House Price Prediction Using Supervised ML Regression Models

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Contents

1 Introduction

1.1 Background

Real estate is a lucrative business. Thousands of houses are sold every day. There are some questions every buyer asks themselves like: What is the actual price that this house deserves? Am I paying a fair price? In this project, a machine learning model is proposed to predict a house price based on data related to the house (its size, the year it was built in, etc.). During the development and evaluation of our model, I will show the code used for each step followed by its output. In this study, Python programming language with a number of Python packages will be used. The codes used in this project can be found here.

1.2 Objective

This project will be focused on **prediction**. The main objectives of this project are as follows:

- To apply data preprocessing and preparation techniques in order to obtain clean data.
- To build at least three supervised machine learning regression models that are able to predict house prices based on house features.
- To analyze and compare model's performance in order to choose the best model.

2 Data

In this study, we will use a housing dataset presented by De Cock (2011). This dataset describes the sales of residential units in Ames, Iowa starting from 2006 until 2010. The dataset contains a large number of variables that are involved in determining a house price. We obtained a .csv copy of the data from here.

2.1 Data Description

The dataset contains 2930 records (rows) and 82 features (columns).

Here, we will provide a brief description of dataset features. Since the number of features is large (82), we will attach the original data description file to this paper for more information about the dataset. It can be downloaded also from here. Now, we will mention the feature name with a short description of its meaning.

Feature	Description
MSSubClass	The type of the house involved in the sale
MSZoning	The general zoning classification of the sale
LotFrontage	Linear feet of street connected to the house
LotArea	Lot size in square feet
Street	Type of road access to the house
Alley	Type of alley access to the house
LotShape	General shape of the house
LandContour	House flatness
Utilities	Type of utilities available
LotConfig	Lot configuration
LandSlope	House Slope
Neighborhood	Locations within Ames city limits
Condition1	Proximity to various conditions
Condition2	Proximity to various conditions (if more than one is present)
BldgType	House type
HouseStyle	House style
OverallQual	Overall quality of material and finish of the house
OverallCond	Overall condition of the house
YearBuilt	Construction year
YearRemodAdd	Remodel year (if no remodeling nor addition, same as YearBuilt)
RoofStyle	Roof type
RoofMatl	Roof material
Exterior1st	Exterior covering on house
Exterior2nd	Exterior covering on house (if more than one material)
MasVnrType	Type of masonry veneer
MasVnrArea	Masonry veneer area in square feet
ExterQual	Quality of the material on the exterior
ExterCond	Condition of the material on the exterior
Foundation	Foundation type
BsmtQual	Basement height
BsmtCond	Basement Condition
BsmtExposure	Refers to walkout or garden level walls
BsmtFinType1	Rating of basement finished area
BsmtFinSF1	Type 1 finished square feet
BsmtFinType2	Rating of basement finished area (if multiple types)
BsmtFinSF2	Type 2 finished square feet
BsmtUnfSF	Unfinished basement area in square feet
TotalBsmtSF	Total basement area in square feet
Heating	Heating type
HeatingQC	Heating quality and condition
CentralAir	Central air conditioning
Electrical	Electrical system type
1stFlrSF	First floor area in square feet

Feature	Description
2ndFlrSF	Second floor area in square feet
LowQualFinSF	Low quality finished square feet in all floors
GrLivArea	Above-ground living area in square feet
BsmtFullBath	Basement full bathrooms
BsmtHalfBath	Basement half bathrooms
FullBath	Full bathrooms above ground
HalfBath	Half bathrooms above ground
Bedroom	Bedrooms above ground
Kitchen	Kitchens above ground
KitchenQual	Kitchen quality
TotRmsAbvGrd	Total rooms above ground (excluding bathrooms)
Functional	Home functionality
Fireplaces	Number of fireplaces
FireplaceQu	Fireplace quality
GarageType	Garage location
GarageYrBlt	Year garage was built in
GarageFinish	Interior finish of the garage
GarageCars	Size of garage (in car capacity)
GarageArea	Garage size in square feet
GarageQual	Garage quality
GarageCond	Garage condition
PavedDrive	How driveway is paved
WoodDeckSF	Wood deck area in square feet
OpenPorchSF	Open porch area in square feet
EnclosedPorch	Enclosed porch area in square feet
3SsnPorch	Three season porch area in square feet
ScreenPorch	Screen porch area in square feet
PoolArea	Pool area in square feet
PoolQC	Pool quality
Fence	Fence quality
MiscFeature	Miscellaneous feature
MiscVal	Value of miscellaneous feature
MoSold	Sale month
YrSold	Sale year
SaleType	Sale type
SaleCondition	Sale condition

2.2 Reading the Dataset

The first step is reading the dataset from the csv file we downloaded. We will use the read_csv() function from Pandas Python package:

```
import pandas as pd import numpy as np dataset

= pd.read_csv("AmesHousing.csv")
```

2.3 Getting A Feel of the Dataset

Let's display the first few rows of the dataset to get a feel of it:

```
# Configuring float numbers format pd.options.display.float_format =
'{:20.2f}'.format dataset.head(n=5)
```

Order	PID	MS SubClass	MS Zoning	Lot Frontage	Lot Area
1	526301100	20	RL	141.00	31770
2	526350040	20	RH	80.00	11622
3	526351010	20	RL	81.00	14267
4	526353030	20	RL	93.00	11160
5	527105010	60	RL	74.00	13830

Street	Alley	Lot Shape	Land Contour	Utilities	Lot Config
Pave	NaN	IR1	Lvl	AllPub	Corner
Pave	NaN	Reg	Lvl	AllPub	Inside
Pave	NaN	IR1	Lvl	AllPub	Corner
Pave	NaN	Reg	Lvl	AllPub	Corner
Pave	NaN	IR1	Lvl	AllPub	Inside

Land Slope	Neighborhood	Condition 1	Condition 2	Bldg Type	House Style
Gtl	NAmes	Norm	Norm	1Fam	1Story
Gtl	NAmes	Feedr	Norm	1Fam	1Story
Gtl	NAmes	Norm	Norm	1Fam	1Story
Gtl	NAmes	Norm	Norm	1Fam	1Story
Gtl	Gilbert	Norm	Norm	1Fam	2Story

Overall Qual	Overall Cond	Year Built	Year Remod/Add	Roof Style	Roof Matl
6	5	1960	1960	Hip	CompShg
5	6	1961	1961	Gable	CompShg
6	6	1958	1958	Hip	CompShg
7	5	1968	1968	Hip	CompShg
5	5	1997	1998	Gable	CompShg

Exterior 1st	Exterior 2nd	Mas Vnr Type	Mas Vnr Area	Exter Qual	Exter Cond
BrkFace	Plywood	Stone	112.00	TA	TA
VinylSd	VinylSd	None	0.00	TA	TA
Wd Sdng	Wd Sdng	BrkFace	108.00	TA	TA
BrkFace	BrkFace	None	0.00	Gd	TA
VinylSd	VinylSd	None	0.00	TA	TA

Foundation	Bsmt Qual	Bsmt Cond	Bsmt Exposure	BsmtFin Type 1	BsmtFin SF 1
CBlock	TA	Gd	Gd	BLQ	639.00
CBlock	TA	TA	No	Rec	468.00
CBlock	TA	TA	No	ALQ	923.00
CBlock	TA	TA	No	ALQ	1065.00
PConc	Gd	TA	No	GLQ	791.00

BsmtFin Type 2	BsmtFin SF 2	Bsmt Unf SF	Total Bsmt SF	Heating	Heating QC
Unf	0.00	441.00	1080.00	GasA	Fa
LwQ	144.00	270.00	882.00	GasA	TA
Unf	0.00	406.00	1329.00	GasA	TA
Unf	0.00	1045.00	2110.00	GasA	Ex
Unf	0.00	137.00	928.00	GasA	Gd

Central Air	Electrical	1st Flr SF	2nd Flr SF	Low Qual Fin SF	Gr Liv Area
Y	SBrkr	1656	0	0	1656
Y	SBrkr	896	0	0	896
Y	SBrkr	1329	0	0	1329
Y	SBrkr	2110	0	0	2110
Y	SBrkr	928	701	0	1629

Bsmt Full Bath	Bsmt Half Bath	Full Bath	Half Bath	Bedroom AbvGr	Kitchen AbvGr
1.00	0.00	1	0	3	1
0.00	0.00	1	0	2	1
0.00	0.00	1	1	3	1
1.00	0.00	2	1	3	1
0.00	0.00	2	1	3	1

Kitchen Qual	TotRms AbvGrd	Functional	Fireplaces	Fireplace Qu	Garage Type
TA	7	Typ	2	Gd	Attchd
TA	5	Typ	0	NaN	Attchd
Gd	6	Typ	0	NaN	Attchd
Ex	8	Typ	2	TA	Attchd
TA	6	Typ	1	TA	Attchd

Garage Yr Blt	Garage Finish	Garage Cars	Garage Area	Garage Qual	Garage Cond
1960.00	Fin	2.00	528.00	TA	TA
1961.00	Unf	1.00	730.00	TA	TA
1958.00	Unf	1.00	312.00	TA	TA
1968.00	Fin	2.00	522.00	TA	TA
1997.00	Fin	2.00	482.00	TA	TA

Paved Drive	Wood Deck SF	Open Porch SF	Enclosed Porch	3Ssn Porch	Screen Porch
P	210	62	0	0	0
Y	140	0	0	0	120
Y	393	36	0	0	0
Y	0	0	0	0	0
Y	212	34	0	0	0

Pool Area	Pool QC	Fence	Misc Feature	Misc Val	Mo Sold
0	NaN	NaN	NaN	0	5
0	NaN	MnPrv	NaN	0	6
0	NaN	NaN	Gar2	12500	6
0	NaN	NaN	NaN	0	4
0	NaN	MnPrv	NaN	0	3

Yr Sold	Sale Type	Sale Condition	SalePrice
2010	WD	Normal	215000
2010	WD	Normal	105000
2010	WD	Normal	172000
2010	WD	Normal	244000
2010	WD	Normal	189900

Now, let's get statistical information about the numeric columns in our dataset. We want to know the mean, the standard deviation, the minimum, the maximum, and the 50th percentile (the median) for *each numeric column* in the dataset:

```
dataset.describe(include=[np.number], percentiles=[.5]) \
    .transpose().drop("count", axis=1)
```

	mean	std	min	50%	max
Order	1465.50	845.96	1.00	1465.50	2930.00
PID	714464496.99	188730844.65	526301100.00	535453620.00	1007100110.00
MS SubClass	57.39	42.64	20.00	50.00	190.00
Lot Frontage	69.22	23.37	21.00	68.00	313.00
Lot Area	10147.92	7880.02	1300.00	9436.50	215245.00
Overall Qual	6.09	1.41	1.00	6.00	10.00
Overall Cond	5.56	1.11	1.00	5.00	9.00
Year Built	1971.36	30.25	1872.00	1973.00	2010.00
Year Remod/Add	1984.27	20.86	1950.00	1993.00	2010.00
Mas Vnr Area	101.90	179.11	0.00	0.00	1600.00
BsmtFin SF 1	442.63	455.59	0.00	370.00	5644.00
BsmtFin SF 2	49.72	169.17	0.00	0.00	1526.00
Bsmt Unf SF	559.26	439.49	0.00	466.00	2336.00
Total Bsmt SF	1051.61	440.62	0.00	990.00	6110.00
1st Flr SF	1159.56	391.89	334.00	1084.00	5095.00
2nd Flr SF	335.46	428.40	0.00	0.00	2065.00
Low Qual Fin SF	4.68	46.31	0.00	0.00	1064.00

	mean	std	min	50%	max
Gr Liv Area	1499.69	505.51	334.00	1442.00	5642.00
Bsmt Full Bath	0.43	0.52	0.00	0.00	3.00
Bsmt Half Bath	0.06	0.25	0.00	0.00	2.00
Full Bath	1.57	0.55	0.00	2.00	4.00
Half Bath	0.38	0.50	0.00	0.00	2.00
Bedroom AbvGr	2.85	0.83	0.00	3.00	8.00
Kitchen AbvGr	1.04	0.21	0.00	1.00	3.00
TotRms AbvGrd	6.44	1.57	2.00	6.00	15.00
Fireplaces	0.60	0.65	0.00	1.00	4.00
Garage Yr Blt	1978.13	25.53	1895.00	1979.00	2207.00
Garage Cars	1.77	0.76	0.00	2.00	5.00
Garage Area	472.82	215.05	0.00	480.00	1488.00
Wood Deck SF	93.75	126.36	0.00	0.00	1424.00
Open Porch SF	47.53	67.48	0.00	27.00	742.00
Enclosed Porch	23.01	64.14	0.00	0.00	1012.00
3Ssn Porch	2.59	25.14	0.00	0.00	508.00
Screen Porch	16.00	56.09	0.00	0.00	576.00
Pool Area	2.24	35.60	0.00	0.00	800.00
Misc Val	50.64	566.34	0.00	0.00	17000.00
Mo Sold	6.22	2.71	1.00	6.00	12.00
Yr Sold	2007.79	1.32	2006.00	2008.00	2010.00
SalePrice	180796.06	79886.69	12789.00	160000.00	755000.00

From the table above, we can see, for example, that the average lot area of the houses in our dataset is 10,147.92 ft2 with a standard deviation of 7,880.02 ft2. We can see also that the minimum lot area is 1,300 ft2 and the maximum lot area is 215,245 ft2 with a median of 9,436.5 ft2. Similarly, we can get a lot of information about our dataset variables from the table.

Then, we move to see statistical information about the non-numerical columns in our dataset:

```
dataset.describe(include=[np.object]).transpose() \ .drop("count", axis=1)
```

	unique	top	freq
MS Zoning	7	RL	2273
Street	2	Pave	2918
Alley	2	Grvl	120
Lot Shape	4	Reg	1859
Land Contour	4	Lvl	2633
Utilities	3	AllPub	2927
Lot Config	5	Inside	2140
Land Slope	3	Gtl	2789
Neighborhood	28	NAmes	443
Condition 1	9	Norm	2522

	unique	top	freq
Condition 2	8	Norm	2900
Bldg Type	5	1Fam	2425
House Style	8	1Story	1481
Roof Style	6	Gable	2321
Roof Matl	8	CompShg	2887
Exterior 1st	16	VinylSd	1026
Exterior 2nd	17	VinylSd	1015
Mas Vnr Type	5	None	1752
Exter Qual	4	TA	1799
Exter Cond	5	TA	2549
Foundation	6	PConc	1310
Bsmt Qual	5	TA	1283
Bsmt Cond	5	TA	2616
Bsmt Exposure	4	No	1906
BsmtFin Type 1	6	GLQ	859
BsmtFin Type 2	6	Unf	2499
Heating	6	GasA	2885
Heating QC	5	Ex	1495
Central Air	2	Y	2734
Electrical	5	SBrkr	2682
Kitchen Qual	5	TA	1494
Functional	8	Typ	2728
Fireplace Qu	5	Gd	744
Garage Type	6	Attchd	1731
Garage Finish	3	Unf	1231
Garage Qual	5	TA	2615
Garage Cond	5	TA	2665
Paved Drive	3	Y	2652
Pool QC	4	Gd	4
Fence	4	MnPrv	330
Misc Feature	5	Shed	95
Sale Type	10	WD	2536
Sale Condition	6	Normal	2413

In the table we got, count represents the number of non-null values in each column, unique represents the number of unique values, top represents the most frequent element, and freq represents the frequency of the most frequent element.

2.4 Data Cleaning

2.4.1 Dealing with Missing Values

We should deal with the problem of missing values because some machine learning models don't accept data with missing values. Firstly, let's see the number of missing values in our dataset. We want to see the number and the percentage of missing values for each column that actually contains missing values.

```
# Getting the number of missing values in each column num_missing =
dataset.isna().sum()
# Excluding columns that contains 0 missing values num_missing =
num_missing[num_missing > 0] # Getting the percentages of missing
values percent_missing = num_missing * 100 / dataset.shape[0]
# Concatenating the number and perecentage of missing values
# into one dataframe and sorting it pd.concat([num_missing,
percent_missing], axis=1, keys=['Missing Values', 'Percentage']).\
sort_values(by="Missing Values", ascending=False)
```

	Missing Values	Percentage
Pool QC	2917	99.56
Misc Feature	2824	96.38
Alley	2732	93.24
Fence	2358	80.48
Fireplace Qu	1422	48.53
Lot Frontage	490	16.72
Garage Cond	159	5.43
Garage Qual	159	5.43
Garage Finish	159	5.43
Garage Yr Blt	159	5.43
Garage Type	157	5.36
Bsmt Exposure	83	2.83
BsmtFin Type 2	81	2.76
BsmtFin Type 1	80	2.73
Bsmt Qual	80	2.73
Bsmt Cond	80	2.73
Mas Vnr Area	23	0.78
Mas Vnr Type	23	0.78
Bsmt Half Bath	2	0.07
Bsmt Full Bath	2	0.07
Total Bsmt SF	1	0.03
Bsmt Unf SF	1	0.03
Garage Cars	1	0.03
Garage Area	1	0.03
BsmtFin SF 2	1	0.03
BsmtFin SF 1	1	0.03
Electrical	1	0.03

Now we start dealing with these missing values.

Pool QC The percentage of missing values in Pool QC column is 99.56% which is very high. We think that a missing value in this column denotes that the corresponding house doesn't have a pool. To verify this, let's take a look at the values of Pool Area column:

```
dataset["Pool Area"].value_counts()
```

	Pool Area
0	2917
561	1
555	1
519	1
800	1
738	1
648	1
576	1
512	1
480	1
444	1
368	1
228	1
144	1

We can see that there are 2917 entries in Pool Area column that have a value of 0. This verifies our hypothesis that each house without a pool has a missing value in Pool QC column and a value of 0 in Pool Area column. So let's fill the missing values in Pool QC column with "No Pool":

```
dataset["Pool QC"].fillna("No Pool", inplace=True)
```

Misc Feature The percentage of missing values in Pool QC column is 96.38% which is very high also. Let's take a look at the values of Misc Val column:

```
dataset["Misc Val"].value_counts()
```

	Misc Val
0	2827
400	18
500	13
450	9
600	8
700	7
2000	7
650	3
1200	3

	Misc Val
1500	3
4500	2
2500	2
480	2
3000	2
12500	1
300	1
350	1
8300	1
420	1
80	1
54	1
460	1
490	1
3500	1
560	1
17000	1
15500	1
750	1
800	1
900	1
1000	1
1150	1
1300	1
1400	1
1512	1
6500	1
455	1
620	1

We can see that Misc Val column has 2827 entries with a value of 0. Misc Feature has 2824 missing values. Then, as with Pool QC, we can say that each house without a “miscellaneous feature” has a missing value in Misc Feature column and a value of 0 in Misc Val column. So let’s fill the missing values in Misc Feature column with "No Feature":

```
dataset['Misc Feature'].fillna('No feature', inplace=True)
```

Alley, Fence, and Fireplace Qu According to the dataset documentation, NA in Alley, Fence, and Fireplace Qu columns denotes that the house doesn’t have an alley, fence, or fireplace. So we fill in the missing values in these columns with "No Alley", "No Fence", and "No Fireplace" accordingly:

```
dataset['Alley'].fillna('No Alley', inplace=True) dataset['Fence'].fillna('No Fence',
inplace=True) dataset['Fireplace Qu'].fillna('No Fireplace', inplace=True)
```

Lot Frontage As we saw previously, Lot Frontage represents the linear feet of street connected to the house. So we assume that the missing values in this column indicates that the house is not connected to any street, and we fill in the missing values with 0:

```
dataset['Lot Frontage'].fillna(0, inplace=True)
```

Garage Cond, Garage Qual, Garage Finish, Garage Yr Blt, Garage Type, Garage Cars, and Garage Area According to the dataset documentation, NA in Garage Cond, Garage Qual, Garage Finish, and Garage Type indicates that there is no garage in the house. So we fill in the missing values in these columns with "No Garage". We notice that Garage Cond, Garage Qual, Garage Finish, Garage Yr Blt columns have 159 missing values, but Garage Type has 157 and both Garage Cars and Garage Area have one missing value. Let's take a look at the row that contains the missing value in Garage Cars:

```
garage_columns = [col for col in dataset.columns if col.startswith("Garage")] dataset[dataset['Garage Cars'].isna()][garage_columns]
```

	Garage Type	Garage Yr Blt	Garage Finish	Garage Cars
2236	Detchd	nan	NaN	nan

	Garage Area	Garage Qual	Garage Cond
2236	nan	NaN	NaN

We can see that this is the same row that contains the missing value in Garage Area, and that all garage columns except Garage Type are null in this row, so we will fill the missing values in Garage Cars and Garage Area with 0.

We saw that there are 2 rows where Garage Type is not null while Garage Cond, Garage Qual, Garage Finish, and Garage Yr Blt columns are null. Let's take a look at these two rows: dataset[~pd.isna(dataset['Garage Type']) & pd.isna(dataset['Garage Qual'])][garage_columns]

	Garage Type	Garage Yr Blt	Garage Finish	Garage Cars
1356	Detchd	nan	NaN	1.00
2236	Detchd	nan	NaN	nan

	Garage Area	Garage Qual	Garage Cond
1356	360.00	NaN	NaN
2236	nan	NaN	NaN

We will replace the values of Garage Type with "No Garage" in these two rows also.
For Garage Yr Blt, we will fill in missing values with 0 since this is a numerical column:

```
dataset['Garage Cars'].fillna(0, inplace=True) dataset['Garage Area'].fillna(0,
inplace=True)

dataset.loc[~pd.isna(dataset['Garage Type']) & pd.isna(dataset['Garage Qual']), "Garage
                    Type"] = "No Garage"

                              for col in ['Garage Type', 'Garage Finish', 'Garage Qual', 'Garage Cond']:
        dataset[col].fillna('No Garage', inplace=True) dataset['Garage Yr Blt'].fillna(0,

inplace=True)
```

Bsmt Exposure, BsmtFin Type 2, BsmtFin Type 1, Bsmt Qual, Bsmt Cond, Bsmt Half Bath, Bsmt Full Bath, Total Bsmt SF, Bsmt Unf SF, BsmtFin SF 2, and BsmtFin SF 1 According to the dataset documentation, NA in any of the first five of these columns indicates that there is no basement in the house. So we fill in the missing values in these columns with "No Basement". We notice that the first five of these columns have 80 missing values, but BsmtFin Type 2 has 81, Bsmt Exposure has 83, Bsmt Half Bath and Bsmt Full Bath each has 2, and each of the others has 1. Let's take a look at the rows where Bsmt Half Bath is null:

```
bsmt_columns = [col for col in dataset.columns if "Bsmt" in col] dataset[dataset['Bsmt Half
Bath'].isna()][bsmt_columns]
```

	Bsmt Qual	Bsmt Cond	Bsmt Exposure	BsmtFin Type 1	BsmtFin SF 1
1341	NaN	NaN	NaN	NaN	nan
1497	NaN	NaN	NaN	NaN	0.00

	BsmtFin Type 2	BsmtFin SF 2	Bsmt Unf SF	Total Bsmt SF
1341	NaN	nan	nan	nan
1497	NaN	0.00	0.00	0.00

	Bsmt Full Bath	Bsmt Half Bath
1341	nan	nan
1497	nan	nan

We can see that these are the same rows that contain the missing values in Bsmt Full Bath, and that one of these two rows is contains the missing value in each of Total Bsmt SF, Bsmt Unf

SF, BsmtFin SF 2, and BsmtFin SF 1 columns. We notice also that Bsmt Exposure, BsmtFin Type 2, BsmtFin Type 1, Bsmt Qual, and Bsmt Cond are null in these rows, so we will fill the missing values in Bsmt Half Bath, Bsmt Full Bath, Total Bsmt SF, Bsmt Unf SF, BsmtFin SF 2, and BsmtFin SF 1 columns with 0.

We saw that there are 3 rows where Bsmt Exposure is null while BsmtFin Type 1, Bsmt Qual, and Bsmt Cond are not null. Let's take a look at these three rows:

```
dataset[~pd.isna(dataset['Bsmt Cond']) & pd.isna(dataset['Bsmt
            Exposure'])][bsmt_columns]
```

	Bsmt Qual	Bsmt Cond	Bsmt Exposure	BsmtFin Type 1	BsmtFin SF 1
66	Gd	TA	NaN	Unf	0.00
1796	Gd	TA	NaN	Unf	0.00
2779	Gd	TA	NaN	Unf	0.00

	BsmtFin Type 2	BsmtFin SF 2	Bsmt Unf SF	Total Bsmt SF
66	Unf	0.00	1595.00	1595.00
1796	Unf	0.00	725.00	725.00
2779	Unf	0.00	936.00	936.00

	Bsmt Full Bath	Bsmt Half Bath
66	0.00	0.00
1796	0.00	0.00
2779	0.00	0.00

We will fill in the missing values in Bsmt Exposure for these three rows with "No". According to the dataset documentation, "No" for Bsmt Exposure means "No Exposure":

Let's now take a look at the row where BsmtFin Type 2 is null while BsmtFin Type 1, Bsmt Qual, and Bsmt Cond are not null:

```
dataset[~pd.isna(dataset['Bsmt Cond']) & pd.isna(dataset['BsmtFin Type
            2'])][bsmt_columns]
```

	Bsmt Qual	Bsmt Cond	Bsmt Exposure	BsmtFin Type 1	BsmtFin SF 1
444	Gd	TA	No	GLQ	1124.00

	BsmtFin Type 2	BsmtFin SF 2	Bsmt Unf SF	Total Bsmt SF
444	NaN	479.00	1603.00	3206.00

	Bsmt Full Bath	Bsmt Half Bath
444	1.00	0.00

We will fill in the missing value in BsmtFin Type 2 for this row with "Unf". According to the dataset documentation, "Unf" for BsmtFin Type 2 means “Unfinished”:

```
for col in ["Bsmt Half Bath", "Bsmt Full Bath", "Total Bsmt SF", "Bsmt Unf SF",
                "BsmtFin SF 2", "BsmtFin SF 1"]:
    dataset[col].fillna(0, inplace=True)

dataset.loc[~pd.isna(dataset['Bsmt Cond']) & pd.isna(dataset['Bsmt Exposure']), "Bsmt
                Exposure"] = "No"
dataset.loc[~pd.isna(dataset['Bsmt Cond']) & pd.isna(dataset['BsmtFin Type 2']), "BsmtFin
                Type 2"] = "Unf"

for col in ["Bsmt Exposure", "BsmtFin Type 2",
                    "BsmtFin Type 1", "Bsmt Qual", "Bsmt Cond"]:
    dataset[col].fillna("No Basement", inplace=True)
```

Mas Vnr Area and Mas Vnr Type Each of these two columns have 23 missing values. We will fill in these missing values with "None" for Mas Vnr Type and with 0 for Mas Vnr Area. We use "None" for Mas Vnr Type because in the dataset documentation, "None" for Mas Vnr Type means “None” (i.e. no masonry veneer):

```
dataset['Mas Vnr Area'].fillna(0, inplace=True) dataset['Mas Vnr
Type'].fillna("None", inplace=True)
```

Electrical This column has one missing value. We will fill in this value with the mode of this column:

```
dataset['Electrical'].fillna(dataset['Electrical'].mode()[0], inplace=True)
```

Now let’s check if there is any remaining missing value in our dataset:

```
dataset.isna().values.sum() 0
```

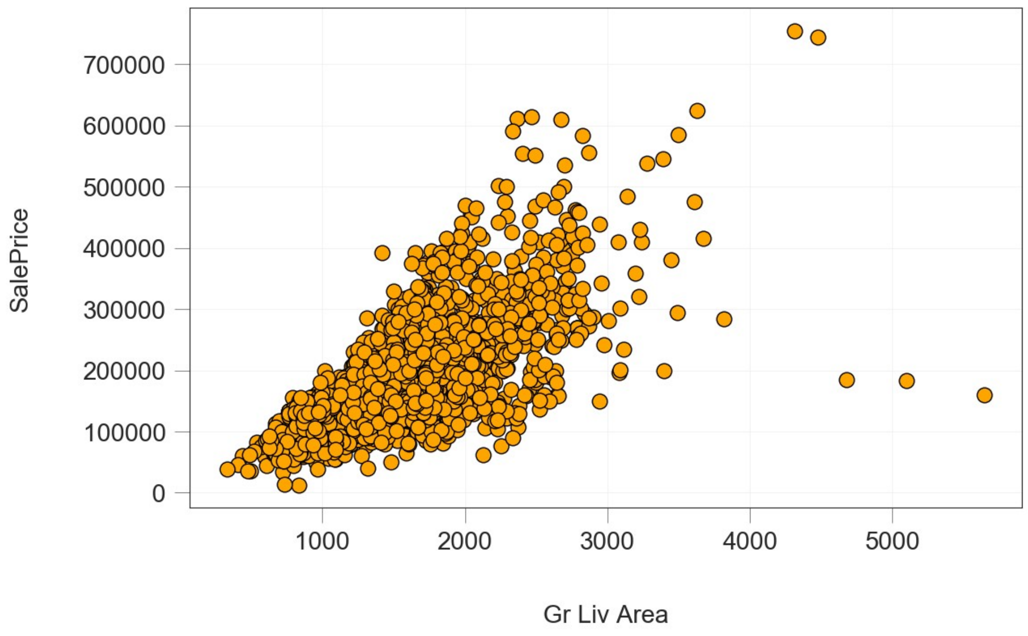
This means that our dataset is now complete; it doesn’t contain any missing value anymore.

2.5 Outlier Removal

In the paper in which our dataset was introduced by De Cock (2011), the author states that there are five unusual values and outliers in the dataset, and encourages the removal of these outliers. He suggested plotting SalePrice against Gr Liv Area to spot the outliers. We will do that now:

```
from matplotlib import pyplot as plt
import seaborn as sns

plt.scatter(x=dataset['Gr Liv Area'], y=dataset['SalePrice'], color="orange",
                    edgecolors="#000000", linewidths=0.5);
plt.xlabel("Gr Liv Area"); plt.ylabel("SalePrice");
```



We can clearly see the five values meant by the author in the plot above. Now, we will remove them from our dataset. We can do so by keeping data points that have Gr Liv Area less than 4,000. But first we take a look at the dataset rows that correspond to these unusual values:

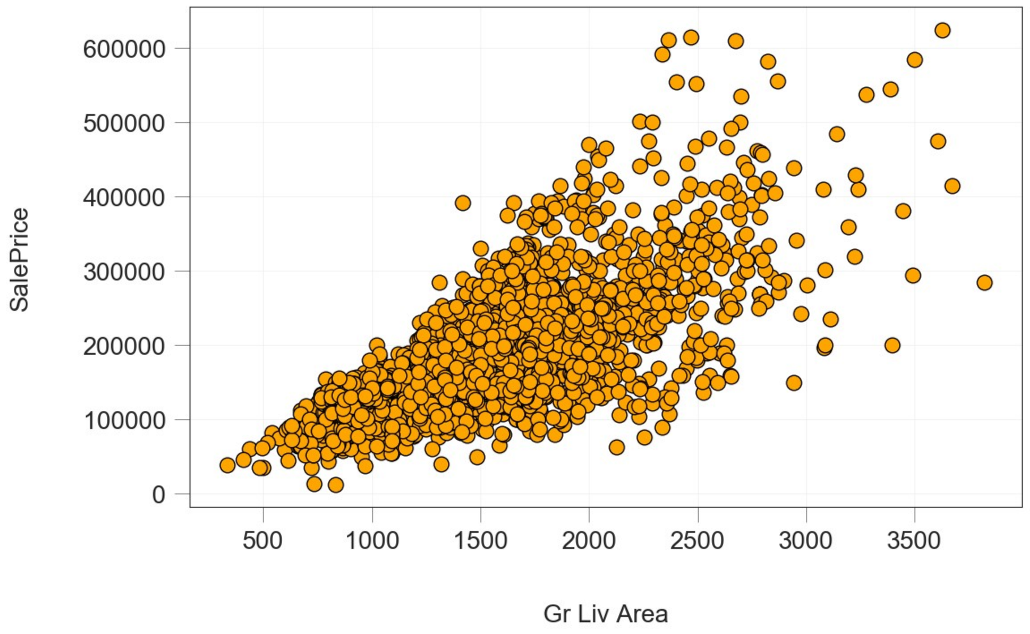
```
outlirt_columns = ["Gr Liv Area"] + \
                    [col for col in dataset.columns if "Sale" in col]
dataset[dataset["Gr Liv Area"] > 4000][outlirt_columns]
```

	Gr Liv Area	Sale Type	Sale Condition	SalePrice
1498	5642	New	Partial	160000
1760	4476	WD	Abnorml	745000
1767	4316	WD	Normal	755000
2180	5095	New	Partial	183850
2181	4676	New	Partial	184750

Now we remove them:

```
dataset = dataset[dataset["Gr Liv Area"] < 4000]
```

```
plt.scatter(x=dataset['Gr Liv Area'], y=dataset['SalePrice'], color="orange",
                    edgecolors="#000000", linewidths=0.5);
plt.xlabel("Gr Liv Area"); plt.ylabel("SalePrice");
```



To avoid problems in modeling later, we will reset our dataset index after removing the outlier rows, so no gaps remain in our dataset index:

```
dataset.reset_index(drop=True, inplace=True)
```

2.6 Deleting Some Unimportant Columns

We will delete columns that are not useful in our analysis. The columns to be deleted are Order and PID:

```
dataset.drop(['Order', 'PID'], axis=1, inplace=True)
```

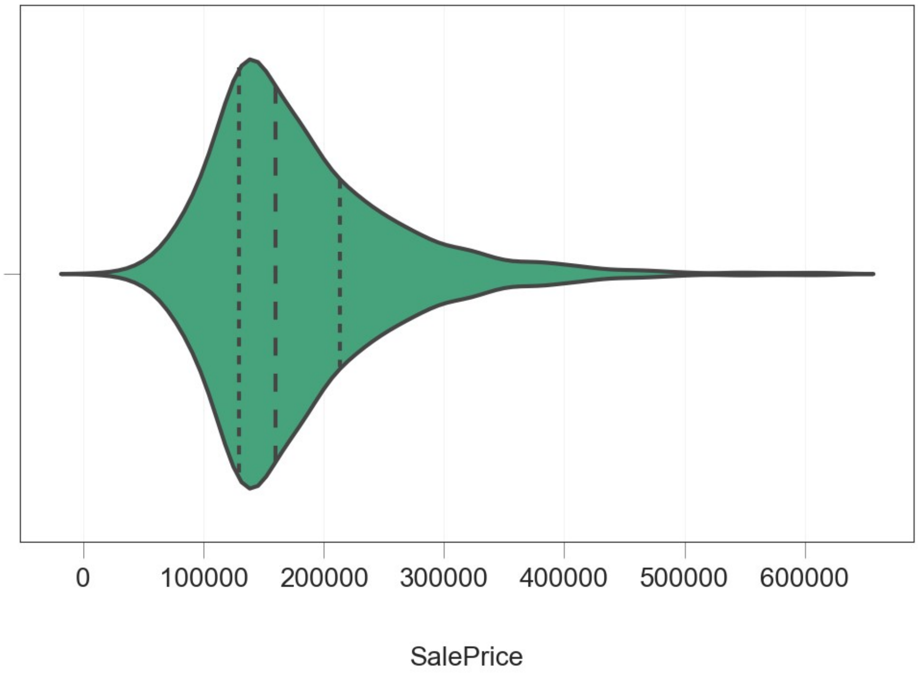
3 Exploratory Data Analysis

In this section, we will explore the data using visualizations. This will allow us to understand the data and the relationships between variables better, which will help us build a better model.

3.1 Target Variable Distribution

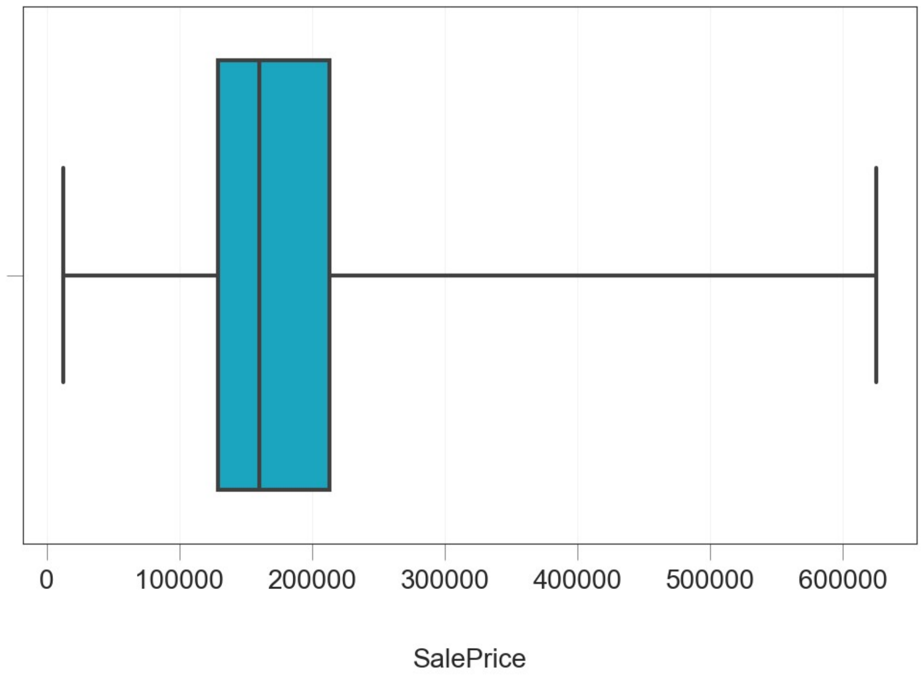
Our dataset contains a lot of variables, but the most important one for us to explore is the target variable. We need to understand its distribution. First, we start by plotting the violin plot for the target variable. The width of the violin represents the frequency. This means that if a violin is the widest between 300 and 400, then the area between 300 and 400 contains more data points than other areas:

```
sns.violinplot(x=dataset['SalePrice'], inner="quartile", color="#36B37E");
```



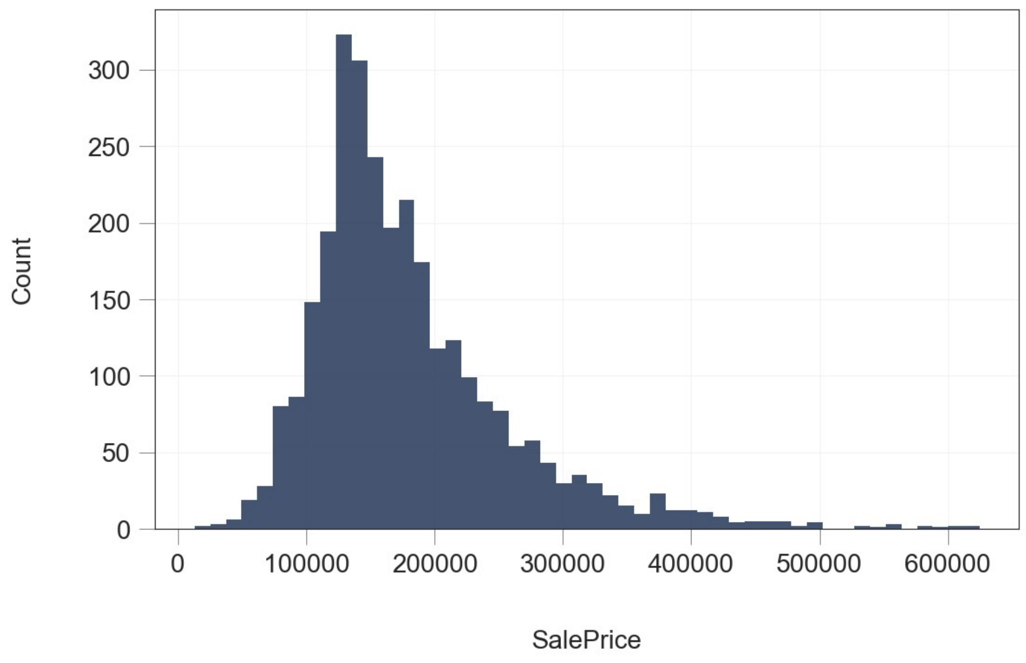
We can see from the plot that most house prices fall between 100,000 and 250,000. The dashed lines represent the locations of the three quartiles Q1, Q2 (the median), and Q3. Now let's see the box plot of SalePrice:

```
sns.boxplot(dataset['SalePrice'], whis=10, color="#00B8D9");
```



This shows us the minimum and maximum values of SalePrice. It shows us also the three quartiles represented by the box and the vertical line inside of it. Lastly, we plot the histogram of the variable to see a more detailed view of the distribution:

```
sns.distplot(dataset['SalePrice'], kde=False, color="#172B4D",
             hist_kws={"alpha": 0.8});
plt.ylabel("Count");
```



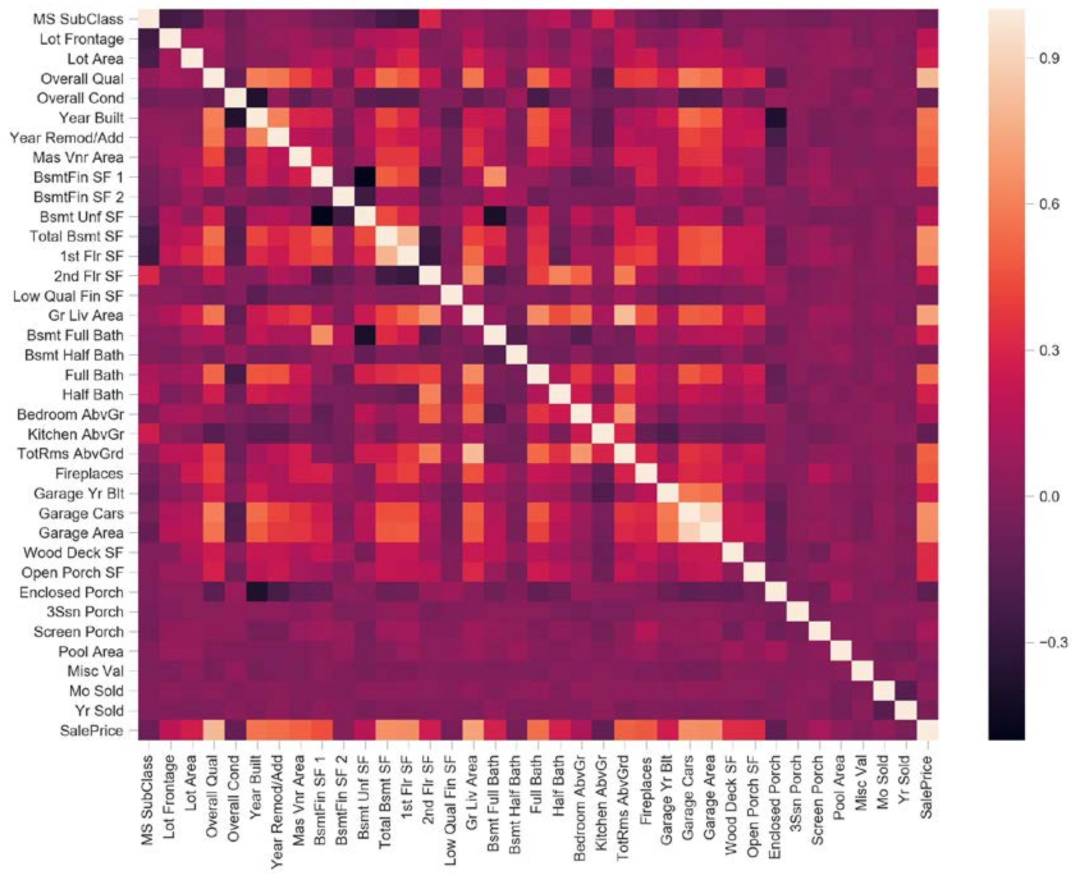
3.2 Correlation Between Variables

We want to see how the dataset variables are correlated with each other and how predictor variables are correlated with the target variable. For example, we would like to see how Lot Area and SalePrice are correlated: Do they increase and decrease together (positive correlation)? Does one of them increase when the other decrease or vice versa (negative correlation)? Or are they not correlated?

Correlation is represented as a value between -1 and +1 where +1 denotes the highest positive correlation, -1 denotes the highest negative correlation, and 0 denotes that there is no correlation.

We will show correlation between our dataset variables (numerical and boolean variables only) using a heatmap graph:

```
fig, ax = plt.subplots(figsize=(12,9)) sns.heatmap(dataset.corr(), ax=ax);
```



We can see that there are many correlated variables in our dataset. Wwe notice that Garage Cars and Garage Area have high positive correlation which is reasonable because when the garage area increases, its car capacity increases too. We see also that Gr Liv Area and TotRms AbvGrd are highly positively correlated which also makes sense because when living area above ground increases, it is expected for the rooms above ground to increase too.

Regarding negative correlation, we can see that Bsmt Unf SF is negatively correlated with BsmtFin SF 1, and that makes sense because when we have more unfinished area, this means that we have less finished area. We note also that Bsmt Unf SF is negatively correlated with Bsmt Full Bath which is reasonable too.

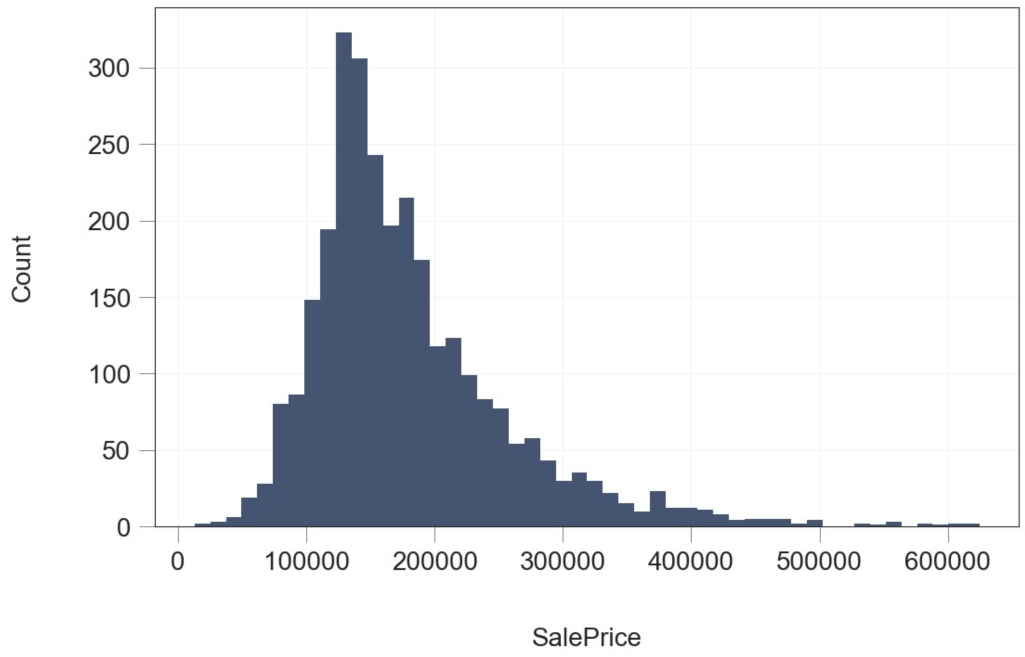
Most importantly, we want to look at the predictor variables that are correlated with the target variable (SalePrice). By looking at the last row of the heatmap, we see that the target variable is highly positively correlated with Overall Qual and Gr Liv Area. We see also that the target variable is positively correlated with Year Built, Year Remod/Add, Mas Vnr Area, Total Bsmt SF, 1st Flr SF, Full Bath, Garage Cars, and Garage Area.

3.2.1 Relationships Between the Target Variable and Other Variables

High Positive Correlation Firstly, we want to visualize the relationships between the target variable and the variables that are highly and positively correlated with it, according to what we saw in the heatmap.

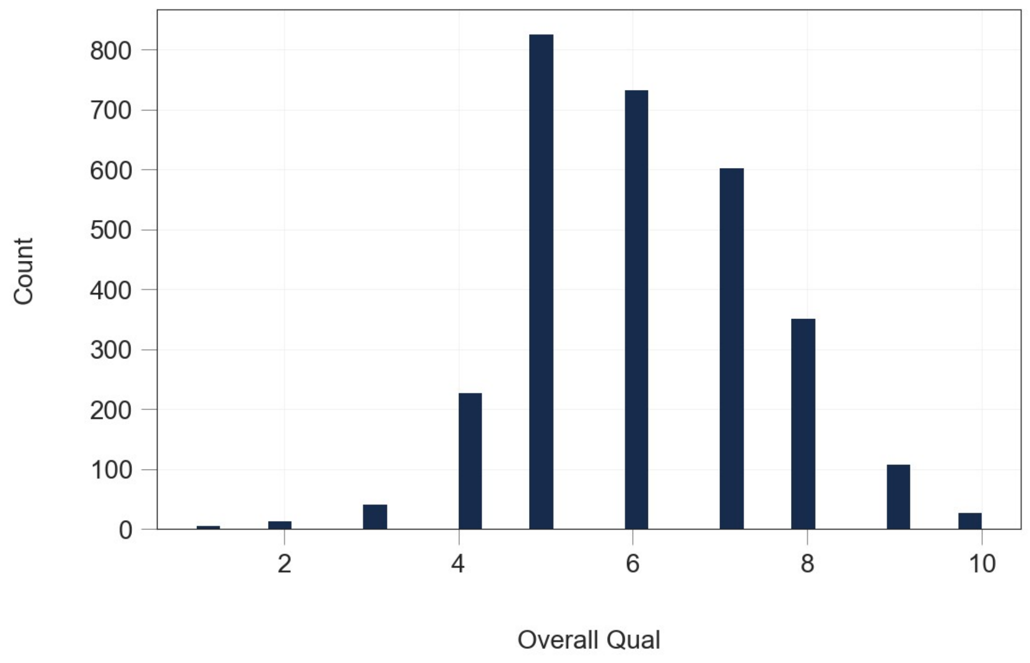
Namely, these variables are Overall Qual and Gr Liv Area. We start with the relationship between the target variable and Overall Qual, but before that, let’s see the distribution of each of them. Let’s start with the target variable SalePrice:

```
sns.distplot(dataset['SalePrice'], kde=False, color="#172B4D",
             hist_kws={"alpha": 0.8});
plt.ylabel("Count");
```



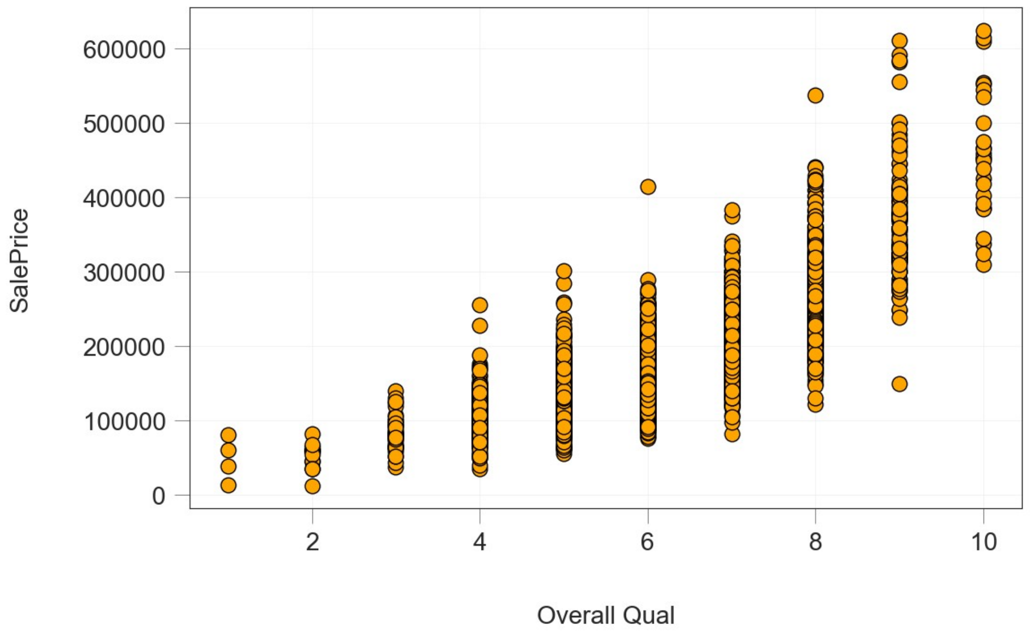
We can see that most house prices fall between 100,000 and 200,000. We see also that there is a number of expensive houses to the right of the plot. Now, we move to see the distribution of Overall Qual variable:

```
sns.distplot(dataset['Overall Qual'], kde=False, color="#172B4D",
             hist_kws={"alpha": 1});
plt.ylabel("Count");
```



We see that Overall Qual takes an integer value between 1 and 10, and that most houses have an overall quality between 5 and 7. Now we plot the scatter plot of SalePrice and Overall Qual to see the relationship between them:

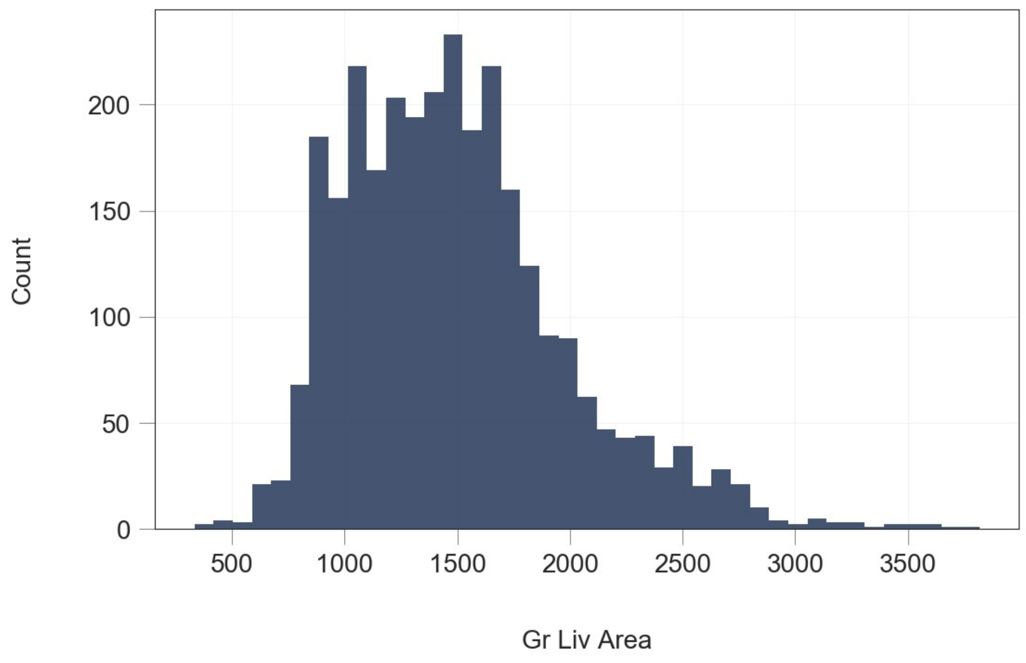
```
plt.scatter(x=dataset['Overall Qual'], y=dataset['SalePrice'], color="orange",
            edgecolors="#000000", linewidths=0.5);
plt.xlabel("Overall Qual"); plt.ylabel("SalePrice");
```



We can see that they are truly positively correlated; generally, as the overall quality increases, the sale price increases too. This verifies what we got from the heatmap above.

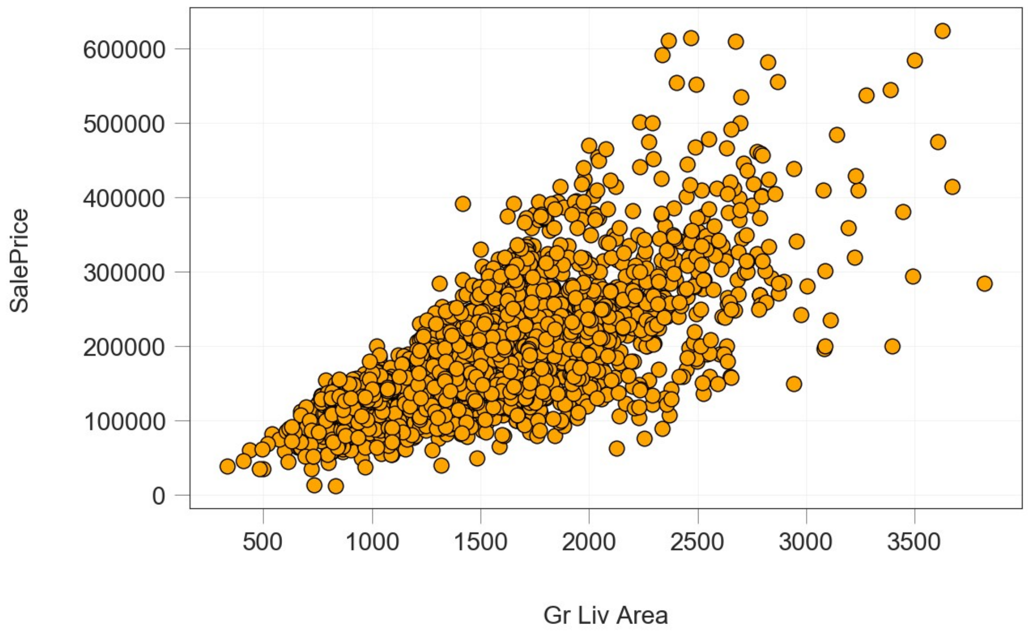
Now, we want to see the relationship between the target variable and Gr Liv Area variable which represents the living area above ground. Let us first see the distribution of Gr Liv Area:

```
sns.distplot(dataset['Gr Liv Area'], kde=False, color="#172B4D",
                    hist_kws={"alpha": 0.8});
plt.ylabel("Count");
```



We can see that the above-ground living area falls approximately between 800 and 1800 ft2. Now, let us see the relationship between Gr Liv Area and the target variable:

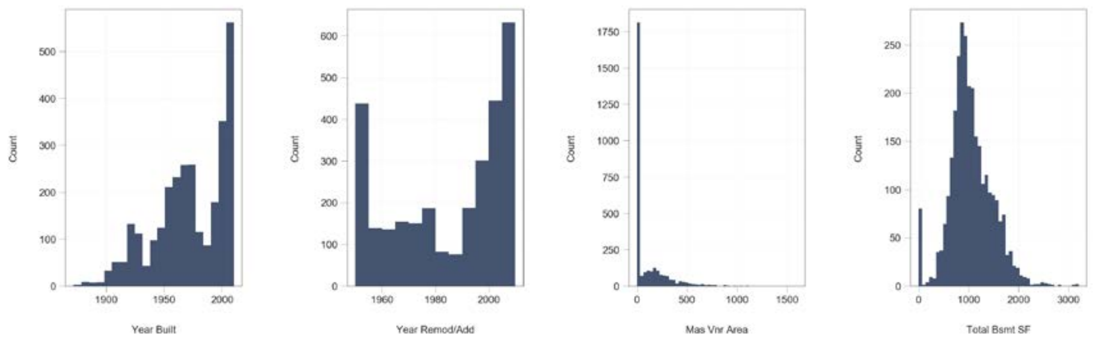
```
plt.scatter(x=dataset['Gr Liv Area'], y=dataset['SalePrice'], color="orange",
                    edgecolors="#000000", linewidths=0.5);
plt.xlabel("Gr Liv Area"); plt.ylabel("SalePrice");
```



The scatter plot above shows clearly the strong positive correlation between Gr Liv Area and SalePrice verifying what we found with the heatmap.

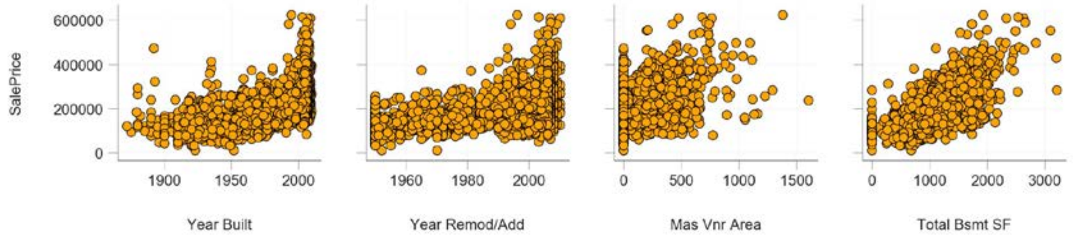
Moderate Positive Correlation Next, we want to visualize the relationship between the target variable and the variables that are positively correlated with it, but the correlation is not very strong. Namely, these variables are Year Built, Year Remod/Add, Mas Vnr Area, Total Bsmt SF, 1st Flr SF, Full Bath, Garage Cars, and Garage Area. We start with the first four. Let us see the distribution of each of them:

```
fig, axes = plt.subplots(1, 4, figsize=(18,5)) fig.subplots_adjust(hspace=0.5,
wspace=0.6) for ax, v in zip(axes.flat, ["Year Built", "Year Remod/Add",
                                        "Mas Vnr Area", "Total Bsmt SF"]):
    sns.distplot(dataset[v], kde=False, color="#172B4D", hist_kws={"alpha": 0.8},
                ax=ax)
    ax.set(ylabel="Count");
```



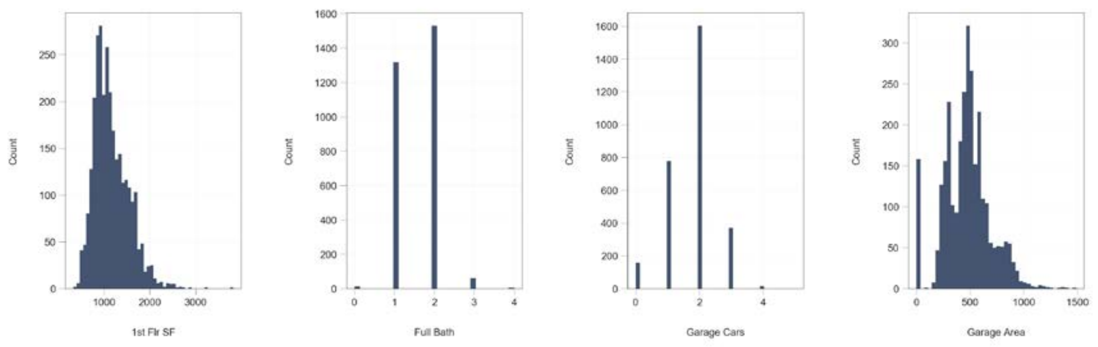
Now let us see their relationships with the target variable using scatter plots:

```
x_vars = ["Year Built", "Year Remod/Add", "Mas Vnr Area", "Total Bsmt SF"] g =
sns.PairGrid(dataset, y_vars=["SalePrice"], x_vars=x_vars);
                                        g.map(plt.scatter, color="orange", edgecolors="#000000", linewidths=0.5);
```



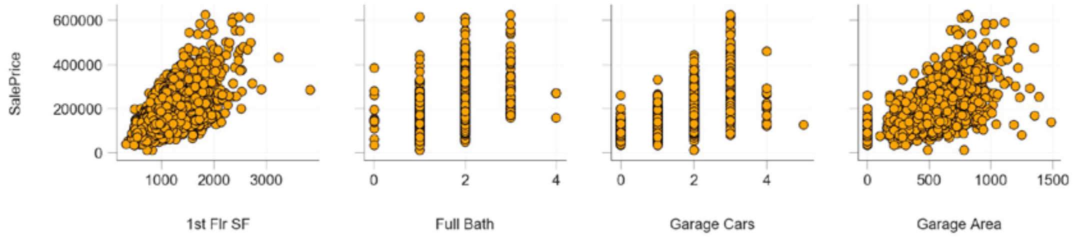
Next, we move to the last four. Let us see the distribution of each of them:

```
fig, axes = plt.subplots(1, 4, figsize=(18,5))
fig.subplots_adjust(hspace=0.5, wspace=0.6) for ax, v in zip(axes.flat,
["1st Flr SF", "Full Bath",
                                                          "Garage Cars", "Garage Area"]):
    sns.distplot(dataset[v], kde=False, color="#172B4D", hist_kws={"alpha": 0.8},
                        ax=ax);
    ax.set(ylabel="Count");
```



And now let us see their relationships with the target variable:

```
x_vars = ["1st Flr SF", "Full Bath", "Garage Cars", "Garage Area"] g =
sns.PairGrid(dataset, y_vars=["SalePrice"], x_vars=x_vars);
                        g.map(plt.scatter, color="orange", edgecolors="#000000", linewidths=0.5);
```

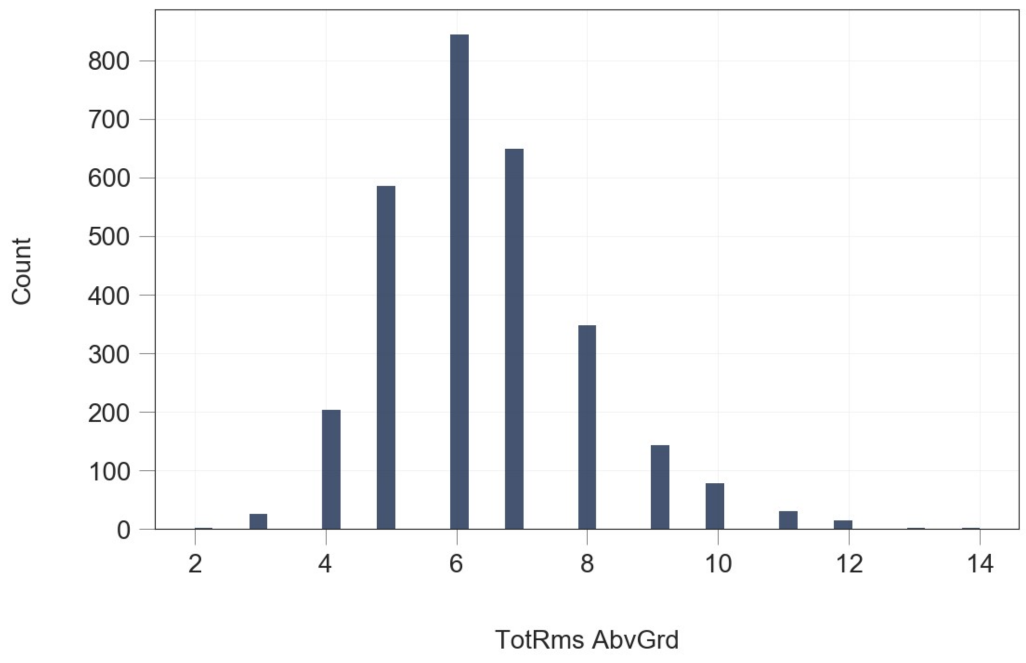


From the plots above, we can see that these eight variables are truly positively correlated with the target variable. However, it's apparent that they are not as highly correlated as Overall Qual and Gr Liv Area.

3.2.2 Relationships Between Predictor Variables

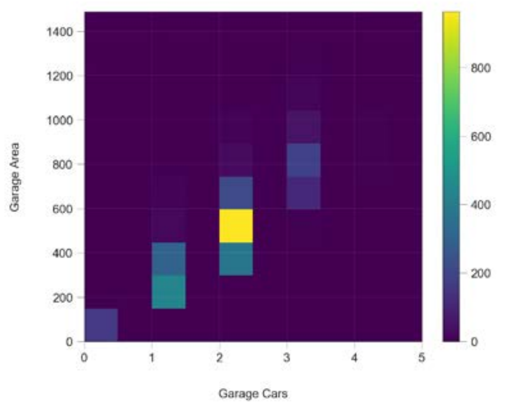
Positive Correlation Apart from the target variable, when we plotted the heatmap, we discovered a high positive correlation between Garage Cars and Garage Area and between Gr Liv Area and TotRms AbvGrd. We want to visualize these correlations also. We've already seen the distribution of each of them except for TotRms AbvGrd. Let us see the distribution of TotRms AbvGrd first:

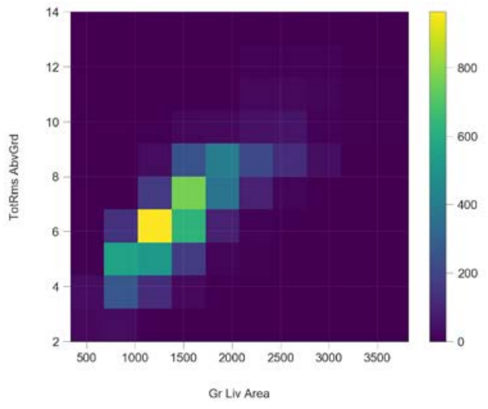
```
sns.distplot(dataset['TotRms AbvGrd'], kde=False, color="#172B4D",
                hist_kws={"alpha": 0.8});
plt.ylabel("Count");
```



Now, we visualize the relationship between Garage Cars and Garage Area and between Gr Liv Area and TotRms AbvGrd:

```
plt.rc("grid", linewidth=0.05) fig, axes = plt.subplots(1, 2,
figsize=(15,5)) fig.subplots_adjust(hspace=0.5,
wspace=0.4) h1 = axes[0].hist2d(dataset["Garage Cars"],
                                dataset["Garage Area"], cmap="viridis");
axes[0].set(xlabel="Garage Cars", ylabel="Garage Area")
plt.colorbar(h1[3], ax=axes[0]); h2 = axes[1].hist2d(dataset["Gr Liv
Area"], dataset["TotRms AbvGrd"], cmap="viridis");
axes[1].set(xlabel="Gr Liv Area", ylabel="TotRms AbvGrd")
plt.colorbar(h1[3], ax=axes[1]); plt.rc("grid", linewidth=0.25)
```

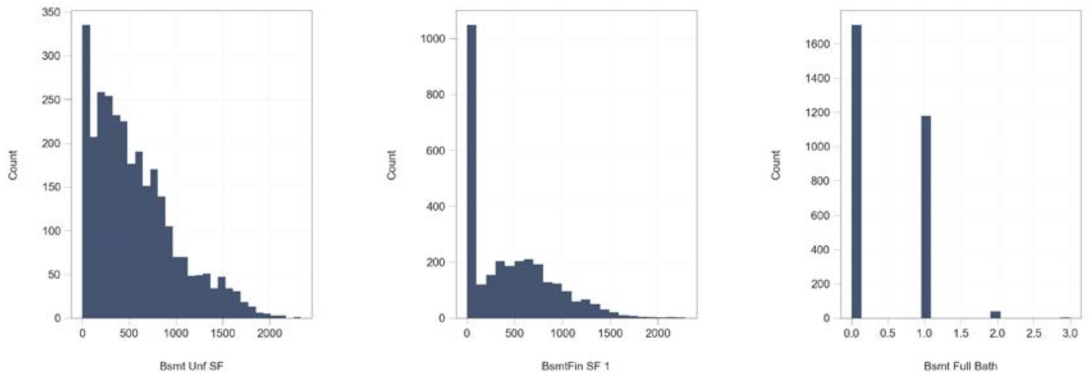




We can see the strong correlation between each pair. For Garage Cars and Garage Area, we see that the highest concentration of data is when Garage Cars is 2 and Garage Area is approximately between 450 and 600 ft2. For Gr Liv Area and TotRms AbvGrd, we notice that the highest concentration is when Garage Liv Area is roughly between 800 and 2000 ft2 and TotRms AbvGrd is 6.

Negative Correlation When we plotted the heatmap, we also discovered a significant negative correlation between Bsmt Unf SF and BsmtFin SF 1, and between Bsmt Unf SF and Bsmt Full Bath. We also want to visualize these correlations. Let us see the distribution of these variables first:

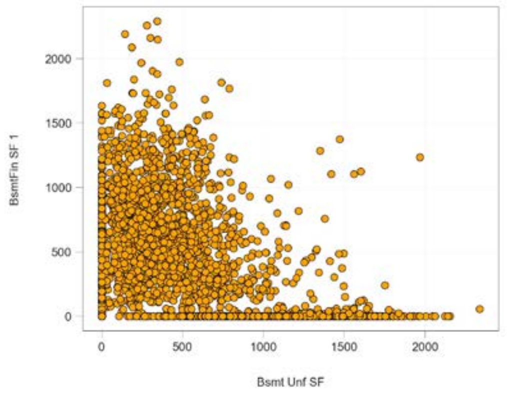
```
fig, axes = plt.subplots(1, 3, figsize=(16,5)) fig.subplots_adjust(hspace=0.5, wspace=0.6)
for ax, v in zip(axes.flat, ["Bsmt Unf SF", "BsmtFin SF 1", "Bsmt Full Bath"]):
sns.distplot(dataset[v], kde=False, color="#172B4D", hist_kws={"alpha": 0.8}, ax=ax);
ax.set(ylabel="Count")
```

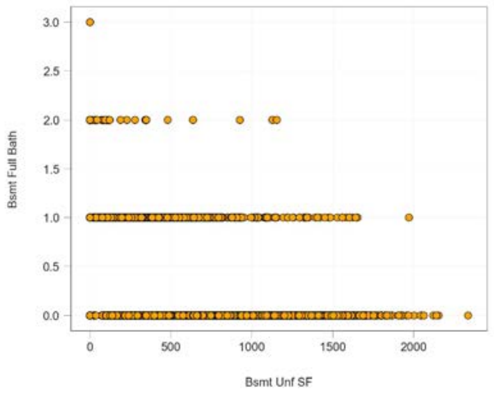


Now, we visualize the relationship between each pair using scatter plots:

```
fig, axes = plt.subplots(1, 2, figsize=(15,5)) fig.subplots_adjust(hspace=0.5, wspace=0.4)
axes[0].scatter(dataset["Bsmt Unf SF"], dataset["BsmtFin SF 1"], color="orange",
edgecolors="#000000", linewidths=0.5);
```

```
axes[0].set(xlabel="Bsmt Unf SF", ylabel="BsmtFin SF 1"); axes[1].scatter(dataset["Bsmt
Unf SF"], dataset["Bsmt Full Bath"], color="orange", edgecolors="#000000",
linewidths=0.5);
axes[1].set(xlabel="Bsmt Unf SF", ylabel="Bsmt Full Bath");
```





From the plots, we can see the negative correlation between each pair of these variables.

We will use the information we got from exploratory data analysis in this section, we will use it in feature engineering in the next section.

3.3 Feature Engineering

In this section, we will use the insights from Exploratory Data Analysis section to engineer the features of our dataset.

3.3.1 Creating New Derived Features

Firstly, we noticed a high positive correlation between the target variable SalePrice and each of Overall Qual and Gr Liv Area. This gives an indication that the latter two features are very important in predicting the sale price. So, we will create polynomial features out of these features: For each one of these features, we will derive a feature whose values are the squares of original values, and another feature whose values are the cubes of original values. Moreover, we will create a feature whose values are the product of our two features values:

```
for f in ["Overall Qual", "Gr Liv Area"]: dataset[f + "_p2"] =
    dataset[f] ** 2 dataset[f + "_p3"] = dataset[f] ** 3
dataset["OverallQual_GrLivArea"] = \ dataset["Overall Qual"] *
    dataset["Gr Liv Area"]
```

Also, we noticed that there are some predictor features that are highly correlated with each other. To avoid the Multicollinearity problem, we will delete one feature from each pair of highly correlated predictors. We have two pairs: the first consists of Garage Cars and Garage Area, and the other consists of Gr Liv Area and TotRms AbvGrd. For the first pair, we will remove Garage Cars feature; from the second pair, we will remove TotRms AbvGrd feature:

```
dataset.drop(["Garage Cars", "TotRms AbvGrd"], axis=1, inplace=True)
```

3.3.2 Dealing with Ordinal Variables

There are some ordinal features in our dataset. For example, the Bsmt Cond feature has the following possible values:

```
print("Unique values in 'Bsmt Cond' column:") print(dataset['Bsmt
Cond'].unique().tolist())
```

```
Unique values in 'Bsmt Cond' column:
['Gd', 'TA', 'No Basement', 'Po', 'Fa', 'Ex']
```

Where “Gd” means “Good”, “TA” means “Typical”, “Po” means “Poor”, “Fa” means “Fair”, and “Ex” means “Excellent” according to the dataset documentation. But the problem is that machine learning models will not know that this feature represents a ranking; it will be treated as other categorical features. So to solve this issue, we will map each one of the possible values of this feature to a number. We will map "No Basement" to 0, "Po" to 1, "Fa" to 2, "TA" to 3, "Gd" to 4, and "Ex" to 5.

The ordinal features in the dataset are: Exter Qual, Exter Cond, Bsmt Qual, Bsmt Cond, Bsmt Exposure, BsmtFin Type 1, BsmtFin Type 2, Heating QC, Central Air, Kitchen Qual, Functional, Fireplace Qu, GarageFinish, Garage Qual, Garage Cond, Pool QC, Land Slope and Fence. We will map the values of each of them to corresponding numbers as described for Bsmt Cond above and in accordance with the dataset documentation:

```
mp = {'Ex':4,'Gd':3,'TA':2,'Fa':1,'Po':0} dataset['Exter Qual'] =
dataset['Exter Qual'].map(mp) dataset['Exter Cond'] = dataset['Exter
Cond'].map(mp) dataset['Heating QC'] = dataset['Heating QC'].map(mp)
dataset['Kitchen Qual'] = dataset['Kitchen Qual'].map(mp)

mp = {'Ex':5,'Gd':4,'TA':3,'Fa':2,'Po':1,'No Basement':0} dataset['Bsmt Qual'] =
dataset['Bsmt Qual'].map(mp) dataset['Bsmt Cond'] = dataset['Bsmt
Cond'].map(mp) dataset['Bsmt Exposure'] = dataset['Bsmt Exposure'].map(
      {'Gd':4,'Av':3,'Mn':2,'No':1,'No Basement':0})

mp = {'GLQ':6,'ALQ':5,'BLQ':4,'Rec':3,'LwQ':2,'Unf':1,'No Basement':0} dataset['BsmtFin Type 1']
= dataset['BsmtFin Type 1'].map(mp) dataset['BsmtFin Type 2'] = dataset['BsmtFin Type
2'].map(mp) dataset['Central Air'] = dataset['Central Air'].map({'Y':1,'N':0}) dataset['Functional'] =
dataset['Functional'].map(
      {'Typ':7,'Min1':6,'Min2':5,'Mod':4,'Maj1':3,
        'Maj2':2,'Sev':1,'Sal':0}) dataset['Fireplace Qu'] =
dataset['Fireplace Qu'].map(
      {'Ex':5,'Gd':4,'TA':3,'Fa':2,'Po':1,'No Fireplace':0}) dataset['Garage Finish'] =
dataset['Garage Finish'].map(
        {'Fin':3,'RFn':2,'Unf':1,'No Garage':0}) dataset['Garage Qual'] =
dataset['Garage Qual'].map(
        {'Ex':5,'Gd':4,'TA':3,'Fa':2,'Po':1,'No Garage':0}) dataset['Garage Cond'] =
dataset['Garage Cond'].map(
        {'Ex':5,'Gd':4,'TA':3,'Fa':2,'Po':1,'No Garage':0}) dataset['Pool QC'] = dataset['Pool
QC'].map(
        {'Ex':4,'Gd':3,'TA':2,'Fa':1,'No Pool':0}) dataset['Land Slope'] =
dataset['Land Slope'].map(
        {'Sev': 2, 'Mod': 1, 'Gtl': 0}) dataset['Fence'] =
dataset['Fence'].map(
                {'GdPrv':4,'MnPrv':3,'GdWo':2,'MnWw':1,'No Fence':0})
```

3.3.3 One-Hot Encoding for Categorical Features

Machine learning models accept only numbers as input, and since our dataset contains categorical features, we need to encode them in order for our dataset to be suitable for modeling. We will encode our categorical features using one-hot encoding technique which transforms the categorical variable into a number of binary variables based on the number of unique categories in the categorical variable; each of the resulting binary variables has only 0 and 1 as its possible values. Pandas package provides a convenient function get_dummies() that can be used for performing one-hot encoding on our dataset.

To see what will happen to our dataset, let us take for example the variable Paved Drive which indicates how the driveway is paved. It has three possible values: Y which means for “Paved”, P which means “Partial Pavement”, and N which means “Dirt/Gravel”. Let us take a look at Paved Drive value for the first few rows in our dataset:

```
dataset[['Paved Drive']].head()
```

```
     Paved Drive
0    P
1    Y
2    Y
3    Y
4    Y
```

Now, we perform one-hot encoding:

```
dataset = pd.get_dummies(dataset)
```

Let us see what has happened to the Paved Drive variable by looking at the same rows above:

```
pavedDrive_oneHot = [c for c in dataset.columns if c.startswith("Paved")]
dataset[pavedDrive_oneHot].head()
```

	Paved Drive_N	Paved Drive_P	Paved Drive_Y
0	0	1	0
1	0	0	1
2	0	0	1
3	0	0	1
4	0	0	1

We can see for example that a value of P in the original Paved Drive column is converted to 1 in Paved Drive_P and zeros in Paved Drive_N and Paved Drive_Y after one-hot encoding.

All categorical columns are converted in the same way.

Now, after we have cleaned and prepared our dataset, it is ready for modeling.

4 Prediction Type and Modeling Techniques

In this section, we choose the type of machine learning prediction that is suitable to our problem. We want to determine if this is a regression problem or a classification problem. In this project, we want to predict the *price* of a house given information about it. The price we want to predict is a continuous value; it can be any real number. This can be seen by looking at the target variable in our dataset SalePrice:

```
dataset[['SalePrice']].head()
```

	SalePrice
0	215000
1	105000
2	172000
3	244000
4	189900

That means that the prediction type that is appropriate to our problem is **regression**.

Now we move to choose the modeling techniques we want to use. There are a lot of techniques available for regression problems like Linear Regression, Ridge Regression, Artificial Neural Networks, Decision Trees, Random Forest, etc. However, most advanced techniques are beyond the scope of this project. We will test three linear regression models which will be variations that cover a simple linear regression as a baseline, adds polynomial effects, and uses a regularization technique and then choose the technique(s) that yield the best results. All models will use the same training and test splits and same cross-validation method called GridSearchCV(). The techniques that we will try are:

4.1 Ridge Regression

This is a method of estimating the coefficients of multiple-regression models in scenarios where independent variables are highly correlated.

4.2 Lasso Regression

This is a regression analysis method that performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of the resulting statistical model.

4.3 Elastic Net

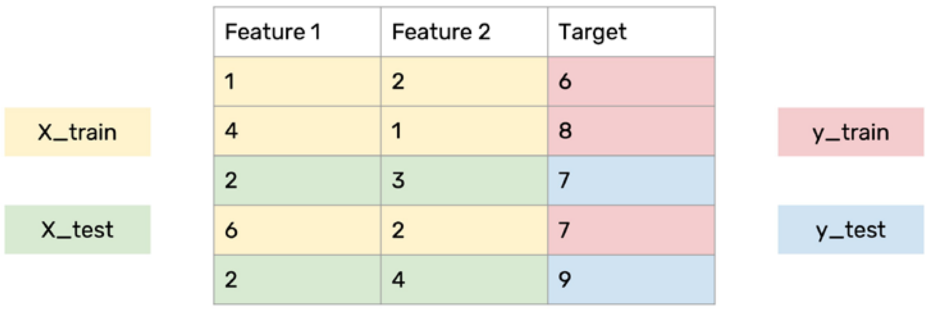
This is a regularized regression method that linearly combines the L1 and L2 penalties of the lasso and ridge methods.

5 Model Building and Evaluation

In this part, we will build our prediction model: we will choose algorithms for each of the techniques we mentioned in the previous section. After we build the model, we will evaluate its performance and results.

5.1 Feature Scaling

In order to make all algorithms work properly with our data, we need to scale the features in our dataset. For that, we will use a helpful function named StandardScaler() from the popular Scikit-Learn Python package. This function standardizes features by subtracting the mean and scaling to unit variance. It works on each feature independently. For a value *x* of some feature *F*, the StandardScaler() function performs the following operation:



Feature 1	Feature 2	Target
1	2	6
4	1	8
2	3	7
6	2	7
2	4	9

Figure 10: train_test_split() operation

$$z = \frac{x - \mu}{s}$$

where *z* is the result of scaling *x*, *μ* is the mean of feature *F*, and *s* is the standard deviation of *F*.

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
# We need to fit the scaler to our data before transformation dataset.loc[:, dataset.columns
!= 'SalePrice'] = scaler.fit_transform( dataset.loc[:, dataset.columns != 'SalePrice'])
```

5.2 Splitting the Dataset

As usual for supervised machine learning problems, we need a training dataset to train our model and a test dataset to evaluate the model. So we will split our dataset randomly into two parts, one for training and the other for testing. For that, we will use another function from Scikit-Learn called train_test_split():

```
from sklearn.model_selection import train_test_split
```

```
X_train, X_test, y_train, y_test = train_test_split( dataset.drop('SalePrice', axis=1),
        dataset[['SalePrice']], test_size=0.25, random_state=3)
```

We specified the size of the test set to be 25% of the whole dataset. This leaves 75% for the training dataset. Now we have four subsets: X_train, X_test, y_train, and y_test. Later we will use X_train and y_train to train our model, and X_test and y_test to test and evaluate the model. X_train and X_test represent features (predictors); y_train and y_test represent the target. From now on, we will refer to X_train and y_train as the training dataset, and to X_test and y_test as the test dataset. Figure 10 shows an example of what train_test_split() does.

5.3 Modeling Approach

For each one of the techniques mentioned in the previous section Ridge Regression, Lasso Regression and Elastic Net), we will follow these steps to build a model:

- Choose an algorithm that implements the corresponding technique
- Search for an effective parameter combination for the chosen algorithm
- Create a model using the found parameters
- Train (fit) the model on the training dataset
- Test the model on the test dataset and get the results

5.3.1 Searching for Effective Parameters

To find the best values for our parameters, we will examine many parameter combinations and choose the combination that gives the best score. Scikit-Learn provides a useful function for that purpose: GridSearchCV(). Sometimes, when the number of parameter combinations is large, GridSearchCV() can take very long time to run. In that case, in addition to GridSearchCV(), we can use RandomizedSearchCV() which is similar to GridSearchCV() but instead of using all parameter combinations, it picks a number of random combinations specified by n_iter. However, the three models we'll test should not take very long in execution and therefore we most probably won't need RandomizedSearchCV().

5.4 Performance Metric

For evaluating the performance of our models, we will use mean absolute error (MAE). If $\hat{y}_i$ is the predicted value of the *i*-th element, and *y* is the corresponding true value, then for all *n* elements, RMSE is calculated as:

$$\text{MAE}(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

However, we'll also check R Squared (coefficient of determination) regression score (r2_score), just out of curiosity. If SS_{res} is the sum of squares of the residual errors and SS_{tot} is the total sum of the errors, r2_score is calculated as:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

5.5 Modeling

5.5.1 Ridge Regression

This model has the following syntax:

```
Ridge(alpha=1.0, fit_intercept=True, normalize=False, copy_X=True, max_iter=None, tol=0.001,
        solver=auto, random_state=None)
```

Firstly, we will use GridSearchCV() to search for the best model parameters in a parameter space provided by us. The parameter alpha represents the regularization strength, fit_intercept determines whether to calculate the intercept for this model, and solver controls which solver to use in the computational routines.

```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Ridge

parameter_space = {
    "alpha": [1, 10, 100, 290, 500],
    "fit_intercept": [True, False],
    "solver": ['svd', 'cholesky', 'lsqr', 'sparse_cg', 'sag', 'saga'],
}

clf = GridSearchCV(Ridge(random_state=3), parameter_space, n_jobs=4, cv=3,
                   scoring="neg_mean_absolute_error")

clf.fit(X_train, y_train)
print("Best parameters:")
print(clf.best_params_)
```

```
Best parameters:
{'alpha': 290, 'fit_intercept': True, 'solver': 'cholesky'}
```

We defined the parameter space above using reasonable values for chosen parameters. Then we used GridSearchCV() with 3 folds (cv=3). Now we build our Ridge model with the best parameters found:

```
ridge_model = Ridge(random_state=3, **clf.best_params_)
```

Then we train our model using our training set (X_train and y_train):

```
ridge_model.fit(X_train, y_train);
```

Finally, we test our model on X_test. Then we evaluate the model performance by comparing its predictions with the actual true values in y_test using the MAE metric as we described above:

```
from sklearn.metrics import mean_absolute_error

y_pred = ridge_model.predict(X_test) ridge_mae =
mean_absolute_error(y_test, y_pred)
print("Ridge MAE =", ridge_mae)
print ("Ridge r2_score =", r2_score(y_test, y_pred))
```

```
Ridge MAE = 15270.463549642733
Ridge r2_score = 0.905076
```

5.5.2 Lasso Regression

This model has the following syntax:

```
Lasso(alpha=1.0, fit_intercept=True, normalize=False, precompute= False, copy_X=True,
max_iter=1000, tol=0.001, warm_start= False, positive= False, random_state=None,
selection='cyclic')
```

Firstly, we will use GridSearchCV() to search for the best model parameters in a parameter space provided by us. The parameter alpha represents the regularization strength, fit_intercept determines whether to calculate the intercept for this model, and solver controls which solver to use in the computational routines.

```
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Lasso

parameter_space = {
    "alpha": [1, 10, 100, 290, 500],
    "fit_intercept": [True, False],
}

clf = GridSearchCV(Lasso(random_state=3), parameter_space, n_jobs=4, cv=3,
                   scoring="neg_mean_absolute_error")
```

```
clf.fit(X_train, y_train)
print("Best parameters:")
print(clf.best_params_)
```

```
Best parameters:
{'alpha': 290, 'fit_intercept': True, 'solver': 'cholesky'}
```

We defined the parameter space above using reasonable values for chosen parameters. Then we used GridSearchCV() with 3 folds (cv=3). Now we build our Lasso model with the best parameters found:

```
lasso_model = Lasso(random_state=3, **clf.best_params_)
```

Then we train our model using our training set (X_train and y_train):

```
lasso_model.fit(X_train, y_train);
```

Finally, we test our model on X_test. Then we evaluate the model performance by comparing its predictions with the actual true values in y_test using the MAE metric as we described above:

```
from sklearn.metrics import mean_absolute_error

y_pred = lasso_model.predict(X_test)
lasso_mae = mean_absolute_error(y_test, y_pred)
print("Lasso MAE =", lasso_mae)
print ("Lasso r2_score =", r2_score(y_test, y_pred))
```

```
Lasso MAE = 15270.463549642733
Lasso r2_score = 0.910009
```

5.5.3 Elastic Net

This model has the following syntax:

```
ElasticNet(alpha=1.0, l1_ratio=0.5, fit_intercept=True, normalize=False, precompute=False,
max_iter=1000, copy_X=True, tol=0.0001, warm_start=False, positive=False, random_state=None,
selection=cyclic)
```

Firstly, we will use GridSearchCV() to search for the best model parameters in a parameter space provided by us. The parameter alpha is a constant that multiplies the penalty terms, l1_ratio determines the amount of L1 and L2 regularizations, fit_intercept is the same as
Ridge’s.

```
from sklearn.linear_model import ElasticNet

parameter_space = {
    "alpha": [1, 10, 100, 280, 500],
    "l1_ratio": [0.5, 1],
    "fit_intercept": [True, False],
}

clf = GridSearchCV(ElasticNet(random_state=3), parameter_space, n_jobs=4, cv=3,
                                    scoring="neg_mean_absolute_error")

clf.fit(X_train, y_train)
print("Best parameters:")
print(clf.best_params_)
```

```
Best parameters:
{'alpha': 280, 'fit_intercept': True, 'l1_ratio': 1}
```

We defined the parameter space above using reasonable values for chosen parameters. Then we used GridSearchCV() with 3 folds (cv=3). Now we build our Ridge model with the best parameters found:

```
elasticNet_model = ElasticNet(random_state=3, **clf.best_params_)
```

Then we train our model using our training set (X_train and y_train):

```
elasticNet_model.fit(X_train, y_train);
```

Finally, we test our model on X_test. Then we evaluate the model performance by comparing its predictions with the actual true values in y_test using the MAE metric as we described above:

```
y_pred = elasticNet_model.predict(X_test) elasticNet_mae =
mean_absolute_error(y_test, y_pred)
print("Elastic Net MAE =", elasticNet_mae)
print ("Elastic Net r2_score =", r2_score(y_test, y_pred))
```

```
Elastic Net MAE = 14767.90981933659
Elastic Net r2_score = 0.910005
```

6 Analysis and Comparison

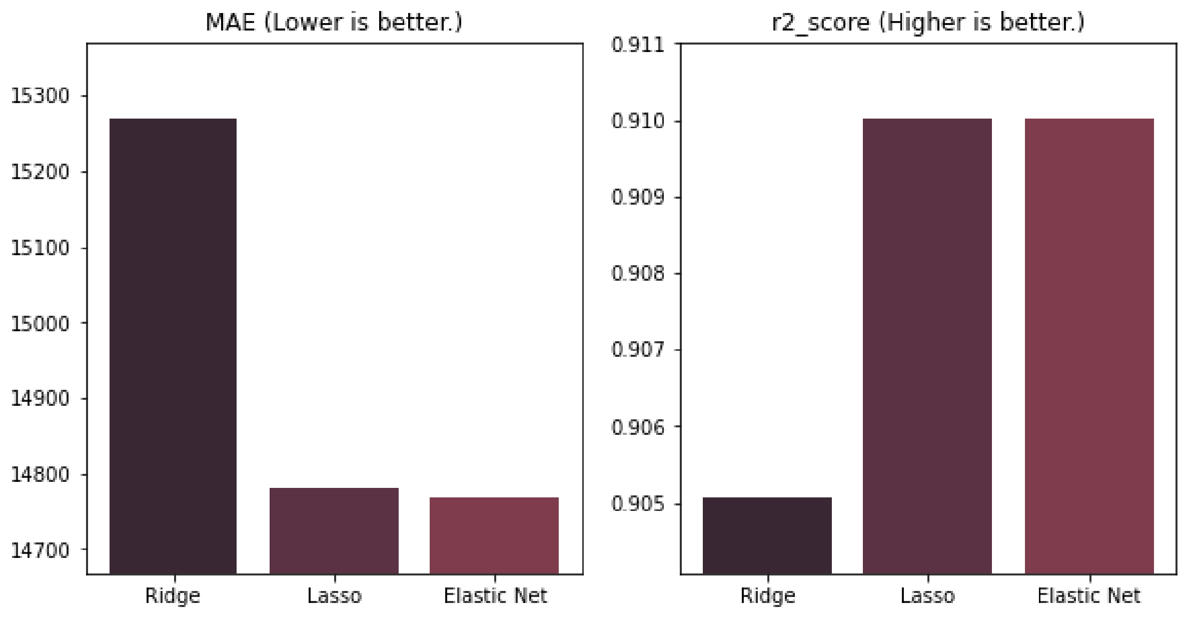
In the previous section, we created three models: for each model we searched for good parameters, constructed the model using those parameters, trained (fitted) the model to our training data (X_train and y_train), then tested the model on our test data (X_test) and finally, we evaluated the model performance by comparing the model predictions with the true values in y_test. We used the mean absolute error (MAE) to evaluate model performance and also checked r2_score of each model just out of curiosity.

Using the results we got in the previous section, we present a table that shows the mean absolute error (MAE) and r2_score for each model when applied to the test set X_test. The table is sorted ascendingly according to MAE score.

Model	MAE	r2_score
Elastic Net	14767.91	0.910005
Lasso	14780.04	0.910009
Ridge	15270.46	0.905076

We also present a graph that visualizes the table contents:

```
colors = ["#392834", "#5a3244", "#7e3c4d"]
model = ['Ridge', 'Lasso', 'Elastic Net']
mae = [15270.46, 14780.04, 14767.91]
r2 = [0.905076, 0.910009, 0.910005]
fig, axs = plt.subplots(1, 2, figsize=(10, 5), sharey=False)
axs[0].bar(model, mae, color=colors)
axs[0].set_ylim(min(mae)-100, max(mae)+100)
axs[0].set_title('MAE (Lower is better.)')
axs[1].bar(model, r2, color=colors)
axs[1].set_ylim(min(r2)-.001, max(r2)+.001)
axs[1].set_title('r2_score (Higher is better.)')
```



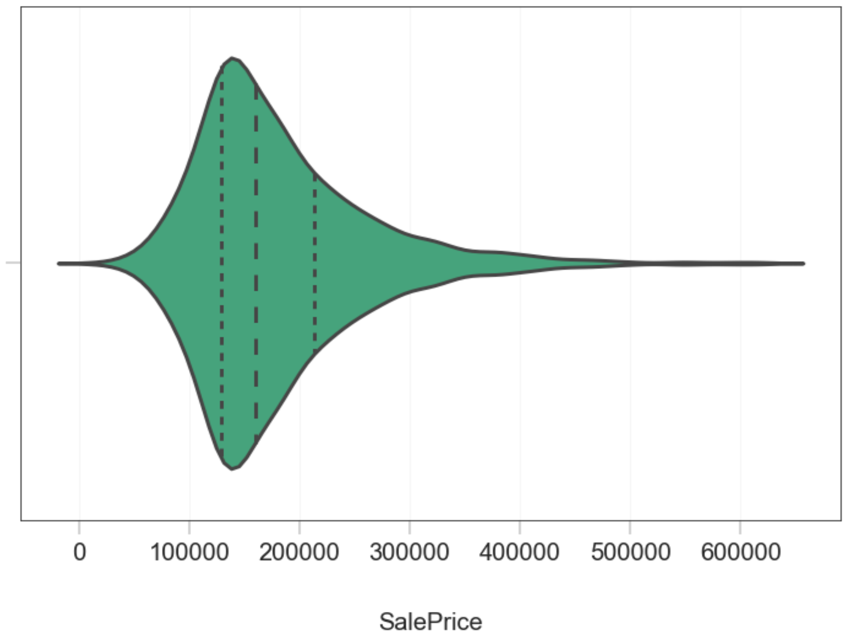
By looking at the table and the graphs, we can see that Elastic Net model has the smallest MAE, 14767.91 followed by Lasso Regression model with a little larger error of 14780.04. After that, Ridge comes with 15656.38. We see similar trend with r2_score where higher score is better.

So, in our experiment, the best model is Elastic Net and the worst model is Ridge Regression. We can see that the difference in MAE between the best model and the worst model is significant.

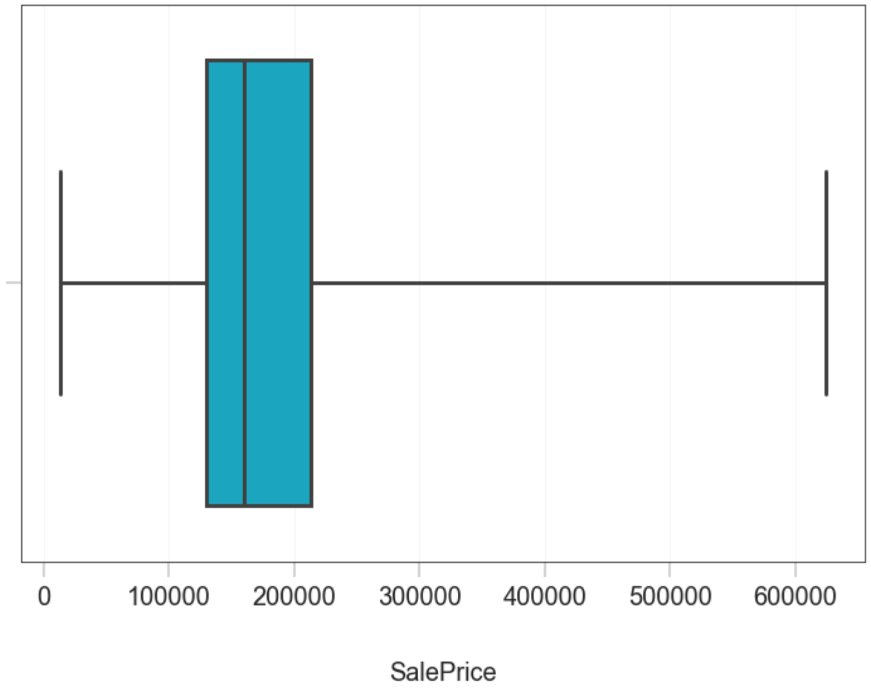
6.1 Performance Interpretation

We chose the mean absolute error (MAE) as our performance metric to evaluate and compare models and r2_score just out of curiosity. MAE presents a value that is easy to understand; it shows the average value of model error. For example, for our Elastic Net model, its MAE is 14767.91 which means that on average, Elastic Net will predict a value that is bigger or smaller than the true value by 14767.91. Now to understand how good this MAE is, we need to know the range and distribution of the data. In our case, we need to see the values of the target variable SalePrice which contains the actual house prices. Let's see the violin plot, box plot, and histogram of SalePrice in our dataset:

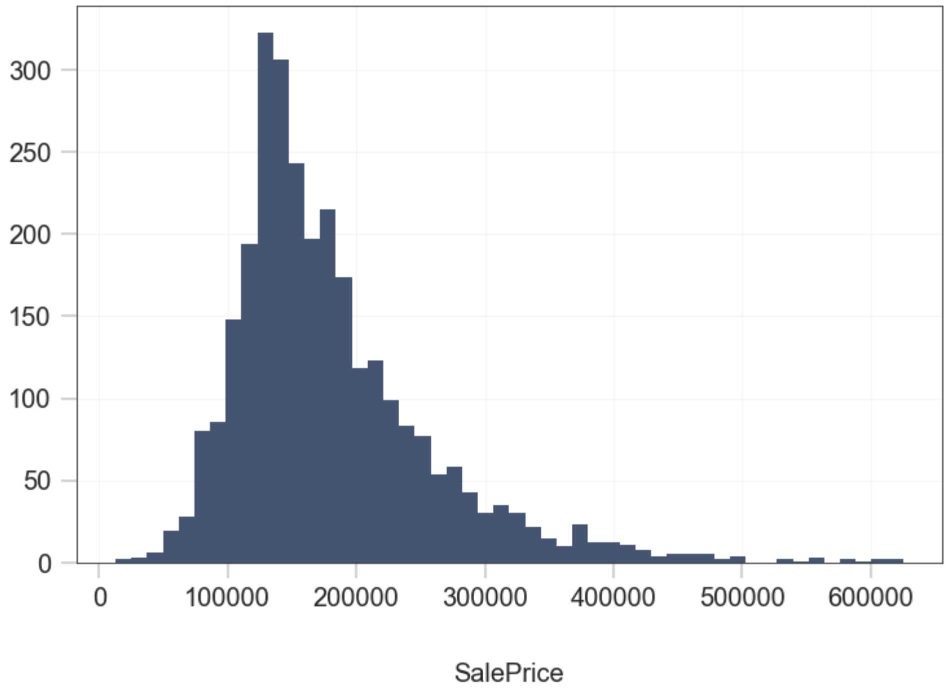
```
sns.violinplot(x=dataset['SalePrice'], inner="quartile", color="#36B37E");
```



```
sns.boxplot(dataset['SalePrice'], whis=10, color="#00B8D9");
```



```
sns.distplot(dataset['SalePrice'], kde=False,
            color="#172B4D", hist_kws={"alpha": 0.8});
```



From the three plots above, we can understand the distribution of SalePrice. Now let's get some numerical statistical information about it:

```
y_train.describe(include=[np.number])
```

	SalePrice
count	2193.00
mean	179846.69
std	79729.38
min	12789.00
25%	128500.00
50%	159895.00
75%	214000.00
max	625000.00

We can see that the mean is 179,846.69 and the median is 159,895. We can see also that the first quartile is 128,500; this means that 75% of the data is larger than this number. Now looking at Elastic Net error of 14,767.91, we can say that an error of about 14,000 is good for data whose mean is 159,895 and whose 75% of it is larger than 128,500.

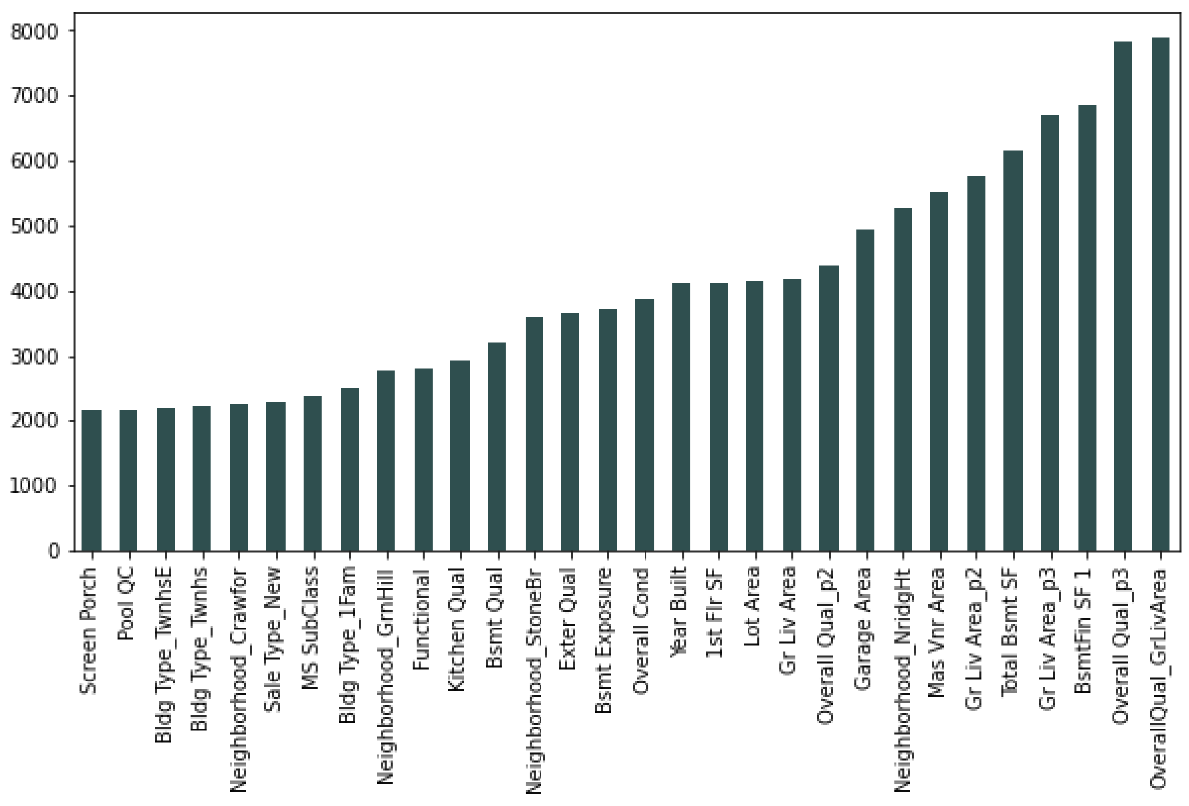
6.2 Feature Importance

Although none of the models we used provide the ability to see the importance of each feature in the dataset after fitting the model, I've tried to extract those feature importance using the code below. We will look at the feature importance provided by all the three models that we've used. We have 242 features in our data which is a big number, so we will take a look at the 30 most important features.

6.2.1 Ridge

Let's discover the most important features as determined by Ridge model:

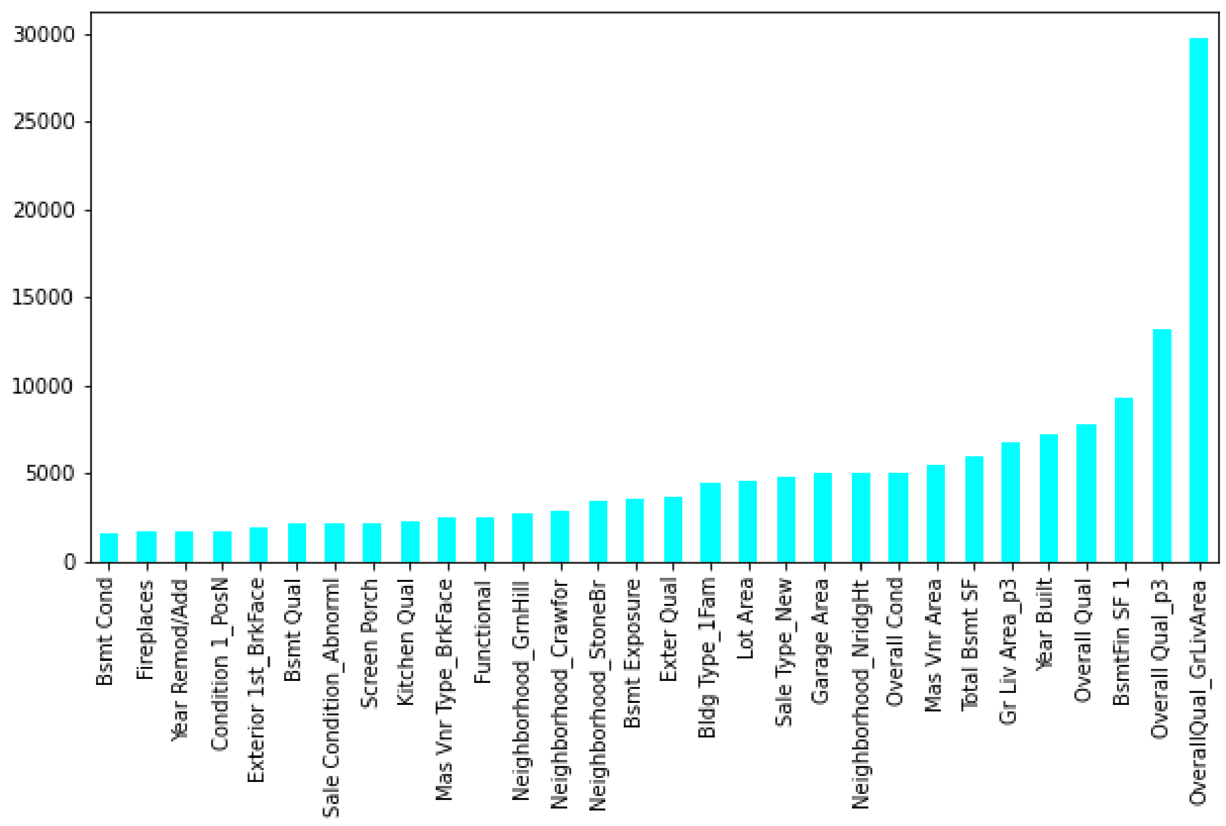
```
feature_importance = pd.Series(index = X_train.columns, data = np.abs(ridge_model.coef_[0]))
n_selected_features = (feature_importance>0).sum()
print('{0:d} features, reduction of {1:2.2f}%'.format(
    n_selected_features,(1-n_selected_features/len(feature_importance))*100))
feature_importance.sort_values().tail(30).plot(kind = 'bar', figsize = (10, 5), color = 'darkslategrey')
```



6.2.2 Lasso

Now let's find the most important features as determined by our Lasso Regression model:

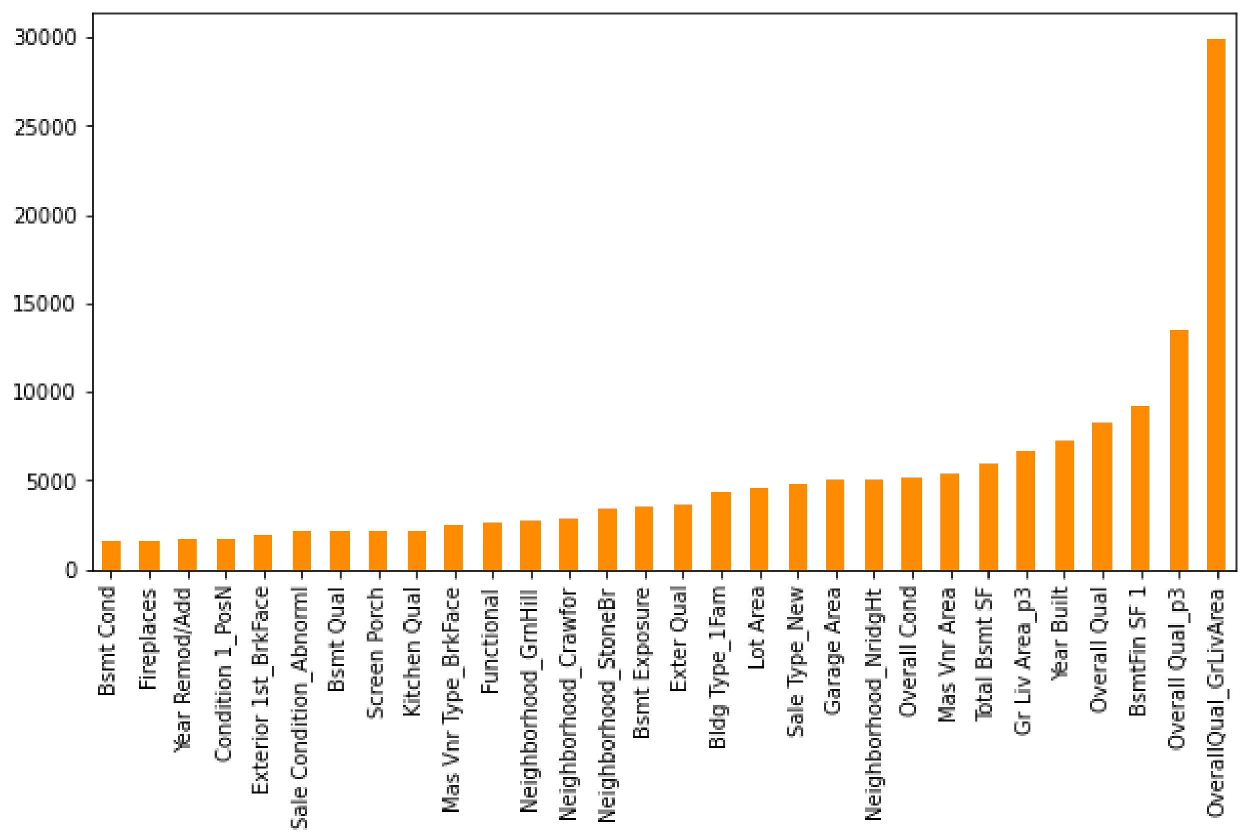
```
lasso_feature_importance = pd.Series(index = X_train.columns, data = np.abs(lasso_model.coef_))
n_selected_features = (feature_importance>0).sum()
print('{0:d} features, reduction of {1:2.2f}%'.format(
    n_selected_features,(1-n_selected_features/len(feature_importance))*100))
lasso_feature_importance.sort_values().tail(30).plot(kind = 'bar', figsize = (10, 5), color = 'cyan')
```



6.2.3 Elastic Net

And finally, let's see the most important features as determined by our Elastic Net model:

```
elastic_feature_importance = pd.Series(index = X_train.columns, data = np.abs(elasticNet_model.coef_))
 n_selected_features = (feature_importance>0).sum()
print('{0:d} features, reduction of {1:2.2f}%'.format(
    n_selected_features,(1-n_selected_features/len(feature_importance))*100))
 elastic_feature_importance.sort_values().tail(30).plot(kind = 'bar', figsize = (10, 5), color = 'darkorange')
```



6.2.4 Common Important Features

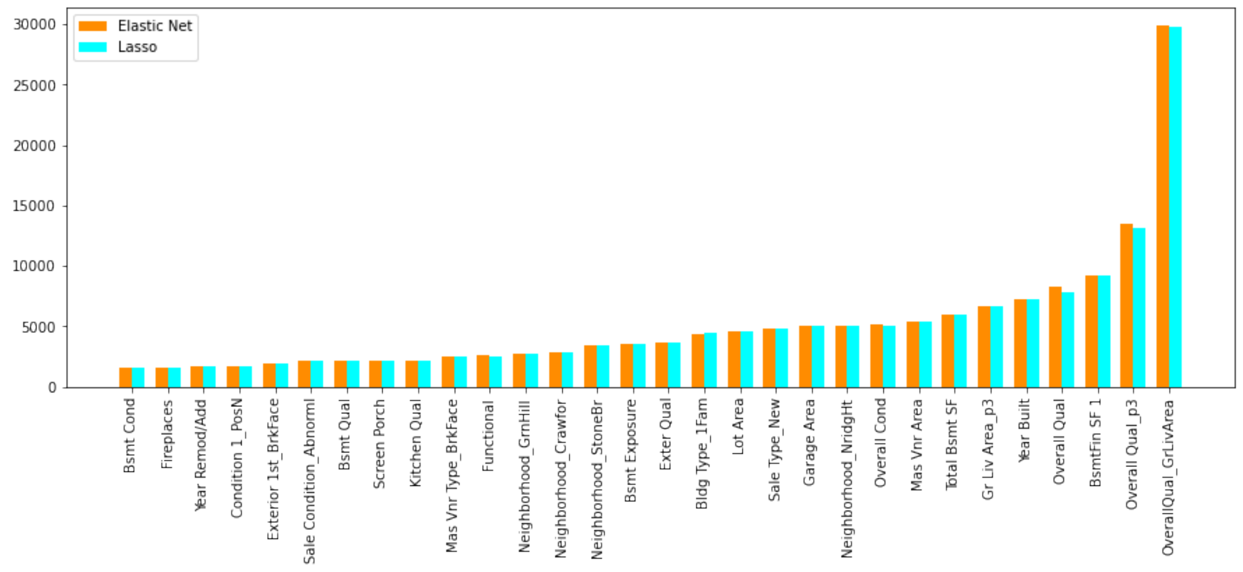
Now, let us see which features are among the most important features for both Elastic Net and Lasso, and let's find out the difference in their importance regarding the two models:

```
common_imp_feat = [x for x in elastic_feature_importance.sort_values().tail(30).index
                if x in lasso_feature_importance.sort_values().tail(30).index]
commImpFeat_elastic_scores = [elastic_feature_importance.sort_values().tail(30)[x]
                    for x in common_imp_feat]
commImpFeat_lasso_scores = [lasso_feature_importance.sort_values().tail(30)[x]
                    for x in common_imp_feat]

ind = np.arange(len(commImpFeat_elastic_scores))
width = 0.35

fig, ax = plt.subplots(figsize=(15, 5))
ax.bar(ind - width/2, commImpFeat_elastic_scores, width, color='darkorange', label='Elastic Net');
ax.bar(ind + width/2, commImpFeat_lasso_scores, width, color='cyan', label='Lasso')
ax.set_xticks(ind);
ax.set_xticklabels(common_imp_feat);
ax.legend();
```

```
plt.xticks(rotation=90);
```



7 Key Findings

We observe that Overall quality of material and finish of the house (Overall Qual) matter less in price prediction compared to living area above-ground in square feet (GrLivArea). We see that Lasso and Elastic Net perform way better than Ridge on our data. It is interesting to see that the difference in Mean Absolute Error of Lasso and Elastic Net is significant, while the difference in their coefficient of determination regression score (r2_score) is negligible. It is clear that Elastic Net performs best among the three models that we tried in this project.

8 Conclusion

In this project, we built several regression models to predict the price of some house given some of the house features. We evaluated and compared each model to determine the one with highest performance. We also looked at how these models rank the features according to their importance. We followed the data science process starting with getting, cleaning and preprocessing the data, followed by exploring the data and building models, then evaluating the results and communicating them with visualizations.

As a recommendation, I would advise to use this model (or a version of it trained with more recent data) by people who want to buy a house in the area covered by the dataset to have an idea about the actual price. The model can be used also with datasets that cover different cities and areas provided that they contain the same features. I also suggest that people take into consideration the features that were deemed as most important as seen in the previous section; this might help them estimate the house price better.

Since, the scope of this project is limited to supervised machine learning regression techniques, the methodology is inherently flawed in the sense that more advanced machine learning techniques could not be used for better accuracy in prediction. However, I've tried my best on interpretation of all three models using feature importance. I would be revisiting this project again with more advanced machine learning techniques like Neural Networks and Gradient Boosting, focusing more on prediction while doing my best regarding interpretation.