



Statistical Methods for Quantitative MS-Based Proteomics:

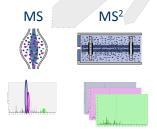
1. Identification

Lieven Clement

Statistics and Genomics Seminar, UCBerkeley, California

Challenges in Label Free MS-based Quatitative proteomics

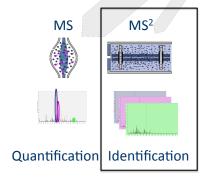




Quantification Identification

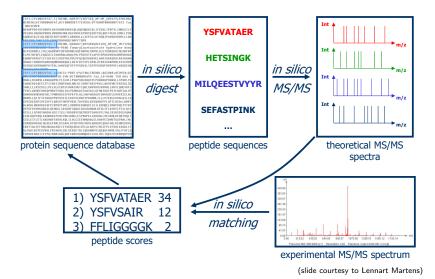
Challenges in Label Free MS-based Quatitative proteomics







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



| | Called Bad | Called Correct | |
|-------------|------------|----------------|-----------------------|
| Bad hit | TN | FP | <i>m</i> ₀ |
| Correct hit | FN | TP | m_1 |
| Total | NR | R | т |



Callad Dad Callad Camara

Random Variables

Constant

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



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

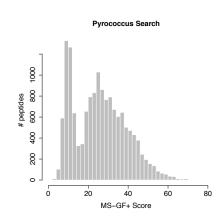


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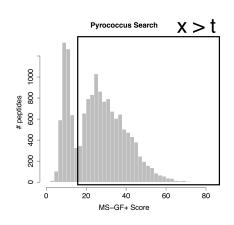
$$FDP = \frac{FP}{FP + TP}$$
. But is unkown! (FDP: false discovery proportion) $FDR = E\left[\frac{FP}{FP + TP}\right]$. (FDR: false discovery rate)



Search engines return score that discriminates good from bad matches

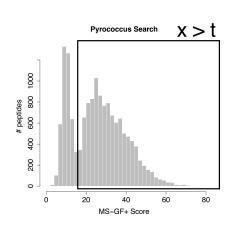


Search engines return score that discriminates good from bad matches



Score threshold *t*?

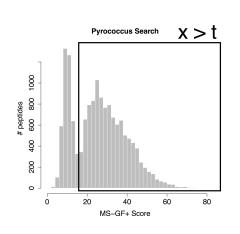
Search engines return score that discriminates good from bad matches



Score threshold
$$t$$
?
 $f(x) = \pi_0 f_0(x) + (1 - \pi_0) f_1(x)$

$$FDR(t) = Pr[FP|x \ge t]$$

Search engines return score that discriminates good from bad matches



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

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$$\int\limits_{-\infty}^{x=t}f(x)=\pi_0\int\limits_{-\infty}^{x=t}f_0(x)+(1-\pi_0)\int\limits_{-\infty}^{x=t}f_1(x)$$

$$F(x) = \pi_0 F_0(t) + (1 - \pi_0) F_1(t)$$

$$\mathsf{FDR}(t) = rac{\pi_0[1-F_0(t)]}{1-F(t)}$$

lieven.clement@ugent.be



Link to Benjamini Hochberg FDR

Bayesian FDR

$$FDR(t) = \frac{\pi_0 [1 - F_0(t)]}{1 - F(t)}$$

BH for one sided test

$$FDR(t) = \frac{mp(t)}{\#t_i \ge t}$$

with

- m the number of tests
- p(t) the p-value corresponding to a test statistic with value t



Link to Benjamini Hochberg FDR

Bayesian FDR

$$FDR(t) = \frac{\pi_0 [1 - F_0(t)]}{1 - F(t)}$$

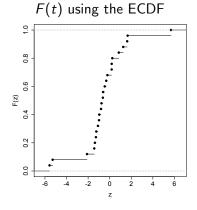
BH for one sided test

$$FDR(t) = \frac{mp(t)}{\#t_i \ge t} = \frac{1 - F_0(t)}{\frac{\#t_i \ge t}{m}} = \frac{1 - F_0(t)}{1 - F(t)}$$

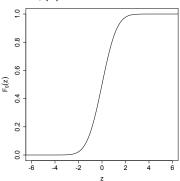
- Use theoretical distribution for $p(t) = 1 F_0(t)$
- Conservative estimate $\pi_0 = 1$
- ECDF: $1 F(t) = \frac{\#t_i \ge t}{m}$



• Benjamini Hochberg 1995:

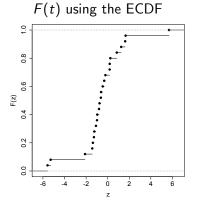


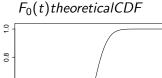
 $F_0(t)$ theoreticalCDF

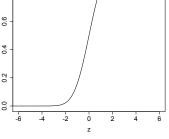




• Benjamini Hochberg 1995:

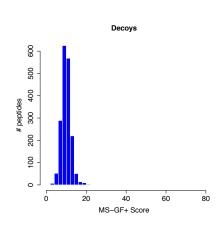




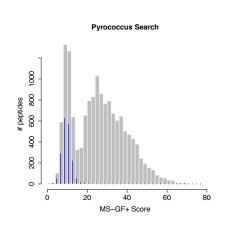


• How to define $F_0(t)$ in proteomics?

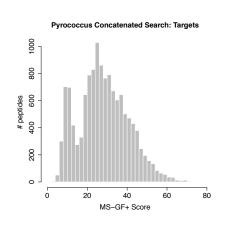




- Searching against decoy databases to generate representative bad hits
- Reversed databases are a popular choice



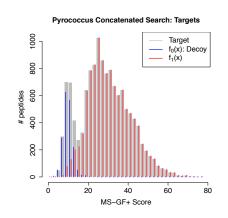
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- Assumption that bad hits have an equal probability to map on forward (target) and reverse database (decoy)

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

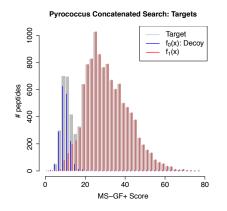




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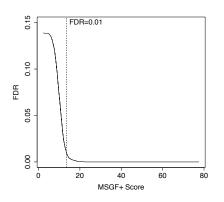
- Score cuttoff?
- Competitive Target decoy:

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

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

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





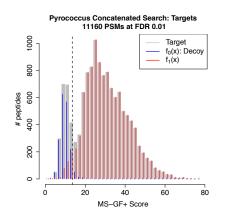
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$$\widehat{\mathsf{FDR}}(x) = \frac{\#decoys}{\#targets} \frac{\frac{\#decoys}{\#decoys}}{\frac{\#targets}{\#targets}} \frac{X \ge x}{\#targets}$$

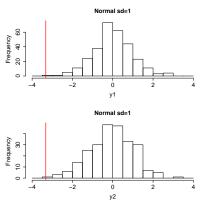
$$\widehat{\mathsf{FDR}}(x) = \hat{\pi}_0 \frac{1 - \bar{F}_0(x)}{1 - \bar{F}(x)}$$

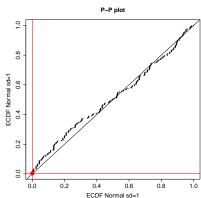


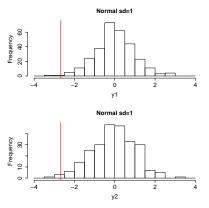
We have to evaluate that

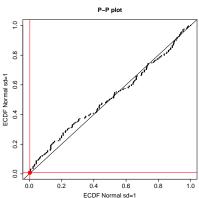
- The decoys are good simulations of the targets: compare $\bar{F}_0(x)$ with $\bar{F}(x)$
- $\hat{\pi}_0 = \frac{\#decoys}{\#targets}$ are a good estimator for π_0 .
- We will use Probability-Probability-plots for this purpose.
- They plot the ECDFs from two samples in function of each other.

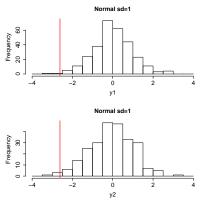


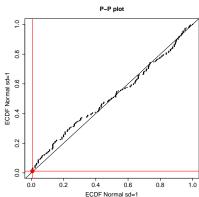


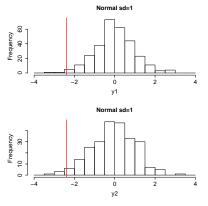


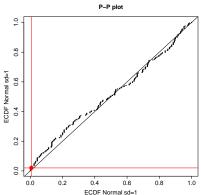


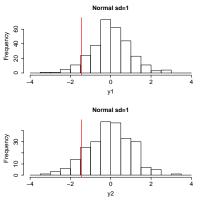


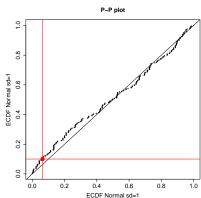


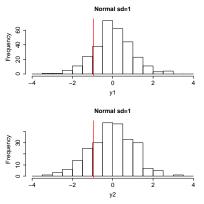


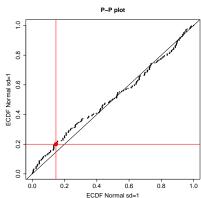




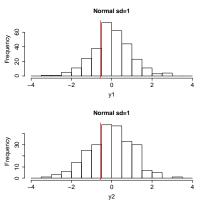


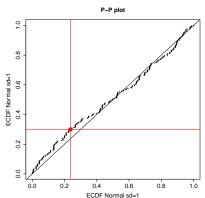




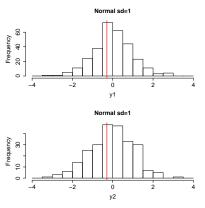


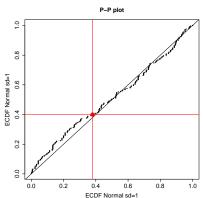


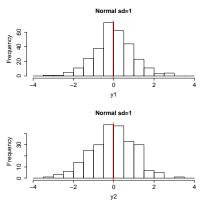


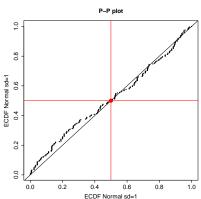




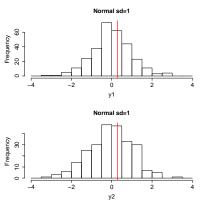


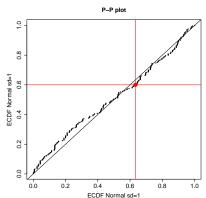


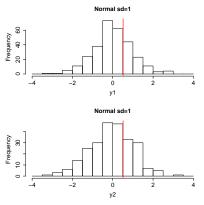


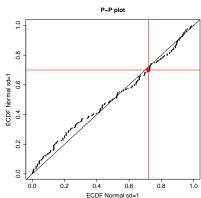


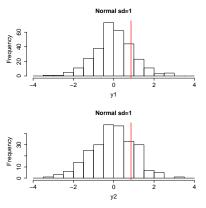


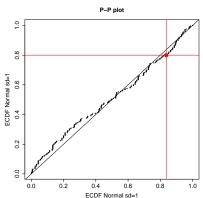


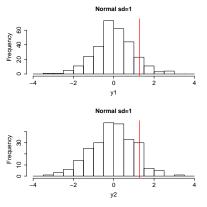


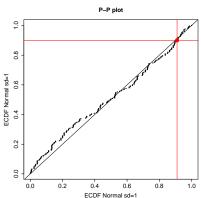


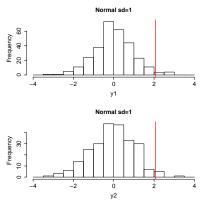


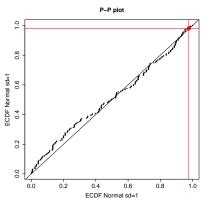


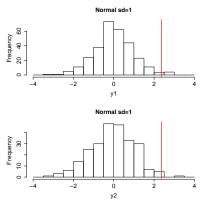


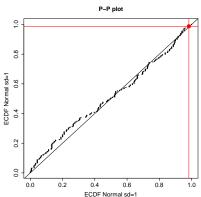




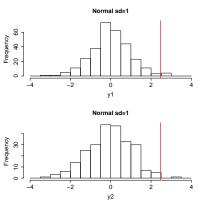


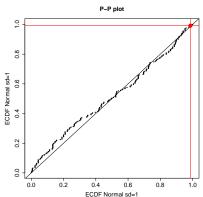




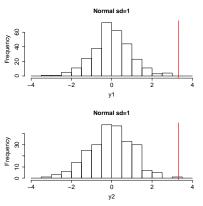


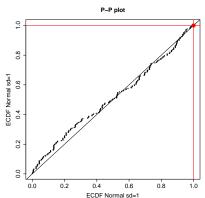




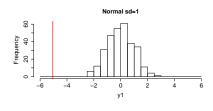


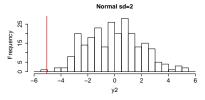


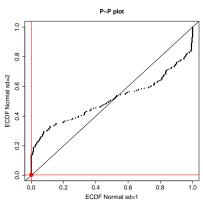




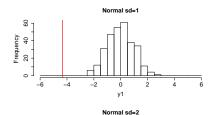


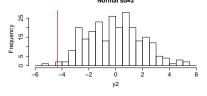


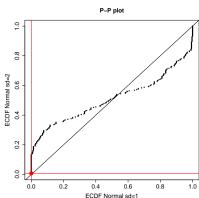




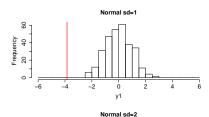


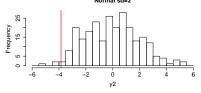


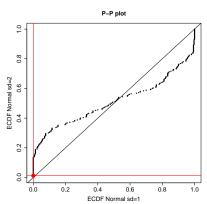




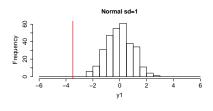


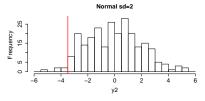


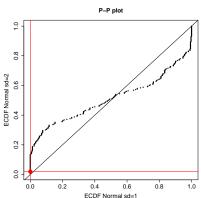




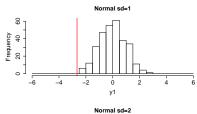


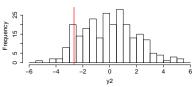


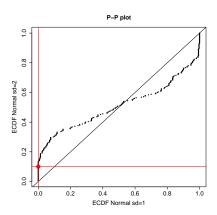




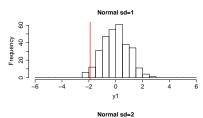


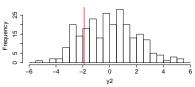


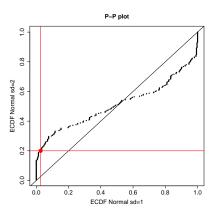




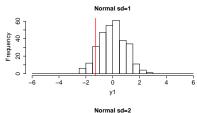


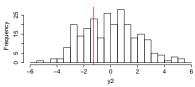


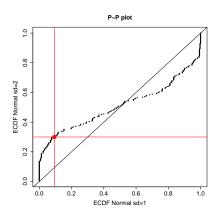




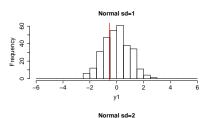


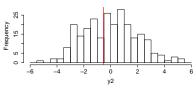


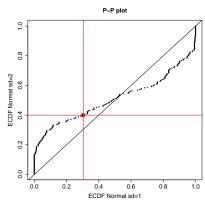




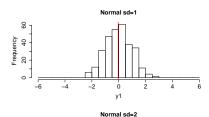


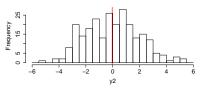


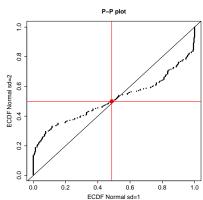




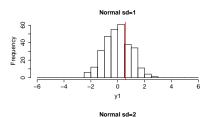


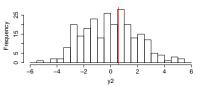


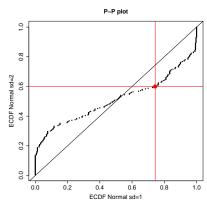




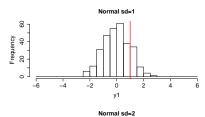


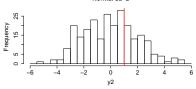


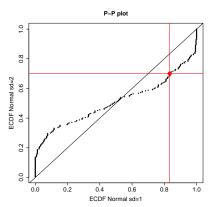




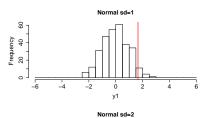


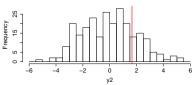


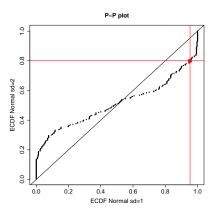




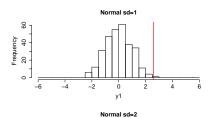


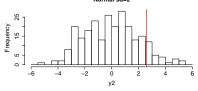


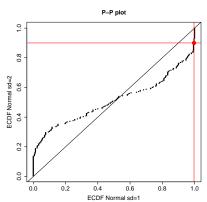




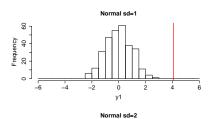


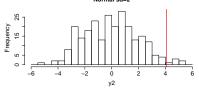


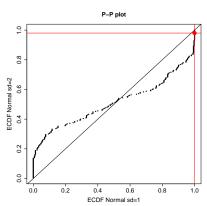




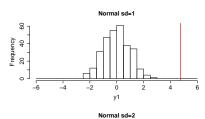


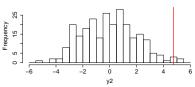


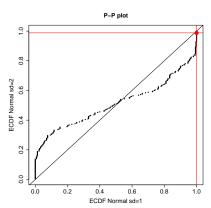




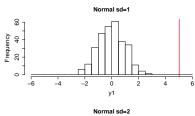


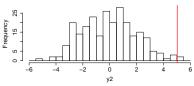


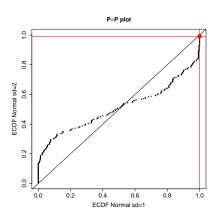




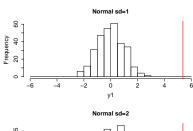


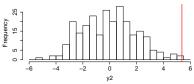


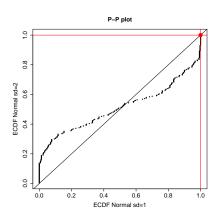




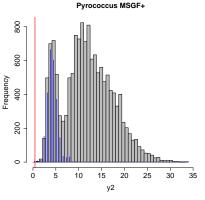


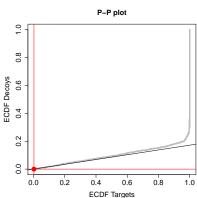












What about π_0 ?



