

# task2-houseprice

July 8, 2024

## 1 House Price Prediction

```
[1]: import pandas as pd
import warnings
warnings.filterwarnings('ignore')
```

```
[2]: house_df = pd.read_csv("HousePricePrediction.xlsx - Sheet1.csv")
```

```
[3]: house_df.head()
```

```
[3]:   Id  MSSubClass MSZoning  LotArea LotConfig BldgType  OverallCond  \
0    0           60       RL    8450     Inside    1Fam           5
1    1           20       RL    9600        FR2    1Fam           8
2    2           60       RL   11250     Inside    1Fam           5
3    3           70       RL    9550     Corner    1Fam           5
4    4           60       RL   14260        FR2    1Fam           5

      YearBuilt  YearRemodAdd Exterior1st  BsmtFinSF2  TotalBsmtSF  SalePrice
0         2003         2003     VinylSd         0.0         856.0   208500.0
1         1976         1976     MetalSd         0.0        1262.0   181500.0
2         2001         2002     VinylSd         0.0         920.0   223500.0
3         1915         1970     Wd Sdng         0.0         756.0  140000.0
4         2000         2000     VinylSd         0.0        1145.0  250000.0
```

```
[4]: house_df.shape
```

```
[4]: (2919, 13)
```

```
[5]: house_df.drop_duplicates(inplace=True)
```

```
[6]: house_df.shape
```

```
[6]: (2919, 13)
```

```
[7]: house_df.columns
```

```
[7]: Index(['Id', 'MSSubClass', 'MSZoning', 'LotArea', 'LotConfig', 'BldgType',  
        'OverallCond', 'YearBuilt', 'YearRemodAdd', 'Exterior1st', 'BsmtFinSF2',  
        'TotalBsmtSF', 'SalePrice'],  
        dtype='object')
```

```
[8]: house_df.drop(columns = ['Id'], inplace = True)
```

```
[9]: house_df.shape
```

```
[9]: (2919, 12)
```

```
[10]: house_df.isna().sum()
```

```
[10]: MSSubClass      0  
      MSZoning      4  
      LotArea      0  
      LotConfig     0  
      BldgType      0  
      OverallCond   0  
      YearBuilt     0  
      YearRemodAdd  0  
      Exterior1st   1  
      BsmtFinSF2    1  
      TotalBsmtSF   1  
      SalePrice    1459  
      dtype: int64
```

```
[11]: from sklearn.impute import SimpleImputer  
  
      imputer = SimpleImputer(strategy='mean')  
  
      imputer.fit(house_df[['SalePrice']])
```

```
[11]: SimpleImputer()
```

```
[12]: imputer.statistics_    # all null values of saleprice will be replaced by mean  
      ↪ of salePrice which is 180921.1958
```

```
[12]: array([180921.19589041])
```

```
[13]: house_df['SalePrice'] = imputer.transform(house_df[['SalePrice']])
```

```
[14]: house_df.isna().sum()
```

```
[14]: MSSubClass      0  
      MSZoning      4  
      LotArea      0
```

```

LotConfig      0
BldgType       0
OverallCond    0
YearBuilt      0
YearRemodAdd   0
Exterior1st    1
BsmtFinSF2     1
TotalBsmtSF    1
SalePrice      0
dtype: int64

```

```
[15]: house_df = house_df.fillna(0)
```

```
[16]: house_df.isna().sum()  #we have replaced the rest null values with 0. now we
    ↪ dont have have null values
```

```
[16]: MSSubClass      0
MSZoning             0
LotArea             0
LotConfig           0
BldgType            0
OverallCond         0
YearBuilt           0
YearRemodAdd        0
Exterior1st         0
BsmtFinSF2          0
TotalBsmtSF         0
SalePrice           0
dtype: int64

```

```
[17]: house_df.describe()
```

```
[17]:
```

	MSSubClass	LotArea	OverallCond	YearBuilt	YearRemodAdd	\
count	2919.000000	2919.000000	2919.000000	2919.000000	2919.000000	
mean	57.137718	10168.114080	5.564577	1971.312778	1984.264474	
std	42.517628	7886.996359	1.113131	30.291442	20.894344	
min	20.000000	1300.000000	1.000000	1872.000000	1950.000000	
25%	20.000000	7478.000000	5.000000	1953.500000	1965.000000	
50%	50.000000	9453.000000	5.000000	1973.000000	1993.000000	
75%	70.000000	11570.000000	6.000000	2001.000000	2004.000000	
max	190.000000	215245.000000	9.000000	2010.000000	2010.000000	

  

	BsmtFinSF2	TotalBsmtSF	SalePrice
count	2919.000000	2919.000000	2919.000000
mean	49.565262	1051.417266	180921.195890
std	169.179104	441.120498	56174.332503
min	0.000000	0.000000	34900.000000

25%	0.000000	793.000000	163000.000000
50%	0.000000	989.000000	180921.195890
75%	0.000000	1302.000000	180921.195890
max	1526.000000	6110.000000	755000.000000

```
[18]: import matplotlib.pyplot as plt
import seaborn as sns
```

```
[19]: sns.set_style('darkgrid')
sns.boxplot(house_df, y = 'LotArea');
```



```
[20]: import numpy as np

Q1 = np.percentile(house_df['LotArea'], 25, interpolation = 'midpoint')
Q3 = np.percentile(house_df['LotArea'], 75, interpolation = 'midpoint')

IQR = Q3 - Q1
```

```
[21]: lowerBound = Q1 - 1.5 * IQR
upperBound = Q1 + 1.5 * IQR
```

```
[22]: df = house_df[(house_df.LotArea < upperBound) & (house_df.LotArea > lowerBound)]
df
```

```
[22]:
```

	MSSubClass	MSZoning	LotArea	LotConfig	BldgType	OverallCond	YearBuilt	\
0	60	RL	8450	Inside	1Fam	5	2003	
1	20	RL	9600	FR2	1Fam	8	1976	
2	60	RL	11250	Inside	1Fam	5	2001	
3	70	RL	9550	Corner	1Fam	5	1915	
6	20	RL	10084	Inside	1Fam	5	2004	
...	...	...	...	...	...	...	...	
2913	160	RM	1526	Inside	Twnhs	5	1970	
2914	160	RM	1936	Inside	Twnhs	7	1970	
2915	160	RM	1894	Inside	TwnhsE	5	1970	
2917	85	RL	10441	Inside	1Fam	5	1992	
2918	60	RL	9627	Inside	1Fam	5	1993	

	YearRemodAdd	Exterior1st	BsmtFinSF2	TotalBsmtSF	SalePrice
0	2003	VinylSd	0.0	856.0	208500.00000
1	1976	MetalSd	0.0	1262.0	181500.00000
2	2002	VinylSd	0.0	920.0	223500.00000
3	1970	Wd Sdng	0.0	756.0	140000.00000
6	2005	VinylSd	0.0	1686.0	307000.00000
...	...	...	...	...	...
2913	1970	CemntBd	0.0	546.0	180921.19589
2914	1970	CemntBd	0.0	546.0	180921.19589
2915	1970	CemntBd	0.0	546.0	180921.19589
2917	1992	HdBoard	0.0	912.0	180921.19589
2918	1994	HdBoard	0.0	996.0	180921.19589

[2550 rows x 12 columns]

```
[23]: df.MSZoning.unique()
```

```
[23]: array(['RL', 'RM', 'C (all)', 'FV', 'RH'], dtype=object)
```

```
[24]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2550 entries, 0 to 2918
Data columns (total 12 columns):
#   Column          Non-Null Count  Dtype
---  -
0   MSSubClass      2550 non-null   int64
1   MSZoning        2550 non-null   object
2   LotArea         2550 non-null   int64
3   LotConfig       2550 non-null   object
4   BldgType        2550 non-null   object
5   OverallCond     2550 non-null   int64
6   YearBuilt       2550 non-null   int64
7   YearRemodAdd    2550 non-null   int64
```

```

8 Exterior1st    2550 non-null    object
9 BsmtFinSF2    2550 non-null    float64
10 TotalBsmtSF   2550 non-null    float64
11 SalePrice     2550 non-null    float64
dtypes: float64(3), int64(5), object(4)
memory usage: 259.0+ KB

```

```
[25]: cat_cols = df.select_dtypes('object').columns.tolist() # gives us all the
      ↪ columns that are categorical
```

```
[26]: cat_cols
```

```
[26]: ['MSZoning', 'LotConfig', 'BldgType', 'Exterior1st']
```

```
[28]: from sklearn.preprocessing import OneHotEncoder

encoder = OneHotEncoder(sparse_output=False, handle_unknown='ignore')

encoder.fit(df[cat_cols])
```

```
[28]: OneHotEncoder(handle_unknown='ignore', sparse_output=False)
```

```
[29]: encoded_cols = encoder.get_feature_names_out(cat_cols)
      encoded_cols
```

```
[29]: array(['MSZoning_C (all)', 'MSZoning_FV', 'MSZoning_RH', 'MSZoning_RL',
            'MSZoning_RM', 'LotConfig_Corner', 'LotConfig_CulDSac',
            'LotConfig_FR2', 'LotConfig_FR3', 'LotConfig_Inside',
            'BldgType_1Fam', 'BldgType_2fmCon', 'BldgType_Duplex',
            'BldgType_Twnhs', 'BldgType_TwnhsE', 'Exterior1st_AsbShng',
            'Exterior1st_AsphShn', 'Exterior1st_BrkComm',
            'Exterior1st_BrkFace', 'Exterior1st_CBlock', 'Exterior1st_CemntBd',
            'Exterior1st_HdBoard', 'Exterior1st_ImStucc',
            'Exterior1st_MetalSd', 'Exterior1st_Plywood', 'Exterior1st_Stucco',
            'Exterior1st_VinylSd', 'Exterior1st_Wd Sdng',
            'Exterior1st_WdShing'], dtype=object)
```

```
[30]: df[encoded_cols] = encoder.transform(df[cat_cols])
      df
```

```
[30]:
```

	MSSubClass	MSZoning	LotArea	LotConfig	BldgType	OverallCond	YearBuilt	\
0	60	RL	8450	Inside	1Fam	5	2003	
1	20	RL	9600	FR2	1Fam	8	1976	
2	60	RL	11250	Inside	1Fam	5	2001	
3	70	RL	9550	Corner	1Fam	5	1915	
6	20	RL	10084	Inside	1Fam	5	2004	
...	...	...	...	...	...	...	...	

2913	160	RM	1526	Inside	Twnhs	5	1970
2914	160	RM	1936	Inside	Twnhs	7	1970
2915	160	RM	1894	Inside	TwnhsE	5	1970
2917	85	RL	10441	Inside	1Fam	5	1992
2918	60	RL	9627	Inside	1Fam	5	1993

	YearRemodAdd	Exterior1st	BsmtFinSF2	...	Exterior1st_CBlock	\
0	2003	VinylSd	0.0	...	0.0	
1	1976	MetalSd	0.0	...	0.0	
2	2002	VinylSd	0.0	...	0.0	
3	1970	Wd Sdng	0.0	...	0.0	
6	2005	VinylSd	0.0	...	0.0	
...	...	...	...	...	...	
2913	1970	CemntBd	0.0	...	0.0	
2914	1970	CemntBd	0.0	...	0.0	
2915	1970	CemntBd	0.0	...	0.0	
2917	1992	HdBoard	0.0	...	0.0	
2918	1994	HdBoard	0.0	...	0.0	

	Exterior1st_CemntBd	Exterior1st_HdBoard	Exterior1st_ImStucc	\
0	0.0	0.0	0.0	
1	0.0	0.0	0.0	
2	0.0	0.0	0.0	
3	0.0	0.0	0.0	
6	0.0	0.0	0.0	
...	...	...	...	
2913	1.0	0.0	0.0	
2914	1.0	0.0	0.0	
2915	1.0	0.0	0.0	
2917	0.0	1.0	0.0	
2918	0.0	1.0	0.0	

	Exterior1st_MetalSd	Exterior1st_Plywood	Exterior1st_Stucco	\
0	0.0	0.0	0.0	
1	1.0	0.0	0.0	
2	0.0	0.0	0.0	
3	0.0	0.0	0.0	
6	0.0	0.0	0.0	
...	...	...	...	
2913	0.0	0.0	0.0	
2914	0.0	0.0	0.0	
2915	0.0	0.0	0.0	
2917	0.0	0.0	0.0	
2918	0.0	0.0	0.0	

	Exterior1st_VinylSd	Exterior1st_Wd Sdng	Exterior1st_WdShing
0	1.0	0.0	0.0

1	0.0	0.0	0.0
2	1.0	0.0	0.0
3	0.0	1.0	0.0
6	1.0	0.0	0.0
...	...	...	...
2913	0.0	0.0	0.0
2914	0.0	0.0	0.0
2915	0.0	0.0	0.0
2917	0.0	0.0	0.0
2918	0.0	0.0	0.0

[2550 rows x 41 columns]

```
[31]: df.drop(columns=cat_cols, inplace=True)
df
```

```
[31]:
```

	MSSubClass	LotArea	OverallCond	YearBuilt	YearRemodAdd	BsmtFinSF2	\
0	60	8450	5	2003	2003	0.0	
1	20	9600	8	1976	1976	0.0	
2	60	11250	5	2001	2002	0.0	
3	70	9550	5	1915	1970	0.0	
6	20	10084	5	2004	2005	0.0	
...	...	...	...	...	...	...	
2913	160	1526	5	1970	1970	0.0	
2914	160	1936	7	1970	1970	0.0	
2915	160	1894	5	1970	1970	0.0	
2917	85	10441	5	1992	1992	0.0	
2918	60	9627	5	1993	1994	0.0	

	TotalBsmtSF	SalePrice	MSZoning_C (all)	MSZoning_FV	...	\
0	856.0	208500.00000	0.0	0.0	...	
1	1262.0	181500.00000	0.0	0.0	...	
2	920.0	223500.00000	0.0	0.0	...	
3	756.0	140000.00000	0.0	0.0	...	
6	1686.0	307000.00000	0.0	0.0	...	
...	...	...	...	...	...	
2913	546.0	180921.19589	0.0	0.0	...	
2914	546.0	180921.19589	0.0	0.0	...	
2915	546.0	180921.19589	0.0	0.0	...	
2917	912.0	180921.19589	0.0	0.0	...	
2918	996.0	180921.19589	0.0	0.0	...	

	Exterior1st_CBlock	Exterior1st_CemntBd	Exterior1st_HdBoard	\
0	0.0	0.0	0.0	
1	0.0	0.0	0.0	
2	0.0	0.0	0.0	
3	0.0	0.0	0.0	



6	0.0	0.0	0.0
...	...	...	...
2913	0.0	1.0	0.0
2914	0.0	1.0	0.0
2915	0.0	1.0	0.0
2917	0.0	0.0	1.0
2918	0.0	0.0	1.0

	Exterior1st_ImStucc	Exterior1st_MetalSd	Exterior1st_Plywood	\
0	0.0	0.0	0.0	
1	0.0	1.0	0.0	
2	0.0	0.0	0.0	
3	0.0	0.0	0.0	
6	0.0	0.0	0.0	
...	...	...	...	
2913	0.0	0.0	0.0	
2914	0.0	0.0	0.0	
2915	0.0	0.0	0.0	
2917	0.0	0.0	0.0	
2918	0.0	0.0	0.0	

	Exterior1st_Stucco	Exterior1st_VinylSd	Exterior1st_Wd Sdng	\
0	0.0	1.0	0.0	
1	0.0	0.0	0.0	
2	0.0	1.0	0.0	
3	0.0	0.0	1.0	
6	0.0	1.0	0.0	
...	...	...	...	
2913	0.0	0.0	0.0	
2914	0.0	0.0	0.0	
2915	0.0	0.0	0.0	
2917	0.0	0.0	0.0	
2918	0.0	0.0	0.0	

	Exterior1st_WdShing
0	0.0
1	0.0
2	0.0
3	0.0
6	0.0
...	...
2913	0.0
2914	0.0
2915	0.0
2917	0.0
2918	0.0

[2550 rows x 37 columns]

```
[32]: df.columns
```

```
[32]: Index(['MSSubClass', 'LotArea', 'OverallCond', 'YearBuilt', 'YearRemodAdd',
        'BsmtFinSF2', 'TotalBsmtSF', 'SalePrice', 'MSZoning_C (all)',
        'MSZoning_FV', 'MSZoning_RH', 'MSZoning_RL', 'MSZoning_RM',
        'LotConfig_Corner', 'LotConfig_CulDSac', 'LotConfig_FR2',
        'LotConfig_FR3', 'LotConfig_Inside', 'BldgType_1Fam', 'BldgType_2fmCon',
        'BldgType_Duplex', 'BldgType_Twnhs', 'BldgType_TwnhsE',
        'Exterior1st_AsbShng', 'Exterior1st_AsphShn', 'Exterior1st_BrkComm',
        'Exterior1st_BrkFace', 'Exterior1st_CBlock', 'Exterior1st_CemntBd',
        'Exterior1st_HdBoard', 'Exterior1st_ImStucc', 'Exterior1st_MetalSd',
        'Exterior1st_Plywood', 'Exterior1st_Stucco', 'Exterior1st_VinylSd',
        'Exterior1st_Wd Sdng', 'Exterior1st_WdShing'],
        dtype='object')
```

```
[33]: X = df.drop(columns = 'SalePrice')
      y = df['SalePrice']
```

```
[36]: from sklearn.preprocessing import MinMaxScaler

      scaler = MinMaxScaler()

      scaler.fit(X)
```

```
[36]: MinMaxScaler()
```

```
[37]: X[:] = scaler.transform(X)  # FOR data normalisation or standardisation i.e.,
      ↪ bringing the data into one scale with 1 as highest value and 0 as lowest
```

```
[38]: X
```

```
[38]:
```

	MSSubClass	LotArea	OverallCond	YearBuilt	YearRemodAdd	BsmtFinSF2	\
0	0.235294	0.574722	0.500	0.949275	0.883333	0.0	
1	0.000000	0.669411	0.875	0.753623	0.433333	0.0	
2	0.235294	0.805270	0.500	0.934783	0.866667	0.0	
3	0.294118	0.665294	0.500	0.311594	0.333333	0.0	
6	0.000000	0.709263	0.500	0.956522	0.916667	0.0	
...	...	...	...	...	...	...	
2913	0.823529	0.004611	0.500	0.710145	0.333333	0.0	
2914	0.823529	0.038370	0.750	0.710145	0.333333	0.0	
2915	0.823529	0.034911	0.500	0.710145	0.333333	0.0	
2917	0.382353	0.738658	0.500	0.869565	0.700000	0.0	
2918	0.235294	0.671634	0.500	0.876812	0.733333	0.0	
	TotalBsmtSF	MSZoning_C (all)	MSZoning_FV	MSZoning_RH	...	\	

0	0.266999	0.0	0.0	0.0	...
1	0.393637	0.0	0.0	0.0	...
2	0.286962	0.0	0.0	0.0	...
3	0.235808	0.0	0.0	0.0	...
6	0.525889	0.0	0.0	0.0	...
...	...	...	...	...	...
2913	0.170306	0.0	0.0	0.0	...
2914	0.170306	0.0	0.0	0.0	...
2915	0.170306	0.0	0.0	0.0	...
2917	0.284467	0.0	0.0	0.0	...
2918	0.310667	0.0	0.0	0.0	...

	Exterior1st_CBlock	Exterior1st_CemntBd	Exterior1st_HdBoard	\
0	0.0	0.0	0.0	
1	0.0	0.0	0.0	
2	0.0	0.0	0.0	
3	0.0	0.0	0.0	
6	0.0	0.0	0.0	
...	...	...	...	
2913	0.0	1.0	0.0	
2914	0.0	1.0	0.0	
2915	0.0	1.0	0.0	
2917	0.0	0.0	1.0	
2918	0.0	0.0	1.0	

	Exterior1st_ImStucc	Exterior1st_MetalSd	Exterior1st_Plywood	\
0	0.0	0.0	0.0	
1	0.0	1.0	0.0	
2	0.0	0.0	0.0	
3	0.0	0.0	0.0	
6	0.0	0.0	0.0	
...	...	...	...	
2913	0.0	0.0	0.0	
2914	0.0	0.0	0.0	
2915	0.0	0.0	0.0	
2917	0.0	0.0	0.0	
2918	0.0	0.0	0.0	

	Exterior1st_Stucco	Exterior1st_VinylSd	Exterior1st_Wd Sdng	\
0	0.0	1.0	0.0	
1	0.0	0.0	0.0	
2	0.0	1.0	0.0	
3	0.0	0.0	1.0	
6	0.0	1.0	0.0	
...	...	...	...	
2913	0.0	0.0	0.0	
2914	0.0	0.0	0.0	

2915	0.0	0.0	0.0
2917	0.0	0.0	0.0
2918	0.0	0.0	0.0

	Exterior1st_WdShing
0	0.0
1	0.0
2	0.0
3	0.0
6	0.0
...	...
2913	0.0
2914	0.0
2915	0.0
2917	0.0
2918	0.0

[2550 rows x 36 columns]

```
[39]: from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳ random_state=42)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
[39]: ((2040, 36), (510, 36), (2040,), (510,))
```

```
[40]: from sklearn.linear_model import LinearRegression

model = LinearRegression()

model.fit(X_train, y_train)
```

```
[40]: LinearRegression()
```

```
[41]: y_pred = model.predict(X_test)
y_test[:5]
```

```
[41]: 67      226000.00000
226      290000.00000
2546     180921.19589
268      120500.00000
2174     180921.19589
Name: SalePrice, dtype: float64
```

```
[42]: y_pred[:5]
```

```
[42]: array([205612., 202536., 174344., 138276., 212236.])
```

```
[43]: from sklearn.metrics import mean_absolute_error  
mean_absolute_error(y_test, y_pred)
```

```
[43]: 29950.854539349984
```

```
[44]: from sklearn.linear_model import Lasso  
  
lasso_reg = Lasso(alpha=50, max_iter=100, tol = 0.1)  
  
lasso_reg.fit(X_train, y_train)
```

```
[44]: Lasso(alpha=50, max_iter=100, tol=0.1)
```

```
[45]: lasso_pred = lasso_reg.predict(X_test)  
mean_absolute_error(y_test, lasso_pred)
```

```
[45]: 29916.55331889878
```

```
[ ]:
```