House Price Prediction Using Machine Learning Techniques

Ammar Alyousfi

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Contents

1 Introduction

Thousands of houses are sold everyday. There are some questions every buyer asks himself like: What is the actual price that this house deserves? Am I paying a fair price? In this paper, 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, we will show the code used for each step followed by its output. This will facilitate the reproducibility of our work. In this study, Python programming language with a number of Python packages will be used.

1.1 Goals of the Study

The main objectives of this study are as follows:

- To apply data preprocessing and preparation techniques in order to obtain clean data
- To build machine learning models able to predict house price based on house features
- To analyze and compare models performance in order to choose the best model

1.2 Paper Organization

This paper is organized as follows: in the next section, section 2, we examine studies related to our work from scientific journals. In section 3, we go through data preparation including data cleaning, outlier removal, and feature engineering. Next in section 4, we discuss the type of our problem and the type of machine-learning prediction that should be applied; we also list the prediction techniques that will be used. In section 5, we choose algorithms to implement the techniques in section 4; we build models based on these algorithms; we also train and test each model. In section 6, we analyze and compare the results we got from section 5 and conclude the paper.

2 Literature Review

In this section, we look at five recent studies that are related to our topic and see how models were built and what results were achieved in these studies.

2.1 Stock Market Prediction Using Bayesian-Regularized Neural Networks

In a study done by Ticknor (2013), he used Bayesian regularized articial neural network to predict the future operation of financial market. Specifically, he built a model to predict future stock prices. The input of the model is previous stock statistics in addition to some financial technical data. The output of the model is the next-day closing price of the corresponding stocks.

The model proposed in the study is built using Bayesian regularized neural network. The weights of this type of networks are given a probabilistic nature. This allows the network to penalize very complex models (with many hidden layers) in an automatic manner. This in turn will reduce the overfitting of the model.

The model consists of a feedforward neural network which has three layers: an input layer, one hidden layer, and an output layer. The author chose the number of neurons in the hidden layer based on experimental methods.The input data of the model is normalized to be between `-1` and `1`, and this opertion is reversed for the output so the predicted price appears in the appropriate scale.

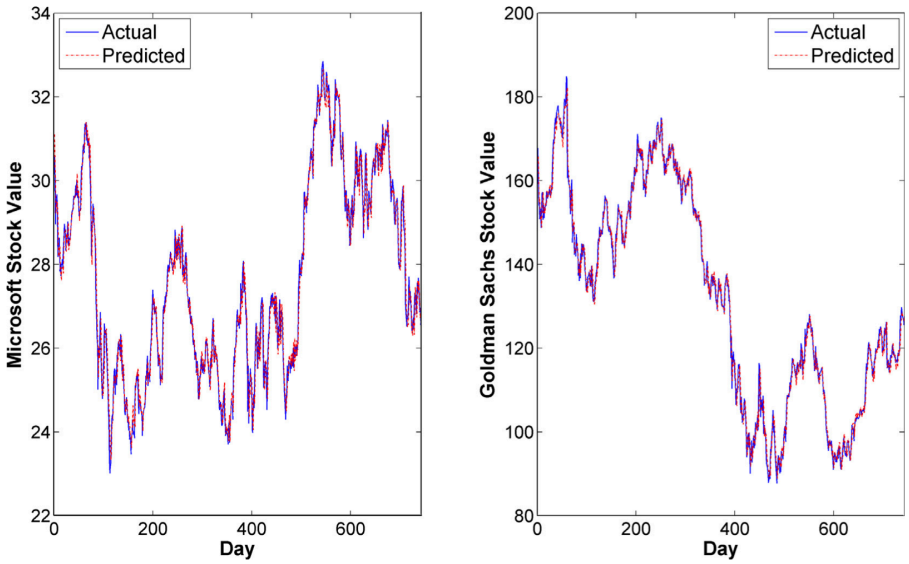


Figure 1: Predicted vs. actual price

The data that was used in this study was obtained from Goldman Sachs Group (GS), Inc. and Microsoft Corp. (MSFT) . The data covers 734 trading days (4 January 2010 to 31 December 2012). Each instance of the data consisted of daily statistics: low price, high price, opening price, close price, and trading volume. To facilitate the training and testing of the model, this data was split into training data and test data with 80% and 20% of the original data, respectively. In addition to the daily-statistics variables in the data, six more variables were created to reflect financial indicators.

The performance of the model were evaluated using mean absolute percentage error (MAPE) performance metric. MAPE was calculated using this formula:

$$MAPE = \frac{\sum_{i=1}^{r}(\text{abs}(y_i - p_i)/y_i)}{r} \times 100 \tag{1}$$

where p_i is the predicted stock price on day i, y_i is the actual stock price on day i, and r is the number of trading days.

When applied on the test data, The model achieved a MAPE score of `1.0561` for MSFT part, and `1.3291` for GS part. Figure 1 shows the actual values and predicted values for both GS and MSFT data.

2.2 Stock Market Prediction Using A Machine Learning Model

In another study done by Hegazy, Soliman, and Salam (2014), a system was proposed to predict daily stock market prices. The system combines particle swarm optimization (PSO) and least square support vector machine (LS-SVM), where PSO was used to optimize LV-SVM.

The authors claim that in most cases, artificial neural networks (ANNs) are subject to the overfitting problem. They state that support vector machines algorithm (SVM) was developed as an alternative that doesn't suffer from overfitting. They attribute this advantage to SVMs being based on the solid foundations of VC-theory. They further elaborate that LS-SVM method was reformulation of traditional SVM method that uses a regularized least squares function with equality

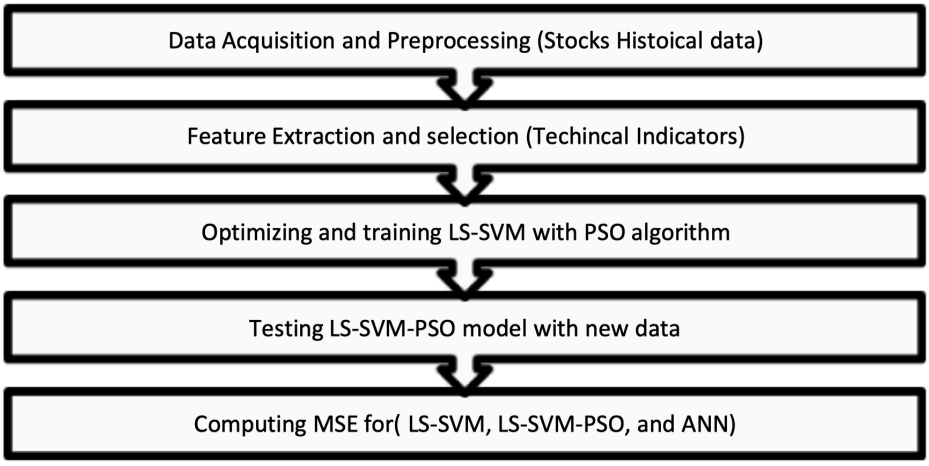


Figure 2: The structure of the model used

constraints to obtain a linear system that satisfies Karush-Kuhn-Tucker conditions for getting an optimal solution.

The authors describe PSO as a popular evolutionary optimization method that was inspired by organism social behavior like bird flocking. They used it to find the optimal parameters for LS-SVM. These parameters are the cost penalty C, kernel parameter γ, and insensitive loss function ϵ.

The model proposed in the study was based on the analysis of historical data and technical financial indicators and using LS-SVM optimized by PSO to predict future daily stock prices. The model input was six vectors representing the historical data and the technical financial indicators. The model output was the future price. The model used is represented in Figure 2.

Regarding the technical financial indicators, five were derived from the raw data: relative strength index (RSI), money flow index (MFI), exponential moving average (EMA), stochastic oscillator (SO), and moving average convergence/divergence (MACD). These indicators are known in the domain of stock market.

The model was trained and tested using datasets taken from https://finance.yahoo.com/. The datasets were from Jan 2009 to Jan 2012 and include stock data for many companies like Adobe and HP. All datasets were partitioned into a training set with 70% of the data and a test set with 30% of the data. Three models were trained and tested: LS-SVM-PSO model, LS-SVM model, and ANN model. The results obtained in the study showed that LS-SVM-PSO model had the best performance. Figure 3 shows a comparison between the mean square error (MSE) of the three models for the stocks of many companies.

2.3 House Price Prediction Using Multilevel Model and Neural Networks

A different study was done by Feng and Jones (2015) to preduct house prices. Two models were built: a multilevel model (MLM) and an artificial neural network model (ANN). These two models were compared to each other and to a hedonic price model (HPM).

The multilevel model integrates the micro-level that specifies the relationships between houses within a given neighbourhood, and the macro-level equation which specifies the relationships between neighbouhoods. The hedonic price model is a model that estimates house prices using

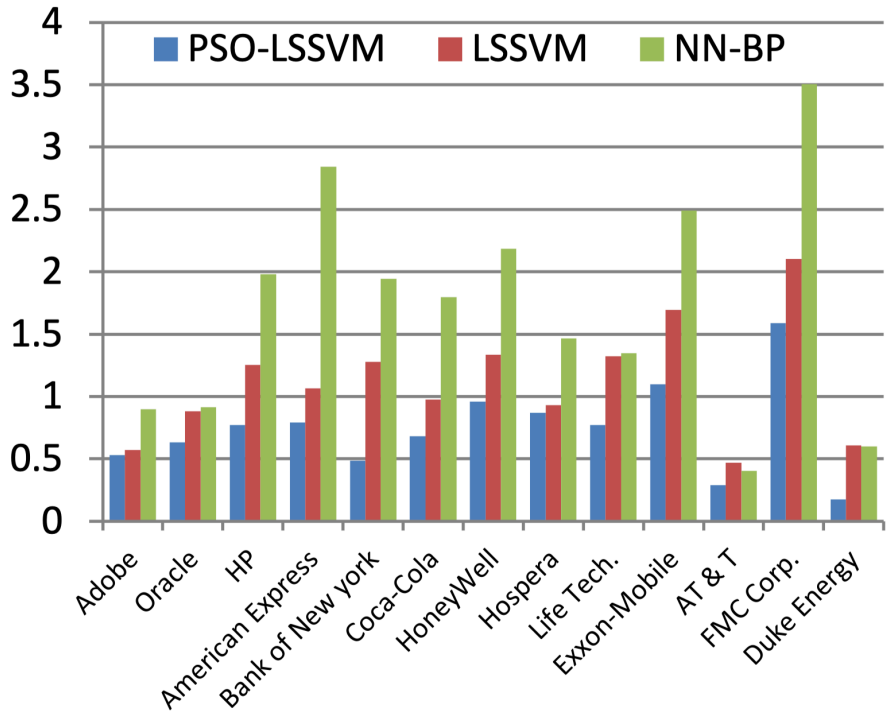


Figure 3: MSE comparison

some attributes such as the number of bedrooms in the house, the size of the house, etc.

The data used in the study contains house prices in Greater Bristol area between 2001 and 2013. Secondary data was obtained from the Land Registry, the Population Census and Neighbourhood Statistics to be used in order to make the models suitable for national usage. The authors listed many reasons on why they chose the Greater Bristol area such as its diverse urban and rural blend and its different property types. Each record in the dataset contains data about a house in the area: it contains the address, the unit postcode, property type, the duration (freehold or leasehold), the sale price, the date of the sale, and whether the house was newly-built when it was sold. In total, the dataset contains around $65,000$ entries. To enable model training and testing, the dataset was divided into a training set that contains data about house sales from 2001 to 2012, and a test set that contains data about house sales in 2013.

The three models (MLM, ANN, and HPM) were tested using three senarios. In the first senario, locational and measured neighbourhood attributes were not included in the data. In the second senario, grid references of house location were included in the data. In the third senario, measured neighbourhood attributes were included in the data. The models were compared in goodness of fit where R^2 was the metric, predictive accuracy where mean absolute error (MAE) and mean absolute percentage error (MAPE) were the metrics, and explanatory power. HPM and MLM models were fitted using MLwiN software, and ANN were fitted using IBM SPSS software. Figure 4 shows the performance of each model regarding fit goodness and predictive accuracy. It shows that MLM model has better performance in general than other models.

COMPARISONS OF GOODNESS-OF-FIT

	R^2 (training set)	R^2 (test set)
HPM1	0.39	0.23
MLM1	0.75	0.75
ANN1	0.39	0.23
HPM2	0.43	0.3
MLM2	0.75	0.75
ANN2	0.41	0.26
HPM3	0.68	0.65
MLM3	0.75	0.74
ANN3	0.69	0.67

COMPARISON OF PREDICTIVE ACCURACY

Test set	MAE (lnP)	MAPE (lnP)	MAE (raw price)	MAPE (raw price)
HPM1	0.319	5.89%	80.4	30.9%
MLM1	0.178	3.29%	48.6	17.5%
ANN1	0.318	5.85%	80.1	30.0%
HPM2	0.304	5.61%	77.0	29.4%
MLM2	0.178	3.29%	48.6	17.5%
ANN2	0.313	5.76%	79.0	29.8%
HPM3	0.210	3.89%	25.3	20.7%
MLM3	0.178	3.30%	48.8	17.6%
ANN3	0.216	4.00%	55.7	20.9%

Figure 4: Model performance comparison

2.4 Composition of Models and Feature Engineering to Win Algorithmic Trading Challenge

A study done by de Abril and Sugiyama (2013) introduced the techniques and ideas used to win Algorithmic Trading Challenge, a competition held on Kaggle. The goal of the competition was to develop a model that can predict the short-term response of order-driven markets after a big liquidity shock. A liquidity shock happens when a trade or a sequence of trades causes an acute shortage of liquidity (cash for example).

The challenge data contains a training dataset and a test dataset. The training dataset has around `754,000` records of trade and quote observations for many securities of London Stock Exchange before and after a liquidity shock. A trade event happens when shares are sold or bought, whereas a quote event happens when the ask price or the best bid changes.

A separate model was built for bid and another for ask. Each one of these models consists of `K` random-forest sub-models. The models predict the price at a particular future time.

The authors spent much effort on feature engineering. They created more than `150` features. These features belong to four categories: price features, liquidity-book features, spread features (bid/ask spread), and rate features (arrival rate of orders/quotes). They applied a feature selection algorithm to obtain the optimal feature set (F_b) for bid sub-models and the optimal feature set (F_a) of all ask sub-models. The algorithm applied eliminates features in a backward manner in order to get a feature set with reasonable computing time and resources.

Three instances of the final model proposed in the study were trained on three datasets; each one of them consists of `50,000` samples sampled randomly from the training dataset. Then, the three models were applied to the test dataset. The predictions of the three models were then averaged to obtain the final prediction. The proposed method achieved a RMSE score of `0.77` approximately.

2.5 Using K-Nearest Neighbours for Stock Price Prediction

Alkhatib, Najadat, Hmeidi, and Shatnawi (2013) have done a study where they used the k-nearest neighbours (KNN) algorithm to predict stock prices. In this study, they expressed the stock prediction problem as a similarity-based classification, and they represented the historical stock data as well as test data by vectors.

The authors listed the steps of predicting the closing price of stock market using KNN as follows:

- The number of neaerest neighbours is chosen

	kNN algorithm for K = 5		
Company	**Total squared RMS error**	**RMS error**	**Average error**
AIEI	0.263151	0.0378176	-5.43E-09
AFIN	0.2629177	0.0363482	-1.01E-08
APOT	22.74533	0.3372338	2.50E-08
IREL	1.2823397	0.1046908	4.27E-08
JOST	0.17963	0.0300444	1.508E-08

Figure 5: Prediction performance evaluation

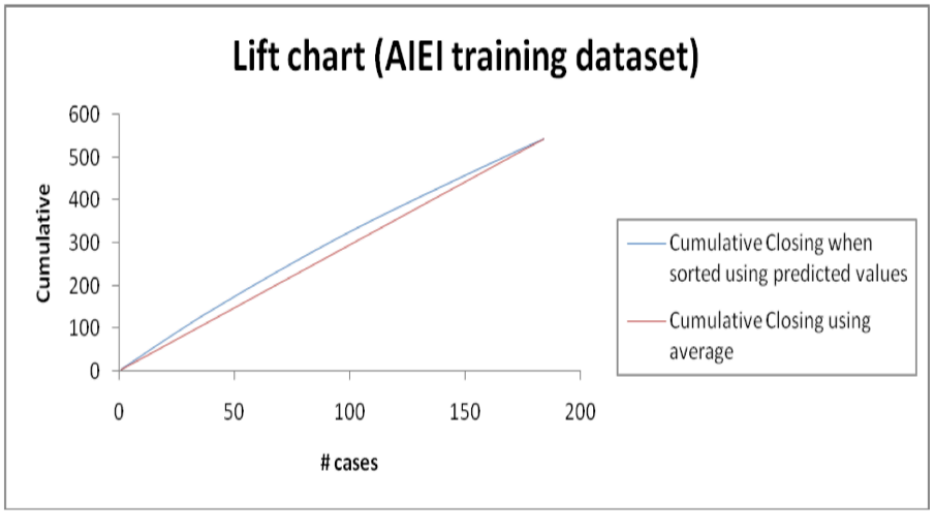


Figure 6: AIEI lift graph

- The distance between the new record and the training data is computed
- Training data is sorted according to the calculated distance
- Majority voting is applied to the classes of the k nearest neighbours to determine the predicted value of the new record

The data used in the study is stock data of five companies listed on the Jordanian stock exchange. The data range is from 4 June 2009 to 24 December 2009. Each of the five companies has around 200 records in the data. Each record has three variables: closing price, low price, and high price. The author stated that the closing price is the most important feature in determining the prediction value of a stock using KNN.

After applying KNN algorithm, the authors summarized the prediction performance evaluation using different metrics in a the table shown in Figure 5.

The authors used lift charts also to evaluate the performance of their model. Lift chart shows the improvement obtained by using the model compared to random estimation. As an example, the lift graph for AIEI company is shown in Figure 6. The area between the two lines in the graph is an indicator of the goodness of the model.

Figure 7 shows the relationship between the actual price and predicted price for one year for the same company.

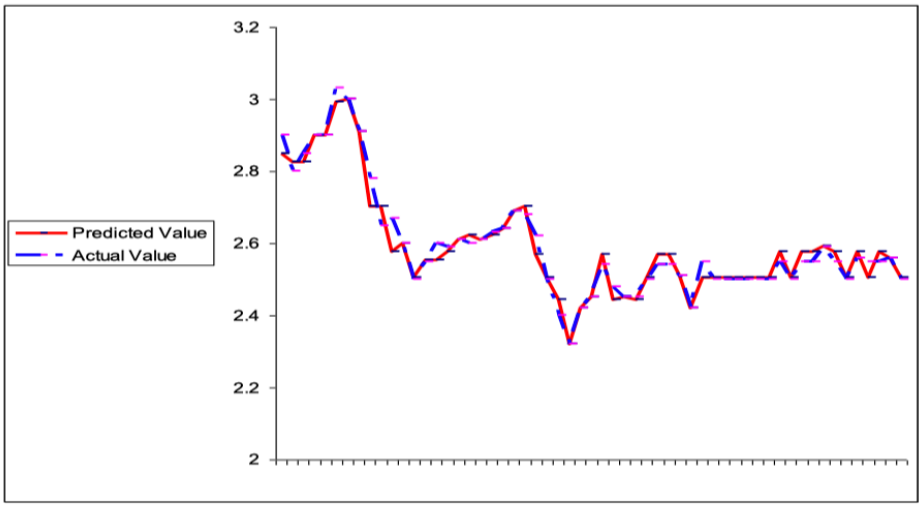


Figure 7: Relationship between actual and predicted price for AIEI

3 Data Preparation

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 https://www.kaggle.com/prevek18/ames-housing-dataset.

3.1 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 https://www.kaggle.com/c/house-prices-advanced-regression-techniques/data). 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

Feature	Description
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
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

Feature	Description
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

3.2 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")
```

3.3 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
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
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

	unique	top	freq
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.

3.4 Data Cleaning

3.4.1 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

	Missing Values	Percentage
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 verfies 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
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
```

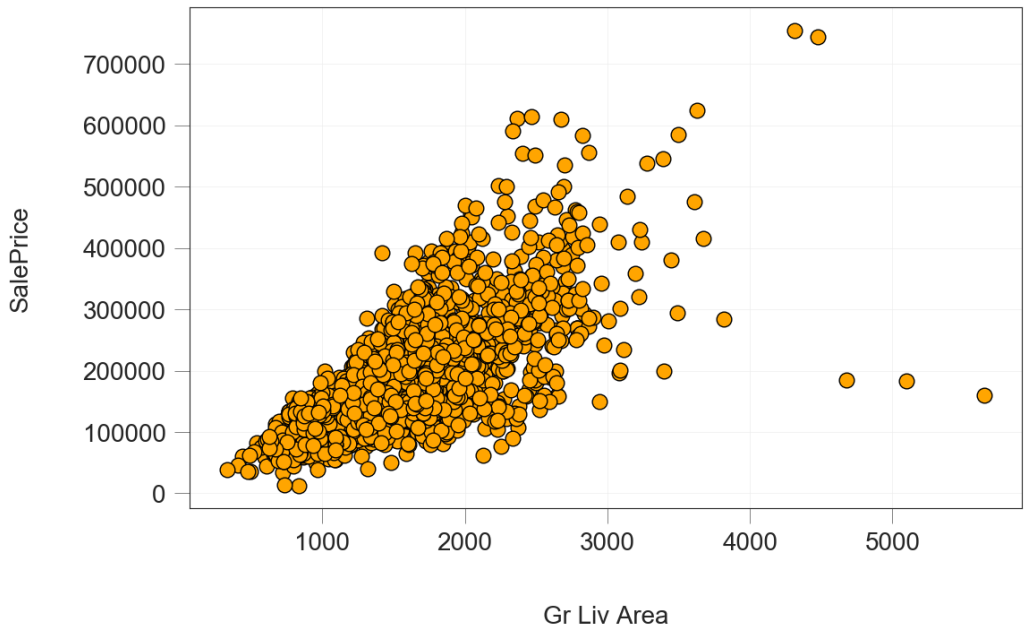
This means that our dataset is now complete; it doesn't contain any missing value anymore.

3.5 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 outliars. 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 authour 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:

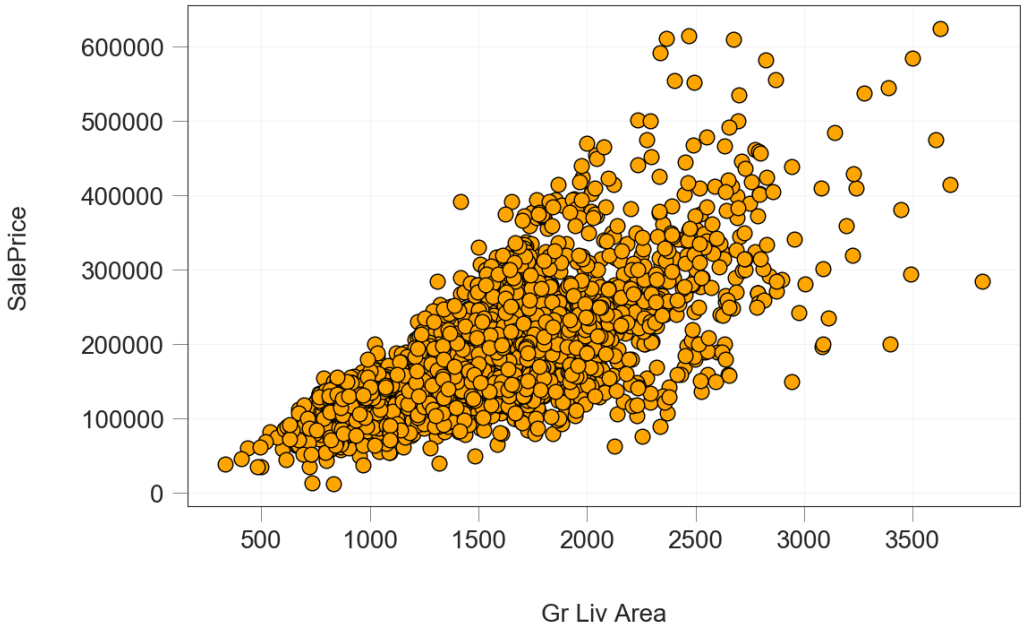
```
outlirt_columns = ["Gr Liv Area"] + \
                  [col for col in dataset.columns if "Sale" in col]
dataset[dataset["Gr Liv Area"] > 4000][outlirt_columns]
```

	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)
```

3.6 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)
```

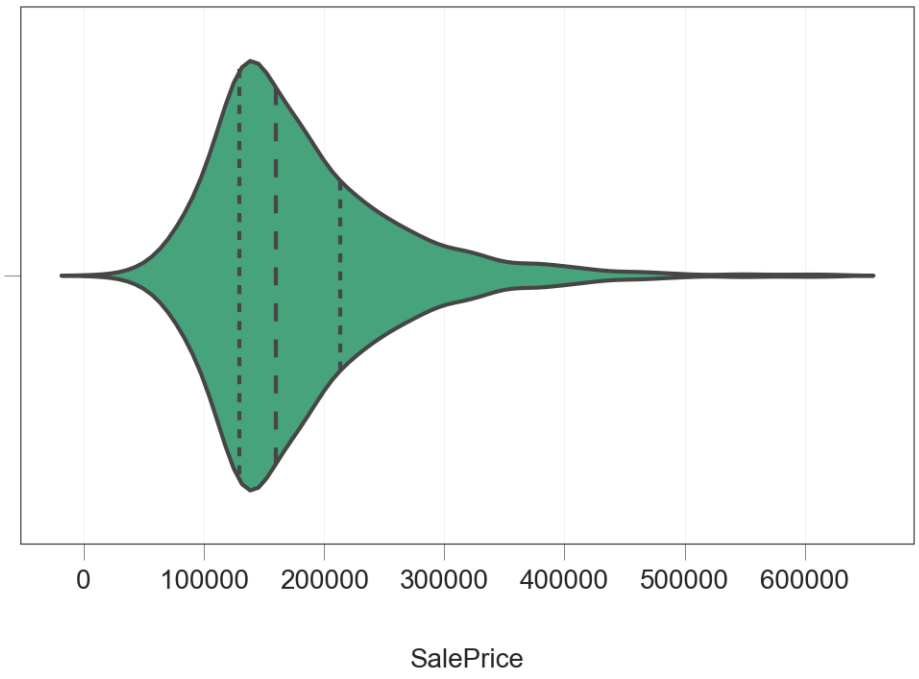
4 Exploratory Data Analysis

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.

4.1 Target Variable Distribution

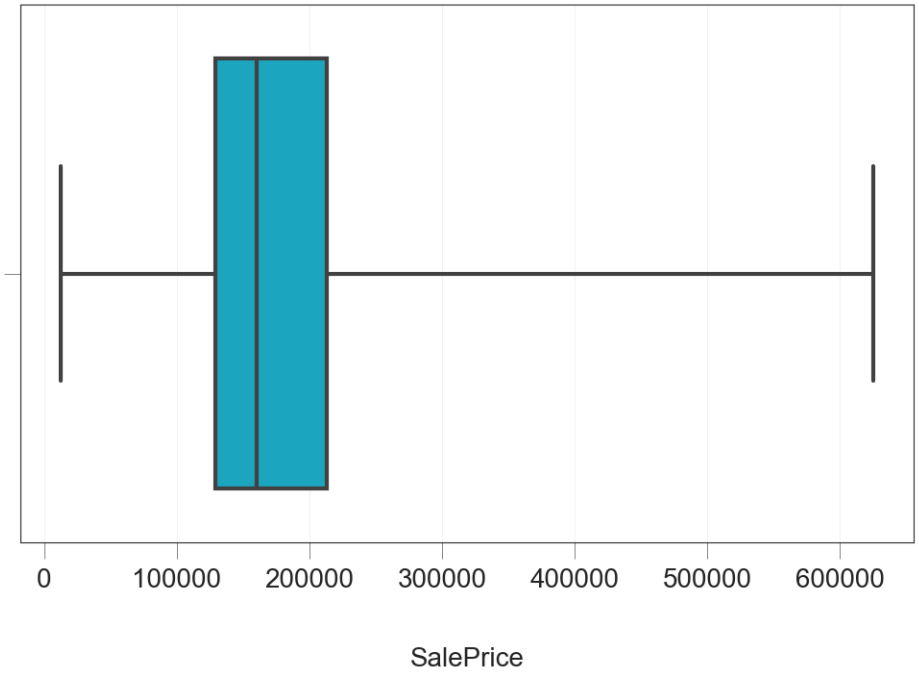
Our dataset contains a lot of variables, but the most important one for us to explore is the target variable. We need to understand its distribution. First, we start by plotting the violin plot for the target variable. The width of the violin represents the frequency. This means that if a violin is the 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");
```



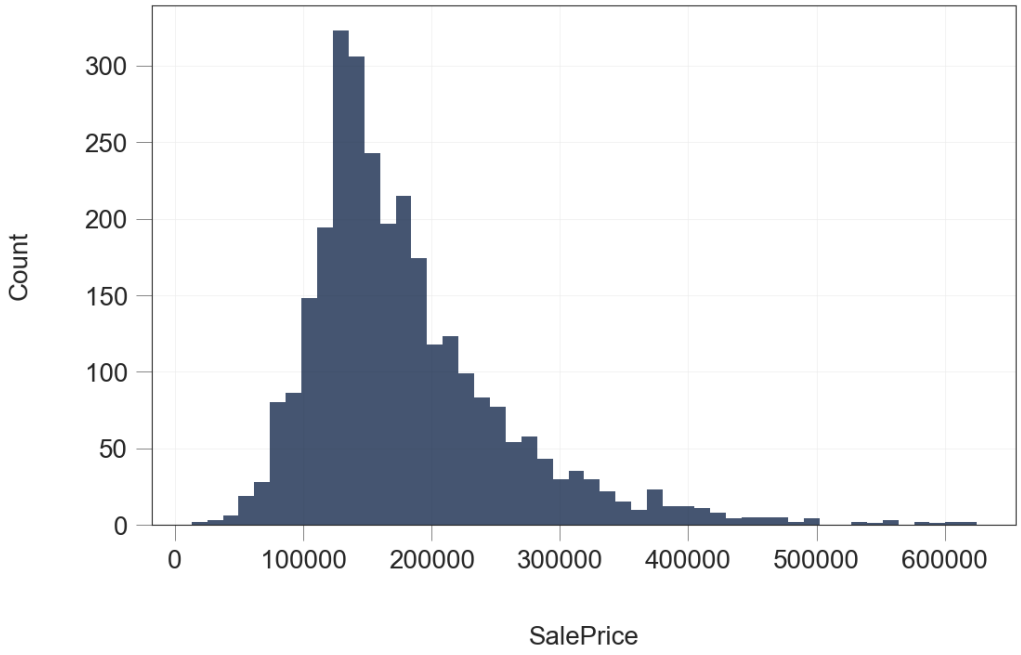
We can see from the plot that most house prices fall between 100,000 and 250,000. The dashed lines represent the locations of the three quartiles Q1, Q2 (the median), and Q3. Now let's see the box plot of `SalePrice`:

```
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");
```



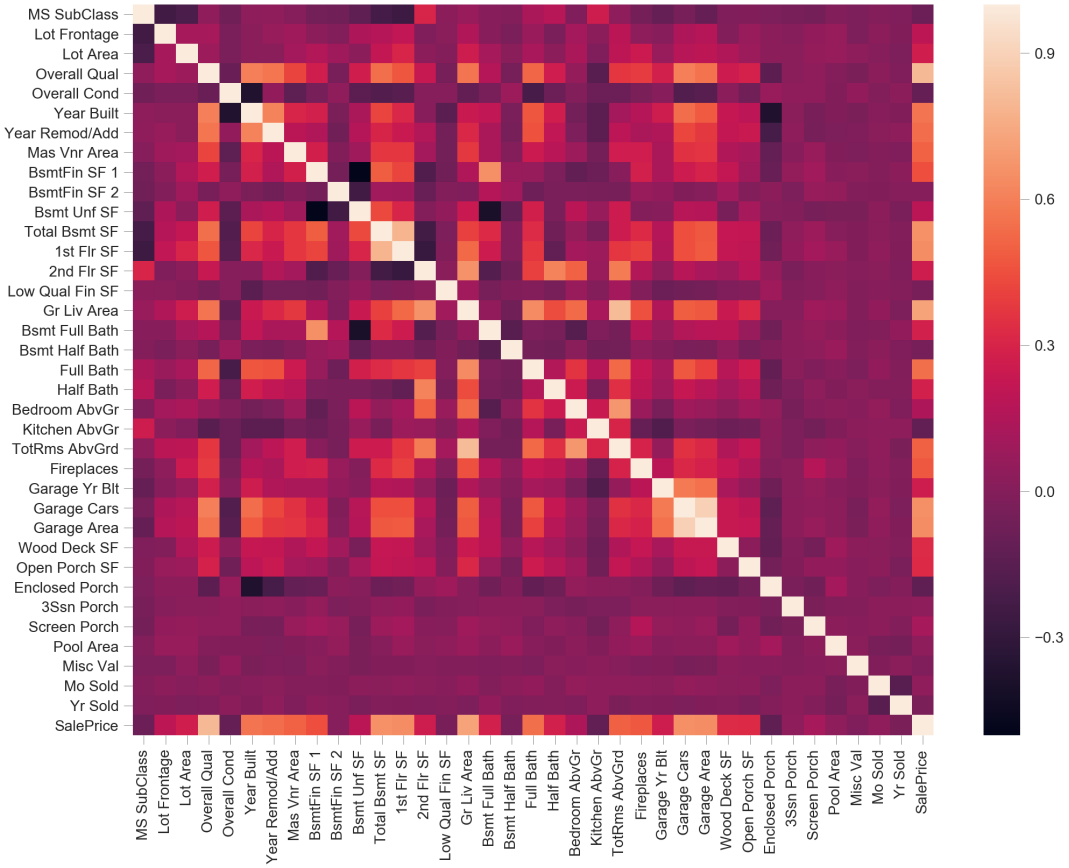
4.2 Correlation Between Variables

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.

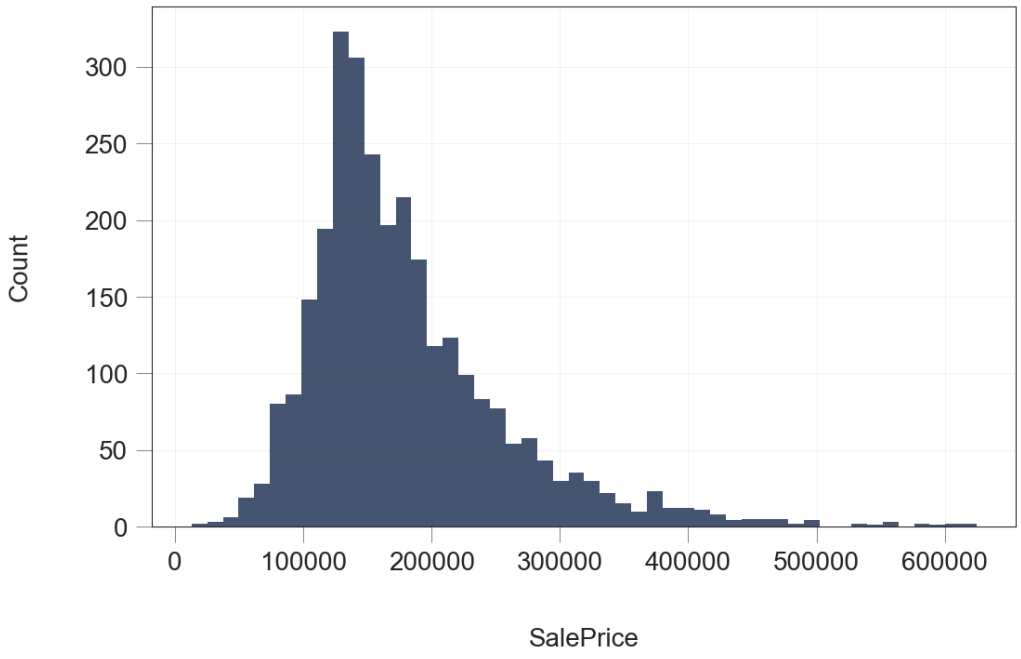
Most importantly, we want to look at the predictor variables that are correlated with the target variable (`SalePrice`). By looking at the last row of the heatmap, we see that the target variable is highly positively correlated with `Overall Qual` and `Gr Liv Area`. We see also that the target variable 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`.

4.2.1 Relatioships Between the Target Variable and Other Varibles

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

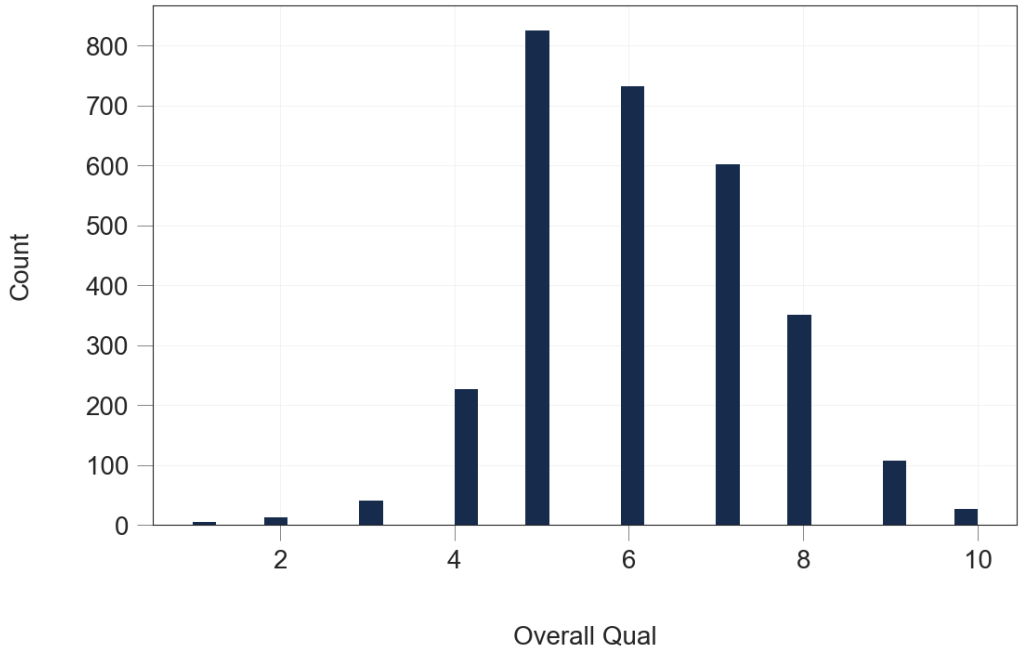
in the heatmap. Namely, these variables are `Overall Qual` and `Gr Liv Area`. We start with the relatioship between the target variable and `Overall Qual`, but before that, let's see the distribution of each of them. Let's start with the target variable `SalePrice`:

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



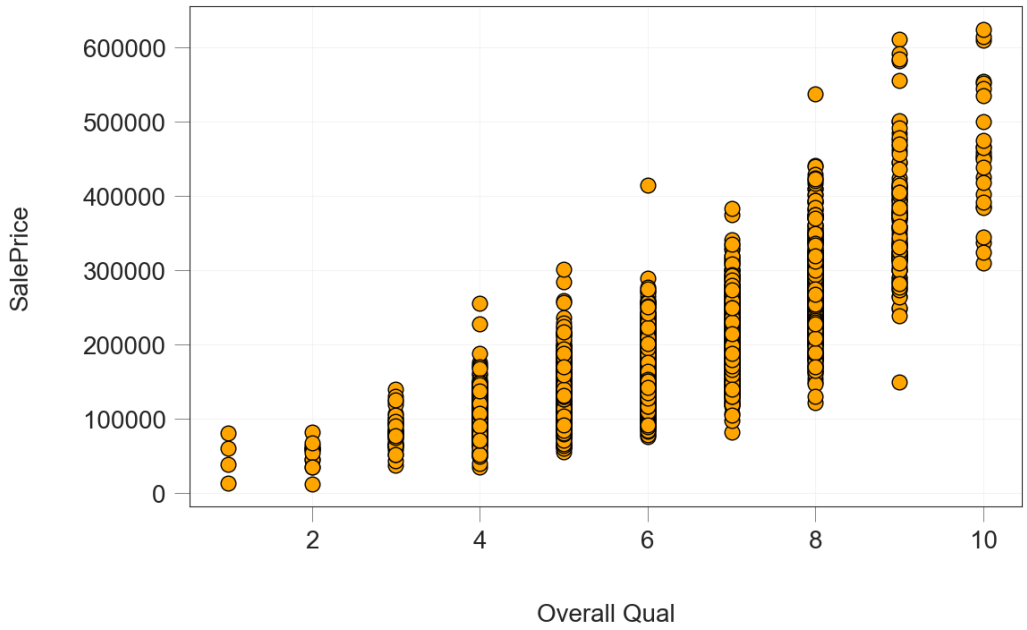
We can see that most house prices fall between 100,000 and 200,000. We see also that there is a number of expensive houses to the right of the plot. Now, we move to see the distribution of `Overall Qual` variable:

```
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:

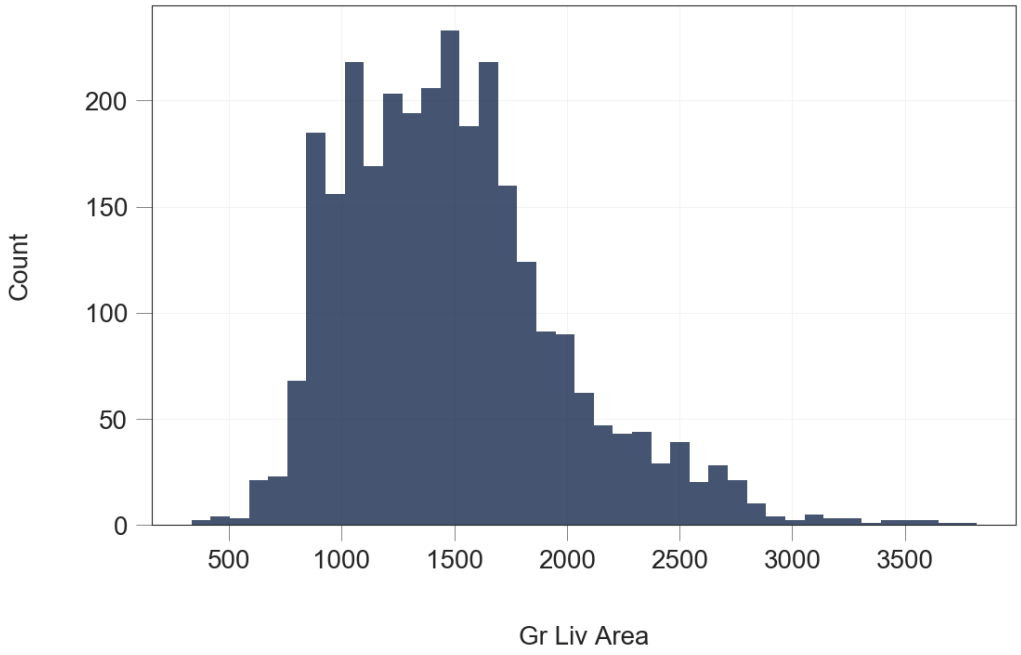
```
plt.scatter(x=dataset['Overall Qual'], y=dataset['SalePrice'],
            color="orange", edgecolors="#000000", linewidths=0.5);
plt.xlabel("Overall Qual"); plt.ylabel("SalePrice");
```



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

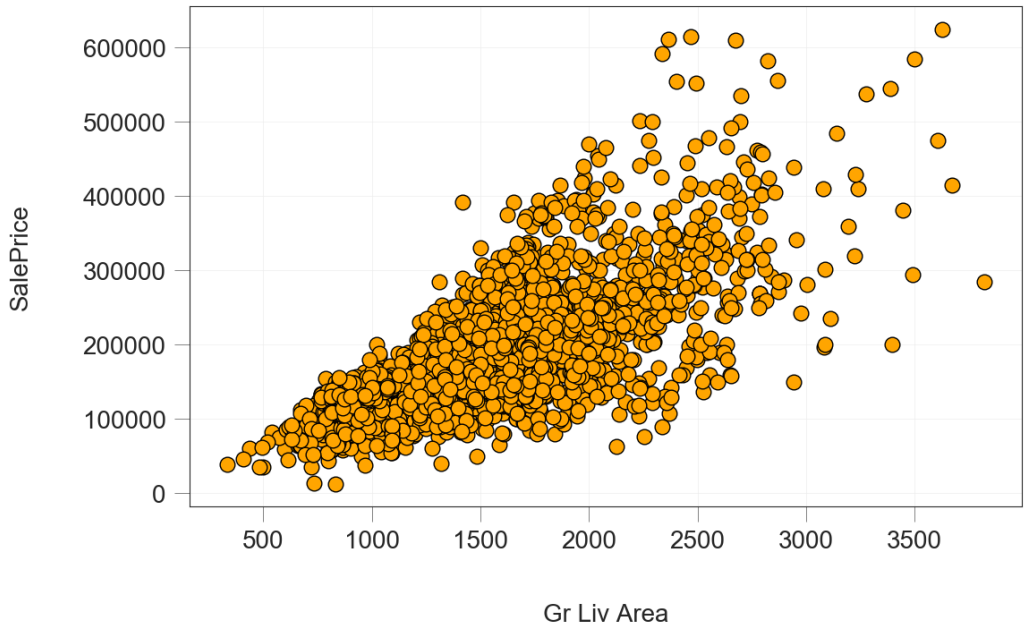
Now, we want to see the relationship between the target variable and `Gr Liv Area` variable which represents the living area above ground. Let us first see the distribution of `Gr Liv Area`:

```
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:

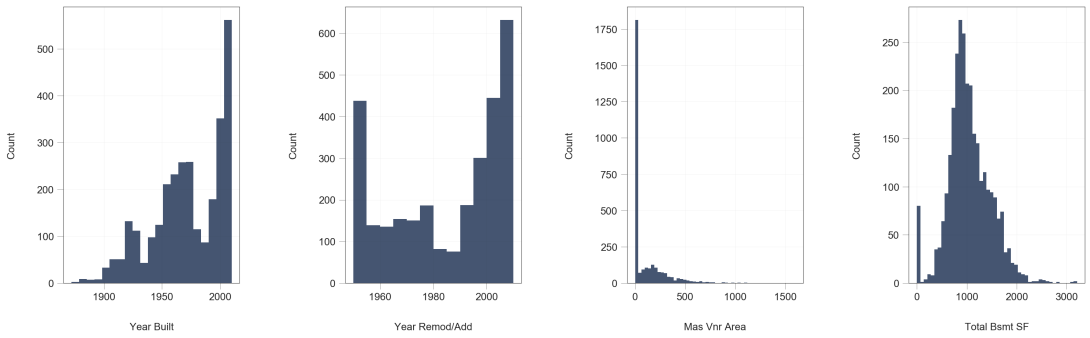
```
plt.scatter(x=dataset['Gr Liv Area'], y=dataset['SalePrice'],
            color="orange", edgecolors="#000000", linewidths=0.5);
plt.xlabel("Gr Liv Area"); plt.ylabel("SalePrice");
```



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

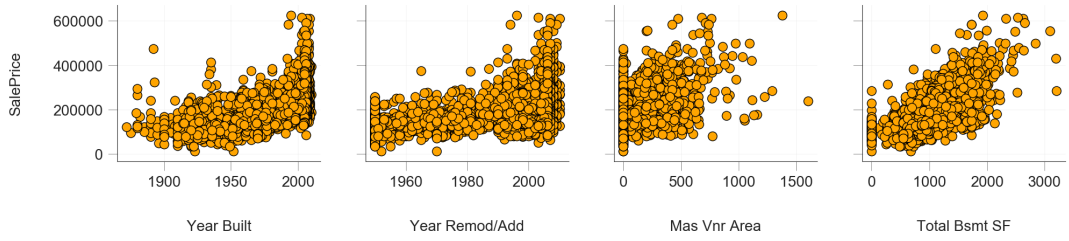
Moderate Positive Correlation Next, we want to visualize the relationship between the target variable and the variables that are positively correlated with it, but the correlation is not very strong. Namely, these variables are `Year Built`, `Year Remod/Add`, `Mas Vnr Area`, `Total Bsmt SF`, `1st Flr 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");
```



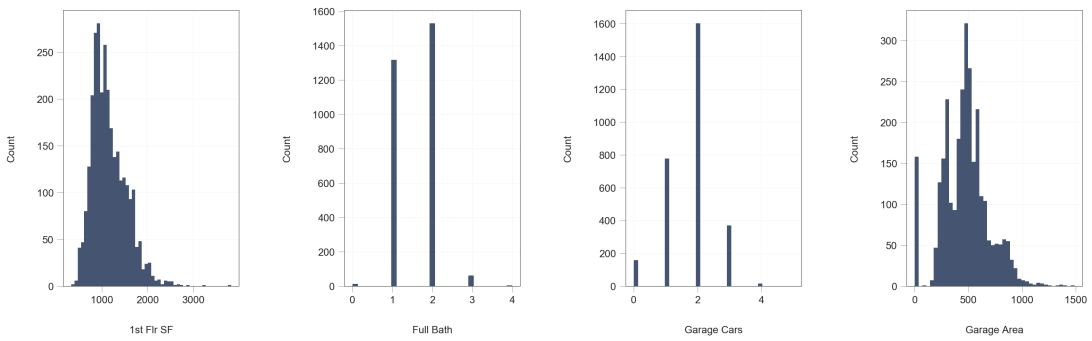
Now let us see their relationships with the target variable using scatter plots:

```
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);
```



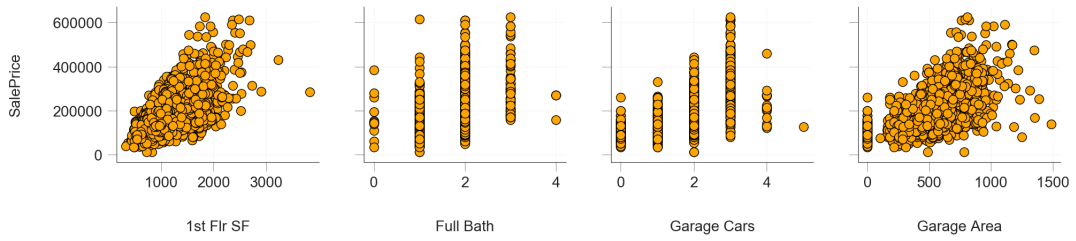
Next, we move to the last four. Let us see the distribution of each of them:

```
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);
```

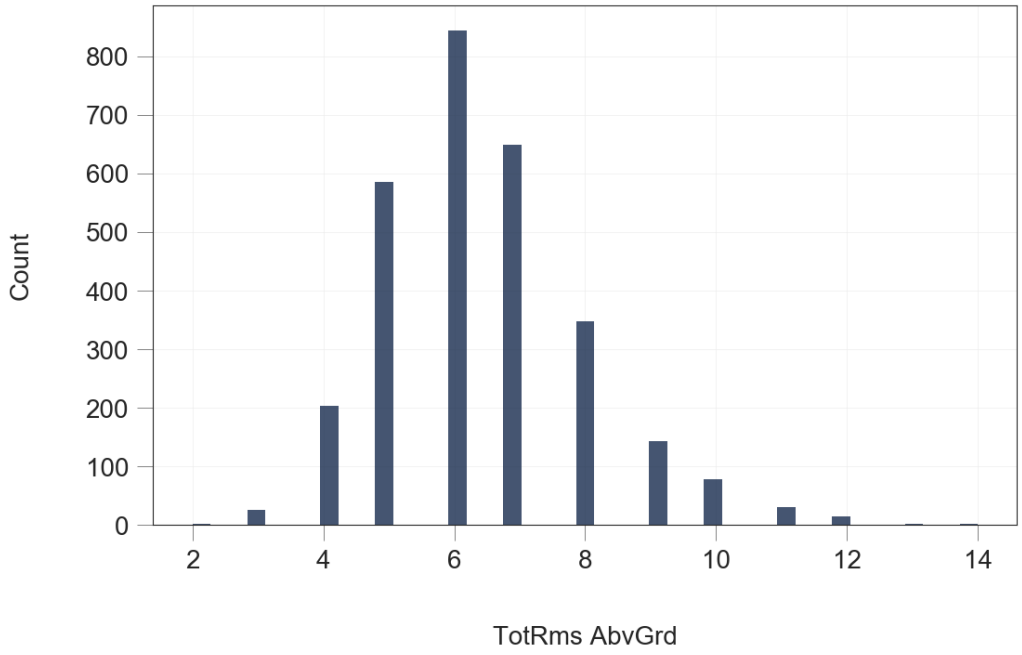


From the plots above, we can see that these eight variables are truly positively correlated with the target variable. However, it's apparent that they are not as highly correlated as `Overall Qual` and `Gr Liv Area`.

4.2.2 Relatioships Between Predictor Variables

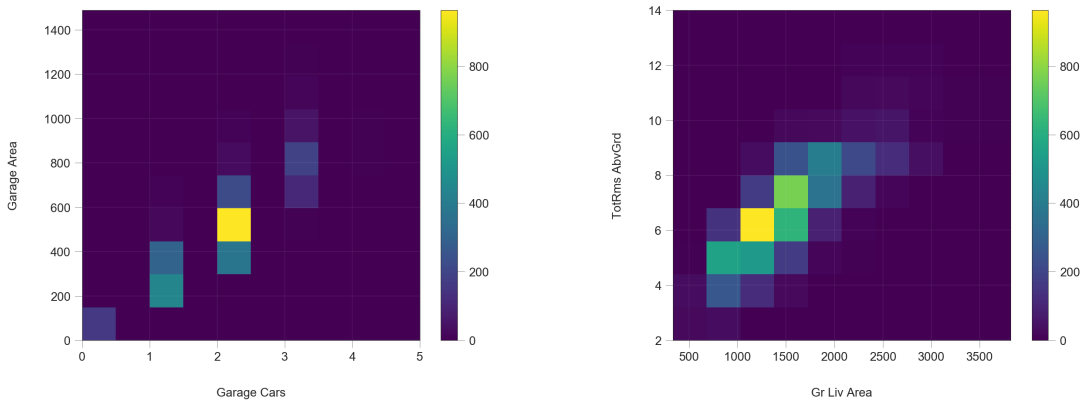
Positive Correlation Apart from the target variable, when we plotted the heatmap, we discovered a high positive correlation between `Garage Cars` and `Garage Area` and between `Gr Liv Area` and `TotRms AbvGrd`. We want to visualize these correlations also. We've already seen the distribution of each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

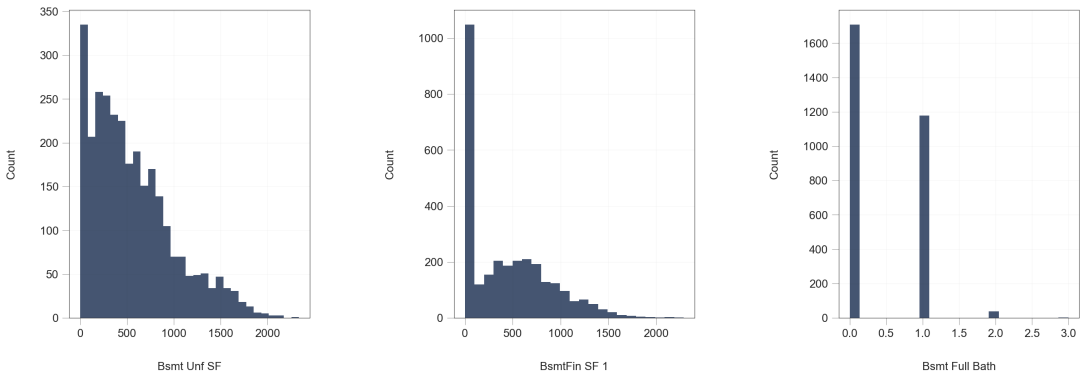
```
plt.rc("grid", linewidth=0.05)
fig, axes = plt.subplots(1, 2, figsize=(15,5))
fig.subplots_adjust(hspace=0.5, wspace=0.4)
h1 = axes[0].hist2d(dataset["Garage Cars"],
                    dataset["Garage Area"],
                    cmap="viridis");
axes[0].set(xlabel="Garage Cars", ylabel="Garage Area")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

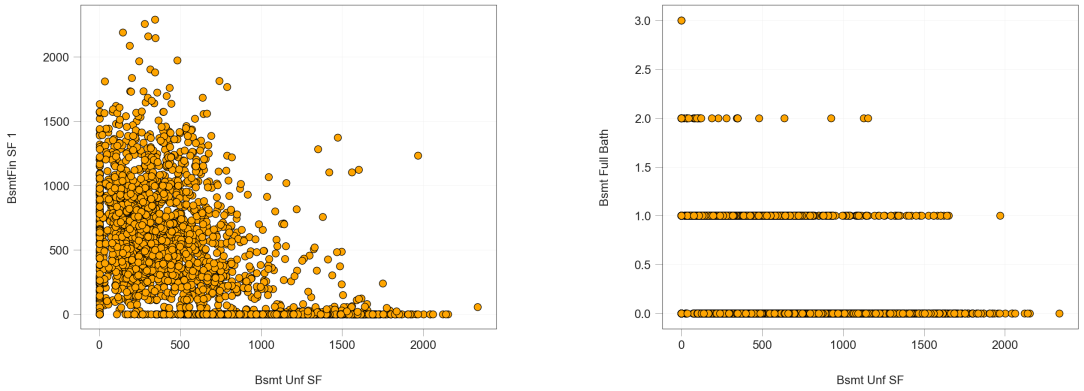
Negative Correlation When we plotted the heatmap, we also discovered a significant negative correlation between `Bsmt Unf SF` and `BsmtFin SF 1`, and between `Bsmt Unf SF` and `Bsmt Full Bath`. We also want to visualize these correlations. Let us see the distribution of these variables first:

```
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.

4.3 Feature Engineering

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

4.3.1 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)
```

4.3.2 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})
```

4.3.3 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 column are converted in the same way.

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

5 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 ragression 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 vatiable 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. In this project, we will test many modeling techniques, and then choose the technique(s) that yield the best results. The techniques that we will try are:

5.0.1 1. Linear Regression

This technique models the relationship between the target variable and the independent variables (predictors). It fits a linear model with coefficients to the data in order to minimize the residual sum of squares between the target variable in the dataset, and the predicted values by the linear approximation.

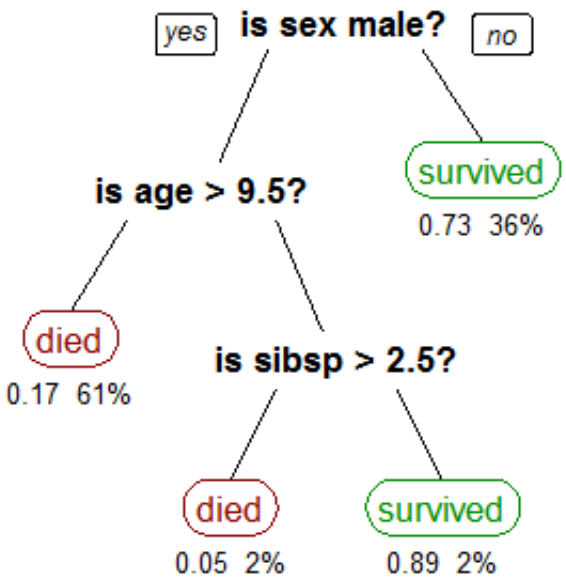


Figure 8: Predicting who survived when the Titanic sank

5.0.2 2. Nearest Neighbors

Nearest Neighbors is a type of instance-based learning. For this technique, the model tries to find a number (k) of training examples closest in distance to a new point, and predict the output for this new point from these closest neighbors. k can be a user-defined number (k-nearest neighbors), or vary based on the local density of points (radius-based neighbors). The distance metric used to measure the closeness is mostly the Euclidean distance.

5.0.3 3. Support Vector Regression

Support vector machines (SVM) are a set of methods that can be used for classification and regression problems. When they are used for regression, we call the technique Support Vector Regression.

5.0.4 4. Decision Trees

For this technique, the goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. An example of a simple decision tree for predicting who survived when the Titanic sank is shown in Figure 8:

5.0.5 5. Neural Networks

Neural network is a machine learning model that tries to mimic the way of working of the biological brain. A neural network consists of multiple layers. Each layer consists of a number of nodes. The nodes of each layer are connected to the nodes of adjacent layers. Each node can be activated

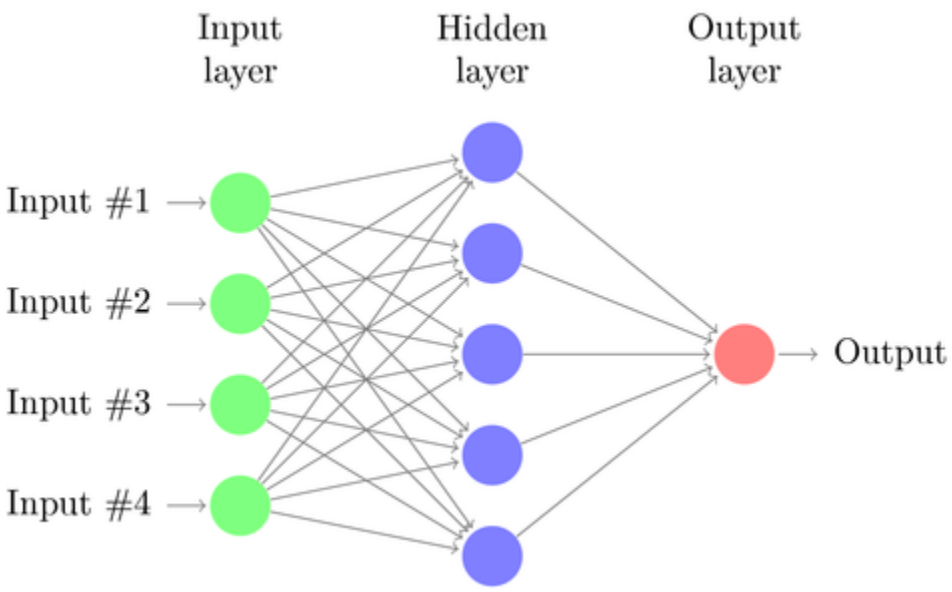


Figure 9: A neural network

or not based on its inputs and its activation function. An example of a neural network is shown in Figure 9:

5.0.6 6. Random Forest

Bagging is an ensemble method where many base models are used with a randomized subset of data to reduce the variance of a the base model.

5.0.7 7. Gradient Boosting

Boosting is also an ensemble method where weak base models are used to create a strong model that reduces bias and variance of the base model.

Each one of these techniques has many algorithmic implementation. *We will choose algorithm(s) for each of these techniques* in the next section.

6 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.

6.1 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:

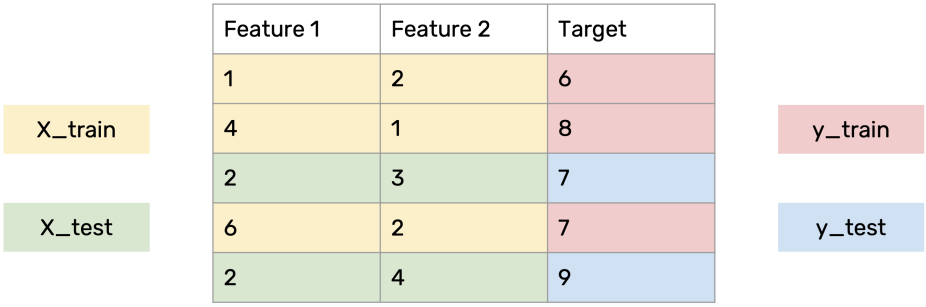


Figure 10: train_test_split() operation

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

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'])
```

6.2 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.

6.3 Modeling Approach

For each one of the techniques mentioned in the previous section (Linear Regression, Nearest Neighbor, Support Vector Machines, etc.), 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

6.3.1 Searching for Effective Parameters

Using Scikit-Learn, we can build a decision-tree model for example as follows:

```
model = DecisionTreeRegressor(max_depth=14, min_samples_split=5, max_features=20)
```

We can do this but to probably achieve a better performance if we choose better values for the parameters `max_depth`, `min_samples_split`, and `max_features`. To do so, 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()`. So for the example above, we will do the following:

```
parameter_space = {
    "max_depth": [7, 15],
    "min_samples_split": [5, 10],
    "max_features": [30, 45]
}

clf = GridSearchCV(DecisionTreeRegressor(), parameter_space, cv=4,
                   scoring="neg_mean_absolute_error")

clf.fit(X_train, y_train)
```

The code above will test the decision-tree model using all the parameter combinations. It will use *cross validation* with 4 folds and it will use the mean absolute error for scoring and comparing different parameter combinations. At the end, it will provide us with the best parameter combination that achieved the best score so we can use it to build our model.

Sometimes, when the number of parameter combinations is large, `GridSearchCV()` can take very long time to run. So in addition to `GridSearchCV()`, we will sometimes 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`. For the example above, we can use `RandomizedSearchCV()` as follows:

```
clf = RandomizedSearchCV(DecisionTreeRegressor(), parameter_space, cv=4,
                         scoring="neg_mean_absolute_error", n_iter=100)
```

This will make `RandomizedSearchCV()` pick 100 parameter combinations randomly.

6.4 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:

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

6.5 Modeling

6.5.1 Linear Regression

For Linear Regression, we will choose three algorithmic implementations: Ridge Regression and Elastic Net. We will use the implementations provided in the Scikit-Learn package of these algorithms.

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)
```

```
Ridge MAE = 15270.463549642733
```

2. 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)
```

```
Elastic Net MAE = 14767.90981933659
```

6.5.2 Nearest Neighbors

For Nearest Neighbors, we will use an implementation of the k-nearest neighbors (KNN) algorithm provided by Scikit-Learn package.

The KNN model has the following syntax:

```
KNeighborsRegressor(n_neighbors=5, weights=uniform, algorithm=auto,
                    leaf_size=30, p=2, metric=minkowski, metric_params=None,
                    n_jobs=None, **kwargs)
```

Firstly, we will use `GridSearchCV()` to search for the best model parameters in a parameter space provided by us. The parameter `n_neighbors` represents `k` which is the number of neighbors to use, `weights` determines the weight function used in prediction: `uniform` or `distance`, `algorithm` specifies the algorithm used to compute the nearest neighbors, `leaf_size` is passed to `BallTree` or `KDTree` algorithm. It can affect the speed of the construction and query, as well as the memory required to store the tree.

```
from sklearn.neighbors import KNeighborsRegressor

parameter_space = {
    "n_neighbors": [9, 10, 11,50],
    "weights": ["uniform", "distance"],
    "algorithm": ["ball_tree", "kd_tree", "brute"],
    "leaf_size": [1,2,20,50,200]
}

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

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

```
Best parameters:
{'algorithm': 'ball_tree', 'leaf_size': 1, 'n_neighbors': 10, 'weights': 'distance'}
```

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:

```
knn_model = KNeighborsRegressor(**clf.best_params_)
```

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

```
knn_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 = knn_model.predict(X_test)
knn_mae = mean_absolute_error(y_test, y_pred)
print("K-Nearest Neighbors MAE =", knn_mae)
```

```
K-Nearest Neighbors MAE = 22780.14347886256
```

6.5.3 Support Vector Regression

For Support Vector Regression (SVR), we will use one of three implementations provided by the Scikit-Learn package.

The SVR model has the following syntax:

```
SVR(kernel=rbf, degree=3, gamma=auto_deprecated, coef0=0.0, tol=0.001,
    C=1.0, epsilon=0.1, shrinking=True, cache_size=200, verbose=False, max_iter=-1)
```

Firstly, we will use `GridSearchCV()` to search for the best model parameters in a parameter space provided by us. The parameter `kernel` specifies the kernel type to be used in the algorithm, `degree` represents the degree of the polynomial kernel `poly`, `gamma` is the kernel coefficient for `rbf`, `poly` and `sigmoid` kernels, `coef0` is independent term in kernel function, and `C` is the penalty parameter of the error term.

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import SVR

parameter_space = \
    {
        "kernel": ["poly", "linear", "rbf", "sigmoid"],
        "degree": [3, 5],
        "coef0": [0, 3, 7],
        "gamma":[1e-3, 1e-1, 1/X_train.shape[1]],
        "C": [1, 10, 100],
    }

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

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

```
Best parameters:
{'C': 100, 'coef0': 3, 'degree': 5, 'gamma': 0.004132231404958678, 'kernel': 'poly'}
```

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 Support Vector Regression model with the best parameters found:

```
svr_model = SVR(**clf.best_params_)
```

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

```
svr_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 = svr_model.predict(X_test)
svr_mae = mean_absolute_error(y_test, y_pred)
print("Support Vector Regression MAE =", svr_mae)
```

```
Support Vector Regression MAE = 12874.92786950232
```

6.5.4 Decision Tree

For Decision Tree (DT), we will use an implementations provided by the Scikit-Learn package.

The Decision Tree model has the following syntax:

```
DecisionTreeRegressor(criterion=mse, splitter=best, max_depth=None,
                      min_samples_split=2, min_samples_leaf=1,
                      min_weight_fraction_leaf=0.0, max_features=None,
                      random_state=None, max_leaf_nodes=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, presort=False)
```

Firstly, we will use `GridSearchCV()` to search for the best model parameters in a parameter space provided by us. The parameter `criterion` specifies the function used to measure the quality of a split, `min_samples_split` determines the minimum number of samples required to split an internal node, `min_samples_leaf` determines the minimum number of samples required to be at a leaf node, and `max_features` controls the number of features to consider when looking for the best split.

```
from sklearn.tree import DecisionTreeRegressor

parameter_space = \
    {
        "criterion": ["mse", "friedman_mse", "mae"],
        "min_samples_split": [5, 18, 29, 50],
        "min_samples_leaf": [3, 7, 15, 25],
        "max_features": [20, 50, 150, 200, X_train.shape[1]],
```

```
        }

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

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

```
Best parameters:
{'criterion': 'mse', 'max_features': 242, 'min_samples_leaf': 7, 'min_samples_split': 18}
```

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 Decision Tree model with the best parameters found:

```
dt_model = DecisionTreeRegressor(**clf.best_params_)
```

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

```
dt_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 = dt_model.predict(X_test)
dt_mae = mean_absolute_error(y_test, y_pred)
print("Decision Tree MAE =", dt_mae)
```

```
Decision Tree MAE = 20873.949425979506
```

6.5.5 Neural Network

For Neural Network (NN), we will use an implementations provided by the Scikit-Learn package.

The Neural Network model has the following syntax:

```
MLPRegressor(hidden_layer_sizes=(100, ), activation=relu, solver=adam,
             alpha=0.0001, batch_size=auto, learning_rate=constant,
             learning_rate_init=0.001, power_t=0.5, max_iter=200, shuffle=True,
             random_state=None, tol=0.0001, verbose=False, warm_start=False,
             momentum=0.9, nesterovs_momentum=True, early_stopping=False,
             validation_fraction=0.1, beta_1=0.9, beta_2=0.999, epsilon=1e-08,
             n_iter_no_change=10)
```

Firstly, we will use `GridSearchCV()` to search for the best model parameters in a parameter space provided by us. The parameter `hidden_layer_sizes` is a list where its ith element represents the number of neurons in the ith hidden layer, `activation` specifies the activation function for the hidden layer, `solver` determines the solver for weight optimization, and `alpha` represents L2 regularization penalty.

```
from sklearn.neural_network import MLPRegressor

parameter_space = \
    {
        "hidden_layer_sizes": [(7,)*3, (19,), (100,), (154,)],
        "activation": ["identity", "logistic", "tanh", "relu"],
        "solver": ["lbfgs"],
        "alpha": [1, 10, 100],
    }

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

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

```
Best parameters:
{'activation': 'identity', 'alpha': 1, 'hidden_layer_sizes': (154,), 'solver': 'lbfgs'}
```

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 Neural Network model with the best parameters found:

```
nn_model = MLPRegressor(**clf.best_params_)
```

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

```
nn_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 = nn_model.predict(X_test)
nn_mae = mean_absolute_error(y_test, y_pred)
print("Neural Network MAE =", nn_mae)
```

```
Neural Network MAE = 15656.581467633143
```

6.5.6 Random Forest

For Random Forest (RF), we will use an implementations provided by the Scikit-Learn package.

The Random Forest model has the following syntax:

```
RandomForestRegressor(n_estimators=warn, criterion=mse, max_depth=None,
                      min_samples_split=2, min_samples_leaf=1,
                      min_weight_fraction_leaf=0.0, max_features=auto,
                      max_leaf_nodes=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, bootstrap=True, oob_score=False,
                      n_jobs=None, random_state=None, verbose=0, warm_start=False)
```

Firstly, we will use `GridSearchCV()` to search for the best model parameters in a parameter space provided by us. The parameter `n_estimators` specifies the number of trees in the forest, `bootstrap` determines whether bootstrap samples are used when building trees. `criterion`, `max_depth`, `min_samples_split`, `min_samples_leaf`, `max_features` are the same as those of the decision tree model.

```
from sklearn.ensemble import RandomForestRegressor

parameter_space = \
    {
        "n_estimators": [10, 100, 300, 600],
        "criterion": ["mse", "mae"],
        "max_depth": [7, 50, 254],
        "min_samples_split": [2, 5],
        "min_samples_leaf": [1, 5],
        "max_features": [19, 100, X_train.shape[1]],
        "bootstrap": [True, False],
    }

clf = RandomizedSearchCV(RandomForestRegressor(random_state=3),
                         parameter_space, cv=3, n_jobs=4,
                         scoring="neg_mean_absolute_error",
                         n_iter=10, random_state=3)

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

```
Best parameters:
{'n_estimators': 600, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_features': 19, 'max_
```

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 Random Forest model with the best parameters found:

```
rf_model = RandomForestRegressor(**clf.best_params_)
```

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

```
rf_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 = rf_model.predict(X_test)
rf_mae = mean_absolute_error(y_test, y_pred)
print("Random Forest MAE =", rf_mae)
```

```
Random Forest MAE = 14506.456657559198
```

6.5.7 Gradient Boosting

For Gradient Boosting (GB), we will use the renowned XGBoost implementations.

XGBoost model has the following syntax:

```
XGBRegressor(max_depth=3, learning_rate=0.1, n_estimators=100, silent=True,
             objective='reg:linear', booster='gbtree', n_jobs=1, nthread=None,
             gamma=0, min_child_weight=1, max_delta_step=0, subsample=1,
             colsample_bytree=1, colsample_bylevel=1, reg_alpha=0, reg_lambda=1,
             scale_pos_weight=1, base_score=0.5, random_state=0, seed=None,
             missing=None, importance_type='gain', **kwargs)
```

Firstly, we will use `GridSearchCV()` to search for the best model parameters in a parameter space provided by us. The parameter `max_depth` sets the maximum depth of a tree, `learning_rate` represents the step size shrinkage used in updating weights, `n_estimators` specifies the number of boosted trees to fit, `booster` determines which booster to use, `gamma` specifies the minimum loss reduction required to make a further partition on a leaf node of the tree, `subsample` is subsample ratio of the training instances; this subsampling will occur once in every boosting iteration, `colsample_bytree` specifies the subsample ratio of columns when constructing each tree, `colsample_bylevel` specifies the subsample ratio of columns for each split, in each level, `reg_alpha` is L1 regularization term, and `reg_lambda` is L2 regularization term.

```
from xgboost import XGBRegressor

parameter_space = \
    {
        "max_depth": [4, 5, 6],
        "learning_rate": [0.005, 0.009, 0.01],
        "n_estimators": [700, 1000, 2500],
        "booster": ["gbtree",],
        "gamma": [7, 25, 100],
        "subsample": [0.3, 0.6],
        "colsample_bytree": [0.5, 0.7],
        "colsample_bylevel": [0.5, 0.7,],
        "reg_alpha": [1, 10, 33],
        "reg_lambda": [1, 3, 10],
    }

clf = RandomizedSearchCV(XGBRegressor(random_state=3),
                         parameter_space, cv=3, n_jobs=4,
                         scoring="neg_mean_absolute_error",
                         random_state=3, n_iter=10)

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

```
Best parameters:
{'subsample': 0.3, 'reg_lambda': 3, 'reg_alpha': 33, 'n_estimators': 2500, 'max_depth': 6, 'lea
```

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 XGBoost model with the best parameters found:

```
xgb_model = XGBRegressor(**clf.best_params_)
```

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

```
xgb_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 = xgb_model.predict(X_test)
xgb_mae = mean_absolute_error(y_test, y_pred)
print("XGBoost MAE =", xgb_mae)
```

```
XGBoost MAE = 12556.67524760929
```

7 Analysis and Comparison

In the previous section, we created many models: for each model, we searched for good parameters then we constructed the model using those parameters, then 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.

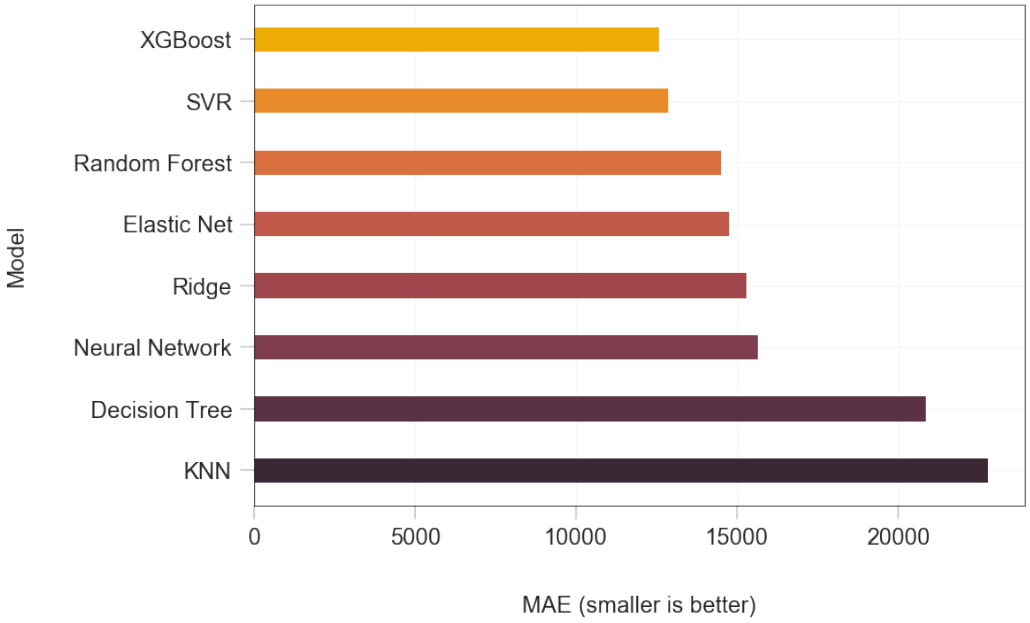
Using the results we got in the previous section, we present a table that shows the mean absolute error (MAE) for each model when applied to the test set `X_test`. The table is sorted ascendingly according to MAE score.

Model	MAE
XGBoost	12556.68
Support Vector Regression (SVR)	12874.93
Random Forest	14506.46
Elastic Net	14767.91
Ridge	15270.46
Neural Network	15656.38
Decision Tree	20873.95
K-Nearest Neighbors (KNN)	22780.14

We also present a graph that visualizes the table contents:

```
x = ['KNN', 'Decision Tree', 'Neural Network', 'Ridge',
     'Elastic Net', 'Random Forest', 'SVR', 'XGBoost']
y = [22780.14, 20873.95, 15656.38, 15270.46, 14767.91,
     14506.46, 12874.93, 12556.68]
```

```
colors = ["#392834", "#5a3244", "#7e3c4d", "#a1484f",
          "#c05949", "#d86f3d", "#e88b2b", "#edab06"]
fig, ax = plt.subplots()
plt.barh(y=range(len(x)), tick_label=x, width=y, height=0.4, color=colors);
ax.set(xlabel="MAE (smaller is better)", ylabel="Model");
```



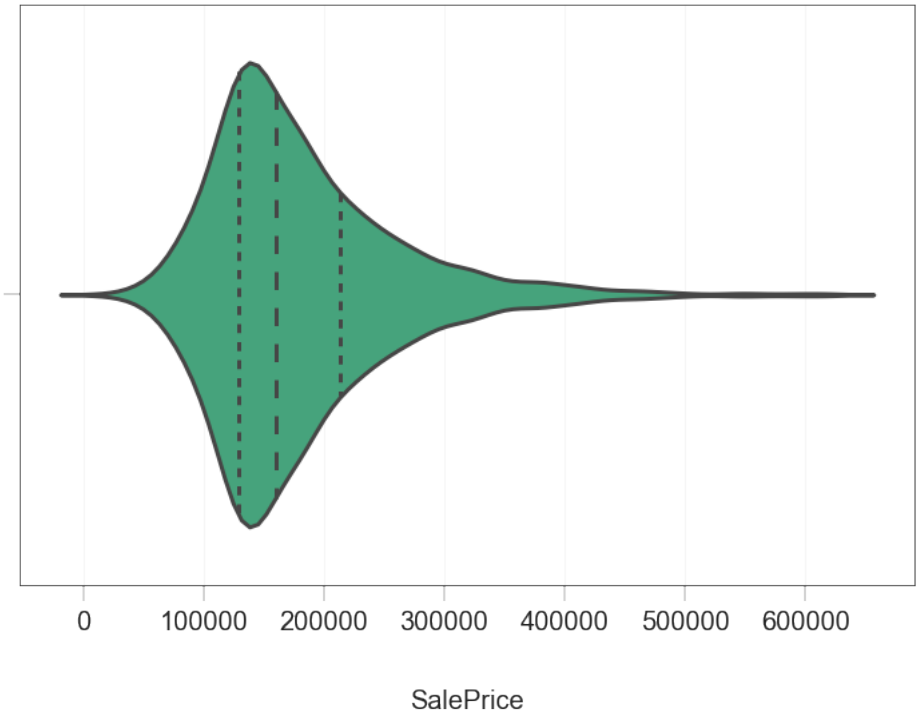
By looking at the table and the graph, we can see that XGBoost model has the smallest MAE, `12556.68` followed by Support Vector Regression model with a little larger error of `12974.93`. After that, Random Forest and Elastic Net models come with similar errors: `14506.46` and `14767.91` respectively. Then come Ridge and Neural Network models with close errors: `15270.46` and `15656.38` respectively. Then comes Decision Tree model with MAE of `20873.95`, and at last, the K-Nearest Neighbors model with an error of `22780.14`.

So, in our experiment, the best model is XGBoost and the worst model is K-Nearest Neighbors. We can see that the difference in MAE between the best model and the worst model is significant; the best model has almost half of the error of the worst model.

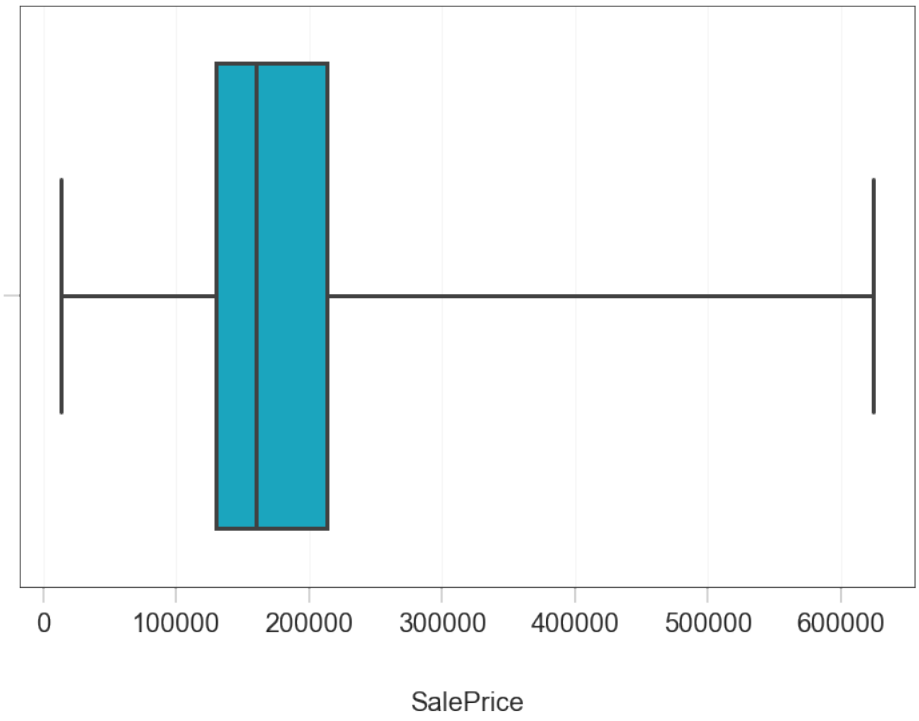
7.1 Performance Interpretation

We chose the mean absolute error (MAE) as our performance metric to evaluate and compare models. MAE presents a value that is easy to understand; it shows the average value of model error. For example, for our XGBoost model, its MAE is `12556.68` which means that on average, XGBoost will predict a value that is bigger or smaller than the true value by `12556.68`. 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:

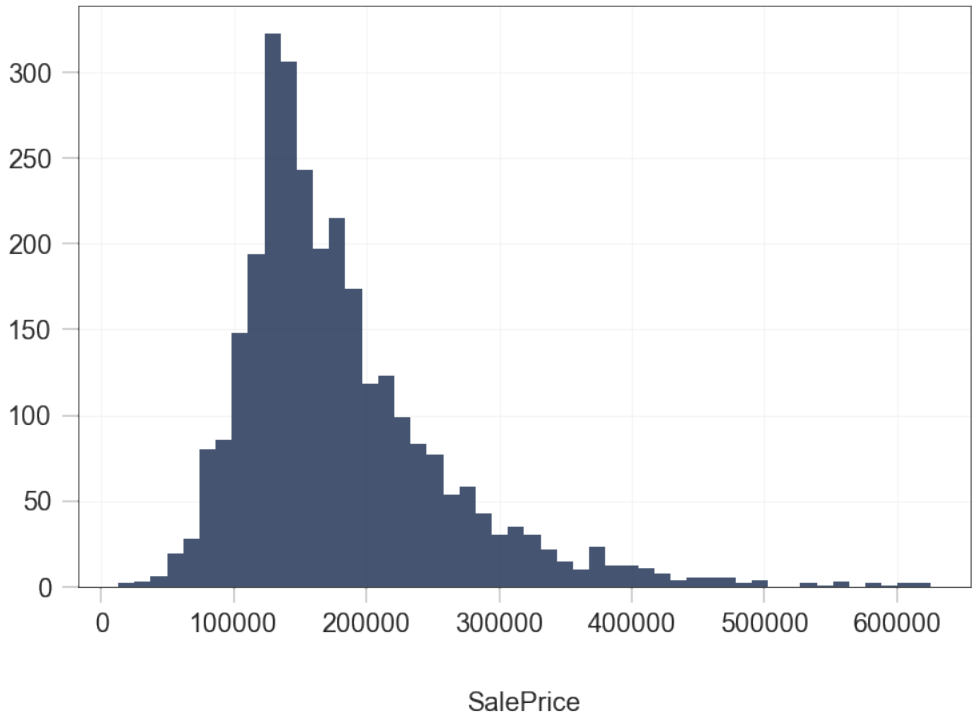
```
sns.violinplot(x=dataset['SalePrice'], inner="quartile", color="#36B37E");
```




```
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 XGBoost error of `12,556.68`, we can say that an error of about `12,000` is good for data whose mean is `159,895` and whose 75% of it is larger than `128,500`.

7.2 Feature Importances

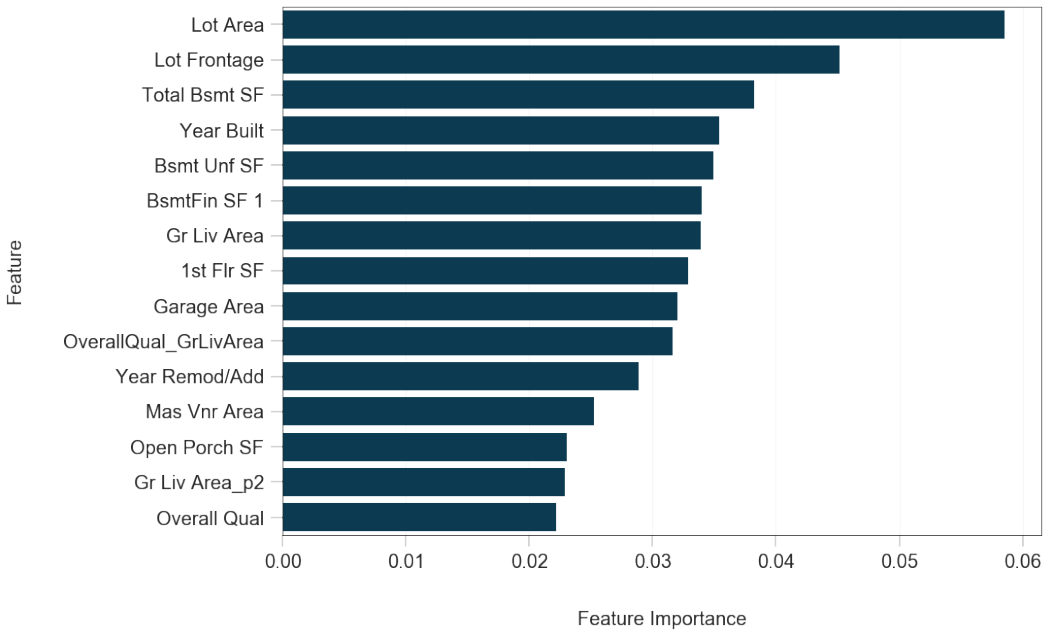
Some of the models we used provide the ability to see the importance of each feature in the dataset after fitting the model. We will look at the feature importances provided by both XGBoost and Random Forest models. We have 242 features in our data which is a big number, so we will take a look at the 15 most important features.

7.2.1 XGBoost

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

```
xgb_feature_importances = xgb_model.feature_importances_
xgb_feature_importances = pd.Series(
    xgb_feature_importances, index=X_train.columns.values
    ).sort_values(ascending=False).head(15)

fig, ax = plt.subplots(figsize=(7, 5))
sns.barplot(x=xgb_feature_importances,
            y=xgb_feature_importances.index,
            color="#003f5c");
plt.xlabel('Feature Importance');
plt.ylabel('Feature');
```

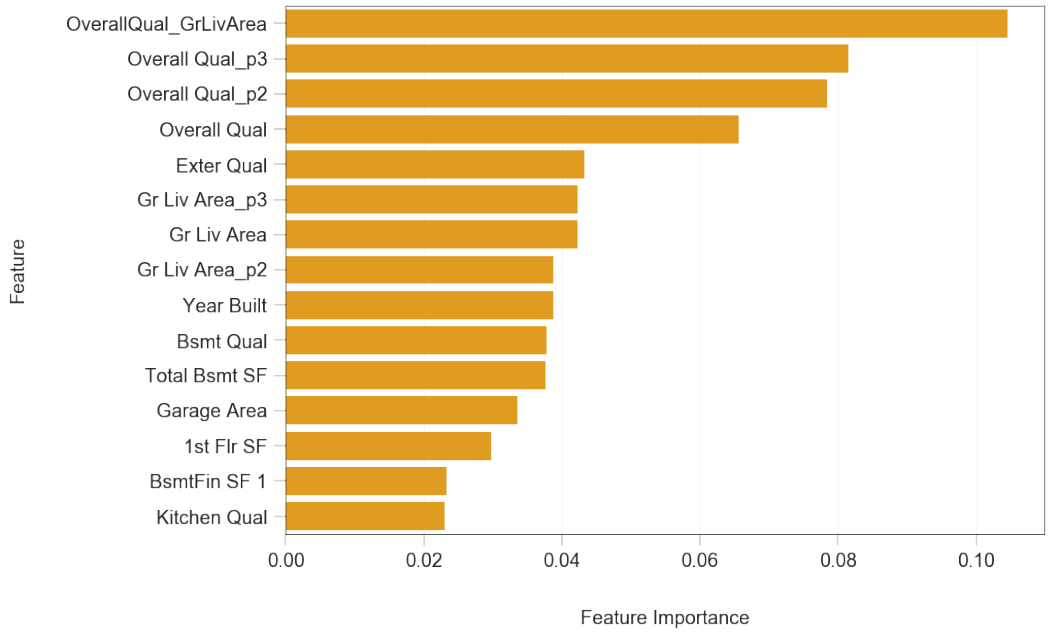


7.2.2 Random Forest

Now, let's see the most important features as for Random Forest model:

```
rf_feature_importances = rf_model.feature_importances_
rf_feature_importances = pd.Series(
    rf_feature_importances, index=X_train.columns.values
    ).sort_values(ascending=False).head(15)

fig, ax = plt.subplots(figsize=(7,5))
sns.barplot(x=rf_feature_importances,
            y=rf_feature_importances.index,
            color="#ffa600");
plt.xlabel('Feature Importance');
plt.ylabel('Feature');
```



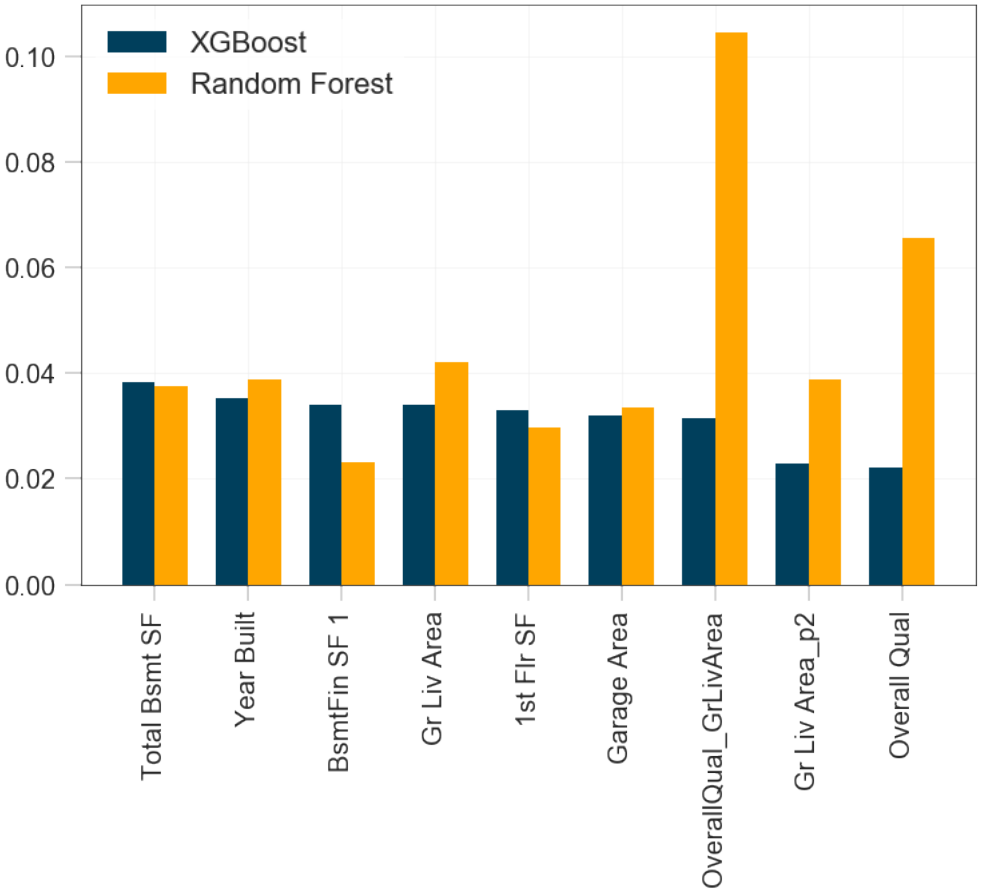
7.2.3 Common Important Features

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

```
common_imp_feat = [x for x in xgb_feature_importances.index
                   if x in rf_feature_importances.index]
commImpFeat_xgb_scores = [xgb_feature_importances[x]
                          for x in common_imp_feat]
commImpFeat_rf_scores = [rf_feature_importances[x]
                         for x in common_imp_feat]
```

```
ind = np.arange(len(commImpFeat_xgb_scores))
width = 0.35

fig, ax = plt.subplots()
ax.bar(ind - width/2, commImpFeat_xgb_scores, width,
       color='#003f5c', label='XGBoost');
ax.bar(ind + width/2, commImpFeat_rf_scores, width,
       color='#ffa600', label='Random Forest')
ax.set_xticks(ind);
ax.set_xticklabels(common_imp_feat);
ax.legend();
plt.xticks(rotation=90);
```



8 Conclusion

In this paper, we built serveral regression models to predict the price of some house given some of the house features. We eveluated and compared each model to determine the one with highest performance. We also looked at how some models rank the features according to their importance. In this paper, we followed the data science process starting with getting the data, then 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, we 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. We 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.

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