Recurrent Neural Network

Oct 2^{nd} & 5^{th}, 2017

ADL x MLDS

Yun-Nung (Vivian) Chen

HTTP://ADL.MIULAB.TW

HTTP://MLDS.MIULAB.TW

國立臺灣大學 National Taiwan University

Slides credited from Hung-Yi Lee & Richard Socher

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

Applications
- Sequential Input
- Sequential Output
  - Aligned Sequential Pairs (Tagging)
  - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

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

Applications
- Sequential Input
- Sequential Output
  - Aligned Sequential Pairs (Tagging)
  - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

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"

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

Applications

- Sequential Input
- Sequential Output
  - Aligned Sequential Pairs (Tagging)
  - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

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 $(n\text{-}1)$ 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

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

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 ……

$$P(\text{ jumped } | \text{ dog }) = \cancel{0}\ \ 0.0001$$

$$P(\text{ ran } | \text{ cat }) = \cancel{0}\ \ 0.0001$$

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.

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

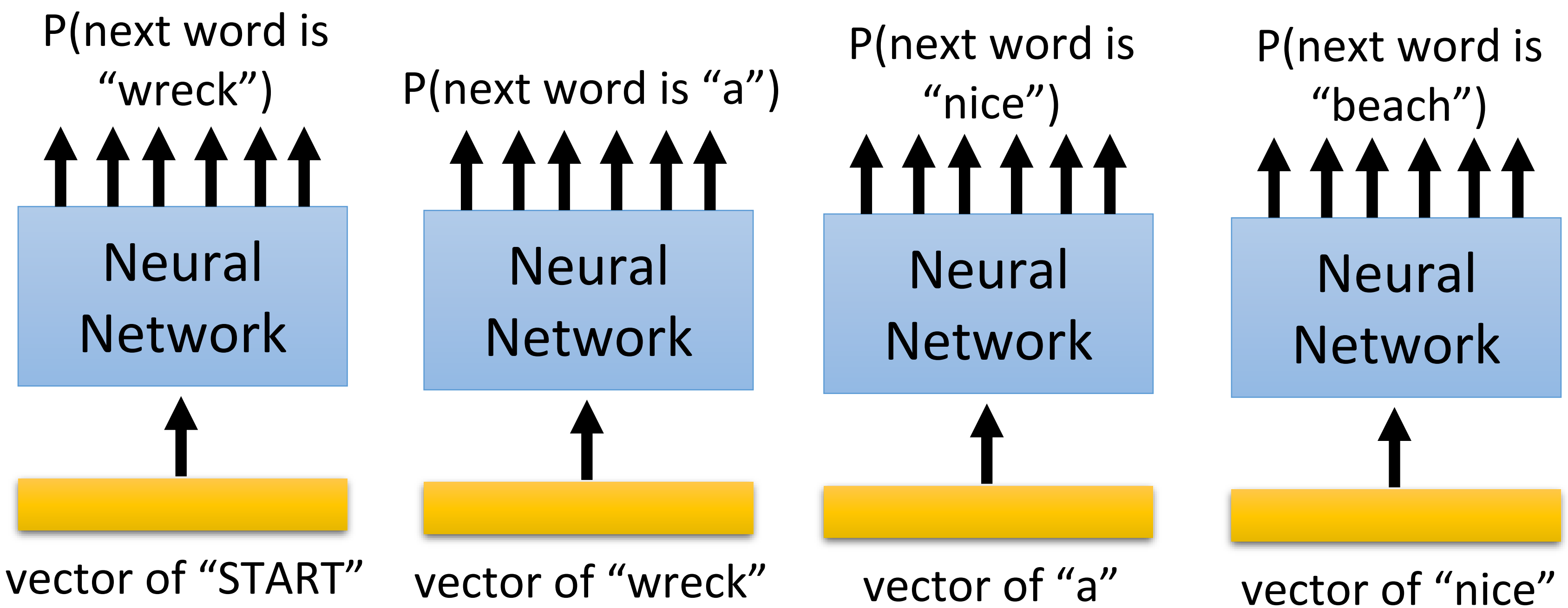
Applications

- Sequential Input
- Sequential Output
  - Aligned Sequential Pairs (Tagging)
  - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

Neural Language Modeling

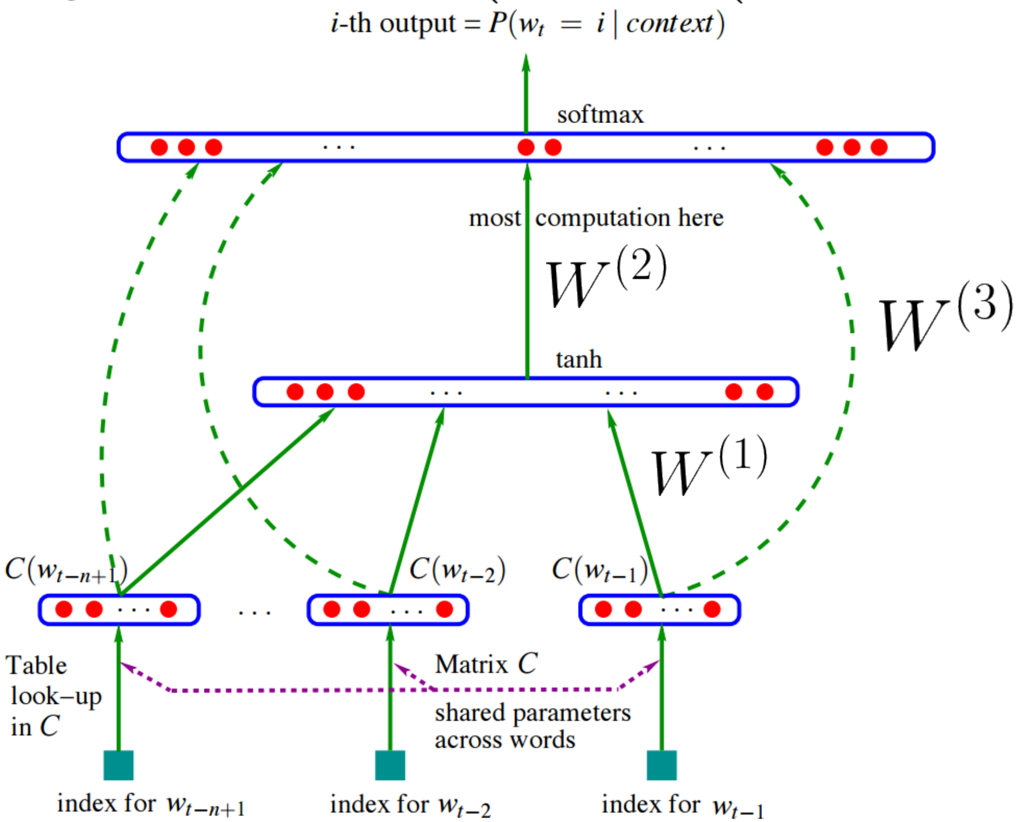
Idea: estimate $P(w_i \mid w_{i-(n-1)}, \cdots, w_{i-1})$ not from count, but from the NN prediction

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



Neural Language Modeling

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

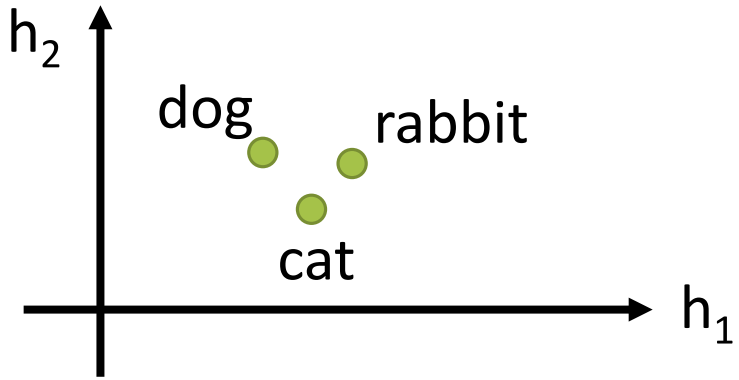


Probability distribution of the next word

context vector

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

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

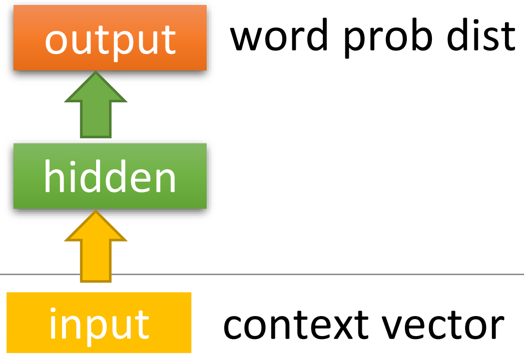
Applications
- Sequential Input
- Sequential Output
  - Aligned Sequential Pairs (Tagging)
  - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

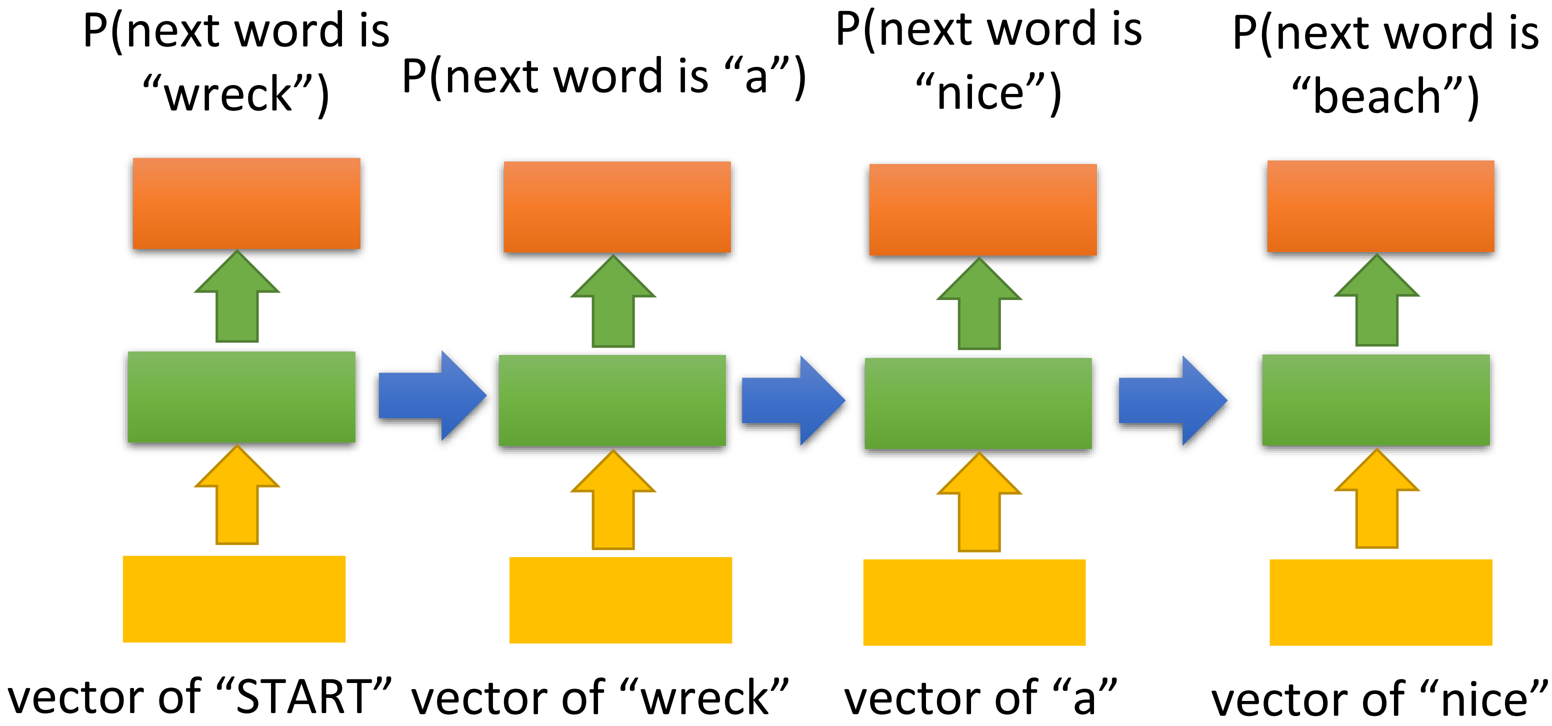
Recurrent Neural Network

Idea: condition the neural network on all previous words and tie the weights at each time step

Assumption: temporal information matters

RNN Language Modeling





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

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

Applications

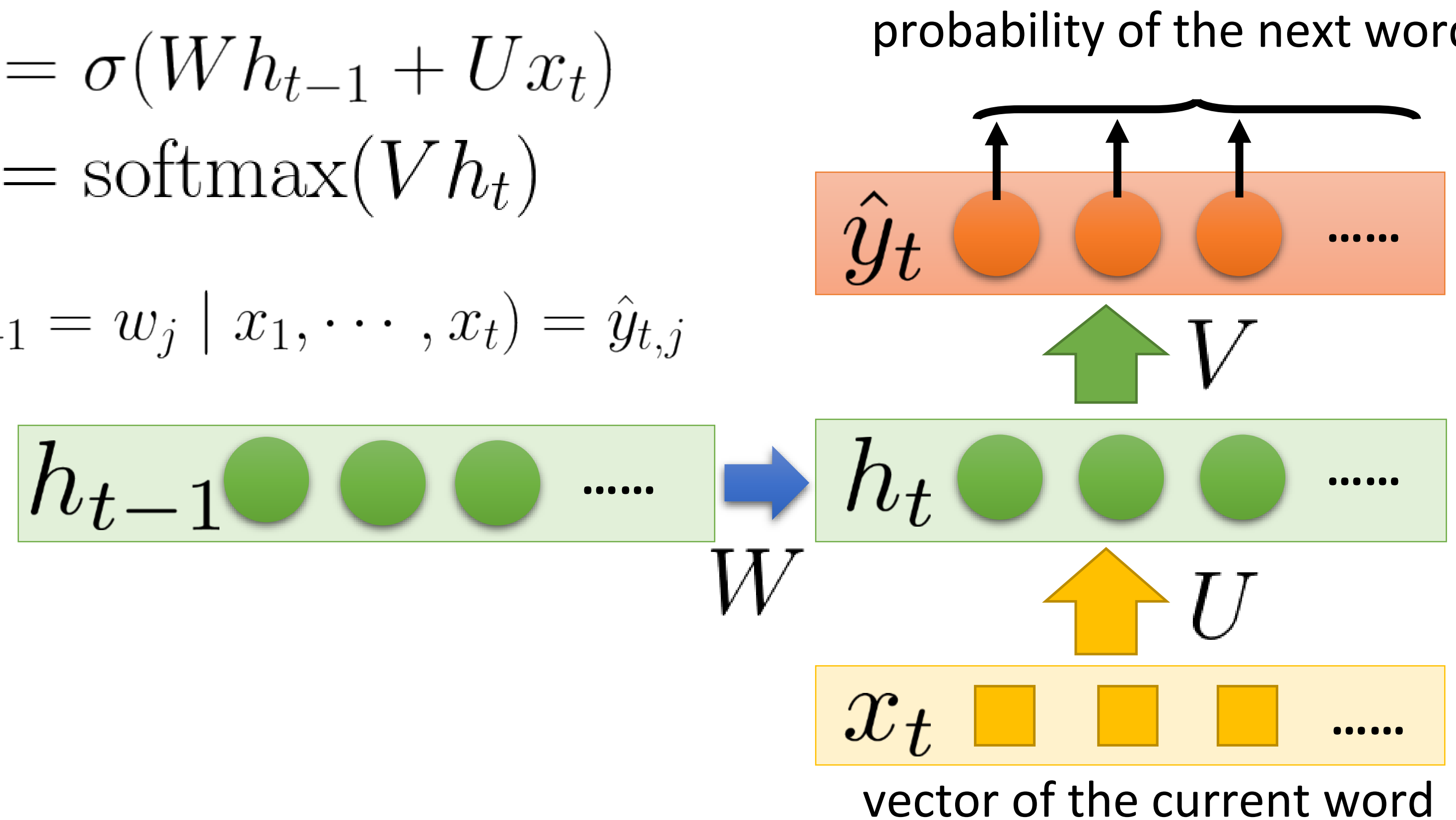
- Sequential Input
- Sequential Output
  - Aligned Sequential Pairs (Tagging)
  - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

RNNLM Formulation

At each time step,

$$h_t = \sigma(W h_{t-1} + U x_t)$$
$$\hat{y}_t = \mathrm{softmax}(V h_t)$$

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



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

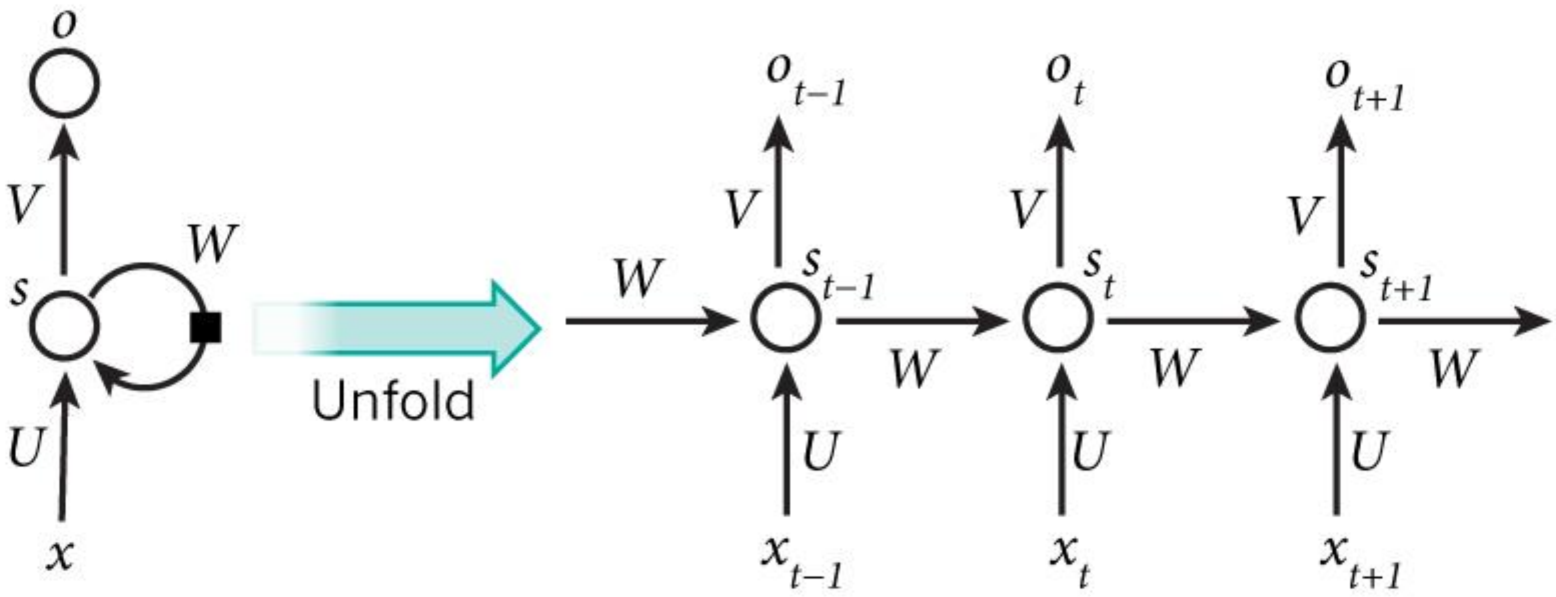
Applications
- Sequential Input
- Sequential Output
  - Aligned Sequential Pairs (Tagging)
  - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

Recurrent Neural Network Definition

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

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

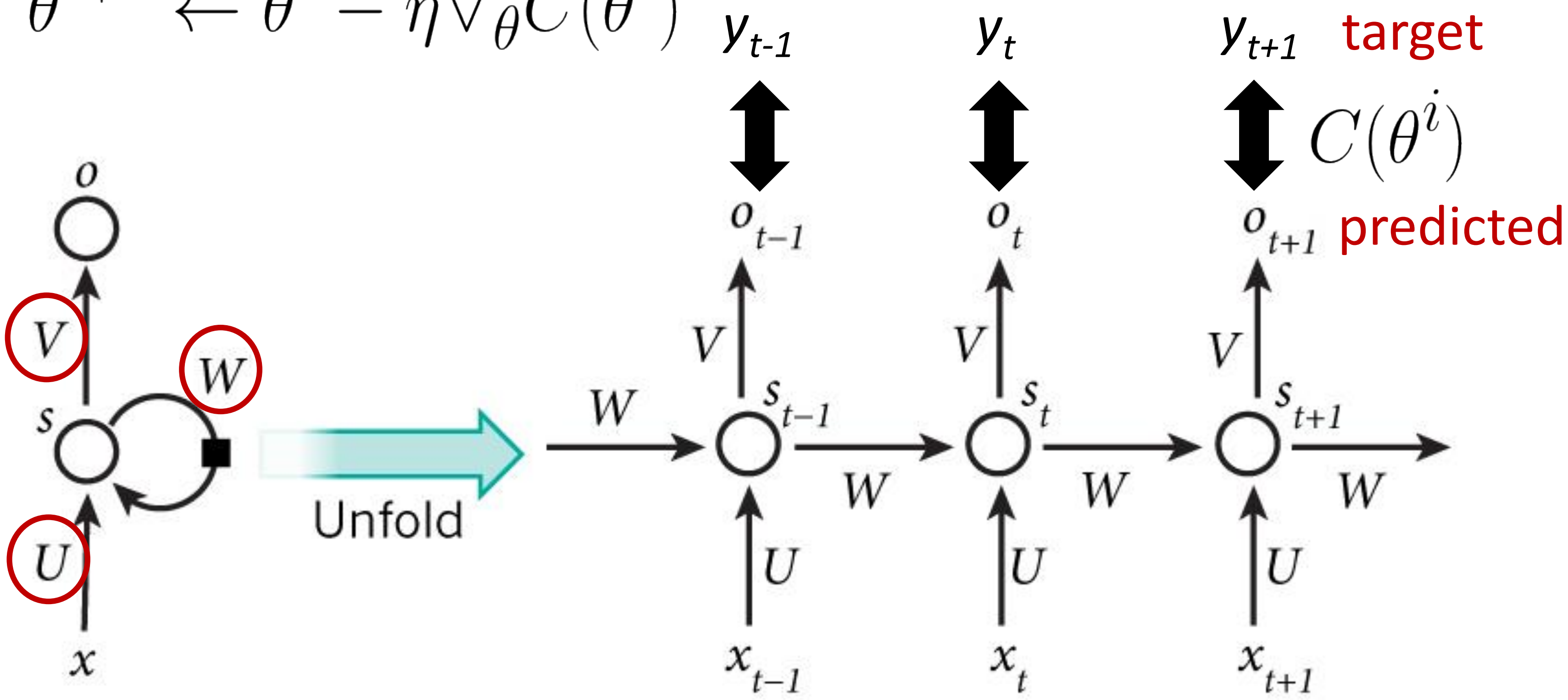
$$o_t = \mathrm{softmax}(V s_t)$$



Model Training

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

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



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

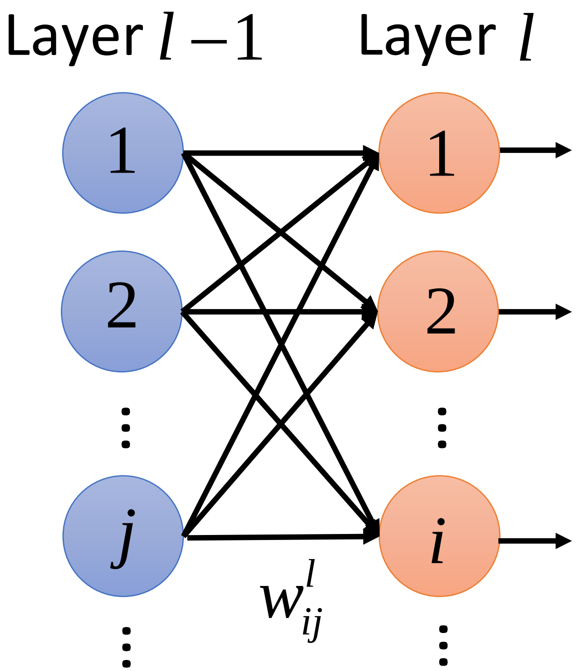
Applications
- Sequential Input
- Sequential Output
  - Aligned Sequential Pairs (Tagging)
  - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

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

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



Backward Pass

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

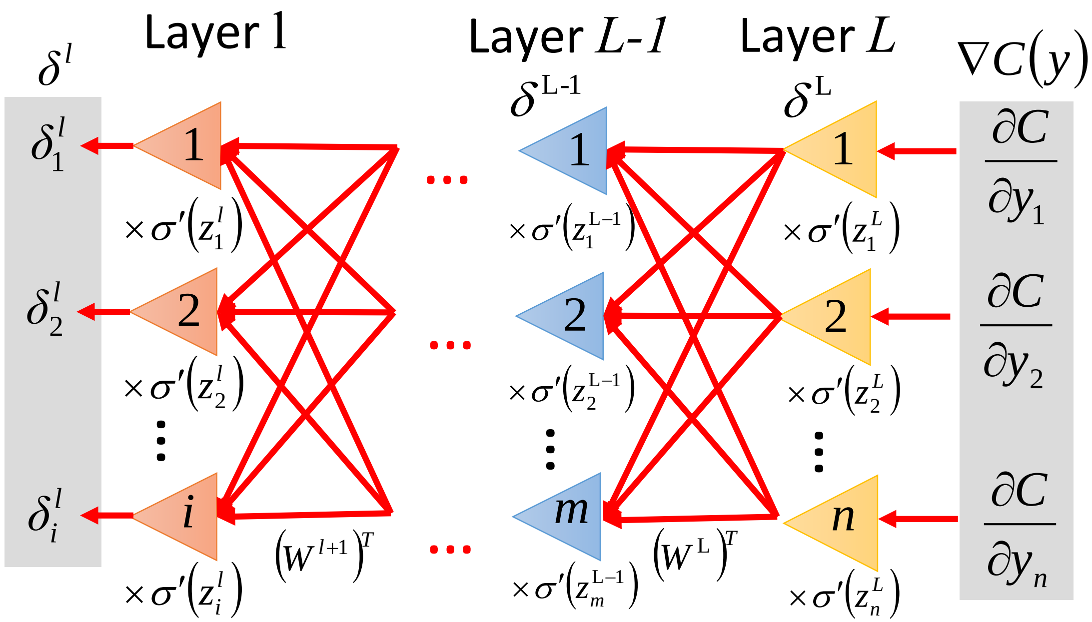
Forward Pass

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

Backpropagation

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

δ_i^l Error signal

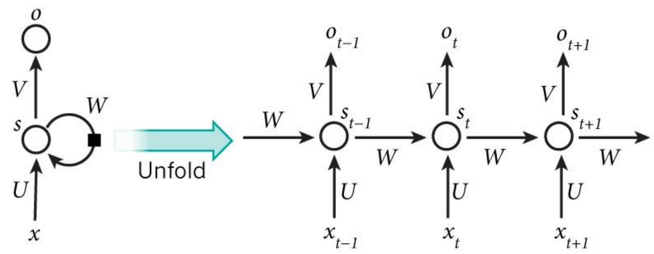


Backward Pass

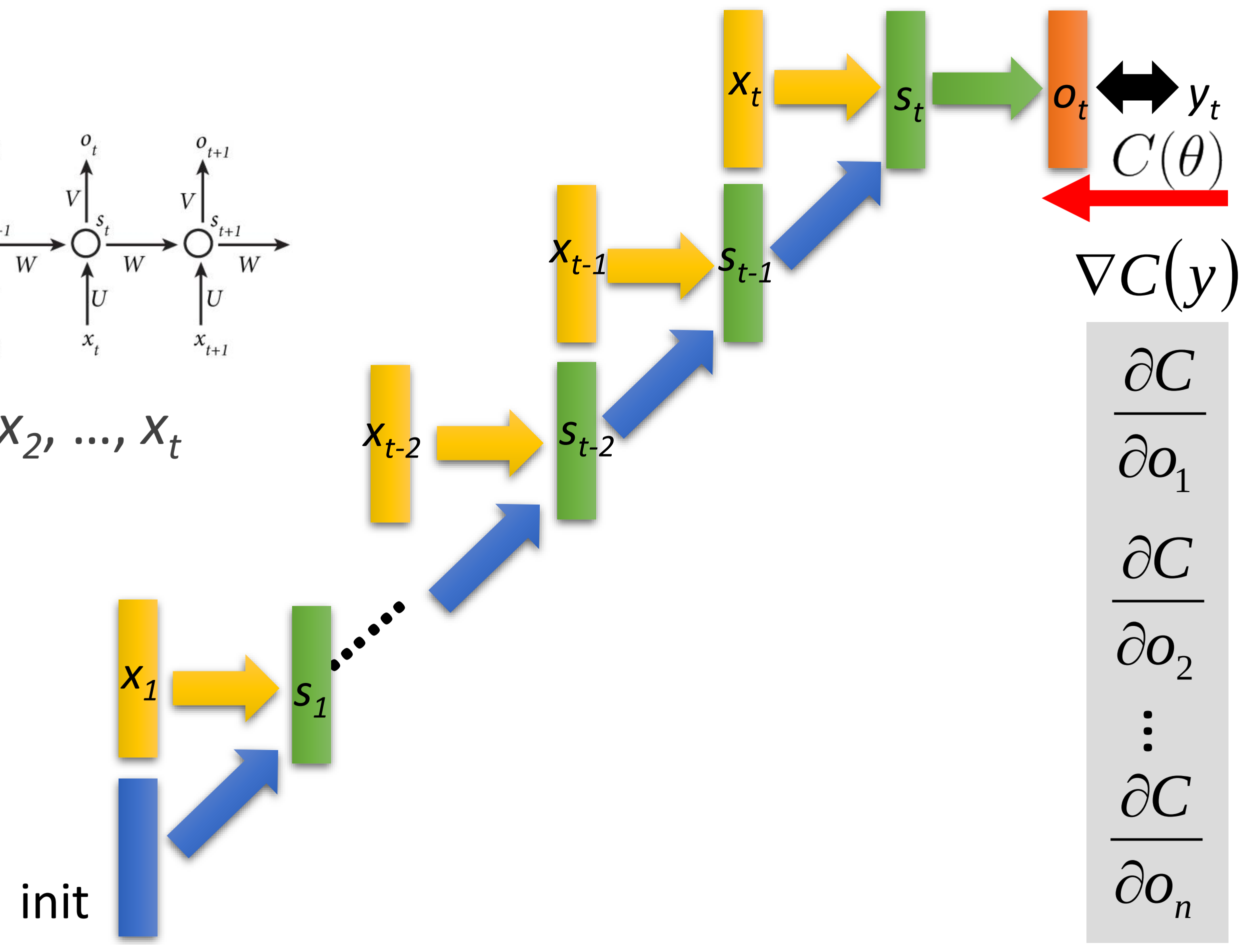
$$\delta^L = \sigma'(z^L) \odot \nabla C(y)$$
$$\delta^{L-1} = \sigma'(z^{L-1}) \odot (W^L)^T \delta^L$$
$$\vdots$$
$$\delta^l = \sigma'(z^l) \odot (W^{l+1})^T \delta^{l+1}$$
$$\vdots$$

Backpropagation through Time (BPTT)

Unfold

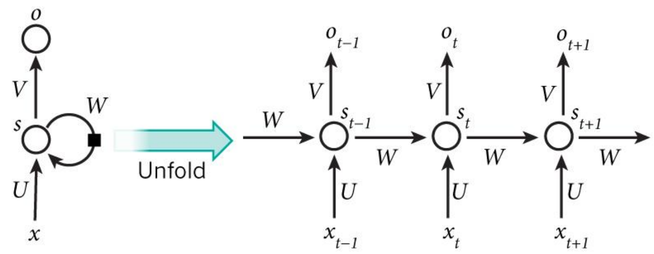


- Input: init, x_1, x_2, …, x_t
- Output: o_t
- Target: y_t

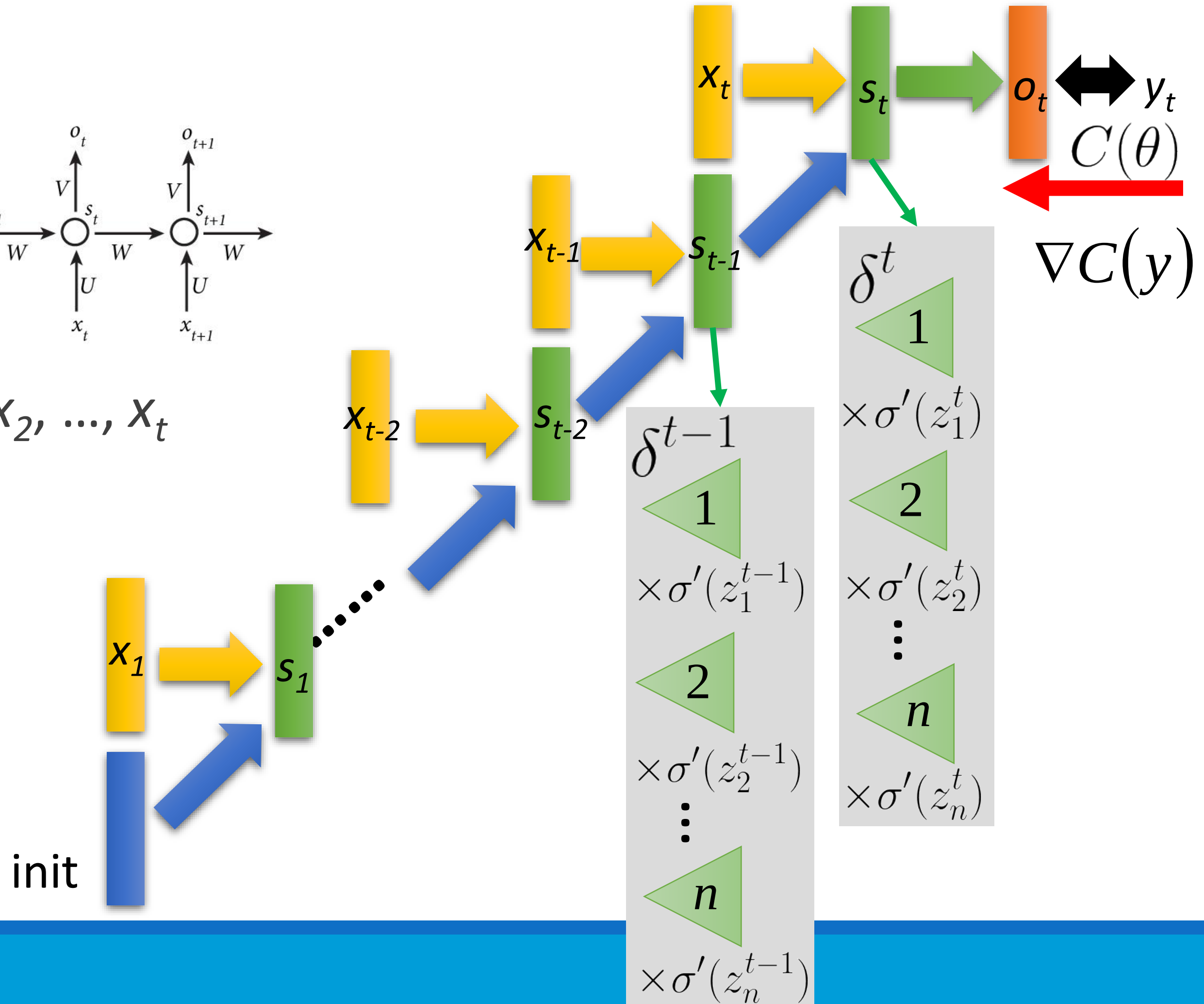


Backpropagation through Time (BPTT)

Unfold

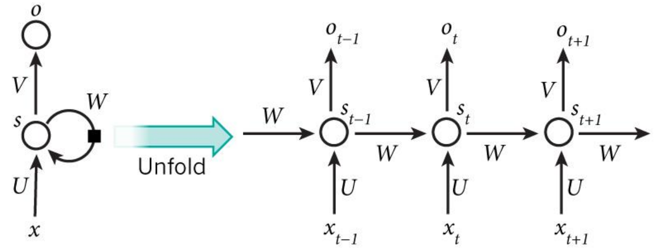


- Input: init, x_1, x_2, …, x_t
- Output: o_t
- Target: y_t

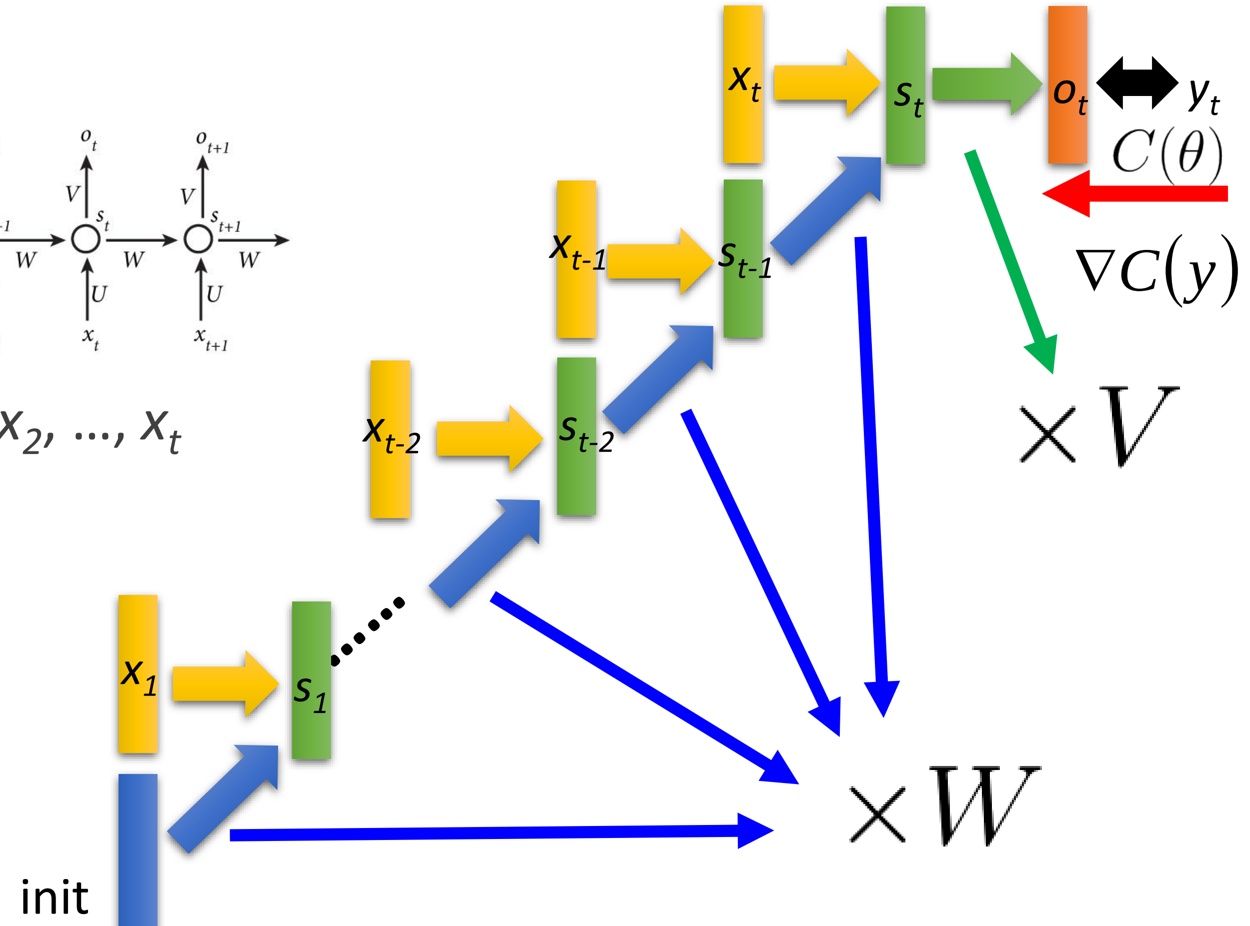


Backpropagation through Time (BPTT)

Unfold

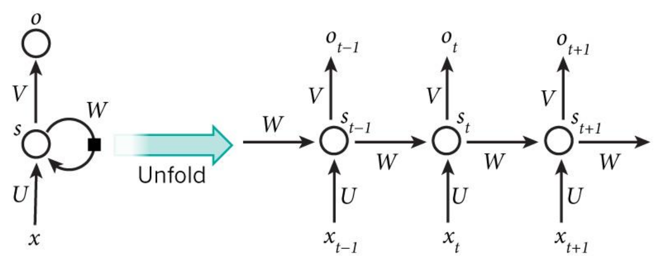


- Input: init, x_1, x_2, …, x_t
- Output: o_t
- Target: y_t

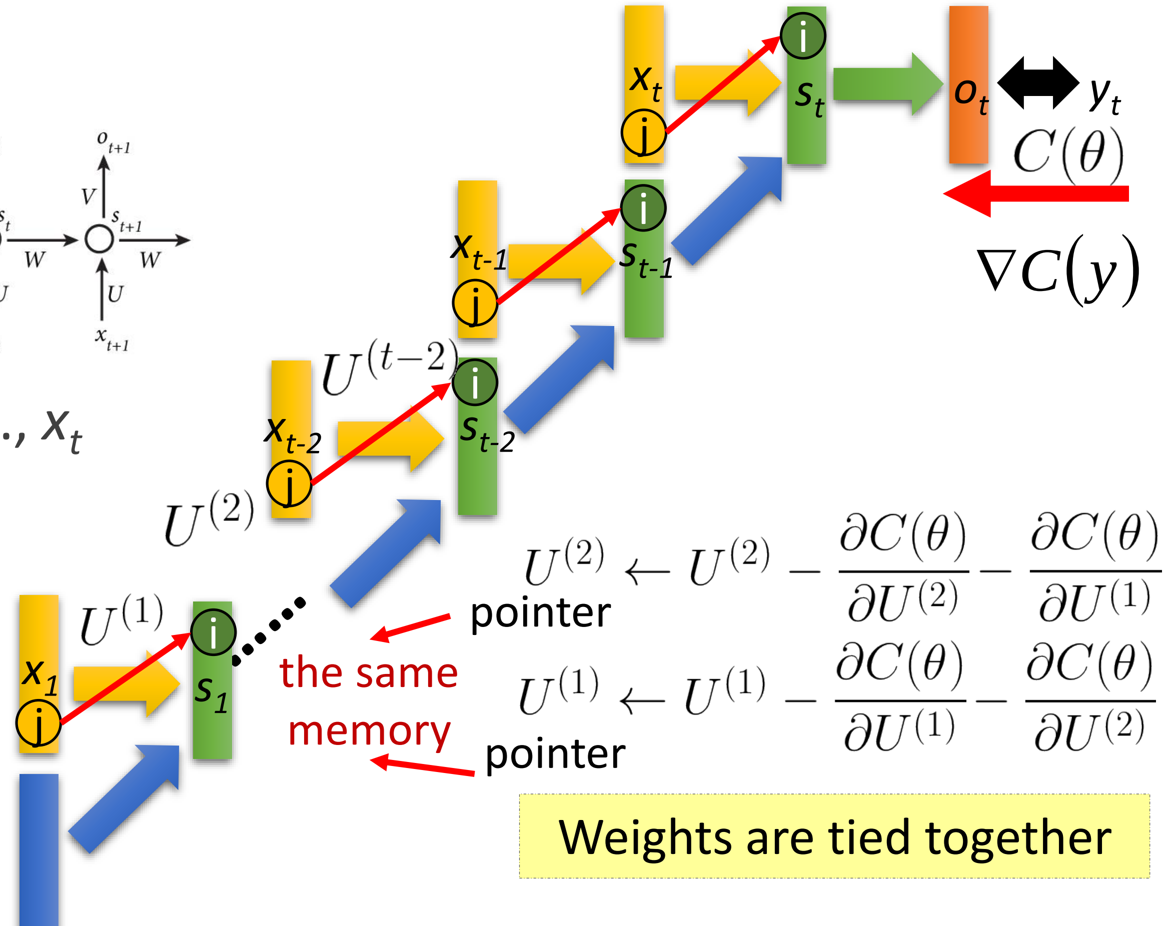


Backpropagation through Time (BPTT)

Unfold



- Input: init, $x_1, x_2, \ldots, x_t$
- Output: o_t
- Target: y_t



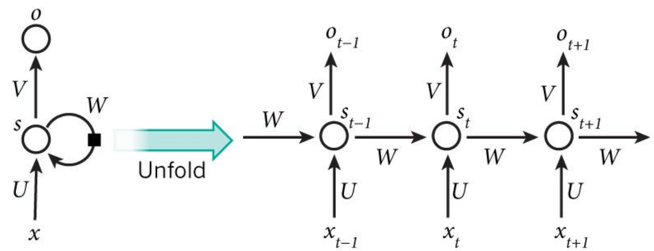
$$U^{(2)} \leftarrow U^{(2)} - \frac{\partial C(\theta)}{\partial U^{(2)}} - \frac{\partial C(\theta)}{\partial U^{(1)}}$$

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

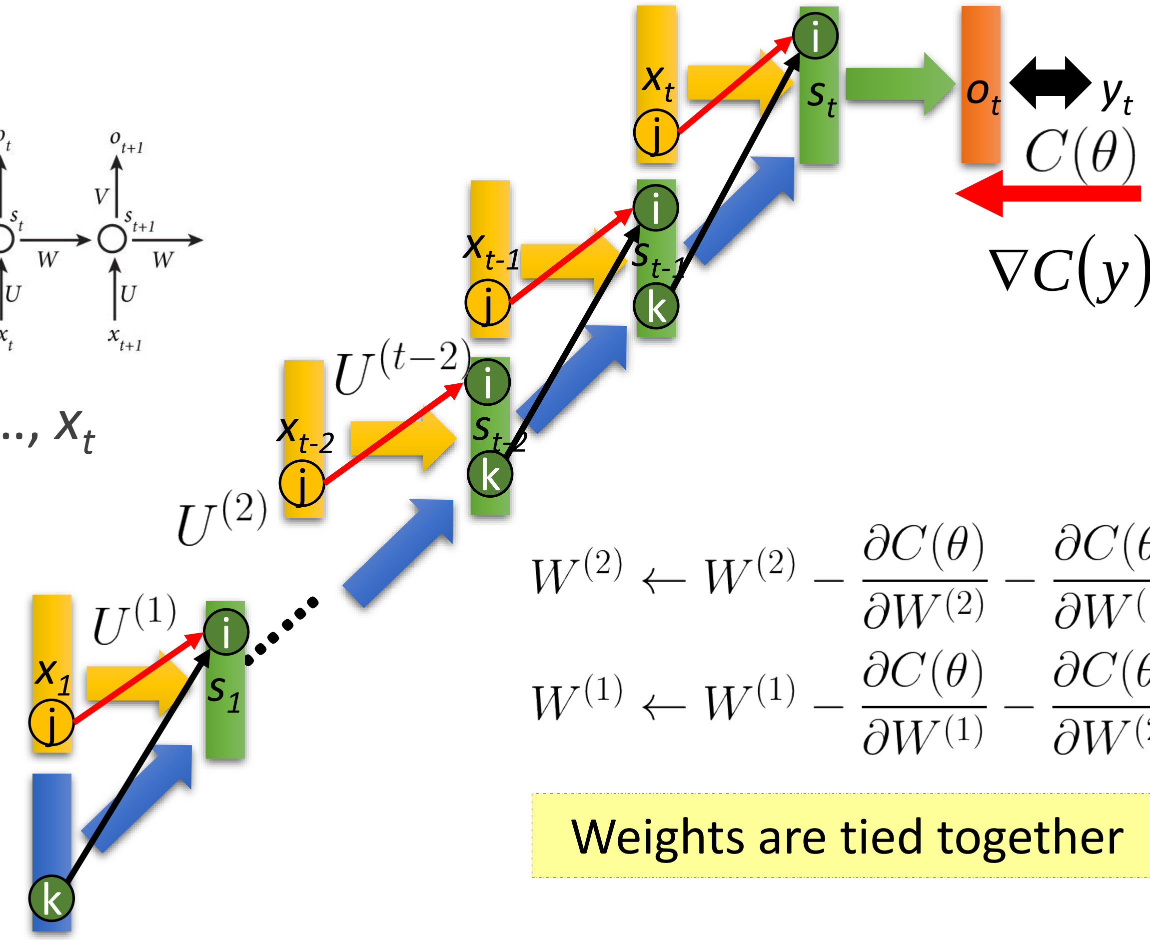
Weights are tied together

Backpropagation through Time (BPTT)

Unfold



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



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

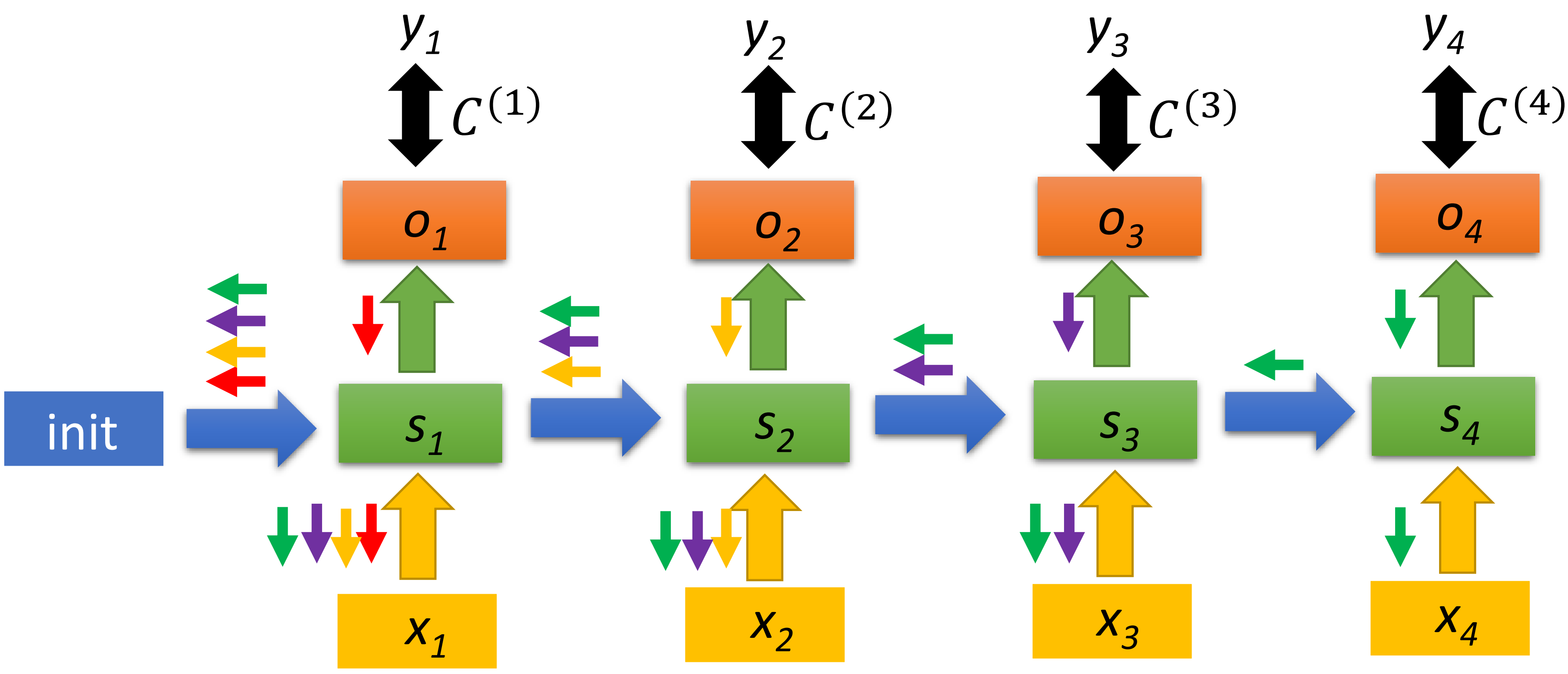
$$W^{(1)} \leftarrow W^{(1)} - \frac{\partial C(\theta)}{\partial W^{(1)}} - \frac{\partial C(\theta)}{\partial W^{(2)}}$$

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 $C^{(1)}$



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**

Applications

- Sequential Input
- Sequential Output
  - Aligned Sequential Pairs (Tagging)
  - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

RNN Training Issue

The gradient is a product of Jacobian matrices, each associated with a step in the forward computation

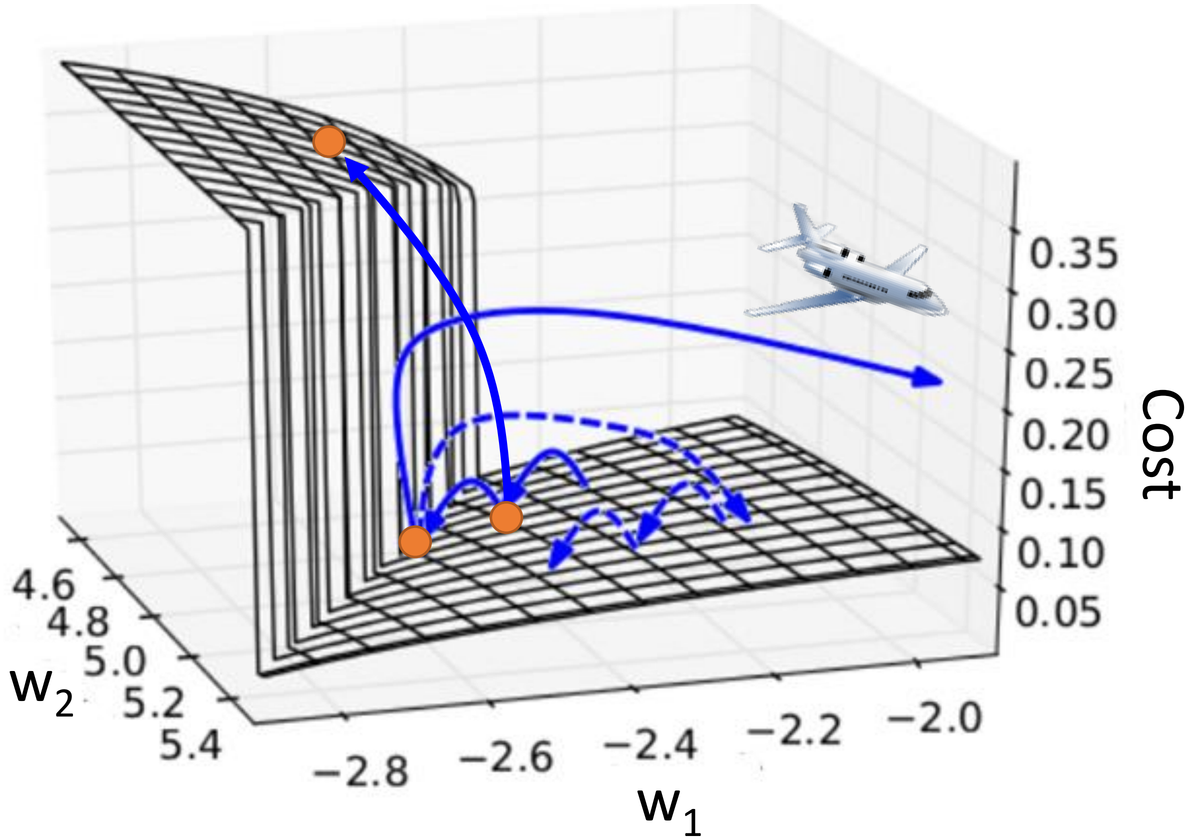
Multiply the <u>same</u> matrix at each time step during backprop

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

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]

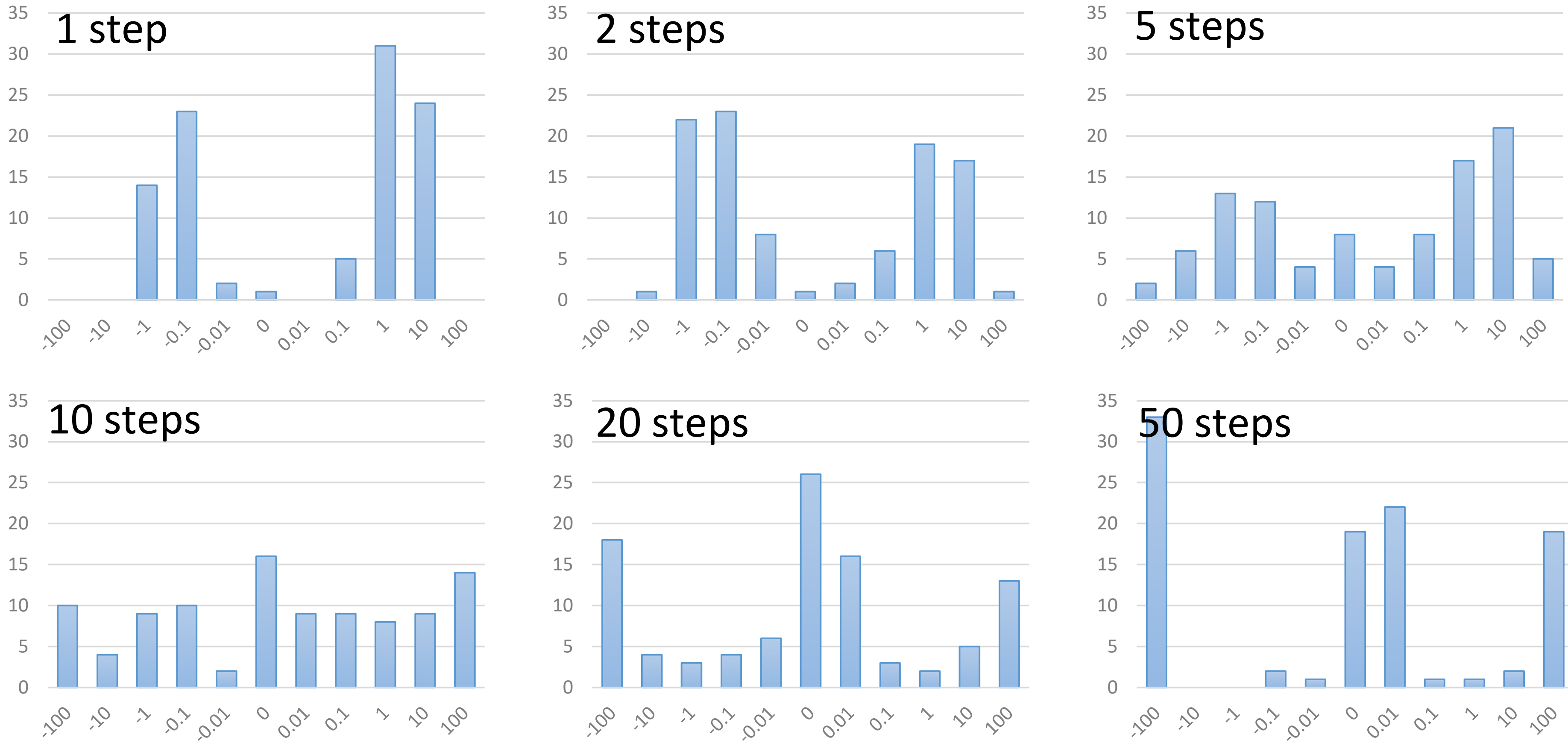
Rough Error Surface



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]

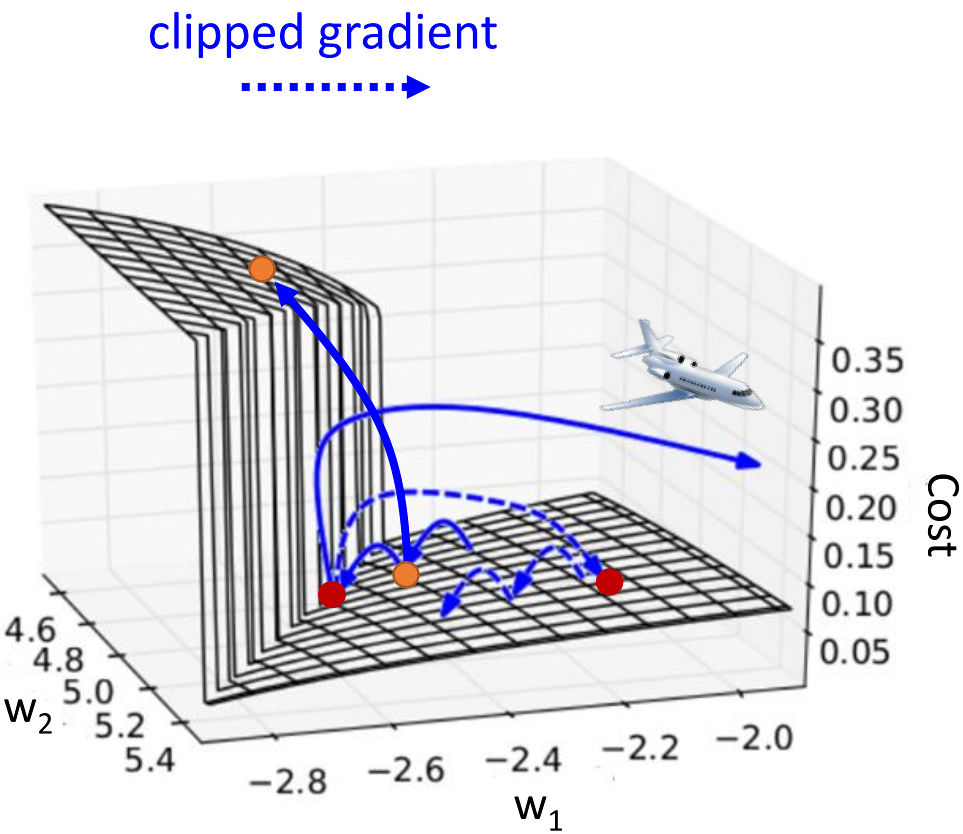
Vanishing/Exploding Gradient Example



Possible Solutions

Recurrent Neural Network

Exploding Gradient: Clipping



Idea: control the gradient value to avoid exploding

Algorithm 1 Pseudo-code for norm clipping

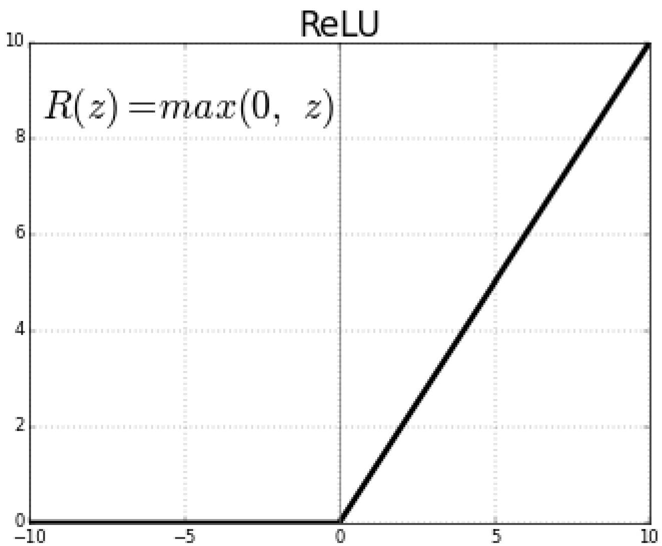
$\hat{\mathbf{g}} \leftarrow \frac{\partial \mathcal{E}}{\partial \theta}$
if $\|\hat{\mathbf{g}}\| \geq \mathit{threshold}$ **then**
  $\hat{\mathbf{g}} \leftarrow \frac{\mathit{threshold}}{\|\hat{\mathbf{g}}\|} \hat{\mathbf{g}}$
end if

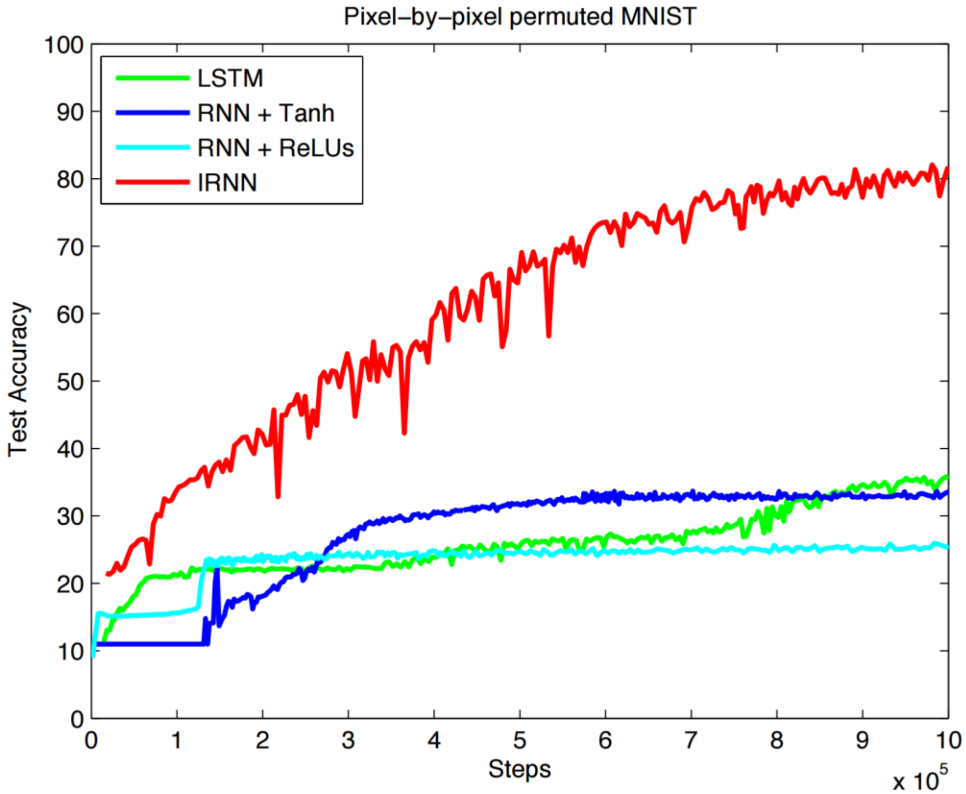
Parameter setting: values from half to ten times the average can still yield convergence

Vanishing Gradient: Initialization + ReLU

IRNN

- initialize all W as identity matrix I
- use ReLU for activation functions

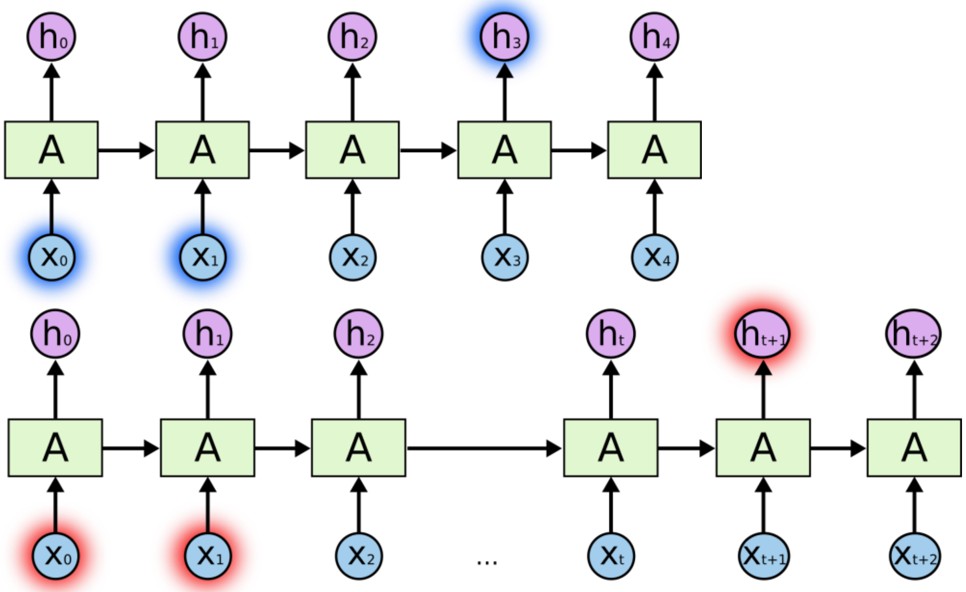




Vanishing Gradient: Gating Mechanism

RNN models temporal sequence information

- can handle “long-term dependencies” *in theory*



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

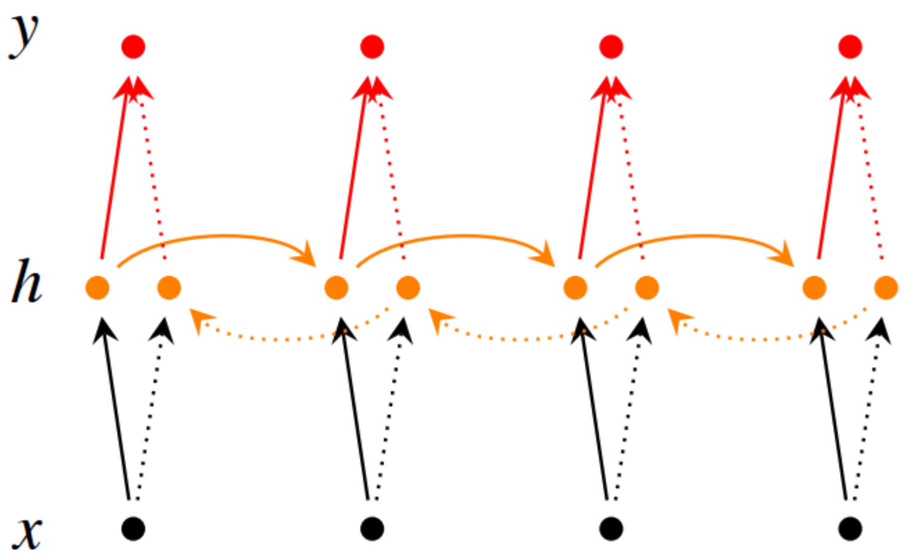
Issue: RNN cannot handle such “long-term dependencies” in practice due to vanishing gradient
→ apply the gating mechanism to directly encode the long-distance information

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Extension

Recurrent Neural Network

Bidirectional RNN



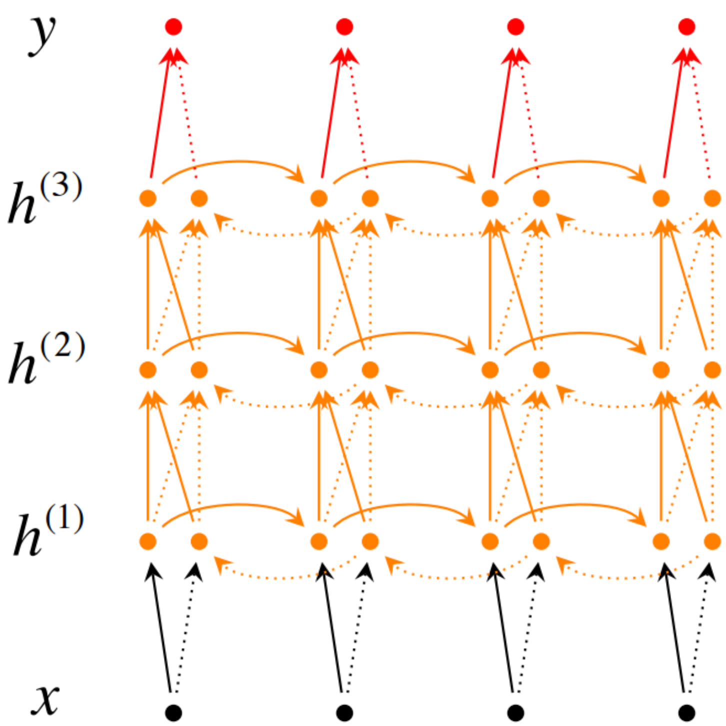
$$\overrightarrow{h}_t = f(\overrightarrow{W} x_t + \overrightarrow{V} \overrightarrow{h}_{t-1} + \overrightarrow{b})$$

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

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

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

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

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

Applications
- Sequential Input
- Sequential Output
  - Aligned Sequential Pairs (Tagging)
  - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

How to Frame the Learning Problem?

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

$$f : X \to Y$$

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

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

Applications
- **Sequential Input**
- Sequential Output
  - Aligned Sequential Pairs (Tagging)
  - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

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)

N-dim

這 (this) $\begin{bmatrix} 0.2 & 0.6 & 0.3 & \cdots & 0.4 \end{bmatrix}$

規格 (specification) $\begin{bmatrix} 0.9 & 0.8 & 0.1 & \cdots & 0.1 \end{bmatrix}$

有 (have) $\begin{bmatrix} 0.1 & 0.3 & 0.1 & \cdots & 0.7 \end{bmatrix}$

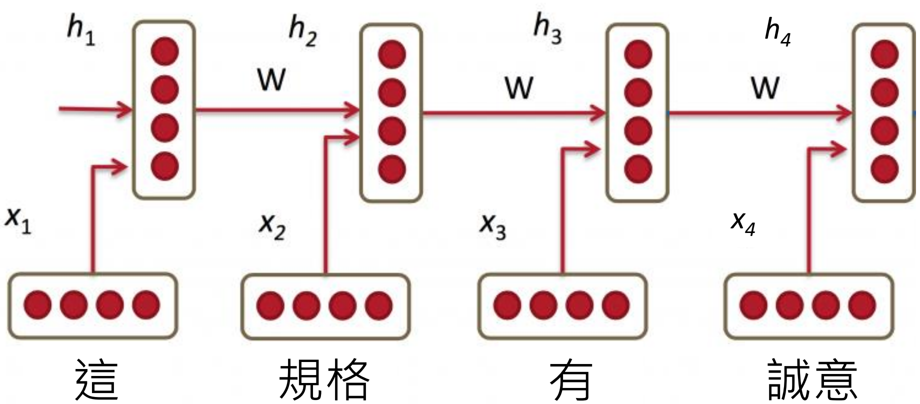
誠意 (sincerity) $\begin{bmatrix} 0.5 & 0.0 & 0.6 & \cdots & 0.4 \end{bmatrix}$

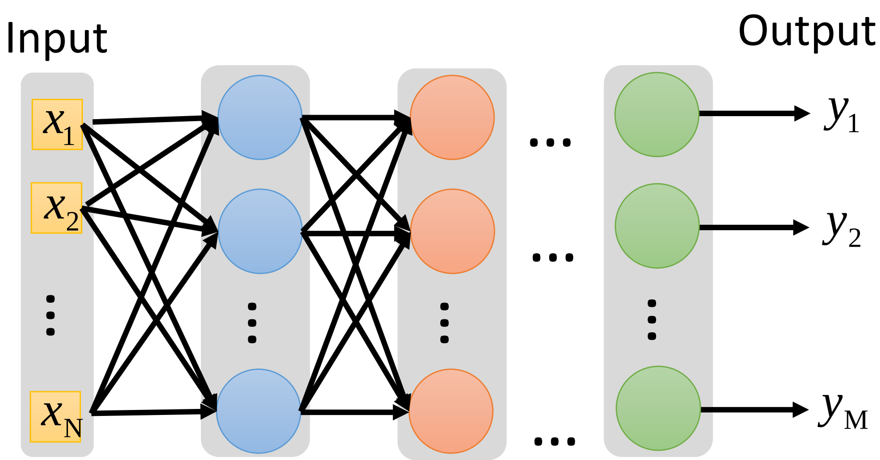
How to compute $\vec{x} = \begin{bmatrix} x_1 & x_2 & x_3 & \cdots & x_N \end{bmatrix}$

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 the input of classification tasks

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

Applications

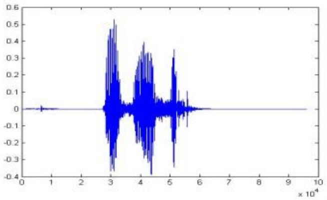
- Sequential Input
- **Sequential Output**
  - Aligned Sequential Pairs (Tagging)
  - Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)

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

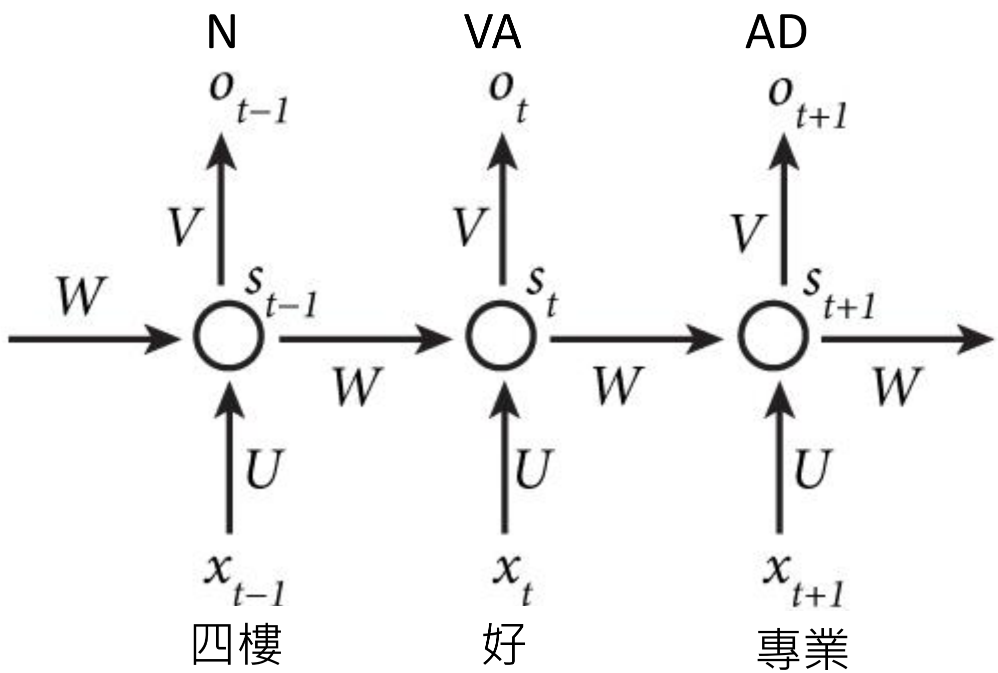
Applications

- 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

Outline

Language Modeling
- N-gram Language Model
- Feed-Forward Neural Language Model
- Recurrent Neural Network Language Model (RNNLM)

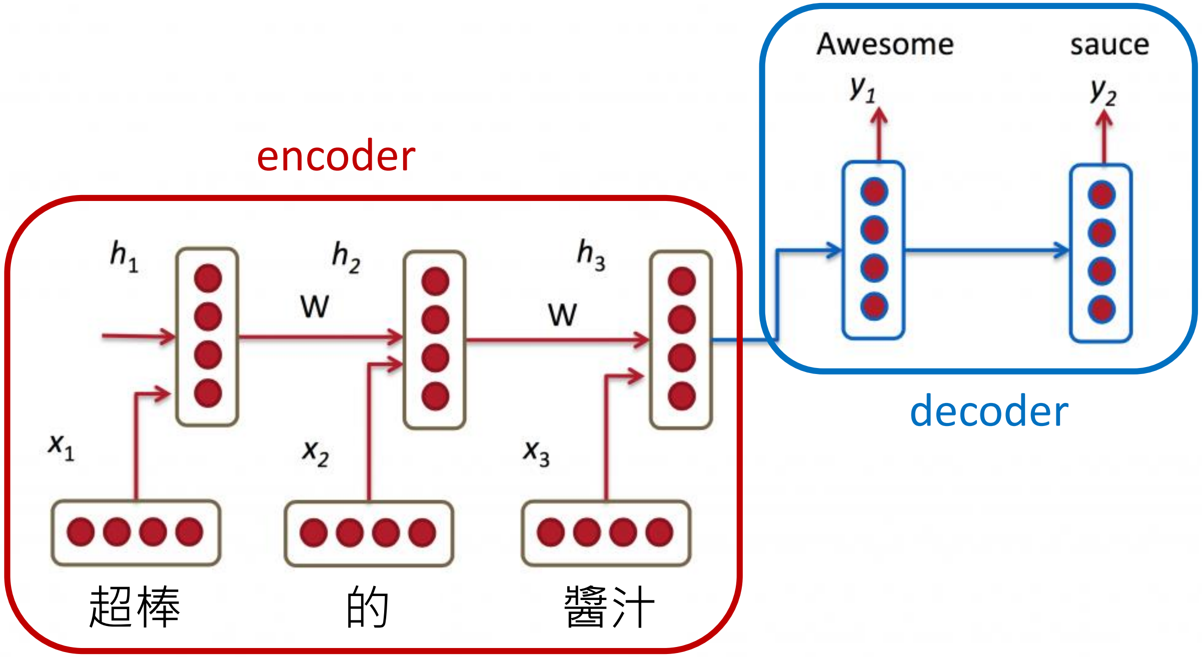
Recurrent Neural Network
- Definition
- Training via Backpropagation through Time (BPTT)
- Training Issue

Applications
- Sequential Input
- Sequential Output
  - Aligned Sequential Pairs (Tagging)
  - **Unaligned Sequential Pairs (Seq2Seq/Encoder-Decoder)**

Machine Translation

Cascade two RNNs, one for encoding and one for decoding

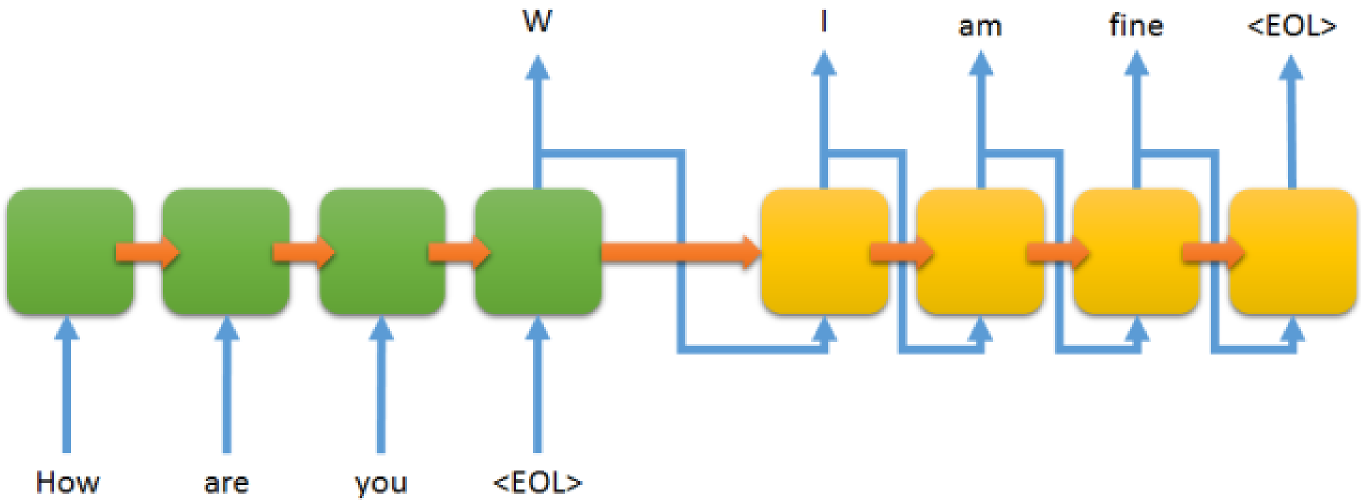
- Input: word sequences in the source language
- Output: word sequences in the target language



Chit-Chat Dialogue Modeling

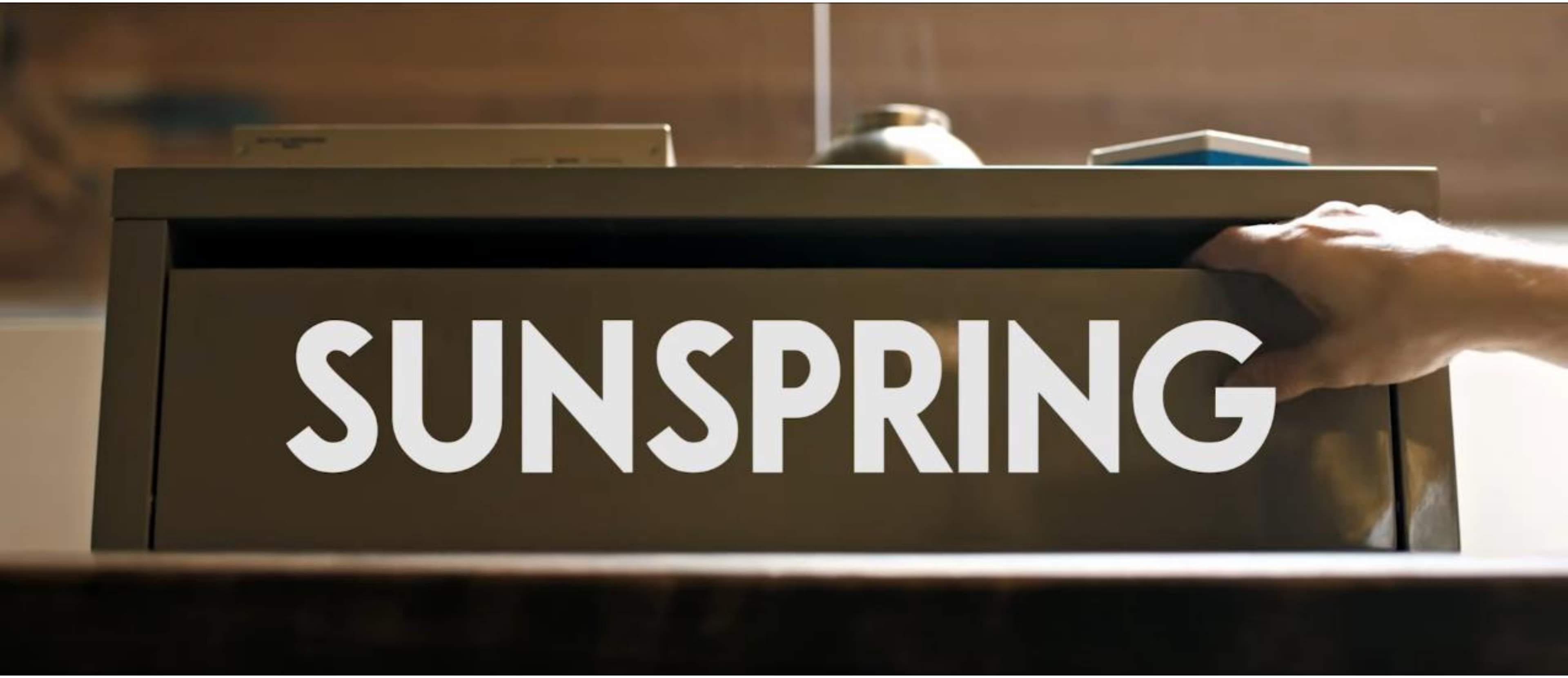
Cascade two RNNs, one for encoding and one for decoding

- 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

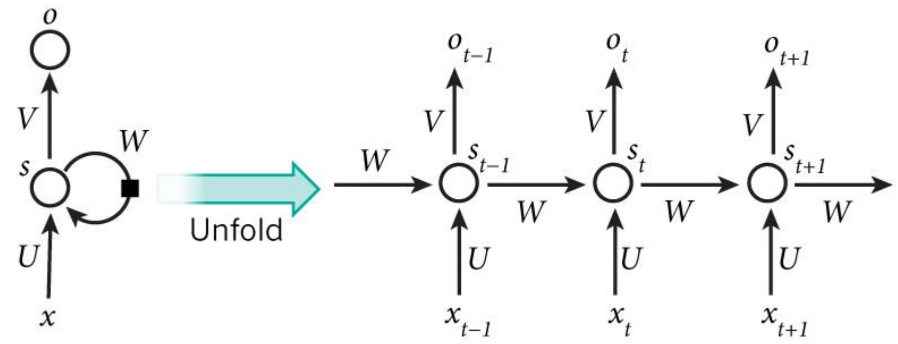


https://www.youtube.com/watch?v=LY7x2Ihqj

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

Applications

- Sequential Input: Sequence-Level Embedding
- Sequential Output: Tagging / Seq2Seq (Encoder-Decoder)