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

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

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

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

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

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

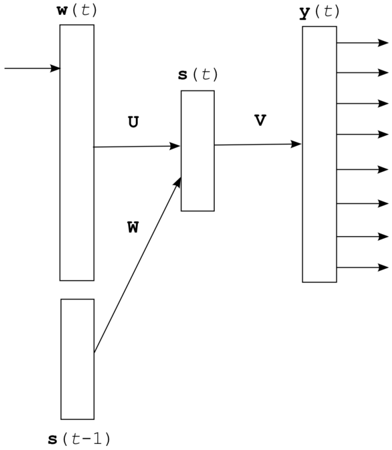
Recurrent Neural Network

- 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 sigmoid / tanh
- $s(t)$ 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

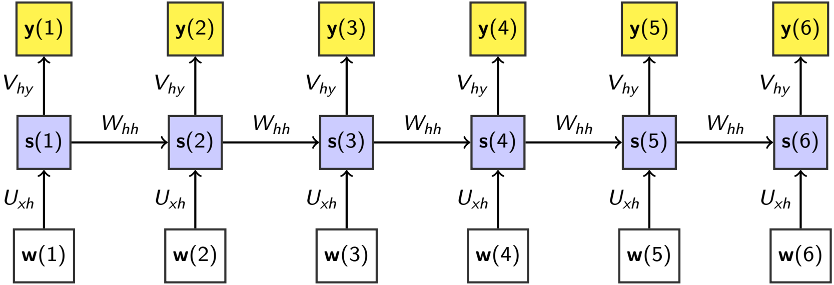
Single time step in RNN:



- 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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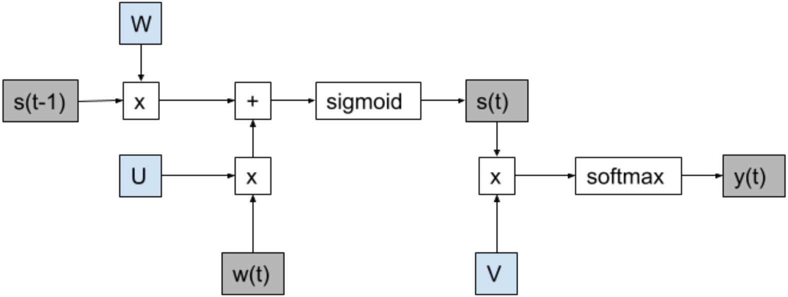
Part 3: Training RNN Language Models

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
- As with feedforward networks we have two passes:

  Forward pass : collect the values to make a prediction (for each time step)

  Backward pass : back-propagate the error gradients (through each time step)

Training of RNNLM

Forward pass

- In the forward pass we compute a hidden state $s(t)$ based on previous states $1, \ldots, t-1$
  - $s(t) = f(U_{xh} \cdot w(t) + W_{hh} \cdot s(t-1))$
  - $s(t) = f(U_{xh} \cdot w(t) + W_{hh} \cdot f(U_{xh} \cdot w(t) + W_{hh} \cdot s(t-2)))$
  - $s(t) = f(U_{xh} \cdot w(t) + W_{hh} \cdot$ $f(U_{xh} \cdot w(t) + W_{hh} \cdot f(U_{xh} \cdot w(t) + W_{hh} \cdot s(t-3))))$
  - etc.
- Let us assume f is linear, e.g. $f(x) = x$.
- Notice how we have to compute $W_{hh} \cdot W_{hh} \cdot \ldots = \prod_i W_{hh}$
- By examining this repeated matrix multiplication we can show that the norm of $W_{hh} \to \infty$ (explodes)
- This is why f is set to a function that returns a bounded value (sigmoid / tanh)

Training of RNNLM

Backward pass

- 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

Backward pass

- 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

Backward pass

- 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:

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

Training of RNNLM

Backward pass

- 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.

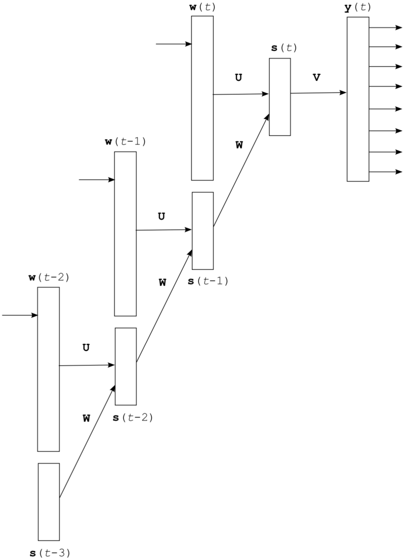
Training of RNNLM: Backpropagation through time

Backward pass

- 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

Backward pass

- 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 (less likely if we use sigmoid / tanh)
- 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

Backward pass

- 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: Gated Recurrent Units

Interpolation for hidden units

u: use history or forget history

- For RNN state $s(t) \in \mathbb{R}^h$ create a binary vector $u \in \{0,1\}^h$

$$u_i = \begin{cases} 1 & \text{use the new hidden state (standard RNN update)} \\ 0 & \text{copy previous hidden state and ignore RNN update} \end{cases}$$

- Create an intermediate hidden state $\tilde{s}(t)$ where f is tanh:

$$\tilde{s}(t) = f(U_{xh} \cdot w(t) + W_{hh} \cdot s(t-1))$$

- Use the binary vector u to interpolate between copying prior state $s(t-1)$ and using new state $\tilde{s}(t)$:

$$s(t) = (1-u) \odot s(t-1) + u \odot \tilde{s}(t)$$

$\odot$ is elementwise multiplication

Interpolation for hidden units

r: reset or retain each element of hidden state vector

- For RNN state $s(t-1) \in \mathbb{R}^h$ create a binary vector $r \in \{0,1\}^h$

$$r_i = \begin{cases} 1 & \text{if } s_i(t-1) \text{ should be used} \\ 0 & \text{if } s_i(t-1) \text{ should be ignored} \end{cases}$$

- Modify intermediate hidden state $\tilde{s}(t)$ where f is tanh:

$$\tilde{s}(t) = f(U_{xh} \cdot w(t) + W_{hh} \cdot (r \odot s(t-1)))$$

- Use the binary vector u to interpolate between $s(t-1)$ and $\tilde{s}(t)$:

$$s(t) = (1-u) \odot s(t-1) + u \odot \tilde{s}(t)$$

Interpolation for hidden units

Learning u and r

- Instead of binary vectors $u \in \{0,1\}^h$ and $r \in \{0,1\}^h$ we want to *learn* u and r
- Let $u \in [0,1]^h$ and $r \in [0,1]^h$
- Learn these two h dimensional vectors using equations similar to the RNN hidden state equation:

$$
\begin{aligned}
u(t) &= \sigma\left(U^u_{xh} \cdot w(t) + W^u_{hh} \cdot s(t-1)\right) \\
r(t) &= \sigma\left(U^r_{xh} \cdot w(t) + W^r_{hh} \cdot s(t-1)\right)
\end{aligned}
$$

- The sigmoid function σ ensures that each element of u and r is between $[0,1]$
- The *use history* u and *reset element* r vectors use different parameters U^u, W^u and U^r, W^r

Interpolation for hidden units

Gated Recurrent Unit (GRU)

- Putting it all together:

$$
\begin{aligned}
u(t) &= \sigma\left(U^u_{xh} \cdot w(t) + W^u_{hh} \cdot s(t-1)\right) \\
r(t) &= \sigma\left(U^r_{xh} \cdot w(t) + W^r_{hh} \cdot s(t-1)\right) \\
\tilde{s}(t) &= \tanh(U_{xh} \cdot w(t) + W_{hh} \cdot (r(t) \odot s(t-1))) \\
s(t) &= (1 - u(t)) \odot s(t-1) + u(t) \odot \tilde{s}(t)
\end{aligned}
$$

Interpolation for hidden units

Long Short-term Memory (LSTM)

- Split up $u(t)$ into two different gates $i(t)$ and $f(t)$:

$$
\begin{aligned}
i(t) &= \sigma\left(U^i_{xh} \cdot w(t) + W^i_{hh} \cdot s(t-1)\right) \\
f(t) &= \sigma\left(U^f_{xh} \cdot w(t) + W^f_{hh} \cdot s(t-1)\right) \\
r(t) &= \sigma\left(U^r_{xh} \cdot w(t) + W^r_{hh} \cdot s(t-1)\right) \\
\tilde{s}(t) &= \tanh(U_{xh} \cdot w(t) + W_{hh} \cdot \underbrace{s(t-1)}_{\text{GRU:}r(t)\odot s(t-1)}) \\
\hat{s}(t) &= \underbrace{f(t) \odot s(t-1) + i(t) \odot \tilde{s}(t)}_{\text{GRU:}(1-u(t))\odot s(t-1)+u(t)\odot\tilde{s}(t)} \\
s(t) &= r(t) \odot \tanh\left(\hat{s}(t)\right)
\end{aligned}
$$

- So LSTM is a GRU plus an extra U_{xh}, W_{hh} and tanh.
- **Q**: what happens if $f(t)$ is set to $1 - i(t)$? **A**: read [3]

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Part 5: 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

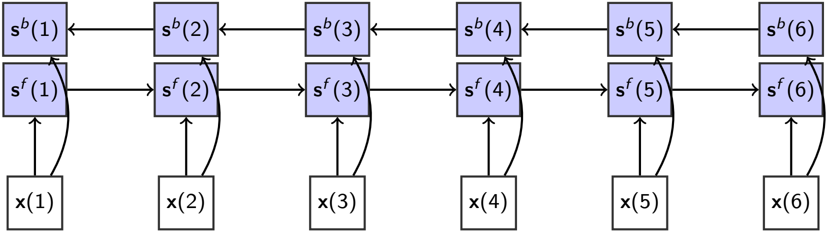
RNN for tagging

- 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

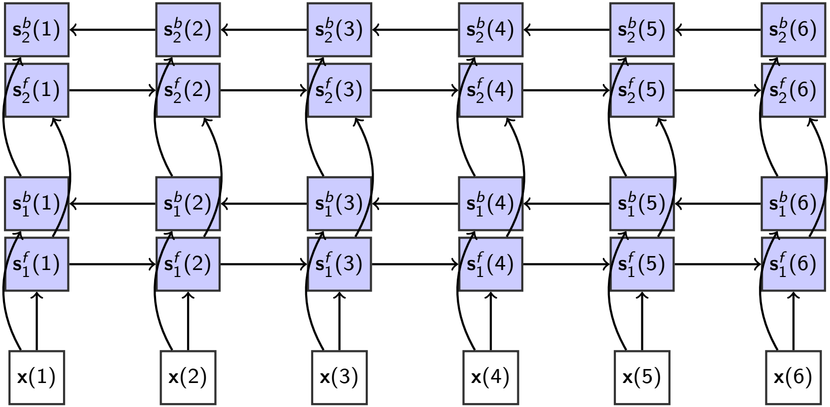
Fig. from [2]



Bidirectional RNN

Bidirectional RNNs can be Stacked

Fig. from [2]



Two Bidirectional RNNs stacked on top of each other

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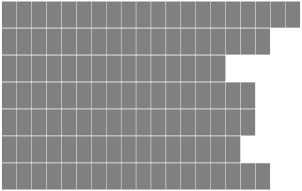
Part 6: Training RNNs on GPUs

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]

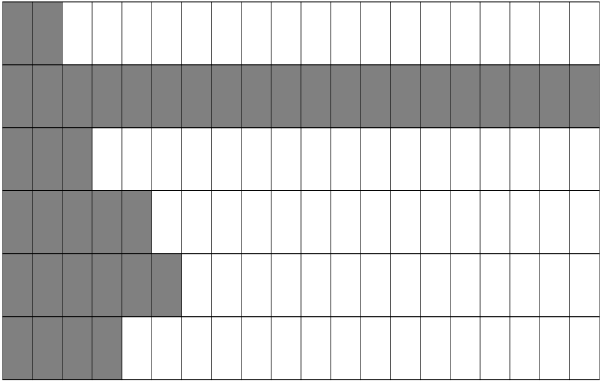
A *mask* matrix may be used to aid with computations that ignore the padded zeros.

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.

[3] Klaus Greff, Rupesh Kumar Srivastava, Jan Koutník, Bas R. Steunebrink, Jürgen Schmidhuber
LSTM: A Search Space Odyssey
2017.

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