Midterm Proposals

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Stanford University, Spring 2016, STATS 205

Overview

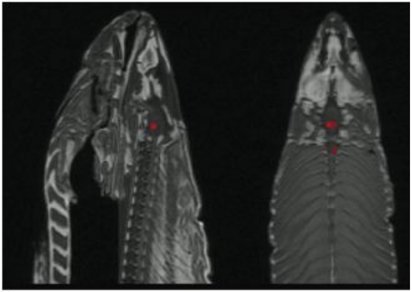
- 16 projects
- 10 singles, 6 pairs
- Wide range:
  - Medicine (microbiome, lung cancer, genetics)
  - Environment (seafood, global warming)
  - Sports (basketball and baseball)
  - Conflict predictions in the Congo
  - Police killings
  - University rankings
  - Virtual Architecture
  - Digital humanities
  - Natural language processing
  - Linear smoothers
  - Finance

Overview

- Very creative, some a bit too ambitious
- Try to start simple, and make it more complicated as you go along
- Do it stepwise, so that you always know which step doesn't work
- Otherwise, in the end you won't know where the problem is, and you'll have to start from scratch

A Dead Fish Can See

- Scientists put a dead fish in a fMRI scanner
- They measured brain activation of the dead fish while showing photos of human faces



Source: Bennet et al. (2009)

Multiple Comparison Problem

- What happened? Random noise from scanner
- The problem is that we are testing around 130,000 voxels in a typical fMRI scan
- Using the common significance level $\alpha = 0.05$, we will see 6,500 discoveries just by chance alone
- We have to adjust for this multiple testing problem
- Here are the common tools and R functions
- For detailed treatment take for instance Stats 300C

Multiple Comparison Problem

- We have four types of outcomes in multiple testing:

	H_0 accepted	H_0 rejected	Total
H_0 true	U	V	n_0
H_0 false	T	S	$n - n_0$
	$n - R$	R	n

- U, V, S, T are unobserved random variables
- R is an observed random variable
- **Familywise Error Rate**: Classical multiple comparison procedures aim to control

$$\text{FWER} = P(V \geq 1)$$

- Holm's procedure is not as conservative as Bonferroni; we typically make more rejections (have more power)
- Holm's procedure can always be used instead of Bonferroni

Multiple Comparison Problem

- The FWER makes sense when we are testing a small number of hypotheses
- For example, in comparing six or ten different treatments, it is very reasonable to control the probability of returning even one ineffective treatment
- If we are testing millions of hypotheses at once, for example in genome-wide association studies, and making a **false discovery** is not the end of the world
- We prefer to return some **false positives** along with many potentially interesting genes, because this enables scientists to follow these leads and to distinguish the important genes from the false discoveries

Multiple Comparison Problem

	H_0 accepted	H_0 rejected	Total
H_0 true	U	V	n_0
H_0 false	T	S	$n - n_0$
	$n - R$	R	n

- False discovery proportion (FDP):

$$\mathrm{FDP} = \begin{cases} V/R & \text{if } R \geq 1 \\ 0 & \text{otherwise} \end{cases}$$

- We observe R, we do not observe V, and so FDP is an unobserved random variable
- **False Discovery Rate** controls the expectation

$$\mathrm{FDR} = \mathrm{E}(\mathrm{FDP})$$

Multiple Comparison Problem

- Consider what it means to control **FDR**: if we repeat our experiment many times, on average we control the FDP
- This is **not** a statement about our **individual experiment**, and does not say much about the chance of having our FDP exceed a certain threshold
- **FWER**, on the other hand, does control for an **individual experiment**

Reproducible Reserach

- Create a github repository for your project
- Do version control every day
- Keep track of everything
- Do all the anlaysis in a Rmd
- Never try out things without writing them down in a script!
- Some examples: (link)

References

- Candes (2016). Lecture Notes (link)
- R function: `p.adjust`
- Bennet et al. (2009). Salmon Poster. (link)