



Statistical Methods for Quantitative MS-Based Proteomics:

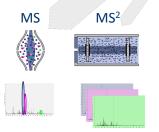
1. Identification & False discovery rate

Lieven Clement

Statistics and Genomics Seminar, UCBerkeley, California

Challenges in Label Free MS-based Quantitative Proteomics

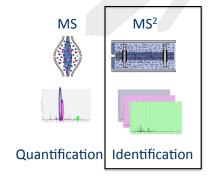




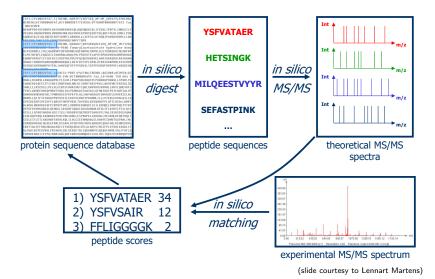
Quantification Identification

Challenges in Label Free MS-based Quantitative Proteomics





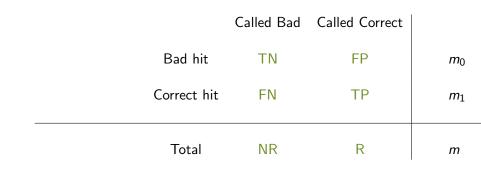
Identification



	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





Random Variables

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



		Called Bad	Called Correct	
	Bad hit	TN	FP	<i>m</i> ₀
Unobservable	Correct hit	FN	TP	m_1
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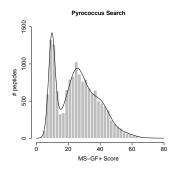
$$FDP = \frac{FP}{FP + TP}$$
. But is unknown! (FDP: false discovery proportion)



		Called Bad	Called Correct	
	Bad hit	TN	FP	m_0
Unobservable	Correct hit	FN	TP	m_1
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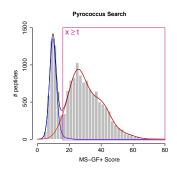
$$FDR = E \left[\frac{FP}{FP + TP} \right]$$
. (FDR: false discovery rate)





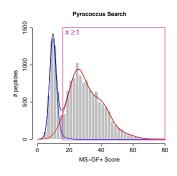






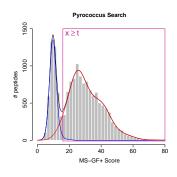
$$f(x) = \pi_0 f_0(x) + (1 - \pi_0) f_1(x)$$





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

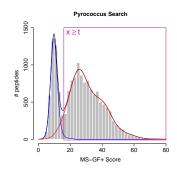


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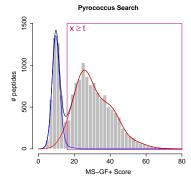
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$$P_{\cdot}[x \geq t] = \int_{t}^{\infty} f_{\cdot}(x)$$



How to estimate FDR?

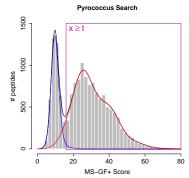


$$P_{\cdot}[x \geq t] = \int_{t}^{\infty} f_{\cdot}(x)$$

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



How to estimate FDR?



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

$$P_{\cdot}[x \geq t] \approx \frac{\#x \geq t}{m}$$

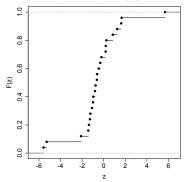
$$FDR(t) = E\left[\frac{FP}{FP + TP}\right] = \frac{m\pi_0 P[x \ge t|FP]}{mP[x \ge t]}$$

$$\widehat{FDR}(t) = \frac{m\pi_0 P[x \ge t|FP]}{\#x \ge t}$$



• $F(t) = \int\limits_{-\infty}^t f(x)$ using the Empirical cumulative distribution

function (ECDF):
$$\bar{F}(t)$$

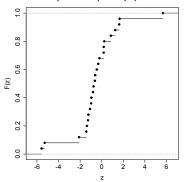


$$\rightarrow \widehat{FDR}(t) = \frac{m\pi_0 P[x \ge t|FP]}{\#x \ge t} = \frac{\pi_0 P[x \ge t|FP]}{\frac{\#x \ge t}{m}} = \frac{\pi_0 [1 - F(t)]}{1 - \bar{F}(t)}$$



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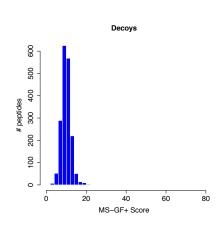
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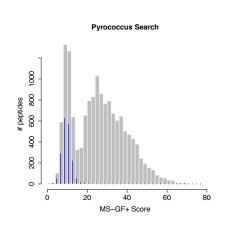
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• How to characterize $F_0(t)$ and π_0 in proteomics?

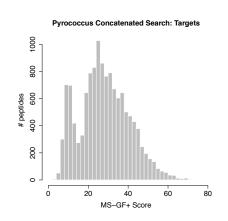




- Searching against decoy databases to generate representative bad hits
- Reversed databases are a popular choice



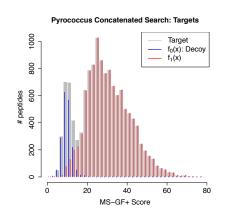
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- Assumption that bad hits have an equal probability to map on forward (target) and reverse database (decoy)

$$\hat{\pi}_0 = \frac{\# \textit{decoys}}{\# \textit{targets}}$$

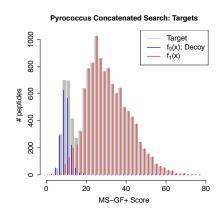




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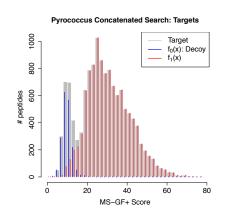


Score cuttoff?

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

Competitive Target - decoy:

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



Score cuttoff?

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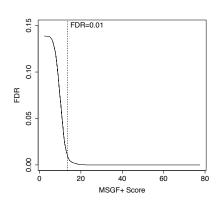
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$$\widehat{\mathsf{FDR}}(x) = \hat{\pi}_0 \frac{1 - \bar{F}_0(x)}{1 - \bar{F}(x)}$$





Score cuttoff?

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

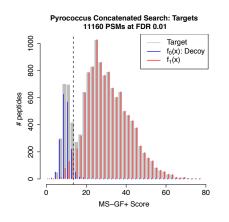
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$$\widehat{\mathsf{FDR}}(x) = \hat{\pi}_0 \frac{1 - \bar{F}_0(x)}{1 - \bar{F}(x)}$$





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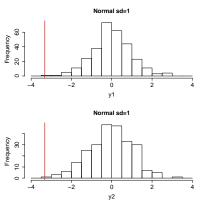


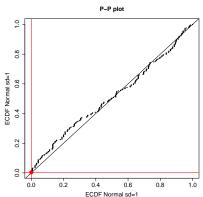
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We have to evaluate that

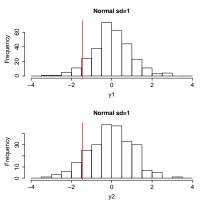
- The decoys are good simulations of the targets: compare $\bar{F}_0(x)$ with $\bar{F}(x)$
- $\hat{\pi}_0 = \frac{\#decoys}{\#targets}$ is a good estimator for π_0 .
- We will use Probability-Probability-plots for this purpose.
- They plot the ECDFs from two samples in function of each other.

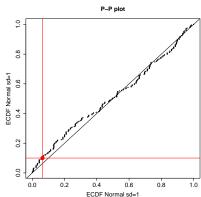


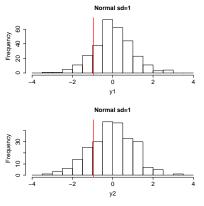


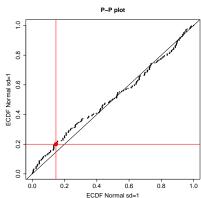


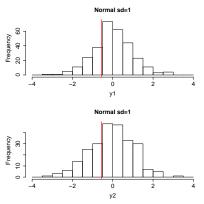


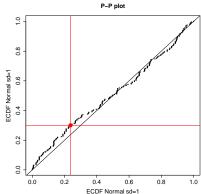


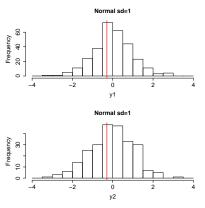


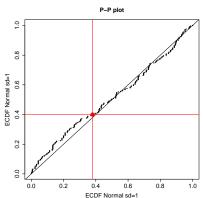


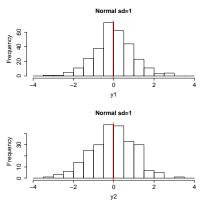


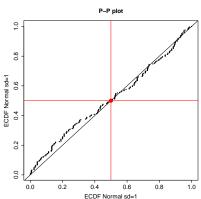




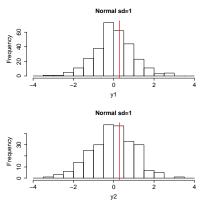


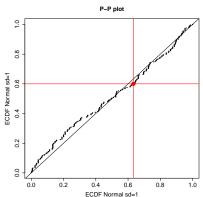


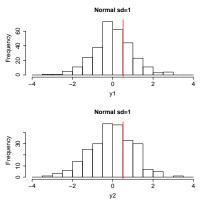


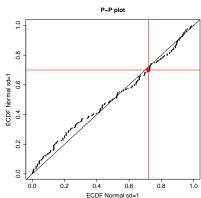


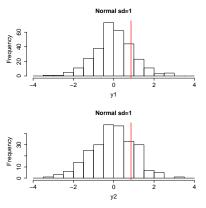


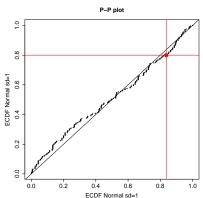


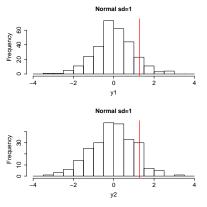


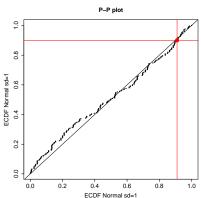


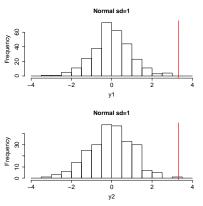


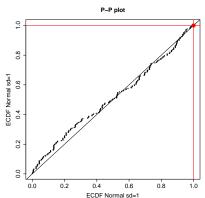




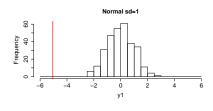


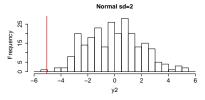


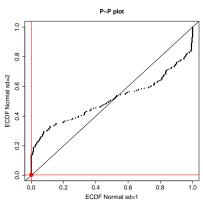




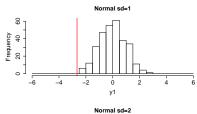


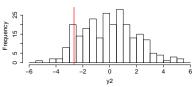


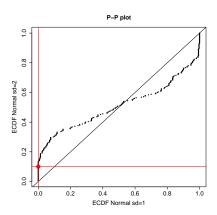




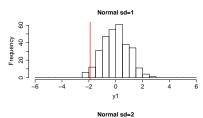


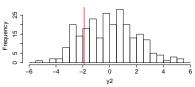


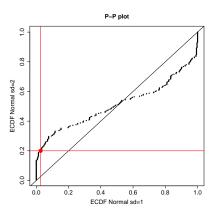




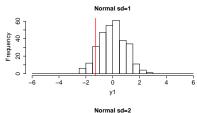


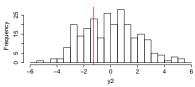


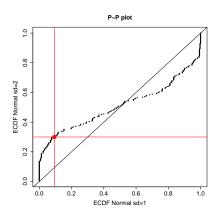




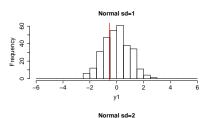


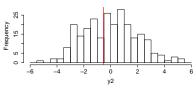


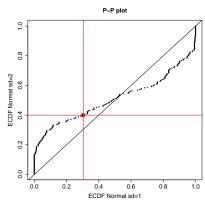




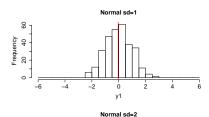


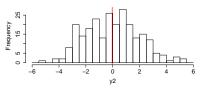


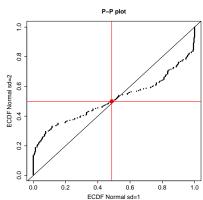




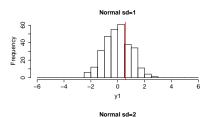


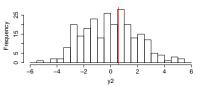


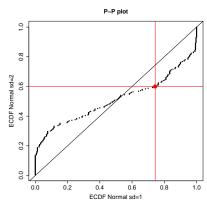




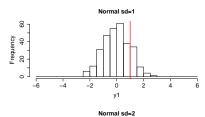


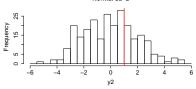


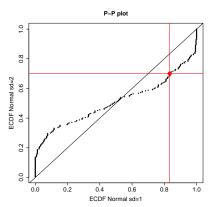




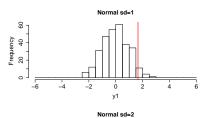


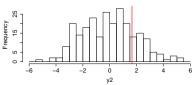


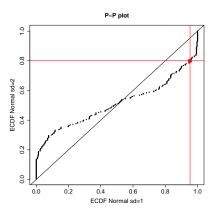




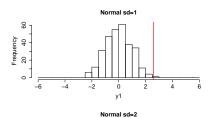


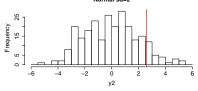


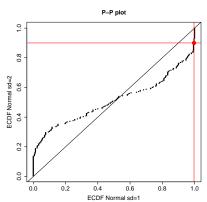




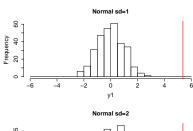


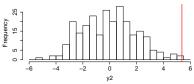


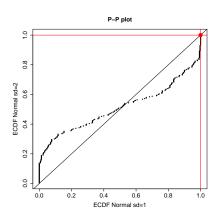




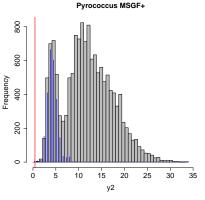


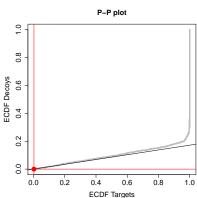


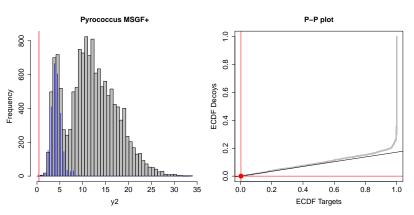












What about $\hat{\pi}_0$?



