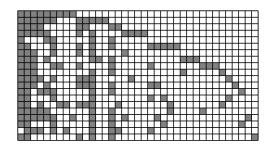
Structured Variational Autoencoders for the Beta-Bernoulli Process

Jeffrey Ling, Rachit Singh, Finale Doshi-Velez Harvard University

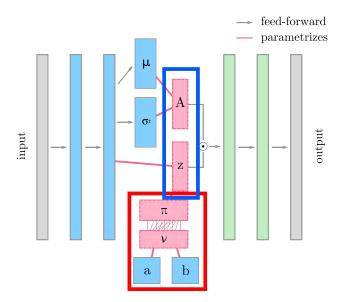
NIPS 2017 Advances in Approximate Bayesian Inference

Indian Buffet Processes



$$egin{aligned}
u_k &\sim \mathsf{Beta}(lpha,1); \pi_k = \prod_{j=1}^k
u_j \ & z_{n,k} \sim \mathsf{Bern}(\pi_k) \ & \mathbf{A}_n &\sim \mathcal{N}(\mathbf{0},\mathbf{I}_{K^+}) \ & \mathbf{x}_n &\sim p_{ heta}(\mathbf{x}_n|\mathbf{Z}_n\odot\mathbf{A}_n) \end{aligned}$$

Structured Variational Inference



Results

	MNIST IWAE		Omniglot IWAE	
Model	Train	Test	Train	Test
MF-IBP BBVI	102.6	104.5	129.4	134.5
$\operatorname{MF-IBP}$ Gumbel	94.2	96.4	125.0	129.5
S-IBP BBVI	93.8	96.2	115.2	124.5
$\operatorname{S-IBP}$ Gumbel	81.7	86.5	101.4	113.0

MNIST Features

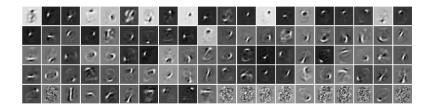


Figure: Features learned from a linear IBP model applied to MNIST

Summary

- We use neural networks to amortize IBP inference for arbitrary likelihoods
- Structured posteriors outperform mean-field VI
- ► Code: github.com/rachtsingh/ibp_vae
- Come to our poster!