House Price Prediction (Regression)

March 18, 2025

1 1. Import Libraries and Dataset

1.1 a. Import Libraries

[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

from scipy.stats import norm
from scipy import stats

import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

1.2 b. Read the Dataset

Data source: https://www.kaggle.com/competitions/house-prices-advanced-regression-techniques/data

[6]:
```
# Read the dataset:
df_train = pd.read_csv('house_train.csv')
df_test = pd.read_csv('house_test.csv')
```

[8]:
```
df_train
```

[8]:
```
          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
…     …          …       …           …        …    …     …       …
1455  1456          60       RL         62.0     7917   Pave   NaN      Reg
1456  1457          20       RL         85.0    13175   Pave   NaN      Reg
1457  1458          70       RL         66.0     9042   Pave   NaN      Reg
```

```
1458  1459          20       RL         68.0     9717   Pave   NaN      Reg
1459  1460          20       RL         75.0     9937   Pave   NaN      Reg

     LandContour Utilities  … PoolArea PoolQC  Fence MiscFeature MiscVal  \
0            Lvl    AllPub  …        0    NaN    NaN         NaN       0
1            Lvl    AllPub  …        0    NaN    NaN         NaN       0
2            Lvl    AllPub  …        0    NaN    NaN         NaN       0
3            Lvl    AllPub  …        0    NaN    NaN         NaN       0
4            Lvl    AllPub  …        0    NaN    NaN         NaN       0
…            …         …  …      …     …     …         …       …
1455         Lvl    AllPub  …        0    NaN    NaN         NaN       0
1456         Lvl    AllPub  …        0    NaN  MnPrv         NaN       0
1457         Lvl    AllPub  …        0    NaN  GdPrv        Shed    2500
1458         Lvl    AllPub  …        0    NaN    NaN         NaN       0
1459         Lvl    AllPub  …        0    NaN    NaN         NaN       0

     MoSold YrSold  SaleType  SaleCondition  SalePrice
0         2   2008        WD         Normal     208500
1         5   2007        WD         Normal     181500
2         9   2008        WD         Normal     223500
3         2   2006        WD        Abnorml     140000
4        12   2008        WD         Normal     250000
…       …      …         …            …          …
1455      8   2007        WD         Normal     175000
1456      2   2010        WD         Normal     210000
1457      5   2010        WD         Normal     266500
1458      4   2010        WD         Normal     142125
1459      6   2008        WD         Normal     147500

[1460 rows x 81 columns]
```

[10]:
```
df_test
```

[10]:
```
        Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0     1461          20       RH         80.0    11622   Pave   NaN      Reg
1     1462          20       RL         81.0    14267   Pave   NaN      IR1
2     1463          60       RL         74.0    13830   Pave   NaN      IR1
3     1464          60       RL         78.0     9978   Pave   NaN      IR1
4     1465         120       RL         43.0     5005   Pave   NaN      IR1
…     …          …      …          …      …     …   …      …
1454  2915         160       RM         21.0     1936   Pave   NaN      Reg
1455  2916         160       RM         21.0     1894   Pave   NaN      Reg
1456  2917          20       RL        160.0    20000   Pave   NaN      Reg
1457  2918          85       RL         62.0    10441   Pave   NaN      Reg
1458  2919          60       RL         74.0     9627   Pave   NaN      Reg

     LandContour Utilities  … ScreenPorch PoolArea PoolQC  Fence  \
```

```
0             Lvl    AllPub  …         120         0    NaN  MnPrv
1             Lvl    AllPub  …           0         0    NaN    NaN
2             Lvl    AllPub  …           0         0    NaN  MnPrv
3             Lvl    AllPub  …           0         0    NaN    NaN
4             HLS    AllPub  …         144         0    NaN    NaN
…          …       …   …         …       …     …     …
1454          Lvl    AllPub  …           0         0    NaN    NaN
1455          Lvl    AllPub  …           0         0    NaN    NaN
1456          Lvl    AllPub  …           0         0    NaN    NaN
1457          Lvl    AllPub  …           0         0    NaN  MnPrv
1458          Lvl    AllPub  …           0         0    NaN    NaN

     MiscFeature MiscVal MoSold  YrSold  SaleType  SaleCondition
0            NaN       0      6    2010        WD         Normal
1           Gar2   12500      6    2010        WD         Normal
2            NaN       0      3    2010        WD         Normal
3            NaN       0      6    2010        WD         Normal
4            NaN       0      1    2010        WD         Normal
…          …     …     …     …      …           …
1454         NaN       0      6    2006        WD         Normal
1455         NaN       0      4    2006        WD        Abnorml
1456         NaN       0      9    2006        WD        Abnorml
1457        Shed     700      7    2006        WD         Normal
1458         NaN       0     11    2006        WD         Normal

[1459 rows x 80 columns]
```

1.3 c. Selecting Important columns on the Dataframe

[13]:
```python
print(df_train.columns)
```

```
Index(['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')
```

[15]:
```
# Selecting the important columns from two DataFrames:
df_train = df_train[['LotArea', 'YearBuilt', 'OverallQual', 'OverallCond',␣
 ↪'RoofMatl', 'ExterQual', 'BedroomAbvGr', 'GrLivArea', 'MiscFeature',␣
 ↪'GarageArea', 'KitchenQual', 'SaleCondition', 'SalePrice']]
df_test = df_test[['LotArea', 'YearBuilt', 'OverallQual', 'OverallCond',␣
 ↪'RoofMatl', 'ExterQual', 'BedroomAbvGr', 'GrLivArea', 'MiscFeature',␣
 ↪'GarageArea', 'KitchenQual', 'SaleCondition']]
```

[17]:
```
df_train
```

[17]:
```
      LotArea  YearBuilt  OverallQual  OverallCond RoofMatl ExterQual  \
0        8450       2003            7            5  CompShg        Gd
1        9600       1976            6            8  CompShg        TA
2       11250       2001            7            5  CompShg        Gd
3        9550       1915            7            5  CompShg        TA
4       14260       2000            8            5  CompShg        Gd
…         …          …           …           …       …         …
1455     7917       1999            6            5  CompShg        TA
1456    13175       1978            6            6  CompShg        TA
1457     9042       1941            7            9  CompShg        Ex
1458     9717       1950            5            6  CompShg        TA
1459     9937       1965            5            6  CompShg        Gd

      BedroomAbvGr  GrLivArea MiscFeature  GarageArea KitchenQual  \
0                3       1710         NaN         548          Gd
1                3       1262         NaN         460          TA
2                3       1786         NaN         608          Gd
3                3       1717         NaN         642          Gd
4                4       2198         NaN         836          Gd
…              …          …           …           …           …
1455             3       1647         NaN         460          TA
1456             3       2073         NaN         500          TA
1457             4       2340        Shed         252          Gd
1458             2       1078         NaN         240          Gd
1459             3       1256         NaN         276          TA

     SaleCondition  SalePrice
0           Normal     208500
1           Normal     181500
2           Normal     223500
3          Abnorml     140000
4           Normal     250000
…              …          …
1455        Normal     175000
```

```
1456         Normal     210000
1457         Normal     266500
1458         Normal     142125
1459         Normal     147500

[1460 rows x 13 columns]
```

2 2. Exploratory Data Analysis (EDA) for Train Set

2.1 a. Check Dataset Information

[21]:
```python
# Check data information:
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 13 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   LotArea        1460 non-null   int64
 1   YearBuilt      1460 non-null   int64
 2   OverallQual    1460 non-null   int64
 3   OverallCond    1460 non-null   int64
 4   RoofMatl       1460 non-null   object
 5   ExterQual      1460 non-null   object
 6   BedroomAbvGr   1460 non-null   int64
 7   GrLivArea      1460 non-null   int64
 8   MiscFeature    54 non-null     object
 9   GarageArea     1460 non-null   int64
 10  KitchenQual    1460 non-null   object
 11  SaleCondition  1460 non-null   object
 12  SalePrice      1460 non-null   int64
dtypes: int64(8), object(5)
memory usage: 148.4+ KB
```

- There is missing value on MiscFeature

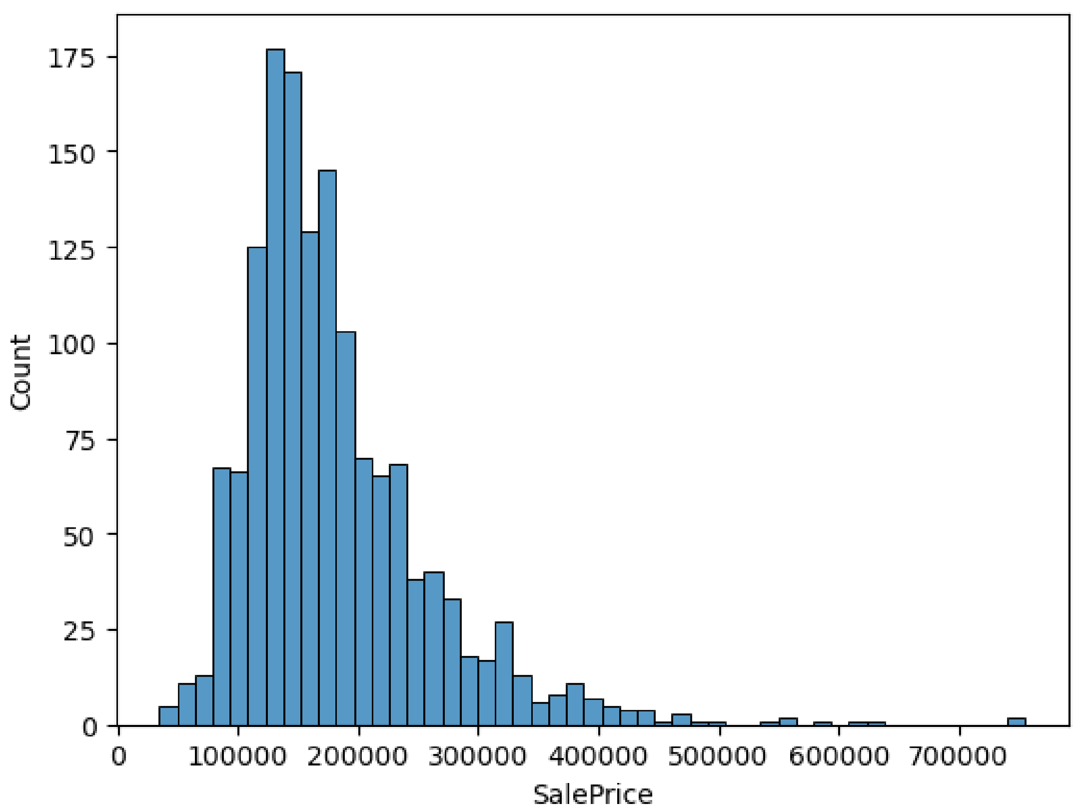
[24]:
```python
# Check data statistical summary:
df_train.describe()
```

[24]:
```
            LotArea    YearBuilt  OverallQual  OverallCond  BedroomAbvGr  \
count   1460.000000  1460.000000  1460.000000  1460.000000   1460.000000
mean   10516.828082  1971.267808     6.099315     5.575342      2.866438
std     9981.264932    30.202904     1.382997     1.112799      0.815778
min     1300.000000  1872.000000     1.000000     1.000000      0.000000
25%     7553.500000  1954.000000     5.000000     5.000000      2.000000
50%     9478.500000  1973.000000     6.000000     5.000000      3.000000
```

```
75%     11601.500000  2000.000000     7.000000     6.000000      3.000000
max    215245.000000  2010.000000    10.000000     9.000000      8.000000

         GrLivArea   GarageArea      SalePrice
count  1460.000000  1460.000000    1460.000000
mean   1515.463699   472.980137  180921.195890
std     525.480383   213.804841   79442.502883
min     334.000000     0.000000   34900.000000
25%    1129.500000   334.500000  129975.000000
50%    1464.000000   480.000000  163000.000000
75%    1776.750000   576.000000  214000.000000
max    5642.000000  1418.000000  755000.000000
```

2.2 b. Histogram of Target Variable (Sale Price)

[27]:
```python
# Show distribution of "SalePrice" column:
sns.histplot(df_train['SalePrice'])
plt.show()
```



- The sale prices is not normally distributed.
- The data appears to be skewed (positively/negatively) and may contain outliers.

- This suggests that the sale prices are not evenly distributed around the mean, which could impact statistical analyses that assume normality. So, preprocessing is needed before further analysis.

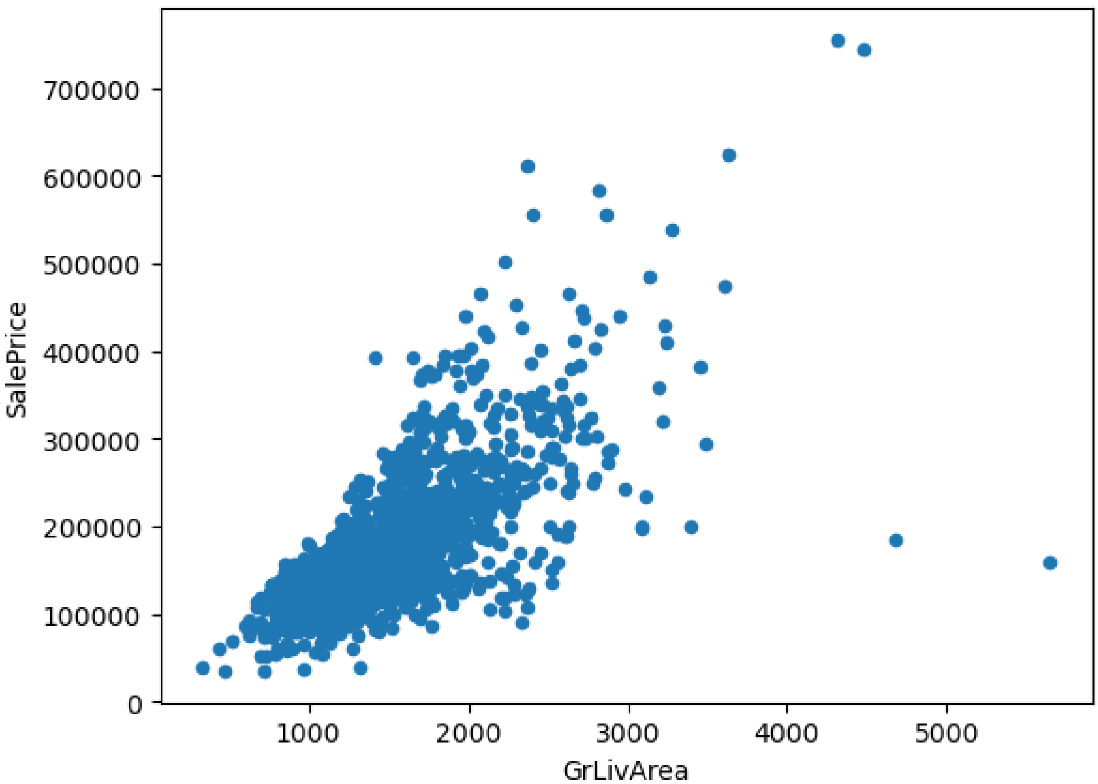
[29]:
```
# Calculate skewness and kurtosis values:
# Skewness: a statistical measure used to assess how much the data distribution
↪is skewed or asymmetric
# Kurtosis: a statistical measure used to assess how much the data distribution
↪has long tails (outliers) and a sharp peak (peakedness) compared to a normal
↪distribution (Gaussian distribution or bell-shaped distribution)

print (f"Skewness: {df_train['SalePrice'].skew()}")
print (f"Kurtosis: {df_train['SalePrice'].kurt()}")
```

```
Skewness: 1.8828757597682129
Kurtosis: 6.536281860064529
```

- The skewness value of 1.88 suggests that the data is positively skewed (right-skewed). This means that most of the sale prices are clustered towards the lower end, with a few higher-priced outliers.
- In other words, there are more lower-priced properties, and fewer high-priced properties that stretch the distribution to the right.
- The kurtosis value of 6.54 is significantly greater than 3 (which represents a normal distribution's kurtosis). This indicates that the distribution has heavy tails and a sharper peak, which means there are outliers or extreme values present in your data.

2.3 c. Scatter Plot of GrLivArea vs Target Variable (Sale Price)

[34]:
```
df_train.plot.scatter(x='GrLivArea', y='SalePrice')
plt.show()
```



- The larger the area, the price tends to be the higher .
- There is an anomaly where large areas have low prices.

[37]:
```python
# Check the data anomaly:

df_train[(df_train['GrLivArea'] > 4000) & (df_train['SalePrice'] < 200000) |
        ((df_train['GrLivArea'] > 4000) & (df_train['SalePrice'] > 700000))]
```

[37]:

	LotArea	YearBuilt	OverallQual	OverallCond	RoofMatl	ExterQual	\
523	40094	2007	10	5	CompShg	Ex	
691	21535	1994	10	6	WdShngl	Ex	
1182	15623	1996	10	5	CompShg	Gd	
1298	63887	2008	10	5	ClyTile	Ex	

	BedroomAbvGr	GrLivArea	MiscFeature	GarageArea	KitchenQual	\
523	3	4676	NaN	884	Ex	
691	4	4316	NaN	832	Ex	
1182	4	4476	NaN	813	Ex	
1298	3	5642	NaN	1418	Ex	

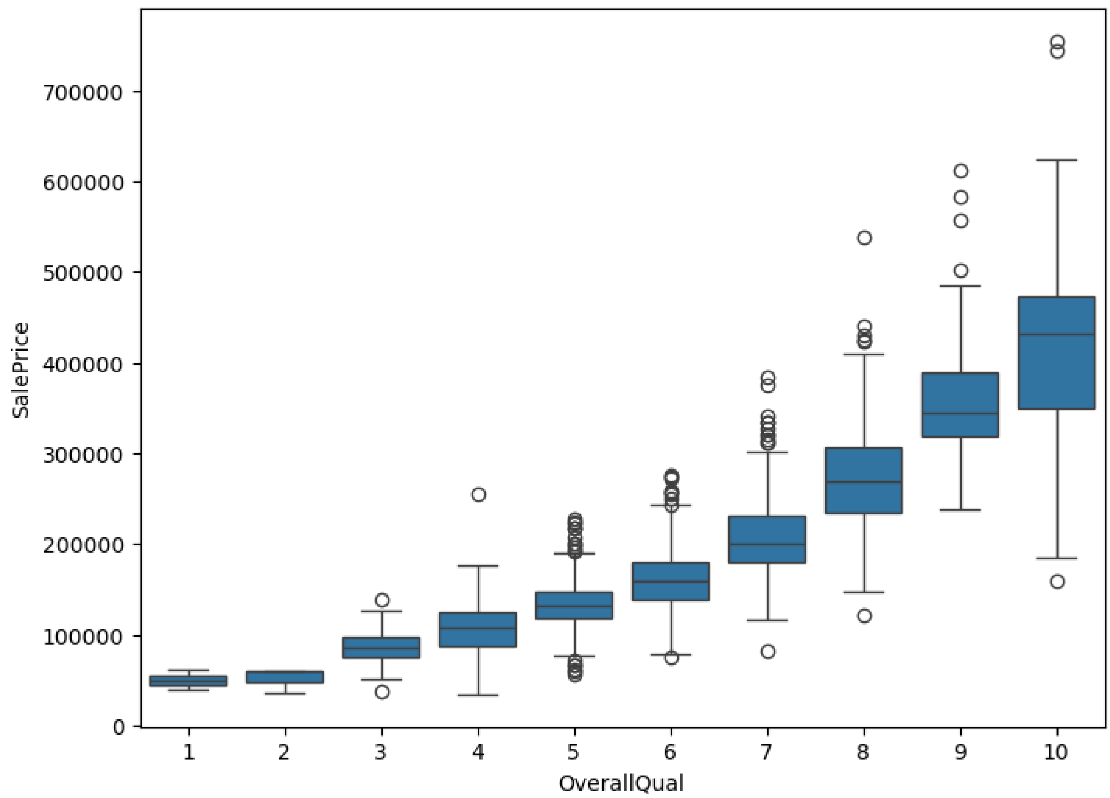
	SaleCondition	SalePrice
523	Partial	184750

```
691         Normal     755000
1182       Abnorml     745000
1298       Partial     160000
```

- There are two houses with exceptionally high selling prices (over 700,000) and two with very low selling prices (under 200,000), all having a GrLivArea of more than 4,000.
- Interestingly, the houses sold at very low prices are actually larger (around 4,600 and 5,600 square feet). Upon closer inspection, the low-priced houses were sold under a partial sale condition, suggesting they were likely unfinished.
- In contrast, the high-priced house has a smaller area than the other two, possibly due to other factors such as house quality or location influencing the price.

2.4 d. Boxplot of OverallQual vs Target Variable (Sale Price)

[41]:
```
data = pd.concat([df_train['SalePrice'], df_train['OverallQual']], axis=1)
f, ax = plt.subplots(figsize=(8, 6))
fig = sns.boxplot(x='OverallQual', y="SalePrice", data=data)
plt.show()
```



- As the OverallQual (represents the overall quality of the house) increases, the SalePrice also tends to increase.

- There are several outliers, particularly for high-quality houses (OverallQual of 9 and 10). For OverallQual = 10, there is an extreme outlier with a SalePrice exceeding 700,000 or under 200,000.

[43]:
```
# Check the anomaly or outliers:

df_train[((df_train['OverallQual'] == 10) & (df_train['SalePrice'] < 200000)) |
         ((df_train['OverallQual'] == 10) & (df_train['SalePrice'] > 700000))]
```

[43]:
```
      LotArea  YearBuilt  OverallQual  OverallCond RoofMatl ExterQual  \
523     40094       2007           10            5  CompShg        Ex
691     21535       1994           10            6  WdShngl        Ex
1182    15623       1996           10            5  CompShg        Gd
1298    63887       2008           10            5  ClyTile        Ex

      BedroomAbvGr  GrLivArea MiscFeature  GarageArea KitchenQual  \
523              3       4676         NaN         884          Ex
691              4       4316         NaN         832          Ex
1182             4       4476         NaN         813          Ex
1298             3       5642         NaN        1418          Ex

     SaleCondition  SalePrice
523        Partial     184750
691         Normal     755000
1182       Abnorml     745000
1298       Partial     160000
```

- Houses with high OverallQual but low Sale Price (< 200,000) is houses with a partial sale condition, where the house is likely to be sold before completion and still under construction (unfinished work)
- Two other houses have high OverallQual and very high prices (>700,000): One of the houses was sold in normal conditions with an overall condition rating of 6 and features a high-quality luxury roof made of wood, which is aesthetic and eco-friendly, making it expensive. Meanwhile, the other house was sold under an abnormal sale condition, suggesting that it could be a luxury property or possess unique high-end features.

2.5 e. Boxplot of YearBuilt vs Target Variable (Sale Price)

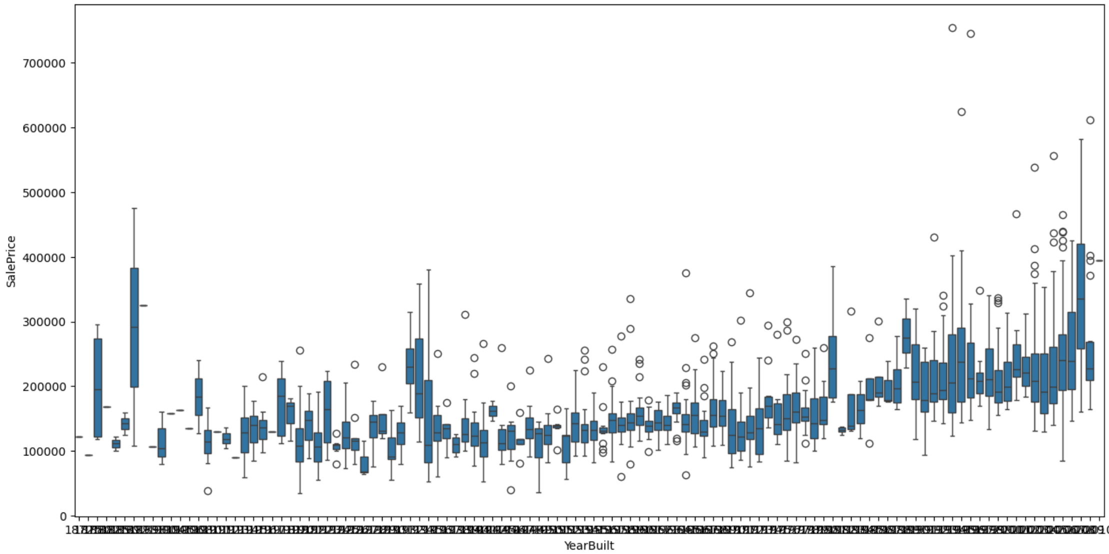
[48]:
```
print(df_train['YearBuilt'].min(), df_train['YearBuilt'].max())
```

```
1872 2010
```

The oldest house was built in 1872, while the newest one was built in 2010.

[51]:
```
# Check whether there is a correlation between the year of manufacture and the␣
↪sale price:

data = pd.concat([df_train['SalePrice'], df_train['YearBuilt']], axis=1)
```

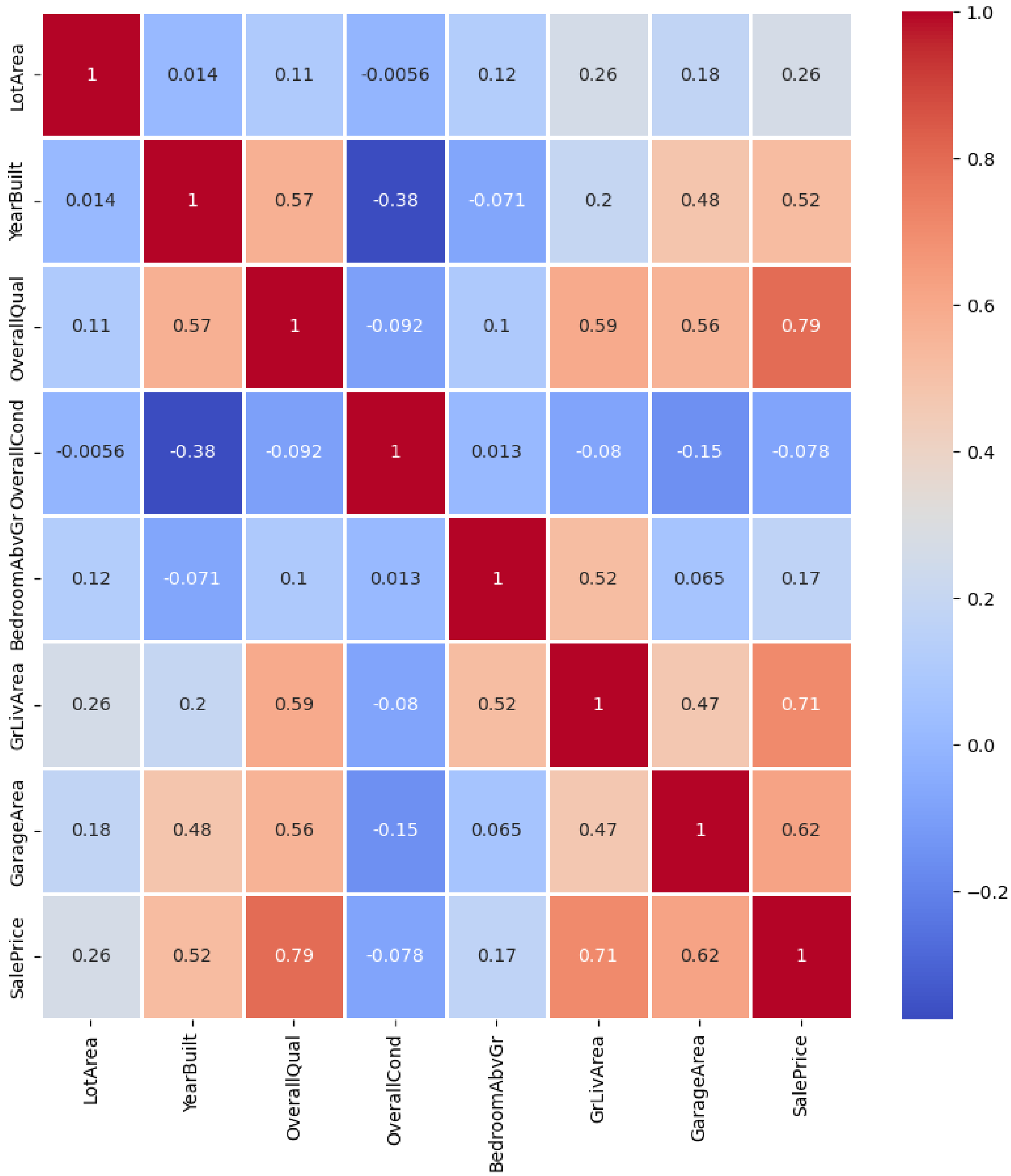
```
f, ax = plt.subplots(figsize=(16, 8))
fig = sns.boxplot(x='YearBuilt', y='SalePrice', data=data)
plt.show()
```



There is no correlation between the year a house was built (Year Built) and Sale Price.

2.6 f. Correlation among Variables

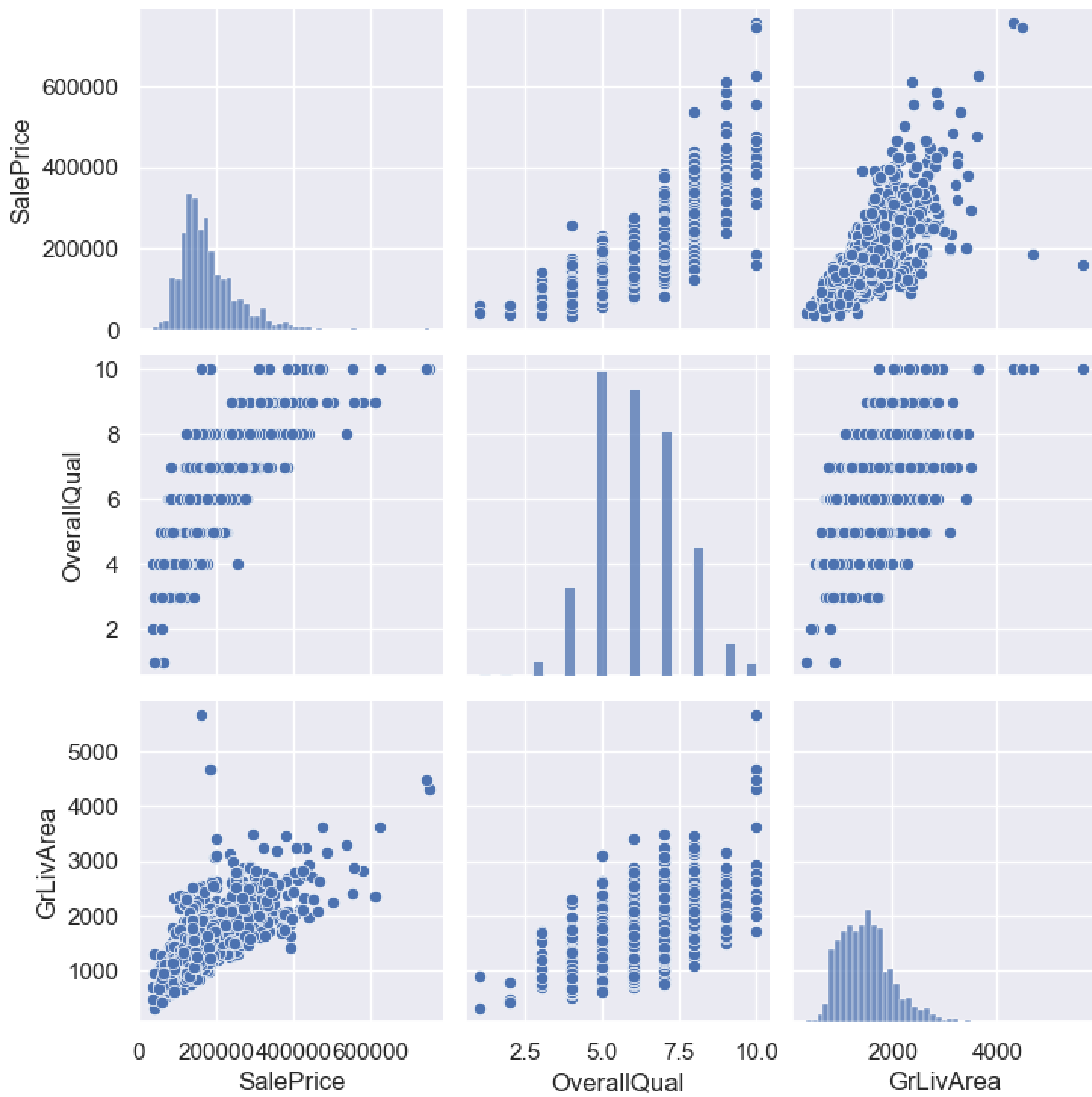
[54]:
```
# Correlation map among variables:

plt.figure(figsize=(10,10))
ax = sns.heatmap(df_train.select_dtypes(exclude = 'object').corr(), cmap =␣
 ↪'coolwarm', annot=True, linewidth=2)
plt.show()
```



Insight: There is a positive correlation between Overall Quality (0.79) or GrLiving Area (0.71) and Sale Price.

[56]:
```
# Pairplot between three variables:

sns.set()
cols = ['SalePrice', 'OverallQual', 'GrLivArea']
sns.pairplot(df_train[cols], size = 2.5)
```

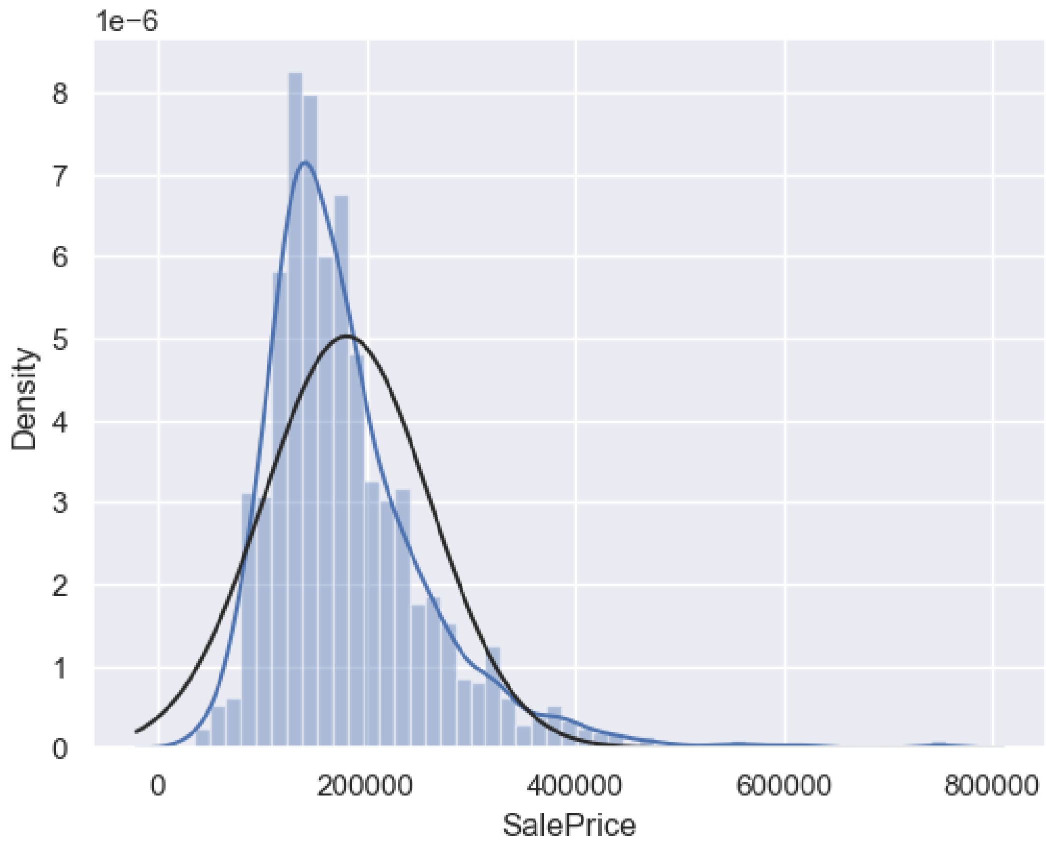
```
plt.show()
```



- Strong positive correlation between Sale Price and Overall Quality and GrLiving Area.
- Moderate correlation between Overall Quality and GrLiving Area: higher quality houses tend to be larger, but size is not the only factor.
- Sale Price and GrLiving Area are right-skewed distributions.

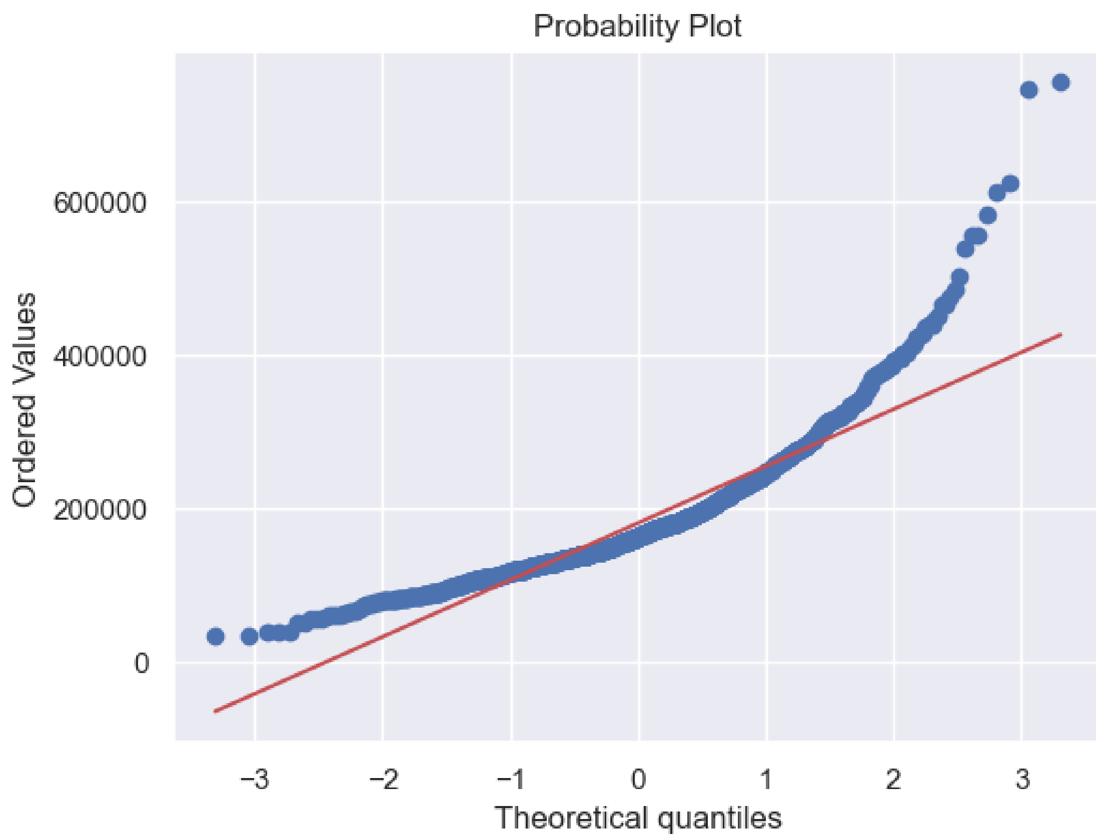
2.7 g. Distribution of Target Variable (SalePrice column)

[59]:
```
sns.distplot(df_train['SalePrice'], fit = norm)
plt.show()
```



The sale prices is not normally distributed. So, preprocessing (transformation) is needed before further analysis.

[62]:
```
# Re-check the SalePrice using QQ-plot (Quantile-Quantile plot) whether the␣
 ↪data follows a normal distribution:
fig = plt.figure()
res = stats.probplot(df_train['SalePrice'], plot=plt)
plt.show()
```



- The SalePrice is NOT normally distributed and is right-skewed with high-priced outliers.

- Log transformation can be applied to reduce this skewness.

3 3. Data Preprocessing

3.1 a. Log Transformation for Target Variable (Sale Price)

[67]:
```
df_train_tf = df_train.copy()      #copy the original dataframe
```

[68]:
```
# Before applying the transformation to the entire dataset, we first test it on
 ↪two data points, one of which is an outlier:

# Before transformation:
print(755000 - 180000)

print("")

# After transformation:
print(np.log1p(755000))
```

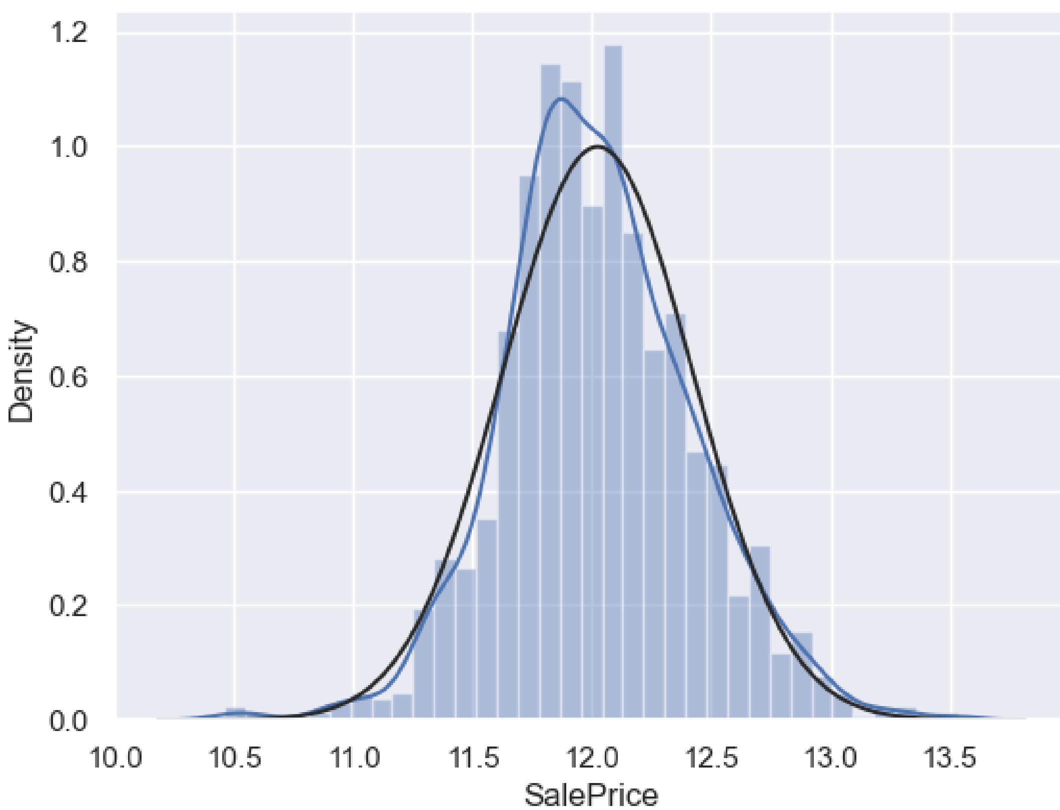
```
print(np.log1p(180000))

print("")
print(np.log1p(755000) - np.log1p(180000))
```

```
575000

13.534474352733596
12.100717685412471

1.4337566673211253
```

- The difference between the two saleprices before the transformation is 575,000 (LARGE).
- The difference between the two saleprices after the transformation is 1.44 (SMALL).

[70]:
```
# Apply Log Transformation to SalePrice column:
df_train_tf['SalePrice'] = np.log1p(df_train['SalePrice'])
```

[71]:
```
# Re-check the distribution:
sns.distplot(df_train_tf['SalePrice'], fit = norm)
plt.show()
```



This confirms that the transformation effectively made SalePrice more normally distributed. Statistical models and machine learning algorithms typically perform better when the data follows a normal distribution.

3.2 b. Merge Train and Test Data

[74]:
```
ntrain = df_train_tf.shape[0]
ntest = df_test.shape[0]
y_train = df_train_tf.SalePrice.values
all_data = pd.concat((df_train_tf, df_test)).reset_index(drop=True)
all_data.drop(['SalePrice'], axis=1, inplace=True)
print("all_data size is : {}".format(all_data.shape))
```

```
all_data size is : (2919, 12)
```

[75]:
```
all_data
```

[75]:
```
      LotArea  YearBuilt  OverallQual  OverallCond RoofMatl ExterQual  \
0        8450       2003            7            5  CompShg        Gd
1        9600       1976            6            8  CompShg        TA
2       11250       2001            7            5  CompShg        Gd
3        9550       1915            7            5  CompShg        TA
4       14260       2000            8            5  CompShg        Gd
…         …          …           …           …       …        …
2914     1936       1970            4            7  CompShg        TA
2915     1894       1970            4            5  CompShg        TA
2916    20000       1960            5            7  CompShg        TA
2917    10441       1992            5            5  CompShg        TA
2918     9627       1993            7            5  CompShg        TA

      BedroomAbvGr  GrLivArea MiscFeature  GarageArea KitchenQual  \
0                3       1710         NaN       548.0          Gd
1                3       1262         NaN       460.0          TA
2                3       1786         NaN       608.0          Gd
3                3       1717         NaN       642.0          Gd
4                4       2198         NaN       836.0          Gd
…               …          …           …           …          …
2914             3       1092         NaN         0.0          TA
2915             3       1092         NaN       286.0          TA
2916             4       1224         NaN       576.0          TA
2917             3        970        Shed         0.0          TA
2918             3       2000         NaN       650.0          TA

     SaleCondition
0           Normal
1           Normal
2           Normal
```

```
3          Abnorml
4           Normal
…             …
2914        Normal
2915       Abnorml
2916       Abnorml
2917        Normal
2918        Normal

[2919 rows x 12 columns]
```

[76]:
```
all_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2919 entries, 0 to 2918
Data columns (total 12 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   LotArea        2919 non-null   int64
 1   YearBuilt      2919 non-null   int64
 2   OverallQual    2919 non-null   int64
 3   OverallCond    2919 non-null   int64
 4   RoofMatl       2919 non-null   object
 5   ExterQual      2919 non-null   object
 6   BedroomAbvGr   2919 non-null   int64
 7   GrLivArea      2919 non-null   int64
 8   MiscFeature    105 non-null    object
 9   GarageArea     2918 non-null   float64
 10  KitchenQual    2918 non-null   object
 11  SaleCondition  2919 non-null   object
dtypes: float64(1), int64(6), object(5)
memory usage: 273.8+ KB
```

There are three columns that have missing values: MiscFeature, GarageArea, and KitchenQual.

3.3 c. Handling Missing Value Analysis and Imputation

[79]:
```
# Check the proportion of missing value in the dataset:
total = all_data.isnull().sum().sort_values(ascending=False)
percent = (all_data.isnull().sum()/all_data.isnull().count() * 100).
↪sort_values(ascending=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
missing_data
```

[79]:
```
               Total    Percent
MiscFeature     2814  96.402878
GarageArea         1   0.034258
```

```
KitchenQual        1    0.034258
LotArea            0    0.000000
YearBuilt          0    0.000000
OverallQual        0    0.000000
OverallCond        0    0.000000
RoofMatl           0    0.000000
ExterQual          0    0.000000
BedroomAbvGr       0    0.000000
GrLivArea          0    0.000000
SaleCondition      0    0.000000
```

- Miscfeature has 2814 missing values.
- Garage Area and Kitchen Quality have 1 missing value.

3.3.1 MiscFeature column

[83]:
```python
# Count each unique value in MiscFeature column:
all_data['MiscFeature'].value_counts()
```

[83]:
```
MiscFeature
Shed    95
Gar2     5
Othr     4
TenC     1
Name: count, dtype: int64
```

[85]:
```python
# The rows with null values are filled with "NA":
all_data['MiscFeature'] = all_data['MiscFeature'].fillna('NA')
```

3.3.2 GarageArea column

[89]:
```python
all_data['GarageArea'].value_counts()
```

[89]:
```
GarageArea
0.0       157
576.0      97
440.0      96
240.0      69
484.0      68
         …
872.0       1
923.0       1
192.0       1
1025.0      1
272.0       1
Name: count, Length: 603, dtype: int64
```

[92]:
```python
# The rows with null values are filled with 0 (No Garage):
all_data['GarageArea'] = all_data['GarageArea'].fillna(0)
```

3.3.3 KitchenQual column

[95]:
```python
all_data['KitchenQual'].value_counts()
```

[95]:
```
KitchenQual
TA    1492
Gd    1151
Ex     205
Fa      70
Name: count, dtype: int64
```

[100]:
```python
# The rows with null values are filled with mode (the most frequently occurring␣
↪value):
all_data['KitchenQual'] = all_data['KitchenQual'].
↪fillna(all_data['KitchenQual'].mode()[0])
```

[103]:
```python
# Check the remaining missing values (if any):
all_data_na = (all_data.isnull().sum() / len(all_data)) * 100
all_data_na = all_data_na.drop(all_data_na[all_data_na == 0].index).
↪sort_values(ascending=False)
missing_data = pd.DataFrame({'Missing Ratio' :all_data_na})
missing_data.head()
```

[103]:
```
Empty DataFrame
Columns: [Missing Ratio]
Index: []
```

[106]:
```python
all_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2919 entries, 0 to 2918
Data columns (total 12 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   LotArea       2919 non-null   int64
 1   YearBuilt     2919 non-null   int64
 2   OverallQual   2919 non-null   int64
 3   OverallCond   2919 non-null   int64
 4   RoofMatl      2919 non-null   object
 5   ExterQual     2919 non-null   object
 6   BedroomAbvGr  2919 non-null   int64
 7   GrLivArea     2919 non-null   int64
 8   MiscFeature   2919 non-null   object
 9   GarageArea    2919 non-null   float64
```

```
 10  KitchenQual    2919 non-null   object
 11  SaleCondition  2919 non-null   object
dtypes: float64(1), int64(6), object(5)
memory usage: 273.8+ KB
```

There is no missing value. All data is complete.

3.4 d. Change the Categorical Data Type

[113]:
```python
# Change the data type to string:
all_data['OverallQual'] = all_data['OverallQual'].astype(str)
all_data['OverallCond'] = all_data['OverallCond'].astype(str)
```

[115]:
```python
all_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2919 entries, 0 to 2918
Data columns (total 12 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   LotArea        2919 non-null   int64
 1   YearBuilt      2919 non-null   int64
 2   OverallQual    2919 non-null   object
 3   OverallCond    2919 non-null   object
 4   RoofMatl       2919 non-null   object
 5   ExterQual      2919 non-null   object
 6   BedroomAbvGr   2919 non-null   int64
 7   GrLivArea      2919 non-null   int64
 8   MiscFeature    2919 non-null   object
 9   GarageArea     2919 non-null   float64
 10  KitchenQual    2919 non-null   object
 11  SaleCondition  2919 non-null   object
dtypes: float64(1), int64(4), object(7)
memory usage: 273.8+ KB
```

- The data type is changed from integer to object/string because the data is in the form of ordinal categorical, not numerical.
- After being converted to object/string, label encoding is applied before processing with machine learning

3.5 e. Label Encoding

[119]:
```python
tmp_data = all_data.copy()
```

[121]:
```python
from sklearn.preprocessing import LabelEncoder
cols = ('OverallQual', 'OverallCond', 'ExterQual', 'KitchenQual') # ordinal␣
 ↪categorical data
encoders = {}
```

```
for c in cols:
    lbl = LabelEncoder() # create encoder objects
    lbl.fit(list(tmp_data[c].values)) # encoder objects learn their data
    tmp_data[c] = lbl.transform(list(tmp_data[c].values)) # encoder object␣
↪change their data
    encoders[c] = lbl # save each encoder for deployment

# shape
print('Shape tmp_data: {}'.format(tmp_data.shape))
```

```
Shape tmp_data: (2919, 12)
```

[122]:
```
tmp_data
```

[122]:
```
      LotArea  YearBuilt  OverallQual  OverallCond RoofMatl  ExterQual  \
0        8450       2003            7            4  CompShg          2
1        9600       1976            6            7  CompShg          3
2       11250       2001            7            4  CompShg          2
3        9550       1915            7            4  CompShg          3
4       14260       2000            8            4  CompShg          2
…         …          …           …           …        …          …
2914     1936       1970            4            6  CompShg          3
2915     1894       1970            4            4  CompShg          3
2916    20000       1960            5            6  CompShg          3
2917    10441       1992            5            4  CompShg          3
2918     9627       1993            7            4  CompShg          3

      BedroomAbvGr  GrLivArea MiscFeature  GarageArea  KitchenQual  \
0                3       1710          NA       548.0            2
1                3       1262          NA       460.0            3
2                3       1786          NA       608.0            2
3                3       1717          NA       642.0            2
4                4       2198          NA       836.0            2
…              …          …          …           …           …
2914             3       1092          NA         0.0            3
2915             3       1092          NA       286.0            3
2916             4       1224          NA       576.0            3
2917             3        970        Shed         0.0            3
2918             3       2000          NA       650.0            3

     SaleCondition
0           Normal
1           Normal
2           Normal
3          Abnorml
4           Normal
```

```
…            …
2914        Normal
2915       Abnorml
2916       Abnorml
2917        Normal
2918        Normal

[2919 rows x 12 columns]
```

3.6 f. Distribution analysis for feature columns (to see skewness)

[126]:
```
from scipy.stats import norm, skew

# for numerical columns:
numeric_feats = tmp_data.dtypes[tmp_data.dtypes != "object"].index

# Check the skew of all numerical features
skewed_feats = tmp_data[numeric_feats].apply(lambda x: skew(x.dropna())).
 ↪sort_values(ascending=False)
print("\nSkewness in numerical features: \n")
skewness = pd.DataFrame({'Skew' :skewed_feats})
skewness
```

```
Skewness in numerical features:
```

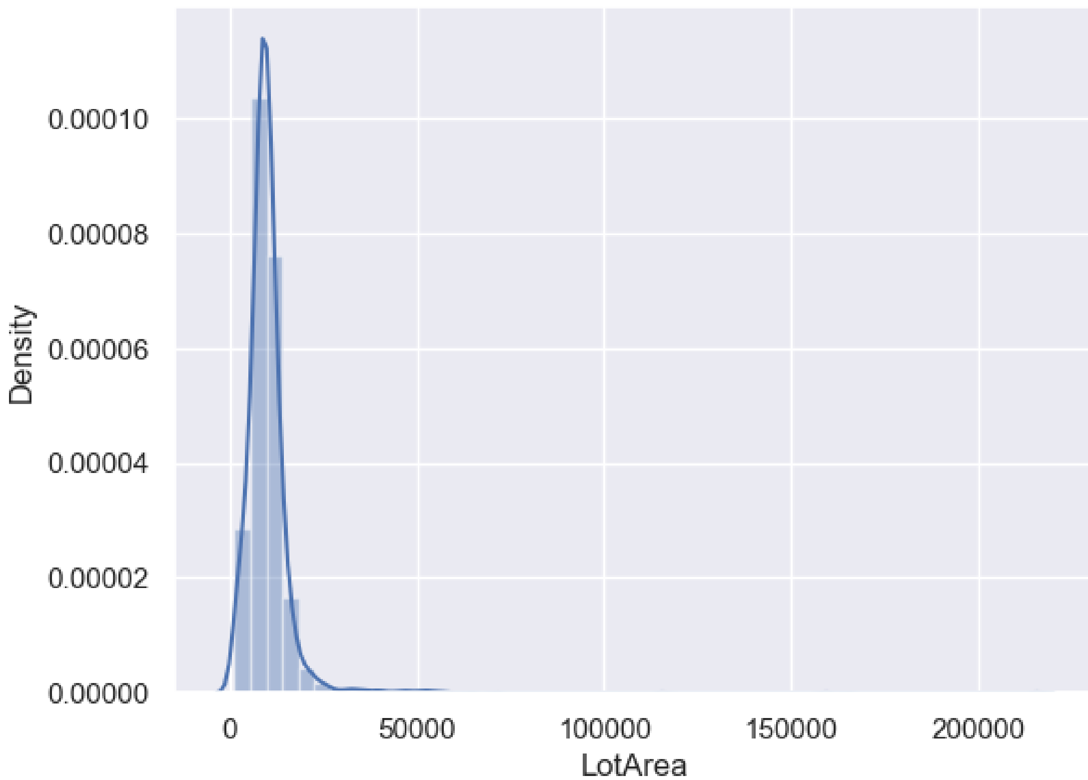
[126]:

	Skew
LotArea	12.822431
GrLivArea	1.269358
OverallCond	0.570312
BedroomAbvGr	0.326324
GarageArea	0.239257
OverallQual	-0.326653
YearBuilt	-0.599806
KitchenQual	-1.448023
ExterQual	-1.801409

- Lot Area is highly right-skewed, so it needs to be transformed to prevent the model from underfitting.
- Meanwhile, GrLivArea, KitchenQual, and ExterQual which have moderate skewness, also need to be transformed to prevent the model from overfitting.

3.6.1 Lot Area

[130]:
```
# lot Area column distribution:
sns.distplot(tmp_data['LotArea'])
plt.show()
```



[131]:
```
tmp_data['LotArea'].describe()
```

[131]:
```
count      2919.000000
mean      10168.114080
std        7886.996359
min        1300.000000
25%        7478.000000
50%        9453.000000
75%       11570.000000
max      215245.000000
Name: LotArea, dtype: float64
```

The smallest lot area is 1,300, with a maximum of up to 215,245, and an average of 10,168.

3.7 g. Box Cox Transformation for feature columns with skewness >0.75 atau <-0.75

[136]:
```
skewness = skewness[abs(skewness['Skew']) > 0.75]
print("There are {} skewed numerical features to Box Cox transform".
 ↪format(skewness.shape[0]))
```

```
There are 4 skewed numerical features to Box Cox transform
```

[138]:
```
# Box Cox transformation:
from scipy.special import boxcox1p

skewed_features = skewness.index
lam = 0.20
for feat in skewed_features:
    tmp_data[feat] = boxcox1p(tmp_data[feat], lam)
```

[140]:
```
# features to be transformed:
skewed_features
```

[140]:
```
Index(['LotArea', 'GrLivArea', 'KitchenQual', 'ExterQual'], dtype='object')
```

[142]:
```
# results:
tmp_data
```

[142]:
```
        LotArea  YearBuilt  OverallQual  OverallCond RoofMatl  ExterQual  \
0     25.503637       2003            7            4  CompShg   1.228655
1     26.291998       1976            6            7  CompShg   1.597540
2     27.300424       2001            7            4  CompShg   1.228655
3     26.259338       1915            7            4  CompShg   1.597540
4     28.868815       2000            8            4  CompShg   1.228655
…           …        …          …          …      …        …
2914  17.719351       1970            4            6  CompShg   1.597540
2915  17.619961       1970            4            4  CompShg   1.597540
2916  31.239346       1960            5            6  CompShg   1.597540
2917  26.821947       1992            5            4  CompShg   1.597540
2918  26.309578       1993            7            4  CompShg   1.597540

      BedroomAbvGr  GrLivArea MiscFeature  GarageArea  KitchenQual  \
0                3  17.162564          NA       548.0     1.228655
1                3  15.856944          NA       460.0     1.597540
2                3  17.356042          NA       608.0     1.228655
3                3  17.180669          NA       642.0     1.228655
4                4  18.303173          NA       836.0     1.228655
…              …        …          …        …          …
2914             3  15.262547          NA         0.0     1.597540
2915             3  15.262547          NA       286.0     1.597540
2916             4  15.729901          NA       576.0     1.597540
```

```
2917             3  14.788544        Shed         0.0      1.597540
2918             3  17.867539          NA       650.0      1.597540

     SaleCondition
0           Normal
1           Normal
2           Normal
3          Abnorml
4           Normal
…             …
2914        Normal
2915       Abnorml
2916       Abnorml
2917        Normal
2918        Normal

[2919 rows x 12 columns]
```

[144]:
```
# Check the skewness of all numerical features:
skewed_feats = tmp_data[numeric_feats].apply(lambda x: skew(x.dropna())).
 ↪sort_values(ascending=False)
print("\nSkew in numerical features: \n")
skewness = pd.DataFrame({'Skew' :skewed_feats})
skewness
```

```
Skew in numerical features:
```

[144]:
```
                  Skew
OverallCond   0.570312
LotArea       0.496692
BedroomAbvGr  0.326324
GarageArea    0.239257
GrLivArea     0.230000
OverallQual  -0.326653
YearBuilt    -0.599806
KitchenQual  -2.156088
ExterQual    -2.778802
```

3.8 h. One-Hot Encoding for non-ordinal categorical columns

[147]:
```
tmp_data
```

[147]:
```
        LotArea  YearBuilt  OverallQual  OverallCond RoofMatl  ExterQual  \
0     25.503637       2003            7            4  CompShg   1.228655
1     26.291998       1976            6            7  CompShg   1.597540
```

```
2     27.300424      2001           7           4  CompShg   1.228655
3     26.259338      1915           7           4  CompShg   1.597540
4     28.868815      2000           8           4  CompShg   1.228655
…         …       …          …         …      …         …
2914  17.719351      1970           4           6  CompShg   1.597540
2915  17.619961      1970           4           4  CompShg   1.597540
2916  31.239346      1960           5           6  CompShg   1.597540
2917  26.821947      1992           5           4  CompShg   1.597540
2918  26.309578      1993           7           4  CompShg   1.597540

      BedroomAbvGr  GrLivArea MiscFeature  GarageArea  KitchenQual  \
0                3  17.162564          NA       548.0     1.228655
1                3  15.856944          NA       460.0     1.597540
2                3  17.356042          NA       608.0     1.228655
3                3  17.180669          NA       642.0     1.228655
4                4  18.303173          NA       836.0     1.228655
…             …          …         …          …           …
2914             3  15.262547          NA         0.0     1.597540
2915             3  15.262547          NA       286.0     1.597540
2916             4  15.729901          NA       576.0     1.597540
2917             3  14.788544        Shed         0.0     1.597540
2918             3  17.867539          NA       650.0     1.597540

     SaleCondition
0           Normal
1           Normal
2           Normal
3          Abnorml
4           Normal
…             …
2914        Normal
2915       Abnorml
2916       Abnorml
2917        Normal
2918        Normal

[2919 rows x 12 columns]
```

[149]:
```
tmp_data = pd.get_dummies(tmp_data, drop_first=True) # one hot encoding for
 ↪other categorical data
print(tmp_data.shape)
```

```
(2919, 25)
```

[151]:
```
# Check the results:
tmp_data
```

[151]:

```
        LotArea  YearBuilt  OverallQual  OverallCond  ExterQual  BedroomAbvGr  \
0     25.503637       2003            7            4   1.228655             3
1     26.291998       1976            6            7   1.597540             3
2     27.300424       2001            7            4   1.228655             3
3     26.259338       1915            7            4   1.597540             3
4     28.868815       2000            8            4   1.228655             4
…           …         …           …          …         …          …
2914  17.719351       1970            4            6   1.597540             3
2915  17.619961       1970            4            4   1.597540             3
2916  31.239346       1960            5            6   1.597540             4
2917  26.821947       1992            5            4   1.597540             3
2918  26.309578       1993            7            4   1.597540             3

      GrLivArea  GarageArea  KitchenQual  RoofMatl_CompShg  …  \
0     17.162564       548.0     1.228655              True  …
1     15.856944       460.0     1.597540              True  …
2     17.356042       608.0     1.228655              True  …
3     17.180669       642.0     1.228655              True  …
4     18.303173       836.0     1.228655              True  …
…           …          …          …              …  …
2914  15.262547         0.0     1.597540              True  …
2915  15.262547       286.0     1.597540              True  …
2916  15.729901       576.0     1.597540              True  …
2917  14.788544         0.0     1.597540              True  …
2918  17.867539       650.0     1.597540              True  …

      RoofMatl_WdShngl  MiscFeature_NA  MiscFeature_Othr  MiscFeature_Shed  \
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
…                  …             …               …               …
2914             False            True             False             False
2915             False            True             False             False
2916             False            True             False             False
2917             False           False             False              True
2918             False            True             False             False

      MiscFeature_TenC  SaleCondition_AdjLand  SaleCondition_Alloca  \
0                False                  False                 False
1                False                  False                 False
2                False                  False                 False
3                False                  False                 False
4                False                  False                 False
…                  …                    …                   …
2914             False                  False                 False
```

```
2915             False                  False                  False
2916             False                  False                  False
2917             False                  False                  False
2918             False                  False                  False

      SaleCondition_Family  SaleCondition_Normal  SaleCondition_Partial
0                    False                  True                  False
1                    False                  True                  False
2                    False                  True                  False
3                    False                 False                  False
4                    False                  True                  False
…                      …                     …                      …
2914                 False                  True                  False
2915                 False                 False                  False
2916                 False                 False                  False
2917                 False                  True                  False
2918                 False                  True                  False

[2919 rows x 25 columns]
```

There is an additional columns from 12 to 25 (from RoofMatl, MiscFeature, and SaleCondition columns)

[154]:
```python
# save the encoding result columns for later use:
one_hot_columns = tmp_data.columns
```

3.9 i. Scaling

[157]:
```python
# Check the value range:
tmp_data
```

[157]:
```
        LotArea  YearBuilt  OverallQual  OverallCond  ExterQual  BedroomAbvGr  \
0     25.503637       2003            7            4   1.228655             3
1     26.291998       1976            6            7   1.597540             3
2     27.300424       2001            7            4   1.228655             3
3     26.259338       1915            7            4   1.597540             3
4     28.868815       2000            8            4   1.228655             4
…           …         …           …           …          …             …
2914  17.719351       1970            4            6   1.597540             3
2915  17.619961       1970            4            4   1.597540             3
2916  31.239346       1960            5            6   1.597540             4
2917  26.821947       1992            5            4   1.597540             3
2918  26.309578       1993            7            4   1.597540             3

       GrLivArea  GarageArea  KitchenQual  RoofMatl_CompShg  …  \
0      17.162564       548.0     1.228655              True  …
1      15.856944       460.0     1.597540              True  …
```

```
2     17.356042       608.0     1.228655              True  …
3     17.180669       642.0     1.228655              True  …
4     18.303173       836.0     1.228655              True  …
…         …          …          …               …   …
2914  15.262547         0.0     1.597540              True  …
2915  15.262547       286.0     1.597540              True  …
2916  15.729901       576.0     1.597540              True  …
2917  14.788544         0.0     1.597540              True  …
2918  17.867539       650.0     1.597540              True  …

      RoofMatl_WdShngl  MiscFeature_NA  MiscFeature_Othr  MiscFeature_Shed  \
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
…                  …             …                 …                 …
2914             False            True             False             False
2915             False            True             False             False
2916             False            True             False             False
2917             False           False             False              True
2918             False            True             False             False

      MiscFeature_TenC  SaleCondition_AdjLand  SaleCondition_Alloca  \
0                False                  False                 False
1                False                  False                 False
2                False                  False                 False
3                False                  False                 False
4                False                  False                 False
…                  …                     …                     …
2914             False                  False                 False
2915             False                  False                 False
2916             False                  False                 False
2917             False                  False                 False
2918             False                  False                 False

      SaleCondition_Family  SaleCondition_Normal  SaleCondition_Partial
0                    False                  True                  False
1                    False                  True                  False
2                    False                  True                  False
3                    False                 False                  False
4                    False                  True                  False
…                      …                     …                     …
2914                 False                  True                  False
2915                 False                 False                  False
2916                 False                 False                  False
2917                 False                  True                  False
```

```
2918                    False                       True                      False

[2919 rows x 25 columns]
```

[159]:
```
# Use a robust scaler to reduce the impact of outliers in each column (far␣
↪range of values):
from sklearn.preprocessing import RobustScaler
scaler = RobustScaler()
scaler.fit(tmp_data)
tmp_data = scaler.transform(tmp_data)
```

[161]:
```
tmp_data
```

[161]:
```
array([[-0.25487439,  0.63157895,  0.5        , …,  0.        ,
         0.        ,  0.        ],
       [ 0.03551351,  0.06315789,  0.        , …,  0.        ,
         0.        ,  0.        ],
       [ 0.40696091,  0.58947368,  0.5        , …,  0.        ,
         0.        ,  0.        ],
       …,
       [ 1.85783766, -0.27368421, -0.5        , …,  0.        ,
        -1.        ,  0.        ],
       [ 0.2307166 ,  0.4        , -0.5        , …,  0.        ,
         0.        ,  0.        ],
       [ 0.04198905,  0.42105263,  0.5        , …,  0.        ,
         0.        ,  0.        ]])
```

4 4. Split Data Training dan Testing

[164]:
```
X_train = tmp_data[:ntrain]
X_test = tmp_data[ntrain:]

X_train.shape, X_test.shape, y_train.shape
```

[164]:
```
((1460, 25), (1459, 25), (1460,))
```

5 6. Modelling

[167]:
```
from sklearn.model_selection import KFold, cross_val_score
from sklearn.metrics import make_scorer, r2_score

# Cross validation:
def test_model(model, X_train=X_train, y_train=y_train):    # create a function
    cv = KFold(n_splits = 4, shuffle=True, random_state = 45)    # 4x cross␣
↪validation, shuffle
```

```
    r2 = make_scorer(r2_score)

    r2_val_score = cross_val_score(model, X_train, y_train, cv=cv, scoring =␣
↪r2)  # calculate R2
    score = [r2_val_score.mean()]
    return score
```

5.1 a. Linear Regression

[170]:
```
import sklearn.linear_model as linear_model
LR = linear_model.LinearRegression()
test_model(LR)
```

[170]: [0.8240757196006232]

5.2 b. Lasso Regression

[173]:
```
lasso = linear_model.Lasso(alpha=1e-4)
test_model(lasso)
```

[173]: [0.8335074727025339]

5.3 c. Random Forest

[176]:
```
random_forest = linear_model.Ridge(alpha=1)
test_model(random_forest)
```

[176]: [0.8363080677683358]

Lasso and Random Forest Regression show better regression compared to others

5.4 d. Support Vector Regression

[180]:
```
from sklearn.svm import SVR
svr_reg = SVR(kernel= 'rbf')
test_model(svr_reg)
```

[180]: [0.8245841296419294]

5.5 e. XGBoost

[182]:
```
!pip install --upgrade xgboost
```

```
Requirement already satisfied: xgboost in c:\users\62817\anaconda3\lib\site-
packages (3.0.0)
Requirement already satisfied: numpy in c:\users\62817\anaconda3\lib\site-
```

```
packages (from xgboost) (1.26.4)
Requirement already satisfied: scipy in c:\users\62817\anaconda3\lib\site-
packages (from xgboost) (1.13.1)
```

[184]:
```
import xgboost

xgb_reg = xgboost.XGBRegressor()
test_model(xgb_reg)
```

[184]:
```
[0.815044432921986]
```

5.6 f. Optimize the model: Lasso Regression vs Random Forest

Lasso Regression

[187]:
```
from sklearn.model_selection import GridSearchCV

param_grid = {'alpha': [1e-4, 1e-3, 1e-2, 0.1, 1, 10]}
grid_search = GridSearchCV(linear_model.Lasso(), param_grid, cv=5)
grid_search.fit(X_train, y_train)

print(f"Best Alpha: {grid_search.best_params_['alpha']}")
```

```
Best Alpha: 0.001
```

[188]:
```
from sklearn.linear_model import Lasso

lasso_best = Lasso(alpha=0.001)
lasso_best.fit(X_train, y_train)
```

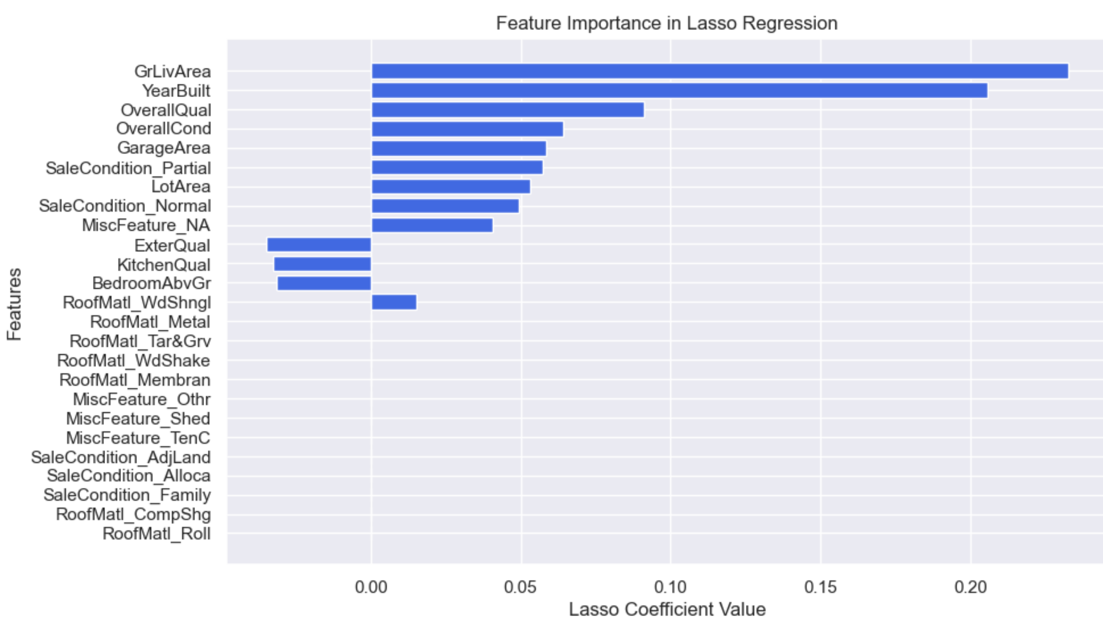
[188]:
```
Lasso(alpha=0.001)
```

[189]:
```
from sklearn.model_selection import cross_val_score

cv_scores = cross_val_score(lasso_best, X_train, y_train, cv=5, scoring='r2')

print(f"Cross-Validation R² Scores: {cv_scores}")
print(f"Mean R² Score: {cv_scores.mean():.4f}")
print(f"Standard Deviation: {cv_scores.std():.4f}")
```

```
Cross-Validation R² Scores: [0.87173941 0.85853769 0.83866367 0.86223495
0.78697472]
Mean R² Score: 0.8436
Standard Deviation: 0.0303
```

[190]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```python
from sklearn.linear_model import Lasso

# Train Lasso model:
lasso = Lasso(alpha=0.001)
lasso.fit(X_train, y_train)

# create feature coefficients:
lasso_coefs = lasso.coef_

# Create DataFrame for visualization:
# Replace X_train.columns with one_hot_columns
lasso_importance_df = pd.DataFrame({'Feature': one_hot_columns, 'Importance':␣
↪lasso_coefs})
lasso_importance_df = lasso_importance_df.sort_values(by='Importance',␣
↪ascending=False, key=abs)  # Sort by absolute value

# Visualization:
plt.figure(figsize=(10,6))
plt.barh(lasso_importance_df['Feature'], lasso_importance_df['Importance'],␣
↪color='royalblue')
plt.xlabel('Lasso Coefficient Value')
plt.ylabel('Features')
plt.title('Feature Importance in Lasso Regression')
plt.gca().invert_yaxis()
plt.show()

# Show the most influential features:
print(lasso_importance_df.head(10))  # Top 10 the important features
```



```
                  Feature  Importance
6               GrLivArea    0.232665
1               YearBuilt    0.205813
2             OverallQual    0.091143
3             OverallCond    0.064278
7              GarageArea    0.058531
24  SaleCondition_Partial    0.057317
0                 LotArea    0.053069
23   SaleCondition_Normal    0.049281
16         MiscFeature_NA    0.040732
4               ExterQual   -0.034696
```

Random Forest

[192]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor

param_grid = {
    'n_estimators': [100, 300, 500],
    'max_depth': [10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt']
}

rf = RandomForestRegressor()
grid_search = GridSearchCV(rf, param_grid, cv=5, scoring='r2', n_jobs=-1)
grid_search.fit(X_train, y_train)

# Best parameters
print(grid_search.best_params_)
```

```
{'max_depth': 30, 'max_features': 'sqrt', 'min_samples_leaf': 1,
'min_samples_split': 2, 'n_estimators': 300}
```

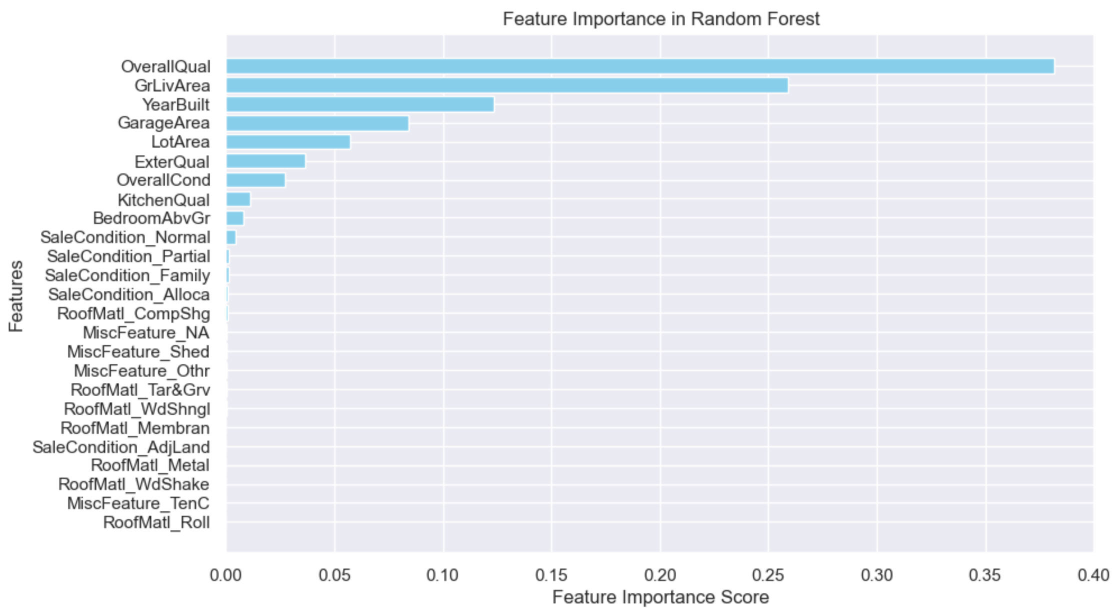
[193]:
```
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestRegressor

# Use the best parameters from GridSearchCV
best_rf = RandomForestRegressor(
    max_depth=30,
    max_features='sqrt',
    min_samples_leaf=1,
    min_samples_split=2,
    n_estimators=500,
    random_state=42
```

```
)

# Perform cross-validation
scores = cross_val_score(best_rf, X_train, y_train, cv=5, scoring='r2')

print("Mean Cross-Validation R²:", scores.mean())
print("Standard Deviation:", scores.std())
```

```
Mean Cross-Validation R²: 0.8500130283032352
Standard Deviation: 0.011010251796251471
```

[194]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor

# Let X_train be the features and y_train be the target
rf = RandomForestRegressor(n_estimators=500, random_state=42)
rf.fit(X_train, y_train)

# Get the important features:
importances = rf.feature_importances_

# **Get feature names from the training data**
# Assuming one_hot_columns contains the feature names from before the scaling␣
↪step
feature_names = one_hot_columns

# Create DataFrame for visualization:
feature_importance_df = pd.DataFrame({'Feature': feature_names, 'Importance':␣
↪importances})
feature_importance_df = feature_importance_df.sort_values(by='Importance',␣
↪ascending=False)

# Show the results:
plt.figure(figsize=(10, 6))
plt.barh(feature_importance_df['Feature'], feature_importance_df['Importance'],␣
↪color='skyblue')
plt.xlabel('Feature Importance Score')
plt.ylabel('Features')
plt.title('Feature Importance in Random Forest')
plt.gca().invert_yaxis()
plt.show()

print(feature_importance_df.head(10))  # Top 10 the important features
```



	Feature	Importance
2	OverallQual	0.381875
6	GrLivArea	0.259145
1	YearBuilt	0.123283
7	GarageArea	0.084152
0	LotArea	0.057279
4	ExterQual	0.036430
3	OverallCond	0.027518
8	KitchenQual	0.011399
5	BedroomAbvGr	0.008284
23	SaleCondition_Normal	0.004296

Based on the cross-validation results, both models perform well, but: - Random Forest has a slightly higher mean R2 score (0.8496 vs. 0.8436 for Lasso), indicating it might generalize slightly better. - Additionally, the standard deviation for Random Forest is lower (0.0142 vs. 0.0303), suggesting it is more stable across different validation splits.

Thus, since after tuning Random Forest has higher and more stable R^2, it is the best choice to predict SalePrice.

6 7. Try to predict new data with the Lasso regression model (because the r2 score is the highest compared to other algorithms)

[198]:
```
pd.DataFrame(tmp_data)    #created in dataframe form
```

[198]:

	0	1	2	3	4	5	6	7	8	9	\
0	-0.254874	0.631579	0.5	0.0	-1.0	0.0	0.395595	0.265625	-1.0	0.0	

```
1      0.035514  0.063158  0.0  3.0  0.0  0.0 -0.305745 -0.078125  0.0  0.0
2      0.406961  0.589474  0.5  0.0 -1.0  0.0  0.499525  0.500000 -1.0  0.0
3      0.023483 -1.221053  0.5  0.0  0.0  0.0  0.405320  0.632812 -1.0  0.0
4      0.984668  0.568421  1.0  0.0 -1.0  1.0  1.008295  1.390625 -1.0  0.0
…         …        …   …   …   …   …        …         …   …   …
2914 -3.122167 -0.063158 -1.0  2.0  0.0  0.0 -0.625037 -1.875000  0.0  0.0
2915 -3.158777 -0.063158 -1.0  0.0  0.0  0.0 -0.625037 -0.757812  0.0  0.0
2916  1.857838 -0.273684 -0.5  2.0  0.0  1.0 -0.373989  0.375000  0.0  0.0
2917  0.230717  0.400000 -0.5  0.0  0.0  0.0 -0.879657 -1.875000  0.0  0.0
2918  0.041989  0.421053  0.5  0.0  0.0  0.0  0.774286  0.664062  0.0  0.0

      …   15   16   17   18   19   20   21   22   23   24
0     …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
1     …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
2     …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
3     …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0 -1.0  0.0
4     …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
…    …  …  …  …  …  …  …  …  …  …  …
2914  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
2915  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0 -1.0  0.0
2916  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0 -1.0  0.0
2917  …  0.0 -1.0  0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0
2918  …  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0

[2919 rows x 25 columns]
```

[199]:
```python
# random forest model:
from sklearn.ensemble import RandomForestRegressor

random_forest = RandomForestRegressor(n_estimators=500, random_state=42)

# Training the model with training data:
model = random_forest.fit(X_train, y_train)
```

[200]:
```python
tmp_data[0]
```

[200]:
```
array([-0.25487439,  0.63157895,  0.5       ,  0.        , -1.        ,
        0.        ,  0.39559454,  0.265625  , -1.        ,  0.        ,
        0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
        0.        ,  0.        ,  0.        ,  0.        ,  0.        ,
        0.        ,  0.        ,  0.        ,  0.        ,  0.        ])
```

[201]:
```python
# Predict data to -0
model.predict(tmp_data[0].reshape(1,-1))
```

[201]:
```
array([12.23591967])
```

[202]:
```
# Predicted sale price:
np.expm1(12.25771747)
```

[202]:
```
210599.33513183476
```

[207]:
```
# compare the predicted sale price with the actual house price:
y_train
```

[207]:
```
array([12.24769912, 12.10901644, 12.31717117, …, 12.49313327,
       11.86446927, 11.90159023])
```

[208]:
```
# The actual sale price for first row houses in training data:
np.expm1(12.24769912)
```

[208]:
```
208500.00075632462
```

[209]:
```
# try to input new data to predict how much the house will cost
new_data = {'LotArea': [8000],
             'YearBuilt':[2010],
             'OverallQual':['8'],
             'OverallCond':['7'],
             'GrLivArea':[2000],
            'MiscFeature':['Shed'],
            'ExterQual' :['Gd'],
            'RoofMatl' : ['Compshg'],
            'SaleCondition' : ['Normal'],
             'GarageArea': [500],
             'KitchenQual': ['Gd'],}
```

[211]:
```
tmp = pd.DataFrame(new_data)
tmp
```

[211]:
```
   LotArea  YearBuilt OverallQual OverallCond  GrLivArea MiscFeature  \
0     8000       2010           8           7       2000        Shed

  ExterQual RoofMatl SaleCondition  GarageArea KitchenQual
0        Gd  Compshg        Normal         500          Gd
```

[212]:
```
new_data_tf = new_data.copy()
```

[213]:
```
# label encoding for new data
new_data_tf['OverallQual'] = encoders['OverallQual'].
 ↪transform(tmp['OverallQual'])[0]
new_data_tf['OverallCond'] = encoders['OverallCond'].
 ↪transform(tmp['OverallCond'])[0]
new_data_tf['ExterQual'] = encoders['ExterQual'].transform(tmp['ExterQual'])[0]
```

```
new_data_tf['KitchenQual'] = encoders['KitchenQual'].
↪transform(tmp['KitchenQual'])[0]
```

[214]:
```
# transformasi boxcox untuk kolom LotArea, GrLivArea, dan KitchenQual
new_data_tf['LotArea'] = boxcox1p(tmp['LotArea'], lam)[0]
new_data_tf['GrLivArea'] = boxcox1p(tmp['GrLivArea'], lam)[0]
new_data_tf['KitchenQual'] = boxcox1p(new_data_tf['KitchenQual'], lam)
new_data_tf['ExterQual'] = boxcox1p(new_data_tf['ExterQual'], lam)
```

[215]:
```
tmp = pd.DataFrame(new_data_tf)
```

[216]:
```
tmp = pd.get_dummies(tmp, columns = ['MiscFeature', 'RoofMatl',␣
↪'SaleCondition'])
tmp
```

[216]:
```
     LotArea  YearBuilt  OverallQual  OverallCond  GrLivArea  ExterQual  \
0  25.171636       2010            8            6  17.867539   1.228655

   GarageArea  KitchenQual  MiscFeature_Shed  RoofMatl_Compshg  \
0         500     1.228655              True              True

   SaleCondition_Normal
0                  True
```

[217]:
```
# Adding missing columns to new data:
for kolom in one_hot_columns:
    if kolom not in tmp.columns:
        tmp[kolom] = 0
```

[218]:
```
tmp = tmp.reindex(columns=one_hot_columns, fill_value=0)
```

[219]:
```
tmp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1 entries, 0 to 0
Data columns (total 25 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   LotArea                1 non-null      float64
 1   YearBuilt              1 non-null      int64
 2   OverallQual            1 non-null      int32
 3   OverallCond            1 non-null      int32
 4   ExterQual              1 non-null      float64
 5   BedroomAbvGr           1 non-null      int64
 6   GrLivArea              1 non-null      float64
 7   GarageArea             1 non-null      int64
 8   KitchenQual            1 non-null      float64
```

```
 9   RoofMatl_CompShg       1 non-null      int64
 10  RoofMatl_Membran       1 non-null      int64
 11  RoofMatl_Metal         1 non-null      int64
 12  RoofMatl_Roll          1 non-null      int64
 13  RoofMatl_Tar&Grv       1 non-null      int64
 14  RoofMatl_WdShake       1 non-null      int64
 15  RoofMatl_WdShngl       1 non-null      int64
 16  MiscFeature_NA         1 non-null      int64
 17  MiscFeature_Othr       1 non-null      int64
 18  MiscFeature_Shed       1 non-null      bool
 19  MiscFeature_TenC       1 non-null      int64
 20  SaleCondition_AdjLand  1 non-null      int64
 21  SaleCondition_Alloca   1 non-null      int64
 22  SaleCondition_Family   1 non-null      int64
 23  SaleCondition_Normal   1 non-null      bool
 24  SaleCondition_Partial  1 non-null      int64
dtypes: bool(2), float64(4), int32(2), int64(17)
memory usage: 310.0 bytes
```

[220]:

```
# Scaling
tmp_scaled = scaler.transform(tmp.loc[0].values.reshape(1,-1))
```

[221]:

```
# house price prediction for new data
y = np.expm1(model.predict(tmp_scaled))
print(y)
```

```
[264503.94660399]
```

[222]:

```
new_data['SalePrice'] = y
```

[223]:

```
# show the predicted new house:
pd.DataFrame(new_data)
```

[223]:

```
   LotArea  YearBuilt  OverallQual  OverallCond  GrLivArea MiscFeature  \
0     8000       2010            8            7       2000        Shed

  ExterQual RoofMatl SaleCondition  GarageArea KitchenQual      SalePrice
0        Gd  Compshg        Normal         500          Gd  264503.946604
```

Random Forest Regression model is performing well with a Mean R^2 of 0.8496, but there might still be room for improvement. Here are some strategies to enhance its performance: 1. Check Feature Importance & remove irrelevant features, but before removing the feature, try running the model with and without certain features, then compare its performance. 2. Experiment with ensemble learning (stacking/blending). 3. Look for external data that can provide more insights into house prices, for example, macroeconomic data (Inflation, interest rates, average salary), more detailed location data (crime rate, school quality, transportation).