Answering House Prices Questions based on Advanced Regression Techniques

October 11, 2024

1 Answering House Prices Questions using Advanced Regression Techniques

1.1 Background

As a Udemy Data Scientist Nanodegree Program student, I'm tasked with writing a blog post and a kernel following the CRISP-DM process. In my blog post, I'll take a fresh approach by adhering to the CRISP-DM process to address three fundamental questions often posed in the housing markets, using the Ames dataset as a case study.

The Kaggle House Prices - Advanced Regression Techniques competition is a fantastic playground for budding data scientists like myself. It challenges us to predict house prices in Ames, Iowa, leveraging 79 predictor variables through machine learning models. This well-analyzed dataset has received over 20,000 submissions, making it an excellent resource for developing and showcasing our skills.

The notebook and source code are available here:

- Blog post: https://blog.anibalhsanchez.com/en/blogging/85-answering-house-prices-questions-using-advanced-regression-techniques.html
- Repository: https://github.com/anibalsanchez/answering-house-prices-questions-based-on-adva

1.2 Objectives

In my blog post, I'll take a fresh approach by adhering to the CRISP-DM process to address three fundamental questions often posed in the housing markets, using the Ames dataset as a case study.

1.2.1 What are the main house price ranges?

Identify the primary price ranges for houses in the dataset. It's essential to identify the specific price ranges encompassing most homes and their distribution. This information will help segment the housing market and tailor the analysis to the most relevant price ranges.

1.2.2 Which areas can you locate these price ranges?

Determine the areas or neighborhoods where these price ranges are concentrated. It is crucial to identify the geographic areas or neighborhoods associated with different price ranges.

I can uncover patterns and identify undervalued or overvalued regions by mapping price ranges to specific areas.

1.2.3 What variables best predict the price range of each home?

Identify the key variables that best predict the price range of each home. Determining the most influential variables that accurately predict the price range for individual homes.

Following the CRISP-DM process, I'll systematically analyze and preprocess the data, build predictive models, and present the findings in a comprehensive blog post and notebook. This project will allow me to showcase my skills, including data exploration, feature engineering, model selection, and result interpretation.

1.3 Exploring the Data

To start the project, I imported the packages, defined the global variables, and read the Ames, Iowa train dataset CSV file.

[76]:
```
import numpy as np
import pandas as pd
from math import expm1
from IPython.display import display # Allows the use of display() for DataFrames
import matplotlib.pyplot as plt
import seaborn as sns

import plotly.offline as py
from plotly.offline import iplot, init_notebook_mode
import plotly.graph_objs as go

head_n_of_records = 5
seed = 42

init_notebook_mode(connected = True) # Required to use plotly offline in␣
 ↪jupyter notebook

plt.style.use('bmh')
sns.set_style({'axes.grid':False})

# Ignore warnings
import warnings
warnings.filterwarnings(action="ignore", category=FutureWarning)

# Define a color-blind friendly palette
# Using a palette from ColorBrewer which is designed to be color-blind friendly
colorblind_palette = sns.color_palette("colorblind", n_colors=8)

# Show all rows and colums
pd.options.display.max_rows = None
pd.options.display.max_columns = None
```

```
%matplotlib inline

study_data = pd.read_csv("train.csv")
study_data_num_rows, study_data_num_columns = (
    study_data.shape
)

# Display markdown formatted output like bold, italic bold etc.'''
from IPython.display import Markdown
def display_md(string):
    display(Markdown(string))

display_md('### Preview of Train Data')
display(study_data.head(n=head_n_of_records))
```

1.3.1 Preview of Train Data

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

  LandContour Utilities LotConfig LandSlope Neighborhood Condition1  \
0         Lvl    AllPub    Inside       Gtl      CollgCr       Norm
1         Lvl    AllPub       FR2       Gtl      Veenker      Feedr
2         Lvl    AllPub    Inside       Gtl      CollgCr       Norm
3         Lvl    AllPub    Corner       Gtl      Crawfor       Norm
4         Lvl    AllPub       FR2       Gtl      NoRidge       Norm

  Condition2 BldgType HouseStyle  OverallQual  OverallCond  YearBuilt  \
0       Norm     1Fam     2Story            7            5       2003
1       Norm     1Fam     1Story            6            8       1976
2       Norm     1Fam     2Story            7            5       2001
3       Norm     1Fam     2Story            7            5       1915
4       Norm     1Fam     2Story            8            5       2000

   YearRemodAdd RoofStyle RoofMatl Exterior1st Exterior2nd MasVnrType  \
0          2003     Gable  CompShg     VinylSd     VinylSd    BrkFace
1          1976     Gable  CompShg     MetalSd     MetalSd        NaN
2          2002     Gable  CompShg     VinylSd     VinylSd    BrkFace
3          1970     Gable  CompShg     Wd Sdng     Wd Shng        NaN
4          2000     Gable  CompShg     VinylSd     VinylSd    BrkFace

   MasVnrArea ExterQual ExterCond Foundation BsmtQual BsmtCond BsmtExposure  \
0       196.0        Gd        TA      PConc       Gd       TA           No
```

```
1         0.0        TA        TA     CBlock       Gd       TA           Gd
2       162.0        Gd        TA      PConc       Gd       TA           Mn
3         0.0        TA        TA     BrkTil       TA       Gd           No
4       350.0        Gd        TA      PConc       Gd       TA           Av

  BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  BsmtUnfSF  TotalBsmtSF  \
0          GLQ         706          Unf           0        150          856
1          ALQ         978          Unf           0        284         1262
2          GLQ         486          Unf           0        434          920
3          ALQ         216          Unf           0        540          756
4          GLQ         655          Unf           0        490         1145

  Heating HeatingQC CentralAir Electrical  1stFlrSF  2ndFlrSF  LowQualFinSF  \
0    GasA        Ex          Y      SBrkr       856       854             0
1    GasA        Ex          Y      SBrkr      1262         0             0
2    GasA        Ex          Y      SBrkr       920       866             0
3    GasA        Gd          Y      SBrkr       961       756             0
4    GasA        Ex          Y      SBrkr      1145      1053             0

   GrLivArea  BsmtFullBath  BsmtHalfBath  FullBath  HalfBath  BedroomAbvGr  \
0       1710             1             0         2         1             3
1       1262             0             1         2         0             3
2       1786             1             0         2         1             3
3       1717             1             0         1         0             3
4       2198             1             0         2         1             4

   KitchenAbvGr KitchenQual  TotRmsAbvGrd Functional  Fireplaces FireplaceQu  \
0             1          Gd             8        Typ           0         NaN
1             1          TA             6        Typ           1          TA
2             1          Gd             6        Typ           1          TA
3             1          Gd             7        Typ           1          Gd
4             1          Gd             9        Typ           1          TA

  GarageType  GarageYrBlt GarageFinish  GarageCars  GarageArea GarageQual  \
0     Attchd       2003.0          RFn           2         548         TA
1     Attchd       1976.0          RFn           2         460         TA
2     Attchd       2001.0          RFn           2         608         TA
3     Detchd       1998.0          Unf           3         642         TA
4     Attchd       2000.0          RFn           3         836         TA

  GarageCond PavedDrive  WoodDeckSF  OpenPorchSF  EnclosedPorch  3SsnPorch  \
0         TA          Y           0           61              0          0
1         TA          Y         298            0              0          0
2         TA          Y           0           42              0          0
3         TA          Y           0           35            272          0
4         TA          Y         192           84              0          0

   ScreenPorch  PoolArea PoolQC Fence MiscFeature  MiscVal  MoSold  YrSold  \
```

```
0            0         0    NaN   NaN         NaN        0       2    2008
1            0         0    NaN   NaN         NaN        0       5    2007
2            0         0    NaN   NaN         NaN        0       9    2008
3            0         0    NaN   NaN         NaN        0       2    2006
4            0         0    NaN   NaN         NaN        0      12    2008

  SaleType SaleCondition  SalePrice
0       WD        Normal     208500
1       WD        Normal     181500
2       WD        Normal     223500
3       WD       Abnorml     140000
4       WD        Normal     250000
```

[77]:
```
display_md('**Shape of our train data:**')
display(study_data.shape)

display_md('**Name of our variables:**')
display(study_data.columns.values)
```

Shape of our train data:

```
(1460, 81)
```

Name of our variables:

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

1.4 Feature set Exploration

The Ames, Iowa train dataset has 79 variables in total, including the SalePrice variable, which is our target variable. The remaining variables are used for clustering and characterization.

In this list, I briefly describe each feature and its type (Categorical, Ordinal, or Numeric).

Name	Description	Type
MSSubClass	Identifies the type of dwelling involved in the sale	Categorical
MSZoning	Identifies the general zoning classification of the sale	Categorical
LotFrontage	Linear feet of street connected to property	Numeric
LotArea	Lot size in square feet	Numeric
Street	Type of road access to property	Categorical
Alley	Type of alley access to property	Categorical
LotShape	General shape of property	Ordinal
LandContour	Flatness of the property	Categorical
Utilities	Type of utilities available	Categorical
LotConfig	Lot configuration	Categorical
LandSlope	Slope of property	Ordinal
Neighborhood	Physical locations within Ames city limits	Categorical
Condition1	Proximity to various conditions	Categorical
Condition2	Proximity to various conditions (if more than one is present)	Categorical
BldgType	Type of dwelling	Categorical
HouseStyle	Style of dwelling	Categorical
OverallQual	Rates the overall material and finish of the house	Ordinal
OverallCond	Rates the overall condition of the house	Ordinal
YearBuilt	Original construction date	Numeric
YearRemodAdd	Remodel date (same as construction date if no remodeling or additions)	Numeric
RoofStyle	Type of roof	Categorical
RoofMatl	Roof material	Categorical
Exterior1st	Exterior covering on house	Categorical
Exterior2nd	Exterior covering on house (if more than one material)	Categorical
MasVnrType	Masonry veneer type	Categorical
MasVnrArea	Masonry veneer area in square feet	Numeric
ExterQual	Evaluates the quality of the material on the exterior	Ordinal
ExterCond	Evaluates the present condition of the material on the exterior	Ordinal
Foundation	Type of foundation	Categorical
BsmtQual	Evaluates the height of the basement	Ordinal
BsmtCond	Evaluates the general condition of the basement	Ordinal
BsmtExposure	Refers to walkout or garden level walls	Ordinal
BsmtFinType1	Rating of basement finished area	Ordinal
BsmtFinSF1	Type 1 finished square feet	Numeric
BsmtFinType2	Rating of basement finished area (if multiple types)	Ordinal

Name	Description	Type
BsmtFinSF2	Type 2 finished square feet	Numeric
BsmtUnfSF	Unfinished square feet of basement area	Numeric
TotalBsmtSF	Total square feet of basement area	Numeric
Heating	Type of heating	Categorical
HeatingQC	Heating quality and condition	Ordinal
CentralAir	Central air conditioning	Categorical
Electrical	Electrical system	Categorical
1stFlrSF	First Floor square feet	Numeric
2ndFlrSF	Second floor square feet	Numeric
LowQualFinSF	Low quality finished square feet (all floors)	Numeric
GrLivArea	Above grade (ground) living area square feet	Numeric
BsmtFullBath	Basement full bathrooms	Numeric
BsmtHalfBath	Basement half bathrooms	Numeric
FullBath	Full bathrooms above grade	Numeric
HalfBath	Half baths above grade	Numeric
BedroomAbvGr	Bedrooms above grade (does NOT include basement bedrooms)	Numeric
KitchenAbvGr	Kitchens above grade	Numeric
KitchenQual	Kitchen quality	Ordinal
TotRmsAbvGrd	Total rooms above grade (does not include bathrooms)	Numeric
Functional	Home functionality (Assume typical unless deductions are warranted)	Ordinal
Fireplaces	Number of fireplaces	Numeric
FireplaceQu	Fireplace quality	Ordinal
GarageType	Garage location	Categorical
GarageYrBlt	Year garage was built	Numeric
GarageFinish	Interior finish of the garage	Ordinal
GarageCars	Size of garage in car capacity	Numeric
GarageArea	Size of garage in square feet	Numeric
GarageQual	Garage quality	Ordinal
GarageCond	Garage condition	Ordinal
PavedDrive	Paved driveway	Ordinal
WoodDeckSF	Wood deck area in square feet	Numeric
OpenPorchSF	Open porch area in square feet	Numeric
EnclosedPorch	Enclosed porch area in square feet	Numeric
3SsnPorch	Three season porch area in square feet	Numeric
ScreenPorch	Screen porch area in square feet	Numeric
PoolArea	Pool area in square feet	Numeric
PoolQC	Pool quality	Ordinal
Fence	Fence quality	Ordinal
MiscFeature	Miscellaneous feature not covered in other categories	Categorical
MiscVal	$Value of miscellaneous feature	Numeric
MoSold	Month Sold (MM)	Numeric
YrSold	Year Sold (YYYY)	Numeric

Name	Description	Type
SaleType	Type of sale	Categorical
SaleCondition	Condition of sale	Categorical

[78]:
```
# Definition of Features Types

categorical_features = ["MSSubClass", "MSZoning", "Street", "LandContour",␣
 ↪"Utilities", "LotConfig", "Neighborhood", "Condition1", "Condition2",␣
 ↪"BldgType", "HouseStyle", "RoofStyle", "RoofMatl", "Exterior1st",␣
 ↪"Exterior2nd", "Foundation", "Heating", "CentralAir", "Electrical",␣
 ↪"GarageType", "SaleType", "SaleCondition"]
numerical_features = ["LotArea", "YearBuilt", "YearRemodAdd", "MasVnrArea",␣
 ↪"BsmtFinSF1", "BsmtFinSF2", "BsmtUnfSF", "TotalBsmtSF", "1stFlrSF",␣
 ↪"2ndFlrSF", "LowQualFinSF", "GrLivArea", "BsmtFullBath", "BsmtHalfBath",␣
 ↪"FullBath", "HalfBath", "BedroomAbvGr", "KitchenAbvGr", "TotRmsAbvGrd",␣
 ↪"Fireplaces", "GarageYrBlt", "GarageCars", "GarageArea", "WoodDeckSF",␣
 ↪"OpenPorchSF", "EnclosedPorch", "3SsnPorch", "ScreenPorch", "PoolArea",␣
 ↪"MiscVal", "MoSold", "YrSold"]
ordinal_features = ["LotShape", "LandSlope", "OverallQual", "OverallCond",␣
 ↪"ExterQual", "ExterCond", "BsmtQual", "BsmtCond", "BsmtExposure",␣
 ↪"BsmtFinType1", "BsmtFinType2", "HeatingQC", "KitchenQual", "Functional",␣
 ↪"GarageFinish", "GarageQual", "GarageCond", "PavedDrive"]
```

1.5 Outliers Removal

In the competition "Ames Iowa Housing Dataset - Special Notes", there is a specific requirement to remove outlier observations.

SPECIAL NOTES: There are 5 observations that an instructor may wish to remove from the data set before giving it to students (a plot of SALE PRICE versus GR LIV AREA will indicate them quickly). Three of them are true outliers (Partial Sales that likely don't represent actual market values) and two of them are simply unusual sales (very large houses priced relatively appropriately). I would recommend removing any houses with more than 4000 square feet from the data set (which eliminates these 5 unusual observations) before assigning it to students.

The following code takes care of this point.

[79]:
```
def scatter_plot(x, y, title, xaxis, yaxis, size, c_scale):
    trace = go.Scatter(
    x = x,
    y = y,
    mode = 'markers',
    marker = dict(color = y, size = size, showscale = True, colorscale =␣
 ↪c_scale))
    layout = go.Layout(hovermode= 'closest', title = title, xaxis = dict(title␣
 ↪= xaxis), yaxis = dict(title = yaxis))
    fig = go.Figure(data = [trace], layout = layout)
```

```
    return iplot(fig)

scatter_plot(study_data.GrLivArea, study_data.SalePrice, 'GrLivArea vs␣
 ↪SalePrice', 'GrLivArea', 'SalePrice', 10, 'Rainbow')
```

[80]:
```
# Drop observations where GrLivArea is greater than 4000 sq.ft
study_data.drop(study_data[study_data.GrLivArea>4000].index, inplace = True)
study_data.reset_index(drop = True, inplace = True)
```

[81]:
```
scatter_plot(study_data.GrLivArea, study_data.SalePrice, 'GrLivArea vs␣
 ↪SalePrice', 'GrLivArea', 'SalePrice', 10, 'Rainbow')
```

1.6 Normalization of Skewed Distributions

1.6.1 Skewness of SalePrice

Since algorithms can be sensitive to skewed distributions and may underperform if the data range isn't properly normalized, I show the **skewness of SalePrice** and its normalization using the natural logarithm transformation, specifically log(1 + x) (base e).

[82]:
```
def plot_histogram(x, title, yaxis, color):
    trace = go.Histogram(x = x,
                         marker = dict(color = color))
    layout = go.Layout(hovermode= 'closest', title = title, yaxis = dict(title␣
 ↪= yaxis))
    fig = go.Figure(data = [trace], layout = layout)
    return iplot(fig)

sale_price_array = study_data.SalePrice
title = 'Distribution of SalePrice with skewness (skewness: {:0.4f})'.
 ↪format(sale_price_array.skew())
plot_histogram(sale_price_array, title, 'Abs Frequency', 'darkred')

sale_price_array = np.log1p(sale_price_array)

# Update the sales prices with the normalized value
study_data['SalePrice'] = sale_price_array

title = 'Distribution of SalePrice removing skewness (skewness: {:0.4f})'.
 ↪format(sale_price_array.skew())
plot_histogram(sale_price_array, title, 'Abs Frequency', 'green')
```

1.6.2 Skewness of Explanatory Variables

Now, it is time to analyze the skewness of explanatory variables. I show the skewness of explanatory variables in the following bar plot.

[83]:
```
def bar_plot(x, y, title, yaxis, c_scale):
    trace = go.Bar(
    x = x,
    y = y,
    marker = dict(color = y, colorscale = c_scale))
    layout = go.Layout(hovermode= 'closest', title = title, yaxis = dict(title␣
 ↪= yaxis))
    fig = go.Figure(data = [trace], layout = layout)
    return iplot(fig)

def show_explanetory_variables_skewness(process_data):
    skew_study_data = process_data[numerical_features].skew()
    skew_merged = pd.DataFrame(data = skew_study_data, columns = ['Skewness'])
    skew_merged_sorted = skew_merged.sort_values(ascending = False, by =␣
 ↪'Skewness')
    bar_plot(skew_merged_sorted.index, skew_merged_sorted.Skewness, 'Skewness␣
 ↪in Explanatory Variables', 'Skewness', 'Bluered')

show_explanetory_variables_skewness(study_data)
```

The graph shows that many variables are skewed, predominantly to the right. To address this, I apply the natural logarithm transformation to variables with skewness greater than 0.75, using this threshold to improve their distributions.

[84]:
```
display_md('**Features to be transformed (skewness>0.75):**')

skew_study_data = study_data[numerical_features].skew()
filtered_skew_study_data = skew_study_data[skew_study_data>0.75]
skewed_columns = filtered_skew_study_data.index.values

display(skewed_columns)

for col in skewed_columns:
    col_values = np.log1p(study_data[col])
    study_data[col] = col_values
```

Features to be transformed (skewness>0.75):

```
array(['LotArea', 'MasVnrArea', 'BsmtFinSF2', 'BsmtUnfSF', '1stFlrSF',
       '2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtHalfBath',
       'KitchenAbvGr', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch',
       '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal'], dtype=object)
```

1.7 Assessing Missing Data in Each Column

Several columns have a high proportion of missing values, making them outliers. To address this, I apply a 6% threshold to filter out mostly empty columns.

[85]:
```
column_missing_data_percentage = {}
column_missing_data_threshold = 6

print(
    f"* The threshold for acceptable missing data in a column is␣
 ↪{column_missing_data_threshold}%. Most features meet this criteria, with␣
 ↪only a few exceeding it. Those features that exceed the threshold are␣
 ↪notably distinct from the majority."
)

for index, feature in enumerate(study_data.columns):
    counts = study_data[feature].value_counts(dropna=False)
    percentages = counts / study_data_num_rows * 100

    if np.nan not in percentages.index:
        column_missing_data_percentage[feature] = 0
        continue

    column_missing_data_percentage[feature] = percentages[np.nan]

    print(
        f"{feature} attribute with more than {percentages[np.nan] :03.2f}% NaN"
    )

    # Investigate patterns in the amount of missing data in each column.
    if percentages[np.nan] < column_missing_data_threshold:
        continue

    print(
        f"---> {index} - {feature} with missing data that exceeds the threshold␣
 ↪of {column_missing_data_threshold}%"
    )

    # plt.figure()
    # counts.plot.bar(title=feature, grid=True)
```

```
* The threshold for acceptable missing data in a column is 6%. Most features
meet this criteria, with only a few exceeding it. Those features that exceed the
threshold are notably distinct from the majority.
LotFrontage attribute with more than 17.74% NaN
---> 3 - LotFrontage with missing data that exceeds the threshold of 6%
Alley attribute with more than 93.49% NaN
---> 6 - Alley with missing data that exceeds the threshold of 6%
MasVnrType attribute with more than 59.66% NaN
---> 25 - MasVnrType with missing data that exceeds the threshold of 6%
MasVnrArea attribute with more than 0.55% NaN
BsmtQual attribute with more than 2.53% NaN
BsmtCond attribute with more than 2.53% NaN
```

```
BsmtExposure attribute with more than 2.60% NaN
BsmtFinType1 attribute with more than 2.53% NaN
BsmtFinType2 attribute with more than 2.60% NaN
Electrical attribute with more than 0.07% NaN
FireplaceQu attribute with more than 47.26% NaN
---> 57 - FireplaceQu with missing data that exceeds the threshold of 6%
GarageType attribute with more than 5.55% NaN
GarageYrBlt attribute with more than 5.55% NaN
GarageFinish attribute with more than 5.55% NaN
GarageQual attribute with more than 5.55% NaN
GarageCond attribute with more than 5.55% NaN
PoolQC attribute with more than 99.38% NaN
---> 72 - PoolQC with missing data that exceeds the threshold of 6%
Fence attribute with more than 80.55% NaN
---> 73 - Fence with missing data that exceeds the threshold of 6%
MiscFeature attribute with more than 96.03% NaN
---> 74 - MiscFeature with missing data that exceeds the threshold of 6%
```

As a result of the previous analysis, the following columns are identified to be dropped:

- Alley
- Fence
- FireplaceQu
- LotFrontage
- MasVnrType
- MiscFeature
- PoolQC

[86]:
```
removed90_NaN_feats_study_data = pd.DataFrame(study_data)

for feature in ["LotFrontage", "Alley", "MasVnrType", "FireplaceQu", "PoolQC",␣
 ↪"Fence", "MiscFeature"]:
    removed90_NaN_feats_study_data.drop(feature, axis=1, inplace=True)

display(removed90_NaN_feats_study_data.head(n=head_n_of_records))
```

```
   Id  MSSubClass MSZoning   LotArea Street LotShape LandContour Utilities  \
0   1          60       RL  9.042040   Pave      Reg         Lvl    AllPub
1   2          20       RL  9.169623   Pave      Reg         Lvl    AllPub
2   3          60       RL  9.328212   Pave      IR1         Lvl    AllPub
3   4          70       RL  9.164401   Pave      IR1         Lvl    AllPub
4   5          60       RL  9.565284   Pave      IR1         Lvl    AllPub

  LotConfig LandSlope Neighborhood Condition1 Condition2 BldgType HouseStyle  \
0    Inside       Gtl      CollgCr       Norm       Norm     1Fam     2Story
1       FR2       Gtl      Veenker      Feedr       Norm     1Fam     1Story
2    Inside       Gtl      CollgCr       Norm       Norm     1Fam     2Story
3    Corner       Gtl      Crawfor       Norm       Norm     1Fam     2Story
4       FR2       Gtl      NoRidge       Norm       Norm     1Fam     2Story
```

	OverallQual	OverallCond	YearBuilt	YearRemodAdd	RoofStyle	RoofMatl
0	7	5	2003	2003	Gable	CompShg
1	6	8	1976	1976	Gable	CompShg
2	7	5	2001	2002	Gable	CompShg
3	7	5	1915	1970	Gable	CompShg
4	8	5	2000	2000	Gable	CompShg

	Exterior1st	Exterior2nd	MasVnrArea	ExterQual	ExterCond	Foundation	BsmtQual
0	VinylSd	VinylSd	5.283204	Gd	TA	PConc	Gd
1	MetalSd	MetalSd	0.000000	TA	TA	CBlock	Gd
2	VinylSd	VinylSd	5.093750	Gd	TA	PConc	Gd
3	Wd Sdng	Wd Shng	0.000000	TA	TA	BrkTil	TA
4	VinylSd	VinylSd	5.860786	Gd	TA	PConc	Gd

	BsmtCond	BsmtExposure	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2
0	TA	No	GLQ	706	Unf	0.0
1	TA	Gd	ALQ	978	Unf	0.0
2	TA	Mn	GLQ	486	Unf	0.0
3	Gd	No	ALQ	216	Unf	0.0
4	TA	Av	GLQ	655	Unf	0.0

	BsmtUnfSF	TotalBsmtSF	Heating	HeatingQC	CentralAir	Electrical	1stFlrSF
0	5.017280	856	GasA	Ex	Y	SBrkr	6.753438
1	5.652489	1262	GasA	Ex	Y	SBrkr	7.141245
2	6.075346	920	GasA	Ex	Y	SBrkr	6.825460
3	6.293419	756	GasA	Gd	Y	SBrkr	6.869014
4	6.196444	1145	GasA	Ex	Y	SBrkr	7.044033

	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath
0	6.751101	0.0	7.444833	1	0.000000	2
1	0.000000	0.0	7.141245	0	0.693147	2
2	6.765039	0.0	7.488294	1	0.000000	2
3	6.629363	0.0	7.448916	1	0.000000	1
4	6.960348	0.0	7.695758	1	0.000000	2

	HalfBath	BedroomAbvGr	KitchenAbvGr	KitchenQual	TotRmsAbvGrd	Functional
0	1	3	0.693147	Gd	8	Typ
1	0	3	0.693147	TA	6	Typ
2	1	3	0.693147	Gd	6	Typ
3	0	3	0.693147	Gd	7	Typ
4	1	4	0.693147	Gd	9	Typ

	Fireplaces	GarageType	GarageYrBlt	GarageFinish	GarageCars	GarageArea
0	0	Attchd	2003.0	RFn	2	548
1	1	Attchd	1976.0	RFn	2	460
2	1	Attchd	2001.0	RFn	2	608
3	1	Detchd	1998.0	Unf	3	642

```
4           1     Attchd       2000.0          RFn           3         836

  GarageQual GarageCond PavedDrive  WoodDeckSF  OpenPorchSF  EnclosedPorch  \
0         TA         TA          Y    0.000000     4.127134       0.000000
1         TA         TA          Y    5.700444     0.000000       0.000000
2         TA         TA          Y    0.000000     3.761200       0.000000
3         TA         TA          Y    0.000000     3.583519       5.609472
4         TA         TA          Y    5.262690     4.442651       0.000000

   3SsnPorch  ScreenPorch  PoolArea  MiscVal  MoSold  YrSold SaleType  \
0        0.0          0.0       0.0      0.0       2    2008       WD
1        0.0          0.0       0.0      0.0       5    2007       WD
2        0.0          0.0       0.0      0.0       9    2008       WD
3        0.0          0.0       0.0      0.0       2    2006       WD
4        0.0          0.0       0.0      0.0      12    2008       WD

  SaleCondition  SalePrice
0        Normal  12.247699
1        Normal  12.109016
2        Normal  12.317171
3       Abnorml  11.849405
4        Normal  12.429220
```

1.7.1 Imputing Missing Values

After the previous steps, the columns now contain 94% meaningful values.

I applied a simple imputer to complete the dataset to ensure compatibility with estimators that require all values to be numerical.

Numerical features are imputed with their mean value, while the remaining features are imputed with the most frequent value.

[87]:
```
from sklearn.impute import SimpleImputer

numerical_imputer = SimpleImputer(strategy="mean")
ordinal_imputer = SimpleImputer(strategy="most_frequent")
categorical_imputer = SimpleImputer(strategy="most_frequent")

numerical_feats_with_NaN = [
    "MasVnrArea", # attribute with more than 0.55% NaN
    "GarageYrBlt", # attribute with more than 5.55% NaN
]

ordinal_feats_with_NaN = [
    "BsmtQual", # attribute with more than 2.53% NaN
    "BsmtCond", # attribute with more than 2.53% NaN
    "BsmtExposure", # attribute with more than 2.60% NaN
    "BsmtFinType1", # attribute with more than 2.53% NaN
```

```
    "BsmtFinType2", # attribute with more than 2.60% NaN
    "GarageFinish", # attribute with more than 5.55% NaN
    "GarageQual", # attribute with more than 5.55% NaN
    "GarageCond" # attribute with more than 5.55% NaN
]

categorical_feats_with_NaN = [
    "Electrical", # attribute with more than 0.07% NaN
    "GarageType", # attribute with more than 5.55% NaN
]

all_feats_with_NaN = numerical_feats_with_NaN + ordinal_feats_with_NaN +␣
 ↪categorical_feats_with_NaN

non_id_study_data = removed90_NaN_feats_study_data.reset_index(drop=True)
for feature in all_feats_with_NaN:
    non_id_study_data.drop(feature, axis=1, inplace=True)

numerical_imputed_study_data = numerical_imputer.
 ↪fit_transform(removed90_NaN_feats_study_data[numerical_feats_with_NaN])
ordinal_imputed_study_data = ordinal_imputer.
 ↪fit_transform(removed90_NaN_feats_study_data[ordinal_feats_with_NaN])
categorical_imputed_study_data = categorical_imputer.
 ↪fit_transform(removed90_NaN_feats_study_data[categorical_feats_with_NaN])

imputed_study_data  = pd.DataFrame(
    np.column_stack([numerical_imputed_study_data, ordinal_imputed_study_data,␣
 ↪categorical_imputed_study_data]),
    columns=all_feats_with_NaN
)

imputed_study_data = pd.concat([
    non_id_study_data,
    imputed_study_data
], axis=1)

columns_order = list(removed90_NaN_feats_study_data.columns)
imputed_study_data = imputed_study_data[columns_order]

display(imputed_study_data.head(n=head_n_of_records))
```

	Id	MSSubClass	MSZoning	LotArea	Street	LotShape	LandContour	Utilities	\
0	1	60	RL	9.042040	Pave	Reg	Lvl	AllPub	
1	2	20	RL	9.169623	Pave	Reg	Lvl	AllPub	
2	3	60	RL	9.328212	Pave	IR1	Lvl	AllPub	
3	4	70	RL	9.164401	Pave	IR1	Lvl	AllPub	
4	5	60	RL	9.565284	Pave	IR1	Lvl	AllPub	

```
  LotConfig LandSlope Neighborhood Condition1 Condition2 BldgType HouseStyle  \
0    Inside       Gtl      CollgCr       Norm       Norm     1Fam     2Story
1       FR2       Gtl      Veenker      Feedr       Norm     1Fam     1Story
2    Inside       Gtl      CollgCr       Norm       Norm     1Fam     2Story
3    Corner       Gtl      Crawfor       Norm       Norm     1Fam     2Story
4       FR2       Gtl      NoRidge       Norm       Norm     1Fam     2Story

   OverallQual  OverallCond  YearBuilt  YearRemodAdd RoofStyle RoofMatl  \
0            7            5       2003          2003     Gable  CompShg
1            6            8       1976          1976     Gable  CompShg
2            7            5       2001          2002     Gable  CompShg
3            7            5       1915          1970     Gable  CompShg
4            8            5       2000          2000     Gable  CompShg

  Exterior1st Exterior2nd MasVnrArea ExterQual ExterCond Foundation BsmtQual  \
0     VinylSd     VinylSd   5.283204        Gd        TA      PConc       Gd
1     MetalSd     MetalSd        0.0        TA        TA     CBlock       Gd
2     VinylSd     VinylSd    5.09375        Gd        TA      PConc       Gd
3     Wd Sdng     Wd Shng        0.0        TA        TA     BrkTil       TA
4     VinylSd     VinylSd   5.860786        Gd        TA      PConc       Gd

  BsmtCond BsmtExposure BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  \
0       TA           No          GLQ         706          Unf         0.0
1       TA           Gd          ALQ         978          Unf         0.0
2       TA           Mn          GLQ         486          Unf         0.0
3       Gd           No          ALQ         216          Unf         0.0
4       TA           Av          GLQ         655          Unf         0.0

   BsmtUnfSF  TotalBsmtSF Heating HeatingQC CentralAir Electrical  1stFlrSF  \
0   5.017280          856    GasA        Ex          Y      SBrkr  6.753438
1   5.652489         1262    GasA        Ex          Y      SBrkr  7.141245
2   6.075346          920    GasA        Ex          Y      SBrkr  6.825460
3   6.293419          756    GasA        Gd          Y      SBrkr  6.869014
4   6.196444         1145    GasA        Ex          Y      SBrkr  7.044033

   2ndFlrSF  LowQualFinSF  GrLivArea  BsmtFullBath  BsmtHalfBath  FullBath  \
0  6.751101           0.0   7.444833             1      0.000000         2
1  0.000000           0.0   7.141245             0      0.693147         2
2  6.765039           0.0   7.488294             1      0.000000         2
3  6.629363           0.0   7.448916             1      0.000000         1
4  6.960348           0.0   7.695758             1      0.000000         2

   HalfBath  BedroomAbvGr  KitchenAbvGr KitchenQual  TotRmsAbvGrd Functional  \
0         1             3      0.693147          Gd             8        Typ
1         0             3      0.693147          TA             6        Typ
2         1             3      0.693147          Gd             6        Typ
3         0             3      0.693147          Gd             7        Typ
```

```
4         1             4      0.693147          Gd             9        Typ

   Fireplaces GarageType GarageYrBlt GarageFinish  GarageCars  GarageArea  \
0           0     Attchd      2003.0          RFn           2         548
1           1     Attchd      1976.0          RFn           2         460
2           1     Attchd      2001.0          RFn           2         608
3           1     Detchd      1998.0          Unf           3         642
4           1     Attchd      2000.0          RFn           3         836

  GarageQual GarageCond PavedDrive  WoodDeckSF  OpenPorchSF  EnclosedPorch  \
0         TA         TA          Y    0.000000     4.127134       0.000000
1         TA         TA          Y    5.700444     0.000000       0.000000
2         TA         TA          Y    0.000000     3.761200       0.000000
3         TA         TA          Y    0.000000     3.583519       5.609472
4         TA         TA          Y    5.262690     4.442651       0.000000

   3SsnPorch  ScreenPorch  PoolArea  MiscVal  MoSold  YrSold SaleType  \
0        0.0          0.0       0.0      0.0       2    2008       WD
1        0.0          0.0       0.0      0.0       5    2007       WD
2        0.0          0.0       0.0      0.0       9    2008       WD
3        0.0          0.0       0.0      0.0       2    2006       WD
4        0.0          0.0       0.0      0.0      12    2008       WD

  SaleCondition  SalePrice
0        Normal  12.247699
1        Normal  12.109016
2        Normal  12.317171
3       Abnorml  11.849405
4        Normal  12.429220
```

[88]:
```
missing_values_per_row = imputed_study_data.isnull().sum(axis=1)
print(f"To confirm {missing_values_per_row.max()} Missing Values per Row")
```

```
To confirm 0 Missing Values per Row
```

1.8 Normalizing Numerical Features

In addition to transforming highly skewed features, it is good practice to scale numerical features to a [0, 1] range. While this normalization does not alter the shape of each feature's distribution, it ensures that all features are treated equally when applying supervised learners.

[89]:
```
from sklearn.preprocessing import StandardScaler

scaled_study_data = pd.DataFrame(imputed_study_data)
min_max_scaler = StandardScaler()  # default=(0, 1)
scaled_study_data[numerical_features] = min_max_scaler.
 ↪fit_transform(scaled_study_data[numerical_features])
```

```
display(scaled_study_data.head(n=head_n_of_records))
```

```
   Id  MSSubClass MSZoning   LotArea Street LotShape LandContour Utilities  \
0   1          60       RL -0.127817   Pave      Reg         Lvl    AllPub
1   2          20       RL  0.120797   Pave      Reg         Lvl    AllPub
2   3          60       RL  0.429834   Pave      IR1         Lvl    AllPub
3   4          70       RL  0.110623   Pave      IR1         Lvl    AllPub
4   5          60       RL  0.891805   Pave      IR1         Lvl    AllPub

  LotConfig LandSlope Neighborhood Condition1 Condition2 BldgType HouseStyle  \
0    Inside       Gtl      CollgCr       Norm       Norm     1Fam     2Story
1       FR2       Gtl      Veenker      Feedr       Norm     1Fam     1Story
2    Inside       Gtl      CollgCr       Norm       Norm     1Fam     2Story
3    Corner       Gtl      Crawfor       Norm       Norm     1Fam     2Story
4       FR2       Gtl      NoRidge       Norm       Norm     1Fam     2Story

   OverallQual  OverallCond  YearBuilt  YearRemodAdd RoofStyle RoofMatl  \
0            7            5   1.053769      0.880629     Gable  CompShg
1            6            8   0.159469     -0.427190     Gable  CompShg
2            7            5   0.987524      0.832191     Gable  CompShg
3            7            5  -1.860986     -0.717817     Gable  CompShg
4            8            5   0.954402      0.735316     Gable  CompShg

  Exterior1st Exterior2nd  MasVnrArea ExterQual ExterCond Foundation BsmtQual  \
0     VinylSd     VinylSd    1.207011        Gd        TA      PConc       Gd
1     MetalSd     MetalSd   -0.811344        TA        TA     CBlock       Gd
2     VinylSd     VinylSd    1.134633        Gd        TA      PConc       Gd
3     Wd Sdng     Wd Shng   -0.811344        TA        TA     BrkTil       TA
4     VinylSd     VinylSd    1.427666        Gd        TA      PConc       Gd

  BsmtCond BsmtExposure BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  \
0       TA           No          GLQ    0.625446          Unf   -0.355892
1       TA           Gd          ALQ    1.257846          Unf   -0.355892
2       TA           Mn          GLQ    0.113946          Unf   -0.355892
3       Gd           No          ALQ   -0.513805          Unf   -0.355892
4       TA           Av          GLQ    0.506871          Unf   -0.355892

   BsmtUnfSF  TotalBsmtSF Heating HeatingQC CentralAir Electrical  1stFlrSF  \
0  -0.339062    -0.472456    GasA        Ex          Y      SBrkr -0.805990
1   0.003303     0.512947    GasA        Ex          Y      SBrkr  0.433256
2   0.231214    -0.317122    GasA        Ex          Y      SBrkr -0.575842
3   0.348751    -0.715166    GasA        Gd          Y      SBrkr -0.436663
4   0.296484     0.228976    GasA        Ex          Y      SBrkr  0.122612

   2ndFlrSF  LowQualFinSF  GrLivArea  BsmtFullBath  BsmtHalfBath  FullBath  \
0  1.185669     -0.133789   0.548227      1.114055     -0.241689  0.800349
1 -0.867410     -0.133789  -0.378408     -0.819275      4.040898  0.800349
2  1.189908     -0.133789   0.680880      1.114055     -0.241689  0.800349
```

```
3  1.148647     -0.133789   0.560689      1.114055     -0.241689 -1.026153
4  1.249303     -0.133789   1.314119      1.114055     -0.241689  0.800349

   HalfBath  BedroomAbvGr  KitchenAbvGr KitchenQual  TotRmsAbvGrd Functional  \
0  1.231823      0.165909     -0.207905          Gd      0.927120        Typ
1 -0.758781      0.165909     -0.207905          TA     -0.314155        Typ
2  1.231823      0.165909     -0.207905          Gd     -0.314155        Typ
3 -0.758781      0.165909     -0.207905          Gd      0.306482        Typ
4  1.231823      1.392121     -0.207905          Gd      1.547757        Typ

   Fireplaces GarageType  GarageYrBlt GarageFinish  GarageCars  GarageArea  \
0   -0.951673     Attchd     1.023874          RFn    0.315804    0.360672
1    0.610487     Attchd    -0.101720          RFn    0.315804   -0.054591
2    0.610487     Attchd     0.940496          RFn    0.315804    0.643806
3    0.610487     Detchd     0.815430          Unf    1.656362    0.804249
4    0.610487     Attchd     0.898808          RFn    1.656362    1.719716

  GarageQual GarageCond PavedDrive  WoodDeckSF  OpenPorchSF  EnclosedPorch  \
0         TA         TA          Y   -0.943983     0.849493      -0.404890
1         TA         TA          Y    1.253310    -1.070556      -0.404890
2         TA         TA          Y   -0.943983     0.679251      -0.404890
3         TA         TA          Y   -0.943983     0.596590       2.840004
4         TA         TA          Y    1.084573     0.996280      -0.404890

   3SsnPorch  ScreenPorch  PoolArea   MiscVal    MoSold    YrSold SaleType  \
0  -0.128701    -0.293206 -0.058688 -0.190752 -1.603837  0.137472       WD
1  -0.128701    -0.293206 -0.058688 -0.190752 -0.491667 -0.615009       WD
2  -0.128701    -0.293206 -0.058688 -0.190752  0.991227  0.137472       WD
3  -0.128701    -0.293206 -0.058688 -0.190752 -1.603837 -1.367490       WD
4  -0.128701    -0.293206 -0.058688 -0.190752  2.103397  0.137472       WD

  SaleCondition  SalePrice
0        Normal  12.247699
1        Normal  12.109016
2        Normal  12.317171
3       Abnorml  11.849405
4        Normal  12.429220
```

1.9 Bivariate Analysis of the SalePrice

To gain a deeper understanding of the Ames, Iowa dataset, I conducted a bivariate analysis of SalePrice. The results provide valuable insights into the features that could significantly influence the analysis.

This analysis highlights the top 10 variables with the highest correlation to SalePrice, both positive and negative. For this analysis, categorical and ordinal features are encoded to the [0, 1] range.

[90]:
```
from sklearn.preprocessing import LabelEncoder

df_corr = pd.DataFrame(study_data)

object_columns = df_corr.select_dtypes(include=['object']).columns

for col in object_columns:
    label_encoder = LabelEncoder()
    df_corr[col] = label_encoder.fit_transform(df_corr[col])

display(df_corr.head(n=head_n_of_records))

df_corr = df_corr.corr()

display_md('**Best 10 Positively Correlated Variables:**')
display(df_corr['SalePrice'].sort_values(ascending = False)[:11])

display_md('**Best 10 Negatively Correlated Variables:**')
display(df_corr['SalePrice'].sort_values(ascending = False)[-10:])
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	\
0	1	60	3	65.0	9.042040	1	2	3	
1	2	20	3	80.0	9.169623	1	2	3	
2	3	60	3	68.0	9.328212	1	2	0	
3	4	70	3	60.0	9.164401	1	2	0	
4	5	60	3	84.0	9.565284	1	2	0	

	LandContour	Utilities	LotConfig	LandSlope	Neighborhood	Condition1	\
0	3	0	4	0	5	2	
1	3	0	2	0	24	1	
2	3	0	4	0	5	2	
3	3	0	0	0	6	2	
4	3	0	2	0	15	2	

	Condition2	BldgType	HouseStyle	OverallQual	OverallCond	YearBuilt	\
0	2	0	5	7	5	2003	
1	2	0	2	6	8	1976	
2	2	0	5	7	5	2001	
3	2	0	5	7	5	1915	
4	2	0	5	8	5	2000	

	YearRemodAdd	RoofStyle	RoofMatl	Exterior1st	Exterior2nd	MasVnrType	\
0	2003	1	0	12	13	1	
1	1976	1	0	8	8	3	
2	2002	1	0	12	13	1	
3	1970	1	0	13	15	3	
4	2000	1	0	12	13	1	

	MasVnrArea	ExterQual	ExterCond	Foundation	BsmtQual	BsmtCond	\
0	5.283204	2	4	2	2	3	
1	0.000000	3	4	1	2	3	
2	5.093750	2	4	2	2	3	
3	0.000000	3	4	0	3	1	
4	5.860786	2	4	2	2	3	

	BsmtExposure	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2	\
0	3	2	706	5	0.0	
1	1	0	978	5	0.0	
2	2	2	486	5	0.0	
3	3	0	216	5	0.0	
4	0	2	655	5	0.0	

	BsmtUnfSF	TotalBsmtSF	Heating	HeatingQC	CentralAir	Electrical	\
0	5.017280	856	1	0	1	4	
1	5.652489	1262	1	0	1	4	
2	6.075346	920	1	0	1	4	
3	6.293419	756	1	2	1	4	
4	6.196444	1145	1	0	1	4	

	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	BsmtHalfBath	\
0	6.753438	6.751101	0.0	7.444833	1	0.000000	
1	7.141245	0.000000	0.0	7.141245	0	0.693147	
2	6.825460	6.765039	0.0	7.488294	1	0.000000	
3	6.869014	6.629363	0.0	7.448916	1	0.000000	
4	7.044033	6.960348	0.0	7.695758	1	0.000000	

	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	KitchenQual	TotRmsAbvGrd	\
0	2	1	3	0.693147	2	8	
1	2	0	3	0.693147	3	6	
2	2	1	3	0.693147	2	6	
3	1	0	3	0.693147	2	7	
4	2	1	4	0.693147	2	9	

	Functional	Fireplaces	FireplaceQu	GarageType	GarageYrBlt	GarageFinish	\
0	6	0	5	1	2003.0	1	
1	6	1	4	1	1976.0	1	
2	6	1	4	1	2001.0	1	
3	6	1	2	5	1998.0	2	
4	6	1	4	1	2000.0	1	

	GarageCars	GarageArea	GarageQual	GarageCond	PavedDrive	WoodDeckSF	\
0	2	548	4	4	2	0.000000	
1	2	460	4	4	2	5.700444	
2	2	608	4	4	2	0.000000	
3	3	642	4	4	2	0.000000	
4	3	836	4	4	2	5.262690	

```
   OpenPorchSF  EnclosedPorch  3SsnPorch  ScreenPorch  PoolArea  PoolQC  \
0     4.127134       0.000000        0.0          0.0       0.0       3
1     0.000000       0.000000        0.0          0.0       0.0       3
2     3.761200       0.000000        0.0          0.0       0.0       3
3     3.583519       5.609472        0.0          0.0       0.0       3
4     4.442651       0.000000        0.0          0.0       0.0       3

   Fence  MiscFeature  MiscVal  MoSold  YrSold  SaleType  SaleCondition  \
0      4            4      0.0       2    2008         8              4
1      4            4      0.0       5    2007         8              4
2      4            4      0.0       9    2008         8              4
3      4            4      0.0       2    2006         8              0
4      4            4      0.0      12    2008         8              4

   SalePrice
0  12.247699
1  12.109016
2  12.317171
3  11.849405
4  12.429220
```

Best 10 Positively Correlated Variables:

```
SalePrice       1.000000
OverallQual     0.819240
GrLivArea       0.732807
GarageCars      0.680408
GarageArea      0.655212
TotalBsmtSF     0.641553
1stFlrSF        0.611030
FullBath        0.590919
YearBuilt       0.588977
YearRemodAdd    0.568986
GarageYrBlt     0.544005
Name: SalePrice, dtype: float64
```

Best 10 Negatively Correlated Variables:

```
LotShape       -0.273934
BsmtExposure   -0.299405
MasVnrType     -0.310619
HeatingQC      -0.425864
FireplaceQu    -0.465384
GarageType     -0.504519
KitchenQual    -0.530470
ExterQual      -0.584138
BsmtQual       -0.588815
GarageFinish   -0.604917
Name: SalePrice, dtype: float64
```

1.10 Reaching the Final Train Data

At this point, the dataset is mainly ready to target the objectives of this analysis. To enrich the dataset further and help reach valuable conclusions, I added the following features based on the existing ones:

- TotalSF: This feature represents the total living area in the house by adding up the basement, first-floor, and second-floor square footage.
- YrBltAndRemod: This combines the years since the house was built and any major renovations, giving a comprehensive view of its age and updates.
- Total_Bathrooms: This feature sums up the total number of bathrooms, including full and half bathrooms, in both the main living area and the basement.
- QualCond: This combines the house's overall quality and overall condition into a single score.
- ExterQualCond: This merges the quality and condition of the house's exterior into one feature.
- GarageQualCond: This combines the quality and condition of the garage into a single feature.
- BsmtQualCond: This merges the quality and condition of the basement into one feature.
- hasPool: This binary feature indicates whether the house has a pool.
- hasGarage: This binary feature indicates whether the house has a garage.
- hasBsmt: This binary feature indicates whether the house has a basement.
- hasFireplace: This binary feature indicates whether the house has a fireplace.
- house_age: This calculates the age of the house by subtracting the year it was built from the year it was sold.
- garage_age: This calculates the age of the garage by subtracting the year it was built from the year it was sold.
- old_house: This binary feature indicates whether the house was built before 1900.

[91]:
```
final_study_data = pd.DataFrame(scaled_study_data)

final_study_data['TotalSF'] = final_study_data['TotalBsmtSF'] +␣
 ↪final_study_data['1stFlrSF'] + final_study_data['2ndFlrSF']
final_study_data['YrBltAndRemod'] = final_study_data['YearBuilt'] +␣
 ↪final_study_data['YearRemodAdd']
final_study_data['Total_Bathrooms'] = (final_study_data['FullBath']
                                + (0.5 * final_study_data['HalfBath'])
                                + final_study_data['BsmtFullBath']
                                + (0.5 * final_study_data['BsmtHalfBath'])
                               )

final_study_data['QualCond'] = final_study_data.OverallQual * 100 +␣
 ↪final_study_data.OverallCond
final_study_data['ExterQualCond'] = final_study_data.ExterQual +␣
 ↪final_study_data.ExterCond
final_study_data['GarageQualCond'] = final_study_data.GarageQual +␣
 ↪final_study_data.GarageCond
final_study_data['BsmtQualCond'] = final_study_data.BsmtQual + final_study_data.
 ↪BsmtCond
```

```
final_study_data['hasPool'] = final_study_data['PoolArea'].apply(lambda x: 1 if␣
 ↪x > 0 else 0)
final_study_data['hasGarage'] = final_study_data['GarageArea'].apply(lambda x:␣
 ↪1 if x > 0 else 0)
final_study_data['hasBsmt'] = final_study_data['TotalBsmtSF'].apply(lambda x: 1␣
 ↪if x > 0 else 0)
final_study_data['hasFireplace'] = final_study_data['Fireplaces'].apply(lambda␣
 ↪x: 1 if x > 0 else 0)

final_study_data['house_age'] = final_study_data.YrSold - final_study_data.
 ↪YearBuilt
final_study_data['garage_age'] = final_study_data.YrSold - final_study_data.
 ↪GarageYrBlt
final_study_data['old_house'] = np.where(final_study_data.YearBuilt < 1900, 1,␣
 ↪0)

display(final_study_data.head(n=head_n_of_records))
```

```
   Id  MSSubClass MSZoning   LotArea Street LotShape LandContour Utilities  \
0   1          60       RL -0.127817   Pave      Reg         Lvl    AllPub
1   2          20       RL  0.120797   Pave      Reg         Lvl    AllPub
2   3          60       RL  0.429834   Pave      IR1         Lvl    AllPub
3   4          70       RL  0.110623   Pave      IR1         Lvl    AllPub
4   5          60       RL  0.891805   Pave      IR1         Lvl    AllPub

  LotConfig LandSlope Neighborhood Condition1 Condition2 BldgType HouseStyle  \
0    Inside       Gtl      CollgCr       Norm       Norm     1Fam     2Story
1       FR2       Gtl      Veenker      Feedr       Norm     1Fam     1Story
2    Inside       Gtl      CollgCr       Norm       Norm     1Fam     2Story
3    Corner       Gtl      Crawfor       Norm       Norm     1Fam     2Story
4       FR2       Gtl      NoRidge       Norm       Norm     1Fam     2Story

   OverallQual  OverallCond  YearBuilt  YearRemodAdd RoofStyle RoofMatl  \
0            7            5   1.053769      0.880629     Gable  CompShg
1            6            8   0.159469     -0.427190     Gable  CompShg
2            7            5   0.987524      0.832191     Gable  CompShg
3            7            5  -1.860986     -0.717817     Gable  CompShg
4            8            5   0.954402      0.735316     Gable  CompShg

  Exterior1st Exterior2nd  MasVnrArea ExterQual ExterCond Foundation BsmtQual  \
0     VinylSd     VinylSd    1.207011        Gd        TA      PConc       Gd
1     MetalSd     MetalSd   -0.811344        TA        TA     CBlock       Gd
2     VinylSd     VinylSd    1.134633        Gd        TA      PConc       Gd
3     Wd Sdng     Wd Shng   -0.811344        TA        TA     BrkTil       TA
4     VinylSd     VinylSd    1.427666        Gd        TA      PConc       Gd

  BsmtCond BsmtExposure BsmtFinType1  BsmtFinSF1 BsmtFinType2  BsmtFinSF2  \
```

```
0       TA           No          GLQ    0.625446          Unf   -0.355892
1       TA           Gd          ALQ    1.257846          Unf   -0.355892
2       TA           Mn          GLQ    0.113946          Unf   -0.355892
3       Gd           No          ALQ   -0.513805          Unf   -0.355892
4       TA           Av          GLQ    0.506871          Unf   -0.355892

   BsmtUnfSF  TotalBsmtSF Heating HeatingQC CentralAir Electrical  1stFlrSF  \
0  -0.339062    -0.472456    GasA        Ex          Y      SBrkr -0.805990
1   0.003303     0.512947    GasA        Ex          Y      SBrkr  0.433256
2   0.231214    -0.317122    GasA        Ex          Y      SBrkr -0.575842
3   0.348751    -0.715166    GasA        Gd          Y      SBrkr -0.436663
4   0.296484     0.228976    GasA        Ex          Y      SBrkr  0.122612

   2ndFlrSF  LowQualFinSF  GrLivArea  BsmtFullBath  BsmtHalfBath  FullBath  \
0  1.185669     -0.133789   0.548227      1.114055     -0.241689  0.800349
1 -0.867410     -0.133789  -0.378408     -0.819275      4.040898  0.800349
2  1.189908     -0.133789   0.680880      1.114055     -0.241689  0.800349
3  1.148647     -0.133789   0.560689      1.114055     -0.241689 -1.026153
4  1.249303     -0.133789   1.314119      1.114055     -0.241689  0.800349

   HalfBath  BedroomAbvGr  KitchenAbvGr KitchenQual  TotRmsAbvGrd Functional  \
0  1.231823      0.165909     -0.207905          Gd      0.927120        Typ
1 -0.758781      0.165909     -0.207905          TA     -0.314155        Typ
2  1.231823      0.165909     -0.207905          Gd     -0.314155        Typ
3 -0.758781      0.165909     -0.207905          Gd      0.306482        Typ
4  1.231823      1.392121     -0.207905          Gd      1.547757        Typ

   Fireplaces GarageType  GarageYrBlt GarageFinish  GarageCars  GarageArea  \
0   -0.951673     Attchd     1.023874          RFn    0.315804    0.360672
1    0.610487     Attchd    -0.101720          RFn    0.315804   -0.054591
2    0.610487     Attchd     0.940496          RFn    0.315804    0.643806
3    0.610487     Detchd     0.815430          Unf    1.656362    0.804249
4    0.610487     Attchd     0.898808          RFn    1.656362    1.719716

  GarageQual GarageCond PavedDrive  WoodDeckSF  OpenPorchSF  EnclosedPorch  \
0         TA         TA          Y   -0.943983     0.849493      -0.404890
1         TA         TA          Y    1.253310    -1.070556      -0.404890
2         TA         TA          Y   -0.943983     0.679251      -0.404890
3         TA         TA          Y   -0.943983     0.596590       2.840004
4         TA         TA          Y    1.084573     0.996280      -0.404890

   3SsnPorch  ScreenPorch  PoolArea   MiscVal    MoSold    YrSold SaleType  \
0  -0.128701    -0.293206 -0.058688 -0.190752 -1.603837  0.137472       WD
1  -0.128701    -0.293206 -0.058688 -0.190752 -0.491667 -0.615009       WD
2  -0.128701    -0.293206 -0.058688 -0.190752  0.991227  0.137472       WD
3  -0.128701    -0.293206 -0.058688 -0.190752 -1.603837 -1.367490       WD
4  -0.128701    -0.293206 -0.058688 -0.190752  2.103397  0.137472       WD
```

```
  SaleCondition  SalePrice   TotalSF  YrBltAndRemod  Total_Bathrooms  \
0        Normal  12.247699 -0.092777       1.934398         2.409470
1        Normal  12.109016  0.078793      -0.267722         1.622132
2        Normal  12.317171  0.296944       1.819716         2.409470
3       Abnorml  11.849405 -0.003182      -2.578803        -0.412333
4        Normal  12.429220  1.600891       1.689718         2.409470

   QualCond ExterQualCond GarageQualCond BsmtQualCond  hasPool  hasGarage  \
0       705          GdTA           TATA         GdTA        0          1
1       608          TATA           TATA         GdTA        0          0
2       705          GdTA           TATA         GdTA        0          1
3       705          TATA           TATA         TAGd        0          1
4       805          GdTA           TATA         GdTA        0          1

   hasBsmt  hasFireplace  house_age  garage_age  old_house
0        0             0  -0.916296   -0.886401          1
1        1             1  -0.774477   -0.513288          1
2        0             1  -0.850052   -0.803024          1
3        0             1   0.493497   -2.182920          1
4        1             1  -0.816930   -0.761335          1
```

1.10.1 Preparing Categorical Variables for Supervised Learning

Finally, I need to convert non-numeric columns (without any inherent order) into numerical values to complete the data preprocessing. This conversion is crucial for the learning algorithms to work effectively. I use one-hot encoding, which creates binary (0 or 1) columns for each category, ensuring no ordinal relationship is implied. This can be done conveniently with the pandas `get_dummies` method.

[92]:
```
def one_hot_encode(final_data):
    categorical_features = [
        "MSSubClass", "MSZoning", "Street", "LandContour", "Utilities",␣
↪"LotConfig", "Neighborhood", "Condition1", "Condition2", "BldgType",␣
↪"HouseStyle", "RoofStyle", "RoofMatl", "Exterior1st", "Exterior2nd",␣
↪"Foundation", "Heating", "CentralAir", "Electrical", "GarageType",␣
↪"SaleType", "SaleCondition"
    ]
    ordinal_features = [
        "LotShape", "LandSlope", "OverallQual", "OverallCond", "ExterQual",␣
↪"ExterCond", "BsmtQual", "BsmtCond", "BsmtExposure", "BsmtFinType1",␣
↪"BsmtFinType2", "HeatingQC", "KitchenQual", "Functional", "GarageFinish",␣
↪"GarageQual", "GarageCond", "PavedDrive",
        # Engineered Qual Features
        "QualCond", "ExterQualCond", "GarageQualCond", "BsmtQualCond"
    ]

    onehot1_study_data = pd.get_dummies(data = final_data, columns =␣
↪categorical_features)
```

```
    return pd.get_dummies(data = onehot1_study_data, columns = ordinal_features)

encoded_study_data = one_hot_encode(final_study_data)
display(encoded_study_data.head(n=head_n_of_records))
```

```
   Id   LotArea  YearBuilt  YearRemodAdd  MasVnrArea  BsmtFinSF1  BsmtFinSF2  \
0   1 -0.127817   1.053769      0.880629    1.207011    0.625446   -0.355892
1   2  0.120797   0.159469     -0.427190   -0.811344    1.257846   -0.355892
2   3  0.429834   0.987524      0.832191    1.134633    0.113946   -0.355892
3   4  0.110623  -1.860986     -0.717817   -0.811344   -0.513805   -0.355892
4   5  0.891805   0.954402      0.735316    1.427666    0.506871   -0.355892

   BsmtUnfSF  TotalBsmtSF  1stFlrSF  2ndFlrSF  LowQualFinSF  GrLivArea  \
0  -0.339062    -0.472456 -0.805990  1.185669     -0.133789   0.548227
1   0.003303     0.512947  0.433256 -0.867410     -0.133789  -0.378408
2   0.231214    -0.317122 -0.575842  1.189908     -0.133789   0.680880
3   0.348751    -0.715166 -0.436663  1.148647     -0.133789   0.560689
4   0.296484     0.228976  0.122612  1.249303     -0.133789   1.314119

   BsmtFullBath  BsmtHalfBath  FullBath  HalfBath  BedroomAbvGr  KitchenAbvGr  \
0      1.114055     -0.241689  0.800349  1.231823      0.165909     -0.207905
1     -0.819275      4.040898  0.800349 -0.758781      0.165909     -0.207905
2      1.114055     -0.241689  0.800349  1.231823      0.165909     -0.207905
3      1.114055     -0.241689 -1.026153 -0.758781      0.165909     -0.207905
4      1.114055     -0.241689  0.800349  1.231823      1.392121     -0.207905

   TotRmsAbvGrd  Fireplaces  GarageYrBlt  GarageCars  GarageArea  WoodDeckSF  \
0      0.927120   -0.951673     1.023874    0.315804    0.360672   -0.943983
1     -0.314155    0.610487    -0.101720    0.315804   -0.054591    1.253310
2     -0.314155    0.610487     0.940496    0.315804    0.643806   -0.943983
3      0.306482    0.610487     0.815430    1.656362    0.804249   -0.943983
4      1.547757    0.610487     0.898808    1.656362    1.719716    1.084573

   OpenPorchSF  EnclosedPorch  3SsnPorch  ScreenPorch  PoolArea   MiscVal  \
0     0.849493      -0.404890  -0.128701    -0.293206 -0.058688 -0.190752
1    -1.070556      -0.404890  -0.128701    -0.293206 -0.058688 -0.190752
2     0.679251      -0.404890  -0.128701    -0.293206 -0.058688 -0.190752
3     0.596590       2.840004  -0.128701    -0.293206 -0.058688 -0.190752
4     0.996280      -0.404890  -0.128701    -0.293206 -0.058688 -0.190752

     MoSold    YrSold  SalePrice   TotalSF  YrBltAndRemod  Total_Bathrooms  \
0 -1.603837  0.137472  12.247699 -0.092777       1.934398         2.409470
1 -0.491667 -0.615009  12.109016  0.078793      -0.267722         1.622132
2  0.991227  0.137472  12.317171  0.296944       1.819716         2.409470
3 -1.603837 -1.367490  11.849405 -0.003182      -2.578803        -0.412333
4  2.103397  0.137472  12.429220  1.600891       1.689718         2.409470

   hasPool  hasGarage  hasBsmt  hasFireplace  house_age  garage_age  \
```

```
0        0          1        0             0  -0.916296   -0.886401
1        0          0        1             1  -0.774477   -0.513288
2        0          1        0             1  -0.850052   -0.803024
3        0          1        0             1   0.493497   -2.182920
4        0          1        1             1  -0.816930   -0.761335

   old_house  MSSubClass_20  MSSubClass_30  MSSubClass_40  MSSubClass_45  \
0          1          False          False          False          False
1          1           True          False          False          False
2          1          False          False          False          False
3          1          False          False          False          False
4          1          False          False          False          False

   MSSubClass_50  MSSubClass_60  MSSubClass_70  MSSubClass_75  MSSubClass_80  \
0          False           True          False          False          False
1          False          False          False          False          False
2          False           True          False          False          False
3          False          False           True          False          False
4          False           True          False          False          False

   MSSubClass_85  MSSubClass_90  MSSubClass_120  MSSubClass_160  \
0          False          False           False           False
1          False          False           False           False
2          False          False           False           False
3          False          False           False           False
4          False          False           False           False

   MSSubClass_180  MSSubClass_190  MSZoning_C (all)  MSZoning_FV  MSZoning_RH  \
0           False           False             False        False        False
1           False           False             False        False        False
2           False           False             False        False        False
3           False           False             False        False        False
4           False           False             False        False        False

   MSZoning_RL  MSZoning_RM  Street_Grvl  Street_Pave  LandContour_Bnk  \
0         True        False        False         True            False
1         True        False        False         True            False
2         True        False        False         True            False
3         True        False        False         True            False
4         True        False        False         True            False

   LandContour_HLS  LandContour_Low  LandContour_Lvl  Utilities_AllPub  \
0            False            False             True              True
1            False            False             True              True
2            False            False             True              True
3            False            False             True              True
4            False            False             True              True
```

```
   Utilities_NoSeWa  LotConfig_Corner  LotConfig_CulDSac  LotConfig_FR2  \
0             False             False              False          False
1             False             False              False           True
2             False             False              False          False
3             False              True              False          False
4             False             False              False           True

   LotConfig_FR3  LotConfig_Inside  Neighborhood_Blmngtn  \
0          False              True                 False
1          False             False                 False
2          False              True                 False
3          False             False                 False
4          False             False                 False

   Neighborhood_Blueste  Neighborhood_BrDale  Neighborhood_BrkSide  \
0                 False                False                 False
1                 False                False                 False
2                 False                False                 False
3                 False                False                 False
4                 False                False                 False

   Neighborhood_ClearCr  Neighborhood_CollgCr  Neighborhood_Crawfor  \
0                 False                 True                 False
1                 False                False                 False
2                 False                 True                 False
3                 False                False                  True
4                 False                False                 False

   Neighborhood_Edwards  Neighborhood_Gilbert  Neighborhood_IDOTRR  \
0                 False                False                 False
1                 False                False                 False
2                 False                False                 False
3                 False                False                 False
4                 False                False                 False

   Neighborhood_MeadowV  Neighborhood_Mitchel  Neighborhood_NAmes  \
0                 False                False               False
1                 False                False               False
2                 False                False               False
3                 False                False               False
4                 False                False               False

   Neighborhood_NPkVill  Neighborhood_NWAmes  Neighborhood_NoRidge  \
0                 False                False                 False
1                 False                False                 False
2                 False                False                 False
3                 False                False                 False
4                 False                False                  True
```

```
   Neighborhood_NridgHt  Neighborhood_OldTown  Neighborhood_SWISU  \
0                 False                 False               False
1                 False                 False               False
2                 False                 False               False
3                 False                 False               False
4                 False                 False               False

   Neighborhood_Sawyer  Neighborhood_SawyerW  Neighborhood_Somerst  \
0                False                 False                 False
1                False                 False                 False
2                False                 False                 False
3                False                 False                 False
4                False                 False                 False

   Neighborhood_StoneBr  Neighborhood_Timber  Neighborhood_Veenker  \
0                 False                False                 False
1                 False                False                  True
2                 False                False                 False
3                 False                False                 False
4                 False                False                 False

   Condition1_Artery  Condition1_Feedr  Condition1_Norm  Condition1_PosA  \
0              False             False             True            False
1              False              True            False            False
2              False             False             True            False
3              False             False             True            False
4              False             False             True            False

   Condition1_PosN  Condition1_RRAe  Condition1_RRAn  Condition1_RRNe  \
0            False            False            False            False
1            False            False            False            False
2            False            False            False            False
3            False            False            False            False
4            False            False            False            False

   Condition1_RRNn  Condition2_Artery  Condition2_Feedr  Condition2_Norm  \
0            False              False             False             True
1            False              False             False             True
2            False              False             False             True
3            False              False             False             True
4            False              False             False             True

   Condition2_PosA  Condition2_PosN  Condition2_RRAe  Condition2_RRAn  \
0            False            False            False            False
1            False            False            False            False
2            False            False            False            False
3            False            False            False            False
```

```
4           False           False           False           False

   Condition2_RRNn  BldgType_1Fam  BldgType_2fmCon  BldgType_Duplex  \
0            False           True            False            False
1            False           True            False            False
2            False           True            False            False
3            False           True            False            False
4            False           True            False            False

   BldgType_Twnhs  BldgType_TwnhsE  HouseStyle_1.5Fin  HouseStyle_1.5Unf  \
0           False            False              False              False
1           False            False              False              False
2           False            False              False              False
3           False            False              False              False
4           False            False              False              False

   HouseStyle_1Story  HouseStyle_2.5Fin  HouseStyle_2.5Unf  HouseStyle_2Story  \
0              False              False              False               True
1               True              False              False              False
2              False              False              False               True
3              False              False              False               True
4              False              False              False               True

   HouseStyle_SFoyer  HouseStyle_SLvl  RoofStyle_Flat  RoofStyle_Gable  \
0              False            False           False             True
1              False            False           False             True
2              False            False           False             True
3              False            False           False             True
4              False            False           False             True

   RoofStyle_Gambrel  RoofStyle_Hip  RoofStyle_Mansard  RoofStyle_Shed  \
0              False          False              False           False
1              False          False              False           False
2              False          False              False           False
3              False          False              False           False
4              False          False              False           False

   RoofMatl_CompShg  RoofMatl_Membran  RoofMatl_Metal  RoofMatl_Roll  \
0              True             False           False          False
1              True             False           False          False
2              True             False           False          False
3              True             False           False          False
4              True             False           False          False

   RoofMatl_Tar&Grv  RoofMatl_WdShake  RoofMatl_WdShngl  Exterior1st_AsbShng  \
0             False             False             False                False
1             False             False             False                False
2             False             False             False                False
```

```
3             False             False             False                False
4             False             False             False                False

   Exterior1st_AsphShn  Exterior1st_BrkComm  Exterior1st_BrkFace  \
0                False                False                False
1                False                False                False
2                False                False                False
3                False                False                False
4                False                False                False

   Exterior1st_CBlock  Exterior1st_CemntBd  Exterior1st_HdBoard  \
0               False                False                False
1               False                False                False
2               False                False                False
3               False                False                False
4               False                False                False

   Exterior1st_ImStucc  Exterior1st_MetalSd  Exterior1st_Plywood  \
0                False                False                False
1                False                 True                False
2                False                False                False
3                False                False                False
4                False                False                False

   Exterior1st_Stone  Exterior1st_Stucco  Exterior1st_VinylSd  \
0              False               False                 True
1              False               False                False
2              False               False                 True
3              False               False                False
4              False               False                 True

   Exterior1st_Wd Sdng  Exterior1st_WdShing  Exterior2nd_AsbShng  \
0                False                False                False
1                False                False                False
2                False                False                False
3                 True                False                False
4                False                False                False

   Exterior2nd_AsphShn  Exterior2nd_Brk Cmn  Exterior2nd_BrkFace  \
0                False                False                False
1                False                False                False
2                False                False                False
3                False                False                False
4                False                False                False

   Exterior2nd_CBlock  Exterior2nd_CmentBd  Exterior2nd_HdBoard  \
0               False                False                False
1               False                False                False
```

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

   Exterior2nd_ImStucc  Exterior2nd_MetalSd  Exterior2nd_Other  \
0                False                False              False
1                False                 True              False
2                False                False              False
3                False                False              False
4                False                False              False

   Exterior2nd_Plywood  Exterior2nd_Stone  Exterior2nd_Stucco  \
0                False              False               False
1                False              False               False
2                False              False               False
3                False              False               False
4                False              False               False

   Exterior2nd_VinylSd  Exterior2nd_Wd Sdng  Exterior2nd_Wd Shng  \
0                 True                False                False
1                False                False                False
2                 True                False                False
3                False                False                 True
4                 True                False                False

   Foundation_BrkTil  Foundation_CBlock  Foundation_PConc  Foundation_Slab  \
0              False              False              True            False
1              False               True             False            False
2              False              False              True            False
3               True              False             False            False
4              False              False              True            False

   Foundation_Stone  Foundation_Wood  Heating_Floor  Heating_GasA  \
0             False            False          False          True
1             False            False          False          True
2             False            False          False          True
3             False            False          False          True
4             False            False          False          True

   Heating_GasW  Heating_Grav  Heating_OthW  Heating_Wall  CentralAir_N  \
0         False         False         False         False         False
1         False         False         False         False         False
2         False         False         False         False         False
3         False         False         False         False         False
4         False         False         False         False         False

   CentralAir_Y  Electrical_FuseA  Electrical_FuseF  Electrical_FuseP  \
0          True             False             False             False
```

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

   Electrical_Mix  Electrical_SBrkr  GarageType_2Types  GarageType_Attchd  \
0           False              True              False               True
1           False              True              False               True
2           False              True              False               True
3           False              True              False              False
4           False              True              False               True

   GarageType_Basment  GarageType_BuiltIn  GarageType_CarPort  \
0               False               False               False
1               False               False               False
2               False               False               False
3               False               False               False
4               False               False               False

   GarageType_Detchd  SaleType_COD  SaleType_CWD  SaleType_Con  \
0              False         False         False         False
1              False         False         False         False
2              False         False         False         False
3               True         False         False         False
4              False         False         False         False

   SaleType_ConLD  SaleType_ConLI  SaleType_ConLw  SaleType_New  SaleType_Oth  \
0           False           False           False         False         False
1           False           False           False         False         False
2           False           False           False         False         False
3           False           False           False         False         False
4           False           False           False         False         False

   SaleType_WD  SaleCondition_Abnorml  SaleCondition_AdjLand  \
0         True                 False                 False
1         True                 False                 False
2         True                 False                 False
3         True                  True                 False
4         True                 False                 False

   SaleCondition_Alloca  SaleCondition_Family  SaleCondition_Normal  \
0                 False                False                 True
1                 False                False                 True
2                 False                False                 True
3                 False                False                False
4                 False                False                 True

   SaleCondition_Partial  LotShape_IR1  LotShape_IR2  LotShape_IR3  \
```

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

   LotShape_Reg  LandSlope_Gtl  LandSlope_Mod  LandSlope_Sev  OverallQual_1  \
0          True           True          False          False          False
1          True           True          False          False          False
2         False           True          False          False          False
3         False           True          False          False          False
4         False           True          False          False          False

   OverallQual_2  OverallQual_3  OverallQual_4  OverallQual_5  OverallQual_6  \
0          False          False          False          False          False
1          False          False          False          False           True
2          False          False          False          False          False
3          False          False          False          False          False
4          False          False          False          False          False

   OverallQual_7  OverallQual_8  OverallQual_9  OverallQual_10  OverallCond_1  \
0           True          False          False           False          False
1          False          False          False           False          False
2           True          False          False           False          False
3           True          False          False           False          False
4          False           True          False           False          False

   OverallCond_2  OverallCond_3  OverallCond_4  OverallCond_5  OverallCond_6  \
0          False          False          False           True          False
1          False          False          False          False          False
2          False          False          False           True          False
3          False          False          False           True          False
4          False          False          False           True          False

   OverallCond_7  OverallCond_8  OverallCond_9  ExterQual_Ex  ExterQual_Fa  \
0          False          False          False         False         False
1          False           True          False         False         False
2          False          False          False         False         False
3          False          False          False         False         False
4          False          False          False         False         False

   ExterQual_Gd  ExterQual_TA  ExterCond_Ex  ExterCond_Fa  ExterCond_Gd  \
0          True         False         False         False         False
1         False          True         False         False         False
2          True         False         False         False         False
3         False          True         False         False         False
4          True         False         False         False         False
```

```
   ExterCond_Po  ExterCond_TA  BsmtQual_Ex  BsmtQual_Fa  BsmtQual_Gd  \
0         False          True        False        False         True
1         False          True        False        False         True
2         False          True        False        False         True
3         False          True        False        False        False
4         False          True        False        False         True

   BsmtQual_TA  BsmtCond_Fa  BsmtCond_Gd  BsmtCond_Po  BsmtCond_TA  \
0        False        False        False        False         True
1        False        False        False        False         True
2        False        False        False        False         True
3         True        False         True        False        False
4        False        False        False        False         True

   BsmtExposure_Av  BsmtExposure_Gd  BsmtExposure_Mn  BsmtExposure_No  \
0            False            False            False             True
1            False             True            False            False
2            False            False             True            False
3            False            False            False             True
4             True            False            False            False

   BsmtFinType1_ALQ  BsmtFinType1_BLQ  BsmtFinType1_GLQ  BsmtFinType1_LwQ  \
0             False             False              True             False
1              True             False             False             False
2             False             False              True             False
3              True             False             False             False
4             False             False              True             False

   BsmtFinType1_Rec  BsmtFinType1_Unf  BsmtFinType2_ALQ  BsmtFinType2_BLQ  \
0             False             False             False             False
1             False             False             False             False
2             False             False             False             False
3             False             False             False             False
4             False             False             False             False

   BsmtFinType2_GLQ  BsmtFinType2_LwQ  BsmtFinType2_Rec  BsmtFinType2_Unf  \
0             False             False             False              True
1             False             False             False              True
2             False             False             False              True
3             False             False             False              True
4             False             False             False              True

   HeatingQC_Ex  HeatingQC_Fa  HeatingQC_Gd  HeatingQC_Po  HeatingQC_TA  \
0          True         False         False         False         False
1          True         False         False         False         False
2          True         False         False         False         False
3         False         False          True         False         False
4          True         False         False         False         False
```

```
   KitchenQual_Ex  KitchenQual_Fa  KitchenQual_Gd  KitchenQual_TA  \
0           False           False            True           False
1           False           False           False            True
2           False           False            True           False
3           False           False            True           False
4           False           False            True           False

   Functional_Maj1  Functional_Maj2  Functional_Min1  Functional_Min2  \
0            False            False            False            False
1            False            False            False            False
2            False            False            False            False
3            False            False            False            False
4            False            False            False            False

   Functional_Mod  Functional_Sev  Functional_Typ  GarageFinish_Fin  \
0           False           False            True             False
1           False           False            True             False
2           False           False            True             False
3           False           False            True             False
4           False           False            True             False

   GarageFinish_RFn  GarageFinish_Unf  GarageQual_Ex  GarageQual_Fa  \
0              True             False          False          False
1              True             False          False          False
2              True             False          False          False
3             False              True          False          False
4              True             False          False          False

   GarageQual_Gd  GarageQual_Po  GarageQual_TA  GarageCond_Ex  GarageCond_Fa  \
0          False          False           True          False          False
1          False          False           True          False          False
2          False          False           True          False          False
3          False          False           True          False          False
4          False          False           True          False          False

   GarageCond_Gd  GarageCond_Po  GarageCond_TA  PavedDrive_N  PavedDrive_P  \
0          False          False           True         False         False
1          False          False           True         False         False
2          False          False           True         False         False
3          False          False           True         False         False
4          False          False           True         False         False

   PavedDrive_Y  QualCond_101  QualCond_103  QualCond_203  QualCond_205  \
0          True         False         False         False         False
1          True         False         False         False         False
2          True         False         False         False         False
3          True         False         False         False         False
```

```
4          True         False         False         False         False

   QualCond_302  QualCond_303  QualCond_304  QualCond_305  QualCond_306  \
0         False         False         False         False         False
1         False         False         False         False         False
2         False         False         False         False         False
3         False         False         False         False         False
4         False         False         False         False         False

   QualCond_307  QualCond_308  QualCond_402  QualCond_403  QualCond_404  \
0         False         False         False         False         False
1         False         False         False         False         False
2         False         False         False         False         False
3         False         False         False         False         False
4         False         False         False         False         False

   QualCond_405  QualCond_406  QualCond_407  QualCond_408  QualCond_409  \
0         False         False         False         False         False
1         False         False         False         False         False
2         False         False         False         False         False
3         False         False         False         False         False
4         False         False         False         False         False

   QualCond_502  QualCond_503  QualCond_504  QualCond_505  QualCond_506  \
0         False         False         False         False         False
1         False         False         False         False         False
2         False         False         False         False         False
3         False         False         False         False         False
4         False         False         False         False         False

   QualCond_507  QualCond_508  QualCond_509  QualCond_603  QualCond_604  \
0         False         False         False         False         False
1         False         False         False         False         False
2         False         False         False         False         False
3         False         False         False         False         False
4         False         False         False         False         False

   QualCond_605  QualCond_606  QualCond_607  QualCond_608  QualCond_609  \
0         False         False         False         False         False
1         False         False         False          True         False
2         False         False         False         False         False
3         False         False         False         False         False
4         False         False         False         False         False

   QualCond_703  QualCond_704  QualCond_705  QualCond_706  QualCond_707  \
0         False         False          True         False         False
1         False         False         False         False         False
2         False         False          True         False         False
```

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

   QualCond_708  QualCond_709  QualCond_804  QualCond_805  QualCond_806  \
0         False         False         False         False         False
1         False         False         False         False         False
2         False         False         False         False         False
3         False         False         False         False         False
4         False         False         False          True         False

   QualCond_807  QualCond_808  QualCond_809  QualCond_902  QualCond_905  \
0         False         False         False         False         False
1         False         False         False         False         False
2         False         False         False         False         False
3         False         False         False         False         False
4         False         False         False         False         False

   QualCond_1005  QualCond_1009  ExterQualCond_ExEx  ExterQualCond_ExGd  \
0          False          False               False               False
1          False          False               False               False
2          False          False               False               False
3          False          False               False               False
4          False          False               False               False

   ExterQualCond_ExTA  ExterQualCond_FaFa  ExterQualCond_FaTA  \
0               False               False               False
1               False               False               False
2               False               False               False
3               False               False               False
4               False               False               False

   ExterQualCond_GdGd  ExterQualCond_GdTA  ExterQualCond_TAEx  \
0               False                True               False
1               False               False               False
2               False                True               False
3               False               False               False
4               False                True               False

   ExterQualCond_TAFa  ExterQualCond_TAGd  ExterQualCond_TAPo  \
0               False               False               False
1               False               False               False
2               False               False               False
3               False               False               False
4               False               False               False

   ExterQualCond_TATA  GarageQualCond_ExEx  GarageQualCond_ExTA  \
0               False                False                False
1                True                False                False
```

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

   GarageQualCond_FaFa  GarageQualCond_FaPo  GarageQualCond_FaTA  \
0                False                False                False
1                False                False                False
2                False                False                False
3                False                False                False
4                False                False                False

   GarageQualCond_GdGd  GarageQualCond_GdTA  GarageQualCond_PoPo  \
0                False                False                False
1                False                False                False
2                False                False                False
3                False                False                False
4                False                False                False

   GarageQualCond_TAFa  GarageQualCond_TAGd  GarageQualCond_TATA  \
0                False                False                 True
1                False                False                 True
2                False                False                 True
3                False                False                 True
4                False                False                 True

   BsmtQualCond_ExGd  BsmtQualCond_ExTA  BsmtQualCond_FaFa  BsmtQualCond_FaPo  \
0              False              False              False              False
1              False              False              False              False
2              False              False              False              False
3              False              False              False              False
4              False              False              False              False

   BsmtQualCond_FaTA  BsmtQualCond_GdFa  BsmtQualCond_GdGd  BsmtQualCond_GdTA  \
0              False              False              False               True
1              False              False              False               True
2              False              False              False               True
3              False              False              False              False
4              False              False              False               True

   BsmtQualCond_TAFa  BsmtQualCond_TAGd  BsmtQualCond_TATA
0              False              False              False
1              False              False              False
2              False              False              False
3              False               True              False
4              False              False              False
```

1.11 Findings in the Ames, Iowa Housing Market

1.11.1 What are the main house price ranges?

To determine the main house price ranges in the Ames, Iowa dataset, I used three clustering approaches to analyze the SalePrice values. Clustering helps to group similar house prices, and these methods can provide different insights:

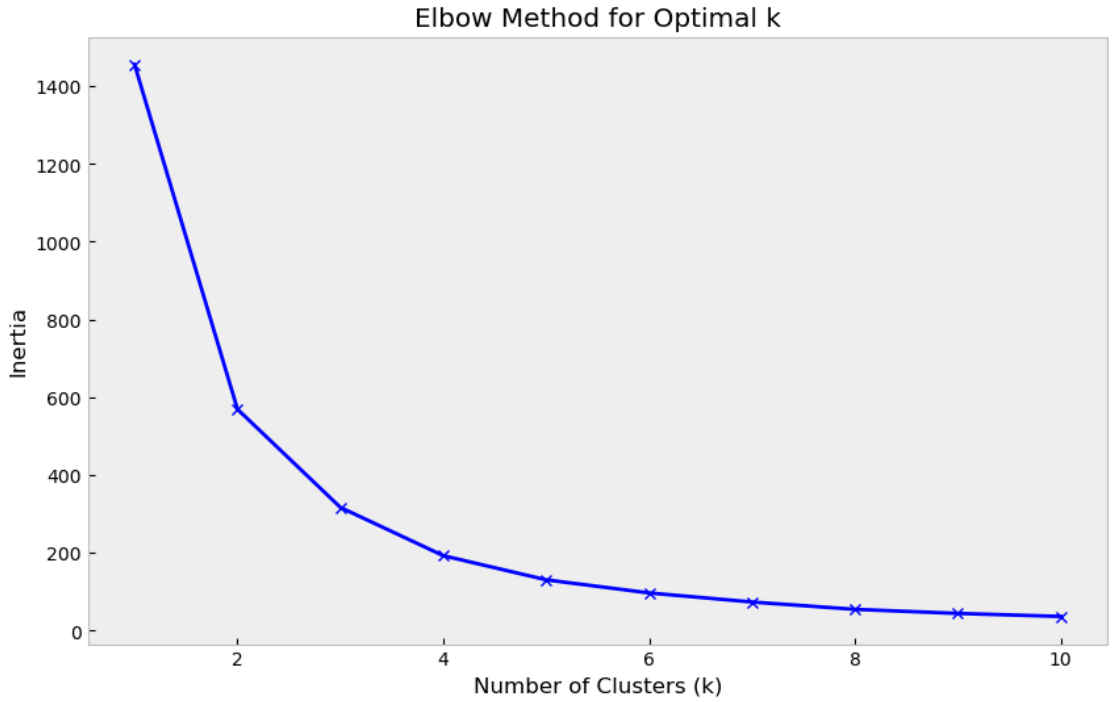
- **K-means Clustering + Elbow Optimization**: This method uses K-means clustering to group houses based on their prices. The Elbow Optimization technique helps determine the optimal number of clusters by finding where adding more doesn't significantly improve the fit.
- **K-means Clustering + Silhouette Optimization**: Similar to the above method, K-means clustering is used. However, it leverages Silhouette Optimization to measure how similar each house is to its own cluster compared to others. This helps identify the ideal number of clusters for the best grouping.
- **Gaussian Mixture Model + Bayesian Information Criterion (BIC) Score**: This method uses a Gaussian Mixture Model (GMM) to group house prices. GMM allows clusters to take various shapes, unlike K-means which assumes spherical clusters. The BIC score helps to select the best model by balancing the fit and complexity, ensuring the most appropriate number of clusters.

[93]:
```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

clustering_data = pd.DataFrame(final_study_data)
sale_prices = clustering_data[['SalePrice']].values

# Before clustering, we need to scale the SalePrices
standard_scaler = StandardScaler()
scaled_sale_prices = standard_scaler.fit_transform(sale_prices)
```

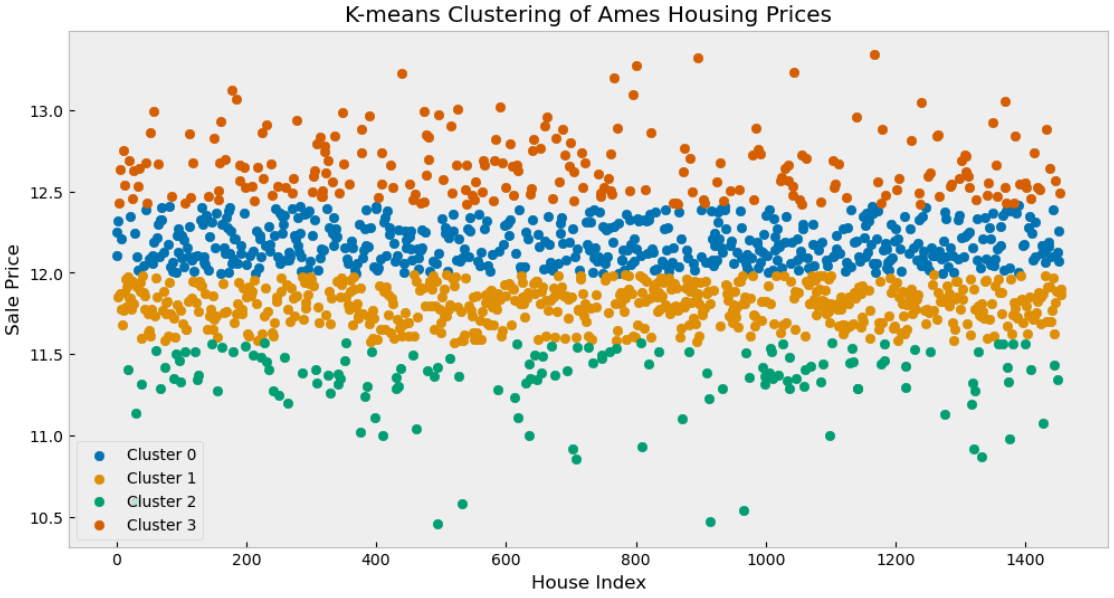
K-means Clustering + Elbow Optimization of Ames Housing Prices

[94]:
```
inertias = []
K = range(1, 11)

for k in K:
    kmeans = KMeans(n_clusters=k, random_state=seed)
    kmeans.fit(scaled_sale_prices)
    inertias.append(kmeans.inertia_)

plt.figure(figsize=(10, 6))
plt.plot(K, inertias, 'bx-')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal k')
plt.show()

# Based on the elbow curve, let's choose an appropriate number of clusters
```

```
# For this example, let's say we choose 4 clusters
n_clusters = 4

kmeans = KMeans(n_clusters=n_clusters, random_state=seed)
kmeans.fit(scaled_sale_prices)

# Add cluster labels to the original dataframe
clustering_data = pd.DataFrame(final_study_data)
clustering_data['Cluster'] = kmeans.labels_

# Calculate the mean price for each cluster
cluster_means = clustering_data.groupby('Cluster')['SalePrice'].mean().
 ↪sort_values()

for cluster, mean_price in cluster_means.items():
    print(f"Cluster {cluster}: Mean Price = ${expm1(mean_price):.2f}")

# Visualize the clusters
plt.figure(figsize=(12, 6))
for i in range(n_clusters):
    cluster_data = clustering_data[clustering_data['Cluster'] == i]
    plt.scatter(cluster_data.index, cluster_data['SalePrice'], label=f'Cluster␣
 ↪{i}', color=colorblind_palette[i])

plt.xlabel('House Index')
plt.ylabel('Sale Price')
plt.title('K-means Clustering of Ames Housing Prices')
plt.legend()
plt.show()
```



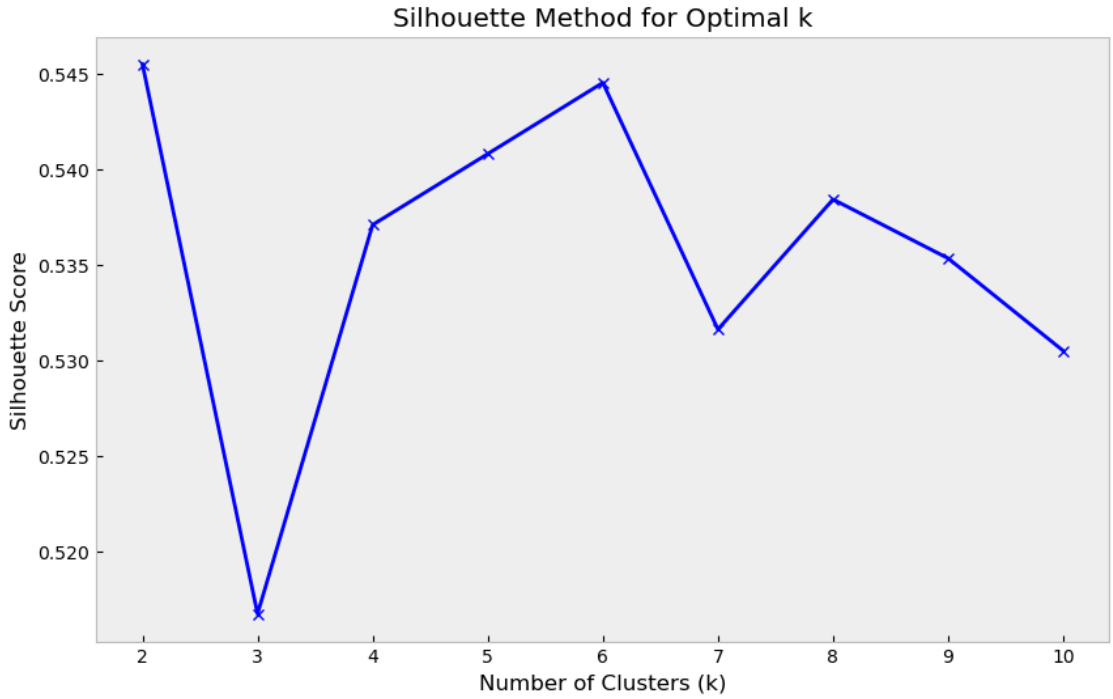

```
Cluster 2: Mean Price = $83958.98
Cluster 1: Mean Price = $133851.67
Cluster 0: Mean Price = $194839.43
Cluster 3: Mean Price = $312264.64
```



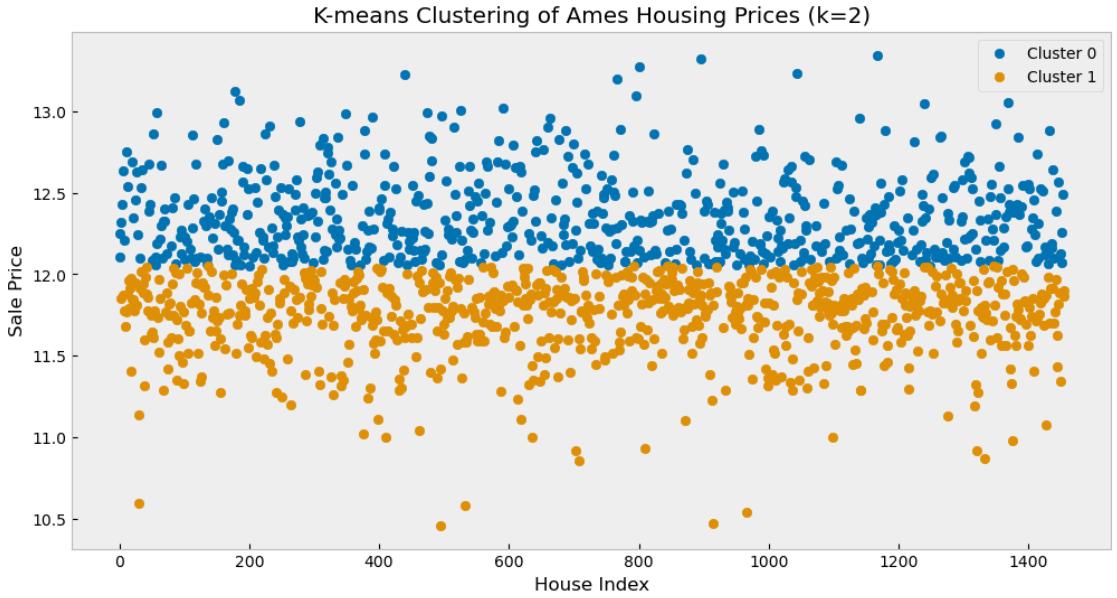
K-means Clustering + Silhouette Optimization of Ames Housing Prices

[95]:
```
from sklearn.metrics import silhouette_score

# Calculate silhouette scores for different numbers of clusters
silhouette_scores = []
K = range(2, 11)  # Start from 2 clusters as silhouette score is not defined␣
 ↪for 1 cluster

for k in K:
    kmeans = KMeans(n_clusters=k, random_state=seed)
    kmeans.fit(scaled_sale_prices)
    score = silhouette_score(scaled_sale_prices, kmeans.labels_)
    silhouette_scores.append(score)

# Plot the silhouette scores
plt.figure(figsize=(10, 6))
plt.plot(K, silhouette_scores, 'bx-')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Method for Optimal k')
plt.show()

# Find the optimal number of clusters (highest silhouette score)
optimal_k = K[silhouette_scores.index(max(silhouette_scores))]
print(f"Optimal number of clusters: {optimal_k}")

# Perform K-means clustering with the optimal number of clusters
kmeans = KMeans(n_clusters=optimal_k, random_state=seed)
kmeans.fit(scaled_sale_prices)

# Add cluster labels to the original dataframe
clustering_data = pd.DataFrame(final_study_data)
clustering_data['Cluster'] = kmeans.labels_

# Calculate the mean price for each cluster
cluster_means = clustering_data.groupby('Cluster')['SalePrice'].mean().
 ↪sort_values()

# Print the mean prices for each cluster
for cluster, mean_price in cluster_means.items():
    print(f"Cluster {cluster}: Mean Price = ${expm1(mean_price):.2f}")

# Visualize the clusters
plt.figure(figsize=(12, 6))
for i in range(optimal_k):
    cluster_data = clustering_data[clustering_data['Cluster'] == i]
```

```
    plt.scatter(cluster_data.index, cluster_data['SalePrice'], label=f'Cluster␣
 ↪{i}', color=colorblind_palette[i])

plt.xlabel('House Index')
plt.ylabel('Sale Price')
plt.title(f'K-means Clustering of Ames Housing Prices (k={optimal_k})')
plt.legend()
plt.show()
```



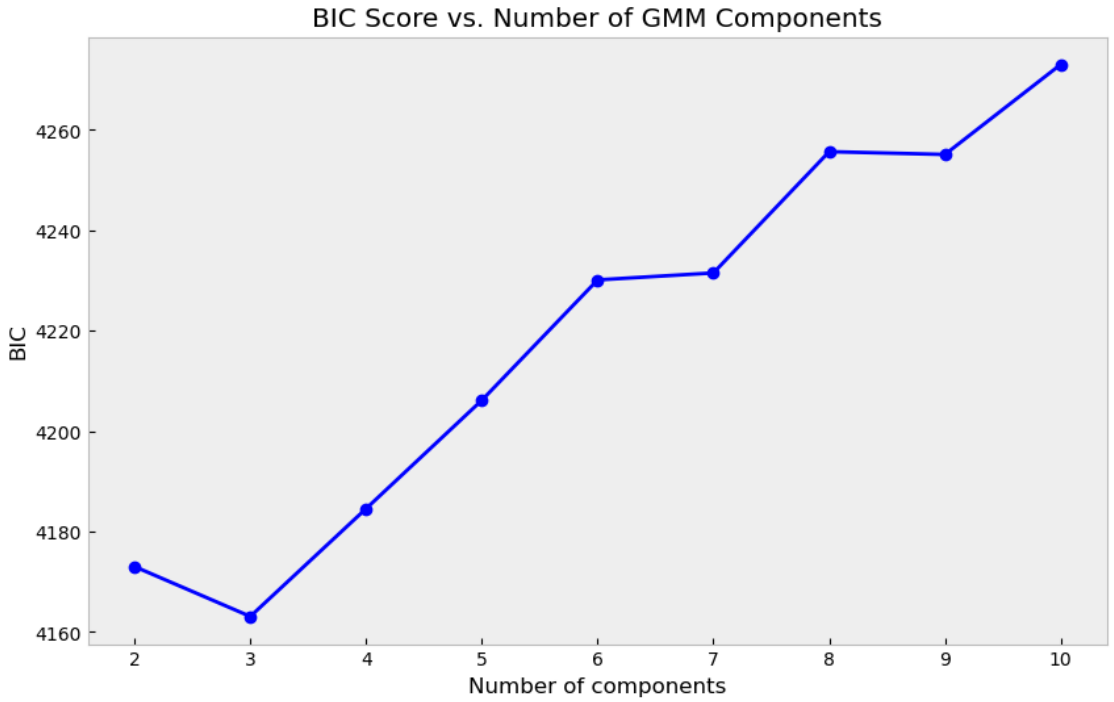

```
Optimal number of clusters: 2
Cluster 1: Mean Price = $125567.91
Cluster 0: Mean Price = $233574.83
```



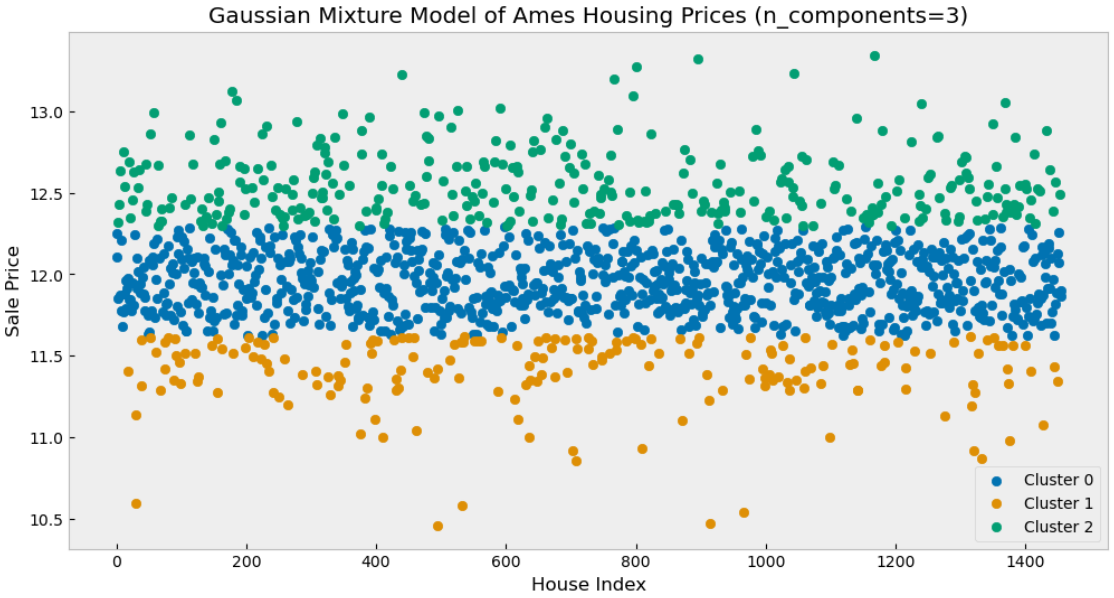
1.12 Gaussian Mixture Model + BIC Score of Ames Housing Prices

[96]:
```
from sklearn.mixture import GaussianMixture

# Calculate BIC and silhouette scores for different numbers of components
n_components_range = range(2, 11)
bic = []
silhouette_scores = []

for n_components in n_components_range:
    # Fit a Gaussian Mixture Model
    gmm = GaussianMixture(n_components=n_components, random_state=seed)
    gmm.fit(scaled_sale_prices)

    # Calculate BIC score
    bic.append(gmm.bic(scaled_sale_prices))

# Plot the BIC scores
plt.figure(figsize=(10, 6))
plt.plot(n_components_range, bic, 'bo-')
plt.xlabel('Number of components')
plt.ylabel('BIC')
plt.title('BIC Score vs. Number of GMM Components')
plt.show()

# Find the optimal number of components (lowest BIC score)
optimal_n_components = n_components_range[bic.index(min(bic))]
```

```
print(f"The optimal number of components based on BIC:␣
 ↪{optimal_n_components}\n")

# Fit the final GMM model with the optimal number of components
gmm = GaussianMixture(n_components=optimal_n_components, random_state=seed)
gmm.fit(scaled_sale_prices)

# Add cluster labels to the original dataframe
gmm_clustering_data = pd.DataFrame(final_study_data)
gmm_clustering_data['Cluster'] = gmm.predict(scaled_sale_prices)

# Calculate the mean price for each cluster
cluster_sale_price = gmm_clustering_data.groupby('Cluster')['SalePrice']
cluster_means = cluster_sale_price.mean().sort_values()
cluster_mins = cluster_sale_price.min()
cluster_maxs = cluster_sale_price.max()

# Visualize the clusters
plt.figure(figsize=(12, 6))
for i in range(optimal_n_components):
    cluster_data = gmm_clustering_data[gmm_clustering_data['Cluster'] == i]
    plt.scatter(cluster_data.index, cluster_data['SalePrice'], label=f'Cluster␣
 ↪{i}', color=colorblind_palette[i])

plt.xlabel('House Index')
plt.ylabel('Sale Price')
plt.title(f'Gaussian Mixture Model of Ames Housing Prices␣
 ↪(n_components={optimal_n_components})')
plt.legend()
plt.show()
```




```
The optimal number of components based on BIC: 3
```



1.12.1 SalePrice Clustering Results

Using three different clustering methods to analyze the SalePrice values in the Ames, Iowa dataset, I identified various clusters:

- K-means Clustering + Elbow Optimization: Grouped houses into 4 clusters.
- K-means Clustering + Silhouette Optimization: Grouped houses into 2 clusters.
- Gaussian Mixture Model + Bayesian Information Criterion (BIC) Score: Grouped houses into 3 clusters.

To simplify the analysis and provide a clearer view of the housing market, I chose to use the results from the GMM+BIC method, defining three distinct housing segments based on their sale price ranges:

- **Luxury Homes Segment**: These are the high-end, more expensive homes.
- **Mid-Range Homes Segment**: These average-priced homes fall in the middle range.
- **Budget Homes Segment**: These are the more affordable, lower-priced homes.

[97]:
```
#
# Define cluster labels to present the business conclussion
#
# cluster 1: Mean Price = $89484.06 [$35K - $111K]
# cluster 0: Mean Price = $155502.32 [$112K - $218K]
# cluster 2: Mean Price = $282697.23 [$219K - $625K]
#
cluster_labels = [
    "Mid-Range Homes Segment",
    "Budget Homes Segment",
    "Luxury Homes Segment",
]

# Print the mean prices for each cluster
for cluster, mean_price in cluster_means.items():
    print(f"{cluster_labels[cluster]} (cluster {cluster}): Mean Price =␣
 ↪${expm1(mean_price)/1000:.0f}K [${expm1(cluster_mins[cluster])/1000:.0f}K -␣
 ↪${expm1(cluster_maxs[cluster])/1000:.0f}K]")
```

```
Budget Homes Segment (cluster 1): Mean Price = $89K [$35K - $111K]
Mid-Range Homes Segment (cluster 0): Mean Price = $156K [$112K - $218K]
Luxury Homes Segment (cluster 2): Mean Price = $283K [$219K - $625K]
```

Main House Price Ranges in Ames, Iowa This classification helps understand the housing market by segmenting it into easily understandable price ranges.

Segment	Mean Price	Minimum Price	Maximum Price
Luxury Homes	$283K	$219K	$625K
Mid-Range Homes	$156K	$112K	$218K
Budget Homes	$89K	$35K	$111K

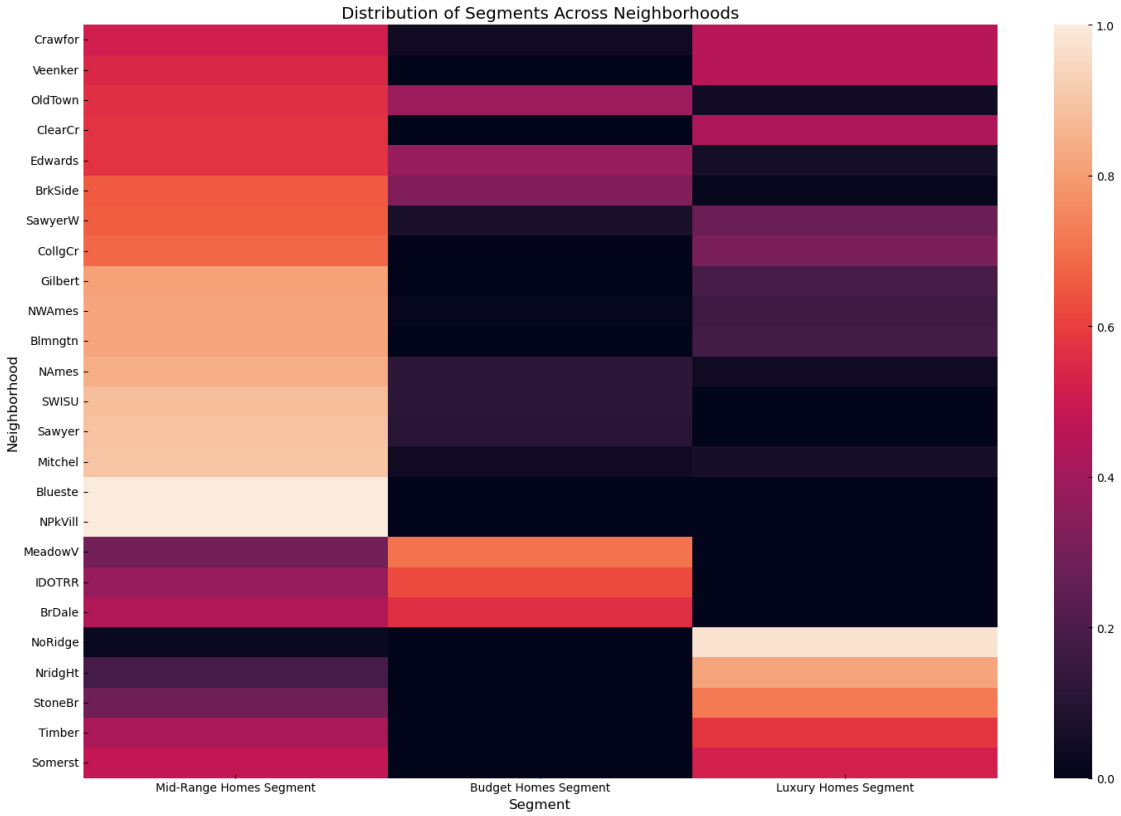
1.13 Which Areas Can You Locate These Price Ranges?

Based on the segmentation of budget, mid-range, and luxury homes, I can now identify the top neighborhoods where these houses are located. This helps us understand where different types of homes are most commonly found in the Ames, Iowa, housing market.

[98]:
```
# Analyze the distribution of clusters across neighborhoods
neighborhood_clusters = gmm_clustering_data.groupby('Neighborhood')['Cluster'].
 ↪value_counts(normalize=True).unstack()

# Fill NaN values with 0
neighborhood_clusters = neighborhood_clusters.fillna(0)

# Sort neighborhoods by the most prevalent cluster
dominant_cluster = neighborhood_clusters.idxmax(axis=1)
neighborhood_clusters['Dominant_Cluster'] = dominant_cluster
neighborhood_clusters = neighborhood_clusters.
 ↪sort_values(by=['Dominant_Cluster'] + list(neighborhood_clusters.columns[:
 ↪-1]))

# Identify top neighborhoods for each cluster
top_neighborhoods = {}
for cluster in range(3):
    top_neighborhoods[cluster] = neighborhood_clusters[cluster].nlargest(5)

for cluster, neighborhoods in top_neighborhoods.items():
    print(f"\nTop 5 neighborhoods for {cluster_labels[cluster]}:")
    for neighborhood, proportion in neighborhoods.items():
        print(f"  {neighborhood}: {proportion:.2f}")

# Plot the distribution of clusters across neighborhoods
plt.figure(figsize=(15, 10))
ax = sns.heatmap(neighborhood_clusters.iloc[:, :-1])
ax.set_xticklabels(cluster_labels)
plt.title('Distribution of Segments Across Neighborhoods')
plt.ylabel('Neighborhood')
plt.xlabel('Segment')
plt.tight_layout()
plt.show()
```

```
Top 5 neighborhoods for Mid-Range Homes Segment:
  Blueste: 1.00
  NPkVill: 1.00
  Mitchel: 0.90
  Sawyer: 0.89
  SWISU: 0.88
```

```
Top 5 neighborhoods for Budget Homes Segment:
  MeadowV: 0.71
  IDOTRR: 0.62
  BrDale: 0.56
  OldTown: 0.39
  Edwards: 0.38

Top 5 neighborhoods for Luxury Homes Segment:
  NoRidge: 0.97
  NridgHt: 0.82
  StoneBr: 0.72
  Timber: 0.58
  Somerst: 0.52
```



These are the top 5 neighborhoods for each segment:

- **Luxury Homes Segment**: These neighborhoods are known for their expensive houses.
  - NoRidge
  - NridgHt
  - StoneBr
  - Timber
  - Somerst

- **Mid-Range Homes Segment**: These neighborhoods feature homes with average prices that fall in the middle range.
  - Blueste
  - NPkVill
  - Mitchel
  - Sawyer
  - SWISU
- **Budget Homes Segment**: These neighborhoods are characterized by more affordable, lower-priced houses.
  - MeadowV
  - IDOTRR
  - BrDale
  - OldTown
  - Edwards

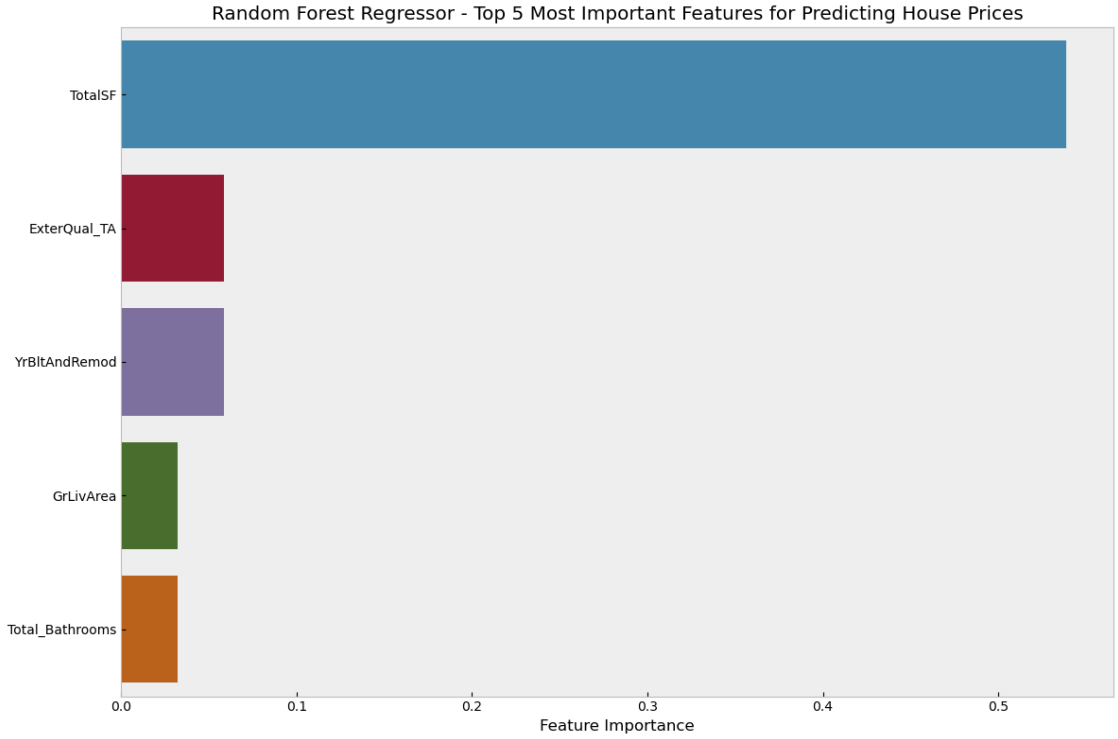
1.14 What features best predict the price range of each home?

To determine which features most accurately predict the price range of each home, I analyzed the overall housing market and the previously identified segments: budget, mid-range, and luxury homes. This approach allows me to identify the main factors influencing the entire market and the specific segments.

I used the Random Forest Regressor, AdaBoost Regressor, and a Decision Tree Regressor to pinpoint the key features. For this analysis, I used the default settings of these regressors, but further studies could explore other models and fine-tune the parameters for even better results.

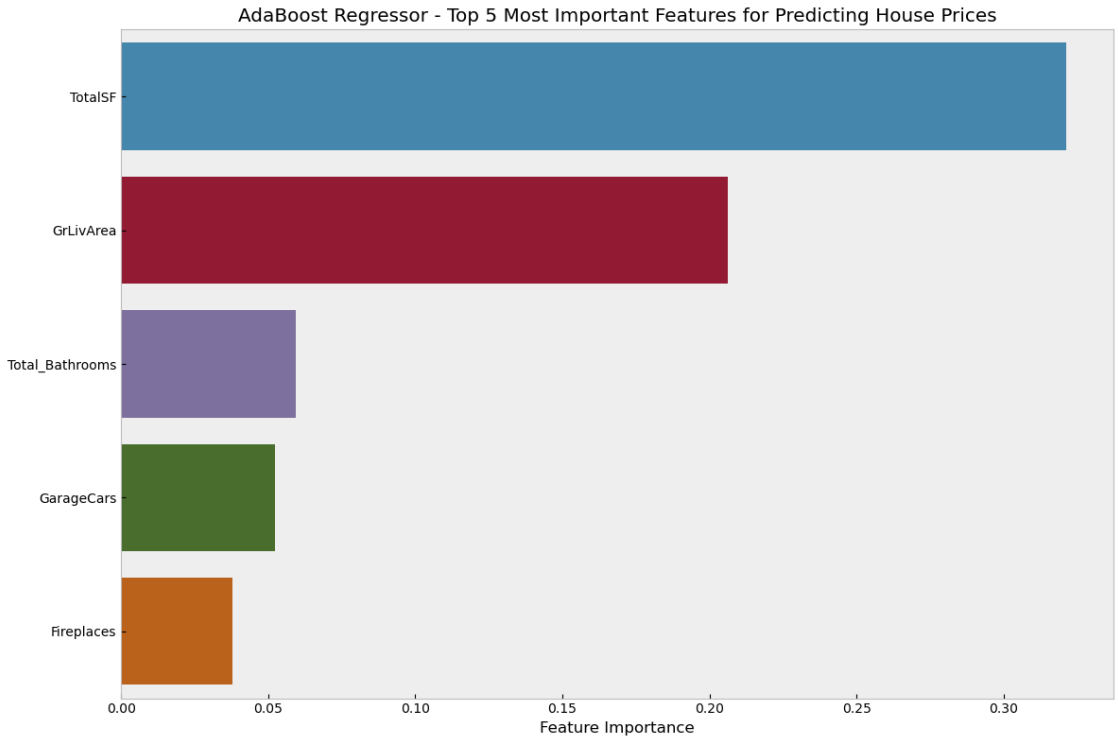
[99]:
```
from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestRegressor, AdaBoostRegressor
from sklearn.tree import DecisionTreeRegressor

# Separate features and target
X = encoded_study_data.drop('SalePrice', axis=1)
y = encoded_study_data['SalePrice']

def regresor_fit_and_print(title, X, y, regressor):
    """
    Fit and print a regressor results
    """
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=seed)
    regressor.fit(X_train, y_train)

    importances = regressor.feature_importances_
    feature_importances = pd.Series(importances, index=X.columns).
 ↪sort_values(ascending=False)

    plt.figure(figsize=(12, 8))
```

```
    sns.barplot(x=feature_importances.values[:5], y=feature_importances.index[:
↪5])
    plt.title(title + ' - Top 5 Most Important Features for Predicting House␣
↪Prices')
    plt.xlabel('Feature Importance')
    plt.tight_layout()
    plt.show()

    print(title + " - Top 5 most important features:")
    for i, (feature, importance) in enumerate(feature_importances[:5].items(),␣
↪1):
        print(f"{i}. {feature}: {importance:.4f}")

random_forest_regressor = RandomForestRegressor(random_state=seed)
regresor_fit_and_print("Random Forest Regressor", X, y, random_forest_regressor)

ada_boost_regressor = AdaBoostRegressor(random_state=seed)
regresor_fit_and_print("AdaBoost Regressor", X, y, ada_boost_regressor)

decision_tree_regressor = DecisionTreeRegressor(random_state=seed)
regresor_fit_and_print("Decision Tree Regressor", X, y, decision_tree_regressor)
```

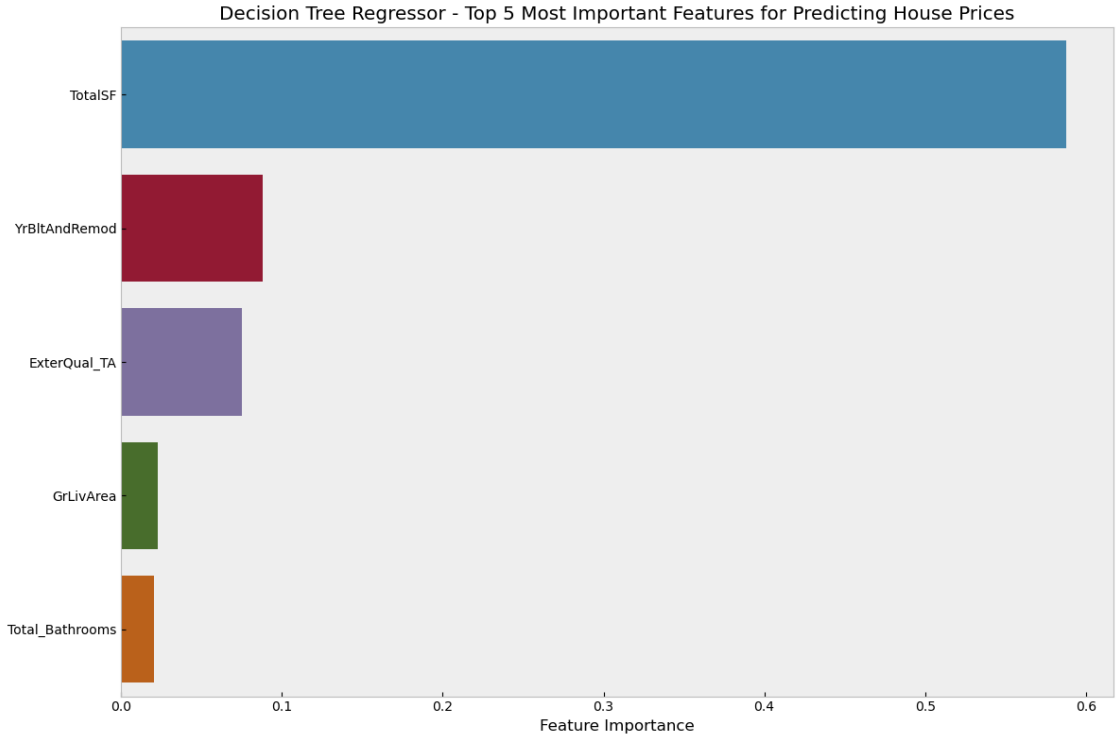



```
Random Forest Regressor - Top 5 most important features:
```

1. TotalSF: 0.5387
2. ExterQual_TA: 0.0587
3. YrBltAndRemod: 0.0585
4. GrLivArea: 0.0321
5. Total_Bathrooms: 0.0320



AdaBoost Regressor - Top 5 most important features:
1. TotalSF: 0.3212
2. GrLivArea: 0.2062
3. Total_Bathrooms: 0.0593
4. GarageCars: 0.0524
5. Fireplaces: 0.0379




```
Decision Tree Regressor - Top 5 most important features:
1. TotalSF: 0.5877
2. YrBltAndRemod: 0.0880
3. ExterQual_TA: 0.0751
4. GrLivArea: 0.0227
5. Total_Bathrooms: 0.0205
```

According to the results from these regressors, here are the top 7 features that drive housing prices in the general market:

- Random Forest Regressor:
  - TotalSF: Total square footage of the house.
  - ExterQual_TA: Quality of the exterior material (Average/Typical).
  - YrBltAndRemod: Combined years since the house was built and any renovations.
  - GrLivArea: Above-ground living area.
  - Total_Bathrooms: Total number of bathrooms in the house.
  - YearBuilt: The year the house was built.
  - GarageArea: Size of the garage.
- AdaBoost Regressor:
  - TotalSF: Total square footage of the house.
  - GrLivArea: Above-ground living area.
  - Total_Bathrooms: Total number of bathrooms in the house.
  - GarageCars: Number of cars the garage can hold.
  - Fireplaces: Number of fireplaces in the house.
  - GarageYrBlt: The year the garage was built.

  - GarageArea: Size of the garage.
- Decision Tree Regressor:
  - TotalSF: Total square footage of the house.
  - YrBltAndRemod: Combined years since the house was built and any renovations.
  - ExterQual_TA: Quality of the exterior material.
  - GrLivArea: Above-ground living area.
  - Total_Bathrooms: Total number of bathrooms in the house.
  - KitchenAbvGr: Number of kitchens above ground.
  - BsmtFinSF1: Finished square footage of the basement.

1.14.1 Conclusions

Based on the results from these regressors, I conclude that several key factors strongly influence the sale price of homes:

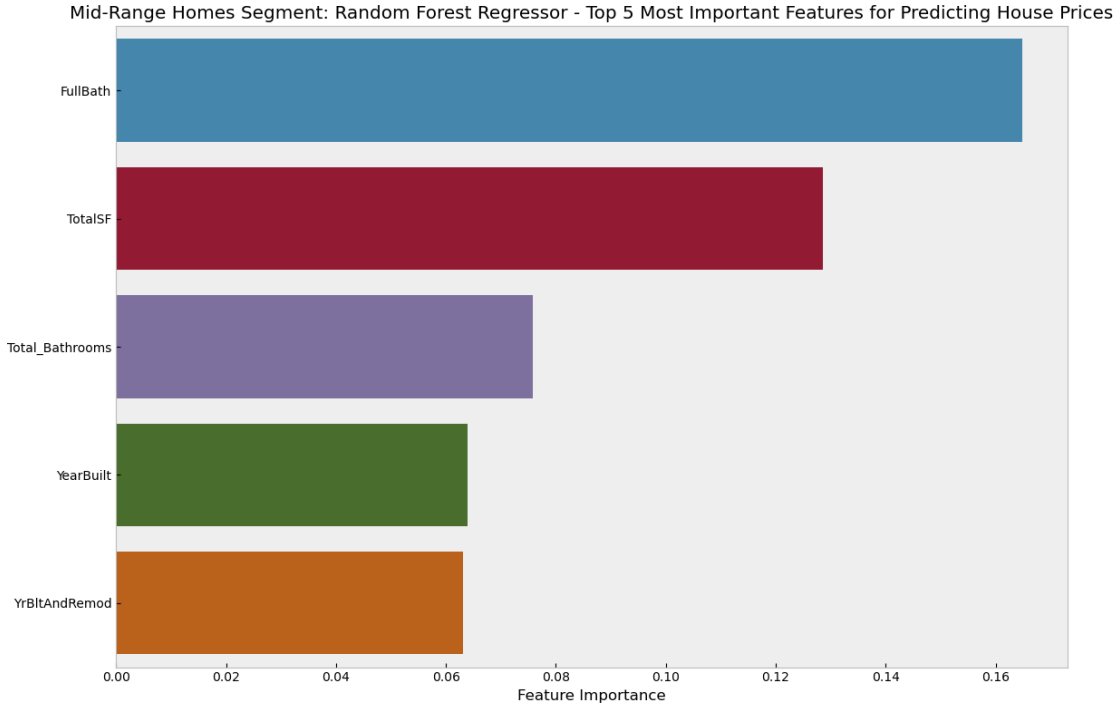
- **House Surface**: Total square footage and above-ground living area are crucial in determining home value.
- **Garage Characteristics**: The size of the garage, the number of cars it can hold, and the year it was built are significant predictors of price.
- **House Age**: The year the house was built and the combined years since any renovations are influential factors.
- **Total Bathrooms**: The total number of bathrooms in the house also significantly predicts price.

Understanding these features helps to focus on what truly matters when evaluating home prices.

1.14.2 Sale Price Predictors for Budget, Mid-Range, and Luxury Homes

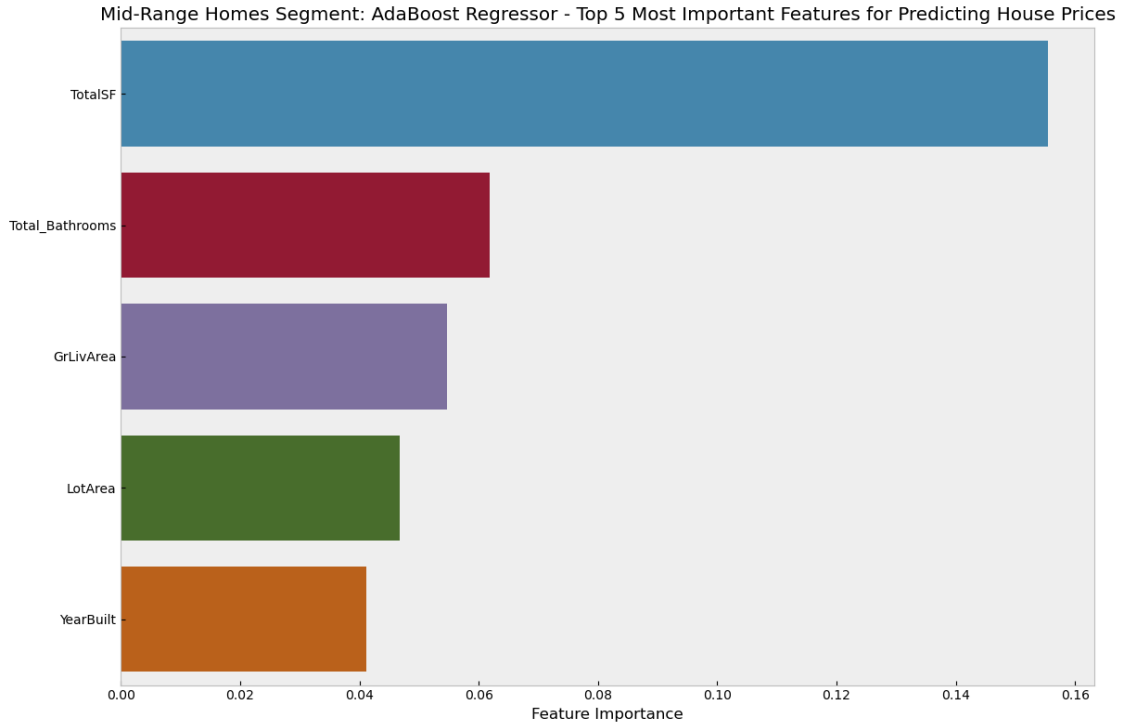
I repeated the analysis for each category to understand the different factors influencing the sale price of homes in the budget, mid-range, and luxury segments. This advanced study reveals the various considerations that buyers might prioritize within each segment.

[ ]:
```
for i in range(optimal_n_components):
    cluster_data = gmm_clustering_data[gmm_clustering_data['Cluster'] == i]
    final_cluster_data = one_hot_encode(cluster_data)
    X_cluster = final_cluster_data.drop(columns=['SalePrice'])
    y_cluster = final_cluster_data['SalePrice']

    random_forest_regressor = RandomForestRegressor(random_state=seed)
    regresor_fit_and_print(f"{cluster_labels[i]}: Random Forest Regressor",␣
↪X_cluster, y_cluster, random_forest_regressor)

    ada_boost_regressor = AdaBoostRegressor(random_state=seed)
    regresor_fit_and_print(f"{cluster_labels[i]}: AdaBoost Regressor",␣
↪X_cluster, y_cluster, ada_boost_regressor)

    decision_tree_regressor = DecisionTreeRegressor(random_state=seed)
    regresor_fit_and_print(f"{cluster_labels[i]}: Decision Tree Regressor",␣
↪X_cluster, y_cluster, decision_tree_regressor)
```

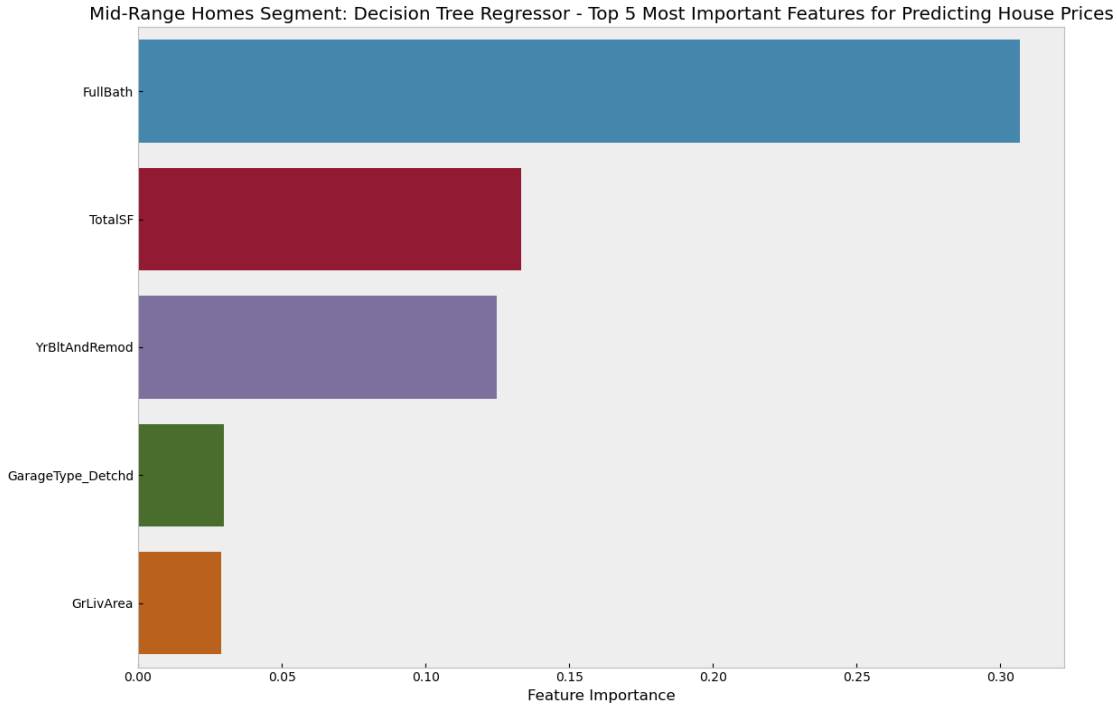


Mid-Range Homes Segment: Random Forest Regressor - Top 5 most important features:

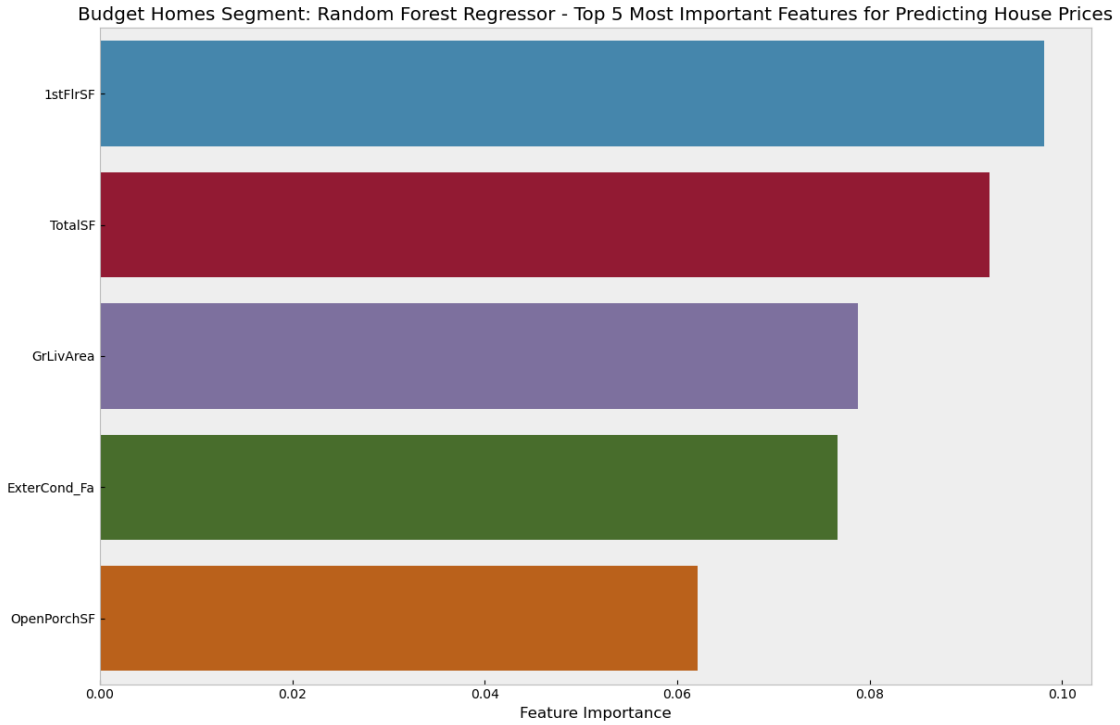
1. FullBath: 0.1648
2. TotalSF: 0.1285
3. Total_Bathrooms: 0.0758
4. YearBuilt: 0.0640
5. YrBltAndRemod: 0.0631



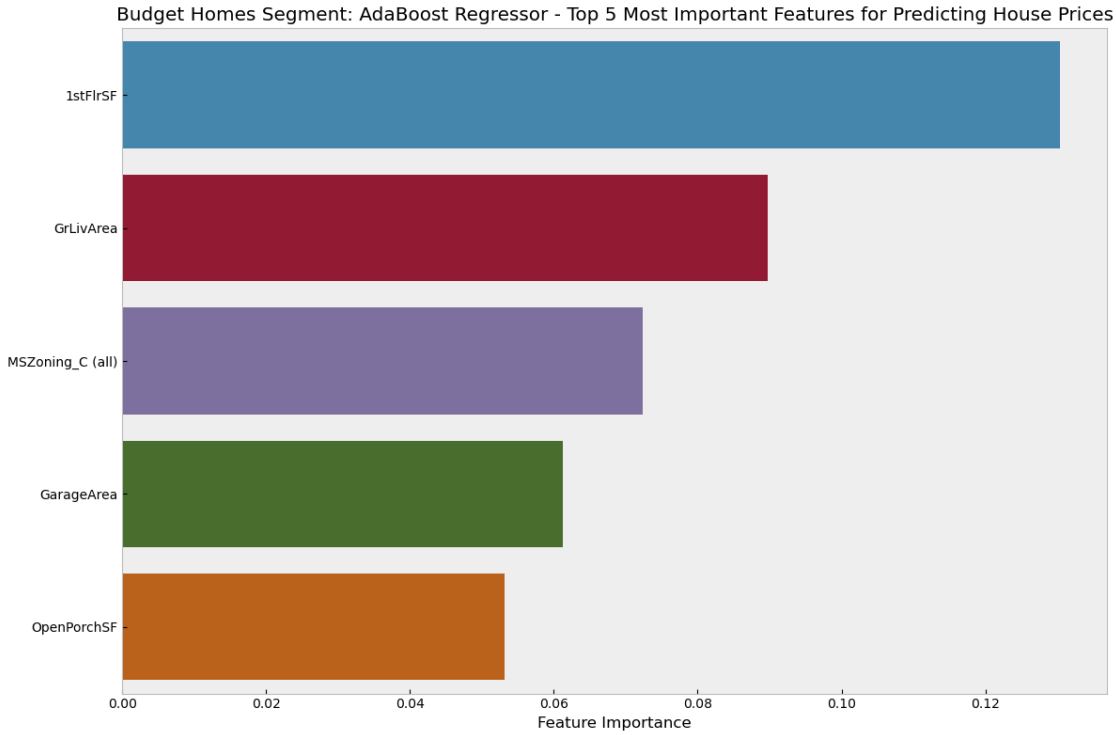

```
Mid-Range Homes Segment: AdaBoost Regressor - Top 5 most important features:
1. TotalSF: 0.1554
2. Total_Bathrooms: 0.0618
3. GrLivArea: 0.0548
4. LotArea: 0.0467
5. YearBuilt: 0.0412
```



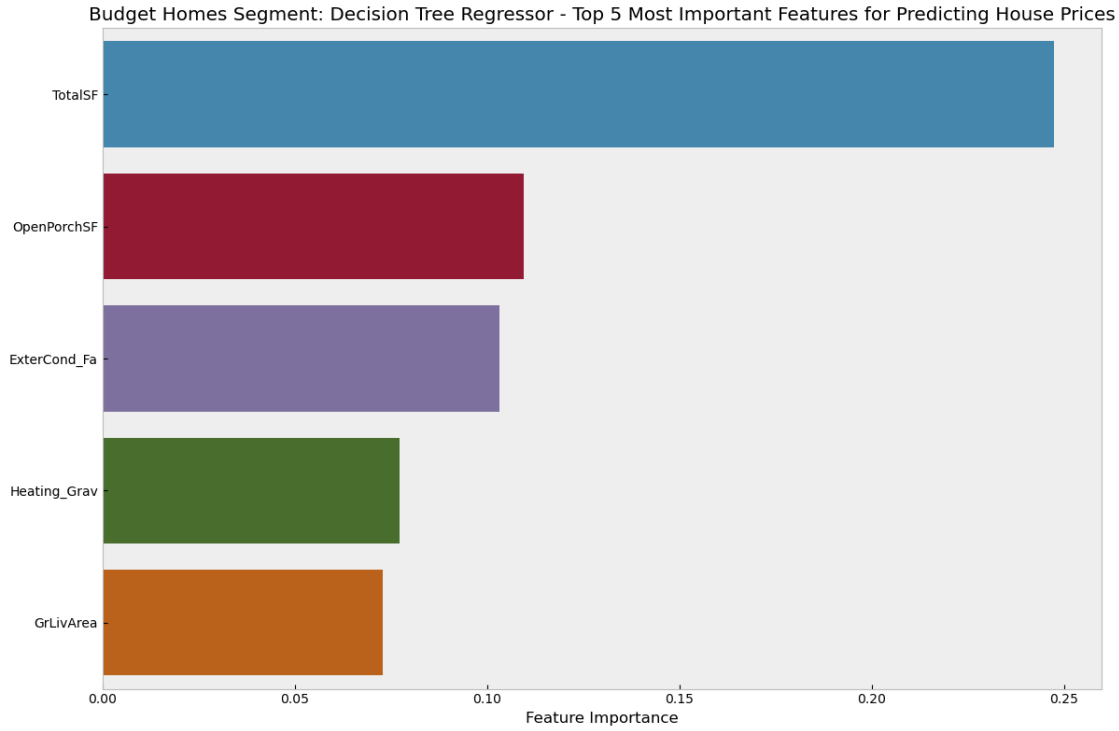

```
Mid-Range Homes Segment: Decision Tree Regressor - Top 5 most important
features:
1. FullBath: 0.3068
2. TotalSF: 0.1332
3. YrBltAndRemod: 0.1247
4. GarageType_Detchd: 0.0299
5. GrLivArea: 0.0290
```



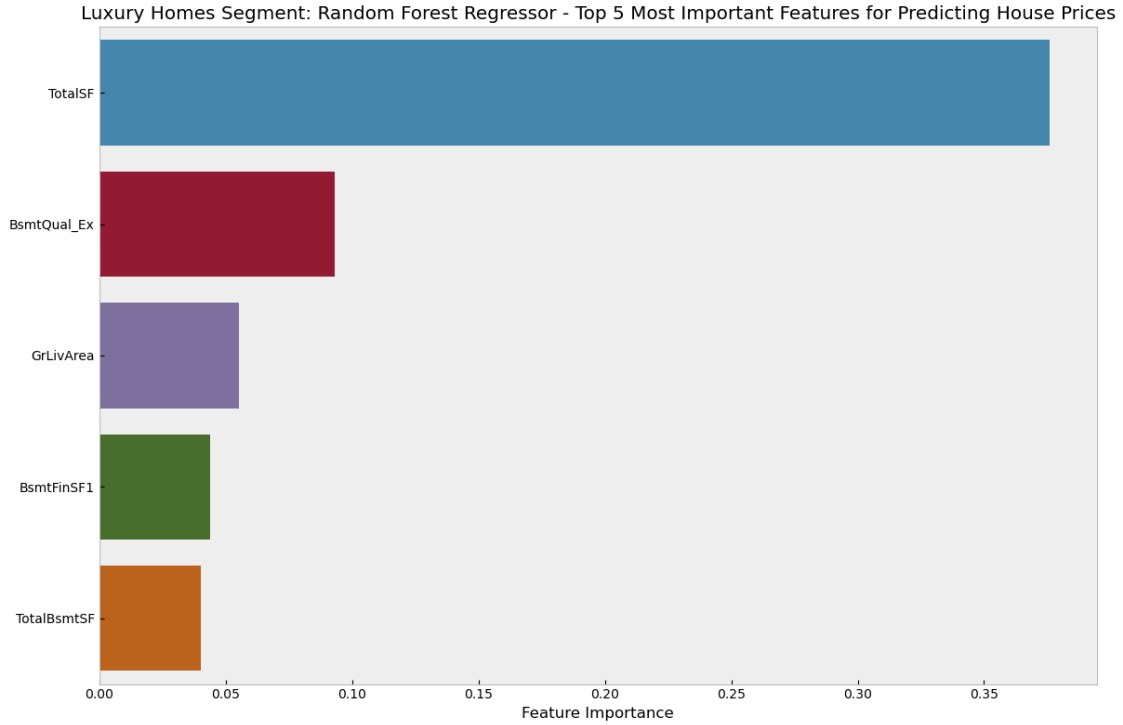

```
Budget Homes Segment: Random Forest Regressor - Top 5 most important features:
1. 1stFlrSF: 0.0982
2. TotalSF: 0.0924
3. GrLivArea: 0.0788
4. ExterCond_Fa: 0.0767
5. OpenPorchSF: 0.0622
```



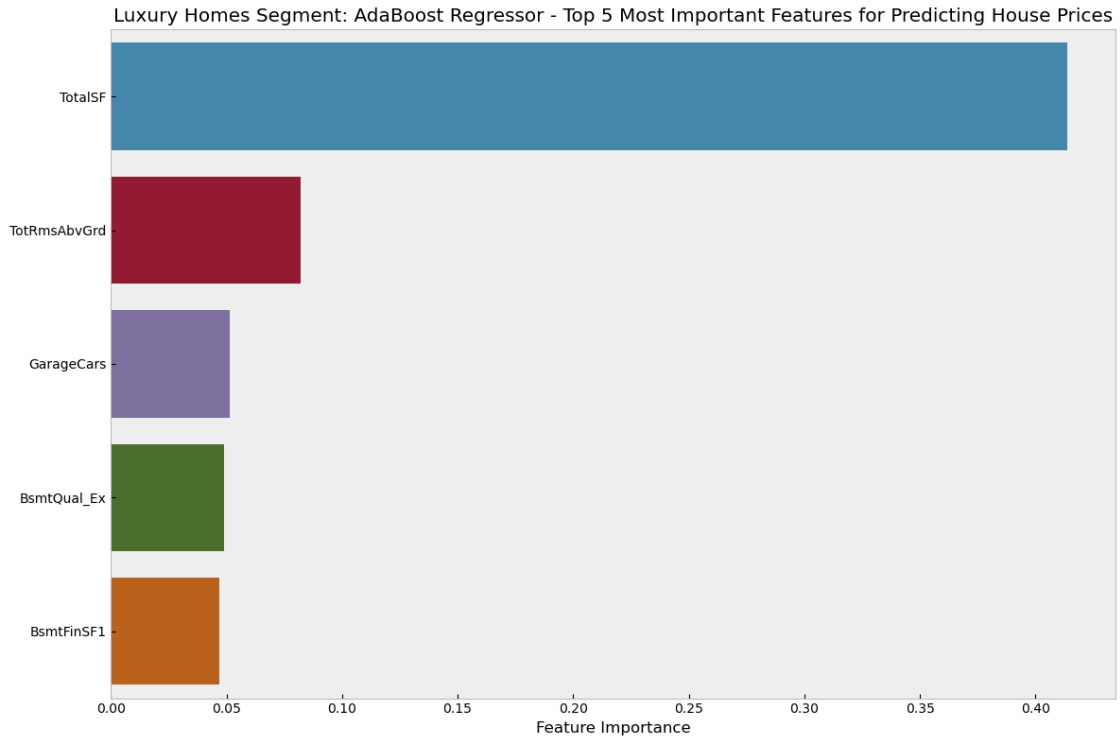

```
Budget Homes Segment: AdaBoost Regressor - Top 5 most important features:
1. 1stFlrSF: 0.1304
2. GrLivArea: 0.0897
3. MSZoning_C (all): 0.0724
4. GarageArea: 0.0612
5. OpenPorchSF: 0.0532
```



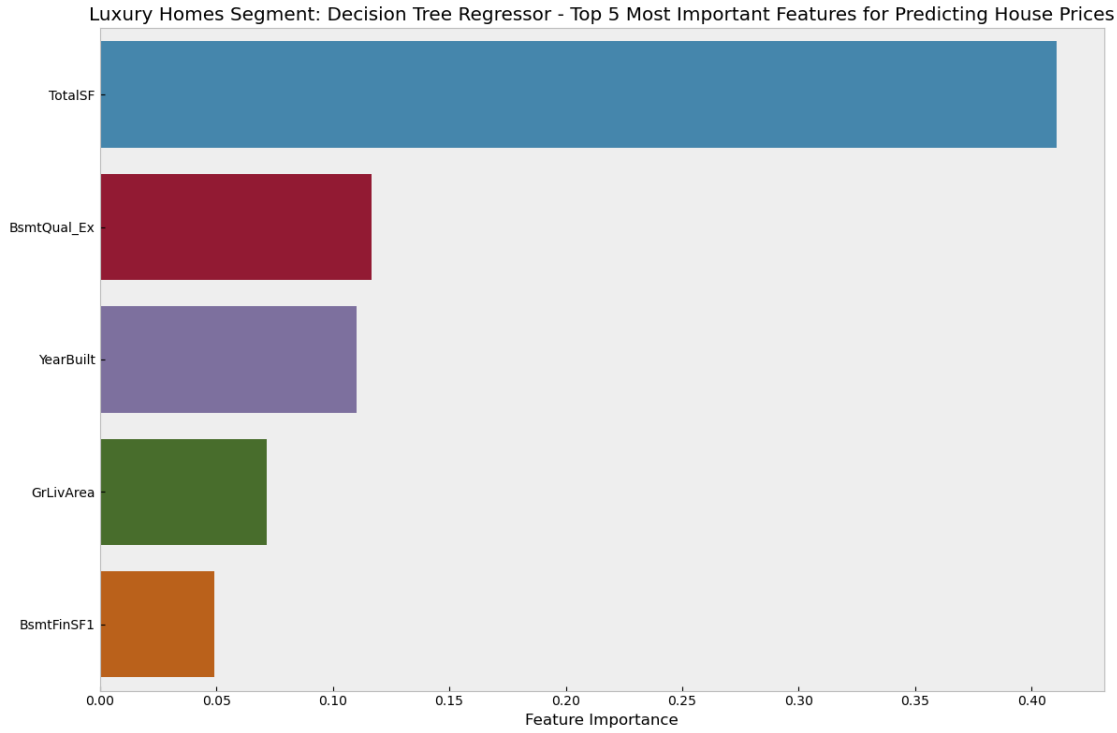

```
Budget Homes Segment: Decision Tree Regressor - Top 5 most important features:
1. TotalSF: 0.2474
2. OpenPorchSF: 0.1096
3. ExterCond_Fa: 0.1031
4. Heating_Grav: 0.0772
5. GrLivArea: 0.0728
```




```
Luxury Homes Segment: Random Forest Regressor - Top 5 most important features:
1. TotalSF: 0.3759
2. BsmtQual_Ex: 0.0930
3. GrLivArea: 0.0551
4. BsmtFinSF1: 0.0438
5. TotalBsmtSF: 0.0403
```




```
Luxury Homes Segment: AdaBoost Regressor - Top 5 most important features:
1. TotalSF: 0.4139
2. TotRmsAbvGrd: 0.0821
3. GarageCars: 0.0514
4. BsmtQual_Ex: 0.0488
5. BsmtFinSF1: 0.0467
```




```
Luxury Homes Segment: Decision Tree Regressor - Top 5 most important features:
1. TotalSF: 0.4106
2. BsmtQual_Ex: 0.1165
3. YearBuilt: 0.1103
4. GrLivArea: 0.0718
5. BsmtFinSF1: 0.0489
```

1.14.3 Conclusions

From the top 5 most essential features for budget, mid-range, and luxury homes, we notice some variables previously identified for the general market. By excluding these general commonalities, we can delve deeper and identify patterns that specifically increase the sale price within each segment. Here are my findings:

- **Luxury Homes Segment**
  - **Livable Basement Finished Surface** (BsmtFinSF1 and TotalBsmtSF) and the height of the basement (BsmtQual). Excellent quality basements (100+ inches) add significant value.
  - **Total Rooms Above Grade**: More rooms (excluding bathrooms) increase the home's value.
- **Mid-Range Homes Segment**
  - **Full Bathrooms Above Grade** (FullBath): More full bathrooms on the main floors significantly impact the sale price.
  - **Detached Garage Location** (GarageType Detchd): Detached garages are valuable in this segment.

- **Budget Homes Segment**:
  - **Open Porch Area** (OpenPorchSF): Larger open porch areas contribute to higher prices.
  - **First Floor Area** (1stFlrSF): A more extensive first-floor area adds value.
  - **Exterior Material Condition** (ExterCond): The condition of the exterior material, mainly if it's excellent or fair, impacts the sale price.

Understanding these specific drivers within each segment helps us better predict and evaluate home prices based on various characteristics and amenities. Further studies could refine these insights and explore additional features influencing housing prices.

1.14.4 Parting Thoughts

What started as a simple assignment for the Udemy Data Scientist Nanodegree Program was an incredible learning journey. I applied various data science techniques, including:

- Setting clear objectives
- Exploring and visualizing data
- Identifying and removing outliers
- Addressing skewed distributions
- Handling missing data
- Normalizing numerical features
- Conducting bivariate analysis
- Extracting insights from the Ames, Iowa housing market

This experience deepened my understanding of the data science workflow and the CRISP-DM process. It answered the initial questions and sparked my curiosity about further exploration in the field.

1.15 LICENSE