```
# 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/CSV/titanic1.csv"

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

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving titanic1.csv to titanic1 (1).csv
The dimension of the table is:  (891, 12)
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

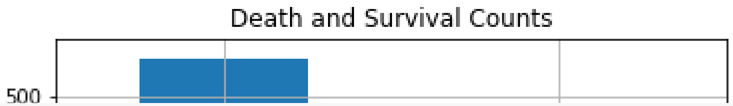
```
df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN

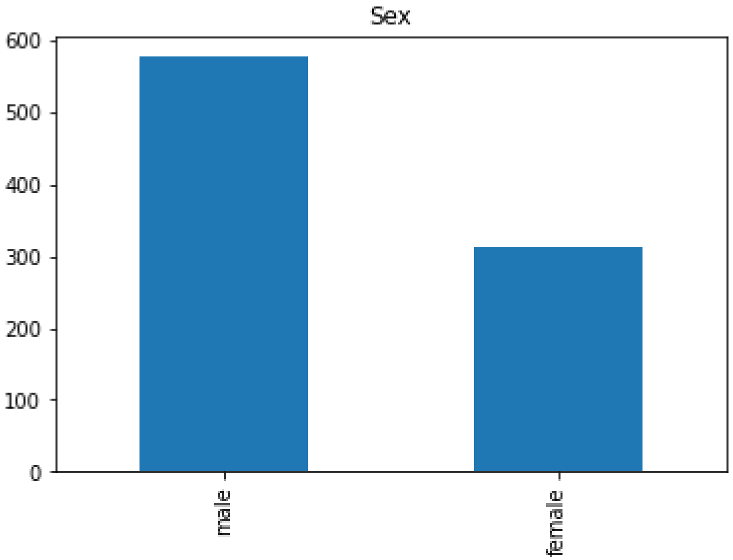
```
df.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

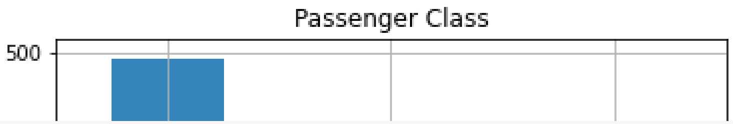
```
#Now we have a general idea of the data set contents.
df['Survived'].value_counts().plot(kind='bar', title='Death and Survival Counts',grid=True)
plt.show()
```



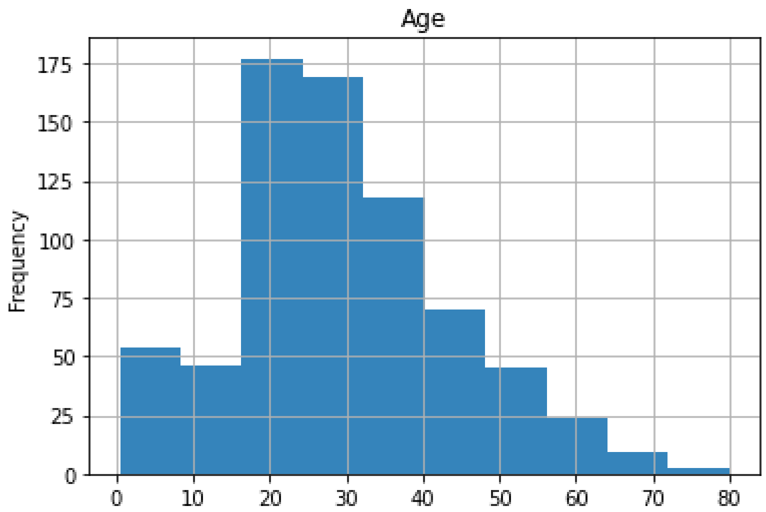

```
#From this,we infer that majority of people did not survive the accident.
df['Sex'].value_counts().plot(kind='bar', title='Sex')
plt.show()
```



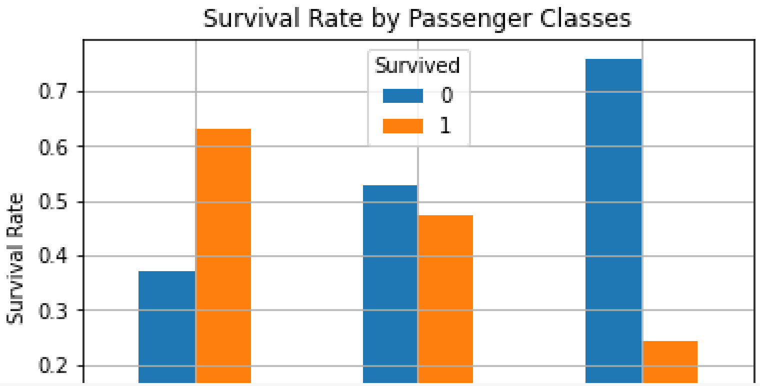

```
#It can be infered that the majority of people in the ship were male.
df['Pclass'].value_counts().plot(kind='bar', title='Passenger Class',alpha=0.90,grid=True)
plt.show()
```




```
#It can be infered that the largest number of passengers were in class 3 followed by class 1 and class 2.

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



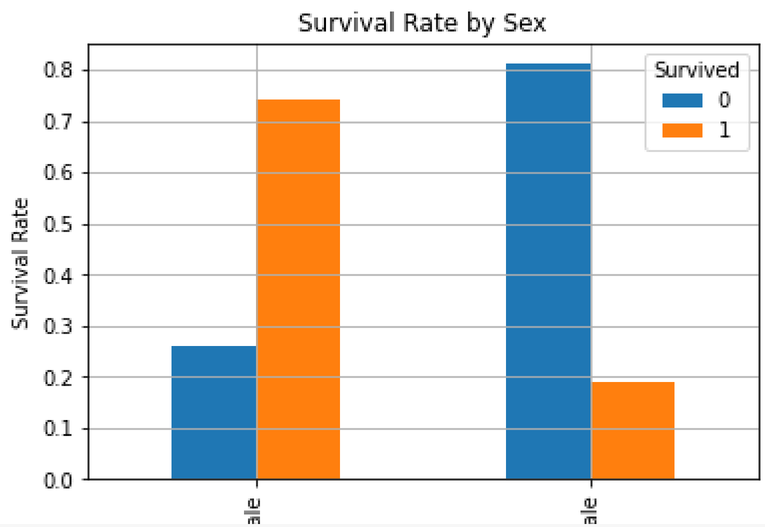

```
#It can be infered that majority of passengers were in the age group 15-30 years.
#Feature1 : Passenger Class
# finding survival rate in the passenger class
rel_1=pd.crosstab(df['Pclass'],df['Survived'])
rel_1_normalize = rel_1.div(rel_1.sum(1).astype(float), axis=0)
rel_1_normalize.plot(kind='bar',title='Survival Rate by Passenger Classes',stacked=False,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	Cabin	Embarked	Age_complete	Embarke
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S	22.0	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C	38.0	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S	26.0	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S	35.0	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S	35.0	
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q	NaN	
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S	54.0	
7	8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S	2.0	
8	9	1	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S	27.0	
9	10	1	2	Nasser, Mrs. Nicholas (Adele	female	14.0	1	0	237736	30.0708	NaN	C	14.0	

```
# 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=False,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
```

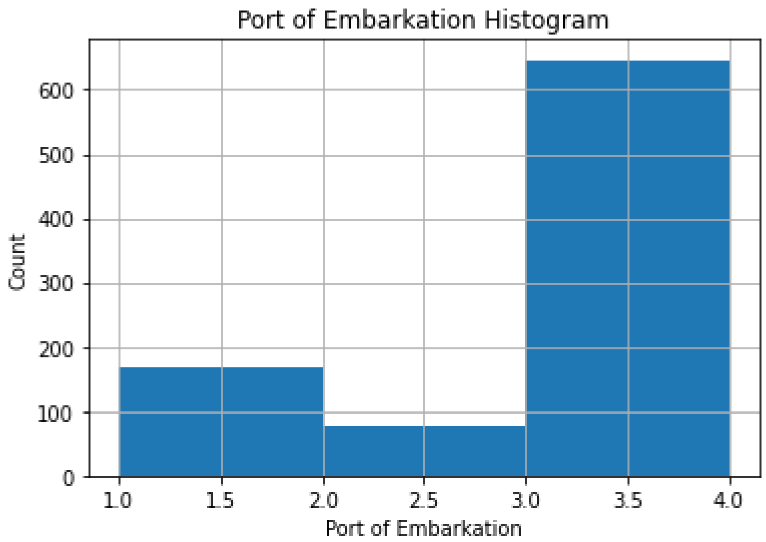
```
#Plot survival rate by Sex and Pclass:
male_rel=pd.crosstab(male['Pclass'],male['Survived'])
male_rel_normalize=male_rel.div(male_rel.sum(1).astype(float),axis=0)
```

```
male_rel_normalize.plot(kind='bar',title='Survival rate of male by passenger classes',stacked='True',grid='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='True',grid='True'
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, 2, 3]
```

```
#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()
```



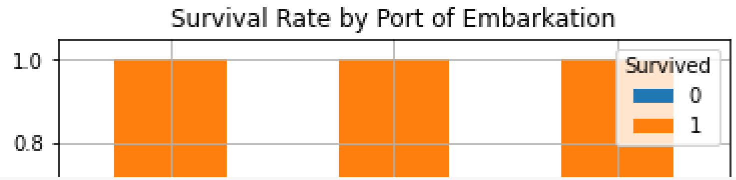

```
#Feature3: Embarked
# To check invalid embarked values
df[df['Embarked'].isnull()]
```

PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Age_complete	Embarked_Value	Sex_Val

```
#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())
print(embarked_locs)

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

```
[1, 2, 3]
['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',stacked='True')
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	Cabin	Embarked	Age_complete	Embarke
5	6	0	3	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q	NaN	

Williams, Mr. Charles

```
#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(x.median()))
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
```

42	43	0	3	Kraeff, Mr. Theodor	male	NaN	0	0	349253	7.8958	NaN	C	NaN

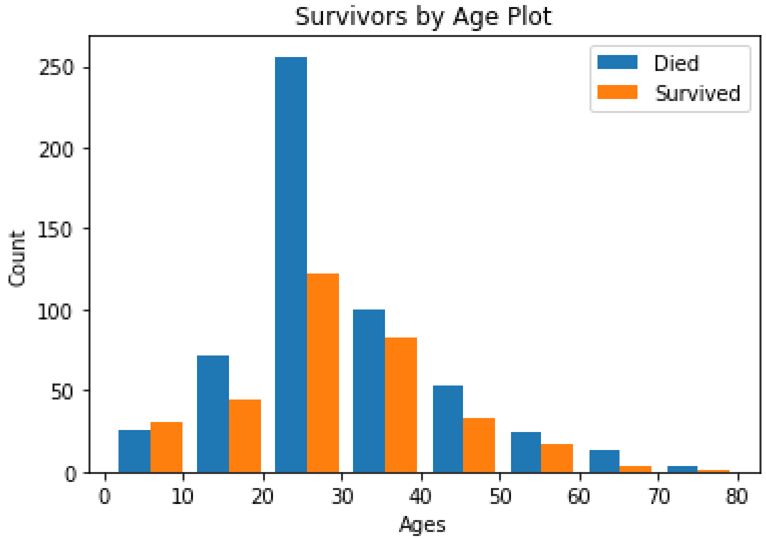
```
# to check any nan age
df[df['Age_complete'].isnull()].head(10)
```

PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Age_complete	Embarked_Value	Sex_Val

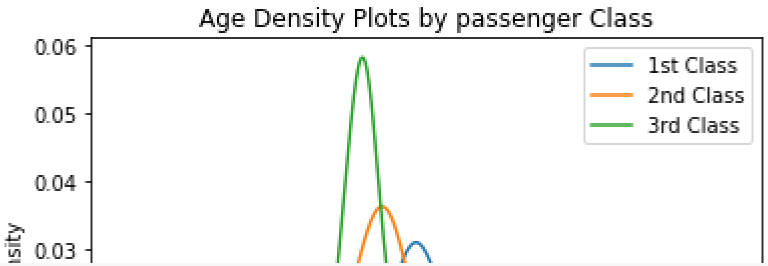
```
age_survived=df[df['Survived']==1]['Age_complete']
age_not_survived = df[df['Survived'] == 0]['Age_complete']
max_age=max(df['Age_complete'])
print('survived :',len(age_survived))
print('died :',len(age_not_survived))

plt.hist([age_not_survived,age_survived],bins=8,range=(1, max_age),stacked=False)
plt.title('Survivors by Age Plot')
```

```
plt.title('Survivors by Age Plot')
plt.xlabel('Ages')
plt.ylabel('Count')
plt.legend(('Died','Survived'),loc='best')
plt.show()
```

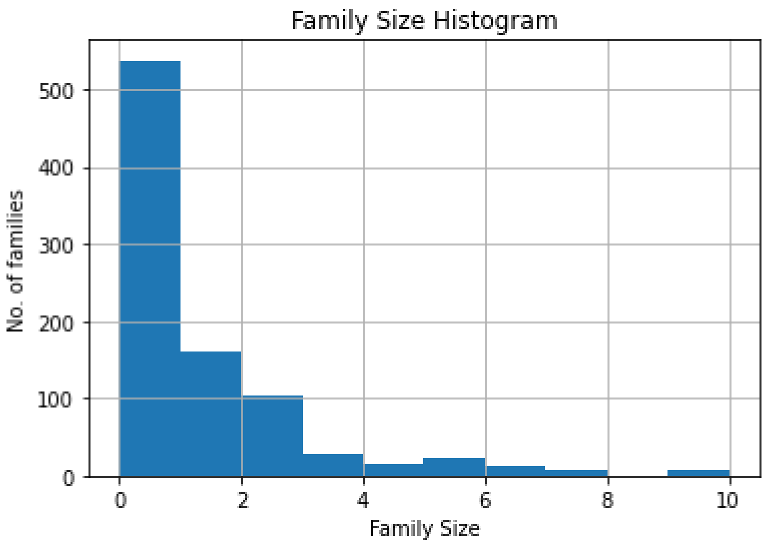
```
survived : 342
died : 549
```




```
#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()
```



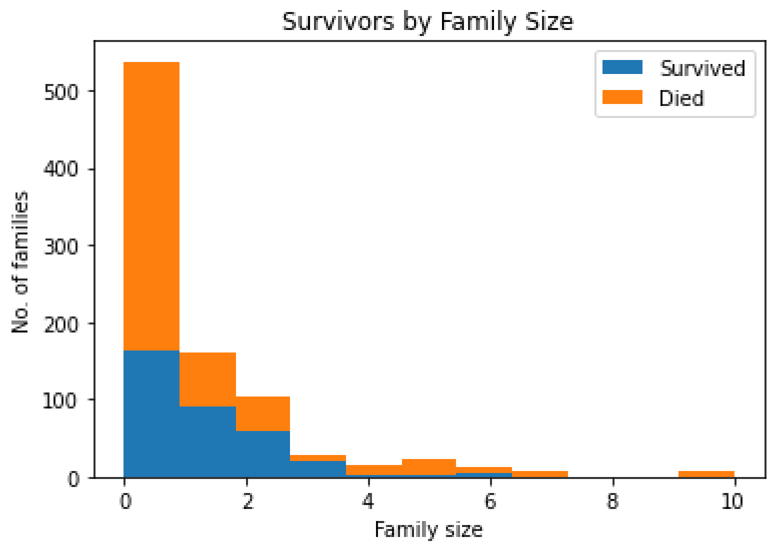

```
#Thus we see the first class passengers were generally older then second class passengers,
#which in turn were older than third class passengers.
#Feature5 : Family Size
#We define a new feature FamilySize that is the sum of Parch (number of parents or children on board) and
#SibSp (number of siblings 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_sizes_max),stacked
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_Value'],axis=1)
train_df=df
df.head(10)
df.columns
```

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

```
train_df.head()
```

```
train_df.head()
```

	Survived	Pclass	Fare	Sex_Val	Age_complete	Family_Size
0	0	3	7.2500	1	22.0	1
1	1	1	71.2833	0	38.0	1
2	1	3	7.9250	0	26.0	0
3	1	1	53.1000	0	35.0	1
4	0	3	8.0500	1	35.0	0

```
# 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_state=7)
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
```

```
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_state=7)
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)
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_state=7)
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)

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