CS 6501 Natural Language Processing

Recurrent Neural Networks

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Overview

1. Recurrent Neural Networks
2. RNN Language Modeling
3. Challenge of Training RNNs
4. Variants of RNNs
5. Applications

Recurrent Neural Networks

RNNs

A simple RNN is defined as

$$\boldsymbol{h}_t = \boldsymbol{f}(\boldsymbol{x}_t, \boldsymbol{h}_{t-1}) \tag{1}$$

where $\boldsymbol{x}_t$ and $\boldsymbol{h}_t$ is the input and hidden state at time t, and $\boldsymbol{b}$ is the bias. $\mathbf{W}_h$ and $\mathbf{W}_i$ are the weight matrices for hidden states and inputs respectively.

Transition Function

For the simplest case, f is an element-wise sigmoid function as

$$\boldsymbol{f}(\boldsymbol{x}_t, \boldsymbol{h}_{t-1}) = \boldsymbol{f}(\mathbf{W}_h \boldsymbol{h}_{t-1} + \mathbf{W}_i \boldsymbol{x}_t + \boldsymbol{b}) \tag{2}$$

Unfolding RNNs

Recursive:

$$\boldsymbol{h}_t = f(\boldsymbol{x}_t, \boldsymbol{h}_{t-1}) \tag{3}$$

Unfolded:

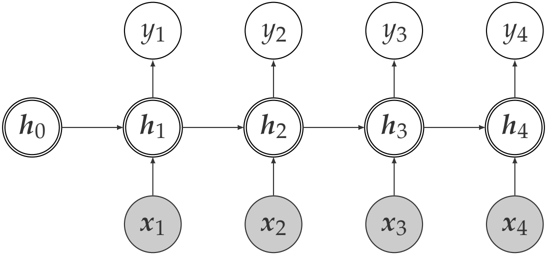
$$\begin{aligned}
\boldsymbol{h}_t &= f(\boldsymbol{x}_t, f(\boldsymbol{x}_{t-1}, \boldsymbol{h}_{t-2})) \\
&= f(\boldsymbol{x}_t, f(\boldsymbol{x}_{t-1}, f(\boldsymbol{x}_{t-2}, \boldsymbol{h}_{t-3}))) \\
&= \cdots \\
&= f(\boldsymbol{x}_t, f(\boldsymbol{x}_{t-1}, f(\boldsymbol{x}_{t-2}, \cdots f(\boldsymbol{x}_1, \boldsymbol{h}_0) \cdots)))
\end{aligned} \tag{4}$$

Base Condition

$$h_t = f(x_t, f(x_{t-1}, f(x_{t-2}, \cdots f(x_1, h_0) \cdots))) \qquad (5)$$

- h_0: zero vector or parameter
- x_1: input at time $t = 1$

Plot



Output

Loss at single time step t

$$L_t(y_t, \hat{y}_t) = \|y_t - \hat{y}_t\|_2^2 \tag{6}$$

where y_t and $\hat{y}_t = g(\boldsymbol{h}_t)$ are the ground truth and predicted output respectively.

The total loss is given as

$$\ell = \sum_{t=1}^{T} L_t \tag{7}$$

RNN Language Modeling

RNN Language Models

For a given sentence $\{x_1, \ldots, x_T\}$, the input at time t is word embedding $\boldsymbol{x}_t$. The probability distribution of next word X_{t+1}

$$P(X_{t+1} = x) = \frac{\exp(\boldsymbol{w}_{o,x}^\top \boldsymbol{h}_t)}{\sum_{x'} \exp(\boldsymbol{w}_{o,x'}^\top \boldsymbol{h}_t)} \tag{8}$$

where $\boldsymbol{w}_{o,x}$ is the output weight vector related to word x.

Special Cases

$$\{\texttt{start}, x_1, \ldots, x_T, \texttt{stop}\}$$

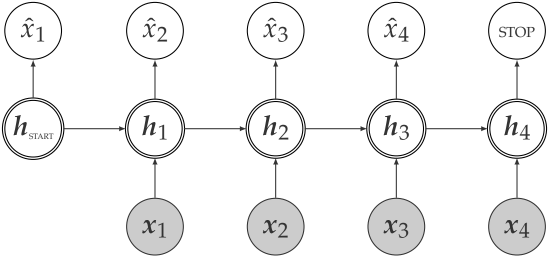
At time $t = 1$

$$P(X_1 = x) \propto \exp(\boldsymbol{w}_{o,x}^\top \boldsymbol{h}_{\texttt{start}}) \tag{9}$$

At time $t = T$

$$P(X_T = \texttt{stop}) \propto \exp(\boldsymbol{w}_{o,x}^\top \boldsymbol{h}_T) \tag{10}$$

Plot



$\hat{x}_1$
$\hat{x}_2$
$\hat{x}_3$
$\hat{x}_4$
STOP
h_{START}
h_1
h_2
h_3
h_4
x_1
x_2
x_3
x_4

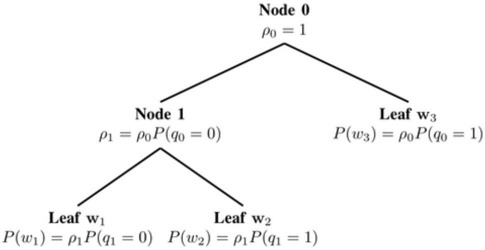
Normalization Term

$$P(X_{t+1} = x) = \frac{\exp(\boldsymbol{w}_{o,x}^{\top}\boldsymbol{h}_t)}{\sum_{x'} \exp(\boldsymbol{w}_{o,x'}^{\top}\boldsymbol{h}_t)} \quad (11)$$

Options:

- Negative sampling (x)
- Hierarchical softmax
- Class-factored softmax

Hierarchical Softmax



Class-factored Softmax: Definition

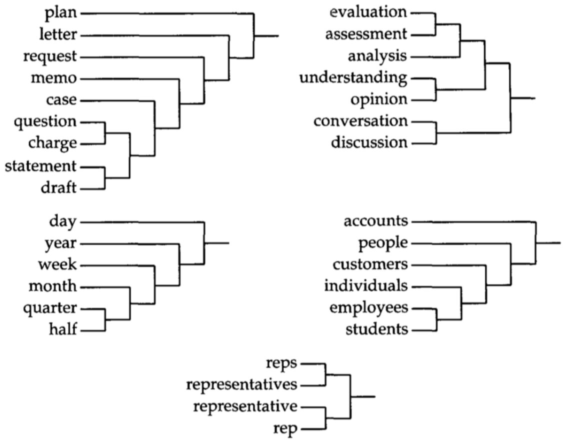
- Partition the vocab into K classes $\{\mathscr{C}_1, \ldots, \mathscr{C}_K\}$, such that $\mathscr{V} = \cup \mathscr{C}_k$ and $\mathscr{C}_k \cap \mathscr{C}_{k'} = \emptyset$ for any $k' \neq k$
- Define the probability distribution of word as

$$\begin{aligned} P(X_{t+1} = x; \boldsymbol{h}_t) = & P(X_{t+1} = x, C_{t+1} = c; \boldsymbol{h}_t) \\ = & P(X_{t+1} = x \mid C_{t+1} = c; \boldsymbol{h}_t) \\ & \cdot P(C_{t+1} = c \mid \boldsymbol{h}_t) \end{aligned} \tag{12}$$

[Baltescu and Blunsom, 2014]

Class-factored Softmax: Word clusters

Brown clusters



[Brown et al., 1992]

Plot

Computational Complexity

Model	Training/Decoding
Standard	$\mathcal{O}(\lvert\mathcal{V}\rvert \cdot D)$
Hierarchical	$\mathcal{O}(\log \lvert\mathcal{V}\rvert \cdot D)$
Class-factored	$\mathcal{O}(\sqrt{\lvert\mathcal{V}\rvert} \cdot D)$

Table: Computational complexities of different softmax functions.

Challenge of Training RNNs

Backpropagation Through Time

The algorithm used to train RNNs is called *Backpropagation Through Time* [Rumelhart et al., 1985, BPTT].

Consider the gradient of ℓ with respect to the network parameters $\boldsymbol{\theta} = \{\mathbf{W}_h, \mathbf{W}_i, \boldsymbol{b}\}$,

$$\frac{\partial \ell}{\partial \boldsymbol{\theta}} = \sum_{t=1}^{T} \frac{\partial L_t}{\partial \boldsymbol{\theta}} \tag{13}$$

Gradients

For each time step t, we have

$$\frac{\partial L_t}{\partial \boldsymbol{\theta}} = \sum_{i=1}^{t} \frac{\partial L_t}{\partial \boldsymbol{h}_t} \frac{\partial \boldsymbol{h}_t}{\partial \boldsymbol{h}_i} \frac{\partial \boldsymbol{h}_i}{\partial \boldsymbol{\theta}} \tag{14}$$

where both $\frac{\partial L_t}{\partial \boldsymbol{h}_t}$ and $\frac{\partial \boldsymbol{h}_i}{\partial \boldsymbol{\theta}}$ are the intermediate gradients

Gradients (Cont.)

Computation of $\frac{\partial \boldsymbol{h}_t}{\partial \boldsymbol{h}_i}$ requires the chain rule in calculus,

$$\frac{\partial \boldsymbol{h}_t}{\partial \boldsymbol{h}_i} = \prod_{j=i+1}^{t} \frac{\partial \boldsymbol{h}_j}{\partial \boldsymbol{h}_{j-1}}. \tag{15}$$

which can be justified by the unfolded version of $\boldsymbol{h}_t$

$$
\begin{aligned}
\boldsymbol{h}_t &= f(\boldsymbol{x}_t, f(\boldsymbol{x}_{t-1}, \boldsymbol{h}_{t-2})) \\
&= f(\boldsymbol{x}_t, f(\boldsymbol{x}_{t-1}, f(\boldsymbol{x}_{t-2}, \boldsymbol{h}_{t-3}))) \\
&= \cdots \\
&= f(\boldsymbol{x}_t, f(\boldsymbol{x}_{t-1}, f(\boldsymbol{x}_{t-2}, \cdots f(\boldsymbol{x}_1, \boldsymbol{h}_0) \cdots))) \qquad (16)
\end{aligned}
$$

Challenges

$$\frac{\partial \boldsymbol{h}_t}{\partial \boldsymbol{h}_i} = \prod_{j=i+1}^{t} \frac{\partial \boldsymbol{h}_j}{\partial \boldsymbol{h}_{j-1}}. \tag{17}$$

- vanishing gradients
- exploding gradients

[Pascanu et al., 2013]

Exploding Gradients

Solution: **norm clipping** [Pascanu et al., 2013].

Consider the gradient $\boldsymbol{g} = \frac{\partial \ell}{\partial \boldsymbol{\theta}}$,

$$\hat{\boldsymbol{g}} \leftarrow \tau \cdot \frac{\boldsymbol{g}}{\|\boldsymbol{g}\|} \tag{18}$$

when $\|\boldsymbol{g}\| > \tau$. Usually, $\tau = 3$ or 5 in practice.

Vanishing Gradients

Solution:

- initialize parameters carefully
- replace hidden state function $\sigma()$ with other options
  - LSTM [Hochreiter and Schmidhuber, 1997]
  - GRU [Cho et al., 2014]

Long Short-Term Memory

$$\boldsymbol{i}_t = \sigma(\mathbf{W}_{xi}\boldsymbol{x}_t + \mathbf{W}_{hi}\boldsymbol{h}_{t-1} + \mathbf{W}_{ci}\boldsymbol{c}_{t-1} + \boldsymbol{b}_i) \quad (19)$$

$$\boldsymbol{f}_t = \sigma(\mathbf{W}_{xf}\boldsymbol{x}_t + \mathbf{W}_{hf}\boldsymbol{h}_{t-1} + \mathbf{W}_{cf}\boldsymbol{c}_{t-1} + \boldsymbol{b}_f) \quad (20)$$

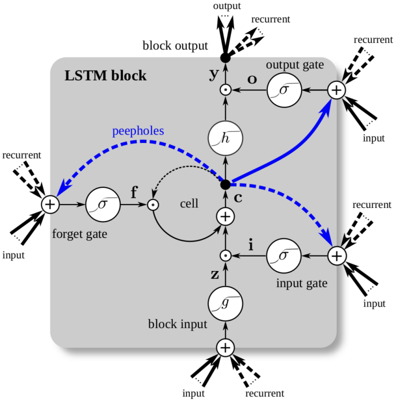
$$\boldsymbol{c}_t = \boldsymbol{f}_t \circ \boldsymbol{c}_{t-1} + \boldsymbol{i}_t \circ \tanh(\mathbf{W}_{xc}\boldsymbol{x}_t + \mathbf{W}_{hc}\boldsymbol{h}_{t-1} + \boldsymbol{b}_c) \quad (21)$$

$$\boldsymbol{o}_t = \sigma(\mathbf{W}_{xo}\boldsymbol{x}_t + \mathbf{W}_{ho}\boldsymbol{h}_{t-1} + \mathbf{W}_{co}\boldsymbol{c}_t + \boldsymbol{b}_o) \quad (22)$$

$$\boldsymbol{h}_t = \boldsymbol{o}_t \circ \tanh(\boldsymbol{c}_t) \quad (23)$$

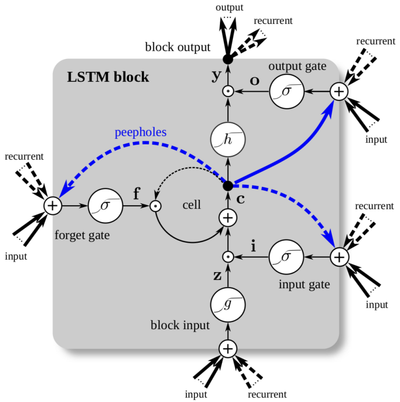
$\circ$ is the element-wise multiplication [Graves, 2013]

LSTM



output
recurrent
block output
recurrent
LSTM block
y
o
output gate
σ
input
peepholes
h
recurrent
f
cell
c
σ
forget gate
recurrent
input
i
σ
z
input gate
input
g
block input
input
recurrent

LSTM



- Forget gate f_t — discounting on the memory cell
- Peephole connections (connections in blue color) [Gers and Schmidhuber, 2000]

A Simple LSTM

A LSTM without forget gate and peephole connections

$$\begin{aligned}
\boldsymbol{i}_t &= \sigma(\mathbf{W}_{xi}\boldsymbol{x}_t + \mathbf{W}_{hi}\boldsymbol{h}_{t-1} + \boldsymbol{b}_i) && (24)\\
\boldsymbol{o}_t &= \sigma(\mathbf{W}_{xo}\boldsymbol{x}_t + \mathbf{W}_{ho}\boldsymbol{h}_{t-1} + \boldsymbol{b}_o) && (25)\\
\boldsymbol{c}_t &= \boldsymbol{c}_{t-1} + \boldsymbol{i}_t \circ \tanh(\mathbf{W}_{xc}\boldsymbol{x}_t + \mathbf{W}_{hc}\boldsymbol{h}_{t-1} + \boldsymbol{b}_c) && (26)\\
\boldsymbol{h}_t &= \boldsymbol{o}_t \circ \tanh(\boldsymbol{c}_t) && (27)
\end{aligned}$$

[Greff et al., 2017]

Gated Recurrent Units

A gated recurrent unit (GRU) was proposed in [Cho et al., 2014].

$$
\begin{aligned}
\boldsymbol{r}_t &= \sigma(\mathbf{W}_{rx}\boldsymbol{x}_t + \mathbf{W}_{rh}\boldsymbol{h}_{t-1}) && (28)\\
\tilde{\boldsymbol{h}}_t &= \tanh(\mathbf{W}_{hx}\boldsymbol{x}_t + \mathbf{W}_{hr}(\boldsymbol{r}_t \odot \boldsymbol{h}_{t-1})) && (29)\\
\boldsymbol{z}_t &= \sigma(\mathbf{W}_{zx}\boldsymbol{x}_t + \mathbf{W}_{zh}\boldsymbol{h}_{t-1}) && (30)\\
\boldsymbol{h}_t &= (1 - \boldsymbol{z}_t) \odot \boldsymbol{h}_{t-1} + \boldsymbol{z}_t \odot \tilde{\boldsymbol{h}}_t && (31)\\
& && (32)
\end{aligned}
$$

Empirical results show GRU units are *comparable* to LSTM units [Chung et al., 2014].

Variants of RNNs

Overview

- Bi-directional RNNs
- Stacked (*or* Multi-layer) LSTM
- Memory networks [Weston et al., 2014]
- Recurrent neural network grammars [Dyer et al., 2016]

Bi-directional RNNs

To construct a bi-directional RNN, we need another uni-directional RNN running from the end of the sequence to the beginning, as

$$\boldsymbol{u}_t = f(\boldsymbol{x}_t, \boldsymbol{u}_{t+1}). \tag{33}$$

where $\boldsymbol{u}_t$ is the hidden state at time t in this new model.

[Schuster and Paliwal, 1997]

Stacked LSTM

Use the hidden state $\boldsymbol{h}_t^{(k)}$ from the current layer as input $\boldsymbol{x}_t^{(k+1)}$ to the next layer [Sutskever et al., 2014],

$$\boldsymbol{x}_t^{(k+1)} = \boldsymbol{h}_t^{(k)}. \tag{34}$$

[Sutskever et al., 2014]

Applications

Applications

- Language modeling
- POS tagging
- Named entity recognition
- Code switch
- ...

NER

Example

`Atlantis touched down at Kennedy Space Center`

NER

Example

[Atlantis]$_{\text{MSIC}}$ touched down at [Kennedy Space Center]$_{\text{LOC}}$

NER

Example

`[Atlantis]`$_{\text{MSIC}}$ `touched down at [Kennedy Space Center]`$_{\text{LOC}}$

Tag set

- B: beginning
- I: inside
- O: outside

Category

- Person
- Location
- Organization
- Msic

NER

Example

`[Atlantis]`$_{\text{MSIC}}$ `touched down at [Kennedy Space Center]`$_{\text{LOC}}$

Tag set

- B: beginning
- I: inside
- O: outside

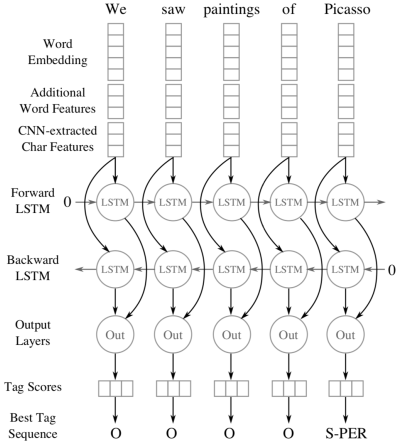
Category

- Person
- Location
- Organization
- Msic

Atlantis	touched	down	at	Kennedy	Space	Center	.
B_{MSIC}	O	O	O	B_{LOC}	I_{LOC}	I_{LOC}	O

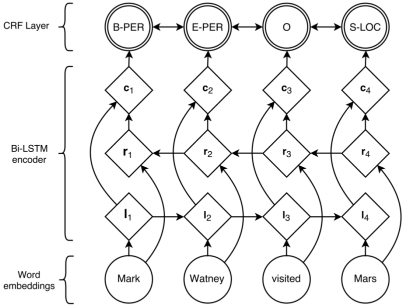
NER (Cont.)

As classification



NER (Cont.)

As sequential modeling (CRFs)



Summary

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Reference

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