

# STAT 30850 Project Proposal

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## Overview

There are many scenarios where hypothesis testing is performed sequentially as new data becomes available through time. Streaming data is common in many modern applications such as high frequency stock trading, novel results from clinical trials, and large-scale advertisement experiments conducted by Google and Facebook. In this context one would like to test multiple hypothesis on the data as its streaming in, while still retaining adequate FDR control, similarly to approaches developed for non-streaming data. Here we propose to extend and apply Bayesian methods for FDR control in an online testing setting.

## Initial Proposal of Model

Suppose that time  $t \in \{0, 1, \dots, \tau\}$ , and that test statistics  $X_t$  are independently distributed under the mixture model:

$$X_t \sim \pi_0 \cdot N(\mu_0, \sigma_0^2) + (1 - \pi_0) \cdot N(\mu_1, \sigma_1^2)$$

We will further simplify this and obtain the p-values for each of the data points  $P_t$ . We wish to use all datapoints prior to  $\tau$  to estimate the proportion of nulls ( $\pi_0$ ) before we switch to a Bayesian FDR method (such as Storey's method). Note that as we proceed through the data stream, all of the p-values  $P_0, \dots, P_t$  can be used to update our estimate of the true proportion of nulls. Note that in the above setting we assume that the true proportion of nulls ( $\pi_0$ ) does not vary with time. We also define the rejection region of the p-values as  $[0, \gamma]$ .

Thus our initial estimate of the proportion of nulls will be (according to Storey):

$$\hat{\pi}_0^\tau(\lambda) = \frac{\#\{p_i > \lambda\}}{(1 - \lambda)\tau}$$

And more generally our updated estimates will be:

$$\hat{\pi}_0^t(\lambda) = \frac{\#\{p_i > \lambda\}}{(1 - \lambda)t}$$

Then we can define our similar data-adaptive FDR and pFDR estimators at time  $t > \tau$  as:

$$FDR_\lambda^t(\gamma) = \frac{\hat{\pi}_0^t(\lambda)\gamma}{(1 - \lambda)(R(\gamma) \vee 1)}$$

$$pFDR_\lambda^t(\gamma) = \frac{\hat{\pi}_0^t(\lambda)\gamma}{(1 - \lambda)(R(\gamma) \vee 1)(1 - (1 - \gamma)^t)}$$

## Questions Proposed

- $\tau$  : which time-step to switch to the Bayesian FDR model? What model to use prior to this model? Or should we not even switch and just reject everything before  $\tau$ ?
- $\pi_0$  : How many nulls are there relative to the signals within the data? Are we able to detect the signals even when there are very few of them?
- $\mu_1 \gg \mu_0$  : The relative strength of the signals vs. the nulls. How weakly can we classify signals?
- Calculating  $\lambda_{best}$  : Storey formulates a method (Section 9) to compute the optimal value of  $\lambda$  for a given set of data. How could recalculating this value according to streaming data affect FDR? Recalculate for most recent "chunk" of time or aggregate through time?
- Clustering of Signals : How does the method react to clusters of signals together?

## References

1. Storey, John. *A direct approach to false discovery rates*. 2002. *Journal of the Royal Statistical Society*