Load " titanic_data". Survived as your y variable, and the other variables as your x variables. The goal is to build a model to predict whether a person survives or not.

```
import pandas as pd
import numpy as np
from sklearn import preprocessing
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
import seaborn as sns
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
#import the data
data=pd.read_csv("/content/drive/MyDrive/DataMining/Files/titanic_data.csv")
#explore the data
data.info()
data.columns
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

```
#Hitmap to check the null or drop columns
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(20,20))
sns.heatmap(data.isnull()) ##to visualize the missing values
data.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: int64
```

The data.info() indicates that three colums lack some data and may require some data wrangling, if possible. - Age : 177 values missing (likely) - Cabin : 687 values missing (unlikely) - Embarked : 2 values missing (easy)

```
data
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen \Carrie\""	female	NaN	1	2	W./C. 6607	23.4500	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	Q

891 rows × 12 columns

```
data.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

The provides two immediate observations:

Survival rate: only 38% of the 891 passengers survived

Age: the average age of all passengers was 29.7 years with a strong StDev of 14.5 years

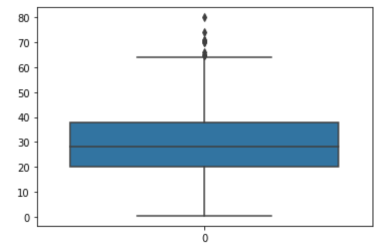
The data is about the Titanic passengers. The goal is to predict whether a passenger survives or not (1/0). The dataset provides the titanic passenger information. It includes 891 records and 12 fields. Input Variables:

survival:(Numeric) Survival 0 = No, 1 = Yes Name: (Categorical) Name of the person pclass: (Numeric) Ticket class 1 = 1st, 2 = 2nd, 3 = 3rd sex: (Categorical) Sex Male or Female
Age: (Numeric) Age in years
sibsp: (Numeric) number of siblings / spouses aboard the Titanic
parch: (Numeric) number of parents / children aboard the Titanic
ticket: (Categorical) Ticket number
fare: (Numeric) Passenger fare

cabin: (Categirical) Cabin number
embarked: (Categorical) Port of Embarkation C = Cherbourg, Q = Queenstown, S = Southampton

```
#Cleaning Dataset, dropped 'Ticket' and 'Cabin' for our prediction model as they might have zero or low influence on 'Survived'
```

```
data=data.drop(["Ticket", "Cabin"],axis=1)
sns.boxplot(data=data["Age"])
median_age=data["Age"].median()
data["Age"]=data["Age"].fillna(median_age)
data["Embarked"].value_counts()
data["Embarked"] = data["Embarked"].fillna("S")
```




```
#1. Can some important info be extracted from the name column? Use that in your models.
"""Yes, the titles can be extracted from the name column"""
data['Title'] = data.Name.str.extract(' ([A-Za-z]+)\.', expand=False)
data["Title"].value_counts()
```

```
Mr          517
Miss        182
Mrs         125
Master       40
Dr            7
Rev           6
Mlle          2
Major         2
Col           2
Countess      1
Capt          1
Ms            1
Sir           1
Lady          1
Mme           1
Don           1
Jonkheer      1
Name: Title, dtype: int64
```

```
data['Title'] = data['Title'].replace(['Lady', 'Countess', 'Capt', 'Col', 'Don', 'Dr', 'Major', 'Rev', 'Sir', 'Jonkheer', 'Dona'], 'Rare')
data['Title'] = data['Title'].replace('Mlle', 'Miss')
data['Title'] = data['Title'].replace('Ms', 'Miss')
data['Title'] = data['Title'].replace('Mme', 'Mrs')
data[['Title', 'Survived']].groupby(['Title'], as_index=False).mean()
```

	Title	Survived
0	Master	0.575000
1	Miss	0.702703
2	Mr	0.156673
3	Mrs	0.793651
4	Rare	0.347826

```
data=data.drop(['PassengerId','Name'], axis=1)
```

```
data
```

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Title
0	0	3	male	22.0	1	0	7.2500	S	Mr
1	1	1	female	38.0	1	0	71.2833	C	Mrs
2	1	3	female	26.0	0	0	7.9250	S	Miss
3	1	1	female	35.0	1	0	53.1000	S	Mrs
4	0	3	male	35.0	0	0	8.0500	S	Mr
...	...	...	...	...	...	...	...	...	...
886	0	2	male	27.0	0	0	13.0000	S	Rare
887	1	1	female	19.0	0	0	30.0000	S	Miss
888	0	3	female	28.0	1	2	23.4500	S	Miss
889	1	1	male	26.0	0	0	30.0000	C	Mr
890	0	3	male	32.0	0	0	7.7500	Q	Mr

891 rows × 9 columns

```
#create dummy variables
#['Sex','Embarked','Title']
temp=pd.get_dummies(data[['Sex','Embarked','Title']], drop_first=True)
data=data.drop(['Sex','Embarked','Title'],axis=1)
data = pd.concat([data,temp],axis=1)

#Separate the x and y variables

x=data.drop(["Survived"],axis=1)
y=data['Survived'] # Survive is the y column
```

```
y
```

```
0      0
1      1
2      1
3      1
4      0
      ..
886    0
887    1
888    0
889    1
890    0
Name: Survived, Length: 891, dtype: int64
```

```
##train and test split
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=101)
```

```
x_train
```

	Pclass	Age	SibSp	Parch	Fare	Sex_male	Embarked_Q	Embarked_S	Title_Miss	Title_Mr	Title_Mrs	Title_Rare
520	1	30.0	0	0	93.5000	0	0	1	1	0	0	0
510	3	29.0	0	0	7.7500	1	1	0	0	1	0	0
446	2	13.0	0	1	19.5000	0	0	1	1	0	0	0
2	3	26.0	0	0	7.9250	0	0	1	1	0	0	0
691	3	4.0	0	1	13.4167	0	0	0	1	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
575	3	19.0	0	0	14.5000	1	0	1	0	1	0	0
838	3	32.0	0	0	56.4958	1	0	1	0	1	0	0
337	1	41.0	0	0	134.5000	0	0	0	1	0	0	0
523	1	44.0	0	1	57.9792	0	0	0	0	0	1	0
863	3	28.0	8	2	69.5500	0	0	1	1	0	0	0

623 rows × 12 columns

```
#2 Fit a logistic regression model.
# Show precision, recall, F-score, and confusion matrix and interpret the results.
```

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

y_pred = logreg.predict(x_test)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/linear_model/_logistic.py:818: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

```
len(y_pred)
```

```
268
```

```
from sklearn.metrics import confusion_matrix
confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)

from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred))
```

```
[[137  17]
 [ 37  77]]
              precision    recall  f1-score   support

           0       0.79      0.89      0.84       154
           1       0.82      0.68      0.74       114

    accuracy                           0.80       268
   macro avg       0.80      0.78      0.79       268
weighted avg       0.80      0.80      0.79       268
```

```
#3. Try Linear Regression here
#Separate the x and y variables
x=data.drop(["Survived"],axis=1)
y=data['Survived']

## Train and test split
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=101)
```

```
from sklearn.linear_model import LinearRegression
lm=LinearRegression()
lm.fit(x_train,y_train)
```

```
LinearRegression()
```

```
x_test
```

	Pclass	Age	SibSp	Parch	Fare	Sex_male	Embarked_Q	Embarked_S	Title_Miss	Title_Mr	Title_Mrs	Title_Rare
331	1	45.5	0	0	28.5000	1	0	1	0	1	0	0
700	1	18.0	1	0	227.5250	0	0	0	0	0	1	0
748	1	19.0	1	0	53.1000	1	0	1	0	1	0	0
751	3	6.0	0	1	12.4750	1	0	1	0	0	0	0
481	2	28.0	0	0	0.0000	1	0	1	0	1	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
388	3	28.0	0	0	7.7292	1	1	0	0	1	0	0
416	2	34.0	1	1	32.5000	0	0	1	0	0	1	0
407	2	3.0	1	1	18.7500	1	0	1	0	0	0	0
482	3	50.0	0	0	8.0500	1	0	1	0	1	0	0
829	1	62.0	0	0	80.0000	0	0	1	0	0	1	0

268 rows × 12 columns

```
predictions = lm.predict(x_test)
```

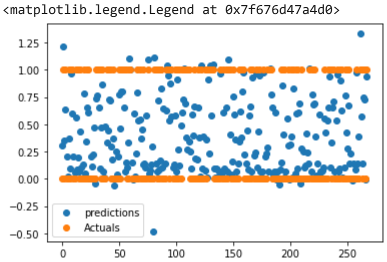
```
len(predictions)
```

```
268
```

```
x_test_plt=np.arange(0,len(x_test),1)
```

```
import matplotlib.pyplot as plt
plt.scatter(x_test_plt,predictions,label="predictions")
plt.scatter(x_test_plt,y_test,label="Actuals")
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f676d47a4d0>
```



We can not do linear regression here as the prediction values are not between 0 and 1

```
#4. Build KNN Model
```

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import Pipeline
from sklearn.metrics import (f1_score,confusion_matrix,
                             precision_score,recall_score, classification_report)
pipe = Pipeline([('a', MinMaxScaler()), ('b', KNeighborsClassifier())])
```

```
x_test
```

Pclass	Age	SibSp	Parch	Fare	Sex_male	Embarked_Q	Embarked_S	Title_Miss	Title_Mr	Title_Mrs	Title_Rare

```
pipe.fit(x_train, y_train)
```

```
Pipeline(steps=[('a', MinMaxScaler()), ('b', KNeighborsClassifier())])
```

```
Pipeline(steps=[('a', MinMaxScaler()), ('b', KNeighborsClassifier())])
```

748	1	19.0	1	0	53.1000	1	0	1	0	1	0	0

```
x_test
```

	Pclass	Age	SibSp	Parch	Fare	Sex_male	Embarked_Q	Embarked_S	Title_Miss	Title_Mr	Title_Mrs	Title_Rare
331	1	45.5	0	0	28.5000	1	0	1	0	1	0	0
700	1	18.0	1	0	227.5250	0	0	0	0	0	1	0
748	1	19.0	1	0	53.1000	1	0	1	0	1	0	0
751	3	6.0	0	1	12.4750	1	0	1	0	0	0	0
481	2	28.0	0	0	0.0000	1	0	1	0	1	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
388	3	28.0	0	0	7.7292	1	1	0	0	1	0	0
416	2	34.0	1	1	32.5000	0	0	1	0	0	1	0
407	2	3.0	1	1	18.7500	1	0	1	0	0	0	0
482	3	50.0	0	0	8.0500	1	0	1	0	1	0	0
829	1	62.0	0	0	80.0000	0	0	1	0	0	1	0

268 rows × 12 columns

```
y_pred_pipe=pipe.predict(x_test)
```

```
y_pred_pipe
```

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

```
c_matrix = pd.DataFrame(confusion_matrix(y_test, y_pred_pipe,labels=[0,1]),
                                     index=['true:0', 'true:1'],  columns=['pred:0', 'pred:1'] )
print (c_matrix)
```

```
        pred:0  pred:1
true:0     137      17
true:1      42      72
```

For KNN model:

- True negative is 137, means predict a passenger is not survived when the passenger is actually not survived
- False positive is 17, means predict a passenger is survived when the passenger is actually survived
- False negative is 42, means predict a passenger is not survived when the passenger is actually survived
- True positive is 72, means predict a passenger is survived when the passenger is actually survived

```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
from math import sqrt
```

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(x_train)
scaled_x_test=scaler.transform(x_test)
scaled_x_train=scaler.transform(x_train)
```

```
##5. Grid Search for optimal solution
```

```
from sklearn.model_selection import GridSearchCV
model = KNeighborsRegressor()

grid_params = {
    'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
    'weights': ['distance'],
    'metric': ['euclidean', 'manhattan']
}
```

```
gs = GridSearchCV(KNeighborsRegressor(),
                  grid_params,
                  verbose=1,
                  cv=3,
                  n_jobs=-1)

gs_results = gs.fit(scaled_x_train, y_train)
```

```
Fitting 3 folds for each of 20 candidates, totalling 60 fits
```

```
scaled_x_test
```

```
array([[0.        , 0.61266649, 0.        , ..., 1.        , 0.        ,
        0.        ],
       [0.        , 0.23892362, 0.125     , ..., 0.        , 1.        ,
        0.        ],
       [0.        , 0.25251427, 0.125     , ..., 1.        , 0.        ,
        0.        ],
       ...,
       [0.5       , 0.03506388, 0.125     , ..., 0.        , 0.        ,
        0.        ],
       [1.        , 0.67382441, 0.        , ..., 1.        , 0.        ,
        0.        ],
       [0.        , 0.8369122 , 0.        , ..., 0.        , 1.        ,
        0.        ]])
```

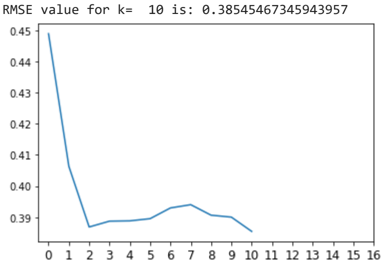
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 13 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Survived    891 non-null    int64  
 1   Pclass      891 non-null    int64  
 2   Age         891 non-null    float64
 3   SibSp       891 non-null    int64  
 4   Parch       891 non-null    int64  
 5   Fare        891 non-null    float64
 6   Sex_male    891 non-null    uint8  
 7   Embarked_Q  891 non-null    uint8  
 8   Embarked_S  891 non-null    uint8  
 9   Title_Miss  891 non-null    uint8  
 10  Title_Mr    891 non-null    uint8  
 11  Title_Mrs   891 non-null    uint8  
 12  Title_Rare  891 non-null    uint8  
dtypes: float64(2), int64(4), uint8(7)
memory usage: 48.0 KB
```

```
#7. What happens when K=N? Check the model performance on the training and testing data. Here, N=No of data points in the training set.
rmse_val = []
for K in range(1,12):  # used 12 based on 12 variables in the dataset
    model = KNeighborsRegressor(n_neighbors = K)
    model.fit(scaled_x_train, y_train)  #fit the model
    pred=model.predict(scaled_x_test) #make prediction on test set
    error = sqrt(mean_squared_error(y_test,pred)) #calculate rmse
    rmse_val.append(error) #store rmse values
    print('RMSE value for k= ' , K-1 , 'is:', error)

plt.plot(rmse_val)
plt.xticks([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16],fontsize=12)
plt.show()
```

```
RMSE value for k=  0 is: 0.4488792012484348
RMSE value for k=  1 is: 0.4063396858522528
RMSE value for k=  2 is: 0.3868699071282999
RMSE value for k=  3 is: 0.38874079151161206
RMSE value for k=  4 is: 0.3888367650451102
RMSE value for k=  5 is: 0.3895398484524251
RMSE value for k=  6 is: 0.3929782716926476
RMSE value for k=  7 is: 0.39402901154648307
RMSE value for k=  8 is: 0.3906616783038156
RMSE value for k=  9 is: 0.3900344416479675
RMSE value for k=  10 is: 0.38545467345943957
```



We created elbow grapgh and we can clearly see the slope change is maximum at point 2. So we will use k=2

```
pred = gs.predict(scaled_x_test)
error = sqrt(mean_squared_error(y_test,pred)) #calculate rmse
rmse_val.append(error) #store rmse values
print('RMSE value for k= ' , gs_results.best_estimator_.n_neighbors , 'is:', error)
```

```
RMSE value for k=  10 is: 0.38352844434979055
```

So based on the grid search we can say the optimum value of RMSE is at k=10 which would give best model prediction

```
gs_results.best_score_
```

```
gs_results.best_estimator_
gs_results.best_params_
```

```
{'metric': 'euclidean', 'n_neighbors': 10, 'weights': 'distance'}
```

```
#6. What happens when K=1? Check the model performance on the training and testing data.
rmse_val=[]
for K in range(1,12):  # used 12 based on 12 variables in the dataset
    model = KNeighborsRegressor(n_neighbors = 1)
    model = KNeighborsRegressor(n_neighbors = 1)
    model.fit(scaled_x_train, y_train)  #fit the model
    pred=model.predict(scaled_x_test) #make prediction on test set
    error = sqrt(mean_squared_error(y_test,pred)) #calculate rmse
    rmse_val.append(error) #store rmse values
    print('RMSE value for k= ' , K-1 , 'is:', error)

plt.plot(rmse_val)
plt.xticks([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16],fontsize=12)
plt.show()
```

```
RMSE value for k=  0 is: 0.4488792012484348
RMSE value for k=  1 is: 0.4488792012484348
RMSE value for k=  2 is: 0.4488792012484348
RMSE value for k=  3 is: 0.4488792012484348
RMSE value for k=  4 is: 0.4488792012484348
RMSE value for k=  5 is: 0.4488792012484348
RMSE value for k=  6 is: 0.4488792012484348
RMSE value for k=  7 is: 0.4488792012484348
RMSE value for k=  8 is: 0.4488792012484348
RMSE value for k=  9 is: 0.4488792012484348
RMSE value for k=  10 is: 0.4488792012484348
```