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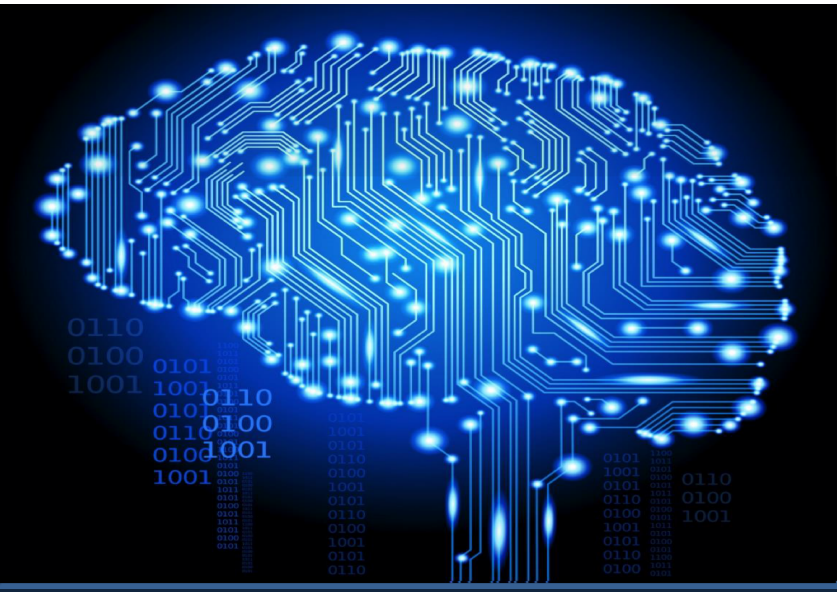

DL: Recurrent Neural Networks

Reference

- [Goodfellow et al. (2016)] I. Goodfellow, Y. Bengio, and A. Courville, Deep learning, The MIT Press, 2016.
- [Hinton. (2015)] G. Hinton, Online course on Neural Networks for Machine Learning.

  https://www.coursera.org/learn/neural-networks
- [Larochelle. (2014)] H. Larochelle, Online course on Neural Networks.

  http://info.usherbrooke.ca/hlarochelle/neural_networks/content.html
- [Gavves. (2017)] E. Gavves, UvA Deep Learning Course.

  http://uvadlc.github.io/
- Borrows slides (some modified) from Larochelle & Gavves

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Lecture Overview

- Recurrent Neural Networks (RNN) for sequences
- Backpropagation Through Time (BPTT)
- Vanishing and Exploding Gradients and Remedies
- RNNs using Long Short-Term Memory (LSTM)
- Applications of Recurrent Neural Networks

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Recurrent Neural Networks

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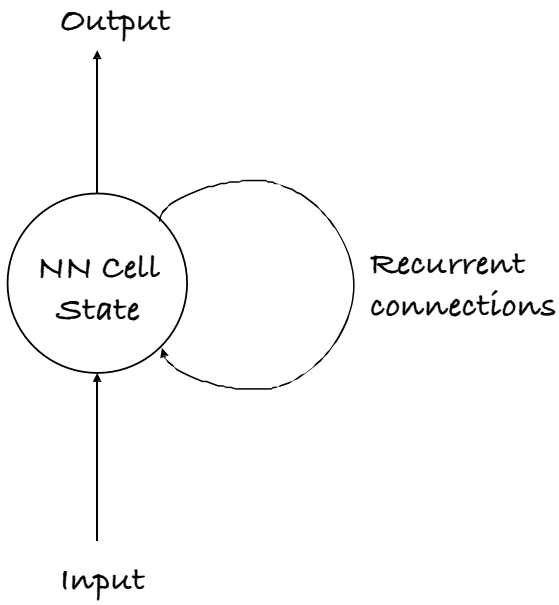
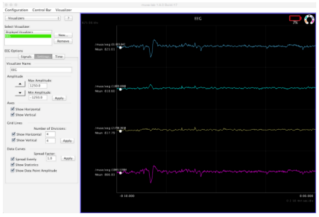


Examples of Sequential Data and Time Series

- Videos
- Stock Exchange
- Biological Measurement
- Climate Measurement
- Market Analysis
- Speech /Music
- Use Behavior in Websites



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Sequences

- Next data depend on previous data
  - Each data point on the previous ones and their distribution changes over time
  - How to model temporal dependencies, especially high-dim complex data?
- Sequences might be of arbitrary length
  - How to model dependencies at different temporal scales?
  - How to make a model that works for **both** 10 sec and 10 min sequences?
- Cycles in our computational graph
  - How to learn with cycles?
- Unclear how to assign credit to past time steps
  - Which of the infinite past time steps is responsible for this observed present?
- Chaotic behavior
  - How do we account for all possible effects of small changes in past sequence?

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Solution!

- What makes sequences special?

Challenges	Inductive Bias
Non iid data	State models, Chain rule of Probabilities
Arbitrary length	Sharing weights
Credit assignment problem	Backpropagation through time
Chaotic behavior	LSTM, GRU

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A sequence of probabilities

- Sequences are by definition non iid
  - p(He is a student) = p(He) p(is|He) p(a|He is) p(student|He is a)
  - p(She is also a student) = p(She) p(is|She) p(also|She is) p(a|She is also) p(student|She is also a)
- Compute likelihood by decomposing with chain rule of probabilities

$$\Pr(x) = \prod_i \Pr(x_i | x_{i-T}, \dots, x_{i-1})$$

- Model each term $\Pr(x_i | x_{i-T}, \dots, x_{i-1})$ separately

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Memory

- To have the past influence present we must keep a summary of the past
  - A representation of the past
- At time step t project all information $1, \dots, t$ on a state (latent) space c_t with shared parameters θ
- Then, at time step $t+1$ re-use the parameters θ and the previous c_t

$$c_{t+1} = h(x_{t+1}, c_t; \theta)$$

- Recurrent parameters θ are the shared for all timesteps $t = 0, \dots$

$$c_{t+1} = h(x_{t+1}, h(x_t, h(x_{t-1}, \dots, h(x_1, c_0; \theta); \theta); \theta); \theta)$$

- Sharing parameters through time enables sequences of arbitrary lengths

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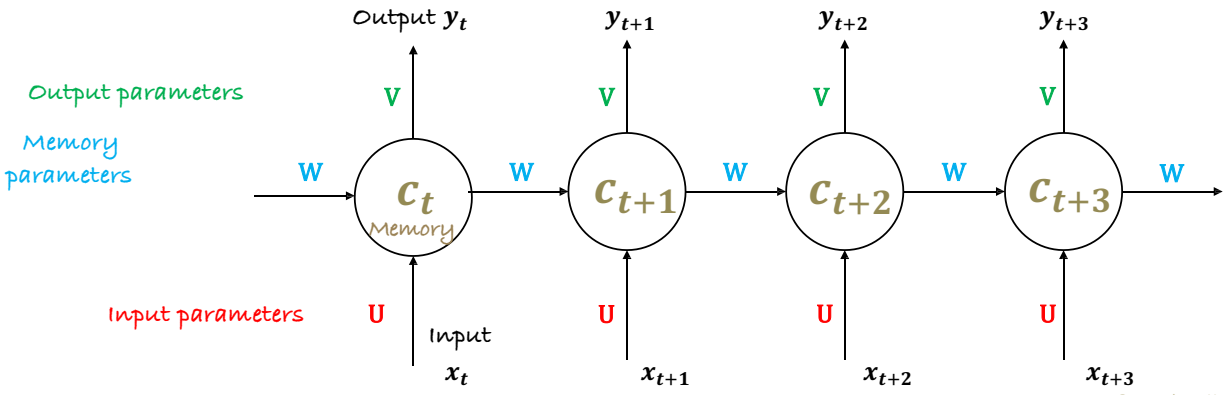
Memory as a Graph

- Simplest model
  - Input with parameters U
  - Memory embedding with parameters W
  - Output with parameters V



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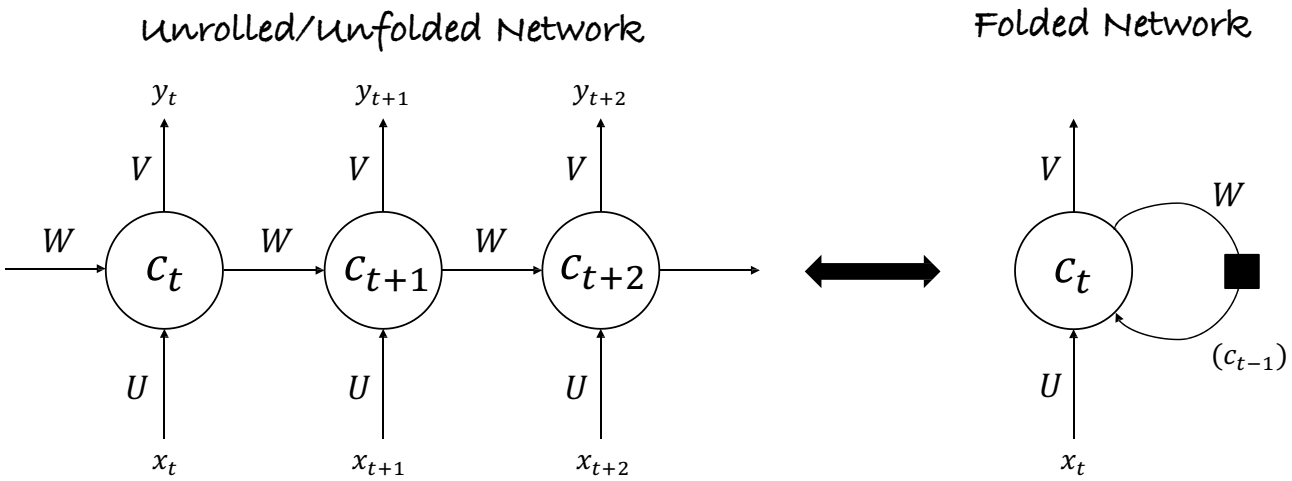
Folding the memory



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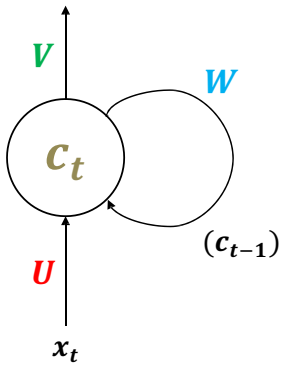
Recurrent Neural Network (RNN)

- Only two equations

$$c_t = \tanh(b + U\, x_t + W\, c_{t-1})$$
$$y_t = \mathrm{softmax}(a + V\, c_t)$$



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Recurrent Neural Networks

- Putting things together!
- A memory of 3 units [Hyperparameter that we choose like layer size]
  - $c_t: [3\times1], W: [3\times3]$
- An input projection of 3 dimensions
  - $U: [3\times5]$
- An output projections of 10 dimensions
  - $V: [10\times3]$

$$b = 0,\ a = 0$$

$$c_t = \tanh(U\, x_t + W\, c_{t-1})$$

$$y_t = \text{softmax}(V\, c_t)$$

$$\mathcal{L} = \sum_t \mathcal{L}_t(y_t, l_t)$$

$$U \cdot x_{t=4} = \begin{bmatrix} 0.1 & -0.3 & 1.2 & 0.6 & -0.8 \\ -0.2 & 0.4 & 0.5 & 0.9 & -0.1 \\ -0.1 & 0.2 & -0.7 & -0.8 & 0.3 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.6 \\ 0.9 \\ -0.8 \end{bmatrix} = U^{(4)}$$

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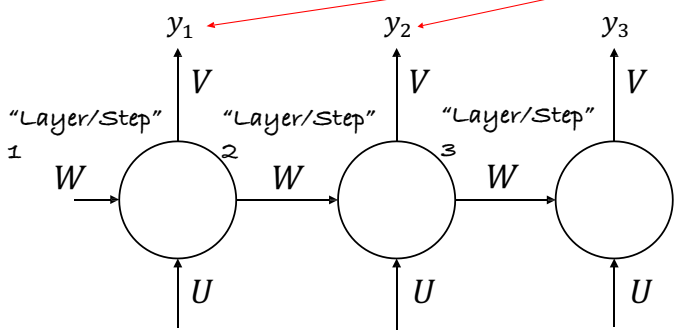
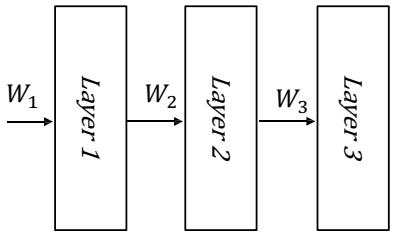
Rolled Network vs. Multi-layer Network?

- What is really different?
  - Steps instead of layers
  - Step parameters shared whereas in a Multi-Layer Network they are different

- Sometimes intermediate outputs are not even needed
- Removing them, we almost end up to a standard Neural Network



3-gram Unrolled Recurrent Network



3-layer Neural Network

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Training Recurrent Networks

- Cross-entropy loss

$$P = \prod_{t,k} y_{tk}^{l_{tk}} \Longrightarrow \mathcal{L} = -\log P = \sum_t \mathcal{L}_t = -\frac{1}{T}\sum_t l_t \log y_t$$

- Backpropagation Through Time (BPTT)
  - Basically, chain rule again for $\frac{d\mathcal{L}}{dV}, \frac{d\mathcal{L}}{dU}, \frac{d\mathcal{L}}{dW}$ → the same algorithm
  - Shared computations complicate the chain rule!
  - Only difference: Gradients survive over time steps
    - Gradients flow not from a single path of previous layer like in MLP
    - The recurrence in the chain rule hides multiple dependencies

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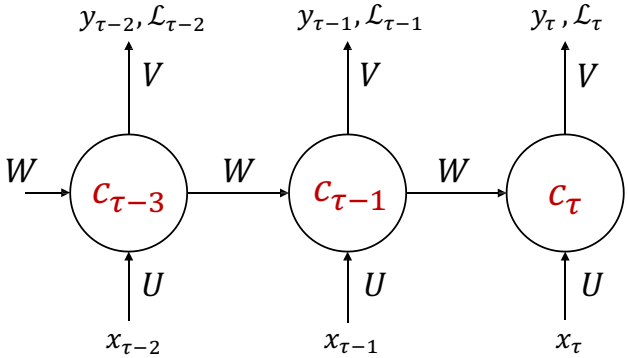
Backpropagation Through Time: An Example

- $\frac{\partial \mathcal{L}}{\partial V}, \frac{\partial \mathcal{L}}{\partial W}, \frac{\partial \mathcal{L}}{\partial U}$
- Let's focus on the final step τ

$$\frac{\partial \mathcal{L}_\tau}{\partial V}, \frac{\partial \mathcal{L}_\tau}{\partial W}, \frac{\partial \mathcal{L}_\tau}{\partial U}$$

Step by step explanation at:
http://www.wildml.com/2015/10/recurrent-neural-networks- tutorial-part-3-backpropagation-through-time-and-vanishing- gradients/

$$c_t = \tanh(b + Ux_t + Wc_{t-1})$$
$$y_t = \text{softmax}(a + Vc_t)$$
$$\mathcal{L} = -\sum_t l_t \log y_t = \sum_t \mathcal{L}_t$$



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Backpropagation Through Time

$$\frac{\partial \text{softmax}(\boldsymbol{z})_j}{\partial z_i} = \text{softmax}(\boldsymbol{z})_i(\delta_{ij} - \text{softmax}(\boldsymbol{z})_j)$$

$$\frac{\partial}{\partial \alpha^{(L)}(x)_c} - \ln f(x)_y = \frac{-1}{f(x)_y}\frac{\partial f(x)_y}{\partial \alpha^{(L)}(x)_c}$$
$$= \frac{-1}{f(x)_y} f(x)_y(\delta_{yc} - f(x)_c) = -(1_{(y=c)} - f(x)_c)$$

$$\frac{\partial \mathcal{L}_\tau}{\partial c_\tau} = \left(\frac{\partial \alpha_\tau}{\partial c_\tau}\right)^T \frac{\partial \mathcal{L}_\tau}{\partial \alpha_\tau} = \left(\frac{\partial (V c_\tau)}{\partial c_\tau}\right)^T \cdot [-(l_\tau - y_\tau)] = V^T(y_\tau - l_\tau)$$

$$\frac{\partial \mathcal{L}_\tau}{\partial V} = \frac{\partial \mathcal{L}_\tau}{\partial \alpha_\tau}\frac{\partial \alpha_\tau}{\partial V} = (y_\tau - l_\tau) \cdot \frac{\partial (V c_\tau)}{\partial V} = (y_\tau - l_\tau) \cdot c_\tau^T$$

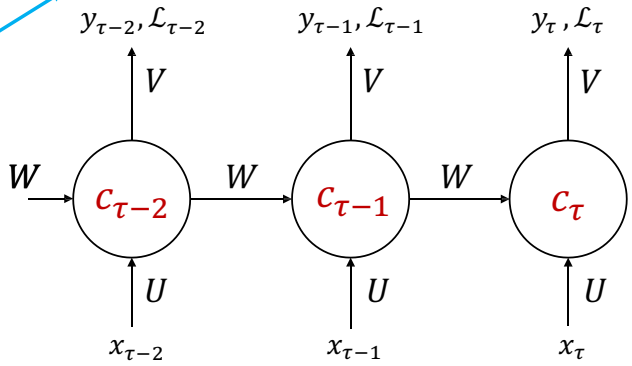
$$\frac{\partial \mathcal{L}}{\partial \alpha_t} = \frac{\partial \mathcal{L}_t}{\partial \alpha_t}\frac{\partial \mathcal{L}}{\partial \mathcal{L}_t} = y_t - l_t$$

$$\frac{\partial L}{\partial a_l} = \left(\frac{\partial a_{l+1}}{\partial a_l}\right)^T \cdot \frac{\partial L}{\partial a_{l+1}}$$
$$\frac{\partial L}{\partial \theta_l} = \frac{\partial a_l}{\partial \theta_l} \cdot \left(\frac{\partial L}{\partial a_l}\right)^T$$
$$\frac{\partial L}{\partial \theta_l^T} = \frac{\partial a_l}{\partial \theta_l^T} \cdot \left(\frac{\partial L}{\partial a_l}\right)$$

$$\mathcal{L} = \sum_t \mathcal{L}_t \rightarrow \frac{\partial \mathcal{L}}{\partial \mathcal{L}_t} = 1$$

$$\frac{\partial}{\partial \boldsymbol{x}}(\boldsymbol{c}^T\boldsymbol{x}) = \boldsymbol{c}$$
$$\frac{\partial}{\partial \boldsymbol{x}}(\mathbf{A}\boldsymbol{x}) = \mathbf{A}$$
$$\frac{\partial}{\partial \mathbf{A}}(\mathbf{A}^T\boldsymbol{x}) = \boldsymbol{x}$$
$$\frac{\partial}{\partial \mathbf{A}}(\mathbf{A}\boldsymbol{x}) = \boldsymbol{x}^T$$

$$c_t = \tanh(b + Ux_t + Wc_{t-1})$$
$$\alpha_t = a + Vc_t$$
$$y_t = \text{softmax}(\alpha_t)$$
$$\mathcal{L} = -\sum_t l_t \log y_t = \sum_t \mathcal{L}_t$$



Backpropagation Through Time

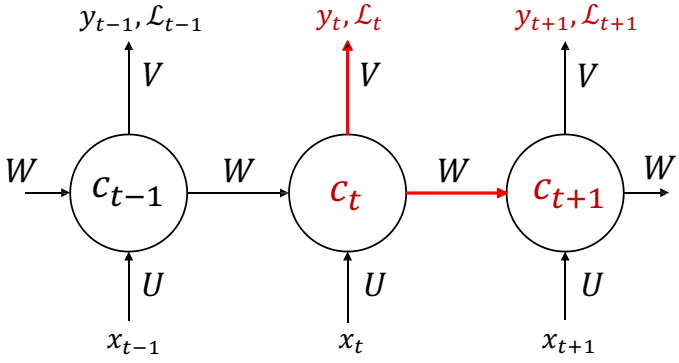
- c_t has as descendants both c_{t+1} and y_t
  - $\frac{\partial f(\varphi(x),\psi(x))}{\partial x} = \frac{\partial f}{\partial \varphi}\frac{\partial \varphi}{\partial x} + \frac{\partial f}{\partial \psi}\frac{\partial \psi}{\partial x}$

$$\frac{\partial \mathcal{L}}{\partial c_t} = \left(\frac{\partial c_{t+1}}{\partial c_t}\right)^T \frac{\partial \mathcal{L}}{\partial c_{t+1}} + \left(\frac{\partial \alpha_t}{\partial c_t}\right)^T \frac{\partial \mathcal{L}}{\partial \alpha_t} = \left(\frac{\partial c_{t+1}}{\partial c_t}\right)^T \frac{\partial \mathcal{L}}{\partial c_{t+1}} + \left(\frac{\partial \alpha_t}{\partial c_t}\right)^T \frac{\partial \mathcal{L}_t}{\partial \alpha_t} = W^T \text{diag}(1 - c_{t+1}^2)\frac{\partial \mathcal{L}}{\partial c_{t+1}} + V^T(y_t - l_t)$$

In $\mathcal{L}$, only $\mathcal{L}_t$ and $\mathcal{L}_{t+1}$ depends on c_t

$$a = \tanh(x) \rightarrow a' = 1 - a^2$$

$$c_t = \tanh(b + Ux_t + Wc_{t-1})$$
$$\alpha_t = a + Vc_t$$
$$y_t = \text{softmax}(\alpha_t)$$
$$\mathcal{L} = -\sum_t l_t \log y_t = \sum_t \mathcal{L}_t$$

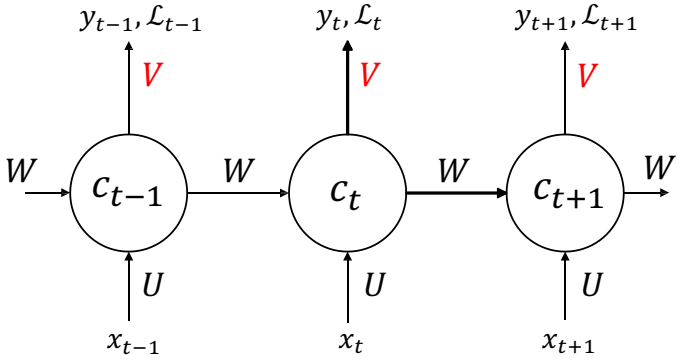


Backpropagation Through Time

$$\frac{\partial \mathcal{L}}{\partial V} = \sum_{t=1}^{\tau} \frac{\partial \mathcal{L}}{\partial \mathcal{L}_t} \frac{\partial \mathcal{L}_t}{\partial \alpha_t} \frac{\partial \alpha_t}{\partial V} = (l_t - y_t) \cdot \frac{\partial (V c_t)}{\partial V} = \sum_{t=1}^{\tau} (y_t - l_t) \cdot c_t^T$$

$$\frac{\partial \mathcal{L}}{\partial a} = \sum_{t=1}^{\tau} \frac{\partial \mathcal{L}}{\partial \mathcal{L}_t} \left(\frac{\partial \alpha_t}{\partial a}\right)^T \frac{\partial \mathcal{L}_t}{\partial \alpha_t} = \sum_{t=1}^{\tau} \boldsymbol{I} \cdot (y_t - l_t) = \sum_{t=1}^{\tau} (y_t - l_t)$$

$$c_t = \tanh(b + U x_t + W c_{t-1})$$
$$\alpha_t = a + V c_t$$
$$y_t = \mathrm{softmax}(\alpha_t)$$
$$\mathcal{L} = -\sum_t l_t \log y_t = \sum_t \mathcal{L}_t$$



Backpropagation Through Time

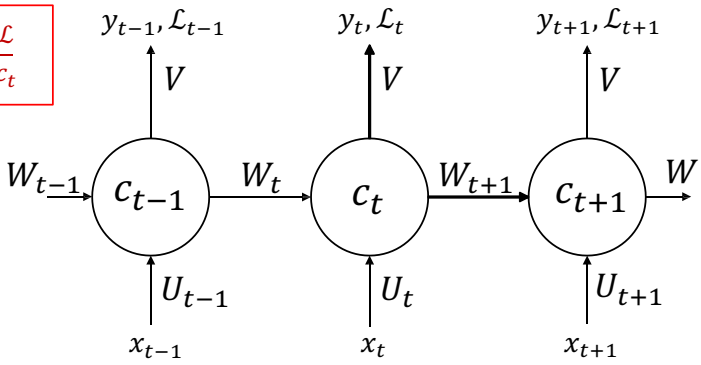
$$\frac{\partial \mathcal{L}}{\partial U} = \sum_{t=1}^{\tau} \frac{\partial \mathcal{L}}{\partial U_t} = \sum_{t=1}^{\tau} \frac{\partial \mathcal{L}}{\partial c_t} \left(\frac{\partial c_t}{\partial U_t}\right)^T = \sum_{t=1}^{\tau} \frac{\partial \mathcal{L}}{\partial c_t} \cdot diag(1 - c_t^2) \cdot x_t^T$$

$$\frac{\partial \mathcal{L}}{\partial W} = \sum_{t=1}^{\tau} \frac{\partial \mathcal{L}}{\partial W_t} = \sum_{t=1}^{\tau} \frac{\partial \mathcal{L}}{\partial c_t} \left(\frac{\partial c_t}{\partial W_t}\right)^T = \sum_{t=1}^{\tau} \frac{\partial \mathcal{L}}{\partial c_t} \cdot \mathrm{diag}(1 - c_t^2) \cdot c_{t-1}^T$$

$$\frac{\partial \mathcal{L}}{\partial b} = \sum_{t=1}^{\tau} \frac{\partial \mathcal{L}}{\partial b_t} = \sum_{t=1}^{\tau} \left(\frac{\partial c_t}{\partial b_t}\right)^T \frac{\partial \mathcal{L}}{\partial c_t} = \sum_{t=1}^{\tau} \mathrm{diag}(1 - c_t^2) \cdot \frac{\partial \mathcal{L}}{\partial c_t}$$

The $\frac{\partial \mathcal{L}}{\partial W}$ operator used in calculus takes into account the contribution of W to the value of $\mathcal{L}$ due to **all** edges in the computational graph. To resolve this ambiguity, we introduce dummy variables W_t that are defined to be copies of W but with each W_t used only at time step t. We may then use $\frac{\partial \mathcal{L}}{\partial W_t}$ to denote the contribution of the weights at time step t to the gradient.

$$c_t = \tanh(b_t + U_t x_t + W_t c_{t-1})$$
$$\alpha_t = a + V c_t$$
$$y_t = \mathrm{softmax}(\alpha_t)$$
$$\mathcal{L} = -\sum_t l_t \log y_t = \sum_t \mathcal{L}_t$$



Challenge of long-term dependencies

- Vanishing gradients
  - After a few time steps the gradients become almost 0
- Exploding gradients
  - After a few time steps the gradients become huge
- Can't capture long-term dependencies

$$\frac{\partial \mathcal{L}_t}{\partial \boldsymbol{W}} = \sum_{i=0}^{t} \frac{\partial \mathcal{L}_t}{\partial y_t} \frac{\partial y_t}{\partial \boldsymbol{s}_t} \frac{\partial \boldsymbol{s}_t}{\partial \boldsymbol{s}_i} \frac{\partial \boldsymbol{s}_i}{\partial \boldsymbol{W}} = \sum_{i=0}^{t} \frac{\partial \mathcal{L}_t}{\partial y_t} \frac{\partial y_t}{\partial \boldsymbol{s}_t} \left(\prod_{j=i+1}^{t} \frac{\partial \boldsymbol{s}_j}{\partial \boldsymbol{s}_{j-1}} \right) \frac{\partial \boldsymbol{s}_i}{\partial \boldsymbol{W}}$$

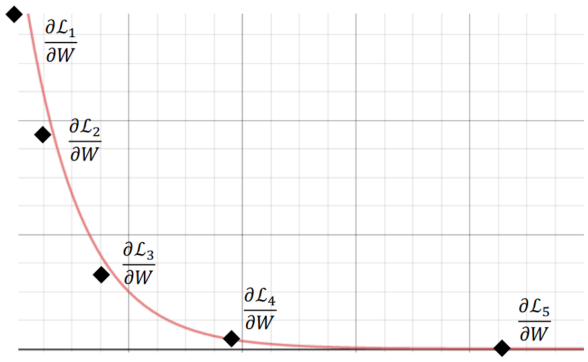
  - To make it simpler, assume that $c_t = W \cdot c_{t-1}$ and W admits an eigendecomposition of the form $W = V \Lambda V^{-1}$, then

$$c_t = W \cdot c_{t-1} = W^t \cdot c_0 = V \Lambda^{\mathrm{t}} V^{-1} \cdot c_0$$

    - The eigenvalues are raised to the power of t causing eigenvalues with magnitude less than one to decay to zero and eigenvalues with magnitude greater than one to explode. Any component of c_0 that is not aligned with the largest eigenvector will eventually be discarded.

Vanishing gradients

- Exponentially smaller contribution of longer-term terms
  - Model emphasizes on shorter-term terms as they have larger gradients
- Can be undesirable if the 'distant past' is a key factor



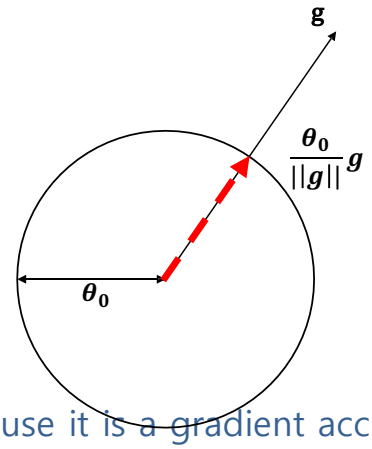
Source: http://uvadlc.github.io/

Gradient clipping for exploding gradients

- Scale the gradients to a threshold

Pseudocode

1. $g \leftarrow \frac{\partial \mathcal{L}}{\partial W}$
2. if $||g|| > \theta_0$:
   $g \leftarrow \frac{\theta_0}{||g||} g$
   else:
   print("Do nothing")



- Simple, but works!
- We cannot rescale vanishing gradients because it is a gradient accuracy issue
  - A vanishing gradient does not count as a gradient in the first place

Source: http://uvadlc.github.io/

Advanced RNNs

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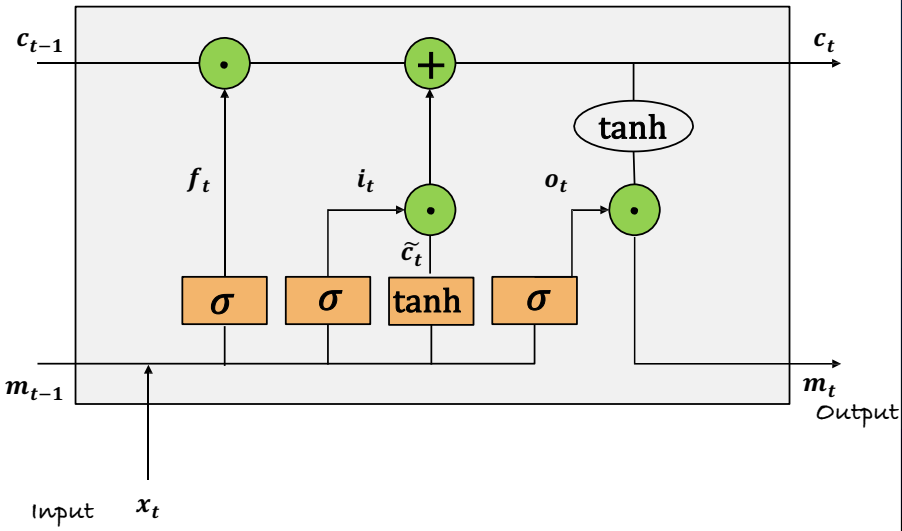


How to fix the vanishing gradients?

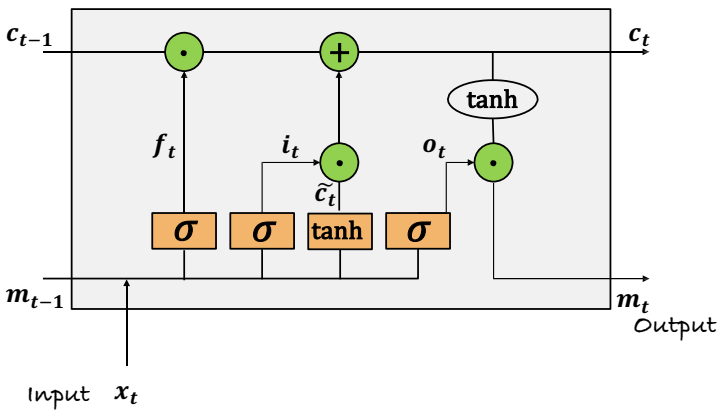
- Error signal over time must have not too large, not too small norm
- Solution: have an activation function with derivative equal to 1
  - $\frac{\partial c_t}{\partial c_{t-1}} = 1$ (Identify function)
- Remove immediate nonlinear relation between c_t and c_{t-1}
  - Replace tanh between c_t and c_{t-1} with identity
  - By doing so, gradients do not become too small not too large
- Also, avoid continuous overwriting of state
  - Modulate the importance of new input by a gate
  - Modulate the importance of new output by a gate
  - Modulate the importance of past memories by a gate

$$c_t = \tanh(b + U\, x_t + W\, c_{t-1})$$
$$y_t = \text{softmax}(a + V\, c_t)$$

Source: http://uvadlc.github.io/

Long Short-Term Memory (LSTM: Beefed up RNN)

$$i_t = \sigma(b^{(i)} + U^{(i)} x_t + W^{(i)} m_{t-1})$$
$$f_t = \sigma(b^{(f)} + U^{(f)} x_t + W^{(f)} m_{t-1})$$
$$o_t = \sigma(b^{(o)} + U^{(o)} x_t + W^{(o)} m_{t-1})$$
$$\tilde{c}_t = \tanh(b^{(g)} + U^{(g)} x_t + W^{(g)} m_{t-1})$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$
$$m_t = \tanh(c_t) \odot o_t$$

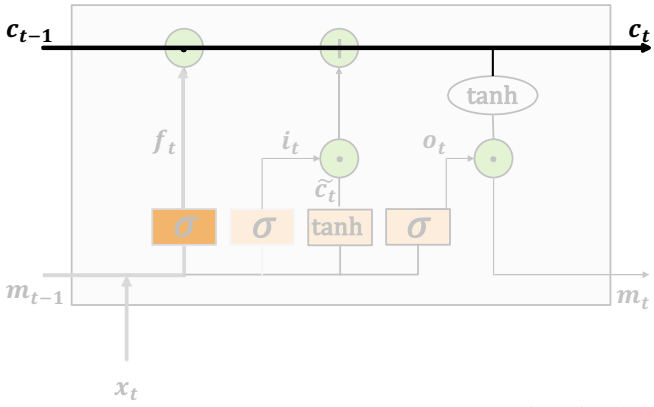


Long Short-Term Memory (LSTM: Beefed up RNN)

- The cell state carries the essential information over time

Cell state line

$$i_t = \sigma(b^{(i)} + U^{(i)}x_t + W^{(i)}m_{t-1})$$
$$f_t = \sigma(b^{(f)} + U^{(f)}x_t + W^{(f)}m_{t-1})$$
$$o_t = \sigma(b^{(o)} + U^{(o)}x_t + W^{(o)}m_{t-1})$$
$$\tilde{c}_t = \tanh(b^{(g)} + U^{(g)}x_t + W^{(g)}m_{t-1})$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$
$$m_t = \tanh(c_t) \odot o_t$$

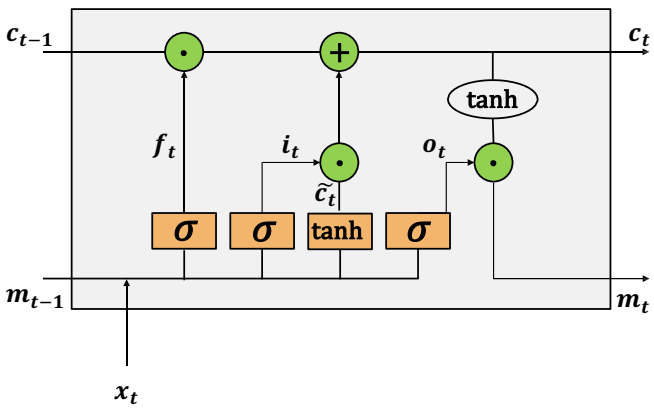


Source: http://uvadlc.github.io/

LSTM nonlinearities

- $\sigma \in (0,1)$ control gate – something like a switch
- $\tanh \in (-1,1)$: recurrent nonlinearity

$$i_t = \sigma(b^{(i)} + U^{(i)}x_t + W^{(i)}m_{t-1})$$
$$f_t = \sigma(b^{(f)} + U^{(f)}x_t + W^{(f)}m_{t-1})$$
$$o_t = \sigma(b^{(o)} + U^{(o)}x_t + W^{(o)}m_{t-1})$$
$$\tilde{c}_t = \tanh(b^{(g)} + U^{(g)}x_t + W^{(g)}m_{t-1})$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$
$$m_t = \tanh(c_t) \odot o_t$$



Source: http://uvadlc.github.io/

LSTM Step (1): Forget gate

- E.g. Model the sentence "Yesterday she slapped me. Today she loves me."
- Decide what to forget and what to remember for the new memory
  - Sigmoid 1 → Remember everything
  - Sigmoid 0 → Forget everything

$$i_t = \sigma(b^{(i)} + U^{(i)}x_t + W^{(i)}m_{t-1})$$

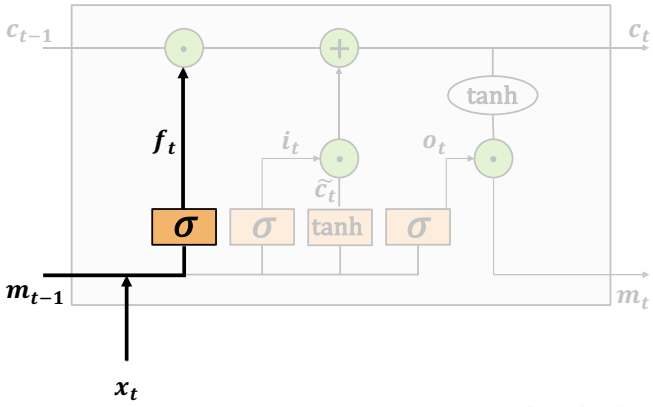
$$f_t = \sigma(b^{(f)} + U^{(f)}x_t + W^{(f)}m_{t-1})$$

$$o_t = \sigma(b^{(o)} + U^{(o)}x_t + W^{(o)}m_{t-1})$$

$$\tilde{c}_t = \tanh\left(b^{(g)} + U^{(g)}x_t + W^{(g)}m_{t-1}\right)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

$$m_t = \tanh(c_t) \odot o_t$$



Source: http://uvadlc.github.io/

LSTM Step (2): Input gate

- Decide what new information should you add to the new memory
  - Modulate the input i_t
  - Generate candidate memories $\tilde{c}_t$

$$i_t = \sigma(b^{(i)} + U^{(i)}x_t + W^{(i)}m_{t-1})$$

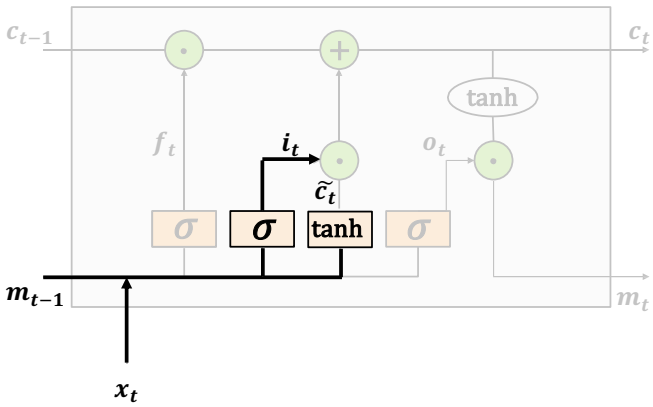
$$f_t = \sigma(b^{(f)} + U^{(f)}x_t + W^{(f)}m_{t-1})$$

$$o_t = \sigma(b^{(o)} + U^{(o)}x_t + W^{(o)}m_{t-1})$$

$$\tilde{c}_t = \tanh\left(b^{(g)} + U^{(g)}x_t + W^{(g)}m_{t-1}\right)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

$$m_t = \tanh(c_t) \odot o_t$$

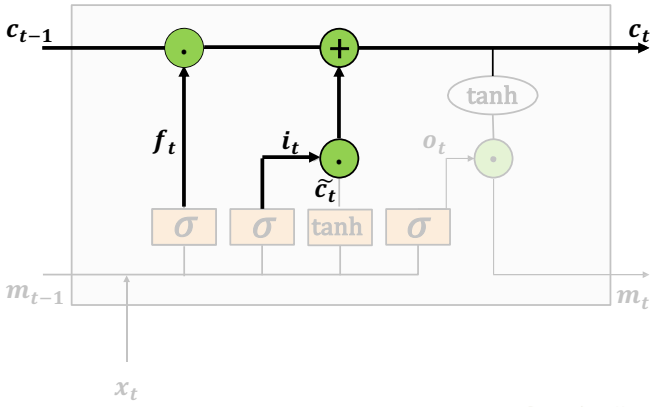


Source: http://uvadlc.github.io/

LSTM Step (3): Cell gate

- Compute and update the current cell state c_t
  - Depends on the previous cell state
  - What we decide to forget
  - What inputs we allow
  - The candidate memories

$$i_t = \sigma(b^{(i)} + U^{(i)}x_t + W^{(i)}m_{t-1})$$
$$f_t = \sigma(b^{(f)} + U^{(f)}x_t + W^{(f)}m_{t-1})$$
$$o_t = \sigma(b^{(o)} + U^{(o)}x_t + W^{(o)}m_{t-1})$$
$$\tilde{c}_t = \tanh(b^{(g)} + U^{(g)}x_t + W^{(g)}m_{t-1})$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$
$$m_t = \tanh(c_t) \odot o_t$$

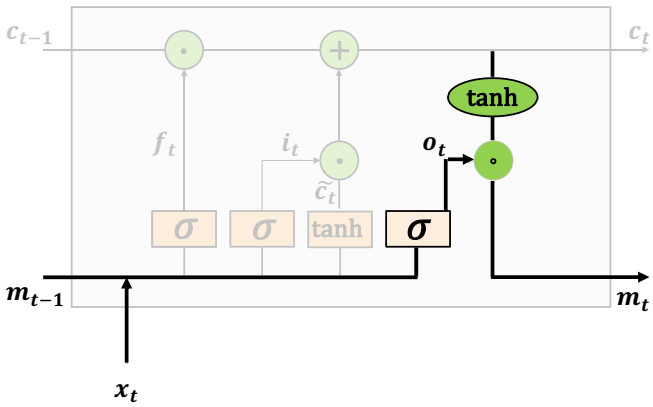


Source: http://uvadlc.github.io/

LSTM Step (4): Output gate

- Modulate the output
  - Does the cell state contain something relevant? → Sigmoid 1
- Generate the new memory

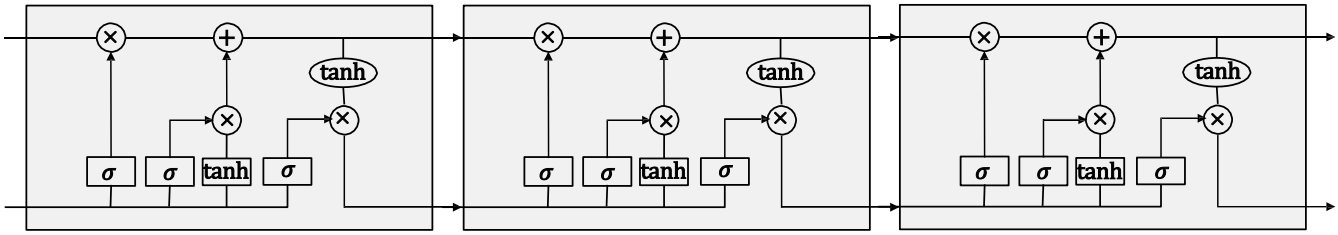
$$i_t = \sigma(b^{(i)} + U^{(i)}x_t + W^{(i)}m_{t-1})$$
$$f_t = \sigma(b^{(f)} + U^{(f)}x_t + W^{(f)}m_{t-1})$$
$$o_t = \sigma(b^{(o)} + U^{(o)}x_t + W^{(o)}m_{t-1})$$
$$\tilde{c}_t = \tanh(b^{(g)} + U^{(g)}x_t + W^{(g)}m_{t-1})$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$
$$m_t = \tanh(c_t) \odot o_t$$



Source: http://uvadlc.github.io/

LSTM Unrolled Network

- Macroscopically very similar to standard RNNs
- The engine is a bit different (more complicated)
  - Because of their gates LSTMs capture long and short term dependencies

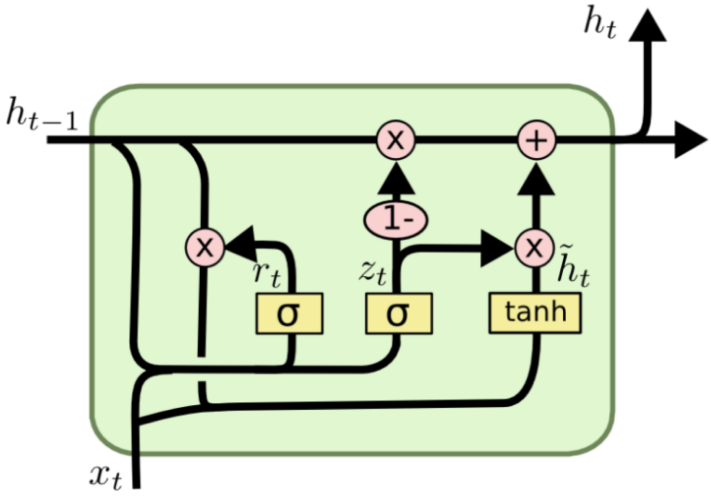


Source: http://uvadlc.github.io/

Gated Recurrent Units (GRU)

- Gated Recurrent Units (GRU)

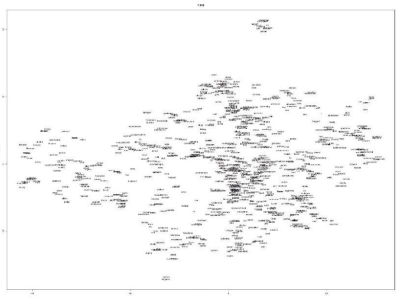
$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$
$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t])$$
$$\tilde{h}_t = \tanh(W \cdot [r_t * h_{t-1}, x_t])$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

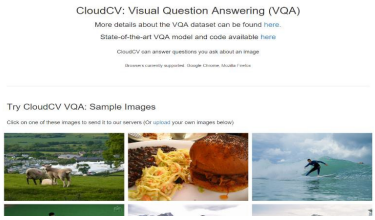


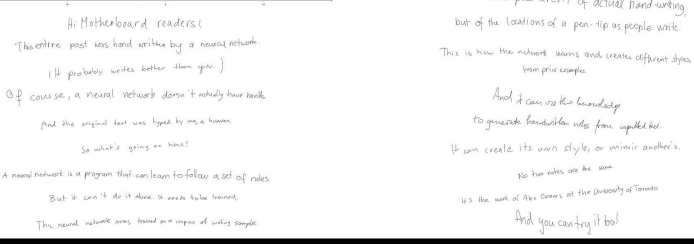
Applications of Recurrent Networks

Prof. Saerom Park

NeuralTalk and Walk, recognition, text description of the image while walking

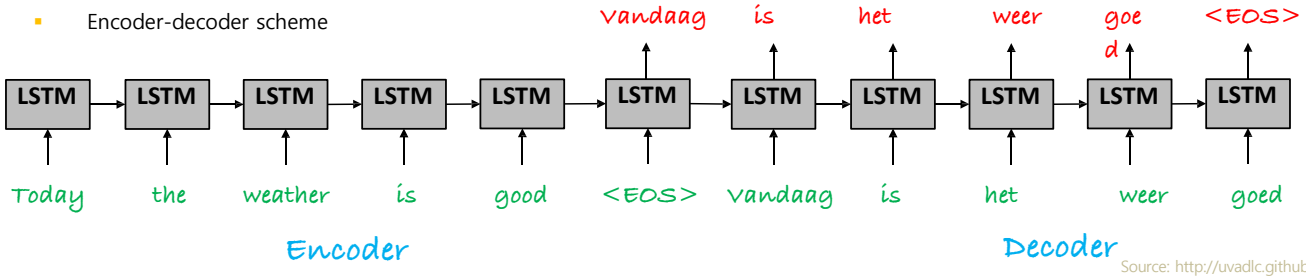






Machine Translation

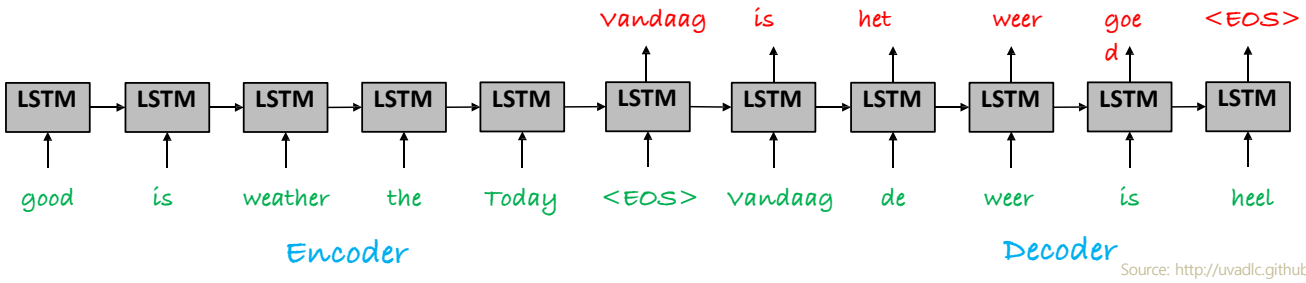
- The phrase in the source language is one sequence
  - "Today the weather is good"
- The phrase in the target language is also a sequence
  - "Vandaag is het weer goed"
- Problems
  - no perfect word alignment, sentence length might differ
- Solution
  - Encoder-decoder scheme



Source: http://uvadlc.github.io/

Better Machine Translation

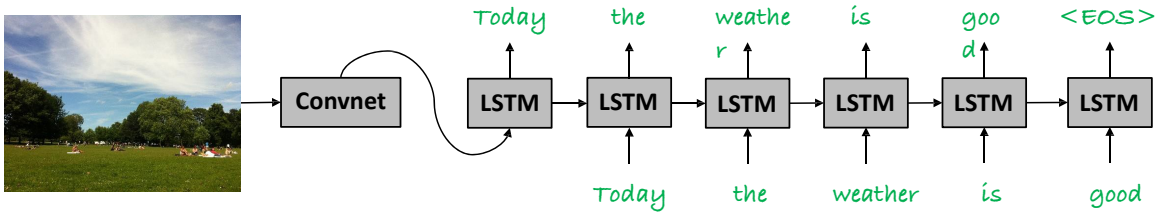
- It might even pay off reversing the source sentence
  - The first target words will be closer to their respective source words
- The encoder and decoder parts can be modelled with different LSTMs
- Deep LSTM



Source: http://uvadlc.github.io/

Image captioning

- An image is a thousand words, literally!
- Pretty much the same as machine transation
- Replace the encoder part with the output of a Convnet
  - E.g. use Alexnet or a VGG16 network
- Keep the decoder part to operate as a translator



Source: http://uvadlc.github.io/

Image captioning demo

- https://milhidaka.github.io/chainer-image-caption/

Generating image caption demo

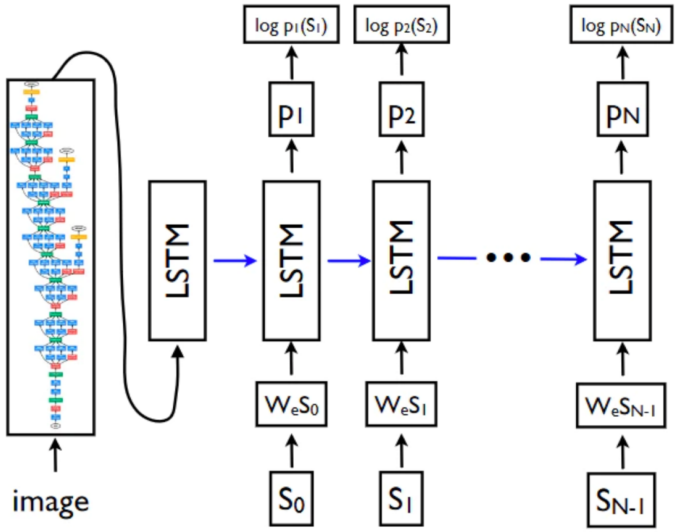
Input image (can drag-drop image file):

파일 선택 선택된 파일 없음

Generate caption

Load models > Analyze image > Generate text

```
Generated caption will be shown here.
```



Source: http://uvadlc.github.io/

Reading material & references

- http://www.deeplearningbook.org/
  - Part II: Chapter 13,14

Source: http://uvadlc.github.io/