In [ ]:
```
import pandas as pd
import numpy as np
import os.path as osp
import matplotlib.pyplot as plt
import seaborn as sns
import os
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
import statsmodels.api as sm
import datetime

db_dir = os.getcwd()
df = pd.read_csv(db_dir + r'/data/train.csv')
df.head()
```

Out[ ]:

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

5 rows × 81 columns

Data cleanup

In [ ]:
```
#Explore the dataset to see what NA actually means per column

#Qualitative data
#Alley N/A can be recoded to none instead of N/A to show no access to alley
#MasVnrType can be recoded to none instead of N/A to show no vanier type
#All basement data can be recoded to none instead of N/A to show no basement
#fireplace data can be recoded to none instead of N/A to show no fireplace
#All garage data can be recoded to none instead of N/A to show no garage
#Fence data can be recoded to none instead of N/A to show no fence
#MiscFeature data can be recoded to none instead of N/A to show no missing feature

#for electrical there is only one value that is missing so we add the most common value to that column

#Quantitative data
#perform mice on quantitative data
```

In [ ]:
```
# Fill in Missing values with either null or 0 depending on the data type
for col in df.columns:
    if df[col].dtype == "object":
        df[col].fillna('None', inplace=True)
    else:
        df[col].fillna(0, inplace=True)
```

In [ ]:
```
# Perform MICE on quantitative data
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer

numerical_cols = df.select_dtypes(include=[np.number]).columns
imputer = IterativeImputer(max_iter=10, random_state=0)
df[numerical_cols] = imputer.fit_transform(df[numerical_cols])
```

In [ ]:
```
#Proceed only if there are no missing values
df.isnull().sum()
```

Out[ ]:
```
Id               0
MSSubClass       0
MSZoning         0
LotFrontage      0
LotArea          0
                ..
MoSold           0
YrSold           0
SaleType         0
SaleCondition    0
SalePrice        0
Length: 81, dtype: int64
```

Data Cleaning

In [ ]:
```
#perform logic checks on the data

# Get today's date for year checks
today_year = datetime.datetime.today().year

# Initialize a set to keep track of unique indices of rows with errors
error_indices = set()

# Inline logical checks without adding new columns

# LotFrontage check
lot_frontage_errors = df[df['LotFrontage'] <= 0]
if not lot_frontage_errors.empty:
    print("Errors in LotFrontage (should be positive):")
    print(lot_frontage_errors[['LotFrontage']])
    print("Explanation: LotFrontage must be a positive number. The above rows have invalid LotFrontage values.\n")
    error_indices.update(lot_frontage_errors.index)

# LotArea check
lot_area_errors = df[df['LotArea'] <= 0]
if not lot_area_errors.empty:
    print("Errors in LotArea (should be positive):")
    print(lot_area_errors[['LotArea']])
    print("Explanation: LotArea must be a positive number. The above rows have invalid LotArea values.\n")
    error_indices.update(lot_area_errors.index)

# Street check
valid_Street = {'Grvl', 'Pave'}
street_errors = df[~df['Street'].isin(valid_Street)]
if not street_errors.empty:
    print("Errors in Street (must be either 'Grvl' or 'Pave'):")
    print(street_errors[['Street']])
    print("Explanation: Street must be either 'Grvl' (Gravel) or 'Pave' (Paved). The above rows have invalid Street
    error_indices.update(street_errors.index)

# YearRemodAdd check
year_remod_add_errors = df[
    (df['YearRemodAdd'] < df['YearBuilt']) |
    (df['YearRemodAdd'] > today_year)
]
if not year_remod_add_errors.empty:
    print("Errors in YearRemodAdd (must be between YearBuilt and the current year):")
    print(year_remod_add_errors[['YearBuilt', 'YearRemodAdd']])
    print(f"Explanation: YearRemodAdd must be between YearBuilt and {today_year}. The above rows have invalid YearR
    error_indices.update(year_remod_add_errors.index)

# GarageYrBlt check
garage_yr_blt_errors = df[
    (df['GarageYrBlt'] < df['YearBuilt']) |
    (df['GarageYrBlt'] > today_year)
]
if not garage_yr_blt_errors.empty:
    print("Errors in GarageYrBlt (must be between YearBuilt and the current year):")
    print(garage_yr_blt_errors[['YearBuilt', 'GarageYrBlt']])
    print(f"Explanation: GarageYrBlt must be between YearBuilt and {today_year}. The above rows have invalid Garage
    error_indices.update(garage_yr_blt_errors.index)

# Electrical check
valid_Electrical = {'SBrkr', 'FuseA', 'FuseF', 'FuseP', 'Mix'}
electrical_errors = df[~df['Electrical'].isin(valid_Electrical)]
if not electrical_errors.empty:
    print("Errors in Electrical (must be one of 'SBrkr', 'FuseA', 'FuseF', 'FuseP', 'Mix'):")
    print(electrical_errors[['Electrical']])
```

```
    print("Explanation: Electrical must be one of 'SBrkr', 'FuseA', 'FuseF', 'FuseP', or 'Mix'. The above rows have
    error_indices.update(electrical_errors.index)

# Final Output
if len(error_indices) == 0:
    print("All rows are valid according to the specified checks.")
else:
    print(f"Total number of rows with errors: {len(error_indices)}")
    print("Some rows have errors as detailed above.")
```

```
Errors in LotFrontage (should be positive):
      LotFrontage
7             0.0
12            0.0
14            0.0
16            0.0
24            0.0
...           ...
1429          0.0
1431          0.0
1441          0.0
1443          0.0
1446          0.0

[259 rows x 1 columns]
Explanation: LotFrontage must be a positive number. The above rows have invalid LotFrontage values.

Errors in GarageYrBlt (must be between YearBuilt and the current year):
      YearBuilt  GarageYrBlt
29       1927.0       1920.0
39       1955.0          0.0
48       1920.0          0.0
78       1968.0          0.0
88       1915.0          0.0
...         ...          ...
1414     1923.0       1922.0
1418     1963.0       1962.0
1449     1970.0          0.0
1450     1974.0          0.0
1453     2006.0          0.0

[90 rows x 2 columns]
Explanation: GarageYrBlt must be between YearBuilt and 2024. The above rows have invalid GarageYrBlt values.

Errors in Electrical (must be one of 'SBrkr', 'FuseA', 'FuseF', 'FuseP', 'Mix'):
     Electrical
1379       None
Explanation: Electrical must be one of 'SBrkr', 'FuseA', 'FuseF', 'FuseP', or 'Mix'. The above rows have invalid Ele
ctrical values.

Total number of rows with errors: 343
Some rows have errors as detailed above.
```

In [ ]:

```
#Removing rows where there are errors, specifically where Garage year built is not built between today and the

# Get today's date for year checks
today_year = datetime.datetime.today().year

# Show the total number of rows before deletion
rows_before = df.shape[0]
print(f"Total rows before deletion: {rows_before}")

# GarageYrBlt check - identify rows to be deleted
garage_yr_blt_errors = df[
    (df['GarageYrBlt'] < df['YearBuilt']) |
    (df['GarageYrBlt'] > today_year)
]

# Remove rows with GarageYrBlt errors
if not garage_yr_blt_errors.empty:
    print(f"Removing {len(garage_yr_blt_errors)} rows due to invalid GarageYrBlt values.")
    df = df.drop(garage_yr_blt_errors.index)

# Show the total number of rows after deletion
rows_after = df.shape[0]
print(f"Total rows after deletion: {rows_after}")
```

```
Total rows before deletion: 1460
Removing 90 rows due to invalid GarageYrBlt values.
Total rows after deletion: 1370
```

Create interaction terms

In [ ]:
```
# List of columns involved in interactions that need one-hot encoding
interaction_categorical_columns = ['BsmtFinType1', 'Neighborhood', 'KitchenQual', 'ExterQual']

# Perform one-hot encoding only on these specific columns
df_interaction_encoded = pd.get_dummies(df, columns=interaction_categorical_columns, drop_first=True, dtype=np.floa

# Ensure the relevant columns are numeric
df_interaction_encoded['OverallQual'] = pd.to_numeric(df_interaction_encoded['OverallQual'], errors='coerce')
df_interaction_encoded['GrLivArea'] = pd.to_numeric(df_interaction_encoded['GrLivArea'], errors='coerce')
df_interaction_encoded['YearBuilt'] = pd.to_numeric(df_interaction_encoded['YearBuilt'], errors='coerce')
df_interaction_encoded['GarageYrBlt'] = pd.to_numeric(df_interaction_encoded['GarageYrBlt'], errors='coerce')
df_interaction_encoded['TotalBsmtSF'] = pd.to_numeric(df_interaction_encoded['TotalBsmtSF'], errors='coerce')
df_interaction_encoded['1stFlrSF'] = pd.to_numeric(df_interaction_encoded['1stFlrSF'], errors='coerce')
df_interaction_encoded['GarageCars'] = pd.to_numeric(df_interaction_encoded['GarageCars'], errors='coerce')
df_interaction_encoded['GarageArea'] = pd.to_numeric(df_interaction_encoded['GarageArea'], errors='coerce')
df_interaction_encoded['LotArea'] = pd.to_numeric(df_interaction_encoded['LotArea'], errors='coerce')
df_interaction_encoded['YearRemodAdd'] = pd.to_numeric(df_interaction_encoded['YearRemodAdd'], errors='coerce')

# Create interaction terms
df_interaction_encoded['OverallQual_x_GrLivArea'] = df_interaction_encoded['OverallQual'] * df_interaction_encoded[
df_interaction_encoded['YearBuilt_x_GarageYrBlt'] = df_interaction_encoded['YearBuilt'] * df_interaction_encoded['G
df_interaction_encoded['TotalBsmtSF_x_1stFlrSF'] = df_interaction_encoded['TotalBsmtSF'] * df_interaction_encoded['

if 'BsmtFinType1_GLQ' in df_interaction_encoded.columns:
    df_interaction_encoded['BsmtFinSF1_x_BsmtFinType1_GLQ'] = df_interaction_encoded['BsmtFinSF1'] * df_interaction_

df_interaction_encoded['GarageCars_x_GarageArea'] = df_interaction_encoded['GarageCars'] * df_interaction_encoded['

if 'Neighborhood_NoRidge' in df_interaction_encoded.columns:
    df_interaction_encoded['Neighborhood_NoRidge_x_OverallQual'] = df_interaction_encoded['Neighborhood_NoRidge'] *

if 'KitchenQual_TA' in df_interaction_encoded.columns:
    df_interaction_encoded['KitchenQual_TA_x_GrLivArea'] = df_interaction_encoded['KitchenQual_TA'] * df_interactio

if 'ExterQual_Gd' in df_interaction_encoded.columns:
    df_interaction_encoded['ExterQual_Gd_x_TotalBsmtSF'] = df_interaction_encoded['ExterQual_Gd'] * df_interaction_

if 'BsmtQual_Gd' in df_interaction_encoded.columns:
    df_interaction_encoded['BsmtQual_Gd_x_BsmtFinSF1'] = df_interaction_encoded['BsmtQual_Gd'] * df_interaction_enc

if 'Neighborhood_NridgHt' in df_interaction_encoded.columns:
    df_interaction_encoded['Neighborhood_NridgHt_x_GrLivArea'] = df_interaction_encoded['Neighborhood_NridgHt'] * d

# Display the interaction terms created
interaction_terms = df_interaction_encoded.filter(regex='_x_')
print("Interaction Terms Created:")
print(interaction_terms.head())

# Print the total number of interaction terms created
print(f"Total number of interaction terms created: {interaction_terms.shape[1]}")
```

```
Interaction Terms Created:
   OverallQual_x_GrLivArea  YearBuilt_x_GarageYrBlt  TotalBsmtSF_x_1stFlrSF  \
0                  11970.0                4012009.0                732736.0
1                   7572.0                3904576.0               1592644.0
2                  12502.0                4004001.0                846400.0
3                  12019.0                3826170.0                726516.0
4                  17584.0                4000000.0               1311025.0

   BsmtFinSF1_x_BsmtFinType1_GLQ  GarageCars_x_GarageArea  \
0                          706.0                   1096.0
1                            0.0                    920.0
2                          486.0                   1216.0
3                            0.0                   1926.0
4                          655.0                   2508.0

   Neighborhood_NoRidge_x_OverallQual  KitchenQual_TA_x_GrLivArea  \
0                                 0.0                         0.0
1                                 0.0                      1262.0
2                                 0.0                         0.0
3                                 0.0                         0.0
4                                 8.0                         0.0

   ExterQual_Gd_x_TotalBsmtSF  Neighborhood_NridgHt_x_GrLivArea
0                       856.0                               0.0
1                         0.0                               0.0
2                       920.0                               0.0
3                         0.0                               0.0
4                      1145.0                               0.0
Total number of interaction terms created: 9
```

Creating categorical dummy variables on remaining values

In [ ]:
```
# List of remaining columns that need one-hot encoding
remaining_categorical_columns = df.select_dtypes(include=['object']).columns.difference(interaction_categorical_col

# Perform one-hot encoding on the remaining categorical columns
df_encoded = pd.get_dummies(df_interaction_encoded, columns=remaining_categorical_columns, drop_first=True, dtype=n

# Display the final DataFrame with all interactions and one-hot encoded columns
print("Final DataFrame with One-Hot Encoded Columns and Interaction Terms:")
print(df_encoded.columns)
```

```
Final DataFrame with One-Hot Encoded Columns and Interaction Terms:
Index(['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual',
       'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1',
       ...
       'SaleType_CWD', 'SaleType_Con', 'SaleType_ConLD', 'SaleType_ConLI',
       'SaleType_ConLw', 'SaleType_New', 'SaleType_Oth', 'SaleType_WD',
       'Street_Pave', 'Utilities_NoSeWa'],
      dtype='object', length=265)
```

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

```
<class 'pandas.core.frame.DataFrame'>
Index: 1370 entries, 0 to 1459
Columns: 265 entries, Id to Utilities_NoSeWa
dtypes: float64(265)
memory usage: 2.8 MB
```

Creating additional interaction terms & transformations

In [ ]:
```
# List of interaction terms to create
interaction_terms = [
    ('OverallQual', 'GrLivArea'),
    ('YearBuilt', 'GarageArea'),
    ('TotalBsmtSF', '1stFlrSF'),
    ('GarageCars', 'GarageArea'),
    ('OverallQual', 'TotalBsmtSF'),
    ('GrLivArea', 'GarageCars'),
    ('YearBuilt', 'OverallQual'),
    ('YearRemodAdd', 'TotalBsmtSF'),
    ('FullBath', 'BedroomAbvGr'),
    ('Fireplaces', 'GarageCars'),
    ('TotRmsAbvGrd', 'YearBuilt'),
    ('GarageYrBlt', 'TotalBsmtSF'),
    ('BsmtFinSF1', 'BsmtUnfSF'),
    ('LotArea', 'GrLivArea'),
```

```
    ('BsmtFullBath', 'HalfBath')
]

# Create interaction terms in the DataFrame
for term1, term2 in interaction_terms:
    interaction_name = f'{term1}_x_{term2}'
    if term1 in df_encoded.columns and term2 in df_encoded.columns:
        df_encoded[interaction_name] = df_encoded[term1] * df_encoded[term2]
```

In [ ]:
```
# Create interaction terms in the DataFrame
for term1, term2 in interaction_terms:
    interaction_name = f'{term1}_x_{term2}'
    if term1 in df_encoded.columns and term2 in df_encoded.columns:
        df_encoded[interaction_name] = df_encoded[term1] * df_encoded[term2]

# Logarithmic Transformation: apply log to skewed features
log_transformed_columns = ['LotArea', 'GrLivArea', '1stFlrSF', 'TotalBsmtSF', 'GarageArea']
for col in log_transformed_columns:
    df_encoded[f'log_{col}'] = np.log1p(df_encoded[col])

# Square Root Transformation: apply sqrt to features with high variance
sqrt_transformed_columns = ['LotArea', 'GrLivArea', '1stFlrSF', 'TotalBsmtSF', 'GarageArea']
for col in sqrt_transformed_columns:
    df_encoded[f'sqrt_{col}'] = np.sqrt(df_encoded[col])

# Exponential Transformation: apply exp to features that might benefit from it
exp_transformed_columns = ['OverallQual']
for col in exp_transformed_columns:
    df_encoded[f'exp_{col}'] = np.exp(df_encoded[col])
```

In [ ]:
```
new_columns = df_encoded.filter(regex='_x_|log_|sqrt_|exp_').columns
print(f"New interaction and transformed terms added: {list(new_columns)}")
print(f"Total predictors now in df_encoded: {len(df_encoded.columns)}")
```

```
New interaction and transformed terms added: ['OverallQual_x_GrLivArea', 'YearBuilt_x_GarageYrBlt', 'TotalBsmtSF_x_1
stFlrSF', 'BsmtFinSF1_x_BsmtFinType1_GLQ', 'GarageCars_x_GarageArea', 'Neighborhood_NoRidge_x_OverallQual', 'Kitchen
Qual_TA_x_GrLivArea', 'ExterQual_Gd_x_TotalBsmtSF', 'Neighborhood_NridgHt_x_GrLivArea', 'YearBuilt_x_GarageArea', 'O
verallQual_x_TotalBsmtSF', 'GrLivArea_x_GarageCars', 'YearBuilt_x_OverallQual', 'YearRemodAdd_x_TotalBsmtSF', 'FullB
ath_x_BedroomAbvGr', 'Fireplaces_x_GarageCars', 'TotRmsAbvGrd_x_YearBuilt', 'GarageYrBlt_x_TotalBsmtSF', 'BsmtFinSF1
_x_BsmtUnfSF', 'LotArea_x_GrLivArea', 'BsmtFullBath_x_HalfBath', 'log_LotArea', 'log_GrLivArea', 'log_1stFlrSF', 'lo
g_TotalBsmtSF', 'log_GarageArea', 'sqrt_LotArea', 'sqrt_GrLivArea', 'sqrt_1stFlrSF', 'sqrt_TotalBsmtSF', 'sqrt_Garag
eArea', 'exp_OverallQual']
Total predictors now in df_encoded: 288
```

Building the initial model

In [ ]:
```
# Define the target variable and predictors
y = df_encoded['SalePrice']
X = df_encoded.drop(columns=['SalePrice'])

# Add a constant to the model (for intercept)
X = sm.add_constant(X)

# Build and fit the OLS regression model
ols_model = sm.OLS(y, X).fit()

# Print the model summary
print("OLS Regression Model Summary:")
print(ols_model.summary())

# Calculate and print Train/Test MSE and MAPE
from sklearn.metrics import mean_squared_error, mean_absolute_percentage_error
from sklearn.model_selection import train_test_split

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=42)

# Predict on Train data
y_train_pred = ols_model.predict(X_train)
train_mse = mean_squared_error(y_train, y_train_pred)
train_mape = mean_absolute_percentage_error(y_train, y_train_pred) * 100

print(f'Train MSE: {train_mse}')
print(f'Train MAPE: {train_mape}')

# Predict on Test data
y_test_pred = ols_model.predict(X_test)
test_mse = mean_squared_error(y_test, y_test_pred)
```

```
test_mape = mean_absolute_percentage_error(y_test, y_test_pred) * 100

print(f'Test MSE: {test_mse}')
print(f'Test MAPE: {test_mape}')
```

```
OLS Regression Model Summary:
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.946
Model:                            OLS   Adj. R-squared:                  0.932
Method:                 Least Squares   F-statistic:                     67.79
Date:                Thu, 15 Aug 2024   Prob (F-statistic):               0.00
Time:                        19:52:38   Log-Likelihood:                -15395.
No. Observations:                1370   AIC:                         3.135e+04
Df Residuals:                    1088   BIC:                         3.283e+04
Df Model:                         281
Covariance Type:            nonrobust
==========================================================================================
                               coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
const                     1.198e+07   8.25e+06      1.452      0.147   -4.21e+06    2.82e+07
Id                           0.0008      1.500      0.001      1.000      -2.942       2.943
MSSubClass                 -71.4726     84.309     -0.848      0.397    -236.899      93.954
LotFrontage                 11.5938     22.273      0.521      0.603     -32.109      55.297
LotArea                      2.7067      0.745      3.633      0.000       1.245       4.169
OverallQual               8.441e+04   5.96e+04      1.417      0.157   -3.25e+04    2.01e+05
OverallCond               6240.3225    882.069      7.075      0.000    4509.573    7971.072
YearBuilt                -6382.1429   4202.420     -1.519      0.129   -1.46e+04    1863.622
YearRemodAdd              -146.2835    140.422     -1.042      0.298    -421.812     129.245
MasVnrArea                   8.2652      5.496      1.504      0.133      -2.520      19.050
BsmtFinSF1                 -81.6327     78.979     -1.034      0.302    -236.600      73.335
BsmtFinSF2                 -82.7803     78.600     -1.053      0.292    -237.005      71.445
BsmtUnfSF                  -88.4144     79.337     -1.114      0.265    -244.086      67.257
TotalBsmtSF               -252.8106    236.611     -1.068      0.286    -717.075     211.454
1stFlrSF                   -88.2673    125.812     -0.702      0.483    -335.129     158.595
2ndFlrSF                    56.3690     50.765      1.110      0.267     -43.239     155.977
LowQualFinSF                14.9122     54.145      0.275      0.783     -91.327     121.152
GrLivArea                  -16.9604     74.890     -0.226      0.821    -163.905     129.984
BsmtFullBath              4095.4059   2177.017      1.881      0.060    -176.221    8367.033
BsmtHalfBath              2296.9860   2885.706      0.796      0.426   -3365.193    7959.165
FullBath                  5207.4671   5064.761      1.028      0.304   -4730.337    1.51e+04
HalfBath                  3683.0822   2406.971      1.530      0.126   -1039.747    8405.912
BedroomAbvGr             -2667.8596   2675.230     -0.997      0.319   -7917.053    2581.333
KitchenAbvGr             -9299.4264   7079.225     -1.314      0.189   -2.32e+04    4591.053
TotRmsAbvGrd             -7694.1961   4.17e+04     -0.185      0.854   -8.95e+04    7.41e+04
Fireplaces                3774.7419   4493.042      0.840      0.401   -5041.265    1.26e+04
GarageYrBlt              -6650.9226   4092.590     -1.625      0.104   -1.47e+04    1379.340
GarageCars                -460.4906   7242.756     -0.064      0.949   -1.47e+04    1.38e+04
GarageArea                  43.1143    425.759      0.101      0.919    -792.287     878.515
WoodDeckSF                   8.9624      5.636      1.590      0.112      -2.096      20.020
OpenPorchSF                  2.5423     11.559      0.220      0.826     -20.138      25.223
EnclosedPorch               22.0077     12.561      1.752      0.080      -2.638      46.654
3SsnPorch                   39.7378     20.742      1.916      0.056      -0.960      80.436
ScreenPorch                 43.4253     11.781      3.686      0.000      20.310      66.541
PoolArea                   433.1381    213.769      2.026      0.043      13.691     852.585
MiscVal                      3.5487      7.092      0.500      0.617     -10.366      17.464
MoSold                    -421.2031    233.303     -1.805      0.071    -878.977      36.571
YrSold                    -26.8846     493.327     -0.054      0.957    -994.864     941.095
BsmtFinType1_BLQ          2295.6400   2700.291      0.850      0.395   -3002.728    7594.008
BsmtFinType1_GLQ         -8631.7060   4136.615     -2.087      0.037   -1.67e+04    -515.060
BsmtFinType1_LwQ         -3870.7178   3675.437     -1.053      0.293   -1.11e+04    3341.030
BsmtFinType1_None         1.003e+05   8.55e+04      1.172      0.241   -6.76e+04    2.68e+05
BsmtFinType1_Rec            14.5600   2937.224      0.005      0.996   -5748.706    5777.826
BsmtFinType1_Unf         -7688.3301   3710.911     -2.072      0.039    -1.5e+04    -406.978
Neighborhood_Blueste      5380.5558   1.86e+04      0.289      0.772   -3.11e+04    4.19e+04
Neighborhood_BrDale      -5374.7241   1.13e+04     -0.476      0.634   -2.75e+04    1.68e+04
Neighborhood_BrkSide       478.3001   9830.068      0.049      0.961   -1.88e+04    1.98e+04
Neighborhood_ClearCr     -7064.7428   9244.934     -0.764      0.445   -2.52e+04    1.11e+04
Neighborhood_CollgCr     -1.215e+04   7515.511     -1.616      0.106   -2.69e+04    2601.452
Neighborhood_Crawfor         1.3e+04   8779.250      1.481      0.139   -4221.663    3.02e+04
Neighborhood_Edwards     -2.255e+04   8211.256     -2.747      0.006   -3.87e+04   -6442.314
Neighborhood_Gilbert      -1.14e+04   7924.388     -1.438      0.151   -2.69e+04    4151.999
Neighborhood_IDOTRR      -5626.0482   1.12e+04     -0.502      0.616   -2.76e+04    1.63e+04
Neighborhood_MeadowV     -1.738e+04   1.15e+04     -1.507      0.132      -4e+04    5247.294
Neighborhood_Mitchel     -1.879e+04   8384.412     -2.242      0.025   -3.52e+04   -2342.677
Neighborhood_NAmes       -1.519e+04   8044.580     -1.889      0.059    -3.1e+04     592.018
Neighborhood_NPkVill      4093.8322   1.33e+04      0.308      0.758    -2.2e+04    3.02e+04
Neighborhood_NWAmes      -1.324e+04   8204.686     -1.614      0.107   -2.93e+04    2855.354
Neighborhood_NoRidge     -2.367e+05   4.13e+04     -5.727      0.000   -3.18e+05   -1.56e+05
Neighborhood_NridgHt     -4.253e+04   1.53e+04     -2.787      0.005   -7.25e+04   -1.26e+04
Neighborhood_OldTown     -9873.5705   9948.807     -0.992      0.321   -2.94e+04    9647.448
Neighborhood_SWISU       -1.347e+04   1.01e+04     -1.337      0.182   -3.32e+04    6296.623
Neighborhood_Sawyer      -1.256e+04   8252.741     -1.521      0.128   -2.87e+04    3637.024
Neighborhood_SawyerW     -8549.6870   8051.478     -1.062      0.289   -2.43e+04    7248.494
Neighborhood_Somerst     -7561.2707   8969.262     -0.843      0.399   -2.52e+04        1e+04
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Neighborhood_StoneBr	3.499e+04	8297.408	4.217	0.000	1.87e+04	5.13e+04
Neighborhood_Timber	-7694.1184	8226.462	-0.935	0.350	-2.38e+04	8447.408
Neighborhood_Veenker	1879.0483	1.04e+04	0.181	0.856	-1.85e+04	2.22e+04
KitchenQual_Fa	-1.64e+04	6529.100	-2.512	0.012	-2.92e+04	-3591.100
KitchenQual_Gd	-1.626e+04	3366.474	-4.830	0.000	-2.29e+04	-9655.027
KitchenQual_TA	-5530.9369	6710.388	-0.824	0.410	-1.87e+04	7635.829
ExterQual_Fa	1.281e+04	1.49e+04	0.860	0.390	-1.64e+04	4.21e+04
ExterQual_Gd	-1.269e+04	8937.671	-1.420	0.156	-3.02e+04	4844.180
ExterQual_TA	-8756.9498	5892.985	-1.486	0.138	-2.03e+04	2805.952
OverallQual_x_GrLivArea	2.1783	2.130	1.023	0.307	-2.000	6.357
YearBuilt_x_GarageYrBlt	3.4354	2.120	1.621	0.105	-0.724	7.595
TotalBsmtSF_x_1stFlrSF	-0.0263	0.012	-2.180	0.029	-0.050	-0.003
BsmtFinSF1_x_BsmtFinType1_GLQ	21.3614	5.107	4.183	0.000	11.340	31.383
GarageCars_x_GarageArea	2.3716	12.578	0.189	0.850	-22.308	27.051
Neighborhood_NoRidge_x_OverallQual	3.239e+04	5246.125	6.174	0.000	2.21e+04	4.27e+04
KitchenQual_TA_x_GrLivArea	-7.2549	3.795	-1.912	0.056	-14.700	0.191
ExterQual_Gd_x_TotalBsmtSF	3.9636	4.728	0.838	0.402	-5.313	13.240
Neighborhood_NridgHt_x_GrLivArea	28.8000	7.411	3.886	0.000	14.258	43.342
Alley_None	998.0886	4463.094	0.224	0.823	-7759.156	9755.333
Alley_Pave	1234.0919	6197.137	0.199	0.842	-1.09e+04	1.34e+04
BldgType_2fmCon	-6475.7626	1.35e+04	-0.479	0.632	-3.3e+04	2.01e+04
BldgType_Duplex	-9980.5916	8192.140	-1.218	0.223	-2.61e+04	6093.589
BldgType_Twnhs	-2943.6170	1.05e+04	-0.282	0.778	-2.35e+04	1.76e+04
BldgType_TwnhsE	-1451.4060	9260.409	-0.157	0.875	-1.96e+04	1.67e+04
BsmtCond_Gd	2192.8724	5208.103	0.421	0.674	-8026.189	1.24e+04
BsmtCond_None	1.003e+05	8.55e+04	1.172	0.241	-6.76e+04	2.68e+05
BsmtCond_Po	2.544e+04	1.73e+04	1.467	0.143	-8585.255	5.95e+04
BsmtCond_TA	4538.3456	4334.605	1.047	0.295	-3966.787	1.3e+04
BsmtExposure_Gd	1.048e+04	2909.917	3.600	0.000	4767.333	1.62e+04
BsmtExposure_Mn	-2007.8153	2893.318	-0.694	0.488	-7684.930	3669.300
BsmtExposure_No	-3085.8906	2084.109	-1.481	0.139	-7175.218	1003.437
BsmtExposure_None	-1.101e+04	2.1e+04	-0.523	0.601	-5.23e+04	3.03e+04
BsmtFinType2_BLQ	-6689.3469	7158.440	-0.934	0.350	-2.07e+04	7356.563
BsmtFinType2_GLQ	-4490.4632	9225.764	-0.487	0.627	-2.26e+04	1.36e+04
BsmtFinType2_LwQ	-8441.4258	6959.244	-1.213	0.225	-2.21e+04	5213.632
BsmtFinType2_None	-1.072e+05	3.66e+04	-2.927	0.003	-1.79e+05	-3.53e+04
BsmtFinType2_Rec	-5426.6149	6738.055	-0.805	0.421	-1.86e+04	7794.437
BsmtFinType2_Unf	-1954.6235	7109.447	-0.275	0.783	-1.59e+04	1.2e+04
BsmtQual_Fa	-1567.5842	6260.931	-0.250	0.802	-1.39e+04	1.07e+04
BsmtQual_Gd	-6198.2722	3196.329	-1.939	0.053	-1.25e+04	73.395
BsmtQual_None	1.003e+05	8.55e+04	1.172	0.241	-6.76e+04	2.68e+05
BsmtQual_TA	-3240.0845	3993.925	-0.811	0.417	-1.11e+04	4596.582
CentralAir_Y	5494.8364	4373.701	1.256	0.209	-3087.006	1.41e+04
Condition1_Feedr	8124.0590	5089.433	1.596	0.111	-1862.155	1.81e+04
Condition1_Norm	1.528e+04	4188.787	3.648	0.000	7062.496	2.35e+04
Condition1_PosA	5290.4620	9583.878	0.552	0.581	-1.35e+04	2.41e+04
Condition1_PosN	1.966e+04	7302.393	2.692	0.007	5327.060	3.4e+04
Condition1_RRAe	-6740.1396	8665.173	-0.778	0.437	-2.37e+04	1.03e+04
Condition1_RRAn	1.252e+04	6689.697	1.872	0.062	-606.209	2.56e+04
Condition1_RRNe	-877.0464	1.61e+04	-0.054	0.957	-3.26e+04	3.08e+04
Condition1_RRNn	1.599e+04	1.21e+04	1.323	0.186	-7731.160	3.97e+04
Condition2_Feedr	-9127.8844	2.35e+04	-0.389	0.697	-5.52e+04	3.69e+04
Condition2_Norm	-2142.1637	2.02e+04	-0.106	0.915	-4.17e+04	3.74e+04
Condition2_PosA	1.533e+04	4.31e+04	0.356	0.722	-6.93e+04	9.99e+04
Condition2_PosN	-2.362e+05	2.89e+04	-8.162	0.000	-2.93e+05	-1.79e+05
Condition2_RRAe	-6e+04	6.9e+04	-0.870	0.385	-1.95e+05	7.53e+04
Condition2_RRAn	-1.446e+04	3.01e+04	-0.481	0.631	-7.34e+04	4.45e+04
Condition2_RRNn	-1825.5077	3.07e+04	-0.060	0.953	-6.2e+04	5.83e+04
Electrical_FuseF	-3749.6198	6165.591	-0.608	0.543	-1.58e+04	8348.174
Electrical_FuseP	2.003e+04	2.2e+04	0.912	0.362	-2.31e+04	6.31e+04
Electrical_Mix	2.544e+04	1.73e+04	1.467	0.143	-8585.255	5.95e+04
Electrical_None	-277.9635	2.27e+04	-0.012	0.990	-4.48e+04	4.43e+04
Electrical_SBrkr	-594.4409	2933.791	-0.203	0.839	-6350.970	5162.088
ExterCond_Fa	1527.3498	2.44e+04	0.063	0.950	-4.64e+04	4.94e+04
ExterCond_Gd	-2150.6172	2.38e+04	-0.091	0.928	-4.88e+04	4.45e+04
ExterCond_TA	3314.0832	2.38e+04	0.139	0.889	-4.33e+04	4.99e+04
Exterior1st_BrkComm	-1.497e+04	2.67e+04	-0.562	0.574	-6.73e+04	3.73e+04
Exterior1st_BrkFace	1.118e+04	1.29e+04	0.870	0.385	-1.4e+04	3.64e+04
Exterior1st_CBlock	-1.096e+04	1.39e+04	-0.790	0.429	-3.82e+04	1.62e+04
Exterior1st_CemntBd	7790.2488	1.88e+04	0.415	0.678	-2.91e+04	4.46e+04
Exterior1st_HdBoard	-1.18e+04	1.31e+04	-0.902	0.367	-3.75e+04	1.39e+04
Exterior1st_ImStucc	-3.997e+04	2.68e+04	-1.491	0.136	-9.26e+04	1.26e+04
Exterior1st_MetalSd	-2022.6728	1.51e+04	-0.134	0.893	-3.16e+04	2.76e+04
Exterior1st_Plywood	-1.003e+04	1.3e+04	-0.773	0.440	-3.55e+04	1.54e+04
Exterior1st_Stone	1.726e+04	2.49e+04	0.693	0.488	-3.16e+04	6.61e+04
Exterior1st_Stucco	-4621.0611	1.42e+04	-0.327	0.744	-3.24e+04	2.31e+04
Exterior1st_VinylSd	-4188.5653	1.34e+04	-0.312	0.755	-3.05e+04	2.22e+04
Exterior1st_Wd Sdng	-8340.2907	1.27e+04	-0.658	0.511	-3.32e+04	1.65e+04
Exterior1st_WdShing	-6466.9773	1.37e+04	-0.473	0.636	-3.33e+04	2.03e+04
Exterior2nd_AsphShn	1.375e+04	2.18e+04	0.629	0.529	-2.91e+04	5.66e+04

Exterior2nd_Brk Cmn	1.71e+04	1.95e+04	0.878	0.380	-2.11e+04	5.53e+04
Exterior2nd_BrkFace	7955.3967	1.33e+04	0.599	0.549	-1.81e+04	3.4e+04
Exterior2nd_CBlock	-1.096e+04	1.39e+04	-0.790	0.429	-3.82e+04	1.62e+04
Exterior2nd_CmentBd	-696.6179	1.84e+04	-0.038	0.970	-3.68e+04	3.54e+04
Exterior2nd_HdBoard	1.587e+04	1.25e+04	1.269	0.205	-8665.945	4.04e+04
Exterior2nd_ImStucc	2.036e+04	1.41e+04	1.439	0.151	-7406.376	4.81e+04
Exterior2nd_MetalSd	1.198e+04	1.46e+04	0.823	0.411	-1.66e+04	4.05e+04
Exterior2nd_Other	-3.209e+04	2.54e+04	-1.263	0.207	-8.2e+04	1.78e+04
Exterior2nd_Plywood	1.369e+04	1.22e+04	1.120	0.263	-1.03e+04	3.77e+04
Exterior2nd_Stone	-5065.5168	1.78e+04	-0.284	0.776	-4e+04	2.99e+04
Exterior2nd_Stucco	1.22e+04	1.35e+04	0.901	0.368	-1.44e+04	3.88e+04
Exterior2nd_VinylSd	1.013e+04	1.28e+04	0.789	0.430	-1.51e+04	3.53e+04
Exterior2nd_Wd Sdng	1.567e+04	1.21e+04	1.294	0.196	-8085.697	3.94e+04
Exterior2nd_Wd Shng	1.055e+04	1.26e+04	0.837	0.403	-1.42e+04	3.53e+04
Fence_GdWo	2593.5323	4655.844	0.557	0.578	-6541.917	1.17e+04
Fence_MnPrv	6027.8364	3826.709	1.575	0.116	-1480.729	1.35e+04
Fence_MnWw	-3685.9102	7649.009	-0.482	0.630	-1.87e+04	1.13e+04
Fence_None	3771.7311	3492.262	1.080	0.280	-3080.599	1.06e+04
FireplaceQu_Fa	-1047.6412	6513.125	-0.161	0.872	-1.38e+04	1.17e+04
FireplaceQu_Gd	4892.3867	5035.116	0.972	0.331	-4987.250	1.48e+04
FireplaceQu_None	7787.6739	5892.276	1.322	0.187	-3773.836	1.93e+04
FireplaceQu_Po	1.009e+04	7564.394	1.334	0.183	-4753.230	2.49e+04
FireplaceQu_TA	4968.5643	5226.490	0.951	0.342	-5286.575	1.52e+04
Foundation_CBlock	3942.7833	3395.627	1.161	0.246	-2719.936	1.06e+04
Foundation_PConc	6057.4435	3474.402	1.743	0.082	-759.843	1.29e+04
Foundation_Slab	-1921.7700	1.08e+04	-0.178	0.858	-2.31e+04	1.92e+04
Foundation_Stone	1.095e+04	1.23e+04	0.887	0.375	-1.33e+04	3.52e+04
Foundation_Wood	-2.304e+04	1.38e+04	-1.666	0.096	-5.02e+04	4094.383
Functional_Maj2	-9218.1227	1.59e+04	-0.580	0.562	-4.04e+04	2.2e+04
Functional_Min1	3970.9326	8420.062	0.472	0.637	-1.26e+04	2.05e+04
Functional_Min2	1575.6485	8658.529	0.182	0.856	-1.54e+04	1.86e+04
Functional_Mod	5919.4060	1.05e+04	0.563	0.573	-1.47e+04	2.65e+04
Functional_Sev	-3.998e+04	2.8e+04	-1.428	0.154	-9.49e+04	1.5e+04
Functional_Typ	1.291e+04	7472.084	1.728	0.084	-1748.060	2.76e+04
GarageCond_Fa	7.607e+04	3.81e+04	1.997	0.046	1332.896	1.51e+05
GarageCond_Gd	7.512e+04	3.92e+04	1.917	0.056	-1782.230	1.52e+05
GarageCond_Po	8.068e+04	4.05e+04	1.992	0.047	1217.159	1.6e+05
GarageCond_TA	7.402e+04	3.8e+04	1.948	0.052	-544.409	1.49e+05
GarageFinish_RFn	-132.5074	1838.743	-0.072	0.943	-3740.392	3475.377
GarageFinish_Unf	-1472.6542	2287.874	-0.644	0.520	-5961.799	3016.490
GarageQual_Fa	-8.224e+04	3.42e+04	-2.401	0.017	-1.49e+05	-1.5e+04
GarageQual_Gd	-7.412e+04	3.49e+04	-2.124	0.034	-1.43e+05	-5644.180
GarageQual_Po	-1.145e+05	4.14e+04	-2.768	0.006	-1.96e+05	-3.33e+04
GarageQual_TA	-7.483e+04	3.4e+04	-2.200	0.028	-1.42e+05	-8095.615
GarageType_Attchd	1.333e+04	1.1e+04	1.212	0.226	-8258.925	3.49e+04
GarageType_Basment	2.143e+04	1.26e+04	1.701	0.089	-3292.329	4.61e+04
GarageType_BuiltIn	1.236e+04	1.14e+04	1.082	0.280	-1.01e+04	3.48e+04
GarageType_CarPort	1.592e+04	1.47e+04	1.084	0.278	-1.29e+04	4.47e+04
GarageType_Detchd	1.522e+04	1.1e+04	1.385	0.166	-6343.752	3.68e+04
Heating_GasA	2.465e+04	2.45e+04	1.004	0.315	-2.35e+04	7.28e+04
Heating_GasW	2.973e+04	2.55e+04	1.164	0.245	-2.04e+04	7.98e+04
Heating_Grav	2.681e+04	3.03e+04	0.884	0.377	-3.27e+04	8.63e+04
Heating_OthW	1.221e+04	3.49e+04	0.350	0.727	-5.63e+04	8.07e+04
Heating_Wall	3.08e+04	2.84e+04	1.084	0.279	-2.5e+04	8.66e+04
HeatingQC_Fa	3653.9588	4692.543	0.779	0.436	-5553.500	1.29e+04
HeatingQC_Gd	-3635.1547	2017.069	-1.802	0.072	-7592.941	322.631
HeatingQC_Po	-1.006e+04	2.55e+04	-0.395	0.693	-6e+04	3.99e+04
HeatingQC_TA	-2784.1582	2021.503	-1.377	0.169	-6750.644	1182.328
HouseStyle_1.5Unf	9753.0031	9398.708	1.038	0.300	-8688.642	2.82e+04
HouseStyle_1Story	2792.7499	4952.922	0.564	0.573	-6925.610	1.25e+04
HouseStyle_2.5Fin	-1.356e+04	1.46e+04	-0.931	0.352	-4.21e+04	1.5e+04
HouseStyle_2.5Unf	-7652.3404	1.04e+04	-0.738	0.461	-2.8e+04	1.27e+04
HouseStyle_2Story	-2082.3882	3470.911	-0.600	0.549	-8892.826	4728.049
HouseStyle_SFoyer	1919.7429	7059.892	0.272	0.786	-1.19e+04	1.58e+04
HouseStyle_SLvl	4637.8914	5987.650	0.775	0.439	-7110.757	1.64e+04
LandContour_HLS	8180.6581	5171.089	1.582	0.114	-1965.777	1.83e+04
LandContour_Low	-1.042e+04	6407.181	-1.626	0.104	-2.3e+04	2155.035
LandContour_Lvl	5209.6721	3800.014	1.371	0.171	-2246.514	1.27e+04
LandSlope_Mod	6830.3181	3967.189	1.722	0.085	-953.888	1.46e+04
LandSlope_Sev	-3.981e+04	1.12e+04	-3.570	0.000	-6.17e+04	-1.79e+04
LotConfig_CulDSac	7663.1319	3073.015	2.494	0.013	1633.426	1.37e+04
LotConfig_FR2	-6869.2161	3816.909	-1.800	0.072	-1.44e+04	620.120
LotConfig_FR3	-1.393e+04	1.17e+04	-1.191	0.234	-3.69e+04	9021.022
LotConfig_Inside	-264.3333	1720.275	-0.154	0.878	-3639.765	3111.098
LotShape_IR2	5883.1363	4026.798	1.461	0.144	-2018.032	1.38e+04
LotShape_IR3	4097.7108	8333.807	0.492	0.623	-1.23e+04	2.04e+04
LotShape_Reg	319.5856	1589.069	0.201	0.841	-2798.401	3437.572
MSZoning_FV	5.465e+04	1.33e+04	4.124	0.000	2.86e+04	8.07e+04
MSZoning_RH	3.895e+04	1.38e+04	2.831	0.005	1.2e+04	6.6e+04
MSZoning_RL	4.058e+04	1.19e+04	3.413	0.001	1.72e+04	6.39e+04

```
MSZoning_RM                   3.672e+04   1.14e+04      3.217      0.001    1.43e+04    5.91e+04
MasVnrType_BrkFace            4740.8569   6362.734      0.745      0.456   -7743.760    1.72e+04
MasVnrType_None               4619.6640   6442.908      0.717      0.474   -8022.267    1.73e+04
MasVnrType_Stone              7982.3512   6749.267      1.183      0.237   -5260.702    2.12e+04
MiscFeature_None              5.826e+04   1.12e+05      0.522      0.602   -1.61e+05    2.77e+05
MiscFeature_Othr              6.936e+04   1.14e+05      0.611      0.542   -1.53e+05    2.92e+05
MiscFeature_Shed              5.461e+04   1.07e+05      0.512      0.609   -1.55e+05    2.64e+05
MiscFeature_TenC              3.705e+04   1.07e+05      0.346      0.730   -1.73e+05    2.47e+05
PavedDrive_P                 -2142.4344   5818.524     -0.368      0.713   -1.36e+04    9274.363
PavedDrive_Y                  3619.8169   3930.028      0.921      0.357   -4091.474    1.13e+04
PoolQC_Fa                    -5.155e+04   3.94e+04     -1.308      0.191   -1.29e+05    2.58e+04
PoolQC_Gd                    -2.786e+04   3.61e+04     -0.773      0.440   -9.86e+04    4.29e+04
PoolQC_None                   2.028e+05   1.16e+05      1.745      0.081   -2.52e+04    4.31e+05
RoofMatl_CompShg              4.792e+05   1.03e+05      4.666      0.000    2.78e+05    6.81e+05
RoofMatl_Membran              5.454e+05   1.08e+05      5.069      0.000    3.34e+05    7.57e+05
RoofMatl_Metal                5.297e+05   1.07e+05      4.945      0.000     3.2e+05     7.4e+05
RoofMatl_Roll                 4.787e+05   1.05e+05      4.559      0.000    2.73e+05    6.85e+05
RoofMatl_Tar&Grv              4.846e+05   1.04e+05      4.645      0.000     2.8e+05    6.89e+05
RoofMatl_WdShake              4.786e+05   1.05e+05      4.580      0.000    2.74e+05    6.84e+05
RoofMatl_WdShngl              5.176e+05   1.03e+05      5.013      0.000    3.15e+05     7.2e+05
RoofStyle_Gable               5186.4218   1.74e+04      0.298      0.766    -2.9e+04    3.94e+04
RoofStyle_Gambrel             2000.3971   1.96e+04      0.102      0.919   -3.65e+04    4.05e+04
RoofStyle_Hip                 4840.3474   1.75e+04      0.277      0.782   -2.94e+04    3.91e+04
RoofStyle_Mansard             1.128e+04   2.13e+04      0.529      0.597   -3.05e+04    5.31e+04
RoofStyle_Shed                7.987e+04   3.37e+04      2.368      0.018    1.37e+04    1.46e+05
SaleCondition_AdjLand         2.643e+04   2.34e+04      1.129      0.259   -1.95e+04    7.24e+04
SaleCondition_Alloca          8849.1300   9175.890      0.964      0.335   -9155.313    2.69e+04
SaleCondition_Family          -945.8270   5755.515     -0.164      0.869   -1.22e+04    1.03e+04
SaleCondition_Normal          7450.0986   2878.935      2.588      0.010    1801.207    1.31e+04
SaleCondition_Partial         -1.48e+04    1.4e+04     -1.059      0.290   -4.22e+04    1.26e+04
SaleType_CWD                  4663.1206    1.2e+04      0.389      0.697   -1.89e+04    2.82e+04
SaleType_Con                  1.571e+04   1.62e+04      0.967      0.334   -1.62e+04    4.76e+04
SaleType_ConLD                2.048e+04   1.04e+04      1.961      0.050      -9.936     4.1e+04
SaleType_ConLI               -1665.7739    1.2e+04     -0.139      0.889   -2.52e+04    2.18e+04
SaleType_ConLw                -679.8350   1.21e+04     -0.056      0.955   -2.45e+04    2.31e+04
SaleType_New                   3.28e+04   1.45e+04      2.265      0.024    4387.350    6.12e+04
SaleType_Oth                  1.953e+04   2.24e+04      0.871      0.384   -2.44e+04    6.35e+04
SaleType_WD                  -2154.7655   3974.798     -0.542      0.588   -9953.902    5644.371
Street_Pave                   4.447e+04   1.52e+04      2.924      0.004    1.46e+04    7.43e+04
Utilities_NoSeWa             -3.722e+04   2.45e+04     -1.522      0.128   -8.52e+04    1.08e+04
YearBuilt_x_GarageArea           0.1911      0.204      0.936      0.349      -0.209       0.592
OverallQual_x_TotalBsmtSF        4.6626      2.529      1.844      0.066      -0.300       9.625
GrLivArea_x_GarageCars           1.5311      3.678      0.416      0.677      -5.687       8.749
YearBuilt_x_OverallQual        -45.0495     30.523     -1.476      0.140    -104.939      14.840
YearRemodAdd_x_TotalBsmtSF       0.2453      0.145      1.691      0.091      -0.039       0.530
FullBath_x_BedroomAbvGr        303.7953   1606.430      0.189      0.850   -2848.257    3455.847
Fireplaces_x_GarageCars        849.9059   1955.984      0.435      0.664   -2988.021    4687.833
TotRmsAbvGrd_x_YearBuilt         4.8460     21.111      0.230      0.818     -36.576      46.268
GarageYrBlt_x_TotalBsmtSF        0.0418      0.148      0.282      0.778      -0.249       0.333
BsmtFinSF1_x_BsmtUnfSF          -0.0158      0.006     -2.684      0.007      -0.027      -0.004
LotArea_x_GrLivArea             -0.0007      0.000     -2.985      0.003      -0.001      -0.000
BsmtFullBath_x_HalfBath      -2941.0698   2511.113     -1.171      0.242   -7868.243    1986.103
log_LotArea                   1.967e+04   1.61e+04      1.222      0.222   -1.19e+04    5.12e+04
log_GrLivArea                 -6.05e+04    1.2e+05     -0.504      0.614   -2.96e+05    1.75e+05
log_1stFlrSF                  -1.89e+05    1.7e+05     -1.109      0.268   -5.23e+05    1.45e+05
log_TotalBsmtSF               7.792e+04   6.72e+04      1.160      0.246   -5.39e+04     2.1e+05
log_GarageArea                 1.85e+05   9.49e+04      1.949      0.052   -1242.026    3.71e+05
sqrt_LotArea                  -440.0389    420.330     -1.047      0.295   -1264.788     384.710
sqrt_GrLivArea                3881.5954   1.26e+04      0.309      0.758   -2.08e+04    2.86e+04
sqrt_1stFlrSF                 2.178e+04   2.12e+04      1.026      0.305   -1.99e+04    6.34e+04
sqrt_TotalBsmtSF             -1.763e+04   1.07e+04     -1.653      0.099   -3.86e+04    3293.480
sqrt_GarageArea              -3.552e+04   1.79e+04     -1.982      0.048   -7.07e+04    -354.024
exp_OverallQual                  1.6199      0.606      2.672      0.008       0.430       2.809
==============================================================================
Omnibus:                      308.659   Durbin-Watson:                   1.985
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            11841.431
Skew:                           0.159   Prob(JB):                         0.00
Kurtosis:                      17.399   Cond. No.                     9.69e+17
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 1.31e-18. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
Train MSE: 329902990.40326095
Train MAPE: 6.574591672754486
Test MSE: 359782528.8679208
Test MAPE: 7.068066960622021
```

Testing on initial model

In [ ]:
```
from scipy.stats import norm

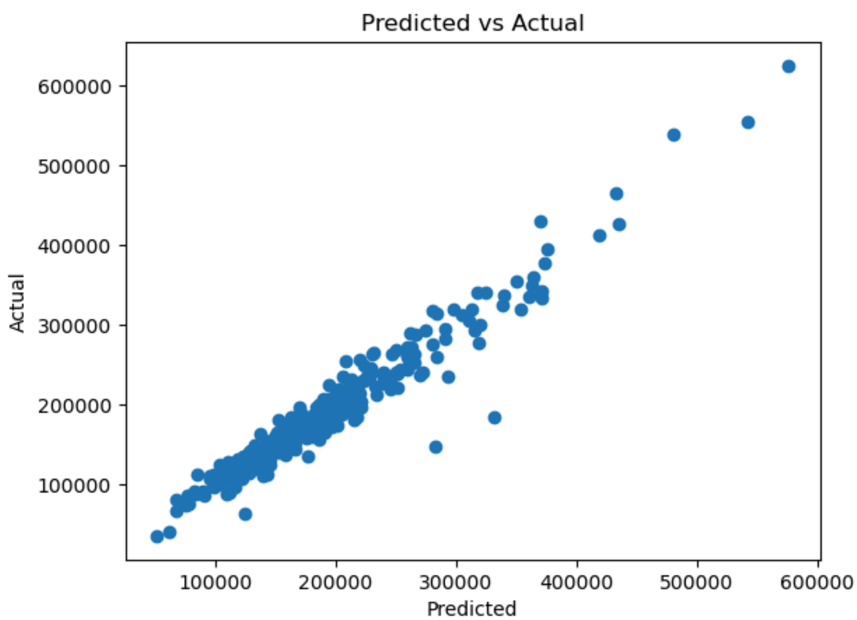
# 1. Predicted vs Actual Values Plot
plt.scatter(y_test_pred, y_test)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Predicted vs Actual")
plt.show()

# 2. QQ Plot
plt.figure(figsize=(6,6))
sm.qqplot(ols_model.resid, line='45', fit=True)
plt.title("Normal Q-Q plot")
plt.show()

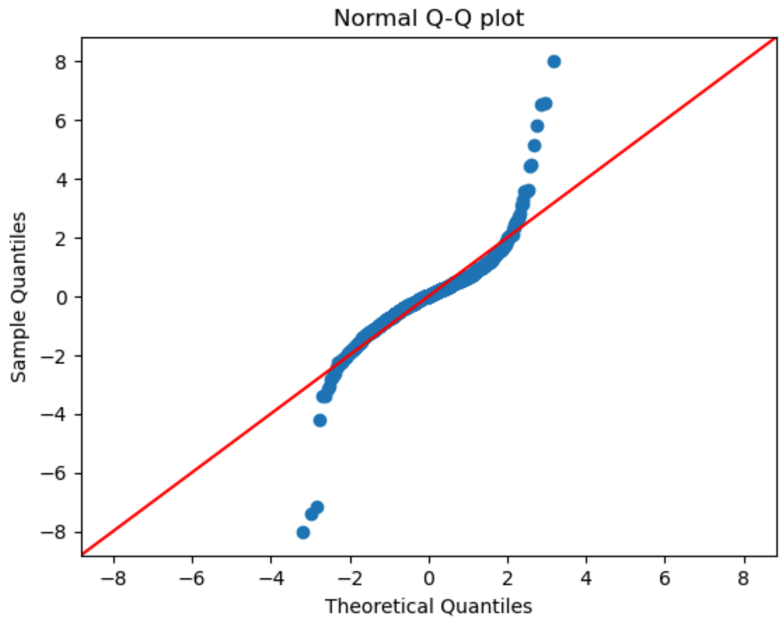
# 3. Residuals vs Fitted Values
plt.scatter(ols_model.fittedvalues, ols_model.resid)
plt.axhline(0, color='red', linestyle='--')
plt.xlabel('Fitted values')
plt.ylabel('Residuals')
plt.title('Residuals vs Fitted Values')
plt.show()

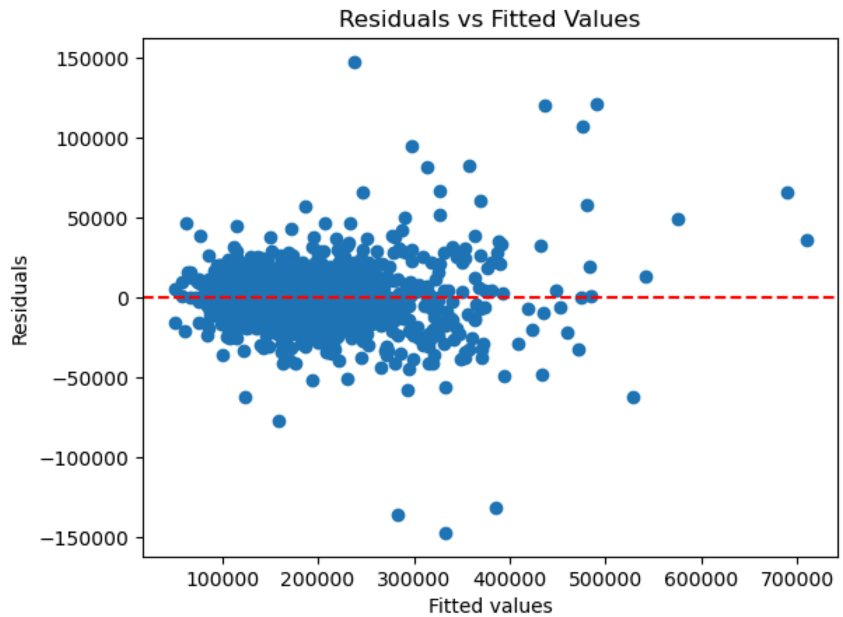
# Total number of predictors (excluding the intercept)
num_predictors = X.shape[1] - 1  # Subtract 1 to exclude the constant column

print(f'Total number of predictors in the model: {num_predictors}')
```




```
<Figure size 600x600 with 0 Axes>
```






```
Total number of predictors in the model: 287
```

In [ ]:

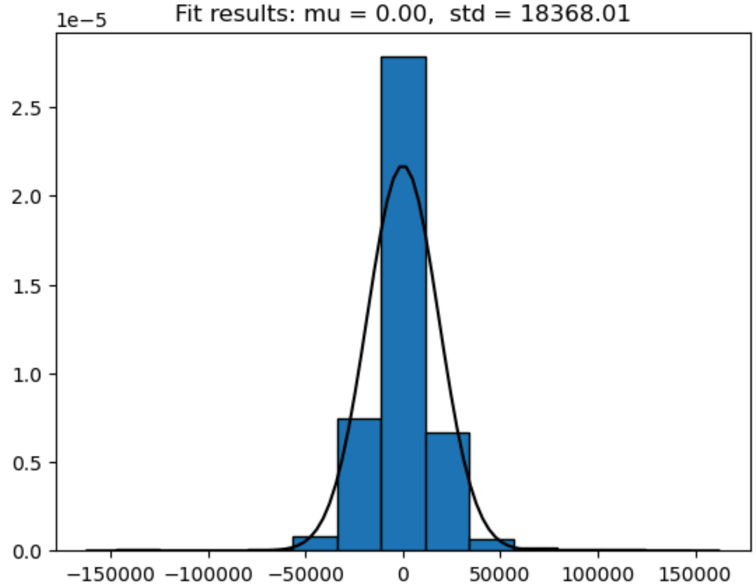
```python
# 4. Density Plot of Residuals
residuals = ols_model.resid

# Fit a normal distribution to the data:
mean, std = norm.fit(residuals)

# Plot the histogram
plt.hist(residuals, bins=13, edgecolor='black', density=True)

# Generate a PDF based on the fitted distribution
xmin, xmax = plt.xlim()
x = np.linspace(xmin, xmax, 100)
p = norm.pdf(x, mean, std)
plt.plot(x, p, color='black')
title = "Fit results: mu = %.2f,  std = %.2f" % (mean, std)
plt.title(title)

plt.show()
```



Perform lasso regression on model

In [ ]:
```
import patsy
from sklearn.linear_model import Lasso, LassoCV
from sklearn.metrics import mean_squared_error, mean_absolute_percentage_error

# Clean up all column names
df_encoded.columns = (
    df_encoded.columns
    .str.replace(' ', '_')              # Replace spaces with underscores
    .str.replace('[^A-Za-z0-9_]', '', regex=True)  # Remove any characters that are not alphanumeric or underscores
    .str.replace('^[0-9]', 'n', regex=True)  # Replace any column names starting with a number with 'n' followed by
)

# Check the cleaned column names
print(df_encoded.columns)
```

```
Index(['Id', 'MSSubClass', 'LotFrontage', 'LotArea', 'OverallQual',
       'OverallCond', 'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1',
       ...
       'log_GrLivArea', 'log_1stFlrSF', 'log_TotalBsmtSF', 'log_GarageArea',
       'sqrt_LotArea', 'sqrt_GrLivArea', 'sqrt_1stFlrSF', 'sqrt_TotalBsmtSF',
       'sqrt_GarageArea', 'exp_OverallQual'],
      dtype='object', length=288)
```

In [ ]:
```
# Step 1: Define the target variable and predictors
y_initial = df_encoded['SalePrice']
X_initial = df_encoded.drop(columns=['SalePrice'])

# Add a constant to the model (for intercept)
X_initial = sm.add_constant(X_initial)

# Split the data into training and testing sets
X_train_initial, X_test_initial, y_train_initial, y_test_initial = train_test_split(X_initial, y_initial, test_size

# Step 2: Perform Lasso Regression with Cross-Validation to find the best alpha
lasso_cv_model_initial = LassoCV(cv=10, random_state=42)  # Using Cross-Validation to find the best alpha
lasso_cv_model_initial.fit(X_train_initial, y_train_initial)

# Get the best alpha
best_alpha_initial = lasso_cv_model_initial.alpha_
print(f'Best alpha (Initial Lasso): {best_alpha_initial}')

# Step 3: Fit the Lasso Regression with the best alpha
lasso_model_initial = Lasso(alpha=best_alpha_initial)
lasso_model_initial.fit(X_train_initial, y_train_initial)

# Step 4: Make predictions on the training and testing data
lasso_train_predictions_initial = lasso_model_initial.predict(X_train_initial)
lasso_test_predictions_initial = lasso_model_initial.predict(X_test_initial)

# Step 5: Calculate and display Train/Test MSE and MAPE for Lasso
```

```
lasso_train_mse_initial = mean_squared_error(y_train_initial, lasso_train_predictions_initial)
lasso_train_mape_initial = mean_absolute_percentage_error(y_train_initial, lasso_train_predictions_initial) * 100

lasso_test_mse_initial = mean_squared_error(y_test_initial, lasso_test_predictions_initial)
lasso_test_mape_initial = mean_absolute_percentage_error(y_test_initial, lasso_test_predictions_initial) * 100

print(f'LASSO Training MSE (Initial): {lasso_train_mse_initial}')
print(f'LASSO Training MAPE (Initial): {lasso_train_mape_initial}')
print(f'LASSO Testing MSE (Initial): {lasso_test_mse_initial}')
print(f'LASSO Testing MAPE (Initial): {lasso_test_mape_initial}')
```

```
Best alpha (Initial Lasso): 722214625.7287824
LASSO Training MSE (Initial): 2848017848.5601506
LASSO Training MAPE (Initial): 20.003391892126043
LASSO Testing MSE (Initial): 2457516485.695716
LASSO Testing MAPE (Initial): 20.073289776083406
```

Conclusion: Lasso regression makes model worse than initial model

Ridge regression on initial model

In [ ]:
```
from sklearn.linear_model import RidgeCV, Ridge
# Step 1: Define the target variable and predictors
y_ridge = df_encoded['SalePrice']
X_ridge = df_encoded.drop(columns=['SalePrice'])

# Add a constant to the model (for intercept)
X_ridge = sm.add_constant(X_ridge)

# Split the data into training and testing sets
X_train_ridge, X_test_ridge, y_train_ridge, y_test_ridge = train_test_split(X_ridge, y_ridge, test_size=0.25, rando

# Step 2: Perform Ridge Regression with Cross-Validation to find the best alpha
alphas = np.logspace(-6, 6, 13)  # A wide range of alphas to consider
ridge_cv_model = RidgeCV(alphas=alphas, cv=10, scoring='neg_mean_squared_error')  # Using Cross-Validation to find
ridge_cv_model.fit(X_train_ridge, y_train_ridge)

# Get the best alpha
best_alpha_ridge = ridge_cv_model.alpha_
print(f'Best alpha (Ridge): {best_alpha_ridge}')

# Step 3: Fit the Ridge Regression with the best alpha
ridge_model = Ridge(alpha=best_alpha_ridge)
ridge_model.fit(X_train_ridge, y_train_ridge)

# Step 4: Make predictions on the training and testing data
ridge_train_predictions = ridge_model.predict(X_train_ridge)
ridge_test_predictions = ridge_model.predict(X_test_ridge)

# Step 5: Calculate and display Train/Test MSE and MAPE for Ridge
ridge_train_mse = mean_squared_error(y_train_ridge, ridge_train_predictions)
ridge_train_mape = mean_absolute_percentage_error(y_train_ridge, ridge_train_predictions) * 100

ridge_test_mse = mean_squared_error(y_test_ridge, ridge_test_predictions)
ridge_test_mape = mean_absolute_percentage_error(y_test_ridge, ridge_test_predictions) * 100



# Get the coefficients from the Ridge model
ridge_coefficients = pd.Series(ridge_model.coef_, index=X_train_ridge.columns)

# Filter to keep only the predictors that were retained by Ridge (i.e., non-zero coefficients)
included_predictors_ridge = ridge_coefficients[ridge_coefficients != 0].index

# Subset the training data to include only these predictors
X_train_included_ridge = X_train_ridge[included_predictors_ridge]
X_test_included_ridge = X_test_ridge[included_predictors_ridge]

# Add a constant to the model (for intercept)
X_train_included_ridge = sm.add_constant(X_train_included_ridge)
X_test_included_ridge = sm.add_constant(X_test_included_ridge)

# Refit an OLS model using only the predictors retained by Ridge
ols_model_ridge = sm.OLS(y_train_ridge, X_train_included_ridge).fit()

# Print the model summary
print("OLS Regression Model Summary with Ridge Predictors:")
print(ols_model_ridge.summary())
```

```
print(f'Ridge Training MSE: {ridge_train_mse}')
print(f'Ridge Training MAPE: {ridge_train_mape}')
print(f'Ridge Testing MSE: {ridge_test_mse}')
print(f'Ridge Testing MAPE: {ridge_test_mape}')
```

```
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.67841e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.44293e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.57454e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.24448e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.82335e-25): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.22647e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.26137e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.07406e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.01568e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.12989e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.67415e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.43952e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.57156e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.41354e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.8197e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.24362e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.25828e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.07391e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.01484e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.27308e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.64188e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.41307e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.54493e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.43144e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.78421e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.21907e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.23455e-22): result may not be accurate.
```

```
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.07257e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.00676e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.18673e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.55811e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.33903e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.42174e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.14276e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.5282e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.15428e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.17031e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.06441e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.50706e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.8843e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.02862e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.72254e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.28337e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.25047e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.23714e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.44015e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.62916e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.01211e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.78811e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.9886e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.29663e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.11736e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.20355e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
```

```
x (rcond=9.76995e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.32674e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.00076e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.47751e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.5475e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.23026e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.0489e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.98347e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.68736e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.37125e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.48847e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.90038e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.74791e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.59757e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.50094e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.51928e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.99883e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.40118e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.48834e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.13577e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.57266e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.83463e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.79912e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.68987e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.68935e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.33731e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.60869e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
```

```
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.06077e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.6084e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.37044e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.61511e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.21483e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.51638e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.72139e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.52831e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.54633e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.70788e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
```

```
Best alpha (Ridge): 1000000.0
OLS Regression Model Summary with Ridge Predictors:
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.963
Model:                            OLS   Adj. R-squared:                  0.949
Method:                 Least Squares   F-statistic:                     70.82
Date:                Thu, 15 Aug 2024   Prob (F-statistic):               0.00
Time:                        19:52:41   Log-Likelihood:                -11358.
No. Observations:                1027   AIC:                         2.327e+04
Df Residuals:                     752   BIC:                         2.462e+04
Df Model:                         274
Covariance Type:            nonrobust
========================================================================================================
                                           coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------------------
const                                 3.961e+06   7.05e+06      0.562      0.574   -9.87e+06    1.78e+07
Id                                      -0.0500      1.540     -0.032      0.974      -3.074       2.974
MSSubClass                             -93.4596     89.420     -1.045      0.296    -269.003      82.083
LotFrontage                             14.2284     23.608      0.603      0.547     -32.118      60.575
LotArea                                 -1.6104      0.939     -1.715      0.087      -3.454       0.233
OverallQual                          -3.938e+04   6.42e+04     -0.613      0.540   -1.65e+05    8.67e+04
OverallCond                           6160.4579    964.321      6.388      0.000    4267.377    8053.538
YearBuilt                            -4980.1454   4614.364     -1.079      0.281    -1.4e+04    4078.421
YearRemodAdd                           -97.4265    152.716     -0.638      0.524    -397.227     202.374
MasVnrArea                               4.4011      6.126      0.718      0.473      -7.626      16.428
BsmtFinSF1                            -129.9241     83.945     -1.548      0.122    -294.718      34.870
BsmtFinSF2                            -139.0685     83.741     -1.661      0.097    -303.463      25.326
BsmtUnfSF                             -139.2076     84.200     -1.653      0.099    -304.503      26.087
TotalBsmtSF                           -407.7733    251.610     -1.621      0.106    -901.715      86.168
nstFlrSF                               132.4917    130.484      1.015      0.310    -123.665     388.649
nndFlrSF                                97.2342     53.304      1.824      0.069      -7.408     201.877
LowQualFinSF                            81.3859     56.170      1.449      0.148     -28.882     191.654
GrLivArea                              313.0091     88.955      3.519      0.000     138.380     487.638
BsmtFullBath                          1325.9634   2302.019      0.576      0.565   -3193.184    5845.111
BsmtHalfBath                          1082.6700   3034.140      0.357      0.721   -4873.722    7039.062
FullBath                              1.217e+04   5180.708      2.349      0.019    1998.179    2.23e+04
HalfBath                              3001.2254   2502.717      1.199      0.231   -1911.917    7914.368
BedroomAbvGr                           527.0135   2708.445      0.195      0.846   -4789.998    5844.025
KitchenAbvGr                         -1.024e+04   7578.030     -1.351      0.177   -2.51e+04    4637.937
TotRmsAbvGrd                         -3758.6862     4.7e+04     -0.080      0.936   -9.59e+04    8.84e+04
Fireplaces                           -1862.0445   4668.316     -0.399      0.690    -1.1e+04    7302.437
GarageYrBlt                          -5477.6127   4482.125     -1.222      0.222   -1.43e+04    3321.353
GarageCars                           -1.257e+04   7352.897     -1.710      0.088    -2.7e+04    1863.532
GarageArea                            -179.2303    451.752     -0.397      0.692   -1066.075     707.614
WoodDeckSF                              11.4267      6.155      1.857      0.064      -0.656      23.510
OpenPorchSF                              0.6775     11.799      0.057      0.954     -22.485      23.840
EnclosedPorch                           23.4077     13.921      1.681      0.093      -3.921      50.737
nSsnPorch                               44.0933     19.547      2.256      0.024       5.721      82.466
ScreenPorch                             52.0971     12.250      4.253      0.000      28.048      76.146
PoolArea                              2844.6682    958.374      2.968      0.003     963.262    4726.075
MiscVal                                 10.8915      7.069      1.541      0.124      -2.986      24.769
MoSold                                -197.7997    246.703     -0.802      0.423    -682.107     286.508
YrSold                                 -54.9372    521.669     -0.105      0.916   -1079.038     969.164
BsmtFinType1_BLQ                      1340.0847   2853.589      0.470      0.639   -4261.863    6942.032
BsmtFinType1_GLQ                     -9321.9815   4457.860     -2.091      0.037   -1.81e+04    -570.651
BsmtFinType1_LwQ                      -914.0067   3941.762     -0.232      0.817   -8652.173    6824.160
BsmtFinType1_None                     1.312e+05   6.99e+04      1.878      0.061   -5934.856    2.68e+05
BsmtFinType1_Rec                       191.3321   3240.040      0.059      0.953   -6169.266    6551.930
BsmtFinType1_Unf                     -6328.5047   4049.661     -1.563      0.119   -1.43e+04    1621.481
Neighborhood_Blueste                  3140.4510   2.23e+04      0.141      0.888   -4.07e+04    4.69e+04
Neighborhood_BrDale                    989.8840   1.17e+04      0.084      0.933    -2.2e+04     2.4e+04
Neighborhood_BrkSide                  1.078e+04   1.07e+04      1.004      0.316   -1.03e+04    3.19e+04
Neighborhood_ClearCr                 -3277.3152   9600.475     -0.341      0.733   -2.21e+04    1.56e+04
Neighborhood_CollgCr                  -1.08e+04   7846.217     -1.376      0.169   -2.62e+04    4606.641
Neighborhood_Crawfor                  2.269e+04   9433.759      2.406      0.016    4174.236    4.12e+04
Neighborhood_Edwards                 -1.307e+04   8693.687     -1.503      0.133   -3.01e+04    4001.390
Neighborhood_Gilbert                 -6320.3523   8369.818     -0.755      0.450   -2.28e+04    1.01e+04
Neighborhood_IDOTRR                  -2095.5141   1.19e+04     -0.176      0.861   -2.55e+04    2.13e+04
Neighborhood_MeadowV                 -1.261e+04   1.19e+04     -1.064      0.288   -3.59e+04    1.07e+04
Neighborhood_Mitchel                 -7222.0483   8956.698     -0.806      0.420   -2.48e+04    1.04e+04
Neighborhood_NAmes                   -8369.6007   8519.478     -0.982      0.326   -2.51e+04    8355.187
Neighborhood_NPkVill                  -811.3117   1.37e+04     -0.059      0.953   -2.77e+04     2.6e+04
Neighborhood_NWAmes                  -1.169e+04   8660.074     -1.350      0.178   -2.87e+04    5313.819
Neighborhood_NoRidge                  1.948e+04      5e+04      0.390      0.697   -7.86e+04    1.18e+05
Neighborhood_NridgHt                 -3.267e+04   1.64e+04     -1.992      0.047   -6.49e+04    -470.356
Neighborhood_OldTown                  1095.1972   1.07e+04      0.102      0.919     -2e+04    2.21e+04
Neighborhood_SWISU                   -1689.0609   1.08e+04     -0.157      0.875   -2.28e+04    1.94e+04
Neighborhood_Sawyer                  -3596.7253   8692.581     -0.414      0.679   -2.07e+04    1.35e+04
Neighborhood_SawyerW                 -6331.0514   8358.531     -0.757      0.449   -2.27e+04    1.01e+04
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Neighborhood_Somerst	-778.1823	9383.631	-0.083	0.934	-1.92e+04	1.76e+04
Neighborhood_StoneBr	3.315e+04	8430.032	3.932	0.000	1.66e+04	4.97e+04
Neighborhood_Timber	-1.128e+04	8873.816	-1.272	0.204	-2.87e+04	6137.335
Neighborhood_Veenker	5629.8704	1.08e+04	0.521	0.602	-1.56e+04	2.68e+04
KitchenQual_Fa	-1.506e+04	7070.129	-2.130	0.033	-2.89e+04	-1179.599
KitchenQual_Gd	-1.098e+04	3525.160	-3.116	0.002	-1.79e+04	-4063.179
KitchenQual_TA	-7130.7010	7241.736	-0.985	0.325	-2.13e+04	7085.721
ExterQual_Fa	-1150.1880	1.69e+04	-0.068	0.946	-3.43e+04	3.2e+04
ExterQual_Gd	1.075e+04	9805.212	1.097	0.273	-8497.145	3e+04
ExterQual_TA	-1047.3790	6270.891	-0.167	0.867	-1.34e+04	1.13e+04
OverallQual_x_GrLivArea	8.3656	2.359	3.547	0.000	3.735	12.996
YearBuilt_x_GarageYrBlt	2.7007	2.319	1.165	0.245	-1.852	7.253
TotalBsmtSF_x_1stFlrSF	-0.0054	0.013	-0.418	0.676	-0.031	0.020
BsmtFinSF1_x_BsmtFinType1_GLQ	24.1363	5.531	4.364	0.000	13.278	34.994
GarageCars_x_GarageArea	33.0820	13.018	2.541	0.011	7.527	58.637
Neighborhood_NoRidge_x_OverallQual	-2509.5753	6391.271	-0.393	0.695	-1.51e+04	1e+04
KitchenQual_TA_x_GrLivArea	-1.6738	4.156	-0.403	0.687	-9.833	6.485
ExterQual_Gd_x_TotalBsmtSF	-10.1517	5.294	-1.918	0.056	-20.545	0.241
Neighborhood_NridgHt_x_GrLivArea	18.5934	7.813	2.380	0.018	3.257	33.930
Alley_None	3581.0058	4840.994	0.740	0.460	-5922.463	1.31e+04
Alley_Pave	-98.3702	6917.672	-0.014	0.989	-1.37e+04	1.35e+04
BldgType_2fmCon	-3679.2184	1.44e+04	-0.255	0.799	-3.2e+04	2.46e+04
BldgType_Duplex	-4932.9651	8757.334	-0.563	0.573	-2.21e+04	1.23e+04
BldgType_Twnhs	-1297.8383	1.12e+04	-0.115	0.908	-2.34e+04	2.08e+04
BldgType_TwnhsE	4269.0698	9992.937	0.427	0.669	-1.53e+04	2.39e+04
BsmtCond_Gd	-1259.4018	5937.044	-0.212	0.832	-1.29e+04	1.04e+04
BsmtCond_None	1.312e+05	6.99e+04	1.878	0.061	-5934.857	2.68e+05
BsmtCond_TA	2638.0426	5197.125	0.508	0.612	-7564.557	1.28e+04
BsmtExposure_Gd	1.415e+04	3057.794	4.626	0.000	8142.323	2.01e+04
BsmtExposure_Mn	-2214.4635	2976.798	-0.744	0.457	-8058.285	3629.358
BsmtExposure_No	-2931.3676	2064.416	-1.420	0.156	-6984.071	1121.336
BsmtExposure_None	1.312e+05	6.99e+04	1.878	0.061	-5934.857	2.68e+05
BsmtFinType2_BLQ	-1170.5603	8122.404	-0.144	0.885	-1.71e+04	1.48e+04
BsmtFinType2_GLQ	2260.8490	9823.676	0.230	0.818	-1.7e+04	2.15e+04
BsmtFinType2_LwQ	-6737.0604	7789.823	-0.865	0.387	-2.2e+04	8555.325
BsmtFinType2_None	-9.725e+04	3.98e+04	-2.442	0.015	-1.75e+05	-1.91e+04
BsmtFinType2_Rec	-7109.1652	7337.031	-0.969	0.333	-2.15e+04	7294.333
BsmtFinType2_Unf	-5372.5423	7975.597	-0.674	0.501	-2.1e+04	1.03e+04
BsmtQual_Fa	-1.121e+04	6996.831	-1.602	0.110	-2.49e+04	2526.303
BsmtQual_Gd	-8073.9249	3344.273	-2.414	0.016	-1.46e+04	-1508.704
BsmtQual_None	1.312e+05	6.99e+04	1.878	0.061	-5934.857	2.68e+05
BsmtQual_TA	-5538.5434	4318.109	-1.283	0.200	-1.4e+04	2938.438
CentralAir_Y	7122.7214	5117.106	1.392	0.164	-2922.790	1.72e+04
Condition1_Feedr	6021.9934	5271.313	1.142	0.254	-4326.246	1.64e+04
Condition1_Norm	1.301e+04	4410.205	2.950	0.003	4353.522	2.17e+04
Condition1_PosA	9883.2049	1.07e+04	0.924	0.356	-1.11e+04	3.09e+04
Condition1_PosN	2.21e+04	7869.734	2.808	0.005	6648.362	3.75e+04
Condition1_RRAe	-1.213e+04	8489.380	-1.428	0.154	-2.88e+04	4540.643
Condition1_RRAn	9828.1616	7169.020	1.371	0.171	-4245.510	2.39e+04
Condition1_RRNe	-5935.3633	2.02e+04	-0.294	0.769	-4.56e+04	3.37e+04
Condition1_RRNn	2108.8773	1.62e+04	0.130	0.897	-2.98e+04	3.4e+04
Condition2_Feedr	-3.349e+04	2.59e+04	-1.293	0.196	-8.43e+04	1.74e+04
Condition2_Norm	-1.516e+04	1.98e+04	-0.765	0.445	-5.41e+04	2.37e+04
Condition2_PosA	4.873e+04	4.21e+04	1.158	0.247	-3.39e+04	1.31e+05
Condition2_PosN	-5.805e+04	3e+04	-1.937	0.053	-1.17e+05	788.742
Condition2_RRAe	4.8e+05	1.01e+06	0.475	0.635	-1.5e+06	2.46e+06
Condition2_RRAn	-3.315e+04	2.83e+04	-1.170	0.242	-8.88e+04	2.25e+04
Condition2_RRNn	-1.478e+04	2.9e+04	-0.510	0.610	-7.16e+04	4.21e+04
Electrical_FuseF	-6145.6022	6823.446	-0.901	0.368	-1.95e+04	7249.666
Electrical_FuseP	-2.101e+04	2.51e+04	-0.836	0.404	-7.04e+04	2.83e+04
Electrical_None	1.471e+04	2.05e+04	0.716	0.474	-2.56e+04	5.5e+04
Electrical_SBrkr	-2716.7120	3227.892	-0.842	0.400	-9053.463	3620.038
ExterCond_Fa	2.21e+04	2.37e+04	0.932	0.352	-2.44e+04	6.86e+04
ExterCond_Gd	6587.6267	2.22e+04	0.297	0.767	-3.7e+04	5.01e+04
ExterCond_TA	1.156e+04	2.23e+04	0.519	0.604	-3.22e+04	5.53e+04
Exterior1st_BrkComm	-3.353e+04	2.83e+04	-1.183	0.237	-8.92e+04	2.21e+04
Exterior1st_BrkFace	7811.1301	1.48e+04	0.529	0.597	-2.12e+04	3.68e+04
Exterior1st_CBlock	703.3103	1.39e+04	0.051	0.960	-2.65e+04	2.79e+04
Exterior1st_CemntBd	-3.931e+04	2.04e+04	-1.931	0.054	-7.93e+04	659.901
Exterior1st_HdBoard	-1.455e+04	1.52e+04	-0.955	0.340	-4.45e+04	1.54e+04
Exterior1st_ImStucc	-1.801e+04	2.65e+04	-0.679	0.497	-7.01e+04	3.41e+04
Exterior1st_MetalSd	1078.5929	1.67e+04	0.065	0.948	-3.16e+04	3.38e+04
Exterior1st_Plywood	-1.177e+04	1.53e+04	-0.771	0.441	-4.17e+04	1.82e+04
Exterior1st_Stone	-3278.2127	2.48e+04	-0.132	0.895	-5.19e+04	4.54e+04
Exterior1st_Stucco	-1.736e+04	1.68e+04	-1.034	0.301	-5.03e+04	1.56e+04
Exterior1st_VinylSd	-1422.3341	1.52e+04	-0.094	0.925	-3.13e+04	2.84e+04
Exterior1st_Wd_Sdng	-9300.5143	1.46e+04	-0.637	0.524	-3.8e+04	1.94e+04
Exterior1st_WdShing	519.2130	1.56e+04	0.033	0.973	-3.01e+04	3.12e+04
Exterior2nd_AsphShn	7993.7097	2.16e+04	0.369	0.712	-3.45e+04	5.05e+04
Exterior2nd_Brk_Cmn	3.098e+04	2.14e+04	1.446	0.148	-1.11e+04	7.3e+04

Exterior2nd_BrkFace	1.202e+04	1.47e+04	0.820	0.412	-1.68e+04	4.08e+04
Exterior2nd_CBlock	703.3103	1.39e+04	0.051	0.960	-2.65e+04	2.79e+04
Exterior2nd_CmentBd	4.559e+04	1.96e+04	2.323	0.020	7056.726	8.41e+04
Exterior2nd_HdBoard	1.625e+04	1.38e+04	1.178	0.239	-1.08e+04	4.33e+04
Exterior2nd_ImStucc	1.794e+04	1.6e+04	1.119	0.264	-1.35e+04	4.94e+04
Exterior2nd_MetalSd	7901.5562	1.55e+04	0.510	0.610	-2.25e+04	3.83e+04
Exterior2nd_Other	-4.542e+04	2.4e+04	-1.891	0.059	-9.26e+04	1736.990
Exterior2nd_Plywood	1.752e+04	1.37e+04	1.275	0.203	-9451.734	4.45e+04
Exterior2nd_Stone	-6315.1362	1.78e+04	-0.355	0.722	-4.12e+04	2.86e+04
Exterior2nd_Stucco	2.218e+04	1.47e+04	1.510	0.132	-6660.078	5.1e+04
Exterior2nd_VinylSd	1.05e+04	1.39e+04	0.755	0.450	-1.68e+04	3.78e+04
Exterior2nd_Wd_Sdng	1.469e+04	1.32e+04	1.114	0.266	-1.12e+04	4.06e+04
Exterior2nd_Wd_Shng	6151.8922	1.38e+04	0.444	0.657	-2.1e+04	3.33e+04
Fence_GdWo	5348.6500	4945.466	1.082	0.280	-4359.911	1.51e+04
Fence_MnPrv	4158.7162	4163.628	0.999	0.318	-4014.999	1.23e+04
Fence_MnWw	1580.1470	8612.495	0.183	0.854	-1.53e+04	1.85e+04
Fence_None	2991.2055	3764.971	0.794	0.427	-4399.898	1.04e+04
FireplaceQu_Fa	-4646.0336	6860.384	-0.677	0.498	-1.81e+04	8821.748
FireplaceQu_Gd	1189.9536	5336.544	0.223	0.824	-9286.341	1.17e+04
FireplaceQu_None	-2871.1485	6096.433	-0.471	0.638	-1.48e+04	9096.903
FireplaceQu_Po	1.034e+04	7988.245	1.294	0.196	-5344.856	2.6e+04
FireplaceQu_TA	2189.5801	5546.146	0.395	0.693	-8698.190	1.31e+04
Foundation_CBlock	1223.6738	3916.976	0.312	0.755	-6465.834	8913.182
Foundation_PConc	2493.1700	3952.700	0.631	0.528	-5266.469	1.03e+04
Foundation_Slab	5243.3242	1.07e+04	0.488	0.626	-1.59e+04	2.63e+04
Foundation_Stone	3766.1310	1.27e+04	0.296	0.768	-2.12e+04	2.88e+04
Foundation_Wood	-4.897e+04	1.57e+04	-3.115	0.002	-7.98e+04	-1.81e+04
Functional_Maj2	-2846.4619	1.56e+04	-0.182	0.855	-3.35e+04	2.78e+04
Functional_Min1	1.983e+04	9480.105	2.091	0.037	1216.656	3.84e+04
Functional_Min2	1.958e+04	9518.483	2.057	0.040	890.414	3.83e+04
Functional_Mod	1983.8672	1.08e+04	0.184	0.854	-1.92e+04	2.32e+04
Functional_Typ	2.54e+04	8169.772	3.109	0.002	9359.824	4.14e+04
GarageCond_Fa	1.775e+04	4.34e+04	0.409	0.683	-6.75e+04	1.03e+05
GarageCond_Gd	2.555e+04	4.65e+04	0.549	0.583	-6.58e+04	1.17e+05
GarageCond_Po	2.26e+04	4.62e+04	0.489	0.625	-6.81e+04	1.13e+05
GarageCond_TA	1.609e+04	4.35e+04	0.370	0.712	-6.94e+04	1.02e+05
GarageFinish_RFn	1052.6174	1915.809	0.549	0.583	-2708.353	4813.588
GarageFinish_Unf	1296.5495	2354.025	0.551	0.582	-3324.692	5917.791
GarageQual_Fa	-4.322e+04	4.11e+04	-1.052	0.293	-1.24e+05	3.74e+04
GarageQual_Gd	-4.172e+04	4.25e+04	-0.981	0.327	-1.25e+05	4.18e+04
GarageQual_Po	-2.101e+04	2.51e+04	-0.836	0.404	-7.04e+04	2.83e+04
GarageQual_TA	-3.481e+04	4.1e+04	-0.848	0.397	-1.15e+05	4.57e+04
GarageType_Attchd	2.424e+04	1.06e+04	2.293	0.022	3486.746	4.5e+04
GarageType_Basment	2.339e+04	1.25e+04	1.865	0.063	-1229.426	4.8e+04
GarageType_BuiltIn	2.727e+04	1.11e+04	2.460	0.014	5509.912	4.9e+04
GarageType_CarPort	2.286e+04	1.48e+04	1.545	0.123	-6192.598	5.19e+04
GarageType_Detchd	2.772e+04	1.06e+04	2.626	0.009	6999.554	4.84e+04
Heating_GasA	3.121e+04	2.3e+04	1.355	0.176	-1.4e+04	7.64e+04
Heating_GasW	4.467e+04	2.43e+04	1.840	0.066	-2976.715	9.23e+04
Heating_Grav	2.371e+04	3.37e+04	0.703	0.482	-4.25e+04	8.99e+04
Heating_OthW	2.622e+04	3.32e+04	0.791	0.429	-3.89e+04	9.13e+04
Heating_Wall	2.955e+04	2.67e+04	1.106	0.269	-2.29e+04	8.2e+04
HeatingQC_Fa	3695.2784	5560.821	0.665	0.507	-7221.301	1.46e+04
HeatingQC_Gd	315.9297	2157.199	0.146	0.884	-3918.919	4550.778
HeatingQC_Po	7517.9022	2.37e+04	0.318	0.751	-3.9e+04	5.4e+04
HeatingQC_TA	-2141.4688	2153.572	-0.994	0.320	-6369.197	2086.259
HouseStyle_15Unf	4853.0139	9520.248	0.510	0.610	-1.38e+04	2.35e+04
HouseStyle_1Story	591.4449	5142.297	0.115	0.908	-9503.519	1.07e+04
HouseStyle_25Fin	-1.256e+04	2.87e+04	-0.438	0.661	-6.88e+04	4.37e+04
HouseStyle_25Unf	-5324.9242	1.13e+04	-0.470	0.638	-2.75e+04	1.69e+04
HouseStyle_2Story	1287.7100	3698.915	0.348	0.728	-5973.718	8549.138
HouseStyle_SFoyer	-2022.8336	7604.944	-0.266	0.790	-1.7e+04	1.29e+04
HouseStyle_SLvl	3160.8868	6354.226	0.497	0.619	-9313.245	1.56e+04
LandContour_HLS	-5901.4797	5895.542	-1.001	0.317	-1.75e+04	5672.198
LandContour_Low	-2.395e+04	6767.888	-3.539	0.000	-3.72e+04	-1.07e+04
LandContour_Lvl	-8714.6981	4340.235	-2.008	0.045	-1.72e+04	-194.280
LandSlope_Mod	3459.1169	4204.032	0.823	0.411	-4793.917	1.17e+04
LandSlope_Sev	-2.825e+04	1.23e+04	-2.302	0.022	-5.23e+04	-4159.378
LotConfig_CulDSac	490.2394	3231.956	0.152	0.879	-5854.489	6834.968
LotConfig_FR2	-1.063e+04	3916.651	-2.714	0.007	-1.83e+04	-2940.082
LotConfig_FR3	-2.54e+04	1.38e+04	-1.843	0.066	-5.25e+04	1658.603
LotConfig_Inside	-2010.9680	1863.881	-1.079	0.281	-5669.997	1648.061
LotShape_IR2	-2070.7884	4100.959	-0.505	0.614	-1.01e+04	5979.901
LotShape_IR3	-3158.0542	8314.535	-0.380	0.704	-1.95e+04	1.32e+04
LotShape_Reg	-76.5405	1644.665	-0.047	0.963	-3305.221	3152.140
MSZoning_FV	2.98e+04	1.54e+04	1.929	0.054	-529.242	6.01e+04
MSZoning_RH	1.867e+04	1.61e+04	1.157	0.248	-1.3e+04	5.03e+04
MSZoning_RL	2.043e+04	1.41e+04	1.450	0.147	-7224.451	4.81e+04
MSZoning_RM	1.526e+04	1.35e+04	1.132	0.258	-1.12e+04	4.17e+04
MasVnrType_BrkFace	4960.0906	6847.815	0.724	0.469	-8483.017	1.84e+04

```
MasVnrType_None                    3093.2608   7001.885      0.442      0.659   -1.07e+04    1.68e+04
MasVnrType_Stone                   1.218e+04   7283.592      1.672      0.095   -2122.730    2.65e+04
MiscFeature_None                   1.078e+06   2.01e+06      0.536      0.592   -2.87e+06    5.03e+06
MiscFeature_Shed                   1.071e+06   2.01e+06      0.532      0.595   -2.88e+06    5.02e+06
MiscFeature_TenC                   1.333e+06   2.02e+06      0.661      0.509   -2.63e+06    5.29e+06
PavedDrive_P                      -5668.4712   6931.929     -0.818      0.414   -1.93e+04    7939.762
PavedDrive_Y                      -3836.9635   4574.681     -0.839      0.402   -1.28e+04    5143.701
PoolQC_Fa                          -2.66e+05   1.15e+05     -2.316      0.021   -4.92e+05   -4.05e+04
PoolQC_Gd                         -4.495e+05   2.01e+05     -2.238      0.025   -8.44e+05   -5.53e+04
PoolQC_None                        1.547e+06   5.11e+05      3.029      0.003    5.44e+05    2.55e+06
RoofMatl_CompShg                   8.696e+05    2.9e+05      3.001      0.003    3.01e+05    1.44e+06
RoofMatl_Membran                   9.799e+05   2.93e+05      3.344      0.001    4.05e+05    1.56e+06
RoofMatl_Metal                      9.46e+05   2.92e+05      3.236      0.001    3.72e+05    1.52e+06
RoofMatl_Roll                      8.658e+05   2.91e+05      2.976      0.003    2.95e+05    1.44e+06
RoofMatl_TarGrv                    8.801e+05   2.92e+05      3.017      0.003    3.07e+05    1.45e+06
RoofMatl_WdShake                   8.483e+05    2.9e+05      2.930      0.003     2.8e+05    1.42e+06
RoofMatl_WdShngl                   8.999e+05   2.88e+05      3.124      0.002    3.34e+05    1.47e+06
RoofStyle_Gable                    2.943e+04   2.39e+04      1.232      0.218   -1.75e+04    7.63e+04
RoofStyle_Gambrel                  3.084e+04   2.57e+04      1.198      0.231   -1.97e+04    8.14e+04
RoofStyle_Hip                      2.694e+04    2.4e+04      1.124      0.261   -2.01e+04     7.4e+04
RoofStyle_Mansard                  3.422e+04   2.72e+04      1.258      0.209   -1.92e+04    8.76e+04
RoofStyle_Shed                       4.8e+05   1.01e+06      0.475      0.635    -1.5e+06    2.46e+06
SaleCondition_AdjLand              2.016e+04   2.22e+04      0.909      0.363   -2.34e+04    6.37e+04
SaleCondition_Alloca              -4956.3923   8870.481     -0.559      0.576   -2.24e+04    1.25e+04
SaleCondition_Family              -1698.7320   6291.997     -0.270      0.787   -1.41e+04    1.07e+04
SaleCondition_Normal               6008.7846   2990.871      2.009      0.045     137.335    1.19e+04
SaleCondition_Partial              -1.49e+04    1.3e+04     -1.148      0.251   -4.04e+04    1.06e+04
SaleType_CWD                       5.759e+04   2.04e+04      2.818      0.005    1.75e+04    9.77e+04
SaleType_Con                       2.008e+04   1.46e+04      1.375      0.170   -8599.293    4.88e+04
SaleType_ConLD                     2.252e+04   1.11e+04      2.029      0.043     728.924    4.43e+04
SaleType_ConLI                     1.222e+04   1.25e+04      0.978      0.328   -1.23e+04    3.67e+04
SaleType_ConLw                    -1098.7667   1.12e+04     -0.098      0.922   -2.32e+04     2.1e+04
SaleType_New                       3.751e+04   1.35e+04      2.782      0.006     1.1e+04     6.4e+04
SaleType_Oth                       2.478e+04   2.02e+04      1.230      0.219   -1.48e+04    6.43e+04
SaleType_WD                        1660.9373   3928.227      0.423      0.673   -6050.658    9372.533
Street_Pave                        2.256e+04   1.59e+04      1.416      0.157   -8717.552    5.38e+04
Utilities_NoSeWa                  -1.429e+04   2.31e+04     -0.618      0.537   -5.97e+04    3.11e+04
YearBuilt_x_GarageArea               -0.0782      0.216     -0.361      0.718      -0.503       0.347
OverallQual_x_TotalBsmtSF             5.1256      2.607      1.966      0.050       0.007      10.244
GrLivArea_x_GarageCars               -3.5769      3.825     -0.935      0.350     -11.085       3.932
YearBuilt_x_OverallQual              14.6590     32.900      0.446      0.656     -49.928      79.246
YearRemodAdd_x_TotalBsmtSF            0.1961      0.155      1.265      0.206      -0.108       0.500
FullBath_x_BedroomAbvGr           -2220.7290   1643.387     -1.351      0.177   -5446.901    1005.442
Fireplaces_x_GarageCars             998.9151   2051.728      0.487      0.626   -3028.881    5026.711
TotRmsAbvGrd_x_YearBuilt              3.0931     23.739      0.130      0.896     -43.510      49.696
GarageYrBlt_x_TotalBsmtSF             0.2034      0.157      1.298      0.195      -0.104       0.511
BsmtFinSF1_x_BsmtUnfSF               -0.0163      0.006     -2.560      0.011      -0.029      -0.004
LotArea_x_GrLivArea                   0.0007      0.000      2.219      0.027     8.3e-05       0.001
BsmtFullBath_x_HalfBath             783.0573   2612.487      0.300      0.764   -4345.578    5911.693
log_LotArea                       -2159.7795   1.85e+04     -0.117      0.907   -3.85e+04    3.42e+04
log_GrLivArea                      5.567e+05   1.48e+05      3.760      0.000    2.66e+05    8.47e+05
log_1stFlrSF                       6.365e+04   1.79e+05      0.355      0.723   -2.89e+05    4.16e+05
log_TotalBsmtSF                    1.409e+05   7.41e+04      1.901      0.058   -4589.888    2.86e+05
log_GarageArea                    -6.353e+04   9.65e+04     -0.658      0.511   -2.53e+05    1.26e+05
sqrt_LotArea                        470.0764    485.523      0.968      0.333    -483.066    1423.219
sqrt_GrLivArea                    -6.133e+04   1.55e+04     -3.968      0.000   -9.17e+04    -3.1e+04
sqrt_1stFlrSF                     -6061.2577   2.21e+04     -0.274      0.784   -4.94e+04    3.73e+04
sqrt_TotalBsmtSF                  -2.467e+04    1.2e+04     -2.058      0.040   -4.82e+04   -1134.408
sqrt_GarageArea                    1.896e+04    1.8e+04      1.052      0.293   -1.64e+04    5.43e+04
exp_OverallQual                      -1.0967      0.702     -1.563      0.118      -2.474       0.281
==============================================================================
Omnibus:                      217.218   Durbin-Watson:                   1.921
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2910.810
Skew:                           0.561   Prob(JB):                         0.00
Kurtosis:                      11.171   Cond. No.                     1.27e+16
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 6.24e-15. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
Ridge Training MSE: 653517053.3198816
Ridge Training MAPE: 9.893959967022031
Ridge Testing MSE: 1149982084.600799
Ridge Testing MAPE: 11.062642950621454
```

In [ ]:

```python
# Get the coefficients from the Ridge model
ridge_coefficients = pd.Series(ridge_model.coef_, index=X_train_ridge.columns)

# Count how many predictors were deleted (coefficients set to zero)
```

```
num_deleted_predictors_ridge = (ridge_coefficients == 0).sum()

# Count how many predictors were kept (coefficients not set to zero)
num_kept_predictors_ridge = (ridge_coefficients != 0).sum()

# Print the results
print(f'Number of predictors deleted by Ridge: {num_deleted_predictors_ridge}')
print(f'Number of predictors kept by Ridge: {num_kept_predictors_ridge}')
```

```
Number of predictors deleted by Ridge: 5
Number of predictors kept by Ridge: 283
```

Ridge regression while dropping the data transformations

In [ ]:

```
import numpy as np
import pandas as pd
import statsmodels.api as sm
from sklearn.linear_model import Ridge, RidgeCV
from sklearn.metrics import mean_squared_error, mean_absolute_percentage_error
from sklearn.model_selection import train_test_split

# Step 1: Define the target variable and predictors, dropping the transformation variables
# List of transformation columns to drop
transformation_columns = [
    'log_LotArea', 'log_GrLivArea', 'log_1stFlrSF', 'log_TotalBsmtSF', 'log_GarageArea',
    'sqrt_LotArea', 'sqrt_GrLivArea', 'sqrt_1stFlrSF', 'sqrt_TotalBsmtSF', 'sqrt_GarageArea',
    'exp_OverallQual'
]

# Define the target variable and predictors
y_ridge = df_encoded['SalePrice']
X_ridge = df_encoded.drop(columns=['SalePrice'] + transformation_columns)

# Add a constant to the model (for intercept)
X_ridge = sm.add_constant(X_ridge)

# Split the data into training and testing sets
X_train_ridge, X_test_ridge, y_train_ridge, y_test_ridge = train_test_split(X_ridge, y_ridge, test_size=0.25, rando

# Step 2: Perform Ridge Regression with Cross-Validation to find the best alpha
alphas = np.logspace(-6, 6, 13)
ridge_cv_model = RidgeCV(alphas=alphas, cv=10).fit(X_train_ridge, y_train_ridge)

# Get the best alpha
best_alpha_ridge = ridge_cv_model.alpha_
print(f'Best alpha (Ridge): {best_alpha_ridge}')

# Step 3: Fit the Ridge Regression with the best alpha
ridge_model = Ridge(alpha=best_alpha_ridge)
ridge_model.fit(X_train_ridge, y_train_ridge)

# Step 4: Make predictions on the training and testing data
ridge_train_predictions = ridge_model.predict(X_train_ridge)
ridge_test_predictions = ridge_model.predict(X_test_ridge)

# Step 5: Calculate and display Train/Test MSE and MAPE for Ridge
ridge_train_mse = mean_squared_error(y_train_ridge, ridge_train_predictions)
ridge_train_mape = mean_absolute_percentage_error(y_train_ridge, ridge_train_predictions) * 100

ridge_test_mse = mean_squared_error(y_test_ridge, ridge_test_predictions)
ridge_test_mape = mean_absolute_percentage_error(y_test_ridge, ridge_test_predictions) * 100

print(f'Ridge Training MSE: {ridge_train_mse}')
print(f'Ridge Training MAPE: {ridge_train_mape}')
print(f'Ridge Testing MSE: {ridge_test_mse}')
print(f'Ridge Testing MAPE: {ridge_test_mape}')

# Step 6: Count total predictors and predictors dropped by Ridge regression
coef_ridge = ridge_model.coef_

# Total predictors (excluding the intercept)
total_predictors = len(coef_ridge)

# Predictors with coefficients effectively reduced to zero
predictors_dropped = np.sum(np.isclose(coef_ridge, 0))

print(f'Total predictors used: {total_predictors}')
print(f'Total predictors dropped by Ridge regression: {predictors_dropped}')
```

```
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.67855e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.44305e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.57463e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.24452e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.82393e-25): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.22651e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.26145e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.07409e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.01578e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.12985e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.67496e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.44019e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.57221e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.41358e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.82361e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.24419e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.2588e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.07396e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.01553e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.27626e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.64634e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.41704e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.55016e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.43152e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.8202e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.22236e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.23763e-22): result may not be accurate.
```

```
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.07276e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.0131e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.20734e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.56136e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.34451e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.43924e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.14233e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.79107e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.15894e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.17522e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.06659e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.92589e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.02446e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.02162e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.73446e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.29946e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.25177e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.72067e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.43641e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.81175e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.02545e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.30745e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.29223e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.31787e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.00409e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.2428e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
```

```
x (rcond=1.00159e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.53518e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.28592e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.74683e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.57936e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.25891e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.27096e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.86241e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.82876e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.80603e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.91976e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.00706e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.73853e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.78033e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.8684e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.78512e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.10093e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.52691e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.67277e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.39931e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.75422e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.01285e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.93481e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.83208e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.8427e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.47258e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.74171e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
```

```
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.1769e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.69387e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.52715e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.65218e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.97641e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.64441e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.75723e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.61155e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.64355e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.80861e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
Best alpha (Ridge): 100.0
Ridge Training MSE: 461176243.6481745
Ridge Training MAPE: 8.22330032332195
Ridge Testing MSE: 1082499341.8054051
Ridge Testing MAPE: 10.122704604882529
Total predictors used: 277
Total predictors dropped by Ridge regression: 5
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.61126e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.61126e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
```

Conclusion: Use Ridge regression after dropping the data transformation as it has the best fit between MSE and MAPE so there is not too much overfitting but enough predictability

In [ ]:

```python
import pandas as pd
import statsmodels.api as sm
from sklearn.linear_model import Ridge
import numpy as np
# Assuming X_train_ridge and y_train_ridge are already defined

# Define and train the Ridge model
alphas = np.logspace(-6, 6, 13)  # A wide range of alphas to consider
ridge_cv_model = RidgeCV(alphas=alphas, cv=10, scoring='neg_mean_squared_error')  # Using Cross-Validation to find
ridge_cv_model.fit(X_train_ridge, y_train_ridge)

# Get the best alpha
best_alpha_ridge = ridge_cv_model.alpha_
ridge_model = Ridge(alpha=best_alpha_ridge)
ridge_model.fit(X_train_ridge, y_train_ridge)

# Get the coefficients from the Ridge model
ridge_coefficients = pd.Series(ridge_model.coef_, index=X_train_ridge.columns)

# Filter to keep only the predictors that were retained by Ridge (i.e., non-zero coefficients)
included_predictors_ridge = ridge_coefficients[ridge_coefficients != 0].index

# Subset the training data to include only these predictors
X_train_included_ridge = X_train_ridge[included_predictors_ridge]

# Add a constant to the model (for intercept)
X_train_included_ridge = sm.add_constant(X_train_included_ridge)

# Refit an OLS model using only the predictors retained by Ridge
ols_model_ridge = sm.OLS(y_train_ridge, X_train_included_ridge).fit()

# Print the model summary
```

```
print("OLS Regression Model Summary with Ridge Predictors:")
print(ols_model_ridge.summary())
```

```
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.67855e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.44305e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.57463e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.24452e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.82393e-25): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.22651e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.26145e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.07409e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.01578e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.12985e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.67496e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.44019e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.57221e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.41358e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.82361e-24): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.24419e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.2588e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.07396e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.01553e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.27626e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.64634e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.41704e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.55016e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.43152e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.8202e-23): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.22236e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.23763e-22): result may not be accurate.
```

```
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.07276e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.0131e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.20734e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.56136e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.34451e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.43924e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.14233e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.79107e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.15894e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.17522e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.06659e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.92589e-22): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.02446e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.02162e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.73446e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.29946e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.25177e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.72067e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.43641e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.81175e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.02545e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.30745e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.29223e-21): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.31787e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.00409e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.2428e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
```

```
x (rcond=1.00159e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.53518e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.28592e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.74683e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.57936e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=1.25891e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.27096e-20): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.86241e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.82876e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.80603e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.91976e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.00706e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.73853e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.78033e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.8684e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.78512e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.10093e-19): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.52691e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.67277e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.39931e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.75422e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.01285e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.93481e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.83208e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.8427e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.47258e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.74171e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
```

```
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=9.1769e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=7.69387e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.52715e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.65218e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.97641e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.64441e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.75723e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.61155e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=8.64355e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=6.80861e-17): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.8022e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
/opt/anaconda3/lib/python3.11/site-packages/sklearn/linear_model/_ridge.py:216: LinAlgWarning: Ill-conditioned matri
x (rcond=5.8022e-18): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
```

```
OLS Regression Model Summary with Ridge Predictors:
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.961
Model:                            OLS   Adj. R-squared:                  0.947
Method:                 Least Squares   F-statistic:                     70.74
Date:                Thu, 15 Aug 2024   Prob (F-statistic):               0.00
Time:                        19:52:44   Log-Likelihood:                -11386.
No. Observations:                1027   AIC:                         2.330e+04
Df Residuals:                     763   BIC:                         2.460e+04
Df Model:                         263
Covariance Type:            nonrobust
========================================================================================================
                                     coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------------------
const                           5.316e+06   7.11e+06      0.748      0.455   -8.64e+06    1.93e+07
Id                                -0.0270      1.560     -0.017      0.986      -3.088       3.035
MSSubClass                      -105.5593     88.856     -1.188      0.235    -279.990      68.872
LotFrontage                       23.0852     23.701      0.974      0.330     -23.442      69.613
LotArea                           -0.1683      0.571     -0.295      0.768      -1.289       0.952
OverallQual                     2.662e+04   6.16e+04      0.432      0.666   -9.44e+04    1.48e+05
OverallCond                     6150.1115    978.734      6.284      0.000    4228.781    8071.442
YearBuilt                      -4238.5558   4648.252     -0.912      0.362   -1.34e+04    4886.326
YearRemodAdd                    -111.3043    153.409     -0.726      0.468    -412.458     189.850
MasVnrArea                         5.4227      6.205      0.874      0.382      -6.758      17.604
BsmtFinSF1                      -203.2946     77.965     -2.608      0.009    -356.346     -50.244
BsmtFinSF2                      -212.7418     77.747     -2.736      0.006    -365.366     -60.118
BsmtUnfSF                       -214.4685     78.179     -2.743      0.006    -367.939     -60.998
TotalBsmtSF                     -629.9678    233.584     -2.697      0.007   -1088.512    -171.423
nstFlrSF                          -7.2866      9.807     -0.743      0.458     -26.539      11.966
nndFlrSF                           2.2046      8.529      0.258      0.796     -14.539      18.948
LowQualFinSF                     -10.1929     20.733     -0.492      0.623     -50.893      30.507
GrLivArea                        -17.1312     12.752     -1.343      0.180     -42.164       7.902
BsmtFullBath                    1503.0169   2333.716      0.644      0.520   -3078.249    6084.283
BsmtHalfBath                    2124.2299   3080.897      0.689      0.491   -3923.810    8172.270
FullBath                        8490.6558   5140.801      1.652      0.099   -1601.138    1.86e+04
HalfBath                        2868.8260   2512.551      1.142      0.254   -2063.507    7801.159
BedroomAbvGr                    -819.8219   2693.432     -0.304      0.761   -6107.238    4467.595
KitchenAbvGr                    -1.14e+04   7668.388     -1.486      0.138   -2.65e+04    3656.921
TotRmsAbvGrd                    3.132e+04   4.51e+04      0.695      0.487   -5.72e+04     1.2e+05
Fireplaces                       347.4564   4719.120      0.074      0.941   -8916.545    9611.458
GarageYrBlt                    -5020.3211   4521.643     -1.110      0.267   -1.39e+04    3856.017
GarageCars                     -5671.5089   4964.122     -1.142      0.254   -1.54e+04    4073.449
GarageArea                       293.4568    417.580      0.703      0.482    -526.286    1113.199
WoodDeckSF                        15.4008      6.150      2.504      0.012       3.328      27.473
OpenPorchSF                        6.5511     11.907      0.550      0.582     -16.823      29.925
EnclosedPorch                     30.7354     13.958      2.202      0.028       3.334      58.137
nSsnPorch                         48.1266     19.757      2.436      0.015       9.342      86.911
ScreenPorch                       54.9175     12.403      4.428      0.000      30.569      79.266
PoolArea                        3637.4235    927.632      3.921      0.000    1816.411    5458.437
MiscVal                           12.3593      7.136      1.732      0.084      -1.650      26.368
MoSold                          -384.4998    248.950     -1.544      0.123    -873.208     104.208
YrSold                           -88.9520    530.398     -0.168      0.867   -1130.164     952.260
BsmtFinType1_BLQ                2280.3698   2895.417      0.788      0.431   -3403.559    7964.299
BsmtFinType1_GLQ               -7621.6728   4501.286     -1.693      0.091   -1.65e+04    1214.702
BsmtFinType1_LwQ                -356.0379   3991.376     -0.089      0.929   -8191.420    7479.344
BsmtFinType1_None               4962.0142   7074.945      0.701      0.483   -8926.655    1.89e+04
BsmtFinType1_Rec                1728.0323   3260.244      0.530      0.596   -4672.082    8128.146
BsmtFinType1_Unf               -3596.6013   4065.854     -0.885      0.377   -1.16e+04    4384.987
Neighborhood_Blueste            5862.9804   2.11e+04      0.278      0.781   -3.55e+04    4.72e+04
Neighborhood_BrDale             4731.4557   1.14e+04      0.414      0.679   -1.77e+04    2.72e+04
Neighborhood_BrkSide             1.32e+04   1.04e+04      1.269      0.205   -7216.554    3.36e+04
Neighborhood_ClearCr            3533.6087   9378.934      0.377      0.706   -1.49e+04    2.19e+04
Neighborhood_CollgCr           -5237.0666   7300.465     -0.717      0.473   -1.96e+04    9094.316
Neighborhood_Crawfor            2.433e+04   8957.904      2.716      0.007    6742.583    4.19e+04
Neighborhood_Edwards           -8429.0298   8237.152     -1.023      0.306   -2.46e+04    7741.142
Neighborhood_Gilbert             743.5869   7758.408      0.096      0.924   -1.45e+04     1.6e+04
Neighborhood_IDOTRR             3936.4453   1.16e+04      0.340      0.734   -1.88e+04    2.67e+04
Neighborhood_MeadowV           -1.213e+04   1.18e+04     -1.031      0.303   -3.52e+04     1.1e+04
Neighborhood_Mitchel           -1366.3360   8505.367     -0.161      0.872   -1.81e+04    1.53e+04
Neighborhood_NAmes             -2979.2792   8032.689     -0.371      0.711   -1.87e+04    1.28e+04
Neighborhood_NPkVill            4582.9022   1.38e+04      0.333      0.739   -2.24e+04    3.16e+04
Neighborhood_NWAmes            -4462.1901   8153.918     -0.547      0.584   -2.05e+04    1.15e+04
Neighborhood_NoRidge           -1.893e+04   4.87e+04     -0.389      0.698   -1.15e+05    7.67e+04
Neighborhood_NridgHt           -2.971e+04   1.57e+04     -1.889      0.059   -6.06e+04    1159.702
Neighborhood_OldTown            4558.0093   1.04e+04      0.437      0.663   -1.59e+04    2.51e+04
Neighborhood_SWISU             -2830.7007   1.04e+04     -0.272      0.786   -2.33e+04    1.76e+04
Neighborhood_Sawyer             1427.2710   8219.963      0.174      0.862   -1.47e+04    1.76e+04
Neighborhood_SawyerW             112.5469   7749.663      0.015      0.988   -1.51e+04    1.53e+04
Neighborhood_Somerst            5414.8997   8959.177      0.604      0.546   -1.22e+04     2.3e+04
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Neighborhood_StoneBr	3.666e+04	8078.868	4.538	0.000	2.08e+04	5.25e+04
Neighborhood_Timber	-3833.1172	8396.524	-0.457	0.648	-2.03e+04	1.26e+04
Neighborhood_Veenker	1.035e+04	1.04e+04	0.991	0.322	-1.02e+04	3.09e+04
KitchenQual_Fa	-1.612e+04	7174.007	-2.247	0.025	-3.02e+04	-2037.810
KitchenQual_Gd	-1.175e+04	3577.536	-3.284	0.001	-1.88e+04	-4726.203
KitchenQual_TA	-5334.7698	7294.548	-0.731	0.465	-1.97e+04	8984.997
ExterQual_Fa	-2818.0860	1.7e+04	-0.165	0.869	-3.63e+04	3.06e+04
ExterQual_Gd	5814.2148	9712.502	0.599	0.550	-1.33e+04	2.49e+04
ExterQual_TA	-1320.1258	6183.611	-0.213	0.831	-1.35e+04	1.08e+04
OverallQual_x_GrLivArea	10.2585	1.824	5.624	0.000	6.678	13.839
YearBuilt_x_GarageYrBlt	2.4654	2.338	1.055	0.292	-2.124	7.055
TotalBsmtSF_x_1stFlrSF	0.0073	0.005	1.382	0.167	-0.003	0.018
BsmtFinSF1_x_BsmtFinType1_GLQ	21.8946	5.547	3.947	0.000	11.006	32.783
GarageCars_x_GarageArea	9.3812	7.328	1.280	0.201	-5.004	23.766
Neighborhood_NoRidge_x_OverallQual	3212.6759	6251.739	0.514	0.607	-9059.975	1.55e+04
KitchenQual_TA_x_GrLivArea	-3.5267	4.169	-0.846	0.398	-11.711	4.658
ExterQual_Gd_x_TotalBsmtSF	-5.9220	5.210	-1.137	0.256	-16.150	4.306
Neighborhood_NridgHt_x_GrLivArea	20.5530	7.830	2.625	0.009	5.182	35.924
Alley_None	1912.2649	4909.389	0.390	0.697	-7725.248	1.15e+04
Alley_Pave	-2250.4760	6950.218	-0.324	0.746	-1.59e+04	1.14e+04
BldgType_2fmCon	1236.0506	1.43e+04	0.086	0.931	-2.69e+04	2.93e+04
BldgType_Duplex	-3506.5722	8873.974	-0.395	0.693	-2.09e+04	1.39e+04
BldgType_Twnhs	-5372.5850	1.08e+04	-0.499	0.618	-2.65e+04	1.57e+04
BldgType_TwnhsE	3137.4856	9915.989	0.316	0.752	-1.63e+04	2.26e+04
BsmtCond_Gd	-712.0380	5987.266	-0.119	0.905	-1.25e+04	1.1e+04
BsmtCond_None	4962.0143	7074.945	0.701	0.483	-8926.655	1.89e+04
BsmtCond_TA	3129.2237	5232.102	0.598	0.550	-7141.801	1.34e+04
BsmtExposure_Gd	1.348e+04	3107.892	4.337	0.000	7377.935	1.96e+04
BsmtExposure_Mn	-3157.8763	3012.139	-1.048	0.295	-9070.940	2755.187
BsmtExposure_No	-3290.1796	2084.888	-1.578	0.115	-7382.977	802.618
BsmtExposure_None	4962.0143	7074.945	0.701	0.483	-8926.655	1.89e+04
BsmtFinType2_BLQ	-3295.1571	8245.757	-0.400	0.690	-1.95e+04	1.29e+04
BsmtFinType2_GLQ	907.0268	9932.976	0.091	0.927	-1.86e+04	2.04e+04
BsmtFinType2_LwQ	-8034.0228	7902.562	-1.017	0.310	-2.35e+04	7479.323
BsmtFinType2_None	-2.899e+04	2.44e+04	-1.189	0.235	-7.68e+04	1.89e+04
BsmtFinType2_Rec	-8289.5799	7446.491	-1.113	0.266	-2.29e+04	6328.462
BsmtFinType2_Unf	-5960.4891	8097.767	-0.736	0.462	-2.19e+04	9936.058
BsmtQual_Fa	-6744.8069	7022.176	-0.961	0.337	-2.05e+04	7040.273
BsmtQual_Gd	-5703.7864	3378.542	-1.688	0.092	-1.23e+04	928.555
BsmtQual_None	4962.0143	7074.945	0.701	0.483	-8926.655	1.89e+04
BsmtQual_TA	-3300.3415	4347.873	-0.759	0.448	-1.18e+04	5234.872
CentralAir_Y	7196.5897	5132.927	1.402	0.161	-2879.746	1.73e+04
Condition1_Feedr	6070.0386	5328.474	1.139	0.255	-4390.170	1.65e+04
Condition1_Norm	1.299e+04	4471.071	2.905	0.004	4212.725	2.18e+04
Condition1_PosA	1.075e+04	1.08e+04	0.993	0.321	-1.05e+04	3.2e+04
Condition1_PosN	1.843e+04	7984.356	2.308	0.021	2757.048	3.41e+04
Condition1_RRAe	-8259.1951	8609.218	-0.959	0.338	-2.52e+04	8641.372
Condition1_RRAn	1.118e+04	7252.453	1.542	0.124	-3055.645	2.54e+04
Condition1_RRNe	-1.371e+04	2.05e+04	-0.668	0.505	-5.4e+04	2.66e+04
Condition1_RRNn	767.7759	1.65e+04	0.046	0.963	-3.17e+04	3.32e+04
Condition2_Feedr	-2.512e+04	2.63e+04	-0.955	0.340	-7.67e+04	2.65e+04
Condition2_Norm	-8813.5388	2.01e+04	-0.439	0.661	-4.83e+04	3.06e+04
Condition2_PosA	1.069e+04	4.1e+04	0.261	0.794	-6.97e+04	9.11e+04
Condition2_PosN	-6.838e+04	2.95e+04	-2.317	0.021	-1.26e+05	-1.05e+04
Condition2_RRAe	6.582e+05	1.02e+06	0.646	0.518	-1.34e+06	2.66e+06
Condition2_RRAn	-2.625e+04	2.87e+04	-0.913	0.361	-8.27e+04	3.02e+04
Condition2_RRNn	-3736.9143	2.93e+04	-0.128	0.899	-6.13e+04	5.38e+04
Electrical_FuseF	-1.176e+04	6819.223	-1.725	0.085	-2.51e+04	1623.438
Electrical_FuseP	-64.5749	2.48e+04	-0.003	0.998	-4.87e+04	4.85e+04
Electrical_None	1.433e+04	2.08e+04	0.688	0.492	-2.66e+04	5.52e+04
Electrical_SBrkr	-2959.8429	3264.770	-0.907	0.365	-9368.842	3449.156
ExterCond_Fa	1.877e+04	2.39e+04	0.787	0.432	-2.81e+04	6.56e+04
ExterCond_Gd	3445.7087	2.23e+04	0.154	0.877	-4.03e+04	4.72e+04
ExterCond_TA	8469.7729	2.24e+04	0.378	0.706	-3.55e+04	5.25e+04
Exterior1st_BrkComm	-2.329e+04	2.86e+04	-0.815	0.415	-7.93e+04	3.28e+04
Exterior1st_BrkFace	8834.5938	1.5e+04	0.590	0.556	-2.06e+04	3.82e+04
Exterior1st_CBlock	1245.0154	1.41e+04	0.089	0.929	-2.64e+04	2.88e+04
Exterior1st_CemntBd	-3.824e+04	2.06e+04	-1.860	0.063	-7.86e+04	2126.690
Exterior1st_HdBoard	-1.19e+04	1.54e+04	-0.772	0.440	-4.22e+04	1.84e+04
Exterior1st_ImStucc	-1.39e+04	2.69e+04	-0.517	0.605	-6.67e+04	3.89e+04
Exterior1st_MetalSd	5428.8166	1.69e+04	0.322	0.748	-2.77e+04	3.86e+04
Exterior1st_Plywood	-1.03e+04	1.54e+04	-0.667	0.505	-4.06e+04	2e+04
Exterior1st_Stone	-5544.2632	2.43e+04	-0.228	0.820	-5.33e+04	4.22e+04
Exterior1st_Stucco	-1.676e+04	1.68e+04	-0.998	0.319	-4.97e+04	1.62e+04
Exterior1st_VinylSd	575.2612	1.54e+04	0.037	0.970	-2.96e+04	3.08e+04
Exterior1st_Wd_Sdng	-6836.6621	1.48e+04	-0.463	0.643	-3.58e+04	2.21e+04
Exterior1st_WdShing	1620.6042	1.58e+04	0.103	0.918	-2.94e+04	3.26e+04
Exterior2nd_AsphShn	9387.3226	2.19e+04	0.428	0.669	-3.37e+04	5.24e+04
Exterior2nd_Brk_Cmn	2.687e+04	2.15e+04	1.249	0.212	-1.54e+04	6.91e+04
Exterior2nd_BrkFace	1.231e+04	1.48e+04	0.830	0.407	-1.68e+04	4.14e+04

Exterior2nd_CBlock	1245.0154	1.41e+04	0.089	0.929	−2.64e+04	2.88e+04
Exterior2nd_CmentBd	4.698e+04	1.98e+04	2.375	0.018	8149.936	8.58e+04
Exterior2nd_HdBoard	1.629e+04	1.39e+04	1.169	0.243	−1.11e+04	4.36e+04
Exterior2nd_ImStucc	1.829e+04	1.62e+04	1.127	0.260	−1.36e+04	5.01e+04
Exterior2nd_MetalSd	6143.3676	1.57e+04	0.392	0.695	−2.46e+04	3.69e+04
Exterior2nd_Other	−4.319e+04	2.44e+04	−1.771	0.077	−9.1e+04	4674.699
Exterior2nd_Plywood	1.876e+04	1.39e+04	1.349	0.178	−8535.026	4.61e+04
Exterior2nd_Stone	−5428.2917	1.8e+04	−0.302	0.763	−4.07e+04	2.99e+04
Exterior2nd_Stucco	2.184e+04	1.48e+04	1.472	0.141	−7278.271	5.1e+04
Exterior2nd_VinylSd	1.111e+04	1.41e+04	0.790	0.430	−1.65e+04	3.87e+04
Exterior2nd_Wd_Sdng	1.471e+04	1.34e+04	1.101	0.271	−1.15e+04	4.09e+04
Exterior2nd_Wd_Shng	5253.8813	1.4e+04	0.376	0.707	−2.22e+04	3.27e+04
Fence_GdWo	7086.1633	4981.560	1.422	0.155	−2693.027	1.69e+04
Fence_MnPrv	5206.1242	4213.704	1.236	0.217	−3065.706	1.35e+04
Fence_MnWw	2030.0395	8692.907	0.234	0.815	−1.5e+04	1.91e+04
Fence_None	4513.3258	3794.475	1.189	0.235	−2935.525	1.2e+04
FireplaceQu_Fa	−5306.2682	6931.121	−0.766	0.444	−1.89e+04	8300.064
FireplaceQu_Gd	659.2844	5370.231	0.123	0.902	−9882.897	1.12e+04
FireplaceQu_None	−1398.8962	6137.075	−0.228	0.820	−1.34e+04	1.06e+04
FireplaceQu_Po	9865.3738	8076.789	1.221	0.222	−5989.994	2.57e+04
FireplaceQu_TA	943.9994	5576.248	0.169	0.866	−1e+04	1.19e+04
Foundation_CBlock	89.5911	3876.120	0.023	0.982	−7519.535	7698.717
Foundation_PConc	2933.5095	3962.520	0.740	0.459	−4845.226	1.07e+04
Foundation_Slab	−500.3122	1.06e+04	−0.047	0.962	−2.14e+04	2.04e+04
Foundation_Stone	−2127.1026	1.15e+04	−0.185	0.854	−2.48e+04	2.05e+04
Foundation_Wood	−4.745e+04	1.59e+04	−2.980	0.003	−7.87e+04	−1.62e+04
Functional_Maj2	2581.7167	1.58e+04	0.163	0.870	−2.85e+04	3.37e+04
Functional_Min1	2.181e+04	9530.662	2.289	0.022	3101.733	4.05e+04
Functional_Min2	2.256e+04	9473.085	2.382	0.017	3967.444	4.12e+04
Functional_Mod	6153.6737	1.08e+04	0.568	0.570	−1.51e+04	2.74e+04
Functional_Typ	2.846e+04	8193.479	3.474	0.001	1.24e+04	4.45e+04
GarageCond_Fa	−1.488e+04	4.23e+04	−0.352	0.725	−9.79e+04	6.81e+04
GarageCond_Gd	−6462.6284	4.57e+04	−0.141	0.888	−9.61e+04	8.32e+04
GarageCond_Po	−9409.9798	4.51e+04	−0.209	0.835	−9.8e+04	7.92e+04
GarageCond_TA	−1.807e+04	4.24e+04	−0.427	0.670	−1.01e+05	6.51e+04
GarageFinish_RFn	1241.7222	1945.729	0.638	0.524	−2577.895	5061.339
GarageFinish_Unf	1248.9250	2389.372	0.523	0.601	−3441.599	5939.449
GarageQual_Fa	−768.9287	3.99e+04	−0.019	0.985	−7.9e+04	7.75e+04
GarageQual_Gd	−421.4267	4.14e+04	−0.010	0.992	−8.16e+04	8.08e+04
GarageQual_Po	−64.5749	2.48e+04	−0.003	0.998	−4.87e+04	4.85e+04
GarageQual_TA	8331.4183	3.98e+04	0.209	0.834	−6.98e+04	8.65e+04
GarageType_Attchd	2.366e+04	1.07e+04	2.208	0.028	2629.189	4.47e+04
GarageType_Basment	2.55e+04	1.27e+04	2.004	0.045	517.523	5.05e+04
GarageType_BuiltIn	2.527e+04	1.12e+04	2.252	0.025	3238.918	4.73e+04
GarageType_CarPort	2.364e+04	1.5e+04	1.571	0.117	−5895.826	5.32e+04
GarageType_Detchd	2.633e+04	1.07e+04	2.463	0.014	5346.076	4.73e+04
Heating_GasA	4.775e+04	2.3e+04	2.073	0.038	2540.799	9.3e+04
Heating_GasW	5.864e+04	2.41e+04	2.429	0.015	1.13e+04	1.06e+05
Heating_Grav	4.251e+04	3.38e+04	1.259	0.208	−2.38e+04	1.09e+05
Heating_OthW	3.818e+04	3.35e+04	1.139	0.255	−2.76e+04	1.04e+05
Heating_Wall	5.047e+04	2.66e+04	1.897	0.058	−1767.381	1.03e+05
HeatingQC_Fa	4099.4452	5652.586	0.725	0.469	−6997.022	1.52e+04
HeatingQC_Gd	−811.7147	2165.666	−0.375	0.708	−5063.087	3439.657
HeatingQC_Po	1024.7181	2.39e+04	0.043	0.966	−4.6e+04	4.8e+04
HeatingQC_TA	−2217.3528	2189.839	−1.013	0.312	−6516.178	2081.473
HouseStyle_15Unf	1.007e+04	9276.081	1.085	0.278	−8143.700	2.83e+04
HouseStyle_1Story	2255.8064	4972.605	0.454	0.650	−7505.805	1.2e+04
HouseStyle_25Fin	−1.13e+04	2.89e+04	−0.391	0.696	−6.8e+04	4.54e+04
HouseStyle_25Unf	−9297.5336	1.15e+04	−0.810	0.418	−3.18e+04	1.32e+04
HouseStyle_2Story	136.7184	3734.159	0.037	0.971	−7193.727	7467.163
HouseStyle_SFoyer	−158.7461	7186.516	−0.022	0.982	−1.43e+04	1.39e+04
HouseStyle_SLvl	7566.4068	6042.227	1.252	0.211	−4294.955	1.94e+04
LandContour_HLS	−3889.1223	5865.659	−0.663	0.508	−1.54e+04	7625.624
LandContour_Low	−2.154e+04	6836.441	−3.151	0.002	−3.5e+04	−8118.850
LandContour_Lvl	−5970.6836	4366.015	−1.368	0.172	−1.45e+04	2600.144
LandSlope_Mod	5572.2900	4213.506	1.322	0.186	−2699.151	1.38e+04
LandSlope_Sev	−3.81e+04	1.2e+04	−3.177	0.002	−6.16e+04	−1.46e+04
LotConfig_CulDSac	1494.4646	3272.071	0.457	0.648	−4928.866	7917.795
LotConfig_FR2	−8918.4686	3952.940	−2.256	0.024	−1.67e+04	−1158.539
LotConfig_FR3	−2.39e+04	1.4e+04	−1.709	0.088	−5.13e+04	3555.408
LotConfig_Inside	−2216.2608	1861.685	−1.190	0.234	−5870.894	1438.372
LotShape_IR2	1096.0070	4014.602	0.273	0.785	−6784.970	8976.984
LotShape_IR3	338.3592	8428.420	0.040	0.968	−1.62e+04	1.69e+04
LotShape_Reg	−1173.2787	1645.595	−0.713	0.476	−4403.711	2057.153
MSZoning_FV	2.503e+04	1.55e+04	1.614	0.107	−5417.375	5.55e+04
MSZoning_RH	1.577e+04	1.61e+04	0.980	0.327	−1.58e+04	4.73e+04
MSZoning_RL	1.767e+04	1.42e+04	1.246	0.213	−1.02e+04	4.55e+04
MSZoning_RM	9955.9219	1.35e+04	0.735	0.463	−1.66e+04	3.66e+04
MasVnrType_BrkFace	4237.1193	6949.633	0.610	0.542	−9405.552	1.79e+04
MasVnrType_None	2939.7157	7097.634	0.414	0.679	−1.1e+04	1.69e+04

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MasVnrType_Stone                  1.232e+04   7379.554      1.670      0.095   -2162.863    2.68e+04
MiscFeature_None                  1.435e+06   2.03e+06      0.707      0.480   -2.55e+06    5.42e+06
MiscFeature_Shed                  1.427e+06   2.03e+06      0.703      0.482   -2.56e+06    5.41e+06
MiscFeature_TenC                  1.795e+06   2.04e+06      0.882      0.378    -2.2e+06    5.79e+06
PavedDrive_P                     -1859.2373   6878.778     -0.270      0.787   -1.54e+04    1.16e+04
PavedDrive_Y                     -1646.8272   4469.612     -0.368      0.713   -1.04e+04    7127.370
PoolQC_Fa                        -3.848e+05   1.09e+05     -3.522      0.000   -5.99e+05    -1.7e+05
PoolQC_Gd                        -6.516e+05   1.92e+05     -3.391      0.001   -1.03e+06   -2.74e+05
PoolQC_None                       1.942e+06   4.97e+05      3.908      0.000    9.66e+05    2.92e+06
RoofMatl_CompShg                  3.342e+05   2.57e+05      1.302      0.193    -1.7e+05    8.38e+05
RoofMatl_Membran                   4.47e+05   2.61e+05      1.714      0.087    -6.5e+04    9.59e+05
RoofMatl_Metal                    4.114e+05    2.6e+05      1.584      0.114   -9.86e+04    9.21e+05
RoofMatl_Roll                     3.266e+05   2.58e+05      1.268      0.205   -1.79e+05    8.32e+05
RoofMatl_TarGrv                   3.365e+05   2.58e+05      1.303      0.193   -1.71e+05    8.44e+05
RoofMatl_WdShake                  3.111e+05   2.56e+05      1.215      0.225   -1.92e+05    8.14e+05
RoofMatl_WdShngl                  3.799e+05   2.56e+05      1.483      0.139   -1.23e+05    8.83e+05
RoofStyle_Gable                   1.415e+04    2.4e+04      0.591      0.555   -3.29e+04    6.12e+04
RoofStyle_Gambrel                 1.583e+04   2.58e+04      0.615      0.539   -3.47e+04    6.64e+04
RoofStyle_Hip                     1.215e+04   2.41e+04      0.505      0.614   -3.51e+04    5.94e+04
RoofStyle_Mansard                 2.179e+04   2.74e+04      0.796      0.426   -3.19e+04    7.55e+04
RoofStyle_Shed                    6.582e+05   1.02e+06      0.646      0.518   -1.34e+06    2.66e+06
SaleCondition_AdjLand             2.465e+04   2.24e+04      1.099      0.272   -1.94e+04    6.87e+04
SaleCondition_Alloca             -1181.6566   8918.767     -0.132      0.895   -1.87e+04    1.63e+04
SaleCondition_Family             -1618.3668   6403.144     -0.253      0.801   -1.42e+04      1.1e+04
SaleCondition_Normal              6362.6445   3042.423      2.091      0.037     390.132    1.23e+04
SaleCondition_Partial            -8515.6966    1.31e+04    -0.651      0.515   -3.42e+04    1.72e+04
SaleType_CWD                      5.014e+04   2.07e+04      2.421      0.016    9489.794    9.08e+04
SaleType_Con                      2.424e+04   1.48e+04      1.633      0.103   -4894.041    5.34e+04
SaleType_ConLD                    1.896e+04   1.11e+04      1.709      0.088   -2817.483    4.07e+04
SaleType_ConLI                    4872.1468   1.24e+04      0.393      0.694   -1.95e+04    2.92e+04
SaleType_ConLw                      69.8048   1.14e+04      0.006      0.995   -2.23e+04    2.24e+04
SaleType_New                      3.407e+04   1.36e+04      2.502      0.013    7341.400    6.08e+04
SaleType_Oth                      2.447e+04   2.05e+04      1.194      0.233   -1.58e+04    6.47e+04
SaleType_WD                       2280.4184   3988.559      0.572      0.568   -5549.433    1.01e+04
Street_Pave                       2.577e+04   1.58e+04      1.635      0.102   -5164.734    5.67e+04
Utilities_NoSeWa                 -1.988e+04   2.35e+04     -0.848      0.397   -6.59e+04    2.62e+04
YearBuilt_x_GarageArea              -0.1494      0.215     -0.695      0.487      -0.572       0.273
OverallQual_x_TotalBsmtSF            4.7756      2.446      1.952      0.051      -0.026       9.577
GrLivArea_x_GarageCars               1.6051      3.548      0.452      0.651      -5.360       8.571
YearBuilt_x_OverallQual            -20.5785     31.655     -0.650      0.516     -82.719      41.562
YearRemodAdd_x_TotalBsmtSF           0.1858      0.155      1.198      0.231      -0.119       0.490
FullBath_x_BedroomAbvGr           -951.8019   1627.789     -0.585      0.559   -4147.279    2243.676
Fireplaces_x_GarageCars            583.7097   2068.675      0.282      0.778   -3477.261    4644.680
TotRmsAbvGrd_x_YearBuilt           -14.8052     22.796     -0.649      0.516     -59.555      29.945
GarageYrBlt_x_TotalBsmtSF            0.2317      0.153      1.519      0.129      -0.068       0.531
BsmtFinSF1_x_BsmtUnfSF              -0.0131      0.006     -2.095      0.037      -0.025      -0.001
LotArea_x_GrLivArea                  0.0005      0.000      1.612      0.107      -0.000       0.001
BsmtFullBath_x_HalfBath             39.0325   2637.781      0.015      0.988   -5139.138    5217.203
==============================================================================
Omnibus:                      228.705   Durbin-Watson:                   1.916
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             3345.497
Skew:                           0.588   Prob(JB):                         0.00
Kurtosis:                      11.764   Cond. No.                     1.27e+16
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 6.24e-15. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

In [ ]:

```python
import pandas as pd

# Load the test data
test_data = pd.read_csv(db_dir + r'/data/test.csv')
# Assuming 'included_predictors_ridge' is defined and contains the features retained by Ridge
X_test_included_ridge = test_data[included_predictors_ridge]

# Add a constant for the intercept
X_test_included_ridge = sm.add_constant(X_test_included_ridge)
# Predict using the OLS model
ridge_predictions = ols_model_ridge.predict(X_test_included_ridge)

# Display the predictions
print(ridge_predictions)
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
Cell In[24], line 6
      4 test_data = pd.read_csv(db_dir + r'/data/test.csv')
      5 # Assuming 'included_predictors_ridge' is defined and contains the features retained by Ridge
----> 6 X_test_included_ridge = test_data[included_predictors_ridge]
      8 # Add a constant for the intercept
      9 X_test_included_ridge = sm.add_constant(X_test_included_ridge)

File /opt/anaconda3/lib/python3.11/site-packages/pandas/core/frame.py:3899, in DataFrame.__getitem__(self, key)
   3897     if is_iterator(key):
   3898         key = list(key)
-> 3899     indexer = self.columns._get_indexer_strict(key, "columns")[1]
   3901 # take() does not accept boolean indexers
   3902 if getattr(indexer, "dtype", None) == bool:

File /opt/anaconda3/lib/python3.11/site-packages/pandas/core/indexes/base.py:6115, in Index._get_indexer_strict(sel
f, key, axis_name)
   6112 else:
   6113     keyarr, indexer, new_indexer = self._reindex_non_unique(keyarr)
-> 6115 self._raise_if_missing(keyarr, indexer, axis_name)
   6117 keyarr = self.take(indexer)
   6118 if isinstance(key, Index):
   6119     # GH 42790 - Preserve name from an Index

File /opt/anaconda3/lib/python3.11/site-packages/pandas/core/indexes/base.py:6179, in Index._raise_if_missing(self,
key, indexer, axis_name)
   6176     raise KeyError(f"None of [{key}] are in the [{axis_name}]")
   6178 not_found = list(ensure_index(key)[missing_mask.nonzero()[0]].unique())
-> 6179 raise KeyError(f"{not_found} not in index")

KeyError: "['nstFlrSF', 'nndFlrSF', 'nSsnPorch', 'BsmtFinType1_BLQ', 'BsmtFinType1_GLQ', 'BsmtFinType1_LwQ', 'BsmtFi
nType1_None', 'BsmtFinType1_Rec', 'BsmtFinType1_Unf', 'Neighborhood_Blueste', 'Neighborhood_BrDale', 'Neighborhood_B
rkSide', 'Neighborhood_ClearCr', 'Neighborhood_CollgCr', 'Neighborhood_Crawfor', 'Neighborhood_Edwards', 'Neighborho
od_Gilbert', 'Neighborhood_IDOTRR', 'Neighborhood_MeadowV', 'Neighborhood_Mitchel', 'Neighborhood_NAmes', 'Neighborh
ood_NPkVill', 'Neighborhood_NWAmes', 'Neighborhood_NoRidge', 'Neighborhood_NridgHt', 'Neighborhood_OldTown', 'Neighb
orhood_SWISU', 'Neighborhood_Sawyer', 'Neighborhood_SawyerW', 'Neighborhood_Somerst', 'Neighborhood_StoneBr', 'Neigh
borhood_Timber', 'Neighborhood_Veenker', 'KitchenQual_Fa', 'KitchenQual_Gd', 'KitchenQual_TA', 'ExterQual_Fa', 'Exte
rQual_Gd', 'ExterQual_TA', 'OverallQual_x_GrLivArea', 'YearBuilt_x_GarageYrBlt', 'TotalBsmtSF_x_1stFlrSF', 'BsmtFinS
F1_x_BsmtFinType1_GLQ', 'GarageCars_x_GarageArea', 'Neighborhood_NoRidge_x_OverallQual', 'KitchenQual_TA_x_GrLivAre
a', 'ExterQual_Gd_x_TotalBsmtSF', 'Neighborhood_NridgHt_x_GrLivArea', 'Alley_None', 'Alley_Pave', 'BldgType_2fmCon',
'BldgType_Duplex', 'BldgType_Twnhs', 'BldgType_TwnhsE', 'BsmtCond_Gd', 'BsmtCond_None', 'BsmtCond_TA', 'BsmtExposure
_Gd', 'BsmtExposure_Mn', 'BsmtExposure_No', 'BsmtExposure_None', 'BsmtFinType2_BLQ', 'BsmtFinType2_GLQ', 'BsmtFinTyp
e2_LwQ', 'BsmtFinType2_None', 'BsmtFinType2_Rec', 'BsmtFinType2_Unf', 'BsmtQual_Fa', 'BsmtQual_Gd', 'BsmtQual_None',
'BsmtQual_TA', 'CentralAir_Y', 'Condition1_Feedr', 'Condition1_Norm', 'Condition1_PosA', 'Condition1_PosN', 'Conditi
on1_RRAe', 'Condition1_RRAn', 'Condition1_RRNe', 'Condition1_RRNn', 'Condition2_Feedr', 'Condition2_Norm', 'Conditio
n2_PosA', 'Condition2_PosN', 'Condition2_RRAe', 'Condition2_RRAn', 'Condition2_RRNn', 'Electrical_FuseF', 'Electrica
l_FuseP', 'Electrical_None', 'Electrical_SBrkr', 'ExterCond_Fa', 'ExterCond_Gd', 'ExterCond_TA', 'Exterior1st_BrkCom
m', 'Exterior1st_BrkFace', 'Exterior1st_CBlock', 'Exterior1st_CemntBd', 'Exterior1st_HdBoard', 'Exterior1st_ImStuc
c', 'Exterior1st_MetalSd', 'Exterior1st_Plywood', 'Exterior1st_Stone', 'Exterior1st_Stucco', 'Exterior1st_VinylSd',
'Exterior1st_Wd_Sdng', 'Exterior1st_WdShing', 'Exterior2nd_AsphShn', 'Exterior2nd_Brk_Cmn', 'Exterior2nd_BrkFace',
'Exterior2nd_CBlock', 'Exterior2nd_CmentBd', 'Exterior2nd_HdBoard', 'Exterior2nd_ImStucc', 'Exterior2nd_MetalSd', 'E
xterior2nd_Other', 'Exterior2nd_Plywood', 'Exterior2nd_Stone', 'Exterior2nd_Stucco', 'Exterior2nd_VinylSd', 'Exterio
r2nd_Wd_Sdng', 'Exterior2nd_Wd_Shng', 'Fence_GdWo', 'Fence_MnPrv', 'Fence_MnWw', 'Fence_None', 'FireplaceQu_Fa', 'Fi
replaceQu_Gd', 'FireplaceQu_None', 'FireplaceQu_Po', 'FireplaceQu_TA', 'Foundation_CBlock', 'Foundation_PConc', 'Fou
ndation_Slab', 'Foundation_Stone', 'Foundation_Wood', 'Functional_Maj2', 'Functional_Min1', 'Functional_Min2', 'Func
tional_Mod', 'Functional_Typ', 'GarageCond_Fa', 'GarageCond_Gd', 'GarageCond_Po', 'GarageCond_TA', 'GarageFinish_RF
n', 'GarageFinish_Unf', 'GarageQual_Fa', 'GarageQual_Gd', 'GarageQual_Po', 'GarageQual_TA', 'GarageType_Attchd', 'Ga
rageType_Basment', 'GarageType_BuiltIn', 'GarageType_CarPort', 'GarageType_Detchd', 'Heating_GasA', 'Heating_GasW',
'Heating_Grav', 'Heating_OthW', 'Heating_Wall', 'HeatingQC_Fa', 'HeatingQC_Gd', 'HeatingQC_Po', 'HeatingQC_TA', 'Hou
seStyle_15Unf', 'HouseStyle_1Story', 'HouseStyle_25Fin', 'HouseStyle_25Unf', 'HouseStyle_2Story', 'HouseStyle_SFoye
r', 'HouseStyle_SLvl', 'LandContour_HLS', 'LandContour_Low', 'LandContour_Lvl', 'LandSlope_Mod', 'LandSlope_Sev', 'L
otConfig_CulDSac', 'LotConfig_FR2', 'LotConfig_FR3', 'LotConfig_Inside', 'LotShape_IR2', 'LotShape_IR3', 'LotShape_R
eg', 'MSZoning_FV', 'MSZoning_RH', 'MSZoning_RL', 'MSZoning_RM', 'MasVnrType_BrkFace', 'MasVnrType_None', 'MasVnrTyp
e_Stone', 'MiscFeature_None', 'MiscFeature_Shed', 'MiscFeature_TenC', 'PavedDrive_P', 'PavedDrive_Y', 'PoolQC_Fa',
'PoolQC_Gd', 'PoolQC_None', 'RoofMatl_CompShg', 'RoofMatl_Membran', 'RoofMatl_Metal', 'RoofMatl_Roll', 'RoofMatl_Tar
Grv', 'RoofMatl_WdShake', 'RoofMatl_WdShngl', 'RoofStyle_Gable', 'RoofStyle_Gambrel', 'RoofStyle_Hip', 'RoofStyle_Ma
nsard', 'RoofStyle_Shed', 'SaleCondition_AdjLand', 'SaleCondition_Alloca', 'SaleCondition_Family', 'SaleCondition_No
rmal', 'SaleCondition_Partial', 'SaleType_CWD', 'SaleType_Con', 'SaleType_ConLD', 'SaleType_ConLI', 'SaleType_ConL
w', 'SaleType_New', 'SaleType_Oth', 'SaleType_WD', 'Street_Pave', 'Utilities_NoSeWa', 'YearBuilt_x_GarageArea', 'Ove
rallQual_x_TotalBsmtSF', 'GrLivArea_x_GarageCars', 'YearBuilt_x_OverallQual', 'YearRemodAdd_x_TotalBsmtSF', 'FullBat
h_x_BedroomAbvGr', 'Fireplaces_x_GarageCars', 'TotRmsAbvGrd_x_YearBuilt', 'GarageYrBlt_x_TotalBsmtSF', 'BsmtFinSF1_x
_BsmtUnfSF', 'LotArea_x_GrLivArea', 'BsmtFullBath_x_HalfBath'] not in index"
```