

Part I: Normalization & Summarization

Lieven Clement

Proteomics Data Analysis Shortcourse

Outline

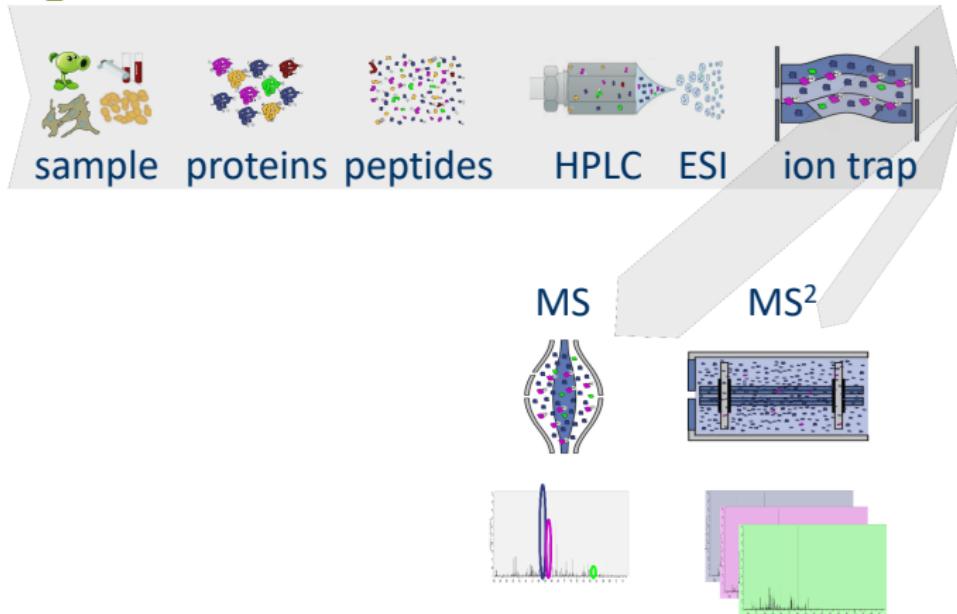
① Introduction

- ① Label free MS based Quantitative Proteomics Workflow and Challenges

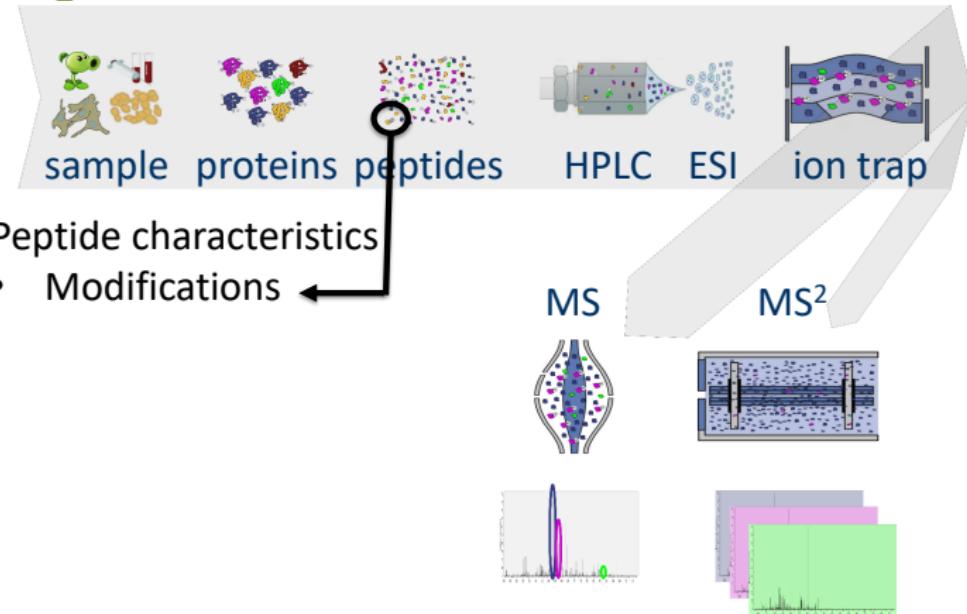
② Preprocessing

- ① Filtering
- ② Log transformation
- ③ Normalization
- ④ Summarization

Challenges in Label Free Quantitative Proteomics

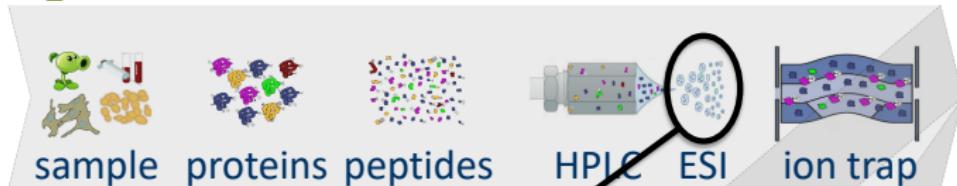


Challenges in Label Free Quantitative Proteomics



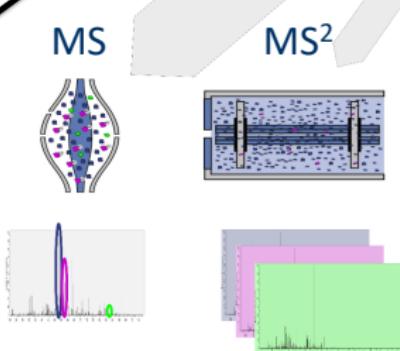
Quantification Identification

Challenges in Label Free Quantitative Proteomics



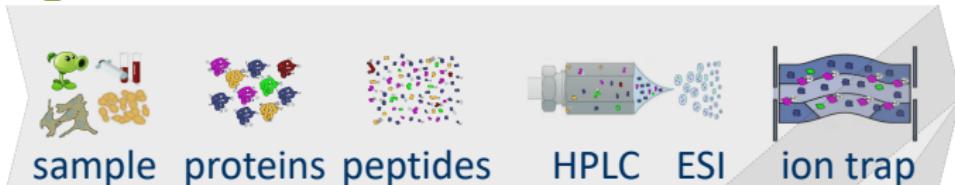
Peptide characteristics

- Modifications
- Ionisation efficiency
 - Outliers
 - Huge variability



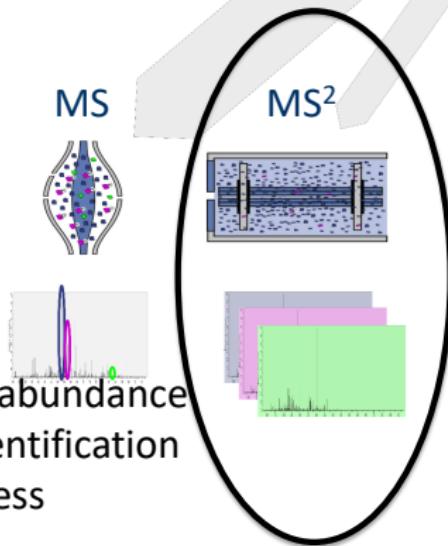
Quantification Identification

Challenges in Label Free Quantitative Proteomics

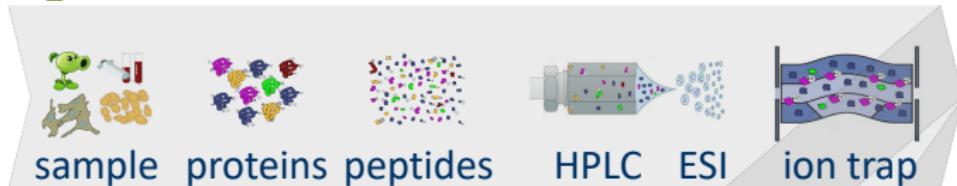


Peptide characteristics

- Modifications
- Ionisation efficiency
 - Outliers
 - Huge variability
- MS² selection on peptide abundance
 - Context dependent Identification
 - Non-random missingness

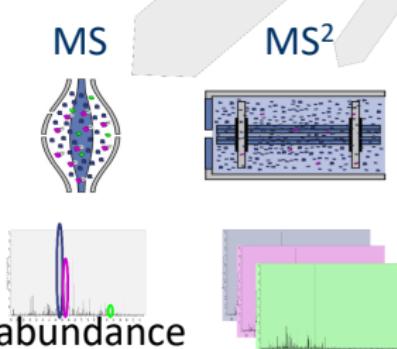


Challenges in Label Free Quantitative Proteomics



Peptide characteristics

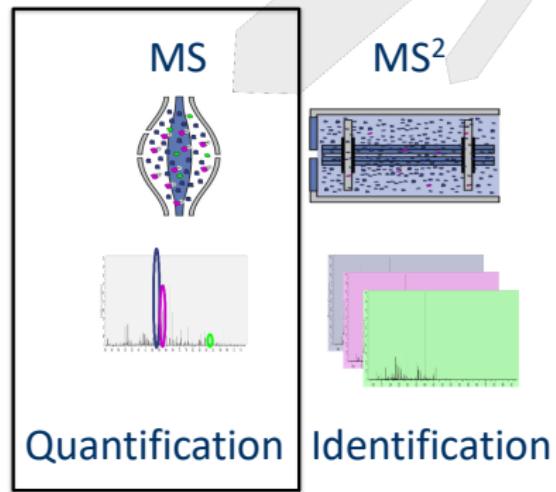
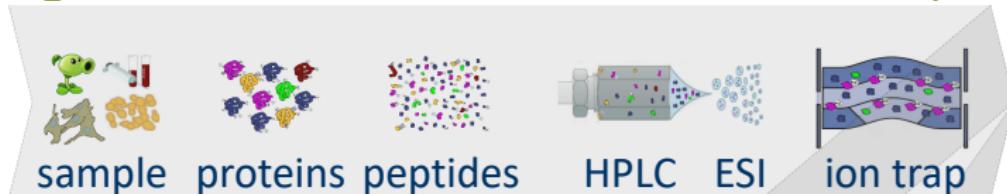
- Modifications
- Ionisation efficiency
 - Outliers
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Unbalanced peptides identifications across samples and messy data

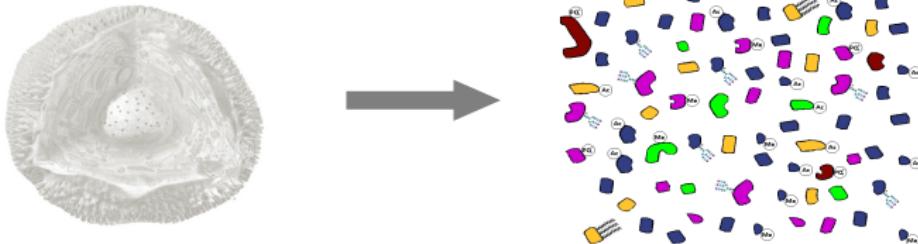


Challenges in Label Free MS-based Quantitative proteomics



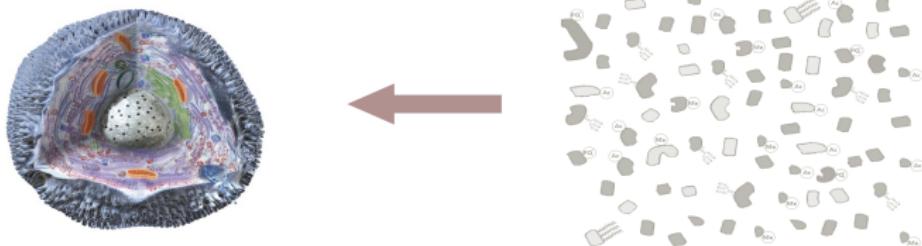
Challenges in Label Free MS-based Quantitative proteomics

MS-based proteomics returns **peptides**: pieces of proteins

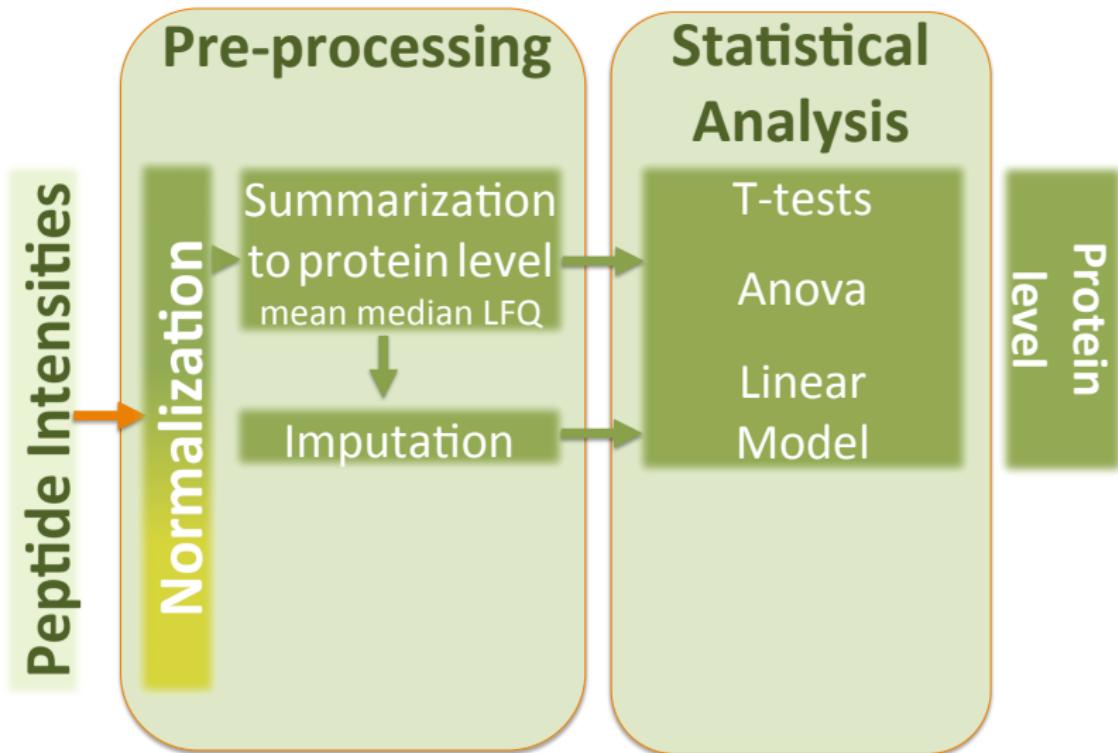


Challenges in Label Free MS-based Quantitative proteomics

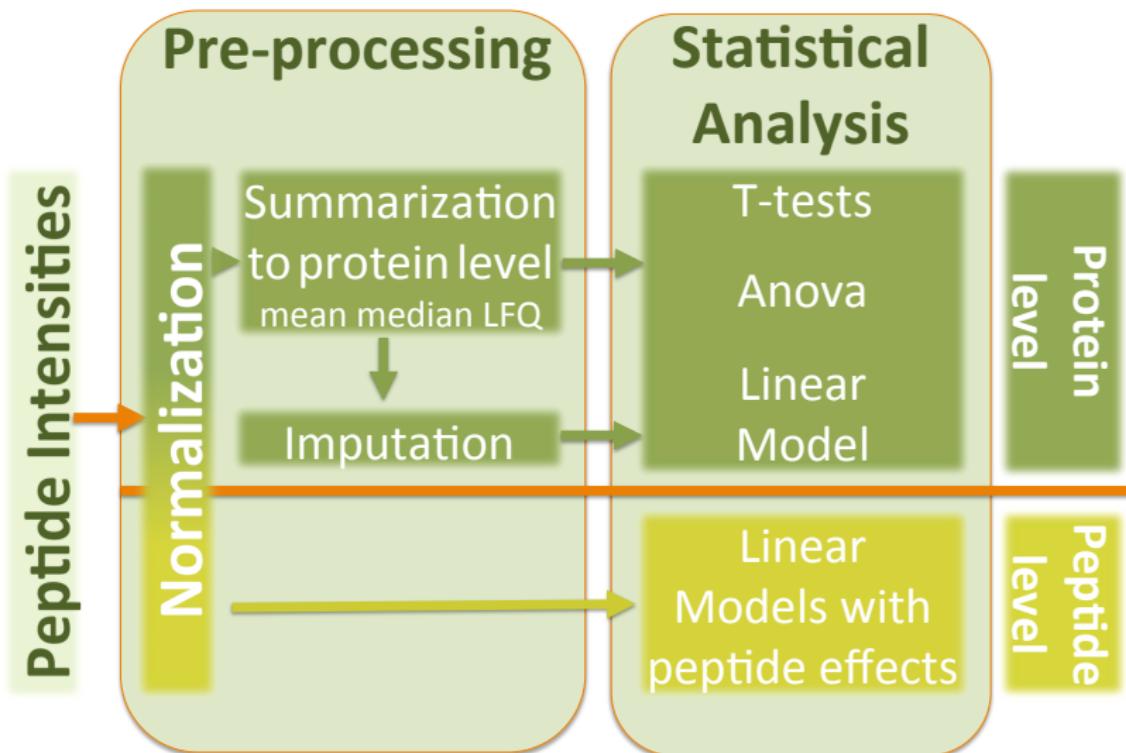
We need information on protein level!



Label-free Quantitative Proteomics Data Analysis Pipelines



Label-free Quantitative Proteomics Data Analysis Pipelines



CPTAC Spike-in Study

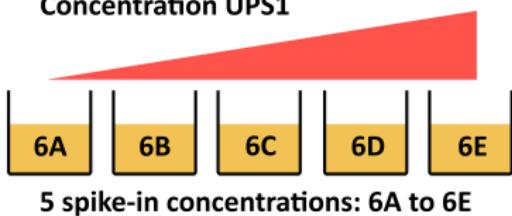
Digested
UPS1 protein mix



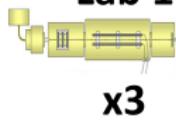
Digested
yeast proteins



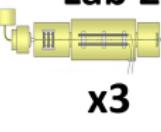
Concentration UPS1



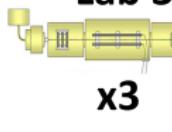
Lab 1



Lab 2



Lab 3



- Same trypsin-digested yeast proteome background in each sample
 - Trypsin-digested Sigma UPS1 standard: 48 different human proteins spiked in at 5 different concentrations (treatment A-E)
 - Samples repeatedly run on different instruments in different labs
 - After MaxQuant search with match between runs option
 - 41% of all proteins are quantified in all samples
 - 6.6% of all peptides are quantified in all samples
- vast amount of missingness

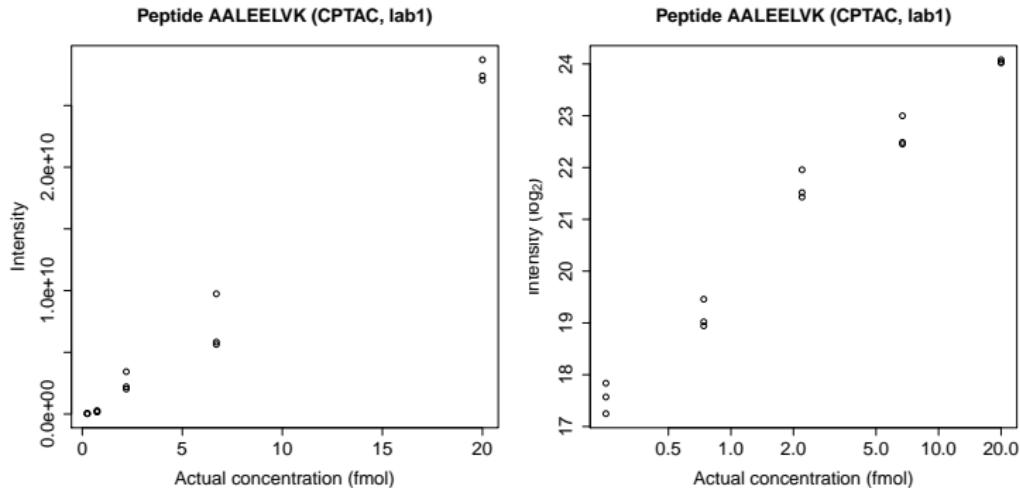
Preprocessing

- Typical preprocessing steps
 - 1 Filtering
 - 2 Log-transformation
 - 3 Normalization
 - 4 (Summarization)
- Many methods exist

Filtering

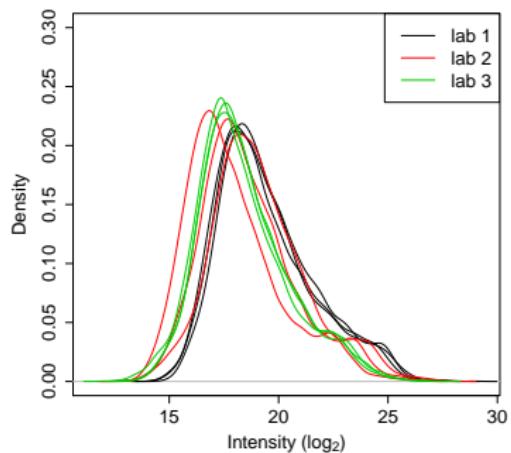
- Reverse sequences
- Only identified by modification site (only modified peptides detected)
- Razor peptides: non-unique peptides assigned to the protein group with the most other peptides
- Contaminants
- Peptides few identifications
- Proteins that are only identified with one or a few peptides
- Filtering does not induce bias if the criterion is independent from the downstream data analysis!

Log-transformation

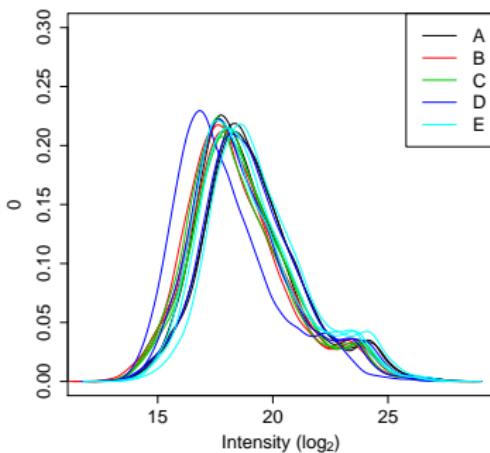


Variability more equal upon log transformation: often multiplicative error structure of intensity-based read-outs

Raw peptide intensity (CPTAC D)



Raw peptide intensity (CPTAC lab2)



Even in very clean synthetic dataset (same background, only 48 UPS proteins can be different) the marginal peptide intensity distribution across samples can be quite distinct

- Considerable effects between and within labs for replicate samples
- Considerable effects between samples with different spike-in concentration
- Normalization is needed



Mean or median?

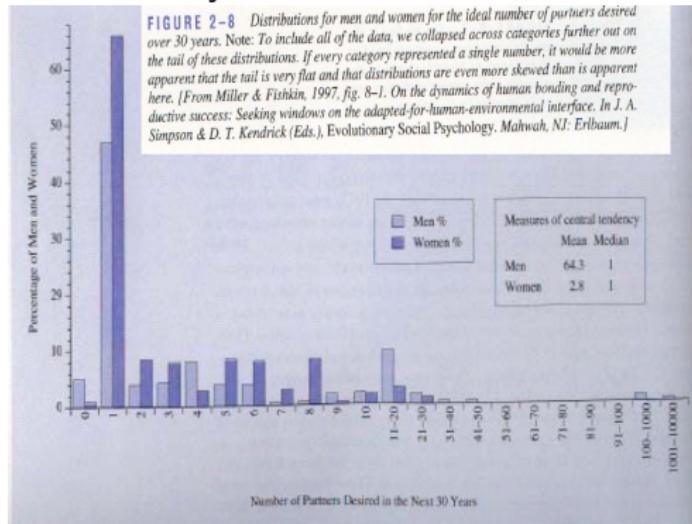
- Over a period of 30 years males desire to have on average 64.3 partners and females 2.8. (Miller and Fishkin, 1997)

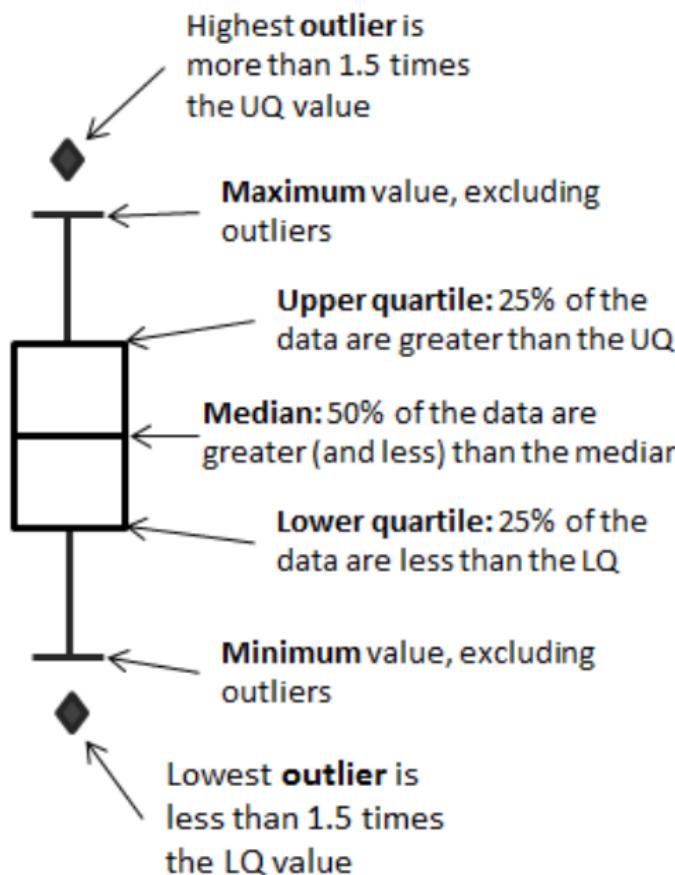
Mean or median?

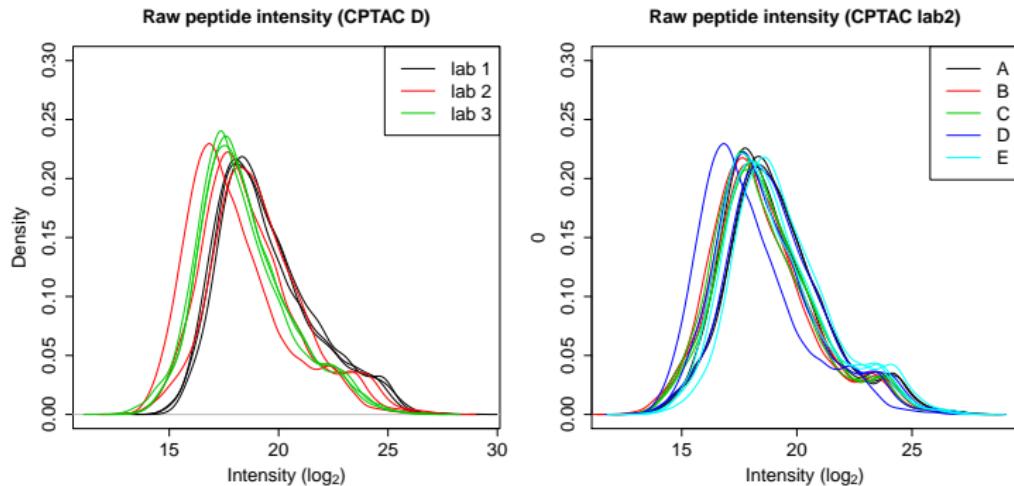
- Over a period of 30 years males desire to have on average 64.3 partners and females 2.8. (Miller and Fishkin, 1997)
- Over a period of 30 years males, is the median of the number of desired partners is 1 for both males and females. (Miller and Fishkin, 1997)

Mean or median?

Mean is very sensitive to outliers!





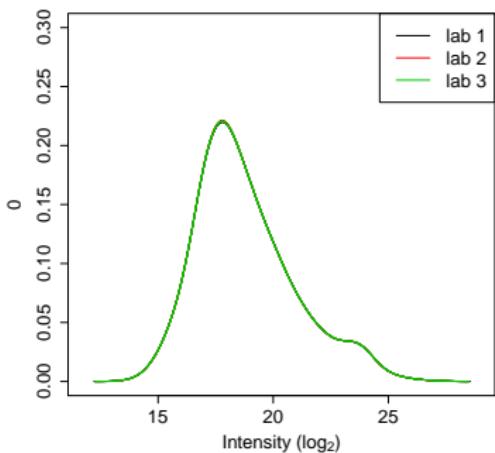


Even in very clean synthetic dataset (same background, only 48 UPS proteins can be different) the marginal peptide intensity distribution across samples can be quite distinct

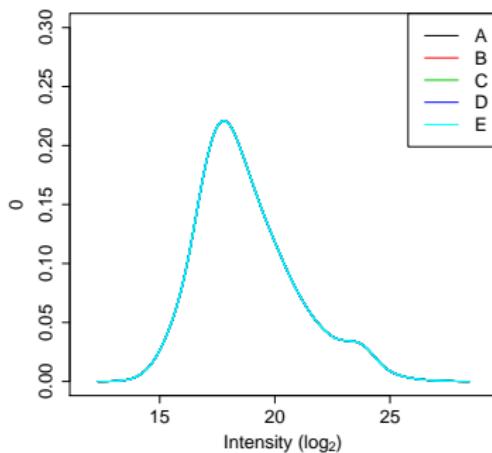
- Considerable effects between and within labs for replicate samples
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- Normalization is needed



QQ-normalized peptide intensity (CPTAC D)



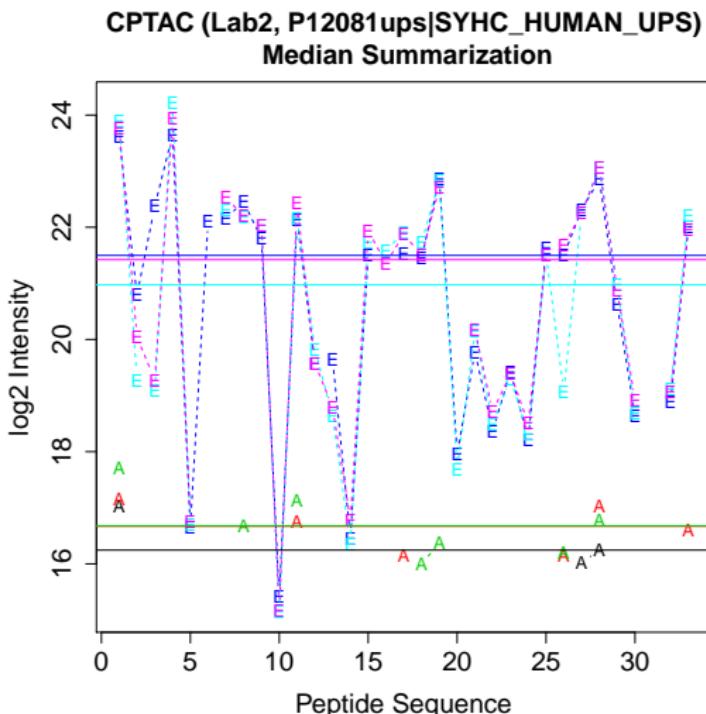
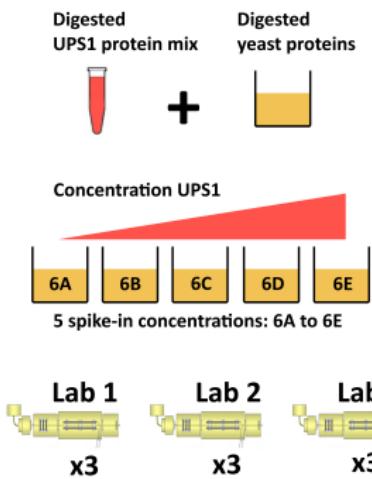
QQ-normalized peptide intensity (CPTAC lab2)



Even in very clean synthetic dataset (same background, only 48 UPS proteins can be different) the marginal peptide intensity distribution across samples can be quite distinct

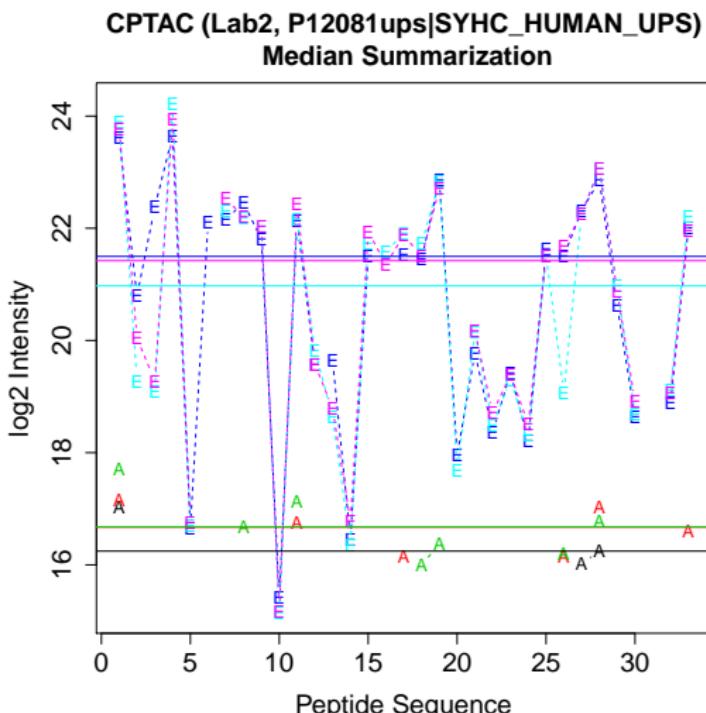
- Considerable effects between and within labs for replicate samples
 - Considerable effects between samples with different spike-in concentration
- Normalization is needed, e.g. **quantile normalization**

Summarization



Summarization

- Strong peptide effect
- Unbalanced peptide identification
- Summarization bias
- Different precision of protein level summaries



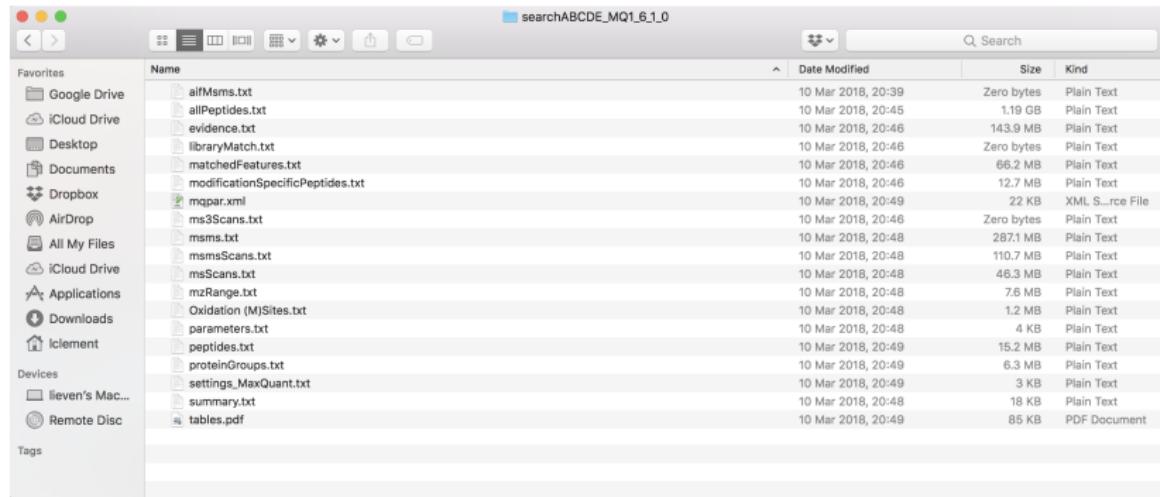
Impact of summarization?

Subsample of cptac study

- Lab 3
 - Spike in concentration A vs B
 - Two group comparison
-
- ① Median summarization
 - ② MaxLFQ (MaxQuant)
 - ③ Robust summarization:

$$y_{sp} = \beta_p^{\text{pep}} + \beta_s^{\text{sample}} + \epsilon_{sp}$$

MaxQuant output



A screenshot of a Mac OS X Finder window titled "searchABCDE_MQ1_6.1_0". The window displays a list of files and folders from a search result. The left sidebar shows "Favorites" with links to Google Drive, iCloud Drive, Desktop, Documents, Dropbox, AirDrop, All My Files, iCloud Drive, Applications, Downloads, and Clement. The main pane lists files under "Name" and "Date Modified" columns.

Name	Date Modified	Size	Kind
aifMsms.txt	10 Mar 2018, 20:39	Zero bytes	Plain Text
allPeptides.txt	10 Mar 2018, 20:45	1.19 GB	Plain Text
evidence.txt	10 Mar 2018, 20:46	143.9 MB	Plain Text
libraryMatch.txt	10 Mar 2018, 20:46	Zero bytes	Plain Text
matchedFeatures.txt	10 Mar 2018, 20:46	66.2 MB	Plain Text
modificationSpecificPeptides.txt	10 Mar 2018, 20:46	12.7 MB	Plain Text
mqpar.xml	10 Mar 2018, 20:49	22 KB	XML S...rc File
ms3Scans.txt	10 Mar 2018, 20:46	Zero bytes	Plain Text
msms.txt	10 Mar 2018, 20:48	287.1 MB	Plain Text
msmsScans.txt	10 Mar 2018, 20:48	110.7 MB	Plain Text
msScans.txt	10 Mar 2018, 20:48	46.3 MB	Plain Text
mzRange.txt	10 Mar 2018, 20:48	7.6 MB	Plain Text
Oxidation (M)Sites.txt	10 Mar 2018, 20:48	1.2 MB	Plain Text
parameters.txt	10 Mar 2018, 20:48	4 KB	Plain Text
peptides.txt	10 Mar 2018, 20:49	15.2 MB	Plain Text
proteinGroups.txt	10 Mar 2018, 20:49	6.3 MB	Plain Text
settings_MaxQuant.txt	10 Mar 2018, 20:49	3 KB	Plain Text
summary.txt	10 Mar 2018, 20:48	18 KB	Plain Text
tables.pdf	10 Mar 2018, 20:49	85 KB	PDF Document

MaxLFQ summarization

a

```
>P63208
MPSIKLQSSDGEIFEVDVIEIAKQSVTIKTMLEDLGMDDEGDD
DPVPLPNVNNAILKKVIQWCTHKDDPPPFEDDENKEKRTDD
IPVWDQEFLKVDQGTLFEELILAANYLDIKGLLDVTCKTVANM
IKGKTPEEIRKTFNIKNDFTEEEEAQVRKENQWCEEK
```

b

Peptide species	Sequence	Charge	Mod.
P ₁	LQSSDGEIFEVDVIEIAK	2	–
P ₂	LQSSDGEIFEVDVIEIAK	3	–
P ₃	RTDDIPVWDQEFLK	2	–
P ₄	TVANMIK	2	–
P ₅	TVANMIK	2	Oxid.
P ₆	TPEEIRK	3	–
P ₇	NDFTEEEEAQVR	2	–

c

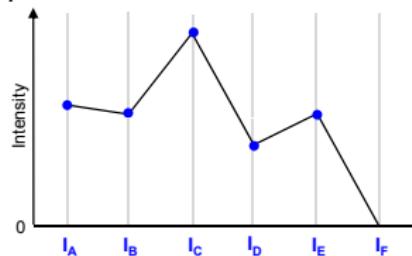
Sample	P ₁	P ₂	P ₃	P ₄	P ₅	P ₆	P ₇
A	+						+
B		+	+				+
C	+	+	+	+		+	+
D	+	+		+		+	+
E		+		+			+
F	+				+		

d

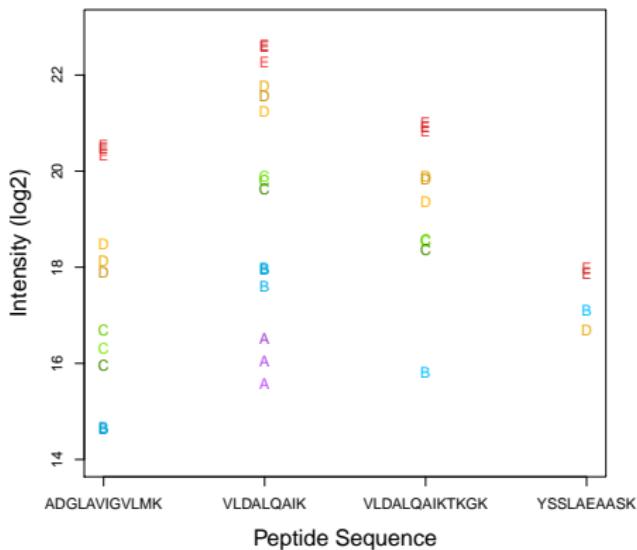
A	r_{BA}					
B	r_{CA}		r_{CB}			
C	r_{DA}	r_{DB}	r_{DC}			
D	r_{EA}	r_{EB}	r_{EC}	r_{ED}		
E	r_{FA}	r_{FB}	r_{FC}	r_{FD}	r_{FE}	
A	r_{BA}	r_{CA}	r_{CB}	r_{DA}	r_{EA}	r_{FA}
B		r_{CA}	r_{CB}	r_{DB}	r_{EB}	r_{FB}
C			r_{CB}	r_{DC}	r_{EC}	r_{FD}
D				r_{DC}	r_{ED}	r_{FE}
E					r_{ED}	r_{FE}
F						r_{FE}

e

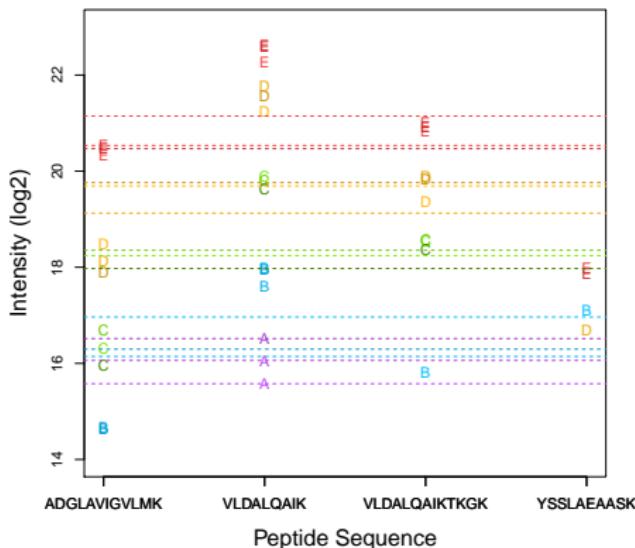
$$\begin{array}{lll} r_{BA} = I_B / I_A & r_{CA} = I_C / I_A & r_{CB} = I_C / I_B \\ r_{DA} = I_D / I_A & r_{DB} = I_D / I_B & r_{DC} = I_D / I_C \\ r_{EC} = I_E / I_C & r_{ED} = I_E / I_D & I_F = 0 \end{array}$$

f

Summarisation with peptide based model



Summarisation with peptide based model



Protein by protein analysis of peptide data with linear model

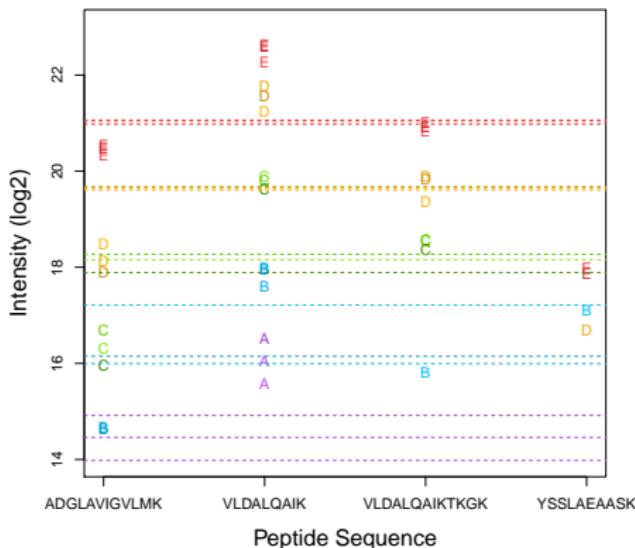
peptide level

$$y_{sp} = \epsilon_{sp}$$

protein level

$$\beta_s^{\text{sample}}$$

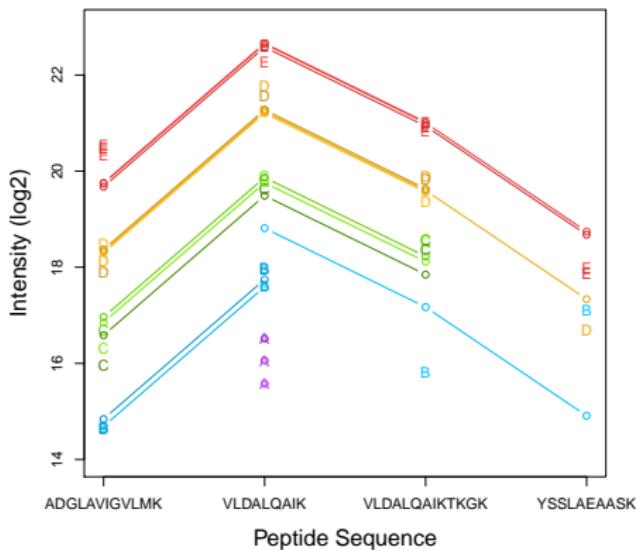
Summarisation with peptide based model



Protein by protein analysis of peptide data with linear model

$$\text{peptide level} \qquad \qquad \text{protein level}$$
$$y_{sp} = \beta_p^{\text{pep}} + \epsilon_{sp} \quad + \quad \beta_s^{\text{sample}}$$

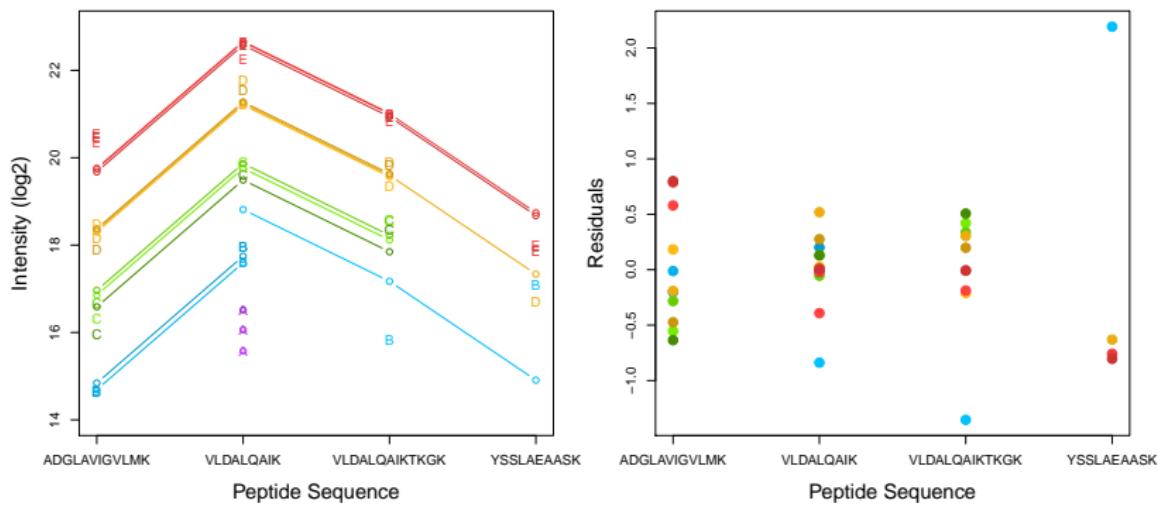
Summarisation with peptide based model



Protein by protein analysis of peptide data with linear model

$$\text{peptide level} \quad \text{protein level}$$
$$y_{sp} = \beta_p^{\text{pep}} + \epsilon_{sp} \quad + \quad \beta_s^{\text{sample}}$$

Summarisation with peptide based model

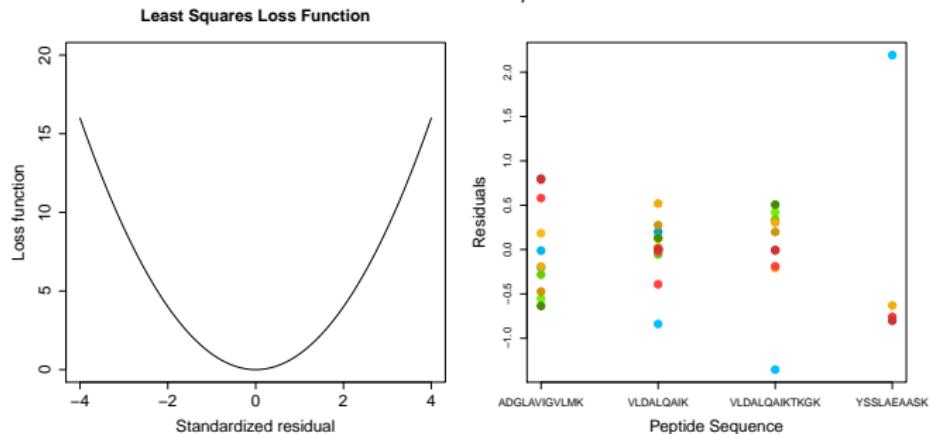


Protein by protein analysis of peptide data with linear model

$$\text{Estimation} \rightarrow \operatorname{argmin}_{\beta_{1\dots P}^{\text{pep}}, \beta_{1\dots n}^{\text{samp}}} \left[\sum_{i=1}^n \sum_p^P (y_{ip} - \beta_p^{\text{pep}} - \beta_i^{\text{samp}})^2 \right]$$

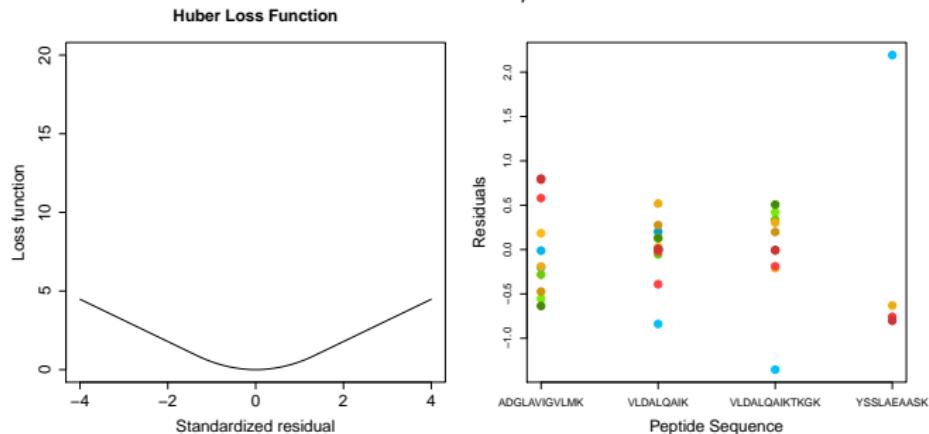
Robust estimation using observation weights

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



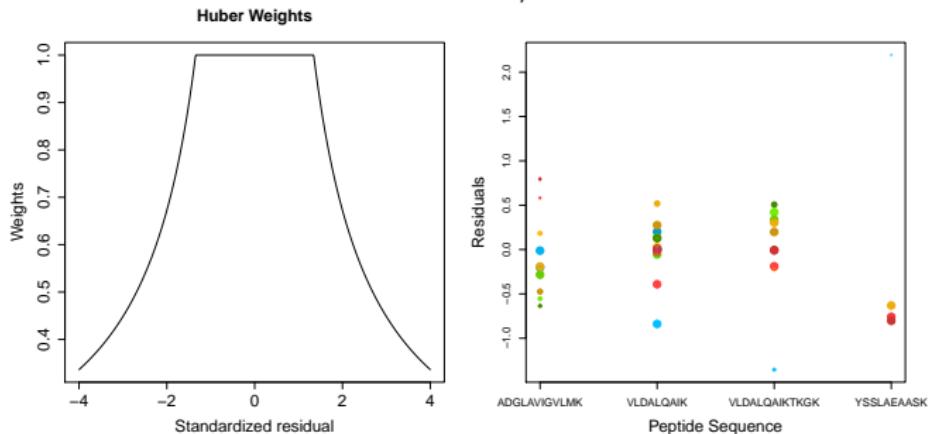
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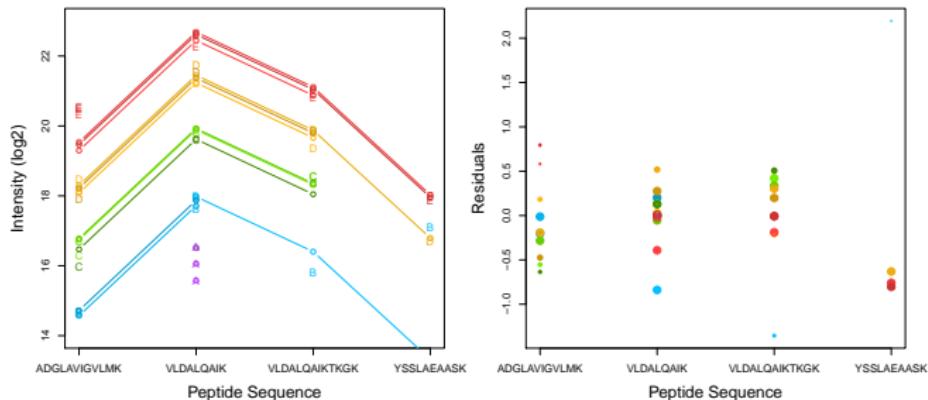


- Iteratively fit model with observation weights $w(\epsilon_{ip})$

$$\operatorname{argmin}_{\beta_1^{\text{pep}}, \dots, \beta_P^{\text{pep}}, \beta_1^{\text{samp}}, \dots, \beta_n^{\text{samp}}} \left[\sum_{i=1}^n \sum_{p=1}^P w(\epsilon_{ip}) (y_{ip} - \beta_p^{\text{pep}} - \beta_i^{\text{samp}})^2 \right]$$

Robust estimation using observation weights

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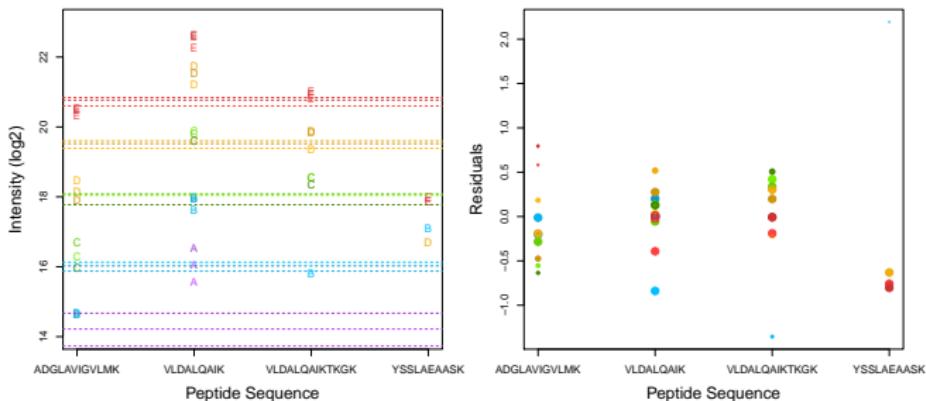


- Iteratively fit model with observation weights $w(\epsilon_{ip})$

$$\operatorname{argmin}_{\beta_1^{\text{pep}}, \dots, \beta_P^{\text{pep}}, \beta_1^{\text{samp}}, \dots, \beta_n^{\text{samp}}} \left[\sum_{i=1}^n \sum_{p=1}^P w(\epsilon_{ip}) (y_{ip} - \beta_p^{\text{pep}} - \beta_i^{\text{samp}})^2 \right]$$

Robust estimation using observation weights

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- Iteratively fit model with observation weights $w(\epsilon_{ip})$

$$\operatorname{argmin}_{\beta_1^{\text{pep}}, \dots, \beta_P^{\text{pep}}, \beta_1^{\text{samp}}, \dots, \beta_n^{\text{samp}}} \left[\sum_{i=1}^n \sum_{p=1}^P w(\epsilon_{ip}) (y_{ip} - \beta_p^{\text{pep}} - \beta_i^{\text{samp}})^2 \right]$$

