prediction-project-codsoft-task-1

October 30, 2023

Titanic Survival Prediction Project-Giriraju B

Import Data from csv file

[223]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score,\
confusion_matrix, ConfusionMatrixDisplay, RocCurveDisplay
```

[224]:
```
df=pd.read_csv('/content/Titanic Data set.csv')
```

[225]:
```
df.head()
```

[225]:
```
   PassengerId  Survived  Pclass  \
0          892         0       3
1          893         1       3
2          894         0       2
3          895         0       3
4          896         1       3

                                           Name     Sex   Age  SibSp  Parch  \
0                              Kelly, Mr. James    male  34.5      0      0
1              Wilkes, Mrs. James (Ellen Needs)  female  47.0      1      0
2                     Myles, Mr. Thomas Francis    male  62.0      0      0
3                              Wirz, Mr. Albert    male  27.0      0      0
4  Hirvonen, Mrs. Alexander (Helga E Lindqvist)  female  22.0      1      1

    Ticket     Fare Cabin Embarked
0   330911   7.8292   NaN        Q
1   363272   7.0000   NaN        S
2   240276   9.6875   NaN        Q
3   315154   8.6625   NaN        S
4  3101298  12.2875   NaN        S
```

[226]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  418 non-null    int64
 1   Survived     418 non-null    int64
 2   Pclass       418 non-null    int64
 3   Name         418 non-null    object
 4   Sex          418 non-null    object
 5   Age          332 non-null    float64
 6   SibSp        418 non-null    int64
 7   Parch        418 non-null    int64
 8   Ticket       418 non-null    object
 9   Fare         417 non-null    float64
 10  Cabin        91 non-null     object
 11  Embarked     418 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 39.3+ KB
```

[227]:
```
df.isnull().sum()
```

[227]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age             86
SibSp            0
Parch            0
Ticket           0
Fare             1
Cabin          327
Embarked         0
dtype: int64
```

Data wrangling

[228]:
```
df['Age'].fillna(df['Age'].mean(),inplace=True)
```

[229]:
```
df['Fare'].fillna(df['Fare'].mean(),inplace=True)
```

[230]:
```
df['Embarked'].fillna(df['Embarked'].mode()[0],inplace=True)
```

[231]:
```
df.drop(columns=['Cabin'], inplace=True)
```

[232]:
```python
df.isnull().sum()
```

[232]:
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

[233]:
```python
df.describe()
```

[233]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   418.000000  418.000000  418.000000  418.000000  418.000000
mean   1100.500000    0.363636    2.265550   30.272590    0.447368
std     120.810458    0.481622    0.841838   12.634534    0.896760
min     892.000000    0.000000    1.000000    0.170000    0.000000
25%     996.250000    0.000000    1.000000   23.000000    0.000000
50%    1100.500000    0.000000    3.000000   30.272590    0.000000
75%    1204.750000    1.000000    3.000000   35.750000    1.000000
max    1309.000000    1.000000    3.000000   76.000000    8.000000

            Parch        Fare
count  418.000000  418.000000
mean     0.392344   35.627188
std      0.981429   55.840500
min      0.000000    0.000000
25%      0.000000    7.895800
50%      0.000000   14.454200
75%      0.000000   31.500000
max      9.000000  512.329200
```

[234]:
```python
df['Survived'].value_counts()
```

[234]:
```
0    266
1    152
Name: Survived, dtype: int64
```

[235]:
```python
df['Sex'].value_counts()
```

[235]:
```
male      266
female    152
```

```
Name: Sex, dtype: int64
```

So we can understand all the males died on saving females,lol!!

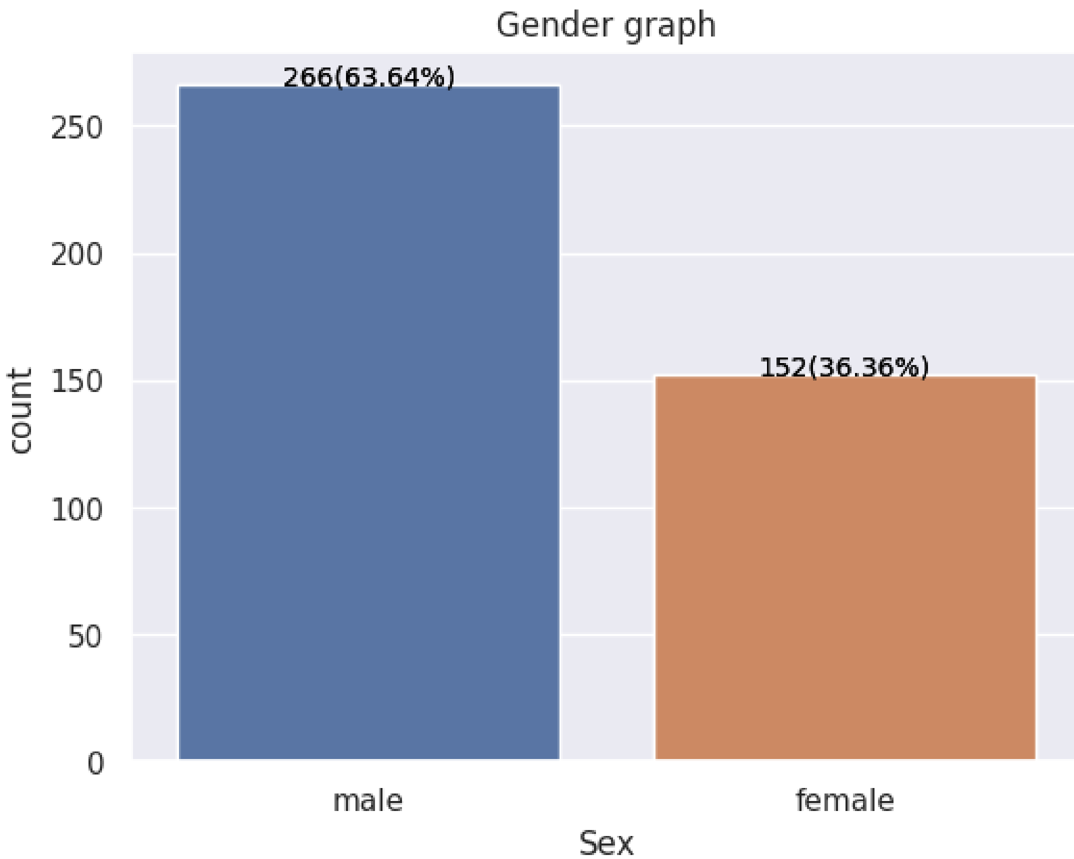
[236]:
```
df['Embarked'].value_counts()
```

[236]:
```
S    270
C    102
Q     46
Name: Embarked, dtype: int64
```

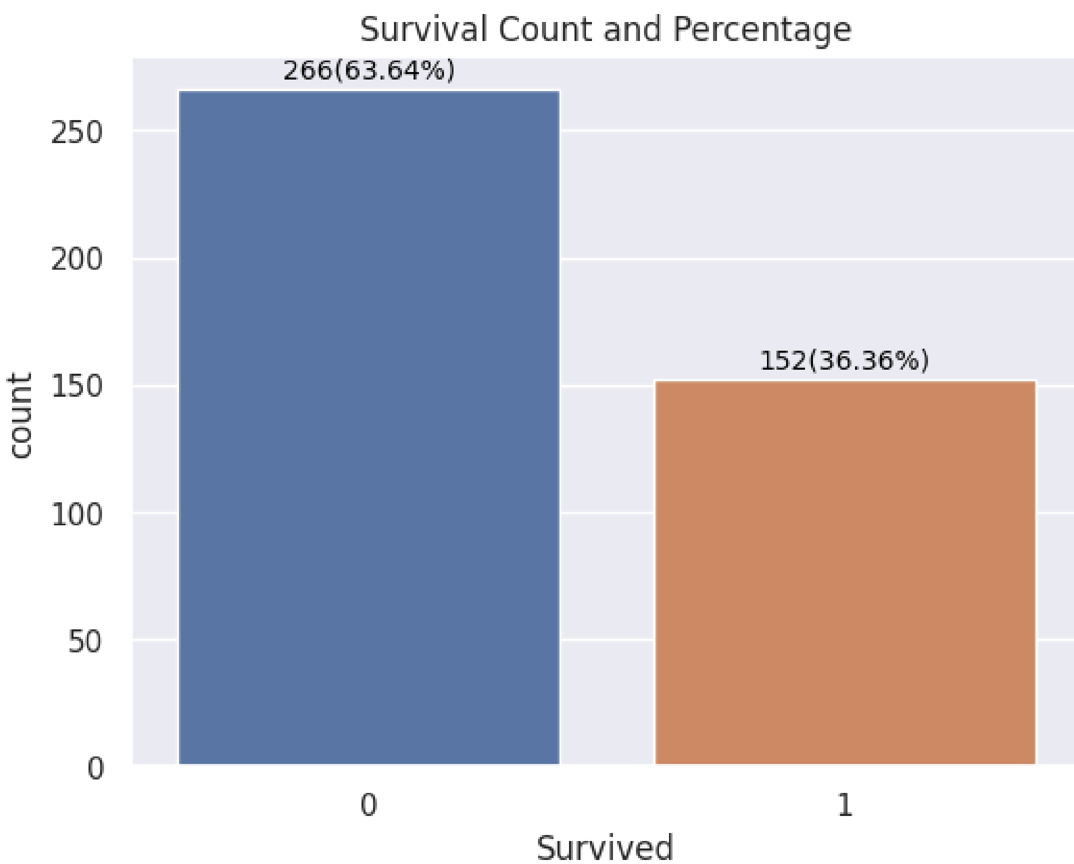
Data visualization

[237]:
```
sns.set()
```

[238]:
```
sns.countplot(x='Sex',data=df)
plt.title('Gender graph')

ax = sns.countplot(x='Sex', data=df)


total = len(df['Sex'])
for p in ax.patches:
    count = p.get_height()
    percentage = 100 * count / total
    x = p.get_x() + p.get_width() / 2
    y = p.get_height() + 0.05
    ax.annotate(f'{int(count)}({percentage:.2f}%)', (x, y), ha='center',␣
 ↪fontsize=10, color='black')


plt.title('Gender graph')


plt.show()
```



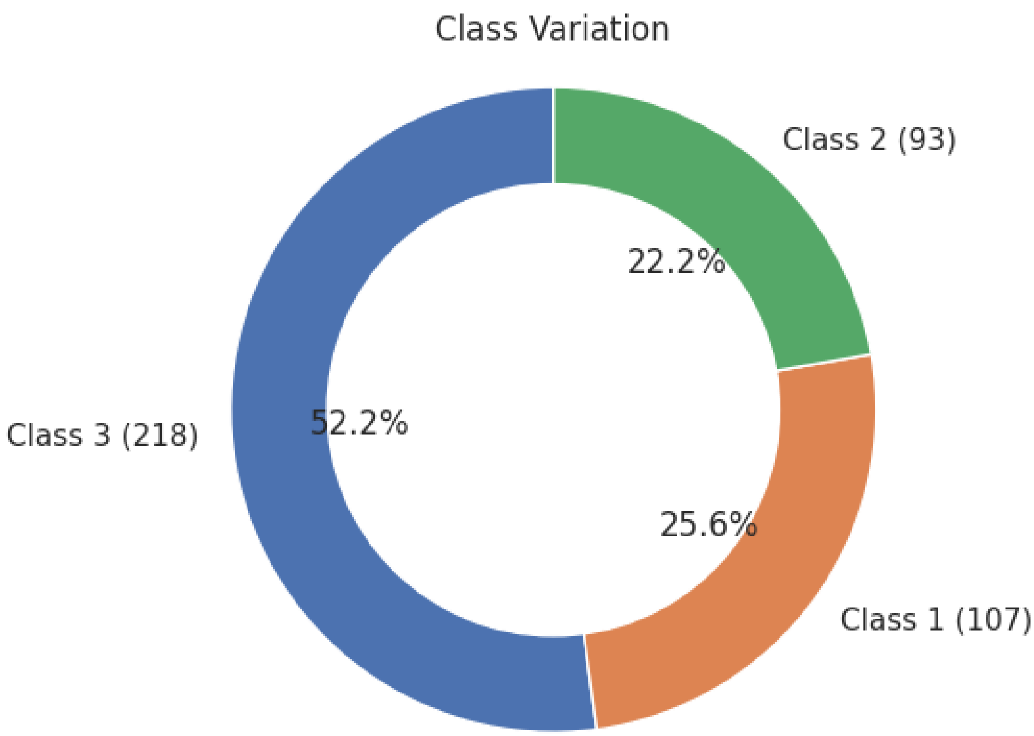
[239]:
```
ax = sns.countplot(x='Survived', data=df)


total = len(df['Survived'])
for p in ax.patches:
    count = p.get_height()
    percentage = 100 * count / total
    x = p.get_x() + p.get_width() / 2
    y = p.get_height() + 5
    ax.annotate(f'{int(count)}({percentage:.2f}%)', (x, y), ha='center',␣
 ↪fontsize=10, color='black')

plt.title('Survival Count and Percentage')

plt.show()
```



[240]:
```
class_counts = df['Pclass'].value_counts()


plt.pie(class_counts, labels=[f'Class {i} ({count})' for i, count in␣
↪class_counts.iteritems()], autopct='%1.1f%%', startangle=90,␣
↪wedgeprops=dict(width=0.4))


centre_circle = plt.Circle((0,0),0.70,fc='white')
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

plt.axis('equal')

plt.title('Class Variation')

plt.show()
```

```
<ipython-input-240-f1b15da63cbd>:4: FutureWarning: iteritems is deprecated and
will be removed in a future version. Use .items instead.
```

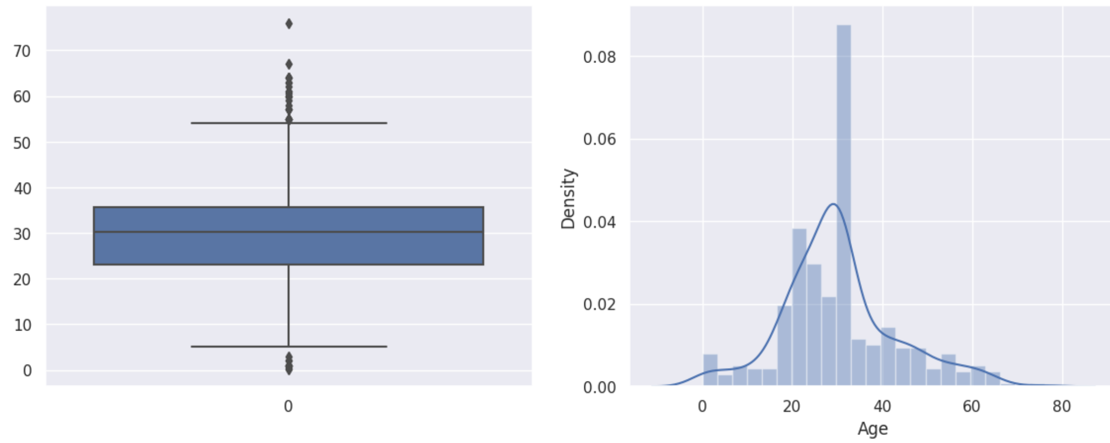
```
  plt.pie(class_counts, labels=[f'Class {i} ({count})' for i, count in
class_counts.iteritems()], autopct='%1.1f%%', startangle=90,
wedgeprops=dict(width=0.4))
```



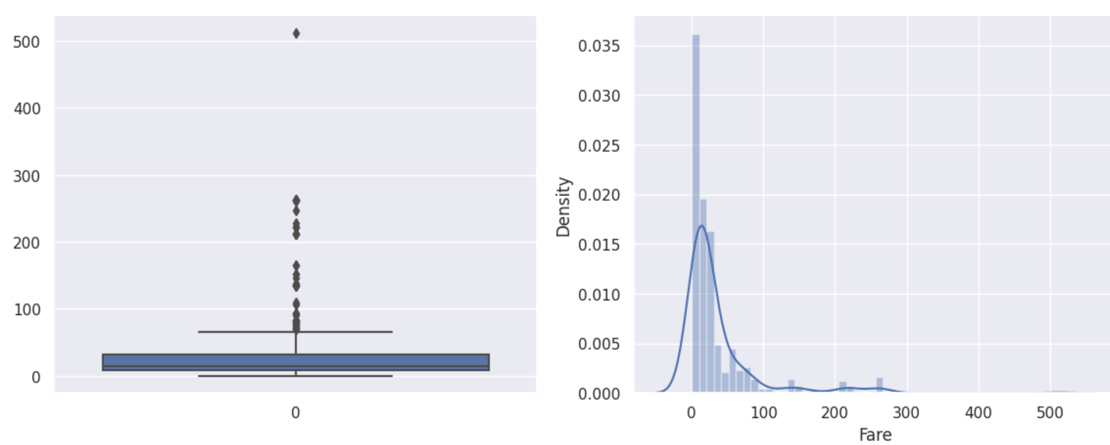
[241]:
```
Age_Fare = ['Age', 'Fare']
for column in Age_Fare:
    plt.figure(figsize=(14,5))
    plt.subplot(1,2,1)
    ax = sns.boxplot(df[column])

    plt.subplot(1,2,2)
    ax = sns.distplot(df[column])
    plt.show()
```

```
<ipython-input-241-1fc3ed409439>:8: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751
```

```
  ax = sns.distplot(df[column])
```



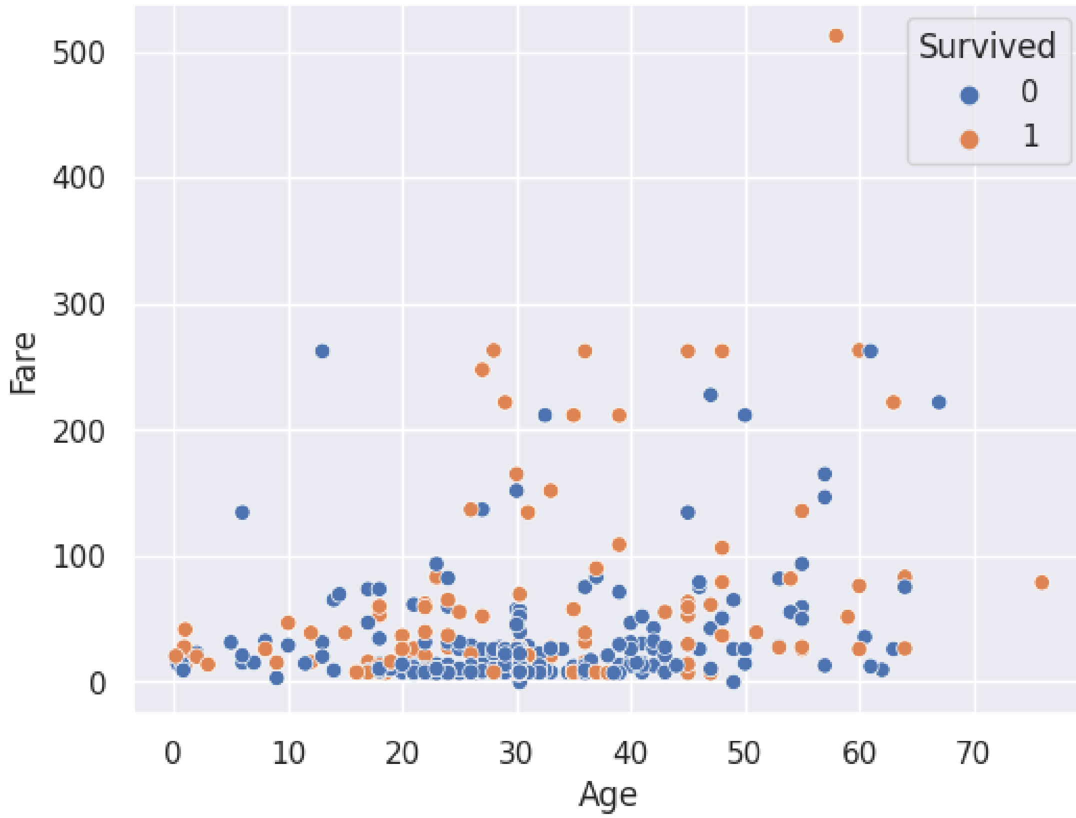

```
<ipython-input-241-1fc3ed409439>:8: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  ax = sns.distplot(df[column])
```



- In the ‘Age’ variable, there are some outliers present. The distribution of ages indicates that the majority of passengers fell within the age range of 20 to 40 years old.

- Regarding the 'Fare' variable, it exhibits several outliers, suggesting that there were passengers who paid significantly higher fares. Additionally, the distribution of fares is right-skewed, indicating that the majority of passengers paid lower fares, with a few paying much higher amounts.

[242]:
```
sns.scatterplot(data=df, x='Age', y='Fare', hue='Survived')
plt.show()
```



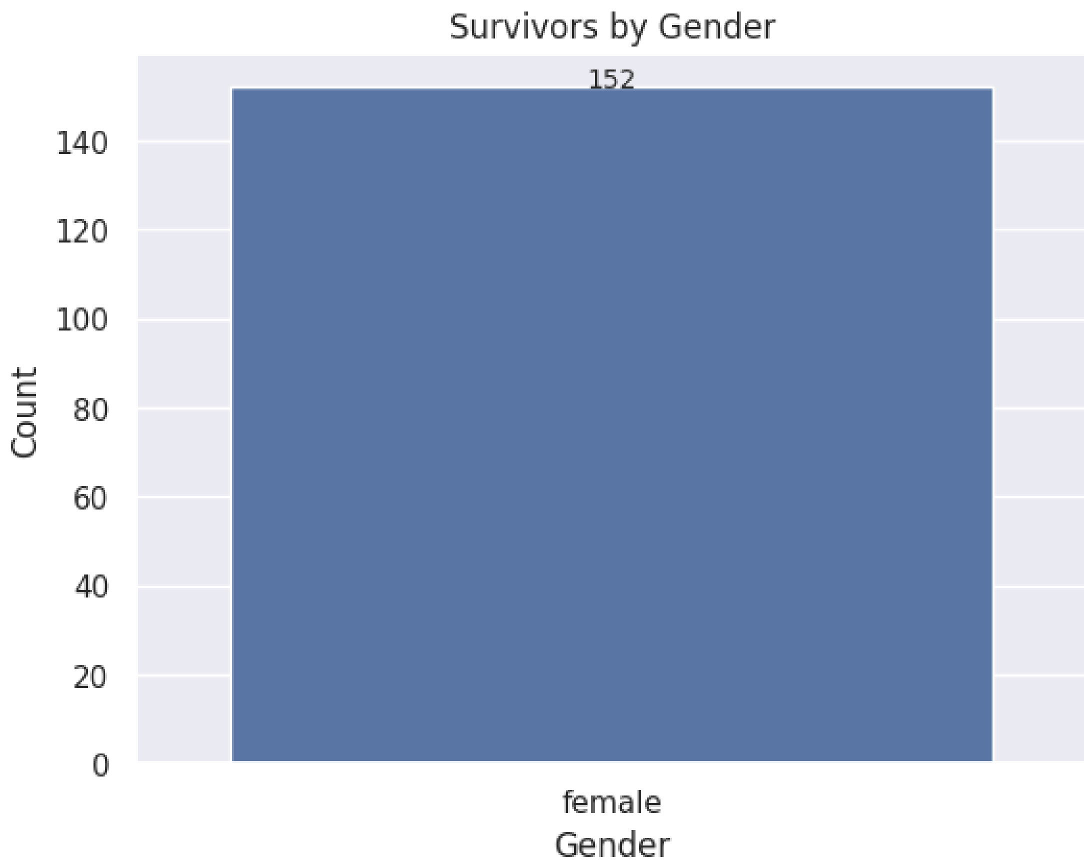
The scatterplot shows that the passengers with high fares had more chance of survival

To count & Visualise by Survived by people

Survived by Gender

[243]:
```
ax = sns.countplot(x='Sex', data=df[df['Survived'] == 1])
total_survived = len(df[df['Survived'] == 1])

for p in ax.patches:
    count = p.get_height()
    x = p.get_x() + p.get_width() / 2
    y = p.get_height() + 0.05
    ax.annotate(f'{int(count)}', (x, y), ha='center', fontsize=10)
```

```
plt.title('Survivors by Gender')
plt.xlabel('Gender')
plt.ylabel('Count')

plt.show()
```



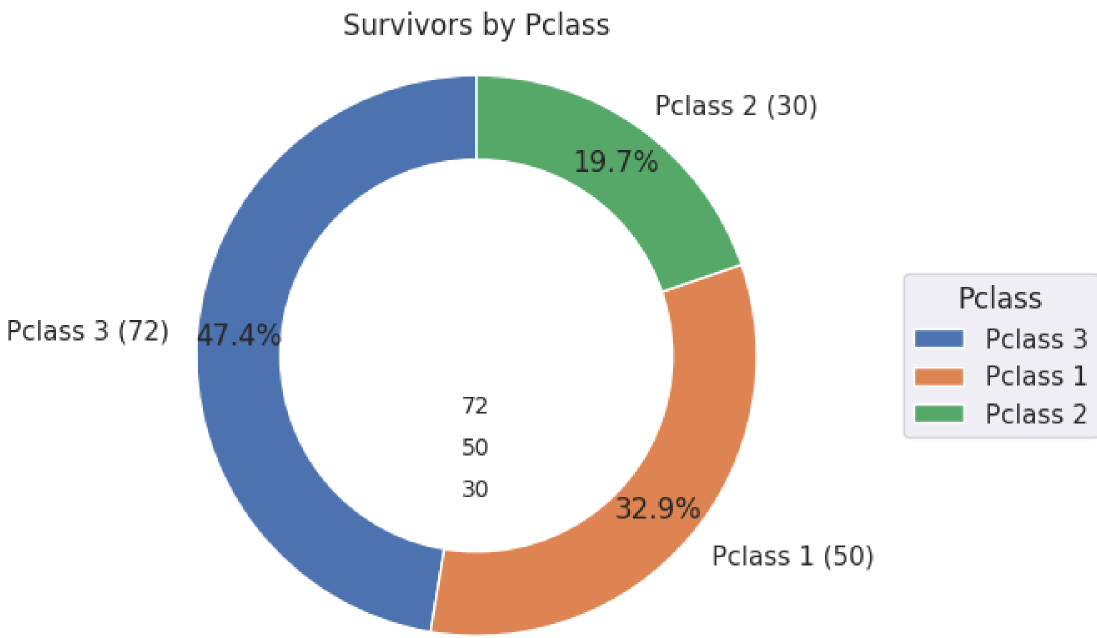
So, by the above graph you can see only females are alive in the titanic accident.By this we can confirm they followed "Womens and children first" if *an* accident occurs!!

Survived by Pclass

[244]:
```
survived_by_pclass = df[df['Survived'] == 1]['Pclass'].value_counts()

plt.pie(survived_by_pclass, labels=[f'Pclass {i} ({count})' for i, count in␣
↪survived_by_pclass.iteritems()],
        autopct='%1.1f%%', startangle=90, pctdistance=0.85,␣
↪wedgeprops=dict(width=0.4))

centre_circle = plt.Circle((0, 0), 0.70, fc='white')
```

```
fig = plt.gcf()
fig.gca().add_artist(centre_circle)

plt.axis('equal')
plt.legend([f'Pclass {i}' for i in survived_by_pclass.index], title='Pclass',␣
↪loc='center left', bbox_to_anchor=(1, 0, 0.5, 1))

for i, count in enumerate(survived_by_pclass):
    plt.text(0, -0.2 - i*0.15, f'{int(count)}', ha='center', fontsize=10)


plt.title('Survivors by Pclass')
plt.show()
```

```
<ipython-input-244-32ea0026edd4>:3: FutureWarning: iteritems is deprecated and
will be removed in a future version. Use .items instead.
  plt.pie(survived_by_pclass, labels=[f'Pclass {i} ({count})' for i, count in
survived_by_pclass.iteritems()],
```



Data value replacing with numbers

[245]:
```
df.new=df.replace({'Sex':{'male':'0','female':'1'},'Embarked':{'S':'0','C':
↪'1','Q':'2'}})
```

```
<ipython-input-245-b067cfad61b6>:1: UserWarning: Pandas doesn't allow columns to
be created via a new attribute name - see https://pandas.pydata.org/pandas-
```

```
docs/stable/indexing.html#attribute-access
  df.new=df.replace({'Sex':{'male':'0','female':'1'},'Embarked':{'S':'0','C':'1'
,'Q':'2'}})
```

Separating Features and Target

[246]:
```python
X=df.new.drop(columns=['PassengerId', 'Name', 'Ticket'])
Y=df.new['Survived']
```

[247]:
```python
print(X)
```

```
     Survived  Pclass Sex       Age  SibSp  Parch      Fare Embarked
0           0       3   0  34.50000      0      0    7.8292        2
1           1       3   1  47.00000      1      0    7.0000        0
2           0       2   0  62.00000      0      0    9.6875        2
3           0       3   0  27.00000      0      0    8.6625        0
4           1       3   1  22.00000      1      1   12.2875        0
..        …       …  ..       …    …    …       …      …
413         0       3   0  30.27259      0      0    8.0500        0
414         1       1   1  39.00000      0      0  108.9000        1
415         0       3   0  38.50000      0      0    7.2500        0
416         0       3   0  30.27259      0      0    8.0500        0
417         0       3   0  30.27259      1      1   22.3583        1

[418 rows x 8 columns]
```

[248]:
```python
print(Y)
```

```
0      0
1      1
2      0
3      0
4      1
      ..
413    0
414    1
415    0
416    0
417    0
Name: Survived, Length: 418, dtype: int64
```

Training data & testing data

[249]:
```python
X_train, X_test,Y_train, Y_test = train_test_split(X,Y,test_size=0.2,
 ↪random_state=2)
```

[250]:
```python
print(X.shape,X_train.shape,X_test.shape)
```

```
(418, 8) (334, 8) (84, 8)
```

Model Training

Logistics Regression

[251]:
```
model = LogisticRegression()
```

[252]:
```
model.fit(X_train,Y_train)
```

[252]:
```
LogisticRegression()
```

Model Evaluation

Accuracy Score

[253]:
```
X_train_prediction=model.predict(X_train)
```

[254]:
```
print(X_train_prediction)
```

```
[1 1 0 0 1 1 0 0 0 1 0 0 1 0 0 0 1 0 1 0 1 0 1 1 0 0 0 0 0 1 0 0 0 0 0 0 0
 1 1 1 0 0 0 1 0 0 0 1 0 1 0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 1 0 1 0 1 1 1 0 1
 0 1 0 0 0 0 0 0 0 0 0 0 0 1 1 0 1 1 0 1 0 0 0 0 0 0 0 1 0 1 1 1 0 1 0 1 0
 1 1 0 0 0 0 1 1 0 1 0 0 1 1 0 1 0 0 0 0 0 0 1 0 0 1 0 0 1 0 0 1 0 1 1 0 0
 0 0 1 1 1 0 0 1 1 0 1 1 0 0 0 0 0 0 0 1 1 0 0 1 1 1 1 0 1 0 0 0 0 1 0 1 1
 1 0 1 0 0 0 1 0 0 0 1 0 1 0 0 0 0 0 0 0 1 1 1 1 0 0 0 0 1 0 0 1 0 0 1 0 0
 1 0 1 0 0 0 0 0 1 0 0 0 1 1 0 0 0 1 1 0 1 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 1
 0 1 1 1 1 0 0 0 1 1 0 0 1 0 1 1 0 0 0 0 1 0 0 0 0 0 1 0 0 1 1 0 1 1 0 0 0
 0 0 0 0 1 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 1 1 0 1 1 0 0 0 1 1 1
 1]
```

[255]:
```
Training_data_accuracy= accuracy_score(Y_train,X_train_prediction)
print('Accuracy Score of training data: ',Training_data_accuracy)
```

```
Accuracy Score of training data:  1.0
```

[256]:
```
X_test_prediction=model.predict(X_test)
Test_data_accuracy= accuracy_score(Y_test,X_test_prediction)
print('Accuracy Score of testing data: ',Test_data_accuracy)
```

```
Accuracy Score of testing data:  1.0
```

Neighbour Classfier

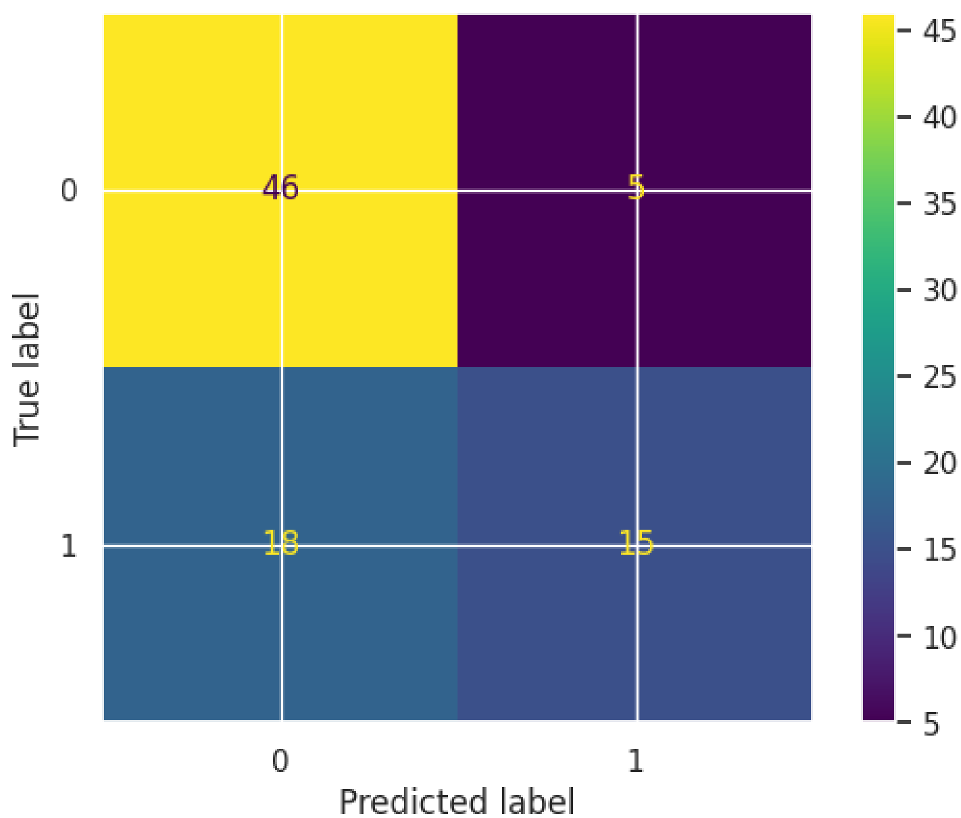
[257]:
```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier()
knn.fit(X_train,Y_train)
Y_pred_knn = knn.predict(X_test)
```

[258]:
```
print('Accuracy: ', accuracy_score(Y_test, Y_pred_knn))
print('Precision: ', precision_score(Y_test, Y_pred_knn))
```

```
print('Recall: ', recall_score(Y_test, Y_pred_knn))
print('F1 Score: ', f1_score(Y_test, Y_pred_knn))
```

```
Accuracy:  0.7261904761904762
Precision:  0.75
Recall:  0.45454545454545453
F1 Score:  0.5660377358490566
```

[260]:
```
cm = confusion_matrix(Y_test, Y_pred_knn, labels=knn.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=knn.classes_)
disp.plot();
```



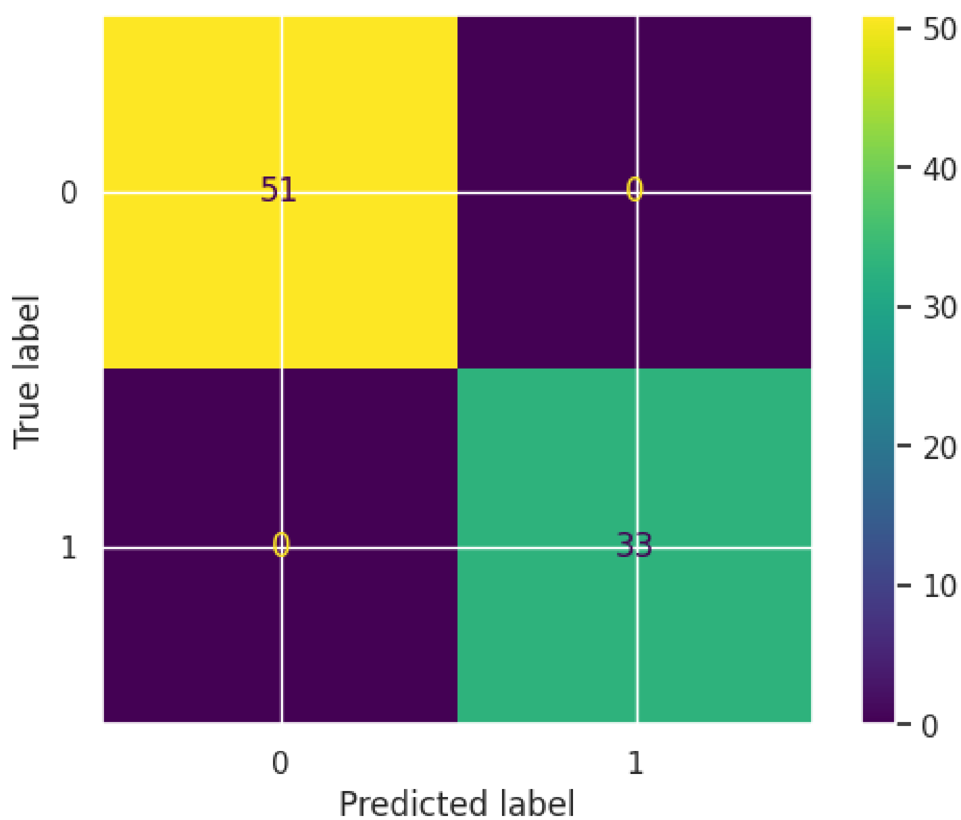
[261]:
```
from sklearn.tree import DecisionTreeClassifier

tree = DecisionTreeClassifier()
tree.fit(X_train,Y_train)
y_pred_tree = tree.predict(X_test)
```

[262]:
```
print('Accuracy: ', accuracy_score(Y_test, y_pred_tree))
print('Precision: ', precision_score(Y_test, y_pred_tree))
print('Recall: ', recall_score(Y_test, y_pred_tree))
```

```python
print('F1 Score: ', f1_score(Y_test, y_pred_tree))
```

```
Accuracy:  1.0
Precision:  1.0
Recall:  1.0
F1 Score:  1.0
```

[263]:
```python
cm = confusion_matrix(Y_test, y_pred_tree, labels=tree.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=tree.classes_)
disp.plot();
```



Summary:

The treemap visualization indicates that the Decision Tree model achieved perfect accuracy in predicting passenger survival solely based on their gender. This is because all females survived the Titanic disaster, while all males did not.

Key statistics:

- 36.36% of passengers survived the Titanic disaster.
- 63.64% of passengers did not survive.

Gender-based survival:

- All females survived.
- None of the males survived.

Class-based survival:

- Passengers in Class 3 and 2 had a lower chance of survival.

Model Performance: Both the Logistic Regression and Decision Tree models achieved 100% accuracy.

`**Thank You !!**`