Deep Learning

13. Recurrent Neural Networks

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So far...

1. Perceptron, MLP, Gradient Descent (Backpropagation)

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2. CNNs (visualizing and understanding)

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2. CNNs (visualizing and understanding)
3. 'Feedforward Neural networks'

Feedforward NNs: some observations

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1. Size of the i/p is fixed(?!)
2. Successive i/p are i.i.d.
3. Processing of successive i/p is independent of each other

Consider 'auto-completion' task

Q deep|

G deep — Search with Google

🕓 **kuldeep birdar**

Q deep**ika padukone**

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Q deep**ak bagga**

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① Successive i/p are not independent

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3. Same underlying task at different 'time instances'

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1. Successive i/p are not independent
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4. Sequence Learning Problems

Sequence Learning Tasks: Example
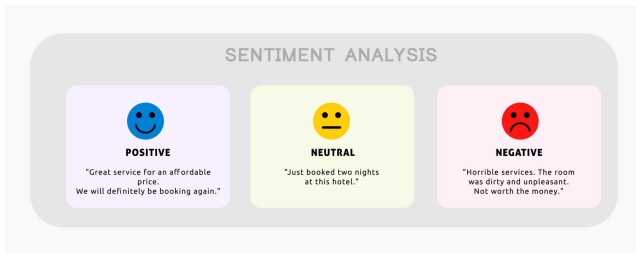
Sentiment Analysis (Source)

Sequence Learning Tasks: Example
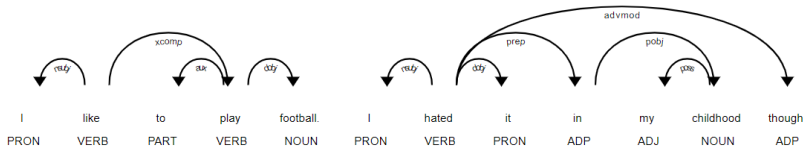
POS-Tagging (Source:Kaggle)

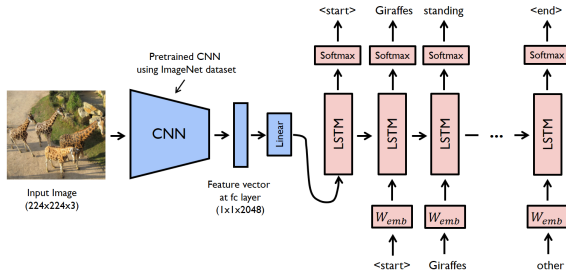# Sequence Learning Tasks: Example
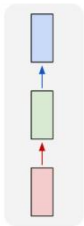

Action Recognition (Source)

Image Captioning(Source)

Sequence Learning Tasks: Variations
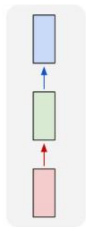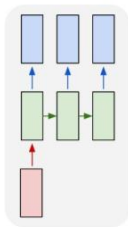
one to one

Source

Sequence Learning Tasks: Variations

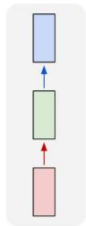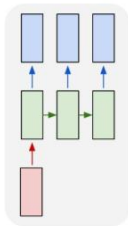one to one   one to many

Source

Sequence Learning Tasks: Variations

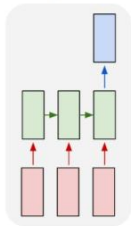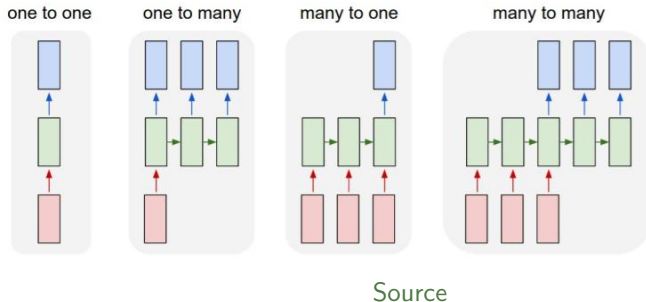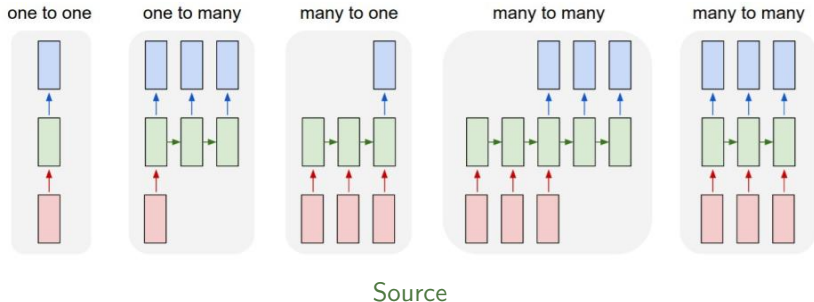one to one   one to many   many to one

Source

Sequence Learning Tasks: Variations

Source

Sequence Learning Tasks: Variations

| one to one | one to many | many to one | many to many | many to many |

Source

Recurrent Neural Networks (RNN)

1. NNs designed to solve sequence learning tasks

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2. Characteristics
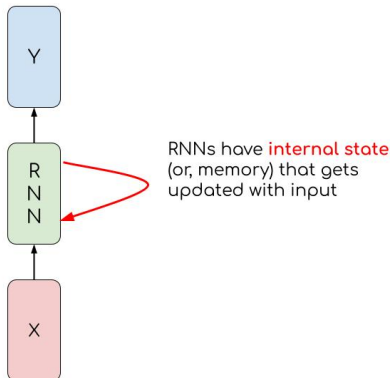   1. Model the dependence among the i/p

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    1. Model the dependence among the i/p
    2. Handle variable length of i/p
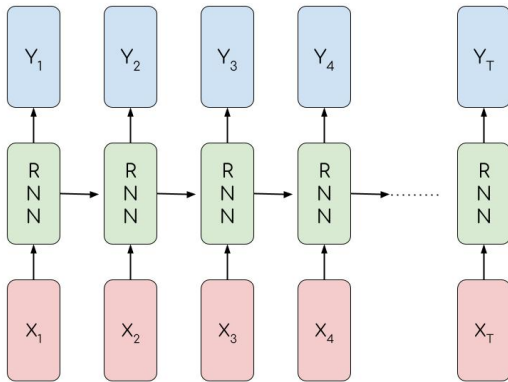
Recurrent Neural Networks (RNN)

1. NNs designed to solve sequence learning tasks
2. Characteristics
   1. Model the dependence among the i/p
   2. Handle variable length of i/p
   3. Same function applied at all time instances

RNNs: internal state

RNNs have **internal state** (or, memory) that gets updated with input

RNNs: unfolding

RNNs

1. Apply the same transformation at every time step $\rightarrow$ 'Recurrent' NNs

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③ Initial recurrent state $h_0 \in \mathbb{R}^{\mathbb{Q}}$

RNNs

1. Apply the same transformation at every time step $\rightarrow$ 'Recurrent' NNs
2. i/p sequence $x_t \in \mathbb{R}^{\mathbb{D}}$
3. Initial recurrent state $h_0 \in \mathbb{R}^{\mathbb{Q}}$
4. RNN model computes sequence of recurrent states iteratively
   $h_t = \phi(x_t, h_{t-1}; w)$

RNNs
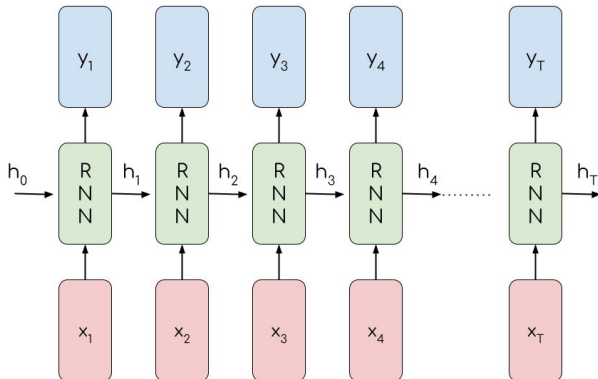
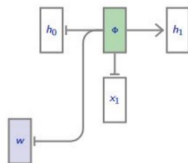# Elmon RNN (1990)

1. Start with $h_0 = 0$

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3. $y_t = softmax(W_{hy}.h_t + b_y)$

RNNs as computational graph

1. Use the same set of parameters at each time step

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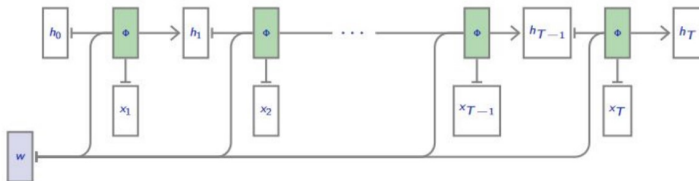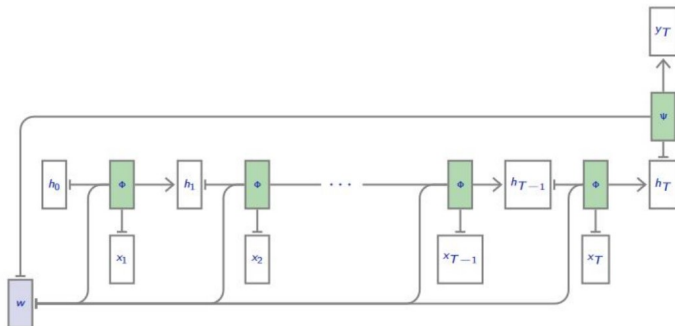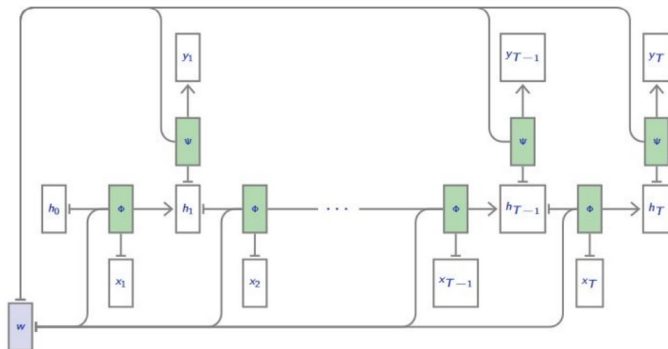
RNNs as computational graph

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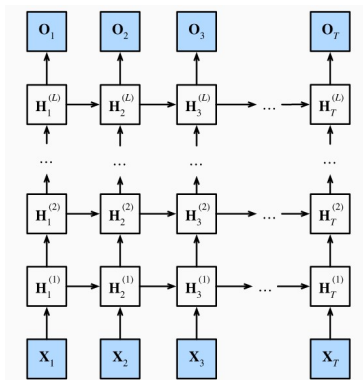
RNNs as computational graph

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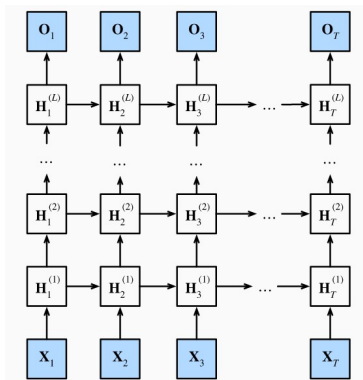2. Flexible to realize different variants (with some tricks!)

Multi-layered RNNs

1. Stack multiple RNNs between i/p and o/p layers

Source

Multi-layered RNNs

1. Stack multiple RNNs between i/p and o/p layers

2. $H_t^{(l)} = W_{xh}^{(l)} \cdot H_t^{(l-1)} + W_{hh}^{(l)} \cdot H_{t-1}^{(l)} + b_h^{(l)}$
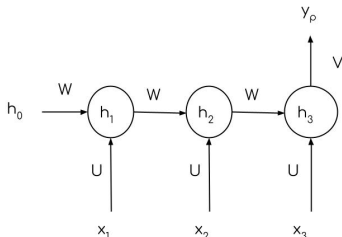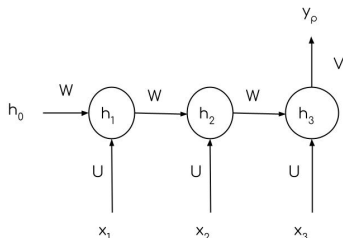

Source

Backpropagation Through Time (BPTT)

1. Consider a many-to-one variant RNN (e.g. sentiment analysis)

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2. Let's separate the parameters into U, V, and W

Backpropagation Through Time (BPTT)

1. Let's now perform SGD (assume loss L is formulated on y_p)
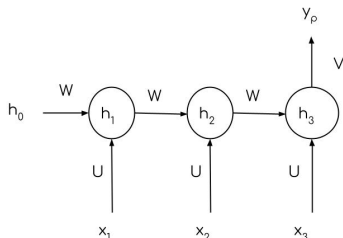
Backpropagation Through Time (BPTT)

1. Let's now perform SGD (assume loss L is formulated on y_p)

2. $\rightarrow$ we need to compute $\frac{\partial L}{\partial V}$, $\frac{\partial L}{\partial W}$, and $\frac{\partial L}{\partial U}$
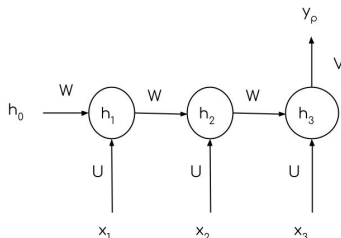
Backpropagation Through Time (BPTT)

① $\frac{\partial L}{\partial V} = \frac{\partial L}{\partial y_p}\frac{\partial y_p}{\partial V} =$
$\frac{\partial L}{\partial y_p} \cdot \frac{\partial y_p}{\partial z_3} \cdot \frac{\partial z_3}{\partial V}$
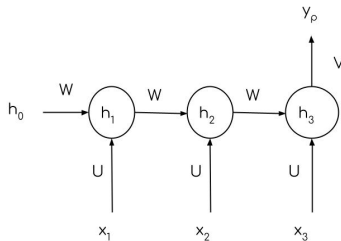
Backpropagation Through Time (BPTT)

1. $\frac{\partial L}{\partial V} = \frac{\partial L}{\partial y_p} \frac{\partial y_p}{\partial V} =$
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2. $y_p = softmax(z_3)$ and
   $z_3 = V \cdot h_3 + b_y$
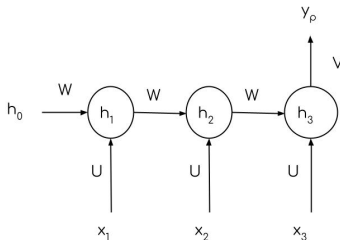
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3. Since we know that
   h_3, b_y are independent of
   V, we can compute $\frac{\partial L}{\partial V}$
   in a single step
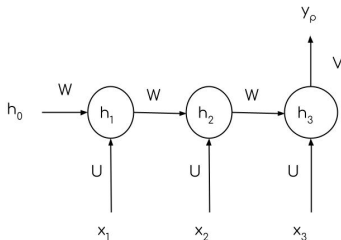
Backpropagation Through Time (BPTT)

1. Let's now consider $\frac{\partial L}{\partial W}$
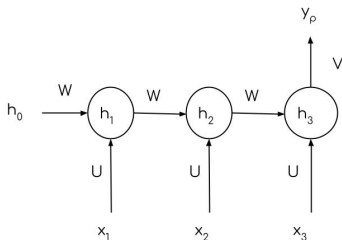
Backpropagation Through Time (BPTT)

1. Let's now consider $\frac{\partial L}{\partial W}$
2. There are multiple 'W's in the computational graph!
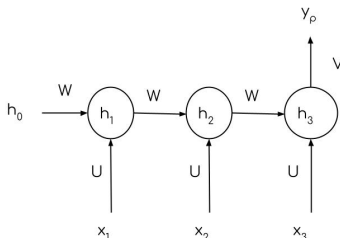
Backpropagation Through Time (BPTT)
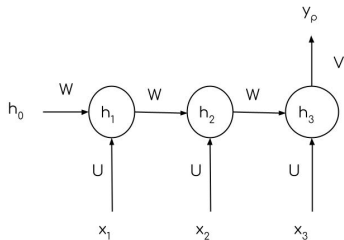
1. For ease of understanding
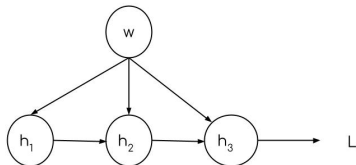
Backpropagation Through Time (BPTT)
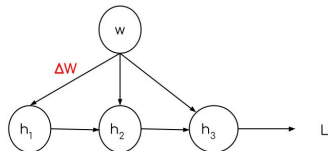
1. Δw change in W$\rightarrow$
   $\left(\frac{\partial h_1}{\partial W} \cdot \Delta w \right)$ change in h_1

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2. Δw change in $W \rightarrow$
   $\left(\frac{\partial h_2}{\partial W} \cdot \Delta w\right)$ change in h_2
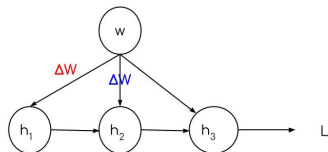
Backpropagation Through Time (BPTT)

1. Δw change in W→
   $\left(\frac{\partial h_1}{\partial W} \cdot \Delta w \right)$ change in h_1

2. Δw change in $W \to$
   $\left(\frac{\partial h_2}{\partial W} \cdot \Delta w \right)$ change in h_2

3. Δw change in W→
   $\left(\frac{\partial h_3}{\partial W} \cdot \Delta w \right)$ change in h_3
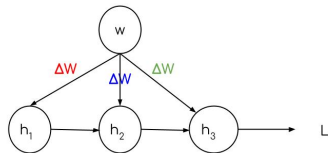
Backpropagation Through Time (BPTT)

1. $\Delta L =$
   $\frac{\partial L}{\partial h_1} \cdot \Delta h_1 + \frac{\partial L}{\partial h_2} \cdot \Delta h_2 + \frac{\partial L}{\partial h_3} \cdot \Delta h_3$

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2. $\frac{\partial L}{\partial W} = \frac{\partial L}{\partial h_1}\frac{\partial h_1}{\partial W} + \frac{\partial L}{\partial h_2}\frac{\partial h_2}{\partial W} + \frac{\partial L}{\partial h_3}\frac{\partial h_3}{\partial W}$

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2. $\frac{\partial L}{\partial W} = \textcolor{red}{\frac{\partial L}{\partial h_1} \frac{\partial h_1}{\partial W}} + \textcolor{blue}{\frac{\partial L}{\partial h_2} \frac{\partial h_2}{\partial W}} + \textcolor{green}{\frac{\partial L}{\partial h_3} \frac{\partial h_3}{\partial W}}$

3. $\textcolor{green}{\frac{\partial L}{\partial h_3}} = \frac{\partial L}{\partial y_p} \frac{\partial y_p}{\partial h_3}$
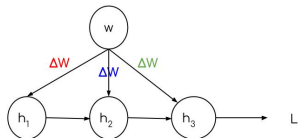
4. $\frac{\partial L}{\partial h_2} = ?$

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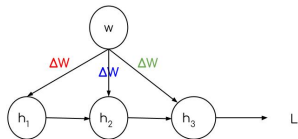
2. $\frac{\partial L}{\partial W} = \frac{\partial L}{\partial h_1} \frac{\partial h_1}{\partial W} + \frac{\partial L}{\partial h_2} \frac{\partial h_2}{\partial W} + \frac{\partial L}{\partial h_3} \frac{\partial h_3}{\partial W}$

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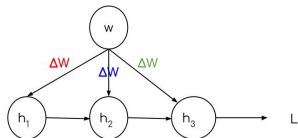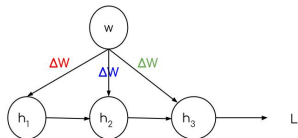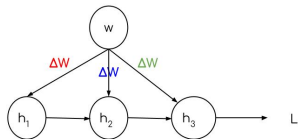
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③ $\frac{\partial L}{\partial h_3} = \frac{\partial L}{\partial y_p} \frac{\partial y_p}{\partial h_3}$

④ $\frac{\partial L}{\partial h_2} = ?$

⑤ $\frac{\partial L}{\partial h_2} = \frac{\partial L}{\partial h_3} \frac{\partial h_3}{\partial h_2}$

⑥ $\frac{\partial L}{\partial h_1} = \frac{\partial L}{\partial h_3} \frac{\partial h_3}{\partial h_1} = \frac{\partial L}{\partial h_3} \frac{\partial h_3}{\partial h_2} \frac{\partial h_2}{\partial h_1}$

Backpropagation Through Time (BPTT)

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Backpropagation Through Time (BPTT)

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2. $\dfrac{\partial L}{\partial h_2} = \dfrac{\partial L}{\partial h_3}\dfrac{\partial h_3}{\partial h_2}$

3. $\dfrac{\partial L}{\partial h_1} = \dfrac{\partial L}{\partial h_3}\dfrac{\partial h_3}{\partial h_1} = \dfrac{\partial L}{\partial h_3}\dfrac{\partial h_3}{\partial h_2}\dfrac{\partial h_2}{\partial h_1}$

4. $\dfrac{\partial L}{\partial W} = \dfrac{\partial L}{\partial h_3}\dfrac{\partial h_3}{\partial h_2}\dfrac{\partial h_2}{\partial h_1}\dfrac{\partial h_1}{\partial W} +$
   $\dfrac{\partial L}{\partial h_3}\dfrac{\partial h_3}{\partial h_2}\dfrac{\partial h_2}{\partial W} + \dfrac{\partial L}{\partial h_3}\dfrac{\partial h_3}{\partial W}$
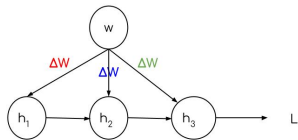
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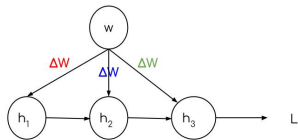
4. $\dfrac{\partial L}{\partial W} = \dfrac{\partial L}{\partial h_3}\dfrac{\partial h_3}{\partial h_2}\dfrac{\partial h_2}{\partial h_1}\dfrac{\partial h_1}{\partial W} +$
   $\dfrac{\partial L}{\partial h_3}\dfrac{\partial h_3}{\partial h_2}\dfrac{\partial h_2}{\partial W} + \dfrac{\partial L}{\partial h_3}\dfrac{\partial h_3}{\partial W}$

5.

$$\frac{\partial L}{\partial W} = \sum_{k=1}^{3} \frac{\partial L}{\partial h_3} \frac{\partial h_3}{\partial h_k} \frac{\partial h_k}{\partial W}$$

Backpropagation Through Time (BPTT)

① $\frac{\partial L}{\partial W} = \frac{\partial L}{\partial h_1}\frac{\partial h_1}{\partial W} + \frac{\partial L}{\partial h_2}\frac{\partial h_2}{\partial W} + \frac{\partial L}{\partial h_3}\frac{\partial h_3}{\partial W}$
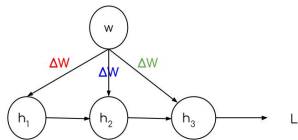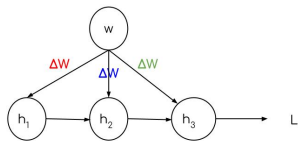
② $\frac{\partial L}{\partial h_2} = \frac{\partial L}{\partial h_3}\frac{\partial h_3}{\partial h_2}$

③ $\frac{\partial L}{\partial h_1} = \frac{\partial L}{\partial h_3}\frac{\partial h_3}{\partial h_1} = \frac{\partial L}{\partial h_3}\frac{\partial h_3}{\partial h_2}\frac{\partial h_2}{\partial h_1}$

④ $\frac{\partial L}{\partial W} = \frac{\partial L}{\partial h_3}\frac{\partial h_3}{\partial h_2}\frac{\partial h_2}{\partial h_1}\frac{\partial h_1}{\partial W} +$
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⑤
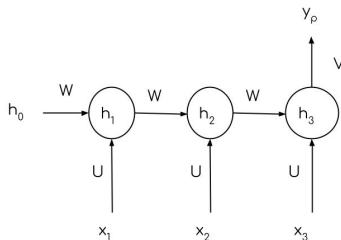$$\frac{\partial L}{\partial W} = \sum_{k=1}^{3} \frac{\partial L}{\partial h_3}\frac{\partial h_3}{\partial h_k}\frac{\partial h_k}{\partial W}$$

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$$\frac{\partial L}{\partial W} = \sum_{k=1}^{3} \frac{\partial L}{\partial h_3}\left(\prod_{j=k+1}^{3}\frac{\partial h_j}{\partial h_{j-1}}\right)\frac{\partial h_k}{\partial W}$$
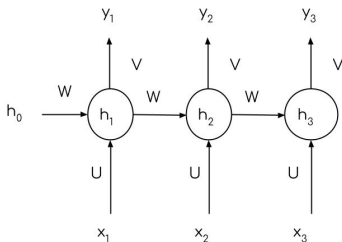
Backpropagation Through Time (BPTT)

1. Similarly $\frac{\partial L}{\partial U}$

Backpropagation Through Time (BPTT)

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2. Full sequence is one training example (although there is an error computed at each time step)

Backpropagation Through Time (BPTT)

1. Consider a many-to-many variant RNN (e.g. PoS tagging)
2. Total error is the sum of errors at each time step
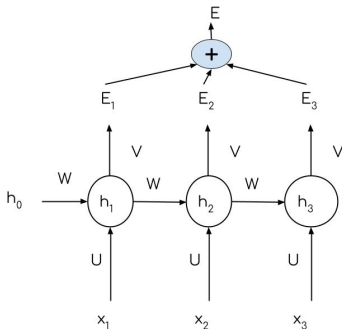
Backpropagation Through Time (BPTT)

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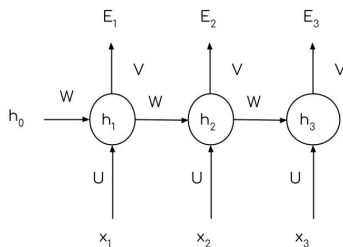
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4. Leads to Vanishing Gradient problem!
5. No impact of earlier time steps at later times (difficult to learn long-term dependencies!)

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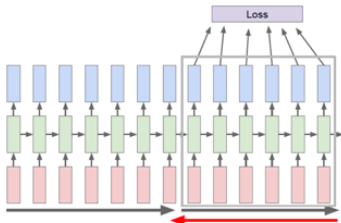   - Gradient clipping

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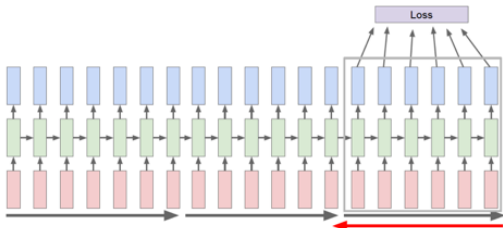4. Better initialization, Regularization, short time sequences (Truncation)

Backpropagation Through Time (BPTT)
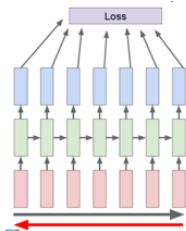
Truncated BPTT (CS231n)

Handling long-term dependencies

1. Architectural modifications to RNNs

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   - LSTM (1997 by Sepp Hochreiter and Jürgen Schmidhuber; Improved by Gers et al. in 2000)
   - GRU (Cho et al. 2014)

LSTM

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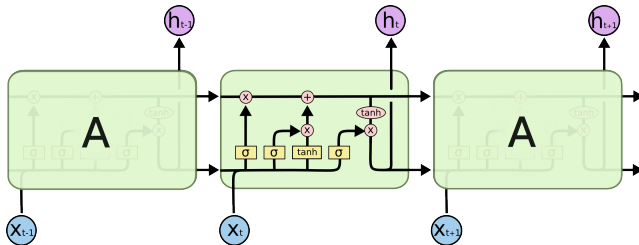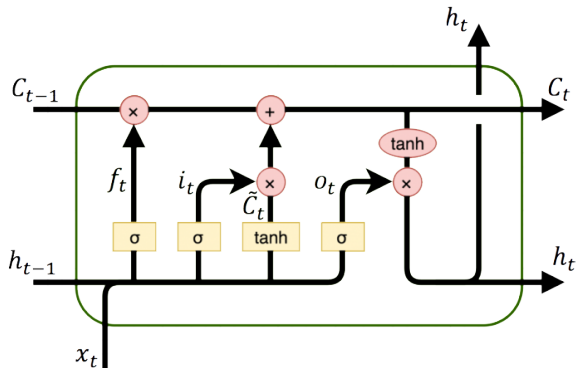   - Gates are dynamically computed based on the context

LSTM
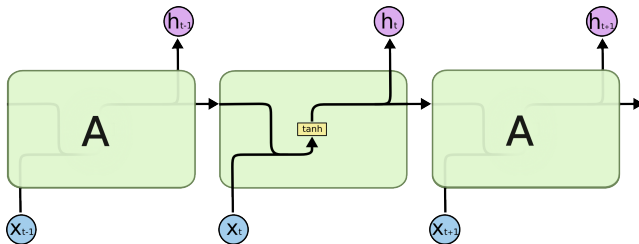
RNNs are chain of repeating moduels. Basic RNN (Colah's blog)
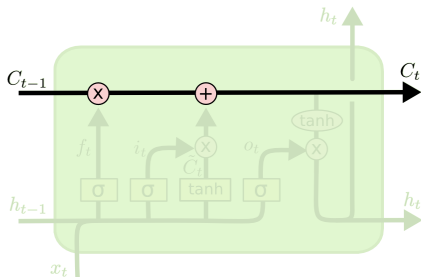
LSTM

RNNs are chain of repeating moduels. LSTM (Colah's blog)
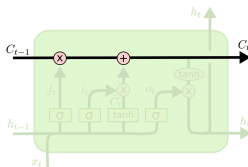
LSTM

The LSTM node. (Colah's blog)

LSTM: The cell state

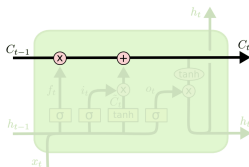Cell state in LSTM (Colah's blog)

LSTM: The cell state

1. Info. can flow through unchanged

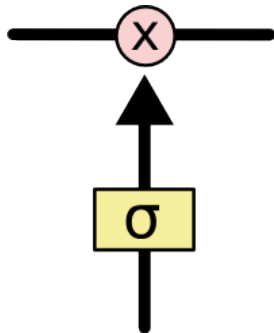

Cell state in LSTM (Colah's blog)

LSTM: The cell state

1. Info. can flow through unchanged

2. Gates can add/remove information to cell state
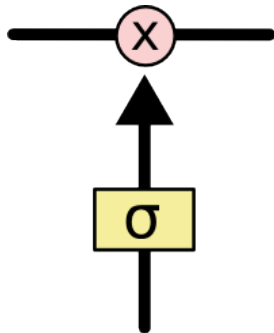

Cell state in LSTM (Colah's blog)

LSTM: The gates

1. Sigmoid neural nets (o/p numbers in [0, 1])

Cell state in LSTM (Colah's blog)

LSTM: The gates

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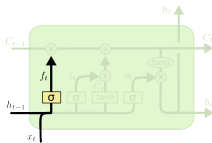2. Point-wise multiplication operation

Cell state in LSTM (Colah's blog)

LSTM: The forget gate

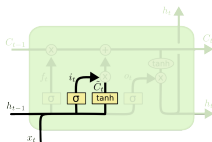1. Decides what to throw away from cell state (e.g. forgetting the gender of old subject in light of a new one)

$$f_t = \sigma \left(W_f \cdot [h_{t-1}, x_t] + b_f \right)$$

Forget gate in LSTM (Colah's blog)

LSTM: The input gate

1. Next is to decide what new to store in cell state (e.g. add the gender of a new subject)

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

Input gate in LSTM (Colah's blog)

LSTM: The input gate

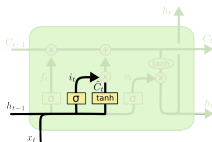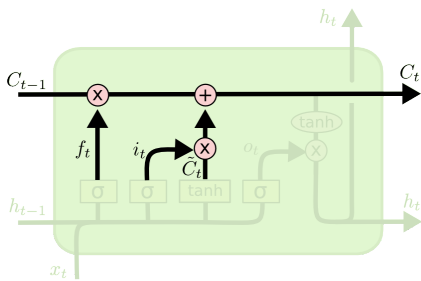1. Next is to decide what new to store in cell state (e.g. add the gender of a new subject)
2. Done in two steps
   - input gate decides what to update
   - A tanh layer creates a candidate cell state

$$i_t = \sigma \left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i \right)$$
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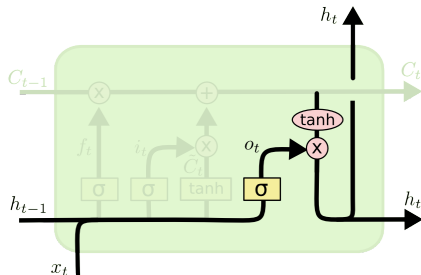
Input gate in LSTM (Colah's blog)

LSTM: The cell state update

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Cell state update in LSTM (Colah's blog)
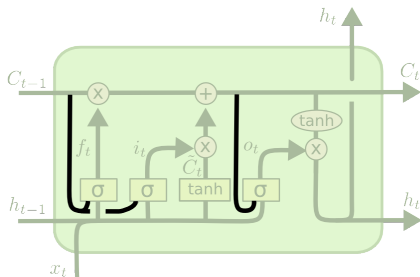
LSTM: The output

$$o_t = \sigma \left(W_o \left[h_{t-1}, x_t \right] + b_o \right)$$
$$h_t = o_t * \tanh \left(C_t \right)$$

Output computation in LSTM (Colah's blog)
e.g. may be a verb that is coming next in case of a language model
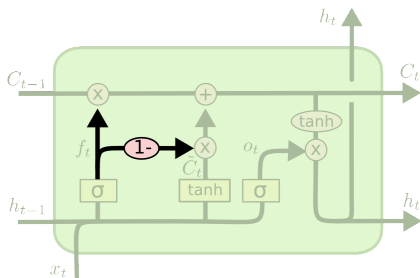
LSTM variant: Peephole connections

$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] + b_f\right)$$
$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] + b_i\right)$$
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] + b_o\right)$$

Variant with gates looking into the Cell state in LSTM by Ger et al. (Colah's blog)
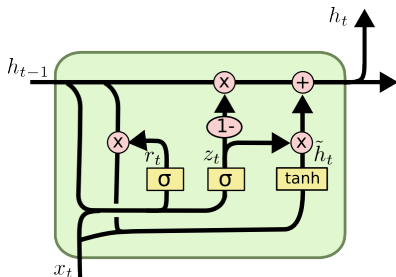
LSTM variant: Coupled i/p and forget gates

$$C_t = f_t * C_{t-1} + (1 - f_t) * \tilde{C}_t$$

Variant with coupled input and forget gates. (Colah's blog)

LSTM → GRU

$$z_t = \sigma \left(W_z \cdot [h_{t-1}, x_t] \right)$$

$$r_t = \sigma \left(W_r \cdot [h_{t-1}, x_t] \right)$$

$$\tilde{h}_t = \tanh \left(W \cdot [r_t * h_{t-1}, x_t] \right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Gated Recurrent Unit (Colah's blog)

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2. Driven applications such as handwriting recognition, ASR, Machine translation, Parsing, image captioning, VQA, etc.
3. Attention and Transformers are becoming more popular lately