# House Price Prediction

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## 1 House Price Prediciton

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Explore the fascinating world of housing price prediction with this synthetic dataset. Perfect for data science enthusiasts, machine learning practitioners, and Kaggle learners, this dataset offers a diverse collection of features, including square footage, bedrooms, bathrooms, neighborhood types, and the year of construction. Immerse yourself in the challenge of predicting house prices and enhance your skills in regression analysis.

Data Set link:https://www.kaggle.com/datasets/muhammadbinimran/housing-price-prediction-data/data

## 2 Importing Libraries

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import datetime as dt
import statsmodels.api as sm
```

[78]:
```
df=pd.read_csv("housing_price_dataset.csv")
df
```

[78]:

| | SquareFeet | Bedrooms | Bathrooms | Neighborhood | YearBuilt | Price |
|---|---|---|---|---|---|---|
| 0 | 2126 | 4 | 1 | Rural | 1969 | 215355.283618 |
| 1 | 2459 | 3 | 2 | Rural | 1980 | 195014.221626 |
| 2 | 1860 | 2 | 1 | Suburb | 1970 | 306891.012076 |
| 3 | 2294 | 2 | 1 | Urban | 1996 | 206786.787153 |
| 4 | 2130 | 5 | 2 | Suburb | 2001 | 272436.239065 |
| … | … | … | … | … | … | … |
| 49995 | 1282 | 5 | 3 | Rural | 1975 | 100080.865895 |
| 49996 | 2854 | 2 | 2 | Suburb | 1988 | 374507.656727 |
| 49997 | 2979 | 5 | 3 | Suburb | 1962 | 384110.555590 |
| 49998 | 2596 | 5 | 2 | Rural | 1984 | 380512.685957 |
| 49999 | 1572 | 5 | 3 | Rural | 2011 | 221618.583218 |

[50000 rows x 6 columns]

## 3 EDA

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

[3]:
```
   SquareFeet  Bedrooms  Bathrooms Neighborhood  YearBuilt          Price
0        2126         4          1        Rural       1969  215355.283618
1        2459         3          2        Rural       1980  195014.221626
2        1860         2          1       Suburb       1970  306891.012076
3        2294         2          1        Urban       1996  206786.787153
4        2130         5          2       Suburb       2001  272436.239065
```

[4]:
```
df.dtypes
```

[4]:
```
SquareFeet        int64
Bedrooms          int64
Bathrooms         int64
Neighborhood     object
YearBuilt         int64
Price           float64
dtype: object
```

[5]:
```
df.shape
```

[5]:
```
(50000, 6)
```

[6]:
```
df.isna().sum()
```

[6]:
```
SquareFeet      0
Bedrooms        0
Bathrooms       0
Neighborhood    0
YearBuilt       0
Price           0
dtype: int64
```

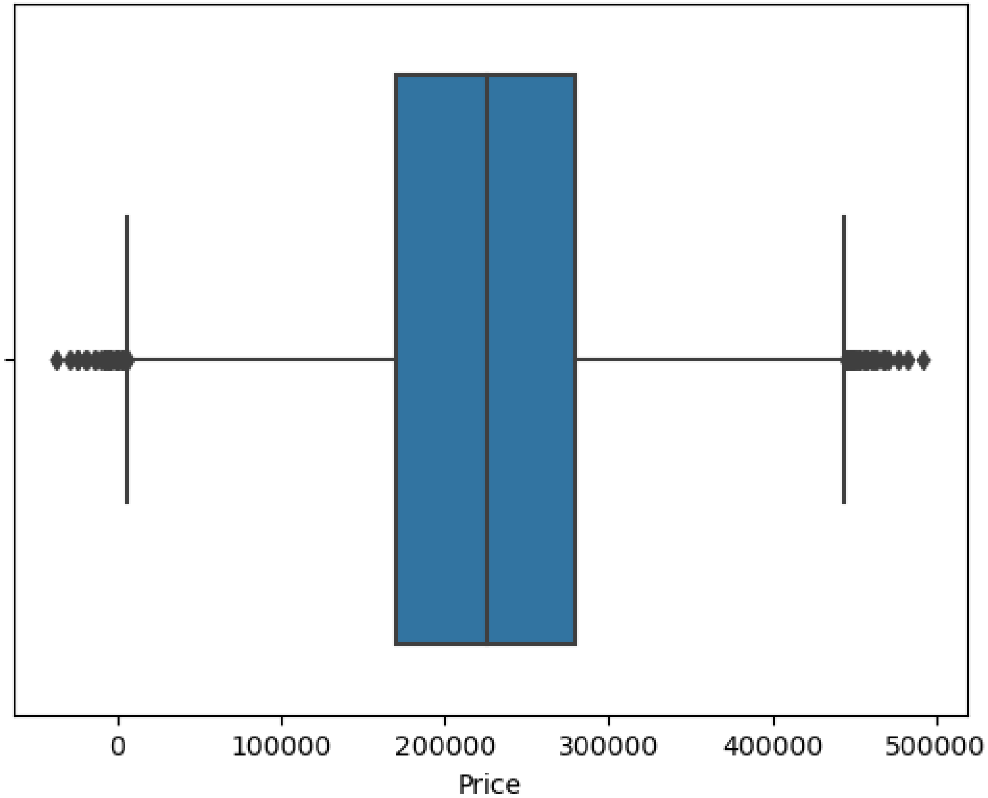
[7]:
```
df.describe()
```

[7]:
```
         SquareFeet      Bedrooms     Bathrooms     YearBuilt          Price
count  50000.000000  50000.000000  50000.000000  50000.000000   50000.000000
mean    2006.374680      3.498700      1.995420   1985.404420  224827.325151
std      575.513241      1.116326      0.815851     20.719377   76141.842966
min     1000.000000      2.000000      1.000000   1950.000000  -36588.165397
25%     1513.000000      3.000000      1.000000   1967.000000  169955.860225
50%     2007.000000      3.000000      2.000000   1985.000000  225052.141166
75%     2506.000000      4.000000      3.000000   2003.000000  279373.630052
```

```
max      2999.000000       5.000000       3.000000    2021.000000   492195.259972
```

[53]:
```
sns.boxplot(x="Price",data=df)
```

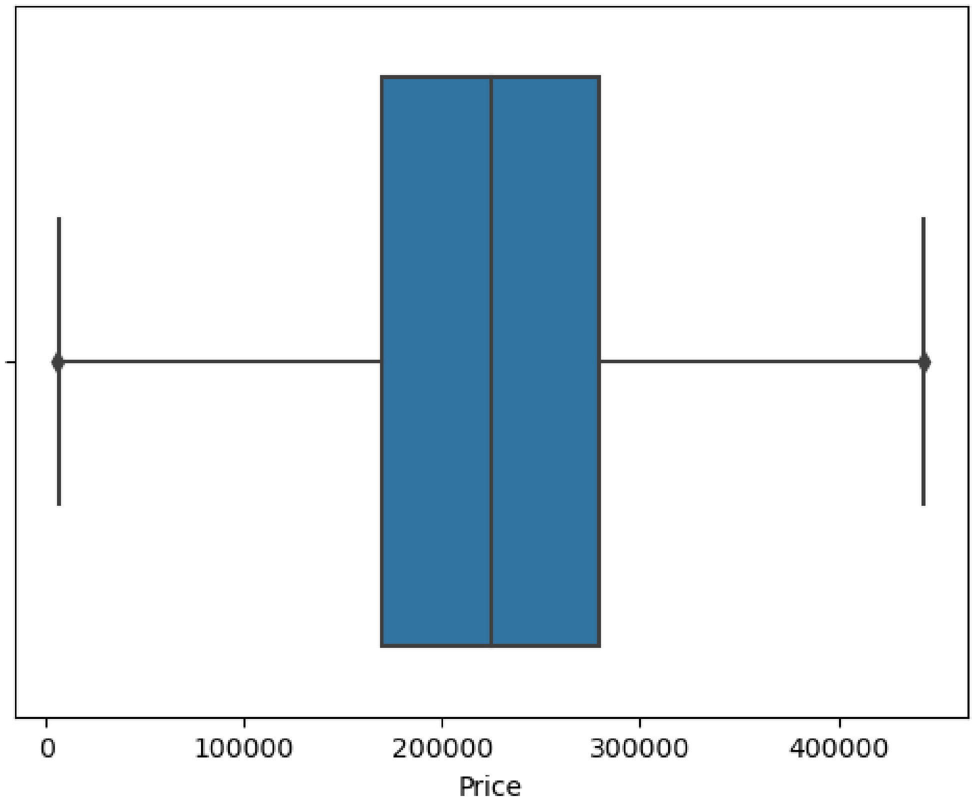
[53]:
```
<Axes: xlabel='Price'>
```




We see that it has outliers so removing outliers

[55]:
```
Q3=df["Price"].quantile(0.75)
Q1=df["Price"].quantile(0.25)
med=df["Price"].median()
IQR=Q3-Q1
upper=Q3+(1.5*IQR)
lower=Q1-(1.5*IQR)
df["Price"]=df["Price"].where(df["Price"]>lower,other=med)
df["Price"]=df["Price"].where(df["Price"]<upper,other=med)
sns.boxplot(x="Price",data=df)
```

[55]:
```
<Axes: xlabel='Price'>
```



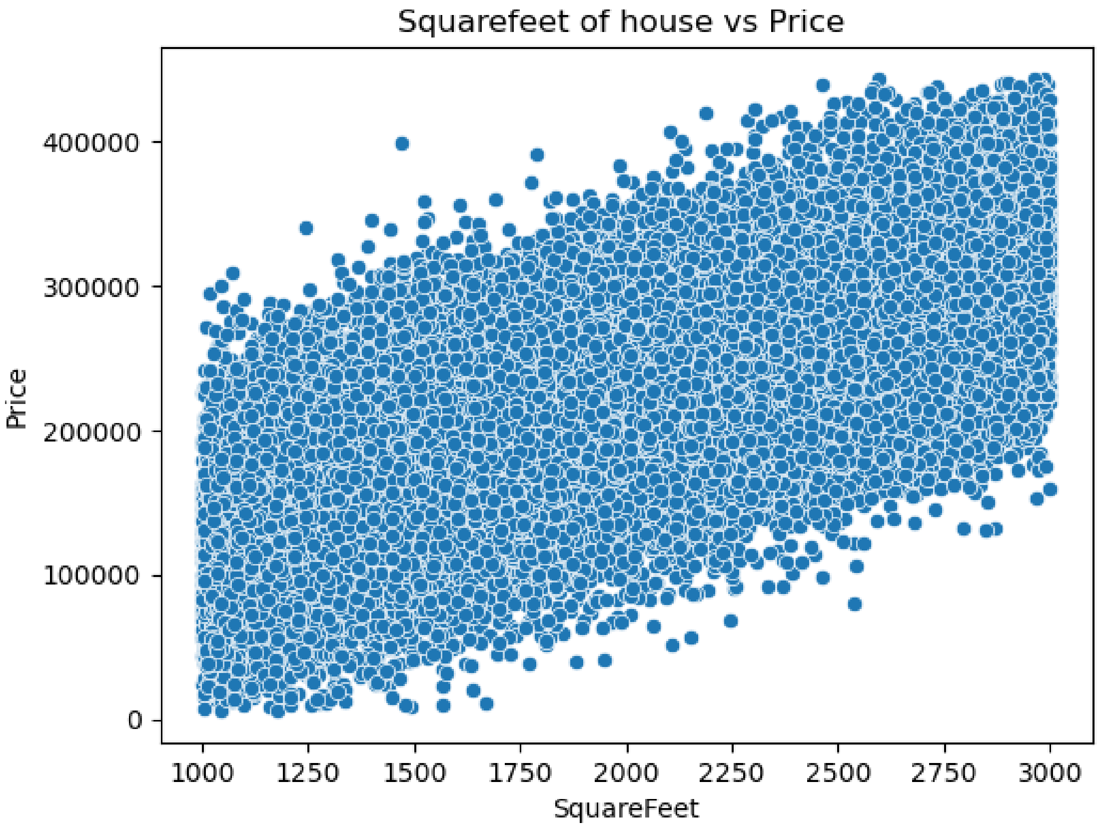

So outliers Removed

# 4 Analysis of House Price with various other features

**squarefeet of house vs price**

[56]:
```
sns.scatterplot(x="SquareFeet",y="Price",data=df)
plt.title("Squarefeet of house vs Price ")
```

[56]: `Text(0.5, 1.0, 'Squarefeet of house vs Price ')`




So we see how as we increase the Squarefeet of house the price increases as expected

**Number of Bedrooms vs Price**

[57]:
```
df["Bedrooms"].value_counts()
```

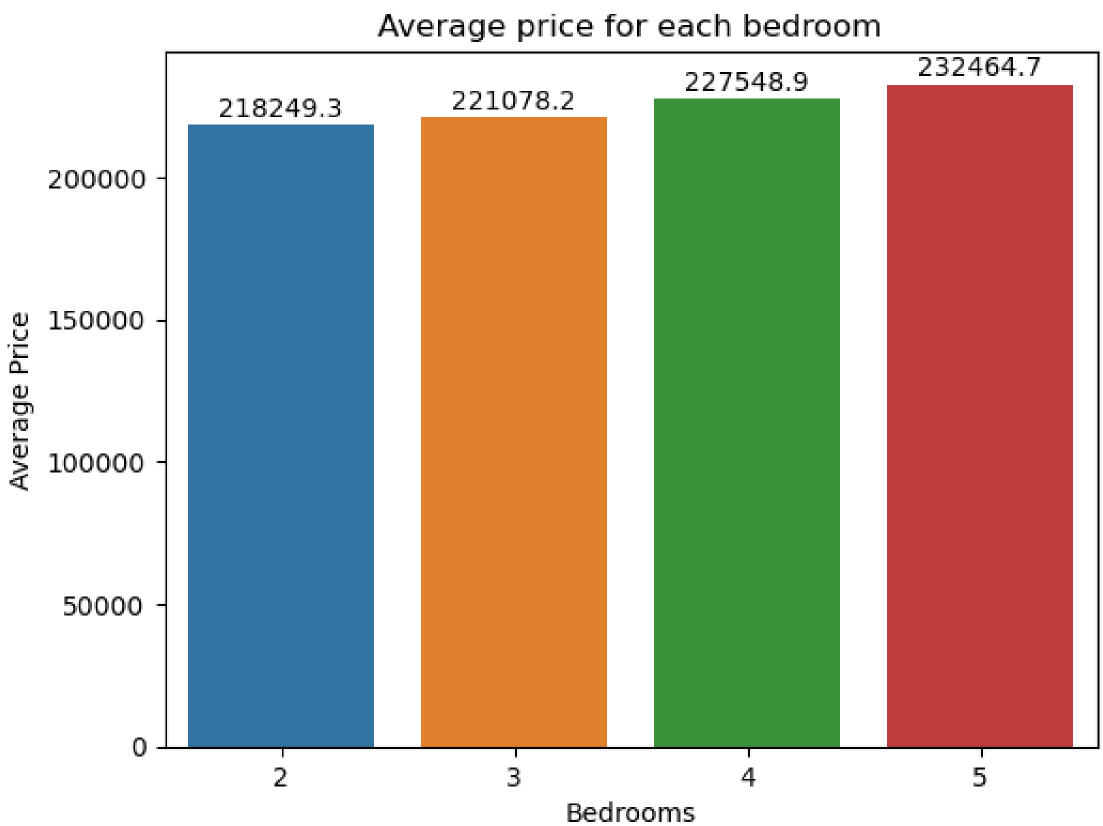
[57]:
```
3    12661
5    12468
2    12436
4    12435
Name: Bedrooms, dtype: int64
```

[58]:
```
bed=pd.DataFrame(df.groupby(by="Bedrooms")["Price"].mean().
 ↪reset_index(name="Average Price"))
bed
```

[58]:

| | Bedrooms | Average Price |
|---|---|---|
| 0 | 2 | 218249.252067 |
| 1 | 3 | 221078.202916 |
| 2 | 4 | 227548.914442 |
| 3 | 5 | 232464.690840 |

[59]:
```
sns.barplot(x="Bedrooms",y="Average Price",data=bed)
plt.title("Average price for each bedroom")
for index, value in enumerate(bed["Average Price"]):
    plt.text(index, value + 1000, f"{value:.1f}", ha='center', va='bottom')

plt.show()
```




We can see that as number of bedrooms increase the Average price also starts to increase

### Number of Bathrooms vs Price

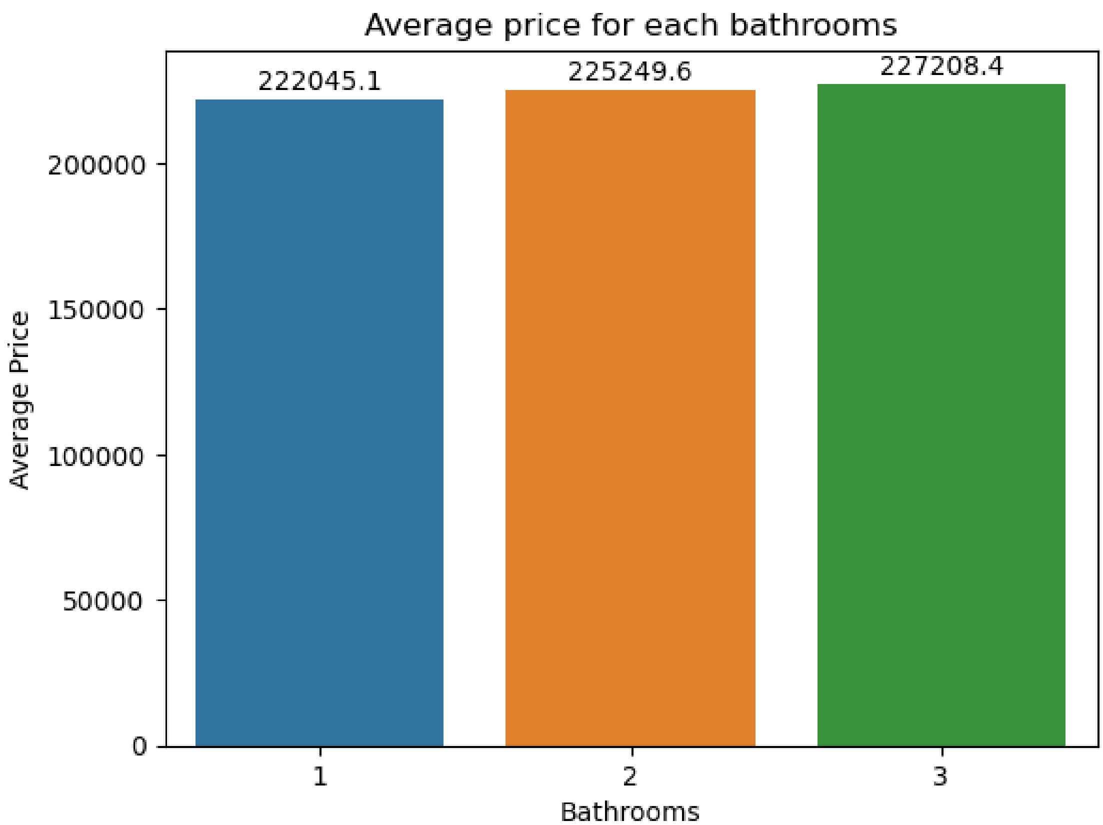
[60]:
```
df["Bathrooms"].value_counts()
```

[60]:
```
1    16755
2    16719
3    16526
Name: Bathrooms, dtype: int64
```

[61]:
```
bath=pd.DataFrame(df.groupby(by="Bathrooms")["Price"].mean().
 ↪reset_index(name="Average Price"))
bath
```

[61]:
```
   Bathrooms  Average Price
0          1  222045.094838
1          2  225249.613104
2          3  227208.368439
```

[62]:
```
sns.barplot(x="Bathrooms",y="Average Price",data=bath)
plt.title("Average price for each bathrooms")
for index, value in enumerate(bath["Average Price"]):
    plt.text(index, value + 1000, f"{value:.1f}", ha='center', va='bottom')

plt.show()
```




We can see how as we increase the number of bathrooms the Average Price increases

**Neighborhood vs Average Price**

[63]:
```
df["Neighborhood"].value_counts()
```

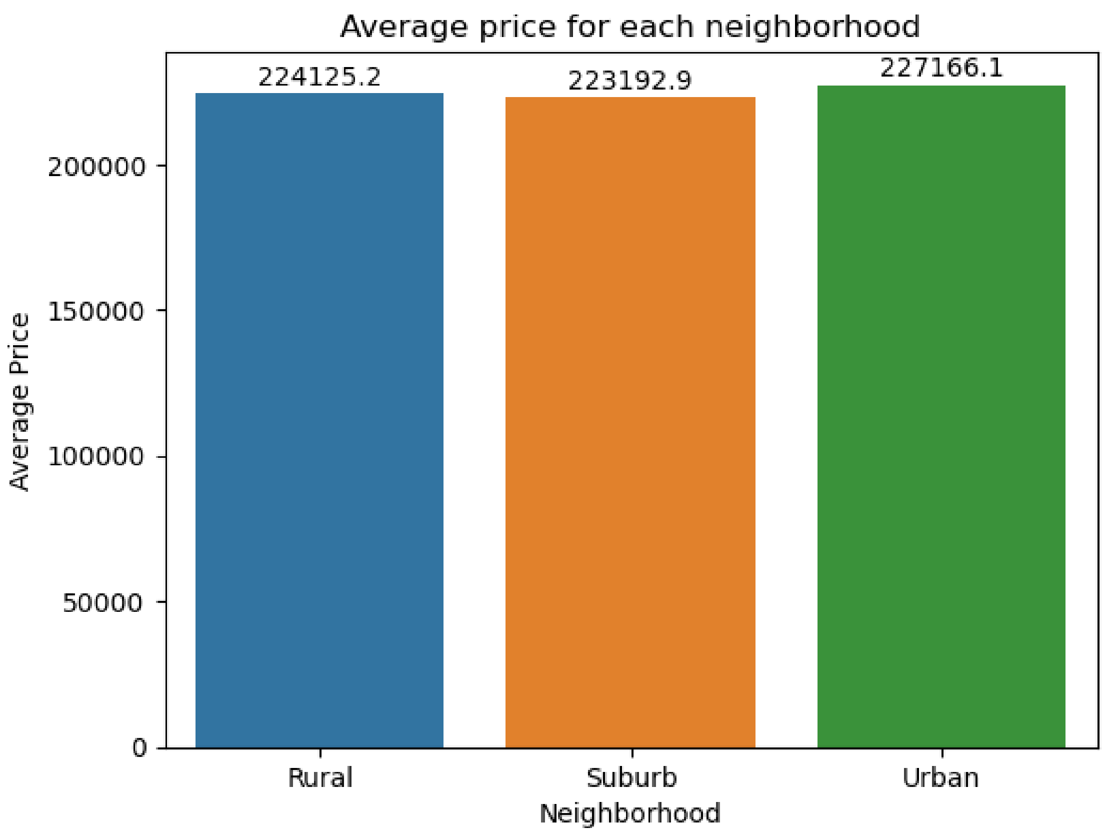
[63]:
```
Suburb    16721
Rural     16676
Urban     16603
Name: Neighborhood, dtype: int64
```

[64]:
```
neighbour=pd.DataFrame(df.groupby(by="Neighborhood")["Price"].mean().
  ↪reset_index(name="Average Price"))
neighbour
```

[64]:

| | Neighborhood | Average Price |
|---|---|---|
| 0 | Rural | 224125.178580 |
| 1 | Suburb | 223192.948028 |
| 2 | Urban | 227166.089281 |

[65]:
```
sns.barplot(x="Neighborhood",y="Average Price",data=neighbour)
plt.title("Average price for each neighborhood")
for index, value in enumerate(neighbour["Average Price"]):
    plt.text(index, value + 1000, f"{value:.1f}", ha='center', va='bottom')

plt.show()
```




We can see how the suburb and rural almost is same but Urban has slightly Higher Average prices

**Bathrooms and bedrooms with Avg prices**

[66]:
```
result = pd.crosstab(df["Bedrooms"], df["Bathrooms"], values=df["Price"],
 ↪aggfunc=np.mean)
result
```

[66]:
```
Bathrooms              1              2              3
Bedrooms
2          215886.544085  218562.827360  220404.115749
3          219351.799315  221262.999634  222641.779733
4          224743.774128  227479.904192  230408.868379
5          228413.876000  233710.084748  235262.003348
```

we can see that number of bathrooms along with number of bedroom increasing proportionally increase the average Price

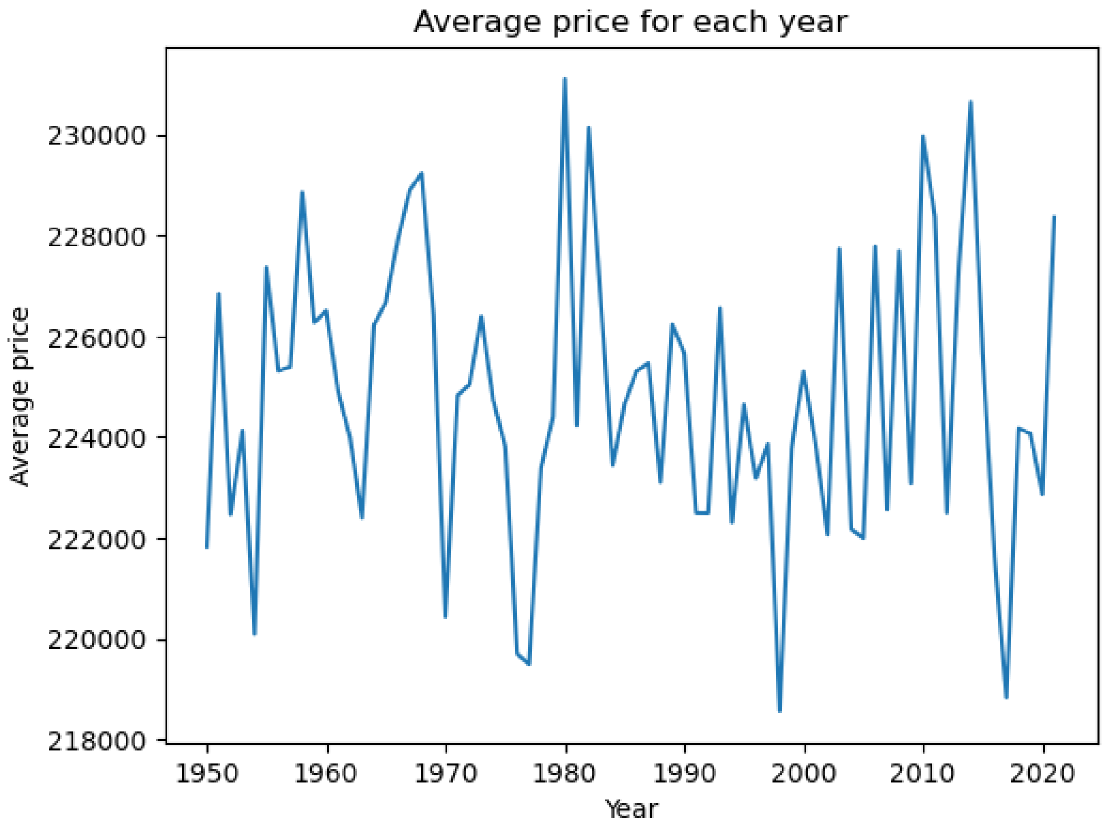
**Year vs Average Price**

[67]:
```
year_means = df.groupby("YearBuilt")["Price"].mean().reset_index()
year_means.columns = ["Year", "Average price"]
year_means
```

[67]:
```
    Year  Average price
0   1950  221824.023360
1   1951  226840.452189
2   1952  222467.013806
3   1953  224131.036288
4   1954  220090.184532
..   …            …
67  2017  218834.416354
68  2018  224177.614510
69  2019  224064.205270
70  2020  222865.659902
71  2021  228354.411635

[72 rows x 2 columns]
```

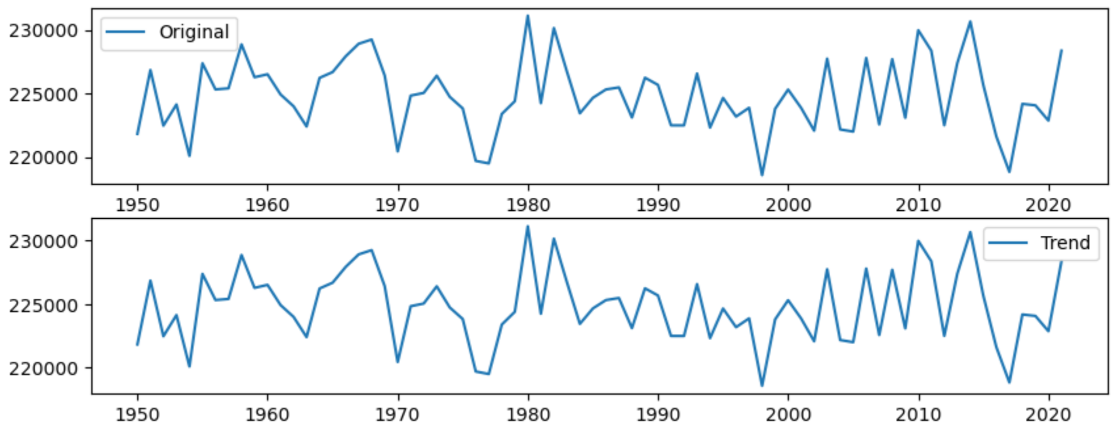
[68]:
```
sns.lineplot(x="Year",y="Average price",data=year_means)
plt.title("Average price for each year")
```

[68]:
```
Text(0.5, 1.0, 'Average price for each year')
```




[69]:
```
year_means['Year'] = pd.to_datetime(year_means['Year'], format='%Y')
year_means.set_index('Year', inplace=True)

result = sm.tsa.seasonal_decompose(year_means['Average price'],␣
 ↪model='additive')

plt.figure(figsize=(10, 8))

plt.subplot(411)
plt.plot(year_means['Average price'], label='Original')
plt.legend()

plt.subplot(412)
plt.plot(result.trend, label='Trend')
plt.legend()
```

[69]: <matplotlib.legend.Legend at 0x1c6aaebaa10>




We can see how average price has been varied over years and is currently up the trend and was low for certain years before around 2019 we may assume covid was also a factor for the same

**ALL vs price**

[79]:
```
df["Neighborhood"]=df["Neighborhood"].map({"Rural":1,"Suburb":2,"Urban":3})
df
```

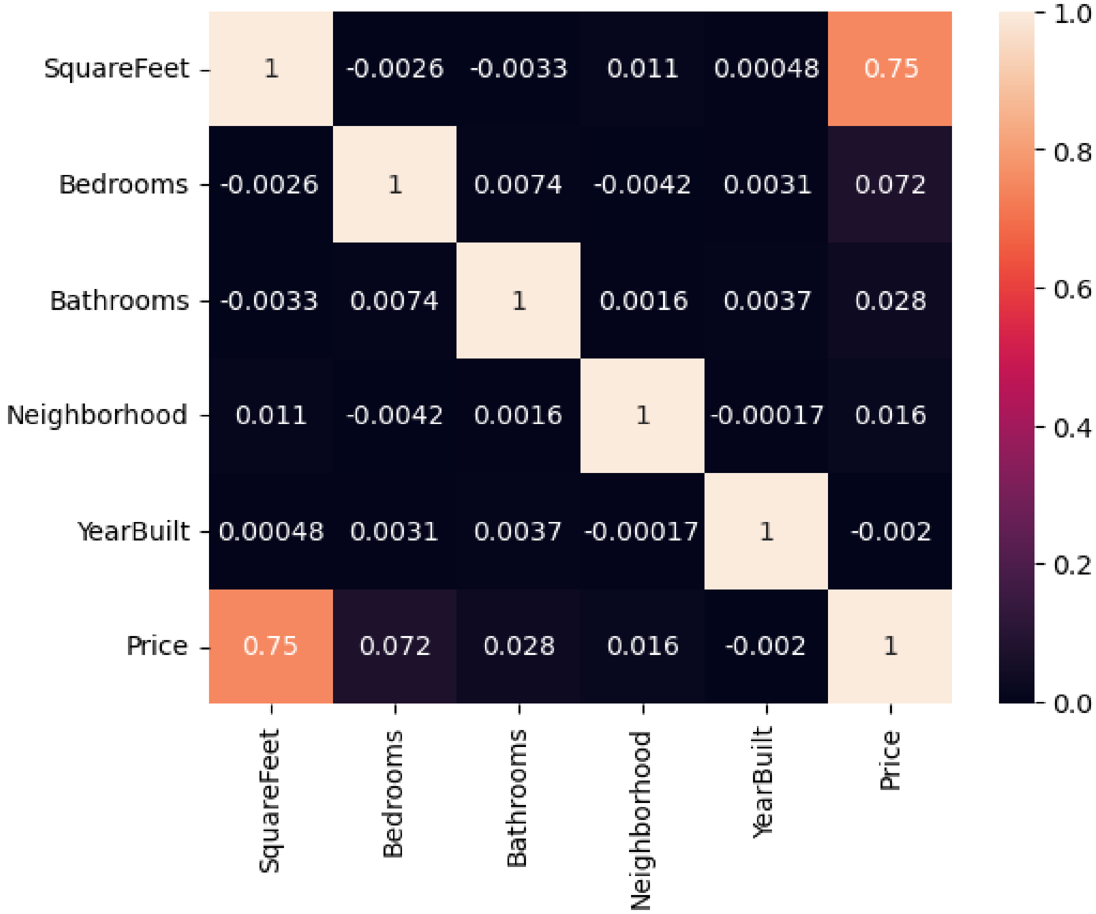
[79]:

| | SquareFeet | Bedrooms | Bathrooms | Neighborhood | YearBuilt | Price |
|---|---|---|---|---|---|---|
| 0 | 2126 | 4 | 1 | 1 | 1969 | 215355.283618 |
| 1 | 2459 | 3 | 2 | 1 | 1980 | 195014.221626 |
| 2 | 1860 | 2 | 1 | 2 | 1970 | 306891.012076 |
| 3 | 2294 | 2 | 1 | 3 | 1996 | 206786.787153 |
| 4 | 2130 | 5 | 2 | 2 | 2001 | 272436.239065 |
| … | … | … | … | … | … | … |
| 49995 | 1282 | 5 | 3 | 1 | 1975 | 100080.865895 |
| 49996 | 2854 | 2 | 2 | 2 | 1988 | 374507.656727 |
| 49997 | 2979 | 5 | 3 | 2 | 1962 | 384110.555590 |
| 49998 | 2596 | 5 | 2 | 1 | 1984 | 380512.685957 |
| 49999 | 1572 | 5 | 3 | 1 | 2011 | 221618.583218 |

[50000 rows x 6 columns]

[71]:
```
sns.heatmap(data=df.corr(),cbar=True,annot=True)
```

[71]: <Axes: >




we see how year built is negatively correlated with price

## 5 House Price Prediction Model

Now let's move on to training a Machine Learning model to predict House Price. I'll start by dividing the data into training and testing sets:

[81]:
```
x=df.iloc[:,0:5]
y=df.iloc[:,5]

from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,
                                           test_size=0.2,
                                           random_state=4)
```

Now let's train the model using the random forest Regressor algorithm(we are prediciting the continuous value):

[82]:
```
from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor()
model.fit(x, y)
```

[82]:
```
RandomForestRegressor()
```

Now let's have a look at the accuracy of the model:

[83]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error
predictions = model.predict(xtest)
mae = mean_absolute_error(ytest, predictions)
print("Mean Absolute Error:", mae)
```

```
Mean Absolute Error: 15716.284350803104
```

## 6 Now let's test the model by making predictions:

[84]:
```
print("House Price Prediction : ")
a = int(input("SquareFeet of the house (Thousands): "))
b = int(input("Number of Bedrooms(2,3,4,5): "))
c = int(input("Number of Bathrooms(1,2,3): "))
d = int(input("Year Built(from 1950 to 2020): "))
e = float(input("neighbourhood (Rural = 1, Suburban = 2, Urban=3) : "))

features = np.array([[a, b, c, d, e]])
print("The Price for your house may come up to(+_15716.284350803104 ) = ",
 ↪model.predict(features))
```

```
House Price Prediction :
SquareFeet of the house (Thousands): 2175
Number of Bedrooms(2,3,4,5): 3
Number of Bathrooms(1,2,3): 2
Year Built(from 1950 to 2020): 2017
neighbourhood (Rural = 1, Suburban = 2, Urban=3) : 3
The Price for your house may come up to(+_15716.284350803104 ) =
[269745.70155346]
```

```
C:\ProgramData\anaconda3\lib\site-packages\sklearn\base.py:420: UserWarning: X
does not have valid feature names, but RandomForestRegressor was fitted with
feature names
  warnings.warn(
```

## 7 Summary

House Price Prediction means based on certain Features affecting the Price of the Houses we Predict what may be the Price of house,to do so we built and Trained a Model which takes features resposnible for pricing of house and predicts the price of houses