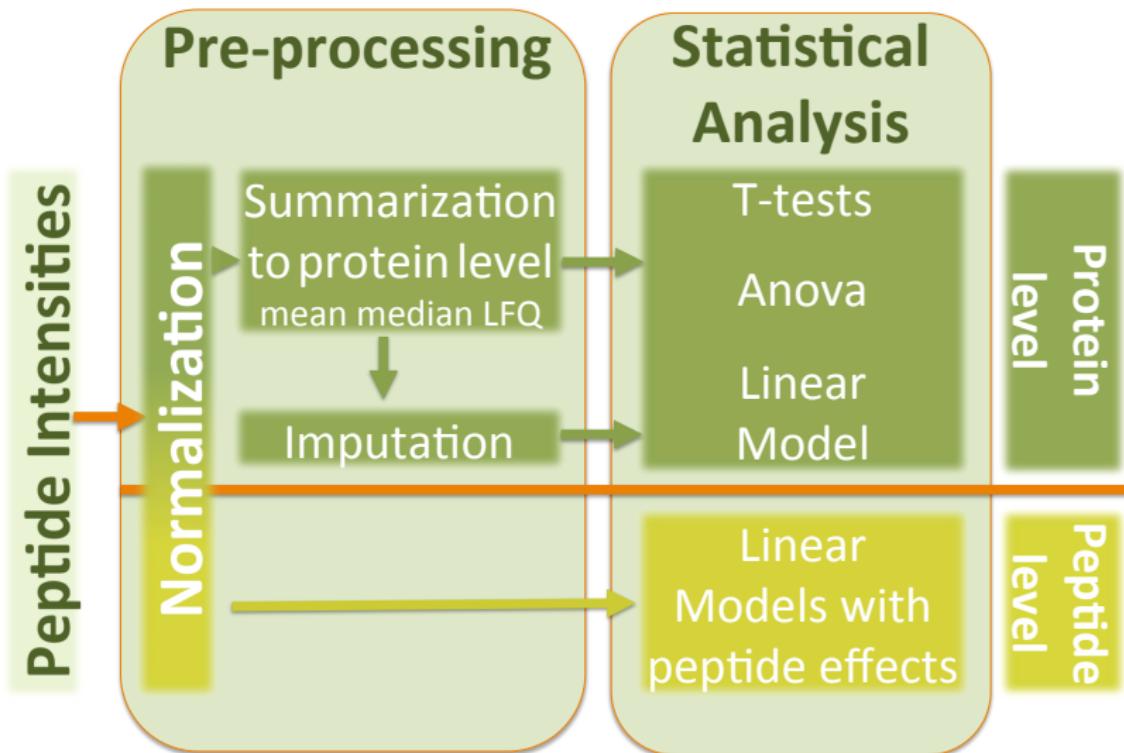


Part II: Statistical Inference

Lieven Clement

Proteomics Data Analysis Shortcourse

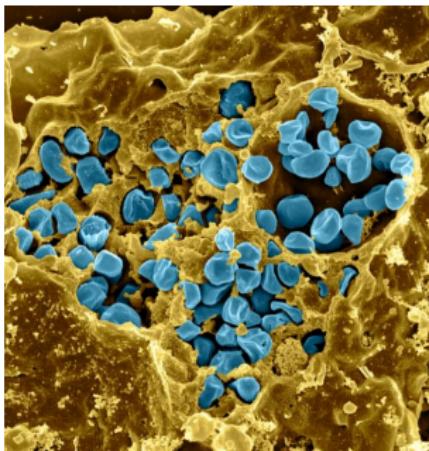
Label-free Quantitative Proteomics Data Analysis Pipelines



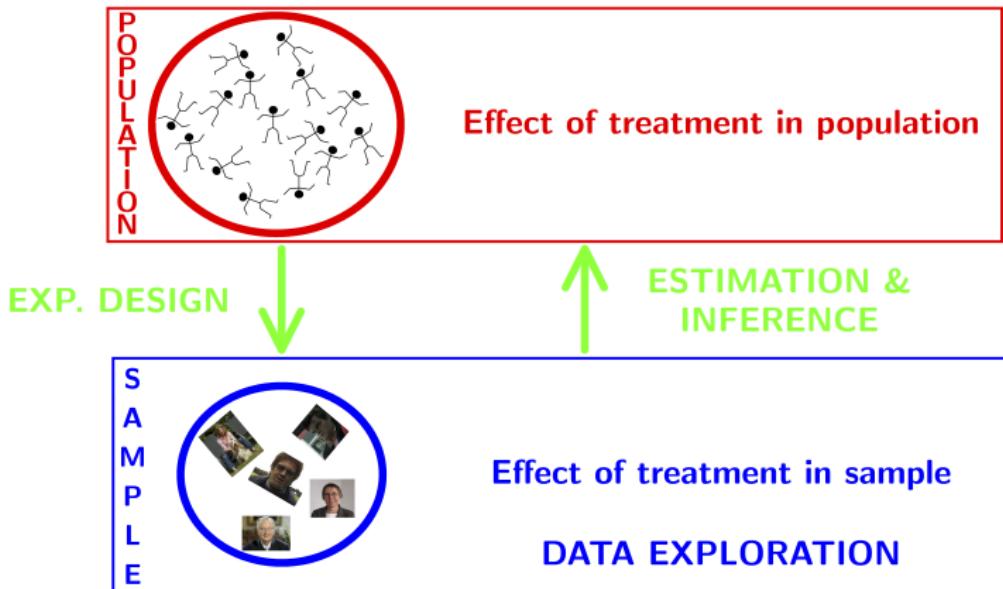
Statistical Inference

- ① Francisella tularensis Example
- ② Hypothesis testing
- ③ Multiple testing
- ④ Moderated statistics
- ⑤ Experimental design
- ⑥ Peptide based models

Francisella tularensis experiment



- Pathogen: causes tularemia
- Metabolic adaptation key for intracellular life cycle of pathogenic microorganisms.
- Upon entry into host cells quick phagosomal escape and active multiplication in cytosolic compartment.
- Francisella is auxotroph for several amino acids, including arginine.
- Inactivation of arginine transporter delayed bacterial phagosomal escape and intracellular multiplication.
- Experiment to assess difference in proteome using 3 WT vs 3 ArgP KO mutants

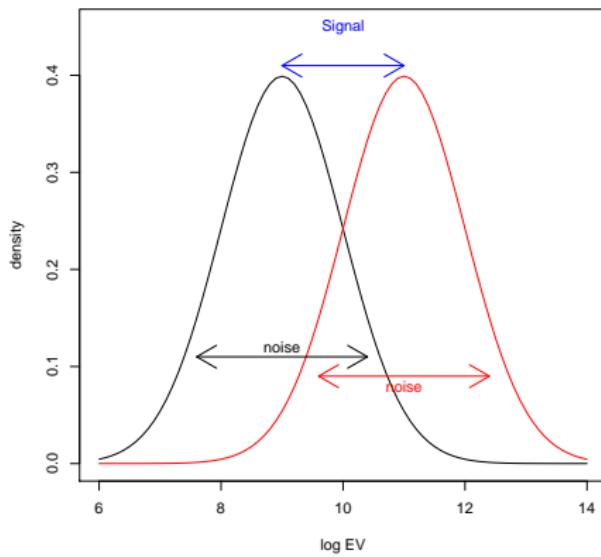


Summarized data structure

- WT vs KO
- 3 vs 3 repeats
- 882 proteins

Protein	WT ₁	WT ₂	WT ₃	KO ₁	KO ₂	KO ₃
gi 118496616	29.83	29.77	29.91	29.70	29.86	29.80
gi 118496617	31.28	31.23	31.51	31.30	31.51	31.76
gi 118496635	32.39	32.27	32.24	32.25	32.14	32.22
gi 118496636	30.74	30.54	30.64	30.65	30.49	30.60
gi 118496637	29.56	29.35	29.56	29.30	29.24	29.14
gi 118498323	31.38	30.52	30.62	31.04	27.38	NA
:	:	:	:	:	:	:

Hypothesis testing: a single protein



$$\Delta = \bar{z}_{p1} - \bar{z}_{p2}$$

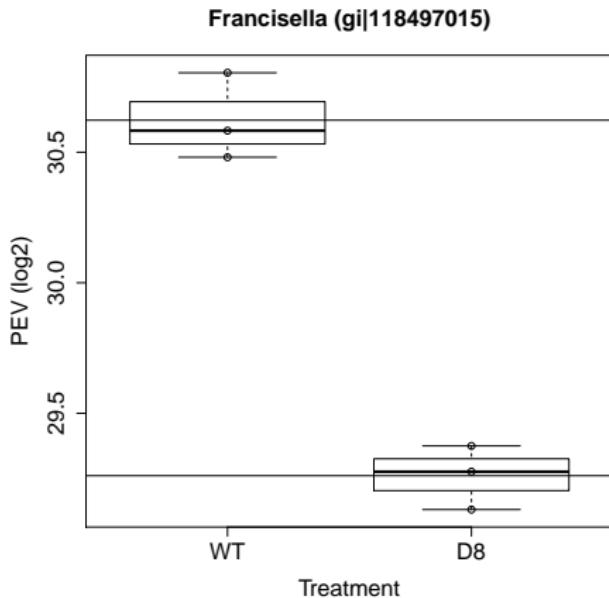
$$T_g = \frac{\Delta}{\text{se}_\Delta}$$

$$T_g = \frac{\overbrace{\text{signal}}^{\text{mean}}}{\overbrace{\text{Noise}}^{\text{SD}}}$$

If we can assume equal variance in both treatment groups:

$$\text{se}_\Delta = \text{SD} \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$$

Hypothesis testing: a single protein



$$t = \frac{\widehat{\log_2 FC}}{se_{\log_2 \widehat{FC}}} = \frac{-1.4}{0.118} = -11.9$$

Is $t = -11.9$ indicating that there is an effect?

How likely is it to observe $t = -11.8$ when there is no effect of the argP KO on the protein expression?

Null hypothesis and alternative hypothesis

- In general we start from **alternative hypothesis** H_A : we want to show an effect of the KO on a protein
 - On average the protein abundance in WT is different from that in KO

Null hypothesis and alternative hypothesis

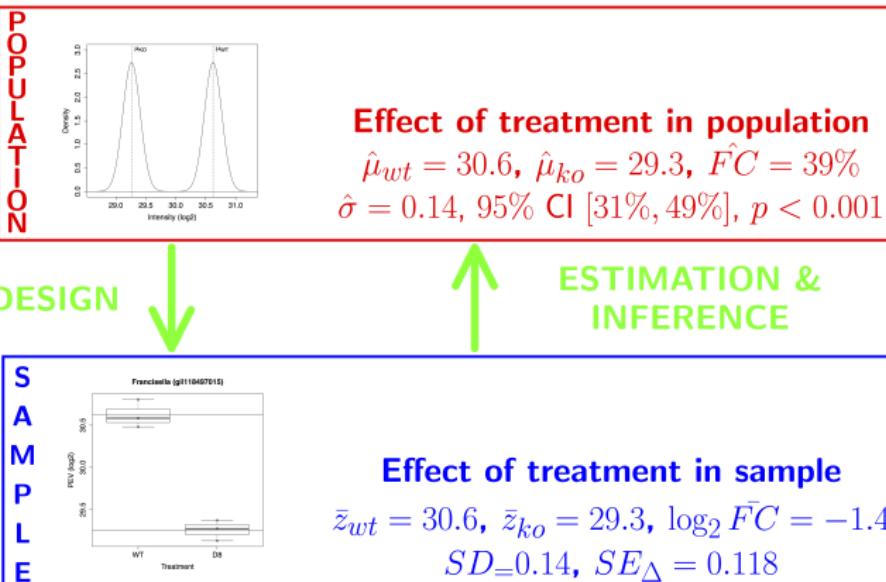
- In general we start from **alternative hypothesis** H_A : we want to show an effect of the KO on a protein
 - On average the protein abundance in WT is different from that in KO
- But, we will assess it by falsifying the opposite: **null hypothesis** H_0
 - On average the protein abundance in WT is equal to that in KO

Two Sample t-test

```
data: z by treat
t = -11.449, df = 4, p-value = 0.0003322
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-1.031371 -1.691774
sample estimates:
mean in group D8 mean in group WT
29.26094      30.62251
```

- How likely is it to observe an equal or more extreme effect than the one observed in the sample when the null hypothesis is true?
- When we make assumptions about the distribution of our test statistic we can quantify this probability: **p-value**. The p-value will only be calculated correctly if the underlying assumptions hold!
- When we repeat the experiment, the probability to observe a fold change more extreme than a 2.6 fold ($\log_2 FC = -1.36$) down or up regulation by random chance (if H_0 is true) is 3 out of 10.000.
- If the p-value is below a significance threshold α we reject the null hypothesis. **We control the probability on a false positive result at the α -level (type I error)**

Hypothesis testing: a single protein



Multiple hypothesis testing

Problem of multiple hypothesis testing

- Consider testing DA for all $m = 882$ proteins simultaneously
 - What if we assess each individual test at level α ?
- Probability to have a false positive among all m simultaneous tests >>> $\alpha = 0.05$

Suppose that 600 proteins are non-DA, then we could expect to discover on average $600 \times 0.05 = 30$ false positive proteins. Hence, we are bound to call false positive proteins each time we run the experiment.

FDR: False discovery rate

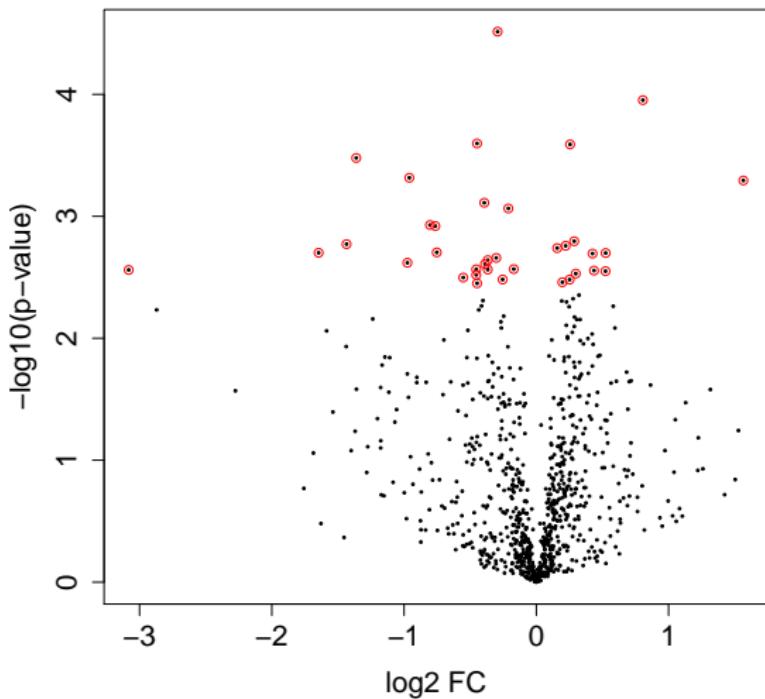
- FDR: Expected proportion of false positives on the total number of positives you return.
- An FDR of 1% means that on average we expect 1% false positive proteins in the list of proteins that are called significant.
- Defined by Benjamini and Hochberg in 1995

$$\text{FDR}(|t_{\text{thres}}|) = E \left[\frac{FP}{FP + TP} \right] = \frac{\pi_0 Pr(|T| \geq t_{\text{thres}} | H_0)}{Pr(|T| \geq t_{\text{thres}})}$$

$$\text{FDR}_{\text{BH}}(|t_{\text{thres}}|) = \frac{1 \times p_{t_{\text{thres}}}}{\# |t_i| \geq t_{\text{thres}}}$$

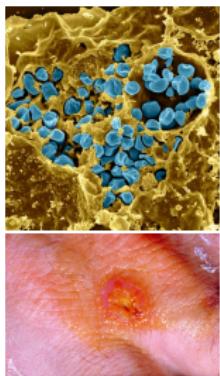
- FDR adjusted p-values can be calculated (e.g. Perseus, R, ...)

Ordinary t-test

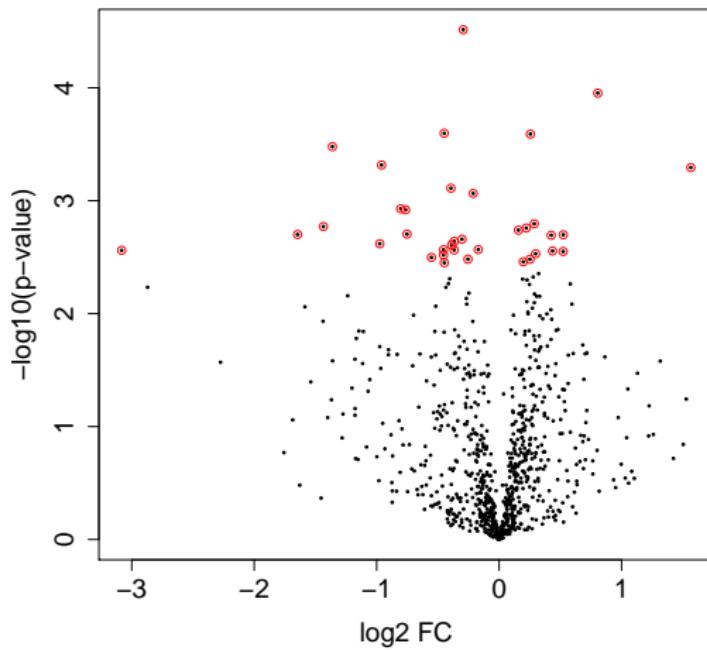


Moderated Statistics

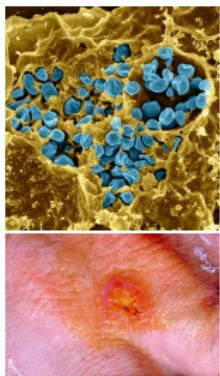
Problems with ordinary t-test



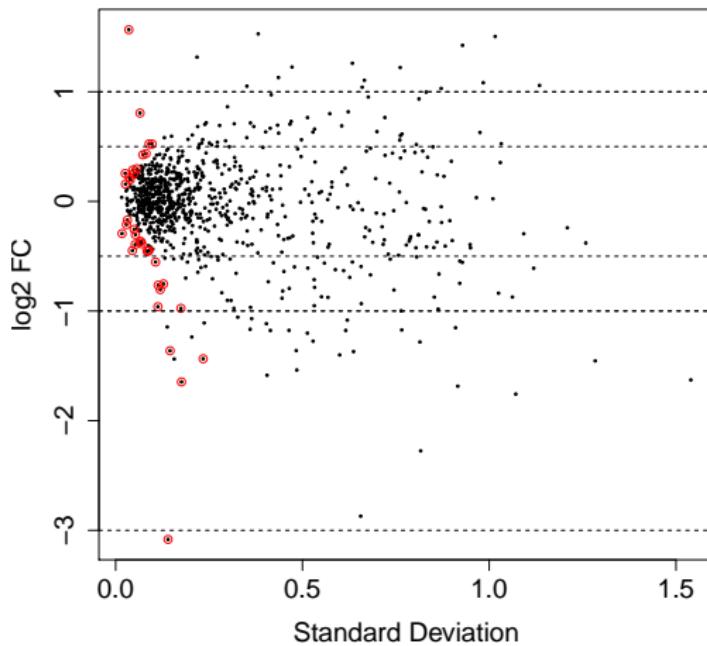
Ordinary t-test



Problems with ordinary t-test

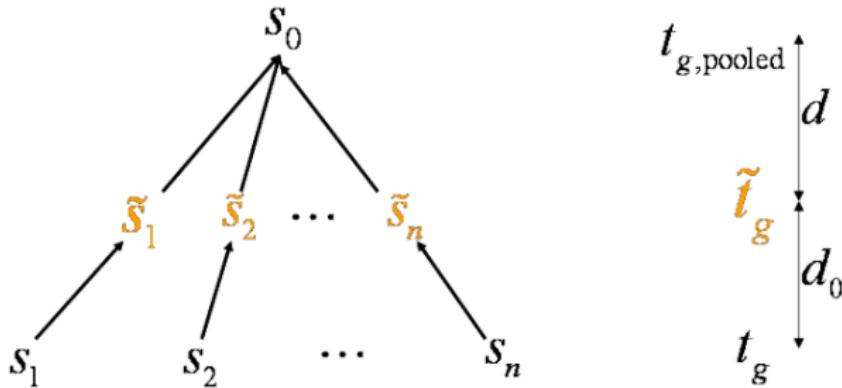


Original t-test



Shrinkage of the variance and moderated t-statistics

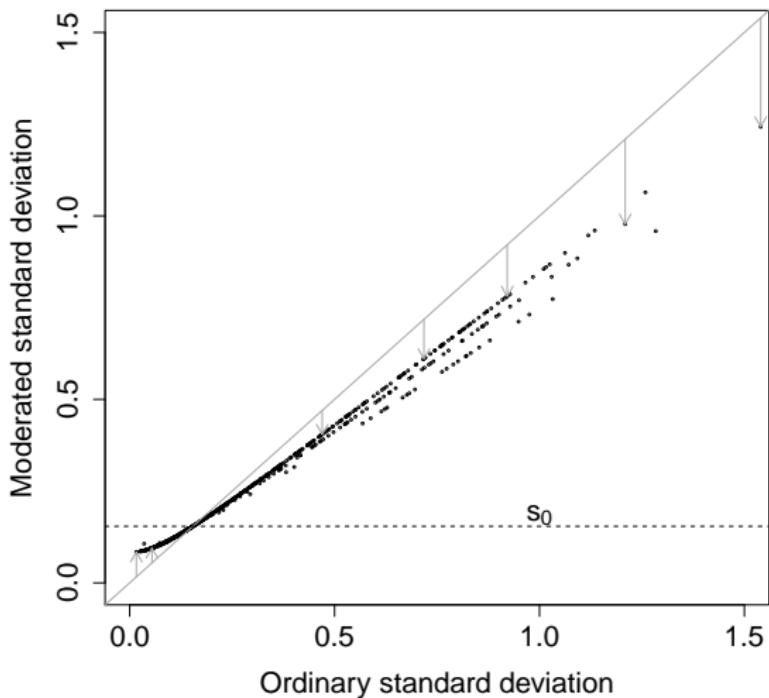
Shrinkage of Standard Deviations



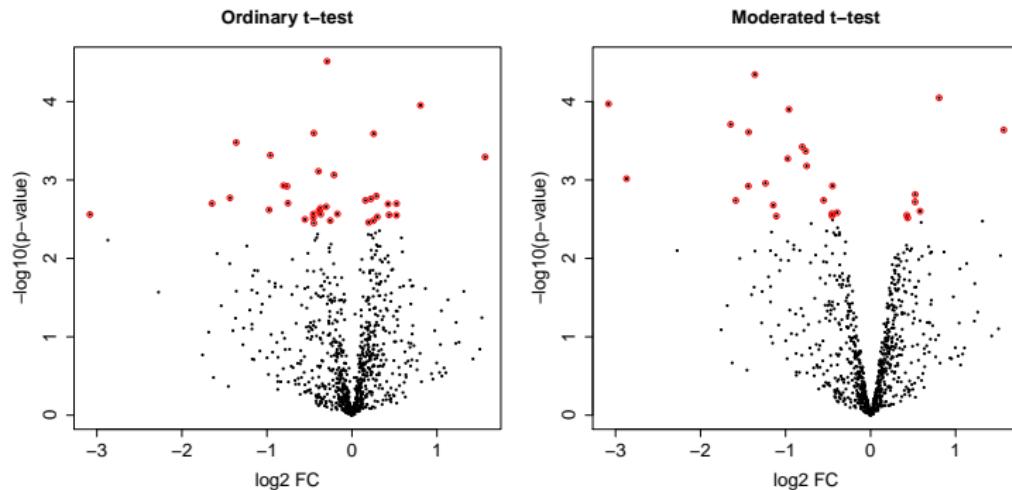
The data decides whether \tilde{t}_g

should be closer to $t_{g,\text{pooled}}$ or to t_g

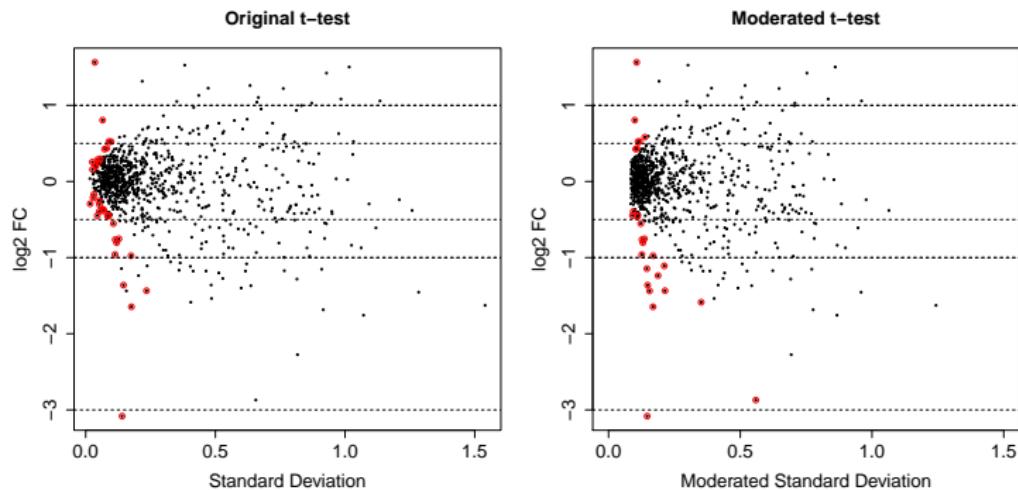
Shrinkage of the variance with limma

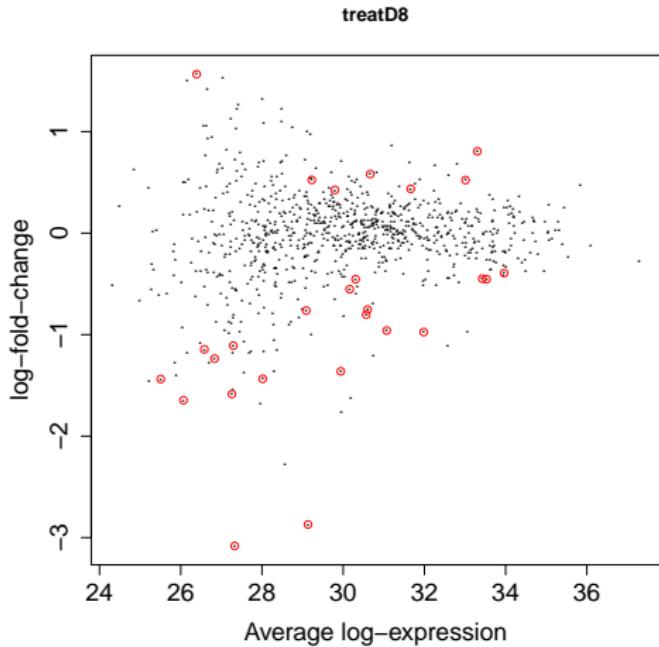


Problems with ordinary t-test solved by moderated EB t-test



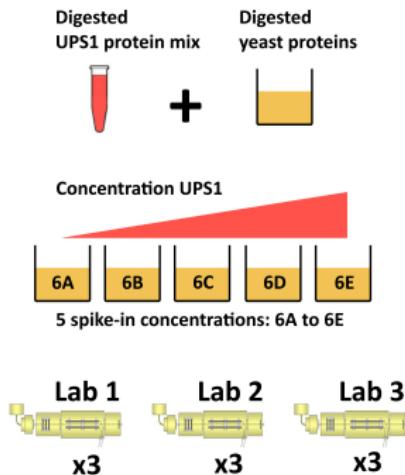
Problems with ordinary t-test solved by moderated EB t-test





Peptide-based models

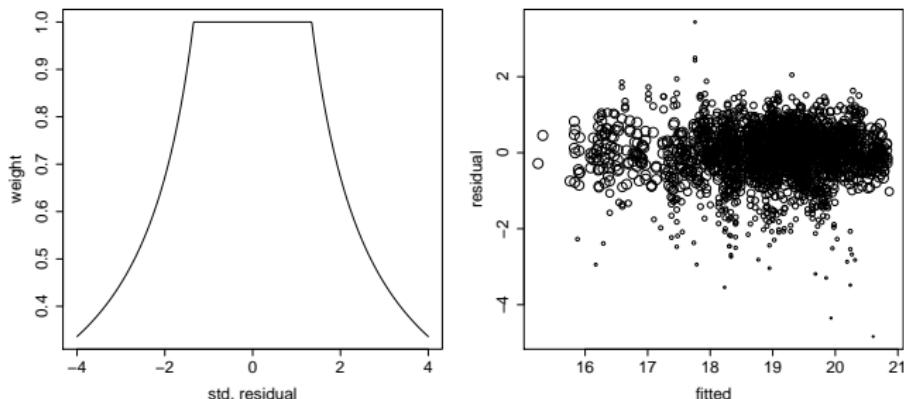
Inference with Peptide Based Methods



- Protein by protein analysis of peptide level data with linear model
 $y_{pept} \sim peptide + treatment + lab$
- Variance estimation in the literature:
 protein-wise (LM) or via limma-style EB (LM-Sq).
- t-tests on model parameters

Extension I: Robust estimation using observation weights (Ex I: LM-Sq-Rob)

- Outlying peptide intensities: incorrect peptide identification, post-translational modifications, ...

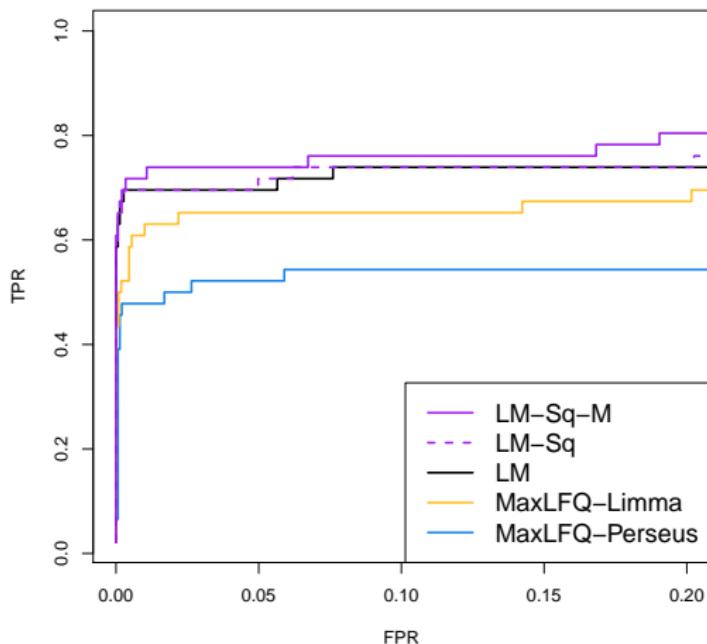


- Iteratively fit model with observation weights $w(d_{ijp})$

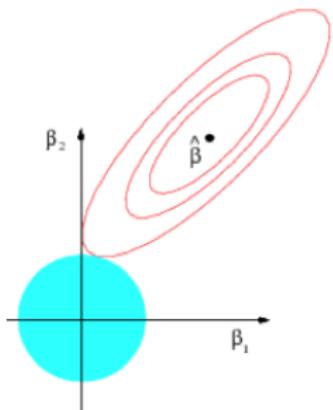
$$\operatorname{argmin} \left[\sum_{i=1}^n \sum_{j=p}^{P_j} w(d_{ijp}) \left(y_{ijp} - \mathbf{x}_i^T \boldsymbol{\beta}_j^{\text{treat}} - \beta_{jp}^{\text{pep}} \right)^2 \right]$$



Method performance



Extension II: Ridge regression

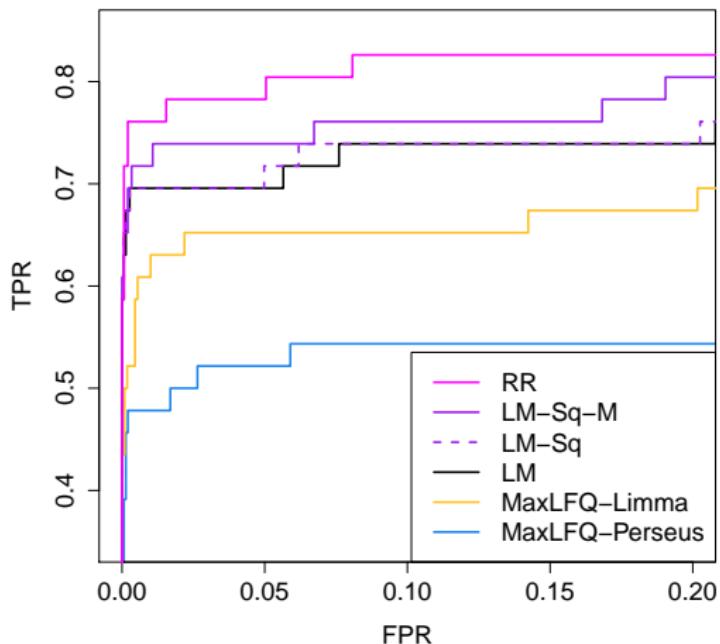


Parameters estimation via ridge regression,
loss function:

$$\operatorname{argmin} \left[\sum_{i=1}^n \sum_{j=1}^{P_j} w(d_{ijp}) \left(y_{ijp} - \mathbf{X}_i^T \boldsymbol{\beta}_j^{\text{treat}} - \beta_{jp}^{\text{pep}} \right)^2 + \lambda_j^{\text{treat}} \sum (\boldsymbol{\beta}_j^{\text{treat}})^2 + \lambda_j^{\text{pep}} \sum (\beta_{jp}^{\text{pep}})^2 \right]$$

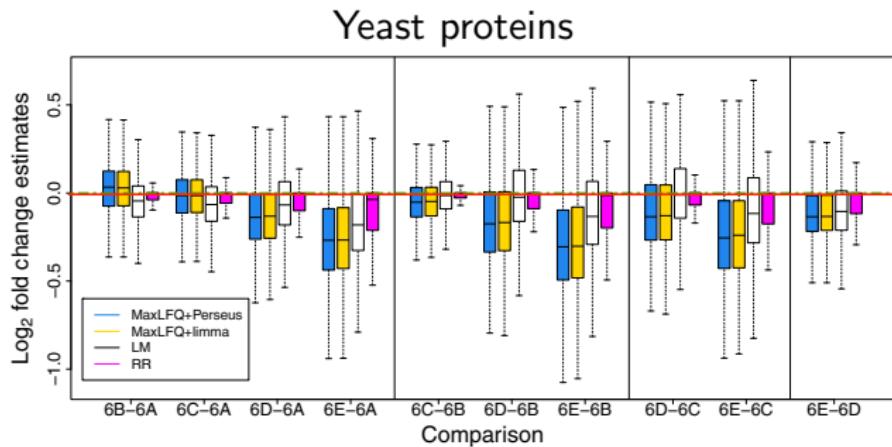
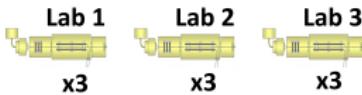
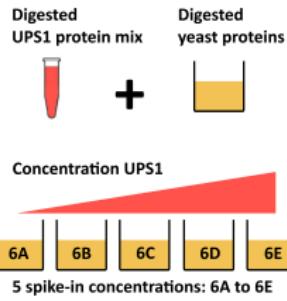
with

- λ_{treat} : penalty term for regularization of parameters of interest
- λ_{pep} : penalty term for regularization of peptide specific parameters



Fold Change Estimates: Accuracy & Precision

Study Design

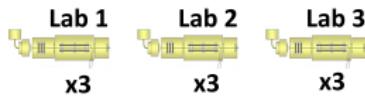
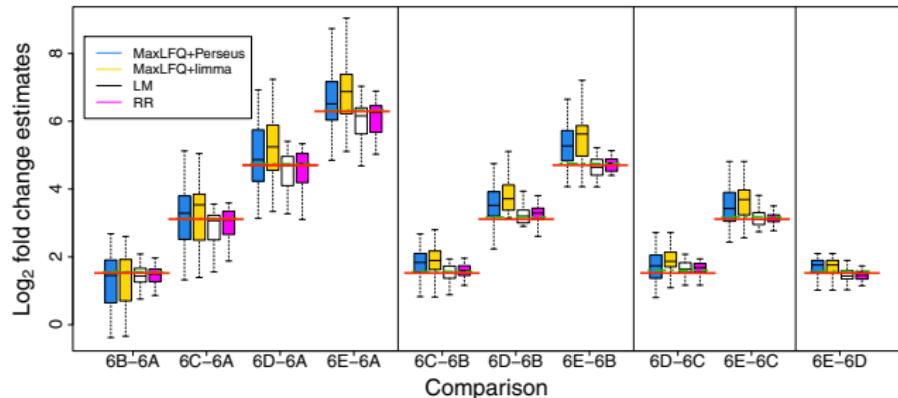
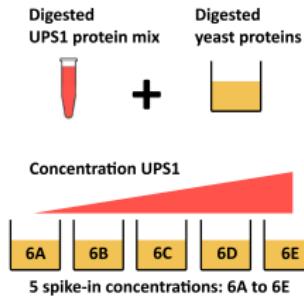


- Shrinkage: more precise and accurate FC estimates
 - Note, negative bias of the log₂ FC estimates as spike-in concentration increases
- Ionization suppression effects + Violation of normalization assumptions

Fold Change Estimates: Accuracy & Precision

Spiked UPS proteins

Study Design



- MaxLFQ- Perseus and MaxLFQ-limma are always more biased and more variable
- Again MSqRob has a higher precision
- Shrinkage does not affect accuracy if there is evidence for DA!

MSqRob

MSqRob for MaxQuant data v 0.8.0 Input Preprocessing Quantification

Select the grouping factor (mostly the "Proteins" column)

Proteins

Select additional annotation columns you want to keep

Protein names

Select fixed effects

genotype

Select random effects

Sequence run scope

Save/Load options:

- Save the model
- Load existing models
- Don't save the model

Select the type of analysis

standard

Number of contrasts you want to test

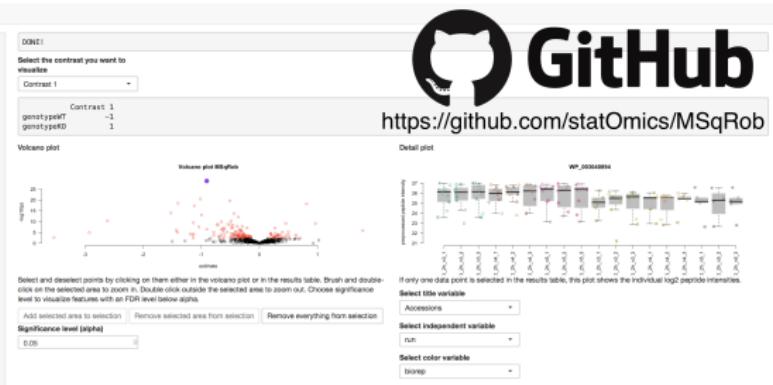
1

Contrast 1

genotypeWT
-1

genotypeKD
1

Go



GitHub

<https://github.com/statOmics/MSqRob>


- Goeminne, L., Gevaert, K. and Clement, L. (2016). Molecular and Cellular Proteomics, 15(2), 657-668
- Goeminne, L., Gevaert, K. and Clement, L. (2017). Journal of Proteomics, In Press.
- <http://dx.doi.org/10.1016/j.jprot.2017.04.004>

Experimental Design

Power?

$$\Delta = \bar{z}_{p1} - \bar{z}_{p2}$$

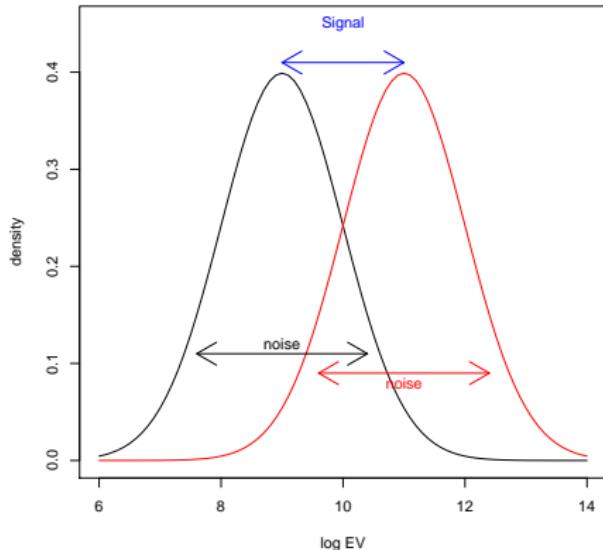
$$T_g = \frac{\Delta}{\text{se}_\Delta}$$

$$T_g = \frac{\widehat{\text{signal}}}{\widehat{\text{Noise}}}$$

If we can assume equal variance in both treatment groups:

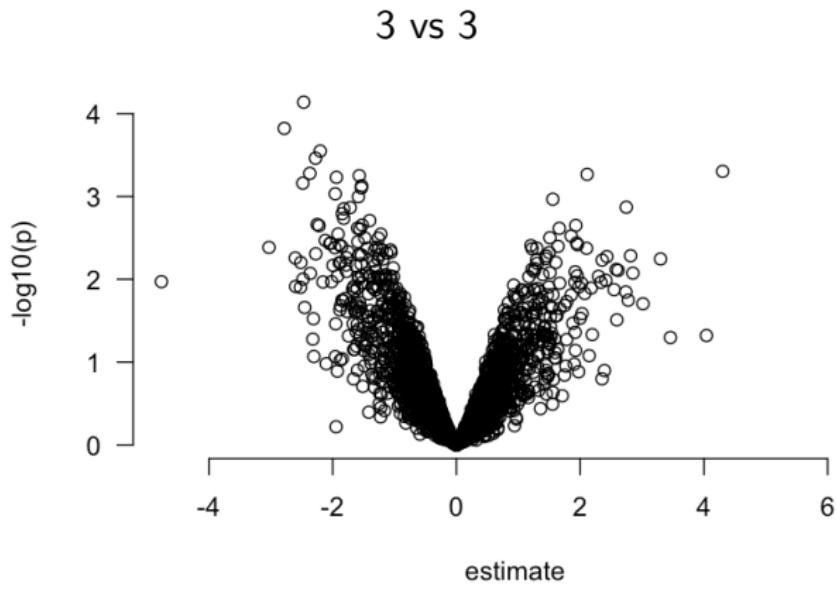
$$\text{se}_\Delta = \text{SD} \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}$$

→ Design: if number of bio-repeats increases we have a higher power!



- Study on tamoxifen treated Estrogen Receptor (ER) positive breast cancer patients
- Proteomes for tumors of patients with good and poor outcome upon recurrence.

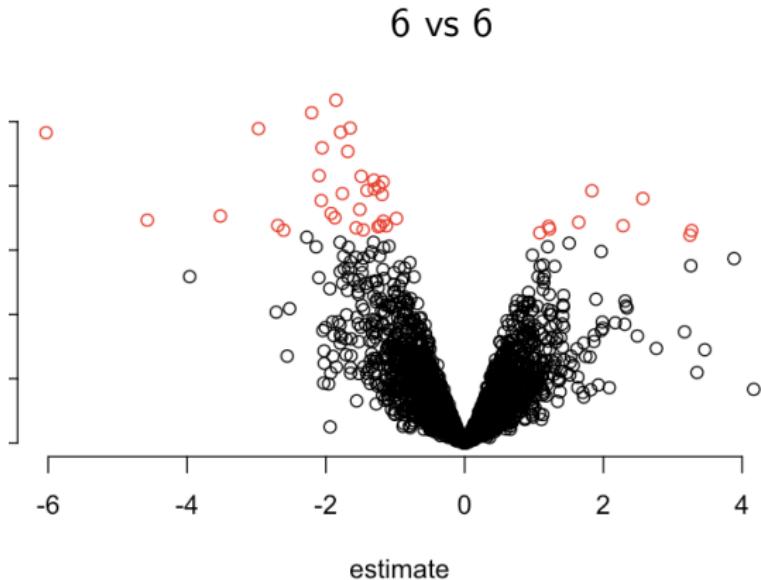
- Study on tamoxifen treated Estrogen Receptor (ER) positive breast cancer patients
- Proteomes for tumors of patients with good and poor outcome upon recurrence.



0 proteins at 5% FDR

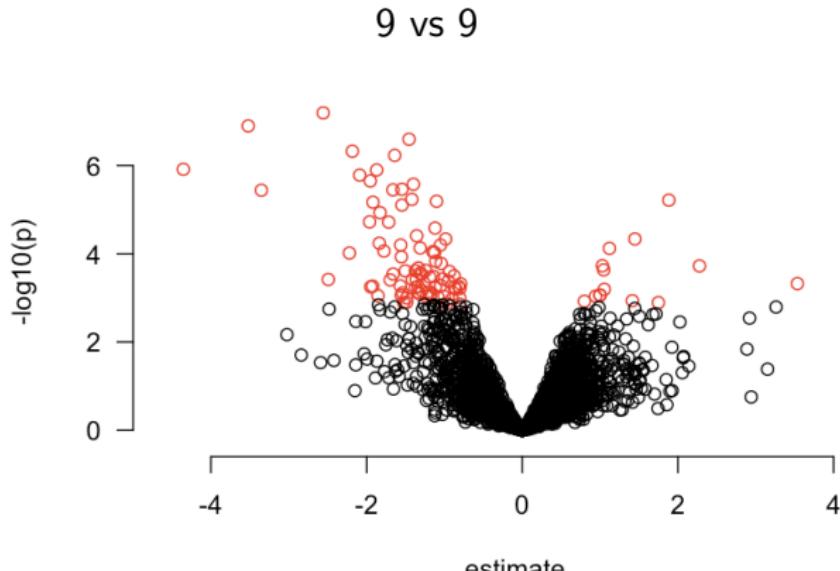


- Study on tamoxifen treated Estrogen Receptor (ER) positive breast cancer patients
- Proteomes for tumors of patients with good and poor outcome upon recurrence.



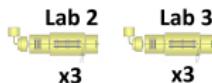
41 proteins at 5% FDR

- Study on tamoxifen treated Estrogen Receptor (ER) positive breast cancer patients
- Proteomes for tumors of patients with good and poor outcome upon recurrence.



96 proteins at 5% FDR

Blocking



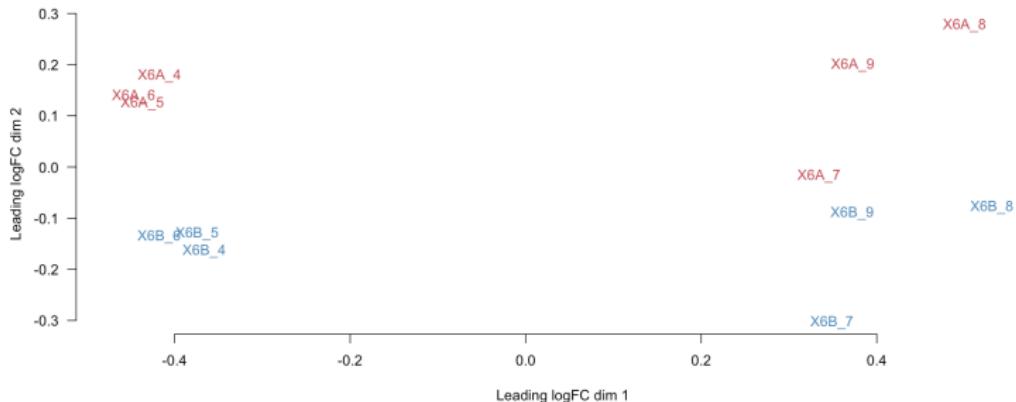
Color variable [?]

condition



MDS plot after full preprocessing [?]

- Plot MDS points
- Plot MDS labels



Experimental Design: Blocking



Sources of variability

$$\sigma^2 = \sigma_{bio}^2 + \sigma_{lab}^2 + \sigma_{extraction}^2 + \sigma_{run}^2 + \dots$$

- Biological: fluctuations in protein level between rats of the same litter, between rats of different litters.
- Technical: cage effect, lab effect, week effect, plasma extraction, MS-run, ...

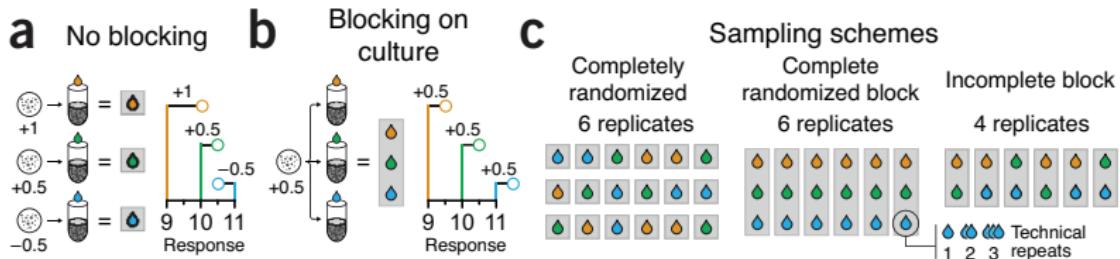


Figure 2 | Blocking improves sensitivity by isolating variation in samples that is independent from treatment effects. **(a)** Measurements from treatment aliquots derived from different cell cultures are differentially offset (e.g., 1, 0.5, -0.5) because of differences in cultures. **(b)** When aliquots are derived from the same culture, measurements are uniformly offset (e.g., 0.5). **(c)** Incorporating blocking in data collection schemes. Repeats within blocks are considered technical replicates. In an incomplete block design, a block cannot accommodate all treatments.

Nature Methods 2014, 11(7) 699–700.

Blocking

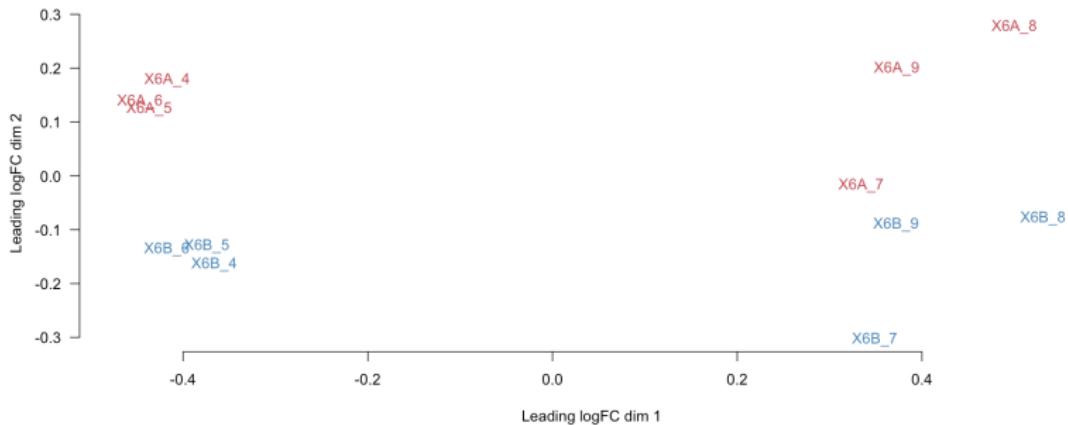
$$\sigma^2 = \sigma^2_{\text{within lab}} + \sigma^2_{\text{between lab}}$$

Color variable [\[?\]](#)

condition

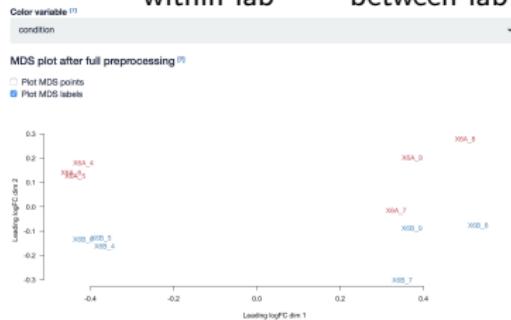
MDS plot after full preprocessing [\[?\]](#)

- Plot MDS points
- Plot MDS labels



Blocking

$$\sigma^2 = \sigma^2_{\text{within lab}} + \sigma^2_{\text{between lab}}$$



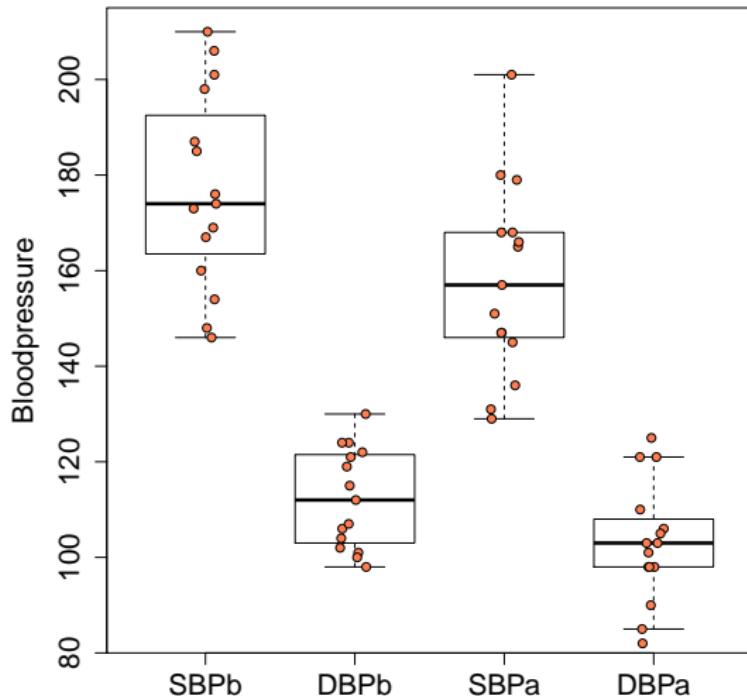
- All treatments of interest are present within block!
- We can estimate the effect of the treatment within block!
- We can isolate the between block variability from the analysis
- linear model:

$$y \sim \text{treatment} + \text{lab}$$

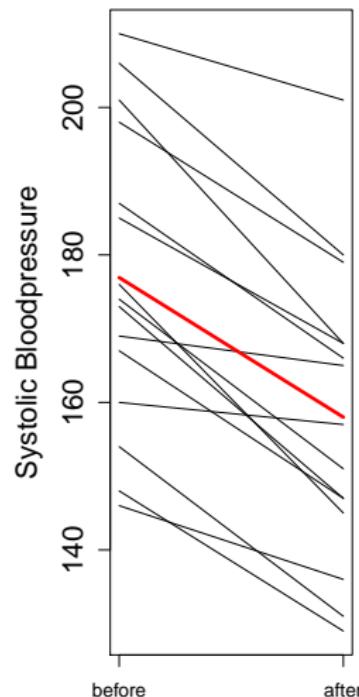
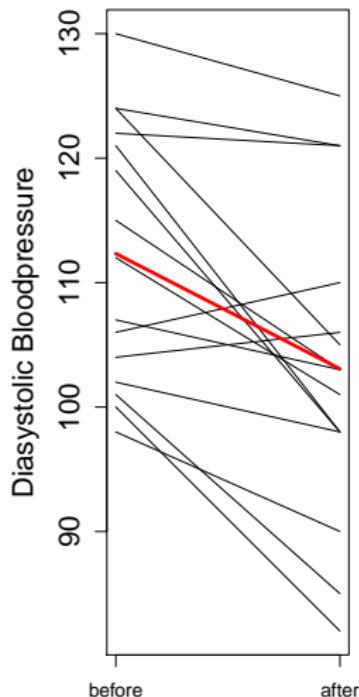
- Not possible with Perseus!



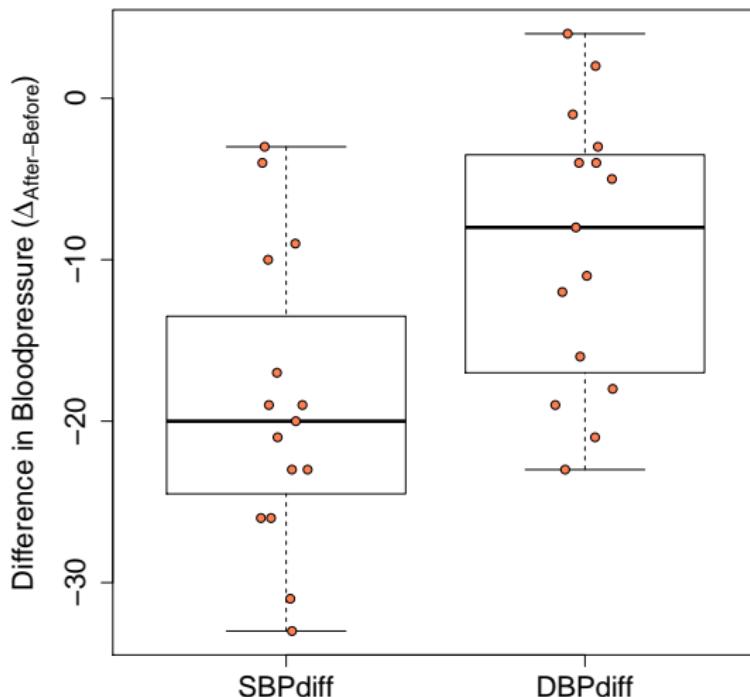
Power gain of blocking



Power gain of blocking



Power gain of blocking



Power gain of blocking

- Completely randomized design: 14 people, 7 baseline BP, 7 BP upon treatment.
- Randomized complete block design: 7 people, 7 baseline BP and BP upon treatment.

Power gain of blocking

Completely randomized design

Call:

```
lm(formula = bp ~ treat, data = captoprilCRD)
```

Residuals:

Min	1Q	Median	3Q	Max
-26.714	-11.643	-3.929	11.179	30.857

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	179.143	7.036	25.461	8.19e-12
treatT	-23.429	9.950	-2.355	0.0364

(Intercept) ***

treatT *

Signif. codes:

0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 18.62 on 12 degrees of freedom

Multiple R-squared: 0.316, Adjusted R-squared: 0.259

F-statistic: 5.544 on 1 and 12 DF, p-value: 0.03641



Power gain of blocking

Randomized complete block design

Call:

```
lm(formula = bp ~ treat + patient, data = captoprilRCB)
```

Residuals:

Min	1Q	Median	3Q	Max
-8	-3	0	3	8

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	213.000	5.442	39.138	1.86e-08
treatT	-15.000	3.848	-3.898	0.008004
patientp2	-38.500	7.200	-5.348	0.001749
patientp3	-29.000	7.200	-4.028	0.006896
patientp4	-47.000	7.200	-6.528	0.000617
patientp5	-48.500	7.200	-6.737	0.000521
patientp6	-45.000	7.200	-6.250	0.000777
patientp7	-29.000	7.200	-4.028	0.006896

(Intercept) ***

treatT **

patientp2 **

patientp3 **

patientp4 ***

patientp5 ***

patientp6 ***

patientp7 **

Signif. codes:

0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ',' 1



Power gain of blocking

Randomized complete block bad analysis

Call:

```
lm(formula = bp ~ treat, data = captoprilRCB)
```

Residuals:

Min	1Q	Median	3Q	Max
-19.143	-11.643	-1.143	5.357	36.857

Coefficients:

	Estimate	Std. Error	t value
(Intercept)	179.143	6.694	26.763
treatT	-15.000	9.466	-1.585
	Pr(> t)		
(Intercept)	4.55e-12 ***		
treatT	0.139		

Signif. codes:

0 '***' 0.001 '**' 0.01 '*' 0.05 '.'
0.1 ' ' 1

Residual standard error: 17.71 on 12 degrees of freedom

Multiple R-squared: 0.173, Adjusted R-squared: 0.1041

F-statistic: 2.511 on 1 and 12 DF, p-value: 0.1391

