

State Space LSTM for NLP

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Introduction

- Significance of LSTMs in sequence modeling.
 - LSTMs' ability to capture long-range dependencies.
 - Applications in natural language processing (NLP).
- Interpretability advantages of state space models.
- **Motivation:** Integrating interpretability of state space models with the power of LSTMs.
- **Reference Paper:** [1] *State Space LSTM Models with Particle MCMC Inference*, Xun Zheng et al., CoRR, 2017

Overview

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- 1 From LSTM and SSM to State Space LSTM (SSL)
- 2 Application of the SSL model to the "Topical SSL" experiment
- 3 Inference with Particle Gibbs
- 4 Results: SSL vs LSTM
- 5 Conclusion

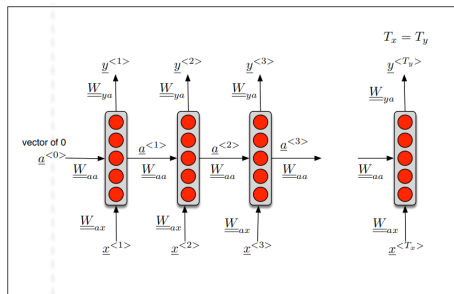
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Recurrent Neural Network: a type of neural network designed to process sequential data

Forward propagation (one hidden layer):

$$s_t = g_1(W_{ss}s_{t-1} + W_{sx}x_t + b_s)$$

$$\hat{y}_t = g_2(W_{ys}s_t + b_y)$$



Back Propagation Through Time (BPTT) and Vanishing Gradient

To train an RNN we need to back-propagate through layers and through time.

$$\frac{\partial \mathcal{L}}{\partial W_{ss}} = \sum_{t=1}^t \frac{\partial \mathcal{L}^{(t)}}{\partial W_{ss}}$$

$$\frac{\partial \mathcal{L}^{(t)}}{\partial W_{ss}} = \sum_{k=0}^t \left(\prod_{i=k+1}^t \frac{\partial s_i}{\partial s_{i-1}} \right) \frac{\partial s_k}{\partial W_{aa}}$$

Vanishing gradient appends when $|\frac{\partial s_i}{\partial s_{i-1}}| < 1$:

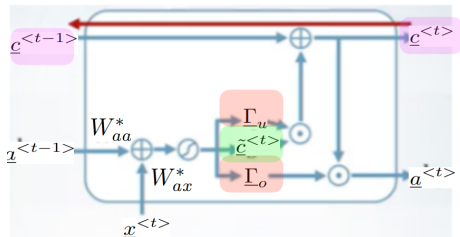
- Contributions from faraway steps vanish and don't affect the training
- Difficult to learn long-range dependencies

LSTM: a type of RNN introduced to learn long-term dependencies

Simplified LSTM:

We add a new path: the **memory cell** c_t

- The candidate cell value \tilde{c}_t is added to the memory cell if the update gate Γ_u is open.
- The hidden state is output if the output gate Γ_o is open



LSTM vs. SSM

Model	Pros	Cons
LSTM	Capture long-term dependencies	Not interpretable
SSM	Interpretable	Cannot capture long-term dependencies due to the Markovian nature of the latent variable process

Table: Comparison of LSTM and SSM

SSL: a combination of SSM and LSTM models

Main idea: we place an LSTM on the latent space to simulate the states z_t . We then generate the observations x_t from a SSM.

Generative process:

- ① $s_t = LSTM(s_{t-1}, z_{t-1})$ (LSTM part)
- ② $z_t | z_{1:t-1} \sim p_\omega(z_t | z_{1:t-1}) =: p_\omega(z; g(s_t))$ (LSTM part)
- ③ $x_t | z_t \sim p_\phi(x; h(z_t))$ (SSM part)

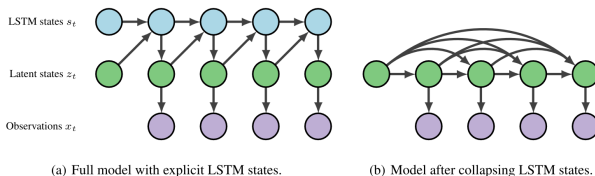


Figure 1: Generative process of SSL.

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Background

Topical SSL:

- $x = (x_1, \dots, x_t, \dots, x_T)$ is a text sequence of length T
- $z = (z_1, \dots, z_t, \dots, z_T)$ is a sequence of unobserved topics characterizing the words in x

Example:

- $x = ("I", "was", "born", "in", "Palaiseau", "in", "1999")$
- $z = ("Pronoun", "Verb", "Verb", "Preposition", "City", "Preposition", "Date")$

Goal: create a generative model. Given a sequence (x_1, \dots, x_t) , we want to predict (x_{t+1}, \dots, x_T) .

Generative Model

x_t and z_t are discrete variables:

- $x_t \in \{1, \dots, N\}$
- $z_t \in \{1, \dots, K\}$

Where N is the size of the vocabulary and K is the number of topics. The SSL model can be written as:

- ① $z_t | z_{1:t-1} \sim \text{Categorical}(\text{softmax}(Ws_t + b))$ (*LSTM*)
- ② $x_t | z_t \sim \text{Categorical}(\phi_{z_t})$ (*SSM*)

Where:

- $\text{softmax}(Ws_t + b) = [p_\omega(z_t = 1 | z_{1:t-1}), \dots, p_\omega(z_t = K | z_{1:t-1})]'$
- $\phi_{z_t} = [p_\phi(x_t = 1 | z_t), \dots, p_\phi(x_t = N | z_t)]'$

Dataset used, pre processing and technical aspects

Dataset:

- IMBD dataset [2] : 25,000 movie reviews, keep $n = 200$ reviews
- Consider the 5000 "top words": $N = 5000$
- Truncation of the sequences: $T = 170$
 - $T_{\text{train}} = 100$
 - $T_{\text{test}} = 70$

LSTM:

- 64 hidden neurons
- Add a dropout layer with $p = 0.2$
- Optimizer: Adam
- z_t variables are one hot encoded in LSTM part

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Particle Gibbs: a way to sample from the variational distribution in EM algorithm

Main idea:

We combine EM algorithm with backpropagation to train the SSL model. For each text and at each iteration of the EM algorithm, we sample $z_{1:T_{\text{train}}}^*$ from the variational distribution in order to compute the MLE of the SSM and the LSTM. To sample $z_{1:T_{\text{train}}}^*$ we use an algorithm called **Particle Gibbs**.

Particle Gibbs Inference

- Sequential Monte Carlo (SMC) method
- Particle Gibbs inference for sampling from joint posterior
- No factorization assumptions

Particle Gibbs Inference

Algorithm Inference with Particle Gibbs

Require: P : number of particles, T : length of the sequence

- 1: Initialize $z_0^p = z_0$ and $\alpha_0^p = \frac{1}{P}$ for $p = 1, \dots, P$
 - 2: **for** $t = 1, \dots, T$ **do**
 - 3: Fix reference path: set $a_{t-1}^1 = 1$ and $z_{1:t}^1 = z_{1:t}^*$ from the previous iteration
 - 4: **for** $p = 2, \dots, P$ **do**
 - 5: Sample ancestors $a_{t-1}^p \sim \alpha_{t-1}$
 - 6: **end for**
 - 7: **for** $p = 2, \dots, P$ **do**
 - 8: Sample particles $z_t^p \sim \gamma_t^p$ and set $z_{1:t}^p = (z_{1:t-1}^{a_{t-1}^p}, z_t^p)$
 - 9: **end for**
 - 10: **for** $p = 1, \dots, P$ **do**
 - 11: Compute normalized weights α_t^p
 - 12: **end for**
 - 13: **end for**
 - 14: Sample $r \sim \alpha_T$
 - 15: **return** the particle path $z_{1:T}^{a_T^r}$
-

Particle Gibbs Inference

Recall:

- $\text{softmax}(Ws_t + b) = [p_\omega(z_t = 1|z_{1:t-1}), \dots, p_\omega(z_t = K|z_{1:t-1})]'$
- $\phi_{z_t} = [p_\phi(x_t = 1|z_t), \dots, p_\phi(x_t = N|z_t)]'$

Let $\phi = [\phi_1, \dots, \phi_K] \in \mathbb{R}^{N \times K}$, such as $\phi[i, j] = p_\phi(x_t = i|z_t = j)$. Here:

- $\alpha_t = p(x_t|z_{1:t-1}) \propto \sum_{k=1}^K \text{softmax}(Ws_t + b)[k] \odot \phi_k$: unnormalized distribution on $\{1, \dots, N\}$
- $\gamma_t = p(z_t|z_{1:t-1}, x_t) \propto \text{softmax}(Ws_t + b) \odot \phi[x_t, 1 : K]$: unnormalized distribution on $\{1, \dots, K\}$

Training Loop

Algorithm Training Loop for Topical SSL

Require: S_x : set of training sequences, P : number of particles, K : number of topics, N : size of the vocabulary, n : number of training samples, n_epochs : number of epochs, n_iter_EM : number of EM iterations

```

1: for  $i = 1, \dots, n$  do
2:    $z_{1:T_{\text{train}}}^* \sim \text{i.i.d } \mathcal{U}\{1, \dots, K\}$ 
3: end for
4: for epoch = 1, ...,  $n\_epochs$  do
5:    $S_{z_{1:T_{\text{train}}}^*} = [ ]$ 
6:   for  $i = 1, \dots, n$  do
7:     for iter_EM = 1, ...,  $n\_iter\_EM$  do
8:       Compute  $z_{1:T_{\text{train}}}^*$  by Particle Gibbs using previous  $z_{1:T_{\text{train}}}^*$ 
9:       Train LSTM with  $z_{1:T_{\text{train}}}^*$  by back-propagation
10:      Compute the MLE of the SSM on  $S_x[1 : i]$  and  $(S_{z_{1:T_{\text{train}}}^*}[1 : i - 1], z_{1:T_{\text{train}}}^*)$ 
11:    end for
12:    Add  $z_{1:T_{\text{train}}}^*$  to  $S_{z_{1:T_{\text{train}}}^*}$ 
13:  end for
14: end for

```

Implementation Details

- All the algorithms coded in `pytorch`
 - GPU usage for LSTM
 - CPU usage for other parts
- $n_epochs = 5$ and $n_iter_EM = 1$ (computational constraint)
- $P = 10$
- $K \in \{10, 50, 100\}$
- Evaluation metric: perplexity - exponential of the categorical cross entropy

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Perplexity curve for the LSTM model

Baseline

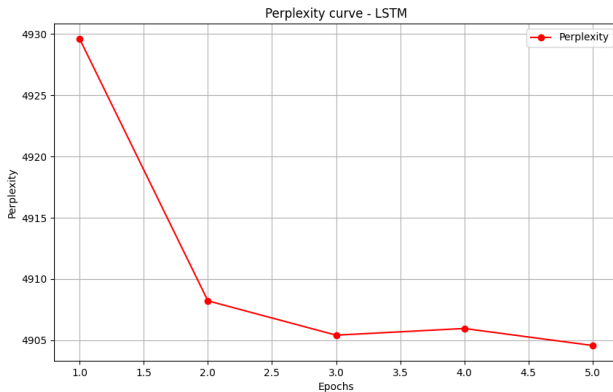
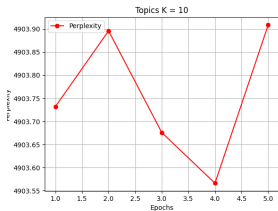
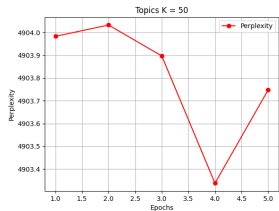


Figure: Perplexity through epochs for standard LSTM

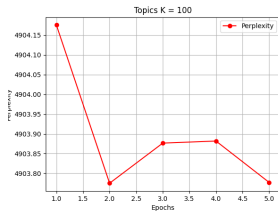
Perplexity curves for the SSL model



10 Topics



50 Topics



100 Topics

Topics Visualization (Interpretability)

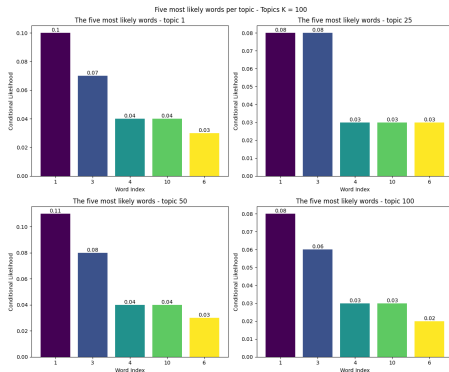


Figure: Latent Topics Visualization

Key insight: Conditionally on topic 50, the third word in the vocabulary is the second word most likely to appear, with a conditional probability of 0.08.

Conclusion: pros and cons of SSL

Pros:

- Similar performances to the LSTM model on our dataset. In the article, LSTM provides better results, but the amount of data is much greater
- Results are interpretable (main advantage)

Cons:

- Computational complexity: assuming that all internal operations can be performed in constant time (which is not the case), the algorithmic complexity of the Particle Gibbs algorithm is $\mathcal{O}(P + T(P - 1)^2P)$ for a single observation.
- Concretely, with the same set-up: about 5 minutes to run one epoch with LSTM versus about 4 hours with SSL.
- Choice of K : K too high can lead to overfitting whereas K too low can lead to underfitting

References



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Q & A

Thank you!
Questions?