PowerExplorer Manual

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Abstract

This vignette demonstrates the applications of R package PowerExplorer as the power and sample size estimation tool for RNA-Seq and quantitative proteomics data.

PowerExplorer contains following main features:

- Estimation of power based on the current setting
- Prediction of power according to the future settings (e.g. increasing sample size)
- Visualizations of estimation and prediction results

Introduction

Power and sample size estimation is still one of the important principles in designing next-generation sequencing experiments to discover differential expressions, a few methods on power estimation for RNA-Seq data have been studied, while the one specialized for proteomics data has not yet been developed. PowerExploreris a power estimation and prediction tool currently applicable to RNA-Seq and quantitative proteomics experiments. The calculation procedure starts with estimating the distribution parameters of each gene or protein (following referred as entry for simplicity) accordingly, with the obtained prior distribution of each entry, a specified amount of simulations are executed to generate data (read counts for RNA-Seq and peptide abundance for proteomics) repetitively for each entry based on null and alternative hypotheses. Furthermore, the corresponding statistical tests (t-test or Wald-test) are performed and the test statistics are collected, eventually the result statistics will be summarized to calculate the statistical power.

Prepare Input Data

For both RNA-Seq (gene expression levels) and quantitative proteomics (peptide abundance levels) datasets, the data matrix should be arranged as entries in rows and samples in columns, for example:

```
library(PowerExplorer)
data("exampleRNASeqData")
head(exampleRNASeqData$dataMatrix[,1:6])
#>
          Sample\_A\_1 Sample\_A\_2 Sample\_A\_3 Sample\_A\_4 Sample\_A\_5 Sample\_B\_1
#> Gene_1
                  469
                              324
                                           38
                                                     1059
                                                                   64
#> Gene 2
                   84
                              276
                                          263
                                                      182
                                                                  181
                                                                               737
#> Gene 3
                  293
                              173
                                          272
                                                       123
                                                                  475
                                                                               169
#> Gene_4
                  310
                              209
                                          550
                                                       212
                                                                  394
                                                                              1064
                                                                               293
#> Gene_5
                   82
                              141
                                          216
                                                      202
                                                                  494
#> Gene_6
                  583
                                          137
                                                       179
                                                                               884
                               98
                                                                  214
```

A grouping vector indicating the sample groups to which all the samples belong should also be created, for example:

Note that the grouping vector length should be equal to the column number of the data matrix, all groups conventionally should have the same number of samples, otherwise the tool will automatically even all the sample numbers to the least number to achieve equal groups.

Run Estimation

Here we use a randomly generated proteomics dataset exampleProteomicsData as an example to estimate the current power of the dataset. The input dataset is named as dataMatrix and the grouping vector as groupVec.

To run the estimation, apart from the input, we still need to specify the following parameters:

- isLogTransformed: FALSE; the input data is not log-transformed.
- dataType: "RNA-Seq"; the datatype can be declared as "Proteomics" or "RNA-Seq".
- minlfc: 0.5; the threshold of Log2 Fold Change, proteins with lower LFC will be discarded.
- alpha: 0.05; the controlled false positive (Type I Error) rate.
- ST: 50; the simulation of each protein entry will be run 50 times (ST>50 is recommended).
- seed: 345; the seed of the random variables to maintain the reproducibility.
- showProcess: FALSE; no detailed processes will be shown, set to TRUE if debug is needed.
- saveSimulatedData: FALSE; if TRUE, save the simulated data in ~/savedData directory.

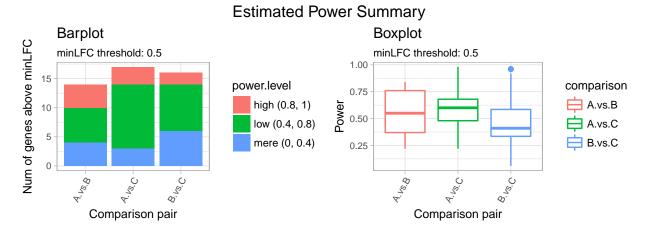
The results will be summaried in barplot, boxplot and summary table.

A part of the output should look like this:

```
##----- Wed Jan 17 16:50:25 2018 -----##
O of 110 entries are filtered due to excessive zero counts
[1]START ESTIMATION
Estimating NB parameters by DESeq2...
Number of groups:
Number of replicates:
Number of simulations:
                           50
Min. Log Fold Change:
                           0.5
False Postive Rate:
                           0.05
Transformed:
Power Estimation between group A and group B:
Quantiles of absolute Log2 Fold Change:
                     20%
                                                50%
                                                        60%
                                                                 70%
                                                                          80%
                                                                                   90%
                                                                                          100%
            10%
                              30%
                                      40%
0.00000 0.05000 0.08000 0.13000 0.16000 0.20000 0.26525 0.31550 0.39000 0.57800 1.80000
14 of 110 genes are over minLFC threshold 0.5:
                                                     =====] 100% of All Simulations Completed...
##----- wed Jan 17 16:50:34 2018 -----##
##----- wed Jan 17 16:50:34 2018 -----##
Estimating cut-off statistics with false positive rate: 0.05
OVERALL ESTIMATED POWER: 0.5486
```

Visualization

The estimated results can be summarized using plotEstimatedPower, the only input needed is the estimatedPower, which should be the estimated power object returned from estimateCurrentPower.



Comp.	Gene Num.	Avg. Power	H (0.8, 1)	L (0.4, 0.8)	M (0, 0.4)
A.vs.B	14	0.55	4 (28.57%)	6 (42.86%)	4 (28.57%)
A.vs.C	17	0.59	3 (17.65%)	11 (64.71%)	3 (17.65%)
B.vs.C	16	0.47	2 (12.5%)	8 (50%)	6 (37.5%)

The graph contains 3 plots, the barplot vertically shows the number of genes/proteins above the minLFC threshold, columns indicates the comparison pairs, each column presents the proportions of three power levels in three colours as indicated in the legend power.level; The boxplot shows the overall power distribution of each comparsion; And the summary table summarize the power in a numerical way with the same information shown in the previous two plots.

Run Predictions

With the same dataset, to run a prediction, a few more parameters are needed:

- isLogTransformed: FALSE; the input data is not log-transformed.
- dataType: "RNA-Seq"; the datatype can be declared as "Proteomics" or "RNA-Seq".
- rangeSimNumRep: the power of replicate number 5 to 20 will be predicted.
- alpha: 0.05; the controlled false positive rate.
- ST: 30; the statistical test and data simulation of each protein entry will be run 30 times (ST>50 is recommended).
- seed: 345; specify the seed of the random variables to maintain the reproducibility.
- showProcess: FALSE; no detailed processes will be shown, set to TRUE if debug is needed.
- saveSimulatedData: FALSE; if TRUE, save the simulated data in root/savedData directory.

Similar to the estimation process, however, the simulations will be excuted with each sample size specified in rangeSimNumRep. (Note: the term sample size in this vignette refers to the replicate number of each group/case)

A part of the output should look like this:

```
##---- Thu Jan 18 10:27:46 2018 ----##
O of 110 entries are filtered due to excessive zero counts
[!]START ESTIMATION
Estimating NB parameters by DESeq2...
Number of groups:
Number of replicates:
                         5, 10, 15, 20
Number of simulations:
                         30
False Postive Rate:
                         0.05
Transformed:
(1 / 4) Simulation with 5 replicates per group:
Power Estimation between group A and group B:
                                                ======] 100% of All Simulations Completed...
##---- Thu Jan 18 10:28:21 2018 -----##
Power Estimation between group A and group C:
                                                 =====] 100% of All Simulations Completed...
##---- Thu Jan 18 10:28:56 2018 ----##
Power Estimation between group B and group C:
                                                       ] 74% of All Simulations Completed...
>> [=======
```

Visualization

The predicted results can be summaried using plotPredictedPower. The input should be the predicted power object returned from predictSampleSizePower, the summary can be optionally visualized by setting the following parameters:

- plotType: power-samplesize-foldchange relationship can be visualized optionally between "lineplot" and "heatmap".
- minLFC and maxLFC: to observe power in a specific range of LFC
- LFCscale: to determine the LFC scale of the observation

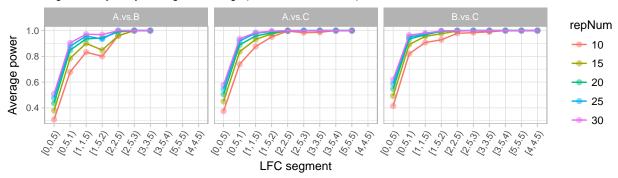
Line Plot

Lineplot (LFCscale = 0.5):

```
data("examplePredictedPower")
plotPredictedPower(examplePredictedPower, plotType = "lineplot", LFCscale = 0.5)
```

Average Predicted Power within LFC ranges

segmented by every 0.5 Log2FoldChange (minLFC: 0, maxLFC: 5)



	repNum:10	repNum:15	repNum:20	repNum:25	repNum:30
A.vs.B	0.8	0.84	0.88	0.89	0.91
A.vs.C	0.88	0.91	0.93	0.94	0.94
B.vs.C	0.9	0.93	0.94	0.95	0.96

Lineplot is one of the optional outputs of plotPredictedPower, the output contains a lineplot and a summary table. For each comparison, the lineplot shows the power tendency across each Log2 Fold Change segment, which resulted from a complete LFC list divided by a specified LFCscale. Each dot on the lines stands for the average power (y-axis) of the genes within the LFC range (x-axis), and the colours indicate the average power of the certain sample size as shown in the legend besides the plot. In addition, a summary table below shows the average power of each comparison across the sample sizes.

For instance, the line plot here shows the average power of four sample sizes (5 to 30, step=5) in LFCscale of 0.5, the LFC range is between 0 and 5, each LFC segment shows the average power of the entries with the

LFC in this range, here the higher LFC has higher power, additionally as the repNum (sample size) shown with different colours, the average power of each LFC range increases with the larger sample sizes.

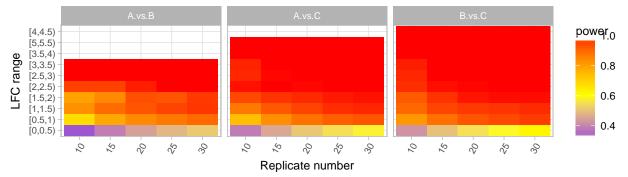
Heatmap

Heatmap (LFCscale = 0.5):

```
data("examplePredictedPower")
plotPredictedPower(examplePredictedPower, plotType = "heatmap", LFCscale = 0.5)
```

Average Predicted Power within LFC ranges

segmented by every 0.5 Log2FoldChange (minLFC: 0, maxLFC: 5)



	repNum:10	repNum:15	repNum:20	repNum:25	repNum:30
A.vs.B	0.8	0.84	0.88	0.89	0.91
A.vs.C	0.88	0.91	0.93	0.94	0.94
B.vs.C	0.9	0.93	0.94	0.95	0.96

The heatmap option presents the power predictions in the similar way, vertically each heatmap shows overall LFC level of a comparison, sometimes a certain range shows blank space, since the result LFC vary in different comparison pairs. The average power of each LFC range is scaled with colours between blue and red, the middle value (0.6) is coloured as yellow, as shown in the colour bar on the right. For example, this graph shows the power increases with larger sample sizes. The same summary table is also shown on the bottom.