```
# import packages needed for the procedure
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
#Coding for importing csv files in Google colab
from google.colab import files
import io
uploaded = files.upload()
df = pd.read_csv(io.BytesIO(uploaded['titanic1.csv']))
# read data as data
#df = pd.read_csv("/home/cyborg/Desktop/Workshop on DA and ML for IIIT internship students/Day 4-7/C

# check the dimension of t1he table
print("The dimension of the table is: ",df.shape)
# check the columns
df.columns
```

Choose Files titanic1.csv

- **titanic1.csv**(n/a) - 60302 bytes, last modified: 1/26/2020 - 100% done

```
Saving titanic1.csv to titanic1.csv
The dimension of the table is:  (891, 12)
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

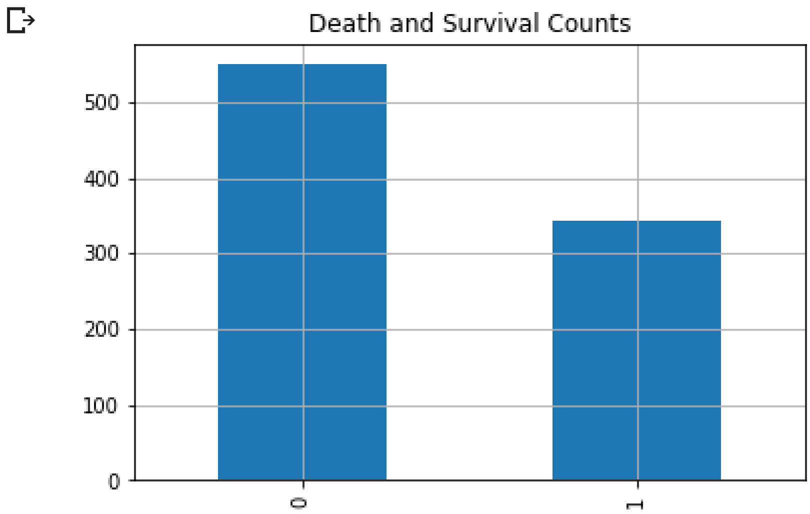
```
df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabi
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	Na
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C8
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	Na

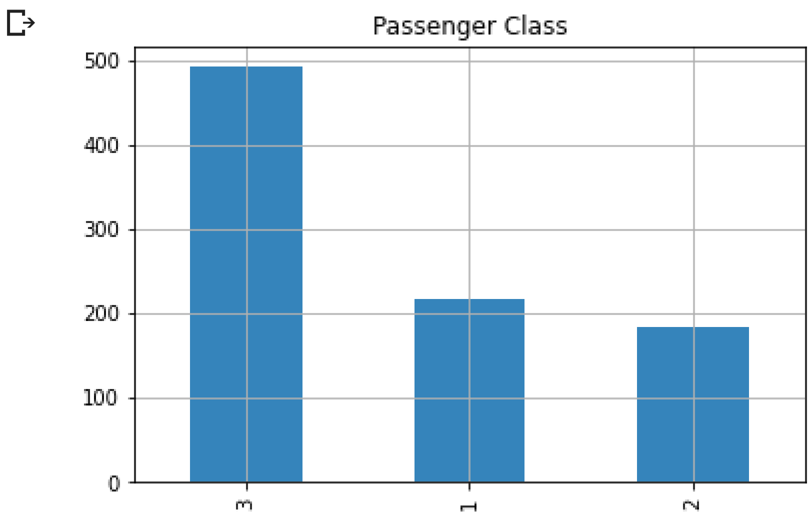
```
df.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000

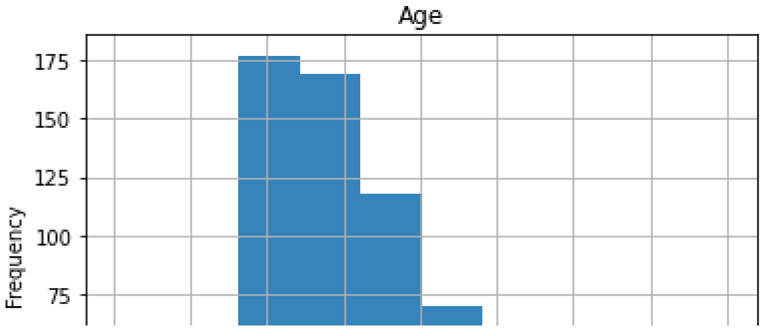
```
#Now we have a general idea of the data set contents.
df['Survived'].value_counts().plot(kind='bar', title='Death and Survival Counts',grid=True)
plt.show()
```



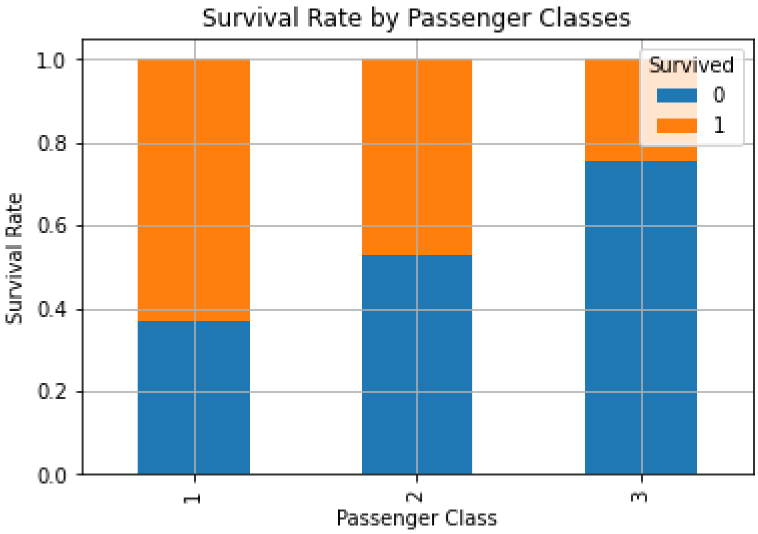

```
#From this,we infer that majority of people did not survive the accident.
df['Sex'].value_counts().plot(kind='bar', title='Sex')
plt.show()


#It can be infered that the majority of people in the ship were male.
df['Pclass'].value_counts().plot(kind='bar', title='Passenger Class',alpha=0.90,grid=True)
plt.show()
```




```
#It can be infered that the largest number of passengers were in class 3 followed by class 1 and cla

df['Age'].plot(kind='hist',title='Age',alpha=0.90,grid=True)
plt.show()
```



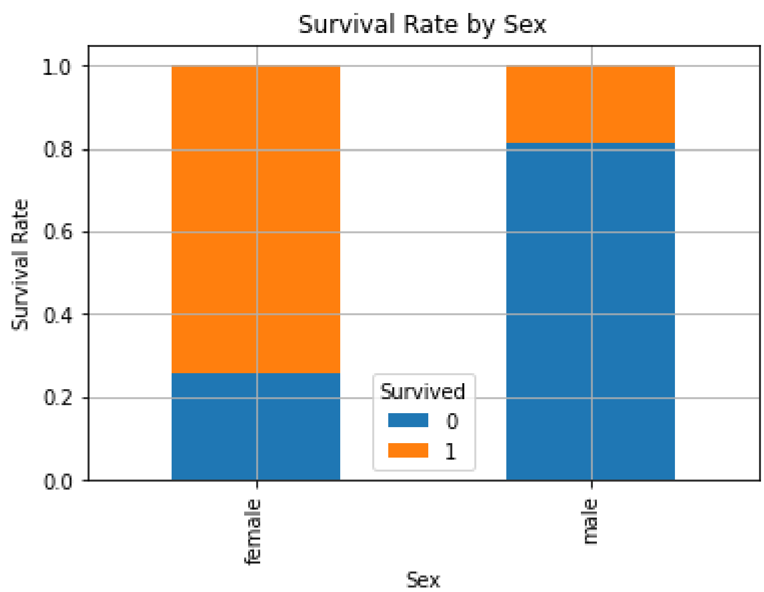

```
#It can be infered that majority of passengers were in the age group 15-30 years.
#Feature1 : Passenger Class
# finding survival rate in the passenger class
rel_1=pd.crosstab(df['Pclass'],df['Survived'])
rel_1_normalize = rel_1.div(rel_1.sum(1).astype(float), axis=0)
rel_1_normalize.plot(kind='bar',title='Survival Rate by Passenger Classes',stacked=True,grid=True)
plt.xlabel('Passenger Class')
plt.ylabel('Survival Rate')
plt.show()
```




```
#Those in First Class has the highest chance for survival.
#Feature2 : Sex
#We'll need to map Sex from a string to a number to prepare it for machine learning algorithms.
sexes = sorted(df['Sex'].unique())
genders_mapping = dict(zip(sexes, range(0, len(sexes) + 1)))
df['Sex_Val'] = df['Sex'].map(genders_mapping).astype(int)
df.head(10)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabi
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	Na
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C8
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	Na
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C12
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	Na
				Moran							

```
# to find survival rate by sex
rel_2=pd.crosstab(df['Sex'],df['Survived'])
rel_2_normalize=rel_2.div(rel_2.sum(1).astype(float),axis=0)
rel_2_normalize.plot(kind='bar',title='Survival Rate by Sex',stacked=True,grid=True)
plt.xlabel('Sex')
plt.ylabel('Survival Rate')
plt.show()
```



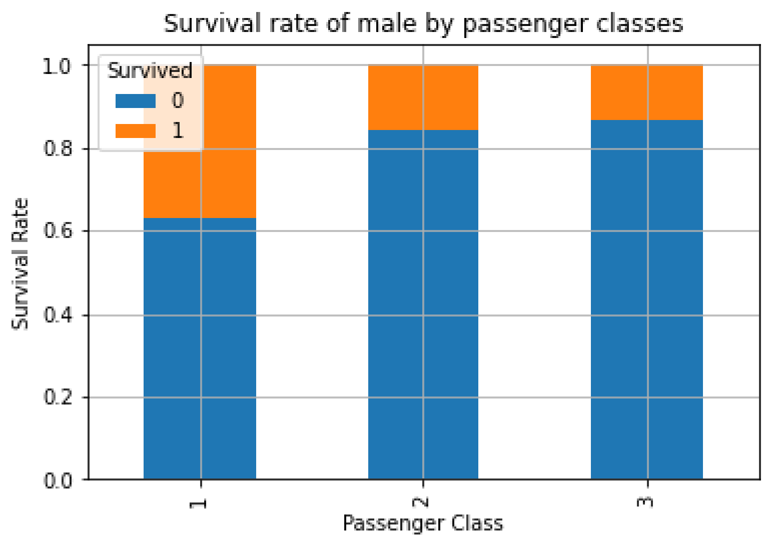

```
#The majority of females survived, whereas the majority of males did not.
#Count males and females in each Pclass:
# Get the unique values of Pclass:
passenger_classes = sorted(df['Pclass'].unique())
passenger_classes
```

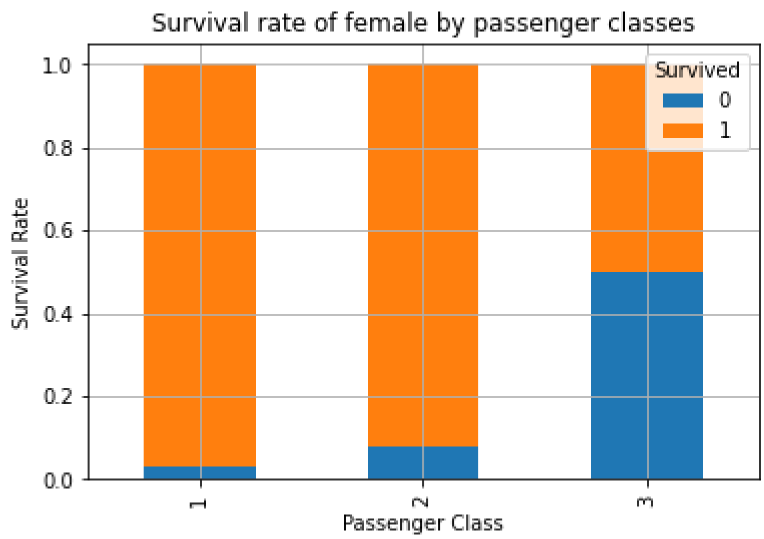
```
[1, 2, 3]
```

```
for i in passenger_classes:
        print ('M : ',i ,len(df[(df['Sex'] == 'male')  & (df['Pclass'] == i)]))
        print ('F : ',i ,len(df[(df['Sex'] =='female') & (df['Pclass'] == i)]))
male=df[df['Sex']=='male']
female=df[df['Sex']=='female']
```

```
M :  1 122
F :  1 94
M :  2 108
F :  2 76
M :  3 347
F :  3 144
```

```
#Plot survival rate by Sex and Pclass:
male_rel=pd.crosstab(male['Pclass'],male['Survived'])
male_rel_normalize=male_rel.div(male_rel.sum(1).astype(float),axis=0)
male_rel_normalize.plot(kind='bar',title='Survival rate of male by passenger classes',stacked='True'
plt.xlabel('Passenger Class')
plt.ylabel('Survival Rate')
plt.show()
female_rel=pd.crosstab(female['Pclass'],female['Survived'])
female_rel_normalize=female_rel.div(female_rel.sum(1).astype(float),axis=0)
female_rel_normalize.plot(kind='bar',title='Survival rate of female by passenger classes',stacked='T
plt.xlabel('Passenger Class')
plt.ylabel('Survival Rate')
plt.show()
```

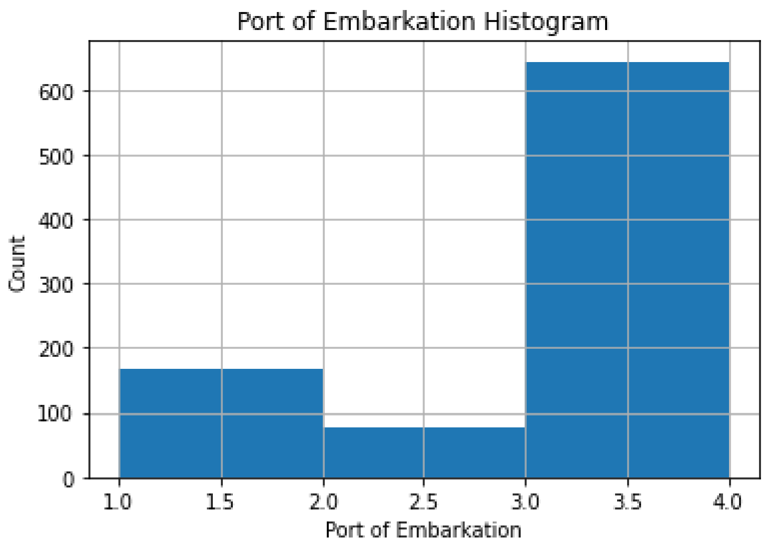




```
#We make a new column 'Embarked_Value'and replace C,Q,S with 1,2,3
#so that we can carry out our machine learning algorithms on it.
df['Embarked_Value']=df['Embarked']
df['Embarked_Value'].replace(['C','Q','S'],[1,2,3],inplace=True)
embarked_locs = sorted(df['Embarked_Value'].unique())
embarked_locs
#df.head(10)
```

```
[1.0, 2.0, 3.0, nan]
```

```
#Visualization of embarkpoints
df['Embarked_Value'].plot(kind='hist',bins=3,range=(1,4),grid='True')
plt.title('Port of Embarkation Histogram')
plt.xlabel('Port of Embarkation')
plt.ylabel('Count')
plt.show()
```




```
#Feature3: Embarked
# To check invalid embarked values
df[df['Embarked'].isnull()]
```

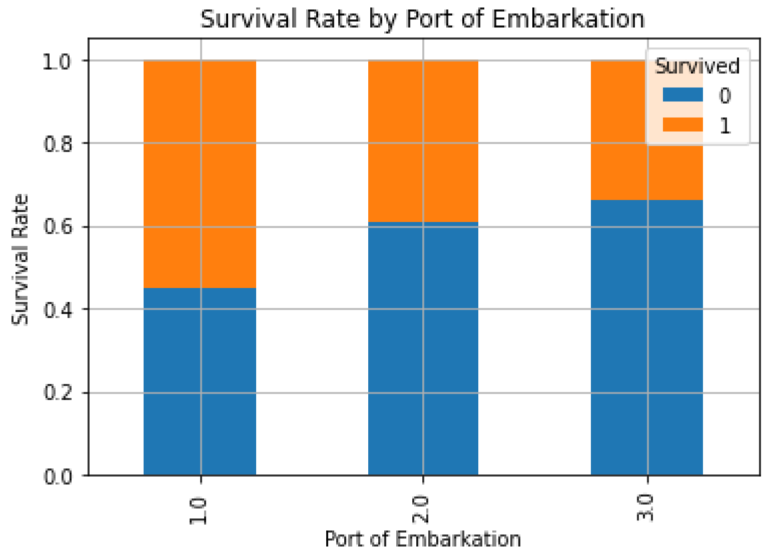
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Eml
61	62	1	1	Icard, Miss. Amelie	female	38.0	0	0	113572	80.0	B28	
829	830	1	1	Stone, Mrs. George Nelson (Martha Evelyn)	female	62.0	0	0	113572	80.0	B28	

```
#Thus we can see that the Embarked Column is missing certain values, which have to be filled
#otherwise it may cause problems during the application of machine learning algorithms.
#Since the majority of passengers embarked in 'S': 3,
#we assign the missing values in Embarked to 'S':
df['Embarked_Value']=df['Embarked_Value'].fillna(3)
df['Embarked']=df['Embarked'].fillna('S')

embarked_locs = sorted(df['Embarked_Value'].unique())
```

```
embarked_locs = sorted(df['Embarked_Value'].unique())
print(embarked_locs)

embarked_locs1 = sorted(df['Embarked'].unique())
print(embarked_locs1)
```

```
[1.0, 2.0, 3.0]
['C', 'Q', 'S']
```

```
# We have removed all nan successfully
# Now we can see the survival rate by port of embarkment
embarked_rel=pd.crosstab(df['Embarked_Value'],df['Survived'])
embarked_rel_normalize=embarked_rel.div(embarked_rel.sum(1).astype(float),axis=0)
embarked_rel_normalize.plot(kind='bar',title='Survival Rate by Port of Embarkation',grid='True',stac
plt.xlabel('Port of Embarkation')
plt.ylabel('Survival Rate')
plt.show()
```




```
#Feature4 : Age
# check null ages
df[df['Age'].isnull()].head(10)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cal
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	N
17	18	1	2	Williams, Mr. Charles Eugene	male	NaN	0	0	244373	13.0000	N
19	20	1	3	Masselmani, Mrs. Fatima	female	NaN	0	0	2649	7.2250	N
26	27	0	3	Emir, Mr. Farred Chehab	male	NaN	0	0	2631	7.2250	N

```
#Here also many ages are missing. So we assign the missing ages the median values
#of the age according to their sex and passenger class.
df['Age_complete'] = df['Age']
df['Age_complete']=df['Age_complete'].groupby([df['Sex_Val'],df['Pclass']]).apply(lambda x: x.fillna
df['Age_complete'].head(10)
```

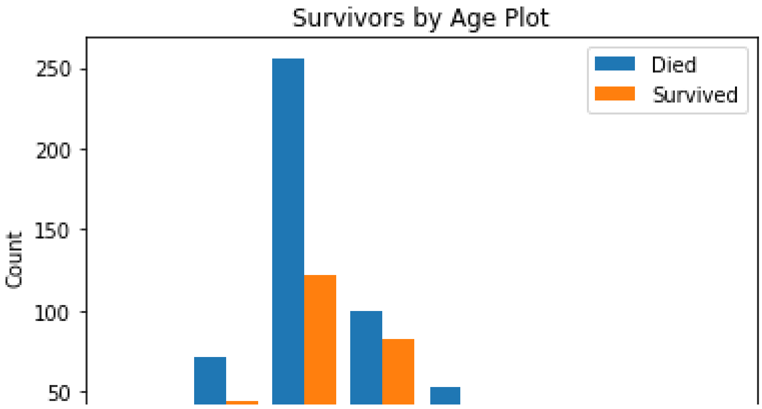
```
0    22.0
1    38.0
2    26.0
3    35.0
4    35.0
5    25.0
6    54.0
7     2.0
8    27.0
9    14.0
Name: Age_complete, dtype: float64
```

```
# to check any nan age
df[df['Age_complete'].isnull()].head(10)
```

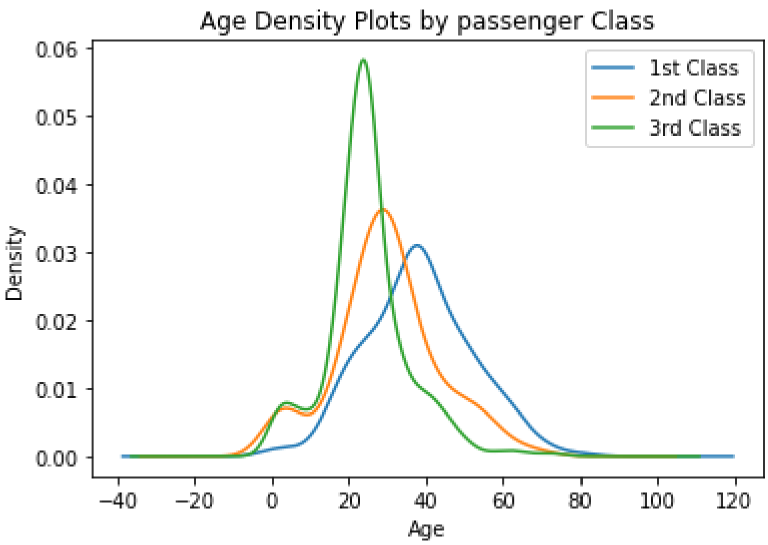
PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	S

```
age_survived=df[df['Survived']==1]['Age_complete']
age_not_survived = df[df['Survived'] == 0]['Age_complete']
max_age=max(df['Age_complete'])
print('survived :',len(age_survived))
print('died :',len(age_not_survived))

plt.hist([age_not_survived,age_survived],bins=8,range=(1, max_age),stacked=False)
plt.title('Survivors by Age Plot')
plt.xlabel('Ages')
plt.ylabel('Count')
plt.legend(('Died','Survived'),loc='best')
plt.show()
```

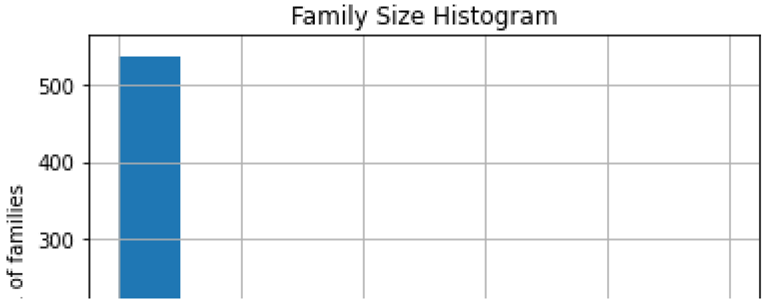
```
survived : 342
died : 549
```




```
#For more detailed analysis,we draw the age density plots.
for i in passenger_classes :
        df.Age_complete[df.Pclass==i].plot(kind='density')
plt.title('Age Density Plots by passenger Class')
plt.xlabel('Age')
plt.legend(('1st Class', '2nd Class', '3rd Class'), loc='best')
plt.show()
```

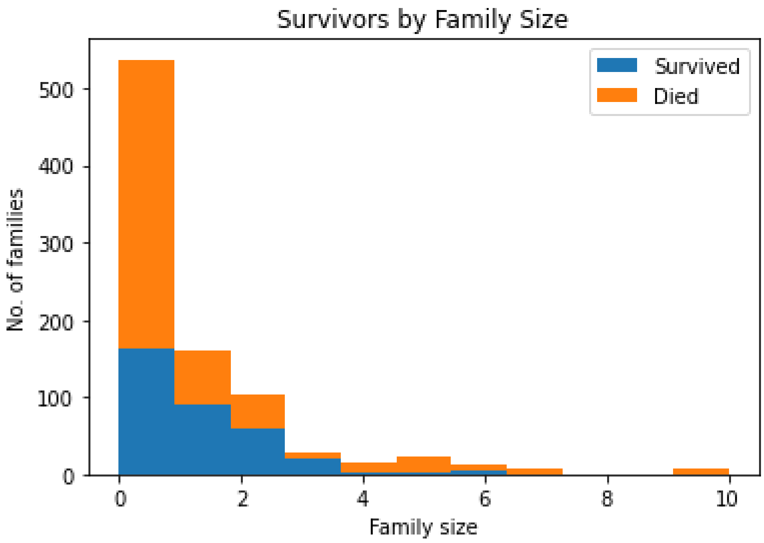



```
#Thus we see the first class passengers were generally older then second class passengers,
#which in turn were older than third class passengers.
#Feature5 : Family Size
#We define a new feature FamilySize that is the sum of Parch (number of parents or children on board
#SibSp (number of siblings or spouses):

df['Family_Size'] = df['SibSp'] + df['Parch']
df['Family_Size'].hist(bins=10)
plt.xlabel('Family Size')
plt.ylabel('No. of families')
plt.title('Family Size Histogram')
plt.show()
```




```
family_sizes=sorted(df['Family_Size'].unique())
family_sizes_max=max(family_sizes)
family_size_survived=df[df['Survived']==1]['Family_Size']
family_size_not_survived=df[df['Survived']==0]['Family_Size']
print('survived :',len(family_size_survived))
print('died :',len(family_size_not_survived))
plt.hist([family_size_survived,family_size_not_survived],bins=family_sizes_max+1,range=(0, family_si
plt.legend(('Survived','Died'), loc='best')
plt.xlabel('Family size')
plt.ylabel('No. of families')
plt.title('Survivors by Family Size')
plt.show()
```

```
survived : 342
died : 549
```




```
df.dtypes[df.dtypes.map(lambda x: x == 'object')]

#df=df.drop(['Name','Sex','Ticket','Cabin','Embarked','SibSp','Parch','PassengerId','Age','Embarked_
train_df=df
df.head(10)
df.columns
```

```
Index(['Survived', 'Pclass', 'Fare', 'Sex_Val', 'Age_complete', 'Family_Size'], dtype='object'
```

```
train_df.head()
```

	Survived	Pclass	Fare	Sex_Val	Age_complete	Family_Size
0	0	3	7.2500	1	22.0	1

```
# fields to be considered for ML
df.columns
```

```
Index(['Survived', 'Pclass', 'Fare', 'Sex_Val', 'Age_complete', 'Family_Size'], dtype='object'
```

```
#Load libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import model_selection
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier, export_graphviz
from sklearn.model_selection import train_test_split
```

```
from sklearn.preprocessing import LabelEncoder
var_mod = []
le = LabelEncoder()
for i in var_mod:
    df[i] = le.fit_transform(df[i])
```

Model 1 ML model considering the dependant variables of all fields except the independant variable **Survived** ['Pclass', 'Fare', 'Sex_Val', 'Age_complete', 'Family_Size']

```
#Training and Testing dataset
array = df.values
X = array[:,1:]
Y = array[:,0]
Y=Y.astype('int')
x_train, x_test, y_train, y_test = model_selection.train_test_split(X, Y, test_size=0.2, random_stat
df.columns
```

```
Index(['Survived', 'Pclass', 'Fare', 'Sex_Val', 'Age_complete', 'Family_Size'], dtype='object'
```

```
model = LogisticRegression()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.770949720670391
```

False negative: 38 (We predicted a negative result and it was positive)

```
model = DecisionTreeClassifier()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7821229050279329
```

```
model = RandomForestClassifier(n_estimators=100)
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7932960893854749
```

Model 2- ML model considering the dependant variables of all fields except the independant variable **Survived** ['Pclass', 'Fare', 'Sex_Val']

```
array = df.values
X = array[:,1:4]
Y = array[:,0]
Y=Y.astype('int')
x_train, x_test, y_train, y_test = model_selection.train_test_split(X, Y, test_size=0.2, random_stat
df.columns
```

```
Index(['Survived', 'Pclass', 'Fare', 'Sex_Val', 'Age_complete', 'Family_Size'], dtype='object'
```

Double-click (or enter) to edit

```
model = LogisticRegression()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7262569832402235
```

Double-click (or enter) to edit

```
model = DecisionTreeClassifier()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7988826815642458
```

Double-click (or enter) to edit

```
model = RandomForestClassifier(n_estimators=100)
model.fit(x_train,y_train)
```

```
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7988826815642458
```

Model 3- ML model considering the dependant variables of all fields except the independant variable **Survived** ['Pclass', 'Fare']

```
array = df.values
X = array[:,1:3]
Y = array[:,0]
Y=Y.astype('int')
x_train, x_test, y_train, y_test = model_selection.train_test_split(X, Y, test_size=0.2, random_stat
df.columns
```

```
Index(['Survived', 'Pclass', 'Fare', 'Sex_Val', 'Age_complete', 'Family_Size'], dtype='object'
```

Double-click (or enter) to edit

```
model = LogisticRegression()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7262569832402235
```

Double-click (or enter) to edit

```
model = DecisionTreeClassifier()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7374301675977654
```

Double-click (or enter) to edit

```
model = RandomForestClassifier(n_estimators=100)
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7430167597765364
```

Double-click (or enter) to edit

```
from sklearn.linear_model import LogisticRegression
logmodel = LogisticRegression()
logmodel.fit(x_train,y_train)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

Double-click (or enter) to edit

```
predictions = logmodel.predict(x_test)
from sklearn.metrics import classification_report
print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.72      0.90      0.80       110
           1       0.74      0.45      0.56        69

    accuracy                           0.73       179
   macro avg       0.73      0.67      0.68       179
weighted avg       0.73      0.73      0.71       179
```

The accuracy of the model develped is 73%

it is not bad!

confusion matrix

```
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test, predictions)
```

```
array([[99, 11],
       [38, 31]])
```

True positive: 99 (We predicted a positive result and it was positive)

True negative: 31 (We predicted a negative result and it was negative)

False positive: 11 (We predicted a positive result and it was negative)