



Slides adapted from Jordan Boyd-Graber

Machine Learning: Chenhao Tan University of Colorado Boulder

Logistics

- HW3 available on Github, due on October 18
- Final project team formation due by October 9

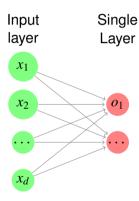
Outline

Recap

Layers for Structured Data

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Logistic Regression as a Single-layer Neural Network



- What is the activation used in logistic regression?
- What is the objective function used in logistic regression?

Forward propagation algorithm

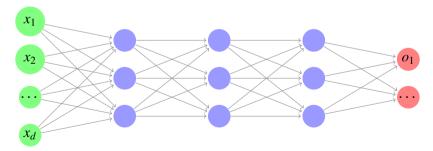
How do we make predictions based on a multi-layer neural network? Store the biases for layer l in b^l , weight matrix in W^l

$$W^1, b^1$$
 W^2, b^2 W^3, b^3 W^4, b^4

$$W^2, b^2$$

$$W^3, b^3$$

$$oldsymbol{W}^4, oldsymbol{b}^4$$

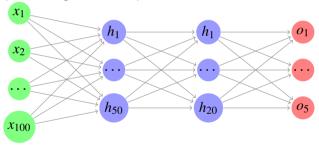


Forward propagation algorithm

Suppose your network has L layers Make prediction for an instance x

- 1: Initialize $a^0 = x$
- 2: **for** l=1 to L **do**
- 3: $z^{l} = W^{l}a^{l-1} + b^{l}$
- 4: $a^l = g^l(z^l) // g^l$ represents a nonlinear activation
- 5: end for
- 6: The prediction \hat{y} is simply a^L

How many parameters are there in the following feed-forward neural networks (assuming no biases)?



- A. 100 * 50 + 50 * 20 + 20 * 5
- B. 100 * 50 + 50 + 50 * 20 + 20 + 20 * 5 + 5

Neural networks in a nutshell

- Training data $S_{\text{train}} = \{(\boldsymbol{x}, y)\}$
- Network architecture (model)

$$\hat{y} = f_w(\boldsymbol{x})$$

Loss function (objective function)

$$\mathcal{L}(y,\hat{y})$$

Learning (next lecture)

Which of the following statements is true? (Suppose that training data is large.)

- A. In training, K-nearest neighbors takes shorter time than neural networks.
- B. In training, K-nearest neighbors takes longer time than neural networks.
- C. In testing, K-nearest neighbors takes shorter time than neural networks.
- D. In testing, K-nearest neighbors takes longer time than neural networks.

Outline

Recap

Layers for Structured Data

Spatial information



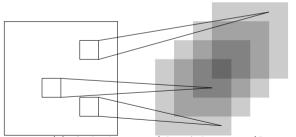
https://www.reddit.com/r/aww/comments/6ip2la/before_and_after_she_was_told_she_was_a_good_girl/

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Convolutional Layers

Sharing parameters across patches

input image output feature maps



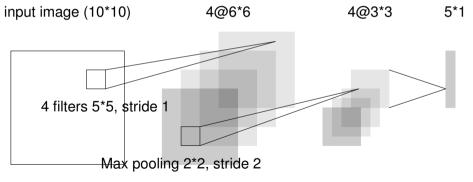
$$a_{i'j'} = \sum_{i=1}^{k} \sum_{j=1}^{k} w_{ij} x_{ij}$$

- Number of filters
- Filter shape
- Stride size

https://github.com/davidstutz/latex-resources/blob/master/tikz-convolutional-layer/convolutional-layer.tex

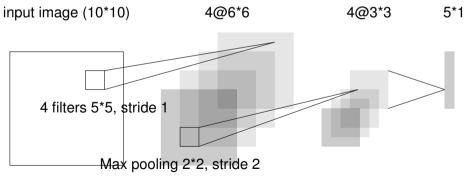
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A concrete example (assuming no biases, convolution with 4 filters, ReLU, max pooling, and finally a fully-connected softmax layer)



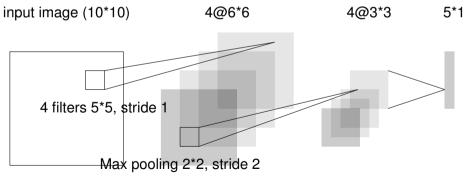
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How many parameters are there in the following convolutional neural networks? (assuming no biases, convolution with 4 filters, ReLU, max pooling, and finally a fully-connected softmax layer)



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How many ReLU operations are performed on the forward pass? (assuming no biases, convolution with 4 filters, ReLU, max pooling, and finally a fully-connected softmax layer)



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Sequential information "My words fly up, my thoughts remain below: Words without thoughts never to heaven go."

—Hamlet

Sequential information "My words fly up, my thoughts remain below: Words without thoughts never to heaven go."

-Hamlet

- language
- activity history

Sequential information "My words fly up, my thoughts remain below: Words without thoughts never to heaven go."

-Hamlet

- language
- activity history

$$x=(x_1,\ldots,x_T)$$

Recurrent Layers

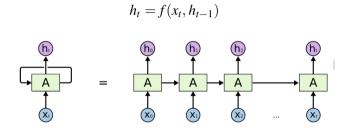
Sharing parameters along a sequence

$$h_t = f(x_t, h_{t-1})$$

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Recurrent Layers

Sharing parameters along a sequence

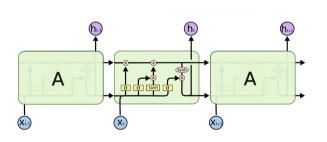


https://colah.github.io/posts/2015-08-Understanding-LSTMs/

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Long short-term memory

A commonly used recurrent neural network in natural language processing



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

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

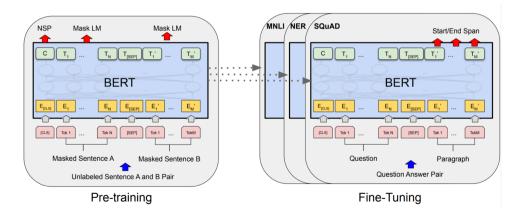
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

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

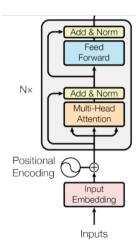
$$h_t = o_t * tanh(C_t)$$

Transformer



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Transformer



Wrap up

Neural networks

- Network architecture (a lot more then fully connected layers)
 - Convulutional layer
 - Recurrent layer
- Loss function

What is missing?

- How to find good weights?
- How to make the model work (regularization, even more architecture, etc)?

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