Applied Deep Learning

Recurrent Neural Network

September 22nd, 2022 http://adl.miulab.tw

National Taiwan University
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Outline

- Language Modeling
  - N-gram Language Model
  - Feed-Forward Neural Language Model
  - Recurrent Neural Network Language Model (RNNLM)
- Recurrent Neural Network
  - Definition
  - Training via Backpropagation through Time (BPTT)
  - Training Issue
  - Extension
- RNN Applications
  - Sequential Input
  - Sequential Output
    - Aligned Sequential Pairs (Tagging)
    - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

3

Language Modeling
語言模型

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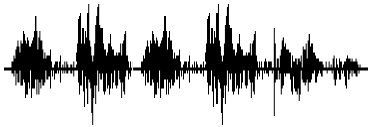
5 Language Modeling

- Goal: estimate the probability of a word sequence

$$P(w_1, \cdots, w_m)$$

- Example task: determinate whether a sequence is grammatical or makes more sense



recognize speech
or
wreck a nice beach

If P(recognize speech)
> P(wreck a nice beach)

Output = “recognize speech”

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7

N-Gram Language Modeling

- Goal: estimate the probability of a word sequence

$$P(w_1, \cdots, w_m)$$

- N-gram language model
  - Probability is conditioned on a window of (*n*-1) previous words

$$P(w_1, \cdots, w_m) = \prod_{i=1}^{m} P(w_i \mid w_1, \cdots, w_{i-1}) \approx \prod_{i=1}^{m} P(w_i \mid w_{i-(n-1)}, \cdots, w_{i-1})$$

  - Estimate the probability based on the training data

$$P(\text{beach}|\text{nice}) = \frac{C(\text{nice each})}{C(\text{nice})}$$

Count of “nice beach” in the training data

Count of “nice” in the training data

Issue: some sequences may not appear in the training data

N-Gram Language Modeling

- Training data:
  - The dog ran ……
  - The cat jumped ……

P(jumped | dog) = ~~0~~ 0.0001

P(ran | cat) = ~~0~~ 0.0001

give some small probability
→ smoothing

- The probability is not accurate.
- The phenomenon happens because we cannot collect all the possible text in the world as training data.

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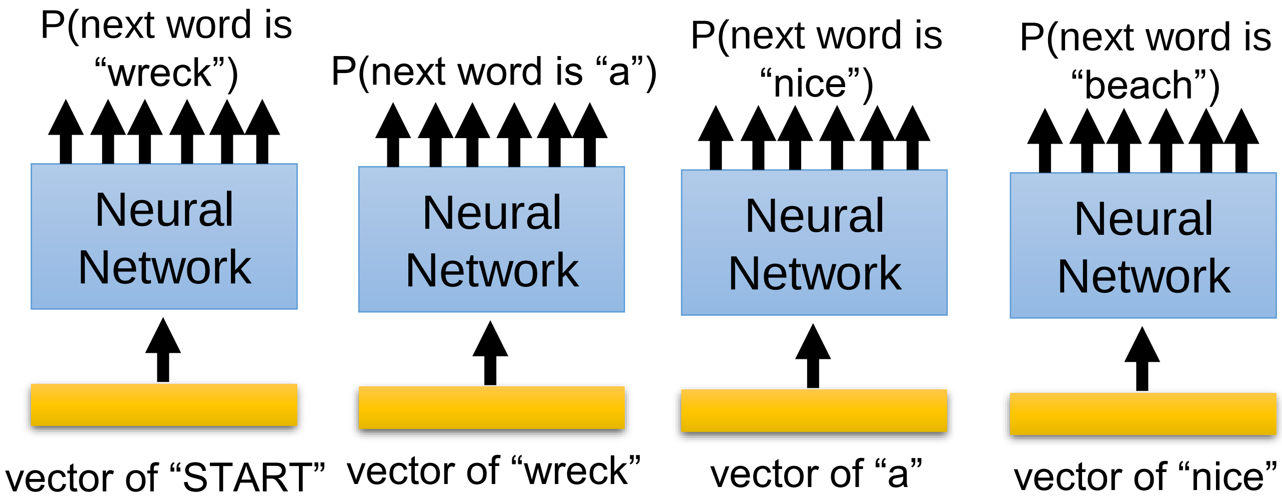
Neural Language Modeling

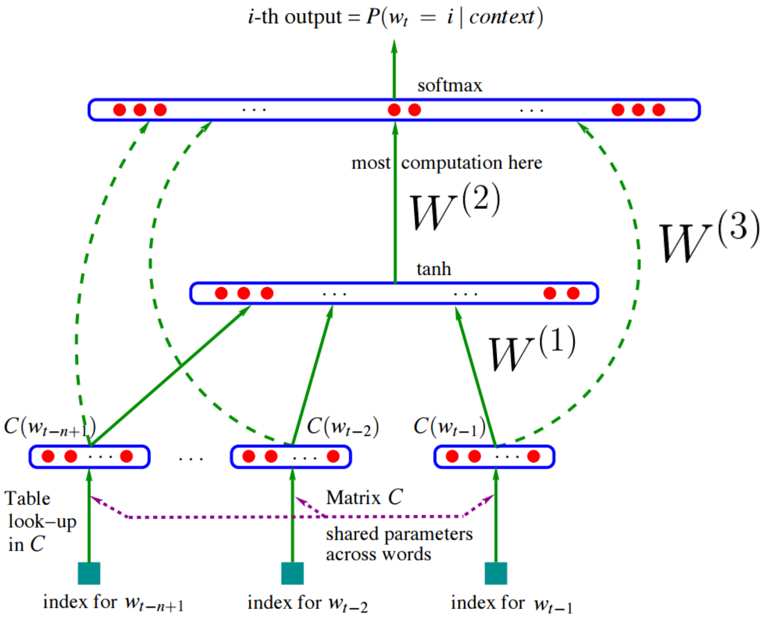
- Idea: estimate $P(w_i \mid w_{i-(n-1)}, \cdots, w_{i-1})$ not from count, but from NN prediction

P("wreck a nice beach") = P(wreck | START) P(a | wreck) P(nice | a) P(beach | nice)

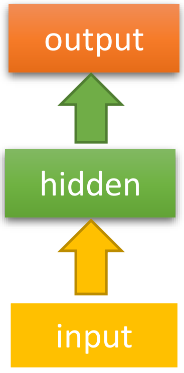


Neural Language Modeling

$$\hat{y} = \mathrm{softmax}(W^{(2)}\sigma(W^{(1)}x + b^{(1)}) + W^{(3)}x + b^{(3)})$$



Probability distribution of the next word

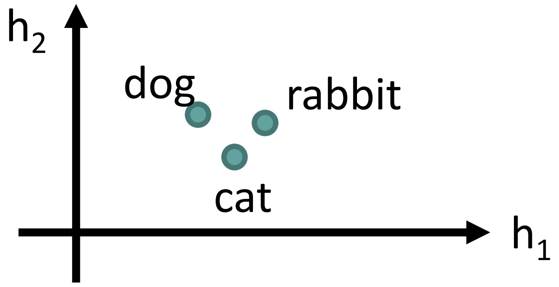


context vector

Bengio et al., “A Neural Probabilistic Language Model,” in *JMLR*, 2003.

Neural Language Modeling

- The input layer (or hidden layer) of the related words are close



  - If P(jump | dog) is large, P(jump | cat) increase accordingly (even there is not "… cat jump …" in the data)

Smoothing is automatically done

Issue: fixed context window for conditioning

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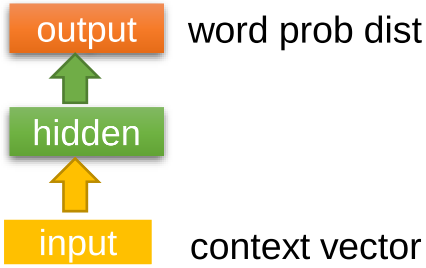
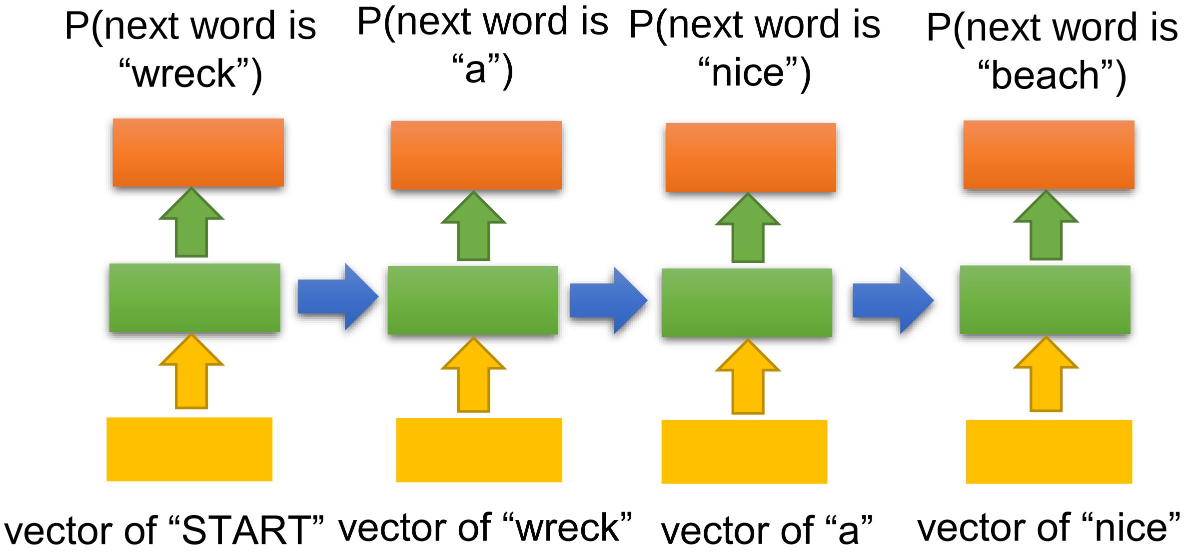
Recurrent Neural Network

- Idea: condition the neural network on <u>all previous words</u> and <u>tie the weights</u> at each time step
- Assumption: temporal information matters

RNN Language Modeling





Idea: pass the information from the previous hidden layer to leverage all contexts

16

Recurrent Neural Network

詳細解析鼎鼎大名的RNN

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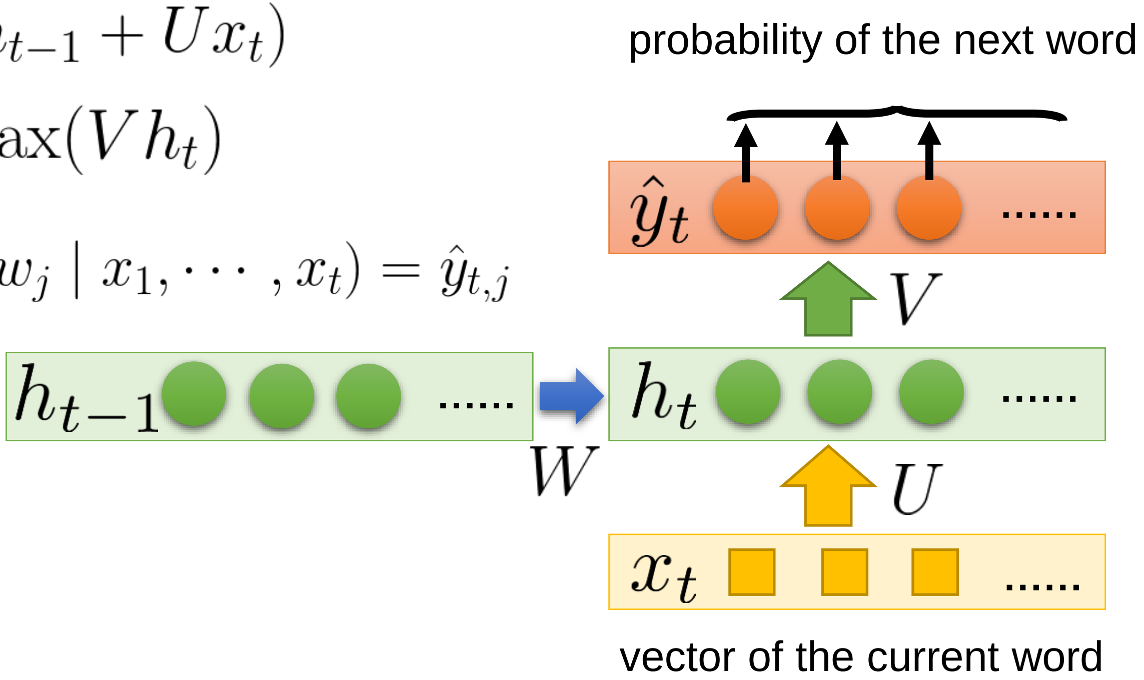
RNNLM Formulation

- At each time step,

$$h_t = \sigma(Wh_{t-1} + Ux_t)$$

$$\hat{y}_t = \text{softmax}(Vh_t)$$

$$P(x_{t+1} = w_j \mid x_1, \cdots, x_t) = \hat{y}_{t,j}$$



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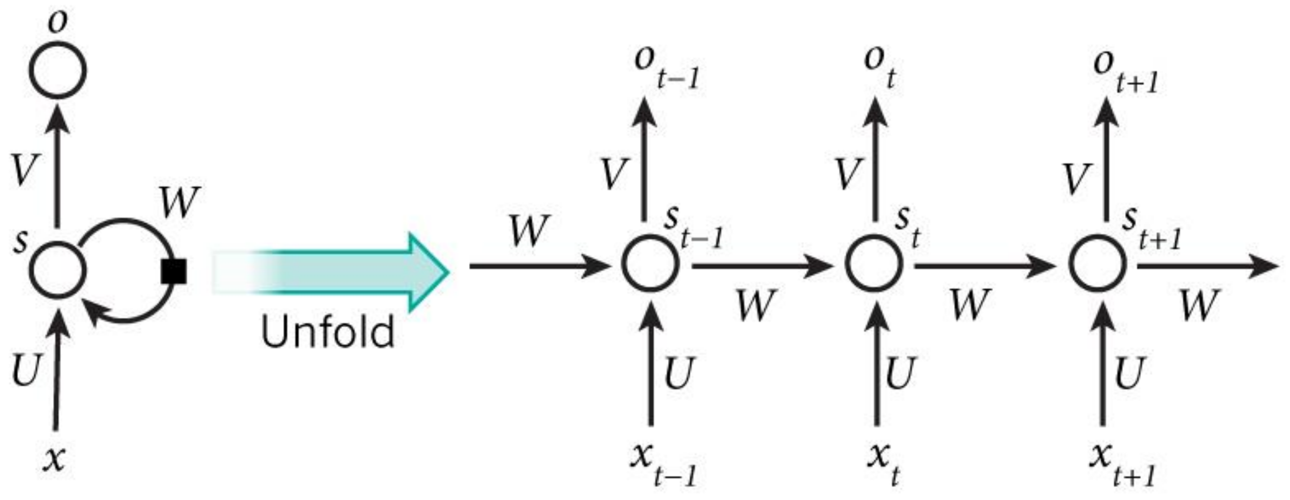
Recurrent Neural Network Definition

$$s_t = \sigma(W s_{t-1} + U x_t)$$
$$o_t = \mathrm{softmax}(V s_t)$$

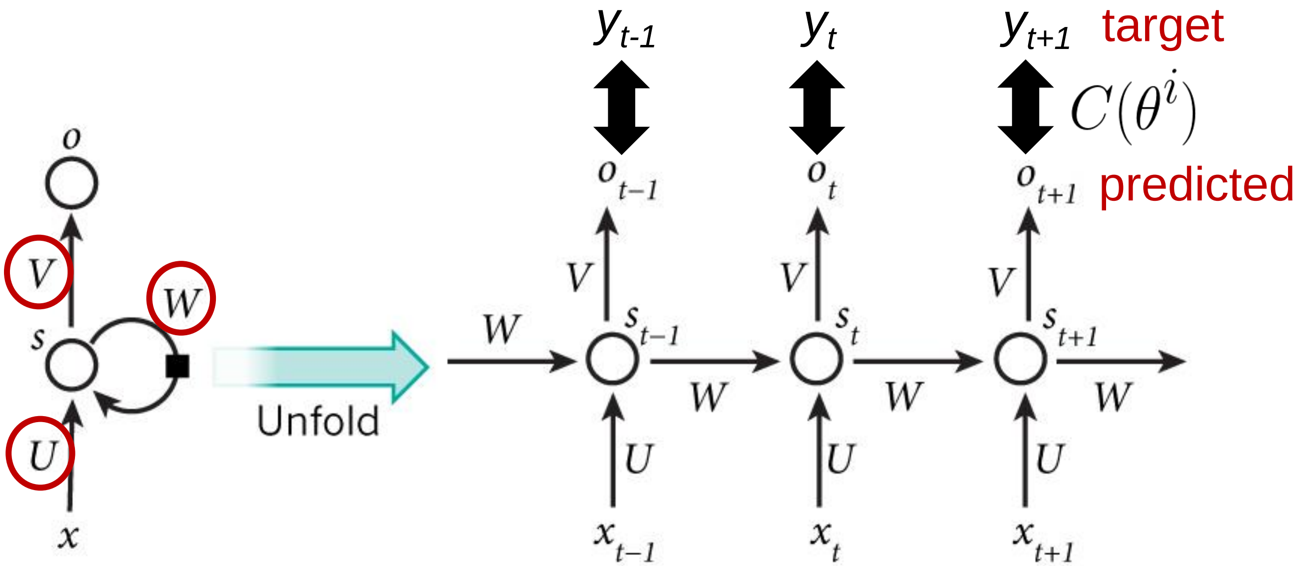
$\sigma(\cdot)$: tanh, ReLU



Model Training

- All model parameters $\theta = \{U, V, W\}$ can be updated by

$$\theta^{i+1} \leftarrow \theta^i - \eta \nabla_\theta C(\theta^i)$$



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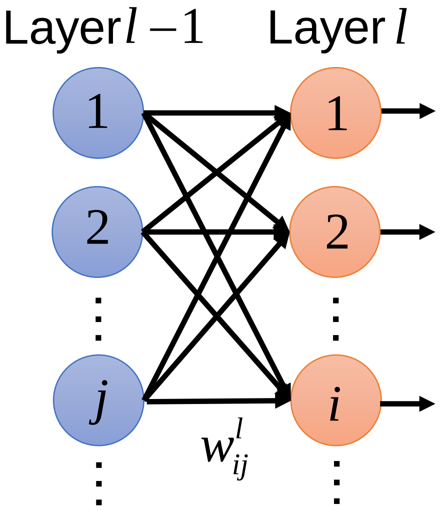
Backpropagation

$$\frac{\partial C(\theta)}{\partial w_{ij}^l} = \boxed{\frac{\partial C(\theta)}{\partial z_i^l}}\ \boxed{\frac{\partial z_i^l}{\partial w_{ij}^l}}$$



$\boxed{\delta_i^l}$ Error signal

$$\boxed{\begin{cases} a_j^{l-1} & l > 1 \\ x_j & l = 1 \end{cases}}$$

Backward Pass

$$\delta^L = \sigma'(z^L) \odot \nabla C(y)$$
$$\delta^{L-1} = \sigma'(z^{L-1}) \odot (W^L)^T \delta^L$$
$$\vdots$$
$$\delta^l = \sigma'(z^l) \odot (W^{l+1})^T \delta^{l+1}$$
$$\vdots$$

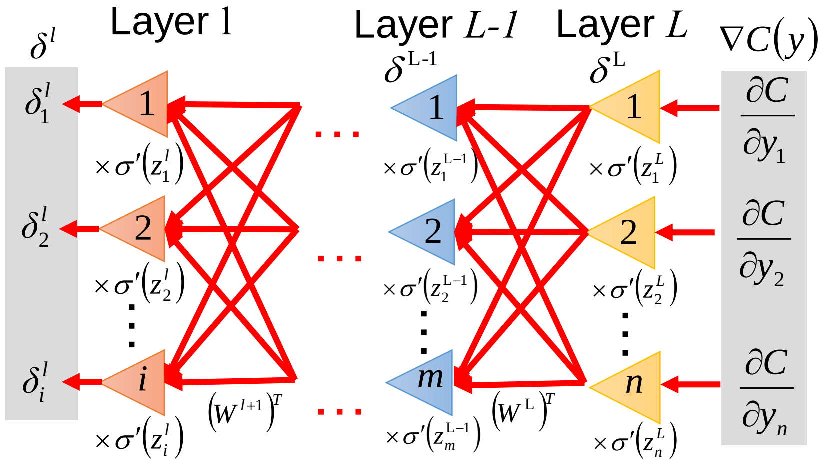
Forward Pass

$$z^1 = W^1 x + b^1$$
$$a^1 = \sigma(z^1)$$
$$\vdots$$
$$z^l = W^l a^{l-1} + b^l$$
$$a^l = \sigma(z^l)$$
$$\vdots$$

Backpropagation

$$\frac{\partial C(\theta)}{\partial w_{ij}^{l}} = \boxed{\frac{\partial C(\theta)}{\partial z_i^{l}}} \frac{\partial z_i^{l}}{\partial w_{ij}^{l}}$$

$\boxed{\delta_i^l}$ Error signal

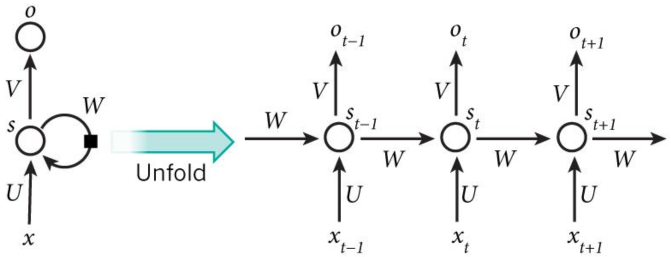


<u>Backward Pass</u>

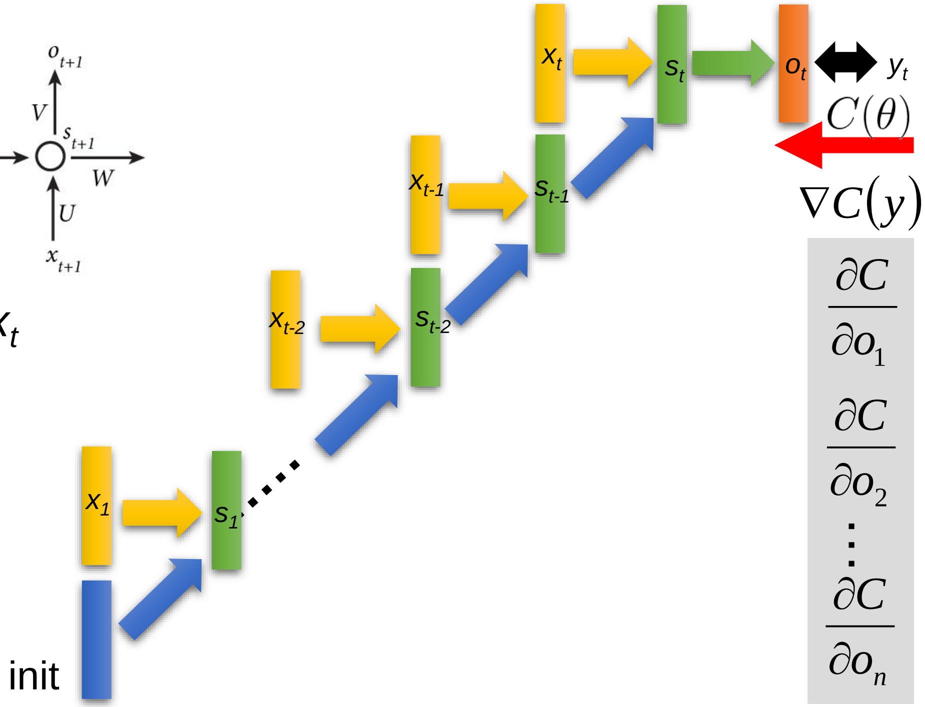
$$\delta^L = \sigma'(z^L) \odot \nabla C(y)$$
$$\delta^{L-1} = \sigma'(z^{L-1}) \odot (W^L)^T \delta^L$$
$$\vdots$$
$$\delta^l = \sigma'(z^l) \odot (W^{l+1})^T \delta^{l+1}$$
$$\vdots$$

Backpropagation through Time (BPTT)

- Unfold

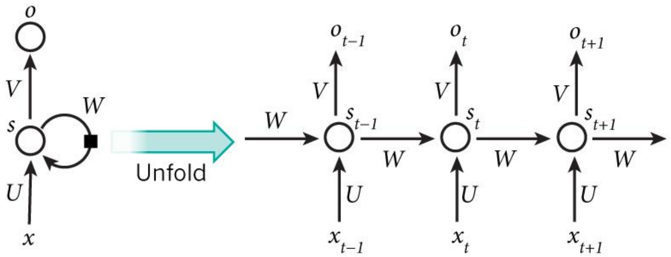


  - Input: init, x_1, x_2, …, x_t
  - Output: o_t
  - Target: y_t



Backpropagation through Time (BPTT)

- Unfold



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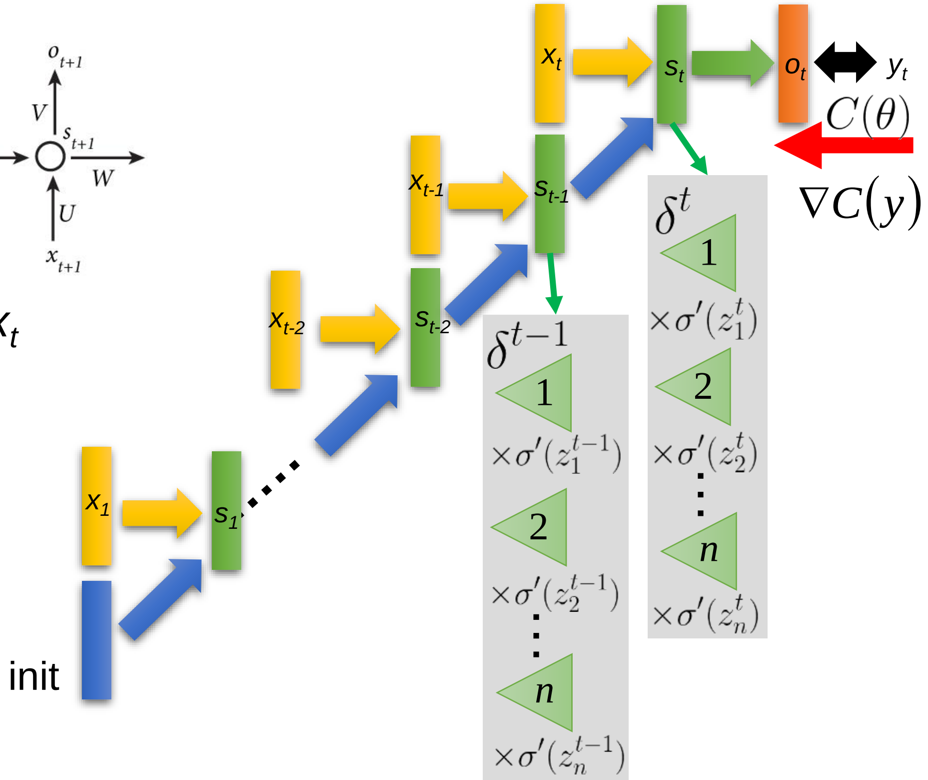
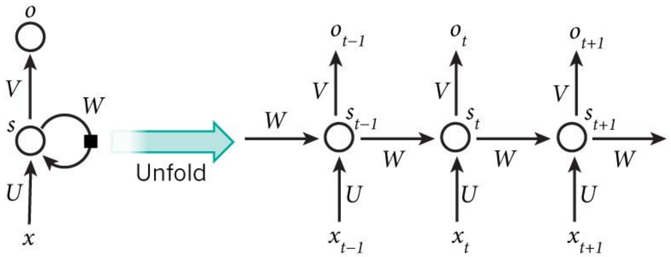


Backpropagation through Time (BPTT)

- Unfold



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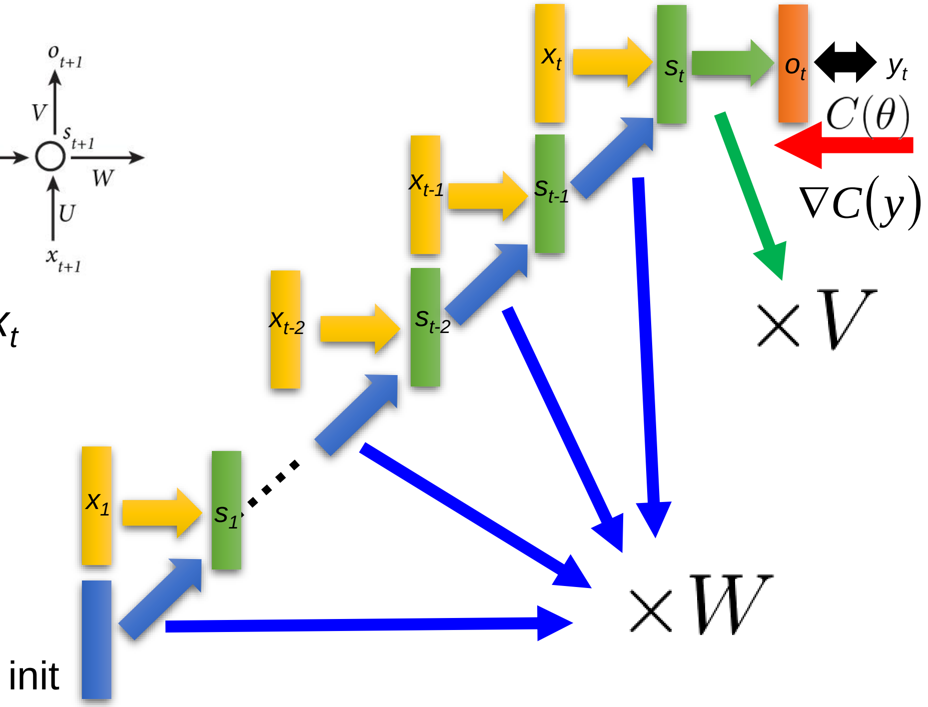
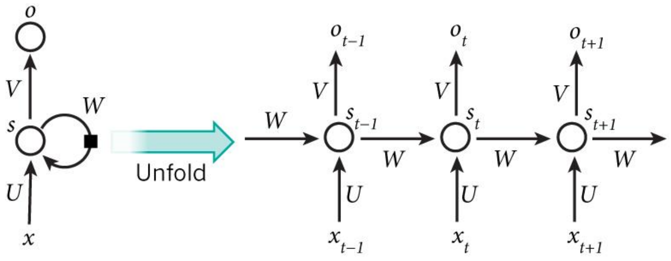
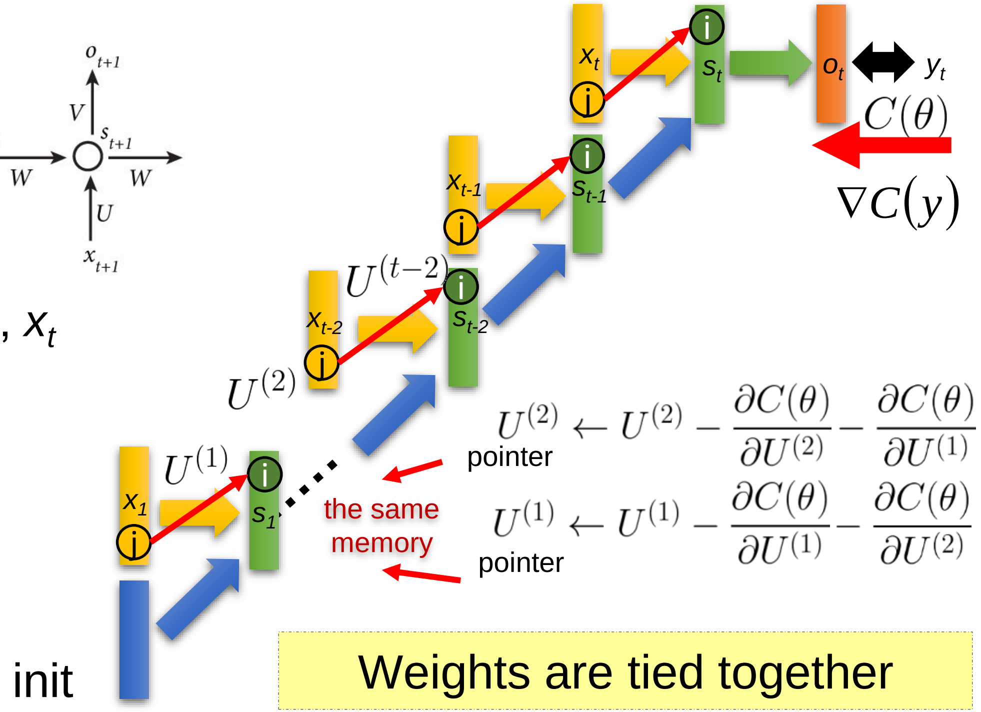


Backpropagation through Time (BPTT)

- Unfold



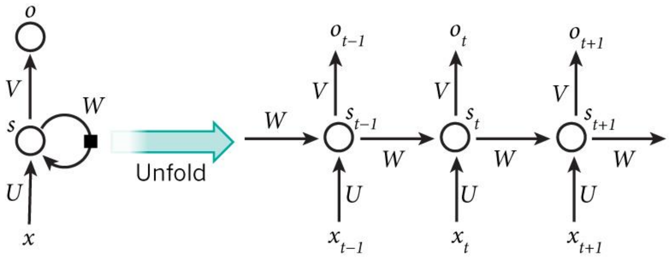
  - Input: init, x_1, x_2, …, x_t
  - Output: o_t
  - Target: y_t



Weights are tied together

Backpropagation through Time (BPTT)

- Unfold



  - Input: init, x_1, x_2, …, x_t
  - Output: o_t
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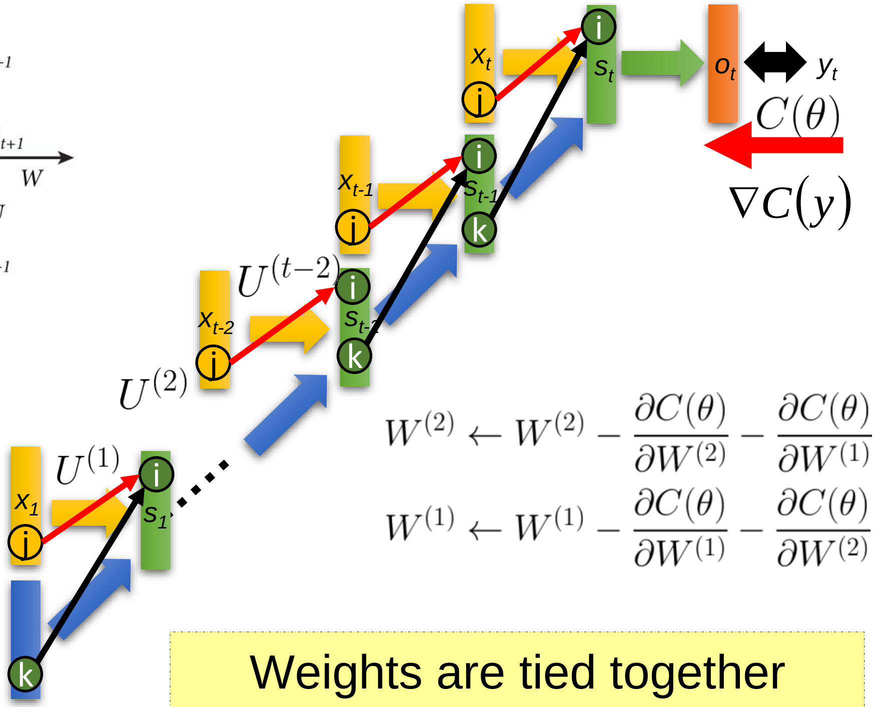


$$W^{(2)} \leftarrow W^{(2)} - \frac{\partial C(\theta)}{\partial W^{(2)}} - \frac{\partial C(\theta)}{\partial W^{(1)}}$$

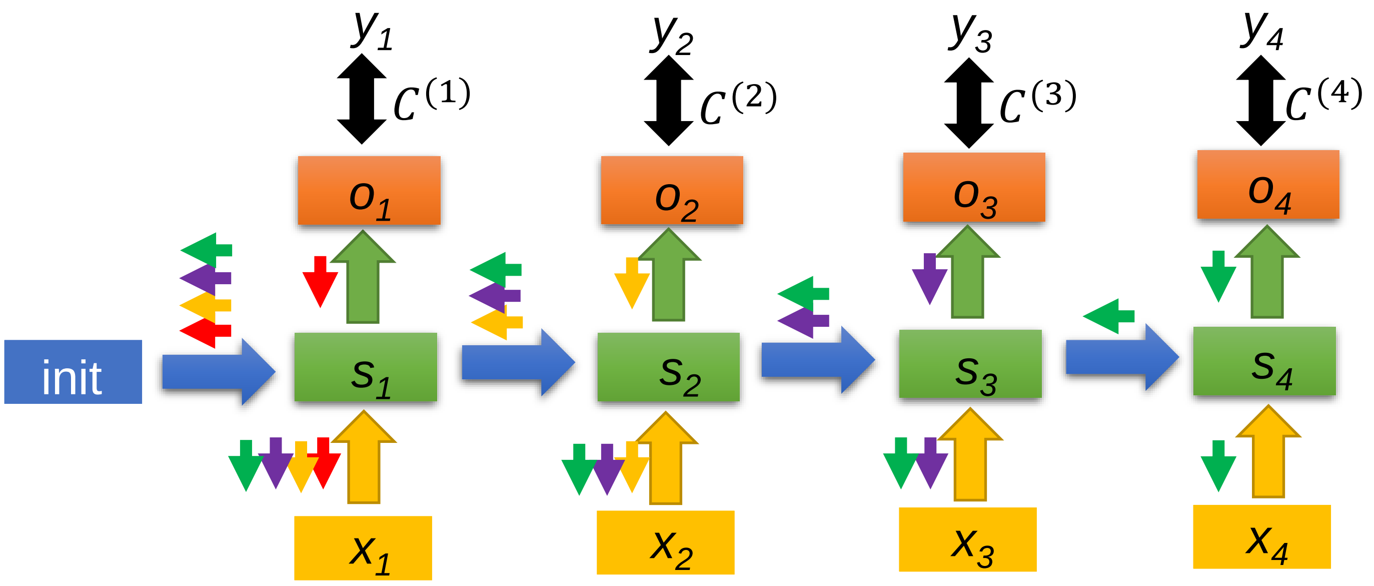
$$W^{(1)} \leftarrow W^{(1)} - \frac{\partial C(\theta)}{\partial W^{(1)}} - \frac{\partial C(\theta)}{\partial W^{(2)}}$$

Weights are tied together

BPTT

Forward Pass: Compute s_1, s_2, s_3, s_4 ……

Backward Pass: For $C^{(4)}$ For $C^{(3)}$ For $C^{(2)}$ For $C^{(1)}$



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RNN Training Issue

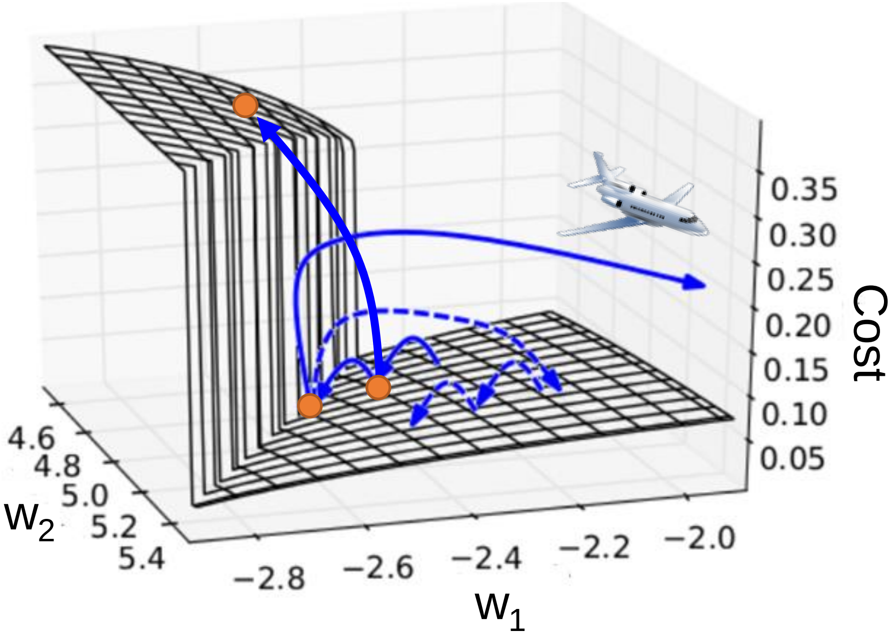
- The gradient is a product of Jacobian matrices, each associated with a step in the forward computation
- Multiply the same matrix at each time step during backprop

$$\delta^l = \sigma'(z^l) \odot \boxed{(W^{l+1})^T} \delta^{l+1}$$

The gradient becomes very small or very large quickly
→ **vanishing or exploding gradient**

Bengio et al., “Learning long-term dependencies with gradient descent is difficult,” *IEEE Trans. of Neural Networks*, 1994. [link]
Pascanu et al., “On the difficulty of training recurrent neural networks,” in *ICML*, 2013. [link]

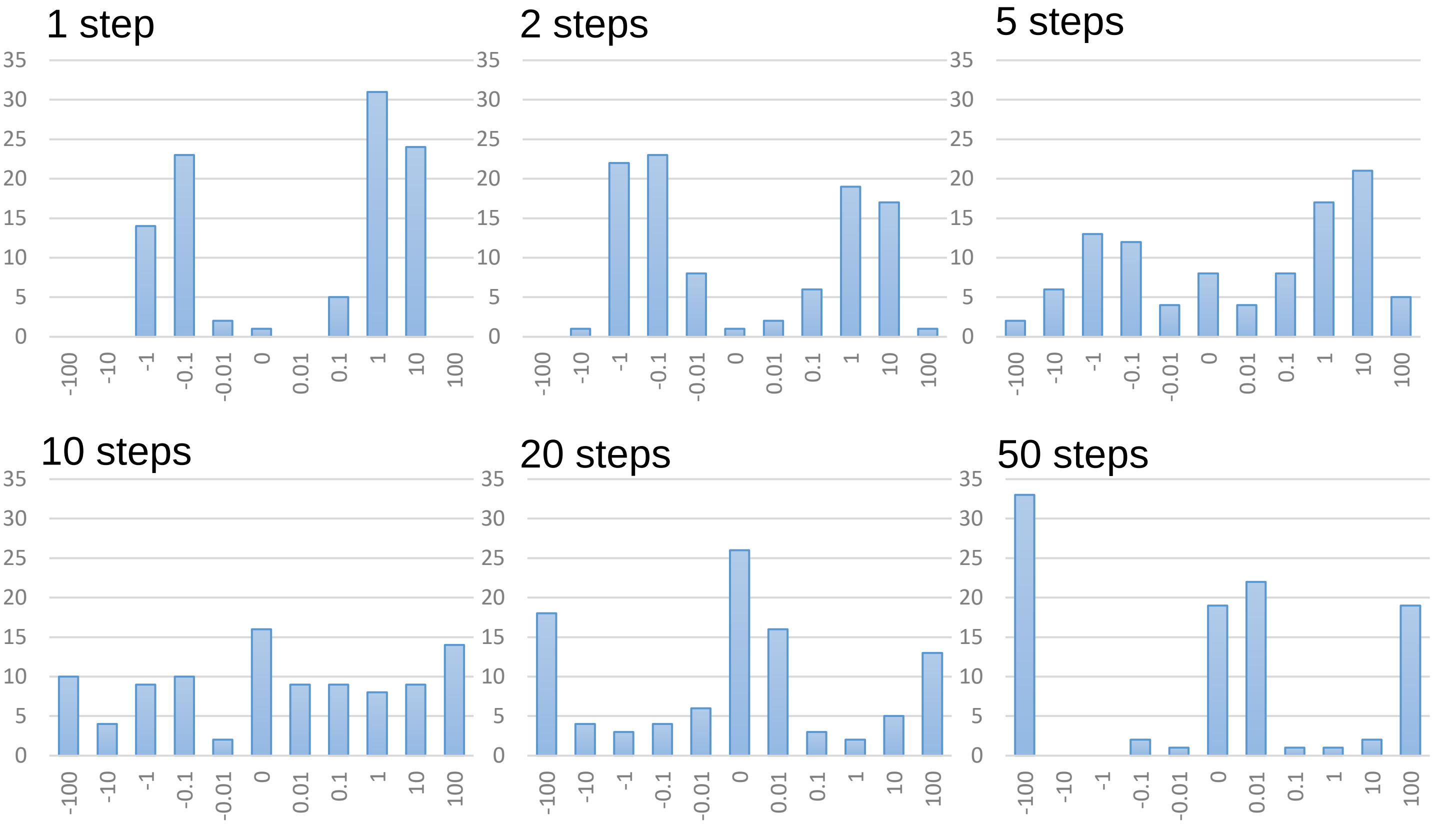
Rough Error Surface



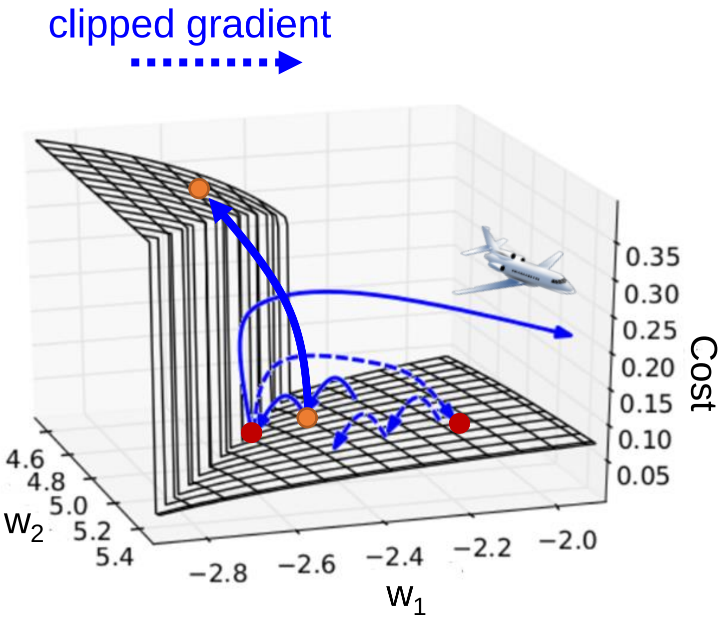
The error surface is either very flat or very steep

Bengio et al., “Learning long-term dependencies with gradient descent is difficult,” *IEEE Trans. of Neural Networks*, 1994. [link]
Pascanu et al., “On the difficulty of training recurrent neural networks,” in *ICML*, 2013. [link]

Vanishing/Exploding Gradient Example



Solution for Exploding Gradient: Clipping



Idea: control the gradient value to avoid exploding

Algorithm 1 Pseudo-code for norm clipping

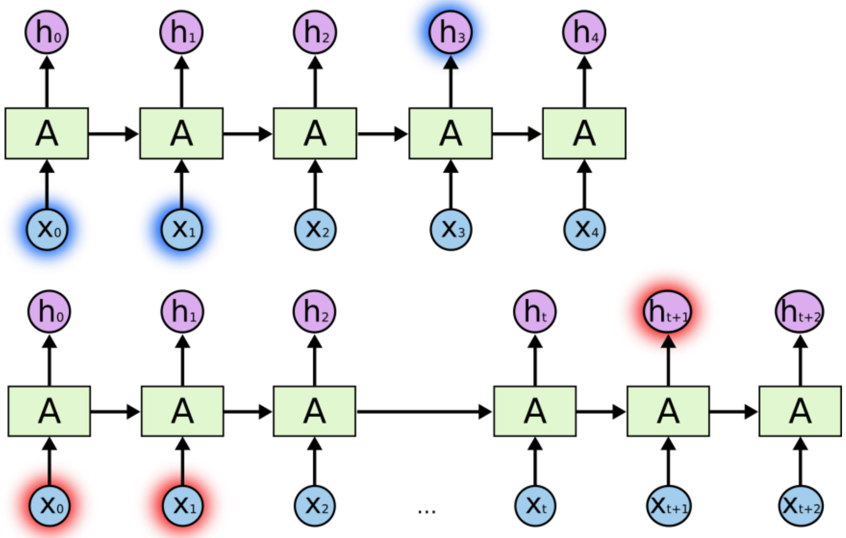
$\hat{\mathbf{g}} \leftarrow \frac{\partial \mathcal{E}}{\partial \theta}$
if $\|\hat{\mathbf{g}}\| \geq threshold$ **then**
  $\hat{\mathbf{g}} \leftarrow \frac{threshold}{\|\hat{\mathbf{g}}\|} \hat{\mathbf{g}}$
end if

Parameter setting: values from half to ten times the average can still yield convergence

Pascanu et al., "On the difficulty of training recurrent neural networks," in *ICML*, 2013. [link]

Solution for Vanishing Gradient: Gating

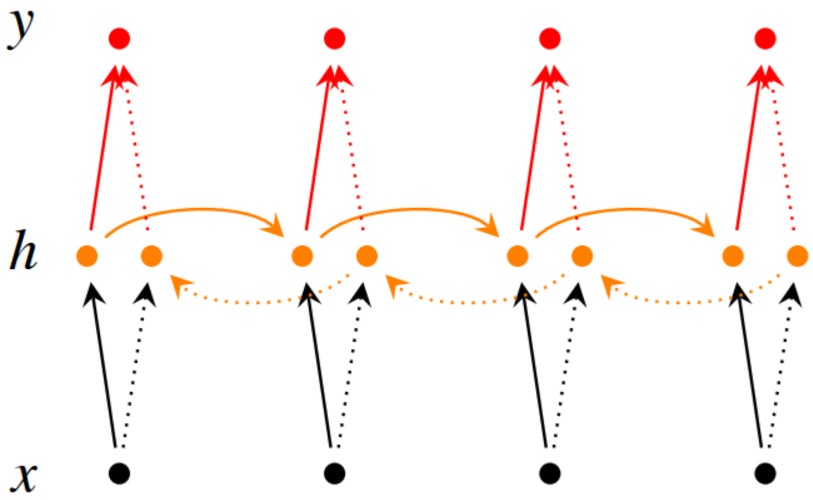
- RNN models temporal sequence information
  - can handle “long-term dependencies” *in theory*



“I grew up in France…
I speak fluent *French*.”

Issue: RNN cannot handle “long-term dependencies” due to vanishing gradient
→ gating directly encodes long-distance information

Extension: Bidirectional RNN



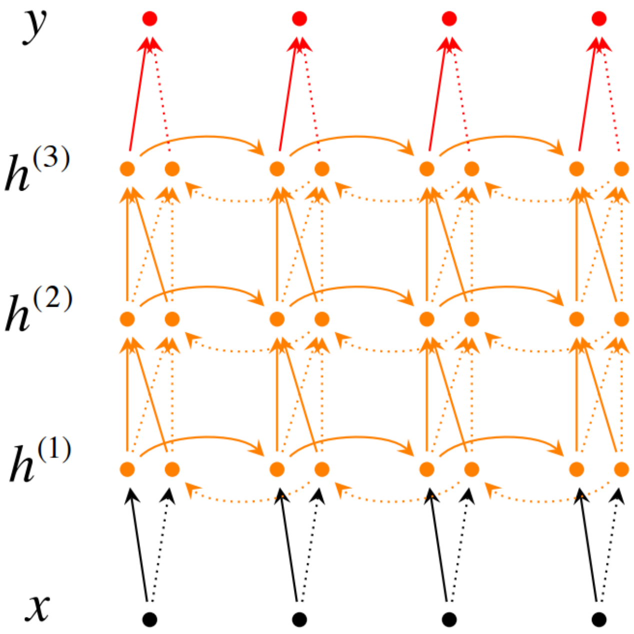
$$\overrightarrow{h}_t = f(\overrightarrow{W} x_t + \overrightarrow{V} \overrightarrow{h}_{t-1} + \overrightarrow{b})$$

$$\overleftarrow{h}_t = f(\overleftarrow{W} x_t + \overleftarrow{V} \overleftarrow{h}_{t+1} + \overleftarrow{b})$$

$$y_t = g(U[\overrightarrow{h}_t ; \overleftarrow{h}_t] + c)$$

$h = \left[\overrightarrow{h}; \overleftarrow{h}\right]$ represents (summarizes) the past and future around a single token

Extension: Deep Bidirectional RNN



$$\overrightarrow{h}_t^{(i)} = f(\overrightarrow{W}^{(i)} h_t^{(i-1)} + \overrightarrow{V}^{(i)} \overrightarrow{h}_{t-1}^{(i)} + \overrightarrow{b}^{(i)})$$

$$\overleftarrow{h}_t^{(i)} = f(\overleftarrow{W}^{(i)} h_t^{(i-1)} + \overleftarrow{V}^{(i)} \overleftarrow{h}_{t+1}^{(i)} + \overleftarrow{b}^{(i)})$$

$$y_t = g(U[\overrightarrow{h}_t^{(L)}; \overleftarrow{h}_t^{(L)}] + c)$$

Each memory layer passes an intermediate representation to the next

39

RNN Applications
RNN各式應用情境

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How to Frame the Learning Problem?

- The learning algorithm f is to map the input domain X into the output domain Y

$$f : X \rightarrow Y$$

- Input domain: word, word sequence, audio signal, click logs
- Output domain: single label, sequence tags, tree structure, probability distribution

Network design should leverage input and output domain properties

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Input Domain – Sequence Modeling

- Idea: aggregate the meaning from all words into a vector
- Method:
  - Basic combination: average, sum
  - Neural combination:
    - ✓ Recursive neural network (RvNN)
    - ✓ Recurrent neural network (RNN)
    - ✓ Convolutional neural network (CNN)

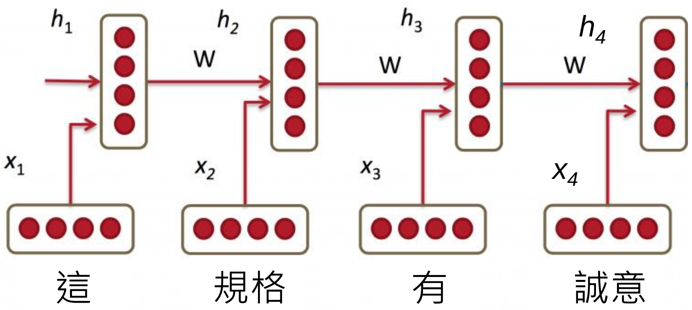
$$\begin{array}{cc} & \overbrace{\hphantom{\begin{bmatrix} 0.2 & 0.6 & 0.3 & \cdots & 0.4 \end{bmatrix}}}^{N\text{-dim}} \\ \text{這 (this)} & \begin{bmatrix} 0.2 & 0.6 & 0.3 & \cdots & 0.4 \end{bmatrix} \\ \text{規格 (specification)} & \begin{bmatrix} 0.9 & 0.8 & 0.1 & \cdots & 0.1 \end{bmatrix} \\ \text{有 (have)} & \begin{bmatrix} 0.1 & 0.3 & 0.1 & \cdots & 0.7 \end{bmatrix} \\ \text{誠意 (sincerity)} & \begin{bmatrix} 0.5 & 0.0 & 0.6 & \cdots & 0.4 \end{bmatrix} \end{array}$$

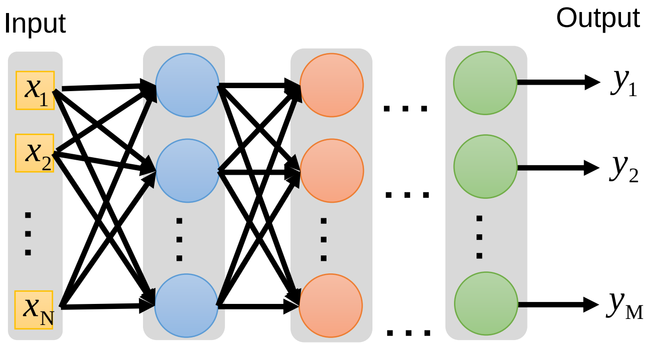
How to compute $\vec{x} = \begin{bmatrix} x_1 & x_2 & x_3 & \cdots & x_N \end{bmatrix}$

Sentiment Analysis

- Encode the sequential input into a vector using RNN

$$\vec{x} = \begin{bmatrix} x_1 & x_2 & x_3 & \cdots & x_N \end{bmatrix}$$





RNN considers temporal information to learn sentence vectors as classifier's input

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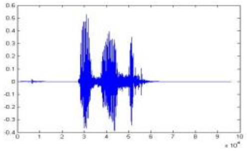
Output Domain – Sequence Prediction

- POS Tagging

“推薦我台大後門的餐廳” → 推薦/VV 我/PN 台大/NR 後門/NN 的/DEG 餐廳/NN

- Speech Recognition



→ “大家好”

- Machine Translation

“How are you doing today?” → “你好嗎?”

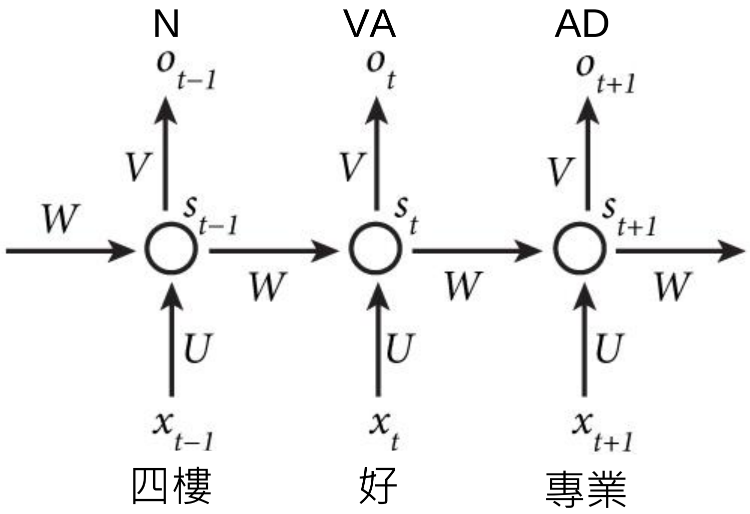
The output can be viewed as a sequence of classification

Outline

- Language Modeling
  - N-gram Language Model
  - Feed-Forward Neural Language Model
  - Recurrent Neural Network Language Model (RNNLM)
- Recurrent Neural Network
  - Definition
  - Training via Backpropagation through Time (BPTT)
  - Training Issue
  - Extension
- RNN Applications
  - Sequential Input
  - Sequential Output
    - **Aligned Sequential Pairs (Tagging)**
    - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

POS Tagging

- Tag a word at each timestamp
  - Input: word sequence
  - Output: corresponding POS tag sequence



Natural Language Understanding (NLU)

- Tag a word at each timestamp
  - Input: word sequence
  - Output: IOB-format slot tag and intent tag

<START>	just	sent	email	to	bob	about	fishing	this	weekend	<END>
O	O	O	O	O	B-contact_name	O	B-subject	I-subject	I-subject	send_email

→ send_email(contact_name="bob", subject="fishing this weekend")

Temporal orders for input and output are the same

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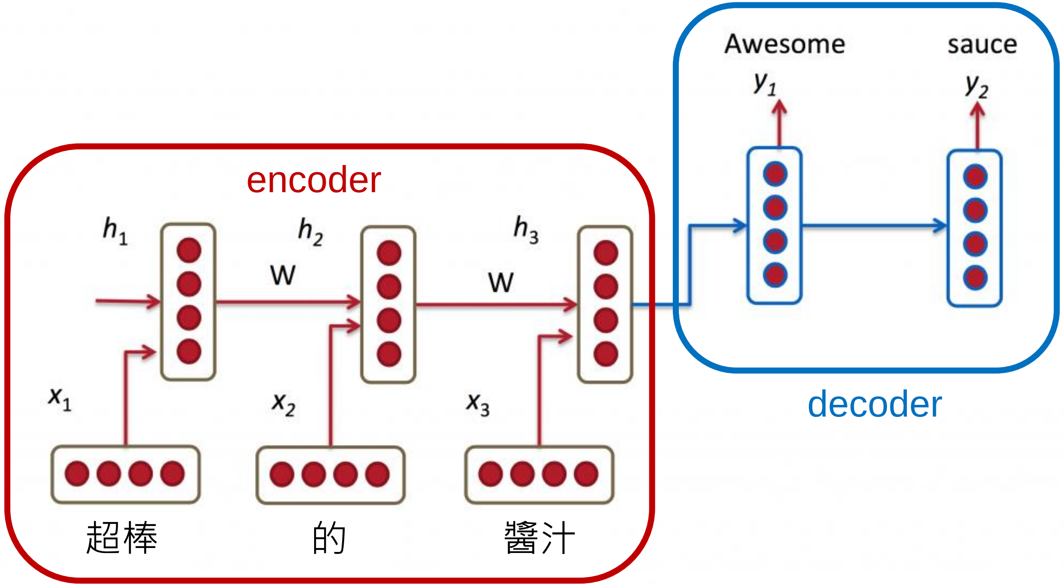
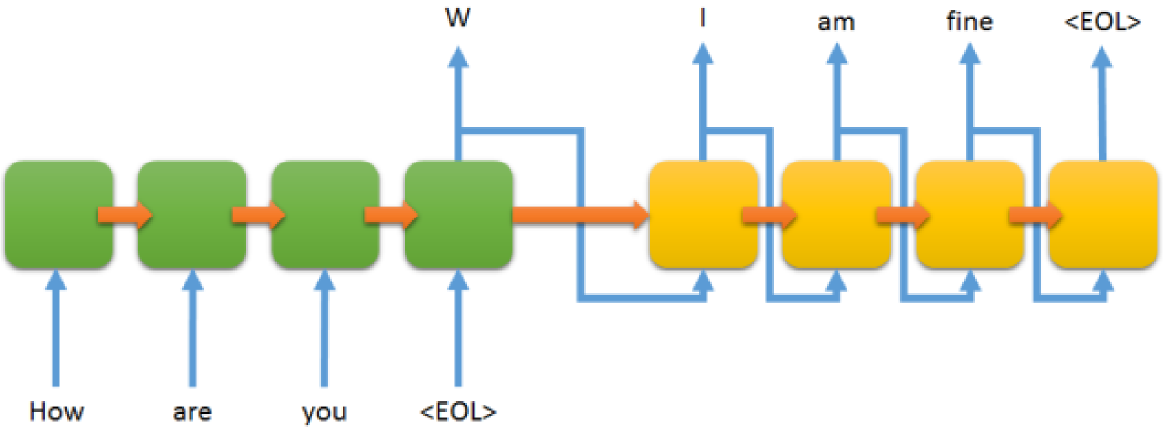
Machine Translation

- Cascade two RNNs, one for encoding and one for decoding
    - Input: word sequences in the source language
    - Output: word sequences in the target language



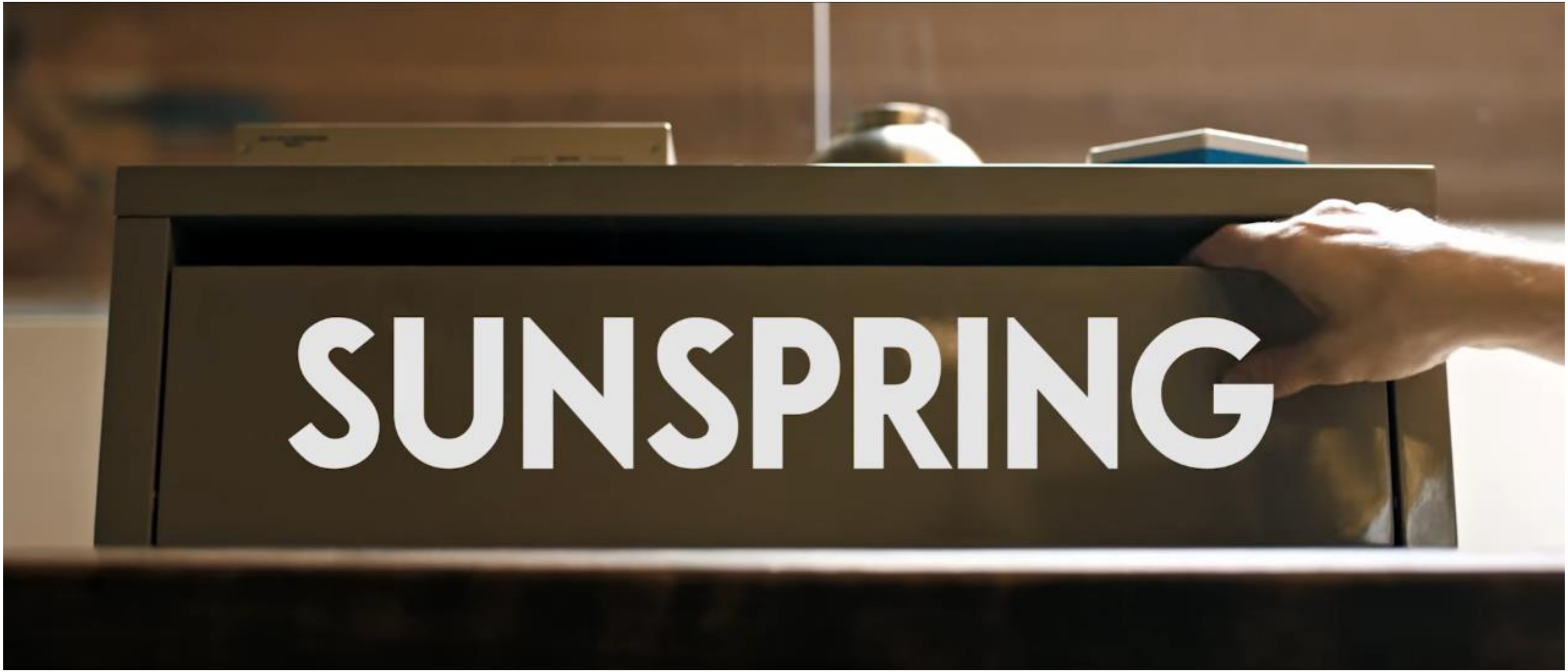
Chit-Chat Dialogue Modeling

- Cascade two RNNs, one for encoding and one for decoding
  - Input: word sequences in the question
  - Output: word sequences in the response



Temporal ordering for input and output may be different

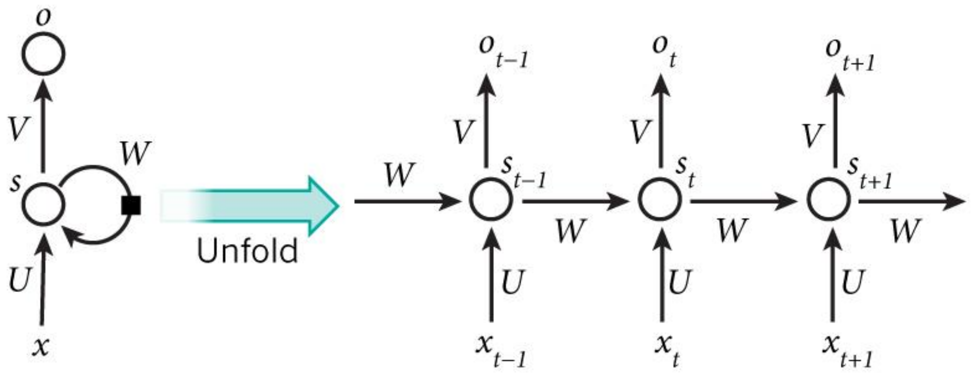
Sci-Fi Short Film - SUNSPRING



Concluding Remarks

- Language Modeling
  - RNNLM
- Recurrent Neural Networks
  - Definition

$$s_t = \sigma(W s_{t-1} + U x_t)$$
$$o_t = \mathrm{softmax}(V s_t)$$



  - Backpropagation through Time (BPTT)
  - Vanishing/Exploding Gradient
- RNN Applications
  - Sequential Input: Sequence-Level Embedding
  - Sequential Output: Tagging / Seq2Seq (Encoder-Decoder)