ABSTRACT

I will talk about two projects I have been working on. The first is FDR control for ordered hypothesis testing. Given an ordered list of $n$ hypotheses, ranked from mostly likely to least likely to be a signal from prior studies, our aim is to select a data-dependent cutoff $k$ and declare the first $k$ hypotheses to be statistically significant while bounding the false discovery rate (FDR). Generalizing several existing methods, we develop a family of "accumulation tests" to choose a cutoff $k$ that adapts to the amount of signal at the top of the ranked list. Depending on how much we trust the prior ranking, we also consider a test rule that combines the cutoff $k$ with a threshold on p-values.

The second is BIC for functional regression. Here we consider a function-on-scalar setting, where a process of interest (e.g. heart function, blood pressure) changes over time, and we are interested in how it is related to some static features such as SNPs. For such models, we want to establish an information criteria that achieves consistency in model selection. In reality, we observe such a process at discrete time points, so the model is reduced to a multitask regression setting. Suppose we observe the process at $M$ time points, as long as $M$ is large enough, we should expect to get enough information of the process, and the BIC results should not be sensitive to $M$. I will talk about what that means, and our preliminary results on this problem.