

# House Price Prediction - Individual project

## Importing data

The required data and libraries are imported and datasets are analyzed for Null values and their structure

In [6]: `import pandas as pd`

```
house_train = pd.read_csv(r'C:\Users\Riaz\Desktop\MSDS\Predictive Analysis\Week 2\train.
pd.set_option('display.max_columns', None)
print ("The Null values present in dataset\n",house_train[house_train.columns[house_train
print("The house dataset is \n")
print(house_train.info())
```

The Null values present in dataset

```
LotFrontage      259
Alley            1369
MasVnrType        872
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

The house dataset is

<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	588	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)

# Data Adjustments

Data has been adjusted and a new feature created by adding the columns of basement and living area, to come up with the total grand area.

```
In [2]: # Total area including basement

house_train['GrandArea'] = house_train['TotalBsmtSF'] + house_train['GrLivArea']
```

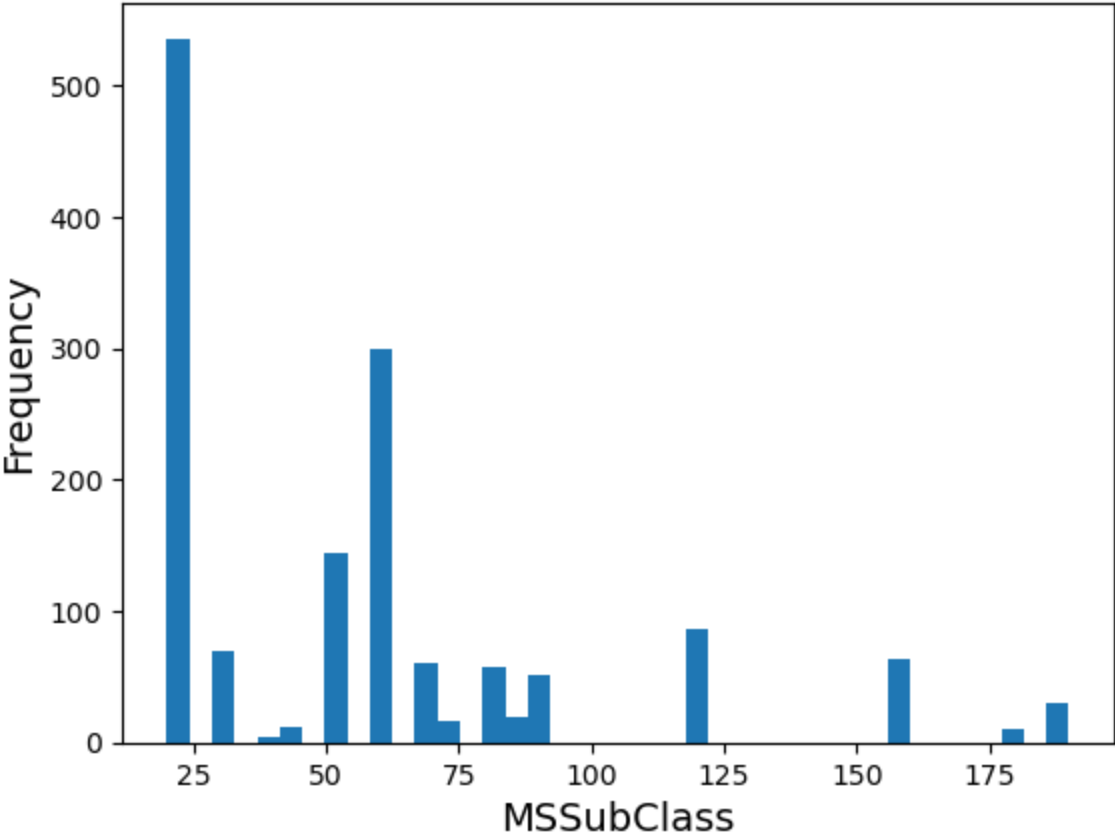
## Visualization

Various visualization like frequency distribution, box plots, bar charts has been plotted for different variables. For better understanding, please refer the accompanying word document.

```
In [3]: import matplotlib.pyplot as plt
plt.title('Frequency Distribution of MSSubClass', fontsize=16)
plt.xlabel('MSSubClass', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
plt.hist(house_train['MSSubClass'],bins=40)

Out[3]: (array([536.,  0.,  69.,  0.,  4., 12.,  0., 144.,  0., 299.,  0.,
        60., 16.,  0., 58., 20., 52.,  0.,  0.,  0.,  0.,  0.,
        0., 87.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0., 63.,
        0.,  0.,  0.,  0., 10.,  0., 30.]),
array([ 20. ,  24.25,  28.5 ,  32.75,  37.  ,  41.25,  45.5 ,  49.75,
        54.  ,  58.25,  62.5 ,  66.75,  71.  ,  75.25,  79.5 ,  83.75,
        88.  ,  92.25,  96.5 , 100.75, 105.  , 109.25, 113.5 , 117.75,
       122.  , 126.25, 130.5 , 134.75, 139.  , 143.25, 147.5 , 151.75,
       156.  , 160.25, 164.5 , 168.75, 173.  , 177.25, 181.5 , 185.75,
       190.  ]),
<BarContainer object of 40 artists>)
```

Frequency Distribution of MSSubClass

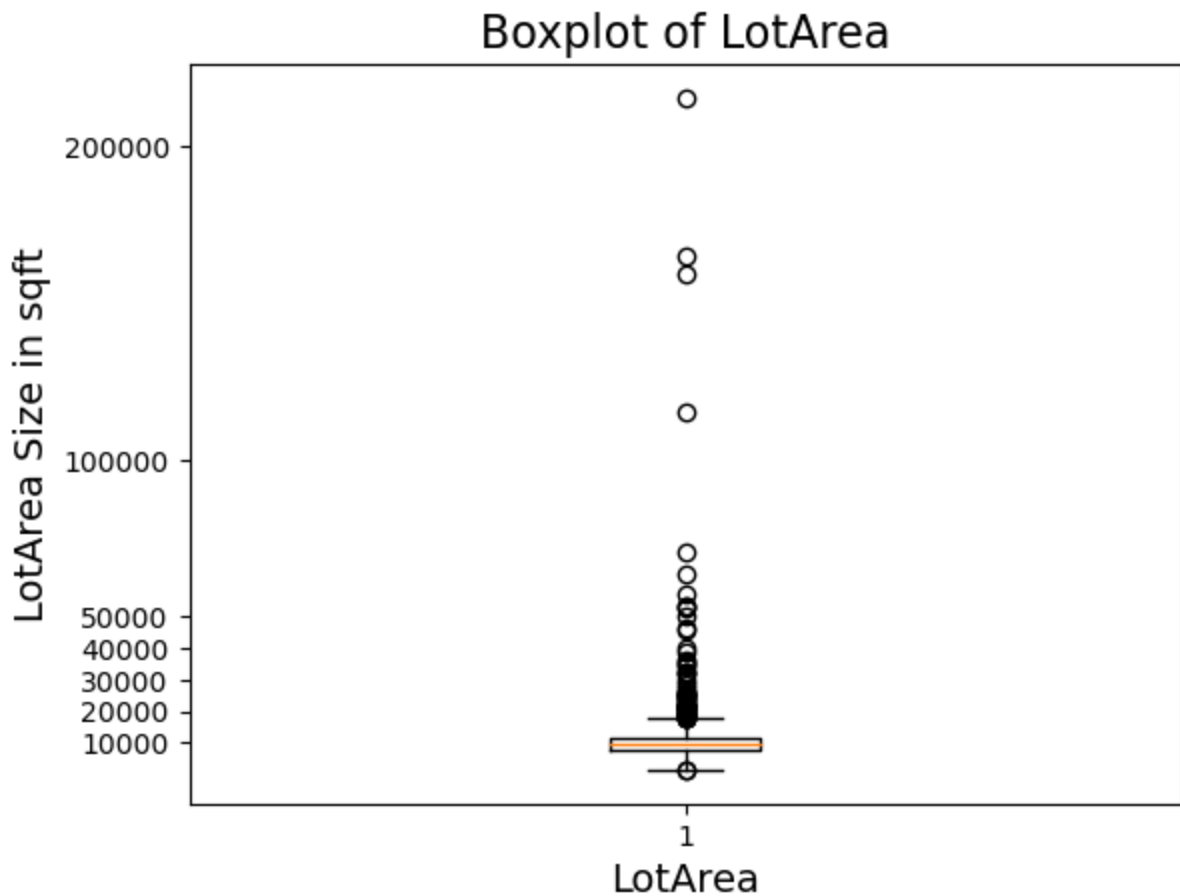


```
In [4]: plt.title('Boxplot of LotArea', fontsize=16)
plt.xlabel('LotArea', fontsize=14)
plt.ylabel('LotArea Size in sqft', fontsize=14)
plt.boxplot(house_train['LotArea'])
plt.yticks([10000,20000,30000,40000,50000,100000,200000])
pd.set_option('display.max_columns', None)
house_train[house_train['LotArea'] > 30000]
```

Out[4]:

	<b>Id</b>	<b>MSSubClass</b>	<b>MSZoning</b>	<b>LotFrontage</b>	<b>LotArea</b>	<b>Street</b>	<b>Alley</b>	<b>LotShape</b>	<b>LandContour</b>	<b>Utilities</b>	<b>LotC</b>	
	<b>53</b>	54	20	RL	68.0	50271	Pave	NaN	IR1	Low	AllPub	I
	<b>171</b>	172	20	RL	141.0	31770	Pave	NaN	IR1	Lvl	AllPub	C
	<b>249</b>	250	50	RL	NaN	159000	Pave	NaN	IR2	Low	AllPub	Cu
	<b>271</b>	272	20	RL	73.0	39104	Pave	NaN	IR1	Low	AllPub	Cu
	<b>313</b>	314	20	RL	150.0	215245	Pave	NaN	IR3	Low	AllPub	I
	<b>335</b>	336	190	RL	NaN	164660	Grvl	NaN	IR1	HLS	AllPub	C
	<b>384</b>	385	60	RL	NaN	53107	Pave	NaN	IR2	Low	AllPub	C
	<b>411</b>	412	190	RL	100.0	34650	Pave	NaN	Reg	Bnk	AllPub	I
	<b>451</b>	452	20	RL	62.0	70761	Pave	NaN	IR1	Low	AllPub	I
	<b>457</b>	458	20	RL	NaN	53227	Pave	NaN	IR1	Low	AllPub	Cu
	<b>523</b>	524	60	RL	130.0	40094	Pave	NaN	IR1	Bnk	AllPub	I
	<b>529</b>	530	20	RL	NaN	32668	Pave	NaN	IR1	Lvl	AllPub	Cu
	<b>661</b>	662	60	RL	52.0	46589	Pave	NaN	IR2	Lvl	AllPub	Cu
	<b>706</b>	707	20	RL	NaN	115149	Pave	NaN	IR2	Low	AllPub	Cu
	<b>769</b>	770	60	RL	47.0	53504	Pave	NaN	IR2	HLS	AllPub	Cu

<b>848</b>	849	50	RL	75.0	45600	Pave	NaN	IR2	Bnk	AllPub	I
<b>1169</b>	1170	60	RL	118.0	35760	Pave	NaN	IR1	Lvl	AllPub	Cu
<b>1184</b>	1185	20	RL	50.0	35133	Grvl	NaN	Reg	Lvl	AllPub	I
<b>1190</b>	1191	190	RL	NaN	32463	Pave	NaN	Reg	Low	AllPub	I
<b>1287</b>	1288	20	RL	NaN	36500	Pave	NaN	IR1	Low	AllPub	I
<b>1298</b>	1299	60	RL	313.0	63887	Pave	NaN	IR3	Bnk	AllPub	C
<b>1396</b>	1397	20	RL	NaN	57200	Pave	NaN	IR1	Bnk	AllPub	I



```
In [5]: house_train_lotarea=house_train[house_train['LotArea'] < 30000]
```

```
In [6]: import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

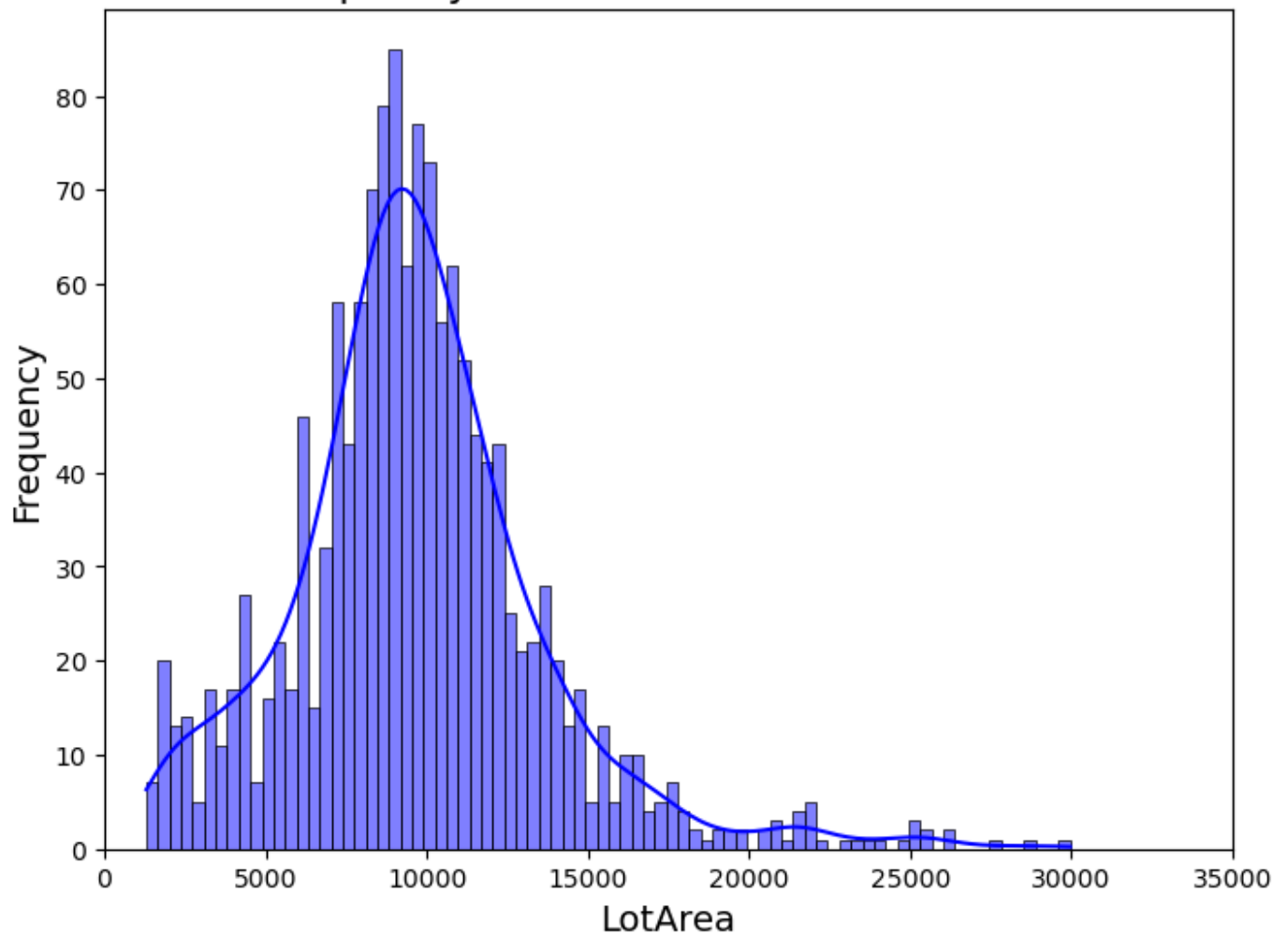
# Set up the plot
plt.figure(figsize=(8, 6))

# Plot a histogram with KDE (Kernel Density Estimate)
sns.histplot(house_train_lotarea['LotArea'], bins=80, kde=True, color='blue')

# Add titles and labels
plt.title('Frequency Distribution Curve of LotArea', fontsize=16)
plt.xlim(0,35000)
plt.xlabel('LotArea', fontsize=14)
plt.ylabel('Frequency', fontsize=14)

# Display the plot
plt.show()
```

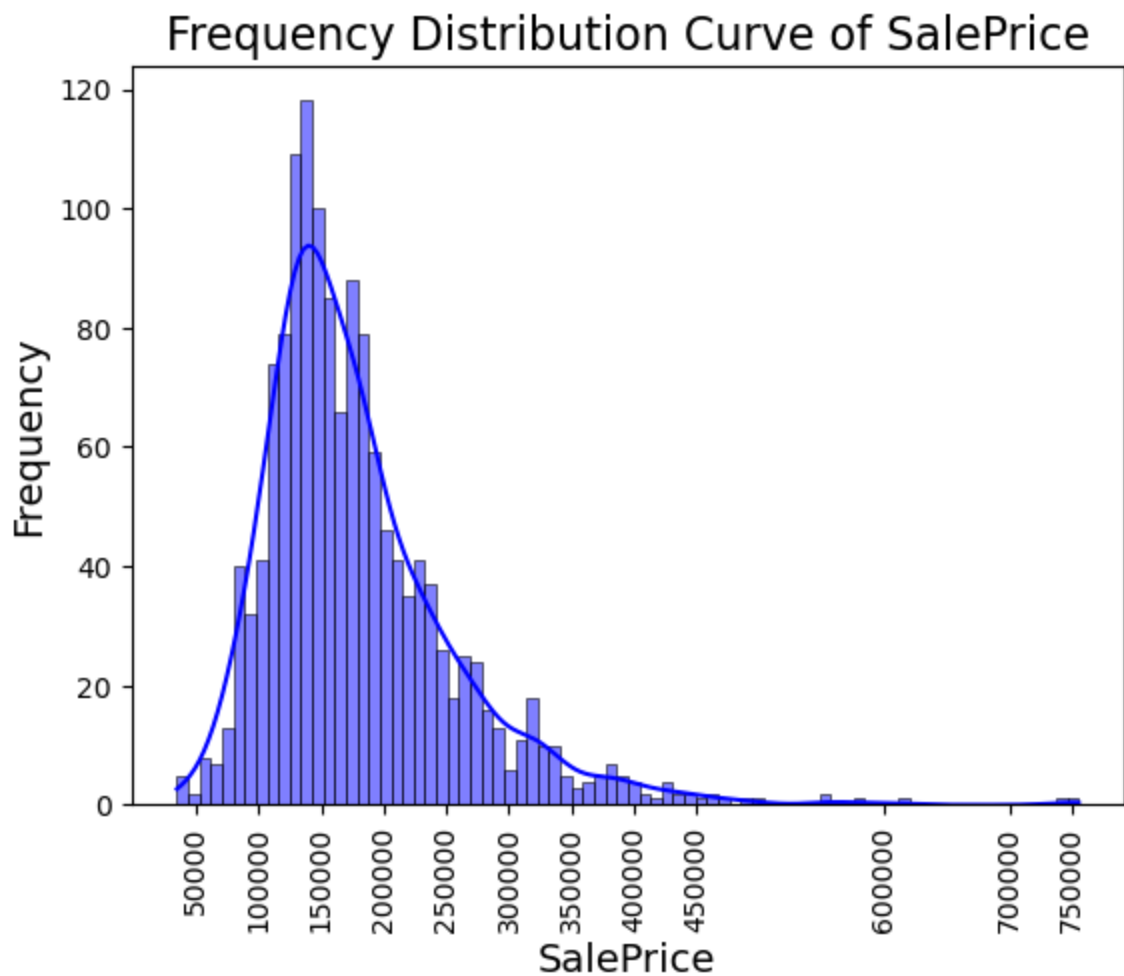
# Frequency Distribution Curve of LotArea



```
In [7]: sns.histplot(house_train_lotarea['SalePrice'], bins=80, kde=True, color='blue')

# Add titles and labels
plt.title('Frequency Distribution Curve of SalePrice', fontsize=16)
plt.xticks([50000, 100000, 150000, 200000, 250000, 300000, 350000, 400000, 450000, 600000, 700000],
plt.xlabel('SalePrice', fontsize=14)
plt.ylabel('Frequency', fontsize=14)

# Display the plot
plt.show()
```



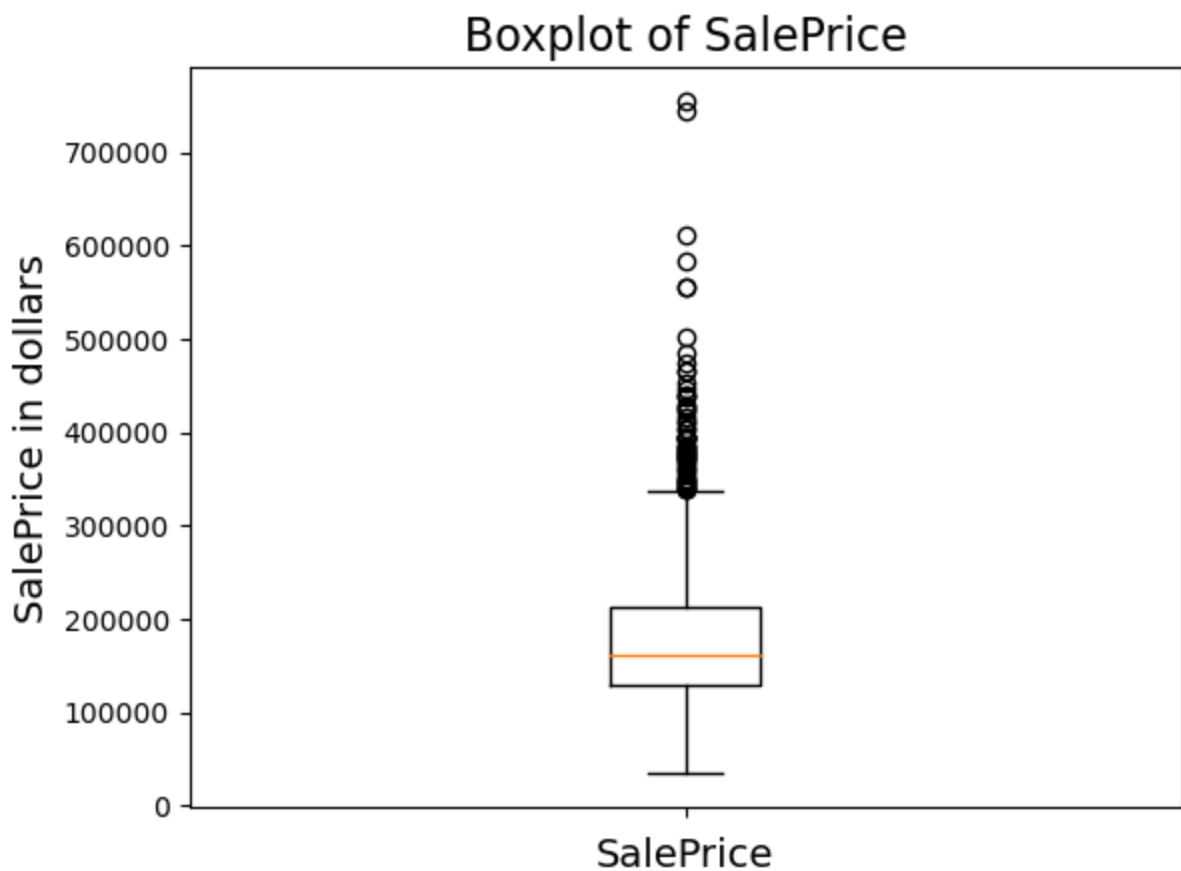
Rows having house sale price more than 400K USD has been displayed and it will be dropped.

```
In [8]: plt.title('Boxplot of SalePrice', fontsize=16)
plt.xticks([50000,100000,150000,200000,250000,300000,350000,400000,450000,600000,700000,
plt.xlabel('SalePrice', fontsize=14)
plt.ylabel('SalePrice in dollars', fontsize=14)
plt.boxplot(house_train_lotarea['SalePrice'])
house_train_lotarea[house_train_lotarea['SalePrice'] > 400000]
```

```
Out[8]:
```

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	LotC
58	59	60	RL	66.0	13682	Pave	NaN	IR2	HLS	AllPub	Cu
161	162	60	RL	110.0	13688	Pave	NaN	IR1	Lvl	AllPub	I
178	179	20	RL	63.0	17423	Pave	NaN	IR1	Lvl	AllPub	Cu
185	186	75	RM	90.0	22950	Pave	NaN	IR2	Lvl	AllPub	I
231	232	60	RL	174.0	15138	Pave	NaN	IR1	Lvl	AllPub	I
278	279	20	RL	107.0	14450	Pave	NaN	Reg	Lvl	AllPub	I
349	350	60	RL	56.0	20431	Pave	NaN	IR2	Lvl	AllPub	I
389	390	60	RL	96.0	12474	Pave	NaN	Reg	Lvl	AllPub	I
440	441	20	RL	105.0	15431	Pave	NaN	Reg	Lvl	AllPub	I
473	474	20	RL	110.0	14977	Pave	NaN	IR1	Lvl	AllPub	I
496	497	20	RL	NaN	12692	Pave	NaN	IR1	Lvl	AllPub	I
515	516	20	RL	94.0	12220	Pave	NaN	Reg	Lvl	AllPub	I

527	528	60	RL	67.0	14948	Pave	NaN	IR1	Lvl	AllPub	I
591	592	60	RL	97.0	13478	Pave	NaN	IR1	Lvl	AllPub	C
664	665	20	RL	49.0	20896	Pave	NaN	IR2	Lvl	AllPub	Cu
691	692	60	RL	104.0	21535	Pave	NaN	IR1	Lvl	AllPub	C
798	799	60	RL	104.0	13518	Pave	NaN	Reg	Lvl	AllPub	I
803	804	60	RL	107.0	13891	Pave	NaN	Reg	Lvl	AllPub	I
898	899	20	RL	100.0	12919	Pave	NaN	IR1	Lvl	AllPub	I
1046	1047	60	RL	85.0	16056	Pave	NaN	IR1	Lvl	AllPub	I
1142	1143	60	RL	77.0	9965	Pave	NaN	Reg	Lvl	AllPub	I
1182	1183	60	RL	160.0	15623	Pave	NaN	IR1	Lvl	AllPub	C
1243	1244	20	RL	107.0	13891	Pave	NaN	Reg	Lvl	AllPub	I
1353	1354	50	RL	56.0	14720	Pave	NaN	IR1	Lvl	AllPub	Cu
1373	1374	20	RL	NaN	11400	Pave	NaN	Reg	Lvl	AllPub	I



Finding out if there are any houses withouch kitchen and it will be dropped subsequently

```
In [9]: print ("There is a house where there are no kitchens\n\n",house_train_lotarea[house_train_lotarea['KitchenAbvGr'] < 1 , 'KitchenAbvGr'] = 1
```

There is a house where there are no kitchens

```
      Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
954  955           90      RL         35.0    9400   Pave   NaN    IR1

      LandContour Utilities LotConfig LandSlope Neighborhood Condition1  \
954           Lvl     AllPub    CulDSac      Gtl      Edwards        Norm
```



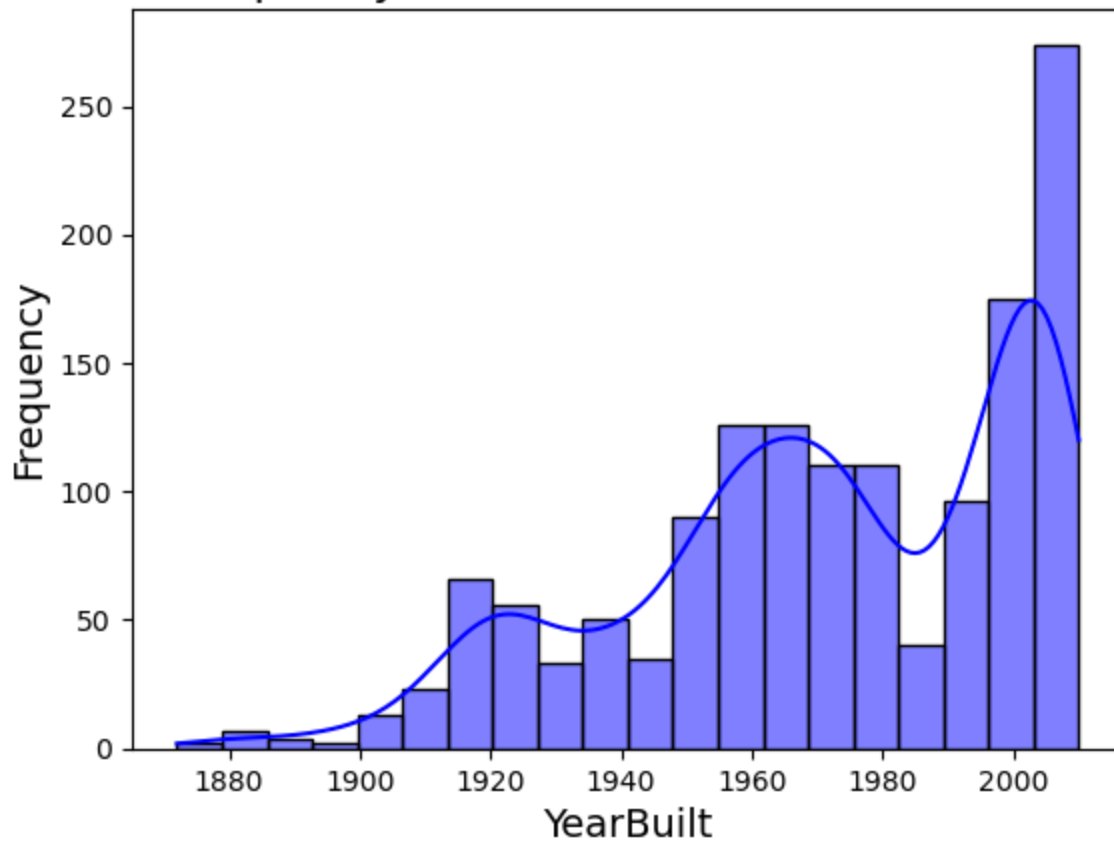
	Condition2	BldgType	HouseStyle	OverallQual	OverallCond	YearBuilt	\
954	Norm	Duplex	SFoyer	6	5	1975	
	YearRemodAdd	RoofStyle	RoofMatl	Exterior1st	Exterior2nd	MasVnrType	\
954	1975	Flat	Tar&Grv	WdShing	Plywood	BrkFace	
	MasVnrArea	ExterQual	ExterCond	Foundation	BsmtQual	BsmtCond	BsmtExposure \
954	250.0	TA	TA	CBlock	Gd	Gd	Gd
	BsmtFinType1	BsmtFinSF1	BsmtFinType2	BsmtFinSF2	BsmtUnfSF	TotalBsmtSF	\
954	GLQ	945	Unf	0	0	945	
	Heating	HeatingQC	CentralAir	Electrical	1stFlrSF	2ndFlrSF	LowQualFinSF \
954	GasA	TA	Y	SBrkr	980	0	0
	GrLivArea	BsmtFullBath	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	\
954	980	0	2	2	0	4	
	KitchenAbvGr	KitchenQual	TotRmsAbvGrd	Functional	Fireplaces	\	
954	0	TA	4	Typ	0		
	FireplaceQu	GarageType	GarageYrBlt	GarageFinish	GarageCars	GarageArea	\
954	NaN	NaN	NaN	NaN	0	0	
	GarageQual	GarageCond	PavedDrive	WoodDeckSF	OpenPorchSF	EnclosedPorch	\
954	NaN	NaN	Y	0	0	0	
	3SsnPorch	ScreenPorch	PoolArea	PoolQC	Fence	MiscFeature	MiscVal \
954	0	0	0	NaN	NaN	NaN	0
	MoSold	YrSold	SaleType	SaleCondition	SalePrice	GrandArea	
954	10	2006	WD	AdjLand	127500	1925	

```
In [10]: sns.histplot(house_train_lotarea['YearBuilt'], bins=20, kde=True, color='blue')

# Add titles and labels
plt.title('Frequency Distribution Curve of YearBuilt', fontsize=16)
plt.xlabel('YearBuilt', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
```

```
Out[10]: Text(0, 0.5, 'Frequency')
```

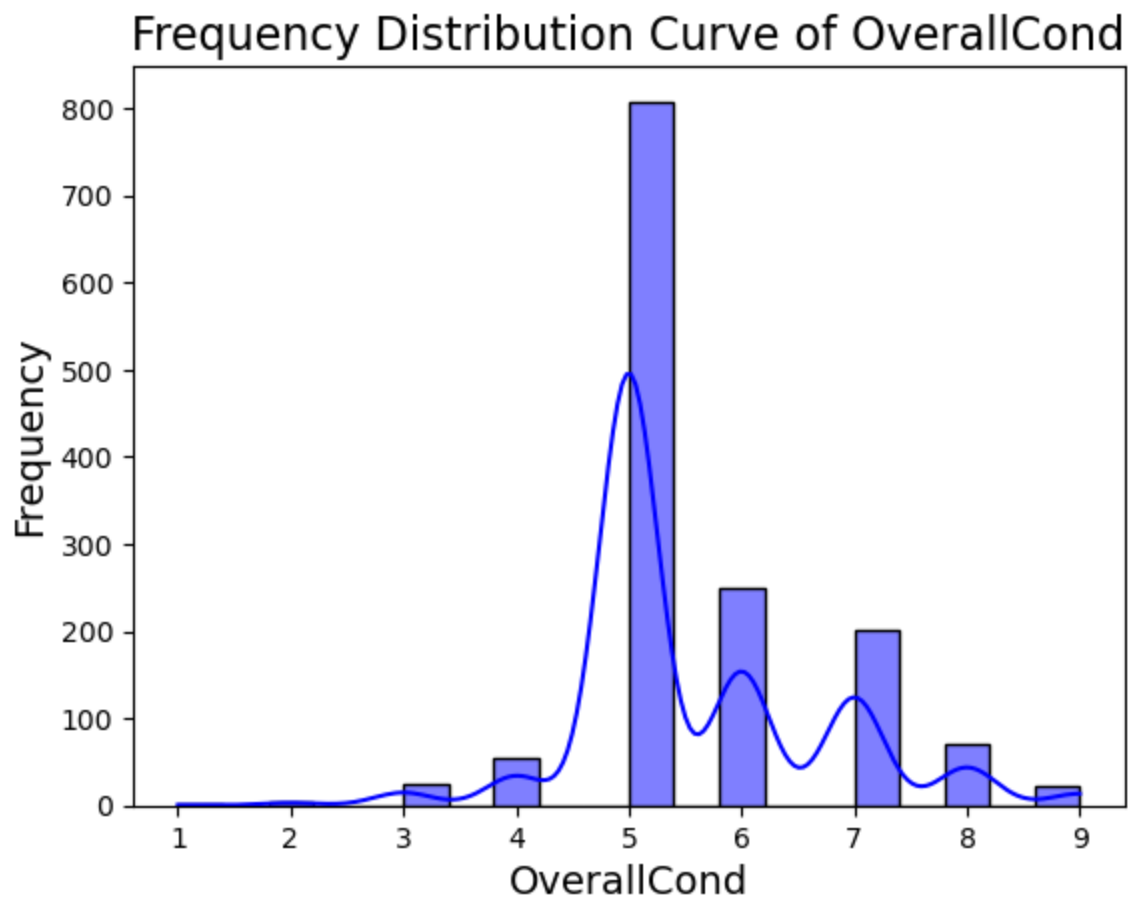
# Frequency Distribution Curve of YearBuilt



```
In [11]: sns.histplot(house_train_lotarea['OverallCond'], bins=20, kde=True, color='blue')

# Add titles and labels
plt.title('Frequency Distribution Curve of OverallCond', fontsize=16)
plt.xlabel('OverallCond', fontsize=14)
plt.ylabel('Frequency', fontsize=14)
```

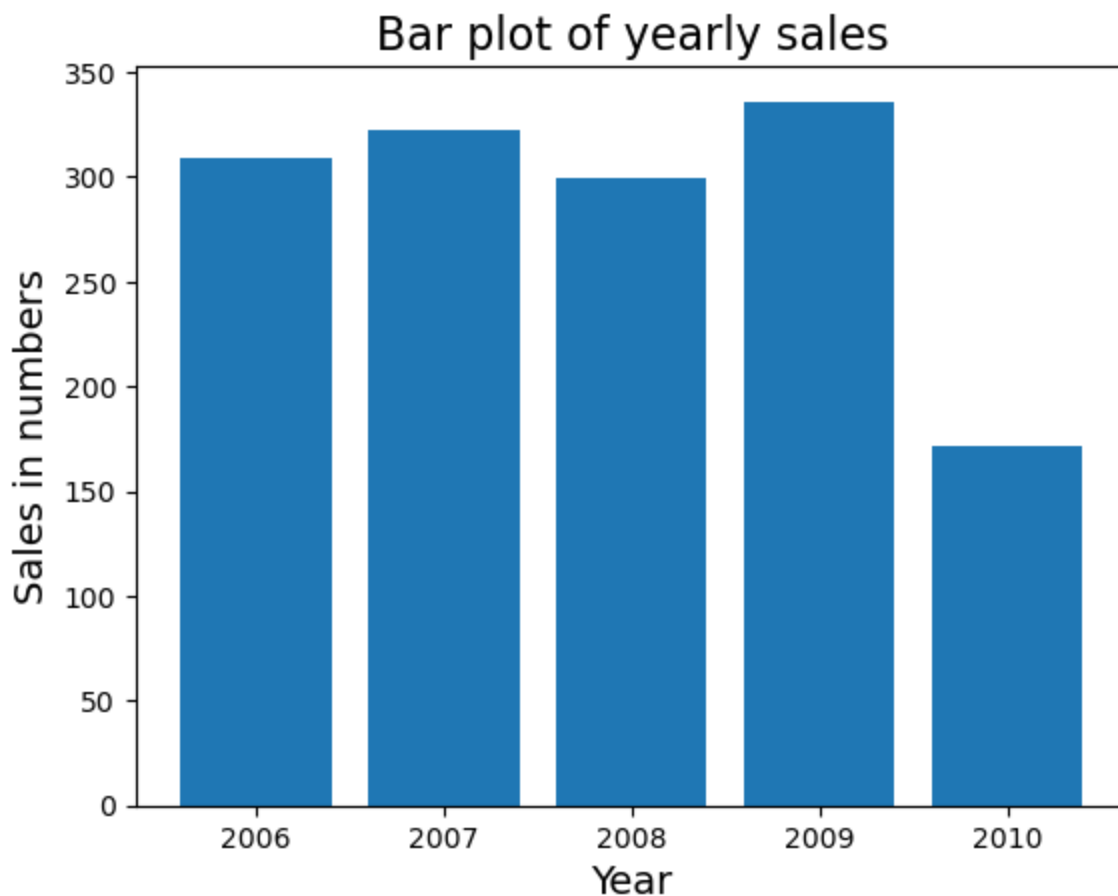
Out[11]: Text(0, 0.5, 'Frequency')



```
In [12]: plt.title('Bar plot of yearly sales', fontsize=16)
#plt.xticks([50000,100000,150000,200000,250000,300000,350000,400000,450000,600000,700000])
plt.xlabel('Year', fontsize=14)
plt.ylabel('Sales in numbers', fontsize=14)

plt.bar(house_train_lotarea.groupby('YrSold')['SalePrice'].count().index,house_train_lot

Out[12]: <BarContainer object of 5 artists>
```



## Data Preparation

The data which does not add value to the model has been found out and will be dropped.

They are determined based on the number of record counts present or on the basic understanding of the real estate market.

```
In [13]: print("Following are the count of columns which do not add any value to the model\n")
print("The count of Utilities column\n",house_train_lotarea['Utilities'].value_counts())
print("The count of Street column\n",house_train_lotarea['Street'].value_counts())
print("The count of PoolQC column\n",house_train_lotarea['PoolQC'].value_counts())
print("The count of Alley column\n",house_train_lotarea['Alley'].value_counts())
print("The count of MiscFeature column\n",house_train_lotarea['MiscFeature'].value_count
print("The count of Fence column\n",house_train_lotarea['Fence'].value_counts())
house_train_lotarea_dropped = house_train_lotarea.drop(['Utilities','Street','PoolQC','A
```

Following are the count of columns which do not add any value to the model

The count of Utilities column

Utilities

AllPub 1437

NoSeWa 1

Name: count, dtype: int64

The count of Street column

Street

Pave 1434

Grvl 4

Name: count, dtype: int64

The count of PoolQC column

PoolQC

Ex 2

Fa 2

Gd 2

```

Name: count, dtype: int64
The count of Alley column
Alley
Grvl      50
Pave      41
Name: count, dtype: int64
The count of MiscFeature column
MiscFeature
Shed      47
Gar2       2
Othr       2
TenC       1
Name: count, dtype: int64
The count of Fence column
Fence
MnPrv     157
GdPrv      59
GdWo       54
MnWw       11
Name: count, dtype: int64

```

NaN values are filled appropriately and for some columns they are dropped

```

In [14]: house_train_lotarea_dropped['MasVnrType'].fillna("None",inplace=True)
house_train_lotarea_dropped['MasVnrArea'].fillna(0,inplace=True)
house_train_lotarea_dropped['FireplaceQu'].fillna("None",inplace=True)
house_train_lotarea_dropped['GarageType'].fillna("None",inplace=True)
house_train_lotarea_dropped['LotFrontage'].fillna(house_train_lotarea_dropped['LotFrontage'].median(),inplace=True)
house_train_lotarea_dropped.drop(['GarageYrBlt','GarageFinish','GarageQual','GarageCond'],inplace=True)

```

```

In [15]: print ("The NAN values after performing above data cleansing\n",house_train_lotarea_dropped.value_counts()
#house_train_lotarea_dropped['BsmtQual'].value_counts()
house_train_lotarea_dropped_1 = house_train_lotarea_dropped.dropna()
house_train_lotarea_dropped_1

```

```

The NAN values after performing above data cleansing
BsmtQual      37
BsmtCond      37
BsmtExposure   38
BsmtFinType1   37
BsmtFinType2   38
Electrical      1
dtype: int64

```

```

Out[15]:

```

	MSSubClass	MSZoning	LotFrontage	LotArea	LotShape	LandContour	LotConfig	LandSlope	Neighborhood
0	60	RL	65.0	8450	Reg	Lvl	Inside	Gtl	Collg
1	20	RL	80.0	9600	Reg	Lvl	FR2	Gtl	Veenl
2	60	RL	68.0	11250	IR1	Lvl	Inside	Gtl	Collg
3	70	RL	60.0	9550	IR1	Lvl	Corner	Gtl	Craw
4	60	RL	84.0	14260	IR1	Lvl	FR2	Gtl	NoRid
...	...	...	...	...	...	...	...	...	...
1455	60	RL	62.0	7917	Reg	Lvl	Inside	Gtl	Gilb
1456	20	RL	85.0	13175	Reg	Lvl	Inside	Gtl	NWArr
1457	70	RL	66.0	9042	Reg	Lvl	Inside	Gtl	Craw
1458	20	RL	68.0	9717	Reg	Lvl	Inside	Gtl	NArr
1459	20	RL	75.0	9937	Reg	Lvl	Inside	Gtl	Edwar

# Correlation matrix

Finding the numerical columns and plotting a correlation matrix.

There is a high correlation between GrLivArea and GrandArea, because previously we calculated GrandArea as the sum of TotalBsmtSF and GrLivArea.

Because of that GrLivArea column will be dropped.

```
In [16]: # Find the columns with numerical type,

col = house_train_lotarea_dropped_1.select_dtypes(include=['number']).columns

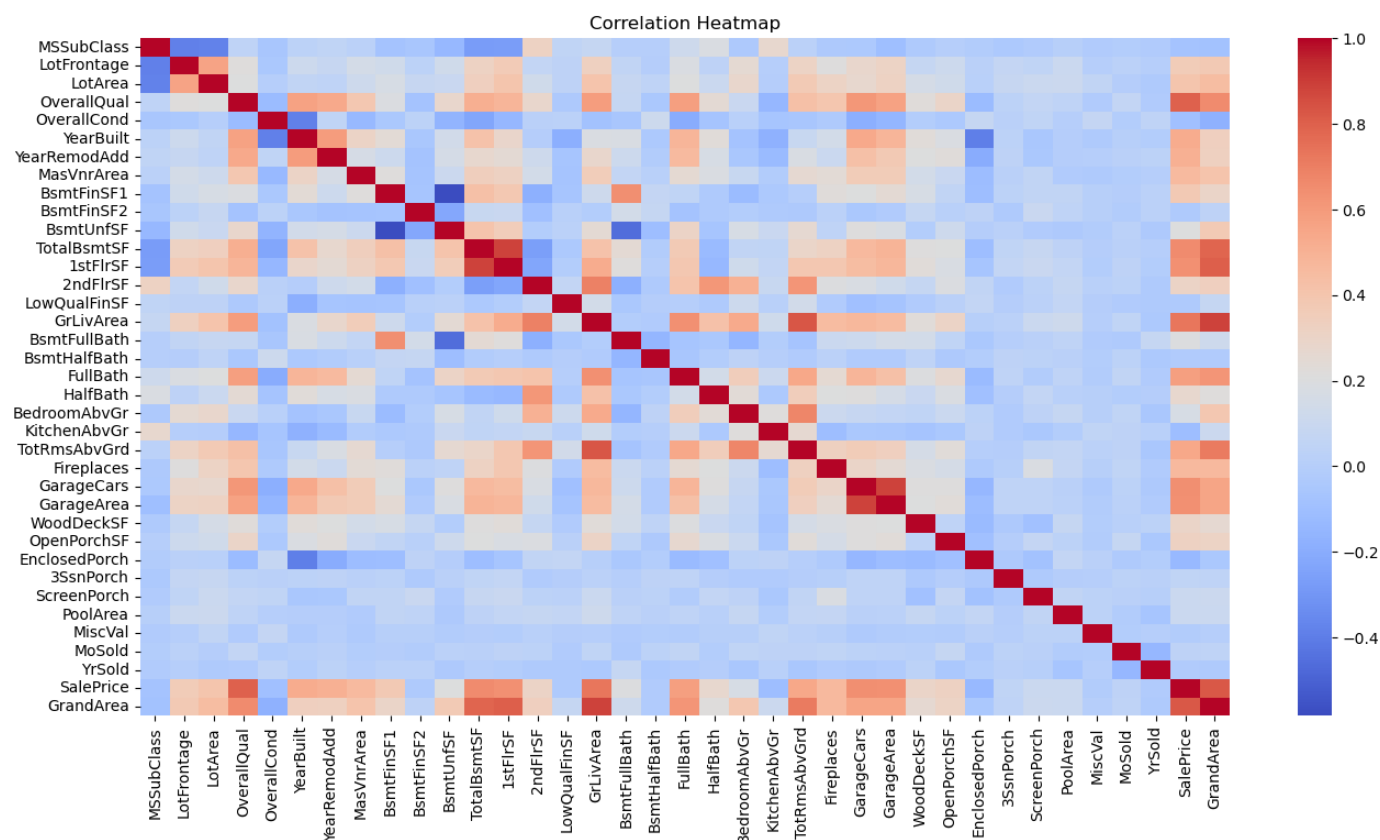
# Correlation between the numerical columns

import seaborn as sns
import matplotlib.pyplot as plt

# Correlation matrix
corr_matrix = house_train_lotarea_dropped_1[col].corr()

plt.figure(figsize=(16, 8))

# Plotting heatmap
sns.heatmap(corr_matrix, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```



```
In [17]: # There is a high correlation between GrLivArea and GrandArea, because previously we cal

house_train_lotarea_dropped_1['GrLivArea'].corr(house_train_lotarea_dropped_1['GrandArea
house_train_lotarea_dropped_2 = house_train_lotarea_dropped_1.drop(['GrLivArea'],axis=1)
house_train_lotarea_dropped_2
```

Out[17]:	MSSubClass	MSZoning	LotFrontage	LotArea	LotShape	LandContour	LotConfig	LandSlope	Neighborho
<b>0</b>	60	RL	65.0	8450	Reg	Lvl	Inside	Gtl	Collg
<b>1</b>	20	RL	80.0	9600	Reg	Lvl	FR2	Gtl	Veenl
<b>2</b>	60	RL	68.0	11250	IR1	Lvl	Inside	Gtl	Collg
<b>3</b>	70	RL	60.0	9550	IR1	Lvl	Corner	Gtl	Craw
<b>4</b>	60	RL	84.0	14260	IR1	Lvl	FR2	Gtl	NoRid
...	...	...	...	...	...	...	...	...	
<b>1455</b>	60	RL	62.0	7917	Reg	Lvl	Inside	Gtl	Gilb
<b>1456</b>	20	RL	85.0	13175	Reg	Lvl	Inside	Gtl	NWArr
<b>1457</b>	70	RL	66.0	9042	Reg	Lvl	Inside	Gtl	Craw
<b>1458</b>	20	RL	68.0	9717	Reg	Lvl	Inside	Gtl	NArr
<b>1459</b>	20	RL	75.0	9937	Reg	Lvl	Inside	Gtl	Edwar

1398 rows × 70 columns

Finding the object value columns alone to do encoding.

Encoding the categorical values using onehotencoder.

```
In [18]: house_train_lotarea_dropped_2['BsmtFinType2'].value_counts()
col_cat = house_train_lotarea_dropped_1.select_dtypes(include=['object']).columns

col_cat = col_cat.tolist()

import pandas as pd
from sklearn.preprocessing import OneHotEncoder

# Initialize the encoder
encoder = OneHotEncoder()

# Fit and transform the data
onehot_encoded = encoder.fit_transform(house_train_lotarea_dropped_1[col_cat])

# Convert to a DataFrame (optional, for better readability)
onehot_df = pd.DataFrame(onehot_encoded.toarray(), columns=encoder.get_feature_names_out(col_cat))
house_train_lotarea_dropped_1.columns
```

```
Out[18]: Index(['MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'LotShape',
        'LandContour', 'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1',
        'Condition2', 'BldgType', 'HouseStyle', 'OverallQual', 'OverallCond',
        'YearBuilt', 'YearRemodAdd', 'RoofStyle', 'RoofMatl', 'Exterior1st',
        'Exterior2nd', 'MasVnrType', 'MasVnrArea', 'ExterQual', 'ExterCond',
        'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1',
        'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF',
        'Heating', 'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF',
        '2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath',
        'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
        'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType',
        'GarageCars', 'GarageArea', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
        'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'MiscVal',
        'MoSold', 'YrSold', 'SaleType', 'SaleCondition', 'SalePrice',
        'GrandArea'],
        dtype='object')
```

Concatenating the encoded values and the numerical values by resetting the index, so that they align properly.

```
In [19]: import pandas as pd
import numpy as np

# Reset the index for both (if necessary)
df1_reset = house_train_lotarea_dropped_1.reset_index(drop=True)
df2_reset = onehot_df.reset_index(drop=True)

# Concatenate using numpy to avoid column alignment issues
concatenated = pd.concat ([df1_reset, df2_reset], axis=1)

#print(result)
modeldata=concatenated.drop(columns=col_cat)
modeldata
```

```
Out[19]:
```

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	Bsm
0	60	65.0	8450	7	5	2003	2003	196.0	
1	20	80.0	9600	6	8	1976	1976	0.0	
2	60	68.0	11250	7	5	2001	2002	162.0	
3	70	60.0	9550	7	5	1915	1970	0.0	
4	60	84.0	14260	8	5	2000	2000	350.0	
...	...	...	...	...	...	...	...	...	...
1393	60	62.0	7917	6	5	1999	2000	0.0	
1394	20	85.0	13175	6	6	1978	1988	119.0	
1395	70	66.0	9042	7	9	1941	2006	0.0	
1396	20	68.0	9717	5	6	1950	1996	0.0	
1397	20	75.0	9937	5	6	1965	1965	0.0	

1398 rows × 255 columns

Splitting the dataset to train and test using 80/20 %.

```
In [20]: from sklearn.model_selection import train_test_split
import pandas as pd

# Features and target variable
X = modeldata.drop(columns=['SalePrice']) # Independent variables (features)
y = modeldata['SalePrice'] # Dependent variable (target)

# Split the data into 80% training and 20% testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Output the results
print("Training Features:\n", X_train)
print("Testing Features:\n", X_test)
print("Training Labels:\n", y_train)
print("Testing Labels:\n", y_test)
```

```
Training Features:
   MSSubClass  LotFrontage  LotArea  OverallQual  OverallCond  YearBuilt \
```



48	60	69.655724	13869	6	6	1997
155	60	110.000000	13688	9	5	2003
756	60	92.000000	9920	7	5	1996
1070	20	70.000000	7560	5	5	1959
303	60	71.000000	7795	7	5	2004
...	...	...	...	...	...	...
1095	190	60.000000	12180	4	4	1941
1130	120	64.000000	5587	8	5	2008
1294	50	56.000000	14720	8	5	1995
860	20	69.655724	7340	4	6	1971
1126	20	37.000000	6951	5	5	1984

	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	\
48	1997	0.0	182	0	612	
155	2004	664.0	1016	0	556	
756	1997	0.0	862	0	255	
1070	1959	0.0	369	0	671	
303	2005	0.0	425	0	291	
...	...	...	...	...	...	
1095	1950	0.0	348	0	324	
1130	2008	186.0	1480	0	120	
1294	1996	579.0	816	0	1217	
860	1971	0.0	322	0	536	
1126	1985	0.0	658	0	218	

	TotalBsmtSF	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	\
48	794	794	676	0	1470	0	
155	1572	1572	1096	0	2668	1	
756	1117	1127	886	0	2013	1	
1070	1040	1040	0	0	1040	0	
303	716	716	716	0	1432	1	
...	...	...	...	...	...	...	
1095	672	672	252	0	924	1	
1130	1600	1652	0	0	1652	1	
1294	2033	2053	1185	0	3238	1	
860	858	858	0	0	858	0	
1126	876	923	0	0	923	1	

	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	\
48	1	2	0	3	1	
155	0	2	1	3	1	
756	0	2	1	3	1	
1070	0	1	0	3	1	
303	0	2	1	3	1	
...	...	...	...	...	...	
1095	0	1	0	2	1	
1130	1	2	0	2	1	
1294	0	2	1	4	1	
860	0	1	0	2	1	
1126	0	1	0	3	1	

	TotRmsAbvGrd	Fireplaces	GarageCars	GarageArea	WoodDeckSF	\
48	6	0	2	388	0	
155	10	2	3	726	400	
756	8	1	2	455	180	
1070	6	0	1	286	140	
303	6	1	2	432	100	
...	...	...	...	...	...	
1095	5	0	1	280	0	
1130	5	1	2	482	162	
1294	9	1	3	666	283	
860	4	0	1	684	0	
1126	5	0	1	264	362	

	OpenPorchSF	EnclosedPorch	3SsnPorch	ScreenPorch	PoolArea	MiscVal	\
48	75	0	0	0	0	0	

155	0	0	0	0	0	0
756	130	0	0	0	0	0
1070	0	252	0	0	0	0
303	51	0	0	0	0	0
...	...	...	...	...	...	...
1095	0	0	0	0	0	0
1130	53	0	153	0	0	0
1294	86	0	0	0	0	0
860	0	0	0	0	0	0
1126	0	0	0	0	0	0

	MoSold	YrSold	GrandArea	MSZoning_C (all)	MSZoning_FV	MSZoning_RH	\
48	7	2007	2264	0.0	0.0	0.0	
155	3	2008	4240	0.0	0.0	0.0	
756	6	2007	3130	0.0	0.0	0.0	
1070	7	2006	2080	0.0	0.0	0.0	
303	7	2009	2148	0.0	0.0	0.0	
...	...	...	...	...	...	...	
1095	7	2010	1596	0.0	0.0	0.0	
1130	11	2008	3252	0.0	0.0	0.0	
1294	3	2010	5271	0.0	0.0	0.0	
860	6	2007	1716	0.0	0.0	0.0	
1126	10	2008	1799	0.0	0.0	0.0	

	MSZoning_RL	MSZoning_RM	LotShape_IR1	LotShape_IR2	LotShape_IR3	\
48	1.0	0.0	0.0	1.0	0.0	
155	1.0	0.0	1.0	0.0	0.0	
756	1.0	0.0	1.0	0.0	0.0	
1070	1.0	0.0	0.0	0.0	0.0	
303	1.0	0.0	1.0	0.0	0.0	
...	...	...	...	...	...	
1095	1.0	0.0	0.0	0.0	0.0	
1130	0.0	1.0	1.0	0.0	0.0	
1294	1.0	0.0	1.0	0.0	0.0	
860	1.0	0.0	1.0	0.0	0.0	
1126	1.0	0.0	1.0	0.0	0.0	

	LotShape_Reg	LandContour_Bnk	LandContour_HLS	LandContour_Low	\
48	0.0	0.0	0.0	0.0	
155	0.0	0.0	0.0	0.0	
756	0.0	0.0	0.0	0.0	
1070	1.0	0.0	0.0	0.0	
303	0.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	1.0	0.0	0.0	0.0	
1130	0.0	0.0	1.0	0.0	
1294	0.0	0.0	0.0	0.0	
860	0.0	0.0	0.0	0.0	
1126	0.0	0.0	0.0	0.0	

	LandContour_Lvl	LotConfig_Corner	LotConfig_CulDSac	LotConfig_FR2	\
48	1.0	1.0	0.0	0.0	
155	1.0	0.0	0.0	0.0	
756	1.0	0.0	1.0	0.0	
1070	1.0	0.0	0.0	0.0	
303	1.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	1.0	0.0	0.0	0.0	
1130	0.0	0.0	0.0	0.0	
1294	1.0	0.0	1.0	0.0	
860	1.0	0.0	0.0	0.0	
1126	1.0	0.0	1.0	0.0	

	LotConfig_FR3	LotConfig_Inside	LandSlope_Gtl	LandSlope_Mod	\
48	0.0	0.0	1.0	0.0	
155	0.0	1.0	1.0	0.0	

756	0.0	0.0	1.0	0.0
1070	0.0	1.0	1.0	0.0
303	0.0	1.0	1.0	0.0
...	...	...	...	...
1095	0.0	1.0	1.0	0.0
1130	0.0	1.0	0.0	1.0
1294	0.0	0.0	1.0	0.0
860	0.0	1.0	1.0	0.0
1126	0.0	0.0	1.0	0.0

	LandSlope_Sev	Neighborhood_Blmngtn	Neighborhood_Blueste	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	0.0	0.0	
1294	0.0	0.0	0.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	Neighborhood_BrDale	Neighborhood_BrkSide	Neighborhood_ClearCr	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	0.0	0.0	
1294	0.0	0.0	0.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	Neighborhood_CollgCr	Neighborhood_Crawfor	Neighborhood_Edwards	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	1.0	
1130	0.0	1.0	0.0	
1294	0.0	0.0	0.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	Neighborhood_Gilbert	Neighborhood_IDOTRR	Neighborhood_MeadowV	\
48	1.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	1.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	0.0	0.0	
1294	0.0	0.0	0.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	Neighborhood_Mitchel	Neighborhood_NAmes	Neighborhood_NPkVill	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	

1070	0.0	1.0	0.0
303	0.0	0.0	0.0
...	...	...	...
1095	0.0	0.0	0.0
1130	0.0	0.0	0.0
1294	0.0	0.0	0.0
860	0.0	1.0	0.0
1126	1.0	0.0	0.0

	Neighborhood_NWAmes	Neighborhood_NoRidge	Neighborhood_NridgHt	\
48	0.0	0.0	0.0	
155	0.0	0.0	1.0	
756	0.0	1.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	0.0	0.0	
1294	0.0	1.0	0.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	Neighborhood_OldTown	Neighborhood_SWISU	Neighborhood_Sawyer	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	0.0	0.0	
1294	0.0	0.0	0.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	Neighborhood_SawyerW	Neighborhood_Somerst	Neighborhood_StoneBr	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	0.0	0.0	
1294	0.0	0.0	0.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	Neighborhood_Timber	Neighborhood_Veenker	Condition1_Artery	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	0.0	0.0	
1294	0.0	0.0	0.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	Condition1_Feedr	Condition1_Norm	Condition1_PosA	Condition1_PosN	\
48	0.0	1.0	0.0	0.0	
155	0.0	1.0	0.0	0.0	
756	0.0	1.0	0.0	0.0	
1070	0.0	1.0	0.0	0.0	

303	0.0	1.0	0.0	0.0
...	...	...	...	...
1095	0.0	1.0	0.0	0.0
1130	0.0	1.0	0.0	0.0
1294	0.0	1.0	0.0	0.0
860	0.0	1.0	0.0	0.0
1126	0.0	1.0	0.0	0.0

	Condition1_RRAe	Condition1_RRAn	Condition1_RRNe	Condition1_RRNn	\
48	0.0	0.0	0.0	0.0	
155	0.0	0.0	0.0	0.0	
756	0.0	0.0	0.0	0.0	
1070	0.0	0.0	0.0	0.0	
303	0.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	0.0	0.0	0.0	0.0	
1130	0.0	0.0	0.0	0.0	
1294	0.0	0.0	0.0	0.0	
860	0.0	0.0	0.0	0.0	
1126	0.0	0.0	0.0	0.0	

	Condition2_Artery	Condition2_Feedr	Condition2_Norm	Condition2_PosA	\
48	0.0	0.0	1.0	0.0	
155	0.0	0.0	1.0	0.0	
756	0.0	0.0	1.0	0.0	
1070	0.0	0.0	1.0	0.0	
303	0.0	0.0	1.0	0.0	
...	...	...	...	...	
1095	0.0	0.0	1.0	0.0	
1130	0.0	0.0	1.0	0.0	
1294	0.0	0.0	1.0	0.0	
860	0.0	0.0	1.0	0.0	
1126	0.0	0.0	1.0	0.0	

	Condition2_PosN	Condition2_RRAe	Condition2_RRAn	Condition2_RRNn	\
48	0.0	0.0	0.0	0.0	
155	0.0	0.0	0.0	0.0	
756	0.0	0.0	0.0	0.0	
1070	0.0	0.0	0.0	0.0	
303	0.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	0.0	0.0	0.0	0.0	
1130	0.0	0.0	0.0	0.0	
1294	0.0	0.0	0.0	0.0	
860	0.0	0.0	0.0	0.0	
1126	0.0	0.0	0.0	0.0	

	BldgType_1Fam	BldgType_2fmCon	BldgType_Duplex	BldgType_Twnhs	\
48	1.0	0.0	0.0	0.0	
155	1.0	0.0	0.0	0.0	
756	1.0	0.0	0.0	0.0	
1070	1.0	0.0	0.0	0.0	
303	1.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	0.0	1.0	0.0	0.0	
1130	0.0	0.0	0.0	0.0	
1294	1.0	0.0	0.0	0.0	
860	1.0	0.0	0.0	0.0	
1126	1.0	0.0	0.0	0.0	

	BldgType_TwnhsE	HouseStyle_1.5Fin	HouseStyle_1.5Unf	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	

...	...	...	...
1095	0.0	1.0	0.0
1130	1.0	0.0	0.0
1294	0.0	1.0	0.0
860	0.0	0.0	0.0
1126	0.0	0.0	0.0

	HouseStyle_1Story	HouseStyle_2.5Fin	HouseStyle_2.5Unf	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	1.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	1.0	0.0	0.0	
1294	0.0	0.0	0.0	
860	1.0	0.0	0.0	
1126	1.0	0.0	0.0	

	HouseStyle_2Story	HouseStyle_SFoyer	HouseStyle_Slvl	RoofStyle_Flat	\
48	1.0	0.0	0.0	0.0	
155	1.0	0.0	0.0	0.0	
756	1.0	0.0	0.0	0.0	
1070	0.0	0.0	0.0	0.0	
303	1.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	0.0	0.0	0.0	0.0	
1130	0.0	0.0	0.0	0.0	
1294	0.0	0.0	0.0	0.0	
860	0.0	0.0	0.0	0.0	
1126	0.0	0.0	0.0	0.0	

	RoofStyle_Gable	RoofStyle_Gambrel	RoofStyle_Hip	RoofStyle_Mansard	\
48	1.0	0.0	0.0	0.0	
155	1.0	0.0	0.0	0.0	
756	1.0	0.0	0.0	0.0	
1070	1.0	0.0	0.0	0.0	
303	1.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	1.0	0.0	0.0	0.0	
1130	0.0	0.0	1.0	0.0	
1294	0.0	0.0	1.0	0.0	
860	1.0	0.0	0.0	0.0	
1126	1.0	0.0	0.0	0.0	

	RoofStyle_Shed	RoofMatl_CompShg	RoofMatl_Metal	RoofMatl_Roll	\
48	0.0	1.0	0.0	0.0	
155	0.0	1.0	0.0	0.0	
756	0.0	1.0	0.0	0.0	
1070	0.0	1.0	0.0	0.0	
303	0.0	1.0	0.0	0.0	
...	...	...	...	...	
1095	0.0	1.0	0.0	0.0	
1130	0.0	1.0	0.0	0.0	
1294	0.0	1.0	0.0	0.0	
860	0.0	1.0	0.0	0.0	
1126	0.0	1.0	0.0	0.0	

	RoofMatl_Tar&Grv	RoofMatl_WdShake	RoofMatl_WdShngl	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	

1095	0.0	0.0	0.0
1130	0.0	0.0	0.0
1294	0.0	0.0	0.0
860	0.0	0.0	0.0
1126	0.0	0.0	0.0

	Exterior1st_AsbShng	Exterior1st_BrkComm	Exterior1st_BrkFace	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	1.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	0.0	0.0	
1294	0.0	0.0	0.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	Exterior1st_CBlock	Exterior1st_CemntBd	Exterior1st_HdBoard	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	1.0	0.0	
1294	0.0	0.0	0.0	
860	0.0	0.0	1.0	
1126	0.0	0.0	1.0	

	Exterior1st_ImStucc	Exterior1st_MetalSd	Exterior1st_Plywood	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	1.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	1.0	0.0	
1130	0.0	0.0	0.0	
1294	0.0	0.0	0.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	Exterior1st_Stone	Exterior1st_Stucco	Exterior1st_VinylSd	\
48	0.0	0.0	1.0	
155	0.0	0.0	1.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	1.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	0.0	0.0	
1294	0.0	0.0	1.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	Exterior1st_Wd Sdng	Exterior1st_WdShing	Exterior2nd_AsbShng	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	

1130	0.0	0.0	0.0
1294	0.0	0.0	0.0
860	0.0	0.0	0.0
1126	0.0	0.0	0.0

	Exterior2nd_AsphShn	Exterior2nd_Brk Cmn	Exterior2nd_BrkFace \
48	0.0	0.0	0.0
155	0.0	0.0	0.0
756	0.0	0.0	0.0
1070	0.0	0.0	0.0
303	0.0	0.0	0.0
...	...	...	...
1095	0.0	0.0	0.0
1130	0.0	0.0	0.0
1294	0.0	0.0	0.0
860	0.0	0.0	0.0
1126	0.0	0.0	0.0

	Exterior2nd_CBlock	Exterior2nd_CmentBd	Exterior2nd_HdBoard \
48	0.0	0.0	0.0
155	0.0	0.0	0.0
756	0.0	0.0	0.0
1070	0.0	0.0	0.0
303	0.0	0.0	0.0
...	...	...	...
1095	0.0	0.0	0.0
1130	0.0	1.0	0.0
1294	0.0	0.0	0.0
860	0.0	0.0	1.0
1126	0.0	0.0	0.0

	Exterior2nd_ImStucc	Exterior2nd_MetalSd	Exterior2nd_Other \
48	0.0	0.0	0.0
155	0.0	0.0	0.0
756	0.0	1.0	0.0
1070	0.0	0.0	0.0
303	0.0	0.0	0.0
...	...	...	...
1095	0.0	1.0	0.0
1130	0.0	0.0	0.0
1294	0.0	0.0	0.0
860	0.0	0.0	0.0
1126	0.0	0.0	0.0

	Exterior2nd_Plywood	Exterior2nd_Stone	Exterior2nd_Stucco \
48	0.0	0.0	0.0
155	0.0	0.0	0.0
756	0.0	0.0	0.0
1070	0.0	0.0	0.0
303	0.0	0.0	0.0
...	...	...	...
1095	0.0	0.0	0.0
1130	0.0	0.0	0.0
1294	0.0	0.0	0.0
860	0.0	0.0	0.0
1126	1.0	0.0	0.0

	Exterior2nd_VinylSd	Exterior2nd_Wd Sdng	Exterior2nd_Wd Shng \
48	1.0	0.0	0.0
155	1.0	0.0	0.0
756	0.0	0.0	0.0
1070	0.0	1.0	0.0
303	1.0	0.0	0.0
...	...	...	...
1095	0.0	0.0	0.0
1130	0.0	0.0	0.0



1294	1.0	0.0	0.0
860	0.0	0.0	0.0
1126	0.0	0.0	0.0

	MasVnrType_BrkCmn	MasVnrType_BrkFace	MasVnrType_None	\
48	0.0	0.0	1.0	
155	0.0	1.0	0.0	
756	0.0	0.0	1.0	
1070	0.0	0.0	1.0	
303	0.0	0.0	1.0	
...	...	...	...	
1095	0.0	0.0	1.0	
1130	0.0	0.0	0.0	
1294	0.0	1.0	0.0	
860	0.0	0.0	1.0	
1126	0.0	0.0	1.0	

	MasVnrType_Stone	ExterQual_Ex	ExterQual_Fa	ExterQual_Gd	\
48	0.0	0.0	0.0	0.0	
155	0.0	0.0	0.0	1.0	
756	0.0	0.0	0.0	1.0	
1070	0.0	0.0	0.0	0.0	
303	0.0	0.0	0.0	1.0	
...	...	...	...	...	
1095	0.0	0.0	0.0	0.0	
1130	1.0	1.0	0.0	0.0	
1294	0.0	0.0	0.0	1.0	
860	0.0	0.0	0.0	0.0	
1126	0.0	0.0	0.0	0.0	

	ExterQual_TA	ExterCond_Ex	ExterCond_Fa	ExterCond_Gd	ExterCond_Po	\
48	1.0	0.0	0.0	0.0	0.0	
155	0.0	0.0	0.0	0.0	0.0	
756	0.0	0.0	0.0	0.0	0.0	
1070	1.0	0.0	0.0	0.0	0.0	
303	0.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	
1095	1.0	0.0	1.0	0.0	0.0	
1130	0.0	0.0	0.0	0.0	0.0	
1294	0.0	0.0	0.0	0.0	0.0	
860	1.0	0.0	0.0	0.0	0.0	
1126	1.0	0.0	0.0	0.0	0.0	

	ExterCond_TA	Foundation_BrkTil	Foundation_CBlock	Foundation_PConc	\
48	1.0	0.0	0.0	1.0	
155	1.0	0.0	0.0	1.0	
756	1.0	0.0	0.0	1.0	
1070	1.0	0.0	1.0	0.0	
303	1.0	0.0	0.0	1.0	
...	...	...	...	...	
1095	0.0	1.0	0.0	0.0	
1130	1.0	0.0	0.0	1.0	
1294	1.0	0.0	0.0	1.0	
860	1.0	0.0	1.0	0.0	
1126	1.0	0.0	1.0	0.0	

	Foundation_Stone	Foundation_Wood	BsmtQual_Ex	BsmtQual_Fa	\
48	0.0	0.0	0.0	0.0	
155	0.0	0.0	1.0	0.0	
756	0.0	0.0	0.0	0.0	
1070	0.0	0.0	0.0	0.0	
303	0.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	0.0	0.0	0.0	0.0	
1130	0.0	0.0	1.0	0.0	
1294	0.0	0.0	0.0	0.0	

860	0.0	0.0	0.0	0.0
1126	0.0	0.0	0.0	0.0

	BsmtQual_Gd	BsmtQual_TA	BsmtCond_Fa	BsmtCond_Gd	BsmtCond_Po	\
48	1.0	0.0	0.0	0.0	0.0	
155	0.0	0.0	0.0	0.0	0.0	
756	1.0	0.0	0.0	0.0	0.0	
1070	0.0	1.0	0.0	0.0	0.0	
303	1.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	
1095	1.0	0.0	0.0	0.0	0.0	
1130	0.0	0.0	0.0	0.0	0.0	
1294	1.0	0.0	0.0	0.0	0.0	
860	0.0	1.0	0.0	0.0	0.0	
1126	0.0	1.0	0.0	0.0	0.0	

	BsmtCond_TA	BsmtExposure_Av	BsmtExposure_Gd	BsmtExposure_Mn	\
48	1.0	1.0	0.0	0.0	
155	1.0	1.0	0.0	0.0	
756	1.0	1.0	0.0	0.0	
1070	1.0	0.0	0.0	0.0	
303	1.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	1.0	0.0	0.0	0.0	
1130	1.0	0.0	1.0	0.0	
1294	1.0	1.0	0.0	0.0	
860	1.0	0.0	0.0	0.0	
1126	1.0	0.0	0.0	0.0	

	BsmtExposure_No	BsmtFinType1_ALQ	BsmtFinType1_BLQ	BsmtFinType1_GLQ	\
48	0.0	0.0	0.0	1.0	
155	0.0	0.0	0.0	1.0	
756	0.0	0.0	0.0	1.0	
1070	1.0	0.0	0.0	0.0	
303	1.0	0.0	0.0	1.0	
...	...	...	...	...	
1095	1.0	0.0	1.0	0.0	
1130	0.0	0.0	0.0	1.0	
1294	0.0	0.0	0.0	1.0	
860	1.0	1.0	0.0	0.0	
1126	1.0	1.0	0.0	0.0	

	BsmtFinType1_LwQ	BsmtFinType1_Rec	BsmtFinType1_Unf	BsmtFinType2_ALQ	\
48	0.0	0.0	0.0	0.0	
155	0.0	0.0	0.0	0.0	
756	0.0	0.0	0.0	0.0	
1070	1.0	0.0	0.0	0.0	
303	0.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	0.0	0.0	0.0	0.0	
1130	0.0	0.0	0.0	0.0	
1294	0.0	0.0	0.0	0.0	
860	0.0	0.0	0.0	0.0	
1126	0.0	0.0	0.0	0.0	

	BsmtFinType2_BLQ	BsmtFinType2_GLQ	BsmtFinType2_LwQ	BsmtFinType2_Rec	\
48	0.0	0.0	0.0	0.0	
155	0.0	0.0	0.0	0.0	
756	0.0	0.0	0.0	0.0	
1070	0.0	0.0	0.0	0.0	
303	0.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	0.0	0.0	0.0	0.0	
1130	0.0	0.0	0.0	0.0	
1294	0.0	0.0	0.0	0.0	
860	0.0	0.0	0.0	0.0	

1126 0.0 0.0 0.0 0.0

	BsmtFinType2_Unf	Heating_GasA	Heating_GasW	Heating_Grav	\
48	1.0	1.0	0.0	0.0	
155	1.0	1.0	0.0	0.0	
756	1.0	1.0	0.0	0.0	
1070	1.0	1.0	0.0	0.0	
303	1.0	1.0	0.0	0.0	
...	...	...	...	...	
1095	1.0	0.0	0.0	1.0	
1130	1.0	1.0	0.0	0.0	
1294	1.0	1.0	0.0	0.0	
860	1.0	1.0	0.0	0.0	
1126	1.0	1.0	0.0	0.0	

	Heating_OthW	HeatingQC_Ex	HeatingQC_Fa	HeatingQC_Gd	HeatingQC_Po	\
48	0.0	0.0	0.0	1.0	0.0	
155	0.0	1.0	0.0	0.0	0.0	
756	0.0	1.0	0.0	0.0	0.0	
1070	0.0	0.0	0.0	0.0	0.0	
303	0.0	1.0	0.0	0.0	0.0	
...	...	...	...	...	...	
1095	0.0	0.0	1.0	0.0	0.0	
1130	0.0	1.0	0.0	0.0	0.0	
1294	0.0	1.0	0.0	0.0	0.0	
860	0.0	0.0	0.0	0.0	0.0	
1126	0.0	0.0	0.0	0.0	0.0	

	HeatingQC_TA	CentralAir_N	CentralAir_Y	Electrical_FuseA	\
48	0.0	0.0	1.0	0.0	
155	0.0	0.0	1.0	0.0	
756	0.0	0.0	1.0	0.0	
1070	1.0	0.0	1.0	1.0	
303	0.0	0.0	1.0	0.0	
...	...	...	...	...	
1095	0.0	1.0	0.0	1.0	
1130	0.0	0.0	1.0	0.0	
1294	0.0	0.0	1.0	0.0	
860	1.0	0.0	1.0	0.0	
1126	1.0	0.0	1.0	0.0	

	Electrical_FuseF	Electrical_FuseP	Electrical_Mix	Electrical_SBrkr	\
48	0.0	0.0	0.0	1.0	
155	0.0	0.0	0.0	1.0	
756	0.0	0.0	0.0	1.0	
1070	0.0	0.0	0.0	0.0	
303	0.0	0.0	0.0	1.0	
...	...	...	...	...	
1095	0.0	0.0	0.0	0.0	
1130	0.0	0.0	0.0	1.0	
1294	0.0	0.0	0.0	1.0	
860	0.0	0.0	0.0	1.0	
1126	0.0	0.0	0.0	1.0	

	KitchenQual_Ex	KitchenQual_Fa	KitchenQual_Gd	KitchenQual_TA	\
48	0.0	0.0	0.0	1.0	
155	1.0	0.0	0.0	0.0	
756	0.0	0.0	0.0	1.0	
1070	0.0	0.0	0.0	1.0	
303	0.0	0.0	1.0	0.0	
...	...	...	...	...	
1095	0.0	1.0	0.0	0.0	
1130	0.0	0.0	1.0	0.0	
1294	0.0	0.0	1.0	0.0	
860	0.0	0.0	0.0	1.0	
1126	0.0	0.0	0.0	1.0	

	Functional_Maj1	Functional_Maj2	Functional_Min1	Functional_Min2	\
48	0.0	0.0	0.0	0.0	
155	0.0	0.0	0.0	0.0	
756	0.0	0.0	0.0	0.0	
1070	0.0	0.0	0.0	0.0	
303	0.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	0.0	0.0	0.0	0.0	
1130	0.0	0.0	0.0	0.0	
1294	0.0	0.0	0.0	0.0	
860	0.0	0.0	0.0	0.0	
1126	0.0	0.0	0.0	0.0	

	Functional_Mod	Functional_Sev	Functional_Typ	FireplaceQu_Ex	\
48	0.0	0.0	1.0	0.0	
155	0.0	0.0	1.0	0.0	
756	0.0	0.0	1.0	0.0	
1070	0.0	0.0	1.0	0.0	
303	0.0	0.0	1.0	0.0	
...	...	...	...	...	
1095	0.0	0.0	1.0	0.0	
1130	0.0	0.0	1.0	0.0	
1294	0.0	0.0	1.0	1.0	
860	0.0	0.0	1.0	0.0	
1126	0.0	0.0	1.0	0.0	

	FireplaceQu_Fa	FireplaceQu_Gd	FireplaceQu_None	FireplaceQu_Po	\
48	0.0	0.0	1.0	0.0	
155	0.0	1.0	0.0	0.0	
756	0.0	0.0	0.0	0.0	
1070	0.0	0.0	1.0	0.0	
303	0.0	1.0	0.0	0.0	
...	...	...	...	...	
1095	0.0	0.0	1.0	0.0	
1130	0.0	1.0	0.0	0.0	
1294	0.0	0.0	0.0	0.0	
860	0.0	0.0	1.0	0.0	
1126	0.0	0.0	1.0	0.0	

	FireplaceQu_TA	GarageType_2Types	GarageType_Attchd	\
48	0.0	0.0	1.0	
155	0.0	0.0	0.0	
756	1.0	0.0	1.0	
1070	0.0	0.0	1.0	
303	0.0	0.0	1.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	0.0	1.0	
1294	0.0	0.0	1.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	1.0	

	GarageType_Basment	GarageType_BuiltIn	GarageType_CarPort	\
48	0.0	0.0	0.0	
155	0.0	1.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	0.0	0.0	
1294	0.0	0.0	0.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	GarageType_Detchd	GarageType_None	PavedDrive_N	PavedDrive_P	\
48	0.0	0.0	0.0	0.0	
155	0.0	0.0	0.0	0.0	
756	0.0	0.0	0.0	0.0	
1070	0.0	0.0	0.0	0.0	
303	0.0	0.0	0.0	0.0	
...	...	...	...	...	
1095	1.0	0.0	0.0	0.0	
1130	0.0	0.0	0.0	0.0	
1294	0.0	0.0	0.0	0.0	
860	1.0	0.0	0.0	0.0	
1126	0.0	0.0	0.0	0.0	

	PavedDrive_Y	SaleType_COD	SaleType_CWD	SaleType_Con	SaleType_ConLD	\
48	1.0	0.0	0.0	0.0	0.0	
155	1.0	0.0	0.0	0.0	0.0	
756	1.0	0.0	0.0	0.0	0.0	
1070	1.0	0.0	0.0	0.0	0.0	
303	1.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	
1095	1.0	0.0	0.0	0.0	0.0	
1130	1.0	0.0	0.0	0.0	0.0	
1294	1.0	0.0	0.0	0.0	0.0	
860	1.0	0.0	0.0	0.0	0.0	
1126	1.0	0.0	0.0	0.0	0.0	

	SaleType_ConLI	SaleType_ConLw	SaleType_New	SaleType_Oth	SaleType_WD	\
48	0.0	0.0	0.0	0.0	1.0	
155	0.0	0.0	0.0	0.0	1.0	
756	0.0	0.0	0.0	0.0	1.0	
1070	0.0	0.0	0.0	0.0	1.0	
303	0.0	0.0	0.0	0.0	1.0	
...	...	...	...	...	...	
1095	0.0	0.0	0.0	0.0	1.0	
1130	0.0	0.0	1.0	0.0	0.0	
1294	0.0	0.0	0.0	0.0	1.0	
860	0.0	0.0	0.0	0.0	1.0	
1126	0.0	0.0	0.0	0.0	1.0	

	SaleCondition_Abnorml	SaleCondition_AdjLand	SaleCondition_Alloca	\
48	0.0	0.0	0.0	
155	0.0	0.0	0.0	
756	0.0	0.0	0.0	
1070	0.0	0.0	0.0	
303	0.0	0.0	0.0	
...	...	...	...	
1095	0.0	0.0	0.0	
1130	0.0	0.0	0.0	
1294	0.0	0.0	0.0	
860	0.0	0.0	0.0	
1126	0.0	0.0	0.0	

	SaleCondition_Family	SaleCondition_Normal	SaleCondition_Partial
48	0.0	1.0	0.0
155	0.0	1.0	0.0
756	0.0	1.0	0.0
1070	0.0	1.0	0.0
303	0.0	1.0	0.0
...	...	...	...
1095	0.0	1.0	0.0
1130	0.0	0.0	1.0
1294	0.0	1.0	0.0
860	0.0	1.0	0.0
1126	0.0	1.0	0.0

[1118 rows x 254 columns]

## Testing Features:

	MSSubClass	LotFrontage	LotArea	OverallQual	OverallCond	YearBuilt	\
78	120	32.000000	4500	6	5	1998	
478	160	21.000000	1890	6	5	1973	
354	60	69.655724	8121	6	5	2000	
594	20	71.000000	7064	5	6	1977	
1255	60	108.000000	14774	9	5	1999	
...	...	...	...	...	...	...	
435	70	34.000000	4571	5	5	1916	
538	60	77.000000	11198	9	5	2005	
350	20	69.655724	9500	6	5	1963	
1159	30	50.000000	9340	4	6	1941	
894	20	313.000000	27650	7	7	1960	

	YearRemodAdd	MasVnrArea	BsmtFinSF1	BsmtFinSF2	BsmtUnfSF	\
78	1998	443.0	1201	0	36	
478	1973	285.0	356	0	316	
354	2000	0.0	0	0	953	
594	1977	153.0	560	0	420	
1255	1999	165.0	0	0	1393	
...	...	...	...	...	...	
435	1950	0.0	0	0	624	
538	2007	245.0	0	0	1122	
350	1963	247.0	609	0	785	
1159	1950	0.0	344	0	328	
894	2007	0.0	425	0	160	

	TotalBsmtSF	1stFlrSF	2ndFlrSF	LowQualFinSF	GrLivArea	BsmtFullBath	\
78	1237	1337	0	0	1337	1	
478	672	672	546	0	1218	0	
354	953	953	711	0	1664	0	
594	980	980	0	0	980	0	
1255	1393	1422	1177	0	2599	0	
...	...	...	...	...	...	...	
435	624	624	720	0	1344	0	
538	1122	1134	1370	0	2504	0	
350	1394	1394	0	0	1394	1	
1159	672	672	0	0	672	1	
894	585	2069	0	0	2069	1	

	BsmtHalfBath	FullBath	HalfBath	BedroomAbvGr	KitchenAbvGr	\
78	0	2	0	2	1	
478	0	1	1	3	1	
354	0	2	1	3	1	
594	0	1	0	3	1	
1255	0	2	1	4	1	
...	...	...	...	...	...	
435	0	1	0	4	1	
538	0	2	1	4	1	
350	0	1	1	3	1	
1159	0	1	0	2	1	
894	0	2	0	4	1	

	TotRmsAbvGrd	Fireplaces	GarageCars	GarageArea	WoodDeckSF	\
78	5	0	2	405	0	
478	7	0	1	264	144	
354	7	1	2	460	100	
594	6	0	2	484	192	
1255	10	1	3	779	668	
...	...	...	...	...	...	
435	7	0	3	513	0	
538	11	1	3	656	144	
350	6	2	2	514	0	
1159	4	0	1	234	0	
894	9	1	2	505	0	

	OpenPorchSF	EnclosedPorch	3SsnPorch	ScreenPorch	PoolArea	MiscVal	\
78	199	0	0	0	0	0	
478	28	0	0	0	0	0	
354	40	0	0	0	0	0	
594	0	0	0	0	0	0	
1255	30	0	0	0	0	0	
...	...	...	...	...	...	...	
435	0	96	0	0	0	0	
538	39	0	0	0	0	0	
350	76	0	0	185	0	0	
1159	113	0	0	0	0	0	
894	0	0	0	0	0	0	

	MoSold	YrSold	GrandArea	MSZoning_C (all)	MSZoning_FV	MSZoning_RH	\
78	3	2006	2574	0.0	0.0	0.0	
478	5	2007	1890	0.0	0.0	0.0	
354	1	2006	2617	0.0	0.0	0.0	
594	7	2009	1960	0.0	0.0	0.0	
1255	5	2010	3992	0.0	0.0	0.0	
...	...	...	...	...	...	...	
435	5	2008	1968	0.0	0.0	0.0	
538	6	2008	3626	0.0	0.0	0.0	
350	7	2009	2788	0.0	0.0	0.0	
1159	8	2009	1344	0.0	0.0	0.0	
894	11	2008	2654	0.0	0.0	0.0	

	MSZoning_RL	MSZoning_RM	LotShape_IR1	LotShape_IR2	LotShape_IR3	\
78	0.0	1.0	0.0	0.0	0.0	
478	0.0	1.0	0.0	0.0	0.0	
354	1.0	0.0	1.0	0.0	0.0	
594	1.0	0.0	0.0	0.0	0.0	
1255	1.0	0.0	1.0	0.0	0.0	
...	...	...	...	...	...	
435	0.0	1.0	0.0	0.0	0.0	
538	1.0	0.0	1.0	0.0	0.0	
350	1.0	0.0	1.0	0.0	0.0	
1159	1.0	0.0	0.0	0.0	0.0	
894	1.0	0.0	0.0	1.0	0.0	

	LotShape_Reg	LandContour_Bnk	LandContour_HLS	LandContour_Low	\
78	1.0	0.0	0.0	0.0	
478	1.0	0.0	0.0	0.0	
354	0.0	0.0	0.0	0.0	
594	1.0	0.0	0.0	0.0	
1255	0.0	0.0	0.0	0.0	
...	...	...	...	...	
435	1.0	0.0	0.0	0.0	
538	0.0	0.0	0.0	0.0	
350	0.0	0.0	0.0	0.0	
1159	1.0	0.0	0.0	0.0	
894	0.0	0.0	1.0	0.0	

	LandContour_Lvl	LotConfig_Corner	LotConfig_CulDSac	LotConfig_FR2	\
78	1.0	0.0	0.0	1.0	
478	1.0	0.0	0.0	0.0	
354	1.0	0.0	0.0	0.0	
594	1.0	0.0	0.0	0.0	
1255	1.0	1.0	0.0	0.0	
...	...	...	...	...	
435	1.0	0.0	0.0	0.0	
538	1.0	0.0	0.0	0.0	
350	1.0	0.0	0.0	0.0	
1159	1.0	0.0	0.0	0.0	
894	0.0	0.0	0.0	0.0	

LotConfig\_FR3 LotConfig\_Inside LandSlope\_Gtl LandSlope\_Mod \

78	0.0	0.0	1.0	0.0
478	0.0	1.0	1.0	0.0
354	0.0	1.0	1.0	0.0
594	0.0	1.0	1.0	0.0
1255	0.0	0.0	1.0	0.0
...	...	...	...	...
435	0.0	1.0	1.0	0.0
538	0.0	1.0	1.0	0.0
350	0.0	1.0	1.0	0.0
1159	0.0	1.0	1.0	0.0
894	0.0	1.0	0.0	1.0

	LandSlope_Sev	Neighborhood_Blmngtn	Neighborhood_Blueste	\
78	0.0	0.0	0.0	
478	0.0	0.0	0.0	
354	0.0	0.0	0.0	
594	0.0	0.0	0.0	
1255	0.0	0.0	0.0	
...	...	...	...	
435	0.0	0.0	0.0	
538	0.0	0.0	0.0	
350	0.0	0.0	0.0	
1159	0.0	0.0	0.0	
894	0.0	0.0	0.0	

	Neighborhood_BrDale	Neighborhood_BrkSide	Neighborhood_ClearCr	\
78	0.0	0.0	0.0	
478	1.0	0.0	0.0	
354	0.0	0.0	0.0	
594	0.0	0.0	0.0	
1255	0.0	0.0	0.0	
...	...	...	...	
435	0.0	0.0	0.0	
538	0.0	0.0	0.0	
350	0.0	0.0	0.0	
1159	0.0	0.0	0.0	
894	0.0	0.0	0.0	

	Neighborhood_CollgCr	Neighborhood_Crawfor	Neighborhood_Edwards	\
78	0.0	0.0	0.0	
478	0.0	0.0	0.0	
354	0.0	0.0	0.0	
594	0.0	0.0	0.0	
1255	0.0	0.0	0.0	
...	...	...	...	
435	0.0	0.0	0.0	
538	0.0	0.0	0.0	
350	0.0	0.0	0.0	
1159	0.0	0.0	1.0	
894	0.0	0.0	0.0	

	Neighborhood_Gilbert	Neighborhood_IDOTRR	Neighborhood_MeadowV	\
78	0.0	0.0	0.0	
478	0.0	0.0	0.0	
354	1.0	0.0	0.0	
594	0.0	0.0	0.0	
1255	0.0	0.0	0.0	
...	...	...	...	
435	0.0	0.0	0.0	
538	0.0	0.0	0.0	
350	0.0	0.0	0.0	
1159	0.0	0.0	0.0	
894	0.0	0.0	0.0	

	Neighborhood_Mitchel	Neighborhood_NAmes	Neighborhood_NPkVill	\
78	1.0	0.0	0.0	



478	0.0	0.0	0.0
354	0.0	0.0	0.0
594	0.0	0.0	0.0
1255	0.0	0.0	0.0
...	...	...	...
435	0.0	0.0	0.0
538	0.0	0.0	0.0
350	0.0	1.0	0.0
1159	0.0	0.0	0.0
894	0.0	1.0	0.0

	Neighborhood_NWAmes	Neighborhood_NoRidge	Neighborhood_NridgHt \
78	0.0	0.0	0.0
478	0.0	0.0	0.0
354	0.0	0.0	0.0
594	0.0	0.0	0.0
1255	0.0	1.0	0.0
...	...	...	...
435	0.0	0.0	0.0
538	0.0	0.0	0.0
350	0.0	0.0	0.0
1159	0.0	0.0	0.0
894	0.0	0.0	0.0

	Neighborhood_OldTown	Neighborhood_SWISU	Neighborhood_Sawyer \
78	0.0	0.0	0.0
478	0.0	0.0	0.0
354	0.0	0.0	0.0
594	0.0	0.0	1.0
1255	0.0	0.0	0.0
...	...	...	...
435	1.0	0.0	0.0
538	0.0	0.0	0.0
350	0.0	0.0	0.0
1159	0.0	0.0	0.0
894	0.0	0.0	0.0

	Neighborhood_SawyerW	Neighborhood_Somerst	Neighborhood_StoneBr \
78	0.0	0.0	0.0
478	0.0	0.0	0.0
354	0.0	0.0	0.0
594	0.0	0.0	0.0
1255	0.0	0.0	0.0
...	...	...	...
435	0.0	0.0	0.0
538	0.0	0.0	1.0
350	0.0	0.0	0.0
1159	0.0	0.0	0.0
894	0.0	0.0	0.0

	Neighborhood_Timber	Neighborhood_Veenker	Condition1_Artery \
78	0.0	0.0	0.0
478	0.0	0.0	0.0
354	0.0	0.0	0.0
594	0.0	0.0	0.0
1255	0.0	0.0	0.0
...	...	...	...
435	0.0	0.0	0.0
538	0.0	0.0	0.0
350	0.0	0.0	0.0
1159	0.0	0.0	0.0
894	0.0	0.0	0.0

	Condition1_Feedr	Condition1_Norm	Condition1_PosA	Condition1_PosN \
78	0.0	1.0	0.0	0.0
478	0.0	1.0	0.0	0.0

354	0.0	1.0	0.0	0.0
594	0.0	1.0	0.0	0.0
1255	0.0	1.0	0.0	0.0
...	...	...	...	...
435	0.0	1.0	0.0	0.0
538	0.0	1.0	0.0	0.0
350	0.0	1.0	0.0	0.0
1159	0.0	1.0	0.0	0.0
894	0.0	0.0	1.0	0.0

	Condition1_RRAe	Condition1_RRAn	Condition1_RRNe	Condition1_RRNn	\
78	0.0	0.0	0.0	0.0	
478	0.0	0.0	0.0	0.0	
354	0.0	0.0	0.0	0.0	
594	0.0	0.0	0.0	0.0	
1255	0.0	0.0	0.0	0.0	
...	...	...	...	...	
435	0.0	0.0	0.0	0.0	
538	0.0	0.0	0.0	0.0	
350	0.0	0.0	0.0	0.0	
1159	0.0	0.0	0.0	0.0	
894	0.0	0.0	0.0	0.0	

	Condition2_Artery	Condition2_Feendr	Condition2_Norm	Condition2_PosA	\
78	0.0	0.0	1.0	0.0	
478	0.0	0.0	1.0	0.0	
354	0.0	0.0	1.0	0.0	
594	0.0	0.0	1.0	0.0	
1255	0.0	0.0	1.0	0.0	
...	...	...	...	...	
435	0.0	0.0	1.0	0.0	
538	0.0	0.0	1.0	0.0	
350	0.0	0.0	1.0	0.0	
1159	0.0	0.0	1.0	0.0	
894	0.0	0.0	1.0	0.0	

	Condition2_PosN	Condition2_RRAe	Condition2_RRAn	Condition2_RRNn	\
78	0.0	0.0	0.0	0.0	
478	0.0	0.0	0.0	0.0	
354	0.0	0.0	0.0	0.0	
594	0.0	0.0	0.0	0.0	
1255	0.0	0.0	0.0	0.0	
...	...	...	...	...	
435	0.0	0.0	0.0	0.0	
538	0.0	0.0	0.0	0.0	
350	0.0	0.0	0.0	0.0	
1159	0.0	0.0	0.0	0.0	
894	0.0	0.0	0.0	0.0	

	BldgType_1Fam	BldgType_2fmCon	BldgType_Duplex	BldgType_Twnhs	\
78	0.0	0.0	0.0	0.0	
478	0.0	0.0	0.0	1.0	
354	1.0	0.0	0.0	0.0	
594	1.0	0.0	0.0	0.0	
1255	1.0	0.0	0.0	0.0	
...	...	...	...	...	
435	1.0	0.0	0.0	0.0	
538	1.0	0.0	0.0	0.0	
350	1.0	0.0	0.0	0.0	
1159	1.0	0.0	0.0	0.0	
894	1.0	0.0	0.0	0.0	

	BldgType_TwnhsE	HouseStyle_1.5Fin	HouseStyle_1.5Unf	\
78	1.0	0.0	0.0	
478	0.0	0.0	0.0	
354	0.0	0.0	0.0	

594	0.0	0.0	0.0
1255	0.0	0.0	0.0
...	...	...	...
435	0.0	0.0	0.0
538	0.0	0.0	0.0
350	0.0	0.0	0.0
1159	0.0	0.0	0.0
894	0.0	0.0	0.0

	HouseStyle_1Story	HouseStyle_2.5Fin	HouseStyle_2.5Unf	\
78	1.0	0.0	0.0	
478	0.0	0.0	0.0	
354	0.0	0.0	0.0	
594	1.0	0.0	0.0	
1255	0.0	0.0	0.0	
...	...	...	...	
435	0.0	0.0	0.0	
538	0.0	0.0	0.0	
350	1.0	0.0	0.0	
1159	1.0	0.0	0.0	
894	1.0	0.0	0.0	

	HouseStyle_2Story	HouseStyle_SFoyer	HouseStyle_Slvl	RoofStyle_Flat	\
78	0.0	0.0	0.0	0.0	
478	1.0	0.0	0.0	0.0	
354	1.0	0.0	0.0	0.0	
594	0.0	0.0	0.0	0.0	
1255	1.0	0.0	0.0	0.0	
...	...	...	...	...	
435	1.0	0.0	0.0	0.0	
538	1.0	0.0	0.0	0.0	
350	0.0	0.0	0.0	0.0	
1159	0.0	0.0	0.0	0.0	
894	0.0	0.0	0.0	0.0	1.0

	RoofStyle_Gable	RoofStyle_Gambrel	RoofStyle_Hip	RoofStyle_Mansard	\
78	0.0	0.0	1.0	0.0	
478	1.0	0.0	0.0	0.0	
354	1.0	0.0	0.0	0.0	
594	1.0	0.0	0.0	0.0	
1255	1.0	0.0	0.0	0.0	
...	...	...	...	...	
435	1.0	0.0	0.0	0.0	
538	0.0	0.0	1.0	0.0	
350	1.0	0.0	0.0	0.0	
1159	0.0	0.0	1.0	0.0	
894	0.0	0.0	0.0	0.0	

	RoofStyle_Shed	RoofMatl_CompShg	RoofMatl_Metal	RoofMatl_Roll	\
78	0.0	1.0	0.0	0.0	
478	0.0	1.0	0.0	0.0	
354	0.0	1.0	0.0	0.0	
594	0.0	1.0	0.0	0.0	
1255	0.0	1.0	0.0	0.0	
...	...	...	...	...	
435	0.0	1.0	0.0	0.0	
538	0.0	1.0	0.0	0.0	
350	0.0	1.0	0.0	0.0	
1159	0.0	1.0	0.0	0.0	
894	0.0	0.0	0.0	0.0	

	RoofMatl_Tar&Grv	RoofMatl_WdShake	RoofMatl_WdShngl	\
78	0.0	0.0	0.0	
478	0.0	0.0	0.0	
354	0.0	0.0	0.0	
594	0.0	0.0	0.0	

1255	0.0	0.0	0.0
...	...	...	...
435	0.0	0.0	0.0
538	0.0	0.0	0.0
350	0.0	0.0	0.0
1159	0.0	0.0	0.0
894	1.0	0.0	0.0

	Exterior1st_AsbShng	Exterior1st_BrkComm	Exterior1st_BrkFace	\
78	0.0	0.0	0.0	
478	0.0	0.0	0.0	
354	0.0	0.0	0.0	
594	0.0	0.0	0.0	
1255	0.0	0.0	0.0	
...	...	...	...	
435	1.0	0.0	0.0	
538	0.0	0.0	0.0	
350	0.0	0.0	0.0	
1159	0.0	0.0	0.0	
894	0.0	0.0	0.0	

	Exterior1st_CBlock	Exterior1st_CemntBd	Exterior1st_HdBoard	\
78	0.0	0.0	0.0	
478	0.0	0.0	1.0	
354	0.0	0.0	0.0	
594	0.0	0.0	0.0	
1255	0.0	0.0	0.0	
...	...	...	...	
435	0.0	0.0	0.0	
538	0.0	0.0	0.0	
350	0.0	0.0	0.0	
1159	0.0	0.0	0.0	
894	0.0	0.0	0.0	

	Exterior1st_ImStucc	Exterior1st_MetalSd	Exterior1st_Plywood	\
78	0.0	0.0	0.0	
478	0.0	0.0	0.0	
354	0.0	0.0	0.0	
594	0.0	0.0	1.0	
1255	0.0	0.0	0.0	
...	...	...	...	
435	0.0	0.0	0.0	
538	0.0	0.0	0.0	
350	0.0	0.0	1.0	
1159	0.0	1.0	0.0	
894	0.0	0.0	0.0	

	Exterior1st_Stone	Exterior1st_Stucco	Exterior1st_VinylSd	\
78	0.0	0.0	1.0	
478	0.0	0.0	0.0	
354	0.0	0.0	1.0	
594	0.0	0.0	0.0	
1255	0.0	0.0	1.0	
...	...	...	...	
435	0.0	0.0	0.0	
538	0.0	0.0	1.0	
350	0.0	0.0	0.0	
1159	0.0	0.0	0.0	
894	0.0	0.0	0.0	

	Exterior1st_Wd Sdng	Exterior1st_WdShng	Exterior2nd_AsbShng	\
78	0.0	0.0	0.0	
478	0.0	0.0	0.0	
354	0.0	0.0	0.0	
594	0.0	0.0	0.0	
1255	0.0	0.0	0.0	

...	...	...	...
435	0.0	0.0	1.0
538	0.0	0.0	0.0
350	0.0	0.0	0.0
1159	0.0	0.0	0.0
894	1.0	0.0	0.0

	Exterior2nd_AsphShn	Exterior2nd_Brk Cmn	Exterior2nd_BrkFace \
78	0.0	0.0	0.0
478	0.0	0.0	0.0
354	0.0	0.0	0.0
594	0.0	0.0	0.0
1255	0.0	0.0	0.0
...	...	...	...
435	0.0	0.0	0.0
538	0.0	0.0	0.0
350	0.0	0.0	0.0
1159	0.0	0.0	0.0
894	0.0	0.0	0.0

	Exterior2nd_CBlock	Exterior2nd_CmentBd	Exterior2nd_HdBoard \
78	0.0	0.0	0.0
478	0.0	0.0	1.0
354	0.0	0.0	0.0
594	0.0	0.0	0.0
1255	0.0	0.0	0.0
...	...	...	...
435	0.0	0.0	0.0
538	0.0	0.0	0.0
350	0.0	0.0	0.0
1159	0.0	0.0	0.0
894	0.0	0.0	0.0

	Exterior2nd_ImStucc	Exterior2nd_MetalSd	Exterior2nd_Other \
78	0.0	0.0	0.0
478	0.0	0.0	0.0
354	0.0	0.0	0.0
594	0.0	0.0	0.0
1255	0.0	0.0	0.0
...	...	...	...
435	0.0	0.0	0.0
538	0.0	0.0	0.0
350	0.0	0.0	0.0
1159	0.0	1.0	0.0
894	0.0	0.0	0.0

	Exterior2nd_Plywood	Exterior2nd_Stone	Exterior2nd_Stucco \
78	0.0	0.0	0.0
478	0.0	0.0	0.0
354	0.0	0.0	0.0
594	1.0	0.0	0.0
1255	0.0	0.0	0.0
...	...	...	...
435	0.0	0.0	0.0
538	0.0	0.0	0.0
350	1.0	0.0	0.0
1159	0.0	0.0	0.0
894	0.0	0.0	0.0

	Exterior2nd_VinylSd	Exterior2nd_Wd Sdng	Exterior2nd_Wd Shng \
78	1.0	0.0	0.0
478	0.0	0.0	0.0
354	1.0	0.0	0.0
594	0.0	0.0	0.0
1255	1.0	0.0	0.0
...	...	...	...

435	0.0	0.0	0.0
538	1.0	0.0	0.0
350	0.0	0.0	0.0
1159	0.0	0.0	0.0
894	0.0	1.0	0.0

	MasVnrType_BrkCmn	MasVnrType_BrkFace	MasVnrType_None	\
78	0.0	1.0	0.0	
478	0.0	1.0	0.0	
354	0.0	0.0	1.0	
594	0.0	1.0	0.0	
1255	0.0	1.0	0.0	
...	...	...	...	
435	0.0	0.0	1.0	
538	0.0	1.0	0.0	
350	0.0	1.0	0.0	
1159	0.0	0.0	1.0	
894	0.0	0.0	1.0	

	MasVnrType_Stone	ExterQual_Ex	ExterQual_Fa	ExterQual_Gd	\
78	0.0	0.0	0.0	0.0	
478	0.0	0.0	0.0	0.0	
354	0.0	0.0	0.0	0.0	
594	0.0	0.0	0.0	0.0	
1255	0.0	0.0	0.0	1.0	
...	...	...	...	...	
435	0.0	0.0	0.0	0.0	
538	0.0	0.0	0.0	1.0	
350	0.0	0.0	0.0	0.0	
1159	0.0	0.0	0.0	0.0	
894	0.0	0.0	0.0	0.0	

	ExterQual_TA	ExterCond_Ex	ExterCond_Fa	ExterCond_Gd	ExterCond_Po	\
78	1.0	0.0	0.0	1.0	0.0	
478	1.0	0.0	0.0	0.0	0.0	
354	1.0	0.0	0.0	0.0	0.0	
594	1.0	0.0	0.0	0.0	0.0	
1255	0.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	
435	1.0	0.0	0.0	0.0	0.0	
538	0.0	0.0	0.0	0.0	0.0	
350	1.0	0.0	0.0	0.0	0.0	
1159	1.0	0.0	0.0	0.0	0.0	
894	1.0	0.0	0.0	0.0	0.0	

	ExterCond_TA	Foundation_BrkTil	Foundation_CBlock	Foundation_PConc	\
78	0.0	0.0	0.0	1.0	
478	1.0	0.0	1.0	0.0	
354	1.0	0.0	0.0	1.0	
594	1.0	0.0	1.0	0.0	
1255	1.0	0.0	0.0	1.0	
...	...	...	...	...	
435	1.0	1.0	0.0	0.0	
538	1.0	0.0	0.0	1.0	
350	1.0	0.0	1.0	0.0	
1159	1.0	0.0	1.0	0.0	
894	1.0	0.0	1.0	0.0	

	Foundation_Stone	Foundation_Wood	BsmtQual_Ex	BsmtQual_Fa	\
78	0.0	0.0	1.0	0.0	
478	0.0	0.0	0.0	0.0	
354	0.0	0.0	0.0	0.0	
594	0.0	0.0	0.0	0.0	
1255	0.0	0.0	0.0	0.0	
...	...	...	...	...	
435	0.0	0.0	0.0	0.0	

538	0.0	0.0	0.0	0.0
350	0.0	0.0	0.0	0.0
1159	0.0	0.0	0.0	0.0
894	0.0	0.0	0.0	0.0

	BsmtQual_Gd	BsmtQual_TA	BsmtCond_Fa	BsmtCond_Gd	BsmtCond_Po	\
78	0.0	0.0	0.0	1.0	0.0	
478	0.0	1.0	0.0	0.0	0.0	
354	1.0	0.0	0.0	0.0	0.0	
594	0.0	1.0	0.0	0.0	0.0	
1255	1.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	
435	0.0	1.0	0.0	0.0	0.0	
538	1.0	0.0	0.0	1.0	0.0	
350	1.0	0.0	0.0	0.0	0.0	
1159	0.0	1.0	0.0	0.0	0.0	
894	1.0	0.0	0.0	0.0	0.0	

	BsmtCond_TA	BsmtExposure_Av	BsmtExposure_Gd	BsmtExposure_Mn	\
78	0.0	0.0	0.0	0.0	
478	1.0	0.0	0.0	0.0	
354	1.0	0.0	0.0	0.0	
594	1.0	0.0	0.0	0.0	
1255	1.0	0.0	0.0	0.0	
...	...	...	...	...	
435	1.0	0.0	0.0	0.0	
538	0.0	0.0	0.0	0.0	
350	1.0	0.0	0.0	0.0	
1159	1.0	0.0	0.0	0.0	
894	1.0	0.0	1.0	0.0	

	BsmtExposure_No	BsmtFinType1_ALQ	BsmtFinType1_BLQ	BsmtFinType1_GLQ	\
78	1.0	0.0	0.0	1.0	
478	1.0	0.0	1.0	0.0	
354	1.0	0.0	0.0	0.0	
594	1.0	0.0	1.0	0.0	
1255	1.0	0.0	0.0	0.0	
...	...	...	...	...	
435	1.0	0.0	0.0	0.0	
538	1.0	0.0	0.0	0.0	
350	1.0	0.0	1.0	0.0	
1159	1.0	0.0	0.0	0.0	
894	0.0	0.0	0.0	1.0	

	BsmtFinType1_LwQ	BsmtFinType1_Rec	BsmtFinType1_Unf	BsmtFinType2_ALQ	\
78	0.0	0.0	0.0	0.0	
478	0.0	0.0	0.0	0.0	
354	0.0	0.0	1.0	0.0	
594	0.0	0.0	0.0	0.0	
1255	0.0	0.0	1.0	0.0	
...	...	...	...	...	
435	0.0	0.0	1.0	0.0	
538	0.0	0.0	1.0	0.0	
350	0.0	0.0	0.0	0.0	
1159	0.0	1.0	0.0	0.0	
894	0.0	0.0	0.0	0.0	

	BsmtFinType2_BLQ	BsmtFinType2_GLQ	BsmtFinType2_LwQ	BsmtFinType2_Rec	\
78	0.0	0.0	0.0	0.0	
478	0.0	0.0	0.0	0.0	
354	0.0	0.0	0.0	0.0	
594	0.0	0.0	0.0	0.0	
1255	0.0	0.0	0.0	0.0	
...	...	...	...	...	
435	0.0	0.0	0.0	0.0	
538	0.0	0.0	0.0	0.0	

350	0.0	0.0	0.0	0.0
1159	0.0	0.0	0.0	0.0
894	0.0	0.0	0.0	0.0

	BsmtFinType2_Unf	Heating_GasA	Heating_GasW	Heating_Grav	\
78	1.0	1.0	0.0	0.0	
478	1.0	1.0	0.0	0.0	
354	1.0	1.0	0.0	0.0	
594	1.0	1.0	0.0	0.0	
1255	1.0	1.0	0.0	0.0	
...	...	...	...	...	
435	1.0	1.0	0.0	0.0	
538	1.0	1.0	0.0	0.0	
350	1.0	1.0	0.0	0.0	
1159	1.0	1.0	0.0	0.0	
894	1.0	1.0	0.0	0.0	

	Heating_OthW	HeatingQC_Ex	HeatingQC_Fa	HeatingQC_Gd	HeatingQC_Po	\
78	0.0	1.0	0.0	0.0	0.0	
478	0.0	0.0	0.0	0.0	0.0	
354	0.0	1.0	0.0	0.0	0.0	
594	0.0	0.0	0.0	0.0	0.0	
1255	0.0	1.0	0.0	0.0	0.0	
...	...	...	...	...	...	
435	0.0	0.0	1.0	0.0	0.0	
538	0.0	1.0	0.0	0.0	0.0	
350	0.0	0.0	0.0	1.0	0.0	
1159	0.0	0.0	0.0	0.0	0.0	
894	0.0	1.0	0.0	0.0	0.0	

	HeatingQC_TA	CentralAir_N	CentralAir_Y	Electrical_FuseA	\
78	0.0	0.0	1.0	0.0	
478	1.0	0.0	1.0	0.0	
354	0.0	0.0	1.0	0.0	
594	1.0	0.0	1.0	0.0	
1255	0.0	0.0	1.0	0.0	
...	...	...	...	...	
435	0.0	1.0	0.0	0.0	
538	0.0	0.0	1.0	0.0	
350	0.0	0.0	1.0	0.0	
1159	1.0	0.0	1.0	0.0	
894	0.0	0.0	1.0	0.0	

	Electrical_FuseF	Electrical_FuseP	Electrical_Mix	Electrical_SBrkr	\
78	0.0	0.0	0.0	1.0	
478	0.0	0.0	0.0	1.0	
354	0.0	0.0	0.0	1.0	
594	0.0	0.0	0.0	1.0	
1255	0.0	0.0	0.0	1.0	
...	...	...	...	...	
435	0.0	0.0	0.0	1.0	
538	0.0	0.0	0.0	1.0	
350	0.0	0.0	0.0	1.0	
1159	0.0	0.0	0.0	1.0	
894	0.0	0.0	0.0	1.0	

	KitchenQual_Ex	KitchenQual_Fa	KitchenQual_Gd	KitchenQual_TA	\
78	0.0	0.0	0.0	1.0	
478	0.0	0.0	0.0	1.0	
354	0.0	0.0	0.0	1.0	
594	0.0	0.0	0.0	1.0	
1255	0.0	0.0	1.0	0.0	
...	...	...	...	...	
435	0.0	0.0	0.0	1.0	
538	1.0	0.0	0.0	0.0	
350	0.0	0.0	0.0	1.0	



1159	0.0	0.0	0.0	1.0
894	0.0	0.0	1.0	0.0

	Functional_Maj1	Functional_Maj2	Functional_Min1	Functional_Min2	\
78	0.0	0.0	0.0	0.0	
478	0.0	0.0	0.0	0.0	
354	0.0	0.0	0.0	0.0	
594	0.0	0.0	0.0	0.0	
1255	0.0	0.0	0.0	0.0	
...	...	...	...	...	
435	0.0	0.0	0.0	0.0	
538	0.0	0.0	0.0	0.0	
350	0.0	0.0	0.0	0.0	
1159	0.0	0.0	0.0	0.0	
894	0.0	0.0	0.0	0.0	

	Functional_Mod	Functional_Sev	Functional_Typ	FireplaceQu_Ex	\
78	0.0	0.0	1.0	0.0	
478	0.0	0.0	1.0	0.0	
354	0.0	0.0	1.0	0.0	
594	0.0	0.0	1.0	0.0	
1255	0.0	0.0	1.0	0.0	
...	...	...	...	...	
435	0.0	0.0	1.0	0.0	
538	0.0	0.0	1.0	0.0	
350	0.0	0.0	1.0	0.0	
1159	0.0	0.0	1.0	0.0	
894	0.0	0.0	1.0	0.0	

	FireplaceQu_Fa	FireplaceQu_Gd	FireplaceQu_None	FireplaceQu_Po	\
78	0.0	0.0	1.0	0.0	
478	0.0	0.0	1.0	0.0	
354	0.0	0.0	0.0	0.0	
594	0.0	0.0	1.0	0.0	
1255	0.0	0.0	0.0	0.0	
...	...	...	...	...	
435	0.0	0.0	1.0	0.0	
538	0.0	1.0	0.0	0.0	
350	0.0	1.0	0.0	0.0	
1159	0.0	0.0	1.0	0.0	
894	0.0	1.0	0.0	0.0	

	FireplaceQu_TA	GarageType_2Types	GarageType_Attchd	\
78	0.0	0.0	1.0	
478	0.0	0.0	0.0	
354	1.0	0.0	1.0	
594	0.0	0.0	0.0	
1255	1.0	0.0	0.0	
...	...	...	...	
435	0.0	0.0	0.0	
538	0.0	0.0	0.0	
350	0.0	0.0	1.0	
1159	0.0	0.0	1.0	
894	0.0	0.0	1.0	

	GarageType_Basment	GarageType_BuiltIn	GarageType_CarPort	\
78	0.0	0.0	0.0	
478	0.0	0.0	0.0	
354	0.0	0.0	0.0	
594	0.0	0.0	0.0	
1255	0.0	1.0	0.0	
...	...	...	...	
435	0.0	0.0	0.0	
538	0.0	1.0	0.0	
350	0.0	0.0	0.0	
1159	0.0	0.0	0.0	

894

0.0

0.0

0.0

	GarageType_Detchd	GarageType_None	PavedDrive_N	PavedDrive_P	\
78	0.0	0.0	0.0	0.0	
478	1.0	0.0	0.0	0.0	
354	0.0	0.0	0.0	0.0	
594	1.0	0.0	0.0	0.0	
1255	0.0	0.0	0.0	0.0	
...	...	...	...	...	
435	1.0	0.0	0.0	0.0	
538	0.0	0.0	0.0	0.0	
350	0.0	0.0	0.0	0.0	
1159	0.0	0.0	1.0	0.0	
894	0.0	0.0	0.0	0.0	

	PavedDrive_Y	SaleType_COD	SaleType_CWD	SaleType_Con	SaleType_ConLD	\
78	1.0	0.0	0.0	0.0	0.0	
478	1.0	0.0	0.0	0.0	0.0	
354	1.0	0.0	0.0	0.0	0.0	
594	1.0	0.0	0.0	0.0	0.0	
1255	1.0	0.0	0.0	0.0	0.0	
...	...	...	...	...	...	
435	1.0	1.0	0.0	0.0	0.0	
538	1.0	0.0	0.0	0.0	0.0	
350	1.0	0.0	0.0	0.0	0.0	
1159	0.0	0.0	0.0	0.0	0.0	
894	1.0	0.0	0.0	0.0	0.0	

	SaleType_ConLI	SaleType_ConLw	SaleType_New	SaleType_Oth	SaleType_WD	\
78	0.0	0.0	0.0	0.0	1.0	
478	0.0	0.0	0.0	0.0	1.0	
354	0.0	0.0	0.0	0.0	1.0	
594	0.0	0.0	0.0	0.0	1.0	
1255	0.0	0.0	0.0	0.0	1.0	
...	...	...	...	...	...	
435	0.0	0.0	0.0	0.0	0.0	
538	0.0	0.0	0.0	0.0	1.0	
350	0.0	0.0	0.0	0.0	1.0	
1159	0.0	0.0	0.0	0.0	1.0	
894	0.0	0.0	0.0	0.0	1.0	

	SaleCondition_Abnorml	SaleCondition_AdjLand	SaleCondition_Alloca	\
78	0.0	0.0	0.0	
478	0.0	0.0	0.0	
354	0.0	0.0	0.0	
594	0.0	0.0	0.0	
1255	0.0	0.0	0.0	
...	...	...	...	
435	1.0	0.0	0.0	
538	0.0	0.0	0.0	
350	0.0	0.0	0.0	
1159	0.0	0.0	0.0	
894	0.0	0.0	0.0	

	SaleCondition_Family	SaleCondition_Normal	SaleCondition_Partial	\
78	0.0	1.0	0.0	
478	0.0	1.0	0.0	
354	0.0	1.0	0.0	
594	0.0	1.0	0.0	
1255	0.0	1.0	0.0	
...	...	...	...	
435	0.0	0.0	0.0	
538	0.0	1.0	0.0	
350	0.0	1.0	0.0	
1159	0.0	1.0	0.0	
894	0.0	1.0	0.0	

```
[280 rows x 254 columns]
Training Labels:
  48      177000
155      412500
756      269790
1070     133700
303      188500
...
1095      80000
1130     392500
1294     410000
860      110000
1126     119500
Name: SalePrice, Length: 1118, dtype: int64
Testing Labels:
  78      153500
478      113000
354      172400
594      135000
1255     333168
...
435      98000
538      325000
350      159000
1159     113000
894      242000
Name: SalePrice, Length: 280, dtype: int64
```

## Models

Following are the two regression models developed for this project,

1. XGBoost
2. Artificial Neural networks

## XGBoost model

After splitting the dataset, XGBoost model libraries are imported and using XGBRegressor class the model is fit and predicted.

The MSE and R Squared is also calculated.

```
In [21]: import xgboost as xgb
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
import pandas as pd
import numpy as np

# Initialize the XGBoost Regressor
xg_reg = xgb.XGBRegressor(objective='reg:squarederror', # Regression task
                          n_estimators=100,           # Number of boosting rounds (tr
                          learning_rate=0.1,          # Step size shrinkage
                          max_depth=3)               # Maximum tree depth
```

```

# Fit the model to training data
xg_reg.fit(X_train, y_train)

# Make predictions on the test set
# Predict on test data
y_pred = xg_reg.predict(X_test)

# Calculate Mean Squared Error
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse}")

# Calculate R-squared
r_squared = xg_reg.score(X_test, y_test)
print(f"R-squared: {r_squared}")

```

Mean Squared Error: 739680079.3796469  
R-squared: 0.8952285051345825

As a part of my learning, GridSearchCV has been used and best parameters are found.

```

In [22]: from sklearn.model_selection import GridSearchCV

# Define the hyperparameter grid
param_grid = {
    'learning_rate': [0.01, 0.1, 0.2, 0.3],
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 4, 5],
}

# Initialize GridSearchCV with XGBRegressor
grid_search = GridSearchCV(estimator=xgb.XGBRegressor(objective='reg:squarederror'),
                           param_grid=param_grid, cv=3, scoring='neg_mean_squared_error')

# Fit the grid search to the data
grid_search.fit(X_train, y_train)

# Best parameters
print("Best Parameters:", grid_search.best_params_)

```

Best Parameters: {'learning\_rate': 0.2, 'max\_depth': 3, 'n\_estimators': 300}

Same XGBoost model has been run once again with the best parameters as found above.

```

In [23]: # Initialize the XGBoost Regressor
xg_reg_cv = xgb.XGBRegressor(objective='reg:squarederror', # Regression task
                             n_estimators=300,           # Number of boosting rounds (tr
                             learning_rate=0.2,          # Step size shrinkage
                             max_depth=3)                # Maximum tree depth

# Fit the model to training data
xg_reg_cv.fit(X_train, y_train)

# Make predictions on the test set
# Predict on test data
y_pred_cv = xg_reg_cv.predict(X_test)

# Calculate Mean Squared Error
mse_cv = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse_cv}")

```

```
# Calculate R-squared
r_squared_cv = xg_reg_cv.score(X_test, y_test)
print(f"R-squared: {r_squared_cv}")
```

Mean Squared Error: 739680079.3796469

R-squared: 0.8992318511009216

One another instance of the same model has been run using RFECV as a part of my learning.

```
In [25]: from sklearn.feature_selection import RFECV

# Initialize XGBoost Regressor
xg_reg_RFECV = xgb.XGBRegressor(objective='reg:squarederror', n_estimators=100, learning_rate=0.1)

# RFECV for automatic feature selection
rfecv_RFECV = RFECV(estimator=xg_reg, step=1, cv=5, scoring='neg_mean_squared_error')
rfecv_RFECV.fit(X_train, y_train)

# Get selected features
selected_features_rfecv = X.columns[rfecv_RFECV.support_]
print(f'Selected Features (RFECV): {selected_features_rfecv}')

# Train model with selected features
X_train_selected = X_train[selected_features_rfecv]
X_test_selected = X_test[selected_features_rfecv]

xg_reg_RFECV.fit(X_train_selected, y_train)
y_pred = xg_reg_RFECV.predict(X_test_selected)

# Calculate Mean Squared Error
mse_rfecv = mean_squared_error(y_test, y_pred)
print(f'Mean Squared Error (RFECV): {mse_rfecv}')

# Calculate R-squared
r_squared_RFECV = xg_reg_RFECV.score(X_test_selected, y_test)
print(f"R-squared: {r_squared_RFECV}")

rmse = np.sqrt(mse_rfecv)
print (rmse)
```

Selected Features (RFECV): Index(['LotArea', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd',

'MasVnrArea', 'BsmtFinSF1', 'TotalBsmtSF', '2ndFlrSF', 'GrLivArea', 'BsmtFullBath', 'FullBath', 'HalfBath', 'KitchenAbvGr', 'TotRmsAbvGrd', 'Fireplaces', 'GarageCars', 'GarageArea', 'WoodDeckSF', 'MoSold', 'GrandArea', 'MSZoning\_RL', 'LandSlope\_Mod', 'Neighborhood\_CollgCr', 'Neighborhood\_Crawfor', 'Neighborhood\_StoneBr', 'ExterQual\_Ex', 'ExterQual\_TA', 'BsmtQual\_Ex', 'BsmtExposure\_Gd', 'BsmtFinType1\_GLQ', 'HeatingQC\_Gd', 'CentralAir\_N', 'KitchenQual\_Ex', 'KitchenQual\_Gd', 'Functional\_Typ', 'FireplaceQu\_Gd', 'GarageType\_Attchd', 'GarageType\_Detachd', 'SaleType\_New', 'SaleCondition\_Abnorml'], dtype='object')

Mean Squared Error (RFECV): 712265048.1892676

R-squared: 0.8991116881370544

26688.294216552462

GridSearchCV has been run once again with the combination of RFECV for my learning purpose

```
In [26]: from sklearn.model_selection import GridSearchCV

# Define the hyperparameter grid
param_grid = {
    'learning_rate': [0.01, 0.1, 0.2, 0.3],
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 4, 5],
```

```

}

# Initialize GridSearchCV with XGBRegressor
grid_search_RFECV = GridSearchCV(estimator=xgb.XGBRegressor(objective='reg:squarederror'
                                                             param_grid=param_grid, cv=3, scoring='neg_mean_squared_error'

# Fit the grid search to the data
grid_search_RFECV.fit(X_train_selected, y_train)

# Best parameters
print("Best Parameters:", grid_search_RFECV.best_params_)

# Initialize the XGBoost Regressor
xg_reg_RFECV = xgb.XGBRegressor(objective='reg:squarederror', # Regression task
                                n_estimators=200,             # Number of boosting rounds (tr
                                learning_rate=0.2,             # Step size shrinkage
                                max_depth=3)                   # Maximum tree depth

# Make predictions on the test set
# Predict on test data
xg_reg_RFECV.fit(X_train_selected, y_train)
y_pred_RFECV = xg_reg_RFECV.predict(X_test_selected)

# Calculate Mean Squared Error
mse_RFECV = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error: {mse_RFECV}")

# Calculate R-squared
r_squared_RFECV = xg_reg_RFECV.score(X_test_selected, y_test)
print(f"R-squared: {r_squared_RFECV}")

```

```

Best Parameters: {'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 200}
Mean Squared Error: 712265048.1892676
R-squared: 0.8892741799354553

```

## ANN model

Standard scaler has been applied to the train and test data, to have a mean of 0 and standard deviation of 1. It helps speed up the learning process by ensuring the network has a more stable and balanced gradient. An additional neural network model has been run.

```

In [27]: import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score

# Standardize the data (this is often useful for neural networks)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Build a simple neural network model for regression
model = Sequential()

# Input layer with 3 input features, one hidden layer with 64 neurons, and output layer
model.add(Dense(64, activation='relu', input_shape=(X_train_scaled.shape[1],)))
model.add(Dense(128, activation='relu')) # 2nd hidden layer

```

```

model.add(Dense(64, activation='relu')) # 3rd hidden layer
model.add(Dense(32, activation='relu')) # 4th hidden layer
model.add(Dense(1)) # Output layer with 1 neuron (for continuous value prediction)

# Compile the model using Mean Squared Error (MSE) as the loss function and Adam optimizer
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
model.fit(X_train_scaled, y_train, epochs=100, batch_size=32, verbose=1)

# Make predictions
y_pred = model.predict(X_test_scaled)

# Calculate and print the Root Mean Squared Error (RMSE)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print(f"Root Mean Squared Error (RMSE): {rmse}")

# Calculate R-squared
r2 = r2_score(y_test, y_pred)

print(f"R-squared: {r2}")

```

C:\Users\Riaz\anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an `input\_shape`/`input\_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```

super().__init__(activity_regularizer=activity_regularizer, **kwargs)

```

```

Epoch 1/100
35/35 ————— 3s 3ms/step - loss: 38733680640.0000
Epoch 2/100
35/35 ————— 0s 2ms/step - loss: 39961980928.0000
Epoch 3/100
35/35 ————— 0s 3ms/step - loss: 39441084416.0000
Epoch 4/100
35/35 ————— 0s 3ms/step - loss: 27071232000.0000
Epoch 5/100
35/35 ————— 0s 2ms/step - loss: 10535130112.0000
Epoch 6/100
35/35 ————— 0s 2ms/step - loss: 6200822784.0000
Epoch 7/100
35/35 ————— 0s 3ms/step - loss: 3546874112.0000
Epoch 8/100
35/35 ————— 0s 2ms/step - loss: 2108351232.0000
Epoch 9/100
35/35 ————— 0s 2ms/step - loss: 1642377472.0000
Epoch 10/100
35/35 ————— 0s 2ms/step - loss: 1227948032.0000
Epoch 11/100
35/35 ————— 0s 2ms/step - loss: 1014454336.0000
Epoch 12/100
35/35 ————— 0s 2ms/step - loss: 980015040.0000
Epoch 13/100
35/35 ————— 0s 2ms/step - loss: 809232576.0000
Epoch 14/100
35/35 ————— 0s 3ms/step - loss: 781222720.0000
Epoch 15/100
35/35 ————— 0s 2ms/step - loss: 674652672.0000
Epoch 16/100
35/35 ————— 0s 3ms/step - loss: 656052736.0000
Epoch 17/100
35/35 ————— 0s 2ms/step - loss: 634472000.0000
Epoch 18/100
35/35 ————— 0s 2ms/step - loss: 480466784.0000
Epoch 19/100
35/35 ————— 0s 2ms/step - loss: 540717440.0000

```

Epoch 20/100	<b>35/35</b>	0s 2ms/step - loss: 475730848.0000
Epoch 21/100	<b>35/35</b>	0s 2ms/step - loss: 478371552.0000
Epoch 22/100	<b>35/35</b>	0s 2ms/step - loss: 448959008.0000
Epoch 23/100	<b>35/35</b>	0s 2ms/step - loss: 415411776.0000
Epoch 24/100	<b>35/35</b>	0s 3ms/step - loss: 367201728.0000
Epoch 25/100	<b>35/35</b>	0s 3ms/step - loss: 389466752.0000
Epoch 26/100	<b>35/35</b>	0s 2ms/step - loss: 367920032.0000
Epoch 27/100	<b>35/35</b>	0s 2ms/step - loss: 346098944.0000
Epoch 28/100	<b>35/35</b>	0s 3ms/step - loss: 346544192.0000
Epoch 29/100	<b>35/35</b>	0s 2ms/step - loss: 364562080.0000
Epoch 30/100	<b>35/35</b>	0s 3ms/step - loss: 372335456.0000
Epoch 31/100	<b>35/35</b>	0s 2ms/step - loss: 289689440.0000
Epoch 32/100	<b>35/35</b>	0s 3ms/step - loss: 297819840.0000
Epoch 33/100	<b>35/35</b>	0s 2ms/step - loss: 243877744.0000
Epoch 34/100	<b>35/35</b>	0s 2ms/step - loss: 270862976.0000
Epoch 35/100	<b>35/35</b>	0s 2ms/step - loss: 251725968.0000
Epoch 36/100	<b>35/35</b>	0s 3ms/step - loss: 322231040.0000
Epoch 37/100	<b>35/35</b>	0s 3ms/step - loss: 265979552.0000
Epoch 38/100	<b>35/35</b>	0s 2ms/step - loss: 289109824.0000
Epoch 39/100	<b>35/35</b>	0s 3ms/step - loss: 262039888.0000
Epoch 40/100	<b>35/35</b>	0s 3ms/step - loss: 244107152.0000
Epoch 41/100	<b>35/35</b>	0s 3ms/step - loss: 243650816.0000
Epoch 42/100	<b>35/35</b>	0s 3ms/step - loss: 255338304.0000
Epoch 43/100	<b>35/35</b>	0s 3ms/step - loss: 208358976.0000
Epoch 44/100	<b>35/35</b>	0s 2ms/step - loss: 235003008.0000
Epoch 45/100	<b>35/35</b>	0s 2ms/step - loss: 246282880.0000
Epoch 46/100	<b>35/35</b>	0s 2ms/step - loss: 213298992.0000
Epoch 47/100	<b>35/35</b>	0s 2ms/step - loss: 192490064.0000
Epoch 48/100	<b>35/35</b>	0s 3ms/step - loss: 196573408.0000
Epoch 49/100	<b>35/35</b>	0s 3ms/step - loss: 198204560.0000
Epoch 50/100	<b>35/35</b>	0s 2ms/step - loss: 207491040.0000
Epoch 51/100	<b>35/35</b>	0s 2ms/step - loss: 178342128.0000
Epoch 52/100	<b>35/35</b>	0s 2ms/step - loss: 186717792.0000



Epoch 53/100	<b>35/35</b>	0s 2ms/step - loss: 223875824.0000
Epoch 54/100	<b>35/35</b>	0s 2ms/step - loss: 155992576.0000
Epoch 55/100	<b>35/35</b>	0s 2ms/step - loss: 222225248.0000
Epoch 56/100	<b>35/35</b>	0s 2ms/step - loss: 164092560.0000
Epoch 57/100	<b>35/35</b>	0s 3ms/step - loss: 183253840.0000
Epoch 58/100	<b>35/35</b>	0s 2ms/step - loss: 177960880.0000
Epoch 59/100	<b>35/35</b>	0s 3ms/step - loss: 167012288.0000
Epoch 60/100	<b>35/35</b>	0s 3ms/step - loss: 184324848.0000
Epoch 61/100	<b>35/35</b>	0s 2ms/step - loss: 180131824.0000
Epoch 62/100	<b>35/35</b>	0s 2ms/step - loss: 219963088.0000
Epoch 63/100	<b>35/35</b>	0s 2ms/step - loss: 159893456.0000
Epoch 64/100	<b>35/35</b>	0s 3ms/step - loss: 156727072.0000
Epoch 65/100	<b>35/35</b>	0s 3ms/step - loss: 137286368.0000
Epoch 66/100	<b>35/35</b>	0s 2ms/step - loss: 146315568.0000
Epoch 67/100	<b>35/35</b>	0s 3ms/step - loss: 146743552.0000
Epoch 68/100	<b>35/35</b>	0s 3ms/step - loss: 141036480.0000
Epoch 69/100	<b>35/35</b>	0s 3ms/step - loss: 171761152.0000
Epoch 70/100	<b>35/35</b>	0s 3ms/step - loss: 156288208.0000
Epoch 71/100	<b>35/35</b>	0s 2ms/step - loss: 157211872.0000
Epoch 72/100	<b>35/35</b>	0s 2ms/step - loss: 133620520.0000
Epoch 73/100	<b>35/35</b>	0s 3ms/step - loss: 169730544.0000
Epoch 74/100	<b>35/35</b>	0s 3ms/step - loss: 142623888.0000
Epoch 75/100	<b>35/35</b>	0s 3ms/step - loss: 155123120.0000
Epoch 76/100	<b>35/35</b>	0s 3ms/step - loss: 138146448.0000
Epoch 77/100	<b>35/35</b>	0s 2ms/step - loss: 133328832.0000
Epoch 78/100	<b>35/35</b>	0s 2ms/step - loss: 120216896.0000
Epoch 79/100	<b>35/35</b>	0s 2ms/step - loss: 137511248.0000
Epoch 80/100	<b>35/35</b>	0s 3ms/step - loss: 136124080.0000
Epoch 81/100	<b>35/35</b>	0s 4ms/step - loss: 126484968.0000
Epoch 82/100	<b>35/35</b>	0s 3ms/step - loss: 109866192.0000
Epoch 83/100	<b>35/35</b>	0s 2ms/step - loss: 116785064.0000
Epoch 84/100	<b>35/35</b>	0s 2ms/step - loss: 115543440.0000
Epoch 85/100	<b>35/35</b>	0s 2ms/step - loss: 126940600.0000

```

Epoch 86/100
35/35 ————— 0s 3ms/step - loss: 144546592.0000
Epoch 87/100
35/35 ————— 0s 2ms/step - loss: 111387008.0000
Epoch 88/100
35/35 ————— 0s 3ms/step - loss: 98769080.0000
Epoch 89/100
35/35 ————— 0s 3ms/step - loss: 116741600.0000
Epoch 90/100
35/35 ————— 0s 3ms/step - loss: 142048272.0000
Epoch 91/100
35/35 ————— 0s 2ms/step - loss: 96497160.0000
Epoch 92/100
35/35 ————— 0s 3ms/step - loss: 130368592.0000
Epoch 93/100
35/35 ————— 0s 3ms/step - loss: 143725472.0000
Epoch 94/100
35/35 ————— 0s 3ms/step - loss: 98900160.0000
Epoch 95/100
35/35 ————— 0s 2ms/step - loss: 117763896.0000
Epoch 96/100
35/35 ————— 0s 3ms/step - loss: 105844224.0000
Epoch 97/100
35/35 ————— 0s 3ms/step - loss: 89482872.0000
Epoch 98/100
35/35 ————— 0s 2ms/step - loss: 86296432.0000
Epoch 99/100
35/35 ————— 0s 2ms/step - loss: 98563528.0000
Epoch 100/100
35/35 ————— 0s 2ms/step - loss: 130962592.0000
9/9 ————— 0s 15ms/step
Root Mean Squared Error (RMSE): 34126.043177258194
R-squared: 0.8350428342819214

```

One another time the same ANN model has been run with the hyperparameter tuning

```

In [62]: #from tensorflow.keras.wrappers.scikit_learn import KerasRegressor
#%pip install tensorflow scikeras scikit-learn

from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from tensorflow.keras.wrappers.scikit_learn import KerasRegressor
from scikeras.wrappers import KerasRegressor
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Define a function to create the model (to use in grid search)
def create_model(neurons=64, hidden_layers=1):
    model_kerasregressor = Sequential()
    model_kerasregressor.add(Dense(neurons, input_dim=X_train_scaled.shape[1], activation='relu'))

    # Add the desired number of hidden layers
    for _ in range(hidden_layers):
        model_kerasregressor.add(Dense(neurons, activation='relu'))

    model_kerasregressor.add(Dense(1)) # Output layer for regression
    model_kerasregressor.compile(optimizer='adam', loss='mean_squared_error')
    return model_kerasregressor

# Wrap Keras model with KerasRegressor
model_kerasregressor = KerasRegressor(build_fn=create_model, epochs=50, batch_size=32, verbose=1)
print(model_kerasregressor)

# Define the grid of hyperparameters to search
param_grid = {
    'model__neurons': [32, 64, 128], # Different neuron counts
    'model__hidden_layers': [1, 2, 3], # Number of hidden layers

```

```

    'batch_size': [16, 32, 64],          # Batch sizes to try
    'epochs': [50, 100, 150]            # Number of epochs to try
}

# Perform the grid search
grid_ann = RandomizedSearchCV(estimator=model_kerasregressor, param_distributions=param_
grid_result = grid_ann.fit(X_train_scaled, y_train)

# Get the best parameters
print(f"Best: {grid_result.best_score_} using {grid_result.best_params_}")

```

```

KerasRegressor(
    model=None
    build_fn=<function create_model at 0x0000021003DE4680>
    warm_start=False
    random_state=None
    optimizer=rmsprop
    loss=None
    metrics=None
    batch_size=32
    validation_batch_size=None
    verbose=0
    callbacks=None
    validation_split=0.0
    shuffle=True
    run_eagerly=False
    epochs=50
)

```

C:\Users\Riaz\anaconda3\Lib\site-packages\scikeras\wrappers.py:925: UserWarning: ``build\_fn`` will be renamed to ``model`` in a future release, at which point use of ``build\_fn`` will raise an Error instead.

X, y = self.\_initialize(X, y)

C:\Users\Riaz\anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an `input\_shape`/`input\_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

super().\_\_init\_\_(activity\_regularizer=activity\_regularizer, \*\*kwargs)

Best: -1264862090.065643 using {'model\_\_neurons': 128, 'model\_\_hidden\_layers': 3, 'epoch s': 150, 'batch\_size': 64}

```

In [64]: best_model = grid_result.best_estimator_
         predictions = best_model.predict(X_test_scaled)

# Calculate and print the Root Mean Squared Error (RMSE)
rmse_randomsearchcv = np.sqrt(mean_squared_error(y_test, predictions))
print(f"Root Mean Squared Error (RMSE): {rmse_randomsearchcv}")

```

```

# Calculate R-squared
r2_randomsearchcv = r2_score(y_test, predictions)

print(f"R-squared: {r2_randomsearchcv}")

```

Root Mean Squared Error (RMSE): 30195.1942335079  
R-squared: 0.8708558082580566

```

In [65]: estimators = [
         ('knn', KNeighborsClassifier()),
         ('rf', RandomForestClassifier(n_estimators=10, random_state=42)),
         ('svr', LinearSVC(random_state=42))
         ]

```

R-squared: 0.8708558082580566

## Result Evaluation

Standard regression evaluation metrics like MAE, MSE, RMSE, and  $R^2$  will be used. Also, the feature importance of XGBRegressor will be explored.

Out of the two different models, XGboost offered a marginal higher performance over ANN,

XGboost Model

Best Parameters: {'learning\_rate': 0.2, 'max\_depth': 3, 'n\_estimators': 200}

Mean Squared Error: 712265048.1892676

Root Mean Squared Error (RMSE): 26688.294216

R-squared: 0.8991116881370544

ANN Model

Best Parameters: -1264862090.065643 using {'model\_neurons': **128**, 'model\_hidden\_layers': 3, 'epochs': 150, 'batch\_size': 64}

Mean Squared Error: 30195.1942335079

Root Mean Squared Error (RMSE): 30195.1942335079

R-squared: 0.8708558082580566

Root Mean Squared Error (RMSE) indicates the XGBoost model prediction is off of 26688 USD, the actual sale value of the house.

Coefficient of Determination is how well the input variables in a regression model explains the variance in the target variable. It varies from 0 to 1 and in the case of XGBoost model, the input variables are able to explain the 89% of the variance in target variable and the rest 11% is unexplained.

## Conclusion

This is an individual project related to housing price prediction from historical prices.

Two different models has been created after performing data preparation and the models are evaluated.

Data visualization has also been completed to understand more about the data.

Please refer this Jupyter notebook with the original word document for easier understanding.