Predicting HDB Resale Prices in Singapore

Using regression models and neural networks

Agenda

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Problem Statement

Problem Description

In recent months, HDB resale prices has been steadily increasing and has become a common discussion topics especially amongst first time young buyers for affordability.

I am curious to understand the **features influencing HDB resale prices** and help potential buyers find out if the current asking prices of HDBs are reasonable by **using regression models to predict HDB prices**.

Why is this a problem?

The increasing cost of living comes to mind for young Singaporeans looking to purchase a home and start a family. This model would serve a guide for them as part of their home purchase decision making process.

How will we tackle the problem

Regression models:

1. Linear
2. Lasso
3. Ridge
4. Random Forest
5. ExtraTrees
6. XGBoost
7. Neural Networks

How will we evaluate the results

Success Metrics: Model performance will be guided by RMSE score. We will seek to find the best performing model based on the lowest score.

Structured data

Over 200,000 rows and 10 features

	month	town	flat_type	block	street_name	storey_range	floor_area_sqm	flat_model	lease_commence_date	remaining_lease	resale_price
0	2017-01	ANG MO KIO	2 ROOM	406	ANG MO KIO AVE 10	10 TO 12	44.0	Improved	1979	61 years 04 months	232000.0
1	2017-01	ANG MO KIO	3 ROOM	108	ANG MO KIO AVE 4	01 TO 03	67.0	New Generation	1978	60 years 07 months	250000.0
2	2017-01	ANG MO KIO	3 ROOM	602	ANG MO KIO AVE 5	01 TO 03	67.0	New Generation	1980	62 years 05 months	262000.0
3	2017-01	ANG MO KIO	3 ROOM	465	ANG MO KIO AVE 10	04 TO 06	68.0	New Generation	1980	62 years 01 month	265000.0
4	2017-01	ANG MO KIO	3 ROOM	601	ANG MO KIO AVE 5	01 TO 03	67.0	New Generation	1980	62 years 05 months	265000.0

Sourced from data.gov.sg

Data Collection

Calling OneMap API

Scraping longitudes and latitudes of:

- the transacted HDBs
- Nearby amenities such as:
  - MRT stations
  - Primary and secondary schools
  - malls

Feature Engineering

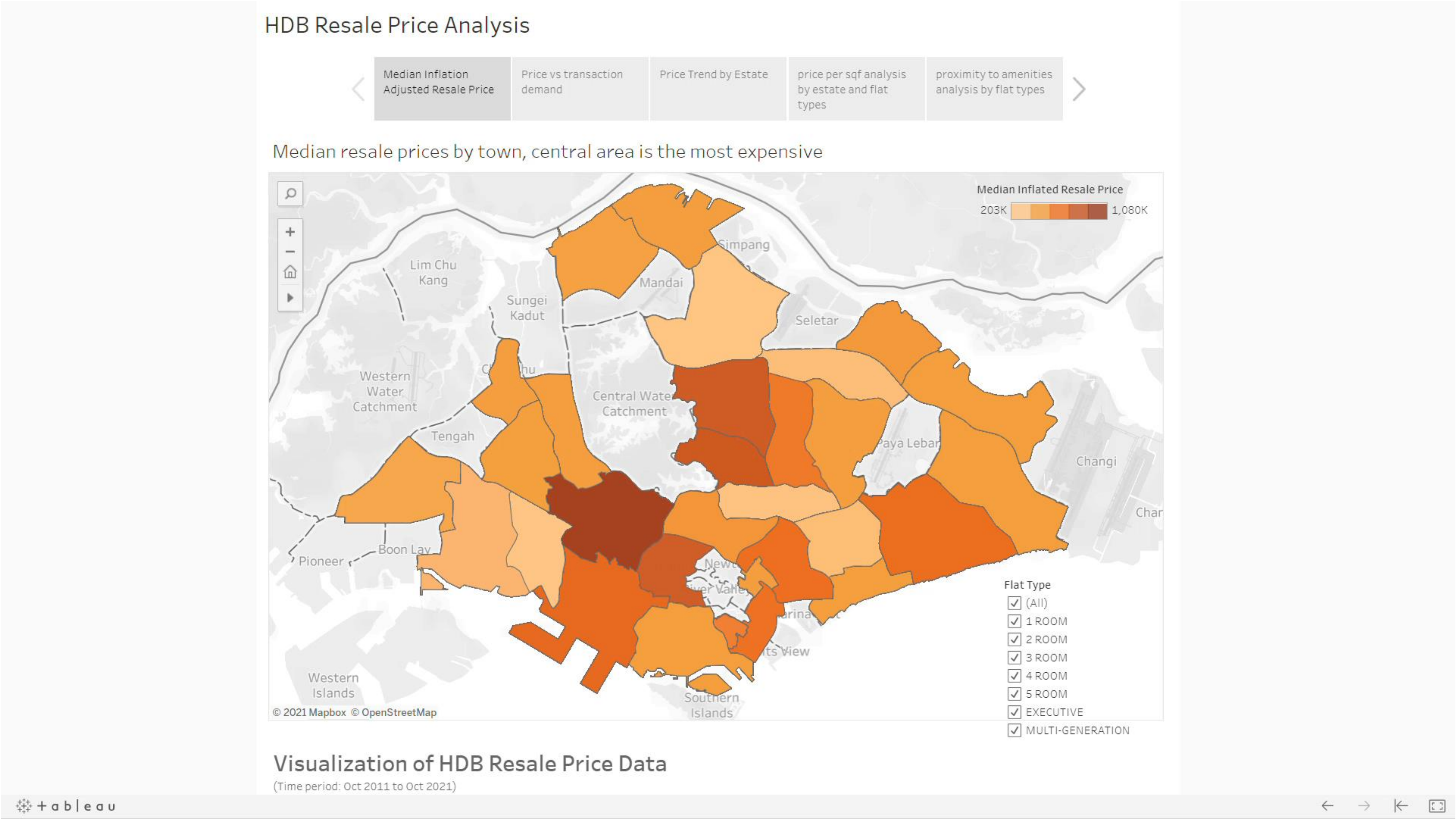
- Created new distance-based features such as:
  - HDB's proximity to nearest
    - MRT station
    - Primary school
    - Secondary school
    - Mall
    - CBD

- Other created features include:
  - Year transacted
  - Resale price per sqf
  - Average storey (floor)
  - Age of HDB
  - Inflation adjusted resale price

Exploratory Data Analysis

Visualized with Tableau

Link to Tableau visualization [here]()



Modeling Process

Baseline Model

- Using mean resale price from train dataset

- Train RMSE: 144,232
- Test RMSE: 142,975

Preprocessing

- Standard Scaler
- Dummify categorical features:
  - Town
  - Flat type
  - Flat model
  - Year transacted

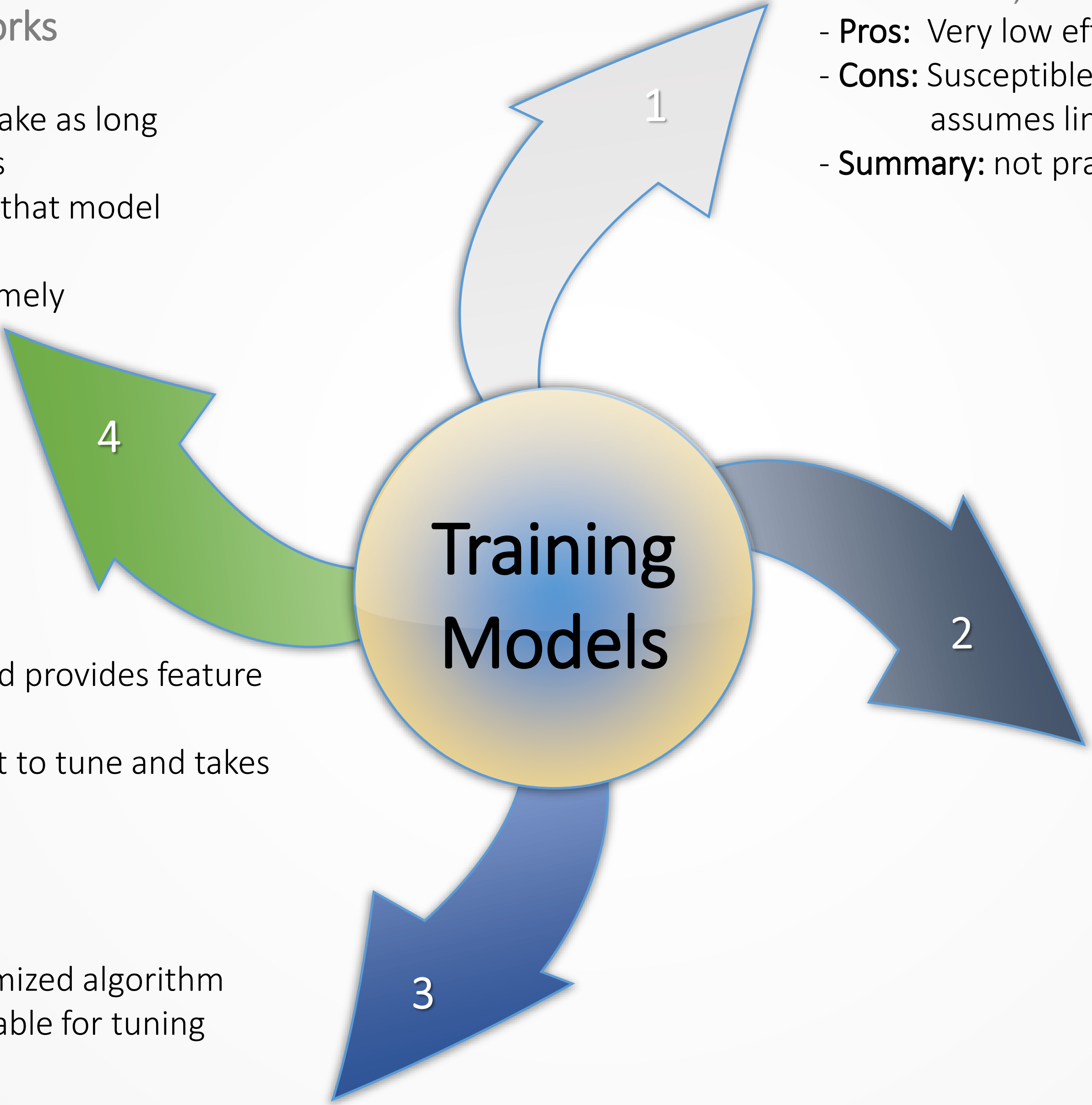
Training Models

- Linear Regression
- Lasso Regression
- Ridge Regression
- Random Forest
- ExtraTrees
- XG Boost
- Feed Forward Neural Network
  - Vanilla model
  - Weight Decay
  - Dropout

Evaluation

- RMSE is our guiding metric

Model Evaluation



Linear Regression

Test RMSE: 52,005

- **Pros:** Very low effort, extremely fast to train
- **Cons:** Susceptible to overfitting and only assumes linear relationship
- **Summary:** not practical in most situations

Regularized Linear Regression

Lasso and Ridge

Test RMSE: 52,005 and 52,792

- **Pros:** Low effort, easy to train
  Alpha hyperparameter helps to reduce likelihood of overfitting
- **Cons:** may increase the bias

Tree-based models

Random Forest & ExtraTrees

Test RMSE: 24,066 and 24,865

- **Pros:** Reasonable RMSE score and provides feature importance for interpretability
- **Cons:** tends to overfit, high effort to tune and takes long time to train

XG Boost

RMSE: 23,372

- **Pros:** medium effort, highly optimized algorithm with many hyperparameters available for tuning
- Best RMSE score

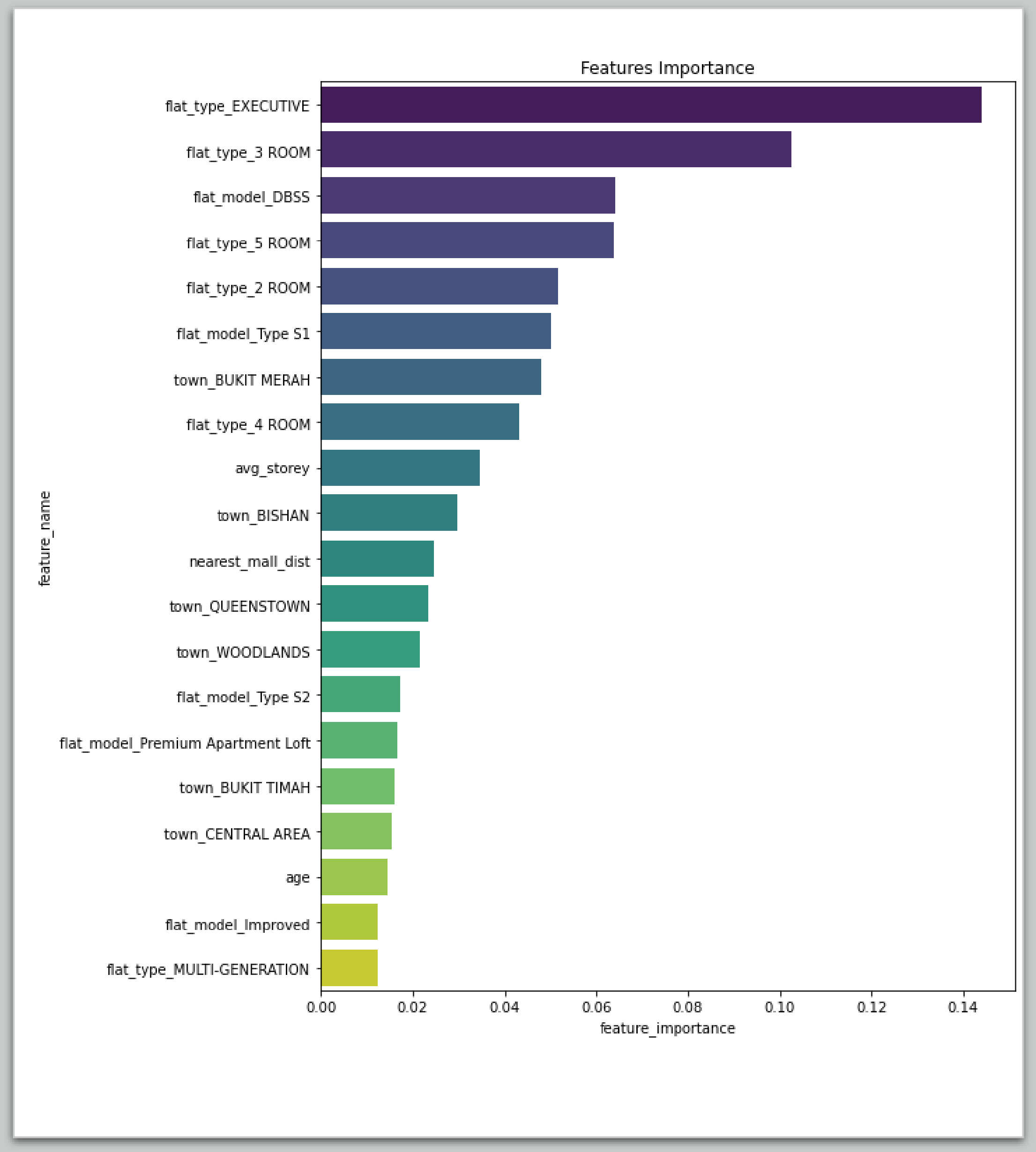
Feed forward neural networks

Test RMSE: 27,645 to 29,626

- **Pros:** Medium effort, doesn't take as long as the tree-based models
- **Cons:** Black box nature means that model isn't easily intepretable
- **Summary:** best used for extremely complex datasets

Feature Importance

- Overall, we had more physical housing features such as flat type and flat model, followed by location-based features like the town in which the HDB apartments were found in.
- Specifically, flat types like executive, 2-room, 3-room and 5-room were in the top 5 features.
- We noticed that towns located in the central part of Singapore made it into the list
- Interestingly, proximity to nearest mall was the only distance-based feature making into the list, which meant that proximity to malls had a greater influence in price than proximity to schools and mrt stations
- Age: HDBs are leasehold in nature, it would be natural that people would want to buy newer flats, thus an important feature



Conclusion and reflections

Tying back to the problem statement

- Using the best model, we discussed the important features which influenced a HDB's resale price
- We successfully ran different regression models in HDB price prediction and concluded that XG Boost performed the best

Model limitations

- HDB prices are driven by macro economic factors like status of the economy and inflation as well as housing policies

Reflections

- Good planning is half the battle
- Understanding the computing resources that you have and plan for contingencies

Next steps/how we can improve

Retrain

Retrain model with more data!
Try other models like support vector regression

Retune

Further tuning on hyperparameters!
- GridSearchCV
- RandomizedSearchCV

Collect

Scrape private residential data (condos)
- Explore the data and test our model's predictive capability

Deploy

Using Flask to develop a web application and deploy model online
- Allow users to input some HDB features and see a price estimate

Update: model is now deployed on Heroku!