USA Housing Price Prediction

Here we will perform many regression algorithms to see the accuracy score (`testing_score`) of the data and compare which model performs the best

1 . Importing Libraries

In [49]:

```
# importing the required libraries

# importing plotting libraries
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# importing data tools
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.pipeline import Pipeline
from sklearn.metrics import r2_score , mean_absolute_error, mean_squared_error
from scipy.stats import pearsonr

# importing data normalisation and standardization tool
from sklearn.preprocessing import StandardScaler , MinMaxScaler, PolynomialFeatures, Labe
lEncoder

# importing algorithms
from sklearn.linear_model import LinearRegression, BayesianRidge , PoissonRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import GradientBoostingRegressor , RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor , ExtraTreeRegressor
from xgboost import XGBRegressor , XGBRFRegressor
```

2 . Importing the Dataset

In [50]:

```
# importing the housing price dataset
housing_df = pd.read_csv("USA_housing_parsed_data.csv")

# verifying the unnamed column doesn't exist for future references
if 'Unnamed: 0' in housing_df.columns:
    housing_df = housing_df.drop(columns=['Unnamed: 0'])
```

3 . Data Exploration & Cleaning

In [51]:

```
housing_df.head(5)
```

Out[51]:

	income	house_area	noof_rooms	noof_bedrooms	population	price	Address	street_address
0	79545.45857	5.682861	7.009188	4.09	23086.80050	1.059034e+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...	208 Michael Ferry Apt. 674

	income	house_area	noof_rooms	noof_bedrooms	population	price	Address	street_address
1	79248.64245	6.002900	6.730821	3.09	40173.07217	1.505891e+06	188 Johnson Views Suite 079\nLake Kathleen, CA...	188 Johnson Views Suite 079
2	61287.06718	5.865890	8.512727	5.13	36882.15940	1.058988e+06	9127 Elizabeth Stravenue\nDanieltown, WI 06482...	9127 Elizabeth Stravenue
3	63345.24005	7.188236	5.586729	3.26	34310.24283	1.260617e+06	USS Barnett\nFPO AP 44820	USS Barnett
4	59982.19723	5.040555	7.839388	4.23	26354.10947	6.309435e+05	USNS Raymond\nFPO AE 09386	USNS Raymond

In [52]:

```
housing_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 15 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   income                  5000 non-null   float64
 1   house_area              5000 non-null   float64
 2   noof_rooms              5000 non-null   float64
 3   noof_bedrooms           5000 non-null   float64
 4   population              5000 non-null   float64
 5   price                   5000 non-null   float64
 6   Address                 5000 non-null   object 
 7   street_address          5000 non-null   object 
 8   city_names              5000 non-null   object 
 9   state_name              5000 non-null   object 
 10  state_abbr              5000 non-null   object 
 11  postal_code             5000 non-null   object 
 12  state_wise category     5000 non-null   int64  
 13  categorized_postal_code 5000 non-null   int64  
 14  cnf_USA_state           5000 non-null   bool   
dtypes: bool(1), float64(6), int64(2), object(6)
memory usage: 551.9+ KB
```

Checking for duplicate values

In [53]:

```
# to check whether there are any duplicated values
housing_df.duplicated().sum()
```

Out[53]:

```
0
```

Checking for missing values

In [54]:

```
housing_df.isna().sum()
```

Out[54]:

```
income                     0
house_area                 0
noof_rooms                 0
noof_bedrooms              0
population                 0
price                      0
Address                    0
street_address             0
city_names                 0
state_name                 0
```

```
state_abbr                  0
postal_code                 0
state_wise category         0
categorized_postal_code     0
cnf_USA_state               0
dtype: int64
```

In [55]:

```
# checking column names
housing_df.columns
```

Out[55]:

```
Index(['income', 'house_area', 'noof_rooms', 'noof_bedrooms', 'population',
       'price', 'Address', 'street_address', 'city_names', 'state_name',
       'state_abbr', 'postal_code', 'state_wise category',
       'categorized_postal_code', 'cnf_USA_state'],
      dtype='object')
```

In [56]:

```
housing_df.head(5)
```

Out[56]:

	income	house_area	noof_rooms	noof_bedrooms	population	price	Address	street_address
0	79545.45857	5.682861	7.009188	4.09	23086.80050	1.059034e+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...	208 Michael Ferry Apt. 674
1	79248.64245	6.002900	6.730821	3.09	40173.07217	1.505891e+06	188 Johnson Views Suite 079\nLake Kathleen, CA...	188 Johnson Views Suite 079
2	61287.06718	5.865890	8.512727	5.13	36882.15940	1.058988e+06	9127 Elizabeth Stravenue\nDanieltown, WI 06482...	9127 Elizabeth Stravenue
3	63345.24005	7.188236	5.586729	3.26	34310.24283	1.260617e+06	USS Barnett\nFPO AP 44820	USS Barnett
4	59982.19723	5.040555	7.839388	4.23	26354.10947	6.309435e+05	USNS Raymond\nFPO AE 09386	USNS Raymond

columns description

- `income` **: average income of the neighborhood**
- `house_area` **: average house area**
- `noof_rooms` **: number of average number of rooms**
- `noof_bedrooms` **: average number of bedrooms**
- `population` **: average population of the area**
- `price` **: the target variable of the final price for all the independent variables**
- `Address` **: this consists of street address followed by '\n' , followed by city name , state abbreviation, and postal code**
- `street_address` **: the locality of the housing area**
- `city_names` **: name of the city**
- `state_name` **: State Name of locality**
- `state_abbr` **: The each State Abbreviation**
- `postal_code` **: It refers to the postal code available in the data**
- `state_wise category` **: categorized by the abbreviation as the city name holds unknown fields and different postal code**
- `categorized_postal_code` **: Postal Code column has been categorized**
- `cnf_USA_state` **: the state that is confirmed as a USA state , as there are only 50 states in USA but here**

we have 62 uniques state names which are not confirmable

Assigning the `'price'` column to a new variable price

In [57]:

```
price = housing_df['price']
housing_df.drop(columns={'price'},inplace=True)
```

In [58]:

```
price
```

Out[58]:

```
0       1.059034e+06
1       1.505891e+06
2       1.058988e+06
3       1.260617e+06
4       6.309435e+05
            ...
4995    1.060194e+06
4996    1.482618e+06
4997    1.030730e+06
4998    1.198657e+06
4999    1.298950e+06
Name: price, Length: 5000, dtype: float64
```

We have removed the `price` column from our data but we will be adjoining it in upcoming cells

Checking for the feature column values and the need for standardizing the values

In [59]:

```
housing_df.head(5)
```

Out[59]:

	income	house_area	noof_rooms	noof_bedrooms	population	Address	street_address	city_names	s
0	79545.45857	5.682861	7.009188	4.09	23086.80050	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...	208 Michael Ferry Apt. 674	Laurabury	
1	79248.64245	6.002900	6.730821	3.09	40173.07217	188 Johnson Views Suite 079\nLake Kathleen, CA...	188 Johnson Views Suite 079	Lake Kathleen	
2	61287.06718	5.865890	8.512727	5.13	36882.15940	9127 Elizabeth Stravenue\nDanieltown, WI 06482...	9127 Elizabeth Stravenue	Danieltown	
3	63345.24005	7.188236	5.586729	3.26	34310.24283	USS Barnett\nFPO AP 44820	USS Barnett	FPO	
4	59982.19723	5.040555	7.839388	4.23	26354.10947	USNS Raymond\nFPO AE 09386	USNS Raymond	FPO	

Verifying if any of the numerical columns are categorical again for confirmation of the data integrity

In [60]:

```
housing_df['noof_bedrooms'].nunique()
```

Out[60]:

```
255
```

In [61]:

```
housing_df['noof_rooms'].nunique()
```

Out[61]:

5000

In [62]:

```
housing_df['house_area'].nunique()
```

Out[62]:

5000

In [63]:

```
housing_df['income'].nunique()
```

Out[63]:

5000

In [64]:

```
housing_df['population'].nunique()
```

Out[64]:

5000

In [65]:

```
housing_df['state_wise category'].nunique()
```

Out[65]:

62

In [66]:

```
housing_df['postal_code'].nunique()
```

Out[66]:

4078

In [67]:

```
housing_df['categorized_postal_code'].nunique()
```

Out[67]:

4078

Now we know that the column `noof_rooms` , `house_area` , `income` , `population` needs to be standardized

- **while the columns `no_of_bdroom` and `state_wise category` are categorical values**

categorizing the address column

In [68]:

```
housing_df.head(5)
```

Out[68]:

	income	house_area	noof_rooms	noof_bedrooms	population	Address	street_address	city_names	s

	income	house_area	noof_rooms	noof_bedrooms	population	Address	street_address	city_names	s
0	79545.45857	5.682861	7.009188	4.09	23086.80050	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...	208 Michael Ferry Apt. 674	Laurabury	
1	79248.64245	6.002900	6.730821	3.09	40173.07217	188 Johnson Views Suite 079\nLake Kathleen, CA...	188 Johnson Views Suite 079	Lake Kathleen	
2	61287.06718	5.865890	8.512727	5.13	36882.15940	9127 Elizabeth Stravenue\nDanieltown, WI 06482...	9127 Elizabeth Stravenue	Danieltown	
3	63345.24005	7.188236	5.586729	3.26	34310.24283	USS Barnett\nFPO AP 44820	USS Barnett	FPO	
4	59982.19723	5.040555	7.839388	4.23	26354.10947	USNS Raymond\nFPO AE 09386	USNS Raymond	FPO	

In [69]:

```
address_col = list(housing_df['Address'])
addr1 = address_col[1]
print(len(address_col))
```

```
5000
```

From this data we can see that `\n` is the divider between these addressses because the left part of the address carries down the in-home address and the right part of the address carries the state and county of the address which we are able to categorize the data

categorizing the address column did not work as expected so we now came to a decision to `drop` the `address` column and proceed with the rest of the data

Drop the Address column

In [70]:

```
housing_df.drop(columns=['Address'],inplace=True)
```

In [71]:

```
housing_df.head(5)
```

Out[71]:

	income	house_area	noof_rooms	noof_bedrooms	population	street_address	city_names	state_name	state_abbr	p
0	79545.45857	5.682861	7.009188	4.09	23086.80050	208 Michael Ferry Apt. 674	Laurabury	Nebraska	NE	
1	79248.64245	6.002900	6.730821	3.09	40173.07217	188 Johnson Views Suite 079	Lake Kathleen	California	CA	
2	61287.06718	5.865890	8.512727	5.13	36882.15940	9127 Elizabeth Stravenue	Danieltown	Wisconsin	WI	
3	63345.24005	7.188236	5.586729	3.26	34310.24283	USS Barnett	FPO	Unknown	AP	
4	59982.19723	5.040555	7.839388	4.23	26354.10947	USNS Raymond	FPO	Unknown	AE	

Add the price column back and see the data as it is

In [72]:

```
housing_df['price'] = price
```

```
housing_df.head(5)
```

Out[72]:

	income	house_area	noof_rooms	noof_bedrooms	population	street_address	city_names	state_name	state_abbr	p
0	79545.45857	5.682861	7.009188	4.09	23086.80050	208 Michael Ferry Apt. 674	Laurabury	Nebraska	NE	
1	79248.64245	6.002900	6.730821	3.09	40173.07217	188 Johnson Views Suite 079	Lake Kathleen	California	CA	
2	61287.06718	5.865890	8.512727	5.13	36882.15940	9127 Elizabeth Stravenue	Danieltown	Wisconsin	WI	
3	63345.24005	7.188236	5.586729	3.26	34310.24283	USS Barnett	FPO	Unknown	AP	
4	59982.19723	5.040555	7.839388	4.23	26354.10947	USNS Raymond	FPO	Unknown	AE	

Lets categorize the no_of_bdroom column because we can see that these are mostly categorical values

In [73]:

```
# categorizing the bedrooms column
housing_df['noof_bedrooms'] = LabelEncoder().fit_transform(housing_df['noof_bedrooms'])
housing_df.head(5)
```

Out[73]:

	income	house_area	noof_rooms	noof_bedrooms	population	street_address	city_names	state_name	state_abbr	p
0	79545.45857	5.682861	7.009188	111	23086.80050	208 Michael Ferry Apt. 674	Laurabury	Nebraska	NE	
1	79248.64245	6.002900	6.730821	60	40173.07217	188 Johnson Views Suite 079	Lake Kathleen	California	CA	
2	61287.06718	5.865890	8.512727	166	36882.15940	9127 Elizabeth Stravenue	Danieltown	Wisconsin	WI	
3	63345.24005	7.188236	5.586729	77	34310.24283	USS Barnett	FPO	Unknown	AP	
4	59982.19723	5.040555	7.839388	125	26354.10947	USNS Raymond	FPO	Unknown	AE	

Lets Now filter the columns and intake only the numercial columns to our df

In [74]:

```
usa_housing_df = housing_df[['income','house_area','population','noof_rooms','noof_bedro
oms',
                              'state_wise category','categorized_postal_code','cnf_USA_st
ate','price']]
usa_housing_df.head(5)
```

Out[74]:

	income	house_area	population	noof_rooms	noof_bedrooms	state_wise category	categorized_postal_code	cnf_USA_state	
0	79545.45857	5.682861	23086.80050	7.009188	111	37	835	True	1
1	79248.64245	6.002900	40173.07217	6.730821	60	8	746	True	1
2	61287.06718	5.865890	36882.15940	8.512727	166	59	3694	True	1
3	63345.24005	7.188236	34310.24283	5.586729	77	4	1814	False	1

	income	house_area	population	noof_rooms	noof_bedrooms	state_wise	categorized_postal_code	cnf_USA_state
4	59982.19723	5.040555	26354.10947	7.839388	125	1	391	False

Conerting boolean values to integer values

In [75]:

```
usa_housing_df['cnf_USA_state'] = usa_housing_df['cnf_USA_state'].astype(int)
```

```
C:\Users\preda\AppData\Local\Temp\ipykernel_29936\3599256225.py:1: SettingWithCopyWarning
:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  usa_housing_df['cnf_USA_state'] = usa_housing_df['cnf_USA_state'].astype(int)
```

let see some correlation features compared to it with the price column

In [76]:

```
usa_housing_df.corr()
```

Out[76]:

	income	house_area	population	noof_rooms	noof_bedrooms	state_wise category	categorized_postal_code
income	1.000000	-0.002007	-0.016234	-0.011032	0.020491	-0.003106	-0.014730
house_area	-0.002007	1.000000	-0.018743	-0.009428	0.006932	0.006094	0.004144
population	-0.016234	-0.018743	1.000000	0.002040	-0.023182	0.004332	0.007819
noof_rooms	-0.011032	-0.009428	0.002040	1.000000	0.451647	-0.021154	0.006964
noof_bedrooms	0.020491	0.006932	-0.023182	0.451647	1.000000	-0.000481	0.025073
state_wise category	-0.003106	0.006094	0.004332	-0.021154	-0.000481	1.000000	0.000700
categorized_postal_code	-0.014730	0.004144	0.007819	0.006964	0.025073	0.000700	1.000000
cnf_USA_state	-0.003140	0.008041	-0.012648	-0.008711	-0.014098	0.420713	-0.025888
price	0.639734	0.452543	0.408556	0.335664	0.167595	-0.004747	-0.001344

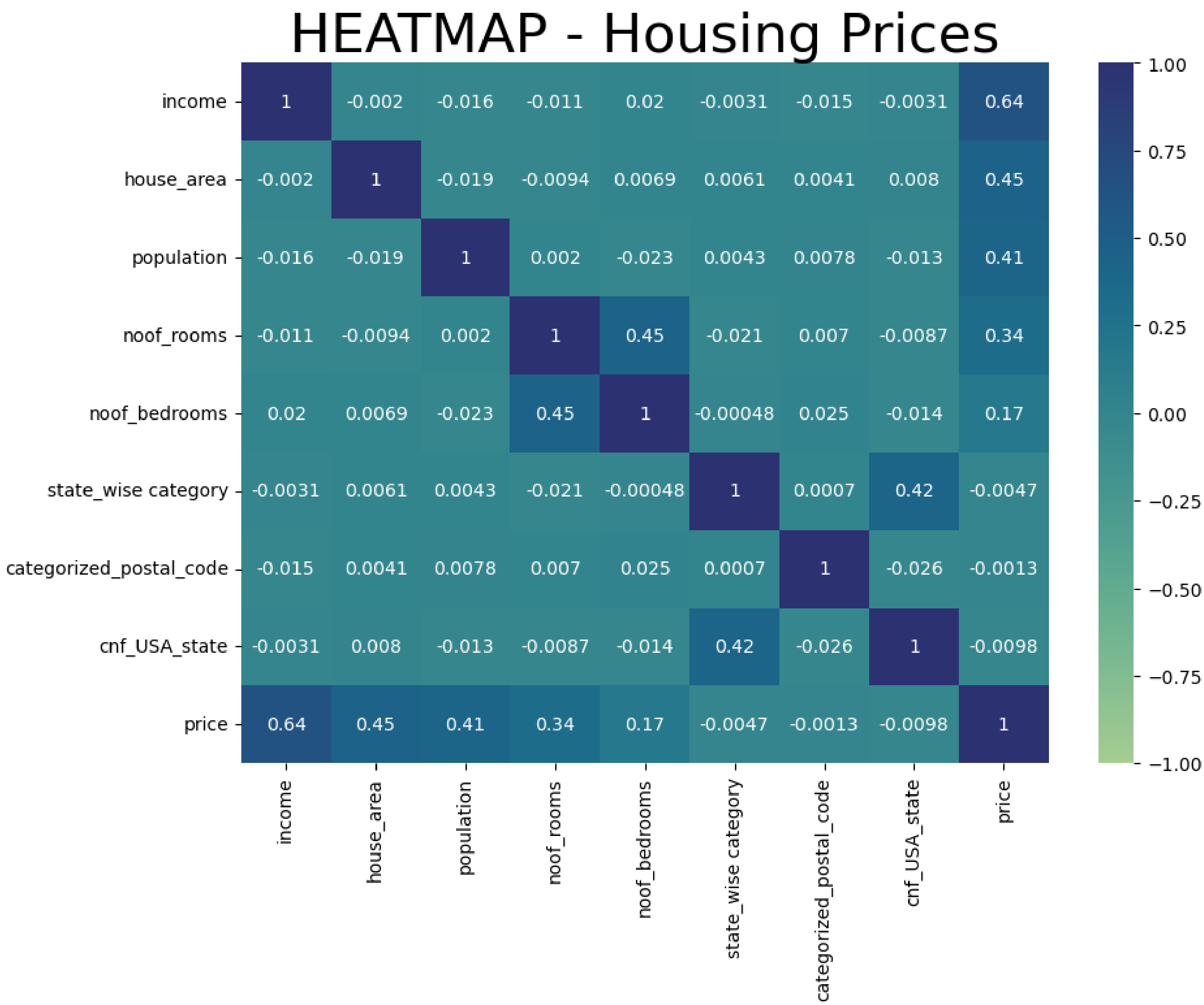
Now let us normalize or standardize the data

Producing a heatmap

In [77]:

```
# heatmap correlation for the housing_df

# plot figure size
plt.figure(figsize=(10,7))

# plotting the heatmap
sns.heatmap(usa_housing_df.corr(),
            annot=True,
            vmin=-1,
            vmax=1,
```

```
            cmap='crest')

# giving the title for the heatmap
plt.title("HEATMAP - Housing Prices",fontsize=30)

# displaying the heatmap
plt.show()
```



- **Here we can see that the column `state_wise_encoded` has lowest of all correlation so I think it would be better if we could include only those features that tend more towards the negative `-1` or positive correlation `+1`**

- **Since we have our new data here we should also check if these new data has any duplicated values in it or missing values or any null values though we couldn't find it in beginning**

In [78]:

```
# opting for the features that I think we be a good fit for the data
df = usa_housing_df[['income','house_area','population','noof_rooms']]
cols = df.columns
cols
```

Out[78]:

```
Index(['income', 'house_area', 'population', 'noof_rooms'], dtype='object')
```

In [79]:

```
# tranforming the numerical continous values into normalized values
```

```
mMs = MinMaxScaler()
normalise_df = mMs.fit_transform(df)
normalise_df
```

Out[79]:

```
array([[0.68682217, 0.44198584, 0.3299422 , 0.50150158],
       [0.68352073, 0.48853836, 0.57596801, 0.46450137],
       [0.48373705, 0.46860901, 0.52858204, 0.70135011],
       ...,
       [0.50713527, 0.67002636, 0.47651494, 0.20853446],
       [0.55841872, 0.4203891 , 0.61128233, 0.51757886],
       [0.53071451, 0.48699729, 0.66708815, 0.47267788]])
```

In [80]:

```
# create a new dataframe that stores the normalized values
new_normalize_df = pd.DataFrame(normalise_df,columns=cols)

# adding the bedroom, state_wise_encoded columns back into the normalized df
new_normalize_df['noof_bedrooms'] = usa_housing_df['noof_bedrooms']
new_normalize_df['state_wise_encoded'] = usa_housing_df['state_wise category']
new_normalize_df['postal_code_categories'] = usa_housing_df['categorized_postal_code']
new_normalize_df
```

Out[80]:

	income	house_area	population	noof_rooms	noof_bedrooms	state_wise_encoded	postal_code_categories
0	0.686822	0.441986	0.329942	0.501502	111	37	835
1	0.683521	0.488538	0.575968	0.464501	60	8	746
2	0.483737	0.468609	0.528582	0.701350	166	59	3694
3	0.506630	0.660956	0.491549	0.312430	77	4	1814
4	0.469223	0.348556	0.376988	0.611851	125	1	391
...	...	...	...	...	...	...	...
4995	0.475738	0.754359	0.326351	0.385619	97	4	1203
4996	0.675097	0.633450	0.366362	0.444024	104	0	3748
4997	0.507135	0.670026	0.476515	0.208534	13	55	1692
4998	0.558419	0.420389	0.611282	0.517579	197	1	2946
4999	0.530715	0.486997	0.667088	0.472678	109	41	1514

5000 rows × 7 columns

In [81]:

```
# adding the target variable to the data
new_normalize_df['price'] = price
new_normalize_df
```

Out[81]:

	income	house_area	population	noof_rooms	noof_bedrooms	state_wise_encoded	postal_code_categories	pı
0	0.686822	0.441986	0.329942	0.501502	111	37	835	1.059034e-
1	0.683521	0.488538	0.575968	0.464501	60	8	746	1.505891e-
2	0.483737	0.468609	0.528582	0.701350	166	59	3694	1.058988e-
3	0.506630	0.660956	0.491549	0.312430	77	4	1814	1.260617e-
4	0.469223	0.348556	0.376988	0.611851	125	1	391	6.309435e-
...	...	...	...	...	...	...	...	
4995	0.475738	0.754359	0.326351	0.385619	97	4	1203	1.060194e-
4996	0.675097	0.633450	0.366362	0.444024	104	0	3748	1.482618e-

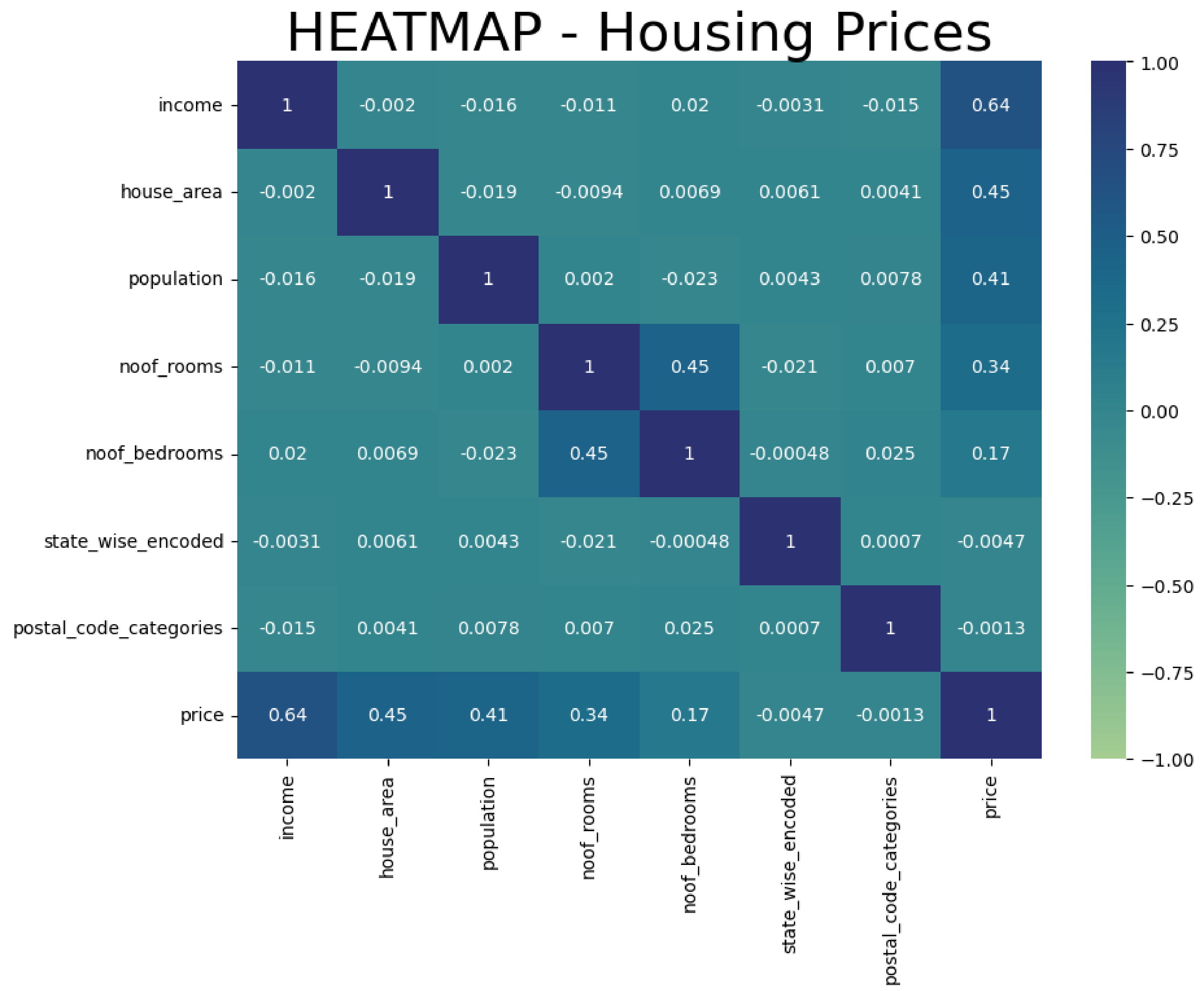
	income	house_area	population	noof_rooms	noof_bedrooms	state_wise_encoded	postal_code_categories	pi
4997	0.507135	0.670026	0.476515	0.208534	13	55	1692	1.030730e
4998	0.558419	0.420389	0.611282	0.517579	197	1	2946	1.198657e-
4999	0.530715	0.486997	0.667088	0.472678	109	41	1514	1.298950e-

5000 rows × 8 columns

Heatmap for the Normalized data

In [82]:

```
# plotting the heatmap
# heatmap correlation for the new_normalize_df

# plot figure size
plt.figure(figsize=(10,7))

# plotting the heatmap
sns.heatmap(new_normalize_df.corr(),
            annot=True,
            vmin=-1,
            vmax=1,
            cmap='crest')

# giving the title for the heatmap
plt.title("HEATMAP - Housing Prices",fontsize=30)

# displaying the heatmap
plt.show()
```



In [83]:

```
# checking the duplicates
new_normalize_df.duplicated().sum()
```

Out[83]:

```
0
```

In [84]:

```
# checking if there is any null values()
new_normalize_df.isna().sum()
```

Out[84]:

```
income                    0
house_area                0
population                0
noof_rooms                0
noof_bedrooms             0
state_wise_encoded        0
postal_code_categories    0
price                     0
dtype: int64
```

Great now we can move forward with the data

4 . Dividing the independent and dependent variables

In [85]:

```
# assigning the features to 'X' independent variable or features
X = new_normalize_df[['income','house_area','population','noof_rooms','noof_bedrooms']]

# dependent variable
y = new_normalize_df['price']
```

In [86]:

```
X
```

Out[86]:

	income	house_area	population	noof_rooms	noof_bedrooms
0	0.686822	0.441986	0.329942	0.501502	111
1	0.683521	0.488538	0.575968	0.464501	60
2	0.483737	0.468609	0.528582	0.701350	166
3	0.506630	0.660956	0.491549	0.312430	77
4	0.469223	0.348556	0.376988	0.611851	125
...	...	...	...	...	...
4995	0.475738	0.754359	0.326351	0.385619	97
4996	0.675097	0.633450	0.366362	0.444024	104
4997	0.507135	0.670026	0.476515	0.208534	13
4998	0.558419	0.420389	0.611282	0.517579	197
4999	0.530715	0.486997	0.667088	0.472678	109

5000 rows × 5 columns

In [87]:

```
y
```

Out[87]:

```
0       1.059034e+06
1       1.505891e+06
2       1.058988e+06
3       1.260617e+06
4       6.309435e+05
            ...
4995    1.060194e+06
4996    1.482618e+06
4997    1.030730e+06
4998    1.198657e+06
4999    1.298950e+06
Name: price, Length: 5000, dtype: float64
```

5 . Standardizing or Normalising the Data

In [88]:

```
# # Using the Standard scalar
# Ss = StandardScaler()

# # transforming the X to Ss
# X_Ss = Ss.fit_transform(X)

# # new standardized data
# print(X_Ss.shape)

# # df
# X_Ss = pd.DataFrame(X_Ss,columns=X.columns)

# # description
# X_Ss.describe()
```

In [89]:

```
# X_Ss
```

In [90]:

```
# # normalized data
# mMs = MinMaxScaler()

# # tranforming the X to mMs
# X_mMs = mMs.fit_transform(X)

# # new normalized values
# print(X_mMs.shape)

# # df
# X_mMs = pd.DataFrame(X_mMs, columns=X.columns)

# # description
# X_mMs.describe()
```

In [91]:

```
# X_mMs
```

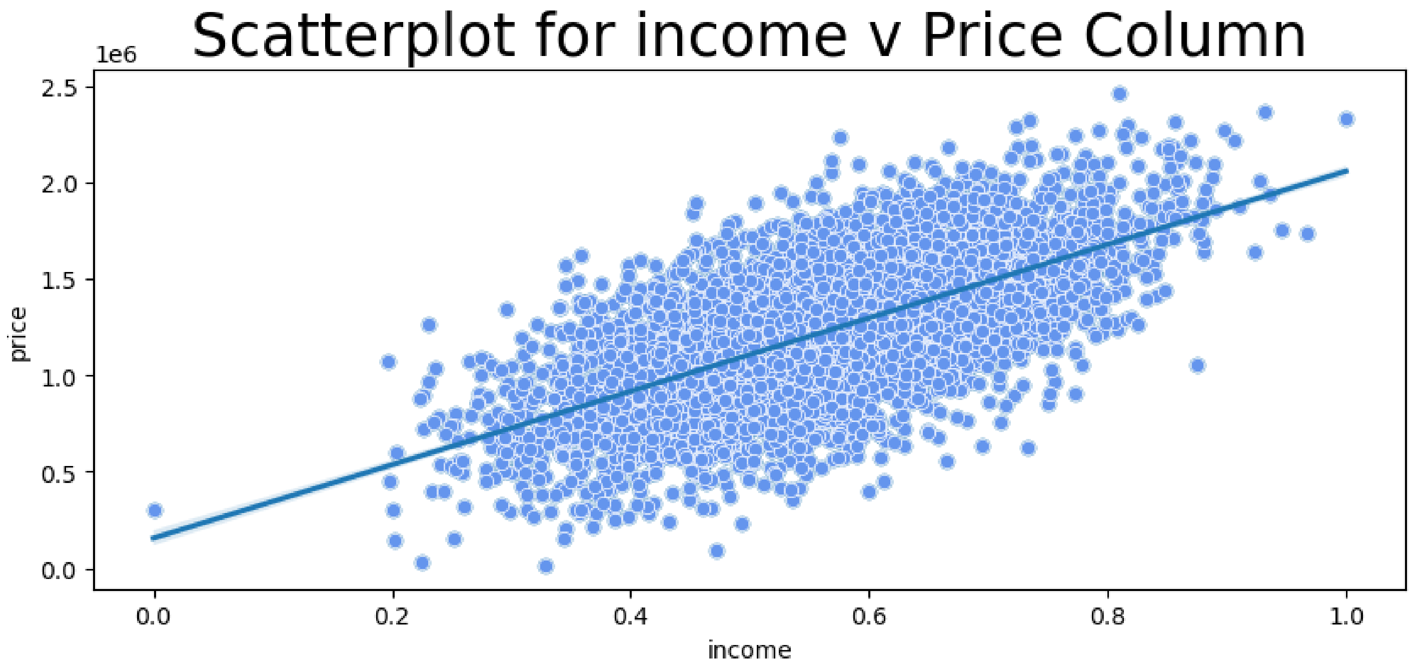
Since we have already proceeded with the above step lets move onto the next step

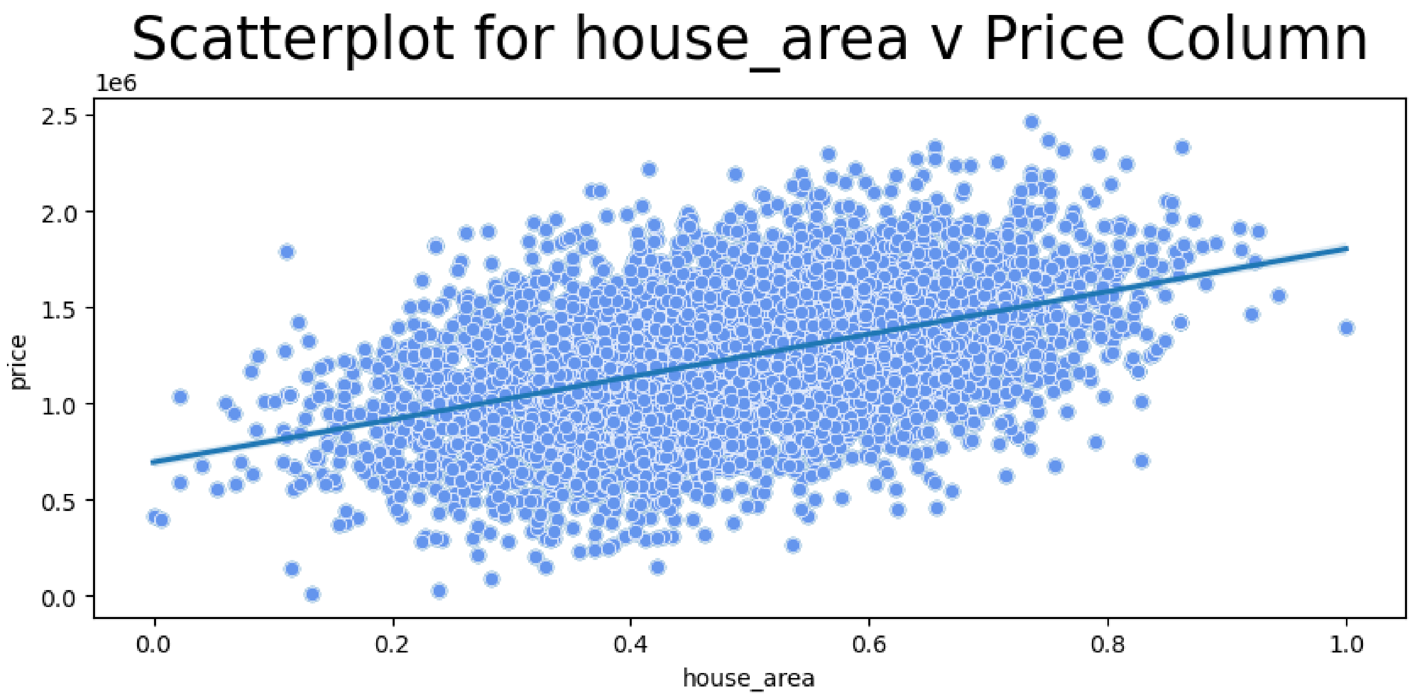
6 . Plotting the Data

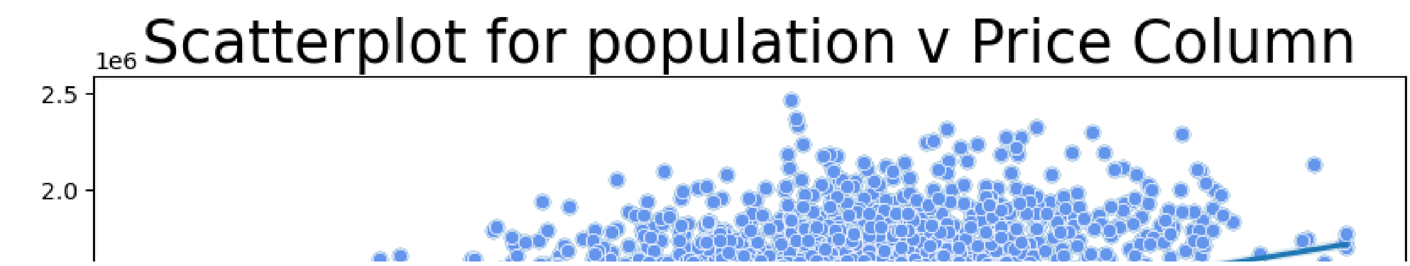
LinePlot

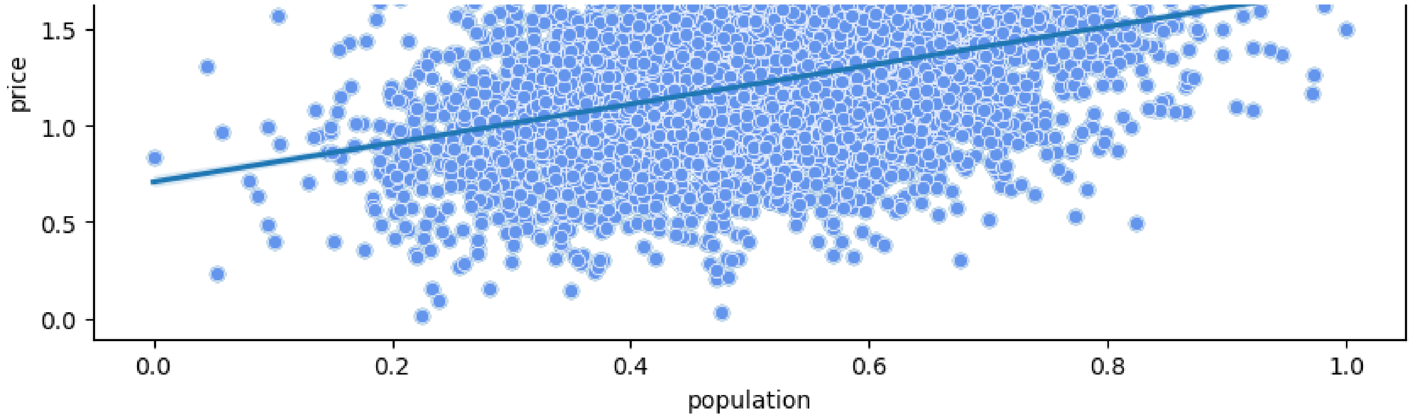
In [92]:

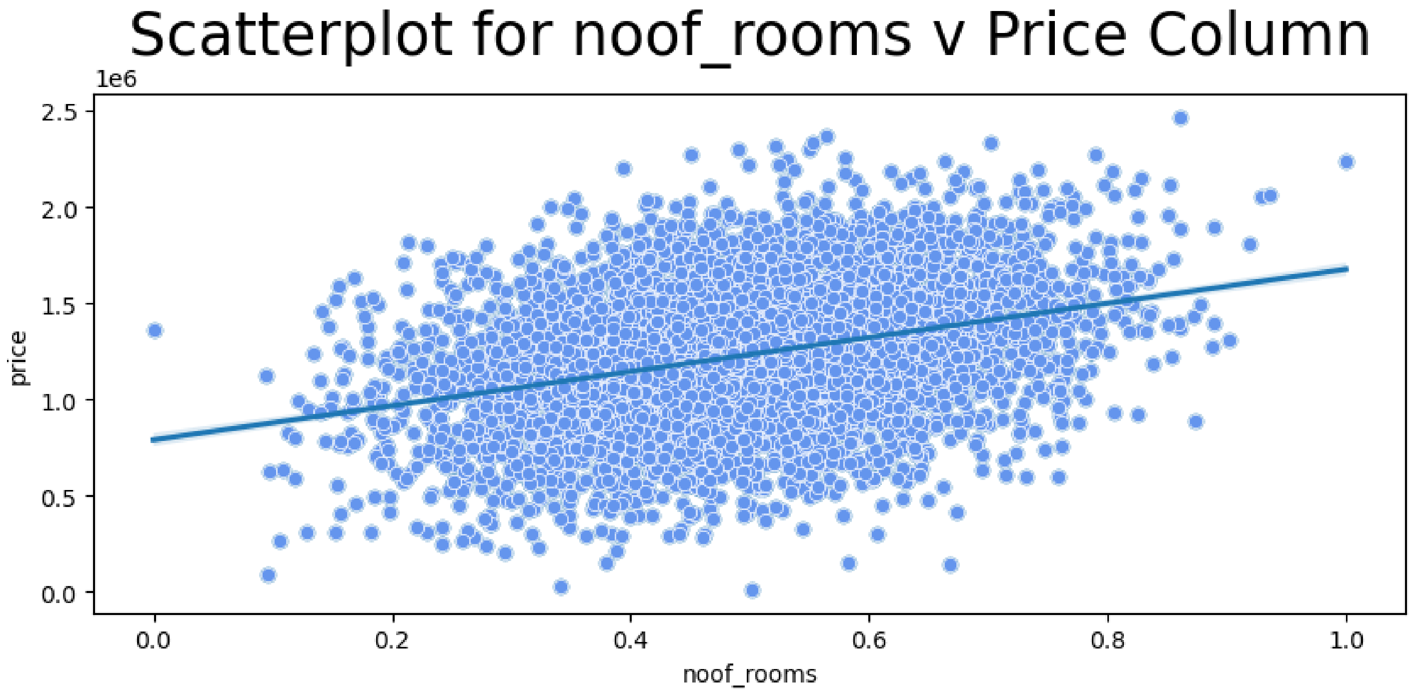
```
# lineplot
for col in X.columns:

    plt.figure(figsize=(10,4))

    ax = sns.regplot(x = X[col] , y = y)

    sns.scatterplot(x = X[col] , y = y, color='cornflowerblue', ax=ax)

    plt.title(f"Scatterplot for {col} v Price Column",fontsize=25)

    plt.show()
```

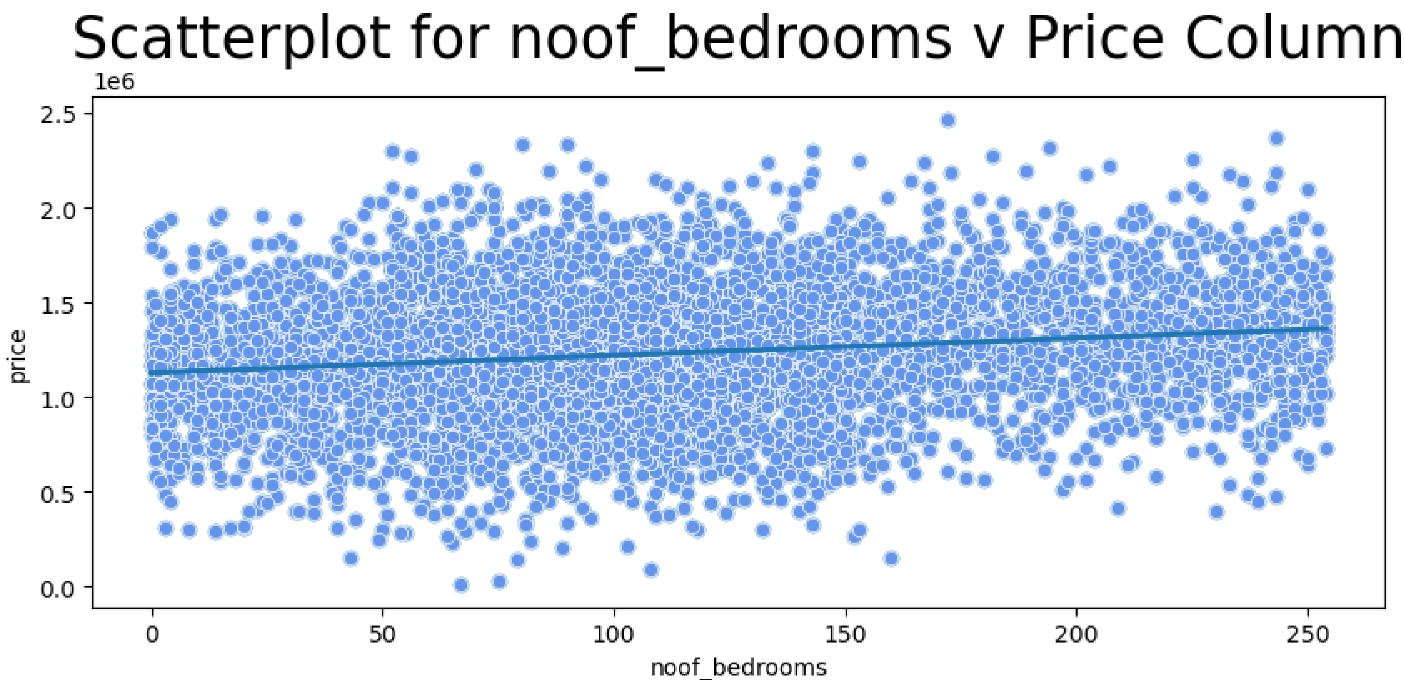












From the above graph we can see that we are having a good correlation with these features however the column `state_wise_encoded` doesnt potray much significance in the data so it would be best if we could remove it

In [93]:

```
# X.drop(columns=['state_wise_encoded'],inplace=True)
# X
```

Splitting the Data into Train and Test Set

In [94]:

```
# splitting the data
(X_train, X_test, y_train, y_test) = train_test_split(X, y , test_size=0.2, random_state
=2020)
print(f"training Data Shape : {X_train.shape,y_train.shape}")
print(f"testing Data Shape : {X_test.shape,y_test.shape}")
```

```
training Data Shape : ((4000, 5), (4000,))
testing Data Shape : ((1000, 5), (1000,))
```

Model Evaluation

We will using various models for fitting and testing and evaluate which model performs best and eventually we can choose that model and proceed with the model with a good test and train scores

In [95]:

```
# various regression models
regression_models = [
    LinearRegression(),
    BayesianRidge(),
    KNeighborsRegressor(),
    DecisionTreeRegressor(),# add parameters GridSearchCV
    PoissonRegressor(),
    RandomForestRegressor(),
    XGBRegressor(),
    XGBRFRegressor(),
    ExtraTreeRegressor(),
    GradientBoostingRegressor()
]
```

In [96]:

```
# initializing a list to store the various different scores for the models
models_scores = []

# a function to see which regression model is best suited for this data
def models_evaluated():
    for reg_model in regression_models:

        # fit the model with the data
        model_eval = reg_model.fit(X_train, y_train)

        # prediciting the y_hat
        model_y_hat = model_eval.predict(X_test)

        # accuracy scores
        # model train score
        model_train_score = model_eval.score(X_train, y_train)
        # model test score
        model_test_score = model_eval.score(X_test, y_test)
        # mse_score
        mse_score = mean_squared_error(y_test,model_y_hat)
        # mae score
        mae_score = mean_absolute_error(y_test,model_y_hat)
        # r2 score
        r2_score_m = r2_score(y_test,model_y_hat)

        # defining the items as list needed for the dict models_scores
        models_scores.append({'Model_Used':str(reg_model.__class__.__name__),
                'training_scores':model_train_score,
                'testing_scores':model_test_score,
              'R2_Score(test)':r2_score_m,
```

```
                'mse_score_test':mse_score,
                'mae_score_test':mae_score})

    #           # appending the values to the dictionary model scores
    #           for key, value in zip(models_scores.keys(), model_scores_list):
    #               models_scores[key].append(value)

    return models_scores
```

In [97]:

```
# converting this dictionary to dataframe
final_models_df = pd.DataFrame(models_evaluated())
final_models_df
```

Out[97]:

	Model_Used	training_scores	testing_scores	R2_Score(test)	mse_score_test	mae_score_test
0	LinearRegression	0.917763	0.918961	0.918961	9.905596e+09	79143.208930
1	BayesianRidge	0.917763	0.918962	0.918962	9.905429e+09	79142.687224
2	KNeighborsRegressor	0.674243	0.436525	0.436525	6.887450e+10	204480.467839
3	DecisionTreeRegressor	1.000000	0.749872	0.749872	3.057361e+10	139293.096409
4	PoissonRegressor	0.873860	0.875668	0.886505	1.387269e+10	91448.012511
5	RandomForestRegressor	0.983795	0.882289	0.882289	1.438801e+10	94054.351749
6	XGBRegressor	0.982309	0.877084	0.877084	1.502422e+10	96371.631711
7	XGBRFRegressor	0.856153	0.801599	0.801599	2.425086e+10	120489.056955
8	ExtraTreeRegressor	1.000000	0.707600	0.707600	3.574053e+10	151059.509972
9	GradientBoostingRegressor	0.928155	0.902326	0.902326	1.193888e+10	85992.784776

In [98]:

```
# sorting the regression models by their testing scores
final_models_df.sort_values(ascending=False, by=['testing_scores'], inplace=True)

# reseting the index
final_models_df.reset_index(inplace=True)

# dropping the index column
final_models_df.drop(columns=['index'],inplace=True)

final_models_df
```

Out[98]:

	Model_Used	training_scores	testing_scores	R2_Score(test)	mse_score_test	mae_score_test
0	BayesianRidge	0.917763	0.918962	0.918962	9.905429e+09	79142.687224
1	LinearRegression	0.917763	0.918961	0.918961	9.905596e+09	79143.208930
2	GradientBoostingRegressor	0.928155	0.902326	0.902326	1.193888e+10	85992.784776
3	RandomForestRegressor	0.983795	0.882289	0.882289	1.438801e+10	94054.351749
4	XGBRegressor	0.982309	0.877084	0.877084	1.502422e+10	96371.631711
5	PoissonRegressor	0.873860	0.875668	0.886505	1.387269e+10	91448.012511
6	XGBRFRegressor	0.856153	0.801599	0.801599	2.425086e+10	120489.056955
7	DecisionTreeRegressor	1.000000	0.749872	0.749872	3.057361e+10	139293.096409
8	ExtraTreeRegressor	1.000000	0.707600	0.707600	3.574053e+10	151059.509972
9	KNeighborsRegressor	0.674243	0.436525	0.436525	6.887450e+10	204480.467839

In [99]:

```
final_models_df['Model_Used']
```

Out[99]:

```
0                BayesianRidge
1             LinearRegression
2    GradientBoostingRegressor
3        RandomForestRegressor
4                 XGBRegressor
5             PoissonRegressor
6               XGBRFRegressor
7        DecisionTreeRegressor
8           ExtraTreeRegressor
9          KNeighborsRegressor
Name: Model_Used, dtype: object
```

We can see that there are 3 models which performed well comparatively than others without using any paramters on the model with accuracies of :

- `1` : `91.89` ,
- `2` : `91.89`,
- `3` : `90.23`

1. **Bayesian Regression**
2. **Linear Regression**
3. **Gradient Boosting Regressor**

And we can see that the rest of the regressors have `overfitting` issues, however let us also try with `Decision Tree Regressor`

Bayesian Regression

In [100]:

```
# bayessian regression initialization and fitting the model
baye_reg_model = BayesianRidge().fit(X_train,y_train)

# yhat bayesian
bayesian_yhat = baye_reg_model.predict(X_test)
```

In [101]:

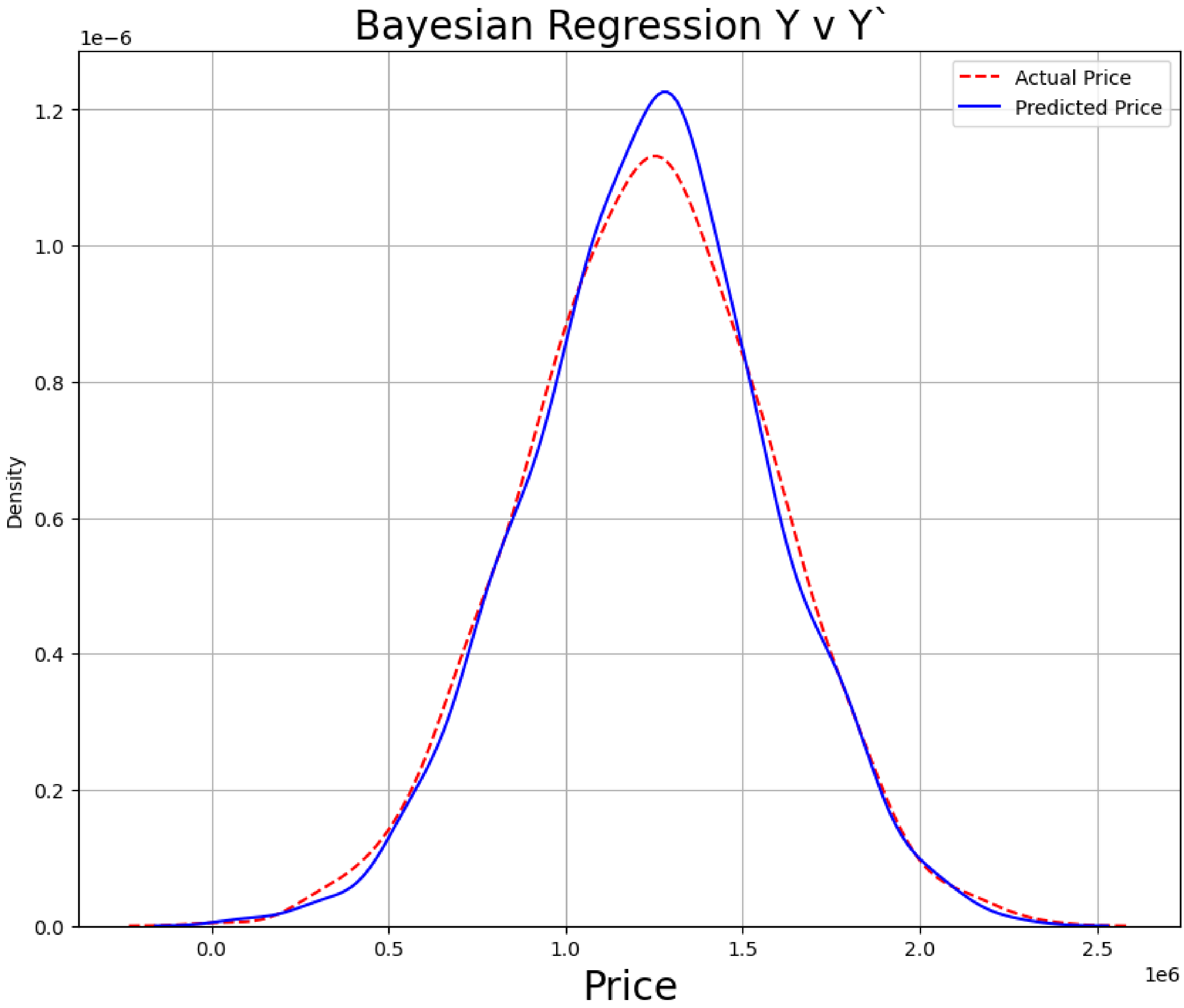
```
# training and testing score

print(f"Training score for Bayesian Regression : {baye_reg_model.score(X_train,y_train)}"
)
print(f"Testing score for Bayesian Regression : {baye_reg_model.score(X_test,y_test)}")
```

```
Training score for Bayesian Regression : 0.9177633232338686
Testing score for Bayesian Regression : 0.9189619005051035
```

In [102]:

```
# Line plot between predicted and actual price

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

ax = sns.kdeplot(y_test, label='Actual Price', color='red', linestyle='--')

sns.kdeplot(bayesian_yhat,label='Predicted Price',color='blue',ax=ax)

plt.title("Bayesian Regression Y v Y` ", fontsize=20)
plt.xlabel("Price",fontsize=20)

plt.grid(True)
plt.legend()
```

```
plt.show()
```



GridSearch CV for bayesian regression

In [103]:

```
# Define the parameter grid
param_grid = {
    'max_iter': [100, 300, 500, 700, 900, 1000],
    'alpha_1': [1e-6, 1e-5, 1e-4],
    'alpha_2': [1e-6, 1e-5, 1e-4],
    'lambda_1': [1e-6, 1e-5, 1e-4],
    'lambda_2': [1e-6, 1e-5, 1e-4],
    'tol': [1e-3, 1e-4, 1e-5]
}
```

In [104]:

```
# gridsearchcv with bayesian regression
grids_cv = GridSearchCV(BayesianRidge(),
                        param_grid=param_grid,
                        scoring='r2', cv=5)

# fitting the model with bayesian gridsearch cv
grids_cv.fit(X_train,y_train)

# prediciting grids_cv
grids_cv_yhat = grids_cv.predict(X_test)
```

```
# display the best parameters from the given
print(grids_cv.best_params_)

# new convertion to df
grid_sch_cv_Brg_df = pd.DataFrame(grids_cv.cv_results_)
```

```
{'alpha_1': 1e-06, 'alpha_2': 1e-06, 'lambda_1': 0.0001, 'lambda_2': 1e-06, 'max_iter': 1
00, 'tol': 0.001}
```

In [105]:

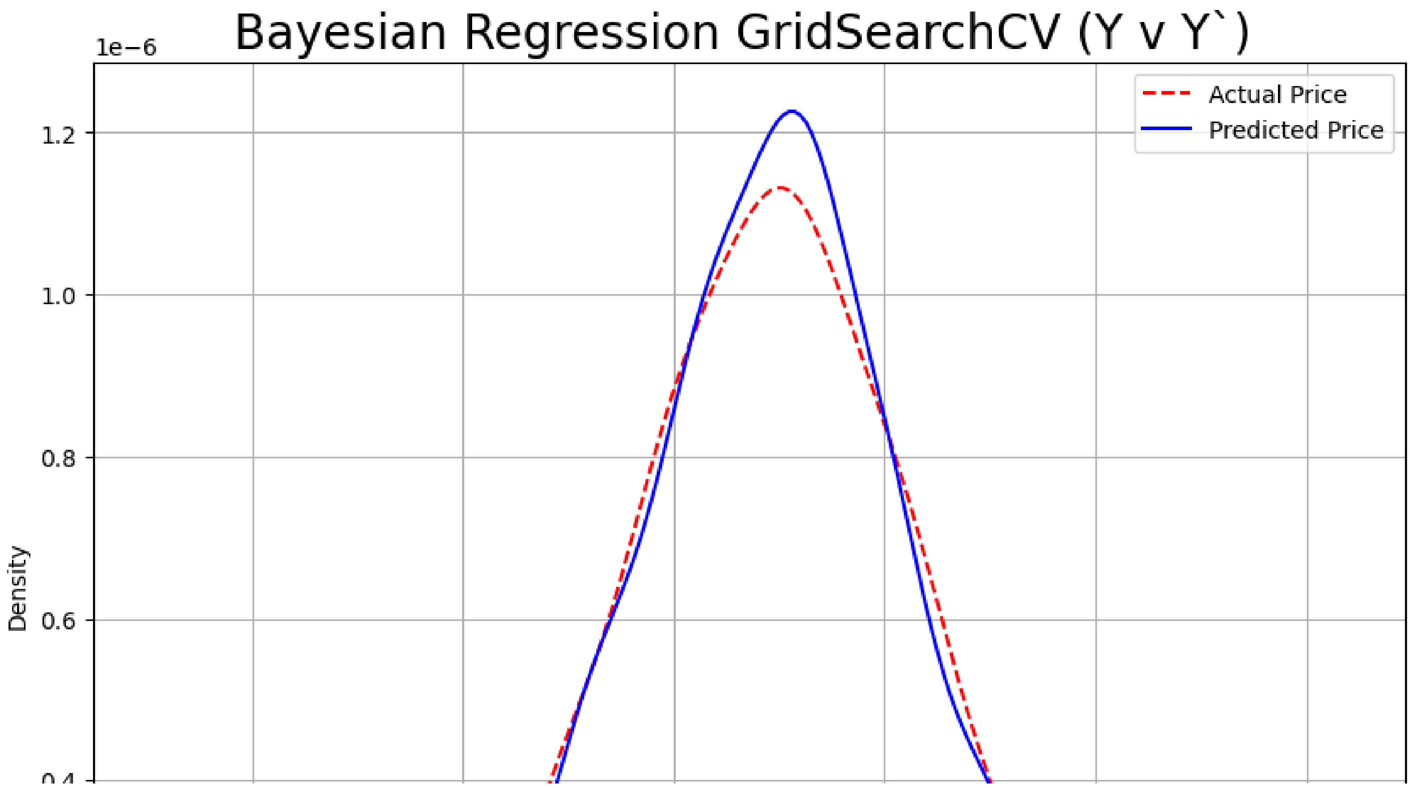
```
# displaying the best ranks out there with there parameters used
grid_sch_cv_Brg_df[grid_sch_cv_Brg_df['rank_test_score']==1].head(2)
```

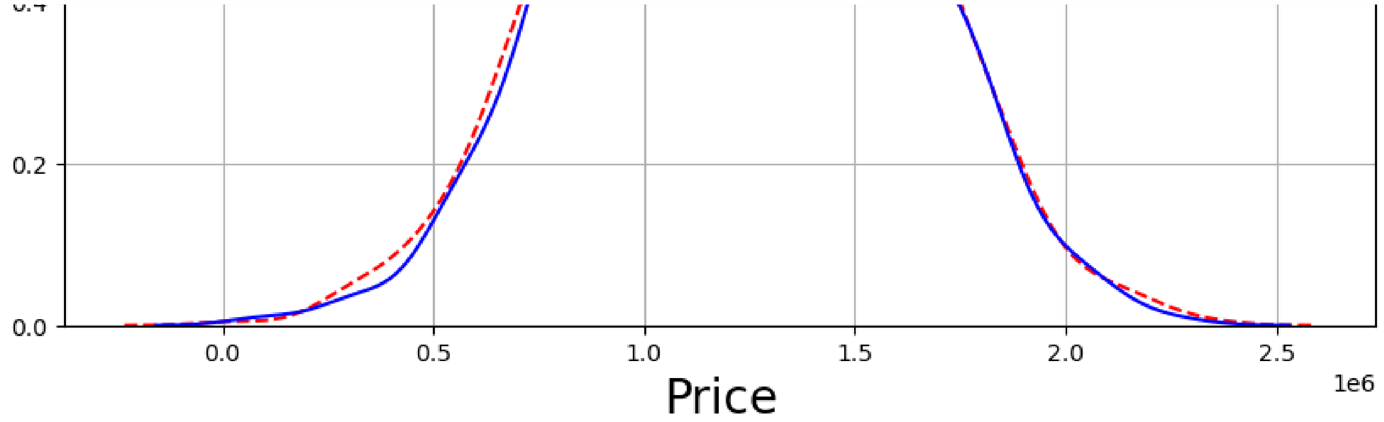
Out[105]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_alpha_1	param_alpha_2	param_lambda_1	param_la
108	0.008796	0.000750	0.002601	0.000493	0.000001	0.000001	0.0001	(
109	0.008119	0.001285	0.002369	0.000554	0.000001	0.000001	0.0001	(

In [106]:

```
# Line plot between predicted and actual price

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

ax = sns.kdeplot(y_test, label='Actual Price', color='red', linestyle='--')

sns.kdeplot(grids_cv_yhat,label='Predicted Price',color='blue',ax=ax)

plt.title("Bayesian Regression GridSearchCV (Y v Y`) ", fontsize=20)
plt.xlabel("Price",fontsize=20)
plt.grid(True)
plt.legend()
plt.show()
```





Polynomial Features for bayesian regression

In [107]:

```
# Define the pipeline
pipeline = Pipeline([
    ('polynomialfeatures', PolynomialFeatures()),
    ('bayesianridge', BayesianRidge())
])

# Define the parameter grid
param_grid = {
    'polynomialfeatures__degree': [1, 2, 3, 4, 5]  # Correct syntax
}
```

In [108]:

```
# gridsearchcv with pipeline1
grid_pipe = GridSearchCV(estimator=pipeline,
                         param_grid=param_grid,
                        scoring='r2',
                        cv=5)

# fitting the model
grid_pipe.fit(X_train,y_train)

# new results
grid_pipe_results = pd.DataFrame(grid_pipe.cv_results_)
```

In [109]:

```
grid_pipe_results
```

Out[109]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_polynomialfeatures__degree	par
0	0.016266	0.002920	0.004585	0.000598	1	{'polynomialfeatures__deg
1	0.025175	0.003801	0.004861	0.002115	2	{'polynomialfeatures__deg
2	0.092376	0.018887	0.005218	0.000988	3	{'polynomialfeatures__deg
3	0.136903	0.024368	0.004817	0.001430	4	{'polynomialfeatures__deg
4	0.243213	0.026408	0.005819	0.000410	5	{'polynomialfeatures__deg

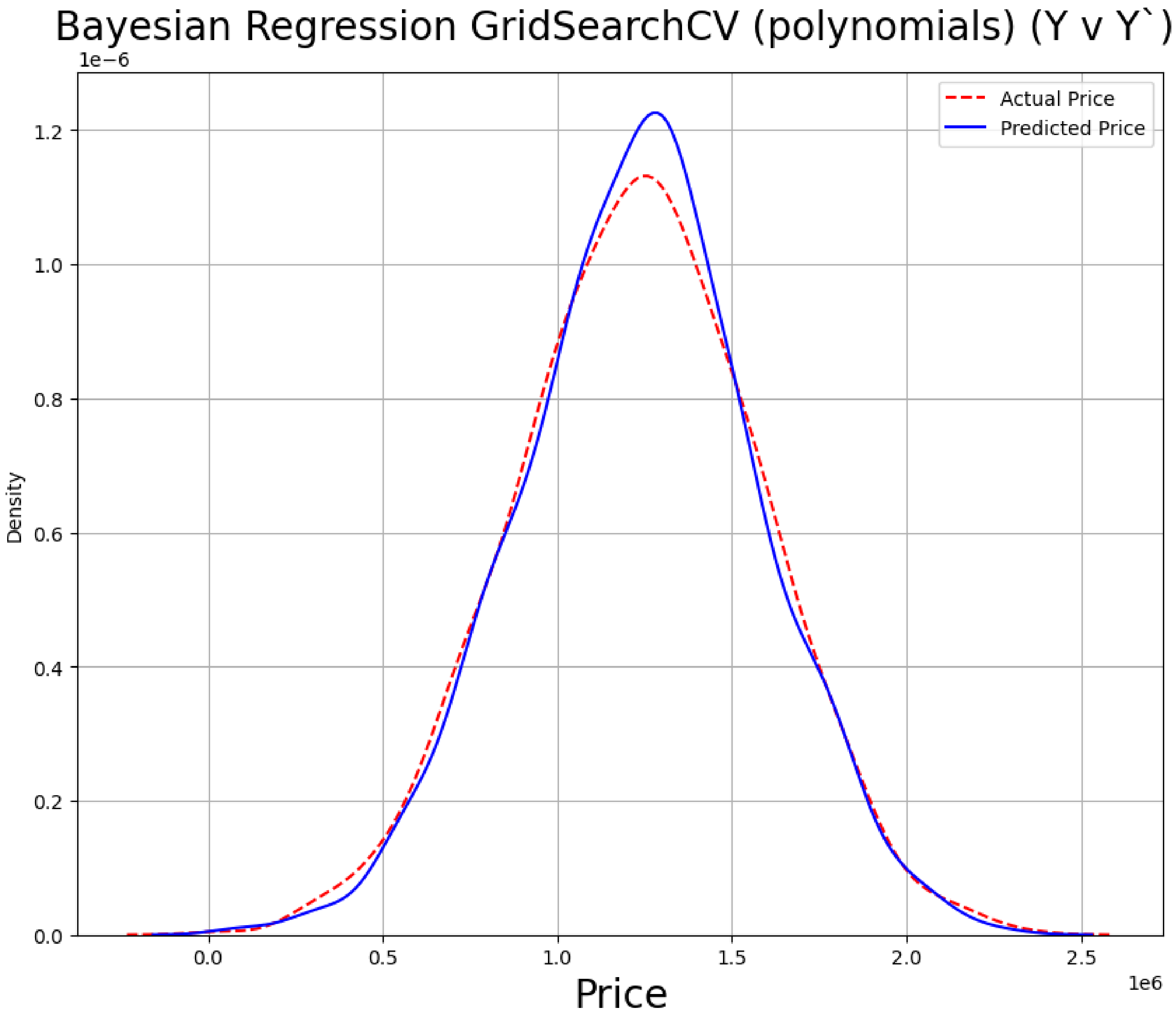
In [110]:

```
# the y predict for the grid with pipeline with polynomial feature
```

```
grid_yhat_pipes = grid_pipe.predict(X_test)
```

In [111]:

```
# Line plot between predicted and actual price

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

ax = sns.kdeplot(y_test, label='Actual Price', color='red', linestyle='--')

sns.kdeplot(grid_yhat_pipes,label='Predicted Price',color='blue',ax=ax)

plt.title("Bayesian Regression GridSearchCV (polynomials) (Y v Y`) ", fontsize=20)
plt.xlabel("Price",fontsize=20)
plt.grid(True)
plt.legend()
plt.show()
```



Linear Regression

In [112]:

```
# initializing linear regression
Lr = LinearRegression()

# fitting the data
Lr.fit(X_train, y_train)

# y_predict - linear regression
```

```
Lr_y_predict = Lr.predict(X_test)

## training and testing score
print(f"Training score for Linear Regression : {Lr.score(X_train,y_train)}")
print(f"Testing score for Linear Regression : {Lr.score(X_test,y_test)}")
```

```
Training score for Linear Regression : 0.917763335495789
Testing score for Linear Regression : 0.9189605362354953
```

In [113]:

```
final_models_df[final_models_df['Model_Used']=='LinearRegression']
```

Out[113]:

	Model_Used	training_scores	testing_scores	R2_Score(test)	mse_score_test	mae_score_test
1	LinearRegression	0.917763	0.918961	0.918961	9.905596e+09	79143.20893

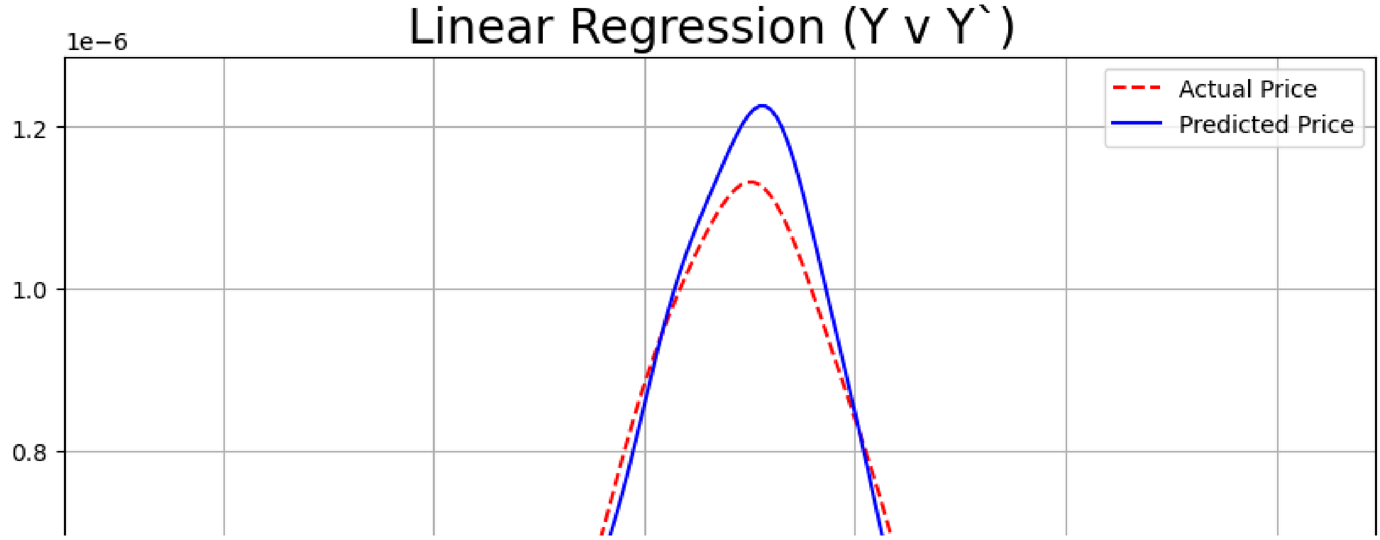
In [114]:

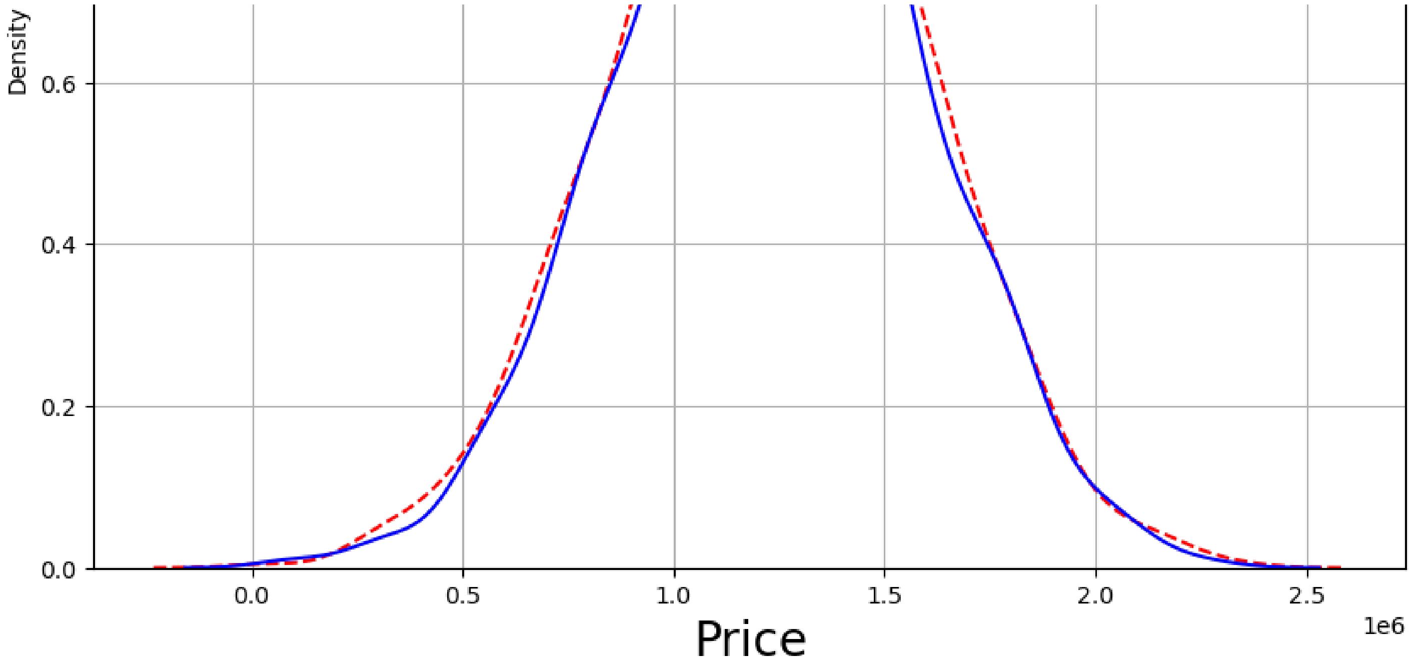
```
# parameters
coef = Lr.coef_
intercept = Lr.intercept_
mse = mean_squared_error(y_test, Lr_y_predict)
r2 = r2_score(y_test, Lr_y_predict)

print(f"Coefficients: {coef}")
print(f"Intercept: {intercept}")
print(f"Mean Squared Error: {mse}")
print(f"R-squared: {r2}")
```

```
Coefficients: [1.94010518e+06 1.14597570e+06 1.05036433e+06 9.14922625e+05
 2.79140754e+01]
Intercept: -1422362.6532700951
Mean Squared Error: 9905595592.651926
R-squared: 0.9189605362354953
```

In [115]:

```
# Line plot between predicted and actual price

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

ax = sns.kdeplot(y_test, label='Actual Price', color='red', linestyle='--')

sns.kdeplot(Lr_y_predict,label='Predicted Price',color='blue',ax=ax)

plt.title("Linear Regression (Y v Y`) ", fontsize=20)
plt.xlabel("Price",fontsize=20)
plt.grid(True)
plt.legend()
plt.show()
```





As you can see both the models have made the best possible outcomes

Gradient Boosting Regressor

In [1]:

```
# # initializing the gradient boosting regressor
# gbr = GradientBoostingRegressor()

# # initializing the parameters for gbr
# # Define the parameter
# gbr_param_grid = { 'n_estimators': [100, 200, 300, 400, 500, 600, 700, 800], # Number of boosting stages
#                   'learning_rate': [0.01, 0.005, 0.1], # Learning rate
#                   'max_depth': [1,2,3], # Maximum depth of the individual trees
#                   'min_samples_split': [2,3,4,5], # Minimum number of samples required to split an internal node
#                   'min_samples_leaf': [1, 2, 3, 4, 5], # Minimum number of samples required to be at a leaf node
#                   'max_features': ['auto', 'sqrt', 'log2'], # Number of features to consider when looking for the best split
#                   'loss': ['squared_error', 'absolute_error', 'huber', 'quantile']
# }

# # initializing the grid search cv
# grid_search_cv = GridSearchCV(estimator = gbr,
#                               param_grid = gbr_param_grid,
#                               cv = 5, scoring='r2',n_jobs=14)

# # fitting the model
# grid_search_cv.fit(X_train, y_train)

# # y_predict for gbr_grid
# gbr_predict = grid_search_cv.predict(X_test)

# print(grid_search_cv.best_params_)

# # outputing the final results into a variable
# final_gbr_model_result = grid_search_cv.cv_results_
```

In [2]:

```
# # converting the result to df from dict
# final_models_df_gbr_model_result = pd.DataFrame.from_dict(final_gbr_model_result)

# final_models_df_gbr_model_result[final_models_df_gbr_model_result['rank_test_score']==1
```

```
]
```

In [3]:

```
# # Line plot between predicted and actual price

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

# ax = sns.kdeplot(y_test, label='Actual Price', color='red', linestyle='--')

# sns.kdeplot(gbr_predict, label='Predicted Price',color='blue',ax=ax)

# plt.title("Gradient Boosting Regression (Y v Y`) ", fontsize=20)
# plt.xlabel("Price",fontsize=20)
# plt.grid(True)
# plt.legend()
# plt.show()
```

Decision Tree Regressor

In [ ]:

```
# paramaters = {
#     'criterion':["squared_error", "friedman_mse", "absolute_error", "poisson"],
#     'splitter' : ["best","random"],
#     'max_depth':[None,1,2,3,4],
#     'min_samples_split':[2,3,4,5],
#     'min_samples_leaf':[1,2,3,4,5],
#     'max_leaf_nodes':[1,2,3,4,5]
# }
```

In [4]:

```
# # initializing the model
# dctr = DecisionTreeRegressor(random_state=53)

# # initializing gridsearchcv
# grid_dctr = GridSearchCV(
#     estimator=dctr,
#     param_grid = parameters,
#     cv=5, n_jobs=13
# )

# # fitting the data
# grid_dctr.fit(X_train,y_train)

# # yhat predict
# grid_dctr_yhat = grid_dctr.predict(X_test)

# # get the best parameters
# print(f"Best Parameters : {grid_dctr.bests_params_}")

# # converting to a df
# grid_dctr_df = pd.DataFrame.from_dict(grid_dctr.cv_results_)
```

In [5]:

```
# grid_dctr_df[grid_dctr_df['rank_test_score']==1]
```