Predicting HDB Resale Price

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DSIF 2

Agenda

Project

- Problem Statement
- Result and conclusion

Lessons Learned

- Geoprocessing
- Mapping
- ML Automation

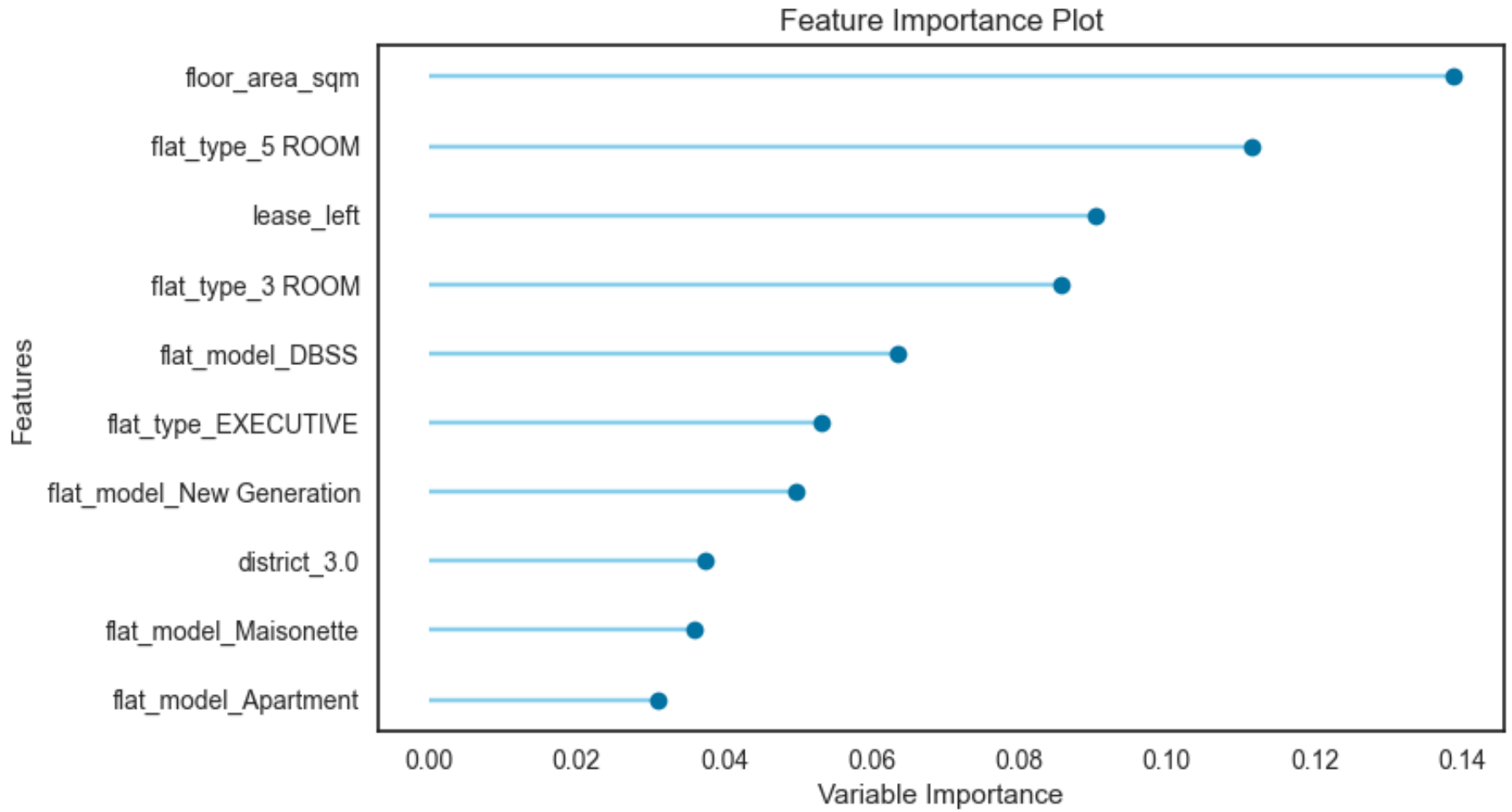
Predicting HDB Resale Price

- Property market is heating up
- Location, location, location
- Test hypothesis with regression model

Predicting HDB Resale Price

- Price data from data.gov.sg
  - HDB property information
  - HDB transacted prices
- Geographical data from onemap.gov.sg
  - Latitude and Longitude
  - Postcode

- **Features added: district code, number of MRT stations, primary school, and shopping centres within 1km.**
- **Random Forest Regressor model is best with RMSE difference of 4.37%**



- **In conclusion, the location features do not affect HDB price too much.**

- **Size, type, and how many years to the end of lease are more important.**

Geoprocessing

- **The earth is not flat**

World Geodetic System 1984 (WGS 84) used by onemap.gov.sg

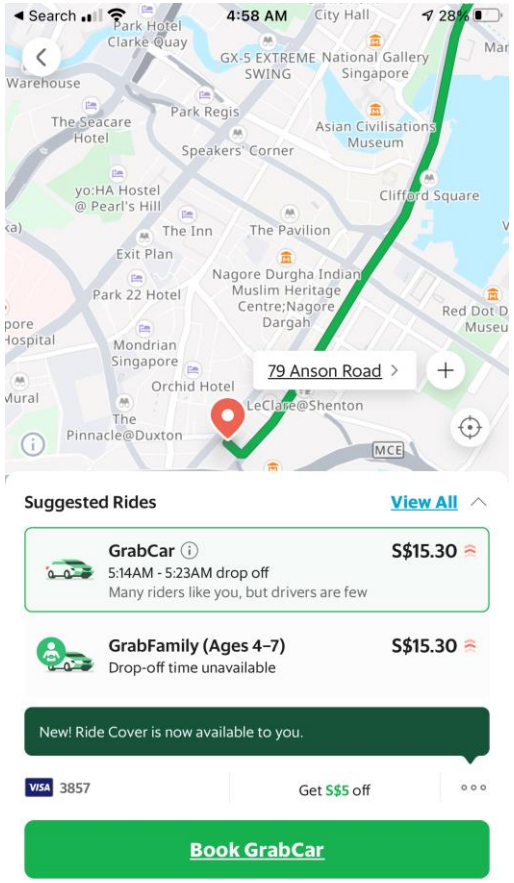
Calculate distance:

```
from pyproj import Geod
from shapely.geometry import Point, LineString
a = POINT (103.95337, 1.34319) # Simei MRT Station
b = POINT (103.98809, 1.38861) # 1 Changi Village Road
geod = Geod(ellps="WGS84")
distance = geod.geometry_length(LineString([a, b]))/1000  # km
```

Singapore is located at latitude 1.28967 and longitude 103.85007

Mapping


StarHub
4:55 AM
28%
General Assembly
See similar places
Tanjong Pagar
EW15
Haji Muhammad
Salleh Mosque
Maxwell Rd
Duxton Rd
Craig Rd
Gopeng St
Tras St
Union St
Straits Blvd
Maxwell Link
Stanley St
Telok Ayer St
General Assembly
4.6 ★★★★½ (73)


Search
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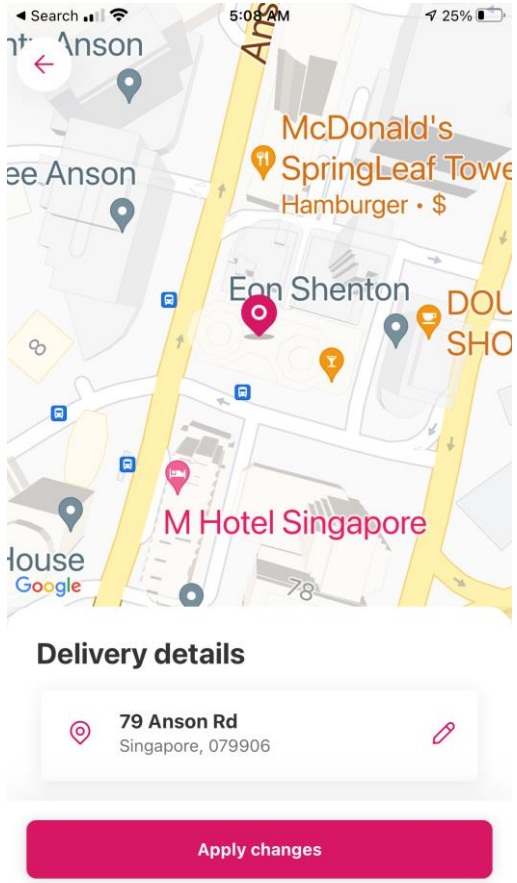
City Hall
28%
Park Hotel Clarke Quay
GX-5 EXTREME SWING
National Gallery Singapore
Warehouse
The Seacare Hotel
Park Regis
Asian Civilisations Museum
Speakers' Corner
yo:HA Hostel @ Pearl's Hill
Clifford Square
The Inn
The Pavilion
Exit Plan
Park 22 Hotel
Nagore Durgha Indian Muslim Heritage Centre;Nagore Dargah
Mondrian Singapore
Orchid Hotel
79 Anson Road
LeClare@Shenton
The Pinnacle@Duxton
MCE
Suggested Rides
View All
GrabCar
S$15.30
5:14AM - 5:23AM drop off
Many riders like you, but drivers are few
GrabFamily (Ages 4–7)
S$15.30
Drop-off time unavailable
New! Ride Cover is now available to you.
VISA 3857
Get S$5 off
Book GrabCar


Search
5:08 AM
25%
McDonald's
SpringLeaf Towe
Hamburger • $
Eon Shenton
M Hotel Singapore
Google
Delivery details
79 Anson Rd
Singapore, 079906
Apply changes

Mapping with Folium

```
import folium

map = folium.Map(location=[1.28967, 103.85007], zoom_start=14)

map
```

ML Automation with pycaret

Sample and Split	Data Preparation	Scale and Transform
• Train Test Split • Sampling	• Impute Missing Values • One-Hot Encoding • Ordinal Encoding • Cardinal Encoding	• Normalization • Transformation

Feature Engineering	Feature Selection	Unsupervised
• Feature Interaction • Polynomial Features • Group Features • Bin Numeric Features	• Feature Importance • Remove Multicollinearity • PCA • Ignore Low Variance	• Create Clusters • Remove Outliers

ML Automation with pycaret

Modules

- Classification
- Regression
- Clustering
- Anomaly Detection
- Natural Language Processing
- Association Rule Mining

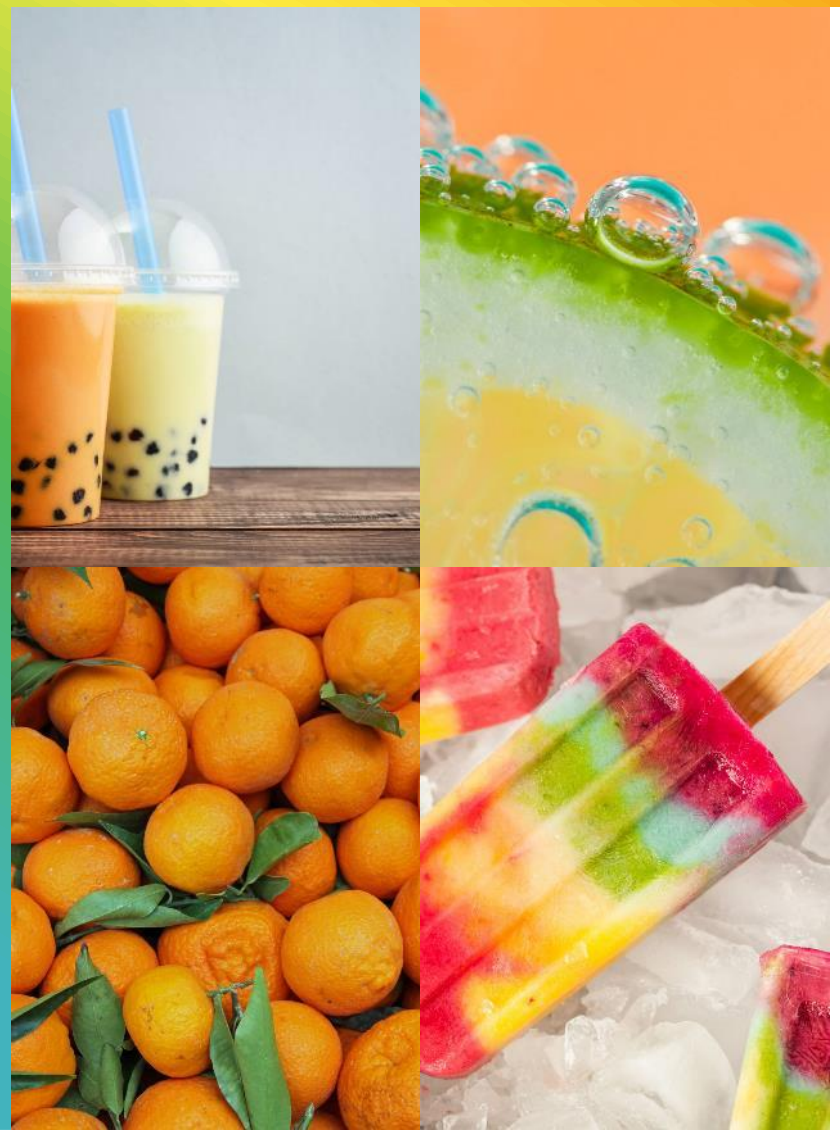
Automation with pycaret

```
from pycaret.regression import *
data = df_price.sample(frac=0.9, random_state=random_seed)
data_unseen = df_price.drop(data.index)
setup(data = data, target = 'resale_price', session_id=42)
best = compare_models(exclude = ['ransac'])
```

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
rf	Random Forest Regressor	23140.7051	1037548773.3689	32206.8675	0.9587	0.0693	0.0521	37.0500
catboost	CatBoost Regressor	24146.2746	1079360778.8293	32848.0380	0.9570	0.0706	0.0542	5.9330
et	Extra Trees Regressor	24662.5136	1171186720.0435	34217.3733	0.9534	0.0739	0.0555	48.6270
xgboost	Extreme Gradient Boosting	26177.1420	1264129702.4000	35548.0387	0.9497	0.0760	0.0587	11.3230
lightgbm	Light Gradient Boosting Machine	29976.8666	1642227201.0760	40520.2103	0.9346	0.0857	0.0668	0.5060
dt	Decision Tree Regressor	30790.2685	1902196054.1036	43610.0498	0.9243	0.0944	0.0693	0.8280

Automation with pycaret

```
rf_reg101 = create_model('rf')
rf_params = {'bootstrap’:[True,False],
             'max_depth’:[5,6,7],
             'max_features':['log2'],
             'max_leaf_nodes':[None],
             'min_impurity_decrease’:[0.0, 0.0001],
             'min_samples_leaf’:[5],
             'min_samples_split':[7],
             'n_estimators':[100]
            }
tuned_rf_reg101 = tune_model(rf_reg101, optimize='RMSE', custom_grid = rf_params)
predict_model(tuned_rf_reg101)
```



Summary

The hypothesis that location and other geodata is a strong price predictor is not true.

Use automation to reduce effort.

https://python-visualization.github.io/folium/

https://pycaret.org/