

# Post-hoc power estimation for topological inference in fMRI

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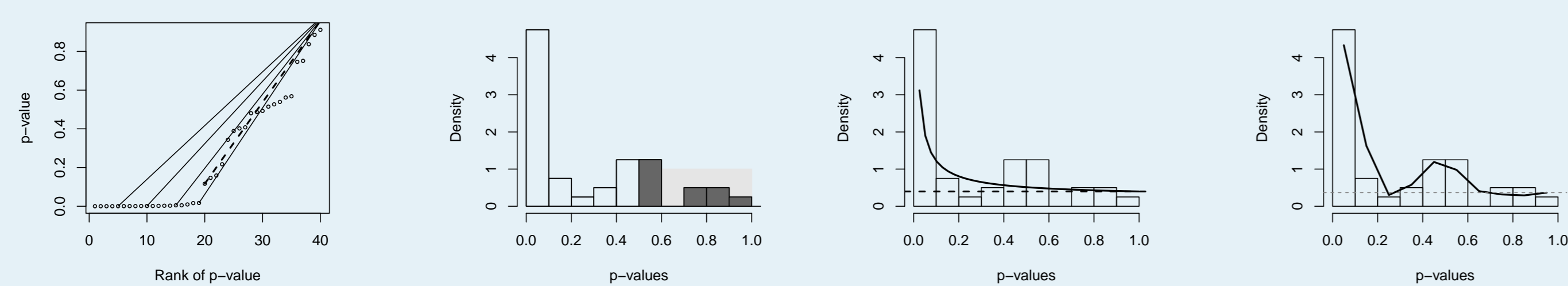
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## Introduction

- Topological inference on clusters or peaks is increasingly being used in neuroimaging.
- Uncorrected topological  $p$ -values can be submitted to any multiple testing procedure to control an excess of type I errors.
- More stringent threshold  $\Rightarrow$  drop in power.
- To meet an acceptable level of power: compute power (and sample size) *a priori*; however, these techniques depend on many unknown parameters.
- Zehetmayer et al. (2010) study post-hoc power in the context of statistical genetics.
- Our goal: estimate the post-hoc power of an fMRI study post-hoc using estimates for the proportion of non-activated features  $\pi_0$ .**
- $\pi_0$  can be estimated using the distribution uncorrected  $p$ -values.
- Topological  $p$ -values can be found using RFT and permutations, both for clusters and for peaks.
- We use permutation  $p$ -values for clusters, and RFT  $p$ -values for peaks.

## Estimating $\pi_0$ , the proportion of null tests



**Benjamini, 2000 - BH:** After sorting the  $p$ -values, the slope  $S_i$  is calculated between the  $i$ th  $p$ -value and the point  $(m+1, 1)$  for ascending  $i$  (solid lines). The first  $i$  for which  $S_i < S_{i-1}$  is considered the first  $p$ -value from the alternative hypothesis (dashed line). Subsequently  $\hat{m}_0$  is estimated as  $\min(m, (1/S - i + 1))$ .

**Storey, 2003 - ST; Storey, 2001 - S:** For a certain  $\lambda$  (here: 0.5),  $\pi_0$  is estimated as the density of  $p$ -values greater than  $\lambda$  (dark grey) divided by the expected density under  $H_0$ ,  $1 - \lambda$  (light grey). Storey, 2003 and Storey, 2001 differ in the way they optimize the choice of  $\lambda$ .

**Pounds, 2003 - PM:** The probability density function is assumed to be a mixture of a uniform distribution (dashed line) and a beta-distribution (solid line), with weight  $\pi_0$  to the uniform distribution. Through maximal likelihood estimation, the optimal weights and parameters for the beta-distribution are estimated.

**Pounds, 2004 - PC:** The probability density function  $\hat{f}(p_i)$  is estimated by applying a loess smoother through the histogram of  $p$ -values (solid line).  $\pi_0$  is then estimated as  $\hat{f}(\max(p_i))$ .

## Estimating post-hoc power

	Declared active	Declared inactive	Total
Truly non-active	$F = \alpha m_0$	$m_0 - \alpha m_0$	$m_0$
Truly active	$T = S - \alpha m_0$	$m_1 - (S - \alpha m_0)$	$m_1$
Total	$S$	$m - S$	$m$

- "Power" True Positive Rate:  $TPR = E(T)/m_1 \Leftrightarrow FPR = E(F)/m_0$
- False Nondiscovery Rate:  $FNR = E[(m_1 - T)/(m_1 - S)]$  if  $S \neq m$  and 0 otherwise  $\Leftrightarrow FDR = E(F)/S$

## Simulations

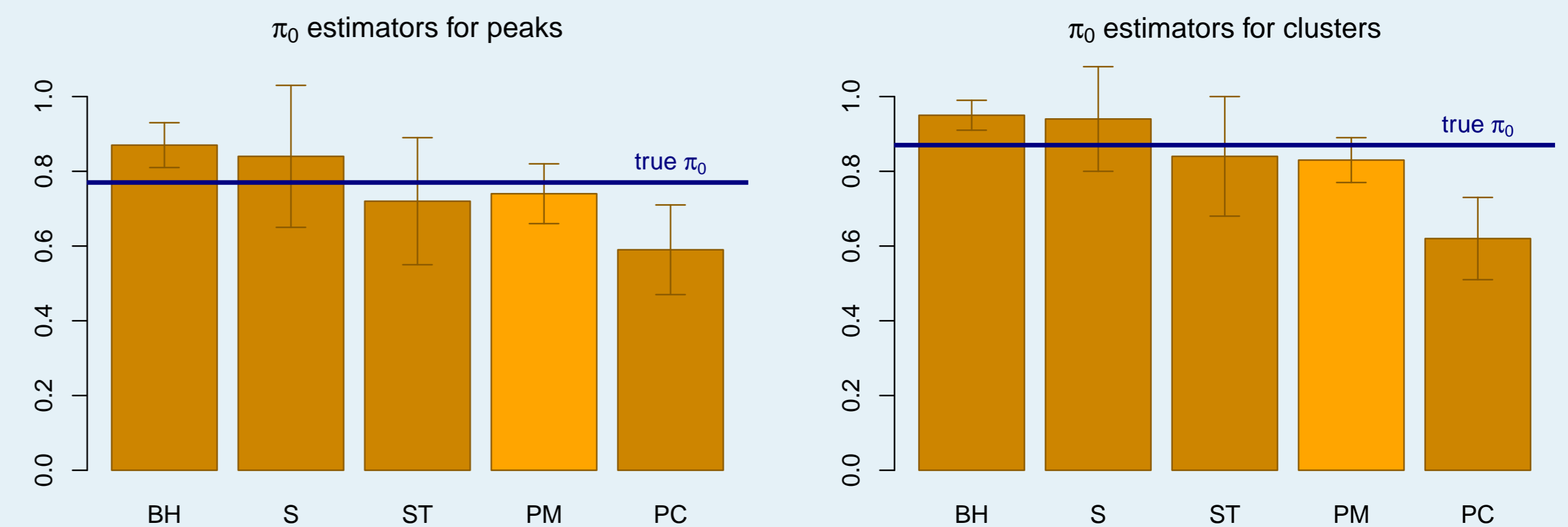
- fMRI data ( $40 \times 40 \times 40 \times 400$ ) are simulated using neuRosim with spatial ( $\sigma = 2.5$ ) and temporal ( $\rho = 0.2$ ) noise.
- 5 regions of  $7 \times 7 \times 7$  voxels are related to the blocked design (20 blocks) with 400 timepoints.
- The signal-to-noise ratio: 0.015.
- A GLM is fit to the data using FSL.
- Excursion threshold:  $P(T_{398} > u) = 0.01$
- Peak and cluster  $p$ -values are calculated.
- 500 simulations have been performed.
- Simulations have been repeated under different conditions for smoothness, excursion threshold, number of activated regions and signal-to-noise ratio's with equal conclusions.

## References and acknowledgements

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 Henson, Shallice, Gorno-Tempini and Dolan (2002). *Cerebral cortex*, 12(2), 178-186.  
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 This work was carried out using the STEVIN Supercomputer Infrastructure at Ghent University, funded by Ghent University, the Flemish Supercomputer Center (VSC), the Hercules Foundation and the Flemish Government  $\hat{a}$  department EW1.

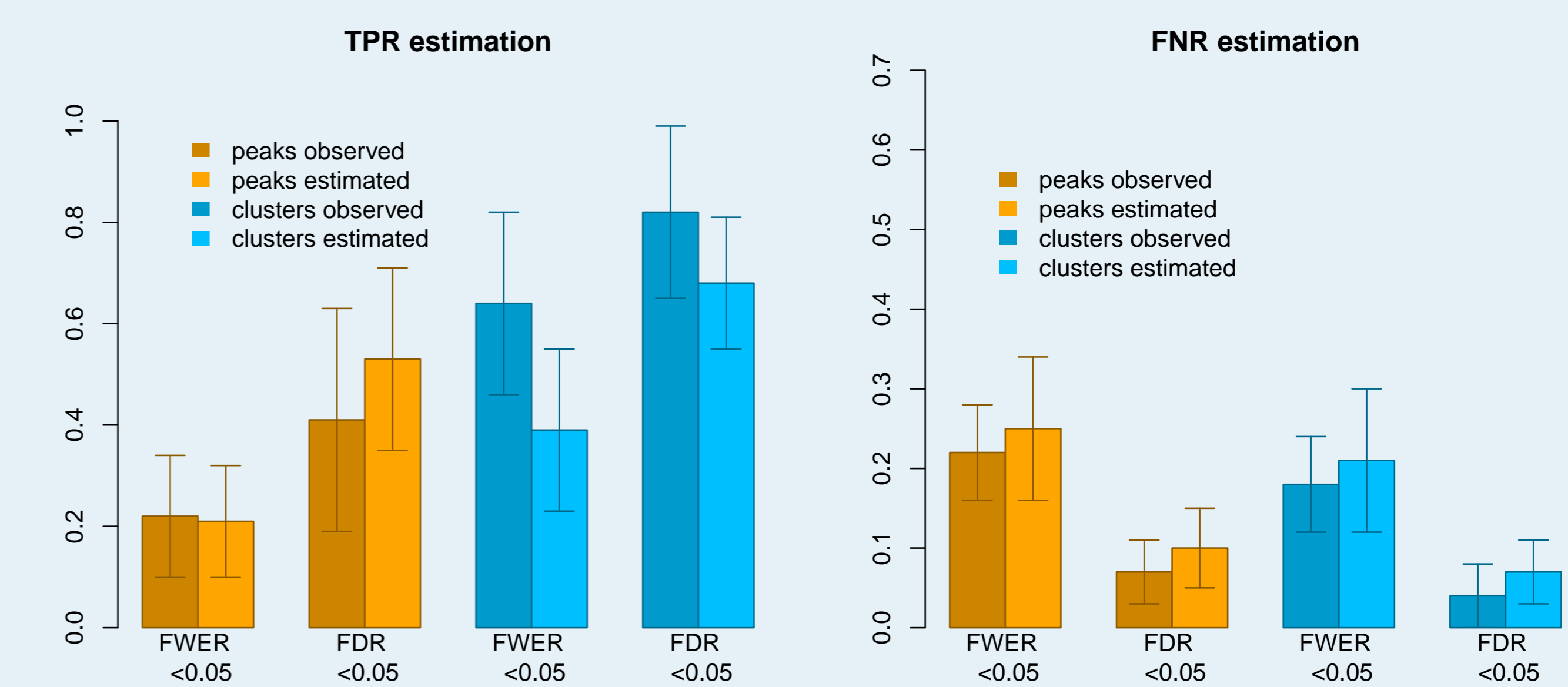
## Evaluation $\pi_0$ estimators on simulated data

### Average estimates of $\hat{\pi}_0$ for the different estimators with their standard deviation.



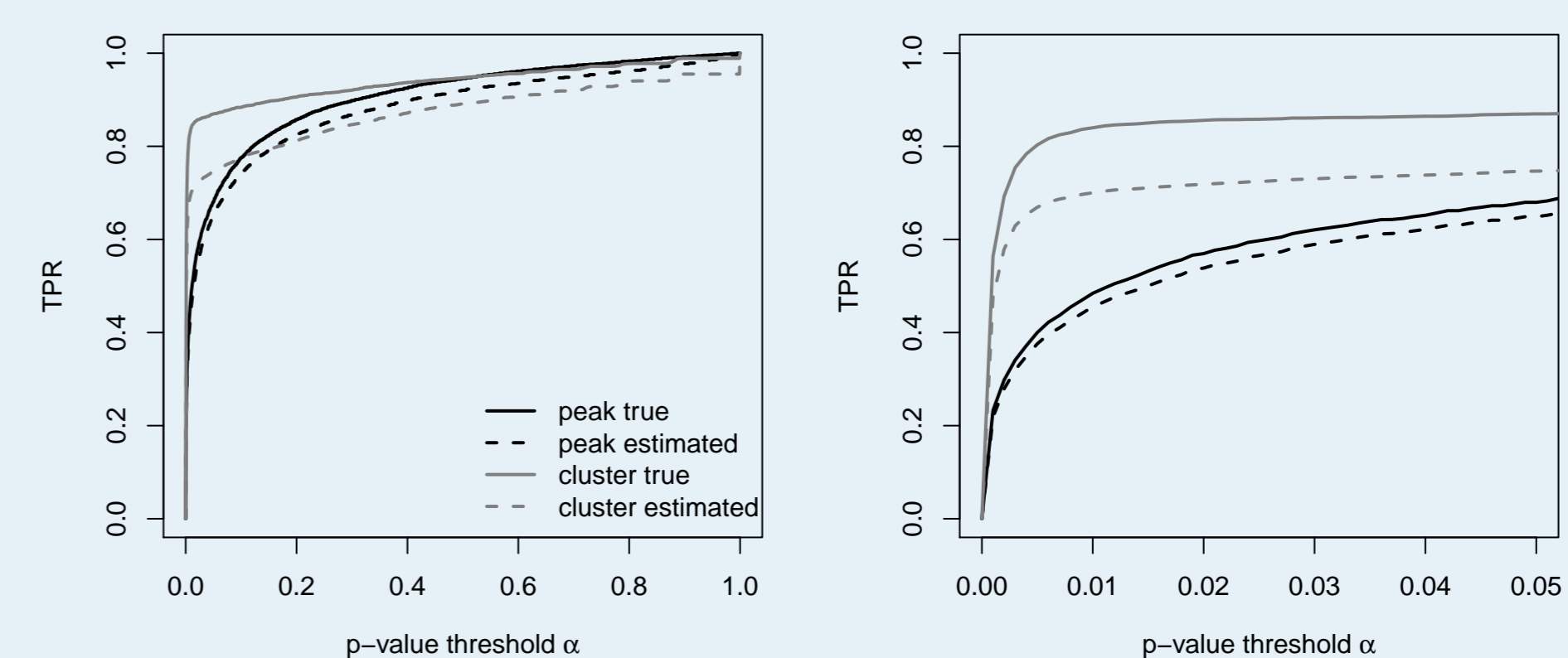
- PM produces best overall performance.

## Evaluation of post-hoc power estimation on simulated data



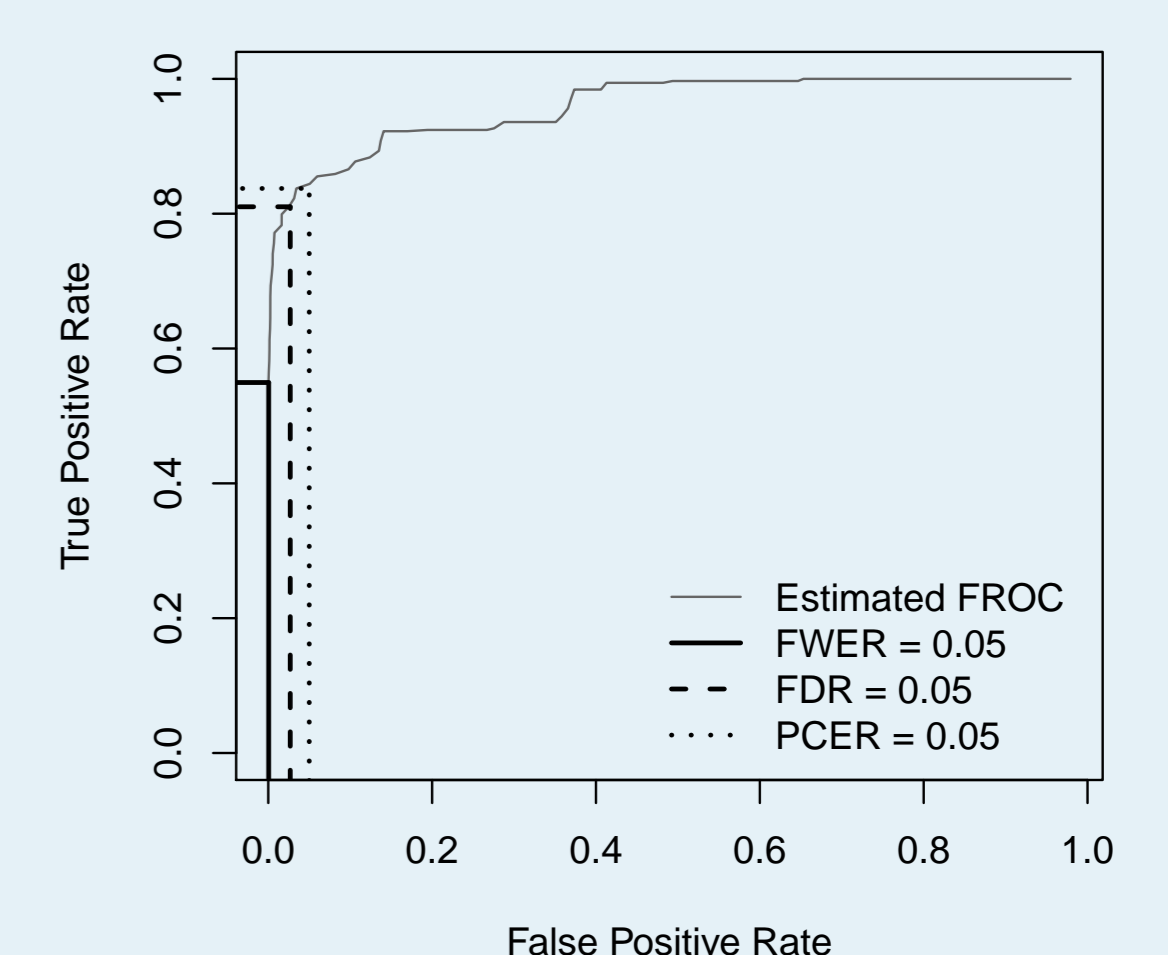
## Estimating the free-receiver operator curve

FROC: TPR is plotted against the FPR for a range of  $p$ -value thresholds



## Real data example

- study by Henson et al., 2002: single-subject event-related design. Average effect of presenting faces.
- 97 peaks discovered
- FWER control  $\alpha = 0.05$ 
  - 35 significant peaks
  - $\widehat{TPR} = 55\%$
  - $\widehat{FNR} = 44\%$
- FDR control  $\alpha = 0.05$ 
  - 52 significant peaks
  - $\widehat{TPR} = 81\%$
  - $\widehat{FNR} = 26\%$



## Discussion and conclusion

- Pounds and Morris (2003) best estimator under different fMRI conditions
- Post-hoc power calculations: For a univariate tests ill-advised (e.g. power always greater than 50% for significant test). For multiple testing, provides useful estimate of proportion of true positives.
- Procedure can be used on any collection of uncorrected  $p$ -values: voxel-based morphometry, diffusion tensor imaging,...
- Henson study: very low power using FWER control  $\Rightarrow$  **call for better balance between sensitivity and specificity.**