An Investigation of Regression Techniques to Predict Housing Prices

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Problem

House price prediction has been an important area of research and has a practical application in real estate. By understanding the factors that contribute to a property's value we are able to accurately predict its the property's value and it can allow real estate agents, buyers, and sellers to make informed decisions.

In this project, We aim to develop a ML model which can accurately predict the price of properties based on various features. The feature list and their description can be found at https://www.kaggle.com/competitions/house-prices-advanced-regression-techniques/data. The goal is to create a model that can estimate the value of a house based on its characteristics and evalute the quality of the model. We will be creating a Random Forest Regression, A Gradiant Booseter Regression and a Polynomial Linear regression.

Results and Conclusion

Regression Type	*MAE*	*Root MSE*	*R2 / EV*
LinearRegression	~18704.58	~28348.17	~0.771157
RandomForestRegressor	~15613.14	~22230.18	~0.85946
GradientBoostingRegressor	~15414.11	~21863.97	~0.86435

All our models did well, but they also had a fair amount of error in price estimation. These models have room for improvement, in that the parameters governing their adaptation can be tweaked. The feature set does have redundant features which could be combined, such as square foot of each level of the house and all contribute to the overall square footage. Upon looking at some of the other submissions for the Kaggle contest, it appears that others had similar results with a .96 EV score being the highest we found among the submissions we inspected.

As with any kind of market, things are worth what people are willing to pay and housing is no different. To some a large kitchen is important, to others a large garage. This personal preference will always make prices somewhat subjective and in the end, it is really about fitting the buyer to the house, which will allow the seller to ask for a higher price.

```
# Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats

# Preprocessing
from sklearn.preprocessing import MinMaxScaler, OrdinalEncoder, StandardScaler

# Modeling
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error
from sklearn.metrics import explained_variance_score as evs
from sklearn.model_selection import train_test_split,cross_val_score

#Allow for inline plotting
```

```
#Allow for inline plotting
%matplotlib inline
```

```
# Loading Data
# If this notebook is re-used these need to be modified

from google.colab import drive
drive.mount('/content/drive')

#df_train = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/train.csv')
#df_test = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/test.csv') # After the model is built this is the data which will be used f

df_train = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Project3/train.csv')
#df_test = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/Project3/test.csv') # After the model is built this is the data which will
df_train.head()

```

```
Mounted at /content/drive
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandCor
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	

5 rows × 81 columns

Data Cleaning and inspection

```
#List columns with NA values
df_train.replace([np.inf, -np.inf], np.nan, inplace=True)
pd.DataFrame(df_train.isna().sum()).sort_values(by=0,ascending=False).head(20)
```

	0
PoolQC	1453
MiscFeature	1406
Alley	1369
Fence	1179
FireplaceQu	690
LotFrontage	259
GarageYrBlt	81
GarageCond	81
GarageType	81
GarageFinish	81
GarageQual	81
BsmtFinType2	38
BsmtExposure	38
BsmtQual	37
BsmtCond	37
BsmtFinType1	37
MasVnrArea	8
MasVnrType	8
Electrical	1
Id	0

```
#Find percent of entires which are na
pd.DataFrame(df_train.isna().mean()*100).sort_values(by=0,ascending=False).head(20)
```

	0
PoolQC	99.520548
MiscFeature	96.301370
Alley	93.767123
Fence	80.753425
FireplaceQu	47.260274
LotFrontage	17.739726
GarageYrBlt	5.547945
GarageCond	5.547945
GarageType	5.547945
GarageFinish	5.547945
GarageQual	5.547945
BsmtFinType2	2.602740
BsmtExposure	2.602740
BsmtQual	2.534247
BsmtCond	2.534247
BsmtFinType1	2.534247
MasVnrArea	0.547945
MasVnrType	0.547945
Electrical	0.068493
Id	0.000000

```
#drop any columns which are above 40% bad
df_train_clean = df_train.drop(columns=df_train.columns[df_train.isna().mean() > 0.40])
```

```
#Check skew to determine mean or median for na columns
df_train_clean.skew(skipna = True)
```

```
<ipython-input-6-96ec2b9820d8>:2: FutureWarning: The default value of numeric_only in DataFrame.skew is deprecated. In a future version,
  df_train_clean.skew(skipna = True)
Id                0.000000
MSSubClass        1.407657
LotFrontage       2.163569
LotArea          12.207688
OverallQual       0.216944
OverallCond       0.693067
YearBuilt        -0.613461
YearRemodAdd     -0.503562
MasVnrArea        2.669084
BsmtFinSF1        1.685503
BsmtFinSF2        4.255261
BsmtUnfSF         0.920268
TotalBsmtSF       1.524255
1stFlrSF          1.376757
2ndFlrSF          0.813030
LowQualFinSF      9.011341
GrLivArea         1.366560
BsmtFullBath      0.596067
BsmtHalfBath      4.103403
FullBath          0.036562
HalfBath          0.675897
BedroomAbvGr      0.211790
KitchenAbvGr      4.488397
TotRmsAbvGrd      0.676341
Fireplaces        0.649565
GarageYrBlt      -0.649415
GarageCars       -0.342549
GarageArea        0.179981
WoodDeckSF        1.541376
OpenPorchSF       2.364342
EnclosedPorch     3.089872
3SsnPorch        10.304342
```

```
ScreenPorch       4.122214
PoolArea         14.828374
MiscVal          24.476794
MoSold            0.212053
YrSold            0.096269
SalePrice         1.882876
dtype: float64
```

```
#
#Deal with NA values at that are still there
# When:
#  skew value is postiive use mean to fill the missing value.
#  skew value is negative use median to fill the missing value.
#  skew value is zero, use either mean or median to fill the missing value.


df_train_clean['LotFrontage'] = df_train_clean['LotFrontage'].fillna(df_train_clean['LotFrontage'].mean())
df_train_clean['MasVnrArea']  = df_train_clean['MasVnrArea'].fillna(df_train_clean['MasVnrArea'].mean())
df_train_clean['GarageYrBlt'] = df_train_clean['GarageYrBlt'].fillna(df_train_clean['GarageYrBlt'].median())
```

```
#
# Fill in enmerated values, these can not be mean or median
#
df_train_clean['MasVnrType']   = df_train_clean['MasVnrType'].fillna(df_train_clean['MasVnrType'].mode()[0])
df_train_clean['BsmtQual']     = df_train_clean['BsmtQual'].fillna(df_train_clean['BsmtQual'].mode()[0])
df_train_clean['BsmtCond']     = df_train_clean['BsmtCond'].fillna(df_train_clean['BsmtCond'].mode()[0])
df_train_clean['BsmtExposure'] = df_train_clean['BsmtExposure'].fillna(df_train_clean['BsmtExposure'].mode()[0])
df_train_clean['BsmtFinType1'] = df_train_clean['BsmtFinType1'].fillna(df_train_clean['BsmtFinType1'].mode()[0])
df_train_clean['BsmtFinType2'] = df_train_clean['BsmtFinType2'].fillna(df_train_clean['BsmtFinType2'].mode()[0])
df_train_clean['Electrical']   = df_train_clean['Electrical'].fillna(df_train_clean['Electrical'].mode()[0])
df_train_clean['GarageType']   = df_train_clean['GarageType'].fillna(df_train_clean['GarageType'].mode()[0])
df_train_clean['GarageFinish'] = df_train_clean['GarageFinish'].fillna(df_train_clean['GarageFinish'].mode()[0])
df_train_clean['GarageQual']   = df_train_clean['GarageQual'].fillna(df_train_clean['GarageQual'].mode()[0])
df_train_clean['GarageCond']   = df_train_clean['GarageCond'].fillna(df_train_clean['GarageCond'].mode()[0])
```

```
df_train_clean.isna().sum()
```

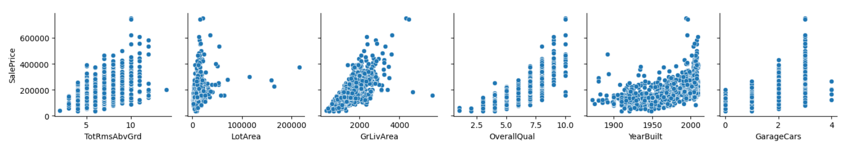
```
Id               0
MSSubClass       0
MSZoning         0
LotFrontage      0
LotArea          0
                ..
MoSold           0
YrSold           0
SaleType         0
SaleCondition    0
SalePrice        0
Length: 76, dtype: int64
```

```
#Get a rough idea of what correlations
# Will dive deeper into this when we clean the data
(df_train_clean.corr()['SalePrice']*100).sort_values(ascending=False)
```

```
<ipython-input-10-b322cba5289c>:3: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future versior
  (df_train_clean.corr()['SalePrice']*100).sort_values(ascending=False)
SalePrice        100.000000
OverallQual       79.098160
GrLivArea         70.862448
GarageCars        64.040920
GarageArea        62.343144
TotalBsmtSF       61.358055
1stFlrSF          60.585218
FullBath          56.066376
TotRmsAbvGrd      53.372316
YearBuilt         52.289733
YearRemodAdd      50.710097
MasVnrArea        47.524132
Fireplaces        46.692884
GarageYrBlt       46.675365
BsmtFinSF1        38.641981
LotFrontage       33.490085
WoodDeckSF        32.441344
2ndFlrSF          31.933380
OpenPorchSF       31.585623
HalfBath          28.410768
LotArea           26.384335
```

```
BsmtFullBath      22.712223
BsmtUnfSF         21.447911
BedroomAbvGr      16.821315
ScreenPorch       11.144657
PoolArea           9.240355
MoSold             4.643225
3SsnPorch          4.458367
BsmtFinSF2        -1.137812
BsmtHalfBath      -1.684415
MiscVal           -2.118958
Id                -2.191672
LowQualFinSF      -2.560613
YrSold            -2.892259
OverallCond       -7.785589
MSSubClass        -8.428414
EnclosedPorch    -12.857796
KitchenAbvGr     -13.590737
Name: SalePrice, dtype: float64
```

```
#Plot some of the possible correlated features, to see trends
g = sns.PairGrid(df_train_clean, x_vars=['TotRmsAbvGrd', 'LotArea', 'GrLivArea', 'OverallQual', 'YearBuilt','GarageCars'], y_vars='SalePri
g = g.map(sns.scatterplot)
plt.show()
```




```
# We need to remove any outliners for the target saleprice
#  to help trian this data

# The IQR (Interquartile Range) method is a way for handling outliers in data
#  that has an abnormal distribution. This method uses the distance between the
#  first quartile and the third quartile as a measure of the distance
#  between the outlier data and the median value in the dataset.

def limit(data, var):
    iqr = data[var].quantile(0.75) - data[var].quantile(0.25)

    lower_limit = data[var].quantile(0.25) - (iqr*1.5)
    upper_limit = data[var].quantile(0.75) + (iqr*1.5)

    return lower_limit, upper_limit


lower_sale, upper_sale = limit(df_train_clean, 'SalePrice')

df_train_clean_noOut = df_train_clean[(df_train_clean.SalePrice > lower_sale)&(df_train_clean.SalePrice < upper_sale)]

print( f"Number of outliers removed: {df_train_clean.shape[0] - df_train_clean_noOut.shape[0]}")
```

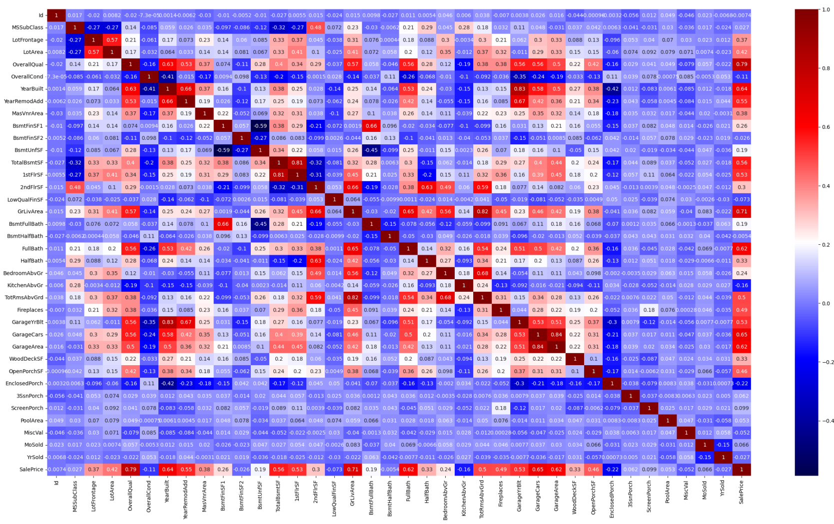
```
Number of outliers removed: 61
```

Feature selection

```
#Isolate numberical features vs categorical features
numer_columns = df_train_clean_noOut.select_dtypes(include=np.number).columns.tolist()
cate_columns = df_train_clean_noOut.select_dtypes(include= ['object']).columns.tolist()

train_numer = df_train_clean_noOut[numer_columns]
train_cate = df_train_clean_noOut[cate_columns]
```

```
#Plot heat map of numerical
plt.figure(figsize=(30,16))
sns.heatmap(train_numer.corr(method = 'spearman'), annot=True, cmap='seismic')
plt.show()
```



```
#List the correlation of the numberical features
(train_numer.corr()['SalePrice']*100).sort_values(ascending=False)
```

```
SalePrice       100.000000
OverallQual      78.429431
GrLivArea        66.132457
GarageCars       62.801307
GarageArea       60.722962
FullBath         57.736866
YearBuilt        56.455801
TotalBsmtSF      54.350839
YearRemodAdd     54.116060
1stFlrSF         52.278499
GarageYrBlt      47.578141
TotRmsAbvGrd     47.229206
Fireplaces       45.300976
MasVnrArea       35.266647
OpenPorchSF      32.579073
2ndFlrSF         31.735811
WoodDeckSF       30.233863
```

```
LotFrontage      29.703460
BsmtFinSF1       29.037668
HalfBath         27.883055
LotArea          24.981193
BsmtUnfSF        22.279549
BsmtFullBath     20.218500
BedroomAbvGr     20.161016
ScreenPorch      10.885107
MoSold            7.047782
PoolArea          4.868221
3SsnPorch         4.332370
BsmtFinSF2        0.715426
Id               -1.198390
MiscVal          -1.287187
BsmtHalfBath     -1.882673
YrSold           -2.824535
OverallCond      -4.800544
LowQualFinSF     -5.808636
MSSubClass       -6.011097
EnclosedPorch   -14.499581
KitchenAbvGr    -14.738505
Name: SalePrice, dtype: float64
```

Encode Catagorical features

```
train_cate.head()
```

	MSZoning	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighl
0	RL	Pave	Reg	Lvl	AllPub	Inside	Gtl	
1	RL	Pave	Reg	Lvl	AllPub	FR2	Gtl	
2	RL	Pave	IR1	Lvl	AllPub	Inside	Gtl	
3	RL	Pave	IR1	Lvl	AllPub	Corner	Gtl	
4	RL	Pave	IR1	Lvl	AllPub	FR2	Gtl	I

5 rows × 38 columns

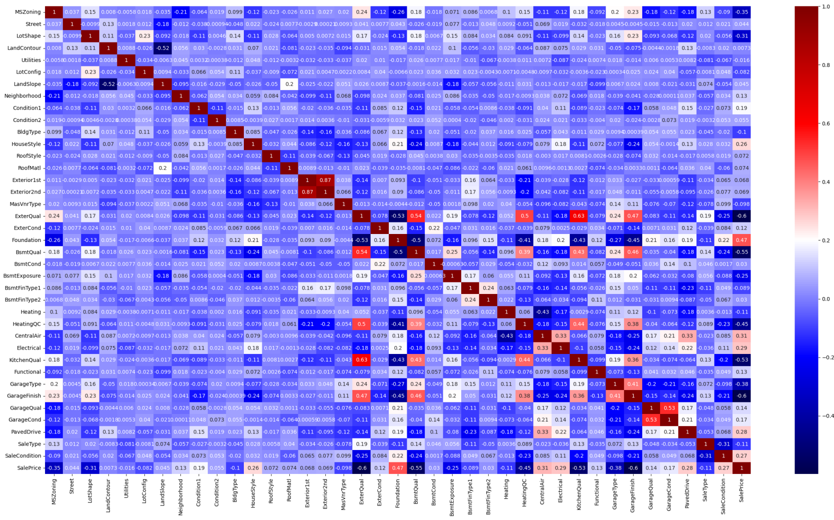
```
# Encode the categorical data
oe= OrdinalEncoder()
cat = oe.fit_transform(train_cate)
#Put back into dataframe
train_cate_enc = pd.DataFrame(cat, columns=train_cate.columns)
train_cate_enc.head()
```

	MSZoning	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope	Neighl
0	3.0	1.0	3.0	3.0	0.0	4.0	0.0	
1	3.0	1.0	3.0	3.0	0.0	2.0	0.0	
2	3.0	1.0	0.0	3.0	0.0	4.0	0.0	
3	3.0	1.0	0.0	3.0	0.0	0.0	0.0	
4	3.0	1.0	0.0	3.0	0.0	2.0	0.0	

5 rows × 38 columns

```
#Add SalePrice and then plot heat map

#Note I had an issue with assigning here, the indexing would mismatch. I had to
# convert the clean, to a numpy array
train_cate_enc['SalePrice'] = df_train_clean_noOut['SalePrice'].to_numpy()
plt.figure(figsize=(30,16))
sns.heatmap(train_cate_enc.corr(method = 'spearman'), annot=True, cmap='seismic')
plt.show()
```



```
1 #List out correlations of categorical features
2 (train_cate_enc.corr(method = 'spearman')['SalePrice']*100).sort_values(ascending=False)
```

```
SalePrice        100.000000
Foundation        47.402608
CentralAir        31.412189
Electrical        29.198416
PavedDrive        27.666618
SaleCondition     27.006789
HouseStyle        26.199275
Condition1        18.890390
GarageCond        16.764506
GarageQual        13.806369
Neighborhood      12.893884
Functional        12.889864
ExterCond         12.484319
RoofMatl           7.381102
RoofStyle          7.173816
Exterior2nd        6.927691
Exterior1st        6.771599
Condition2         5.471580
LandSlope          4.542001
Street             4.389097
BsmtFinType2       3.025599
BsmtCond           3.019515
LandContour        0.726375
```

```
Utilities         -1.579473
LotConfig         -8.221699
BsmtFinType1      -8.881545
MasVnrType        -9.820295
BldgType         -10.131836
Heating          -11.253326
SaleType         -11.280618
BsmtExposure     -24.500278
LotShape         -30.664669
MSZoning         -34.620206
GarageType       -37.727618
HeatingQC        -44.877529
KitchenQual      -52.915015
BsmtQual         -54.981414
GarageFinish     -59.714518
ExterQual        -59.944092
Name: SalePrice, dtype: float64
```

Now that we have an idea of correlation scores, we can set a threshold at which a feature must correlate with the target inorder for us to use it.

```
#Output sizes to show changes in number of columns

print( "Shape before pruning: ")
print( f"train_numer: {train_numer.shape}, train_cate_enc: {train_cate_enc.shape}" )

#Changing this will effect the overall output
corrThresh = .30;

train_numer = train_numer.loc[:,  (train_numer.corr()['SalePrice'] > corrThresh) | (train_numer.corr()['SalePrice'] < -corrThresh) ]
train_cate_enc = train_cate_enc.loc[:,  (train_cate_enc.corr()['SalePrice'] > corrThresh) | (train_cate_enc.corr()['SalePrice'] < -corrThr

print( "Shape after pruning: ")
print( f"train_numer: {train_numer.shape}, train_cate_enc: {train_cate_enc.shape}" )

```

```
Shape before pruning:
train_numer: (1399, 17), train_cate_enc: (1399, 8)
Shape after pruning:
train_numer: (1399, 17), train_cate_enc: (1399, 8)
```

```
print( "Columns selected for each: " )
print( train_numer.columns )
print( train_cate_enc.columns )
```

```
Columns selected for each:
Index(['OverallQual', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'TotalBsmtSF',
       '1stFlrSF', '2ndFlrSF', 'GrLivArea', 'FullBath', 'TotRmsAbvGrd',
       'Fireplaces', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF',
       'OpenPorchSF', 'SalePrice'],
      dtype='object')
Index(['ExterQual', 'Foundation', 'BsmtQual', 'HeatingQC', 'KitchenQual',
       'GarageType', 'GarageFinish', 'SalePrice'],
      dtype='object')
```

```
#Create initial data train set
y = df_train_clean_noOut['SalePrice']
X = pd.concat([train_numer.drop(columns='SalePrice').reset_index(drop=True), train_cate_enc.drop(columns='SalePrice').reset_index(drop=Tru
```

Model Creation

```
#Create and scale teh data sets for random forest regression

#Make sure all input is properly scaled
#scaler = MinMaxScaler()
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train,X_test,y_train,y_test=train_test_split(X_scaled,y,test_size=0.2,random_state=1001) # Use small test size as I have an addional tes
```

Random Forest Regession

```
#Create regressor and train
rf = RandomForestRegressor()
rf.fit(X_train,y_train)
#Run predictions
rf_pred = rf.predict(X_test)
```

```
#Format prediction vs actual
df_comp = pd.DataFrame(rf_pred, columns=['prediction'])
comparison_rf = pd.concat([y_test.reset_index(drop=True),df_comp], axis=1)
comparison_rf.head(10)
```

	SalePrice	prediction
0	137000	123974.80
1	274900	295608.28
2	213000	227243.66
3	55000	92828.00
4	141000	147349.50
5	173000	163303.62
6	112000	152625.33
7	144000	173265.50
8	244600	253366.55
9	336000	292398.54

```
mae = mean_absolute_error(y_test, rf_pred)
ev = evs(y_test, rf_pred)
mse = mean_squared_error(y_test, rf_pred)

print(f"MAE: {mae}")
print(f"rMSE: {np.sqrt(mse)}")
print(f"ev: {ev}")
```

```
MAE: 15613.135102380955
rMSE: 22230.176896536006
ev: 0.8594604867664504
```

The random forest regession had an ~88% explained variance score and about a 14.6k mean absolute error.

Gradient Boosting Regressor

```
#Create regressor and train
gb = GradientBoostingRegressor()
gb.fit(X_train,y_train)
#run predictions
gb_pred = gb.predict(X_test)

#Format prediction vs actual
df_comp = pd.DataFrame(gb_pred, columns=['prediction'])
comparison_gb = pd.concat([y_test.reset_index(drop=True),df_comp], axis=1)
comparison_gb.head(10)
```

	SalePrice	prediction
0	137000	128429.545582

```
mae = mean_absolute_error(y_test, gb_pred)
ev = evs(y_test, gb_pred)
mse = mean_squared_error(y_test, gb_pred)

print(f"MAE: {mae}")
print(f"rMSE: {np.sqrt(mse)}")
print(f"ev: {ev}")

```

```
MAE: 15414.110672017801
rMSE: 21863.970064152334
ev: 0.8643500237248247
```

The Gradient Boosting regession had an ~89% explained variance score and about a 13.8k mean absolute error. This was the best out of the methods we tested.

Linear Regression

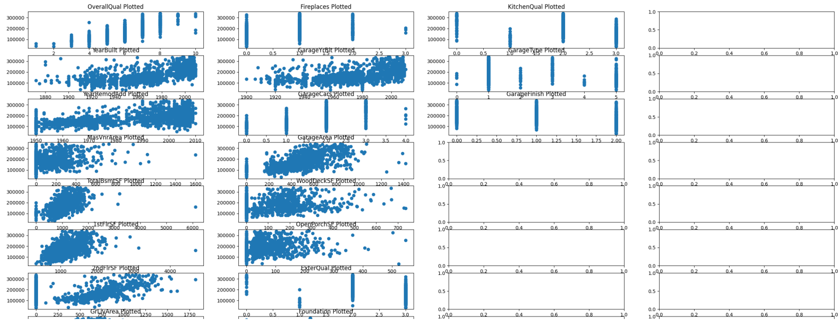
```
countR = 0;
countC = 0;
count = 0

fig, axes = plt.subplots(nrows=10, ncols=4, figsize=(30,16))
for (colname, colval) in X.items():
  row = countR % 10
  col = countC % 4

  axes[row][col].scatter(X[colname], y)
  axes[row][col].set_title( colname + " Plotted")

  countR = countR + 1;
  count = count + 1
  if(count % 10== 0):
    countC = countC + 1;

plt.show()
```




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

```
▾ LinearRegression
LinearRegression()
```

```
poly_reg_y_predicted = poly_reg_model.predict(X_test)
poly_reg_rmse = np.sqrt(mean_squared_error(y_test, poly_reg_y_predicted))
poly_r2_score  = r2_score(y_test, poly_reg_y_predicted)

print( f'MAE: {mean_absolute_error(y_test, poly_reg_y_predicted)}' )
print( f'rMSE: {poly_reg_rmse}' )
print( f'r2: {poly_r2_score}' )


```

```
MAE: 18704.577499952407
rMSE: 28348.171320161167
r2: 0.7711573111010801
```

✓ 0s completed at 9:22 PM