

# Scaling Hidden Markov Language Models

April 30, 2021

# Language Modeling

*‘OpenAI’s new language generator GPT-3 is shockingly good—and completely mindless’*

Will Douglas Heaven (MIT Tech Review)

A common paradigm in modern NLP

- ▶ Large, opaque models
- ▶ Pretrained via language modeling on large data
- ▶ Fine-tuned on small data 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
- ▶ Language requires encoding long-range context

# Language Models

Language models are primarily

- ▶ Transformers
  - ▶ Encode context into a continuous vector with stacks of attention-based neural networks
- ▶ Recurrent neural networks
  - ▶ Encode context into a continuous vector with stacks of nonlinear dynamical systems

Both are difficult to interpret due to model complexity

# Hidden Markov Language Models

- ▶ Interpretability as a design decision
- ▶ Context is encoded as a single integer
- ▶ Interpretable, but thought to be poor language models<sup>1</sup>

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<sup>1</sup>Byus, Bisk, and Choi, 'Bridging HMMs and RNNs through Architectural Transformations'.

# 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
  - ▶ Word alignment for translation
- ▶ Admits tractable exact inference
  - ▶ Strong conditional independence assumptions
  - ▶ Finite set of discrete latent states



# HMM State Sizes

Year	Data	Model	States
1989	Phoneme Segmentation	HMM <sup>2</sup>	7
1994	POS	HMM <sup>3</sup>	76
2005	Activity Monitoring	DMC HMM <sup>4</sup>	1k
2006	2D Image Tracking	Convolutional HMM <sup>5</sup>	100k
2009	LM	Split-POS HMM <sup>6</sup>	450
2016	POS	Neural HMM <sup>7</sup>	37
2016	Web Traffic Analysis	FFT HMM <sup>8</sup>	81
2019	Char LM	Cloned HMM <sup>9</sup>	30k

<sup>2</sup>Lee and Hon, 'Speaker-independent phone recognition using hidden Markov models'.

<sup>3</sup>Merialdo, 'Tagging English Text with a Probabilistic Model'.

<sup>4</sup>Siddiqi and Moore, 'Fast Inference and Learning in Large-State-Space HMMs'.

<sup>5</sup>Movellan, Hershey, and Susskind, *Real-Time Video Tracking Using Convolution HMMs*.

<sup>6</sup>Huang, Eidelman, and Harper, 'Improving A Simple Bigram HMM Part-of-Speech Tagger by Latent Annotation and Self-Training'.

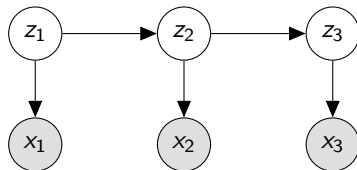
<sup>7</sup>Tran et al., 'Unsupervised Neural Hidden Markov Models'.

<sup>8</sup>Felzenszwalb, Huttenlocher, and Kleinberg, 'Fast Algorithms for Large-State-Space HMMs with Applications to Web Usage Analysis'.

<sup>9</sup>Shen et al., 'Cloned HMMs for Character-Level Language Modeling'.

# 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,  $[\Lambda_t]_{z_{t-1}, z_t} = p(x_t \mid z_t)p(z_t \mid z_{t-1})$

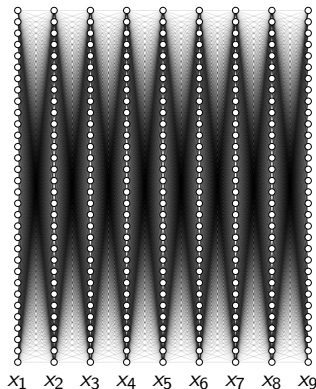
- ▶ Matrix representation of forward algorithm:

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

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

# 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

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

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

- ▶ 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>10</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>10</sup>Srivastava et al., 'Dropout: A Simple Way to Prevent Neural Networks from Overfitting'.

# State Dropout

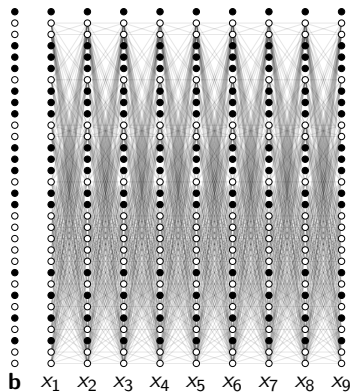
- ▶ At each batch, sample dropout mask  $\mathbf{b} \in \{0, 1\}^Z$
- ▶ Compute distributional parameters by indexing into embeddings  $U, V$

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

(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>11</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>11</sup>Dedieu et al., *Learning higher-order sequential structure with cloned HMMs*.

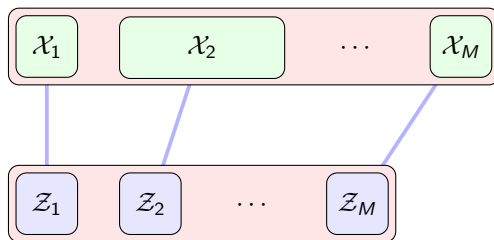
# Block-Sparse Emission Constraints: Alignment

Start with a joint partitioning of both states and words

Indices  $m \in [M]$

State partitions  $\mathcal{Z}_m$

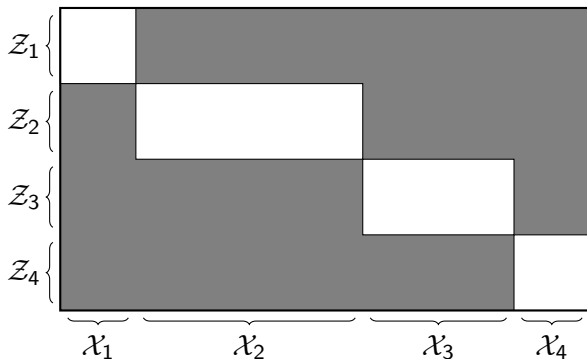
Word partitions  $\mathcal{X}_m$



# Block-Sparse Emission Constraints

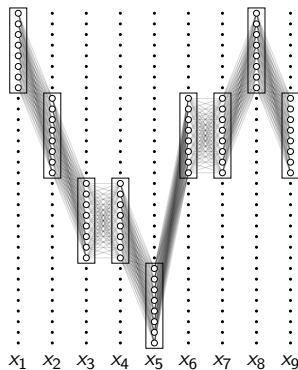
Given the unnormalized emission logits,

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

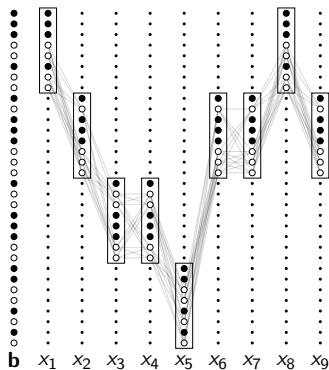


# Block-Sparse Emissions: Inference

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

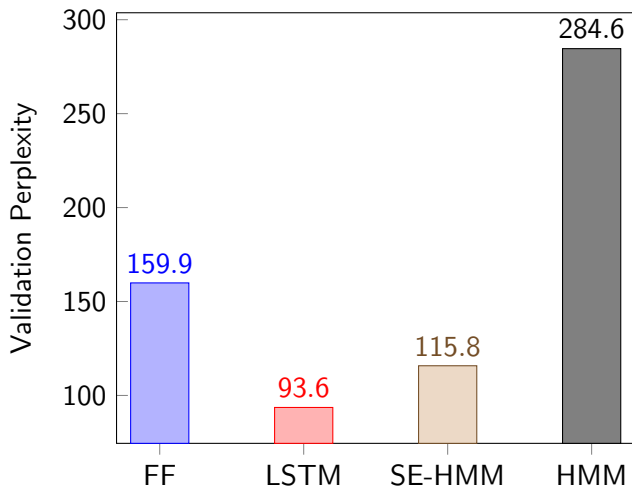
- ▶ A fourth after experiments

## Experiments

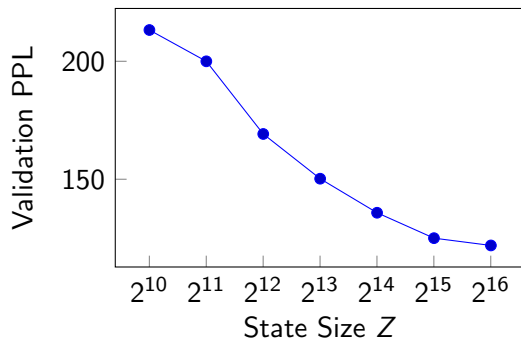
# Experiments

- ▶ Language modeling on Penn Treebank
- ▶ Evaluate perplexity
  - ▶ Function of likelihood
  - ▶ Lower is better
- ▶ Baselines
  - ▶ Feedforward 5-gram model
  - ▶ 2-layer LSTM
  - ▶ A 900 state HMM (Buys et al 2018)
- ▶ Model
  - ▶  $2^{15}$  (32k) state sparse emission HMM (SE-HMM)
  - ▶  $M = 128$  groups (256 states per type), obtained via Brown Clustering
  - ▶ Dropout rate of 0.5 during training

## 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 Decompositions



# Fast Inference with Low-Rank Decompositions

- ▶ 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 decomposition ( $ZR$ )
- ▶ We utilize low-rank decompositions

# Low-Rank Factorization

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

$$\boxed{\alpha^\top} \times \boxed{A} = \boxed{\alpha^\top} \times \boxed{U} \times \boxed{V^\top}$$

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?

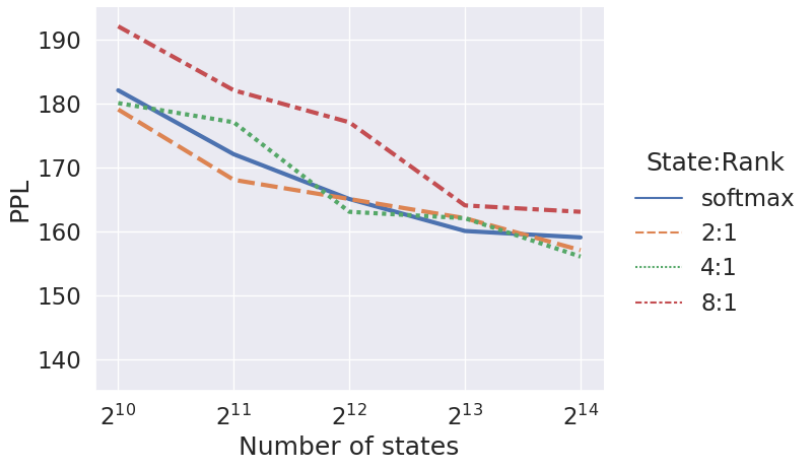
## Experiments

# Experiments

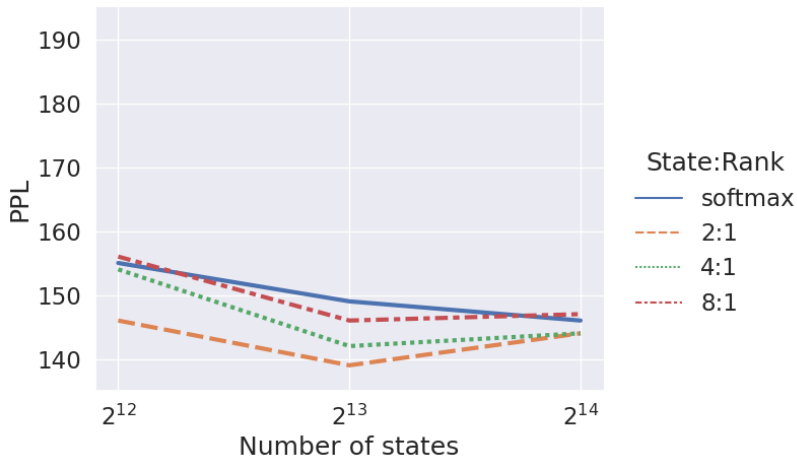
- ▶ Language modeling on PTB
- ▶ Feature map  $\phi(U) = \exp(UW)$ , with learned  $W \in \mathbb{R}^{R \times R}$
- ▶ Baseline: Softmax HMM



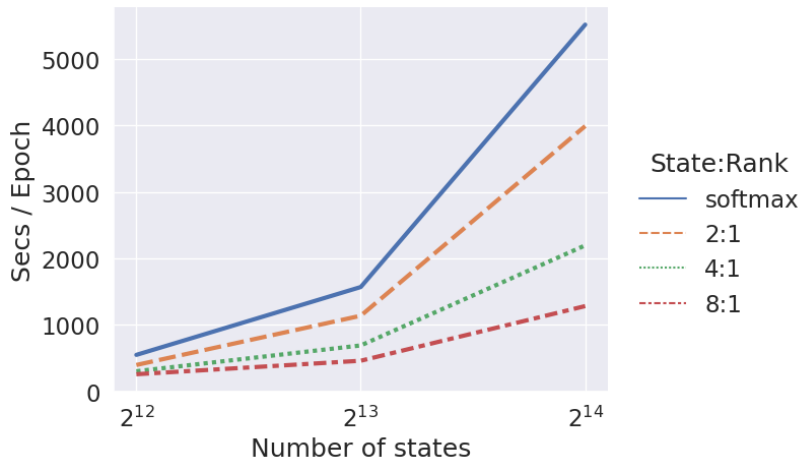
## Scaling on PTB (Validation)



## Further Scaling on PTB with Dropout (Validation)



## Speed Comparison<sup>12</sup>



<sup>12</sup>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 higher than SE-HMM

# Future Work






- ▶ Explore the performance of more complex interpretable models
  - ▶ Switching linear dynamical systems<sup>13</sup>
- ▶ Examine the tradeoffs between

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<sup>13</sup>Foerster et al., 'Intelligible Language Modeling with Input Switched Affine Networks'.

EOS

# Citations

-  Buys, Jan, Yonatan Bisk, and Yejin Choi. 'Bridging HMMs and RNNs through Architectural Transformations'. In: 2018.
-  Dedieu, Antoine et al. *Learning higher-order sequential structure with cloned HMMs*. 2019. arXiv: 1905.00507 [stat.ML].
-  Felzenszwalb, Pedro, Daniel Huttenlocher, and Jon Kleinberg. 'Fast Algorithms for Large-State-Space HMMs with Applications to Web Usage Analysis'. In: *Advances in Neural Information Processing Systems*. Ed. by S. Thrun, L. Saul, and B. Schölkopf. Vol. 16. MIT Press, 2004. URL: <https://proceedings.neurips.cc/paper/2003/file/9407c826d8e3c07ad37cb2d13d1cb641-Paper.pdf>.
-  Foerster, Jakob N. et al. 'Intelligible Language Modeling with Input Switched Affine Networks'. In: *CoRR* abs/1611.09434 (2016). arXiv: 1611.09434. URL: <http://arxiv.org/abs/1611.09434>.
-  Huang, Zhongqiang, Vladimir Eidelman, and Mary Harper. 'Improving A Simple Bigram HMM Part-of-Speech Tagger by Latent Annotation and Self-Training'. In: (June 2009),

# 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!