Housing Price Regression

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==

STEP1: Import required libraries

In [2]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from warnings import filterwarnings
filterwarnings('ignore')
from sklearn.preprocessing import LabelEncoder
```

STEP2: Import file

In [3]:
```
df=pd.read_csv("Housing.csv")
df.head(2)
```

Out[3]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airconditioning	parking	pre
0	13300000	7420	4	2	3	yes	no	no	no	yes	2	
1	12250000	8960	4	4	4	yes	no	no	no	yes	3	

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 545 entries, 0 to 544
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   price             545 non-null    int64 
 1   area              545 non-null    int64 
 2   bedrooms          545 non-null    int64 
 3   bathrooms         545 non-null    int64 
 4   stories           545 non-null    int64 
 5   mainroad          545 non-null    object
 6   guestroom         545 non-null    object
 7   basement          545 non-null    object
 8   hotwaterheating   545 non-null    object
 9   airconditioning   545 non-null    object
 10  parking           545 non-null    int64 
 11  prefarea          545 non-null    object
 12  furnishingstatus  545 non-null    object
dtypes: int64(6), object(7)
memory usage: 55.5+ KB
```

In [5]:
```
df.isnull().sum()
```

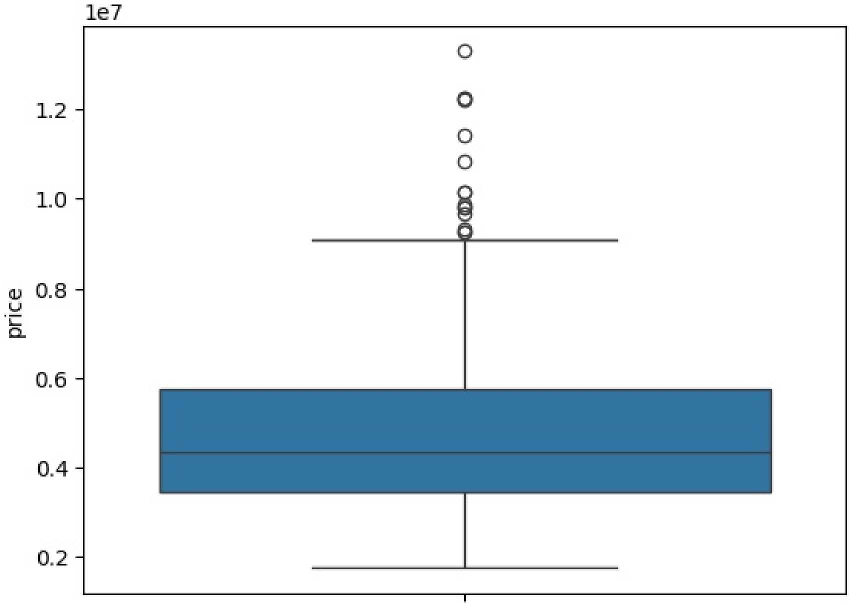
Out[5]:
```
price               0
area                0
bedrooms            0
bathrooms           0
stories             0
mainroad            0
guestroom           0
basement            0
hotwaterheating     0
airconditioning     0
parking             0
prefarea            0
furnishingstatus    0
dtype: int64
```

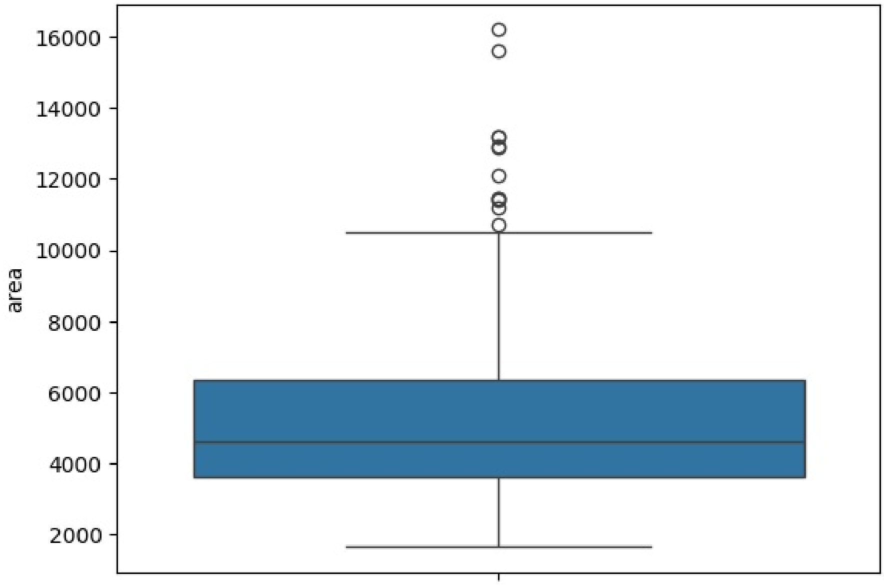
In [5]:
```
# no null values in data
```

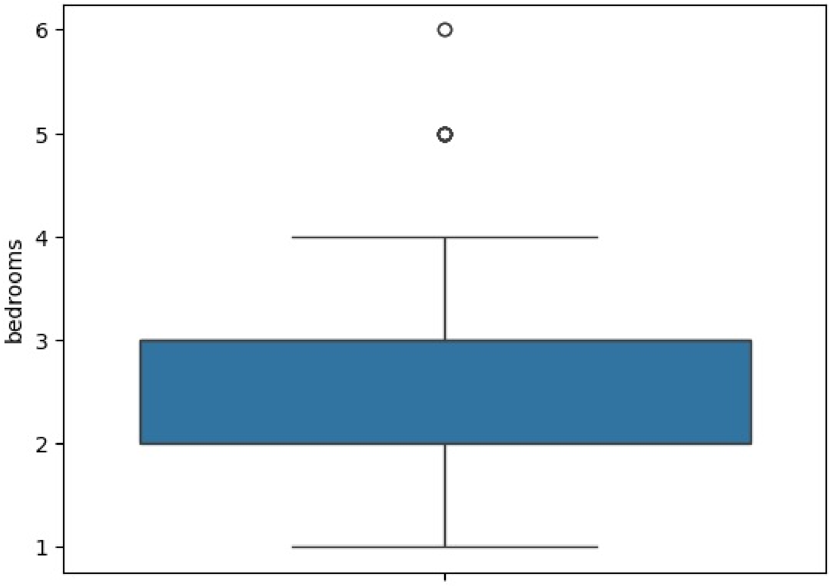
In [6]:
```
#using boxplot to visualise any outliers presence
```

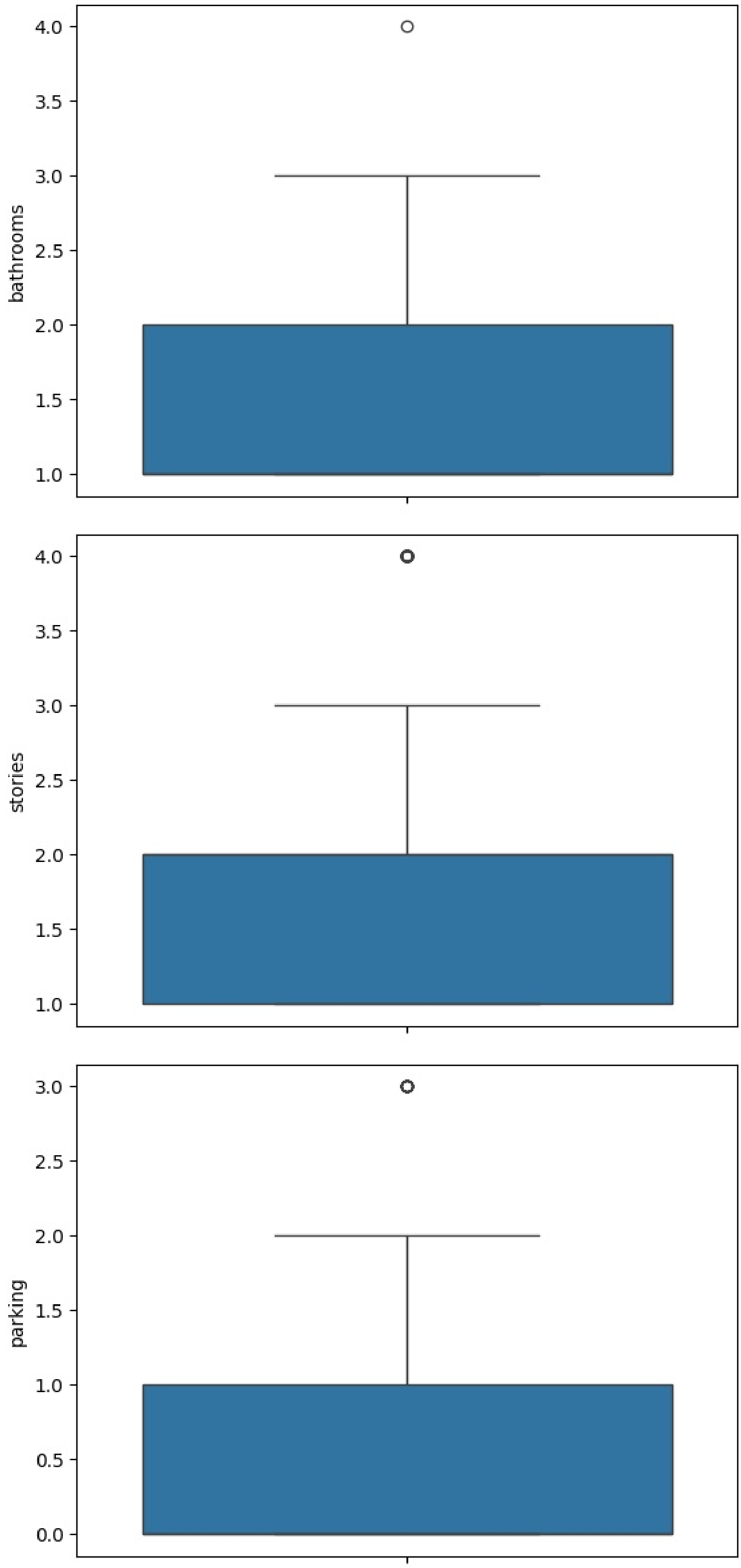
In [6]:
```
df_numeric= df.select_dtypes(include='number')
```

In [7]:
```
for i in df_numeric.columns:
    sns.boxplot(df_numeric[i])
    plt.show()
```









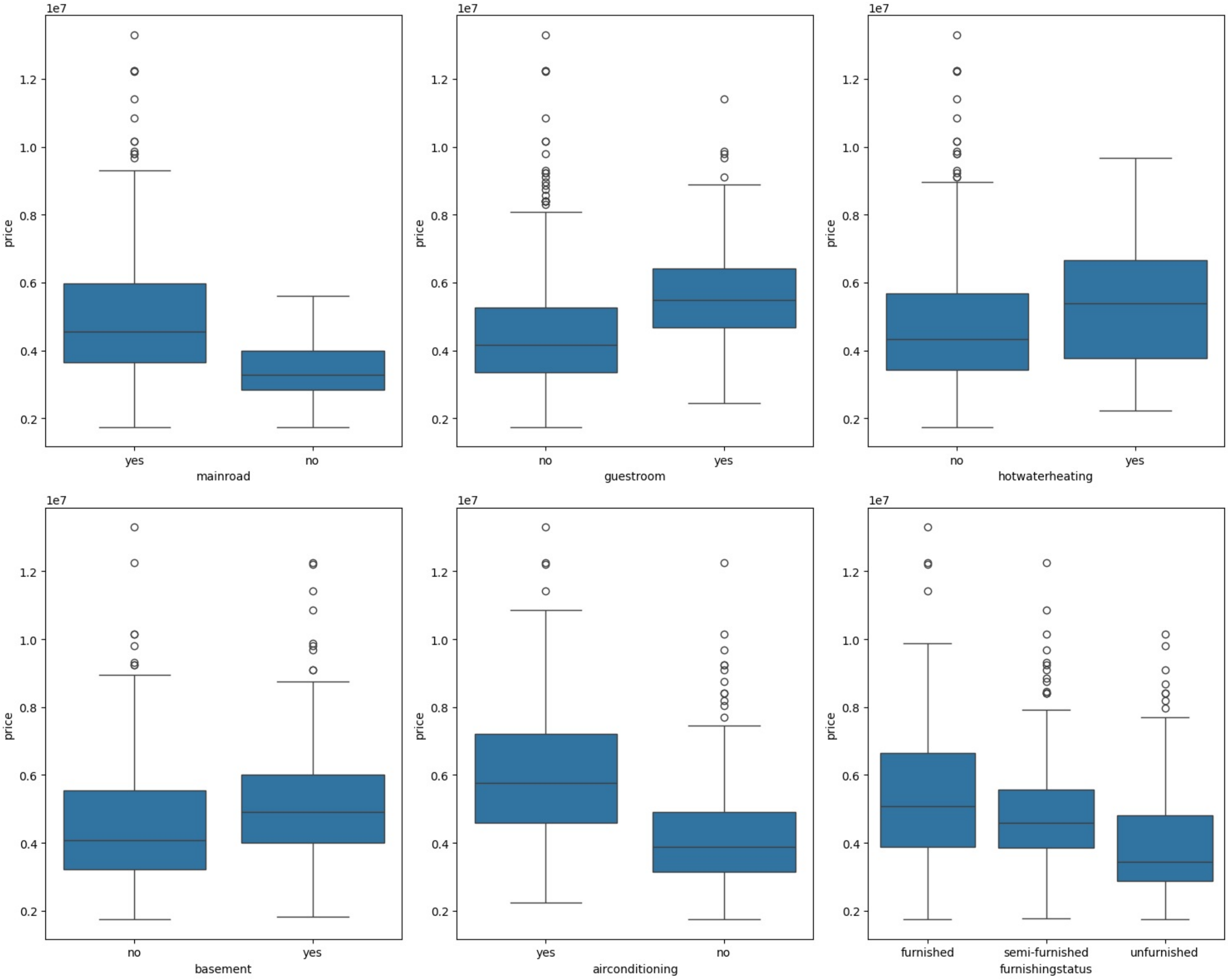
In [9]:
```
# The presence of outliers is indicated
```

In [10]:
```
# since the obeservations are very few.. we try not removing outliers
```

STEP3: visualising numeric variables

In [8]:
```
sns.pairplot(df,diag_kind='kde')
plt.show()
```

In [9]:
```
# bivariant
plt.figure(figsize=(15,12))
plt.subplot(2,3,1)
sns.boxplot(x='mainroad',y='price',data=df)
plt.subplot(2,3,2)
sns.boxplot(x='guestroom',y='price',data=df)
plt.subplot(2,3,3)
sns.boxplot(x='hotwaterheating',y='price',data=df)
plt.subplot(2,3,4)
sns.boxplot(x='basement',y='price',data=df)
plt.subplot(2,3,5)
sns.boxplot(x='airconditioning',y='price',data=df)
plt.subplot(2,3,6)
sns.boxplot(x='furnishingstatus',y='price',data=df)
plt.tight_layout()
plt.show()
```



In [14]:
```
# if we look at the above boxplot the houses which are on mainroad, having guestroom, having hotwater facility,
# with basement, airconditioning and semi furinished and fully furnished are expensive and more than compared t
# houses with not havng most facilities
```

In [10]:
```
df.replace({'yes': 1, "no": 0},inplace=True)
# replacing object variables 'YES' and "NO" to one and zero
```

In [11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 545 entries, 0 to 544
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   price             545 non-null    int64
 1   area              545 non-null    int64
 2   bedrooms          545 non-null    int64
 3   bathrooms         545 non-null    int64
 4   stories           545 non-null    int64
 5   mainroad          545 non-null    int64
 6   guestroom         545 non-null    int64
 7   basement          545 non-null    int64
 8   hotwaterheating   545 non-null    int64
 9   airconditioning   545 non-null    int64
 10  parking           545 non-null    int64
 11  prefarea          545 non-null    int64
 12  furnishingstatus  545 non-null    object
dtypes: int64(12), object(1)
memory usage: 55.5+ KB
```

In [17]:
```
# encoding furnishing status
```

In [12]:
```
encoded_furniture=pd.get_dummies(df['furnishingstatus'],drop_first=True).astype('uint8')
```

In [13]:
```
df= pd.concat([df, encoded_furniture], axis = 1)
df
```

Out[13]:

	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airconditioning	parking
0	13300000	7420	4	2	3	1	0	0	0	1	2
1	12250000	8960	4	4	4	1	0	0	0	1	3
2	12250000	9960	3	2	2	1	0	1	0	0	2
3	12215000	7500	4	2	2	1	0	1	0	1	3
4	11410000	7420	4	1	2	1	1	1	0	1	2
...	...	...	...	...	...	...	...	...	...	...	...
540	1820000	3000	2	1	1	1	0	1	0	0	2
541	1767150	2400	3	1	1	0	0	0	0	0	0
542	1750000	3620	2	1	1	1	0	0	0	0	0
543	1750000	2910	3	1	1	0	0	0	0	0	0
544	1750000	3850	3	1	2	1	0	0	0	0	0

545 rows × 15 columns

In [14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 545 entries, 0 to 544
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   price             545 non-null    int64 
 1   area              545 non-null    int64 
 2   bedrooms          545 non-null    int64 
 3   bathrooms         545 non-null    int64 
 4   stories           545 non-null    int64 
 5   mainroad          545 non-null    int64 
 6   guestroom         545 non-null    int64 
 7   basement          545 non-null    int64 
 8   hotwaterheating   545 non-null    int64 
 9   airconditioning   545 non-null    int64 
 10  parking           545 non-null    int64 
 11  prefarea          545 non-null    int64 
 12  furnishingstatus  545 non-null    object
 13  semi-furnished    545 non-null    uint8 
 14  unfurnished       545 non-null    uint8 
dtypes: int64(12), object(1), uint8(2)
memory usage: 56.5+ KB
```

In [21]:
```
# we can drop furnishingstatus now
```

In [15]:
```
df.drop('furnishingstatus',axis=1,inplace=True)
```

In [16]:
```
# standardising the data
from sklearn.preprocessing import MinMaxScaler
```

In [17]:
```
mm=MinMaxScaler()
df_scaled=pd.DataFrame(mm.fit_transform(df),columns=df.columns)
df_scaled
```

Out[17]:

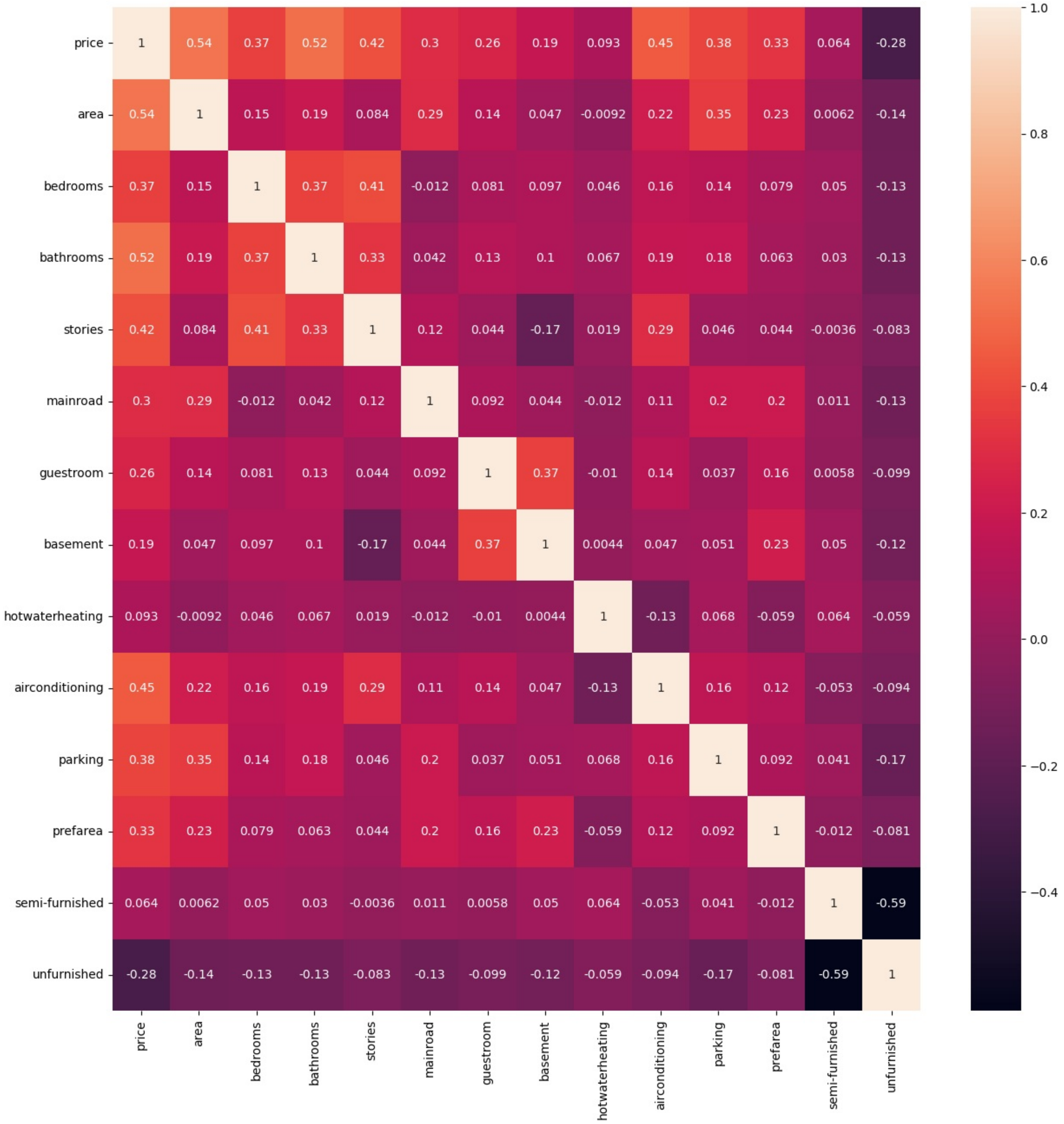
	price	area	bedrooms	bathrooms	stories	mainroad	guestroom	basement	hotwaterheating	airconditioning	park
0	1.000000	0.396564	0.6	0.333333	0.666667	1.0	0.0	0.0	0.0	1.0	0.666
1	0.909091	0.502405	0.6	1.000000	1.000000	1.0	0.0	0.0	0.0	1.0	1.000
2	0.909091	0.571134	0.4	0.333333	0.333333	1.0	0.0	1.0	0.0	0.0	0.666
3	0.906061	0.402062	0.6	0.333333	0.333333	1.0	0.0	1.0	0.0	1.0	1.000
4	0.836364	0.396564	0.6	0.000000	0.333333	1.0	1.0	1.0	0.0	1.0	0.666
...	...	...	...	...	...	...	...	...	...	...	
540	0.006061	0.092784	0.2	0.000000	0.000000	1.0	0.0	1.0	0.0	0.0	0.666
541	0.001485	0.051546	0.4	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.000
542	0.000000	0.135395	0.2	0.000000	0.000000	1.0	0.0	0.0	0.0	0.0	0.000
543	0.000000	0.086598	0.4	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.000
544	0.000000	0.151203	0.4	0.000000	0.333333	1.0	0.0	0.0	0.0	0.0	0.000

545 rows × 14 columns

In [18]:

```
plt.figure(figsize=(15,15))
sns.heatmap(df_scaled.corr(),annot=True)
```

Out[18]: <Axes: >



In [26]:
```
# Area,bathroms,bedrooms,stories with price look to have a good correlation,
```

STEP4: Splitting the Data into Training and Testing Sets

In [19]:
```
from sklearn.model_selection import train_test_split
```

In [20]:
```
X=df_scaled.drop('price',axis=1)
y=df_scaled['price']
```

In [21]:
```
xtrain,xtest,ytrain,ytest= train_test_split(X,y, test_size = 0.2, random_state = 100)
xtrain.shape,xtest.shape,ytrain.shape,ytest.shape
```

Out[21]:
```
((436, 13), (109, 13), (436,), (109,))
```

STEP5: Model Building

In [22]:
```
from sklearn.linear_model import LinearRegression
```

In [26]:
```
lin_reg = LinearRegression()
# train the model with input and output data - train
model = lin_reg.fit(xtrain,ytrain)
```

```
#test the model with input  data - test
y_pred = model.predict(xtest)
lin_reg.fit(xtest,y_pred)
```

Out[26]:

```
LinearRegression
LinearRegression()
```

In [32]:

```
#Model Evaluation
```

In [27]:

```
from sklearn.metrics import mean_squared_error,r2_score
```

In [34]:

```
# model evaluation for training set
y_pred = lin_reg.predict(xtrain)
rmse = (np.sqrt(mean_squared_error(ytrain, y_pred)))
print("rmse:",rmse)
# R square value - training dataset
r2 =  r2_score(ytrain, y_pred)
print("R- Square:",r2)
```

```
rmse: 0.09160650416956634
R- Square: 0.6781789392869301
```

In [35]:

```
# model evaluation for testing set
y_pred = lin_reg.predict(xtest)
rmse = (np.sqrt(mean_squared_error(ytest, y_pred)))
print("rmse:",rmse)
r2 =  r2_score(ytest, y_pred)
print("R- Square:",r2)
```

```
rmse: 0.09191877175078576
R- Square: 0.6806539407870682
```

OLS - model summary

In [36]:

```
import statsmodels.api as sm
model = sm.OLS(y, X).fit()
predictions = model.predict(X) # make the predictions by the model

# Print out the statistics
model.summary()
```

Out[36]:

OLS Regression Results

Dep. Variable:	price	**R-squared (uncentered):**	0.912
Model:	OLS	**Adj. R-squared (uncentered):**	0.909
Method:	Least Squares	**F-statistic:**	421.6
Date:	Mon, 27 Nov 2023	**Prob (F-statistic):**	3.45e-270
Time:	15:07:26	**Log-Likelihood:**	530.67
No. Observations:	545	**AIC:**	-1035.
Df Residuals:	532	**BIC:**	-979.4
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
area	0.3137	0.030	10.399	0.000	0.254	0.373
bedrooms	0.0707	0.026	2.727	0.007	0.020	0.122
bathrooms	0.2531	0.027	9.480	0.000	0.201	0.306
stories	0.1161	0.017	6.974	0.000	0.083	0.149
mainroad	0.0443	0.010	4.260	0.000	0.024	0.065
guestroom	0.0260	0.011	2.281	0.023	0.004	0.048
basement	0.0315	0.009	3.318	0.001	0.013	0.050
hotwaterheating	0.0751	0.019	3.890	0.000	0.037	0.113
airconditioning	0.0756	0.009	8.077	0.000	0.057	0.094
parking	0.0718	0.015	4.721	0.000	0.042	0.102
prefarea	0.0558	0.010	5.574	0.000	0.036	0.075
semi-furnished	0.0009	0.009	0.100	0.921	-0.017	0.019
unfurnished	-0.0292	0.009	-3.075	0.002	-0.048	-0.011

Omnibus:	90.675	**Durbin-Watson:**	1.240
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	232.079
Skew:	0.841	**Prob(JB):**	4.02e-51
Kurtosis:	5.718	**Cond. No.**	11.1

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Building random forest model with all features to find out the feature importance

In [37]:

```
from sklearn.ensemble import RandomForestRegressor

forest = RandomForestRegressor(n_estimators = 100, max_depth = 10)
forest.fit(xtrain,ytrain)
```

Out[37]:

```
▾ RandomForestRegressor
RandomForestRegressor(max_depth=10)
```

In [38]:

```
y_pred=forest.predict(xtest)
```

In [39]:

```
rmse=np.sqrt(mean_squared_error(ytest,y_pred))
rmse
```

Out[39]: 0.0963470346104841

In [40]:

```
r2_score(ytest,y_pred)
```

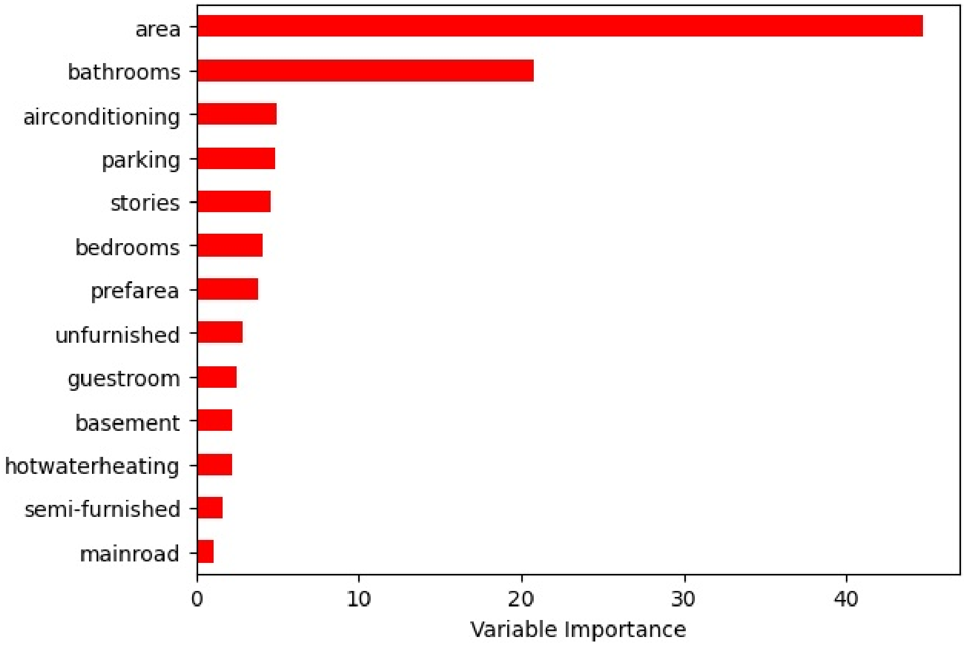
Out[40]: 0.6491432461227882

In [41]:

```
Importance = pd.DataFrame({'Importance':forest.feature_importances_*100}, index=xtrain.columns)
Importance.sort_values('Importance', axis=0, ascending=True).plot(kind='barh', color='r', )
plt.xlabel('Variable Importance')
plt.gca().legend_ = None
```

```
plt.figure(figsize=(20,15))
```

Out[41]: <Figure size 2000x1500 with 0 Axes>



<Figure size 2000x1500 with 0 Axes>

In [42]:
```
Importance.sort_values('Importance', axis=0, ascending=False)
```

Out[42]:

	Importance
area	44.750199
bathrooms	20.754096
airconditioning	4.918742
parking	4.817895
stories	4.517445
bedrooms	4.048446
prefarea	3.763245
unfurnished	2.891752
guestroom	2.485536
basement	2.240064
hotwaterheating	2.205662
semi-furnished	1.588988
mainroad	1.017932

In [43]:
```
# area and bathrooms explain 65 percent variance togetehr considering they are the most important features
```

In [44]:
```
# creating new X based on selective features
# taking features that cpuld give 85% variance together
X_new=df_scaled.drop(['unfurnished','guestroom','basement','hotwaterheating','semi-furnished','mainroad'],axis=
Y=df_scaled['price']
```

In [ ]:

In [48]:
```
from sklearn import metrics
from sklearn.model_selection import KFold
from sklearn.linear_model import Ridge,Lasso
```

In [49]:
```
LR=LinearRegression()
Ridge_R=Ridge(alpha=0.5)
Lasso_R=Lasso(alpha=0.1)
```

In [53]:
```
kf=KFold(n_splits=3,shuffle=True,random_state=2)
for model, name in zip([LR,Ridge_R,Lasso_R],['Ridge','Lasso']):
    rmse=[]
    for train,test in kf.split(X_new,Y):
        x_train,x_test=X_new.iloc[train,:],X_new.iloc[test,:]
        y_train,y_test=Y.iloc[train],Y.iloc[test]
        model.fit(x_train,y_train)
        Y_predict=model.predict(x_test)
```

```
        rmse.append(np.sqrt(metrics.mean_squared_error(y_test,Y_predict)))
    print(rmse)
    print("Cross_Validated_rmse_score: %0.03f (+/- %0.5f) [%s]" % (np.mean(rmse),np.var(rmse,ddof=1),name))
```

```
[1.2334373077647615e-16, 1.661481330599047e-16, 8.773567958375563e-17]
Cross_Validated_rmse_score: 0.000 (+/- 0.00000) [Ridge]
[0.012877039040894732, 0.011901611855598371, 0.012292062950779137]
Cross_Validated_rmse_score: 0.012 (+/- 0.00000) [Lasso]
```

Model Evaluation Summary

Initial Model: Linear Regression with All Features (Scaled) Root Mean Square Error (RMSE): 0.0916 Intermediate Model: Random Forest with All Features RMSE: 0.0958 Final Model: Linear Regression with Ridge and Lasso Regression (Selected Features)

Features selected to account for 85% variance

Ridge Regression:

Cross-Validated RMSE Score: 0.012 (± 0.00000)

Lasso Regression:

Cross-Validated RMSE Score: 0.00 (± 0.00000)

Conclusion

The model initially had an RMSE of 0.0916. A Random Forest model yielded a slightly higher RMSE of 0.0958. Using Ridge and Lasso regression with selected features improved the RMSE significantly. The Cross-Validated RMSE for Ridge Regression is 0.012, while for Lasso Regression it is 0.00. This demonstrates a significant reduction in RMSE, indicating that Ridge and Lasso regression models are more effective.

Measures of a Good Model

Lower RMSE: Indicates better predictive accuracy. Cross-Validation: Ensures the model's reliability and generalizability. Feature Importance: Identifying key features that contribute most to the prediction, improving model interpretability and performance. Variance Explained: Selecting features that explain a high percentage of variance helps in reducing complexity and enhancing model performance.

In [ ]:

In [ ]:

In [ ]: