Scaling Hidden Markov Language Models

Anonymous

2020

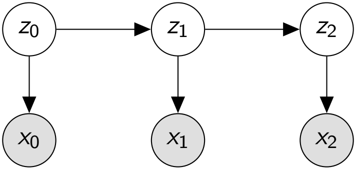
Motivation for HMMs

- Generative process separates the generation of the latent representations from the observed
  - LSTMs couple the two
- Discrete latent representations
  - Improves performance in low-resource classification (citation todo)

HMM LMs

- Previously thought to be very poor language models
  - Improved performance by departing from HMM structure and turning them into RNNs (Buys et al., 2018)
- HMMs performance can be vastly improved by scaling the number of hidden states

HMMs



Joint distribution

$$p(\mathbf{x}, \mathbf{z}; \theta) = \prod_{t=1}^{T} p(x_t \mid z_t) p(z_t \mid z_{t-1})$$

We shorten the emission matrix $p(x_t \mid z_t)$ to $\mathbf{O}$.

Training HMMs

- Computing the likelihood of the observed sentence is $O(T|\mathcal{Z}|^2)$, scaling poorly in the number of states
- Tabular parameterizations of distributions are difficult to optimize
- We present three tricks to mitigate these issues

3 Tricks 4 Scaling HMMs

- A block-sparse emission matrix reduces the computational cost of computing the likelihood
- A compact (neural) parameterization of the transitions and emissions aides optimization
- State dropout further reduces computational cost and reduces overfitting

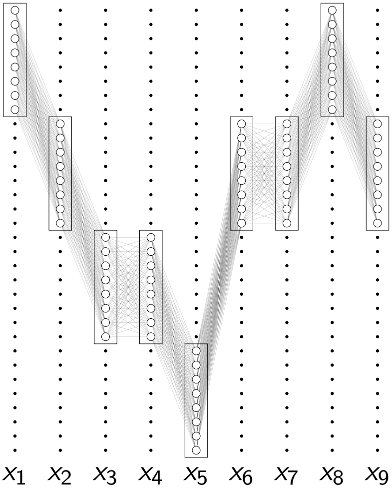
Block-sparse Emissions

- Constrain emissions to

$$\mathbf{O} = \begin{bmatrix} \mathbf{O}^1 & 0 & 0 \\ 0 & \dots & 0 \\ 0 & 0 & \mathbf{O}^M \end{bmatrix}$$

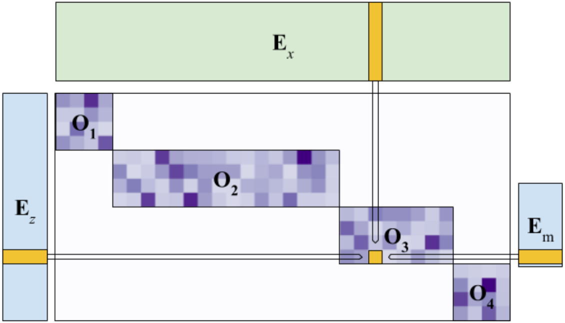
- Each block $\mathbf{O}_m$ contains k latent states and a variable number of tokens
- Results in a serial complexity of $O(Tk^2)$ for computing the likelihood

Block-sparse Emissions



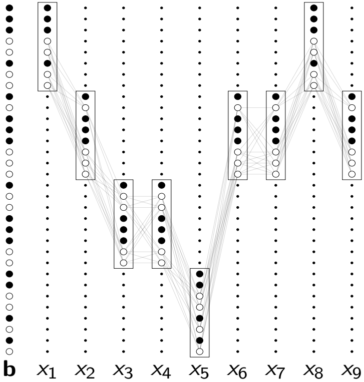
Neural Parameterization

- Compute transition and emission parameters using a neural network
  - State embeddings $\mathbf{E}_z \in \mathbb{R}^{|\mathcal{Z}| \times h/2}$
  - Token embeddings $\mathbf{E}_x \in \mathbb{R}^{|\mathcal{X}| \times h}$
  - Block embeddings $\mathbf{E}_m \in \mathbb{R}^{M \times h/2}$



State Dropout

- Sample a dropout mask $\mathbf{b}_m \in \{0, 1\}^k$ for each block $\mathbf{O}_m$
- Concatenate into a global vector $\mathbf{b} = \langle \mathbf{b}_1, \ldots, \mathbf{b}_M \rangle$



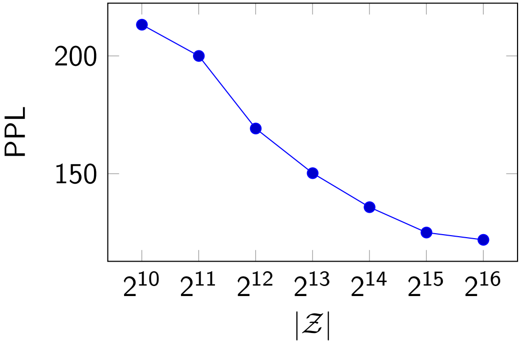
Results on PTB

Model	# Params	Val PPL	Test PPL
KN 5-gram	2M	-	141.2
AWD-LSTM	24M	60.0	57.3
256 FF 5-gram	2.9M	159.9	152.0
2x256 dim LSTM	3.6M	93.6	88.8
HMM+RNN	10M	142.3	-
HMM ($\lvert\mathcal{Z}\rvert$=900)	10M	284.6	-
VL-NHMM ($\lvert\mathcal{Z}\rvert = 2^{15}$)	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-NHMM ($\|\mathcal{Z}\| = 2^{15}$)	13.7M	169.0	158.2

State Size Ablation



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

Bibliography

Jan Buys, Yonatan Bisk, and Yejin Choi. 2018. Bridging hmms and rnns through architectural transformations.