Australian Housing Prices prediction

This dataset can be used to predict hosing prices in Australia. This dataset can be used to find relationships between housing prices and location. This dataset can be used to find relationships between housing prices and features such as size, number of bedrooms, and number of bathrooms

Hint: RealEstateAU_1000_Samples.csv file

Instructions:

1. Use Lifecycle of Data Sciece
2. Use necessary data Preprocess techniques
3. Use various Regression and Classification techniques for comparision
4. Use metrics for regression and classification when needed.
5. Use variosu Pipeline/Hyperparametr tuning techniques for improving performance

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

%matplotlib inline


df = pd.read_csv("/content/RealEstateAU_1000_Samples.csv")
df
```

	index	TID	breadcrumb	category_name	property_type	building_size	land_size	preferred_si:
0	0	1350988	Buy>NT>DARWIN CITY	Real Estate & Property for sale in DARWIN CITY...	House	NaN	NaN	Na
1	1	1350989	Buy>NT>DARWIN CITY	Real Estate & Property for sale in DARWIN CITY...	Apartment	171m²	NaN	171m
2	2	1350990	Buy>NT>DARWIN CITY	Real Estate & Property for sale in DARWIN	Unit	NaN	NaN	Na

df.columns

```
Index(['index', 'TID', 'breadcrumb', 'category_name', 'property_type',
       'building_size', 'land_size', 'preferred_size', 'open_date',
       'listing_agency', 'price', 'location_number', 'location_type',
       'location_name', 'address', 'address_1', 'city', 'state', 'zip_code',
       'phone', 'latitude', 'longitude', 'product_depth', 'bedroom_count',
       'bathroom_count', 'parking_count', 'RunDate'],
      dtype='object')
```

df.drop(["index", "TID", "breadcrumb", "open_date", "phone", "RunDate"], axis = 1, inplace = True)

df.head( )

	category_name	property_type	building_size	land_size	preferred_size	listing_agency	price	location_
0	Real Estate & Property for sale in DARWIN CITY...	House	NaN	NaN	NaN	Professionals - DARWIN CITY	$435,000	13
1	Real Estate & Property for sale in DARWIN CITY...	Apartment	171m²	NaN	171m²	Nick Mousellis Real Estate - Eview Group Member	Offers Over $320,000	139
2	Real Estate & Property for sale in DARWIN CITY...	Unit	NaN	NaN	NaN	Habitat Real Estate - THE GARDENS	$310,000	139
3	Real Estate & Property for sale in DARWIN CITY...	House	NaN	NaN	NaN	Ray White - NIGHTCLIFF	$259,000	13
4	Real Estate & Property for sale in DARWIN CITY...	Unit	201m²	NaN	201m²	Carol Need Real Estate - Fannie Bay	$439,000	139

5 rows × 21 columns

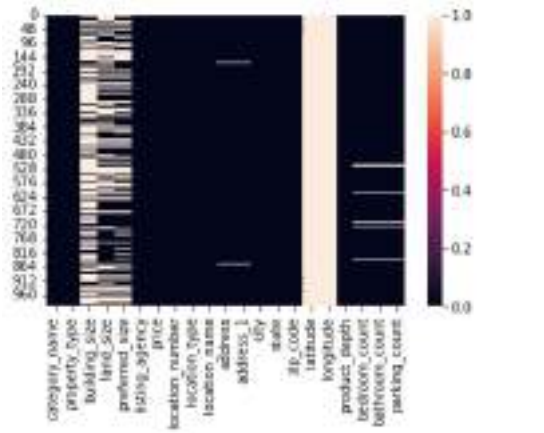
null = df.isnull().sum()
null

```
category_name       0
property_type       0
building_size     720
land_size         467
preferred_size    391
listing_agency      0
price               0
location_number     0
```

```
location_type        0
location_name        0
address             12
address_1           12
city                 0
state                0
zip_code             0
latitude          1000
longitude         1000
product_depth        0
bedroom_count       33
bathroom_count      33
parking_count       33
dtype: int64
```

```
sns.heatmap(df.isnull())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd9dc9788b0>
```



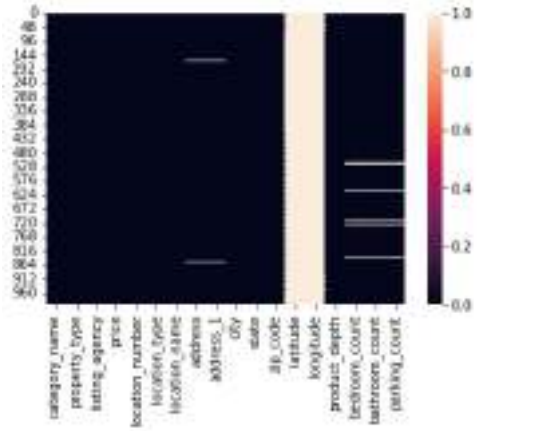
The "Building Size", "Land Size" and "Preferred Size" are sadly columns to drop, since there are too many missing values.

Alternatively, we could create a new DataFrame to be analyzed with Only the Rows that are not Null for the 3 Columns mentioned, but that would reduce the size of our samples, which is already small.

```
df.drop(["preferred_size", "building_size", "land_size"], axis = 1, inplace = True)
```

```
sns.heatmap(df.isnull())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd9dc89d370>
```



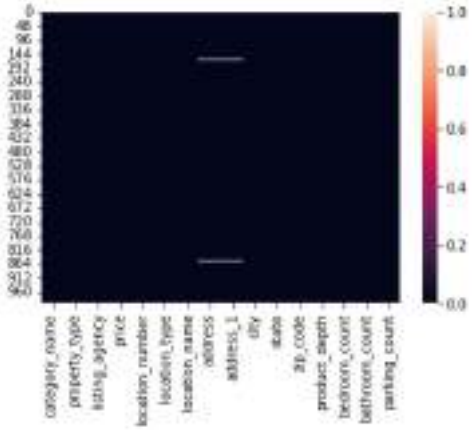

```
df.drop(["longitude", "latitude"], axis = 1, inplace = True)
sns.heatmap(df.isnull())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd9d9a5ffa0>
```

```
df["bedroom_count"].fillna(df["bedroom_count"].mode()[0], inplace = True)
df["bathroom_count"].fillna(df["bedroom_count"].mode()[0], inplace = True)
df["parking_count"].fillna(df["bedroom_count"].mode()[0], inplace = True)
```

```
sns.heatmap(df.isnull())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd9d996f8b0>
```



```
df["category_name"].value_counts()
```

```
Real Estate & Property for sale in DARWIN, NT 0801        816
Real Estate & Property for sale in DARWIN CITY, NT 0800    184
Name: category_name, dtype: int64
```

```
df["property_type"].value_counts()
```

```
House                441
Unit                 230
Apartment            212
Townhouse             38
Residential Land      33
Duplex/Semi-detached  19
Acreage                9
Block Of Units         6
Other                  4
Villa                  4
Studio                 2
Warehouse              1
Lifestyle              1
Name: property_type, dtype: int64
```

```
df["listing_agency"].value_counts()
```

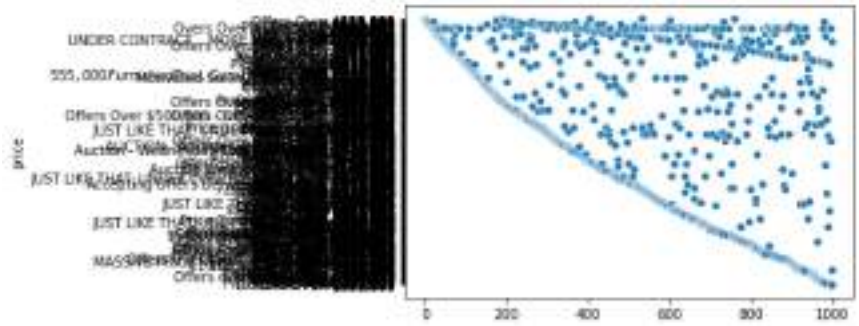
```
Real Estate Central - DARWIN CITY                113
Elders Real Estate - Darwin                       62
Elders Real Estate - Palmerston                   53
Raine & Horne - Darwin                            48
First National Real Estate O'Donoghues - Darwin   41
                                                 ...
Ellis Parker Real Estate - LARRAKEYAH              1
Dunvegan Real Estate - PALMERSTON                  1
Australian Home Partners                           1
buymyplace                                         1
Mercury Real Estate                                1
Name: listing_agency, Length: 85, dtype: int64
```

```
df["city"].value_counts()
```

```
Darwin City        285
Stuart Park         39
Rosebery            37
Bakewell            31
Durack              30
Zuccoli             29
Woodroffe           27
Nightcliff          27
Driver              26
Parap               26
Rapid Creek         25
Bellamack           23
Humpty Doo          20
Johnston            20
Leanyer             19
Gunn                19
Gray                19
Karama              16
Moulden             15
Howard Springs      15
Berrimah            15
Bayview             14
Fannie Bay          14
Farrar              12
Coconut Grove       12
Muirhead            12
The Gardens         11
Lyons               10
Millner             10
Woolner              9
Jingili              9
Herbert              9
Tiwi                 9
Larrakeyah           9
Ludmilla             7
Alawa                7
Anula                7
Wagaman              7
Malak                7
Wulagi               6
Virginia             6
Brinkin              6
Wanguri              6
Berry Springs        6
Moil                 5
Lee Point            4
Nakara               4
Marrara              3
Coolalinga           3
Girraween            3
Bees Creek           3
Cullen Bay           3
The Narrows          1
Knuckey Lagoon       1
Rosebery Heights     1
Marlow Lagoon        1
Name: city, dtype: int64
```

```
sns.scatterplot(data = df["price"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd9d988b610>
```




```
import re

def extract_price(x):
    if x != "":
```

```
        match = re.search(r'\$?\s*(\d+(?:\.\d+)?)[k|m|K|M]\s*', x)

        if match:
            price = match.group(1)
            price = float(price)
            if x[-1].lower() == 'k':
                price *= 1000
            elif x[-1].lower() == 'm':
                price *= 1000000
            return int(price)
        else:
            match = re.sub(r'[^\d]', '', x)

            try:
                return int(match)
            except:
                try:
                    return(float(match))
                except:
                    return  None


df["NumericalPrice"] = df["price"]

df["NumericalPrice"] = df["NumericalPrice"].apply(lambda x: extract_price(x))


pd.options.display.max_columns =  None
pd.options.display.max_rows = None

df[["price", "NumericalPrice"]]
```

960	Offers over $419,000	4.190000e+05
961	Offers over $380,000	3.800000e+05
962	$430,000	4.300000e+05
963	$244,000	2.440000e+05
964	$599,000	5.990000e+05
965	Offers Over $480,000	4.800000e+05
966	$560,000	5.600000e+05
967	$315,000	3.150000e+05
968	$585,000 & $595,000	5.850006e+11
969	$1,550,000	1.550000e+06
970	Offers over $450,000	4.500000e+05
971	Under Offer	NaN
972	Offers Over $630,000	6.300000e+05
973	Price Guide Mid $300,000	3.000000e+05
974	$685,000	6.850000e+05
975	UNDER CONTRACT	NaN
976	$469,000	4.690000e+05
977	Negotiable	NaN
978	$439,000	4.390000e+05
979	$299,000 Negotiable	2.990000e+05
980	$380,000	3.800000e+05
981	Contact Agent	NaN
982	$339,000	3.390000e+05
983	$275,000	2.750000e+05
984	$425,000	4.250000e+05
985	Offers over $370,000	3.700000e+05
986	OFFERS OVER $415,000	4.150000e+05
987	$550,000	5.500000e+05
988	PRICE GUIDE $1,070,000	1.070000e+06
989	Offers over $740,000	7.400000e+05
990	UNDER CONTRACT	NaN
991	$270,000	2.700000e+05
992	$390,000	3.900000e+05
993	$495,000	4.950000e+05
994	UNDER CONTRACT	NaN
995	2 Residence	2.000000e+00
996	$601,000	6.010000e+05
997	$655,000	6.550000e+05
998	$675,000	6.750000e+05
999	$399,000	3.990000e+05

```
c = 0

for x in df["NumericalPrice"]:
  x = str(x)

  if len(x) <= 5:
    x = None

  elif len(x) >= 8:
    count0 = 0

    for n in x:
      if n == "0":
        count0 += 1

    if count0 <= 2:
      x = None

    else:
      x = x[0:6]

  df["NumericalPrice"][c] = x

  c += 1
```

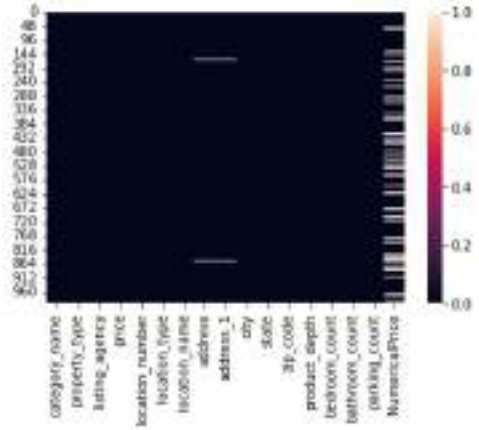
```
<ipython-input-21-e1de7eabf4fa>:22: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df["NumericalPrice"][c] = x
```

```
df[["price", "NumericalPrice"]]
```

960	Offers over $419,000	419000.0
961	Offers over $380,000	380000.0
962	$430,000	430000.0
963	$244,000	244000.0
964	$599,000	599000.0
965	Offers Over $480,000	480000.0
966	$560,000	560000.0
967	$315,000	315000.0
968	$585,000 & $595,000	585000.0
969	$1,550,000	155000.0
970	Offers over $450,000	450000.0
971	Under Offer	NaN
972	Offers Over $630,000	630000.0
973	Price Guide Mid $300,000	300000.0
974	$685,000	685000.0
975	UNDER CONTRACT	NaN
976	$469,000	469000.0
977	Negotiable	NaN
978	$439,000	439000.0
979	$299,000 Negotiable	299000.0
980	$380,000	380000.0
981	Contact Agent	NaN
982	$339,000	339000.0
983	$275,000	275000.0
984	$425,000	425000.0
985	Offers over $370,000	370000.0
986	OFFERS OVER $415,000	415000.0
987	$550,000	550000.0
988	PRICE GUIDE $1,070,000	107000.0
989	Offers over $740,000	740000.0
990	UNDER CONTRACT	NaN
991	$270,000	270000.0
992	$390,000	390000.0
993	$495,000	495000.0
994	UNDER CONTRACT	NaN
995	2 Residence	NaN
996	$601,000	601000.0
997	$655,000	655000.0
998	$675,000	675000.0
999	$399,000	399000.0

```
sns.heatmap(df.isnull())
```

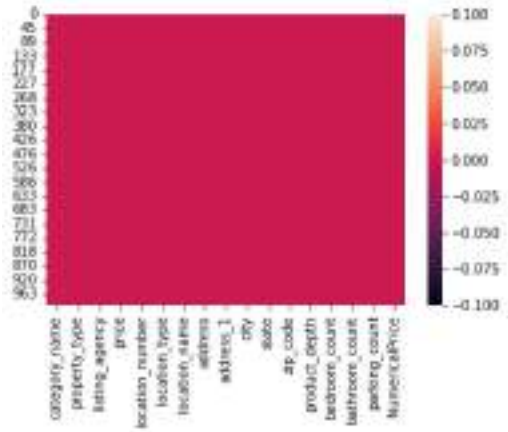
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd9d92f8f70>
```




```
df.dropna(axis = 0, how = "any", inplace = True)
```

```
sns.heatmap(df.isnull())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd9d7928ee0>
```




```
df["NumericalPrice"]
```

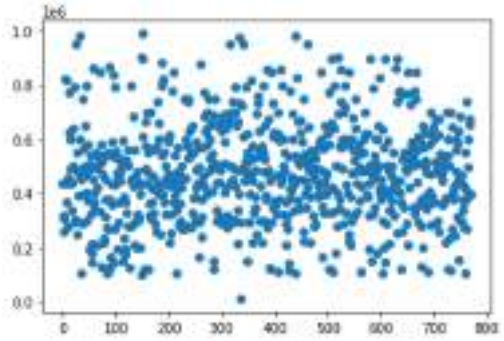
```
966    560000.0
967    315000.0
968    585000.0
969    155000.0
970    450000.0
972    630000.0
973    300000.0
974    685000.0
976    469000.0
978    439000.0
979    299000.0
980    380000.0
982    339000.0
983    275000.0
984    425000.0
985    370000.0
986    415000.0
987    550000.0
988    107000.0
989    740000.0
991    270000.0
992    390000.0
993    495000.0
996    601000.0
997    655000.0
998    675000.0
999    399000.0
Name: NumericalPrice, dtype: float64
```

```
df["NumericalPrice"].astype("float")
```

```
996    601000.0
997    655000.0
998    675000.0
999    399000.0
Name: NumericalPrice, dtype: float64
```

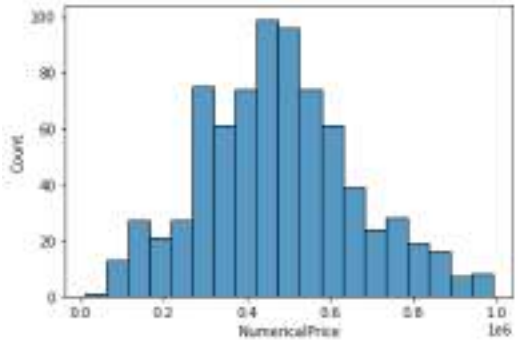
```
plt.scatter(x = [i for i in range(len(df))], y = df["NumericalPrice"].astype("float"))
```

```
<matplotlib.collections.PathCollection at 0x7fd9d788fe20>
```




```
sns.histplot(df["NumericalPrice"].astype("float"))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd9d7919e80>
```




```
df["NumericalPrice"] = df["NumericalPrice"].astype("float")
```

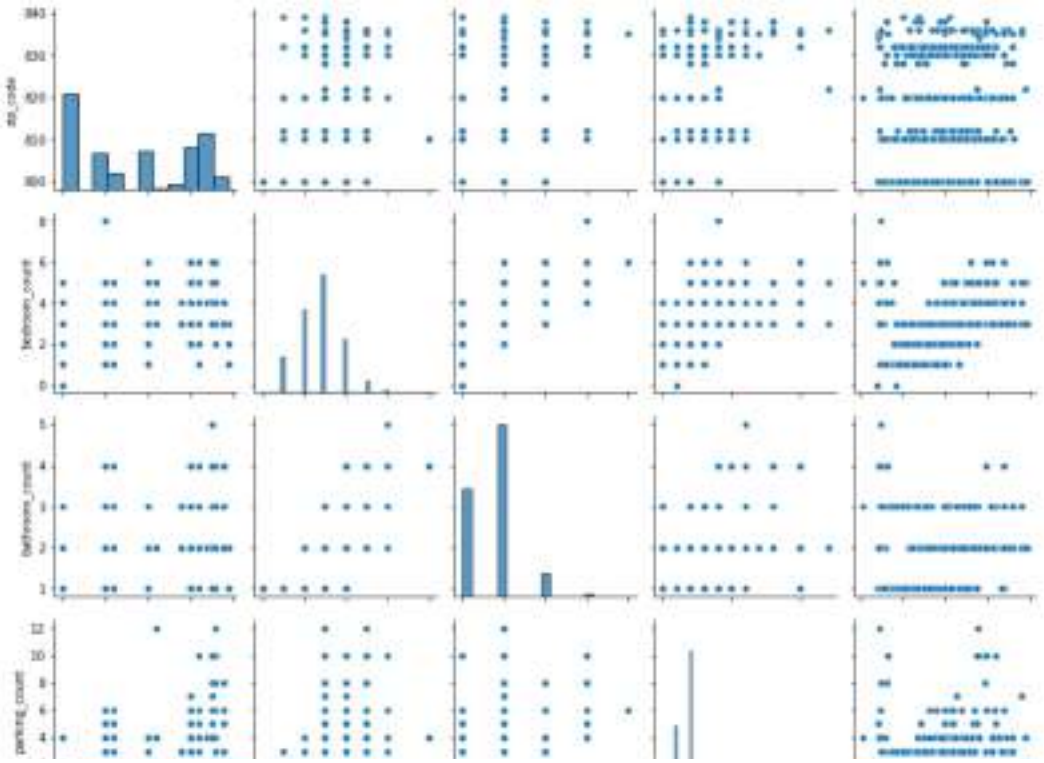
```
df.columns
```

```
Index(['category_name', 'property_type', 'listing_agency', 'price',
       'location_number', 'location_type', 'location_name', 'address',
       'address_1', 'city', 'state', 'zip_code', 'product_depth',
       'bedroom_count', 'bathroom_count', 'parking_count', 'NumericalPrice'],
      dtype='object')
```

```
newdf = df[["property_type", "zip_code", "bedroom_count", "bathroom_count", "parking_count","NumericalPrice"]]
```

```
sns.pairplot(data = newdf)
```

```
<seaborn.axisgrid.PairGrid at 0x7fd9d784a490>
```




```
newdf = pd.get_dummies(newdf)
```

```
newdf.head( )
```

	zip_code	bedroom_count	bathroom_count	parking_count	NumericalPrice	property_type_Acreage	property
0	800	2.0	1.0	1.0	435000.0	0	
1	800	3.0	2.0	2.0	320000.0	0	
2	800	2.0	1.0	1.0	310000.0	0	
3	800	1.0	1.0	0.0	259000.0	0	
4	800	3.0	2.0	2.0	439000.0	0	

The Steps for Building Our Linear Regression Model Are:

1) Create the X Features Variable and Y the Predicted Variable.

2) Split the DataSet into a TrainSet and a TestSet.

3)Fit the Model

4) Use the Model to make Predictions

5) Calculate Errors

6) Evaluate the Model

```
from sklearn.linear_model import LinearRegression as LR
from sklearn.model_selection import train_test_split as TTS
```

```
x = newdf.drop("NumericalPrice", axis = 1, inplace= False)
y = newdf["NumericalPrice"]
```

```
xTrain, xTest, yTrain, yTest = TTS(x, y, test_size = 0.3)
```

```
LR_ = LR()
```

```
LR_.fit(xTrain, yTrain)
```

```
LinearRegression()
```

```
preds = LR_.predict(xTest)
```

```
from sklearn.metrics import mean_squared_error as MSE
from sklearn.metrics import mean_absolute_error as MAE
from sklearn.metrics import r2_score as R2
```

```
mae = MAE(preds, yTest)
mse = MSE(preds, yTest)
rmse = MSE(preds, yTest, squared= False)
r2 = R2(preds, yTest)
```

```
print(mae)
print(mse)
print(rmse)
print(r2)
```

```
110480.09710388833
25126686160.28905
158513.99357876595
-1.9465748442855029
```

As we've Guessed Earlier, by Looking at the Errors, we can conclude that the Linear Regression is not the best Model to fit our Data. Since we have Non-Linear Data, but we Still need to Address a Regression Problem, we will Try out 2 more Models:

1) K Nearest Neighbors Regressor

2) Decision Tree Regressor

The Steps for Building Our Models are pretty much the same with some Variations:

1) Create the X Features Variable and Y the Predicted Variable

2) Split the DataSet into a TrainSet and a TestSet

3) Search for the Best Parameters with the GridSearchCV Method

4) Fit the Model

5) Use the Model to make Predictions

6) Calculate Errors

7) Cross Validate the Model

8) Evaluate the Model

```
#We Resize the Unit of Our Prices for Convenience Purposes
```

```
newdf["RoundedPrice"] = newdf["NumericalPrice"].apply(lambda x: x/100000)
```

```
from sklearn.neighbors import KNeighborsRegressor as KNR
from sklearn.tree import DecisionTreeRegressor as DTR
from sklearn.model_selection import GridSearchCV as GSCV
```

```
x = newdf.drop("RoundedPrice", axis = 1, inplace= False)
y = newdf["RoundedPrice"]
xTrain, xTest, yTrain, yTest = TTS(x, y, test_size = 0.3)
```

```
'\n#Evaluate KNN Neighbors with Elbow Method\n\nScores = []\n\nfor k in range(1, 11):\n    K = KNR(algorithm = "auto", n_neighbors = k, p = 1)\n    K.fit(xTrain, yTr
```

```
'\n#Evaluate KNN Neighbors with Elbow Method\n\nScores = []\n\nfor k in range(1, 11):\n    K = KNR(algorithm = "aut
o", n_neighbors = k, p = 1)\n    K.fit(xTrain, yTrain)\n    Preds = K.predict(xTest)\n    Scores.append(MSE(yTest, Preds,
squared = False))\n\n\nprint(Scores)\n\nplt.plot(Scores)\n'
```

```
Parameters = {'n_neighbors': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
              'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'],
              'p': [1,2]}

KNN = KNR()
```