



TutorialSlide6

STATS5099: Data Mining

Neural networks

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This week's content

- artificial neuron
- activation function
- feedforward neural networks
- gradient descent, backpropagation

Artificial neuron

- Artificial neuron, aka perceptron, is the basic unit of a neural network.

- An artificial neuron consists of input values, weights and a bias, a weighted sum and activation function.

Activation functions

- The purpose of activation functions is to **introduce non-linearities** into the network.

Image source: [Apicella, Andrea, et al. "A survey on modern trainable activation functions." Neural Networks \(2021\).](#)

Activation functions

- The purpose of activation functions is to **introduce non-linearities** into the network.

softmax: generalisation of sigmoid for multi-class classification

$$p_i(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}$$

Two special cases of neural networks

- A neural network with no hidden layer and the linear activation function is simply a linear regression model.
- A neural network with no hidden layer and the logistic/sigmoid activation function is a logistic regression model.

Neural network construction

Image source: <https://yogayya.github.io/DeepLearningCourse/03/MultilayerPerceptron.html>

Neural network construction

- Multi-layer perceptron:** a feedforward neural network with multiple **fully-connected layers** and (at least some nonlinear activation function)

Image source: <https://machinelearninggreek.com/multi-layer-perceptron-neural-network-using-python/>

Fitting feedforward neural networks

- Empirical loss: total cost incurred from incorrect predictions (how well your network performs)

$$R(w) = \frac{1}{n} \sum_{i=1}^n L(y_i, \hat{y}_i) = \frac{1}{n} \sum_{i=1}^n L(y_i, f(x_i, w))$$

- Objective: $w^* = \arg \min_w R(w)$
- Gradient descent:
 - start with a random guess at the weights
 - compute gradient, $\frac{\partial R(w)}{\partial w}$
 - update weights, $w \rightarrow w - \eta \frac{\partial R(w)}{\partial w}$ (learning rate)
 - repeat steps 2-3 until reaching stopping criteria

Fitting feedforward neural networks: gradient descent

one of the local optimal, can't ensure the best optimal

Image source: MIT 6.S191: Introduction to Deep Learning

Fitting (feedforward) neural networks: backpropagation

- Feed loss backwards to tune the model parameters (weights and biases)
- Compute gradients using **chain rule**:

$$\frac{\partial R(w)}{\partial w_2} = \frac{\partial R(w)}{\partial y} * \frac{\partial y}{\partial w_2}$$

Image source: MIT 6.S191: Introduction to Deep Learning

Fitting (feedforward) neural networks: backpropagation

- Feed loss backwards to tune the model parameters (weights and biases)
- Compute gradients using **chain rule**:

$$\frac{\partial R(w)}{\partial w_1} = \frac{\partial R(w)}{\partial y} * \frac{\partial y}{\partial z_1} * \frac{\partial z_1}{\partial w_1}$$

Image source: MIT 6.S191: Introduction to Deep Learning

Training in practice

- Gradient descent algorithm may get "stuck" in local optima.

Image source: Li, Hao, et al. "Visualizing the loss landscape of neural nets."

Training in practice: random initialisation

- Different starting values may lead to different local optima.
- Common practice 1: test multiple starting values
- Common practice 2: Initialise weights to random values near zero; initialise bias to 0

Training in practice: learning rate

- Advanced techniques: adaptive learning rate

Image source: <https://saugatibhattarai.com.np/what-is-gradient-descent-in-machine-learning/>

Training in practice: additional considerations

- Stochastic gradient descent (doesn't let me down)
- Regularisation (avoid overfit)

Pros of deep learning

- Nonlinear activation functions
- Universal Approximation Theorem: neural networks with a single hidden layer can be used to approximate any *continuous* function to any desired precision
- Caveat: the layer may be infeasibly large and may fail to learn and generalize correctly
- Particularly suitable for complex problems such as image classification, natural language processing, and speech recognition

Pros of deep learning

Traditional pattern recognition

Deep learning

Cons of deep learning

- may not be easily interpreted
- typically require a large amount of data to perform well
- can be computationally expensive to train
- training a good neural network can be hard

Next week's plan

Next week (Week 7) will be a reading week.

- Training neural networks in practice
 - learning rate, optimizers
 - regularisation techniques
- Deep learning in R
- Optional topic 1: convolutional neural networks
- Optional topic 2: recurrent neural networks
- Revision quizzes
- Additional topics: deep reinforcement learning, etc.

No tutorial; drop-in Q&A on Friday 12-1pm.

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Tutorial in Week 8 will take place on **Wednesday 12-1pm**. The lecture material will be provided early next week.