Exploratory Data Analysis for House Price Prediction, a Kaggle Project

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Introduction and Objectives

This notebook presents an exploratory data analysis (EDA) of the House Price dataset from Kaggle, which is designed to predict the final sale price of residential homes in Ames, Iowa. The dataset comprises 79 explanatory variables that capture a wide range of characteristics influencing the value of each property, from its physical attributes to neighborhood features.

The primary objectives of this EDA are:

- Understanding the Data: Familiarizing with the structure, types, and summary statistics of the dataset to build a solid foundation for further analysis.
- Identifying Patterns: Recognizing key trends and relationships within the data that could contribute to more accurate predictions.
- Detecting Anomalies: Spotting any inconsistencies or outliers that may affect the robustness of the predictive models.

Generating Insights: Extracting useful insights that can inform data preprocessing and feature engineering steps, ensuring the data is well-prepared for machine learning applications.

By achieving these objectives, this analysis will serve as a critical step toward building an effective model for predicting house prices and enhancing our understanding of the factors that drive property values in Ames, Iowa.

Data Import and Description

Importing Modules

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt # for making plots
import seaborn as sns # for making plots with seaborn

import scipy # for statistical analysis
from scipy.stats import chi2_contingency
from scipy.stats import ttest_ind
from scipy.stats import pearsonr # Pearson Correlation
from scipy import stats # Module for T-test and ANOVA
```

```
import statsmodels.api as sm # Module for OLS Regression
from statsmodels.formula.api import ols  # Module for OLS Regression
from sklearn.impute import SimpleImputer # Module for imputing missing values

from ipywidgets import Button, Output # Module for creating buttons
from IPython.display import display # Module for displaying widgets
```

Virtual Python Environment: base (Python 3.12.4)

Importing the Dataset

The dataset consists of two files: train.csv and test.csv.

- train.csv: 1460 observations, 81 columns, with the target variable being the SalePrice column.
- test.csv: 1459 observations, 80 columns, containing the test data.

The first step is to load the train.csv file and examine its contents.

In [3]:
```
# Read the training data
train_df = pd.read_csv('data/train.csv')
# Drop Id column
train_df = train_df.drop(columns = ['Id'])
```

In [4]:
```
# Inspect first few rows of the datat
train_df.head(6)
```

Out[4]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	U
0	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	
1	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	
2	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	
3	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	
4	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	
5	50	RL	85.0	14115	Pave	NaN	IR1	Lvl	

6 rows × 80 columns

In [5]:
```
# Inspect the data structure
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   MSSubClass     1460 non-null   int64  
 1   MSZoning       1460 non-null   object 
 2   LotFrontage    1201 non-null   float64
 3   LotArea        1460 non-null   int64  
 4   Street         1460 non-null   object 
 5   Alley          91 non-null     object 
 6   LotShape       1460 non-null   object 
 7   LandContour    1460 non-null   object 
 8   Utilities      1460 non-null   object 
 9   LotConfig      1460 non-null   object 
 10  LandSlope      1460 non-null   object 
 11  Neighborhood   1460 non-null   object 
 12  Condition1     1460 non-null   object 
 13  Condition2     1460 non-null   object 
 14  BldgType       1460 non-null   object 
 15  HouseStyle     1460 non-null   object 
 16  OverallQual    1460 non-null   int64  
 17  OverallCond    1460 non-null   int64  
 18  YearBuilt      1460 non-null   int64  
 19  YearRemodAdd   1460 non-null   int64  
 20  RoofStyle      1460 non-null   object 
 21  RoofMatl       1460 non-null   object 
 22  Exterior1st    1460 non-null   object 
 23  Exterior2nd    1460 non-null   object 
 24  MasVnrType     588 non-null    object 
 25  MasVnrArea     1452 non-null   float64
 26  ExterQual      1460 non-null   object 
 27  ExterCond      1460 non-null   object 
 28  Foundation     1460 non-null   object 
 29  BsmtQual       1423 non-null   object 
 30  BsmtCond       1423 non-null   object 
 31  BsmtExposure   1422 non-null   object 
 32  BsmtFinType1   1423 non-null   object 
 33  BsmtFinSF1     1460 non-null   int64  
 34  BsmtFinType2   1422 non-null   object 
 35  BsmtFinSF2     1460 non-null   int64  
 36  BsmtUnfSF      1460 non-null   int64  
 37  TotalBsmtSF    1460 non-null   int64  
 38  Heating        1460 non-null   object 
 39  HeatingQC      1460 non-null   object 
 40  CentralAir     1460 non-null   object 
 41  Electrical     1459 non-null   object 
 42  1stFlrSF       1460 non-null   int64  
 43  2ndFlrSF       1460 non-null   int64  
 44  LowQualFinSF   1460 non-null   int64  
 45  GrLivArea      1460 non-null   int64  
 46  BsmtFullBath   1460 non-null   int64  
 47  BsmtHalfBath   1460 non-null   int64  
 48  FullBath       1460 non-null   int64  
 49  HalfBath       1460 non-null   int64  
 50  BedroomAbvGr   1460 non-null   int64  
 51  KitchenAbvGr   1460 non-null   int64  
 52  KitchenQual    1460 non-null   object 
 53  TotRmsAbvGrd   1460 non-null   int64  
```

```
 54  Functional     1460 non-null   object
 55  Fireplaces     1460 non-null   int64
 56  FireplaceQu    770 non-null    object
 57  GarageType     1379 non-null   object
 58  GarageYrBlt    1379 non-null   float64
 59  GarageFinish   1379 non-null   object
 60  GarageCars     1460 non-null   int64
 61  GarageArea     1460 non-null   int64
 62  GarageQual     1379 non-null   object
 63  GarageCond     1379 non-null   object
 64  PavedDrive     1460 non-null   object
 65  WoodDeckSF     1460 non-null   int64
 66  OpenPorchSF    1460 non-null   int64
 67  EnclosedPorch  1460 non-null   int64
 68  3SsnPorch      1460 non-null   int64
 69  ScreenPorch    1460 non-null   int64
 70  PoolArea       1460 non-null   int64
 71  PoolQC         7 non-null      object
 72  Fence          281 non-null    object
 73  MiscFeature    54 non-null     object
 74  MiscVal        1460 non-null   int64
 75  MoSold         1460 non-null   int64
 76  YrSold         1460 non-null   int64
 77  SaleType       1460 non-null   object
 78  SaleCondition  1460 non-null   object
 79  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(34), object(43)
memory usage: 912.6+ KB
```

The training dataset consists of 1460 observations and 81 columns, including the target variable SalePrice. The columns represent various property features, such as the number of bedrooms, bathrooms, and other attributes that may influence the sale price.

The dataset includes different types of variables: numerical, categorical, and ordinal. Some variables contain missing values that will need to be handled during data preprocessing.

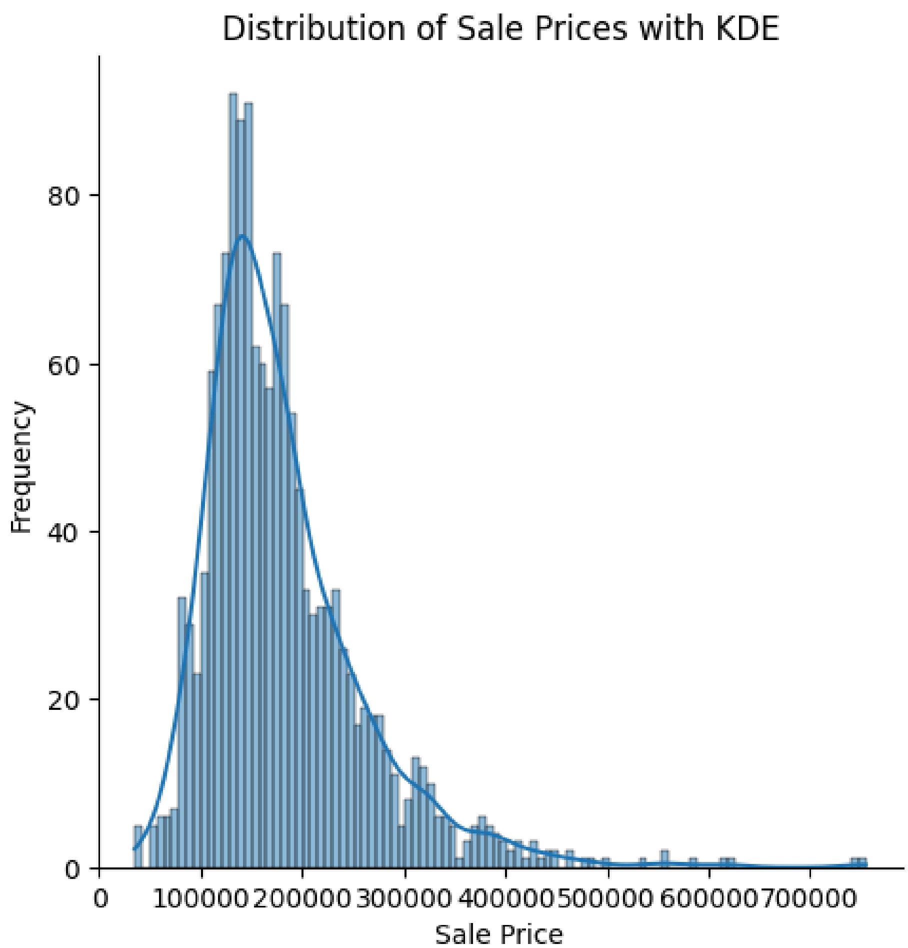
Descriptive Statistics of the Target Variable: SalePrice

In [6]:
```
# Description of the target variable
train_df['SalePrice'].describe()
```

Out[6]:
```
count      1460.000000
mean     180921.195890
std       79442.502883
min       34900.000000
25%      129975.000000
50%      163000.000000
75%      214000.000000
max      755000.000000
Name: SalePrice, dtype: float64
```

In [7]:
```
# Histogram of the target variable with kernel density estimation (KDE)
sns.displot(train_df['SalePrice'], kde=True, bins=100)

# Display the plot
plt.title('Distribution of Sale Prices with KDE')
plt.xlabel('Sale Price')
```

```
plt.ylabel('Frequency')
plt.show()
```



The descriptive statistics of the target variable are as follows:

- Mean: $180,921.20
- Standard Deviation: $79,442.50
- Minimum: $34,900.00
- 25th Percentile: $129,975.00
- Median: $163,000.00
- 75th Percentile: $214,000.00
- Maximum: $755,000.00

In general, the target variable, SalePrice, is right-skewed. The mean is greater than the median, which indicates that the distribution is positively skewed. The minimum value is $34,900.00, whilethemaximumvalueis$755,000.00. The standard deviation is $79,442.50, which indicates that the data points are spread out from the mean.

Data Cleaning and Preprocessing

Inspect Missing Values

First, we will examine the missing values in the dataset to determine the extent of missing data and decide on the appropriate handling strategy.

In [8]:
```python
# Check for missing values
pd.isna(train_df)
```

Out[8]:

	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour
0	False	False	False	False	False	True	False	False
1	False	False	False	False	False	True	False	False
2	False	False	False	False	False	True	False	False
3	False	False	False	False	False	True	False	False
4	False	False	False	False	False	True	False	False
...	...	...	...	...	...	...	...	...
1455	False	False	False	False	False	True	False	False
1456	False	False	False	False	False	True	False	False
1457	False	False	False	False	False	True	False	False
1458	False	False	False	False	False	True	False	False
1459	False	False	False	False	False	True	False	False

1460 rows × 80 columns

Identifying Missing Values: The dataset contains missing values that need to be addressed before proceeding with the analysis. The missing values are distributed across multiple columns, with varying degrees of completeness. The next step is to investigate the missing values in more detail and determine the appropriate imputation strategy.

In [9]:
```python
# Summary of missing values counts in each variable
missing_list = pd.isna(train_df).agg(lambda x: np.sum(x))

# Display only variables that have missing values and counts
var_with_na = list(missing_list[missing_list > 0].index)
count_na = list(missing_list[missing_list > 0].values)

# Create a directory with key and value representing positive variables and NA cc
dict_na = dict(zip(var_with_na, count_na))
```

In [10]:
```python
# Create a data frame with columns, including variable name, NA counts, and NA pe
df_series = {
    "variable": dict_na.keys(),
    "na_count": dict_na.values()
}

df_na = pd.DataFrame(df_series)

# Add a column na_percent
unique_id_count = train_df.shape[0]
df_na["na_percent"] = df_na["na_count"] / unique_id_count * 100
```

```
print(df_na.sort_values(by="na_percent"))
```

```
       variable  na_count  na_percent
9    Electrical         1    0.068493
3    MasVnrArea         8    0.547945
4      BsmtQual        37    2.534247
5      BsmtCond        37    2.534247
7  BsmtFinType1        37    2.534247
6  BsmtExposure        38    2.602740
8  BsmtFinType2        38    2.602740
15   GarageCond        81    5.547945
14   GarageQual        81    5.547945
13 GarageFinish        81    5.547945
12  GarageYrBlt        81    5.547945
11   GarageType        81    5.547945
0   LotFrontage       259   17.739726
10  FireplaceQu       690   47.260274
2    MasVnrType       872   59.726027
17        Fence      1179   80.753425
1         Alley      1369   93.767123
18  MiscFeature      1406   96.301370
16       PoolQC      1453   99.520548
```

The dataset contains missing values in 19 explanatory variables. Among these, the variables with the most missing values (>50% missingness) are:

- PoolQC (99.52% missing): Pool quality
- MiscFeature (96.30% missing): Miscellaneous feature not covered in other categories
- Alley (93.77% missing): Type of alley access to property
- Fence (80.75% missing): Fence quality

These variables have the highest proportion of missing data and will require attention during the data preprocessing phase.

In [11]:

```
# Add a column "datatype"
data_type = train_df.dtypes  # Check data types of variables
df_datatype = pd.DataFrame(data_type)
df_datatype_reset = df_datatype.reset_index() # Change index into a column
df_datatype_reset = df_datatype_reset.rename(columns={"index": "variable", 0: "da

# Join df_datatype_reset and df_na on variable
df_na_datatype = pd.merge(df_na,
                          df_datatype_reset,
                          on="variable",
                          how="left")

df_na_datatype.sort_values(by="na_percent")
```

Out[11]:

	variable	na_count	na_percent	datatype
9	Electrical	1	0.068493	object
3	MasVnrArea	8	0.547945	float64
4	BsmtQual	37	2.534247	object
5	BsmtCond	37	2.534247	object
7	BsmtFinType1	37	2.534247	object
6	BsmtExposure	38	2.602740	object
8	BsmtFinType2	38	2.602740	object
15	GarageCond	81	5.547945	object
14	GarageQual	81	5.547945	object
13	GarageFinish	81	5.547945	object
12	GarageYrBlt	81	5.547945	float64
11	GarageType	81	5.547945	object
0	LotFrontage	259	17.739726	float64
10	FireplaceQu	690	47.260274	object
2	MasVnrType	872	59.726027	object
17	Fence	1179	80.753425	object
1	Alley	1369	93.767123	object
18	MiscFeature	1406	96.301370	object
16	PoolQC	1453	99.520548	object

Handling Missing Data

To handle missing values, I use the following strategy:

- For numeric variables:
  - Impute missing values with the median if missingness is less than 30%.
  - Drop the variable if missingness exceeds 30%.
- For categorical variables:
  - Impute missing values using the mode (most frequent value).

In [12]:

```
# Find categorical variable (aka object)
na_object_index = df_na_datatype["datatype"] == "object"
na_object_variables = df_na_datatype[na_object_index]["variable"].tolist()
non_object_variables = df_na_datatype["datatype"] != "object"
# Store the remaining variables into a list
df_na_float = df_na_datatype[non_object_variables]

na_float_variables = df_na_float["variable"].values.tolist()
```

Impute missing values for categorical variables using the mode (most frequent value).

In [13]:
```
mode_imputer = SimpleImputer(strategy="most_frequent")
train_df[na_object_variables] = mode_imputer.fit_transform(train_df[na_object_var
```

In [14]:
```
sum_na = pd.isna(train_df).agg(lambda x: np.sum(x))  # NA counts before filling
sum_na[sum_na != 0] # Check variables with missing values
```

Out[14]:
```
LotFrontage    259
MasVnrArea       8
GarageYrBlt     81
dtype: int64
```

For numeric variables (float or int), fill missing values with the median if missingness is less than 30%.

In [15]:
```
# Replace missing values in numerical variables with median
numerical_variables = df_na_float["variable"].values.tolist()
train_df[numerical_variables] = train_df[numerical_variables].fillna(train_df[num

# print(train_df_dropna)
sum_na2 = pd.isna(train_df).agg(lambda x: np.sum(x))  # NA counts after filling
sum_na2[sum_na2 != 0] # Check variables with missing values

# Check the data structure after imputing missing values
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 80 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   MSSubClass     1460 non-null   int64  
 1   MSZoning       1460 non-null   object 
 2   LotFrontage    1460 non-null   float64
 3   LotArea        1460 non-null   int64  
 4   Street         1460 non-null   object 
 5   Alley          1460 non-null   object 
 6   LotShape       1460 non-null   object 
 7   LandContour    1460 non-null   object 
 8   Utilities      1460 non-null   object 
 9   LotConfig      1460 non-null   object 
 10  LandSlope      1460 non-null   object 
 11  Neighborhood   1460 non-null   object 
 12  Condition1     1460 non-null   object 
 13  Condition2     1460 non-null   object 
 14  BldgType       1460 non-null   object 
 15  HouseStyle     1460 non-null   object 
 16  OverallQual    1460 non-null   int64  
 17  OverallCond    1460 non-null   int64  
 18  YearBuilt      1460 non-null   int64  
 19  YearRemodAdd   1460 non-null   int64  
 20  RoofStyle      1460 non-null   object 
 21  RoofMatl       1460 non-null   object 
 22  Exterior1st    1460 non-null   object 
 23  Exterior2nd    1460 non-null   object 
 24  MasVnrType     1460 non-null   object 
 25  MasVnrArea     1460 non-null   float64
 26  ExterQual      1460 non-null   object 
 27  ExterCond      1460 non-null   object 
 28  Foundation     1460 non-null   object 
 29  BsmtQual       1460 non-null   object 
 30  BsmtCond       1460 non-null   object 
 31  BsmtExposure   1460 non-null   object 
 32  BsmtFinType1   1460 non-null   object 
 33  BsmtFinSF1     1460 non-null   int64  
 34  BsmtFinType2   1460 non-null   object 
 35  BsmtFinSF2     1460 non-null   int64  
 36  BsmtUnfSF      1460 non-null   int64  
 37  TotalBsmtSF    1460 non-null   int64  
 38  Heating        1460 non-null   object 
 39  HeatingQC      1460 non-null   object 
 40  CentralAir     1460 non-null   object 
 41  Electrical     1460 non-null   object 
 42  1stFlrSF       1460 non-null   int64  
 43  2ndFlrSF       1460 non-null   int64  
 44  LowQualFinSF   1460 non-null   int64  
 45  GrLivArea      1460 non-null   int64  
 46  BsmtFullBath   1460 non-null   int64  
 47  BsmtHalfBath   1460 non-null   int64  
 48  FullBath       1460 non-null   int64  
 49  HalfBath       1460 non-null   int64  
 50  BedroomAbvGr   1460 non-null   int64  
 51  KitchenAbvGr   1460 non-null   int64  
 52  KitchenQual    1460 non-null   object 
 53  TotRmsAbvGrd   1460 non-null   int64  
```

```
 54  Functional     1460 non-null   object
 55  Fireplaces     1460 non-null   int64
 56  FireplaceQu    1460 non-null   object
 57  GarageType     1460 non-null   object
 58  GarageYrBlt    1460 non-null   float64
 59  GarageFinish   1460 non-null   object
 60  GarageCars     1460 non-null   int64
 61  GarageArea     1460 non-null   int64
 62  GarageQual     1460 non-null   object
 63  GarageCond     1460 non-null   object
 64  PavedDrive     1460 non-null   object
 65  WoodDeckSF     1460 non-null   int64
 66  OpenPorchSF    1460 non-null   int64
 67  EnclosedPorch  1460 non-null   int64
 68  3SsnPorch      1460 non-null   int64
 69  ScreenPorch    1460 non-null   int64
 70  PoolArea       1460 non-null   int64
 71  PoolQC         1460 non-null   object
 72  Fence          1460 non-null   object
 73  MiscFeature    1460 non-null   object
 74  MiscVal        1460 non-null   int64
 75  MoSold         1460 non-null   int64
 76  YrSold         1460 non-null   int64
 77  SaleType       1460 non-null   object
 78  SaleCondition  1460 non-null   object
 79  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(34), object(43)
memory usage: 912.6+ KB
```

In summary, I imputed 16 categorical variables with modes and filled 3 numeric variables with the median. The resulting data frame, `train_df` is free of missing values, and contains 1460 observations and 79 explanatory variables.

Identifying and Handling Duplicates

Check for and remove duplicate rows.

In [16]:
```
# Check for and remove duplicate rows
train_df.index.is_unique
```

Out[16]: True

In [17]:
```
# Check for and remove duplicate columns
train_df.columns.is_unique
```

Out[17]: True

In summary, there are no duplicate rows and columns in the dataset.

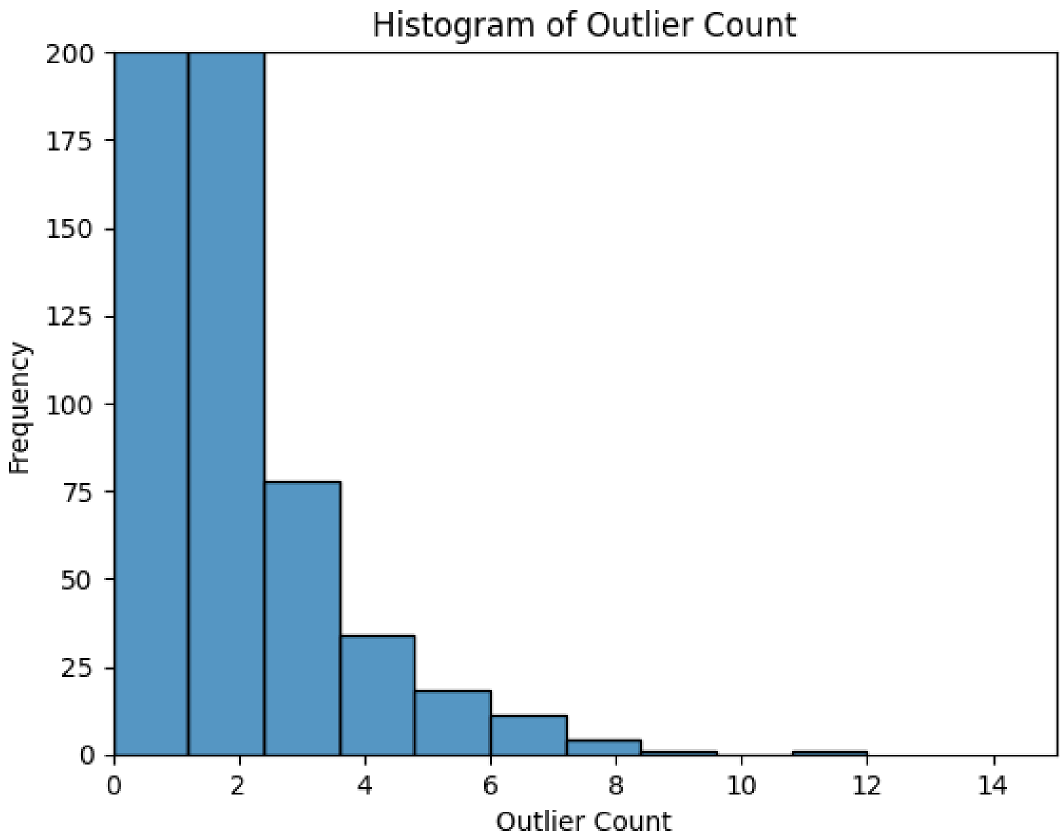
Outlier detection and handling

Investigate potential outliers in numeric variables using the 1.5IQR method. Data points below Q1 - 1.5IQR or above Q3 + 1.5IQR are considered outliers.

In [18]:
```
# Create a function to detect outliers
def detect_outlier(var):
    # Calculate IQR based on the list, x
    q1 = np.quantile(var, 0.25)
    q3 = np.quantile(var, 0.75)
    iqr = q3 - q1

    lower_bound = q1 - 1.5*iqr
    upper_bound = q3 + 1.5*iqr

    outlier = [True if x > upper_bound or x < lower_bound else False for x in var

    return outlier
```

In [19]:
```
# Apply the above function to each numeric variable, and store results in a new d
df_outlier = train_df.select_dtypes(include=[np.number]).apply(detect_outlier)

# Calculate count of outliers in a sample
outlier_count = df_outlier.iloc[:, 1:].sum(axis=1, skipna=True)

# Sort the series
sorted_outlier_count = outlier_count.sort_values(ascending=False)
```

In [20]:
```
# Draw a histogram to represent outlier count
sns.histplot(sorted_outlier_count, bins=10)

# Zoom in 0 - 200 in y axis
plt.ylim(0, 200)
plt.xlim(0, 15)
plt.xlabel("Outlier Count")
plt.ylabel("Frequency")
plt.title("Histogram of Outlier Count")
plt.show()
```



Identify properties with more than 10 outliers by counting the number of outliers for each property. Properties with more than 10 outliers (based on the 1.5*IQR method) will be flagged for further investigation.

In [21]:
```
# Identify sample ID with more than 10 outliers
sample_many_outliers = sorted_outlier_count[sorted_outlier_count >= 5].index
sample_many_outliers_list = sample_many_outliers.to_list()

# Drop samples with 10 or more outliers with index sample_many_outliers_list
train_df_dropna_clean2 = train_df.drop(index=sample_many_outliers_list)

print(train_df_dropna_clean2.shape)  # Check the shape of the data frame
```

```
(1425, 80)
```

In summary, the resulting dataset, `train_df_dropna_clean2`, contains 1425 observations and 79 explanatory variables. It is free of missing values and outliers. The data is now ready for further analysis and modeling.

I want to verify the training dataset before and after outlier removal using NMDS (Non-metric Multidimensional Scaling) to visualize the data distribution. NMDS is a dimensionality reduction technique that can help visualize the similarity between data points in a lower-dimensional space. By comparing the NMDS plots before and after outlier removal, we can assess the impact of outlier removal on the data distribution.

In [22]:
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
```

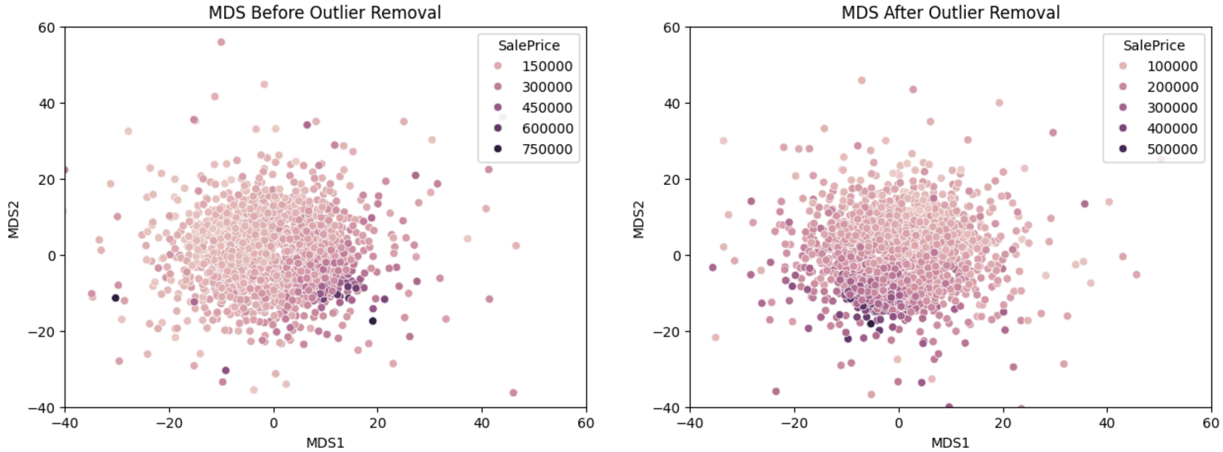
```
from sklearn.decomposition import PCA
from sklearn.metrics import pairwise_distances
from sklearn.manifold import MDS
import seaborn as sns
import matplotlib.pyplot as plt
```

In [23]:
```
# Handle categorical data - convert to numeric using one-hot encoding
train_df_encoded = pd.get_dummies(train_df, drop_first=True)  # Before outlier re
train_df_dropna_clean2_encoded = pd.get_dummies(train_df_dropna_clean2, drop_firs
```

In [24]:
```
# Standardize the numerical data
scaler = StandardScaler()
train_df_encoded_scaled = scaler.fit_transform(train_df_encoded)  # Before outlie
train_df_dropna_clean2_encoded_scaled = scaler.fit_transform(train_df_dropna_clea
```

In [25]:
```
# Calculate the Euclidean distance matrix
distance_matrix = pairwise_distances(train_df_encoded_scaled, metric='euclidean')
distance_matrix2 = pairwise_distances(train_df_dropna_clean2_encoded_scaled, metr
```

In [26]:
```
# Perform MDS on the distance matrix
mds = MDS(n_components=2, dissimilarity='precomputed') # Before outlier removal
train_df_encoded_mds = mds.fit_transform(distance_matrix)  # Before outlier remov

mds2 = MDS(n_components=2, dissimilarity='precomputed') # After outlier removal
train_df_dropna_clean2_encoded_mds = mds2.fit_transform(distance_matrix2)  # Afte

# Create a data frame with MDS results
df_mds = pd.DataFrame(train_df_encoded_mds, columns=['MDS1', 'MDS2']) # Before ou
df_mds2 = pd.DataFrame(train_df_dropna_clean2_encoded_mds, columns=['MDS1', 'MDS2

# Add SalePrice to the data frame
df_mds['SalePrice'] = train_df['SalePrice'].values # Before outlier removal
df_mds2['SalePrice'] = train_df_dropna_clean2['SalePrice'].values # After outlier

# Scatter plot of MDS1 and MDS2 with SalePrice as hue
# Combine the two scatter plots - before and after outlier removal
# Make x-axis and y-axis the same range in two plots
fig, axes = plt.subplots(1, 2, figsize=(15, 5))

sns.scatterplot(data=df_mds, x='MDS1', y='MDS2', hue='SalePrice', ax=axes[0])
axes[0].set_title('MDS Before Outlier Removal')
axes[0].set_xlim(-40, 60)
axes[0].set_ylim(-40, 60)

sns.scatterplot(data=df_mds2, x='MDS1', y='MDS2', hue='SalePrice', ax=axes[1])
axes[1].set_title('MDS After Outlier Removal')
axes[1].set_xlim(-40, 60)
axes[1].set_ylim(-40, 60)

plt.show()
```



Exploratory Analysis

Correlation Analysis

Correlation Between Sale Prices and Categorical Variables

To identify independent, categorial variables that are predictive of the target outcome, I applied T-test and ANOVA to two- and multiple-group variables, respectively, which produced p-values for each variable.

To further assess strength of the relationship, I calculated the effect size using Cohen's d for two-group variables and eta-squared for multiple-group variables.

In [27]:
```
# Identify categorical variables
categorical_vars = train_df_dropna_clean2.select_dtypes(include=['object', 'categ

# Check data types for all the features
data_types_features = train_df_dropna_clean2.dtypes

# Distribution of data types
data_types_features.value_counts()

# Extract categorical variables
categorical_vars_df = train_df_dropna_clean2.select_dtypes(include=['object'])
```

In [28]:
```
# Use T-test to compare sales price between two groups
class_n = categorical_vars_df.nunique()
class_n_df = class_n.to_frame(name="n_groups")

# Identify variables (index) which has only two groups, and store binary variable
binary_variables = class_n_df.index[class_n_df["n_groups"] == 2].to_list()
# Store the rest multi-class variable names into a list
multiclass_variables = class_n_df.index[class_n_df["n_groups"] > 2].to_list()
```

In [29]:
```
# Write a function to implement T-test for binary variable and sales price
def ttest_sales_prices(df, binary_var, target_var='SalePrice'):
    # Split the data into two groups based on the binary variable
```

```
    group1 = df[df[binary_var] == df[binary_var].unique()[0]][target_var]
    group2 = df[df[binary_var] == df[binary_var].unique()[1]][target_var]

    # Perform T-test
    t_stat, p_value = ttest_ind(group1, group2)

    return t_stat, p_value
```

In [30]:
```
# Apply the defined function on binary variables and cleaned data set
ttest_results = []
for var in binary_variables:
    t_stat, p_value = ttest_sales_prices(df=train_df_dropna_clean2, binary_var=va
    ttest_results.append({"variable": var, "stat": t_stat, "p-value": p_value, 'm
```

In [ ]:
```
# Convert the list of dictionaries to a data frame
ttest_results_df = pd.DataFrame(ttest_results)
```

Out[ ]:

	variable	stat	p-value	method
0	Street	1.617747	1.059388e-01	ttest
1	Alley	0.830391	4.064571e-01	ttest
2	Utilities	0.554215	5.795189e-01	ttest
3	CentralAir	10.636956	1.764859e-25	ttest
4	PoolQC	-0.067869	9.458998e-01	ttest

Apply ANOVA test to categorical variables with more than two groups versus sale prices

In [32]:
```
# Write the function to implement ANOVA
def anova_sale_price(df, var, target_var='SalePrice'):
    formula = f'{target_var} ~ C({var})'
    model = ols(formula, data=df).fit()
    anova_results = sm.stats.anova_lm(model, typ=2)

    return anova_results
```

In [33]:
```
# Apply the function to data frame
anova_results = []
for var in multiclass_variables:
    anova_result = anova_sale_price(df=train_df_dropna_clean2, var=var)
    f_value = anova_result.iloc[0,2]
    p_value = anova_result.iloc[0,3]
    anova_results.append({'variable':var, 'stat':f_value, 'p-value':p_value, 'met
```

In [34]:
```
# Convert dictionary to a data frame
anova_df =  pd.DataFrame(anova_results)
```

In [35]:
```
# Combine T-test and ANOVA outputs into a single data frame
frames = [ttest_results_df, anova_df]
combined_results = pd.concat(frames)
# - Create a column of -log(10)p
combined_results['log(10)p'] = -np.log(combined_results['p-value'])
```

In [92]:
```python
# Order the row by -log(10)p and stat
combined_results.sort_values(by=['log(10)p'], ascending=False).head(10)
```

Out[92]:

	variable	stat	p-value	method	log(10)p
5	Neighborhood	76.867613	3.156385e-235	anova	539.958069
15	ExterQual	460.697852	4.975219e-209	anova	479.635815
18	BsmtQual	439.578920	5.571639e-202	anova	463.404500
26	KitchenQual	407.917463	4.217077e-191	anova	438.354611
30	GarageFinish	345.566251	4.883239e-123	anova	281.632158
17	Foundation	119.283705	1.767115e-105	anova	241.202086
24	HeatingQC	97.086753	4.372212e-73	anova	166.613443
21	BsmtFinType1	76.193318	7.364954e-71	anova	161.486809
29	GarageType	66.895535	7.291414e-63	anova	143.076163
12	Exterior1st	23.453370	6.624499e-55	anova	124.751405

Assessing strength of association between categorical variables and SalePrice using Effect Size

In [60]:
```python
# Effect size calculation for T-test using pingouin.compute_effsize() function
import pingouin as pg

# Calculate effect size for T-test
effect_size = []
for var in binary_variables:
    group1 = train_df_dropna_clean2[train_df_dropna_clean2[var] == train_df_dropr
    group2 = train_df_dropna_clean2[train_df_dropna_clean2[var] == train_df_dropr
    effect_size.append({'variable': var, 'd': pg.compute_effsize(group1, group2,
```

In [93]:
```python
# Convert the list of dictionaries to a data frame
effect_size_df = pd.DataFrame(effect_size)

# Add a column that contains variable description from the data_description.txt 1
# Read the data_description.txt file
with open('data/data_description.txt', 'r') as file:
    data_description = file.readlines()

# Create a dictionary with variable names as keys and descriptions as values
var_description = {}
for line in data_description:
    if ':' in line:
        key = line.split(':')[0]
        value = line.split(':')[1].strip()
        var_description[key] = value

# Add a column that contains variable description from the data_description.txt 1
effect_size_df['description'] = effect_size_df['variable'].map(var_description)
```

```python
# Display the data frame
effect_size_df.head(10)
```

Out[93]:

	variable	d	description
0	Street	0.661837	Type of road access to property
1	Alley	0.133179	Type of alley access to property
2	Utilities	[0.5544094131357278]	Type of utilities available
3	CentralAir	1.129632	Central air conditioning
4	PoolQC	[-0.0678924090136919]	Pool quality

In [95]:

```python
# Calculate Eta squared for each variable using pingouin.compute_effsize() functi
eta_squared = []
for var in multiclass_variables:
    formula = f'SalePrice ~ C({var})'
    aov = pg.anova(data=train_df_dropna_clean2, dv='SalePrice', between=var, deta
    eta_squared.append({'variable': var, 'eta_squared': aov['np2'][0]})

# Convert the list of dictionaries to a data frame
eta_squared_df = pd.DataFrame(eta_squared)

# Create a dictionary with variable names as keys and descriptions as values
var_description = {}
for line in data_description:
    if ':' in line:
        key = line.split(':')[0]
        value = line.split(':')[1].strip()
        var_description[key] = value

# Add a column that contains variable description from the data_description.txt f
eta_squared_df['description'] = eta_squared_df['variable'].map(var_description)

# Display the data frame by Eta squared in descending order
eta_squared_df.sort_values(by='eta_squared', ascending=False).head(7)
```

Out[95]:

	variable	eta_squared	description
5	Neighborhood	0.568543	Physical locations within Ames city limits
15	ExterQual	0.493060	Evaluates the quality of the material on the e...
18	BsmtQual	0.481337	Evaluates the height of the basement
26	KitchenQual	0.462710	Kitchen quality
30	GarageFinish	0.327065	Interior finish of the garage
17	Foundation	0.295928	Type of foundation
24	HeatingQC	0.214752	Heating quality and condition

The first step is to calculate the effect size for each categorical variable using the eta-squared (η2) statistic. The eta-squared statistic measures the proportion of variance in the dependent variable (SalePrice) that can be attributed to the independent variable (categorical variable).

The effect size analysis reveals that the top 10 categorical variables with the highest effect sizes are as follows: Neighborhood, ExterQual, KitchenQual, BsmtQual, GarageFinish, HeatingQC, Foundation, CentralAir, PavedDrive, and SaleType. These variables have a strong association with SalePrice, as they explain a significant proportion of the variance in the target variable. The two-group variable, CentralAir, has the highest effect size, indicating a strong relationship with SalePrice.

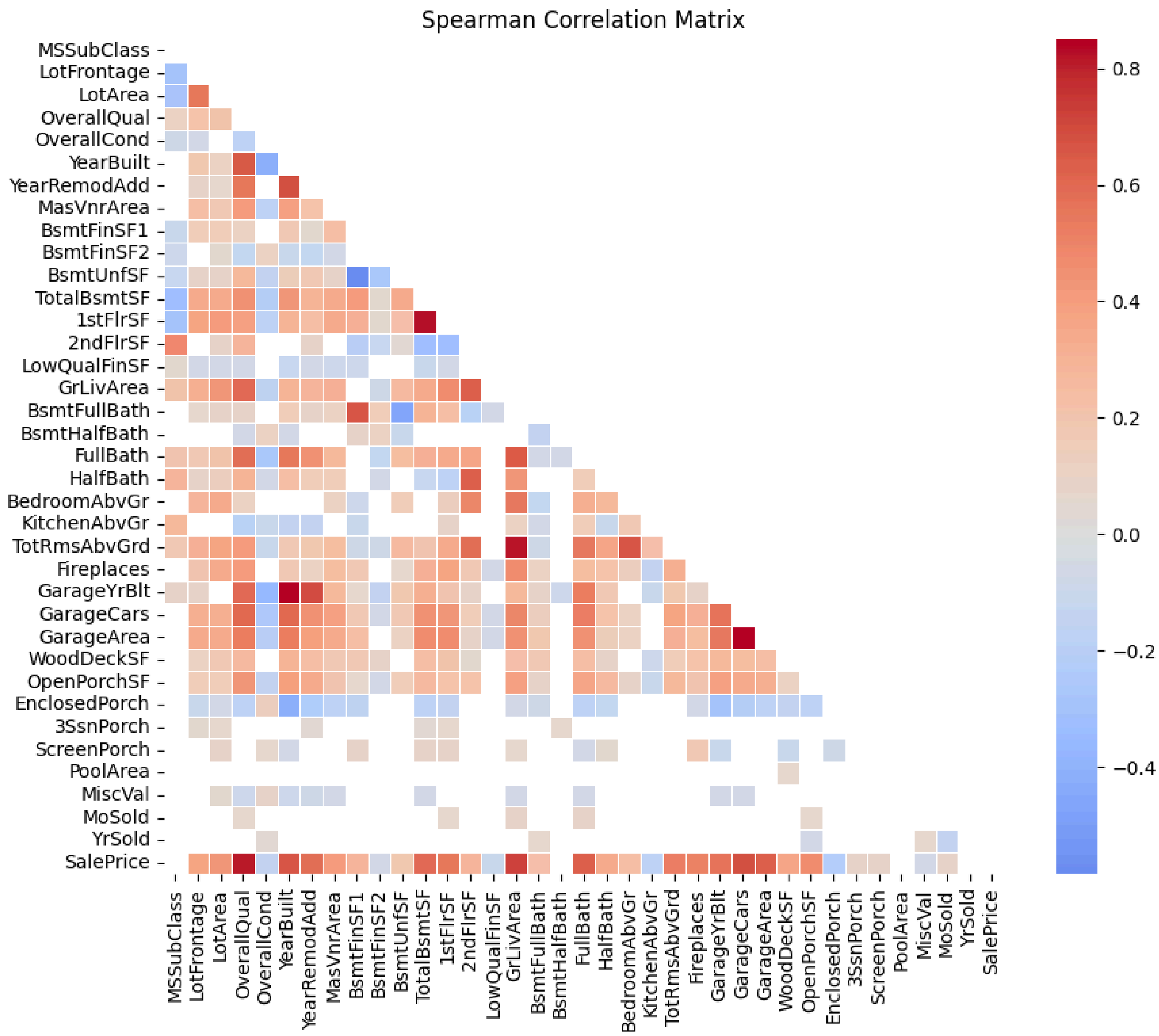
In addition, the effect size analysis provides valuable insights into the categorical variables that are most relevant for predicting house prices in Ames, Iowa.

Correlation between numeric variables and sale prices

In [40]:
```
numeric_vars = train_df_dropna_clean2.select_dtypes(include=[np.number]) # Select
```

In [41]:
```
import pandas as pd
import numpy as np
from scipy.stats import spearmanr

# Assuming numeric_vars is already defined and contains the numeric variables

# Function to compute Spearman correlation matrix and p-values matrix
def spearman_corr_pvalues(df):
    cols = df.columns
    n = len(cols)
    corr_matrix = np.zeros((n, n))
    pval_matrix = np.zeros((n, n))

    for i in range(n):
        for j in range(n):
            corr, pval = spearmanr(df[cols[i]], df[cols[j]])
            corr_matrix[i, j] = corr
            pval_matrix[i, j] = pval

    corr_df = pd.DataFrame(corr_matrix, index=cols, columns=cols)
    pval_df = pd.DataFrame(pval_matrix, index=cols, columns=cols)

    return corr_df, pval_df

# Calculate Spearman correlation matrix and p-values matrix
spearman_corr_matrix, spearman_pval_matrix = spearman_corr_pvalues(numeric_vars)
```

In [85]:
```
# Create heatmap for the correlation matrix
# Mask cells with p-values greater than 0.05
mask = spearman_pval_matrix > 0.05
spearman_corr_matrix_masked = spearman_corr_matrix.copy()
spearman_corr_matrix_masked[mask] = np.nan

# Create a mask for the upper triangle
mask2 = np.triu(np.ones_like(spearman_corr_matrix, dtype=bool))

plt.figure(figsize=(10, 8))
sns.heatmap(spearman_corr_matrix_masked, annot=False, cmap='coolwarm', center=0,
plt.title('Spearman Correlation Matrix')
plt.show()
```



In [101…

```
# Find the variables that are highly correlated with SalePrice
high_corr_vars = spearman_corr_matrix
high_corr_vars = high_corr_vars['SalePrice']
high_corr_vars = high_corr_vars[abs(high_corr_vars) > 0.5]
high_corr_vars = high_corr_vars.sort_values(ascending=False)
high_corr_vars = high_corr_vars.drop('SalePrice') # Remove SalePrice from the lis

# Add columns names to the data frame, with first column as variable and second c
high_corr_vars = high_corr_vars.reset_index()
high_corr_vars.columns = ['variable', 'correlation']

# Create a dictionary with variable names as keys and descriptions as values
var_description = {}
for line in data_description:
    if ':' in line:
        key = line.split(':')[0]
        value = line.split(':')[1].strip()
        var_description[key] = value

# Add a column that contains variable description from the data_description.txt f
high_corr_vars['description'] = high_corr_vars['variable'].map(var_description)

# Display the data frame by Eta squared in descending order
high_corr_vars.sort_values(by="correlation", ascending=False)
```

Out[101…

	variable	correlation	description
0	OverallQual	0.807584	Rates the overall material and finish of the h...
1	GrLivArea	0.719779	Above grade (ground) living area square feet
2	GarageCars	0.684793	Size of garage in car capacity
3	YearBuilt	0.668263	Original construction date
4	GarageArea	0.640978	Size of garage in square feet
5	FullBath	0.630213	Full bathrooms above grade
6	TotalBsmtSF	0.589182	Total square feet of basement area
7	YearRemodAdd	0.578083	Remodel date (same as construction date if no ...
8	GarageYrBlt	0.569145	Year garage was built
9	1stFlrSF	0.555505	First Floor square feet
10	TotRmsAbvGrd	0.514206	Total rooms above grade (does not include bath...
11	Fireplaces	0.507028	Number of fireplaces

The correlation analysis reveals that the top 10 numeric variables with the highest correlation coefficients are as follows: OverallQual, GrLivArea, GarageCars, GarageArea, TotalBsmtSF, 1stFlrSF, FullBath, TotRmsAbvGrd, YearBuilt, and YearRemodAdd. These variables have a strong positive correlation with SalePrice, indicating that they are important predictors of house prices in Ames, Iowa.

Encode Categorical Variables

In [ ]:

```
# Convert categorical variables into dummy variables
train_df_dropna_clean2_dummy = pd.get_dummies(train_df_dropna_clean2, drop_first=
train_df_dropna_clean2_dummy.head()
```

Out[ ]:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd
0	60	65.0	8450	7	5	2003	2003
1	20	80.0	9600	6	8	1976	1976
2	60	68.0	11250	7	5	2001	2002
3	70	60.0	9550	7	5	1915	1970
4	60	84.0	14260	8	5	2000	2000

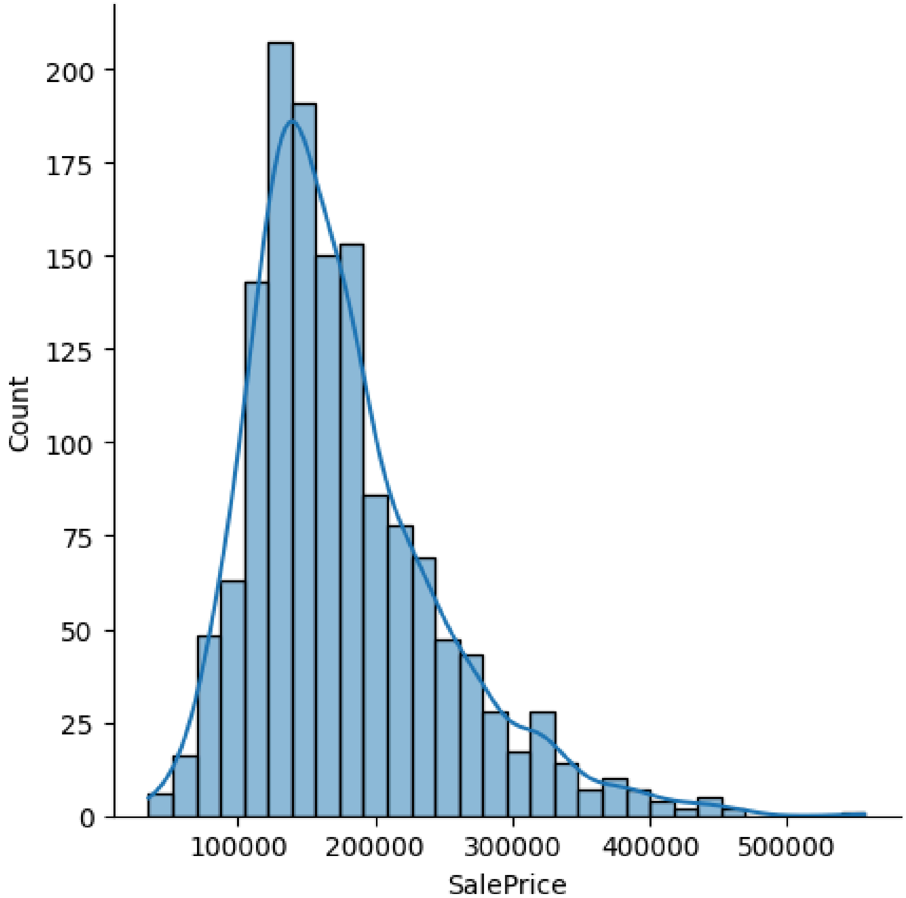
5 rows × 240 columns

Scaling and Normalization

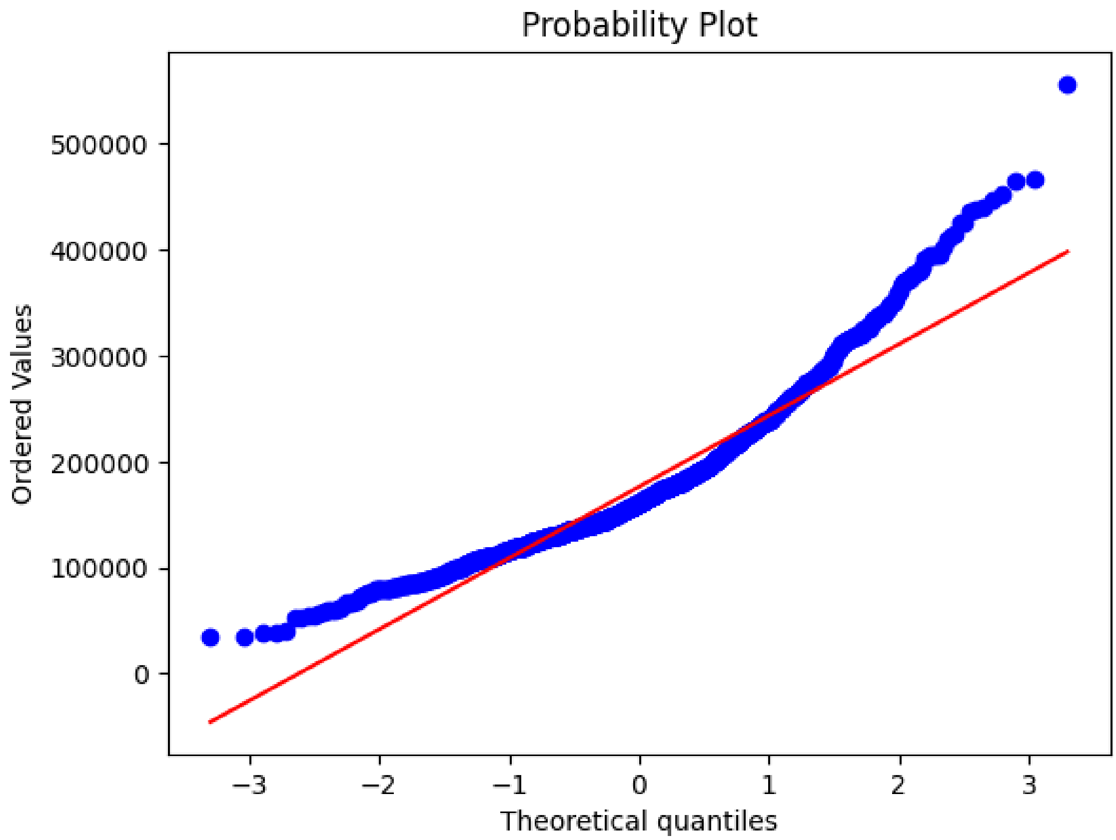
In [45]:

```
# Histogram and normal probability plot for SalePrice
sns.displot(train_df_dropna_clean2['SalePrice'], bins=30, kde=True)
```

```
plt.show()
```

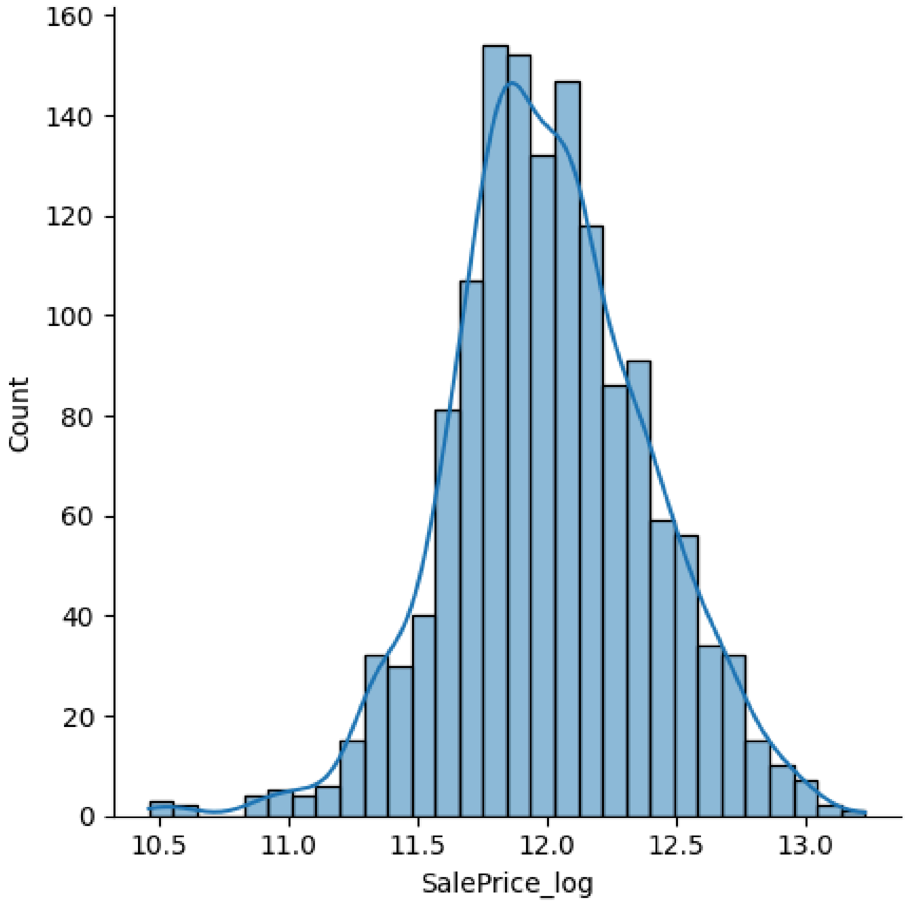


In [46]:
```
# Normal probability plot
stats.probplot(train_df_dropna_clean2['SalePrice'], plot=plt)
plt.show()
```



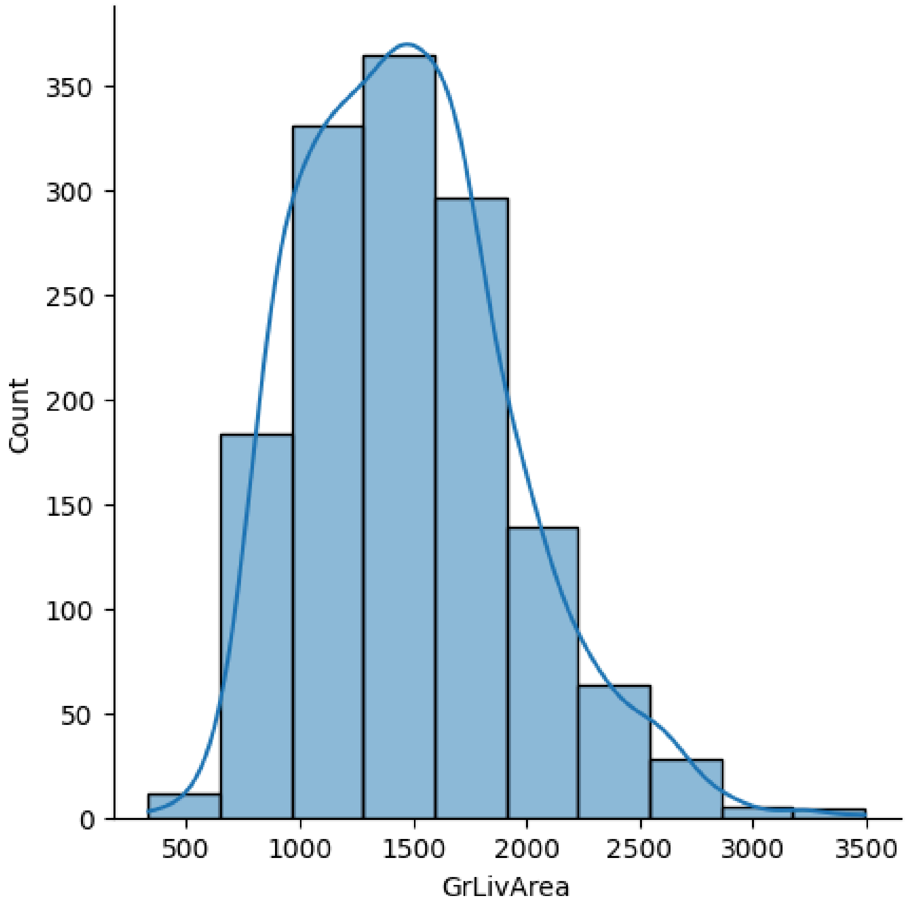
In [47]:
```
# Log transformation of SalePrice
train_df_dropna_clean2['SalePrice_log'] = np.log(train_df_dropna_clean2['SalePric
```

In [48]:
```
# Histogram and normal probability plot for SalePrice_log
sns.displot(train_df_dropna_clean2['SalePrice_log'], bins=30, kde=True)
plt.show()
```

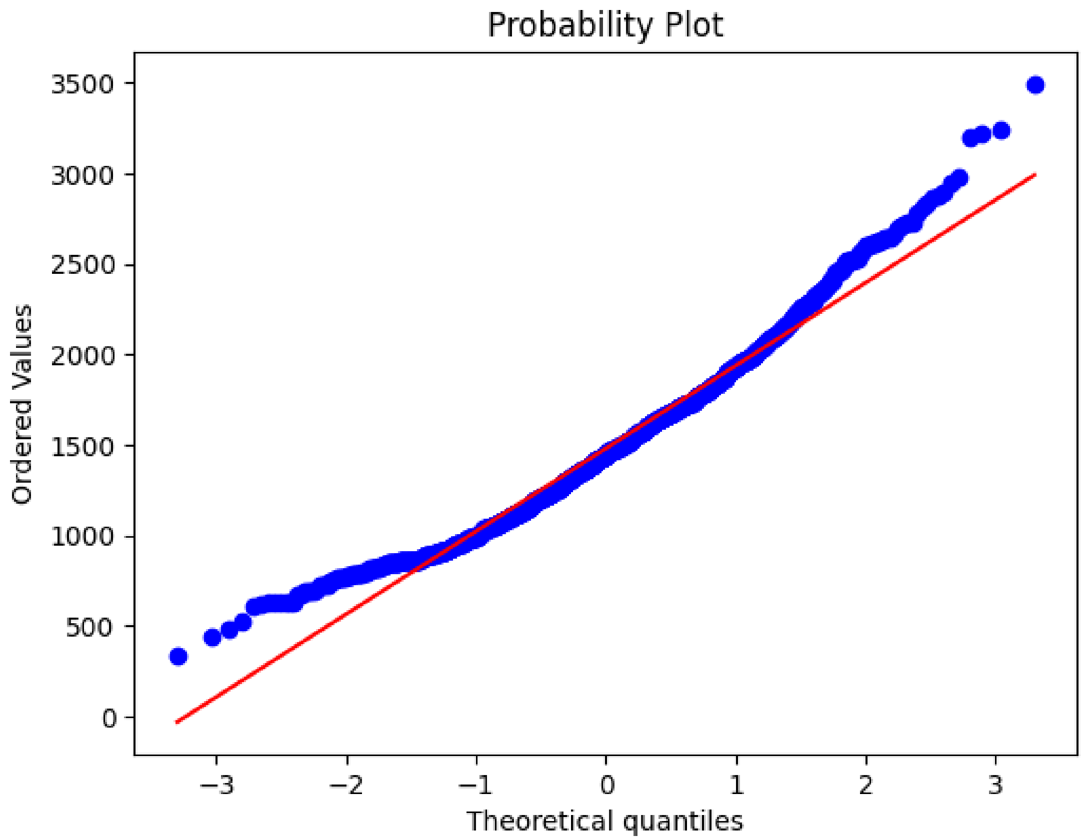


In [49]:

```
# Histogram for 'GrLivArea'
sns.displot(train_df_dropna_clean2['GrLivArea'], bins=10, kde=True)
plt.show()
```



In [50]:
```
# Normal probability plot for 'GrLivArea'
stats.probplot(train_df_dropna_clean2['GrLivArea'], plot=plt)
plt.show()
```

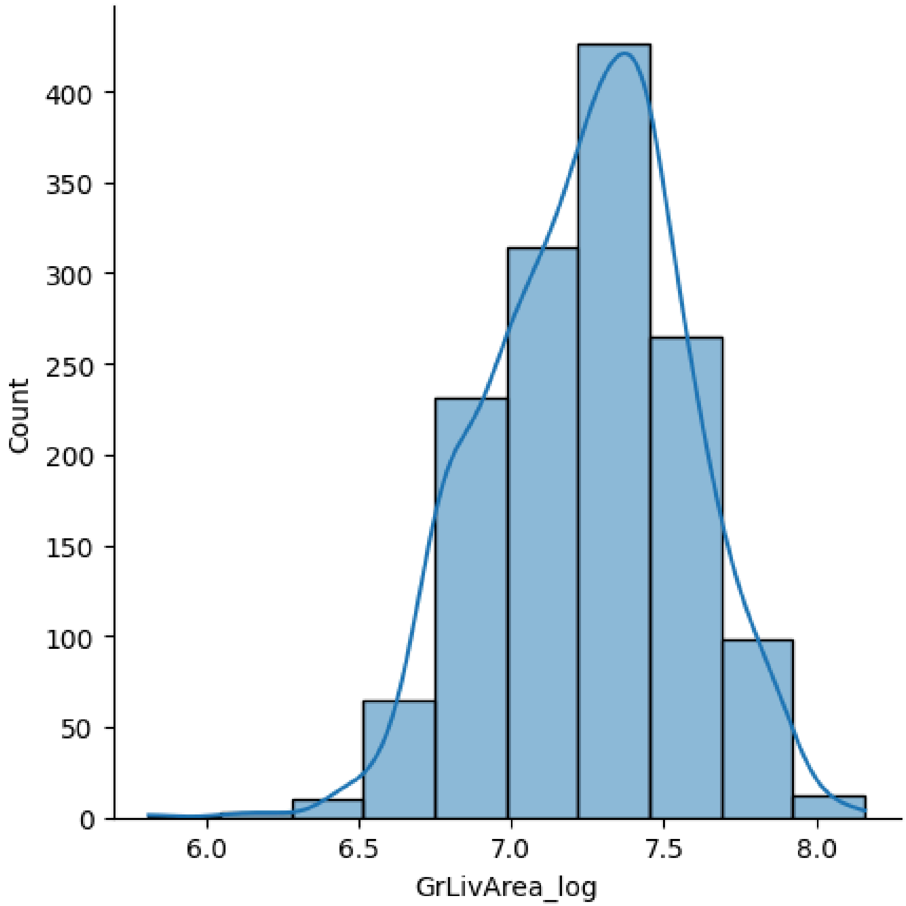


The variable 'GrLivArea' is not normally distributed. The Q-Q plot shows that the data points do not fall on the straight line.

I will apply a log transformation to 'GrLivArea' to make it more normally distributed.

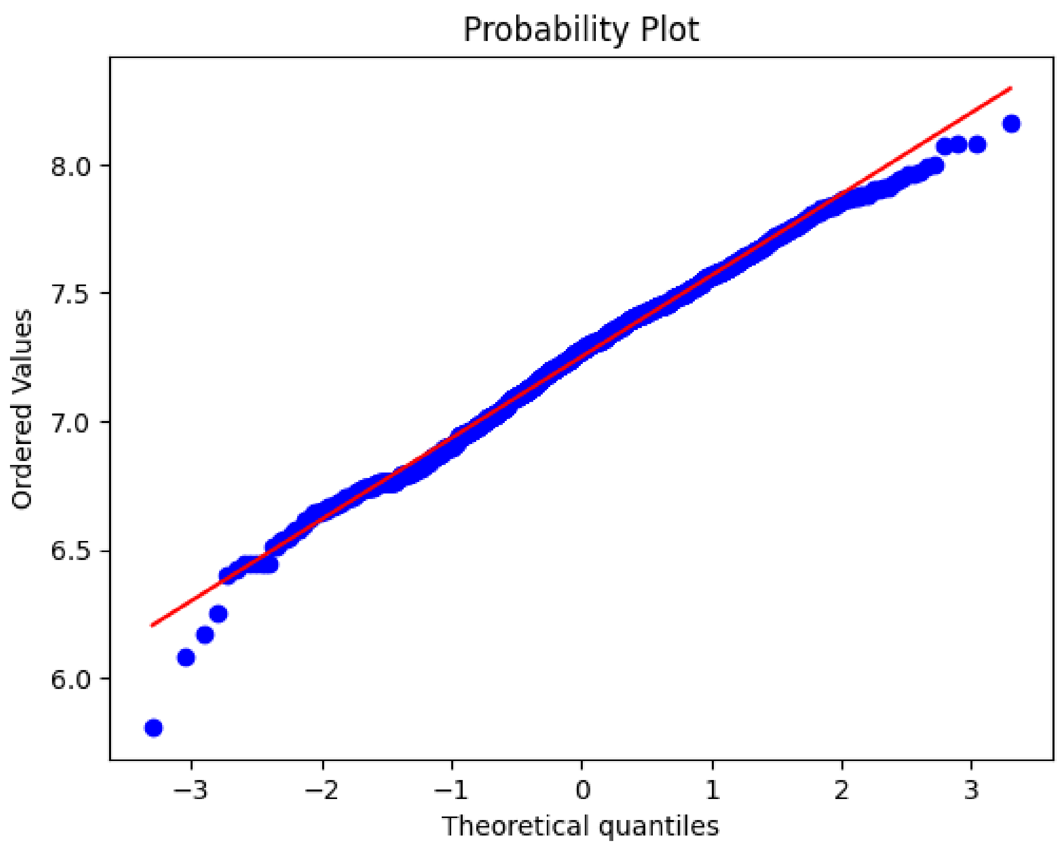
In [51]:
```
# Apply log transformation to 'GrLivArea'
train_df_dropna_clean2['GrLivArea_log'] = np.log(train_df_dropna_clean2['GrLivAre
```

In [52]:
```
# Histogram and normal probability plot for 'GrLivArea_log'
sns.displot(train_df_dropna_clean2['GrLivArea_log'], bins=10, kde=True)
plt.show()
```



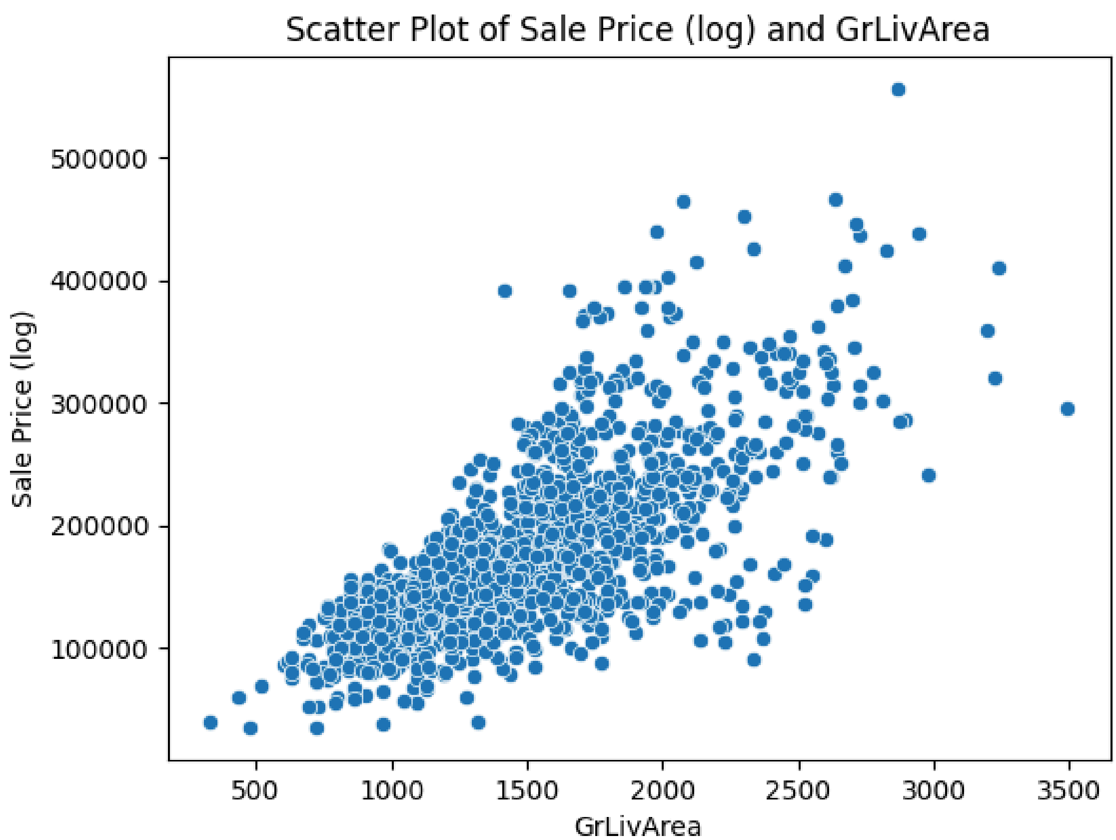
In [53]:

```
# Normal probability plot for 'GrLivArea_log'
stats.probplot(train_df_dropna_clean2['GrLivArea_log'], plot=plt)
plt.show()
```



Investigate the relationship between 'GrLivArea' and 'SalePrice' to check for homoscedasticity and linearity.

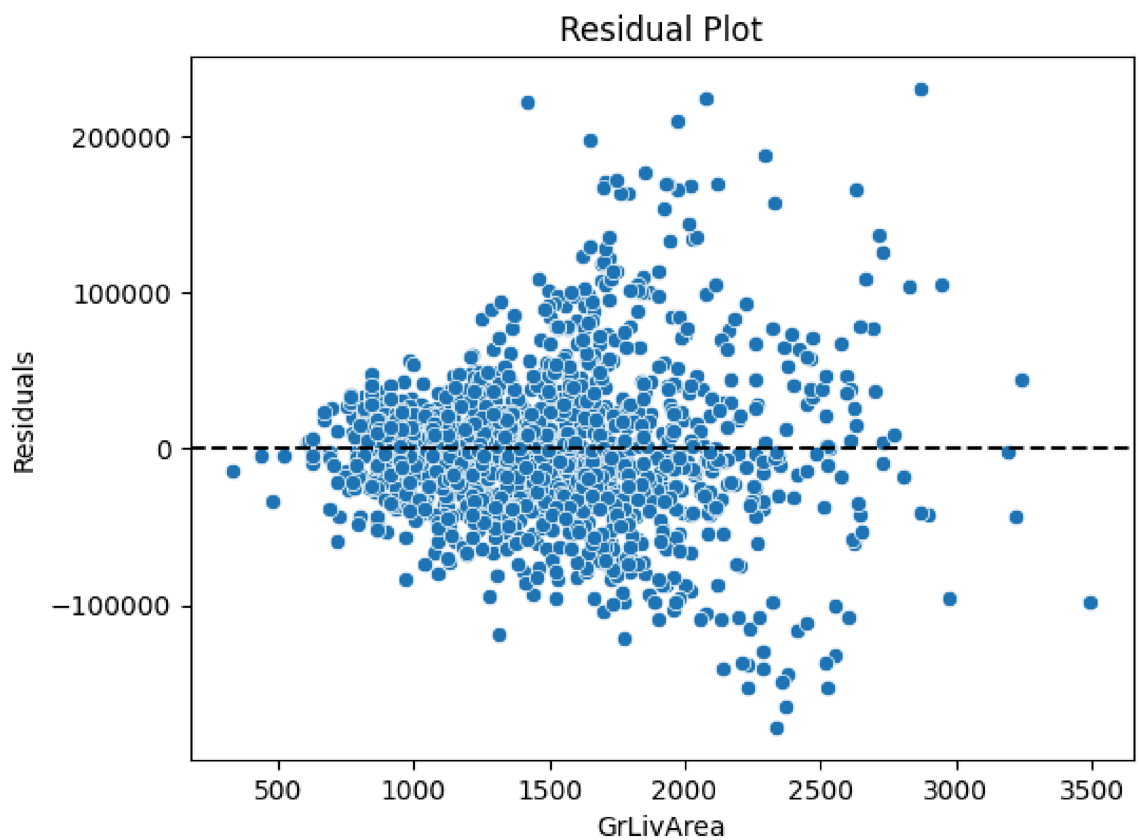
In [54]:
```
# Scatter plot for 'GrLivArea_log' and 'SalePrice'
sns.scatterplot(x='GrLivArea', y='SalePrice', data=train_df_dropna_clean2)

# Add title and labels
plt.title('Scatter Plot of Sale Price (log) and GrLivArea')
plt.xlabel('GrLivArea')
plt.ylabel('Sale Price (log)')
plt.show()
```



In [55]:

```
# Build a linear regression model with 'GrLivArea' as the predictor and 'SalePric
# Import the linear regression model
from sklearn.linear_model import LinearRegression

# Create an instance of the linear regression model
linear_reg = LinearRegression()

# Fit the model
linear_reg.fit(train_df_dropna_clean2[['GrLivArea']], train_df_dropna_clean2['Sal

# Print the coefficients
print('Intercept:', linear_reg.intercept_)
print('Coefficient:', linear_reg.coef_)
# Make predictions
predictions = linear_reg.predict(train_df_dropna_clean2[['GrLivArea']])

# Calculate the residuals
residuals = train_df_dropna_clean2['SalePrice'] - predictions

# Plot the residuals
sns.scatterplot(x=train_df_dropna_clean2['GrLivArea'], y=residuals)
plt.axhline(y=0, color='black', linestyle='--')
plt.title('Residual Plot')
plt.xlabel('GrLivArea')
plt.ylabel('Residuals')
plt.show()
```

```
Intercept: 16944.89212068476
Coefficient: [107.62504592]
```



Feature Analysis and Selection

Feature analysis and selection: Identify features with low variance or high multicollinearity and consider removing them

In [56]:
```
# Using Pandas to calculate variance
numeric_features = train_df_dropna_clean2.select_dtypes(include=[np.number]) # Se

# Calculate variance for each numeric variable
variance_numeric_features = numeric_features.var()
# print(variance_numeric_features)
low_variance_numeric_features = variance_numeric_features[variance_numeric_featu
print(low_variance_numeric_features)  # Variables with low variance
```

```
Index([], dtype='object')
```

In [57]:
```
# Identify features with high multicollinearity

# Compute the correlation matrix
corr_matrix = numeric_features.corr().abs()

# Identify pairs of features with correlation greater than 0.8
high_corr_var = np.where(corr_matrix > 0.8)
high_corr_var = [(corr_matrix.columns[x], corr_matrix.columns[y]) for x, y in zip

# Remove pairs with 'SalePrice' or 'SalePrice_log'
high_corr_var = [x for x in high_corr_var if 'SalePrice' not in x]
high_corr_var = [x for x in high_corr_var if 'SalePrice_log' not in x]
print(high_corr_var)  # Pairs of variables with high correlation
```

```
[('GrLivArea', 'TotRmsAbvGrd'), ('GrLivArea', 'GrLivArea_log'), ('TotRmsAbvGrd',
'GrLivArea_log'), ('GarageCars', 'GarageArea')]
```

In [102…

```python
# Alternative method to identify features with high multicollinearity - Variance
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Create a data frame to store VIF
vif_data = pd.DataFrame()
vif_data["Feature"] = numeric_features.columns

# Calculate VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(numeric_features.values, i) for i in

vif_data.sort_values(by="VIF", ascending=False).head(10)  # Display top 10 featur
```

```
/opt/anaconda3/lib/python3.12/site-packages/statsmodels/stats/outliers_influence.
py:197: RuntimeWarning: divide by zero encountered in scalar divide
  vif = 1. / (1. - r_squared_i)
```

Out[102…

	Feature	VIF
12	1stFlrSF	inf
11	TotalBsmtSF	inf
15	GrLivArea	inf
14	LowQualFinSF	inf
13	2ndFlrSF	inf
8	BsmtFinSF1	inf
9	BsmtFinSF2	inf
10	BsmtUnfSF	inf
35	YrSold	3.752511e+04
37	SalePrice_log	2.654911e+04

VIF Interpretation:

- VIF = 1: No correlation with other variables
- VIF between 1 and 5: Moderate correlation (usually acceptable)
- VIF > 5: High correlation (multicollinearity is likely present)
- VIF > 10: Severe multicollinearity (should be addressed)

VIF values indicate how much the variance of a feature’s coefficient is inflated due to multicollinearity.