REAL ESTATE ANALYSIS

EXTRACT AND UNDERSTAND THE DRIVERS OF HOUSING PRICES IN SINGAPORE

GUIDELINE

1. DATA EXPLORATION
   - Data collection
   - Final dataset
2. TIME SERIES ANALYSIS (from 1990-2020)
   - Understand the evolution of the square meter price
3. DRIVERS EXTRACTION
   - Feature selection methods
4. HOUSING PRICE PREDICTION
   - Compare ML models to understand the role of each feature

1. Data Exploration

Data Collection

Final Dataset

	month	town	floor_area_sqm	flat_type	flat_model	price	storey	top_floor	Postcode	LATITUDE	LONGITUDE	District	mrt_dist	primary_dist	secondary_dist	agency_dist	orchard_dist
0	736846	1	85.00	4	1	600000.00	11	0	310142	1.34	103.85	12	0.44	0.34	0.55	0.59	3.82
1	736846	1	101.00	4	1	700000.00	17	0	310121	1.34	103.85	12	0.16	0.28	0.70	0.82	4.21
2	736846	1	100.00	4	1	780000.00	14	0	310154	1.33	103.85	12	0.17	0.32	0.44	0.33	3.61

Month

```
Start Date : 1990-01
End Date   : 2020-01
```

Town

```
# List of all towns in the dataset (Central Area, Bishan, Geylang...)
df.town.unique()
```

```
array(['ANG MO KIO', 'BEDOK', 'BISHAN', 'BUKIT BATOK', 'BUKIT MERAH',
       'BUKIT TIMAH', 'CENTRAL AREA', 'CHOA CHU KANG', 'CLEMENTI',
       'GEYLANG', 'HOUGANG', 'JURONG EAST', 'JURONG WEST',
       'KALLANG/WHAMPOA', 'MARINE PARADE', 'QUEENSTOWN', 'SENGKANG',
       'SERANGOON', 'TAMPINES', 'TOA PAYOH', 'WOODLANDS', 'YISHUN',
       'LIM CHU KANG', 'SEMBAWANG', 'BUKIT PANJANG', 'PASIR RIS',
       'PUNGGOL'], dtype=object)
```

Flat_type

```
df.flat_type.value_counts()
```

```
4 ROOM                302897
3 ROOM                268309
5 ROOM                166614
EXECUTIVE              61474
2 ROOM                  9530
1 ROOM                  1234
MULTI-GENERATION         498
Name: flat_type, dtype: int64
```

Flat_model

```
df.flat_model.unique()
```

```
array(['improved', 'new generation', 'model a', 'standard', 'simplified',
       'model a-maisonette', 'apartment', 'maisonette', 'terrace',
       '2-room', 'improved-maisonette', 'multi generation',
       'premium apartment', 'adjoined flat', 'premium maisonette',
       'model a2', 'dbss', 'type s1', 'type s2', 'premium apartment loft'],
      dtype=object)
```

Storey

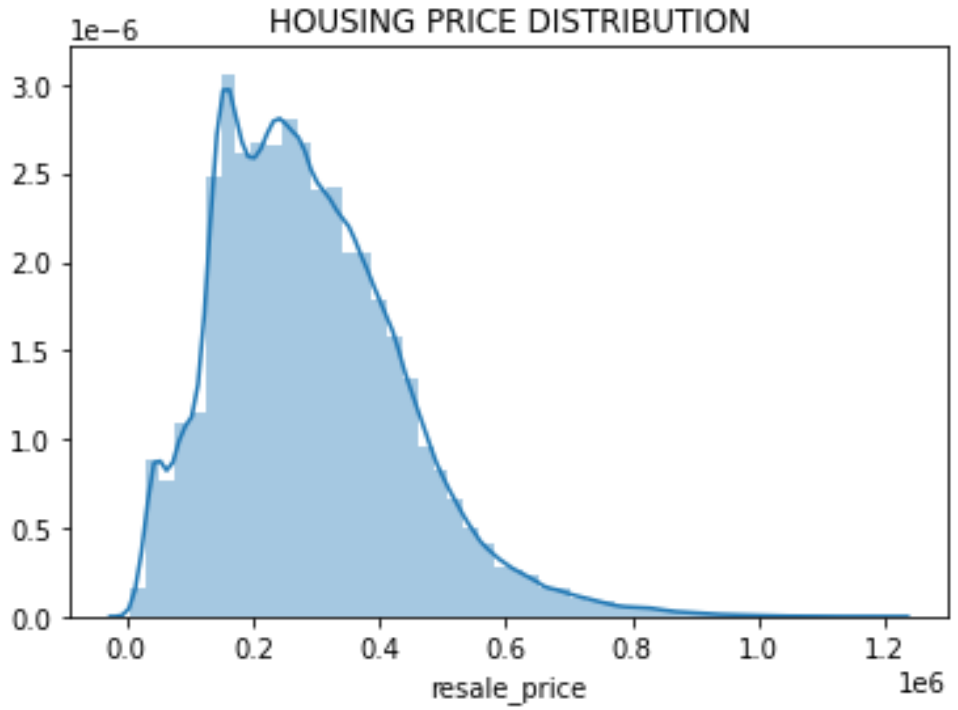
```
df.storey_range.unique()
```

```
array(['10 TO 12', '04 TO 06', '07 TO 09', '01 TO 03', '13 TO 15',
       '19 TO 21', '16 TO 18', '25 TO 27', '22 TO 24', '28 TO 30',
       '31 TO 33', '40 TO 42', '37 TO 39', '34 TO 36', '06 TO 10',
       '01 TO 05', '11 TO 15', '16 TO 20', '21 TO 25', '26 TO 30',
       '36 TO 40', '31 TO 35', '46 TO 48', '43 TO 45', '49 TO 51'],
      dtype=object)
```

Price

count	810556
mean	291045
std	147336
min	5000
25%	180000
50%	272000
75%	380000
max	1205000

Name: resale_price

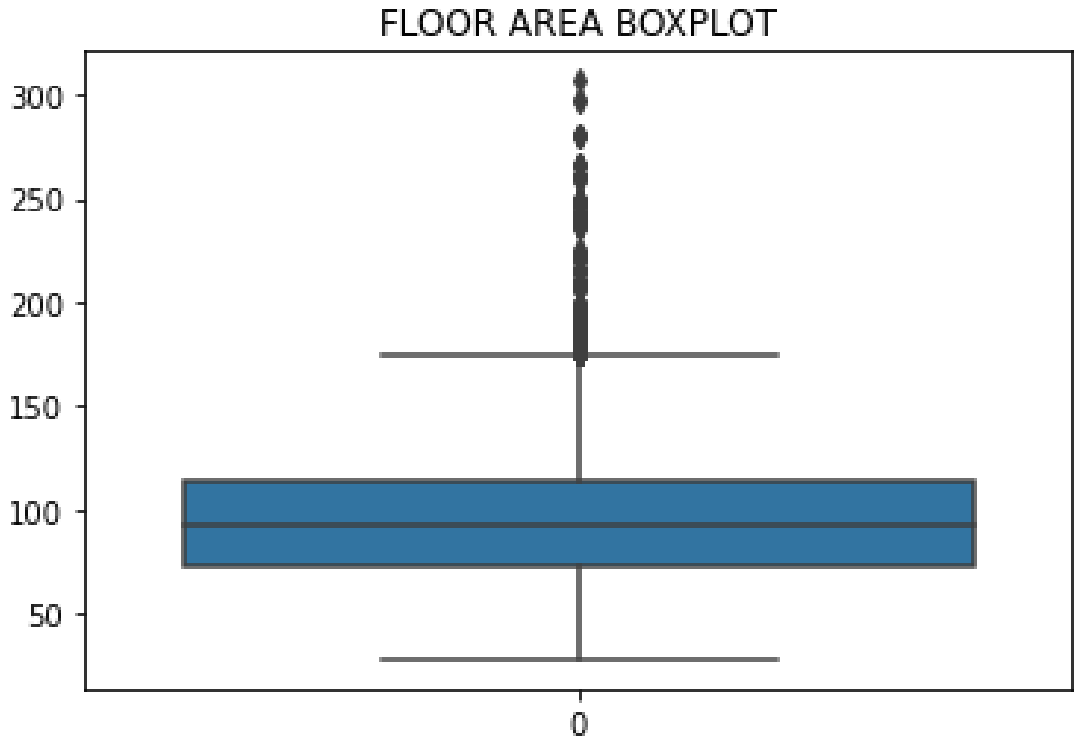


The housing price has a skew distribution. 50% of the houses have been sold between 180,000 and 380,000.

Floor_area_sqm

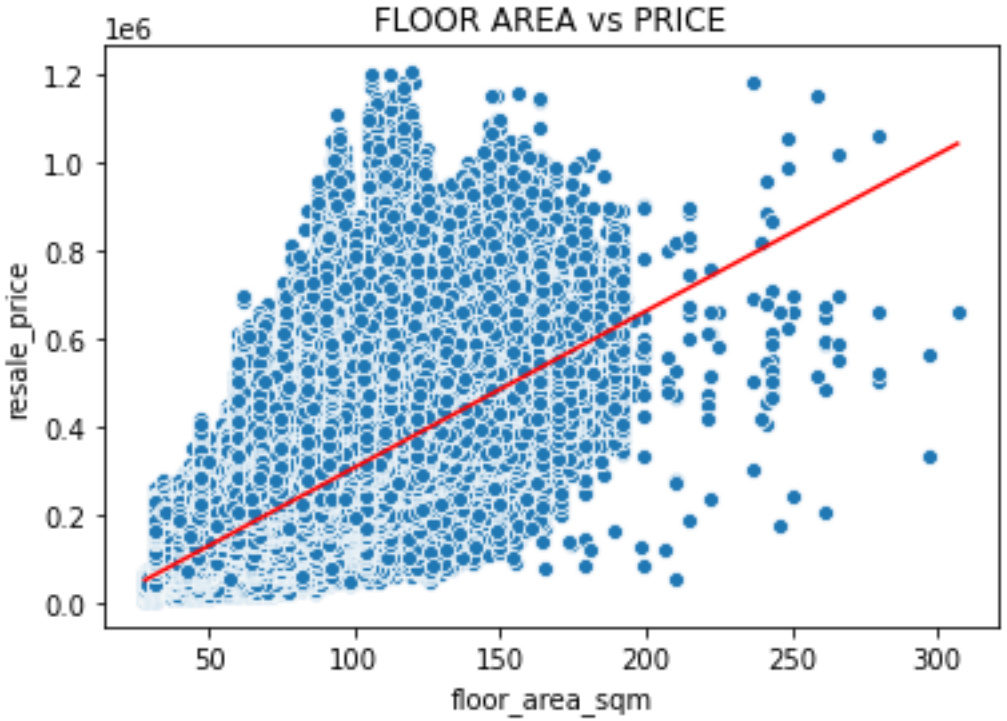
count	810556
mean	96
std	26
min	28
25%	73
50%	93
75%	114
max	307

Name: floor_area_sqm



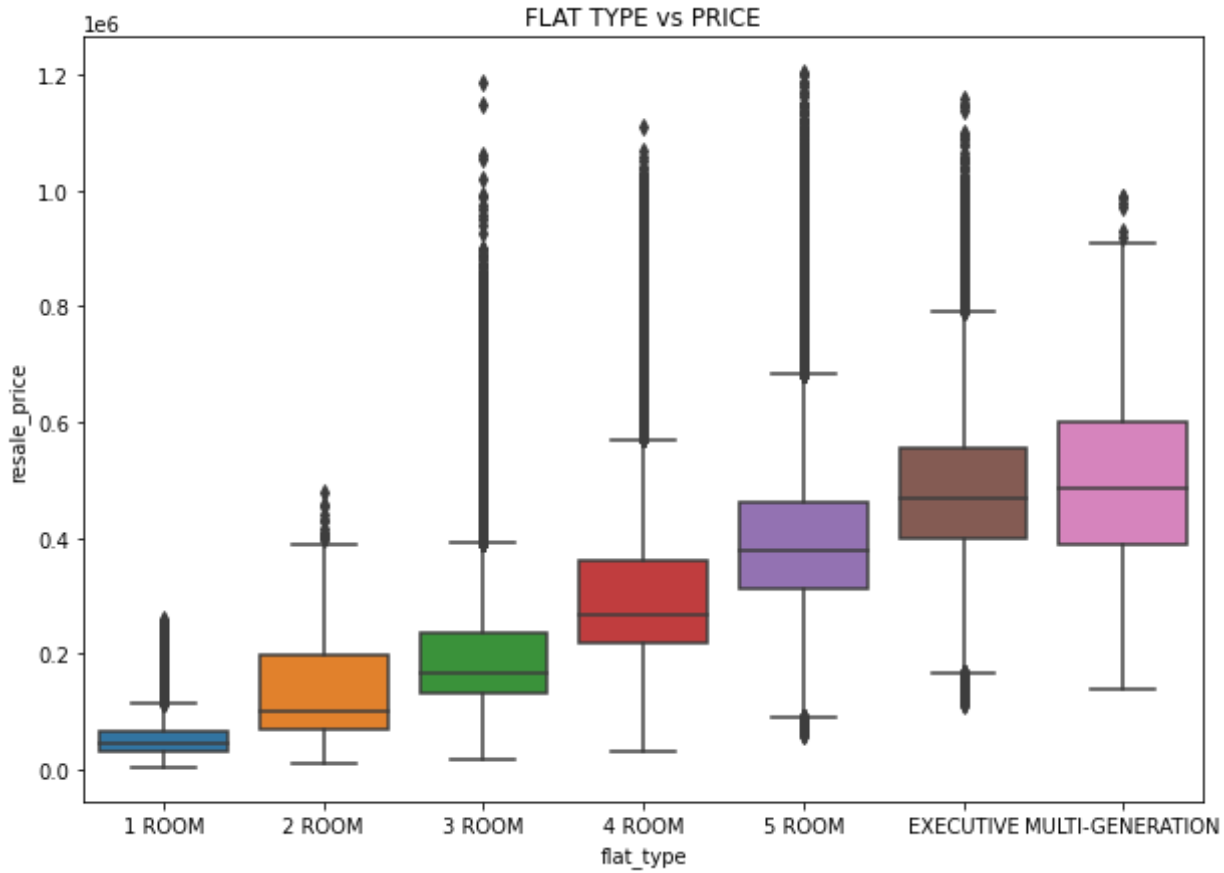
The floor area of the apartments is between 75 to 115 sqm, with an average of 95 sqm per apartment

Floor area vs Price



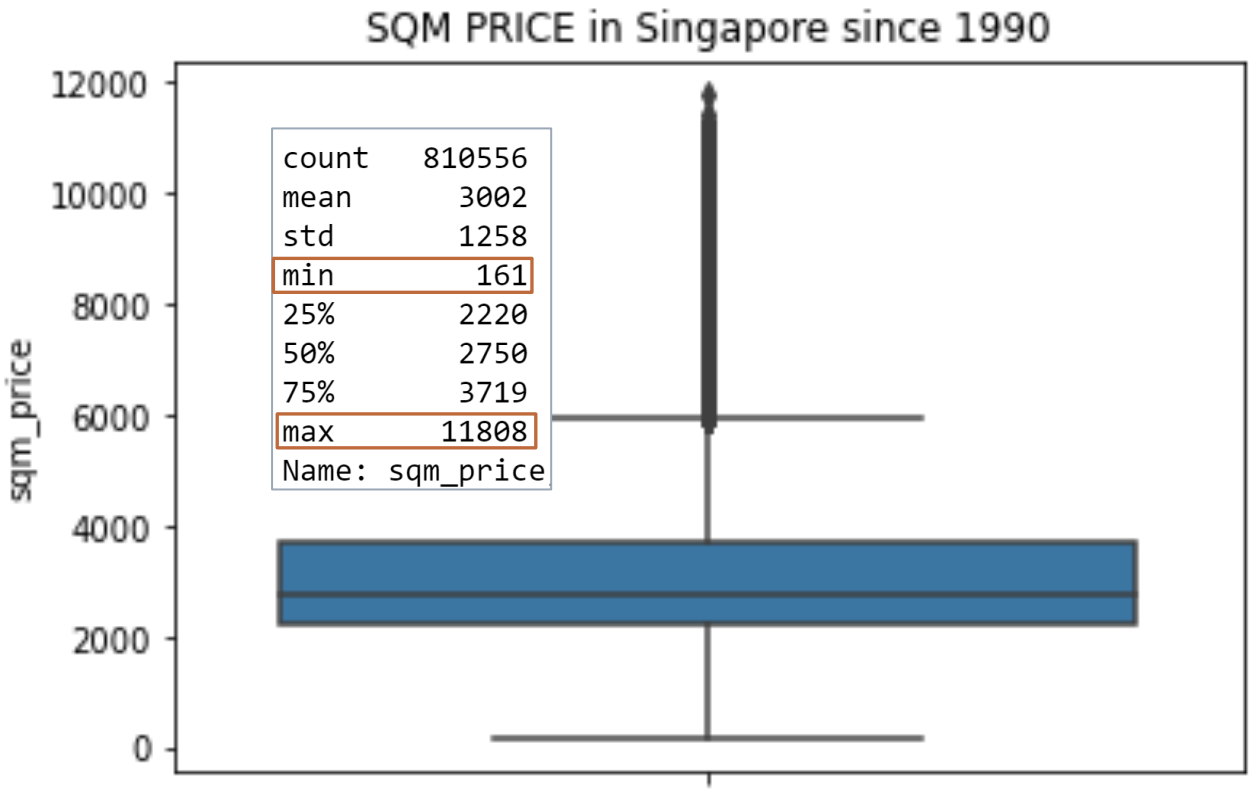
There is a positive correlation between the size of the apartment and its price.
Price increases as the floor area gets bigger.

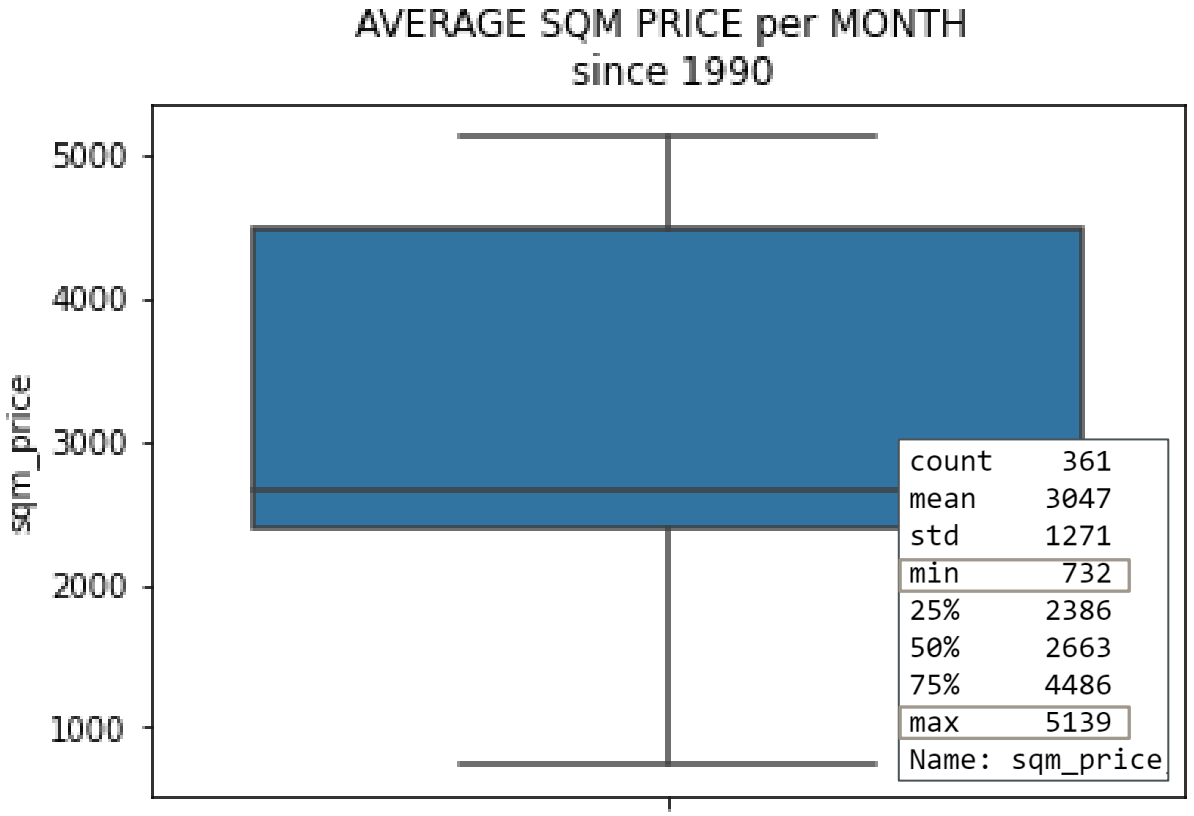
Flat_type vs Price



- There is a positive correlation between the number of rooms (size of the apartment) and its price.
- Executive and Multi-Generation are both premium flat types of respectively 3 and 4 rooms.

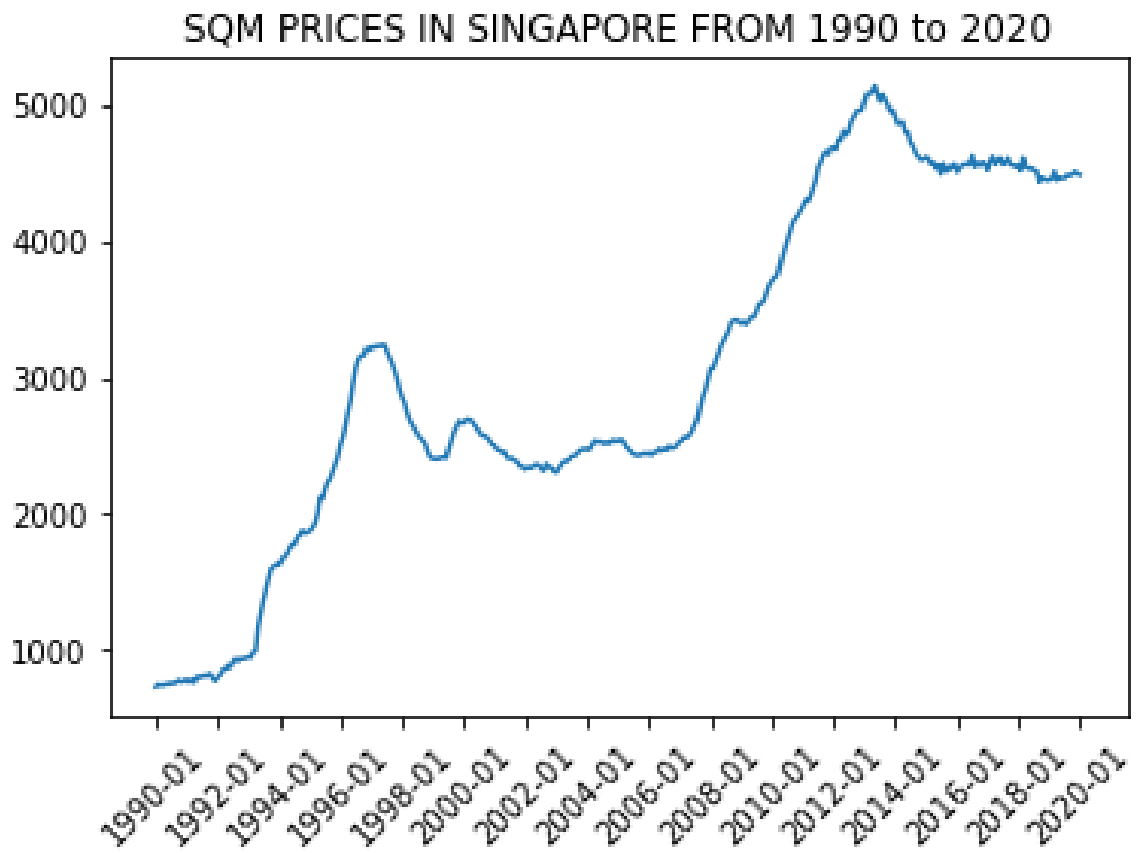
Sqm_price


SQM PRICE in Singapore since 1990
sqm_price
12000
10000
8000
6000
4000
2000
0
count 810556
mean 3002
std 1258
min 161
25% 2220
50% 2750
75% 3719
max 11808
Name: sqm_price

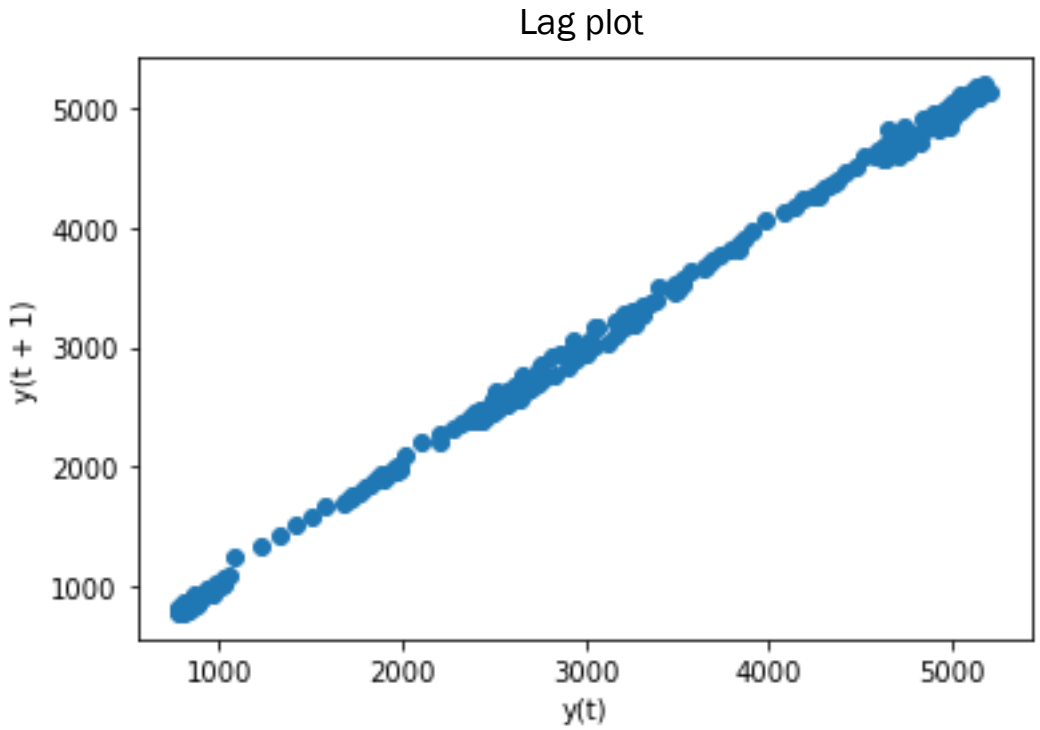

AVERAGE SQM PRICE per MONTH since 1990
sqm_price
5000
4000
3000
2000
1000
count 361
mean 3047
std 1271
min 732
25% 2386
50% 2663
75% 4486
max 5139
Name: sqm_price

2. Time Series Analysis

Evolution of the housing price



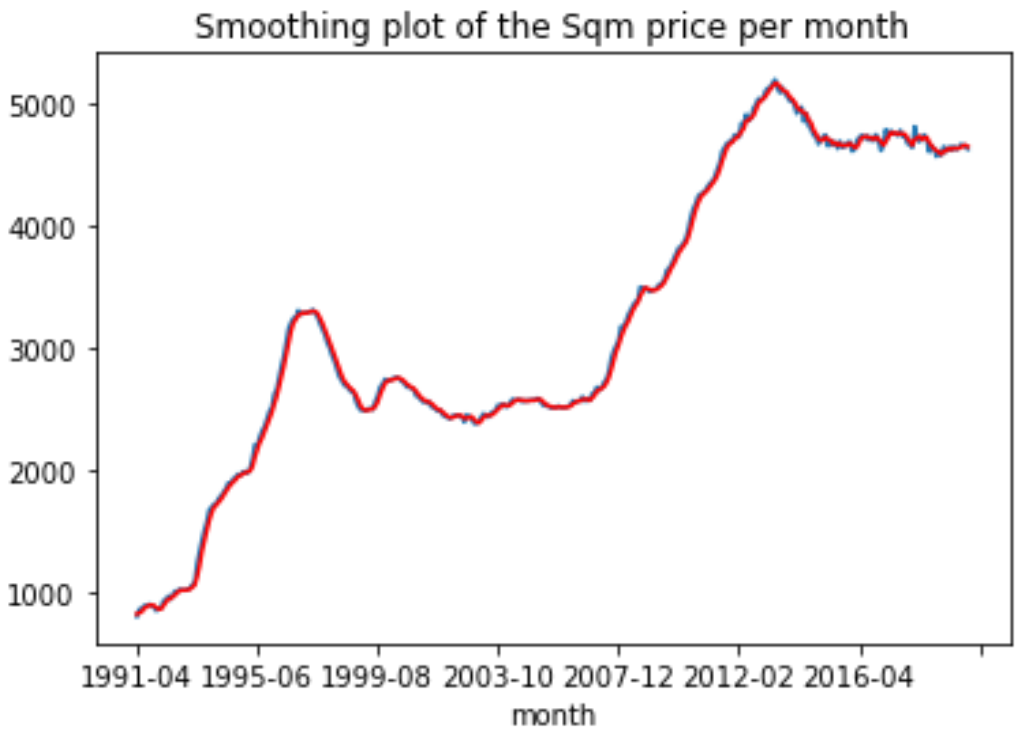
Lag plot

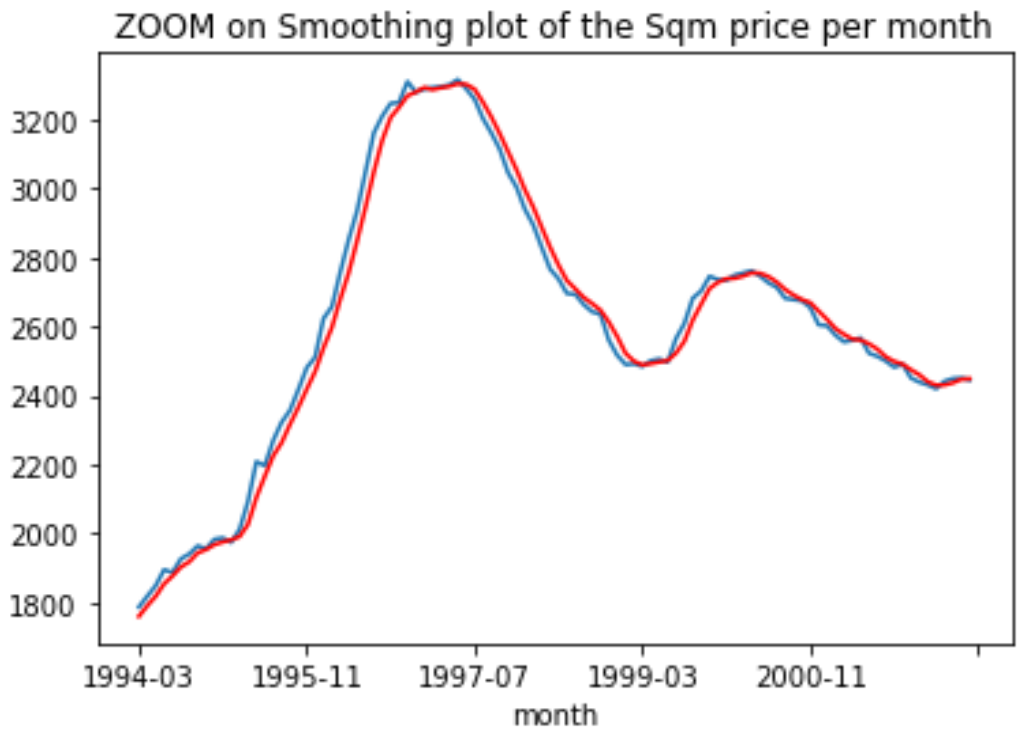


- Time series modeling assumes a relationship between an observation and the previous observation. Previous observations in a time series are called lags.

- We can see a strong positive correlation between the price of the sqm at month t and at month t+1

Moving Average Smoothing



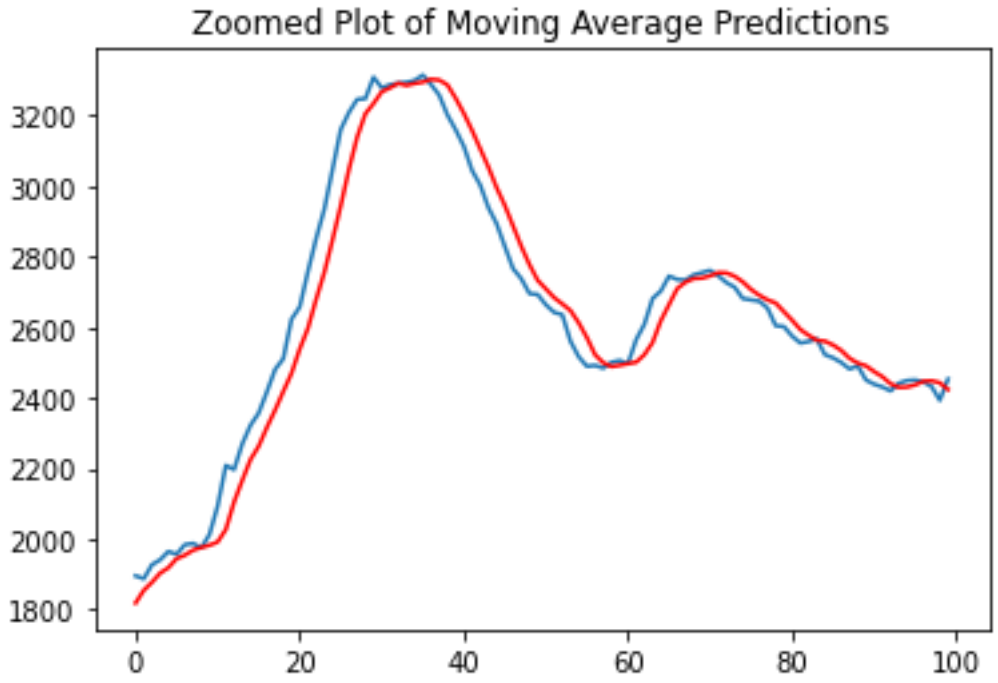


Smoothing is a technique applied to time series to remove the fine-grained variation between time steps.

Moving Average as Prediction

Predict the price for the next period (e.g. month)

- Compute the mean on the historical data and predict the value for the next period (next month)
- As new observations are made available (e.g. monthly), the model can be updated, and a prediction made for the next month



RMSE: 66.85
Abs error: 49.68

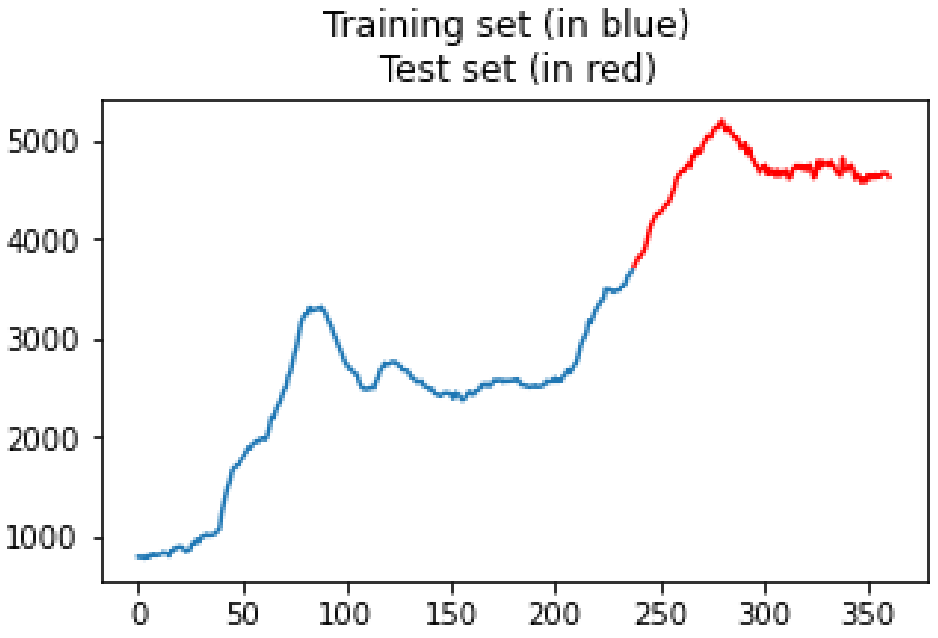
Stationarity in Time Series Data

- The observations in a stationary time series are not dependent on time.
- When a time series is stationary, it can be easier to model.
- Using Augmented Dickey-Fuller test, we accept the null hypothesis that says our real-estate data are not stationary. **THEY DEPEND ON TIME**.

```
ADF Statistic: -1.791865
p-value: 0.384508
Critical Values:
        1%: -3.449
        5%: -2.870
        10%: -2.571
```

Train-Test Split

for Time Series Data

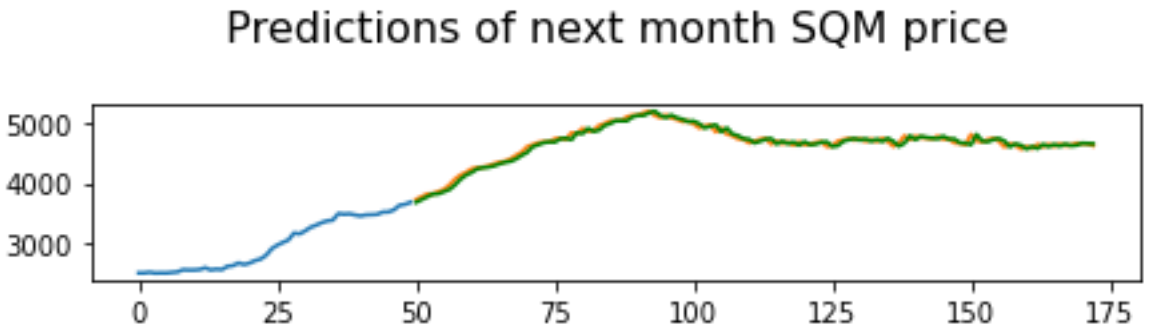


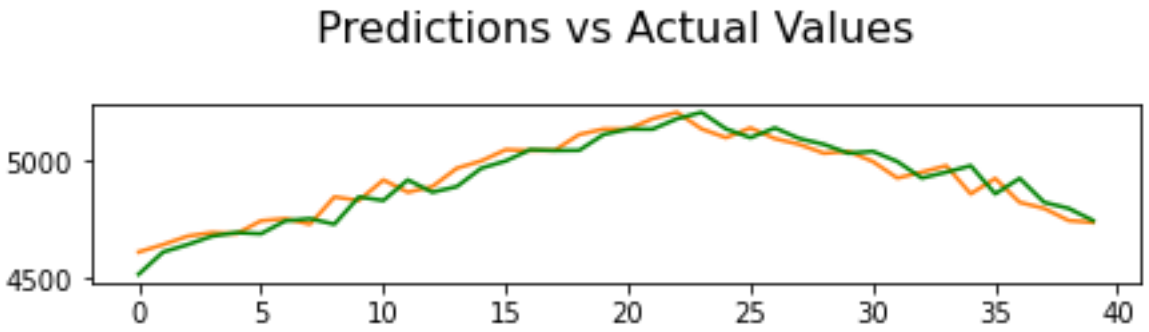
- When training a model we want to make sure that we don't use any information from the test set.
- In blue we can see the training set and in red the test set. Training set use 'historical' data, past data of the train set.

```
Observations: 361 (12 months x 30 years + Jan 2020 = 361)
Training Observations: 238
Testing Observations: 123
```

Persistance model for Forecasting

Predict the sqm price of the next month by taking the price of the previous month






```
Test RMSE: 51.44
Abs error: 42.06
```

	t	t+1
0	nan	786.67
1	786.67	795.15
2	795.15	777.38
3	777.38	773.25
4	773.25	801.76

Regression Modeling for Time Series

Linear Regression using Lags as features

```
RMSE:  47
Abs error: 35.53
```

		1990-04	1990-03	1990-02	1990-01
		1990-05	1990-04	1990-03	1990-02
		1990-06	1990-05	1990-04	1990-03

		lag_1	lag_2	lag_3	lag_4	Y_pred
1990-05	**0**	743.16	743.09	750.40	731.92	754.29
1990-06	**1**	754.29	743.16	743.09	750.40	748.00
1990-07	**2**	748.00	754.29	743.16	743.09	...

We build a linear regression model to predict the price of the next month by using lags as a feature.

Time Series Results

- Using only the historical data, we can estimate the average price of the square meter in Singapore, for the next month, with an absolute error of **35 dollars**.

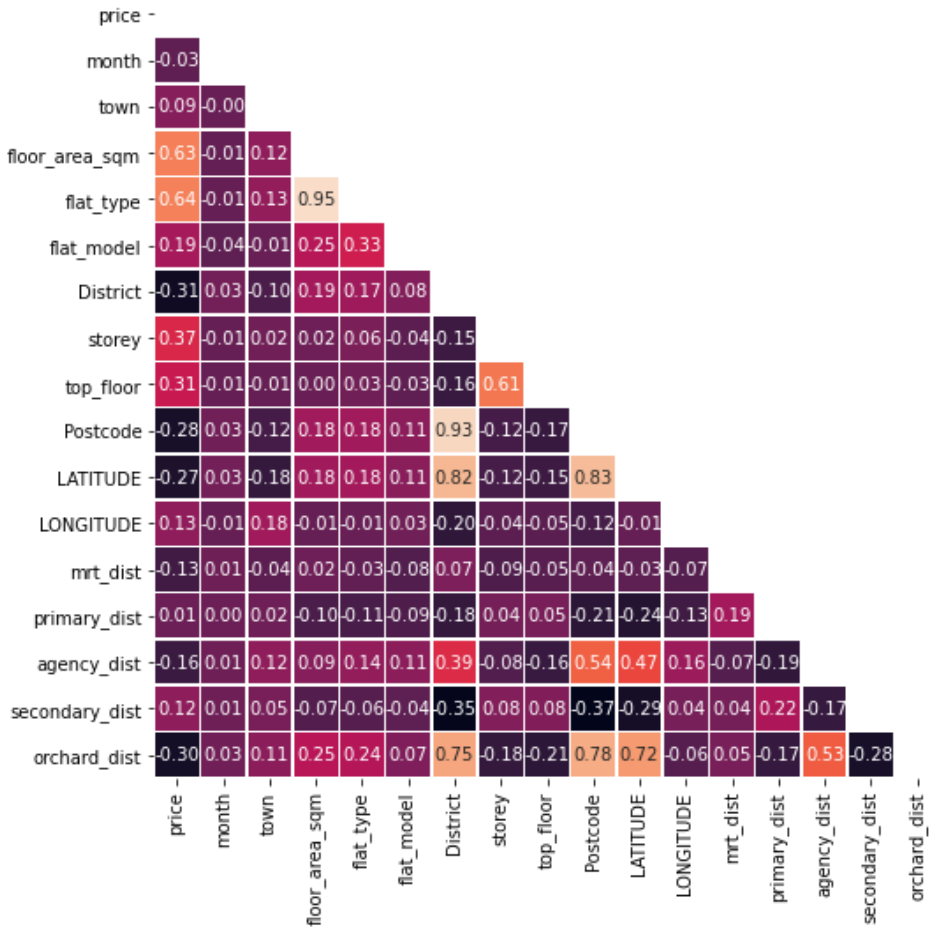
MODELS	MOVING AVERAGE	PERSISTANCE MODEL	REGRESSION MODELING
MAE	49.68	42.06	35.53

- Now, let's try to understand what are the factors that drives the sqm price.

3. Drivers Extraction

What drives the prices of the houses ?

Correlation Matrix

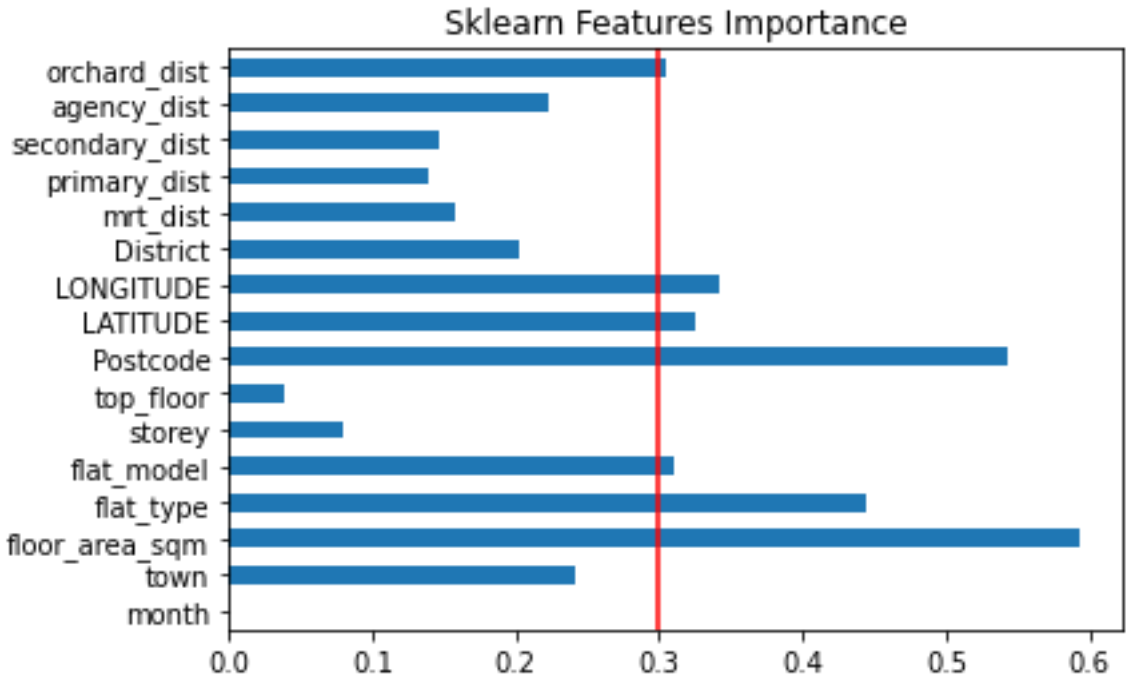


- The first column of the Matrix shows the features correlation with our variable *Price*
  - floor_area_sqm
  - ~~flat_type~~
  - District
  - storey
  - ~~top_floor~~
  - Orchard_dist
- We can spot some redundant features:

  flat_type highly depends on *floor_area_sqm*
  top_floor highly correlated to *storey*
  postcode highly correlated to *latitude*

Features importance

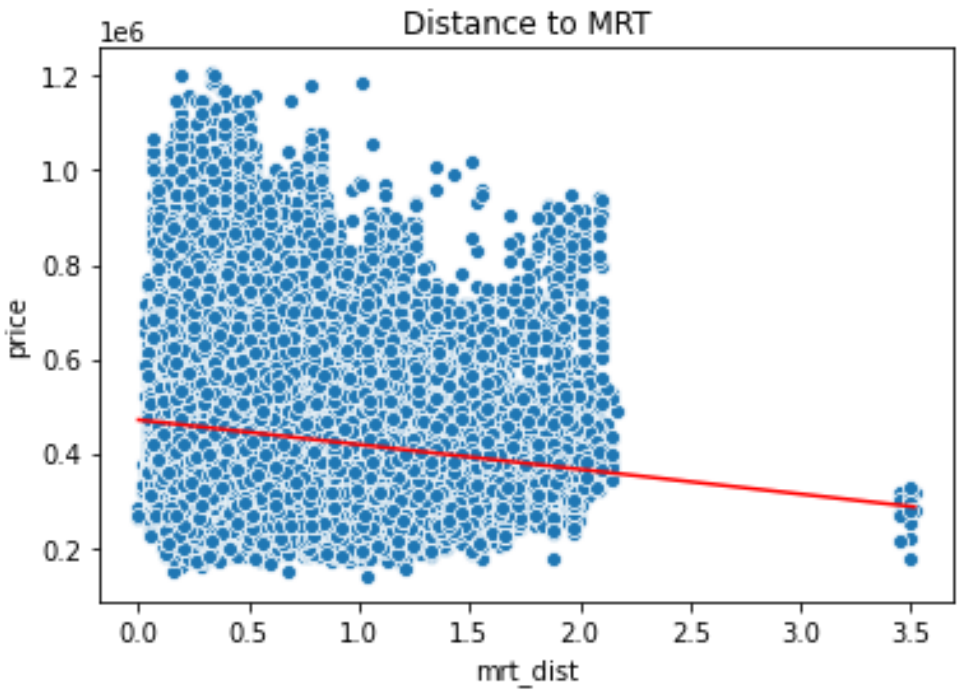
using sklearn.feature_selection

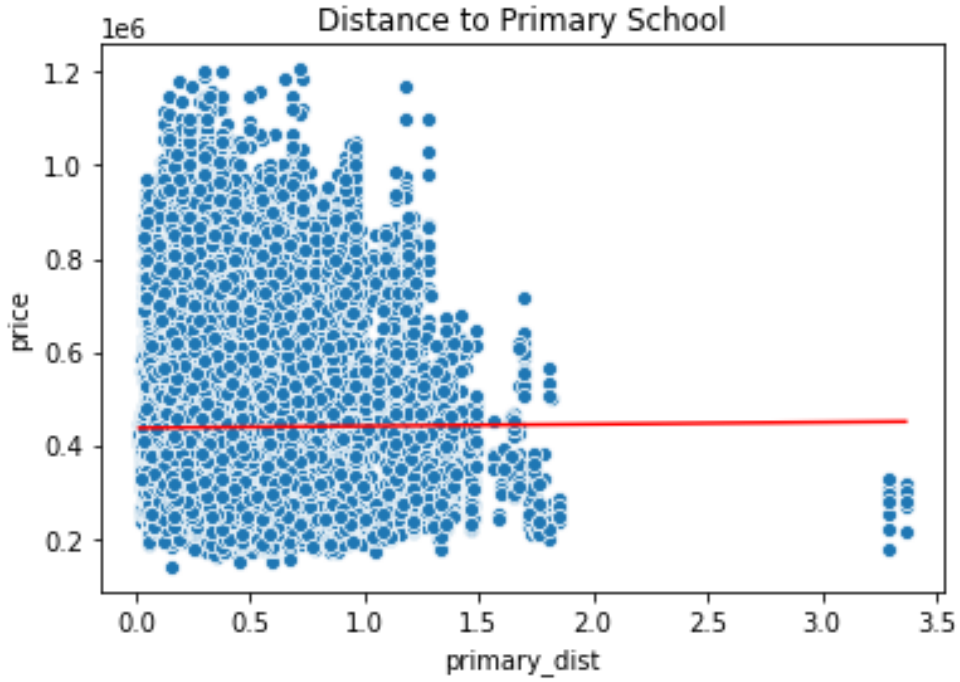


This method estimates the mutual information (entropy) for our target variable *Price*

NOTE

Understand the low influence of distance to POI

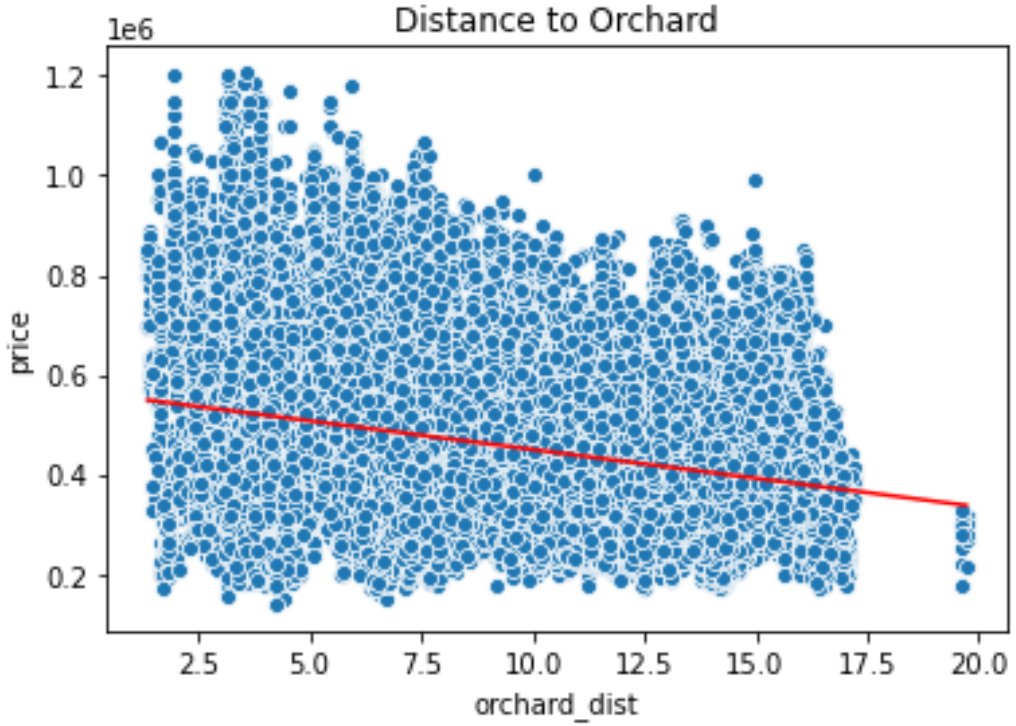




Most of the HDB have direct access to MRT, and schools.
That is why, we can't estimate the influence of the distance to the POIs on *Price*

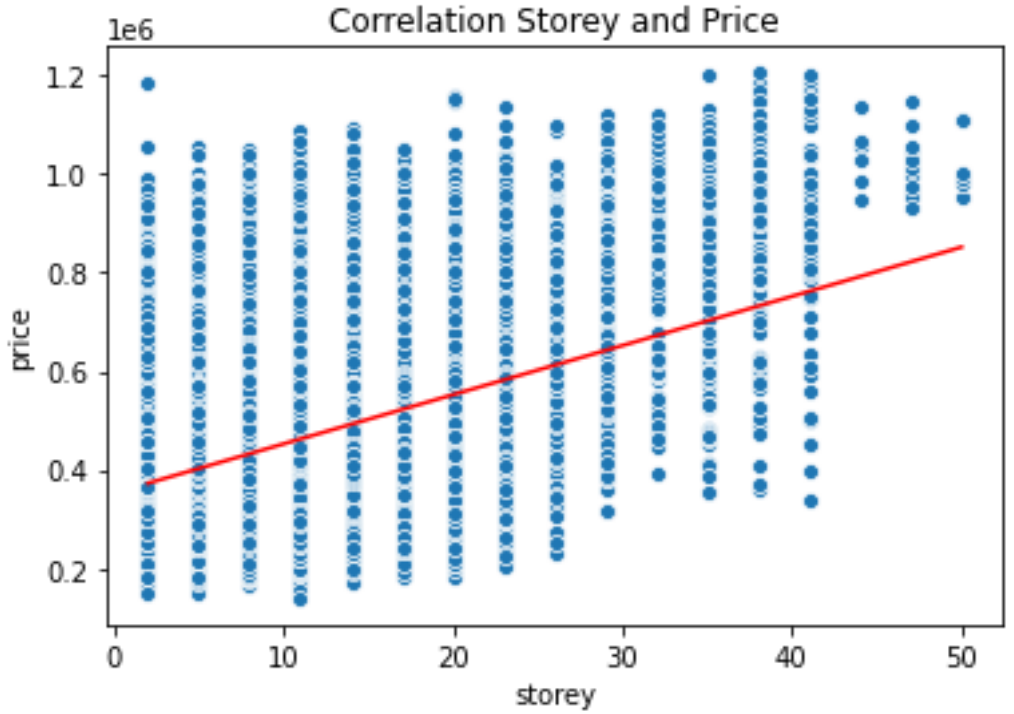
NOTE

Understand the low influence of distance to POI



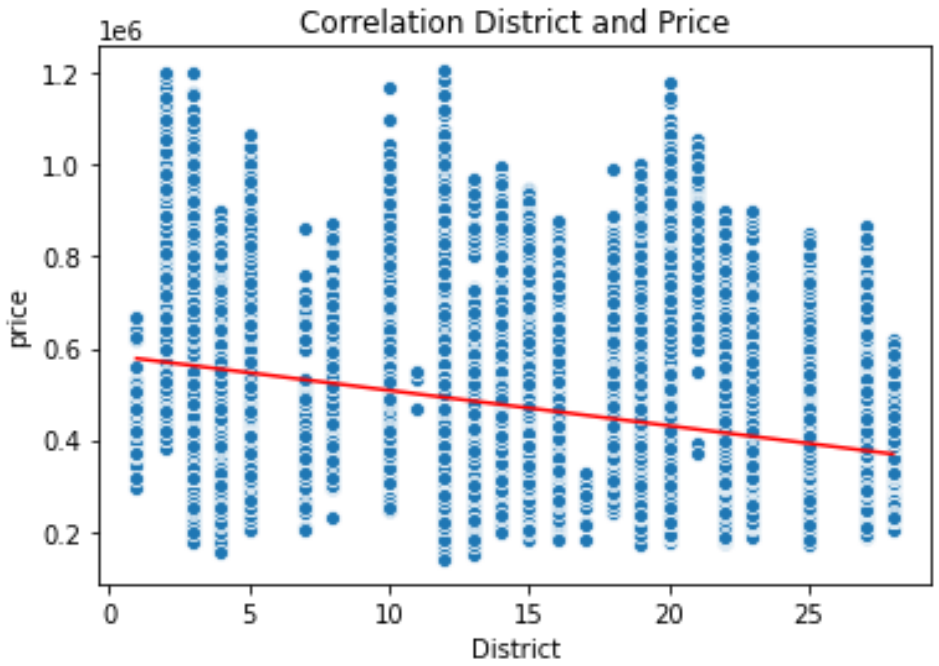
In contrast, the orchard_dist feature have a wider range and can provide more insight on the impact of the distance to Orchard on the *Price*

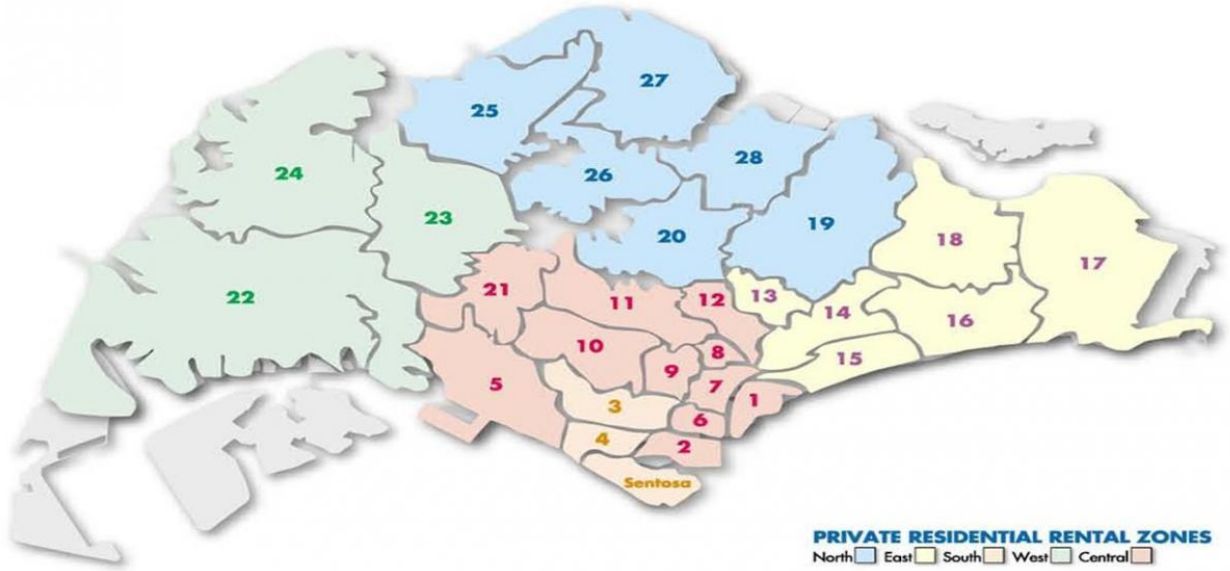
Correlation between Storey and Price



Being located on a higher floor, seems to give value to the apartment

NOTE
Understand the low influence of distance to POI

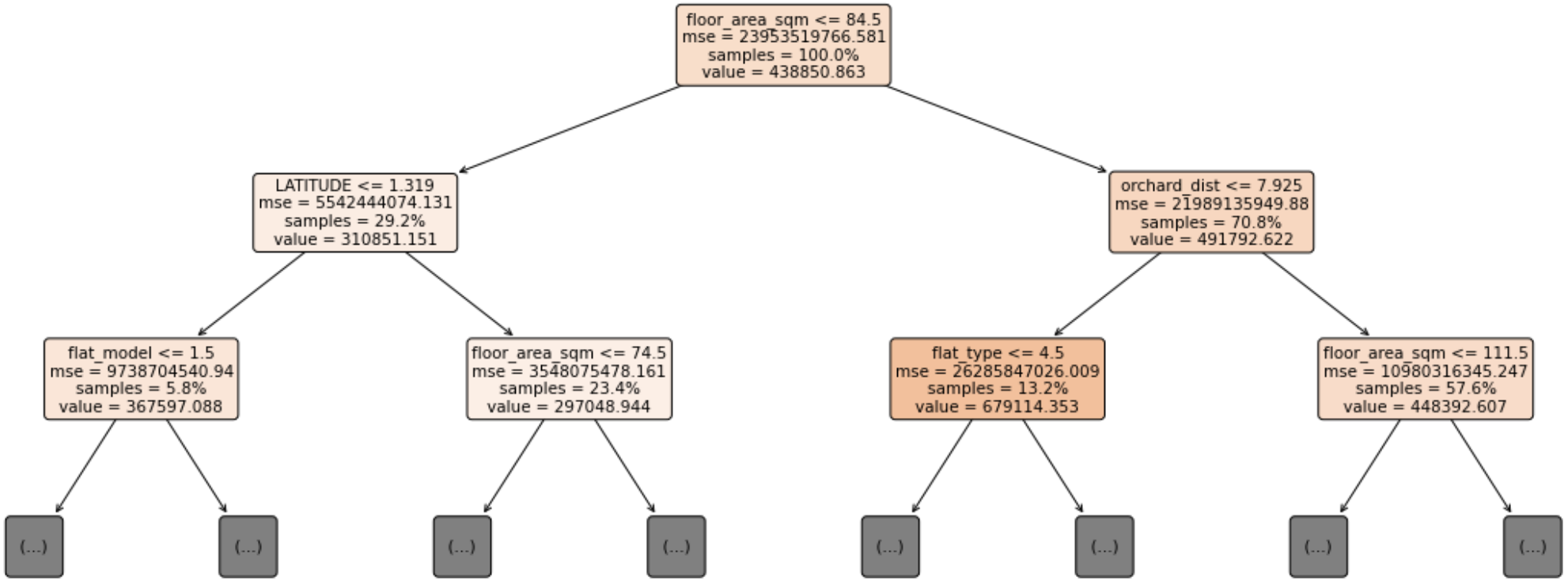




There is a negative correlation between the district number and the price. Higher the # of the district, lower the price is.

Features importance

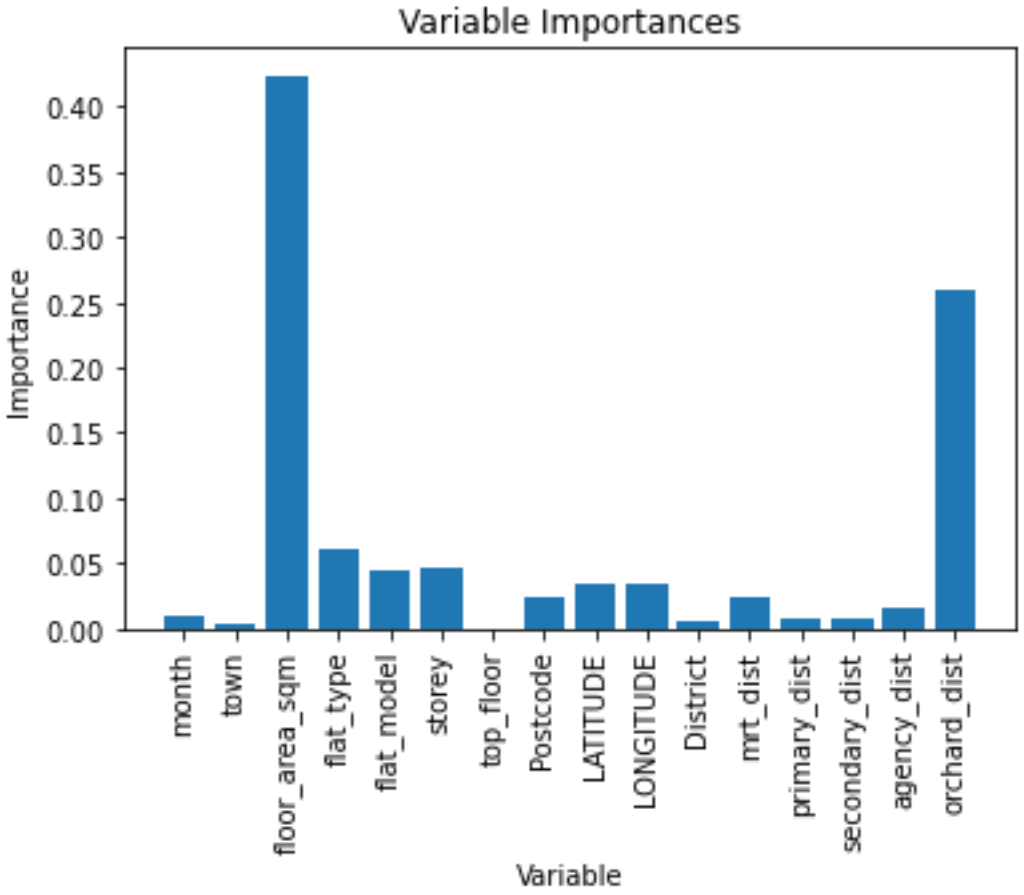
using Random Forest

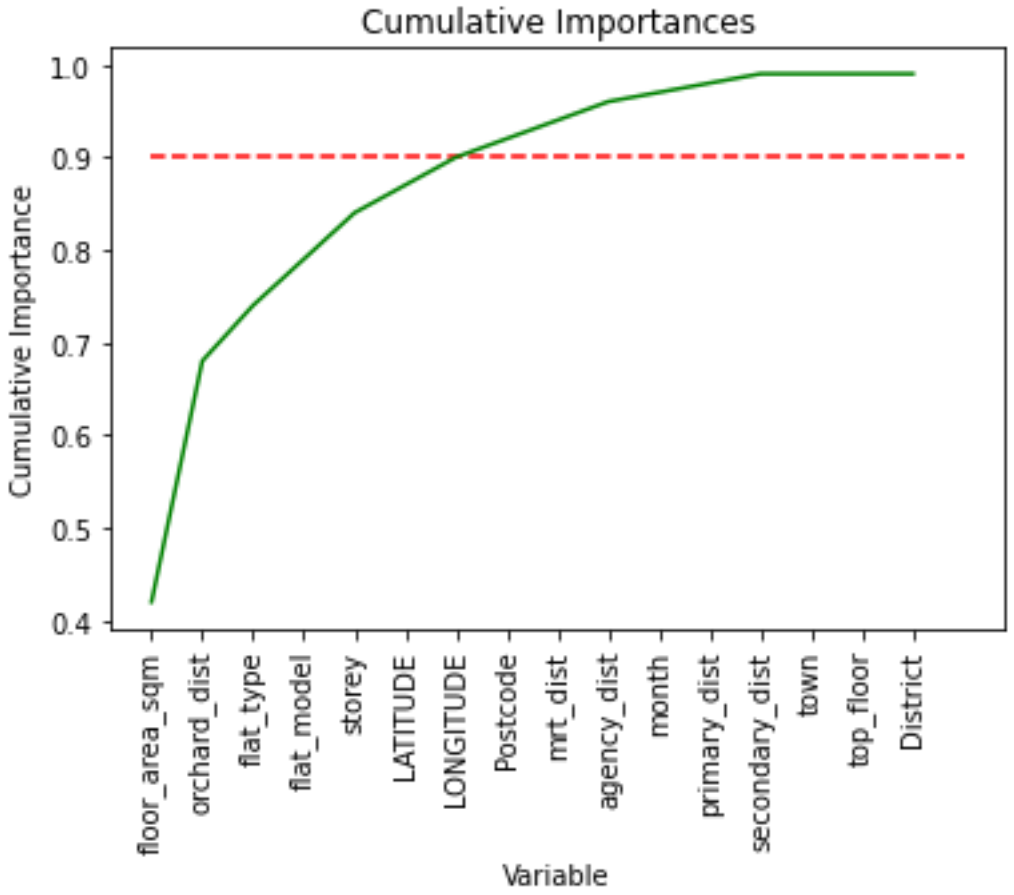


Visualization of a tree from the Random Forest

Features importance

using Random Forest





Drivers Extraction Results

METHODS	CORRELATION MATRIX	SKLEARN FEATURES IMPORTANCE	RANDOM FOREST FEATURES IMPORTANCE
IMPORTANT FEATURES	floor_area_sqm Orchard_dist storey District	floor_area_sqm Orchard_dist flat_model Latitude Longitude	floor_are_sqm Orchard_dist Storey flat_model Latitude Longitude

4. Housing Price Prediction

Linear Regression

FEATURES FROM	CORRELATION MATRIX	SKLEARN FEATURES IMPORTANCE	RANDOM FOREST FEATURES IMPORTANCE	SIMPLEST
R-SCORE	0.72	0.64	0.73	0.70
MAE	63,180	69,988	62,314	65,266

Linear Regression Results

y_pred = 101078 + 4685 ***floor_area_sqm*** - *16852* **orchard_dist** + 7547 * **storey**

```
Intercept         101078
floor_area_sqm      4685
storey              7546
orchard_dist      -16852
dtype: float64
```

We can interpret this equation and say:

The price of an apartment is composed of:

1. A base of $101,078
2. Plus $4,685 for each square meter
3. Minus $16,852 for each km from Orchard MRT
4. Plus $7,546 for each storey

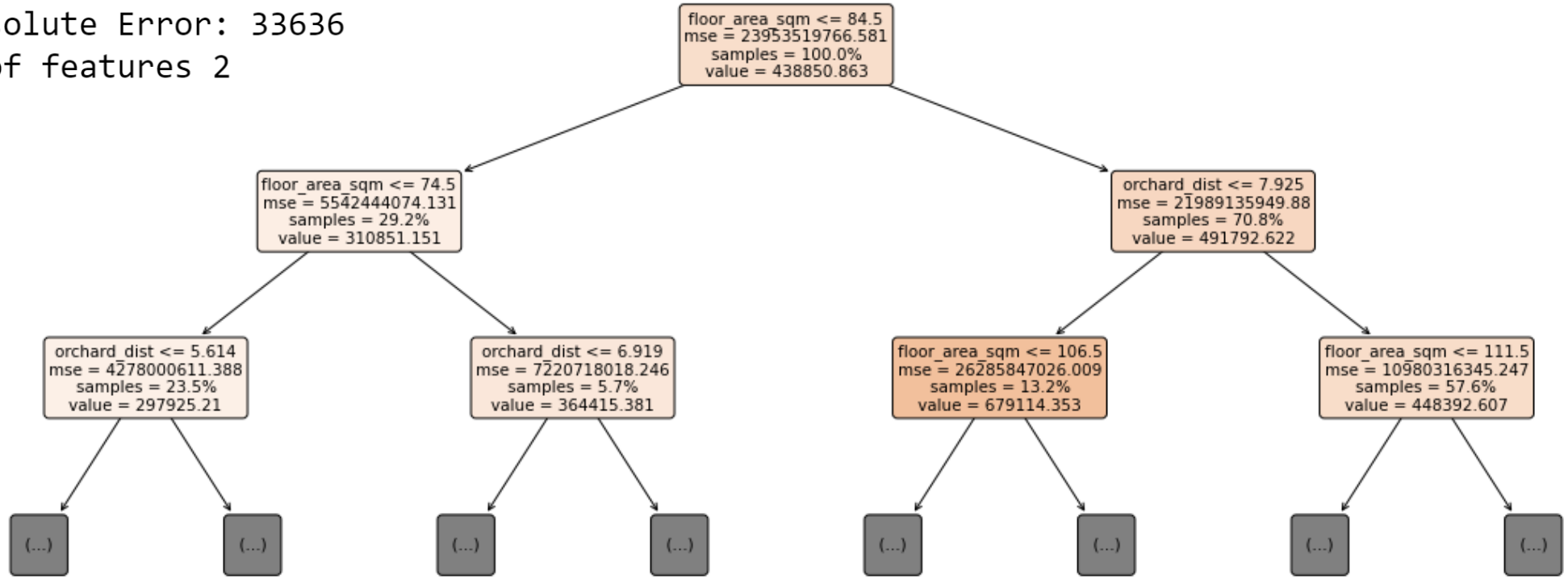
Random Forest

FEATURES FROM	ALL FEATURES	RANDOM FOREST FEATURES	3 MAIN FEATURES (*floor_area, orchard_dist, storey*)	SIMPLEST
# OF FEATURES	16	6	3	2
MAE	20,820	23,776	34,620	33,636

Random Forest

Tree Visualization (*floor_area_sqm, orchard_dist*)

```
Mean Absolute Error: 33636
Number of features 2
```



CONCLUSION

The goal of this project was to understand the key drivers of the prices of the houses in Singapore.

By combining, time series analysis, feature selection techniques and Machine Learning, we estimate the key drivers of the housing price in Singapore to be, in order:

1. The size of the apartment
2. Its distance to the city center (how close to Orchard)
3. Its floor number (higher floor the better)
4. Its location (district, postcode, exact location)

Using these features we estimated the price of the apartments with an error of SGD 30,000.

IMPROVMENTS

- By using the publicly available data of housing in Singapore, we collect data on HDB. The study could be different if mixing public and private housing would have been possible. Althought, note that more than 80% of Singapore population live in HDB.

- A key ratio that I had difficulties to embedded in the study is the Supply and Demand ratio for time analysis. As the supply is possibly computable, I still haven't found a way to estimate the demand.

- As a main result of the study, one of the key element to determine the price of the house is its location. So what make a district attractive ? What are the drivers of the attractiveness of a district ? All these questions could lead to another project...