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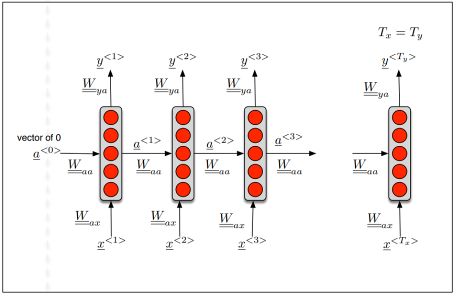
Reccurent Neural Network: a type of neural network designed to process sequential data

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 $|\frac{\partial s_i}{\partial s_{i-1}}| < 1$:

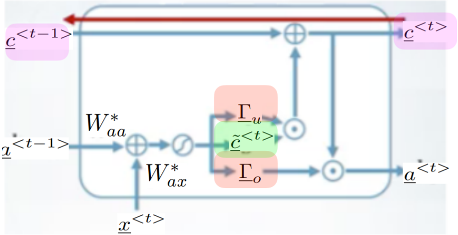
- Contributions from faraway steps vanish and don't affect the training
- Difficult to learn long-range dependencies

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)

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Background

Topical SSL:

- $x = (x_1, \ldots, x_t, \ldots, x_T)$ is a text sequence of lenght T
- $z = (z_1, \ldots, z_t, \ldots, z_T)$ is a sequence of unobserved topics which characterize 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 $(x_1, \ldots, x_t)$, we want to predict $(x_{t+1}, \ldots, x_T)$.

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 $\phi_{z_t} = (p(x = 1|z), \dots, p(x = N|z))'$

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 particules, T: length of the sequence

```
Initialize z_0^p = z_0 and α_0^p = 1/P for p = 1, ..., P
for t = 1, ..., T do
    Fix reference path: set a_{t-1}^1 = 1 and z_{1:t}^1 = z_{1:t}^* from the previous iteration
    for p = 2, ..., P do
        Sample ancestors a_{t-1}^p ~ α_{t-1}
    end for
    for p = 2, ..., P do
        Sample particles z_t^p ~ γ_t^p and set z_{1:t}^p = (z_{1:t-1}^{a_{t-1}^p}, z_t^p)
    end for
    for p = 1, ..., P do
        Compute normalized weights α_t^p
    end for
end for
Sample r ~ α_T
return the particle path z_{1:T}^{a_T^r}
```

Training Loop

Algorithm Training Loop for Topical SSL

Require: S_x: set of training sequences, P: number of particules, 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

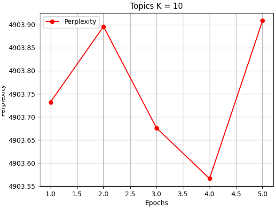
for $i = 1, \dots, n$ **do**
  $z^*_{1:T_{\text{train}}} \sim$ i.i.d $\mathcal{U}\{1, \dots, K\}$
end for
for epoch $= 1, \dots,$ n_epochs **do**
  $S_{z^*_{1:T_{\text{train}}}} = [\,]$
  for $i = 1, \dots, n$ **do**
    for iter_EM $= 1, \dots,$ n_iter_EM **do**
      Compute $z^*_{1:T_{\text{train}}}$ by Particle Gibbs using previous $z^*_{1:T_{\text{train}}}$
      Train LSTM with $z^*_{1:T_{\text{train}}}$ by back-propagation
      Compute the MLE of the SSM on $S_x[1 : i]$ and $(S_{z^*_{1:T_{\text{train}}}}[1 : i-1], z^*_{1:T_{\text{train}}})$
    end for
    Add $z^*_{1:T_{\text{train}}}$ to $S_{z^*_{1:T_{\text{train}}}}$
  end for
end for

Implementation details

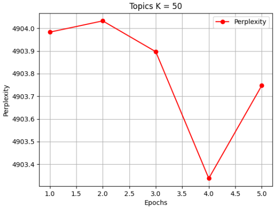
- All the algorithms implemented in `pytorch`
  - GPU usage for LSTM
  - CPU usage for other parts
- n_epochs = 5 and n_iter_EM = 1 (computational constraint)
- $P = 10$
- $K \in \{10, 50, 100\}$

Results

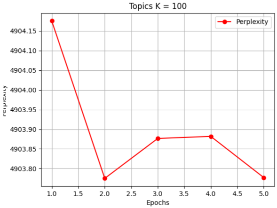
Perplexity Curves



10 Topics



50 Topics



100 Topics

Standard LSTM

Baseline

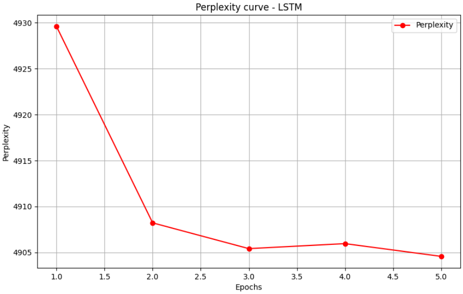


Figure: Perplexity through epochs for standard LSTM

Topics Visualization (Interpretability)

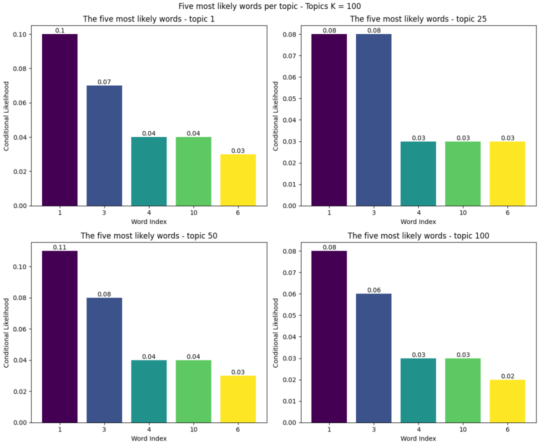


Figure: Latent Topics Visualization

Conclusion

- Key results :
  - Impact of Topical SSL on NLP interpretability
  - Newly proposed inference method can be (much) slower
- Potential extensions :
  - Reduce computing time (parallelization)
  - Better optimization of hyperparameters (number of particles, topics, dropout, ...)

References

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Q & A

Thank you!
Questions?