House Prices Analysis and Prediction

May 1, 2022

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.api import OLS

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error

import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import DataLoader, Dataset
from torchvision import transforms

%matplotlib inline
```

[2]:
```
import warnings
warnings.filterwarnings("ignore")
```

[3]:
```
BASE_COLOR = sns.color_palette()[0]
TEST_SIZE = 0.2
RANDOM_STATE = 42
BATCH_SIZE = 32
LR = 0.01
```

1 Load train and test Datasets

[4]:
```
train_df = pd.read_csv("./data/train.csv")
test_df = pd.read_csv("./data/test.csv")
```

[5]:
```
train_df.head()
```

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

  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5
2         Lvl    AllPub  …        0    NaN   NaN         NaN       0      9
3         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
4         Lvl    AllPub  …        0    NaN   NaN         NaN       0     12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]
```

2 Wrangle train Dataset

2.1 Dropping NaN values

droping NaN value with as follows: - if column has NaN values more than 200 entry will drop that column - if column has NaN values less than 200: - if column is numeric will fillna with the `mean` - if column is categorical will dropit

[6]:
```
nan_cols = train_df.isna().sum()
nan_cols = nan_cols[nan_cols > 0]
nan_cols
```

[6]:
```
LotFrontage      259
Alley           1369
MasVnrType         8
MasVnrArea         8
BsmtQual          37
BsmtCond          37
BsmtExposure      38
BsmtFinType1      37
BsmtFinType2      38
Electrical         1
```

```
FireplaceQu      690
GarageType        81
GarageYrBlt       81
GarageFinish      81
GarageQual        81
GarageCond        81
PoolQC          1453
Fence           1179
MiscFeature     1406
dtype: int64
```

[7]:
```
nan_cols_to_drop = nan_cols[nan_cols > 200]
train_df = train_df.drop(nan_cols_to_drop.index.values, axis='columns')
train_df.head()
```

[7]:
```
   Id  MSSubClass MSZoning  LotArea Street LotShape LandContour Utilities  \
0   1          60       RL     8450   Pave      Reg         Lvl    AllPub
1   2          20       RL     9600   Pave      Reg         Lvl    AllPub
2   3          60       RL    11250   Pave      IR1         Lvl    AllPub
3   4          70       RL     9550   Pave      IR1         Lvl    AllPub
4   5          60       RL    14260   Pave      IR1         Lvl    AllPub

  LotConfig LandSlope  … EnclosedPorch 3SsnPorch ScreenPorch PoolArea  \
0    Inside       Gtl  …             0         0           0        0
1       FR2       Gtl  …             0         0           0        0
2    Inside       Gtl  …             0         0           0        0
3    Corner       Gtl  …           272         0           0        0
4       FR2       Gtl  …             0         0           0        0

  MiscVal  MoSold  YrSold  SaleType  SaleCondition SalePrice
0       0       2    2008        WD         Normal    208500
1       0       5    2007        WD         Normal    181500
2       0       9    2008        WD         Normal    223500
3       0       2    2006        WD        Abnorml    140000
4       0      12    2008        WD         Normal    250000

[5 rows x 75 columns]
```

[8]:
```
nan_cols = train_df.isna().sum()
nan_cols = nan_cols[nan_cols > 0]
# nan_cols
non_numeric_nan_cols = train_df[nan_cols.index.values].select_dtypes('object').
 ↪columns
non_numeric_nan_cols
```

[8]:
```
Index(['MasVnrType', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1',
       'BsmtFinType2', 'Electrical', 'GarageType', 'GarageFinish',
```

```
         'GarageQual', 'GarageCond'],
        dtype='object')
```

[9]:
```
train_df = train_df.drop(non_numeric_nan_cols, axis="columns")
train_df.head()
```

[9]:
```
   Id  MSSubClass MSZoning  LotArea Street LotShape LandContour Utilities  \
0   1          60       RL     8450   Pave      Reg         Lvl    AllPub
1   2          20       RL     9600   Pave      Reg         Lvl    AllPub
2   3          60       RL    11250   Pave      IR1         Lvl    AllPub
3   4          70       RL     9550   Pave      IR1         Lvl    AllPub
4   5          60       RL    14260   Pave      IR1         Lvl    AllPub

  LotConfig LandSlope  … EnclosedPorch 3SsnPorch ScreenPorch PoolArea  \
0    Inside       Gtl  …             0         0           0        0
1       FR2       Gtl  …             0         0           0        0
2    Inside       Gtl  …             0         0           0        0
3    Corner       Gtl  …           272         0           0        0
4       FR2       Gtl  …             0         0           0        0

  MiscVal  MoSold  YrSold  SaleType  SaleCondition SalePrice
0       0       2    2008        WD         Normal    208500
1       0       5    2007        WD         Normal    181500
2       0       9    2008        WD         Normal    223500
3       0       2    2006        WD        Abnorml    140000
4       0      12    2008        WD         Normal    250000

[5 rows x 64 columns]
```

2.2 Checking any duplicates

[10]:
```
train_df[train_df.duplicated()]
```

[10]:
```
Empty DataFrame
Columns: [Id, MSSubClass, MSZoning, LotArea, Street, LotShape, LandContour,
Utilities, LotConfig, LandSlope, Neighborhood, Condition1, Condition2, BldgType,
HouseStyle, OverallQual, OverallCond, YearBuilt, YearRemodAdd, RoofStyle,
RoofMatl, Exterior1st, Exterior2nd, MasVnrArea, ExterQual, ExterCond,
Foundation, BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, TotalBsmtSF, Heating, HeatingQC,
CentralAir, 1stFlrSF, 2ndFlrSF, LowQualFinSF, GrLivArea, BsmtFullBath,
BsmtHalfBath, FullBath, HalfBath, BedroomAbvGr, KitchenAbvGr, KitchenQual,
TotRmsAbvGrd, Functional, Fireplaces, GarageYrBlt, GarageCars, GarageArea,
PavedDrive, WoodDeckSF, OpenPorchSF, EnclosedPorch, 3SsnPorch, ScreenPorch,
PoolArea, MiscVal, MoSold, YrSold, SaleType, SaleCondition, SalePrice]
Index: []

[0 rows x 64 columns]
```

No Duplicated row in the dataset

[11]:
```python
nan_cols = train_df.isna().sum()
nan_cols = nan_cols[nan_cols > 0]
nan_cols
```

[11]:
```
MasVnrArea      8
GarageYrBlt    81
dtype: int64
```

[12]:
```python
train_df['MasVnrArea'].fillna(train_df['MasVnrArea'].mean(), inplace=True)
train_df['GarageYrBlt'].fillna(train_df['GarageYrBlt'].mean(), inplace=True)

nan_cols = train_df.isna().sum()
nan_cols = nan_cols[nan_cols > 0]

assert len(nan_cols) == 0
```

2.3 Inspecting Categorical Columns

[13]:
```python
numeric_cols = train_df.select_dtypes('number').columns
categorical_cols = train_df.select_dtypes('object').columns
```

[14]:
```python
numeric_cols
```

[14]:
```
Index(['Id', 'MSSubClass', 'LotArea', 'OverallQual', 'OverallCond',
       'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
       'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
       'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
       'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',
       'MoSold', 'YrSold', 'SalePrice'],
      dtype='object')
```

[15]:
```python
categorical_cols
```

[15]:
```
Index(['MSZoning', 'Street', 'LotShape', 'LandContour', 'Utilities',
       'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2',
       'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st',
       'Exterior2nd', 'ExterQual', 'ExterCond', 'Foundation', 'Heating',
       'HeatingQC', 'CentralAir', 'KitchenQual', 'Functional', 'PavedDrive',
       'SaleType', 'SaleCondition'],
      dtype='object')
```

2.3.1 MSZoning Analysis

[16]:
```
train_df['MSZoning'].value_counts(normalize=True).sort_values(ascending=False)
```

[16]:
```
RL         0.788356
RM         0.149315
FV         0.044521
RH         0.010959
C (all)    0.006849
Name: MSZoning, dtype: float64
```

MSZoning has a hig bias twards the **Residential Low Density** and **Residential Medium Density** zoning types.

2.3.2 HouseStyle Analysis

[17]:
```
train_df['HouseStyle'].value_counts(normalize=True).sort_values(ascending=False)
```

[17]:
```
1Story    0.497260
2Story    0.304795
1.5Fin    0.105479
SLvl      0.044521
SFoyer    0.025342
1.5Unf    0.009589
2.5Unf    0.007534
2.5Fin    0.005479
Name: HouseStyle, dtype: float64
```

HouseStyle has major proportions twards **One Story**, **Two Story** and **One and one-half story: 2nd level unfinished**

2.3.3 Functional Analysis

[18]:
```
train_df['Functional'].value_counts(normalize=True).sort_values(ascending=False)
```

[18]:
```
Typ     0.931507
Min2    0.023288
Min1    0.021233
Mod     0.010274
Maj1    0.009589
Maj2    0.003425
Sev     0.000685
Name: Functional, dtype: float64
```

Functional column has large proportion twards **Typical Functionality**

2.3.4 SaleCondition Analysis

[19]:
```
train_df['SaleCondition'].value_counts(normalize=True).
 ↪sort_values(ascending=False)
```

[19]:
```
Normal     0.820548
Partial    0.085616
Abnorml    0.069178
Family     0.013699
Alloca     0.008219
AdjLand    0.002740
Name: SaleCondition, dtype: float64
```

SaleCondition has large proportion in being **Normal**

2.3.5 Heating Analysis

[20]:
```
train_df['Heating'].value_counts(normalize=True).sort_values(ascending=False)
```

[20]:
```
GasA     0.978082
GasW     0.012329
Grav     0.004795
Wall     0.002740
OthW     0.001370
Floor    0.000685
Name: Heating, dtype: float64
```

Heating columns has large proportion twards **Gas forced warm air furnace**

2.4 Cleaning Categorical Columns

[21]:
```
## MSZoning Column
train_df['zone_low_density'] = train_df['MSZoning'] == "RL"

## HouseStyle Column
train_df['one_story_style'] = train_df['HouseStyle'] == '1Story'
train_df['two_story_style'] = train_df['HouseStyle'] == '2Story'
train_df['one_half_story_style'] = train_df['HouseStyle'] == '1.5Fin'

## Functional Column
train_df['typical_functionality'] = train_df['Functional'] == 'Typ'

## Sale Condition
train_df['sale_normal_condition'] = train_df['SaleCondition'] == 'Normal'

## Heating Column
train_df['gas_heating'] = train_df['Heating'] == 'GasA'
```

```python
## conver to numeric values
cols = ['zone_low_density', 'one_story_style', 'two_story_style',␣
 ↪'typical_functionality',
        'one_half_story_style', 'gas_heating', 'sale_normal_condition']

train_df[cols] = train_df[cols].astype('int')

train_df[
    ['zone_low_density', 'one_story_style', 'two_story_style',␣
 ↪'typical_functionality',
     'one_half_story_style', 'gas_heating', 'sale_normal_condition']
].head()
```

[21]:

```
   zone_low_density  one_story_style  two_story_style  typical_functionality  \
0                 1                0                1                      1
1                 1                1                0                      1
2                 1                0                1                      1
3                 1                0                1                      1
4                 1                0                1                      1

   one_half_story_style  gas_heating  sale_normal_condition
0                     0            1                      1
1                     0            1                      1
2                     0            1                      1
3                     0            1                      0
4                     0            1                      1
```

2.5 Inspecting Numerical Columns

[22]:

```python
numeric_cols
```

[22]:

```
Index(['Id', 'MSSubClass', 'LotArea', 'OverallQual', 'OverallCond',
       'YearBuilt', 'YearRemodAdd', 'MasVnrArea', 'BsmtFinSF1', 'BsmtFinSF2',
       'BsmtUnfSF', 'TotalBsmtSF', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF',
       'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath',
       'BedroomAbvGr', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces',
       'GarageYrBlt', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',
       'MoSold', 'YrSold', 'SalePrice'],
      dtype='object')
```

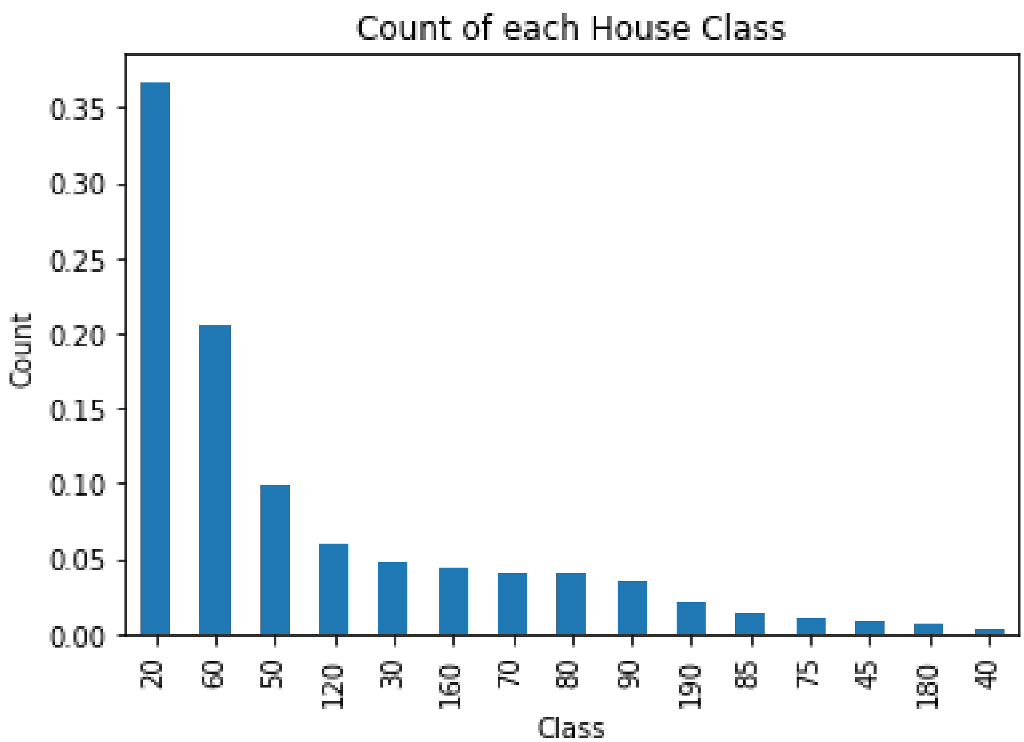
2.5.1 MSSubClass Analysis

- **20 1-STORY 1946 & NEWER ALL STYLES**
- 30 1-STORY 1945 & OLDER
- 40 1-STORY W/FINISHED ATTIC ALL AGES
- 45 1-1/2 STORY - UNFINISHED ALL AGES

- 50 1-1/2 STORY FINISHED ALL AGES
- **60 2-STORY 1946 & NEWER**
- 70 2-STORY 1945 & OLDER
- 75 2-1/2 STORY ALL AGES
- 80 SPLIT OR MULTI-LEVEL
- 85 SPLIT FOYER
- 90 DUPLEX - ALL STYLES AND AGES
- 120 1-STORY PUD (Planned Unit Development) - 1946 & NEWER
- 150 1-1/2 STORY PUD - ALL AGES
- 160 2-STORY PUD - 1946 & NEWER
- 180 PUD - MULTILEVEL - INCL SPLIT LEV/FOYER
- 190 2 FAMILY CONVERSION - ALL STYLES AND AGES

this column must be conveted to be **categorical column**

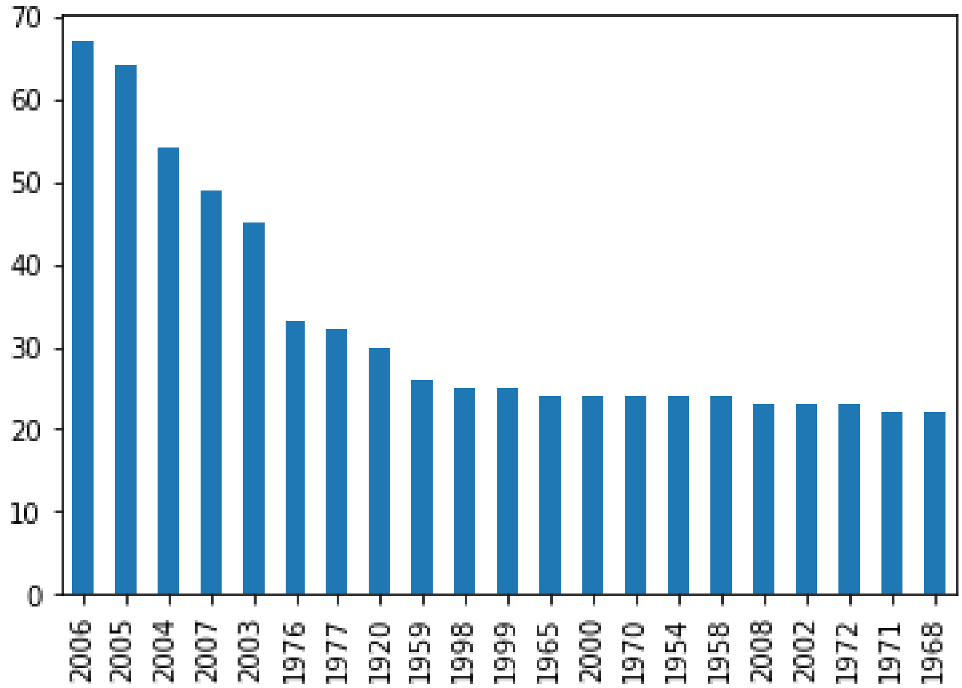
[23]:
```
train_df['MSSubClass'] = train_df['MSSubClass'].astype('object')

train_df['MSSubClass'].value_counts(normalize=True).plot(kind='bar')
plt.title("Count of each House Class")
plt.xlabel('Class')
plt.ylabel('Count');
```



2.5.2 YearBuilt Analysis

[24]:
```
(train_df['YearBuilt'].value_counts()
 [train_df['YearBuilt'].value_counts() > 20]
).plot(kind='bar')
```

[24]: <AxesSubplot:>



2.5.3 YearRemodAdd Analysis

[25]:
```
train_df['time_taken_to_remodel'] = train_df['YearRemodAdd'] -␣
 ↪train_df['YearBuilt']
train_df['time_taken_to_remodel'].describe()
```

[25]:
```
count    1460.000000
mean       13.597945
std        24.476465
min         0.000000
25%         0.000000
50%         0.000000
75%        20.000000
max       123.000000
Name: time_taken_to_remodel, dtype: float64
```

[26]:
```
train_df['time_taken_to_sell'] = train_df['YrSold'] - train_df['YearBuilt']
train_df['time_taken_to_sell'].describe()
```

[26]:
```
count    1460.000000
mean       36.547945
std        30.250152
min         0.000000
25%         8.000000
50%        35.000000
75%        54.000000
max       136.000000
Name: time_taken_to_sell, dtype: float64
```

[27]:
```
train_df['time_taken_to_sell_after_remodel'] = train_df['YrSold'] -
 ↪train_df['YearRemodAdd']
train_df['time_taken_to_sell_after_remodel'].describe()
```

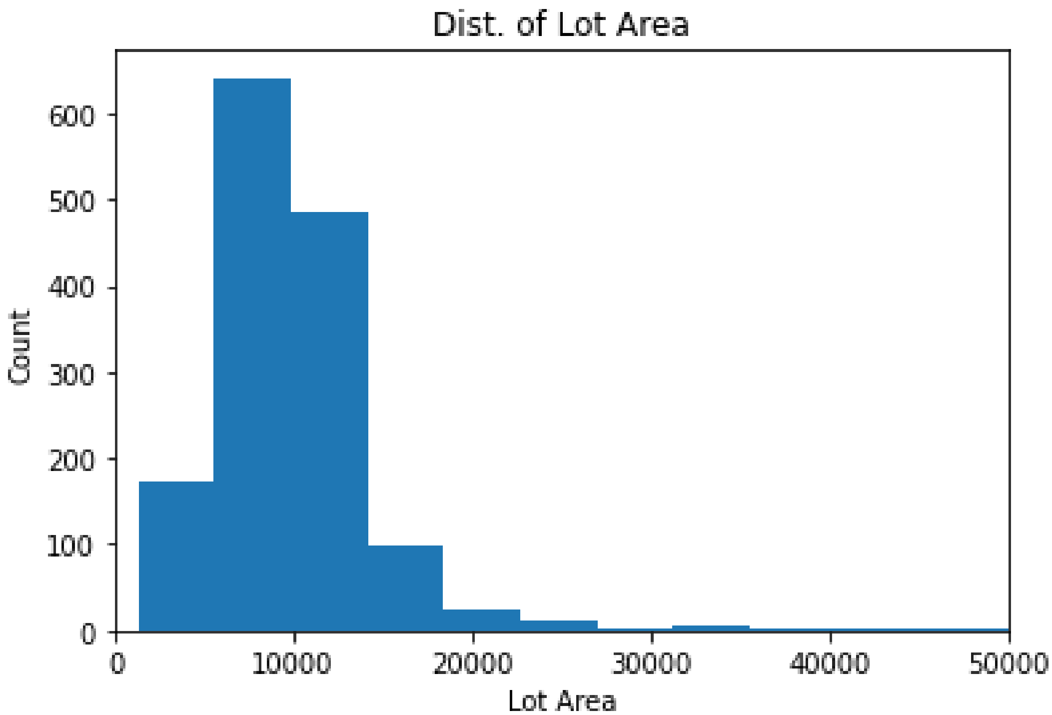
[27]:
```
count    1460.000000
mean       22.950000
std        20.640653
min        -1.000000
25%         4.000000
50%        14.000000
75%        41.000000
max        60.000000
Name: time_taken_to_sell_after_remodel, dtype: float64
```

on average it took **36 Years** to sell a house and **22 Year** to sell a house that has been **ReModeled**

2.5.4 LotArea Analysis

[28]:
```
train_df['LotArea'].plot(kind='hist', bins=50)
plt.title("Dist. of Lot Area")
plt.xlabel("Lot Area")
plt.ylabel('Count')
plt.xlim([0, 50_000]);

print(train_df['LotArea'].describe())
```

```
count      1460.000000
mean      10516.828082
std        9981.264932
min        1300.000000
25%        7553.500000
50%        9478.500000
75%       11601.500000
max      215245.000000
Name: LotArea, dtype: float64
```

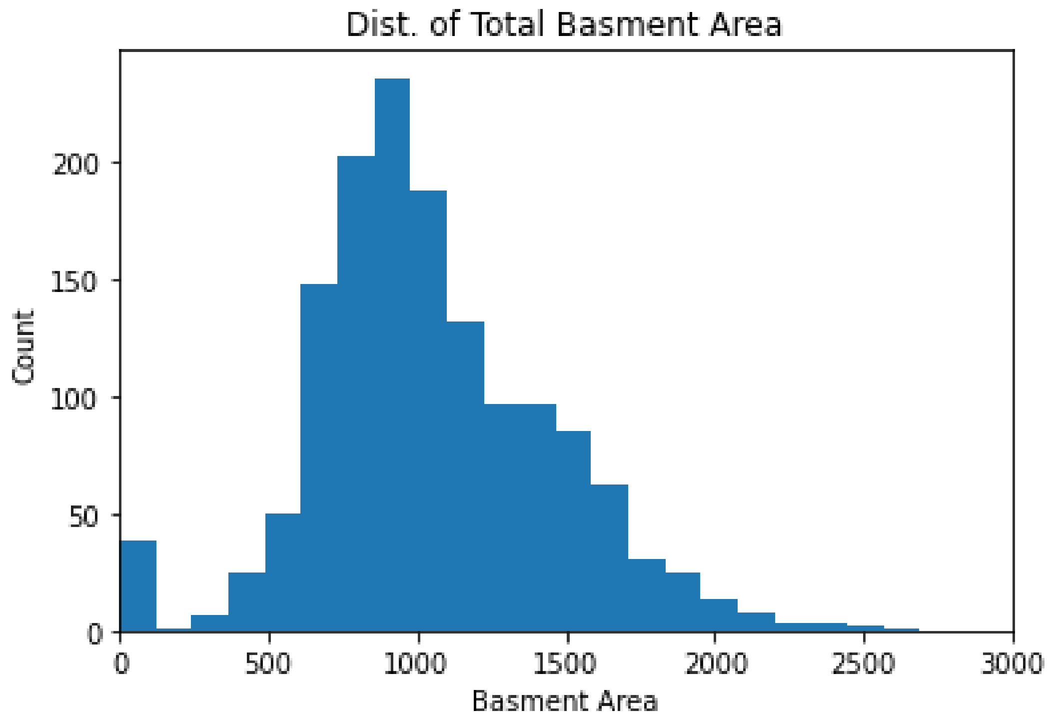


most of the houses has a Lot Area around **5,000** to **15,000** square feet

2.5.5 TotalBsmtSF

[29]:
```
print(train_df['TotalBsmtSF'].describe())

train_df['TotalBsmtSF'].plot(kind='hist', bins=50)
plt.title("Dist. of Total Basment Area")
plt.xlabel("Basment Area")
plt.ylabel('Count');

plt.xlim([0, 3000]);
```

```
count    1460.000000
mean     1057.429452
std       438.705324
min         0.000000
25%       795.750000
50%       991.500000
75%      1298.250000
max      6110.000000
Name: TotalBsmtSF, dtype: float64
```



most of the houses has a Basment Area from **500** to **1500**

2.5.6 Bedroom and Bathroom Analysis

[30]:
```
train_df['BedroomAbvGr'].value_counts()
```

[30]:
```
3    804
2    358
4    213
1     50
5     21
6      7
0      6
8      1
Name: BedroomAbvGr, dtype: int64
```

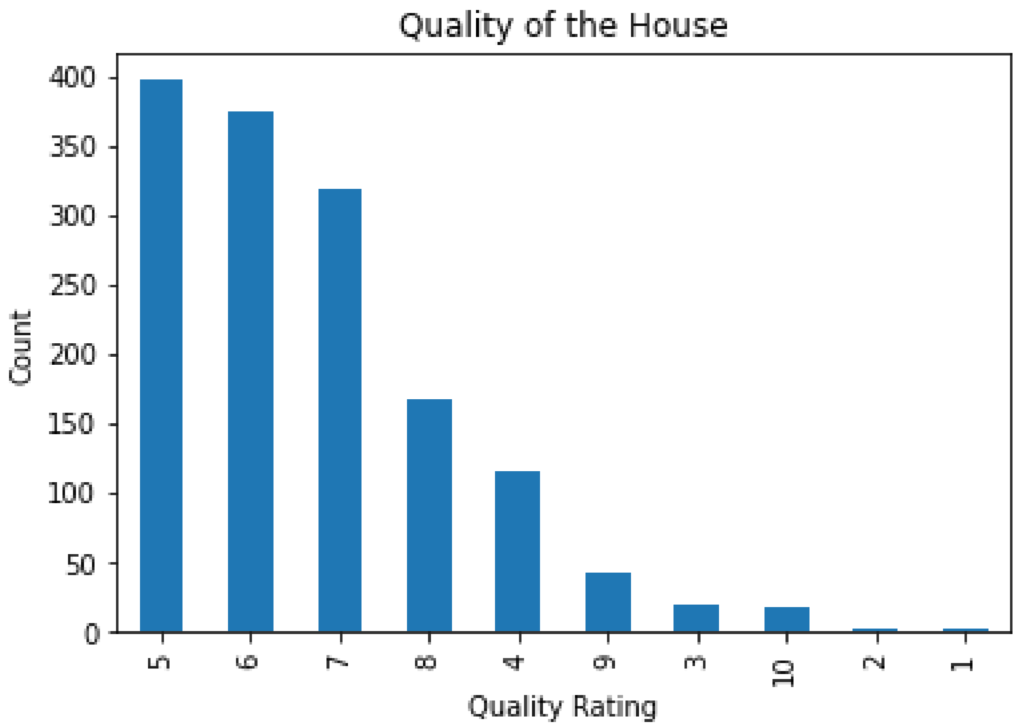
[31]:
```
train_df['FullBath'].value_counts()
```

[31]:
```
2    768
1    650
3     33
0      9
Name: FullBath, dtype: int64
```

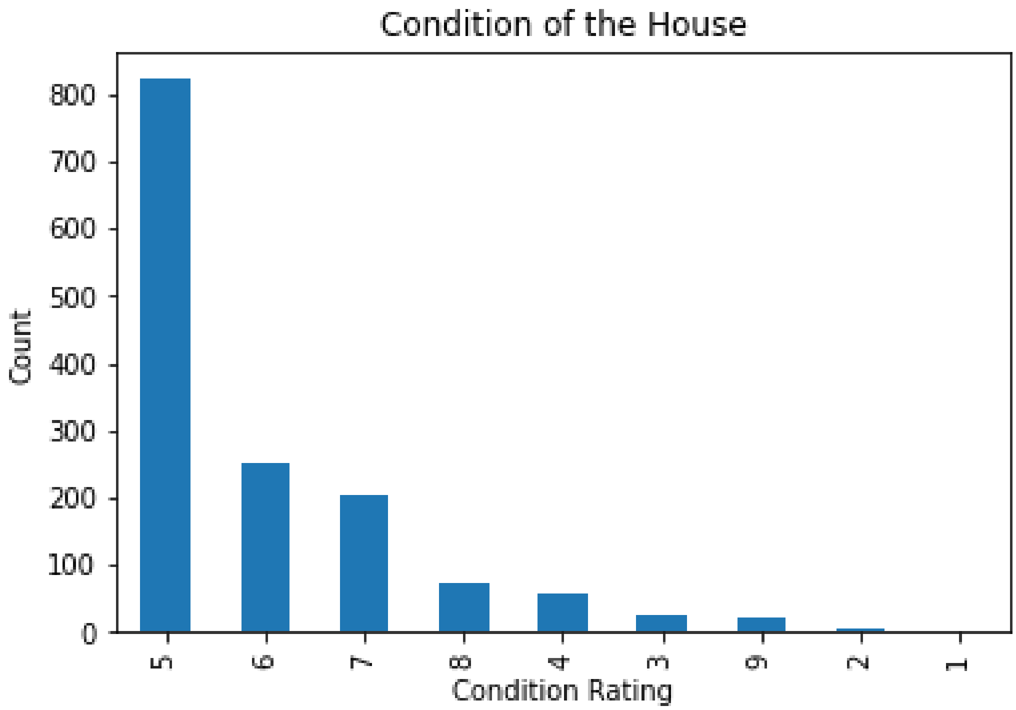
most of the house have a **3, 2 or 4** bedrooms above the grade and **2 or 1** bathroom above the grade

2.5.7 OverallQual and OverallCond Analysis

[32]:
```
train_df['OverallQual'].value_counts().plot(kind='bar');
plt.title("Quality of the House")
plt.xlabel("Quality Rating")
plt.ylabel("Count");
```



[33]:
```
train_df['OverallCond'].value_counts().plot(kind='bar')
plt.title("Condition of the House")
plt.xlabel("Condition Rating")
plt.ylabel("Count");
```

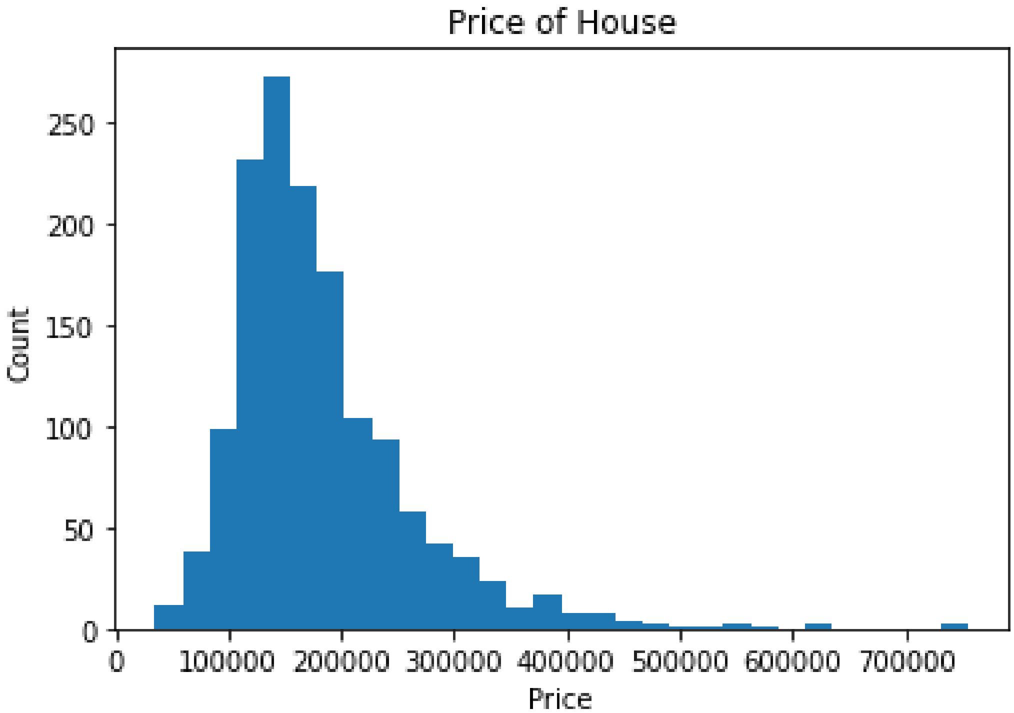


most of the houses have a rating condition and quality around **5 or 6**

2.5.8 SalePrice Analysis

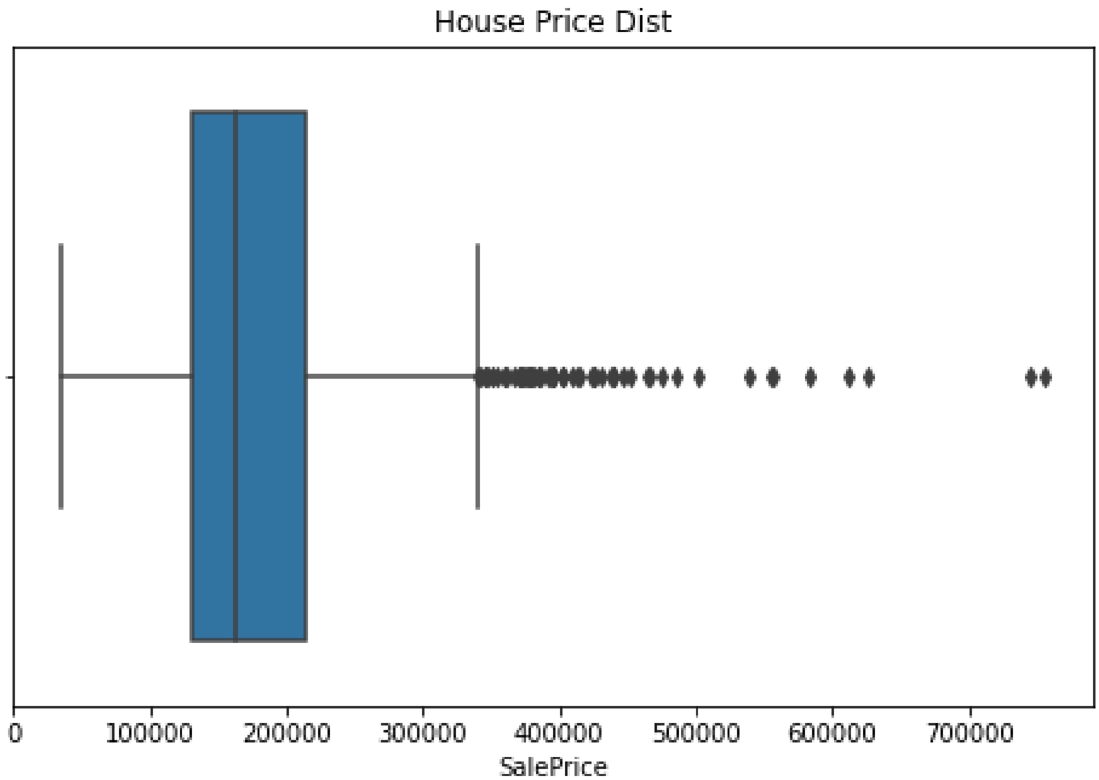
[34]:
```
print(train_df['SalePrice'].describe())

train_df['SalePrice'].plot(kind='hist', bins=30)
plt.title("Price of House")
plt.xlabel("Price")
plt.ylabel("Count");
```

```
count      1460.000000
mean     180921.195890
std       79442.502883
min       34900.000000
25%      129975.000000
50%      163000.000000
75%      214000.000000
max      755000.000000
Name: SalePrice, dtype: float64
```



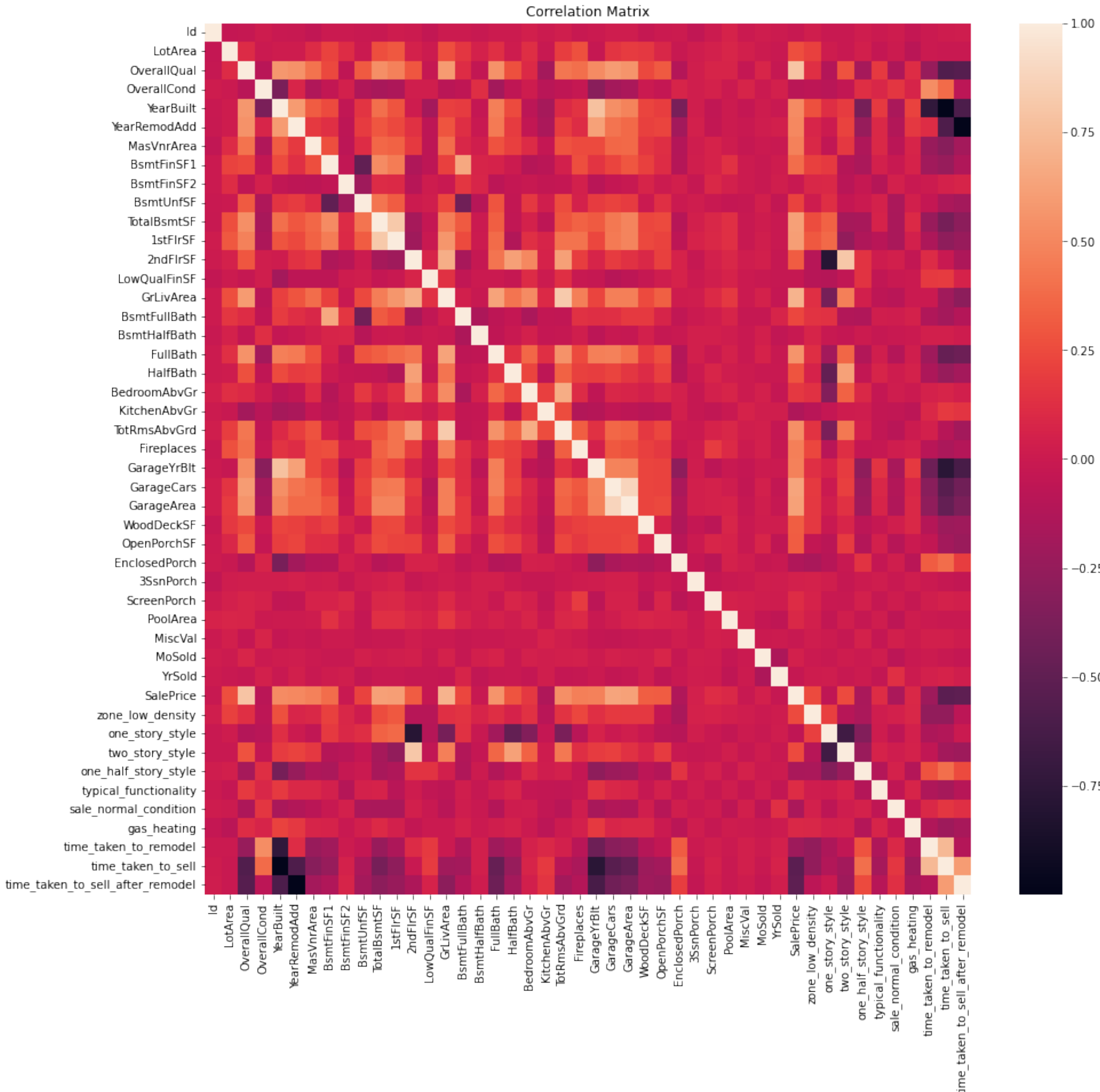
most houses has price ranging between **1,000,000** to **2,500,000** us dollars

[35]:
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=train_df, x='SalePrice')
plt.title("House Price Dist");
```



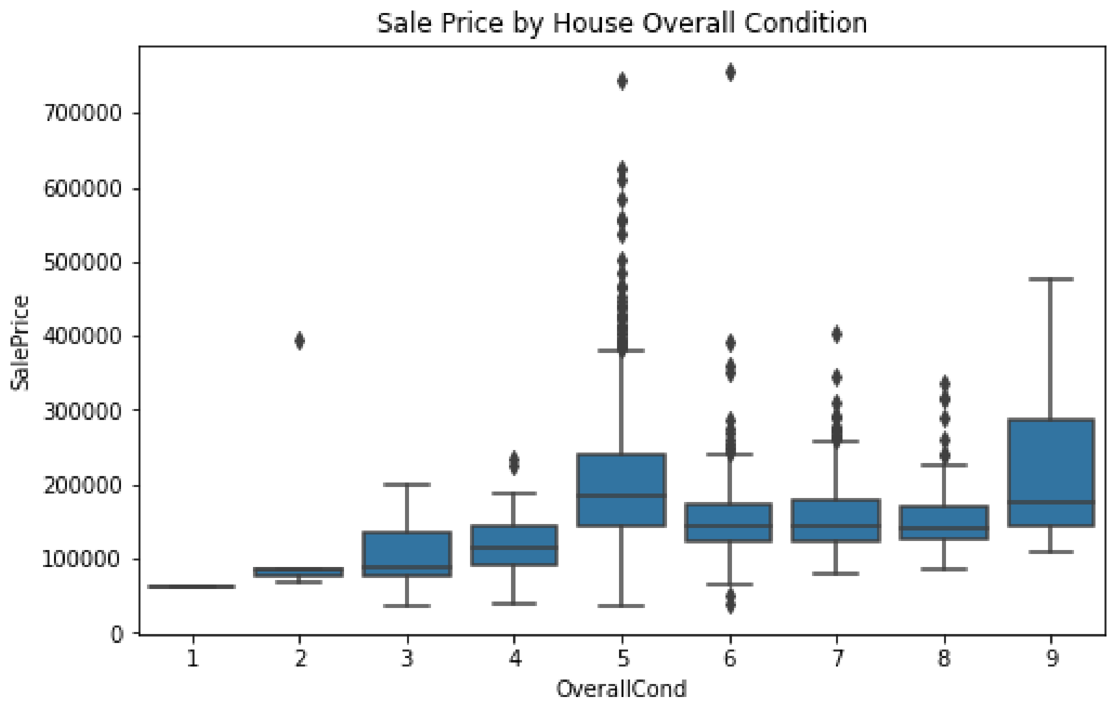
2.5.9 Corrletation Matrix in the Dataset

[36]:
```
corr = train_df.corr()

fig, ax = plt.subplots(nrows=1, figsize=(15, 14))
sns.heatmap(corr, ax=ax)
ax.set_title("Correlation Matrix");
```



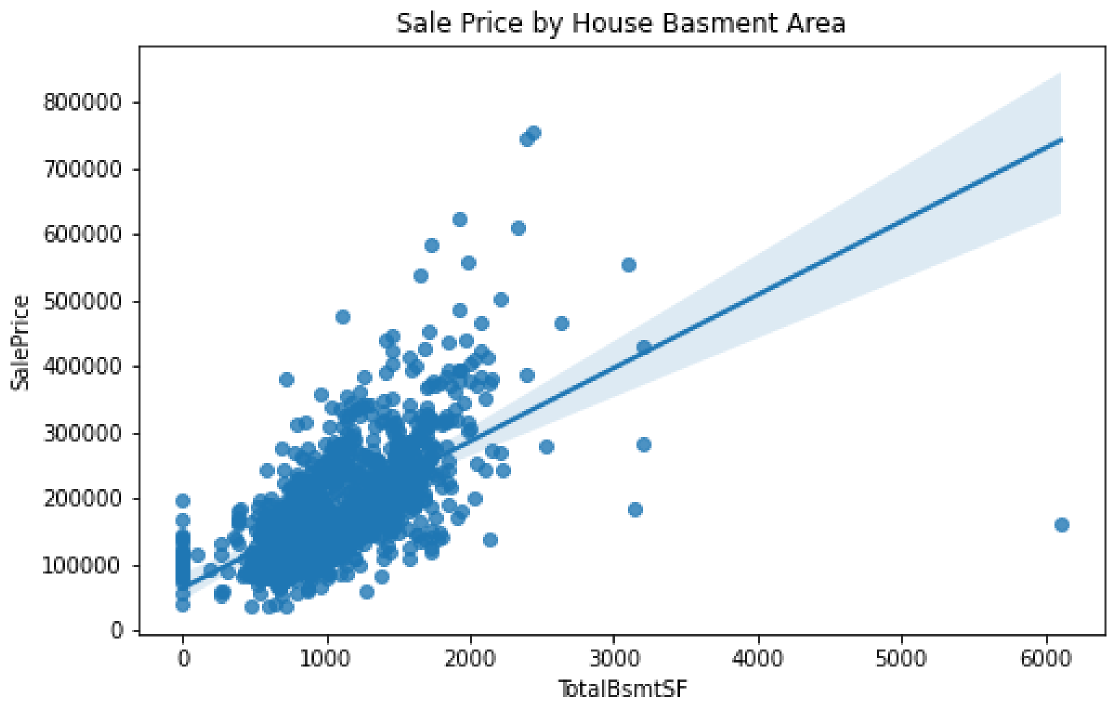
2.5.10 SalePrice vs OverallCond

[37]:
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=train_df, x='OverallCond', y='SalePrice', color=BASE_COLOR);
plt.title("Sale Price by House Overall Condition");
```



2.5.11 SalePrice vs TotalBsmtSF

[38]:
```
plt.figure(figsize=(8, 5))
sns.regplot(data=train_df, x='TotalBsmtSF', y='SalePrice', color=BASE_COLOR);
plt.title("Sale Price by House Basment Area");
```

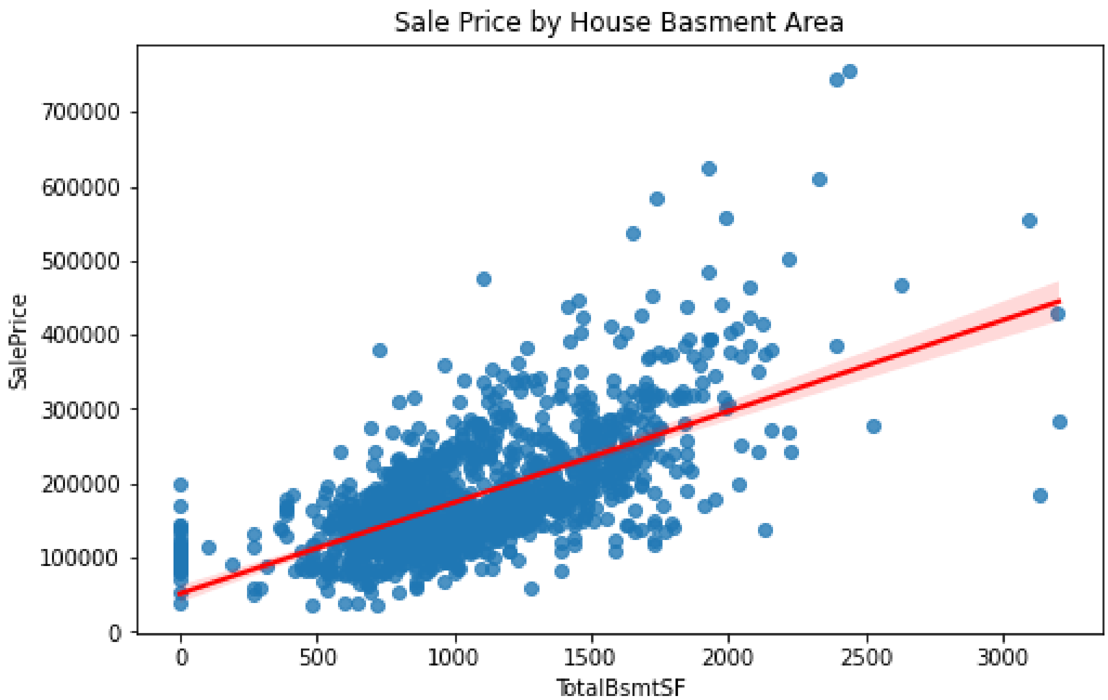


the relation shows existance of outlier point at **6000** so, it would be better it we remove it

[39]:
```
train_df.drop(train_df[train_df['TotalBsmtSF'] > 5000].index, inplace=True)
train_df[train_df['TotalBsmtSF'] > 5000]
```

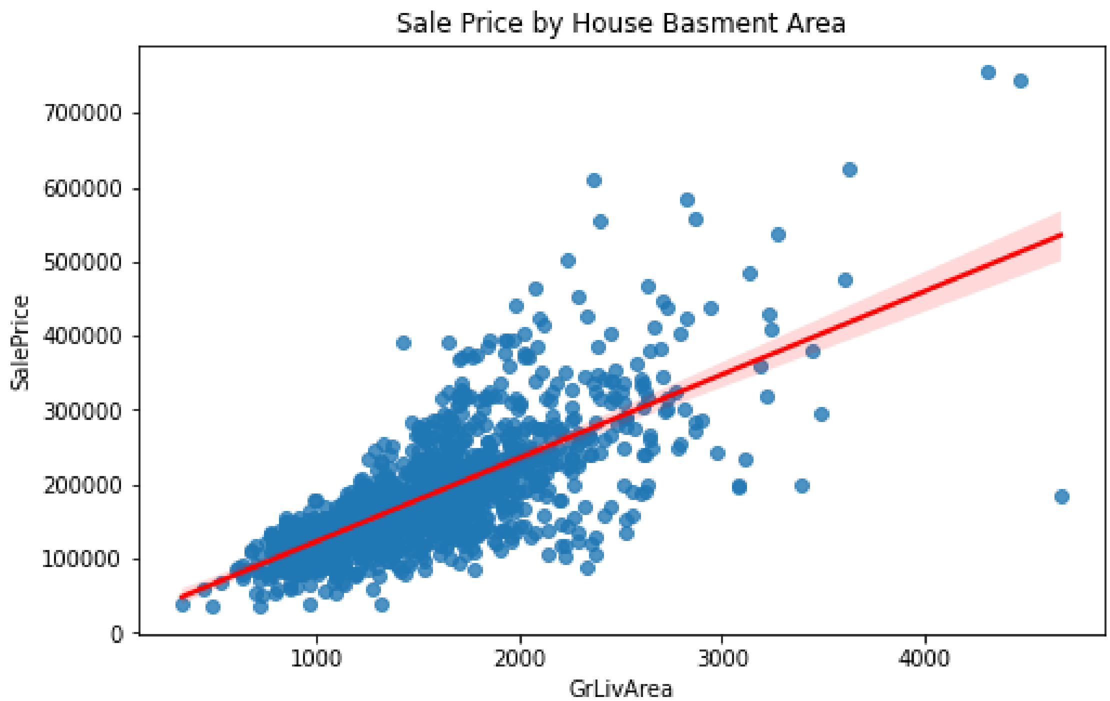
[39]:
```
Empty DataFrame
Columns: [Id, MSSubClass, MSZoning, LotArea, Street, LotShape, LandContour,
Utilities, LotConfig, LandSlope, Neighborhood, Condition1, Condition2, BldgType,
HouseStyle, OverallQual, OverallCond, YearBuilt, YearRemodAdd, RoofStyle,
RoofMatl, Exterior1st, Exterior2nd, MasVnrArea, ExterQual, ExterCond,
Foundation, BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, TotalBsmtSF, Heating, HeatingQC,
CentralAir, 1stFlrSF, 2ndFlrSF, LowQualFinSF, GrLivArea, BsmtFullBath,
BsmtHalfBath, FullBath, HalfBath, BedroomAbvGr, KitchenAbvGr, KitchenQual,
TotRmsAbvGrd, Functional, Fireplaces, GarageYrBlt, GarageCars, GarageArea,
PavedDrive, WoodDeckSF, OpenPorchSF, EnclosedPorch, 3SsnPorch, ScreenPorch,
PoolArea, MiscVal, MoSold, YrSold, SaleType, SaleCondition, SalePrice,
zone_low_density, one_story_style, two_story_style, one_half_story_style,
typical_functionality, sale_normal_condition, gas_heating,
time_taken_to_remodel, time_taken_to_sell, time_taken_to_sell_after_remodel]
Index: []

[0 rows x 74 columns]
```

[40]:
```
plt.figure(figsize=(8, 5))
sns.regplot(data=train_df, x='TotalBsmtSF', y='SalePrice',␣
 ↪line_kws=dict(color='r'));
plt.title("Sale Price by House Basment Area");
```



2.5.12 SalePrice vs GrLivArea

[41]:
```
plt.figure(figsize=(8, 5))
sns.regplot(data=train_df,  x='GrLivArea', y='SalePrice',␣
 ↪line_kws=dict(color='r'));
plt.title("Sale Price by House Basment Area");
```

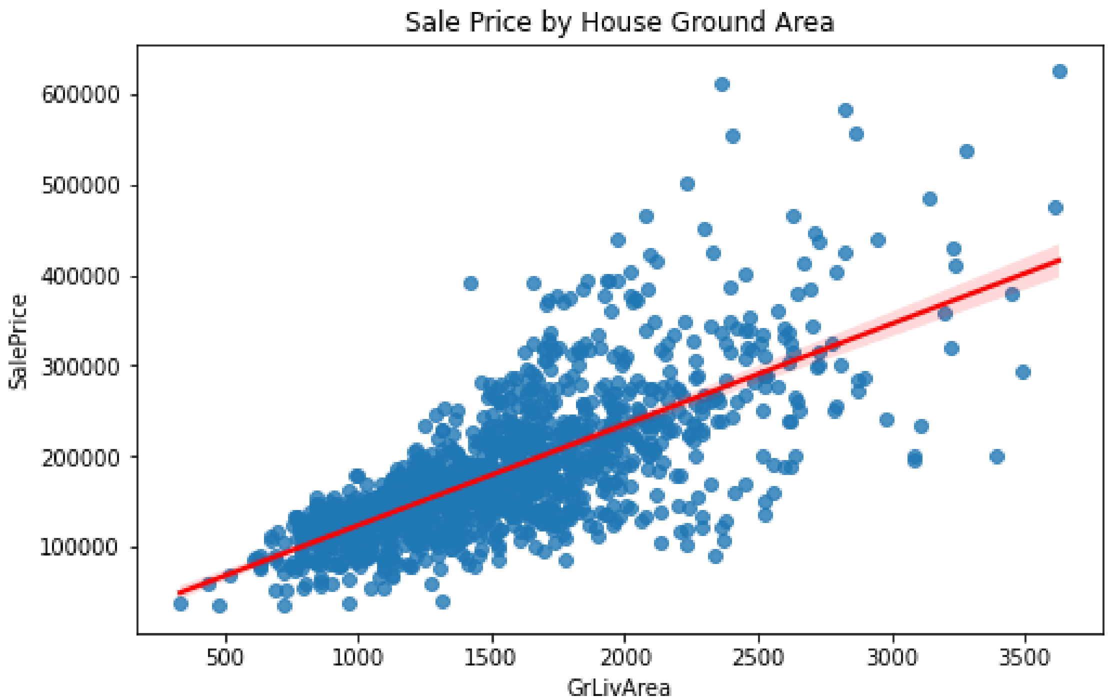


there is outliers in the GrLivArea greater than **4000** so removing it

[42]:
```
train_df.drop(train_df[train_df['GrLivArea'] > 4000].index, inplace=True)
train_df[train_df['GrLivArea'] > 4000]
```

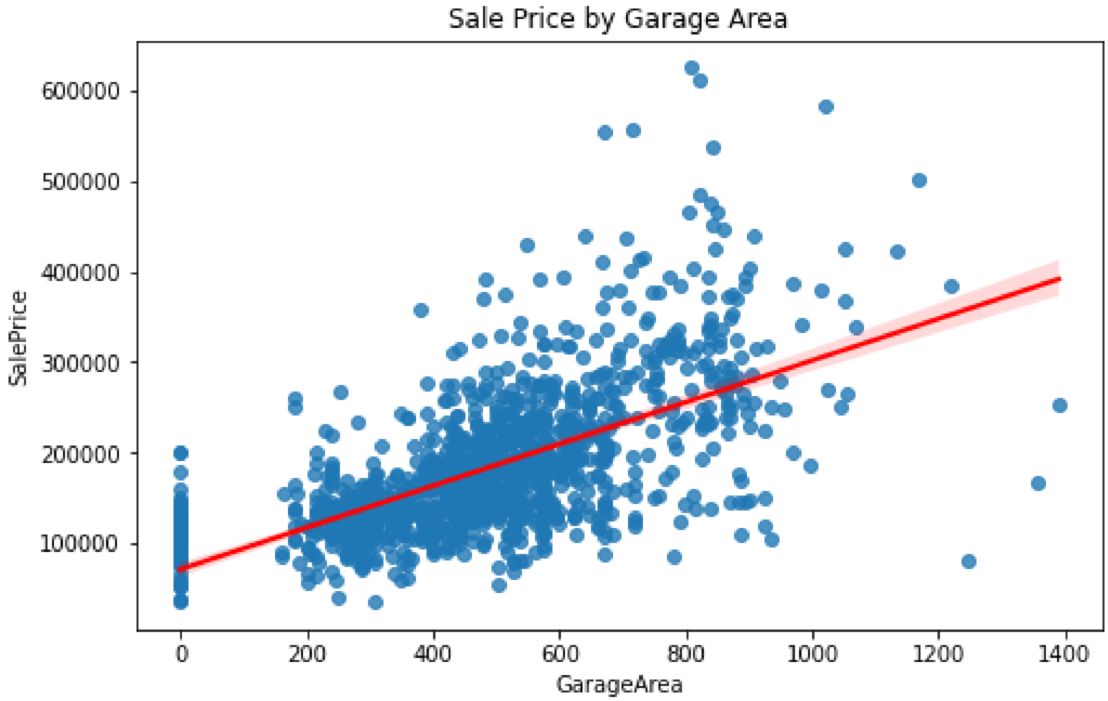
[42]:
```
Empty DataFrame
Columns: [Id, MSSubClass, MSZoning, LotArea, Street, LotShape, LandContour,
Utilities, LotConfig, LandSlope, Neighborhood, Condition1, Condition2, BldgType,
HouseStyle, OverallQual, OverallCond, YearBuilt, YearRemodAdd, RoofStyle,
RoofMatl, Exterior1st, Exterior2nd, MasVnrArea, ExterQual, ExterCond,
Foundation, BsmtFinSF1, BsmtFinSF2, BsmtUnfSF, TotalBsmtSF, Heating, HeatingQC,
CentralAir, 1stFlrSF, 2ndFlrSF, LowQualFinSF, GrLivArea, BsmtFullBath,
BsmtHalfBath, FullBath, HalfBath, BedroomAbvGr, KitchenAbvGr, KitchenQual,
TotRmsAbvGrd, Functional, Fireplaces, GarageYrBlt, GarageCars, GarageArea,
PavedDrive, WoodDeckSF, OpenPorchSF, EnclosedPorch, 3SsnPorch, ScreenPorch,
PoolArea, MiscVal, MoSold, YrSold, SaleType, SaleCondition, SalePrice,
zone_low_density, one_story_style, two_story_style, one_half_story_style,
typical_functionality, sale_normal_condition, gas_heating,
time_taken_to_remodel, time_taken_to_sell, time_taken_to_sell_after_remodel]
Index: []

[0 rows x 74 columns]
```

[43]:
```
plt.figure(figsize=(8, 5))
sns.regplot(data=train_df, x='GrLivArea', y='SalePrice',␣
 ↪line_kws=dict(color='r'));
plt.title("Sale Price by House Ground Area");
```



2.5.13 GarageArea vs SalePrice

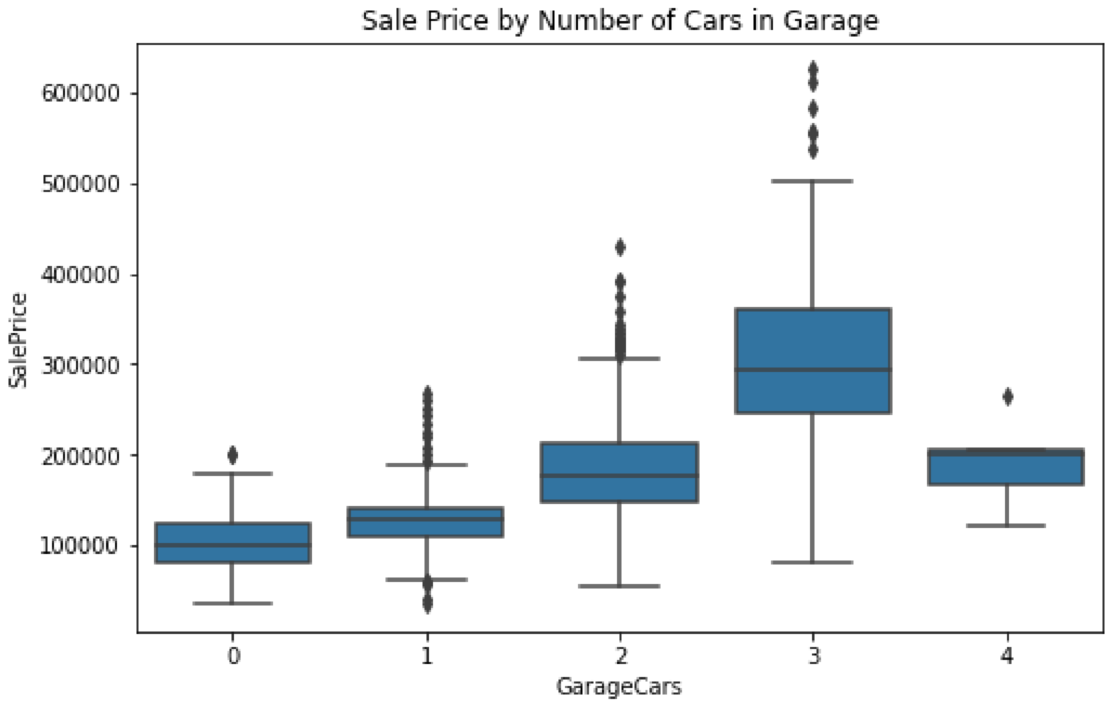
[44]:
```
plt.figure(figsize=(8, 5))
sns.regplot(data=train_df, x='GarageArea', y='SalePrice',␣
 ↪line_kws=dict(color='r'));
plt.title("Sale Price by Garage Area");
```



positive correlation indicating an increase in price as the garage area increases.

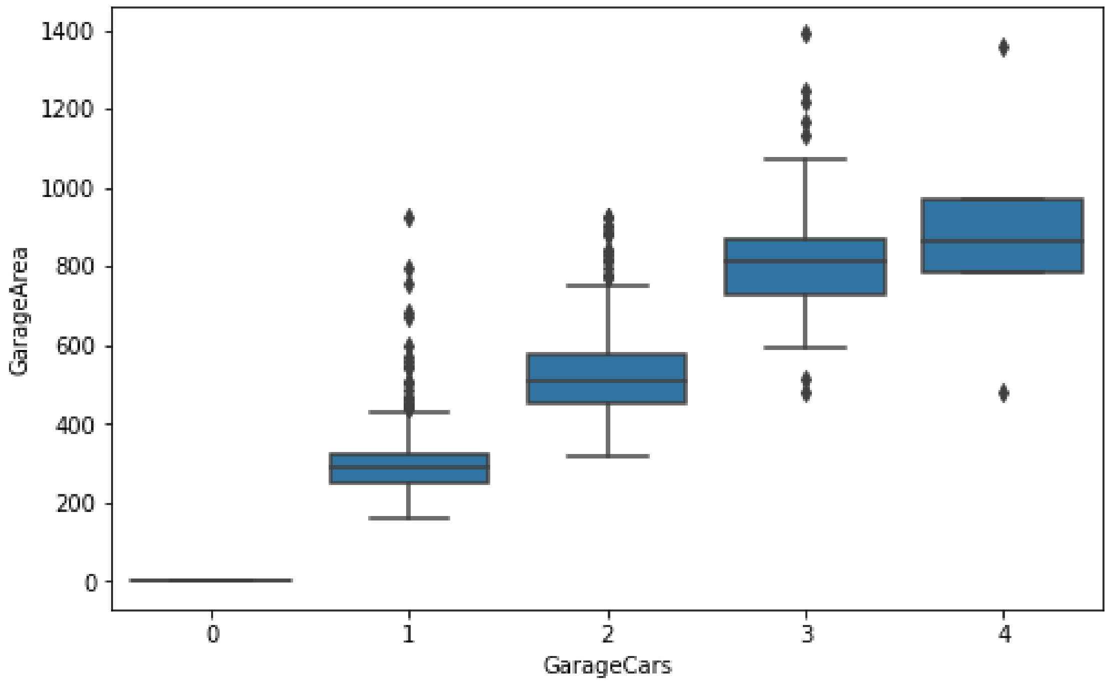
2.5.14 GarageCars vs SalePrice

[45]:
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=train_df, x='GarageCars', y='SalePrice', color=BASE_COLOR);
plt.title("Sale Price by Number of Cars in Garage");
```



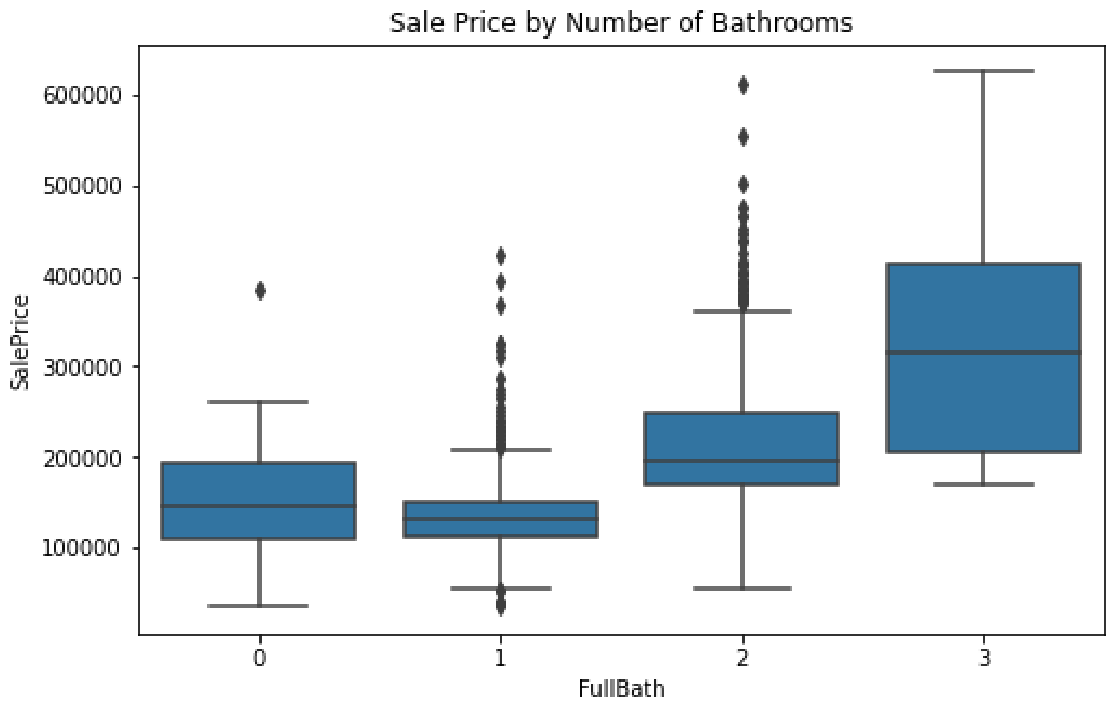
positive correlation indicating an increase in price as number of cars garage can fit increases

[46]:
```
## GarageCars vs GarageArea
## False correlation or colinearity in the dataset
## Does make sense

plt.figure(figsize=(8, 5))
sns.boxplot(data=train_df, x='GarageCars', y='GarageArea', color=BASE_COLOR);
```



2.5.15 SalePrice vs FullBath

[47]:
```
plt.figure(figsize=(8, 5))
sns.boxplot(data=train_df, x='FullBath', y='SalePrice', color=BASE_COLOR);
plt.title("Sale Price by Number of Bathrooms");
```



[ ]:

3 Statmodels OLS Model Analysis

[48]:
```
ols_df = train_df.select_dtypes('number')
ols_df.head()
```

[48]:

	Id	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	\
0	1	8450	7	5	2003	2003	196.0	
1	2	9600	6	8	1976	1976	0.0	
2	3	11250	7	5	2001	2002	162.0	
3	4	9550	7	5	1915	1970	0.0	
4	5	14260	8	5	2000	2000	350.0	

	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	…	zone_low_density	one_story_style	\
0	706	0	150	…	1	0	
1	978	0	284	…	1	1	
2	486	0	434	…	1	0	
3	216	0	540	…	1	0	
4	655	0	490	…	1	0	

	two_story_style	one_half_story_style	typical_functionality	\
0	1	0	1	

```
1                0                    0                     1
2                1                    0                     1
3                1                    0                     1
4                1                    0                     1

   sale_normal_condition  gas_heating  time_taken_to_remodel  \
0                      1            1                      0
1                      1            1                      0
2                      1            1                      1
3                      0            1                     55
4                      1            1                      0

   time_taken_to_sell  time_taken_to_sell_after_remodel
0                   5                                 5
1                  31                                31
2                   7                                 6
3                  91                                36
4                   8                                 8

[5 rows x 46 columns]
```

[49]:
```
ols_df = ols_df.drop(['YrSold', 'YearBuilt', 'YearRemodAdd', 'Id'],␣
↪axis='columns')
ols_df
```

[49]:
```
      LotArea  OverallQual  OverallCond  MasVnrArea  BsmtFinSF1  BsmtFinSF2  \
0        8450            7            5       196.0         706           0
1        9600            6            8         0.0         978           0
2       11250            7            5       162.0         486           0
3        9550            7            5         0.0         216           0
4       14260            8            5       350.0         655           0
…           …          …           …          …           …
1455     7917            6            5         0.0           0           0
1456    13175            6            6       119.0         790         163
1457     9042            7            9         0.0         275           0
1458     9717            5            6         0.0          49        1029
1459     9937            5            6         0.0         830         290

      BsmtUnfSF  TotalBsmtSF  1stFlrSF  2ndFlrSF  …  zone_low_density  \
0           150          856       856       854  …                 1
1           284         1262      1262         0  …                 1
2           434          920       920       866  …                 1
3           540          756       961       756  …                 1
4           490         1145      1145      1053  …                 1
…           …          …        …       …   …                …
1455        953          953       953       694  …                 1
1456        589         1542      2073         0  …                 1
```

```
1457        877         1152       1188       1152  …                 1
1458          0         1078       1078          0  …                 1
1459        136         1256       1256          0  …                 1

      one_story_style  two_story_style  one_half_story_style  \
0                   0                1                     0
1                   1                0                     0
2                   0                1                     0
3                   0                1                     0
4                   0                1                     0
…                 …               …                    …
1455                0                1                     0
1456                1                0                     0
1457                0                1                     0
1458                1                0                     0
1459                1                0                     0

      typical_functionality  sale_normal_condition  gas_heating  \
0                         1                      1            1
1                         1                      1            1
2                         1                      1            1
3                         1                      0            1
4                         1                      1            1
…                       …                    …          …
1455                      1                      1            1
1456                      0                      1            1
1457                      1                      1            1
1458                      1                      1            1
1459                      1                      1            1

      time_taken_to_remodel  time_taken_to_sell  \
0                         0                   5
1                         0                  31
2                         1                   7
3                        55                  91
4                         0                   8
…                       …                 …
1455                      1                   8
1456                     10                  32
1457                     65                  69
1458                     46                  60
1459                      0                  43

      time_taken_to_sell_after_remodel
0                                    5
1                                   31
2                                    6
```

```
3                                  36
4                                   8
…                               …
1455                                7
1456                               22
1457                                4
1458                               14
1459                               43

[1456 rows x 42 columns]
```

[50]:
```python
ols_df['intercept'] = 1
```

[51]:
```python
ols_model = OLS(ols_df['SalePrice'], ols_df.drop('SalePrice', axis='columns'))
result = ols_model.fit()
result.summary()
```

[51]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:              SalePrice   R-squared:                       0.870
Model:                            OLS   Adj. R-squared:                  0.866
Method:                 Least Squares   F-statistic:                     248.8
Date:                Sun, 01 May 2022   Prob (F-statistic):               0.00
Time:                        01:35:18   Log-Likelihood:                -16959.
No. Observations:                1456   AIC:                         3.400e+04
Df Residuals:                    1417   BIC:                         3.420e+04
Df Model:                          38
Covariance Type:            nonrobust
================================================================================
====================
                                       coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
--------------------
LotArea                              0.5892      0.082      7.168      0.000
0.428       0.750
OverallQual                         1.4e+04    980.392     14.279      0.000
1.21e+04    1.59e+04
OverallCond                       4810.6610    864.986      5.562      0.000
3113.871    6507.451
MasVnrArea                          28.7187      4.871      5.896      0.000
19.163      38.274
BsmtFinSF1                          20.2892      2.144      9.464      0.000
16.084      24.495
BsmtFinSF2                           0.3289      3.650      0.090      0.928
```

					-6.830	7.488
BsmtUnfSF	-0.2817	1.969	-0.143	0.886	-4.145	3.582
TotalBsmtSF	20.3364	2.826	7.196	0.000	14.793	25.880
1stFlrSF	23.5409	5.308	4.435	0.000	13.129	33.953
2ndFlrSF	28.9580	5.521	5.245	0.000	18.128	39.788
LowQualFinSF	-18.3571	12.279	-1.495	0.135	-42.445	5.730
GrLivArea	34.1418	4.674	7.305	0.000	24.974	43.310
BsmtFullBath	1188.0415	2142.964	0.554	0.579	-3015.682	5391.765
BsmtHalfBath	-6472.7349	3345.912	-1.935	0.053	-1.3e+04	90.739
FullBath	-1839.3572	2303.181	-0.799	0.425	-6357.367	2678.653
HalfBath	-1745.3871	2214.303	-0.788	0.431	-6089.052	2598.278
BedroomAbvGr	-1.179e+04	1379.653	-8.545	0.000	-1.45e+04	-9082.100
KitchenAbvGr	-2.403e+04	3983.327	-6.034	0.000	-3.18e+04	-1.62e+04
TotRmsAbvGrd	5593.5981	1013.354	5.520	0.000	3605.763	7581.433
Fireplaces	1842.6362	1457.101	1.265	0.206	-1015.671	4700.943
GarageYrBlt	106.9927	56.099	1.907	0.057	-3.053	217.038
GarageCars	3023.0111	2356.422	1.283	0.200	-1599.439	7645.461
GarageArea	18.5384	8.052	2.302	0.021	2.743	34.334
WoodDeckSF	15.2935	6.518	2.346	0.019	2.508	28.079
OpenPorchSF	27.3756	12.513	2.188	0.029	2.829	51.922
EnclosedPorch	11.2541	13.682	0.823	0.411	-15.585	38.093
3SsnPorch	10.4082	25.354	0.411	0.681	-39.328	60.144
ScreenPorch	38.0293	13.973	2.722	0.007	10.620	65.439
PoolArea	-3.5168	21.287	-0.165	0.869	-45.275	38.241

```
MiscVal                                -1.0412      1.505     -0.692      0.489
-3.993       1.911
MoSold                                -16.9945    276.902     -0.061      0.951
-560.176     526.188
zone_low_density                     6488.6639   2135.912      3.038      0.002
2298.775    1.07e+04
one_story_style                      6570.5700   3002.646      2.188      0.029
680.461    1.25e+04
two_story_style                     -2732.2378   4015.387     -0.680      0.496
-1.06e+04    5144.504
one_half_story_style                  659.9872   3689.555      0.179      0.858
-6577.590    7897.564
typical_functionality                1.371e+04   3210.058      4.272      0.000
7415.270       2e+04
sale_normal_condition               -7827.3892   2033.137     -3.850      0.000
-1.18e+04   -3839.107
gas_heating                         -4403.7303   5333.956     -0.826      0.409
-1.49e+04    6059.570
time_taken_to_remodel                 -18.4268     29.553     -0.624      0.533
-76.399      39.546
time_taken_to_sell                   -226.4515     38.136     -5.938      0.000
-301.261    -151.642
time_taken_to_sell_after_remodel  -208.0247     37.895     -5.490      0.000
-282.361    -133.689
intercept                           -2.603e+05   1.13e+05     -2.308      0.021
-4.81e+05   -3.91e+04
==============================================================================
Omnibus:                      422.947   Durbin-Watson:                   2.035
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4012.154
Skew:                           1.071   Prob(JB):                         0.00
Kurtosis:                      10.845   Cond. No.                     1.01e+16
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is  3e-21. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
"""
```

4 Sklearn Models Analysis

[52]:
```
features_cols = [
    "time_taken_to_sell",
    "OverallQual",
    "OverallCond",
```

```
    "MasVnrArea",
    "TotalBsmtSF",
    "GrLivArea",
    "BedroomAbvGr",
    "TotRmsAbvGrd",
    "GarageArea",
    "ScreenPorch",
    "zone_low_density",
    "typical_functionality",
    "sale_normal_condition",
]
```

[53]:
```
features_df = train_df[features_cols]
features_df.head()
```

[53]:
```
   time_taken_to_sell  OverallQual  OverallCond  MasVnrArea  TotalBsmtSF  \
0                   5            7            5       196.0          856
1                  31            6            8         0.0         1262
2                   7            7            5       162.0          920
3                  91            7            5         0.0          756
4                   8            8            5       350.0         1145

   GrLivArea  BedroomAbvGr  TotRmsAbvGrd  GarageArea  ScreenPorch  \
0       1710             3             8         548            0
1       1262             3             6         460            0
2       1786             3             6         608            0
3       1717             3             7         642            0
4       2198             4             9         836            0

   zone_low_density  typical_functionality  sale_normal_condition
0                 1                      1                      1
1                 1                      1                      1
2                 1                      1                      1
3                 1                      1                      0
4                 1                      1                      1
```

[54]:
```
X = features_df.values
y = train_df['SalePrice']
```

[55]:
```
sc = StandardScaler()

X = sc.fit_transform(X)
X
```

[55]:
```
array([[-1.04612544,  0.66564559, -0.51746143, …,  0.51903606,
         0.27156272,  0.46516048],
       [-0.18625648, -0.06470858,  2.17654515, …,  0.51903606,
```

```
         0.27156272,  0.46516048],
       [-0.97998167,  0.66564559, -0.51746143, …,  0.51903606,
         0.27156272,  0.46516048],
       …,
       [ 1.07047507,  0.66564559,  3.07454735, …,  0.51903606,
         0.27156272,  0.46516048],
       [ 0.77282812, -0.79506274,  0.38054077, …,  0.51903606,
         0.27156272,  0.46516048],
       [ 0.21060611, -0.79506274,  0.38054077, …,  0.51903606,
         0.27156272,  0.46516048]])
```

[56]:
```
x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=TEST_SIZE,
                                                    random_state=RANDOM_STATE)

assert x_train.shape[1] == x_test.shape[1]
```

4.1 Linear Model

[57]:
```
lm = LinearRegression()
lm.fit(x_train, y_train)
lm_preds = lm.predict(x_test)

print("R2 Score for Linear Model : ", lm.score(x_test, y_test))
print("RMSE for Linear Model : ", np.sqrt(mean_squared_error(y_test, lm_preds)))
```

```
R2 Score for Linear Model :  0.8464733772982462
RMSE for Linear Model :  28386.122329701033
```

4.2 RandomForest Model

[58]:
```
rf_model = RandomForestRegressor()
rf_model.fit(x_train, y_train)
rf_preds = rf_model.predict(x_test)

print("R2 Score for Random Forest Model : ", rf_model.score(x_test, y_test))
print("RMSE for Random Forest Model : ", np.sqrt(mean_squared_error(y_test,␣
 ↪rf_preds)))
```

```
R2 Score for Random Forest Model :  0.8718567738601649
RMSE for Random Forest Model :  25933.554655943077
```

4.3 DecisionTreeRegressor Model

[59]:
```
dt_model = DecisionTreeRegressor()
dt_model.fit(x_train, y_train)
dt_preds = dt_model.predict(x_test)
```

```
print("R2 Score for Decision Tree Model : ", rf_model.score(x_test, y_test))
print("RMSE for Decision Tree Model : ", np.sqrt(mean_squared_error(y_test,␣
↪dt_preds)))
```

```
R2 Score for Decision Tree Model :  0.8718567738601649
RMSE for Decision Tree Model :  39583.2371666652
```

Random Forest Model is the best till this moment with **RMSE = 25126.752** and **R2 = 0.8797** and I will use to predict the test dataframe

4.4 Generating Prediction on Test DataFrame

4.4.1 Cleaning Test Dataset like in Train Dataset

[60]:
```
## MSZoning Column
test_df['zone_low_density'] = test_df['MSZoning'] == "RL"

## HouseStyle Column
test_df['one_story_style'] = test_df['HouseStyle'] == '1Story'
test_df['two_story_style'] = test_df['HouseStyle'] == '2Story'
test_df['one_half_story_style'] = test_df['HouseStyle'] == '1.5Fin'

## Functional Column
test_df['typical_functionality'] = test_df['Functional'] == 'Typ'

## Sale Condition
test_df['sale_normal_condition'] = test_df['SaleCondition'] == 'Normal'

## Heating Column
test_df['gas_heating'] = test_df['Heating'] == 'GasA'

## conver to numeric values
cols = ['zone_low_density', 'one_story_style', 'two_story_style',␣
↪'typical_functionality',
        'one_half_story_style', 'gas_heating', 'sale_normal_condition']

test_df[cols] = test_df[cols].astype('int')

# test_df[
#     ['zone_low_density', 'one_story_style', 'two_story_style',␣
↪'typical_functionality',
#      'one_half_story_style', 'gas_heating', 'sale_normal_condition']
# ].head()
```

[61]:
```
test_df['time_taken_to_sell'] = test_df['YrSold'] - test_df['YearBuilt']
```

[62]:
```
test_features_df = test_df[features_cols]
test_features_df.head()
```

[62]:
```
   time_taken_to_sell  OverallQual  OverallCond  MasVnrArea  TotalBsmtSF  \
0                  49            5            6         0.0        882.0
1                  52            6            6       108.0       1329.0
2                  13            5            5         0.0        928.0
3                  12            6            6        20.0        926.0
4                  18            8            5         0.0       1280.0

   GrLivArea  BedroomAbvGr  TotRmsAbvGrd  GarageArea  ScreenPorch  \
0        896             2             5       730.0          120
1       1329             3             6       312.0            0
2       1629             3             6       482.0            0
3       1604             3             7       470.0            0
4       1280             2             5       506.0          144

   zone_low_density  typical_functionality  sale_normal_condition
0                 0                      1                      1
1                 1                      1                      1
2                 1                      1                      1
3                 1                      1                      1
4                 1                      1                      1
```

[63]:
```
test_features_df.isna().sum()
```

[63]:
```
time_taken_to_sell        0
OverallQual               0
OverallCond               0
MasVnrArea               15
TotalBsmtSF               1
GrLivArea                 0
BedroomAbvGr              0
TotRmsAbvGrd              0
GarageArea                1
ScreenPorch               0
zone_low_density          0
typical_functionality     0
sale_normal_condition     0
dtype: int64
```

[64]:
```
test_features_df['MasVnrArea'].fillna(test_features_df['MasVnrArea'].mean(),␣
 ↪inplace=True)
test_features_df['TotalBsmtSF'].fillna(test_features_df['TotalBsmtSF'].mean(),␣
 ↪inplace=True)
test_features_df['GarageArea'].fillna(test_features_df['GarageArea'].mean(),␣
 ↪inplace=True)

assert len(test_features_df.isna().sum()[test_features_df.isna().sum() != 0])␣
 ↪== 0
```

[65]:
```python
X_test = test_features_df.values
X_test = sc.fit_transform(X_test)
X_test
```

[65]:
```
array([[ 0.41378443, -0.75110125,  0.40076604, …, -1.79693781,
         0.27416383,  0.46021084],
       [ 0.51239787, -0.05487716,  0.40076604, …,  0.55650229,
         0.27416383,  0.46021084],
       [-0.76957685, -0.75110125, -0.49741776, …,  0.55650229,
         0.27416383,  0.46021084],
       …,
       [ 0.31517099, -0.75110125,  1.29894985, …,  0.55650229,
         0.27416383, -2.17291708],
       [-0.73670571, -0.75110125, -0.49741776, …,  0.55650229,
         0.27416383,  0.46021084],
       [-0.76957685,  0.64134693, -0.49741776, …,  0.55650229,
         0.27416383,  0.46021084]])
```

4.4.2 Evaluating Best Machine Learning Model.

[66]:
```python
test_preds = rf_model.predict(X_test)
test_preds
```

[66]:
```
array([129459.  , 154134.5 , 172650.33, …, 151392.5 , 113305.   ,
       233236.3 ])
```

[67]:
```python
test_df['SalePrice'] = test_preds
test_df[['Id', 'SalePrice']].head()
```

[67]:

	Id	SalePrice
0	1461	129459.00
1	1462	154134.50
2	1463	172650.33
3	1464	190920.00
4	1465	210673.91

[68]:
```python
## exporting the predictions to csv
test_df[['Id', 'SalePrice']].to_csv('predictions_1.csv', index=False)
```

4.5 PyTorch Neural Network Model

[69]:
```python
class HouseDataset(Dataset):
    def __init__(self, x_data, y_data, transform=None):
        """
        Args:
            x_data (np.ndarray) : x_train data array
```

```
            y_data (np.ndarray) : y_train data array
            transform (callable, optional): Optional transform to be applied
                on a sample.
        """

        self.x_data = x_data
        self.y_data = y_data
        self.transform = transform

    def __len__(self):
        return self.x_data.shape[0]

    def __getitem__(self, idx):
        if torch.is_tensor(idx):
            idx = idx.tolist()

        if not isinstance(self.y_data, np.ndarray):
            self.y_data = np.array(self.y_data)

        x_sample = self.x_data[idx]
        y_sample = self.y_data[idx]

        if self.transform is not None:
            x_sample = self.transform(x_sample)

        return x_sample, y_sample


train_ds = HouseDataset(x_train, y_train)
train_dl = DataLoader(train_ds, batch_size=BATCH_SIZE, shuffle=True)

sample = next(iter(train_dl))
sample[0], sample[1]
```

[69]:
```
(tensor([[ 1.4673e+00,  6.6565e-01,  1.2785e+00, -5.7750e-01, -7.8313e-01,
           2.7081e-01,  1.6591e-01, -3.1416e-01,  3.5123e-01, -2.7061e-01,
          -1.9266e+00,  2.7156e-01,  4.6516e-01],
         [-1.0131e+00,  2.8567e+00, -5.1746e-01,  3.4103e+00,  3.8405e+00,
           2.2682e+00, -1.0603e+00,  9.2712e-01,  1.5687e+00, -2.7061e-01,
           5.1904e-01,  2.7156e-01,  4.6516e-01],
         [ 5.0825e-01, -7.9506e-01, -5.1746e-01, -5.7750e-01, -2.5501e+00,
          -7.7017e-01,  1.6591e-01, -9.3479e-01, -2.2253e+00, -2.7061e-01,
           5.1904e-01, -3.6824e+00,  4.6516e-01],
         [ 7.8319e-02, -7.9506e-01,  3.8054e-01, -1.4761e-01, -1.1810e-01,
          -1.0158e+00,  1.6591e-01, -9.3479e-01,  2.0312e+00, -2.7061e-01,
           5.1904e-01,  2.7156e-01,  4.6516e-01],
         [ 1.4673e+00, -7.9506e-01,  1.2785e+00, -5.7750e-01, -3.0256e-01,
```

```
 -3.8358e-01,  1.6591e-01, -3.1416e-01,  5.8662e-02, -2.7061e-01,
 -1.9266e+00,  2.7156e-01,  4.6516e-01],
[ 2.7675e-01, -7.9506e-01, -5.1746e-01, -5.7750e-01,  2.1684e-01,
  3.8156e-01,  1.6591e-01,  9.2712e-01, -5.7839e-01, -2.7061e-01,
  5.1904e-01, -3.6824e+00,  4.6516e-01],
[ 1.8973e+00, -6.4709e-02,  3.8054e-01, -5.7750e-01, -7.4915e-01,
 -4.5308e-02,  1.6591e-01,  1.5478e+00, -2.2253e+00, -2.7061e-01,
 -1.9266e+00,  2.7156e-01,  4.6516e-01],
[ 1.0043e+00, -7.9506e-01,  1.2785e+00, -5.7750e-01, -6.2536e-01,
 -7.8225e-01,  1.6591e-01, -9.3479e-01, -2.9054e-01,  4.5852e+00,
 -1.9266e+00,  2.7156e-01,  4.6516e-01],
[-7.1541e-01,  1.3960e+00, -5.1746e-01, -5.7750e-01,  6.9498e-01,
 -3.4129e-01, -1.0603e+00, -9.3479e-01, -4.5154e-02, -2.7061e-01,
  5.1904e-01,  2.7156e-01,  4.6516e-01],
[-1.2115e+00,  1.3960e+00, -5.1746e-01,  1.1194e+00,  1.2896e+00,
  1.3178e+00,  1.6591e-01,  9.2712e-01,  1.4979e+00, -2.7061e-01,
  5.1904e-01,  2.7156e-01, -2.1498e+00],
[ 5.7440e-01, -7.9506e-01, -5.1746e-01, -5.7750e-01,  8.0663e-01,
 -2.4867e-01,  1.6591e-01, -3.1416e-01, -5.5480e-01, -2.7061e-01,
  5.1904e-01,  2.7156e-01,  4.6516e-01],
[-1.8626e-01, -6.4709e-02,  1.2785e+00,  4.0672e-01,  2.2412e-01,
 -7.9232e-01,  1.6591e-01, -3.1416e-01,  1.5304e-01, -2.7061e-01,
  5.1904e-01,  2.7156e-01,  4.6516e-01],
[-1.0461e+00,  6.6565e-01, -5.1746e-01,  1.0742e+00, -1.2781e-01,
  1.0863e+00,  1.6591e-01,  9.2712e-01,  1.8849e+00, -2.7061e-01,
  5.1904e-01,  2.7156e-01,  4.6516e-01],
[-1.1453e+00,  1.3960e+00, -5.1746e-01, -5.7750e-01, -8.3409e-01,
 -1.8625e-01,  1.6591e-01, -3.1416e-01, -3.2357e-01, -2.7061e-01,
  5.1904e-01,  2.7156e-01,  4.6516e-01],
[-1.1453e+00,  1.3960e+00, -5.1746e-01, -5.7750e-01,  1.0081e+00,
 -8.1551e-02,  1.6591e-01,  3.0648e-01,  6.5324e-01, -2.7061e-01,
  5.1904e-01,  2.7156e-01,  4.6516e-01],
[-1.1453e+00, -6.4709e-02, -5.1746e-01,  8.7054e-01,  7.5566e-01,
 -2.9096e-01, -1.0603e+00, -3.1416e-01, -5.4591e-02, -2.7061e-01,
  5.1904e-01,  2.7156e-01,  4.6516e-01],
[-1.1784e+00, -6.4709e-02, -5.1746e-01, -1.5893e-01, -3.8023e-01,
  8.5876e-01,  1.3921e+00,  1.5478e+00,  9.2694e-01, -2.7061e-01,
  5.1904e-01,  2.7156e-01,  4.6516e-01],
[ 2.1061e-01, -6.4709e-02,  3.8054e-01, -5.7750e-01,  2.0713e-01,
 -7.4601e-01,  1.6591e-01, -9.3479e-01, -4.1323e-01, -2.7061e-01,
  5.1904e-01,  2.7156e-01,  4.6516e-01],
[-1.5318e-01, -6.4709e-02,  3.8054e-01,  2.1440e-01, -8.7536e-01,
 -1.6209e-01,  1.6591e-01, -3.1416e-01, -1.4897e-01, -2.7061e-01,
  5.1904e-01,  2.7156e-01,  4.6516e-01],
[ 1.7319e+00, -7.9506e-01,  1.2785e+00, -5.7750e-01, -5.6954e-01,
 -1.8223e-01,  1.6591e-01,  3.0648e-01,  4.9280e-01, -2.7061e-01,
  5.1904e-01,  2.7156e-01,  4.6516e-01],
```

```
        [-1.0131e+00, -6.4709e-02, -5.1746e-01,  3.8409e-01, -4.9187e-01,
         -1.3259e+00, -2.2865e+00, -1.5554e+00, -2.4335e-01, -2.7061e-01,
         -1.9266e+00,  2.7156e-01,  4.6516e-01],
        [-1.2115e+00,  6.6565e-01,  3.8054e-01, -5.7750e-01, -4.2877e-01,
          5.1243e-01,  1.6591e-01,  3.0648e-01,  5.0224e-01, -2.7061e-01,
         -1.9266e+00,  2.7156e-01, -2.1498e+00],
        [-1.2115e+00, -6.4709e-02, -5.1746e-01, -1.9286e-01,  5.1295e-01,
         -4.9231e-01, -1.0603e+00, -9.3479e-01,  4.7393e-01, -2.7061e-01,
         -1.9266e+00,  2.7156e-01, -2.1498e+00],
        [ 5.0825e-01, -7.9506e-01, -5.1746e-01, -5.7750e-01, -1.6180e+00,
         -2.9498e-01,  1.6591e-01, -3.1416e-01,  4.7393e-01, -2.7061e-01,
          5.1904e-01, -3.6824e+00,  4.6516e-01],
        [-1.2115e+00,  1.3960e+00, -5.1746e-01, -1.7024e-01,  6.0518e-01,
         -3.8761e-01,  1.6591e-01, -3.1416e-01,  3.7955e-01, -2.7061e-01,
         -1.9266e+00,  2.7156e-01, -2.1498e+00],
        [ 6.0747e-01, -7.9506e-01, -1.4155e+00, -5.7750e-01, -5.8168e-01,
         -2.4062e-01,  1.6591e-01,  3.0648e-01, -1.0172e+00, -2.7061e-01,
         -1.9266e+00,  2.7156e-01,  4.6516e-01],
        [ 1.3681e+00, -7.9506e-01,  1.2785e+00, -5.7750e-01, -8.1468e-01,
         -1.2715e+00, -1.0603e+00, -9.3479e-01, -1.3759e+00, -2.7061e-01,
         -1.9266e+00,  2.7156e-01,  4.6516e-01],
        [-1.0792e+00,  6.6565e-01, -5.1746e-01,  1.9226e+00, -4.4333e-01,
         -7.2588e-01,  1.6591e-01, -3.1416e-01, -1.5841e-01, -2.7061e-01,
          5.1904e-01,  2.7156e-01,  4.6516e-01],
        [-1.1784e+00,  6.6565e-01, -5.1746e-01,  8.9868e-03,  9.1585e-01,
         -1.5806e-01,  1.6591e-01, -3.1416e-01,  3.9787e-02, -2.7061e-01,
         -1.9266e+00,  2.7156e-01, -2.1498e+00],
        [ 2.4368e-01, -6.4709e-02,  3.8054e-01, -5.7750e-01,  1.1319e+00,
          7.6815e-01, -1.0603e+00, -3.1416e-01,  5.0224e-01, -2.7061e-01,
          5.1904e-01, -3.6824e+00,  4.6516e-01],
        [-1.2011e-01, -6.4709e-02,  3.8054e-01,  8.6489e-01, -2.3443e-02,
         -7.6816e-01,  1.6591e-01, -3.1416e-01, -5.6423e-01, -2.7061e-01,
          5.1904e-01,  2.7156e-01, -2.1498e+00],
        [-7.8155e-01, -6.4709e-02, -5.1746e-01,  1.6424e-02, -2.9770e-01,
          4.3189e-01,  1.6591e-01,  3.0648e-01, -2.6836e-03, -2.7061e-01,
          5.1904e-01,  2.7156e-01,  4.6516e-01]], dtype=torch.float64),
tensor([178000, 466500,  93000, 148500, 130000, 143900, 128000, 119900, 180000,
        325624, 165000, 148000, 284000, 178000, 201000, 194700, 214000, 140000,
        159500, 112000, 140000, 227875, 185000, 130000, 229456,  93000, 105000,
        187500, 182000, 190000, 125000, 201000]))
```

[70]:
```
class NNet(nn.Module):
    def __init__(self, input_size: int, hidden_sizes: list, output_size: int=1)␣
 ↪-> None:
        super().__init__()

        self.fc1 = nn.Linear(input_size, hidden_sizes[0])
```

```python
        self.fc2 = nn.Linear(hidden_sizes[0], hidden_sizes[1])
        self.fc3 = nn.Linear(hidden_sizes[1], hidden_sizes[2])
        self.fc4 = nn.Linear(hidden_sizes[2], output_size)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = F.relu(self.fc3(x))
        out = self.fc4(x)

        return out

class RMSELoss(nn.Module):
    def __init__(self):
        super().__init__()

        self.mse = nn.MSELoss()

    def forward(self, y_pred, y_true):
        return torch.sqrt(self.mse(y_pred, y_true))
```

[71]:
```python
def train(train_dl, model, optimizer, criterion, epochs=100) -> list:
    losses = []

    print("{:<8}|{:>15}".format("Epoch", "Loss"))
    print("="*24)
    epoch_loss = 0

    for epoch in range(epochs):
        epoch_losses = []
        for x_batch, y_batch in train_dl:

            y_preds = model(x_batch.float())
            loss = criterion(y_preds, y_batch.float())

            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            epoch_loss += loss.item()
            epoch_losses.append(loss.item())

        losses.append(np.mean(epoch_losses))

        if epoch % 10 == 0:
            print("{:<8}|{:>15}".format(epoch, round(np.mean(epoch_losses), 3)))
```

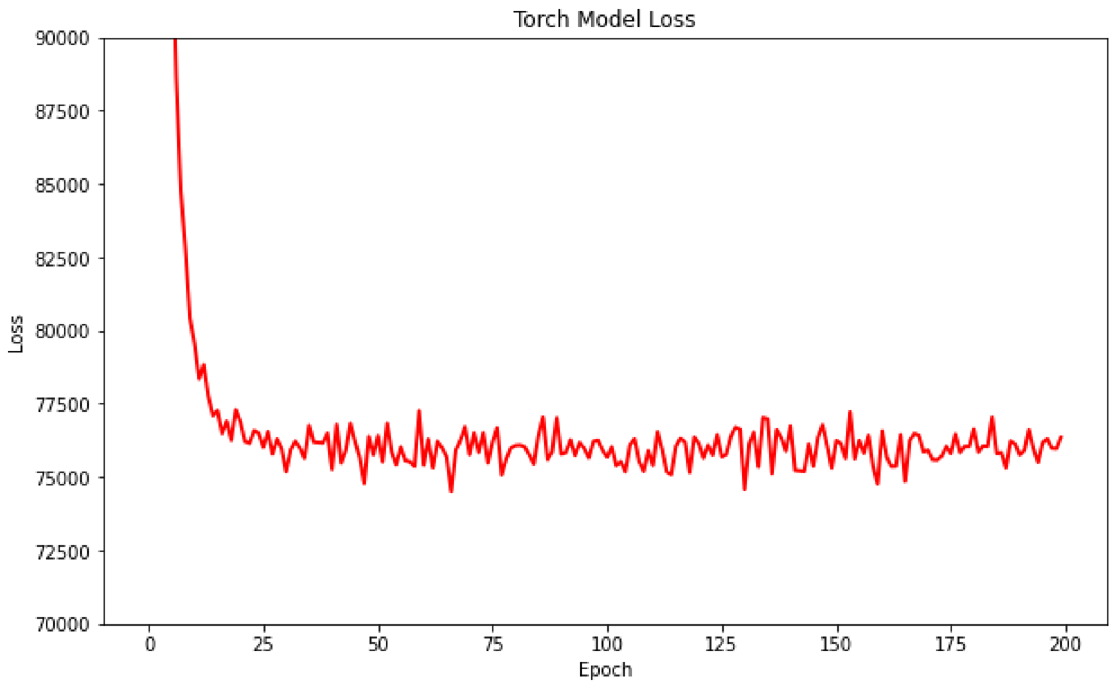
```
    return losses
```

[72]:
```
## initializing mode
n_feaures = x_train.shape[1]
hidden_sizes = [32, 16, 8]
output_size = 1

model = NNet(n_feaures, hidden_sizes, output_size)

print(model)

## training Model
optimizer = optim.Adam(model.parameters(), lr=LR)
criterion = RMSELoss()

losses = train(train_dl, model, optimizer, criterion, epochs=200)
```

```
NNet(
  (fc1): Linear(in_features=13, out_features=32, bias=True)
  (fc2): Linear(in_features=32, out_features=16, bias=True)
  (fc3): Linear(in_features=16, out_features=8, bias=True)
  (fc4): Linear(in_features=8, out_features=1, bias=True)
)
Epoch    |            Loss
========================
0        |      196045.524
10       |       79553.088
20       |       76881.525
30       |       75187.745
40       |       75267.642
50       |        76417.62
60       |       75412.843
70       |       75768.498
80       |       76077.083
90       |       75788.585
100      |       75680.965
110      |       75396.359
120      |       76147.532
130      |       74582.772
140      |       76748.031
150      |        76243.72
160      |       76572.471
170      |       75917.212
180      |       76640.626
190      |       75758.835
```

[73]:
```
%matplotlib inline

fig, ax = plt.subplots(nrows=1, figsize=(10, 6))

ax.plot(losses, 'r-', lw=2)
ax.set_title("Torch Model Loss")
ax.set_xlabel("Epoch")
ax.set_ylabel("Loss");
ax.set_ylim([70000, 90000])
```

[73]: (70000.0, 90000.0)



[ ]:
```
```