Neural Network and application in Finance

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Machine Learning

Neural Networks

Slides mostly adapted from Tom Mithcell, Han and Kamber

Artificial Neural Networks

- Computational models inspired by the human brain:
  - Algorithms that try to mimic the brain.
  - Massively parallel, distributed system, made up of simple processing units (neurons)
  - Synaptic connection strengths among neurons are used to store the acquired knowledge.
  - Knowledge is acquired by the network from its environment through a learning process

History

- late-1800's - Neural Networks appear as an analogy to biological systems
- 1960's and 70's – Simple neural networks appear
  - Fall out of favor because the perceptron is not effective by itself, and there were no good algorithms for multilayer nets
- 1986 – Backpropagation algorithm appears
  - Neural Networks have a resurgence in popularity
  - More computationally expensive

Properties

- Inputs are flexible
  - any real values
  - Highly correlated or independent
- Target function may be discrete-valued, real-valued, or vectors of discrete or real values
  - Outputs are real numbers between 0 and 1
- Resistant to errors in the training data
- Long training time
- Fast evaluation
- The function produced can be difficult for humans to interpret

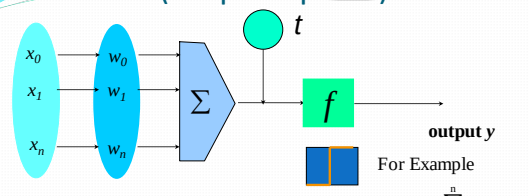
When to consider neural networks

- Input is high-dimensional discrete or raw-valued
- Output is discrete or real-valued
- Output is a vector of values
- Possibly noisy data
- Form of target function is unknown
- Human readability of the result is not important

Examples:

- Speech phoneme recognition
- Image classification
- Financial prediction

A Neuron (= a perceptron)



Input vector x **weight vector w** **weighted sum** **Activation function**

For Example $y = \text{sign}(\sum_{i=0}^{n} w_i x_i - t)$

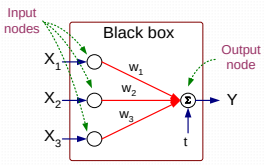
- The *n*-dimensional input vector **x** is mapped into variable y by means of the scalar product and a nonlinear function mapping

Perceptron

- Basic unit in a neural network
- Linear separator
- Parts
  - N inputs, x_1 ... x_n
  - Weights for each input, w_1 ... w_n
  - A bias input x_0 (constant) and associated weight w_0
  - Weighted sum of inputs, $y = w_0x_0 + w_1x_1 + ... + w_nx_n$
  - A threshold function or activation function,
    - i.e 1 if y > t, -1 if y <= t

Artificial Neural Networks (ANN)

- Model is an assembly of inter-connected nodes and weighted links
- Output node sums up each of its input value according to the weights of its links
- Compare output node against some threshold t



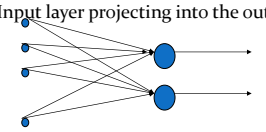
Perceptron Model

$$Y = I(\sum_i w_i x_i - t) \quad \text{or}$$

$$Y = sign(\sum_i w_i x_i - t)$$

Different Network Topologies

- Single layer feed-forward networks
  - Input layer projecting into the output layer

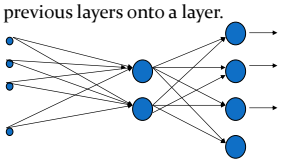


Single layer network

Input layer Output layer

Different Network Topologies

- Multi-layer feed-forward networks
  - One or more hidden layers. Input projects only from previous layers onto a layer.

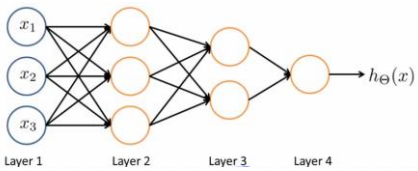


2-layer or 1-hidden layer *fully connected* network

Input layer Hidden layer Output layer

Different Network Topologies

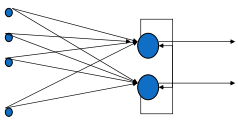
- Multi-layer feed-forward networks



Input layer Hidden layers Output layer

Different Network Topologies

- Recurrent networks
  - A network with feedback, where some of its inputs are connected to some of its outputs (discrete time).



Recurrent network

Input layer

Output layer

Multilayer Networks

The class of functions representable by perceptrons is limited

$$\text{Out}(\mathbf{x}) = g\left(\mathbf{w}^{\mathrm{T}}\mathbf{x}\right) = g\left(\sum_j w_j x_j\right)$$

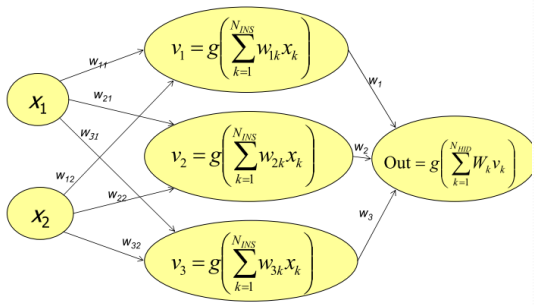
Use a wider representation !

$$\text{Out}(\mathbf{x}) = g\left(\sum_j W_j g\left(\sum_k w_{jk} x_{jk}\right)\right)$$

This is a nonlinear function
Of a linear combination
Of non linear functions
Of linear combinations of inputs

A 1-HIDDEN LAYER NET

$N_{INPUTS} = 2$ $N_{HIDDEN} = 3$

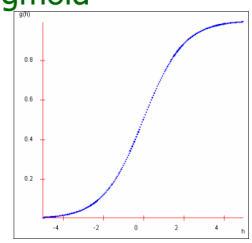


Multi-layer Networks

- Linear units inappropriate
  - No more expressive than a single layer
- Introduce non-linearity
  - Threshold not differentiable
- Use sigmoid function

The Sigmoid

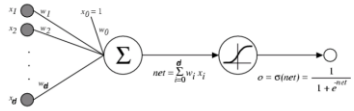
$$g(h) = \frac{1}{1+\exp(-h)}$$



Now we choose ***w*** to minimize

$$\sum_{i=1}^{R} \left[y_i - \text{Out}(\mathbf{x}_i)\right]^2 = \sum_{i=1}^{R} \left[y_i - g(\mathbf{w}^{\mathrm{T}}\mathbf{x}_i)\right]^2$$

Sigmoid Unit



$\sigma(x)$ is the sigmoid function/activation function (also linear, threshold)

$$\frac{1}{1+e^{-x}}$$

Nice property: $\frac{d\sigma(x)}{dx} = \sigma(x)(1-\sigma(x))$ Differentiable

We can derive gradient decent rules to train

- One sigmoid unit
- *Multilayer networks* of sigmoid units → Backpropagation

Backpropagation

$$\text{Out}(x) = g\left(\sum_j W_j g\left(\sum_k w_{jk} x_k\right)\right)$$

Find a set of weights $\{W_j\}, \{w_{jk}\}$

to minimize

$$\sum_i (y_i - \text{Out}(x_i))^2$$

by gradient descent.

That's it!
That's the backpropagation algorithm.

Backpropagation

- Iteratively process a set of training tuples & compare the network's prediction with the actual known target value
- For each training tuple, the weights are modified to **minimize the mean squared error** between the network's prediction and the actual target value
- Modifications are made in the "**backwards**" direction: from the output layer, through each hidden layer down to the first hidden layer, hence "**backpropagation**"
- Steps
  - Initialize weights (to small random #s) and biases in the network
  - Propagate the inputs forward (by applying activation function)
  - Backpropagate the error (by updating weights and biases)
  - Terminating condition (when error is very small, etc.)

How A Multi-Layer Neural Network Works?

- The **inputs** to the network correspond to the attributes measured for each training tuple
- Inputs are fed simultaneously into the units making up the **input layer**
- They are then weighted and fed simultaneously to a **hidden layer**
- The number of hidden layers is arbitrary, although usually only one
- The weighted outputs of the last hidden layer are input to units making up the **output layer**, which emits the network's prediction
- The network is **feed-forward** in that none of the weights cycles back to an input unit or to an output unit of a previous layer
- From a statistical point of view, networks perform **nonlinear regression**: Given enough hidden units and enough training samples, they can closely approximate any function

Neural Network as a Classifier

- Weakness
  - Long training time
  - Require a number of parameters typically best determined empirically, e.g., the network topology or "structure."
  - Poor interpretability: Difficult to interpret the symbolic meaning behind the learned weights and of "hidden units" in the network
- Strength
  - High tolerance to noisy data
  - Ability to classify untrained patterns
  - Well-suited for continuous-valued inputs and outputs
  - Successful on a wide array of real-world data
  - Algorithms are inherently parallel
  - Techniques have recently been developed for the extraction of rules from trained neural networks

Ứng dụng NN
Dự báo bankruptcy

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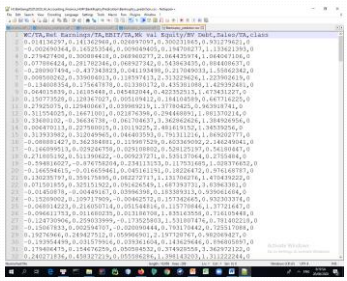
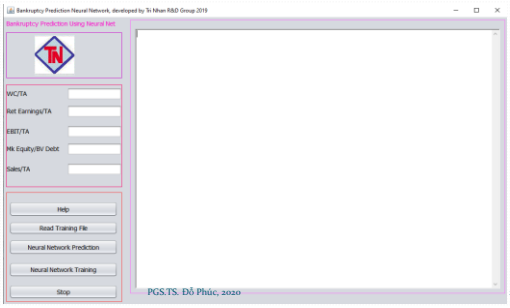
Dữ liệu: bankruptcy



Bankruptcy Prediction using NN



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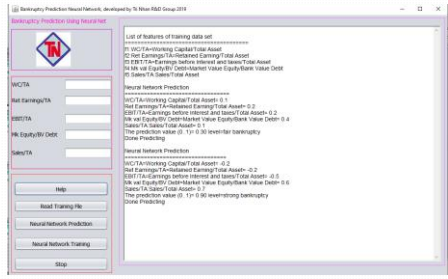
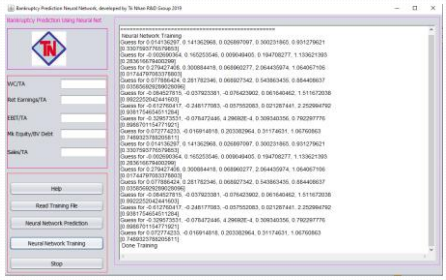
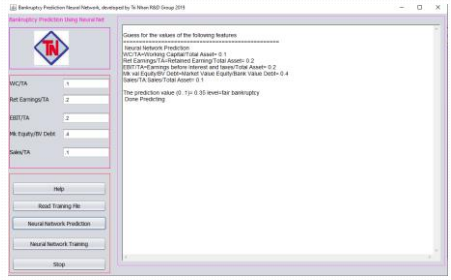


Huấn luyện mạng NN



Vận hành mạng NN- fair bankruptcy



Vận hành mạng NN- strong bankruptcy