

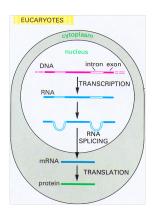


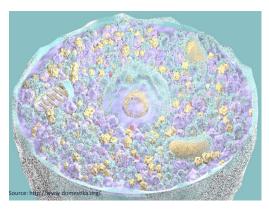
Statistical Methods for Quantitative MS-Based Proteomics:

1. Identification & False discovery rate

Lieven Clement

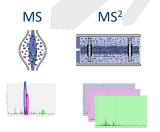
Proteomics Data Analysis Shortcourse





Challenges in Label Free MS-based Quantitative Proteomics

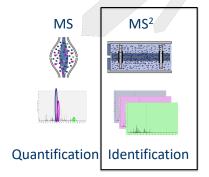




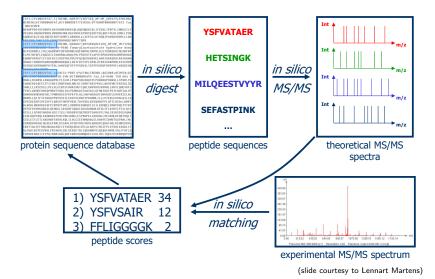
Quantification Identification

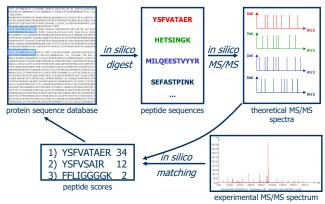
Challenges in Label Free MS-based Quantitative Proteomics

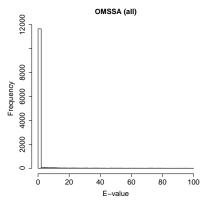




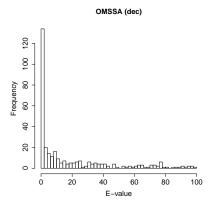
Identification



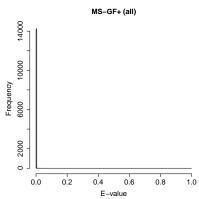


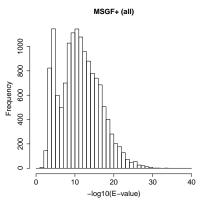












Probability that a random hit produces a higher score that the observed PSM score.

• A bad hit is the random hit with the best score so it is also bound to have a low E-value.



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- If we look at E-values for all PSMs they are only useful as a score.



- A bad hit is the random hit with the best score so it is also bound to have a low E-value.
- If we look at E-values for all PSMs they are only useful as a score.
- We should know the distribution of the maximum score of random hits when we want to do the statistics.



Table of Outcomes

	Called Bad	Called Correct	
Bad hit	TN	FP	m_0
Correct hit	FN	TP	m_1
Total	NR	R	т

- TN: number of true negatives
- FP: number of false positives
- FN: number of false negatives
- TP: number of true positives
- NR: number of non-rejections, R: number of rejections



Table of Outcomes

		Called Bad	Called Correct	
Unobservable	Bad hit	TN	FP	m_0
	Correct hit	FN	TP	m_1
Observable	Total	NR	R	m

 $FDP = \frac{FP}{FP+TP}$. But is unknown! (FDP: false discovery proportion)



Table of Outcomes

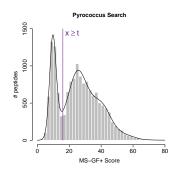
		Called Bad	Called Correct	
Unobservable	Bad hit	TN	FP	m_0
	Correct hit	FN	TP	m_1
Observable	Total	NR	R	т

$$FDR = E \left[\frac{FP}{FP+TP} \right]$$
. (FDR: false discovery rate)

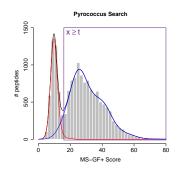




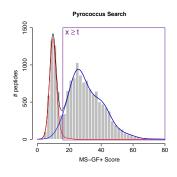






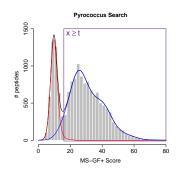


$$f(x) = \pi_0 f_0(x) + (1 - \pi_0) f_1(x)$$

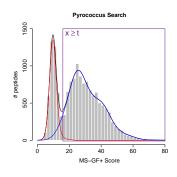


$$f(x) = \pi_0 f_0(x) + (1 - \pi_0) f_1(x)$$

$$FDR(t) = E\left[\frac{FP}{FP+TP}\right]$$

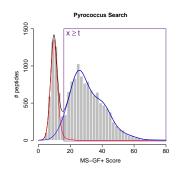


Score threshold t? $f(x) = \pi_0 f_0(x) + (1 - \pi_0) f_1(x)$ $\mathsf{FDR}(t) = E \left[\frac{\mathit{FP}}{\mathit{FP} + \mathit{TP}} \right]$ $\mathsf{FDR}(t) = \frac{\mathit{mP[FP]P[x \ge t|FP]}}{\mathit{mP[x \ge t]}}$



Score threshold t? $f(x) = \pi_0 f_0(x) + (1 - \pi_0) f_1(x)$ $FDR(t) = E \left[\frac{FP}{FP + TP} \right]$ $FDR(t) = \frac{mP[FP]P[x \ge t|FP]}{mP[x \ge t]}$

 $FDR(t) = \frac{\pi_0 P_0[x \ge t]}{P[x > t]}$



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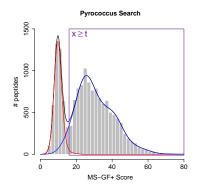
$$FDR(t) = \frac{mP[FP]P[x \ge t|FP]}{mP[x \ge t]}$$

$$FDR(t) = \frac{\pi_0 P_0[x \ge t]}{P[x > t]}$$

$$P_{\cdot}[x \ge t] = \int_{t}^{\infty} f_{\cdot}(x) dx$$



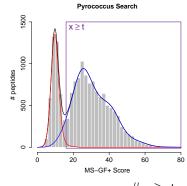
How to estimate FDR?



$$FDR(t) = E\left[\frac{FP}{FP+TP}\right]$$
$$= \frac{\pi_0 P_0[x \ge t]}{P[x \ge t]}$$

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How to estimate FDR?



$$\hat{P}[x \ge t] = \frac{\#x \ge t}{m} \qquad \Rightarrow \qquad$$

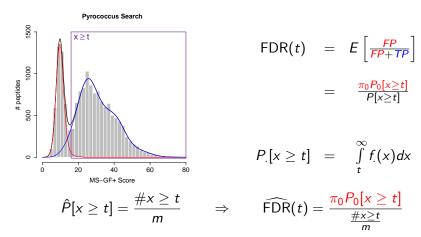
$$FDR(t) = E\left[\frac{FP}{FP+TP}\right]$$
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$$P[x \ge t] = \int_{t}^{\infty} f(x) dx$$

$$\widehat{\mathsf{FDR}}(t) = \frac{\pi_0 P_0[x \ge t]}{\frac{\#x \ge t}{m}}$$

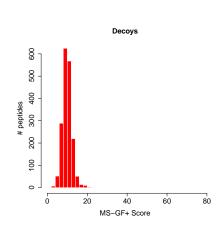


How to estimate FDR?

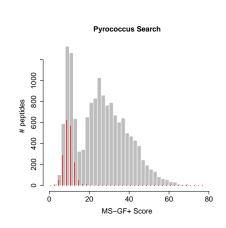


How to characterize $f_0(t)$ and π_0 in proteomics?

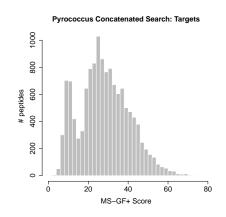




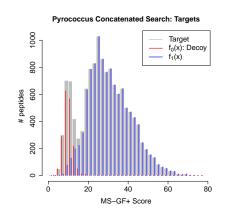
- Search against decoy database to generate representative bad hits
- Reversed databases are popular



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- Concatenated search



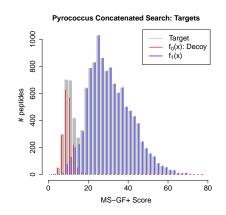
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$$\hat{\pi}_0 = rac{\# extit{decoys}}{\# extit{targets}}$$



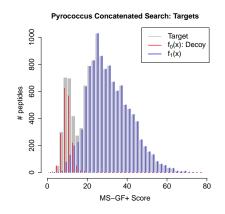


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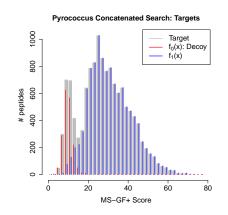
• Score cuttoff: $FDR(x) = E \left[\frac{FP}{FP+TP} \right]$





• Competitive Target - decoy:

$$\widehat{\mathsf{FDR}}(x) = \frac{\#\mathsf{decoys}|X \ge x}{\#\mathsf{targets}|X \ge x}$$



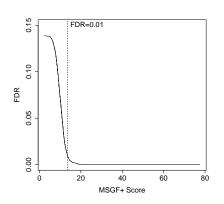
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$$\widehat{\text{FDR}}(x) = \frac{\#\text{decoys}|X \ge x}{\#\text{targets}|X \ge x}$$

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$$\widehat{\text{FDR}}(x) = \hat{\pi}_0 \frac{f_0(x) dx}{\int_t^{+\infty} f(x) dx}$$

$$\widehat{\text{FDR}}(x) = \hat{\pi}_0 \frac{\hat{P}_0[X \ge x]}{\hat{P}[X > x]}$$



• Competitive Target - decoy:

$$\widehat{FDR}(x) = \frac{\# decoys | X \ge x}{\# targets | X \ge x}$$

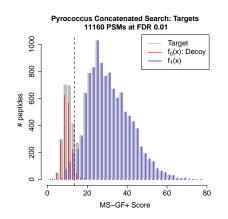
$$\widehat{FDR}(x) = \frac{\# decoys}{\# targets} \frac{\# decoys | X \ge x}{\# decoys}$$

$$\frac{\# decoys}{\# targets | X \ge x}$$

$$\frac{\# decoys}{\# decoys}$$

$$\frac{\# decoys}{\# decoy$$

 $\widehat{\mathsf{FDR}}(x) = \hat{\pi}_0 \frac{P_0[X \ge x]}{\hat{p}[X > x]}$



Competitive Target - decoy:

$$\widehat{\text{FDR}}(x) = \frac{\# decoys | X \ge x}{\# targets | X \ge x}$$

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$$\widehat{\text{FDR}}(x) = \hat{\pi}_0 \frac{\int_{t}^{t} f_0(x) dx}{\int_{t}^{t} f(x) dx}$$

$$\widehat{\text{FDR}}(x) = \hat{\pi}_0 \frac{\hat{P}_0[X \ge x]}{\hat{P}[X > x]}$$

Assess TDA assumptions

We have to evaluate that

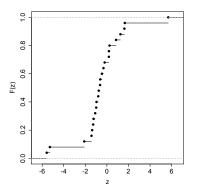
• The decoys are good simulations of the bad target hits: compare distributions $F_0(x)$ with F(x)

$$F_0(x) = \int_{-\infty}^t f_0(x) dx \quad \leftrightarrow \quad F(x) = \int_{-\infty}^t f(x) dx$$

- $\hat{\pi}_0 = \frac{\#decoys}{\#targets}$ is a good estimator for π_0 .
- We will use Probability-Probability-plots (PP-plot) for this purpose.

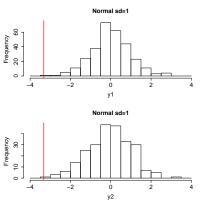


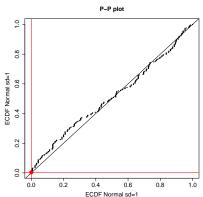
- To make PP-plots we need estimates for $F_0(x)$ and F(x).
- The empirical cumulative distribution (ECDF) is used for that purpose



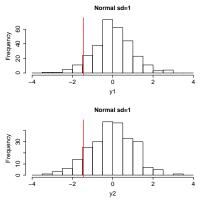
$$\hat{F}_0(x) = \frac{\#decoys|X \le x}{\#decoys}, \quad \hat{F}(x) = \frac{\#targets|X \le x}{\#targets}$$

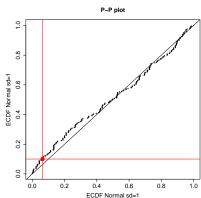


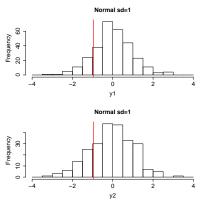


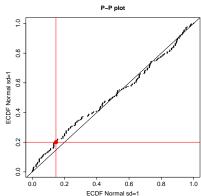


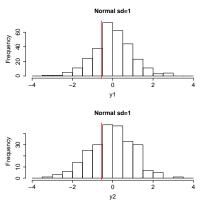


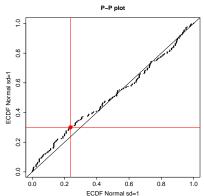


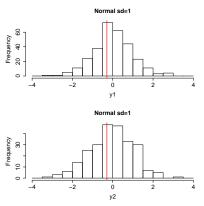


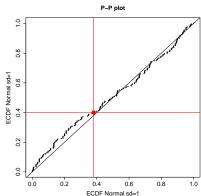


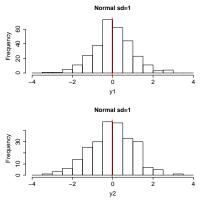


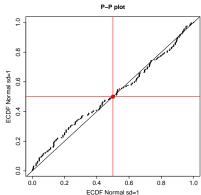




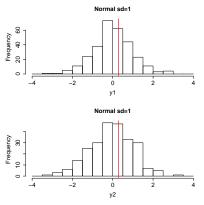


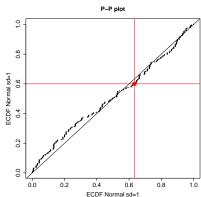


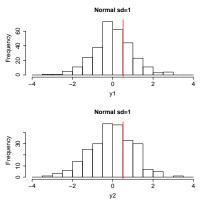


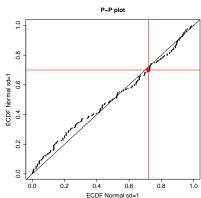


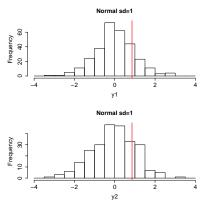


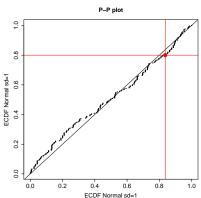


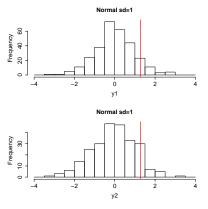


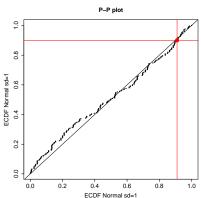


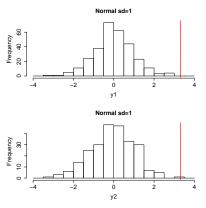


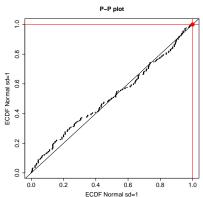


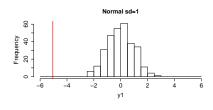


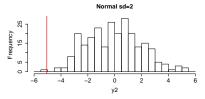


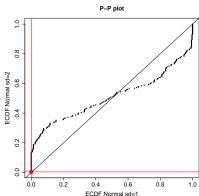




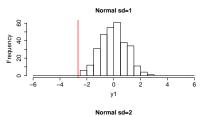


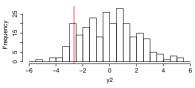


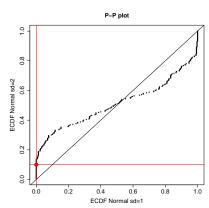




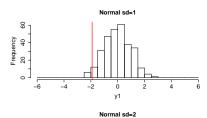


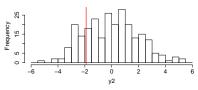


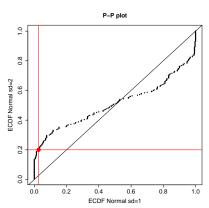




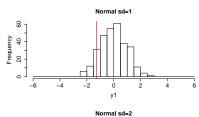


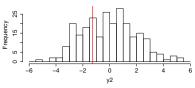


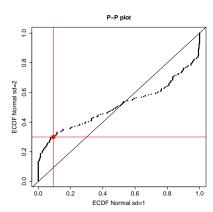




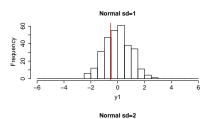


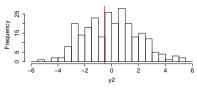


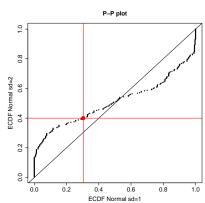




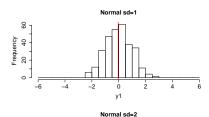


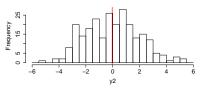


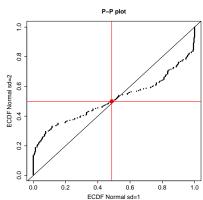




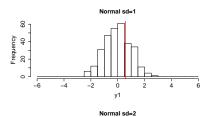


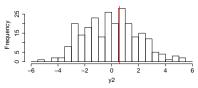


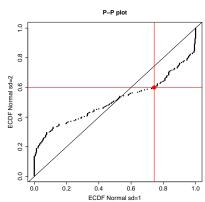




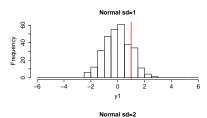


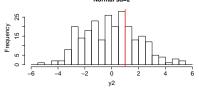


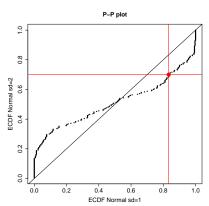




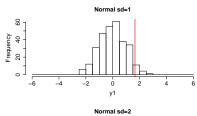


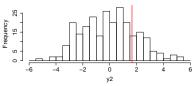


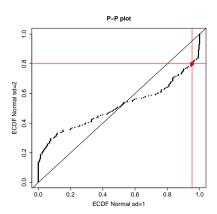




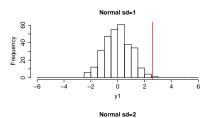


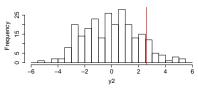


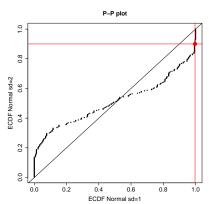




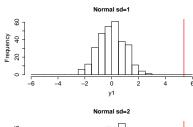


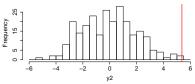


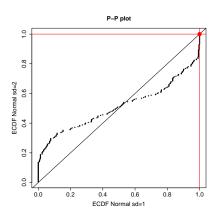




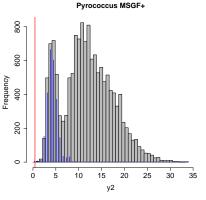


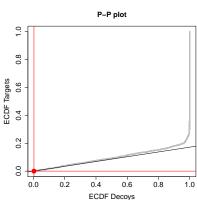




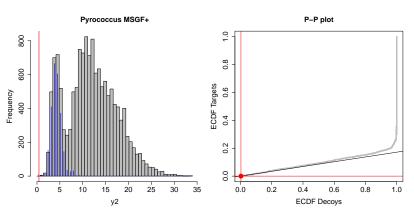












What about $\hat{\pi}_0$?



