Assignment 1

Name: Arnab Sen Roll: 510519006

(i) Download data

Data downloaded and stored at drive.bold text

```
from google.colab import drive
In [272...
         drive.mount('/content/drive')
         Drive already mounted at /content/drive; to attempt to forcibly remount, call
         drive.mount("/content/drive", force_remount=True).
         BASE_PATH = '/content/drive/MyDrive/Colab_Notebooks/ML_DRIVE/Assign_1/dataset'
In [273...
In [274... 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 [275...
           dataset = pd.read_csv(f"{BASE_PATH}/train.csv")
           scaler = StandardScaler()
In [276...
           dataset.head()
Out[276]:
               ld
                   MSSubClass MSZoning LotFrontage LotArea
                                                                 Street Alley
                                                                               LotShape
                                                                                          LandContour
                                                                                                       Utilit
            0
                1
                            60
                                       RL
                                                   65.0
                                                           8450
                                                                   Pave
                                                                         NaN
                                                                                    Reg
                                                                                                         Allf
                            20
                                       RL
                                                   0.08
                                                           9600
                                                                         NaN
                                                                                                         AllF
            1
                2
                                                                   Pave
                                                                                    Reg
                                                                                                   Lvl
                                                          11250
            2
                3
                            60
                                       RL
                                                   68.0
                                                                                     IR1
                                                                   Pave
                                                                         NaN
                                                                                                   Lvl
                                                                                                         Allf
                            70
                                                   60.0
                                                           9550
                                                                                     IR1
                                       RL
                                                                   Pave
                                                                         NaN
                                                                                                   Lvl
                                                                                                         AIII
                5
                            60
                                       RL
                                                   84.0
                                                          14260
                                                                  Pave
                                                                         NaN
                                                                                     IR1
                                                                                                   Lvl
                                                                                                         Allf
```

5 rows × 81 columns

(iii) Linear Regression

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

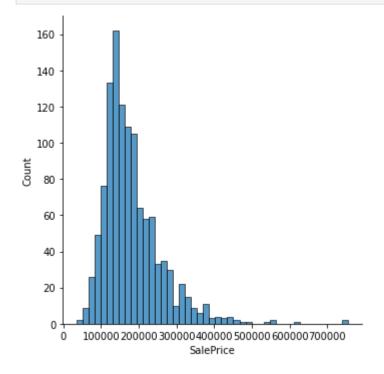
Remove the missing rows corresponding to only SalePrice and LotArea columns.

```
In [277... df = dataset.loc[:, ['SalePrice', 'LotArea']].dropna()
```

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

```
In [278... train_df, test_df = train_test_split(df, test_size=0.2)
```

```
In [279... sns.displot(train_df['SalePrice']);
```



In [280... train_df.head()

1453

Out[280]:		SalePrice	LotArea
	599	151000	1950
	44	141000	7945
	802	189000	8199
	1438	149700	7407

```
In [281... test_df.head()
```

84500

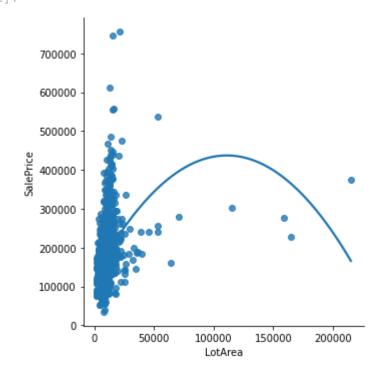
17217

Out [281

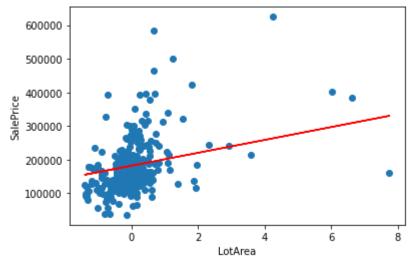
]:		SalePrice	LotArea
	75	91000	1596
	53	385000	50271
	906	255000	13501
	1366	193000	9179
	1104	106000	2016

Scatter plot to see the relationship between SalePrice and LotArea.

```
In [282... # ci: used to specify the size of the interval
sns.lmplot(x ="LotArea", y ="SalePrice", data = train_df, ci=None, order=2)
Out[282]: <seaborn.axisgrid.FacetGrid at 0x7f28068e4bd0>
```



```
plt.plot(X_test, y_pred, color ='r')
plt.show()
```



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

(iv) Multiple Regression

Model 1: LotFrontage, LotArea

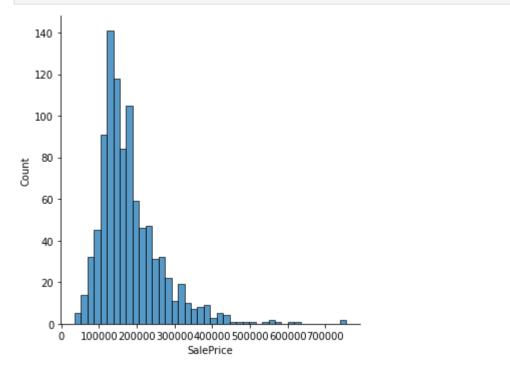
```
In [287... lot_area_weights = [] # required for question (vii)
In [288... df = dataset.loc[:, ['SalePrice', 'LotArea', 'LotFrontage']].dropna()
In [289... train_df, test_df = train_test_split(df, test_size=0.2)
In [290... train_df.head()
```

Out[290]:		SalePrice	LotArea	LotFrontage
	467	146500	9480	79.0
	119	163990	8461	65.0
	875	303477	9000	75.0
	480	326000	16033	98.0
	906	255000	13501	116.0

```
In [291... test_df.head()
```

Out[291]:		SalePrice	LotArea	LotFrontage
	1071	154000	11700	78.0
	946	143000	8163	70.0
	755	172500	3230	34.0
	30	40000	8500	50.0
	570	142600	13101	74.0

```
In [292... sns.displot(train_df['SalePrice']);
```



```
In [293...
variables = ['LotArea', 'LotFrontage']
X_train = np.array(train_df[variables])
X_train = scaler.fit_transform(X_train)
y_train = np.array(train_df[['SalePrice']])

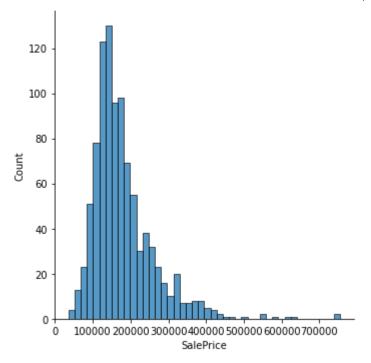
X_test = np.array(test_df[variables])
X_test = scaler.fit_transform(X_test)
y_test = np.array(test_df[['SalePrice']])
```

```
In [294... model = LinearRegression()
                         new_model = model.fit(X_train, y_train)
In [295... y_pred = new_model.predict(X_test)
                         r2_score_m1 = new_model.score(X_test, y_test)
                         mse_m1 = mean_squared_error(y_test, y_pred)
                         print("[Model 1] r2 score:", r2_score_m1) # same as sklearn.metrics.r2_score
                         print("[Model 1] mean squared error:", mse_m1)
                         [Model 1] r2 score: 0.18894409589343242
                         [Model 1] mean squared error: 4465301087.46941
In [296...
                        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:
                                                                                             18003.076786530026
                         LotArea
                        LotFrontage
                                                                                             21198.762404965273
                         Model 2: LotFrontage, LotArea, OverallOual, OverallCond
                        df = dataset.loc[:, ['SalePrice', 'LotArea', 'LotFrontage', 'OverallQual', '
In [297...
                        train_df, test_df = train_test_split(df, test_size=0.2)
In [298...
In [299...
                         train_df.head()
                                         SalePrice LotArea LotFrontage OverallQual OverallCond
Out[299]:
                           1420
                                             179900
                                                                    11700
                                                                                                  90.0
                                                                                                                                   6
                                                                                                                                                                6
                                                                                                                                                                5
                                86
                                              174000
                                                                    11911
                                                                                                122.0
                           1403
                                              282922
                                                                   15256
                                                                                                  49.0
                                                                                                                                   8
                                                                                                                                                                5
                              267
                                             179500
                                                                     8400
                                                                                                   60.0
                                                                                                                                   5
                                                                                                                                                                8
                              248
                                              180000
                                                                    11317
                                                                                                  72.0
                                                                                                                                   7
                                                                                                                                                                5
In [300...
                         test_df.head()
                                         SalePrice LotArea LotFrontage OverallQual OverallCond
Out[300]:
                              588
                                              143000
                                                                    25095
                                                                                                   65.0
                                                                                                                                   5
                                                                                                                                                                8
                            1121
                                              212900
                                                                   10084
                                                                                                  84.0
                                                                                                                                   7
                                                                                                                                                                5
                             847
                                              133500
                                                                   15523
                                                                                                   36.0
                                                                                                                                   5
                                                                                                                                                                6
                           1204
                                              153500
                                                                   10140
                                                                                                   78.0
                                                                                                                                   5
                                                                                                                                                                6
                           1050
                                             176485
                                                                     8993
                                                                                                  73.0
                                                                                                                                   7
                                                                                                                                                                5
```

```
file:///home/arnab/Desktop/Notes/ML/lab/ass-01/linear_multiple.html
```

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

In [301...



```
In [302... 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 [303... model = LinearRegression()
         new_model = model.fit(X_train, y_train)
In [304... y_pred = new_model.predict(X_test)
         r2_score_m2 = new_model.score(X_test, y_test)
         mse_m2 = mean_squared_error(y_test, y_pred)
         print("[Model 2] r2 score:", r2_score_m2) # same as sklearn.metrics.r2_score
         print("[Model 2] mean squared error:", mse_m2)
         [Model 2] r2 score: 0.7043508132745866
         [Model 2] mean squared error: 2052790517.6136389
In [305...
         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
                                    8862.459778565702
```

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

10739.146228055622

62472.4520137272

135.6182336392569

LotFrontage

OverallOual

OverallCond

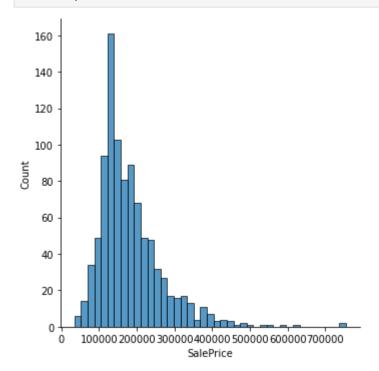
```
In [306... df = dataset.loc[:, ['SalePrice', 'LotArea', 'LotFrontage', 'OverallQual', 'Over
In [307... train_df, test_df = train_test_split(df, test_size=0.2)
In [308...
                                                            train_df.head()
                                                                                                  SalePrice LotArea LotFrontage OverallQual OverallCond 1stFlrSF
                                                                                                                                                                                                                                                                                                                                                                                                                                                          GrLivArea
Out[308]:
                                                                 1075
                                                                                                                                                                                                                                                                                                                       7
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    1740
                                                                                                            219500
                                                                                                                                                                13125
                                                                                                                                                                                                                                          75.0
                                                                                                                                                                                                                                                                                                                                                                                          6
                                                                                                                                                                                                                                                                                                                                                                                                                                 960
                                                                                                             190000
                                                                                                                                                                                                                                                                                                                                                                                                                            1888
                                                                        446
                                                                                                                                                                16492
                                                                                                                                                                                                                                     137.0
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                                                                            93
                                                                                                            133900
                                                                                                                                                                   7200
                                                                                                                                                                                                                                          60.0
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                                                                        503
                                                                                                            289000
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                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     1801
                                                                                                                                                                15602
                                                                                                                                                                                                                                                                                                                                                                                                                            1801
                                                                        371
                                                                                                            134432
                                                                                                                                                                17120
                                                                                                                                                                                                                                          80.0
                                                                                                                                                                                                                                                                                                                        4
                                                                                                                                                                                                                                                                                                                                                                                           4
                                                                                                                                                                                                                                                                                                                                                                                                                             1120
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                     1588
```

In [309... test_df.head()

0u	t	3	0	9]	

	SalePrice	LotArea	LotFrontage	OverallQual	OverallCond	1stFlrSF	GrLivArea
595	319000	11302	69.0	8	5	1826	1826
365	147000	10690	59.0	5	7	672	1344
440	555000	15431	105.0	10	5	2402	2402
289	153575	8730	60.0	6	7	698	1396
981	336000	12203	98.0	8	5	1276	2612

In [310... sns.displot(train_df['SalePrice']);



```
In [311... variables = ['LotArea', 'LotFrontage', 'OverallQual', 'OverallCond', '1stFlrSF
X_train = np.array(train_df[variables])
```

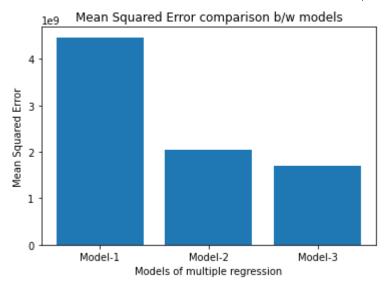
```
X_train = scaler.fit_transform(X_train)
         y_train = np.array(train_df[['SalePrice']])
         X_test = np.array(test_df[variables])
         X_test = scaler.fit_transform(X_test)
         y_test = np.array(test_df[['SalePrice']])
In [312... model = LinearRegression()
         new_model = model.fit(X_train, y_train)
In [313... y_pred = new_model.predict(X_test)
         r2_score_m3 = new_model.score(X_test, y_test)
         mse_m3 = mean_squared_error(y_test, y_pred)
         print("[Model 3] r2 score:", r2_score_m3) # same as sklearn.metrics.r2_score
         print("[Model 3] mean squared error:", mse_m3)
         [Model 3] r2 score: 0.7180087039489944
         [Model 3] mean squared error: 1704631344.9561703
         print("Weights/Coefficients:\n")
In [314...
         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:
                                    7057.920345774349
         LotArea
         LotFrontage
                                    -303.05755787223825
         OverallQual
                                    46592.153445790944
         OverallCond
                                    1552.500016010084
         1stFlrSF
                                    12198.610608555135
         GrLivArea
                                    22959.99196815228
```

(v) Compare the Mean squared Error, R2 score

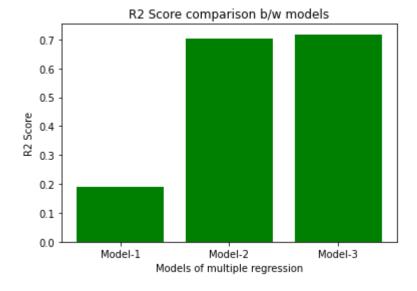
Comparing R2 score

Comparing Mean Squared Error

```
In [315... plt.xlabel("Models of multiple regression")
   plt.ylabel("Mean Squared Error")
   plt.title("Mean Squared Error comparison b/w models")
   plt.bar(["Model-1", "Model-2", "Model-3"], [mse_m1, mse_m2, mse_m3])
   plt.show()
```



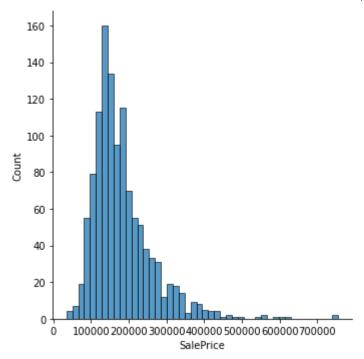
```
In [316... plt.xlabel("Models of multiple regression")
    plt.ylabel("R2 Score")
    plt.title("R2 Score comparison b/w models")
    plt.bar(["Model-1", "Model-2", "Model-3"], [r2_score_m1, r2_score_m2, r2_score_plt.show()
```



(vi) Multiple Regression (contd.)

Model 4: LotArea, Street

```
In [317... 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 [318... test_df.head()

0ι	+	Г	0	1	0	٦
Vι	I L		0	Т	0	

	SalePrice	LotArea	Street_GrvI	Street_Pave
217	107000	9906	0	1
1242	170000	10625	0	1
945	124900	8820	0	1
1357	149900	12537	0	1
163	103200	5500	0	1

In [319... train_df.head()

Out[319]:

	SalePrice	LotArea	Street_GrvI	Street_Pave
393	100000	7446	0	1
776	221500	11210	0	1
552	255500	11146	0	1
1304	130000	3363	0	1
1420	179900	11700	0	1

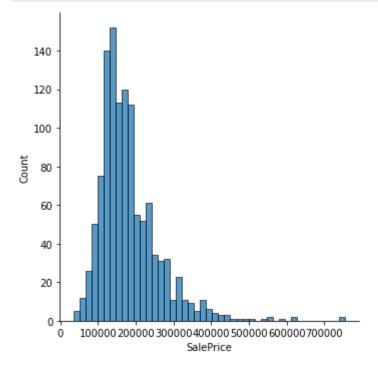
```
In [320... variables = train_df.columns.array[1:]
    X_train = np.array(train_df[variables])
    X_train = scaler.fit_transform(X_train)
    y_train = np.array(train_df[['SalePrice']])
    X_test = np.array(test_df[variables])
    X_test = scaler.fit_transform(X_test)
    y_test = np.array(test_df[['SalePrice']])
```

```
In [321... model = LinearRegression()
```

```
new_model = model.fit(X_train, y_train)
In [322...
         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("[Model 4] r2 score:", r2_score_m4) # same as sklearn.metrics.r2_score
         print("[Model 4] mean squared error:", mse_m4)
         [Model 4] r2 score: 0.03592748703897697
         [Model 4] mean squared error: 4941760310.846153
In [323... 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
                                    24258.824360028957
         Street_Grvl
                                    -2.103931852980475e+18
         Street_Pave
                                    -2.103931852980467e+18
```

Model 5: LotArea, OverallCond, Street, Neighborhood

```
In [324...
df = dataset.loc[:, ['SalePrice', 'LotArea', 'OverallCond', 'Street', 'Neighbo:
    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 [325... train_df.head()
```

Out[325]:		SalePrice	LotArea	OverallCond	Street_GrvI	Street_Pave	Neighborhood_Blmngtn	Neighbo
	233	128200	10650	6	0	1	0	
	1281	180000	8049	5	0	1	0	
	938	239799	8760	5	0	1	0	
	762	215200	8640	5	0	1	0	
	1414	207000	13053	7	0	1	0	

5 rows × 30 columns

								,
In [326	test_	df.head()						
Out[326]:		SalePrice	LotArea	OverallCond	Street_GrvI	Street_Pave	Neighborhood_Blmngtn	Neighbo
	741	142000	6768	8	0	1	0	
	570	142600	13101	5	0	1	0	
	1271	185750	9156	7	0	1	0	
	190	315000	10570	8	0	1	0	
	503	289000	15602	8	0	1	0	

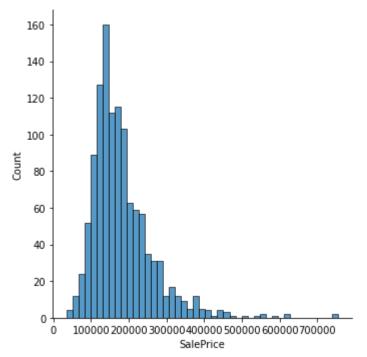
5 rows × 30 columns

```
4
In [327...
          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 [328... model = LinearRegression()
          new_model = model.fit(X_train, y_train)
In [329... 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)
          print("[Model 5] r2 score:", r2_score_m5) # same as sklearn.metrics.r2_score
          print("[Model 5] mean squared error:", mse_m5)
          [Model 5] r2 score: -5.462117067358696e+25
          [Model 5] mean squared error: 2.842884981217866e+35
In [330... 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
                          15977.35125907898
OverallCond
                          8291.768367203786
Street Grvl
                          1.4985119376798313e+18
Street_Pave
                          1.4985119376798364e+18
Neighborhood_Blmngtn
                          -4.903717487170676e+17
Neighborhood_Blueste
                          -1.9325335685306864e+17
Neighborhood_BrDale
                           -4.5146677589772614e+17
Neighborhood BrkSide
                          -8.996195991429783e+17
Neighborhood_ClearCr
                          -6.354281091819452e+17
Neighborhood_CollgCr
                          -1.38718857898456e+18
Neighborhood_Crawfor
                          -8.29265873648037e+17
Neighborhood_Edwards
                          -1.1737896044948403e+18
Neighborhood Gilbert
                           -1.0715370892887411e+18
Neighborhood_IDOTRR
                          -7.630041994550884e+17
Neighborhood_MeadowV
                          -5.4331163342291085e+17
Neighborhood_Mitchel
                          -8.292658736480454e+17
Neighborhood NAmes
                          -1.668231901758573e+18
Neighborhood NPkVill
                          -3.8551098844421715e+17
Neighborhood_NWAmes
                          -1.0479394302686234e+18
Neighborhood_NoRidge
                          -7.744933160441996e+17
Neighborhood NridgHt
                          -1.055879084370892e+18
Neighborhood_OldTown
                          -1.252827625423997e+18
Neighborhood_SWISU
                          -6.210894177653805e+17
Neighborhood_Sawyer
                          -1.0399237608182981e+18
Neighborhood_SawyerW
                          -9.278812597095914e+17
Neighborhood Somerst
                           -1.102011597387187e+18
Neighborhood_StoneBr
                          -6.21089417765355e+17
Neighborhood_Timber
                          -7.513181019235105e+17
Neighborhood_Veenker
                          -4.306426636943415e+17
```

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

```
In [331... 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 [332... train_df.head()

Out[332]:

	SalePrice	LotArea	OverallCond	1stFlrSF	YearBuilt	Street_GrvI	Street_Pave	Neighborhoo
405	150000	9991	4	1620	1976	0	1	
890	122900	8064	7	672	1949	0	1	
1256	301500	14303	5	1987	1994	0	1	
1219	91500	1680	5	672	1971	0	1	
1067	167900	9760	6	798	1964	0	1	

5 rows × 32 columns

In [333... test_df.head()

Out[333]:

		SalePrice	LotArea	OverallCond	1stFlrSF	YearBuilt	Street_GrvI	Street_Pave	Neighborhoo
	981	336000	12203	5	1276	1998	0	1	
	798	485000	13518	5	1966	2008	0	1	
	464	124000	8430	5	1040	1978	0	1	
	1136	119000	9600	5	1032	1950	0	1	
	401	164990	8767	5	1310	2005	0	1	

5 rows × 32 columns

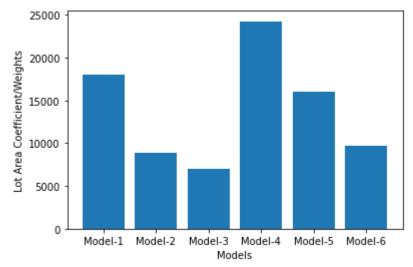
```
In [334... variables = train_df.columns.array[1:]
    X_train = np.array(train_df[variables])
    X_train = scaler.fit_transform(X_train)
    y_train = np.array(train_df[['SalePrice']])
```

```
X_test = np.array(test_df[variables])
         X_test = scaler.fit_transform(X_test)
         y_test = np.array(test_df[['SalePrice']])
In [335... model = LinearRegression()
         new_model = model.fit(X_train, y_train)
In [336... 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)
         print("[Model 6] r2 score:", r2_score_m6) # same as sklearn.metrics.r2_score
         print("[Model 6] mean squared error:", mse_m6)
         [Model 6] r2 score: -5.457098552528068e+22
         [Model 6] mean squared error: 2.9030478443896677e+32
         print("Weights/Coefficients:\n")
In [337...
         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
                                    9649.838114536089
         OverallCond
                                    12909.33574022097
         1stFlrSF
                                    30241.98159192617
         YearBuilt
                                    21322.116831710307
         Street_Grvl
                                    1.4247004510097416e+16
                                    1.4247004510100894e+16
         Street_Pave
         Neighborhood_Blmngtn
                                    1.2550049681081134e+16
         Neighborhood_Blueste
                                    4768071901278653.0
         Neighborhood_BrDale
                                    1.1629152423225832e+16
         Neighborhood_BrkSide
                                    2.3344491948968852e+16
         Neighborhood_ClearCr
                                    1.5323920108050198e+16
         Neighborhood_CollgCr
                                    3.4754750569005932e+16
         Neighborhood_Crawfor
                                    2.071847555367409e+16
         Neighborhood_Edwards
                                    2.9957268640653976e+16
         Neighborhood_Gilbert
                                    2.624539095563849e+16
         Neighborhood IDOTRR
                                    1.8243589062267188e+16
                                    1.1138880501593168e+16
         Neighborhood_MeadowV
         Neighborhood_Mitchel
                                    1.9661991313214108e+16
         Neighborhood_NAmes
                                    4.106259003253796e+16
         Neighborhood_NPkVill
                                    8244365020842694.0
         Neighborhood_NWAmes
                                    2.484694393799061e+16
                                    1.910880037530304e+16
         Neighborhood_NoRidge
         Neighborhood_NridgHt
                                    2.5657672105554464e+16
         Neighborhood_OldTown
                                    3.106551603276723e+16
         Neighborhood_SWISU
                                    1.4588657808779264e+16
         Neighborhood Sawver
                                    2.4429099010471972e+16
         Neighborhood_SawyerW
                                    2.400235701786597e+16
         Neighborhood_Somerst
                                    2.8269572137679916e+16
         Neighborhood StoneBr
                                    1.567769358324218e+16
         Neighborhood_Timber
                                    1.8243589062273212e+16
         Neighborhood_Veenker
                                    1.0625094527151932e+16
```

(vi) Compare the feature "LotArea" weights/coefficients

for all the six trained models and plot a graph using the Matplotlib library.

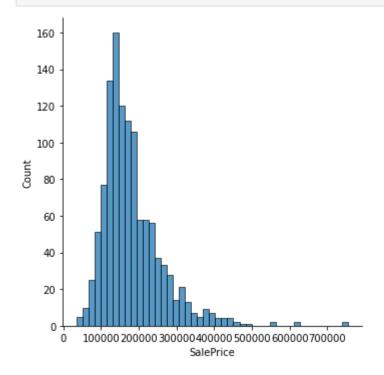
```
In [338... x_values = [f"Model-{x}" for x in range(1, 7)]
y_values = lot_area_weights
plt.bar(x_values, y_values)
plt.ylabel('Lot Area Coefficient/Weights')
plt.xlabel('Models')
plt.show()
```



(vii) Polynomial regression

DegrDegree 2ee 2

```
In [339... df = dataset.loc[:, ['SalePrice', 'LotArea']].dropna()
    train_df, test_df = train_test_split(df, test_size=0.2)
    sns.displot(train_df['SalePrice']);
```



```
train_df.head()
In [340...
               SalePrice LotArea
Out[340]:
           720
                 275000
                           6563
                 116500
                           7207
           960
                 181000
                          17043
           124
            17
                  90000
                          10791
           591
                 451950
                          13478
In [341...
          test_df.head()
                SalePrice LotArea
Out[341]:
            908
                  131000
                            8885
           1283
                  139000
                            9400
           1193
                  165000
                            4500
            998
                   91000
                            9786
            83
                  126500
                            8892
In [342...
         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 [343...
         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 [344...
         y_pred = new_model.predict(poly.fit_transform(X_test))
          r2_score_poly = r2_score(y_test, y_pred)
          mse_poly = mean_squared_error(y_test, y_pred)
          print("[Poly] r2 score:", r2_score_poly)
          print("[Poly] mean squared error:", mse_poly)
          [Poly] r2 score: 0.14151946740561616
          [Poly] mean squared error: 5232502359.016333
In [345...
          sns.scatterplot(X_test.reshape(-1), y_test.reshape(-1))
          sns.lineplot(X_test.reshape(-1), y_pred.reshape(-1), color = 'red')
```

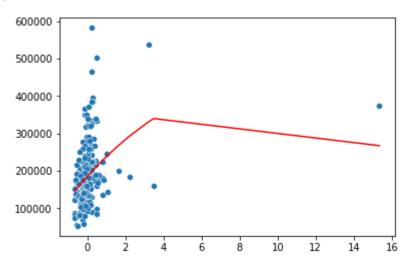
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarnin g: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments wit hout an explicit keyword will result in an error or misinterpretation.

FutureWarning

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarnin g: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments wit hout an explicit keyword will result in an error or misinterpretation.

FutureWarning

Out[345]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2806baa490>



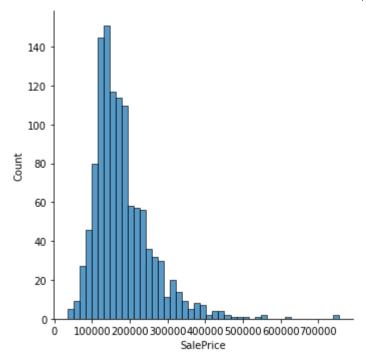
```
In [346... print("Weights/Coefficients:\n", new_model.coef_.reshape(-1))
Weights/Coefficients:
```

cignes/coerricients.

[0. 56060.78192413 -3300.9838299]

Degree 3

```
In [347...
df = dataset.loc[:, ['SalePrice', 'LotArea']].dropna()
    train_df, test_df = train_test_split(df, test_size=0.2)
    sns.displot(train_df['SalePrice']);
```



In [348... train_df.head()

Out[348]:		SalePrice	LotArea
	1112	129900	7100
	697	123500	6420
	1079	126000	8775
	89	123600	8070

115000

10434

In [349... test_df.head()

1125

Out[349]:		SalePrice	LotArea
	385	192000	3182
	896	106500	8765
	622	135000	7064
	162	220000	12182
	1400	120000	6000

```
In [350... 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']])
```

```
poly = PolynomialFeatures(degree = 3)
In [351...
          X_poly = poly.fit_transform(X_train)
          poly.fit(X_poly, y_train)
         model = LinearRegression()
          new_model = model.fit(X_poly, y_train)
In [352...
         y_pred = new_model.predict(poly.fit_transform(X_test))
          r2_score_poly = r2_score(y_test, y_pred)
         mse_poly = mean_squared_error(y_test, y_pred)
          print("[Poly Deg 3] r2 score:", r2_score_poly)
          print("[Poly Deg 3] mean squared error:", mse_poly)
          [Poly Deg 3] r2 score: 0.08977086485503138
          [Poly Deg 3] mean squared error: 5829891043.974915
In [353... sns.scatterplot(X_test.reshape(-1), y_test.reshape(-1))
          sns.lineplot(X_test.reshape(-1), y_pred.reshape(-1), color = 'red')
         /usr/local/lib/python3.7/dist-packages/seaborn/ decorators.py:43: FutureWarnin
         g: Pass the following variables as keyword args: x, y. From version 0.12, the
         only valid positional argument will be `data`, and passing other arguments wit
         hout an explicit keyword will result in an error or misinterpretation.
           FutureWarning
         /usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarnin
         g: Pass the following variables as keyword args: x, y. From version 0.12, the
         only valid positional argument will be `data`, and passing other arguments wit
         hout an explicit keyword will result in an error or misinterpretation.
           FutureWarning
          <matplotlib.axes._subplots.AxesSubplot at 0x7f28078b2910>
Out[3531:
          600000
          500000
          400000
          300000
          200000
          100000
                                              10
                                                    12
                                                          14
In [354...
          new_model.coef_
                                     69593.45503156, -12804.01331804,
          array([[
Out[354]:
                      503.8040302511)
In [355...
         print("Weights/Coefficients:\n", new_model.coef_.reshape(-1))
         Weights/Coefficients:
                             69593.45503156 -12804.01331804
                                                                503.804030251
          Γ
```