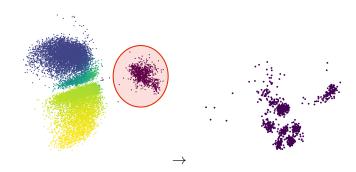
Iterative Latent Spaces for Interpretable High-Dimensional Modeling

Jackson Loper, David Blei, and Liam Paninski Columbia University





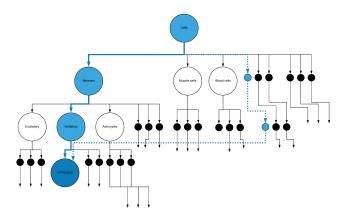
No two-dimensional space can smoothly represent the full diversity of cells.

Latent-variable generative modelling is a natural idea

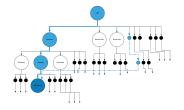
Especially natural for multi-modality data.

$$\mathbb{P}(X_1, X_2, X_3, \cdots) = \int \left(\left(\prod_i \mathbb{P}(X_i | Z) \right) \mu(dZ) \right)$$

Put them together



A fully generative model for all the features of the data



- T cell type at finest resolution
- $Z_n \sim q(z; heta_{T,n})$ for each group n that T is a member of
- $X_g \sim p\left(x; f_g\left(Z_1 \cdots Z_N\right)\right)$ for each feature g

Empirical results

Tasic, Bosiljka, Zizhen Yao, Kimberly A. Smith, Lucas Graybuck, Thuc Nghi Nguyen, Darren Bertagnolli, Jeff Goldy et al. "Shared and distinct transcriptomic cell types across neocortical areas." bioRxiv (2017): 229542.

Empirical results

- Amortized variational inference
- Zero-inflated negative binomial distribution for gene expression

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Method	Train	Test
Factor analysis $k = 16$	-4.2	-4.2
Factor analysis $k = 64$	-4.1	-4.3
HNBPF $k=2$	-5.7	-5.7
HNBPF $k = 16$	-3.8	-3.9
HNBPF $k = 64$	-3.8	-5.7
ZINB-NN $k = 2$	-3.6	-3.6
ILS $k = 2 + 2$	-3.5	-3.5
ILS $k = 2 + 2$	-3.5	-3.5

More flexible, but still interpretable

