SFU NatLangLab

Natural Language Processing

Anoop Sarkar
anoopsarkar.github.io/nlp-class

Simon Fraser University

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Part 1: Long distance dependencies

Long distance dependencies

Example

- He doesn't have very much confidence in himself
- She doesn't have very much confidence in herself

n-gram Language Models: $P(w_i \mid w_{i-n+1}^{i-1})$

$$\begin{aligned} P(\text{himself} &\mid \text{confidence}, \text{in}) \\ P(\text{herself} &\mid \text{confidence}, \text{in}) \end{aligned}$$

What we want: $P(w_i \mid w_{<i})$

$$\begin{aligned} P(\text{himself} &\mid \text{He}, \ldots, \text{confidence}) \\ P(\text{herself} &\mid \text{She}, \ldots, \text{confidence}) \end{aligned}$$

Long distance dependencies

Other examples

- **Selectional preferences**: *I ate lunch with a fork* vs. *I ate lunch with a backpack*
- **Topic**: *Babe Ruth was able to touch the home plate yet again* vs. *Lucy was able to touch the home audiences with her humour*
- **Register**: Consistency of register in the entire sentence, e.g. informal (Twitter) vs. formal (scientific articles)

Language Models

Chain Rule and ignore some history: the trigram model

$$
\begin{aligned}
& p(w_1, \ldots, w_n) \\
& \quad \approx \quad p(w_1)p(w_2 \mid w_1)p(w_3 \mid w_1, w_2) \ldots p(w_n \mid w_{n-2}, w_{n-1}) \\
& \quad \approx \quad \prod_t p(w_{t+1} \mid w_{t-1}, w_t)
\end{aligned}
$$

How can we address the long-distance issues?

- Skip *n*-gram models. Skip an arbitrary distance for *n*-gram context.
- Variable *n* in *n*-gram models that is adaptive
- **Problems**: Still "all or nothing". Categorical rather than soft.

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Part 2: Neural Language Models

Neural Language Models

Use Chain rule and approximate using a neural network

$$p(w_1, \ldots, w_n) \approx \prod_t p(w_{t+1} \mid \underbrace{\phi(w_1, \ldots, w_t)}_{\text{capture history with vector } s(t)})$$

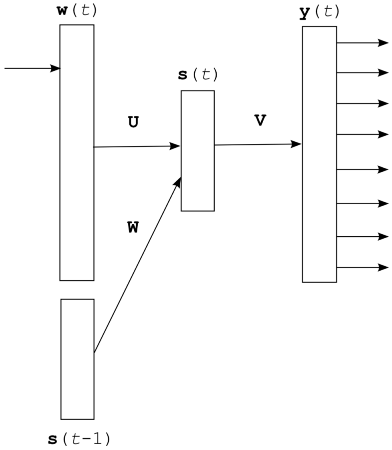
Recurrent Neural Network

- Let y be the output w_{t+1} for current word w_t and history $w_1, \ldots, w_t$
- $s(t) = f(U_{xh} \cdot w(t) + W_{hh} \cdot s(t-1))$ where f is a sigmoid
- $s(t)$ encapsulates history using single vector of size h
- Output word at time step w_{t+1} is provided by $y(t)$
- $y(t) = g(V_{hy} \cdot s(t))$ where g is softmax

Neural Language Models

Recurrent Neural Network

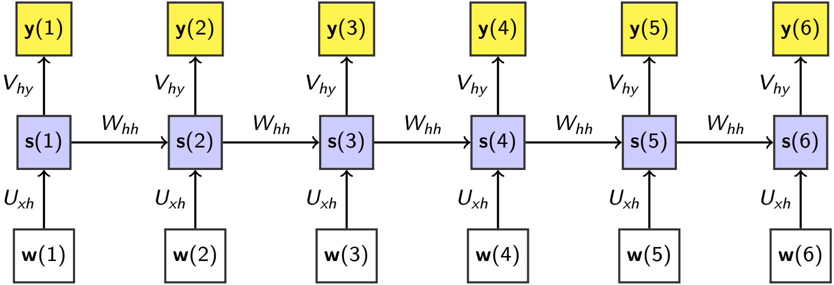
Single time step in RNN:



- Input layer is a one hot vector and output layer **y** have the same dimensionality as vocabulary (10K-200K).
- One hot vector is used to look up word embedding **w**
- "Hidden" layer **s** is orders of magnitude smaller (50-1K neurons)
- U is the matrix of weights between input and hidden layer
- V is the matrix of weights between hidden and output layer
- Without recurrent weights W, this is equivalent to a bigram feedforward language model

Neural Language Models

Recurrent Neural Network



What is stored and what is computed:

- Model parameters: $\mathbf{w} \in \mathbb{R}^x$ (word embeddings);
  $U_{xh} \in \mathbb{R}^{x \times h}$; $W_{hh} \in \mathbb{R}^{h \times h}$; $V_{hy} \in \mathbb{R}^{h \times y}$ where $y = |\mathcal{V}|$.
- Vectors computed during forward pass: $\mathbf{s}(t) \in \mathbb{R}^h$; $\mathbf{y}(t) \in \mathbb{R}^y$ and each $\mathbf{y}(t)$ is a probability over vocabulary $\mathcal{V}$.

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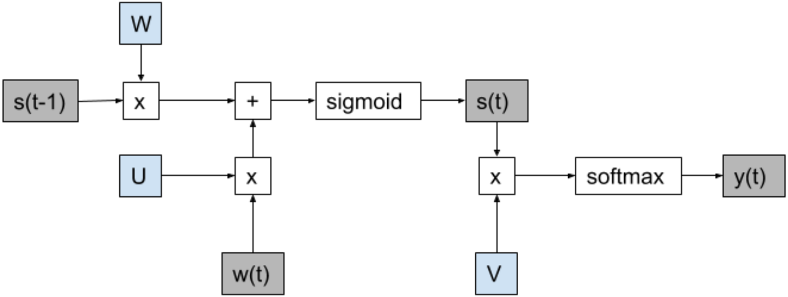
Part 3: Training RNN Language Models

Computational Graph for an RNN Language Model



Training of RNNLM

- The training is performed using Stochastic Gradient Descent (SGD)
- We go through all the training data iteratively, and update the weight matrices U, W and V (after processing every word)
- Training is performed in several "epochs" (usually 5-10)
- An epoch is one pass through the training data

Training of RNNLM

- Gradient of the error vector in the output layer $\mathbf{e}_o(t)$ is computed using a cross entropy criterion:

$$\mathbf{e}_o(t) = \mathbf{d}(t) - \mathbf{y}(t)$$

- $\mathbf{d}(t)$ is a target vector that represents the word $w(t+1)$ represented as a one-hot (1-of-$\mathcal{V}$) vector

Training of RNNLM

- Weights V between the hidden layer $s(t)$ and the output layer $y(t)$ are updated as

$$V^{(t+1)} = V^{(t)} + \mathbf{s}(t) \cdot \mathbf{e}_o(t) \cdot \alpha$$

- where α is the learning rate

Training of RNNLM

- Next, gradients of errors are propagated from the output layer to the hidden layer

$$\mathbf{e}_h(t) = d_h(\mathbf{e}_o \cdot V, t)$$

- where the error vector is obtained using function $d_h()$ that is applied element-wise:

$$d_{hj} = x \cdot s_j(t)(1 - s_j(t))$$

Training of RNNLM

- Weights U between the input layer $w(t)$ and the hidden layer $s(t)$ are then updated as

$$U^{(t+1)} = U^{(t)} + \mathbf{w}(t) \cdot \mathbf{e}_h(t) \cdot \alpha$$

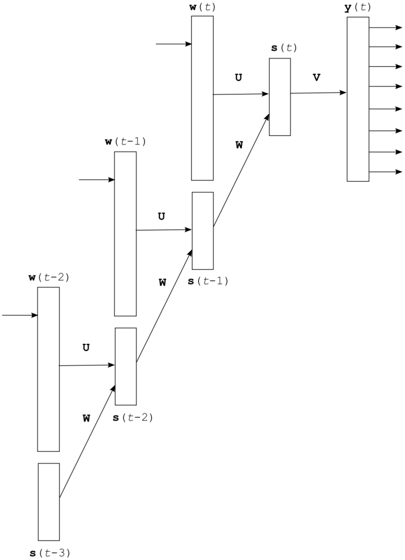
- Similarly the word embeddings **w** can also be updated using the error gradient.

Training of RNNLM: Backpropagation through time

- The recurrent weights W are updated by unfolding them in time and training the network as a deep feedforward neural network.
- The process of propagating errors back through the recurrent weights is called Backpropagation Through Time (BPTT).

Training of RNNLM: Backpropagation through time

Fig. from [1]: RNN unfolded as a deep feedforward network 3 time steps back in time



Training of RNNLM: Backpropagation through time

- Error propagation is done recursively as follows (it requires the states of the hidden layer from the previous time steps τ to be stored):

$$\mathbf{e}(t-\tau-1) = d_h(\mathbf{e}_h(t-\tau) \cdot W, t-\tau-1)$$

- The error gradients quickly vanish as they get backpropagated in time (in rare cases the errors can explode)
- We use gated RNNs to stop gradients from vanishing or exploding.
- Popular gated RNNs are *long short-term memory* RNNs aka LSTMs and *gated recurrent units* aka GRUs.

Training of RNNLM: Backpropagation through time

- The recurrent weights W are updated as:

$$W^{(t+1)} = W^{(t)} + \sum_{z=0}^{T} \mathbf{s}(t-z-1) \cdot \mathbf{e}_h(t-z) \cdot \alpha$$

- Note that the matrix W is changed in one update at once, not during backpropagation of errors.

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Part 4: Sequence prediction using RNNs

Representation: finding the right parameters

Problem: Predict ?? using context, $P(?? \mid \texttt{context})$

Profits/N soared/V at/P Boeing/?? Co. , easily topping forecasts on Wall Street , as their CEO Alan Mulally announced first quarter results .

Representation: history

- The input is a tuple: $(x_{[1:n]}, i)$ [ignoring y_{-1} for now]
- $x_{[1:n]}$ are the n words in the input
- i is the index of the word being tagged
- For example, for $x_4 =$ Boeing
- We can use an RNN to summarize the entire context at $i = 4$
  - $x_{[1:i-1]} =$ (Profits, soared, at)
  - $x_{[i+1:n]} =$ (Co., easily, ..., results, .)

Locally normalized RNN taggers

Log-linear model over history, tag pair (h, t)

$$\log \Pr(y \mid h) = \mathbf{w} \cdot \mathbf{f}(h, y) - log \sum_{y'} \exp\left(\mathbf{w} \cdot \mathbf{f}(h, y')\right)$$

$\mathbf{f}(h, y)$ is a vector of feature functions

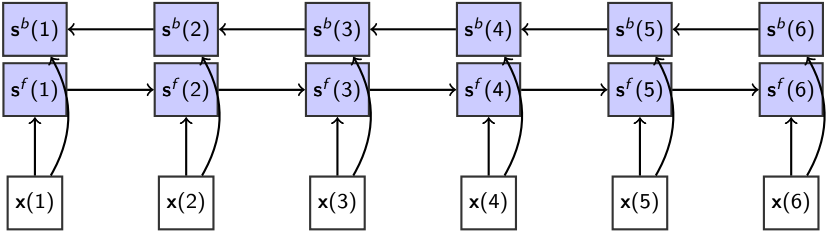
RNN for tagging

- Replace $\mathbf{f}(h, y)$ with RNN hidden state $s(t)$
- Define the output logprob: $\log \Pr(y \mid h) = \log y(t)$
- $y(t) = g(V \cdot s(t))$ where g is softmax
- In neural LMs the output $y \in \mathcal{V}$ (vocabulary)
- In sequence tagging using RNNs the output $y \in \mathcal{T}$ (tagset)

$$\log \Pr(y_{[1:n]} \mid x_{[1:n]}) = \sum_{i=1}^{n} \log \Pr(y_i \mid h_i)$$

Bidirectional RNNs

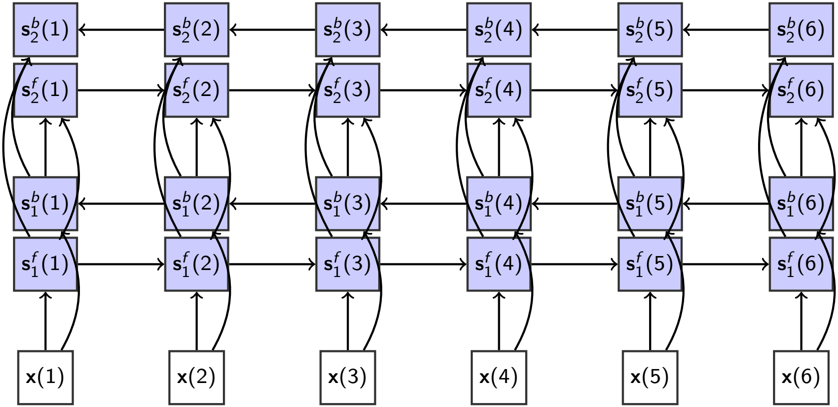
Fig. from [2]



Bidirectional RNN

Bidirectional RNNs can be Stacked

Fig. from [2]



Two Bidirectional RNNs stacked on top of each other

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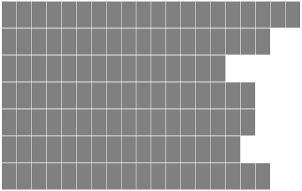
Part 5: Training RNNs on GPUs

Parallelizing RNN computations

Fig. from [2]

Apply RNNs to *batches* of sequences

Present the data as a 3D tensor of $(T \times B \times F)$. Each dynamic update will now be a matrix multiplication.



Binary Masks

Fig. from [2]

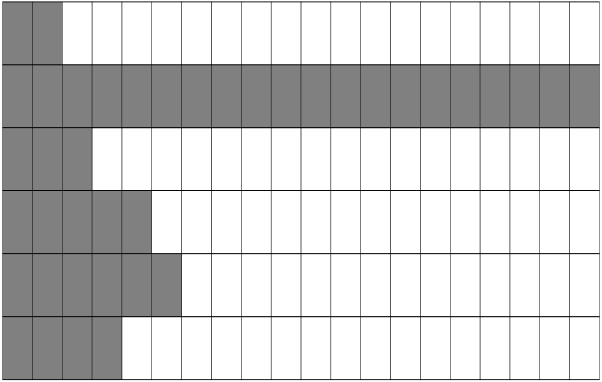
A *mask* matrix may be used to aid with computations that ignore the padded zeros.

1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0

Binary Masks

Fig. from [2]

It may be necessary to (partially) sort your data.



[1] Tomas Mikolov
Recurrent Neural Networks for Language Models. Google Talk.
2010.

[2] Philemon Brakel
MLIA-IQIA Summer School notes on RNNs
2015.

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