Bangkok & Metropolitan Area
Price Prediction

Data Science Immersive Course
Project 2

Problem Statement

X

Real Estate Consulting Firm

Scenario

Given that
we're real estate consulting firm whose clients are leading real estate developers in Bangkok and Metropolitan Area

As real estate market is bouncing back from Covid financial crisis. **Our clients trying to explore possibility launching projects in 2,500 prospective areas** (Test Data) given from client and client marketing team wants to know proper pricing in those areas that reflect **from existing estate data**. (Train Data)

So that, the marketing team could get glimpse of margin, worthiness of investment for each projects based on predicted data to rank priority of prospective areas.

Prospect Audience: Client Marketing Team

PRUKSA

ORIGIN

SANSIRI

PROPERTY PERFECT

Real Estate Developers

Our Plan

Find out

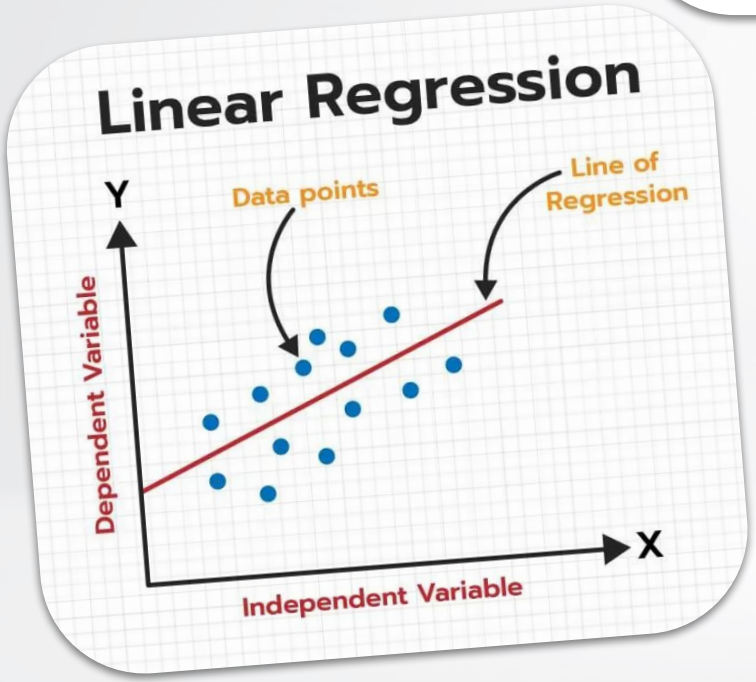
1. **Price Prediction Model** for 2,500 potential project location from existing real estate data

2. **Crucial Price Indicating Factors** that matter in real estate industry (i.e. premise features)

3. **Recommendation** for further studies and Business strategy/execution suggestion

Methodology

1. **Price Prediction Model** for 2,500 potential project location from existing real estate data



Multiple Linear Regression

Approach for modelling the relationship between a scalar response (Response variable) and explanatory variables (Features)

Assumptions associated with a linear regression model:

1. **Linearity**: The relationship between X and the mean of Y is linear.
2. **Independence**: Observations are independent of each other.
3. **Normality**: For any fixed value of X, Y is normally distributed.
4. **Equality of Variance**: If the residuals do not fan out in a triangular fashion that means that the equal variance assumption is met.

***With L1 regularization (Lasso) if needed in a model**

Methodology Process

2 Datasets

Train set (23 Features)
Test (All Features w/o Price)

Period: Year 1993-2022

14,271 rows, 23 columns
2,500 rows, 22 columns

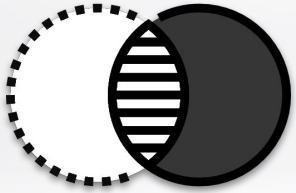
EDA

Exploratory Data Analysis

Data Cleansing

Data Imputation
(i.e. filling/dropping missing values, filtering out odd ones)

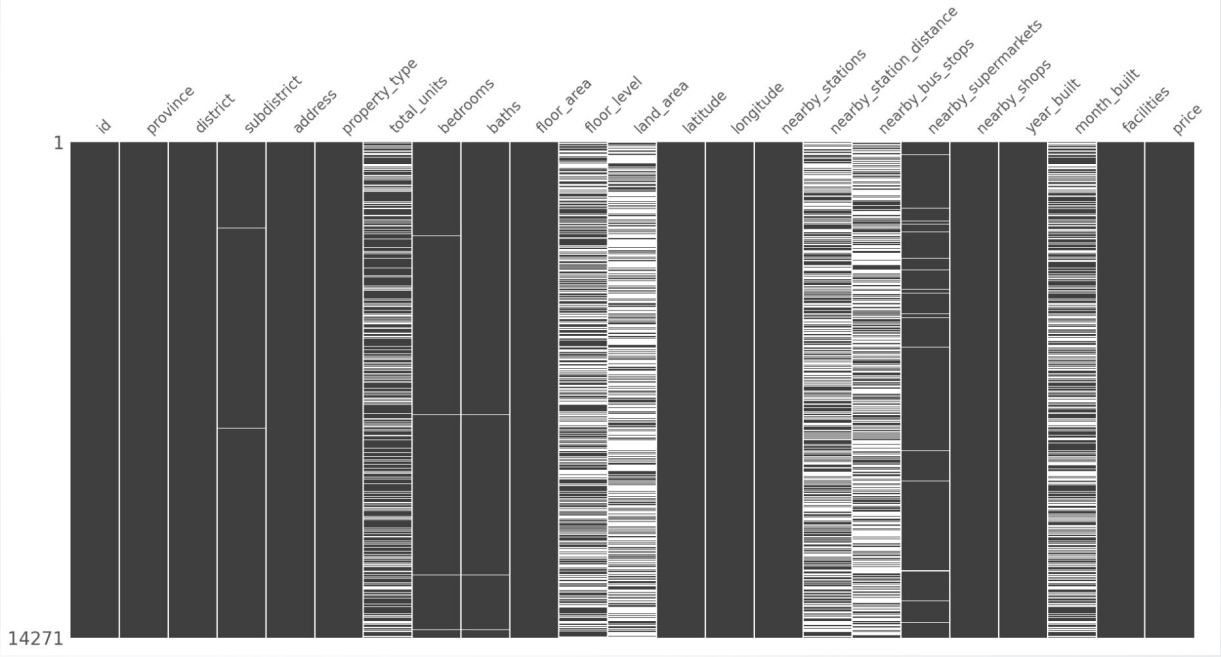
Feature Selection
Feature Engineering



Modeling & Prediction

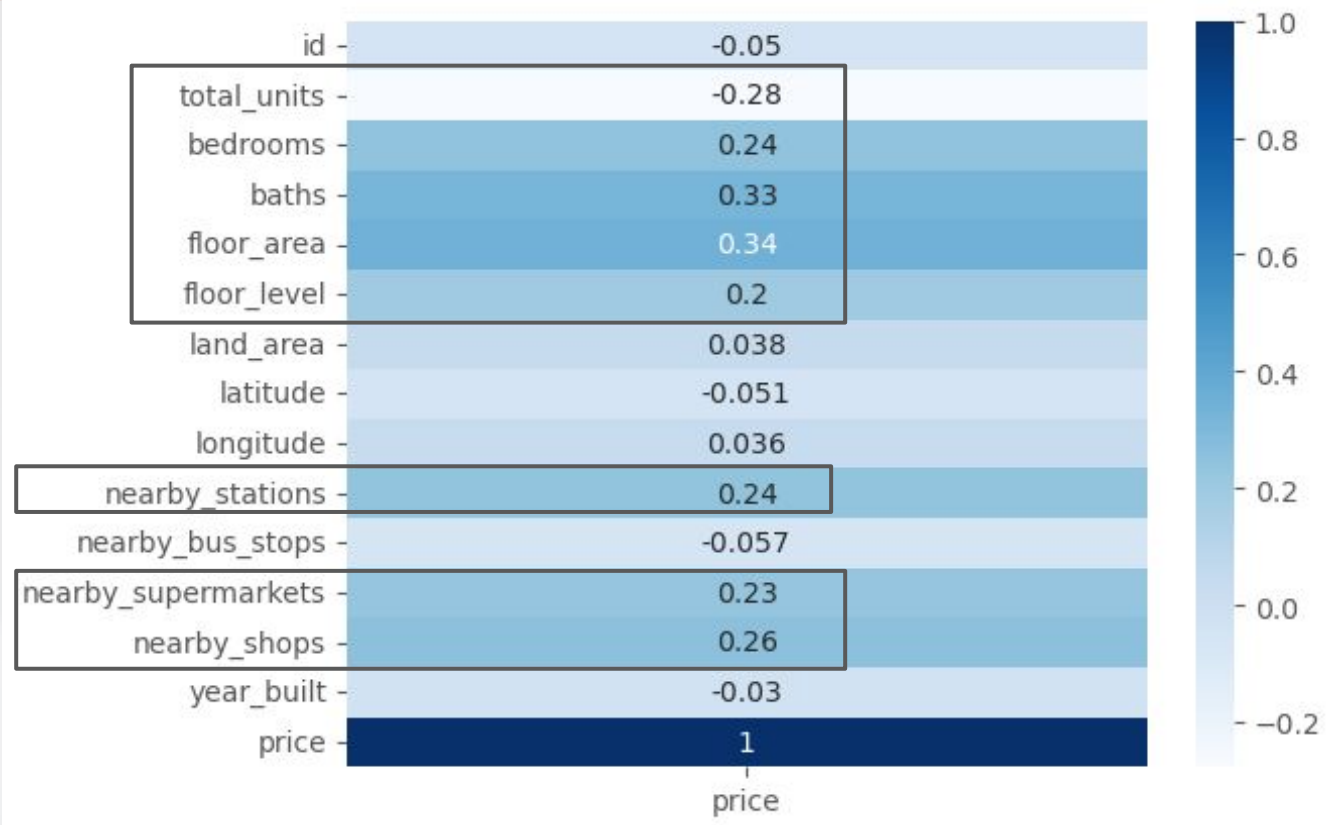
Exploratory Data Analysis: Matrix


```
RangeIndex: 14271 entries, 0 to 14270
Data columns (total 23 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   id                       14271 non-null  int64
 1   province                 14271 non-null  object
 2   district                 14271 non-null  object
 3   subdistrict              14260 non-null  object
 4   address                  14271 non-null  object
 5   property_type            14271 non-null  object
 6   total_units              10509 non-null  float64
 7   bedrooms                 14228 non-null  float64
 8   baths                    14236 non-null  float64
 9   floor_area               14271 non-null  int64
 10  floor_level              8093 non-null   float64
 11  land_area                4917 non-null   float64
 12  latitude                 14271 non-null  float64
 13  longitude                14271 non-null  float64
 14  nearby_stations          14271 non-null  int64
 15  nearby_station_distance  7228 non-null   object
 16  nearby_bus_stops         6009 non-null   float64
 17  nearby_supermarkets      13885 non-null  float64
 18  nearby_shops             14271 non-null  int64
 19  year_built               14271 non-null  int64
 20  month_built              8397 non-null   object
 21  facilities               14271 non-null  object
 22  price                    14271 non-null  int64
dtypes: float64(9), int64(6), object(8)
memory usage: 2.5+ MB
```



***Missing values will be fill with avg. of each features**

Exploratory Data Analysis: Correlation



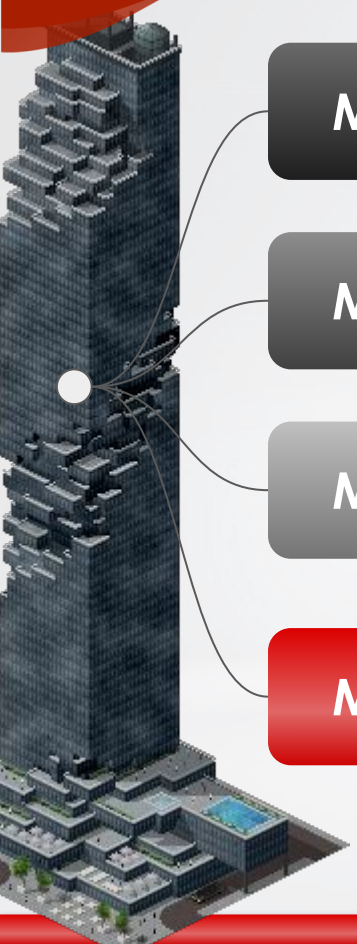
Medium and up correlation to price (both +,-)

Total_units
Bedrooms
Baths
Floor_area
Floor_level
Nearby_stations
Nearby_supermarkets
Nearby_shops

8 Numeric Features

***Red color indicates features that has missing values**

Prediction Model



Model 1	Null Model : predicting with avg. value in train set	1 Feature
Model 2	Only Latitude & Longitude represent location features + Numeric features	14 Features
Model 3	Province and District represent location features + Numeric features	14 Features
Model 4	Model 2+3 improvement > adding more features, ignore unnecessary features	19 Features

Model 1 : Null Model

Features

id	province	district	sub-district	address
property type	total units	bedrooms	baths	floor area
floor level	land area	latitude	longitude	nearby stations
nearby station distance	nearby bus stop	nearby supermarket	nearby shops	year built
	month built	facilities	price	

Regularization

L1: Lasso	L2: Ridge

Model 2 : Lat & Long for location features + Numeric F.

Features

id	province	district	sub-district	address
D property type	total units	bedrooms	baths	floor area
floor level	land area	latitude	longitude	nearby stations
nearby station distance	nearby bus stop	nearby supermarket	nearby shops	year built
	month built	C facilities	price	

Regularization

L1: Lasso	L2: Ridge	Elastic Net

Feature Engineering

- D — Dummify
- C — Count (iterate through items)

Model 3 : Province & District features + Numeric F.

Features

id	D province	D district	sub-district	address
D property type	total units	bedrooms	baths	floor area
floor level	land area	latitude	longitude	nearby stations
nearby station distance	nearby bus stop	nearby supermarket	nearby shops	year built
	month built	C facilities	price	

Regularization

L1: Lasso	L2: Ridge	Elastic Net

Feature Engineering

- D — Dummify
- C — Count (iterate through items)

Model 4 : Model 2+3 Improvement

Features

id	D province	D district	sub-district	address
D property type	total units	bedrooms	baths	floor area
NEW floor level	NEW land area	latitude	longitude	nearby stations
C nearby station distance NEW	nearby bus stop	nearby supermarket	nearby shops	year built
	month built	C facilities	price	

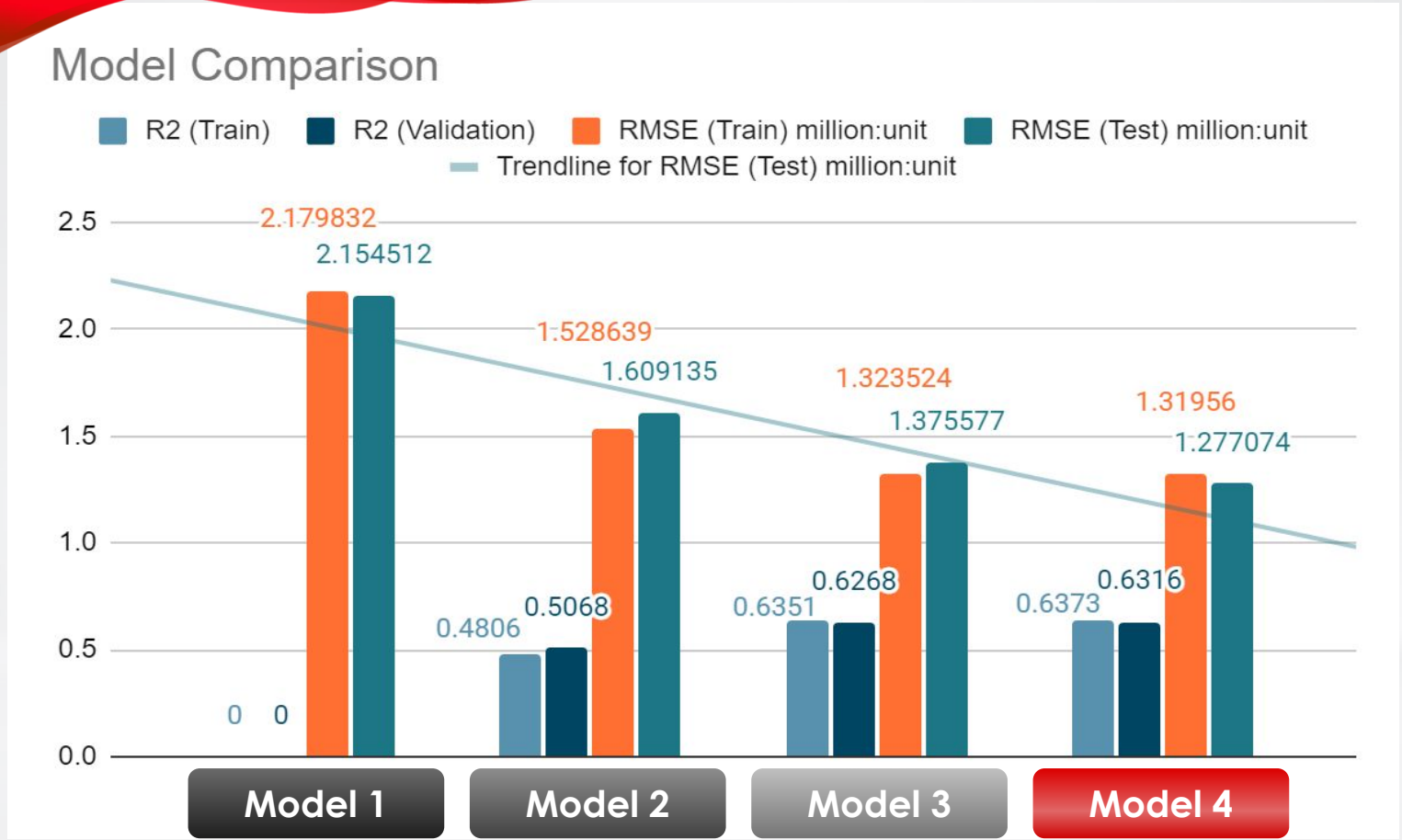
Regularization

L1: Lasso	L2: Ridge	Elastic Net

Feature Engineering

- D — Dummify
- C — Count (iterate through items)

Model Performance



Conclusion

After deploying 4 models,

Model#4 is surely perform best but might be unrealistic in term of generalization trading off with preciseness improvement from **Model#3 — (i.e. 19 features vs 14 features)**

Whlist Model#3 has drastic different score from **Model#2** given that they have equal no. of features which proof that Province and Subdistrict are better representative of location features than Latitude and Longitude or the latter 2 are needed engineering before fitting with the model.

For further studies, We could dive deep into Latitude & Longitude feature engineering for better prediction are could try fill missing values with other tactics rather than just Avg. value.

Business recommendation

Vital Price Determiners

Greater, better (+ve)

Floor Area (Usable Area)
Bedroom
Bathroom
Year Built (newer is better)
Nearby shops (counts)
Facility (counts)
BTS > MRT > ARL > SRT nearby counts

Greater, worsen (-ve)

Total Units

Strategy Recommendation

Real Estate Developers may focus on floor area (usable area) > land area and try not to squeeze in too much total units as it will be effect the price. In Addition, customer convenience for living (facility, transportation and shop nearby) also play key roles in marking up price for real estate project.

Thank you