

House Prediction Task-1

Use a dataset that includes information about housing prices and features like square footage, number of bedrooms, etc. to train a model that can predict the price of a new house

House price prediction is a machine learning task that involves using historical data to build a model capable of estimating the prices of houses based on various features or attributes. This process is essential for real estate, financial planning, and investment decisions. Here's an explanation of the key steps involved in house price prediction:

panda,numpy,matplotlib,seaborn,sklearn are the basic libraries used in the email spam filtering natural language tool kit used to study the data which means a mail and visualized the data in the different graphical form(pictorial representation and here we are using the linear regression to predict the price of a new house

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
In [4]: file_path="C:\\Users\\prade\\OneDrive\\Documents\\DATASCIENCE\\Intern DataS
Hp_df=pd.read_csv(file_path)
Hp_df
```

Out[4]:

| | id | date | price | bedrooms | bathrooms | sqft_living | sqft_lot |
|-------|------------|-----------------|----------|----------|-----------|-------------|----------|
| 0 | 7129300520 | 20141013T000000 | 221900.0 | 3 | 1.00 | 1180 | 5650 |
| 1 | 6414100192 | 20141209T000000 | 538000.0 | 3 | 2.25 | 2570 | 7242 |
| 2 | 5631500400 | 20150225T000000 | 180000.0 | 2 | 1.00 | 770 | 10000 |
| 3 | 2487200875 | 20141209T000000 | 604000.0 | 4 | 3.00 | 1960 | 5000 |
| 4 | 1954400510 | 20150218T000000 | 510000.0 | 3 | 2.00 | 1680 | 8080 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| 21608 | 263000018 | 20140521T000000 | 360000.0 | 3 | 2.50 | 1530 | 1131 |
| 21609 | 6600060120 | 20150223T000000 | 400000.0 | 4 | 2.50 | 2310 | 5813 |
| 21610 | 1523300141 | 20140623T000000 | 402101.0 | 2 | 0.75 | 1020 | 1350 |
| 21611 | 291310100 | 20150116T000000 | 400000.0 | 3 | 2.50 | 1600 | 2388 |
| 21612 | 1523300157 | 20141015T000000 | 325000.0 | 2 | 0.75 | 1020 | 1076 |

21613 rows × 21 columns



```
In [5]: Columns= Hp_df.shape[1]
Rows=Hp_df.shape[0]
print('Number of columns : ',Columns)
print('Number of Rows   : ',Rows)
```

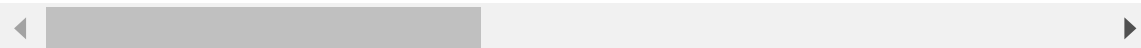
```
Number of columns : 21
Number of Rows   : 21613
```

```
In [6]: Hp_df.head()
```

Out[6]:

| | id | date | price | bedrooms | bathrooms | sqft_living | sqft_lot | floor |
|---|------------|-----------------|----------|----------|-----------|-------------|----------|-------|
| 0 | 7129300520 | 20141013T000000 | 221900.0 | 3 | 1.00 | 1180 | 5650 | 1 |
| 1 | 6414100192 | 20141209T000000 | 538000.0 | 3 | 2.25 | 2570 | 7242 | 2 |
| 2 | 5631500400 | 20150225T000000 | 180000.0 | 2 | 1.00 | 770 | 10000 | 1 |
| 3 | 2487200875 | 20141209T000000 | 604000.0 | 4 | 3.00 | 1960 | 5000 | 1 |
| 4 | 1954400510 | 20150218T000000 | 510000.0 | 3 | 2.00 | 1680 | 8080 | 1 |

5 rows × 21 columns

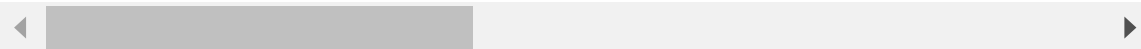


```
In [7]: Hp_df.tail()
```

Out[7]:

| | id | date | price | bedrooms | bathrooms | sqft_living | sqft_lot |
|-------|------------|-----------------|----------|----------|-----------|-------------|----------|
| 21608 | 263000018 | 20140521T000000 | 360000.0 | 3 | 2.50 | 1530 | 1131 |
| 21609 | 6600060120 | 20150223T000000 | 400000.0 | 4 | 2.50 | 2310 | 5813 |
| 21610 | 1523300141 | 20140623T000000 | 402101.0 | 2 | 0.75 | 1020 | 1350 |
| 21611 | 291310100 | 20150116T000000 | 400000.0 | 3 | 2.50 | 1600 | 2388 |
| 21612 | 1523300157 | 20141015T000000 | 325000.0 | 2 | 0.75 | 1020 | 1076 |

5 rows × 21 columns



```
In [8]: Hp_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21613 entries, 0 to 21612
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype  
---  -
 0   id                    21613 non-null  int64  
 1   date                  21613 non-null  object  
 2   price                 21613 non-null  float64 
 3   bedrooms              21613 non-null  int64  
 4   bathrooms             21613 non-null  float64 
 5   sqft_living           21613 non-null  int64  
 6   sqft_lot              21613 non-null  int64  
 7   floors                21613 non-null  float64 
 8   waterfront            21613 non-null  int64  
 9   view                  21613 non-null  int64  
10   condition             21613 non-null  int64  
11   grade                 21613 non-null  int64  
12   sqft_above            21613 non-null  int64  
13   sqft_basement         21613 non-null  int64  
14   yr_built              21613 non-null  int64  
15   yr_renovated          21613 non-null  int64  
16   zipcode               21613 non-null  int64  
17   lat                   21613 non-null  float64 
18   long                  21613 non-null  float64 
19   sqft_living15         21613 non-null  int64  
20   sqft_lot15            21613 non-null  int64  
dtypes: float64(5), int64(15), object(1)
memory usage: 3.5+ MB
```

```
In [9]: Hp_df.dtypes
```

```
Out[9]: id                    int64
date                      object
price                    float64
bedrooms                 int64
bathrooms                float64
sqft_living              int64
sqft_lot                 int64
floors                   float64
waterfront               int64
view                     int64
condition                int64
grade                    int64
sqft_above               int64
sqft_basement            int64
yr_built                 int64
yr_renovated             int64
zipcode                  int64
lat                      float64
long                     float64
sqft_living15            int64
sqft_lot15              int64
dtype: object
```

```
In [10]: Hp_df.describe(include='all').T
```

Out[10]:

| | count | unique | top | freq | mean | std |
|---------------|---------|--------|-----------------|------|-------------------|-----------------|
| id | 21613.0 | NaN | NaN | NaN | 4580301520.864988 | 2876565571.3120 |
| date | 21613 | 372 | 20140623T000000 | 142 | NaN | NaN |
| price | 21613.0 | NaN | NaN | NaN | 540088.141767 | 367127.1964 |
| bedrooms | 21613.0 | NaN | NaN | NaN | 3.370842 | 0.9300 |
| bathrooms | 21613.0 | NaN | NaN | NaN | 2.114757 | 0.7701 |
| sqft_living | 21613.0 | NaN | NaN | NaN | 2079.899736 | 918.4408 |
| sqft_lot | 21613.0 | NaN | NaN | NaN | 15106.967566 | 41420.5115 |
| floors | 21613.0 | NaN | NaN | NaN | 1.494309 | 0.5399 |
| waterfront | 21613.0 | NaN | NaN | NaN | 0.007542 | 0.0865 |
| view | 21613.0 | NaN | NaN | NaN | 0.234303 | 0.7663 |
| condition | 21613.0 | NaN | NaN | NaN | 3.40943 | 0.6507 |
| grade | 21613.0 | NaN | NaN | NaN | 7.656873 | 1.1754 |
| sqft_above | 21613.0 | NaN | NaN | NaN | 1788.390691 | 828.0909 |
| sqft_basement | 21613.0 | NaN | NaN | NaN | 291.509045 | 442.5750 |
| yr_built | 21613.0 | NaN | NaN | NaN | 1971.005136 | 29.3734 |
| yr_renovated | 21613.0 | NaN | NaN | NaN | 84.402258 | 401.679 |
| zipcode | 21613.0 | NaN | NaN | NaN | 98077.939805 | 53.5050 |
| lat | 21613.0 | NaN | NaN | NaN | 47.560053 | 0.1385 |
| long | 21613.0 | NaN | NaN | NaN | -122.213896 | 0.1408 |
| sqft_living15 | 21613.0 | NaN | NaN | NaN | 1986.552492 | 685.3913 |
| sqft_lot15 | 21613.0 | NaN | NaN | NaN | 12768.455652 | 27304.1796 |

```
In [13]: Hp_df.drop('id',axis=1,inplace=True)
```

```

-----
--
KeyError                                Traceback (most recent call last)
Cell In[13], line 1
----> 1 Hp_df.drop('id',axis=1,inplace=True)

File ~\anaconda3\Lib\site-packages\pandas\core\frame.py:5258, in DataFrame.drop(self, labels, axis, index, columns, level, inplace, errors)
    5110 def drop(
    5111     self,
    5112     labels: IndexLabel = None,
    (...)
    5119     errors: IgnoreRaise = "raise",
    5120 ) -> DataFrame | None:
    5121     """
    5122     Drop specified labels from rows or columns.
    5123
    (...)
    5256         weight 1.0      0.8
    5257     """
-> 5258     return super().drop(
    5259         labels=labels,
    5260         axis=axis,
    5261         index=index,
    5262         columns=columns,
    5263         level=level,
    5264         inplace=inplace,
    5265         errors=errors,
    5266     )

File ~\anaconda3\Lib\site-packages\pandas\core\generic.py:4549, in NDFrame.drop(self, labels, axis, index, columns, level, inplace, errors)
    4547 for axis, labels in axes.items():
    4548     if labels is not None:
-> 4549         obj = obj._drop_axis(labels, axis, level=level, errors=errors)
    4551 if inplace:
    4552     self._update_inplace(obj)

File ~\anaconda3\Lib\site-packages\pandas\core\generic.py:4591, in NDFrame._drop_axis(self, labels, axis, level, errors, only_slice)
    4589     new_axis = axis.drop(labels, level=level, errors=errors)
    4590     else:
-> 4591     new_axis = axis.drop(labels, errors=errors)
    4592     indexer = axis.get_indexer(new_axis)
    4594 # Case for non-unique axis
    4595 else:

File ~\anaconda3\Lib\site-packages\pandas\core\indexes\base.py:6699, in Index.drop(self, labels, errors)
    6697 if mask.any():
    6698     if errors != "ignore":
-> 6699         raise KeyError(f"{list(labels[mask])} not found in axis")
    6700     indexer = indexer[~mask]
    6701 return self.delete(indexer)

KeyError: '['id'] not found in axis"

```

```
In [ ]: Hp_df.head()
```

```
In [ ]: from sklearn.preprocessing import LabelEncoder  
le=LabelEncoder()  
le
```

```
In [ ]: Hp_df['date']=le.fit_transform(Hp_df['date'])  
Hp_df['date'].dtype
```

Exploratory Data Analysis[EDA]

count the number of houses with unique floor values.

```
In [ ]: Hp_df['floors'].value_counts()
```

```
In [ ]: Hp_df['floors'].value_counts().unique()
```

```
In [ ]: Hp_df['floors'].value_counts().to_frame()
```

```
In [ ]: Hp_df.hist(bins=40,figsize=(15,15))  
plt.show()
```

Determine whether houses with a waterfront view or without a waterfront view_ have more price outliers.

```
In [ ]: sns.boxplot(data=Hp_df,x=Hp_df['waterfront'],y=Hp_df['price'])  
plt.show()
```

Determine if the feature sqft_above is negatively or positively correlated_ with price.

```
In [ ]: sns.regplot(data=Hp_df,x=Hp_df['sqft_above'],y=Hp_df['price'])  
plt.show()
```

```
In [ ]: sns.boxplot(data=Hp_df,x=Hp_df['sqft_basement'],y=Hp_df['price'])  
plt.show()
```

```
In [ ]: sns.barplot(data=Hp_df,x=Hp_df['floors'],y=Hp_df['price'])  
plt.show()
```

```
In [ ]: sns.histplot(data=Hp_df,x=Hp_df['grade'],y=Hp_df['price'])  
plt.show()
```

```
In [ ]: sns.barplot(data=Hp_df,x=Hp_df['grade'],y=Hp_df['price'])
plt.show()
```

```
In [ ]: corr_matrix= Hp_df.corr()
fig, ax = plt.subplots(figsize=(15, 10))
ax = sns.heatmap(corr_matrix,annot=True,
                 linewidths=0.5,fmt=".2f",cmap="viridis");
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top- 0.5)
```

```
In [ ]: correlation_values = Hp_df.drop('price', axis=1).corrwith(Hp_df['price'])
correlation_values.plot(kind='bar', grid=True, figsize=(10, 6), title="Corr
plt.show()
```

```
In [ ]: Hp_df.skew()
```

splitting the data set

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

X=np.array(Hp_df.drop(columns="price"))
y=np.array(Hp_df.drop(columns='price'))
space=Hp_df["sqft_living"]
price=Hp_df["price"]
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25,random_st
print(f"the shape of x_train is : {X_train.shape}")
print(f'the shape of x_test is : {X_test.shape}')
print(f'the shape of y_tain is : {y_train.shape}')
print(f'the shape of y_test is {y_test.shape}')
```

```
In [ ]: from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score,mean_absolute_error
model3=LinearRegression()
model3.fit(X_train,y_train)
y_pred3=model3.predict(X_test)
print(f'R2 Score is : {r2_score(y_test,y_pred3)}')
print(f'Mae is : {mean_absolute_error(y_test,y_pred3)}')
```

```
In [ ]: plt.scatter(X_train, y_train, color='red')
plt.plot(X_train, y_train, color='blue')
plt.title("visualization--")
plt.xlabel('space')
plt.ylabel('price')
plt.show()
```



```
In [ ]: plt.scatter(X_test, y_test, label='Actual data',color='blue')
plt.plot(X_test, y_test, color='red')
plt.title("visualization")
plt.xlabel('space')
plt.ylabel('price')
plt.show()
```

In []:

In []:

In []: