HW 4

This assignment covers Linear Classification methods

DO NOT ERASE MARKDOWN CELLS AND INSTRUCTIONS IN YOUR HW submission

- **Q** - QUESTION
- **A** - Where to input your answer

Instructions

Keep the following in mind for all notebooks you develop:

- Structure your notebook.
- Use headings with meaningful levels in Markdown cells, and explain the questions each piece of code is to answer or the reason it is there.
- Make sure your notebook can always be rerun from top to bottom.
- Please start working on this assignment as soon as possible. If you are a beginner in Python this might take a long time. One of the objectives of this assignment is to help you learn python and scikit-learn package.
- See README.md for homework submission instructions

Related Tutorials

Refreshers

- Intro to Machine Learning w scikit-learn
- A tutorial on statistical-learning for scientific data processing

Classification Approaches

- Logistic Regression with Sklearn
- KNN with sklearn

Modeling

- Cross-validation
- Plot Confursion Matrix with Sklearn
- Confusion Matrix Display

Data Processing

Q1 Get training data from the dataframe

1. Load mobile_data.csv from ```data'' folder into the dataframe
2. Assign values of `price_range` column to `y`
3. Drop 'price_range' column from data frame,
4. Assign remaining df column values to x
5. Print the head of the dataframe

A1 Replace ??? with code in the code cell below

In [ ]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from matplotlib import pyplot as plt
from sklearn.preprocessing import StandardScaler

#Read the mobile_data.csv file using the appropriate separator as input to read_csv
df = pd.read_csv('../data/mobile_data.csv', sep=',')

df.head()
```

Out[ ]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	n_cor
0	842	0	2.2	0	1	0	7	0.6	188	
1	1021	1	0.5	1	0	1	53	0.7	136	
2	563	1	0.5	1	2	1	41	0.9	145	
3	615	1	2.5	0	0	0	10	0.8	131	
4	1821	1	1.2	0	13	1	44	0.6	141	

5 rows × 21 columns

In [ ]:
```
# Code to assign values of "price_range" column to y variable
y = df.price_range.values
```

In [ ]:
```
# Drop "price_range" column from dataframe
df.drop(columns=['price_range'], inplace=True)

# Assign remaining columns to x variable
x = df.values
```

In [ ]:
```
# Show head of dataframe with "price_range" column dropped
df.head()
```

Out[ ]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep	mobile_wt	n_cor
0	842	0	2.2	0	1	0	7	0.6	188	
1	1021	1	0.5	1	0	1	53	0.7	136	
2	563	1	0.5	1	2	1	41	0.9	145	
3	615	1	2.5	0	0	0	10	0.8	131	
4	1821	1	1.2	0	13	1	44	0.6	141	

Q2:

1. Check number of null values per column in the x dataframe.

A2 Replace ??? with code in the code cell below

In [ ]:

```
# The provided code was to manipulate the x variable but I found using the "df" dat

# Check for nan values in "df" dataframe
df.isna().sum()
```

Out[ ]:

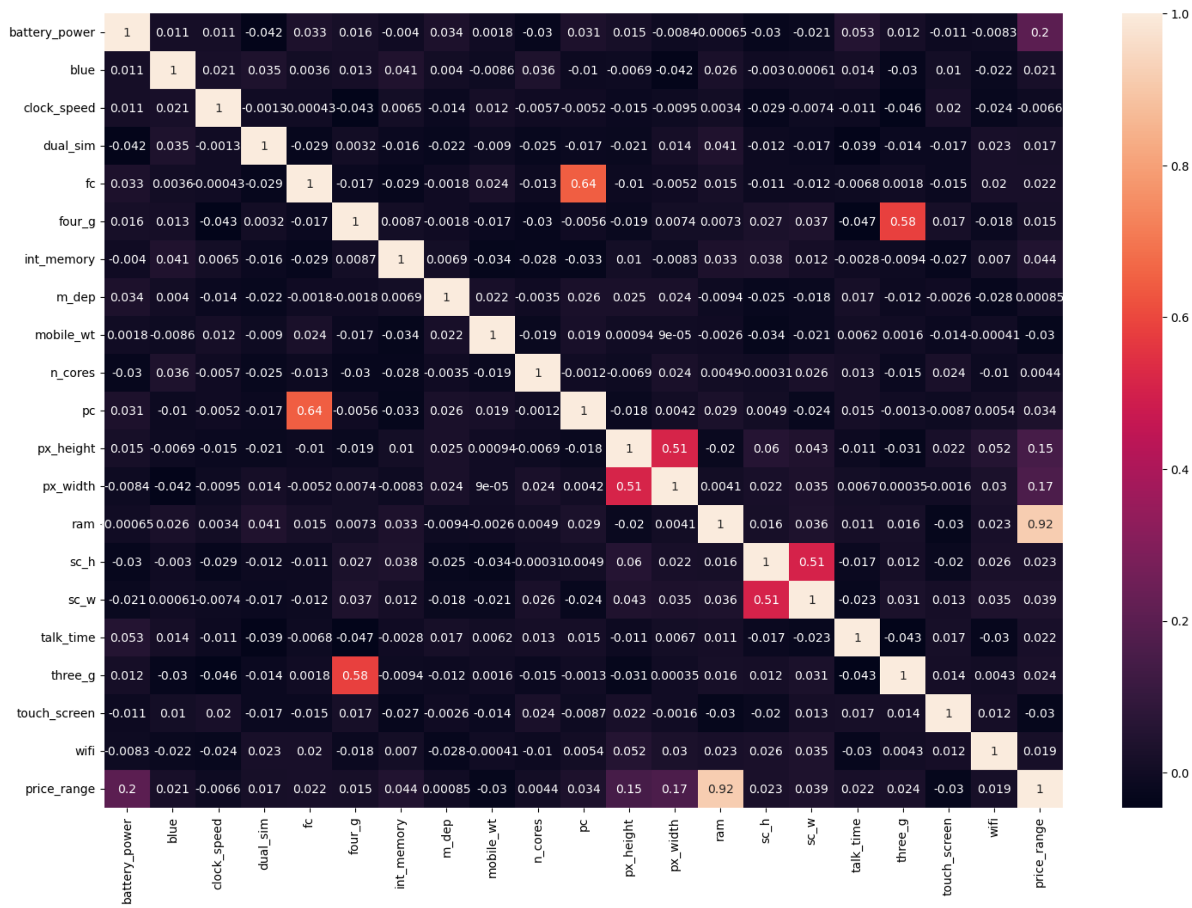
```
battery_power    0
blue             0
clock_speed      0
dual_sim         0
fc               0
four_g           0
int_memory       0
m_dep            0
mobile_wt        0
n_cores          0
pc               0
px_height        0
px_width         0
ram              0
sc_h             0
sc_w             0
talk_time        0
three_g          0
touch_screen     0
wifi             0
dtype: int64
```

Q3.1 Use seaborn heatmap chart to visualize the correlations between the columns. Replace ??? with code in the code cell below

A3.1

In [ ]:
```python
import seaborn as sns

# Create new dataframe still containing price_range column for determining correlat
df2 = pd.read_csv('../data/mobile_data.csv', sep=',')

# Create correlation matrix to fix heatmap to
corr_matrix = df2.corr()

# Specify size of heatmap generated
plt.figure(figsize=(18,12))

# generate heatmap
sns.heatmap(corr_matrix, annot=True)
```

Out[ ]: <Axes: >



Q3.2 List columns that correlate the most with the 'price_range' column.

Note: For this dataset any column that has correlation factor over or near 0.1 can be considered as a good predictor/ feature.

A3.2 The columns that most correlate with the "price_range" column are (from greatest to least correlated) ram (0.92), battery_power (0.2), px_width (0.17), and px_height (0.15). All other columns have a correlation to the "price_range" column that is less than |0.1| <- absolute value

Q3.3 Update the 'x' dataframe defined earlier in Q1 with your selected features/columns for 'price_range'.

A3.3 Replace ??? with code in the code cell below

In [ ]:
```
# A3 Part 3:

# Limit dataframe to 4 most correlated columns
df = df[['battery_power', 'px_height', 'px_width', 'ram']]

# verify dataframe contains only focus columns
print(df.head())

# reassign focus column values to x variable
x = df.values
```

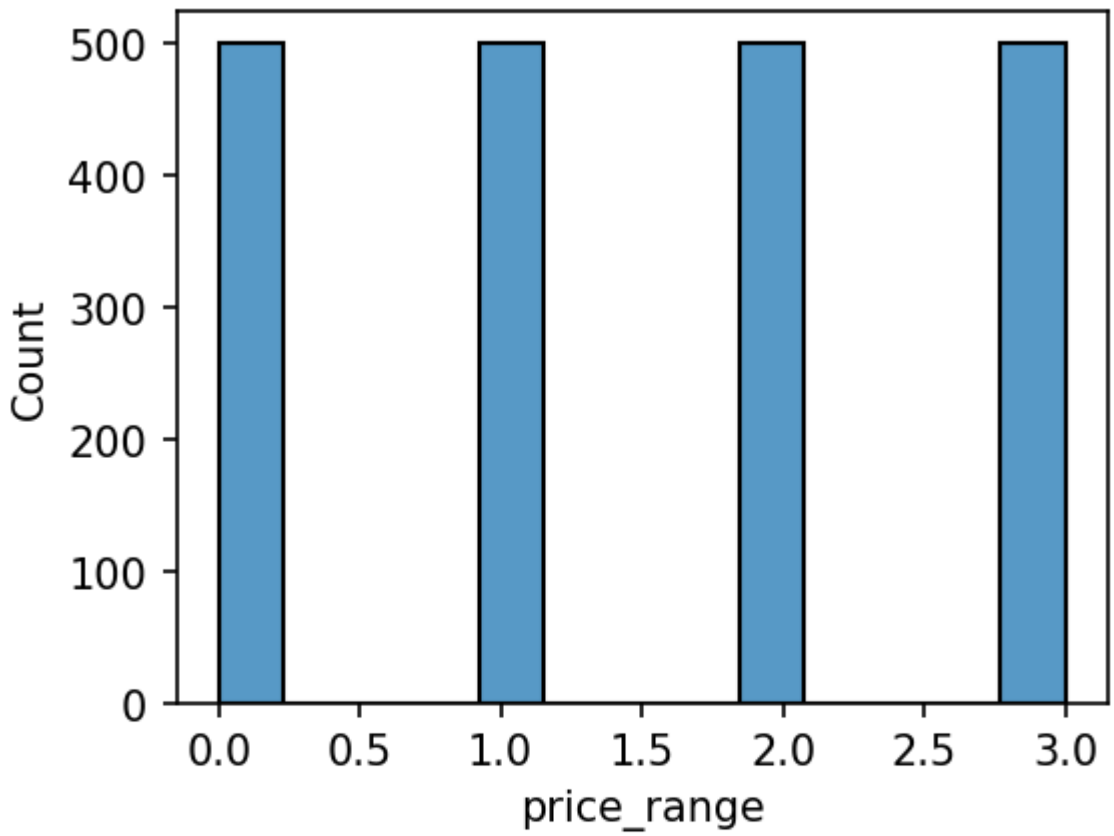
```
   battery_power  px_height  px_width   ram
0            842         20       756  2549
1           1021        905      1988  2631
2            563       1263      1716  2603
3            615       1216      1786  2769
4           1821       1208      1212  1411
```

Q4: Use seaborn *histplot* to plot a distribution graph for the price_range column

A4 Replace ??? with code in the code cell below

In [ ]:
```
plt.figure(figsize=(4,3),dpi=150)
sns.histplot(data=df2['price_range'])
```

Out[ ]:
```
<Axes: xlabel='price_range', ylabel='Count'>
```

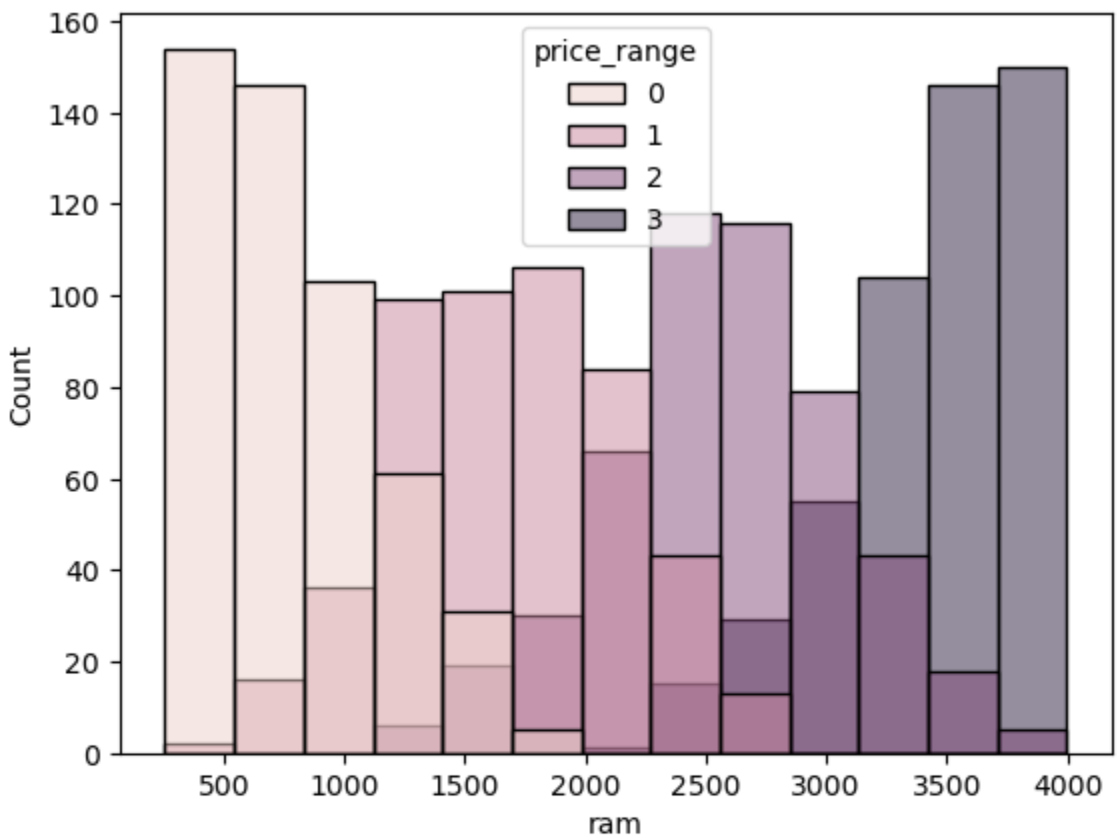


Q5: Use seaborn *histplot* to present the relation between _price*range* and the *ram* of a mobile

A5 Replace ??? with code in the cell below

In [ ]:
```
# I set the x-axis to measure "ram" and set the hue to "price_range",
# and you can see from the resulting histplot does show that (generally
# speaking), as the ram of the mobile increases, so too does the price_range
sns.histplot(data=df2, x="ram", hue="price_range")
```

Out[ ]:
```
<Axes: xlabel='ram', ylabel='Count'>
```



Q6:

1. Use StandardScaler from sklearn to transform the x dataframe.
2. Split dataset into train and test data use train_test_split with test_size = 0.2 and random_state = 42
3. Check the number of instance in the train and test set.
4. Check the number of instance per class in train and test set using ytrain and ytest

A6 Replace ??? with code in the code cell below

In [ ]:
```
# create StandardScaler instance
scaler = StandardScaler()

# fit scaler to x data
scaler.fit(x)

# transform x data and store in same variable
x = scaler.transform(x)
```

In [ ]:
```
xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.2, random_state=4
```

In [ ]:
```
print(len(xtrain), len(ytrain))
print(len(xtest), len(ytest))
```

```
1600 1600
400 400
```

In [ ]:
```
ytrain.shape
```

Out[ ]: (1600,)

In [ ]:
```
ytest.shape
```

Out[ ]: (400,)

Classification Model 1: Logistic Regression

Here, we fit Logistic Regression model to the train dataset using K-fold cross validation

Q7 Train Logistic Regression Model

1. Create a logistic regression model using sklearn linear_model library.
2. Fit the model with the train data
3. Get the score from the model using test data
4. Plot confusion matrix using ConfusionMatrixDisplay, see Visualization with Display Objects example.

A7 Replace ??? with code in the code cell below

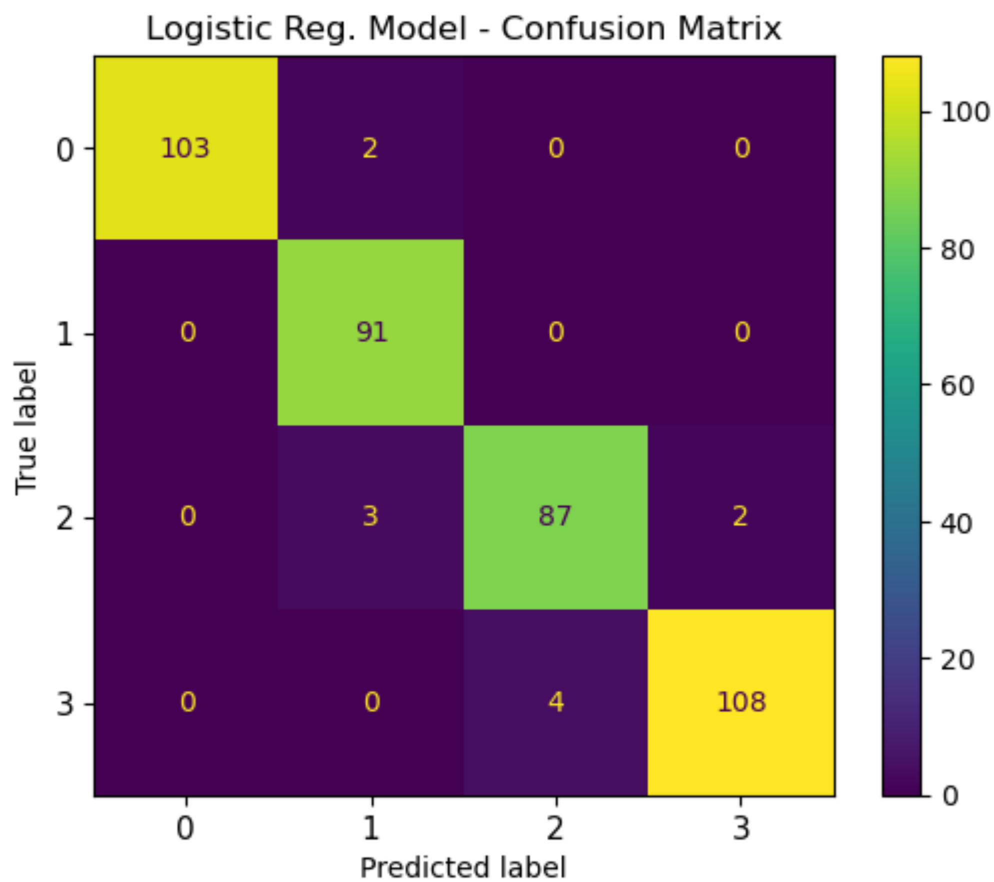
In [ ]:
```
from sklearn.metrics import ConfusionMatrixDisplay
import matplotlib.pyplot as plt

# Create a logistic regression model using sklearn library
clf = LogisticRegression()

# Fit model with training data
clf.fit(xtrain, ytrain)
```

Out[ ]:
```
▾ LogisticRegression

LogisticRegression()
```

In [ ]:
```
#print score for test data
clf.score(xtest, ytest)
```

Out[ ]: 0.9725

In [ ]:
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay

# create a prediction to compare to true labels
y_pred = clf.predict(xtest)

# create confusion matrix comparing predictions to true labels
cm = confusion_matrix(ytest, y_pred, labels=clf.classes_)

# fit confusion matrix to a visual graph
matrix = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=clf.classes_)
matrix.plot()

# tweak display graph appearance
plt.title("Logistic Reg. Model - Confusion Matrix")
plt.xticks([0,1,2,3], [0,1,2,3], fontsize=11)
plt.yticks([0,1,2,3], [0,1,2,3], fontsize=11)
plt.show()
```



Q8: Train Logistic Regression Model using cross-validation on *xtrain, ytrain* data.

- Apply K fold cross validation technique for the model training (cross_val_score), and set K to 5 or 10.
- Print the different scores from different folds

A8: Replace ??? with code in the code cell below

In [ ]:
```
from sklearn.model_selection import cross_val_score

# Use sklearn for 5 fold cross validation

# create LR model and fit it to training data
scores_log = LogisticRegression()
scores_log.fit(xtrain, ytrain)

# print the scores from different folds
print('Score with 5 folds: ', cross_val_score(scores_log, xtrain, ytrain, cv=5))
print('Score with 10 folds: ', cross_val_score(scores_log, xtrain, ytrain, cv=10))
```

```
Score with 5 folds:  [0.95625  0.953125 0.959375 0.95625  0.953125]
Score with 10 folds:  [0.93125 0.96875 0.96875 0.95    0.95    0.98125 0.975   0.93
125 0.9375
 0.95625]
```

Classification Model 2: K Nearest Neighbor Classifier

Here, we learn how to fit KNN on the train dataset using k-fold cross validation, and evaluate its classification accuracy on the train dataset using confusion matrix.

Q9 Build a KNN Classification Model for the dataset as following:

1. Create a KNN model using sklearn library, and initialize n_neighbors as described in documentation.
2. Fit the model with the train data
3. Predict the values from test data
4. Print out the score from training and test data
5. Repeat Step 1.- 4. for a range of `n_neighbors` values (k in kNN) from 1 to 30.

A9 Replace ??? with code in the code cell below

In [ ]:
```
from sklearn.neighbors import KNeighborsClassifier


# Define KNN model
for k in range(1,31):

    knn = KNeighborsClassifier(n_neighbors=k)

    #Fit KNN model on xtrain, ytrain from above
    knn.fit(xtrain, ytrain)
    #predict y values from xtest
    y_pred = knn.predict(xtest)

    #print score for test data
    print("K: ",k,"Train Score: ",knn.score(xtrain, ytrain), "Test Score: ",knn.sco
```

```
K:  1 Train Score:  1.0 Test Score:  0.8875
K:  2 Train Score:  0.933125 Test Score:  0.8675
K:  3 Train Score:  0.955 Test Score:  0.915
K:  4 Train Score:  0.92625 Test Score:  0.895
K:  5 Train Score:  0.930625 Test Score:  0.915
K:  6 Train Score:  0.92 Test Score:  0.91
K:  7 Train Score:  0.924375 Test Score:  0.91
K:  8 Train Score:  0.91875 Test Score:  0.9175
K:  9 Train Score:  0.92625 Test Score:  0.9225
K:  10 Train Score:  0.91875 Test Score:  0.9175
K:  11 Train Score:  0.9225 Test Score:  0.925
K:  12 Train Score:  0.92 Test Score:  0.9225
K:  13 Train Score:  0.924375 Test Score:  0.93
K:  14 Train Score:  0.92 Test Score:  0.91
K:  15 Train Score:  0.923125 Test Score:  0.915
K:  16 Train Score:  0.921875 Test Score:  0.915
K:  17 Train Score:  0.9225 Test Score:  0.915
K:  18 Train Score:  0.92 Test Score:  0.9025
K:  19 Train Score:  0.919375 Test Score:  0.9125
K:  20 Train Score:  0.9175 Test Score:  0.905
K:  21 Train Score:  0.91875 Test Score:  0.9
K:  22 Train Score:  0.92 Test Score:  0.9075
K:  23 Train Score:  0.916875 Test Score:  0.915
K:  24 Train Score:  0.92 Test Score:  0.9
K:  25 Train Score:  0.920625 Test Score:  0.9125
K:  26 Train Score:  0.92375 Test Score:  0.9125
K:  27 Train Score:  0.921875 Test Score:  0.915
K:  28 Train Score:  0.920625 Test Score:  0.9125
K:  29 Train Score:  0.91875 Test Score:  0.92
K:  30 Train Score:  0.913125 Test Score:  0.91
```

Q9 Part 2:

What is the best `n_neighbors` ? Why?

A9 The "n_neighbors" with the best test score was 13 neighbors (0.93)

Q10.

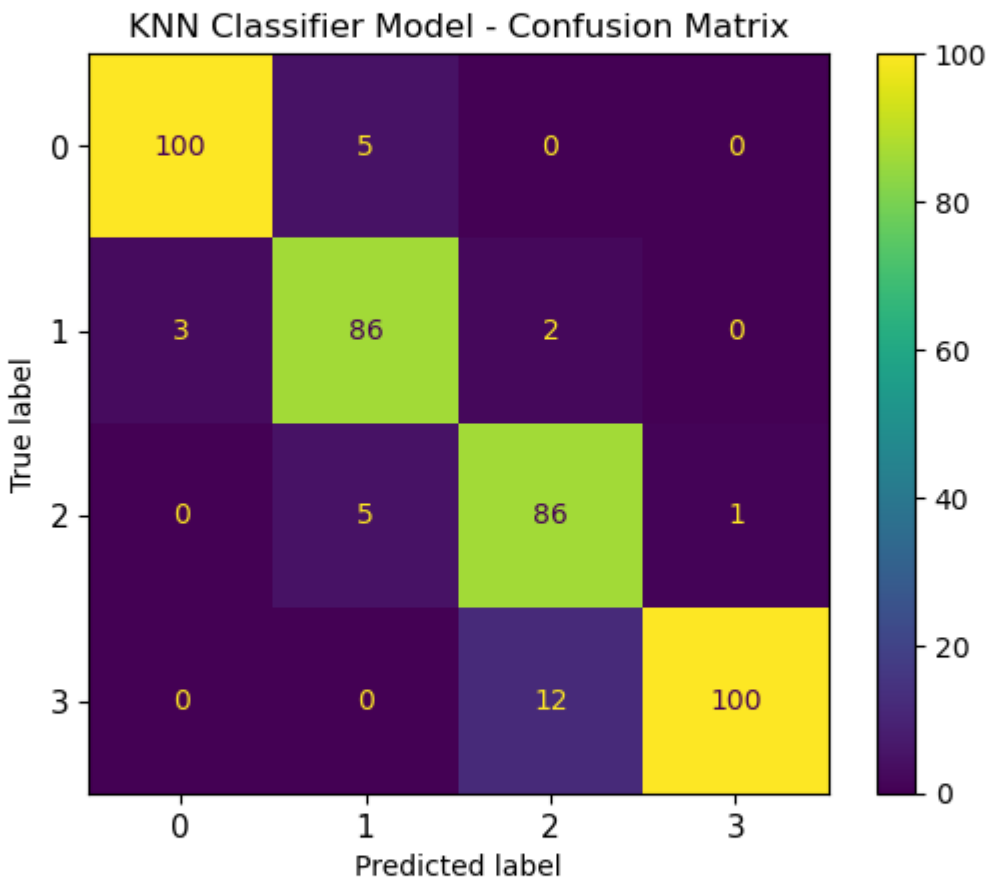
1. Create a KNN Classifier model using the best value of k found from previous question.
2. Train the model using xtrain, ytrain values.
3. Plot confusion matrix for the xtest and ytest, using ConfusionMatrixDisplay, see Visualization with Display Objects example.

A10 Replace ??? with code in the code cell below

In [ ]:
```
knn_best = KNeighborsClassifier(n_neighbors=13)

knn_best.fit(xtrain, ytrain)
```

Out[ ]:
```
▾        KNeighborsClassifier
KNeighborsClassifier(n_neighbors=13)
```

In [ ]:
```
y_pred = knn_best.predict(xtest)

cm = confusion_matrix(ytest, y_pred, labels=knn_best.classes_)

#plt.figure()
matrix = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=knn_best.classe
matrix.plot()
plt.title("KNN Classifier Model - Confusion Matrix")
plt.xticks([0,1,2,3], [0,1,2,3], fontsize=11)
plt.yticks([0,1,2,3], [0,1,2,3], fontsize=11)
plt.show()
```



Q11 Train KNN classifier using cross-validation approach, sklearn.cross_validation tutorial.

Note:

Try a range of `n_neighbors` values (k in kNN) from 1 to 30.

A11 Replace ??? with code in the code cell below **

In [ ]:
```python
# Define KNN model
from sklearn.model_selection import cross_val_score

for k in range(1, 31):
    #Define KNN model
    knn_crossval = KNeighborsClassifier(n_neighbors=k)
    knn_crossval.fit(xtrain, ytrain)

    # Use sklearn for 5 fold cross validation
    scores_cv= cross_val_score(knn_crossval, xtrain, ytrain, cv=5)

    # print the scores from different folds
    print('Score with ', k, ' folds: ', scores_cv)
```

```
Score with  1  folds:  [0.834375 0.8375   0.865625 0.859375 0.865625]
Score with  2  folds:  [0.85     0.85     0.84375 0.84375 0.85    ]
Score with  3  folds:  [0.88125  0.878125 0.85     0.846875 0.85625 ]
Score with  4  folds:  [0.875    0.865625 0.846875 0.853125 0.85    ]
Score with  5  folds:  [0.8625   0.890625 0.8625   0.86875  0.85625 ]
Score with  6  folds:  [0.86875  0.890625 0.865625 0.878125 0.85    ]
Score with  7  folds:  [0.88125  0.8875   0.865625 0.865625 0.865625]
Score with  8  folds:  [0.8875   0.871875 0.88125  0.865625 0.859375]
Score with  9  folds:  [0.875    0.88125  0.890625 0.8625   0.878125]
Score with  10  folds:  [0.86875  0.890625 0.896875 0.871875 0.86875 ]
Score with  11  folds:  [0.859375 0.909375 0.903125 0.884375 0.86875 ]
Score with  12  folds:  [0.8625   0.8875   0.9125   0.878125 0.86875 ]
Score with  13  folds:  [0.875    0.890625 0.915625 0.875    0.88125 ]
Score with  14  folds:  [0.859375 0.903125 0.915625 0.8625   0.86875 ]
Score with  15  folds:  [0.875    0.903125 0.921875 0.871875 0.86875 ]
Score with  16  folds:  [0.875    0.9      0.909375 0.8625   0.871875]
Score with  17  folds:  [0.8875   0.915625 0.909375 0.878125 0.871875]
Score with  18  folds:  [0.8875   0.909375 0.896875 0.871875 0.88125 ]
Score with  19  folds:  [0.8875   0.915625 0.890625 0.875    0.884375]
Score with  20  folds:  [0.890625 0.90625  0.890625 0.875    0.86875 ]
Score with  21  folds:  [0.884375 0.925    0.89375  0.88125  0.8875  ]
Score with  22  folds:  [0.89375  0.915625 0.8875   0.878125 0.865625]
Score with  23  folds:  [0.88125  0.91875  0.890625 0.9      0.865625]
Score with  24  folds:  [0.896875 0.90625  0.884375 0.890625 0.8625  ]
Score with  25  folds:  [0.8875   0.915625 0.89375  0.90625  0.8625  ]
Score with  26  folds:  [0.884375 0.903125 0.884375 0.89375  0.875   ]
Score with  27  folds:  [0.890625 0.91875  0.90625  0.9      0.878125]
Score with  28  folds:  [0.884375 0.909375 0.890625 0.8875   0.88125 ]
Score with  29  folds:  [0.884375 0.909375 0.9      0.890625 0.890625]
Score with  30  folds:  [0.890625 0.90625  0.884375 0.884375 0.88125 ]
```

Comparison

Q12 Compare the two models (trained using xtrain,ytrain) in terms of score.

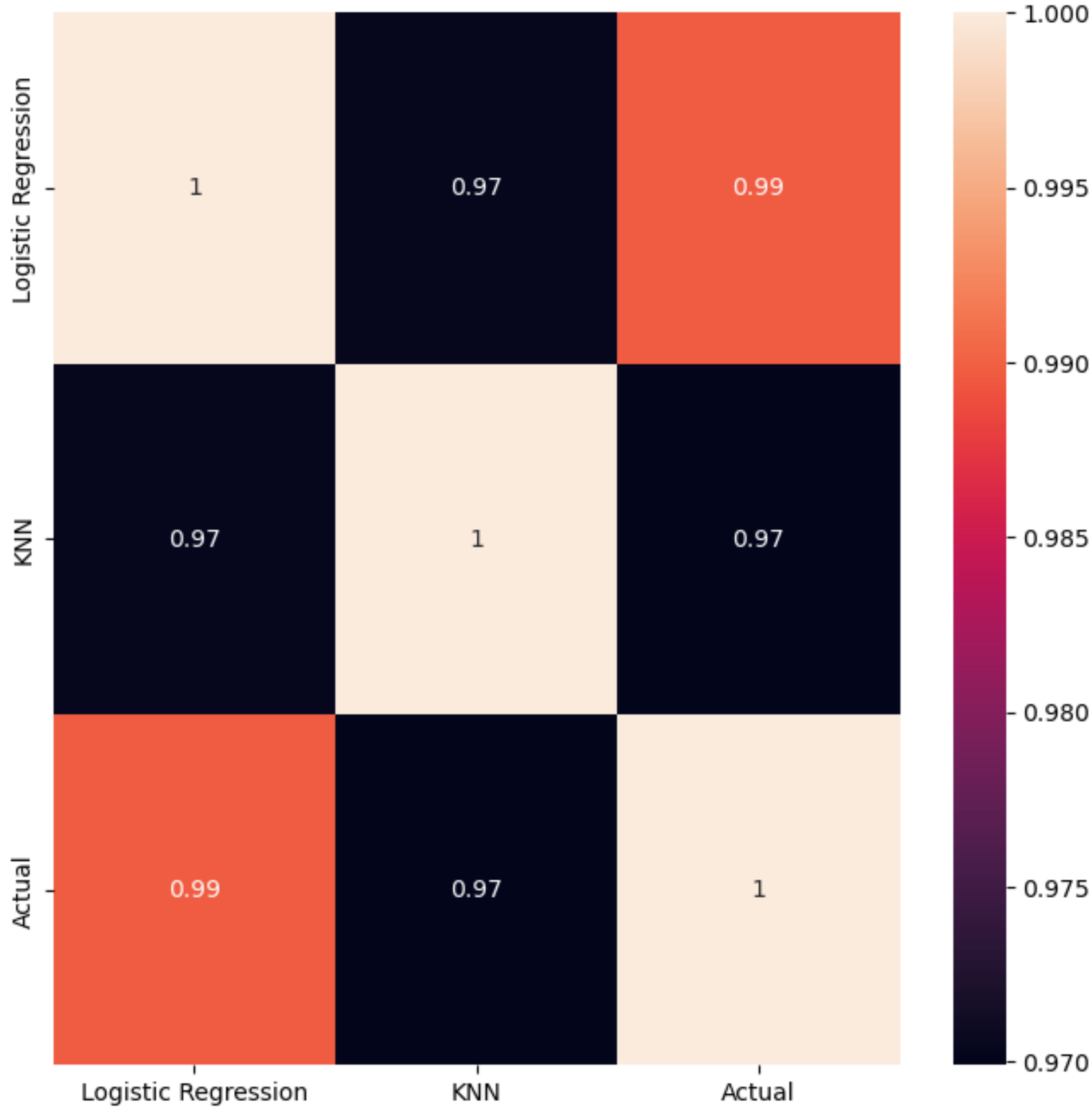
- Train two different models on Train data
- Predict xtest using the trained models
- Make a correlation matrix between ytest and predicted ytest values from the two Models
- Your resulting matrix should be `3x3 correlation matrix` for xtest, ytest data
  - The matrix is symmetric
  - It will provide the correlation between two models predictions plus ytest
  - Hint: You can create a new dataframe using these values and use corr() function for creating the corelation matrix. Use meaningful column name while creating the dataframe.

A12 Replace ??? with code in the code cell below

In [ ]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Predict Train dataset using logistic reg
clf= LogisticRegression()
clf.fit(xtrain, ytrain)
ypred_clf = clf.predict(xtest)

# Predict Train dataset using KNN
knn = KNeighborsClassifier(n_neighbors=29)
knn.fit(xtrain, ytrain)
ypred_knn = knn.predict(xtest)

print(ytest.shape, ypred_clf.shape, ypred_knn.shape)
# Create a dataframe using the predicted results from the models
df = pd.DataFrame({'Logistic Regression':ypred_clf, 'KNN':ypred_knn, 'Actual':ytest

# compute correlation
corr_matrix = df.corr()

# Now use seaborn library to plot the heatmap correlation matrix
plt.figure(figsize=(8,8))
sns.heatmap(corr_matrix, annot=True)
```

```
(400,) (400,) (400,)
```

Out[ ]:
```
<Axes: >
```


Logistic Regression
KNN
Actual
1
0.97
0.99
0.97
1
0.97
0.99
0.97
1
Logistic Regression
KNN
Actual
1.000
0.995
0.990
0.985
0.980
0.975
0.970