# Data Preprocessing & Regression Model

November 1, 2024

[4]:
```
# required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler, MinMaxScaler
import scipy.stats as stats
from sklearn.model_selection import train_test_split
from scipy.stats import norm
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

## 1 I- Data Preprocessing

#### 1.0.1 1- Loading the data

[5]:
```
# Load the Excel file
file_path = "C:\\Users\\elmou\\OneDrive\\Desktop\\bcg␣
↪assignement\\Take-home-case-Data-analyst.xlsx"
sheet_name = "data"

# Read the data into a DataFrame
df = pd.read_excel(file_path, sheet_name=sheet_name)

# Check the data
df.head()
```

[5]:
```
     id  sub_ms_class zoning_ms  frontge_lot  area_lot streetname alleyname  \
0   128            45        RM         55.0      4388       Pave       NaN
1   456            20        RL         80.0      9600       Pave       NaN
2  1324            30        RL         50.0      5330       Pave       NaN
3   218            70        RM         57.0      9906       Pave      Grvl
4  1182           120        RM         64.0      5587       Pave       NaN

  shape_lot contour_land    util  ... poolarea poolqc fence miscfeature  \
```

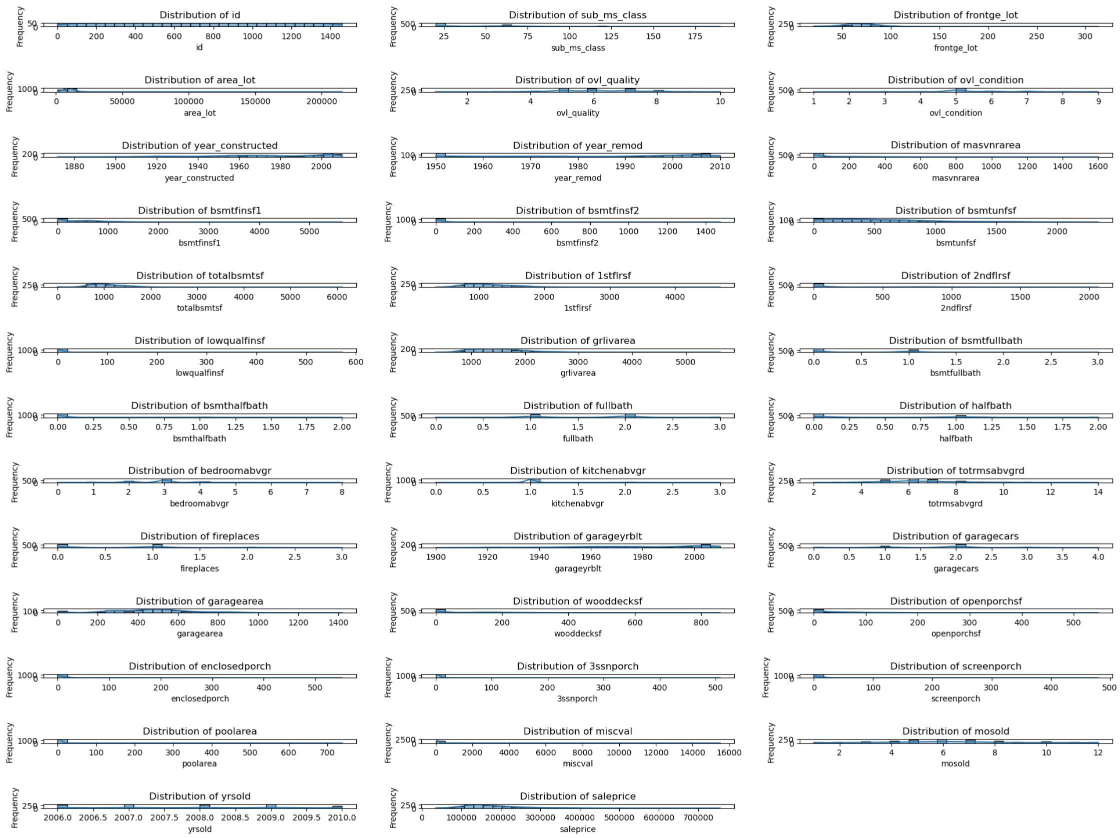
```
0        IR1          Bnk   AllPub  ...        0    NaN   NaN          NaN
1        Reg          Lvl   AllPub  ...        0    NaN   NaN          NaN
2        Reg          HLS   AllPub  ...        0    NaN   NaN          NaN
3        Reg          Lvl   AllPub  ...        0    NaN   NaN          NaN
4        IR1          HLS   AllPub  ...        0    NaN   NaN          NaN

  miscval mosold yrsold  saletype  salecondition  saleprice
0       0      6   2007        WD         Normal      87000
1       0      9   2007        WD         Normal     175500
2       0     12   2009        WD         Normal      82500
3       0      9   2006        WD         Family     107000
4       0     11   2008       New        Partial     392500

[5 rows x 81 columns]
```

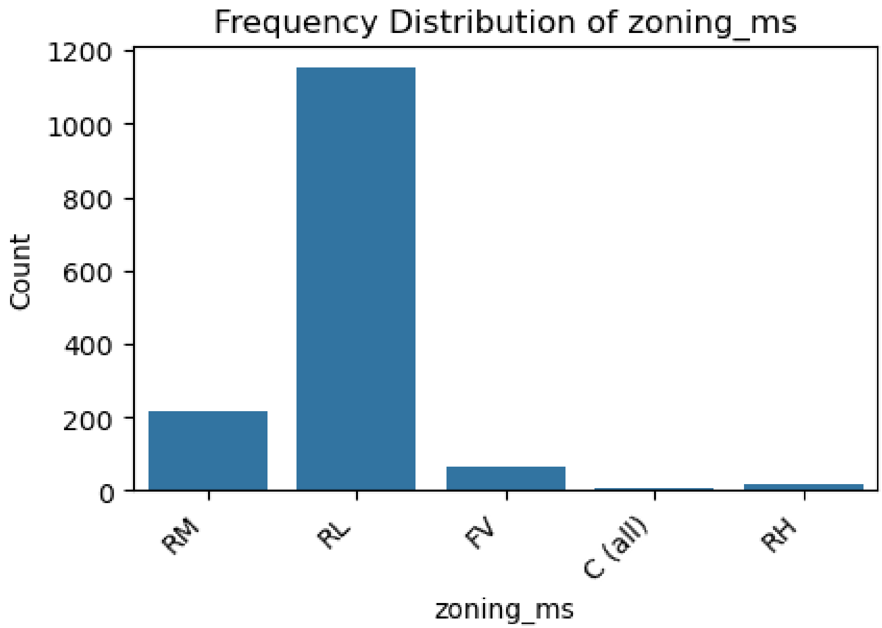
[8]:

```python
print("Data Types for Each Column:")
print(df.dtypes)

# Identify numeric columns and plot histograms
numeric_columns = df.select_dtypes(include=['int64', 'float64']).columns

plt.figure(figsize=(20, 15))  # Larger figure for visibility
n_rows = (len(numeric_columns) + 2) // 3  # Calculate number of rows needed

for i, column in enumerate(numeric_columns, 1):
    plt.subplot(n_rows, 3, i)
    sns.histplot(df[column], kde=True, bins=30)  # Plot histogram with KDE
    plt.title(f'Distribution of {column}')
    plt.xlabel(column)
    plt.ylabel('Frequency')

plt.tight_layout(pad=3.0)  # Adjust layout
plt.show()

# Identify categorical columns and plot count distributions
categorical_columns = df.select_dtypes(include=['object']).columns

for column in categorical_columns:
    plt.figure(figsize=(5, 3))
    sns.countplot(data=df, x=column)
    plt.title(f'Frequency Distribution of {column}')
    plt.xticks(rotation=45, ha='right')  # Rotate x-ticks
    plt.xlabel(column)
    plt.ylabel('Count')
    plt.show()
```

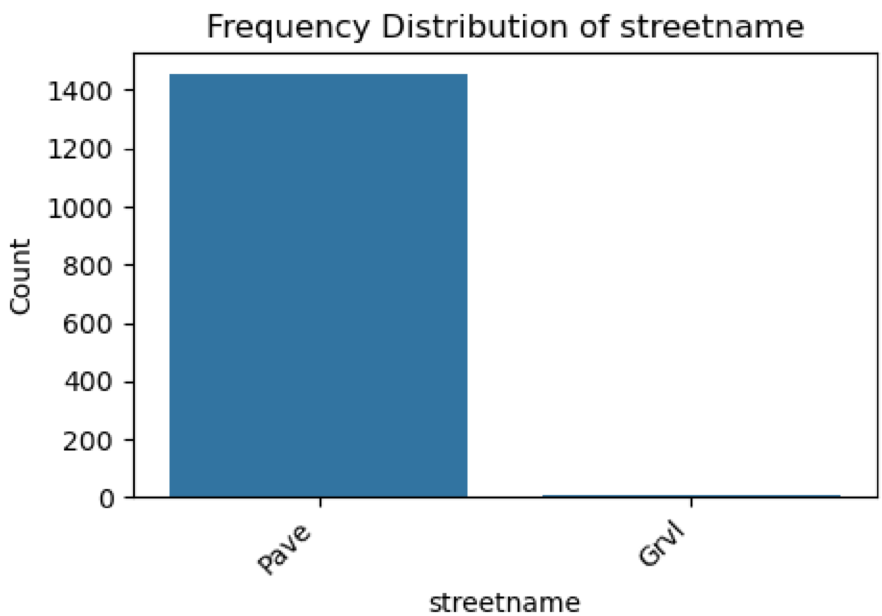
```
Data Types for Each Column:
id                 int64
```

```
sub_ms_class       int64
zoning_ms         object
frontge_lot      float64
area_lot           int64
                   ...
mosold             int64
yrsold             int64
saletype          object
salecondition     object
saleprice          int64
Length: 81, dtype: object
```

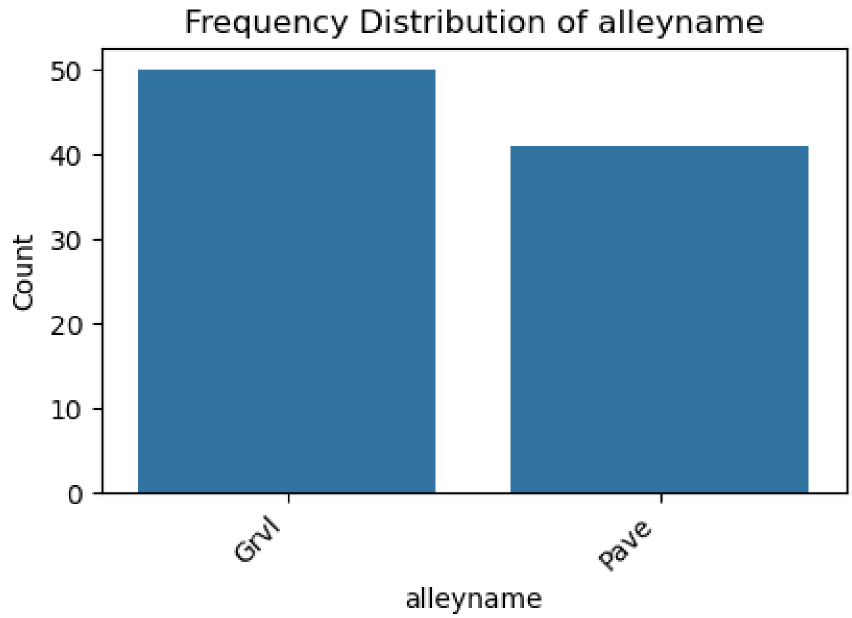


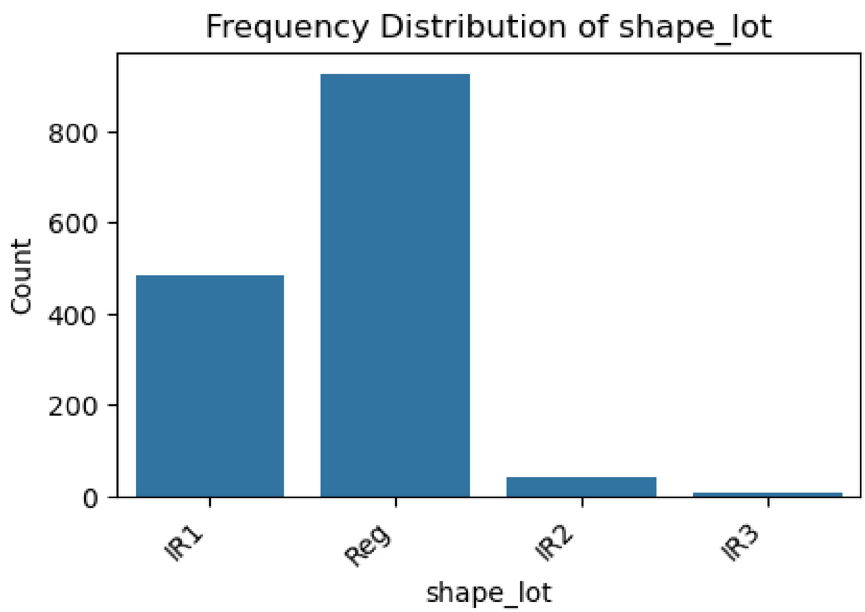


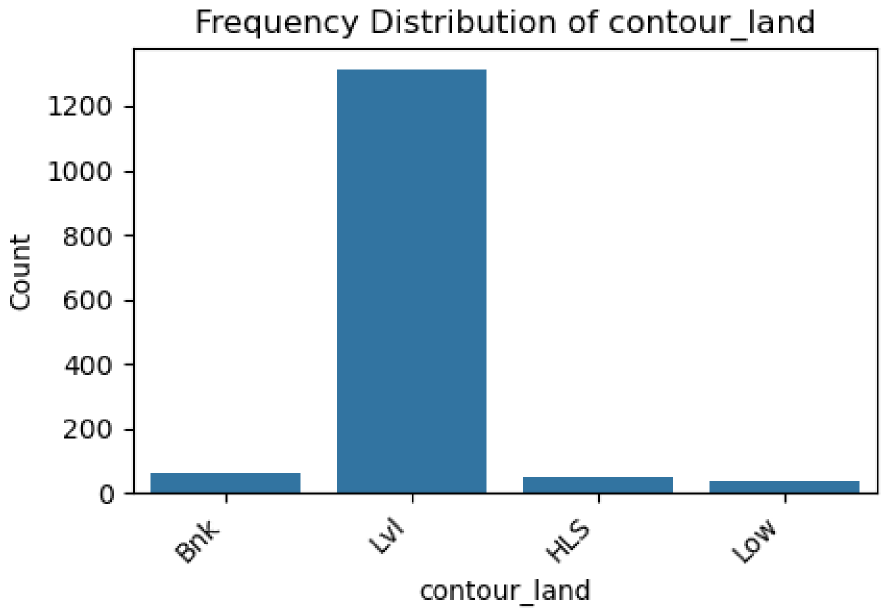
Frequency Distribution of zoning_ms
Count
0
200
400
600
800
1000
1200
RM
RL
FV
C (all)
RH
zoning_ms

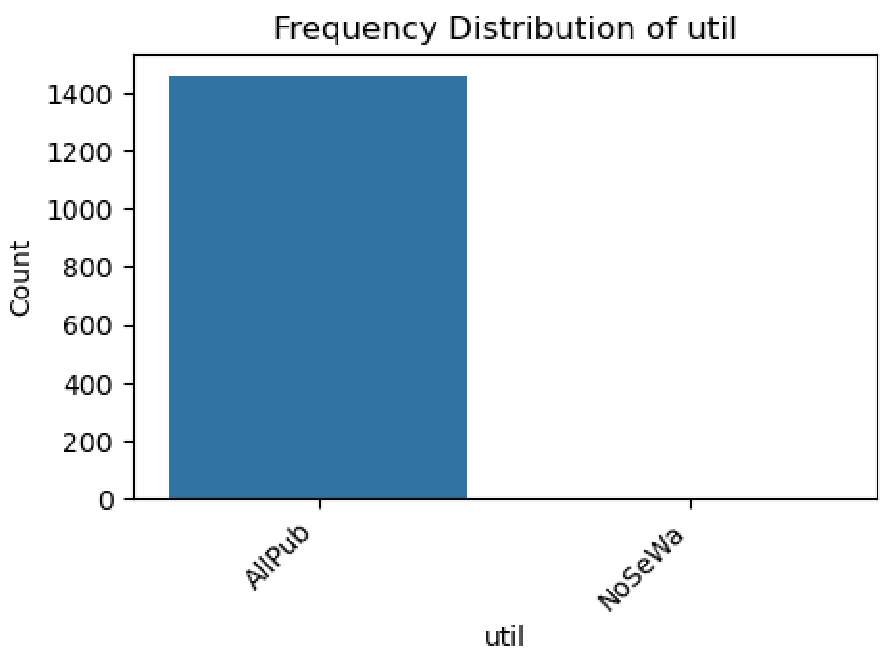



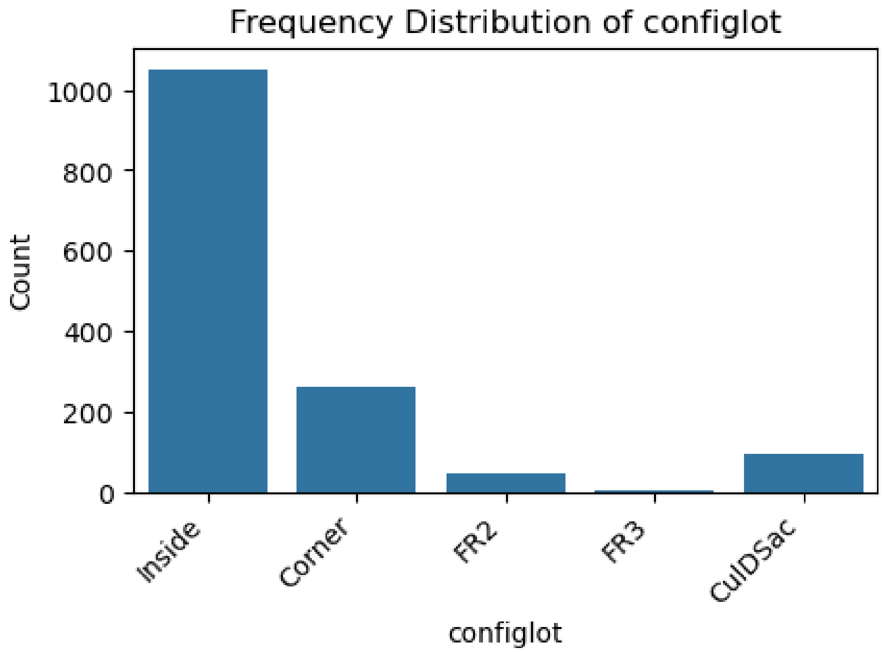
Frequency Distribution of streetname
Count
0
200
400
600
800
1000
1200
1400
Pave
Grvl
streetname

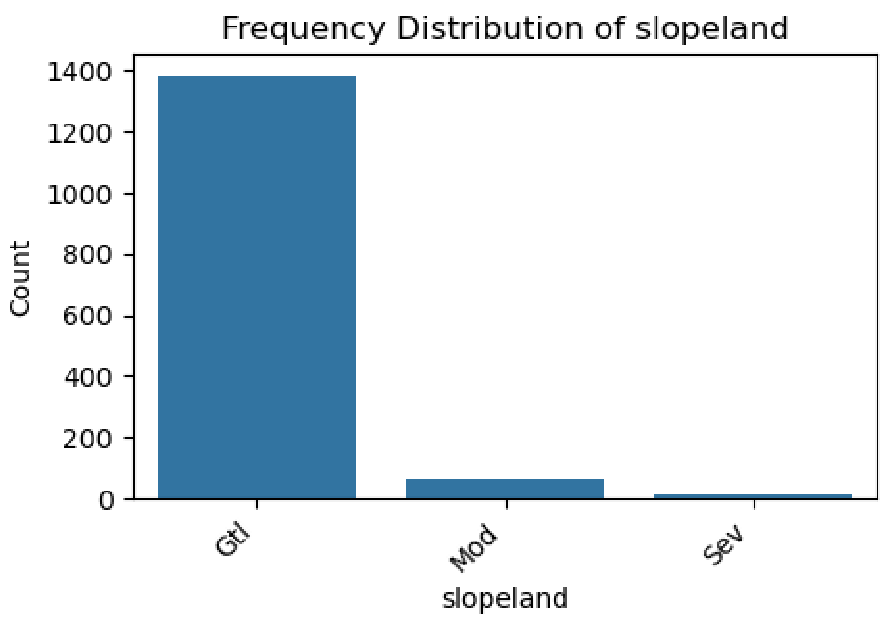

Frequency Distribution of alleyname
50
40
30
20
10
0
Count
Grvl
Pave
alleyname

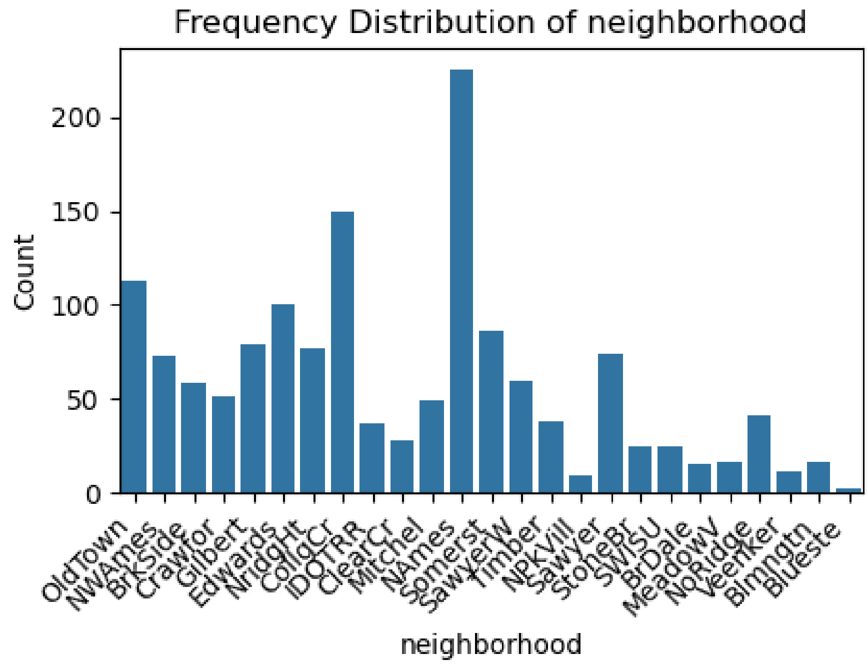

Frequency Distribution of shape_lot
800
600
400
200
0
Count
IR1
Reg
IR2
IR3
shape_lot

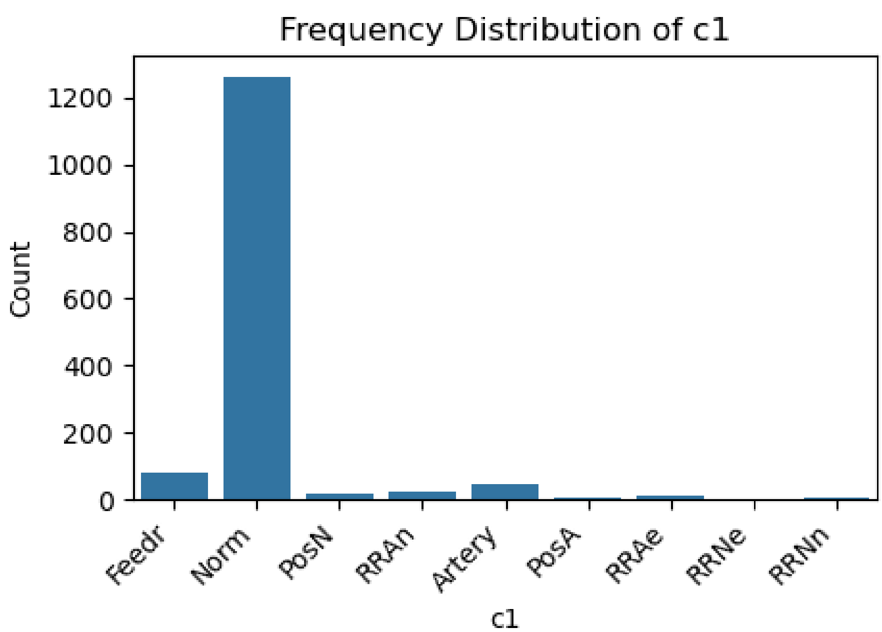

Frequency Distribution of contour_land
Count
1200
1000
800
600
400
200
0
Bnk
Lvl
HLS
Low
contour_land

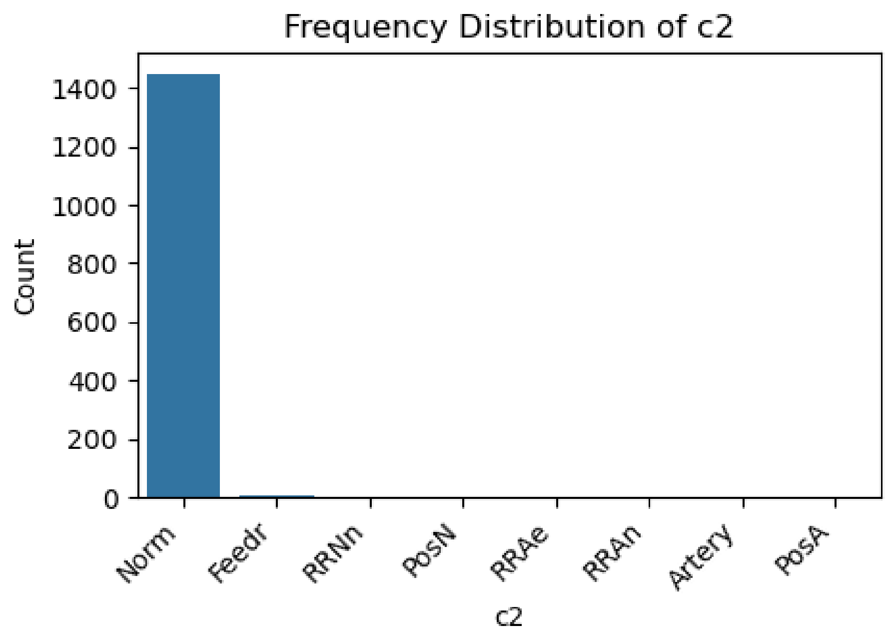

Frequency Distribution of util
Count
1400
1200
1000
800
600
400
200
0
AllPub
NoSeWa
util

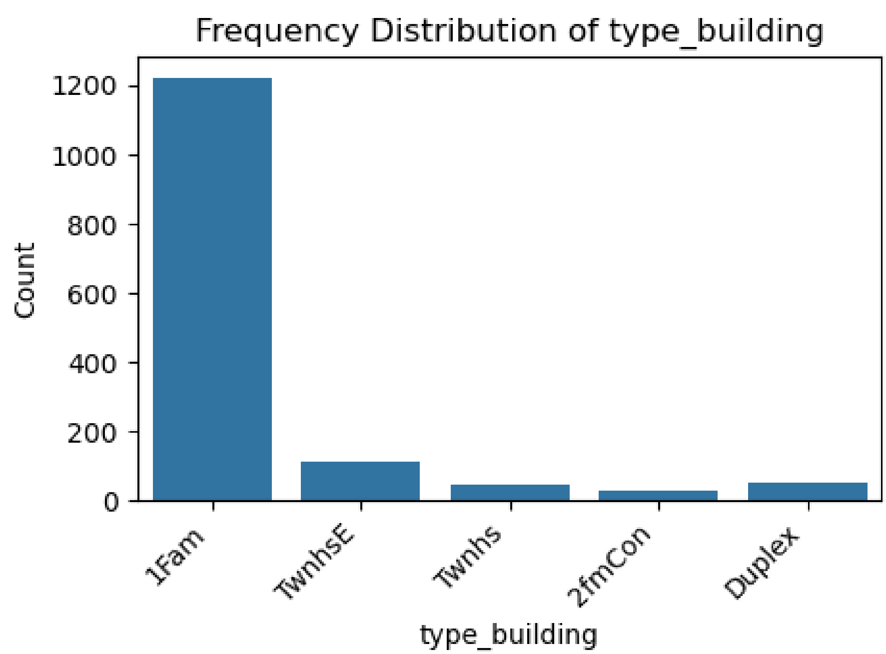

Frequency Distribution of configlot
Count
1000
800
600
400
200
0
Inside
Corner
FR2
FR3
CulDSac
configlot

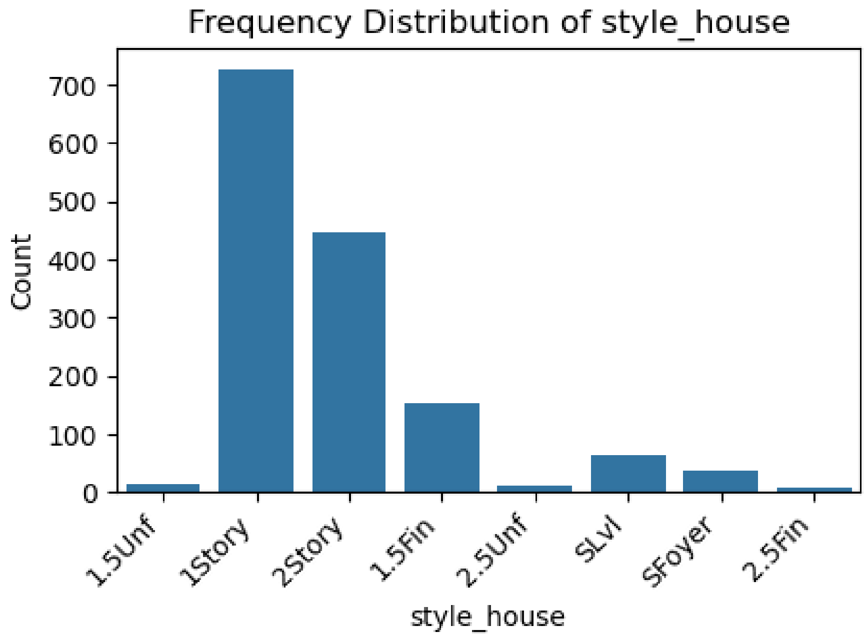

Frequency Distribution of slopeland
Count
1400
1200
1000
800
600
400
200
0
Gtl
Mod
Sev
slopeland

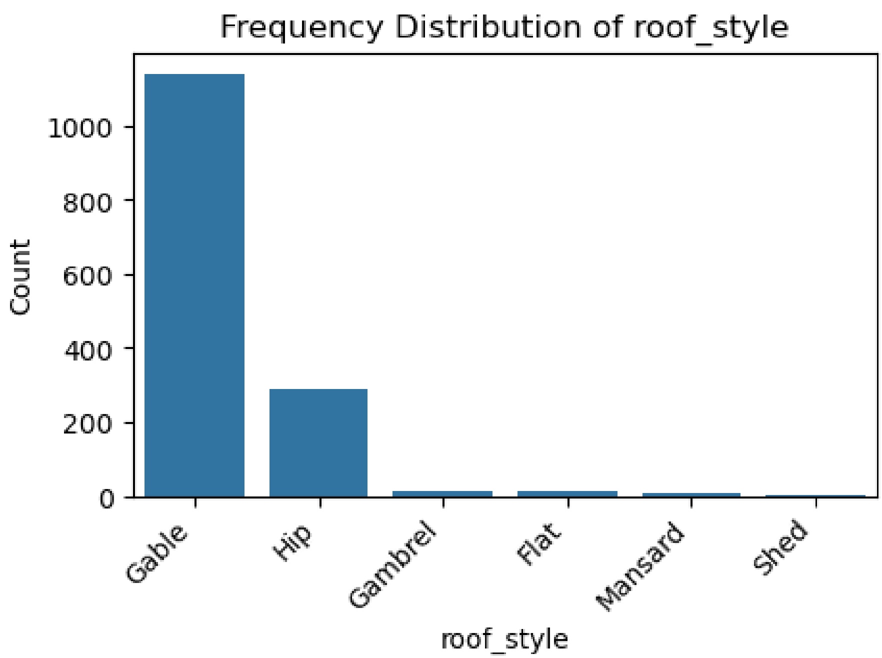

Frequency Distribution of neighborhood
Count
0
50
100
150
200
OldTown
NWAmes
BrkSide
Crawfor
Gilbert
Edwards
NridgHt
CollgCr
IDOTRR
ClearCr
Mitchel
NAmes
Somerst
SawyerW
Timber
NPkVill
Sawyer
StoneBr
SWISU
BrDale
MeadowV
NoRidge
Veenker
Blmngtn
Blueste
neighborhood

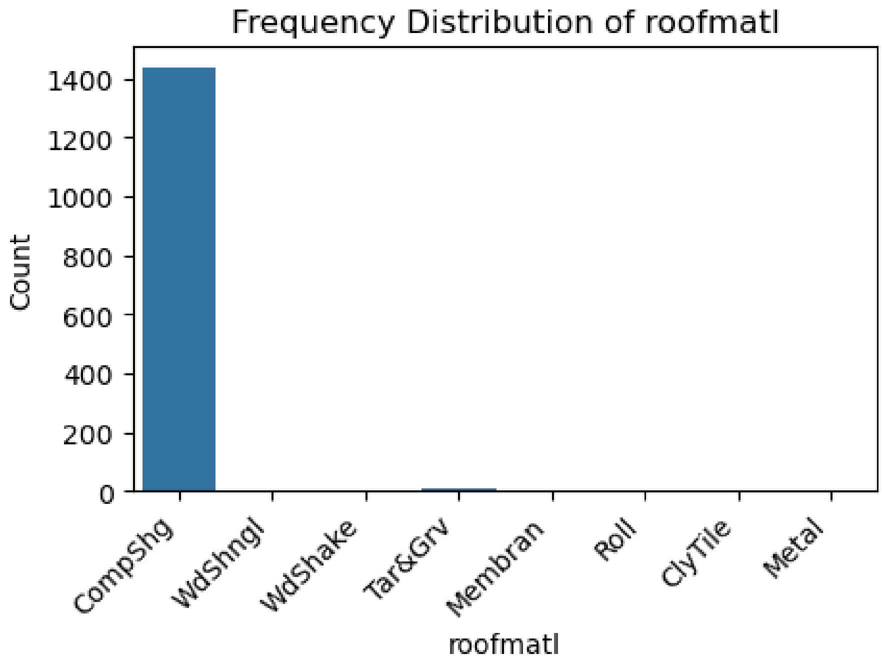

Frequency Distribution of c1
Count
0
200
400
600
800
1000
1200
Feedr
Norm
PosN
RRAn
Artery
PosA
RRAe
RRNe
RRNn
c1

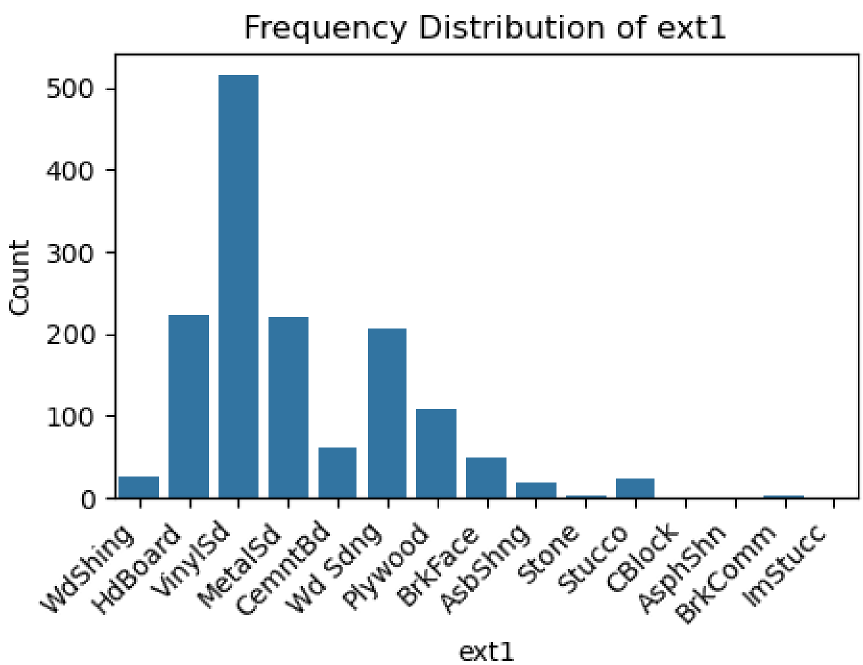

Frequency Distribution of c2
Count
0
200
400
600
800
1000
1200
1400
Norm
Feedr
RRNn
PosN
RRAe
RRAn
Artery
PosA
c2

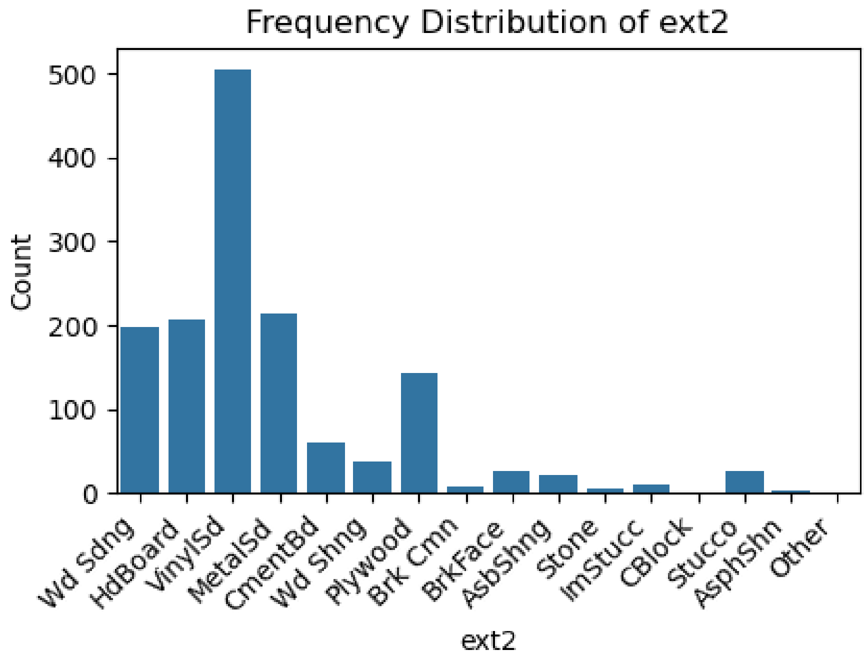

Frequency Distribution of type_building
Count
0
200
400
600
800
1000
1200
1Fam
TwnhsE
Twnhs
2fmCon
Duplex
type_building


Frequency Distribution of style_house
Count
0
100
200
300
400
500
600
700
1.5Unf
1Story
2Story
1.5Fin
2.5Unf
SLvl
SFoyer
2.5Fin
style_house

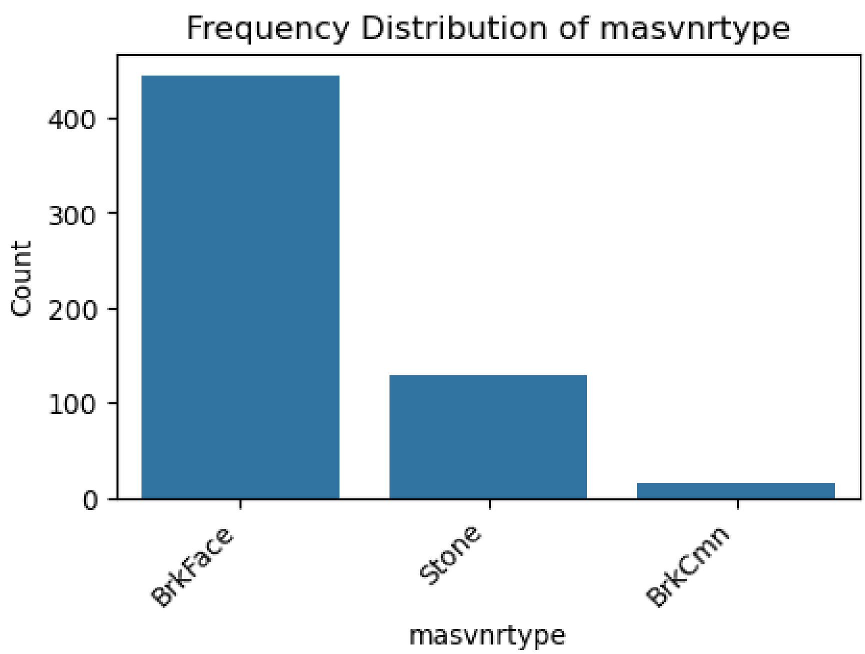

Frequency Distribution of roof_style
Count
0
200
400
600
800
1000
Gable
Hip
Gambrel
Flat
Mansard
Shed
roof_style


Frequency Distribution of roofmatl
Count
0
200
400
600
800
1000
1200
1400
CompShg
WdShngl
WdShake
Tar&Grv
Membran
Roll
ClyTile
Metal
roofmatl

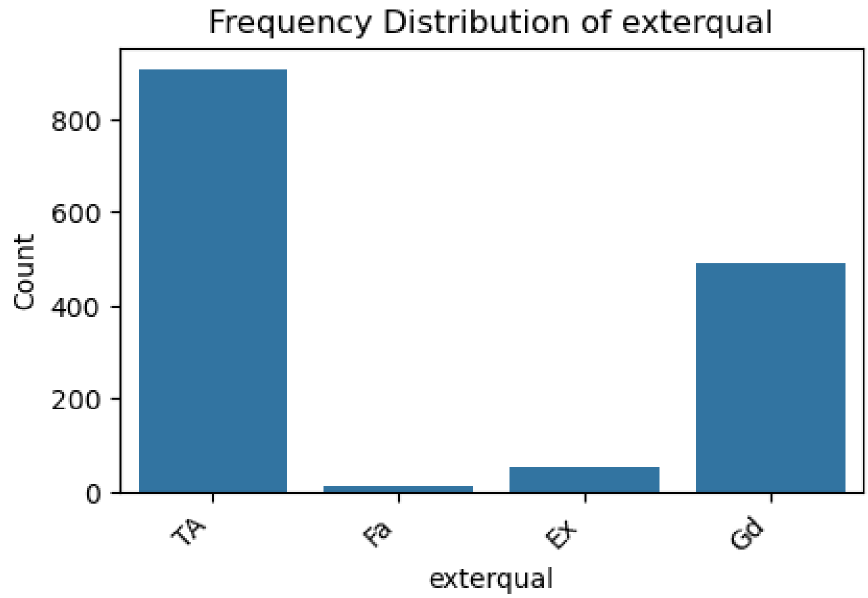

Frequency Distribution of ext1
Count
0
100
200
300
400
500
WdShing
HdBoard
VinylSd
MetalSd
CemntBd
Wd Sdng
Plywood
BrkFace
AsbShng
Stone
Stucco
CBlock
AsphShn
BrkComm
ImStucc
ext1



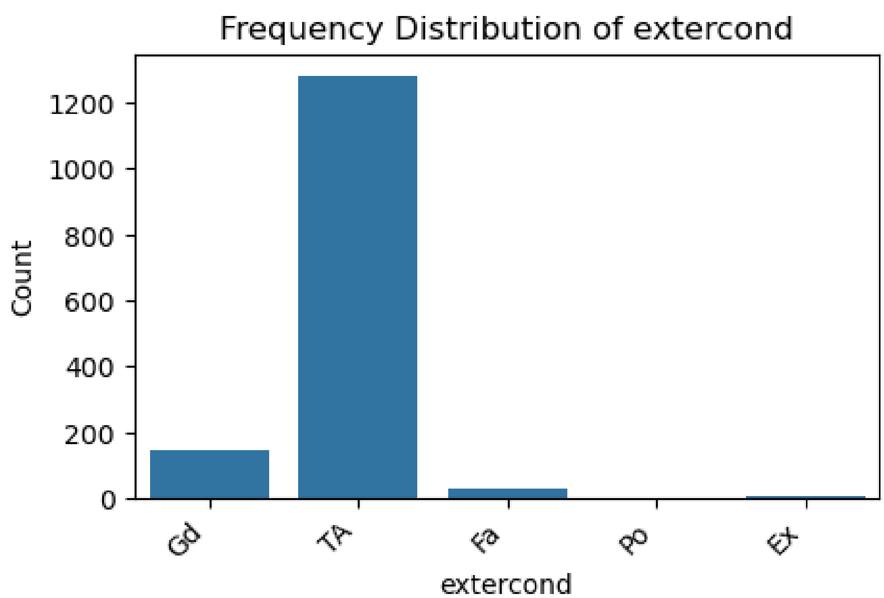
Frequency Distribution of ext2
Count
0
100
200
300
400
500
Wd Sdng
HdBoard
VinylSd
MetalSd
CmentBd
Wd Shng
Plywood
Brk Cmn
BrkFace
AsbShng
Stone
ImStucc
CBlock
Stucco
AsphShn
Other
ext2

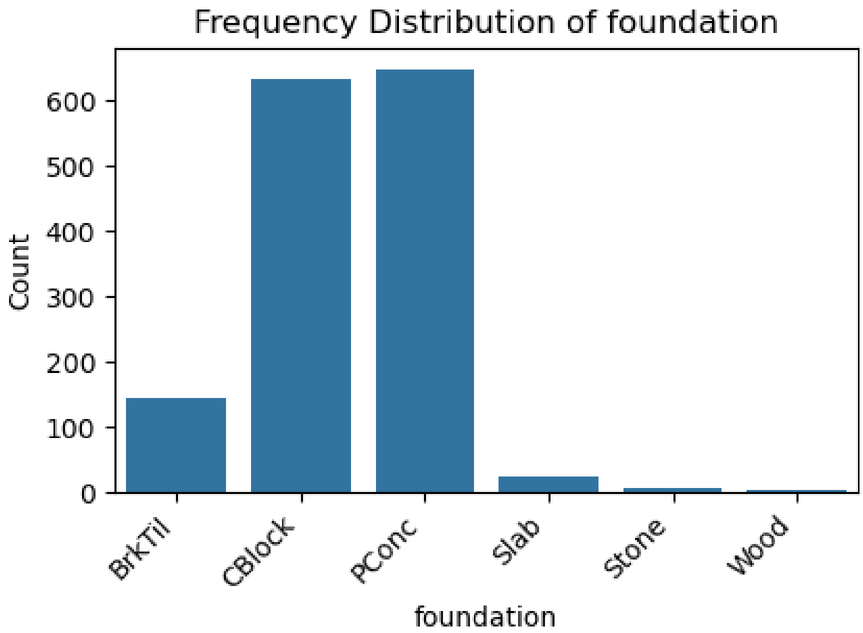
Frequency Distribution of masvnrtype
Count
0
100
200
300
400
BrkFace
Stone
BrkCmn
masvnrtype

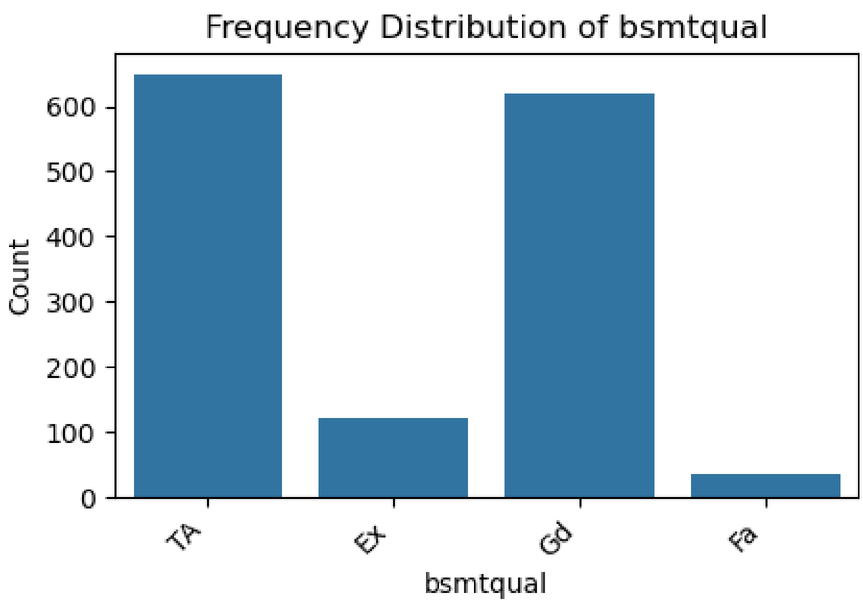


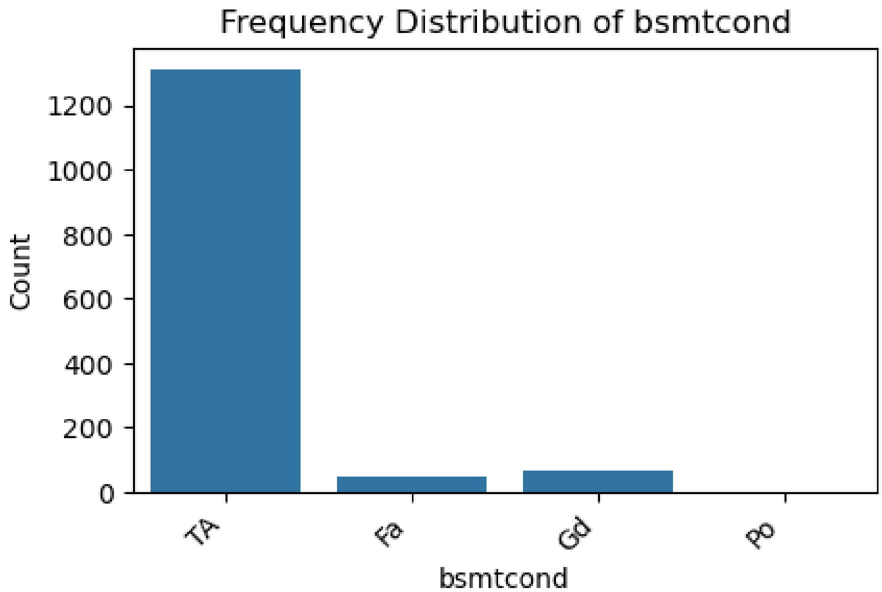
Frequency Distribution of exterqual
Count
0
200
400
600
800
TA
Fa
Ex
Gd
exterqual

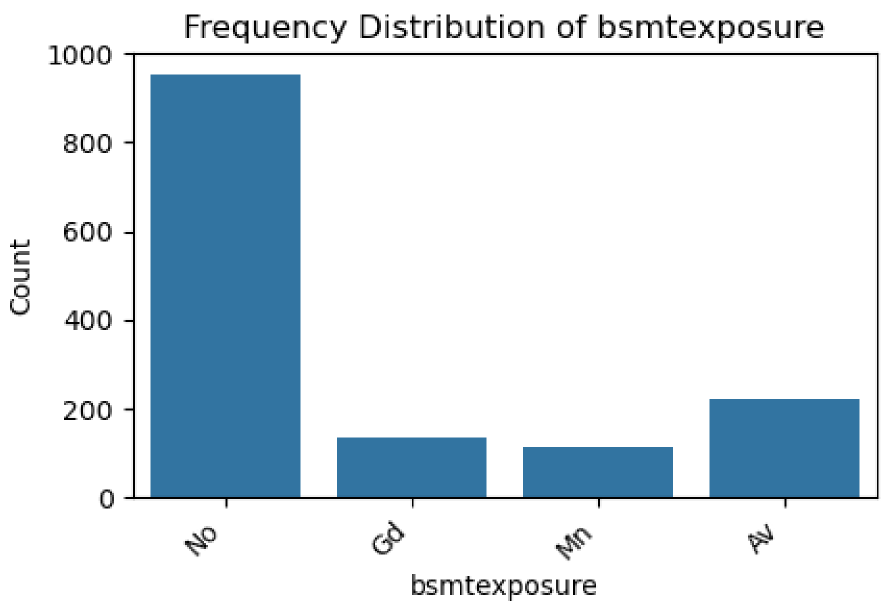



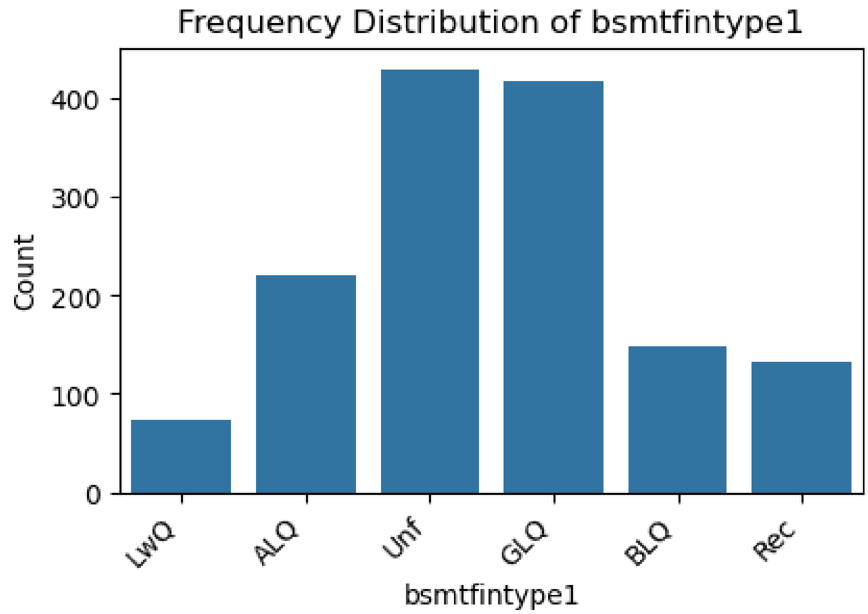
Frequency Distribution of extercond
Count
0
200
400
600
800
1000
1200
Gd
TA
Fa
Po
Ex
extercond

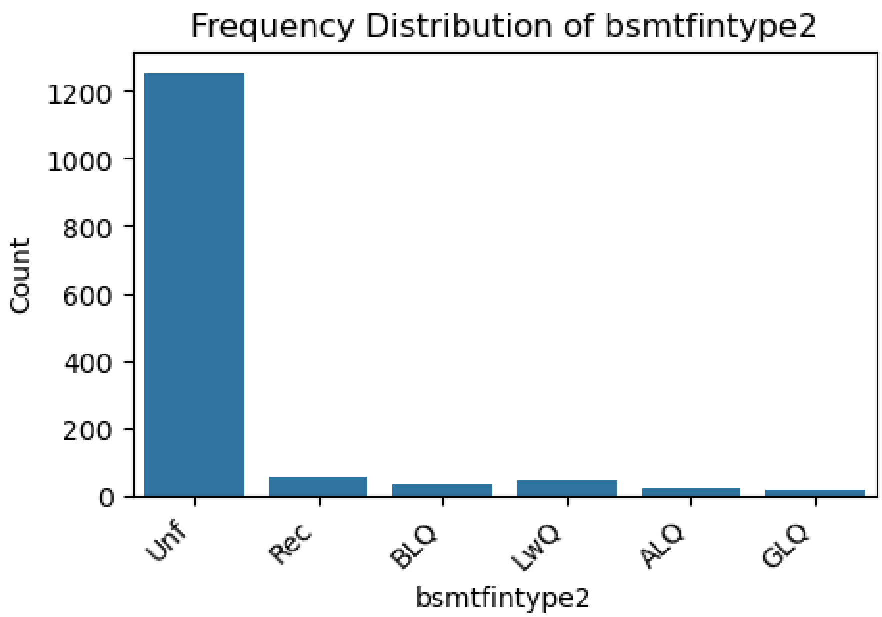

Frequency Distribution of foundation
Count
0
100
200
300
400
500
600
BrkTil
CBlock
PConc
Slab
Stone
Wood
foundation

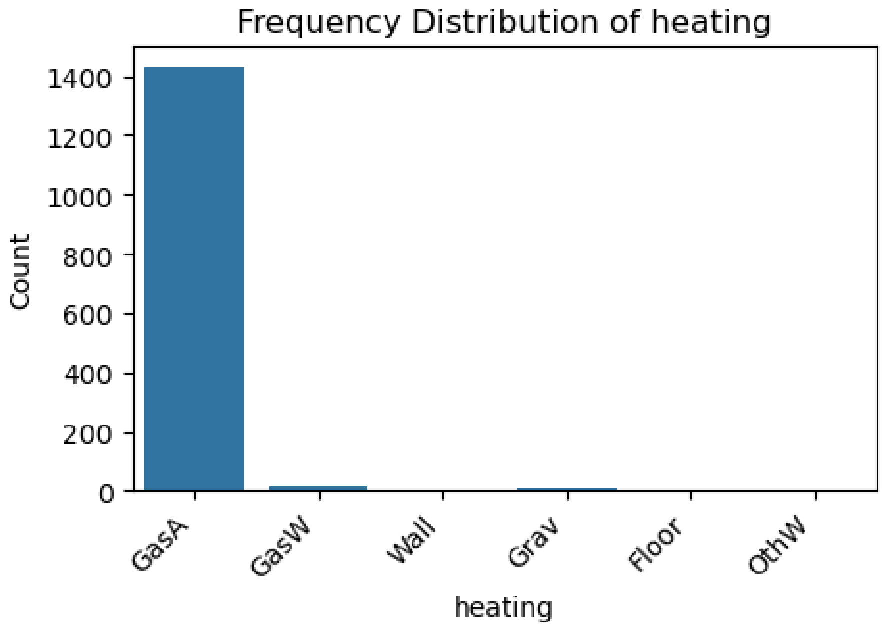

Frequency Distribution of bsmtqual
Count
0
100
200
300
400
500
600
TA
Ex
Gd
Fa
bsmtqual

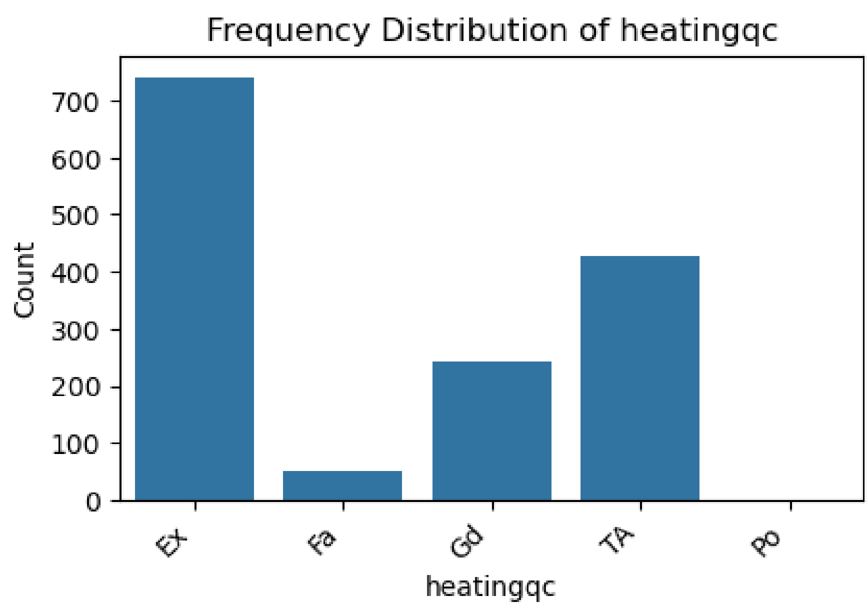

Frequency Distribution of bsmtcond
Count
1200
1000
800
600
400
200
0
TA
Fa
Gd
Po
bsmtcond

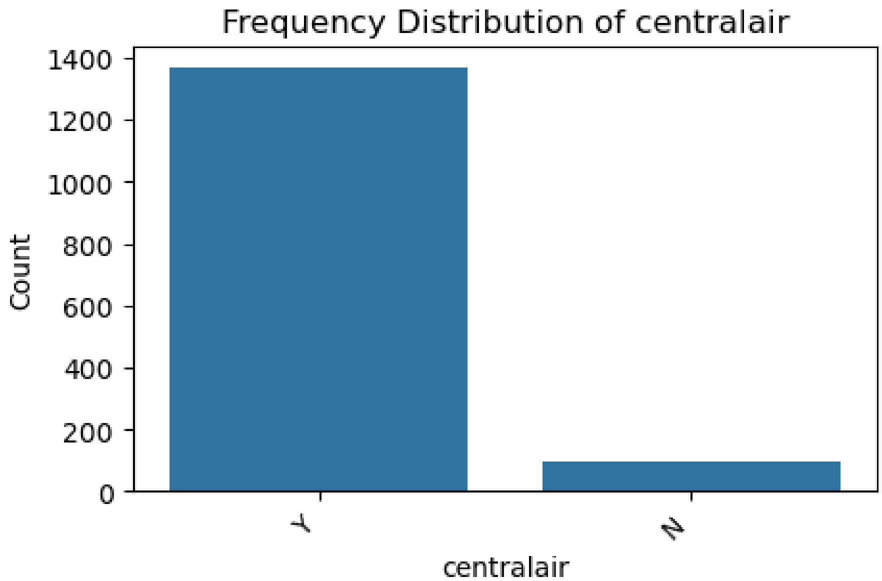

Frequency Distribution of bsmtexposure
Count
1000
800
600
400
200
0
No
Gd
Mn
Av
bsmtexposure

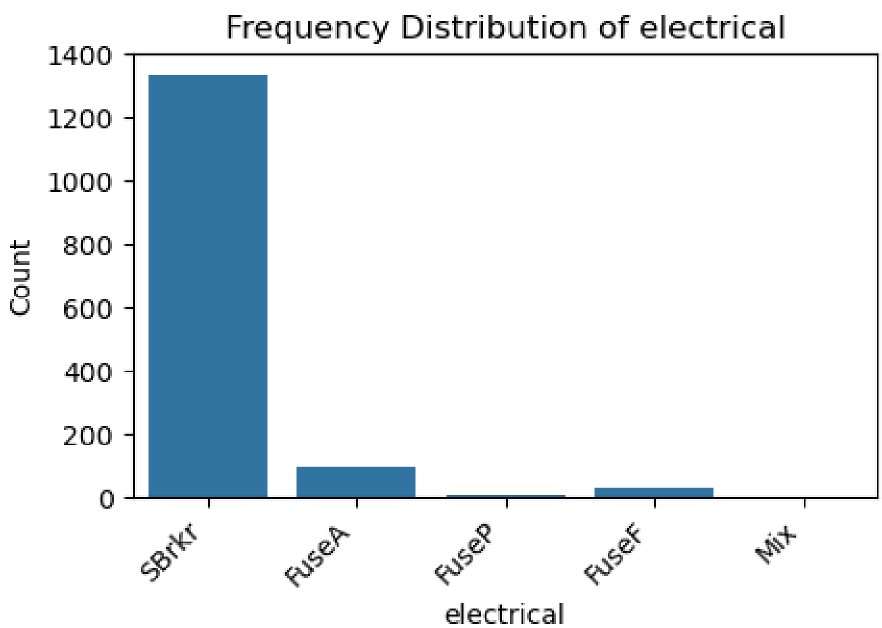

Frequency Distribution of bsmtfintype1
Count
0
100
200
300
400
LwQ
ALQ
Unf
GLQ
BLQ
Rec
bsmtfintype1

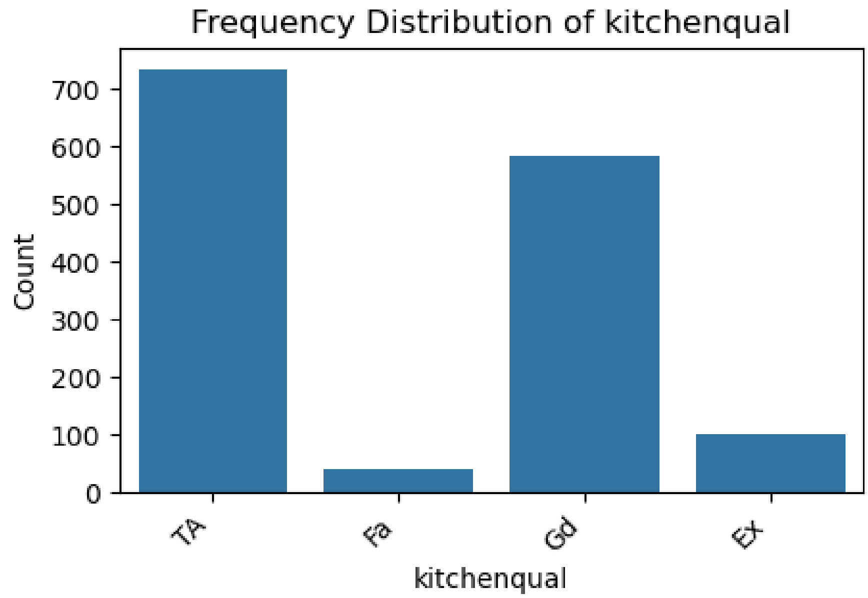

Frequency Distribution of bsmtfintype2
Count
0
200
400
600
800
1000
1200
Unf
Rec
BLQ
LwQ
ALQ
GLQ
bsmtfintype2

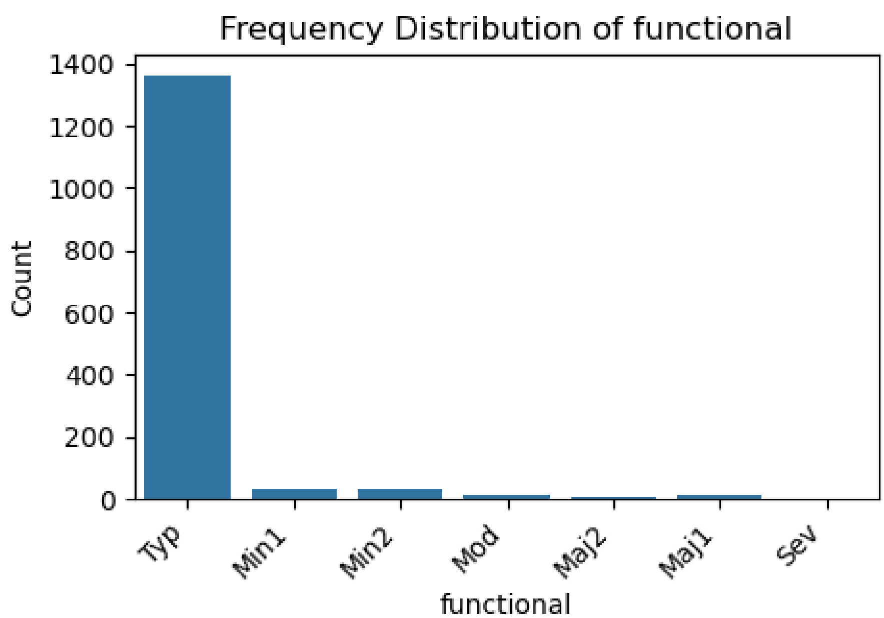

Frequency Distribution of heating
1400
1200
1000
800
600
400
200
0
Count
GasA
GasW
Wall
Grav
Floor
OthW
heating

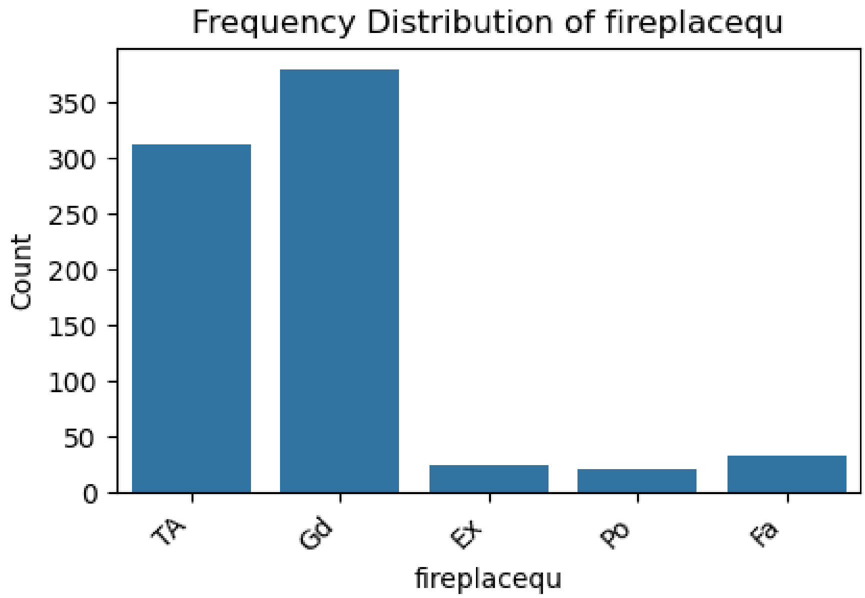

Frequency Distribution of heatingqc
700
600
500
400
300
200
100
0
Count
Ex
Fa
Gd
TA
Po
heatingqc

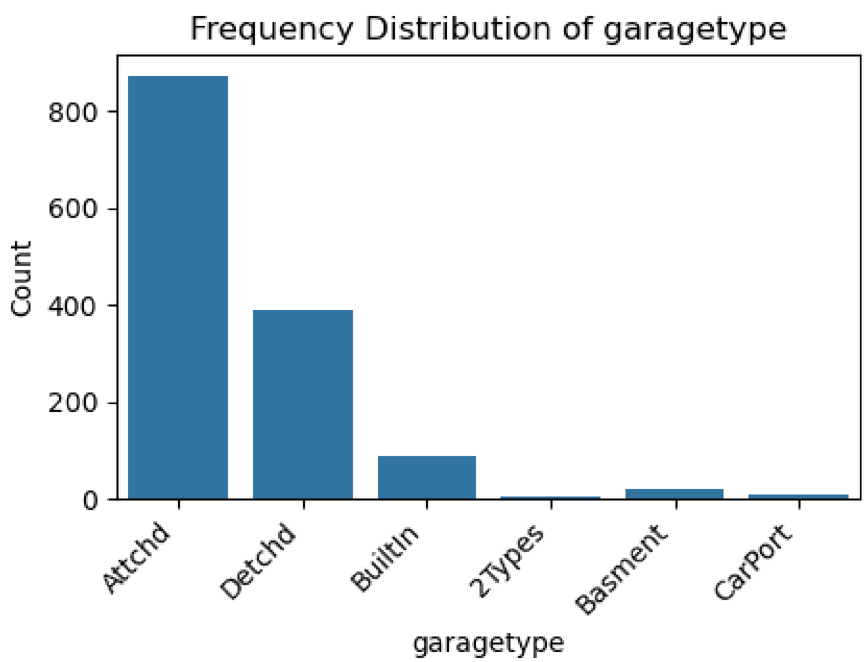

Frequency Distribution of centralair
Count
1400
1200
1000
800
600
400
200
0
Y
N
centralair

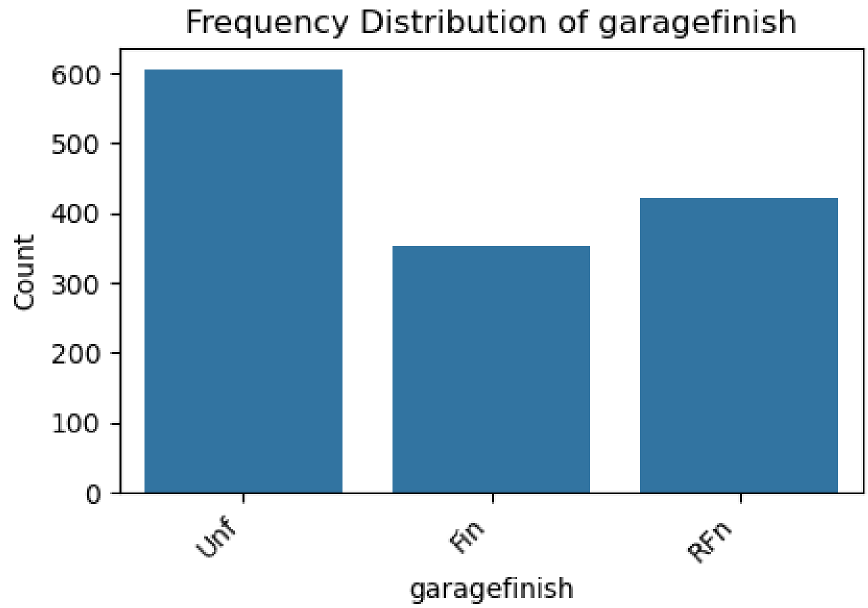

Frequency Distribution of electrical
Count
1400
1200
1000
800
600
400
200
0
SBrkr
FuseA
FuseP
FuseF
Mix
electrical

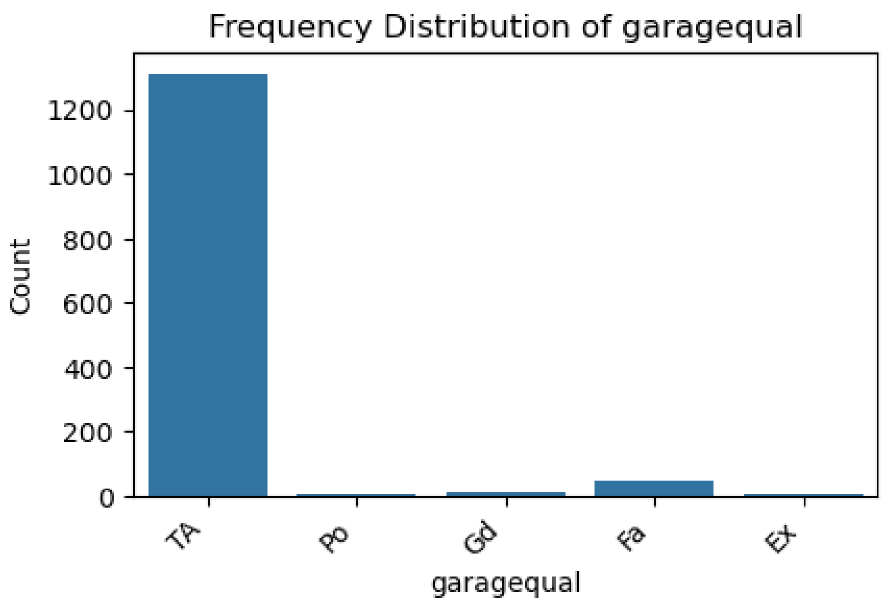

Frequency Distribution of kitchenqual
Count
0
100
200
300
400
500
600
700
TA
Fa
Gd
Ex
kitchenqual

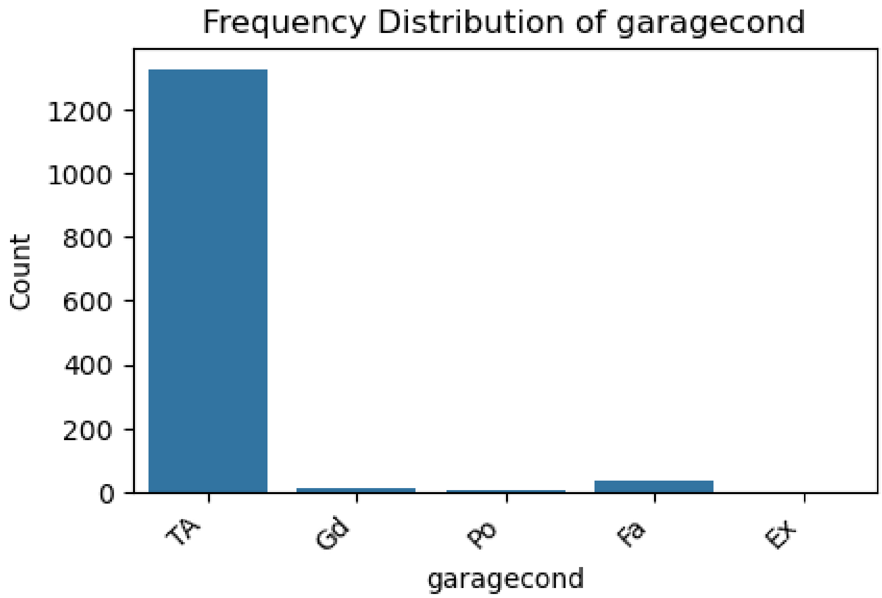

Frequency Distribution of functional
Count
0
200
400
600
800
1000
1200
1400
Typ
Min1
Min2
Mod
Maj2
Maj1
Sev
functional

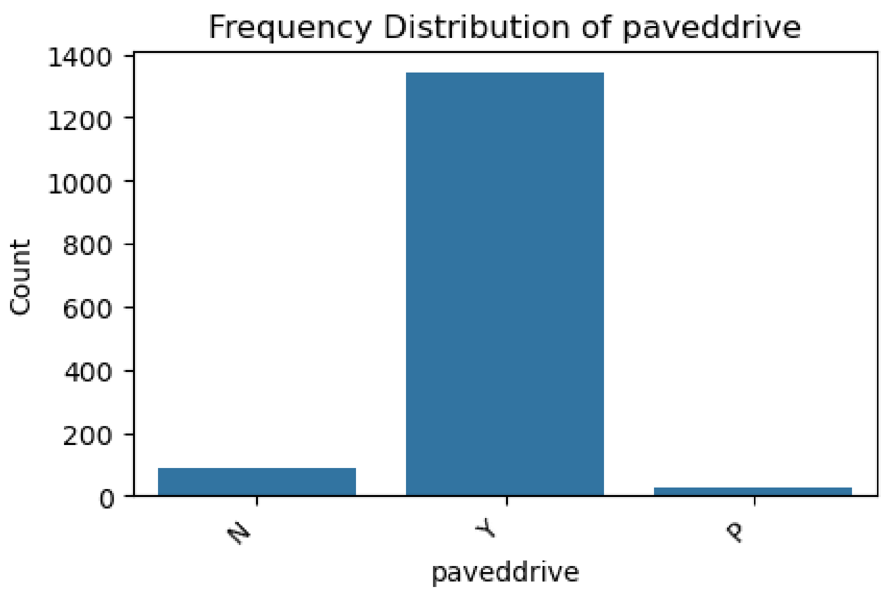

Frequency Distribution of fireplacequ
Count
350
300
250
200
150
100
50
0
TA
Gd
Ex
Po
Fa
fireplacequ

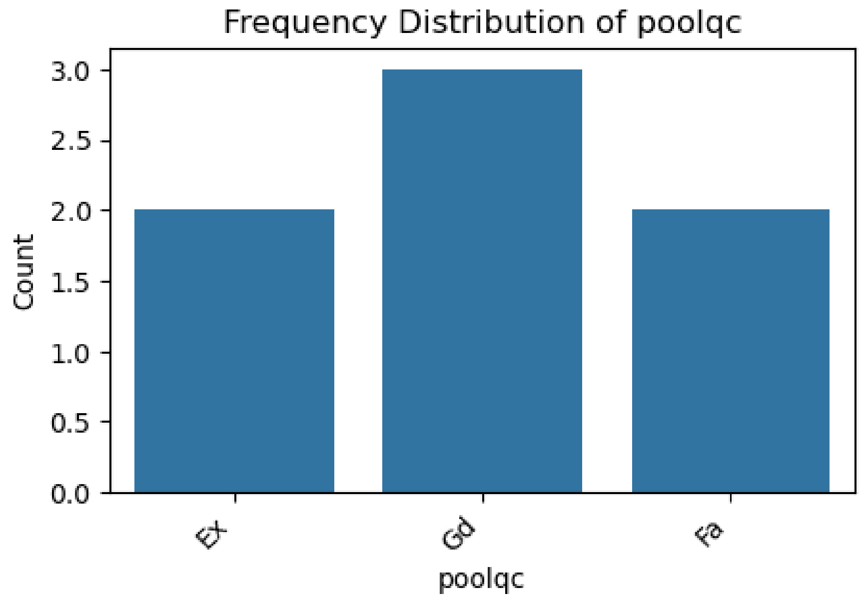

Frequency Distribution of garagetype
Count
800
600
400
200
0
Attchd
Detchd
BuiltIn
2Types
Basment
CarPort
garagetype

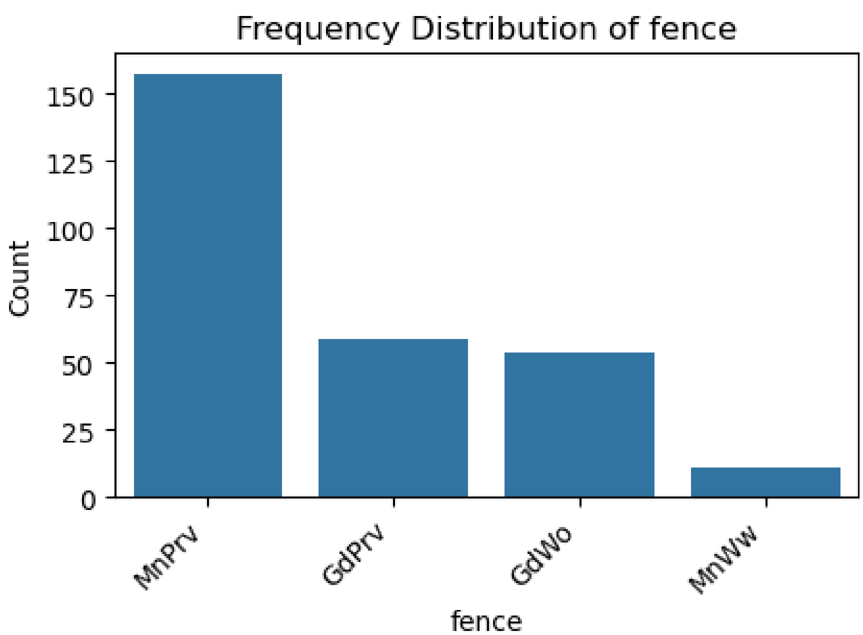

Frequency Distribution of garagefinish
600
500
400
300
200
100
0
Count
Unf
Fin
RFn
garagefinish

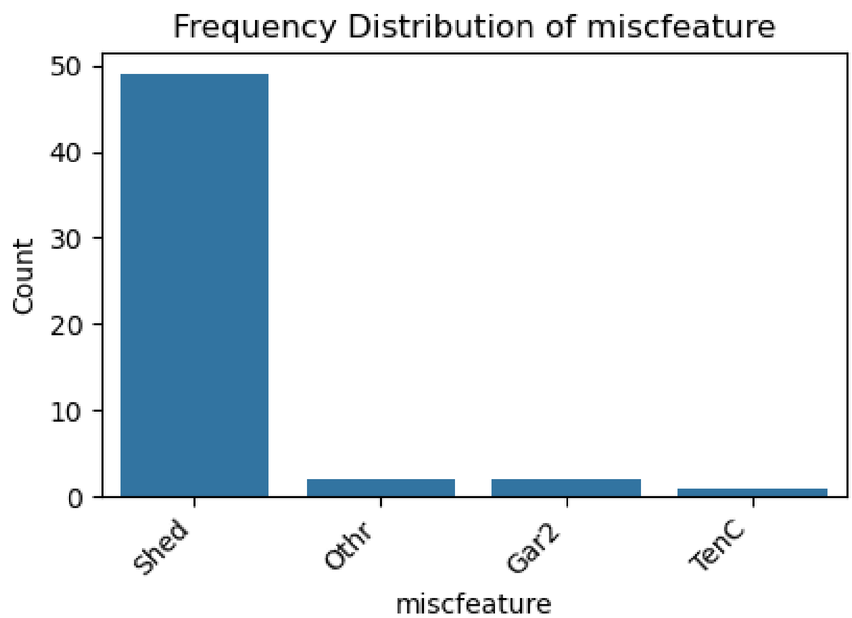

Frequency Distribution of garagequal
1200
1000
800
600
400
200
0
Count
TA
Po
Gd
Fa
Ex
garagequal

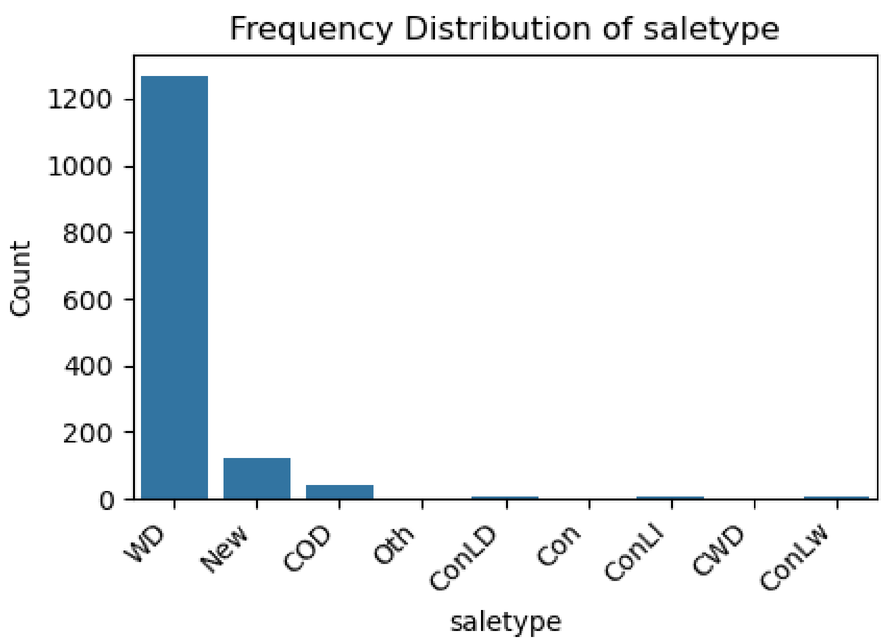

Frequency Distribution of garagecond
Count
0
200
400
600
800
1000
1200
TA
Gd
Po
Fa
Ex
garagecond

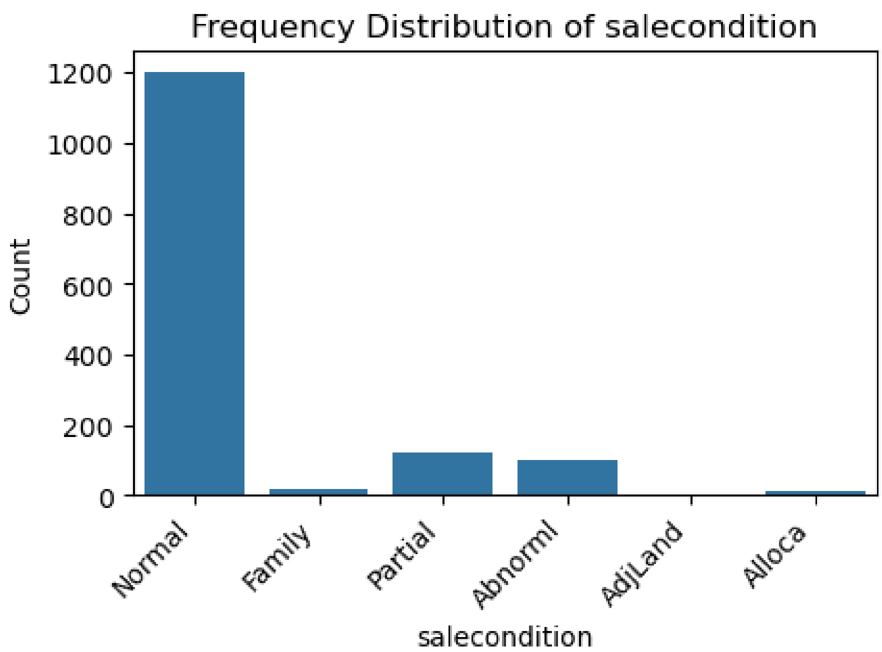

Frequency Distribution of paveddrive
Count
0
200
400
600
800
1000
1200
1400
N
Y
P
paveddrive


Frequency Distribution of poolqc
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Count
Ex
Gd
Fa
poolqc


Frequency Distribution of fence
150
125
100
75
50
25
0
Count
MnPrv
GdPrv
GdWo
MnWw
fence


Frequency Distribution of miscfeature
Count
50
40
30
20
10
0
Shed
Othr
Gar2
TenC
miscfeature


Frequency Distribution of saletype
Count
1200
1000
800
600
400
200
0
WD
New
COD
Oth
ConLD
Con
ConLI
CWD
ConLw
saletype




### 1.0.2 2- finding vriables with missing values

[10]:
```
# Check for missing values
missing_values = df.isnull().sum()

# Filter columns with missing values
missing_values = missing_values[missing_values > 0]

# Convert to DataFrame for better display
missing_values_df = missing_values.reset_index()
missing_values_df.columns = ['Column Name', 'Missing Values']

# Calculate percentage of missing values
missing_values_df['Percentage'] = (missing_values_df['Missing Values'] /␣
 ↪len(df)) * 100

# Sort DataFrame by percentage
missing_values_df = missing_values_df.sort_values(by='Percentage',␣
 ↪ascending=False)

missing_values_df
```

[10]:

| | Column Name | Missing Values | Percentage |
|---|---|---|---|
| 16 | poolqc | 1453 | 99.520548 |
| 18 | miscfeature | 1406 | 96.301370 |

```
1       alleyname         1369   93.767123
17          fence         1179   80.753425
2       masvnrtype         872   59.726027
10     fireplacequ         690   47.260274
0      frontge_lot         259   17.739726
11      garagetype          81    5.547945
12     garageyrblt          81    5.547945
13    garagefinish          81    5.547945
14      garagequal          81    5.547945
15      garagecond          81    5.547945
8     bsmtfintype2          38    2.602740
6     bsmtexposure          38    2.602740
7     bsmtfintype1          37    2.534247
5         bsmtcond          37    2.534247
4         bsmtqual          37    2.534247
3       masvnrarea           8    0.547945
9       electrical           1    0.068493
```

For variables with missing values greater than 45%, it is preferable to delete them and treat them as if they never existed. This approach is better than imputing values, as none of these variables are truly important. Since most of them do not represent significant aspects to consider when purchasing a house, variables with over 90% missing values may indicate potential outliers

[12]:
```python
threshold = 0.55 * len(df)  # Threshold for missing values
df = df.dropna(thresh=threshold, axis=1)  # Drop columns with too many missing␣
↪values
df = df.drop(columns=['id'])  # Remove 'id' column

df.head()
```

[12]:
```
   sub_ms_class zoning_ms  frontge_lot  area_lot streetname shape_lot  \
0            45        RM         55.0      4388       Pave       IR1
1            20        RL         80.0      9600       Pave       Reg
2            30        RL         50.0      5330       Pave       Reg
3            70        RM         57.0      9906       Pave       Reg
4           120        RM         64.0      5587       Pave       IR1

  contour_land   util configlot slopeland  ... enclosedporch 3ssnporch  \
0          Bnk  AllPub    Inside       Gtl  ...             0         0
1          Lvl  AllPub    Inside       Gtl  ...             0         0
2          HLS  AllPub    Inside       Gtl  ...             0         0
3          Lvl  AllPub    Inside       Gtl  ...            60         0
4          HLS  AllPub    Inside       Mod  ...             0       153

  screenporch poolarea miscval  mosold  yrsold  saletype  salecondition  \
0           0        0       0       6    2007        WD         Normal
1           0        0       0       9    2007        WD         Normal
2           0        0       0      12    2009        WD         Normal
```

```
3            0         0        0        9     2006        WD         Family
4            0         0        0       11     2008       New        Partial

  saleprice
0     87000
1    175500
2     82500
3    107000
4    392500

[5 rows x 74 columns]
```

[14]:
```
# Check for missing values and summarize
missing_values = df.isnull().sum()
missing_values = missing_values[missing_values > 0]
missing_values_df = missing_values.reset_index()
missing_values_df.columns = ['Column Name', 'Missing Values']

# Calculate and sort the percentage of missing values
missing_values_df['Percentage'] = (missing_values_df['Missing Values'] /␣
 ↪len(df)) * 100
missing_values_df = missing_values_df.sort_values(by='Percentage',␣
 ↪ascending=False)

missing_values_df  # Display results
```

[14]:

| | Column Name | Missing Values | Percentage |
|---|---|---|---|
| 0 | frontge_lot | 259 | 17.739726 |
| 8 | garagetype | 81 | 5.547945 |
| 9 | garageyrblt | 81 | 5.547945 |
| 10 | garagefinish | 81 | 5.547945 |
| 11 | garagequal | 81 | 5.547945 |
| 12 | garagecond | 81 | 5.547945 |
| 4 | bsmtexposure | 38 | 2.602740 |
| 6 | bsmtfintype2 | 38 | 2.602740 |
| 2 | bsmtqual | 37 | 2.534247 |
| 3 | bsmtcond | 37 | 2.534247 |
| 5 | bsmtfintype1 | 37 | 2.534247 |
| 1 | masvnrarea | 8 | 0.547945 |
| 7 | electrical | 1 | 0.068493 |

### 1.0.3 3- Correlation Analysis and Feature Reduction

[20]:
```
# Get categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns.tolist()

# Display unique values for each categorical column
```

```python
for col in categorical_cols:
    print(f"{col}: {df[col].unique()}")
```

```
zoning_ms: ['RM' 'RL' 'FV' 'C (all)' 'RH']
streetname: ['Pave' 'Grvl']
shape_lot: ['IR1' 'Reg' 'IR2' 'IR3']
contour_land: ['Bnk' 'Lvl' 'HLS' 'Low']
util: ['AllPub' 'NoSeWa']
configlot: ['Inside' 'Corner' 'FR2' 'FR3' 'CulDSac']
slopeland: ['Gtl' 'Mod' 'Sev']
neighborhood: ['OldTown' 'NWAmes' 'BrkSide' 'Crawfor' 'Gilbert' 'Edwards'
'NridgHt'
 'CollgCr' 'IDOTRR' 'ClearCr' 'Mitchel' 'NAmes' 'Somerst' 'SawyerW'
 'Timber' 'NPkVill' 'Sawyer' 'StoneBr' 'SWISU' 'BrDale' 'MeadowV'
 'NoRidge' 'Veenker' 'Blmngtn' 'Blueste']
c1: ['Feedr' 'Norm' 'PosN' 'RRAn' 'Artery' 'PosA' 'RRAe' 'RRNe' 'RRNn']
c2: ['Norm' 'Feedr' 'RRNn' 'PosN' 'RRAe' 'RRAn' 'Artery' 'PosA']
type_building: ['1Fam' 'TwnhsE' 'Twnhs' '2fmCon' 'Duplex']
style_house: ['1.5Unf' '1Story' '2Story' '1.5Fin' '2.5Unf' 'SLvl' 'SFoyer'
'2.5Fin']
roof_style: ['Gable' 'Hip' 'Gambrel' 'Flat' 'Mansard' 'Shed']
roofmatl: ['CompShg' 'WdShngl' 'WdShake' 'Tar&Grv' 'Membran' 'Roll' 'ClyTile'
 'Metal']
ext1: ['WdShing' 'HdBoard' 'VinylSd' 'MetalSd' 'CemntBd' 'Wd Sdng' 'Plywood'
 'BrkFace' 'AsbShng' 'Stone' 'Stucco' 'CBlock' 'AsphShn' 'BrkComm'
 'ImStucc']
ext2: ['Wd Sdng' 'HdBoard' 'VinylSd' 'MetalSd' 'CmentBd' 'Wd Shng' 'Plywood'
 'Brk Cmn' 'BrkFace' 'AsbShng' 'Stone' 'ImStucc' 'CBlock' 'Stucco'
 'AsphShn' 'Other']
exterqual: ['TA' 'Fa' 'Ex' 'Gd']
extercond: ['Gd' 'TA' 'Fa' 'Po' 'Ex']
foundation: ['BrkTil' 'CBlock' 'PConc' 'Slab' 'Stone' 'Wood']
bsmtqual: ['TA' 'Ex' 'Gd' nan 'Fa']
bsmtcond: ['TA' 'Fa' nan 'Gd' 'Po']
bsmtexposure: ['No' 'Gd' 'Mn' 'Av' nan]
bsmtfintype1: ['LwQ' 'ALQ' 'Unf' 'GLQ' 'BLQ' 'Rec' nan]
bsmtfintype2: ['Unf' 'Rec' 'BLQ' nan 'LwQ' 'ALQ' 'GLQ']
heating: ['GasA' 'GasW' 'Wall' 'Grav' 'Floor' 'OthW']
heatingqc: ['Ex' 'Fa' 'Gd' 'TA' 'Po']
centralair: ['Y' 'N']
electrical: ['SBrkr' 'FuseA' 'FuseP' 'FuseF' 'Mix' nan]
kitchenqual: ['TA' 'Fa' 'Gd' 'Ex']
functional: ['Typ' 'Min1' 'Min2' 'Mod' 'Maj2' 'Maj1' 'Sev']
garagetype: [nan 'Attchd' 'Detchd' 'BuiltIn' '2Types' 'Basment' 'CarPort']
garagefinish: [nan 'Unf' 'Fin' 'RFn']
garagequal: [nan 'TA' 'Po' 'Gd' 'Fa' 'Ex']
garagecond: [nan 'TA' 'Gd' 'Po' 'Fa' 'Ex']
paveddrive: ['N' 'Y' 'P']
```

```
saletype: ['WD' 'New' 'COD' 'Oth' 'ConLD' 'Con' 'ConLI' 'CWD' 'ConLw']
salecondition: ['Normal' 'Family' 'Partial' 'Abnorml' 'AdjLand' 'Alloca']
```

[24]:
```
df_encoded = df.copy()

# nominal and ordinal variables
nominal_vars = ['zoning_ms', 'streetname', 'shape_lot', 'contour_land', 'util',
                'configlot', 'slopeland', 'neighborhood', 'c1', 'c2',␣
 ↪'type_building',
                'style_house', 'roof_style', 'roofmatl', 'ext1', 'ext2',␣
 ↪'centralair',
                'paveddrive', 'saletype', 'salecondition', 'foundation',␣
 ↪'heating',
                'garagetype', 'electrical']

ordinal_vars = ['exterqual', 'extercond', 'bsmtqual', 'bsmtcond', 'bsmtexposure',
                'bsmtfintype1', 'bsmtfintype2', 'heatingqc', 'kitchenqual',
                'garagequal', 'garagecond', 'garagefinish', 'functional']

# Encode ordinal variables
le = LabelEncoder()
for col in ordinal_vars:
    df_encoded[col] = le.fit_transform(df_encoded[col])

# One-hot encode nominal variables
df_encoded = pd.get_dummies(df_encoded, columns=nominal_vars, drop_first=True)

# Display the first few rows of the encoded dataframe
df_encoded.head()
```

[24]:
```
   sub_ms_class  frontge_lot  area_lot  ovl_quality  ovl_condition  \
0            45         55.0      4388            5              7
1            20         80.0      9600            7              6
2            30         50.0      5330            4              7
3            70         57.0      9906            4              4
4           120         64.0      5587            8              5

   year_constructed  year_remod  masvnrarea  exterqual  extercond  ...  \
0              1930        1950         0.0          3          2  ...
1              1973        1973       320.0          3          4  ...
2              1940        1950         0.0          1          4  ...
3              1925        1950         0.0          3          4  ...
4              2008        2008       186.0          0          4  ...

   heating_Wall  garagetype_Attchd  garagetype_Basment  garagetype_BuiltIn  \
0         False              False               False               False
1         False               True               False               False
```

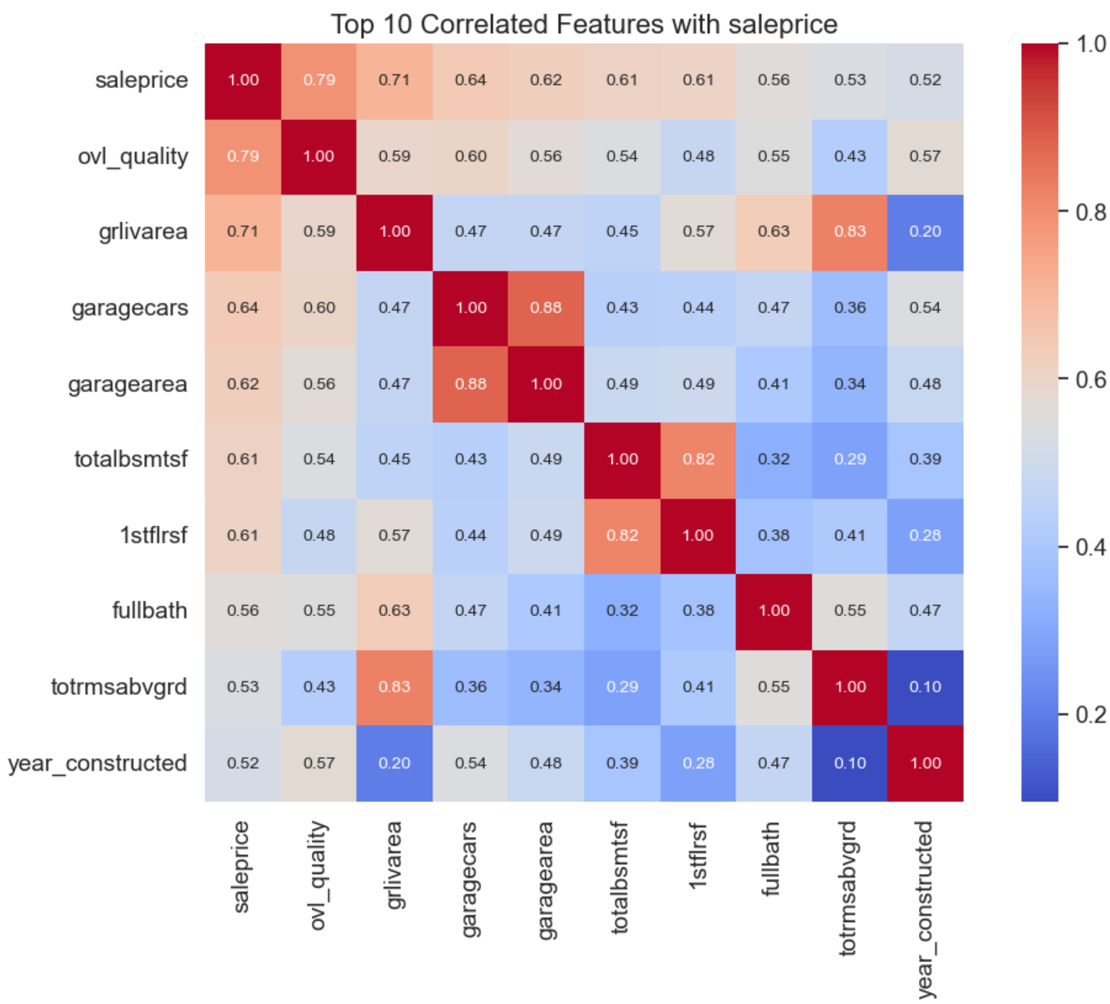
```
2          False              False              False              False
3          False              False              False              False
4          False               True              False              False

   garagetype_CarPort  garagetype_Detchd  electrical_FuseF  electrical_FuseP  \
0               False              False             False             False
1               False              False             False             False
2               False              False             False             False
3               False               True             False             False
4               False              False             False             False

   electrical_Mix  electrical_SBrkr
0           False              True
1           False              True
2           False              True
3           False              True
4           False              True

[5 rows x 194 columns]
```

[26]:

```
corrmat = df_encoded.corr()

# Specify the target variable
target_variable = 'saleprice'


k = 10
cols = corrmat.nlargest(k, target_variable)[target_variable].index

# Calculate the correlation matrix for these top 'k' variables
cm = np.corrcoef(df_encoded[cols].values.T)

# Set up the seaborn font and plot size
sns.set(font_scale=1.25)
plt.figure(figsize=(12, 8))

# Create a heatmap
hm = sns.heatmap(cm,
                 cbar=True,
                 annot=True,
                 square=True,
                 fmt='.2f',
                 annot_kws={'size': 10},
                 yticklabels=cols.values,
                 xticklabels=cols.values,
                 cmap='coolwarm')
```

```
plt.title(f'Top {k} Correlated Features with {target_variable}', fontsize=16)
```

[26]:
```
Text(0.5, 1.0, 'Top 10 Correlated Features with saleprice')
```




**Interpretation of Most Correlated Variables**

1. **Strong Correlation with** `SalePrice`:
   - `OverallQual`, `GrLivArea`, and `TotalBsmtSF` are strongly correlated with `SalePrice`, indicating that these variables are key drivers of the property's sale price.
2. **Garage Features**:
   - `GarageCars` and `GarageArea` are also strongly correlated (correlation 0.88). This is logical, as both variables provide similar information about garage capacity.
   - **Decision**: We will keep `GarageCars`, as it has a higher correlation with `SalePrice` compared to `GarageArea`.
3. **Basement and First Floor Area**:

- TotalBsmtSF and 1stFlrSF are also highly correlated (correlation  0.82). Both measure area-related features of the house.
- **Decision**: We will keep TotalBsmtSF, as it shows a higher correlation with SalePrice.

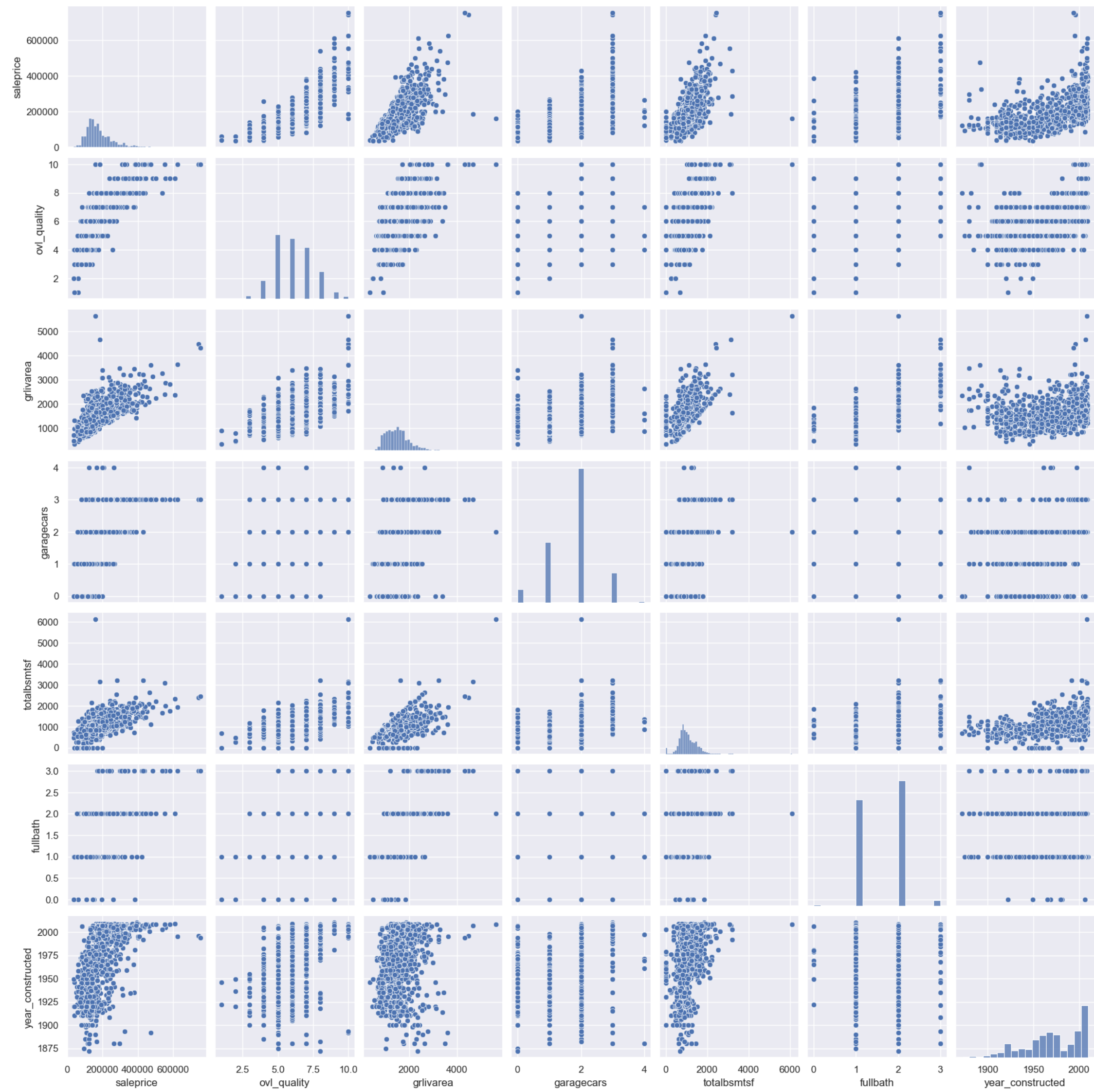
4. **Total Rooms and Living Area**:
   - TotRmsAbvGrd and GrLivArea are another highly related pair. Since GrLivArea represents the total living area, it covers the same information more comprehensively.
   - **Decision**: We will keep GrLivArea due to its stronger correlation with SalePrice. **'SalePrice'**.

### 1.0.4 4- Scatter Plots Analysis

In this section, we will create scatter plots to analyze the relationships between the target variable SalePrice and several features from the dataset. Scatter plots are useful for visualizing the correlation and distribution of data points.

[28]:
```
sns.set()
cols = ['saleprice', 'ovl_quality', 'grlivarea', 'garagecars', 'totalbsmtsf',␣
↪'fullbath', 'year_constructed']
sns.pairplot(df_encoded[cols], size = 2.5)
plt.show()
```

```
C:\Users\elmou\anaconda3\envs\ml_env\Lib\site-packages\seaborn\axisgrid.py:2100:
UserWarning: The `size` parameter has been renamed to `height`; please update
your code.
  warnings.warn(msg, UserWarning)
```




**Insights from Scatter Plots** The scatter plots provide additional insights beyond our initial understanding of the data:

- **TotalBsmtSF vs. GrLivArea**:
  One notable observation from this plot is the linear pattern formed by the data points. This creates a distinct boundary where most points are concentrated below the line. It is logical that the basement area (`TotalBsmtSF`) would not exceed the above-ground living area (`GrLivArea`). While it is possible for the two areas to be equal, it is quite uncommon for the basement area to surpass the living area above ground.

- **SalePrice vs. YearBuilt**:
  The relationship between `SalePrice` and `YearBuilt` is intriguing. At the lower end of the scatter plot, there appears to be a subtle exponential trend, suggesting that older houses may have lower sale prices. Conversely, this trend can also be observed in the upper limit of the

cloud of dots, indicating that more recent builds tend to command higher prices. Notably, the points corresponding to the most recent years are positioned above this upper trend line, highlighting the accelerating increase in property prices in the current market.

#### 1.0.5 5- Missing data

Returning to the issue of missing values, before addressing them, we should analyze whether they exhibit a pattern or are random. Identifying a pattern in the missing data can guide us in filling in these gaps more effectively. Conversely, if the missing values appear to be random, our decisions regarding how to handle them could significantly impact the integrity of our dataset. # ### Applying Findings from the Correlation Study

Based on our previous correlation analysis, we identified some highly correlated variables that provide redundant information. Therefore, to simplify the dataset and reduce multicollinearity, we will drop the following columns:

- **'GarageArea'**: We will keep **'GarageCars'** as it showed a higher correlation with **'SalePrice'**.
- **'1stFlrSF'**: We decided to retain **'TotalBsmtSF'** since it better captures the total living area.
- **'TotRmsAbvGrd'**: We will keep **'GrLivArea'** for representing living space more comprehensively.

This step will help to maintain a more concise dataset while preserving key information for analysis.

[29]:
```python
cols_to_drop = ['garagearea', '1stflrsf', 'totrmsabvgrd']
df = df.drop(columns=cols_to_drop)
```

**Let's review the updated list of features and their missing values**

[28]:
```python
# Check for missing values and create a summary DataFrame
missing_values = df.isnull().sum()
missing_values = missing_values[missing_values > 0]
missing_values_df = missing_values.reset_index()
missing_values_df.columns = ['Column Name', 'Missing Values']

# Calculate and sort percentage of missing values
missing_values_df['Percentage'] = (missing_values_df['Missing Values'] /␣
↪len(df)) * 100
missing_values_df = missing_values_df.sort_values(by='Percentage',␣
↪ascending=False)

# Display the DataFrame
missing_values_df
```

[28]:

| | Column Name | Missing Values | Percentage |
|---|---|---|---|
| 0 | frontge_lot | 259 | 17.739726 |
| 8 | garagetype | 81 | 5.547945 |
| 9 | garageyrblt | 81 | 5.547945 |
| 10 | garagefinish | 81 | 5.547945 |

```
11    garagequal            81    5.547945
12    garagecond            81    5.547945
4    bsmtexposure           38    2.602740
6    bsmtfintype2           38    2.602740
2        bsmtqual           37    2.534247
3        bsmtcond           37    2.534247
5    bsmtfintype1           37    2.534247
1      masvnrarea            8    0.547945
7      electrical            1    0.068493
```

- **Frontge_Lot**: Given that the `frontge_lot` column has approximately 17% missing data and is not critical for our analysis, we will remove this column from the dataset.
- **Electrical**: We have just one missing observation in `'electrical'`. Since it's only one, we will remove this single observation and keep the variable.
- **GarageX Variables**: The `'GarageX'` variables have the same number of missing entries, likely referring to the same set of observations. Given that these missing values constitute only about 5%, we will not spend excessive time delving into them. Considering that the most critical information about garages is captured by `'GarageCars'`, and the missing values are not substantial, we'll remove these `'GarageX'` variables.
- **BsmtX Variables**: A similar rationale applies to the `'BsmtX'` variables. We'll remove these variables as well.
- **MasVnrArea**: For `'masvnrarea'`, we will fill in the missing values with `0`, assuming that a missing entry indicates no masonry veneer area.area.

[439]:
```
#correlation_test = df_encoded[['masvnrarea', 'year_constructed', 'saleprice']].
↪corr()
#correlation_subset = correlation_test.loc[['masvnrarea', 'year_constructed'],␣
↪['year_constructed', 'saleprice']]

#correlation_subset
```

[30]:
```
# Dropping columns with missing data as per the analysis
columns_to_drop = ['garagetype', 'garageyrblt', 'garagefinish', 'garagequal',
                   'garagecond', 'bsmtexposure', 'bsmtfintype2', 'bsmtqual',
                   'bsmtcond', 'bsmtfintype1','frontge_lot']



df.drop(columns=columns_to_drop, inplace=True)

# Dropping the single missing value in 'electrical'
df.dropna(subset=['electrical'], inplace=True)

# Filling missing values in 'masvnrarea' with 0 using .loc
df.loc[:, 'masvnrarea'] = df['masvnrarea'].fillna(0)
```

**Final Check for Remaining Missing Values**

[32]:
```python
missing_values = df.isnull().sum()

missing_values = missing_values[missing_values > 0]

missing_values_df = missing_values.reset_index()
missing_values_df.columns = ['Column Name', 'Missing Values']

missing_values_df['Percentage'] = (missing_values_df['Missing Values'] /␣
 ↪len(df)) * 100

missing_values_df = missing_values_df.sort_values(by='Percentage',␣
 ↪ascending=False)

missing_values_df
```

[32]:
```
Empty DataFrame
Columns: [Column Name, Missing Values, Percentage]
Index: []
```

### 1.0.6 6 Identifying Outliers

Now that we have resolved the missing values, we will look for outliers in our dataset.

First, we need to define a threshold to identify an observation as an outlier. We will standardize the data (mean = 0, standard deviation = 1) for the `SalePrice` variable. Then, we will visualize the lower and upper ranges to see how `SalePrice` looks.

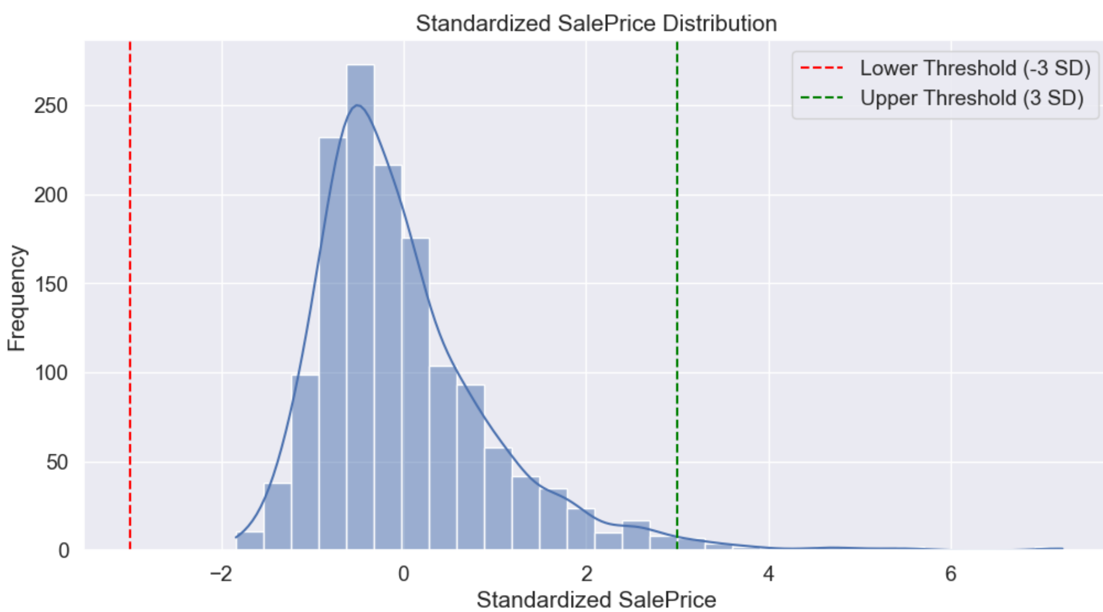
The general approach will include the following steps: 1. Standardize the `SalePrice` data. 2. Define the outlier thr 3. Print the lower and upper outer ranges of the distribution.e4holds. 3. Visualize the distribution of `SalePrice`.

Let's proceed with the implementation.

[34]:
```python
scaler = StandardScaler()

saleprice_scaled = scaler.fit_transform(df[['saleprice']])
lower_threshold = -3  # 3 standard deviations below the mean
upper_threshold = 3   # 3 standard deviations above the mean

low_range = saleprice_scaled[saleprice_scaled[:, 0].argsort()][:10]
high_range = saleprice_scaled[saleprice_scaled[:, 0].argsort()][-10:]

print("Outer range (low) of the distribution:")
print(low_range.flatten())  # Print first 10 values of the lower range

print("\nOuter range (high) of the distribution:")
print(high_range.flatten())
```

```
plt.figure(figsize=(12, 6))
sns.histplot(saleprice_scaled, bins=30, kde=True)
plt.axvline(lower_threshold, color='red', linestyle='--', label='Lower Threshold␣
 ↪(-3 SD)')
plt.axvline(upper_threshold, color='green', linestyle='--', label='Upper␣
 ↪Threshold (3 SD)')
plt.title('Standardized SalePrice Distribution')
plt.xlabel('Standardized SalePrice')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```

```
Outer range (low) of the distribution:
[-1.83820775 -1.83303414 -1.80044422 -1.78282123 -1.77400974 -1.62295562
 -1.6166617  -1.58519209 -1.58519209 -1.57269236]

Outer range (high) of the distribution:
[3.82758058 4.0395221  4.49473628 4.70872962 4.728631   5.06034585
 5.42191907 5.58987866 7.10041987 7.22629831]
```




**Analyzing Outliers in SalePrice** Now that we have identified the outlier values in the `SalePrice`, particularly those above 7 in the standardized scale, we will further investigate these observations.

To do this, we will create scatter plots to visualize the relationships between `SalePrice` and three different variables: 1. `Overall Quality` (`ovl_quality`) 2. `Ground Living Area` (`grlivarea`) 3. `Total Basement Area` (`totalbsm`)

This analysis will help us determine if the high `SalePrice` values are reasonable given the other attributes.

Let's proceed with the scatter plots.

[36]:
```
#Create scatter plots for saleprice against key features
plt.figure(figsize=(18, 5))

# Scatter plot for saleprice vs Overall Quality
plt.subplot(1, 3, 1)
sns.scatterplot(x=df['ovl_quality'], y=df['saleprice'])
plt.title('SalePrice vs Overall Quality')
plt.xlabel('Overall Quality')
plt.ylabel('SalePrice')

# Scatter plot for saleprice vs GrLivArea
plt.subplot(1, 3, 2)
sns.scatterplot(x=df['grlivarea'], y=df['saleprice'])
plt.title('SalePrice vs Ground Living Area')
plt.xlabel('Ground Living Area (GrLivArea)')
plt.ylabel('SalePrice')

# Scatter plot for saleprice vs Total Basement Area
plt.subplot(1, 3, 3)
sns.scatterplot(x=df['totalbsmtsf'], y=df['saleprice'])
plt.title('SalePrice vs Total Basement Area')
plt.xlabel('Total Basement Area (TotalBsmtSF)')
plt.ylabel('SalePrice')

plt.tight_layout()
plt.show()
```


### 1.0.7 Outlier Analysis Results

Upon examining the scatter plots, we made several observations regarding the data points:

1. **Ground Living Area** (`GrLivArea`):

- The two values with the largest `GrLivArea` appear to be outliers. They significantly deviate from the majority of the data points and do not align with the overall trend.
- One possible explanation for this discrepancy is that these values may correspond to agricultural areas, which could account for their relatively low sale prices. Given that these points do not represent typical cases, we will classify them as outliers and proceed to remove them from our dataset.

2. **Sale Price Observations**:
   - The two observations at the top of the plot, which correspond to the highest `saleprice` values (around 7.something), do not appear to be outliers in the same sense. While they are notably high, they seem to follow the established trend of the data.
   - Therefore, we will retain these two observations in our dataset, as they may represent valid, high-value properties.

In summary, we will remove the two outlier observations related to `GrLivArea` while keeping the high sale price values.

[38]:
```
# Identify outliers based on GrLivArea and SalePrice
outlier_condition = (df['grlivarea'] > 4000) & (df['saleprice'] < 200000)
outliers = df[outlier_condition]

print("Identified Outliers:")
print(outliers)
```

```
Identified Outliers:
     sub_ms_class zoning_ms  area_lot streetname shape_lot contour_land  \
491            60        RL     63887       Pave       IR3          Bnk
558            60        RL     40094       Pave       IR1          Bnk

       util configlot slopeland neighborhood  ... enclosedporch 3ssnporch  \
491  AllPub    Corner       Gtl      Edwards  ...             0         0
558  AllPub    Inside       Gtl      Edwards  ...             0         0

    screenporch poolarea  miscval  mosold  yrsold  saletype salecondition  \
491           0      480        0       1    2008       New       Partial
558           0        0        0      10    2007       New       Partial

    saleprice
491    160000
558    184750

[2 rows x 63 columns]
```

[40]:
```
# Now, remove we the outliers
df = df[~outlier_condition]
```

## 2 II - Regression

**1. Assumptions of Regression** Before proceeding with regression analysis, it is essential to verify that the following assumptions are met:

1. **Normality**:
   - The residuals (errors) of the regression model should be normally distributed. This can be assessed using graphical methods (such as Q-Q plots) and statistical tests (like the Shapiro-Wilk test).
2. **Homoscedasticity**:
   - The variance of the residuals should be constant across all levels of the independent variables. This can be evaluated by plotting residuals against fitted values and looking for any patterns.
3. **Linearity**:
   - There should be a linear relationship between the independent variables and the dependent variable. This can be examined using scatter plots and correlation coefficients.
4. **Absence of Correlated Errors**:
   - The residuals should be independent of one another. This assumption can be checked using the Durbin-Watson test or by inspecting residual plots.

**Study of Linearity for SalePrice**

[42]:
```
sns.distplot(df['saleprice'], fit=norm)
plt.title('SalePrice Distribution with Normal Fit')
plt.xlabel('SalePrice')
plt.ylabel('Density')
plt.show()

# Q-Q plot for SalePrice
fig = plt.figure()
res = stats.probplot(df['saleprice'], plot=plt)
plt.title('Q-Q Plot of SalePrice')
plt.xlabel('Theoretical Quantiles')
plt.ylabel('Sample Quantiles')
plt.show()
```

```
C:\Users\elmou\AppData\Local\Temp\ipykernel_2696\308076736.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['saleprice'], fit=norm)
```


SalePrice Distribution with Normal Fit
1e−6
Density
SalePrice
0
200000
400000
600000
800000
1
2
3
4
5
6
7
8

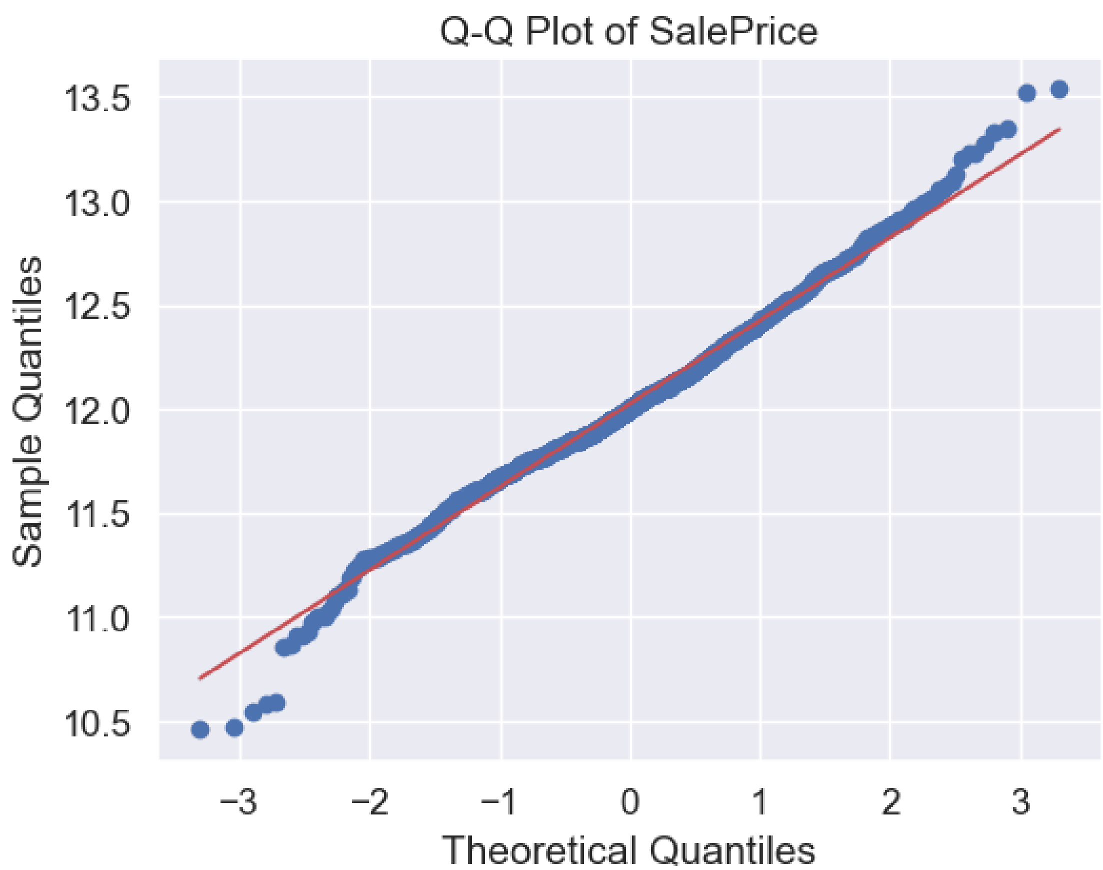

**Remark on SalePrice Normality** The distribution of `'SalePrice'` is not normal. It exhibits **peakedness** and **positive skewness**, and does not align with the diagonal line in the Q-Q plot.

In cases of positive skewness, log transformations often work well to normalize the data. To apply this transformation, we will take the natural logarithm of the `'SalePrice'` variable as follows:

[44]:
```
df['saleprice'] = np.log(df['saleprice'])
```

[46]:
```
sns.distplot(df['saleprice'], fit=norm)
plt.title('SalePrice Distribution with Normal Fit')
plt.xlabel('SalePrice')
plt.ylabel('Density')
plt.show()

# Q-Q plot for SalePrice
fig = plt.figure()
res = stats.probplot(df['saleprice'], plot=plt)
plt.title('Q-Q Plot of SalePrice')
plt.xlabel('Theoretical Quantiles')
plt.ylabel('Sample Quantiles')
plt.show()
```

```
C:\Users\elmou\AppData\Local\Temp\ipykernel_2696\2379746249.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['saleprice'], fit=norm)
```

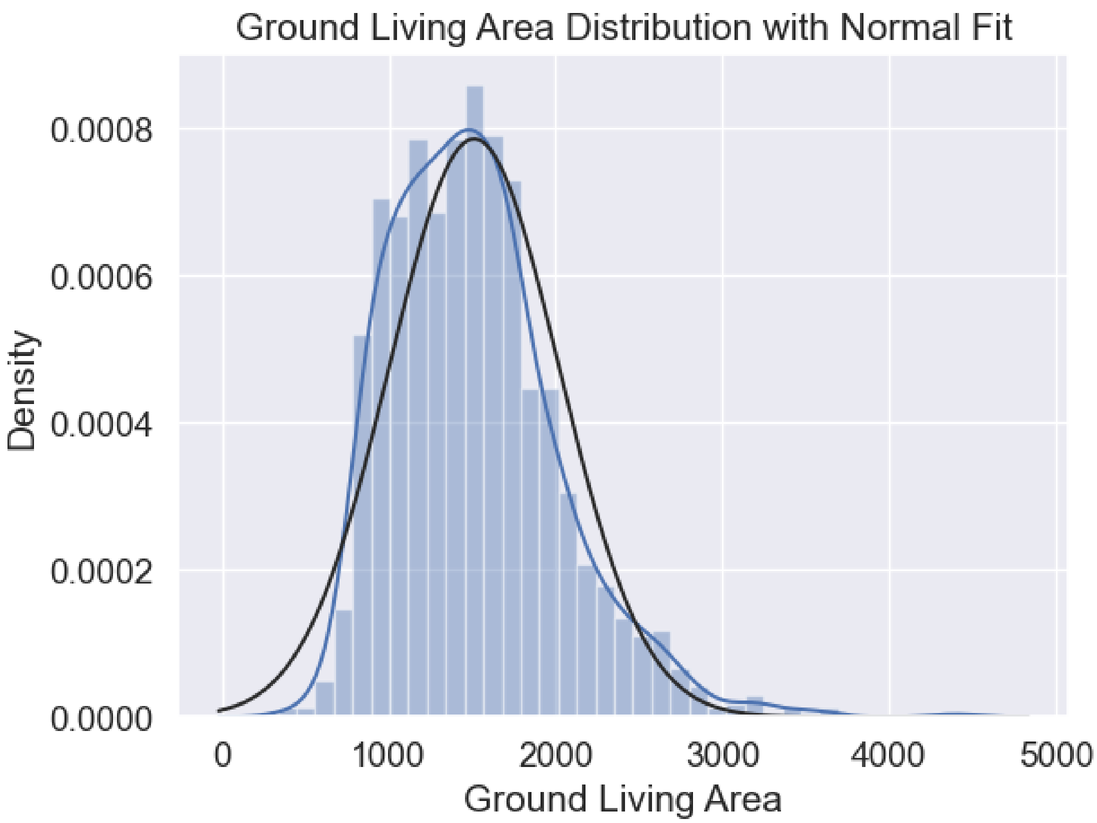


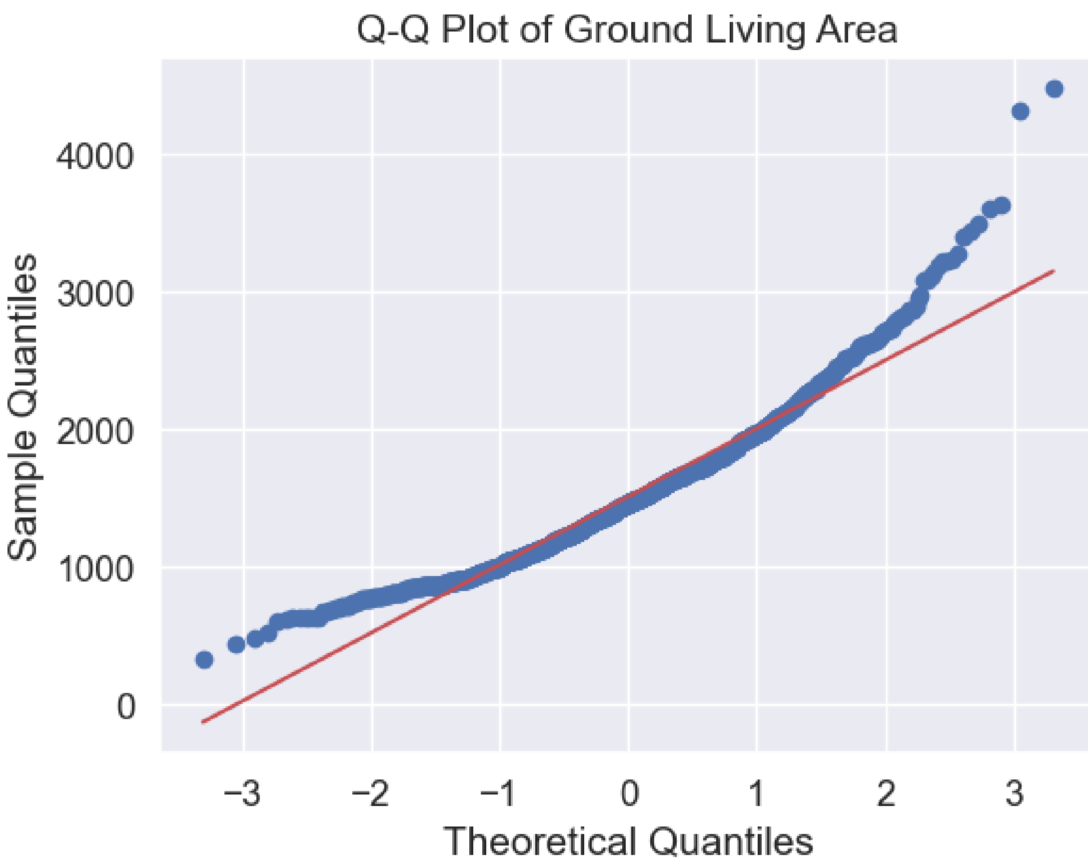

**Study of Linearity for GrLivArea**

[48]:
```
sns.distplot(df['grlivarea'], fit=norm)
plt.title('Ground Living Area Distribution with Normal Fit')
plt.xlabel('Ground Living Area')
plt.ylabel('Density')
plt.show()

# Q-Q plot for Ground Living Area
fig = plt.figure()
res = stats.probplot(df['grlivarea'], plot=plt)
plt.title('Q-Q Plot of Ground Living Area')
plt.xlabel('Theoretical Quantiles')
plt.ylabel('Sample Quantiles')
plt.show()
```

```
C:\Users\elmou\AppData\Local\Temp\ipykernel_2696\3827227883.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
```

```
Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['grlivarea'], fit=norm)
```



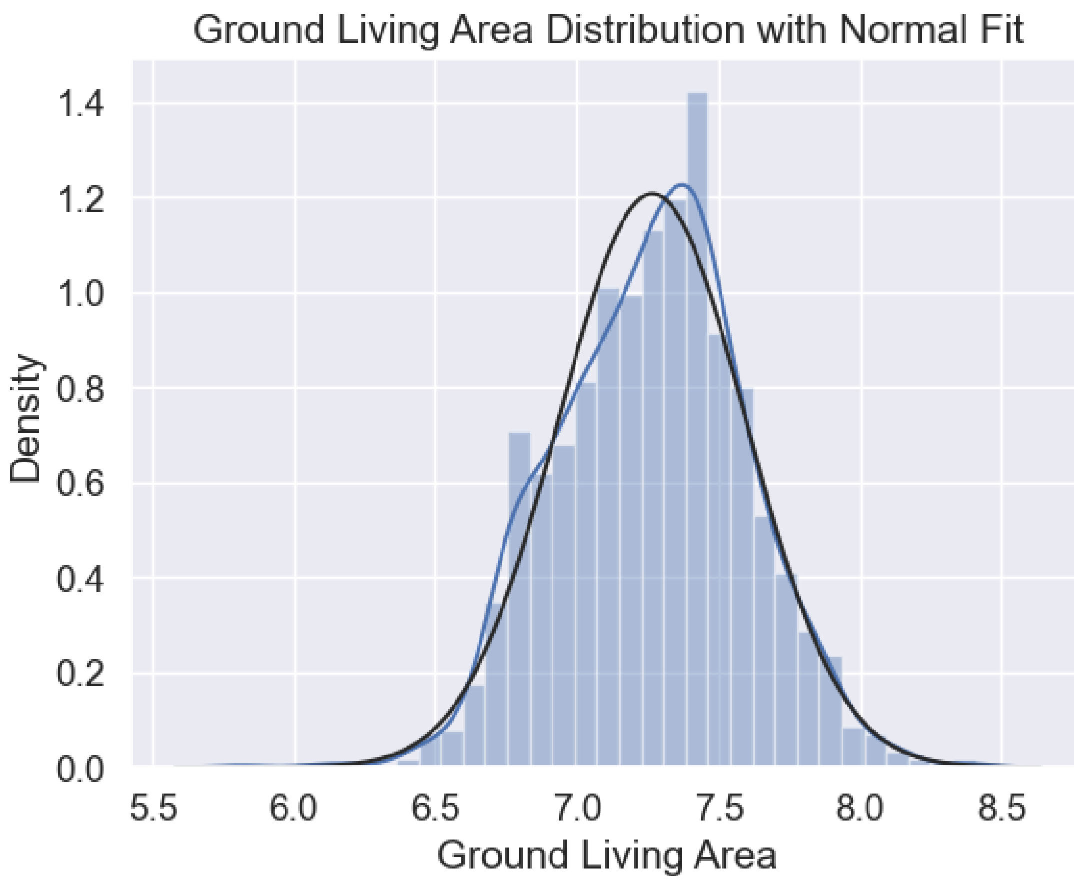


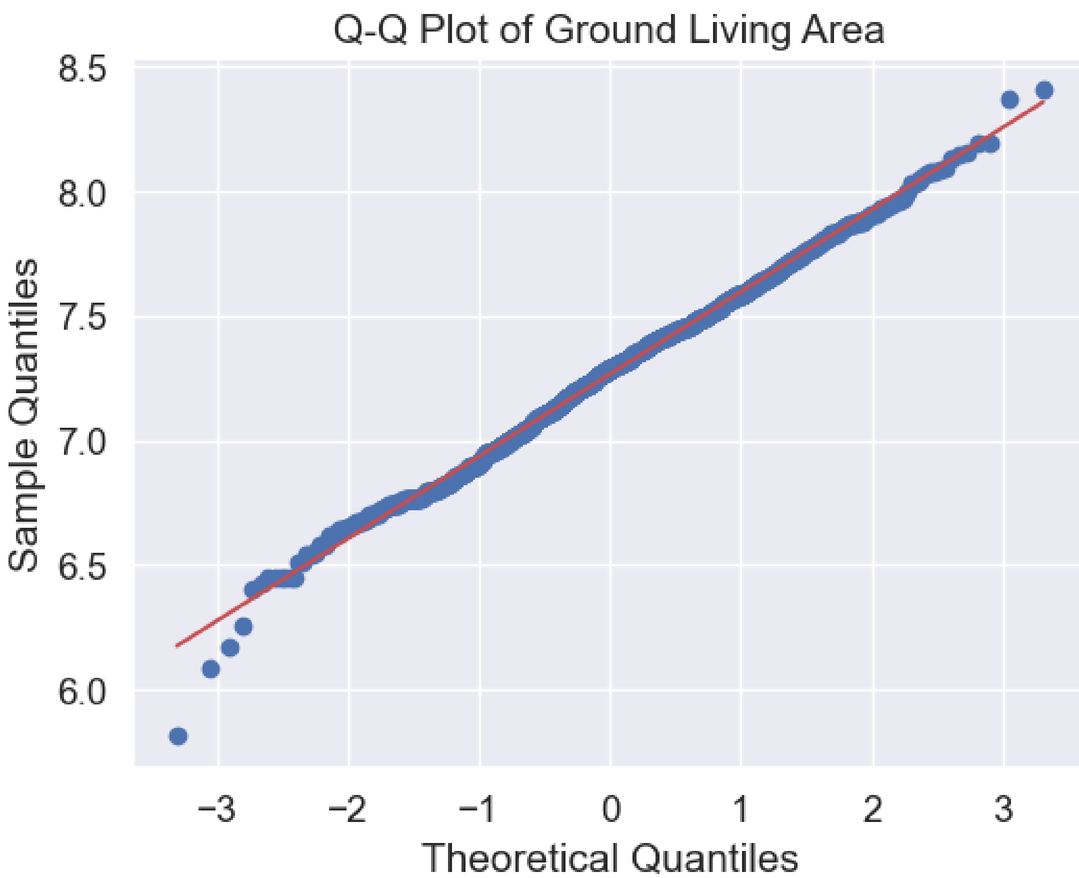

[50]:
```
df['grlivarea'] = np.log(df['grlivarea'])
```

[52]:
```
sns.distplot(df['grlivarea'], fit=norm)
plt.title('Ground Living Area Distribution with Normal Fit')
plt.xlabel('Ground Living Area')
plt.ylabel('Density')
plt.show()

# Q-Q plot for Ground Living Area
fig = plt.figure()
res = stats.probplot(df['grlivarea'], plot=plt)
plt.title('Q-Q Plot of Ground Living Area')
plt.xlabel('Theoretical Quantiles')
plt.ylabel('Sample Quantiles')
plt.show()
```

```
C:\Users\elmou\AppData\Local\Temp\ipykernel_2696\3827227883.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
```

```
Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['grlivarea'], fit=norm)
```

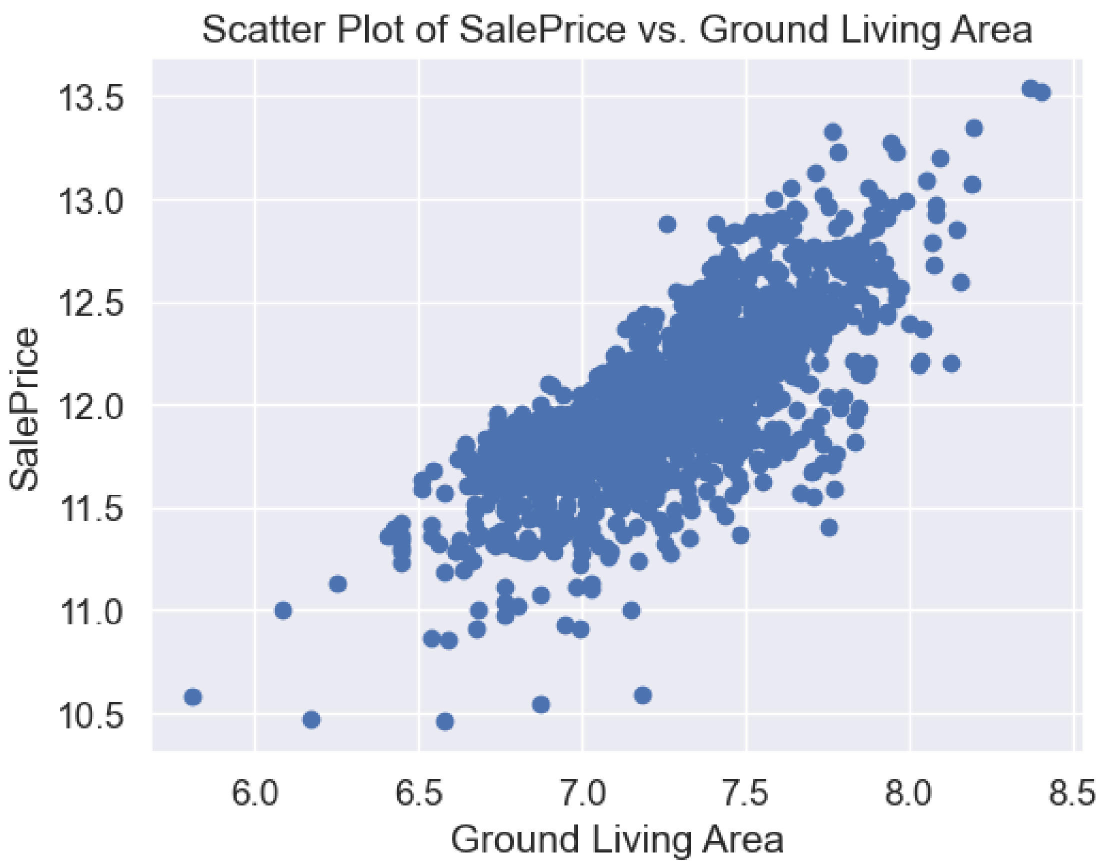





To test for homoscedasticity, we can utilize graphical methods to assess the dispersion of residuals across levels of the independent variable. In a homoscedastic distribution, the residuals should exhibit a constant variance. If the residuals display patterns such as cones (with small dispersion on one side and large dispersion on the other) or diamonds (indicating a concentration of points at the center), it suggests a departure from equal dispersion.

In this analysis, we will start by examining the relationship between `'SalePrice'` and `'grlivarea'`. The scatter plot will help us visualize any potential patterns in the dispersion of the data points.

[54]:
```
plt.scatter(df['grlivarea'], df['saleprice'])
plt.title('Scatter Plot of SalePrice vs. Ground Living Area')
plt.xlabel('Ground Living Area')
plt.ylabel('SalePrice')
plt.show()
```




We can conclude that the condition of homoscedasticity has been met.

### 2.0.1 2. Feature Scaling, Mapping, and One-Hot Encoding

To prepare our data for regression, we need to standardize the scales of continuous variables, map ordinal variables to numeric scales, and apply one-hot encoding to categorical variables.

[56]:
```
categorical_cols = df.select_dtypes(include=['object']).columns.tolist()

#unique values to help determine if they are ordinal or nominal
for col in categorical_cols:
    print(f"{col}: {df[col].unique()}")

#print(df.columns.tolist())
```

```
zoning_ms: ['RM' 'RL' 'FV' 'C (all)' 'RH']
streetname: ['Pave' 'Grvl']
shape_lot: ['IR1' 'Reg' 'IR2' 'IR3']
contour_land: ['Bnk' 'Lvl' 'HLS' 'Low']
util: ['AllPub' 'NoSeWa']
configlot: ['Inside' 'Corner' 'FR2' 'FR3' 'CulDSac']
```

```
slopeland: ['Gtl' 'Mod' 'Sev']
neighborhood: ['OldTown' 'NWAmes' 'BrkSide' 'Crawfor' 'Gilbert' 'Edwards'
'NridgHt'
 'CollgCr' 'IDOTRR' 'ClearCr' 'Mitchel' 'NAmes' 'Somerst' 'SawyerW'
 'Timber' 'NPkVill' 'Sawyer' 'StoneBr' 'SWISU' 'BrDale' 'MeadowV'
 'NoRidge' 'Veenker' 'Blmngtn' 'Blueste']
c1: ['Feedr' 'Norm' 'PosN' 'RRAn' 'Artery' 'PosA' 'RRAe' 'RRNe' 'RRNn']
c2: ['Norm' 'Feedr' 'RRNn' 'PosN' 'RRAe' 'RRAn' 'Artery' 'PosA']
type_building: ['1Fam' 'TwnhsE' 'Twnhs' '2fmCon' 'Duplex']
style_house: ['1.5Unf' '1Story' '2Story' '1.5Fin' '2.5Unf' 'SLvl' 'SFoyer'
'2.5Fin']
roof_style: ['Gable' 'Hip' 'Gambrel' 'Flat' 'Mansard' 'Shed']
roofmatl: ['CompShg' 'WdShngl' 'WdShake' 'Tar&Grv' 'Membran' 'Roll' 'Metal']
ext1: ['WdShing' 'HdBoard' 'VinylSd' 'MetalSd' 'CemntBd' 'Wd Sdng' 'Plywood'
 'BrkFace' 'AsbShng' 'Stone' 'Stucco' 'CBlock' 'AsphShn' 'BrkComm'
 'ImStucc']
ext2: ['Wd Sdng' 'HdBoard' 'VinylSd' 'MetalSd' 'CmentBd' 'Wd Shng' 'Plywood'
 'Brk Cmn' 'BrkFace' 'AsbShng' 'Stone' 'ImStucc' 'CBlock' 'Stucco'
 'AsphShn' 'Other']
exterqual: ['TA' 'Fa' 'Ex' 'Gd']
extercond: ['Gd' 'TA' 'Fa' 'Po' 'Ex']
foundation: ['BrkTil' 'CBlock' 'PConc' 'Slab' 'Stone' 'Wood']
heating: ['GasA' 'GasW' 'Wall' 'Grav' 'Floor' 'OthW']
heatingqc: ['Ex' 'Fa' 'Gd' 'TA' 'Po']
centralair: ['Y' 'N']
electrical: ['SBrkr' 'FuseA' 'FuseP' 'FuseF' 'Mix']
kitchenqual: ['TA' 'Fa' 'Gd' 'Ex']
functional: ['Typ' 'Min1' 'Min2' 'Mod' 'Maj2' 'Maj1' 'Sev']
paveddrive: ['N' 'Y' 'P']
saletype: ['WD' 'New' 'COD' 'Oth' 'ConLD' 'Con' 'ConLI' 'CWD' 'ConLw']
salecondition: ['Normal' 'Family' 'Partial' 'Abnorml' 'AdjLand' 'Alloca']
```

[58]:

```python
df_encod = df.copy()

# Ordinal features
ordinal_features = [
    'exterqual', 'extercond', 'heatingqc', 'kitchenqual',
    'functional', 'paveddrive', 'slopeland', 'centralair'
]

# Categorical features
categorical_features = [
    'zoning_ms', 'streetname', 'shape_lot', 'contour_land', 'util',
    'configlot', 'neighborhood', 'c1', 'c2', 'type_building', 'style_house',
    'roof_style', 'roofmatl', 'ext1', 'ext2', 'foundation', 'heating',
    'electrical', 'saletype', 'salecondition'
]
```

```python
# Encode ordinal variables using LabelEncoder
le = LabelEncoder()
for col in ordinal_features:
    df_encod[col] = le.fit_transform(df_encod[col])

#One-hot encode nominal variables
df_encod = pd.get_dummies(df_encod, columns=categorical_features,
 ↪drop_first=True)

# Display the first few rows of the encoded dataframe
df_encod.head()
```

[58]:

```
   sub_ms_class  area_lot  slopeland  ovl_quality  ovl_condition  \
0            45      4388          0            5              7
1            20      9600          0            7              6
2            30      5330          0            4              7
3            70      9906          0            4              4
4           120      5587          1            8              5

   year_constructed  year_remod  masvnrarea  exterqual  extercond  ...  \
0              1930        1950         0.0          3          2  ...
1              1973        1973       320.0          3          4  ...
2              1940        1950         0.0          1          4  ...
3              1925        1950         0.0          3          4  ...
4              2008        2008       186.0          0          4  ...

   saletype_ConLI  saletype_ConLw  saletype_New  saletype_Oth  saletype_WD  \
0           False           False         False         False         True
1           False           False         False         False         True
2           False           False         False         False         True
3           False           False         False         False         True
4           False           False          True         False        False

   salecondition_AdjLand  salecondition_Alloca  salecondition_Family  \
0                  False                 False                 False
1                  False                 False                 False
2                  False                 False                 False
3                  False                 False                  True
4                  False                 False                 False

   salecondition_Normal  salecondition_Partial
0                  True                  False
1                  True                  False
2                  True                  False
3                 False                  False
4                 False                   True
```

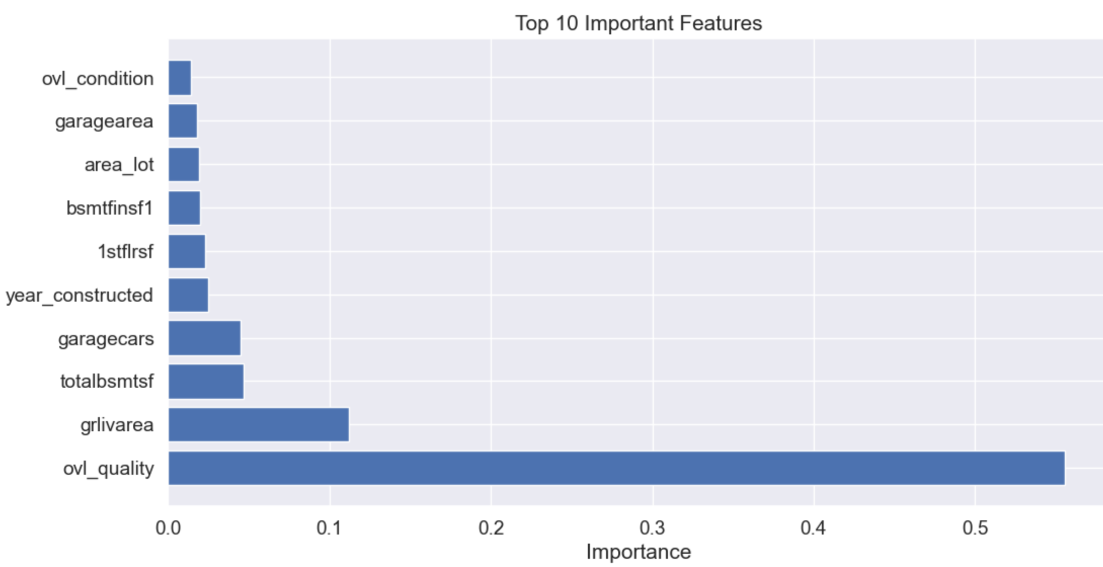
```
[5 rows x 176 columns]
```

### 2.0.2 3. Dividing Data into Training and Test Sets (70-30 Split)

To evaluate the performance of our model, we will split the data into training and test sets. A 70-30 split ratio is chosen, where 70% of the data will be used for training, and the remaining 30% will be used for testing. This split ensures that we have sufficient data for both model training and validation.

[60]:
```
# Define features and target
X = df_encod.drop('saleprice', axis=1)
y = df_encod['saleprice']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)

# Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Fit Random Forest model for feature importance
rf = RandomForestRegressor(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

# Get feature importances and sort
importances = rf.feature_importances_
feature_importance_df = pd.DataFrame({'Feature': X.columns, 'Importance':␣
↪importances})
feature_importance_df = feature_importance_df.sort_values(by='Importance',␣
↪ascending=False)

# Plot top 10 important features
plt.figure(figsize=(12, 6))
plt.barh(feature_importance_df['Feature'].head(10),␣
↪feature_importance_df['Importance'].head(10))
plt.xlabel('Importance')
plt.title('Top 10 Important Features')
plt.show()

# Select top n important features
top_n = 10
important_features = feature_importance_df['Feature'].head(top_n).values

# Create new DataFrames with only the important features
X_train_important = X_train[important_features]
```

```
X_test_important = X_test[important_features]

# Scale important features
X_train_important_scaled = scaler.fit_transform(X_train_important)
X_test_important_scaled = scaler.transform(X_test_important)

# Convert scaled features back to DataFrame
X_train_important_scaled_df = pd.DataFrame(X_train_important_scaled,␣
↪columns=important_features)
X_test_important_scaled_df = pd.DataFrame(X_test_important_scaled,␣
↪columns=important_features)

# Display the first few rows of the scaled important training data
print(X_train_important_scaled_df.head())

# Display the shape of the new training and test sets
print("Important Training set size:", X_train_important.shape)
print("Important Test set size:", X_test_important.shape)
```




```
   ovl_quality  grlivarea  totalbsmtsf  garagecars  year_constructed  \
0    -1.486991  -0.720857    -0.787390   -0.969231         -1.047584
1    -0.766475  -0.821288    -0.080539    0.335454         -0.150451
2     1.395070   0.124796     1.045096    0.335454          1.178634
3    -0.766475   0.216003    -2.559359    0.335454          0.281501
4    -0.045960  -0.673190     0.202685    0.335454          1.145407

   1stflrsf  bsmtfinsf1  area_lot  garagearea  ovl_condition
0 -1.033460   -1.000751 -0.400378   -0.938850      -0.537207
```

```
1 -0.189321    0.190385  0.245066    0.074098      -0.537207
2  0.894081   -1.000751  0.053015    1.418557      -0.537207
3  1.017745   -1.000751 -0.316136   -0.312664      -0.537207
4 -0.041462   -1.000751  0.216223    0.074098      -0.537207
Important Training set size: (1019, 10)
Important Test set size: (438, 10)
```

### 2.0.3 4. Training the Model

We'll start by training a linear regression model using the `LinearRegression` class from `sklearn.linear_model`. The goal is to predict `SalePrice` using the relevant features after preparing and encoding the data.

[62]:
```
model = LinearRegression()
model.fit(X_train_important, y_train)
```

[62]:
```
LinearRegression()
```

### 2.0.4 5. Evaluating the Model

Now that we have trained our model, we will use several regression metrics to evaluate its performance on the test set:

1. **Mean Absolute Error (MAE)**
2. **Mean Squared Error (MSE)**
3. **Root Mean Squared Error (RMSE)**
4. **R-squared (R²)**

These metrics will give us a well-rounded view of the model's performance.

[64]:
```
# Making predictions
y_pred = model.predict(X_test_important)

# Calculating evaluation metrics
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

# Displaying the results
print("Mean Absolute Error (MAE):", mae)
print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("R-squared (R²):", r2)
```

```
Mean Absolute Error (MAE): 0.0962940982726615
Mean Squared Error (MSE): 0.01833831850308669
Root Mean Squared Error (RMSE): 0.13541904778533442
R-squared (R²): 0.8789923317259267
```

The evaluation metrics for this regression model indicate that it's performing quite well overall. Let's break down what each of these metrics means for our model's performance:

**Mean Absolute Error (MAE): 0.0952** The MAE tells us how far off, on average, our predictions are from the actual values. In this case, an MAE of 0.0952 means that our predictions are typically about 9.52% off. While this indicates some room for improvement, it still shows that the model is fairly precise in its predictions.

**Mean Squared Error (MSE): 0.0177** The MSE gives us a sense of the average of the squared differences between our predicted and actual values. A lower MSE generally indicates fewer errors, and here we see a value of 0.0177. While this isn't as low as we'd like, it does suggest that the model is doing a decent job at capturing the data patterns.

**Root Mean Squared Error (RMSE): 0.1330** RMSE, which is the square root of the MSE, provides an error measure in the same units as the `SalePrice`. With an RMSE of 0.1330, this suggests that our predictions are off by about 13.30% on average. This indicates a moderate level of accuracy, highlighting areas where the model could be improved.

**R-squared ($R^2$): 0.8832** $R^2$ tells us how much of the variance in `SalePrice` our model is able to explain. Here, the value is 88.32%, which is quite good. This means that our model captures a significant portion of the variation in `SalePrice`, indicating that it has learned some valuable patterns from the data. However, there's still some room for the model to improve its explanatory power.

Overall, while the model shows good potential and performs reasonably well, there's definitely an opportunity to refine it further for even better predictions.

[66]:
```python
# Get the coefficients
coefficients = model.coef_

# Create a DataFrame for better visualization
feature_names = X_train_important.columns
coef_df = pd.DataFrame({'Feature': feature_names, 'Coefficient': coefficients})

# Sort the DataFrame by absolute coefficient values for better insight
coef_df['Absolute Coefficient'] = coef_df['Coefficient'].abs()
coef_df = coef_df.sort_values(by='Absolute Coefficient', ascending=False)

print(coef_df.head(10))
```

```
            Feature  Coefficient  Absolute Coefficient
1         grlivarea     0.452401              0.452401
0       ovl_quality     0.083848              0.083848
9     ovl_condition     0.065637              0.065637
3        garagecars     0.032854              0.032854
4  year_constructed     0.003454              0.003454
2        totalbsmtsf     0.000127              0.000127
8        garagearea     0.000123              0.000123
```

```
6        bsmtfinsf1     0.000103             0.000103
5          1stflrsf     0.000005             0.000005
7          area_lot     0.000003             0.000003
```

### 2.0.5 Export Scaled Data for Use in Future Models

[68]:
```python
top_n = 8
important_features = feature_importance_df['Feature'].head(top_n).values
important_features
```

[68]:
```
array(['ovl_quality', 'grlivarea', 'totalbsmtsf', 'garagecars',
       'year_constructed', '1stflrsf', 'bsmtfinsf1', 'area_lot'],
      dtype=object)
```

[70]:
```python
X1 = df[important_features]
X1.head()
```

[70]:

| | ovl_quality | grlivarea | totalbsmtsf | garagecars | year_constructed |
|---|---|---|---|---|---|
| 0 | 5 | 6.733402 | 672 | 0 | 1930 |
| 1 | 7 | 7.124478 | 1242 | 2 | 1973 |
| 2 | 4 | 6.562444 | 420 | 0 | 1940 |
| 3 | 4 | 7.191429 | 686 | 1 | 1925 |
| 4 | 8 | 7.409742 | 1600 | 2 | 2008 |

| | 1stflrsf | bsmtfinsf1 | area_lot |
|---|---|---|---|
| 0 | 840 | 116 | 4388 |
| 1 | 1242 | 916 | 9600 |
| 2 | 708 | 280 | 5330 |
| 3 | 810 | 0 | 9906 |
| 4 | 1652 | 1480 | 5587 |

[72]:
```python
#X_scaled = scaler.fit_transform(X1) ## without saleprice
X_scaled_df = pd.DataFrame(X1, columns=X1.columns)
X_scaled_df.to_csv('scaled_housing_data.csv', index=False)
```

[ ]:
```python

```