



Bayesian Non-Parametrics

Advanced Machine Learning for NLP Jordan Boyd-Graber

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- So typically use multinomial distribution as the base distribution
- Remember multinomial:

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Draw document word counts

$$\phi_d \sim \Theta$$
 (6)

$$w_d \sim \phi_d$$
 (7)

Extending DPMM for text: HDP

- Topic models can use multiple topics per document
- Mixture model can only use one
- HDP is the non-parametric extension

Hierarchical Dirichlet Process

• Draw a global distribution over topics (e.g., $H \equiv Dir(\alpha)$)

$$G_0 \sim \mathsf{DP}(\gamma, H)$$
 (8)