CS 760: Machine Learning - Fall 2020

Homework 5: Nearest Neighbors & Naive Bayes

Due: 11/12/2020

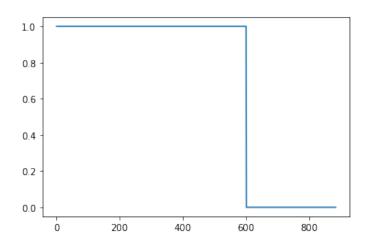
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Problem 1

- (a) I chose the KNN variant that, weights = 'uniform', metric = 'euclidean'
 The data should be min-max normalized before computing. The Accuracy is 81%.
 KNN.py = https://github.com/z-zijie/2020Fall/blob/master/COMP760/Homework5/KNN.py
- (b) Euclidean distance. Because this metric is more intuitive.

(c)



- (d) The best choice of K is 5.
- (e) We can use the voting ratio to decide reliability.

Problem 2

- (a) Bayes.py = https://github.com/z-zijie/2020Fall/blob/master/COMP760/Homework5/Bayes.py
- (b) Passenger Class, Gender, Siblings/Spouses and Parents/Children are Bernoulli. Age and Fare are Gaussian.
- (c) x = [1, 1, 22, 1, 0, 71.2833], survived.
- (d) If prediction=survived, confidence = P(survived|x)/P(survived|x) + P(NOT survived|x).

Problem 3

I prefer Random Forest, because this algorithm is very interpretable.

KNN

```
import numpy as np
from sklearn.model_selection import train_test_split
data = np.delete(np.genfromtxt('titanic_data.csv', delimiter=','), 0, 0)
X = data[:,1:]
y_label = data[:,0]
# transform
for i in range(X.shape[1]):
     if i == 1:
         continue
    X[:,i] \,=\, (X[:,i] \,-\, np.min(X[:,i]))/(np.max(X[:,i]) \,-\, np.min(X[:,i]))
       \mathsf{X}[:,i] \,=\, \big(\mathsf{X}[:,i] \,-\, \mathsf{np.mean}\big(\mathsf{X}[:,i]\big)\big) \,\,/\,\, \mathsf{np.std}\big(\mathsf{X}[:,i]\big)
# metric = 'manhattan'
def dis(x,y):
     ans = np.sum(np.abs(y-x))
     if ans == 0:
         return 1e-10
     return ans
# metric = 'euclidean'
def 12(x,y):
     ans = np.linalg.norm(x-y)
     if ans == 0:
         return 1e-10
     return ans
# KNN
import heapq
def knn_predict(k, x, dataset, label):
    N = len (dataset)
     h = []
     for i in range(N):
          distance = I2(x, dataset[i])
     \begin{array}{lll} & \text{heapq.heappush(h, (distance, i))} \\ & \text{ans} = [\text{heapq.heappop(h)[1]} & \text{for i in } \text{range(min(k,N))}] \end{array}
     p = sum([label[i] \ for \ i \ in \ ans])/len(ans)
     if (p >= 0.5):
          return 1
     return 0
i = 13
k = 5
# KFold
ans = np.zeros(len(X))
k = 5
from sklearn.model_selection import KFold
kf = KFold(n_splits = 10, shuffle = True)
kf.get_n_splits(X)
for train_index, test_index in kf.split(X):
     X_{train}, X_{test} = X[train_{index}], X[test_{index}]
     y\_train \;,\;\; y\_test \;=\; y\_label [\; train\_index \,] \;,\;\; y\_label [\; test\_index \,]
     for i in range(len(test_index)):
         ans[test\_index[i]] = (knn\_predict(k, X\_test[i], X\_train, y\_train) == y\_test[i])
accuracy = sum(ans)/len(ans)
print(accuracy)
# personal data
data = np.delete (np.genfromtxt('titanic_data.csv', delimiter=','), 0, 0)
x = np.array([1, 1, 22, 1, 0, 71.2833])
xx = data[:,1:]
# transform
for i in range(len(x)):
     if i == 1:
         continue
     x[i] = (x[i] - np.min(xx[:,i]))/(np.max(xx[:,i]) - np.min(xx[:,i]))
```

```
# predict p = [knn\_predict(k, x, X, y\_label) for k in range(1,X.shape[0])] import matplotlib.pyplot as plt plt.plot(p)
```

Bayes

```
import numpy as np
from sklearn.model_selection import train_test_split
# import data
data = np.delete(np.genfromtxt('titanic_data.csv', delimiter=','), 0, 0)
X = data[:,1:]
y_label = data[:,0]
import math
def gaussian (val, mean, var):
              ans = math.exp(-(val-mean)*(val-mean)/(2*var))
              ans = ans/math.sqrt(2*math.pi*var)
              return ans
def fit (dataset , label):
              index\_survived = np.where(label == 1)[0]
              index_not_survived = np.where(label==0)[0]
              p_survived = len(index_survived) / len(label)
             # BernoulliNB
              Bernoulli_feature = [0, 1, 3, 4]
              p_estimate_0 = [] # NOT survived
              p_estimate_1 = [] # survived
for feature in Bernoulli_feature:
                            p_feature_0 = []
                            p\_feature\_1 \ = \ [\,]
                            value = np.unique(dataset[:, feature])
                           K = len(value)
                            for val in value:
                                          p_feature_0.append(len(1+np.where((dataset[:, feature]==val) & (label==0))[0])/(append(len(1+np.where((dataset[:, feature]==val)) & (label==0)(append(len(1+np.where((dataset[:, feature]==val)) & (label==0)(append(len(
             K+len(index_not_survived)))
                                          p_{eq} = 1.append(len(1+np.where((dataset[:, feature]==val) & (label==1))[0])/(articles)
             K+len (index_survived)))
                            p_estimate_0 .append(p_feature_0)
                            p_estimate_1 .append (p_feature_1)
             # GaussianNB
               Gaussian_feature = [2, 5]
               Gaussian_parameter_0 = []
              Gaussian_parameter_1 = []
              dataset_0 = dataset[index_not_survived]
              dataset_1 = dataset[index_survived]
              for feature in Gaussian_feature:
                            {\tt Gaussian\_parameter\_0.append} \ ( \verb[np.mean(dataset\_0[:, feature]) \ , \ np.var(dataset\_0[:, featu
              feature])])
                            Gaussian_parameter_1.append([np.mean(dataset_1[:, feature]), np.var(dataset_1[:,
              feature])])
              return p_estimate_0, p_estimate_1, Gaussian_parameter_0, Gaussian_parameter_1, p_survived
              , dataset , label
def predictNB(x, estimate):
              dataset = estimate[5]
              label = estimate[6]
               Bernoulli_feature = [0, 1, 3, 4]
              Gaussian_feature = [2, 5]
             # survived
              p = estimate [4]
               p_{estimate_1} = estimate[1]
              Gaussian_parameter_1 = estimate[3]
```

```
for i in range(len(Bernoulli_feature)):
         feature = Bernoulli_feature[i]
         unique_feature = np.unique(dataset[:, feature]).tolist()
         if x[feature] in unique_feature:
            j = unique_feature.index(x[feature])
            j = len (unique_feature)-1
           j = np.where(np.unique(dataset[:,feature]) == x[feature])[0][0]
#
        p = p * p_estimate_1[i][j]
    for i in range(len(Gaussian_feature)):
         feature = Gaussian_feature[i]
        Mean = Gaussian_parameter_1[i][0]
        \mathsf{Var} = \mathsf{Gaussian\_parameter\_1[i][1]}
        p = p * gaussian(x[feature], Mean, Var)
    p_survived = p
    # NOT survived
    p = 1 - estimate [4]
    p_estimate_0 = estimate[0]
    Gaussian_parameter_0 = estimate[2]
    for i in range(len(Bernoulli_feature)):
         feature = Bernoulli_feature[i]
         unique_feature = np.unique(dataset[:, feature]).tolist()
         if x[feature] in unique_feature:
            j = unique_feature.index(x[feature])
            j = len (unique_feature)-1
           j = np.where(np.unique(dataset[:, feature]) = x[feature])[0][0]
#
        p = p * p_estimate_0[i][j]
    for i in range(len(Gaussian_feature)):
        feature = Gaussian_feature[i]
        Mean = Gaussian_parameter_0[i][0]
        Var = Gaussian\_parameter\_0\,[\,i\,][\,1\,]
        p = p * gaussian(x[feature], Mean, Var)
    p_not_survived = p
    if p_survived > p_not_survived:
        return 1
    return 0
\# estimate = fit (X, y_label)
# predictNB(X[1], estimate)
from sklearn.model_selection import KFold
ans = np.zeros(len(X))
kf = KFold(n_splits = 10, shuffle = True)
kf.get_n_splits(X)
for train_index , test_index in kf.split(X):
    X_{train}, X_{test} = X[train_{index}], X[test_{index}]
    y_train , y_test = y_label[train_index], y_label[test_index]
    estimate = fit(X_train, y_train)
    for i in range(len(test_index)):
        ans[test\_index[i]] = (predictNB(X\_test[i], estimate) == y\_test[i])
accuracy = sum(ans)/len(ans)
print(accuracy)
# personal data
estimate = fit(X, y_label)
x = np.array([1, 1, 22, 1, 0, 71.2833])
print(predictNB(x, estimate))
```