

# Data Analysis 3

## Neural Networks

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November 18, 2018

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Artificial Neural Networks

# Artificial Neural Networks

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# Artificial Neural Networks

- Artificial Neural Networks (ANN) are models of the human nervous system.

## Human nervous system

- The system is composed of cells, called neurons.
- The neurons are connected to other neurons using synapses.
- The strength of the synapses is affected by learning (external stimuli).

## Artificial Neural Networks

- The system is composed of nodes, called neurons.
- These neurons are units of computation that:
  - Receive the inputs from other neurons.
  - Processes these inputs (computes).
  - Set its output.
- The computation process is affected by the input weights and activation function.
- The weights are analogous to the strength of the synapse.
- The weights are affected by the learning process.

- The neural networks ability to learn is based on the architecture of the network.
  - Single-layer neural network.
  - Multi-layer neural network.
  - Recurrent neural networks.
  - Kohonen Maps (Self Organized Maps).
  - Convolution networks.
  - Deep neural networks.
  - ...
  -
- The learning is done by presenting the test instances to the network and correction of the output according to the expected output by weight adjusting.

# Artificial Neural Networks

## Single-layer Neural Network: The Perceptron

- The basic architecture of neural network.
- The structure has two layers.
  - The input layer has one node for each input attribute.
  - The input node only transmit the input value to the output node.
  - The connection between input and output nodes are weighted.
  - The output layer consist of one output neuron.
  - The output neuron computes the output value.
- The class labels are from the set of  $\{-1, +1\}$ .

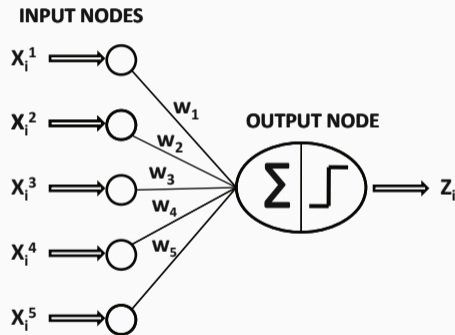


Figure 1: The Perceptron

# Artificial Neural Networks - Single-layer Neural Network

- The weighted inputs are transformed into output value.
- The value is drawn from the set  $\{-1, +1\}$ .
- The value may be interpreted as the perceptron prediction of the class variable.
- The weights  $W = \{w_1, \dots, w_d\}$  are modified when the predicted output does not match expected value.

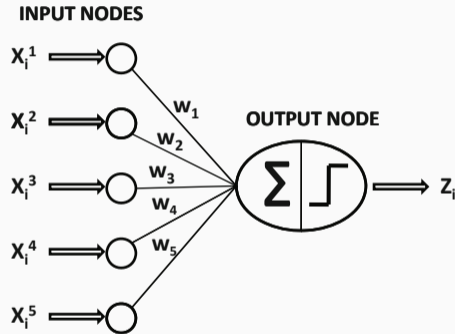


Figure 2: The Perceptron

# Artificial Neural Networks - Single-layer Neural Network

- The function learned by the perceptron is referred as *activation function*.
- The function is usually signed linear function (e.g. weighted sum).
- The  $W = \{w_1, \dots, w_d\}$  are the weights for the connections of  $d$  different inputs to the output neuron.
- The  $d$  is also the dimensionality of the data.
- The  $b$  is the bias associated with the activation function.
- The output  $z_i \in \{-1, +1\}$  is for the data record  $\bar{X}_i = (x_i^1, \dots, x_i^d)$  computed as follows:

$$z_i = \text{sign} \left\{ \sum_{j=1}^d w_j x_i^j + b \right\} = \text{sign} \{ \bar{W} \cdot \bar{X}_i + b \}$$



# Artificial Neural Networks - Single-layer Neural Network

$$z_i = \text{sign} \left\{ \sum_{j=1}^d w_j x_i^j + b \right\} = \text{sign} \{ \bar{W} \cdot \bar{X}_i + b \}$$

- The difference between the prediction of the class value  $z_i$  and the real class value  $y_i$  is  $(y_i - z_i) \in \{-2, 0, 2\}$ .
- The result is 0 when the prediction and reality is the same.
- The weight vector  $\bar{W}$  and bias  $b$  need to be updated, based on the error  $(y_i - z_i)$ .
- The learning process is iterative.
- The weight update rule for  $i$ -th input point  $\bar{X}_i$  in  $t$ -th iteration is as follows:

$$\bar{W}^{t+1} = \bar{W}^t + \eta(y_i - z_i)\bar{X}_i$$

- The  $\eta$  is the learning rate that regulate the learning speed of the network.
- Each cycle per input points in the learning phase is referred as an *epoch*.

# Artificial Neural Networks - Single-layer Neural Network

$$\bar{W}^{t+1} = \bar{W}^t + \eta(y_i - z_i)\bar{X}_i$$

- The incremental term  $(y_i - z_i)\bar{X}_i$  is the approximation of the negative of the gradient of the least-squares prediction error  $(y_i - z_i)^2 = (y_i - \text{sign}(\bar{W} \cdot \bar{X}_i - b))^2$
- The update is performed on a tuple-by-tuple basis not a global over whole dataset.
- The perceptron may be considered a modified version of a gradient descent method that minimizes the squared error of prediction.
- The size of the  $\eta$  affect the speed of the convergence and the quality of the solution.
  - The higher value of  $\eta$  means faster convergence, but suboptimal solution may be found.
  - Lower values of  $\eta$  results in higher-quality solutions with slow convergence.
- In practice,  $\eta$  is decreased systematically with increasing number of epochs performed.
- Higher values at the beginning allows bigger jumps in weight space and lower values later allows precise setting of the weights.

# Artificial Neural Networks

## Multi-layer Neural Network

- The perceptron, with only one computational neuron produces only a linear model.
- Multi-layer perceptron adds a hidden layer beside the input and output layer.
- The hidden layer itself may consist of different type of topologies (e.g. several layers).
- The output of nodes in one layer feed the inputs of the nodes in the next layer - this behavior is called *feed-forward network*.
- The nodes in one layer are fully connected to the neurons in the previous layer.

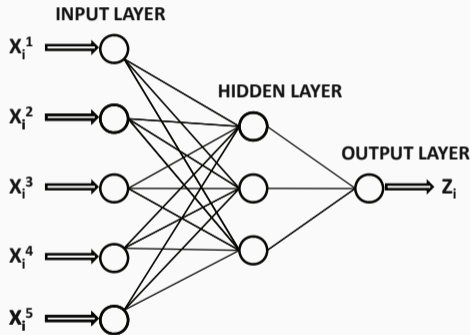


Figure 3: Multi-layer neural network

# Artificial Neural Networks - Multi-layer Neural Network

- The topology of the multi-layer feed-forward network is determined automatically.
- The perceptron may be considered as a single-layer feed-forward neural network.
- The number of layers and the number of nodes in each layer have to be determined manually.
- Standard multi-layer network uses only one hidden layer, i.e. this is considered as a two-layer feed forward neural network.
- The activation function is not limited to linear signed weighted sum, other functions such as logistic, sigmoid or hyperbolic tangents are allowed.

# Artificial Neural Networks - Multi-layer Neural Network

Sigmoid/Logistic function  $\sigma(x) = \frac{1}{1+e^{-x}}$

TanH  $\tanh(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})}$

ReLU (Rectified linear unit)  $f(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ x & \text{for } x \geq 0 \end{cases}$

Sinc  $f(x) = \begin{cases} 1 & \text{for } x = 0 \\ \frac{\sin(x)}{x} & \text{for } x \neq 0 \end{cases}$

Gaussian  $f(x) = e^{-x^2}$

Softmax  $\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}}$

## Learning algorithm

- The learning phase is more complicated than the one in perceptron.
- The biggest problem is to get the error in the hidden layer, because the direct class label is not defined on this level.
- Some kind of *feedback* is required from the nodes in the forward layer to the nodes in earlier layers about the *expected* outputs and corresponding errors.
- This principle is realized in the *back-propagation* algorithm.

## Back-propagation algorithm

- *Forward phase:*
  - The input is fed into input neurons.
  - The computed values are propagated using the current weights to the next layers.
  - The final predicted output is compared with the class label and the error is determined.
- *Backward phase:*
  - The main goal is to learn weights in the backward direction by providing the error estimation from later layers to the earlier layers.
  - The estimation in the hidden layer is computed as a function of the error estimate and weight is the layers ahead.
  - The error is estimated again using the gradient method.
  - The process is complicated by the using of non-linear functions in the inner nodes.

Other learning algorithms:

- Gradient descent
- Stochastic Gradient Descent
  - Momentum
  - Averaging
  - AdaGrad
  - RMSProp
  - Adam
- Newton's method
- Conjugate gradient
- Quasi-Newton method
- Levenberg-Marquardt algorithm



# Artificial Neural Networks - Multi-layer Neural Network

- The multi-layer neural network is more powerful than kernel SVM in its ability to capture arbitrary functions.
- It has ability not only to capture decision boundaries of arbitrary shapes, but also noncontiguous class distribution with different decision boundaries in different regions.
- With increasing number of nodes and layers, virtually any function may be approximated.
- **The neural networks are universal function approximators.**
- This generality brings several challenges that have to be dealt with:
  - The design of the topology presents many trade-off challenges for the analyst.
  - Higher number of nodes and layers provides greater generality but also the risk of over-fitting.
  - There is very little guidance provided from the data.
  - The neural network has poor interpretability associated with the classification process.
  - The learning process is very slow and sensitive to the noise.
  - Larger networks has very slow learning process.

## Recurrent Neural Network

- A class of artificial neural network where connections between units form a directed cycle.
- This structure allows the dynamic temporal behavior or memory.
- Such network are able to deal with sequences of inputs as sequences not isolated inputs.
- Several types are defined in the literature:
  - **Fully recurrent network** - basic architecture with recurrent connection in each level and time-varying activation function.
  - **Recursive neural network** - the network that applies the same weights recursively over a graph-like structure. Designed for representation of the structures like logical terms.
  - **Hopfield network** with proper learning method it is a robust content-addressable memory. Its variations include the bidirectional associative memory.
  - **Echo state network** - a special RNN that has sparsely connected random hidden layer. Only the weights of the output neuron may be changed during training.
- Training is performed by gradient descent or global optimization techniques.

# Artificial Neural Networks

## Self-organizing Map

- A special class of the neural network that is used for unsupervised learning.
- The structure of neurons is a plane with squared or hexagonal grid.
- Each node contains a  $d$ -dimensional vector - a value of the neuron.
- The training of the network is realized as a searching for the closest neuron in feature space (the winner) and moving the neuron value towards the input neuron.
- The neighborhood of the winner is modified too when the size of the move is inversely proportional to the distance from the winner.

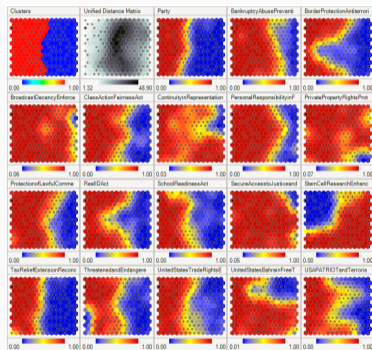


Figure 4: Self-organizing Map

## Convolutional neural network

- A version of MLP that is inspired by the visual perception of animals.
- Instead of fully connected layers it deals with the image processing with different structure.
- The layers of a CNN have neurons arranged in 3 dimensions: width, height and depth.
- The neurons inside a layer are only connected to a small region of the layer before it, called a receptive field (filters).
- CNNs exploit spatially local correlation by enforcing a local connectivity pattern between neurons of adjacent layers.
- Stacking many layers leads to non-linear "filters" that become increasingly "global".
- This allows the network to first create good representations of small parts of the input, then assemble representations of larger areas from them.
- Each filter is replicated across the entire visual field with the same parametrization (weight vector and bias) and form a feature map.
- Features are detected regardless of their position in the visual field.

# Artificial Neural Networks - Convolutional neural network

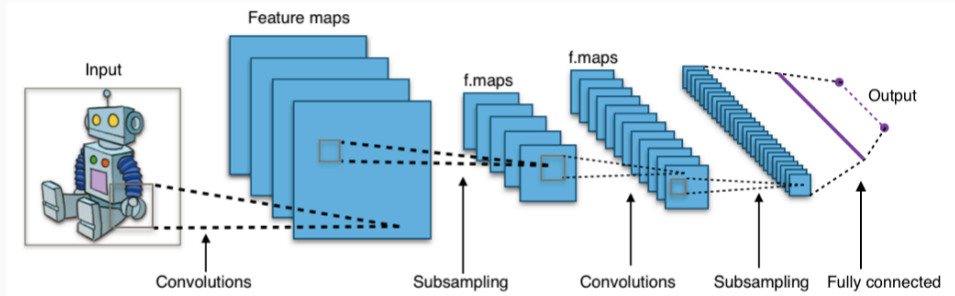


Figure 5: Typical CNN (source Wikipedia)

Questions?