

# Institute of Technology of Cambodia

# Department of Applied Mathematics and Statistics

Project: Condo for Sale in Cambodia

Subject: Programming for Data Science

Lecturer: CHAN Sophal

#### Group 5:

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# 1. Project Description and Objective



Condo for Sale in Cambodia is to provide a high-quality, affordable, and convenient living space for individuals and families. And we choose this topic because we want to use some techniques to interpret and make prediction price of condo. We will study on the variable that make effect to predicting price.

# 2. Dataset and Variable Description

After we scraped dataset by using web scraping technique and regular expression technique. There exist 1547 rows with 15 columns. There exist 15 variables as following:

Ad ID	Category	Locations	Posted	Size(m2)	Bedroom	Bathroom	Link	Title	Price	Post Description	Sub Location	Bedrooms	Bathrooms	Floor
8538993	Condo for Sale	Phnom Penh	06-Jul- 23	34	NaN	NaN	https://www.khmer24.com/en/property/new- condo	New condo for sell	\$58,000	Very special promotion!! Full price \$58,000 bu	Toul Kork	1.0	1.0	6.0
8517524	Condo for Sale	Phnom Penh	06-Jul- 23	58	NaN	NaN	https://www.khmer24.com/en/property/vista- cond	Vista Condo Aeon2 Urgent	\$75,000	ឌុននូសម្រាប់លក់ VISTA Condo\n\r\n(English Belo	Sen Sok	NaN	NaN	19.0
9617339	Condo for Sale	Phnom Penh	03-Jul- 23	34	NaN	NaN	https://www.khmer24.com/en/property/condo- uk-5	Condo UK 548 for Sales	\$42,000	បន្ទប់ឌុននូប្រភេទ Studio (UK Condo 548)\n\rកណ្	NaN	NaN	NaN	15.0
9617339	Condo for Sale	Phnom Penh	03-Jul- 23	34	NaN	NaN	https://www.khmer24.com/en/property/condo- %E1%	Condo សម្រាប់ដូល/Condo for Rent (The Peak Priv	\$800	Property Code: VBRE00586\n\r\nCondo សម្រាប់ដូល	Chamkar Mon	1.0	NaN	NaN
8134344	Condo for Sale	Phnom Penh	09-Apr- 23	57	NaN	NaN	https://www.khmer24.com/en/property/condo- for	Condo for sale 57m2	\$72,000	Fully furnished condo for sale / rent \n\nOwne	NaN	1.0	1.0	9.0



# 3. Data Preprocessing



## 3.1 Data Cleaning

Dropped some features that not affected to predicting and building model.

df\_new.head()

	Locations	Posted	Size(m2)	Price	Sub Location	Bedrooms	Bathrooms	Floor
0	Phnom Penh	06-Jul-23	34	\$58,000	Toul Kork	1.0	1.0	6.0
1	Phnom Penh	06-Jul-23	58	\$75,000	Sen Sok	NaN	NaN	19.0
2	Phnom Penh	03-Jul-23	34	\$42,000	NaN	NaN	NaN	15.0
3	Phnom Penh	03-Jul-23	34	\$800	Chamkar Mon	1.0	NaN	NaN
4	Phnom Penh	09-Apr-23	57	\$72,000	NaN	1.0	1.0	9.0

# 3.1.1 Format Data Type

```
# Format Data type
df_new['Size(m2)']=df_new['Size(m2)'].astype(float)
df_new['Floor']=pd.to_numeric(df_new['Floor'], errors='coerce')
df_new['Price']=df_new['Price'].str.replace('$','').str.replace(',','').astype(float)
```

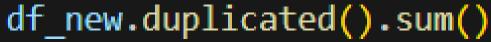
### 3.1.2 Checking missing values

Locations	0
Posted	0
Size(m2)	0
Price	0
Sub Location	931
Bedrooms	766
Bathrooms	1025
Floor	864

Sub Location 60.181 % Missing Values Bedrooms 49.515 % Missing Values Bathrooms 66.257 % Missing Values Floor 55.85 % Missing Values

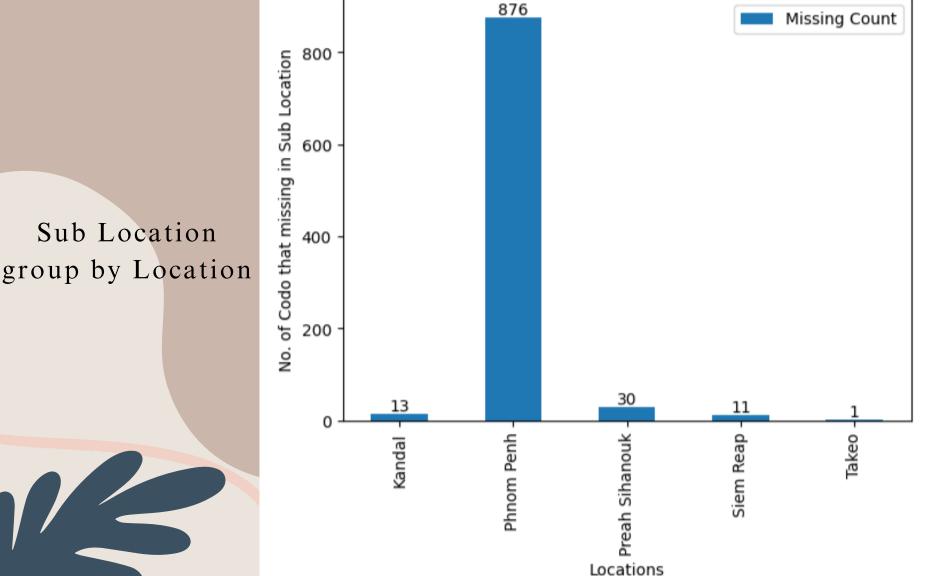


#### 3.1.3 Checking Duplicated



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- Based on my research, you can see that some of the sub places where most condos are in each province are:
- Phnom Penh: Chamkar Mon, Chraoy Chongvar, Tuol Kouk, Doun Penh, Saensokh
- Preah Sihanouk: Sihanoukville, Prey Nob
- Takeo: Daun Keo
- Siem Reap: Svay Dangkum, Sala Kamreuk, Slor Kram
- Kandal: Takhmao



Sub Location



#### 3.1.5 Fill missing value in Feature Sub Location

```
default_sub_locations = {
    "Phnom Penh": "Chamkar Mon",
    "Preah Sihanouk": "Sihanoukville",
    "Takeo": "Daun Keo",
    "Siem Reap": "Svay Dangkum",
    "Kandal": "Takhmao"
} # create a dictionary of default sub locations
df_new["Sub Location"] = df_new["Sub Locations].fillna(df_new["Locations "].map(default_sub_locations))
```



# Label Encoder: Categorical feature Location and Sub Location

	Locations	Posted	Size(m2)	Price	<b>Sub Location</b>	Bedrooms	Bathrooms	Floor
0	1	2023-07-06	34.0	58000.0	15	1.0	1.0	6.0
1	1	2023-07-06	58.0	75000.0	11	NaN	NaN	19.0
2	1	2023-07-03	34.0	42000.0	1	NaN	NaN	15.0
3	1	2023-07-03	34.0	800.0	1	1.0	NaN	NaN
4	1	2023-04-09	57.0	72000.0	1	1.0	1.0	9.0

# 3.1.7 Fixing missing values on Features Bedrooms, Bathrooms and Floor

```
import numpy as np
imputer = KNNImputer(n_neighbors=5,weights="distance")
```

```
hew3=pd.DataFrame(np.round(imputer.fit_transform(df_new2[['Locations ','Size(m2)', 'Price', 'Sub Location', 
'Bedrooms', 'Bathrooms', 'Floor']])),columns=['Locations ','Size(m2)', 'Price', 'Sub Location', 
'Bedrooms', 'Bathrooms', 'Floor'], dtype=int)
```



```
df_new3['Size(m2)'] = df_new3['Size(m2)'].astype(float)
df_new3['Price'] = df_new3['Price'].astype(float)
```

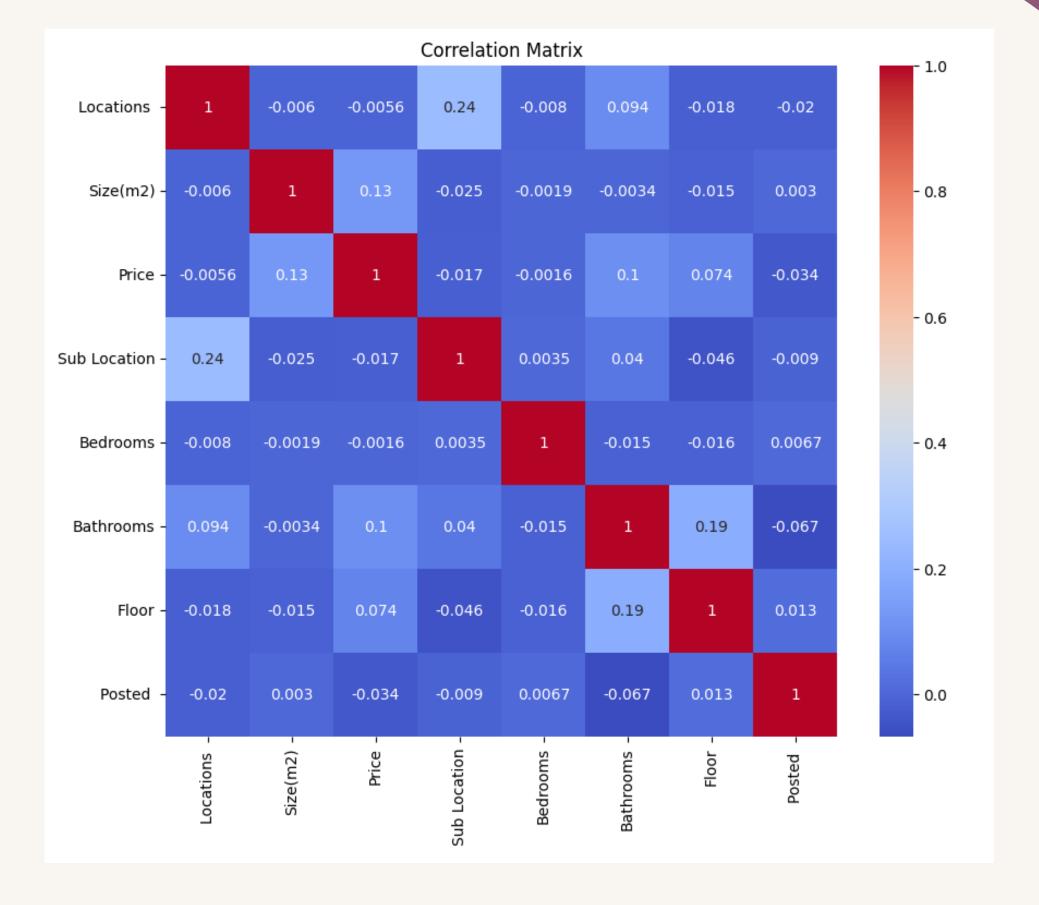
```
#
    Column
                Non-Null Count
                               Dtype
                1506 non-null
    Locations
                               int32
    Size(m2)
                1506 non-null
                               float64
    Price
                1506 non-null
                               float64
    Sub Location 1506 non-null
                               int32
    Bedrooms
                1506 non-null
                               int32
    Bathrooms
                               int32
                1506 non-null
    Floor
                1506 non-null
                               int32
dtypes: float64(2), int32(5)
```

#### Drop duplicate values

df\_new1.drop\_duplicates(subset=df\_new1, keep='first', inplace =True)



#### Heatmap





# 3.1.9 Checking Outliers

	Size(m2)	Price	Sub Location	Bedrooms	Bathrooms	Floor
20	45.0	0.0	1	1	1	38
22	175.0	914985.0	1	4	4	26
23	50.0	84375.0	1	1	1	45
32	154.0	999000.0	0	2	3	26
39	166.0	330000.0	1	3	2	77
1489	127.0	323000.0	1	3	2	26
1497	47.0	68000.0	1	44	1	10
1498	354.0	488000.0	1	60	4	20
1502	298616.0	17900.0	1	2	1	8
1503	119.0	350000.0	11	3	2	24
255 ro	ws × 6 co	lumns				

We found outliers 255 rows and 6 columns by using IQR.



Remove outliers.

```
# Remove outliers from the DataFrame
df_new3 = df_new3[~outliers]
df_new3.shape

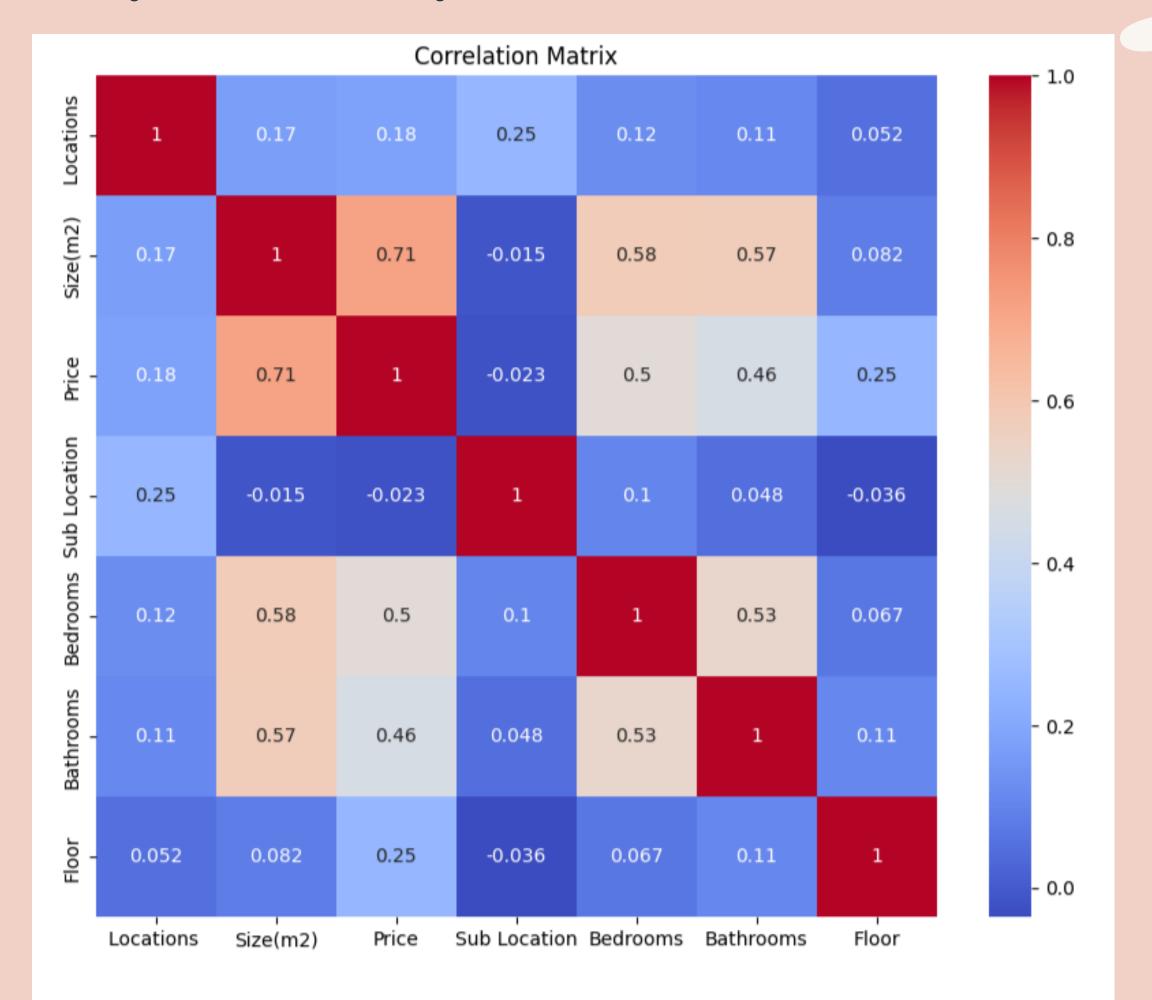
(1251, 8)
```

And then we decided to drop the condos that have price less than 5000.

```
df_new3 = df_new3.drop(df_new3[df_new3['Price'] < 5000].index)</pre>
```

# 4. Exploratory Data Analysis

Heatmap





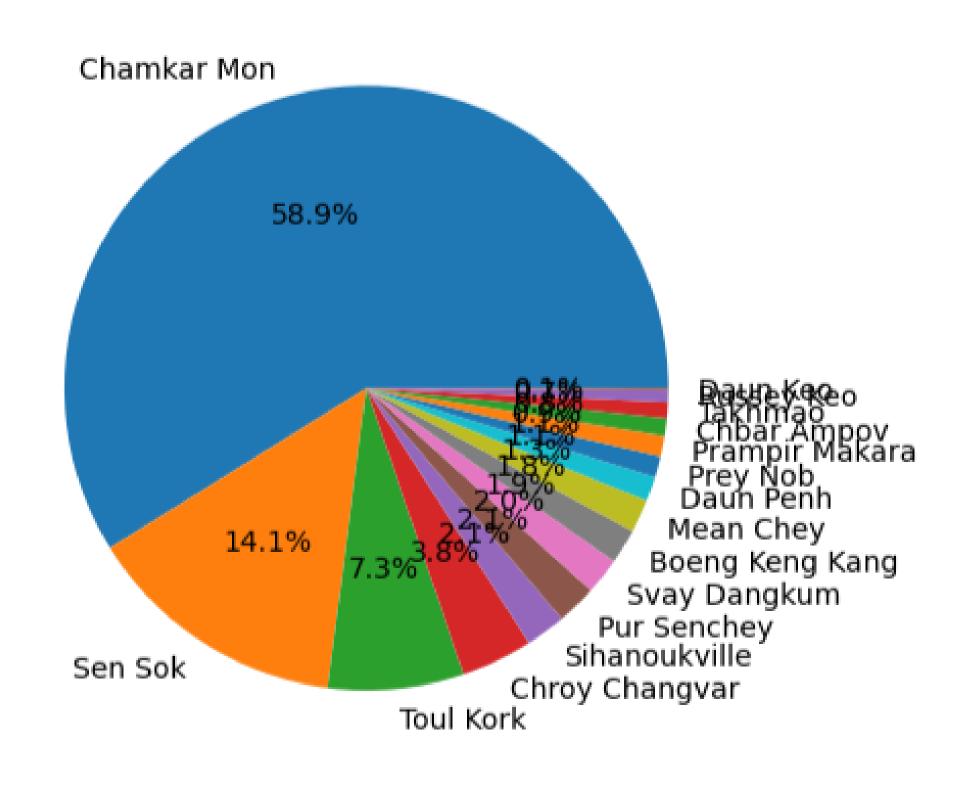
Sub location that has the most condo for sale is Chamkar Mon in location Phnom Penh.

Locations	Sub Location	
Kandal	Takhmao	9
Phnom Penh	Chamkar Mon	631
	Sen Sok	151
	Toul Kork	78
	Chroy Changvar	41
	Pur Senchey	23
	Boeng Keng Kang	20
	Mean Chey	19
	Daun Penh	14
	Prampir Makara	12
	Chbar Ampov	10
	Russey Keo	7
Preah Sihanouk	Sihanoukville	23
	Prey Nob	12
Siem Reap	Svay Dangkum	21
Takeo	Daun Keo	1



#### Pie-chat









Analyze average price base on location.

#### Price by Location:

Locations

Kandal 29962.777778

Phnom Penh 86807.785288

Preah Sihanouk 82840.342857

Siem Reap 146414.190476

Takeo 225000.000000





Analyze average price base on sub location.

Price by Sub Loca Sub Location	tion:
Boeng Keng Kang	100850.000000
Chamkar Mon	86680.153724
Chbar Ampov	75608.800000
Chroy Changvar	92284.390244
Daun Keo	225000.000000
Daun Penh	105792.714286
Mean Chey	78157.789474
Prampir Makara	130383.333333
Prey Nob	95624.333333
Pur Senchey	66147.782609
Russey Keo	45047.428571
Sen Sok	94555.172185
Sihanoukville	76170.434783
Svay Dangkum	146414.190476
Takhmao	29962.777778
Toul Kork	69633.961538





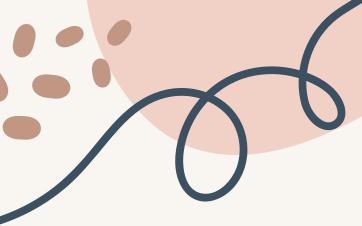


Analyze average price base on floor.

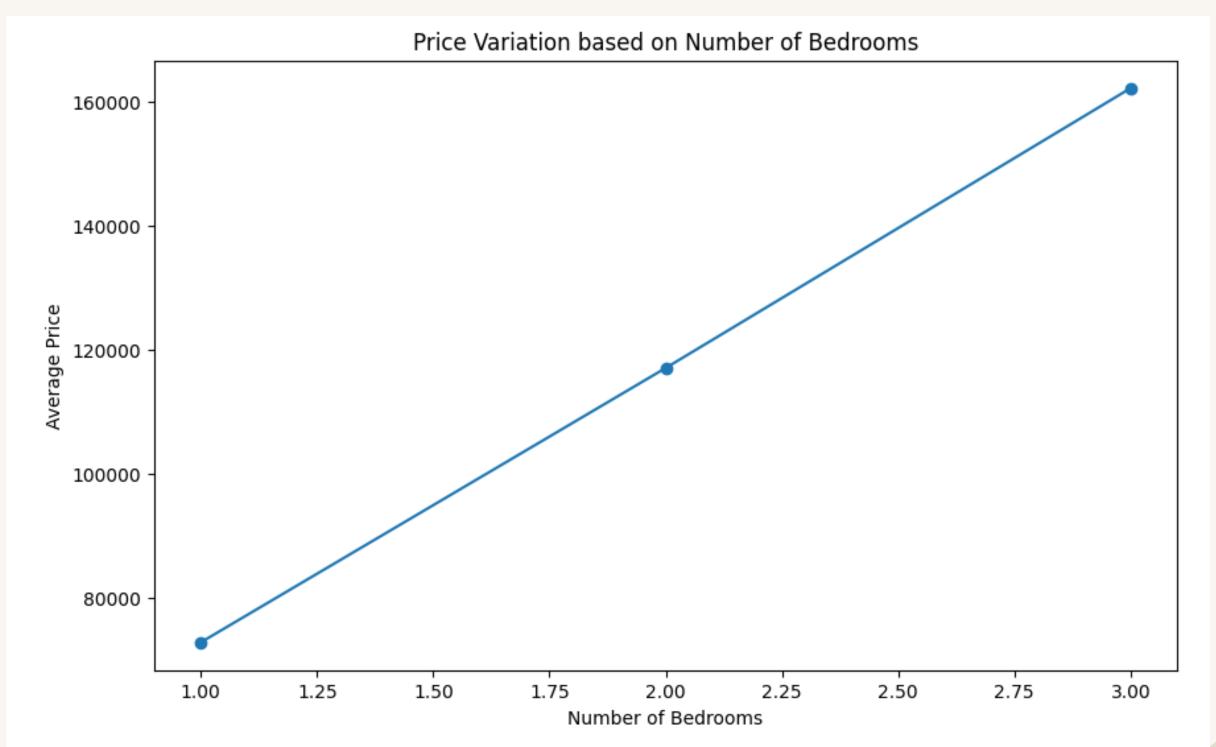
```
Average price by floor level:
 Floor
       82910.083333
      116238.800000
       39423.562500
       53521.444444
       60932.966667
       78249.102041
       77925.235294
       69979.493506
      103633.296296
10
       76441.785714
11
       79324.053763
12
       76538.789474
13
       80385.771429
14
       91191.490909
15
       84509.900000
16
      100460.909091
17
       93367.949153
18
      110694.600000
19
      107668.594595
      125886.352941
21
      119452.450000
22
      114025.666667
23
       76560.357143
      116414.333333
24
      124199.900000
26
       86181.142857
27
      127840.000000
      125149.454545
      102988.888889
30
       90372.500000
31
      113600.000000
```



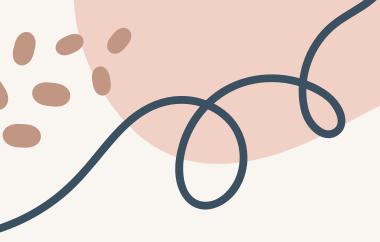




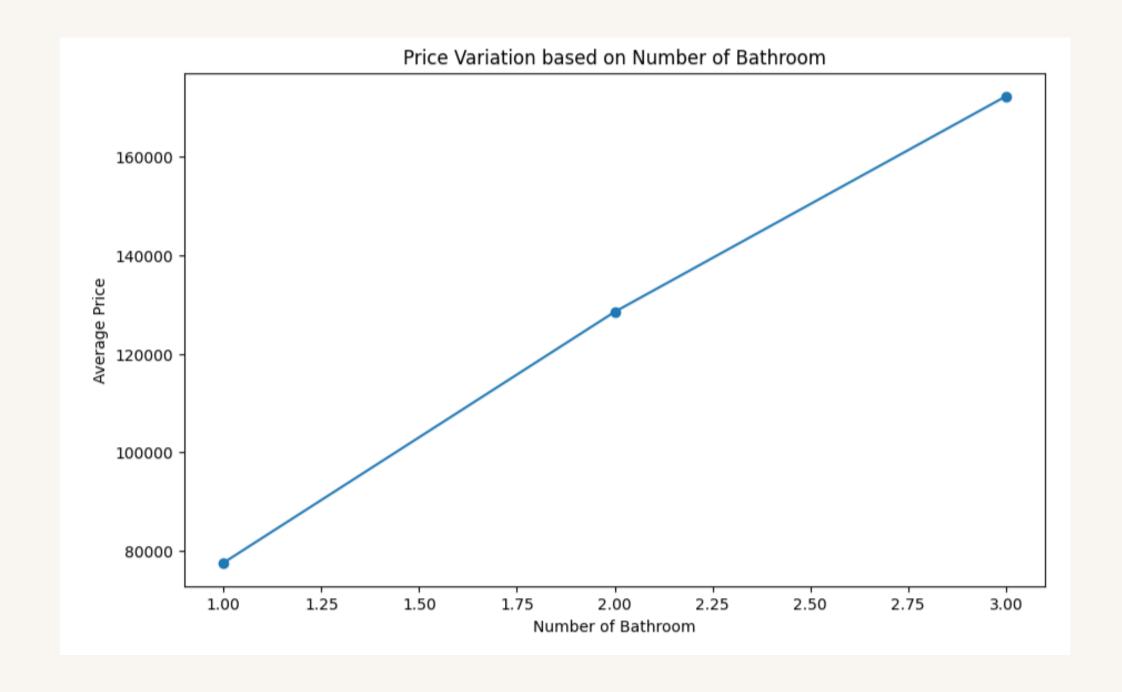
#### Price variation base on bedrooms.





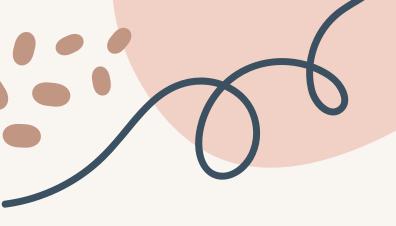


### Price variation base on bathrooms.

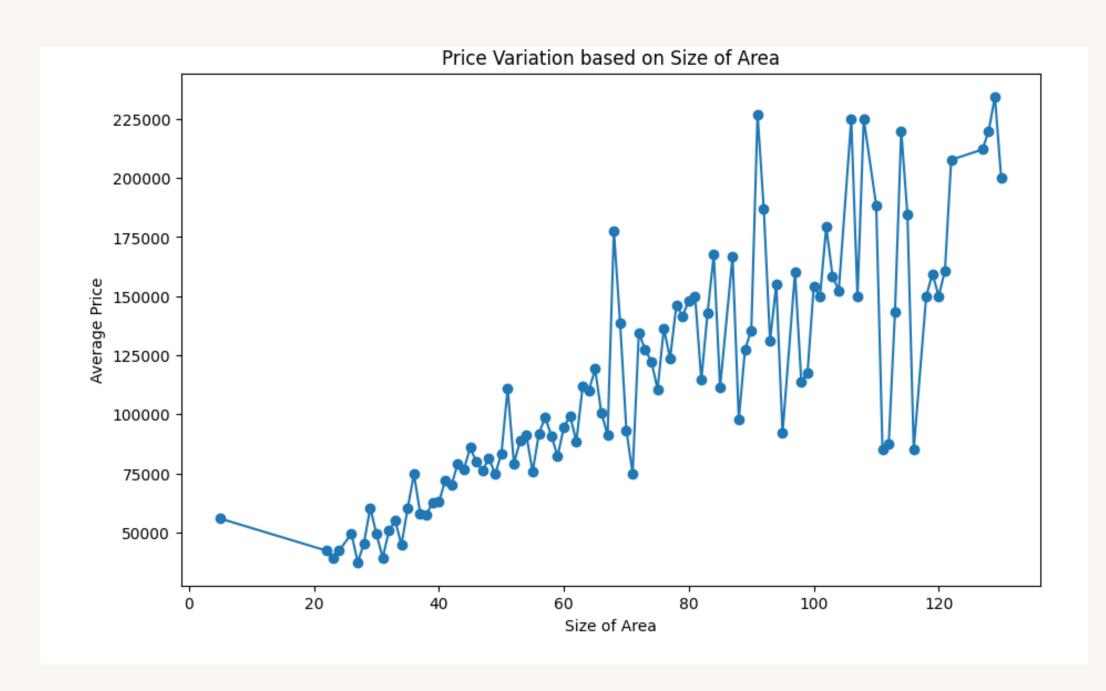








# Price variation base on size.

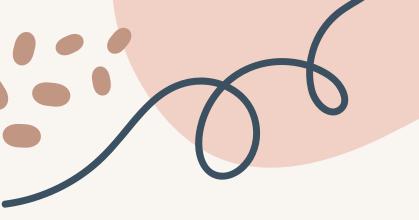






# 5. Feature Engineering

```
from sklearn.feature_selection import SelectFromModel
from sklearn.ensemble import RandomForestRegressor
from catboost import CatBoostRegressor
X = df_new3[['Locations ', 'Size(m2)', 'Sub Location', 'Bedrooms',
       'Bathrooms', 'Floor']]
y = df new3['Price']
model = RandomForestRegressor()
selector = SelectFromModel(model)
X new = selector.fit transform(X, y)
selected_features = X.columns[selector.get_support()]
correlation_selection = df_new3[selected_features.tolist() + ['Price']].corr()
print(correlation selection)
          Size(m2)
                       Floor
                                 Price
Size(m2) 1.000000 0.081549 0.713162
          0.081549 1.000000 0.248376
Floor
Price
          0.713162 0.248376 1.000000
```



# We do dummy on categorical feature.

	Size(m2)	Price	Bedrooms	Bathrooms	Floor	Locations _Kandal	Locations _Phnom Penh	Locations _Preah Sihanouk	Locations _Siem Reap	Locations _Takeo	 Sub Location_Mean Chey	Sub Location_Prampir Makara
0	34.0	58000.0	1	1	6	False	True	False	False	False	 False	False
1	58.0	75000.0	1	1	19	False	True	False	False	False	 False	False
2	34.0	42000.0	1	1	15	False	True	False	False	False	 False	False
4	57.0	72000.0	1	1	9	False	True	False	False	False	 False	False
5	33.0	59000.0	1	1	25	False	True	False	False	False	 False	False

5 rows × 26 columns

Sub Location_Prey Nob	Sub Location_Pur Senchey	Sub Location_Russey Keo	Sub Location_Sen Sok	Sub Location_Sihanoukville	Sub Location_Svay Dangkum	Sub Location_Takhmao	Sub Location_Toul Kork
False	False	False	False	False	False	False	True
False	False	False	True	False	False	False	False
False	False	False	False	False	False	False	False
False	False	False	False	False	False	False	False
False	False	False	False	False	False	False	False





# Data scaling

		Size(m2)	Price	Bedrooms	Bathrooms	Floor
Ī	0	-0.878176	-0.623373	-0.627318	-0.454026	-1.135238
	1	0.189176	-0.264111	-0.627318	-0.454026	1.024581
	2	-0.878176	-0.961501	-0.627318	-0.454026	0.360021
	4	0.144703	-0.327510	-0.627318	-0.454026	-0.636818
	5	-0.922649	-0.602240	-0.627318	-0.454026	2.021420
	1496	-1.056068	-1.005880	-0.627318	-0.454026	-0.802958
	1499	-0.433446	-0.581107	-0.627318	-0.454026	-0.304538
	1500	-0.967122	-1.574358	-0.627318	-0.454026	-0.802958
	1504	-0.967122	-1.637757	-0.627318	-0.454026	0.692301
	1505	-0.967122	-0.591673	-0.627318	-0.454026	0.193882







## Select and Split data to training and testing.

```
X = new_df_dummies_and_scaler.drop(columns=["Price"])
y = new_df_dummies_and_scaler["Price"]
X.shape, y.shape

((1072, 25), (1072,))
```

```
x_train - > (857, 25)
x_test - > (215, 25)
y_train - > (857,)
y_test - > (215,)
```



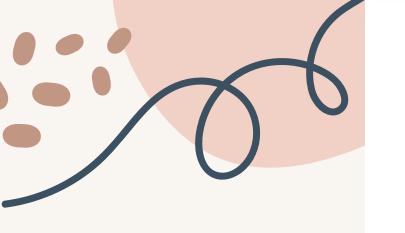


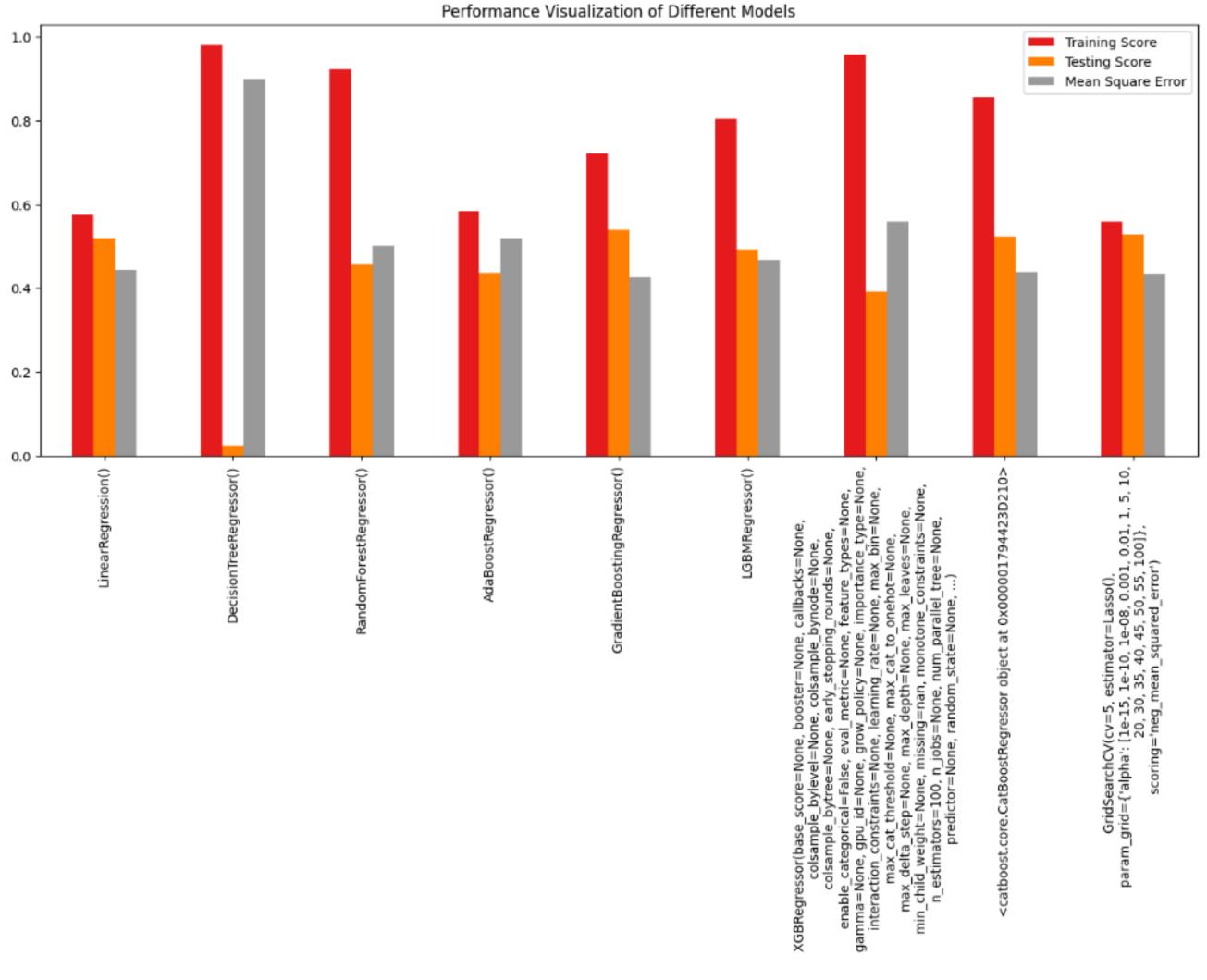
# 6. Model Selection

0         LinearRegression()         0.574740         0.518607         0.444076           1         DecisionTreeRegressor()         0.980405         0.025413         0.899039           2         RandomForestRegressor()         0.922320         0.457235         0.500692           3         AdaBoostRegressor()         0.583103         0.437667         0.518743           4         GradientBoostingRegressor()         0.721175         0.539468         0.424833           5         LGBMRegressor()         0.803285         0.492251         0.468390           6         XGBRegressor(base_score=None, booster=None, ca         0.957994         0.393075         0.559878           7 <catboost.core.catboostregressor 0x0<="" at="" object="" th="">          0.856320         0.524492         0.438648           8         GridSparchCV/cv=5         estimator=Lasso() In         0.559526         0.528684         0.434781</catboost.core.catboostregressor>		Algorithms	Training Score	Testing Score	Mean Square Error
2       RandomForestRegressor()       0.922320       0.457235       0.500692         3       AdaBoostRegressor()       0.583103       0.437667       0.518743         4       GradientBoostingRegressor()       0.721175       0.539468       0.424833         5       LGBMRegressor()       0.803285       0.492251       0.468390         6       XGBRegressor(base_score=None, booster=None, ca       0.957994       0.393075       0.559878         7 <catboost.core.catboostregressor 0x0<="" at="" object="" th="">       0.856320       0.524492       0.438648</catboost.core.catboostregressor>	0	LinearRegression()	0.574740	0.518607	0.444076
3       AdaBoostRegressor()       0.583103       0.437667       0.518743         4       GradientBoostingRegressor()       0.721175       0.539468       0.424833         5       LGBMRegressor()       0.803285       0.492251       0.468390         6       XGBRegressor(base_score=None, booster=None, ca       0.957994       0.393075       0.559878         7 <catboost.core.catboostregressor 0x0<="" at="" object="" td="">       0.856320       0.524492       0.438648</catboost.core.catboostregressor>	1	DecisionTreeRegressor()	0.980405	0.025413	0.899039
4         GradientBoostingRegressor()         0.721175         0.539468         0.424833           5         LGBMRegressor()         0.803285         0.492251         0.468390           6         XGBRegressor(base_score=None, booster=None, ca         0.957994         0.393075         0.559878           7 <catboost.core.catboostregressor 0x0<="" at="" object="" th="">         0.856320         0.524492         0.438648</catboost.core.catboostregressor>	2	RandomForestRegressor()	0.922320	0.457235	0.500692
5         LGBMRegressor()         0.803285         0.492251         0.468390           6         XGBRegressor(base_score=None, booster=None, ca         0.957994         0.393075         0.559878           7 <catboost.core.catboostregressor 0x0<="" at="" object="" th="">         0.856320         0.524492         0.438648</catboost.core.catboostregressor>	3	AdaBoostRegressor()	0.583103	0.437667	0.518743
6 XGBRegressor(base_score=None, booster=None, ca       0.957994       0.393075       0.559878         7 <catboost.core.catboostregressor 0x0<="" at="" object="" td="">       0.856320       0.524492       0.438648</catboost.core.catboostregressor>	4	GradientBoostingRegressor()	0.721175	0.539468	0.424833
7 <catboost.core.catboostregressor 0.438648<="" 0.524492="" 0.856320="" 0x0="" at="" object="" th=""><th>5</th><th>LGBMRegressor()</th><th>0.803285</th><th>0.492251</th><th>0.468390</th></catboost.core.catboostregressor>	5	LGBMRegressor()	0.803285	0.492251	0.468390
	6	XGBRegressor(base_score=None, booster=None, ca	0.957994	0.393075	0.559878
9 GridSparchCV/cv=5 petimator=Lacen() \n	7	<catboost.core.catboostregressor 0x0<="" at="" object="" th=""><th>0.856320</th><th>0.524492</th><th>0.438648</th></catboost.core.catboostregressor>	0.856320	0.524492	0.438648
• Ondocurency (cv = 5, estimator = Lasso(), wr 0.555520 0.520004 0.454701	8	GridSearchCV(cv=5, estimator=Lasso(),\n	0.559526	0.528684	0.434781

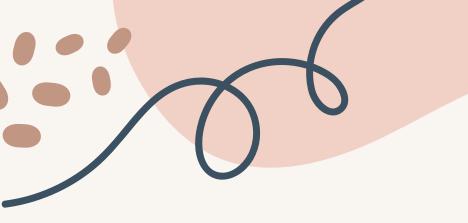












# 7. Decision making

In terms of all models that we tested, it is the best that we choose the GradientBoostingRegressor Model.





