Genome analysis

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unifiedWMWqPCR: the unified Wilcoxon–Mann–Whitney test for analyzing RT-qPCR data in R

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ABSTRACT

Motivation: Recently, De Neve *et al.* proposed a modification of the Wilcoxon–Mann–Whitney (WMW) test for assessing differential expression based on RT-qPCR data. Their test, referred to as the unified WMW (uWMW) test, incorporates a robust and intuitive normalization and quantifies the probability that the expression from one treatment group exceeds the expression from another treatment group. However, no software package for this test was available yet.

Results: We have developed a Bioconductor package for analyzing RT-qPCR data with the uWMW test. The package also provides graphical tools for visualizing the effect sizes.

Availability and implementation: The unifiedWMWqPCR package and its user documentation can be obtained through Bioconductor. **Contact:** JanR.DeNeve@UGent.be

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1 INTRODUCTION

Conventional approaches for analyzing RT-qPCR data first adopt a separate normalization step, e.g. using the Bioconductor package SLqPCR (Kohl, 2007), before assessing differential expression. This preprocessing step can obscure the interpretation of the statistical test. Furthermore, the type I error can be inflated, as the additional uncertainty associated with normalization is typically ignored. If C_q^1 denotes a quantification cycle associated with treatment group 1 and C_q^2 a quantification cycle associated with group 2 for a particular feature (typically a gene or a microRNA), then the unified Wilcoxon–Mann–Whitney (uWMW) test considers the null hypothesis

$$H_0: \mathbf{P}(C_a^1 \leq C_a^2) = \Delta, \tag{1}$$

where the probability $P(x \le y) := P(x < y) + 0.5P(x = y)$ allows for tied quantification cycles. If there is no need for normalization, under the null hypothesis of no-treatment effect, $\Delta = 0.5$ and the ordinary Wilcoxon–Mann–Whitney (WMW) test can be used. However, because of errors in the fluorescence quantification or differences in the amount of starting material and enzymatic efficiencies, among other reasons, $\Delta \ne 0.5$ even in the absence

of a treatment effect, and hence, normalization is required. The uWMW test consists of the following steps: (i) estimate Δ based on housekeeping features or on all features when housekeeping features are not available. The latter approach assumes up- and downregulation to be balanced; (ii) perform an adjusted WMW test to test H_0 (1) while accounting for the additional uncertainty caused by estimating Δ from the data; and (iii) provide standard errors and P-values.

 H_0 (1) can be equivalently expressed in terms of odds and odds ratio's (ORs) as follows

$$H_0: \operatorname{odds}(C_a^1 \leq C_a^2) = \Delta' \Leftrightarrow H_0: \operatorname{log} \operatorname{OR}(C_a^1 \leq C_a^2) = 0,$$
 (2)

where
$$odds(A) = P(A)/[1 - P(A)], \ \Delta' = \Delta/(1 - \Delta),$$
 and $OR(C_q^1 \le C_q^2) = odds(C_q^1 \le C_q^2)/\Delta'.$

2 SOFTWARE FEATURES

The unifiedWMWqPCR package is developed for R (R Core Team, 2013) and is a part of the Bioconductor environment (Gentleman *et al.*, 2004); both are freely available. The package includes a user's tutorial and can be installed on all major platforms.

2.1 Usage

The main function uWMW typically requires two inputs: (i) a data matrix where the rows indicate the features, the columns indicate the samples and each cell gives the raw (i.e. nonnormalized) C_q values and (ii) a binary vector with length equal to the number of columns of the data matrix indicating the two treatment groups. However, other input formats such as data frames or qPCRset objects from the Bioconductor package HTqPCR (Dvinge and Bertone, 2009) are also allowed. A vector with the names of housekeeping features for estimating Δ can be given as an optional argument. In the absence of housekeeping features, all features are used for the estimation of Δ ; see De Neve et al. (2013) for more details. For more information on the other optional arguments, we refer to the R help files.

2.2 Example

We consider the neuroblastoma NB dataset of Mestdagh *et al.* (2009) to illustrate the basic functionality of the package. The data consist of 323 miRNA features measured in 22 and

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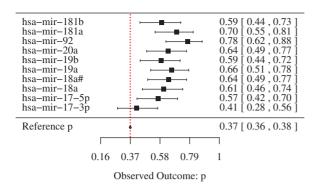


Fig. 1. Forest plot of the microRNAs associated with the miR-17-92 and miR-181 cluster

39 samples for the MYCN amplified (MNA) and MYCN single copy (MNSC) group, respectively. We refer to the unifiedWMWqPCR vignette for more information. Following De Neve *et al.* (2013), we assess null hypothesis (2) using all features for estimating Δ as follows:

```
> library('unifiedWMWqPCR')
> data(NBmat)
> dim(NBmat)
[1] 323 61
> table(NBgroups)
NBgroups
MNA MNSC
22 39
> uWMW.out <- uWMW(NBmat, groups = NBgroups)
> uWMW.out
unified Wilcoxon-Mann-Whitney test
with overall normalization
number of features: 323
Fitted probabilities: P(MNA < MNSC) + 0.5 P(MNA = MNSC)</pre>
```

Estimated log odds ratio's (logor), corresponding standard errors (se), odds ratio's (or), test statistics and *P*-values can be extracted as follows:

The estimated log $OR(C_q^{MNA} \leq C_q^{MNSC})$ for hsa-let-7a is given by 0.78, and it is significantly different from 0 at the 5% level of significance. The *p.adjust* function (R, 2013) can be used to adjust the *P*-values for multiple testing.

For visualization, the function *forestplot* can be used to draw a forest plot of a selection of microRNAs; see Figure 1. The estimated probabilities in (1) as well as their (unadjusted) 95% confidence intervals are plotted. The diamond on the bottom gives the estimate and confidence interval of Δ with which the probabilities should be compared with.

```
> selection.miRNA <- c("hsa-mir-17-3p", "hsa-mir-17-5p", "hsa-mir-18a", 
+ "hsa-mir-18a#", "hsa-mir-19a", "hsa-mir-19b", 
+ "hsa-mir-20a", "hsa-mir-92", "hsa-mir-181a", "hsa-mir-181b") 
> selection.id <- match(selection.miRNA, names(uWMW.out)) 
> forestplot(uWMW.out, estimate = "p", order = selection.id)
```

As the uWMW test is in essence obtained by fitting a probabilistic index model (Thas *et al.*, 2012), the estimated coefficients of the model and the estimated variance—covariance matrix can also be extracted.

For more details on the package and its available plots, we refer to the unifiedWMWqPCR vignette and help-files.

2.3 Performance

As the uWMW test implies fitting a regression model to a dataset with n_1n_2N rows and N columns (where N is the total number of features and n_i the number of samples in group i), its efficient implementation is an important property of the package. Analyzing a small dataset of 20 features with 10 replicates for each treatment group takes <0.2 s, whereas a large dataset of 1000 features with 100 replicates for each treatment group takes <30 s on an Intel 2.5 GHz CPU with 4 GB RAM.

3 CONCLUSION

This article presents the Bioconductor unifiedWMWqPCR package. It provides an extension of the WMW test so that a separate normalization preprocessing step is no longer required before assessing differential expression. In addition to *P*-values, the package also provides informative plots to visualize treatment effects.

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Conflict of Interest: none declared.

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