ABSTRACT

AI APPROACHES TO UNDERSTAND HUMAN DECEPTIONS, PERCEPTIONS, AND PERSPECTIVES IN SOCIAL MEDIA

by
Chih-Yuan Li

Social media platforms have created virtual space for sharing user generated information, connecting, and interacting among users. However, there are research and societal challenges: 1) The users are generating and sharing the disinformation 2) It is difficult to understand citizens' perceptions or opinions expressed on wide variety of topics; and 3) There are overloaded information and echo chamber problems without overall understanding of the different perspectives taken by different people or groups.

This dissertation addresses these three research challenges with advanced AI and Machine Learning approaches. To address the fake news, as deceptions on the facts, this dissertation presents Machine Learning approaches for fake news detection models, and a hybrid method for topic identification, whether they are fake or real.

To understand the user's perceptions or attitude toward some topics, this study analyzes the sentiments expressed in social media text. The sentiment analysis of posts can be used as an indicator to measure how topics are perceived by the users and how their perceptions as a whole can affect decision makers in government and industry, especially during the COVID-19 pandemic. It is difficult to measure the public perception of government policies issued during the pandemic. The citizen responses to the government policies are diverse, ranging from security or goodwill to confusion, fear, or anger. This dissertation provides a near real-time approach to track and monitor public reactions toward government policies by continuously collecting and analyzing Twitter posts about

the COVID-19 pandemic.

To address the social media's overwhelming number of posts, content echo-chamber, and information isolation issue, this dissertation provides a multiple view-based summarization framework where the same contents can be summarized according to different perspectives. This framework includes components of choosing the perspectives, and advanced text summarization approaches.

The proposed approaches in this dissertation are demonstrated with a prototype system to continuously collect Twitter data about COVID-19 government health policies and provide analysis of citizen concerns toward the policies, and the data is analyzed for fake news detection and for generating multiple-view summaries.

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by
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CHAPTER 1

INTRODUCTION

1.1 Motivation

Social media platforms, such as Twitter, Facebook, Instagram, Reddit, etc. have become important sources for users to share and obtain substantial amounts of information, including but not limited to announcements of socio-political events, alerts concerning natural or man-made disasters, updates on the spread of worldwide pandemics, etc. Especially during the COVID-19 pandemic, these platforms became important tools for communicating and commenting.

The opinions of social media users can now be easily expressed on social media platforms. However, although it has become easier to share and retrieve information on social media, it has also become increasingly harder to verify the authenticity of the posted information. Due to the convenience of accessing social media and sharing posts, many users might distribute fake news due to evil intentions, ignorance, personal gain, or entertainment. For example, while the COVID-19 pandemic has led to an unprecedented loss of lives and economic disruptions, fake news about COVID-19 has also become a serious issue. Some people have accepted mistaken reports that garlic, alcohol, or vitamins could prevent and/or cure COVID-19. This in turn might have led them to ignore warnings about wearing masks and staying socially distanced, potentially leading to their infection, hospitalization, or even death. Fake news has also claimed that COVID-19 is a hoax, not worse than the "normal" flu, and vaccinations are not effective or even dangerous.

This flood of fake news has been termed an "Infodemic" [1], i.e., the appearance of too much misleading information during a disease outbreak. Social media users will have reduced access to authentic information, while being exposed to inflammatory content and fake disinformation. This phenomenon will cause confusion of citizens and conflicts in society [2][3]. There are currently several challenges in fake news research on social media. It is challenging to accurately identify fake news in social media posts. It is also infeasible for in-time human identification because the amount of fake news data is substantial and overwhelming. Besides, topics discussed in real news might be manipulated or even fabricated in fake news. Thus, the first goal in this dissertation is to identify fake news on social media and help stop the spread, by building Machine Learning and Deep Learning detection models.

Over the course of the COVID-19 pandemic, government authorities have had to formulate policies, guidelines, actions, or measures, ranging from directives for preventing the spread of the disease, to economic measures for minimizing adverse impacts. These policies or directives addressed activities of personal preventive care, such as washing hands, social distancing, or mask mandates, and economic, educational, and social restrictions by enforcing business and school closings, housing eviction suspensions, etc. Many of these policies were intended to control the spread, but ended up limiting economic and social activities. These policies were repeatedly enacted and changed on short notice, impacting not only disease control but also public attitudes.

For example, China enforced an extreme COVID-19 measure called the “zero-COVID policy,” locking down entire cities, restricting their citizens’ movement for prolonged periods, forcing people into isolation and quarantine, and subjecting them to continuous testing and surveillance [4]. While such policies were intended to prevent the disease's spread, citizens have expressed diverse responses and shown different attitudes toward them. Many citizens reacted to these policies with anxiety, depression, panic, and fear, as well as anger. When a large international retail chain in China faced a sudden lockdown, panicked customers tried to exit the store as quickly as possible, fearing quarantine, isolation, and enforced testing [5]. Capturing users' perceptions is important in order to identify their confidence in, e.g., government policies, especially when a disaster or worldwide pandemic hits. In order to engender faith of citizens in government policies, it is often necessary for government authorities to carry out relevant policies in an efficient and effective manner [6].

However, it is difficult to capture diverse perceptions of social media users, because citizens' perceptions of government performance are likely a reflection of a number of factors that are beyond objective performance measures. Thus, understanding how citizens perceive government performance is important. The process that citizens use to compose their perceptions into an overall evaluation of effectiveness is little known [7]. Therefore, it is a challenging task to determine whether or not these public health policies achieved the intended impact. This requires systematic data collection and scientific studies, which can be very time-consuming. In order to overcome such challenges, the second goal of this dissertation is to track the public's attitudes toward these COVID-19 government policies in real time, by continuously collecting Twitter posts related to the COVID-19 pandemic, and analyzing the concerns expressed by the posts in both temporal and geographical manners. This can be a gauge for assessing the impact of these government policies, and evaluating citizens' perceptions on social media.

As social media platforms have become major sources for users to share or retrieve information, abundant information and data items exist in the platforms, such as fake news, government health policies, and other current topics and events. The volume of the posts on social media platforms is very large. For example, Twitter has around 450 million monthly active users, and 6,000 tweets were posted on average every second in 2022 [8]. If we extrapolate the tweet counts, we derive that there are 360,000 tweets posted every minute, 518 million tweets a day, and 189 billion tweets a year!

Due to the large volume, it is infeasible to rely on humans to review the tweets for investigating a certain topic, e.g., identifying fake news to prevent their spread, comprehending government health policies to combat the pandemic, etc. In addition, unlike news or coherent documents, single posts on social media are short, but sets of posts contain voluminous, dispersed, and incoherent content from many users. Such contents of posts convey many aspects of the same events without coherent perspectives, as users would express different opinions, experiences, attitudes, and emotions about the same events. It may be inadequate to review voluminous social media posts with only a single summary. Therefore, this dissertation provides readers with a framework to generate summaries based on different view perspectives.

1.2 Contributions

In this section, we present our approaches and solutions to deal with the research issues and challenges discussed in the previous section.

1.2.1 Fake News Detection and Feature Analysis about COVID-19

In order to help curb the rampant "health information disorder [9]," we need to identify fake news first. We present Machine Learning and Deep Learning approaches to distinguish between fake news and real news. We used Long short-term memory (LSTM) [10], Bidirectional Encoder Representations from Transformers (BERT) [11], and DistilBERT [12] as our Deep Learning algorithms. To train Deep Learning models, we utilized three publicly available fake news datasets. Two of them were news-based, and were collected before the COVID-19 pandemic. The third one was a set of social media posts of fake news and real news on COVID-19, which is our main focus.

To further realize the features of fake news posts generated and shared on social media amid the COVID-19 pandemic, we applied Natural Language Processing (NLP) techniques, and implemented behavioral and sentiment analyses focusing on the third dataset about COVID-19. We use the term "behavioral features" for features that are directly the result of a choice by the user, e.g., whether to use a "#hashtag" for a certain word, or to provide a hint about how the user feels about an issue (concern levels). A number of behavioral features were analyzed and compared between fake news and real news, including post lengths, sentiments, concern levels, and the use of hashtags (e.g., #COVID) and mentions (e.g., @WHO).

To investigate how influential the features could be toward fake news detection, we built Deep Learning models based on feature elimination. Moreover, we built topic identification models to identify the topics manipulated in fake news and the topics discussed in real news about COVID-19. A number of interesting topics were identified, half of which were common between fake news and real news. Our experiment also showed that fake news exhibits a relatively more consistent writing style.

To better distinguish between fake news and real news regarding COVID-19, we are raising five research questions in this chapter:

1) Is there a difference of the expressed sentiments between fake news and real news of social media posts regarding COVID-19? Besides, if such a difference exists, is it statistically significant?
2) What are the differences between fake news and real news with regards to easily measurable features, such as number of words and number and use of hashtags and mentions in a posting, and can these features contribute to better accuracy in fake news detection?
3) Are there differences in the topic structure of fake news compared to real news, and what are the main topics for COVID-19 in both?
4) How good are the results when we use transfer learning with models trained with fake news datasets that predate COVID-19 when tested with a COVID-19 fake news dataset?
5) Do the extracted features help improve model robustness?

The work in this subsection makes the following contributions:

1) Our fake news detection models achieved better performances than previous studies.
2) We found that the identified behavioral features can contribute to distinguishing

between fake news and real news.

3) We determined that half of the identified topics are common in fake news and real news. This shows that the existence of fake news could make readers confused and make them mistake fake news for real news.
4) We found that fake news causes significantly more concerns among citizens, and the "concern levels" of fake news and real news are significantly different.

Part of the work presented in this subsection was published in [13].

1.2.2 Analysis of Citizens' Reactions Towards Government Policies

To track the public's attitudes toward government health policies about COVID-19 in real time, we built a Public Health Policy Perception Monitoring and Awareness Platform as a near-real-time tracking system of citizen reactions toward the policies. This platform's objective is to elucidate the public perception of COVID-19 health policies as an indirect indicator of policy impact in a near-real-time manner.

The traditional policy outcome assessment or impact study methods involve well-designed surveys or observational data collected over a long period of time [14]. In contrast, this platform has the advantage of being much faster by continuously collecting citizen-generated Twitter data about health policies, and analyzing the sentiments expressed by each policy tweet. In addition, the platform intends to enhance public awareness of health policies through visual browsing and summarization tools.

To measure public perceptions towards public health policies, we limited our inquiry to the coarse-grained measures of whether Twitter users felt positive, negative, or neutral about them and to what extent. As news reports expressed enough evidence that reactions were mostly negative, we quantified these attitudes as "concern levels." *A priori*, there is no reason why all reactions to COVID-19 policies should be negative. While many citizens might feel restricted by indoor facemask mandates, others might experience an increased degree of safety, because their fellow citizens are also masked. While some working parents might feel burdened by having their children at home, other parents would appreciate that the danger of infection to their children is reduced by school closings.

The concern levels can be instructive for government policymakers who have had the difficult task of balancing the expected positive effects with the actual impact of policies. Keeping track of public concern levels is challenging due to different policy types, and different occurrence patterns, e.g., temporal trends, regional variations, etc. Fine-grained monitoring of concern levels is necessary because government agencies promulgate policies at different levels (federal, state, county, city/town). In a rapidly changing environment, monitoring public perceptions of health policies needs to be continuous, so that it can be useful for understanding the policy's impact on citizens.

Our system for health policy monitoring aims to answer the following research questions:

1) What government policies engendered the highest and the lowest concern levels in citizens?
2) How have citizens' concern levels about different health policies changed during the progression of the pandemic?
3) Is the concern level trend positively correlated with the infection/death case trends?
4) Is there a notable difference in the public's attitude toward health policies among US states?

5) What kinds of public health policies are issued by different regions/towns, and how many?
6) Are there any notable health policy differences among different regions/towns?
7) What are summaries of particular policies?

In this work, we make the following contributions:

(1) We have developed a working prototype system for our Public Health Policy Perception Monitoring and Awareness Platform that continuously collects Twitter data relating to COVID health policies. It provides analysis by near real-time tracking of citizen concerns towards government policies through sentiment analysis and policy awareness capabilities.
(2) The provision of concern level trends could serve as a speedy source of information to identify resistance or acceptance of launched COVID-19 policies among citizens. Tracking the concern level trends over time in all US states can help local government agencies to gauge the reactions of citizens to particular policies and compare them across different states or cities. Uncovering negative public perceptions and concerns towards a health policy could provide useful feedback to identify problematic policies and to fine-tune them to address any arising tensions between citizens and government agencies.
(3) Situational awareness components of public health policies provide policy transparency to citizens. There have been many policies and measures mandated and recommended by different local governments during the pandemic. Keeping track of multiple policies is challenging. The tracking capabilities and spatial analysis of policies by types and quantities show

different city/state-level foci of policies. In addition, policies that are stated mostly as long text documents could be challenging to digest by citizens with limited time and without a legal background. Using AI-based text summarization models, the system can provide the public with summarized policy text documents to enhance the citizens' understanding of policy contents.

The work presented in this subsection was published in [15].

1.2.3 Multiple View-based Summarization Framework

In order to summarize social media dataset posts, and provide summaries based on different perspectives or viewpoints, we built a Multiple View Summarization Framework (MVSF). Our MVSF is able to generate summaries of the same social media dataset that reflect different perspectives, based on each user's interests or viewpoints. For example, one summary view can be entity focused. For COVID-19 related posts, a summary can be generated about Pfizer vaccines, while an election summary can be about a specific candidate. Another summary may focus on significant events. For this, users might be interested in a summary of activities discussed relatively more often in the dataset, e.g., what a campaign candidate has done or lied about. Alternatively, a summary view can focus on highly influential posts that are most often shared or liked. The other summary views may focus on emotions expressed, or on specific geographical areas or timelines. Users might be interested in a summary of negative sentiments only, about governments, authorities, or minorities. In some cases, it would be helpful to intersect different views, and generate a summary with multiple view filters, e.g., a summary on one candidate that shows negative sentiments only.

We present (1) Entity-based summarization (E), (2) Triple Distance-based summarization (D), and (3) Social Feature-based Summarization (SF), which can be combined with (i) Sentiment-based (S), (ii) Geographical-based (G), and (iii) Timeline-based (T) summarization. These view summaries are capable of uncovering different aspects in posts. For instance, an Entity view summary focuses on the main entities in the dataset (main subjects or main objects). A negative sentiment view allows a user to retrieve a summary of the negative perspective only. Besides, our views can be combined (e.g., S+E, or S+D) to generate different and even more fine-grained summaries.

We extracted <subject, predicate, object> triples (<SPO>) (Sintek and Decker 2002) to obtain the events and activities of a social media post. We then applied view-based summarization, identified top groups of actions and entities, and ranked triples. Our view-based summaries have better Rouge F-1 scores [16] than those generated by extractive and abstractive summarization models from the literature.

The work in this subsection makes the following contributions:

(1) We built a Multiple View Summarization Framework to generate multiple-view summaries of different summarization methods. According to Rouge scores, our summaries show better performances than those generated by existing models.

(2) The summarization views may focus on the different aspects of user interests to generate summaries from different perspectives, such as social feature-based, entity-based, contextual-based, etc. They can be applied as a single view, or be combined from multiple views.

(3) Our summarization method can be applied to any text datasets. Therefore, our methods are capable to summarize any discussion topics from any platforms,

such as fake news, government policies, BBC news items, etc.

Part of the work presented in this subsection was accepted by the Flairs-36 conference [17] and is currently in press.

1.2.4 Prototype System

In this dissertation research, we built a prototype system, i.e., a web app that implements the approaches introduced in the previous sections, including fake news detection, tracking of concern levels toward government COVID-19 policies, and mapping of policy summaries on the US state level and city level. Our prototype system is accessible at http://ai4sg.njit.edu/ai4sg/ , Retrieved on January 1st 2023.

1.3 Dissertation Overview

Chapter 2 provides prior work and background information relevant to this dissertation. Chapter 3 presents our study of employing a Deep Learning model for fake news detection, and a hybrid model for news topic identification. Chapter 4 reports on the implementation of our Public Health Policy Perception Monitoring and Awareness Platform as a near-real-time tracking system of citizen reactions toward health policies. Chapter 5 describes our study of a multiple-view summarization framework to generate different view-based summaries. Chapter 6 presents a prototype application that utilizes the solutions of Chapter 3, Chapter 4, and Chapter 5. Chapter 7 concludes this dissertation, and describes ideas for future work.

CHAPTER 2

RELATED WORK

2.1 Human Behavior on Social Media

In social media, the word “social” means that users interact with others by sharing and receiving information, and “media” means a medium of communication and interactions [18]. In today’s world, many humans rely on social media platforms such as Twitter, Facebook, Instagram, etc., to find and connect with each other [19]. Social media has created new styles for humans to communicate and interact. Instead of meeting in-person or sending mails that take days to deliver, humans now share speedy communications and updates with family and friends around the world [20]. People find friends or communities that share similar interests, experiences, or backgrounds [21]. They watch, read, study, and spread news, information, and awareness to a large audience with great speed [22]. Social media users express their thoughts, or ideas freely, as an outlet for self-expression and creativity, and even find companions to turn some ideas into reality, e.g., making a video together [23]. They network with recruiters to find a job [24], or develop and start a business to establish an income flow [25]. People can seek emotional support online when they feel depressed [26]. These are positive human behaviors making use of the convenience and advantages of social media. Especially during the COVID-19 pandemic, when social distancing was required and physical meetings were thus limited, social media provided a high degree of convenience and comfort for people to adapt to the difficult situation [27].

However, there are also negative human behaviors on social media. People can easily compare their lives with other people’s lives on social media. They may draw the conclusion that their lives are easier and more luxurious, which might lead to jealousy and depression [28]. Social media have been used to spread negativity, violence, and rumors, which has led to an increase of confusion, conflicts, and violence in society [29]. Users easily disguise themselves for projecting a better image by using fake photos and/or exaggerated self-descriptions in their profiles [30] [31]. Users are easily involved in trolling or cyberbullying, being the victims and perpetrators of fake news and deceptions at the same time [32]. Besides the mentioned negative human behaviors, we will further describe cheating and deception on social media with literature references in the following section.

2.2 Human Deceptions in Virtual Space

Deception can be defined as the projection of an inaccurate or false image of knowledge, intentions, or motivations [33]. The appearance and existence of misleading/deceptive contents are the productions of human deception [34]. Deception is common among human interactions [35], which can be intentional such as in the case of lying, incorrect self-presentation, or withholding important information. Deception has spread to social media, whereby users willfully post incorrect statements on different online platforms. In many cases, an act of human deception can be categorized as lying to increase reputation or appear more attractive, lying to protect the feelings of others, lying for self-protection to avoid punishment, lying to oneself, i.e., self-deception, and lying to intentionally cause hurt to others [36].

Given the ease of accessing social media, it is easy for individuals to deceive one another [37]. On social media, human deceptions are expressed in different forms, such as text messages, images, audios, and videos. For example, users might exaggerate their height on their profiles, or use another person's picture as the profile picture in order to appear more attractive [38]. Besides manipulating profiles, social media users also generate and share fake content to gain attention and/or try to earn an improved reputation [39][40].

Due to the rapid spread of social content, misleading information could benefit users by gaining attention and attracting more users to join groups or become followers and thus contribute to the respectability of the deception. According to [18], fake contents spread six times faster than facts do, as they sound more exciting and novel. Users are also more likely to share such messages, especially when they confirm their pre-existing attitudes and prejudices. Social media users are more inclined to accept information that fits into their worldview [41]. This is commonly referred as echo chamber effect [42]. We will review three kinds of online deception in the following subsections.

2.2.1 Misinformation

Misinformation is an objective social phenomenon, which appears in the social operation environment [43]. Misinformation usually refers to the information that is widely circulated either intentionally or unintentionally, without supporting facts, confirmation, or clarification [44]. According to (Wu et al 2019) [45], misinformation is fake or misleading and spreads unintentionally. According to (Guess and Lyons 2020) [46], misinformation is defined as constituting a claim that contradicts or distorts common understandings of verifiable facts. Misinformation has developed into a concern not only in the social sciences, e.g., sociology and journalism [47], but also in the field of computer science and other technical fields [48]. For example, digital misinformation has become so pervasive in online social media that it has been listed by the World Economic Forum as one of the main threats to human society [49].

2.2.2 Disinformation

Disinformation is distinct from misinformation and is defined as the subset of misinformation that is *deliberately* propagated [50]. While misinformation may be unintentional, disinformation is spread intentionally and is meant to deceive [51] [52].

2.2.3 Deepfake

As we have mentioned earlier in this section, human deceptions are expressed in different forms, such as text messages, images, audios, and videos. With the easy access to the audio and visual content on social media, it has become possible to use open-source trained models, especially Deep Learning models [53], to synthesize the content. The synthesized content is now called Deepfakes [54], i.e., the product of artificial intelligence applications that merge, combine, replace, and superimpose images and video clips to create fake videos that appear authentic [55]. This is especially targeting human faces, allowing to easily create new identities or change only some specific attributes of a real face in a video [56]. Deepfakes have become threats by being used to disseminate disinformation, revenge porn, financial frauds, hoaxes, and to disrupt government functioning [57].

2.2.4 Fake News

Even though "fake news" has become common, there is still no agreement on its definition. Allcott et al. [58] defined fake news as "news articles that are intentionally and verifiably false and could mislead readers." Lazer et al. [41] defined fake news as "fabricated information that mimics news media content." Another definition [59] says that fake news "is false or misleading information presented as news. It often has the aim of damaging the reputation of a person or entity, or making money through advertising revenue." Some prior work saw satire news as fake news since the contents are false, even though satire is often entertaining and reveals its own purpose to the readers [60][61][62][63]. Although the definitions vary, it is important to recognize that they all exclude unintentional reporting mistakes [64][65][66][67].

Trusting fake news can even cause fatalities. In March 2020, in the beginning of the COVID-19 pandemic, in Iran, nearly 300 people died and more than 1000 were sickened after ingesting methanol, because of a fake news message “alcohol can wash and sanitize the digestive system” [68]. In the study of [69], the author presented COVID-19 fake news items, including “transmission via mosquito bites,” “temperature as a cure,” “youthful immunity,” etc. Such information might cause fatalities directly, and might make the situation worse by not seeking out legitimate remedies. Fake news can also cause street riots. In Feb 2020 in the central Ukrainian town of Novi Sanzhary, a fake news email, purportedly from the Ministry of Health, provoked panic by claiming that some of the evacuees from the town were infected with the virus. This led to local residents burning tires, blocking roads, and clashing with the hundreds of policemen who were urgently dispatched to disperse them [70].

The availability of curated fake news datasets is one of the fundamental factors for building an effective fake news detection model. Currently there exists a number of available fake news datasets: Benjamin Political Dataset [71][72], Burfoot Satire News Dataset [73], BuzzFeed News [74], Credbank Dataset [75], Fake News Challenge Dataset [76], FakeNewsNet [77], etc.

2.3 Fake News Detection

In order to reduce the impact of misleading information, we need to identify them first. We introduce different types to identify such misleading content in the following sections.

2.3.1 Authoritative Fact Checking

Professional staff are recruited by government authorities, tech companies, reputable news organizations, book publishers, etc. to perform fact checking. Facebook provides technologies to detect posts that are likely to be misleading (or have the potential to cause harm). Facebook has been working with the International Fact Checking Network (IFCN) [78], a nonprofit housed at the Poynter Institute, to recruit and manage an army of fact checkers who flag misinformation in Facebook posts [79]. The fact checkers consider whether users on Facebook and Instagram report a post as fake news, or the post itself engenders disbelief. In those cases, the Facebook fact-checkers will identify and review the content on their own [80]. They will review such a post and rate its accuracy, which may involve calling sources, consulting public data, authenticating images, verifying videos, etc. The fact-checkers apply ratings, including *False, Altered, Partly False, Missing Context, Satire*, and *True*. The ratings are defined in [81]. If content is rated *False* or *Altered*, which characterizes the most inaccurate content, it results in the most aggressive actions by dramatically reducing the distribution [80], while lesser actions are reserved for *Partly False* and *Missing Context* ratings. They will not assign labels or restrictions to content rated *Satire* or *True*. If an account repeatedly shares content rated as *False* or *Altered*, it is placed under restrictions for a given time period. This will limit the ability of the users to distribute fake news, and remove their ability to monetize their postings and attract advertisers. Therefore, the spread of misleading information will be curtailed to a certain degree.

2.3.2 Bot and Software Approaches

Besides humans, social bots are another source of creating and spreading misleading information [82] [83]. For example, the COVID-19 infodemic is driven partially by Twitter bots [84]. Almost 25% of COVID-19-related tweets contained some misleading information [85]. On the other hand, social bots are also available tools to fight disinformation online. Currently, there are a number of bot tools that help fight against online disinformation.

Bot Sentinel [86] is developed to detect and track troll bots and untrustworthy Twitter accounts. It uses machine learning and artificial intelligence to study Twitter accounts, and to classify them as trustworthy or untrustworthy, to identify bots. It then stores those accounts in a database to track each account daily [87].

Hoaxy (Hoaxy2beta) [88], a web-based tool, visualizes the spread of articles online. It searches for claims and fact-checking going back to 2016. It tracks the sharing of links to stories from low-credibility sources and independent fact-checking organizations. It also calculates a bot score, which is a measure of the likely level of automation [89] (Hoaxy).

Botometer is a web-based program that uses machine learning to classify Twitter accounts as bot or human [90]. It looks at features of a profile including friends, social network structure, temporal activity, language, and sentiment. Botometer outputs an overall bot score (0-5) that provides a measure of the likelihood that the account is a bot.

Check by Meedan [91], a fact-checking tool enabled the open-source collection of tips through WhatsApp regarding misinformation in Africa, India, and Brazil. Its algorithms identify content based on its similarity to flagged misinformation, and can prioritize certain types of information based on the user's preferences [92].

The Factual [93] is a mainly automated mobile app and browser extension that scores news content based on "the extent and quality of its sources," "the expertise of the journalist," "the opinionated nature of the language used," and "the historical reputation of the sight." [94] It ranks the content on a 0-100 scale to measure the quality. The tool rates news quality based on diversity of sources, author expertise, language used, etc.

There are several other available automated bot tools that can help fight online disinformation [92][95].

2.3.3 Machine Learning and Other Automated Approaches

Supervised Machine Learning algorithms such as Decision Tree, Random Forest, Support Vector Machine [96], Logistic Regression, K-nearest Neighbors are extensively used for fake news detection [97][98][99][100][101][102][103]. Bojjireddy et al. (2021) [104] presented a Machine Learning approach to recognizing misinformation, specifically using presidential election and COVID-19 related fake news [71][105][106][107][108]. They applied several Machine Learning approaches – Multinomial Naïve Bayes (MNB), Support Vector Machine (SVM) [96], Multilayer Perceptron, Decision Tree, Random Forest, and Gradient Boosting (GB) as technical solutions for automating the detection of fake news and misleading contents.

In recent years, Deep Learning has gained a favorable reputation in the areas of speech recognition and visual object recognition [109][110][111]. Machine Learning techniques require humans to reduce the complexity of the data and make patterns more visible (e.g., by adding combined features) for algorithms to work well. Deep Learning algorithms can be fed with raw data, and they can discover the representations without the need for human feature engineering [110][112]. Ali et al. (2021) [113] investigated the robustness of different Deep Learning architecture choices, e.g., Multilayer Perceptron (MLP), Convolutional Neural Networks (CNN) [114] (Yamashita et al 2018), Recurrent Neural Networks (RNN) and a recently proposed Hybrid CNN-RNN combination. Their experiments based on the Kaggle fake-news dataset [105], ISOT dataset [115], and LIAR dataset [116] suggest that RNNs are robust as compared to other architectures. Li et al. (2021) [117] proposed an unsupervised method based on an autoencoder [118] to detect fake news in the MediaEval 2016 fake news dataset [119]. The detection was based on features including text content, images, propagation information, and user information (followers, likes) of published news.

In this Dissertation, we applied Deep Learning approaches for fake news detection. Using Deep Learning models eliminates the need for domain expertise and hard-core feature extraction [112]. Second, Deep Learning outperforms other techniques if the data size is large. Third, when there is a lack of domain understanding for feature introspection, Deep Learning stands out, as there is less worry about the need for feature engineering with it [120].

2.3.4 Regulatory Approaches

In March 2017, German government tabled a proposal to impose hefty fines (of up to €50 million) on social media companies that fail to take down illegal content quickly enough [121]. The draft law would give social media platforms 24 hours to delete the most blatant cases [122]. For less offensive content, the time allowed would be extended to one week - with the clock starting once the first complaint is filed. The proposal entered into Network Enforcement Law in 2021 [123]. Other European governments - including the British government - have acted more cautiously, limiting themselves to calls for additional voluntary measures [121].

The European Commission has already pushed Facebook, Twitter, YouTube, and Microsoft to sign up to a code of conduct [124] that aims to tackle online hate speech and take down the majority of potentially illegal content within 24 hours. Many fear this code of conduct might become a blueprint for regulating fabricated content online.

In the United Kingdom, the Culture, Media, and Sport Committee set up a Fake News Inquiry, and evidence was submitted [125] by 79 experts and organizations. However, the inquiry was closed when the election was called.

In the Czech Republic, officials are monitoring fake news directly. Ahead of the country's general election in October, the Czech government has set up a "specialized analytical and communications unit" [126] within the Ministry of the Interior that, as part of its work to monitor threats to internal security, will also target "dis-information campaigns." According to the Ministry, it will "not force the 'truth' on anyone, or censor media content." Rather, as the unit's Twitter page explains, it will assess whether the disinformation seriously affects internal security, and, if so, it will respond by publicizing available facts and data that disprove the fake story. Whatever happens in Europe sets an important global precedent. In Singapore, the laws to tackle the "scourge of fake news" were kicked in 2019 [127]. Since the outbreak of the COVID-19 pandemic, the U.S. Federal government has started considering introducing legislation to make it an offence to spread harmful misinformation [128].

2.4 User Perceptions and Sentiments in Social Media

Social media has been a window to understanding human perceptions, such as sentiments, emotions, attitudes, etc. There have been studies conducted to mine these perceptions for different use cases, e.g., brand monitoring and marketing research [129] [130] [131], customer reviews [132] [133] [134] [135], product review [136], social media monitoring [137] [138], workforce analytics and employee engagement monitoring [139] [140] [141].

A 2017 study [142] found approximately 7000 papers published on sentiment analysis by 2016, including work on sarcasm detection, emotion mining, and sentiment analysis applications. In industry, sentiment analysis is implemented for pattern identification and accurate data-driven predictions [143], providing solutions to different real-life problems, such as stock market prediction [144], political elections forecasting [145], crisis management [146], individual and collective emotional response communication [147], etc. In the study of Asur and Huberman [148], they argued that a deep understanding of social media communications could be helpful for accurate predictions of future activities and events. Twitter posts have also been used for cluster analysis by a cognitive pattern recognition system [149], which picks real-time information about road-traffic events prior to any mainstream reporting channels.

Sentiment analysis is a discipline that aims to extract qualitative characteristics from users' text data, such as sentiments, opinions, thoughts, and behavioral intent [150]. Social media texts are particularly useful for sentiment analysis research [148]. They are (1) used to express a standpoint and (2) filled with subjective text. Soon after Twitter was launched in 2006, social and computer scientists used Twitter data for sentiment detection and analysis research [151].

2.4.1 Approaches to Sentiment Analysis of Social Media Data

In this section, we list a number of sentiment analysis approaches, and related work on the health-related sentiments expressed in social media.

2.4.1.1 Rule-based and Lexicon-based approach This is a practical approach that analyzes text without training or using Machine Learning models. The sentiment analysis results from this approach are a set of rules based on how text is labeled, e.g., positive, negative, and neutral. The rules are also known as lexicons. Therefore, a rule-based approach is also called a lexicon-based approach [152].

This approach uses a valence dictionary [153] of a sentiment analysis model to label each word as "negative," "positive," or "neutral." The labels can also be in the form of numbers, positive number as positive sentiment, negative number as negative sentiment, or zero as neutral sentiment. The models use either the majority of labels or the sum or a normalization of number labels to determine the sentiment expressed by a segment of text.

VADER (Valence Aware Dictionary for Sentiment Reasoning) [154] is one of the lexicon-based sentiment analysis tool. VADER is sensitive to both polarity (positive/negative), and intensity (strength) of emotion. It relies on its valence dictionary and maps lexical features to emotional polarity and intensity, which are known as sentiment scores. Besides understanding sentiments expressed by the basic context of words, VADER also understands negations, and the sentiment emphasis/intensity by the use of punctuation and capitalizations. VADER returns sentiments expressed by the text based on a compound score which is computed by the normalization of lexicon scores in the text.

Textblob [155] uses semantic labels (emoticons, exclamation marks, emojis, etc.) to help with fine-grained sentiment analysis. It returns both polarity (between -1 and 1) and subjectivity (between 0 and 1) of an input phrase, which indicates the weights of personal opinion and factual opinion in the text. The higher the subjectivity of the text, the more the personal opinion is expressed as opposed to the factual opinion.

SentiWordNet [156] is another lexical resource for supporting sentiment classification tasks. It uses the WordNet [157] database to obtain the part-of-speech tag, lemma, and synonym set of each word in the text. For each word, SentiWordNet obtains it sentiment (positive, negative, neutral) score for the first word in the synonym set. Then SentiWordNet calculates the sentiment as the difference of positive and negative scores.

2.4.1.2 Pattern-based Approach This is an approach that recognizes sentiment by relying on writing pattern-related features, which capture the syntax and semantic of the opinionated sentences [158]. In the work of [159], (Bouazizi and Ohtsuki, 2017) proposed an approach that relies on writing patterns, and special unigrams to classify tweets into 7 different classes (“love”, “happiness”, “fun”, “neutral”, “hate”, “sadness” and “anger”.). The features selected and applied in their work for sentiment classification include:

- sentiment-related features (number of positive/negative/capitalized words, emoticons, and hashtags),
- punctuation features (number of punctuations, words, and characters),
- syntactic and stylistic features (use of content words such as nouns, verbs, adjectives and objectives, and use of non-content words such as particles, interjections, pronouns, and negations),
- semantic features (use of opinion words, expressions, highly sentimental words, uncertainty words, and active and passive forms),
- unigram features (hypernym of words by wordNet),

- top words (top-occurrence words),
- pattern-related features (part-of-speech tags of words).

Their proposed work reached up to 60.2% accuracy on the multi-class classification.

2.4.1.3 Machine Learning Approach In the past decade, there has been significant research on Twitter sentiment classification using Machine Learning algorithms such as Naïve Bayes [160] (Bennett 2000), Support Vector Machines [96], Convolutional Neural Networks [114] (Yamashita et al 2018), and Sentiment Specific Word Embeddings [161]. Meanwhile, sentiment analysis of tweets often must tackle issues such as under-specificity, noise, and multilingual content. Singh et al. [162] proposed a heterogeneous multi-layer network-based representation. Their work addressed the issues of under-specificity (text limits), noisy text (presence of short forms, long forms, misspellings, etc.), and multilingual content and provided better classification performance.

2.4.2 Perception Studies on Public Health in Social Media Data

Ji et al. [163] presented an application of Twitter sentiment analysis to track disease outbreak paths, and used sentiment analysis to calculate the users' concern levels. It provides trending analysis and geographic evolution of disease evolutions and people's concern levels, following the sentiments on swine flu, measles, listeria, and tuberculosis cases.

Survey-based research is naturally limited in data points and delayed in availability. Furthermore, the focus of such research might be different even when COVID-19 is a topic. For example, Kravitz-Wirtz et al. [164] used a survey that was completed by 2870 participants to gauge the depth of concern about the secondary effects of COVID-19 relating to firearm violence. While our research analyzes public reactions towards government policies, their interest is in determining the degree to which citizens are worried about bodily harm perpetrated by other citizens in the form of home invasions, robberies, etc., indirectly caused by COVID-19. Another small study [165] based on a survey with 538 inputs in the Philippines tried to determine the level of panic, health anxiety, and related feelings experienced by citizens. The study found a geographic difference, namely a “difference in the avoidance behavior between residents inside Metro Manila and outside Metro Manila”.

The Centers for Disease Control and Prevention (CDC) provided a COVID Data Tracker [166] as the primary source of information about cases, deaths, hospitalizations, and vaccinations, as well as state-issued prevention measures such as mask mandates, bar closures, restaurant closures, stay-at-home orders, etc. These state-level measures are counted and shown on a map. This is similar to our policy awareness component. However, the concern levels or reactions by the public to these measures are not tracked in their work.

Mittal et al. [167] used a lexicon-based sentiment analysis tool [154] on the collected Twitter data regarding COVID-19. Their work identified a significant and positive connection between global infections/deaths and negative tweets and between global recoveries and negative/positive tweets. Hung et al. [168] also applied a lexicon-based sentiment analysis tool to investigate the sentiments of tweets regarding COVID-19. Their work included using a bag-of-word representation to identify the topic discussions in the tweets during a one-month period. Their study found five COVID-19-related topics, and they identified the U.S. states expressing the most negative sentiments and the most positive sentiments. In our work, we utilize a fine-tuned sentiment analysis tool that considers both the meaning of each word and the structure of the input phrases. Our work involves ten COVID-19 related policies during a ten-month period.

Yadav and Vishwakarma [169] proposed a deep-learning model to extract three different categories of sentiments. Their work provides feedback to government and health officials to help deal with future outbreaks. In the work of Yu et al. [170], they presented an interactive visual analytic system for reflecting and analyzing public sentiment and detecting sentiment fluctuation triggers on social media. Their system adopted a lexicon-based sentiment analysis tool to uncover public opinion about COVID-19 events. Basiri et al. [171] found that the coronavirus attracted the attention of people from different countries at different times with varying intensities. The sentiments in their tweets were correlated with the news and events that occurred in their countries, including the numbers of new infections, recoveries, and deaths. They also showed that different social media platforms have a great impact on evoking citizens' awareness regarding the importance of this pandemic. By extracting around 12,741 tweets with the keyword "Indialockdown" from 5 to 17 April 2020 and by applying two lexicon-based sentiment analysis tools, Gupta et al. [172] showed that a majority of Indian citizens supported the decision to impose a lockdown implemented by the Indian government.

During the early stages of the outbreak of this pandemic, Naseem et al. [173] annotated their 90,000 collected tweets with three categories, negative, neutral, and positive. They reported several critical findings. For example, they discovered that citizens favored a lockdown earlier in the pandemic. However, sentiment shifted by mid-March. Their study showed that there is a need to develop a proactive approach to fight against the spread of negative sentiments on social media platforms during any pandemic.

Chen et al. [174] described a multilingual COVID-19 dataset for studying online conversation dynamics. For example, the policy of social distancing has caused changes to public access to physical/social environments for gaining information and updates. Lopez et al. [175] collected daily tweets about COVID-19 in multiple languages to explore the citizens' perceptions regarding the pandemic. The study was aimed at identifying public sentiments towards the pandemic and how the responses varied over time, by country, and by language. However, the published datasets include the analyzed sentiments or Named Entity data, not the raw tweet text data or social features, such as retweets. Thus, it is hard to verify the sentimental analysis results. In addition, claims about policy perceptions are not presented in their study.

Prominent politicians' emotions expressed on social media were also analyzed during this period. Yaqub [176] performed a sentiment analysis of tweets by President Trump during the early spread of the COVID-19 pandemic. The work identified a negative correlation between the sentiments expressed by Trump's posts and the infection cases in the US. A transition from positive to negative sentiments in his posts about China and the coronavirus was discovered as well.

The National Institutes of Health (NIH) provides open-access data and computational resources to address COVID-19 [177], with available datasets from the US CDC [166], JHU [178], and the European CDC [179]. These data sources present daily numbers of newly reported COVID-19 cases and deaths worldwide. However, the daily updates provided in [179] were discontinued on 17 December 2020.

Most of these reviewed studies were conducted based on static datasets and either provide the situation awareness of the disease status, such as cases of infections, death counts, and vaccination rates, or they provide sentiments (negative or positive tweet counts) toward particular measures such as lockdown policies [172] or prevention measures, as with the CDC data [166]. A few studies reported large-scale data collections [175], but the analyses were rudimentary in showing the sentiment counts of different tweets by region and by language.

We summarized the COVID-19 datasets mentioned in this section together with their goals and limitations in **Table 2.1**. In contrast to the cited studies, our policy monitoring and situation awareness platform features continuous tweet data collection and analysis of sentiments, to provide multi-policy monitoring of public perceptions of the governments' prevention and other pandemic-related policies. It also supports the users' policy awareness of government measures.

Table 2.1 COVID-19 Datasets in the Related Work

Papers	Dataset	Study Focus	Limitations
Kravitz-Wirtz et al. [164]	Survey responses by 2,870 participants	The concerns about bodily harm through crimes indirectly caused by COVID-19 provide important information for social and public safety.	Self-reported survey data is limited in number, duration, and spatial coverage. Not a continuous monitoring and findings might not be generalizable to other states.
Nicomedesa et al. [165]	A survey data with 538 inputs in Philippines	It determined the level of panic, health anxiety and related feelings experienced by citizens directly caused by COVID-19 pandemic.	Small input set, no timeline information, no continuous monitoring data.
Centers for Disease Control and Prevention [166]	Surveillance data on disease: deaths, cases, hospitalization, vaccinations, mobility, news events	Allows to have disease awareness, the state and county level counts of prevention. measures, and location of COVID news events.	Limited to the prevention measure counts, no other policies are covered. Data on the state measures is not available as of early April 2022.

Mittal et al. [167]	50,000 Tweets collected daily in March 2020	The study identified a positive and significant relationship between (a) global infections and negative tweets, (b) global deaths and negative tweets, (c) recoveries and negative tweets, and (d) recoveries and positive tweets. No significant association could be found between (e) infections and positive tweets and (f) deaths and positive tweets.	The data was limited to a short period, without geographical information.
Yadav and Vishwakarma [169]	4,118 tweets located in USA (1,135), Brazil (1,029), India (765), Russia (564), and South Africa (625), between Feb 9th and June 7th, 2020	This study proposed a deep language-independent approach to extract the positive, negative, and neutral sentiments from the collected tweets.	Focused only on a short period of Twitter data, which doesn't reflect the entire population of any country.
Yu et al. [170]	60,000 tweets related to COVID-19 between 4/19 and 6/13, 2020	This study presented a lexicon-based and interactive visual analytic system for analyzing public sentiment and detecting sentiment fluctuation triggers on social media.	The system does not support real-time data, thus, users can only obtain a visual analysis of historical data.
Hung et al. [168]	902,138 tweets between 3/20 and 4/19, 2020	This study analyzed discussions on Twitter related to COVID-19	
Gupta et al. [172]	12,000 tweets	Using sentiment analysis, the study shows the lockdown policy is supported in India.	Its study shows one lockdown policy reaction in India, but the data is limited for one policy during the collection period.
Dong et al. [180]	40,162 worldwide cases, 908 deaths between 1/22 and 2/9 2020	Provided an online real-time interactive dashboard in January 2020. It included more detailed data down to the city level, for the USA, Canada, and Australia.	No information other than daily and cumulative cases, recovery, and deaths was included.

Chen et al. [181]	50 million multi-lingual tweets on coronavirus from Jan 28 to May 8, 2020	This study described a multilingual COVID-19 dataset for studying online conversation dynamics (English, Spanish, Indonesian, French, Portuguese, Japanese, Thai, Italian, Turkish) .	While the dataset is multi-lingual, the keywords and accounts tracked have been mostly in English. There is a significant bias in favor of English Tweets.
Lopez et al. [175]	6,468,526 tweets between January 22nd and March 13th, 2020.	The continuous data collection to share sentiments in Tweets in different languages.	Published data is on summary values only on sentiments and named entities. Only a relatively small percentage of collected tweets contain geolocation information. No specified government policy about tweets.
Gupta et al. [172]	Over 252 million Twitter posts from 1/28/2020 to 6/1/2022, with temporal and geographical information	This study reports the descriptive statistics of the attributes, temporal distribution, and geographic representation of a COVID-19 dataset. It helps to understand both global and local conversations and social sentiments in real-time, at a large scale.	The relevant government policy is limited to vaccine.
Vidgen et al. [182]	159,320 tweets with human annotation based on the 1,000 most used hashtags extracted during the beginning of the COVID-19 pandemic	The data is used to create a classifier that detects and categorizes tweets into four classes: Hostility against East Asia, Criticism of East Asia, Discussions of East Asian prejudice, Neutral class.	Not directly a study of policy, but important to study impact of racial discrimination during COVID. It could be further distinguished by countries in East Asia.
Alsudias & Rayson [183]	10,828 Arabic tweets multi-labeled and manually annotated, with location	This data is used for Arabic COVID-19 fake news and hate speech detection.	The data was limited to a short period, to detect human reactions to COVID-19 but did not directly measure COVID-19

	information, collected during Dec. 2019		policy related reactions.
Li et al. (Our work in this Dissertation)	16 million tweets about COVID-19 policies used for this study between July 2020 and May 2021. (20M Total tweets collected as of Nov. 7th, 2022)	Working system for the continuous data collection of tweets on multiple policies to provide policy-related citizen concern tracking, and geospatial and temporal trends. Policy summaries and comparative policy focus are provided for policy awareness.	The datasets are collected with static policy sets. System needs an ability to dynamically choose the policies for which tweets are collected (e.g., add new user-selected policy) to monitor any emerging public health issues. Also, the data is limited to the US.

2.5 Social Media Content Summarization

In this section, we introduce general social media summarization approaches, with different applications, as well as existing summarization work on social media in the literature.

2.5.1 General Summarization Approach

Researchers distinguish general summarization approaches between abstractive methods and extractive methods [184]. Abstractive summarization generates a summary by capturing the prominent ideas of the source text. The summaries contain new sentences that were not in the original text. Currently there is a number of existing abstractive summarization models, including: bart-large-cnn [185], T5 [186], FactSumm [187], FAIRSEQ [188], PEGASUS [189], XNLG [190], ChatGPT [191], Gpt-2 [192], etc.

On the other hand, extractive summarization selects a subset of the sentences that are able to best represent the original document. The existing extractive summarization models in the literature include: BertSum [193], SBert [194], RankSum [195], HAHSum [196], NeRoBERTa [197], DebateSum [198], MemSum [199], Gensim [200], etc.

Joshi et al. [195] proposed a method based on LDA [201] topic modeling and word embeddings [202] for the extractive summarization of single documents. Their work based on CNN/*Daily Mail* datasets [203] achieved state-of-the-art performance at the time. LDA and word embeddings are effective for identifying topics by finding frequent words when sentences are coherent. However, when sentences are not coherent, which often happens in social media, extra contextual information is needed [204].

According to (Rudra et al. 2015) [205], it is beneficial to work with tweet fragments rather than entire tweets. In this Dissertation, we work on the extractive summarization along with this tweet post fragment approach.

2.5.2 Social Media Summarization Approach

Algorithms for social media summarization have been proposed, e.g., ([206] [207] [208] [209] [210] [211] [212] [213]). Yadav et al. [206] used reinforced learning along with attention layer and a deep learning-based model, by using the Recurrent Neural Network (RNN), and Bi-LSTM network for summarization task. Their proposed work achieved state-of-the-art performance when evaluated with BLEU and ROUGE scores. Modhe et al. [207] made use of TF-IDF algorithm to obtain both single-post and multi-post summaries of Twitter posts based on the rankings of words and a user-defined threshold. Geng et al. [208] proposed a microblogging cluster stream (Microblog Cluster Vectors) and a ranking method, by using K-means clustering [214] and query-lexical-rank to generate a query-focused extractive summary of Twitter data. Dutta et al. [210] performed the first systematic analysis of summarizing Twitter posts during disasters. They found that different algorithms applied to the same input would yield summaries with significant differences, which is similar to our results. Olariu et al. [211] introduced a Twitter Online Word Graph Summarizer, which is the first online abstractive summarization algorithm. In their experiment, a set of related tweets generates a quality summary. However, when applied to unrelated tweets, the generated summary lacks any meaning. This happens because event-related signals (in their case, bigrams) stand out when analyzing similar tweets, The summarizer built the word graph from trigrams to solve the issue.

2.5.3 Other Summarization Approach

Gunaratna et al. (2017) [215] selected related features among entities while maintaining the diversity and saliency of features within entity sets. By selecting (i) inter-entity facts that are similar and (ii) intra-entity facts that are important and diverse, the approach summarizes facts about a collection of entities. Entity summarization has been categorized into extractive and non-extractive methods. Among extractive methods, the summarization is further divided into single-entity and multi-entity categories. For single-entity categories, Gunaratna et al. (2015) [216] proposed FACES to incorporate diversity in summarization. For multiple-entity categories, FACES-E (Gunaratna et al. 2016) [217] uses focus term detection and aligns these focus terms to ontology classes and entities present in knowledge graphs [218]. FACES-E showed the usefulness of type-computed literals in creating comprehensive entity summaries. For the non-extractive categories, REMES was introduced [219] to maximize relatedness of facts between entity summaries and importance and diversity of facts within each entity summary. One of our views performs entity-based summarization.

Unlike most of the approaches in literature that focus on a single aspect, our work, based on different summarization views, is able to identify variant summary perspectives from tweet posts. Moreover, these views can be either utilized alone or combined to generate fine-grained summaries.

CHAPTER 3

FAKE NEWS DETECTION AND FAKE NEWS TOPIC IDENTIFICATION

While social media platforms have provided an easy access to sharing, commenting, and spreading content, especially during the global COVID-19 pandemic, an ongoing "Infodemic" due to the spread of fake news regarding the pandemic has also been a global issue. The existence of fake news impacts different aspects of our daily lives, including politics, public health, economic activities, etc. Readers could mistake fake news for real news, and consequently have less access to authentic information. This phenomenon will likely cause confusion of citizens and conflicts in society. Currently, there are major challenges in fake news research. It is challenging to accurately identify fake news in social media posts. In-time human identification is infeasible as the amount of fake news data is over-whelming. Besides, topics discussed in fake news are hard to identify due to their similarity to real news.

The goal of this chapter is to identify fake news on social media to help stop the spread. For this purpose, we developed different datasets to make three types of larger datasets from integrating different data sources. Second, we trained Fake New detection models to compare ML and DL models. Third, we analyzed and discovered features that differentiate in fake news from real news items. These features, word count, character count, hashtag count, mention count and sentiment integer label are into the sentence embeddings in BERT model to train the detection models. We present Deep Learning approaches for fake news detection. Our detection models achieved higher accuracy than previous studies using Machine Learning models. Before training our models, we analyzed features that can be used to differentiate between fake news and real news items. When we added them into the sentence embeddings of BERT, we found that they affected the model performance. We applied a hybrid-method and built models for recognizing topics from posts. We found that half of the identified topics were overlapping in fake news and real news, which could increase confusion when distinguishing between fake news and real news.

3.1 Approaches

In this section, we present our approaches to detect fake news and identify topics in the news items. **Figure 3.1** shows the two experimental processes we conducted. We will discuss the methods and the experiments in detail in the following subsections. For experiment 1, we compare baseline models with the detection models we trained, LSTM, DistilBERT, and BERT to identify which model is the best performing based on the different datasets. Then we perform the second experiment, by adding feature analysis results into the best-performing model.

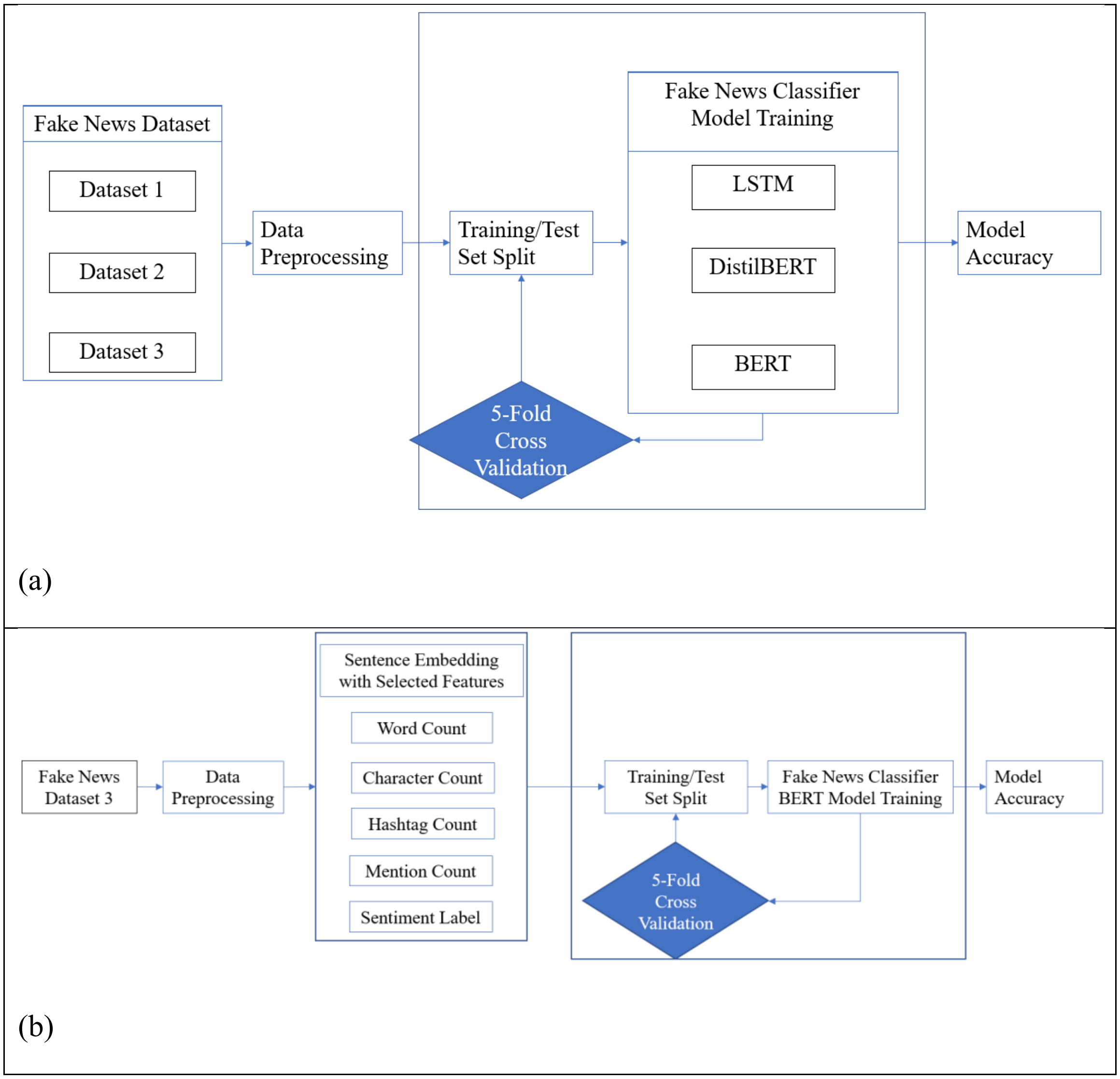


Figure 3.1 Fake News Detection Pipeline. (a) Experiment 1: Basic Classification Models. (b) BERT Model with Sentence Embeddings with Additional Selected Features.

3.1.1 Datasets

To create a large training dataset, we combined multiple sources of publicly available fake news data.

Dataset 1 & Dataset 2: Data items collected from a political dataset [71], a Kaggle dataset [105], fakeorreal [106], and from Kaggle fakereal [107] contain both news titles and news content text of fake news and real news. Data items collected from Politifact

[108] [220] contain only news titles of fake news and real news. These data items were collected before the COVID-19 pandemic. We grouped the news titles together as dataset 1 (DS1), and the news content text items as dataset 2 (DS2). Therefore, DS1 includes news titles, with 69,027 fake news items and 84,232 real news items. DS2 includes news content text items, with 37,115 fake news and 66,067 real news items.

Dataset 3. As our main interest in this chapter is in fake news about COVID-19, we used a third dataset, published by [221], that contains 4,480 real news and 4,080 fake news items. Fake news items were collected from Facebook and Instagram posts, tweets, public statements, and press releases. They were verified as fake news by various fact-checking sites ([220], [222], [223]), and by tools such as Google fact-check-explorer [224], and International Fact-Checking Network [78]. These sites present determinations on posts about COVID-19 and other generic topics, whether the items are fake or real. The real news items were from Twitter, using official and verified Twitter handles, including WHO (World Health Organization), CDC (Centers for Disease Control and Prevention), ICMR (Indian Council of Medical Research), etc. Each post was read by a human, and was marked as real news if it contained useful information on COVID-19. We call this dataset "DS3." Fake news and real news examples are shown in **Table 3.1**. We present summaries of our 3 fake news datasets in **Table 3.2**.

Table 3.1 Sample News Items in DS3

Text	Label
Florida Governor Ron DeSantis Botches COVID-19 Response - By banning Corona beer in order to flatten pandemic curve.	Fake
Masks can help prevent the spread of when they are widely used in public. When you wear a mask, you can help protect those around you. When others wear one, they can help protect people around them incl. you.	Real
Americans With Coronavirus Symptoms Are Being Asked To Cough Directly Onto President Trump	Fake

The main mode of transmission of is through droplets and it is possible that infected smokers may blow droplets carrying the virus when they exhale. Regardless of you should steer clear of second-hand smoke as it may cause various health problems.	Real
Justin Trudeau Resigns Amidst Coronavirus Pandemic	Fake
The positive rate has fallen a lot since early April. Back then it was ~20%. Now it's more like 4-5-6%. A lot of that change has been driven by the rising tests and plummeting positive rates in the northeast.	Real
Experts Call Out Claims That Cow Dung/Urine, Yoga, AYUSH Can Prevent Or Treat COVID-19	Fake
Georgia is particularly worrisome. The state had not seen a large rise in reported deaths despite rising infections and a steep hospitalization curve. Today the state reported its second-highest deaths since the beginning of the pandemic and the highest number since April 7.	Real

Table 3.2 Fake News Dataset Summaries

Dataset	Features	Sources	Number of Records
DS1	News Title	[71] [105][106][107] [108][220]	69,027 fake items, 84,232 real items.
DS2	News Content	[71][105][106][107]	37,115 fake items, 66,067 real items.
DS3	Social Media Posts from Twitter, Facebook, and Instagram, and public statements, and press release.	[221]	4,080 fake items, 4,480 real items.

3.1.1.1 Topic Identification Experiment In order to understand DS3 further, we perform topic analysis to discover topics and present descriptive understanding in DS3. The purpose that we performed topic identification is as follows. We would like to explore the topics discussed in real news and in fake news. If there are many common topics in both, they would be more likely to confuse readers, because the readers would mistake fake news for real news. We compared the topics in fake news posts with those in real news posts. During text preprocessing for this task, for each input news item, we removed stop words, numbers, and punctuations, lowercased each letter, and lemmatized each word. We then applied a hybrid method by using Latent Dirichlet Allocation (LDA) [201] and BERT [11].

LDA represents documents as random mixtures over latent topics, where each topic is characterized by a distribution over words [201]. It is effective for identifying topics by finding frequent words when sentences are coherent. However, when text is not coherent, extra contextual information is needed to comprehensively represent the idea of a text item. As social media posts often do not form complete sentences, LDA needs to be augmented by another mechanism. The transformer encoder of BERT reads the entire sequence of words at a time. This characteristic allows the model to learn the context of a word based on its surroundings (left and right of the word). By combining the probabilistic topic assignment vector from LDA with the sentence embedding vector from BERT, we can augment semantic information with con-textual topic information.

The concatenated vectors of LDA and BERT will yield high-dimensional spaces, which arise as a way of modeling datasets with many features. However, the number of features can exceed the number of observations, and the calculations become difficult. To deal with this issue, an autoencoder [118] is used to learn a lower dimensional latent space representation of the concatenated vector. The latent space is a representation of compressed data in which similar data points are closer together in space. The low dimensional latent space aims to capture the most important features required to learn and represent the input data. We implemented K-Means clustering [214] on the latent space representations, and we assigned contextual topics to the clusters. To decide on the best number of topic clusters, we applied the coherence score metric [225]. Coherence score is a measure of scoring a single topic by measuring the degree of semantic similarity between words in each topic. A higher coherence score indicates a higher degree of likeness in the meaning of the words within each topic.

Based on our topic models with topic cluster numbers from three to ten (**Table 3.3**), we achieved the highest coherence scores for both fake news items and real news items when the topic cluster number was set to six. Therefore, we clustered both into six topics. We generated word clouds and observed that half of the six topics overlapped between real news and fake news. These are "people and vaccine" (**Figure 3.2**a and **Figure 3.3**e), "pandemic situation in India" (**Figure 3.2**c and **Figure 3.3**d), and "state's critical cases" (**Figure 3.2**f and **Figure 3.3**c). We derived these results by calculating the common words and similarity rates between fake news topics and real news topics. We define the similarity rate as:

DEFINITION 3.1. Similarity Rate between two word clouds

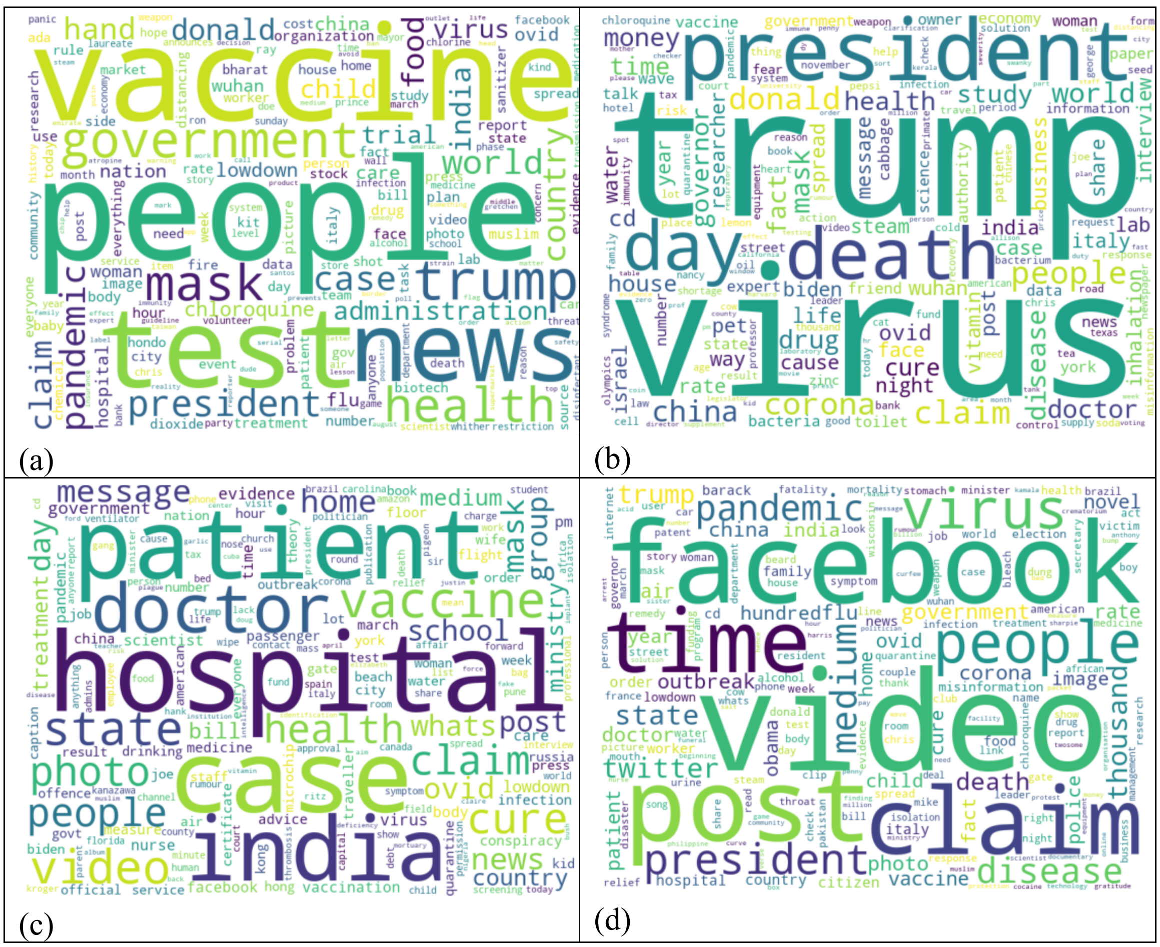
$$Similarity\ Rate\ = \frac{Common\ Word\ Count\ in\ two\ Word\ Clouds}{Avg\ (word\ count\ in\ wordCloud1,\ \ word\ count\ in\ wordCloud2)} \qquad \text{(Equation 3.1)}$$

For example, there are 10,751 words in **Figure 3.2**a, and 9,499 words in **Figure 3.3**e. They have 6,557 words in common. Their similarity rate is 64.7%. The similarity rate of **Figure 3.2**c (6,351 words) and **Figure 3.3**d (7,054 words) is 67% (4,488 common words). The similarity rate of **Figure 3.2**f (10,418 words) and **Figure 3.3**c (11,752 words) is 66% (7,388 common words). Among 36 pairs of 6 fake news topics and 6 real news topics, these three are the only pairs that have a similarity rate above 50%.

Another finding based on our experiments is that fake news has higher coherence scores than real news for all given topic numbers (**Table 3.3**), which means that in fake news words from the same topic are more closely related and have a higher degree of semantic similarity. This implies that compared with real news, fake news might have a more consistent writing style [226].

Table 3.3 Coherence Scores for Between 3 and 10 Topic Clusters of Fake News and Real News in DS3

Topics	Fake news	Real news
3	0.58	0.37
4	0.63	0.29
5	0.57	0.42
6	0.65	0.49
7	0.58	0.45
8	0.56	0.35
9	0.58	0.44
10	0.55	0.42



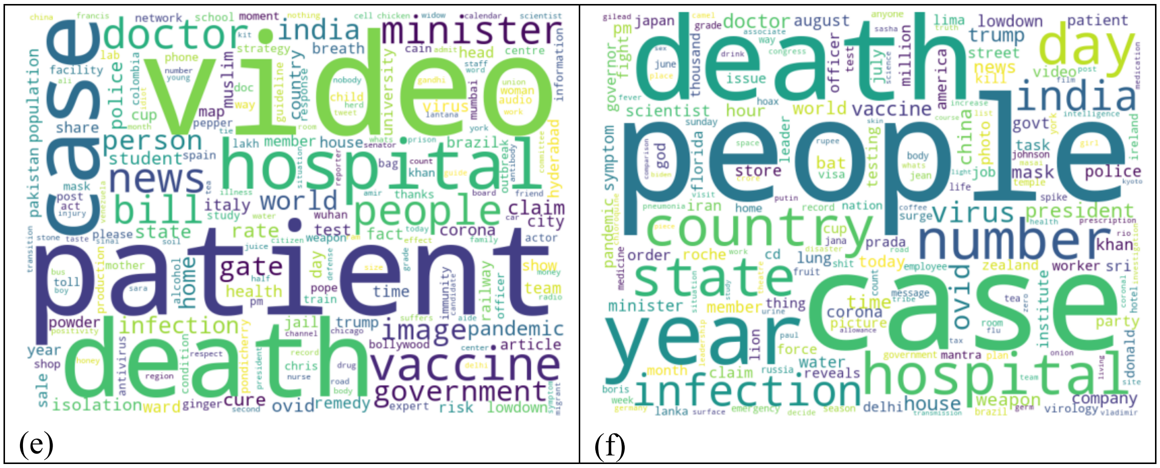
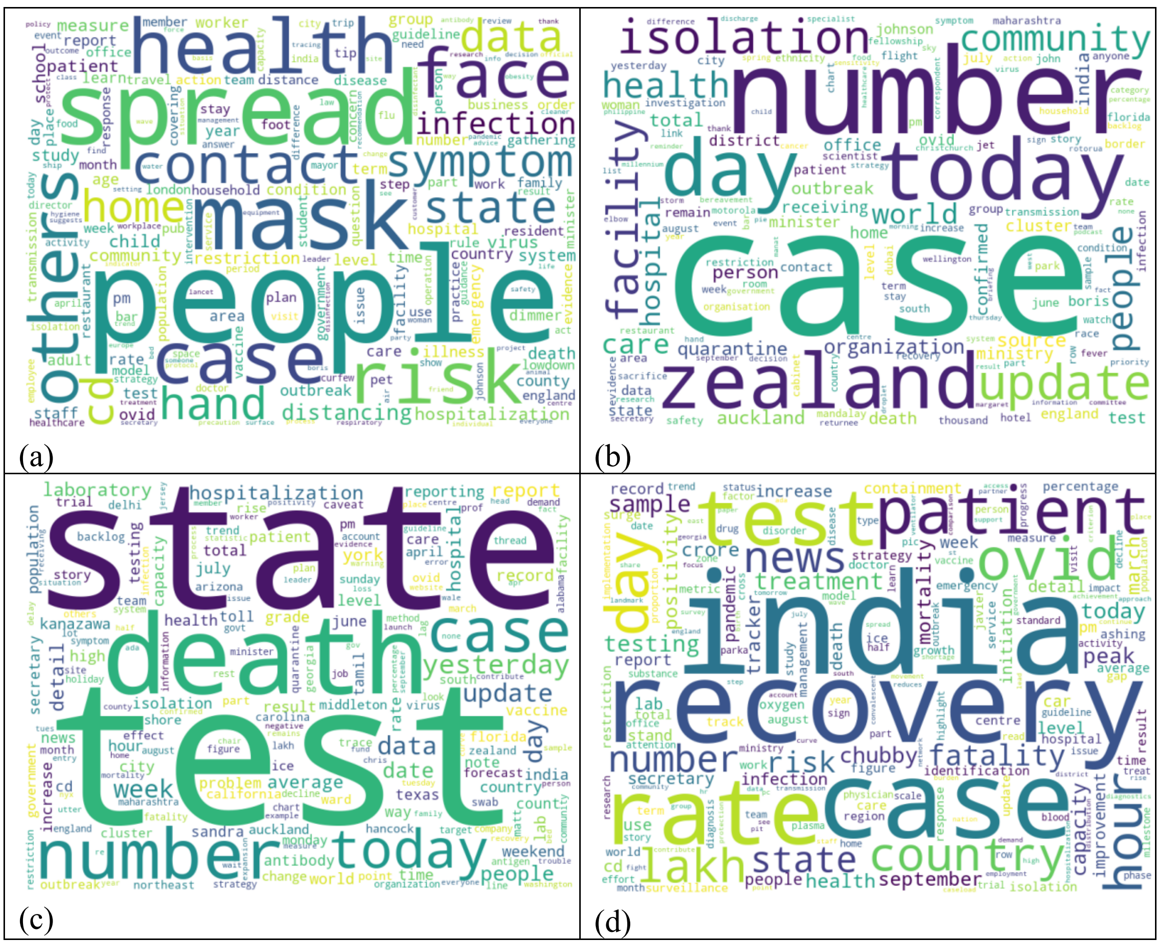


Figure 3.2 Word clouds generated from identified topics in fake news items in DS3



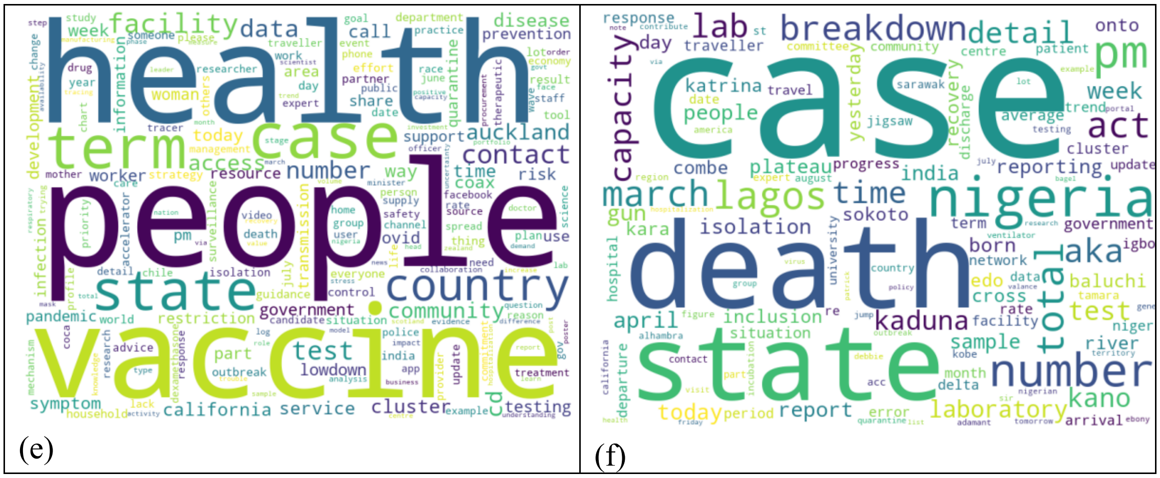


Figure 3.3 Word clouds generated from identified topics in real news items in DS3.

3.1.1.2 Features of Post Length We found that real news items are on average 40% longer than fake news items (175 char vs. 125 chars; 29.89 words vs. 20.7 words) in DS3. We hypothesize that to defend the facts, scientists/authorities might need to draft longer paragraphs of clear and precise content. For example, to combat a fake news item such as "Garlic can be used to cure COVID-19," it may be necessary to cite results from previously published studies that contradict this claim.

3.1.1.3 Features of Hashtags and Mentions We perform analysis on hashtags and mentions to study the use of difference of hashtags and mentioned in fake news posts and real news posts. There are two purposes for the extraction of hashtags and mentions. First, we would like to see whether/how they are used differently in fake news and real news. Second, if there are differences of use observed, how would these features impact the detection model performance after being added into model's embeddings upon model training. We used Python regular expressions to capture any word starting with a "#" (hashtag), or a "@" (mention of a Twitter user). There were hashtags expressing the same meaning, but in different representations, such as “Covid_19” and “covid19.” We lowercased each hashtag and removed the punctuations (**Table 3.4**).

Table 3.4 Examples Of Hashtag Cleaning

Original Hashtag	Processed Hashtag
Covid_19	covid19
CoronaVirusFacts	coronavirusfacts
NYCLockdown	nyclockdown

Figure 3.4 and **Figure 3.5** show the top 30 hashtags used in fake news and real news in DS3. In fake news, there are 2,021 hashtags, 794 of which are unique, while in real news there are a total of 4,743 hashtags, 386 of which are unique. One interesting finding is the wording used for the pandemic. In fake news, “coronavirus” is used more often than “covid19,” while in real news, “covid19” is a more popular usage. **Figure 3.6** and **Figure 3.7** show the bar graphs of the top 30 hashtags that exist only in fake news vs only in real news. In fake news, hashtags tend to contain substrings such as “trump,” “wuhan,” “virus,” “fact,” “check.” In real news, hashtags contain inspiring messages such as “takeresponsibility,” “covidupdates,” “coronaupdates,” “wearamask,” “slowthespread,” and “reopeningsafely.”

We also looked into the accounts mentioned. **Figure 3.8** and **Figure 3.9** present the bar graphs of the top 30 mentions in fake news and in real news. In fake news, there are 669 mentions, 486 of which are unique, while in real news, there are 2,090 mentions, 568 of which are unique. In fake news, the top mentions are often politically related: “realDonalTrump,” “narandramodi” (Indian Prime Minister), “factchecknet,” “PMOIndia” (Prime Minister Office India), while in real news, top mentions are related to public health experts or institutes: “MoHFW_INDIA” (Ministry of Health and Family Welfare of India), "ICMRDELHI" (India Council of Medical Research), "DrTedros" (Director General of WHO), and "drharshvardhan" (An Indian Otorhinolaryngologist).

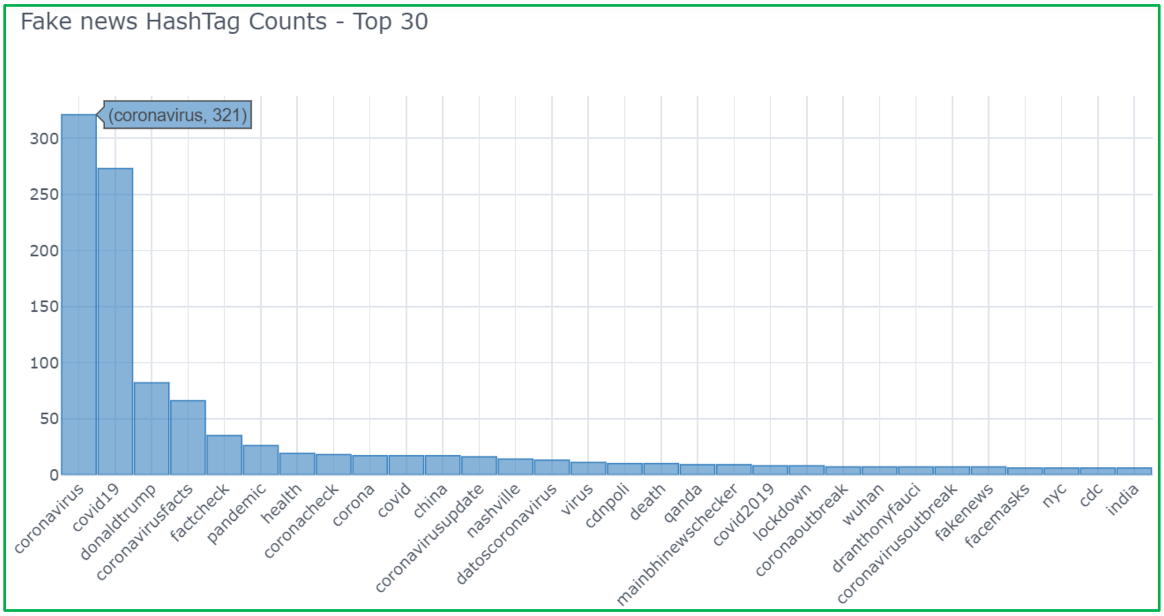


Figure 3.4 Bar graph showing top 30 hashtags used in fake news

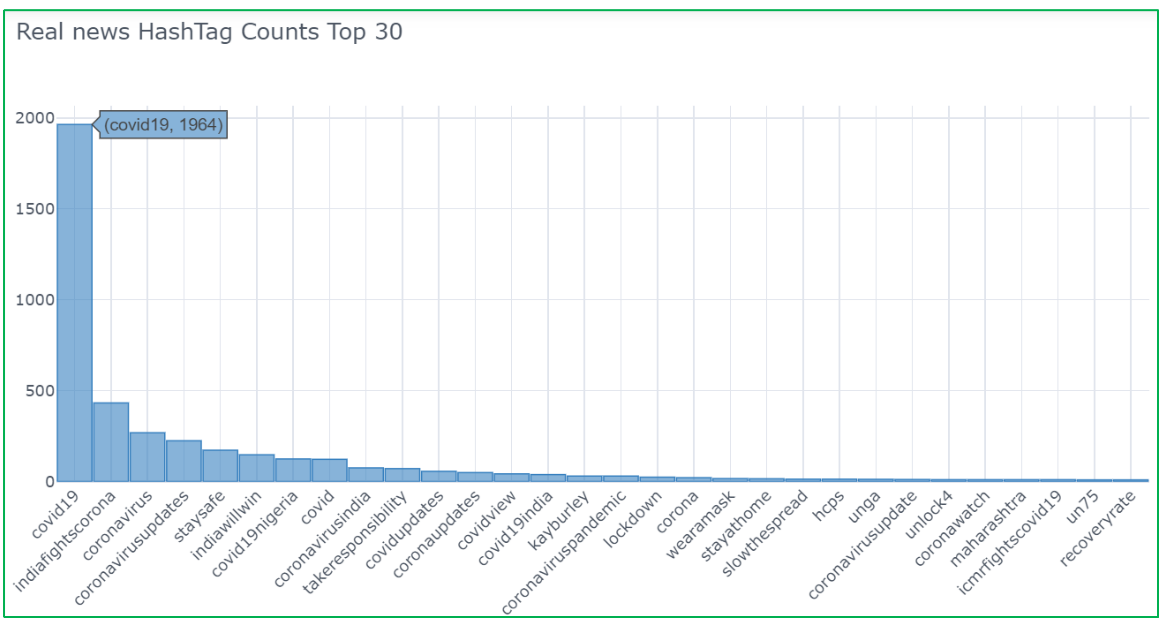


Figure 3.5 Bar graph showing top 30 hashtags used in real news

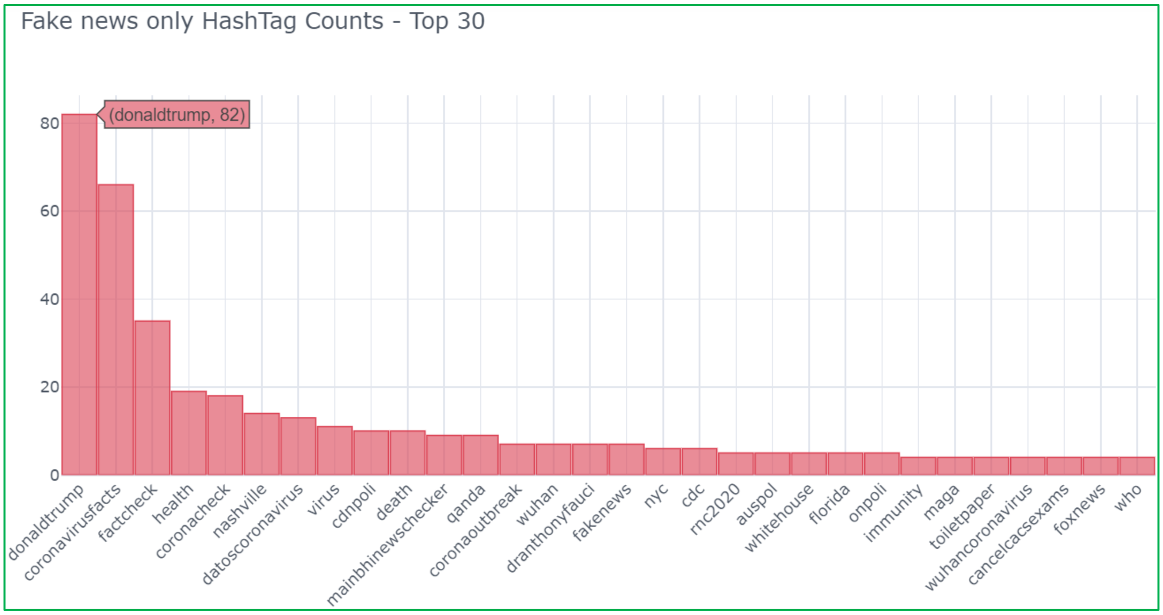


Figure 3.6 Bar graph of top 30 hashtags occurring only in fake news

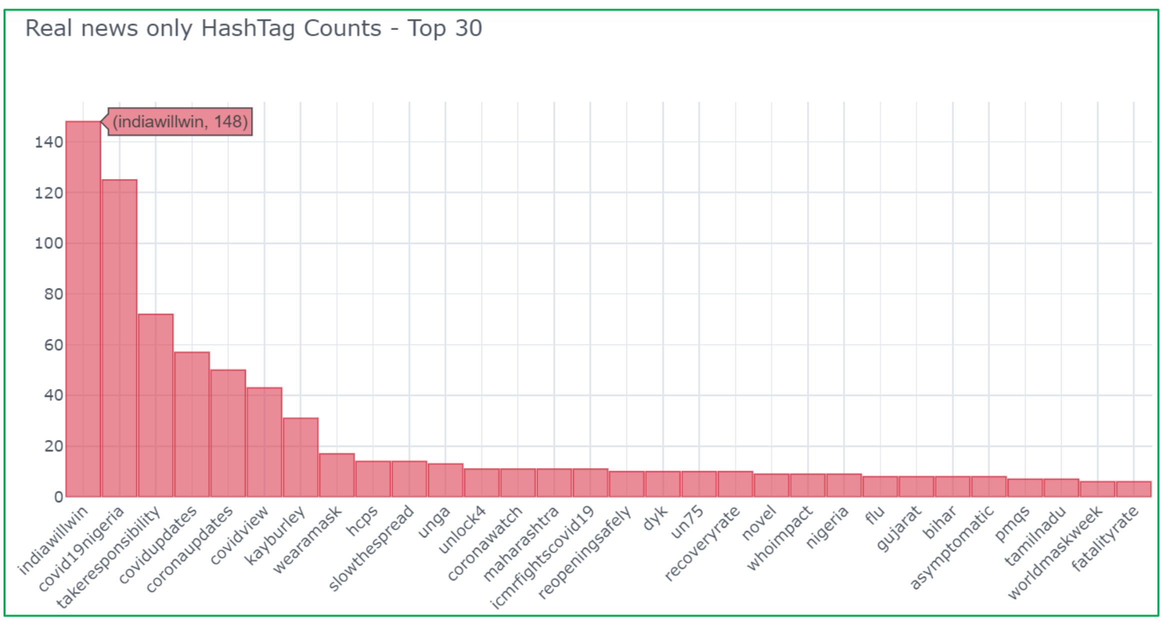


Figure 3.7 Bar graph of top 30 hashtags occurring only in real news

We also did a normalization experiment, based on the count difference between fake news (4,080) and real news (4,480). Since the dataset is class-wise balanced, the comparison results between fake news and real news discussed above did not change.

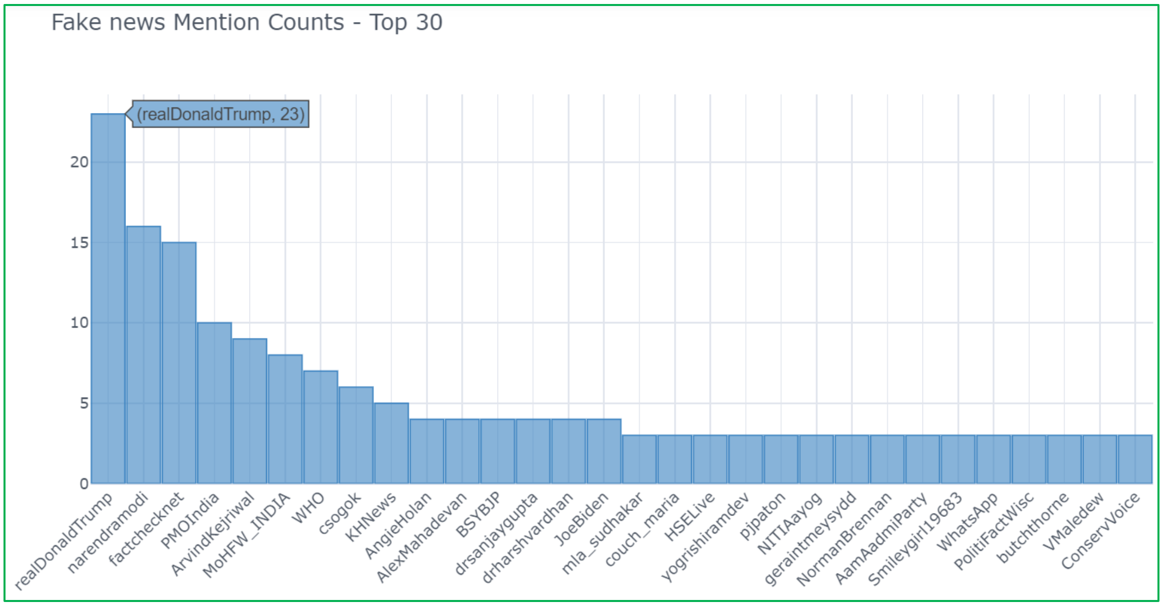


Figure 3.8 Bar graph showing top 30 mentions in fake news

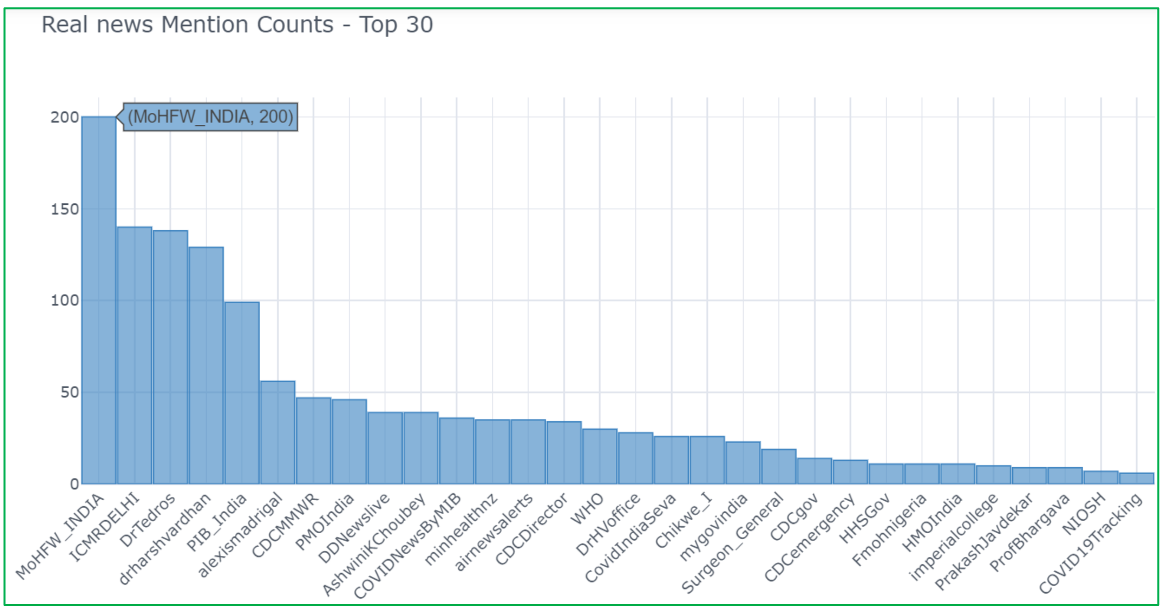


Figure 3.9 Bar graph showing top 30 mentions in real news

3.1.1.4 Features of Sentiment Analysis and Concern Levels Analysis In order to determine the emotional impact of news items and monitor the concerns expressed by fake news and real news, we applied a sentiment analysis tool to each data item in DS3. A number of sentiment analysis tools are described in the literature. We considered the

VADER [154], Stanford Sentiment Analyzer [227], and TextBlob [155]. In order to decide which sentiment analysis tool to use, we performed three initial experiments. First, we conducted a human evaluation of a sample of 100 randomly collected tweets regarding COVID-19 [228]. Three research group members participated in this evaluation. Every member worked independently to label each tweet either with 0 as “Negative,” 2 as “Neutral,” or 4 as “Positive” sentiment. We computed a combined result of the human labelers by a majority vote.

Second, in order to identify the degree of agreement among the three sets of human-labeled sentiments, we computed the Inter-rater reliability based on Krippendorff’s alpha [229]. We compared the sentiments of the combined human result with those generated by the Stanford Sentiment Analyzer, VADER, and TextBlob. Among the 100 tweets, 91 agreed with a human majority vote, while there was no agreement for the remaining 9. Among the 91 tweets, there were 51 for which TextBlob and the combined human results agreed on the same sentiments, 58 for VADER, and 43 for the Stanford Sentiment Analyzer. Therefore, the accuracy of our human evaluation for TextBlob is 56% (51/91), for VADER, it is 63.7% (58/91), and for the Stanford Sentiment Analyzer, it is 47.2% (43/91). We utilized an online calculator [230] to obtain the value of alpha, which was computed as 0.485. Third, according to [231], data with an alpha < 0.667 should be discarded, which meant it did not matter which tool we selected. Based on the prior studies, the Stanford Sentiment Analyzer has the best accuracy among the three, with 80.7% [227], while VADER has an accuracy of 76.8%, and TextBlob is 68.8% [232]. Therefore, we chose the Stanford Sentiment Analyzer.

The Stanford Sentiment Analyzer uses a fine-grained analysis based on both words and labeled phrasal parse trees to train a Recursive Neural Tensor Network (RNTN) model. The approach of RNTN is shown in **Figure 3.10**. In order to derive the sentiment (p2) of a phrase, the RNTN uses a compositionality function g(.) to compute parent node vectors from child node vectors (**Figure 3.10**). To compute the sentiment (p1) of the sub-phrase, it uses the function g(.) with the sentiments of its children b and c. For each node (a, b, and c), the analyzer uses varied features for classifying its sentiment. Therefore, the sentiment computed by the RNTN model is based on (1) the sentiment values of each word, and (2) the sentiment of the parse-tree structure composed from the sentiment values of words and sub-phrases. Furthermore, these characteristics enable the model to capture some sophisticated features, such as sarcasm and negation expressed by input phrases.

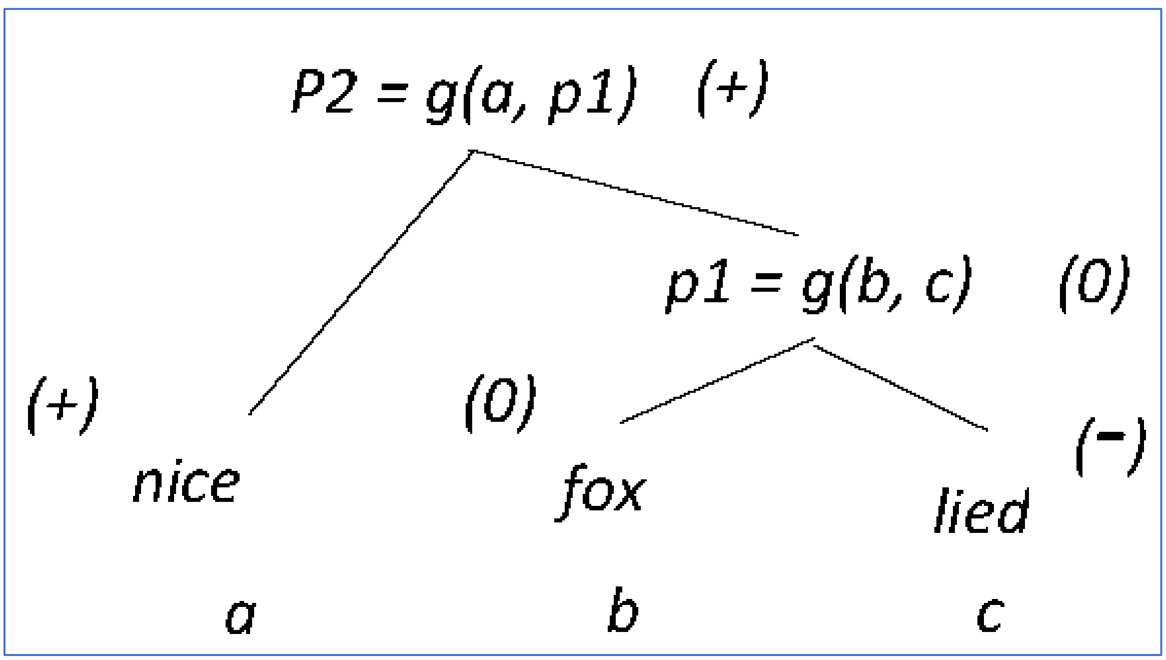


Figure 3.10 Approach of Recursive Neural Network Model, based on [227], predicting the sentiment classes of "Negative" (-), "Neutral" (0), and "Positive" (+). Sentiment classes in the figure are examples, not actual computed output.

Each input phrase is classified as belonging to one of five sentiment classes: "Very Negative," "Negative," "Neutral," "Positive," or "Very Positive." **Table 3.5** shows examples of sentiments of the dataset tweets classified by the Stanford Sentiment Analyzer. For our study, we used only three sentiment classes. A positive sentiment was assigned to a tweet if it was classified as positive or very positive by the Stanford Sentiment Analyzer. Similarly, a tweet was assigned a negative sentiment when it was classified as either negative or very negative. The neutral sentiment of a tweet remained neutral.

Table 3.5 Examples of the Five Sentiment Classes, Taken from the Dataset DS3.

Text	Sentiment
A voice recording on WhatsApp claims there will be 900 deaths a day at the peak of the new coronavirus outbreak, one third will be children with no underlying health conditions, ambulances won't be sent to people struggling to breathe, and all ice rinks are now being used as mor...	Very Negative
Obama Calls Trumps Coronavirus Response A Chaotic Disaster	Negative
In May we did not break 30k cases in a day. Today the South alone reported 32830.	Negative
India spraying pesticides at night to prevent COVID19.	Neutral
Our daily update is published. States reported 586k tests 28k cases and 224 deaths.	Neutral
It is best to shave your beard to avoid being infected by the coronavirus.	Positive
For example, once a successful vaccine has been identified WHOs strategic advisory group will provide recommendations for their appropriate and fair use. The allocation of vaccines is proposed to be rolled out in two phases-@DrTedros #COVID19	Positive
Foundation is truly one of the most inspirational forces of social change	Very Positive

In order to monitor concerns expressed from the posts, we performed a "concern level" analysis. The formula for computing the concern level was defined by Ji et al. [163],

DEFINITION 3.2 Concern Level.

$$\text{Concern Level} = \frac{N}{N+P} \qquad \text{Equation 3.2}$$

where N is the count of tweets with negative and very negative sentiments,

$\sum_{i=1}^{n} \quad neg(twi)$; P is the count of tweets with positive and very positive sentiments, $\sum_{i=1}^{n} \quad pos(twi)$. The functions neg() and pos() are appropriate sentiment indicator functions applied to the i-th tweet tw_i. The higher the concern level toward a new item set is, the more negative sentiments are expressed, relative to the total number of news items with some emotive polarity value. We define emotive tweets as T = N + P, i.e., the total number of news items with a polarity sentiment. This excludes the neutral sentiment tweets, neuT, that lack the emotive polarity perspective towards a policy. The fraction of neutral tweets (neuT) among all tweets shows the magnitude of indifference toward a news item set, while the proportion of emotive tweets (T) among all news items shows the level of emotional reactions to it.

In order to identify if the difference between the concern levels in fake news and real news is significant, we calculated a Z-score using the concern level formula in Definition 3.2:

DEFINITION 3.3 Z-score calculation.

C_F (Concern Level in Fake News) = $\frac{N_F}{T_F}$ Equation 3.3

C_R (Concern Level in Real News) = $\frac{N_R}{T_R}$ Equation 3.4

C_T (Concern Level Combined) = $\frac{(N_F + N_R)}{(T_F + T_R)}$ Equation 3.5

std ($C_F - C_R$) = $sqrt((C_T * \frac{(1 - C_T)}{T_F}) + (C_T * \frac{(1 - C_T)}{T_R}))$ Equation 3.6

Z-score = $\frac{abs(C_F - C_R)}{std(C_F - C_R)}$ Equation 3.7

Where:

N_F = Negative Tweets, Fake News
T_F = Total Tweets, Fake News
N_R = Negative Tweets, Real News
T_R = Total Tweets, Real News

We then did a lookup of a two-tailed p-value from the Z-score and considered a p-value ***less than 0.05*** to indicate statistical significance.

3.1.1.5 Statistics regarding DS3 We present (in **Table 3.6**) a summary of the statistics of DS3. The table includes post counts, average word counts, average character counts, training/test split, sentiment distribution, total hashtag counts, unique hashtag counts, total mention counts, and unique mention counts.

Table 3.6 Statistics regarding DS3

		fake news items	real news items
Counts and Length of Posts	Post Counts	4,080	4,480
	AVG Word Counts per post	20.7	29.89
	AVG Char Counts per post	125	175
Training/Test Split		80% for training and 20% for testing. 5-fold cross validation.	
Sentiment Distribution	Very Negative	2,512	1,794
	Negative	247	553
	Neutral	240	677
	Positive	503	716
	Very Positive	578	740
Hashtags		Totally 2,021, 794 out of which are unique.	Totally 4,743, 386 out of which are unique.
Mentions		Totally 669, 486 out of which are unique.	Totally 2,090, 568 out of which are unique.

3.1.2 Fake News Detection Models

For fake news detection, we trained LSTM [10], BERT [11] , and DistilBERT [12] models.

LSTM (long short term memory) is a specific recurrent neural network (RNN) that can handle long term dependencies and in turn solve the problem of vanishing gradient. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals, and the three gates regulate the flow of information into and out of the cell. One-hot encoding is used for word embedding and vector representation.

BERT is a powerful Deep Learning system based on the first deeply bidirectional model. It is used for both pretrained language modelling and Classification model. It uses bidirectional transformers, such that a transformer is used for converting a sequence using an encoder and a decoder into another sequence. As opposed to directional models, which read the input text sequentially (left to right or right to left), the transformer encoder reads the entire input text at once. This characteristic allows the model to learn the context of a word based on its left and right neighboring words. This large-scale pre-trained language model can be used for embedding the input sentences for other ML and DL models for their input. BERT model is also used for classification model.

DistilBERT is a pre-trained version of BERT. DistilBERT leverages knowledge distillation during a pretraining phase. Thus, DistilBERT has fewer parameters than the Bert model (bert-base-uncased) by 40%, while it retains 97% of its language understanding capabilities and runs 60% faster [12]. From BERT the token-type embeddings and the poolers are removed while the number of layers is reduced by a factor of 2.

For each model, we performed 5-fold cross validation. In this chapter, we used three datasets, and trained each of the LSTM, BERT, DistilBERT models with each dataset. Therefore, we will describe nine training regimens.

3.2 Experimental Results

3.2.1 Fake News Detection - Experiment 1

In experiment 1, we used three datasets and trained each of the LSTM, BERT, DistilBERT models with each dataset. Therefore, there are nine training regimens. The performance results of our Deep Learning models are shown in **Table 3.7**. In our experiments, fake news detection with BERT, outperformed the other models on all three datasets. Compared with other approaches, the BERT models, namely BERT1 based on DS1 and BERT3 based on DS3, achieved higher accuracy than the models by [104] and [221], respectively, as presented below in **Table 3.8** and **Table 3.9.**

Table 3.7 Performance of Our Trained Deep Learning Models

Model Accuracy	LSTM	BERT	DistilBERT
DS1	86.64%	**93.5%**	70.4%
DS2	89.29%	**97.05%**	81.5%
DS3	87.21%	**95.61%**	75.37%

Table 3.8 Accuracy of BERT and LSTM Models and Previous ML Approaches on DS1

Model (BO = Bojjireddy et al., 2021)	**Accuracy**
Multinomial Naïve Bayes (BO)	78.87%
Gradient Boosting (BO)	79.72%
Decision Tree (BO)	81.58%
Random Forest (BO)	86.39%
LSTM trained on DS1	86.64%
Support Vector Machine (BO)	87.35%
Multilayer Perceptron (BO)	87.75%
BERT trained on DS1	**93.5%**

Table 3.9 Accuracy of BERT and LSTM and Previous ML Approaches on DS3

Model	**Accuracy**
Decision Tree (Patwa et al., 2021)	85.23%
Gradient Boost (Patwa et al., 2021)	86.82%
LSTM trained on DS3	87.21%
Logistic Regression (Patwa et al., 2021)	92.76%
Support Vector Machine (Patwa et al., 2021)	93.46%
BERT trained on DS3	**95.61%**

Table 3.10 Performance of BERT Models Trained with Our Datasets

Model Accuracy	DS1	DS2	DS3
BERT1 = BERT trained on DS1	**93.52%**	73.74%	42.65%
BERT2 = BERT trained on DS2	39.15%	**97.05%**	46.5%
BERT3 = BERT trained on DS3	48.27%	38.73%	**95.61%**

We evaluated our BERT models on the other two datasets that they were not trained on (**Table 3.10**, the non-diagonal values). Each of the three models was trained with DS1, DS2, and DS3. We used pre-trained BERT, and each model was fully trained with embeddings and classification. However, experiment 1 shows that the models were not adapting well between different domains, because the datasets are intrinsically different in their nature. DS1 and DS2 are news-based and from the time before COVID-19, while DS3 is social network-based, and about COVID-19.

3.2.2 Sentiment Analysis of DS3

Table 3.11 presents the statistical results of sentiment analysis on DS3. The fake news items result in a higher concern level than real news items by 10% (72% vs. 62%). By Definition 3.2, we obtained a Z-score of 9.3. A lookup in Social Science Statistics [233] of a two-tailed p-value from the Z-score identified a ***p-value < 0.00001***. Thus, the difference of concern indices between fake news and real news is highly **significant.** This result shows that fake news expressed more negative emotions.

Table 3.11 Statistical Results of Sentiment Analysis on DS3

	fake news items	real news items
Very Negative (VN)	2,512	1,794
Negative (Neg)	247	553
Neutral (Neu)	240	677
Positive (Pos)	503	716
Very Positive (VP)	578	740
Concern Index (CI)	0.72	0.62

3.2.3 BERT model detection for DS3 with feature embeddings and selection – Experiment 2

In order to evaluate how the identified features impacted the model performance, in this subsection, we performed the second detection experiment with feature embeddings along with feature elimination. We added features to form the feature analysis component, which includes *sentiment*, *number of words*, *number of characters*, *number of hashtags*, and *number of mentions* (discussed and analyzed in subsection 3.1.1) for each post in DS3. We will use the term "identified features" to include these five features. To investigate how the identified features would influence the fake news detection, we added them (in numerical format) into the sentence embeddings of BERT model training. Each input sequence processed by BERT is tokenized, and each token is converted into an integer id. BERT itself has a dictionary with 30,254 rows, and each row contains exactly one token and a corresponding id.

In order to avoid id duplicates in the embeddings, we used the sum of 31,000 and the sentiment value of the sentence as the token id of the sentiment. For the sentiments, we converted "Very negative" and "Negative" to 0, "Neutral" to 2, and "Very Positive" and "Positive" to 4. Correspondingly, 32,000 is added to the number of words in the sentence as the token id of the word count. In a similar manner, 33,000 is used to offset the character count from the token ids used by BERT. Next, 34,000 is added to the hashtag count and 35,000 is added for the mentions count. For example, a fake news item in DS3 "*Washington Examiner Editor Loses Head Up His Ass #washington #josephbiden #covid19*" is encoded as follows. This sentence expressed a negative sentiment. Thus, the token id of sentiment is 31,000 (0+31,000). The token id of word count is 32,011 (11 words + 32,000). The token id of character count is 33,082 (82 chars + 33,000). The token id of hashtag count is 34,003

(3 hashtags + 34,000). The token id of its mention count is 35,000 (0 mentions + 35,000).

As shown in **Figure 3.11**, the input sequence *"Washington Examiner Editor Loses Up His Ass #washington #josephbiden #covid19"* is tokenized, and each token is converted into numerical data, stored in the first list shown in **Figure 3.11**. We them appended the converted numerical data of five features to the list **(underlined and bold in the second list in Figure 3.11)**. The token ids 101 and 102 are ids of special tokens "[CLS]" and "[SEP]" for BERT to represent the input properly.

We then trained BERT detection models with these new embeddings that included identified features. We obtained an accuracy of *94.72%*, which is however slightly lower than the model without the embeddings of the identified features, *95.61%* presented in experiment 1 in section 3.2.1.

Washington Examiner Editor Loses Head Up His Ass #washington #josephbiden #covid19

token ids of BERT sentence embedding**:** [101**,** 2899, 19684, 3559, 12386, 2132, 2039, 2010, 4632, 1001, 2899, 1001, 3312, 17062, 2368, 1001, 2522, 17258, 16147, 102**]**

tokens id of BERT sentence embedding **after we added the identified features**: **[**101, 2899, 19684, 3559, 12386, 2132, 2039, 2010, 4632, 1001, 2899, 1001, 3312, 17062, 2368, 1001, 2522, 17258, 16147, **31000, 32011, 33082, 34003, 35000,** 102**]**

Figure 3.11 Token Embeddings of Input Sequence in BERT.

In addition to adding the identified features into the embeddings, we also trained models on text with either hashtags removed, or mentions removed, or both hashtags and mentions removed, and evaluated model performance. Namely, we performed sensitivity analysis [234], consisting of (1) remove hashtags, but keep mentions, (2) keep hashtags, but remove mentions, and (3) remove both hashtags and mentions.

To be precise, removing a hashtag means that the word that is preceded by the character "#" is completely removed. Out of 8,560 data rows in DS3, there are 286 rows containing mentions, and 648 rows containing hashtags. A finding here is that in DS3 there is no data row containing both a mention and a hashtag.

As shown in **Table 3.12,** "Text with Hashtag Eliminated" means the hashtags were deleted from the post set. For example, by removing hashtags from *"Washington Examiner Editor Loses Up His Ass #washington #josephbiden #covid19,"* we obtained *"Washington Examiner Editor Loses Up His Ass."* The same applies to "Text with Mention eliminated." In those cases, if we added the feature of hashtag into embeddings, the appended number default to 34,000 instead of 34,003.

In **Table 3.12**, the row "Embeddings of Original Text" represented the embeddings converted from the original text, without identified features appending the embeddings, no matter whether hashtags and/or mentioned are removed from the text or not. The row of "Embeddings of Original Text **plus** identified features" means that we appended the embeddings of original text with five identified features, according to whether the hashtags and/or mentions are removed from the text or not.

Table 3.12 BERT Model Performance on DS3 with Feature Embeddings and Elimination

	Original Text	Text with Hashtag Eliminated	Text with Mention eliminated	Text with Hashtag and Mention Eliminated
Embeddings of Original Post Text	**95.61%**	95.03%	95.41%	94.81%
Embeddings of Original Post Text **plus** identified features	**94.72%**	93.91%	94.36%	92.22%

Based on the experimental results in **Table 3.12**, we have a number of findings from this experiment. First, the accuracies of models with the identified features embedded do not reflect improvements over the models without the identified features embedded. Second, the models trained on the original text without hashtag/mention eliminated performed best, the models trained on the text with both hashtags and mentioned eliminated had the lowest accuracy, and the models trained on text with either hashtag or mention eliminated had accuracy in between. Third, although the uses of hashtags and mentions differ between fake news and real news, the influence of hashtags and mentions towards fake news detection is not significant. This might be due to the low percentage of data rows containing hashtags or mentions.

3.3 Discussion

Fake news circulating on social media, no matter whether created by mistake or intention, has created trust issues among citizens and discord in society. We built Deep Learning models for fake news detection based on different domains of datasets. While our BERT models achieved state-of-the-art results compared with previous studies, we found that the models did not do well when evaluated on the other two datasets. To detect COVID-related fake news with models trained with non-COVID datasets, appropriate adjustments for transfer learning will be required. The DS2 dataset was constructed for this research, and thus no comparison with published research is possible. Among all our experiments, the BERT2 model showed the best performance.

We built topic identification models to identify topics in both fake news and real news in DS3. We found that half of the identified topics were overlapping across the news items. Such overlap of news topics across real news and fake news can add difficulties for citizens to distinguish between fake news and real news. We performed behavioral and sentiment analysis on DS3 and identified a number of feature differences between fake news items and real news items. The features include length of post, Concern Index, use of hashtags, and use of mentions. We hypothesized that such differences could help distinguish fake news from real news. For this purpose, we built BERT detection models for DS3 with the features (in numerical format) concatenated into the sentence embeddings. Unfortunately, we obtained slightly lower accuracy than for models built without the features added into the sentence embeddings. As BERT was pre-trained using plain text only, additional features in numerical data might not help improve model accuracy. Besides, the numbers applied were out-of-vocabulary (OOV) for BERT's sentence embeddings. Therefore, the numbers in the embeddings were not meaningful, and could even be interpreted as noise by BERT.

One result that challenged our intuitions was that fake news achieved higher coherence scores than real news. A possible explanation might be that real news will often be supported by a "proof," while fake news spreaders often try convincing the world by simple language that is often repeated.

Part of the work presented in this subsection is published in [13].

CHAPTER 4

PUBLIC PERCEPTIONS IN SOCIAL MEDIA: APPLICATION FOR PUBLIC HEALTH POLICY MONITORING

4.1 Introduction - Public Health Policy Perception Monitoring

Since the start of the COVID-19 pandemic, government authorities have responded by issuing new public health policies, many of which were intended to contain its spread but ended up limiting economic and social activities. The citizen responses to these policies are diverse, ranging from goodwill to fear and anger. It is challenging to determine whether or not these public health policies achieved the intended impact. This evaluation of policy impacts on the targeted goal requires systematic data collection (e.g., surveys) and scientific studies, which can be very time-consuming. To overcome such challenges, in this chapter, we provide an alternative approach to continuously monitor and dynamically make sense of how public health policies impact citizens.

The proposed public policy impact understanding is achieved through continuous collection of Twitter posts related to COVID-19 policies and analysis of the public reaction or perceptions expressed in their posts with advanced data analysis such as Machine Learning and Artificial Intelligence with trending analysis, geospatial analysis, and text summarization analysis. The overall architecture of proposed approach is shown in **Figure 4.1**.

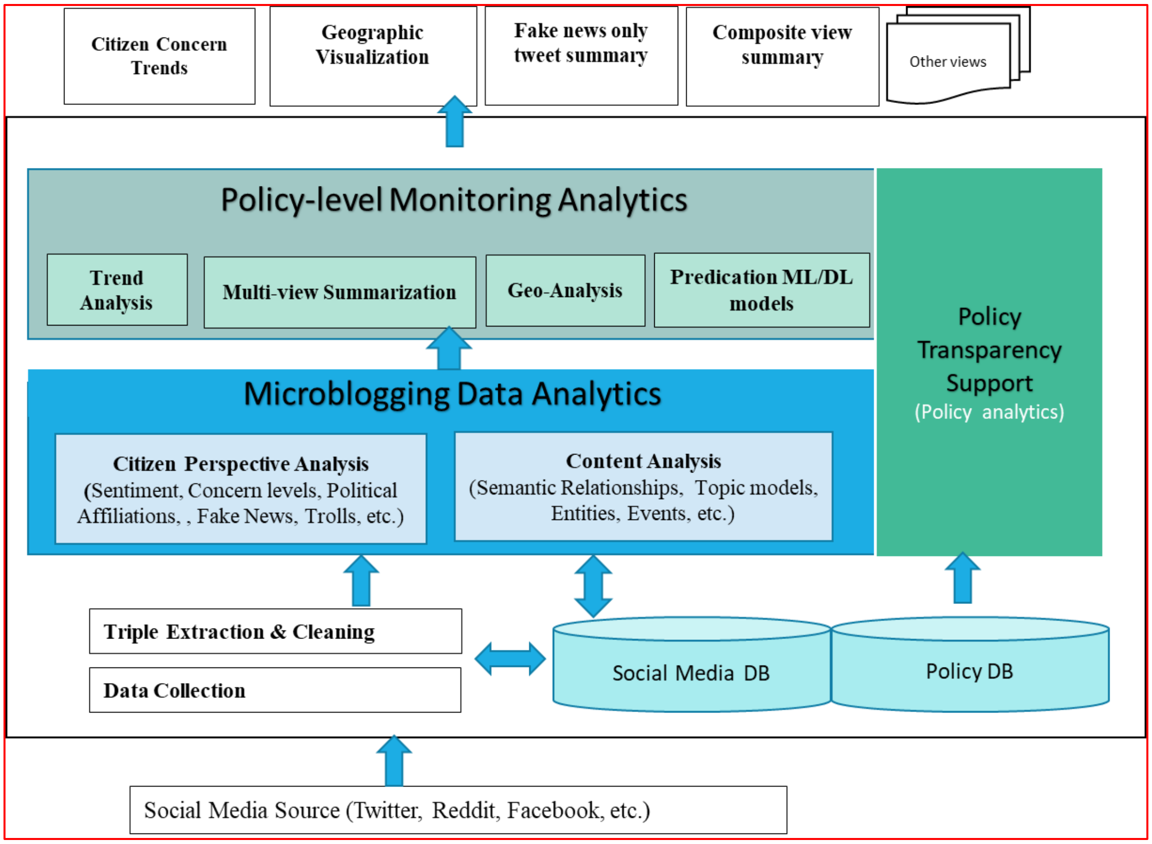


Figure 4.1 Architecture of Public Health Policy Monitoring on Citizens Impact

We have developed a web-based system that collects tweets daily and generates timelines and geographical displays of citizens' "concern levels." Tracking the public reactions towards different policies can help government officials assess the policy impacts in a more dynamic and real-time manner. For this chapter, we collected and analyzed over 16 million tweets related to ten policies over a 10-month period. We obtained a number of findings; for example, the "COVID-19 (General)" and "Ventilators" policies engendered the highest concern levels, while the "Face Coverings" policy caused the lowest. Nine out of ten policies exhibited significant changes in concern levels during the observation period.

4.2 Public Health Policy Perception Monitoring

In this section, we present the Public Health Policy Perception Monitoring component as well as experimental results. This section is organized as follows. In subsection 4.2.1, we introduce the source and collection of the dataset. We present three sentiment analysis tools and justify our choice of one of them based on human evaluation in subsection 4.2.2. In subsection 4.2.3, we discuss the formula to compute concern levels. We present the visualization of concern level trends for each policy in subsection 4.2.4. In subsection 4.2.5, we analyze the changes in concern levels over time and identify the significance of these changes. We then investigate the relationship between concern levels and pandemic progress during our study period. In subsection 4.2.6, we visualize the monthly concern levels of policies in US states and present the information in geographical maps. We present the readable summaries of our collected policy tweets in different and combined view perspectives in subsection 4.2.7.

4.2.1 Datasets

The data used in the chapter has been collected from Twitter. We were interested in the COVID-19 related health policies as well as other relevant protocols. We search tweets related to COVID- policies. **Table 4.1** shows the policy types, the keywords used, and the total tweet counts for each policy. Between August 2020 and March 2021, we collected 16,680,266 tweets. We performed tweet searches by using the official Twitter search API [235] using the keywords in **Table 4.1**. We collected English tweets only from the U.S. by restricting the search by setting the parameters “lang: en” and “place_country: US” to focus on the public health policies in the U.S. While we understand that COVID-19 is a global concern, policy decisions are local. Therefore, our methodology and analyses are designed to encompass a locality that is useful for a set of policy makers and the relevant public. However, this framework can be extended to any region or any language. We present tweet samples for each policy in **Table 4.2**.

Table 4.1 Policy Names, Search Terms, and Tweet Counts (The Counts are Based on Data Collected between Aug. 2020 and Mar. 2021)

Policy	**Search Terms**	**Tweet Count**
COVID-19 (General)	COVID COVID19 corona coronavirus	2,689,099
Face Coverings	face (mask OR covering)	2,842,246
Business Closing	business (closing OR shutdown)	2,655,381
School Closing	school (closing OR shutdown)	2,648,275
Economic Impact	CARES act OR stimulus check OR coronavirus economy	2,579.479
Quarantine	quarantine OR self isolation OR lockdown	1,813,622
Contact Tracing	contact (tracing OR tracking)	1,789,444
Testing	test corona virus	1,771,197
Ventilators	ventilator COVID	303,215
Social Distancing	socialdistancing social distancing	165,208
TOTAL		**16,680,266**

Table 4.2 Tweet Examples for Each Policy

COVID-19 (General)	Great example of ongoing medical education in the wake of restricted travel and meetings #COVID19 Thank you for sharing. We need more of the same!
	Me too. I took it, along with the family. Personal choice for each of us. I get the apprehension. CDC doesnt make it any better. But my whole point was Dr are treating everything as covid erroneously at the sake of misdiagnosing other things.
	We are getting ready to open on August 15! So.....to give us a little more time the store will be closed this Friday and Saturday! We will post all the changes due to Covid ASAP. The apples are looking lovely.
Face Coverings	We letting these beasts make masks mandatory. This is all about obedience, no fucking evidence supporting the effectiveness of masks against contracting covid. Niggas is wearing tissue paper for face mask but as long as you a good sheep and comply it's all good.
	Wear a Mask! Californians must wear a face-covering in high-risk settings.
	Miss Princess! Customizable Face Masks with PM2.5 Activated Carbon Filters!
Business	Attached is an article that @TheSlideJob wrote about him (after the video)

Closing	and what he did when our family business was shutdown from COVID-19. He will do almost anything to race!
	Interesting that the president of the U.S. is hunkering in a bunker under the W.H. instead of addressing the nation? Tear gassing peaceful protestor's yet, when your ppl protested the closing of business's due to COVID. You allowed machine gun carrying nasty rude ppl to cont. on?
	Bull ! Like Walmart isn't our Myrtle beach. Covid mart has been open every since the virus started and they have curbside service. Beshear is scared of Walmart's lawyers! While everyone that owns other business was made to shutdown! Typical democrat.
School Closing	Day 1 of our COVID-19 school shutdown and there was abundant evidence of our @PosProject theme this week: #LoveofLearning Everyone worked so hard to make sure our wee Turtles have what they need to keep growing while they are away.
	15yo grandson says COVID cases at school are up. School in Raytown may be closing soon.
	After more than week of classes, a Fort Bend ISD elementary school is closing its doors and shifting to online learning due to a significant" risk of COVID-19 on campus.
Economic Impact	The reason the country went in the tank was the democrat leaders in their states locking everyone and thing down. That's what killed our economy. There's study after study that show lockdowns didn't help with covid
	We might retest Covid lows. Anything can happen. Still a lot of stubborn inflation and a horrible economy is not priced in. We bottom when Bored Ape is a zero, GME is at 15, and BTC trades at 3000.
	People can make money when the virus is under control. Imagine that. With Covid-19 Under Control, China's Economy Surges Ahead.
Quarantine	Iran becomes the first country to report a second wave of coronavirus infections as cases hit a record high after easing lockdown and has so far reported 164,270 cases and 8,071 deaths.
	The World Health Organization has announced that dogs cannot contract Covid-19. Dogs previously held in quarantine can now be released. To be clear, WHO let the dogs out.
	Crazy how essential workers never got any hazard pay for going to work during quarantine especially after I got sick twice with covid. First time I was out for a month and second time I was out for 2 months. What happened to that $25,000 heroes pay? It was let go.
Contact Tracing	Contact tracing shows high risk for coronavirus spread in churches
	WHO urged countries to continue to test, isolate, and treat COVID pts.. Contact-tracing & quarantining to help reduce transmission. face masks, physical distance in public, handwashing. These measures can flatten the curve without lockdowns, regardless of drugs.
	I just completed a free certificate on COVID-19 Contact Tracing - you can too. If you are still looking for a summer job, this could be worth 5 h of your time.
Testing	Getting the vaccine does NOT prevent a positive COVID test. It's like the

	flu shot. You can still get the flu. You can still get COVID but the symptoms and fighting it isn't severe
	Negative covid test. I got the results today but I had an ER visit yesterday morning for asthma like symptoms. Doing much better but I never had asthma before so it was a bit scary.
	In need of a #COVID19 test? Come to McDonough Middle School. If you're in need of a ride call 860.550.7540
Ventilators	After more than 3 weeks on a ventilator while fighting COVID-19, this man says convalescent plasma saved his life.
	Corpus people really out here thinking covid-19 is a hoax. I've seen multiple people say let's just get it so we can get it over with. If they tell me I have it I'm not gonna believe them & continue about my life. You all are a bunch of fools. Have fun with that ventilator sis.
	Just found out my cousin has Covid and is on a ventilator. Please send positive vibes.
Social Distancing	It took a little work, but we have the pets practicing Social Distancing
	As if social distancing, working from home & home school don't already mess up your sense of days- this reminded me of when I woke up for school on the wkends.... need 2 stay on top of this calendar & make sure dates/days match to avoid confusion
	Practicing social distancing. Even us newsies are doing it with ya.

For continuous monitoring, we used a Python script to perform data collection once per minute. The results are appended to a file for each search category, and the files are saved in a directory organized by search date. At the end of each day, the daily datasets are analyzed with sentiment classification software to automatically label each tweet with a sentiment category (positive, negative, or neutral). The results are stored in a relational database for further analysis and visualization. The experiments and results presented in chapter is based on data collected from August 2020 to May 2021. However, data collection has been continuous beyond the study period and ongoing. We provide a link to a dataset of tweets with sentiment annotation for the time period covered by this chapter, http://ai4sg.njit.edu/data/ai4sg_raw_data.csv Retrieved on January 1st, 2023.

4.2.2 Concern Level Analysis

In order to monitor and track citizens' concerns about government policies, we performed the sentiment analysis on each microblog post with the sentiment analysis as part of the component on **Figure 4.1**. Using the sentiment analysis results, the system computes the "concern level" for each policy by using the formula in **Definition 3.2**.

$$\text{Concern Level of policy i} = \frac{Ni}{Ni+Pi} \qquad \text{Equation 3.8}$$

where N_i is the count of tweets with negative and very negative sentiments in policy i, $\sum_{i=1}^{n} \quad neg(twi)$; P_i is the count of tweets with positive and very positive sentiments in policy i, $\sum_{i=1}^{n} \quad pos(twi)$.

We analyzed the concern levels for different government policies to understand citizens' reactions to official policies, actions, and measures. We annotated the policy-related tweets with sentiment labels and calculated the concern levels. To analyze citizens' concern levels by US State, it is important to have accurate and standardized information about the tweet author's geographic location. Unfortunately, among the raw tweets that we collected, only approximately 7% contained usable location information including the tweet author's US State. Part of the tweet processing pipeline, besides sentiment annotation, uses other tweet metadata to attempt to properly associate the tweet with a US State. Tweet attributes such as "city," "location," "state_name," and "state_id" were examined and mapped to standardized state ids whenever possible. With this additional processing, the percentage of tweets with usable state locations increased from 7% to approximately 21%. With the US State information in the tweets, we were able to build a "concern map," and observe the concern levels by state. Due to the low percentage of tweets that could be tagged with geographical information, we summarized the concern level by month for each state instead of based on a daily basis.

4.2.3 Monitoring Levels of Concern

We tracked the daily concern levels about different COVID-19 related government policies. **Figure 4.2** shows the concern level trend for each policy between August 2020 and March 2021. According to the trends, we report the following findings. (The concern levels toward each policy are tracked on a daily basis and are visualized on our platform site, http://ai4sg.njit.edu/ai4sg/SentimentByPolicy Retrieved on January 1st, 2023.)

We observed that the concern level about "COVID-19 (General)" is higher than it is for individual policies. On the other hand, the concern level for "Face Coverings" has stayed relatively low throughout the period. Meanwhile, the concern level trend of "Economic Impact" stayed quite stable but was relatively higher than the concern levels for other individual policies throughout the period. The drop in the concern level about *Quarantine at the end of October was due to a data collection issue during that time.*

Figure 4.2 Concern Level Trends of All Policies

In **Table 4.3**, we demonstrate the mean concern level for each policy between August 2020 and May 2021, in descending order. Besides COVID-19 (General), Ventilators, Economic Impact, and Contact Tracing show the highest mean concern levels over time. On the other hand, the mean concern level of Face Coverings was the lowest among all and was the only one under 0.7.

Table 4.3 Average Concern Levels between Aug. 2020 and May 2021

Policy	**Mean Concern Level (8/1/20 – 5/23/21)**
COVID-19 (General)	0.839060
Ventilators	0.777519
Economic Impact	0.773728
Contact Tracing	0.768422
Business Closing	0.740154
Testing	0.737642
Social Distancing	0.727610
School Closing	0.724288
Quarantine	0.723680
Face Coverings	0.642787

4.2.4 Concern Level Trend Analysis

We examined the concern levels over time by computing summary statistics, namely mean and standard deviation for concern levels for each policy. In addition, we compared the mean concern levels for the first week of the time frame with the mean concern level for the last week of the time frame. The statistics are demonstrated in **Table 4.4**.

Table 4.4 Statistical Significance Tests (N Means Negative Tweet Count, P Means Positive, C Means Concern Level, S Means Start Week, and E Means End Week)

	Start Week (2020/07/27 – 2020/08/02)			**End Week (2021/05/17 – 2021/05/23)**				
	N_S	**$N_S + P_S$**	**C_S**	**N_E**	**$N_E + P_E$**	**C_E**	**Z-score**	**p-value**

Business Closing	44,969	60,351	0.7451	47,513	63,500	0.7482	1.259	0.2
Economic Impact	47,116	60,669	0.7766	44,115	57,505	0.7672	3.873	0.0
Contact Tracing	33,355	43,022	0.7753	35,337	44,769	0.7893	5.032	0.0
COVID-19 (General)	19,730	22,383	0.8815	58,265	67,593	0.8620	7.433	0.0
Face Coverings	47,130	68,079	0.6923	43,022	67,791	0.6346	22.489	0.0
Quarantine	32,669	43,741	0.7469	27,320	38,037	0.7182	9.236	0.0
School Closing	43,364	57,875	0.7493	46,029	63,343	0.7267	8.935	0.0
Social Distancing	8,070	11,252	0.7172	1,250	1,683	0.7427	2.176	0.0
Testing	37,346	48,732	0.7664	29,672	41,201	0.7202	15.834	0.0
Ventilators	11,150	14,275	0.7811	8,526	9,744	0.8750	18.569	0.0

Our examination showed statistically significant changes in concern levels over time for most of the policies, except for the business closing and social distancing policies. We considered concern levels from 27 July 2020 to 23 May 2021 for this computation. We calculated a Z-score using the formula in **Definition 3.3.**

Except for Business Closing, all the policies experienced significant changes in concern levels as shown in **Table 4.4**: Economic Impact (-1.21%, from 0.7766 to 0.7672), Contact Tracing (1.81%, *from 0.7753 to 0.7893*), COVID-19 (General) (-2.21%, *from 0.8815 to 0.8620*), Face Coverings (-8.33%, *from 0.6923 to 0.6346*), Quarantine (-3.84%, *from 0.7469 to 0.7182*), School Closing (-3.02%, *from 0.7493 to 0.7267*), Social Distancing (3.56%, *from 0.7172 to 0.7427*), Testing (-6.03%, *from 0.7664 to 0.7202*) and Ventilators (12.02%, *from 0.7811 to 0.875*).

4.2.5 Relationship between Pandemic Progress and Concern Levels

An important objective in our research was to understand the relationship between the progress of the pandemic, i.e., daily, and cumulative confirmed cases as well as deaths, and the levels of citizen concerns about the various defined policies. How did the hard data of the pandemic affect the measured levels of concern, if at all?

We investigated the association strengths with a trend visualization method by plotting concern levels for COVID-19 policy tweets, and normalized values of COVID-19 cases and confirmed deaths over time as shown in **Figure 4.3**. There was little fluctuation of the concern level trend of COVID-19 (General) (shown as a blue line), while the normalized infections (orange line) and deaths (green line) fluctuated drastically between November 2020 and March 2021. Based on this information, we were not able to identify any meaningful correlation between the progress of the pandemic and the levels of citizen concern.

Instead, we computed correlation coefficients between confirmed cases, deaths, and concern levels for each of the policies. Correlations were computed using the raw daily concern values, weekly mean concern levels values, and monthly mean concern level values. In **Table 4.5**, we demonstrate correlations of daily infections and deaths for each policy with concern levels. We computed [236] the p-values for the correlations with a two-tailed p-value for the data for 243 days (Aug. 2020 – Mar. 2021). We marked all the non-significant p values in *italics*, using a cut-off value of $p = 0.05$.

We note that only three correlations are positive. Namely, an increase in daily deaths led to an increase of concerns about Quarantine, School Closing, and Social Distancing. However, these three correlations are statistically not significant. Among the seventeen negative correlations, three are not significant, while the other fourteen are significant. It is counterintuitive that (for example) an increase in daily confirmed cases would lead to a decrease of concern about Economic Impact (with $r = -0.252$).

The findings from the negative associations between concern levels of policies and the daily deaths or daily infection cases are that when there is increased deaths or infection cases, the negativity towards some policies decreases. This shows the seemingly counterintuitive association directionality makes more sense. The concern-level tracking of different policy impacts on citizens and the COVID-19 progress are shown on a daily basis on our prototype system available at (http://ai4sg.njit.edu/ai4sg/COVID).

Table 4.5 Correlation Coefficients for Daily Confirmed Cases and Daily Deaths with Concern Levels about Each Policy between Aug. 2020 and March 2021

Concern by Policy	Daily Confirmed Cases	p-value	Daily Deaths	p-value
Business Closing	-0.385	0.0	-0.010	*0.876*
Economic Impact	-0.252	0.0	-0.282	0.0
Contact Tracing	-0.401	0.0	-0.231	0.0
COVID-19 (General)	-0.513	0.0	-0.262	0.0
Face Coverings	-0.442	0.0	-0.213	0.0
Quarantine	-0.229	0.0	0.055	*0.393*
School Closing	-0.389	0.0	0.079	*0.219*
Social Distancing	-0.080	*0.214*	0.097	*0.131*
Testing	-0.402	0.0	-0.388	0.0
Ventilators	-0.272	0.0	-0.030	*0.641*

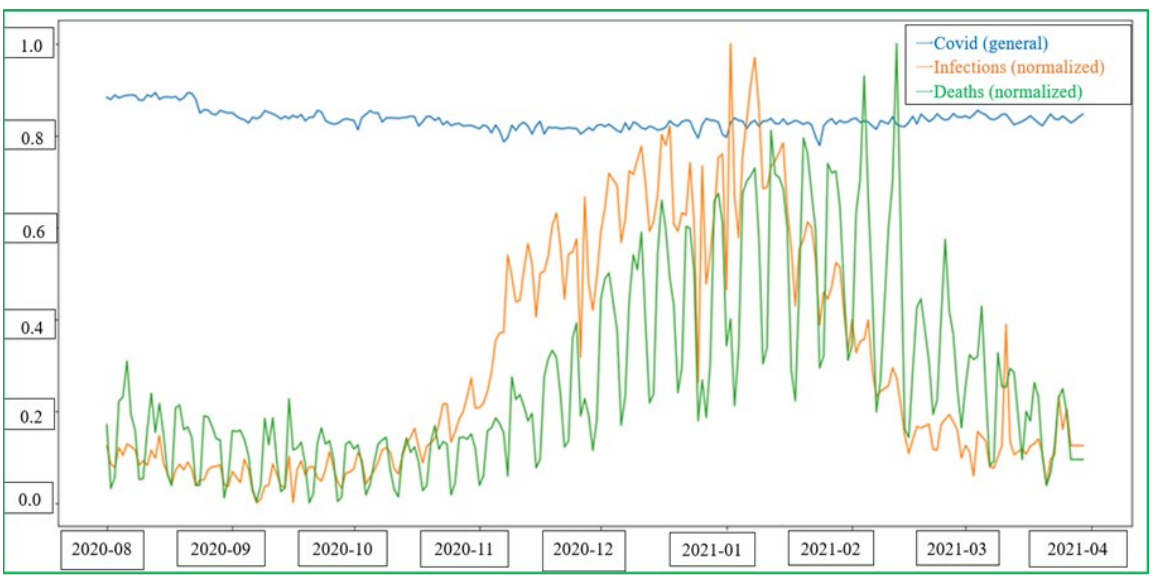


Figure 4.3 Comparison of the progress of the pandemic and the levels of citizen concerns. Blue: COVID-19 (General) Concern Level; Orange: Infections (normalized); Green: Deaths (normalized)

4.2.6 Public Concern Map by Policy

Over the whole period of data collection, we observed that states with large populations tended to fluctuate to a smaller degree than states with small populations. For example, in

Wyoming, which has a population of *578,759*, the concern levels between August 2020 and May 2021 were varying widely: 0.91, 0.80, 0.82, 0.88, 0.83, 0.76, 0.97, 0.87, 0.76 and 0.93. However, these values were computed from small numbers of tweets. Thus, the concern level of 0.93 for May 2021 is based on only 25 negative tweets. In comparison, for the same month, the concern level of California, which has 39.5 million residents, was 0.83, but it was based on 3,963 negative tweets. Texas, which has 29.2 million people, had a comparable concern level to California of 0.84, based on 3,712 negative tweets. The concern level of 0.97 in Wyoming, which was recorded in Feb. 2021, is the highest observed in any state and in any category. The lowest concern level was recorded in Minnesota as 0.68 for March 2021. Even though Minnesota, which has 5.7 million residents, is ten times more populous than Wyoming, this result was based on only 69 negative tweets. All these numbers are for COVID-19 (General). For individual policies, values are notably lower.

For concerns about masks ("Face Coverings"), Idaho and New Hampshire were at the low end of the spectrum in May 2021, at 0.57 and 0.43 respectively. However, the state of Wyoming, which is a neighboring state of Idaho, had a concern level at the high end of its range, with a value of 0.86, based on 18 negative tweets. With the stored data, a concern map can be computed for each policy for each month. The concern map shown in **Figure 4.4** illustrates the concern levels of each state regarding Face Coverings in May 2021. We demonstrated a progression of concern in the US states from November 2020 to January 2021 in **Figure 4.5**. While citizens entered the holiday season of 2020, they expressed more concern in December than November. After the holiday season was over and entering the first month of 2021, the expressed concerns in most of the US states dropped.

For Economic Impact in April 2021, Mississippi had the countrywide highest concern level of 0.85, but based on only 118 negative tweets. South Dakota and North Dakota had the lowest concern levels about the economy at 0.65 and 0.70 respectively. We could not discern any obvious regional patterns.

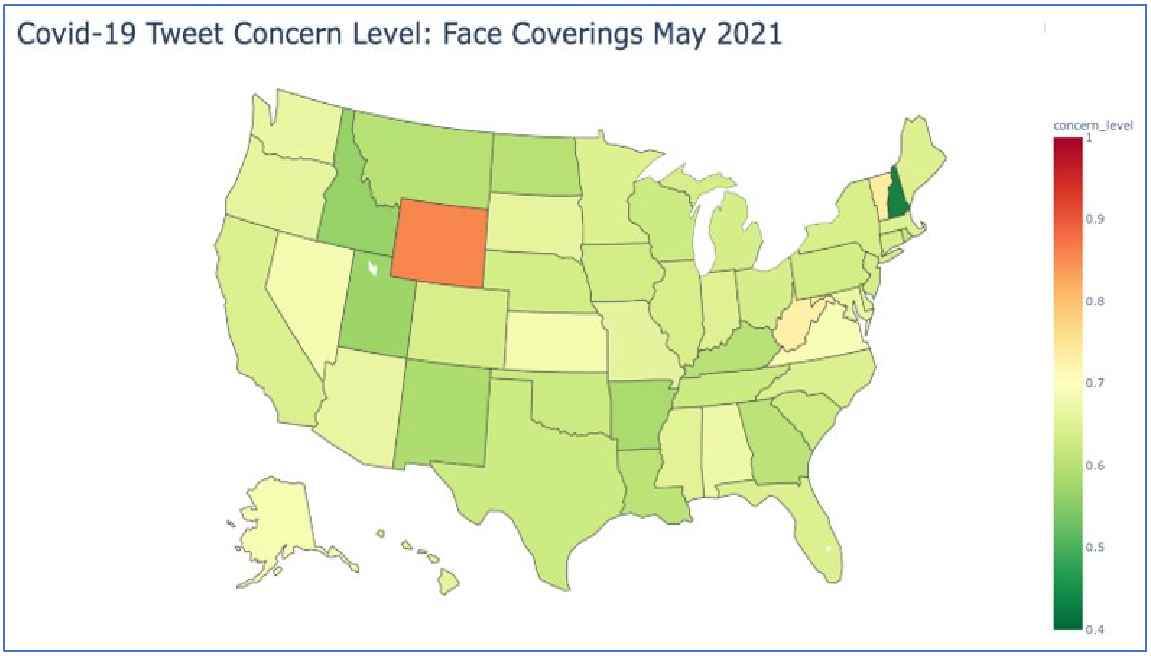


Figure 4.4 Concern Levels by State for Face Coverings in May 2021

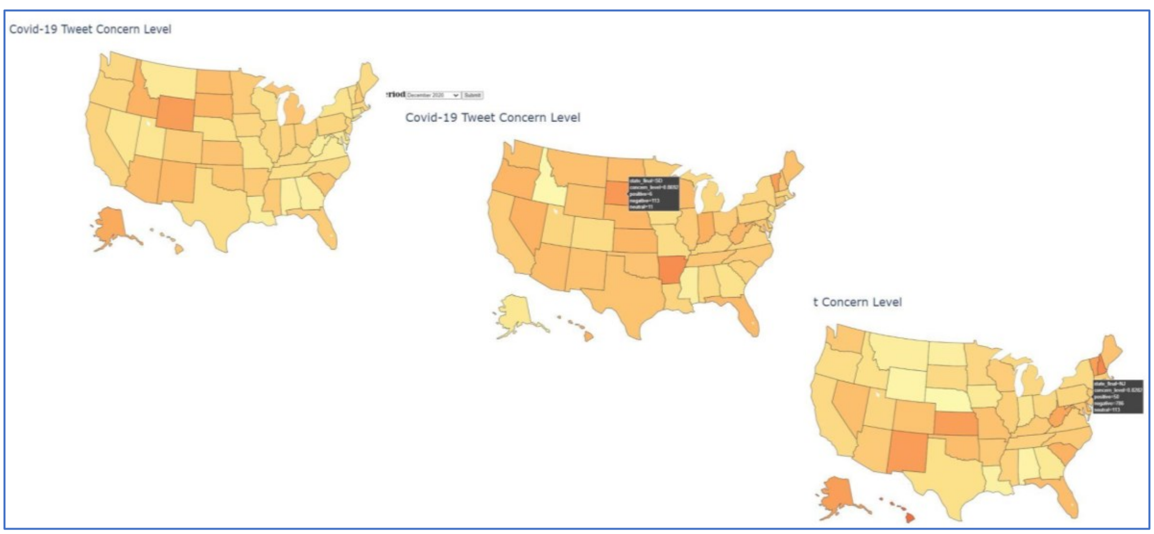


Figure 4.5 Temporal progression of the concern maps by US state (Nov 20 – Jan 21).

We expected that concern maps for Economic Impact would have clearly differentiated red (Republican) and blue (Democrat) states. Given the instability of values for small states, we chose California as a representative of the blue states and Texas as the prototypical red state. We then compared concern levels for all ten months. However, the results *contradicted* our expectations. First, we noticed that values were relatively stable throughout the period. In California, the values varied from 0.75 to 0.79. For Texas, the values were between 0.76 and 0.79. Furthermore, the absolute value of the difference in each month between the two states was never larger than 0.02.

One of our expectations was narrowly fulfilled. We hypothesized that "high tech states" produce more tweet activity than rural states. We summed the total numbers of tweets in each of the ten largest states by population and set them in relation to the numbers of citizens, which is shown in **Table 4.6**. New York and California, the home states of many computing startups, lead the pack at 19% and 14% respectively. The other large states vary between 9% and 13%, with Texas, Illinois, and Pennsylvania coming close to California.

Table 4.6 Tweet Activity

State	Total Tweets	Tweets/Population in '000
New York	3,687	19%
California	5,658	14%
Texas	3,888	13%
Illinois	1,719	13%
Pennsylvania	1,678	13%
Florida	2,674	12%
Georgia	1,336	12%
Ohio	1,368	11%
Michigan	994	10%
North Carolina	988	9%

4.2.7 Policy-based Microblog Summarization

In this subsection, we present the summaries of the collected policy tweets, and brief our developed summarization methods. We will present the detailed summarization methods in Chapter 5. Our summarization framework is able to generate summaries of different perspectives and composed perspectives of the same microblog data sets.

For a policy tweet set, we first decide a view or a combined view from the view set we are interested in to form the summary, e.g., policy, emotion, fake news, etc., and filtered the tweets accordingly. Then we applied our summarization algorithms, which are Entity-based, Social-Feature-based and Distance (Content)-based algorithms. The different algorithms focus on different perspectives of the input data, and can provide summaries on the focus. We present an overall algorithm as follows:

I. Ts = an input tweet set on policy and views (e.g., negative sentiment)

II. S = select (summarization algorithm from Entity, Social-Feature, or Distance)

III. L = Output Length

IV. Summary = S (Ts, L)

Therefore, we can obtain a summary of composed view perspectives from the data. We collected tweets of COVID-19 vaccination policy that were posted on Twitter in October 2022, and present the summaries in different (composed) views.

Table 4.7 Summary of Vaccination Policy Tweets in ***Entity*** View

It is very convenient for the pharmaceutical companies to disclude the first few weeks after vaccination in studies if the vaccine increases the likelihood of injury/death or increases the susceptibility of contracting covid (or causes covid) immediately after receiving a shot. The vaccine does prevent infection in some people (mostly helps w severity of disease) & also reduces the likelihood of long Covid in those who are vaccinated. I was never under the impression that the vaccine prevented me from

spreading COVID. Fact the vaccine I prevent Covid, and I prevent transmission. There is a lot of evidence that the vaccine reduces the severity of covid Vaccine was over 90 percent effective at preventing covid but because of the slow roll out and resisters the virus was able to find new hosts and mutate to become vaccine evasive. Once the MRNA vaccine rolls out zero covid will be a thing of the past Plus, the vaccines on the list actually prevent the underlying illness unlike the Covid vaccine. The vaccine was 95 percent effective in preventing infection of the early version of covid, but was never tested on transmission to others. The vaccine was 95 percent effective in preventing infection for you of the early version of covid, but was never tested for how contagious you would be. The vaccine was 95 percent effective in preventing infection for you of the early version of covid, but was never tested for how contagious you would be. BBC News – India vaccine maker destroys 100 million doses of expired Covid jab.

Table 4.8 Summary of Vaccination Policy Tweets in ***Entity* + *Negative Sentiment*** View

Its quite simple – republicans listened to ex-game show hosts who told them to eat horse wormer & that covid was just a bad cold & to refuse the vaccine. Despite knowing the COVID vaccine I stop the spread of the virus, King County Executive is keeping the mandate in effect for employees and volunteers. Are you concerned about citizens who could of had a Covid vaccination but declined it for personal freedom reasons and subsequently died of Covid? The vaccine does prevent infection in some people (mostly helps w severity of disease) & also reduces the likelihood of long Covid in those who are vaccinated. The Flu vaccine only contains the Flu vaccine- and it is highly recommended this year as we look to be headed for a bad season. The vaccine lessened the severity of my illness and I am glad I didn't suffer anything other than a bad cold because I got jabbed - 3 times. Its sad thought that most future Covid deaths might result from the politically motivated vaccine deniers listening to the American affiliate of Russian State TV? Once the MRNA vaccine rolls out zero covid will be a thing of the past And- Will Covid vaccination stop transmission of the Covid virus? COVID-19 Vaccine Induced Myocarditis A Proven Cause of Death? The COVID vaccine has been proven to minimize the spread and severity of the deadly disease. BBC News - India vaccine maker destroys 100 million doses of expired Covid jab.

Table 4.9 Summary of Vaccination Policy Tweets in ***Distance*** View

I got the COVID bivalent shot in one arm and the flu quadrivalent vaccine in the other arm yesterday. Maybe I misunderstood- long covid by definition ate vaccine side effects. This tool was essential in how managed our COVID vaccination roll out and focus around equity and hard to reach areas. Before we had a vaccine, many cases of myocarditis in teens & athletes was documented after they contracted covid-19. Ill give you some history. You're now playing revisionist history here. Hendersonville-based company calling itself Med Choice LLC, offering handwritten medical waivers personally reviewed and signed by a licensed physician."$139 for a vaccine waiver because youre afraid of needles? UK provided 5 and up. Insightful talk by Dr. The pandemic was a step backward for Tuberculosis>30 vaccines for COVID in 3 years Only 1 TB vaccine since 1921 = BCG (and no vaccines to curb pulmonary transmissions) I would love to see a cure for cancer, but this is so clickbaity Vote Republican to stop this madness. I had a case of COVID before any vaccination against COVID was available (

Feb 2020). The children whom you injected with an emergency use authorized vaccine would not be eligible for any COVID vaccine in Denmark (limited to those aged Last booster knocked me on my arse too. Once the COVID pandemic became a political dog whistle we lost our best chance to control it. Earlier I saw a commercial on the in partnership with regarding the covid vaccine and boosters.

Table 4.10 Summary of Vaccination Policy Tweets in ***Distance*** **+** ***Negative Sentiment*** View

Maybe I misunderstood- long covid by definition ate vaccine side effects. Covid shots were never intended to stop the virus! Allegedly the Pfizer CEO admitted that the vaccine was never tested to prevent infection or stop the spread of COVID Why is the federal government hiding COVID injury data? Doctors rip basis of Surgeon General Ladapos latest anti-COVID vaccine advice Insightful talk by Dr. The pandemic was a step backward for Tuberculosis>30 vaccines for COVID in 3 years Only 1 TB vaccine since 1921 = BCG (and no vaccines to curb pulmonary transmissions) Unless emerg vaccine approval was threatened by effective conventional drugs. CDC caught using same PR firm as Pfizer and Moderna to boost health communication" during covid scamdemic Well they voted down funding to prepare for the next pandemic! If your COVID vaccine left you feeling terrible, it probably offered you better protection, new study suggests Last booster knocked me on my arse too. Once the COVID pandemic became a political dog whistle we lost our best chance to control it. This is an OAN news correspondent showing weird path slides and calling it vaccine sickness Tom Cotton is against vaccine mandates even when COVID-19 pandemic is raging and/or appearing in different variants in spite of such mandates having proven effective in preventing deaths while hospitalized. Trump won and you know it Fuck Pfizer Anthony Fauci belongs in prison Rachel Levine is a man COVID is the flu with a better PR budget Ned Segal, Parag Agrawal and Vijaya Gadde are now unemployed losers. How much money did government give Big Pharma for a half-baked, over-hyped Covid vaccine?

We present the summaries of the vaccination policy tweets posted where were posted in October 2022 in four different composed view perspectives, **Entity View, Entity + Negative Sentiment View, Distance View, Distance + Negative Sentiment View**, in **Table 4.7**, **Table 4.8**, **Table 4.9**, and **Table 4.10**, respectively. These different view summaries can help provide summaries of large social media dataset, and help readers to understand the voluminous posts in different and composed perspectives expressed by the social media users. Our summarization algorithms can summarize any input text in any length and generate summary in a customized length. In this case, each summary is 250±10 word long.

4.3 Public Health Policy Awareness

During the pandemic, many different types of government policies and measures were issued. Having an awareness of the rapidly changing government actions and policies during a public health crisis such as the COVID-19 pandemic may provide critical and useful information, at the right time, to citizens and businesses in terms of their obligations and their rights. There are websites, such as the IMF policy tracker [237], following economic policies by different country governments to limit the human and economic impact of the COVID-19 pandemic. This is a global country-wide policy tracker where all policies are listed as text. The municipal city government responses to COVID-19 have been shared through the NLC (National League of Cities) Local Action Tracker [238], which allows different city responses to be searched for and browsed. These tools provide the information needed for global and local leaders to manage the many pandemic-related issues. But textual legal policies are difficult to comprehend, and the comparative policy analysis across different cities or states is challenging.

To enhance public health policy awareness, we used the dataset of 5,295 pandemic-related policies or local actions in 23 distinct policy areas collected from the National League of Cities (NLC) and Bloomberg Philanthropies [238]. The policy analysis in **Figure 4.6** shows the distribution of different types of policies. Policies for Prevention/Flattening the Curve comprise the highest total policy count of 947. These include face covering, quarantine/self-isolation, social distancing, COVID-19 testing, ventilators, etc. The second-highest policy type is Government Operations, with a total count of 631, including policies related to emergency services operations, first responders, and frontline medical workers across the country, who continue to provide essential services combating the pandemic. The Housing policy category, with a total count of 521, was the third policy, and so on.

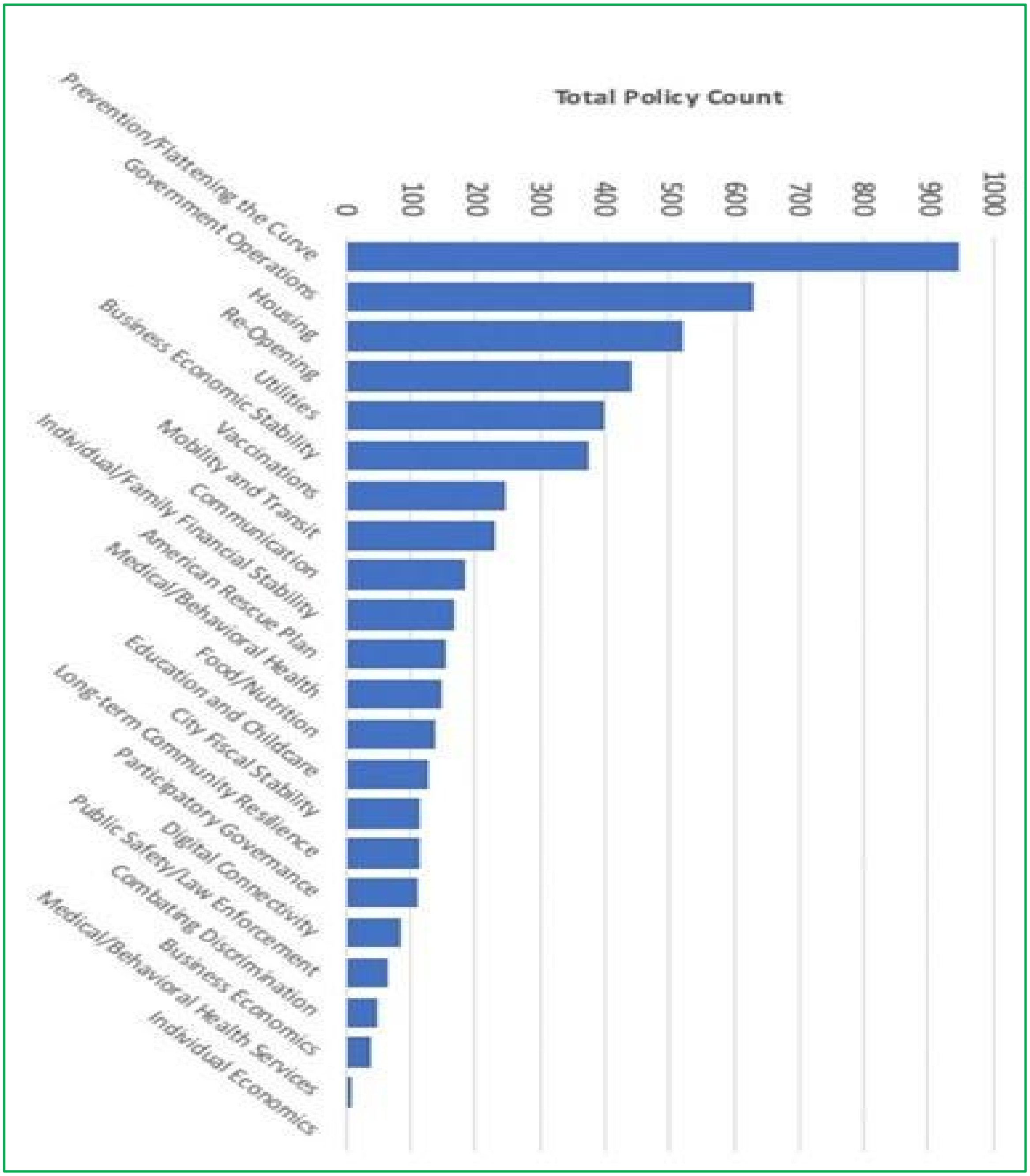


Figure 4.6 Public Health Policy types during COVID-19 Pandemic

4.3.1 Policy Mapping and Filtering

The policy tracking map implemented in [238] helps to browse local actions taken by cities around the country to respond to the pandemic. We have developed a prototype spatial browsing tool for policies in which the policies can be filtered by policy area, state, city, and action date, as shown in **Figure 4.7** and **Figure 4.8**. For example, the map in **Figure 4.7** shows the housing policy counts that were issued by each state, while the map in **Figure 4.8** shows the transportation/mobility-related policies by state. The two maps show that the transit and mobility policies are more prominent in NY (25 counts) compared to the housing policies (8 counts), while in California, there are more housing policies (128) than transit/mobility-related policies (38). The filtering by policy types shows the different policy emphases in different states to address local needs. The prototype spatial browsing tool we have developed is available at the platform site (http://ai4sg.njit.edu/ai4sg/PolicyMaps , accessed 28 Oct 2022).

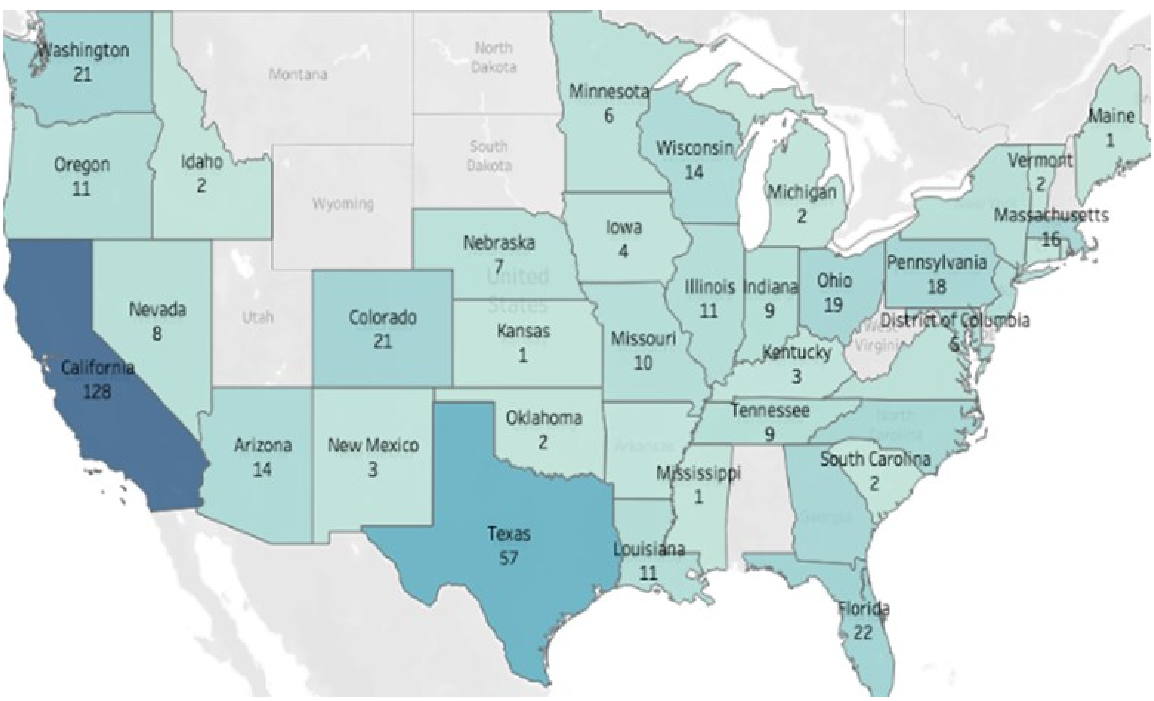


Figure 4.7 Housing Policy counts by State

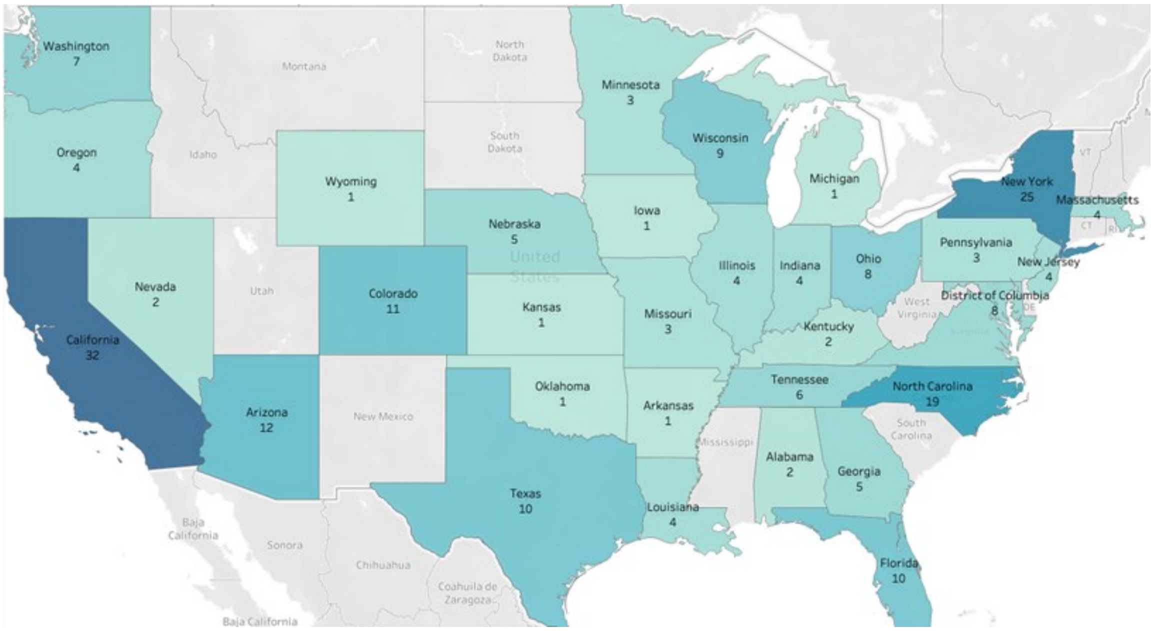


Figure 4.8 Transit/Mobility Policy counts by State

4.3.2 Policy Summarization Tool

Pandemic policies pose many challenges to the reader. As demonstrated in our study, there are many policies, and they are often expressed as long documents of legal text. To make it easier for the casual user to navigate this environment, we did a preliminary analysis of the usability of text summarization tools for health policies. To determine the most appropriate method to use, we conducted experiments with four existing pretrained text-summarization machine learning models. Specifically, we tested Bart using Pytorch [185], T5 using TensorFlow [186], Gensim with TextRank [200], and GPT-2 Transformers [192]. The result of our test runs on several text samples taken from our policy database were compared by members of our research group, and the agreement was that Bart and T5 summarization models produced the best summarization outcomes. Furthermore, based on our human evaluation, we did not discern a significant difference in the summarization quality between Bart using Pytorch and T5 using TensorFlow. Thus, we randomly chose to work with Bart to summarize the policy descriptions.

The summarization with Bart resulted in a compression rate of 0.6295. The compression rate was calculated as the total number of words of the summarized text divided by the total number of words of the original text. A compression rate equal to 0.6295 means there was an average 37.04% reduction of the original text size. **Table 4.11** shows examples of the summarization of policies by Bart and T5. These summaries are not intended for lawyers, who often need to argue about a single word in a legal text, but for quickly navigating an overwhelmingly complex patchwork of different government regulations.

Table 4.11 Policy Summarization Results with Original Policy Description

Original Policy Text	***Summarized Policy by Bart***	***Summarized Policy by T5***
Mayor Todd Gloria announced today that the state will provide more than $45.5 million in assistance for San Diego residents unable to pay rent due to the impacts of COVID-19. Together, this week's funding and the direct federal funding announced previously amounts to nearly $87.9 million in relief for families and individuals who've been devastated financially by the pandemic. This is on top of $13.75 million in emergency rental assistance that helped 3,717 San Diego households in 2020.	The state will provide more than $45.5 million in assistance for San Diego residents unable to pay rent due to the impacts of COVID-19 . This is on top of $13.75 million in emergency rental assistance that helped 3,717 San Diego households .	The state will provide more than $45.5 million in assistance for residents unable to pay rent . this is on top of $13.75 million in emergency rental assistance that helped 3,717 households in 2020.
In an effort to provide security and much-needed assistance for San Diegans struggling due to the ongoing COVID-19 pandemic, Mayor Todd Gloria announced today that the City will be making	Mayor Todd Gloria announced today that the City will be making more than $42 million in emergency rental assistance available to	San Diegans struggling due to ongoing COVID-19 pandemic will receive emergency rental assistance . mayor

more than $42 million in emergency rental assistance available to San Diego residents and that he will bring forward a proposal to extend eviction protections for renters and businesses to the City Council on Tuesday.	San Diego residents . Gloria will bring forward a proposal to extend eviction protections for renters and businesses to the City Council on Tuesday .	will bring forward proposal to extend eviction protections to the city council on Thursday.
Mayor Kevin L. Faulconer and San Diego Housing Commission (SDHC) President and CEO Richard C. Gentry today called for San Diego landlords to rent their units to San Diegans experiencing homelessness, including seniors and veterans, in an effort that builds on the successful Housing Our Heroes initiative. The call to action supports Operation Shelter to Home at the San Diego Convention Center, where case managers are working to find permanent housing for individuals experiencing homelessness. With more rental units, housing navigators at the convention center will have more options to match individuals most ready for independent living to a home.	Mayor Kevin L. Faulconer and SDHC President and CEO Richard C. Gentry call for San Diego landlords to rent their units to San Diegans experiencing homelessness . Housing navigators at the San Diego Convention Center will have more options to match individuals most ready for independent living to a home .	housing navigators' at the convention center will have more options to match individuals most ready for independent living to a home .
The emergency law temporarily halting evictions in the City of San Diego was passed unanimously and goes into effect immediately. It will last until May 31st. Tenants must demonstrate a substantial decrease in income or medical expenses caused by COVID-19 in order to qualify. It will not relieve a tenant of their requirement to pay rent or restrict a landlord from recovering rent at a future time.	Emergency law temporarily halting evictions in the City of San Diego was passed unanimously and goes into effect immediately . Tenants must demonstrate a substantial decrease in income or medical expenses caused by COVID-19.	the law temporarily halts evictions in the City of San Diego . it goes into effect immediately and will last until may 31st .

4.4 Discussion

Based on the results derived from our experiments on public health policy concern tracking between August 2020 and March 2021, we have discovered a number of findings, which include:

i. The levels of citizens' concerns about the disease itself appear higher than the levels of concern about individual policies throughout the period of investigation. As shown in **Figure 4.2**, among all the policies, "Ventilators" engendered the highest concern level at 0.77, except for COVID-19 (General) at 0.84. The concern level about Ventilators was relatively high in two periods throughout the time of the study. One was between August and September 2020, when the COVID death cases were on the rise. The second peak was in January 2021, after the holiday season was over, with surging infections and deaths. The Face Coverings policy was associated with a concern level of 0.64. Its concern levels were the lowest and the only one under 0.7 throughout the period, despite the mask shortage in the early stages of the pandemic [239]. This result implies that citizens might not have cared much about wearing masks. Besides, the concern level trend of Economic Impact remained fairly stable but relatively higher among all individual policies. Many industries were impacted during this period. The recreational sector especially registered high job losses [240], as citizens would reduce the frequency of traveling or going out to avoid becoming infected.

ii. By comparing the concern levels in the first week with those in the last week of our date range, we found that the concern levels about policies concerning Economic Impact, COVID-19 (General), Face Coverings, Quarantine, School Closing, and Testing exhibited negative changes, while Business Closing, Contact Tracing, Social Distancing, and Ventilators showed positive changes. Except for Business Closing, these changes are all statistically significant. This finding implied that citizens might have adapted to a new normal, even with rising case numbers [241] amid the pandemic.

iii. While the trend of case numbers of infections and deaths showed notable fluctuations, the concern level of COVID-19 (General) stayed relatively constant throughout the study period. In other words, no meaningful correlation between the progress of the pandemic and the levels of citizens' concern was identified.

iv. We expected to see a geographic distribution of concerns that reflects the political divide of the country. However, we were not able to confirm this.

The characteristic of capturing sophisticated features made the Stanford Sentiment Analyzer a strong candidate for our sentiment analysis. However, no analysis tool is perfect. A limitation of the Stanford Sentiment Analyzer is that it lacks multipolarity analysis. An input phrase might express multiple polarities based on different aspects mentioned in a post. If we obtain only one composed result of several expressed sentiments, this could be misleading. For example, the phrase "This restaurant provides excellent food but poor service" expresses a positive sentiment about the food but a negative sentiment about the service. Currently, we are working on a novel sentiment analysis algorithm that reports multiple polarities when an input phrase discusses multiple aspects with different sentiments.

Our built Public Health Policy Perception Monitoring and Awareness Platform overcomes challenges in prior works and extends our preliminary study [242] with capabilities of continuous monitoring of citizen perceptions of health policies to serve as an indirect indicator of measuring the impact and potential acceptance or resistance of health-related policies. **Table 4.12** shows improvements carried out in our work.

Table 4.12 Our Improvements to Prior Limitations

Limitations in Prior Studies	**Our improvements**
Prior work focused on single policy in a fixed dataset.	We work with 10 different policies and continuously collected data.
Prior work was limited to concern tracking using perceived sentiments towards the disease itself.	We focus not only on the concerns about the disease, but also on the citizens' perceptions and attitudes towards the government policies regarding the COVID-19 pandemic.
Prior work conducted survey-based research, which is naturally limited in data points and delayed in availability.	We collect data and generate analysis results daily in a near real time manner, and show on our web dashboard.
Prior work did not provide details about citizens' reactions to policies in time and space.	We continuously collect tweets for analyzing and understanding citizens' concerns toward disease and government actions in both geographical and temporal manner.
Prior work used lexicon-based sentiment tool, which considers sentiment by bag of word representation but ignores the context of the phrase.	We utilize a fine-tuned sentiment analysis tool that generates sentiment values that are a composition of each word's meaning and input phrase structure.
It provides a policy specific portal to understand policy details.	Our platform provides the aggregated policies of different local measures and analyzes them to compare across cities or states.
Each policy text is presented as issued.	Each policy text can be accessed as a summarized text for enhancing the content understanding.

Besides this, we have also achieved several novel breakthroughs in our work. The generated results from the continuous monitoring data and analyses can help governments and citizens get insights to adapt to a "new normal" in a post-pandemic era. The correlation between policy concern levels and pandemic progress statistics helps citizens to understand if or how life is impacted. Our system allows us to quickly retrieve and access the results for a desired period. For example, one can examine the previous holiday seasons' results to better prepare for the upcoming holiday seasons. It is possible to quickly extend our work when a new relevant government policy is issued. Users of our system can rapidly react and apply our work to novel pandemics or similar urgent situations occurring in the future.

Our study also has some limitations. First, the datasets are collected with static policy sets. If a new public health issue emerges, the system needs the ability to dynamically choose the policies for which tweets are collected (e.g., add a new user-selected policy) to monitor it. Second, the collected data is limited to the US. Third, the concern levels depend on the sentiment analysis results, which are not perfect. We used the Stanford Sentiment Analyzer, which has the highest accuracy among alternative tools but with lower human agreement scores compared with other approaches. Thus, there is a great deal of uncertainty in the sentiment associated with the tweets. Any system that relies on the currently available sentiment analysis tools would be subject to this kind of uncertainty due to the technical limitations and human subject variabilities. An important theoretical implication of this research is that refined measures for concern levels could be introduced, e.g., weighted and/or relative measures, as was hinted in subsection 4.2.3. Such an analysis goes beyond the scope of this dissertation. The most important practical implication is that near-real-time monitoring and processing of re-actions to policies is possible and provides a powerful capability that goes beyond what is publicly available at the current time.

CHAPTER 5

MULTIPLE VIEW-BASED SUMMARIZATION OF SOCIAL MEDIA

In recent years, microblogging sites, such as Twitter, Facebook, Reddit, etc. have become major news sources. They provide abundant information about current topics and events. Thousands of posts are shared every second. When a user desires to investigate one specific topic, it is usually not feasible due to the large numbers of posts. Besides, posts show different biases, viewpoints, perspectives, and emotions. People tend to follow certain groups with a similar viewpoint or perspective, creating the phenomenon of echo chamber or information isolation.

To address the social media's overwhelmingly large volume of posts, content echo-chamber, and information isolation issue, this dissertation provides a multiple view-based summarization framework (MVSF) where the same social media contents can be summarized according to different group's perspectives. This framework includes components of choosing the perspectives, and advanced text summarization approaches as shown in the MVSF architecture (**Figure 5.1**).

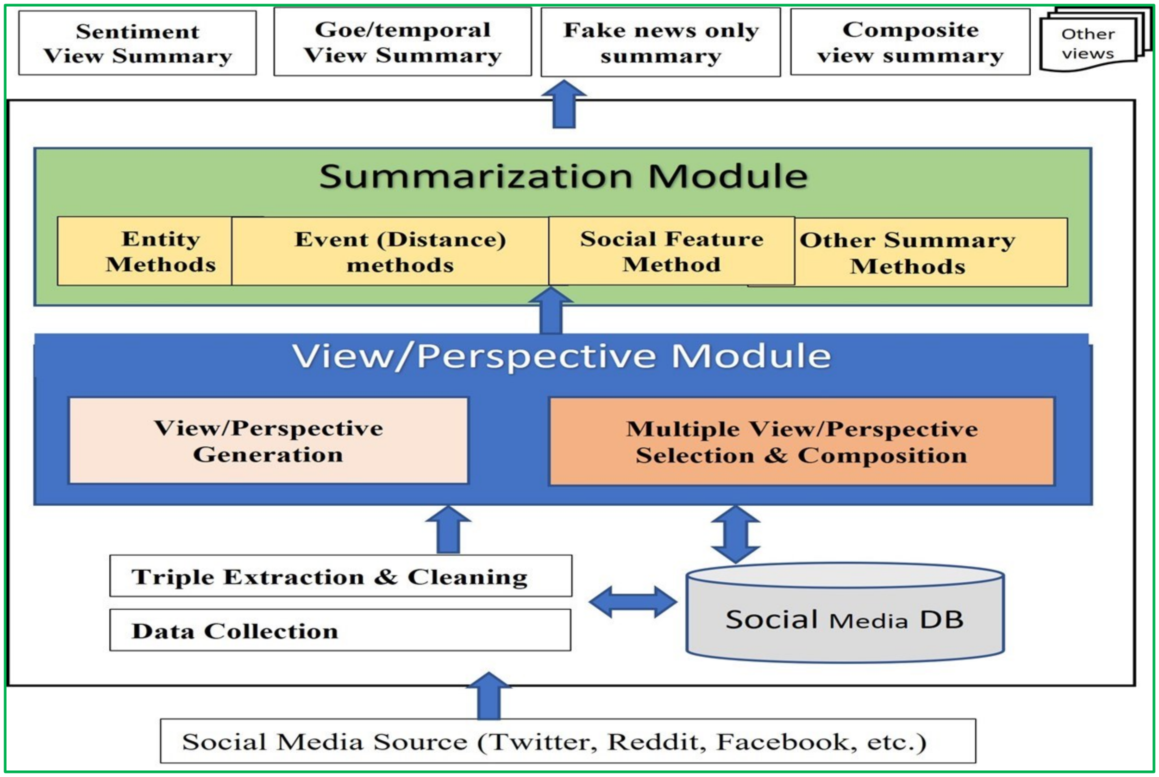


Figure 5.1 Multiple View Summarization Framework (MVSF)

Summaries using different views/perspectives can be easily compared to understand different groups' perspectives without just consuming only contents of similar perspectives. Social media posts from different users, time, or locations may carry different biases, viewpoints, perspectives, and emotions. Therefore, the proposed multiple view summarization framework allows users to select different views and different summarization models, and to be able to combine them to generate unique fine-grained summaries.

For the microblogging summarization, we proposed three different summarization methods: 1) Entity-centered summarization, 2) Social feature-oriented (follower count and retweet count) summarization, 3) Distance-based (triple-based event) summarization, computed using the Euclidian distance from the center of all triple embeddings.

(Embeddings are computed with BERT). For different perspective taking, or views, we consider views by (i) Sentiment, (ii) Geo-location, (iii) Timeline. The power lies in the view composition component where different views can be composed to provide fine-grained summaries. For instance, the summarization can be made from the perspectives of combined negative views from NY State, or fake news view with positive sentiments only during December 2020, etc. In this Chapter, we provide three proposed microblogging summarization algorithms, and compare their performance with other summarization approaches existing in the literature, e.g., BertSum, SBert, etc. Our results were shown to be better than these published extractive and abstractive summarization models, using Rouge Scores. We apply the MVSF-based multiple view summarization approach to a set of COVID-19 vaccine related Twitter posts, and show the different views of the same dataset.

5.1 Multiple View Summarization

Our multiple view summarization components shown in **Figure 5.1** is introduced in this section. Social media posts cover divergent and conflicting aspects (views or perspectives) by different users, even on a particular topic or event (e.g., elections, pandemics, disasters, etc.). Some users post messages expressing reactions to public policies, others comment on election results, etc. For infectious diseases, fears concerning disease spread or users' experiences with symptoms may be expressed. Our multiple view summarization framework addresses these diverse aspects of Twitter users that need to be reflected in the summarization results. The same social media dataset on one particular topic can be summarized by multiple summaries according to the different perspectives, which we call views. The architecture of our multiple view summarization framework is in **Figure 5.1**.

5.1.1 Data Collection, Cleaning and Triple Extraction

Microblogging sites, such as Twitter, are used for data collection on a particular topic. We first apply standard text-preprocessing to clean the dataset. Social media users are often more interested in tweets that describe events or activities [243]. Therefore, we focus on <SPO> triples describing events or activities. We used the Stanford Open IE model [245] to extract <SPO> knowledge triples from sentences. Their classifier splits a sentence into a set of logically entailed shorter clauses. The algorithm predicts at each step whether an edge should yield a new independent clause [246]. To achieve a unified text representation, we lowercased each extracted triple.

5.2 Perspective Taking Analytics

In this section, we describe the process of discovering each different perspective or view that can be individually applied and/or combined together to be included in summaries. Throughout the view(s), we can obtain summaries of different perspectives expressed from the same dataset of social media posts.

5.2.1 Sentiment View Summarization

Each social media post can be analyzed with the perspective of the sentiment expressed. This Sentiment-based Summarization view (S) looks for triples expressing a certain sentiment (e.g., negative/positive/neutral). We applied the Sentiment Analyzer mentioned in **section 3.1.1.4** on each input post. We can choose to focus only on the triples with a specific sentiment, for example, a summary of negative sentiment towards a mandatory policy during the COVID-19 pandemic.

5.2.2 Fake News View Summarization

As we presented in **Chapter 3**, social media platforms have been flooded with fake news, which confused citizens, and caused conflicts, by limiting them from accessing authentic information. Therefore, it would be beneficial to summarize the large amount of fake news items and obtain a readable summary to realize what the fake news is about to contain the spread of fake news. To achieve this, we can apply the fake news detection models to the social media posts and collect those labelled as fake news for this fake news-view (F) summarization.

5.2.3 Political View Summarization

The Political View-based Summarization view allows users to obtain readable summaries based on the political types, e.g., Left-Wing, or Right-Wing. Normally left-wing and right-wing would have opposite opinions on the posts of the same topic, e.g., gun-control, abortion, etc. This summarization view can provide readers with a readable summary based on the selected political type of the social media posts. This view summarization can be achieved by training a binary detection model to distinguish between the political alignments of posts.

5.2.4 Temporal View Summarization

The Temporal View-based Summarization view (T) focuses on triples in a temporal manner. This view can be discovered based on the timeline information of posts. This view would allow users to obtain the summary based on a specific time period. Besides, this view allows users to read and compare summaries in different periods for an ongoing event, e.g., the summary of government' lockdown policy in the beginning of the COVID-19 pandemic vs. the lockdown policy 6 months after the pandemic outbreak, which could be used to evaluate the effectiveness of the policy and the progress of the pandemic.

5.2.5 Geolocation View Summarization

The Geolocation-based Summarization view (G) focuses on triples in a geographical manner, and generates summary based on specific locations, or in different administrative level, such as country, state/province, county, city, borough, etc. Therefore, this view can provide readers with a summary of a desired area, or let users compare the summaries of the same government policy but in different state locations. This view can be discovered based on geographical location information of posts or user profile information.

5.2.6 View Composition

In previous subsections, we discussed a number of available views that can be applied to form different summaries of the same dataset posts. The views can be used individually to obtain the summaries, respectively. In addition, our framework provides the flexibility to combine the different views to create more focused summaries. Therefore, for a dataset, our framework can generate summaries based on each view respectively, selected views combined, or all views combined. For example, we can generate a summary of left-wing and negative sentiment fake news during an election period in California.

5.3 Our Microblogging Summarization Methods

5.3.1 Entity-based Summarization

In Entity-based Summarization (E), the entities define the primary people or subjects for obtaining summaries. Unlike other research where the user provides the entities of interest (e.g., "JF Kennedy"), we start with social media data mentioning a vast number of entities, and have to discover the most interesting or prominent entities mentioned in the microblogging posts, coming from large group of people distributed from the globe.

Important entities can appear in different events, marked by different predicates/actions. Thus, we identify predicates expressing similar/identical meanings with different words, such as "offer," "offered," "provide," and "provided," all of which express a similar meaning of "giving something to someone." Groups of semantically similar verbs can be subsumed by one root verb, using the appropriate synset from WordNet [157]. A synset is a set of one or more synonyms. A word might have multiple meanings and appear in different synsets. We identified the frequent events by selecting triples whose root verbs occur more often than a threshold θ. Given a triple set TS= {ts1, ts2, …} where tsi= (s, p, o), find tsi= (s, root(p), o). We select triples that have frequent root verbs root(p). Then the second task in this view is to identify important entities to focus on. Each triple includes two entities, a subject, and an object. To identify the best summary, we experimented with assigning different weights (α) to the subjects and objects. We select the top-scoring $\mathbf{m_E}$ triples and the corresponding original sentences. We present the pseudo code that calculates subject scores and object scores in **Table 5.1**.

$$\boldsymbol{TripleScore} = \alpha * (Subject\ Score) + (1 - \alpha) * (Object\ Score) \qquad \text{Equation (5.1)}$$

and α ∈ [0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0]

Table 5.1 Pseudo Code to Count the Subject Score and Object Score for Each Subject and Object respectively in Triple Set.

```
subjectWord = [ ] // a list that collects all words in triple subjects
objectWord = [ ] // a list that collects all words in triple objects

for each subject s, object o, triple t in triple set ST: // s is the subject of triple t in ST,
                                                          // o is the object of triple t in ST
        subjectWord.extend (s.split(" "))
        objectWord.extend (o.split(" "))

for each word x in subjectWord:
        label x with an integer score of its frequency in subjectWord

for each word y in objectWord:
        label y with an integer score of its frequency in objectWord

for each subject s, object o, triple t in triple set ST: // s is the subject of triple t in ST,
                                                          // o is the object of triple t in ST
        Subject Score of s = highest score of the word in s
        Object Score of o = highest score of the word in o
```

5.3.1.1 Entity-based Summarization View Process We will focus on details of Entity summarization in this subsection. For triples using verbs expressing similar/identical meanings with different words or tense forms, we replaced the verbs as follows. We lemmatized each verb and used WordNet to find its root verb synset. A word might have multiple meanings, and each synset expresses a meaning. For example, the meaning of the word "die" is different when applied to a human, a computer, or a star in the Milky Way. To disambiguate the meaning of a predicate and find the closest synsets, we compared two methods and used a human evaluator to determine the better one. The first method is the Lesk algorithm [247]. Given a verb and the triple where it occurs, Lesk returns a synset that represents the meaning in its context. However, Lesk often failed at finding the correct synset. Among a set of 80 randomly picked triples, only 37 verb synsets were correctly identified. The second method was that we selected "v.01" (primary meaning) as the synset for each verb and use human evaluation. Even though this is a simple approach, it produced a better result. Therefore, we used the “v.01” meaning for each verb to find the root synset. For each verb synset vx.v.01, we identified its hypernym (superclass) chain until reaching the root. We present the program to identify the synset hierarchy in **Figure 5.2**, and an example synset hierarchy in **Figure 5.3** where all verbs are be summarized by “transfer.” If a root verb occurs fewer times than a threshold, then all corresponding triples are deleted.

```
highestSuperclass = [ ]

for v in tripleVerb:
   currentV = v + ’.v.01’ // we apply v.01 (most natural) synset to all triple verbs

   while ( len(wordNet.synset(currentV).hypernyms())==1 ):
      currentV = wordNet.synset(currentV).hypernyms() //replace current synset with its direct superclass synset

   highestSuperclass.append(currentV)
```

Figure 5.2 Pseudo code to find the root verb synset by using WordNet.

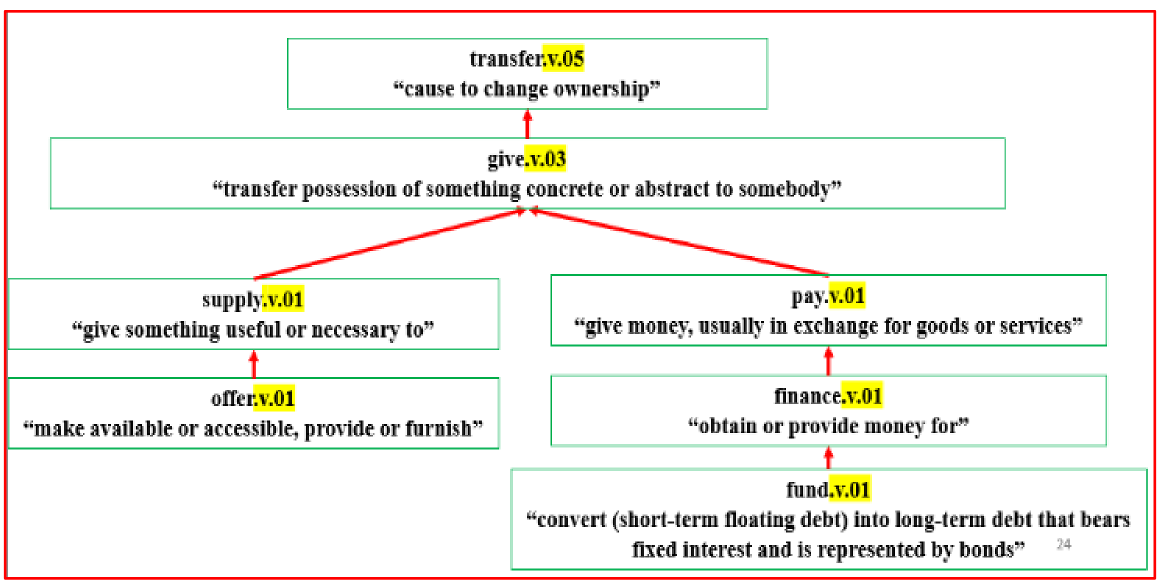


Figure 5.3 All verbs are summarized by "transfer.”

The Entity-based summarization is based on the entities (subject/object) that occur most often in the triple sets. To identify the frequencies of meaningful words, we first removed numbers, stop words, and words with fewer than three characters. Next, we lemmatized each word. If a pre-processed subject or object becomes an empty string, we remove the whole triple. If a pre-processed subject consisted of more than two words, we removed all except for the last two words.

We labelled each subject with its frequency in the triple set. If there are two words in a subject, we obtained the subject score from the word with the higher frequency. If there are 77 occurrences of "covid" and 100 of "vaccine," then the subject score of "covid" is 77 and of "vaccine" is 100, and for "covid vaccine" it is also 100. We apply the same method to objects to obtain object scores. The preprocessing and score calculation of triple entities is shown in **Table 5.2**.

Table 5.2 Pseudo Code of Preprocessing and Score Calculation of Triple Entities

```
def preprocess (entity):
        entity = remove stop words and numbers from entity
        if (length of entity) < three characters:
                entity = empty string
        entity = lemmatization (entity)
        return entity

subjectWord = [ ] // a list that collects all words in triple subjects
objectWord = [ ] // a list that collects all words in triple objects

for each subject s, object o, triple t in triple set ST: // s is the subject of triple t in ST,
                                                       // o is the object of triple t in ST
        s = preprocess (s)
        o = preprocess (o)
        if s == empty string or o == empty string:
                remove t from ST

        s = s.split(" ")[:-2] // if s have more than two words,
                            // remove all except for the last two words


        subjectWord.extend (s.split(" "))
        objectWord.extend (o.split(" "))
```

```
for each word x in subjectWord:
        label x with an integer score of its frequency in subjectWord

for each word y in objectWord:
        label y with an integer score of its frequency in objectWord

for each subject s, object o, triple t in triple set ST: // s is the subject of triple t in ST,
                                                          // o is the object of triple t in ST
        Subject Score of s = highest score of the word in s
        Object Score of o = highest score of the word in o
```

5.3.2 Triple Distance-based Summarization

In the Triple Distance-based Summarization view (D), we represent the meaning of a triple sentence. To create sentence representations, we use the embeddings of each word, based on which we calculate the embeddings of the whole sentence. We use BERT [11] sentence embeddings. BERT reads the entire input sequence of words at one time. This characteristic allows BERT to learn the contextual information of each word based on its neighbor (left and right) words. We then used an autoencoder [118], to learn a 32-dimensional vector representation of each triple. This ensures that we achieve a lower dimensional representation of the information [204]. Instead of focusing on specific entities, we produced a summary based on important contextual information conveyed by the whole triples. We identified the centroid, which is the average of all triple vectors in the cleaned triple set (see Cleaning Process in subsection 5.5.4). For each triple t, its vector representation v is:

$v_t = [v_{t1}, v_{t2}, v_{t3}, \ldots, v_{t32}]$ Equation (5.2)

The centroid vector vc of all triple vectors is:

$v_c = \frac{1}{n}(\sum_{t=1}^{n} v_t) = [v_{c1}, v_{c2}, v_{c3}, \ldots, v_{c32}]$ Equation (5.3)

where n is the triple count.

The Euclidean distance d from a triple t to the centroid c is:

$\boldsymbol{d}_{tc} = sqrt(\sum_{i=1}^{32} (v_{ti} - v_{ci})^2)$ Equation (5.4)

We selected $\mathbf{m_{SD}}$ triples with the shortest distances to the centroid c. The original sentences corresponding to the selected triples were recovered to form the summary.

5.3.3 Social Feature-based Summarization

In the Social Feature-based Summarization (SF) view, we exploit the social network signals (i.e., user's followers, retweet count) to identify the saliences of tweets. (Liu et al. 2012) [243] stated that a tweet is more important if (1) it has been retweeted many times, and (2) it is posted by a user with many followers. They defined the salience score of a tweet as the multiplication of retweet count, user follower count and readability. Our goal is to identify summaries with social prominence on social media. Thus, we modified the formula and defined the salience score of a tweet:

$$\boldsymbol{Salience\ Score} = \begin{cases} follower + retweet * 707, & follower > 0 \\ 0, & follower = 0 \end{cases}$$ Equation (5.5)

where 707 is the average number of followers of a user on Twitter [244]. When a post is retweeted, there will be on average 707 people who will see it. We rank triples based on the scores of their original tweets, and select the $\mathbf{m_{SF}}$ top-scoring triples. The corresponding original sentences of the triples are selected to form the summary.

5.4 Evaluation of Microblogging Summarization Methods

In order to evaluate our microblogging summarizations methods, and multiple view summarizations, we compared them with the summaries generated by extractive and abstractive summarization models from the literature. Extractive models are BertSum [193] and SBert [194], which are variants of BERT that we used in one of the views. Abstractive summarization models are bart-large-cnn [185] and T5 [186], which according to [15], generate better summaries compared with TextRank [200] and GPT-2 [192]. To our knowledge, there is no gold standard social media dataset with corresponding summaries for evaluating the summary performance. To work around this, we used a dataset of BBC news items [248] with their human-generated summaries for performance evaluation.

The BBC dataset contains 2,225 news documents, covering five categories (business, entertainment, sport, politics, tech). Each document is paired with an extractive human summary. In this experiment, we selected 20 news documents from the business category. As this dataset doesn't have social signals, geolocations, timelines, we could not apply the SF view, G view nor T view.

Each of the generated summaries is approximately 300 words long, which applies to our methods and the published models. We used Rouge scores as the evaluation metrics, which compare a (model/method view) summary against a gold standard summary, in 1-gram, 2-gram, and longest common subsequence (LCS) units.

All of our view summaries perform better than those by the models shown in **Table 5.3**. The view (S+D) performed best with the highest score for 1-gram and LCS, while the view (D) performed best for 2-gram. Both view (E) and (S+E) achieve the best performances when α = 0.7. This result shows that the text summaries generated by our views are more consistent with the gold standard summaries than existing models. We show the Rogue scores for each α value of view (E) and view (S+E) in **Table 5.4** and **Table 5.5**, respectively.

We observed that the summaries are notably different, especially between view E and view D. Either with or without view S, there is **NO** overlapping sentence between view E and view D. There are **two** sentences common in D and S+D, and **three** sentences common in view E and view S+E.

Table 5.3 Rouge Scores of Summarization Models

Rouge Score	1-gram	2-gram	LCS
View (E), α = 0.7	0.465	0.310	0.444
View (D)	0.557	**0.427**	0.551
View (S+D)	**0.58**	0.416	**0.572**
View (S+E), α = 0.7	0.459	0.299	0.433
BertSum	0.406	0.174	0.394
SBert	0.444	0.152	0.428
bart-large-cnn	0.402	0.150	0.394
T5	0.304	0.104	0.304

Table 5.4 Rouge Scores of Summaries of View (E) with Different α

Rouge Score	1-gram	2-gram	LCS
α = 0.0 (0.0*subject score + 1.0*object score)	0.410	0.230	0.394
α = 0.1 (0.1*subject score + 0.9*object score)	0.414	0.235	0.406
α = 0.2 (0.2*subject score + 0.8*object score)	0.441	0.268	0.417
α = 0.3 (0.3*subject score + 0.7*object score)	0.451	0.287	0.428
α = 0.4 (0.4*subject score + 0.6*object score)	0.443	0.271	0.420
α = 0.5 (0.5*subject score + 0.5*object score)	0.453	0.291	0.430
α = 0.6 (0.6*subject score + 0.4*object score)	0.461	0.301	0.433
α = 0.7 (0.7*subject score + 0.3*object score)	**0.465**	**0.310**	**0.444**
α = 0.8 (0.8*subject score + 0.2*object score)	0.450	0.285	0.425

α = 0.9 (0.9*subject score + 0.1*object score)	0.431	0.259	0.407
α = 1.0 (1.0*subject score + 0.0*object score)	0.455	0.297	0.430

Table 5.5 Rouge Scores of Summaries of View (S+E) with Different α

Rouge Score	1-gram	2-gram	LCS
α = 0.0 (0.0*subject score + 1.0*object score)	0.459	0.298	0.431
α = 0.1 (0.1*subject score + 0.9*object score)	0.455	0.295	0.430
α = 0.2 (0.2*subject score + 0.8*object score)	0.454	0.294	0.429
α = 0.3 (0.3*subject score + 0.7*object score)	0.455	0.295	0.430
α = 0.4 (0.4*subject score + 0.6*object score)	0.453	0.291	0.426
α = 0.5 (0.5*subject score + 0.5*object score)	0.452	0.291	0.426
α = 0.6 (0.6*subject score + 0.4*object score)	0.457	0.297	0.431
α = 0.7 (0.7*subject score + 0.3*object score)	**0.459**	**0.299**	**0.433**
α = 0.8 (0.8*subject score + 0.2*object score)	0.440	0.285	0.418
α = 0.9 (0.9*subject score + 0.1*object score)	0.435	0.265	0.413
α = 1.0 (1.0*subject score + 0.0*object score)	0.431	0.261	0.408

5.5 Application of MVSF Approaches towards COVID-19 Vaccine Tweet Summarization

In this section, we apply our summarization framework to a dataset of COVID-19 Vaccine Tweet as a case study.

5.5.1 Data

We used a dataset [249] of 18,047 tweets about the COVID vaccines Pfizer/BioNTech, Sinopharm, Sinovac, Moderna, Oxford/AstraZeneca (AZ), Covaxin, and Sputnik V. We identified the vaccine types by the hashtags in the posts.

This dataset contains social features, geographical and temporal information. Therefore, besides view (S), the summarization distinguished by view (G) and view (T) can be used in combination with view (E), view (SF), view (D) based summarization as well.

5.5.2 Preprocessing on Geographical Information

For each string value, either non-empty or empty, in column **"user_loc"** in the dataset **(Figure 5.4)**, which represent the users' locations on profile, we first used a Python library, ***GoogleTranslator*** [250] translate non-English string to English, e.g., ***"Trkiye"*** to ***"Turkey."*** Then we used a Python library, ***geopy*** [251] to identify the location information, and the administrative level same and above the location. For example, for ***"Mumbai, India,"*** we will obtain ***"Mumbai, Mumbai Suburban, Maharashtra, India."*** Therefore, when a city information is identified, the county, state/province, and country of the city will be altogether retrieved.

user_loc
Egypt
London, England
Mumbai, India
Trkiye

Figure 5.4 User location information in the data set.

5.5.3 Text Preprocessing

We performed text preprocessing, which includes removing the non-ASCII codes, URLs, redundant spaces, and punctuation. We assigned to each post an integer *post index*, starting from 0. Next, we performed sentence tokenization [252] to split posts into sentences, because a post may contain multiple sentences. We assigned to each sentence an integer *sentence index* (typically between 0 and 3). It is beneficial to work with post fragments (sentences) rather than entire posts [205]. This sentence tokenization is used for tracing back to the corresponding original sentences from the selected knowledge triples. **Table 5.6** shows an example of a processed post with two sentences. We obtained 28,242 sentences from 18,047 posts.

Table 5.6 A Post with Two Sentences in the Dataset

post index	post text	sentence index	sentence text
484	A shipment of Sputnik V vaccine arrived in Vietnam. The handover ceremony took place at Noi Bai airport.	0	A shipment of Sputnik V vaccine arrived in Vietnam.
		1	The handover ceremony took place at Noi Bai airport.

5.5.4 Triple Extraction and Cleaning Process

Using triple extraction methods (OpenIE) [245] from the Stanford CoreNLP package [253], we extracted 101,432 triples, and linked them to their sentence and post indices (**Table 5.7**).

Table 5.7 Extracted Triples and Index Labels

post index	sentence index	triple index	subject	verb	Object
484	0	0	shipment	arrived in	vietnam
484	1	0	handover ceremony	took place at	noi bai aiport

We then discuss our "semantic" cleaning and summarization process. We removed triples where "be," or "have" and their tense forms are the verbs, as these are auxiliary verbs that carry little meaning. This reduced the triple set from 101,432 down to 67,049 elements. There were duplicate triples derived from the same sentence, but with different lengths (**Figure 5.5**). To deal with this issue, for triples from the same post, same sentence, and with the same verb, we eliminated all but the one triple that retains the most details (words) of the sentence. This reduced the triple set down to 16,270, which is the input for each summarization method.

subject	relation	object	word
argentinas drug regulator	approved	use for children	7
argentinas drug regulator	approved	use	5
argentinas drug regulator	approved	use of sinopharm coronavirus vaccine for children	11
argentinas drug regulator	approved	use of sinopharm coronavirus vaccine	9

Figure 5.5 Remove Redundant Triples. All except for the one with the most words (highlight) are removed.

5.5.5 Experimental Results

We present our experimental results of summarization in two parts. One is using the proposed summarization methods, Entity (E), Distance (D), and Social-Feature (SF) without perspective taking. The other one is taking Geographical Perspective (G) and combining with methods (E), (D) or (SF), and generating summaries in composed View (G+E), View (G+D) and View (G+SF) based in the United States of America, along with different administrative levels.

5.5.5.1 Summaries of Our Proposed Summarization Methods As opposed to geographical perspective in **5.5.5.2 USA-based Summary**, here we don't perform any view/perspective filtering. Therefore, in this summarization, we use all the 16,270 triples (from the previous subsection) extracted from posts whose "*user_loc"* columns (**subsection 5.5.2**) are either non-empty or empty.

We show the knowledge graph [218] summarization of the summary triples in view (E) in **Figure 5.6**. The size of each node is proportional to its degree. The color of an edge expresses the sentiment expressed from the triple, red (1) for "Negative," yellow (2) for

“Neutral,” and green (3) for “Positive.” The rule of sentiment integer index applies to the sentiment columns in coming tables, (1) for “Negative,” (2) for “Neutral,” and (3) for “Positive.”. A node with a higher degree is larger than the one with a lower degree. The thickness of an edge represents its ranking. The thicker an edge is, the higher ranking (i.e., higher (triple/salience) score, shorter distance to the centroid) the triple is in the summary set. Therefore, from the triple set (after subject/object preprocessing) in view (E), we selected the top-scoring $\mathbf{m_E}$ triples with their corresponding sentences, such that the total number of words in the sentences was approximately 300. The details of summary triples of this view are in **Table 5.8**. The corresponding original sentences of summary triples are shown **Table 5.9**.

For views (D) and (SF), we generated summaries from 16,270 triples (after Cleaning Process of Extracted Triples). The goal was again to retain $\mathbf{m_{SD}}$ and $\mathbf{m_{SF}}$ top-ranking triples to generate ~300-word readable summaries. The triple knowledge graphs of view (D) and view (SF) are in **Figure 5.7** and **Figure 5.8**, respectively. The summary details are in **Table 5.10** and **Table 5.12**, and corresponding original sentences of summary triples are in **Table 5.11** and **Table 5.13**, respectively.

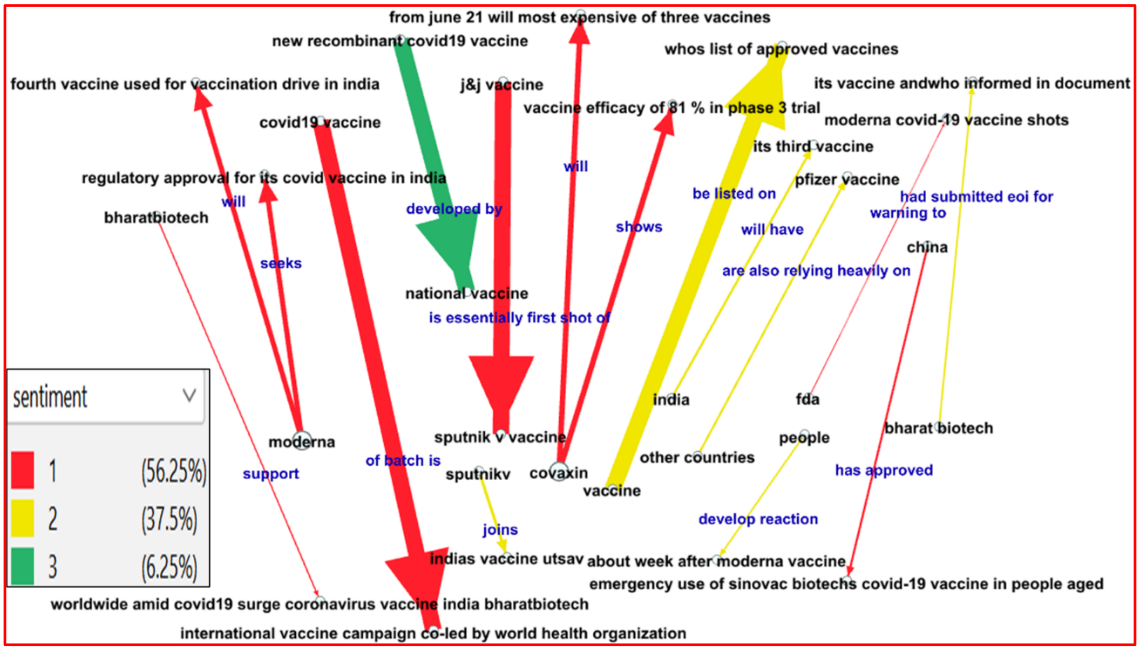


Figure 5.6 Knowledge Graph Visualization of Summary Triples of View (E)

Table 5.8 Summary Triples of View (E), Their Triple Scores, Sentiments, and Vaccines Mentioned, in Ranking Order

tripleS	sentiment	tripleScore	vaccine
j&j vaccine is essentially first shot of sputnik v vaccine	1	1646	sputnik
new recombinant covid19 vaccine developed by national vaccine	3	1646	sinopharm
covid19 vaccine of batch is international vaccine campaign co-led by world health organization	1	1646	sinopharm
vaccine be listed on whos list of approved vaccines	2	1646	covaxin
covaxin shows vaccine efficacy of 81 % in phase 3 trial	1	1153.2	covaxin
covaxin will from june 21 will most expensive of three vaccines	1	1153.2	covaxin
moderna seeks regulatory approval for its covid vaccine in india	1	1129.4	moderna
moderna will fourth vaccine used for vaccination drive in india	1	1129.4	moderna
sputnikv joins indias vaccine utsav	2	1028.6	sputnik
india will have its third vaccine	2	1002.7	sputnik
china has approved emergency use of sinovac biotechs covid-19 vaccine in people aged	1	999.2	sinovac
other countries are also relying heavily on pfizer vaccine	2	994.3	pfizer
bharat biotech had submitted eoi for its vaccine andwho informed in document	2	978.2	covaxin
people develop reaction about week after moderna vaccine	2	974	moderna
bharatbiotech support worldwide amid covid19 surge coronavirus vaccine india bharatbiotech	1	962.8	covaxin
fda warning to moderna covid-19 vaccine shots	1	939.7	moderna pfizer

Table 5.9 Summary Sentence Text of View (E), in Temporal Order

Other countries in the Middle East, including Saudi Arabia, Qatar, Kuwait, and Oman, are also relying heavily on the Pfizer vaccine, developed by the US company PfizerVaccine. This is also another validation of Sputnik V pioneering technology as J&J vaccine is essentially a first shot of Sputnik V vaccine (Ad 26 - human adenoviral vector 26). Covaxin shows vaccine efficacy of 81% in phase 3 trial. About a week after the Moderna vaccine, some people develop a reaction. The new recombinant COVID19 vaccine, developed by the National Vaccine &Serum Institute, a R&D center of Sinopharms bioscience subsidiary the China National Biotec Group, got approval from the National Medical Products Administration on Apr. 9. SputnikV joins Indias vaccine utsav. Once DCGI approves SputnikV, India will have its third vaccine after Covishield and Covaxin. Bharat Biotech announces COVAXIN capacity expansion to support vaccination campaigns in India & worldwide amid COVID19 surge Coronavirus Vaccine India BharatBiotech. The first batch of COVID19 vaccine supplied by Chinas Sinopharm to COVAX, the international vaccine campaign co-led by the World Health Organization, was officially rolled off the production line on Tuesday. China has approved emergency use of Sinovac Biotechs COVID-19 vaccine in people aged between 3 and 17. From June 21 Covaxin will be the most expensive of the three vaccines which will be available in private hospitals. The vaccine is yet to be listed on the WHOs list of approved vaccines. FDA adds warning to Pfizer, Moderna Covid-19 vaccine shots to indicate the rare risk of heart inflammation after its use Pfizer Moderna COVID19 Vaccine US FDA. Moderna seeks regulatory approval for its Covid vaccine in India. Moderna will be the fourth vaccine to be used for the vaccination drive in India. Bharat Biotech had submitted EOI (Expression of Interest) on April 19 for its vaccine and WHO informed in a document that the assessment status for Covaxin is ongoing.

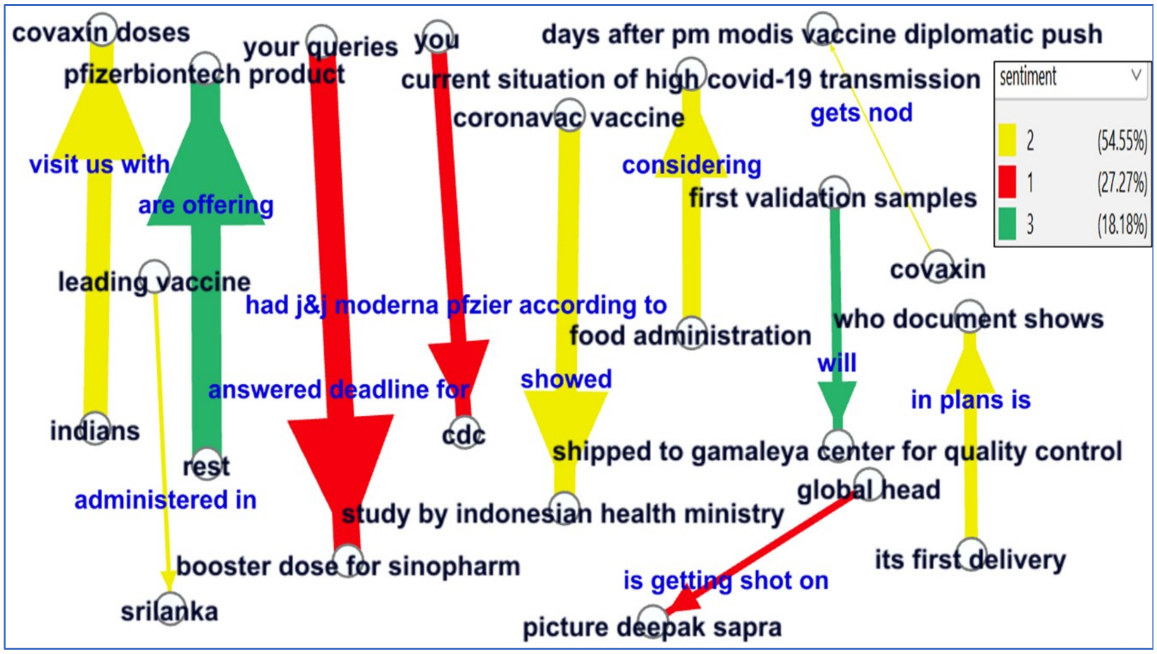


Figure 5.7 Knowledge Graph Visualization of Summary Triples of View (D)

Table 5.10 Summary Triples of View (D), Their Distances to the Centroid, Sentiments, and Vaccines, in Ranking Order

tripleS	sentiment	distance	vaccine
rest are offering pfizerbiontech product	3	2.14519871	moderna pfizer
your queries answered deadline for booster dose for sinopharm	1	2.18289661	pfizer sinopharm
indians visit us with covaxin doses	2	2.19706129	covaxin
coronavac vaccine showed study by indonesian health ministry	2	2.23561892	sinovac
food administration considering current situation of high covid-19 transmission	2	2.25889658	sinovac
you had j&j moderna pfzier according to cdc	1	2.28808198	moderna
its first delivery in plans is who document shows	2	2.30615778	sinopharm sinovac
first validation samples will shipped to gamaleya center for quality control	3	2.30836552	sputnik
global head is getting shot on picture deepak sapra	1	2.31143843	sputnik
leading vaccine administered in srilanka	2	2.34467295	sinopharm
covaxin gets nod days after pm modis vaccine diplomatic push	2	2.36003974	covaxin

Table 5.11 Summary Sentence Text of View (D), in Temporal Order

The Food and Drug Administration on Wednesday gave its approval for Sinovac use on the elderly after considering the recommendation of the experts and the current situation of high Covid-19 transmission and limited available vaccines. The Moderna Covid19 jab is now available at 11 of 38 vaccination centres in Singapore, while the rest are offering the PfizerBioNTech product. The CoronaVac vaccine developed by the Chinese biopharmaceutical company Sinovac Biotech has effectively reduced the risk of COVID19 symptoms in medical workers by 94%, showed a study by the Indonesian Health Ministry. On the picture Deepak Sapra, Global Head of Custom Pharma Services at drreddys Laboratories is getting a shot of Sputnik V in Hyderabad. unless you had J&J) Moderna Pfizer As of today154199664 Americans are fully vaccinated, according to the CDC! The first validation samples taken from the produced batch will be shipped to the Gamaleya Center for quality control. The WorldHealthOrganizations pandemic programme plans to ship 100 million doses of the Sinovac and Sinopharm COVID19 shots by the end of next month, mostly to Africa and Asia, in its first delivery of Chinese vaccines, a WHO document shows. Your queries answered Deadline for booster dose for Sinopharm announced, if you received vaccine over six months PfizerBiontech COVID19. USA doesnt recognise Indian vaccine COVAXIN PM Modi has gone to US and possibly he took doses of COVAXIN Whether all Indians are allowed to visit US with COVAXIN doses? days after PM Modis vaccine diplomatic push, Covaxin gets WHO nod; propaganda by anti-govt voices falls flat. Sinopharm approved for travel to UK From Nov.22, the Sinopharm vaccine will be added to the UKs list of approved vaccines for inbound travel, benefiting more fully vaccinated people travelling from to Sinopharm is the leading vaccine administered in SriLanka.

We found that our different views yielded completely different triple sets. Each corresponding original sentence in our summary views is also unique, which means there is no common sentence among our views. The sentiments are represented by integers, 1 for negative, 2 for neutral, and 3 for positive. In view (D), more than half of the summary triples are neutral, while in views (E) and (SF), more than half are negative. The AstraZeneca (AZ) vaccine is not mentioned in any of our summaries. In view (D), each vaccine except for AZ is evenly mentioned 2 to 3 times. In view (SF), Covaxin and Sputnik V are mentioned most frequently, 14 and 9 times respectively, among 24 triples. In view (E), Covaxin, Moderna and Sputnik V are mentioned most frequently, 5, 4, and 3 times among 16 triples. In general, Covaxin and Sputnik V are the most frequently mentioned in our summaries. We present the statistics of views in **Table 5.14**. The average length of summary sentences of view (D) is the longest among the three views.

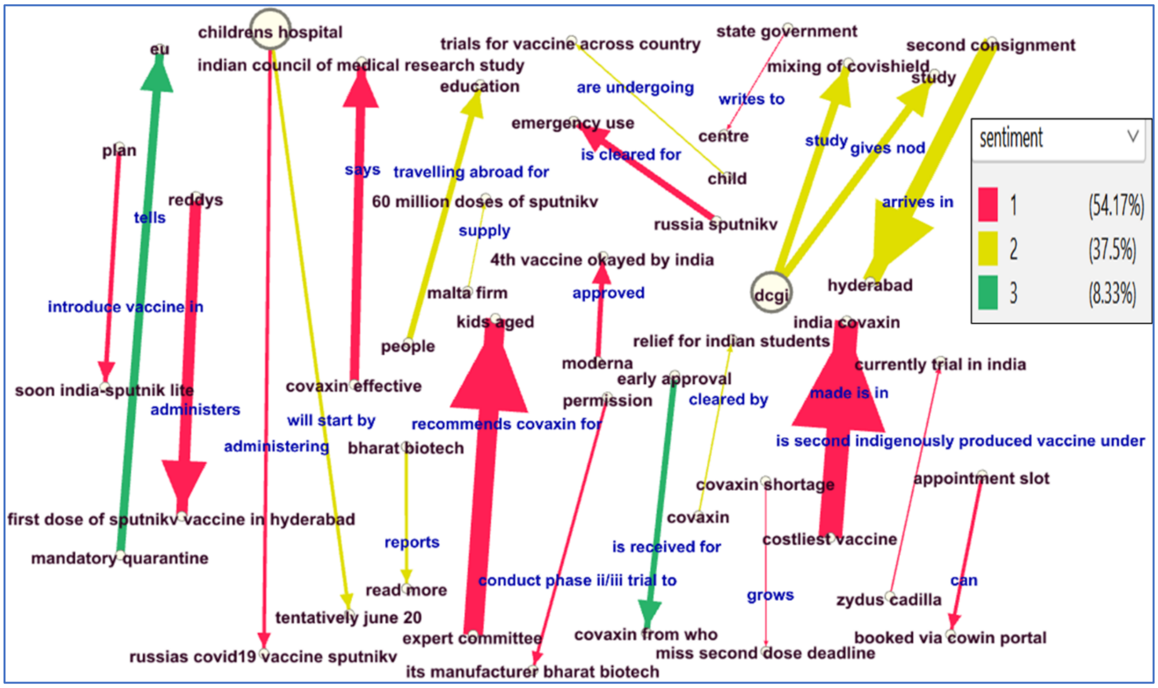


Figure 5.8 Knowledge Graph Visualization of Summary Triples of View (SF)

Table 5.12 Summary Triples of View (SF), Their Salience Score, Sentiment, and Vaccine Mentioned, in Ranking Order

tripleS	sentiment	salienceScore	vaccines
costliest vaccine made is in india covaxin	1	17677188	covaxin
expert committee recommends covaxin for kids aged	1	17669984	covaxin
second consignment arrives in hyderabad	2	17663692	sputnik
reddys administers first dose of sputnikv vaccine in hyderabad	1	17654508	sputnik
covaxin effective says indian council of medical research study	1	17650360	covaxin
mandatory quarantine tells eu	3	17648991	covaxin
dcgi gives nod study	2	17648798	covaxin
dcgi study mixing of covishield	2	17648798	covaxin
russia sputnikv is cleared for emergency use	1	17646035	sputnik
people travelling abroad for education	2	17644721	covaxin
early approval is received for covaxin from who	3	17644721	covaxin
moderna approved 4th vaccine okayed by india	1	17642612	moderna
plan introduce vaccine in soon india-sputnik lite	1	17641774	sputnik
appointment slot can booked via cowin portal	1	17639753	sputnik
childrens hospital will start by tentatively june 20	2	17639753	sputnik
childrens hospital administering russias covid19 vaccine sputnikv	1	17639753	sputnik
bharat biotech reports read more	2	17638980	covaxin
permission conduct phase ii/iii trial to its manufacturer bharat biotech	1	17638935	covaxin
child are undergoing trials for vaccine across country	2	17636214	covaxin
zydus cadilla is second indigenously produced vaccine under currently trial in india	1	17636214	covaxin
covaxin cleared by relief for indian students	2	17636201	covaxin
state government writes to centre	1	17635505	sputnik
malta firm supply 60 million doses of sputnikv	2	17635505	sputnik
covaxin shortage grows miss second dose deadline	1	17635458	covaxin

Table 5.13 Summary Sentence Text of View (SF), in Temporal Order

India gets third coronavirus vaccine as Russias SputnikV is cleared for emergency use CovidVaccine. Dr Reddys administers first dose of the SputnikV vaccine in Hyderabad The second consignment of SputnikV arrives in Hyderabad, Telangana. There are plans to introduce single-dose vaccine soon in India-Sputnik Lite. JustIn. A PIL has been moved in Delhi High Court challenging Centres notification which has accorded permission to conduct the Phase II/III clinical trial of Covaxin in the age group 2 to 18 years to its manufacturer Bharat Biotech. Bharat Biotech Amid Travel Fears NDTVs Shonakshi Chakravarty reports Read more. Malta firm wants to supply 60 million doses of SputnikV to Haryana, state government writes to Centre. Assam Covaxin Shortage Grows Into Crisis, Some Miss Second Dose Deadline. Made in India Covaxin is the third costliest vaccine globally. The appointment slots can be booked via CoWIN portal, according to the hospital administration. Delhis Madhukar Rainbow Childrens Hospital will start administering Russias COVID19 vaccine SputnikV, tentatively by June 20. children are undergoing trials for the vaccine across the country. After Covaxin, Zydus Cadilla is the second indigenously produced vaccine for children currently under trial in India. This will also benefit people travelling abroad for education, jobs or business. I request for your kind intervention so that an early approval is received for Covaxin from WHO. Moderna approved for emergency use, 4th vaccine okayed by India COVID19Vaccine. Accept Covishield, Covaxin Or Face Mandatory Quarantine, India Tells EU. COVAXIN effective against DeltaPlus variant of COVID19, says Indian Council of Medical Research study. DCGI gives nod to study mixing of Covishield and Covaxin. Subject Expert Committee recommends Covaxin for kids aged between 2 and 18 NDTVs Meher Pandey reports. Covaxin Cleared By UK, Relief For Indian Students

And Tourists.

Table 5.14 Statistics about Each view. # Means "Count."

	Summary Triple #	Summary Sentence #	Word # in Sentences	Avg word # per sentence
SF	24	21	290	13.81
E	16	16	314	19.63
D	11	11	295	26.82

SF-based summaries are more likely to contain summary triples from the same sentences, as this view is based on the user's follower counts and retweet counts. In this view, the average length of summary sentences is the shortest among the three views. This might indicate that worldwide popular users normally generate short posts, which might tend to appeal to social media readers.

5.5.5.2 World-based Summary In this subsection, we generate the World-based summaries of combined view (G+E), view (G+SF) and view (G+D), respectively. Out of the whole data set 18,047 tweets (101,432 extracted triples), 15,217 tweets (87,685 triples) have country labels in column *"user_loc,"* which means these posts have country information. The goal was again to retain top-ranking triples to generate ~300-word readable summaries. **Table 5.15**, **Table 5.16**, and **Table 5.17** present the summary triples, sentiments, users' located states, mentioned vaccines, and rankings of view (G+E), view (G+D), and view (G+SF), respectively. **Figure 5.9**, **Figure 5.10**, and **Figure 5.11** show the knowledge graph of triple summary for view (G+E), view (G+D), and view (G+SF), respectively. We show the summary text of view (G+E), view (G+D), and view (G+SF) in **Table 5.18**, **Table 5.19**, and **Table 5.20**, respectively. Based on the summary triples, we identified a number of findings of the Worldwide summary. The summary triples are mainly based in India, and talked about Covaxin, which is India' state vaccine. The summaries are negative sentiment based. All three views have no triple in common, which shows again different views would generate different summaries. The average sentence length in view (G+D) is the longest among three views, while that of view (G+SF) is the shortest (**Table 5.21**).

Table 5.15 Summary Triples of View (G+E) Worldwide based, Their Sentiments, Countries, Vaccines, and Triple Scores in Ranking Order.

triple_string	sentiment	country	vaccines	tripleScore
j&j vaccine is essentially first shot of sputnik v vaccine	1	Russia	sputnik	1442.4
sinopharm covid19 vaccine be imported as alternative vaccines	1	Thailand	astrazeneca sinopharm sinovac	1442.4
covid19 vaccine of batch is international vaccine campaign co-led by world health organization	1	China	sinopharm	1442.4
vaccine be listed on whos list of approved vaccines	2	India	covaxin	1442.4
covaxin gets nod days after pm modis vaccine diplomatic push	2	India	covaxin	994.4
covaxin seems most effective lasting vaccine against delta variant	3	India	covaxin	994.4
moderna begin first human trials of mrna vaccine for hiv	1	Kenya	moderna	964.3
moderna announces development of new vaccine	2	United States	moderna	964.3
1st 30k doses are arriving tonight initial deliveries of s 20m doses of vaccine	1	Canada	pfizer	877.5
sputnikv will third covid-19 vaccine	2	India	sputnik	876.8
china donated additional 600000 doses of sinopharm covid-19 vaccine	2	China	sinopharm	873.3
india has granted emergency approval to russian sputnik vaccine	1	India	sputnik	859.3
other countries are also relying heavily on pfizer vaccine	2	India	pfizer	857.2
bharat biotech supply 20 million doses of covaxin vaccine coronavirusvaccine bharatbiotech covaxin brazil	1	India	covaxin	851.6
most people attending vaccine clinics	2	Canada	moderna pfizer	845.3
bharatbiotech releases efficacy data on efficacy of vaccine recorded at 81 percent	1	India	covaxin	825.7

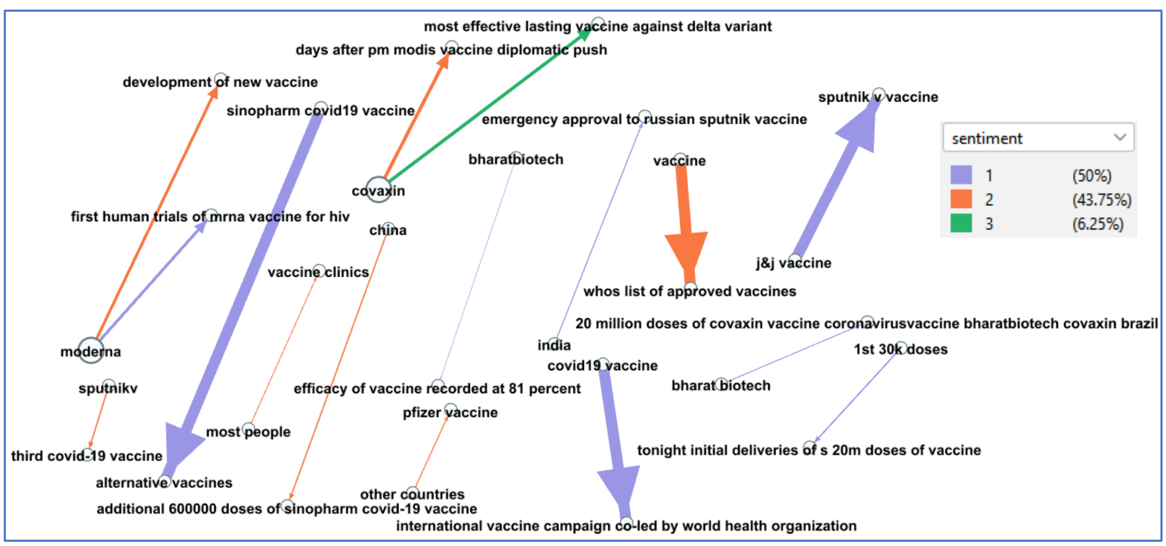


Figure 5.9 Knowledge Graph Visualization of Summary Triples of View (G+E)

Table 5.16 Summary Triples of View (G+D) Worldwide based, Their Sentiments, Countries, Vaccines, and Distances to the Centroid in Ranking Order

triple_string	sentiment	country	vaccines	distance_from_centroid
central govt recently gave bharatbiotech permission	1	India	covaxin	2.34055931
indonesia aims regional vaccine	1	China	sinovac	2.34248747
nstworld israel will receive doses in return	3	Malaysia	pfizer	2.34300991
earlier gamaleya center study making it ne of worlds for other vaccines	2	Russia	sputnik	2.39248674
cdcgov now recommends covid19 boostershots for eligible americans	1	United States	moderna pfizer	2.40120728
govt produce covaxin	2	India	covaxin	2.43127986
company testing can administered as two shots	2	India	covaxin	2.43814039
uk could conceivably restrict astrazeneca vaccine you can see	1	United Kingdom	astrazeneca moderna	2.47913781
state has reportedly received fresh consignment of 693210 doses of covaxin	3	India	covaxin	2.5362459
moderna vaccines remain amid even surging deltavariant cases	1	United States	moderna pfizer	2.54453472
variants are circulating oxfordastrazeneca	2	Canada	astrazeneca	2.56588994
off modernas booster on signs is u.s. centers for disease control	1	Thailand	moderna	2.58675057
indias covid19 vaccine covaxin will added to uk governments	1	India	covaxin	2.58900752
el salvador extend shots to elderly	2	China	sinovac	2.60050308

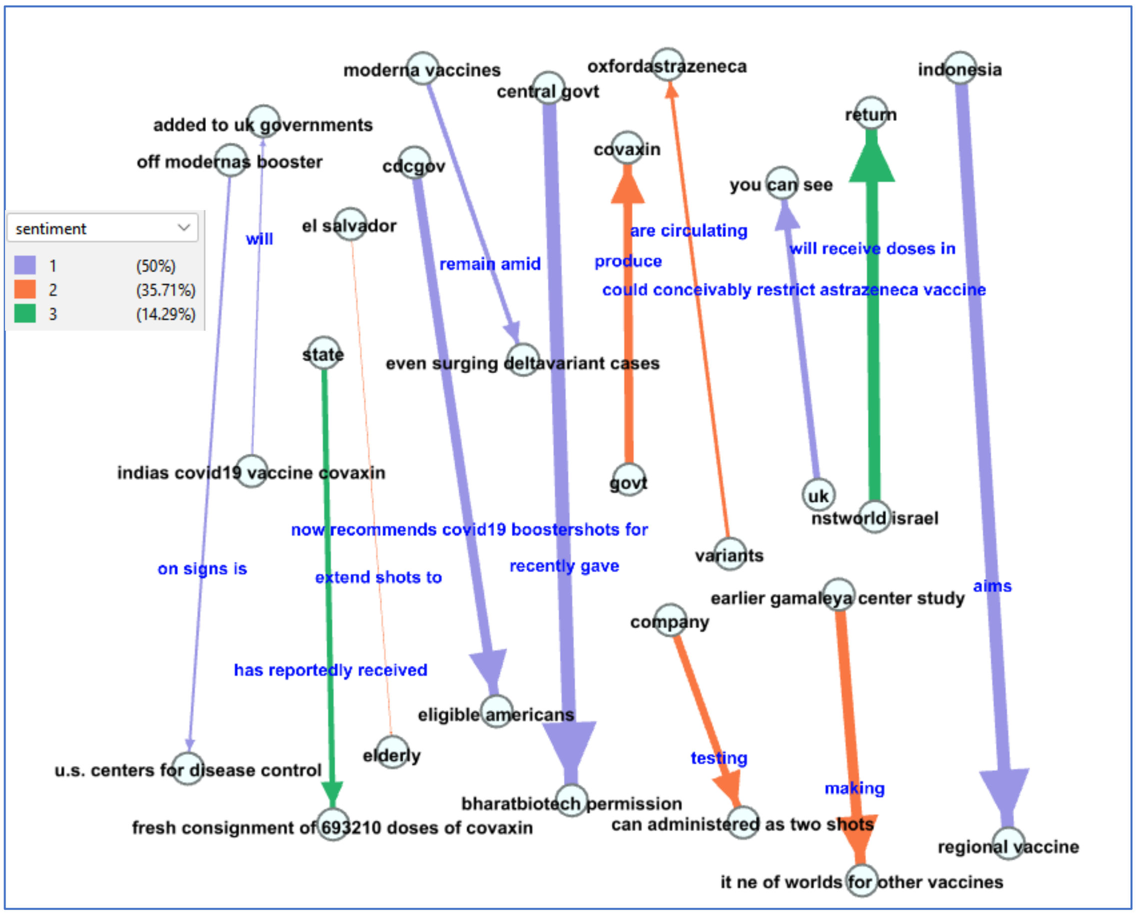


Figure 5.10 Knowledge Graph Visualization of Summary Triples of View (G+D)

Table 5.17 Summary Triples of View (G+SF) Worldwide based, Their Sentiments, Countries, Vaccines, and Salience Scores in Ranking Order

triple_string	sentiment	country	salienceScore	vaccines
costliest vaccine made is in india covaxin	1	India	17761240	covaxin
expert committee recommends covaxin for kids aged	1	India	17754939	covaxin
second consignment arrives in hyderabad	2	India	17747804	sputnik
reddys administers first dose of sputnikv vaccine in hyderabad	1	India	17737906	sputnik
covaxin effective says indian council of medical research study	1	India	17735111	covaxin
dcgi gives nod study	2	India	17734409	covaxin
dcgi study mixing of covishield	2	India	17734409	covaxin
mandatory quarantine tells eu	3	India	17732959	covaxin
russia sputnikv is cleared covidvaccine for emergency use	1	India	17729419	sputnik
early approval is received for covaxin from who	3	India	17728724	covaxin
people travelling abroad for education	2	India	17728724	covaxin
covaxin shortage grows miss second dose deadline vaccinationdrive covidvaccine	1	India	17726597	covaxin
moderna approved 4th vaccine okayed by india	1	India	17726592	moderna
plan introduce vaccine in soon india-sputnik lite	1	India	17725888	sputnik
childrens hospital will start by tentatively june 20	2	India	17723064	sputnik
childrens hospital administering russias covid19 vaccine sputnikv	1	India	17723064	sputnik
appointment slot can booked via cowin portal	1	India	17723064	sputnik
permission conduct phase ii/iii trial to its manufacturer bharat biotech	1	India	17722353	covaxin
bharat biotech reports read more	2	India	17722353	covaxin
covaxin cleared by relief for indian students	2	India	17721697	covaxin
lancet peerreview confirms efficacy analysis of bharat biotechs covaxin	1	India	17720286	covaxin
covaxin demonstrates efficacy as per phase-three clinical trials data	1	India	17720286	covaxin
health of minister is mansukh mandaviya	2	India	17720282	covaxin
union minister launches first commercial batch of bharat biotechs covaxin manufactured in gujarats ankleshwar	1	India	17720282	covaxin
zydus cadilla is indigenously produced vaccine under currently trial in india	1	India	17720235	covaxin

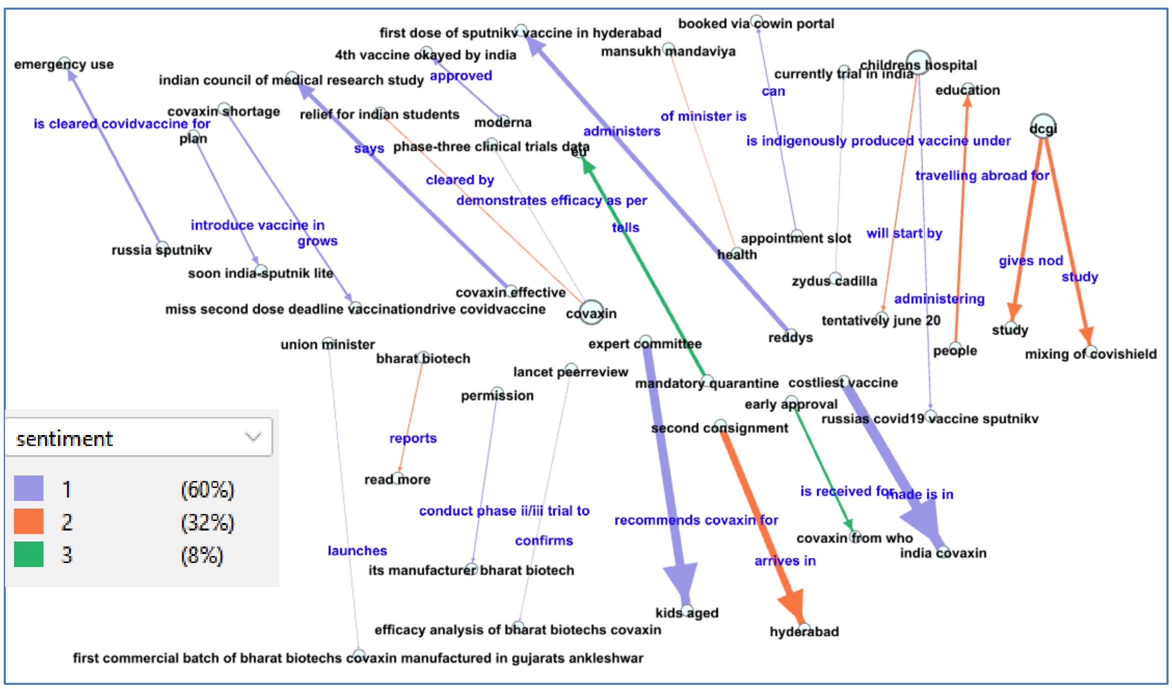


Figure 5.11 Knowledge Graph Visualization of Summary Triples of View (G+SF)

Table 5.18 Worldwide-based Summary Text of View (G+E)

The 1st 30K doses of PfizerBioNTech are arriving across the country tonight & tomorrow initial deliveries of s 20M doses of this vaccine. Other countries in the Middle East, including Saudi Arabia, Qatar, Kuwait and Oman, are also relying heavily on the Pfizer vaccine, developed by the US company PfizerVaccine PfizerBioNTech Israeligovernment MiddleEast COVIDVaccination Bharat Biotech confirms deal with Brazil to supply 20 million doses of COVAXIN vaccine CoronavirusVaccine BharatBiotech Covaxin Brazil This is also another validation of Sputnik V pioneering technology as J&J vaccine is essentially a first shot of Sputnik V vaccine (Ad26 - human adenoviral vector 26). BharatBiotech releases efficacy data on Covaxin, efficacy of the vaccine recorded at 81 percent. If approved, SputnikV will be the third COVID-19 vaccine to be available in India India has granted emergency approval to Russian Sputnik vaccine. The Kings sister had just approved on Thursday the Sinopharm covid19 vaccine be imported into Thailand as alternative vaccines to help the nation cope with the pandemic. The first batch of COVID19 vaccine supplied by Chinas Sinopharm to COVAX, the international vaccine campaign co-led by the World Health Organization, was officially rolled off the production line on Tuesday. The vaccine is yet to be listed on the WHOs list of approved vaccines. ROWPublicHealth announced most people attending vaccine clinics will get the Moderna vaccine, not Pfizer. Moderna is set to begin the first human trials of an mRNA (RNA messenger) vaccine for HIV China on Monday donated additional 600000 doses of the Sinopharm COVID-19 vaccine to Cambodia. Moderna announces the development of a new vaccine that combines its current Covid19 vaccine with a flu shot vacccine. days after PM Modis vaccine diplomatic push, Covaxin gets WHO nod; propaganda by anti-govt voices falls flat. As of now, Covaxin seems to be the most effective & long lasting vaccine against the Delta variant!

Table 5.19 Worldwide-based Summary Text of View (G+D)

Obstatsinc Was offered PfizerBioNTech first. We will beat this virus! Traffic still a bear around PetcoPark for UCSDHealth vaccines. PMOIndia narendramodi took the first dose of Covaxin, developed and made in India by BharatBiotech LargestVaccineDrive new Moderna COVID19 vaccine appointment slots for our new Reed Road site, a partnership with Curative, are NOW OPEN. if you booked an appointment at the CovidVaccine clinic at campnorthend this weekend, the clinic will now use Pfizer and Moderna instead of the JohnsonandJohnson vaccine SpecNews1CLT covid19 cltnews meckcounty If you scheduled a JohnsonandJohnson vaccine appt with cvspharmacy they tell me theyre trying to the fullest extent possible to rescheduled you for a Pfizer or Moderna appt by Sunday . The U.S. sent 2.5 million doses of the Moderna COVID-19 vaccine to Taiwan on Sunday, tripling an earlier pledge. Research led by swathi sangli of AHNtoday, AHNIMres reports what is believed to be the first case of thrombosis with thrombocytopenia after a messenger RNA COVID19 vaccine RNA1273 mRNA moderna unless you had J&J) Moderna Pfzier As of today154199664 Americans are fully vaccinated, according to the CDC! Modernas new vaccine data, expanding testing in the Bay Area, Sonoma Co.s mandate for emergency workers. The plan calls for an extra dose eight months after people get their second shot of the Pfizer or Moderna vaccine. The next DeltaVariant will be bred in an unvaxxed population. National Health

ErinEBillups tells us whos eligible. The booster can be J&J, Moderna, or Pfizer (mix & match strategy) based on results of NIAID-led trial. CDCgov Director signs off on COVID19 boosters for Moderna and johnsonandjohnson The CDCgov has approved Moderna and JohnsonAndJohnson boosters. NIH vs Moderna trial used doses, 100mcg vs 50mcg. pstronski writes in the latest look InsideRussia Im getting my COVID19 booster shot tomorrow at Costco.

Table 5.20 Worldwide-based Summary Text in View (G+SF)

India gets third coronavirus vaccine as Russias SputnikV is cleared for emergency use CovidVaccine Dr Reddys administers first dose of the SputnikV vaccine in Hyderabad The second consignment of SputnikV arrives in Hyderabad, Telangana. There are plans to introduce single-dose vaccine soon in India-Sputnik Lite. JustIn. A PIL has been moved in Delhi High Court challenging Centres notification which has accorded permission to conduct the Phase II/III clinical trial of Covaxin in the age group 2 to 18 years to its manufacturer Bharat Biotech Bharat Biotech Amid Travel Fears NDTVs Shonakshi Chakravarty reports Read more: Assam Covaxin Shortage Grows Into Crisis, Some Miss Second Dose Deadline VaccinationDrive CovidVaccine Made in India Covaxin is the third costliest vaccine globally Delhis Madhukar Rainbow Childrens Hospital will start administering Russias COVID19 vaccine SputnikV, tentatively by June 20. The appointment slots can be booked via CoWIN portal, according to the hospital administration. After Covaxin, Zydus Cadilla is the second indigenously produced vaccine for children currently under trial in India. I request for your kind intervention so that an early approval is received for Covaxin from WHO This will also benefit people travelling abroad for education, jobs or business Moderna approved for emergency use, 4th vaccine okayed by India COVID19Vaccine Accept Covishield, Covaxin Or Face Mandatory Quarantine, India Tells EU COVAXIN effective against DeltaPlus variant of COVID19, says Indian Council of Medical Research study DCGI gives nod to study mixing of Covishield and Covaxin. Union Minister of Health and Family Welfare, Mansukh Mandaviya launches the first commercial batch of Bharat Biotechs Covaxin manufactured in Gujarats Ankleshwar. Subject Expert Committee recommends Covaxin for kids aged between 2 and 18 NDTVs Meher Pandey reports The Lancet peer-review confirms the efficacy analysis of Bharat Biotechs Covaxin. As per phase-three clinical trials data, Covaxin demonstrates 77.8% efficacy against symptomatic COVID19. Covaxin Cleared By UK, Relief For Indian Students And Tourists

Table 5.21 Statistics about Each Worldwide based View. # Means "Count."

	Summary Triple #	Summary Sentence #	Word # in Sentences	Avg word # per sentence
G+SF	25	22	304	13.81
G+E	16	16	305	19.06
G+D	14	14	309	22.07

5.5.5.2 USA-based Summary In this subsection, we generate the USA-based summaries of combined view (G+E), view (G+SF) and view (G+D), respectively. Out of 15,217 tweets (87,685 triples) with country labels in column *"user_loc,"* 1,288 tweets (5,795 triples) are USA-based. The goal was again to retain top-ranking triples to generate ~300-word readable summaries. **Table 5.22**, **Table 5.23**, and **Table 5.24** present the summary triples, sentiments, users' located states, mentioned vaccines, and rankings of view (G+E), view (G+D), and view (G+SF), respectively. Based on the summary triples, we identified a number of findings of the USA summary. First, the summaries are mainly based in the states of New York and California, and District of Columbia. Second the vaccines mentioned are mostly about Moderna and Pfizer, with few Covaxin and SputnikV compared the worldwide summary in previous subsection where vaccines worldwide were included in the summaries with Covaxin and Sputnik V as the majority. Third, the sentiments of the USA summaries are Neutral based, while the worldwide summary are Negative based. Fourth, among the three views, there is only 1 overlapping summary sentence between view (G+SF) and view (G+E). This again proves that our different summarization views generate different summary perspectives. While the average length of summary sentence of view (D) of worldwide-based summary is the longest among three views, the average length of summary sentence of view (G+D) of USA-based summary is the shortest (**Table 5.25**).

Table 5.22 Summary Triples of View (G+E) based in the USA, Their Sentiments, States, Vaccines, and Triple Scores in Ranking Order.

triple_string	sentiment	US state	vaccines	tripleScore
moderna vaccine continue vaccine clinic	2	Indiana	moderna	102.9
moderna applied for full u.s. approval of its covid-19 vaccine for adults	2	District of Columbia	moderna	102.9
moderna expand their vaccine trials	2	New York	moderna pfizer	102.9
moderna seeks u.s. authorization for covid-19 vaccine booster	1	Pennsylvania	moderna	102.9
moderna announces development of new vaccine	2	Idaho	moderna	102.9
moderna are pushing for covid-19 vaccine boostershots	1	New York	moderna pfizer	102.9
moderna asks for fda authorization for reduced dose of its vaccine	1	Texas	moderna	102.9
u.s. fda adds moderna covid vaccines	1	Pennsylvania	moderna pfizer	76.3
us fda focused on covid19 vaccines	2	Arizona	moderna pfizer	76.3
fda mixing covid19 vaccines	2	North Carolina	moderna	76.3
us fda approves covid19 vaccine booster shots	2	Texas	moderna pfizer	76.3
vaccine offers best protection against covid19	3	Wisconsin	moderna pfizer	75.2
allworthit moderna modernas covid vaccine generated double antibodies of similar shot made by pfizer-biontech in research	1	California	moderna	59.9
people receiving pfizerbiontech vaccines	2	New York	moderna pfizer	58.1
company studies safety of vaccine for kids ages 6 months	2	Washington	moderna	51.1

Table 5.23 Summary Triples of View (G+D) based in the USA, Their Sentiments, States, Vaccines, and Distances to the Centroid in Ranking Order.

triple_string	sentiment	US state	vaccines	distance_from_centroid
u.s. tripling earlier pledge	2	Utah	moderna	5.23458694
you had j&j moderna pfzier according to cdc	1	District of Columbia	moderna	5.24666103
next deltavariant will bred in unvaxxed population	1	District of Columbia	moderna	5.40357536
cdcgov has approved moderna boosters	2	Maryland	moderna	5.42056645
nih trial used doses	2	Virginia	moderna	5.53246126
we will beat virus	2	California	moderna	5.56867727
pstronski writes insiderussia in latest look	2	District of Columbia	sputnik	5.5895796
bay area mandate for emergency workers	2	California	moderna	5.64356185
national health erinebillups tells us	2	New York	moderna	5.68547191
plan calls for extra dose	2	Illinois	moderna pfizer	5.69031759
you scheduled johnsonandjohnson vaccine appt with cvspharmacy	2	District of Columbia	moderna pfizer	5.69581813
you booked appointment at covidvaccine clinic at campnorthend	2	South Carolina	moderna pfizer	5.74895379
research led by swathi sangli of ahntoday	2	Pennsylvania	moderna	5.76329135
obstatsinc was offered first pfizerbiontech	2	Vermont	pfizer	5.79600135
pmoindia narendramodi made by bharatbiotech largestvaccinedrive	1	District of Columbia	covaxin	5.80840341
our new reed road site for slots is partnership with curative	1	Texas	moderna	5.81162881
cdcgov director signs off on covid19 boosters for moderna	1	Arizona	moderna	5.84938587
traffic still bear for ucsdhealth vaccines	2	California	moderna	5.8832553
booster pfizer based on results of niaid-led trial	2	Maryland	moderna	5.88736532
pmoindia narendramodi took first dose of covaxin	2	District of Columbia	covaxin	5.90397176
im getting my covid19 booster shot at costco	1	Utah	moderna pfizer	5.90866362

Table 5.24 Summary triples of view (G+SF) based in the USA, Their Sentiments, States, Vaccines, and Salience Scores in Ranking Order

triple_string	sentiment	US state	vaccines	salienceScore
bart classen warns mrna technology used in pfizer	1	California	moderna pfizer	2112730
new research published in microbiology diseases	2	California	moderna pfizer	2112730
covid vaccine could create new potential mechanisms of adverse events	1	California	moderna pfizer	2112730
moderna vaccine stopped msjannie	2	Alabama	moderna	1938507
moderna vaccine talking trash	1	Alabama	moderna	1938507
cancer patient need moderna vaccinereminder to multiplemyeloma	1	District of Columbia	moderna	1598552
tuesday morn ahead gmaevapilgrim shares encouraging news in race vaccinate	1	New York	moderna pfizer	1133197
pfizer vaccine offer protection for years	2	New York	moderna pfizer	1133197
ginger zee brings latest	2	New York	moderna pfizer	1133197
evapilgrim brings latest on that	2	New York	moderna	1131089
jupitermedicalcenter thank you diane	3	New York	moderna pfizer	1057120
moderna did increase igg antibodies after 2 shots	1	District of Columbia	moderna	974978
pfizer only increased roughly ~ 10x	1	District of Columbia	moderna	974978
people receiving vaccine for covid19	2	New York	moderna pfizer	939604
people have died according to reports submitted to federal system	2	New York	moderna pfizer	939604
people receiving pfizerbiontech vaccines	2	New York	moderna pfizer	939604
death occurred according to reports	1	New York	moderna pfizer	939604
cancer patient really need 100 mcg moderna vaccine	1	District of Columbia	moderna	875998
moderna enroll nearly 7000 children	2	New York	moderna	782442
one vaccine is better than another since studies conducted	2	New York	moderna pfizer	776081
people might wonder better than another since studies conducted	2	New York	moderna pfizer	776081
moderna says covid-19 vaccine for south africa strain	1	New York	moderna	718275
woman tested positive for covid19	3	New York	moderna	653277
woman taken her 2nd moderna vaccine shot	2	New York	moderna	653277
fda is investigating around 5 allergic reactions	2	New York	pfizer	638422

Table 5.25 Statistics of Each View in the USA-based Summary. # Means "Count."

	Summary Triple #	Summary Sentence #	Word # in Sentences	Avg word # per sentence
G+SF	25	19	300	15.8
G+E	15	15	278	18.53
G+D	21	20	295	14.75

We further drilled down to state, city, and borough level by using New York state as the case. There are 244 New York state-based tweets and 998 New York state-based triples, out of 1,288 US-based tweets and 5,795 US-based triples. The triple size is reduced to 186 (from 998) after triple artifact cleaning, 83 of which are New York City (NYC)-based, and 39 of which are at known locations outside of NYC (Albany, Buffalo, Ithaca, Yonkers, etc.). For the other 64, it is not known where in New York State they are. Some of the 64 could be in NYC.

For the NYC borough analysis, we checked whether the locations contain exact borough names. Out of 83, we found 12 Manhattan, 3 Brooklyn, 2 Bronx, no Queens nor

Staten Island, and the other 66 are described by terms such "New York, NY," "New York, New York," "NYC," "NYC NY," etc., saying it's New York City but without specifying boroughs.

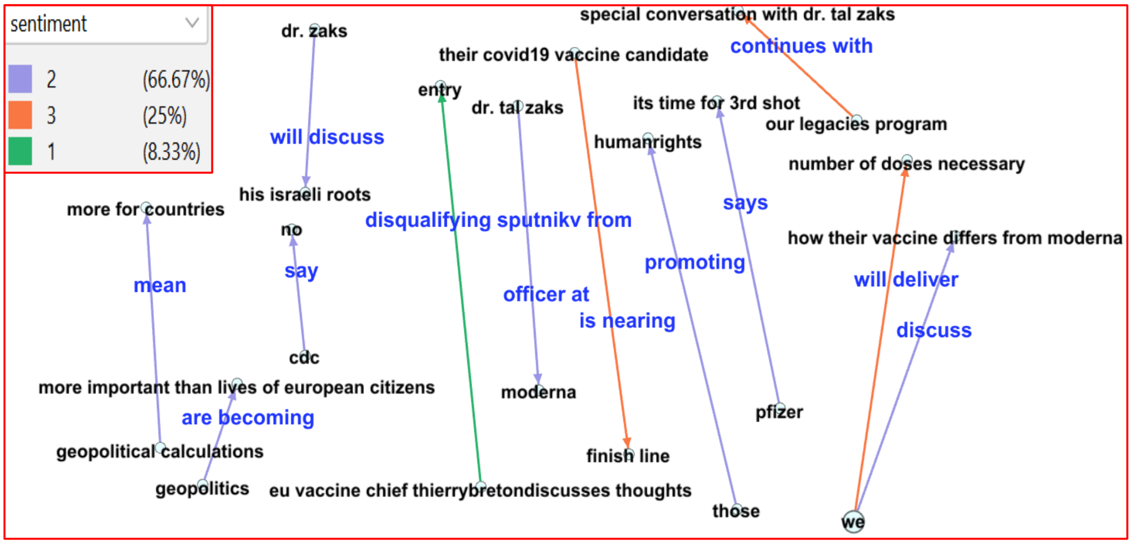


Figure 5.12 Knowledge Graph Visualization of triples based in Manhattan, New York.

Table 5.26 Details of Manhattan-based Triples

sentence	triple_string	userLoc	vaccines	sentiment
This is a proof that geopolitical calculations mean more for some countries than saving human lives!	geopolitical calculations mean more for countries	Manhattan, NY	sputnik	2
How dare those who work behind the scenes to smear efficient vaccines of their competitors pretend to be promoting HumanRights?	those promoting humanrights	Manhattan, NY	sputnik	2
Thats how geopolitics are becoming more important than lives of European citizens.	geopolitics are becoming more important than lives of european citizens	Manhattan, NY	sputnik	2
We will deliver the number of doses necessary to achieve 70% of the adult population being vaccinated by mid-	we will deliver number of doses necessary	Manhattan, NY	sputnik	3

July.				
EU Vaccine Chief ThierryBretondiscusses thoughts on vaccine passports, disqualifying SputnikV from entry, and confidence in herd immunity this summer.	eu vaccine chief thierrybretondiscusses thoughts disqualifying sputnikv from entry	Manhattan, NY	sputnik	1
Franz-Werner Haas, CEO CureVacRNAsays their COVID19 vaccine candidate is nearing the finish line.	their covid19 vaccine candidate is nearing finish line	Manhattan, NY	moderna pfizer	3
We discuss struggles with equipment, manufacturing 300M doses by 2022, and how their vaccine differs from Moderna & Pfizer.	we discuss how their vaccine differs from moderna	Manhattan, NY	moderna pfizer	2
Pfizer says its time for a 3rd shot.	pfizer says its time for 3rd shot	Manhattan, NY	moderna pfizer	2
the CDC & FDA say no.	cdc say no	Manhattan, NY	moderna pfizer	2
Tomorrow our Legacies program continues with a special conversation with Dr. Tal Zaks, Chief Medical Officer at Moderna.	our legacies program continues with special conversation with dr. tal zaks	Battery Park City, Manhattan	moderna	3
Tomorrow our Legacies program continues with a special conversation with Dr. Tal Zaks, Chief Medical Officer at Moderna.	dr. tal zaks officer at moderna	Battery Park City, Manhattan	moderna	2
Dr. Zaks and mattiekahn will discuss his family background, his Israeli and Jewish roots, and his life-saving work.	dr. zaks will discuss his israeli roots	Battery Park City, Manhattan	moderna	2

Table 5.27 Details of Brooklyn and Bronx-based Triples

sentence	triple_string	sentiment	userLoc	vaccines
Hope you all join meand thanks, NYC and New York State!	you join new york state	2	Brooklyn, USA	moderna
Hives have run their course, on the mend!	hives have run their course	2	Brooklyn	moderna
BTW, got my Moderna booster yesterday, feel fine.	btw feel fine	3	Brooklyn, NY	moderna
The CDC is planning to meet today to discuss making that booster available to everyone 18 and older as soon as this weekend if approved.	cdc is planning meet today	2	Bronx, NY	moderna pfizer
	cdc meet today	2	Bronx, NY	moderna pfizer

As the amount borough information is very limited with 12 Manhattan, 3 Brooklyn, and 2 Bronx, we were not able to apply our summarization method views. **Figure 5.12** shows the knowledge graph visualization of triples based in Manhattan, and **Table 5.26** and **Table 5.27** present details of the triples in Manhattan and in Brooklyn and Bronx, respectively. The USA-based summary is based on Pfizer and Moderna vaccines. However, we found almost half (5 out of 12) of the Manhattan triples are about Russian Sputnik V vaccine, with sentences expressing geopolitics-related content.

We then applied view (G+SF) to summarize 83 NYC triples, and obtain 20 summary triples. Compared with the country-wide summary with Pfizer and Moderna based and Neutral sentiment based, the NYC summary shows some differences. First, the NYC summary is related to Russian and China state vaccines besides Moderna and Pfizer (**Table 5.28**). Second, from **Figure 5.13**, the negative sentiment (1, purple) has the same ratio as neutral sentiment (2, Orange). As we look into **Table 5.28** with more details, we found all the summary triples related to Russian Sputnik V vaccines express negative sentiment. This implies that the Russian Troll activities [218] might be still active today. Therefore, it would be beneficial to identify if such sentences spread disinformation.

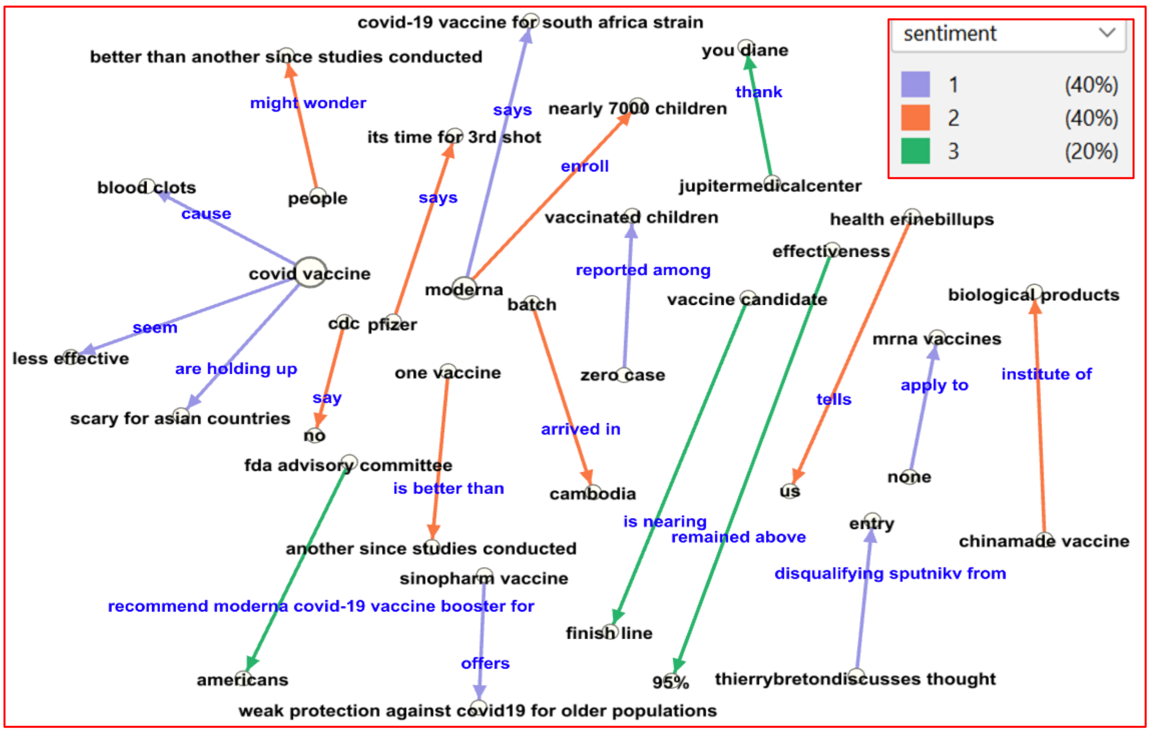


Figure 5.13 Knowledge Graph of NYC Summary Triples in view(G+SF).

Table 5.28 Details of NYC Summary Triples in View (G+SF)

Triple String	sentiment	userLoc	Vaccines
moderna says covid-19 vaccine for south africa strain	1	NYC	moderna
moderna enroll nearly 7000 children	2	New York City	moderna
jupitermedicalcenter thank you diane	3	New York,	moderna

		New York	pfizer
thierrybretondiscusses thought disqualifying sputnikv from entry	1	Manhattan, NY	sputnik
one vaccine is better than another since studies conducted	2	New York City	moderna pfizer
people might wonder better than another since studies conducted	2	New York City	moderna pfizer
covid vaccine cause blood clots	1	New York, NY	sputnik
covid vaccine seem less effective	1	New York, NY	sputnik
none apply to mrna vaccines	1	New York, NY	sputnik
vaccine candidate is nearing finish line	3	Manhattan, NY	moderna pfizer
batch arrived in cambodia	2	New York, NY	sinovac
zero case reported among vaccinated children	1	New York City	moderna
chinamade vaccine institute of biological products	2	New York, NY	sinopharm sinovac
pfizer says its time for 3rd shot	2	Manhattan, NY	moderna pfizer
cdc say no	2	Manhattan, NY	moderna pfizer
covid vaccine are holding up scary for asian countries	1	New York, NY	sinopharm
effectiveness remained above 95%	3	New York, NY	pfizer
sinopharm vaccine offers weak protection against covid19 for older populations	1	New York, NY USA	sinopharm
advisory committee recommend moderna covid-19 vaccine booster for americans	3	New York City	moderna
health erinebillups tells us	2	New York City	moderna

As we looked into the New York State summary, we found it pretty aligned with the country-wide summary on vaccines mentioned and sentiments expressed (**Figure 5.14 Table 5.29**).

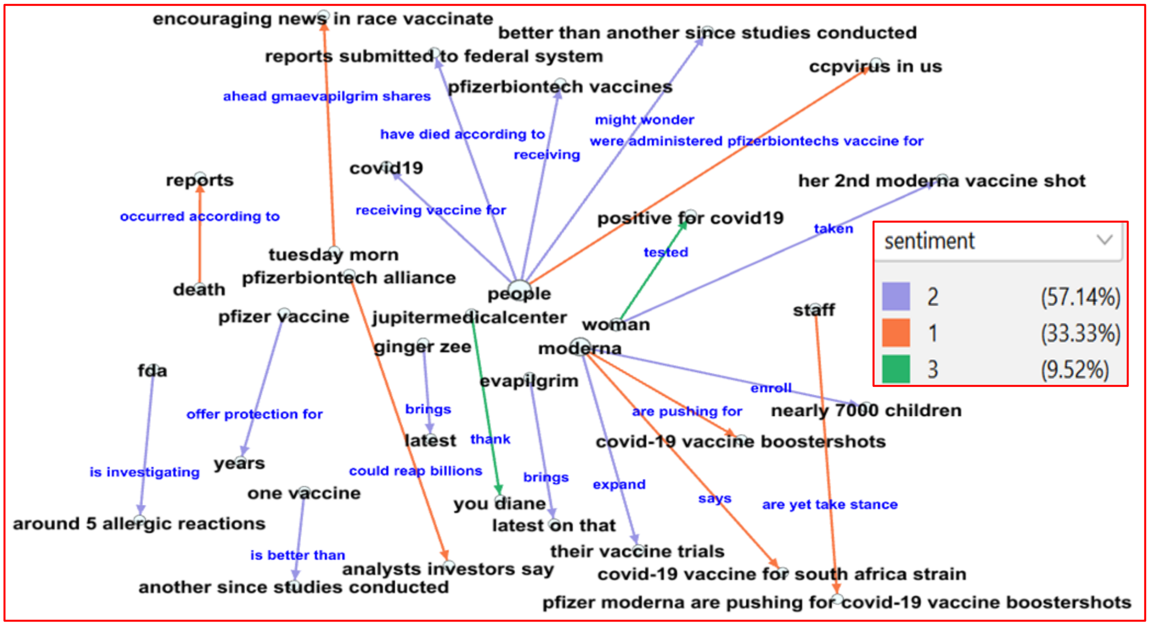


Figure 5.14 Knowledge Graph of New York State Summary Triples in view (G+SF)

Table 5.29 Details of New York State Summary Triples in View (G+SF)

Triple String	sentiment	userLoc	vaccines
people were administered pfizerbiontechs vaccine for ccpvirus in us	1	New York, USA	pfizer
fda is investigating around 5 allergic reactions	2	New York, USA	pfizer
people receiving vaccine for covid19	2	New York, USA	moderna pfizer
people have died according to reports submitted to federal system	2	New York, USA	moderna pfizer
people receiving pfizerbiontech vaccines	2	New York, USA	moderna pfizer
death occurred according to reports	1	New York, USA	moderna pfizer
moderna says covid-19 vaccine for south africa strain	1	NYC	moderna
evapilgrim brings latest on that	2	New York	moderna
moderna enroll nearly 7000 children	2	New York City	moderna
woman tested positive for covid19	3	New York, USA	moderna
woman taken her 2nd moderna vaccine shot	2	New York, USA	moderna
jupitermedicalcenter thank you diane	3	New York,	moderna

		New York	pfizer
one vaccine is better than another since studies conducted	2	New York City	moderna pfizer
people might wonder better than another since studies conducted	2	New York City	moderna pfizer
tuesday morn ahead gmaevapilgrim shares encouraging news in race vaccinate	1	New York	moderna pfizer
pfizer vaccine offer protection for years	2	New York	moderna pfizer
ginger zee brings latest	2	New York	moderna pfizer
moderna expand their vaccine trials	2	New York, USA	moderna pfizer
pfizerbiontech alliance could reap billions analysts investors say	1	New York, USA	moderna pfizer
staff are yet take stance pfizer moderna are pushing for covid-19 vaccine boostershots	1	New York, USA	moderna pfizer
moderna are pushing for covid-19 vaccine boostershots	1	New York, USA	moderna pfizer

5.6 Comparison with ChatGPT

In this section, we present the comparison between the summaries generated by our views (SF), (E) and (D) and by ChatGPT [191], a language model designed to respond to text-based queries and generate natural language response. By using a deep learning Transformer architecture, it learns patterns in language and generate response text in an abstractive way. As a state-of-the-art model just released and available in late 2022, it is worth making a comparison of ChatGPT and our framework. In this section, we presented two experiments.

The first is to contrast our view-based extractive summaries against the abstractive ChatGPT summary, and observe the differences in between. There is an input limit of 3,000 words for ChatGPT. Thus, instead of applying the whole set of 16,270 vaccine triples mentioned in **section 5.2.4**, we used the 83 vaccine triples based in New York City (**section 5.2.6.2**) as the input of ChatGPT and our developed method views, Social Feature view

(SF), Distance view (D) and Entity view (E). According to the low Rouge scores shown in **Table 5.30**, we found that the summaries are very different between each of our views and ChatGPT. We present the summary by ChatGPT in **Table 5.31**, and the summaries by our three views in **Table 5.32** (view SF), **Table 5.33** (view E), and **Table 5.34** (view D).

Table 5.30 Rouge Scores of ChatGPT Summary and Our View-based Summaries

Rouge F-1 Score	1-gram	2-gram	LCS
ChatGPT vs our view SF	0.27	0.06	0.25
ChatGPT vs our view D	0.23	0.06	0.22
ChatGPT vs our view E	0.35	0.14	0.33

Table 5.31 Summary Text by ChatGPT Summarizing 83 NYC-based Triples.

Moderna has developed a COVID-19 vaccine that is effective against the South African strain of the virus. The company is also enrolling nearly 7,000 children for pediatric trials, starting as young as six months. However, some people have experienced adverse reactions to the vaccine, and there have been reports of deaths after receiving the vaccine in Hong Kong. Moderna has also had some legal issues, with the company misspelled on an alleged fake vaccination card and only now challenging the validity of patents used in the vaccine.

Meanwhile, Pfizer-BioNTech's vaccine has been found to set off a persistent immune reaction in the body, leading some to call for a third booster shot. The FDA has amended emergency use authorizations for Pfizer and a skeptical federal circuit panel questioned the validity of Moderna's patents. Johnson & Johnson vaccine recipients are getting a booster shot from Pfizer, and the FDA advisory committee has recommended Moderna's booster shot for seniors and certain populations.

China-made vaccines, such as Sinovac, have been effective in some areas but less so in others, and there are concerns about the weak protection Sinopharm's vaccine offers against COVID-19 for older populations. The EU's drug regulator has found a possible link between rare heart inflammation and Pfizer's vaccine, but the CDC has not yet recommended a third shot.

Overall, the geopolitics of vaccines are becoming more important than the lives of European citizens, as countries jockey for position and make calculations based on human rights and other factors. While the situation remains uncertain, there have been some positive developments, such as Moderna's vaccine appearing safe in teens and preventing COVID-19 hospitalization.

Table 5.32 Summary Text by Our View SF Summarizing 83 NYC-based Triples

Moderna Says Covid-19 Vaccine for South Africa Strain Moderna is looking to enroll nearly 7000 children from six months to 12-years-old for the trial that will take place in the U.S. and Canada. Thank you jupitermedicalcenter thank you Diane! EU Vaccine Chief ThierryBretondiscusses thoughts on vaccine passports, disqualifying SputnikV from entry, and confidence in herd immunity this summer. People might wonder if one vaccine is better than another since studies conducted before the vaccines were rolled out found varying levels of effectiveness. Worry is that all the adenovirus-vector COVID19 vaccines (J&J, AstraZeneca & SputnikV) seem less effective & may cause blood clots. NONE of these issues apply to the mRNA vaccines -- moderna tx & pfizer -- they work, prevent death & theyre safe. Franz-Werner Haas, CEO CureVacRNAsays their COVID19 vaccine candidate is nearing the finish line. The 4th batch of Chinas Sinovac COVID-19 vaccine arrived in Cambodia on Sunday. with Zero cases of covid reported among vaccinated children. China to provide more than 1 billion doses of COVID19 vaccines in 2021 and supply to be further expanded next year as two more China-made vaccines, CanSino and Wuhan Institute of Biological Products, await approval by WHO, after Sinopharm and Sinovac. Pfizer says its time for a 3rd shot. the CDC & FDA say no. The Chinese Sinopharm COVID19 vaccines are holding up against the DeltaVariant -- scary for Asian countries and Brazil, where it has been the lynchpin of their SARSCoV2 responses. Effectiveness remained above 95% regardless of age group, sex, race, or comorbidities. A new study from Hungary found Chinas Sinopharm vaccine offers weak protection against COVID19 for older populations. A US FDA advisory committee voted to recommend the Moderna COVID-19 vaccine booster for some Americans. National Health ErinEBillups tells us whos eligible.

Table 5.33 Summary Text by Our View E Summarizing 83 NYC-based Triples

Moderna Says Covid-19 Vaccine for South Africa Strain Year Old Mother Dies After 2nd Dose of Moderna Vaccine Family - fox13 Moderna vaccine KUTV I feel like Im waiting for the other shoe to drop with this Moderna vaccine. Worry is that all the adenovirus-vector COVID19 vaccines (J&J, AstraZeneca & SputnikV) seem less effective & may cause blood clots. Modernas Covid-19 vaccine appears safe and effective in teens And hope in India as new cases slow down but daily deaths remain high; Singapore could ease curbs June 13; and Sinovac gets boost after proving highly effective in Serrana Brazil after 75% of towns adults got vaccinated. The vaccines made by Pfizer-BioNTech and Moderna set off a persistent immune reaction in the body that may protect against the coronavirus for years. FDA] is poised to amend the emergency use authorizations for the Pfizer & the Moderna COVID19 vaccines Thursday to allow people with compromised immune systems to get a third dose. As the US moves toward booster shots for those who received Pfizer and Moderna doses, a new trial out of South Africa on the efficacy of single dose johnsonandjohnson vaccine. A skeptical Federal Circuit panel questioned Thursday why Moderna only now is challenging the validity of patents used in the COVID19 vaccine when it has been licensing the same technology for use in other vaccines for years. JohnsonAndJohnson COVID19 vaccine recipients are better off getting a booster shot from Pfizer or Moderna, a highly anticipated U.S. study suggested Wednesday. FDA advisory panel endorses Moderna COVID booster shots for seniors and other high-risk groups. A US FDA advisory committee voted to recommend the Moderna COVID-19 vaccine booster for some Americans. CDC’s independent advisory panel voted unanimously to recommend [BoosterShot] doses of Moderna and JohnsonJohnson [COVID19] vaccine for certain populations and allow people to mix-and-match doses.

Table 5.34 Summary Text by Our View D Summarizing 83 NYC-based Triples

We are talking weather covid 19 vaccine moderna sleep pix11news see you at 56 and 10pm! We will deliver the number of doses necessary to achieve 70% of the adult population being vaccinated by mid-July. I feel like Im waiting for the other shoe to drop with this Moderna vaccine. Worry is that all the adenovirus-vector COVID19 vaccines (J&J, AstraZeneca & SputnikV) seem less effective & may cause blood clots. The vaccines made by Pfizer-BioNTech and Moderna set off a persistent immune reaction in the body that may protect against the coronavirus for years. I spoke with CBSNews medical contributor Dr. DavidAgus about that on wcbs880. The Chinese Sinopharm COVID19 vaccines are holding up against the DeltaVariant -- scary for Asian countries and Brazil, where it has been the lynchpin of their SARSCoV2 responses. Combining AstraZenecas COVID19 vaccine with a second dose from either Pfizer-BioNTech or Modernas jab provides good protection, Denmarks State Serum Institute said on Monday. The US CDC could weigh in soon. As the US moves toward booster shots for those who received Pfizer and Moderna doses, a new trial out of South Africa on the efficacy of single dose johnsonandjohnson vaccine. Learn more about third dose eligibility and find a vaccination site near you: Tomorrow our Legacies program continues with a special conversation with Dr. Tal Zaks, Chief Medical Officer at Moderna. Dr. Zaks and mattiekahn will discuss his family background, his Israeli and Jewish roots, and his life-saving work. Moderna misspelled on alleged fake vaccination card; woman visiting Hawaii arrested. CDCgov study finds Moderna vaccine is best at preventing Covid19 hospitalization via politico Bloombergs Josh Wingrove explains why the FDA wants to cut Modernas booster shots in half National Health ErinEBillups tells us whos eligible.

While ChatGPT model weighs the importance of different words or phrases in input triples to generate the abstractive summary, our framework weighs the importance of triples based on the criteria in each view, and generates the output in an extractive way by using corresponding original sentences of the top-ranking triples. Therefore, we obtained low Rouge scores along with different summary representations. Among our three views, the Rouge score of view E with ChatGPT is the highest. This means that the entity-based summary is more similar to the ChatGPT summary compared with social-feature based summary and distance-based summary. By looking into the summaries, we found that the summary generated by ChatGPT discuss important entities such as vaccine brands, organizations, locations, etc., which is the focus of the summary in our Entity-based summarization.

The second experiment with ChatGPT is that we used them as a gold standard summarization tool, and evaluated our summarization views. We assume that "if the Rouge scores of our view summary and ChatGPT summary is approximately equal to the Rouge scores of two ChatGPT summaries, then our summary framework is probably as good as ChatGPT."

We used the first 500 triples out of the 16,270 from section **5.2.4**, and split them into 5 sets evenly. For each set i (1<=i<=5), we generated 2 summaries by ChatGPT, Gi1 and Gi2, and generated summaries SFi, Ei, and Di by our social-feature view, entity view and distance view, respectively. We then compared the summaries and obtained Rouge scores by comparing Gi1 with Gi2, Gi1 with SFi, Gi2 with SFi, Gi1 with Ei, Gi2 with Ei, Gi1 with Di, and Gi2 with Di. After we obtained all n-set scores (n=5), we averaged the Rouge scores by n, and obtained average Rouge Scores, RougeChatGpt, RougeGptSF, RougeGptE, and RougeGptD, to evaluate the performance of our view-generated summaries against ChatGPT. The flowchart of the work process and final average Rogue score representations are shown in **Figure 5.15**. Based on the Rouge scores shown in **Table 5.35**, we found that our assumption is contradicted. There are 16% differences in 1-gram and LCS, and a 10% difference in 2-gram, where RougeChatGpt are higher. Among the three views, the view (SF) reflects the highest scores.

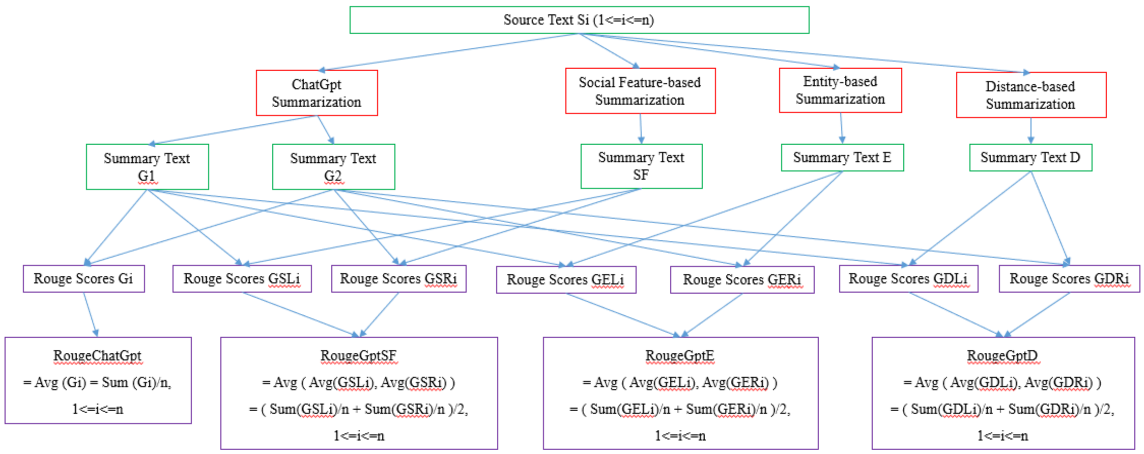


Figure 5.15 Flowchart of triple sets summary comparison of ChatGPT and our method views

Table 5.35 Rouge Scores of between ChatGPT Summaries, and between ChatGPT Summaries and our View Summaries

Rouge F-1 score	1-gram	2-gram	LCS
RougeChatGpt	0.47	0.22	0.44
RougeGptSF	0.31	0.12	0.28
RougeGptE	0.29	0.10	0.27
RogueGptD	0.29	0.10	0.26

5.7 Discussions

Our view-based summarization framework can generate summaries based on the entities, the events, the social features, or the sentiments. The framework provides multiple summaries from the same dataset. View (E) focuses on the entities that occur often in posts. Thus, entities play an important role in the post set. On the other hand, the emphasis may focus on the whole event. Therefore, we rank and select the prominent triples, which are to be included in the view (D). The views can be combined together to further narrow down a set of postings. For instance, we may focus on a summary of entities that is related to negative sentiments or possibly associated with fake news analysis [13]. Therefore, the composability of multiple views is an advantage of our method for users interested in targeted, fine-grained summaries, instead of a model generating “one-size-fits-all” summaries. A difficulty that we encountered in this task was the lack of a gold standard dataset of social media items together with corresponding summaries. Although there are many large social media text corpora, we were unable to find any gold standard for our task.

All the models we selected to compare with are variations of the transformer architecture [254], including encoder-only pre-training (BertSum, SBert) and encoder-decoder pre-training (Bart, T5). One disadvantage of transformers is that when the input sequence is long, the performance of the attention mechanism is undermined [255]. Besides, while our views accept input text of any length, these models all limit the lengths of input sequences. Thus, we had to break long text items into chunks, and combine summarized chunks as output. However, this loses contextual information, which is disadvantageous for abstractive summarization models that generate new sentences not existing in the original text. Therefore, when it comes to the comparison with a gold standard summary based on an extractive method, the performance of an abstractive method may have suffered.

CHAPTER 6

PROTOTYPE APPLICATIONS

In this chapter, we present our prototype web applications that utilize approaches presented in the previous chapters, including fake news detection, health policy tracking analytics and summarization.

6.1 Fake News Detection Applications

We built two fake news evaluator applications, one is used to detect COVID-19 related fake news items, using a passive-aggressive classifier and TF-IDF Vectorizer [256]. The other one is to detect general (non-COVID) related news, which is an SVM model built in our previous work [104]. Users can easily paste any text data item onto the textbox and get a prompt response regarding the authenticity of the data item. For COVID fake news, we got a prompt response of "Detected as Real News" by evaluating "Mask can prevent infection" (**Figure 6.1**) and "Detected as Fake News" by evaluating "Mask is not helping" (**Figure 6.2**), respectively. The results accurately show the reality that the input sentences reflect. We also evaluated general (non-COVID) fake news items and obtained accurate results, shown in **Figure 6.3** and **Figure 6.4**.

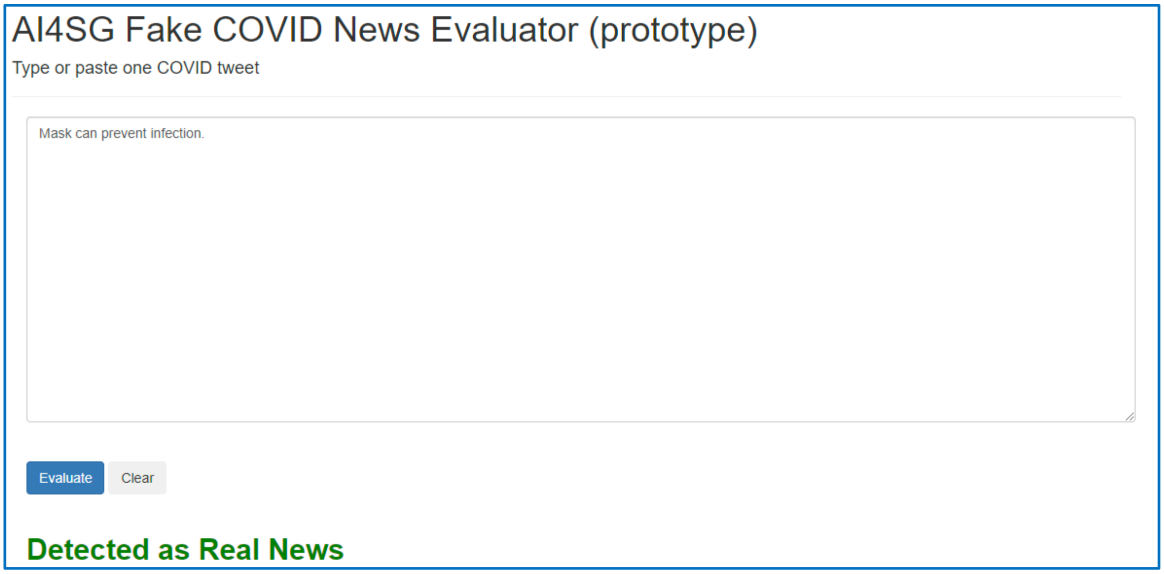


Figure 6.1 Our Prototype System for COVID fake news detection, with a data item evaluated as Real News (http://ai4sg.njit.edu/ai4sg/FakeNews)

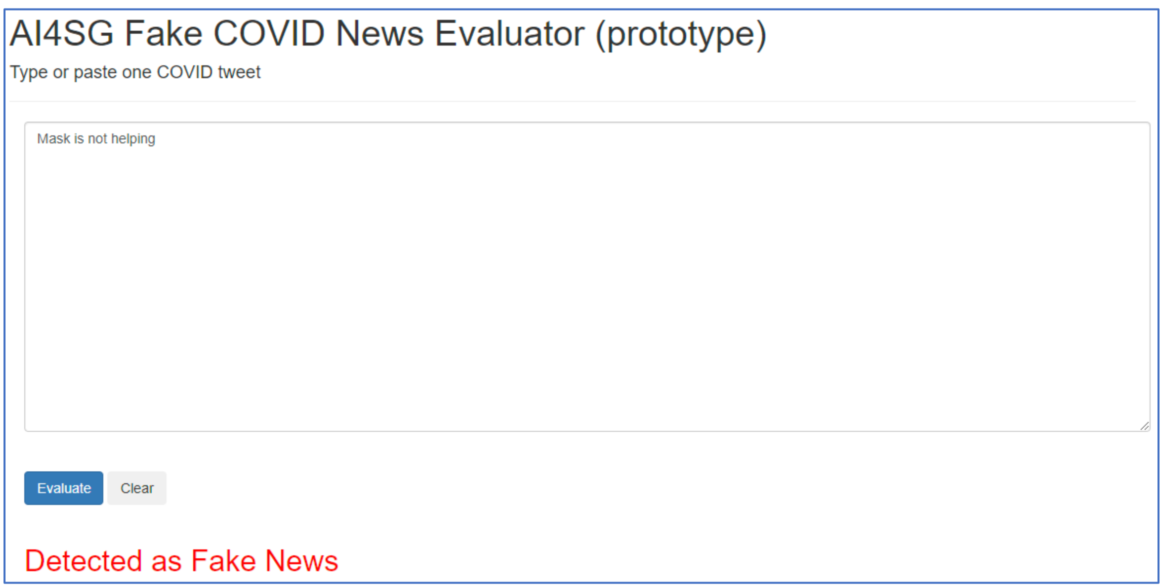


Figure 6.2 Our Prototype System for COVID fake news detection, with a data item evaluated as Fake News (http://ai4sg.njit.edu/ai4sg/FakeNews)

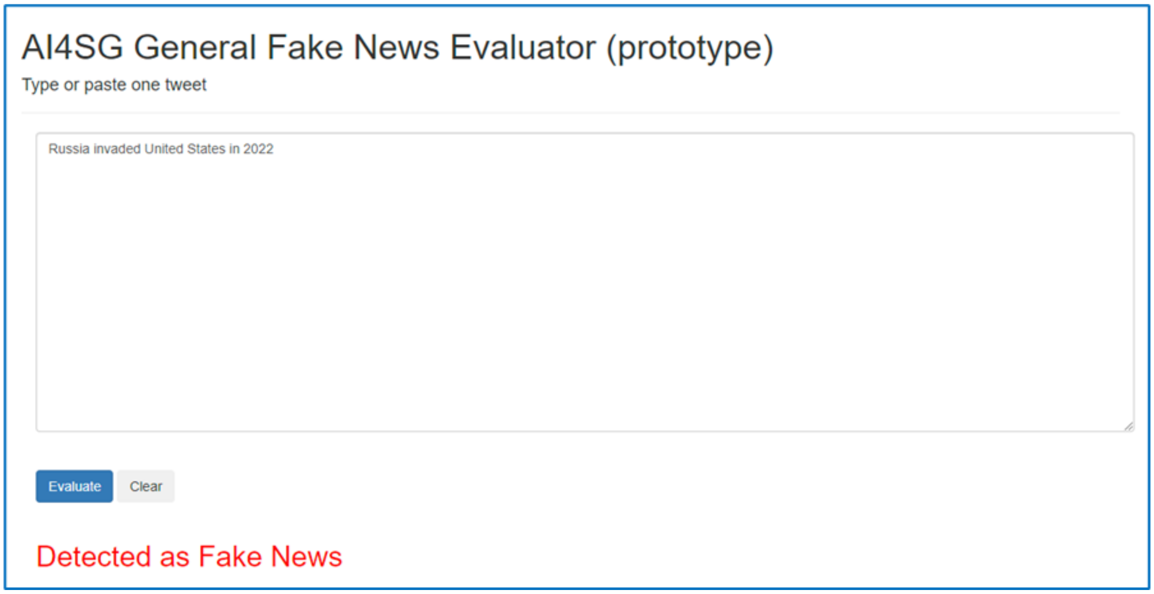


Figure 6.3 Our Prototype System for general (non-COVID) fake news detection, with a data item evaluated as Fake News (http://ai4sg.njit.edu/ai4sg/GeneralFakeNews)

Figure 6.4 Our Prototype System for general (non-COVID) fake news detection, with a data item evaluated as Real News (http://ai4sg.njit.edu/ai4sg/GeneralFakeNews)

We developed this detection app to provide convenient help to users to promptly verify the authenticity of a new item they are confused about. We built this app not only to detect fake news but also to help stop the spread. If a fake news item is recognized, we expect the chance of it being spread out of ignorance will be lower.

6.2 Tracking, Monitoring and Multi-View Summarization on COVID-19 Policies

We have continuously collected and sentiment-analyzed tweets about 12 government health policies about COVID-19, since January 2020, on a daily basis. We have added two new policies, Vaccines and Vaccine Mandates into tracking. Therefore, we expanded the number of policy types from 10 to 12. **Figure 6.5** shows our prototype tracking system, where the concern levels are calculated and presented on a monthly timeline.

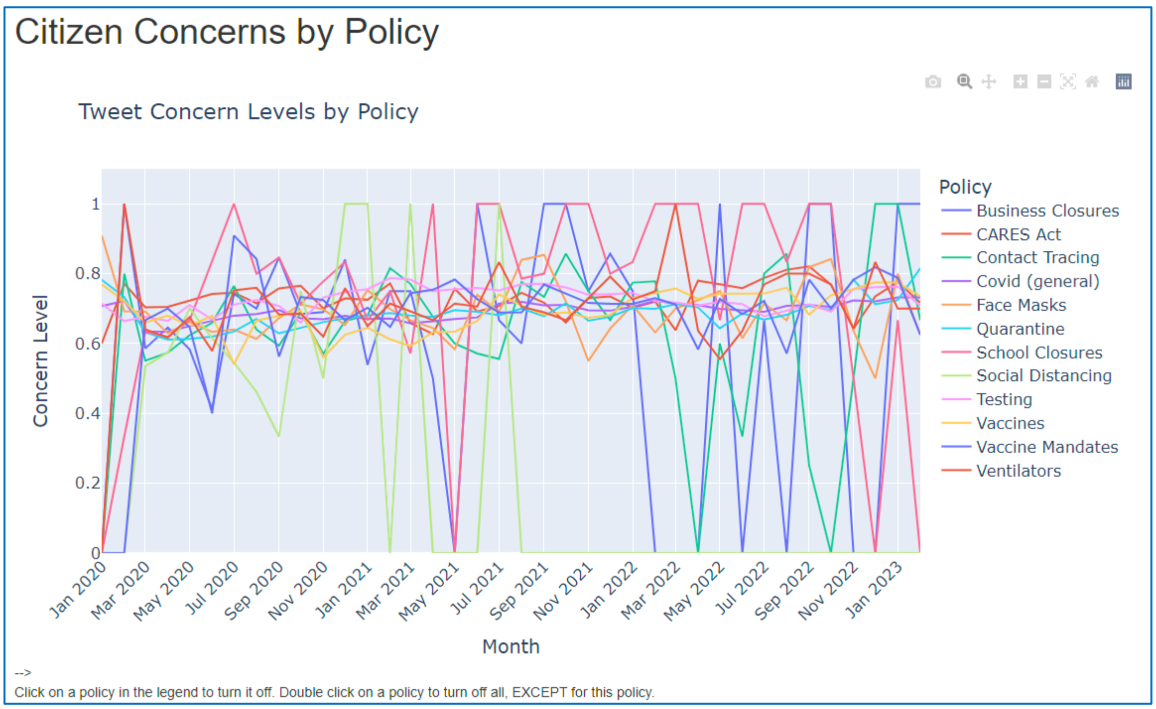


Figure 6.5 Tracking of citizen concerns toward 12 COVID government health policies from January 2020 to March 2023. (http://ai4sg.njit.edu/ai4sg/SentimentByPolicy)

As stated at the bottom of **Figure 6.5**, all policies except for the double clicked one can be turned off for a better observation experience. After double-clicking on "Ventilators," all policies except for "Ventilators" are turned off (**Figure 6.6**). With this built-in feature, users have the convenience of observing the concern level trend of the desired policy.

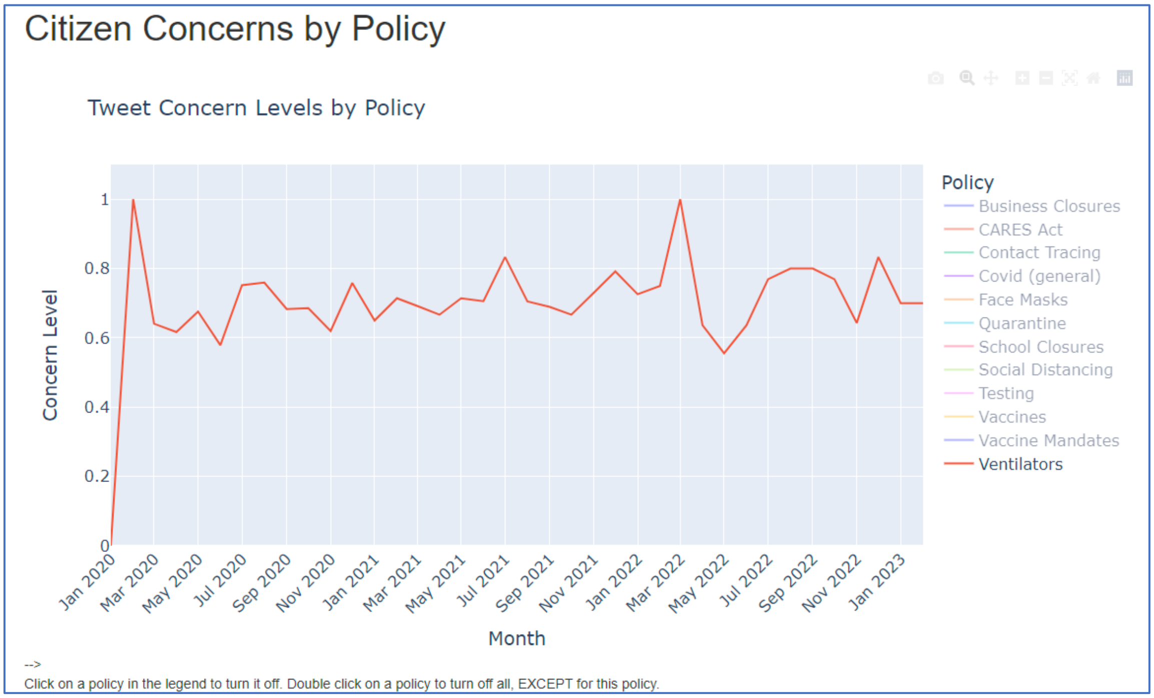


Figure 6.6 Tracking of citizen concern toward "Ventilators" after double-clicking on it.

Next, we present the summaries of "Vaccines" policy tweets posted in October 2022 in four views, (1) Entity View (**Table 6.1**), (2) Entity + Sentiment (Negative) View (**Table 6.2**), (3) Distance View (**Table 6.3**), and (4) Distance + Sentiment (Negative) View (**Table 6.4**).

Table 6.1 Summary of "Vaccines" Policy Tweets Posted in Oct. 2022 in Entity View

It is very convenient for the pharmaceutical companies to disclude the first few weeks after vaccination in studies if the vaccine increases the likelihood of injury/death or increases the susceptibility of contracting covid (or causes covid) immediately after receiving a shot. The vaccine does prevent infection in some people (mostly helps w severity of disease) & also reduces the likelihood of long Covid in those who are vaccinated. I was never under the impression that the vaccine prevented me from spreading COVID. Fact the vaccine didnt prevent Covid, and didnt prevent transmission. There is a lot of evidence that the vaccine reduces the severity of covid Vaccine was over 90 percent effective at preventing covid but because of the slow roll out and resisters the

virus was able to find new hosts and mutate to become vaccine evasive. Once the MRNA vaccine rolls out zero covid will be a thing of the past Plus, the vaccines on the list actually prevent the underlying illness unlike the Covid vaccine. The vaccine was 95 percent effective in preventing infection of the early version of covid, but was never tested on transmission to others. The vaccine was 95 percent effective in preventing infection for you of the early version of covid, but was never tested for how contagious you would be. The vaccine was 95 percent effective in preventing infection for you of the early version of covid, but was never tested for how contagious you would be. BBC News - India vaccine maker destroys 100 million doses of expired Covid jab

Table 6.2 Summary of "Vaccines" Policy Tweets Posted in Oct. 2022 in Entity + Sentiment (Negative) View

Its quite simple - republicans listened to ex-game show hosts who told them to eat horse wormer & that covid was just a bad cold & to refuse the vaccine. Despite knowing the COVID vaccine doesnt stop the spread of the virus, King County Executive is keeping the mandate in effect for employees and volunteers. Are you concerned about citizens who could of had a Covid vaccination but declined it for personal freedom reasons and subsequently died of Covid? The vaccine does prevent infection in some people (mostly helps w severity of disease) & also reduces the likelihood of long Covid in those who are vaccinated. The Flu vaccine only contains the Flu vaccine- and it is highly recommended this year as we look to be headed for a bad season. The vaccine lessened the severity of my illness and I am glad I didn't suffer anything other than a bad cold because I got jabbed - 3 times. Its sad thought that most future Covid deaths might result from the politically motivated vaccine deniers listening to the American affiliate of Russian State TV? Once the MRNA vaccine rolls out zero covid will be a thing of the past And- Will Covid vaccination stop transmission of the Covid virus? COVID-19 Vaccine Induced Myocarditis A Proven Cause of Death? The COVID vaccine has been proven to minimize the spread and severity of the deadly disease. BBC News - India vaccine maker destroys 100 million doses of expired Covid jab

Table 6.3 Summary of "Vaccines" Policy Tweets Posted in Oct. 2022 in Distance View

I got the COVID bivalent shot in one arm and the flu quadrivalent vaccine in the other arm yesterday. Maybe I misunderstood- long covid by definition ate vaccine side effects. This tool was essential in how managed our COVID vaccination roll out and focus around equity and hard to reach areas. Before we had a vaccine, many cases of myocarditis in teens & athletes was documented after they contracted covid-19. Ill give you some history. You're now playing revisionist history here. Hendersonville-based company calling itself Med Choice LLC, offering handwritten medical waivers personally reviewed and signed by a licensed physician."$139 for a vaccine waiver because youre afraid of needles? UK provided 5 and up. Insightful talk by Dr. The pandemic was a step backward for Tuberculosis>30 vaccines for COVID in 3 years Only 1 TB vaccine since 1921 = BCG (and no vaccines to curb pulmonary transmissions) I would love to see a cure for cancer, but this is so clickbaity Vote Republican to stop this madness. I had a case of COVID before any vaccination against COVID was available (Feb 2020). The children whom you injected with an emergency use authorized vaccine would not be eligible for any COVID vaccine in Denmark (limited to those aged Last

booster knocked me on my arse too. Once the COVID pandemic became a political dog whistle we lost our best chance to control it. Earlier I saw a commercial on the in partnership with regarding the covid vaccine and boosters.

Table 6.4 Summary of "Vaccines" Policy Tweets Posted in Oct. 2022 in Distance + Sentiment (Negative) View

Maybe I misunderstood- long covid by definition ate vaccine side effects. Covid shots were never intended to stop the virus! Allegedly the Pfizer CEO admitted that the vaccine was never tested to prevent infection or stop the spread of COVID Why is the federal government hiding COVID injury data? Doctors rip basis of Surgeon General Ladapos latest anti-COVID vaccine advice Insightful talk by Dr. The pandemic was a step backward for Tuberculosis>30 vaccines for COVID in 3 years Only 1 TB vaccine since 1921 = BCG (and no vaccines to curb pulmonary transmissions) Unless emerg vaccine approval was threatened by effective conventional drugs. CDC caught using same PR firm as Pfizer and Moderna to boost health communication" during covid scamdemic Well they voted down funding to prepare for the next pandemic! If your COVID vaccine left you feeling terrible, it probably offered you better protection, new study suggests Last booster knocked me on my arse too. Once the COVID pandemic became a political dog whistle we lost our best chance to control it. This is an OAN news correspondent showing weird path slides and calling it vaccine sickness Tom Cotton is against vaccine mandates even when COVID-19 pandemic is raging and/or appearing in different variants in spite of such mandates having proven effective in preventing deaths while hospitalized. Trump won and you know it Fuck Pfizer Anthony Fauci belongs in prison Rachel Levine is a man COVID is the flu with a better PR budget Ned Segal, Parag Agrawal and Vijaya Gadde are now unemployed losers. How much money did government give Big Pharma for a half-baked, over-hyped Covid vaccine?

6.3 Government Policy Awareness

To enhance public health policy awareness, our system provides a prototype spatial browsing tool in which policies can be filtered by policy area, state, city, and action date. We used the dataset of 5,295 pandemic-related policies or local actions in 23 distinct policy areas collected from the National League of Cities (NLC) local action tracker [238]. The implementation is based on the Tableau tool.

Users can review the counts of policies at the state-level (**Figure 6.7**) and the city level (**Figure 6.8**). Overall, the state of California has the most policies (**Figure 6.7**). The diagram shows that states have different policy priorities. The transit and mobility policies are more prominent in NY (25 counts) (**Figure 6.12**) compared to the housing policies (8 counts) (**Figure 6.10**), while in California, there are more housing policies (128) (**Figure 6.9**) than transit/mobility-related policies (38) (**Figure 6.11**). The map allows us to click the desired state (**Figure 6.13**), and view (**Figure 6.14**) the policy summaries (**Table 6.5**).

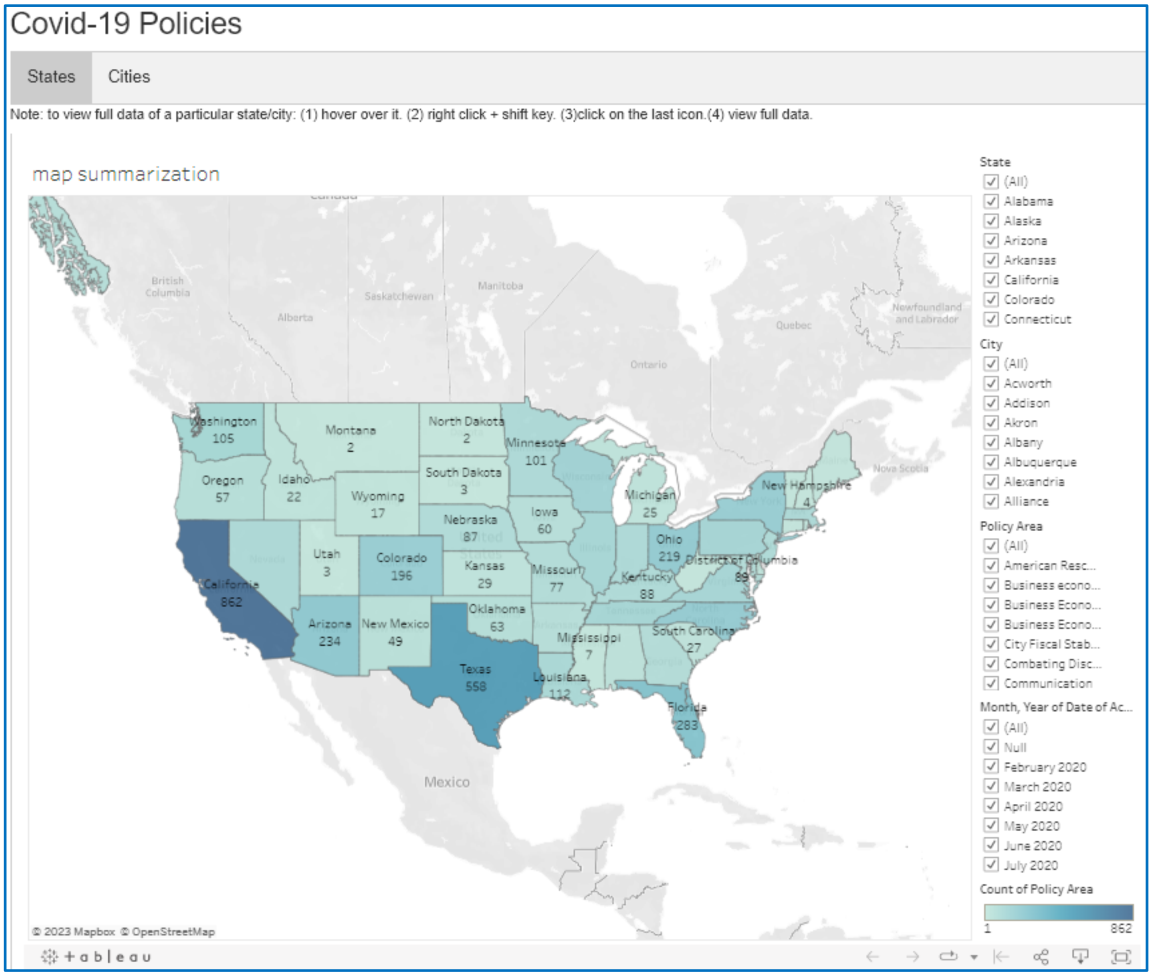


Figure 6.7 Map of Statewide COVID-19 Policy Summary (http://ai4sg.njit.edu/ai4sg/PolicyMaps)

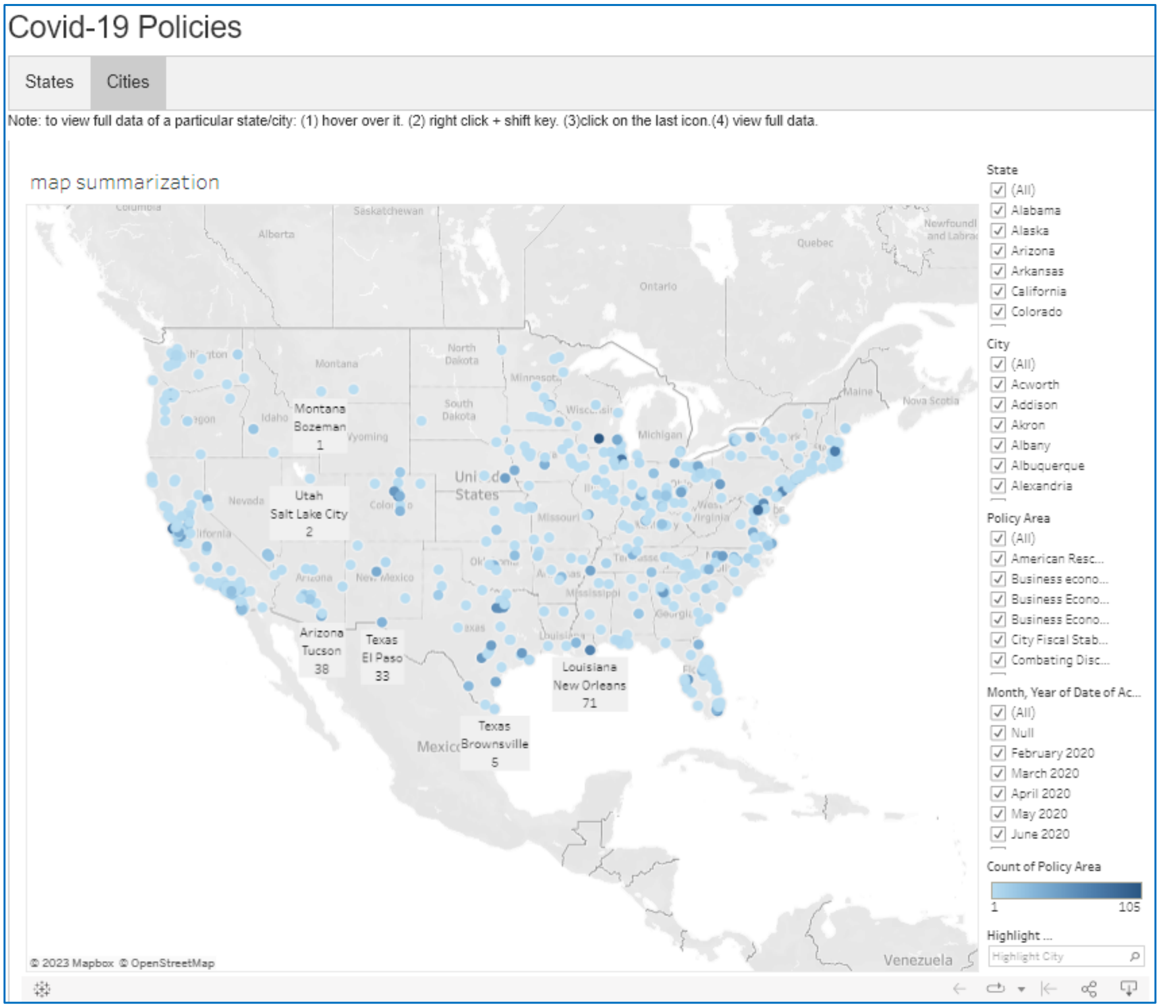


Figure 6.8 Map of Citywide COVID-19 Policy Summary (http://ai4sg.njit.edu/ai4sg/PolicyMaps)

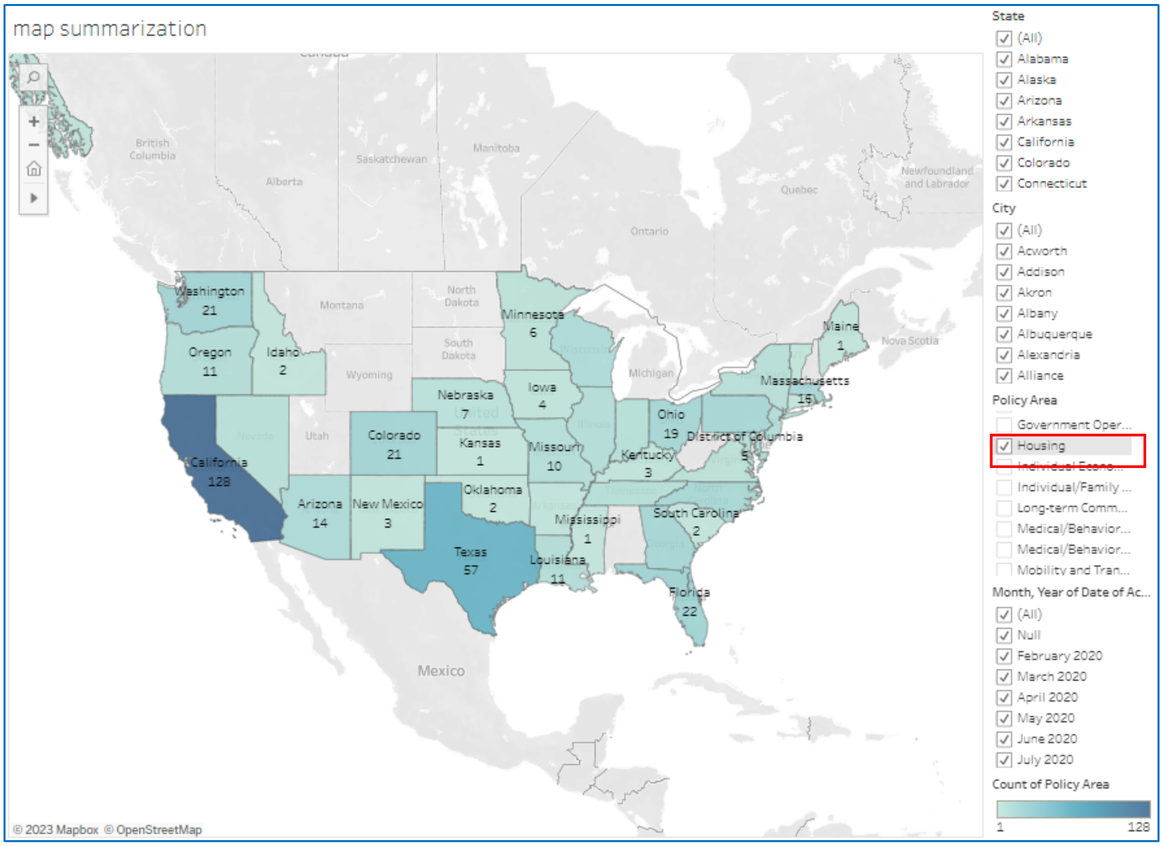


Figure 6.9 Housing Policy Counts in US states.

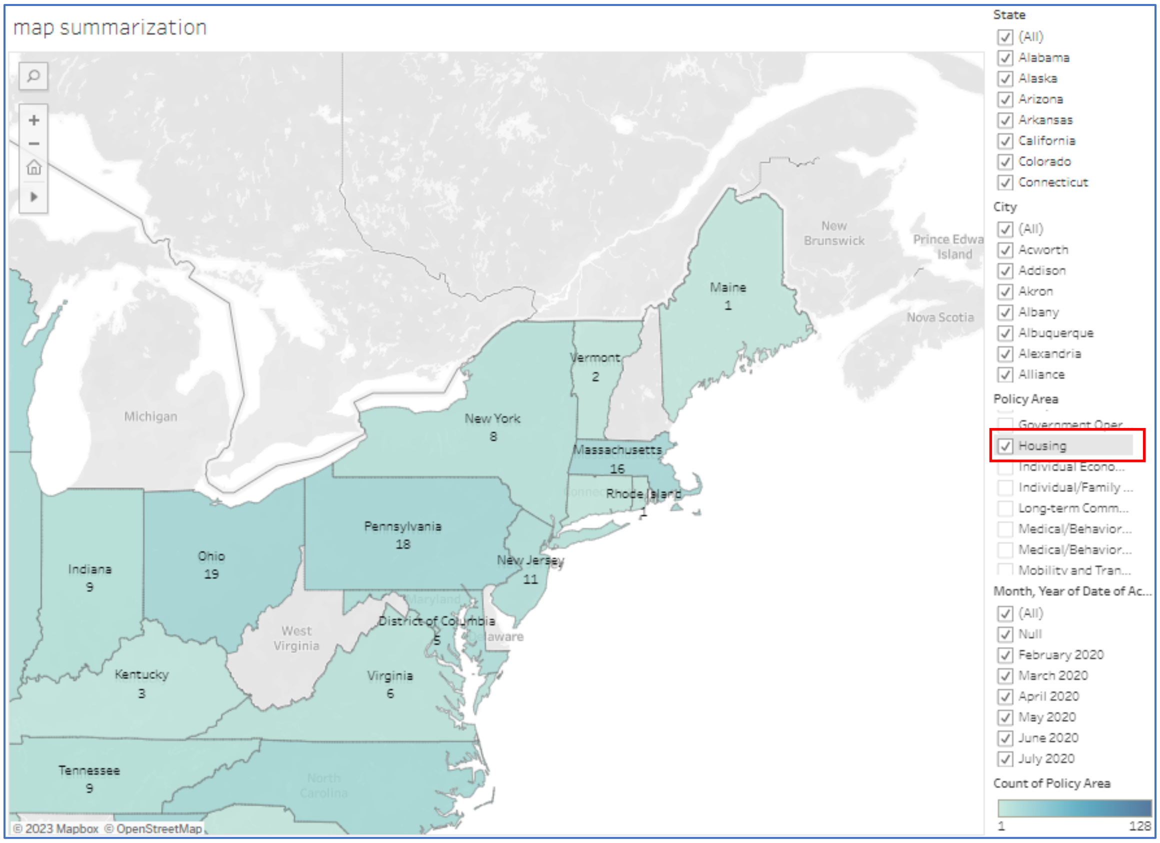


Figure 6.10 Housing Policy Counts among Northeastern States

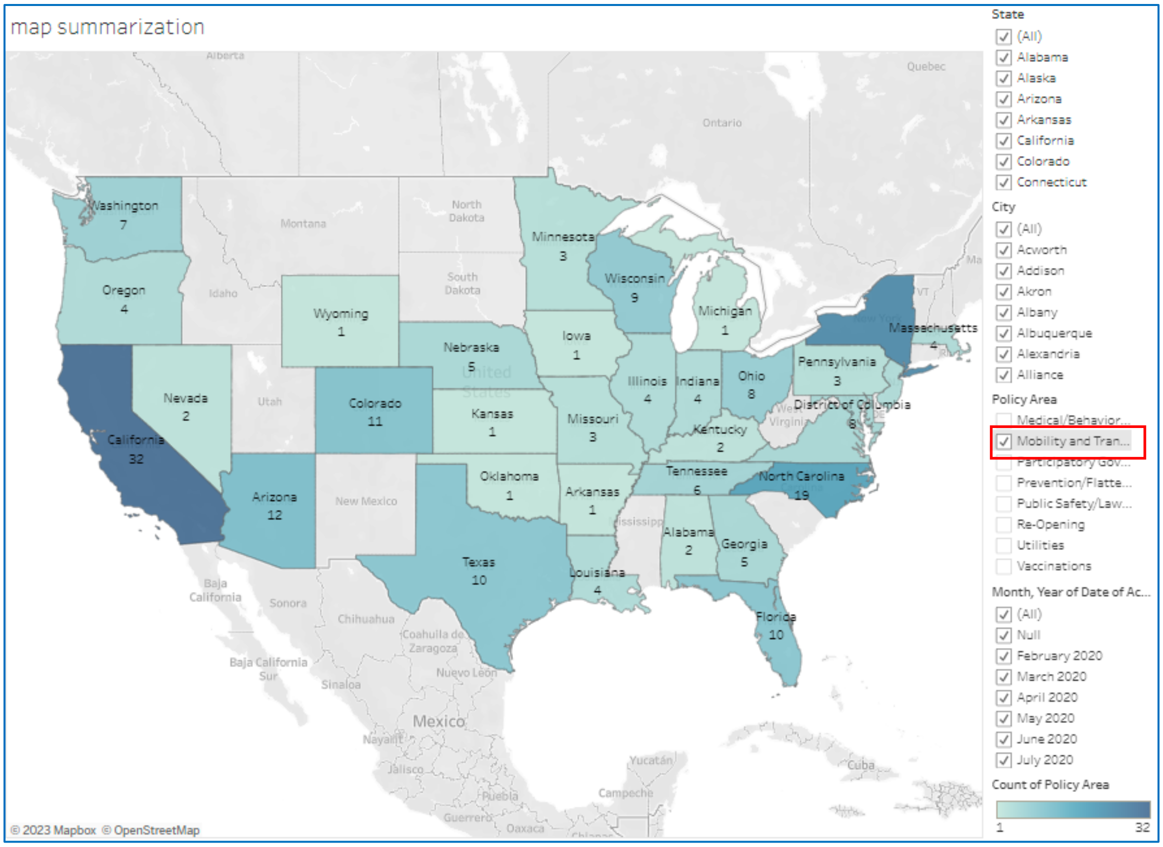


Figure 6.11 Mobility and Transit Policy Counts in US States

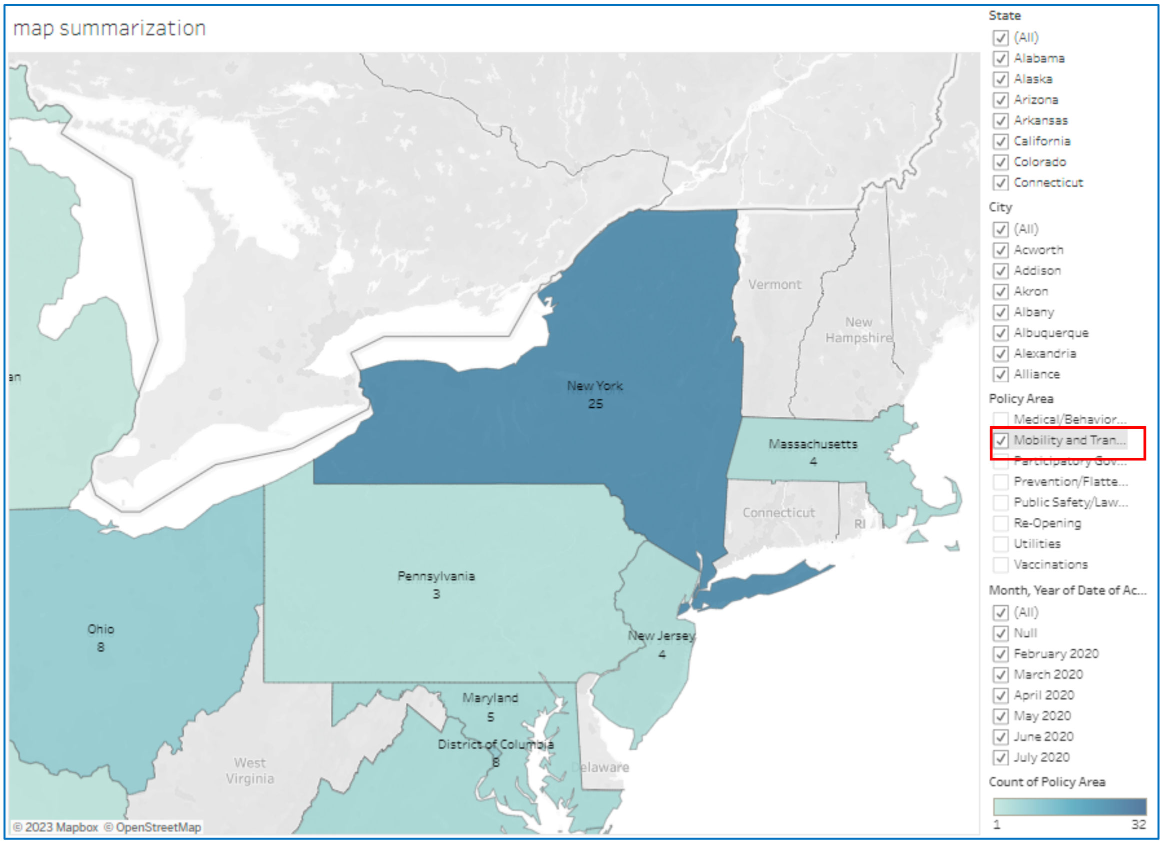


Figure 6.12 Mobility and Transit Policy Counts among Northeastern States

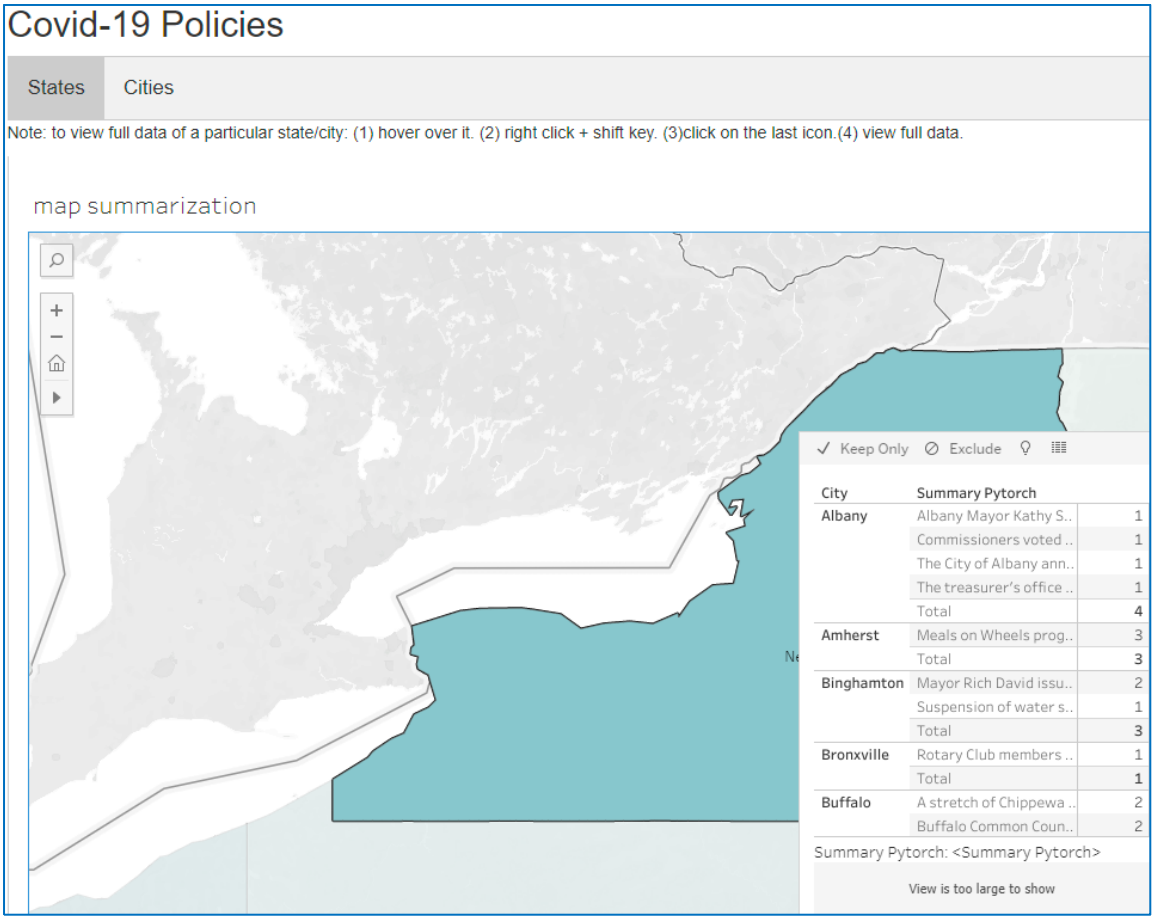


Figure 6.13 Steps to View a New York State Policy Summary

PytorchSummarization_V3.csv State	PytorchSummarization_V3.csv Policy Area	PytorchSummarization_V3.csv City	PytorchSummarization_V3.csv Summary Pytorch
New York	American Rescue Plan	Albany	Commissioners voted 4-2 to use the $22 million dollars of the Rescue Plan on sewer infrastructur...
New York	American Rescue Plan	Buffalo	Mayor Byron Brown unveiled the newest program that will benefit from American Rescue Plan doll...
New York	American Rescue Plan	Oswego	$15,000 grant is being provided to the Oswego Bookmobile to assist with the purchase of a new b...
New York	American Rescue Plan	Syracuse	Mayor Walsh unveiled plans for $123 million in federal aid to the City of Syracuse . Mayor Walsh co...
New York	American Rescue Plan	Buffalo	Buffalo Mayor Byron Brown says the four-point plan focuses on Â'people and placesÂ" and Â'progr...
New York	American Rescue Plan	Oswego	The City of Oswego is using $40,000 in funding from the American Rescue Plan to issue COVID-19...
New York	American Rescue Plan	Oswego	Mayor Billy Barlow announced the recipients of the city of OswegoÂs COVID-19 revival grant progr...
New York	American Rescue Plan	New York	Mayor Bill de Blasio today signed official legislation to make Open Streets a permanent part of Ne...

Figure 6.14 Steps to View a Policy Summary of "American Rescue Plan" in New York State

Table 6.5 Summaries of "American Rescue Plan" Policy in New York State

1. Commissioners voted 4-2 to use the $22 million dollars of the Rescue Plan on sewer infrastructure around the city . The funding will fix issues including lift station repairs and flooding .

2. Mayor Byron Brown unveiled the newest program that will benefit from American Rescue Plan dollars. $3.5 million dollars is going to a minority-owned business support program through the Beverly Gray Business Exchange Center.
3. $15,000 grant is being provided to the Oswego Bookmobile to assist with the purchase of a new bus vehicle to administer the Driving Books Home program . Part of the city's $1.89 million in funding from the American Rescue Plan .
4. Mayor Walsh unveiled plans for $123 million in federal aid to the City of Syracuse . Mayor Walsh committed to work with the Syracuse Common Council to begin deploying funds to the most time sensitive priorities .
5. Buffalo Mayor Byron Brown says the four-point plan focuses on people and places and progress and prosperity with two dozen proposed initiatives to improve equitable growth and inclusion .
6. The City of Oswego is using $40,000 in funding from the American Rescue Plan to issue COVID-19 recovery grants to community organizations in the city .
7. Mayor Billy Barlow announced the recipients of the city of Oswego's COVID-19 revival grant program . Originally, $150,000 was allocated from the $1.89 million the city received from the American Rescue Plan . After receiving approximately 50 applications totaling more than $750,000 in funding requests, the city increased the available funding to $225,000 .
8. Mayor Bill de Blasio today signed official legislation to make Open Streets a permanent part of New York City's urban landscape . Open Streets transformed our city and changed the way we came together as communities .

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

We built deep learning models for fake news detection based on different domains of datasets. Our BERT models exhibited better performance than previous studies. Due to the different nature of datasets, transfer learning with models trained with datasets that were collected before COVID-19 didn't work well with a COVID-19-related dataset. Based on our experiment, adjustments for transfer learning will be required to detect fake news across different domains of datasets.

To further analyze the features of fake news posts generated and shared on social media amid the COVID-19 pandemic, we applied a number of NLP techniques to DS3. We performed behavioral and sentiment analyses. We built topic identification models based on DS3 to recognize topics manipulated in fake news posts and discussed in real news post. We discovered a number of interesting findings that are also summarized in **Table 7.1**:

i. The concern level of fake news is greater than that of real news by 10%. Based on the derived p-value, we identified a significant difference. This result answered the first two questions in the Introduction: fake news expressed more negative emotions, and the difference is **significant**, which shows that fake news can cause negative emotional impacts on citizens and society.

ii. Real news posts are on average 40% longer than fake news. This implies that to recognize fake news, length can provide a hint. Regarding the use and count of hashtags, fake news contains more unique hashtags while real news has more total hashtags. Fake news posters tend to use "coronavirus" to describe the pandemic, while real news users tend to write "COVID19." In fake news, hashtags tend to contain substrings such as “trump,” “wuhan,” “virus,” “fact,” or “check,” while in real news, hashtags contain inspiring messages such as “indiawillwin,” “takeresponsibility,” “COVIDupdates,” “coronaupdates,” “wearamask,” “slowthespread,” “icmfightsCOVID19,” and “reopeningsafely.” When it comes to the use and count of mentions, real news contains more unique mentions and more total mentions than fake news. In fake news, the top mentions are the handles of politicians and fact check sites, while in real news, top mentions are the handles of public health experts and institutes. To further realize whether the identified features of hashtags and mentions help achieve better performance in fake news detection, we built detection models based on feature elimination. The detection model with both features achieved the best accuracy, while the model with both features eliminated showed the worst performance.

iii. By using the best coherence score based on topic numbers between three and ten, we generated six topics for both fake news and real news. We found that half of the identified topics are over-lapping across fake news and real news, including “people and vaccine,” “pandemic situation in India,” and “state’s critical cases.” We also found that fake news has a higher coherence score than real news in our experiments, which shows that fake news seems to have a more consistent writing style.

Table 7.1 Experimental Results and Comparison of fake news and real news in DS3

	Fake news	Real news
Hashtag	More unique hashtags.	More total hashtags. Inspiring and admonishing messages are expressed.
Mention	Top mentions are handles of politicians and fact checking sites.	More unique and total mentions. Top mentions are handles of public health experts and institutes.

Length	Real news posts are on average 40% longer than fake news. This implies that to recognize fake news, length can provide a hint.
Concern level	The concern level of fake news is great than that of real news by 10%. This is a statistically significant difference.
Topic Identification	Six topics were identified in both news items, half of which were overlapping, including “people and vaccine,” “pandemic situation in India,” and “state’s critical cases.” A higher coherence score shows a possibly relatively consistent writing style of fake news.

We have developed a Public Health Policy Perception Monitoring and Awareness Platform that tracks citizens’ concern level trends about 12 different public health policies during the COVID-19 pandemic. Our tools can also enhance the public understanding of government health policies. The concern level tracking revealed that “COVID-19 (General)” and “Ventilators” engendered the highest concern levels, while the “Face Coverings” policy caused the lowest concern levels during the data collection period.

Between the first week and the last week of our data period, the concern levels about “Economic Impact,” “COVID-19 (General),” “Face Coverings,” “Quarantine,” “School Closing,” and “Testing” demonstrated negative changes, while “Business Closing,” “Contact Tracing,” “Social Distancing,” and “Ventilators” underwent positive changes. Moreover, all changes except for “Business Closing” were significant.

Throughout the study period in **Chapter 4**, the concern level of “COVID-19 (General)” stayed relatively stable, even though the trends of both infections and deaths were notably fluctuating. Therefore, no meaningful correlation between the pandemic progress and the concern levels could be identified. This provides an answer to our third research question.

We expected to see a clear difference in concern levels regarding the economy that would reflect the political divide between politically red (Republican) and blue (Democrat) states. However, our experiments showed no evidence supporting this hypothesis.

We reviewed publicly available policies and local actions in 23 distinct policy areas, including 5295 pandemic-related policies [238]. Policies for Prevention/Flattening the Curve occurred most often (947), including rules for face covering, quarantine/self-isolation, social distancing, COVID-19 testing, ventilators, etc. The second most frequent policies dealt with Government Operations, totaling 631, including policies related to emergency services operations, first responders, and frontline medical workers across the country. The Housing policy category, with a total count of 521, ranked third.

The policy awareness tool, however, demonstrated regional differences for the analyzed policies, such as housing-focused policies in California compared to transit/mobility-focused policies in New York.

The summary of the housing policies in **Table 4.11** shows that the California Government provided more funds to help local people, such as tenants, the homeless, etc., to ameliorate the impact of the pandemic. The assistance from the government includes rental reimbursement, extended eviction protection, and accommodations for the homeless.

Our reported results are based on a specific period and concentrate on concern levels and government policies. However, the continuous monitoring capabilities of our system can be used to observe temporal trends and geographic distributions in policy perception. Thus, our platform can provide public perceptions as a near real-time feedback mechanism for policymakers and evaluators to appraise each health policy.

We presented a framework to generate multiple-view summarizations, using different summarization methods. These views may focus on the different aspects or dimensions of interest to generate summaries from different perspectives. The Entity-based summarization focuses on the entities that recur often in posts, thus, playing an important role in the post set. On the other hand, the emphasis may be focused on the whole event, thus, ranking and selecting the prominent triples (events) to be included in the summary. In addition, the user may prefer a negative Sentiment-based summary in contrast to a positive summary, or a fake-content based summary in contrast with verified news, to help suppress fake news.

Thus, a view-based summarization framework can generate summaries based on the entities, the events (whole triples), or the sentiments. The framework can add summarization perspectives to the basic entity or event-based summarization. This framework can provide multiple summaries of the same dataset, based on the desired perspectives. The views can be combined together to further narrow down a set of postings. For instance, we may focus on a summary of entities that is related to negative sentiments that are associated with fake news only, etc. The composability of the multiple-view-based summarization methods is one advantage for users who may be interested in targeted, fine-grained summarizations, instead of a model generating "one size fits all" summaries for a given post set. This may provide different perspective-based summaries. Large sets of social media posts focus on different aspects, even for the same topic. Capturing these perspectives and providing different view summaries is useful to understand the user behaviors for overwhelming data sets.

Our methods can be applied to any text dataset. We have shown that the triple embedding with Distance/similarity-based view summary (D) performs better than Entity-based summarization (E), and the Sentiment-based summary with Distance (S+D) demonstrated a better performance than SBert, BertSum, bart-large-cnn, and T5. We also found that different view summaries generated by different models have few sentences in common. This shows that the different view-based summarization methods focus on the different aspects in a given text.

We are working on achieving better transferability on fake news data among different domains, and building detection models that can identify cross-domain fake news. Based on our detection models, we will build a fact-checking web platform, which will help citizens get an immediate response regarding the authenticity of a news item that is copied and pasted into a window of a web page. The eventual goal of these methods is to serve social media platforms in an invisible manner. By including these machine learning models, social media platforms can decide to reject any messages that are recognized as fake news. Alternatively, they can let suspicious messages pass through to the user community, but provide a pop-up warning to readers that the message is potentially fake news. The second solution would be more acceptable to activists who are concerned about free speech in social media [257].

A limitation in the presented work is the partial analysis of concern levels about COVID vaccines. At the beginning of this study, vaccines did not yet exist. With the wide availability of Pfizer, Moderna, etc. vaccines, the new phenomenon of "political" and personal resistance to vaccine policies has arisen. Thus, unexpected to us, vaccines were not universally welcomed by the population. A simple recording of concern levels about vaccines does not distinguish between citizens concerned about getting access to the shots versus citizens concerned about the negative effects of the vaccines. We plan to perform a more fine-grained analysis of the available social network data about vaccines. The concepts in Chapter 4 could be applied to understand citizens' concerns about entirely different public events and policy actions. Our concern level tracking system could be easily repurposed to analyze tweets for sentiments regarding other policies, e.g., immigration rules, tax cuts, congestion pricing in New York City, or funding for inter-planetary space travel. The possibilities are as broad as the range of government actions and natural events causing them. We plan to expand this dynamic policy data collection capability by allowing users to select new policies to be tracked or by automatically identifying emerging policies to monitor. This will make the platform adjustable for future crisis events.

We are currently integrating the summarization work into a real-time summarization app. By selecting a certain time range and/or topic, the program can return summaries based on even more differentiated views. The methods that we described as well as the gold standard summaries are extractive. In the future, we would like to extend our work to a hybrid (abstractive and extractive) summarization method. We plan to ask humans to generate summaries and build an abstractive gold standard summary of fake news posts.

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