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ABSTRACT

COMPARISON OF DIFFERENT DIFFERENTIAL EXPRESSION ANALYSIS TOOLS FOR RNA-SEQ DATA

**by
Junfei Zhu**

In molecular biology research, RNA-seq is a relatively new method for transcriptome profiling. It utilizes the next generation sequencing technology to provide huge amount information about the variety and abundance of RNA present in an organism of interest at a specific state and a given time. One of the most important tasks of RNA-seq analysis is finding genes that are expressed differently in different subject groups. A lot of differential expression analysis tools for RNA-seq have been developed, but there is no golden standard in this field. In this research, four commonly used tools (DESeq, edgeR, limma, and cuffdiff) are studied by comparing their performances in the normalization of different subject group data, and also in the sensitivity and specificity of selection of genes with differential expression. In addition, their performances on genes which only express in one condition are compared. The data used are SEQC and melanoma. The result shows that in differential expression analysis, DESeq is slightly better than other tools in normalization, while DESeq, edgeR, and limma, in general, display good sensitivity and specificity, and limma outputs less false positive predictions. In cases where genes of interest are absent in one of the conditions, limma has the best performance.

**COMPARISON OF DIFFERENT DIFFERENTIAL
EXPRESSION ANALYSIS TOOLS FOR RNA-SEQ DATA**

by
Junfei Zhu

**A Thesis
Submitted to the Faculty of
New Jersey Institute of Technology
in Partial Fulfillment of the Requirements for the Degree of
Master of Science in Bioinformatics**

Department of Computer Science

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APPROVAL PAGE

**COMPARISON OF DIFFERENT DIFFERENTIAL
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CHAPTER 1

INTRODUCTION

1.1 Objective and Methods

The objective of this study is to compare the performance of some of the most commonly used differential expression tools on RNA-seq data. These tools include DESeq¹, edgeR², limma³ and cuffdiff⁴. Several features such as the normalization, sensitivity and specificity of differential expression analysis, false positive rate, and performance when genes only express on one condition are taken into consideration.

For the normalization comparison, a clustering was carried out based on the samples, and the distribution of the normalized counts was generated by boxplot. Normalization is a process to remove variances in data caused by differences in read coverage or other experimental procedure rather than by real biological differences. If the replicates of normalized data can cluster in the same condition group as the original data, it will be considered that the normalization procedure is acceptable. Also the differences of medians of samples should be reduced by normalization.

For the sensitivity and specificity comparison, SEQC data was used in the study. Since a set of synthetic RNAs from the External RNA Control Consortium (ERCC) at known concentrations is mixed, the accuracy can be tested in different tools. Furthermore, there are around 1000 genes' expression have been test by qT-PCR, a more comprehensive comparison can be conducted.

To test the false positive rate of different tools, samples from the same condition were compared to detect the differential expressed genes. As expected, the distribution of p-value should be uniform⁶.

To test the performance of differential expression analysis tools when only one condition has expressed, such subset of genes were selected, and the ratios of signal to noise were computed⁶. A better model should assign more significant p-values to these genes which have higher ratio of signal to noise.

1.2 Background Information

Instead of microarray, RNA-seq has been used as a powerful tool in transcriptome profiling. One of the key tasks of transcriptome profiling is to quantify the expression levels of each transcript in different conditions, such as normal and cancer, or different time points. Several tools have been developed for this purpose, for example, DESeq, edgeR, limma and cuffdiff. These tools base on different statistics models, such as negative binomial, or Bayes.

For the differential expression detection, there are two important steps. The initial step is normalization. During the preparation of libraries, due to different platform, the library sizes can differ in a large range⁶. To detect the differential expression genes, normalization is a core step⁷. The fundamental assumption for RNA-seq differential expression analysis is the number of reads which are aligned to the genes can present the expression level of these genes. Therefore, there are two biases: sequencing depth and gene length⁸. During the library preparation, larger library sizes will generate more reads. And the longer genes will have more reads aligned. One simple way to figure out the biases is to divide the counts number for each gene by the gene length and library size. FPKM⁴ (Fragments Per Kilobase of exon per Million fragments mapped) is introduced in cuffdiff to deal with such issue. However, according to the experiment experience, there

are always small amount genes which can generate larger proportion of reads⁹. They can affect the library size. It means that the proportions of reads which are generated by genes are dependent on other genes.

After the normalization step, differential expression analysis will be conducted. To model the distribution of number of reads which are aligned to different genes, it is very common to think about Poisson distribution. But for the Poisson distribution, there is only one parameter λ . The mean and variance both equal to λ . However, in the RNA-seq data, the variance is always larger than the mean¹⁰. Instead of Poisson distribution, negative binomial distribution¹¹ is introduced, since in the negative binomial distribution, the variance is not necessary to be equal to mean.

CHAPTER 2

DATASET

2.1 SEQC

The dataset is part of SEQC study. There are two conditions: condition A and condition B. Each condition has five replicates. For condition A, the sample is a mixture of ten human's different cell types (B lymphocyte, brain, breast, cervix, liposarcoma, liver, macrophage, skin, testis, and T lymphocyte). For conditions B, the sample is a mixture of several brain regions from 23 adults. These replicates are technical replicates, because replicates of the same condition are from a single sample. Each sample was mixed with a set of synthetic RNAs from the External RNA Control Consortium (ERCC) at known concentrations. Samples from condition A contain 2% by volume of ERCC mix 1. Samples from condition B contain 2% by volume of ERCC mix 2.

2.2 ERCC RNA Spike-In Mix and qRT-PCR

In the ERCC spike-in control, there are 92 synthetic polyadenylated oligonucleotides of 250-2000 nucleotides long. There are two mixtures, mixture 1 and mixture 2. The 92 synthetic polyadenylated oligonucleotides are divided into four subgroups, A, B, C, and D. Each subgroup has 23 transcripts. And their concentrations ratios in mixture 1 and mixture 2 are 4, 0.5, 0.67 and 1 separately. In the differential expression analysis step, the subgroup D with concentration ratio 1 will be considered as true negative, and other three subgroups are considered as true positive.

Except for the 92 synthetic polyadenylated oligonucleotides, there are around 1000 genes' expressions in eight replicates (four replicates from condition A and four replicates from condition B) have been measure by qRT-PCR technology.

2.3 Melanoma Dataset

There are 14 samples which are divided into six conditions in melanoma dataset. The detailed information is showed in table 2.1. Four comparisons are conducted between these conditions: condition 1 vs. condition 2, condition 1 vs. condition 3, condition 4 vs. condition 6, condition 5 vs. condition 6. To conduct the false positive comparison, pairwise comparisons are carried out between the four replicates in condition 3.

Table 2.1 Description of the Melanoma Dataset

	Index	Description
Condition 1	Index 1	Dermal stem cells in stem cell media
	Index 7	Dermal stem cells in stem cell media
Condition 2	Index 8	Melanocytes in melanocyte media
	Index 9	Melanocytes in melanocyte media
Condition 3	s4	FF144SC p12 in StemPro
	s5	FF160SC p4 in StemPro
	s6	MSC p3 in StemPro
	s7	HMVECnd p4 in StemPro
Condition 4	Index 6	Melanocytes with Notch GFP in stem cell media
	Index 12	Melanocytes with Notch GFP in stem cell media
Condition 5	Index 5	Melanocytes with Notch GFP in melanocyte media
	Index 11	Melanocytes with Notch GFP in melanocyte media
Condition 6	Index 4	Melanocytes with control GFP in melanocyte media
	Index 10	Melanocytes with control GFP in melanocyte media

CHAPTER 3

ALIGNMENT AND GENE COUNTS

3.1 Sequence Alignment

All the sequenced short reads are aligned to human genome hg19.gtf which is downloaded from UCSC. For SEQC dataset, the hg19.gtf file is mixed with ERCC transcript information which is downloaded from Life technology website <http://www.lifetechnologies.com/order/catalog/product/4456740>. Tophat2¹² is used to carry out the alignment task. And the summary of the alignment is generated (Table 3.1, 3.2). The average mapping rate of SEQC dataset is 86.19%. The average mapping rate of melanoma dataset is 82.22%.

Table 3.1 Summary of the Alignment of SEQC Dataset

Sample	Condition	Number of reads	Number of aligned reads	Mapping rate
SRR950078	A_1	200,774,020	175,886,653	87.6%
SRR950079	B_1	222,075,402	187,186,468	84.3%
SRR950080	A_2	183,562,954	159,981,986	87.2%
SRR950081	B_2	224,855,528	195,448,825	86.9%
SRR950082	A_3	134,415,514	106,879,116	79.5%
SRR950083	B_3	226,323,912	194,643,956	86.0%
SRR950084	A_4	250,166,388	214,364,321	85.7%
SRR950085	B_4	188,373,788	164,125,122	87.1%
SRR950086	A_5	143,531,234	126,983,375	88.5%
SRR950087	B_5	121,199,466	108,039,889	89.1%

Table 3.2 Summary of the Alignment of Melanoma Dataset

Index	Condition	Number of reads	Number of mapped reads	Mapping rate
Index 1	1	37,570,912	32,464,567	86.41%
Index 7	1	56,635,435	48,494,193	85.63%
Index 8	2	44,741,908	38,803,621	86.73%
Index 9	2	68,465,092	57,907,439	84.58%
s4	3	45,520,385	35,625,472	78.26%
s5	3	45,501,178	34,288,113	75.36%
s6	3	48,169,747	36,468,083	75.71%
s7	3	51,460,718	39,280,037	76.33%
Index 6	4	136,196,886	123,865,622	90.95%
Index 12	4	51,146,404	41,794,202	81.71%
Index 5	5	29,174,334	23,550,504	80.72%
Index 11	5	44,654,136	37,660,136	84.34%
Index 4	6	33,318,109	27,031,597	81.13%
Index 10	6	37,683,524	31,361,331	83.22%

3.2 Gene Counts

HTSeq was used to generate the raw gene counts from the aligned bam files with the following parameters: -m intersection-strict -s no. With the parameter -m intersection, if there are reads which are aligned to multiple genes, these reads were excluded (Figure 3.1). The distribution of raw counts numbers after log₂ transformation is shown in Figure A.1 and B.1.

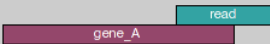


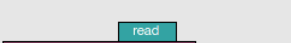
	union	intersection_strict	intersection_nonempty
	gene_A	gene_A	gene_A
	gene_A	no_feature	gene_A
	gene_A	no_feature	gene_A
	gene_A	gene_A	gene_A
	gene_A	gene_A	gene_A
	ambiguous	gene_A	gene_A
	ambiguous	ambiguous	ambiguous

Figure 3.1 Illustration of the effect of the model in HTSeq-count. There are three models in HTSeq-count, and the model of intersection-strict was used in the thesis.

Source: <http://www-huber.embl.de/users/anders/HTSeq/doc/count.html>, accessed September 23, 2013

CHAPTER 4

RESULTS

4.1 Normalization

The first step of differential expression analysis of RNA-seq data is normalization. It is very important to the downstream analysis. To compare the normalization methods of different tools, boxplots of distributions of normalized counts are generated and hierarchical clustering is used based on the normalized counts of each sample⁶. For a good normalization, the hierarchical clustering should group different samples from the same condition into a cluster.

From the boxplots of distributions of normalized counts by different tools (Figure A.2 to A.5 and Figure B.2 to B.5), the distributions of normalized counts by DESeq, limma and cuffdiff are good and very similar to each other. But for edgeR, the distributions of normalized counts do not change compared to raw counts.

During the hierarchical clustering analysis, for the SEQC data, the result shows that all the tools perform very well (Figure C.1). Different replicates from same conditions are grouped together. But when the same clustering is performed in the raw counts, it still can separate samples based on their conditions (Figure 4.1). Admittedly, this method cannot prove the performance of normalization methods. As a result, Dunn cluster validity index⁶ is introduced to compare the clustering. A good clustering is a kind of one, in which, members in the same cluster have a small variance, and the means of different clusters should be different enough. A higher Dunn index indicates better

clustering. As a result, DESeq has a highest Dunn index, while cuffdiff has a lowest Dunn index (Figure E.1).

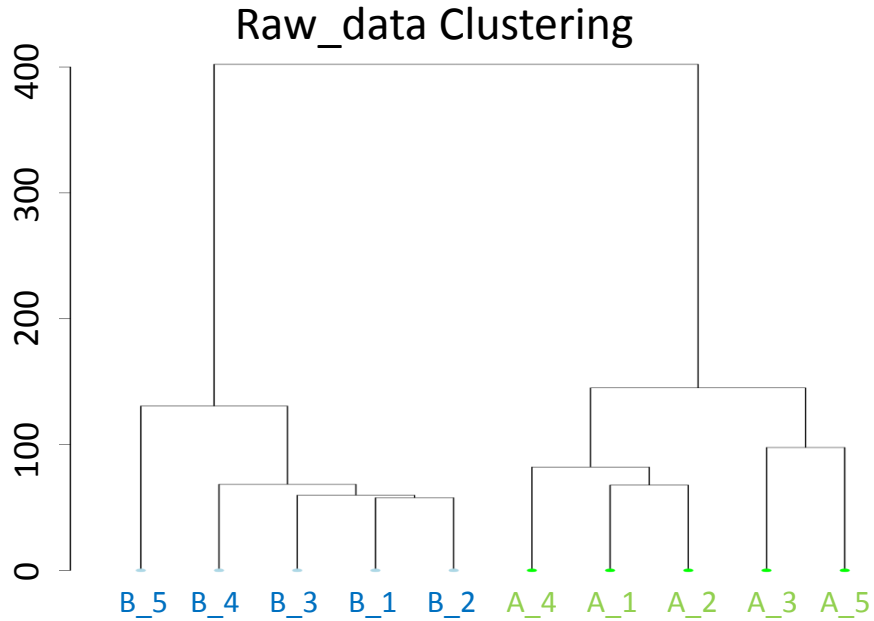


Figure 4.1 Hierarchical clustering based on the raw counts. Hierarchical clustering based only the raw counts of ten samples still can group samples from the same conditions together.

For the melanoma dataset, the result of hierarchical clustering analysis is completely different. In comparison between condition 1 and condition 2, index1 and index8 are grouped together, index7 and index9 are grouped together (Figure D.1). Actually, index1 and index8 are from the same individual, and index7 and index9 are from another individual. In another three comparisons, the performances of the four tools are very similar to each other. Samples from the same conditions are grouped together.

Since around 1000 genes' expression of eight samples in SEQC dataset (four replicates of condition A and four replicates of condition B) has been measured by qRT-PCR, the correlation between the logFC (fold change by log transformation) of

expression measured by qRT-PCR and these differential expression analysis tools can be computed⁶. A higher correlation value indicates a better normalization. DESeq has a largest RMSD correlation 1.94 and limma has a smallest one 1.26 (Figure F.1).

To sum up, there is no big difference in normalization step among these tools except for edgeR. DESeq performs a little better than others.

4.2 Differential Expression Analysis

In the SEQC data, there are total 22425 genes, and the numbers of detected differential expressed genes by different tools are showed in table 4.1. The average percentage of detected differential expressed genes is 71.96%. The overlaps of detected differential expressed genes by different tools are generated. To measure the level of overlap, the overlapping correlation is computed. For two sets, the number of overlapped elements divided by the minimum number of elements between the two sets is computed as the overlapping correlation. The minimum overlapping correlation is 0.94 which indicates that the detected differential expressed genes by different tools are very similar to each other.

Table 4.1 Numbers of Detected Differential Expressed Genes by Tools in SEQC

	Number of Differential Expressed Genes	Total	Percentage
DESeq	16042	22425	0.715362
edgeR	16617	22425	0.741003
limma	17000	22425	0.758082
cuffdiff	14892	22425	0.664080

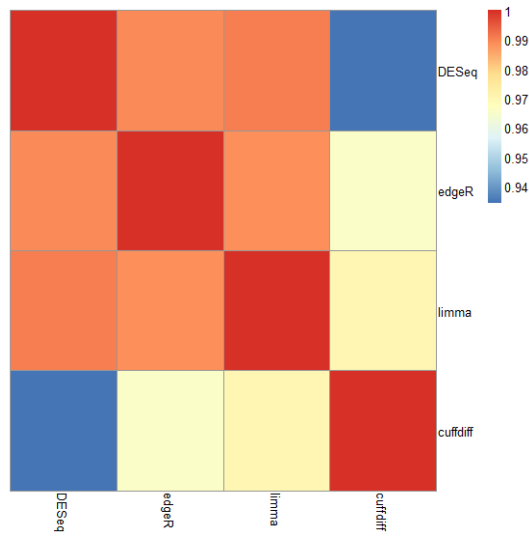


Figure 4.2 Overlapping correlation of differential expressed genes by four tools. The overlapping correlation of DESeq and edgeR is highest.

In the SEQC dataset, there are 92 synthetic oligonucleotides which are mixed into two mixtures. The 92 synthetic oligonucleotides are divided by four groups, and each group has 23 synthetic oligonucleotides. The four groups have different concentration ratios in the two mixtures which are 4, 0.5, 0.67 and 1. In the comparison, the group with concentration ratio 1 is considered as true negative, and others are true positive. The sensitivity and specificity of differential expression detections are showed in Table 4.2. Also the ROC curve was computed (Figure 4.3). edgeR has a higher AUC value 0.793.

Table 4.2 Sensitivity and Specificity of Differential Expression Detection

	DESeq	edgeR	limma	cuffdiff
Total	68	74	73	59
True Positive	58	62	62	48
Sensitivity	84.1%	89.9%	89.9%	69.6%
Specificity	56.5%	47.8%	52.2%	52.2%

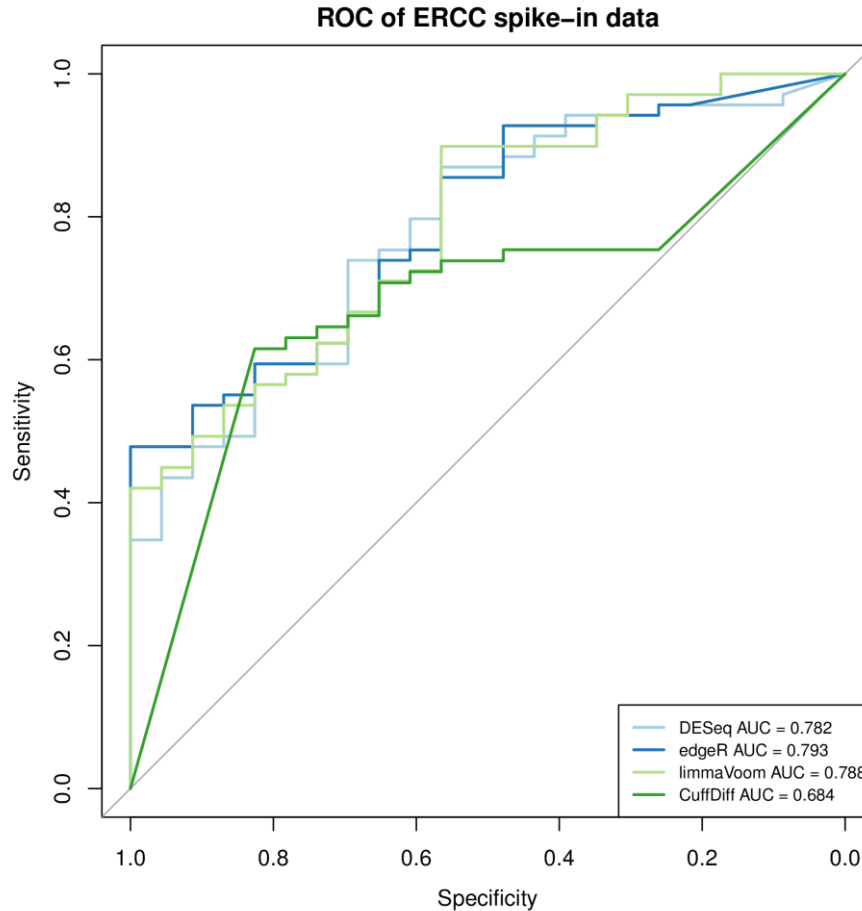


Figure 4.3 ROC analysis of differential expression detection in ERCC control. edgeR has a higher AUC value.

Another comparison is carried out on the around 1000 genes whose expression have been measured by qRT-PCR. First, calculate the log₂ fold change ratios between two conditions. Then set the log₂ fold change ratio 0.5 as the cutoff. It means that genes with log₂ expression change larger than 0.5 are considered as differential expressed genes. Under this assumption, there are total 764 genes are differential expressed. The numbers of detected differential expressed genes by different tools are showed in table 4.2. Furthermore, the ROC curve was also generated (Figure 4.4). The result shows that DESeq and edgeR have higher AUC value 0.888, and cuffdiff has a lower AUC value 0.726.

Table 4.3 Numbers of Detected Differential Expressed Genes in TaqMan Data

True Positive	DESeq	edgeR	limma	cuffdiff
764 (Total 1001)	626	634	635	605

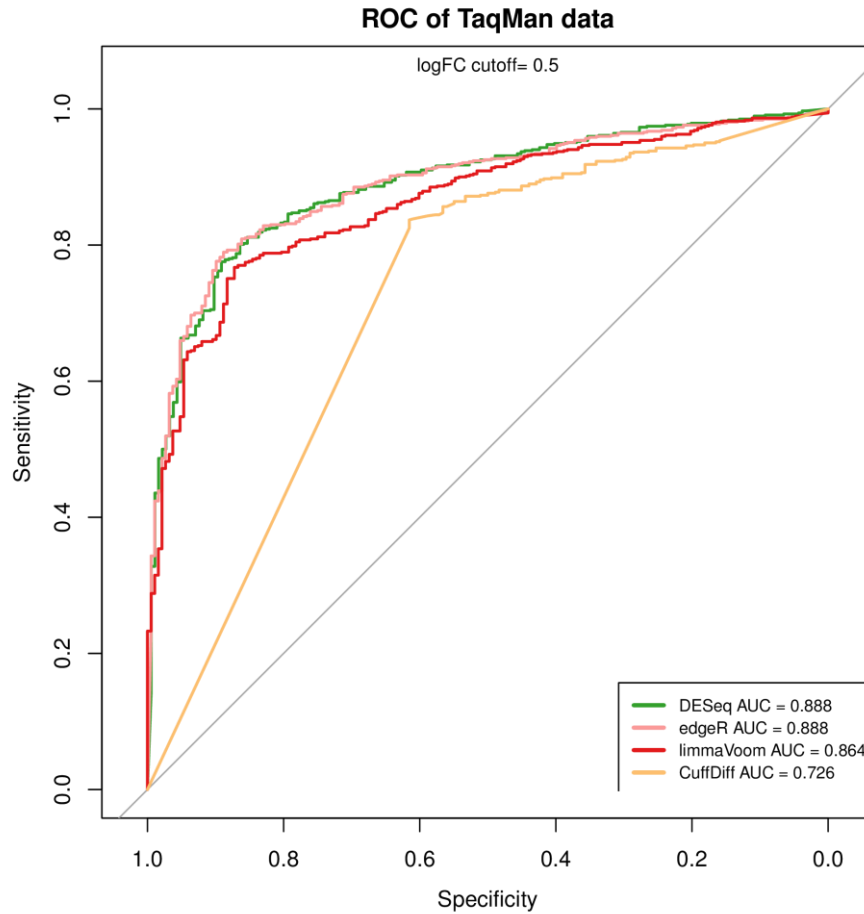


Figure 4.4 ROC analysis of differential expression detection in TaqMan data. DESeq and edgeR have higher AUC values.

For the melanoma dataset, all the four comparisons are conducted by different four tools. And the overlapping correlations are generated (Figure G.1). For the comparison between group 4 and group 6, and comparison between group 5 and group6,

limma detected no differential expressed genes, only three tools' overlapping correlations are computed. The overlapping correlation between DESeq and edgeR is highest 0.87, and the overlapping correlation between limma and cuffdiff is lowest 0.62.

4.3 Test of Type-I Error

During the differential expression analysis, it is better to reduce the type-I error. It means that people do not want to take genes which actually are not differential expressed into consideration. After the differential expression analysis, a biological process will be carried out to test the result. By controlling the type-I error, the cost in the following step can be reduced. To perform the test, samples from the same condition are compared. For SEQC dataset, three comparisons are conducted: A_1 and A_2 vs. A_3 and A_4, A_1 and A_2 vs. A_3, A_4 and A_5, B_1 and B_2 vs. B_3 and B_4. For the melanoma dataset, three comparisons are conducted: s4 and s5 vs. s6 and s7, s4 and s6 vs. s5 and s7, s4 and s7 vs. s5 and s6. As expected, there should be no differential expressing genes. Furthermore, the distributions of p-value which are calculated by different methods should be uniform⁶. As shown in the result (Figure H.1 and H.2), for the SEQC dataset, the p-value is mostly uniform. Due to the noise to signal ratio is very large in the lower 25% expressed genes, the distribution of p-value in these genes is a little different. Compared to other methods, cuffdiff outputs more false positive predictions. But for the melanoma dataset, only limma has very little false positive predictions.

4.4 Performance When Genes Expressed in Only One Condition

During the differential expression analysis, it is very common that there are a lot of genes which only express in only one condition. In such case, it is difficult to carry out

differential express analysis. Differential expression analysis tools cannot simply assign a significant p-value to these genes or do not take them into consideration. To evaluate these genes, an isotonic regression is carried out. The mean and variance of the expression values in only one condition are computed. As expected, the p-value should be consistent with the ratio of mean over standard deviation. As the ratios of mean divided by standard deviation increase, the p-value should be more significant. The advantage of isotonic regression compared with liner regression is that it does not assume any form of the target function. As the result shows, limma performs best in such kind of regression model, while other three methods have pool performances (Figure I.1). The ratio of mean divided by standard deviation 3 was set as a cutoff. Genes that have a ratio larger than 3 were considered as differential expressed. And ROC curve were generated. Limma has the highest AUC value 0.969.

Such test is also carried out in melanoma dataset (Figure I.2 to I.5). But only in comparison between condition 1 and condition 3, limma has very clear pattern as expected.

CHAPTER 5

DISCUSSION

There are several following evaluations can be carried out. Firstly, in the SEQC dataset, the library of each sample is very similar to each other. In the reality, it is very possible that the libraries sizes change a lot among different samples. To test the performance of these tools, the numbers of several samples' reads can be amplified and others can be reduced. Then the differential expression analysis can be conducted to compare their performance. Secondly, during the evaluation of type-I error control, cuffdiff outputs a lot of very significant expressed genes. A clear and deep investigation can be conducted to check whether these genes are actually differential expressed even in the samples of same condition. Thirdly, the sensitivity and specificity comparison based on the melanoma dataset can be conducted. The fold change of the raw counts can be computed, and the genes with log₂ transformation of fold change larger than 3 will be considered as differential expressed. Then, the sensitivity and specificity of these tools can be computed.

APPENDIX A

DISTRIBUTION OF RAW AND NORMALIZED COUNTS OF SEQC DATASET

Figure A.1 to A.5 show the distribution of SEQC dataset's raw and normalized counts.

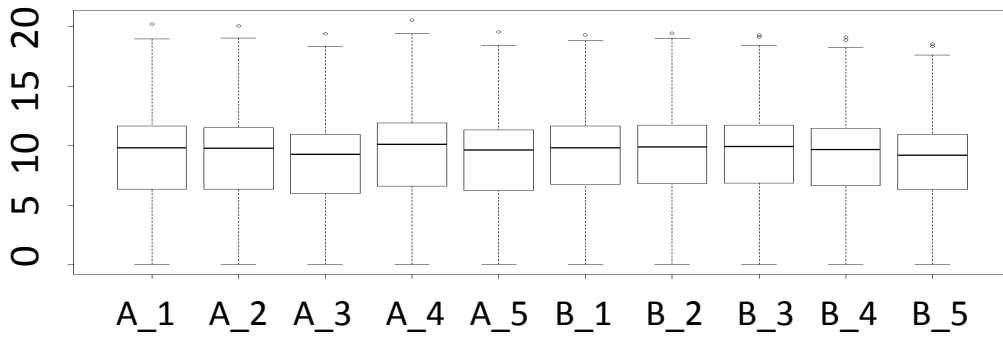


Figure A.1 The distribution of SEQC dataset's raw counts.

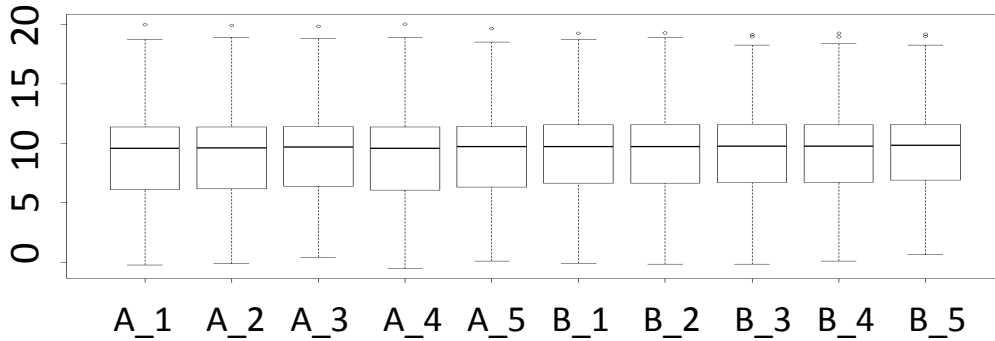


Figure A.2 The distribution of SEQC dataset's normalized counts by DESeq.

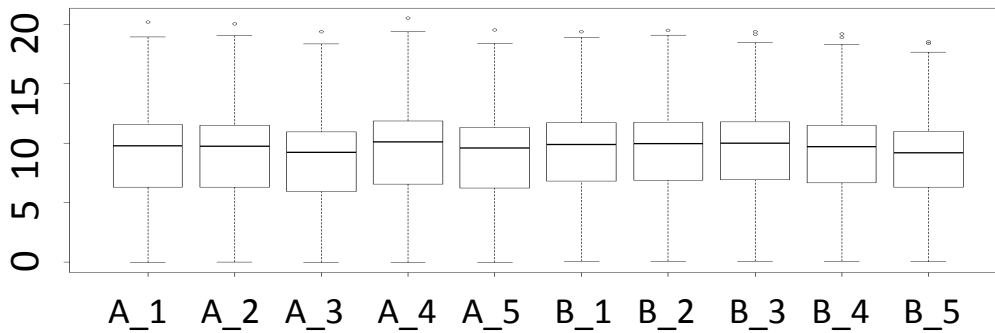


Figure A.3 The distribution of SEQC dataset's normalized counts by edgeR.

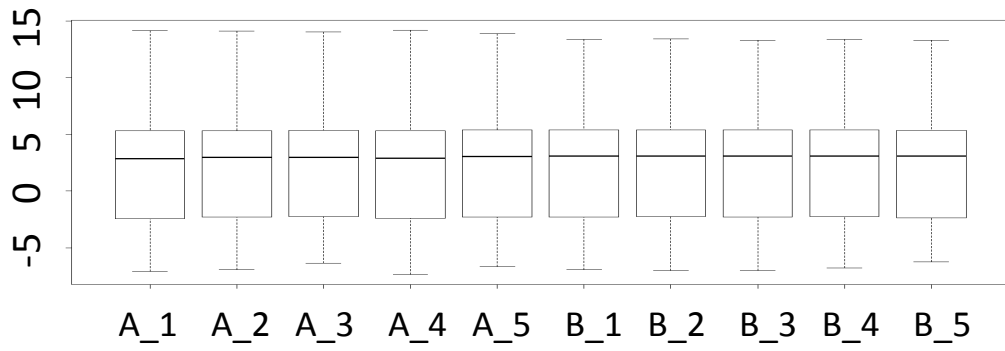


Figure A.4 The distribution of SEQC dataset's normalized counts by limma.

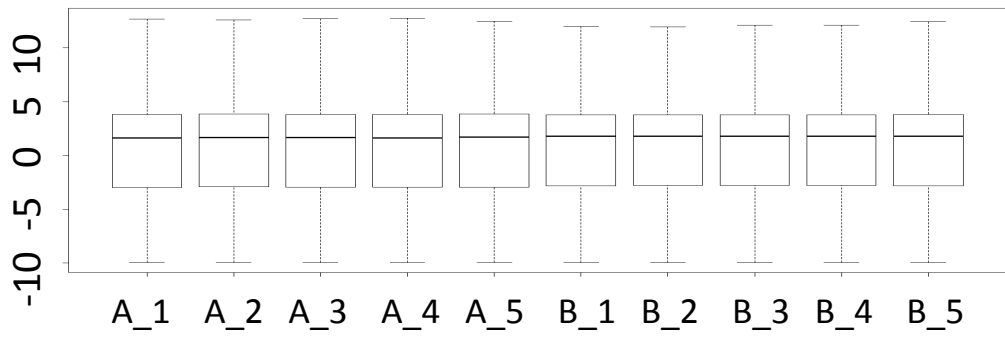


Figure A.5 The distribution of SEQC dataset's normalized counts by cuffdiff.

APPENDIX B

DISTRIBUTION OF RAW AND NORMALIZED COUNTS OF MELANOMA

Figure B.1 to B.5 show the distribution of melanoma dataset's raw and normalized counts (log₂ transformation) in four comparisons.

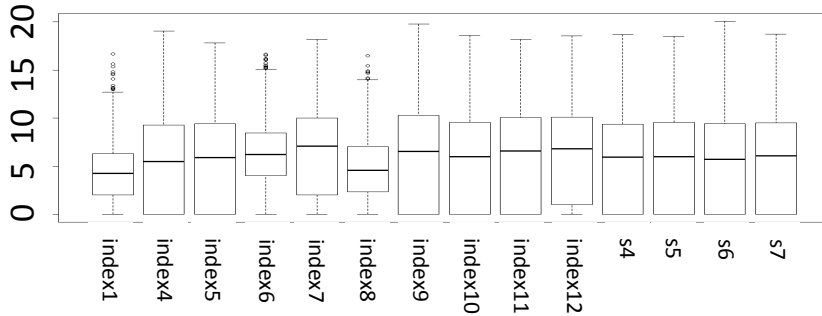


Figure B.1 The distribution of melanoma dataset's raw counts.

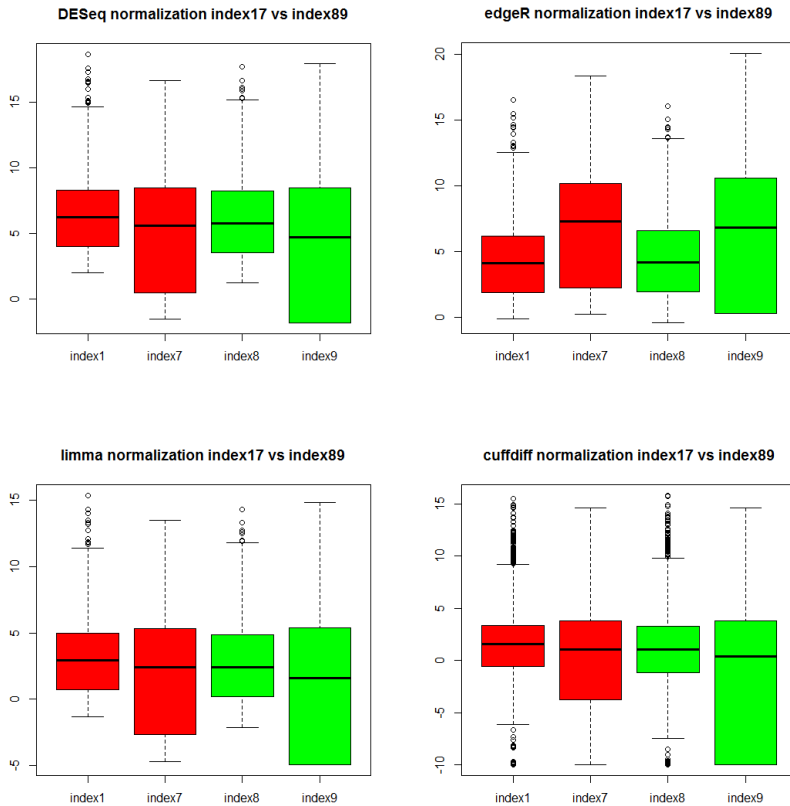


Figure B.2 The distribution of melanoma dataset's normalized counts in comparison 1.

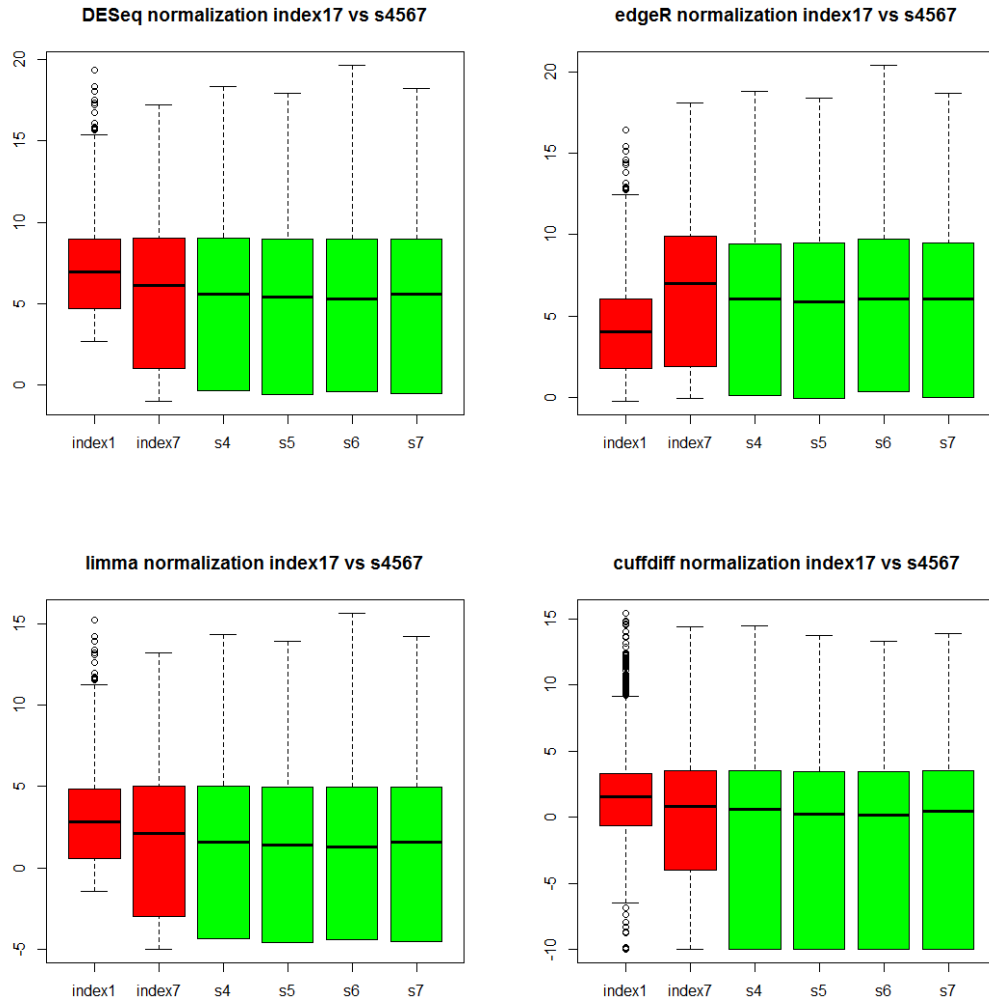


Figure B.3 The distribution of melanoma dataset's normalized counts in comparison 2.

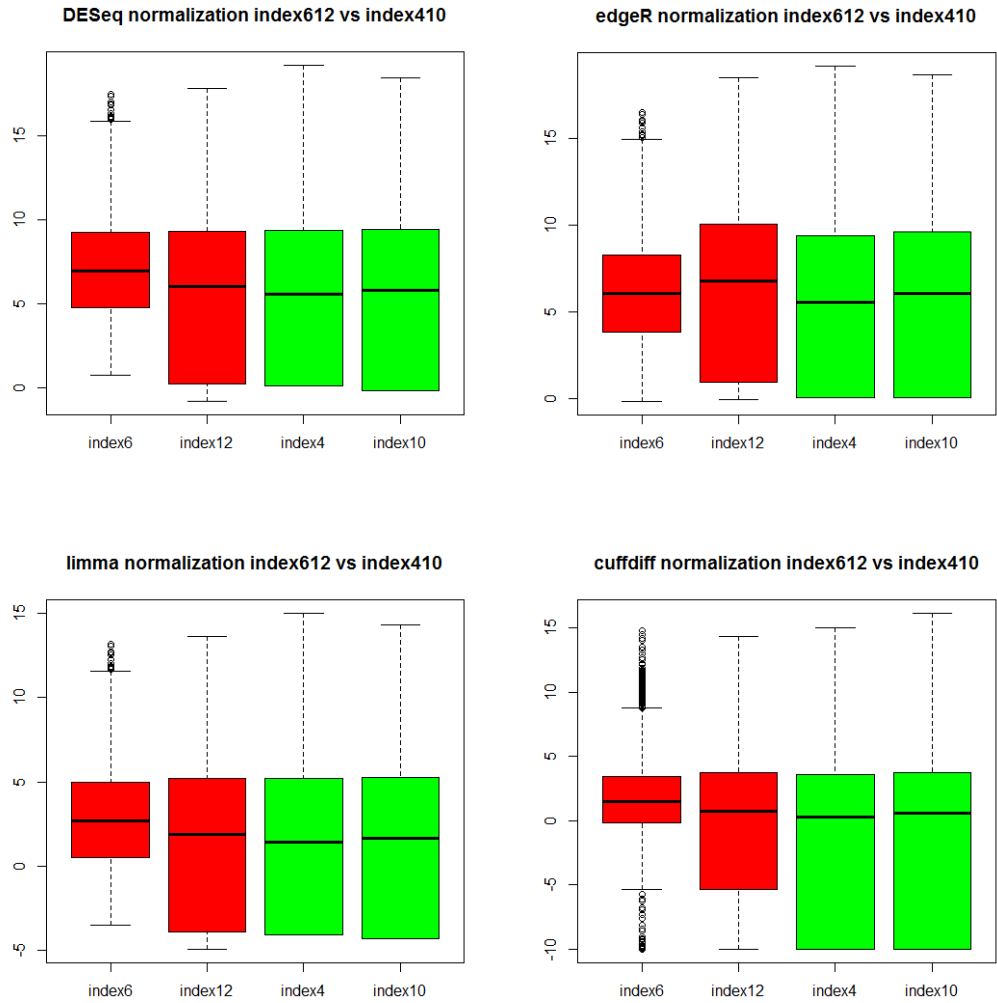


Figure B.4 The distribution of melanoma dataset's normalized counts in comparison 3.

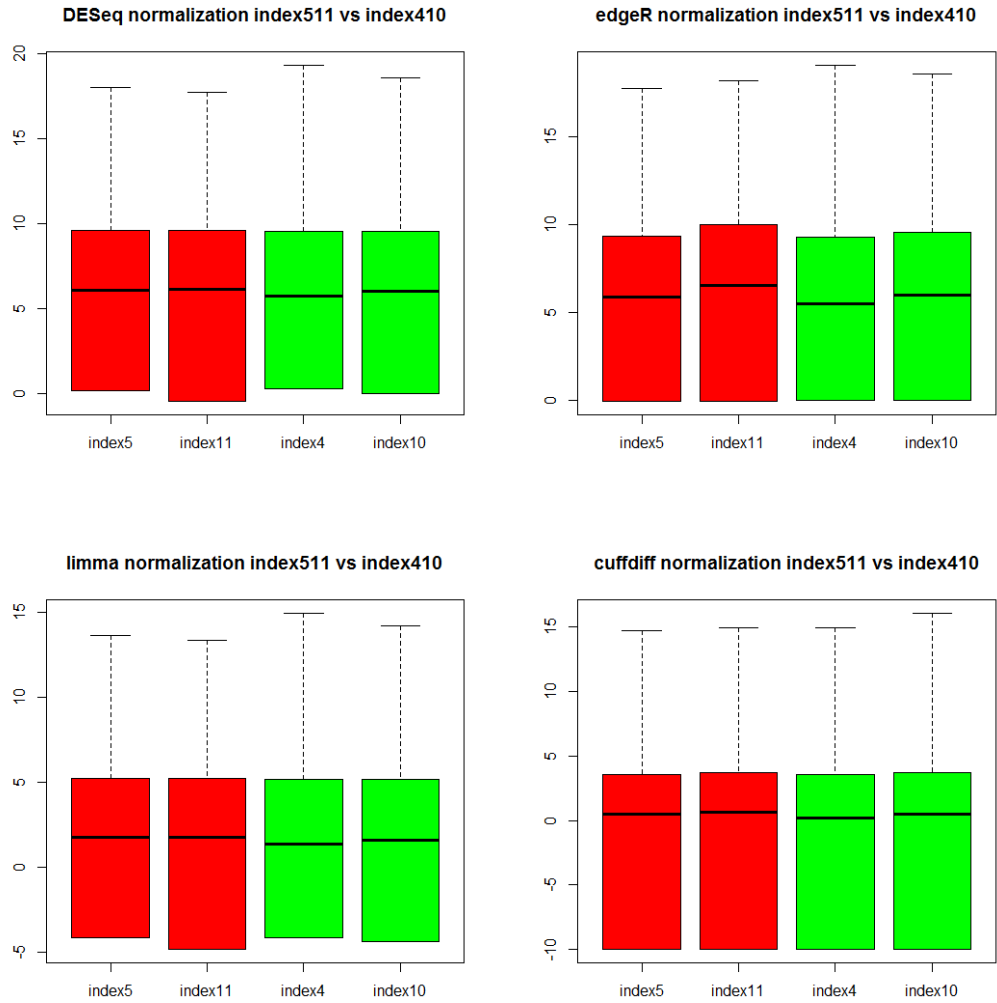


Figure B.5 The distribution of melanoma dataset's normalized counts in comparison 4

APPENDIX C

CLUSTERING OF SEQC

Figure C.1 shows the clustering results based on the normalization counts in SEQC dataset of four tools.

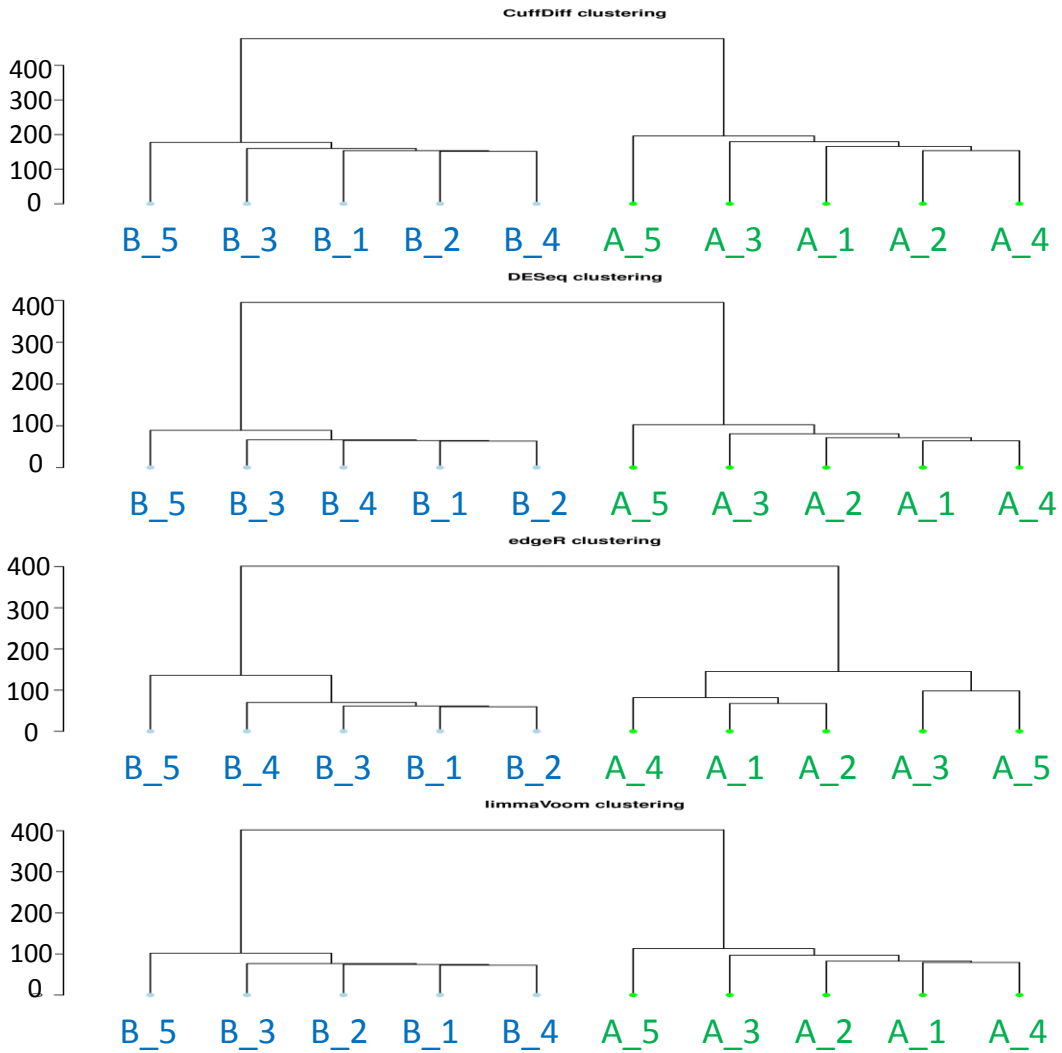


Figure C.1 The clustering based on the normalized counts. The clustering shows that samples from the same conditions are very well grouped together.

APPENDIX D
CLUSTERING OF MELANOMA

Figure D.1 to D. 4 show the clustering results based on the normalization counts in melanoma dataset of four tools.

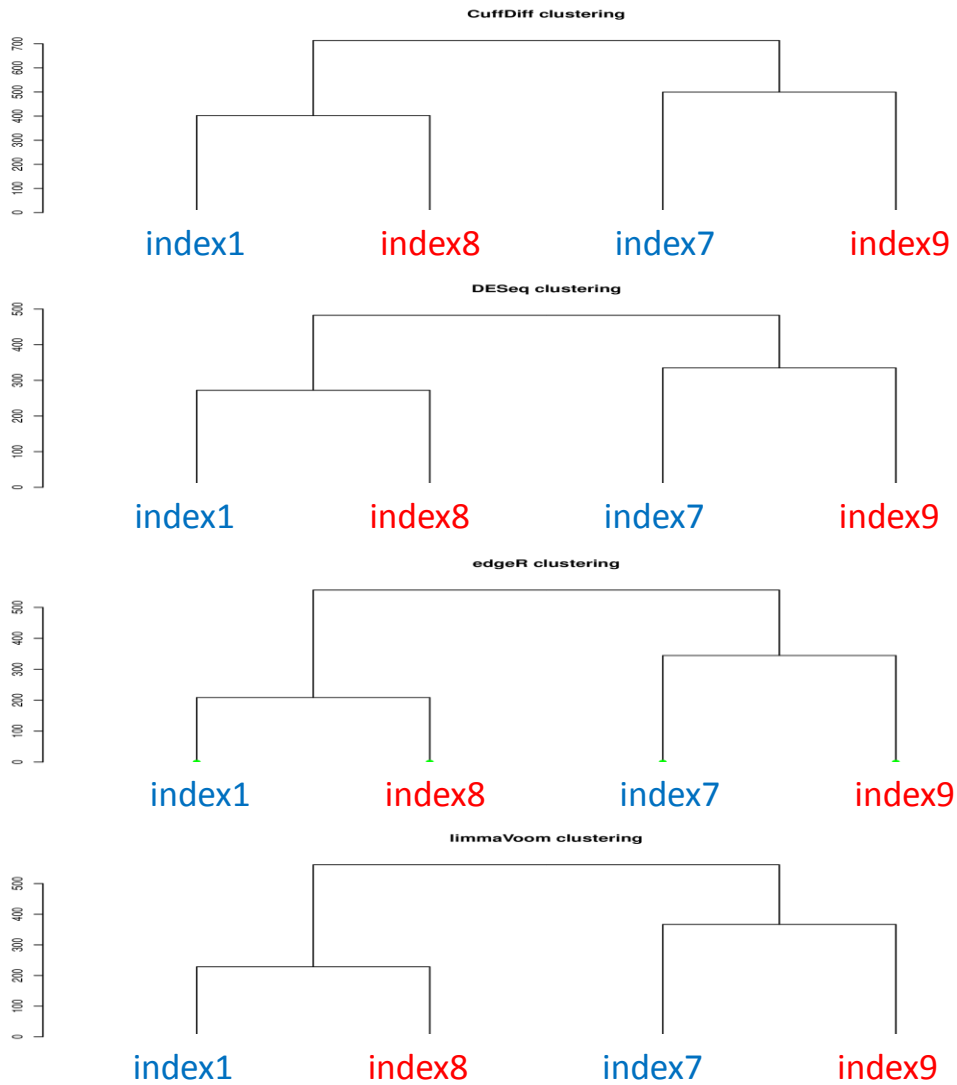


Figure D.1 The clustering based on the normalized counts in comparison between condition 1 and condition 2. Samples from the same individual are grouped together.

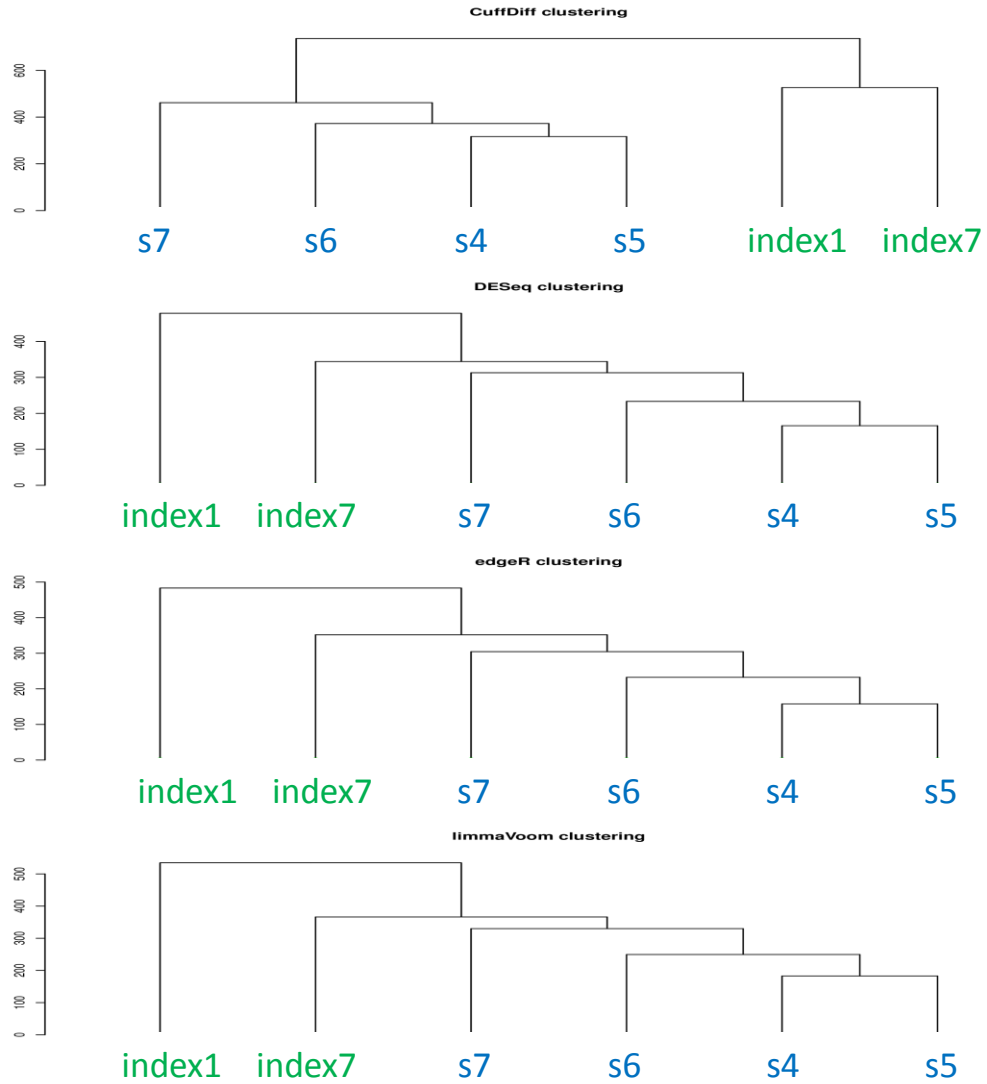


Figure D.2 The clustering based on the normalized counts in comparison between condition 1 and condition 3. The result of cuffdiff can group samples from the same condition together very well.

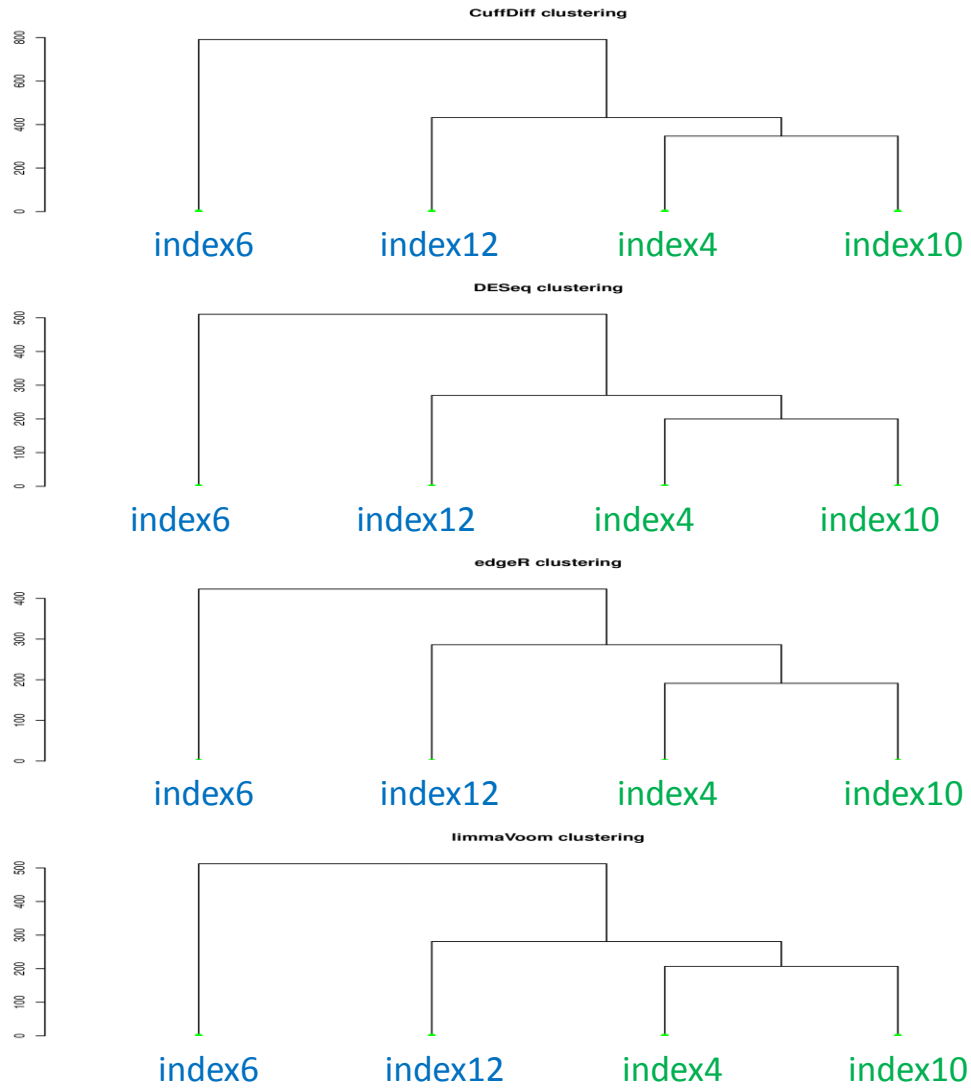


Figure D.3 The clustering based on the normalized counts in comparison between condition 4 and condition 6. The performances of the four tools are same with each other.

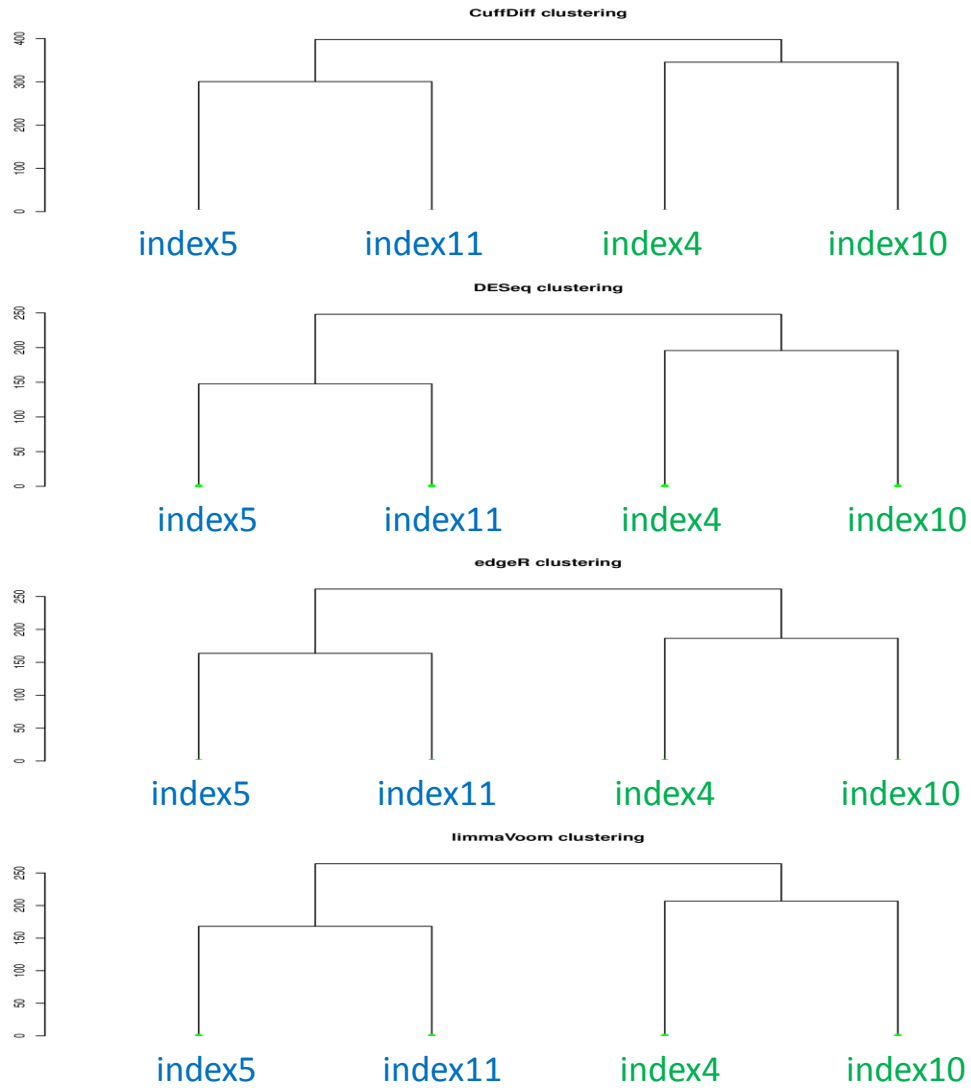


Figure D.4 The clustering based on the normalized counts in comparison between group 5 and group 6. The performances of the four tools are same with each other. Samples from the condition are grouped together.

APPENDIX E

DUNN CLUSTER VALIDITY INDICES

Figure E.1 shows the Dunn cluster validity indices of the clustering.

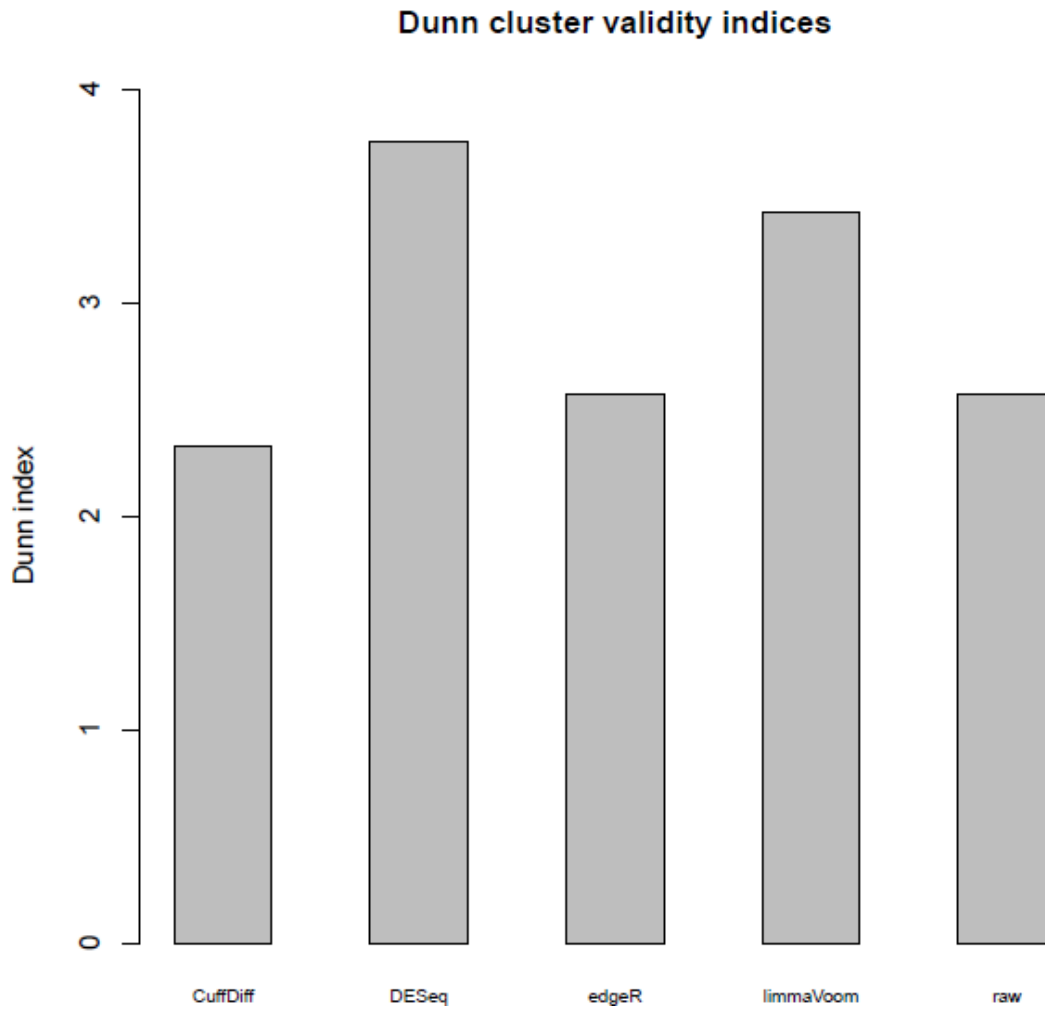


Figure E.1 Dunn index is used to compare the clustering of normalized counts of four differential expression analysis tools, including the raw counts. DESeq and limma have higher Dunn index values.

APPENDIX F

RMSD CORRELATION WITH TAQMAN FOLD CHANGES

Figure F.1 shows the RMSD correlation with TaqMan fold changes.

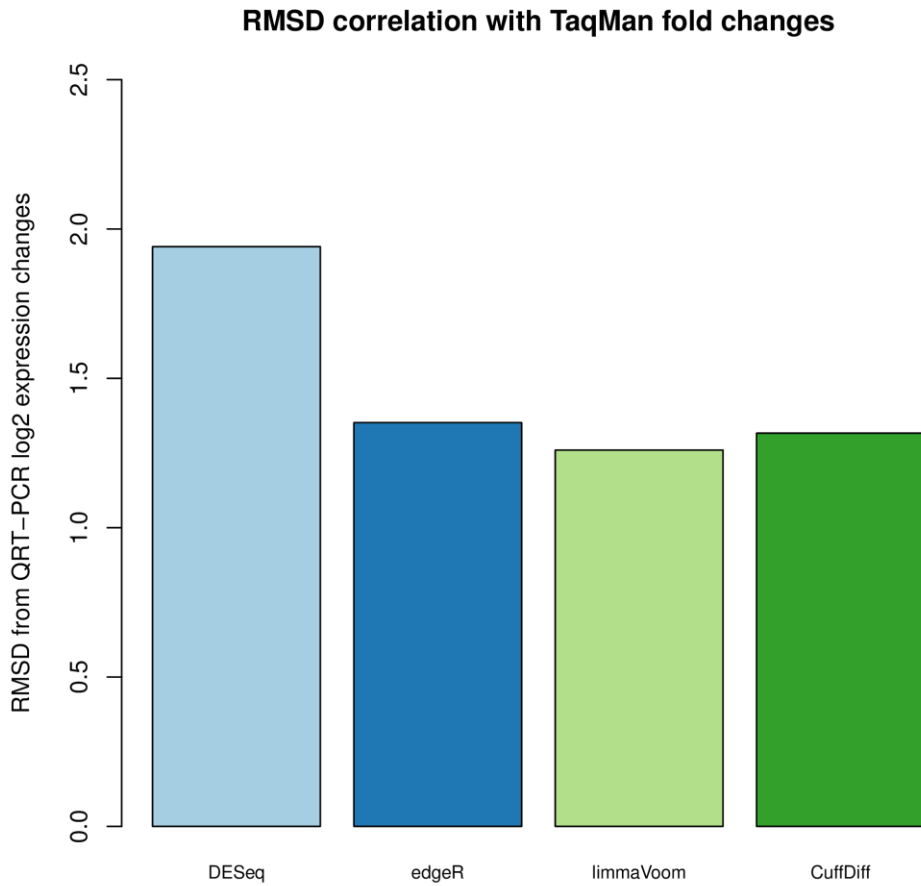


Figure F.1 RMSD correlation with TaqMan fold changes indicates that DESeq has a highest correlation accuracy value.

APPENDIX G

OVERLAPPING CORRELATION OF DIFFERENTIAL EXPRESSION

ANALYSIS TOOLS

Figure G.1 shows the overlapping correlation of detected differential expressed genes by four tools in four comparisons.

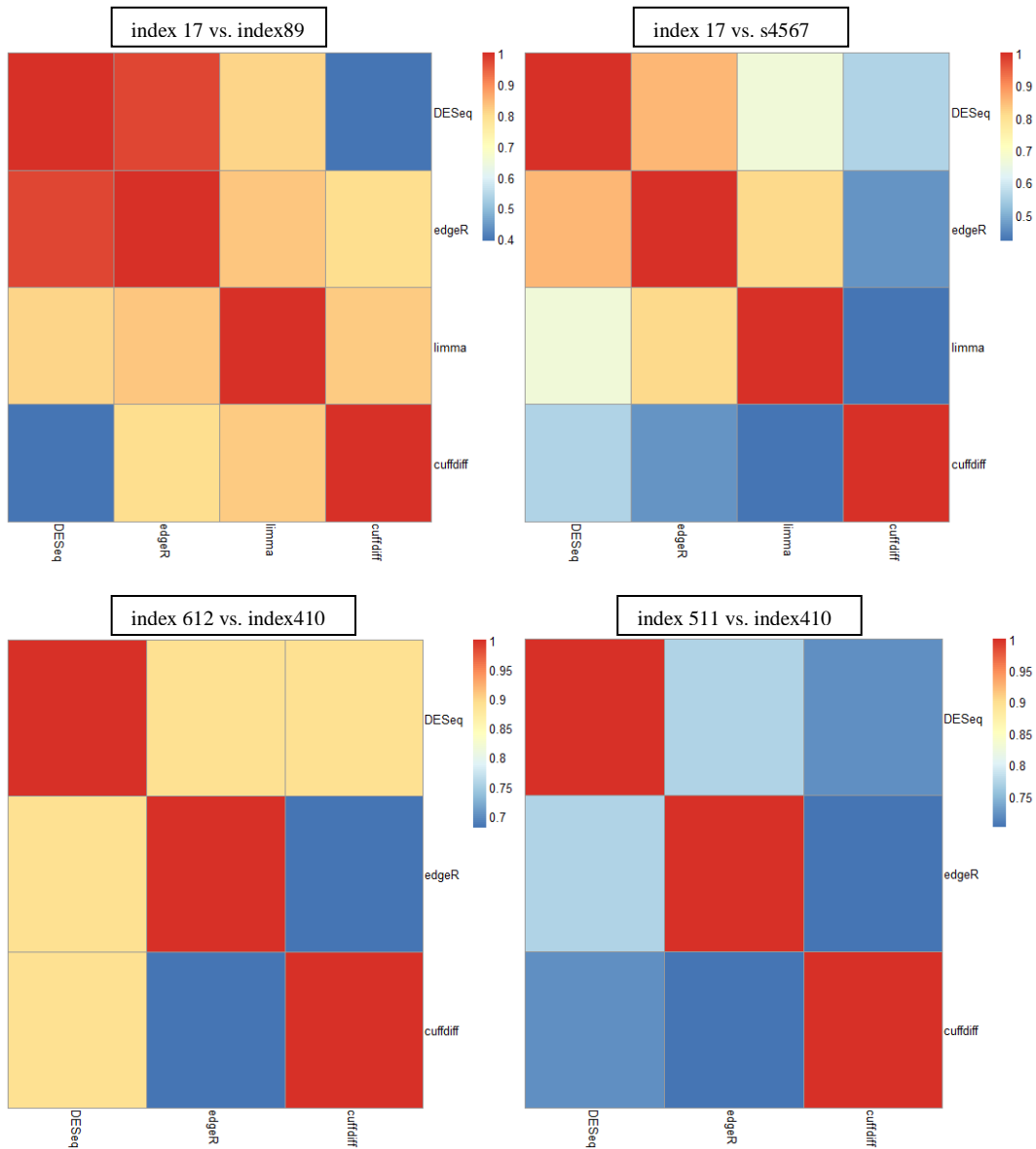


Figure G.1 The overlapping correlation of detected differential expressed genes by four tools in four comparisons. The overlapping correlation between DESeq and edgeR is highest 0.87, and the mapping correlation between limma and cuffdiff is lowest 0.62.

APPENDIX H

DISTRIBUTION OF P VALUES

Figure H.1 to H.2 show the distribution of p.value in different read counts quartiles.

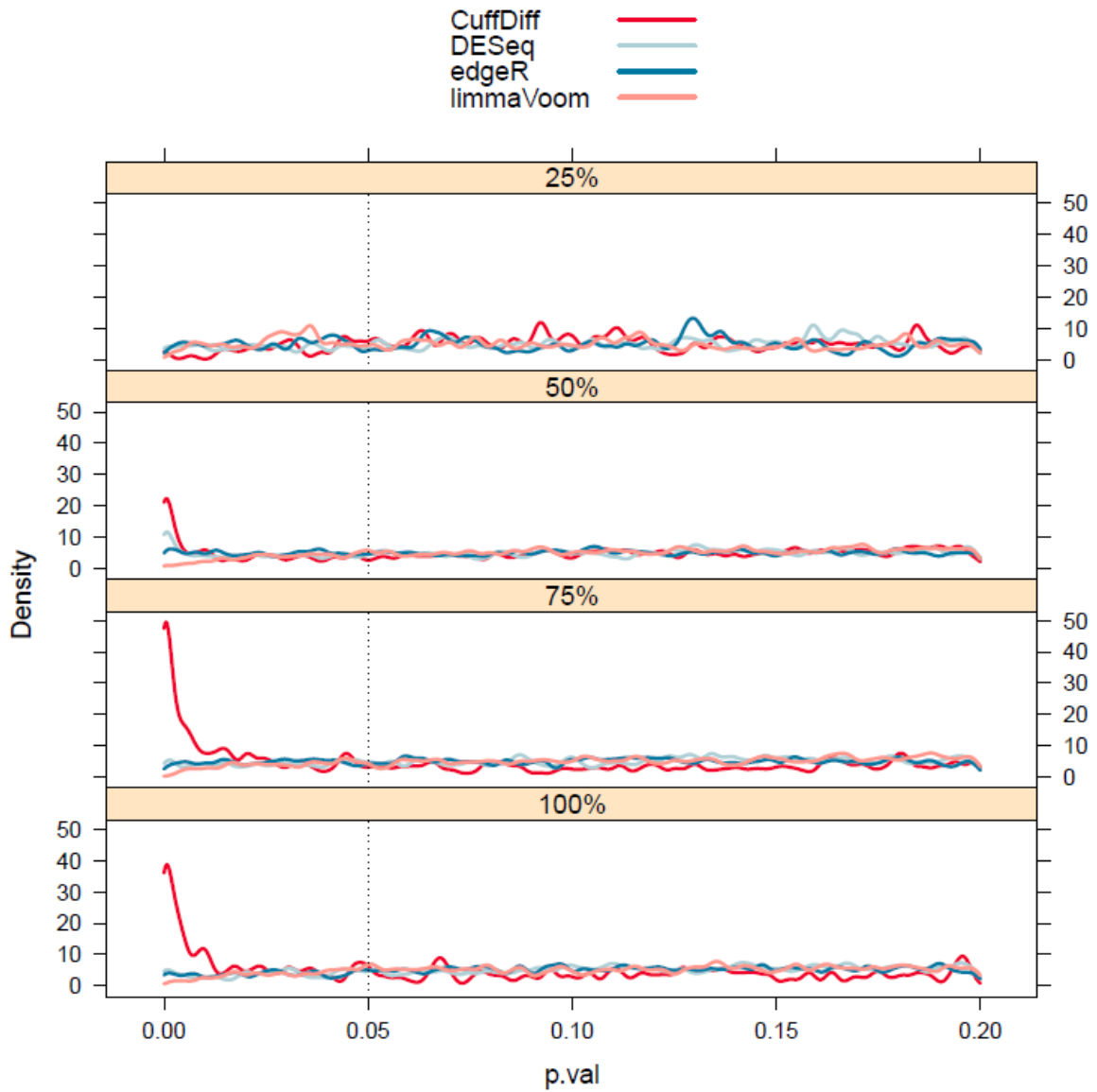


Figure H.1 The distributions of p-value in SEQC dataset are mostly uniform. Compared to other methods, cuffdiff has more false positive predictions.

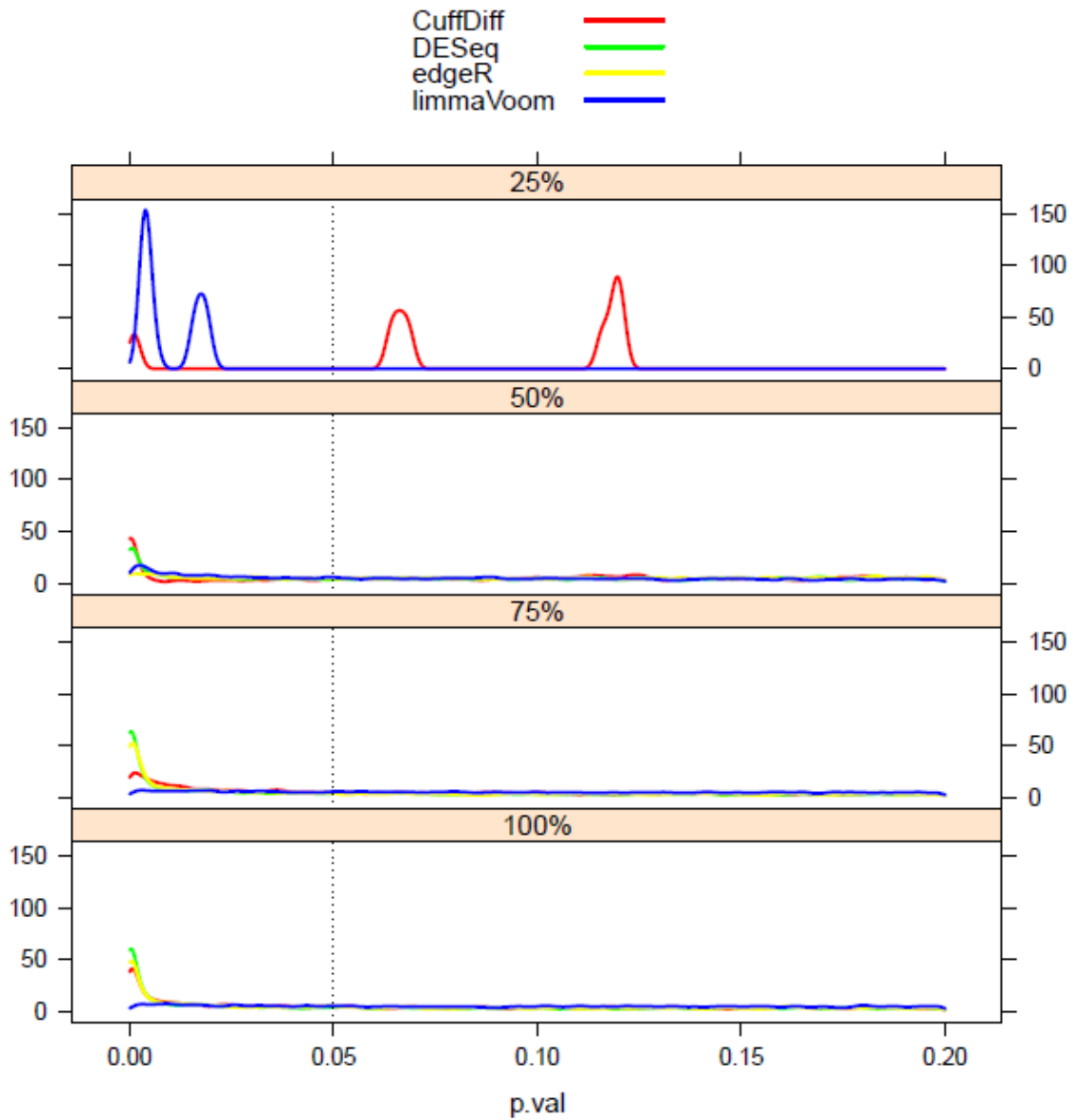


Figure H.2 The distributions of p-value in melanoma dataset are mostly uniform. But only limma has very little false positive predictions.

APPENDIX I

CORRELATION BETWEEN SIGNAL TO NOISE RATIO AND P VALUES

Figure I.1 to I.5 show the correlation between signal to noise ratio and $-\log_{10}$ transformation of p values when genes only express in one condition.

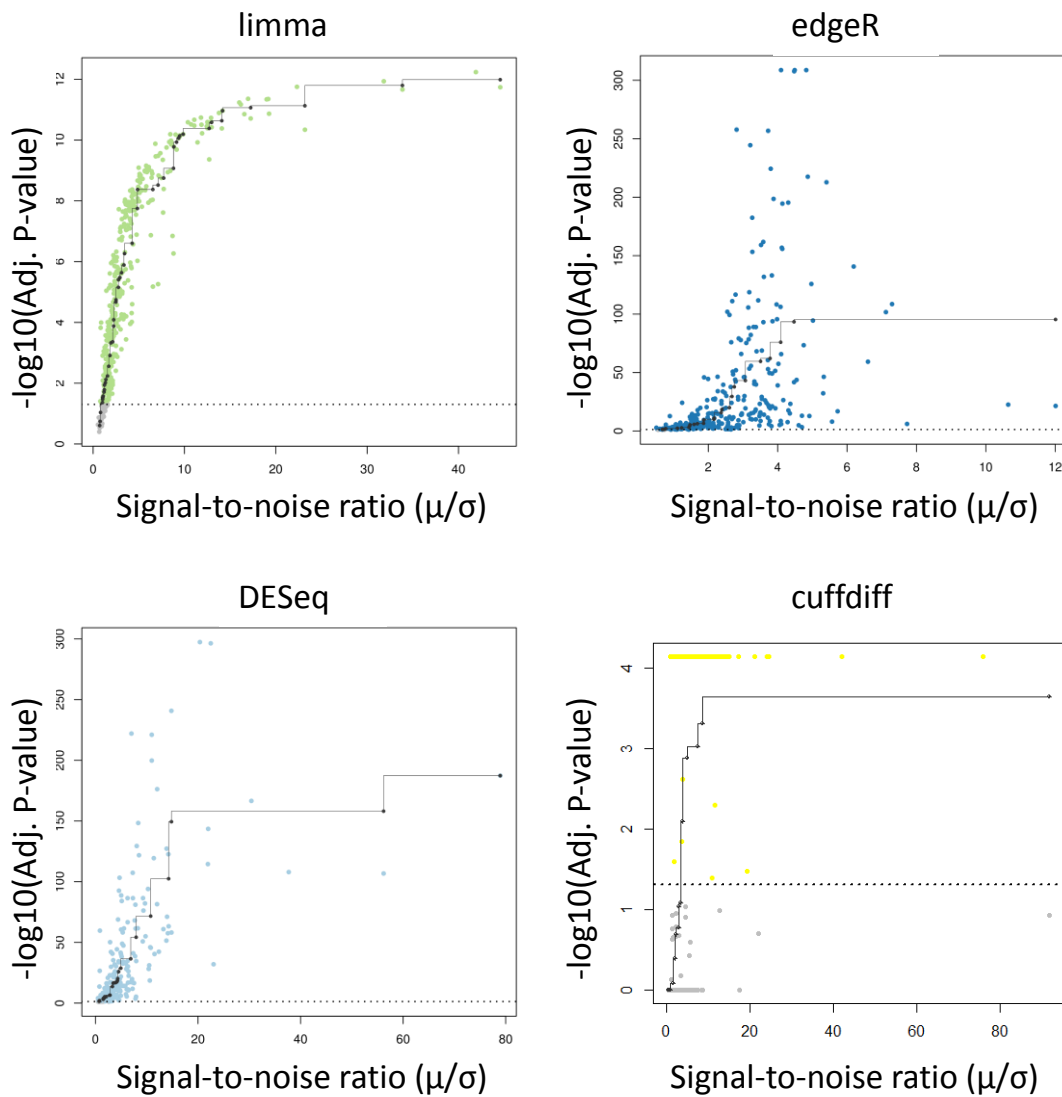


Figure I.1 Limma performs best in the correlation evaluation of SEQC dataset.

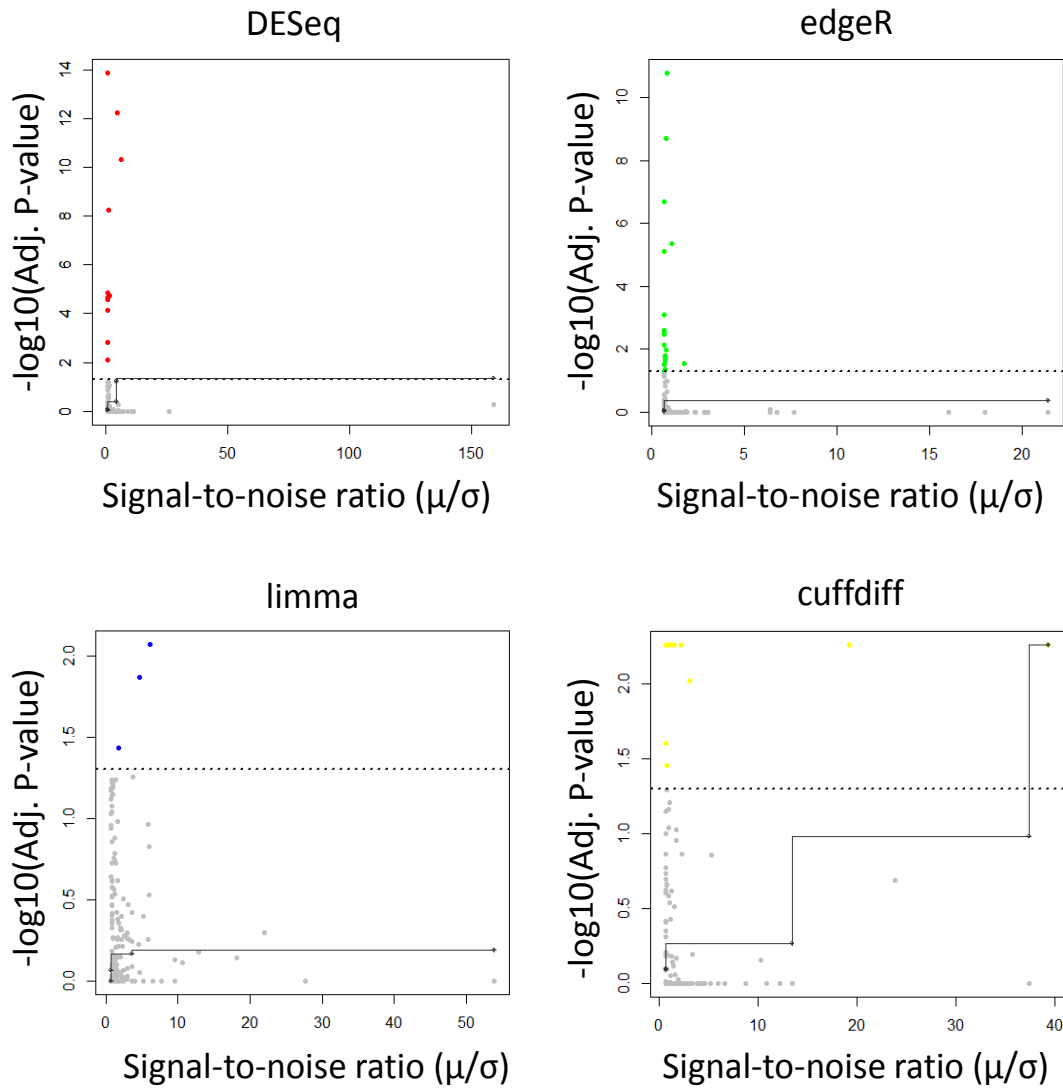


Figure I.2 The correlation between signal to noise ratio and $-\log_{10}$ transformation of p values when genes only express in one condition in comparison between condition 1 and condition 2 of melanoma dataset.

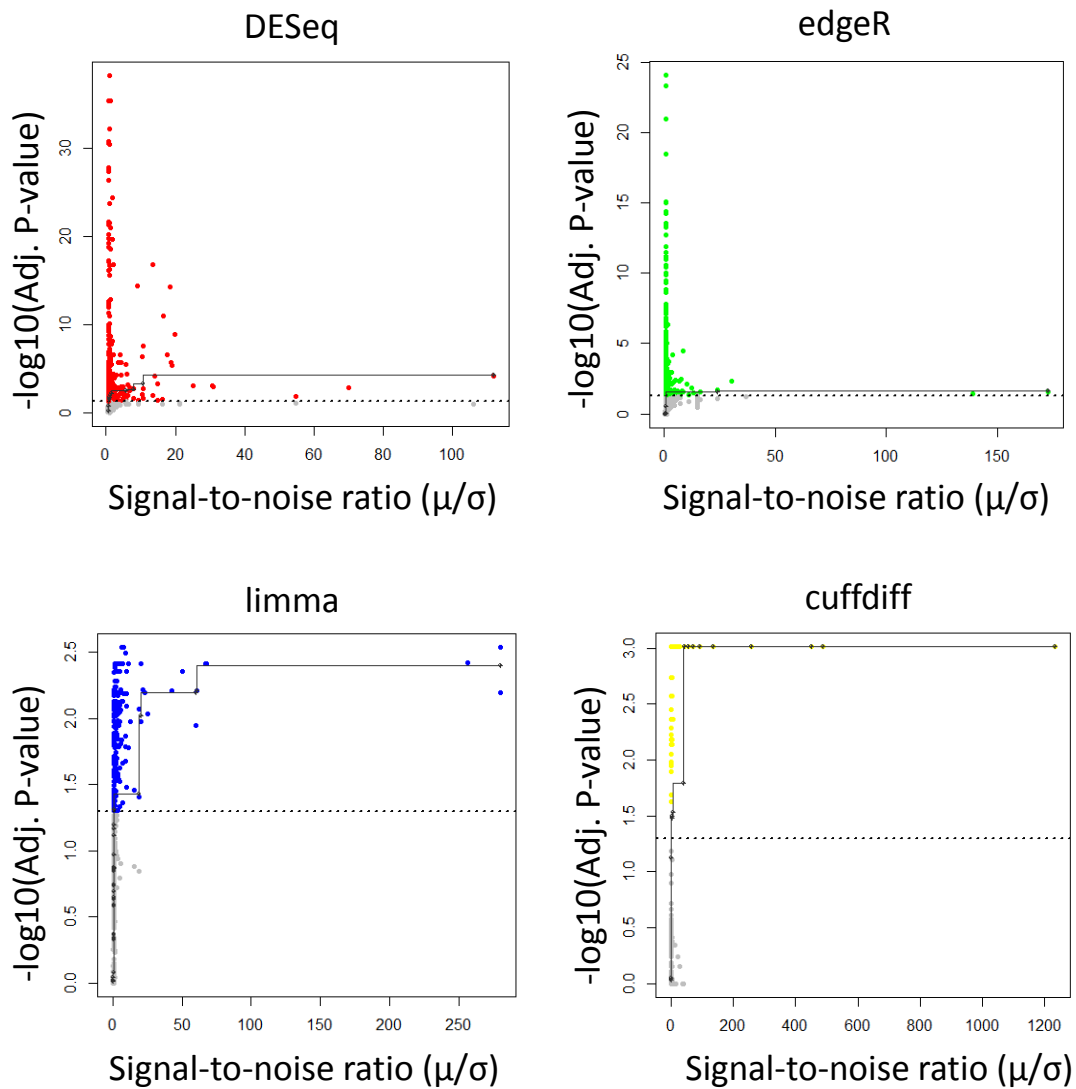


Figure I.3 The correlation between signal to noise ratio and $-\log_{10}$ transformation of p values when genes only express in one condition in comparison between condition 1 and condition 3 of melanoma dataset.

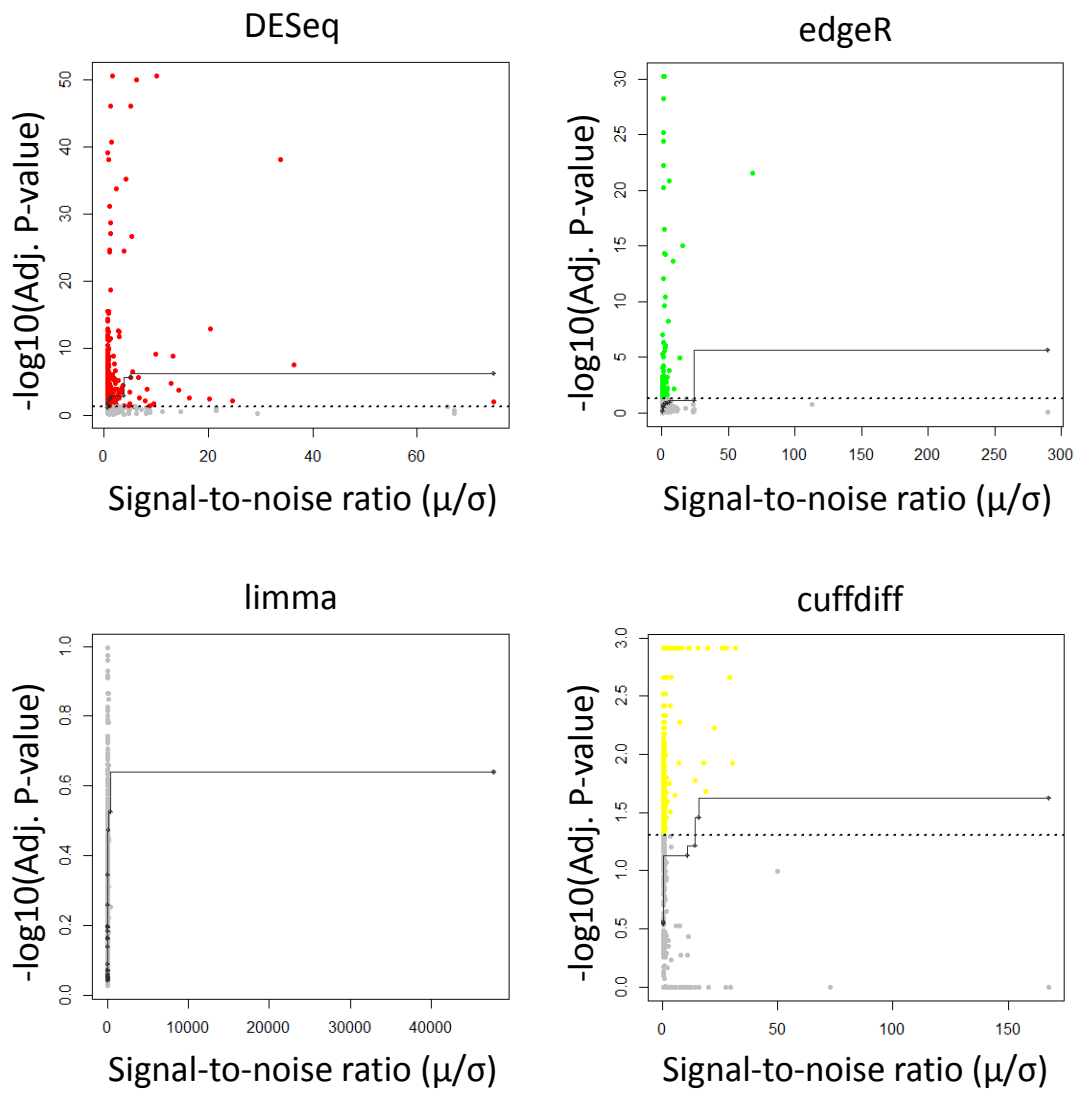


Figure I.4 The correlation between signal to noise ratio and $-\log_{10}$ transformation of p values when genes only express in one condition in comparison between condition 4 and condition 6 of melanoma dataset.

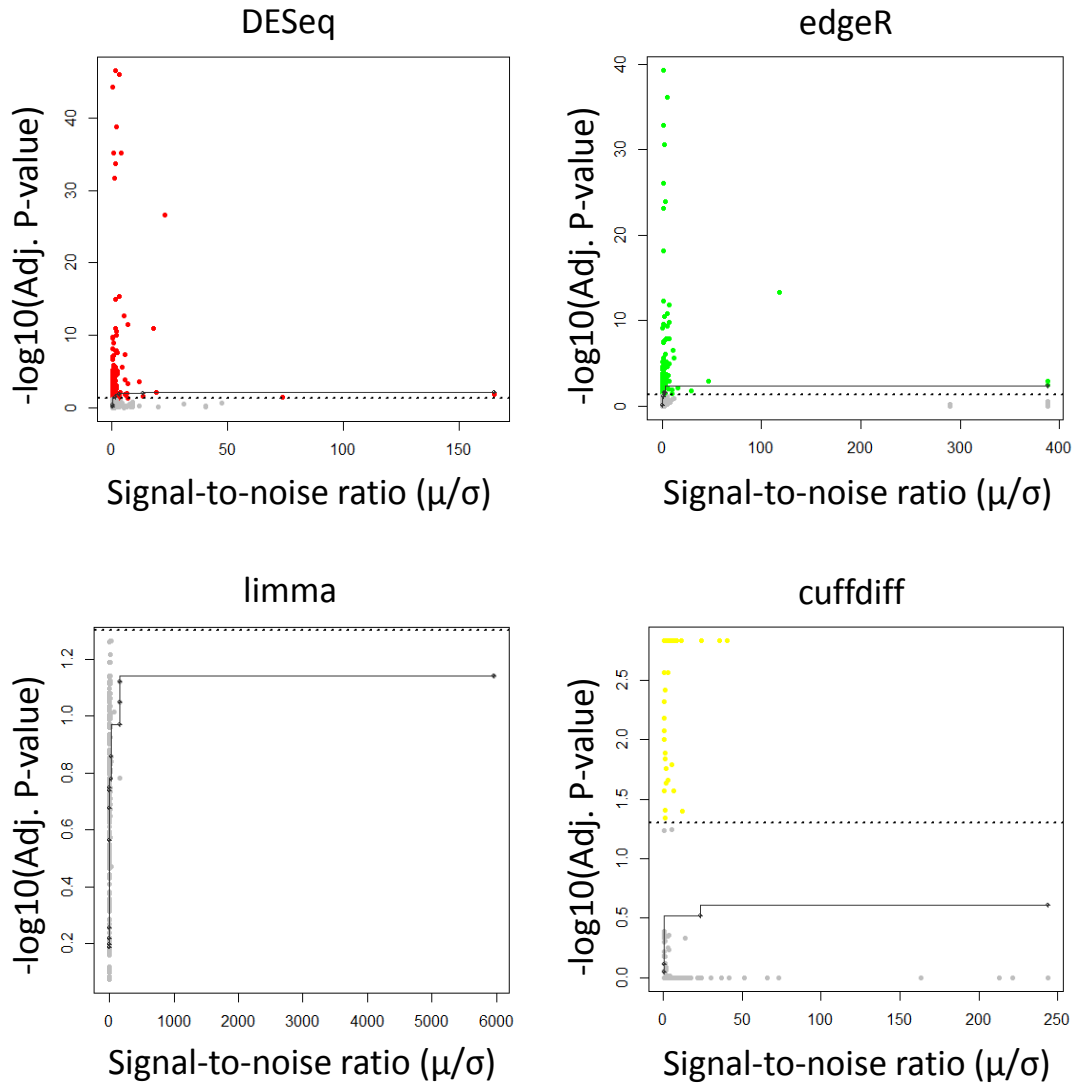


Figure I.5 The correlation between signal to noise ratio and $-\log_{10}$ transformation of p values when genes only express in one condition in comparison between condition 5 and condition 6 of melanoma dataset.

APPENDIX J

ROC CURVE WHEN SIGNAL TO NOISE RATIO 3 IS SET AS CUTOFF

Figure J.1 shows the ROC curve when signal-to-noise ratio 3 is set as cutoff.

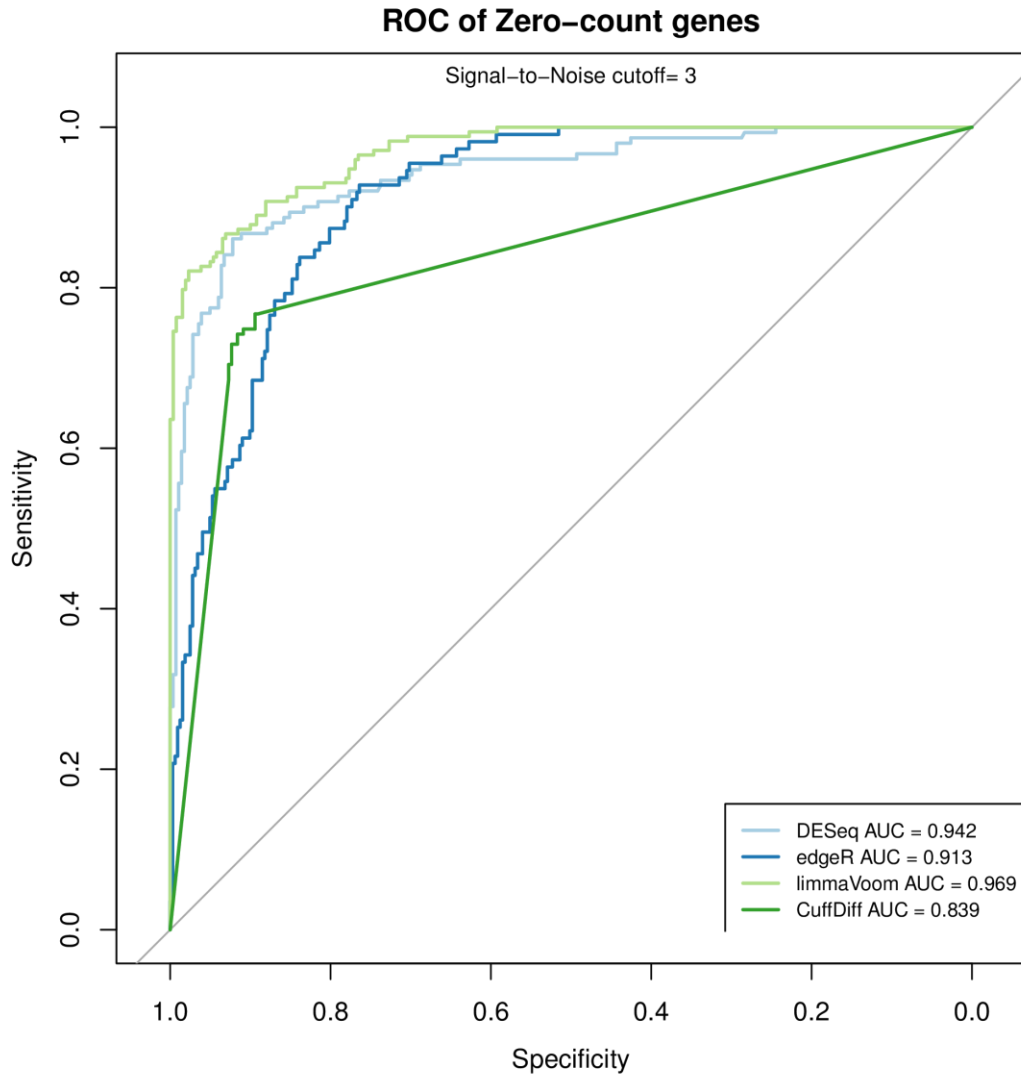


Figure J.1 ROC curve when the cutoff of signal-to-noise ratio is 3. limma has the highest AUC value 0.969.

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