

# PROJECT 3: DATA SPRINT

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# AGENDA

## PROJECT OVERVIEW

Background & Problem Statement  
Objectives  
Data Sources

## DATA PRESENTATION & ANALYSIS

Exploratory Analysis (EDA)  
Feature Engineering  
Insights from the Data

## MODELING & RESULTS

Correlation Analysis – What Drives Price?  
Model Overview  
Model Comparison  
What Singaporeans Really Value in an HDB Home?

## IMPACT & LESSONS

Assumptions & Caveats  
Business Impact & Recommendations  
Lessons Learned & Next Steps  
Retrospective

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# PROJECT OVERVIEW





## BACKGROUND

- Similar HDB flats (same town/size) can differ by S\$100k+ (e.g., S\$400k vs S\$550k).
- Key question: is the gap from floor level, MRT/schools, flat age, or market timing?
- Upfront, explainable pricing helps with faster decisions and fair negotiations.
- We will focus on observable drivers (e.g. flat attributes & location), not opaque or hard-to-interpret features.

**Team goal:** turn raw transactions into simple, defensible insights for everyday use.



## PROBLEM STATEMENT

- HDB resale prices are dynamic and competitive, shifting with buyer preferences, economic conditions, and location demand.
- WOW! agents need to deliver accurate, competitive price estimates across all flat types and neighborhoods.
- Without strong guidance, sellers risk undervaluing and buyers risk overpaying.
- Our goal is to build a transparent, data-driven model to support fair pricing and confident client advice.

# OBJECTIVES

## IDENTIFY KEY PRICE DRIVERS

- Analyze how variables such as flat size, age, location, and proximity to amenities (MRT, schools, malls, hawker centres) influence resale prices

## COMPARE PRICING PATTERNS

- Examine price variations between neighborhoods and flat models to highlight high-value and emerging areas.

## DEVELOP A PREDICTIVE MODEL FOR RESALE PRICE ESTIMATION

- Build and test data-driven models to estimate resale prices based on key property attributes

## VISUALIZE INSIGHTS FOR DECISION-MAKING

- Create interactive dashboards and visual tools to help agents and clients easily interpret price trends and factors

## SUPPORT BUSINESS STRATEGY AND CLIENT ADVISORY

- Use analytical findings to enhance client consultations, improve pricing accuracy, and strengthen WOW!'s market positioning

# DATA SOURCES



## DATASET

**train.csv** -- this data contains all of the training data for our model.

**test.csv** -- this data contains the test data for our model.

**sample\_sub\_reg.csv** -- An example of a correctly formatted submission to evaluate the model accuracy on the test data.



# DATA PRESENTATION & ANALYSIS



# EXPLORATORY DATA ANALYSIS

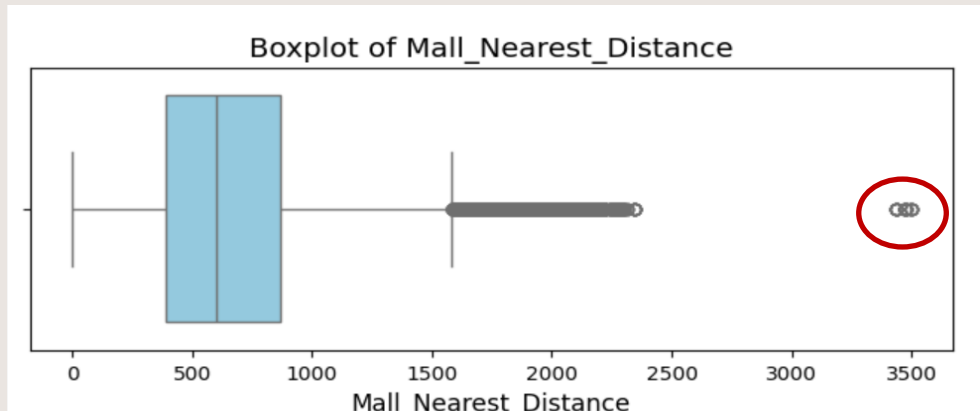
Dataset of 147,976 records and 49 variables

## DATA CLEANING

- **Identifying duplicates**
- **Identifying nulls** (7 columns)
  - Mall\_Nearest\_Distance
  - Mall\_Within\_500m
  - Mall\_Within\_1km
  - Mall\_Within\_2km
  - Hawker\_Within\_500m
  - Hawker\_Within\_1km
  - Hawker\_Within\_2km
- Verifying **data types**
- Checking **outliers**

## DATA HANDLING

- No duplicates found
- Replace nulls with 0 for 'Mall\_Within\_XX km' and 'Hawker\_Within\_XX km'
- Removing rows where by Mall\_Nearest\_Distance are nulls (829 rows)
- Changing data types (date, Boolean) for columns needed
- Remove outliers (Skewed high values)



Example of identifying skewed outliers



# FEATURE ENGINEERING

## (+) ADDED NEW FEATURES

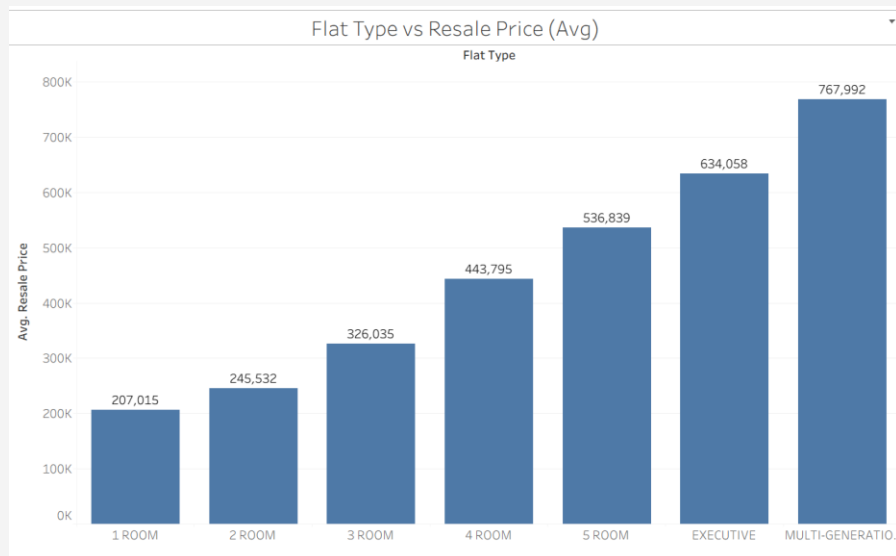
- floor\_level\_range
  - Floor categorised based of flat max floor
- years\_of\_lease\_left
  - 99 years – HDB age
- mrt\_region
  - Classify MRT names into country regions based to URA region guidelines

	mid_storey	max_floor_lvl	floor_level_range
0	11	25	Mid Lower Level
1	8	9	Upper Level
2	14	16	Upper Level
3	3	11	Mid Lower Level
4	2	4	Mid Upper Level
...	...	...	...
150629	5	12	Mid Lower Level
150630	5	16	Mid Lower Level
150631	11	15	Mid Upper Level
150632	8	10	Upper Level
150633	8	12	Mid Upper Level

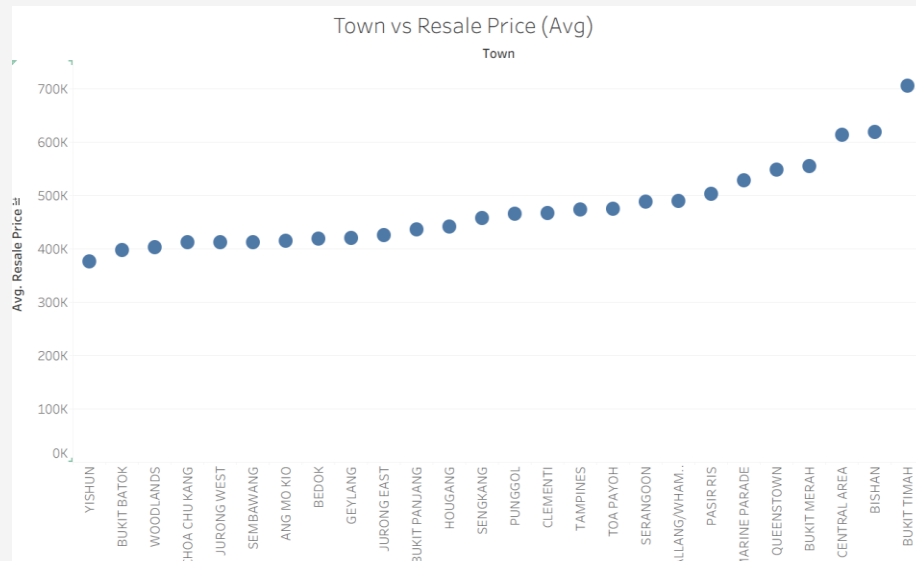
# INSIGHTS FROM THE DATA



Size matters



Location/Town

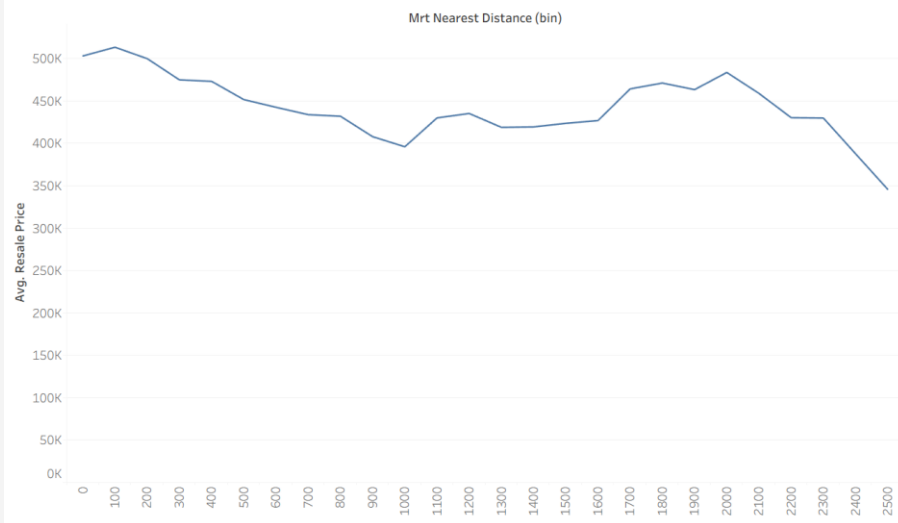


# INSIGHTS FROM THE DATA



## Amenities distance

Mrt Nearest Distance vs Price



## Age of HDB

Lease Commence Date vs Resale Price (Avg)



# MODELING & RESULTS



## (+) CROSS CHECK ON CORRELATIONS BTW FEATURES

## (-) CROSS CHECK ON CORRELATIONS BTW TARGET & FEATURES

# CORRELATION ANALYSIS

	resale_price
floor_area_sqft	0.65669984
commercial	-0.1408056
market_hawker	-0.0059146
multistorey_carpark	-0.0077384
Mall_Within_500m	0.08871682
Mall_Within_1km	0.08580538
Mall_Within_2km	0.11424498
Hawker_Within_500m	0.01278653
Hawker_Within_1km	0.09213981
Hawker_Within_2km	0.18514101
mrt_nearest_distance	-0.1274085
mrt_interchange	0.06455517
pri_sch_nearest_distance	-0.0072261
years_of_lease_left	0.35018899
2 ROOM	-0.1605935
3 ROOM	-0.5061808
4 ROOM	-0.0245584
5 ROOM	0.34785892
EXECUTIVE	0.38477496
Mid Lower Level	0.0087973
Mid Upper Level	0.015815
Upper Level	0.03554236
east	0.02128902
north	-0.1741129
north_east	0.009977
west	-0.1028206

## (1) CORRELATION BETWEEN FEATURES

- Mall/ Hawker within [ 500m | 1km | 2km ]

## (2) CORRELATION BETWEEN FEATURES & TARGET

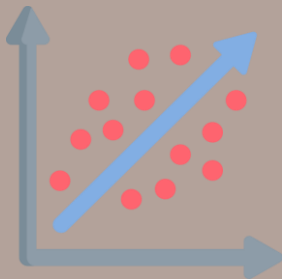
- Market Hawker
  - Multistorey Carpark
  - Pri School Nearest Distance
- } Almost close to 0 with no correlation

# MODEL OVERVIEW

## MODELS USED

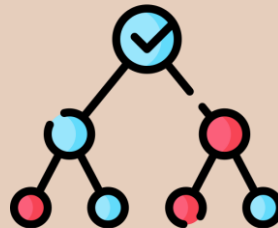
### LINEAR REGRESSION MODEL

"If one factor increases, how much does the price change?"



### XGBOOST

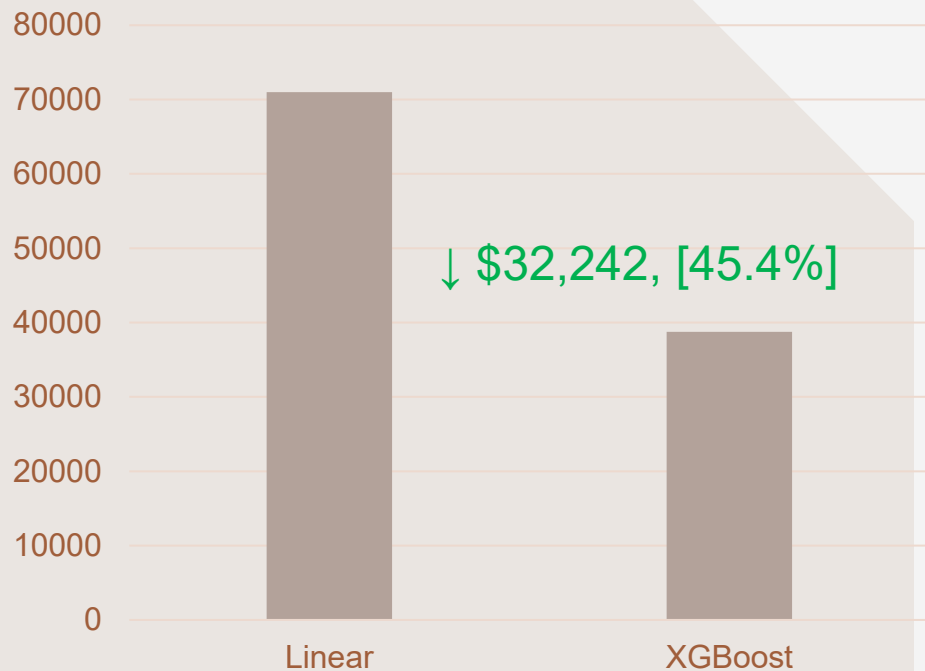
Instead of one line, it builds *hundreds of small trees* that learn from each other's mistakes.



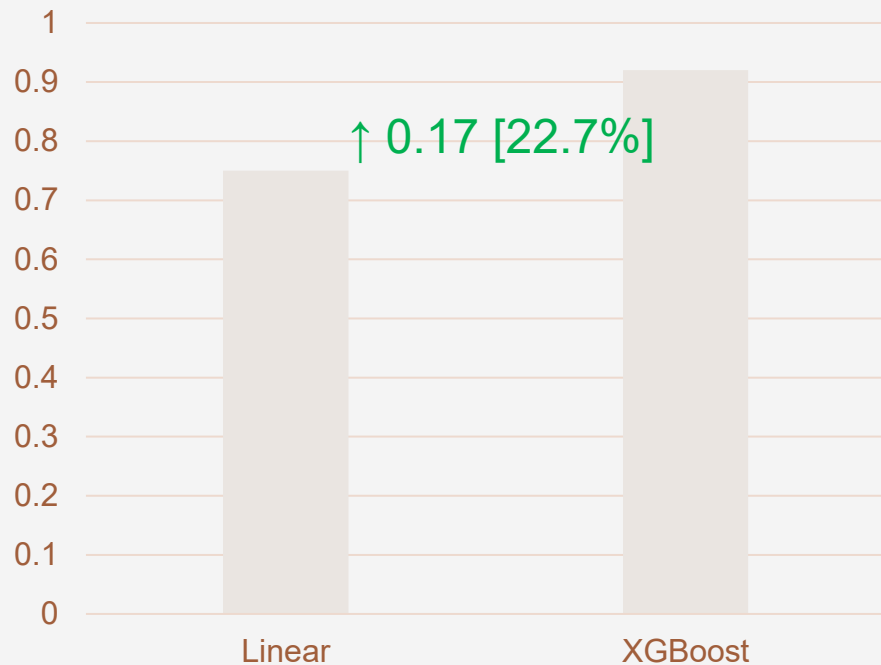


# MODEL COMPARISON

## RMSE

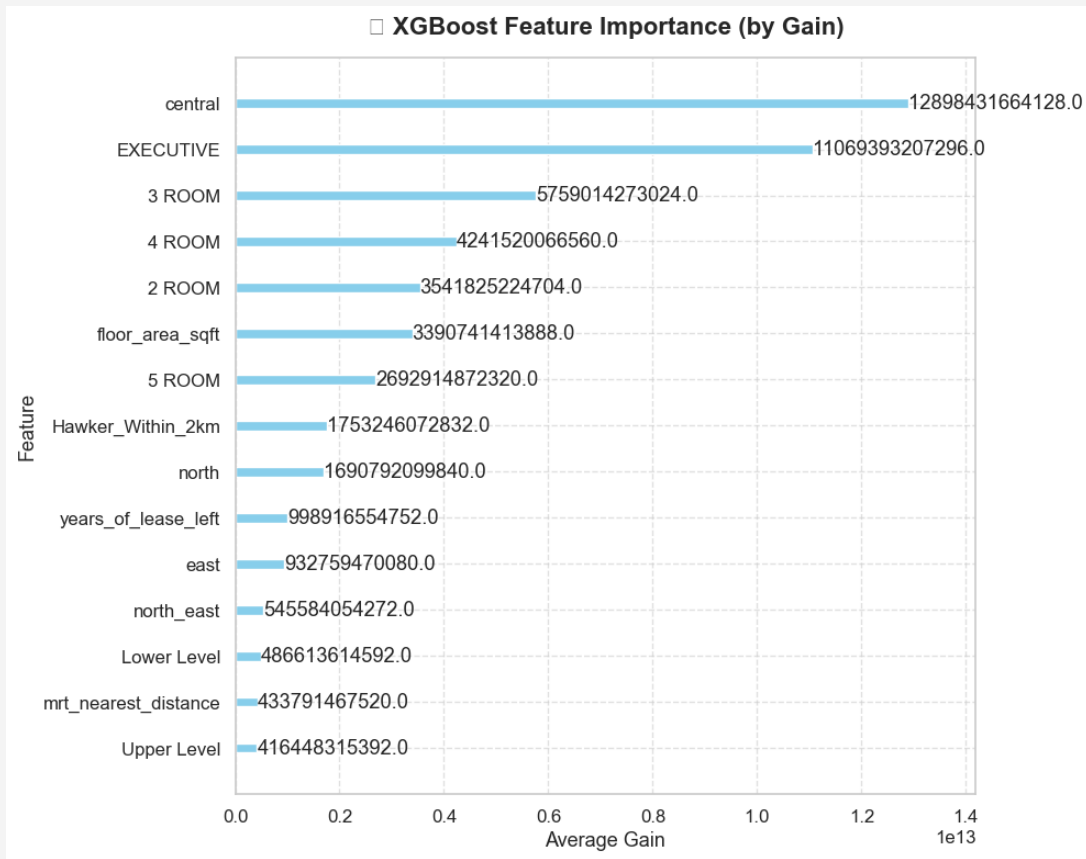


## $R^2$



# What Singaporeans Really Value in an HDB Home?

1. Central is everything
2. **BIGGER** the better
3. Proud Foodies
4. Practical
5. Everyday Conveniences



# IMPACT & LESSONS



# ASSUMPTIONS & CAVEATS



## Assumptions



Market behaves rationally – resale prices reflect measurable factors.



Data sources are reliable and updated.



Past trends represent near-term market patterns.



## Caveats



Uncaptured factors – interior condition and renovation not included.



Approximate proximity – map data, not travel time.



Market shifts – sudden policy or sentiment changes may affect predictions.

# BUSINESS IMPACT & RECOMMENDATIONS



## Data Insights

Enables fair and transparent pricing for both buyers and sellers.



## Model Application

Predictive model allows accurate resale price estimation, reducing guesswork and bias.



## Agent Empowerment

Provides data-backed confidence in negotiations, boosting agent credibility



## Business Impact

Strengthens WOW!'s position as a trusted, analytics-driven real estate brand.



## RECOMMENDATIONS



Integrate model into agent workflow through a Streamlit-based pricing app.



Continuously update data with new transactions to maintain accuracy.

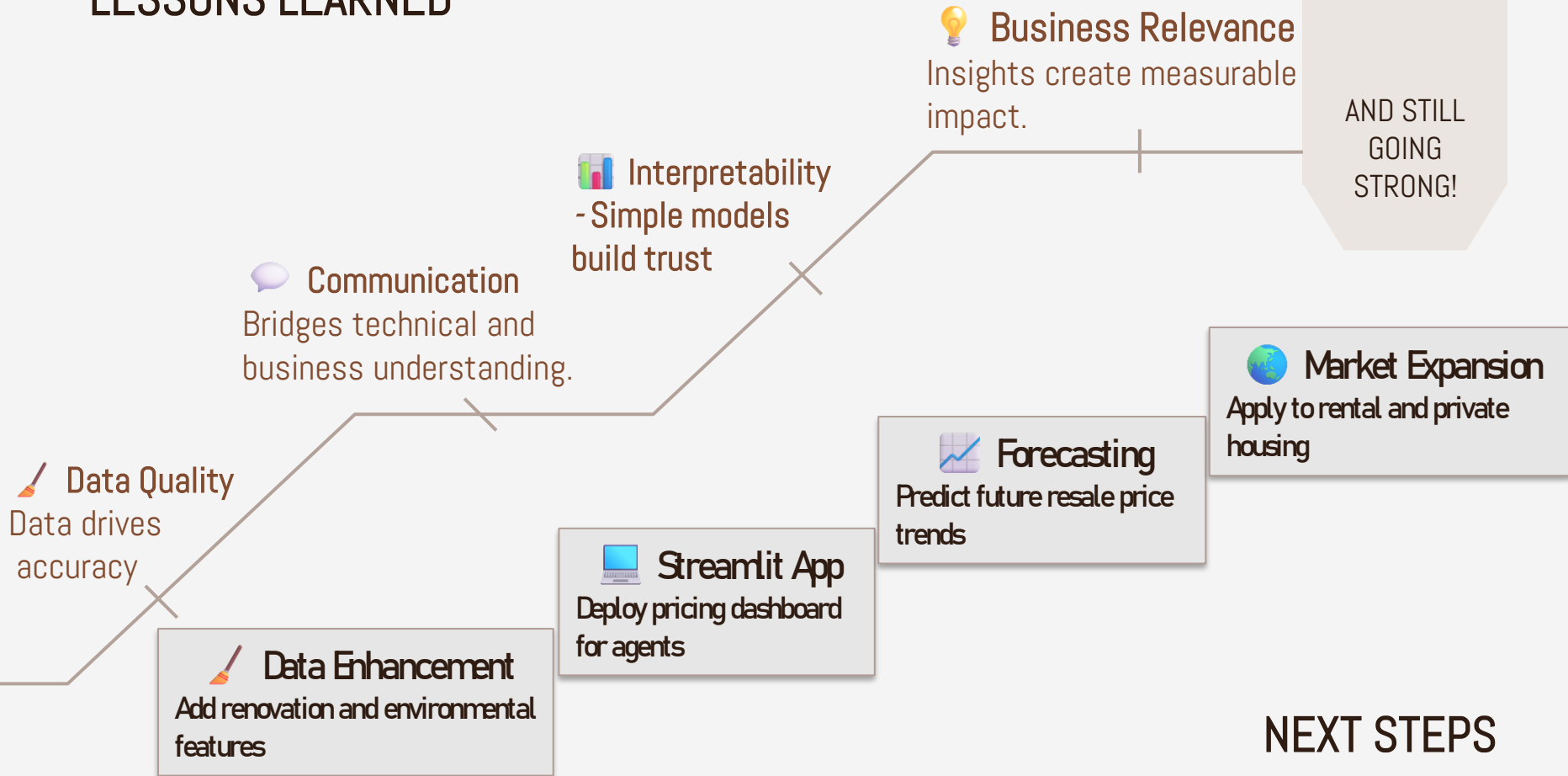


Use results for targeted marketing (e.g., towns with rising demand).



Explore rental and BTO market extensions.

# LESSONS LEARNED



# RETROSPECTIVE

From messy data to actionable insights — our journey combined teamwork, technical depth, way forward and storytelling.



TEAMWORK → What works?

Task division and collaboration



TECHNICAL DEPTH → What must be done?

Correlation and feature selection



WAY FORWARD → To move on or put a pin on it?

Exploration to implementation



STORYTELLING → How can we show/explain?

Make complex analytics insights  
accessible to all audience





STREAMLIT DEMO





QUESTIONS?



A photograph of a modern building facade with a large, bold, dark brown 'THANK YOU' sign. The building has a textured, light-colored concrete or stone surface. Below the sign, there are several rectangular windows with dark frames. The building is set against a light beige background with a large, dark beige geometric shape on the right side.

# THANK YOU

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