Statistics for Bioinformatics

# Detecting differentially expressed genes

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## Principle of differential analysis

#### Two-groups differential analysis with Welch test

- Principle: define a group of interest ("goi", for example hyperdiploidy), and compare it to all other cancer subtypes.
- For each gene *I*, test the null hypothesis of mean equality
  - $H_0: m_{i,goi} = m_{i,others}$
  - *H<sub>A</sub>: m<sub>i,goi</sub> <> m<sub>i,others</sub>*
- A priori, we expect that differential expression will cause a difference between group variances -> we apply Welch rather than Student test.

#### Multi-groups differential analysis with ANOVA

- Test the hypothesis of mean equality between all groups.
- For each gene, analyze the variance and compare the inter-group variance with the intra-group (residual) variance.

#### Multiple testing corrections

- The data set from Den Boer (2009) contains 22,283 probes. We are thus challenging 22,283 times the risk of false positive (considering a gene as significant whereas it is "truly null").
- Different methods have been proposed to control the number of false positives:
  - Bonferoni correction : decrease the significance threshold to alpha / N
  - E-value: compute the expected number of false positives: e-value = p-value \* N
  - FWER: compute P(FP >= 1)
  - q-value: estimate the false discovery rate (proportion of FP among the genes declared significant).

## Welch test results for two-groups differential analysis



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### Negative controls

- It is always useful to check empirically the significance of a selection procedure.
- For this, we can build negative controls, i.e. datasets where no difference is expected between groups.
- 3 negative controls
  - Random normal values. We build a fake expression matrix by generating random numbers following a normal distribution. This perfectly fits the working hypotheses underlying statistical tests (Student, ANOVA, ...) but is not a very realistic image of the biological data.
  - Matrix-wise random permutation of expression values. The distribution of values corresponds to the typical Affymetrix expression sets: left-skewed distribution.
  - Permutation of sample labels. We maintain the structure of the original expression matrix, but the sample labels are re-assigned at random. In principle, the labels are balanced between all the cancer subtypes, and there should be no significant difference between the randomized groups.





### Distribution of P-values from Welch test

- Data set: Den Boer et al. (2009).
- Welch test: hyperdiploid versus other types of Acute Lymphoblastic Leukemia.
- P-value distribution
  - Abscissa: frequency class of the P-value.
  - Ordinate: number of genes falling in this class.
- 3 negative controls
  - Random normal values.
    - Flat distribution, as expected.
  - Matrix-wise random permutation of expression values.
    - Flat distribution, as expected.
  - Permutation of sample labels, analysis of the original expression matrix.
    - Under-representation of low P-values. Strange.
- Original expression matrix.
  - Striking over-representation of the low P-values. This likely corresponds to differentially expressed genes.



Permuted sample labels

DenBoer, 2009



 Data source: Den Boer et al. 2009. A subtype of childhood acute lymphoblastic leukaemia with poor treatment outcome: a genome-wide classification study. Lancet Oncol 10(2): 125-134.

### Distribution of P-values from Welch test

- Data set: Den Boer et al. (2009).
- Welch test: hyperdiploid versus other types of Acute Lymphoblastic Leukemia.
- Volcano plots
  - Abscissa: difference between the means
  - Ordinate: significance of the test.
- 3 negative controls
  - Random normal values.
    - All significances are negative.
  - Matrix-wise random permutation of expression values.
    - 7 probesets are slightly significant.
  - Permutation of sample labels, analysis of the original expression matrix.
    - All significances are negative.
- Original expression matrix.
  - 2133 probesets are declared significant (differentially expressed) with E-value <= 1.</li>





Permuted sample labels

Den Boer 2009, hyperdiploid versus others



#### Data source: Den Boer et al. 2009. A subtype of childhood acute lymphoblastic leukaemia with poor treatment outcome: a genome-wide classification study. Lancet Oncol 10(2): 125-134.

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0

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-0.4

sig = -log10(E-value)

Random normal values

Matrix-wise permuted expression values