```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

```
# Load the dataset
data = pd.read_csv('/content/tested.csv')
```

```
data
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	892	0	3	Kelly, Mr. James	1	34.50000	0	0	330911	7.8292	1
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	0	47.00000	1	0	363272	7.0000	2
2	894	0	2	Myles, Mr. Thomas Francis	1	62.00000	0	0	240276	9.6875	1
3	895	0	3	Wirz, Mr. Albert	1	27.00000	0	0	315154	8.6625	2
4	896	1	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	0	22.00000	1	1	3101298	12.2875	2
...	...	...	...	...	...	...	...	...	...	...	...
413	1305	0	3	Spector, Mr. Woolf	1	30.27259	0	0	A.5. 3236	8.0500	2
414	1306	1	1	Oliva y Ocana, Dona. Fermina	0	39.00000	0	0	PC 17758	108.9000	0
415	1307	0	3	Saether, Mr. Simon Sivertsen	1	38.50000	0	0	SOTON/O.Q. 3101262	7.2500	2
416	1308	0	3	Ware, Mr. Frederick	1	30.27259	0	0	359309	8.0500	2
417	1309	0	3	Peter, Master. Michael J	1	30.27259	1	1	2668	22.3583	0

418 rows × 11 columns

Next steps: Generate code with data | View recommended plots

```
len(data)
```

```
418
```

```
data.shape
```

```
(418, 11)
```

```
new_data=data[['Pclass','Sex','Age','Fare','Survived']]
new_data
```

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

418 rows × 5 columns

Next steps: Generate code with new_data View recommended plots

```
print (data.columns,'/n/n/n/n')
data.info()
```

```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Embarked'],
      dtype='object') /n/n/n/n
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 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    int64
 5   Age          418 non-null    float64
 6   SibSp        418 non-null    int64
 7   Parch        418 non-null    int64
 8   Ticket       418 non-null    object
 9   Fare         418 non-null    float64
 10  Embarked     418 non-null    int64
dtypes: float64(2), int64(7), object(2)
memory usage: 36.0+ KB
```

```
data.sample(10)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	
97	989	0	3	Makinen, Mr. Kalle Edvard	1	29.00000	0	0	STON/O 2. 3101268	7
343	1235	1	1	Cardeza, Mrs. James Warburton Martinez (Charlo...	0	58.00000	0	1	PC 17755	512
146	1038	0	1	Hilliard, Mr. Herbert Henry	1	30.27259	0	0	17463	51
180	1072	0	2	McCrie, Mr. James Matthew	1	30.00000	0	0	233478	13
53	945	1	1	Fortune, Miss. Ethel	0	28.00000	3	2	19950	263

```
data.describe()
```

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch
count	418.000000	418.000000	418.000000	418.000000	418.000000	418.000000	418.00000C
mean	1100.500000	0.363636	2.265550	0.636364	30.272590	0.447368	0.392344
std	120.810458	0.481622	0.841838	0.481622	12.634534	0.896760	0.981429
min	892.000000	0.000000	1.000000	0.000000	0.170000	0.000000	0.00000C
25%	996.250000	0.000000	1.000000	0.000000	23.000000	0.000000	0.00000C
50%	1100.500000	0.000000	3.000000	1.000000	30.272590	0.000000	0.00000C
75%	1204.750000	1.000000	3.000000	1.000000	35.750000	1.000000	0.00000C
max	1309.000000	1.000000	3.000000	1.000000	76.000000	8.000000	9.00000C

```
data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Em
0	892	0	3	Kelly, Mr. James	1	34.5	0	0	330911	7.8292	
1	893	1	3	Wilkes, Mrs. James (Ellen Needs)	0	47.0	1	0	363272	7.0000	

Next steps: Generate code with `data` View recommended plots

```
new_data1=new_data.dropna()
new_data1
```

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

418 rows × 5 columns

Next steps: Generate code with `new_data1` View recommended plots

```
data.tail()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket
413	1305	0	3	Spector, Mr. Woolf	1	30.27259	0	0	A.5. 3236
414	1306	1	1	Oliva y Ocana, Dona. Fermina	0	39.00000	0	0	PC 17758 1

```
target=new_data1.Survived
target
```

```
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
```

```
inputs=new_data1.drop('Survived',axis='columns')
inputs
```

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

418 rows × 4 columns

Next steps: Generate code with inputs View recommended plots

```
from sklearn.preprocessing import LabelEncoder
le_sex=LabelEncoder()
inputs['Sex_n']= le_sex.fit_transform(inputs['Sex'])
inputs
```

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

418 rows × 5 columns

Next steps: Generate code with inputs View recommended plots

```
inputs_new=inputs.drop('Sex', axis='columns')
inputs_new
```

	Pclass	Age	Fare	Sex_n
0	3	34.50000	7.8292	1
1	3	47.00000	7.0000	0
2	2	62.00000	9.6875	1
3	3	27.00000	8.6625	1
4	3	22.00000	12.2875	0
...	...	...	...	...
413	3	30.27259	8.0500	1
414	1	39.00000	108.9000	0
415	3	38.50000	7.2500	1
416	3	30.27259	8.0500	1
417	3	30.27259	22.3583	1

418 rows × 4 columns

Next steps: Generate code with `inputs_new` View recommended plots

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(inputs_new, target, test_size=0.1, random_state=42)
len(X_train)
```

```
376
```

```
len(y_test)
```

```
42
```

```
from sklearn.model_selection import cross_val_score
from sklearn import tree
model_DecisionTree=tree.DecisionTreeClassifier()
model_DecisionTree.fit(X_train,y_train)
model_DecisionTree.score(X_test,y_test)
```

```
1.0
```

```
scores_DecisionTree=cross_val_score(tree.DecisionTreeClassifier(),X_train,y_train,cv=10)
scores_DecisionTree
```

```
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])
```

```
scores_DecisionTree.mean()
```

```
1.0
```

```
from sklearn.svm import SVC
model_svm=SVC()
model_svm.fit(X_train,y_train)
model_svm.score(X_test,y_test)
```

```
0.5476190476190477
```

```
scores_svm=cross_val_score(SVC(),X_train,y_train,cv=10)
scores_svm
```

```
array([0.65789474, 0.68421053, 0.68421053, 0.68421053, 0.63157895,
       0.63157895, 0.62162162, 0.64864865, 0.62162162, 0.64864865])
```

```
scores_svm.mean()
```

```
0.6514224751066855
```

```
from sklearn.ensemble import RandomForestClassifier
model_RandomForest=RandomForestClassifier(n_estimators=500)
model_RandomForest.fit(X_train,y_train)
model_RandomForest.score(X_test,y_test)
```

```
1.0
```

```
scores_RandomForest=cross_val_score(RandomForestClassifier(n_estimators=500),X_train,y_train,cv=10)
scores_RandomForest
```

```
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])
```

```
scores_RandomForest.mean()
```

```
1.0
```

```
from sklearn.linear_model import LogisticRegression
model_LogisticRegression=LogisticRegression()
model_LogisticRegression.fit(X_train,y_train)
model_LogisticRegression.score(X_test,y_test)
```

```
1.0
```

```
scores_LogisticRegression=cross_val_score(LogisticRegression(),X_train,y_train,cv=10)
scores_LogisticRegression
```

```
array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])
```

```
scores_LogisticRegression.mean()
```

```
1.0
```

```
predictions = model_RandomForest.predict(X_test)
predictions
```

```
array([0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0,
       1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1])
```

```
y_test
```

```
321    0
324    1
388    0
56     0
153    1
30     0
72     1
82     0
258    1
416    0
9      0
391    1
104    1
414    1
413    0
39     0
412    1
378    0
55     0
406    0
387    0
245    0
409    1
180    0
225    1
113    1
364    1
148    0
337    0
78     0
210    0
367    1
141    1
93     0
222    1
204    0
```

```
79     1
301    0
248    1
75     0
70     1
33     1
Name: Survived, dtype: int64
```

```
import tensorflow as tf
from tensorflow import keras

#I will create a neural network
#I will have same number of neurons as columns, so 2
#we use relu as activation function because is easy to compute relu

model=keras.Sequential([
    keras.layers.Dense(4,input_shape=(4,),activation='relu'),
    keras.layers.Dense(1, activation='sigmoid')

])

#loss is binary_crossentropy because our output is binary, zero and one
#adam is a very commonly used optimizer
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy']
)
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 4)                 20

 dense_1 (Dense)             (None, 1)                 5

=================================================================
Total params: 25 (100.00 Byte)
Trainable params: 25 (100.00 Byte)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

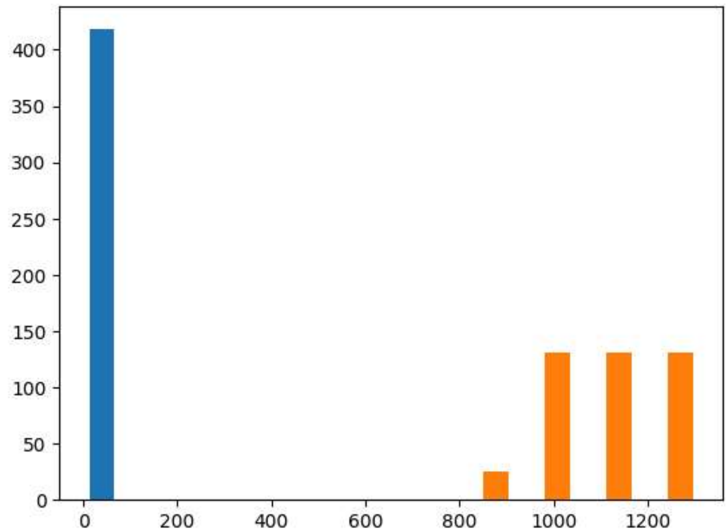
```
epochs = 200
history = model.fit(
    X_train,
    y_train,
    epochs=epochs
)
```

```
Epoch 186/200
12/12 [==============================] - 0s 3ms/step - loss: 0.5963 - accuracy: 0.6436
Epoch 187/200
12/12 [==============================] - 0s 3ms/step - loss: 0.5953 - accuracy: 0.6436
Epoch 188/200
12/12 [==============================] - 0s 3ms/step - loss: 0.5946 - accuracy: 0.6410
Epoch 189/200
12/12 [==============================] - 0s 3ms/step - loss: 0.5939 - accuracy: 0.6410
Epoch 190/200
12/12 [==============================] - 0s 3ms/step - loss: 0.5933 - accuracy: 0.6702
Epoch 191/200
12/12 [==============================] - 0s 3ms/step - loss: 0.5927 - accuracy: 0.6702
Epoch 192/200
12/12 [==============================] - 0s 3ms/step - loss: 0.5919 - accuracy: 0.6729
Epoch 193/200
12/12 [==============================] - 0s 3ms/step - loss: 0.5912 - accuracy: 0.6729
Epoch 194/200
12/12 [==============================] - 0s 4ms/step - loss: 0.5903 - accuracy: 0.6729
Epoch 195/200
12/12 [==============================] - 0s 3ms/step - loss: 0.5897 - accuracy: 0.6782
Epoch 196/200
12/12 [==============================] - 0s 2ms/step - loss: 0.5889 - accuracy: 0.6729
Epoch 197/200
12/12 [==============================] - 0s 2ms/step - loss: 0.5883 - accuracy: 0.6729
Epoch 198/200
12/12 [==============================] - 0s 3ms/step - loss: 0.5875 - accuracy: 0.6676
Epoch 199/200
12/12 [==============================] - 0s 3ms/step - loss: 0.5866 - accuracy: 0.6676
Epoch 200/200
12/12 [==============================] - 0s 3ms/step - loss: 0.5861 - accuracy: 0.6676
```

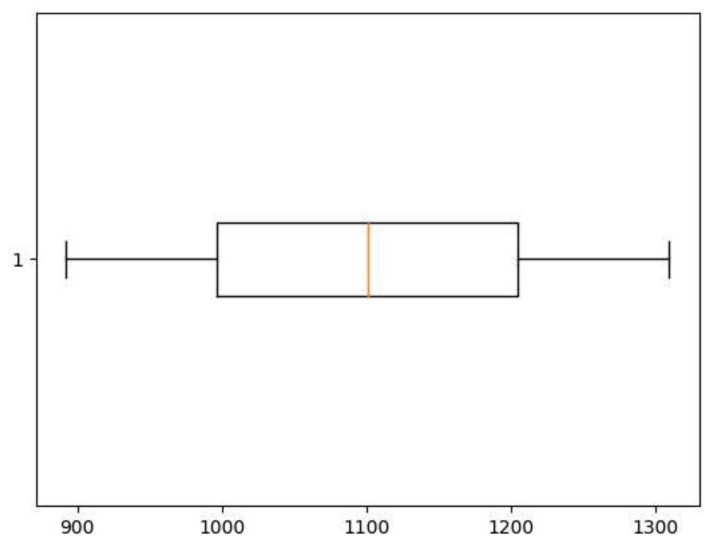
```
epochs = 200
history = model.fit(
    X_test,
    y_test,
    epochs=epochs
)
```

```
Epoch 195/200
2/2 [==============================] - 0s 13ms/step - loss: 0.5247 - accuracy: 0.7381
Epoch 196/200
2/2 [==============================] - 0s 14ms/step - loss: 0.5242 - accuracy: 0.7381
Epoch 197/200
2/2 [==============================] - 0s 13ms/step - loss: 0.5235 - accuracy: 0.7381
Epoch 198/200
2/2 [==============================] - 0s 12ms/step - loss: 0.5230 - accuracy: 0.7381
Epoch 199/200
2/2 [==============================] - 0s 10ms/step - loss: 0.5216 - accuracy: 0.7381
Epoch 200/200
2/2 [==============================] - 0s 12ms/step - loss: 0.5212 - accuracy: 0.7857
```

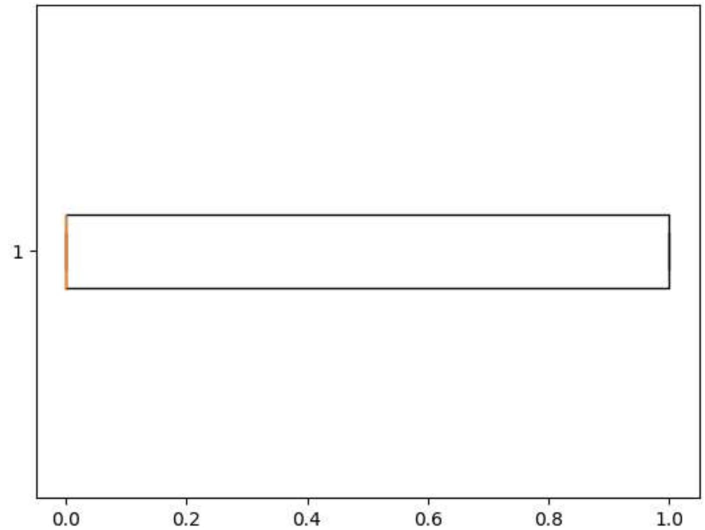
```
import matplotlib.pyplot as plt
plt.hist(data[['Survived','PassengerId']]);
```




```
plt.boxplot(data['PassengerId'],vert=False);
```




```
plt.boxplot(data['Survived'],vert=False);
```




```
data['Survived'].describe()
```

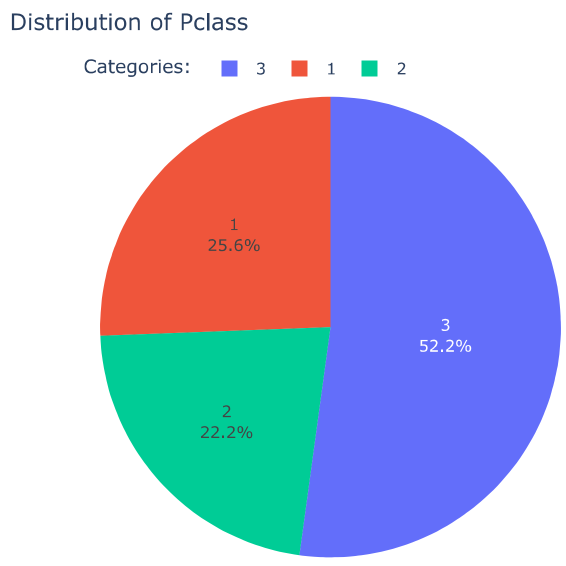
```
count    418.000000
mean       0.363636
std        0.481622
min        0.000000
25%        0.000000
50%        0.000000
75%        1.000000
max        1.000000
Name: Survived, dtype: float64
```

```
data.isna().sum()
```

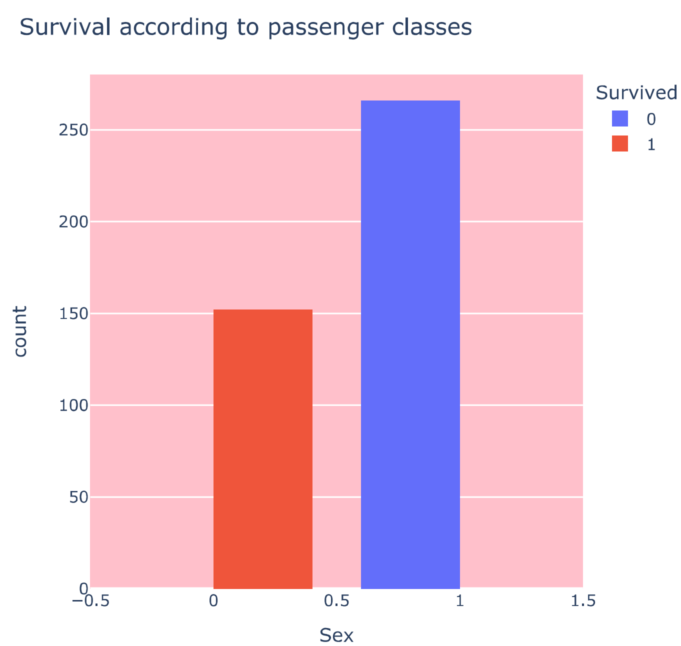
```
PassengerId    0
Survived       0
Pclass         0
Name           0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Embarked       0
dtype: int64
```

```
!pip install plotly
import plotly.express as px

pclass_counts=data.Pclass.value_counts()
fig_pclass_perc=px.pie(data,names=pclass_counts.index,values=pclass_counts.values,title=f'Distribution of Pclass')

fig_pclass_perc.update_traces(textinfo='percent+label')
fig_pclass_perc.update_layout(legend_title_text='Categories:',legend=dict(orientation="h",yanchor="bottom",y=1.02))
fig_pclass_perc.show()
```

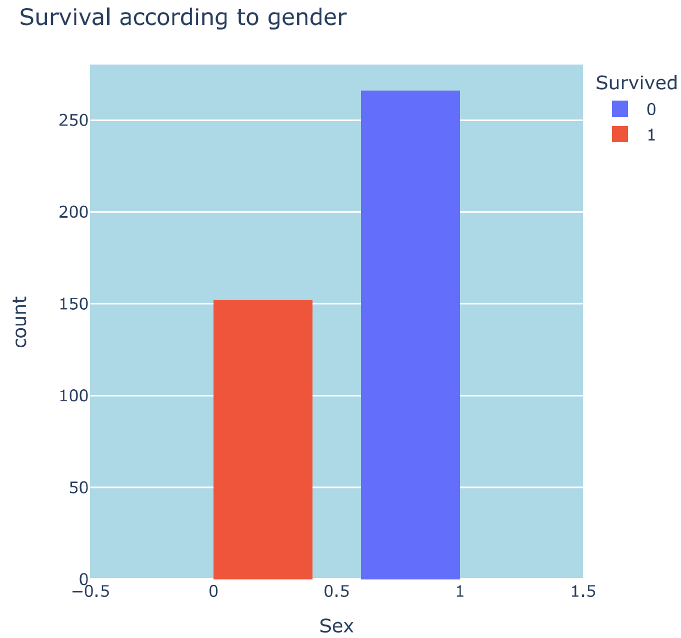
```
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-packages (5.15.
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (fr
```



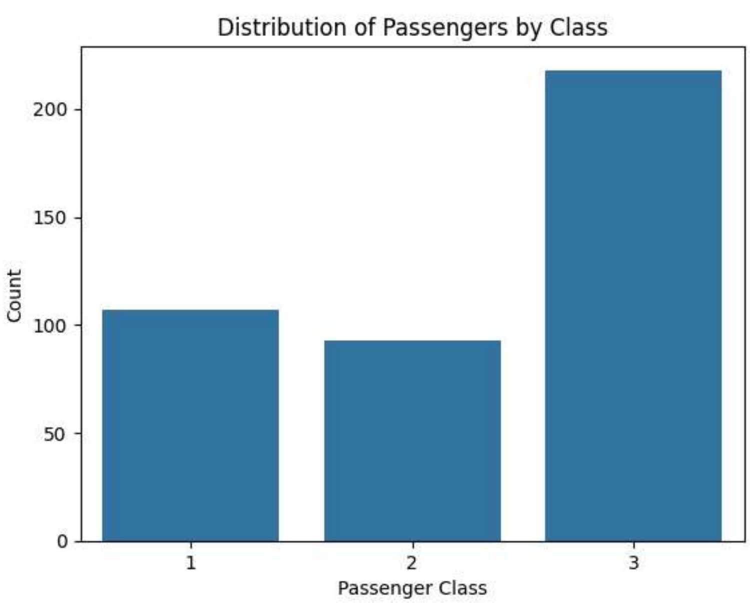

```
#0=male 1= female
ig_pclass_surv=px.histogram(data,x='Pclass',barmode='group',color='Survived')
fig_pclass_surv.update_layout(title='Survival according to passenger classes',plot_bgcolor='pink')
fig_pclass_surv.show()
```



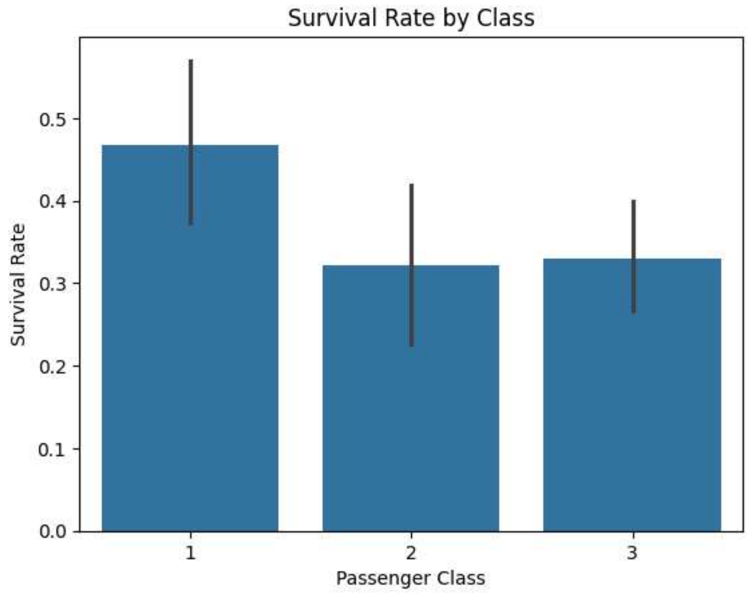

```
fig_pclass_surv=px.histogram(data,x='Sex',barmode='group',color='Survived')
fig_pclass_surv.update_layout(title='Survival according to gender',plot_bgcolor='lightblue')
fig_pclass_surv.show()
```



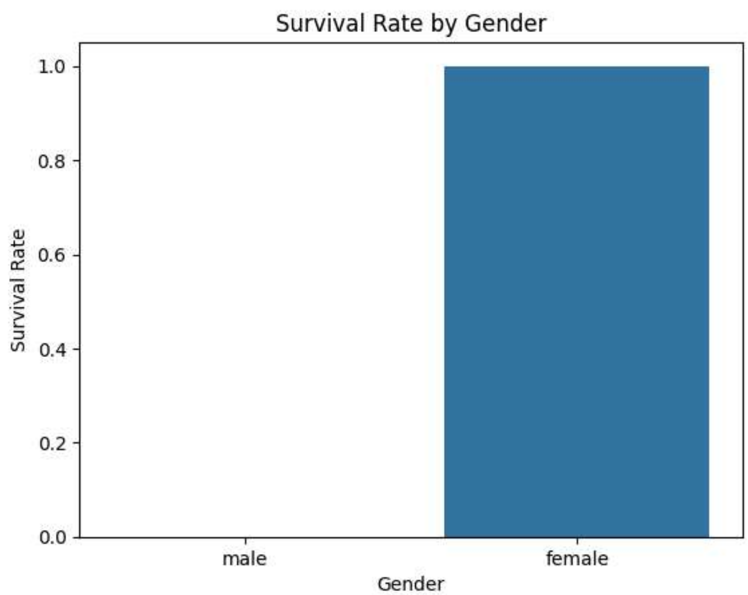

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')

df=pd.read_csv("/content/tested.csv")


sns.countplot(data=df, x='Pclass')
plt.title('Distribution of Passengers by Class')
plt.xlabel('Passenger Class')
plt.ylabel('Count')
plt.show()
```



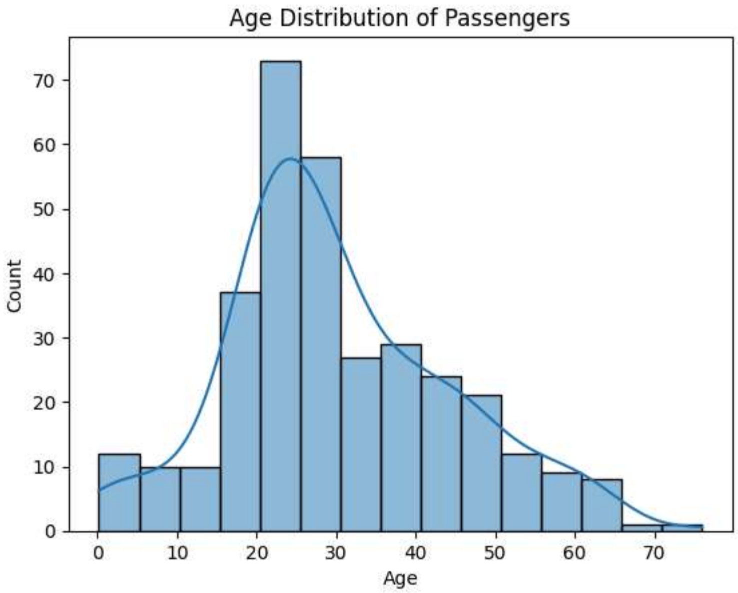

```
sns.barplot(data=df, x='Pclass', y='Survived')
plt.title('Survival Rate by Class')
plt.xlabel('Passenger Class')
plt.ylabel('Survival Rate')
plt.show()
```



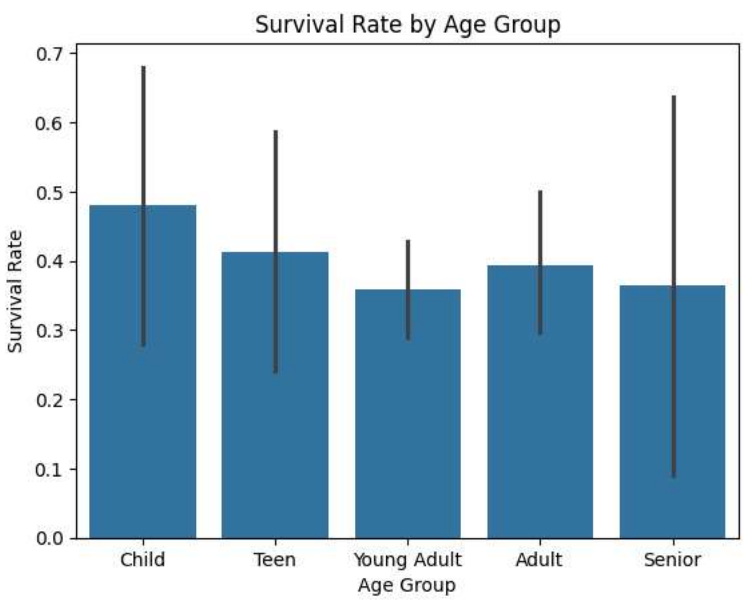

```
sns.barplot(data=df, x='Sex', y='Survived')
plt.title('Survival Rate by Gender')
plt.xlabel('Gender')
plt.ylabel('Survival Rate')
plt.show()
```



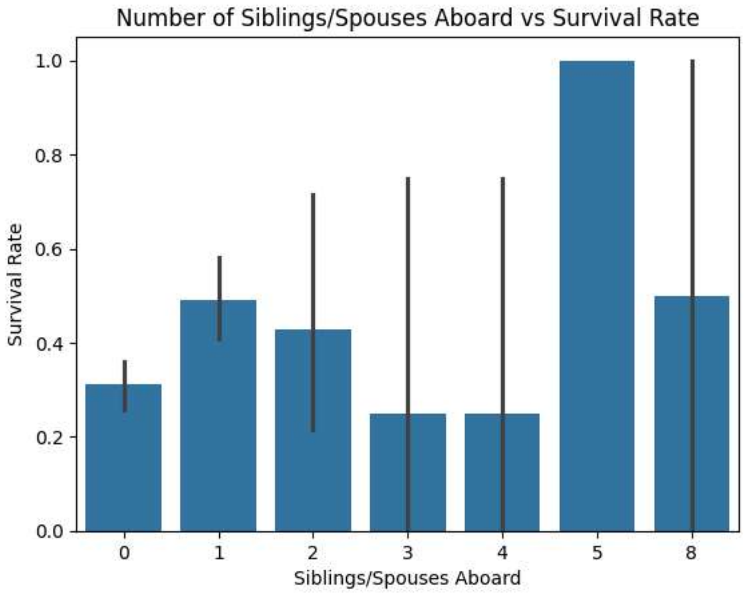

```
sns.histplot(df['Age'].dropna(), kde=True)
plt.title('Age Distribution of Passengers')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



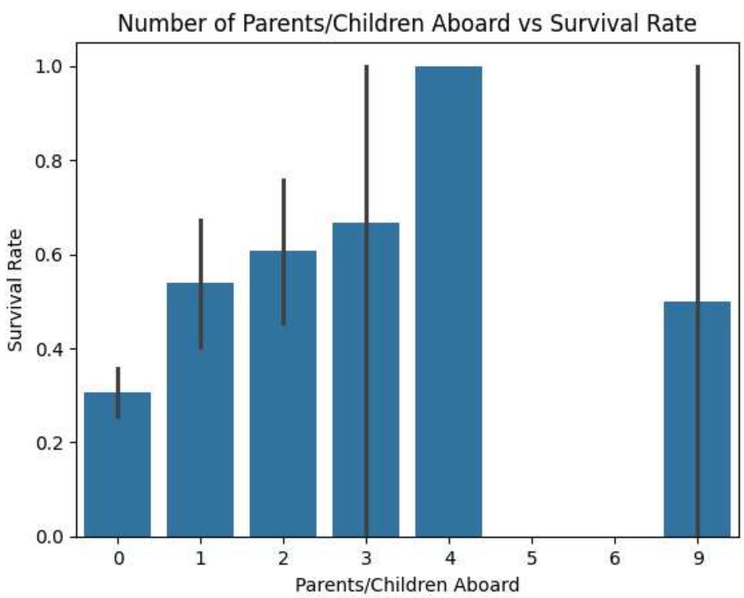

```
df['AgeGroup'] = pd.cut(df['Age'], bins=[0, 12, 18, 35, 60, 80], labels=['Child', 'Teen', 'Young Adult', 'Adult', 'Senior'])
sns.barplot(data=df, x='AgeGroup', y='Survived')
plt.title('Survival Rate by Age Group')
plt.xlabel('Age Group')
plt.ylabel('Survival Rate')
plt.show()
```



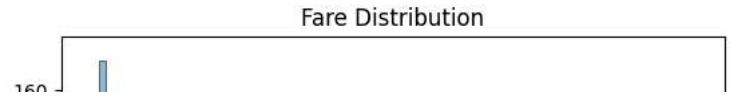

```
sns.barplot(data=df, x='SibSp', y='Survived')
plt.title('Number of Siblings/Spouses Aboard vs Survival Rate')
plt.xlabel('Siblings/Spouses Aboard')
plt.ylabel('Survival Rate')
plt.show()
```




```
sns.barplot(data=df, x='Parch', y='Survived')
plt.title('Number of Parents/Children Aboard vs Survival Rate')
plt.xlabel('Parents/Children Aboard')
plt.ylabel('Survival Rate')
plt.show()
```




```
sns.histplot(df['Fare'], kde=True)
plt.title('Fare Distribution')
plt.xlabel('Fare')
plt.ylabel('Count')
plt.show()
```


Fare Distribution
160