

Project 2 - Singapore Housing Data and Kaggle Challenge

Presented by: Tan Jun Jie, Timothy Chan and Kho Guan Guo
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Agenda

- Problem statement
- Factors for resale price
- Analysis of features affecting resale price
- Modelling: Methodology and Findings
- Conclusions
- Model Limitations
- Recommendations

Introduction: Backdrop

1. Singapore's HDB resale market is becoming increasingly competitive.
2. Buyer, seller and real estate agents are all competing for information.
3. Accurate information is important for decision making.

Problem Statement

Real Estate company needs a model for their agents to

1. Help themselves and clients better understand the **key features** that **affect pricing**.
2. Help **selling clients** know what to expect in terms of pricing in order to **list**.
3. Help **buying clients** **budget** in terms of what features they want from their purchase.

Factors Affecting Resale Price

1. Size
2. Location
3. Age
4. Amenities

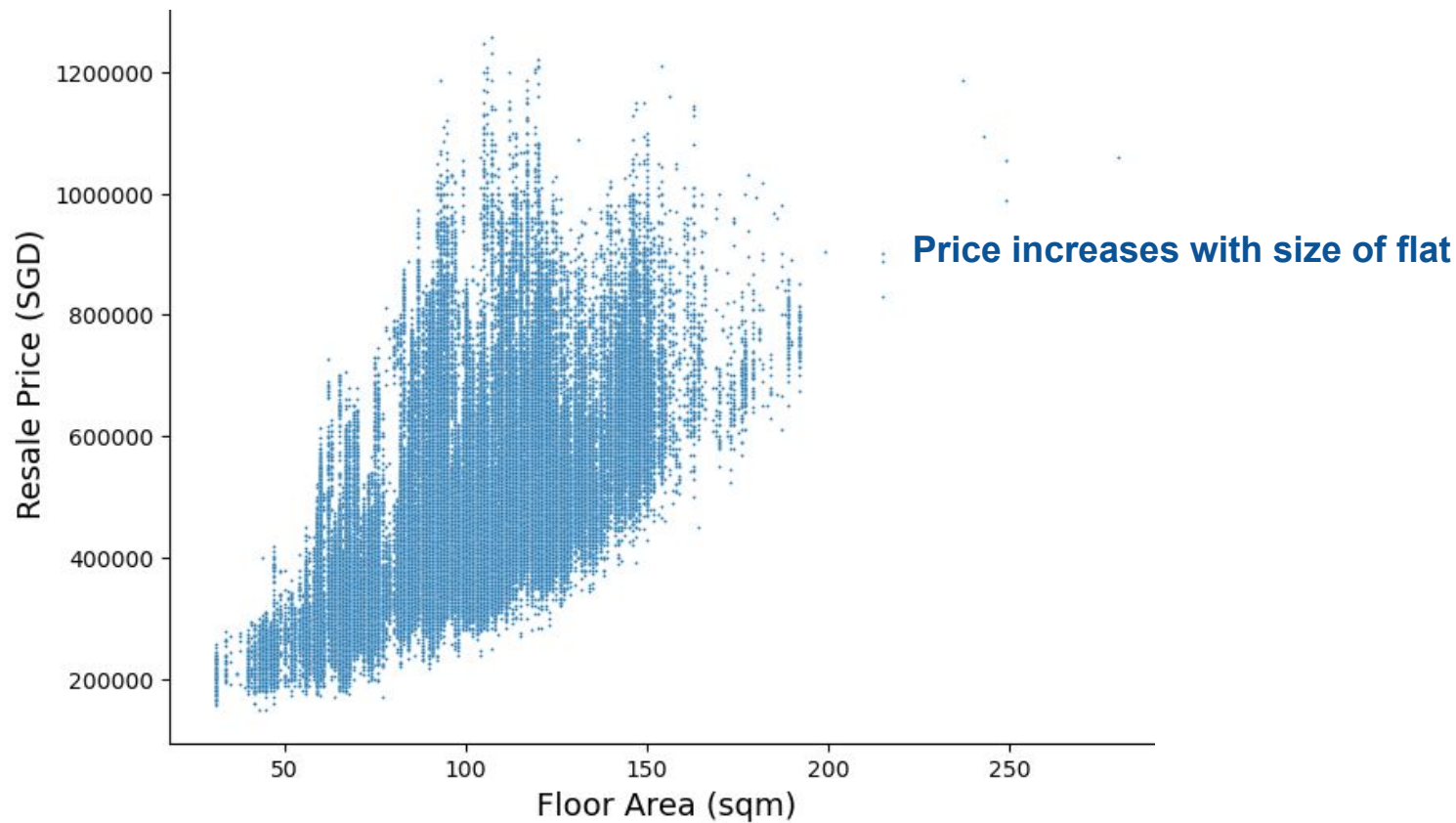
Analysis of features
affecting resale price

resale_price	1
postal	0.78
full_flat_type	0.74
bus_stop_name	0.68
floor_area_sqm	0.66
max_floor_lvl	0.49
planning_area	0.38
mid_storey	0.35
count_of_convenience_within_1km	0.13
bus_stop_nearest_distance	0.034
pri_sch_rank	-0.0035
pri_sch_nearest_distance	-0.013
hawker_nearest_distance	-0.015
average_dist_amenities	-0.062
sec_sch_rank	-0.076
mrt_nearest_distance	-0.13
total_dwelling_units	-0.15
distance_to_cityhall	-0.25
hdb_age	-0.35

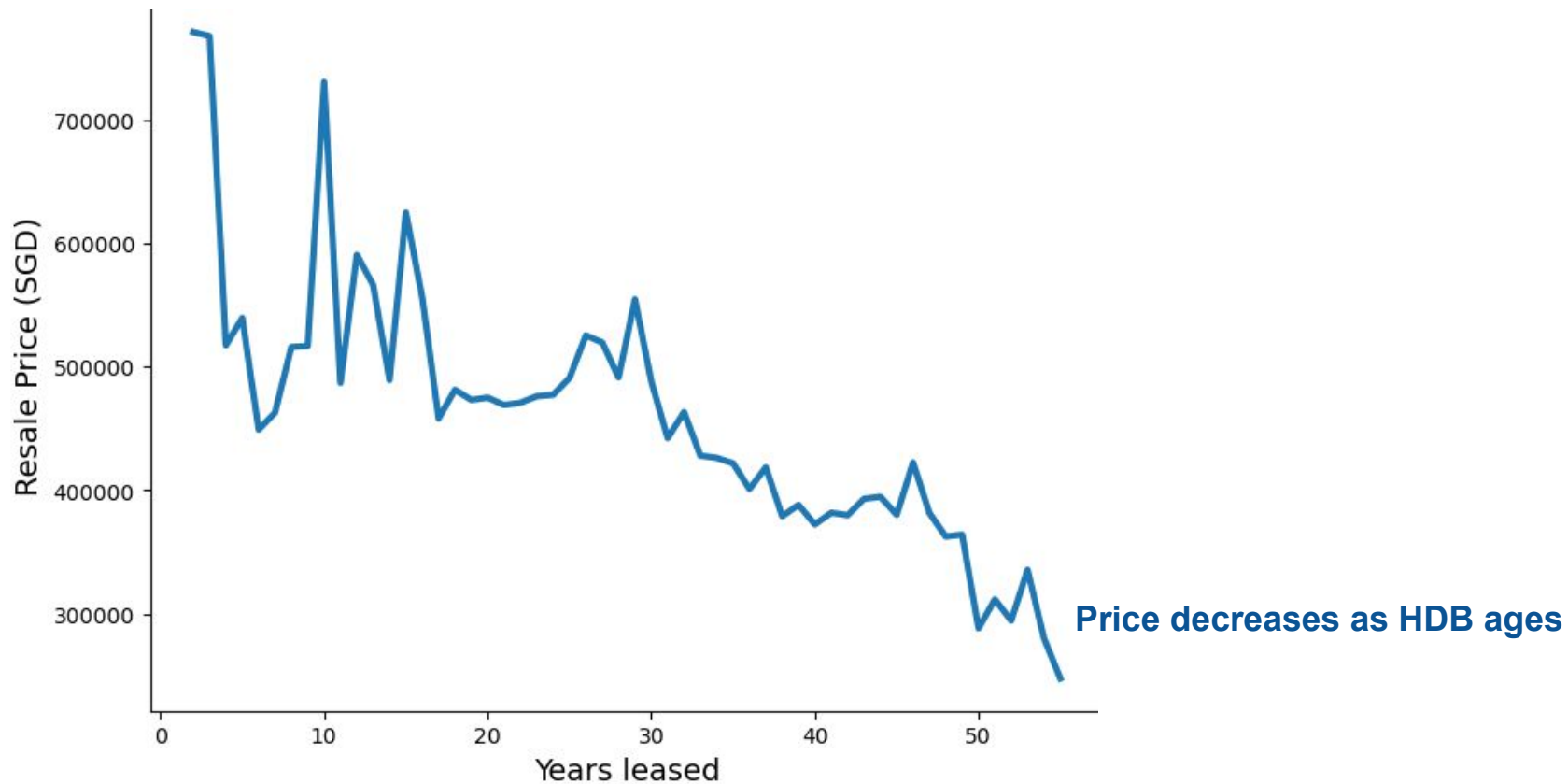
Strongest +ve corr: location, type of flats, size

Strongest -ve corr: age and distance to CBD

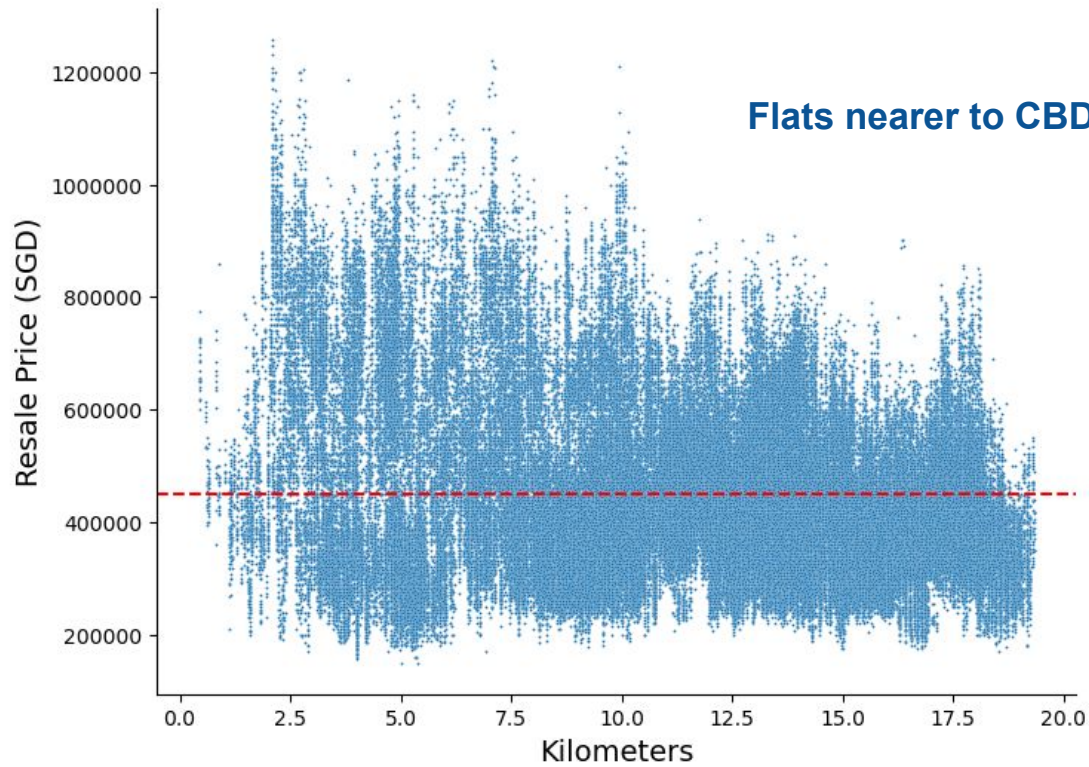
Resale Price vs Floor Area



Average Resale Price vs HDB age

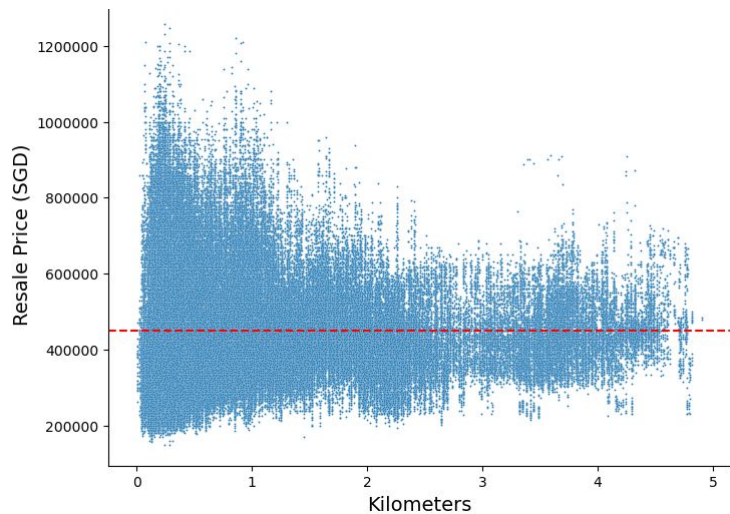


Resale Price vs Distance to City Hall

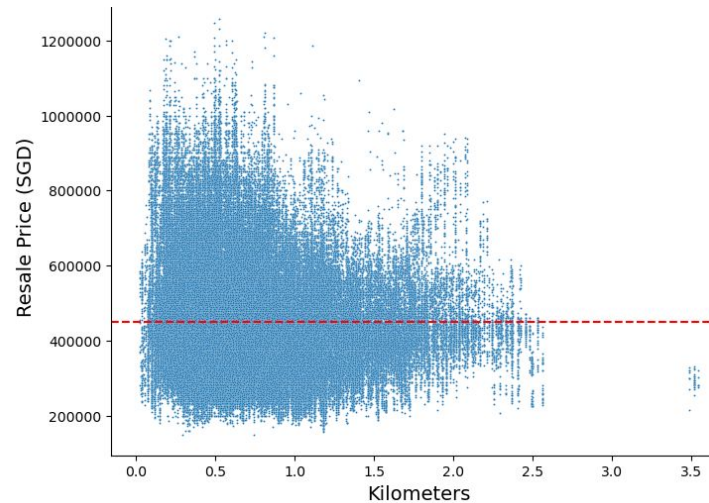


Flats nearer to CBD can command higher prices

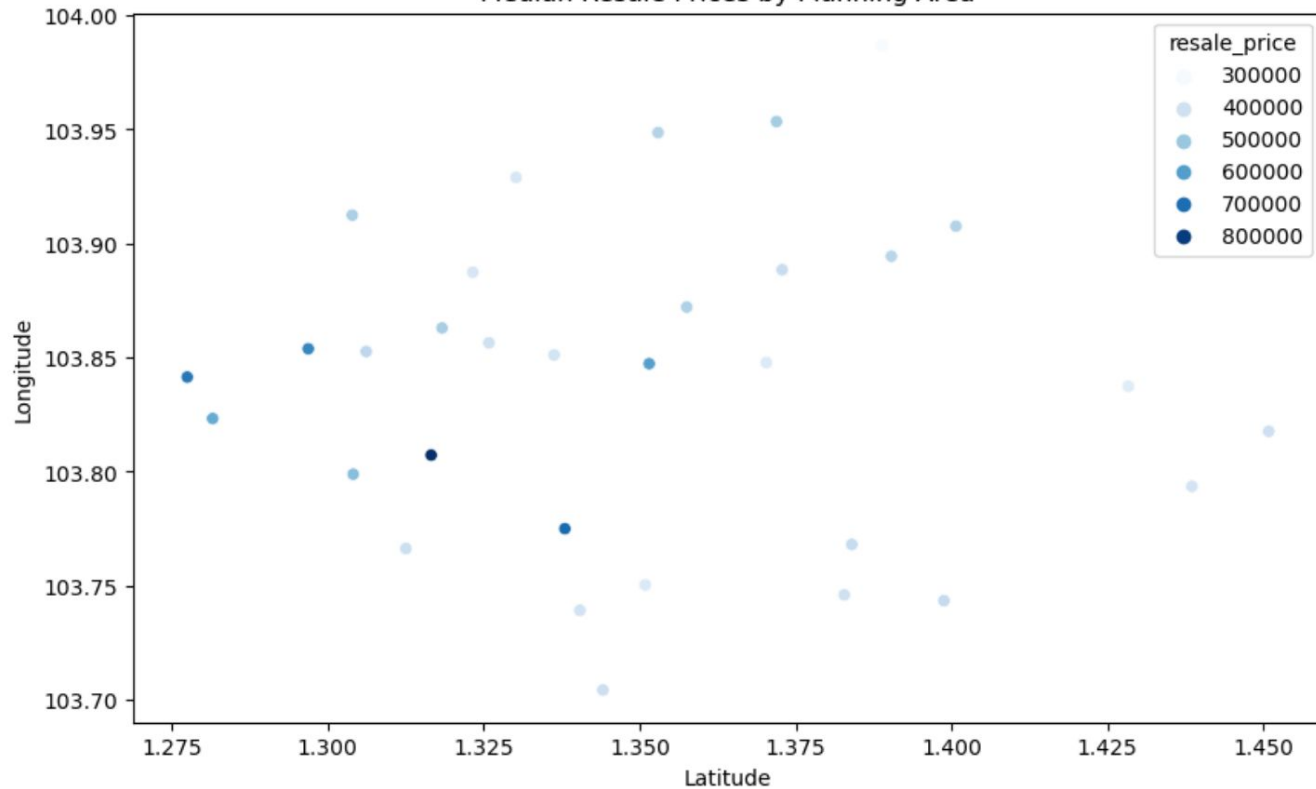
Resale Price vs Distance to Nearest Hawker



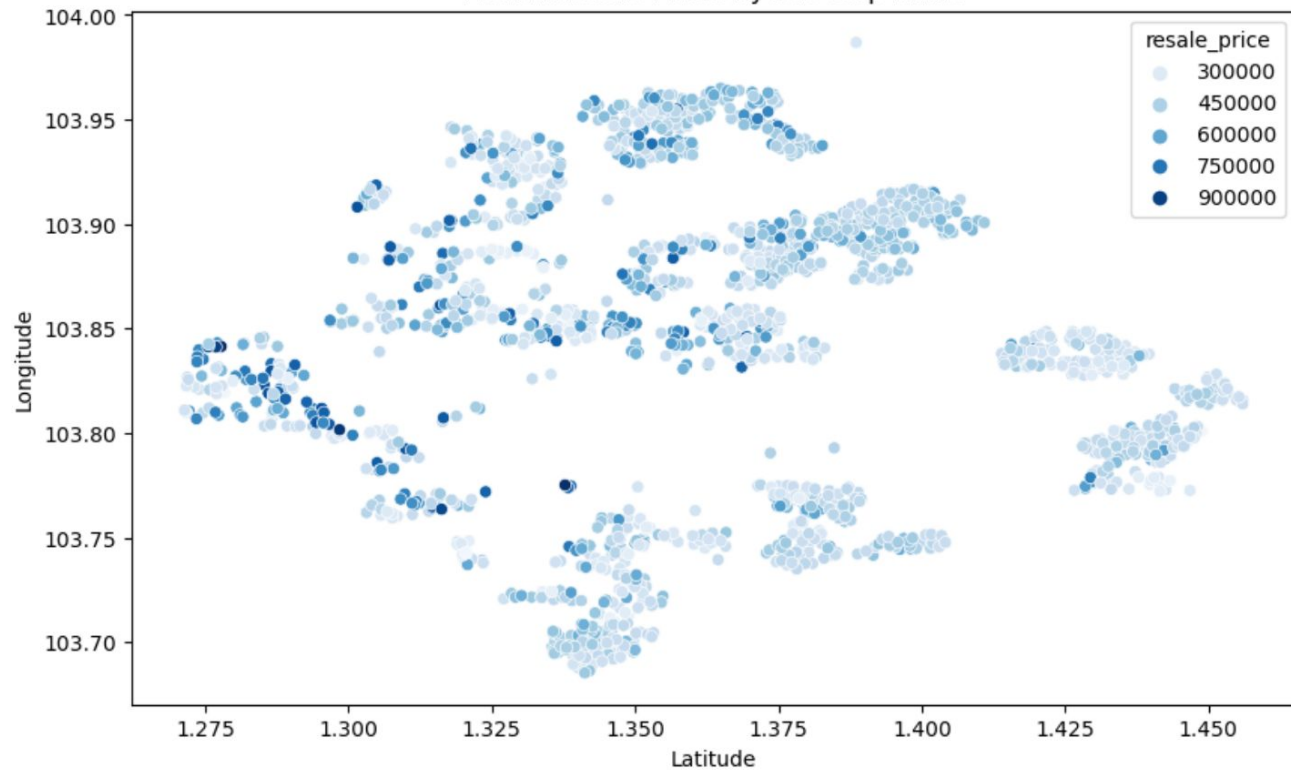
Resale Price vs Distance to Nearest MRT



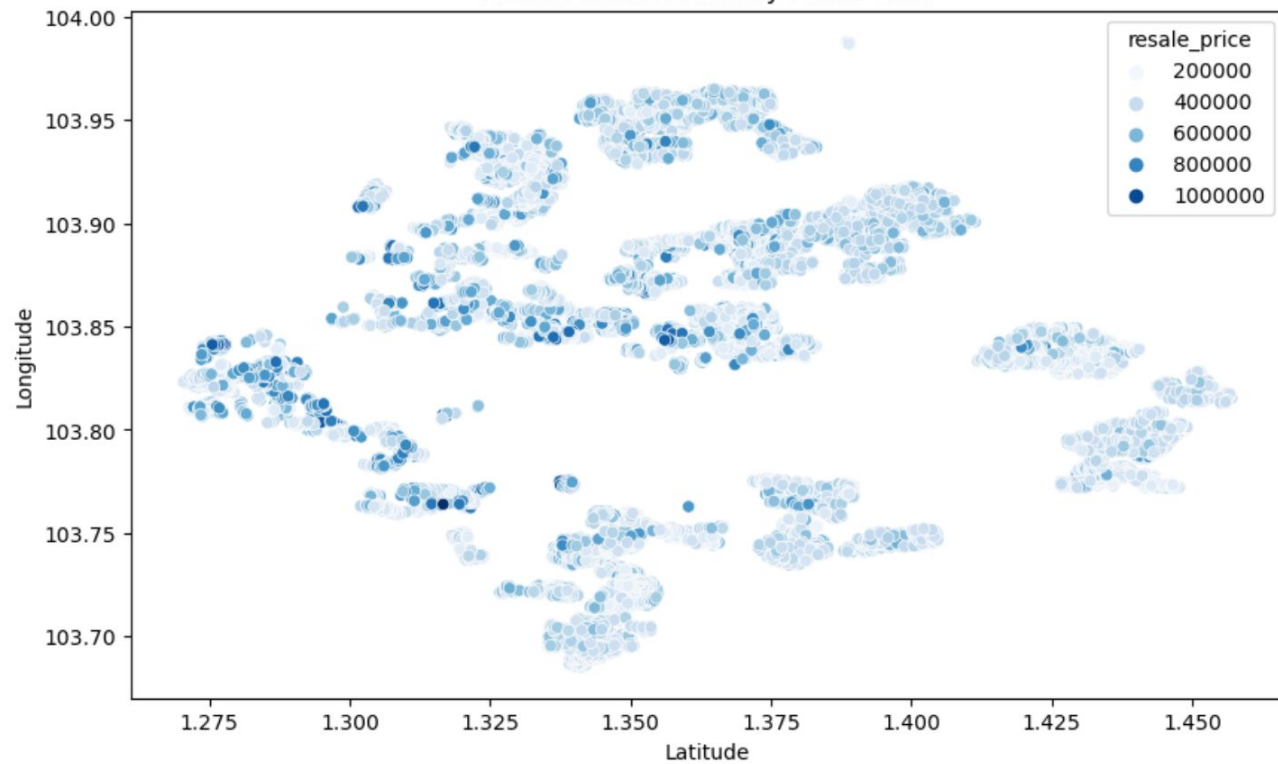
Median Resale Prices by Planning Area



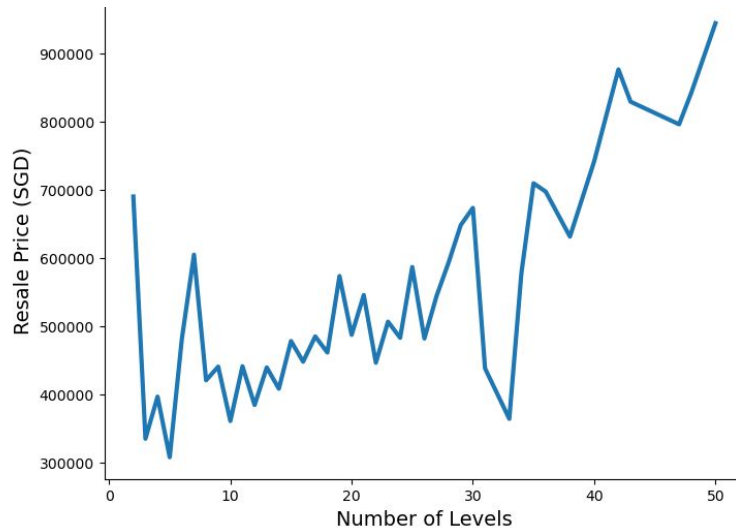
Median Resale Prices by Bus Stop Name



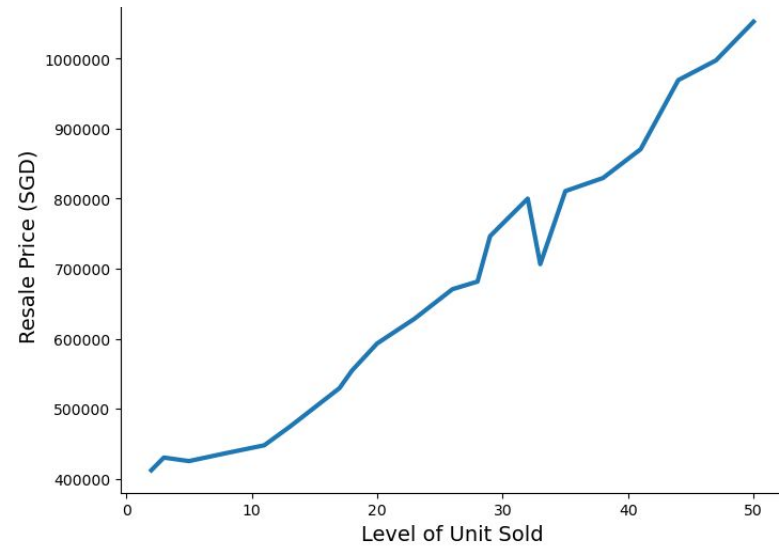
Median Resale Prices by Postal Code



Avg Resale Price vs Number of Levels



Avg Resale Price vs Level Of Unit Sold



Modelling

Linear Regression Model Benchmarking

Model	Number_of_Features	training_RMSE	baseline_RMSE	RidgeCV_RMSE	LassoCV_RMSE	Polynomial_4_train_RMSE	Polynomial_4_baseline_RMSE	Number_of_Poly_Features	Recommend
1	18	\$ 54,860	\$ 54,630	\$ 54,834	\$ 54,859	\$ 37,760	\$ 37,766	7,315	Yes
2	21	\$ 54,849	\$ 54,609	\$ 54,821	\$ 54,849	-	-	-	
3	28	\$ 54,571	\$ 54,314	\$ 54,550	\$ 54,571	-	-	-	

**All model feature inputs have been standard-scaled*

**RMSE - root mean squared error*

Simplicity or Accuracy?

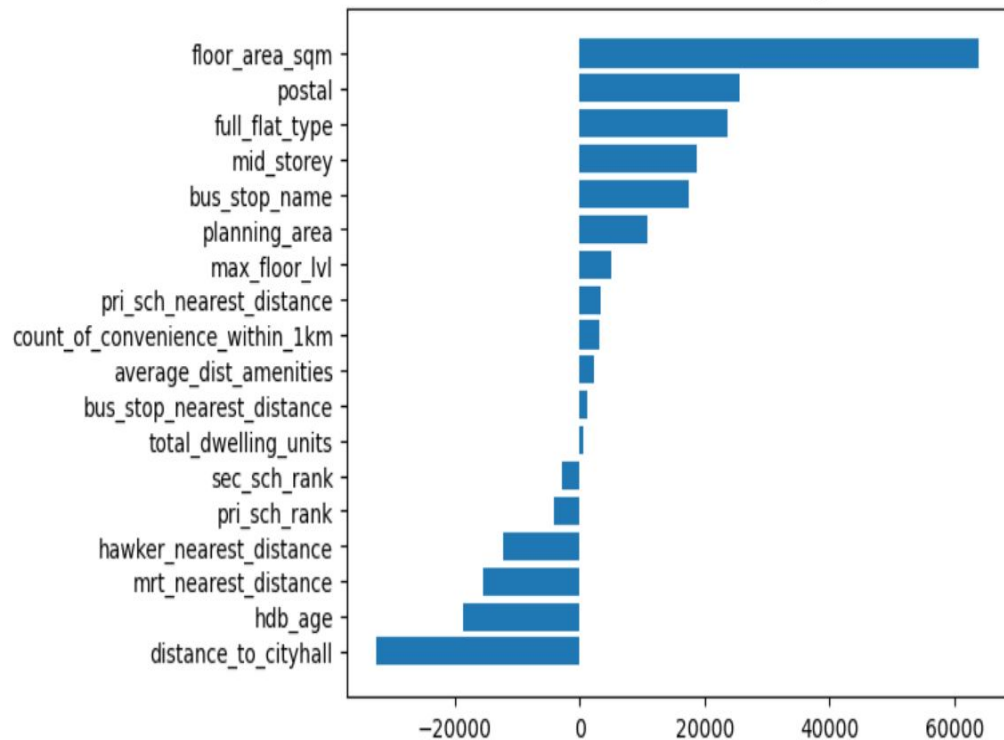
	Simple Model	Complex Model
Number of Features	18	7,315
Model Type	Ordinary Linear Regression	OLS with polynomial degree=4
Interpretability	Intuitive	Only a machine can!
Average Accuracy Score [^]	± 10% error	± 7% error
Types of features	Location, size, amenities, age factors	Location, size, amenities, age, plus interaction features up to a combination of <i>*four</i> features
Utility	Sufficiently Simple	Accuracy

[^]Average accuracy score is based on the R-squared score of each model

^{*}The optimal polynomial degree that produces the minimum error based on the set of 18 features is 4.

Housing Price Premia Ranking

Lasso Coefficients Ranking



“Size” premium

“CityHall” premium

“West” premium

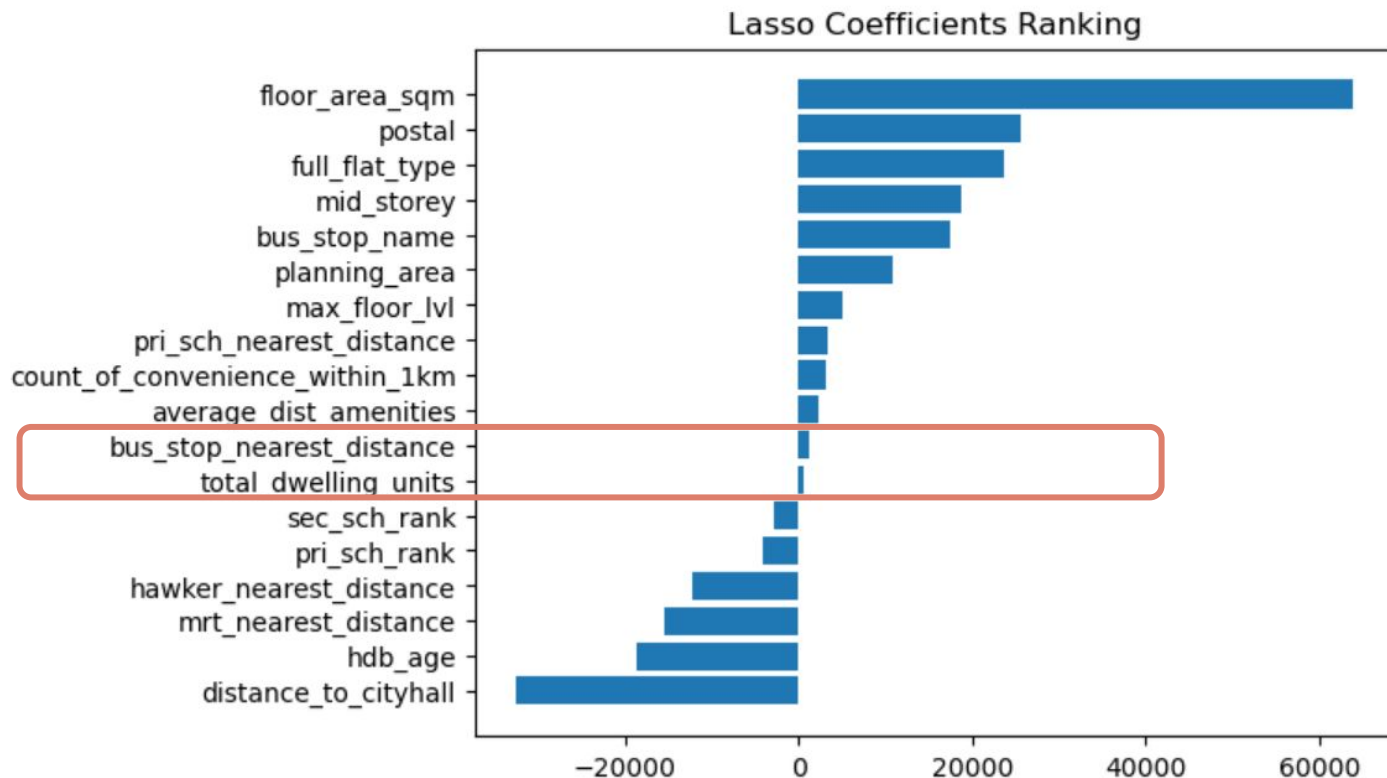
“Height” premium

“Age” premium

“School” premium

“Amenities” premium

Ranking the 18 features, it turns out that **total_dwelling_units** and **bus_stop_nearest_distance** are least significant.



Model Robustness

- No overfitting with consistent out-of-sample testing results
- High accuracy value that explains *at least* 80-90% of resale_price
- 18-feature model is simple to use and understand
- Captures the most important features from the four key factors of housing prices
 - Location
 - Size
 - Amenities
 - Age

Model Conclusions

- Location is not King! SIZE IS KING!
- Size > Location > Age > Amenities
- Locations closer to city centre (“City Hall”) are more expensive and taller!
- Locations in the West tend to command a higher premium
- Among the Amenities, proximity to MRT has the biggest premium
- Proximity to good schools is a bonus, not a primary consideration for most

Model Limitations

- Trained on historical data from 2012-2022. Model will need to be retrained on the new market regime.
- The Simple model with just 18 features does not capture sufficient value-add from feature interaction.
- The Complex polynomial model is unintuitive with 7,315 features despite its accuracy.
- Model can only capture 80-90% of price variation meaning clients still have 10-20% buffer with which they will need to budget for.
- HDB switched the resale housing price index to market forces on 1 January 2013.
 - Demand and supply factors, interest rates and govt policy (HDB cooling measures) not captured.

Recommendations

1. Use simple 18 feature OLS model
 - Clients can expect +/- \$55,000 on the predicted price.
 - Simple and easy to use.
 - Accurately captures the predictive value of the 4 mentioned factors.
2. Agents can advise clients based on a structure given in this model. Size > Location > Age > Amenities.
3. Accurate budgeting for Buy/Sell advice can be given based on the model. (80-90% accuracy)
4. Use the 4 main features to help client narrow down search or listing parameters for the best results.