Scaling Hidden Markov Language Models

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Hidden Markov Models in NLP

- Historically significant latent variable models
  - Applied to tagging, alignment, and language modeling in the 90s
- Are thought to be very poor language models
  - We show they are not!

Lessons from Large Neural Language Models

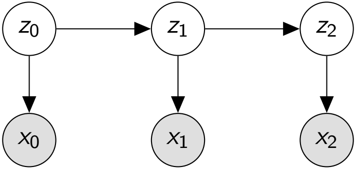
Large models perform better but are . . .

- Slow to train
  - Parallelize computation and use GPUs
- Prone to overfitting
  - Regularize

Apply this to scaling HMMs

HMMs

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



We wish optimize

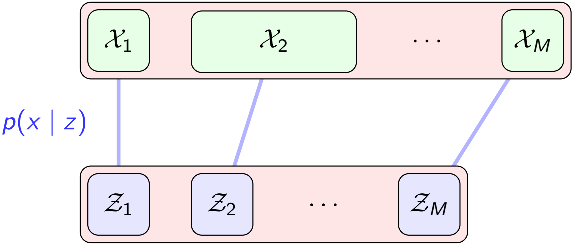
$$p(\mathbf{x}) = \sum_{\mathbf{z}} p(\mathbf{x}, \mathbf{z})$$

3 Tricks for Training Large HMMs

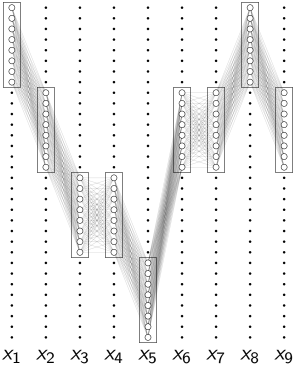
- Block-sparse emission constraints
  ⬆ Speed
- Compact neural parameterization
  ⬆ Generalization
- State dropout
  ⬆ Speed ⬆ Generalization

Block-Sparse Emission Constraints

- Partition words and states jointly
- Words can only be emit by states in same group



Block-sparse Emissions: Effect on Inference

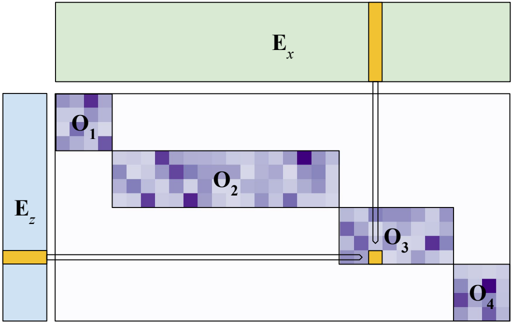


After observing each x_t, only the states in the corresponding group have nonzero probability of occurring

Neural Parameterization

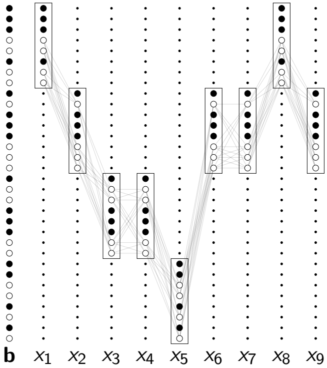
Generate transition and emission distributions using a neural network

- State embeddings $\mathbf{E}_z \in \mathbb{R}^{|\mathcal{Z}| \times h}$
- Token embeddings $\mathbf{E}_x \in \mathbb{R}^{|\mathcal{X}| \times h}$



State Dropout

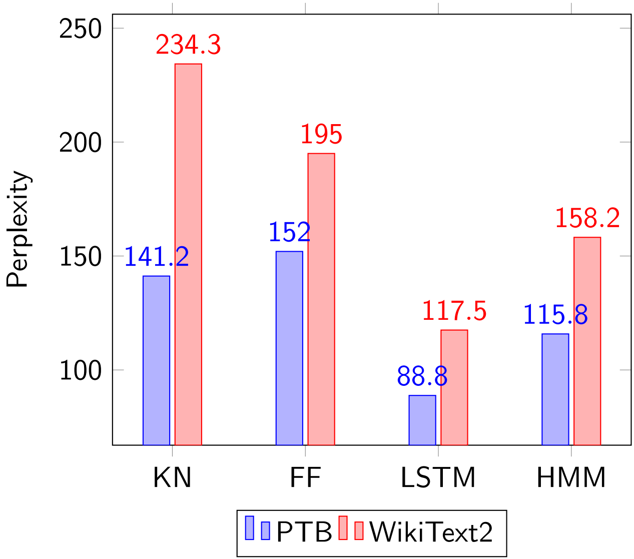
At each batch, sample dropout mask $\mathbf{b} \in \{0,1\}^{|\mathcal{Z}|}$



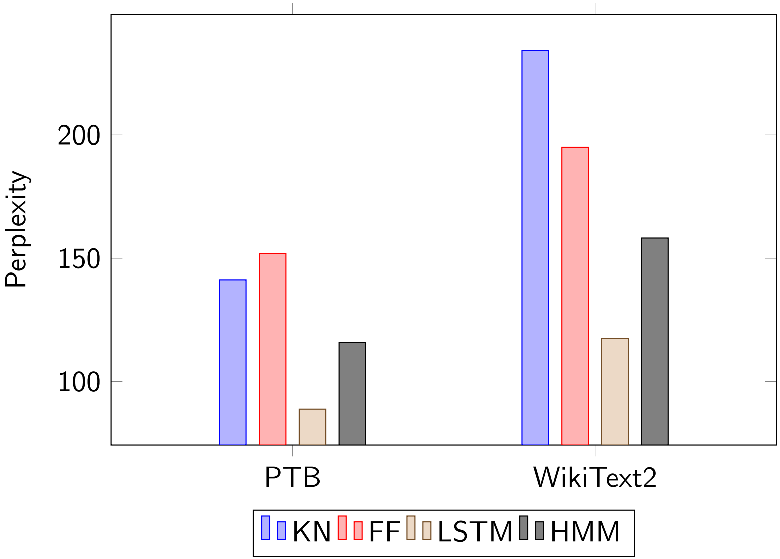
Experiments

- Language modeling on Penn Treebank and Wikitext-2
- Baselines
  - Knesey-Ney 5-gram model
  - Feedforward 5-gram model
  - 2-layer LSTM
- 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 and WT2



Results on PTB and WT2



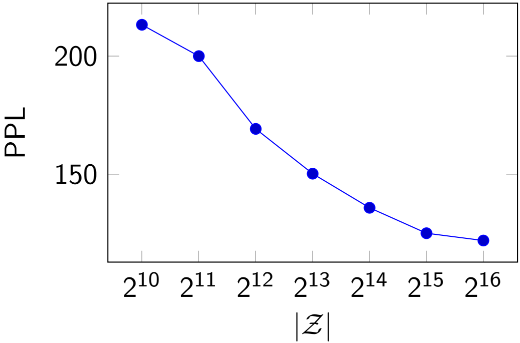
Results on PTB

Model	# Params	Val PPL	Test PPL
KN 5-gram	2M	-	141.2
256 FF 5-gram	2.9M	159.9	152.0
AWD-LSTM	24M	60.0	57.3
2x256 dim LSTM	3.6M	93.6	88.8
HMM ($\lvert\mathcal{Z}\rvert$=900)	10M	284.6	-
VL-HMM ($\lvert\mathcal{Z}\rvert = 2^{15}$)	7.7M	125.0	115.8

Results on WikiText2

Model	# Param	Val PPL	Test PPL
KN 5-gram	5.7M	248.7	234.3
AWD-LSTM	33M	68.6	65.8
256 FF 5-gram	8.8M	210.9	195.0
2x256 LSTM	9.6M	124.5	117.5
VL-HMM ($\lvert\mathcal{Z}\rvert = 2^{15}$)	13.7M	169.0	158.2

State Size Ablation



Perplexity on PTB by state size $|\mathcal{Z}|$ ($\lambda = 0.5$ and $M = 128$)

Other Ablations

Model	Param	Train	Val	Time
VL-HMM (2^{14})	7.2M	115	134	40
- neural param	423M	119	169	14
- state dropout	7.2M	88	157	100

Conclusion

- HMMs can be scaled up to competitive language models
- Introduced 3 tricks for tackling speed and overfitting
- HMMs are cool!

EOS

Citations