ML_Assignment3_Farhana_700735341

Programming elements:
Classification

Assignment:
1. (Titanic Dataset)

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.

Question 1

In [2]:
```
import pandas as pd
import numpy as np
import random as rnd

import warnings # current version generates a bunch of warnings that we'll ignore
warnings.filterwarnings("ignore")

# visualization
import seaborn as sns
import matplotlib.pyplot as plt

# machine learning
from sklearn.linear_model import LogisticRegression, RidgeClassifierCV
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import (RandomForestClassifier, GradientBoostingClassifier)
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score, GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn import preprocessing
```

First of all, imported pandas as pd ,numpy as np,random as rnd, warnings, seaborn as sns, matplotlib.pyplot as plt and import seaborn as sns

from sklearn.linear_model import LogisticRegression, RidgeClassifierCV

from sklearn.svm import SVC, LinearSVC

from sklearn.ensemble import (RandomForestClassifier, GradientBoostingClassifier)

from sklearn.neighbors import KNeighborsClassifier

from sklearn.naive_bayes import GaussianNB

from sklearn.linear_model import Perceptron

from sklearn.linear_model import SGDClassifier

from sklearn.tree import DecisionTreeClassifier

from sklearn.model_selection import cross_val_score, GridSearchCV from sklearn.metrics import accuracy_score

from sklearn import preprocessing

#Question-1 (TITANIC DATASET)

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

train_df.head()

The datasets are read using read_csv() and Sex and Embark are replaced with numerical values for finding the correlation heatmap shows the correlation and Sex has the highest value of the correlation.

```
In [5]:  train_df = pd.read_csv('train.csv')
         train_df.head()
```

Out[5]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

```
]:  #1.. correlation between 'survived' (target column) and 'sex' column for the Titanic use case in class.
    #      a. Why should we keep this feature?

    #print(pd.pivot_table(train_df, index = 'Survived', columns = 'Sex',
                    #  values = 'Ticket' ,aggfunc ='count'))

    train_df[["Sex", "Survived"]].groupby(['Sex'], as_index=False).mean().sort_values(by='Survived', ascending=False)
    #a. Survived: Most of the people died,  only around 300 people survived.
    # Sex: There were more males than females aboard the ship, roughly double the amount.
    #Most of the women survived, and the majority of the male died .
```

#1.. correlation between 'survived' (target column) and 'sex' column for the Titanic use case in class.

a. Why should we keep this feature?

#print(pd.pivot_table(train_df, index = 'Survived', columns = 'Sex',

values = 'Ticket' ,aggfunc ='count'))

train_df[["Sex", "Survived"]].groupby(['Sex'], as_index=False).mean().sort_values(by='Survived', ascending=False)

#a. Survived: Most of the people died, only around 300 people survived.

Sex: There were more males than females aboard the ship, roughly double the amount.

#Most of the women survived, and the majority of the male died .

Output will be as

Out[6]:

	Sex	Survived
0	female	0.742038
1	male	0.188908

In [7]:
```
a = preprocessing.LabelEncoder()
train_df['Sex'] = a.fit_transform(train_df.Sex.values)
train_df['Survived'].corr(train_df['Sex'])
```

Output is -0.5433513806577552

In [8]:
```
mat = train_df.corr()
print(mat)
```

mat = train_df.corr()

print(mat)

Output for the above code is

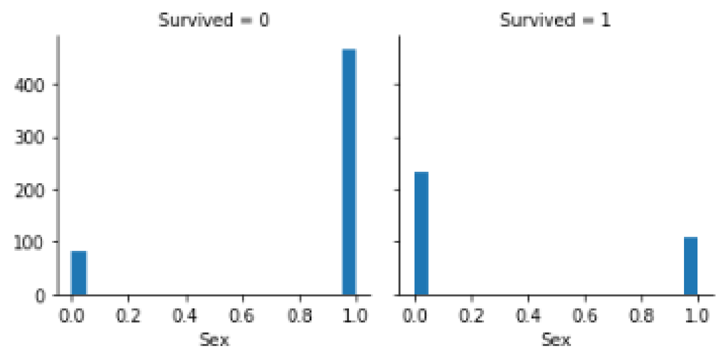
```
             PassengerId  Survived    Pclass       Sex       Age     SibSp  \
PassengerId     1.000000 -0.005007 -0.035144  0.042939  0.036847 -0.057527
Survived       -0.005007  1.000000 -0.338481 -0.543351 -0.077221 -0.035322
Pclass         -0.035144 -0.338481  1.000000  0.131900 -0.369226  0.083081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

                Parch      Fare
PassengerId -0.001652  0.012658
Survived     0.081629  0.257307
Pclass       0.018443 -0.549500
Sex         -0.245489 -0.182333
Age         -0.189119  0.096067
SibSp        0.414838  0.159651
Parch        1.000000  0.216225
Fare         0.216225  1.000000
```

#2.. two visualizations to describe or show correlations g = sns.FacetGrid(train_df, col='Survived')

g.map(plt.hist, 'Sex', bins=20)

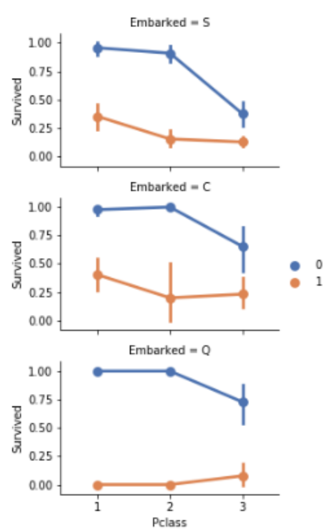
```
In [9]:  #2.. two visualizations to describe or show correlations
         g = sns.FacetGrid(train_df, col='Survived')
         g.map(plt.hist, 'Sex', bins=20)
```

```
Out[9]: <seaborn.axisgrid.FacetGrid at 0x2147b49cc48>
```




```
In [10]:  grid = sns.FacetGrid(train_df, row='Embarked', size=2.2, aspect=1.6)
          grid.map(sns.pointplot, 'Pclass', 'Survived', 'Sex', palette='deep')
          grid.add_legend()
```

```
Out[10]: <seaborn.axisgrid.FacetGrid at 0x2147c170c48>
```

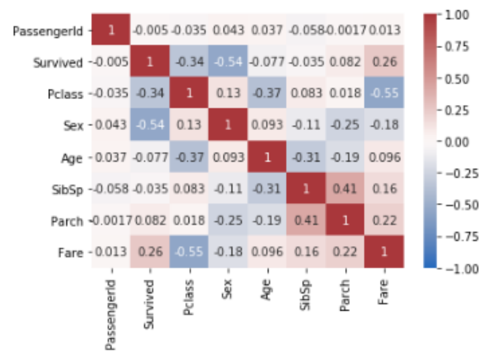


In [11]:
```python
train_df.corr().style.background_gradient(cmap="Greens")
```

Out[11]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
PassengerId	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

In [12]:
```python
sns.heatmap(mat, annot=True, vmax=1, vmin=-1, center=0, cmap='vlag')
plt.show()
```



In [13]:
```python
#3.. Implementing Naive Bayes method using scikit-Learn library and report the accuracy

from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
```

In [15]:
```python
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')
```

In [16]:
```python
# 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_test, y_train, y_test = train_test_split(train, labels, test_size=0.2, random_state=0)
```

In [17]:
```
# Gaussian Naive Bayes
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)

y_pred = classifier.predict(X_test)

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

```
              precision    recall  f1-score   support

         0.0       0.77      0.84      0.80        82
         1.0       0.75      0.66      0.70        61

    accuracy                           0.76       143
   macro avg       0.76      0.75      0.75       143
weighted avg       0.76      0.76      0.76       143

[[69 13]
 [21 40]]
accuracy is 0.7622377622377622
```

#Question-2 (GLASS DATASET)

#1.. Implementing Naïve Bayes method using scikit-learn library.

a. Use the glass dataset available

Train_test_split() is used to split the training and testing data and random state=0 gives the same testing and training split every time.

In [19]:
```
#1.. Implementing Naïve Bayes method using scikit-learn library.
#     a. Use the glass dataset available

glass = pd.read_csv('glass.csv')
glass.head()
```

Out[19]:

	RI	Na	Mg	Al	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

In [20]:
```
glass.corr().style.background_gradient(cmap="Greens")
```

Out[20]:

	RI	Na	Mg	Al	Si	K	Ca	Ba	Fe	Type
RI	1.000000	-0.191885	-0.122274	-0.407326	-0.542052	-0.289833	0.810403	-0.000386	0.143010	-0.164237
Na	-0.191885	1.000000	-0.273732	0.156794	-0.069809	-0.266087	-0.275442	0.326603	-0.241346	0.502898
Mg	-0.122274	-0.273732	1.000000	-0.481799	-0.165927	0.005396	-0.443750	-0.492262	0.083060	-0.744993
Al	-0.407326	0.156794	-0.481799	1.000000	-0.005524	0.325958	-0.259592	0.479404	-0.074402	0.598829
Si	-0.542052	-0.069809	-0.165927	-0.005524	1.000000	-0.193331	-0.208732	-0.102151	-0.094201	0.151565
K	-0.289833	-0.266087	0.005396	0.325958	-0.193331	1.000000	-0.317836	-0.042618	-0.007719	-0.010054
Ca	0.810403	-0.275442	-0.443750	-0.259592	-0.208732	-0.317836	1.000000	-0.112841	0.124968	0.000952
Ba	-0.000386	0.326603	-0.492262	0.479404	-0.102151	-0.042618	-0.112841	1.000000	-0.058692	0.575161
Fe	0.143010	-0.241346	0.083060	-0.074402	-0.094201	-0.007719	0.124968	-0.058692	1.000000	-0.188278
Type	-0.164237	0.502898	-0.744993	0.598829	0.151565	-0.010054	0.000952	0.575161	-0.188278	1.000000

In [21]:
```
y=glass['Type'].values
```

In [22]:
```
#1b. Use train_test_split to create training and testing part.
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size = 0.30, random_state = 0)
```

#1b. Use train_test_split to create training and testing part.

In [23]:
```
# Evaluating the model on testing part using score and
# 1. Gaussian Naive Bayes
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(x_train, y_train)

y_pred = classifier.predict(x_test)

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

```
              precision    recall  f1-score   support

           1       0.39      0.86      0.54        21
           2       0.50      0.12      0.19        26
           3       0.00      0.00      0.00         7
           5       0.00      0.00      0.00         2
           6       0.67      1.00      0.80         2
           7       0.88      1.00      0.93         7

    accuracy                           0.46        65
   macro avg       0.41      0.50      0.41        65
weighted avg       0.44      0.46      0.37        65

[[18  1  0  0  1  1]
 [21  3  1  1  0  0]
 [ 7  0  0  0  0  0]
 [ 0  2  0  0  0  0]
 [ 0  0  0  0  2  0]
 [ 0  0  0  0  0  7]]
accuracy is 0.46153846153846156
```

Multinomial Naive Bayes and Gaussian Naive Bayes gives accurate values in Naive Bayes

#Question-3

```
In [24]:  #1. Implement linear SVM method using scikit library
          #      a. Use the glass dataset available
          # Support Vector Machine's
          from sklearn.svm import SVC, LinearSVC

          classifier = LinearSVC()
          classifier.fit(x_train, y_train)

          y_pred = classifier.predict(x_test)

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

```
              precision    recall  f1-score   support

           1       0.43      1.00      0.60        21
           2       0.50      0.12      0.19        26
           3       0.00      0.00      0.00         7
           5       0.00      0.00      0.00         2
           6       0.00      0.00      0.00         2
           7       0.78      1.00      0.88         7

    accuracy                           0.48        65
   macro avg       0.28      0.35      0.28        65
weighted avg       0.42      0.48      0.36        65

[[21  0  0  0  0  0]
 [21  3  0  0  1  1]
 [ 7  0  0  0  0  0]
 [ 0  2  0  0  0  0]
 [ 0  1  0  0  0  1]
 [ 0  0  0  0  0  7]]
accuracy is 0.47692307692307695
```

#1. Implement linear SVM method using scikit library

a. Use the glass dataset available

Support Vector Machine's

from sklearn.svm import SVC, LinearSVC

classifier = LinearSVC()

classifier.fit(x_train, y_train)

y_pred = classifier.predict(x_test)

Summary of the predictions made by the classifier

print(classification_report(y_test, y_pred))

print(confusion_matrix(y_test, y_pred))

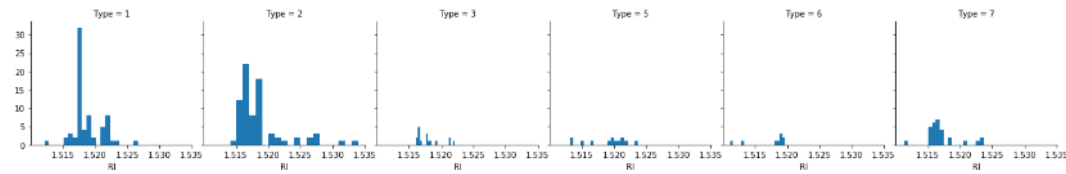
Accuracy score

from sklearn.metrics import accuracy_score

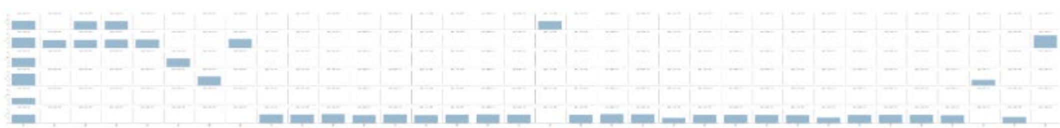
print('accuracy is',accuracy_score(y_pred,y_test))

#Do at least two visualizations to describe or show correlations in the Glass Dataset

In [25]:
```
#Do at least two visualizations to describe or show correlations in the Glass Dataset
g = sns.FacetGrid(glass, col='Type')
g.map(plt.hist,'RI',bins=20)
```
Out[25]: <seaborn.axisgrid.FacetGrid at 0x2147c6b92c8>



In [26]:
```
grid = sns.FacetGrid(glass, row='Type',col='Ba',height=2.2,aspect=1.6)
grid.map(sns.barplot,'Al','Ca',alpha=.5,ci=None)
grid.add_legend()
```
Out[26]: <seaborn.axisgrid.FacetGrid at 0x2147caff288>



In [ ]:
```
#Which algorithm you got better accuracy? Can you justify why?
#Gaussian Naive Bayes algorithm gives better accuracy than other algorithms. This is used when features are not discreet.
```

GitHUB Link: https://github.com/AishaFar/ML_Assignment3_Farhana_700735341/

Video Link:

https://youtu.be/mY6EB_6wdt8