91258 Natural Language Processing

Lesson 11. "More than One" Neuron

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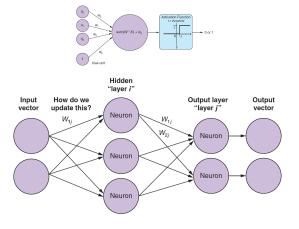
Previously ► The perceptron ► Intro to neural networks

Backpropagation (brief)

Table of Contents	
Backpropagation (brief)	
Keras	
Some Guidelines	
Chapter 5 of Lane et al. (2019)	

Weight Updating

Learning in a "simple" perceptron vs a fully-connected network



(Lane et al., 2019, p. 158, 168)

Backpropagation (of the errors)

A better activation function

Step function:
$$f(\vec{x}) = \begin{cases} 1 & \text{if } \sum_{i=0}^{n} x_i w_i > \text{threshold} \\ 0 & \text{otherwise} \end{cases}$$

Sigmoid function: non-linear³ and continuously differentiable

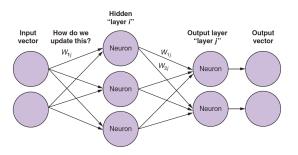
$$S(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

■Let us see



Non-linear o model non-linear relationships Continuously differentiable o partial derivatives wrt various variables to update the weights

Backpropagation (of the errors)



- ► The error is computed on the output vector
- ► How much error did W_{1i} "contribute"?
- ▶ "Path": $W_{1i} \rightarrow [W_{1j}, W_{2j}] \rightarrow output$

Backpropagation

Differentiating to adjust

Squared error⁴

$$SE = (y - f(x))^2 \tag{2}$$

Mean squared error

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y - f(x))^{2}$$
 (3)

Calculus chain rule

$$f(g(x))' = F'(x) = f'(g(x))g'(x)$$
 (4)

With (4) we can find the derivative of the actfunct \forall unit wrt its input.

Plain words: find the contribution of a weight to the error and adjust it!

(no further math)

¹Remember: aka linear regression

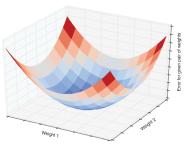
³The change of the output is not proportional to the change of the input.

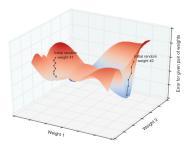
²Notice that the first W_{1i} should be W_{1i}

⁴In (Lane et al., 2019, p. 171) they say this is MSE; but there is no mean

Backpropagation (of the errors)

 $\sim\!\!\text{Gradient}$ descent: minimising the error





Convex error curve

Non-convex error curve

(Lane et al., 2019, p. 173-174)

Keras

Addressing Local minima

Batch learning

- ► Aggregate the error for the batch
- ► Update the weight at the end
- ightharpoonup ightharpoonup hard to find global minimum

Stochastic gradient descent

- ► Look at the error for each single instance
- ► Update the weights right away
- $lackbox{}{} o$ more likely to make it to the global minimum

Mini-batch

- ► Much smaller batch, combining the best of the two worlds
- ightharpoonup Fast as batch, resilient as stochastic gradient descent

Important parameter: learning rate α

A parameter to define at what extent should we "correct" the error

Some Popular Libraries

There are many high- and low-level libraries in multiple languages

- ► PyTorch
 - Community-driven; https://pytorch.org/
- ► Theano
- ► TensorFlow

Google Brain; https://www.tensorflow.org/

► Others

We will use **Keras**; https://keras.io/

What is Keras

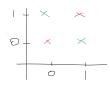
- ► High-level wrapper with an accessible API for Python
- ► Gives access to three alternative backends
 - ► TensorFlow
 - ► CNTK (MS)

Some Guidelines

Keras

Logical exclusive OR (XOR) in Keras

inp	out	outpu
0	0	0
0	1	1
1	0	1
1	1	0





- ► First dense layer
 - ► 2 inputs, 10 units
 - ► 30 parameters
 - ► 2 × 10 → 20
 - ▶ But we also have the bias! That's 10 more weights
- ► Second dense layer
 - ► 10 inputs, 1 unit
 - ▶ 11 parameters

Now we can compile the model

■ Let us see

Design Decisions

Activation functions

Sigmoid

ReLU Rectified linear unit (and variations)

tanh Hyperbolic tangent

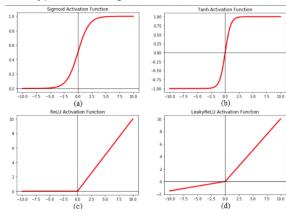


Figure source: (Kandel and Castelli, 2020)

Design Decisions

Activation functions

- ► Sigmoid
- ► ReLU (rectified linear unit)
- ► tanh (hyperbolic tangent)

Learning rate

- ► Choosing one in advance
- ▶ Use **momentum** to perform dynamic adjustments

Dropout

► Ignore randomly-chosen weights in a training pass to prevent overfitting

Regularisation

► Dampen a weight from growing/shrinking too far from the rest to prevent overfitting

References

Kandel, I. and M. Castelli

2020. Transfer learning with convolutional neural networks for diabetic retinopathy image classification. a review. *Applied Sciences*, 10(6).

Lane, H., C. Howard, and H. Hapkem 2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.

Normalisation

Example House classification.

Input number of bedrooms, last selling price
Output Likelihood of selling
Vector input_vec = [4, 12000]

All input dimensions should have comparable values

Ideally, all features should be in the range [-1,1] or [0,1]

Typical normalisation: mean normalization, feature scaling, coefficient of variation

NLP typically uses TF–IDF, one-hot encoding, word2vec (already normalised)