CS3802--Machine Learning Algorithms Lab

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Exercise 2

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a) Use the house_pred.csv file to build a multiple linear regression model. sklearn shall be used to fit the model. Perform necessary preprocessing and check for outliers and multi-collinearity. Apply the same set of preprocessing to the test.csv and use the data to predict the house price. The evaluation criteria will be Root Mean Squared Error

Importing the necessary libraries

In [ ]:
```
import pandas as pd
from statsmodels.stats.outliers_influence import variance_inflation_factor as VI
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import math
```

Reading the dataset

In [ ]:
```
data = pd.read_csv('house_pred.csv')
data.head()
```

Out[ ]:

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

5 rows × 81 columns

In [ ]:
```
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     1452 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
```

Pre-Processing

Remove outliers using IQR method

The `IQR_Removal` function takes a DataFrame (`df`) as input and performs the following steps:

1. **Initialization:**
   - Retrieves column names from the DataFrame (`columns = df.columns`).
2. **Iterate Through Columns:**
   - For each column (`col`) in the DataFrame:
     - Skips the 'SalePrice' column.
3. **Check Column Type:**
   - Verifies if the column is not of type 'object' (i.e., numerical).
4. **Remove Outliers Using IQR:**
   - Calculates the first quartile (Q1), third quartile (Q3), and Interquartile Range (IQR) for the numerical column.
   - Filters rows to keep only those within the range of `(Q1 - 1.5 * IQR)` to `(Q3 + 1.5 * IQR)` .
5. **Return Updated DataFrame:**
   - Returns the DataFrame with outliers removed from numerical columns.

In [ ]:
```
def IQR_Removal(df):

    columns = df.columns
    for col in columns:
        if col == 'SalePrice':
            continue
        typeCol = str(df[col].dtype)
        if typeCol != 'object':
            Q1 = df[col].quantile(0.25)
            Q3 = df[col].quantile(0.75)
            iqr = Q3 - Q1
            df = df[(df[col] >= Q1 - 1.5*iqr) & (df[col] <= Q3 + 1.5*iqr)]
    return df
```

Remove columns with only one unique value and columns with null ratio >= 0.30

The `ThresholdandND_columnRemoval` function takes a DataFrame (`df`) as input and performs the following steps:

1. **Calculate Length and Columns:**
   - Retrieves the length of the DataFrame (`N = len(df)`) and column names (`columns = df.columns`).
2. **Iterate Through Columns:**
   - For each column (`col`) in the DataFrame:
     - Checks if the number of unique values in the column is equal to 1. If true, drops the column as it lacks diversity.
3. **Check Null Ratio:**
   - Calculates the ratio of null values in the column (`notnull = df[col].isnull().sum()`) and checks if it is greater than or equal to 30%.
   - If true, drops the column as it exceeds the specified null ratio threshold.
4. **Return Updated DataFrame:**
   - Returns the DataFrame with columns removed based on the threshold and no-diversity criteria.

In [ ]:
```
def ThresholdandND_columnRemoval(df):

    N = len(df)
    columns = df.columns
    for col in columns:
        if (len(df[col].unique()) == 1):
            df = df.drop([col], axis=1)
            continue
        notnull = df[col].isnull().sum()
        ratio = notnull / N
        if (ratio >= 0.30):
            df = df.drop([col], axis=1)
    return df
```

Handle null values by either removing rows or filling with mean/median

The `Handling_NullValues` function takes a DataFrame (`df`) as input and performs the following steps:

1. **Iterate Through Columns:**
   - For each column (`col`) in the DataFrame:
     - Checks the data type of the column (`typeCol = str(df[col].dtype)`).
2. **Handle Null Values for Object Type:**
   - If the column type is 'object' (categorical):
     - Removes rows with null values for that column (`df = df[df[col].notna()]`).
3. **Handle Null Values for Numeric Type:**
   - If the column type is numeric:
     - Calculates mean, median, and standard deviation of the column (`mean = df[col].mean()` , `median = df[col].median()` , `standard_deviation = df[col].std()`).
4. **Partial Median Change (PMC) Criteria:**
   - Calculates Partial Median Change (PMC) using the formula `pmc = (3 * (mean - median)) / standard_deviation` .
   - If PMC is greater than or equal to 0.4 or less than or equal to -0.4:
     - Fills null values with the median (`df[col] = df[col].fillna(median)`).
   - Otherwise:
     - Fills null values with the mean (`df[col] = df[col].fillna(mean)`).
5. **Return Updated DataFrame:**
   - Returns the DataFrame with missing values handled based on data type and PMC criteria.

In [ ]:
```
def Handling_NullValues(df):

    columns = df.columns
    for col in columns:
        typeCol = str(df[col].dtype)
        if typeCol == 'object':
            df = df[df[col].notna()]
        else:
            mean = df[col].mean()
            median = df[col].median()
            standard_deviation = df[col].std()
            pmc = (3 * (mean - median)) / standard_deviation
            if pmc >= 0.4 or pmc <= -0.4:
                df[col] = df[col].fillna(median)
            else:
                df[col] = df[col].fillna(mean)
    return df
```

Perform one-hot encoding for categorical columns

The `OneHotEncoding_objects` function encodes categorical (object-type) columns using one-hot encoding:

1. **Iterate Through Columns:**
   - For each column (`col`) in the DataFrame:
     - Check if the column type is 'object'.
2. **One-Hot Encode Object Columns:**
   - If the column is 'object':
     - Use `pd.get_dummies` to create one-hot encoded columns.
3. **Rename and Join Encoded Columns:**
   - Rename the new columns by appending the original column name as a prefix.
   - Join the one-hot encoded columns to the original DataFrame.
4. **Drop Original Object Column:**
   - Drop the original object-type column.
5. **Return Updated DataFrame:**
   - Returns the DataFrame with one-hot encoded object-type columns.

In [ ]:
```
def OneHotEncoding_objects(df):

    columns = df.columns
    for col in columns:
        typeCol = str(df[col].dtype)
        if typeCol == 'object':
            enc = pd.get_dummies(df[col])
            encCol = enc.columns
            newColumns = {}
            for i in range(0, len(encCol)):
                newColumns[encCol[i]] = col + encCol[i]
            enc.rename(columns=newColumns, inplace=True)
            df = df.join(enc)
            df = df.drop([col], axis=1)
    return df
```

Result of Pre-Processing

In [ ]:
```
dataFeatures = OneHotEncoding_objects(IQR_Removal(Handling_NullValues(Thresholda
dataFeatures.head()
```

Out[ ]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAd
0	1	60	65.0	8450	7	5	2003	200
2	3	60	68.0	11250	7	5	2001	200
4	5	60	84.0	14260	8	5	2000	200
6	7	20	75.0	10084	8	5	2004	200
10	11	20	70.0	11200	5	5	1965	196

5 rows × 211 columns

Variance Inflation Factor Filter

The `VIF_Filter` function performs VIF filtering to remove multicollinear variables:

1. **Initialize Variables:**
   - Identify common columns between training and testing data (`xCol`).
   - Exclude the 'Id' column.
2. **VIF Calculation Loop:**
   - Continuously iterate until convergence.
   - Calculate VIF values for each variable in `xCol` .
   - If a variable has VIF greater than 3 or if VIF is 'inf', 'nan', or '0.0', remove the variable.
   - Repeat the process until no variable is removed.
3. **Return Result:**
   - Return the list of selected variables (`xCol`) and their corresponding VIF values.

In [ ]:

```
def VIF_Filter(df, dfTest):
    """
    Perform VIF filtering to remove multicollinear variables
    """
    xCol = list(set(list(df.columns)) & set(list(dfTest.columns)))
    xCol.remove('Id')

    while(1):
        finished = True
        xVal = df[xCol].copy()
        xVal['intercept'] = 1

        # Calculate VIF values
        vif = pd.DataFrame()
        vif['variable'] = xVal.columns
        vif['vif'] = [VIF(xVal.values, i) for i in range(xVal.shape[1])]

        for i in range(0, len(vif)):
            var = str(vif.iloc[i, 0])
            val = str(vif.iloc[i, 1])

            if var == 'intercept':
```

```
                continue
            elif val == 'inf' or val == 'nan' or val == '0.0':
                xCol.remove(var)
                finished = False
                break
            else:
                val = float(val)
                if val > 3:
                    xCol.remove(var)
                    finished = False
                    break

        if finished:
            return xCol, vif
```

Pre-Processing 'test.csv'

In [ ]:
```
import warnings

# Load testing data
testingdata = pd.read_csv('test.csv')

# Preprocess testing features
testingFeatures = OneHotEncoding_objects(IQR_Removal(Handling_NullValues(Threshc

# Ignore warnings during VIF filtering
with warnings.catch_warnings():
    warnings.filterwarnings("ignore", category=RuntimeWarning)

    # Perform VIF filtering
    columns, vif = VIF_Filter(dataFeatures, testingFeatures)
```

In [ ]:
```
testingdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 256 entries, 0 to 255
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             256 non-null    int64  
 1   MSSubClass     256 non-null    int64  
 2   MSZoning       256 non-null    object 
 3   LotFrontage    207 non-null    float64
 4   LotArea        256 non-null    int64  
 5   Street         256 non-null    object 
 6   Alley          16 non-null     object 
 7   LotShape       256 non-null    object 
 8   LandContour    256 non-null    object 
 9   Utilities      256 non-null    object 
 10  LotConfig      256 non-null    object 
 11  LandSlope      256 non-null    object 
 12  Neighborhood   256 non-null    object 
 13  Condition1     256 non-null    object 
 14  Condition2     256 non-null    object 
 15  BldgType       256 non-null    object 
 16  HouseStyle     256 non-null    object 
 17  OverallQual    256 non-null    int64  
 18  OverallCond    256 non-null    int64  
 19  YearBuilt      256 non-null    int64  
 20  YearRemodAdd   256 non-null    int64  
 21  RoofStyle      256 non-null    object 
 22  RoofMatl       256 non-null    object 
 23  Exterior1st    256 non-null    object 
 24  Exterior2nd    256 non-null    object 
 25  MasVnrType     254 non-null    object 
 26  MasVnrArea     254 non-null    float64
 27  ExterQual      256 non-null    object 
 28  ExterCond      256 non-null    object 
 29  Foundation     256 non-null    object 
 30  BsmtQual       251 non-null    object 
 31  BsmtCond       251 non-null    object 
 32  BsmtExposure   251 non-null    object 
 33  BsmtFinType1   251 non-null    object 
 34  BsmtFinSF1     256 non-null    int64  
 35  BsmtFinType2   251 non-null    object 
 36  BsmtFinSF2     256 non-null    int64  
 37  BsmtUnfSF      256 non-null    int64  
 38  TotalBsmtSF    256 non-null    int64  
 39  Heating        256 non-null    object 
 40  HeatingQC      256 non-null    object 
 41  CentralAir     256 non-null    object 
 42  Electrical     255 non-null    object 
 43  1stFlrSF       256 non-null    int64  
 44  2ndFlrSF       256 non-null    int64  
 45  LowQualFinSF   256 non-null    int64  
 46  GrLivArea      256 non-null    int64  
 47  BsmtFullBath   256 non-null    int64  
 48  BsmtHalfBath   256 non-null    int64  
 49  FullBath       256 non-null    int64  
 50  HalfBath       256 non-null    int64  
 51  BedroomAbvGr   256 non-null    int64  
 52  KitchenAbvGr   256 non-null    int64  
 53  KitchenQual    256 non-null    object 
 54  TotRmsAbvGrd   256 non-null    int64  
```

```
 55  Functional     256 non-null    object 
 56  Fireplaces     256 non-null    int64  
 57  FireplaceQu    132 non-null    object 
 58  GarageType     242 non-null    object 
 59  GarageYrBlt    242 non-null    float64
 60  GarageFinish   242 non-null    object 
 61  GarageCars     256 non-null    int64  
 62  GarageArea     256 non-null    int64  
 63  GarageQual     242 non-null    object 
 64  GarageCond     242 non-null    object 
 65  PavedDrive     256 non-null    object 
 66  WoodDeckSF     256 non-null    int64  
 67  OpenPorchSF    256 non-null    int64  
 68  EnclosedPorch  256 non-null    int64  
 69  3SsnPorch      256 non-null    int64  
 70  ScreenPorch    256 non-null    int64  
 71  PoolArea       256 non-null    int64  
 72  PoolQC         3 non-null      object 
 73  Fence          54 non-null     object 
 74  MiscFeature    6 non-null      object 
 75  MiscVal        256 non-null    int64  
 76  MoSold         256 non-null    int64  
 77  YrSold         256 non-null    int64  
 78  SaleType       256 non-null    object 
 79  SaleCondition  256 non-null    object 
dtypes: float64(3), int64(34), object(43)
memory usage: 160.1+ KB
```

Checking the Correlation Matrix

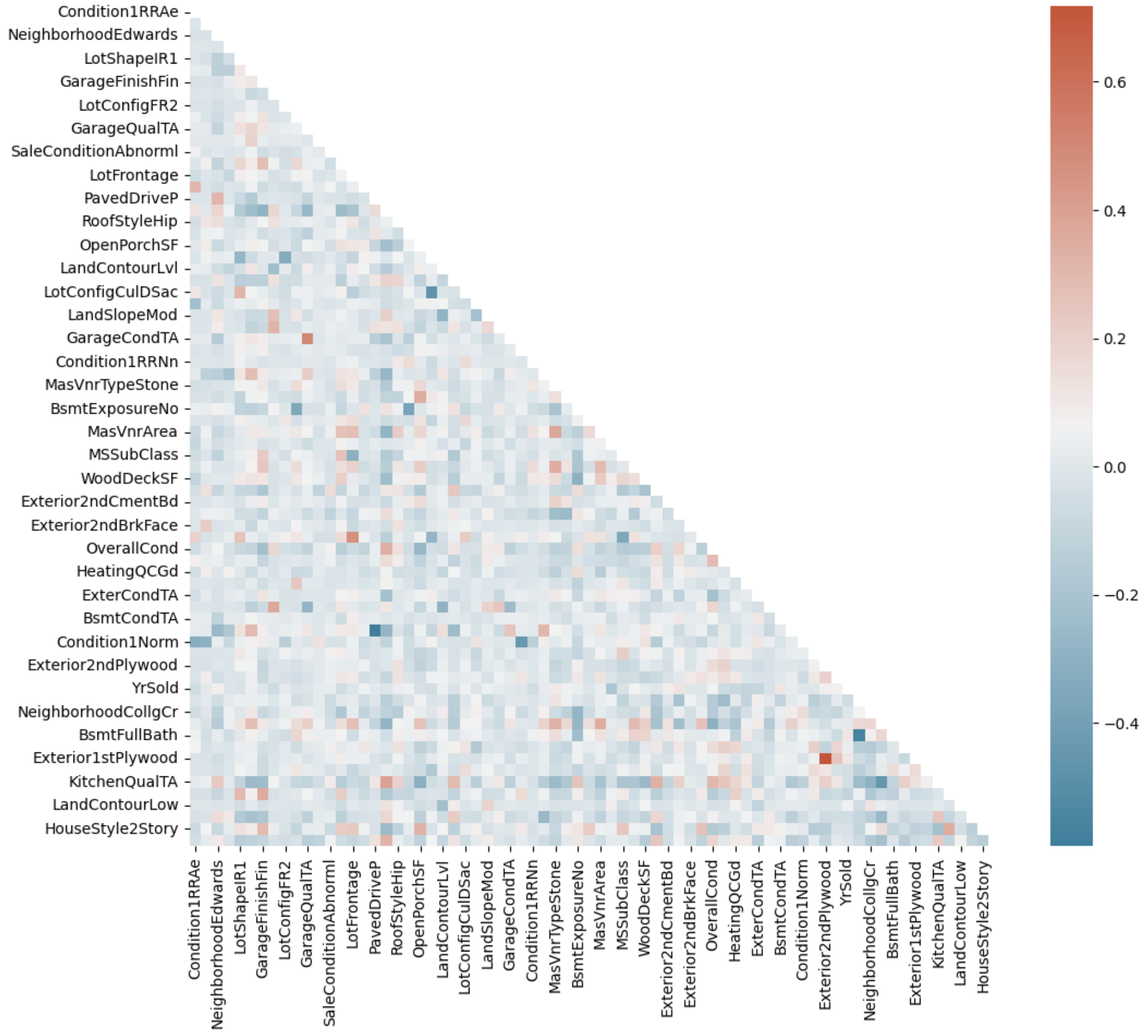
In [ ]:

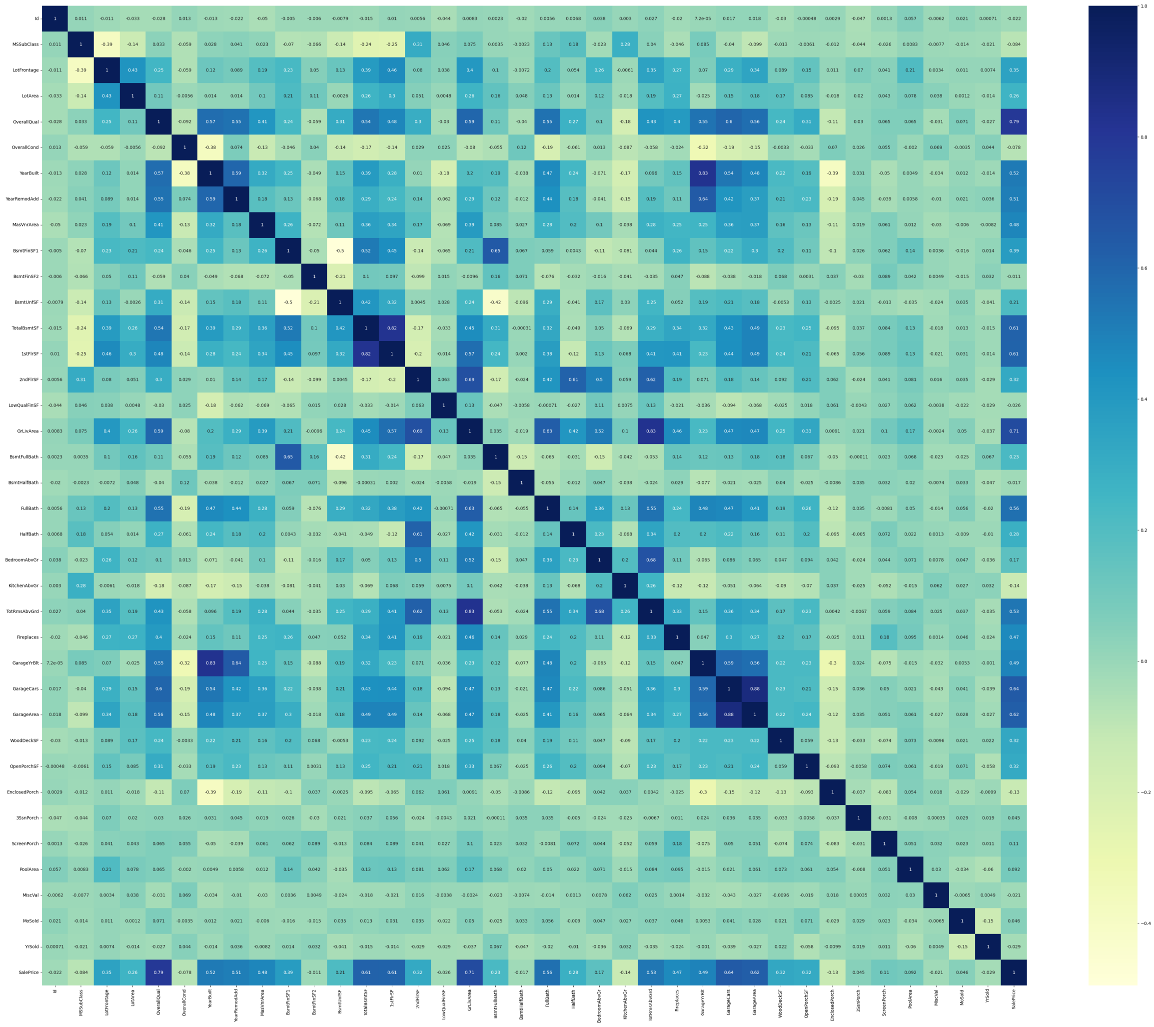
```
corr = dataFeatures[columns].corr()
f, ax = plt.subplots(figsize=(12, 10))
mask = np.triu(np.ones_like(corr, dtype=bool))
cmap = sns.diverging_palette(230, 20, as_cmap=True)
sns.heatmap(corr, mask=mask, cmap=cmap)

plt.figure(figsize=(50,40))
sns.heatmap(data.corr(),cmap='YlGnBu',annot=True)
```

```
C:\Users\ADITHYA VEDHAMANI\AppData\Local\Temp\ipykernel_22156\726974904.py:8: F
utureWarning: The default value of numeric_only in DataFrame.corr is deprecate
d. In a future version, it will default to False. Select only valid columns or
specify the value of numeric_only to silence this warning.
  sns.heatmap(data.corr(),cmap='YlGnBu',annot=True)
```

Out[ ]: `<Axes: >`


Condition1RRAe
NeighborhoodEdwards
LotShapeIR1
GarageFinishFin
LotConfigFR2
GarageQualTA
SaleConditionAbnorml
LotFrontage
PavedDriveP
RoofStyleHip
OpenPorchSF
LandContourLvl
LotConfigCulDSac
LandSlopeMod
GarageCondTA
Condition1RRNn
MasVnrTypeStone
BsmtExposureNo
MasVnrArea
MSSubClass
WoodDeckSF
Exterior2ndCmentBd
Exterior2ndBrkFace
OverallCond
HeatingQCGd
ExterCondTA
BsmtCondTA
Condition1Norm
Exterior2ndPlywood
YrSold
NeighborhoodCollgCr
BsmtFullBath
Exterior1stPlywood
KitchenQualTA
LandContourLow
HouseStyle2Story
0.6
0.4
0.2
0.0
−0.2
−0.4



Training the Model

In [ ]:
```
y = dataFeatures['SalePrice']
x = dataFeatures[columns]
reg = LinearRegression()
reg.fit(x, y)
```

Out[ ]:
```
▾ LinearRegression
LinearRegression()
```

Displaying Intercept and Coefficients

In [ ]:
```
print("Intercept:", reg.intercept_)
print("Coefficients:", reg.coef_)
```

```
Intercept: -566917.8580690894
Coefficients: [-1.57711414e+04  1.32971812e+04 -2.67501451e+04  5.21445057e+03
 -2.39607583e+03  2.93856461e+03  3.12080992e+03 -5.32503660e+04
 -8.94714751e+03  1.20560786e+04  1.88673061e+04 -2.87203024e+04
 -5.64392258e+03  1.00729126e+04  9.82912962e+01 -6.17545122e+03
  8.98969107e+03 -1.20285265e+04  3.89001815e+03  2.27162374e+03
  1.39588993e+02  9.80415896e+02 -2.71854062e+03 -9.17949758e+03
  1.37339396e+04  2.02702194e+03  3.16750482e+03  2.34743133e+04
  8.93240293e+03  8.45627875e+03 -2.03708706e+03  1.15154948e+04
  1.22058974e+04 -1.88631613e+03 -3.06491910e+03  1.79400780e+04
  2.65323975e+01  2.14121302e+02 -3.38942045e+01  4.25261561e+04
  3.08037356e+01 -2.00278063e+04  2.29757066e+04 -4.99318903e+03
  1.33939104e+04  2.84232810e+00  1.10509814e+03 -4.87501234e+03
 -2.52204486e+03 -3.14075611e+04  5.90141701e+03  3.34160814e+04
  6.56613036e+03  6.17328835e+03  1.67158704e+04 -3.32221216e+03
 -1.14442408e+04 -1.03347382e+04  3.04093258e+02  4.52477626e+00
 -1.45071215e+04  9.70129762e+01  1.34038083e+04 -1.49094129e+04
 -1.26345238e+04 -2.44353869e+04 -1.60452435e+04 -8.02346780e+03
 -2.60960050e+04 -4.11666524e+03  1.51006563e+04  4.04101400e+03]
```

Value Prediction for testing values

In [ ]:
```
x_test = testingFeatures[columns]
y_forTest = reg.predict(x_test)
y_forTest
```

Out[ ]:
```
array([156910.95597128, 196095.1155866 , 290000.        , 257465.65795365,
       215930.43833661, 117729.54611827, 157929.09774169, 112788.30773603,
       203056.6342366 , 201607.59668333, 205403.97562943, 196841.90837206,
       186651.49273272, 190876.08984555, 163396.10665655, 129969.74775075,
       168945.27357892, 236784.27544071, 177159.52202618, 133799.07461602,
       213086.2615363 , 167419.39661206, 224112.67426623, 190805.78921758,
       223773.63588556, 185306.17394746, 192574.78071109, 202935.3398293 ,
       227990.45535069, 196990.8027346 , 184096.70610627, 214848.55829687,
       166765.49429272, 199349.77392345, 207672.18751235,  97551.44422994,
       173946.35026734])
```

RMSE value for the training dataset of price prediction

In [ ]:
```
y_pred = reg.predict(x)
rmse = math.sqrt(mean_squared_error(y, y_pred))
print("RMSE:", rmse)
```

```
RMSE: 23494.364349139858
```

R Square Score for Multiple Regression

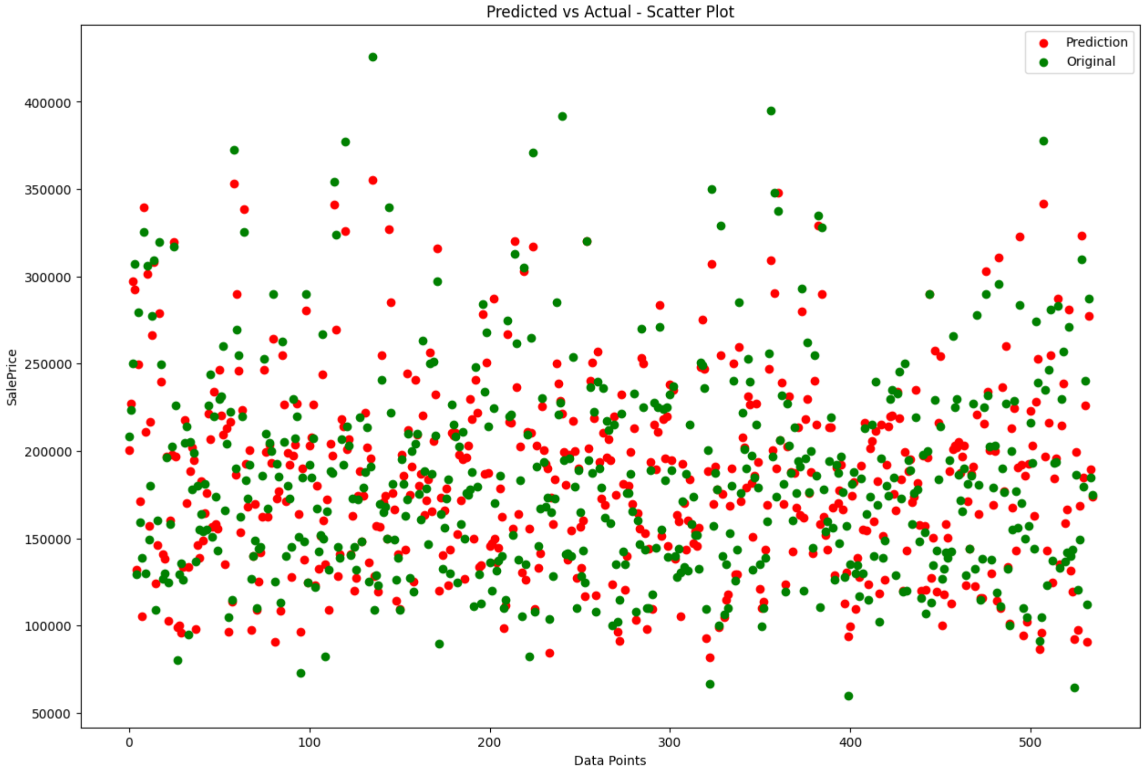
In [ ]:
```
r_square = reg.score(x, y)
print("R-Square:", r_square)
```

```
R-Square: 0.8444619024729351
```

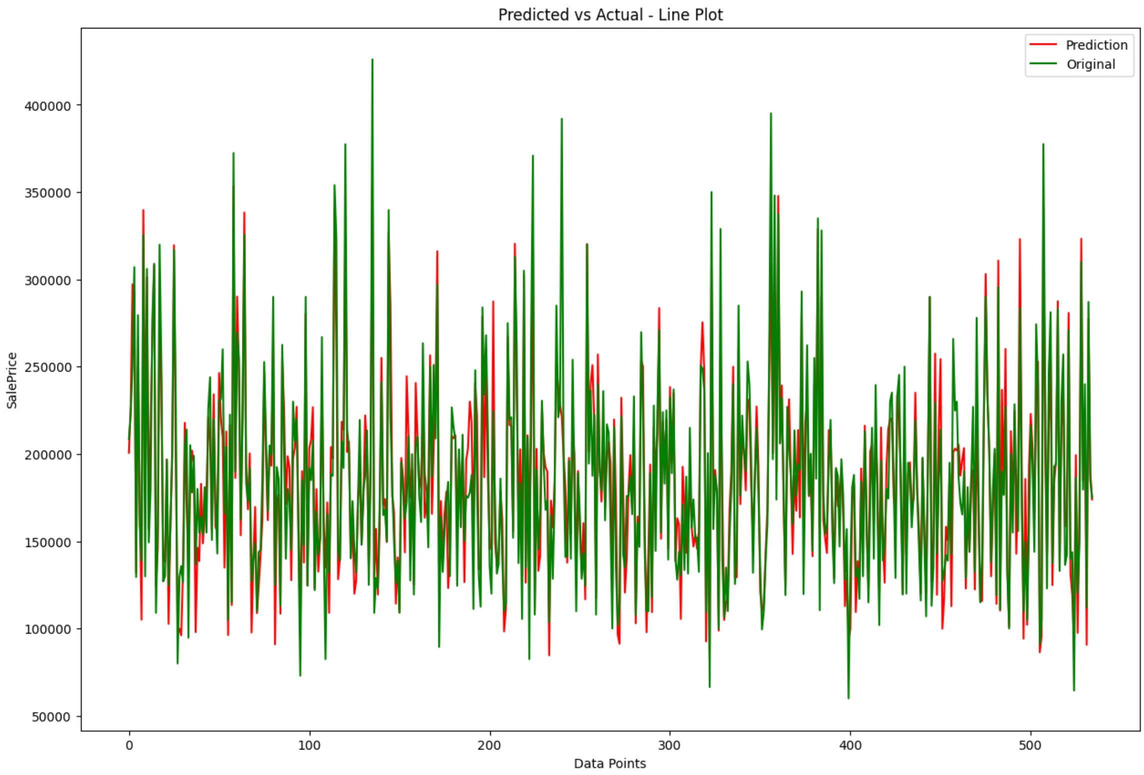
Predicted vs Actual Graph

In [ ]:
```
# Scatter Plot
plt.figure(figsize=(15, 10))
plt.scatter(range(len(y_pred)), y_pred, c='r', label='Prediction')
```

```
plt.scatter(range(len(y)), y, c='g', label='Original')
plt.legend()
plt.title("Predicted vs Actual - Scatter Plot")
plt.xlabel("Data Points")
plt.ylabel("SalePrice")
plt.show()
```



In [ ]:
```
# Line Plot
plt.figure(figsize=(15, 10))
plt.plot(y_pred, c='r', label='Prediction')
plt.plot(y.values, c='g', label='Original')
plt.legend()
plt.title("Predicted vs Actual - Line Plot")
plt.xlabel("Data Points")
plt.ylabel("SalePrice")
plt.show()
```


Predicted vs Actual - Line Plot
Prediction
Original
SalePrice
400000
350000
300000
250000
200000
150000
100000
50000
0
100
200
300
400
500
Data Points