Data preprocessing

```
In [1]:
```

```
#first we will clean the data
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
train=pd.read_csv(r'C:\Users\Pranav\Desktop\Prachi\titanic-dataset\titanic\train.csv')
test=pd.read_csv(r'C:\Users\Pranav\Desktop\Prachi\titanic-dataset\titanic\test.csv')
gender=pd.read_csv(r'C:\Users\Pranav\Desktop\Prachi\titanic-dataset\titanic\gender_submission.csv')
```

In [3]:

```
train.info()
```

```
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
#
    Column
                 Non-Null Count
    PassengerId 891 non-null
                                  int64
     Survived
                  891 non-null
                                  int64
1
                  891 non-null
2
    Pclass
                                  int64
 3
    Name
                  891 non-null
                                  object
 4
    Sex
                  891 non-null
                                  object
                 714 non-null
                                  float64
 5
    Age
                  891 non-null
    SibSp
 6
                                  int64
 7
     Parch
                  891 non-null
                                  int64
     Ticket
                  891 non-null
                                  object
                  891 non-null
                                  float64
    Fare
                 204 non-null
10 Cabin
                                  object
11 Embarked
                  889 non-null
                                  object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

<class 'pandas.core.frame.DataFrame'>

In [4]:

```
row=train.shape[0]
r_null=train.isnull().sum()
r_null
```

Out[4]:

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: int64	

```
In [5]:
r_null/row*100
Out[5]:
PassengerId    0.000000
```

Survived 0.000000 0.000000 Pclass Name 0.000000 0.000000 Sex Age 19.865320 SibSp 0.000000 0.000000 Parch 0.000000 Ticket Fare 0.000000 Cabin 77.104377 Embarked 0.224467

dtype: float64

In [6]:

```
train=train.drop(columns=['Cabin'],axis=1) #to drop null values columns #axis=1 is for columns 0 is for rows
```

In [7]:

```
train['Age']=train['Age'].fillna(train['Age'].mean()) #filling the null values by mean value of age column
```

In [8]:

```
train['Embarked']=train['Embarked'].fillna(train['Embarked'].mode()[0])# using mode function to fill categorical values
```

In [9]:

```
train.isnull().sum() # dataset is fully cleaned with no null values
```

Out[9]:

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

In [10]:

```
#now cleaning test data
test.info()
```

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

<class 'pandas.core.frame.DataFrame'>

```
In [11]:
row=test.shape[0]
r_null=test.isnull().sum()
r_null
Out[11]:
                 0
PassengerId
Survived
                 0
Pclass
                 a
Name
                 0
Sex
                86
Age
SibSp
                0
Parch
                 0
Ticket
                 0
Fare
                1
Cabin
               327
Embarked
                 0
dtype: int64
In [12]:
test=test.drop(columns=['Cabin'],axis=1) #to drop null values columns #axis=1 is for columns 0 is for rows
In [13]:
test['Age']=test['Age'].fillna(test['Age'].mean()) #filling the null values by mean value of age column
In [14]:
test['Fare']=train['Fare'].fillna(train['Fare'].mean())
In [15]:
r_null/row*100 # test data is cleaned
Out[15]:
PassengerId
                0.000000
Survived
                0.000000
Pclass
                0.000000
                0.000000
Name
                0.000000
Sex
Age
               20.574163
SibSp
                0.000000
                0.000000
Parch
                0.000000
Ticket
Fare
                0.239234
Cabin
               78.229665
Embarked
                0.000000
dtype: float64
In [16]:
gender.info() # gender has no null values
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 2 columns):
                Non-Null Count Dtype
# Column
0 PassengerId 418 non-null
                                  int64
 1 Survived
                  418 non-null
                                  int64
dtypes: int64(2)
memory usage: 6.7 KB
In [2]:
train.info()
```

In [17]:

```
#Now the data preprocessing starts- We are converting categorical data into numerical data by labelencoding
from sklearn.preprocessing import LabelEncoder #sklearn is a library, label encoder is a function of sklearn
le=LabelEncoder()
object_list=train.select_dtypes(include=['object']).columns
for i in object_list:
    train[i]=le.fit_transform(train[i])#converting string data into numerical
```

In [18]:

```
train.info()
```

```
RangeIndex: 891 entries, 0 to 890
Data columns (total 11 columns):
                  Non-Null Count Dtype
#
    Column
0
     PassengerId 891 non-null
                                  int64
     Survived
                  891 non-null
                                  int64
1
                  891 non-null
                                  int64
     Pclass.
 3
     Name
                  891 non-null
                                  int32
 4
                  891 non-null
                                  int32
     Sex
 5
                  891 non-null
                                  float64
     Age
                  891 non-null
     SibSp
                                  int64
 6
 7
     Parch
                  891 non-null
                                  int64
 8
     Ticket
                  891 non-null
                                  int32
                  891 non-null
     Fare
                                  float64
 10 Embarked
                  891 non-null
                                  int32
dtypes: float64(2), int32(4), int64(5)
memory usage: 62.8 KB
```

<class 'pandas.core.frame.DataFrame'>

In [19]:

```
#for test dataset
from sklearn.preprocessing import LabelEncoder #sklearn is a library, label encoder is a function of sklearn
le=LabelEncoder()
object_list=test.select_dtypes(include=['object']).columns
for i in object_list:
    test[i]=le.fit_transform(test[i])
```

In [20]:

test.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
#
    Column
                  Non-Null Count
                                  Dtype
     PassengerId 418 non-null
                                  int64
a
 1
     Survived
                  418 non-null
                                  int64
     Pclass
                  418 non-null
                                  int64
 3
     Name
                  418 non-null
                                  int32
                  418 non-null
 4
                                  int32
     Sex
 5
     Age
                  418 non-null
                                  float64
 6
     SibSp
                  418 non-null
                                  int64
                  418 non-null
 7
     Parch
                                  int64
                  418 non-null
 8
     Ticket
                                  int32
                  418 non-null
                                  float64
     Fare
 10 Embarked
                  418 non-null
                                  int32
dtypes: float64(2), int32(4), int64(5)
memory usage: 29.5 KB
```

```
In [21]:
```

```
train.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 11 columns):
 # Column
                                    Non-Null Count
                                                                     Dtype
 a
         PassengerId 891 non-null
                                                                      int64
  1
          Survived
                                     891 non-null
                                                                      int64
                                     891 non-null
          Pclass
                                                                      int64
                                     891 non-null
                                                                      int32
  3
         Name
  4
         Sex
                                     891 non-null
                                                                      int32
  5
          Age
                                     891 non-null
                                                                      float64
  6
          SibSp
                                     891 non-null
                                                                      int64
                                     891 non-null
          Parch
                                                                      int64
  8
         Ticket
                                     891 non-null
                                                                      int32
  9
         Fare
                                     891 non-null
                                                                      float64
  10 Embarked
                                     891 non-null
                                                                      int32
dtypes: float64(2), int32(4), int64(5)
memory usage: 62.8 KB
In [25]:
#slicing data(we use slicing method for the target variable "survived"
#column separated from the train data as well as test data)
                                                        # select all rows but exclude column 1 "survived"
x_train=train.iloc[:,2:]
y_train=train.iloc[:,:2] #[rows , columns][: means all rows included and :2 means 0:2 2
#columns which is 0 and 1 excluding 2nd column]
x_test=test.iloc[:,2:]
y_test=test.iloc[:,:2]
In [26]:
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x_train=sc.fit_transform(x_train) #will transform column according to model
x_test=sc.transform(x_test) #will transform model according to column
In [27]:
x_train
Out[27]:
array([[ 0.82737724, -1.31021659, 0.73769513, ..., 0.91896631,
              -0.50244517, 0.58595414],
[-1.56610693, -0.99141018, -1.35557354, ..., 1.28262456,
                  0.78684529, -1.9423032 ],
              [ 0.82737724, -0.35768524, -1.35557354, ..., 1.64628282, -0.48885426, 0.58595414],
               [\ 0.82737724,\ -0.12441226,\ -1.35557354,\ \ldots,\ 1.67617254,
                -0.17626324, 0.58595414],
              [-1.56610693, -1.41518943, 0.73769513, ..., -1.64656796,
              -0.04438104, -1.9423032 ],
[ 0.82737724, -0.87477369, 0.73769513, ..., 0.63501397, -0.49237783, -0.67817453]])
In [28]:
x_test
Out[28]:
\verb"array" ([[ \ 0.82737724, \ -0.92920405, \ \ 0.73769513, \ \dots, \ -0.92921469, \ \ 0.73769513, \ \dots, \ -0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.92921469, \ \ 0.9292
                 -0.50244517, -0.67817453],
               [\ 0.82737724,\ -0.16329109,\ -1.35557354,\ \ldots,\ -0.58548291,
                  0.78684529, 0.58595414],
              [-0.36936484, -0.68426742, 0.73769513, ..., -1.32276267, -0.48885426, -0.67817453],
               [0.82737724, -0.43933078, 0.73769513, ..., 0.03721958,
                 -0.48633742, 0.58595414],
              [ 0.82737724, -0.23716087, 0.73769513, ..., -0.59046453, 0.00595568, 0.58595414],
               [\ 0.82737724,\ -0.55596728,\ 0.73769513,\ \ldots,\ -1.16335083,
                 -0.38667072, -1.9423032 ]])
```

```
In [29]:
```

y_train

Out[29]:

	Passengerld	Survived
0	1	0
1	2	1
2	3	1
3	4	1
4	5	0
886	887	0
887	888	1
888	889	0
889	890	1
890	891	0

891 rows × 2 columns

In [57]:

y_test

Out[57]:

	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	3	206	1	34.50000	0	0	152	7.2500	1
1	3	403	0	47.00000	1	0	221	71.2833	2
2	2	269	1	62.00000	0	0	73	7.9250	1
3	3	408	1	27.00000	0	0	147	53.1000	2
4	3	178	0	22.00000	1	1	138	8.0500	2
413	3	353	1	30.27259	0	0	267	0.0000	2
414	1	283	0	39.00000	0	0	324	7.9250	0
415	3	332	1	38.50000	0	0	346	8.0500	2
416	3	384	1	30.27259	0	0	220	32.5000	2
417	3	302	1	30.27259	1	1	105	13.0000	0

418 rows × 9 columns

In [30]:

```
y_train=y_train.drop(columns=['PassengerId'],axis=1)
```

In [31]:

```
y_test=y_test.drop(columns=['PassengerId'],axis=1)
```

```
In [33]:
```

```
y_train #total rows in y_train should match y_test
```

Out[33]:

	Survivea
0	0
1	1
2	1
3	1
4	0
886	0
887	1
888	0
889	1
890	0

891 rows × 1 columns

In [34]:

```
#from sklearn.model_selection import train_test_split #use when data is 100%
#x_train,x_test,y_train,y_test=train_test_split(X,y,test_size=0.3,range_state+0)
```

In [35]:

```
#preparing model to check the dependency of survival on all the columns
from sklearn.linear_model import Ridge, Lasso, LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor

list_algo = [LinearRegression(), Ridge(), Lasso(), KNeighborsRegressor(), DecisionTreeRegressor()]

for algo in list_algo:
    model=algo
    model.fit(x_train, y_train)
    y_pred=model.predict(x_test)
    print(f'The score of {algo} is {algo.score(x_test,y_test)*100}%')
```

The score of LinearRegression() is 66.99864409093249%
The score of Ridge() is 66.96051313044707%
The score of Lasso() is -0.17636684303348193%
The score of KNeighborsRegressor() is 43.51127819548872%
The score of DecisionTreeRegressor() is -19.924812030075188%

In []:

In []:

In []: