COMP4220: Machine Learning, Spring 2022, Assignment 4

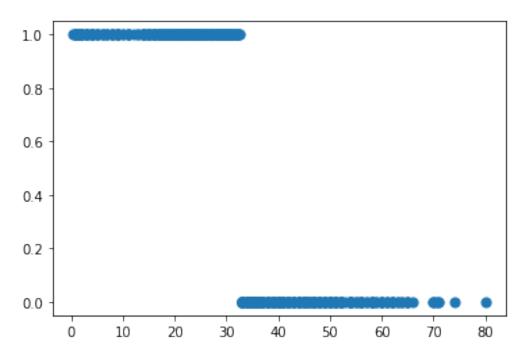
Please submit one pdf file for all questions.

```
1. KMeans:
#importing the libraries --add any additional libraries you will need
import numpy as np
import pandas as pd
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
X train = pd.read csv("titanic.csv")
# removing the columns not of interest
X train = X train.drop(['PassengerId','Name','Ticket',
'Cabin', 'Embarked', 'Pclass', 'SibSp', 'Sex', 'Parch', 'Fare'], axis=1)
# removing rows of data with NaN
X train = X train[X train['Age'].notna()]
X train.isnull().values.any()
X train.fillna(0, inplace=True)
a) Define X and y from the training data. Answer provided. Print X and y to see
data.
X = X train.drop(['Survived'], 1).astype(float)
y = X train['Survived']
print(X.shape)
(714, 1)
print(y.shape)
(714,)
b) Perform KMeans on X
kmeans = KMeans(n clusters=k, random state=42)
y kmeans = kmeans.fit predict(X)
centroids = kmeans.cluster centers
print(centroids)
[[44.60150376]
 [20.85082589]]
```

c) Plot the prediction for X

```
centers = kmeans.cluster_centers_
plt.scatter(X, y_kmeans, s=50, cmap='viridis')
```

<matplotlib.collections.PathCollection at 0x7f157c1e7e50>



d) Compute the accuracy

```
correct = 0
```

```
prediction = kmeans.predict(X)
```

pred_df = pd.DataFrame({'actual': y, 'prediction': prediction})
print(pred_df)

	actual	prediction
0	0	1
1	1	0
2 3	1	1
3	1	0
4	0	Θ
885	Θ	0
886	Θ	1
887	1	1
889	1	1
890	0	1

[714 rows x 2 columns]

2. Classification using SVM

This is data collected from brain waves collection during a pain detection research project.

```
import numpy as np
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.svm import LinearSVC
painData = pd.read csv("pain.csv")
painData = painData.drop(['SubjectID','Index','Date', 'Time'], axis=1)
painData
            PainType
                           TP9
                                       AF7
                                                  AF8
                                                             TP10
Right Axis
         severe pain 68.847656 -73.242188
                                            18.066406
                                                       27.832031
25.390625
         severe pain 44.921875 -235.351562
                                            36.621094
                                                       27.832031
4.394531
         severe pain -11.230469 -81.054688 45.410156
                                                       29.296875
12.207031
3
         severe pain -2.929688
                                 17.089844
                                            33.203125
                                                       24.902344
44.433594
                     10.253906 -58.105469
                                            32.226562
                                                       14.648438
         severe pain
0.976562
. . .
                                                              . . .
19148 moderate pain
                      0.000000 -358.886719 35.644531
                                                        6.347656
19.042969
19149 moderate pain 17.089844 -14.648438
                                            39.550781
                                                       40.039062
38.085938
19150 moderate pain 14.648438 -72.265625 27.343750
                                                       38.085938
71.777344
19151
      moderate pain -0.488281 -693.847656 20.507812
                                                       22.949219
56.152344
19152 moderate pain -0.976562 -813.964844 27.343750
                                                       26.855469
2.900000
       label
```

3.0 3.0 3.0 3.0
3.0
2.0 2.0 2.0

```
19151
         2.0
19152
         NaN
[19153 rows x 7 columns]
The label column is the target, and pain type is an explanation.
a) Get X and y from painData above. X is TP9 and Right Axis. Y is label.
painData = painData.dropna(how='any',axis=0)
X = painData[['TP9', 'Right Axis']]
#y = painData[painData['label'].notna()]
y = painData[['label']]
print(X.shape, y.shape)
(19152, 2) (19152, 1)
painData['y'].isnull().values.any()
a) Using a regularization parameter of c=1 and c=100, using a LinearSVC.
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
scaler = StandardScaler()
svm clf1 = LinearSVC(C=1, loss="hinge", random state=42)
svm clf2 = LinearSVC(C=100, loss="hinge", random state=42)
b) Scale the dataset using a pipeline
scaled svm clf1 = Pipeline([
                   ("scaler", scaler),
                   ("linear svc", svm_clf1),
])
scaled svm clf2 = Pipeline([
                   ("scaler", scaler),
                   ("linear svc", svm clf2),
1)
c) Plot dataset using the regularization parameter of c=1 and c=100
scaled svm clf1.fit(X, y)
scaled svm clf2.fit(X, y)
Pipeline(steps=[('scaler', StandardScaler()),
                 ('linear svc',
                  LinearSVC(C=100, loss='hinge', random state=42))])
```

3. Decision Trees:

Using the same dataset above, meaning X and y

```
a) Print the shape of X and y
print(X.shape, y.shape)
(19152, 2) (19152, 1)
b) Train using a decision tree classifier
from sklearn.tree import DecisionTreeClassifier
tree clf = DecisionTreeClassifier(max depth=2, random state=42)
tree clf.fit(X,y)
DecisionTreeClassifier(max depth=2, random state=42)
c) Visualize the dataset
import os
PROJECT ROOT DIR = "."
CHAPTER ID = "decision trees"
IMAGES PATH = os.path.join(PROJECT ROOT DIR, "images", CHAPTER ID)
os.makedirs(IMAGES PATH, exist ok=True)
os.makedirs(IMAGES PATH, exist ok=True)
from graphviz import Source
from sklearn.tree import export graphviz
export graphviz(
    tree clf,
    out file=os.path.join(IMAGES PATH, "painData.dot"),
    feature names=None,
    class names=None,
    rounded=True,
    filled=True
)
d) Plot the decision boundaries of the dataset
#skipped
4. Ensemble Classifier and Random forest
Run on pain.csv
a) Run a voting classifier that includes logistic regression, random forest
classifier and SVM
from sklearn.model selection import train test split
X_train, X_test, y_train, y_test = train_test_split(X, y,
random state=42)
```

from sklearn.ensemble import RandomForestClassifier

from sklearn.ensemble import VotingClassifier

```
from sklearn.linear model import LogisticRegression
from sklearn.svm import SVC
log clf = LogisticRegression(solver="lbfgs", random state=42)
rnd clf = RandomForestClassifier(n estimators=100, random state=42)
svm clf = SVC(gamma="scale", random state=42)
voting clf = VotingClassifier(
    estimators=[('lr', log_clf), ('rf', rnd_clf), ('svc', svm clf)],
    voting='hard')
b) Print the accuracy scores
from sklearn.metrics import accuracy_score
import warnings
warnings.filterwarnings('ignore')
for clf in (log clf, rnd clf, svm clf, voting clf):
  clf.fit(X train,y train)
  y_pred = clf.predict(X_test)
  print(clf.__class__.__name__, accuracy_score(y_test, y pred))
LogisticRegression 0.39807852965747703
RandomForestClassifier 0.6038011695906432
SVC 0.6203007518796992
VotingClassifier 0.5925229741019215
```