COMP4432 Machine Learning

Tutorial Questions on Neural Networks (with reference answers)

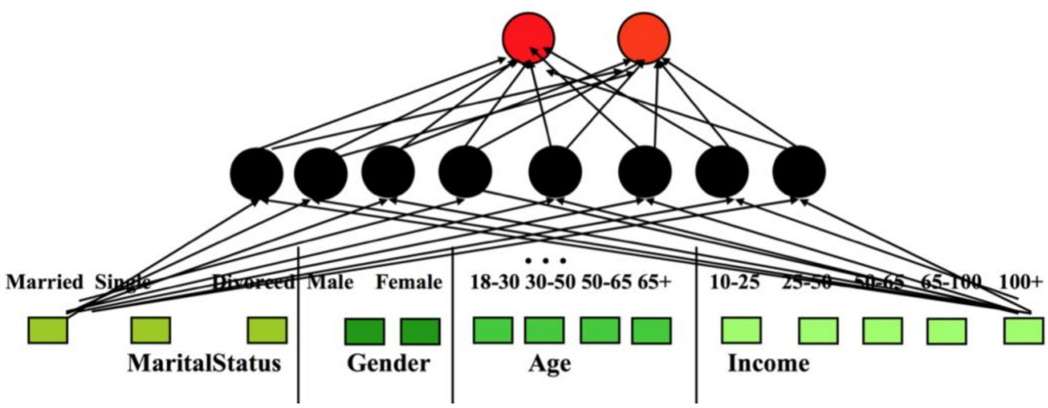
1. Suppose we want to classify potential bank customers as good creditors or bad creditors for loan applications. We have a training dataset describing past customers using the following attributes:
   - Marital status {married, single, divorced}
   - Gender {male, female}
   - Age{[18..30[, [30..50[, [50..65[, [65+]}
   - Income {[10K..25K[, [25K..50K[, [50K..65K[, [65K..100K[, [100K+]}

   a) Design a 3-layer neural network (i.e. 1 input layer, 1 hidden layer and 1 output layer) that could be trained to predict the credit rating of an applicant.

   b) How many learnable parameters (interconnection weights) are there in the neural network when the hidden layer consists of 8 nodes?

Answer:

a) As we have 2 classes, i.e., good creditor and bad creditor, we want to have 2 output nodes, with training output value pairs (1, 0) and (0, 1) to describe them respectively. Note that using 1 output node is also okay (using 1 to denote good creditor and 0 to denote bad creditor) but the training could be harder. Similarly, we need to use 3 input nodes, 2 input nodes, 4 input nodes and 5 input nodes for the attribute "Marital Status", "Gender", "Age" and "Income" respectively, altogether 14 input nodes. For the number of hidden nodes, it is generally required to be smaller than that of input nodes to avoid overfitting. The weights are initialized with random small values, e.g. -0.1<value<+0.1.



b) The number of learnable parameters of input-to-hidden is $(14+1)\times 8+(8+1)\times 2$.

2. For the single layer perceptron using sigmoid output, derive the learning rule based on the error/loss function in slide 11 of the MLP lecture notes.

$$y^t = sigmoid(w^t x^t)$$

$$E^t(\mathbf{w}|\mathrm{x}^t, \mathrm{r}^t) = -r^t log y^t - (1 - r^t)\log(1 - y^t)$$

$$\Delta w_j^t = \eta(r^t - y^t)x_j^t$$

Ans.

$E^t(\mathbf{w}|\mathrm{x}^t, \mathrm{r}^t) = -r^t log y^t - (1 - r^t)\log(1 - y^t)$

$\frac{\partial}{\partial w_j^t} E^t(\mathbf{w}|\mathrm{x}^t, \mathrm{r}^t) = \frac{\partial}{\partial w_j^t}[-r^t log y^t - (1 - r^t)\log(1 - y^t)]$

$= -r^t \frac{1}{y^t} \cdot \frac{\partial}{\partial w_j^t} y^t - (1 - r^t)\frac{1}{1 - y^t}\left(-\frac{\partial}{\partial w_j^t} y^t\right)$

$= \left[-r^t \frac{1}{y^t} + (1 - r^t)\frac{1}{1 - y^t}\right] \cdot \left[y^t(1 - y^t) \cdot \frac{\partial}{\partial w_j^t}[w^t x^t]\right]$

$= \left(-\frac{r^t}{y^t} + \frac{1 - r^t}{1 - y^t}\right) \cdot [y^t(1 - y^t) \cdot x_j^t]$

$= \left(\frac{-r^t(1 - y^t) + y^t(1 - r^t)}{y^t(1 - y^t)}\right) \cdot [y^t(1 - y^t) \cdot x_j^t]$

$= -(r^t - r^t y^t - y^t + r^t y^t) \cdot x_j^t$

$= -[r^t - y^t] \cdot x_j^t$

Hence,

$\Delta w_j^t = -\eta \frac{\partial E^t(\mathbf{w}|\mathrm{x}^t, \mathrm{r}^t)}{\partial w_j^t} = \eta(r^t - y^t)x_j^t.$