Property Price Prediction

Problem Statement

A key challenge for property sellers is to determine the sale price of the property. The ability to predict the exact property value is beneficial for property investors as well as for buyers to plan their finances according to the price trend. The property prices depend on the number of features like the property area, basement square footage, year built, number of bedrooms, and so on. Regression analysis can be useful in predicting the price of the house.

Data Definition

Dwell_Type: Identifies the type of dwelling involved in the sale

Zone_Class: Identifies the general zoning classification of the sale

LotFrontage: Linear feet of street-connected to the property

LotArea: Lot size is the lot or parcel side where it adjoins a street, boulevard or access way

Road_Type: Type of road access to the property

Alley: Type of alley access to the property

Property_Shape: General shape of the property

LandContour: Flatness of the property

LotConfig: Lot configuration

LandSlope: Slope of property

Neighborhood: Physical locations within Ames city limits

Condition1: Proximity to various conditions

Condition2: Proximity to various conditions (if more than one is present)

Dwelling_Type: Type of dwelling

HouseStyle: Style of dwelling

OverallQual: Rates the overall material and finish of the house

OverallCond: Rates the overall condition of the house

YearBuilt: Original construction date

YearRemodAdd: Remodel date (same as construction date if no remodeling or additions)

RoofStyle: Type of roof

RoofMatl: Roof material

Exterior1st: Exterior covering on the house

Exterior2nd: Exterior covering on the house (if more than one material)

MasVnrType: Masonry veneer type

MasVnrArea: Masonry veneer area in square feet

ExterQual: Evaluates the quality of the material on the exterior

ExterCond: Evaluates the present condition of the material on the exterior

Foundation: Type of foundation

BsmtQual: Evaluates the height of the basement

BsmtCond: Evaluates the general condition of the basement

BsmtExposure: Refers to walkout or garden level walls

BsmtFinType1: Rating of basement finished area

BsmtFinSF1: Type 1 finished square feet

BsmtFinType2: Rating of basement finished area (if multiple types)

BsmtFinSF2: Type 2 finished square feet

BsmtUnfSF: Unfinished square feet of the basement area

TotalBsmtSF: Total square feet of the basement area

Heating: Type of heating

HeatingQC: Heating quality and condition

CentralAir: Central air conditioning

Electrical: Electrical system

1stFlrSF: First Floor square feet

2ndFlrSF: Second floor square feet

LowQualFinSF: Low quality finished square feet (all floors)

GrLivArea: Above grade (ground) living area square feet

BsmtFullBath: Basement full bathrooms

BsmtHalfBath: Basement half bathrooms

FullBath: Full bathrooms above grade

HalfBath: Half baths above grade

Bedroom: Bedrooms above grade (does NOT include basement bedrooms)

Kitchen: Kitchens above grade

KitchenQual: Kitchen quality

TotRmsAbvGrd: Total rooms above grade (does not include bathrooms)

Functional: Home functionality (Assume typical unless deductions are warranted)

Fireplaces: Number of fireplaces

FireplaceQu: Fireplace quality

GarageType: Garage location

GarageYrBlt: Year garage was built

GarageFinish: Interior finish of the garage

GarageCars: Size of garage in car capacity

GarageArea: Size of garage in square feet

GarageQual: Garage quality

GarageCond: Garage condition

PavedDrive: Paved driveway

WoodDeckSF: Wood deck area in square feet

OpenPorchSF: Open porch area in square feet

EnclosedPorch: Enclosed porch area in square feet

3SsnPorch: Three season porch area in square feet

ScreenPorch: Screen porch area in square feet

PoolArea: Pool area in square feet

PoolQC: Pool quality

Fence: Fence quality

MiscFeature: Miscellaneous feature not covered in other categories

MiscVal: Value of miscellaneous feature

MoSold: Month Sold (MM)

YrSold: Year Sold (YYYY)

SaleType: Type of sale

SaleCondition: Condition of sale

Icon Legends

Inferences from outcome

Additional Reads

Lets do it

Quick Tips

Table of Contents

1. Import Libraries

In [1]:
```
# We use 'Numpy'for mathematical operations on large, multi-dimensional arrays and matrices
# 'Pandas' is used for data manipulation and analysis
import numpy as np
import pandas as pd

# To check the data type we import 'is_string_dtype' and 'is_numeric_dtype'
from pandas.api.types import is_string_dtype
from pandas.api.types import is_numeric_dtype

# 'Matplotlib' is a data visualization library for 2D and 3D plots
import matplotlib.pyplot as plt
%matplotlib inline

# seaborn is used for plotting statistical graphics
import seaborn as sns

#  To build and analyze various statistical models we use 'Statsmodels'
import statsmodels
import statsmodels.api as sm
from statsmodels.compat import lzip
import statsmodels.stats.api as sms
import statsmodels.formula.api as smf
from statsmodels.formula.api import ols
from statsmodels.tools.eval_measures import rmse
from statsmodels.stats.outliers_influence import variance_inflation_factor

# 'Scikit-learn' (sklearn) emphasizes various regression, classification and clustering algorithms
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn import preprocessing

# To perform scientific computations
from scipy.stats import shapiro
from scipy import stats
```

In [2]:
```
# suppress the warnings
from warnings import filterwarnings
filterwarnings('ignore')

# set the plot size using 'rcParams'
# once the plot size is set using 'rcParams', it sets the size of all the forthcoming plots in the
# 15 and 8 are width and height in inches respectively
plt.rcParams['figure.figsize'] = [10,6]
```


2. Set Options

1. Display complete data frames
2. To avoid the exponential number

In [3]:
```
# display all columns of the dataframe
pd.options.display.max_columns = None

# display all rows of the dataframe
pd.options.display.max_rows = None

# use below code to convert the 'exponential' values to float
np.set_printoptions(suppress=True)
```

3. Read Data

In [4]:
```
# read csv file using pandas
df_property = pd.read_csv('HousePrices.csv')

# display the top 5 rows of the dataframe
df_property.head()
```

Out[4]:

	Id	Dwell_Type	Zone_Class	LotFrontage	LotArea	Road_Type	Alley	Property_Shape	LandContour	Utilities	LotConfi
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	Inside
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	FR2
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	Inside
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	Corner
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	FR2

Lets take a glance at our dataframe and see how it looks

Dimensions of the data

In [5]:
```
# 'shape' function returns a tuple that gives the total number of rows and columns in the data
df_property.shape
```

Out[5]: (1460, 81)

4. Data Analysis and Preparation

Data preparation is the process of cleaning and transforming raw data before building predictive models.

Here, we analyze and perform the following tasks:
1. Check data types. Ensure your data types are correct.
2. We need to change the data types as per requirement If they are not as per business definition
3. Go through the summary statistics
4. Distribution of variables
5. Study the correlation
6. Detect outliers from the data
7. Look for the missing values

4.1 Understand the Dataset

4.1.1 Data Type

The data types in pandas dataframes are the object, float, int64, bool, and datetime64. We should know the data type of each column.

In our dataset, we have a blend of numerical and categorical variables. The numeric variables should have data type 'int'/'float' while categorical variables should have data type 'object'.

1. Check for the data type

In [6]:
```
# 'dtypes' provides the data type for each column
df_property.dtypes
```

Out[6]:

Id	int64
Dwell_Type	int64
Zone_Class	object
LotFrontage	float64
LotArea	int64
Road_Type	object
Alley	object
Property_Shape	object
LandContour	object
Utilities	object
LotConfig	object
LandSlope	object
Neighborhood	object
Condition1	object
Condition2	object
Dwelling_Type	object
HouseStyle	object
OverallQual	int64
OverallCond	int64
YearBuilt	int64
YearRemodAdd	int64
RoofStyle	object
RoofMatl	object
Exterior1st	object
Exterior2nd	object
MasVnrType	object
MasVnrArea	float64
ExterQual	object
ExterCond	object
Foundation	object
BsmtQual	object
BsmtCond	object
BsmtExposure	object
BsmtFinType1	object
BsmtFinSF1	int64
BsmtFinType2	object
BsmtFinSF2	int64
BsmtUnfSF	int64
TotalBsmtSF	int64
Heating	object
HeatingQC	object
CentralAir	object
Electrical	object
1stFlrSF	int64
2ndFlrSF	int64
LowQualFinSF	int64
GrLivArea	int64
BsmtFullBath	int64
BsmtHalfBath	int64
FullBath	int64
HalfBath	int64
BedroomAbvGr	int64
KitchenAbvGr	int64
KitchenQual	object
TotRmsAbvGrd	int64
Functional	object
Fireplaces	int64
FireplaceQu	object
GarageType	object
GarageYrBlt	float64
GarageFinish	object
GarageCars	int64
GarageArea	int64
GarageQual	object
GarageCond	object
PavedDrive	object
WoodDeckSF	int64
OpenPorchSF	int64
EnclosedPorch	int64
3SsnPorch	int64
ScreenPorch	int64
PoolArea	int64
PoolQC	object
Fence	object
MiscFeature	object
MiscVal	int64

```
MoSold                 int64
YrSold                 int64
SaleType              object
SaleCondition         object
Property_Sale_Price    int64
dtype: object
```

From the above output, we can see that 'Dwell_Type', 'OverallQual' and 'OverallCond' have data type as 'int64'.

But as per the data definition, 'Dwell_Type ', 'OverallQual' and 'OverallCond' are categorical variables, so we need to convert these variables data type to 'object'.

Let us convert 'Dwell_Type ', 'OverallQual' and 'OverallCond' to categorical data type

In [7]:
```
df_property['Dwell_Type'] = df_property['Dwell_Type'].astype('O')
df_property['OverallQual'] = df_property['OverallQual'].astype('O')
df_property['OverallCond'] = df_property['OverallCond'].astype('O')
```

In [8]:
```
# 'dtypes' provides the data type for each column
df_property[['Dwell_Type', 'OverallQual', 'OverallCond']].dtypes
```

Out[8]:
```
Dwell_Type     object
OverallQual    object
OverallCond    object
dtype: object
```

Let us now remove the Id column as this will not be necessary for our analysis

In [9]:
```
df_property.drop(['Id'], axis=1, inplace=True)
```

In [10]:
```
df_property.columns
```

Out[10]:
```
Index(['Dwell_Type', 'Zone_Class', 'LotFrontage', 'LotArea', 'Road_Type',
       'Alley', 'Property_Shape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2',
       'Dwelling_Type', 'HouseStyle', 'OverallQual', 'OverallCond',
       'YearBuilt', 'YearRemodAdd', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'MasVnrType', 'MasVnrArea', 'ExterQual', 'ExterCond',
       'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1',
       'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF',
       '2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath',
       'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'Property_Sale_Price'],
      dtype='object')
```


4.1.2 Summary Statistics

Here we take a look at the summary of each attribute. This includes the count, mean, the minimum and maximum values as well as some percentiles for numeric variables and count, unique, top, frequency for categorical variables.

In our dataset we have numerical as well as categorical variables. Now we check for summary statistics of all the variables.

1. For getting the statistical summary of numerical variables we use the describe()

In [11]:
```
# by default the describe function returns the summary of numerical variables
df_property.describe()
```

Out[11]:

enAbvGr	TotRmsAbvGrd	Fireplaces	GarageYrBlt	GarageCars	GarageArea	WoodDeckSF	OpenPorchSF	EnclosedPorch
0.000000	1460.000000	1460.000000	1379.000000	1460.000000	1460.000000	1460.000000	1460.000000	1460.000000
1.046575	6.517808	0.613014	1978.506164	1.767123	472.980137	94.244521	46.660274	21.954110
0.220338	1.625393	0.644666	24.689725	0.747315	213.804841	125.338794	66.256028	61.119149
0.000000	2.000000	0.000000	1900.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1.000000	5.000000	0.000000	1961.000000	1.000000	334.500000	0.000000	0.000000	0.000000
1.000000	6.000000	1.000000	1980.000000	2.000000	480.000000	0.000000	25.000000	0.000000
1.000000	7.000000	1.000000	2002.000000	2.000000	576.000000	168.000000	68.000000	0.000000
3.000000	14.000000	3.000000	2010.000000	4.000000	1418.000000	857.000000	547.000000	552.000000

The above output displays the summary statistics of all the numeric variables like mean, median, standard deviation, minimum, and the maximum values, the first and third quantiles.

We can see that the LotFrontage ranges from 21 feet to 313 feet, with mean 70 feet. We can see that the minimum pool area is 0 sq.ft. and this means that not all houses have pools and yet have been considered to calculate the mean pool area. Also the count for LotFrontage is less than the total number of observations which indicates the presence of missing values.

2. For getting the statistical summary of categorical features we use the describe(include = object)

In [12]:
```
# summary of categorical variables
df_property.describe(include = object)
```

Out[12]:

entralAir	Electrical	KitchenQual	Functional	FireplaceQu	GarageType	GarageFinish	GarageQual	GarageCond	PavedDrive
1460	1459	1460	1460	770	1379	1379	1379	1379	1460
2	5	4	7	5	6	3	5	5	3
Y	SBrkr	TA	Typ	Gd	Attchd	Unf	TA	TA	Y
1365	1334	735	1360	380	870	605	1311	1326	1340

In [13]:
```
df_property["Dwell_Type"].value_counts().count()
```

Out[13]: 15

The summary statistics for categorical variables contains information about the total number of observations, number of unique classes, the most occurring class, and its frequency.:

Lets understand the outputs of the above table using variable 'Property_Shape'
count: Number of observations = 1460
unique: Number of unique classes in the column = 4 classes
top: The most occurring class = Reg
frequency: Frequency of the most repeated class; out of 1460 observations Reg has a frequency of 925
It is visible that some of the variables have count less than total number of observations which indicates the presence of missing values.

As, the variable `PoolQC` has only 7 non-zero values out of 1460 observations. And also the variable `PoolArea` contains the area of these 7 pools, we will remove the variables `PoolQC` and `PoolArea` .

In [14]:
```
# use drop() to drop the redundant variables
# 'axis = 1' drops the corresponding columns
df_property = df_property.drop(['PoolQC', 'PoolArea'], axis= 1)

# re-check the shape of the dataframe
df_property.shape
```

Out[14]:
```
(1460, 78)
```

4.1.3 Distribution of Variables

Check the distribution of all the variables.

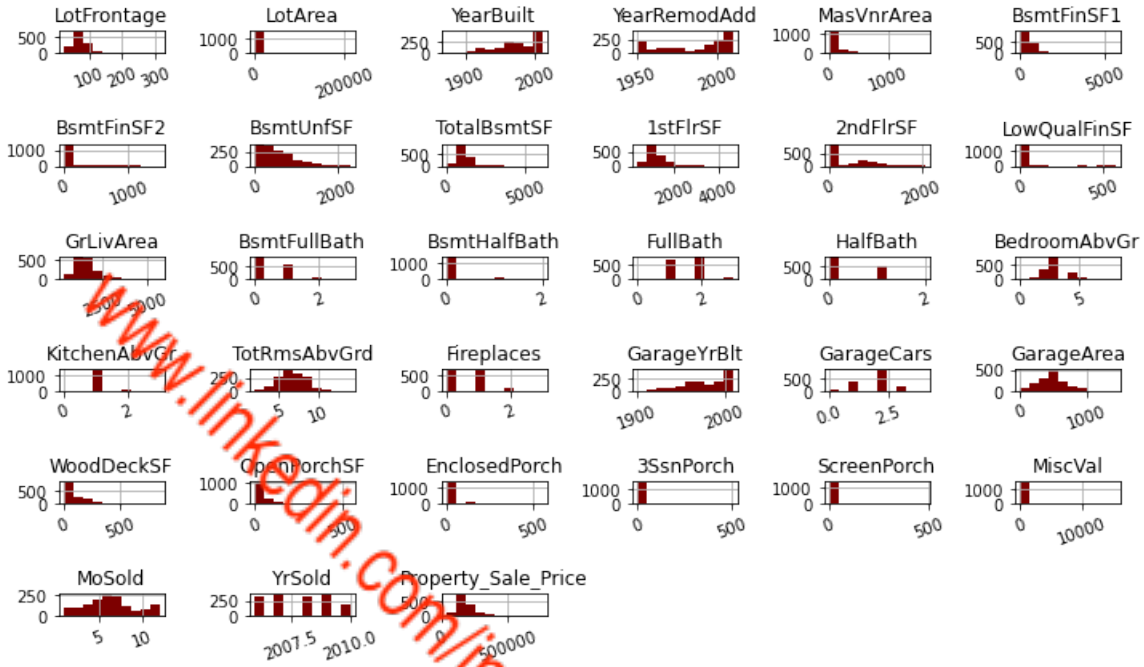
1. Distribution of numeric variables

We plot the histogram to check the distribution of the variables.

In [15]:
```
# filter the numerical features in the dataset using select_dtypes()
# include=np.number is used to select the numeric features
df_numeric_features = df_property.select_dtypes(include=np.number)

# display the numeric features
df_numeric_features.columns
```

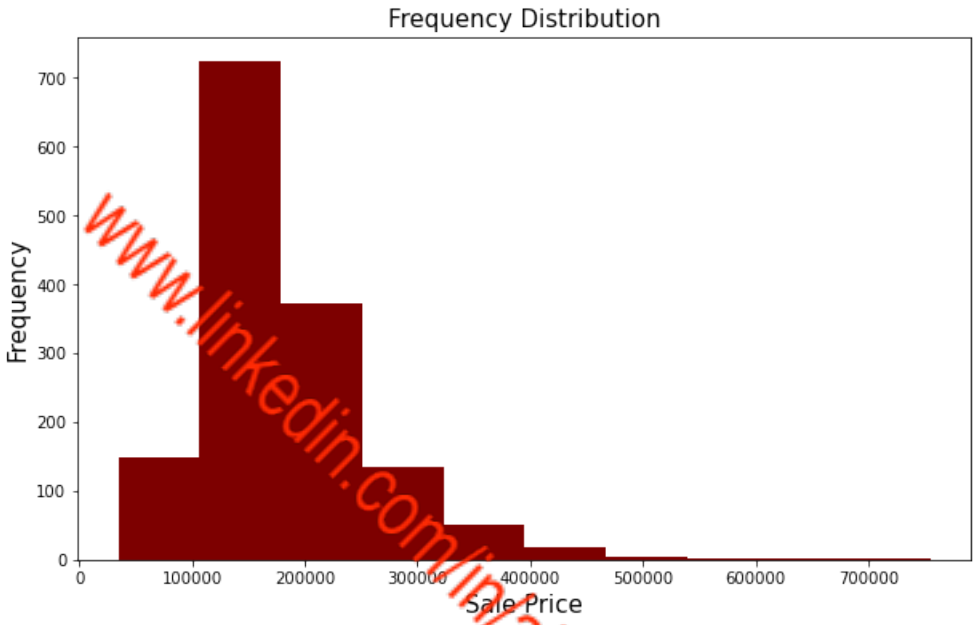
Out[15]:
```
Index(['LotFrontage', 'LotArea', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea',
       'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF',
       '2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath',
       'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd',
       'Fireplaces', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF',
       'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'MiscVal',
       'MoSold', 'YrSold', 'Property_Sale_Price'],
      dtype='object')
```

In [16]:
```
# plot the histogram of numeric variables
# hist() by default considers the numeric variables only,
# rotate the x-axis labels by 20 degree using the parameter, 'xrot'
df_property.hist(xrot = 20, color = "maroon")

# adjust the subplots
plt.tight_layout()

# display the plot
plt.show()
```

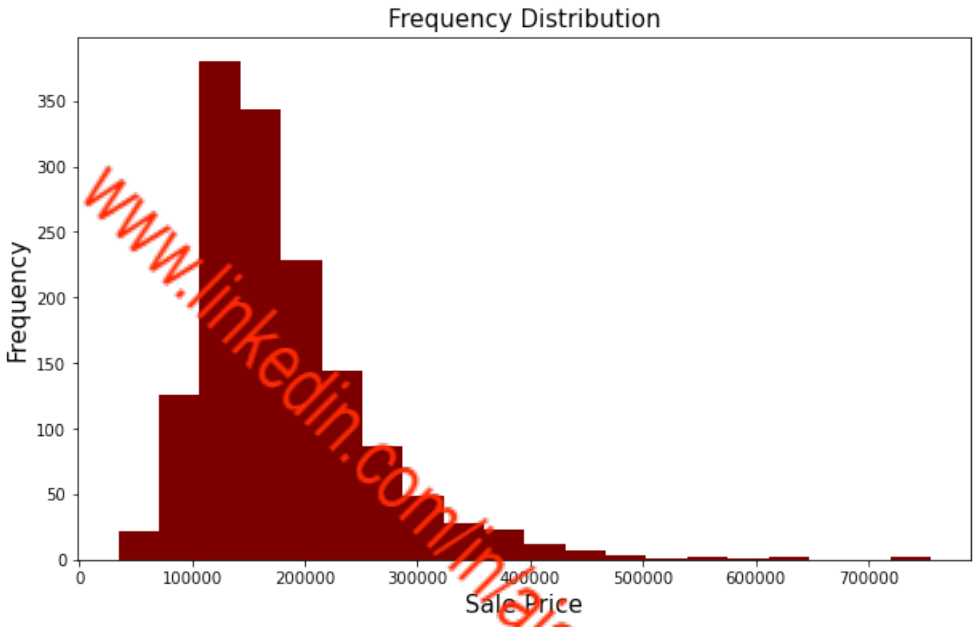


Visualize the target variable

In [17]:
```
# Sale Price Frequency Distribution
# set the xlabel and the fontsize
plt.xlabel("Sale Price", fontsize=15)

# set the ylabel and the fontsize
plt.ylabel("Frequency", fontsize=15)

# set the title of the plot
plt.title("Frequency Distribution", fontsize=15)

# plot the histogram for the target variable
plt.hist(df_property["Property_Sale_Price"], color = 'maroon')
plt.show()
```



In [18]:
```
# Sale Price Frequency Distribution
#Tableau bins are containers of equal size that store data values corresponding to or fitting in bi
# set the xlabel and the fontsize
plt.xlabel("Sale Price", fontsize=15)

# set the ylabel and the fontsize
plt.ylabel("Frequency", fontsize=15)

# set the title of the plot
plt.title("Frequency Distribution", fontsize=15)

# plot the histogram for the target variable
plt.hist(df_property["Property_Sale_Price"], color = 'maroon',bins=20)
plt.show()
```



The above plot shows that the target variable 'Property_Sale_Price' is right skewed (right tailed).

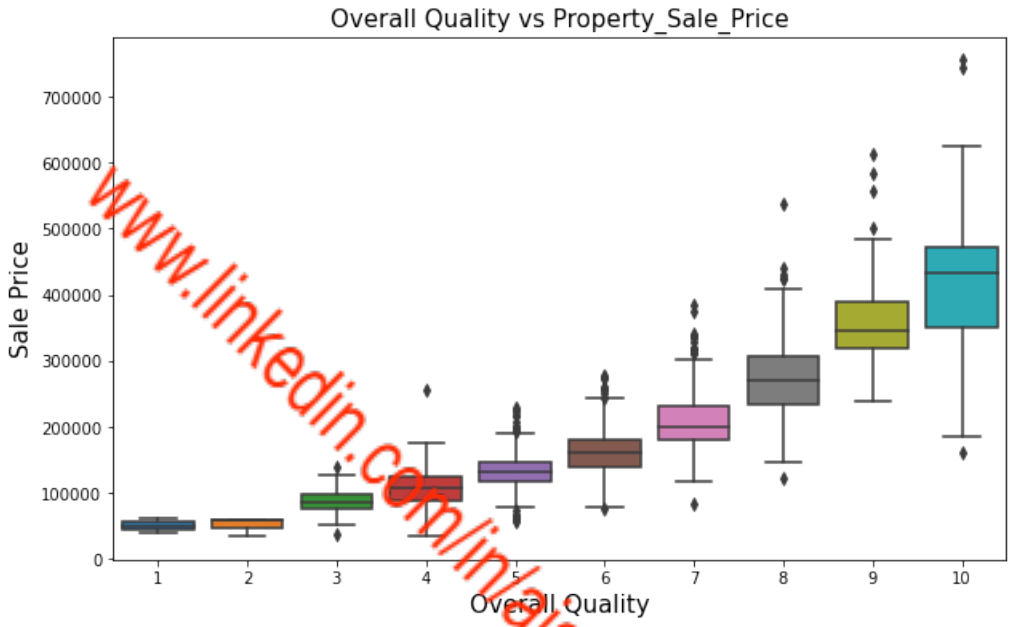
2. Distribution of categorical variables

For the categoric variables, we plot the countplot (Uni-Variate Analysis)

In [19]:
```
# create an empty list to store all the categorical variables
categorical=[]

# check the data type of each variable
for column in df_property:

    # check if the variable has the categorical type
    if is_string_dtype(df_property[column]):

        # append the categorical variables to the list 'categorical'
        categorical.append(column)

# plot the count plot for each categorical variable
# 'figsize' sets the figure size
fig, ax = plt.subplots(nrows=7, ncols=6, figsize = (50, 35))

# plot the count plot using countplot() for each categorical variable
for variable, subplot in zip(categorical, ax.flatten()):
    sns.countplot(df_property[variable], ax = subplot)

# display the plot
plt.show()
```

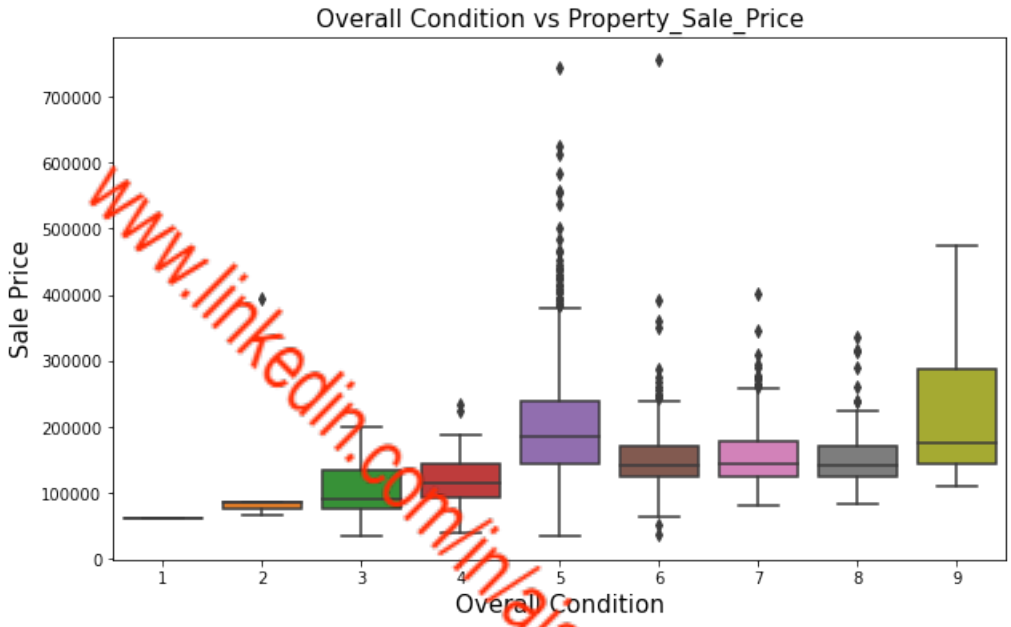
Boxplot of OverallQuality and Property_Sale_Price (Bi-Variate Analysis)

In [20]:
```
# draw the boxplot for OverallQuality and the Property_Sale_Price
sns.boxplot(y="Property_Sale_Price", x="OverallQual", data= df_property)

# set the title of the plot and the fontsize
plt.title("Overall Quality vs Property_Sale_Price", fontsize=15)

# set the xlabel and the fontsize
plt.xlabel("Overall Quality", fontsize=15)

# set the ylabel and the fontsize
plt.ylabel("Sale Price", fontsize=15)

# display the plot
plt.show()
```



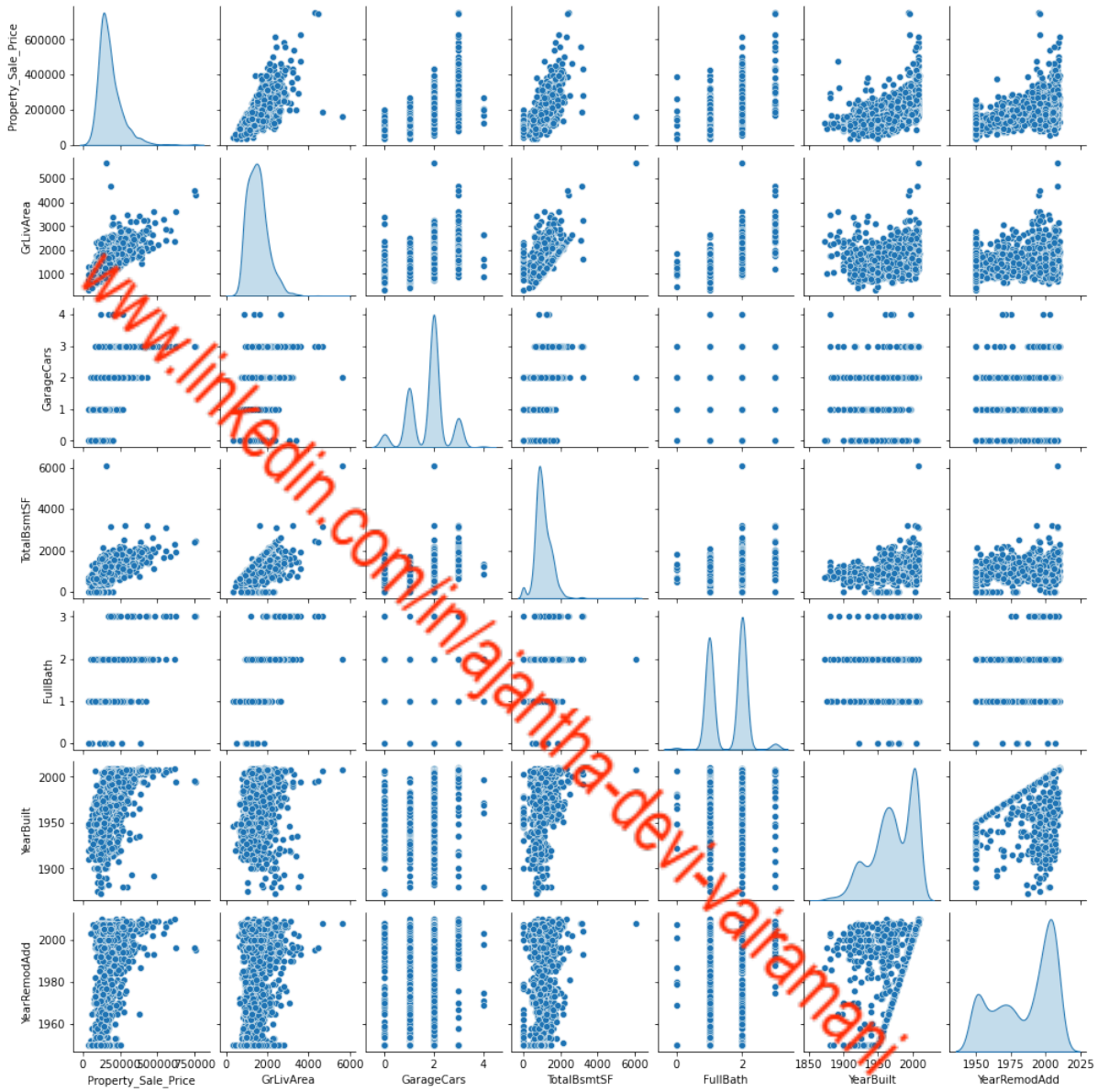
Boxplot of Overall Condition and Property_Sale_Price

In [21]:
```
# draw the boxplot for OverallQuality and the Property_Sale_Price
sns.boxplot(y="Property_Sale_Price", x="OverallCond", data= df_property)

# set the title of the plot and the fontsize
plt.title("Overall Condition vs Property_Sale_Price", fontsize=15)

# set the xlabel and the fontsize
plt.xlabel("Overall Condition", fontsize=15)

# set the ylabel and the fontsize
plt.ylabel("Sale Price", fontsize=15)

# display the plot
plt.show()
```



Draw the pairplot of the numeric variables

In [22]:
```
# Pairplot of numeric variables

# select the columns for the pairplot
columns= ["Property_Sale_Price", "GrLivArea", "GarageCars", "TotalBsmtSF", "FullBath", "YearBuilt",

# draw the pairplot such that the diagonal should be density plot and the other graphs should be sc
sns.pairplot(df_property[columns], size=2, kind= "scatter", diag_kind="kde")

# display the plot
plt.show()
```



4.1.4 Outliers Discovery

In [23]:
```
# plot a boxplot of target variable to detect the outliers
sns.boxplot(df_property['Property_Sale_Price'], color='maroon')

# set plot label
# set text size using 'fontsize'
plt.title('Distribution of Target Variable (Property_Sale_Price)', fontsize = 15)

# display the plot
plt.show()
```

From the above plot we can see that there are outliers present in the target variable 'Property_Sale_Price'. Outliers badly affect the prediction of the regression model and thus, we will remove these outliers.

In [24]:
```
# remove the observations with the house price greater than or equal to 500000
df_property = df_property[df_property['Property_Sale_Price'] < 500000]

# check the dimension of the data
df_property.shape
```

Out[24]: (1451, 78)

4.1.5 Missing Values

If we do not handle the missing values properly then we may end up drawing an inaccurate inference about the data.

Look for the missing values and handle the missing values separately for numerical and categorical values.

Look for the missing values

In [25]:
```
# 'isnull().sum()' returns the number of missing values in each variable
# 'ascending = False': sorts values in the descending order
total_nulls = df_property.isnull().sum().sort_values(ascending = False)

# calculate the percentage of missing values
# 'ascending = False' sorts values in the descending order
percent_null = (df_property.isnull().sum()*100/df_property.isnull().count())
percent_null = percent_null.sort_values(ascending = False)

# concat the 'total_nulls' and 'percent_null' columns
# 'axis = 1' stands for columns
missing_values = pd.concat([total_nulls, percent_null], axis = 1, keys = ['Total Nulls', 'Percentag

# add the column containing data type of each variable
missing_values['Data Type'] = df_property[missing_values.index].dtypes
missing_values
```

Out[25]:

	Total Nulls	Percentage of Missing Values	Data Type
MiscFeature	1397	96.278429	object
Alley	1360	93.728463	object
Fence	1171	80.702963	object
FireplaceQu	690	47.553411	object
LotFrontage	259	17.849759	float64
GarageType	81	5.582357	object
GarageFinish	81	5.582357	object
GarageQual	81	5.582357	object
GarageCond	81	5.582357	object
GarageYrBlt	81	5.582357	float64
BsmtFinType2	38	2.618884	object
BsmtExposure	38	2.618884	object

We can see that 18 variables contain the missing values.

Handle the missing values for numerical variables

In [26]:
```
# filter out the categorical variables and consider only the numeric variables with missing values
num_missing_values = missing_values[(missing_values['Total Nulls'] > 0) & (missing_values['Data Typ
num_missing_values
```

Out[26]:

	Total Nulls	Percentage of Missing Values	Data Type
LotFrontage	259	17.849759	float64
GarageYrBlt	81	5.582357	float64
MasVnrArea	8	0.551344	float64

For the numerical variables, we can replace the missing values by their mean, median or mode as per the requirement.

The variable 'LotFrontage' is right skewed and thus we will fill the missing values with its median value

In [27]:
```
# use the function fillna() to fill the missing values
df_property['LotFrontage'] = df_property['LotFrontage'].fillna(df_property['LotFrontage'].median()
```

We will replace the missing values in the numeric variable `GarageYrBlt` by 0. The missing values in this variable indicates that there are 81 observations for which garage facility is not available.

In [28]:
```
# use the function fillna() to replace missing values in 'GarageYrBlt' with 0
df_property['GarageYrBlt'] = df_property['GarageYrBlt'].fillna(0)
```

The variable 'MasVnrArea' is positively skewed and thus we will fill the missing values with its median value

In [29]:
```
# use the function fillna() to fill the missing values
df_property['MasVnrArea'] = df_property['MasVnrArea'].fillna(df_property['MasVnrArea'].median())
```

Handle the missing values for categorical variables

In [30]:
```
# filter out the numerical variables and consider only the categorical variables with missing value
cat_missing_values = missing_values[(missing_values['Total Nulls'] > 0) & (missing_values['Data Typ
cat_missing_values
```

Out[30]:

	Total Nulls	Percentage of Missing Values	Data Type
MiscFeature	1397	96.278429	object
Alley	1360	93.728463	object
Fence	1171	80.702963	object
FireplaceQu	690	47.553411	object
GarageType	81	5.582357	object
GarageFinish	81	5.582357	object
GarageQual	81	5.582357	object
GarageCond	81	5.582357	object
BsmtFinType2	38	2.618884	object
BsmtExposure	38	2.618884	object
BsmtCond	37	2.549966	object
BsmtFinType1	37	2.549966	object
BsmtQual	37	2.549966	object
MasVnrType	8	0.551344	object
Electrical	1	0.068918	object

In [31]:
```
# according to the data definition, 'NA' denotes the absence of miscellaneous feature
# replace NA values in 'MiscFeature' with a valid value, 'None'
df_property['MiscFeature'] = df_property['MiscFeature'].fillna('None')

# replace NA values in 'Alley' with a valid value, 'No alley access'
df_property['Alley'] = df_property['Alley'].fillna('No alley access')

# replace NA values in 'Fence' with a valid value, 'No Fence'
df_property['Fence'] = df_property['Fence'].fillna('No Fence')

# replace null values in 'FireplaceQu' with a valid value, 'No Fireplace'
df_property['FireplaceQu'] = df_property['FireplaceQu'].fillna('No Fireplace')
```

In [32]:
```
# replace the missing values in the categoric variables representing the garage by `No Garage`
for col in ['GarageType', 'GarageFinish', 'GarageCond', 'GarageQual']:
    df_property[col].fillna('No Garage', inplace = True)
```

In [33]:
```
# according to the data definition, 'NA' denotes the absence of basement in the variabels 'BsmtQual
# replace the missing values in the categoric variables representing the basement by `No Basement`
for col in ['BsmtFinType2', 'BsmtExposure', 'BsmtQual','BsmtCond','BsmtFinType1']:
    df_property[col].fillna('No Basement', inplace = True)
```

In [34]:
```
# according to the data definition, 'NA' denotes the absence of masonry veneer
# replace the missing values in the categorical variable 'MasVnrType' with a value, 'None'
df_property['MasVnrType'] = df_property['MasVnrType'].fillna('None')
```

In [35]:
```
# replace the missing values in the categorical variable 'Electrical' with its mode
mode_electrical = df_property['Electrical'].mode()
df_property['Electrical'].fillna(mode_electrical[0] , inplace = True)
```

4.1.6 Study correlation

To check the correlation between numerical variables, compute a correlation matrix and plot a heatmap for the correlation matrix

Compute a correlation matrix

In [36]:
```
# use the corr() function to generate the correlation matrix of the numeric variables
corrmat = df_property.corr()

# print the correlation matrix
corrmat
```

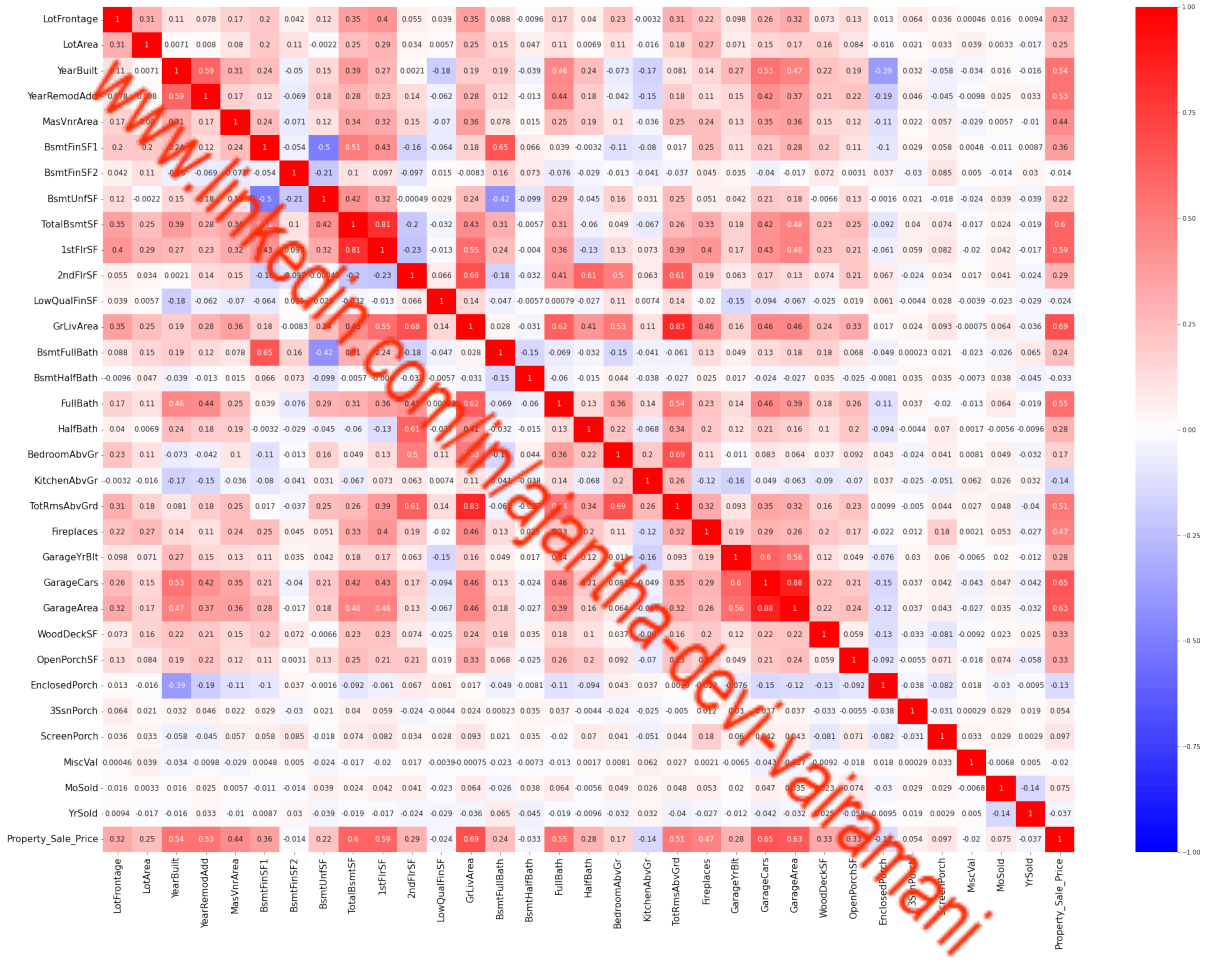
Out[36]:

	LotFrontage	LotArea	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF
LotFrontage	1.000000	0.306226	0.110575	0.078240	0.168580	0.201974	0.041758	0.12234
LotArea	0.306226	1.000000	0.007052	0.007963	0.079576	0.204725	0.113638	-0.00222
YearBuilt	0.110575	0.007052	1.000000	0.590358	0.308832	0.242388	-0.050381	0.14748
YearRemodAdd	0.078240	0.007963	0.590358	1.000000	0.170015	0.120246	-0.069146	0.17996
MasVnrArea	0.168580	0.079576	0.308832	0.170015	1.000000	0.237426	-0.070851	0.11643
BsmtFinSF1	0.201974	0.204725	0.242388	0.120246	0.237426	1.000000	-0.054443	-0.50234
BsmtFinSF2	0.041758	0.113638	-0.050381	-0.069146	-0.070851	-0.054443	1.000000	-0.21168
BsmtUnfSF	0.122341	-0.002229	0.147484	0.179966	0.116437	-0.502348	-0.211681	1.00000
TotalBsmtSF	0.351744	0.253819	0.385072	0.284008	0.340365	0.506796	0.101582	0.42259
1stFlrSF	0.403928	0.293575	0.272635	0.232100	0.318259	0.427145	0.096551	0.32202
2ndFlrSF	0.055154	0.033593	0.002106	0.136997	0.150374	-0.160550	-0.096758	-0.00049
LowQualFinSF	0.038892	0.005727	-0.183659	-0.061920	-0.069527	-0.064339	0.014921	0.02865
GrLivArea	0.352795	0.248741	0.188173	0.283858	0.358948	0.177440	-0.008304	0.24335
BsmtFullBath	0.087810	0.154564	0.185755	0.117521	0.078313	0.652108	0.158017	-0.42140
BsmtHalfBath	-0.009650	0.047356	-0.039128	-0.012512	0.015343	0.065858	0.072546	-0.09905
FullBath	0.166976	0.111174	0.464424	0.436448	0.251721	0.039019	-0.076080	0.28667
HalfBath	0.039602	0.006873	0.239822	0.180804	0.192394	-0.003163	-0.029227	-0.04490
BedroomAbvGr	0.233933	0.114221	0.073171	-0.041872	0.099591	-0.108698	-0.012647	0.16280
KitchenAbvGr	-0.003219	-0.016372	-0.174064	-0.148847	-0.036336	-0.080020	-0.040788	0.03083
TotRmsAbvGrd	0.311321	0.175347	0.081196	0.181722	0.254011	0.016513	-0.036589	0.24899
Fireplaces	0.223229	0.268811	0.140979	0.106649	0.238226	0.245847	0.044752	0.05076
GarageYrBlt	0.097975	0.071133	0.271118	0.145115	0.133385	0.114548	0.035023	0.04219
GarageCars	0.261254	0.145224	0.533519	0.416036	0.351166	0.209144	-0.039581	0.21290
GarageArea	0.317880	0.171107	0.474181	0.366411	0.357034	0.283615	-0.017447	0.18224
WoodDeckSF	0.073205	0.159650	0.223873	0.205597	0.145807	0.202566	0.071761	-0.00658
OpenPorchSF	0.133322	0.084143	0.186221	0.224186	0.122038	0.112177	0.003118	0.12514
EnclosedPorch	0.013371	-0.015829	-0.386450	-0.192517	-0.108352	-0.099877	0.036869	-0.00160
3SsnPorch	0.063617	0.021493	0.032225	0.046070	0.022121	0.028548	-0.030038	0.02119
ScreenPorch	0.035947	0.032825	-0.057585	-0.045230	0.057424	0.037946	0.085238	-0.01750
MiscVal	0.000464	0.039093	-0.033934	-0.009821	-0.029244	0.004795	0.005002	-0.02374
MoSold	0.015944	0.003327	0.016370	0.025102	0.005738	-0.010615	-0.014359	0.03929
YrSold	0.009395	-0.016991	-0.016129	0.033392	-0.010231	0.008691	0.030290	-0.03868
Property_Sale_Price	0.318744	0.252156	0.543898	0.531708	0.436515	0.357076	-0.014028	0.22399

2. Plot the heatmap for the diagonal correlation matrix

A correlation matrix is a symmetric matrix. Plot only the upper triangular entries using a heatmap.

In [37]:
```
# set the plot size
plt.figure(figsize = (35,25))

# plot the heat map
# corr: give the correlation matrix
# cmap: color code used for plotting
# annot_kws: sets the font size of the annotation
# annot: prints the correlation values in the chart
# vmax: gives a maximum range of values for the chart
# vmin: gives a minimum range of values for the chart
sns.heatmap(corrmat, annot = True, vmax = 1.0, vmin = -1.0, cmap = 'bwr', annot_kws = {"size": 11.5

# set the size of x and y axes labels using 'fontsize'
plt.xticks(fontsize = 15)
plt.yticks(fontsize = 15)

# display the plot
plt.show()
```



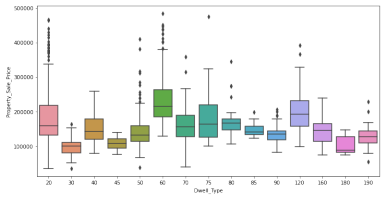
The diagonal represents the correlation of the variable with itself thus all the diagonal entries are '1'. The dark red squares represent the variables with strong positive correlation.

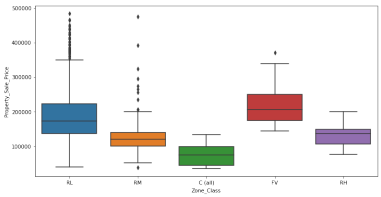
From the above plot we can see that the highest positive correlation (= 0.88) is between the variables 'GarageArea' and 'GarageCars'. Also there is strong positive correlation between the pairs (1StFlrSF, TotalBsmtSF) and (TotRmsAbvGrd, GrlivArea). There may be multicollinearity present.
No two variables have strong negative correlation in the dataset.

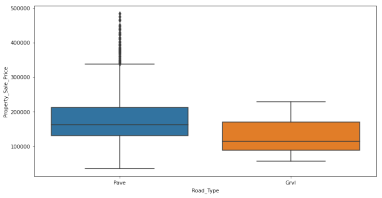
Correlation does not imply causation. In other words, if two variables are correlated, it does not mean that one variable caused the other.

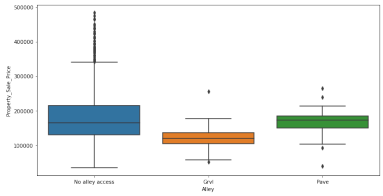
4.1.7 Analyze Relationships Between Target and Categorical Variables

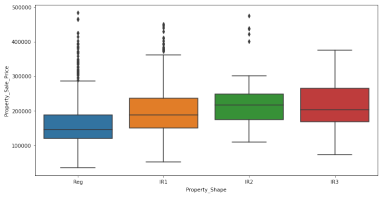
In [38]:
```
# create an empty list to store all the categorical variables
categorical=[]

# check the data type of each variable
for column in df_property:

    # check if the variable has the categorical type
    if is_string_dtype(df_property[column]):

        # append the categorical variables to the list 'categorical'
        categorical.append(column)

# plot the count plot for each categorical variable
# 'figsize' sets the figure size
fig, ax = plt.subplots(nrows = 14, ncols = 3, figsize = (40, 100))

# plot the boxplot for each categoric and target variable
for variable, subplot in zip(categorical, ax.flatten()):
    sns.boxplot(x = variable, y = 'Property_Sale_Price', data = df_property, ax = subplot)

# display the plot
plt.show()
```

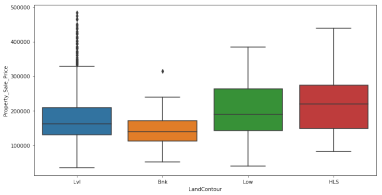


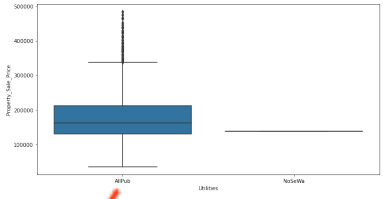


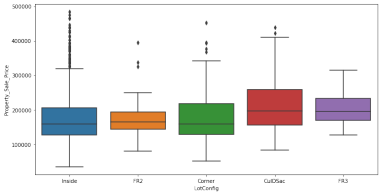


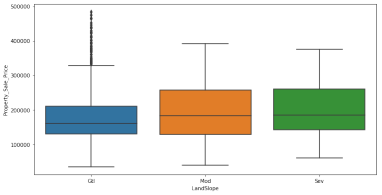


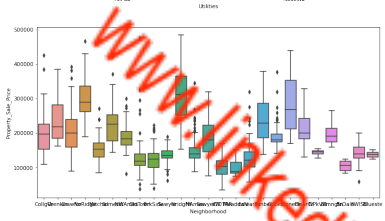


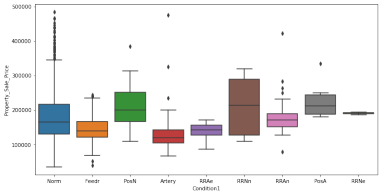


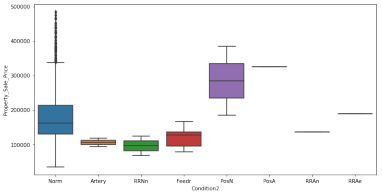


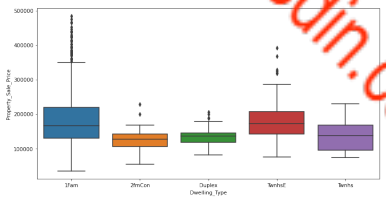


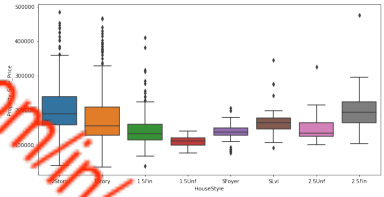


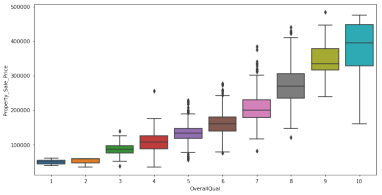


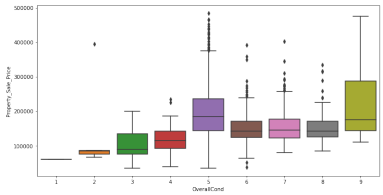


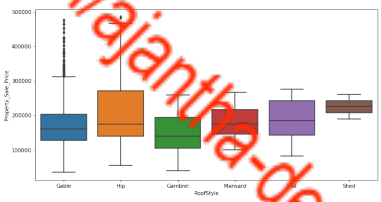


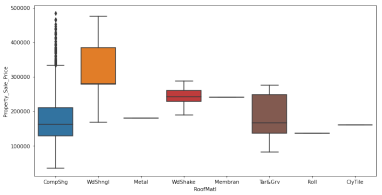


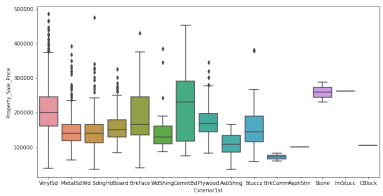


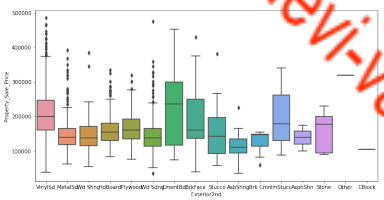


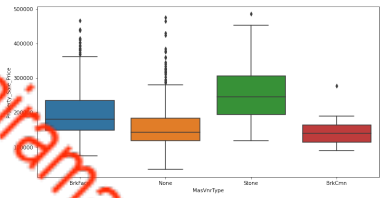


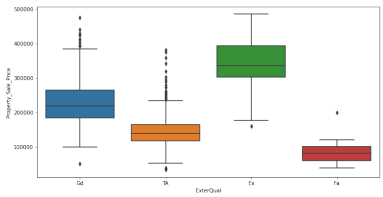


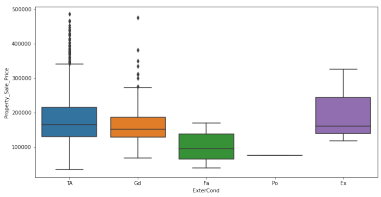


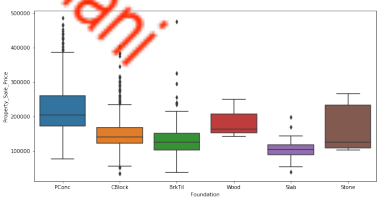


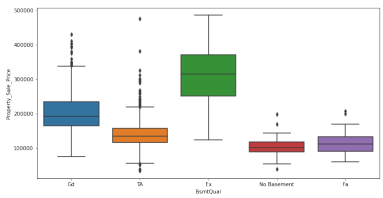


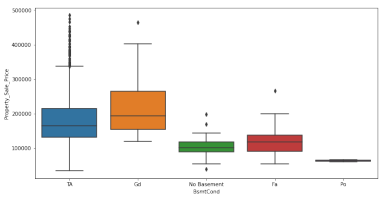


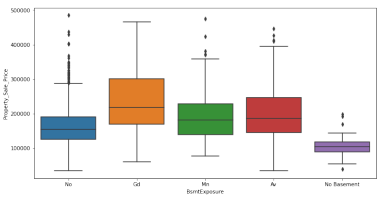


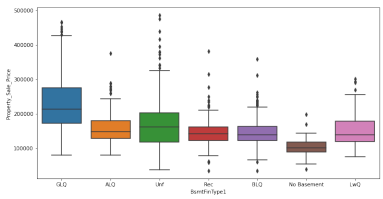


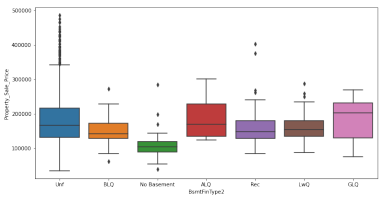


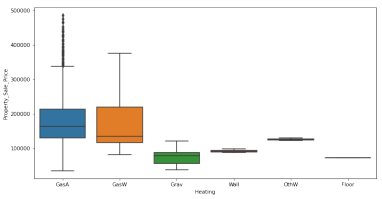


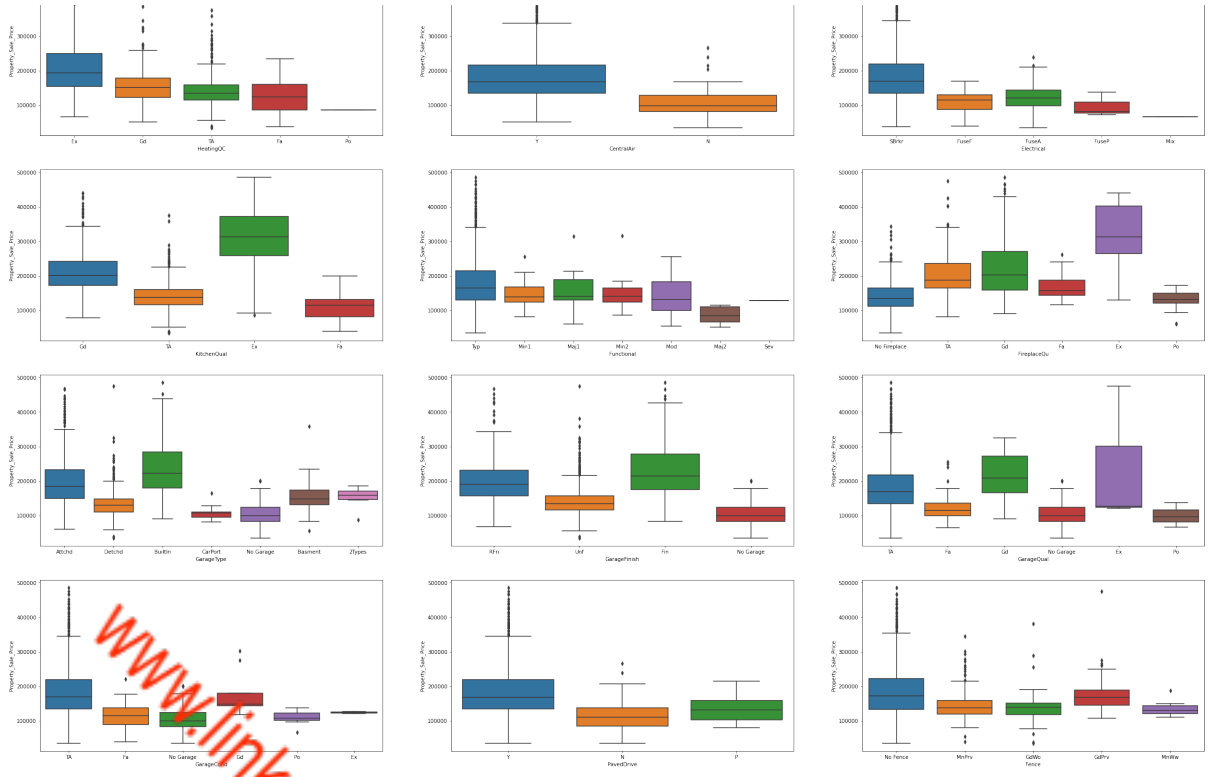












It can be seen that most of the categorical variables have an effect on the sale price of the property. The median sale price rises exponentially with respect to the rating of the overall quality of the material used.

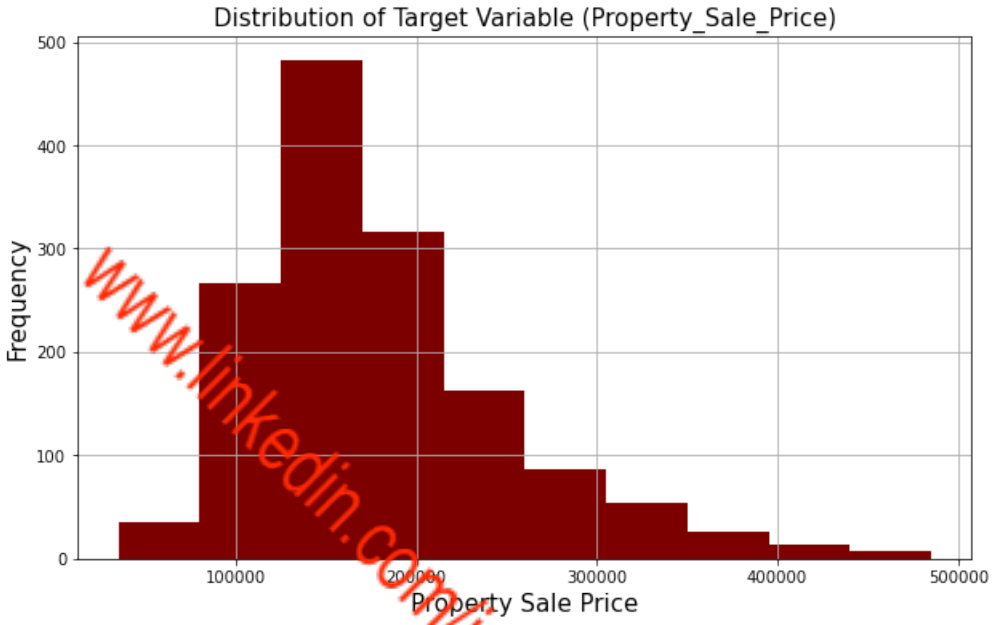
4.2 Data Preparation

4.2.1 Check for Normality

Plot a histogram and also perform the Shapiro-Wilk test

We use the function `hist()` from the matplotlib library to plot a histogram

In [39]:
```
# check the distribution of target variable
df_property.Property_Sale_Price.hist(color = 'maroon')

# add plot and axes labels
# set text size using 'fontsize'
plt.title('Distribution of Target Variable (Property_Sale_Price)', fontsize = 15)
plt.xlabel('Property Sale Price', fontsize = 15)
plt.ylabel('Frequency', fontsize = 15)

# display the plot
plt.show()
```



We can see that the variable 'Property_Sale_Price' is positively skewed and thus we can say that it is not normally distributed.

We should not only make conclusions through visual representations or only using a statistical test but perform multiple ways to get the best insights.

Let us perform from Shapiro-Wilk test to check the normality of the target variable.

The null and alternate hypothesis of Shapiro-Wilk test is as follows:

H_0: The data is normally distributed

H_1: The data is not normally distributed

In [40]:
```
# shapiro() returns the the test statistics along with the p-value of the test
stat, p = shapiro(df_property.Property_Sale_Price)

# print the numeric outputs of the Shapiro-Wilk test upto 3 decimal places
print('Statistics=%.3f, p-value=%.3f' % (stat, p))

# set the level of significance (alpha) to 0.05
alpha = 0.05

# if the p-value is less than alpha print we reject alpha
# if the p-value is greater than alpha print we accept alpha
if p > alpha:
    print('The data is normally distributed (fail to reject H0)')
else:
    print('The data is not normally distributed (reject H0)')
```

```
Statistics=0.919, p-value=0.000
The data is not normally distributed (reject H0)
```

We can see that the p-value is less than 0.05 and thus we reject the null hypothesis. It can be concluded that the data is not normally distributed.

We need to log transform the variable 'Property_Sale_Price' in order to reduce the skewness

Shaprio Wilk Test does not work if the number of observations are more than 5000. However Shapiro Wilk test is more robust than other tests. In case where the observations are more than 5000, other tests like Anderson Darling test or Jarque Bera test may also be used.

If the data is not normally distributed, use log transformation to reduce the skewness and get a near normally distributed data

The log transformation can be used to reduce the skewbess. To log transform the 'Property_Sale_Price' variable we use the function `np.log()` .

In [41]:
```
# log transformation using np.log()
df_property['log_Property_Sale_Price'] = np.log(df_property['Property_Sale_Price'])

# display the top 5 rows of the data
df_property.head()
```

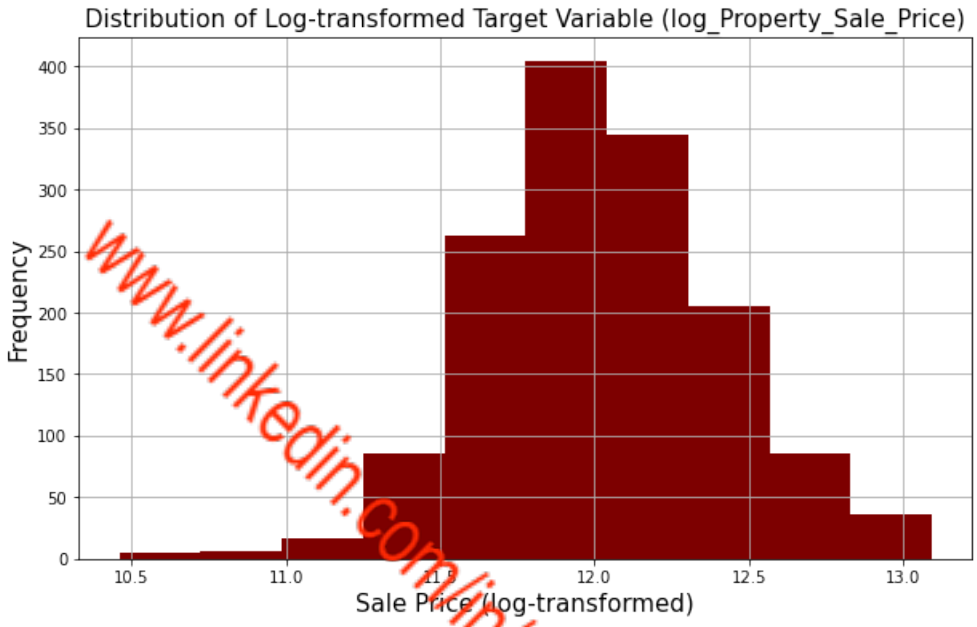
Out[41]:

	Dwell_Type	Zone_Class	LotFrontage	LotArea	Road_Type	Alley	Property_Shape	LandContour	Utilities	LotConfig
0	60	RL	65.0	8450	Pave	No alley access	Reg	Lvl	AllPub	Inside
1	20	RL	80.0	9600	Pave	No alley access	Reg	Lvl	AllPub	FR2
2	60	RL	68.0	11250	Pave	No alley access	IR1	Lvl	AllPub	Inside
3	70	RL	60.0	9550	Pave	No alley access	IR1	Lvl	AllPub	Corner
4	60	RL	84.0	14260	Pave	No alley access	IR1	Lvl	AllPub	FR2

Recheck for normality by plotting histogram and performing Shapiro-Wilk test

Let us first plot a histogram of `log_Property_Sale_Price` .

In [42]:
```
# recheck for normality
# plot the histogram using hist
df_property.log_Property_Sale_Price.hist(color = 'maroon')

# add plot and axes labels
# set text size using 'fontsize'
plt.title('Distribution of Log-transformed Target Variable (log_Property_Sale_Price)', fontsize = 1
plt.xlabel('Sale Price (log-transformed)', fontsize = 15)
plt.ylabel('Frequency', fontsize = 15)

# display the plot
plt.show()
```



It can be seen that the variable log_Property_Sale_Price is near normally distributed. Lets confirm it again by using the Shapiro-Wilk test.

Let us perform Shapiro-Wilk test.

In [43]:
```
# shapiro() returns the the test statistics along with the p-value of the test
stat, p = shapiro(df_property['log_Property_Sale_Price'])

# print the numeric outputs of the Shapiro-Wilk test upto 3 decimal places
print('Statistics=%.3f, p-value=%.3f' % (stat, p))

# set the level of significance (alpha) to 0.05
alpha = 0.05

# if the p-value is less than alpha print we reject alpha
# if the p-value is greater than alpha print we accept alpha
if p > alpha:
    print('The data is normally distributed (fail to reject H0)')
else:
    print('The data is not normally distributed (reject H0)')
```

```
Statistics=0.992, p-value=0.000
The data is not normally distributed (reject H0)
```

In [44]:
```
# find the skewness of the variable log_Property_Sale_Price
df_property['log_Property_Sale_Price'].skew()
```

Out[44]:
```
-0.03836503763294778
```

It can be visually seen that the data has near-normal distribution, but Shapiro-Wilk test does not support the claim.
Note that in reality it might be very tough for your data to adhere to all assumptions your algorithm needs.

4.2.2 Dummy Encode the Categorical Variables

We need to perform dummy encoding on our categorical variables before we proceed; since the method of OLS works only on the numeric data.

Filter numerical and categorical variables

In [45]:
```
# filter out the categorical variables and consider only the numeric variables using (include=np.nu
df_numeric_features = df_property.select_dtypes(include=np.number)

# display the numeric features
df_numeric_features.columns
```

Out[45]:
```
Index(['LotFrontage', 'LotArea', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea',
       'BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF',
       '2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath',
       'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd',
       'Fireplaces', 'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF',
       'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'MiscVal',
       'MoSold', 'YrSold', 'Property_Sale_Price', 'log_Property_Sale_Price'],
      dtype='object')
```

In [46]:
```
# filter out the numerical variables and consider only the categorical variables using (include=obj
df_categoric_features = df_property.select_dtypes(include = object)

# display categorical features
df_categoric_features.columns
```

Out[46]:
```
Index(['Dwell_Type', 'Zone_Class', 'Road_Type', 'Alley', 'Property_Shape',
       'LandContour', 'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood',
       'Condition1', 'Condition2', 'Dwelling_Type', 'HouseStyle',
       'OverallQual', 'OverallCond', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation',
       'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2',
       'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual',
       'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQual',
       'GarageCond', 'PavedDrive', 'Fence', 'MiscFeature', 'SaleType',
       'SaleCondition'],
      dtype='object')
```

Dummy encode the catergorical variables

In [47]:
```
# to create the dummy variables  we use 'get_dummies()' from pandas
# to create (n-1) dummy variables we use 'drop_first = True'
dummy_encoded_variables = pd.get_dummies(df_categoric_features, drop_first = True)
```

Concatenate numerical and dummy encoded categorical variables

In [48]:
```
# concatenate the numerical and dummy encoded categorical variables column-wise
df_property_dummy = pd.concat([df_numeric_features, dummy_encoded_variables], axis=1)

# display data with dummy variables
df_property_dummy.head()
```

Out[48]:

	LotFrontage	LotArea	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	1stl
0	65.0	8450	2003	2003	196.0	706	0	150	856	
1	80.0	9600	1976	1976	0.0	978	0	284	1262	
2	68.0	11250	2001	2002	162.0	486	0	434	920	
3	60.0	9550	1915	1970	0.0	216	0	540	756	
4	84.0	14260	2000	2000	350.0	655	0	490	1145	

In [49]:
```
# check the dimensions of the dataframe
df_property_dummy.shape
```

Out[49]: (1451, 285)

There are various forms of encoding like n-1 dummy encoding, one hot encoding, label encoding, frequency encoding.

We will now train models by fitting a linear regression model using the method of ordinary least square(OLS).

5. Linear Regression (OLS)

5.1 Multiple Linear Regression Full Model with Log Transformed Dependent Variable (OLS)

Follow the steps in order to build the OLS model:

1. Split the data into training and test sets

In [50]:
```
# add the intercept column using 'add_constant()'
df_property_dummy = sm.add_constant(df_property_dummy)

# separate the independent and dependent variables
# drop(): drops the specified columns
X = df_property_dummy.drop(['Property_Sale_Price','log_Property_Sale_Price'], axis = 1)

# extract the target variable from the data set
y = df_property_dummy[['Property_Sale_Price','log_Property_Sale_Price']]

# split data into train data and test data
# what proportion of data should be included in test data is passed using 'test_size'
# set 'random_state' to get the same data each time the code is executed
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 1)

# check the dimensions of the train & test subset for
# print dimension of predictors train set
print("The shape of X_train is:",X_train.shape)

# print dimension of predictors test set
print("The shape of X_test is:",X_test.shape)

# print dimension of target train set
print("The shape of y_train is:",y_train.shape)

# print dimension of target test set
print("The shape of y_test is:",y_test.shape)
```

```
The shape of X_train is: (1015, 284)
The shape of X_test is: (436, 284)
The shape of y_train is: (1015, 2)
The shape of y_test is: (436, 2)
```

2. Build model using sm.OLS().fit()

In [51]:
```
# build a full model using OLS()
# consider the log of sales price as the target variable
# use fit() to fit the model on train data
linreg_logmodel_full = sm.OLS(y_train['log_Property_Sale_Price'], X_train).fit()

# print the summary output
print(linreg_logmodel_full.summary())
```

```
SaleType_ConLw               -0.0588      0.089     -0.664      0.373      -0.174       0.056
SaleType_New                  0.1840      0.092      1.995      0.046       0.003       0.365
SaleType_Oth                  0.2128      0.082      2.585      0.010       0.051       0.374
SaleType_WD                  -0.0259      0.026     -0.998      0.318      -0.077       0.025
SaleCondition_AdjLand         0.2442      0.079      3.074      0.002       0.088       0.400
SaleCondition_Alloca          0.1086      0.048      2.269      0.024       0.015       0.203
SaleCondition_Family          0.0209      0.036      0.580      0.562      -0.050       0.092
SaleCondition_Normal          0.0746      0.015      4.852      0.000       0.044       0.105
SaleCondition_Partial        -0.0909      0.089     -1.025      0.306      -0.265       0.083
==============================================================================
Omnibus:                      248.971   Durbin-Watson:                   1.934
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2118.176
Skew:                          -0.873   Prob(JB):                         0.00
Kurtosis:                       9.858   Cond. No.                     6.16e+19
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 5.77e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

This model explains around 95% of the variation in dependent variable log_Property_Sale_Price.
The Condition Number 6.16e+19 suggests that there is severe multicollinearity in the data.
The Durbin-Watson test statistics is 1.934 i.e. close to 2.0 and thus it indicates that there is no autocorrelation.

Condition Number : Multicollinearity can be checkked by computing the condition number(CN). If condition number is between 100 and 1000, there is moderate multicollinearity, if condition number is less than 100, there is no multicollinearity and if condition number is greater 1000 there is severe multicollinearity in the data.

Durbin-Watson : The Durbin-Watson statistic will always have a value between 0 and 4. A value of 2.0 means that there is no autocorrelation detected in the sample. Values from 0 to less than 2 indicate positive autocorrelation and values from from 2 to 4 indicate negative autocorrelation.

3. Predict the values using test set

In [52]:
```
# predict the 'log_Property_Sale_Price' using predict()
linreg_logmodel_full_predictions = linreg_logmodel_full.predict(X_test)
```

Note that the predicted values are log transformed Property_Sale_Price. In order to get Property_Sale_Price values, we take the antilog of these predicted values by using the function np.exp()

In [53]:
```
# take the exponential of predictions using np.exp()
predicted_Property_Sale_Price = np.exp(linreg_logmodel_full_predictions)

# extract the 'Property_Sale_Price' values from the test data
actual_Property_Sale_Price = y_test['Property_Sale_Price']
```

4. Compute accuracy measures

Now we calculate accuray measures Root-mean-square-error (RMSE), R-squared and Adjusted R-squared.

In [54]:
```
# calculate rmse using rmse()
linreg_logmodel_full_rmse = rmse(actual_Property_Sale_Price, predicted_Property_Sale_Price)

# calculate R-squared using rsquared
linreg_logmodel_full_rsquared = linreg_logmodel_full.rsquared

# calculate Adjusted R-Squared using rsquared_adj
linreg_logmodel_full_rsquared_adj = linreg_logmodel_full.rsquared_adj
```

5. Tabulate the results

In [55]:
```
# create the result table for all accuracy scores
# accuracy measures considered for model comparision are RMSE, R-squared value and Adjusted R-squar
# create a list of column names
cols = ['Model', 'RMSE', 'R-Squared', 'Adj. R-Squared']

# create a empty dataframe of the colums
# columns: specifies the columns to be selected
result_tabulation = pd.DataFrame(columns = cols)

# compile the required information
linreg_logmodel_full_metrics = pd.Series({'Model': "Linreg full model with log of target variable '
                     'RMSE':linreg_logmodel_full_rmse,
                     'R-Squared': linreg_logmodel_full_rsquared,
                     'Adj. R-Squared': linreg_logmodel_full_rsquared_adj
                      })

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a name
result_tabulation = result_tabulation.append(linreg_logmodel_full_metrics, ignore_index = True)

# print the result table
result_tabulation
```

Out[55]:

	Model	RMSE	R-Squared	Adj. R-Squared
0	Linreg full model with log of target variable	37726.465264	0.952066	0.935193

We will also build a linear regression model without performing log transformation on the target variable.

5.2 Multiple Linear Regression Full Model without Log Transformed Target Variable (OLS)

In this section we build a full model with linear regression using OLS (Ordinary Least Square) technique. By full model we indicate that we consider all the independent variables that are present in the dataset.

In this case, we do not consider any kind of transformation on the dependent variable, we use the 'Property_Sale_Price' variable as it is.

We have already done train and test split while building the previous model.

1. Build model using sm.OLS().fit()

In [56]:
```
# build a OLS model using function OLS()
# Property_Sale_Price is our target variable
# use fit() to fit the model on train data
linreg_nolog_model = sm.OLS(y_train['Property_Sale_Price'], X_train).fit()

# print the summary output
print(linreg_nolog_model.summary())
```

```
SaleType_ConLw           -4344.9221   1.55e+04      -0.322      0.747   -3.08e+04    2.21e+04
SaleType_New              4.648e+04   1.81e+04       2.569      0.010     1.1e+04     8.2e+04
SaleType_Oth               1.97e+04   1.61e+04       1.220      0.223    -1.2e+04    5.14e+04
SaleType_WD               -2501.2060  5086.113      -0.492      0.623   -1.25e+04    7483.505
SaleCondition_AdjLand     3.552e+04   1.56e+04       2.279      0.023    4921.109    6.61e+04
SaleCondition_Alloca      1.516e+04   9390.749       1.615      0.107   -3271.244    3.36e+04
SaleCondition_Family      6119.6006   7084.668       0.864      0.388   -7788.538       2e+04
SaleCondition_Normal      8378.0761   3015.314       2.779      0.006    2458.616    1.43e+04
SaleCondition_Partial    -2.404e+04   1.74e+04      -1.382      0.167   -5.82e+04    1.01e+04
==============================================================================
Omnibus:                      157.801   Durbin-Watson:                   1.973
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2312.526
Skew:                          -0.058   Prob(JB):                         0.00
Kurtosis:                      10.394   Cond. No.                     6.16e+19
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 5.77e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```


This model explains around 94% of the variation in dependent variable Property_Sale_Price.
The Durbin-Watson test statistics is 1.973 and indicates that there is no autocorrelation.
The Condition Number 6.16e+19 suggests that there is severe multicollinearity in the data.

2. Predict the values using test set

In [57]:
```
# predict the 'Property_Sale_Price' using predict()
linreg_nolog_model_predictions = linreg_nolog_model.predict(X_test)
```

3. Compute accuracy measures

Now we calculate accuray measures Root-mean-square-error (RMSE), R-squared and Adjusted R-squared.

In [58]:
```
# calculate rmse using rmse()
linreg_nolog_model_rmse = rmse(actual_Property_Sale_Price, linreg_nolog_model_predictions)

# calculate R-squared using rsquared
linreg_nolog_model_rsquared = linreg_nolog_model.rsquared

# calculate Adjusted R-Squared using rsquared_adj
linreg_nolog_model_rsquared_adj = linreg_nolog_model.rsquared_adj
```

4. Tabulate the results

In [59]:
```
# append the result table
# compile the required information
linreg_nolog_model_metrics = pd.Series({'Model': "Linreg full model without log of target variable
                                        'RMSE':linreg_nolog_model_rmse,
                                        'R-Squared': linreg_nolog_model_rsquared,
                                        'Adj. R-Squared': linreg_nolog_model_rsquared_adj

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a name
result_tabulation = result_tabulation.append(linreg_nolog_model_metrics, ignore_index = True)

# print the result table
result_tabulation
```

Out[59]:

	Model	RMSE	R-Squared	Adj. R-Squared
0	Linreg full model with log of target variable	37726.465264	0.952066	0.935193
1	Linreg full model without log of target variable	54970.829645	0.946898	0.928206

If we compare the results in the table we can see that the linreg model withh log of target variable is performing slightly better than the model without log of target variable. Thus we will continue with the target variable 'log_Property_Sale_Price'.

Let us perform feature engineering and take a look at building a linear regression full model by adding new features to the dataset.

5.3 Feature Engineering

It is the process of creating new features using domain knowledge of the data that provides more insight into the data.
Let us create a few features from the existing dataset and build a regression model on the newly created data.

5.3.1 Multiple Linear Regression (Using New Feature) - 1

In order to build the model, we do the following:

1. Create a new feature by using variables 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', and 'GrLivArea'.

Calculate the complete area of the house.
Create a new variable `TotalSF` representing the total square feet area of the house by adding the area of the first floor, second floor, ground level and basement of the house.

In [60]:
```
# create a new variable 'TotalSF' using the variables 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', and '
df_property['TotalSF'] = df_property['TotalBsmtSF'] + df_property['1stFlrSF'] + df_property['2ndFl

# as we have created a new variable using the variables 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF' and
# use 'drop()' to remove the variables
df_property = df_property.drop(["TotalBsmtSF", "1stFlrSF", "2ndFlrSF", "GrLivArea"], axis=1)
```

In [61]:
```
# filter out the categorical variables and consider only the numerical variables using (include=np.
df_numeric_features = df_property.select_dtypes(include=np.number)

# filter out the numerical variables and consider only the categorical variables using (include=obj
df_categoric_features = df_property.select_dtypes(include = object)
```

Dummy encode the catergorical variables

In [62]:
```
# use 'get_dummies()' from pandas to create dummy variables
# use 'drop_first = True' to create (n-1) dummy variables
dummy_encoded_variables = pd.get_dummies(df_categoric_features, drop_first = True)
```

Concatenate numerical and dummy encoded categorical variables

In [63]:
```
# concatenate the numerical and dummy encoded categorical variables column-wise
df_dummy = pd.concat([df_numeric_features, dummy_encoded_variables], axis=1)

# display data with dummy variables
df_dummy.head()
```

Out[63]:

	LotFrontage	LotArea	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	LowQualFinSF	B
0	65.0	8450	2003	2003	196.0	706	0	150	0	
1	80.0	9600	1976	1976	0.0	978	0	284	0	
2	68.0	11250	2001	2002	162.0	486	0	434	0	
3	60.0	9550	1915	1970	0.0	216	0	540	0	
4	84.0	14260	2000	2000	350.0	655	0	490	0	

2. Split the data into train and test sets

In [64]:
```
# add the intercept column using 'add_constant()'
df_dummy = sm.add_constant(df_dummy)

# separate the independent and dependant variables
# drop(): drops the specified columns
# axis=1: specifies that the column is to be dropped
X = df_dummy.drop(['Property_Sale_Price', 'log_Property_Sale_Price'], axis = 1)

# extract the target variable from the data set
y = df_dummy[['Property_Sale_Price','log_Property_Sale_Price']]

# split data into train data and test data
# what proportion of data should be included in test data is specified using 'test_size'
# set 'random_state' to get the same data each time the code is executed
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 1)

# check the dimensions of the train & test subset for
# print dimension of predictors train set
print("The shape of X_train is:",X_train.shape)

# print dimension of predictors test set
print("The shape of X_test is:",X_test.shape)

# print dimension of target train set
print("The shape of y_train is:",y_train.shape)

# print dimension of target test set
print("The shape of y_test is:",y_test.shape)
```

```
The shape of X_train is: (1015, 281)
The shape of X_test is: (436, 281)
The shape of y_train is: (1015, 2)
The shape of y_test is: (436, 2)
```

3. Build model using sm.OLS().fit()

In [65]:
```
# build a full model using OLS()
# consider the target variable 'log_Property_Sale_Price'
# use fit() to fit the model on train data
linreg_feature_1_model = sm.OLS(y_train['log_Property_Sale_Price'], X_train).fit()

# print the summary output
print(linreg_feature_1_model.summary())
```

```
SaleType_ConLI              -0.1460      0.068     -2.162      0.031      -0.278      -0.013
SaleType_ConLw              -0.0399      0.069     -0.582      0.561      -0.175       0.095
SaleType_New                 0.1833      0.092      1.990      0.047       0.002       0.364
SaleType_Oth                 0.2119      0.082      2.578      0.010       0.051       0.373
SaleType_WD                 -0.0261      0.026     -1.008      0.314      -0.077       0.025
SaleCondition_AdjLand        0.2443      0.079      3.077      0.002       0.088       0.400
SaleCondition_Alloca         0.1089      0.048      2.278      0.023       0.015       0.203
SaleCondition_Family         0.0209      0.036      0.580      0.562      -0.050       0.092
SaleCondition_Normal         0.0746      0.015      4.858      0.000       0.044       0.105
SaleCondition_Partial       -0.0905      0.089     -1.021      0.308      -0.264       0.083
==============================================================================
Omnibus:                      248.358   Durbin-Watson:                   1.934
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2114.505
Skew:                          -0.870   Prob(JB):                         0.00
Kurtosis:                       9.853   Cond. No.                     1.26e+16
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.43e-21. This might indicate that there are
```

This model explains around 95% of the variation in dependent variable log_Property_Sale_Price. The Condition Number 1.26e+16 suggests that there is severe multicollinearity in the data. The Durbin-Watson test statistics is 1.934 i.e. close to 2.0 and thus it indicates that there is no autocorrelation.

4. Predict the values using test set

In [66]:
```
# predict the 'log_Property_Sale_Price' using predict()
linreg_feature_1_model_predictions = linreg_feature_1_model.predict(X_test)
```

Note that the predicted values are log transformed Property_Sale_Price. In order to get Property_Sale_Price values, we take the antilog of these predicted values by using the function np.exp()

In [67]:
```
# take the exponential of predictions using np.exp()
predicted_Property_Sale_Price = np.exp(linreg_feature_1_model_predictions)

# extract the 'Property_Sale_Price' values from the test data
actual_Property_Sale_Price = y_test['Property_Sale_Price']
```

5. Compute accuracy measures

Now we calculate accuray measures Root-mean-square-error (RMSE), R-squared and Adjusted R-squared.

In [68]:
```
# calculate rmse using rmse()
linreg_feature_1_model_rmse = rmse(actual_Property_Sale_Price, predicted_Property_Sale_Price)

# calculate R-squared using rsquared
linreg_feature_1_model_rsquared = linreg_feature_1_model.rsquared

# calculate Adjusted R-Squared using rsquared_adj
linreg_feature_1_model_rsquared_adj = linreg_feature_1_model.rsquared_adj
```

6. Tabulate the results

In [69]:
```
# append the accuracy scores to the table
# compile the required information
linreg_feature_1_model_metrics = pd.Series({'Model': "Linreg with new feature (TotalSF) ",
                                            'RMSE': linreg_feature_1_model_rmse,
                                            'R-Squared': linreg_feature_1_model_rsquared,
                                            'Adj. R-Squared': linreg_feature_1_model_rsquared_a

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a name
result_tabulation = result_tabulation.append(linreg_feature_1_model_metrics, ignore_index = True)

# print the result table
result_tabulation
```

Out[69]:

	Model	RMSE	R-Squared	Adj. R-Squared
0	Linreg full model with log of target variable	37726.465264	0.952066	0.935193
1	Linreg full model without log of target variable	54970.829645	0.946898	0.928206
2	Linreg with new feature (TotalSF)	37781.679484	0.952059	0.935271

5.3.2 Multiple Linear Regression (Using New Feature) - 2

In order to build the model, we do the following:

1. Create two new feature by using variables 'Buiding_age' and 'Remodel_age'

In [70]:
```
# 'datetime' is used to perform operations related to date and time
import datetime as dt

# 'now().year' returns the current year
current_year = int(dt.datetime.now().year)
```

In [71]:
```
# create 2 new variables 'Buiding_age' and 'Remodel_age'
Buiding_age = current_year - df_property.YearBuilt
Remodel_age = current_year - df_property.YearRemodAdd
```

In [72]:
```
# append the newly created variables to the dataframe
df_property['Buiding_age'] = Buiding_age
df_property['Remodel_age'] = Remodel_age

# as we have added a new variable using the variables 'YearBuilt' and 'YearRemodAdd', we will drop
# drop the variables using drop()
df_property = df_property.drop(['YearBuilt', 'YearRemodAdd'], axis=1)
```

In [73]:
```
# filter out the categorical variables and consider only the numerical variables using (include=np.
df_numeric_features = df_property.select_dtypes(include=np.number)

# filter out the numerical variables and consider only the categorical variables using (include=obj
df_categoric_features = df_property.select_dtypes(include = object)
```

Dummy encode the catergorical variables

In [74]:
```
# use 'get_dummies()' from pandas to create dummy variables
# use 'drop_first = True' to create (n-1) dummy variables
dummy_encoded_variables = pd.get_dummies(df_categoric_features, drop_first = True)
```

Concatenate numerical and dummy encoded categorical variables

In [75]:
```
# concatenate the numerical and dummy encoded categorical variables column-wise
df_dummy = pd.concat([df_numeric_features, dummy_encoded_variables], axis=1)

# display data with dummy variables
df_dummy.head()
```

Out[75]:

	LotFrontage	LotArea	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	LowQualFinSF	BsmtFullBath	BsmtHalfBath
0	65.0	8450	196.0	706	0	150	0	1	0
1	80.0	9600	0.0	978	0	284	0	0	1
2	68.0	11250	162.0	486	0	434	0	1	0
3	60.0	9550	0.0	216	0	540	0	1	0
4	84.0	14260	350.0	655	0	490	0	1	0

2. Split the data into train and test sets

In [76]:
```
# add the intercept column using 'add_constant()'
df_dummy = sm.add_constant(df_dummy)

# separate the independent and dependent variables
# drop(): drops the specified columns
# axis=1: specifies that the column is to be dropped
X = df_dummy.drop(['Property_Sale_Price','log_Property_Sale_Price'], axis = 1)

# extract the target variable from the data set
y = df_dummy[['Property_Sale_Price','log_Property_Sale_Price']]

# split data into train data and test data
# what proportion of data should be included in test data is specified using 'test_size'
# set 'random_state' to get the same data each time the code is executed
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 1)

# check the dimensions of the train & test subset for
# print dimension of predictors train set
print("The shape of X_train is:",X_train.shape)

# print dimension of predictors test set
print("The shape of X_test is:",X_test.shape)

# print dimension of target train set
print("The shape of y_train is:",y_train.shape)

# print dimension of target test set
print("The shape of y_test is:",y_test.shape)
```

```
The shape of X_train is: (1015, 281)
The shape of X_test is: (436, 281)
The shape of y_train is: (1015, 2)
The shape of y_test is: (436, 2)
```

3. Build model using sm.OLS().fit()

In [77]:
```
# build a OLS model using the function OLS()
# consider the target variable "log_Property_Sale_Price"
# use fit() to fit the model on train data
linreg_feature_2_model = sm.OLS(y_train['log_Property_Sale_Price'], X_train).fit()

# print the summary output
print(linreg_feature_2_model.summary())
```

```
SaleType_ConLw              -0.0599      0.089     -0.682      0.501      -0.235       0.115
SaleType_New                 0.1833      0.092      1.990      0.047       0.002       0.364
SaleType_Oth                 0.2119      0.082      2.578      0.010       0.051       0.373
SaleType_WD                 -0.0261      0.026     -1.008      0.314      -0.077       0.025
SaleCondition_AdjLand        0.2443      0.079      3.077      0.002       0.088       0.400
SaleCondition_Alloca         0.1089      0.048      2.278      0.023       0.015       0.203
SaleCondition_Family         0.0209      0.036      0.580      0.562      -0.050       0.092
SaleCondition_Normal         0.0746      0.015      4.858      0.000       0.044       0.105
SaleCondition_Partial       -0.0905      0.089     -1.021      0.308      -0.264       0.083
==============================================================================
Omnibus:                      248.358   Durbin-Watson:                   1.934
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2114.505
Skew:                          -0.870   Prob(JB):                         0.00
Kurtosis:                       9.853   Cond. No.                     1.28e+16
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.35e-21. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

This model explains around 95% of the variation in dependent variable log_Property_Sale_Price. The Condition Number 1.28e+16 suggests that there is severe multicollinearity in the data. The Durbin-Watson test statistics is 1.934 and indicates that there is no autocorrelation.

4. Predict the values using test set

In [78]:
```
# predict the 'log_Property_Sale_Price' using predict()
linreg_feature_2_model_predictions = linreg_feature_2_model.predict(X_test)
```

Note that the predicted values are log transformed Property_Sale_Price. In order to get Property_Sale_Price values, we take the antilog of these predicted values by using the function np.exp()

In [79]:
```
# take the exponential of predictions using np.exp()
predicted_Property_Sale_Price = np.exp(linreg_feature_2_model_predictions)

# extract the 'Property_Sale_Price' values from the test data
actual_Property_Sale_Price = y_test['Property_Sale_Price']
```

5. Compute accuracy measures

Now we calculate accuray measures Root-mean-square-error (RMSE), R-squared and Adjusted R-squared.

In [80]:
```
# calculate rmse using rmse()
linreg_feature_2_model_rmse = rmse(actual_Property_Sale_Price, predicted_Property_Sale_Price)

# calculate R-squared using rsquared
linreg_feature_2_model_rsquared = linreg_feature_2_model.rsquared

# calculate Adjusted R-Squared using rsquared_adj
linreg_feature_2_model_rsquared_adj = linreg_feature_2_model.rsquared_adj
```

6. Tabulate the results

In [81]:
```
# append the accuracy scores to the table
# compile the required information
linreg_feature_2_model_metrics = pd.Series({'Model': "Linreg with new features (Building_age and Re
                                            'RMSE': linreg_feature_2_model_rmse,
                                            'R-Squared': linreg_feature_2_model_rsquared,
                                            'Adj. R-Squared': linreg_feature_2_model_rsquared_a

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a name
result_tabulation = result_tabulation.append(linreg_feature_2_model_metrics, ignore_index = True)

# print the result table
result_tabulation
```

Out[81]:

	Model	RMSE	R-Squared	Adj. R-Squared
0	Linreg full model with log of target variable	37726.465264	0.952066	0.935193
1	Linreg full model without log of target variable	54970.829645	0.946898	0.928206
2	Linreg with new feature (TotalSF)	37781.679484	0.952059	0.935271
3	Linreg with new features (Building_age and Rem...	38063.992077	0.952059	0.935271

RMSE of the model with new features 'Building_age' and 'Remodel_age' is increased. The value of R-squared and aadjusted R-squared is same as the previous model.

6. Feature Selection

6.1 Variance Inflation Factor

The Variance Inflation Factor (VIF) is used to detect the presence of multicollinearity between the features. The value of VIF equal to 1 indicates that no features are correlated. We calculate the VIF of the numerical independent variables. VIF for the variable V_i is given as:

VIF = 1 / (1 - R-squared)

Where, R-squared is the R-squared of the regression model build by regressing one independent variable (say V_i) on all the remaining independent variables (say V_j, $j \neq i$).

In [82]:
```
# consider the independent variables in the dataframe 'df_property'
# remove the target variables 'Property_Sale_Price' and 'log_Property_Sale_Price' using drop() func
df_property_features = df_property.drop(['Property_Sale_Price', 'log_Property_Sale_Price'], axis =

# filter out the categorical variables and consider only the numerical variables using (include=np.
df_numeric_features_vif = df_property_features.select_dtypes(include=[np.number])

# display the first five observations
df_numeric_features_vif.head()
```

Out[82]:

	LotFrontage	LotArea	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	LowQualFinSF	BsmtFullBath	BsmtHalfBath
0	65.0	8450	196.0	706	0	150	0	1	0
1	80.0	9600	0.0	978	0	284	0	0	1
2	68.0	11250	162.0	486	0	434	0	1	0
3	60.0	9550	0.0	216	0	540	0	1	0
4	84.0	14260	350.0	655	0	490	0	1	0

Calculate the VIF for each numeric variable.

In [83]:
```
# create an empty dataframe to store the VIF for each variable
vif = pd.DataFrame()

# calculate VIF using list comprehension
# use for loop to access each variable
# calculate VIF for each variable and create a column 'VIF_Factor' to store the values
vif["VIF_Factor"] = [variance_inflation_factor(df_numeric_features_vif.values, i) for i in range(df

# create a column of variable names
vif["Features"] = df_numeric_features_vif.columns

# sort the dataframe based on the values of VIF_Factor in descending order
# 'reset_index' resets the index of the dataframe
# 'ascending = False' sorts the data in descending order
# 'drop = True' drops the index that was previously created
vif.sort_values('VIF_Factor', ascending = False).reset_index(drop = True)
```

Out[83]:

	VIF_Factor	Features
0	113.617057	TotalSF
1	92.397837	YrSold
2	85.411954	TotRmsAbvGrd
3	38.944336	GarageCars
4	32.012702	GarageYrBlt
5	31.216275	GarageArea
6	30.844830	KitchenAbvGr
7	29.835340	BedroomAbvGr
8	25.726756	FullBath
9	15.281312	LotFrontage
10	12.389799	Buiding_age
11	12.016293	BsmtUnfSF
12	11.826834	BsmtFinSF1
13	8.395213	Remodel_age
14	6.621128	MoSold
15	3.674500	BsmtFullBath
16	2.851753	Fireplaces
17	2.815314	HalfBath
18	2.613935	LotArea
19	1.873705	WoodDeckSF
20	1.817381	OpenPorchSF
21	1.786236	MasVnrArea
22	1.741937	BsmtFinSF2
23	1.416396	EnclosedPorch
24	1.205339	BsmtHalfBath
25	1.187996	ScreenPorch
26	1.115006	LowQualFinSF
27	1.034145	3SsnPorch
28	1.025051	MiscVal

We can see that the variable 'YrSold' has the highest VIF.
We will remove the variables having VIF greater than 10.
We want to remove the variable for which the remaining variables explain more than 90% of the variation and thus we set the threshold to 10.
The value of threshold is completely experimental i.e. it depends on the business requirements.
One can choose the threshold other than 10.

In [84]:
```
# we will calculate the VIF for each numerical variable
for ind in range(len(df_numeric_features_vif.columns)):

    # create an empty dataframe
    vif = pd.DataFrame()

    # calculate VIF for each variable and create a column 'VIF_Factor' to store the values
    vif["VIF_Factor"] = [variance_inflation_factor(df_numeric_features_vif.values, i) for i in rang

    # create a column of feature names
    vif["Features"] = df_numeric_features_vif.columns

    # filter the variables with VIF greater than 10 and store it in a dataframe 'vif_more_than_10'
    # one can choose the threshold other than 10 (it depends on the business requirements)
    vif_more_than_10 = vif[vif['VIF_Factor'] > 10]

    # if dataframe 'vif_more_than_10' is not empty, then sort the dataframe by VIF values
    # if dataframe 'vif_more_than_10' is empty (i.e. all VIF <= 10), then print the dataframe 'vif
    # 'by' sorts the data using given variable(s)
    # 'ascending = False' sorts the data in descending order
    if(vif_more_than_10.empty == False):
        df_sorted = vif_more_than_10.sort_values(by = 'VIF_Factor', ascending = False)
    else:
        print(vif)
        break

    # if  dataframe 'df_sorted' is not empty, then drop the first entry in the column 'Features' fr
    # select the variable using 'iloc[]'
    # 'axis=1' drops the corresponding column
    #  else print the final dataframe 'vif' with all values after removal of variables with VIF les
    if (df_sorted.empty == False):
        df_numeric_features_vif = df_numeric_features_vif.drop(df_sorted.Features.iloc[0], axis=1)
    else:
        print(vif)
```

	VIF_Factor	Features
0	2.466251	LotArea
1	1.716802	MasVnrArea
2	5.588529	BsmtFinSF1
3	1.333163	BsmtFinSF2
4	4.463709	BsmtUnfSF
5	1.058491	LowQualFinSF
6	3.416672	BsmtFullBath
7	1.173941	BsmtHalfBath
8	1.771201	HalfBath
9	2.475114	Fireplaces
10	7.957664	GarageArea
11	1.828450	WoodDeckSF
12	1.735122	OpenPorchSF
13	1.367396	EnclosedPorch
14	1.026525	3SsnPorch
15	1.170999	ScreenPorch
16	1.014968	MiscVal
17	5.593054	MoSold
18	7.320595	Buiding_age
19	6.843799	Remodel_age

The above dataframe contains all the variables with VIF less than 10.

In order to build the model, we do the following

Now, let us build the model using the categorical variables and the numerical variables obtained from VIF.

1. Concatenate numerical and dummy encoded categorical variables

In [85]:
```
# lets consider the variables obtained from VIF
# use the dummy variables created previously
# concatenate the numerical and dummy encoded categorical variables
df_dummy = pd.concat([df_numeric_features_vif, dummy_encoded_variables], axis=1)

# display data with dummy variables
df_dummy.head()
```

Out[85]:

	LotArea	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	LowQualFinSF	BsmtFullBath	BsmtHalfBath	HalfBath	Fir
0	8450	196.0	706	0	150	0	1	0	1	
1	9600	0.0	978	0	284	0	0	1	0	
2	11250	162.0	486	0	434	0	1	0	1	
3	9550	0.0	216	0	540	0	1	0	0	
4	14260	350.0	655	0	490	0	1	0	1	

2. Split the data into train and test sets

In [86]:
```
# add the intercept column using 'add_constant()'
df_dummy = sm.add_constant(df_dummy)

# consider independent variables
# create a copy of 'df_dummy' and store it as X
X = df_dummy.copy()

# extract the target variable from the data set
y = df_property[['Property_Sale_Price','log_Property_Sale_Price']]

# split data into train data and test data
# what proportion of data should be included in test data is specified using 'test_size'
# set 'random_state' to get the same data each time the code is executed
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 1)

# check the dimensions of the train & test subset for
# print dimension of predictors train set
print("The shape of X_train is:",X_train.shape)

# print dimension of predictors test set
print("The shape of X_test is:",X_test.shape)

# print dimension of target train set
print("The shape of y_train is:",y_train.shape)

# print dimension of target test set
print("The shape of y_test is:",y_test.shape)
```

```
The shape of X_train is: (1015, 272)
The shape of X_test is: (436, 272)
The shape of y_train is: (1015, 2)
The shape of y_test is: (436, 2)
```

3. Build model using sm.OLS().fit()

In [87]:
```
# build a full model using OLS()
# consider the target variable log_Property_Sale_Price
# use fit() to fit the model on train data
linreg_vif_model = sm.OLS(y_train['log_Property_Sale_Price'], X_train).fit()

# print the summary output
print(linreg_vif_model.summary())
```

```
SaleType_New                 0.2269      0.104      2.183      0.029       0.023       0.431
SaleType_Oth                 0.2158      0.093      2.333      0.020       0.034       0.397
SaleType_WD                 -0.0407      0.029     -1.403      0.161      -0.098       0.016
SaleCondition_AdjLand        0.2428      0.090      2.711      0.007       0.067       0.419
SaleCondition_Alloca         0.1594      0.052      3.073      0.002       0.058       0.261
SaleCondition_Family         0.0024      0.041      0.060      0.953      -0.078       0.082
SaleCondition_Normal         0.0667      0.017      3.858      0.000       0.033       0.101
SaleCondition_Partial       -0.1552      0.100     -1.551      0.121      -0.352       0.041
==============================================================================
Omnibus:                      169.966   Durbin-Watson:                   1.946
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1156.308
Skew:                          -0.572   Prob(JB):                    8.15e-252
Kurtosis:                       8.102   Cond. No.                     5.02e+19
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 8.19e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```


This model explains around 93% of the variation in dependent variable log_Property_Sale_Price.
The Condition Number 5.02e+19 suggests that there is severe multicollinearity in the data.
The Durbin-Watson test statistics is 1.946 and indicates that there is no autocorrelation.

4. Predict the values using test set

In [88]:
```
# predict the 'log_Property_Sale_Price' using predict()
linreg_vif_model_predictions = linreg_vif_model.predict(X_test)
```

Note that the predicted values are log transformed Property_Sale_Price. In order to get Property_Sale_Price values, we take the antilog of these predicted values by using the function np.exp()

In [89]:
```
# take the exponential of predictions using np.exp()
predicted_Property_Sale_Price = np.exp(linreg_vif_model_predictions)

# extract the 'Property_Sale_Price' values from the test data
actual_Property_Sale_Price = y_test['Property_Sale_Price']
```

5. Compute accuracy measures

Now we calculate accuray measures Root-mean-square-error (RMSE), R-squared and Adjusted R-squared.

In [90]:
```
# calculate rmse using rmse()
linreg_vif_model_rmse = rmse(actual_Property_Sale_Price, predicted_Property_Sale_Price)

# calculate R-squared using rsquared
linreg_vif_model_rsquared = linreg_vif_model.rsquared

# calculate Adjusted R-Squared using rsquared_adj
linreg_vif_model_rsquared_adj = linreg_vif_model.rsquared_adj
```

6. Tabulate the results

In [91]:
```
# append the accuracy scores to the table
# compile the required information
linreg_vif_model_metrics = pd.Series({'Model': "Linreg with VIF",
                                      'RMSE': linreg_vif_model_rmse,
                                      'R-Squared': linreg_vif_model_rsquared,
                                      'Adj. R-Squared': linreg_vif_model_rsquared_adj})

# append our result table using append()
# ignore_index=True: does not use the index labels
# python can only append a Series if ignore_index=True or if the Series has a name
result_tabulation = result_tabulation.append(linreg_vif_model_metrics, ignore_index = True)

# print the result table
result_tabulation
```

Out[91]:

	Model	RMSE	R-Squared	Adj. R-Squared
0	Linreg full model with log of target variable	37726.465264	0.952066	0.935193
1	Linreg full model without log of target variable	54970.829645	0.946898	0.928206
2	Linreg with new feature (TotalSF)	37781.679484	0.952059	0.935271
3	Linreg with new features (Building_age and Rem...	38063.992077	0.952059	0.935271
4	Linreg with VIF	32980.577734	0.937600	0.916745

From the above table we can see that the linear regression with new features has the lowest RMSE value. Thus, it can be concluded that the linear regression model with new features can be used to predict the price of the house.

The End