The Indian Buffet Process

Bilinear Models

Abstract

For large datasets, we do not want to look at all of the data at once. We consider doing (principled) inference on only a subset of this data. Here no blocked sampling—we still only consider one element of $Z$ at a time.

### Gibbs Sampling

**Uncollapsed Gibbs Sampling:**

- Samples $Z_n$ first and then $A$.
- Integrates out $A$ but integrates out new obs $D$ at a cost of computing whether to add a new feature.
- Advantage: Each iteration is fast to compute.
- Disadvantages: Often slow to mix.

**Collapsed Gibbs Sampling:**

- Integrates out $A$ and keeps a posterior on $A$ for each $Z_n$.
- Requires less computation per iteration but slower to converge to an exact posterior.

### Windowing the Model

- For large datasets, we do not want to look at all of the data at once.
- We consider doing (principled) inference on only a subset of the data.
- Windowing the model allows us to perform fast inference in an important class of bilinear models.

### Experiments on Realworld Data

- The applied 3 samplers to several real-world data sets. The accelerated sampler achieved likelihoods similar to the collapsed sampler orders of magnitude faster.

### Experiments on Synthetic Data

- Data was generated from the prior with $D=10, N=2,600$.
- We ran 5 chains for 1000 iterations on a subset of the data.
- For large datasets, we do not want to look at all of the data at once.

### Conclusions

- Maintaining a posterior within a sampler allows us to perform fast inference in an important class of bilinear models.
- In particular, our approach allows us to scale inference to large Indian Buffet Process models.
- Code is available on my website!