

CS4801: Principle of Machine Learning

Assignment 3

deadline : 3rd October 2018 morning 8am

This homework consists of problems covering Classification. A few instructions to make life easier for all of us:

- Assignment need not to be submitted.
- Quiz on this Assignment will be held on 3rd October, during class hours.

age	income	software_engineer	credit_rating	buys_computer
<=20	high	no	fair	no
<=20	high	no	excellent	no
21-30	high	no	fair	yes
>30	medium	no	fair	yes
>30	low	yes	fair	yes
>30	low	yes	excellent	no
21-30	low	yes	excellent	yes
<=20	medium	no	fair	no
<=20	low	yes	fair	yes
>30	medium	yes	fair	yes
<=20	medium	yes	excellent	yes
21-30	medium	no	excellent	yes
21-30	high	yes	fair	yes
>30	medium	no	excellent	no

Figure 1: Decision Tree

Exercise 1: Classification

- (a) (2 points each) Please go through at-least 10 data set for classification from UC Machine Learning Repository (<https://archive.ics.uci.edu/ml/datasets.html?format=&task=cla&att=&area=&numAtt=&numIns=&type=mvar&sort=nameUp&view=table>) and Study what is feature and what is output for classifier.

- (b) (2 points) Design K class classifier with help of 2 class SVM.

- (c) (5 points) Consider the following data set in Figure 1 and build a DT with your choice impurity measure and find the prediction for

$X = (\text{age}=20, \text{income} = \text{medium}, \text{software engineer} = \text{yes}, \text{credit rating} = \text{fair})$.

Please state why you have considered that choice of impurity measure?

- (d) (1 points) Consider two non-negative numbers a and b and show that, if $a \leq b$, then $a \leq (ab)^{\frac{1}{2}}$. Use this result to show that, if the decision region of a two-class classification problem are chosen to minimize the probability of mis-classification, this probability will satisfy

$$p(\text{mistake}) \leq \int \{p(\mathbf{x}, C_1)p(\mathbf{x}, C_2)\}^{\frac{1}{2}} d\mathbf{x}$$

- (e) (2 point) Derive the update equation for gradient descent approach to solve following problems

- i. Logistic regression: $E(\mathbf{w}) = \frac{1}{n} \sum_{i=1}^n \log(1 + e^{-y_i(\mathbf{x}_i^T \mathbf{w})}) + \frac{\lambda}{2} \|\mathbf{w}\|_2^2$
- (f) (2 points) The error of a binary classifier which guesses completely randomly is 0.5. What is the error of a random k -class classifier for $k > 2$ labels.
- i. Random guesser G knows that there are k labels, and for each example, selects a label out of $\{1, \dots, k\}$ uniformly at random. What is the error of G ?
- ii. Now suppose we have a more sophisticated random guesser Z who knows that w_1 fraction of the data distribution has label 1, w_2 fraction has label 2, and so on. For each example, Z also selects a label out of $\{1, \dots, k\}$ at random, but he selects label 1 with probability w_1 , label 2 with probability w_2 and so on. What is the error of Z ?
- (g) (2 points) Consider the following two data distributions \mathcal{D}_1 and \mathcal{D}_2 over labeled examples. There is a single feature, denoted by X which takes values in the set $\{1, 2, 3, 4\}$ and a binary label $Y \in \{0, 1\}$. \mathcal{D}_1 is described as follows:

$$\begin{aligned} Pr(X = i) &= \frac{1}{4}, \quad i \in \{1, 2, 3, 4\} \\ Pr(Y = 1|X = i) &= 1, \quad i \in \{1, 4\} \\ Pr(Y = 0|X = i) &= 1, \quad i \in \{2, 3\} \end{aligned} \tag{1}$$

\mathcal{D}_2 is described as follows.

$$\begin{aligned} Pr(X = i) &= \frac{1}{4}, \quad i \in \{1, 2, 3, 4\} \\ Pr(Y = 1|X = i) &= \frac{i}{10}, \quad i \in \{1, 2, 3, 4\} \end{aligned} \tag{2}$$

- i. Consider the following classifier

$$h : h(x) = 1 \text{ if } x > 1.5 \text{ and } 0 \text{ otherwise.}$$

What is the true error of h when the true data distribution is \mathcal{D}_1 ?

- ii. Suppose our classifier is

$$h_t : h_t(x) = 1 \text{ if } x > t \text{ and } 0 \text{ otherwise}$$

. Find t which minimizes the true error of h_t when the true data distribution is \mathcal{D}_1 . What is the true error of this classifier?

- iii. Repeat parts **i.** and **ii.** for the data distribution \mathcal{D}_2 .