MACHINE LEARNING LAB

EXERCISE 2

Aim :

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

Algorithm :

1. **Data Preprocessing and Exploration**:
   - Load and preprocess `house_pred.csv`, handling missing values and outliers.
   - Explore data with EDA to understand features and relationships.
2. **Model Building and Evaluation**:
   - Split data into train and validation sets.
   - Use sklearn to build a multiple linear regression model.
   - Train the model and evaluate with RMSE.
3. **Prediction on Test Data**:
   - Apply preprocessing steps to `test.csv`.
   - Use trained model to predict house prices.
   - Evaluate predictions with RMSE.

Code and Output :

In [1]:

```
pip install Numpy==1.23.5
```

```
Requirement already satisfied: Numpy==1.23.5 in c:\users\teju\anaconda3\lib\site-pack
ages (1.23.5)
Note: you may need to restart the kernel to use updated packages.
```

In [2]:

```
import pandas as pd
from statsmodels.stats.outliers_influence import variance_inflation_factor as VIF
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
import math
```

```
C:\Users\TEJU\anaconda3\lib\site-packages\scipy\__init__.py:146: UserWarning: A NumPy
version >=1.16.5 and <1.23.0 is required for this version of SciPy (detected version
1.23.5
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

In [3]:

```
data=pd.read_csv(r"C:\Users\TEJU\Downloads\house_pred (1).csv")
data.head()
```

Out[3]:

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

5 rows × 81 columns

In [4]:

```
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
```

In [5]:

```
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

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

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

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
```

In [6]:

```
df = OneHotEncoding_objects(IQR_Removal(Handling_NullValues(ThresholdandND_columnRem
df
```

Out[6]:

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd
0	1	60	65.0	8450	7	5	2003	2003
2	3	60	68.0	11250	7	5	2001	2002
4	5	60	84.0	14260	8	5	2000	2000
6	7	20	75.0	10084	8	5	2004	2005
10	11	20	70.0	11200	5	5	1965	1965
...	...	...	...	...	...	...	...	...
1447	1448	60	80.0	10000	8	5	1995	1996
1448	1449	50	70.0	11767	4	7	1910	2000

	Id	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd
1451	1452	20	78.0	9262	8	5	2008	2009
1454	1455	20	62.0	7500	7	5	2004	2005
1455	1456	60	62.0	7917	6	5	1999	2000

535 rows × 211 columns

In [7]:

```
def VIF_Filter(df,dfTest):
    xCol = list(set(list(df.columns)) & set(list(dfTest.columns)))
    xCol.remove('Id')
    while(1):
      finished = True
      xVal = df[xCol]
      xVal['intercept'] = 1
      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'):
              xCol.remove(var)
              finished = False
              break
          else:
              val = float(val)
              if val > 3:
                  xCol.remove(var)
                  finished = False
                  break
      if finished == True:
          return xCol, vif
```

In [10]:

```
testdata = pd.read_csv(r"C:\Users\TEJU\Downloads\test (1).csv")
testdf = OneHotEncoding_objects(IQR_Removal(Handling_NullValues(ThresholdandND_colum
columns, vif = VIF_Filter(df,testdf)
```

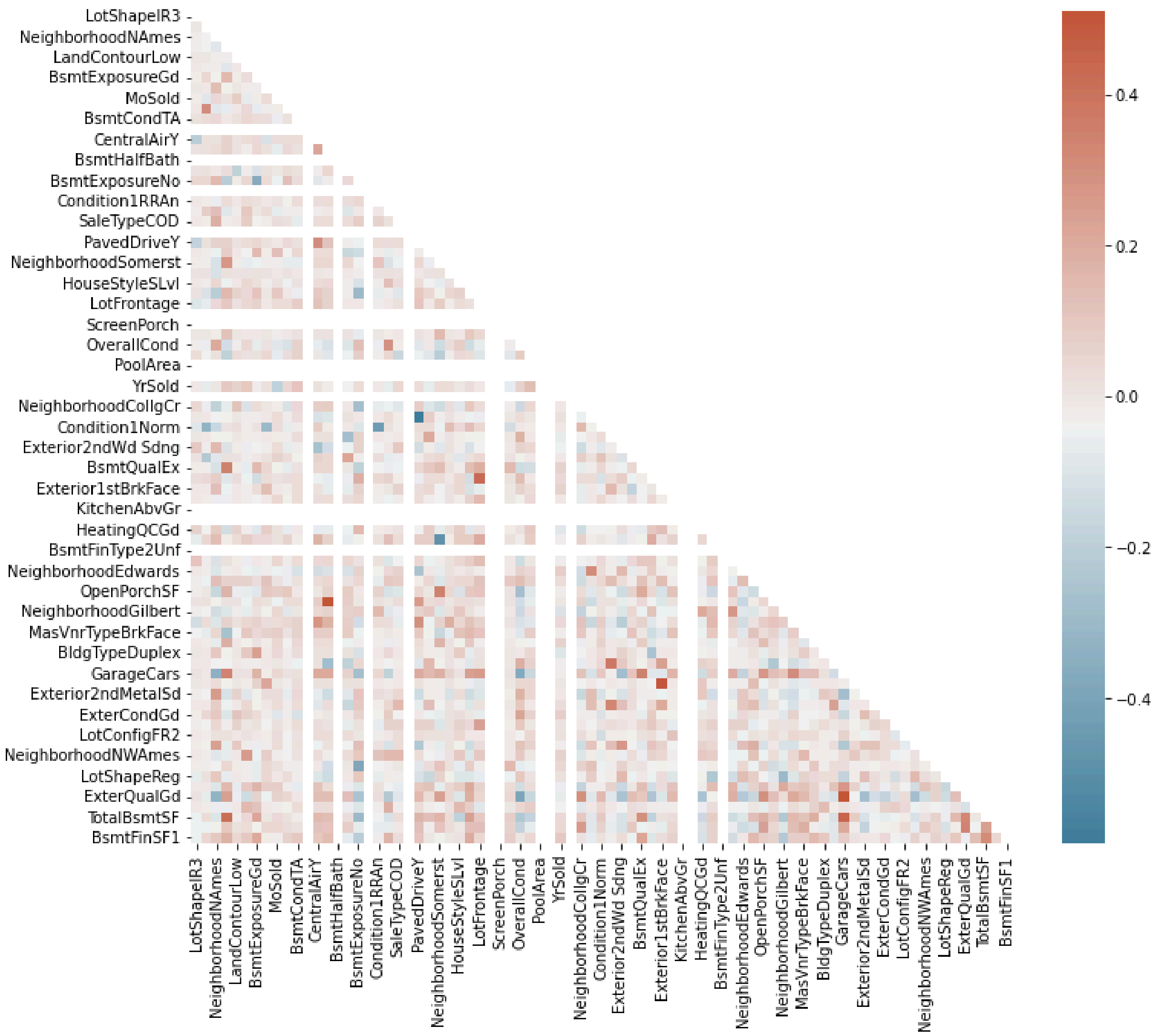
```
C:\Users\TEJU\AppData\Local\Temp/ipykernel_16600/2458712660.py:7: SettingWithCopyWarn
ing:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  xVal['intercept'] = 1
C:\Users\TEJU\anaconda3\lib\site-packages\statsmodels\stats\outliers_influence.py:19
3: RuntimeWarning: divide by zero encountered in double_scalars
  vif = 1. / (1. - r_squared_i)
C:\Users\TEJU\anaconda3\lib\site-packages\statsmodels\regression\linear_model.py:171
5: RuntimeWarning: divide by zero encountered in double_scalars
  return 1 - self.ssr/self.centered_tss
C:\Users\TEJU\anaconda3\lib\site-packages\statsmodels\regression\linear_model.py:171
5: RuntimeWarning: invalid value encountered in double_scalars
  return 1 - self.ssr/self.centered_tss
```

In [12]:

```python
corr = df[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)
```

Out[12]:

```
<AxesSubplot:>
```



In [14]:

```python
y = df['SalePrice']
x = df[columns]
```

```
reg = LinearRegression()
reg.fit(x,y)
```

Out[14]:

```
▾ LinearRegression
LinearRegression()
```

In [15]:

```
reg.intercept_, reg.coef_
```

Out[15]:

```
(-1594359.180326281,
 array([ 1.48196131e+04,  1.79923581e+03, -2.01900480e+04,  8.29220098e+03,
        -3.11602711e+04, -2.13025379e+04,  9.85542569e+03,  1.01402363e+04,
        -4.80839507e+01, -6.51601042e+03,  4.32819720e+03, -1.10285328e-08,
         1.54644927e+03,  1.10831132e+04,  6.89396984e-10, -1.80896810e+03,
         2.60902265e+03,  1.70985004e-10,  9.34399022e+03, -1.51054025e+04,
        -6.89746609e+03, -3.63797881e-12, -1.49015826e+03,  1.58803862e+04,
         2.64284679e+04, -3.24440391e+04, -6.77657514e+03,  2.90603693e+01,
         3.06347254e+02,  6.18456397e-11, -3.81987775e-11, -3.23539744e+04,
         2.95778294e+03,  6.48982182e+02,  1.86446414e-11, -5.02389241e-11,
         7.86574452e+02, -5.45696821e-12, -1.59962832e+02,  6.81430689e+03,
         1.49720747e+04, -3.79134049e+04, -4.44976327e+02,  9.50544655e+03,
         4.79540257e+04,  8.62056422e+03,  2.85956868e+04,  3.30992550e+04,
        -1.31876732e-11,  0.00000000e+00, -6.49579038e+03,  2.00776318e+04,
         3.63797881e-12,  2.90029219e+04, -2.35091579e+04, -8.45164260e+02,
         1.61967148e+02,  1.30491980e+04,  5.67350115e+03,  1.01211579e+03,
         1.12406842e+03,  1.58823688e+04, -1.38634698e+04,  3.17295794e+04,
         2.21720800e+04,  2.02833624e+03,  9.75666077e+03,  1.67018922e+04,
        -4.51834828e+03, -3.87905174e+02, -8.93944758e+03, -1.16442061e+04,
        -3.03759292e+03,  4.98591671e+03,  4.67010521e+02,  1.10556570e+04,
         1.59655180e+04, -1.45586274e+04,  3.33199304e+01,  5.35591104e+03,
         2.33390729e+01]))
```

In [17]:

```
x_test = testdf[columns]
y_forTest = reg.predict(x_test)
y_forTest
```

Out[17]:

```
array([176378.22648779, 208983.52778748, 290000.        , 259602.35385925,
       196874.42652567, 110157.92856467, 142053.28850765, 147620.23703439,
       190748.79104513, 225113.75690499, 174088.87649298, 206004.63007601,
       203899.99223414, 221843.22098781, 178814.32583258, 151970.68978991,
       191895.4718545 , 249476.85597501, 158440.66623878, 131101.521714  ,
       238783.07427756, 165335.360849  , 211234.4214451 , 170922.61185717,
       230529.38276664, 164397.9115744 , 188796.53885744, 196219.72656122,
       228279.65302757, 231189.58306462, 192178.72629544, 196539.36220642,
       174165.52529681, 173215.57956365, 206689.93686828, 115634.04844513,
       174531.9662555 ])
```

In [18]:

```
y_pred = reg.predict(x)
math.sqrt(mean_squared_error(y,y_pred))
```

Out[18]:

```
23373.573363257263
```

In [19]:

```
reg.score(x,y)
```

Out[19]:

```
0.8460571194156481
```

Results :

Therefore, we were successfully able to build the multiple linear regression model and use the train data to predict the house prices in the test data.