Assignment 1

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Date: Aug 12, 2022

(i) Download data

Data downloaded and stored at drive.

```
In [542... 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).
In [543...
         import warnings
         warnings.simplefilter(action='ignore', category=FutureWarning)
In [544... BASE_PATH = '/content/drive/MyDrive/Colab_Notebooks/ML_DRIVE/Assign_1/dataset'
In [545... import numpy as np
         import pandas as pd # read csv files
         from sklearn.model_selection import train_test_split # test and train data spl
         from sklearn.preprocessing import OneHotEncoder
         from sklearn.linear_model import LinearRegression
         from sklearn.preprocessing import StandardScaler
         from sklearn.metrics import mean_squared_error, r2_score
         import seaborn as sns # graph plot
         import matplotlib.pyplot as plt # scatter plot
         from sklearn.preprocessing import PolynomialFeatures # polynomial regression
```

(ii) Reading and formating dataset

Read the dataset in the Pandas data frame. Remove the rows with a missing value. Divide the training.csv into two sets of ratio 80:20 entitled to train and test set respectively.

```
In [546... dataset = pd.read_csv(f"{BASE_PATH}/train.csv")
    scaler = StandardScaler()

In [547... dataset.head()
```

Out [54]

17]:		ld	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utili1
	0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	Allf
	1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	Allf
	2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	Alli
	3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	Alli
	4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	Alli

5 rows × 81 columns

(iii) Linear Regression

Use the linear regression method to estimate the slope and intercept for predicting SalePrice based on LotArea

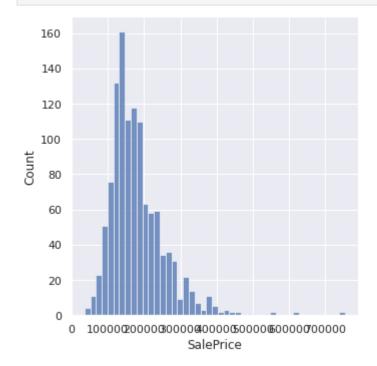
Remove the missing rows corresponding to only SalePrice and LotArea columns.

```
In [548... df = dataset.loc[:, ['SalePrice', 'LotArea']].dropna()
```

Splitting the dataset in 80:20 ratio for fitting the model and then testing.

```
In [549... train_df, test_df = train_test_split(df, test_size=0.2)
```

In [550... sns.displot(train_df['SalePrice']);



```
In [551... train_df.head()
```

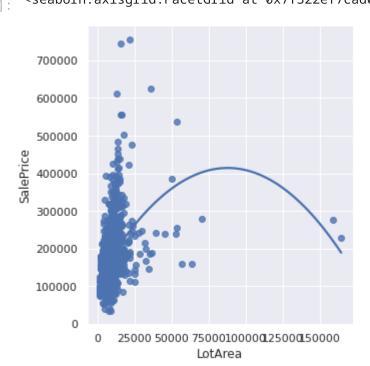
Out[551]:		SalePrice	LotArea
	926	285000	11999
	649	84500	1936
	64	219500	9375
	189	286000	4923
	1421	127500	4043

```
In [552... test_df.head()
```

```
SalePrice LotArea
Out[552]:
             468
                    250000
                               11428
             470
                    212000
                               6820
             968
                     37900
                               5925
                               8846
             376
                    148000
             865
                    148500
                               8750
```

Scatter plot to see the relationship between SalePrice and LotArea.

```
In [553... # ci: used to specify the size of the interval
sns.lmplot(x ="LotArea", y ="SalePrice", data = train_df, ci=None, order=2)
Out[553]: <seaborn.axisgrid.FacetGrid at 0x7f322ef7cad0>
```



```
In [554... X_train = np.array(train_df['LotArea']).reshape(-1, 1) # have one column and a.
X_train = scaler.fit_transform(X_train)
y_train = np.array(train_df['SalePrice']).reshape(-1, 1)
```

```
510519006_assingment_01
          X_test = np.array(test_df['LotArea']).reshape(-1, 1)
          X_test = scaler.fit_transform(X_test)
          y_test = np.array(test_df['SalePrice']).reshape(-1, 1)
In [555... model = LinearRegression()
          new_model = model.fit(X_train, y_train)
          y_pred = new_model.predict(X_test)
In [556...
          plt.xlabel("LotArea")
          plt.ylabel("SalePrice")
          plt.scatter(X_test, y_test)
          plt.plot(X_test, y_pred, color ='r')
          plt.show()
            600000
            500000
            400000
          SalePrice
            300000
            200000
            100000
```

• Coefficient of Determination: With linear regression, the coefficient of determination is equal to the square of the correlation between the x and y variables.

LotArea

10

12

14

```
print("Linear Regression\n========")
In [557...
         print("coefficient of determination (r-squared):", new_model.score(X_test, y_te
         print("intercept:", new_model.intercept_)
         print("slope:", new_model.coef_)
         mse_linear_regression = mean_squared_error(y_test, y_pred)
         print("mean squared error:", mse_linear_regression)
```

2

In [563...

Linear Regression ================

coefficient of determination (r-squared): 0.08266730291019242

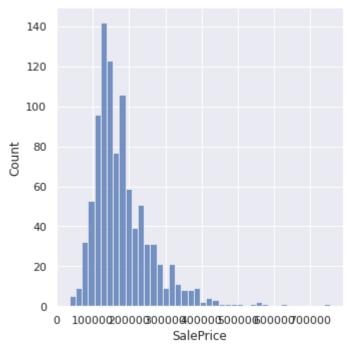
intercept: [181174.69606164] slope: [[20665.83775877]]

mean squared error: 6092303156.234104

(iv) Multiple Regression

Model 1: LotFrontage, LotArea

```
lot_area_weights = [] # required for question (vii)
In [558...
In [559...
          df = dataset.loc[:, ['SalePrice', 'LotArea', 'LotFrontage']].dropna()
In [560...
           train_df, test_df = train_test_split(df, test_size=0.2)
In [561...
           train_df.head()
                  SalePrice LotArea LotFrontage
Out[561]:
            1001
                    86000
                              5400
                                           60.0
             268
                    120500
                              6900
                                           71.0
             204
                    110000
                              3500
                                           50.0
                    113000
            1212
                              9340
                                           50.0
             365
                    147000
                             10690
                                           59.0
In [562...
           test_df.head()
                  SalePrice
                           LotArea LotFrontage
Out[562]:
            1350
                    200000
                             11643
                                           91.0
            1175
                    285000
                             10678
                                           85.0
            1311
                    203000
                              8814
                                           68.0
            1410
                    230000
                             12420
                                           79.0
            1071
                    154000
                             11700
                                           78.0
           sns.displot(train_df['SalePrice']);
```



```
In [564... variables = ['LotArea', 'LotFrontage']
         X_train = np.array(train_df[variables])
         X_train = scaler.fit_transform(X_train)
         y_train = np.array(train_df[['SalePrice']])
         X_test = np.array(test_df[variables])
         X_test = scaler.fit_transform(X_test)
         y_test = np.array(test_df[['SalePrice']])
In [565... model = LinearRegression()
         new_model = model.fit(X_train, y_train)
In [566... y_pred = new_model.predict(X_train)
         r2_m1_train = new_model.score(X_train, y_train)
         mse_m1_train = mean_squared_error(y_train, y_pred)
         print("[Model 1 training] mean squared error:", mse_m1_train)
         print("[Model 1 training] r2 score:", r2_m1_train)
         y_pred = new_model.predict(X_test)
         r2_m1_test = new_model.score(X_test, y_test)
         mse_m1_test = mean_squared_error(y_test, y_pred)
         print("[Model 1 testing] mean squared error:", mse_m1_test)
         print("[Model 1 testing] r2 score:", r2_m1_test)
         [Model 1 training] mean squared error: 5624107998.43659
         [Model 1 training] r2 score: 0.15674940645403534
         [Model 1 testing] mean squared error: 6655777705.427111
         [Model 1 testing] r2 score: 0.17303681161540152
In [567...
         print("Weights/Coefficients:\n")
         for name, weight in zip(variables, new_model.coef_.reshape(-1)):
           if name == 'LotArea':
             lot_area_weights.append(weight)
           print(f"{name.ljust(25)} {weight}")
```

Weights/Coefficients:

LotArea 14461.793682408417 LotFrontage 23384.152426978068

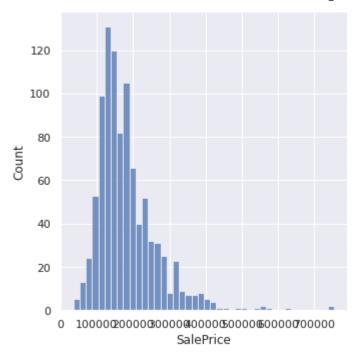


Model 2: LotFrontage, LotArea, OverallQual, OverallCond

```
df = dataset.loc[:, ['SalePrice', 'LotArea', 'LotFrontage', 'OverallQual', '
In [568...
In [569...
                                                        train_df, test_df = train_test_split(df, test_size=0.2)
In [570...
                                                         train_df.head()
                                                                                              SalePrice LotArea LotFrontage OverallQual OverallCond
Out[570]:
                                                                    190
                                                                                                        315000
                                                                                                                                                          10570
                                                                                                                                                                                                                                 70.0
                                                                                                                                                                                                                                                                                                           8
                                                                                                                                                                                                                                                                                                                                                                           8
                                                                                                        206000
                                                                                                                                                                                                                                                                                                           7
                                                                    999
                                                                                                                                                               6762
                                                                                                                                                                                                                                 64.0
                                                                                                                                                                                                                                                                                                                                                                           5
                                                               1241
                                                                                                                                                                                                                                                                                                           7
                                                                                                                                                                                                                                                                                                                                                                           6
                                                                                                        248328
                                                                                                                                                              9849
                                                                                                                                                                                                                                 83.0
                                                                                                                                                                                                                                                                                                           7
                                                                    573
                                                                                                                                                                                                                                                                                                                                                                           5
                                                                                                        170000
                                                                                                                                                               9967
                                                                                                                                                                                                                                 76.0
                                                                                                                                                                                                                                                                                                           7
                                                                        15
                                                                                                        132000
                                                                                                                                                               6120
                                                                                                                                                                                                                                 51.0
                                                                                                                                                                                                                                                                                                                                                                            8
In [571...
                                                         test_df.head()
                                                                                              SalePrice LotArea LotFrontage OverallQual OverallCond
Out[571]:
```

149.0 0.08 30.0 63.0 0.08

In [572... sns.displot(train_df['SalePrice']);



```
In [573... variables = ['LotArea', 'LotFrontage', 'OverallQual', 'OverallCond']
         X_train = np.array(train_df[variables])
         X_train = scaler.fit_transform(X_train)
         y_train = np.array(train_df[['SalePrice']])
         X_test = np.array(test_df[variables])
         X_test = scaler.fit_transform(X_test)
         y_test = np.array(test_df[['SalePrice']])
In [574... | model = LinearRegression()
         new_model = model.fit(X_train, y_train)
In [575... y_pred = new_model.predict(X_train)
         r2_m2_train = new_model.score(X_train, y_train)
         mse_m2_train = mean_squared_error(y_train, y_pred)
         print("[Model 2 training] mean squared error:", mse_m2_train)
         print("[Model 2 training] r2 score:", r2_m2_train)
         y_pred = new_model.predict(X_test)
         r2_m2_test = new_model.score(X_test, y_test)
         mse_m2_test = mean_squared_error(y_test, y_pred)
         print("[Model 2 testing] mean squared error:", mse_m2_test)
         print("[Model 2 testing] r2 score:", r2_m2_test)
         [Model 2 training] mean squared error: 2173743721.3687043
         [Model 2 training] r2 score: 0.6807952868198797
         [Model 2 testing] mean squared error: 2367248284.9225645
         [Model 2 testing] r2 score: 0.6842821691131709
In [576...
         print("Weights/Coefficients:\n")
         for name, weight in zip(variables, new_model.coef_.reshape(-1)):
           if name == 'LotArea':
             lot_area_weights.append(weight)
           print(f"{name.ljust(25)} {weight}")
```

In [581...

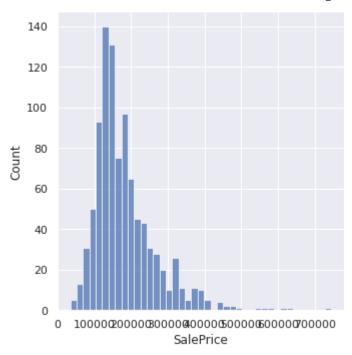
Weights/Coefficients:

LotArea 11136.8044962903 LotFrontage 9244.841249409728 OverallQual 61583.28732019769 OverallCond -102.41031001503097

Model 3: LotFrontage, LotArea, OverallQual, OverallCond, 1stFlrSF, GrLivArea

```
df = dataset.loc[:, ['SalePrice', 'LotArea', 'LotFrontage', 'OverallQual', '
In [577...
In [578...
                                          train_df, test_df = train_test_split(df, test_size=0.2)
In [579...
                                          train_df.head()
                                                                     SalePrice LotArea
                                                                                                                                           LotFrontage
                                                                                                                                                                                         OverallQual
                                                                                                                                                                                                                                        OverallCond
                                                                                                                                                                                                                                                                                        1stFlrSF
                                                                                                                                                                                                                                                                                                                            GrLivArea
Out[579]:
                                                  587
                                                                                                                     8740
                                                                                                                                                                                                                             5
                                                                                                                                                                                                                                                                             6
                                                                                                                                                                                                                                                                                                                                                  860
                                                                             137000
                                                                                                                                                                       74.0
                                                                                                                                                                                                                                                                                                         860
                                              1273
                                                                             177000
                                                                                                                  11512
                                                                                                                                                                   124.0
                                                                                                                                                                                                                              6
                                                                                                                                                                                                                                                                              7
                                                                                                                                                                                                                                                                                                     1357
                                                                                                                                                                                                                                                                                                                                              1357
                                              1379
                                                                             167500
                                                                                                                     9735
                                                                                                                                                                      73.0
                                                                                                                                                                                                                             5
                                                                                                                                                                                                                                                                             5
                                                                                                                                                                                                                                                                                                        754
                                                                                                                                                                                                                                                                                                                                              1394
                                              1151
                                                                             149900
                                                                                                                  17755
                                                                                                                                                                   134.0
                                                                                                                                                                                                                              5
                                                                                                                                                                                                                                                                              4
                                                                                                                                                                                                                                                                                                     1466
                                                                                                                                                                                                                                                                                                                                              1466
                                              1005
                                                                             149900
                                                                                                                      8385
                                                                                                                                                                       65.0
                                                                                                                                                                                                                              5
                                                                                                                                                                                                                                                                              8
                                                                                                                                                                                                                                                                                                         985
                                                                                                                                                                                                                                                                                                                                                  985
In [580...
                                          test_df.head()
                                                                                                                                           LotFrontage
                                                                                                                                                                                          OverallQual
                                                                                                                                                                                                                                        OverallCond
                                                                     SalePrice
                                                                                                          LotArea
                                                                                                                                                                                                                                                                                        1stFlrSF
                                                                                                                                                                                                                                                                                                                            GrLivArea
Out[580]:
                                              1329
                                                                             176500
                                                                                                                      9084
                                                                                                                                                                       63.0
                                                                                                                                                                                                                              7
                                                                                                                                                                                                                                                                             5
                                                                                                                                                                                                                                                                                                         955
                                                                                                                                                                                                                                                                                                                                              1632
                                              1332
                                                                             100000
                                                                                                                      8877
                                                                                                                                                                       67.0
                                                                                                                                                                                                                              4
                                                                                                                                                                                                                                                                             6
                                                                                                                                                                                                                                                                                                        816
                                                                                                                                                                                                                                                                                                                                                  816
                                                  876
                                                                             132250
                                                                                                                                                                                                                                                                                                                                              1040
                                                                                                                  25286
                                                                                                                                                                       94.0
                                                                                                                                                                                                                              4
                                                                                                                                                                                                                                                                             5
                                                                                                                                                                                                                                                                                                     1040
                                              1310
                                                                             335000
                                                                                                                  17500
                                                                                                                                                                   100.0
                                                                                                                                                                                                                              7
                                                                                                                                                                                                                                                                              8
                                                                                                                                                                                                                                                                                                     1902
                                                                                                                                                                                                                                                                                                                                              1902
                                              1255
                                                                             127500
                                                                                                                     6240
                                                                                                                                                                       52.0
                                                                                                                                                                                                                              6
                                                                                                                                                                                                                                                                             6
                                                                                                                                                                                                                                                                                                         959
                                                                                                                                                                                                                                                                                                                                              1367
```

sns.displot(train_df['SalePrice']);



```
In [582... variables = ['LotArea', 'LotFrontage', 'OverallQual', 'OverallCond', '1stFlrSF
         X_train = np.array(train_df[variables])
         X_train = scaler.fit_transform(X_train)
         y_train = np.array(train_df[['SalePrice']])
         X_test = np.array(test_df[variables])
         X_test = scaler.fit_transform(X_test)
         y_test = np.array(test_df[['SalePrice']])
In [583... model = LinearRegression()
         new_model = model.fit(X_train, y_train)
In [584... y_pred = new_model.predict(X_train)
         r2_m3_train = new_model.score(X_train, y_train)
         mse_m3_train = mean_squared_error(y_train, y_pred)
         print("[Model 3 training] mean squared error:", mse_m3_train)
         print("[Model 3 training] r2 score:", r2_m3_train)
         y_pred = new_model.predict(X_test)
         r2_m3_test = new_model.score(X_test, y_test)
         mse_m3_test = mean_squared_error(y_test, y_pred)
         print("[Model 3 testing] mean squared error:", mse_m3_train)
         print("[Model 3 testing] r2 score:", r2_m3_test)
         [Model 3 training] mean squared error: 1705945890.8357406
         [Model 3 training] r2 score: 0.7576982028082635
         [Model 3 testing] mean squared error: 1705945890.8357406
         [Model 3 testing] r2 score: 0.6695918826383475
In [585...
         print("Weights/Coefficients:\n")
         for name, weight in zip(variables, new_model.coef_.reshape(-1)):
           if name == 'LotArea':
             lot_area_weights.append(weight)
           print(f"{name.ljust(25)} {weight}")
```

Weights/Coefficients:

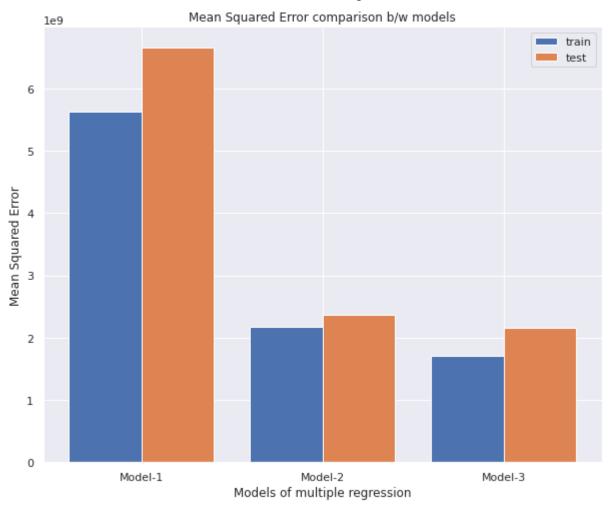
LotArea	6374.9246109743735
LotFrontage	1524.460617406945
OverallQual	47710.77823490351
OverallCond	1440.6205348023514
1stFlrSF	13120.807238707632
GrLivArea	20414.671183909024

(v) Compare the Mean squared Error, R2 score

Comparing R2 score

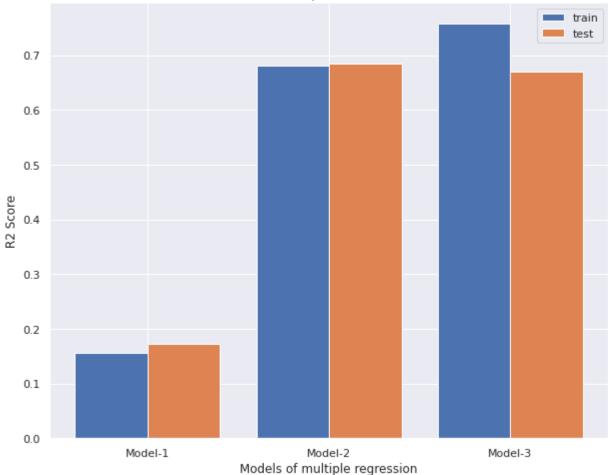
Comparing Mean Squared Error

```
In [586... plt.figure(figsize=(10, 8))
    plt.xlabel("Models of multiple regression")
    plt.ylabel("Mean Squared Error")
    plt.title("Mean Squared Error comparison b/w models")
    x = ["Model-1", "Model-2", "Model-3"]
    x_axis = np.arange(len(x))
    plt.bar(x_axis-0.2, [mse_m1_train, mse_m2_train, mse_m3_train], width=0.4, labe    plt.bar(x_axis+0.2, [mse_m1_test, mse_m2_test, mse_m3_test], width=0.4, label='    plt.xticks(x_axis, x)
    plt.legend()
    plt.show()
```



```
In [587... plt.figure(figsize=(10, 8))
    plt.xlabel("Models of multiple regression")
    plt.ylabel("R2 Score")
    plt.title("R2 Score comparison b/w models")
    plt.bar(x_axis-0.2, [r2_m1_train, r2_m2_train, r2_m3_train], width=0.4, label='
    plt.bar(x_axis+0.2, [r2_m1_test, r2_m2_test, r2_m3_test], width=0.4, label="test")
    plt.xticks(x_axis, x)
    plt.legend()
    plt.show()
```

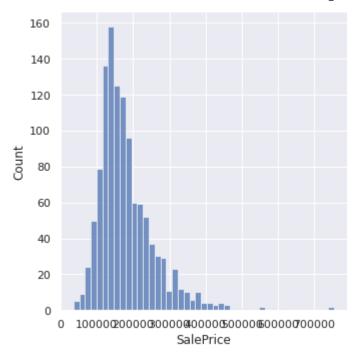
R2 Score comparison b/w models



(vi) Multiple Regression (contd.)

Model 4: LotArea, Street

```
In [588...
df = dataset.loc[:, ['SalePrice', 'LotArea', 'Street']].dropna()
df = pd.get_dummies(df, columns = ['Street'])
train_df, test_df = train_test_split(df, test_size=0.2)
sns.displot(train_df['SalePrice']);
```



In [589... test_df.head()

Out[589]:

	SalePrice	LotArea	Street_GrvI	Street_Pave
913	145000	6270	0	1
1204	153500	10140	0	1
1123	118000	9405	0	1
507	208300	7862	0	1
572	224500	13159	0	1

In [590... train_df.head()

Out[590]:

	SalePrice	LotArea	Street_GrvI	Street_Pave
640	274000	12677	0	1
275	205000	7264	0	1
703	140000	7630	0	1
1425	142000	10721	0	1
691	755000	21535	0	1

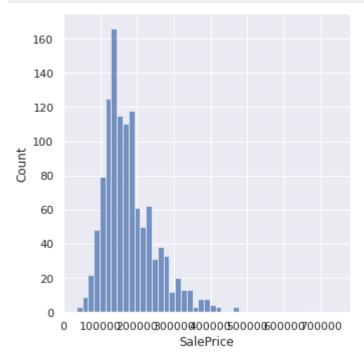
```
In [591... variables = train_df.columns.array[1:]
    X_train = np.array(train_df[variables])
    X_train = scaler.fit_transform(X_train)
    y_train = np.array(train_df[['SalePrice']])
    X_test = np.array(test_df[variables])
    X_test = scaler.fit_transform(X_test)
    y_test = np.array(test_df[['SalePrice']])
```

```
In [592... model = LinearRegression()
   new_model = model.fit(X_train, y_train)
```

```
In [593... y_pred = new_model.predict(X_test)
         r2_score_m4 = new_model.score(X_test, y_test)
         mse_m4 = mean_squared_error(y_test, y_pred)
         print("Weights/Coefficients:\n")
In [594...
         for name, weight in zip(variables, new_model.coef_.reshape(-1)):
           if name == 'LotArea':
              lot_area_weights.append(weight)
           print(f"{name.ljust(25)} {weight}")
         Weights/Coefficients:
         LotArea
                                    23454.428840111013
         Street_Grvl
                                    -3821.8027884244875
         Street_Pave
                                    3821.802788424487
```

Model 5: LotArea, OverallCond, Street, Neighborhood

```
In [595...
df = dataset.loc[:, ['SalePrice', 'LotArea', 'OverallCond', 'Street', 'Neighbor
df = pd.get_dummies(df, columns = ['Street', 'Neighborhood'])
    train_df, test_df = train_test_split(df, test_size=0.2)
    sns.displot(train_df['SalePrice']);
```



```
In [596... train_df.head()
```

Out[596]:		SalePrice	LotArea	OverallCond	Street_GrvI	Street_Pave	Neighborhood_Blmngtn	Neighbo
	846	213000	9317	5	0	1	0	
	1447	240000	10000	5	0	1	0	
	1357	149900	12537	6	0	1	0	
	1407	112000	8780	5	0	1	0	
	1344	155835	11103	5	0	1	0	

5 rows × 30 columns

4								>
In [597	test_	df.head()						
Out[597]:		SalePrice	LotArea	OverallCond	Street_GrvI	Street_Pave	Neighborhood_Blmngtn	Neighbo
	107	115000	6000	5	0	1	0	
	1008	240000	12118	5	0	1	0	
	35	309000	13418	5	0	1	0	
	896	106500	8765	6	0	1	0	
	661	402000	46589	7	0	1	0	

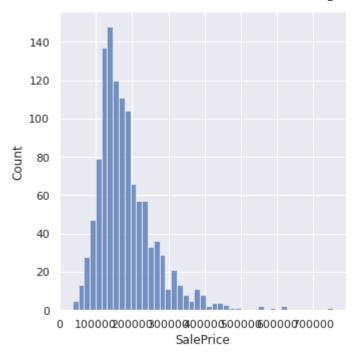
5 rows × 30 columns

```
4
          variables = train_df.columns.array[1:]
In [598...
          X_train = np.array(train_df[variables])
          X_train = scaler.fit_transform(X_train)
          y_train = np.array(train_df[['SalePrice']])
          X_test = np.array(test_df[variables])
          X_test = scaler.fit_transform(X_test)
          y_test = np.array(test_df[['SalePrice']])
In [599... model = LinearRegression()
          new_model = model.fit(X_train, y_train)
In [600... y_pred = new_model.predict(X_test)
          r2_score_m5 = r2_score(y_test, y_pred)
          mse_m5 = mean_squared_error(y_test, y_pred)
In [601...
          print("Weights/Coefficients:\n")
          for name, weight in zip(variables, new_model.coef_.reshape(-1)):
            if name == 'LotArea':
              lot_area_weights.append(weight)
            print(f"{name.ljust(25)} {weight}")
```

```
Weights/Coefficients:
LotArea
                          17232.359311666838
                          5690.487380540634
OverallCond
Street Grvl
                          6.327053544583567e+17
Street_Pave
                          6.327053544583633e+17
Neighborhood_Blmngtn
                          -2.590533868132571e+16
Neighborhood_Blueste
                          -1.0209180430317758e+16
Neighborhood_BrDale
                           -2.6871600147070444e+16
Neighborhood BrkSide
                           -4.901807323061966e+16
Neighborhood_ClearCr
                          -3.1236575892665076e+16
Neighborhood_CollgCr
                          -7.765992363967229e+16
Neighborhood_Crawfor
                          -4.324727727979392e+16
Neighborhood_Edwards
                           -6.237147971180368e+16
Neighborhood Gilbert
                           -5.977162952043296e+16
Neighborhood_IDOTRR
                          -3.710661263538179e+16
Neighborhood_MeadowV
                          -2.036575872723541e+16
Neighborhood_Mitchel
                          -4.267770627300958e+16
Neighborhood NAmes
                          -8.955725171956658e+16
Neighborhood NPkVill
                          -1.9058632514995564e+16
Neighborhood_NWAmes
                          -5.275614016006055e+16
Neighborhood_NoRidge
                          -4.1511898143531064e+16
Neighborhood NridgHt
                          -5.3641645591026664e+16
Neighborhood_OldTown
                          -6.5174816951494e+16
Neighborhood_SWISU
                          -3.0416677914150104e+16
Neighborhood_Sawyer
                          -5.5779937075754104e+16
Neighborhood_SawyerW
                          -4.998417291005957e+16
Neighborhood Somerst
                           -5.5779937075731304e+16
Neighborhood_StoneBr
                          -3.2034101561330188e+16
Neighborhood_Timber
                          -4.151189814354713e+16
Neighborhood_Veenker
                          -2.0365758727225176e+16
```

Model 6: LotArea, OverallCond, Street, 1stFlrSF, Neighborhood, Year

```
In [602... df = dataset.loc[:, ['SalePrice', 'LotArea', 'OverallCond', 'Street', '1stFlrSt
    df = pd.get_dummies(df, columns = ['Street', 'Neighborhood'])
    train_df, test_df = train_test_split(df, test_size=0.2)
    sns.displot(train_df['SalePrice']);
```



In [603... train_df.head()

Out[603]:		SalePrice	LotArea	OverallCond	1stFlrSF	YearBuilt	Street_GrvI	Street_Pave	Neighborhood
	826	109500	6130	6	784	1924	0	1	
	82	245000	10206	5	1563	2007	0	1	
	943	143000	25000	4	1632	1967	0	1	
	771	102000	8877	5	1220	1951	0	1	
	695	176000	13811	6	1137	1987	0	1	

5 rows × 32 columns

4									•
In [604	test_	_df.head())						
Out[604]:		SalePrice	LotArea	OverallCond	1stFlrSF	YearBuilt	Street_GrvI	Street_Pave	Neighborhoo
	659	167000	9937	7	1486	1964	0	1	
	1119	133700	7560	5	1040	1959	0	1	
	28	207500	16321	6	1600	1957	0	1	
	858	152000	10400	5	1370	1976	0	1	
	521	150000	11988	6	1244	1957	0	1	

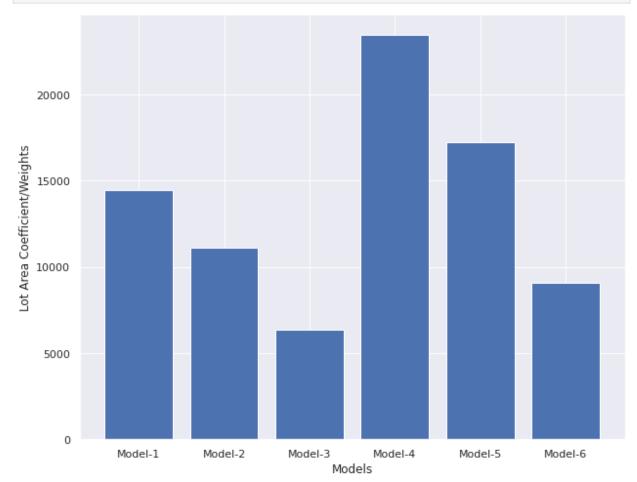
5 rows × 32 columns

```
In [605... variables = train_df.columns.array[1:]
    X_train = np.array(train_df[variables])
    X_train = scaler.fit_transform(X_train)
    y_train = np.array(train_df[['SalePrice']])
```

```
X_test = np.array(test_df[variables])
         X_test = scaler.fit_transform(X_test)
         y_test = np.array(test_df[['SalePrice']])
In [606... model = LinearRegression()
         new_model = model.fit(X_train, y_train)
In [607... y_pred = new_model.predict(X_test)
         r2_score_m6 = r2_score(y_test, y_pred)
         mse_m6 = mean_squared_error(y_test, y_pred)
In [608...
         print("Weights/Coefficients:\n")
         for name, weight in zip(variables, new_model.coef_.reshape(-1)):
           if name == 'LotArea':
             lot_area_weights.append(weight)
           print(f"{name.ljust(25)} {weight}")
         Weights/Coefficients:
                                    9095.208739522406
         LotArea
         OverallCond
                                    12479.243545260257
         1stFlrSF
                                    29698.585808062122
         YearBuilt
                                    19379.890463052205
         Street_Grvl
                                    3227648041608409.5
         Street_Pave
                                    3227648041610349.5
         Neighborhood_Blmngtn
                                    7702836130916101.0
         Neighborhood_Blueste
                                    2828490006877084.5
                                    6898583347436407.0
         Neighborhood_BrDale
         Neighborhood_BrkSide
                                    1.3848294144969926e+16
         Neighborhood_ClearCr
                                    1.0092763613710126e+16
         Neighborhood_CollgCr
                                    2.084761612721487e+16
         Neighborhood_Crawfor
                                    1.3166990150151112e+16
         Neighborhood_Edwards
                                    1.717979040856982e+16
         Neighborhood_Gilbert
                                    1.5569149874755398e+16
         Neighborhood_IDOTRR
                                    1.064513654875348e+16
         Neighborhood_MeadowV
                                    6898583347434978.0
         Neighborhood_Mitchel
                                    1.2737500560328244e+16
         Neighborhood_NAmes
                                    2.3887916947579524e+16
         Neighborhood_NPkVill
                                    5280262405130682.0
         Neighborhood_NWAmes
                                    1.4861610052084344e+16
         Neighborhood_NoRidge
                                    1.0996423440632056e+16
         Neighborhood_NridgHt
                                    1.5908214437482888e+16
         Neighborhood_OldTown
                                    1.8878651880316016e+16
         Neighborhood_SWISU
                                    8875162581757856.0
         Neighborhood_Sawyer
                                    1.423854932814481e+16
         Neighborhood_SawyerW
                                    1.371524149406286e+16
         Neighborhood_Somerst
                                    1.5796218799714458e+16
                                    8654205238571872.0
         Neighborhood_StoneBr
         Neighborhood_Timber
                                    1.0996423440618706e+16
         Neighborhood_Veenker
                                    5280262405133614.0
```

(vi) Compare the feature "LotArea" weights/coefficients for all the six trained models and plot a graph using the Matplotlib library.

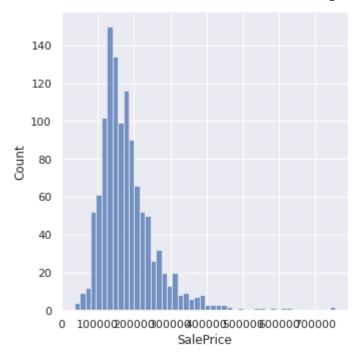
```
In [609... x_values = [f"Model-{x}" for x in range(1, 7)]
    y_values = lot_area_weights
    plt.figure(figsize=(10,8))
    plt.bar(x_values, y_values)
    plt.ylabel('Lot Area Coefficient/Weights')
    plt.xlabel('Models')
    plt.show()
```



(vii) Polynomial regression

DegrDegree 2ee 2

```
In [610... df = dataset.loc[:, ['SalePrice', 'LotArea']].dropna()
    train_df, test_df = train_test_split(df, test_size=0.2)
    sns.displot(train_df['SalePrice']);
```



In [611... train_df.head()

Out[611]:		SalePrice	LotArea
	735	163000	10800
	311	132000	8000
	1021	194000	7406
	881	187500	13758
	1148	116900	5700

In [612... test_df.head()

Out[612]:		SalePrice	LotArea
	1358	177500	2117
	652	191000	8750
	900	110000	7340
	681	159434	4500
	541	248000	11000

```
In [613... variables = train_df.columns.array[1:]
    X_train = np.array(train_df[variables])
    X_train = scaler.fit_transform(X_train)
    y_train = np.array(train_df[['SalePrice']])

    X_test = np.array(test_df[variables])
    X_test = scaler.fit_transform(X_test)
    y_test = np.array(test_df[['SalePrice']])

In [614... poly = PolynomialFeatures(degree = 2)
```

```
X_poly = poly.fit_transform(X_train)
         poly.fit(X_poly, y_train)
         model = LinearRegression()
         new_model = model.fit(X_poly, y_train)
In [615... y_pred = new_model.predict(poly.fit_transform(X_train))
         r2_score_poly = r2_score(y_train, y_pred)
         mse_poly = mean_squared_error(y_train, y_pred)
         print("[Poly training] r2 score:", r2_score_poly)
         print("[Poly training] mean squared error:", mse_poly)
         [Poly training] r2 score: 0.13866776027461258
         [Poly training] mean squared error: 5264230361.419709
In [616... sns.set(rc={'figure.figsize':(11.7,8.27)})
         ax = sns.scatterplot(X_train.reshape(-1), y_train.reshape(-1))
         ax.set_xlabel("LotArea")
         ax.set_ylabel("SalePrice")
         ax.set_title("(Training Data) Polynomial Regression of Degree-2")
         sns.lineplot(X_train.reshape(-1), y_pred.reshape(-1), color = 'red')
```

Out[616]: <matplotlib.axes._subplots.AxesSubplot at 0x7f322ec48f90>

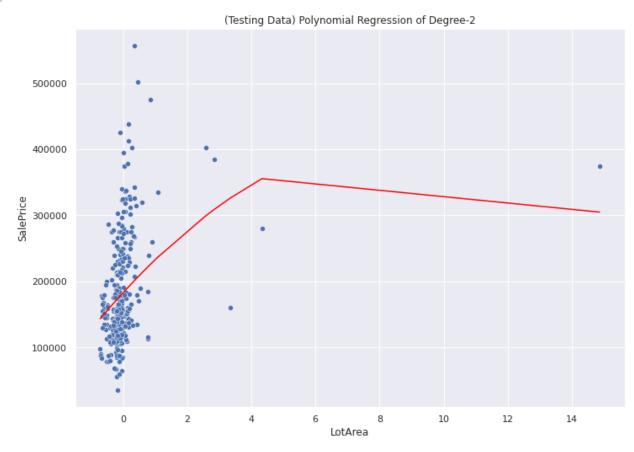


```
[Poly testing] mean squared error: 5954645391.883501

In [619... sns.set(rc={'figure.figsize':(11.7,8.27)})
    ax = sns.scatterplot(X_test.reshape(-1), y_test.reshape(-1))
    ax.set_xlabel("LotArea")
    ax.set_ylabel("SalePrice")
    ax.set_title("(Testing Data) Polynomial Regression of Degree-2")
    sns.lineplot(X_test.reshape(-1), y_pred.reshape(-1), color = 'red')
```

Out[619]: <matplotlib.axes._subplots.AxesSubplot at 0x7f322e5b8410>

[Poly testing] r2 score: 0.1558252665513966

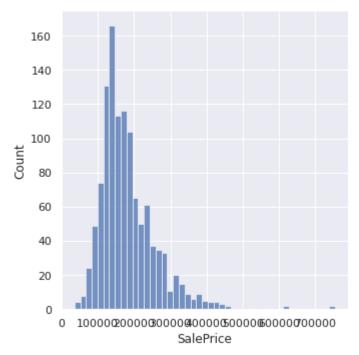


```
In [620... print("(Testing Data) Weights/Coefficients:\n", new_model.coef_.reshape(-1))

(Testing Data) Weights/Coefficients:
        [ 0. 52938.45068525 -3009.53945681]
```

Degree 3

```
In [621... df = dataset.loc[:, ['SalePrice', 'LotArea']].dropna()
  train_df, test_df = train_test_split(df, test_size=0.2)
  sns.displot(train_df['SalePrice']);
```



In [622... train_df.head()

Out[622]:

	SalePrice	LotArea
293	235000	16659
251	235000	4750
539	272000	11423
326	324000	10846
298	175000	11700

In [623... test_df.head()

Out[623]:

	SalePrice	LotArea
1203	213000	9750
1293	162900	10140
605	205000	13600
618	314813	11694
427	109008	8593

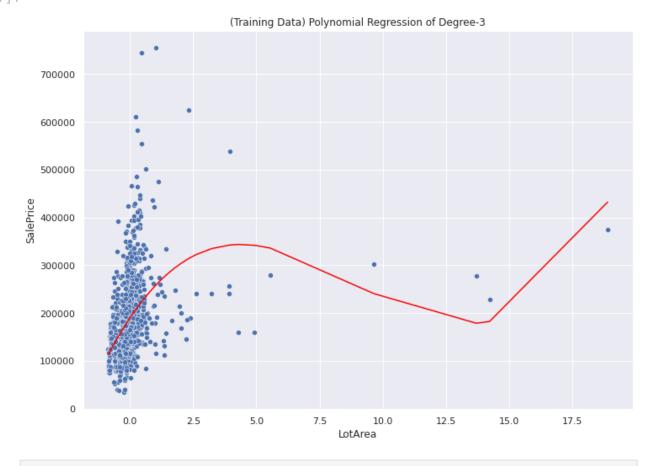
```
In [624...
variables = train_df.columns.array[1:]
X_train = np.array(train_df[variables])
X_train = scaler.fit_transform(X_train)
y_train = np.array(train_df[['SalePrice']])

X_test = np.array(test_df[variables])
X_test = scaler.fit_transform(X_test)
y_test = np.array(test_df[['SalePrice']])
```

```
In [625... poly = PolynomialFeatures(degree = 3)
```

```
X_poly = poly.fit_transform(X_train)
         poly.fit(X_poly, y_train)
         model = LinearRegression()
         new_model = model.fit(X_poly, y_train)
In [626... y_pred = new_model.predict(poly.fit_transform(X_train))
         r2_score_poly = r2_score(y_train, y_pred)
         mse_poly = mean_squared_error(y_train, y_pred)
         print("[Poly training] r2 score:", r2_score_poly)
         print("[Poly training] mean squared error:", mse_poly)
         [Poly training] r2 score: 0.1687319597132202
         [Poly training] mean squared error: 5392311367.540129
In [627... sns.set(rc={'figure.figsize':(11.7,8.27)})
         ax = sns.scatterplot(X_train.reshape(-1), y_train.reshape(-1))
         ax.set_xlabel("LotArea")
         ax.set_ylabel("SalePrice")
         ax.set_title("(Training Data) Polynomial Regression of Degree-3")
         sns.lineplot(X_train.reshape(-1), y_pred.reshape(-1), color = 'red')
```

Out[627]: <matplotlib.axes._subplots.AxesSubplot at 0x7f322e079f90>



```
[Poly testing] r2 score: 0.01985733188443628
[Poly testing] mean squared error: 5393646937.95993
```

```
In [630... sns.set(rc={'figure.figsize':(11.7,8.27)})
    ax = sns.scatterplot(X_test.reshape(-1), y_test.reshape(-1))
    ax.set_xlabel("LotArea")
    ax.set_ylabel("SalePrice")
    ax.set_title("(Testing Data) Polynomial Regression of Degree-3")
    sns.lineplot(X_test.reshape(-1), y_pred.reshape(-1), color = 'red')
```

Out[630]: <matplotlib.axes._subplots.AxesSubplot at 0x7f322dea3910>

