import matplotlib.pyplot as plt
import seaborn as sns

prompt: csv this is my file read the csv file with pytthon

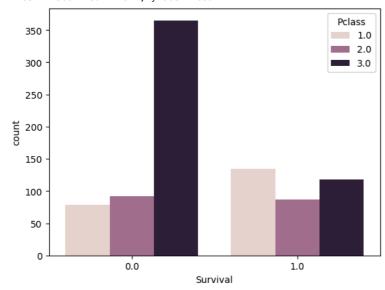
import pandas as pd
Load the dataset
df = pd.read_csv('/content/drive/MyDrive/COMP1816_Titanic_Dataset_Classification.csv')

Display the first few rows of the dataframe print(df.head())

_	0 1 2 3 4	Passe	ngerId 1 2 3 4 5	Pclass 3.0 1.0 3.0 1.0 3.0	Futrelle, Mrs. 3	He: Jacques He	ikkinen, M eath (Lily	Name wen Harris NaN iss. Laina May Peel) liam Henry	Sex male female female female male	\
	0 1 2 3 4	Age 22.0 38.0 26.0 35.0 35.0	SibSp 1.0 1.0 0.0 1.0 0.0	Parch 0.0 0.0 0.0 0.0	Ticket No. A/5 21171 PC 17599 STON/02. 3101282 113803 373450	Fare 7.2500 71.2833 7.9250 53.1000 8.0500	Embarked S C S S	Survival 0.0 1.0 1.0 1.0		

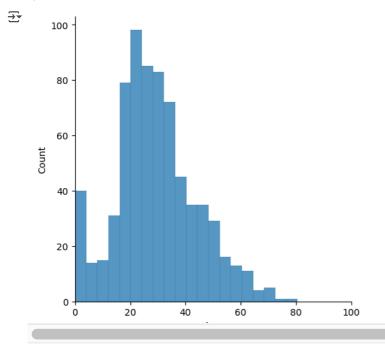
sns.countplot(x='Survival', data= df, hue ='Pclass')





so here it is clear that majority of the people did not survived from the ticketclass 3

```
sns.displot(df['Age'], kde=False)
plt.xlim(0, 100) # Set the x-axis limits
plt.show()
```



df.info()

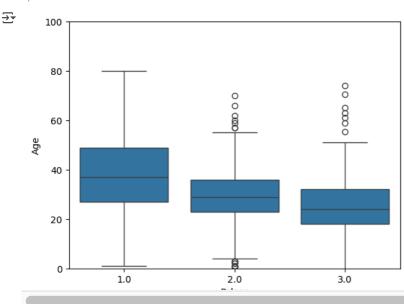
<<re><class 'pandas.core.frame.DataFrame'>
RangeIndex: 890 entries, 0 to 889
Data columns (total 11 columns):

Data	Cotumns (tota	ас ті	L CO CUIIIIS).	
#	Column	Non-	-Null Count	Dtype
0	PassengerId	890	non-null	int64
1	Pclass	880	non-null	float64
2	Name	885	non-null	object
3	Sex	890	non-null	object
4	Age	715	non-null	float64
5	SibSp	888	non-null	float64
6	Parch	888	non-null	float64
7	Ticket No.	888	non-null	object
8	Fare	888	non-null	float64
9	Embarked	884	non-null	object
10	Survival	886	non-null	float64
dtype	es: float64(6)), ir	nt64(1), obj	ect(4)
memo	ry usage: 76.0	6+ KE	3	

df.isnull().sum()



```
sns.boxplot(x='Pclass', y='Age', data=df) plt.ylim(0, 100)    # Set the y-axis limits to 0-100 plt.show()
```



```
# Calculate the mean age for each passenger class
mean_age_by_pclass = df.groupby('Pclass')['Age'].mean()
```

mean_age_by_pclass



Age

Pclass								
1.0	38.149022							
2.0	29.793118							
3.0	33.489801							

```
print(df[df['Pclass']==1]['Age'].mean())
print(df[df['Pclass']==2]['Age'].mean())
print(df[df['Pclass']==3]['Age'].mean())
```

```
38.14902173913043
29.793117647058825
33.48980056980057
```

```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
def fill_in_na_values(cols):
  age = cols[0]
  pclass = cols[1]
  if pd.isnull(age):
    if pclass == 1:
      return round(df[df['Pclass']==1]['Age'].mean())
    elif pclass == 2:
      return round(df[df['Pclass']==2]['Age'].mean())
    else:
      return round(df[df['Pclass']==3]['Age'].mean())
  else:
                   return age
df['Age']=df[['Age', 'Pclass']].apply(fill_in_na_values, axis=1)
```

```
<ipython-input-24-fe67a078db9b>:2: FutureWarning: Series.__getitem__ treating keys as positions is deprecated. In a futu
age = cols[0]
<ipython-input-24-fe67a078db9b>:3: FutureWarning: Series.__getitem__ treating keys as positions is deprecated. In a futu
pclass = cols[1]
```

```
# Fill missing Pclass values (if any)
df['Pclass'].fillna(df['Pclass'].mode()[0], inplace=True)
# Function to fill missing Age values
def fill_in_na_values(cols, df):
    age, pclass = cols
    if pd.isnull(age):
        return round(df[df['Pclass'] == pclass]['Age'].mean())
# Apply function to fill missing Age values
df['Age'] = df[['Age', 'Pclass']].apply(lambda row: fill_in_na_values(row, df), axis=1)
print(df)
          PassengerId
\overline{2}
                        Pclass
                                                                           Name
     0
                                                       Braund, Mr. Owen Harris
                           3.0
                     1
                     2
                           1.0
                                                                            NaN
     1
                                                        Heikkinen, Miss. Laina
     2
                    3
                           3.0
     3
                     4
                           1.0
                                Futrelle, Mrs. Jacques Heath (Lily May Peel)
     4
                    5
                           3.0
                                                      Allen, Mr. William Henry
     885
                  886
                           2.0
                                                         Montvila, Rev. Juozas
     886
                  887
                           1.0
                                                  Graham, Miss. Margaret Edith
                                     Johnston, Miss. Catherine Helen "Carrie"
     887
                  888
                           3.0
     888
                  889
                           1.0
                                                         Behr, Mr. Karl Howell
     889
                  890
                           3.0
                                                           Dooley, Mr. Patrick
                                                               Fare Embarked
             Sex
                   Age
                         SibSp
                                Parch
                                               Ticket No.
                                                                               Survival
                                                            7.2500
    0
            male
                  22.0
                           1.0
                                   0.0
                                                A/5 21171
                                                                            S
                                                                                    0.0
     1
          female
                  38.0
                           1.0
                                   0.0
                                                 PC 17599
                                                           71.2833
                                                                            \Gamma
                                                                                    1.0
     2
                                        STON/02. 3101282
          female
                  26.0
                           0.0
                                   0.0
                                                            7.9250
                                                                            S
                                                                                    1.0
     3
          female
                  35.0
                           1.0
                                   0.0
                                                   113803
                                                           53.1000
                                                                                    1.0
     4
                  35.0
                           0.0
                                   0.0
                                                   373450
                                                            8.0500
                                                                            S
                                                                                    0.0
            male
                                                                                    . . .
             . . .
     885
            male
                  27.0
                           0.0
                                   0.0
                                                   211536
                                                           13.0000
                                                                            S
                                                                                    0.0
     886
          female
                  19.0
                           0.0
                                   0.0
                                                   112053
                                                           30.0000
                                                                                    1.0
     887
                  33.0
                                               W./C. 6607
                                                           23.4500
                                                                            S
                                                                                    0.0
          female
                           1.0
                                   2.0
                                                           30.0000
     888
            male
                  26.0
                           0.0
                                   0.0
                                                   111369
                                                                            C
                                                                                    1.0
                                                            7.7500
     889
            male
                  32.0
                           0.0
                                   0.0
                                                   370376
                                                                            0
                                                                                    0.0
     [890 rows x 11 columns]
```

<ipython-input-25-8fcf2ce5818d>:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[c

df['Pclass'].fillna(df['Pclass'].mode()[0], inplace=True)

df.isnull().sum()

```
₹
                   0
      PassengerId 0
        Pclass
                    0
         Name
                    5
          Sex
                   0
          Age
                   0
         SibSp
                    2
         Parch
                    2
       Ticket No.
                   2
                    2
          Fare
       Embarked
                   6
        Survival
```

```
def fill_in_na_values(cols):
    age = cols[0]
    pclass = cols[1]

if pd.isnull(age):
    if pclass == 1:
        return round(df[df['Pclass']==1]['Age'].mean())
    elif pclass == 2:
```

```
return round(df[df['Pclass']==2]['Age'].mean())
   elif pclass == 3:
     return round(df[df['Pclass']==3]['Age'].mean())
     return age
df['Age']=df[['Age', 'Pclass']].apply(fill_in_na_values, axis=1)
```

<ipython-input-27-d9409739061d>:3: FutureWarning: Series.__getitem__ treating keys as positions is deprecated. In a futu

pclass = cols[1]

df.isnull().sum()



0 PassengerId 0 **Pclass** 0

Name 5

Sex Age 0

0

SibSp 2 Parch 2

Ticket No. 2

Fare 2

Embarked 6 Survival 4

df.dropna(inplace=True)

df.isnull().sum()



0 Passengerld 0

> Pclass 0

Name 0

0 Sex

Age 0

SibSp 0

Parch 0 Ticket No. 0

0 Fare

Embarked 0

Survival 0

df.head()

_		PassengerId		Pclass	Name	Sex	Age	SibSp	Parch	Ticket No.	Fare	Embarked	Survival
	0	1		3.0	Braund, Mr. Owen Harris	male	22.0	1.0	0.0	A/5 21171	7.2500	S	0.0
	2	3	1	3.0	Heikkinen, Miss. Laina	female	26.0	0.0	0.0	STON/02. 3101282	7.9250	S	1.0
	3	4		1.0	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1.0	0.0	113803	53.1000	S	1.0

df.drop(['PassengerId', 'Name', 'Ticket No.'], axis=1, inplace=True)

df.head()

```
₹
        Pclass
                   Sex Age SibSp Parch
                                               Fare Embarked Survival
                  male 22.0
     0
                                             7.2500
                                                             S
                                                                      0.0
            3.0
                                 1.0
                                        0.0
     2
            3.0 female
                       26.0
                                 0.0
                                        0.0
                                              7.9250
                                                             S
                                                                      1.0
     3
            1.0
                       35.0
                                 1.0
                                        0.0
                                            53.1000
                                                             S
                                                                      1.0
                female
                        35.0
                                                             S
                                                                      0.0
            3.0
                  male
                                0.0
                                        0.0
                                             8.0500
```

df['Embarked'].unique()

```
→ array(['S', 'C', 'Q'], dtype=object)
```

```
sex = pd.get_dummies(df['Sex'], drop_first=True).astype(int)
embarked = pd.get_dummies(df['Embarked'], drop_first=True).astype(int)
```

```
print(sex)
print(embarked)
```

```
₹
         male
    0
             1
    2
             0
    3
             0
    4
             1
    6
             1
    886
             0
    887
             0
    888
             1
             1
    889
    [878 rows x 1 columns]
         Q S
         0
             1
    2
         0
            1
    4
6
             1
         0
            1
        0
    885
             1
    886
         0
            1
    887
         0
            1
            0
    888
         0
    889
         1
```

[878 rows x 2 columns]

Double-click (or enter) to edit

```
df = pd.concat([df, sex, embarked], axis=1)
```

Double-click (or enter) to edit

df.head()

₹		Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Survival	male	Q	s	male	Q	s
	0	3.0	male	22.0	1.0	0.0	7.2500	S	0.0	True	False	True	1	0	1
	2	3.0	female	26.0	0.0	0.0	7.9250	S	1.0	False	False	True	0	0	1
	3	1.0	female	35.0	1.0	0.0	53.1000	S	1.0	False	False	True	0	0	1
	4	3.0	male	35.0	0.0	0.0	8.0500	S	0.0	True	False	True	1	0	1
				-										-	

```
# Drop the first occurrences of 'male', 'Q', 'S' but keep the last three
df = df.drop(df.columns[list(df.columns).index('male'):list(df.columns).index('male')+3], axis=1)
```

df.head()

 *		Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Survival
	0	3.0	male	22.0	1.0	0.0	7.2500	S	0.0
	2	3.0	female	26.0	0.0	0.0	7.9250	S	1.0
	3	1.0	female	35.0	1.0	0.0	53.1000	S	1.0
	4	3.0	male	35.0	0.0	0.0	8.0500	S	0.0

sex = pd.get_dummies(df['Sex'], drop_first=True).astype(int) embarked = pd.get_dummies(df['Embarked'], drop_first=True).astype(int)

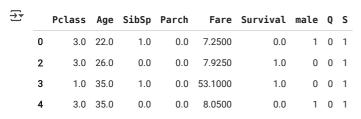
df = pd.concat([df, sex, embarked], axis=1)

df.head()

→	Pclass		Sex	Age	SibSp	Parch	Fare	Embarked	Survival	male	Q	S
	0	3.0	male	22.0	1.0	0.0	7.2500	S	0.0	1	0	1
	2	3.0	female	26.0	0.0	0.0	7.9250	S	1.0	0	0	1
	3	1.0	female	35.0	1.0	0.0	53.1000	S	1.0	0	0	1
	4	3.0	male	35.0	0.0	0.0	8.0500	S	0.0	1	0	1

df.drop(['Sex', 'Embarked'], axis=1, inplace=True)

df.head()



from sklearn.preprocessing import MinMaxScaler from sklearn.model_selection import train_test_split

```
x = df.drop('Survival', axis=1)
```

y = df['Survival']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1)

scaler = MinMaxScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)

from sklearn.preprocessing import MinMaxScaler from sklearn.model_selection import train_test_split

Define X (features) and y (target)

X = df.drop('Survival', axis=1)

y = df['Survival']

Split the last 140 rows as test set, and the rest as training set

 X_{train} , $X_{\text{test}} = X.iloc[:-140]$, X.iloc[-140:] # Last 140 rows for testing

y_train, y_test = y.iloc[:-140], y.iloc[-140:]

Normalize features using MinMaxScaler

scaler = MinMaxScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test) # Use same scaler for test data

from sklearn.svm import SVC

svm= SVC()

```
svm.fit(X_train, y_train)
prediction = svm.predict(X_test)
```

from sklearn.metrics import classification_report, confusion_matrix
print(classification_report(y_test, prediction))
print(confusion_matrix(y_test, prediction))

```
precision
                             recall f1-score
                                                 support
         0.0
                               0.96
                    0.80
                                          0.87
                                                       90
                    0.88
         1.0
                               0.58
                                          0.70
                                                       50
    accuracy
                                          0.82
                                                      140
   macro avg
                    0.84
                               0.77
                                          0.79
                                                      140
                                          0.81
weighted avg
                    0.83
                               0.82
                                                      140
[[86 4]
 [21 29]]
```

from sklearn.model_selection import GridSearchCV
param_grid = {'C': [0.5, 1, 10, 100, 1000], 'gamma': [1, 0.1, 0.01, 0.001, 0.0001]}
grid = GridSearchCV(SVC(), param_grid, verbose=2)
grid.fit(X_train, y_train)
grid_predictions = grid.predict(X_test)

```
Fitting 5 folds for each of 25 candidates, totalling 125 fits
   0.0s

      [CV] END
      .C=0.5, gamma=1; total time=

      [CV] END
      .C=0.5, gamma=1; total time=

      [CV] END
      .C=0.5, gamma=1; total time=

      [CV] END
      .C=0.5, gamma=0.1; total time=

      [CV] END
      .C=0.5, gamma=0.1; total time=

                                                                     0.0s
                                                                     0.05
                                                                     0.05
                                                                     0.05

      [CV] END
      C=0.5, gamma=0.1; total time=

      [CV] END
      C=0.5, gamma=0.1; total time=

                                                                     0.0s
                                                                     0.05
   0.0s

      [CV] END
      C=0.5, gamma=0.01; total time=

      [CV] END
      C=0.5, gamma=0.01; total time=

      [CV] END
      C=0.5, gamma=0.01; total time=

                                                                     0.0s
                                                                     0.05
                                                                     0.05
   0.05
                                                                     0.05

      [CV] END
      C=0.5, gamma=0.001; total time=

      [CV] END
      C=0.5, gamma=0.001; total time=

                                                                     0.05
                                                                     0.05
   0.0s
   [CV] END ......C=0.5, gamma=0.0001; total time=
   0.05

      [CV] END
      C=0.5, gamma=0.0001; total time=

      [CV] END
      C=0.5, gamma=0.0001; total time=

      [CV] END
      C=0.5, gamma=0.0001; total time=

      [CV] END
      C=1, gamma=1; total time=

                                                                     0.05
                                                                     0.0s
                                                                     0.05

      [CV] END
      C=1, gamma=1; total time=

      [CV] END
      C=1, gamma=1; total time=

                                                                     0.05
                                                                     0.05

      [CV] END
      C=1, gamma=1; total time=

      [CV] END
      C=1, gamma=1; total time=

                                                                     0.05
                                                                     0.0s
   0.05
   0.05

      [CV] END
      .C=1, gamma=0.1; total time=

      [CV] END
      .C=1, gamma=0.01; total time=

      [CV] END
      .C=1, gamma=0.01; total time=

      [CV] END
      .C=1, gamma=0.01; total time=

                                                                     0.0s
                                                                     0.05
                                                                     0.05

      [CV] END
      C=1, gamma=0.01; total time=

      [CV] END
      C=1, gamma=0.01; total time=

                                                                     0.05
                                                                     0 00
                                                                     0.0s
   [CV] END ......C=1, gamma=0.01; total time=

      [CV] END
      C=1, gamma=0.001; total time=

      [CV] END
      C=1, gamma=0.001; total time=

                                                                     0.0s
   0.05
   [CV] END ......C=1, gamma=0.001; total time=
                                                                     0.0s
   0.05

      [CV] END
      C=1, gamma=0.0001; total time=

      [CV] END
      C=1, gamma=0.0001; total time=

                                                                     0.05
                                                                     0.05
   0.05
                                                                     0.05

      [CV] END
      C=10, gamma=1; total time=

      [CV] END
      C=10, gamma=1; total time=

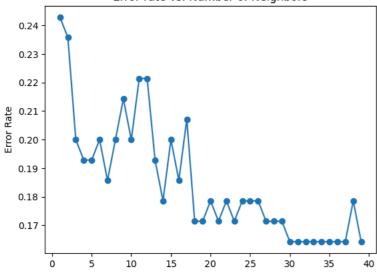
                                                                     0.0s
                                                                     0.05
   [CV] END ......C=10, gamma=1; total time=
                                                                     0.0s
   [CV] END ......C=10, gamma=1; total time=
   0.0s
   [CV] END ......C=10, gamma=0.1; total time=
                                                                     0.0s
   [CV] END ......C=10, gamma=0.1; total time=
                                                                     0.0s
```

print(classification_report(y_test, grid_predictions))
print(confusion_matrix(y_test, grid_predictions))

```
₹
                   precision
                                recall f1-score
                                                    support
              0.0
                        0.81
                                  0.97
                                             0.88
                                                         90
              1.0
                        0.91
                                  0.58
                                             0.71
                                                         50
        accuracy
                                             0.83
                                                        140
                        0.86
                                  0.77
                                             0.79
       macro avg
                                                        140
                        0.84
                                  0.83
                                             0.82
                                                        140
    weighted avg
    [[87 3]
      [21 29]]
Start coding or generate with AI.
from sklearn.linear_model import LogisticRegression
lm = LogisticRegression()
lm.fit(X_train, y_train)
lm\_prediction = lm.predict(X\_test)
print(classification_report(y_test, lm_prediction))
print(confusion_matrix(y_test, lm_prediction))
                   precision
                                recall f1-score
support
              0.0
                        0.83
                                  0.89
                                             0.86
                                                         90
             1.0
                        0.77
                                  0.68
                                             0.72
                                                         50
        accuracy
                                             0.81
                                                        140
       macro avg
                        0.80
                                  0.78
                                             0.79
                                                        140
    weighted avg
                        0.81
                                  0.81
                                            0.81
                                                        140
    [[80 10]
      [16 34]]
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
knn_prediction = knn.predict(X_test)
print(classification_report(y_test, knn_prediction))
print(confusion_matrix(y_test, knn_prediction))
₹
                   precision
                                recall f1-score
                                                    support
              0.0
                                             0.85
                        0.83
                                  0.88
                                                         90
             1.0
                        0.76
                                  0.68
                                             0.72
                                                         50
        accuracy
                                             0.81
                                                        140
       macro avg
                        0.79
                                  0.78
                                             0.78
                                                        140
    weighted avg
                        0.80
                                  0.81
                                             0.80
                                                        140
    [[79 11]
      [16 34]]
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
import numpy as np
error_list = []
# Loop over different values of k (from 1 to 39)
for i in range(1, 40):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train, y_train)
    prediction_i = knn.predict(X_test)
    # Append the error rate for the current k (n_neighbors=i)
    error_list.append(np.mean(prediction_i != y_test))
# Optionally, you could plot or analyze the error_list to see the optimal kprint(error_list)
import matplotlib.pyplot as plt
# Plotting the error rate vs. number of neighbors
plt.plot(range(1, 40), error_list, marker='o')
plt.title('Error rate vs. Number of Neighbors')
plt.xlabel('Number of Neighbors (k)')
plt.ylabel('Error Rate')
plt.show()
```







np.argmin(error_list)

→ 29

error_list[6]

→ 0.18571428571428572

knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
knn_prediction = knn.predict(X_test)
print(classification_report(y_test, knn_prediction))
print(confusion_matrix(y_test, knn_prediction))

→	precision	recall	f1-score	support
0.0 1.0		0.88 0.68	0.85 0.72	90 50
accuracy macro avo weighted avo	0.79	0.78 0.81	0.81 0.78 0.80	140 140 140
[[79 11] [16 34]]				

from sklearn.tree import DecisionTreeClassifier
dtree = DecisionTreeClassifier()
dtree.fit(X_train, y_train)
dtree_prediction = dtree.predict(X_test)
print(classification_report(y_test, dtree_prediction))
print(confusion_matrix(y_test, dtree_prediction))

_		precision	recall	f1-score	support
	0.0	0.90	0.87	0.88	90
	1.0	0.77	0.82	0.80	50
	accuracy			0.85	140
	macro avg	0.84	0.84	0.84	140
	weighted avg	0.85	0.85	0.85	140
	[[78 12] [9 41]]				

from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(X_train, y_train)
rfc_prediction = rfc.predict(X_test)
print(classification_report(y_test, rfc_prediction))

_	р	recision	cision recall		support	
	0.0	0.90	0.90	0.90	90	