



Natural Language Processing

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

$P(\text{himself} \mid \text{confidence, in})$

$P(\text{herself} \mid \text{confidence, in})$

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

$P(\text{himself} \mid \text{He, } \dots, \text{confidence})$

$P(\text{herself} \mid \text{She, } \dots, \text{confidence})$

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

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

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

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

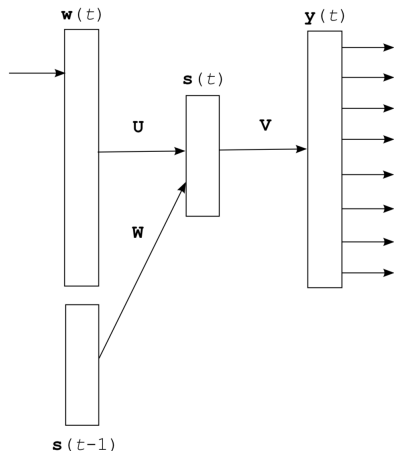
Recurrent Neural Network

- ▶ Let y be the output w_{t+1} for current word w_t and history w_1, \dots, 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

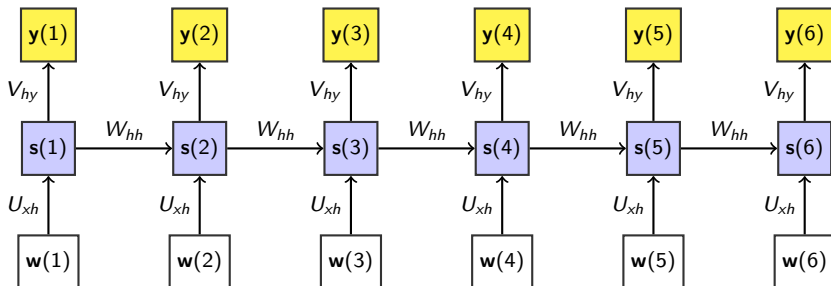
Single time step in RNN:



- ▶ Input layer is a one hot vector and output layer \mathbf{y} have the same dimensionality as vocabulary (10K-200K).
- ▶ One hot vector is used to look up word embedding \mathbf{w}
- ▶ “Hidden” layer \mathbf{s} is orders of magnitude smaller (50-1K neurons)
- ▶ \mathbf{U} is the matrix of weights between input and hidden layer
- ▶ \mathbf{V} is the matrix of weights between hidden and output layer
- ▶ Without recurrent weights \mathbf{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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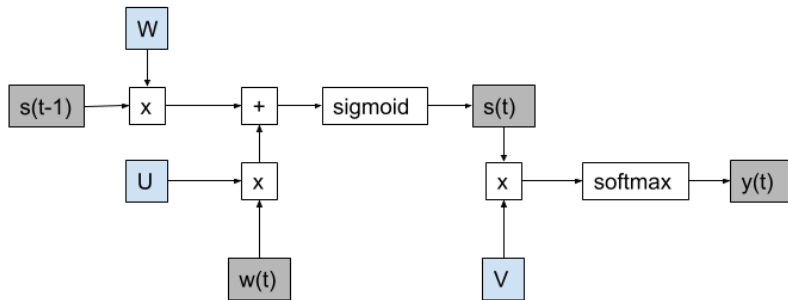
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Part 3: Training RNN Language Models

Neural Language Models

Recurrent Neural Network

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

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

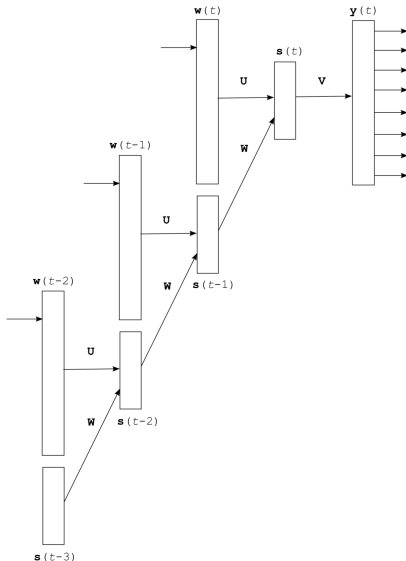
- ▶ Similarly the word embeddings \mathbf{w} can also be updated using the error gradient.

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, $P(?? \mid \text{context})$

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 $x_4 = \text{Boeing}$
- ▶ We can use an RNN to summarize the entire context at $i = 4$
 - ▶ $x_{[1:i-1]} = (\text{Profits, soared, at})$
 - ▶ $x_{[i+1:n]} = (\text{Co., easily, ..., results, .})$

Locally normalized RNN taggers

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

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

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

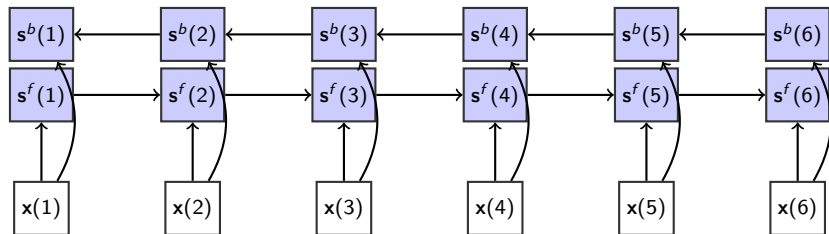
RNN for tagging

- ▶ 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

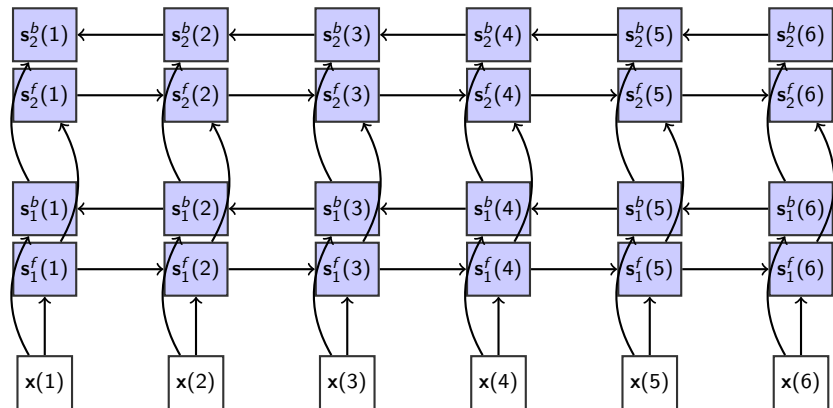
Fig. from [2]



Bidirectional RNN

Bidirectional RNNs can be Stacked

Fig. from [2]



Two Bidirectional RNNs stacked on top of each other

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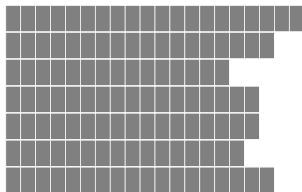
Part 5: Training RNNs on GPUs

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]

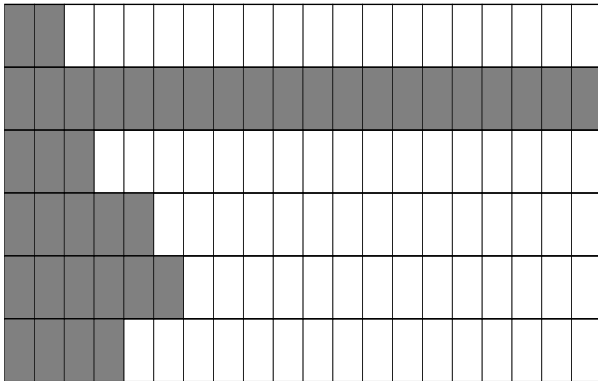
A *mask* matrix may be used to aid with computations that ignore the padded zeros.

| | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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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