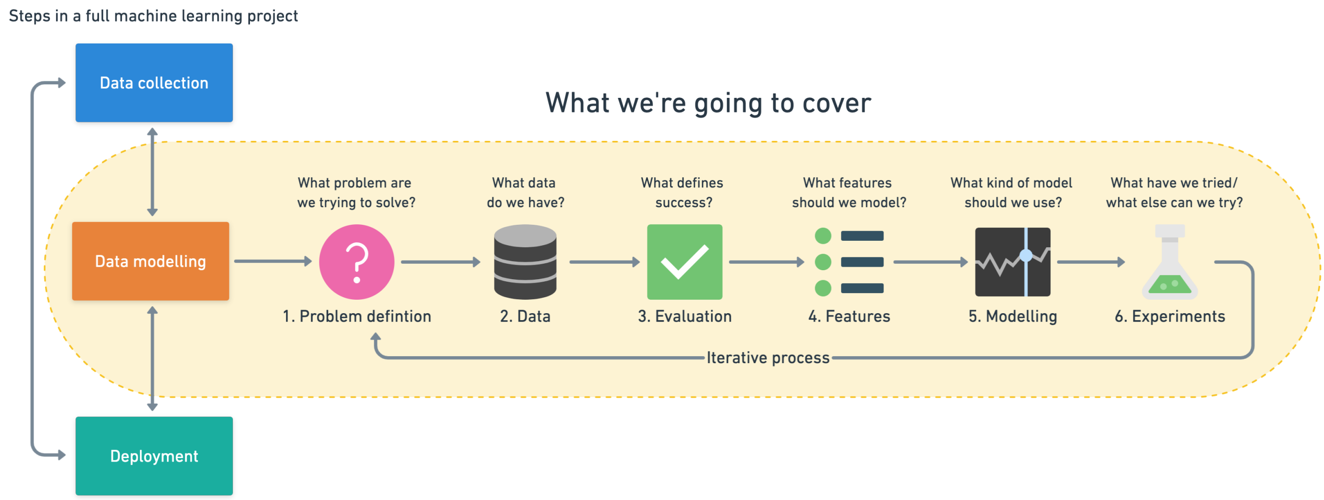
🏡 Housing Market 📈 Analysis 📊: Sales Price Prediction using Feature Engineering, RFs, and Gradient Boosting

In order to anticipate the sales price of homes, a predictive model is created in this notebook after analysis of housing price data. This problem is a regression problem since its objective is to forecast numerical values. Such a situation falls under the category of a regression issue since the objective is to forecast numerical values. The dataset utilized in this analysis is sourced from the [Kaggle House Prices Competition (https://www.kaggle.com/competitions/house-prices-advanced-regression-techniques/data)](https://www.kaggle.com/competitions/house-prices-advanced-regression-techniques/data).

When potential buyers inquire about their ideal home, they typically do not prioritize details such as the basement ceiling height or the nearby east-west railroad. However, an extensive dataset shows that many factors beyond the obvious ones, such as the number of bedrooms or the presence of a white-picket fence, can significantly impact price negotiations. This dataset, which encompasses 79 explanatory variables that cover nearly every aspect of residential properties in Ames, Iowa, can be used to predict the final selling price of each home.

What our task entails

([Reference Link (https://github.com/mrdbourke/zero-to-mastery-ml/blob/master/section-1-getting-ready-for-machine-learning/a-6-step-framework-for-approaching-machine-learning-projects.md)](https://github.com/mrdbourke/zero-to-mastery-ml/blob/master/section-1-getting-ready-for-machine-learning/a-6-step-framework-for-approaching-machine-learning-projects.md))



Since we already possess the dataset, we will proceed with addressing the problem using the following sequential steps: -

1) Problem defination

2) Data

3) EDA & Data Preprocessing

- Importing necessary libraries and loading the dataset.
- Handling duplicates and missing values (NaN).
- Analyzing correlations among variables.
- Normalizing the data through visualization (plots) and statistical tests.

4) Feature Engineering & Modelling

Problem Statement

The goal of this analysis is to increase the accuracy of house sale price predictions by using historical data and its associated features.

Data

Source of Data: [Kaggle Dataset (https://www.kaggle.com/competitions/house-prices-advanced-regression-techniques/data)](https://www.kaggle.com/competitions/house-prices-advanced-regression-techniques/data)

Dean De Cock created the Ames Housing dataset for the purpose of data science education. It is a valuable alternative to the well-known Boston Housing dataset, as it is more contemporary and includes additional features.

The competition provided two datasets:

- **train.csv** - This dataset contains historical records of house sales prices, consisting of approximately 1460 examples. The **target** variable in this dataset is the **SalePrice**.
- **test.csv** - The test dataset, on the other hand, has a sample size of approximately 1458.

Let's start with by importing some python libraries.

In [ ]:

```
# Importing Libraries

import numpy as np
import pandas as pd
import seaborn as sns
import scipy.stats as stats
from scipy.stats import norm
import statsmodels.api as sm
import matplotlib.pyplot as plt
from scipy.stats import skew, norm
from sklearn.neighbors import KNeighborsRegressor
%matplotlib inline

import warnings
warnings.filterwarnings(action="ignore")
```

In [ ]:

```
# Importing data

house_data = pd.read_csv("/content/train.csv")
house_data.rename(columns=lambda x: x.strip().replace(' ', ''), inplace=True)  # Removing
house_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             1460 non-null   int64  
 1   MSSubClass     1460 non-null   int64  
 2   MSZoning       1460 non-null   object 
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64  
 5   Street         1460 non-null   object 
 6   Alley          91 non-null     object 
 7   LotShape       1460 non-null   object 
 8   LandContour    1460 non-null   object 
 9   Utilities      1460 non-null   object 
 10  LotConfig      1460 non-null   object 
 11  LandSlope      1460 non-null   object 
 12  Neighborhood   1460 non-null   object 
 13  Condition1     1460 non-null   object 
 14  Condition2     1460 non-null   object 
 15  BldgType       1460 non-null   object 
 16  HouseStyle     1460 non-null   object 
 17  OverallQual    1460 non-null   int64  
 18  OverallCond    1460 non-null   int64  
 19  YearBuilt      1460 non-null   int64  
 20  YearRemodAdd   1460 non-null   int64  
 21  RoofStyle      1460 non-null   object 
 22  RoofMatl       1460 non-null   object 
 23  Exterior1st    1460 non-null   object 
 24  Exterior2nd    1460 non-null   object 
 25  MasVnrType     1452 non-null   object 
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object 
 28  ExterCond      1460 non-null   object 
 29  Foundation     1460 non-null   object 
 30  BsmtQual       1423 non-null   object 
 31  BsmtCond       1423 non-null   object 
 32  BsmtExposure   1422 non-null   object 
 33  BsmtFinType1   1423 non-null   object 
 34  BsmtFinSF1     1460 non-null   int64  
 35  BsmtFinType2   1422 non-null   object 
 36  BsmtFinSF2     1460 non-null   int64  
 37  BsmtUnfSF      1460 non-null   int64  
 38  TotalBsmtSF    1460 non-null   int64  
 39  Heating        1460 non-null   object 
 40  HeatingQC      1460 non-null   object 
 41  CentralAir     1460 non-null   object 
 42  Electrical     1459 non-null   object 
 43  1stFlrSF       1460 non-null   int64  
 44  2ndFlrSF       1460 non-null   int64  
 45  LowQualFinSF   1460 non-null   int64  
 46  GrLivArea      1460 non-null   int64  
 47  BsmtFullBath   1460 non-null   int64  
 48  BsmtHalfBath   1460 non-null   int64  
 49  FullBath       1460 non-null   int64  
 50  HalfBath       1460 non-null   int64  
 51  BedroomAbvGr   1460 non-null   int64  
 52  KitchenAbvGr   1460 non-null   int64  
 53  KitchenQual    1460 non-null   object 
 54  TotRmsAbvGrd   1460 non-null   int64  
 55  Functional     1460 non-null   object 
```

```
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

Object, float, and int data types make up the majority of the data. There are 81 columns and 1460 rows.

In [ ]:

```
house_data.head(10)
```

Out[3]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl
5	6	50	RL	85.0	14115	Pave	NaN	IR1	Lvl
6	7	20	RL	75.0	10084	Pave	NaN	Reg	Lvl
7	8	60	RL	NaN	10382	Pave	NaN	IR1	Lvl
8	9	50	RM	51.0	6120	Pave	NaN	Reg	Lvl
9	10	190	RL	50.0	7420	Pave	NaN	Reg	Lvl

10 rows × 81 columns

In [ ]:

```
house_data.tail(10)
```

Out[4]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandCon
1450	1451	90	RL	60.0	9000	Pave	NaN	Reg	
1451	1452	20	RL	78.0	9262	Pave	NaN	Reg	
1452	1453	180	RM	35.0	3675	Pave	NaN	Reg	
1453	1454	20	RL	90.0	17217	Pave	NaN	Reg	
1454	1455	20	FV	62.0	7500	Pave	Pave	Reg	
1455	1456	60	RL	62.0	7917	Pave	NaN	Reg	
1456	1457	20	RL	85.0	13175	Pave	NaN	Reg	
1457	1458	70	RL	66.0	9042	Pave	NaN	Reg	
1458	1459	20	RL	68.0	9717	Pave	NaN	Reg	
1459	1460	20	RL	75.0	9937	Pave	NaN	Reg	

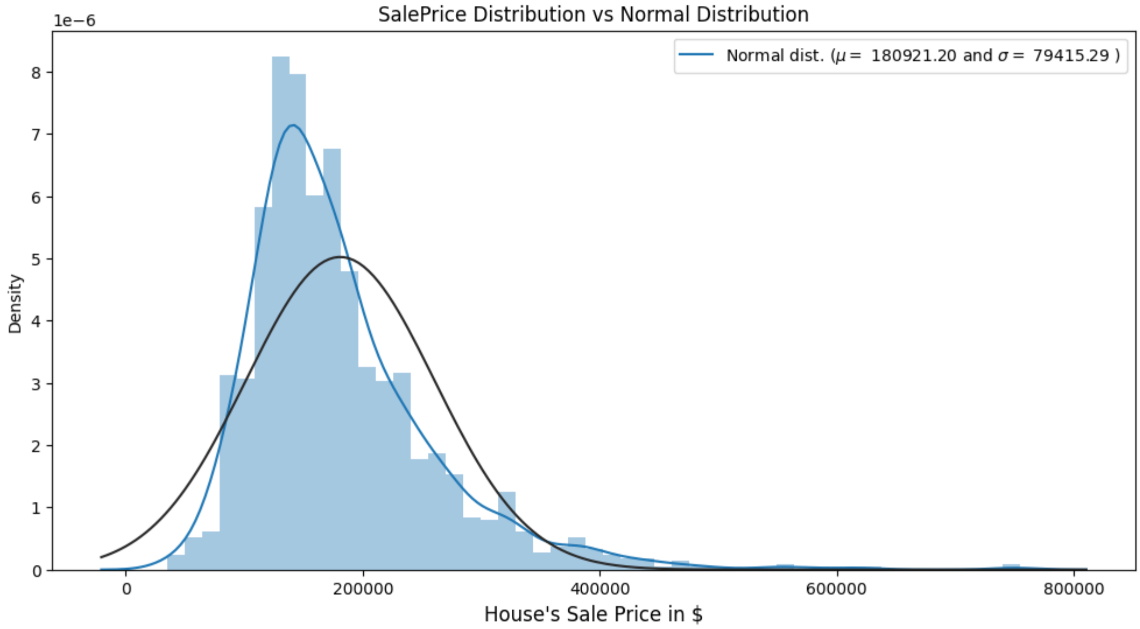
10 rows × 81 columns

Exploratory Data Analysis (EDA) & Visualization

It is important to understand data before working with it. Exploratory data analysis (EDA) is a crucial step in this process. EDA is a combination of visualizations and statistical analysis (uni, bi, and multivariate) that helps us to better understand the data and gain insight into its relationships. Let's explore our target variable and how the other features influence it.

In [ ]:

```
# Fit the data to a normal distribution
mu, sigma = np.mean(house_data['SalePrice']), np.std(house_data['SalePrice'])

# Plot the distribution of SalePrice
plt.figure(figsize=(12, 6))
sns.distplot(house_data['SalePrice'], kde=True, hist=True, fit=norm)
plt.title('SalePrice Distribution vs Normal Distribution', fontsize=12)
plt.xlabel("House's Sale Price in $", fontsize=12)
plt.legend(['Normal dist. ($\mu=$ {:.2f} and $\sigma=$ {:.2f} )'.format(mu, sigma)], loc=
plt.show()
```



In the literature, skewness values between -0.5 and 0.5 and kurtosis values between -2 and 2 are considered acceptable. However, the plot shows that the distribution is not normal, but is highly right-skewed. This is also supported by the Shapiro test for normality, which returned a very small p-value, indicating that we can reject the hypothesis of normality. Despite this, we will leave the distribution as it is for now, as we will address this issue later in the notebook.

In [ ]:

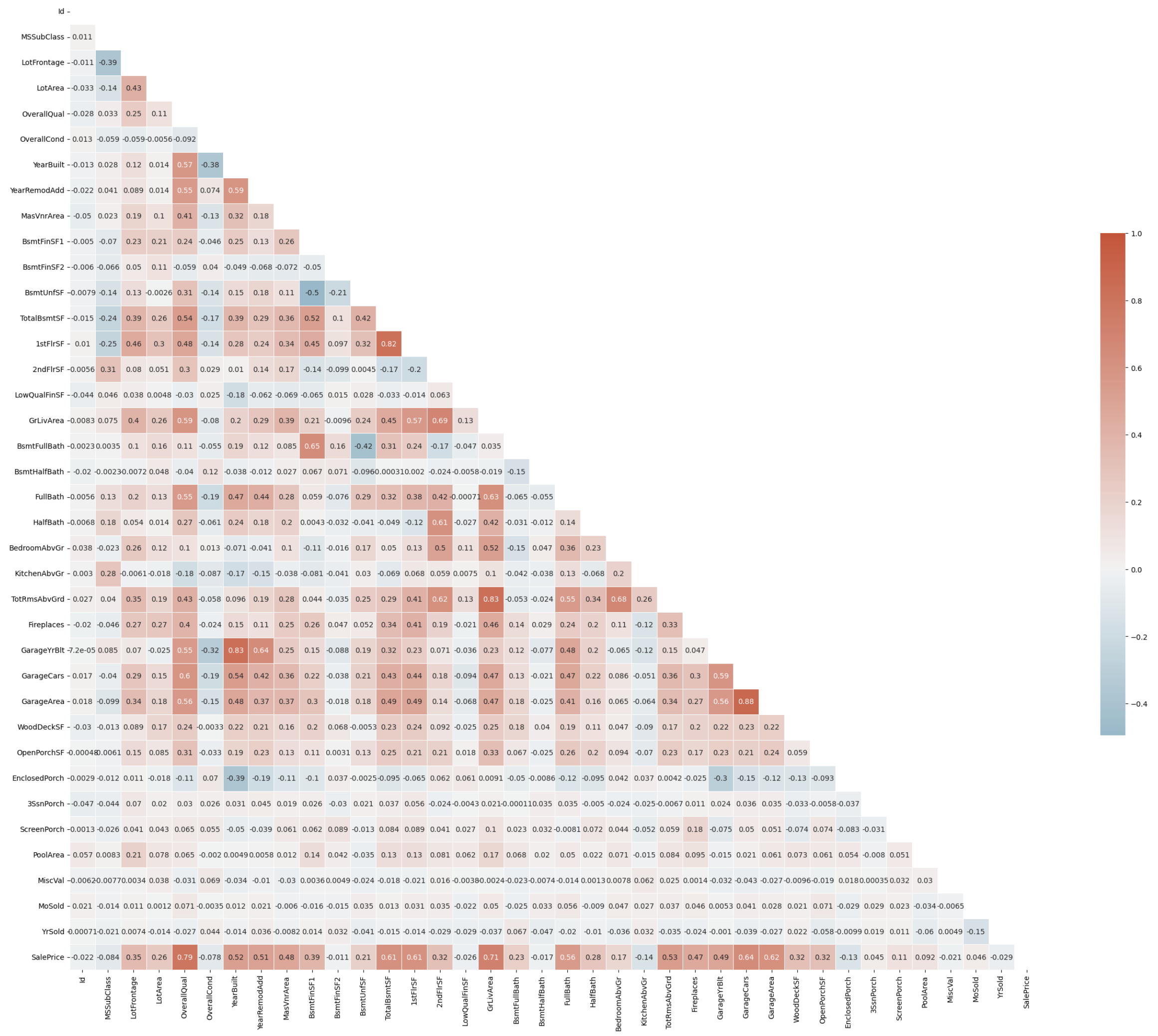
```
# Skew and kurt
from scipy.stats import skew, kurtosis, shapiro

sale_price = house_data['SalePrice']

skewness = skew(np.abs(sale_price))
kurtosis_value = kurtosis(np.abs(sale_price))
shapiro_test = shapiro(sale_price)

print("Skewness: %f" % skewness)
print("Kurtosis: %f" % kurtosis_value)
print("Shapiro_Test: %f" % shapiro_test[0])
print("Shapiro_Test: %f" % shapiro_test[1])
```

```
Skewness: 1.880941
Kurtosis: 6.509812
Shapiro_Test: 0.869673
Shapiro_Test: 0.000000
```

The correlation matrix is a useful tool for identifying the numerical relationships between features. We can use it to see which features are most correlated with our target variable.

In [ ]:

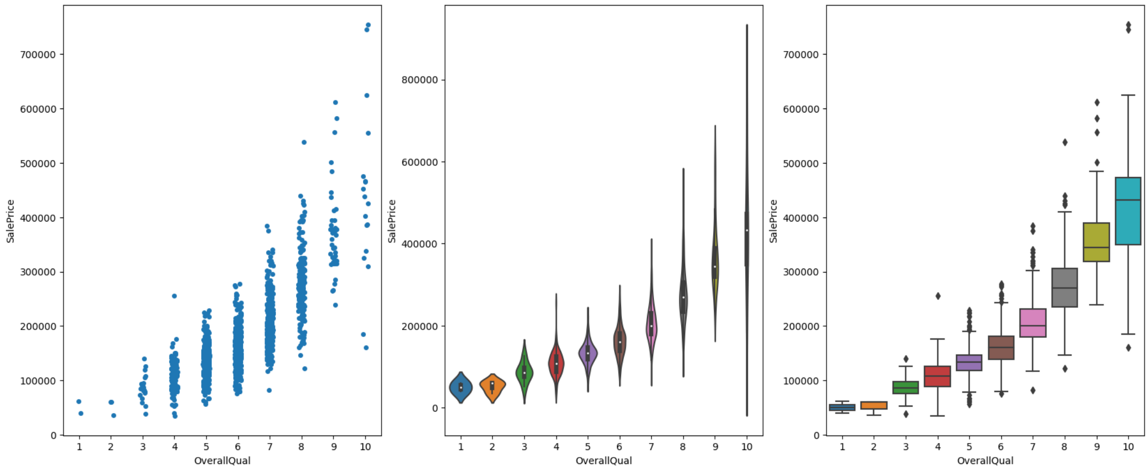
```
# Correlation Matrix
plt.figure(figsize=(30, 25))
corr_matrix = house_data.corr()
mask = np.triu(np.ones_like(corr_matrix, dtype=bool))
cmap = sns.diverging_palette(230, 20, as_cmap=True)
sns.heatmap(corr_matrix, mask=mask, cmap=cmap, vmax=1, center=0, annot=True,
            square=True, linewidths=0.5, cbar_kws={"shrink": 0.5})
plt.show()
```



Now that we have identified the features that are most correlated with our target variable, we can investigate them further.

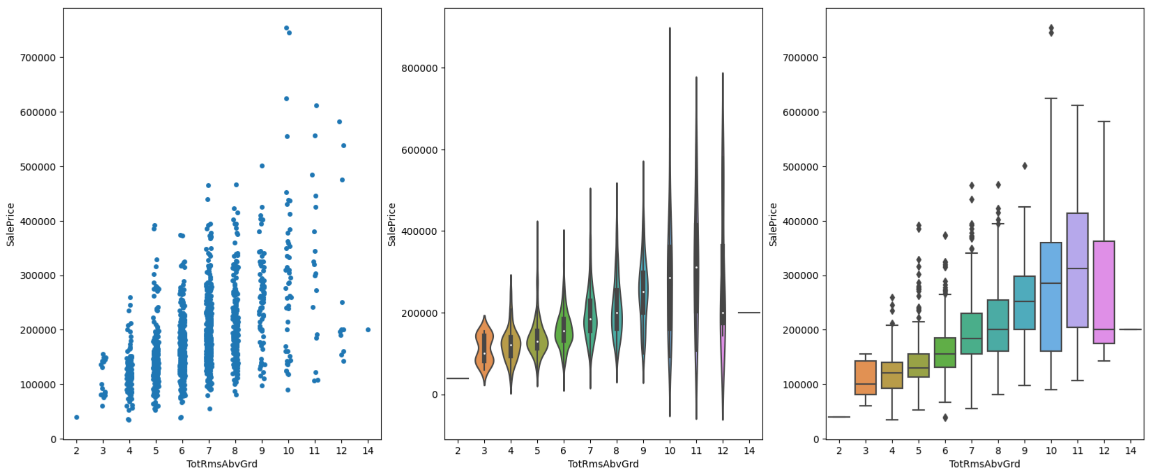
In [ ]:

```
# OverallQuall - SalePrice [Pearson = 0.8]
fig, axes = plt.subplots(1, 3, figsize=(20, 8))

# Strip plot
sns.stripplot(data=house_data, x='OverallQual', y='SalePrice', ax=axes[0])

# Violin plot
sns.violinplot(data=house_data, x='OverallQual', y='SalePrice', ax=axes[1])

# Box plot
sns.boxplot(data=house_data, x='OverallQual', y='SalePrice', ax=axes[2])

plt.show()
```



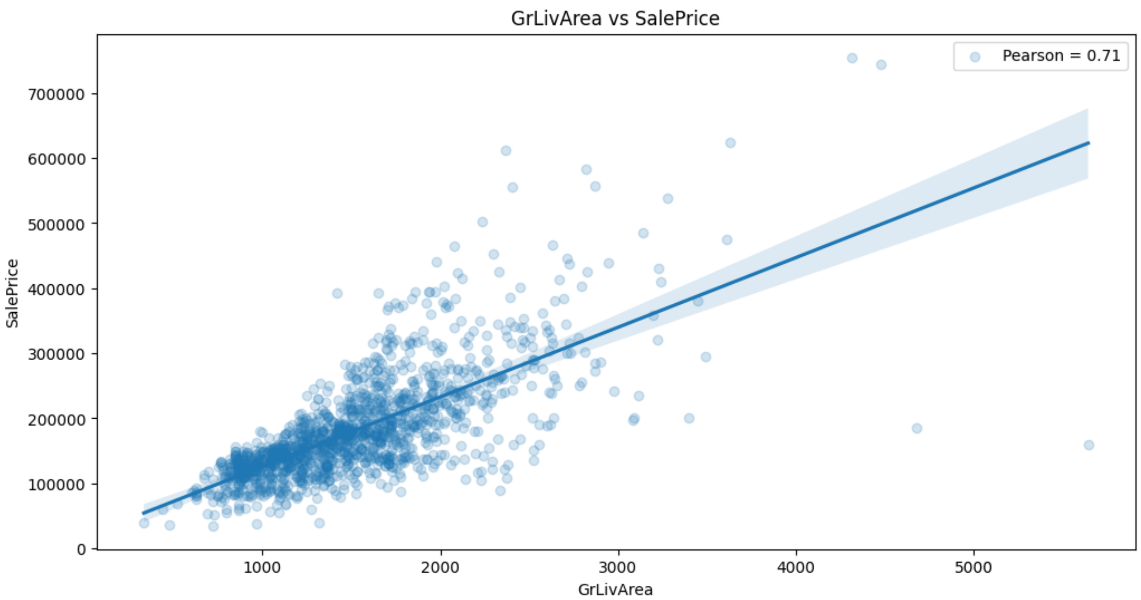
In [ ]:

```
# TotRmsAbvGrd - SalePrice [Pearson = 0.50]

fig, axs = plt.subplots(1, 3, figsize=(20, 8))
sns.stripplot(data=house_data, x='TotRmsAbvGrd', y='SalePrice', ax=axs[0])
sns.violinplot(data=house_data, x='TotRmsAbvGrd', y='SalePrice', ax=axs[1])
sns.boxplot(data=house_data, x='TotRmsAbvGrd', y='SalePrice', ax=axs[2])
plt.show()
```



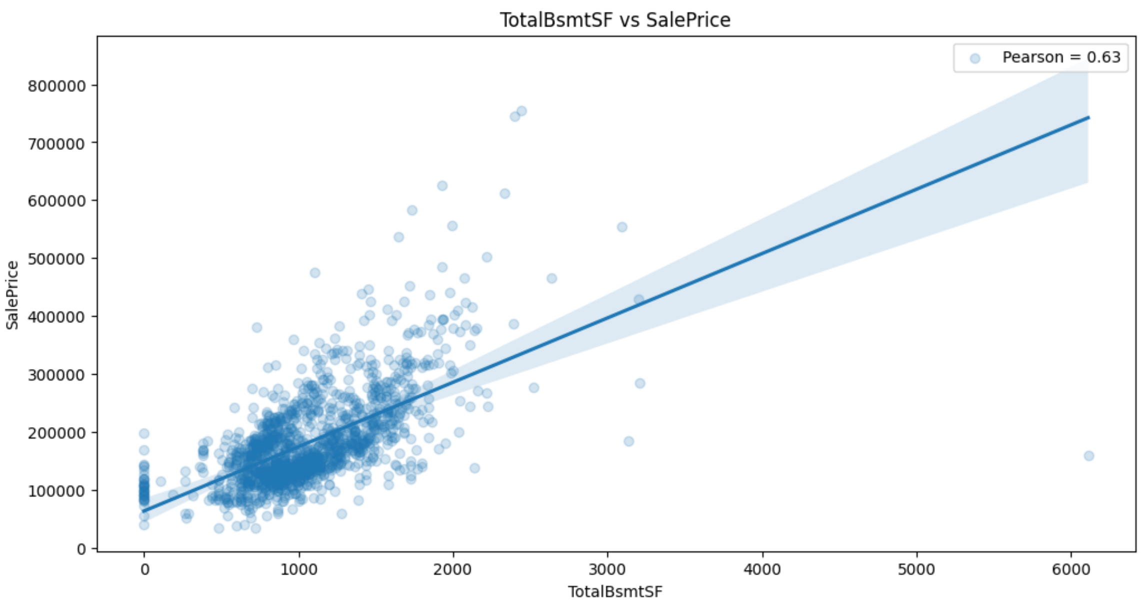
In [ ]:

```
# GrLivArea vs SalePrice [corr = 0.71]

pearson_grliv = 0.71

plt.figure(figsize=(12, 6))
sns.regplot(data=house_data, x='GrLivArea', y='SalePrice', scatter_kws={'alpha': 0.2})
plt.title('GrLivArea vs SalePrice', fontsize=12)
plt.legend(['Pearson = {:.2f}'.format(pearson_grliv)], loc='best')
plt.show()
```



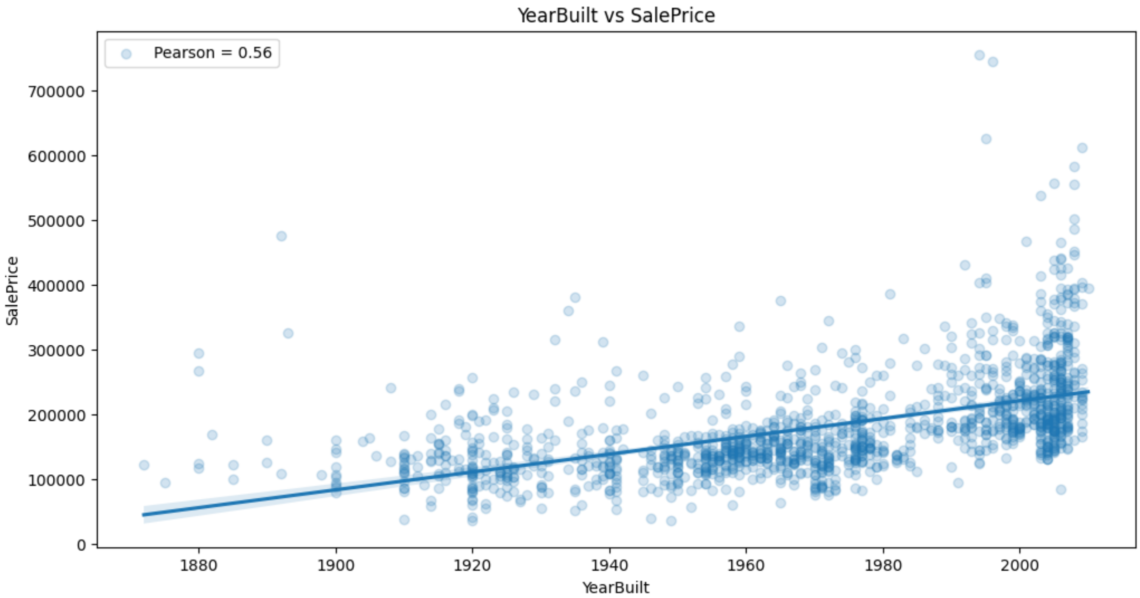
In [ ]:

```
Pearson_TBSF = 0.63

plt.figure(figsize=(12, 6))
sns.regplot(data=house_data, x='TotalBsmtSF', y='SalePrice', scatter_kws={'alpha': 0.2})
plt.title('TotalBsmtSF vs SalePrice', fontsize=12)
plt.legend(['Pearson = {:.2f}'.format(Pearson_TBSF)], loc='best')
plt.show()
```



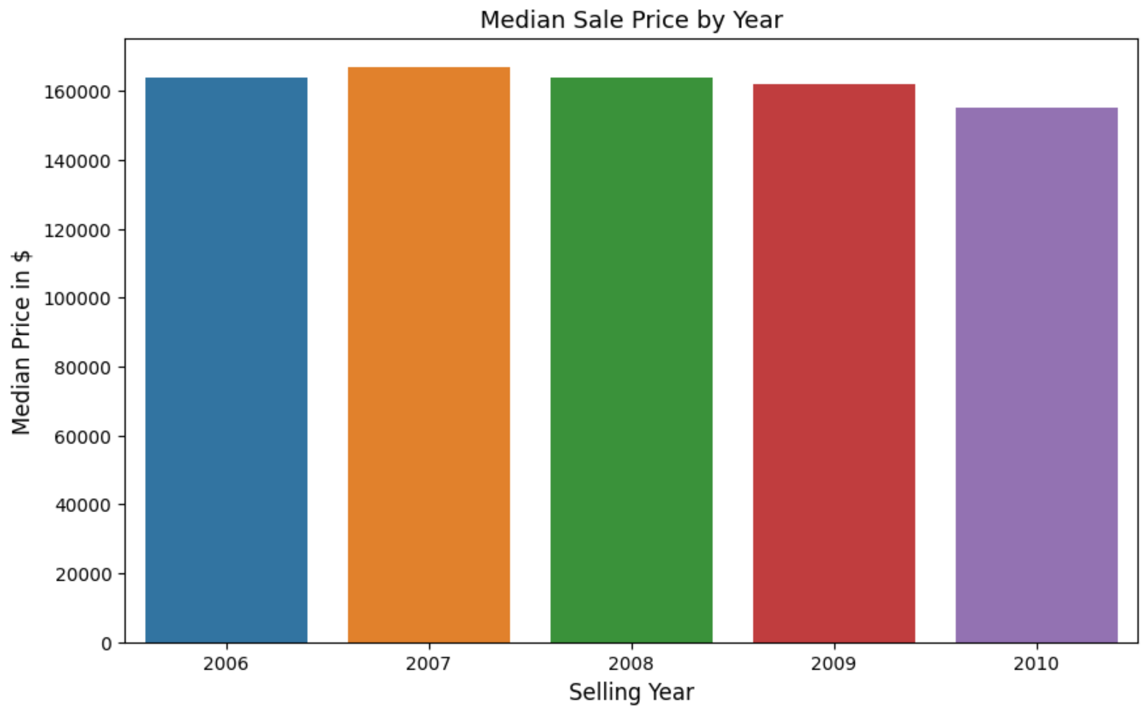
In [ ]:

```
# YearBuilt vs SalePrice

Pearson_YrBlt = 0.56
plt.figure(figsize=(12, 6))
sns.regplot(x=house_data['YearBuilt'], y=house_data['SalePrice'], scatter_kws={'alpha': 0
plt.title('YearBuilt vs SalePrice', fontsize=12)
plt.legend(['Pearson = {:.2f}'.format(Pearson_YrBlt)], loc='best')
plt.show()
```



In [ ]:

```
# Median of Sale Price by Year

plt.figure(figsize=(10, 6))
median_price_by_year = house_data.groupby('YrSold')['SalePrice'].median()
sns.barplot(x=median_price_by_year.index, y=median_price_by_year.values)
plt.title('Median Sale Price by Year', fontsize=13)
plt.xlabel('Selling Year', fontsize=12)
plt.ylabel('Median Price in $', fontsize=12)
plt.show()
```



Data Preprocsessing

Now that we have some understanding of the data, we need to prepare it for modelling. The main steps are: -

- Looking at potential NaN
- Dealing with categorical features (e.g. Dummy coding)
- Normalization

In real-world projects, test data is often not available until the end of the project. This is why it is important to make sure that the test data is similar to the training data so that it can be preprocessed in the same way. In this case, the test data is available but it contains some observations that are not present in the training dataset. This could cause problems if dummy coding is used, as this could lead to inaccurate predictions on the test set. The easiest way to solve this problem is to concatenate the training and test sets, preprocess them together, and then divide them back into separate sets. This ensures that the test data is processed in the same way as the training data, which will help to ensure that the predictions on the test set are accurate.

In [ ]:

```
# Separating Target and Features

test = pd.read_csv("/content/test.csv")

target = house_data['SalePrice']
test_id = test['Id']
test = test.drop(['Id'],axis = 1)
house_data2 = house_data.drop(['SalePrice','Id'], axis = 1)

# Concatenating train & test set

train_test = pd.concat([house_data2,test], axis=0, sort=False)
```

In [ ]:

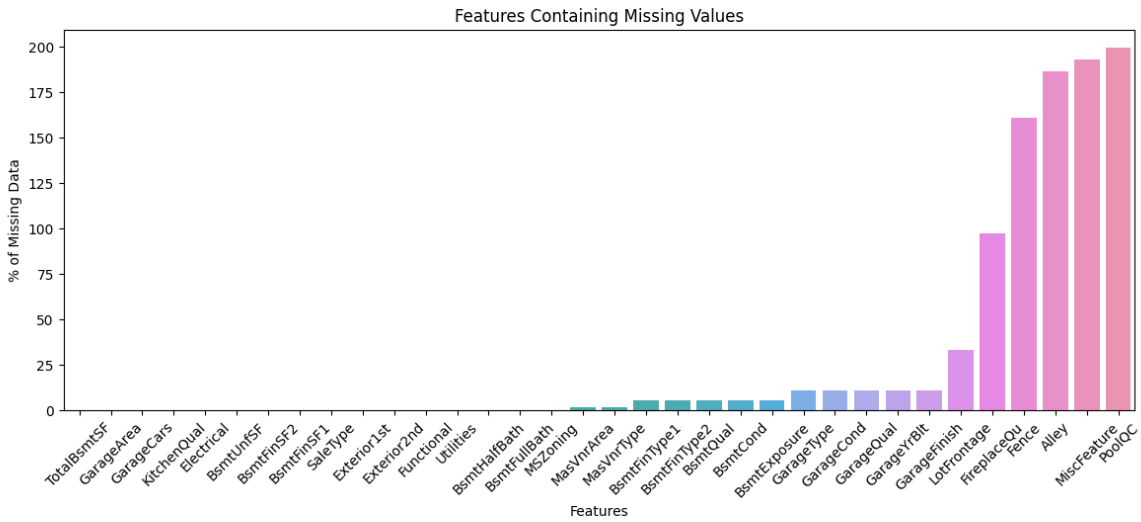
```
# Looking at NaN % within the data

nan_sum = train_test.isna().sum()
nan = pd.DataFrame({
'NaN_sum': nan_sum,
'feat': nan_sum.index,
'Perc(%)': (nan_sum / 1460) * 100
})
nan = nan[nan['NaN_sum'] > 0]
nan = nan.sort_values(by='NaN_sum')
nan['Usability'] = np.where(nan['Perc(%)'] > 20, 'Discard', 'Keep')
nan
```

Out[15]:

	NaN_sum	feat	Perc(%)	Usability
TotalBsmtSF	1	TotalBsmtSF	0.068493	Keep
GarageArea	1	GarageArea	0.068493	Keep
GarageCars	1	GarageCars	0.068493	Keep
KitchenQual	1	KitchenQual	0.068493	Keep
Electrical	1	Electrical	0.068493	Keep
BsmtUnfSF	1	BsmtUnfSF	0.068493	Keep
BsmtFinSF2	1	BsmtFinSF2	0.068493	Keep
BsmtFinSF1	1	BsmtFinSF1	0.068493	Keep
SaleType	1	SaleType	0.068493	Keep
Exterior1st	1	Exterior1st	0.068493	Keep
Exterior2nd	1	Exterior2nd	0.068493	Keep
Functional	2	Functional	0.136986	Keep
Utilities	2	Utilities	0.136986	Keep
BsmtHalfBath	2	BsmtHalfBath	0.136986	Keep
BsmtFullBath	2	BsmtFullBath	0.136986	Keep
MSZoning	4	MSZoning	0.273973	Keep
MasVnrArea	23	MasVnrArea	1.575342	Keep
MasVnrType	24	MasVnrType	1.643836	Keep
BsmtFinType1	79	BsmtFinType1	5.410959	Keep
BsmtFinType2	80	BsmtFinType2	5.479452	Keep
BsmtQual	81	BsmtQual	5.547945	Keep
BsmtCond	82	BsmtCond	5.616438	Keep
BsmtExposure	82	BsmtExposure	5.616438	Keep
GarageType	157	GarageType	10.753425	Keep
GarageCond	159	GarageCond	10.890411	Keep
GarageQual	159	GarageQual	10.890411	Keep
GarageYrBlt	159	GarageYrBlt	10.890411	Keep
GarageFinish	159	GarageFinish	10.890411	Keep
LotFrontage	486	LotFrontage	33.287671	Discard
FireplaceQu	1420	FireplaceQu	97.260274	Discard
Fence	2348	Fence	160.821918	Discard
Alley	2721	Alley	186.369863	Discard
MiscFeature	2814	MiscFeature	192.739726	Discard
PoolQC	2909	PoolQC	199.246575	Discard

In [ ]:

```
# Plotting Nan

fig, ax = plt.subplots(figsize=(14, 5))
sns.barplot(x=nan['feat'], y=nan['Perc(%)'], ax=ax)
ax.set_xticklabels(nan['feat'], rotation=45)
ax.set_title('Features Containing Missing Values')
ax.set_xlabel('Features')
ax.set_ylabel('% of Missing Data')
plt.show()
```



We cannot be certain that all of these NaNs are real missing values. The given description file shows that many of these NaNs represent the absence of something, and therefore are not actually missing values. We can impute these values (for numerical features) or substitute them with data from the file.

In [ ]:

```
# Converting non-numeric predictors stored as numbers into strings
train_test['MSSubClass'] = train_test['MSSubClass'].astype(str)
train_test['YrSold'] = train_test['YrSold'].astype(str)
train_test['MoSold'] = train_test['MoSold'].astype(str)

# Filling categorical NaN values with predetermined replacements
train_test['Functional'].fillna('Typ', inplace=True)
train_test['Electrical'].fillna('SBrkr', inplace=True)
train_test['KitchenQual'].fillna('TA', inplace=True)
train_test['Exterior1st'].fillna(train_test['Exterior1st'].mode()[0], inplace=True)
train_test['Exterior2nd'].fillna(train_test['Exterior2nd'].mode()[0], inplace=True)
train_test['SaleType'].fillna(train_test['SaleType'].mode()[0], inplace=True)
train_test['PoolQC'].fillna('None', inplace=True)
train_test['Alley'].fillna('None', inplace=True)
train_test['FireplaceQu'].fillna('None', inplace=True)
train_test['Fence'].fillna('None', inplace=True)
train_test['MiscFeature'].fillna('None', inplace=True)

train_test['GarageArea'].fillna(0, inplace=True)
train_test['GarageCars'].fillna(0, inplace=True)

train_test['GarageType'].fillna('None', inplace=True)
train_test['GarageFinish'].fillna('None', inplace=True)
train_test['GarageQual'].fillna('None', inplace=True)
train_test['GarageCond'].fillna('None', inplace=True)

train_test['BsmtQual'].fillna('None', inplace=True)
train_test['BsmtCond'].fillna('None', inplace=True)
train_test['BsmtExposure'].fillna('None', inplace=True)
train_test['BsmtFinType1'].fillna('None', inplace=True)
train_test['BsmtFinType2'].fillna('None', inplace=True)

# Checking the remaining features with NaN values
for col in train_test.columns:
    if train_test[col].isnull().sum() > 0:
        print(train_test[col][0])
```

```
0    RL
0    RH
Name: MSZoning, dtype: object
0    65.0
0    80.0
Name: LotFrontage, dtype: float64
0    AllPub
0    AllPub
Name: Utilities, dtype: object
0    BrkFace
0       None
Name: MasVnrType, dtype: object
0    196.0
0      0.0
Name: MasVnrArea, dtype: float64
0    706.0
0    468.0
Name: BsmtFinSF1, dtype: float64
0      0.0
0    144.0
Name: BsmtFinSF2, dtype: float64
0    150.0
0    270.0
Name: BsmtUnfSF, dtype: float64
0    856.0
0    882.0
Name: TotalBsmtSF, dtype: float64
0    1.0
0    0.0
Name: BsmtFullBath, dtype: float64
0    0.0
0    0.0
Name: BsmtHalfBath, dtype: float64
0    2003.0
0    1961.0
Name: GarageYrBlt, dtype: float64
```

In [ ]:

```
# Removing the useless variables
useless = ['GarageYrBlt', 'YearRemodAdd']
train_test = train_test.drop(useless, axis=1)

# Imputing with KNNRegressor (other imputers can also be used)
def impute_knn(df):
    ttn = train_test.select_dtypes(include=[np.number])
    ttc = train_test.select_dtypes(exclude=[np.number])

    cols_nan = ttn.columns[ttn.isna().any()].tolist()  # columns with NaN
    cols_no_nan = ttn.columns.difference(cols_nan).values  # columns without NaN

    for col in cols_nan:
        imp_test = ttn[ttn[col].isna()]  # indices with missing data as the test set
        imp_train = ttn.dropna()  # indices without missing data
        model = KNeighborsRegressor(n_neighbors=5)  # KNR Unsupervised Approach
        knr = model.fit(imp_train[cols_no_nan], imp_train[col])
        ttn.loc[ttn[col].isna(), col] = knr.predict(imp_test[cols_no_nan])

    return pd.concat([ttn, ttc], axis=1)

train_test = impute_knn(train_test)

objects = []
for i in train_test.columns:
    if train_test[i].dtype == object:
        objects.append(i)
train_test.update(train_test[objects].fillna('None'))

# Checking NaN presence
for col in train_test:
    if train_test[col].isna().sum() > 0:
        print(train_test[col].iloc[0])
```

Feature Engineering

Let's combine existing features to create new ones. These could improve the model's performance.

In [ ]:

```
train_test["SqFtPerRoom"] = train_test["GrLivArea"] / (train_test["TotRmsAbvGrd"] +
                                                       train_test["FullBath"] +
                                                       train_test["HalfBath"] +
                                                       train_test["KitchenAbvGr"])

train_test['Total_Home_Quality'] = train_test['OverallQual'] + train_test['OverallCond']

train_test['Total_Bathrooms'] = (train_test['FullBath'] + (0.5 * train_test['HalfBath'])
                               train_test['BsmtFullBath'] + (0.5 * train_test['BsmtHalfBa

train_test["HighQualSF"] = train_test["1stFlrSF"] + train_test["2ndFlrSF"]

# Converting non-numeric predictors stored as numbers into strings

train_test['MSSubClass'] = train_test['MSSubClass'].astype(str)
train_test['YrSold'] = train_test['YrSold'].astype(str)
train_test['MoSold'] = train_test['MoSold'].astype(str)

# Creating dummy variables from categorical features

train_test_dummy = pd.get_dummies(train_test)

# Fetching all numeric features

numeric_features = train_test_dummy.select_dtypes(include=[np.number]).columns
skewed_features = train_test_dummy[numeric_features].apply(lambda x: skew(x)).sort_values
high_skew = skewed_features[skewed_features > 0.5]
skew_index = high_skew.index

# Normalizing skewed features using log transformation

for i in skew_index:
    train_test_dummy[i] = np.log1p(train_test_dummy[i])
```

Let's try to transform our target distribution into a normal distribution. We can do this by using a log transformation. A qq-plot can be used to see the effect of the transformation.

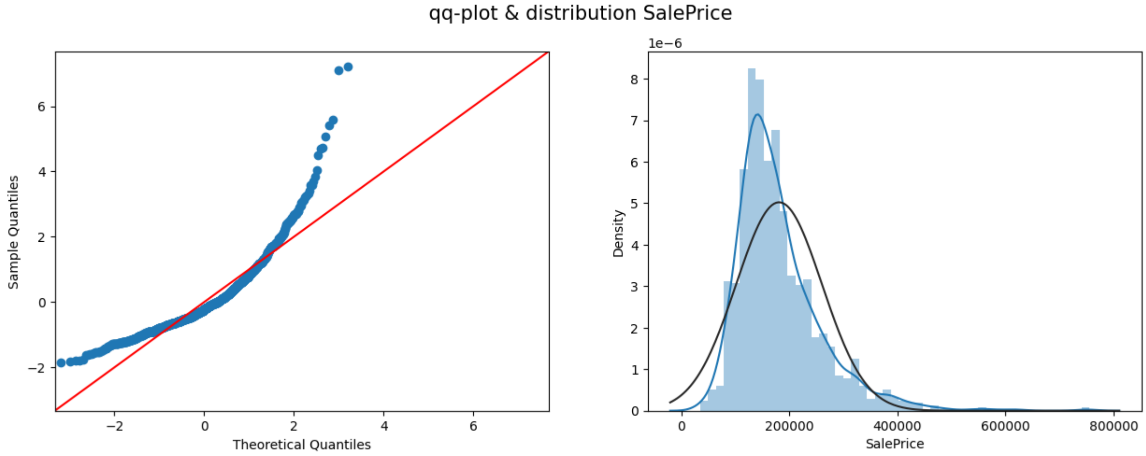
A qq-plot is a graphical method for comparing two probability distributions. It plots the quantiles of one distribution against the quantiles of another distribution. In this case, we will plot the quantiles of the original target distribution against the quantiles of the log-transformed target distribution.

If the transformation has been successful, the qq-plot should be a straight line. This indicates that the two distributions are similar.

If the qq-plot is not a straight line, this indicates that the transformation has not been successful. In this case, we may need to try a different transformation.

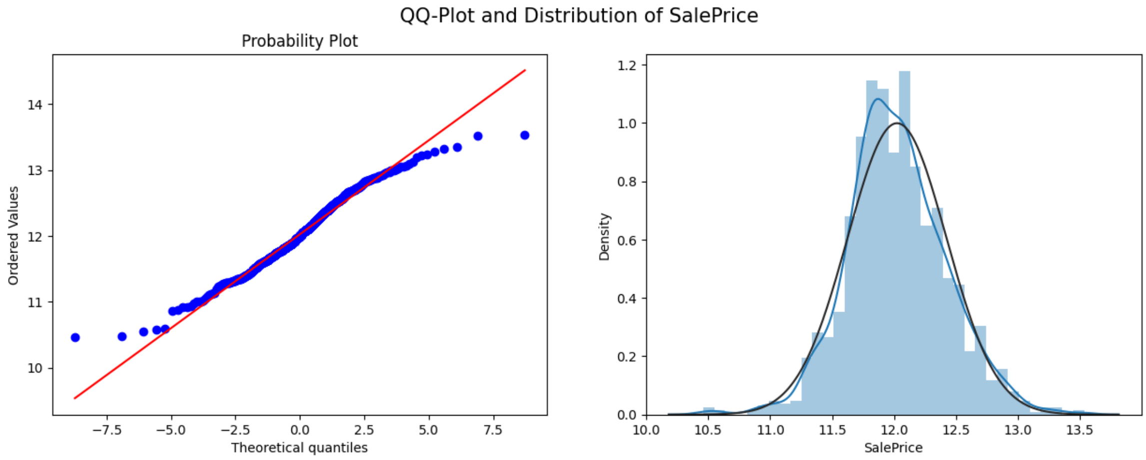
In [ ]:

```
# SalePrice before transformation

fig, ax = plt.subplots(1,2, figsize= (15,5))
fig.suptitle(" qq-plot & distribution SalePrice ", fontsize= 15)

sm.qqplot(target, stats.t, distargs=(4,),fit=True, line="45", ax = ax[0])

sns.distplot(target, kde = True, hist=True, fit = norm, ax = ax[1])
plt.show()
```



In [ ]:

```
# SalePrice after transformation

target_log = np.log1p(target)

fig, ax = plt.subplots(1, 2, figsize=(15, 5))
fig.suptitle("QQ-Plot and Distribution of SalePrice", fontsize=15)

stats.probplot(target_log, dist=stats.t, sparams=(4,), plot=ax[0])
sns.distplot(target_log, kde=True, hist=True, fit=stats.norm, ax=ax[1])
plt.show()
```



Modelling

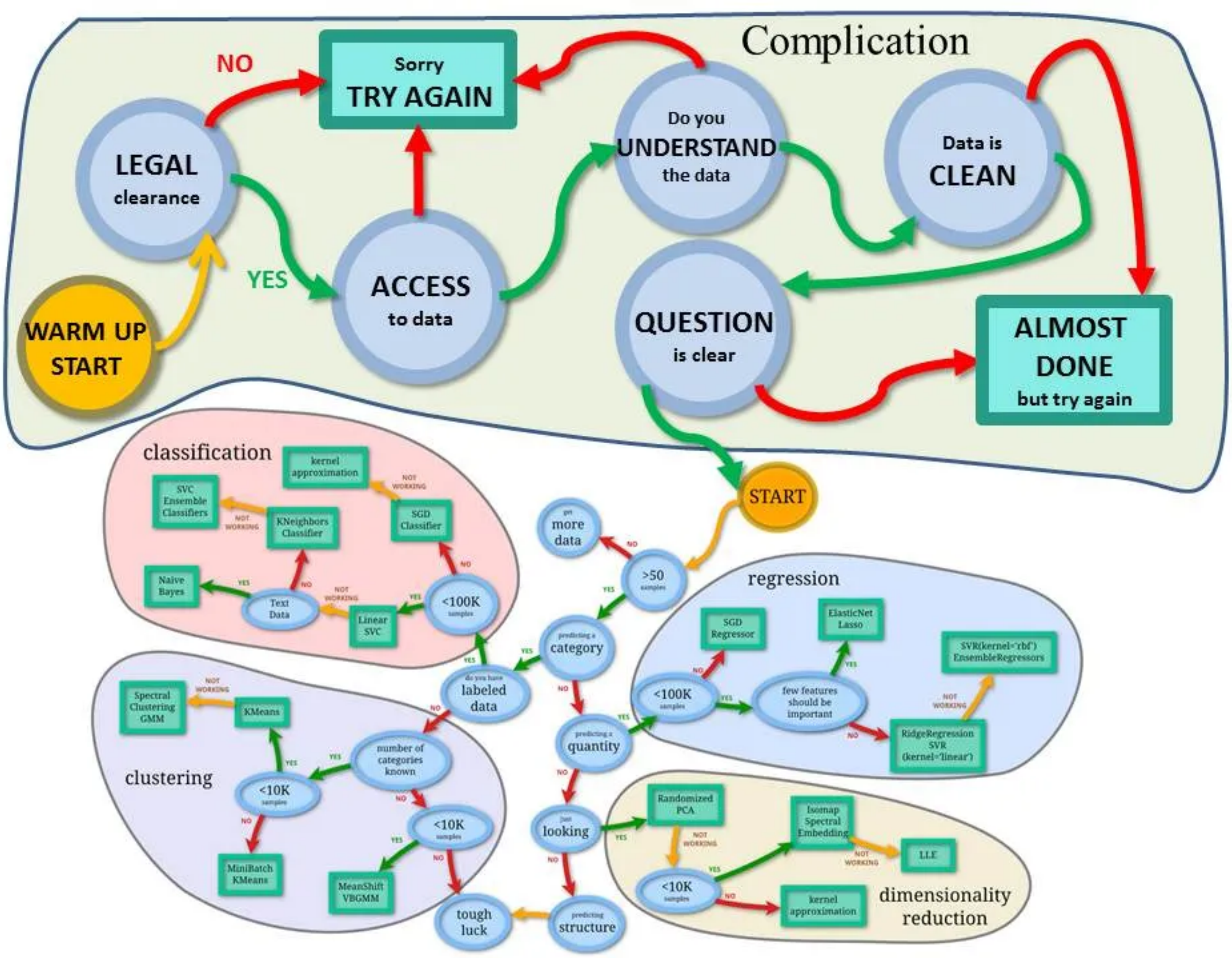
As mentioned in the problem definition, we are trying to predict the sales price of houses. Our goal is to create the best model that predicts the most accurate results.

Which estimator should we use?

We can use the sklearn library to help us choose the right estimator for our model. The sklearn library provides a number of different estimators, each with its own strengths and weaknesses. We can use the graphs provided by the sklearn library to compare the performance of different estimators on our data. This will help us to choose the estimator that is most likely to produce the most accurate results.

Choosing the right estimator for a machine learning problem can be challenging. Different estimators are better suited for different types of data and different problems. The flowchart below provides a rough guide on how to approach problems with regard to which estimators to try on your data.

([Refrence link (https://medium.com/@chris_bour/an-extended-version-of-the-scikit-learn-cheat-sheet-5f46efc6cbb)](https://medium.com/@chris_bour/an-extended-version-of-the-scikit-learn-cheat-sheet-5f46efc6cbb))



In [ ]:

```
pip install shap
```

```
Looking in indexes: https://pypi.org/simple, (https://pypi.org/simple,) ht
tps://us-python.pkg.dev/colab-wheels/public/simple/ (https://us-python.pk
g.dev/colab-wheels/public/simple/)
Collecting shap
  Downloading shap-0.41.0-cp310-cp310-manylinux_2_12_x86_64.manylinux2010_
x86_64.whl (572 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 572.6/572.6 kB 15.5 MB/s eta
0:00:00
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-pac
kages (from shap) (1.22.4)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-pac
kages (from shap) (1.10.1)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/d
ist-packages (from shap) (1.2.2)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-pa
ckages (from shap) (1.5.3)
Requirement already satisfied: tqdm>4.25.0 in /usr/local/lib/python3.10/di
st-packages (from shap) (4.65.0)
Requirement already satisfied: packaging>20.9 in /usr/local/lib/python3.1
0/dist-packages (from shap) (23.1)
Collecting slicer==0.0.7 (from shap)
  Downloading slicer-0.0.7-py3-none-any.whl (14 kB)
Requirement already satisfied: numba in /usr/local/lib/python3.10/dist-pac
kages (from shap) (0.56.4)
Requirement already satisfied: cloudpickle in /usr/local/lib/python3.10/di
st-packages (from shap) (2.2.1)
Requirement already satisfied: llvmlite<0.40,>=0.39.0dev0 in /usr/local/li
b/python3.10/dist-packages (from numba->shap) (0.39.1)
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dis
t-packages (from numba->shap) (67.7.2)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/py
thon3.10/dist-packages (from pandas->shap) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/d
ist-packages (from pandas->shap) (2022.7.1)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/
dist-packages (from scikit-learn->shap) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/pyth
on3.10/dist-packages (from scikit-learn->shap) (3.1.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.8.1->pandas->shap) (1.16.0)
Installing collected packages: slicer, shap
Successfully installed shap-0.41.0 slicer-0.0.7
```

In [ ]:

```
pip install catboost
```

```
Looking in indexes: https://pypi.org/simple, (https://pypi.org/simple,) ht
tps://us-python.pkg.dev/colab-wheels/public/simple/ (https://us-python.pk
g.dev/colab-wheels/public/simple/)
Collecting catboost
  Downloading catboost-1.2-cp310-cp310-manylinux2014_x86_64.whl (98.6 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 98.6/98.6 MB 7.7 MB/s eta 0:
00:00
Requirement already satisfied: graphviz in /usr/local/lib/python3.10/dist-
packages (from catboost) (0.20.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dis
t-packages (from catboost) (3.7.1)
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.10/
dist-packages (from catboost) (1.22.4)
Requirement already satisfied: pandas>=0.24 in /usr/local/lib/python3.10/d
ist-packages (from catboost) (1.5.3)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-pac
kages (from catboost) (1.10.1)
Requirement already satisfied: plotly in /usr/local/lib/python3.10/dist-pa
ckages (from catboost) (5.13.1)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packa
ges (from catboost) (1.16.0)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/py
thon3.10/dist-packages (from pandas>=0.24->catboost) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/d
ist-packages (from pandas>=0.24->catboost) (2022.7.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.
10/dist-packages (from matplotlib->catboost) (1.0.7)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/d
ist-packages (from matplotlib->catboost) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python
3.10/dist-packages (from matplotlib->catboost) (4.39.3)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python
3.10/dist-packages (from matplotlib->catboost) (1.4.4)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.1
0/dist-packages (from matplotlib->catboost) (23.1)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/
dist-packages (from matplotlib->catboost) (8.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.
10/dist-packages (from matplotlib->catboost) (3.0.9)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.1
0/dist-packages (from plotly->catboost) (8.2.2)
Installing collected packages: catboost
Successfully installed catboost-1.2
```

In [ ]:

```
# Importing required libraries
import shap
import xgboost as xgb
from catboost import Pool
from catboost import CatBoostRegressor
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression, BayesianRidge
from sklearn.model_selection import RepeatedKFold
from sklearn.model_selection import KFold, cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingRegressor, RandomForestRegressor
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.metrics import mean_squared_error, mean_absolute_error, mean_squared_log_err
```

To train a model, we first need to split the data into a training set and a test set.

In [ ]:

```
# Train-Test separation
train = train_test_dummy[0:1460]
test = train_test_dummy[1460:]
test['Id'] = test_id

# As for the evaluation function, we need the root mean squared error(RMSE).
# Creation of the RMSE metric:
def rmse(y, y_pred):
    return np.sqrt(mean_squared_error(y, y_pred))

def cv_rmse(model):
    rmse = np.sqrt(-cross_val_score(model, train, target_log, scoring="neg_mean_squared_e
    return rmse
```

In [ ]:

```
# 10 Fold Cross validation
kf = KFold(n_splits=10, random_state=42, shuffle=True)

cv_scores = []
cv_std = []

baseline_models = ['Linear_Reg.', 'Dec_Tree_Reg.','Random_Forest_Reg.', 'Grad_Boost_Reg.'

# Linear Regression
lreg = LinearRegression()
score_lreg = cv_rmse(lreg)
cv_scores.append(score_lreg.mean())
cv_std.append(score_lreg.std())

# Decision Tree Regressor
dtr = DecisionTreeRegressor()
score_dtr = cv_rmse(dtr)
cv_scores.append(score_dtr.mean())
cv_std.append(score_dtr.std())

# Random Forest Regressor
rfr = RandomForestRegressor()
score_rfr = cv_rmse(rfr)
cv_scores.append(score_rfr.mean())
cv_std.append(score_rfr.std())

# Gradient Boost Regressor
gbr = GradientBoostingRegressor()
score_gbr = cv_rmse(gbr)
cv_scores.append(score_gbr.mean())
cv_std.append(score_gbr.std())

# Cat Boost Regressor
catb = CatBoostRegressor()
score_catb = cv_rmse(catb)
cv_scores.append(score_catb.mean())
cv_std.append(score_catb.std())

final_cv_score = pd.DataFrame({'Regressors': baseline_models, 'RMSE_mean': cv_scores, 'RM
```

```
Streaming output truncated to the last 5000 lines.
4:	learn: 0.3514870	total: 36.3ms	remaining: 7.22s
5:	learn: 0.3427397	total: 42.6ms	remaining: 7.06s
6:	learn: 0.3347144	total: 49ms	remaining: 6.96s
7:	learn: 0.3270558	total: 55.7ms	remaining: 6.91s
8:	learn: 0.3189478	total: 62.3ms	remaining: 6.86s
9:	learn: 0.3111859	total: 69ms	remaining: 6.83s
10:	learn: 0.3036006	total: 75.7ms	remaining: 6.81s
11:	learn: 0.2971353	total: 82.5ms	remaining: 6.79s
12:	learn: 0.2905230	total: 88.8ms	remaining: 6.74s
13:	learn: 0.2838031	total: 95.3ms	remaining: 6.71s
14:	learn: 0.2769437	total: 102ms	remaining: 6.7s
15:	learn: 0.2705239	total: 109ms	remaining: 6.69s
16:	learn: 0.2643817	total: 116ms	remaining: 6.69s
17:	learn: 0.2583183	total: 122ms	remaining: 6.68s
18:	learn: 0.2525998	total: 129ms	remaining: 6.66s
19:	learn: 0.2478589	total: 136ms	remaining: 6.66s
20:	learn: 0.2424847	total: 142ms	remaining: 6.64s
21:	learn: 0.2370303	total: 149ms	remaining: 6.63s
```

In [ ]:

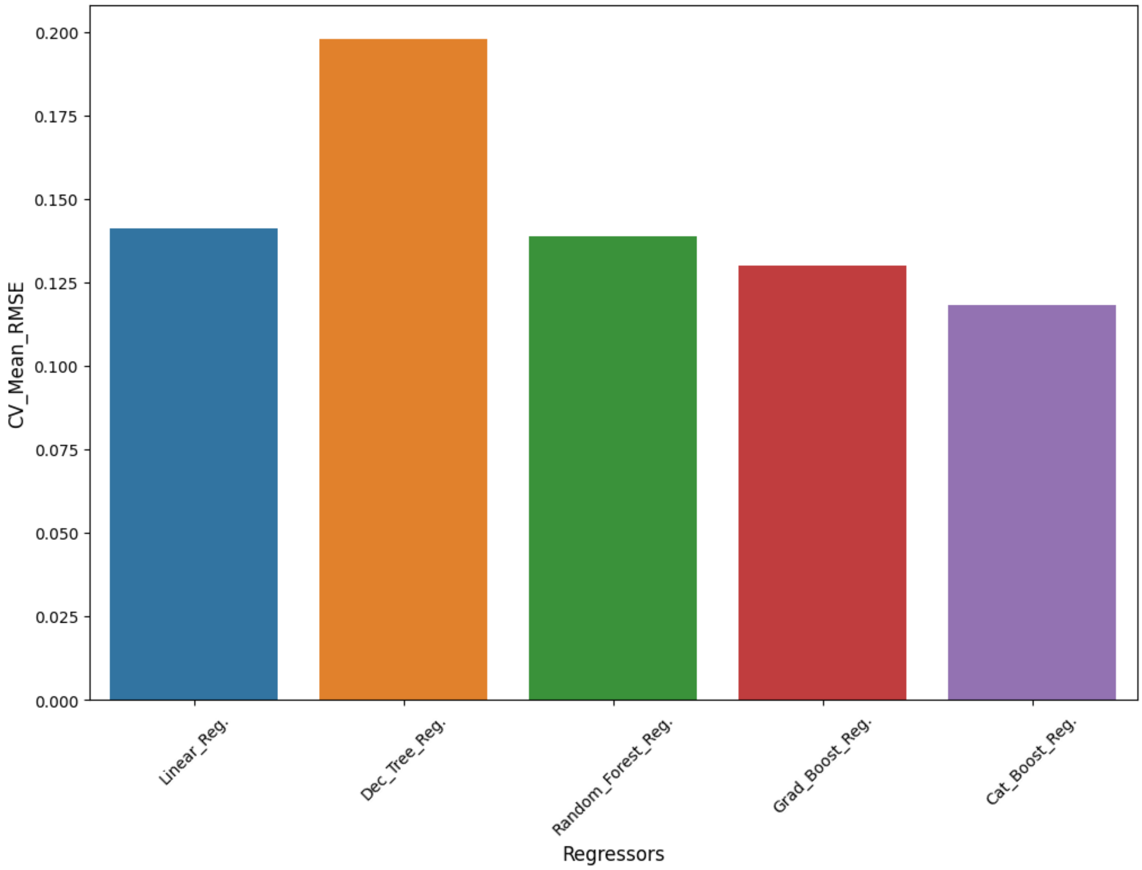
```
final_cv_score
```

Out[27]:

	Regressors	RMSE_mean	RMSE_std
0	Linear_Reg.	0.141219	0.030362
1	Dec_Tree_Reg.	0.198182	0.024794
2	Random_Forest_Reg.	0.139066	0.021911
3	Grad_Boost_Reg.	0.130242	0.020061
4	Cat_Boost_Reg.	0.118386	0.020130

In [ ]:

```
fig, ax = plt.subplots(figsize=(12, 8))
sns.barplot(data=final_cv_score, x='Regressors', y='RMSE_mean', ax=ax)
ax.set_xlabel('Regressors', fontsize=12)
ax.set_ylabel('CV_Mean_RMSE', fontsize=12)
ax.set_xticklabels(ax.get_xticklabels(), rotation=45)

plt.show()
```



We have now developed a model that seems to be working well 😜, as it has a good score and a lower root mean squared error (RMSE). Let's test our model on a test dataset.

Why CatBoostRegressor Model?

The CatBoostRegressor model is chosen for several reasons. First, it is specifically designed to handle categorical variables without the need for manual preprocessing. Second, it is robust to overfitting due to its use of Ordered Boosting and random permutations. Third, it is known for its high performance and competitive results in machine learning competitions. Fourth, it provides automatic parameter tuning, which reduces the need for manual hyperparameter optimization. Fifth, it offers built-in visualization tools that aid in understanding the model and making informed decisions.

Overall, CatBoostRegressor is a popular choice for regression tasks, especially when dealing with categorical features. It simplifies the preprocessing steps and provides good performance out of the box.

In [ ]:

```
# Train-Test split the data
X_train, X_val, y_train, y_val = train_test_split(train, target_log, test_size=0.1, randc

# Create a CatBoostRegressor model
cat_model = CatBoostRegressor()
cat_model.fit(X_train, y_train,
              eval_set=(X_val, y_val),
              plot=True,
              verbose=0)
```

```
MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))
```

Out[29]:

```
<catboost.core.CatBoostRegressor at 0x7fa8ffbb9900>
```

In [ ]:

```
cat_pred = cat_model.predict(X_val)
cat_score = rmse(y_val, cat_pred)
cat_score
```

Out[30]:

```
0.1119668110855348
```

Now, let's examine the top 10 most important variables for our model. This could provide us with additional insight into how the algorithm works and which data it uses most to make its final prediction.

In [ ]:

```
# Features' importance of our model

feat_imp = cat_model.get_feature_importance(prettified=True)
feat_imp
```

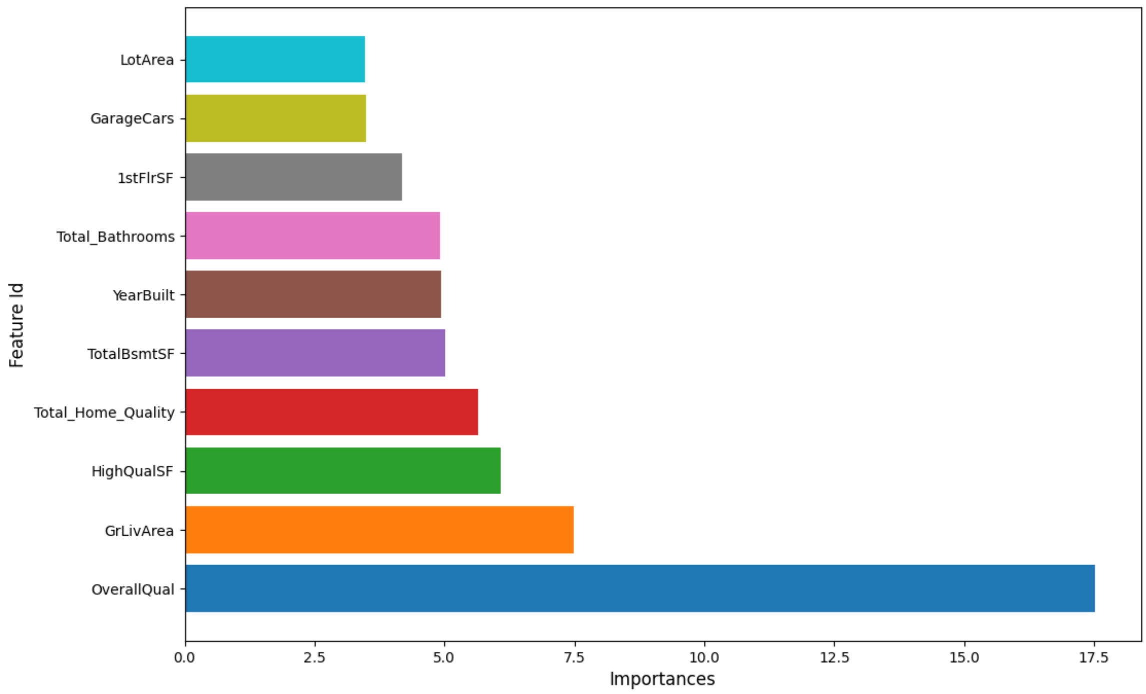
Out[31]:

	Feature Id	Importances
0	OverallQual	17.519965
1	GrLivArea	7.478775
2	HighQualSF	6.089177
3	Total_Home_Quality	5.647646
4	TotalBsmtSF	5.003976
...	...	...
331	MiscFeature_Othr	0.000000
332	MiscFeature_TenC	0.000000
333	SaleType_Con	0.000000
334	SaleType_ConLw	0.000000
335	SaleCondition_Alloca	0.000000

336 rows × 2 columns

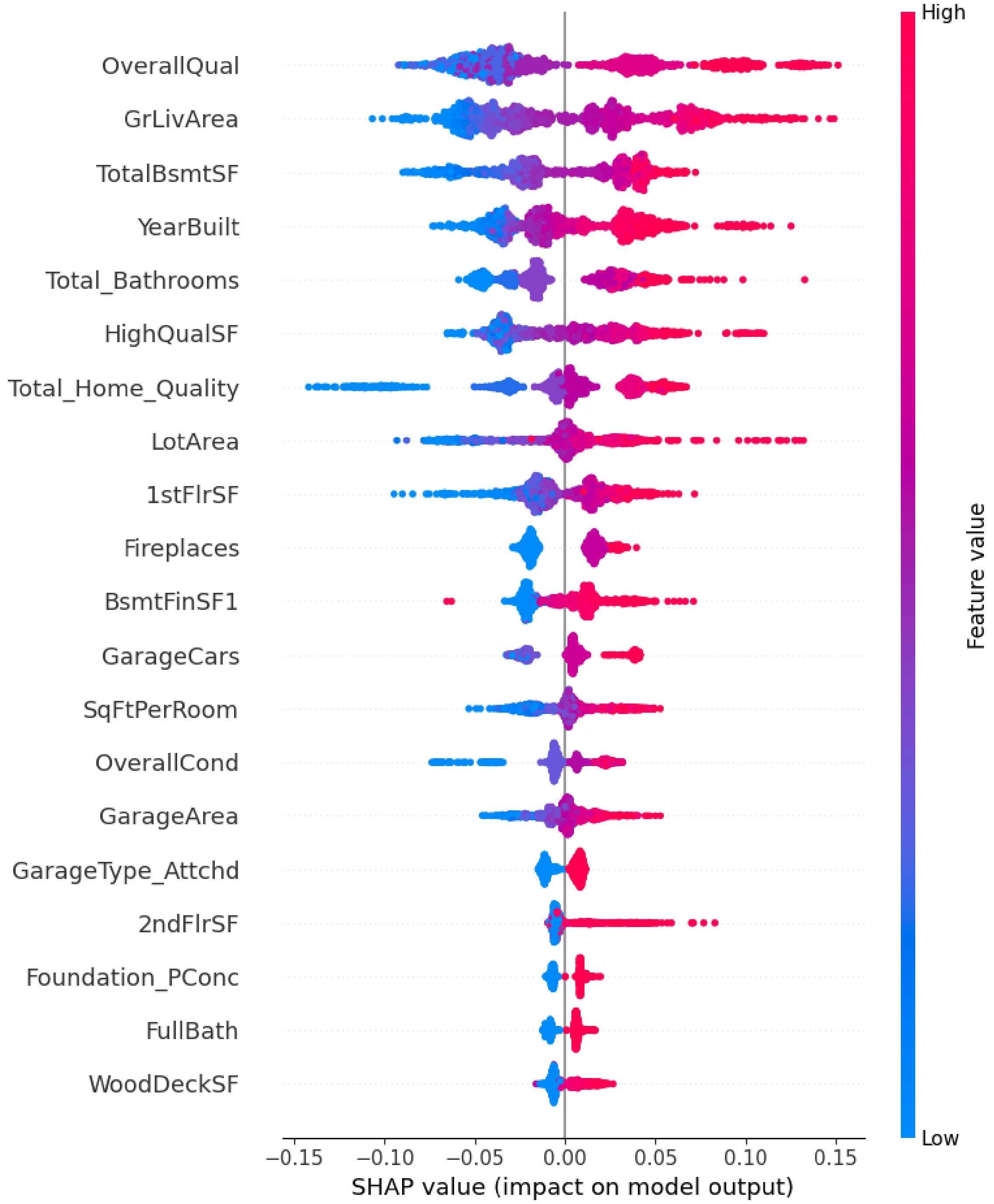
In [ ]:

```
# Plotting top 10 features' importance

# Generate a color map
cmap = plt.get_cmap('tab10')

# Plotting top 10 features' importance
plt.figure(figsize=(12, 8))

# Generate an array of indices for the bars
indices = np.arange(len(feat_imp['Feature Id'][:10]))

# Assign different colors to each bar
colors = [cmap(i) for i in indices]

# Create the bar plot with different colors
plt.barh(indices, feat_imp['Importances'][:10], color=colors)

plt.xlabel('Importances', fontsize=12)
plt.ylabel('Feature Id', fontsize=12)
plt.yticks(indices, feat_imp['Feature Id'][:10])
plt.show()
```



In [ ]:

```
# Feature importance Interactive Plot

train_pool = Pool(X_train)
val_pool = Pool(X_val)

explainer = shap.TreeExplainer(cat_model) # insert your model
shap_values = explainer.shap_values(train_pool) # insert your train Pool object

shap.summary_plot(shap_values, X_train)
```



In [ ]:

```
# Features' Interactions

train_data = Pool(X_train)

interaction = cat_model.get_feature_importance(train_data, type="Interaction")
column_names = X_train.columns.values
interaction_df = pd.DataFrame(interaction, columns=["feature1", "feature2", "importance"]
interaction_df['feature1'] = interaction_df['feature1'].apply(lambda l: column_names[int(
interaction_df['feature2'] = interaction_df['feature2'].apply(lambda l: column_names[int(
interaction_df.head(20)
```

Out[37]:

	feature1	feature2	importance
0	OverallQual	SqFtPerRoom	0.501457
1	GrLivArea	Total_Home_Quality	0.412167
2	OverallQual	BsmtFinSF1	0.408328
3	LotArea	SqFtPerRoom	0.375319
4	OverallQual	GrLivArea	0.371828
5	OverallQual	2ndFlrSF	0.369148
6	YearBuilt	GrLivArea	0.360715
7	Alley_Pave	Exterior1st_BrkFace	0.352348
8	LotArea	OverallQual	0.351644
9	OverallQual	1stFlrSF	0.338377
10	LotArea	YearBuilt	0.334573
11	LotArea	GrLivArea	0.323251
12	OverallQual	Total_Bathrooms	0.320863
13	OverallQual	YearBuilt	0.304562
14	LotArea	1stFlrSF	0.298832
15	LotArea	GarageArea	0.283342
16	LotArea	BsmtFinSF1	0.283037
17	OverallQual	HighQualSF	0.267660
18	LotArea	Neighborhood_BrkSide	0.266989
19	OverallQual	Total_Home_Quality	0.265492

Hyperparameter Optimization

Randomness is often used in machine learning and statistical analysis, such as when shuffling data, initializing weights in neural networks, or splitting data into train and test sets.

To tune the hyperparameters, we will use Random Grid Search. This will allow us to explore different values for the hyperparameters and find the best combination that improves the model score and gives the best results. The default parameters used by CatBoostRegressor are a good starting point for tuning the model. However, it is often possible to improve the performance of the model by optimizing the hyperparameters.

In [ ]:

```
# Catboost default paramters
cat_model.get_all_params()
```

Out[35]:

```
{'nan_mode': 'Min',
 'eval_metric': 'RMSE',
 'iterations': 1000,
 'sampling_frequency': 'PerTree',
 'leaf_estimation_method': 'Newton',
 'grow_policy': 'SymmetricTree',
 'penalties_coefficient': 1,
 'boosting_type': 'Plain',
 'model_shrink_mode': 'Constant',
 'feature_border_type': 'GreedyLogSum',
 'bayesian_matrix_reg': 0.10000000149011612,
 'eval_fraction': 0,
 'force_unit_auto_pair_weights': False,
 'l2_leaf_reg': 3,
 'random_strength': 1,
 'rsm': 1,
 'boost_from_average': True,
 'model_size_reg': 0.5,
 'pool_metainfo_options': {'tags': {}},
 'subsample': 0.800000011920929,
 'use_best_model': True,
 'random_seed': 0,
 'depth': 6,
 'posterior_sampling': False,
 'border_count': 254,
 'classes_count': 0,
 'auto_class_weights': 'None',
 'sparse_features_conflict_fraction': 0,
 'leaf_estimation_backtracking': 'AnyImprovement',
 'best_model_min_trees': 1,
 'model_shrink_rate': 0,
 'min_data_in_leaf': 1,
 'loss_function': 'RMSE',
 'learning_rate': 0.053151000291109085,
 'score_function': 'Cosine',
 'task_type': 'CPU',
 'leaf_estimation_iterations': 1,
 'bootstrap_type': 'MVS',
 'max_leaves': 64}
```

In [ ]:

```
# Preforming a Random Grid Search to find the best combination of parameters

grid = {'iterations': [1000,6000],
        'learning_rate': [0.05, 0.005, 0.0005],
        'depth': [4, 6, 10],
        'l2_leaf_reg': [1, 3, 5, 9]}

final_model = CatBoostRegressor()
randomized_search_result = final_model.randomized_search(grid,
                                                         X = X_train,
                                                         y= y_train,
                                                         verbose = False,
                                                         plot=True)
```

```
MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))

Streaming output truncated to the last 5000 lines.
1004:	learn: 0.1695503	test: 0.1962865 best: 0.1962865 (1004)
total: 3.34s	remaining: 16.6s
1005:	learn: 0.1692497	test: 0.1960053 best: 0.1960053 (1005)
total: 3.35s	remaining: 16.6s
1006:	learn: 0.1689414	test: 0.1957328 best: 0.1957328 (1006)
total: 3.35s	remaining: 16.6s
1007:	learn: 0.1686066	test: 0.1954286 best: 0.1954286 (1007)
total: 3.36s	remaining: 16.6s
1008:	learn: 0.1682819	test: 0.1951488 best: 0.1951488 (1008)
total: 3.36s	remaining: 16.6s
1009:	learn: 0.1679954	test: 0.1948984 best: 0.1948984 (1009)
total: 3.36s	remaining: 16.6s
1010:	learn: 0.1676973	test: 0.1946206 best: 0.1946206 (1010)
total: 3.37s	remaining: 16.6s
1011:	learn: 0.1674342	test: 0.1944184 best: 0.1944184 (1011)
total: 3.37s	remaining: 16.6s
1012:	learn: 0.1671272	test: 0.1941801 best: 0.1941801 (1012)
```

In [39]:

```
# Final Cat-Boost Regressor

params = {'iterations': 6000,
          'learning_rate': 0.005,
          'depth': 4,
          'l2_leaf_reg': 1,
          'eval_metric':'RMSE',
          'early_stopping_rounds': 200,
          'verbose': 200,
          'random_seed': 42}

cat_f = CatBoostRegressor(**params)
cat_model_f = cat_f.fit(X_train,y_train,
                        eval_set = (X_val,y_val),
                        plot=True,
                        verbose = False)

catf_pred = cat_model_f.predict(X_val)
catf_score = rmse(y_val, catf_pred)
```

```
MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))
```

In [40]:

```
#RMSE is a measure of the model's performance, and lower values indicate better performan
catf_score
```

Out[40]:

```
0.11021826071817108
```

In [41]:

```
params = {'n_estimators': 100,
          'max_depth': 4,
          'random_state': 42}

rf = RandomForestRegressor(**params)
rf.fit(X_train, y_train)

rf_pred = rf.predict(X_val)
rf_score = mean_squared_error(y_val, rf_pred, squared=False)
```

Submission(Let's transform the outcome into the desired outcome.)

In [42]:

```
# Test CSV Submission

test_pred = cat_f.predict(test)
submission = pd.DataFrame(test_id, columns = ['Id'])
test_pred = np.expm1(test_pred)
submission['SalePrice'] = test_pred
submission.head()
```

Out[42]:

	Id	SalePrice
0	1461	125610.349414
1	1462	156347.286501
2	1463	183466.622047
3	1464	190687.284287
4	1465	184268.315196

In [43]:

```
# Saving the results in a csv file
submission.to_csv("result.csv", index = False, header = True)
```

Conclusion

In conclusion, there are many parameters that can be changed to improve the accuracy of a model. In this project, we adjusted the parameters of a Cat-Boost Regressor model to achieve a better predicted result.

References

- https://github.com/mrdbourke/zero-to-mastery-ml/blob/master/section-1-getting-ready-for-machine-learning/a-6-step-framework-for-approaching-machine-learning-projects.md (https://github.com/mrdbourke/zero-to-mastery-ml/blob/master/section-1-getting-ready-for-machine-learning/a-6-step-framework-for-approaching-machine-learning-projects.md)
- House Prices Competition using sklearn linear Reg (https://www.kaggle.com/code/onepabs/house-prices-competition-using-sklearn-linear-reg) by JUAN PABLO CONTRERAS
- LightGBM + XGBoost + Catboost (https://www.kaggle.com/code/samratp/lightgbm-xgboost-catboost) by SAMRAT PANDIRI