Scaling Hidden Markov Language Models

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Hidden Markov Models in NLP

- Historically significant latent variable models
- Are thought to be very poor language models
- We show they are not!

Lessons from Large Neural Language Models

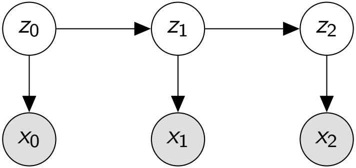
Large models perform better but are ...

1. Slow to train
2. Prone to overfitting

We must overcome these issues when scaling HMMs

HMMs

For times t, model states $z_t \in \mathcal{Z}$, and tokens $x_t \in \mathcal{X}$,



We wish optimize

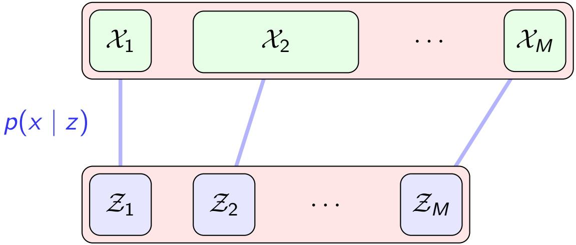
$$p(\mathbf{x}) = \sum_{\mathbf{z}} p(\mathbf{x}, \mathbf{z})$$

3 Techniques for Training Large HMMs

- Block-sparse emission constraints
  - ⇧ Speed
- Compact neural parameterization
  - ⇧ Generalization
- State dropout
  - ⇧ Speed ⇧ Generalization

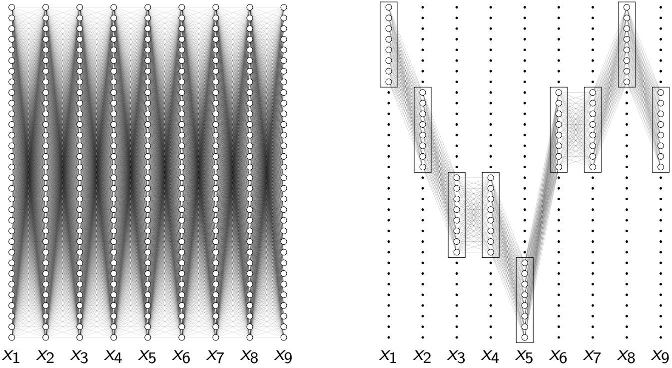
Technique 1: Block-Sparse Emission Constraints

- Reduce cost of marginalization by enforcing structure
- Partition words and states jointly
- Words can only be emit by states in same group



Block-Sparse Emissions: Effect on Inference

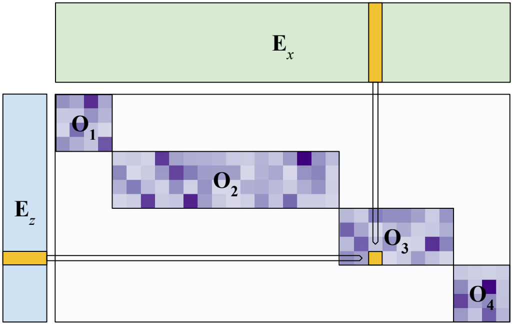
Given each word x_t, only the states in the correct group can occur



(a) No constraints (b) Block-sparse emission

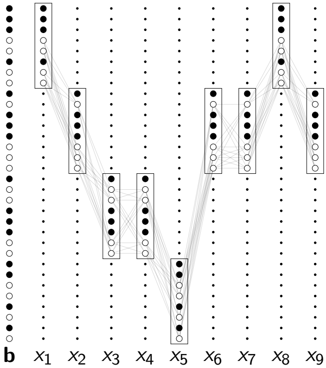
Technique 2: Neural Parameterization

- A neural parameterization allows for parameter sharing
- Generate conditional distributions from state $\mathbf{E}_z$ and token representations $\mathbf{E}_x$



Technique 3: State Dropout

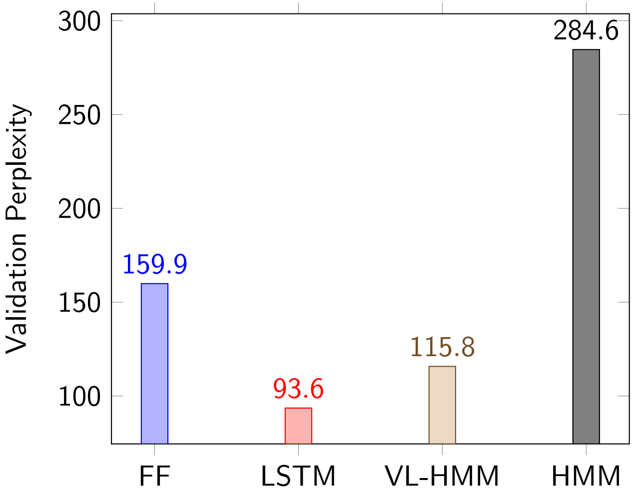
- State dropout encourages broad state usage
- At each batch, sample dropout mask $\mathbf{b} \in \{0,1\}^{|\mathcal{Z}|}$



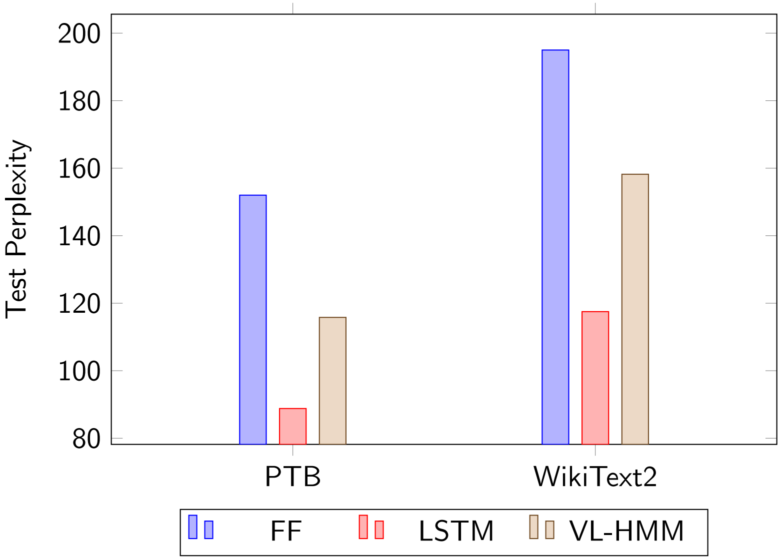
Experiments

- Language modeling on Penn Treebank and Wikitext-2
- Baselines
  - Feedforward 5-gram model
  - 2-layer LSTM
  - A 900 state HMM (Buys et al 2018)
- Model
  - 2^{15} (32k) state very large HMM (VL-HMM)
  - $M = 128$ groups (256 states each), obtained via Brown Clustering
  - Dropout rate of 0.5 during training

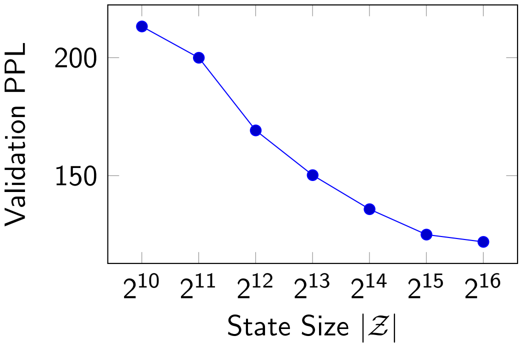
Results on PTB Validation Data



Results on PTB and WT2 Test Data



State Size Ablation



Validation perplexity on PTB by state size ($\lambda = 0.5$ and $M = 128$)

Other Ablations

Model	Param	Train	Val
VL-HMM (2^{14})	7.2M	115	134
- neural param	423M	119	169
- state dropout	7.2M	88	157

Conclusion

- HMMs are competitive language models
- Introduced 3 techniques for tackling speed and overfitting
- A great time to revisit other discrete latent variable models

EOS

Citations