In [1]:
```
%load_ext autoreload
%autoreload 2
```

# Task 1: Problem definition

## Project Description:

The aim of our project is to create a model that allow us to predict the price of hdb using relevant parameters, such as the flat type, size, distance form mrt, etc. We achieved this goal by following the steps below: 1. A suitable dataset with the relevant data and attributes is selected 2. Additional datasets are evaluated and used to enrich the existing dataset. 3. Exploratory data analysis and visualisation are done where data is cleaned and prepared 4. Multiple models are trained and evaluated using RMSE (Root-mean-square error) and MAE (Mean absolute error). 5. The selected model is analysed where the feature importance is evaluated

## Potential use cases:

1. The trained model can be deployed on real estate website such as PropertyGuru, 99.co, where buyers and sellers are able to get the most optimal price estimation before listing or buying.
2. This model can also be used by HDB to real estate agent to find a suitable price when consulting their clients on calculating the valuation of the client's property.

# Task 2: Data collection/curation

We have collected the data we required for our HDB sales price prediction task primarary from data.gov.sg.

**HDB resale price** : https://beta.data.gov.sg/collections/189/datasets/d_8b84c4ee58e3cfc0ece0d773c8ca6abc/view

Besides, we also enriched our dataset using additional data from kaggle as follows:

**HDB coordinate** : https://www.kaggle.com/datasets/mylee2009/singapore-postal-code-mapper **MRT coordinate** : https://www.kaggle.com/datasets/shengjunlim/singapore-mrt-lrt-stations-with-coordinates

The files have been downloaded locally and renamed accordingly.

# Task 3 & 4: Data preparation & Exploratory data analysis and visualization

### Step 1: Import the packages and load resale data

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline


data = pd.read_csv("ResaleflatpricesbasedonregistrationdatefromJan2017onwards.csv")
hdb_locations = pd.read_csv("sg_zipcode_mapper_utf.csv", delimiter=',')
mrt_locations = pd.read_csv("mrt.csv")
```

### Step 2: Data cleaning and EDA

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 177572 entries, 0 to 177571
Data columns (total 11 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   month                177572 non-null  object 
 1   town                 177572 non-null  object 
 2   flat_type            177572 non-null  object 
 3   block                177572 non-null  object 
 4   street_name          177572 non-null  object 
 5   storey_range         177572 non-null  object 
 6   floor_area_sqm       177572 non-null  float64
 7   flat_model           177572 non-null  object 
 8   lease_commence_date  177572 non-null  int64  
 9   remaining_lease      177572 non-null  object 
 10  resale_price         177572 non-null  float64
dtypes: float64(2), int64(1), object(8)
memory usage: 14.9+ MB
```

In [4]:
```
data.head()
```

Out[4]:

| | month | town | flat_type | block | street_name | storey_range | floor_area_sqm | flat_model |
|---|---|---|---|---|---|---|---|---|
| **0** | 2017-01 | ANG MO KIO | 2 ROOM | 406 | ANG MO KIO AVE 10 | 10 TO 12 | 44.0 | Improved |
| **1** | 2017-01 | ANG MO KIO | 3 ROOM | 108 | ANG MO KIO AVE 4 | 01 TO 03 | 67.0 | New Generation |
| **2** | 2017-01 | ANG MO KIO | 3 ROOM | 602 | ANG MO KIO AVE 5 | 01 TO 03 | 67.0 | New Generation |
| **3** | 2017-01 | ANG MO KIO | 3 ROOM | 465 | ANG MO KIO AVE 10 | 04 TO 06 | 68.0 | New Generation |
| **4** | 2017-01 | ANG MO KIO | 3 ROOM | 601 | ANG MO KIO AVE 5 | 01 TO 03 | 67.0 | New Generation |

The data is already cleaned, it does not contain null value, therefore data cleaning is not required.

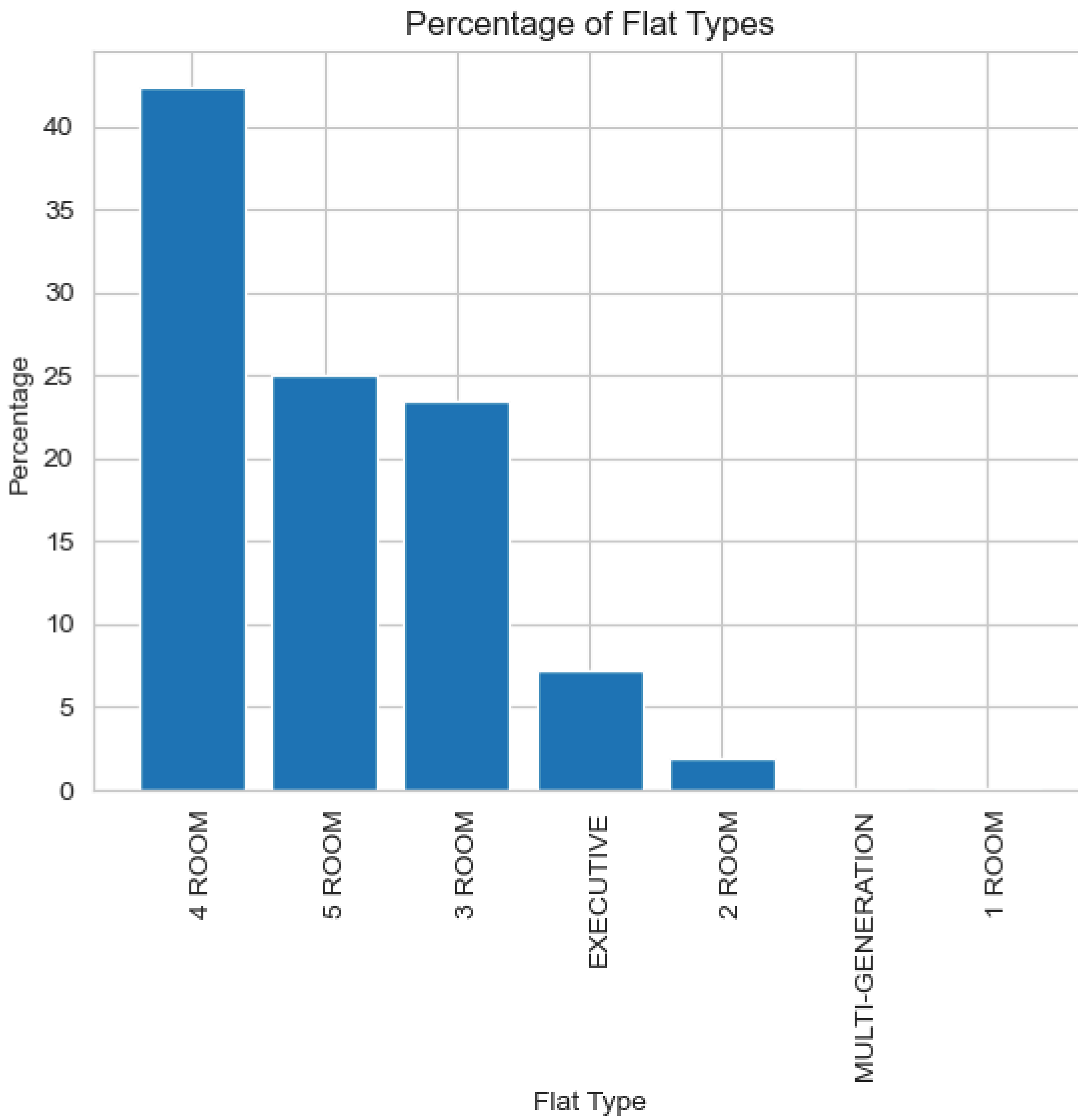
Extract year from the data and filter data to only include data from 2019 to 2023, because we only want to predict he proce of the flat based on the past 4 years of data.

In [5]:

```
data['month'] = pd.to_datetime(data['month'])
data['year'] = list(map(lambda x: x.year, data['month']))

data = data[data['year'] >= 2019]
data = data[data['year'] != 2024]

data['price_per_sqm'] = data['resale_price'] / data['floor_area_sqm']
data['remaining_lease'] = (99 + data['lease_commence_date']) - data['year']
```

In [6]:

```
flat_type_counts = data['flat_type'].value_counts(normalize=True) * 100  # This cal

# Create a bar plot using Matplotlib
plt.bar(flat_type_counts.index, flat_type_counts.values)

plt.xlabel('Flat Type')
plt.ylabel('Percentage')
plt.title('Percentage of Flat Types')
plt.xticks(rotation=90, ha='left', rotation_mode='default')
plt.show()

# # Show the plot
# plt.show()
```

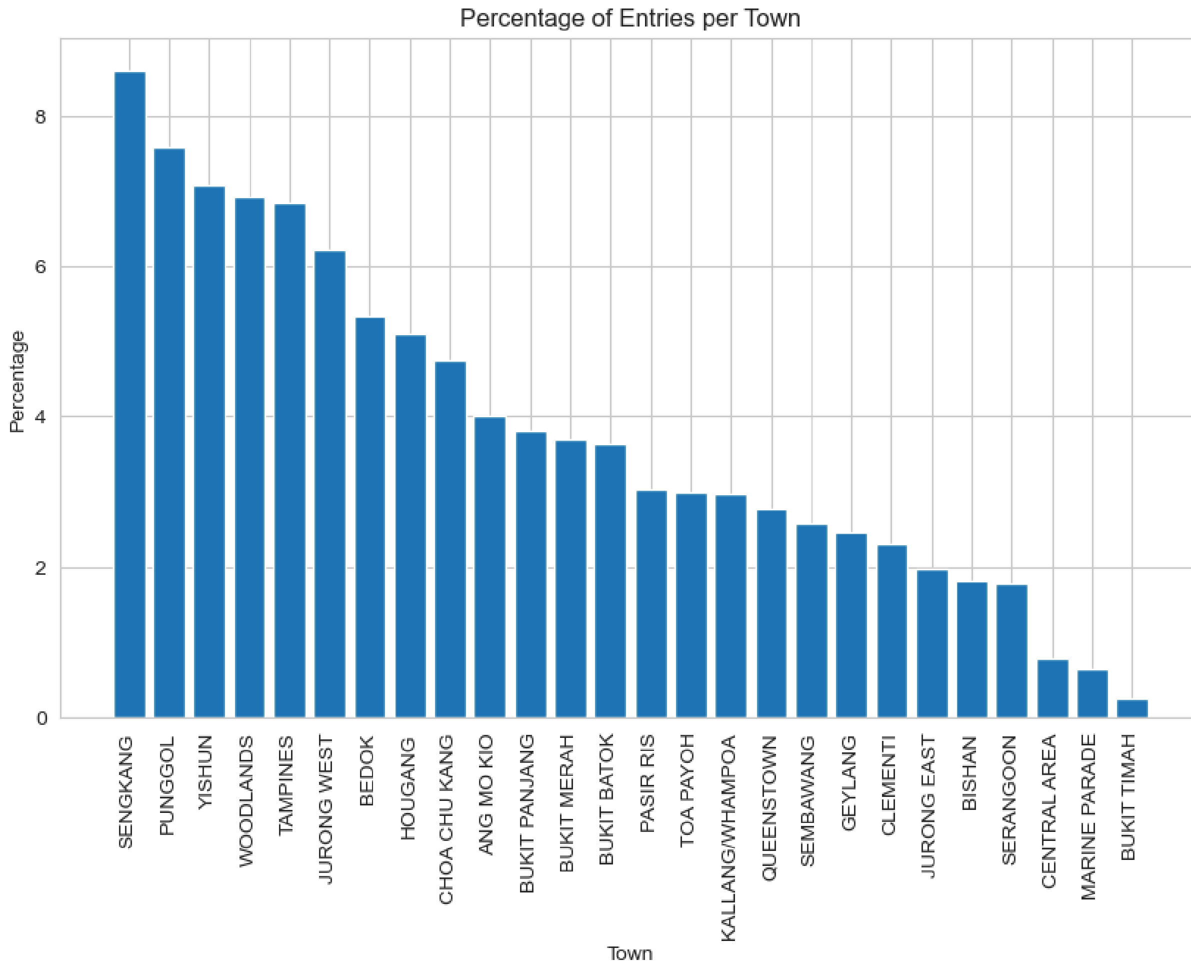



**From the count plot above we can see that there are very little one room, two room and multi-generatin flat(below 5%). therefore we are going to drop these data for our model training.**

In [7]:
```
data = data[data['flat_type'] != "1 ROOM"]
data = data[data['flat_type'] != "2 ROOM"]
data = data[data['flat_type'] != "MULTI-GENERATION"]
```

In [8]:
```
town_counts = data['town'].value_counts()  # Get the counts for each town
total_counts = town_counts.sum()  # Total number of entries
town_percent = (town_counts / total_counts) * 100  # Convert counts to percentage

# Plotting with Matplotlib
plt.figure(figsize=(10, 6))  # Optional: Adjust the size of the figure
plt.bar(town_percent.index, town_percent.values)  # Create a bar chart

plt.xlabel('Town')  # Label for the x-axis
plt.ylabel('Percentage')  # Label for the y-axis
plt.title('Percentage of Entries per Town')  # Title of the plot
```

```
plt.xticks(rotation=90)  # Rotate the x-axis labels for better visibility if needed
plt.show()
```




## From the count plot above we can see that there are very little ales recoed in Central Area, Bukit Timah and Marine Parade(below 1%).therefore we are going to drop these data for our model training.

In [9]:
```
data = data[data['town'] != "CENTRAL AREA"]
data = data[data['town'] != "BUKIT TIMAH"]
data = data[data['town'] != "MARINE PARADE"]
```

## Load the HDB location file, and join with the resale dataframe. This will allow us to calculate the distance from the nearest mrt for each HDB blocks.

In [10]:
```
hdb_locations.rename(columns={"latitude": "lat", "longtitude": "lng",
                              "blk_no": "block", "RD_name": "street_name"},
                     inplace=True)
hdb_locations = hdb_locations[hdb_locations['postal.1'] != 189677]
hdb_locations = hdb_locations[hdb_locations['postal.1'] != 469277]
hdb_locations = hdb_locations[hdb_locations['postal'] != 90027]
hdb_locations = hdb_locations[["postal", "lat", "lng", "block", "street_name", "pos
imputed_data = pd.merge(data, hdb_locations, how='left',
```

```
                   on=['block', 'street_name'])
imputed_data.dropna(inplace=True)
```

In [11]:
```
imputed_data.head()
```

Out[11]:

| | month | town | flat_type | block | street_name | storey_range | floor_area_sqm | flat_model |
|---|---|---|---|---|---|---|---|---|
| **0** | 2019-01-01 | ANG MO KIO | 3 ROOM | 225 | ANG MO KIO AVE 1 | 01 TO 03 | 67.0 | New Generation |
| **1** | 2019-01-01 | ANG MO KIO | 3 ROOM | 174 | ANG MO KIO AVE 4 | 01 TO 03 | 60.0 | Improved |
| **2** | 2019-01-01 | ANG MO KIO | 3 ROOM | 440 | ANG MO KIO AVE 10 | 04 TO 06 | 67.0 | New Generation |
| **3** | 2019-01-01 | ANG MO KIO | 3 ROOM | 174 | ANG MO KIO AVE 4 | 10 TO 12 | 61.0 | Improved |
| **4** | 2019-01-01 | ANG MO KIO | 3 ROOM | 637 | ANG MO KIO AVE 6 | 01 TO 03 | 68.0 | New Generation |

# Data Enrichment

## We will try to enrich the data by calculating the distance of the HDB from MRT stations as we think distance to mrt station might be a good predictor

### Here we will clean the mrt_locations data to remove the unnecessary data

In [12]:
```
mrt_locations.head()
```

Out[12]:

| | Unnamed: 0 | OBJECTID | STN_NAME | STN_NO | geometry | Latitude | Longitude |
|---|---|---|---|---|---|---|---|
| **0** | 0 | 1 | EUNOS MRT STATION | EW7 | POINT (103.9032524667383 1.319778951553637) | 1.319779 | 103.903252 |
| **1** | 1 | 2 | CHINESE GARDEN MRT STATION | EW25 | POINT (103.7325967380734 1.342352820874744) | 1.342353 | 103.732597 |
| **2** | 2 | 3 | KHATIB MRT STATION | NS14 | POINT (103.8329799077383 1.417383370153547) | 1.417383 | 103.832980 |
| **3** | 3 | 4 | KRANJI MRT STATION | NS7 | POINT (103.7621654109002 1.425177698770448) | 1.425178 | 103.762165 |
| **4** | 4 | 5 | REDHILL MRT STATION | EW18 | POINT (103.816816670149 1.289562726402453) | 1.289563 | 103.816817 |

In [13]:
```
mrt_locations.drop(columns=['Unnamed: 0', 'OBJECTID',
                            'geometry', "STN_NO", ], inplace=True)
```

In [14]:
```
mrt_locations.rename(columns={"Latitude": "lat", "Longitude": "lng"}, inplace=True)
```

In [15]:
```
mrt_locations.head()
```

Out[15]:

| | STN_NAME | lat | lng |
|---|---|---|---|
| **0** | EUNOS MRT STATION | 1.319779 | 103.903252 |
| **1** | CHINESE GARDEN MRT STATION | 1.342353 | 103.732597 |
| **2** | KHATIB MRT STATION | 1.417383 | 103.832980 |
| **3** | KRANJI MRT STATION | 1.425178 | 103.762165 |
| **4** | REDHILL MRT STATION | 1.289563 | 103.816817 |

### This is the formula to convert from euclidean distance to earth distance

### Formula taken from https://byteshiva.medium.com/navigate-the-world-a-guide-to-calculating-distances-between-points-on-earth-using-python-and-the-9f3c5c856203

In [16]:
```
def calculate_distance(x, y):
    R = 6371  # Radius of the Earth in kilometers

    lat_a, lon_a = x[0], x[1]
    lat_b, lon_b = y[0], y[1]
```

```
    # Convert latitude and longitude to radians
    lat_a, lon_a, lat_b, lon_b = np.radians([lat_a, lon_a, lat_b, lon_b])

    # Calculate the difference in latitude and longitude
    dlat = lat_b - lat_a
    dlon = lon_b - lon_a

    # Apply the Haversine formula
    a = np.sin(dlat / 2) ** 2 + np.cos(lat_a) * np.cos(lat_b) * np.sin(dlon / 2) **
    c = 2 * np.arctan2(np.sqrt(a), np.sqrt(1 - a))
    distance = R * c

    return distance
```

### Here we import the KNN package to calculate the distance between each HDB block and the nearest mrt

In [17]:
```
from sklearn.neighbors import KNeighborsClassifier

nbrs = KNeighborsClassifier(n_neighbors=1, algorithm='ball_tree',
                            metric=calculate_distance).fit(mrt_locations[['lat', 'l
                                                           mrt_locations['STN_NAME'

imputed_data['mrt_dist'] = nbrs.kneighbors(imputed_data[['lat', 'lng']])[0]

imputed_data['nearest_mrt'] = nbrs.predict(imputed_data[['lat', 'lng']])
```

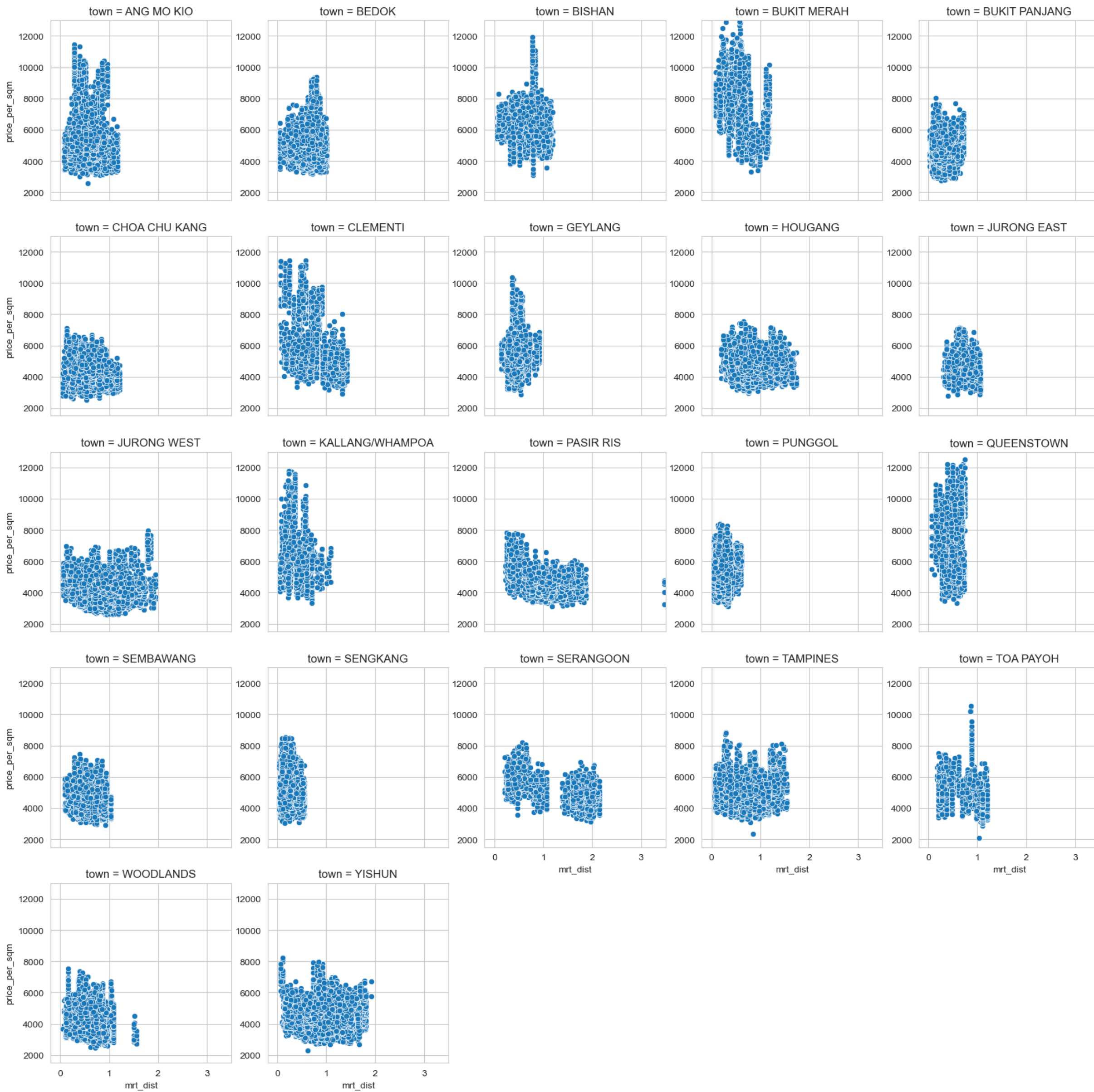
In [18]:
```
imputed_data.head()
```

Out[18]:

| | month | town | flat_type | block | street_name | storey_range | floor_area_sqm | flat_model |
|---|---|---|---|---|---|---|---|---|
| **0** | 2019-01-01 | ANG MO KIO | 3 ROOM | 225 | ANG MO KIO AVE 1 | 01 TO 03 | 67.0 | New Generation |
| **1** | 2019-01-01 | ANG MO KIO | 3 ROOM | 174 | ANG MO KIO AVE 4 | 01 TO 03 | 60.0 | Improved |
| **2** | 2019-01-01 | ANG MO KIO | 3 ROOM | 440 | ANG MO KIO AVE 10 | 04 TO 06 | 67.0 | New Generation |
| **3** | 2019-01-01 | ANG MO KIO | 3 ROOM | 174 | ANG MO KIO AVE 4 | 10 TO 12 | 61.0 | Improved |
| **4** | 2019-01-01 | ANG MO KIO | 3 ROOM | 637 | ANG MO KIO AVE 6 | 01 TO 03 | 68.0 | New Generation |

In [19]:
```
UniqueNames = imputed_data['town'].unique()
```

```
#create a data frame dictionary to store your data frames
DataFrameDict = {elem: pd.DataFrame() for elem in UniqueNames}

for key in DataFrameDict.keys():
    DataFrameDict[key] = imputed_data[imputed_data.town == key]
f = plt.figure(figsize=(20, 20))
for i in range(len(UniqueNames)):
    column = i // 5
    row = i % 5
    axis = f.add_subplot(5, 5, i + 1)
    dataset = UniqueNames[i]
    title = "town = " + dataset
    axis.scatter(DataFrameDict[dataset]['mrt_dist'],
                 DataFrameDict[dataset]['price_per_sqm'],
                 color='#1978b9',
                 edgecolors='white',
                 linewidth=0.5)
    axis.set_xlim([-0.2, 3.5])
    axis.set_ylim([1500, 13000])
    axis.set_xticks([0, 1, 2, 3])
    axis.set_title(title)

    if i >= 17:
        axis.set(xlabel='mrt_dist')
    else:
        axis.tick_params(colors='black', which='major', axis='x', labelcolor='white
    if row == 0:
        axis.set(ylabel='price_per_sqm')
```



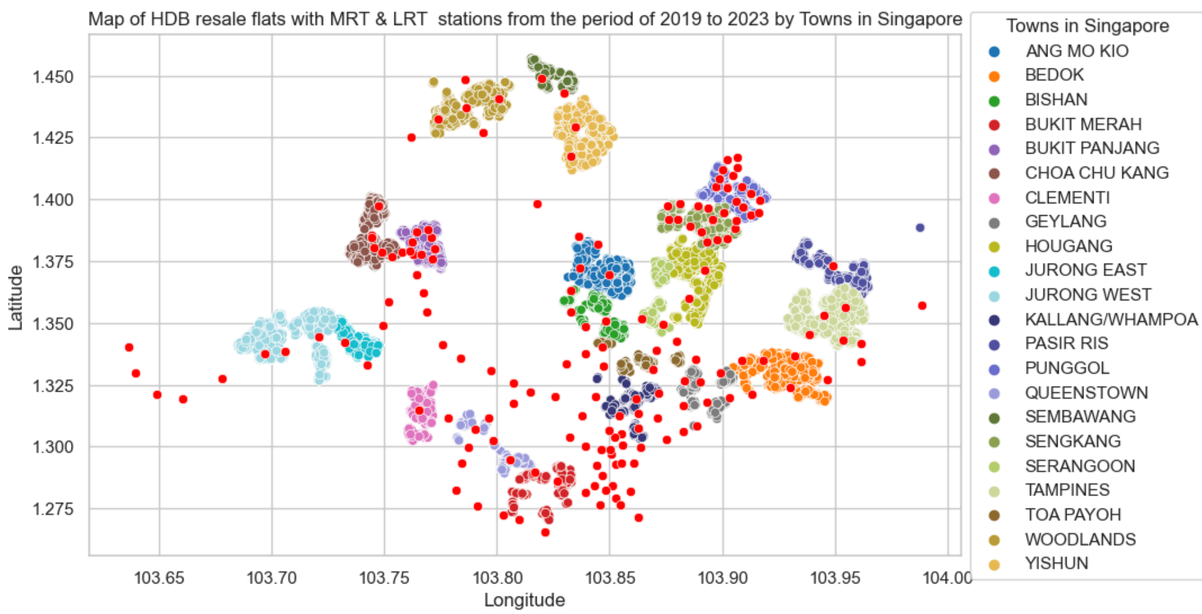

### From the chart of price_per_sqm versus mrt_dist plot we generated for each town, we observed there is not a strong correlation between price and mrt distancefor most of the towns. Thus, the mrt_dist might be a useful predictor when training our model.

# Visualisation

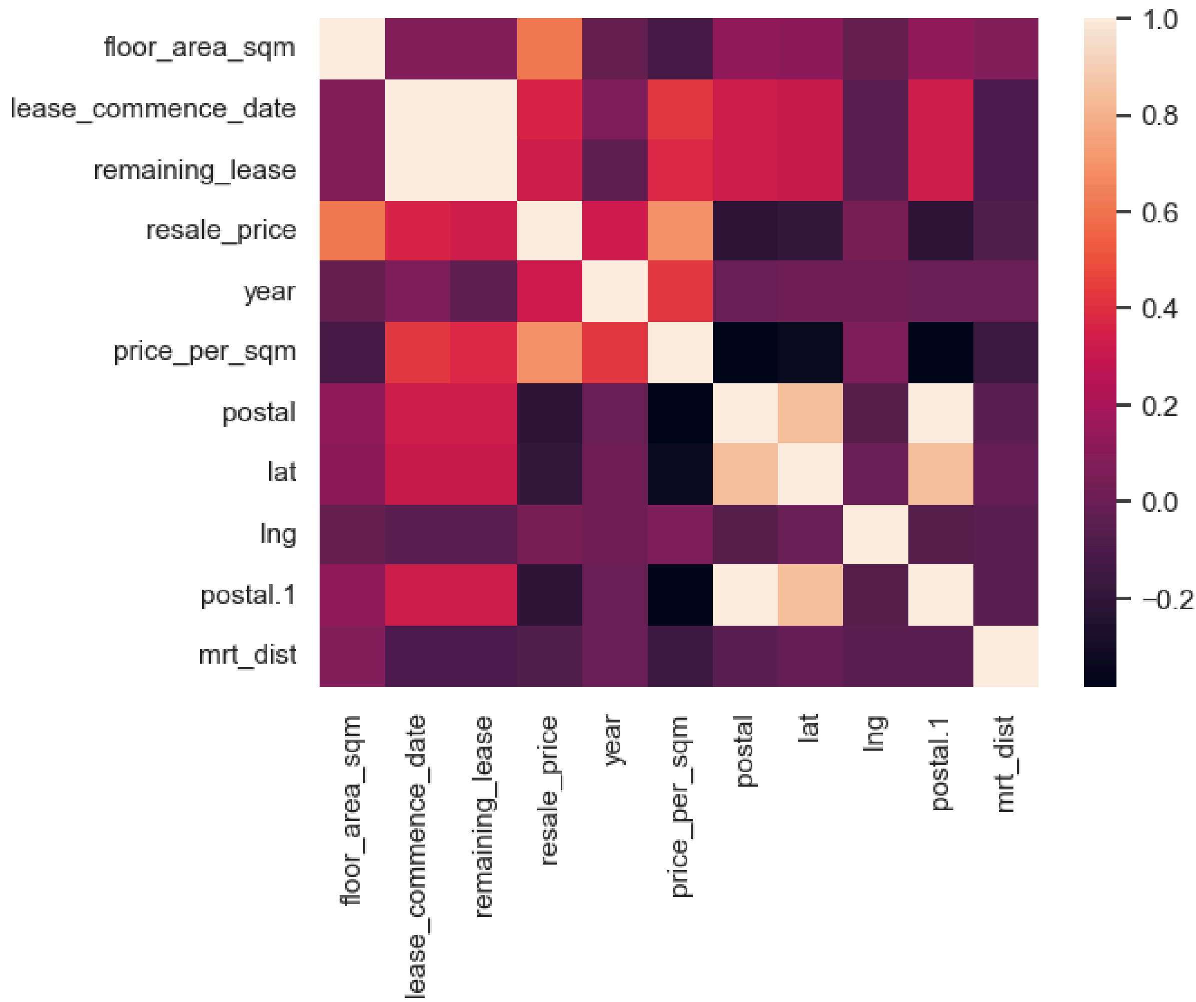
### To visualise the hot spot where of hdb location and their distance to the mrt stations, we have plot the graph below resembling the Singapore map

In [20]:
```
map_town_data = pd.DataFrame({"Latitude": imputed_data["lat"],
                              "Longitude": imputed_data["lng"],
                              "Town": imputed_data["town"]})

train_map_data = pd.DataFrame({"Latitude": mrt_locations["lat"],
                               "Longitude": mrt_locations["lng"]})

custom_palette = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728', '#9467bd', '#8c564b',
```

```
                   '#17becf', '#9edae5', '#393b79', '#5254a3', '#6b6ecf', '#9c9ede',
                   '#cedb9c', '#8c6d31', '#bd9e39', '#e7ba52']

sns.set(style="whitegrid")
plt.figure(figsize=(10, 6))

sns.scatterplot(x="Longitude", y="Latitude", hue="Town", data=map_town_data, palett
sns.scatterplot(x="Longitude", y="Latitude", data=train_map_data, facecolor="red",
plt.legend(title="Towns in Singapore", loc="center left", bbox_to_anchor=(1, 0.5))

plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.title("Map of HDB resale flats with MRT & LRT  stations from the period of 2019

plt.show()
```




In [21]:
```
corr_matrix = imputed_data.select_dtypes(include=['float64', 'int64']).corr()
sns.heatmap(corr_matrix)
plt.show()
```




#### From the heatmap shown above, we theorised that floor_area_sqm and remaining_lease will be a good predictor of resale price, while mrt_dist will not contribute much in predicting the resale_price

# Task 5: Modeling and visualization

### Feature selection for model training

#### To reduce the complexity of the model and prevent model overfitting, we have discarded:

##### 1) features which are too sparse(block & street name)

###### 2) features which are similar(lease commence date) - the value is already calculated and represented by remaining lease

In [22]:
```
data = imputed_data[
    ["month", "town", "flat_type", "storey_range", "floor_area_sqm", "flat_model",
     "resale_price"]]
```

In [23]:
```
data.to_csv('output.csv', index=False)
```

### Step 3: Modelling

### 1) Linear Regression Model

We train a linear regression model as a baseline where we will improve on it using more complicated models which utilises techniques such as cross validation, baggging, stacking and ensembling.

In [24]:
```
data = pd.read_csv('output.csv')
```

In [25]:
```
# Data preparation
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error

# Split data into predictors and target
X = data.drop('resale_price', axis=1)
X = X.drop('month', axis=1)
y = data['resale_price']

# Split the dataset into training (90%) and test (10%) sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_sta
```

### Preprocessing for categorical features

#### Before piping the data into the regression model, we performi 1 hot encoding to transform Categorial data (which are text data) into one hot encoding to match the input format of the Linear Regressor

In [26]:
```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

# Define columns that need encoding
categorical_features = ['town', 'flat_type', 'storey_range', 'flat_model']

# OneHotEncoder for categorical data within a ColumnTransformer
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features)
    ],
    remainder='passthrough'  # Include all other columns in the model unchanged
)

# Create a pipeline that includes preprocessing and the linear model
LR_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', LinearRegression())
])

# Train the model
LR_model.fit(X_train, y_train)

# Predict on the test data
y_pred = LR_model.predict(X_test)
```

```
# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
rmse = (mean_squared_error(y_test, y_pred))**0.5

print('RMSE: {:.2f}'.format(rmse))
print('MAE: {:.2f}'.format(mae))
print('r2: {:.2f}'.format(r2))
```

```
RMSE: 79845.39
MAE: 64428.02
r2: 0.77
```

### 2) Decision Tree

With the baseline identified, we proceeded to experiment with more complex models such as DecisionTreeRegressor. The DecisionTreeRegressor is a versatile machine learning model used for regression tasks that predicts continuous outcomes by splitting data into increasingly homogeneous subsets. It constructs a tree-like model of decisions based on the values of the input features, making it highly interpretable and easy to visualize.

By using the decision tree regressor, we are able to improve the RMSE from 79845 to 54105, with a 47% improvement.

In [27]:
```
from sklearn.tree import DecisionTreeRegressor

DT_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', DecisionTreeRegressor(random_state=42))
])

# Train the model
DT_model.fit(X_train, y_train)

# Predict on the test data
y_pred = DT_model.predict(X_test)

# Evaluate the model

r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
rmse = (mean_squared_error(y_test, y_pred))**0.5

print('RMSE: {:.2f}'.format(rmse))
print('MAE: {:.2f}'.format(mae))
print('r2: {:.2f}'.format(r2))
```

```
RMSE: 54104.85
MAE: 36034.01
r2: 0.90
```

### 3) Hyperparameter tuning on Decision Tree Regressor

Then, the model is finetuned by optimizing the parameters that govern the training process. In the cell below, we test various combinations of hyperparameters to determine the most effective settings for the Decision Tree Regressor including, max_depth, min_samples_split and min_samples_leaf.

It shows significant improvement (6.1%) with the RMSE decreasing from 54105 to 50984.

In [28]:
```
from sklearn.model_selection import GridSearchCV

# Define the parameter grid
param_grid = {
    'regressor__max_depth': [None, 10, 20, 30],  # Maximum number of levels in each
    'regressor__min_samples_split': [2, 10, 20],  # Minimum number of samples requi
    'regressor__min_samples_leaf': [1, 5, 10]  # Minimum number of samples required
}

grid_search = GridSearchCV(estimator=DT_model, param_grid=param_grid, scoring='neg_

# Fit GridSearchCV
grid_search.fit(X_train, y_train)

# Get the best parameters and best score
print("Best parameters:", grid_search.best_params_)
print("Best score:", grid_search.best_score_)

best_model = grid_search.best_estimator_

# Predict on the test data
y_pred = best_model.predict(X_test)

# Evaluate the model

r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
rmse = (mean_squared_error(y_test, y_pred))**0.5

print('RMSE: {:.2f}'.format(rmse))
print('MAE: {:.2f}'.format(mae))
print('r2: {:.2f}'.format(r2))
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
Best parameters: {'regressor__max_depth': None, 'regressor__min_samples_leaf': 1, 'r
egressor__min_samples_split': 10}
Best score: -2702001284.5219145
RMSE: 50984.10
MAE: 34885.60
r2: 0.91
```

## Note: The below part is experimental and requires the installation of additional packages!

In [37]:
```
!pip install autogluon
# !pip install -U scikit-learn==1.4.0
```

### 4) AutoML

By referring to the paper AutoGluon-Tabular, we have tried the best performing AutoML model which is able to automatically select relevant models based on our modelling task (regression) such as KNN, RandomForest, LightGBM, XGBoost. Then, a final model is trained using ensembling where the output of the most performant models are weighted.

By doing so, we are able to reduce the RMSE from 50984 to 25716.

Local Image

In [30]:
```
# Initialisation
from autogluon.tabular import TabularDataset, TabularPredictor

# Train test split
train, test = train_test_split(data, test_size=0.1, random_state=0)
train_data = TabularDataset(train)
test_data = TabularDataset(test)
```

In [31]:
```
label = 'resale_price'
save_path = './AutogluonModels/small'
try:
    predictor = TabularPredictor.load(save_path)
except:
    # Retraining will take around 60 seconds
    presets = ['good_quality', 'optimize_for_deployment']
    predictor = TabularPredictor(label=label, path=save_path).fit(train_data, prese
```

In [32]:
```
predictor.evaluate(test_data)
```

Out[32]:
```
{'root_mean_squared_error': -28650.780324820356,
 'mean_squared_error': -820867213.2211133,
 'mean_absolute_error': -20450.017244982548,
 'r2': 0.9707724441181854,
 'pearsonr': 0.9852810733672099,
 'median_absolute_error': -14724.5625}
```

In [33]:
```
results = predictor.evaluate(test_data)

print('RMSE: {:.2f}'.format(-results['root_mean_squared_error']))
print('MAE: {:.2f}'.format(-results['mean_absolute_error']))
print('r2: {:.2f}'.format(results['r2']))
```

```
RMSE: 28650.78
MAE: 20450.02
r2: 0.97
```

#### Feature importance

By calculating the feature importance scores for the given model via permutation importance, we found that the town and flat_type of the hdb flat have the highest importance when predicting the resale price.

In [34]:
```
predictor.feature_importance(test_data)
```

Out[34]:

| | importance | stddev | p_value | n | p99_high | p99_low |
|---|---|---|---|---|---|---|
| **town** | 106068.756376 | 1667.738286 | 7.331617e-09 | 5 | 109502.652558 | 102634.860194 |
| **flat_type** | 85959.846495 | 1352.574806 | 7.353609e-09 | 5 | 88744.816715 | 83174.876276 |
| **month** | 59488.467628 | 473.545541 | 4.817929e-10 | 5 | 60463.504443 | 58513.430813 |
| **remaining_lease** | 57255.777302 | 1188.005105 | 2.222941e-08 | 5 | 59701.896234 | 54809.658370 |
| **floor_area_sqm** | 43517.972184 | 1176.790124 | 6.410315e-08 | 5 | 45940.999314 | 41094.945054 |
| **flat_model** | 24563.499687 | 502.472489 | 2.100038e-08 | 5 | 25598.097487 | 23528.901888 |
| **mrt_dist** | 18048.738272 | 713.642695 | 2.926930e-07 | 5 | 19518.138445 | 16579.338099 |
| **storey_range** | 16548.739849 | 652.336897 | 2.891413e-07 | 5 | 17891.910536 | 15205.569161 |

# Demo

**With the trained model, we are able to test out our model for our potential users (potential buyer searching for HDB flat near NUS on PropertyGuru):**

In [35]:
```
# Search criteria: a relatively new house near NUS
month = '2024-04-24'
town = 'CLEMENTI'
flat_type = '3 ROOM'
storey_range = '10 TO 12'
floor_area_sqm = 90
flat_model = 'New Generation'
remaining_lease = 90
mrt_distance = 1.0

# hdb_search = data.sample(1)

hdb_search = pd.DataFrame([[month, town, flat_type, storey_range, floor_area_sqm, f
hdb_search
```

Out[35]:

| | month | town | flat_type | storey_range | floor_area_sqm | flat_model | remaining_lease |
|---|---|---|---|---|---|---|---|
| **0** | 2024-04-24 | CLEMENTI | 3 ROOM | 10 TO 12 | 90 | New Generation | 90 |

In [36]:

```
predictor.predict(hdb_search)
```

Out[36]:

```
0    629813.625
Name: resale_price, dtype: float32
```

# Conclusion

In the data preparation stage, we selected the most relevant data by filtering out the outliers. We also enriched the data by calculating the distance of mrt to hdb.

In the EDA stage, we visualised the data to have a better understanding of the data and plotted a correlation matrix in a heatmap. We also preprocessed the data by applying one hot encoding on categorical data.

In the modelling stage, we saw that even simple model like linear regression can get a relatively good prediction. However, we found out that more complex model just as Decision Tree Regression is able to get a better results, and can be further enhance using hyperparameter tuning. Lastly, we also tried out the state of the art model which utilises ensembling for best model performance.

In the feature importance analysis, we also confirmed our hypothesis when calculating the correlation matrix, where mrt_distance does not really contribute in the prediction of sales price.

In conclusion, we have successfully trained a highly accurate sales price prediction model with a 5.1% error (RMSE = 25716, mean = 507,654) after going through the steps of EDA, data enrichment, data preparation and modelling.