Assignment01

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1 Assignment 01

[1]:

```
## install pandas dataframe library

!pip install pandas
```

```
Requirement already satisfied: pandas in
/home/fardeen/Desktop/MachineLearningLab/venv/lib/python3.12/site-packages
(2.2.2)
Requirement already satisfied: numpy>=1.26.0 in
/home/fardeen/Desktop/MachineLearningLab/venv/lib/python3.12/site-packages (from
pandas) (2.0.1)
Requirement already satisfied: python-dateutil>=2.8.2 in
/home/fardeen/Desktop/MachineLearningLab/venv/lib/python3.12/site-packages (from
pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
/home/fardeen/Desktop/MachineLearningLab/venv/lib/python3.12/site-packages (from
pandas) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in
/home/fardeen/Desktop/MachineLearningLab/venv/lib/python3.12/site-packages (from
pandas) (2024.1)
Requirement already satisfied: six>=1.5 in
/home/fardeen/Desktop/MachineLearningLab/venv/lib/python3.12/site-packages (from
python-dateutil>=2.8.2->pandas) (1.16.0)
```

1.1 Question 01 / 02

[6]:

```
import pandas as pd
TRAIN_DATASET_PATH = "../ML_DRIVE/Assignment01/train.csv"

houses_dataframe = pd.read_csv(TRAIN_DATASET_PATH)
```

```
houses_dataframe.head()
```

```
[6]:    Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
     0   1          60       RL         65.0     8450   Pave   NaN      Reg
     1   2          20       RL         80.0     9600   Pave   NaN      Reg
     2   3          60       RL         68.0    11250   Pave   NaN      IR1
     3   4          70       RL         60.0     9550   Pave   NaN      IR1
     4   5          60       RL         84.0    14260   Pave   NaN      IR1

       LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
     0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
     1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5
     2         Lvl    AllPub  …        0    NaN   NaN         NaN       0      9
     3         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
     4         Lvl    AllPub  …        0    NaN   NaN         NaN       0     12

       YrSold  SaleType  SaleCondition  SalePrice
     0   2008        WD         Normal     208500
     1   2007        WD         Normal     181500
     2   2008        WD         Normal     223500
     3   2006        WD        Abnorml     140000
     4   2008        WD         Normal     250000

     [5 rows x 81 columns]
```

1.2 Estimate missing values in the dataframe

First we will drop the columns having at least one 'NAN' value using the dropna() function. Here we will be using the interpolate() method provided by the pandas library to fill the missing values, method used will be forward average for equally spaced values

```
[7]: houses_dataframe=houses_dataframe.dropna(axis=1,thresh=500)
     houses_dataframe=houses_dataframe.interpolate(method="linear",␣
      ↪limit_direction="forward")
     houses_dataframe.columns
```

```
[7]: Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
            'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope',
            'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle',
            'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'RoofStyle',
            'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea',
            'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond',
            'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2',
            'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating', 'HeatingQC',
            'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
            'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
            'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd',
            'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType', 'GarageYrBlt',
            'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond',
            'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch',
            'ScreenPorch', 'PoolArea', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
            'SaleCondition', 'SalePrice'],
           dtype='object')
```

1.3 Question 03

1.4 Estimating Saleprice based on LotArea using Linear Regression

[13]:

```
## Compress the data-frame into ['saleprice','lotarea']

sale_price_lot_area_df = houses_dataframe[['LotArea','SalePrice']]
sale_price_lot_area_df.head()
```

[13]:

```
   LotArea  SalePrice
0     8450     208500
1     9600     181500
2    11250     223500
3     9550     140000
4    14260     250000
```

1.4.1 Before Performing prediction for new values, we need to define our Linear Regression Model

We will import and use the sklearn library for this purpose

[14]:

```
!pip install scikit-learn
```

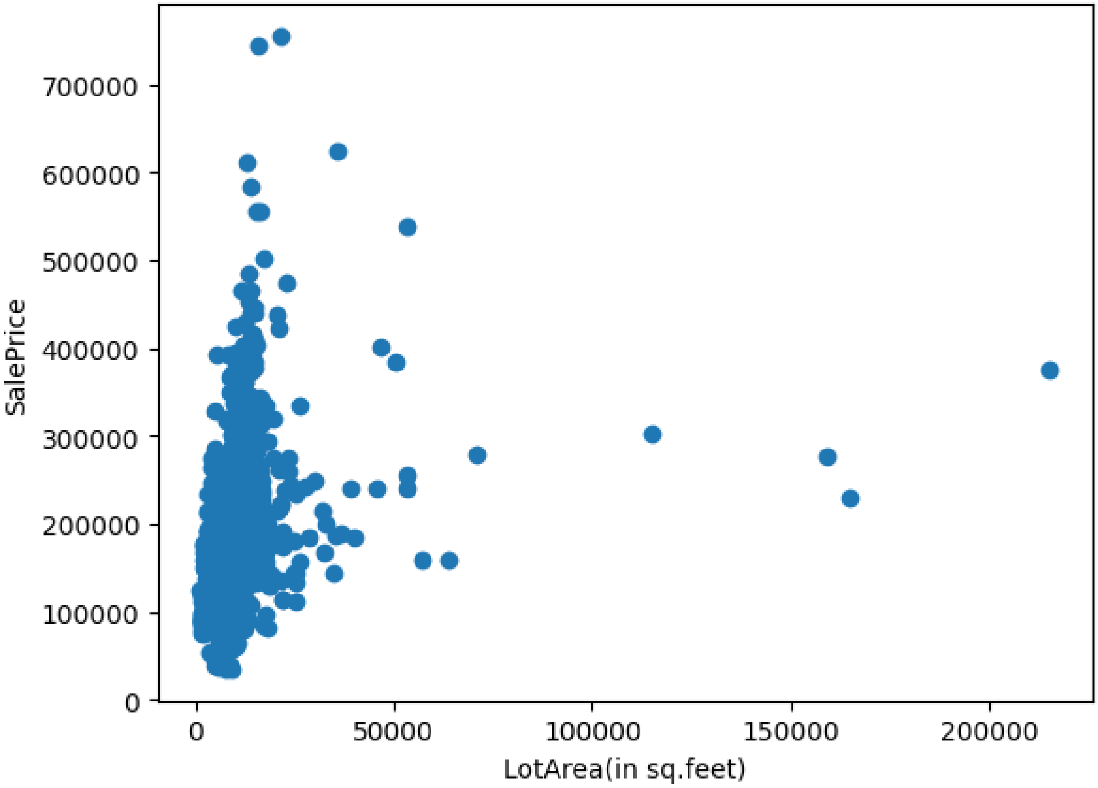
```
Requirement already satisfied: scikit-learn in
/home/fardeen/Desktop/MachineLearningLab/venv/lib/python3.12/site-packages
(1.5.1)
Requirement already satisfied: numpy>=1.19.5 in
/home/fardeen/Desktop/MachineLearningLab/venv/lib/python3.12/site-packages (from
scikit-learn) (2.0.1)
Requirement already satisfied: scipy>=1.6.0 in
/home/fardeen/Desktop/MachineLearningLab/venv/lib/python3.12/site-packages (from
scikit-learn) (1.14.0)
Requirement already satisfied: joblib>=1.2.0 in
/home/fardeen/Desktop/MachineLearningLab/venv/lib/python3.12/site-packages (from
scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/home/fardeen/Desktop/MachineLearningLab/venv/lib/python3.12/site-packages (from
scikit-learn) (3.5.0)
```

[15]:

```
## Plot the saleprice vs lotarea
import matplotlib.pyplot as plt
```

```
plt.
 ↪scatter(x=sale_price_lot_area_df['LotArea'],y=sale_price_lot_area_df['SalePrice'])
plt.xlabel('LotArea(in sq.feet)')
plt.ylabel('SalePrice')
```

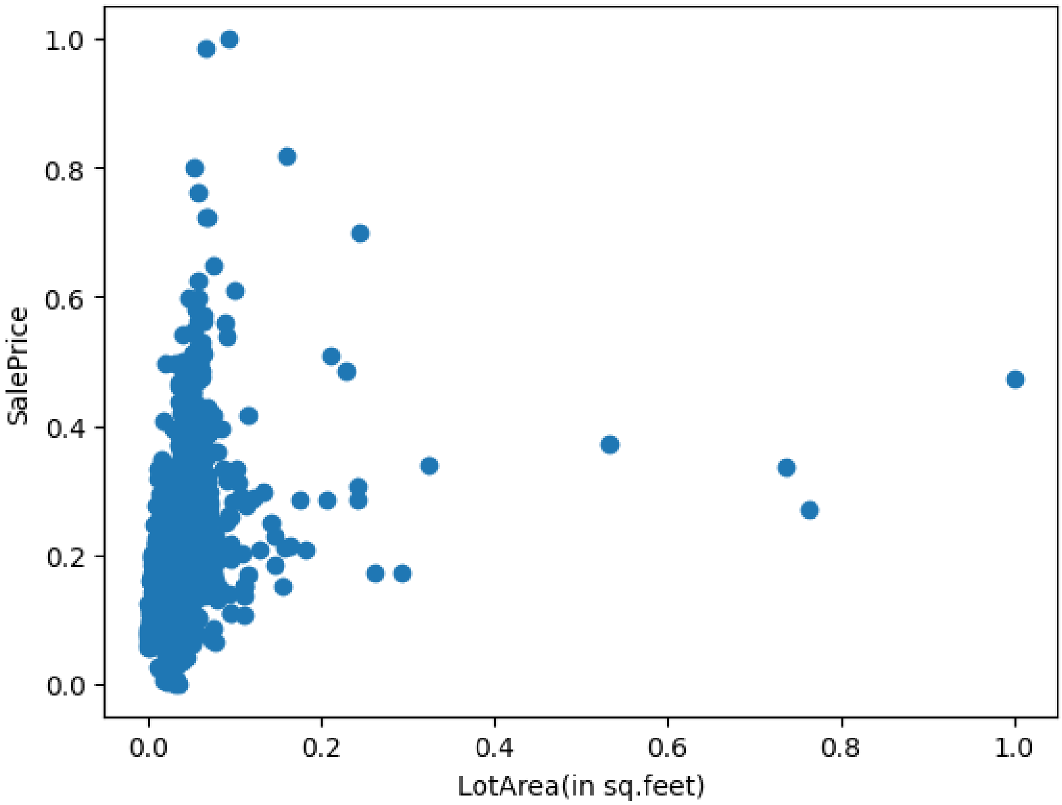
```
[15]: Text(0, 0.5, 'SalePrice')
```



We can observe that the ranges of the X and Y axis are not same, so we can normalise the values of the saleprice and lotarea.

```
[11]: from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler() ## (x-xmin)/(xmax-xmin)
sale_price_lot_area_df=scaler.fit_transform(sale_price_lot_area_df)
sale_price_lot_area_df=pd.
 ↪DataFrame(sale_price_lot_area_df,columns=['LotArea','SalePrice'])
plt.
 ↪scatter(x=sale_price_lot_area_df['LotArea'],y=sale_price_lot_area_df['SalePrice'])
plt.xlabel('LotArea(in sq.feet)')
plt.ylabel('SalePrice')
```

```
[11]: Text(0, 0.5, 'SalePrice')
```



1.4.2 Implementing a utility K-fold cross validator for train-test split

[16]:

```
# Here we will be considering 5 folds
from sklearn.model_selection import KFold
from sklearn.metrics import mean_squared_error

## R2-Score = 1-( RSS/TSS ) ; RSS --> Residual Sum of Squares , TSS --> Total Sum of Squares
'''
    @brief:- Utility function to perform KfoldCross Validation on a dataset
    @param:- model - Estimator
             X_data - Independant Variable
             y_data - Dependant Variable

    @return:- Tuple of size 2, 1st being the average R2 score and the 2nd one being average MSE
'''

def Kfold_util(model,X_data,y_data):
    s_kfold = KFold(n_splits=5)
    model_r2_score = 0
    model_MSE_score = 0
    for i,(train_index,test_index) in enumerate(s_kfold.split(X_data,y_data)):
        print(f"Fold: {i+1}")
        model.fit(X_data[train_index],y_data[train_index])
        r2_score = model.score(X_data[test_index],y_data[test_index])
        y_pred = model.predict(X_data[test_index])
        MSE_score = mean_squared_error(y_data[test_index],y_pred)
        print(f"R2 score is: {r2_score} and MSE is: {MSE_score}")
        model_r2_score += r2_score
        model_MSE_score += MSE_score

    return (model_r2_score/5,model_MSE_score/5)
```

1.5 Implement the model for Linear Regression

[17]:

```
## Note since the y-values will be scaled we will not be using the scaled␣
 ↪values for our model
from sklearn.linear_model import LinearRegression

model = LinearRegression()

X = sale_price_lot_area_df[['LotArea']]
Y = sale_price_lot_area_df[['SalePrice']]

avg_r2_score,avg_MSE = Kfold_util(model,X_data=X.to_numpy(),y_data=Y.to_numpy())

print(f"Average R2-score is :- {avg_r2_score}")
print(f"Average MSE is :- {avg_MSE}")
```

```
Fold: 1
R2 score is: 0.0811255840664582 and MSE is: 5083791990.222536
Fold: 2
R2 score is: -0.09677051342182441 and MSE is: 7206516872.48441
Fold: 3
R2 score is: 0.09034415298115273 and MSE is: 6893188266.548201
Fold: 4
R2 score is: 0.04542629407540688 and MSE is: 4835731884.893979
Fold: 5
R2 score is: 0.06551930527251171 and MSE is: 6266038369.012835
Average R2-score is :- 0.03712896459474102
Average MSE is :- 6057053476.632393
```

Print the slope and intercept

[18]:

```
print(f'Saleprice = {model.coef_[0][0]}*LotArea + {model.intercept_[0]}')
```

```
Saleprice = 1.9554707455489049*LotArea + 160015.64126957097
```

1.6 Question 04 / 05

[19]:

```
## Meta-data checking for non-null vaues
houses_dataframe['LotFrontage'].info()
houses_dataframe['OverallQual'].info()
houses_dataframe['OverallCond'].info()
houses_dataframe['1stFlrSF'].info()
houses_dataframe['GrLivArea'].info()
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 1460 entries, 0 to 1459
Series name: LotFrontage
Non-Null Count  Dtype
--------------  -----
1460 non-null   float64
dtypes: float64(1)
memory usage: 11.5 KB
<class 'pandas.core.series.Series'>
RangeIndex: 1460 entries, 0 to 1459
Series name: OverallQual
Non-Null Count  Dtype
--------------  -----
1460 non-null   int64
dtypes: int64(1)
memory usage: 11.5 KB
<class 'pandas.core.series.Series'>
RangeIndex: 1460 entries, 0 to 1459
Series name: OverallCond
Non-Null Count  Dtype
--------------  -----
1460 non-null   int64
dtypes: int64(1)
memory usage: 11.5 KB
<class 'pandas.core.series.Series'>
RangeIndex: 1460 entries, 0 to 1459
Series name: 1stFlrSF
Non-Null Count  Dtype
--------------  -----
1460 non-null   int64
dtypes: int64(1)
memory usage: 11.5 KB
<class 'pandas.core.series.Series'>
RangeIndex: 1460 entries, 0 to 1459
Series name: GrLivArea
Non-Null Count  Dtype
--------------  -----
1460 non-null   int64
dtypes: int64(1)
```

```
memory usage: 11.5 KB
```

1.6.1 Model 1:- SalePrice based on LotFrontage and LotArea

[20]:

```
X_model1 = houses_dataframe[['LotArea','LotFrontage']]
Y_model1 = houses_dataframe[['SalePrice']]

model1 = LinearRegression()

model1_avg_r2_score,model1_avg_MSE = Kfold_util(model1,X_data=X_model1.
 ↪to_numpy(),y_data=Y_model1.to_numpy())

print(f"Average R2-score of Model 1 is :- {model1_avg_r2_score}")
print(f"Average MSE of Model 1 is :- {model1_avg_MSE}")
```

```
Fold: 1
R2 score is: 0.16662248538019597 and MSE is: 4610769284.887944
Fold: 2
R2 score is: 0.06022044420881212 and MSE is: 6174981130.825078
Fold: 3
R2 score is: 0.12987082205255585 and MSE is: 6593663152.350717
Fold: 4
R2 score is: 0.052979792241372836 and MSE is: 4797466959.203123
Fold: 5
R2 score is: 0.0954056556554943 and MSE is: 6065639346.040892
Average R2-score of Model 1 is :- 0.10101983990768622
Average MSE of Model 1 is :- 5648503974.6615505
```

Print the slope and intercept

[21]:

```
print(f'Saleprice = {model1.coef_[0][0]}*LotArea + {model1.
 ↪coef_[0][1]}*LotFrontage + {model1.intercept_[0]}')
```

```
Saleprice = 1.4451006676919291*LotArea + 963.9269485159833*LotFrontage +
97914.36673373333
```

1.6.2 Model 2:- SalePrice based on LotFrontage, LotArea, OverallQual, OverallCond

[22]:

```
model2 = LinearRegression()

X_model2 =␣
 ↪houses_dataframe[['LotArea','LotFrontage','OverallQual','OverallCond']]
Y_model2 = houses_dataframe[['SalePrice']]

model2_avg_r2_score,model2_avg_MSE = Kfold_util(model2,X_data=X_model2.
 ↪to_numpy(),y_data=Y_model2.to_numpy())

print(f"Average R2-score of Model 2 is :- {model2_avg_r2_score}")
print(f"Average MSE of Model 2 is :- {model2_avg_MSE}")
```

```
Fold: 1
R2 score is: 0.7113617232553542 and MSE is: 1596928735.7894995
Fold: 2
R2 score is: 0.6575961773354837 and MSE is: 2249822451.4958005
Fold: 3
R2 score is: 0.6498657567034967 and MSE is: 2653246571.786378
Fold: 4
R2 score is: 0.6433965130847672 and MSE is: 1806501521.2943513
Fold: 5
R2 score is: 0.6227651796454086 and MSE is: 2529498866.9175787
Average R2-score of Model 2 is :- 0.6569970700049022
Average MSE of Model 2 is :- 2167199629.4567213
```

Print the slope and intercept

[23]:
```
print(f'Saleprice = {model2.coef_[0][0]}*LotArea + {model2.
 ↪coef_[0][1]}*LotFrontage + {model2.coef_[0][2]}*OverallQual +{model2.
 ↪coef_[0][3]}*OverallCond +{model2.intercept_[0]}')
```

```
Saleprice = 1.189847212962575*LotArea + 418.4665742151931*LotFrontage +
42994.96807363269*OverallQual +-867.0796471136888*OverallCond
+-118705.73313785144
```

1.6.3 Model 3:- SalePrice based on LotFrontage, LotArea, OverallQual, OverallCond, 1stFlrSF and GrLivArea

[24]:
```
model3 = LinearRegression()

X_model3 =␣
 ↪houses_dataframe[['LotArea','LotFrontage','OverallQual','OverallCond','1stFlrSF','GrLivArea
Y_model3 = houses_dataframe[['SalePrice']]

model3_avg_r2_score,model3_avg_MSE = Kfold_util(model3,X_data=X_model3.
 ↪to_numpy(),y_data=Y_model3.to_numpy())

print(f"Average R2-score of Model 3 is :- {model3_avg_r2_score}")
print(f"Average MSE of Model 3 is :- {model3_avg_MSE}")
```

```
Fold: 1
R2 score is: 0.7879932254919686 and MSE is: 1172955001.7146173
Fold: 2
R2 score is: 0.7569992404082071 and MSE is: 1596677748.530303
Fold: 3
R2 score is: 0.7612416434303056 and MSE is: 1809262599.0810008
Fold: 4
R2 score is: 0.7326812554452906 and MSE is: 1354197971.775218
Fold: 5
R2 score is: 0.6423236527060292 and MSE is: 2398352077.7665286
Average R2-score of Model 3 is :- 0.7362478034963603
Average MSE of Model 3 is :- 1666289079.7735336
```

Print the slope and intercept

[25]:
```
print(f'Saleprice = {model3.coef_[0][0]}*LotArea + {model3.
 ↪coef_[0][1]}*LotFrontage + {model3.coef_[0][2]}*OverallQual +{model3.
 ↪coef_[0][3]}*OverallCond + {model3.coef_[0][4]}*1stFlrSF + {model3.
 ↪coef_[0][5]}*GrLivArea +{model3.intercept_[0]}')
```

```
Saleprice = 0.6505447246251344*LotArea + 121.80300773461254*LotFrontage +
29613.59960437697*OverallQual +1309.826685552478*OverallCond +
38.79274996548665*1stFlrSF + 45.046292101878805*GrLivArea +-135266.21756742758
```

1.7 Question 06

1.8 Categorical Value Regression

1.8.1 Model 4:- SalePrice based on LotArea and Street

[26]:
```
street_set = set(houses_dataframe['Street'])
street_set
```

[26]:
```
{'Grvl', 'Pave'}
```

Since we have two values for the `Street` feature we can consider a numpy array as a one-hot encoded input feature for estimating `SalePrice`

[27]:
```
## Utility One Hot Encoder

from sklearn.preprocessing import OneHotEncoder

'''
    @brief:- Function transforms the dataframe by converting the categorical␣
 ↪value cols into one-hot encoded form
    @param:- X: Dataframe, col_name:- Categorical Column name
    @return:- Transformed DataFrame
'''
def one_hot_encoder(X,col_name):
    encoder = OneHotEncoder()

    new_df = pd.DataFrame(
        encoder.fit_transform(X[[col_name]]).toarray(),
        columns = encoder.get_feature_names_out()
    )

    X = X.join(new_df)
    X = X.drop(col_name,axis=1) # drop the col_name from the dataframe

    return X
```

[28]:

```
houses_dataframe_pd1 = one_hot_encoder(houses_dataframe,'Street')
houses_dataframe_pd1.head()
```

[28]:

```
   Id  MSSubClass MSZoning  LotFrontage  LotArea LotShape LandContour  \
0   1          60       RL         65.0     8450      Reg         Lvl
1   2          20       RL         80.0     9600      Reg         Lvl
2   3          60       RL         68.0    11250      IR1         Lvl
3   4          70       RL         60.0     9550      IR1         Lvl
4   5          60       RL         84.0    14260      IR1         Lvl

  Utilities LotConfig LandSlope  … ScreenPorch PoolArea MiscVal MoSold  \
0    AllPub    Inside       Gtl  …           0        0       0      2
1    AllPub       FR2       Gtl  …           0        0       0      5
2    AllPub    Inside       Gtl  …           0        0       0      9
3    AllPub    Corner       Gtl  …           0        0       0      2
4    AllPub       FR2       Gtl  …           0        0       0     12

  YrSold  SaleType  SaleCondition  SalePrice  Street_Grvl Street_Pave
0   2008        WD         Normal     208500          0.0         1.0
1   2007        WD         Normal     181500          0.0         1.0
2   2008        WD         Normal     223500          0.0         1.0
3   2006        WD        Abnorml     140000          0.0         1.0
4   2008        WD         Normal     250000          0.0         1.0

[5 rows x 78 columns]
```

[29]:

```
## Street_Grvl and Street_Pave are the two transformed col values
model4 = LinearRegression()

X_model4 = houses_dataframe_pd1[['LotArea','Street_Grvl','Street_Pave']]
Y_model4 = houses_dataframe_pd1[['SalePrice']]

model4_avg_r2_score,model4_avg_MSE = Kfold_util(model4,X_data=X_model4.
 ↪to_numpy(),y_data=Y_model4.to_numpy())

print(f"Average R2-score of Model 4 is :- {model4_avg_r2_score}")
print(f"Average MSE of Model 4 is :- {model4_avg_MSE}")
```

```
Fold: 1
R2 score is: 0.08083987276169624 and MSE is: 5085372725.1058655
Fold: 2
R2 score is: -0.06216483704535136 and MSE is: 6979134400.3638525
Fold: 3
R2 score is: 0.102774623160658 and MSE is: 6798992674.369186
Fold: 4
R2 score is: 0.056929075521841566 and MSE is: 4777460463.1480665
Fold: 5
R2 score is: 0.06650223035586045 and MSE is: 6259447493.116865
```

```
Average R2-score of Model 4 is :- 0.04897619295094098
Average MSE of Model 4 is :- 5980081551.220767
```

Print the slope and intercept

```
[30]: print(f'Saleprice = {model4.coef_[0][0]} * LotArea + {model4.coef_[0][1]} *␣
        ↪Street_Grvl + {model4.coef_[0][2]} * Street_Pave + {model4.intercept_[0]}')
```

```
Saleprice = 2.110142385499554 * LotArea + -64695.324094630705 * Street_Grvl +
64695.32409463071 * Street_Pave + 94246.82591973609
```

1.8.2 Model 5 :- SalePrice based on LotArea, OverallCond, Street, Neighbourhood

```
[31]: houses_dataframe[['LotArea','OverallCond','Neighborhood']]
```

```
[31]:       LotArea  OverallCond Neighborhood
      0        8450            5      CollgCr
      1        9600            8      Veenker
      2       11250            5      CollgCr
      3        9550            5      Crawfor
      4       14260            5      NoRidge
      …         …          …         …
      1455     7917            5      Gilbert
      1456    13175            6       NWAmes
      1457     9042            9      Crawfor
      1458     9717            6        NAmes
      1459     9937            6      Edwards

      [1460 rows x 3 columns]
```

Neighbourhood is another categorical value that needs to be one-hot encoded

```
[32]: print(len(set(houses_dataframe['Neighborhood'])))
```

```
25
```

```
[33]: houses_dataframe_pd2 = one_hot_encoder(houses_dataframe,'Street')
      houses_dataframe_pd2 = one_hot_encoder(houses_dataframe_pd2,'Neighborhood')
      houses_dataframe_pd2.head()
```

```
[33]:    Id  MSSubClass MSZoning  LotFrontage  LotArea LotShape LandContour  \
      0   1          60       RL         65.0     8450      Reg         Lvl
      1   2          20       RL         80.0     9600      Reg         Lvl
      2   3          60       RL         68.0    11250      IR1         Lvl
      3   4          70       RL         60.0     9550      IR1         Lvl
      4   5          60       RL         84.0    14260      IR1         Lvl

        Utilities LotConfig LandSlope  … Neighborhood_NoRidge  \
      0    AllPub    Inside       Gtl  …                  0.0
      1    AllPub       FR2       Gtl  …                  0.0
```

```
2    AllPub    Inside       Gtl  …                  0.0
3    AllPub    Corner       Gtl  …                  0.0
4    AllPub       FR2       Gtl  …                  1.0

  Neighborhood_NridgHt Neighborhood_OldTown Neighborhood_SWISU  \
0                  0.0                  0.0                0.0
1                  0.0                  0.0                0.0
2                  0.0                  0.0                0.0
3                  0.0                  0.0                0.0
4                  0.0                  0.0                0.0

   Neighborhood_Sawyer  Neighborhood_SawyerW  Neighborhood_Somerst  \
0                  0.0                   0.0                   0.0
1                  0.0                   0.0                   0.0
2                  0.0                   0.0                   0.0
3                  0.0                   0.0                   0.0
4                  0.0                   0.0                   0.0

   Neighborhood_StoneBr Neighborhood_Timber Neighborhood_Veenker
0                   0.0                 0.0                  0.0
1                   0.0                 0.0                  1.0
2                   0.0                 0.0                  0.0
3                   0.0                 0.0                  0.0
4                   0.0                 0.0                  0.0

[5 rows x 102 columns]
```

[34]:

```
neighborhood_cols = houses_dataframe_pd2.filter(regex='^Neighborhood_')
neighborhood_cols.head()
```

[34]:

```
   Neighborhood_Blmngtn  Neighborhood_Blueste  Neighborhood_BrDale  \
0                   0.0                   0.0                  0.0
1                   0.0                   0.0                  0.0
2                   0.0                   0.0                  0.0
3                   0.0                   0.0                  0.0
4                   0.0                   0.0                  0.0

   Neighborhood_BrkSide  Neighborhood_ClearCr  Neighborhood_CollgCr  \
0                   0.0                   0.0                   1.0
1                   0.0                   0.0                   0.0
2                   0.0                   0.0                   1.0
3                   0.0                   0.0                   0.0
4                   0.0                   0.0                   0.0

   Neighborhood_Crawfor  Neighborhood_Edwards  Neighborhood_Gilbert  \
0                   0.0                   0.0                   0.0
1                   0.0                   0.0                   0.0
```

```
2                   0.0                   0.0                   0.0
3                   1.0                   0.0                   0.0
4                   0.0                   0.0                   0.0

   Neighborhood_IDOTRR  …  Neighborhood_NoRidge  Neighborhood_NridgHt  \
0                  0.0  …                   0.0                   0.0
1                  0.0  …                   0.0                   0.0
2                  0.0  …                   0.0                   0.0
3                  0.0  …                   0.0                   0.0
4                  0.0  …                   1.0                   0.0

   Neighborhood_OldTown  Neighborhood_SWISU  Neighborhood_Sawyer  \
0                   0.0                 0.0                  0.0
1                   0.0                 0.0                  0.0
2                   0.0                 0.0                  0.0
3                   0.0                 0.0                  0.0
4                   0.0                 0.0                  0.0

   Neighborhood_SawyerW  Neighborhood_Somerst  Neighborhood_StoneBr  \
0                   0.0                   0.0                   0.0
1                   0.0                   0.0                   0.0
2                   0.0                   0.0                   0.0
3                   0.0                   0.0                   0.0
4                   0.0                   0.0                   0.0

   Neighborhood_Timber  Neighborhood_Veenker
0                  0.0                   0.0
1                  0.0                   1.0
2                  0.0                   0.0
3                  0.0                   0.0
4                  0.0                   0.0

[5 rows x 25 columns]
```

[35]:

```python
houses_dataframe_pd2 = pd.
 ↪concat([houses_dataframe_pd2[['LotArea','OverallCond','Street_Grvl','Street_Pave']],neighbo
houses_dataframe_pd2.head()
```

[35]:

```
   LotArea  OverallCond  Street_Grvl  Street_Pave  Neighborhood_Blmngtn  \
0     8450            5          0.0          1.0                   0.0
1     9600            8          0.0          1.0                   0.0
2    11250            5          0.0          1.0                   0.0
3     9550            5          0.0          1.0                   0.0
4    14260            5          0.0          1.0                   0.0

   Neighborhood_Blueste  Neighborhood_BrDale  Neighborhood_BrkSide  \
0                   0.0                  0.0                   0.0
```

```
1                   0.0                  0.0                   0.0
2                   0.0                  0.0                   0.0
3                   0.0                  0.0                   0.0
4                   0.0                  0.0                   0.0

   Neighborhood_ClearCr  Neighborhood_CollgCr  …  Neighborhood_NoRidge  \
0                   0.0                   1.0  …                   0.0
1                   0.0                   0.0  …                   0.0
2                   0.0                   1.0  …                   0.0
3                   0.0                   0.0  …                   0.0
4                   0.0                   0.0  …                   1.0

   Neighborhood_NridgHt  Neighborhood_OldTown  Neighborhood_SWISU  \
0                   0.0                   0.0                 0.0
1                   0.0                   0.0                 0.0
2                   0.0                   0.0                 0.0
3                   0.0                   0.0                 0.0
4                   0.0                   0.0                 0.0

   Neighborhood_Sawyer  Neighborhood_SawyerW  Neighborhood_Somerst  \
0                  0.0                   0.0                   0.0
1                  0.0                   0.0                   0.0
2                  0.0                   0.0                   0.0
3                  0.0                   0.0                   0.0
4                  0.0                   0.0                   0.0

   Neighborhood_StoneBr  Neighborhood_Timber  Neighborhood_Veenker
0                   0.0                  0.0                   0.0
1                   0.0                  0.0                   1.0
2                   0.0                  0.0                   0.0
3                   0.0                  0.0                   0.0
4                   0.0                  0.0                   0.0

[5 rows x 29 columns]
```

[36]:

```
model5 = LinearRegression()

X_model5 = houses_dataframe_pd2
Y_model5 = houses_dataframe_pd1[['SalePrice']]

model5_avg_r2_score,model5_avg_MSE = Kfold_util(model5,X_data=X_model5.
 ↪to_numpy(),y_data=Y_model5.to_numpy())

print(f"Average R2-score of Model 5 is :- {model5_avg_r2_score}")
print(f"Average MSE of Model 5 is :- {model5_avg_MSE}")
```

```
Fold: 1
R2 score is: 0.5841021043157792 and MSE is: 2301009097.833854
```

```
Fold: 2
R2 score is: 0.5261617473778633 and MSE is: 3113434688.9909825
Fold: 3
R2 score is: 0.5665378038610315 and MSE is: 3284688966.9422917
Fold: 4
R2 score is: 0.5250330812935398 and MSE is: 2406113492.1310244
Fold: 5
R2 score is: 0.545123175604145 and MSE is: 3050117194.4170914
Average R2-score of Model 5 is :- 0.5493915824904716
Average MSE of Model 5 is :- 2831072688.0630484
```

1.8.3 Model 6 :- SalePrice based on LotArea, OverallCond, Street, 1stFlrSF, Neighbourhood, Year

[37]:
```
houses_dataframe.columns

## Hmm `Year` is not there but we can use the continuous values of YrSold,␣
 ↪YearBuilt and YearRemodAdd
```

[37]:
```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope',
       'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle',
       'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'RoofStyle',
       'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea',
       'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond',
       'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2',
       'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating', 'HeatingQC',
       'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
       'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd',
       'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType', 'GarageYrBlt',
       'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond',
       'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch',
       'ScreenPorch', 'PoolArea', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

[38]:
```
houses_dataframe_pd3 = houses_dataframe_pd2
houses_dataframe_pd3 = pd.
 ↪concat([houses_dataframe_pd3,houses_dataframe[['1stFlrSF','YearBuilt','YearRemodAdd','YrSol
houses_dataframe_pd3.head()
```

[38]:
```
   LotArea  OverallCond  Street_Grvl  Street_Pave  Neighborhood_Blmngtn  \
0     8450            5          0.0          1.0                   0.0
1     9600            8          0.0          1.0                   0.0
2    11250            5          0.0          1.0                   0.0
3     9550            5          0.0          1.0                   0.0
```

```
4    14260            5          0.0          1.0                   0.0

   Neighborhood_Blueste  Neighborhood_BrDale  Neighborhood_BrkSide  \
0                   0.0                  0.0                   0.0   
1                   0.0                  0.0                   0.0   
2                   0.0                  0.0                   0.0   
3                   0.0                  0.0                   0.0   
4                   0.0                  0.0                   0.0   

   Neighborhood_ClearCr  Neighborhood_CollgCr  …  Neighborhood_Sawyer  \
0                   0.0                   1.0  …                  0.0   
1                   0.0                   0.0  …                  0.0   
2                   0.0                   1.0  …                  0.0   
3                   0.0                   0.0  …                  0.0   
4                   0.0                   0.0  …                  0.0   

   Neighborhood_SawyerW  Neighborhood_Somerst  Neighborhood_StoneBr  \
0                   0.0                   0.0                   0.0   
1                   0.0                   0.0                   0.0   
2                   0.0                   0.0                   0.0   
3                   0.0                   0.0                   0.0   
4                   0.0                   0.0                   0.0   

   Neighborhood_Timber  Neighborhood_Veenker  1stFlrSF  YearBuilt  \
0                  0.0                   0.0       856       2003   
1                  0.0                   1.0      1262       1976   
2                  0.0                   0.0       920       2001   
3                  0.0                   0.0       961       1915   
4                  0.0                   0.0      1145       2000   

   YearRemodAdd  YrSold  
0          2003    2008  
1          1976    2007  
2          2002    2008  
3          1970    2006  
4          2000    2008  

[5 rows x 33 columns]
```

[39]:

```
model6 = LinearRegression()

X_model6 = houses_dataframe_pd3
Y_model6 = houses_dataframe_pd1[['SalePrice']]

model6_avg_r2_score,model6_avg_MSE = Kfold_util(model6,X_data=X_model6.
  ↪to_numpy(),y_data=Y_model6.to_numpy())
```

```
print(f"Average R2-score of Model 6 is :- {model6_avg_r2_score}")
print(f"Average MSE of Model 6 is :- {model6_avg_MSE}")
```

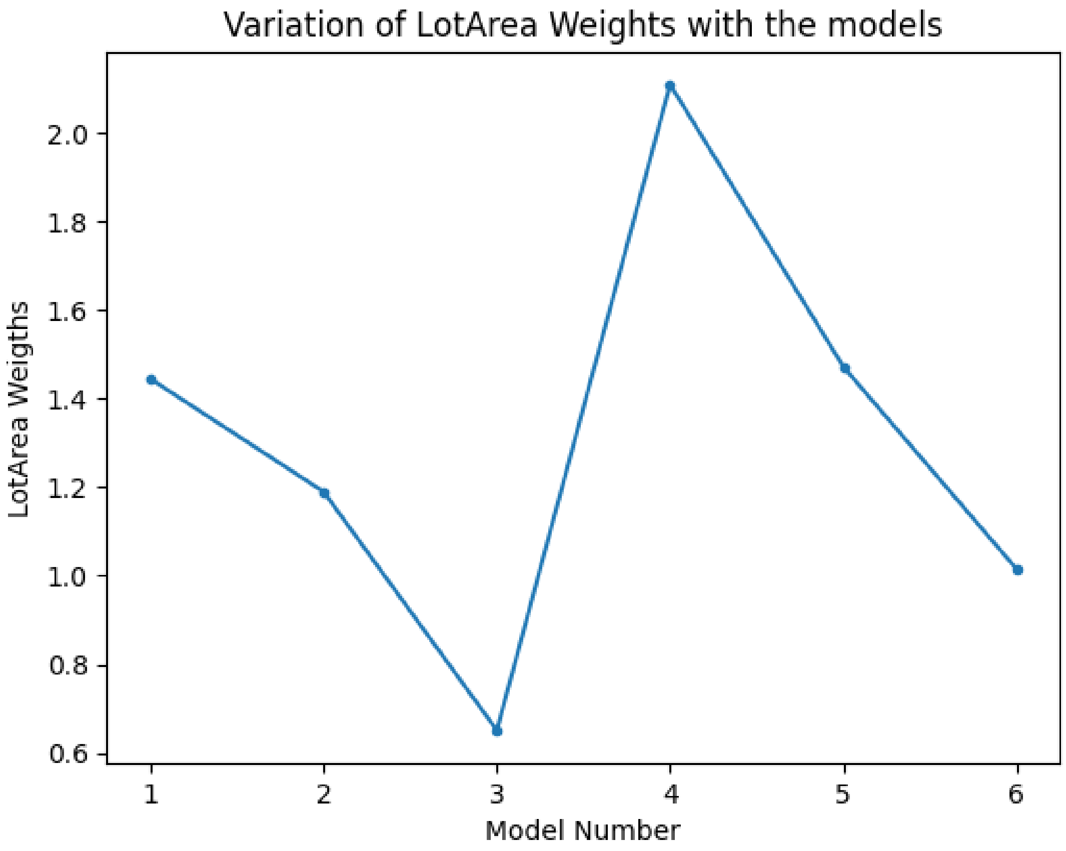
```
Fold: 1
R2 score is: 0.7095584627129405 and MSE is: 1606905508.8314323
Fold: 2
R2 score is: 0.7138242036094097 and MSE is: 1880366658.2457325
Fold: 3
R2 score is: 0.6985593789138491 and MSE is: 2284256138.342621
Fold: 4
R2 score is: 0.6829225245459274 and MSE is: 1606268482.484338
Fold: 5
R2 score is: 0.6451907294515968 and MSE is: 2379127268.740516
Average R2-score of Model 6 is :- 0.6900110598467447
Average MSE of Model 6 is :- 1951384811.328928
```

1.9 Question 07

1.9.1 Comparison of the feature "LotArea" weights/coefficients for all the six trained models

[40]:

```
x_axis = range(1,7)
lot_area_weights = [model1.coef_[0][0],model2.coef_[0][0],model3.
 ↪coef_[0][0],model4.coef_[0][0],model5.coef_[0][0],model6.coef_[0][0]]

plt.plot(x_axis,lot_area_weights,".-")
plt.xlabel("Model Number")
plt.ylabel("LotArea Weigths")
plt.title("Variation of LotArea Weights with the models")
plt.show()
```



1.10 Question 08

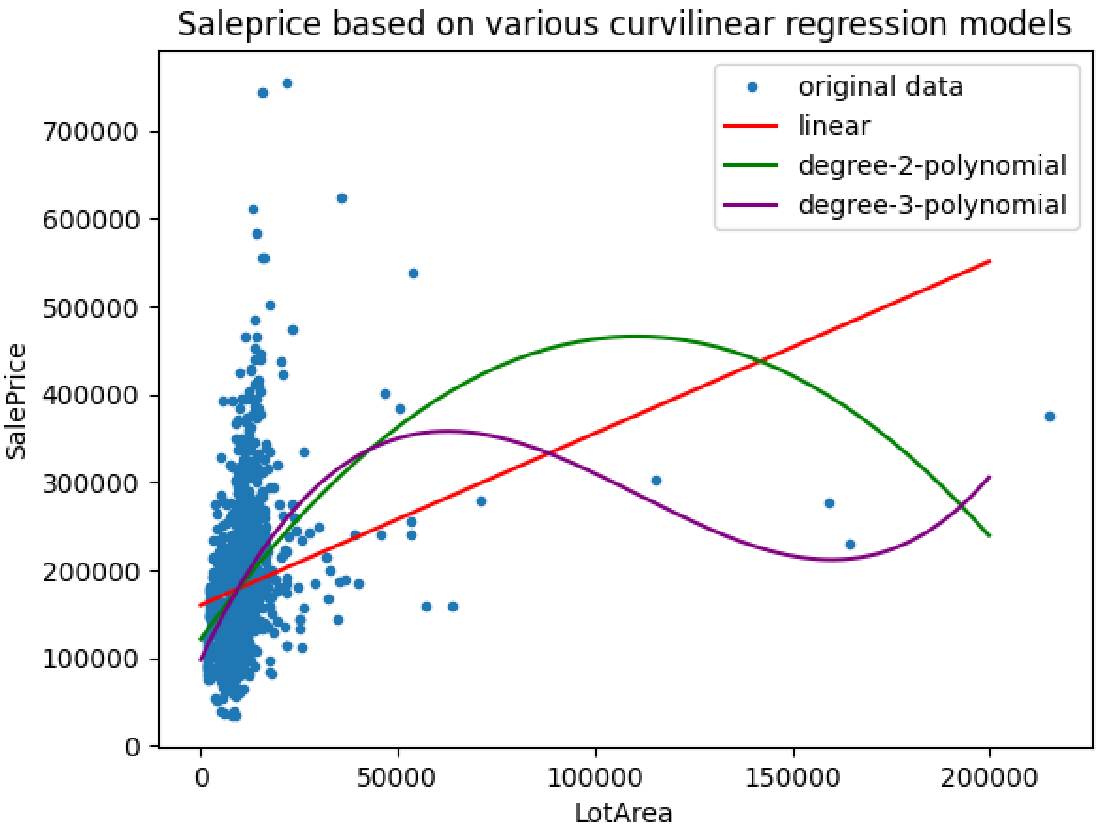
1.10.1 Bonus - Using Polynomial Regression for predicting SalePrice based on LotArea and applying it on the training and test dataset

[41]:
```
sale_price = houses_dataframe[['SalePrice']]
lot_area = houses_dataframe[['LotArea']]
plt.plot(lot_area,sale_price,'.',label="original data")

## define a domain
x_axis = range(0,200000,200)

## Linear Model (degree 1)

linear_model_degree_1 = LinearRegression()
X_data_1 = lot_area[['LotArea']]
Y_data_1 = sale_price[['SalePrice']]
Kfold_util(linear_model_degree_1,X_data_1.to_numpy(),Y_data_1.to_numpy())
linear_model_equation = [linear_model_degree_1.coef_[0][0]*x +␣
 ↪linear_model_degree_1.intercept_[0] for x in x_axis]
```

```python
plt.plot(x_axis,linear_model_equation,'red',label='linear')

curve_model_degree_2 = LinearRegression()
X_data_2 = X_data_1
X_data_2[['LotArea_squared']]=X_data_1[['LotArea']]**2
Y_data_2 = Y_data_1
Kfold_util(curve_model_degree_2,X_data_2.to_numpy(),Y_data_2.to_numpy())
curve_model_2_equation = [curve_model_degree_2.coef_[0][0]*x +␣
 ↪curve_model_degree_2.coef_[0][1]*(x**2) + curve_model_degree_2.intercept_[0]␣
 ↪for x in x_axis]
plt.plot(x_axis,curve_model_2_equation,'green',label='degree-2-polynomial')

curve_model_degree_3 = LinearRegression()
X_data_3 = X_data_2
X_data_3[['LotArea_cubed']] = X_data_1[['LotArea']]**3
Y_data_3 = Y_data_2
Kfold_util(curve_model_degree_3,X_data_3.to_numpy(),Y_data_3.to_numpy())
curve_model_3_equation = [curve_model_degree_3.coef_[0][0]*x +␣
 ↪curve_model_degree_3.coef_[0][1]*(x**2) + curve_model_degree_3.
 ↪coef_[0][2]*(x**3) + curve_model_degree_3.intercept_[0] for x in x_axis]
plt.plot(x_axis,curve_model_3_equation,'purple',label='degree-3-polynomial')

plt.title("Saleprice based on various curvilinear regression models")
plt.legend()
plt.xlabel('LotArea')
plt.ylabel('SalePrice')
plt.show()
```

```
Fold: 1
R2 score is: 0.0811255840664582 and MSE is: 5083791990.222536
Fold: 2
R2 score is: -0.09677051342182441 and MSE is: 7206516872.48441
Fold: 3
R2 score is: 0.09034415298115273 and MSE is: 6893188266.548201
Fold: 4
R2 score is: 0.04542629407540688 and MSE is: 4835731884.893979
Fold: 5
R2 score is: 0.06551930527251171 and MSE is: 6266038369.012835
Fold: 1
R2 score is: 0.1880996406892882 and MSE is: 4491944135.074409
Fold: 2
R2 score is: -0.13326083373331588 and MSE is: 7446282717.562326
Fold: 3
R2 score is: 0.17210416157128516 and MSE is: 6273627436.226067
Fold: 4
R2 score is: 0.08756692413546696 and MSE is: 4622253567.644948
Fold: 5
```

```
R2 score is: 0.10154612807937147 and MSE is: 6024465209.401183
Fold: 1
R2 score is: 0.21551510546124142 and MSE is: 4340264517.273444
Fold: 2
R2 score is: -0.15932525137145825 and MSE is: 7617543398.973908
Fold: 3
R2 score is: 0.18848183298735877 and MSE is: 6149520750.374883
Fold: 4
R2 score is: 0.08050638806129573 and MSE is: 4658021218.90792
Fold: 5
R2 score is: 0.13134466316099958 and MSE is: 5824655020.47448
```



We can clearly see that the higher order polynomials(here cubic) capture the training data more precisely, but it should not be a good indicator for model selection as it may hint at chances of overfitting.

[42]:
```
TEST_DATA_PATH = "../ML_DRIVE/Assignment01/test.csv"

test_df = pd.read_csv(TEST_DATA_PATH)
X_data = test_df[['LotArea']]
```

```
## Linear Model Prediction
test_df[['Linear_SalePrice']] = linear_model_degree_1.predict(X_data.to_numpy())

X_data_2 = X_data
X_data_2[['LotArea_squared']] = X_data[['LotArea']]**2

## Quadratic Model Prediction
test_df[['Quadratic_SalePrice']] = curve_model_degree_2.predict(X_data_2.
 ↪to_numpy())

X_data_3 = X_data_2
X_data_3[['LotArea_cubed']] = X_data[['LotArea']]**3

## Cubic Model Prediction
test_df[['Cubic_SalePrice']] = curve_model_degree_3.predict(X_data_3.to_numpy())
test_df[['Linear_SalePrice','Quadratic_SalePrice','Cubic_SalePrice']]
```

```
[42]:       Linear_SalePrice  Quadratic_SalePrice  Cubic_SalePrice
      0        182742.122274        189993.344744    194862.710030
      1        187914.342396        204567.098660    213283.237485
      2        187059.801681        202186.557959    210330.004739
      3        179527.328369        180735.550583    182745.955495
      4        169802.772351        151800.366145    142881.730423
      …                  …                  …                …
      1454     163801.432633        133245.300499    115795.352440
      1455     163719.302862        132987.673554    115411.178384
      1456     199125.056181        234796.704797    248815.620205
      1457     180432.711324        183358.293784    186210.825113
      1458     178840.958137        178739.167815    180091.665582

      [1459 rows x 3 columns]
```