

CS4641 Spring 2025 Recurrent Neural Networks

Bo Dai School of CSE, Georgia Tech <u>bodai@cc.gatech.edu</u>

Based on Fei-Fei Li & Ehsan Adeli's Slides

Convolution Layer



$$W_{out} = rac{W - F + 2P}{S} + 1$$
 Animation from

Animation from Hochschule der Medien

Pooling (Subsampling)



- Pooling layers simplify / subsample / compress the information in the output from the convolutional layer
- Reduce parameters

Put Everything Together



[LeNet-5, LeCun 1980]

<u>AlexNet (2012)</u>





AlexNet

VGGNet (2014)

- Very Deep CNN
- With only 3*3 conv filters
 - Fewer parameters, deeper nonlinear layers Ο





VGG16

<u>ResNet (2015)</u>

- Very Deep CNN with residual connections
 - 152-layer model for ImageNet
 - ILSVRC'15 classification winner (3.57% top 5 error)
 - Swept all classification and detection competitions in ILSVRC'15 and COCO'15!





Sequence Prediction



texts[0]

Sequence Prediction





Sequence Prediction



I saw the movie with two grown children. Although it was not as clever as Shrek, I thought it was rather good. In a movie theatre surrounded by children who were on spring break, there was not a sound so I know the children all liked it. There parents also seemed engaged. The death and apparent death of characters brought about the appropriate gasps and comments. Hopefully people realize this movie was made for kids.

For a movie that gets no respect there sure are a lot of memorable quotes listed for this gem. Imagine a movie where Joe Piscopo is actually funny! Maureen Stapleton is a scene stealer. The Moroni character is an absolute scream. Watch for Alan "The Skipper" Hale jr. as a police Sgt.



What if the length of sequences varies?

Sequential Regression Algorithms



Linear Regression Pipeline

- Build probabilistic models: Gaussian Distribution + RNN
- 2. Derive loss function: MLE and MAP
- 3. Select optimizer: (Stochastic) GD

Sequential Binary Classification Algorithms



- 1. Build probabilistic models: Bernoulli Distribution + RNN
- 2. Derive loss function: MLE and MAP
- 3. Select optimizer: (Stochastic) Gradient Descent

Sequential Multiclass Logistic Regression Algorithms



- Build probabilistic models: Categorical Distribution + RNN
- 2. Derive loss function: MLE and MAP
- 3. Select optimizer: (Stochastic) Gradient Descent













Simple RNN Cell







Simple RNN Cell





 $\rightarrow \mathbf{h}_{t-1}$

Simple RNN for IMDB Review







More Usages of RNNs



Image Captioning image -> sequence of words

More Usages of RNNs



IMDB text review classification

More Usages of RNNs



Translation

Training of RNNs



Backpropagation Through Unrolling Steps

Simple RNN is not good at long-term dependence



h₁₀₀ is almost irrelevant to
$$\mathbf{x}_1: \frac{\partial \mathbf{h}_{100}}{\partial \mathbf{x}_1}$$
 is near zero.

Gradient Vanishing

Long Short Term Memory (LSTM)



Figures from Christopher Olah's blog

LSTM Cell: Conveyor Belt

The past information directly flows to the future.



LSTM Cell: Forget Gate

A value of zero means "let nothing through."

A value of *one* means "let *everything* through!"



$$f_t = \sigma(W_f x_t + U_f h_{t-1})$$



$$C_t = C_{t-1} \circ f_t + \hat{C}_t \circ i_t$$

LSTM Cell: Input Gate

How much information current context provided.



$$i_t = \sigma(W_i x_t + U_i h_{t-1})$$



$$C_t = C_{t-1} \circ f_t + \hat{C}_t \circ i_t$$

LSTM Cell: New Value

"local" context, only up to immediately preceding state







$$C_t = C_{t-1} \circ f_t + \hat{C}_t \circ i_t$$

LSTM Cell: Update Conveyor Belt



 $C_t = C_{t-1} \circ f_t + \hat{C}_t \circ i_t$

LSTM Cell: Output Gate





 x_t





Auto-differentiation Packages



LSTM vs. ResNet



$$C_t = C_{t-1} \circ f_t + \hat{C}_t \circ i_t$$
LSTM



Similar to ResNet

Other Variants of RNN

Gated Recurrent Unit



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

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Gated Recurrent Unit



Summary

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- RNNs allow a lot of flexibility in architecture design
- Vanilla RNNs are simple but don't work very well
- Backward flow of gradients in RNN can explode or vanish. Exploding is controlled with gradient clipping. Vanishing is controlled with additive interactions (LSTM)

