Introduction	Statistical model	Some results	Conclusion/Future plans
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	SSPA - PIIOL GALA DAS	ed sensitivity a	analysis for
	high-dime	ensional data	
	Maarten van Iterson (B	ioinformatics PhD	Student)

Center for Human and Clinical Genetics Leiden University Medical Center

November 16, 2010

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Introduction	Statistical model	Some results	Conclusion/Future plans

What is the appropriate sample size for an experiment?

- sample variability
- effect size
- proportion of features of interest

Basically two ways:

- simulation study
- pilot data

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adaptive FDR frame work (Benjamini and Hochberg (1995) and Storey (2003))

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- power and sample size analysis
- all estimators are based on p-values or test statistics, the assumption is either normal or Student's t
- currently under development moderated t (limma) and nonparametric approach

implementation of the deconvolution

mixture representation for the test statistics:

$$f(x) = \pi_0 f_0(x) + (1 - \pi_0) \int_{-\infty}^{+\infty} f_0(x - \theta \sqrt{N}) \lambda(\theta) d\theta \qquad (1)$$

deconvolution estimator:

$$\hat{\lambda}(\theta) = \frac{\sqrt{N}}{2\pi} \int_{-\infty}^{+\infty} e^{-it\theta\sqrt{N}} \chi_{\mathcal{K}}(at) \frac{\hat{\chi}_h(t)}{\chi_{f_0}}(t) dt, \qquad (2)$$

related to density using fft and massdist a C-function from the package *stats*.

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Estimation of π_0



On simulated data using method by Langaas et al. (2005).

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Image: A math a math

Estimation of density of effect sizes



Nutrigenomics experiment: using different compounds and exprosure times (van Iterson *et al.* (2009)).

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Power curves



Different expression profiling platforms were compared (van Iterson *et al.* (2009)).

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Introduction	Statistical model	Some results	Conclusion/Future plans

Conclusion:

pilot data-based power and sample size analysis

Future plans:

- moderated t (limma) should be more suitable for small sample sizes
- nonparametric approach, main difficulty nonparametric null; bootstrap high-dimensional data with small sample sizes

M. van Iterson *et al.* Relative power and sample size analysis on gene expression profiling data. (2009), BMC Genomics, **10**.

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