## **ASSIGNMENT – 3**

## 1. (<u>Titanic Dataset</u>)

Fare

0.216225 1.000000

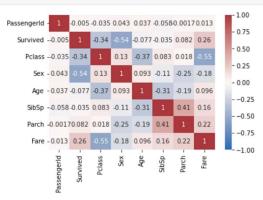
- 1. Find the correlation between 'survived' (target column) and 'sex' column for the Titanic use case in class.
  - a. Do you think we should keep this feature?
- 2. Do at least two visualizations to describe or show correlations.
- 3. Implement Naïve Bayes method using scikit-learn library and report the accuracy.

```
import pandas as pd
import seaborn as sns
from sklearn import preprocessing
import matplotlib.pyplot as plt
df=pd.read_csv("train.csv")
df.head()
   Passengerld Survived Pclass
                                                              Name
                                                                      Sex Age SibSp Parch
                                                                                                      Ticket
                                                                                                               Fare Cabin Embarked
 0
                                                                                                   A/5 21171
                                                                                                             7.2500
                                                                                                                     NaN
                                                                                                                                 S
                    0
                                                 Braund, Mr. Owen Harris
                                                                      male
                                                                          22.0
            2
                            1 Cumings, Mrs. John Bradley (Florence Briggs Th... female 38.0
                                                                                         0
                                                                                                   PC 17599 71.2833
                                                                                                                     C85
                                                                                                                                 C
 2
            3
                                                                                         0 STON/O2. 3101282
                                                                                                                                 S
                                                  Heikkinen, Miss. Laina female 26.0
                                                                                                                     NaN
                                                                                                             7.9250
 3
            4
                                   Futrelle, Mrs. Jacques Heath (Lily May Peel) female 35.0
                                                                                         0
                                                                                                     113803 53.1000
                                                                                                                    C123
                                                                                                                                 S
            5
                                                 Allen, Mr. William Henry male 35.0
                                                                                         0
                                                                                                                                 S
                     0
                                                                                                     373450
                                                                                                             8.0500
                                                                                                                     NaN
le = preprocessing.LabelEncoder()
df['Sex'] = le.fit_transform(df.Sex.values)
df['Survived'].corr(df['Sex'])
-0.543351380657755
matrix = df.corr()
print(matrix)
              PassengerId Survived
                                        Pclass
                                                                        SibSp
                1.000000 -0.005007 -0.035144 0.042939 0.036847 -0.057527
PassengerId
                -0.005007 1.000000 -0.338481 -0.543351 -0.077221 -0.035322
Survived
Pclass
                -0.035144 -0.338481 1.000000 0.131900 -0.369226 0.083081
                0.042939 -0.543351 0.131900 1.000000 0.093254 -0.114631
Sex
                0.036847 -0.077221 -0.369226  0.093254  1.000000 -0.308247
Age
                -0.057527 -0.035322 0.083081 -0.114631 -0.308247 1.000000
SibSp
                -0.001652 0.081629 0.018443 -0.245489 -0.189119 0.414838
Parch
                0.012658 0.257307 -0.549500 -0.182333 0.096067 0.159651
Fare
                 Parch
PassengerId -0.001652 0.012658
Survived
              0.081629 0.257307
Pclass
              0.018443 -0.549500
             -0.245489 -0.182333
Age
             -0.189119 0.096067
SibSp
             0.414838 0.159651
Parch
              1.000000 0.216225
```

#### df.corr().style.background\_gradient(cmap="Greens")

	Passengerld	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
Passengerld	1.000000	-0.005007	-0.035144	0.042939	0.036847	-0.057527	-0.001652	0.012658
Survived	-0.005007	1.000000	-0.338481	-0.543351	-0.077221	-0.035322	0.081629	0.257307
Pclass	-0.035144	-0.338481	1.000000	0.131900	-0.369226	0.083081	0.018443	-0.549500
Sex	0.042939	-0.543351	0.131900	1.000000	0.093254	-0.114631	-0.245489	-0.182333
Age	0.036847	-0.077221	-0.369226	0.093254	1.000000	-0.308247	-0.189119	0.096067
SibSp	-0.057527	-0.035322	0.083081	-0.114631	-0.308247	1.000000	0.414838	0.159651
Parch	-0.001652	0.081629	0.018443	-0.245489	-0.189119	0.414838	1.000000	0.216225
Fare	0.012658	0.257307	-0.549500	-0.182333	0.096067	0.159651	0.216225	1.000000

```
sns.heatmap(matrix, annot=True, vmax=1, vmin=-1, center=0, cmap='vlag')
plt.show()
```



```
#NAive bais

train_raw = pd.read_csv('train.csv')

test_raw = pd.read_csv('test.csv')

# Join data to analyse and process the set as one.

train_raw['train'] = 1

test_raw['train'] = 0

df = train_raw.append(test_raw, sort=False)

features = ['Age', 'Embarked', 'Fare', 'Parch', 'Pclass', 'Sex', 'SibSp']

target = 'Survived'

df = df[features + [target] + ['train']]

# Categorical values need to be transformed into numeric.

df['Sex'] = df['Sex'].replace(["female", "male"], [0, 1])

df('Embarked') = df['Embarked'].replace(['S', 'C', 'Q'], [1, 2, 3])

train = df.query('train == 1')

test = df.query('train == 0')
```

```
# Drop missing values from the train set.
train.dropna(axis=0, inplace=True)
labels = train[target].values

train.drop(['train', target, 'Pclass'], axis=1, inplace=True)
test.drop(['train', target, 'Pclass'], axis=1, inplace=True)
```

```
from sklearn.model_selection import train_test_split, cross_validate
X_train, X_val, Y_train, Y_val = train_test_split(train, labels, test_size=0.2, random_state=1)
import warnings
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats.stats import pearsonr
from sklearn.naive_bayes import GaussianNB
from sklearn.medel_selection import train_test_split
from sklearn.metrics import accuracy_score, recall_score, precision_score, classification_report, confusion_matrix
%matplotlib inline
# Suppress warnings
warnings.filterwarnings("ignore")
classifier = GaussianNB()
{\tt classifier.fit}({\tt X\_train,\ Y\_train})
GaussianNB()
```

```
y_pred = classifier.predict(X_val)

# Summary of the predictions made by the classifier
print(classification_report(Y_val, y_pred))
print(confusion_matrix(Y_val, y_pred))
# Accuracy score
from sklearn.metrics import accuracy_score
print('accuracy is',accuracy_score(Y_val, y_pred))
```

	precision	recall	f1-score	support
0.0	0.79	0.80	0.80	85
1.0	0.70	0.69	0.70	58
accuracy			0.76	143
macro avg	0.75	0.74	0.75	143
weighted avg	0.75	0.76	0.75	143
[[68 17] [18 40]] accuracy is 0	.75524475524	147552		

## 2. (Glass Dataset)

- 1. Implement Naïve Bayes method using scikit-learn library.
  - a. Use the glass dataset available in Link also provided in your assignment.
  - b. Use train\_test\_split to create training and testing part.
- 2. Evaluate the model on testing part using score and

classification\_report(y\_true, y\_pred)

- 1. Implement linear SVM method using scikit library
  - a. Use the glass dataset available in Link also provided in your assignment.
  - b. Use train\_test\_split to create training and testing part.
- 2. Evaluate the model on testing part using score and

classification\_report(y\_true, y\_pred)

```
glass.head()

RI Na Mg AI Si K Ca Ba Fe Type

0 1.52101 13.64 4.49 1.10 71.78 0.06 8.75 0.0 0.0 1

1 1.51761 13.89 3.60 1.36 72.73 0.48 7.83 0.0 0.0 1

2 1.51618 13.53 3.55 1.54 72.99 0.39 7.78 0.0 0.0 1

3 1.51766 13.21 3.69 1.29 72.61 0.57 8.22 0.0 0.0 1

4 1.51742 13.27 3.62 1.24 73.08 0.55 8.07 0.0 0.0 1
```



```
sns.heatmap(matrix, annot=True, vmax=1, vmin=-1, center=0, cmap='vlag')
plt.show()
                                                            -1.00
 Passengerid - 1 -0.005-0.035-0.043-0.037-0.0580.00170.013
                                                            0.75
   Survived -0.005 1 -0.34 -0.54 -0.077-0.035 0.082 0.26
     Pclass --0.035 -0.34 1 0.13 -0.37 0.083 0.018 -0.55
                                                            0.25
       Sex -0.043 -0.54 0.13 1 0.093 -0.11 -0.25 -0.18
                                                           - 0.00
       Age -0.037 -0.077 -0.37 0.093 1 -0.31 -0.19 0.096
                                                           - -0.25
      SibSp --0.058-0.035 0.083 -0.11 -0.31 1 0.41 0.16
                                                          - -0.50
      Parch -0.00170.082 0.018 -0.25 -0.19 0.41 1 0.22
                                                             -0.75
       Fare - 0.013 0.26 -0.55 -0.18 0.096 0.16 0.22
                                                            -1.00
```

```
features = ['R1', 'Na', 'Mg', 'A1', 'Si', 'K', 'Ca', 'Ba', 'Fe']
target = 'Type'

X_train, X_val, Y_train, Y_val = train_test_split(glass[::-1], glass['Type'],test_size=0.2, random_state=1)

classifier = GaussianNB()

classifier.fit(X_train, Y_train)

y_pred = classifier.predict(X_val)

# Summary of the predictions made by the classifier
print(classification_report(Y_val, y_pred))
print(confusion_matrix(Y_val, y_pred))

# Accuracy score
from sklearn.metrics import accuracy_score
print('accuracy is',accuracy_score(Y_val, y_pred))
```

```
precision
                       recall f1-score support
         1
                 0.90
                          0.95
                                   0.92
                                              19
         2
                 0.92
                          0.92
                                   0.92
                                              12
         3
                 1.00
                          0.50
                                   0.67
                                               6
          5
                 0.00
                          0.00
                                   0.00
                                               1
         6
                 1.00
                          1.00
                                   1.00
                                               1
                 0.75
                          0.75
                                   0.75
                                               4
                                   0.84
                                              43
   accuracy
                 0.76
  macro avg
                          0.69
                                   0.71
                                              43
weighted avg
                 0.89
                          0.84
                                   0.85
[[18 1 0 0 0 0]
[ 1 11 0 0 0 [ 1 0 3 2 0
                0]
                0]
 [00000
                1]
[000010]
[000103]]
accuracy is 0.8372093023255814
```

```
: from sklearn.svm import SVC, LinearSVC

classifier = LinearSVC()

classifier.fit(X_train, Y_train)

y_pred = classifier.predict(X_val)

# Summary of the predictions made by the classifier
print(classification_report(Y_val, y_pred))
print(confusion_matrix(Y_val, y_pred))

# Accuracy score
from sklearn.metrics import accuracy_score
print('accuracy is',accuracy_score(Y_val, y_pred))
```

			0131011	Lecali	f1-score	support
	1		1.00	0.95	0.97	19
	2		1.00	0.08	0.15	12
	3		0.25	1.00	0.40	6
	5		0.00	0.00	0.00	1
	6		0.00	0.00	0.00	1
	7		0.00	0.00	0.00	4
accuracy				0.58	43	
macro avg			0.38	0.34	0.25	43
ed av	g		0.76	0.58	0.53	43
0 1	0	0	0]			
1 11	0	0	0]			
0 6	0	0	0]			
0 1	0	0	0]			
0 1	0	0	0]			
0 4	0	0	0]]			
	curac ro av ed av 0 1 1 11 0 6 0 1 0 1	ero avg ed avg 0 1 0 1 11 0 0 6 0 0 1 0 0 1 0 0 4 0	3 5 6 7 7 ccuracy ro avg red avg 0 1 0 0 1 11 0 0 0 6 0 0 0 0 1 0 0 0 0	3 0.25 5 0.00 6 0.00 7 0.00 ccuracy cro avg 0.38 ed avg 0.76 0 1 0 0] 1 11 0 0 0] 0 6 0 0 0] 0 1 0 0]	3 0.25 1.00 5 0.00 0.00 6 0.00 0.00 7 0.00 0.00 ccuracy ro avg 0.38 0.34 ed avg 0.76 0.58 0 1 0 0 0] 1 11 0 0 0] 0 1 0 0 0] 0 1 0 0 0] 0 1 0 0 0] 0 1 0 0 0]	3

# link for video explanation:

https://drive.google.com/drive/folders/1XfywUAFFKZzy7CtwCi5uknu9\_moPL5bh?usp=sharing