Prediction of Singapore HDB price

Introduction

Hi, my name is Mukesh Sharma and I am a big fan of data analysis and data science. Today I am doing analysis and prediction on Singapore resale HDB price. The main content is as follow:

Data wrangling Data Analysis Data preparation for Machine Learning (ML) model input Selecting

the best ML model for prediction of Singapore resale HDB price Case study: how much is the price of resale 4-room HDB in different region of Singapore (Central, East, North, South, and West)

———Prediction of Singapore HDB price_Machine Learning——————

Importing necessary libraries

[260]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import os
import warnings
warnings.filterwarnings("ignore")
```

Data Wrangling And data Preprocessing

First, we observe the dataset and determine which dataset is relevant to our analysis.

[261]:
```
hdb_df = pd.read_csv(r'C:\Users\hp.
↪MUKESH-LF4B6N6\Downloads\ResaleflatpricesbasedonregistrationdatefromJan2017onwards.
↪csv')
```

Head of the dataset

[262]:
```
hdb_df.head()
```

[262]:
```
     month        town flat_type block        street_name storey_range  \
0  2017-01  ANG MO KIO    2 ROOM   406  ANG MO KIO AVE 10     10 TO 12
1  2017-01  ANG MO KIO    3 ROOM   108   ANG MO KIO AVE 4     01 TO 03
2  2017-01  ANG MO KIO    3 ROOM   602   ANG MO KIO AVE 5     01 TO 03
3  2017-01  ANG MO KIO    3 ROOM   465  ANG MO KIO AVE 10     04 TO 06
4  2017-01  ANG MO KIO    3 ROOM   601   ANG MO KIO AVE 5     01 TO 03

   floor_area_sqm      flat_model  lease_commence_date     remaining_lease  \
0            44.0        Improved                 1979  61 years 04 months
```

```
1          67.0  New Generation                  1978  60 years 07 months
2          67.0  New Generation                  1980  62 years 05 months
3          68.0  New Generation                  1980   62 years 01 month
4          67.0  New Generation                  1980  62 years 05 months

   resale_price
0      232000.0
1      250000.0
2      262000.0
3      265000.0
4      265000.0
```

Shape of the dataset

[263]:
```
hdb_df.shape
```

[263]: (166049, 11)

Info of the dataset

[264]:
```
hdb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 166049 entries, 0 to 166048
Data columns (total 11 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   month                166049 non-null  object
 1   town                 166049 non-null  object
 2   flat_type            166049 non-null  object
 3   block                166049 non-null  object
 4   street_name          166049 non-null  object
 5   storey_range         166049 non-null  object
 6   floor_area_sqm       166049 non-null  float64
 7   flat_model           166049 non-null  object
 8   lease_commence_date  166049 non-null  int64
 9   remaining_lease      166049 non-null  object
 10  resale_price         166049 non-null  float64
dtypes: float64(2), int64(1), object(8)
memory usage: 13.9+ MB
```

drop column ['month','street_name','flat_model','lease_commence_date','block'] in my analysis

[265]:
```
# In my analysis, I do not consider street name, block and  flat model is␣
↪relevant (town is sufficient for analysis, as no description of impact of␣
↪the address, e.g., near MRT or not). Some information in flat model are␣
↪either similar to room type (2 room, multi generation, etc.) or it reflected␣
↪how old the unit is, which can be represented by lease commence date and␣
↪remaining lease.Therefore. I will drop this column for my analysis
```

```
hdb_df = hdb_df.drop(['month','street_name','flat_model','lease_commence_date',
↪'block'], axis=1)
```

Rename the columns so it will be clearer

[266]:
```
# Let's rename the column so it will be clearer
hdb_df = hdb_df.rename(columns={'flat_type':'number_of_rooms','storey_range':
↪'storey'})
```

I assume EXECUTIVE is equal to a 6 room (5 room + 1 study room). MULTI-GENERATION is equal to a 5 room (it served the same purpose).

[267]:
```
# I assume EXECUTIVE is equal to a 6 room (5 room + 1 study room).
↪MULTI-GENERATION is equal to a 5 room (it served the same purpose)
hdb_df['number_of_rooms'] = hdb_df['number_of_rooms'].str.
↪replace(r'EXECUTIVE','6 ROOM',regex=True)
hdb_df['number_of_rooms'] = hdb_df['number_of_rooms'].str.
↪replace(r'MULTI-GENERATION','5 ROOM',regex=True)
hdb_df['number_of_rooms'] = hdb_df['number_of_rooms'].str.
↪replace(r'ROOM','',regex=True).astype('int')
```

[268]:
```
# I assume that rather we use floor range, I the possible highest floor within
↪the unit storey range.
hdb_df['storey'] = hdb_df['storey'].str[-2:].astype('int')
```

[269]:
```
# I revise the format of the data in the remaining lease to be quantifiable
↪(change to float).
hdb_df['remaining_lease'] = hdb_df['remaining_lease'].str.split(' ')
hdb_df['remaining_lease'] = hdb_df['remaining_lease'].apply(lambda x:
↪(float(x[0])+(float(x[2])/12)) if (len(x)==4) else float(x[0]))
hdb_df.head()
```

[269]:
```
        town  number_of_rooms  storey  floor_area_sqm  remaining_lease  \
0  ANG MO KIO                2      12            44.0        61.333333
1  ANG MO KIO                3       3            67.0        60.583333
2  ANG MO KIO                3       3            67.0        62.416667
3  ANG MO KIO                3       6            68.0        62.083333
4  ANG MO KIO                3       3            67.0        62.416667

   resale_price
0      232000.0
1      250000.0
2      262000.0
3      265000.0
4      265000.0
```

Check the null values in dataset

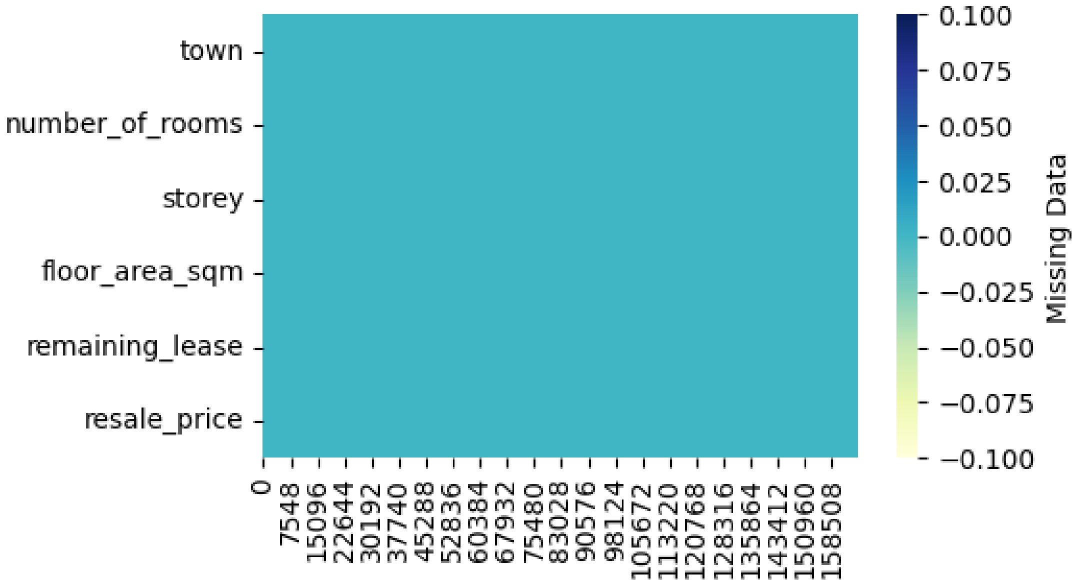
[270]:
```
hdb_df.isna().sum()
```

[270]:

```
town               0
number_of_rooms    0
storey             0
floor_area_sqm     0
remaining_lease    0
resale_price       0
dtype: int64
```

[271]:

```python
plt.figure(figsize=(5,3))
sns.heatmap(hdb_df.isna().transpose(),
            cmap="YlGnBu",
            cbar_kws={'label': 'Missing Data'})
plt.savefig("visualizing_missing_data_with_heatmap_Seaborn_Python.png", dpi=100)
```



Feature Engineering:

[272]:

```python
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
```

[273]:

```python
# Assuming 'df' is your DataFrame
df_encoded = pd.get_dummies(hdb_df, columns=['town'], drop_first=True)
```

[300]:

```python
# Separate features and target variable
X = hdb_df.drop('resale_price', axis=1)
y = hdb_df['resale_price']
```

[301]:
```python
# Identify categorical and numerical features
categorical_features = ['town', 'story']
numerical_features = ['number_of_rooms', 'floor_area_sqm']
```

[302]:
```python
categorical_features
```

[302]:
```
['town', 'story']
```

[303]:
```python
numerical_features
```

[303]:
```
['number_of_rooms', 'floor_area_sqm']
```

[304]:
```python
# Create transformers for preprocessing
numeric_transformer = Pipeline(steps=[
    ('scaler', StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder())
])
```

[306]:
```python
categorical_transformer
```

[306]:
```
Pipeline(steps=[('onehot', OneHotEncoder())])
```

[307]:
```python
# Create column transformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numerical_features),
        ('cat', categorical_transformer, categorical_features)
    ])
```

[308]:
```python
preprocessor
```

[308]:
```
ColumnTransformer(transformers=[('num',
                                 Pipeline(steps=[('scaler', StandardScaler())]),
                                 ['number_of_rooms', 'floor_area_sqm']),
                                ('cat',
                                 Pipeline(steps=[('onehot', OneHotEncoder())]),
                                 ['town', 'story'])])
```

Create an instance of SimpleImputer with mean strategy

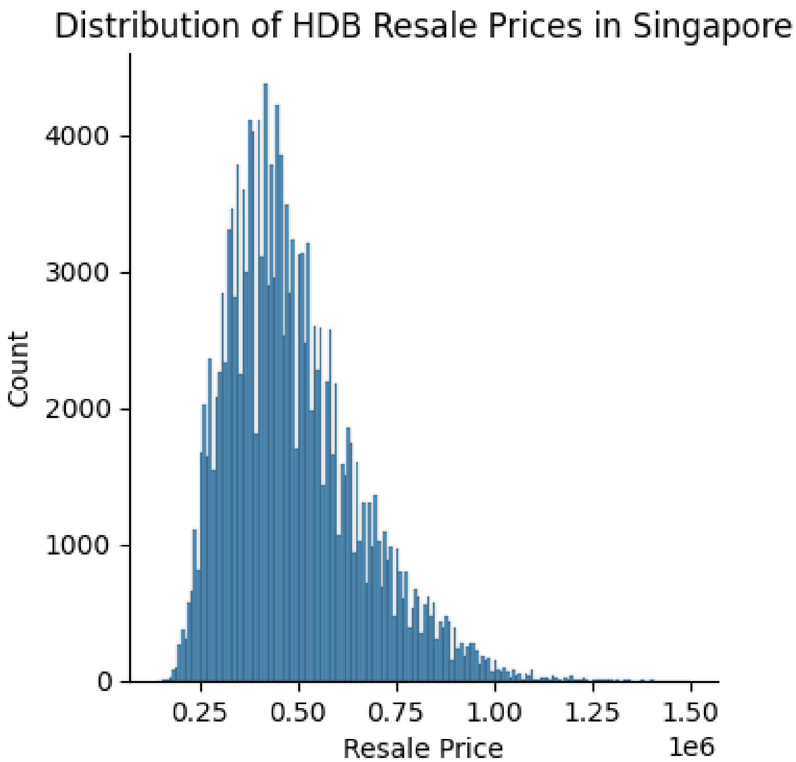
[309]:
```python
from sklearn.impute import SimpleImputer
imp_mean = SimpleImputer(missing_values=np.nan, strategy='mean')
imp_mean
```

[309]:
```
SimpleImputer()
```

HDB Data Analysis

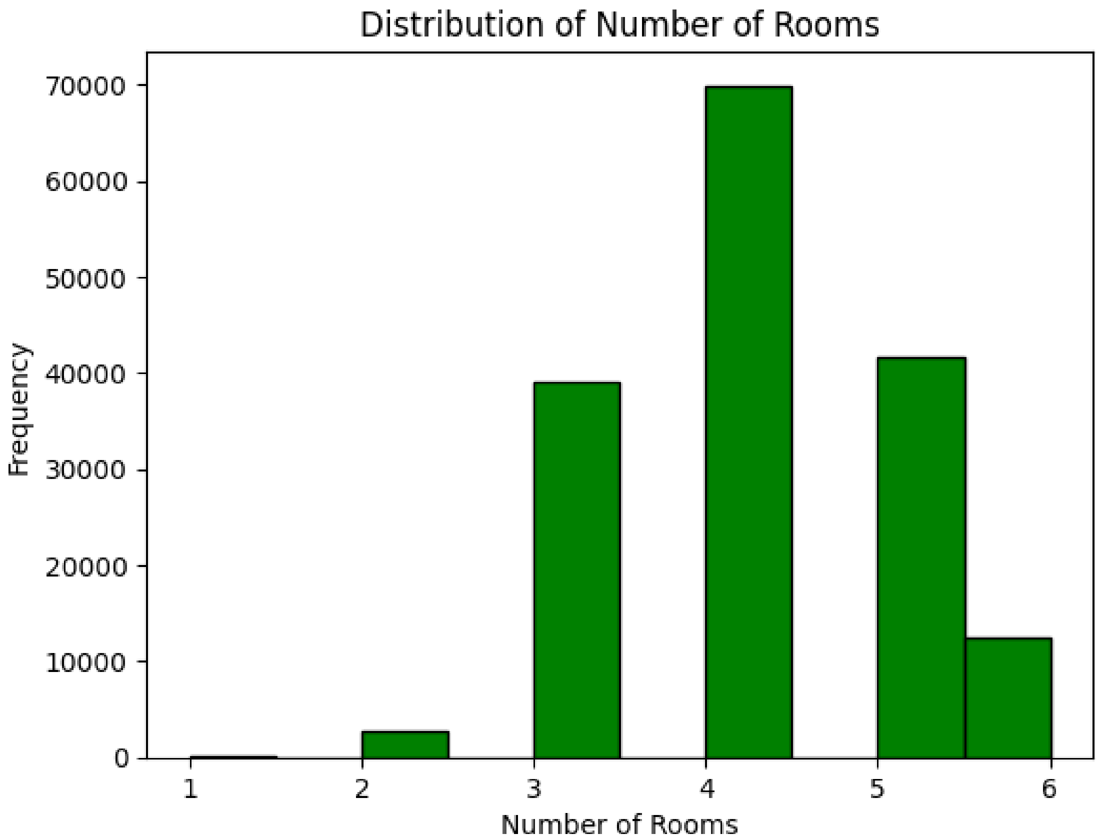
Assuming 'hdb_df' is your DataFrame with the 'resale_price' column

[274]:
```
sns.displot(hdb_df['resale_price'], height=4)
plt.title('Distribution of HDB Resale Prices in Singapore')
plt.xlabel('Resale Price')
plt.ylabel('Count')
plt.show()
```



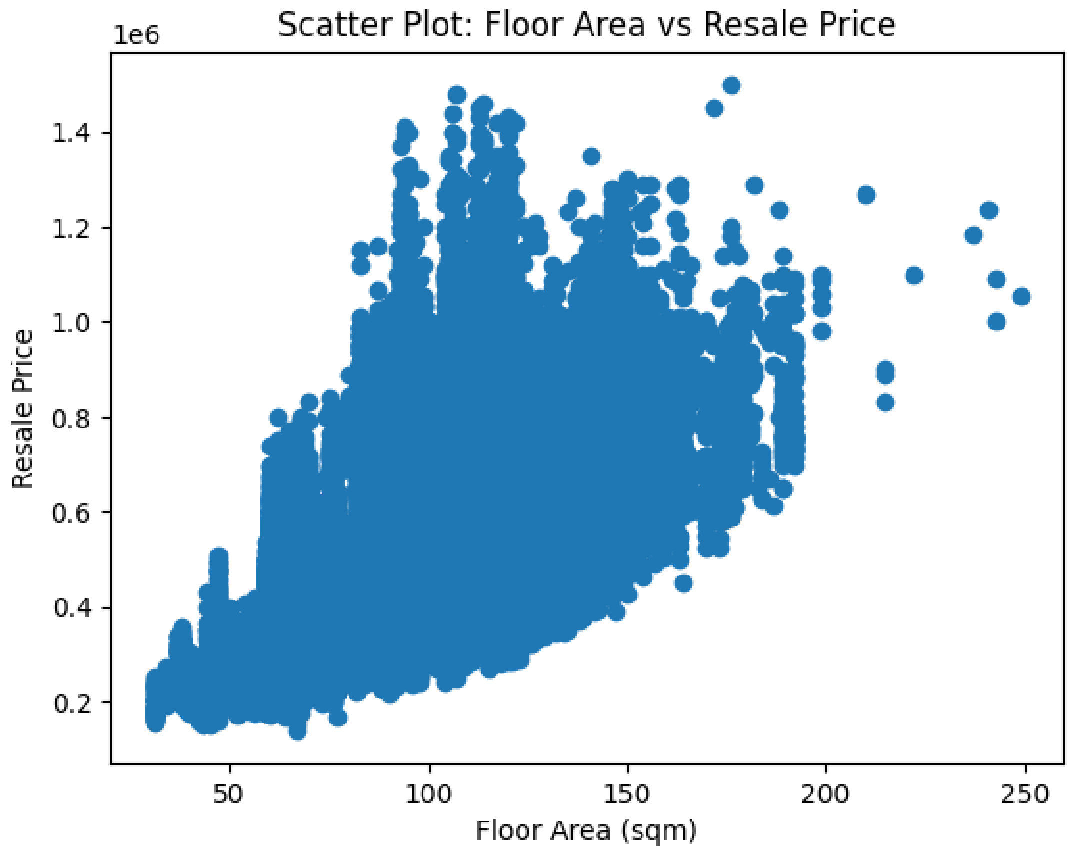
Histogram for 'number_of_rooms'

[310]:
```
plt.hist(hdb_df['number_of_rooms'], bins=10, edgecolor='black', histtype=␣
  ↪'bar', color='green')
plt.title('Distribution of Number of Rooms')
plt.xlabel('Number of Rooms')
plt.ylabel('Frequency')
plt.show()
```



Scatter plot for ‘floor_area_sqm’ vs ‘resale_price’

[276]:
```
plt.scatter(hdb_df['floor_area_sqm'], hdb_df['resale_price'])
plt.title('Scatter Plot: Floor Area vs Resale Price')
plt.xlabel('Floor Area (sqm)')
plt.ylabel('Resale Price')
plt.show()
```



Let see the statistic information of the data

[277]:
```
hdb_df.describe()
```

[277]:
```
       number_of_rooms        storey  floor_area_sqm  remaining_lease  \
count    166049.000000  166049.000000  166049.000000    166049.000000
mean          4.130961       9.767575      97.328697        74.699903
std           0.916981       5.948472      24.024204        13.828198
min           1.000000       3.000000      31.000000        42.250000
25%           3.000000       6.000000      82.000000        63.416667
50%           4.000000       9.000000      93.000000        74.666667
75%           5.000000      12.000000     112.000000        87.833333
max           6.000000      51.000000     249.000000        97.750000

       resale_price
count  1.660490e+05
mean   4.892796e+05
std    1.692389e+05
min    1.400000e+05
25%    3.650000e+05
```

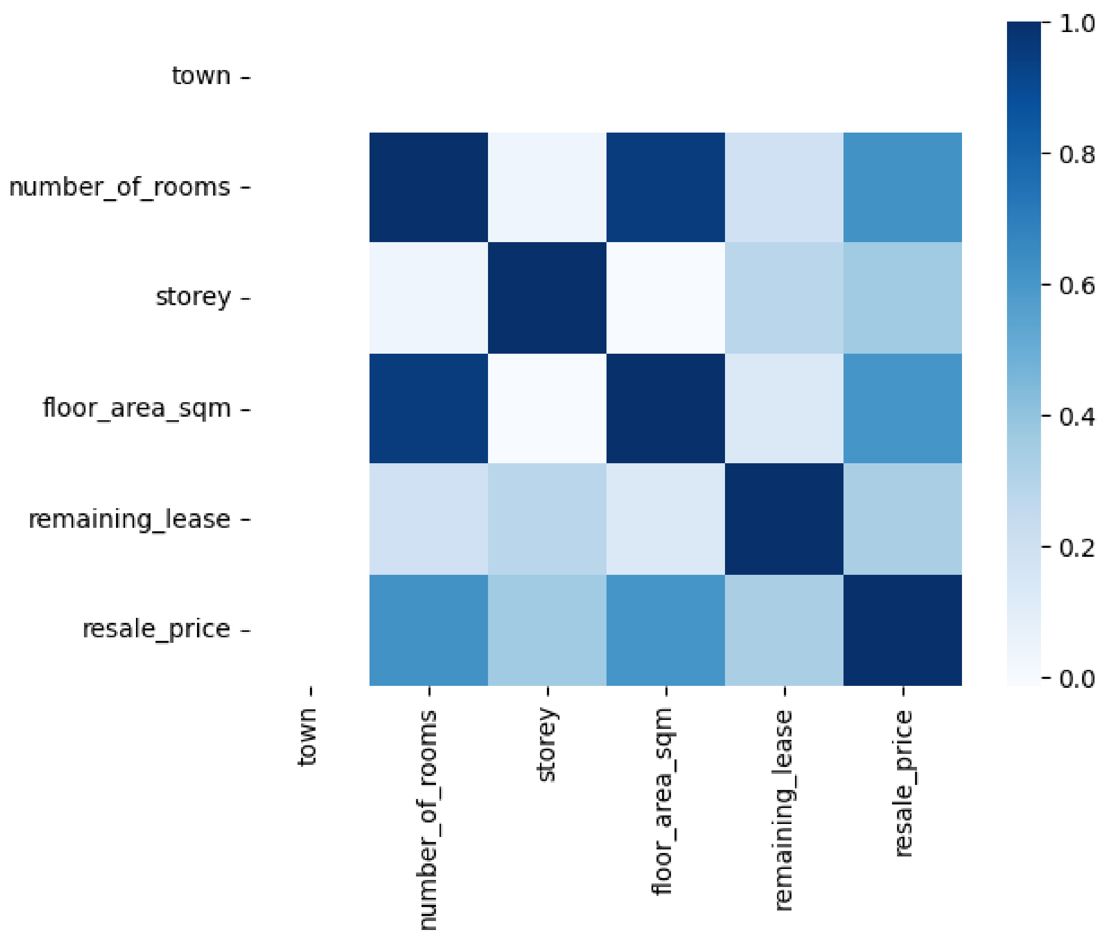
```
50%      4.600000e+05
75%      5.800000e+05
max      1.500000e+06
```

[278]:
```
# Assuming 'column_name' is the column with the issue
hdb_df['town'] = pd.to_numeric(hdb_df['town'], errors='coerce')

# Assuming df is your DataFrame
numeric_columns = hdb_df.select_dtypes(include=['float64', 'int64']).columns
correlation_matrix = hdb_df[numeric_columns].corr()
```

Let us see the relation between each parameters

[279]:
```
sns.heatmap(hdb_df.corr(), cmap="Blues")
```

[279]: <Axes: >



0.4 Machine Learning Models (Regression)

Let start to prepare the date for our machine learning model. My aim here is to determine which model has the highest accuracy in predicting the resale price. The models I will compare are:

Multi Linear Regression

Lasso Regression

Elastic-Net Regression

Decision Tree

Random Forest

[280]:
```
hdb_df['town'].unique()
```

[280]:
```
array([nan])
```

[281]:
```
hdb_df = hdb_df.replace(dict.
 ↪fromkeys(['SEMBAWANG','SENGKANG','WOODLANDS','YISHUN'], 'NORTH'))
hdb_df = hdb_df.replace(dict.fromkeys(['BUKIT MERAH','BUKIT␣
 ↪TIMAH','QUEENSTOWN'], 'SOUTH'))
hdb_df = hdb_df.replace(dict.fromkeys(['BEDOK','GEYLANG','HOUGANG','KALLANG/
 ↪WHAMPOA','PASIR RIS','PUNGGOL','SERANGOON','TAMPINES'], 'EAST'))
hdb_df = hdb_df.replace(dict.fromkeys(['BUKIT BATOK','BUKIT PANJANG','CHOA CHU␣
 ↪KANG','CLEMENTI','JURONG EAST','JURONG WEST'], 'WEST'))
hdb_df = hdb_df.replace(dict.fromkeys(['ANG MO KIO','CENTRAL␣
 ↪AREA','BISHAN','MARINE PARADE','TOA PAYOH'], 'CENTRAL'))
```

[282]:
```
# Let's check whether the data replacement was done properly
hdb_df['town'].unique()
```

[282]:
```
array([nan])
```

[283]:
```
hdb_df = hdb_df.rename(columns={'town':'region'})
```

Simplification of categorical data using One Hot Encoder

[284]:
```
X = hdb_df.iloc[:,:-1].values
y = hdb_df.iloc[:,-1].values
```

[285]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [0])],␣
 ↪remainder='passthrough')
X = np.array(ct.fit_transform(X))
```

[286]:
```
X[1,:]
```

[286]:
```
array([ 1.        ,  3.        ,  3.        , 67.        , 60.58333333])
```

Split the cleaned dataset into the Training set and Test set¶

[287]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
```

[288]:
```
# Import neccessary library to evaluate the performance of each machine␣
↪learning model
from sklearn.metrics import r2_score,mean_absolute_error, mean_squared_error
```

Multi Linear Regression___________________

[289]:
```
from sklearn.linear_model import LinearRegression
mlr = LinearRegression()
mlr.fit(X_train, y_train)
mlr_ypred = mlr.predict(X_test)
mlr_acc = r2_score(y_test,mlr_ypred)
mlr_acc
```

[289]:
```
0.5277903674896878
```

Polynomial Regression___________________

[290]:
```
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
# Let's determine the best degree for polynomial
for n in range(2,5):
    poly_reg = PolynomialFeatures(degree = n)
    X_poly = poly_reg.fit_transform(X_train)
    pr = LinearRegression()
    pr.fit(X_poly, y_train)
    poly_ypred = pr.predict(poly_reg.transform(X_test))
    poly_acc = r2_score(y_test,poly_ypred)
    poly_rmse = np.sqrt(mean_squared_error(y_test,poly_ypred))
    print(r'The accuracy of polynomial regression with degree of {} is {}'.
↪format(n,poly_acc))
    print(r'The RMSE of polynomial regression with degree of {} is {}'.
↪format(n,poly_rmse))
```

```
The accuracy of polynomial regression with degree of 2 is 0.5816221858536264
The RMSE of polynomial regression with degree of 2 is 110086.2851172656
The accuracy of polynomial regression with degree of 3 is 0.5951652190471008
The RMSE of polynomial regression with degree of 3 is 108289.8624375127
The accuracy of polynomial regression with degree of 4 is 0.6058193486879098
The RMSE of polynomial regression with degree of 4 is 106855.4173037394
```

Ridge Regression______________________________

[291]:
```
from sklearn.linear_model import Ridge
ridge_r = Ridge()
ridge_r.fit(X_train, y_train)
ridge_ypred = ridge_r.predict(X_test)
ridge_acc = r2_score(y_test,ridge_ypred)
ridge_acc
```

[291]: 0.5277903431815566

Lasso Regression

[292]:
```
from sklearn.linear_model import Lasso
lasso_r = Lasso(max_iter=100000)
lasso_r.fit(X_train, y_train)
lasso_ypred = lasso_r.predict(X_test)
lasso_acc = r2_score(y_test,lasso_ypred)
lasso_acc
```

[292]: 0.5277904507923076

Elastic Net Regression

[293]:
```
from sklearn.linear_model import ElasticNet
EN_r = ElasticNet()
EN_r.fit(X_train, y_train)
EN_ypred = EN_r.predict(X_test)
EN_acc = r2_score(y_test,EN_ypred)
EN_acc
```

[293]: 0.5256916906731175

Decision Tree Regression

[294]:
```
from sklearn.tree import DecisionTreeRegressor
tree_r = DecisionTreeRegressor()
tree_r.fit(X_train, y_train)
tree_ypred = tree_r.predict(X_test)
tree_acc = r2_score(y_test,tree_ypred)
tree_acc
```

[294]: 0.5253296574844144

Random Forest Regression

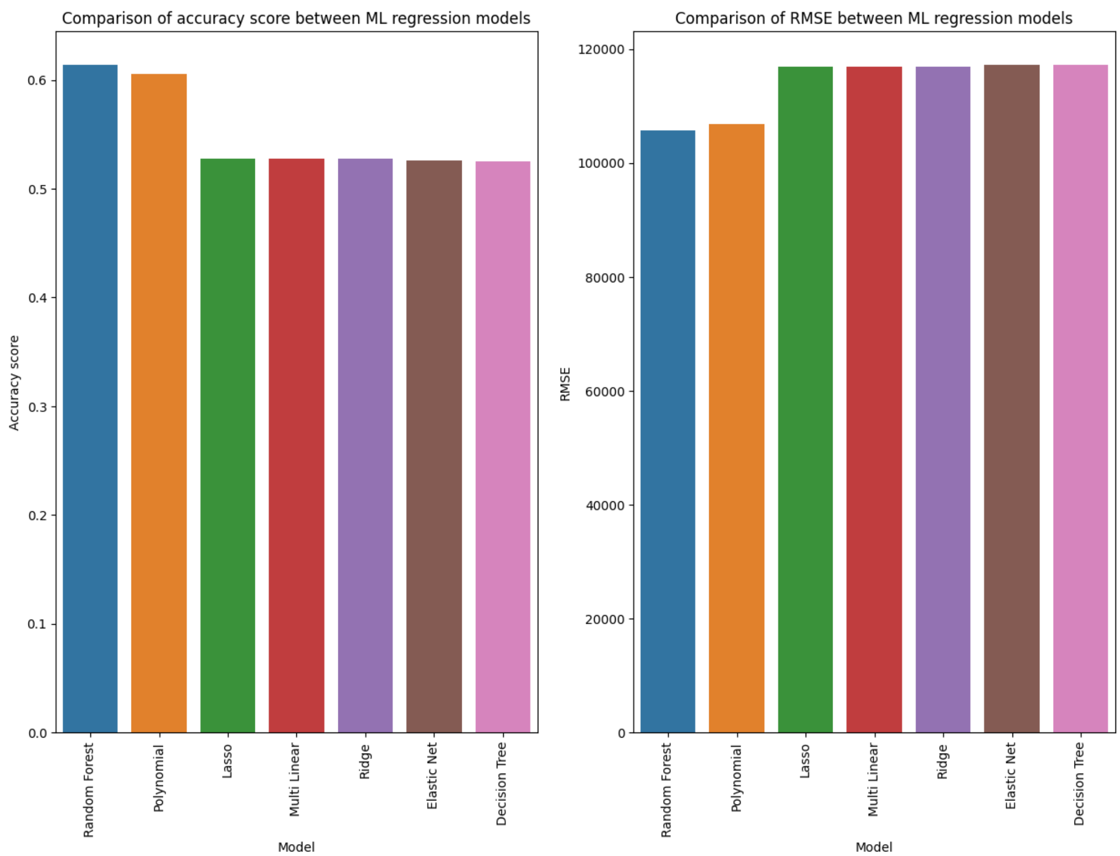
[295]:
```
from sklearn.ensemble import RandomForestRegressor
forest_r = RandomForestRegressor(n_estimators = 10)
forest_r.fit(X_train, y_train)
forest_ypred = forest_r.predict(X_test)
forest_acc = r2_score(y_test,forest_ypred)
forest_acc
```

[295]: 0.6140402086429606

Comparison of different model based on R2-score and RMSE (Root Mean Square Error)

[296]:
```
# Accuracy score for multi linear regression
mlr_acc = r2_score(y_test,mlr_ypred)
mlr_rmse = np.sqrt(mean_squared_error(y_test,mlr_ypred))

# Evaluation for polynomial regression has been calculated in finding the best␣
↪degree
# Evaluation for ridge regression
ridge_acc = r2_score(y_test,ridge_ypred)
ridge_rmse = np.sqrt(mean_squared_error(y_test,ridge_ypred))

# Evaluation for lasso regression
lasso_acc = r2_score(y_test,lasso_ypred)
lasso_rmse = np.sqrt(mean_squared_error(y_test,lasso_ypred))

# Evaluation for elastic net regression
EN_acc = r2_score(y_test,EN_ypred)
EN_rmse = np.sqrt(mean_squared_error(y_test,EN_ypred))

# Evaluation for decision trees regression
tree_acc = r2_score(y_test,tree_ypred)
tree_rmse = np.sqrt(mean_squared_error(y_test,tree_ypred))

# Evaluation for elastic random forest regression
forest_acc = r2_score(y_test,forest_ypred)
forest_rmse = np.sqrt(mean_squared_error(y_test,forest_ypred))

# Let's put it as a list and compare it in a bar chart
model_acc_score = [mlr_acc,poly_acc, ridge_acc, lasso_acc, EN_acc, tree_acc,␣
↪forest_acc]
model_rmse = [mlr_rmse, poly_rmse, ridge_rmse, lasso_rmse, EN_rmse, tree_rmse,␣
↪forest_rmse]
model_list = ['Multi Linear', 'Polynomial', 'Ridge', 'Lasso', 'Elastic Net',␣
↪'Decision Tree', 'Random Forest']
model_result_df = pd.DataFrame(
    {'Model': model_list,
     'Accuracy score': model_acc_score,
     'RMSE': model_rmse
    })
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15,10))
sns.barplot(data=model_result_df, x='Model', y='Accuracy score',␣
↪ax=ax1,order=model_result_df.sort_values('Accuracy score',ascending = False).
↪Model).set_title("Comparison of accuracy score between ML regression models")
```

```
ax1 = ax1.set_xticklabels(ax1.get_xticklabels(), rotation=90)
sns.barplot(data=model_result_df, x='Model', y='RMSE', ax=ax2,␣
↪order=model_result_df.sort_values('RMSE').Model).set_title("Comparison of␣
↪RMSE between ML regression models")
ax2 = ax2.set_xticklabels(ax2.get_xticklabels(), rotation=90)
```



Case study: How much is the price of 4-room HDB in different region?

[297]:
```
import pandas as pd

area = ['Central', 'East', 'North', 'South', 'West']
features = [[0.0,  4, 9, 95.0, 75],
            [ 0.0, 4, 9, 95.0, 75],
            [ 0.0, 4, 9, 95.0, 75],
            [ 1.0,  4, 9, 95.0, 75],
            [0.0, 4, 9, 95.0, 75]]

# Make predictions for each area
resale_prices = [forest_r.predict([feature])[0] for feature in features]

# Create a DataFrame with the results
```

```python
predict_df = pd.DataFrame(list(zip(area, resale_prices)),
                          columns=['Area', 'Predicted HDB price (SGD)'])
predict_df['Predicted HDB price (SGD)'] = predict_df['Predicted HDB price␣
↪(SGD)'].round().astype(int)
```

[298]:
```python
predict_df['Predicted HDB price (SGD)']
```

[298]:
```
0    580900 Central
1    580900 East
2    580900 North
3    580900 South
4    580900 West
Name: Predicted HDB price (SGD), dtype: int32
```

From the model prediction, 4-room HDB at North area is the cheapest option (~SGD 400,000) while South is the most expensive option (~SGD 640,000). Interestengly, according to Singapore map there is no South region, and some areas stated in the South are part of Central as well, as shown in below map Higher cost of HDB located in the Centre and South might be affected by better access and Central Business District (CBD) area is also located in the Central/South region.