```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from warnings import filterwarnings
filterwarnings(action='ignore')

pd.set_option('display.max_columns',10,'display.width',1000)
train = pd.read_csv('train.csv')
test = pd.read_csv('test.csv')
train.head()
```

•	PassengerId	Survived	Pclass	Name	Sex	• • •	Parch	Ticket	Fare	Cał
0	1	0	3	Braund, Mr. Owen Harris	male		0	A/5 21171	7.2500	N
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th	female		0	PC 17599	71.2833	С
2	3	1	3	Heikkinen, Miss. Laina	female		0	STON/O2. 3101282	7.9250	N
4				Futrelle, Mrs.				_		>

train.shape

→ (891, 12)

test.shape

→ (418, 11)

train.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: int6	4

test.isnull().sum()

→	PassengerId	0
	Pclass	0
	Name	0
	Sav	a

Age 86
SibSp 0
Parch 0
Ticket 0
Fare 1
Cabin 327
Embarked 0

dtype: int64

train.describe(include="all")

→		PassengerId	Survived	Pclass	Name	Sex	•••	Parch	Ticket	Fare	Cabin
	count	891.000000	891.000000	891.000000	891	891		891.000000	891	891.000000	204
	unique	NaN	NaN	NaN	891	2		NaN	681	NaN	147
	top	NaN	NaN	NaN	Braund, Mr. Owen Harris	male		NaN	347082	NaN	B96 B98
	freq	NaN	NaN	NaN	1	577		NaN	7	NaN	4
	mean	446.000000	0.383838	2.308642	NaN	NaN		0.381594	NaN	32.204208	NaN
	std	257.353842	0.486592	0.836071	NaN	NaN		0.806057	NaN	49.693429	NaN
	min	1.000000	0.000000	1.000000	NaN	NaN		0.000000	NaN	0.000000	NaN
	25%	223.500000	0.000000	2.000000	NaN	NaN		0.000000	NaN	7.910400	NaN
	50%	446.000000	0.000000	3.000000	NaN	NaN		0.000000	NaN	14.454200	NaN
	75%	668.500000	1.000000	3.000000	NaN	NaN		0.000000	NaN	31.000000	NaN
	max	891.000000	1.000000	3.000000	NaN	NaN		6.000000	NaN	512.329200	NaN

11 rows × 12 columns

train.groupby('Survived').mean()

→		PassengerId	Pclass	Age	SibSp	Parch	Fare
	Survived						
	0	447.016393	2.531876	30.626179	0.553734	0.329690	22.117887
	1	444.368421	1.950292	28.343690	0.473684	0.464912	48.395408

train.corr()

→		PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
	Passengerld	1.000000	-0.005007	-0.035144	0.036847	-0.057527	-0.001652	0.012658
	Survived	-0.005007	1.000000	-0.338481	-0.077221	-0.035322	0.081629	0.257307
	Pclass	-0.035144	-0.338481	1.000000	-0.369226	0.083081	0.018443	-0.549500
	Age	0.036847	-0.077221	-0.369226	1.000000	-0.308247	-0.189119	0.096067
	SibSp	-0.057527	-0.035322	0.083081	-0.308247	1.000000	0.414838	0.159651
	Parch	-0.001652	0.081629	0.018443	-0.189119	0.414838	1.000000	0.216225
	Fare	0.012658	0.257307	-0.549500	0.096067	0.159651	0.216225	1.000000

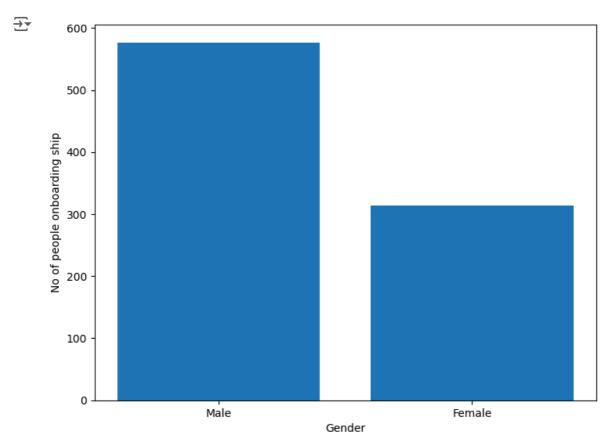
```
male_ind = len(train[train['Sex'] == 'male'])
print("No of Males in Titanic:",male_ind)

No of Males in Titanic: 577

female_ind = len(train[train['Sex'] == 'female'])
print("No of Females in Titanic:",female_ind)

No of Females in Titanic: 314

fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
gender = ['Male','Female']
index = [577,314]
ax.bar(gender,index)
plt.xlabel("Gender")
plt.ylabel("No of people onboarding ship")
plt.show()
```



```
alive = len(train[train['Survived'] == 1])
dead = len(train[train['Survived'] == 0])
```

train.groupby('Sex')[['Survived']].mean()

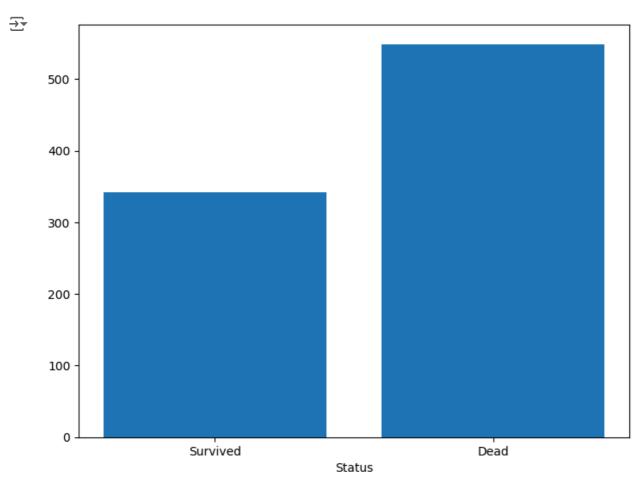
Survived

Sex

female 0.742038

male 0.188908

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
status = ['Survived','Dead']
ind = [alive,dead]
ax.bar(status,ind)
plt.xlabel("Status")
plt.show()
```

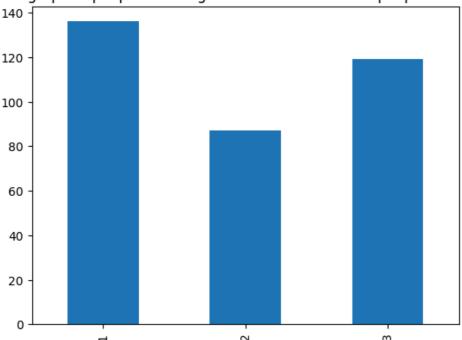


```
plt.figure(1)
train.loc[train['Survived'] == 1, 'Pclass'].value_counts().sort_index().plot.bar()
plt.title('Bar graph of people according to ticket class in which people survived')

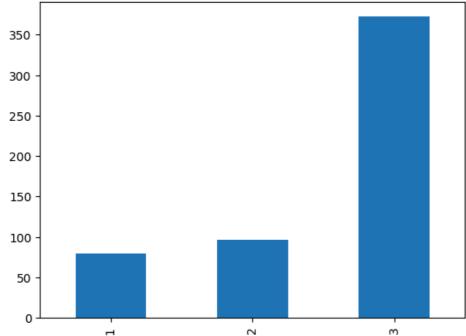
plt.figure(2)
train.loc[train['Survived'] == 0, 'Pclass'].value_counts().sort_index().plot.bar()
plt.title('Bar graph of people according to ticket class in which people couldn\'t survive')
```

Text(0.5, 1.0, "Bar graph of people accrding to ticket class in which people couldn't survive")

Bar graph of people accrding to ticket class in which people survived



Bar graph of people accrding to ticket class in which people couldn't survive

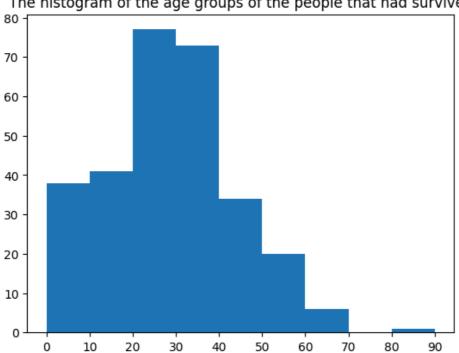


```
plt.figure(1)
age = train.loc[train.Survived == 1, 'Age']
plt.title('The histogram of the age groups of the people that had survived')
plt.hist(age, np.arange(0,100,10))
plt.xticks(np.arange(0,100,10))

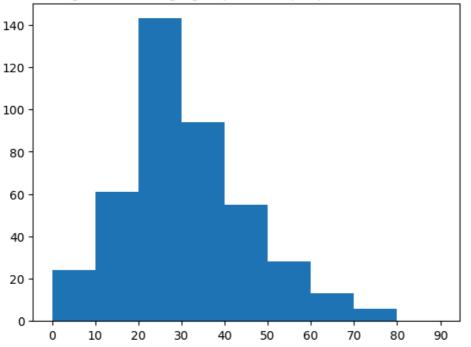
plt.figure(2)
age = train.loc[train.Survived == 0, 'Age']
plt.title('The histogram of the age groups of the people that coudn\'t survive')
plt.hist(age, np.arange(0,100,10))
plt.xticks(np.arange(0,100,10))
```

```
([<matplotlib.axis.XTick at 0x199e3d24f50>,
      <matplotlib.axis.XTick at 0x199e3d24490>,
      <matplotlib.axis.XTick at 0x199e3d1fe10>,
      <matplotlib.axis.XTick at 0x199e3d65a90>,
      <matplotlib.axis.XTick at 0x199e3d67650>,
      <matplotlib.axis.XTick at 0x199e3d699d0>,
      <matplotlib.axis.XTick at 0x199e3d6bc50>,
      <matplotlib.axis.XTick at 0x199e3d6dc10>,
      <matplotlib.axis.XTick at 0x199e3d6fd90>,
      <matplotlib.axis.XTick at 0x199e1532c90>],
     [Text(0, 0, '0'),
      Text(10, 0, '10'),
      Text(20, 0, '20'),
      Text(30, 0, '30'),
      Text(40, 0, '40'),
      Text(50, 0, '50'),
      Text(60, 0, '60'),
      Text(70, 0, '70'),
      Text(80, 0, '80'),
      Text(90, 0, '90')])
```

The histogram of the age groups of the people that had survived



The histogram of the age groups of the people that coudn't survive



train[["SibSp", "Survived"]].groupby(['SibSp'], as_index=False).mean().sort_values(by='Survived', ascend

→		SibSp	Survived
	1	1	0.535885
	2	2	0.464286
	0	0	0.345395
	3	3	0.250000
	4	4	0.166667
	5	5	0.000000
	6	8	0.000000

 $\label{train} train[["Pclass", "Survived"]].group by (['Pclass'], as_index=False).mean().sort_values(by='Survived', ascellations). The property of the prope$

→		Pclass	Survived
	0	1	0.629630
	1	2	0.472826
	2	3	0.242363

train[["Age", "Survived"]].groupby(['Age'], as_index=False).mean().sort_values(by='Age', ascending=True)

→		Age	Survived
	0	0.42	1.0
	1	0.67	1.0
	2	0.75	1.0
	3	0.83	1.0
	4	0.92	1.0
	83	70.00	0.0
	84	70.50	0.0
	85	71.00	0.0
	86	74.00	0.0
	87	80.00	1.0

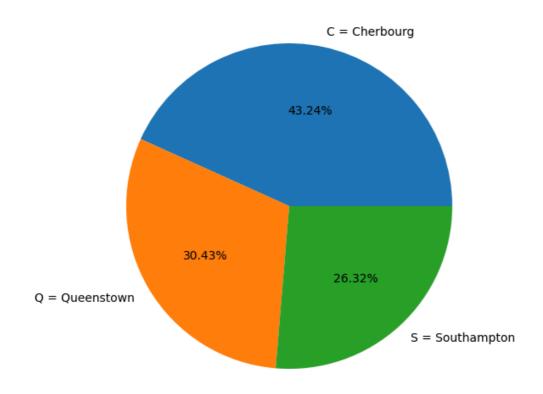
train[["Embarked", "Survived"]].groupby(['Embarked'], as_index=False).mean().sort_values(by='Survived',

→		Embarked	Survived
	0	С	0.553571
	1	Q	0.389610
	2	S	0.336957

88 rows × 2 columns

```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.axis('equal')
l = ['C = Cherbourg', 'Q = Queenstown', 'S = Southampton']
s = [0.553571,0.389610,0.336957]
ax.pie(s, labels = l,autopct='%1.2f%%')
plt.show()
```





test.describe(include="all")

→		PassengerId	Pclass	Name	Sex	Age	 Parch	Ticket	
	count	418.000000	418.000000	418	418	332.000000	 418.000000	418	417.
	unique	NaN	NaN	418	2	NaN	 NaN	363	
	top	NaN	NaN	Kelly, Mr. James	male	NaN	 NaN	PC 17608	
	freq	NaN	NaN	1	266	NaN	 NaN	5	
	mean	1100.500000	2.265550	NaN	NaN	30.272590	 0.392344	NaN	35.
	std	120.810458	0.841838	NaN	NaN	14.181209	 0.981429	NaN	55.
	min	892.000000	1.000000	NaN	NaN	0.170000	 0.000000	NaN	0.
	25%	996.250000	1.000000	NaN	NaN	21.000000	 0.000000	NaN	7.
	50%	1100.500000	3.000000	NaN	NaN	27.000000	 0.000000	NaN	14.
	75%	1204.750000	3.000000	NaN	NaN	39.000000	 0.000000	NaN	31.
	max	1309.000000	3.000000	NaN	NaN	76.000000	 9.000000	NaN	512.

11 rows × 11 columns

```
#Droping Useless Columns
train = train.drop(['Ticket'], axis = 1)
test = test.drop(['Ticket'], axis = 1)
train = train.drop(['Cabin'], axis = 1)
test = test.drop(['Cabin'], axis = 1)
train = train.drop(['Name'], axis = 1)
test = test.drop(['Name'], axis = 1)
#Feature Selection
column_train=['Age','Pclass','SibSp','Parch','Fare','Sex','Embarked']
#training values
X=train[column_train]
#target value
Y=train['Survived']
X['Age'].isnull().sum()
X['Pclass'].isnull().sum()
X['SibSp'].isnull().sum()
X['Parch'].isnull().sum()
X['Fare'].isnull().sum()
X['Sex'].isnull().sum()
X['Embarked'].isnull().sum()
→ 2
X['Age']=X['Age'].fillna(X['Age'].median())
X['Age'].isnull().sum()
→ 0
X['Embarked'] = train['Embarked'].fillna(method ='pad')
X['Embarked'].isnull().sum()
→ 0
d={'male':0, 'female':1}
X['Sex']=X['Sex'].apply(lambda x:d[x])
X['Sex'].head()
\rightarrow
     0
     1
          1
     2
          1
          1
     Name: Sex, dtype: int64
e={'C':0, 'Q':1,'S':2}
X['Embarked']=X['Embarked'].apply(lambda x:e[x])
X['Embarked'].head()
\rightarrow
     0
          2
          0
     1
     2
          2
     3
          2
     Name: Embarked, dtype: int64
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.3,random_state=7)
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model.fit(X_train,Y_train)
Y_pred = model.predict(X_test)
from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,Y_pred))
Accuracy Score: 0.7574626865671642
from sklearn.metrics import accuracy_score,confusion_matrix
confusion_mat = confusion_matrix(Y_test,Y_pred)
print(confusion mat)
→ [[130 26]
      [ 39 73]]
from sklearn.svm import SVC
model1 = SVC()
model1.fit(X_train,Y_train)
pred_y = model1.predict(X_test)
from sklearn.metrics import accuracy score
print("Acc=",accuracy_score(Y_test,pred_y))
Acc= 0.6604477611940298
from sklearn.metrics import accuracy score, confusion matrix, classification report
confusion_mat = confusion_matrix(Y_test,pred_y)
print(confusion mat)
print(classification_report(Y_test,pred_y))
→ [[149
            7]
      [ 84 28]]
                   precision
                                recall f1-score
                                                   support
                        0.64
                                  0.96
                                            0.77
                                                       156
                0
                        0.80
                                  0.25
                1
                                            0.38
                                                       112
                                                       268
         accuracy
                                            0.66
        macro avg
                        0.72
                                  0.60
                                            0.57
                                                       268
     weighted avg
                        0.71
                                  0.66
                                            0.61
                                                       268
from sklearn.neighbors import KNeighborsClassifier
model2 = KNeighborsClassifier(n_neighbors=5)
model2.fit(X_train,Y_train)
y_pred2 = model2.predict(X_test)
from sklearn.metrics import accuracy score
print("Accuracy Score:",accuracy_score(Y_test,y_pred2))
    Accuracy Score: 0.6604477611940298
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
confusion_mat = confusion_matrix(Y_test,y_pred2)
print(confusion_mat)
nnint/classification manant/// tast // mmad2\\
```

print(classification_report(y_test,y_predz))

```
[[127 29]
 [ 62 50]]
               precision
                             recall f1-score
                                                 support
            0
                     0.67
                               0.81
                                          0.74
                                                      156
                     0.63
                               0.45
                                          0.52
                                                      112
                                                      268
                                          0.66
    accuracy
                                          0.63
                                                      268
    macro avg
                     0.65
                               0.63
                               0.66
                                          0.65
                                                      268
weighted avg
                     0.66
```

from sklearn.naive_bayes import GaussianNB
model3 = GaussianNB()
model3.fit(X_train,Y_train)
y_pred3 = model3.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred3))

Accuracy Score: 0.7686567164179104

from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
confusion_mat = confusion_matrix(Y_test,y_pred3)
print(confusion_mat)
print(classification report(Y test,y pred3))

from sklearn.tree import DecisionTreeClassifier
model4 = DecisionTreeClassifier(criterion='entropy',random_state=7)
model4.fit(X_train,Y_train)
y_pred4 = model4.predict(X_test)

from sklearn.metrics import accuracy_score
print("Accuracy Score:",accuracy_score(Y_test,y_pred4))

Accuracy Score: 0.7425373134328358

from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
confusion_mat = confusion_matrix(Y_test,y_pred4)
print(confusion_mat)
print(classification report(Y test,y pred4))

```
→ [[132 24]
     [ 45 67]]
                   precision
                                recall f1-score
                                                    support
                0
                        0.75
                                  0.85
                                             0.79
                                                        156
                1
                        0.74
                                  0.60
                                             0.66
                                                        112
                                             0.74
                                                        268
        accuracy
```

```
macro avg 0.74 0.72 0.73 268 weighted avg 0.74 0.74 0.74 268
```

```
results = pd.DataFrame({
    'Model': ['Logistic Regression', 'Support Vector Machines', 'Naive Bayes', 'KNN' , 'Decision Tree'],
    'Score': [0.75,0.66,0.76,0.66,0.74]})

result_df = results.sort_values(by='Score', ascending=False)
result_df = result_df.set_index('Score')
result_df.head(9)
```

 $\overline{\mathbf{x}}$

Model

Score	
0.76	Naive Bayes
0.75	Logistic Regression
0.74	Decision Tree
0.66	Support Vector Machines
0.66	KNN

Start coding or generate with AI.