

# Scaling Hidden Markov Language Models

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May 13, 2021

# Language Modeling

*'BERT and GPT models change the game for NLP'*

Demi Ajayi (IBM)

Able to achieve strong performance in modern NLP tasks with

- ▶ Large, opaque models
- ▶ Pretrained via language modeling on large data
- ▶ Fine-tuned for downstream task

Language modeling either has useful information for or is a necessary component of downstream tasks

# Language Modeling

How now, brown \_\_\_\_\_

- ▶ Given the words seen so far, predict the next word
- ▶ Requires encoding long-range context
- ▶ Most success with uninterpretable models

# Interpretable Models

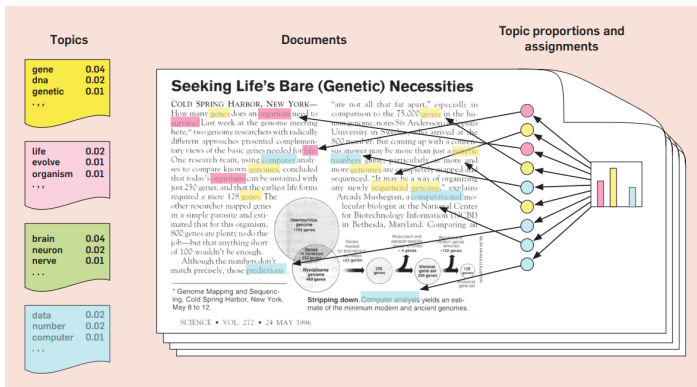
- ▶ Interpretable models give qualitative insight into data
- ▶ Generative models provide interpretability through stories
- ▶ Generative stories provide intermediate decisions

# Interpretable Models: Examples

Examples of interpretable generative models:

- ▶ Topic Model
- ▶ Template Model
- ▶ Entity Language Model

# Interpretable Models: Topic Model<sup>1</sup>



Answers the question

- What is this document broadly about?

<sup>1</sup>Blei, Ng, and Jordan, 'Latent dirichlet allocation'.

# Interpretable Models: Template Model<sup>2</sup>

**Source Entity:** Cotto

type[coffee shop], rating[3 out of 5],  
food[English], area[city centre],  
price[moderate], near[The Portland Arms]

**System Generation:**

Cotto is a coffee shop serving English food  
in the moderate price range. It is located  
near The Portland Arms. Its customer rating is  
3 out of 5.

**Neural Template:**

The ____	is a	providing	
____	is an	serving	____
...	expensive	offering	...
food	in the	price range	It's
cuisine	with a	price bracket	It is
foods	and has a	pricing	The place is
...	...	...	...
located in the		Its customer rating is	
located near	____	Their customer rating is	____
near	...	Customers have rated it	...
...		...	

Answers the question

- ▶ Where did the information in this text come from?

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<sup>2</sup>Wiseman, Shieber, and Rush, 'Learning Neural Templates for Text Generation'.

# Interpretable Models: Entity Model<sup>3</sup>

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[*John*]<sub>1</sub> wanted to go to [*the coffee shop*]<sub>2</sub> in  
[*downtown Copenhagen*]<sub>3</sub>. [*He*]<sub>1</sub> was told that  
[*it*]<sub>2</sub> sold [*the best beans*]<sub>4</sub>.

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Answers the question

- ▶ Who is this text talking about?

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<sup>3</sup>Ji et al., 'Dynamic Entity Representations in Neural Language Models'.



# Performance of Interpretable Generative Models

Generative stories are interpretable because they

- ▶ Decompose data into a sequence of simple decisions

Interpretability is costly

- ▶ Must consider all alternatives for unobserved decisions

Cost of inference limits the size of models

- ▶ Will scaling generative models improve performance while maintaining interpretability?

# Hidden Markov Language Models

- ▶ Interpretability as a design decision
- ▶ Focus on first-order HMMs, where context is encoded as a single integer
- ▶ Thought to be poor language models

# Research Question

To what extent is the performance of HMMs limited by scale and choices in parameterization?

**This work:** Scale HMMs on language modeling using techniques drawn from recent advances in neural networks

## Background: Hidden Markov Models

# Hidden Markov Models (HMMs)

- ▶ Classical models for unsupervised per-word tag induction
  - ▶ Part-of-speech induction<sup>4</sup>
  - ▶ Word alignment for translation<sup>5</sup>
- ▶ Graphical model that admits tractable exact inference
  - ▶ Strong conditional independence assumptions
  - ▶ Simple transition dynamics
  - ▶ Finite set of discrete latent states

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<sup>4</sup>Merialdo, 'Tagging English Text with a Probabilistic Model'.

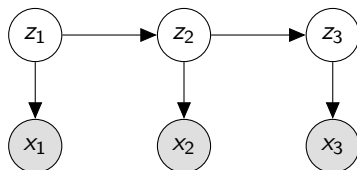
<sup>5</sup>Vogel, Ney, and Tillmann, 'HMM-Based Word Alignment in Statistical Translation'.

# HMM State Sizes

Year	Data	Model	States
1989	Phoneme Segmentation	HMM	7
1994	POS	HMM	76
2005	Activity Monitoring	DMC HMM	1k
2006	2D Image Tracking	Convolutional HMM	100k
2009	LM	Split-POS HMM	450
2016	POS	Neural HMM	37
2016	Web Traffic Analysis	FFT HMM	81
2019	Char LM	Cloned HMM	30k

# Hidden Markov Models (HMMs)

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



This yields the joint distribution

$$p(x, z) = \prod_t p(x_t | z_t) p(z_t | z_{t-1})$$

with

start state	$p(z_1),$
transitions	$p(z_t   z_{t-1}),$
and emissions	$p(x_t   z_t)$

represented as vectors and matrices

# Inference

Given observed  $x = (x_1, \dots, x_T)$  We wish to maximize

$$p(x) = \sum_{z_1} \cdots \sum_{z_T} p(x, z) = \alpha_1^\top \Lambda_2 \Lambda_3 \cdots \Lambda_T \mathbf{1},$$

where we have the

start,  $[\alpha_1]_{z_1} = p(x_1 \mid z_1)p(z_1)$ ,  
and transition operators,  $[\Lambda_t]_{z_{t-1}, z_t} = p(x_t \mid z_t)p(z_t \mid z_{t-1})$

- ▶ Matrix representation of forward algorithm:

$$\alpha_t = \alpha_{t-1} \Lambda_t$$

- ▶ Requires  $O(TZ^2)$  operations in total!



# Transition Operators

We can also express the transition operators  $\Lambda_t$  using the transition matrix  $A \in [0, 1]^{Z \times Z}$  and emissions  $O \in [0, 1]^{Z \times X}$

In particular

the starting alpha

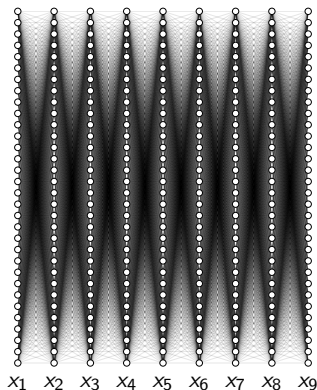
$$\alpha_1 = \pi \circ [O]_{\cdot, x_1},$$

and the transition operators

$$\Lambda_t = A \operatorname{diag}([O]_{\cdot, x_t})$$

# Inference

$$p(x) = \alpha_1^\top \Lambda_2 \cdots \Lambda_T \mathbf{1}$$



- ▶ Each node corresponds to a state
- ▶ Each edge to an entry in the transition operator matrix

## Scaling HMMs

# 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

### 3 Techniques for Training Large HMMs

- ▶ Compact neural parameterization

↑ Generalization

- ▶ State dropout

↑ Speed    ↑ Generalization

- ▶ Block-sparse emission constraints

↑ Speed

- ▶ Will cover a fourth in the second part of this talk

# Technique 1: Neural Parameterization

- ▶ Transition and emission matrices have  $Z^2$  and  $ZX$  entries
- ▶ More states lead to explosion in parameter count
- ▶ Solution: Low dimensional factorization

# Neural Parameterization: Softmax Parameterization

The transition matrix  $A$  is factorized as follows:

$$A \propto \exp \left( U \times V^T \right)$$

with state embeddings  $U, V \in \mathbb{R}^{Z \times D}$

- ▶ Can further parameterize  $U$  or  $V = \text{MLP}(E_u)$
- ▶ Similar for emissions

## Technique 2: State Dropout

- ▶ Dropout is a common technique for regularizing neural networks<sup>6</sup>
  - ▶ Reduces a network's reliance on any particular neuron by via random masking
- ▶ Extend dropout to the states of an HMM
  - ▶ Encourage broad utilization of all states

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<sup>6</sup>Srivastava et al., 'Dropout: A Simple Way to Prevent Neural Networks from Overfitting'.



# State Dropout

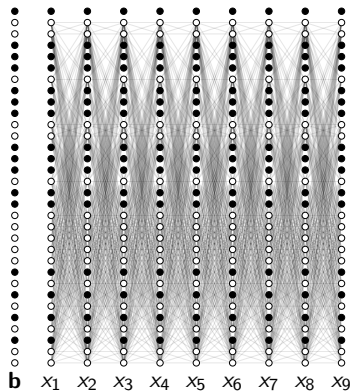
- ▶ At each batch, sample dropout mask  $\mathbf{b} \in \{0, 1\}^Z$
- ▶ Compute distributional parameters by indexing into embeddings  $U, V$

$$\left( \mathbf{b} \circ \begin{array}{|c|} \hline U_{\text{trans}} \\ \hline \end{array} \right) \times \left( \mathbf{b} \circ \begin{array}{|c|} \hline V_{\text{trans}} \\ \hline \end{array} \right)^{\top} \quad \left( \mathbf{b} \circ \begin{array}{|c|} \hline U_{\text{emit}} \\ \hline \end{array} \right) \times \begin{array}{|c|} \hline V_{\text{emit}} \\ \hline \end{array}^{\top}$$

(a) Unnormalized transition logits

(b) Unnormalized emission logits

## State Dropout: Inference



- ▶ Shaded nodes depict dropped states
- ▶ Ignore dropped states during inference

## Technique 3: Block-Sparse Emission Constraints

- ▶ Reduce cost of marginalization by enforcing structure
- ▶ Introduce emission constraints inspired by Cloned HMMs<sup>7</sup>
- ▶ Only allow each word to be emit by a subset of states
- ▶ Cost of inference is quadratic in the size of the largest subset due to sparsity

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<sup>7</sup>Dedieu et al., *Learning higher-order sequential structure with cloned HMMs*.

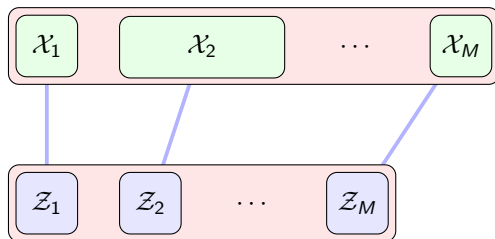
# Block-Sparse Emission Constraints: Alignment

Start with a joint partitioning of both states and words

Indices  $m \in [M]$

State partitions  $\mathcal{Z}_m$

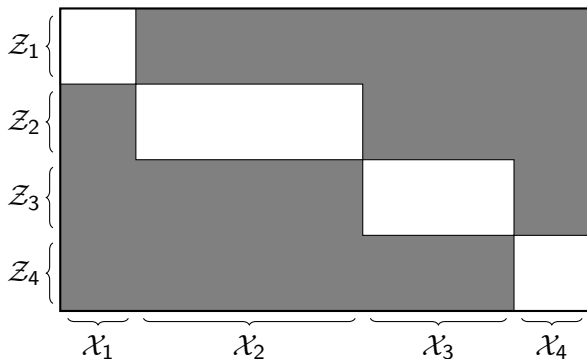
Word partitions  $\mathcal{X}_m$



# Block-Sparse Emission Constraints

Given the unnormalized emission logits,

- ▶ Mask out unaligned state-word entries
- ▶ Normalize rows across words in aligned partition



# Block-Sparse Emissions: Transition Operators

- ▶ The transition operators are defined as

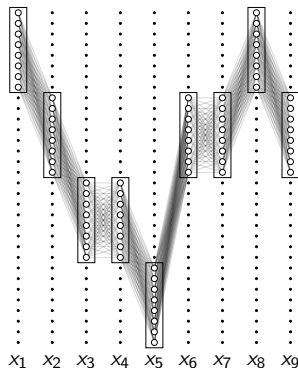
$$\Lambda_t = A \text{diag}([O]_{\cdot, x_t})$$

with transition matrix  $A$  and column of emission matrix  $O$

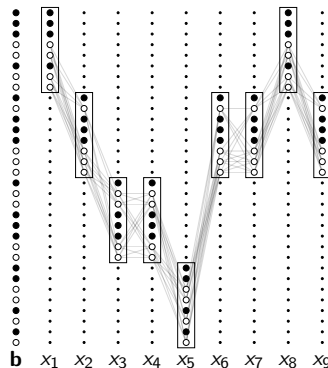
- ▶ Makes the transition operators sparse
  - ▶ Not the transition matrix itself
- ▶ Only affects conditional inference, after observing words  $x$

# Block-Sparse Emissions: Inference

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



(a) Block-sparse emission



(b) With state dropout

# Method Recap

- ▶ Compact neural parameterization

↑ Generalization

- ▶ State dropout

↑ Speed    ↑ Generalization

- ▶ Block-sparse emission constraints

↑ Speed

- ▶ A fourth after experiments



# Experiments

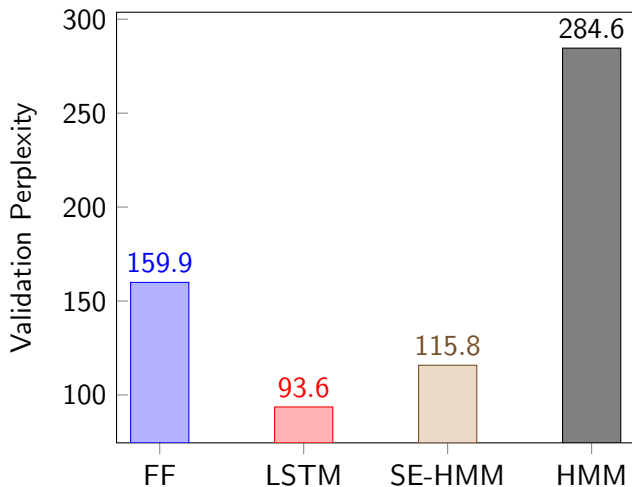
# Experiments

- ▶ Language modeling on Penn Treebank
- ▶ Evaluate perplexity
  - ▶ Function of  $p(x)$
  - ▶ Lower is better
- ▶ Baselines
  - ▶ Feedforward 5-gram model
  - ▶ 2-layer LSTM
  - ▶ A 900 state HMM<sup>8</sup>
- ▶ Model
  - ▶  $2^{15}$  (32k) state sparse emission HMM (SE-HMM)
  - ▶  $M = 128$  groups (256 states per group), obtained via Brown Clustering
  - ▶ Dropout rate of 0.5 during training

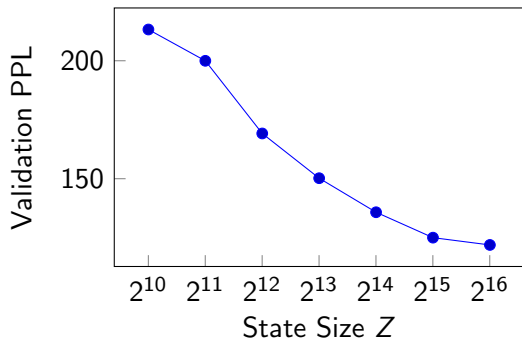
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<sup>8</sup>Byus, Bisk, and Choi, 'Bridging HMMs and RNNs through Architectural Transformations'.

## Results on PTB Validation Data



# State Size Ablation



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

## Other Ablations

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

# Discussion

- ▶ Greatly scaled the state size of HMMs
- ▶ Performance improved with increasing state size
- ▶ Still a large gap between RNNs and HMMs
- ▶ Does the emission sparsity constraint improve computation complexity at the price of accuracy?

# Speeding up HMMs with Low-Rank Factorizations

A work in progress

# Fast Inference with Low-Rank Factorizations

- ▶ The previous approach relied a pre-specified emission sparsity constraint
- ▶ Can we scale inference with a weaker constraint?
- ▶ Exploit structure in the transition matrix to speed up inference



# Inference

Start by unpacking inference to reveal the most expensive step

$$p(x) = \alpha_1^\top \Lambda_2 \Lambda_3 \cdots \Lambda_T \mathbf{1}$$

with

$$\begin{aligned} \text{start,} \quad & [\alpha_1]_{z_1} = p(x_1 \mid z_1)p(z_1), \\ \text{and transition operators,} \quad & [\Lambda_t]_{z_{t-1}, z_t} = p(x_t \mid z_t)p(z_t \mid z_{t-1}) \end{aligned}$$

# Inference

Decompose transition operators into transition matrix  $A$  and emission matrix  $O$

$$\begin{aligned} p(x) &= \alpha_1^\top \Lambda_2 \cdot \Lambda_T \mathbf{1} \\ &= \alpha_1^\top (A \operatorname{diag}([O]_{\cdot, x_2})) \cdots \Lambda_T \mathbf{1} \\ &= \alpha_1^\top A \operatorname{diag}([O]_{\cdot, x_2}) \cdots A \operatorname{diag}([O]_{\cdot, x_T}) \mathbf{1} \end{aligned}$$

where the most expensive steps are the matrix-vector products  $\alpha_t^\top A$ , which take  $O(Z^2)$  computation

# Fast Matrix-Vector Products

- ▶ Goal is to reduce the naive matvec complexity of  $O(Z^2)$
- ▶ Various methods
  - ▶ Sparsity (nnz entries)
  - ▶ Fast Fourier Transform ( $Z \log Z$ )
  - ▶ Low-Rank factorization ( $ZR$ )
- ▶ We utilize low-rank factorizations
- ▶ Connected to work in efficient attention and kernel approximations<sup>9</sup>

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<sup>9</sup>Choromanski et al., *Rethinking Attention with Performers*; Peng et al., *Random Feature Attention*; Blanc and Rendle, *Adaptive Sampled Softmax with Kernel Based Sampling*.

## Low-Rank Factorization

Factor transitions  $A \in [0, 1]^{Z \times Z}$  into product of  $U, V \in \mathbb{R}^{Z \times R}$

$$\boxed{\alpha^\top} \times \boxed{A} = \left( \boxed{\alpha^\top} \times \boxed{U} \right) \times \boxed{V^\top}$$

resulting in two matrix-vector products of cost  $O(ZR)$  each

- ▶ Constraint: Entries of  $A$  must be nonnegative
- ▶ Solution: Use a nonnegative matrix factorization (NMF)

$$A = \phi(U)\phi(V)^\top,$$

with  $\phi : \mathbb{R}^{Z \times R} \rightarrow \mathbb{R}_+^{Z \times R}$

# Method Recap

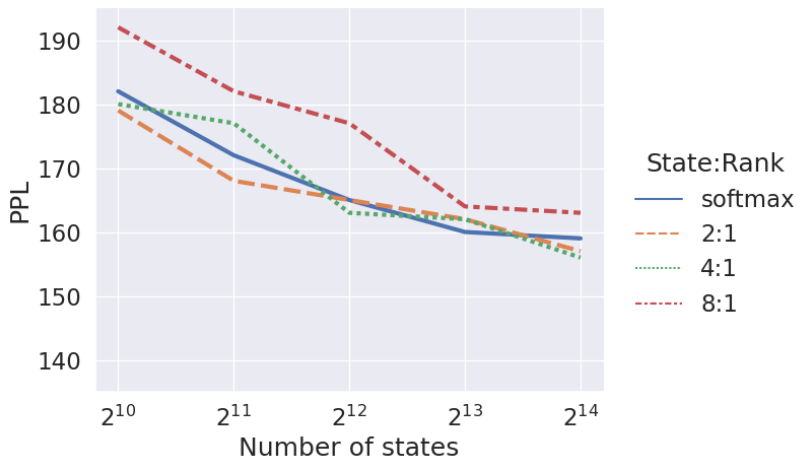
- ▶ Target key  $O(Z^2)$  matvec step in inference
- ▶ Use NMF to reduce cost to  $O(ZR)$
- ▶ How small can  $R$  be relative to  $Z$  without sacrificing accuracy?

# Experiments

# Experiments

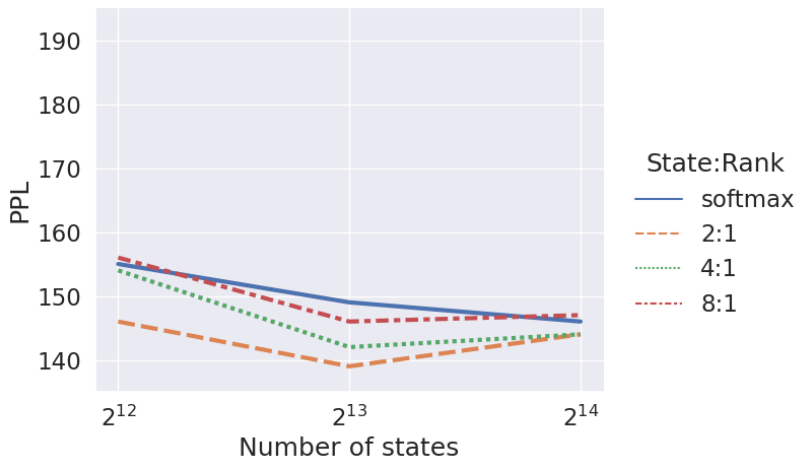
- ▶ Language modeling on PTB
- ▶ Feature map  $\phi(U) = \exp(UW)$ , with learned  $W \in \mathbb{R}^{R \times R}$
- ▶ Baseline: Softmax HMM

## Scaling on PTB (Validation)

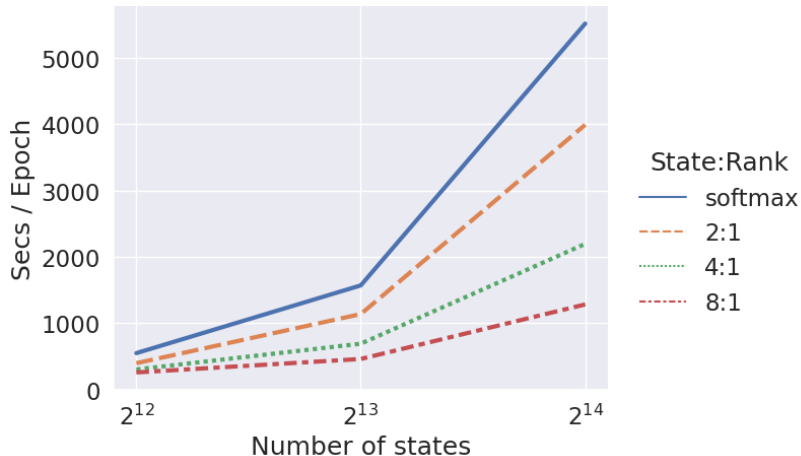




# Further Scaling on PTB with Dropout (Validation)



# Speed Comparison<sup>10</sup>



<sup>10</sup> $2^{14}$  (16k) state SE-HMM takes 506 s/epoch on the same data

# Discussion

- ▶ Reduced computation complexity of inference by 4x with NMF vs softmax HMM
- ▶ Scaling factor not as large as SE-HMM
- ▶ Validation PPL worse than SE-HMM

# Conclusion

- ▶ Extended techniques from neural networks to HMMs
- ▶ Sped up inference using structure in both the emission and transition matrices
- ▶ Demonstrated improvements in perplexity with larger state spaces

# Future Work

- ▶ Explore the performance of more complex interpretable models
  - ▶ Hierarchical HMMs
  - ▶ Factorial HMMs
  - ▶ Probabilistic context-free grammars
  - ▶ Switching linear dynamical systems<sup>11</sup>
  - ▶ Latent vector grammars<sup>12</sup>
- ▶ Explore other structure for fast matrix-vector products and tensor generalizations
  - ▶ FFT-inspired algorithms<sup>13</sup>
- ▶ Other forms of regularization for HMMs
  - ▶ Diversity with DPPs<sup>14</sup>
- ▶ Learn sparsity constraints in SE-HMM
- ▶ Apply sparsity constraints to embedded HMMs<sup>15</sup> for use in approximate inference

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<sup>11</sup>Foerster et al., 'Intelligible Language Modeling with Input Switched Affine Networks'.








<sup>12</sup>Zhao, Zhang, and Tu, 'Gaussian Mixture Latent Vector Grammars'.

<sup>13</sup>Dao et al., 'Kaleidoscope: An Efficient, Learnable Representation For All Structured Linear Maps'.

<sup>14</sup>Qiao et al., 'Diversified Hidden Markov Models for Sequential Labeling'.



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-  Dedieu, Antoine et al. *Learning higher-order sequential structure with cloned HMMs*. 2019. arXiv: 1905.00507 [stat.ML].
-  Foerster, Jakob N. et al. 'Intelligible Language Modeling with

# Generalized Softmax

- Softmax

$$p(z_t \mid z_{t-1}) = \frac{\exp(\mathbf{u}_{z_{t-1}}^\top \mathbf{v}_{z_t})}{\sum_z \exp(\mathbf{u}_{z_{t-1}}^\top \mathbf{v}_z)}$$

- Generalized Softmax

$$p(z_t \mid z_{t-1}) = \frac{K(\mathbf{u}, \mathbf{v})}{\sum_z K(\mathbf{u}, \mathbf{v}_z)} = \frac{\phi(\mathbf{u})^\top \phi(\mathbf{v})}{\sum_z \phi(\mathbf{u})^\top \phi(\mathbf{v}_z)},$$

for positive kernel  $K : \mathbb{R}^D \times \mathbb{R}^D \rightarrow \mathbb{R}_+$  and feature map  $\phi : \mathbb{R}^D \rightarrow \mathbb{R}^R$



# Generalized Softmax: Inference

- ▶ The key  $O(Z^2)$  step in the forward algorithm:

$$p(z_t \mid x_{<t}) = \sum_{z_{t-1}} p(z_t \mid z_{t-1}) p(z_{t-1} \mid x_{<t})$$

- ▶ In matrix form,

$$\gamma_t = \underbrace{\alpha_{t-1}}_{\mathbb{R}^Z} \underbrace{\Lambda}_{\mathbb{R}^{Z \times Z}},$$

where we have the probability of the

current state,	$[\gamma_t]_{z_t} = p(z_t \mid x_{<t}),$
last state,	$[\alpha_{t-1}]_{z_{t-1}} = p(z_{t-1} \mid x_{<t}),$
transition probability,	$[\Lambda]_{z_{t-1}, z_t} = p(z_t \mid z_{t-1})$

# Generalized Softmax: Inference

- ▶ Use generalized softmax in transition distribution

$$[\Lambda]_{z_{t-1}, z_t} = p(z_t \mid z_{t-1}) \propto \phi(\mathbf{u}_{z_{t-1}})^\top \phi(\mathbf{v}_{z_t})$$

- ▶ Allows us to apply associative property of matrix multiplication

$$\begin{aligned}\gamma_t &= \alpha_{t-1} \Lambda \\ &= \alpha_{t-1} (\text{diag}(d) \phi(U) \phi(V)^\top) \\ &= \underbrace{(\alpha_{t-1} \circ d)}_{\mathbb{R}^Z} \underbrace{\phi(U)}_{\mathbb{R}^{Z \times f}} \underbrace{\phi(V)^\top}_{\mathbb{R}^{f \times Z}},\end{aligned}$$

with stacked embeddings  $\phi(U), \phi(V) = [\phi(\mathbf{v}_1), \dots, \phi(\mathbf{v}_Z)]$   
and normalizing constants  $d$

- ▶ Takes  $O(Zf)$  time from left to right!