ABSTRACT

In contemporary applications, it is common to collect very large data sets with the vaguely-defined goal of hypothesis generation. Once a dataset is used to generate a hypothesis, we might wish to test that hypothesis on the same set of data. However, this type of "double dipping" violates a cardinal rule of statistical hypothesis testing: namely, that we must decide what hypothesis to test before looking at the data. When this rule is violated, then standard statistical hypothesis tests (such as t-tests and z-tests) fail to control the selective Type 1 error --- that is, the probability of rejecting the null hypothesis, provided that the null hypothesis holds, and given that we decided to test this null hypothesis.

While double dipping is pervasive throughout many application areas, in this talk I'll focus on the analysis of single-cell RNA-sequencing data. In the first part of my talk, I'll apply ideas from selective inference to enable valid hypothesis testing after hierarchical clustering or k-means clustering. In the second part of my talk, I'll introduce count splitting, an approach to overcome issues associated with double dipping in the context of latent variable estimation for count-valued data.

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