Exploratory_Data_Analysis_Titanic

August 9, 2024

1 Importing the libraries

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
```

2 Loading the dataset

[ ]:
```
data = pd.read_csv('/Users/benfathel/Documents/Work/PRODIGY_DS_02/titanic_data/
↪train.csv')
data
```

[ ]:
```
     PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           …       …     …
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3

                                                 Name     Sex   Age  SibSp  \
0                             Braund, Mr. Owen Harris    male  22.0      1
1    Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                              Heikkinen, Miss. Laina  female  26.0      0
```

```
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                              Allen, Mr. William Henry    male  35.0      0
..                                                  …     …   …    …
886                               Montvila, Rev. Juozas    male  27.0      0
887                        Graham, Miss. Margaret Edith  female  19.0      0
888            Johnston, Miss. Catherine Helen "Carrie"  female   NaN      1
889                               Behr, Mr. Karl Howell    male  26.0      0
890                                 Dooley, Mr. Patrick    male  32.0      0

     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     …               …      …   …      …
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]
```

3 Cleaning the dataset

3.1 Exploring the dataset

[ ]:
```
data.describe()
```

[ ]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
```

```
75%       0.000000   31.000000
max       6.000000  512.329200
```

[ ]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

[ ]:
```
data.isnull().sum()
```

[ ]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

3.2 Handling the missing values

[ ]:
```
round((data.isnull().sum()/data.shape[0])*100,2)
```

[ ]:
```
PassengerId     0.00
Survived        0.00
Pclass          0.00
```

```
Name            0.00
Sex             0.00
Age            19.87
SibSp           0.00
Parch           0.00
Ticket          0.00
Fare            0.00
Cabin          77.10
Embarked        0.22
dtype: float64
```

[ ]:
```
data['Age'].mean()
data['Age'].fillna(data['Age'].mean(), inplace=True)
data['Age'].isnull().sum()
```

```
/var/folders/9s/09g1kdgn5p3fdcwfb0r_hrzh0000gn/T/ipykernel_41264/595731597.py:2:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  data['Age'].fillna(data['Age'].mean(), inplace=True)
```

[ ]:
```
0
```

[ ]:
```
data['Cabin'].fillna(data['Cabin'].mode()[0], inplace=True)
data['Cabin'].isnull().sum()
```

```
/var/folders/9s/09g1kdgn5p3fdcwfb0r_hrzh0000gn/T/ipykernel_41264/49455062.py:1:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  data['Cabin'].fillna(data['Cabin'].mode()[0], inplace=True)
```

[ ]: 0

[ ]:
```
data.describe()
```

[ ]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  891.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   13.002015    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   22.000000    0.000000
50%     446.000000    0.000000    3.000000   29.699118    0.000000
75%     668.500000    1.000000    3.000000   35.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

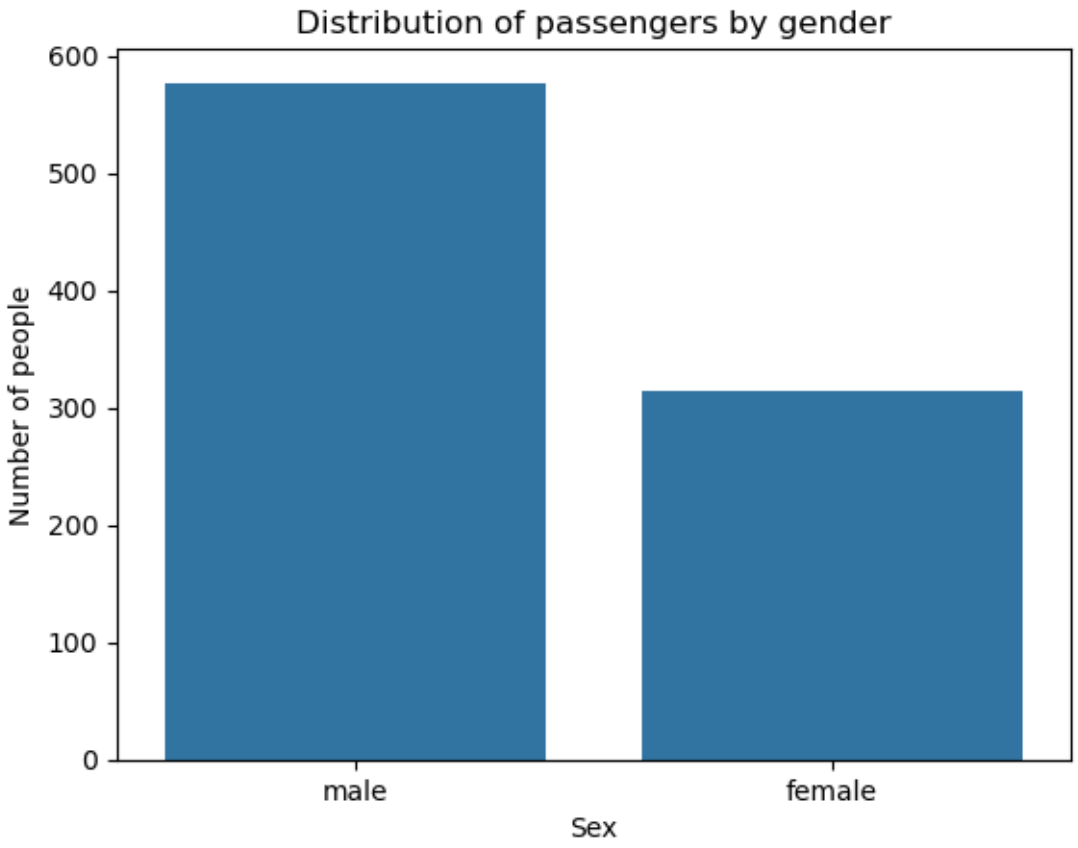
4 Data Visualization

4.1 Distribution of passengers by gender

[ ]:
```
data['Sex'].value_counts()
```

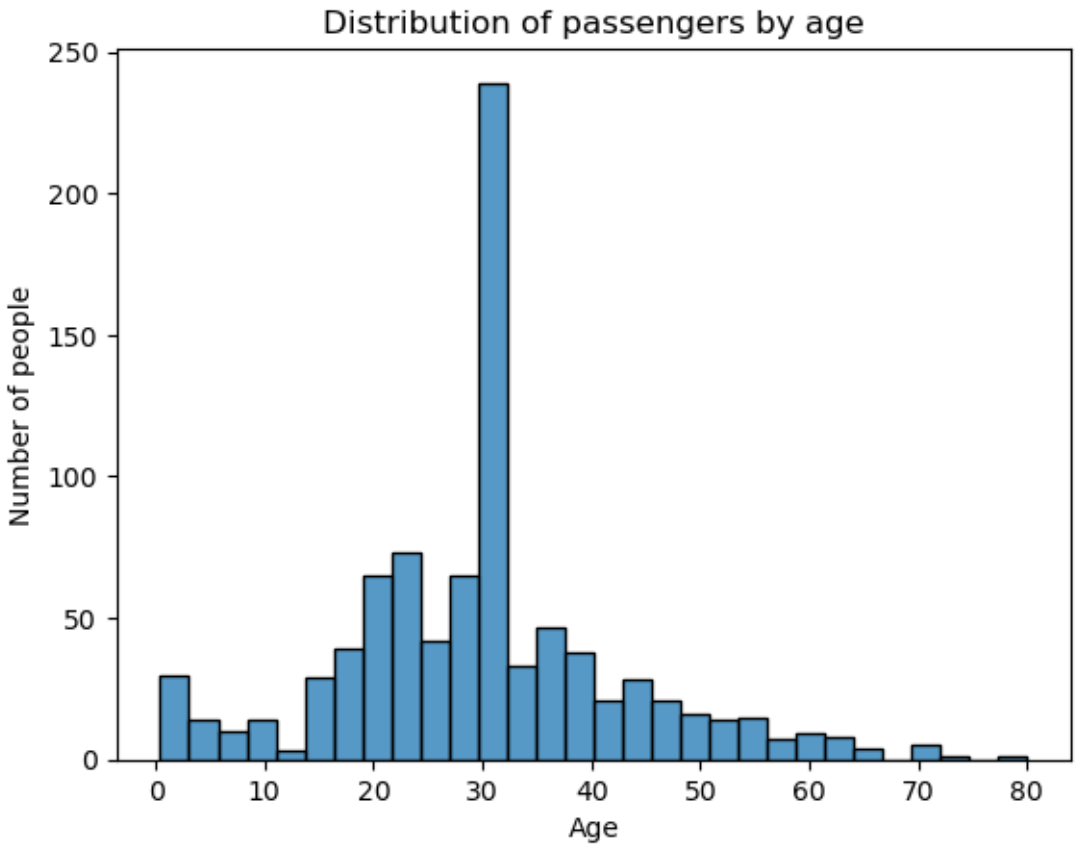
[ ]:
```
Sex
male      577
female    314
Name: count, dtype: int64
```

[ ]:
```
sns.countplot(x='Sex', data=data)
plt.title('Distribution of passengers by gender')
plt.xlabel('Sex')
plt.ylabel('Number of people')
plt.show()
```



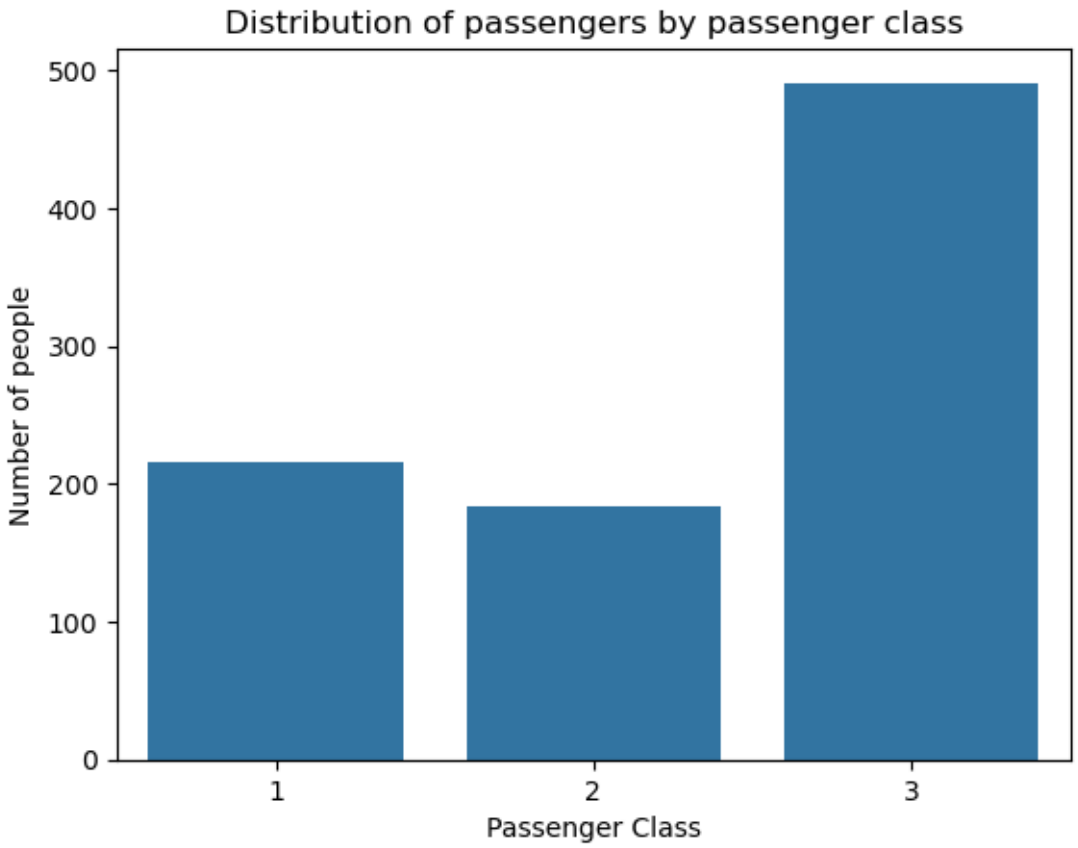
4.2 Distribution of passengers by age

[ ]:
```
sns.histplot(x='Age', data=data)
plt.title('Distribution of passengers by age')
plt.xlabel('Age')
plt.ylabel('Number of people')
plt.show()
```



4.3 Distribution of passengers by passenger class

[ ]:
```
sns.countplot(x='Pclass', data=data)
plt.title('Distribution of passengers by passenger class')
plt.xlabel('Passenger Class')
plt.ylabel('Number of people')
plt.show()
```

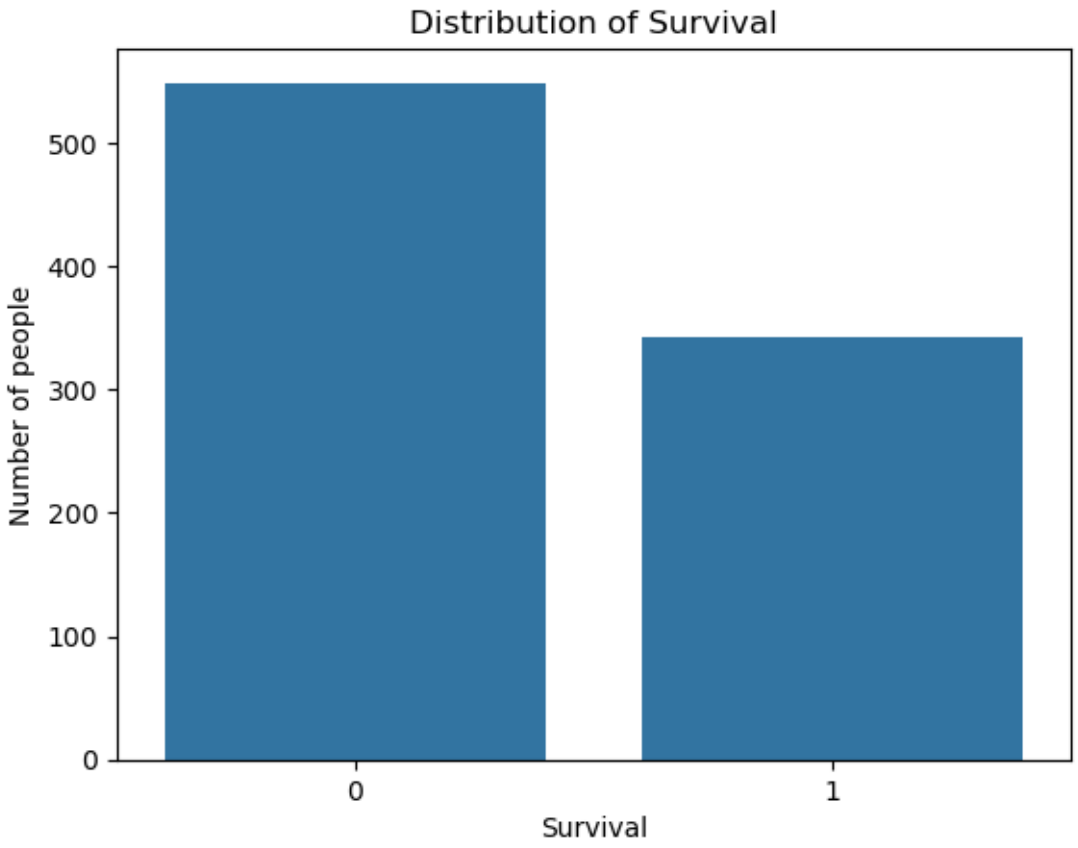


4.4 Survival rate

[ ]:
```
deaths= (data["Survived"] == 0).sum()
print("Deaths ",deaths)
survived= (data["Survived"] == 1).sum()
print("Survived ",survived)
```

```
Deaths  549
Survived  342
```

[ ]:
```
sns.countplot(x='Survived', data=data)
plt.title('Distribution of Survival')
plt.xlabel('Survival')
plt.ylabel('Number of people')
plt.show()
```



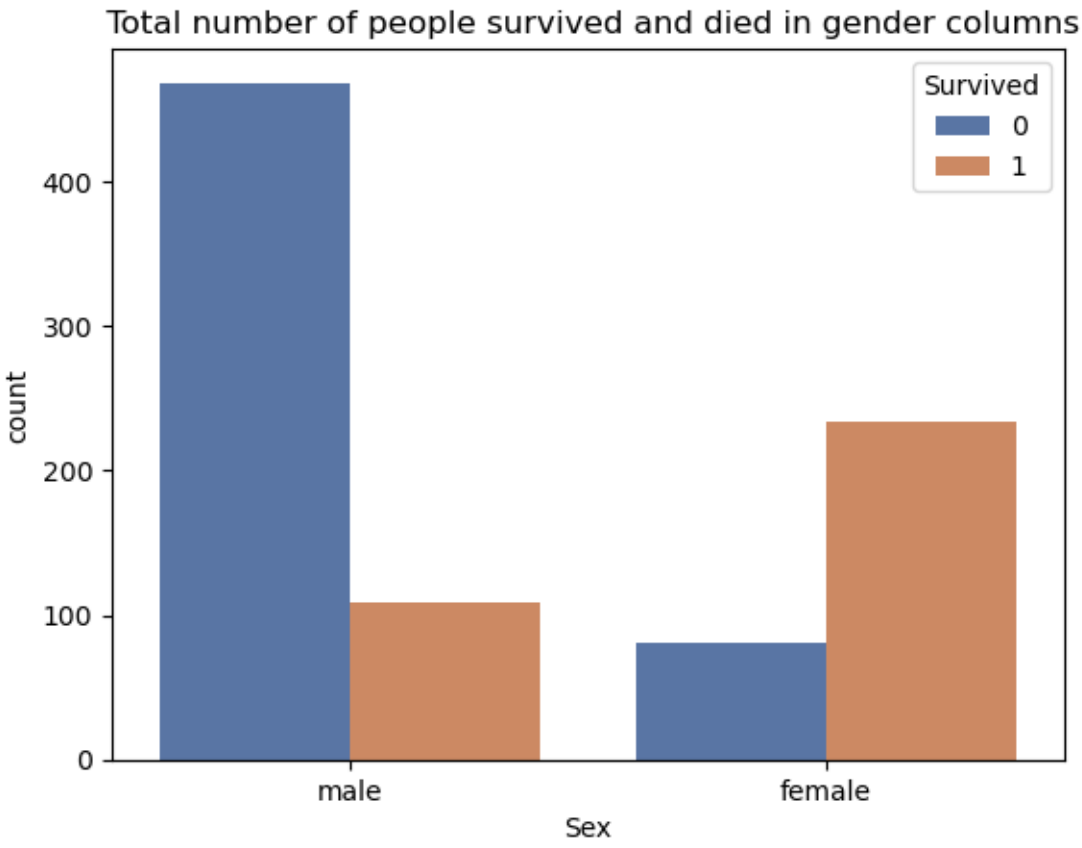
4.5 Survival rate by gender

[ ]:
```
data.groupby(['Survived','Sex'])['Survived'].count()
```

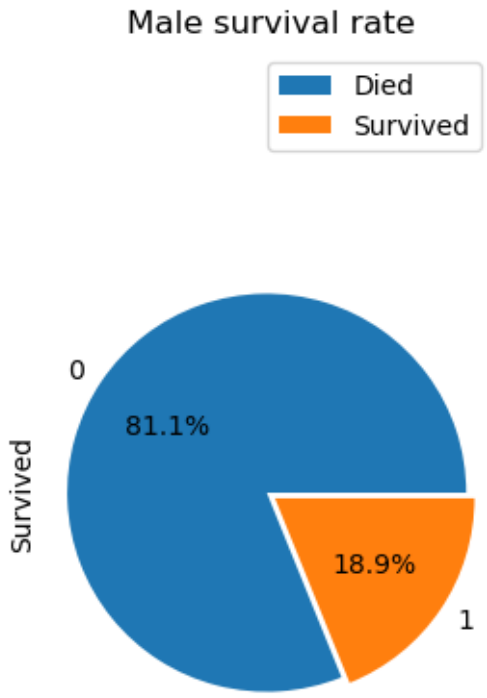
[ ]:
```
Survived  Sex
0         female     81
          male      468
1         female    233
          male      109
Name: Survived, dtype: int64
```

[ ]:
```
sns.countplot(data=data,x='Sex',hue='Survived',palette='deep').set(
title=' Total number of people survived and died in gender columns')
```

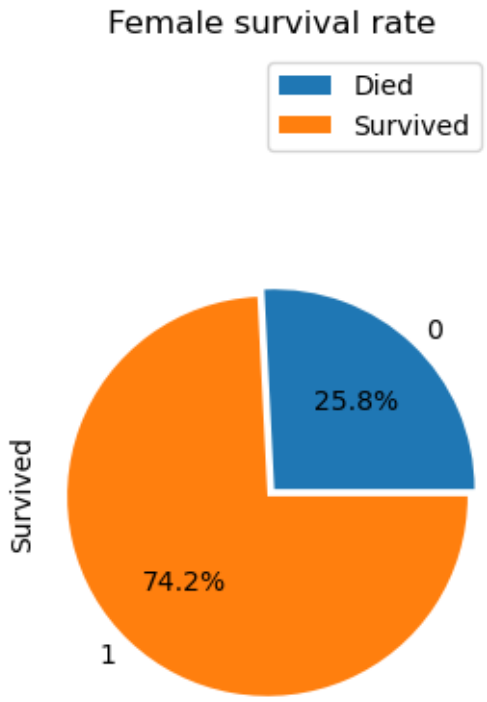
[ ]:
```
[Text(0.5, 1.0, ' Total number of people survived and died in gender columns')]
```



[ ]:
```
data[data['Sex'] == 'male'].Survived.groupby(data.Survived).count().
 ↪plot(kind='pie',
figsize=(3, 6),explode=[0,0.05],autopct='%1.1f%%')
plt.axis('equal')
plt.legend(["Died","Survived"])
plt.title("Male survival rate")
plt.show()
```



[ ]:
```
data[data['Sex'] == 'female'].Survived.groupby(data.Survived).count().
  ↪plot(kind='pie',
figsize=(3, 6),explode=[0,0.05],autopct='%1.1f%%')
plt.axis('equal')
plt.legend(["Died","Survived"])
plt.title("Female survival rate")
plt.show()
```



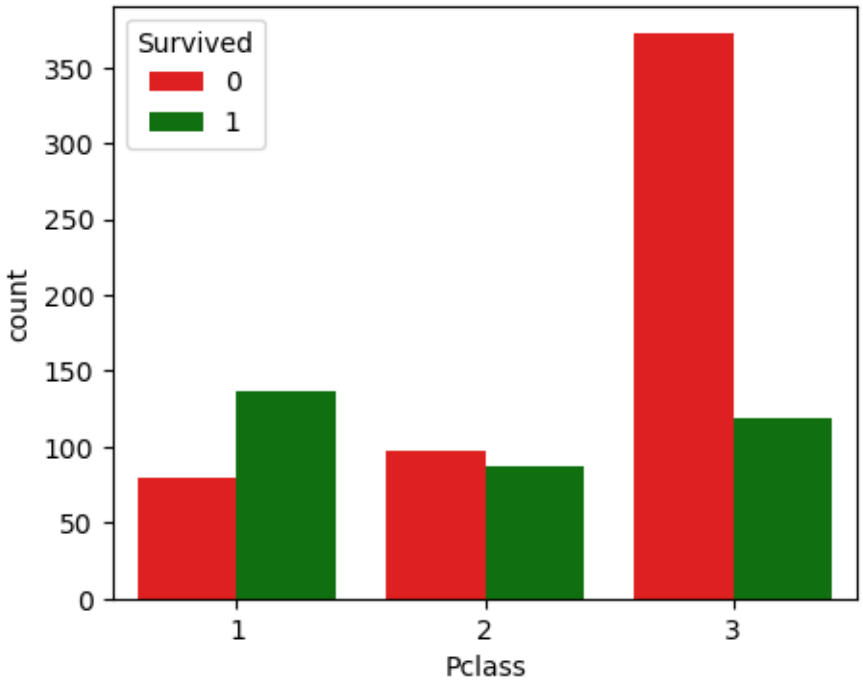
4.6 Survival rate by Passenger class

[ ]:
```
pd.crosstab(data.Pclass, data.Survived, margins=True)
```

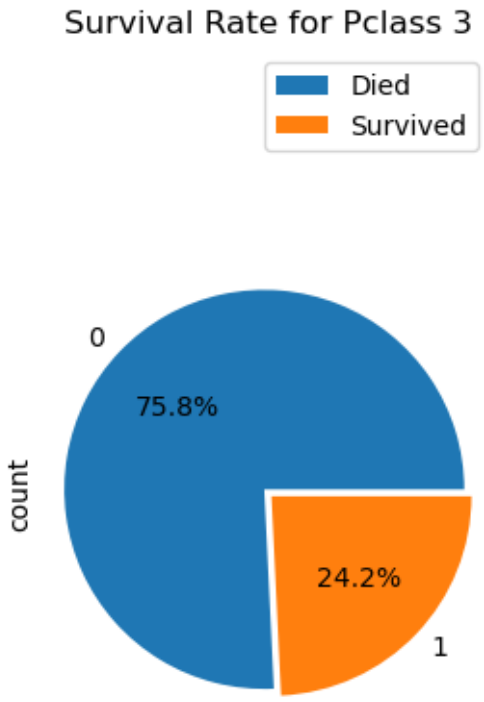
[ ]:
```
Survived    0    1  All
Pclass
1          80  136  216
2          97   87  184
3         372  119  491
All       549  342  891
```

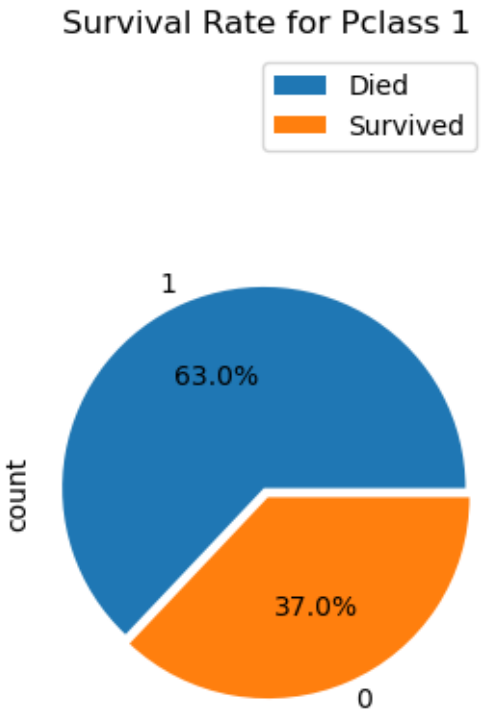
[ ]:
```
fig = plt.figure(figsize=(11, 4))
ax1 = fig.add_subplot(121)
sns.countplot(x = 'Pclass', hue = 'Survived', data = data,␣
 ↪palette=["red","green"])
```

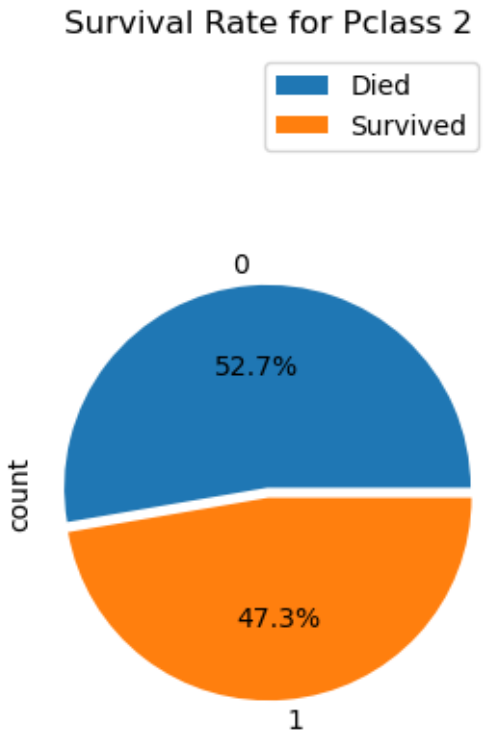
[ ]:
```
<Axes: xlabel='Pclass', ylabel='count'>
```



[ ]:
```
pclasses = data['Pclass'].unique()
for pclass in pclasses:
    pclass_data = data[data['Pclass'] == pclass].Survived.value_counts()
    plt.figure()
    pclass_data.plot(kind='pie', figsize=(3, 6), explode=[0, 0.05], autopct='%1.
 ↪1f%%')
    plt.axis('equal')
    plt.legend(["Died", "Survived"])
    plt.title(f"Survival Rate for Pclass {pclass}")
    plt.show()
```

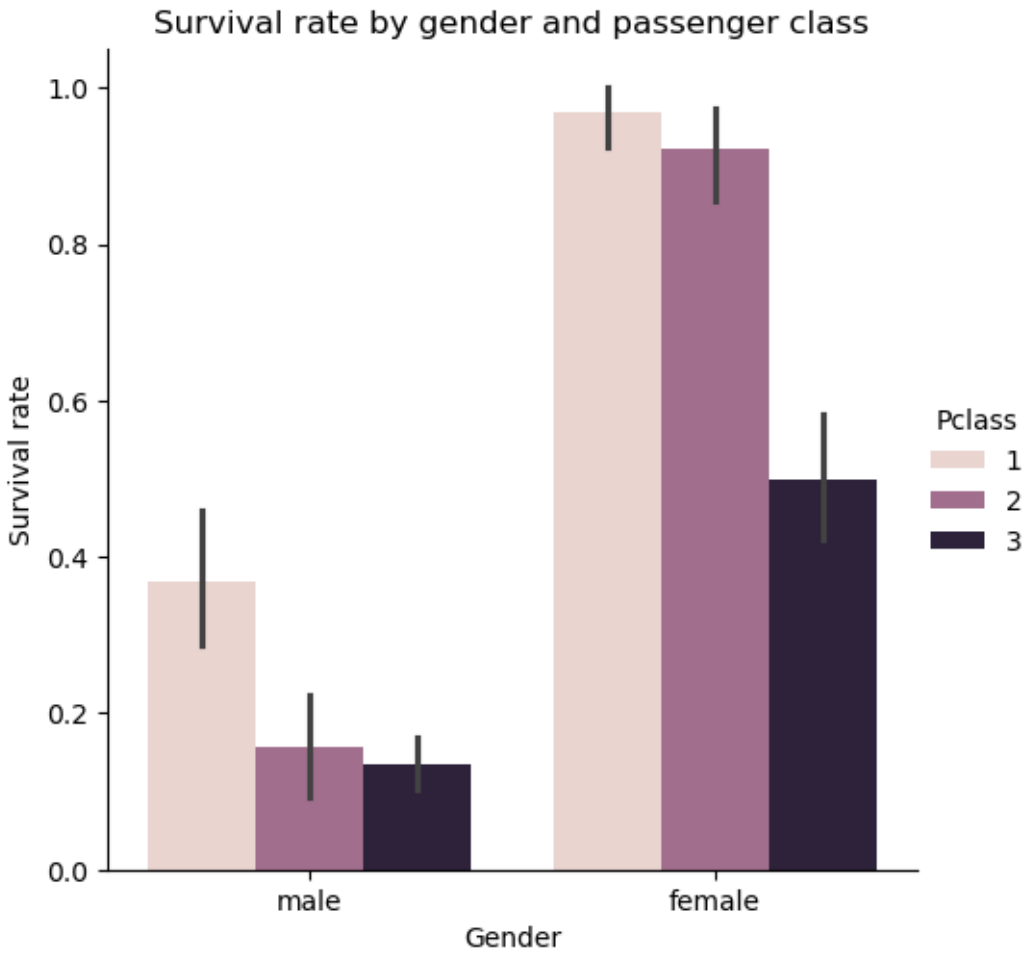

Survival Rate for Pclass 3
Died
Survived
0
75.8%
count
24.2%
1


Survival Rate for Pclass 1
Died
Survived
1
63.0%
count
37.0%
0

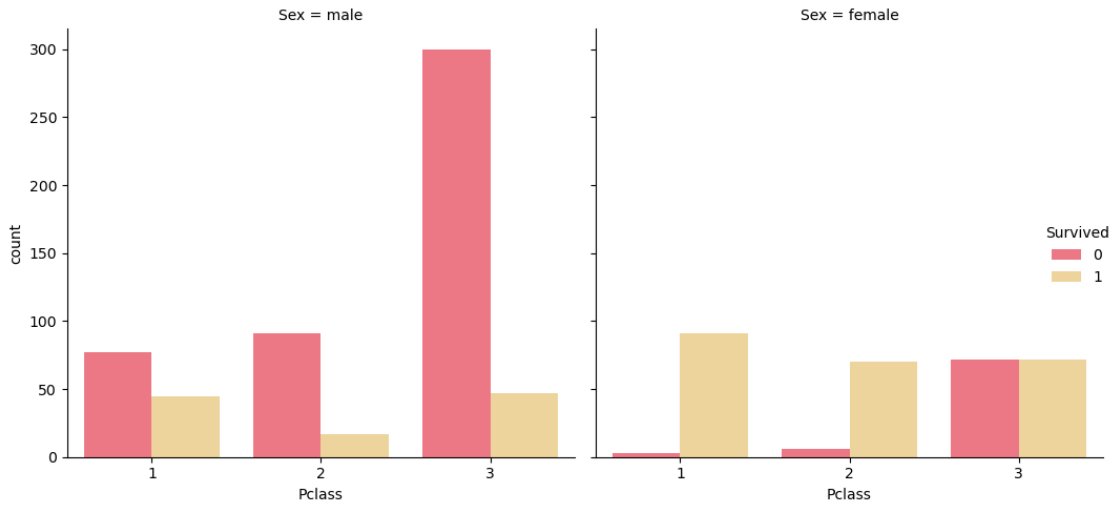


4.7 Survival rate by Gender and Passenger class

[ ]:
```
sns.catplot(x='Sex',y='Survived',hue='Pclass',data=data,kind='bar')
plt.title('Survival rate by gender and passenger class')
plt.xlabel('Gender')
plt.ylabel('Survival rate')
plt.show()
```



[ ]:
```
sns.catplot(x = 'Pclass', hue = 'Survived', col = 'Sex', kind = 'count', data =␣
↪data,palette=["#ff6577", "#f9da8f"] )
plt.tight_layout()
```

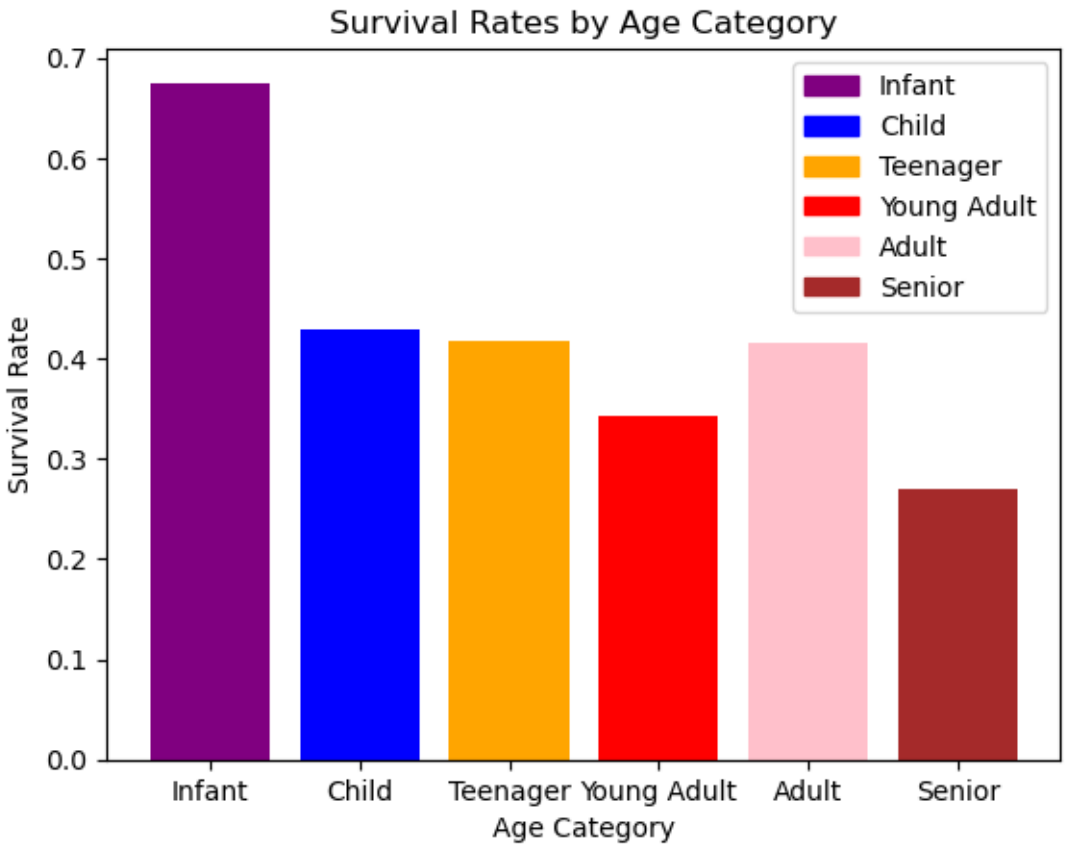


4.8 Survival rate by Age

[ ]:
```
cut_points = [ 0, 5, 12, 20, 35, 60, 100]
label_names = [ 'Infant', "Child", 'Teenager', "Young Adult", 'Adult', 'Senior']
data['Age_categories'] = pd.cut(data['Age'], bins=cut_points,␣
 ↪labels=label_names,right=False)
age_cat_pivot = data.pivot_table(index="Age_categories", values="Survived")
colors = ['purple', 'blue', 'orange', 'red', 'pink', 'brown']
fig, ax = plt.subplots()
bars = ax.bar(age_cat_pivot.index, age_cat_pivot['Survived'], color=colors)
handles = [plt.Rectangle((0, 0), 1, 1, color=colors[i]) for i in
range(len(colors))]
ax.legend(handles, label_names)
ax.set_title('Survival Rates by Age Category')
ax.set_xlabel('Age Category')
ax.set_ylabel('Survival Rate')
```

```
/var/folders/9s/09g1kdgn5p3fdcwfb0r_hrzh0000gn/T/ipykernel_41264/1280162392.py:4
: FutureWarning: The default value of observed=False is deprecated and will
change to observed=True in a future version of pandas. Specify observed=False to
silence this warning and retain the current behavior
  age_cat_pivot = data.pivot_table(index="Age_categories", values="Survived")
```

[ ]:
```
Text(0, 0.5, 'Survival Rate')
```



5 Machine Learning

5.1 Logistic Regression

5.1.1 Working with Age, Gender and Passenger Class individually

[ ]:
```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
y = data['Survived'].values
```

Survival Prediction Model based on Age

[ ]:
```
x_age = data[['Age']].values
lr.fit(x_age, y)
y_pred = lr.predict(x_age)
age_accuracy = accuracy_score(y, y_pred)
print(f"Age Accuracy: {age_accuracy}")
```

```
Age Accuracy: 0.6161616161616161
```

Survival Prediction Model based on Gender

[ ]:
```
x_sex = pd.get_dummies(data[['Sex']]).values
lr.fit(x_sex, y)
y_pred = lr.predict(x_sex)
sex_accuracy = accuracy_score(y,y_pred)
print(f'Sex Accuracy: {sex_accuracy}')
```

```
Sex Accuracy: 0.7867564534231201
```

Survival Prediction Model based on Passenger Class

[ ]:
```
x_pclass = data[['Pclass']].values
lr.fit(x_pclass, y)
y_pred = lr.predict(x_pclass)
pclass_accuracy = accuracy_score(y,y_pred)
print(f'Passenger Class Accuracy: {pclass_accuracy}')
```

```
Passenger Class Accuracy: 0.6790123456790124
```

Comparing the independent variable accuracies

[ ]:
```
pd.DataFrame({'Accuracy':[age_accuracy, sex_accuracy, pclass_accuracy]},␣
 ↪index=['Age', 'Sex', 'Pclass'])
```

[ ]:

	Accuracy
Age	0.616162
Sex	0.786756
Pclass	0.679012

5.1.2 Working with all the independent variables

[ ]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
data['Sex'] = le.fit_transform(data['Sex'])
data['Cabin'] = le.fit_transform(data['Cabin'])
```

[ ]:
```
x = data[['Sex', 'Age', 'Pclass', 'Cabin', 'SibSp', 'Parch']].values
y = data['Survived'].values
train_x, test_x, train_y, test_y = train_test_split(x, y, test_size=0.2,␣
 ↪random_state=0)
lr.fit(train_x,train_y)
y_pred = lr.predict(test_x)
lr_accuracy = accuracy_score(test_y, y_pred)
print(f'Logistic Regression Accuracy: {lr_accuracy}')
```

```
Logistic Regression Accuracy: 0.8212290502793296
```

Confusion Matrix

[ ]:
```
labels = np.unique(test_y)
conf_matrix = confusion_matrix(test_y, y_pred, labels=labels)
pd.DataFrame(conf_matrix, index=labels, columns=labels)
```

[ ]:

	0	1
0	95	15
1	17	52

5.2 KNN

[ ]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(train_x, train_y)
y_pred = knn.predict(test_x)
knn_accuracy = accuracy_score(test_y,y_pred)
print(f'KNN Accuracy: {knn_accuracy}')
```

```
KNN Accuracy: 0.7653631284916201
```

5.3 Random Forest

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(train_x, train_y)
y_pred = rfc.predict(test_x)
rfc_accuracy = accuracy_score(test_y, y_pred)
print(f'Random Forest Accracy: {rfc_accuracy}')
```

```
Random Forest Accracy: 0.7877094972067039
```

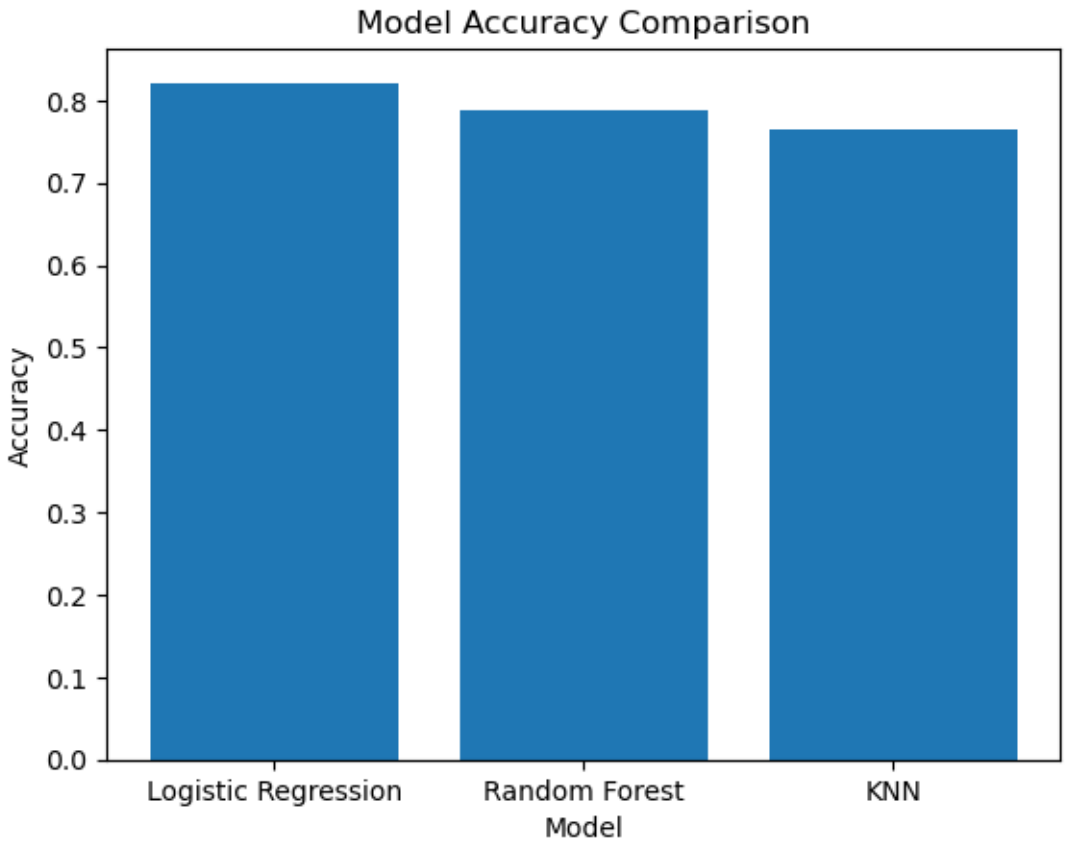
5.4 Comparing the models

[ ]:
```
results = pd.DataFrame({'Model':['Logistic Regression', 'KNN', 'Random␣
↪Forest'], 'Accuracy':[lr_accuracy, knn_accuracy, rfc_accuracy]})
sorted_results = results.sort_values(by='Accuracy', ascending=False)
sorted_results
```

[ ]:

	Model	Accuracy
0	Logistic Regression	0.821229
2	Random Forest	0.787709
1	KNN	0.765363

[ ]:
```
plt.bar(sorted_results['Model'], sorted_results['Accuracy'])
plt.title('Model Accuracy Comparison')
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.show()
```


Model Accuracy Comparison
Accuracy
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Logistic Regression
Random Forest
KNN
Model