Beachfront Bungalows

(Final Project)

Raj Ray

Introduction

- Beachfront Bungalows International – A new realty-services start-up
- Target Market – Tech-Savvy high net-worth individuals
- Services Offered (using Machine Learning and AI) -
  - Property Appraisal for Buyers and Sellers
  - House Price Valuation through Analysis of Existing Listings (Datasets)

Project Goal

o Live Demo - Home appraisal by means of automated object recognition on Smartphones using TensorFlow

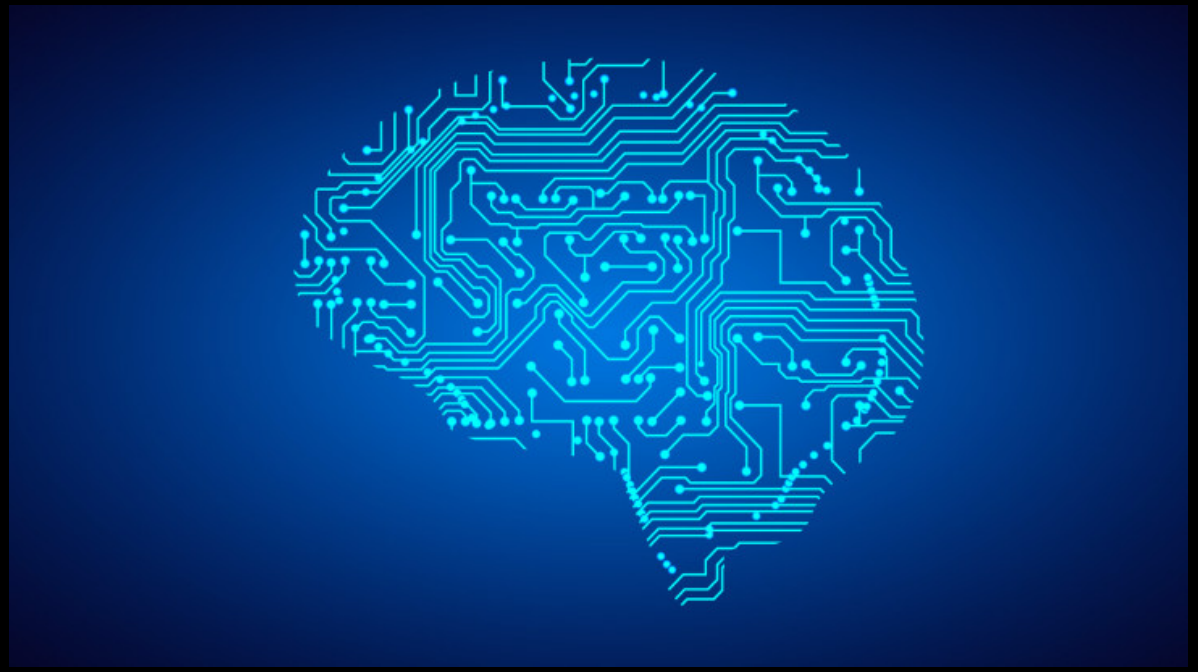
o Computational Analysis – Predictive Analyses of Home Prices using Machine Learning models

- Create, train and test multiple “Supervised ML Models” for regression analysis of past and existing listings
- Derive insights into the performance of different ML models by analyzing prediction accuracies for home prices
- Determine which ML model is best suited for house price valuation based on multiple parameters.

Demo

GitHub Link: https://github.com/tensorflow/tensorflow/tree/master/tensorflow/examples/android

Link to APK File: https://ci.tensorflow.org/view/Nightly/job/nightly-android/lastSuccessfulBuild/artifact/*zip*/archive.zip



Machine Learning Models

Models:

1. Linear Regression
2. Multivariate Regression
3. Decision trees
4. Random Forests
5. Support Vector Machines (SVM)
6. Lasso
7. Ridge
8. K- Nearest Neighbor (K-nn)
9. Gradient Descent Boosting
10. K-fold Grid-Search with Cross Validation

(Note: One-Hot Encoding to transform categorical parameters)

Performance Metric:

1. Correlations
2. Mean-squared error
3. Accuracy

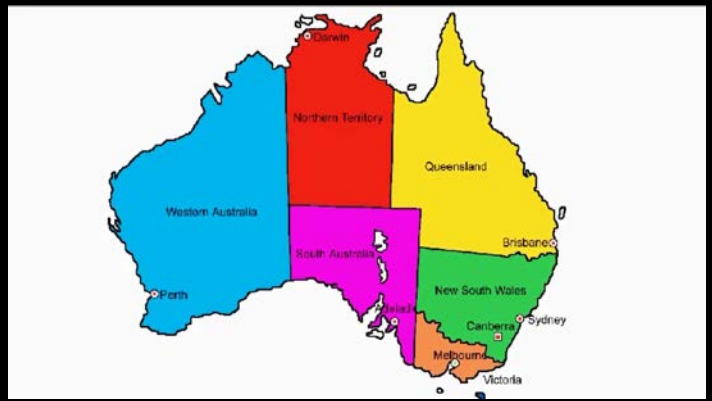
Core Phases:

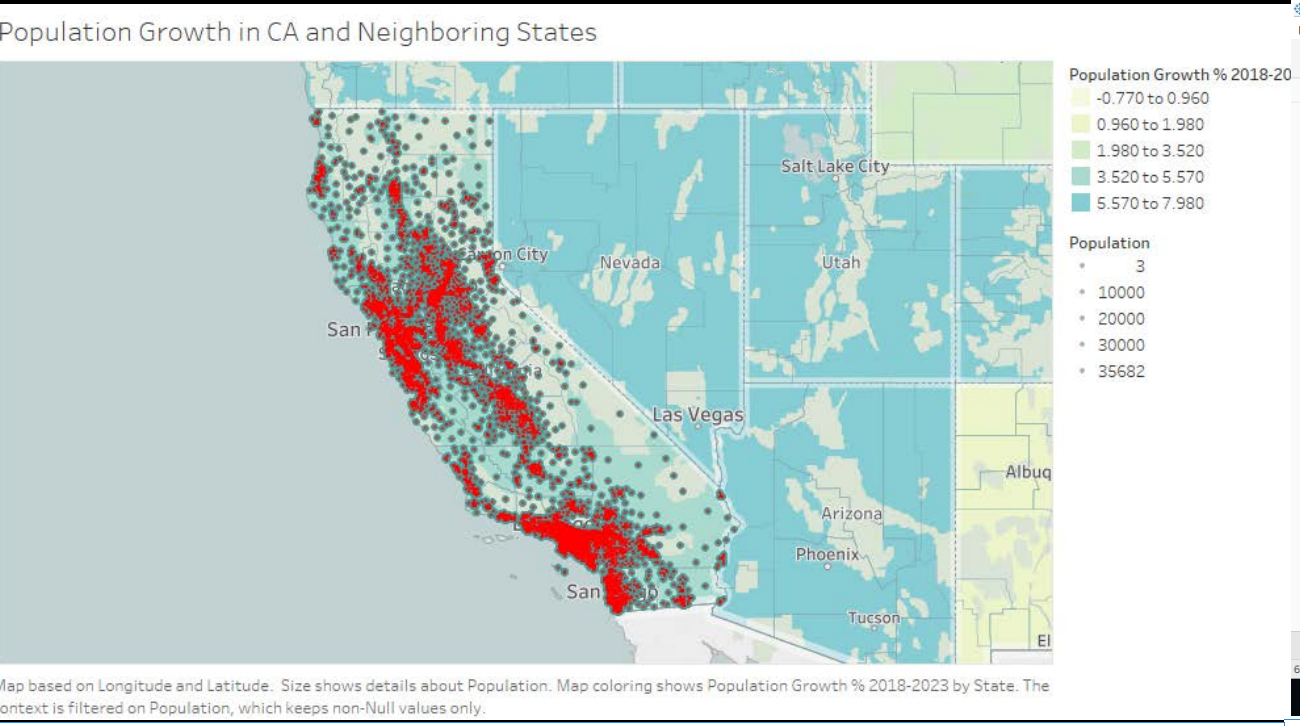
1. Data Input
2. Exploratory Analysis
3. Features and Labels
4. Data Preparation / Cleaning
5. Model Creation
6. Training and Testing
7. Model Fine-Tuning
8. Accuracy Evaluation

Datasets

- US:
  - Coastal Areas Housing Prices in California
  - Data from 1990 California census
  - 20,640 property listings
  - 10 variables each including longitude, latitude, total rooms, proximity to ocean, price etc.
  - Source: Paper published in Statistics & Probability Letters 33.3 (1997): 291-297)

- AUSTRALIA:
  - Coastal Region Housing Prices in Melbourne
  - Data scraped from publicly available weekly listings on www.domain.com.au
  - 14,242 property listings
  - 21 variables each including address, longitude, latitude, suburb, total rooms, bedrooms, bathrooms, lot-size, price, postal code etc.
  - Source – Kaggle.com




Population Growth in CA and Neighboring States
Population Growth % 2018-20
-0.770 to 0.960
0.960 to 1.980
1.980 to 3.520
3.520 to 5.570
5.570 to 7.980
Population
3
10000
20000
30000
35682
Salt Lake City
Nevada
Utah
Las Vegas
Arizona
Phoenix
Tucson
Albuq
Map based on Longitude and Latitude. Size shows details about Population. Map coloring shows Population Growth % 2018-2023 by State. The
ontext is filtered on Population, which keeps non-Null values only.

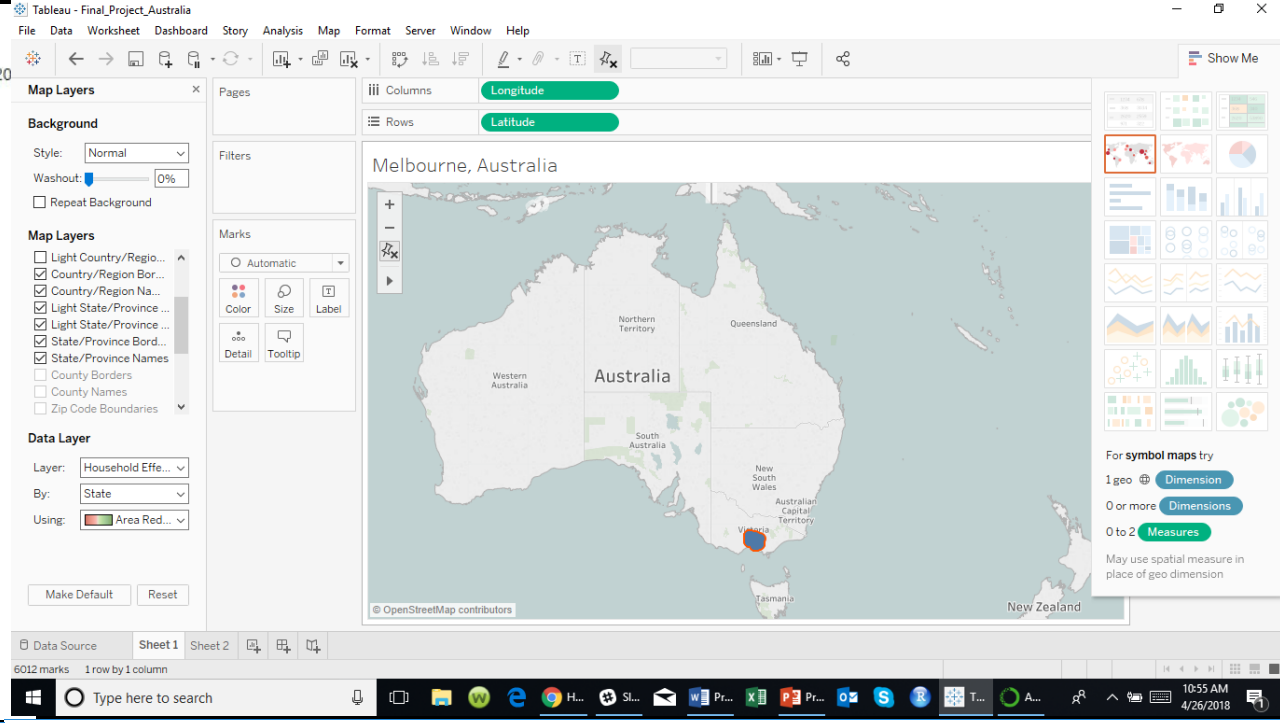


Tableau - Final_Project_Australia
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Show Me
Map Layers
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Map Layers
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State/Province Names
County Borders
County Names
Zip Code Boundaries
Data Layer
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Columns
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Melbourne, Australia
Northern Territory
Queensland
Western Australia
Australia
South Australia
New South Wales
Australian Capital Territory
Victoria
Tasmania
New Zealand
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1 geo Dimension
0 or more Dimensions
0 to 2 Measures
May use spatial measure in place of geo dimension
Data Source
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Sheet 2
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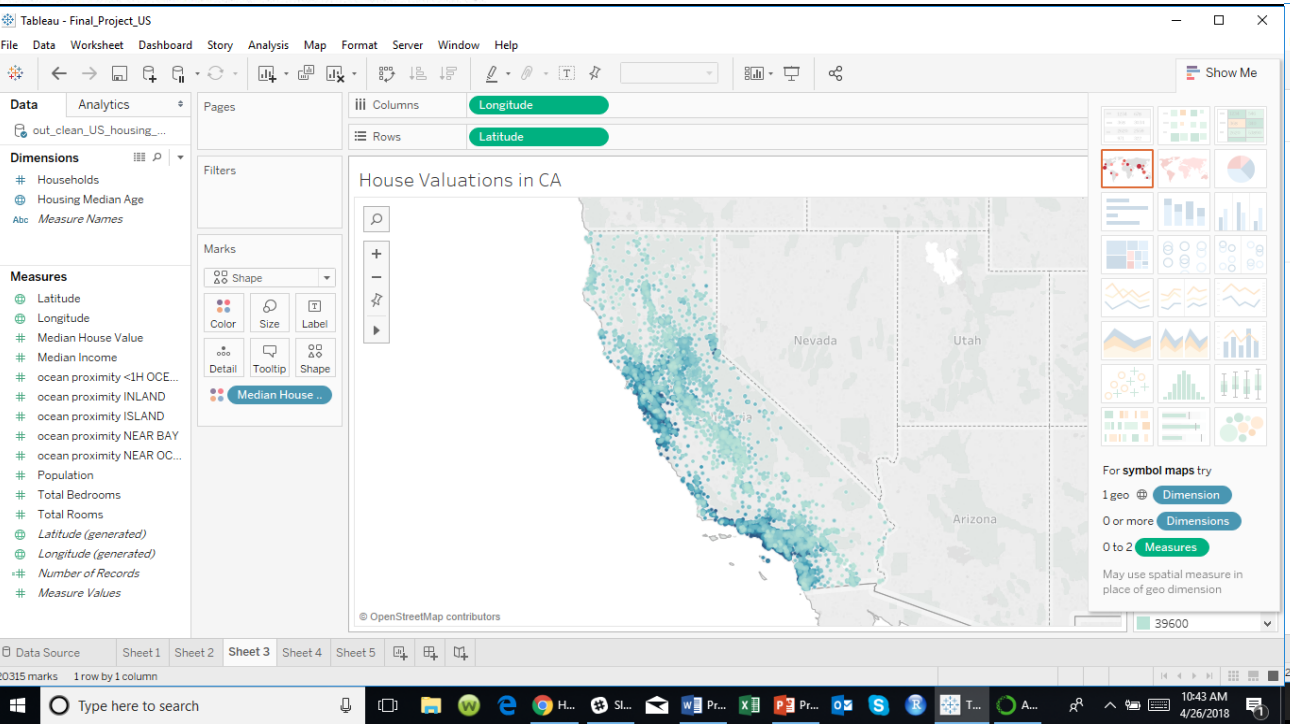
Tableau - Final_Project_US
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ocean proximity NEAR OC...
Population
Total Bedrooms
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House Valuations in CA
Nevada
Utah
Arizona
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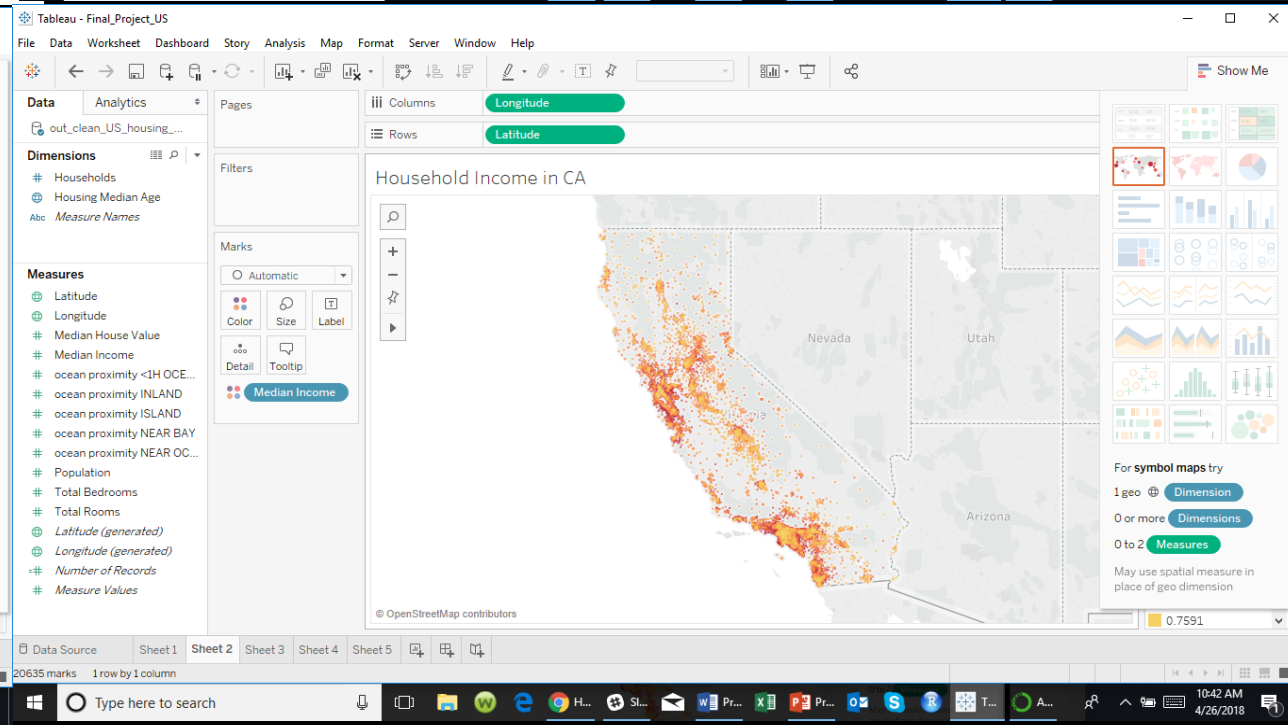
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ocean proximity ISLAND
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Population
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Latitude (generated)
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Household Income in CA
Nevada
Utah
Arizona
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Tableau - Final_Project_Australia

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Data | Analytics

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Dimensions

- Abc Council Area
- Postcode
- Abc Suburb
- Abc Type
- # Year Built
- Abc *Measure Names*

Measures

- # Bathroom
- # Bedrooms
- # Building Area
- # Car
- # Distance
- Latitude
- Longitude
- # Lotsize
- # Price
- # Rooms
- *Latitude (generated)*
- *Longitude (generated)*
- *Number of Records*
- # *Measure Values*

Pages

Filters

Marks

Shape

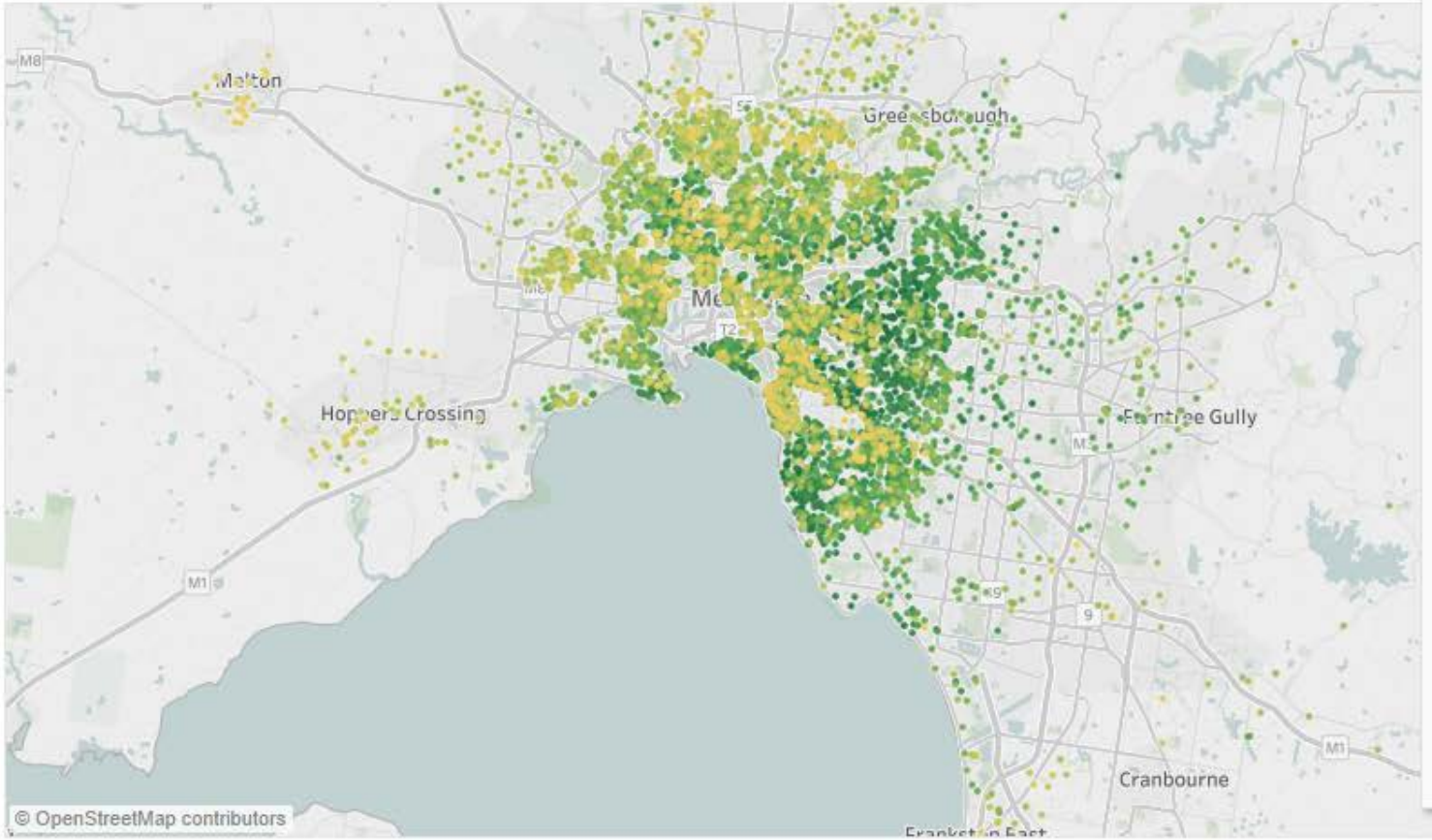
Color | Size | Label | Detail | Tooltip | Shape

Price

Columns: Longitude

Rows: Latitude

High-Priced Homes in Melbourne



For **symbol maps** try

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May use spatial measure in place of geo dimension

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Data Source | Sheet 1 | Sheet 2 | Sheet 3

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Tableau - Final_Project_Australia

File Data Worksheet Dashboard Story Analysis Map Format Server Window Help

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Map Layers

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Map Layers

- [x] Base
- [x] Land Cover
- [ ] Coastline
- [ ] Streets and Highways
- [ ] Light Country/Regio...
- [ ] Light Country/Regio...
- [x] Country/Region Bor...
- [x] Country/Region Na...
- [ ] Light State/Province ...

Data Layer

Layer: Households

By: State

Using: Blue-Gre...

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Pages

Filters

Marks

Automatic

Color Size Label

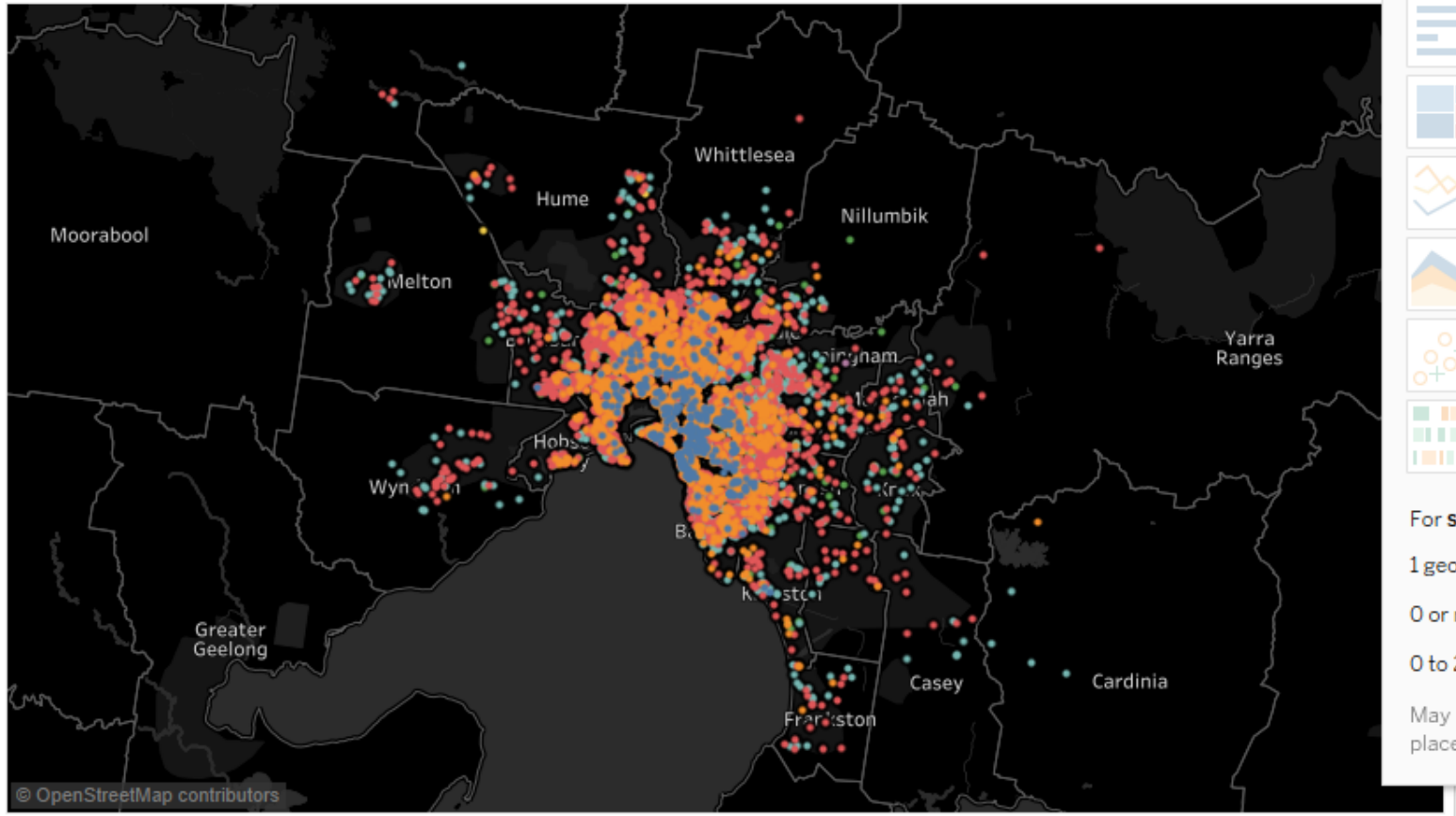
Detail Tooltip

Rooms

Columns: Longitude

Rows: Latitude

# of Rooms per Household



For **symbol maps** try

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May use spatial measure in place of geo dimension

Data Source | Sheet 1 | Sheet 2 | Sheet 3

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Results

ML Model	Mean Squared Error	Accuracy (R2)
Linear Regression	0.4503	0.549
Multivariate Regression	2.17e-13	1.0
	0.0156	0.998
Random Forests	0.0020	0.999
Support Vector Machines	0.8227	0.323
Lasso	0.0008	0.999
Ridge	0.0019	0.998
K-nn	0.81	1.0
Gradient Descent with Boosting	0.1668	.78
K-Fold Grid-Search with Cross-Validation	0.0216	1.0

Conclusions

- Key parameters affecting house price valuation?
  - Location (Zipcode / postal code, proximity to beach)
- Main challenges of machine learning?
  - Large unclean datasets and computational time - Needs GPU or Cloud
- How to improve accuracy and reduce overfitting?
  - Cross-Validation, Lasso / Ridge Regression (Regularization), Scaling, Boosting
- Does overall performance depend on feature selection?
  - Correlated Features and One-Hot Encoding. Drop unrelevant / uncorrelated features
- Effects of k-fold Cross-Validation?
  - Improves over-fitting, Effectively uses small data-sets
- Did certain algorithms perform poorly on both datasets? Why?
  - Yes, Linear Regression because most natural processes tend to be non-linear
- Which supervised models are better for predictive analysis?
  - Yes, Multivariate Regression, Lasso, Ridge, Random Forests performed well.


Thank You