SC1015 Mini Project: Melbourne Housing

REP2 Group 7
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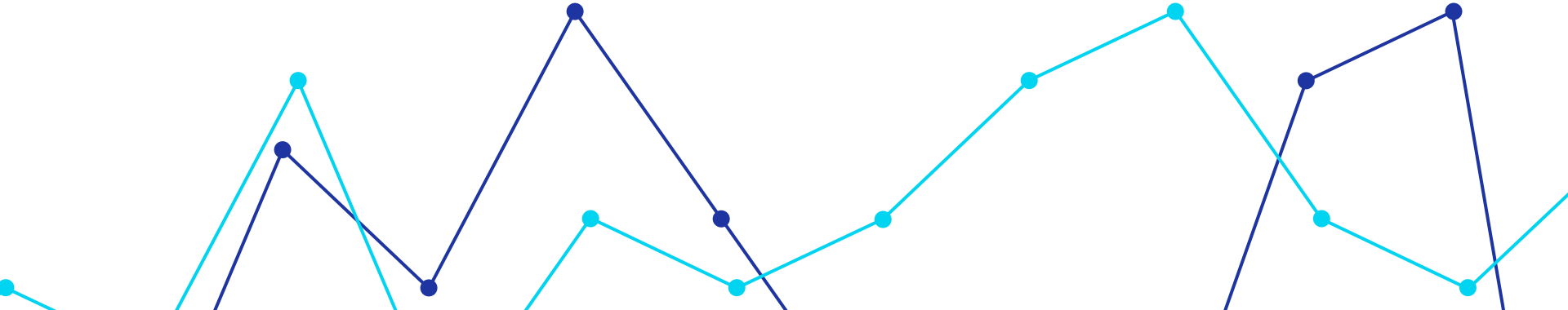

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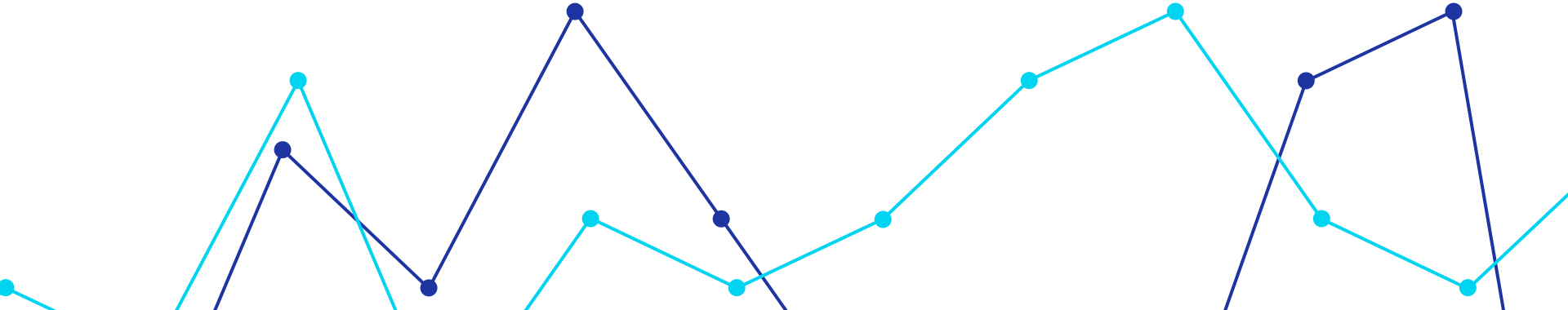
Practical Motivation + Problem Formulation



Practical **MOTIVATION**

Sample **COLLECTION**

Practical Motivation - Relatability to Singapore

- Resilient real estate sector
- Stable economy

2024	2025
9,103	5,438

41.3% ↘

completed private property units

- Supply Constraints
- Strong Demand

Practical Motivation - Relatability to Singapore

Analysis

Understand how different features and locations **impact property prices**

Methodology

Explore methods to **identify emerging high-value areas** and markets

Models

Develop models to **forecast property trends**, helping stakeholders **make decisions**

Comparable Challenges

- Limited Land Supply
- Rising Prices
- Demographic Shifts

Trend Analysis

Problem FORMULATION

Data PREPARATION

Problem Definition

1. Which features have the greatest impact on price?
2. How has the price trend varied across different regions over time, and can we identify emerging high-value areas?
3. How does property age and size influence prediction accuracy in models?

Problem FORMULATION

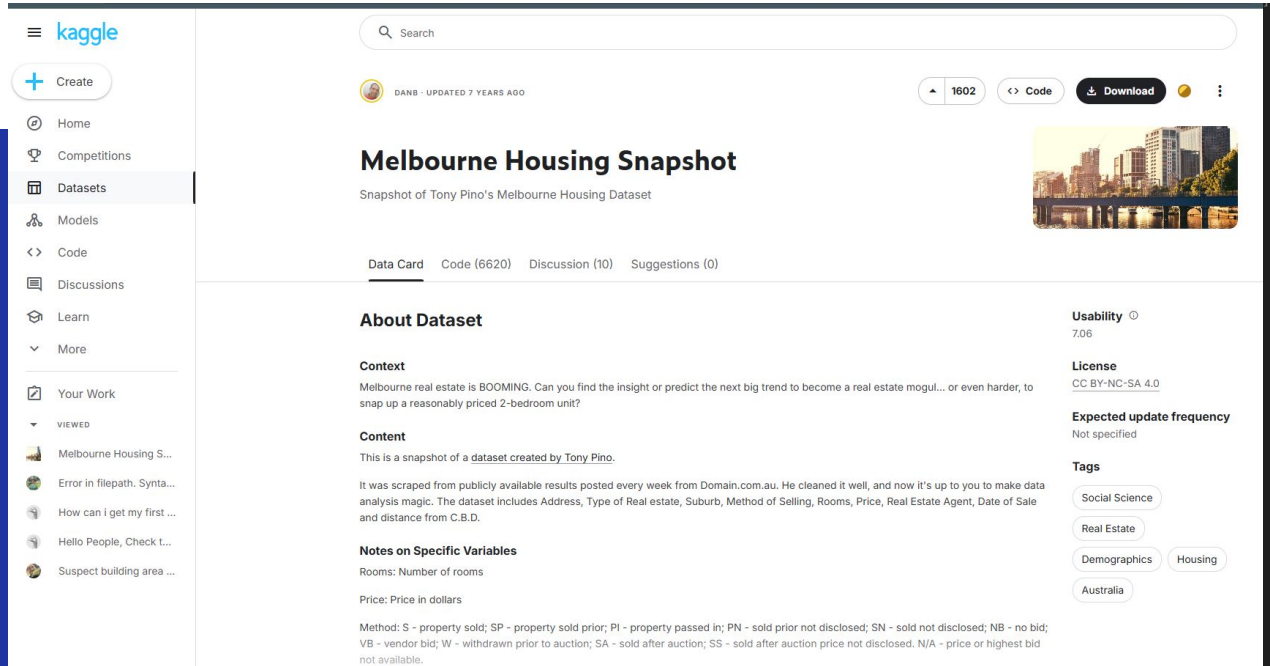
Data PREPARATION

Sample Collection

Raw data is accessed from the Kaggle datasets and extracted via the read_csv Pandas function

A total of 13580 entries, with 21 columns

Contains data on the price, features, location and other attributes




```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13580 entries, 0 to 13579
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Suburb         13580 non-null  object
 1   Address        13580 non-null  object
 2   Rooms          13580 non-null  int64
 3   Type           13580 non-null  object
 4   Price          13580 non-null  float64
 5   Method         13580 non-null  object
 6   SellerG        13580 non-null  object
 7   Date           13580 non-null  object
 8   Distance       13580 non-null  float64
 9   Postcode       13580 non-null  float64
 10  Bedroom2       13580 non-null  float64
 11  Bathroom       13580 non-null  float64
 12  Car            13518 non-null  float64
 13  Landsize       13580 non-null  float64
 14  BuildingArea   7130 non-null   float64
 15  YearBuilt      8205 non-null   float64
 16  CouncilArea    12211 non-null  object
 17  Lattitude      13580 non-null  float64
 18  Longtitude     13580 non-null  float64
 19  Regionname     13580 non-null  object
 20  Propertycount  13580 non-null  float64
dtypes: float64(12), int64(1), object(8)
memory usage: 2.2+ MB
None
```

Problem FORMULATION

Data PREPARATION

Sample Collection

Raw data is accessed from the Kaggle datasets and extracted via the read_csv Pandas function

A total of 13580 entries, with 21 columns

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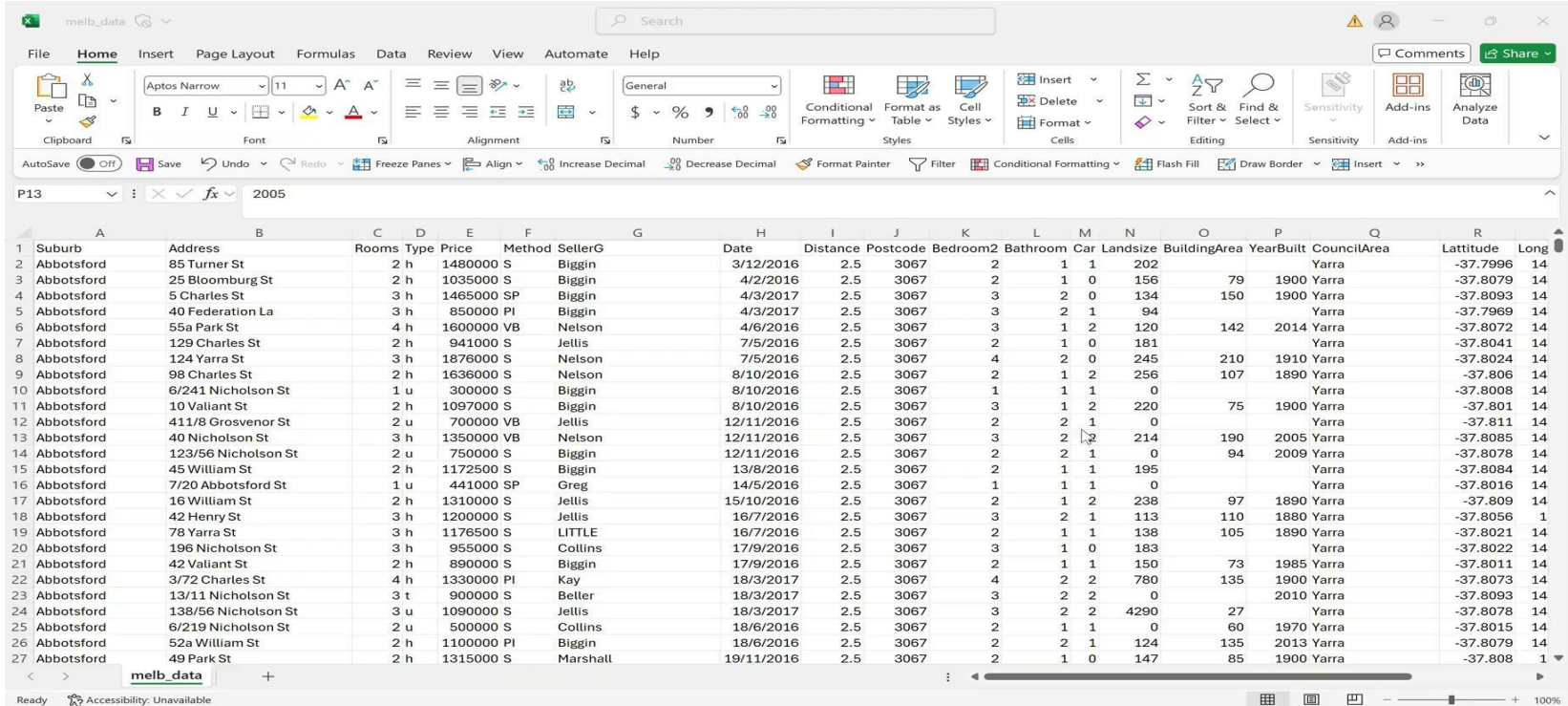

melb_data

	Suburb	Address	Rooms	Type	Price	Method	SellerG	Date	Distance	Postcode	Bedroom2	Bathroom	Car	Landsize	BuildingArea	YearBuilt	CouncilArea	Lattitude	Long
2	Abbotsford	85 Turner St	2	h	1480000	S	Biggin	3/12/2016	2.5	3067	2	1	1	202			Yarra	-37.7996	14
3	Abbotsford	25 Bloomburg St	2	h	1035000	S	Biggin	4/2/2016	2.5	3067	2	1	0	156	79	1900	Yarra	-37.8079	14
4	Abbotsford	5 Charles St	3	h	1465000	SP	Biggin	4/3/2017	2.5	3067	3	2	0	134	150	1900	Yarra	-37.8093	14
5	Abbotsford	40 Federation La	3	h	850000	PI	Biggin	4/3/2017	2.5	3067	3	2	1	94			Yarra	-37.7969	14
6	Abbotsford	55a Park St	4	h	1600000	VB	Nelson	4/6/2016	2.5	3067	3	1	2	120	142	2014	Yarra	-37.8072	14
7	Abbotsford	129 Charles St	2	h	941000	S	Jellis	7/5/2016	2.5	3067	2	1	0	181			Yarra	-37.8041	14
8	Abbotsford	124 Yarra St	3	h	1876000	S	Nelson	7/5/2016	2.5	3067	4	2	0	245	210	1910	Yarra	-37.8024	14
9	Abbotsford	98 Charles St	2	h	1636000	S	Nelson	8/10/2016	2.5	3067	2	1	2	256	107	1890	Yarra	-37.806	14
10	Abbotsford	6/241 Nicholson St	1	u	300000	S	Biggin	8/10/2016	2.5	3067	1	1	1	0			Yarra	-37.8008	14
11	Abbotsford	10 Valiant St	2	h	1097000	S	Biggin	8/10/2016	2.5	3067	3	1	2	220	75	1900	Yarra	-37.801	14
12	Abbotsford	411/8 Grosvenor St	2	u	700000	VB	Jellis	12/11/2016	2.5	3067	2	2	1	0			Yarra	-37.811	14
13	Abbotsford	40 Nicholson St	3	h	1350000	VB	Nelson	12/11/2016	2.5	3067	3	2	2	214	190	2005	Yarra	-37.8085	14
14	Abbotsford	123/56 Nicholson St	2	u	750000	S	Biggin	12/11/2016	2.5	3067	2	2	1	0	94	2009	Yarra	-37.8078	14
15	Abbotsford	45 William St	2	h	1172500	S	Biggin	13/8/2016	2.5	3067	2	1	1	195			Yarra	-37.8084	14
16	Abbotsford	7/20 Abbotsford St	1	u	441000	SP	Greg	14/5/2016	2.5	3067	1	1	1	0			Yarra	-37.8016	14
17	Abbotsford	16 William St	2	h	1310000	S	Jellis	15/10/2016	2.5	3067	2	1	2	238	97	1890	Yarra	-37.809	14
18	Abbotsford	42 Henry St	3	h	1200000	S	Jellis	16/7/2016	2.5	3067	3	2	1	113	110	1880	Yarra	-37.8056	1
19	Abbotsford	78 Yarra St	3	h	1176500	S	LITTLE	16/7/2016	2.5	3067	2	1	1	138	105	1890	Yarra	-37.8021	14
20	Abbotsford	196 Nicholson St	3	h	955000	S	Collins	17/9/2016	2.5	3067	3	1	0	183			Yarra	-37.8022	14
21	Abbotsford	42 Valiant St	2	h	890000	S	Biggin	17/9/2016	2.5	3067	2	1	1	150	73	1985	Yarra	-37.8011	14
22	Abbotsford	3/72 Charles St	4	h	1330000	PI	Kay	18/3/2017	2.5	3067	4	2	2	780	135	1900	Yarra	-37.8073	14
23	Abbotsford	13/11 Nicholson St	3	t	900000	S	Beller	18/3/2017	2.5	3067	3	2	2	0		2010	Yarra	-37.8093	14
24	Abbotsford	138/56 Nicholson St	3	u	1090000	S	Jellis	18/3/2017	2.5	3067	3	2	2	4290	27		Yarra	-37.8078	14
25	Abbotsford	6/219 Nicholson St	2	u	500000	S	Collins	18/6/2016	2.5	3067	2	1	1	0	60	1970	Yarra	-37.8015	14
26	Abbotsford	52a William St	2	h	1100000	PI	Biggin	18/6/2016	2.5	3067	2	2	1	124	135	2013	Yarra	-37.8079	14
27	Abbotsford	49 Park St	2	h	1315000	S	Marshall	19/11/2016	2.5	3067	2	1	0	147	85	1900	Yarra	-37.808	1

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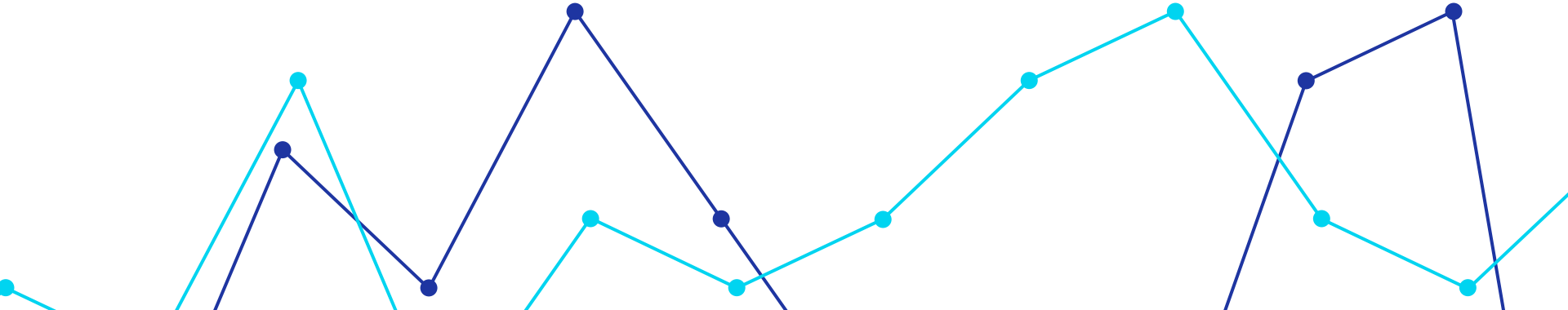
Data Processing + Exploratory Data Analysis

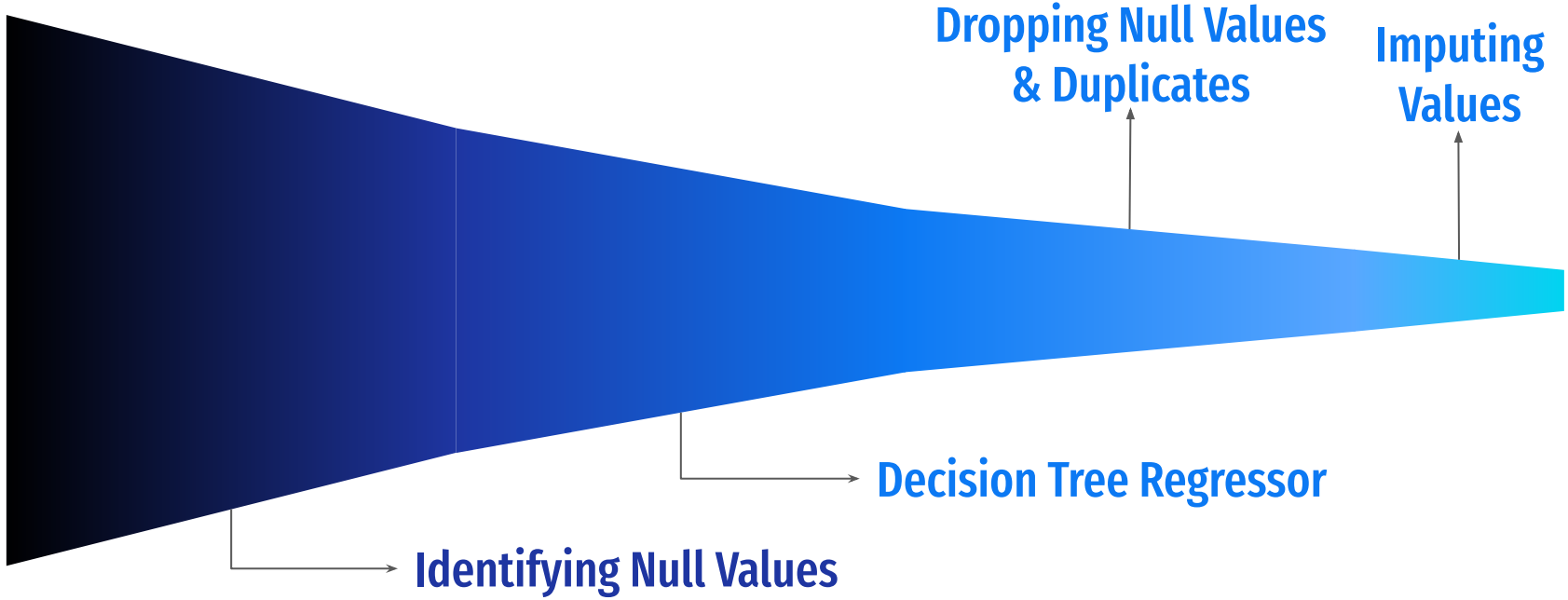


Statistical
DESCRIPTION

Exploratory
ANALYSIS

1. Preliminary Exploration

We adopted a 4 tiered approach for data exploration using statistical tools, before conducting targeted data preparation and cleaning



Statistical
DESCRIPTION

Exploratory
ANALYSIS

a. Identifying Null Values

```
print(housingdata.isnull().sum())
```

```
Suburb          0
Address         0
Rooms           0
Type            0
Price           0
Method          0
SellerG         0
Date            0
Distance        0
Postcode        0
Bedroom2        0
Bathroom        0
Car            62
Landsize        0
BuildingArea 6450
YearBuilt    5375
CouncilArea  1369
Lattitude       0
Longtitude      0
Regionname      0
Propertycount   0
dtype: int64
```

Statistical **DESCRIPTION**

Exploratory **ANALYSIS**

b. Decision Tree Regressor

```
encoder = OrdinalEncoder()
housingdata[categorical] = encoder.fit_transform(housingdata[categorical].astype(str))

X1 = housingdata.drop(columns=["Price"])  # Features
y1= housingdata["Price"]  # Target


model1 = DecisionTreeRegressor(random_state=42)
viz1 = FeatureImportances(model1)
viz1.fit(X1, y1)
```

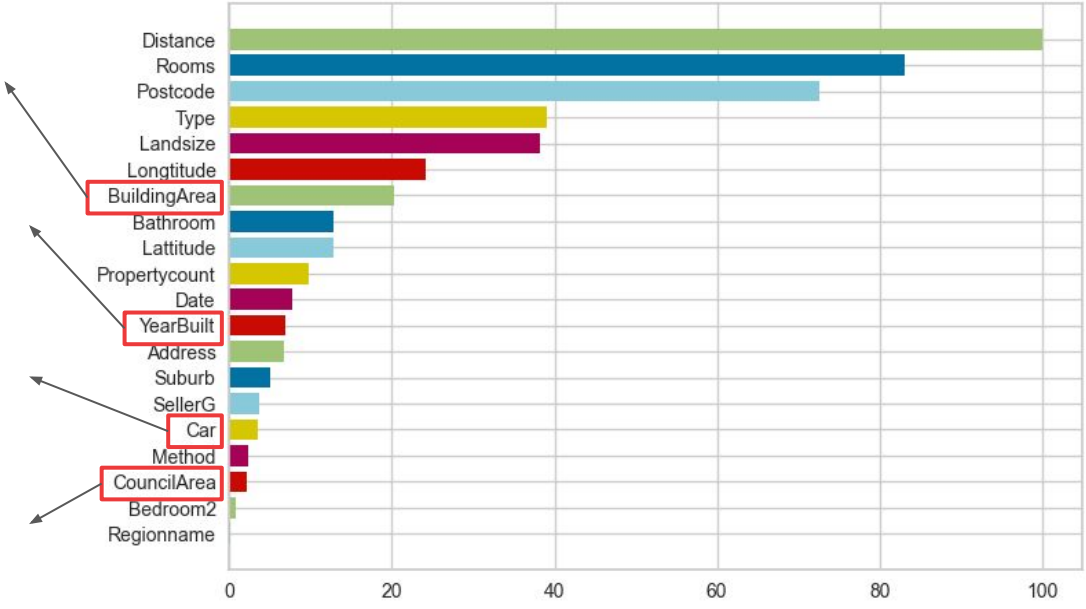
```
FeatureImportances
FeatureImportances(ax=<Axes: >,
                   estimator=DecisionTreeRegressor(random_state=42))
estimator: DecisionTreeRegressor
DecisionTreeRegressor(random_state=42)
DecisionTreeRegressor
DecisionTreeRegressor(random_state=42)
```

47.5% of rows #7 in feature importance

39.6% of rows #12 in feature importance

0.46% of rows #16 in feature importance

10.1% of rows #18 in feature importance



c. Handling NULL Values

Dropping Values

Variable: Car

Drop rows to reduce complexity without sacrificing much information, as its importance in predicting Price is low.

```
# drop rows accordingly
housingdata = housingdata.dropna(subset=['Car'])
```

Imputing Values

Variables: BuildingArea, YearBuilt, CouncilArea

Impute the missing values using the median/mode, grouped by relevant contextual property characteristics (Suburb, Rooms, Type) The number of NULL rows take up a notable percentage of the entire dataset, and the importance of these variables are moderate, hence we opt to impute.

```
# Impute BuildingArea based on median within Suburb + Distance + Rooms
housingdata['BuildingArea'] = housingdata.groupby(['Suburb', 'Rooms', 'Type'])['BuildingArea'].transform(
    lambda x: x.fillna(x.median())
)

# Impute YearBuilt based on Suburb + Type
housingdata['YearBuilt'] = housingdata.groupby(['Suburb', 'Type'])['YearBuilt'].transform(
    lambda x: x.fillna(x.median())
)

# Impute CouncilArea (categorical) based on Suburb
housingdata['CouncilArea'] = housingdata.groupby('Suburb')['CouncilArea'].transform(
    lambda x: x.fillna(x.mode()[0] if not x.mode().empty else 'Unknown')
)
```

Statistical
DESCRIPTION

Exploratory
ANALYSIS

2. Analysis of Numerical Variables

We will analyse the below numerical variables using a Box Plot, Histogram, and Violin Plot.

	Bathroom	Car	Landsize	BuildingArea	YearBuilt
count	13580.000000	13518.000000	13580.000000	7130.000000	8205.000000
mean	1.534242	1.610075	558.416127	151.967650	1964.684217
std	0.691712	0.962634	3990.669241	541.014538	37.273762
min	0.000000	0.000000	0.000000	0.000000	1196.000000
25%	1.000000	1.000000	177.000000	93.000000	1940.000000
50%	1.000000	2.000000	440.000000	126.000000	1970.000000
75%	2.000000	2.000000	651.000000	174.000000	1999.000000
max	8.000000	10.000000	433014.000000	44515.000000	2018.000000

Statistical
DESCRIPTION

Exploratory
ANALYSIS

2. Analysis of Numerical Variables

We will analyse the below numerical variables using a Box Plot, Histogram, and Violin Plot.

	Lattitude	Longtitude	Propertycount
count	13580.000000	13580.000000	13580.000000
mean	-37.809203	144.995216	7454.417378
std	0.079260	0.103916	4378.581772
min	-38.182550	144.431810	249.000000
25%	-37.856822	144.929600	4380.000000
50%	-37.802355	145.000100	6555.000000
75%	-37.756400	145.058305	10331.000000
max	-37.408530	145.526350	21650.000000

Statistical
DESCRIPTION

Exploratory
ANALYSIS

2. Analysis of Numerical Variables

We will analyse the below numerical variables using a Box Plot, Histogram, and Violin Plot.

	Rooms	Price	Distance	Postcode	Bedroom2
count	13580.000000	1.358000e+04	13580.000000	13580.000000	13580.000000
mean	2.937997	1.075684e+06	10.137776	3105.301915	2.914728
std	0.955748	6.393107e+05	5.868725	90.676964	0.965921
min	1.000000	8.500000e+04	0.000000	3000.000000	0.000000
25%	2.000000	6.500000e+05	6.100000	3044.000000	2.000000
50%	3.000000	9.030000e+05	9.200000	3084.000000	3.000000
75%	3.000000	1.330000e+06	13.000000	3148.000000	3.000000
max	10.000000	9.000000e+06	48.100000	3977.000000	20.000000

Statistical
DESCRIPTION

Exploratory
ANALYSIS

2. Analysis of Numerical Variables

We will analyse the below numerical variables using a Box Plot, Histogram, and Violin Plot.

```
Numeric features:
['Rooms', 'Price', 'Distance', 'Postcode', 'Bedroom2', 'Bathroom', 'Car', 'Landsize',
 'BuildingArea', 'YearBuilt', 'Lattitude', 'Longtitude', 'Propertycount']
```

Box Plot — Shows the distribution of price within each variable

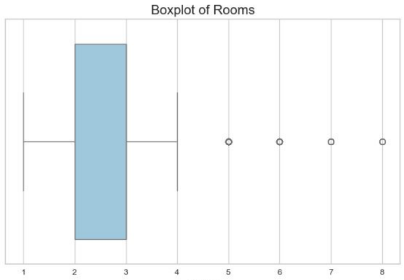
Histogram — Understand the underlying distribution (e.g., normal, skewed) and spread of the data.

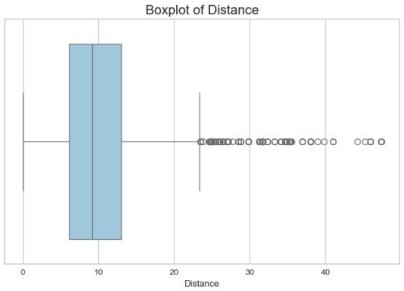
Violin Plot — Better visualize the summary statistics (like median and IQR) and the full distribution shape of the variable

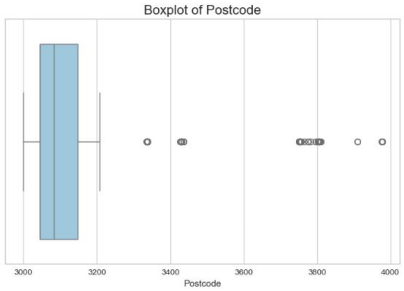
Pattern RECOGNITION

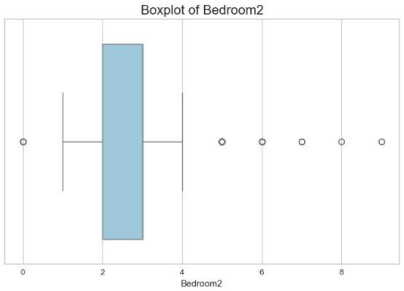
Analytic VISUALIZATION

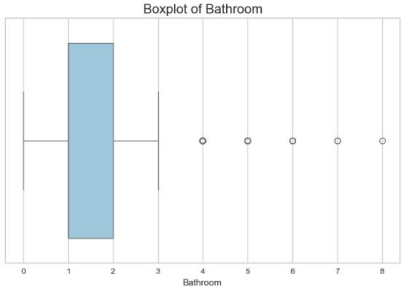
Univariate Visualisation: Boxplot

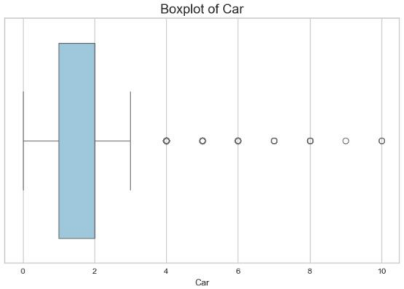


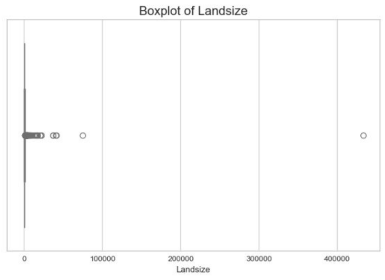


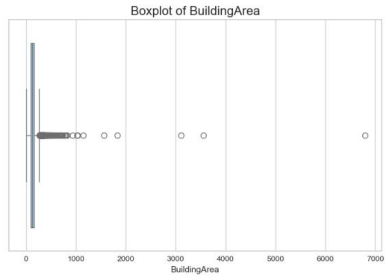


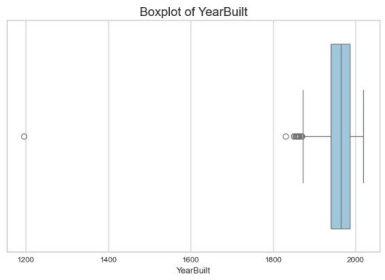


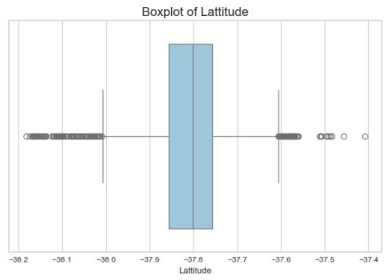


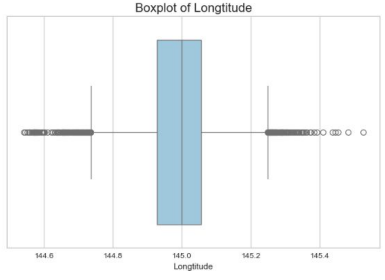


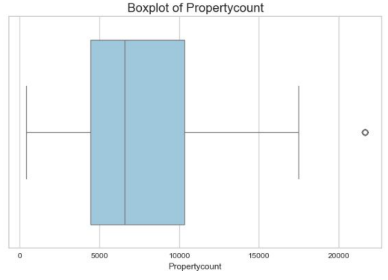








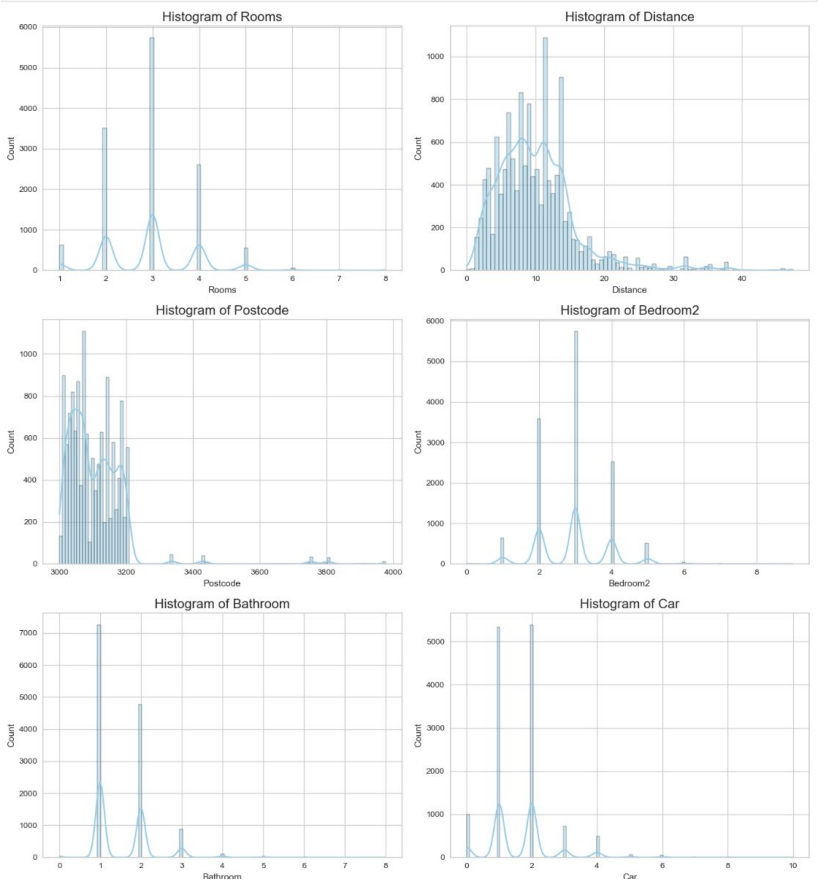


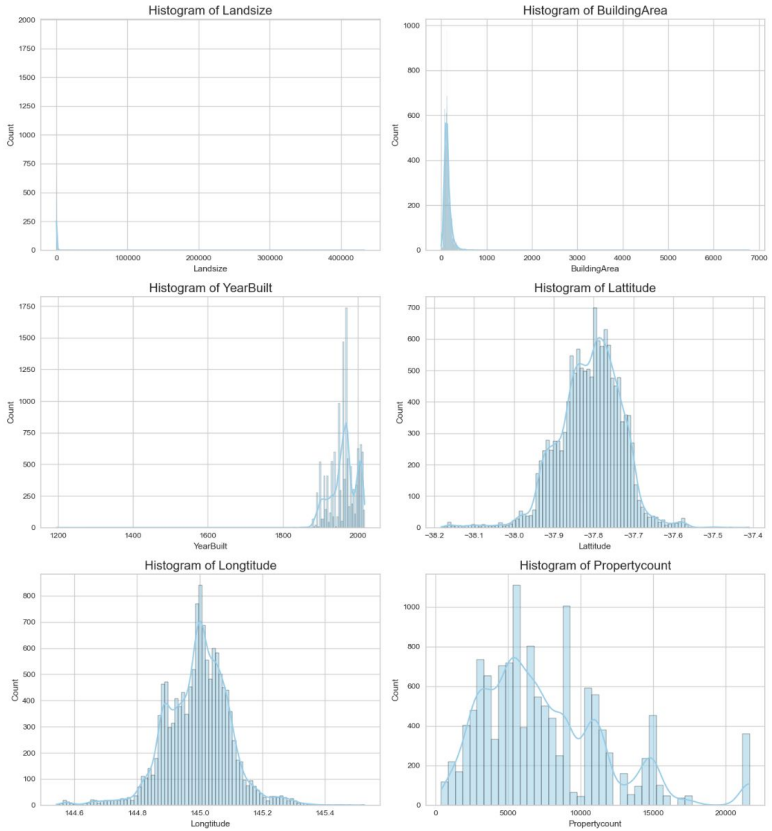


Pattern RECOGNITION

Analytic VISUALIZATION

Univariate Visualisation: Histogram

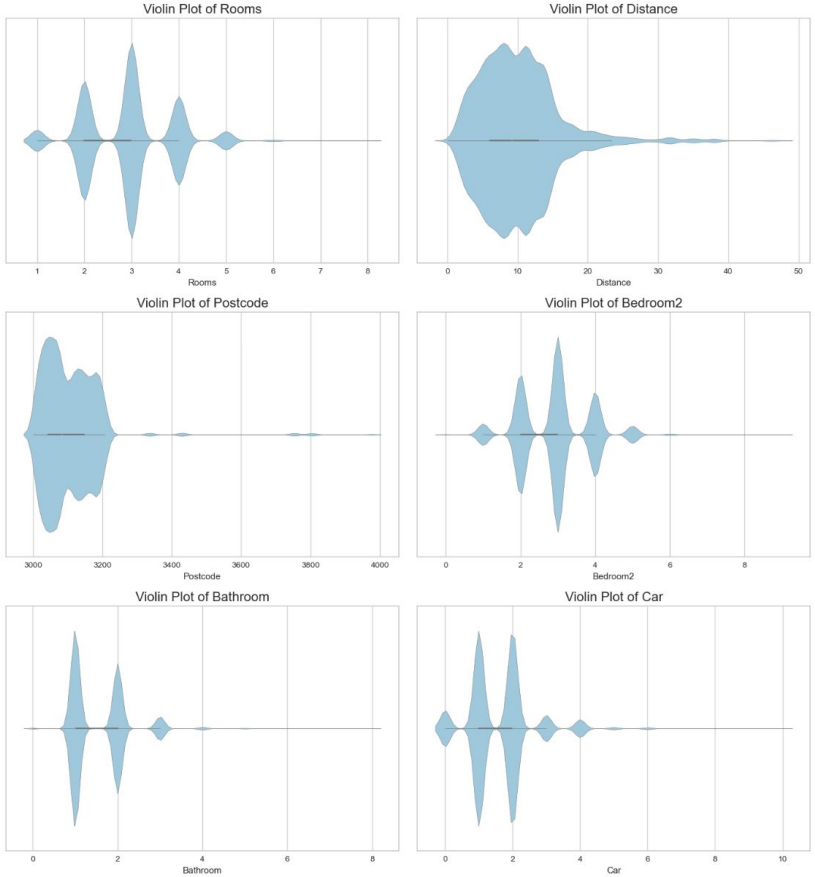


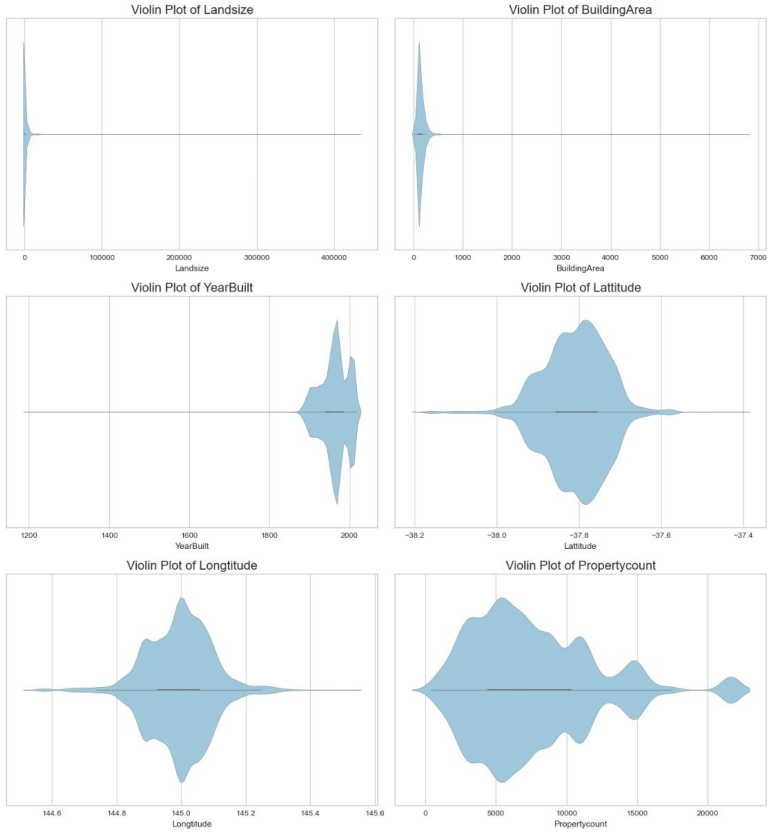


Pattern RECOGNITION

Analytic VISUALIZATION

Univariate Visualisation: Violinplot



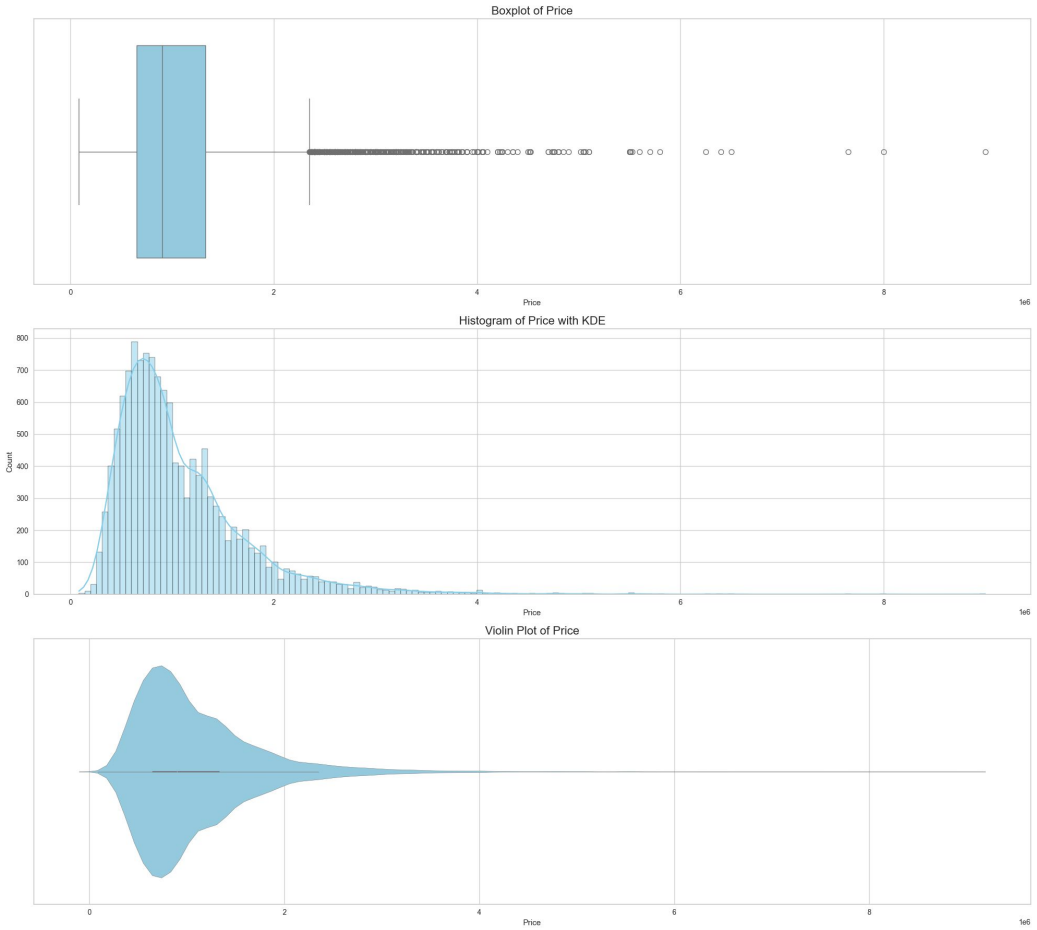


Pattern RECOGNITION

Analytic VISUALIZATION

Univariate Visualisation: Response Variable

Response Variable: Price

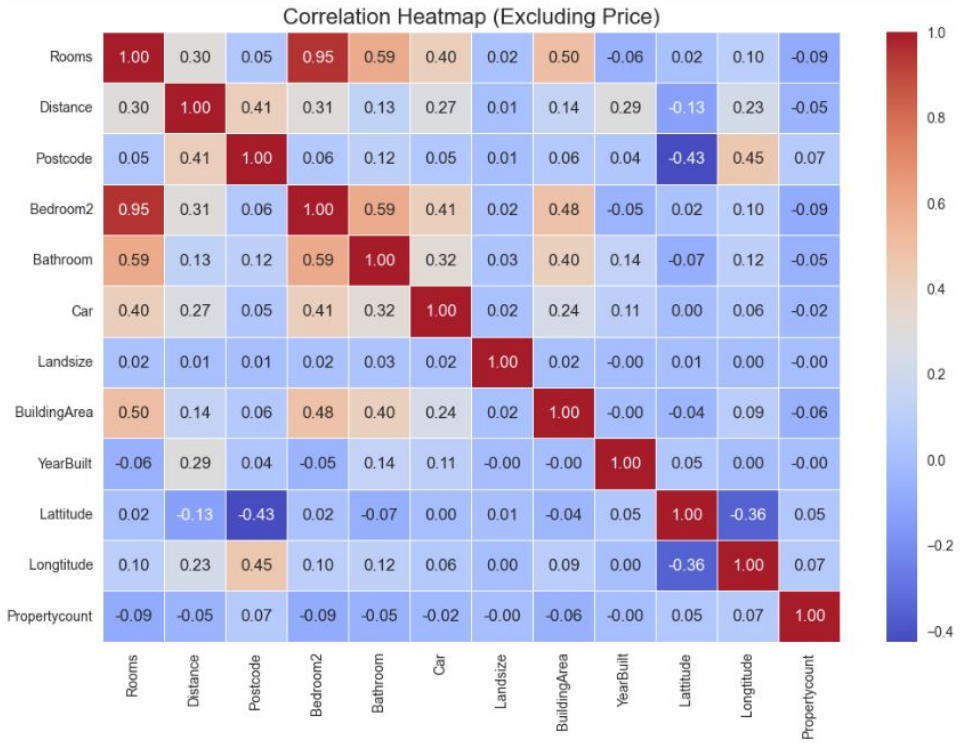


Pattern RECOGNITION

Analytic VISUALIZATION

Bivariate Visualisation

Correlation Heatmap

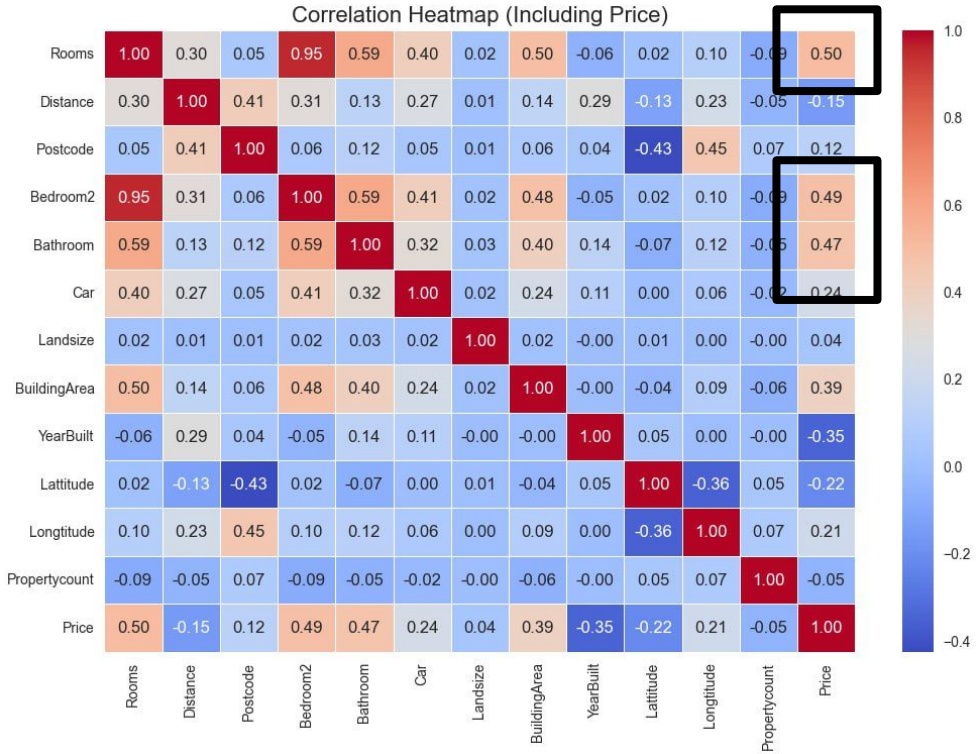


Pattern RECOGNITION

Analytic VISUALIZATION

Bivariate Visualisation

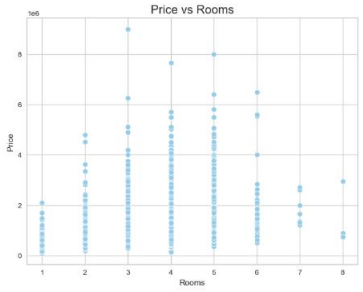
Correlation Heatmap

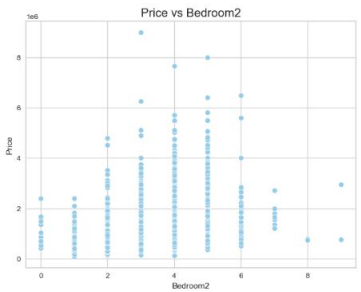


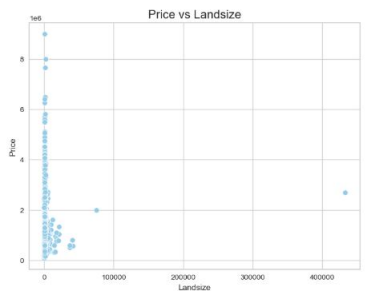
Pattern RECOGNITION

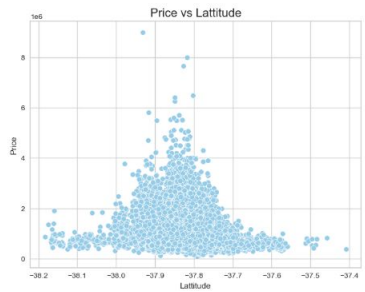
Analytic VISUALIZATION

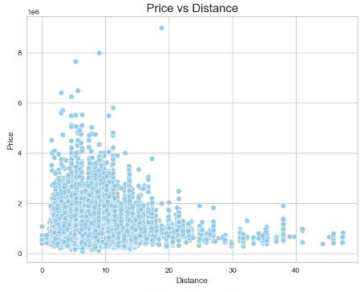
Bivariate Visualisation: Scatter Plot

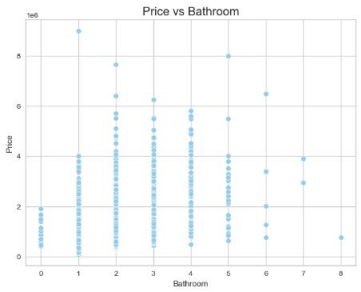


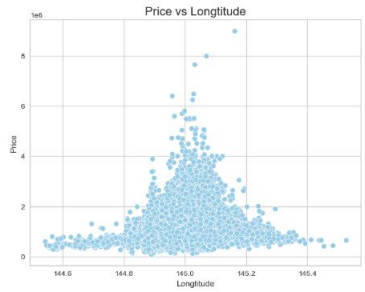


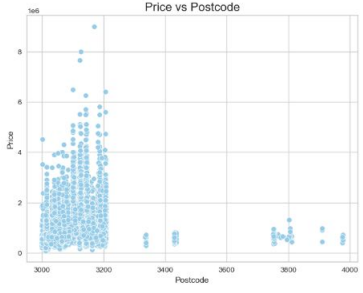


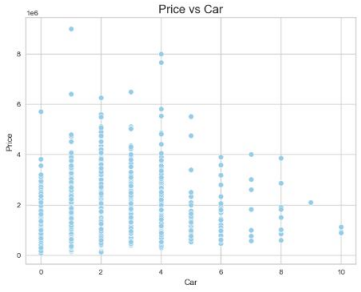


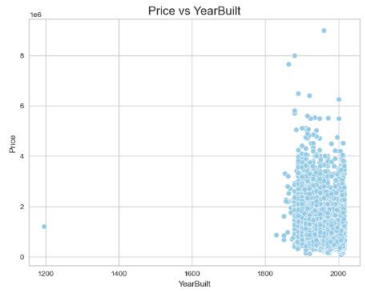












Statistical
DESCRIPTION

Exploratory
ANALYSIS

3. Analysis of Categorical Variables

We will analyse the below categorical variables using a Count Plot, Average Price for each category, as well as a Box Plot.

```
Categorical features:
['Suburb', 'Address', 'Type', 'Method', 'SellerG', 'Date', 'CouncilArea', 'Regionname']
```

Count Plot — Visualizes the frequency and distribution of each category.

Avg Price — Reveal how different categories influence the response variable (Price)

Box Plot — Shows the distribution of price within each category

Pattern RECOGNITION

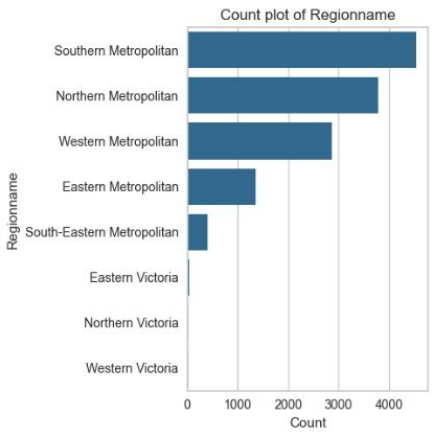
Analytic VISUALIZATION

Univariate Visualization

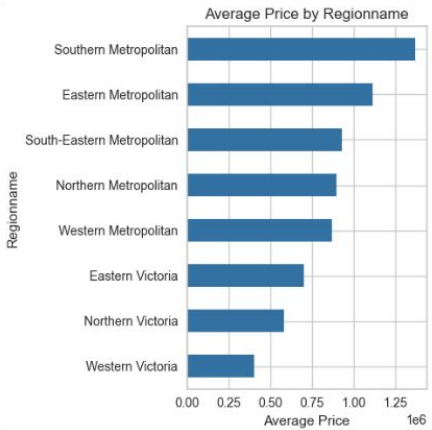
Predictor Variable: Regionname

(using 1 variable as an example)

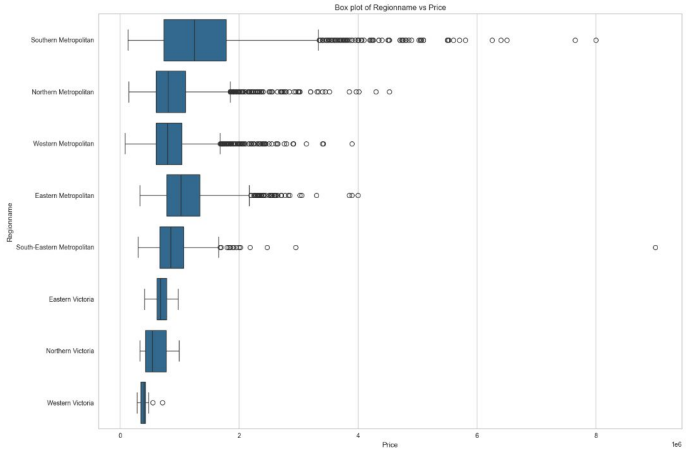
Count Plot



Avg Price

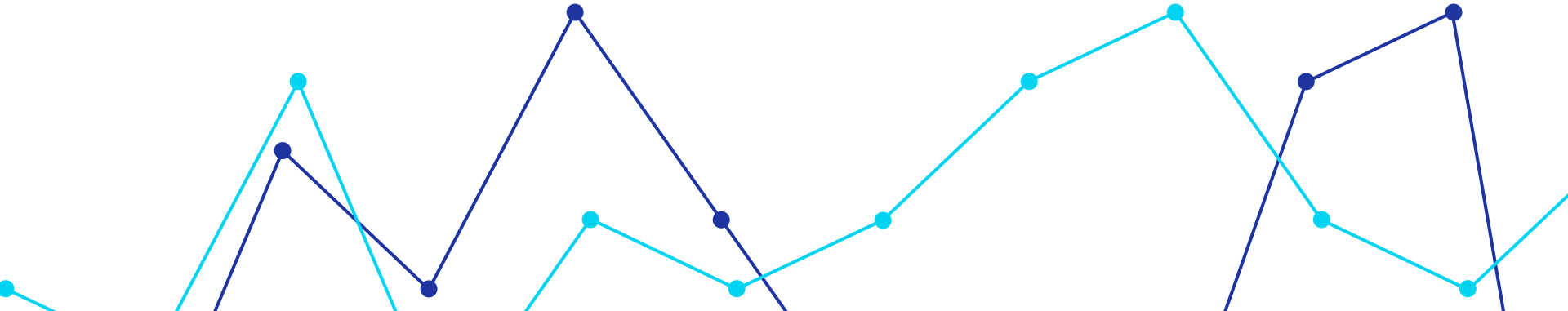


Box Plot



3

Preparation of Variables for Analysis



Dimensionality REDUCTION

Feature ENGINEERING

1. Dimensionality Reduction

How can we reduce the number of unique categories?

	count	unique	top	freq
Suburb	13066	300	Reservoir	359
Address	13066	12874	28 Blair St	3
Type	13066	3	h	9142
Method	13066	5	S	8701
SellerG	13066	263	Nelson	1532
Date	13066	58	27/05/2017	445
CouncilArea	13066	33	nan	1252
Regionname	13066	8	Southern Metropolitan	4547

Dimensionality REDUCTION

Feature ENGINEERING

1. Dimensionality Reduction

How can we reduce the number of unique categories?

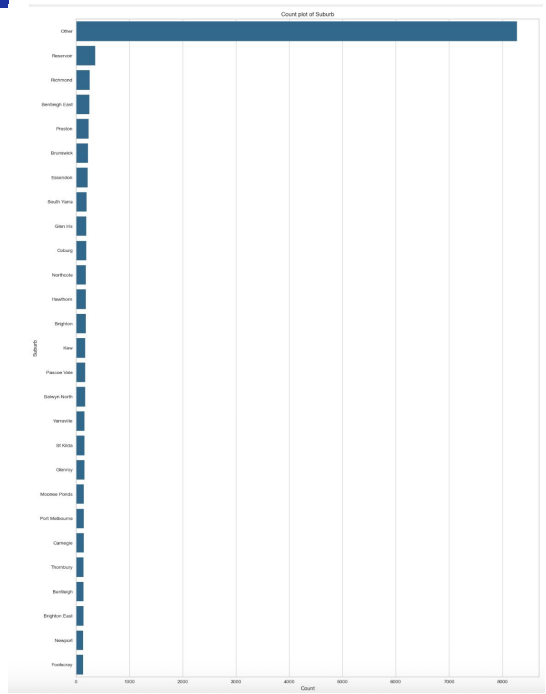
```python
def group_rare_categories(df, column, threshold=0.01):
    # Calculate category counts
    category_counts = df[column].value_counts(normalize=True)

    # Identify categories with frequency less than the threshold
    rare_categories = category_counts[category_counts < threshold].index

    # Replace rare categories with "Other"
    df[column] = df[column].apply(lambda x: 'Other' if x in rare_categories else x)

    return df
```

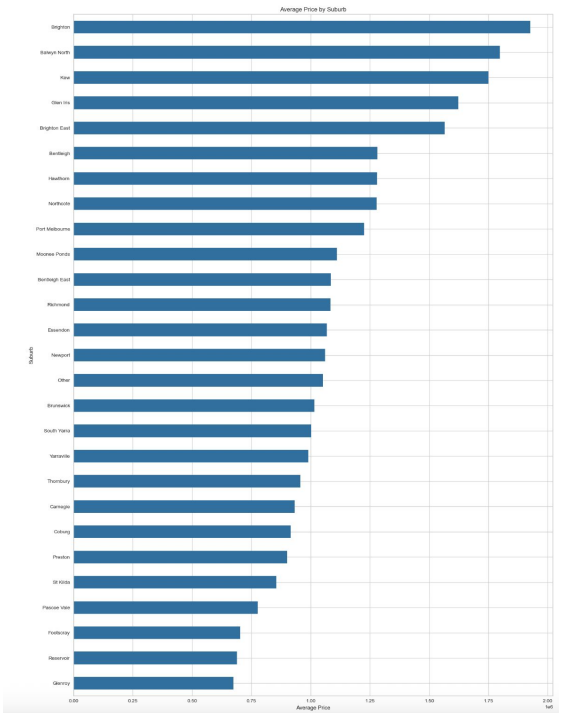
Dimensionality REDUCTION

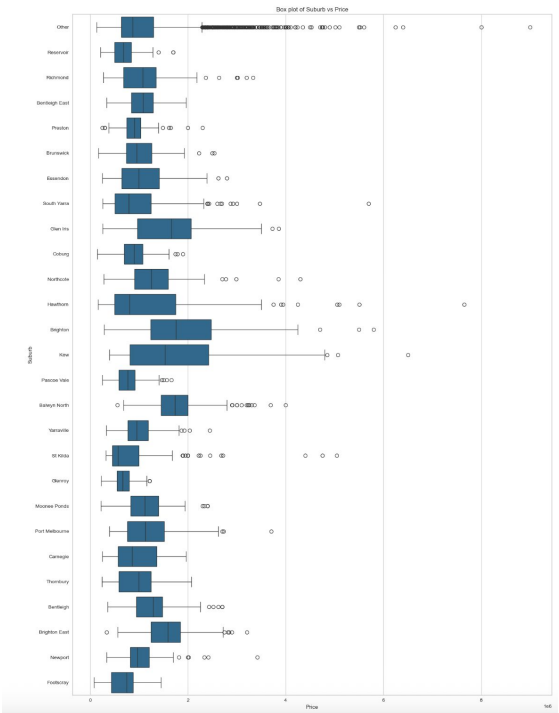
Feature ENGINEERING

1. Dimensionality Reduction: Suburb

How can we reduce the number of unique categories?





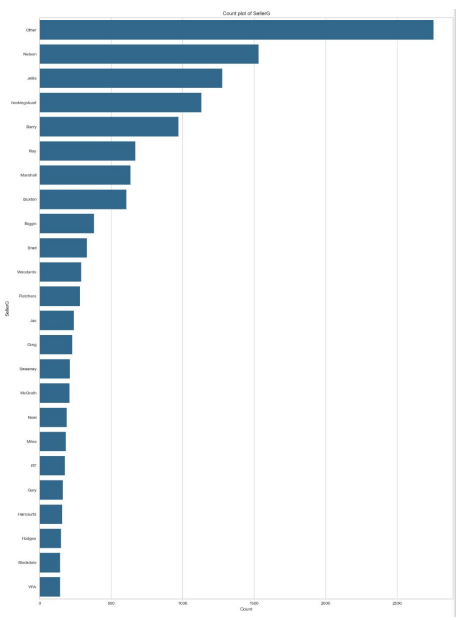


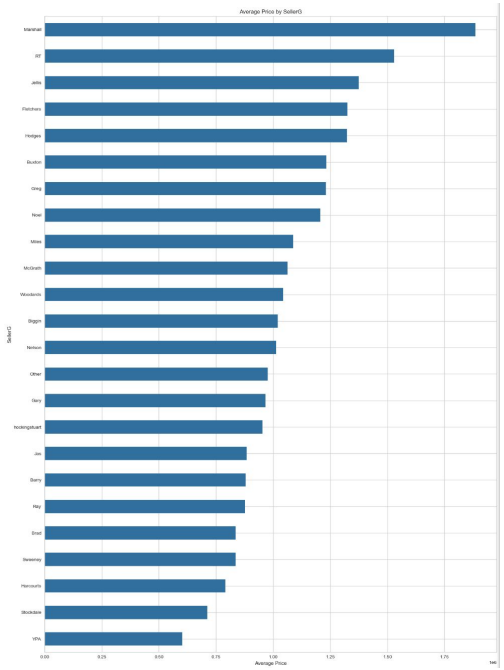
Dimensionality REDUCTION

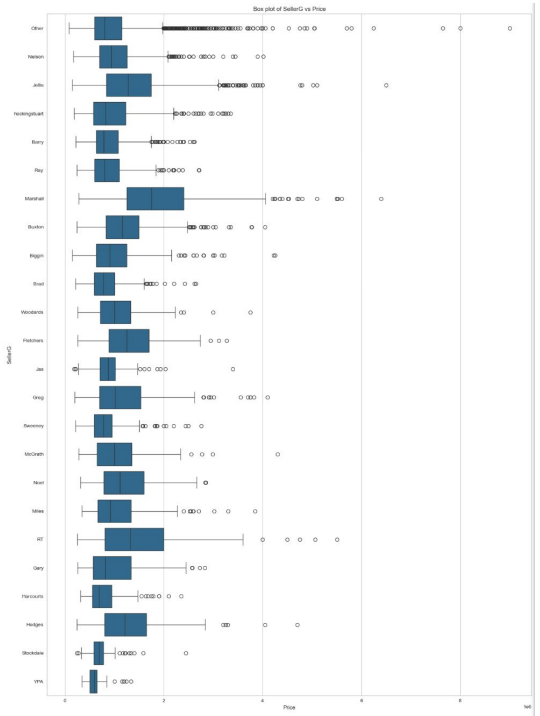
Feature ENGINEERING

1. Dimensionality Reduction: SellerG

How can we reduce the number of unique categories?







1. Dimensionality Reduction: Feature Elimination

How can we reduce the number of unique categories?

```
housingdata = housingdata.drop(columns=['Address'])
```

Dimensionality REDUCTION

Feature ENGINEERING

2. Feature Engineering of 'Date' Variable

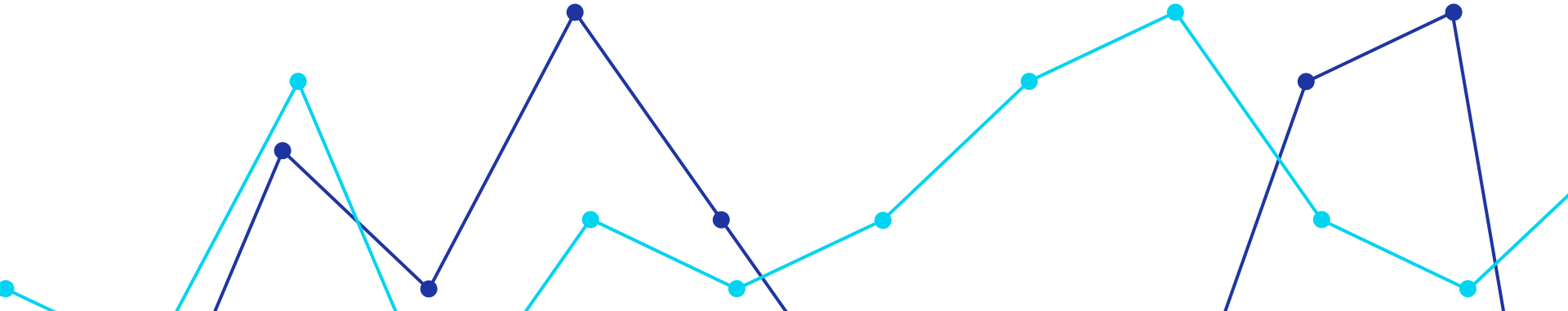
Date
2016-12-03
2016-02-04
2017-03-04
2017-03-04
2016-06-04
...
2017-08-26
2017-08-26
2017-08-26

Facilitate time-based analyses

Year	Month	YearMonth
2016	12	2016-12
2016	2	2016-02
2017	3	2017-03
2017	3	2017-03
2016	6	2016-06
...	...	...
2017	8	2017-08
2017	8	2017-08
2017	8	2017-08

4

Core Analysis



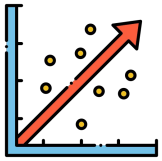
1a. Analysis of Price Predictors

Feature **IMPACT**

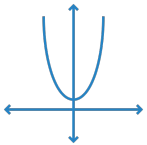
Core **ANALYSIS**

Which features have the highest impact on price based on feature importance?

Linear Regression



Quadratic Regression



Random Forest Regression

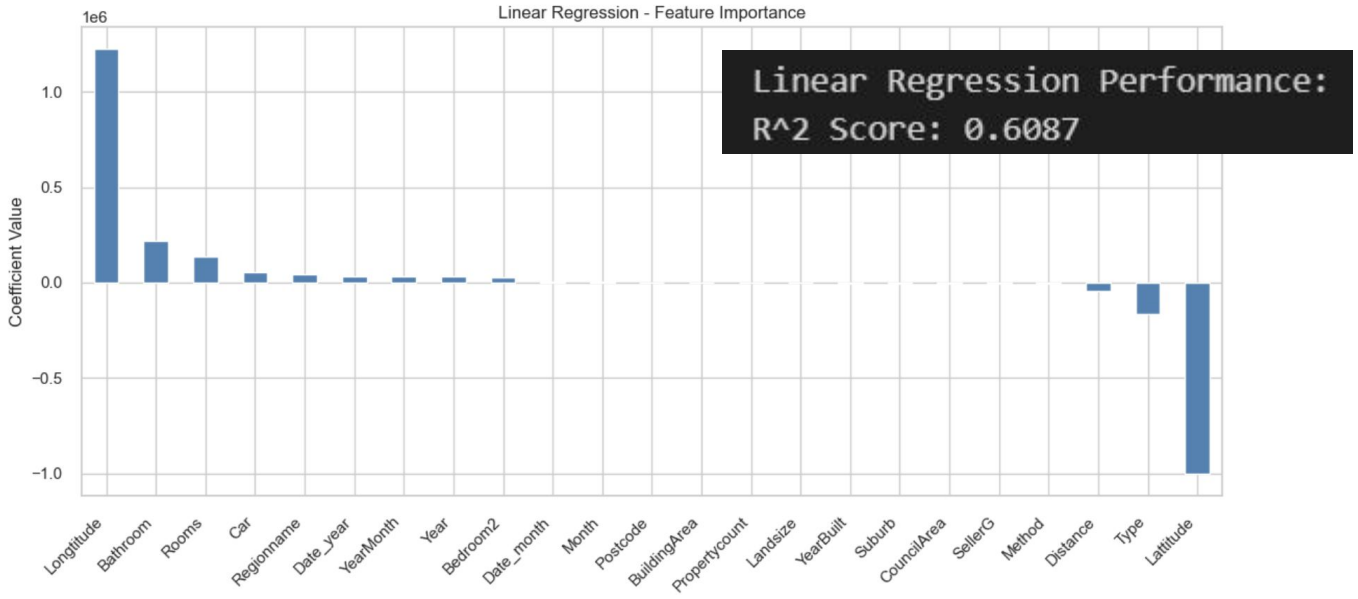
1a. Analysis of Price Predictors

Feature **IMPACT**

Core **ANALYSIS**

Which features have the highest impact on price based on feature importance?

Linear Regression



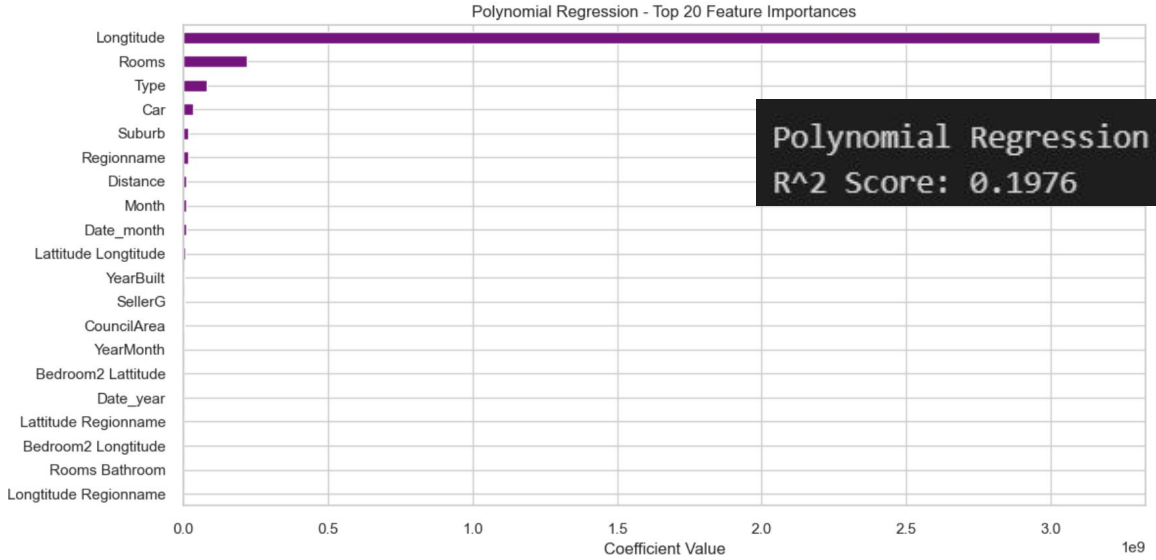
1a. Analysis of Price Predictors

Feature IMPACT

Core ANALYSIS

Which features have the highest impact on price based on feature importance?

Quadratic Regression




```
Polynomial Regression Performance:
R^2 Score: 0.1976
```

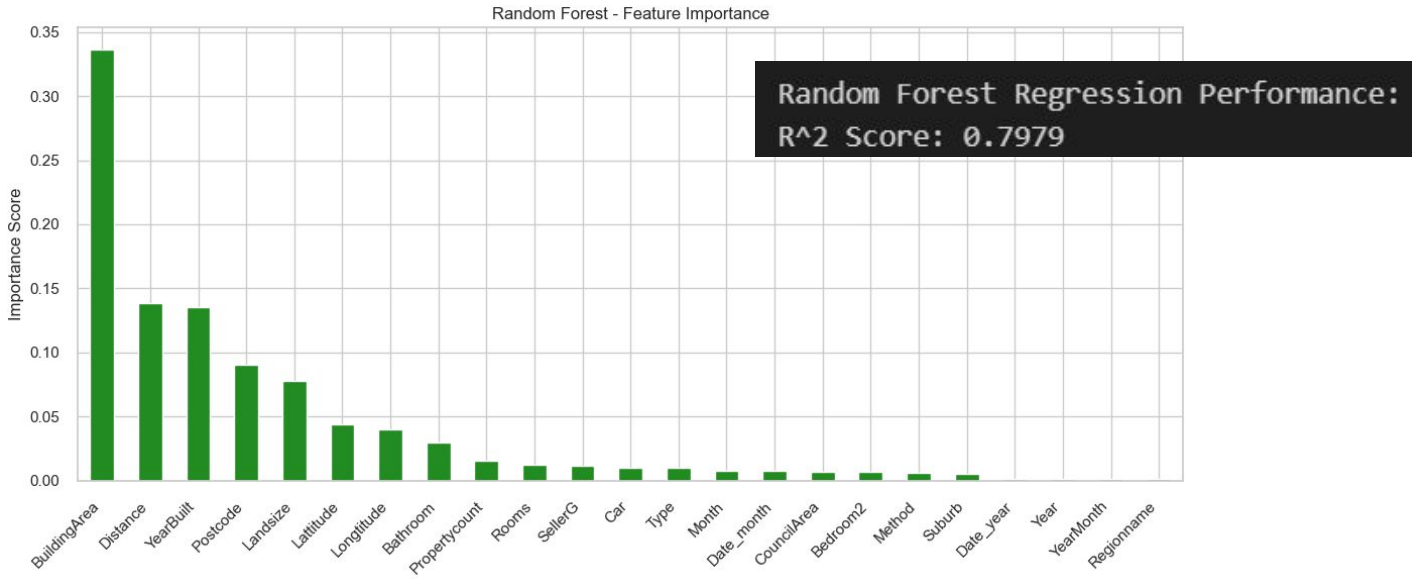
1a. Analysis of Price Predictors

Feature **IMPACT**

Core **ANALYSIS**

Which features have the highest impact on price based on feature importance?

Random Forest Regression

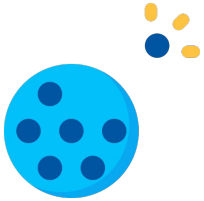


1b. Improvements to the Model

Feature IMPACT

Core ANALYSIS

Which features have the highest impact on price based on feature importance?

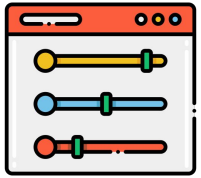


Outliers

- Remove outliers

Feature Engineering

- Encoding variables



Hyperparameter Tuning

```
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5],
}
```

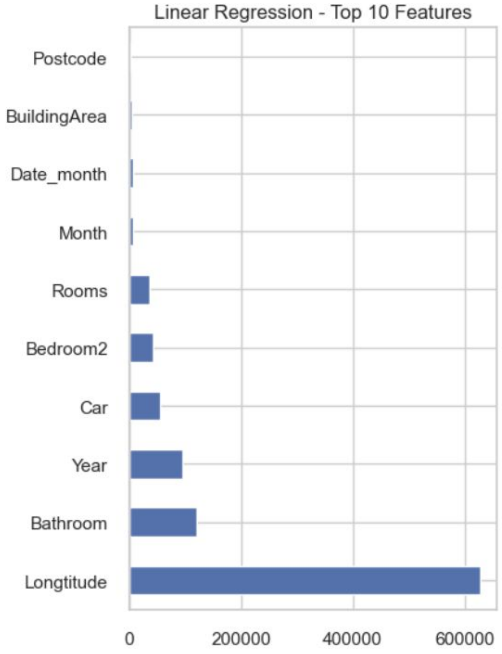
1b. Improvements to the model

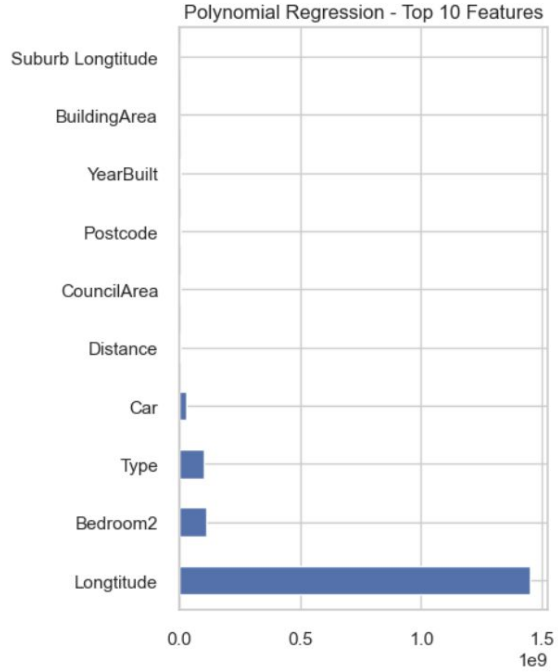
Feature IMPACT

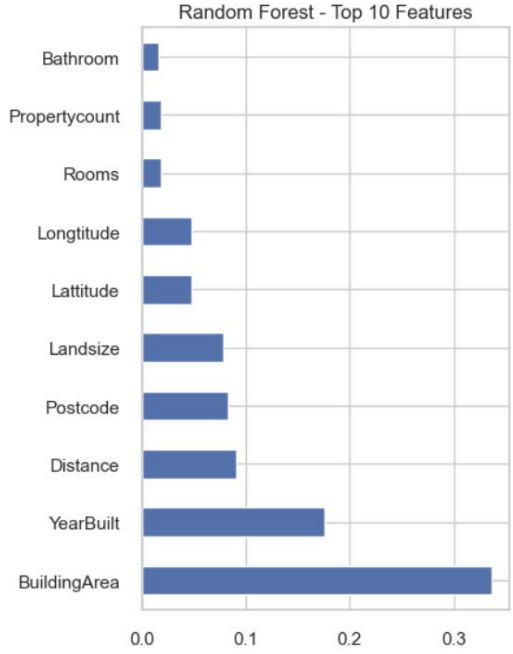
Core ANALYSIS

Which features have the highest impact on price based on feature importance?

```
Fitting 5 folds for each of 12 candidates, totalling 60 fits
```








```
Improved Linear Regression Performance:
R^2 Score: 0.6575
```

```
Improved Polynomial Regression Performance:
R^2 Score: 0.7450
```

```
Tuned Random Forest Performance:
R^2 Score: 0.8000
```

K-Means CLUSTERING

Core ANALYSIS

2. K-Means Clustering of Regions

How has the price trend varied across different regions over time, and can we identify emerging high-value areas?

Average Price

% Change in Price

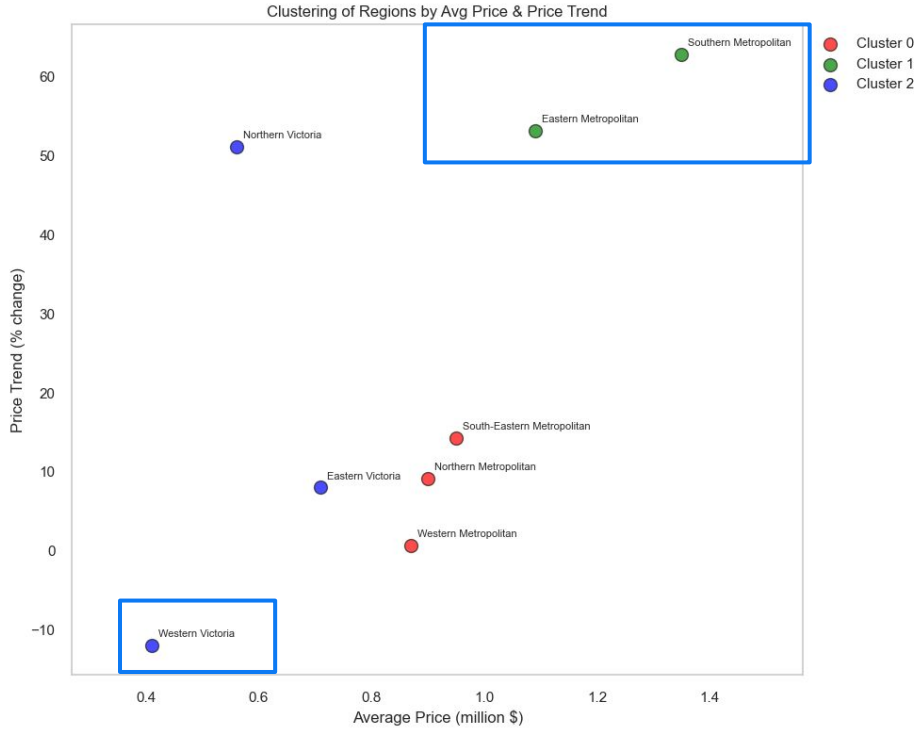
Regionname	FirstDate	LastDate	AvgPrice_M	PctChange	Cluster
Southern Metropolitan	2016-01-28	2017-09-23	1.35	62.85	1
Eastern Metropolitan	2016-02-04	2017-09-23	1.09	53.17	1
Northern Victoria	2017-05-27	2017-09-23	0.56	51.14	2
South-Eastern Metropolitan	2016-02-04	2017-09-23	0.95	14.28	0
Northern Metropolitan	2016-02-04	2017-09-23	0.90	9.12	0
Eastern Victoria	2017-05-27	2017-09-23	0.71	8.02	2
Western Metropolitan	2016-02-04	2017-09-23	0.87	0.69	0
Western Victoria	2017-05-27	2017-09-23	0.41	-11.91	2

K-Means CLUSTERING

Core ANALYSIS

2. K-Means Clustering of Regions

How has the price trend varied across different regions over time, and can we identify emerging high-value areas?



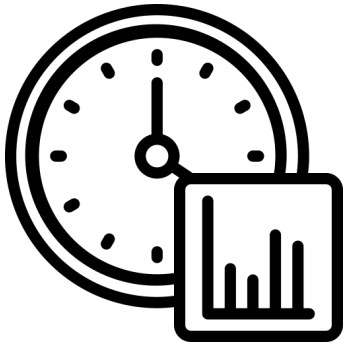
2. Improvements to the Model

Current results only reflect the first date and last date, as well as absolute price change, but instead it should show the changes of the clusters over time

Richer Dataset

Long-term Trends

Time-series Clustering



3. Influence of Variables on Prediction Accuracy

Random FOREST

Core ANALYSIS

How does property age and size influence prediction accuracy in models?

Random Forest Regression

Prediction Errors

```
                Price
count  1.358000e+04
mean   1.075684e+06
```

```
Initial MAE: $176,788.78
Initial MSE: 1.07e+11
RMSE: $326584.15
```

16.5% of average Price

30.5% of average Price

3. Influence of Variables on Prediction Accuracy

Random FOREST

Core ANALYSIS

How does property age and size influence prediction accuracy in models?

Property Age

```
Property Age Error Analysis:
PropertyAge
(-2.001, 9.0]       71067.410175
(9.0, 19.0]         79499.810786
(19.0, 37.0]        66585.052251
(37.0, 46.0]        65962.906458
(46.0, 51.0]        64726.198076
(51.0, 57.0]        73008.901682
(57.0, 67.0]        94876.985238
(67.0, 86.0]       131123.198594
(86.0, 106.0]      122819.075716
(106.0, 821.0]     143251.234171
```

Property Size

```
Landsize Impact:
Smaller properties (<177m²) MAE: $66,342.32
Larger properties (>650m²) MAE: $121,294.82
Error increase: 82.8%

BuildingArea Impact:
Smaller properties (<94m²) MAE: $58,343.37
Larger properties (>164m²) MAE: $142,290.94
Error increase: 143.9%
```

Random FOREST

Core ANALYSIS

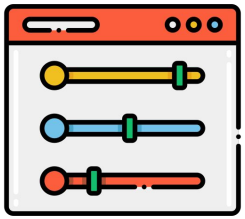
3. Improvements to the Model

How does property age and size influence prediction accuracy in models?

Feature Engineering

```
housingdata['Rooms_Bathroom']
housingdata['Landsize_BuildingArea']
```

- Better capture nuance



Hyperparameter Tuning

```
param_grid = {
    'n_estimators': [200, 300],
    'max_depth': [15, 25, None],
    'min_samples_split': [2, 5]
}
```

- Reduce overfitting

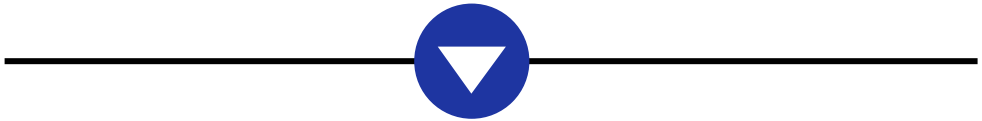
3. Improvements to the Model

Random FOREST

Core ANALYSIS

How does property age and size influence prediction accuracy in models?

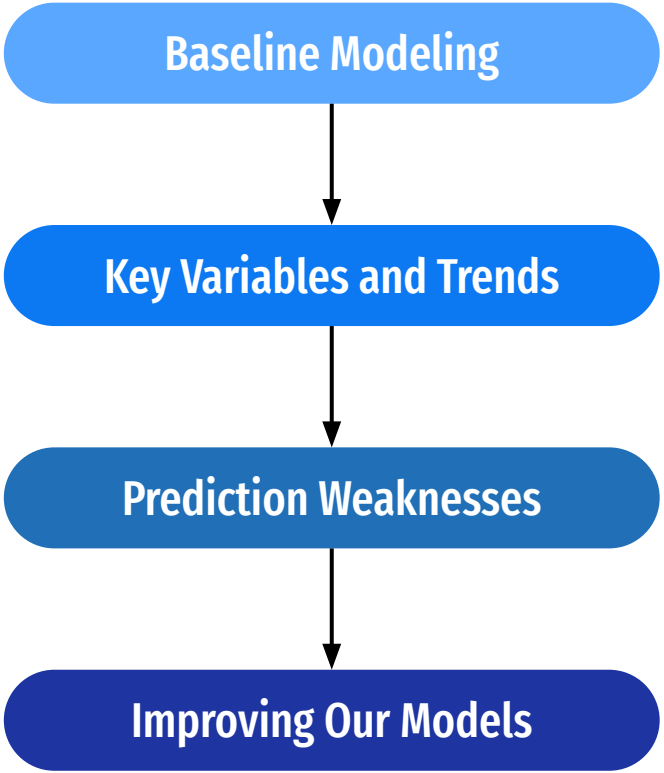
```
Improved MAE: $80,438.03
Improved MSE: 2.34e+10
MAE Improvement: 54.5%
```



Benchmark Conditions

Further Refinement

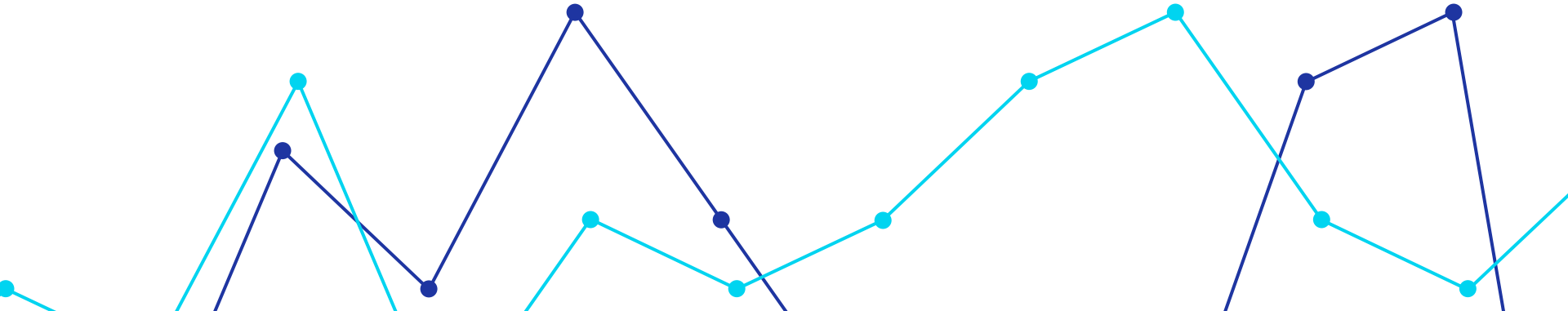
Wrapping Up



Core ANALYSIS

4

Conclusions



Outcome

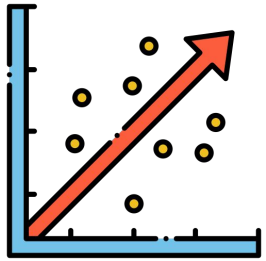
Analytical **OUTCOME**

Key **TAKEAWAYS**

1 Which features have the greatest impact on price?

Influential Predictors Of Price

1. BuildingArea
2. Location-based Features



Random Forest Regression

Linear Regression

Outcome

Analytical **OUTCOME**

Key **TAKEAWAYS**

2

How has the price trend varied across different regions over time, and can we identify emerging high-value areas?

K-Means Clustering

High-Growth Regions	1. Southern Metropolitan 2. Eastern Metropolitan
Declining Regions	1. Western Victoria

Outcome

Analytical **OUTCOME**

Key **TAKEAWAYS**

3

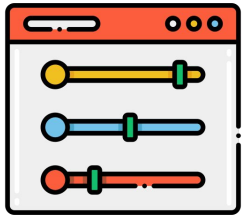
How does property age and size influence prediction accuracy in models?

Model Weaknesses

1. Older Properties
2. Larger Properties

Feature Engineering

+



Hyperparameter Tuning

Model Robustness and Reliance

Conclusions

Analytical **OUTCOME**

Key **TAKEAWAYS**

1. Stakeholders should take note of size and age-related price deviations.

2. Stakeholders should monitor and anticipate growth in certain regions.

Proactive Interventions in Singapore

Thank You!

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