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House Prices - Advanced Regression Techniques

```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split

#Loading train and test datasets
train_data = pd.read_csv('./train.csv')
test_data = pd.read_csv('./test.csv')

#Viewing the contents of the dataset
train_data
```

```
        Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley 
LotShape  \
0        1          60       RL         65.0     8450   Pave   NaN 
Reg   
1        2          20       RL         80.0     9600   Pave   NaN 
Reg   
2        3          60       RL         68.0    11250   Pave   NaN 
IR1   
3        4          70       RL         60.0     9550   Pave   NaN 
IR1   
4        5          60       RL         84.0    14260   Pave   NaN 
IR1   
...    ...         ...      ...          ...      ...    ...   ...
...   
1455  1456          60       RL         62.0     7917   Pave   NaN 
Reg   
1456  1457          20       RL         85.0    13175   Pave   NaN 
Reg   
1457  1458          70       RL         66.0     9042   Pave   NaN 
Reg   
1458  1459          20       RL         68.0     9717   Pave   NaN 
Reg   
1459  1460          20       RL         75.0     9937   Pave   NaN 
Reg   

     LandContour Utilities  ... PoolArea PoolQC Fence MiscFeature 
MiscVal  \
0            Lvl    AllPub  ...        0    NaN   NaN         NaN 
0   
1            Lvl    AllPub  ...        0    NaN   NaN         NaN 
0   
```

```
2             Lvl    AllPub  ...        0    NaN    NaN          NaN
0
3             Lvl    AllPub  ...        0    NaN    NaN          NaN
0
4             Lvl    AllPub  ...        0    NaN    NaN          NaN
0
...           ...       ...  ...      ...    ...    ...          ...
...
1455          Lvl    AllPub  ...        0    NaN    NaN          NaN
0
1456          Lvl    AllPub  ...        0    NaN  MnPrv          NaN
0
1457          Lvl    AllPub  ...        0    NaN  GdPrv         Shed
2500
1458          Lvl    AllPub  ...        0    NaN    NaN          NaN
0
1459          Lvl    AllPub  ...        0    NaN    NaN          NaN
0

     MoSold YrSold  SaleType  SaleCondition  SalePrice
0         2   2008        WD         Normal     208500
1         5   2007        WD         Normal     181500
2         9   2008        WD         Normal     223500
3         2   2006        WD        Abnorml     140000
4        12   2008        WD         Normal     250000
...     ...    ...       ...            ...        ...
1455      8   2007        WD         Normal     175000
1456      2   2010        WD         Normal     210000
1457      5   2010        WD         Normal     266500
1458      4   2010        WD         Normal     142125
1459      6   2008        WD         Normal     147500

[1460 rows x 81 columns]
```

By getting the info on train data, we can see the columns and their datatypes. Our task is to predict housing prices using the attributes **Square footage**, **No. of Bedrooms** & **No. of Bathrooms**

```
train_data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
 1   MSSubClass     1460 non-null   int64
 2   MSZoning       1460 non-null   object
 3   LotFrontage    1201 non-null   float64
```

```
 4   LotArea        1460 non-null   int64
 5   Street         1460 non-null   object
 6   Alley          91 non-null     object
 7   LotShape       1460 non-null   object
 8   LandContour    1460 non-null   object
 9   Utilities      1460 non-null   object
 10  LotConfig      1460 non-null   object
 11  LandSlope      1460 non-null   object
 12  Neighborhood   1460 non-null   object
 13  Condition1     1460 non-null   object
 14  Condition2     1460 non-null   object
 15  BldgType       1460 non-null   object
 16  HouseStyle     1460 non-null   object
 17  OverallQual    1460 non-null   int64
 18  OverallCond    1460 non-null   int64
 19  YearBuilt      1460 non-null   int64
 20  YearRemodAdd   1460 non-null   int64
 21  RoofStyle      1460 non-null   object
 22  RoofMatl       1460 non-null   object
 23  Exterior1st    1460 non-null   object
 24  Exterior2nd    1460 non-null   object
 25  MasVnrType     588 non-null    object
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object
 28  ExterCond      1460 non-null   object
 29  Foundation     1460 non-null   object
 30  BsmtQual       1423 non-null   object
 31  BsmtCond       1423 non-null   object
 32  BsmtExposure   1422 non-null   object
 33  BsmtFinType1   1423 non-null   object
 34  BsmtFinSF1     1460 non-null   int64
 35  BsmtFinType2   1422 non-null   object
 36  BsmtFinSF2     1460 non-null   int64
 37  BsmtUnfSF      1460 non-null   int64
 38  TotalBsmtSF    1460 non-null   int64
 39  Heating        1460 non-null   object
 40  HeatingQC      1460 non-null   object
 41  CentralAir     1460 non-null   object
 42  Electrical     1459 non-null   object
 43  1stFlrSF       1460 non-null   int64
 44  2ndFlrSF       1460 non-null   int64
 45  LowQualFinSF   1460 non-null   int64
 46  GrLivArea      1460 non-null   int64
 47  BsmtFullBath   1460 non-null   int64
 48  BsmtHalfBath   1460 non-null   int64
 49  FullBath       1460 non-null   int64
 50  HalfBath       1460 non-null   int64
 51  BedroomAbvGr   1460 non-null   int64
 52  KitchenAbvGr   1460 non-null   int64
```

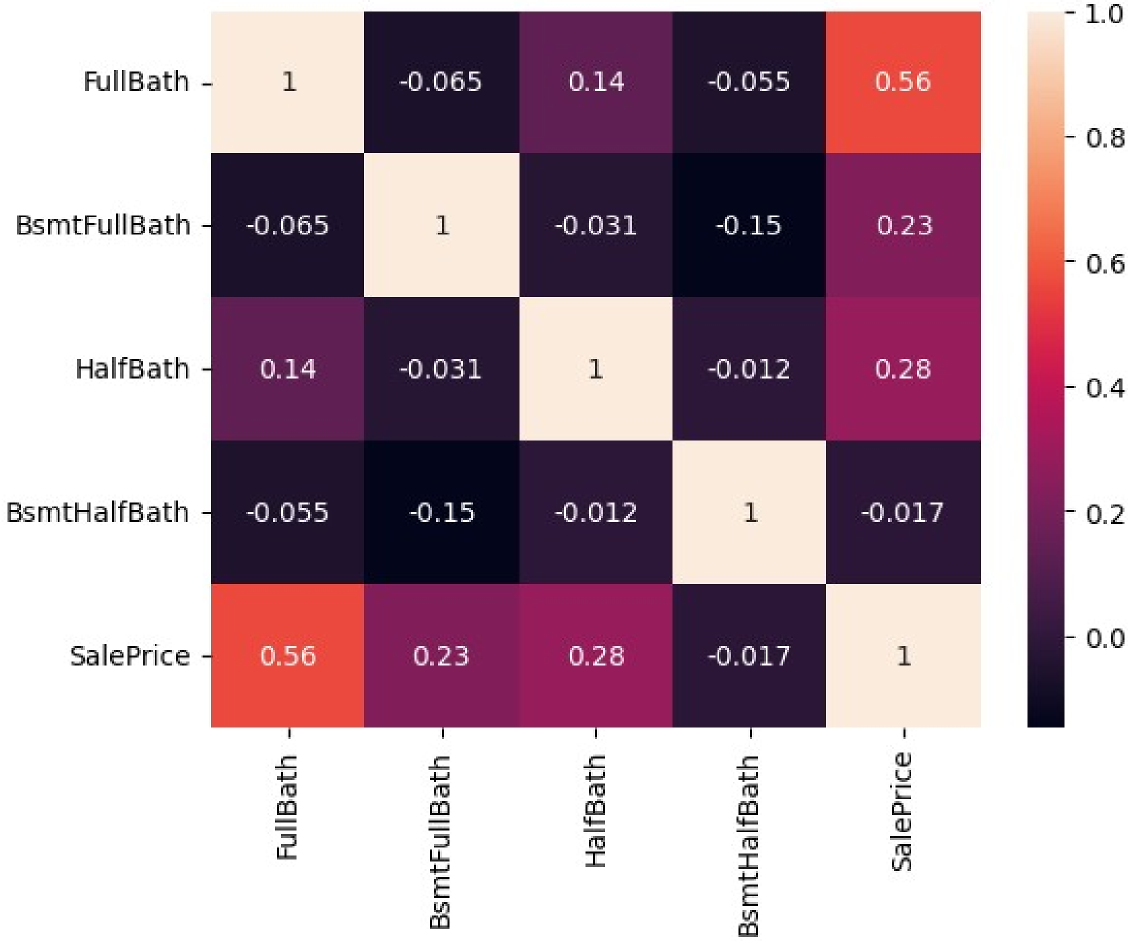
```
 53  KitchenQual    1460 non-null   object
 54  TotRmsAbvGrd   1460 non-null   int64
 55  Functional     1460 non-null   object
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

We can see that the no.of bathrooms is provided in 2 varities: **Full Bathrooms** & **Half Bathrooms** and there are 2 columns for each variant i.e. For Full Bathrooms : **FullBath** & **BsmtFullBath**, For Half Bathrooms : **HalfBath** & **BsmtHalflBath**

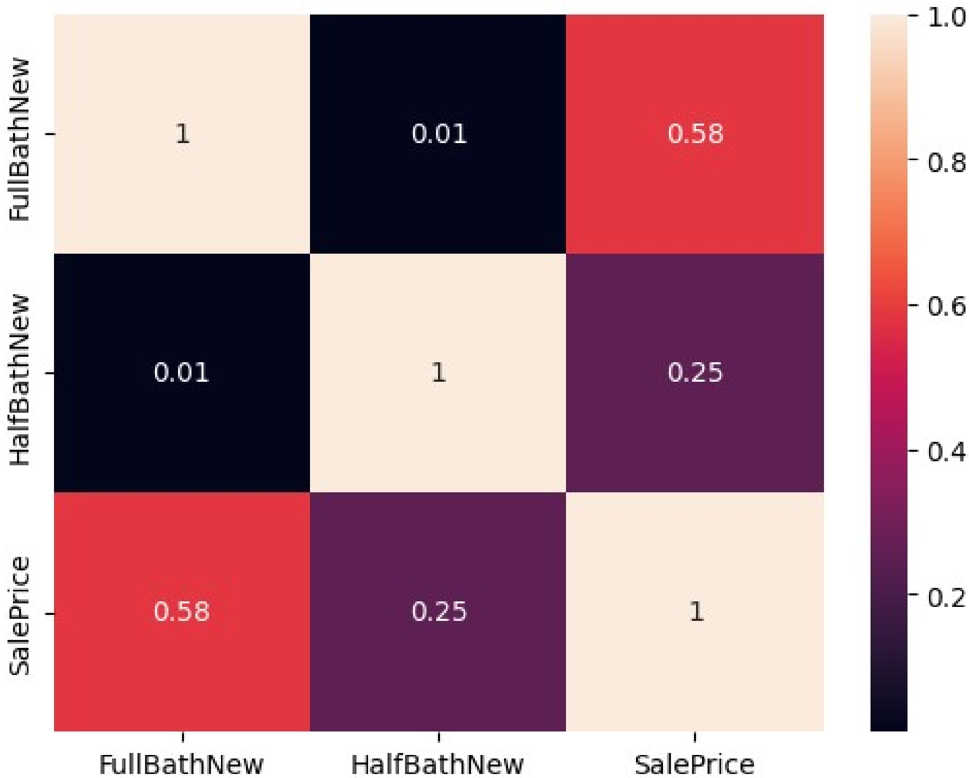
```
# We can find the correlation between the various bathrooms and sales price
bath_sales_df = train_data[['FullBath', 'BsmtFullBath', 'HalfBath', 'BsmtHalfBath', 'SalePrice']]
bath_sales_df
```

	FullBath	BsmtFullBath	HalfBath	BsmtHalfBath	SalePrice
0	2	1	1	0	208500
1	2	0	0	1	181500
2	2	1	1	0	223500
3	1	1	0	0	140000
4	2	1	1	0	250000
...	...	...	...	...	...
1455	2	0	1	0	175000

```
1456          2              1          0              0      210000
1457          2              0          0              0      266500
1458          1              1          0              0      142125
1459          1              1          1              0      147500

[1460 rows x 5 columns]

sns.heatmap(bath_sales_df.corr(), annot=True)
plt.show()
```




```
#We can create new features for each bathroom type (Full or Half)
fullcomb = train_data['FullBath'] + train_data['BsmtFullBath']
halfcomb = train_data['HalfBath'] + train_data['BsmtHalfBath']

bath_sales_new = pd.DataFrame({'FullBathNew':fullcomb,
'HalfBathNew':halfcomb, 'SalePrice':train_data['SalePrice']})
sns.heatmap(bath_sales_new.corr(), annot=True)
plt.show()
```



We can see the correlation is improved with new variables compared to older ones

```
#We need only Square footage, No.of Bedrooms and No.of Bathrooms data
for our ML model
train_data_filt = pd.DataFrame({'LotArea':train_data['LotArea'],
'FullBathComb':fullcomb, 'HalfBathComb':halfcomb,
'Bedrooms':train_data['BedroomAbvGr'],
'SalePrice':train_data['SalePrice']})
train_data_filt.head()
```

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

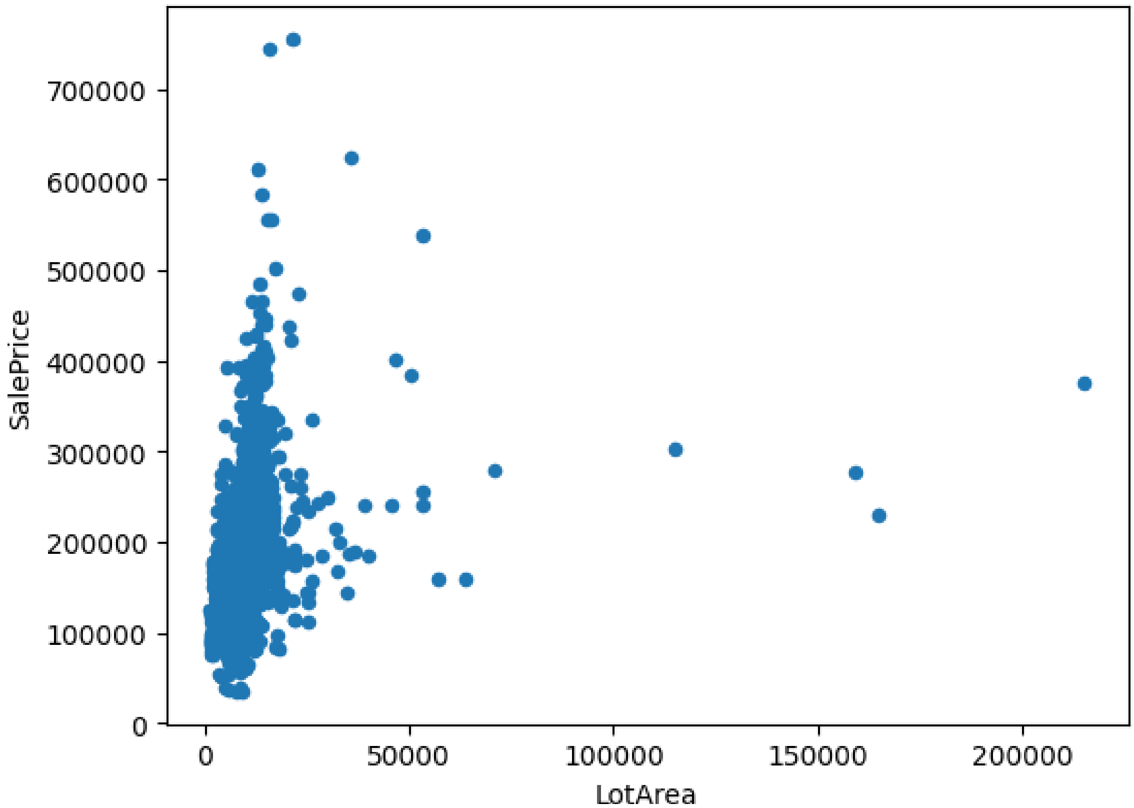
```
# We can see that it has no null values
train_data_filt.isna().sum()
```

```
LotArea         0
FullBathComb    0
HalfBathComb    0
Bedrooms        0
SalePrice       0
dtype: int64
```

We can see the distribution of input parameters against sale price

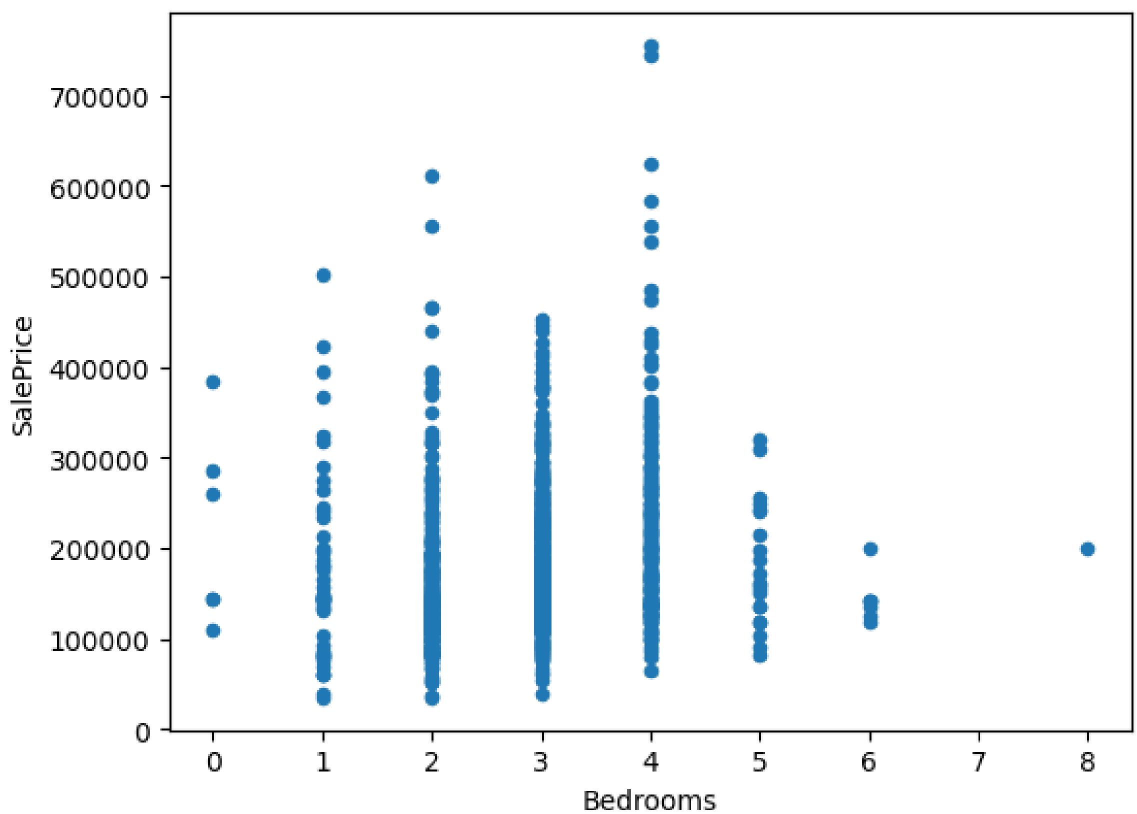
```
train_data_filt.plot(kind='scatter',x='LotArea', y='SalePrice', )
```

```
<Axes: xlabel='LotArea', ylabel='SalePrice'>
```




```
train_data_filt.plot(kind='scatter',x='Bedrooms', y='SalePrice' )
```

```
<Axes: xlabel='Bedrooms', ylabel='SalePrice'>
```




```
train_data_filt.describe()

                 LotArea  FullBathComb  HalfBathComb     Bedrooms
SalePrice
count     1460.000000   1460.000000   1460.000000  1460.000000
1460.000000
mean     10516.828082      1.990411      0.440411     2.866438
180921.195890
std       9981.264932      0.732046      0.554016     0.815778
79442.502883
min       1300.000000      0.000000      0.000000     0.000000
34900.000000
25%       7553.500000      1.000000      0.000000     2.000000
129975.000000
50%       9478.500000      2.000000      0.000000     3.000000
163000.000000
75%      11601.500000      2.000000      1.000000     3.000000
214000.000000
max     215245.000000      6.000000      4.000000     8.000000
755000.000000
```

We can see that there is a huge difference in the mean and deviation values of input parameters (LotArea, FullBathComb, HalfBathComb & Bedrooms). We will apply z-score normalization to normalize these values

```python
train_data_transf =
StandardScaler().fit_transform(train_data_filt.iloc[:, :-1])
train_data_transf
```

```
array([[-0.20714171,  1.37960564,  1.01040607,  0.16377912],
       [-0.09188637,  0.01310345,  1.01040607,  0.16377912],
       [ 0.07347998,  1.37960564,  1.01040607,  0.16377912],
       ...,
       [-0.14781027,  0.01310345, -0.79521555,  1.39002276],
       [-0.08016039,  0.01310345, -0.79521555, -1.06246453],
       [-0.05811155,  0.01310345,  1.01040607,  0.16377912]])
```

```python
x_train_transf = pd.DataFrame(train_data_transf, columns=['LotArea',
'FullBathComb', 'HalfBathComb', 'Bedrooms'])
x_train_transf
```

```
       LotArea  FullBathComb  HalfBathComb  Bedrooms
0    -0.207142      1.379606      1.010406  0.163779
1    -0.091886      0.013103      1.010406  0.163779
2     0.073480      1.379606      1.010406  0.163779
3    -0.096897      0.013103     -0.795216  0.163779
4     0.375148      1.379606      1.010406  1.390023
...        ...           ...           ...       ...
1455 -0.260560      0.013103      1.010406  0.163779
1456  0.266407      1.379606     -0.795216  0.163779
1457 -0.147810      0.013103     -0.795216  1.390023
1458 -0.080160      0.013103     -0.795216 -1.062465
1459 -0.058112      0.013103      1.010406  0.163779

[1460 rows x 4 columns]
```

```python
y_train = train_data_filt['SalePrice']
y_train
```

```
0       208500
1       181500
2       223500
3       140000
4       250000
         ...
1455    175000
1456    210000
1457    266500
1458    142125
1459    147500
Name: SalePrice, Length: 1460, dtype: int64
```

```python
X_train, X_test, y_train, y_test = train_test_split(
    x_train_transf, y_train, test_size=0.25, random_state=42)
```

We will create the linear regression model using sklearn's LinearRegression class module and fit it to our housing data

```
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
lr_model
```

```
LinearRegression()
```

```
#R2 Value
lr_model.score(X_test, y_test)
```

```
0.4529185974643213
```

```
test_data
```

```
        Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley
LotShape  \
0     1461          20       RH         80.0    11622   Pave   NaN
Reg
1     1462          20       RL         81.0    14267   Pave   NaN
IR1
2     1463          60       RL         74.0    13830   Pave   NaN
IR1
3     1464          60       RL         78.0     9978   Pave   NaN
IR1
4     1465         120       RL         43.0     5005   Pave   NaN
IR1
...    ...         ...      ...          ...      ...    ...   ...
...
1454  2915         160       RM         21.0     1936   Pave   NaN
Reg
1455  2916         160       RM         21.0     1894   Pave   NaN
Reg
1456  2917          20       RL        160.0    20000   Pave   NaN
Reg
1457  2918          85       RL         62.0    10441   Pave   NaN
Reg
1458  2919          60       RL         74.0     9627   Pave   NaN
Reg

     LandContour Utilities  ... ScreenPorch PoolArea PoolQC  Fence  \
0            Lvl    AllPub  ...         120        0    NaN  MnPrv
1            Lvl    AllPub  ...           0        0    NaN    NaN
2            Lvl    AllPub  ...           0        0    NaN  MnPrv
3            Lvl    AllPub  ...           0        0    NaN    NaN
4            HLS    AllPub  ...         144        0    NaN    NaN
...          ...       ...  ...         ...      ...    ...    ...
1454         Lvl    AllPub  ...           0        0    NaN    NaN
1455         Lvl    AllPub  ...           0        0    NaN    NaN
1456         Lvl    AllPub  ...           0        0    NaN    NaN
```

```
1457         Lvl    AllPub  ...           0        0    NaN  MnPrv
1458         Lvl    AllPub  ...           0        0    NaN    NaN

     MiscFeature MiscVal MoSold  YrSold  SaleType  SaleCondition
0            NaN       0      6    2010        WD         Normal
1           Gar2   12500      6    2010        WD         Normal
2            NaN       0      3    2010        WD         Normal
3            NaN       0      6    2010        WD         Normal
4            NaN       0      1    2010        WD         Normal
...          ...     ...    ...     ...       ...            ...
1454         NaN       0      6    2006        WD         Normal
1455         NaN       0      4    2006        WD        Abnorml
1456         NaN       0      9    2006        WD        Abnorml
1457        Shed     700      7    2006        WD         Normal
1458         NaN       0     11    2006        WD         Normal

[1459 rows x 80 columns]
```

```
# Testing the model performance
test_data = pd.read_csv('test.csv')
fullcomb_test = test_data['FullBath'] + test_data['BsmtFullBath']
halfcomb_test = test_data['HalfBath'] + test_data['BsmtHalfBath']
test_data_x = pd.DataFrame({'LotArea':test_data['LotArea'],
'FullBathComb':fullcomb_test, 'HalfBathComb':halfcomb_test,
'Bedrooms':test_data['BedroomAbvGr']})
test_data_x
```

```
      LotArea  FullBathComb  HalfBathComb  Bedrooms
0       11622           1.0           0.0         2
1       14267           1.0           1.0         3
2       13830           2.0           1.0         3
3        9978           2.0           1.0         3
4        5005           2.0           0.0         2
...       ...           ...           ...       ...
1454     1936           1.0           1.0         3
1455     1894           1.0           1.0         3
1456    20000           2.0           0.0         4
1457    10441           1.0           1.0         3
1458     9627           2.0           1.0         3

[1459 rows x 4 columns]
```

```
test_data_transf =
StandardScaler().fit_transform(test_data_x.iloc[:, :])
test_data_transf
```

```
array([[ 0.36392912, -1.29367496, -0.82114784, -1.02954254],
       [ 0.89786065, -1.29367496,  1.03375511,  0.17599724],
       [ 0.80964587, -0.0061856 ,  1.03375511,  0.17599724],
       ...,
```

```
       [ 2.05514965, -0.0061856 , -0.82114784,  1.38153702],
       [ 0.12552719, -1.29367496,  1.03375511,  0.17599724],
       [-0.03879049, -0.0061856 ,  1.03375511,  0.17599724]])
```

```
x_test_transf = pd.DataFrame(test_data_transf, columns=['LotArea',
'FullBathComb', 'HalfBathComb', 'Bedrooms'])
x_test_transf
```

```
       LotArea  FullBathComb  HalfBathComb  Bedrooms
0     0.363929     -1.293675     -0.821148 -1.029543
1     0.897861     -1.293675      1.033755  0.175997
2     0.809646     -0.006186      1.033755  0.175997
3     0.032064     -0.006186      1.033755  0.175997
4    -0.971808     -0.006186     -0.821148 -1.029543
...        ...           ...           ...       ...
1454 -1.591330     -1.293675      1.033755  0.175997
1455 -1.599808     -1.293675      1.033755  0.175997
1456  2.055150     -0.006186     -0.821148  1.381537
1457  0.125527     -1.293675      1.033755  0.175997
1458 -0.038790     -0.006186      1.033755  0.175997

[1459 rows x 4 columns]
```

```
x_test_transf = x_test_transf.fillna(0)

y_predict = lr_model.predict(x_test_transf)

prediction_data = pd.DataFrame({'Id':test_data['Id'],
'SalePrice':y_predict})
prediction_data
```

```
        Id      SalePrice
0     1461  114575.795619
1     1462  153043.709580
2     1463  207161.466551
3     1464  199535.514487
4     1465  156458.769683
...    ...            ...
1454  2915  128631.556177
1455  2916  128548.407167
1456  2917  186270.587236
1457  2918  145469.230712
1458  2919  198840.626331

[1459 rows x 2 columns]
```

```
prediction_data.to_csv('prediction.csv', index=False)
```