HW_Classification

February 6, 2022

[1]:
```
from collections import defaultdict
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier as knn
from sklearn.preprocessing import MinMaxScaler as minmax

from sklearn.tree import DecisionTreeClassifier as dt
from sklearn.tree import plot_tree

from sklearn.metrics import confusion_matrix as cm
from sklearn.metrics import plot_confusion_matrix, accuracy_score,␣
 ↪classification_report

import seaborn as sns
```

1 A

[2]:
```
data = pd.read_csv('adult-modified1.csv')
data_dum = pd.get_dummies(data)
```

[3]:
```
data_dum.drop(['income_<=50K'], axis=1,inplace=True)
Y = data_dum.pop('workclass_Self-emp')
X = data_dum.copy()
X.head()
```

[3]:
```
   age  education  hours-per-week  workclass_Private  workclass_Public  \
0   39         13              40                  0                 1
1   50         13              13                  0                 0
2   38          9              40                  1                 0
3   53          7              40                  1                 0
4   28         13              40                  1                 0

   marital-status_Married  marital-status_Single  race_Amer-Indian  \
0                       0                      1                 0
1                       1                      0                 0
2                       0                      1                 0
3                       1                      0                 0
```

```
4                       1                      0                 0

   race_Asian  race_Black  race_Hispanic  race_White  sex_Female  sex_Male  \
0           0           0              0           1           0         1
1           0           0              0           1           0         1
2           0           0              0           1           0         1
3           0           1              0           0           0         1
4           0           1              0           0           1         0

   income_>50K
0            0
1            0
2            0
3            0
4            0
```

[4]:
```
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2)
```

[5]:
```
print('Train Data')
print(x_train.shape)
print(y_train.shape)
print('Test Data')
print(x_test.shape)
print(y_test.shape)
```

```
Train Data
(7529, 15)
(7529,)
Test Data
(1883, 15)
(1883,)
```

#

B

1.1 1

Apply min max scaling to x train and test data

[6]:
```
scaler = minmax()
xtrain_scaled = scaler.fit_transform(x_train)
xtest_scaled = scaler.fit_transform(x_test)
```

Model the data using knn with k=10

[7]:
```
knn_model = knn(n_neighbors=10)
knn_model.fit(xtrain_scaled, y_train)
```

[7]:
```
KNeighborsClassifier(n_neighbors=10)
```

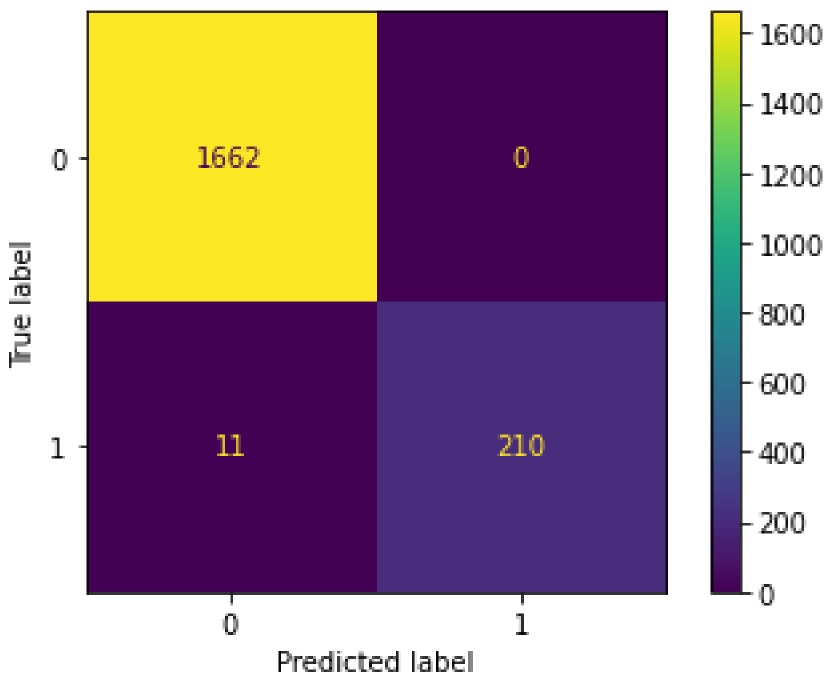
[8]:
```
knn_predictions = knn_model.predict(xtest_scaled)
```

[9]:
```
confusion_mat = cm(knn_predictions, y_test)
```

[10]:
```
plot_confusion_matrix(knn_model, xtest_scaled, y_test)
```

```
/home/gsandoval/.local/lib/python3.10/site-
packages/sklearn/utils/deprecation.py:87: FutureWarning: Function
plot_confusion_matrix is deprecated; Function `plot_confusion_matrix` is
deprecated in 1.0 and will be removed in 1.2. Use one of the class methods:
ConfusionMatrixDisplay.from_predictions or
ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```

[10]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7eff90a92d70>
```



Accuracy for both the training and test sets

[11]:
```
# Training Results
train_predictions = knn_model.predict(xtrain_scaled)
cm(train_predictions, y_train)
```

[11]:
```
array([[6602,   18],
       [   0,  909]])
```

```
[12]: # Testing Results
confusion_mat
```

```
[12]: array([[1662,   11],
             [   0,  210]])
```

1.1.1 PLEASE NOTE

2 and 3 are the same question asked in different ways.

In 2 you ask us to compare different k's and different weights.

In 3 you ask us again to compare with weight of uniform, which was done in 2

1.2 2

```
[13]: k_values = [x for x in range(10,101, 10)]
distance_acc = defaultdict()
```

```
[14]: for k in k_values:
    model = knn(n_neighbors=k, weights='distance')
    model.fit(xtrain_scaled, y_train)
    knn_predictions = knn_model.predict(xtest_scaled)
    accuracy = accuracy_score(y_test, knn_predictions)
    distance_acc[str(k)] = accuracy
```

```
[15]: distance_acc
```

```
[15]: defaultdict(None,
                  {'10': 0.9941582580987786,
                   '20': 0.9941582580987786,
                   '30': 0.9941582580987786,
                   '40': 0.9941582580987786,
                   '50': 0.9941582580987786,
                   '60': 0.9941582580987786,
                   '70': 0.9941582580987786,
                   '80': 0.9941582580987786,
                   '90': 0.9941582580987786,
                   '100': 0.9941582580987786})
```

1.3 3

```
[37]: k_values = [x for x in range(10,101, 10)]
uniform_acc = defaultdict()

for k in k_values:
    model = knn(n_neighbors=k, weights='uniform')
    model.fit(xtrain_scaled, y_train)
    knn_predictions = knn_model.predict(xtest_scaled)
```

```
    accuracy = accuracy_score(y_test, knn_predictions)
    uniform_acc[str(k)] = accuracy

uniform_acc
```

[37]:
```
defaultdict(None,
            {'10': 0.9941582580987786,
             '20': 0.9941582580987786,
             '30': 0.9941582580987786,
             '40': 0.9941582580987786,
             '50': 0.9941582580987786,
             '60': 0.9941582580987786,
             '70': 0.9941582580987786,
             '80': 0.9941582580987786,
             '90': 0.9941582580987786,
             '100': 0.9941582580987786})
```

It appears that all values of k result in identical results. There must be something wrong with the code. I can not figure out where it is wrong.

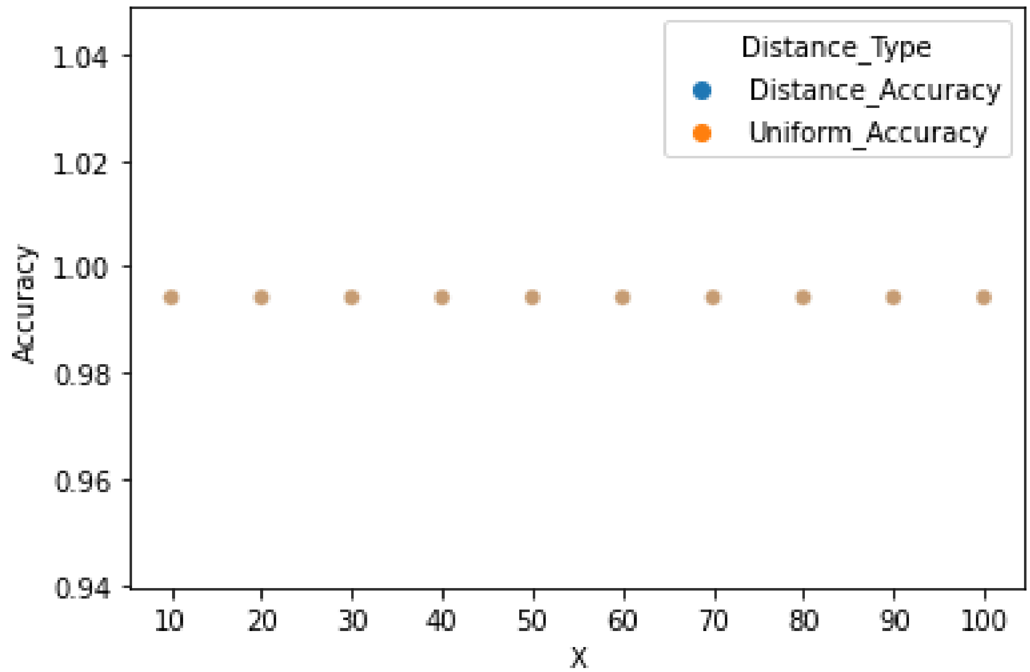
[38]:
```
index1 = distance_acc.keys()
values1 = distance_acc.values()
joint_data = pd.DataFrame(data=values1, index=index1)
joint_data.columns = ['Distance_Accuracy']
```

[39]:
```
joint_data['Uniform_Accuracy'] = uniform_acc.values()
joint_data['X'] = joint_data.index
```

[40]:
```
joint_data = pd.melt(joint_data, id_vars=['X'],
                     value_vars=['Distance_Accuracy', 'Uniform_Accuracy'],
                     var_name='Distance_Type', value_name='Accuracy')
```

[41]:
```
sns.scatterplot(data=joint_data, x='X', y='Accuracy', hue='Distance_Type',
               markers='Distance_Type', alpha=0.5)
```

[41]: <AxesSubplot:xlabel='X', ylabel='Accuracy'>



Please note the distance accuracy does not appear because it lies beneath the Uniform accuracy

2 C

[42]:
```
dt_model = dt()
dt_model.fit(x_train, y_train)
dt_prediction = dt_model.predict(x_test)
accuracy = accuracy_score(y_test, dt_prediction)
dt_cm = cm(y_test, dt_prediction)
report = classification_report(y_test, dt_prediction)
```

[43]:
```
print('Accuracy: ',accuracy)
print('confusion matrix:')
print(dt_cm)
print(report)
```

```
Accuracy:  1.0
confusion matrix:
[[1662    0]
 [   0  221]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1662
           1       1.00      1.00      1.00       221
```

```
    accuracy                           1.00      1883
   macro avg       1.00      1.00      1.00      1883
weighted avg       1.00      1.00      1.00      1883
```

Being that we have a perfect fit on test data, we can see that we have overfit the data. Thus, there is no trade-off at this point.

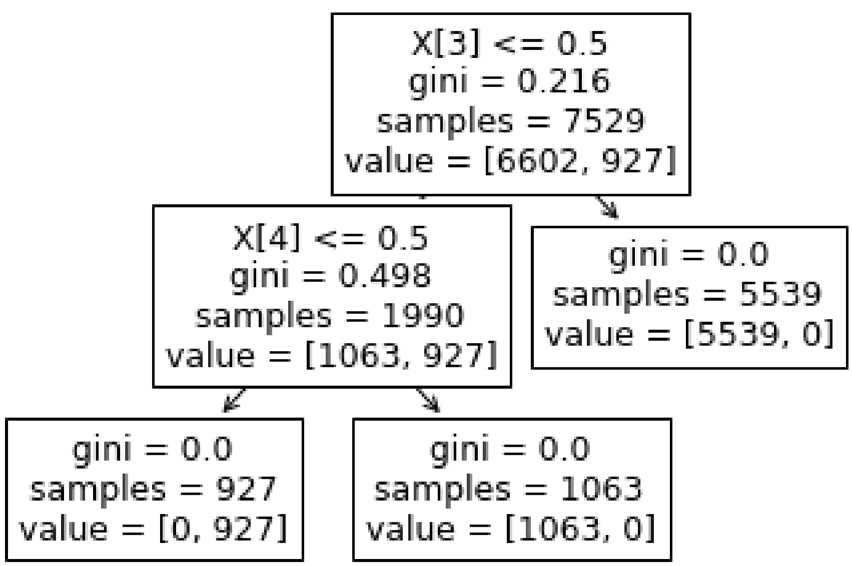
[44]:
```
dt_model = dt(criterion='gini', min_samples_split=10, max_depth=4)
dt_model.fit(x_train, y_train)
dt_prediction = dt_model.predict(x_test)
train_prediction = dt_model.predict(x_train)
train_accuracy = accuracy_score(y_train, train_prediction)
test_accuracy = accuracy_score(y_test, dt_prediction)
dt_cm = cm(y_test, dt_prediction)
report = classification_report(y_test, dt_prediction)
```

[45]:
```
print(f'Train Accuracy: {train_accuracy} | Test Accuracy: {test_accuracy}')
```

```
Train Accuracy: 1.0 | Test Accuracy: 1.0
```

[46]:
```
plot_tree(dt_model)
```

[46]:
```
[Text(0.6, 0.8333333333333334, 'X[3] <= 0.5\ngini = 0.216\nsamples = 7529\nvalue
= [6602, 927]'),
 Text(0.4, 0.5, 'X[4] <= 0.5\ngini = 0.498\nsamples = 1990\nvalue = [1063,
927]'),
 Text(0.2, 0.16666666666666666, 'gini = 0.0\nsamples = 927\nvalue = [0, 927]'),
 Text(0.6, 0.16666666666666666, 'gini = 0.0\nsamples = 1063\nvalue = [1063,
0]'),
 Text(0.8, 0.5, 'gini = 0.0\nsamples = 5539\nvalue = [5539, 0]')]
```



3 D

[47]:
```
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import cross_val_score
```

[48]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as lda
```

3.0.1 Naive Bayes

[49]:
```
nb_model = GaussianNB()
nb_model.fit(x_train, y_train)
scores = cross_val_score(nb_model, x_train, y_train, cv=10)
```

[50]:
```
print('scores: ', scores)
print('avg: ', scores.mean())
```

```
scores:  [0.99867198 0.99335989 0.99601594 0.99734396 0.99734396 0.99468792
 1.         0.99734396 0.99601594 0.99734043]
avg:  0.9968123958068436
```

[51]:
```
test_prediction = nb_model.predict(x_test)
test_accuracy = accuracy_score(y_test, test_prediction)
test_accuracy
```

[51]: 0.9946893255443441

3.0.2 LDA

[52]:
```
lda_model = lda()
lda_model.fit(x_train, y_train)
lda_scores = cross_val_score(lda_model, x_train, y_train, cv=10)
```

[53]:
```
print('scores: ', lda_scores)
print('avg: ', lda_scores.mean())
```

```
scores:  [0.81673307 0.83798141 0.80743692 0.83266932 0.82602922 0.84196547
 0.82735724 0.83532537 0.81407703 0.82579787]
avg:  0.8265372905540957
```

[54]:
```
test_prediction = lda_model.predict(x_test)
test_accuracy = accuracy_score(y_test, test_prediction)
test_accuracy
```

[54]: 0.8422729686670207

LDA performed the worst out of all the models. It is interesting to see that LDA cross validate performed better than the model on the test data.

[ ]:
```

```