Melbourne Housing Price Prediction

Team 2
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Outline

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2. Dataset + Variables
3. Data Preparation
4. Exploratory Data Analysis
5. Models
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   - Ridge
   - Lasso
   - Regression Tree
   - Bagging
   - Random Forest
   - Boosting
6. Conclusion

Objective

- Business Question/Objective
- Why it is important
- Other applications

Dataset

- Kaggle: https://www.kaggle.com/anthonypino/melbourne-housing-market
- 21 columns / 34,009 rows
- Goals:
  - Trying different models to make accurate price prediction
  - Finding important variables influence price the most
  - Giving advice to buyers and sellers
- Variables:
  - 8 characters: Address, Regionname, Type...
  - 7 integers: Rooms, Landsize, YearBuilt...
  - 6 numeric: BuildingArea, Distance...

Variables

Price: Price in Australian dollars

Type:

br - bedroom(s);

h - house,cottage,villa, semi,terrace;

u - unit, duplex;

t - townhouse;

dev site - development site;

o res - other residential.

Address: Address

Distance: Distance from Major City(km)

Latitude: Self explanatory

Longitude: Self explanatory

SellerG: Real Estate Agent

Method:

S - property sold;

SP - property sold prior;

PI - property passed in;

PN - sold prior not disclosed;

SN - sold not disclosed;

NB - no bid;

VB - vendor bid;

W - withdrawn prior to auction;

SA - sold after auction;

SS - sold after auction price not disclosed.

N/A - price or highest bid not available.

Date: Date sold

Regionname: General Region (West, North, etc)

Suburb: Suburb

Propertycount: Number of properties in the suburb.

Rooms: Number of rooms

Bedroom2 : Scraped # of Bedrooms

Bathroom: Number of Bathrooms

Car: Number of carspots

Landsize: Land Size in Metres

BuildingArea: Building Size in Metres

YearBuilt: Year the house was built

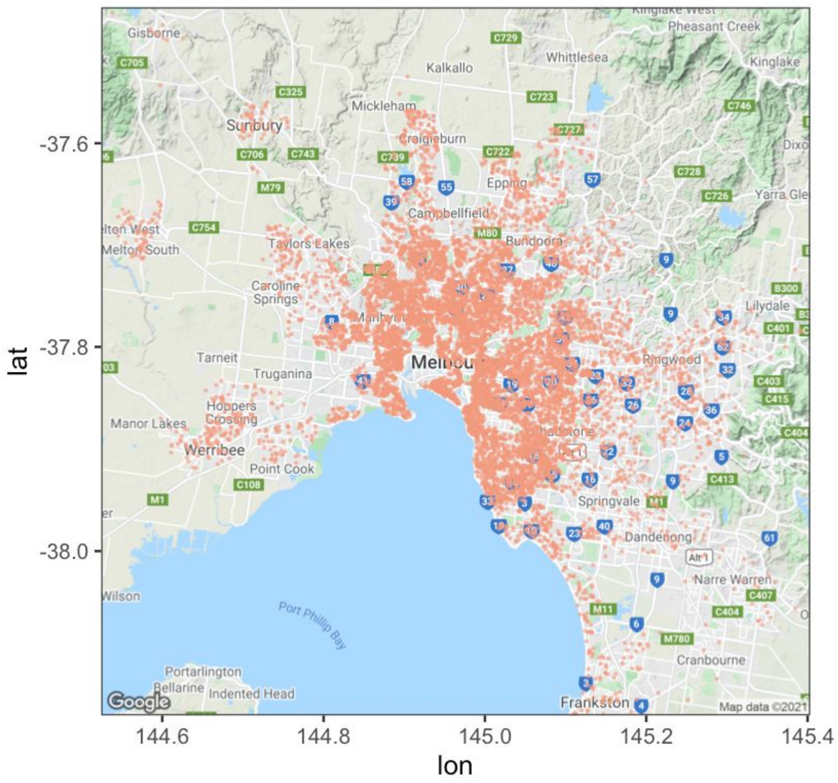
CouncilArea: Governing council for the area

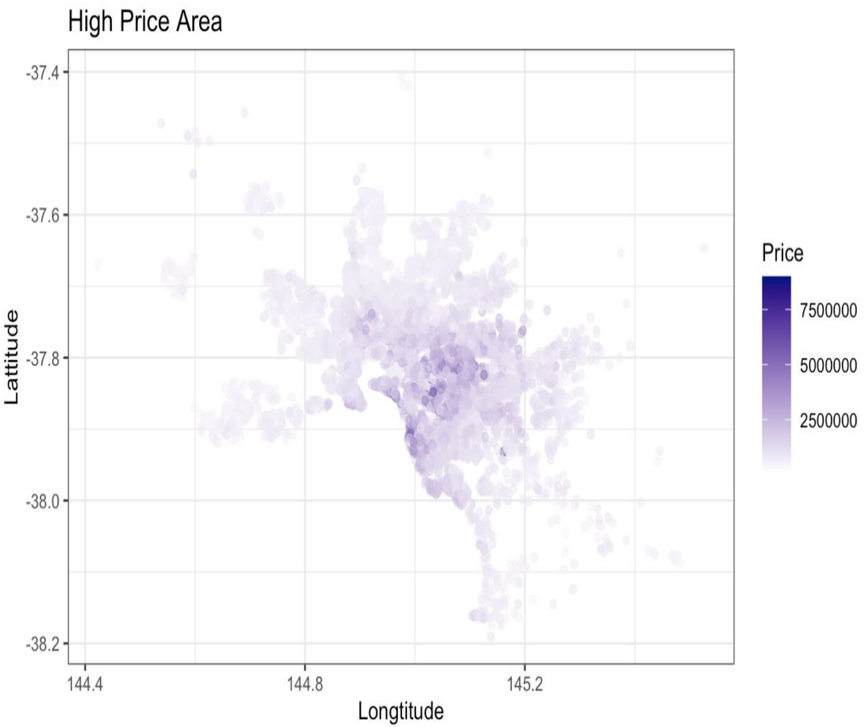
Data Preparation

- Data Formatting
- Null Values
  - Landsize, YearBuilt, Car, Latitude, BuildingArea
- Feature Engineering
  - SellYear, SellMonth
- Factored
  - Type, Method, Regionname, CouncilArea
- Scaling
- Splitting Train/Test (70/30)

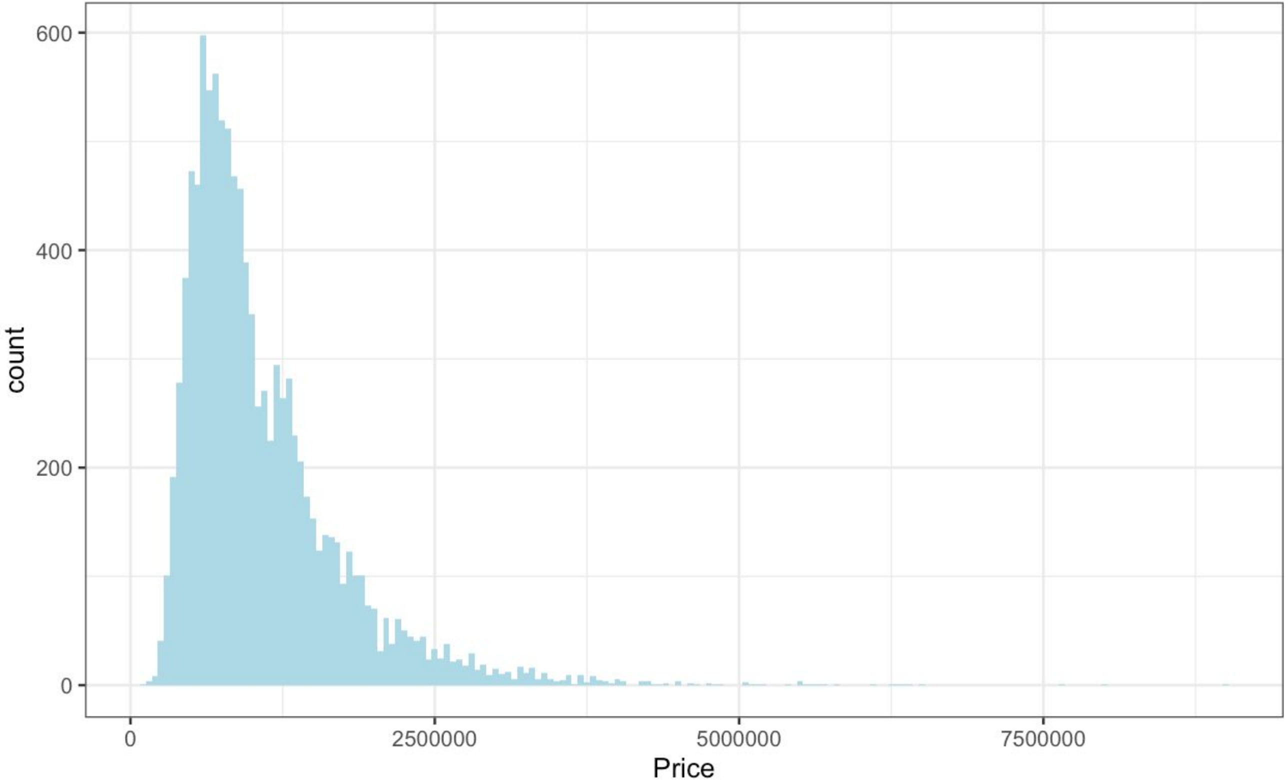
Exploratory Data Analysis

Exploratory Data Analysis



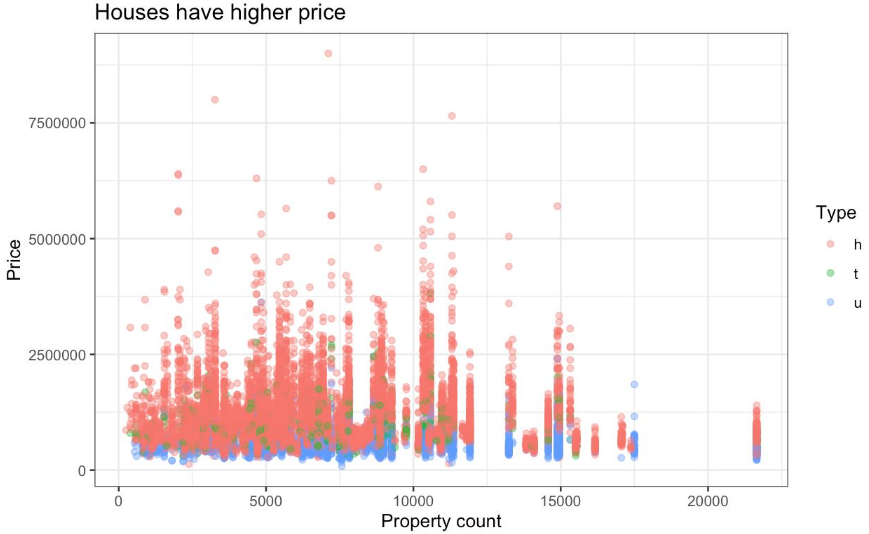


Price Range



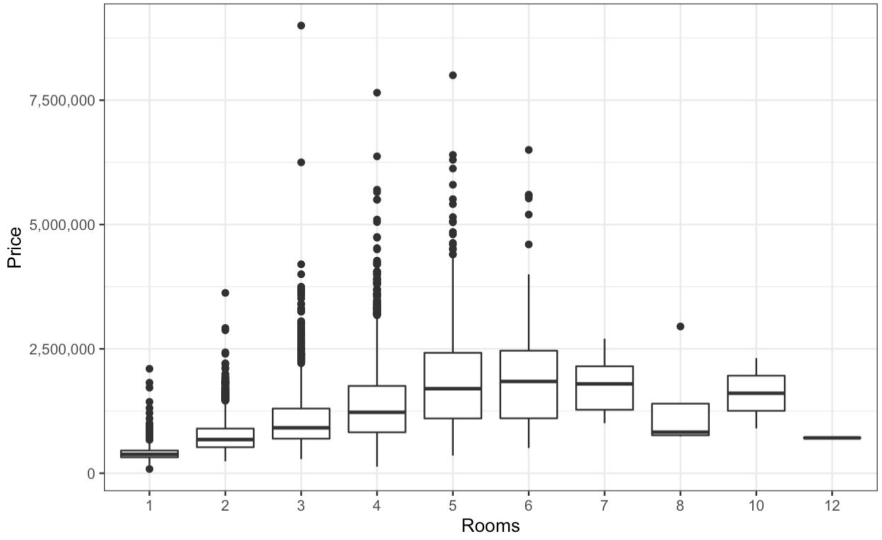
- The majority of those houses lies below $2,500,000

Price vs. Rooms/Types

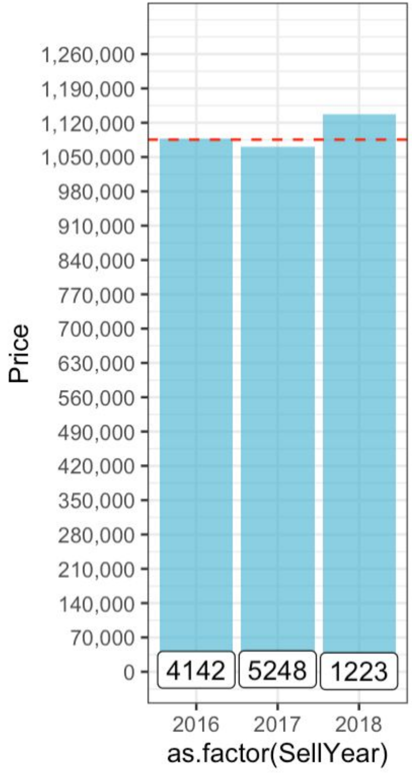


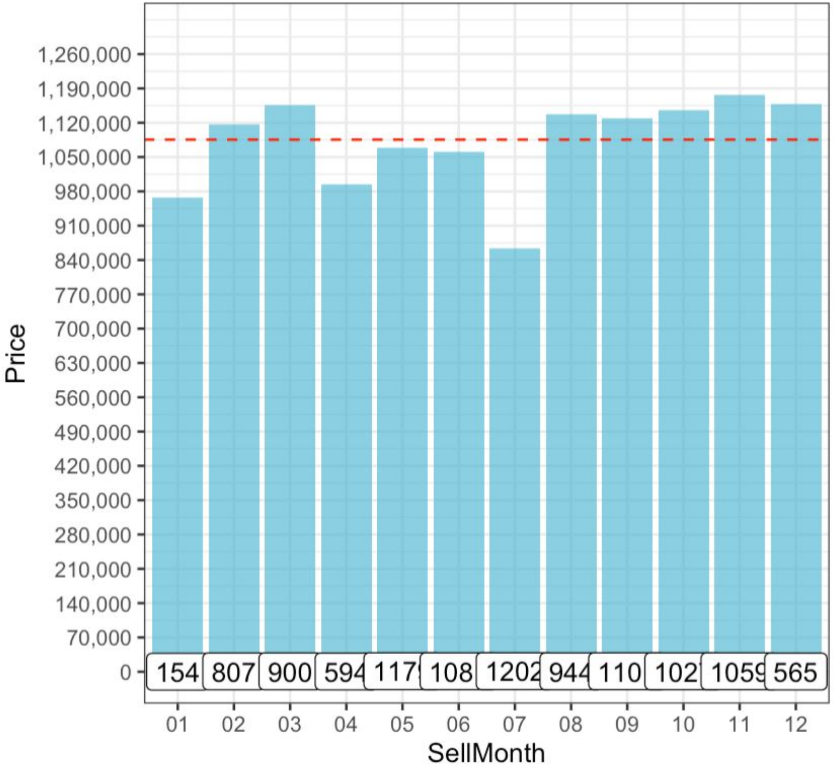
- House is the common type
- House has the highest price

- 4-6 rooms have higher price
- There are some outliers



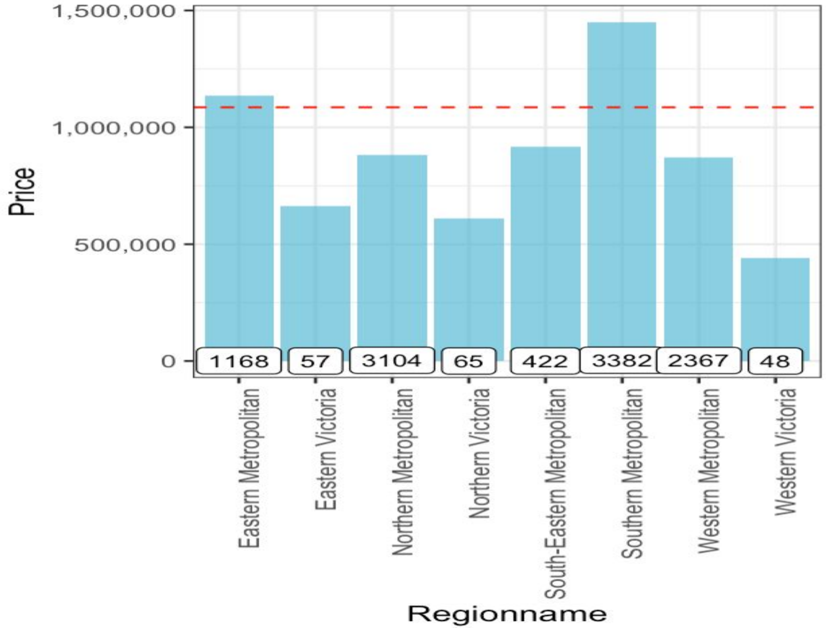
Price vs. Seasons

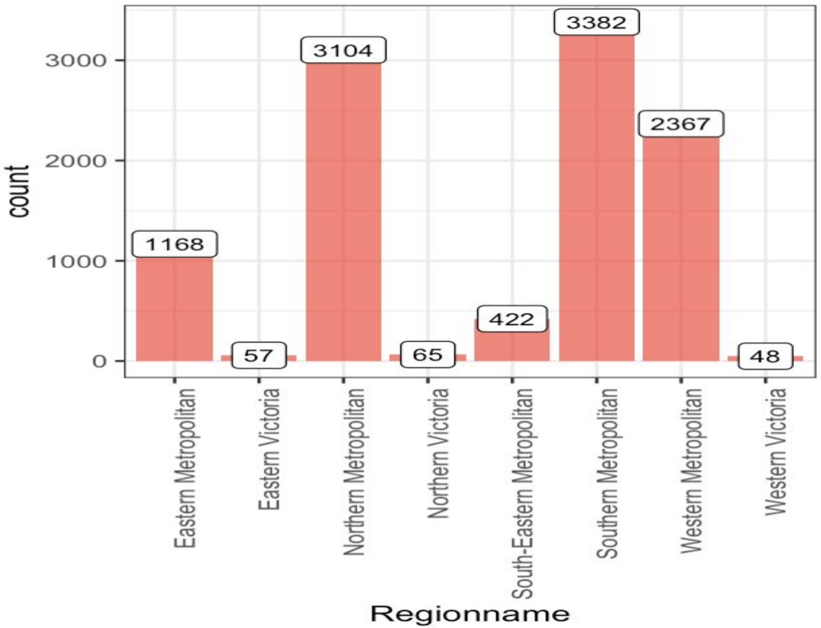




- January April and July have low house price
- Fall has higher house price than other seasons

Price vs. Regions





- Southern Metropolitan has the highest average price and more properties.
- Western Victoria has the lowest house price and least properties.

Linear Regression

Linear regression

- **Model 1**: Full model contains all variables

  Train MSE: 0.3314157 *Test MSE*: 0.3560723

- **Model 2**: Delete insignificant variables

  Train MSE: 0.3362878 *Test MSE*: 0.3626219

- **Model 3**: Combine 'Landsize' and 'Age' to create a interaction model

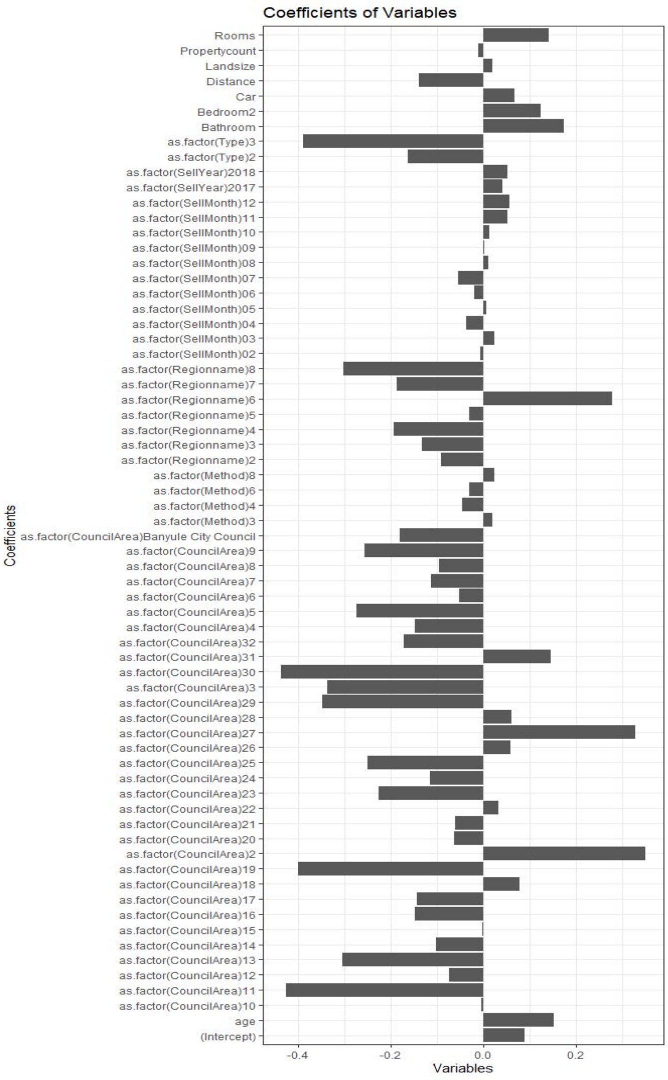
  Train MSE: 0.334264 *Test MSE*: 0.360624

Ridge & Lasso Regression

Ridge regression

- 10 fold cross validation model to find the best lambda
- CouncilArea seemed to have a strongest effect on the price of a house.
    - Boroondara City Council - 2
    - Hume City Council - 11
    - Wyndham City Council - 30

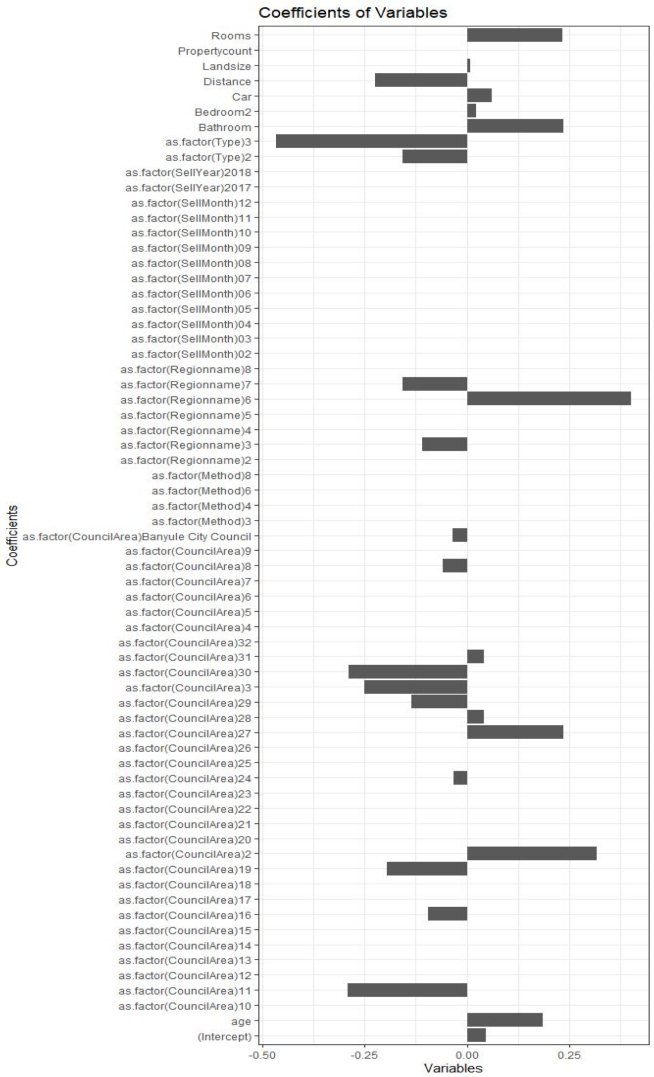
	Train MSE	Test MSE
Ridge	**0.3353068**	**0.3611925**
Lasso	TBD	TBD



Lasso regression

- 10 fold cross validation model to find the best lambda
- Again the CouncilArea, but now Type and Regionname are among the top 3
    - Boroondara City Council - CouncilArea 2
    - Unit style Home - Type 3
    - Southern Metropolitan - Regionname 6

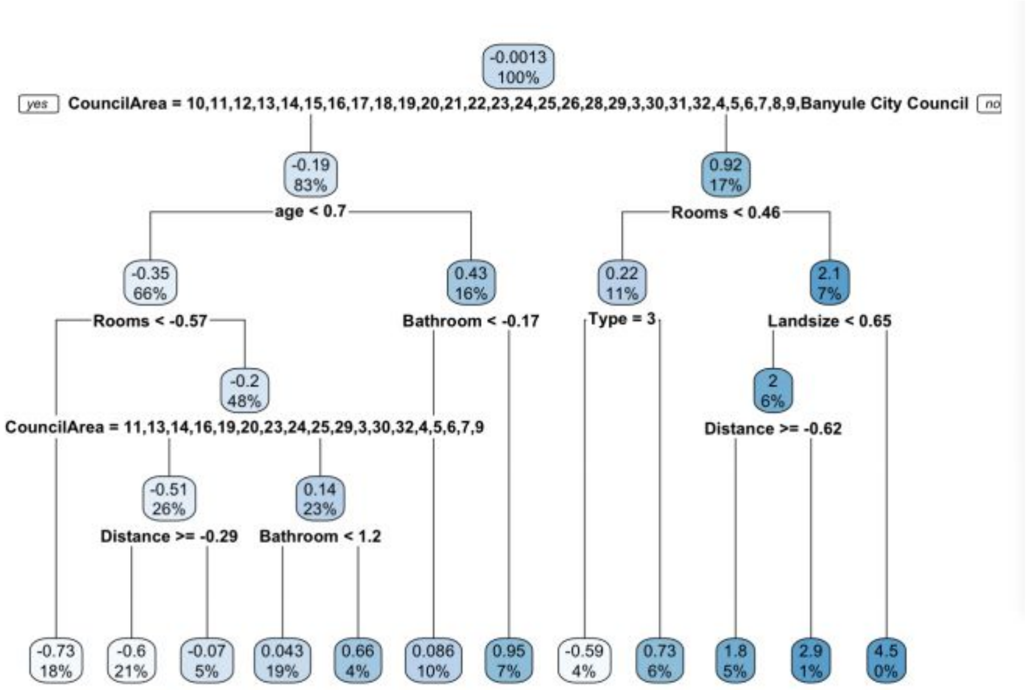
	Train MSE	Test MSE
Lasso	**0.3316269**	**0.3562078**
Ridge	0.3353068	0.3611925



Regression Trees

Regression Tree

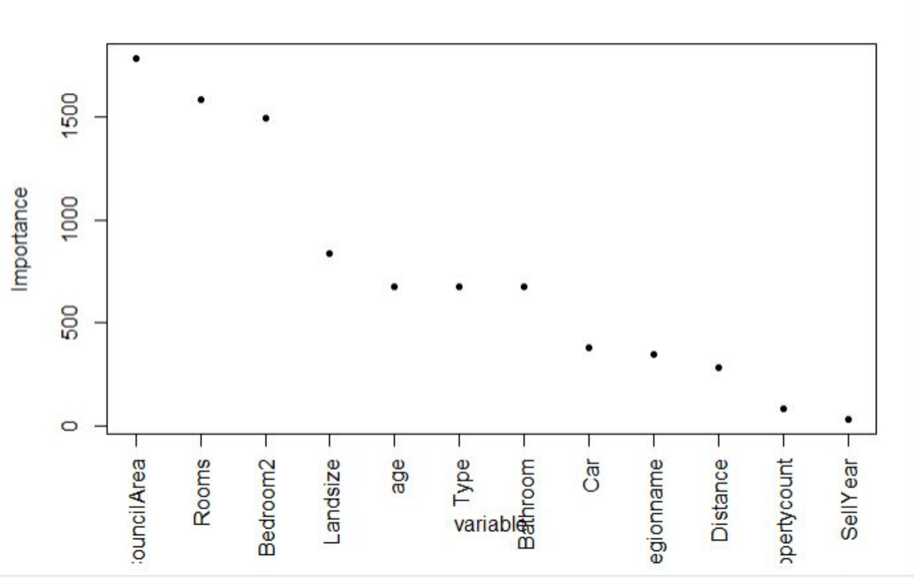
- 12 variables are used to construct the tree with 11 internal nodes resulting in 12 terminal nodes.
- After 10 cross-validation : Train MSE:0.3827 ; Test MSE: 0.4011.



Regression Tree

- The CouncilArea , Rooms and bedrooms seem to have a stronger effect on the price of a house.

```
Variable importance
  CouncilArea        Rooms     Bedroom2     Landsize          age
           20           18           17            9            8
         Type     Bathroom          Car   Regionname     Distance
            8            8            4            4            3
Propertycount
            1
```



Bagging

Bagging

- We use bagging model and set coob = TRUE to use the OOB sample to estimate the test error.
- The test MSE is 0.3442
- The fit of Bagging is better than Regression Tree.

```
Bagging regression trees with 25 bootstrap replications

Call: bagging.data.frame(formula = Price ~ ., data = train, coob = TRUE)

Out-of-bag estimate of root mean squared error:  0.5964
```

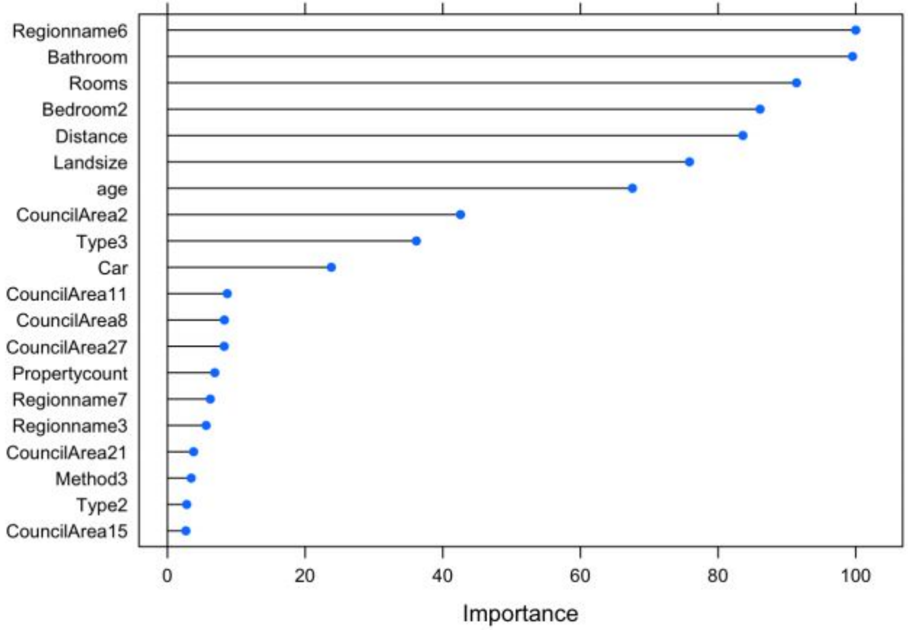
Bagging

- Use caret package performing a 10-fold cross-validated by using bagging model.
- The test MSE is 0.3956.

```
Bagged CART

7431 samples
  14 predictor

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 6688, 6687, 6689, 6686, 6687, 6689,
Resampling results:

  RMSE       Rsquared   MAE
  0.6149614  0.6199037  0.4100107
```

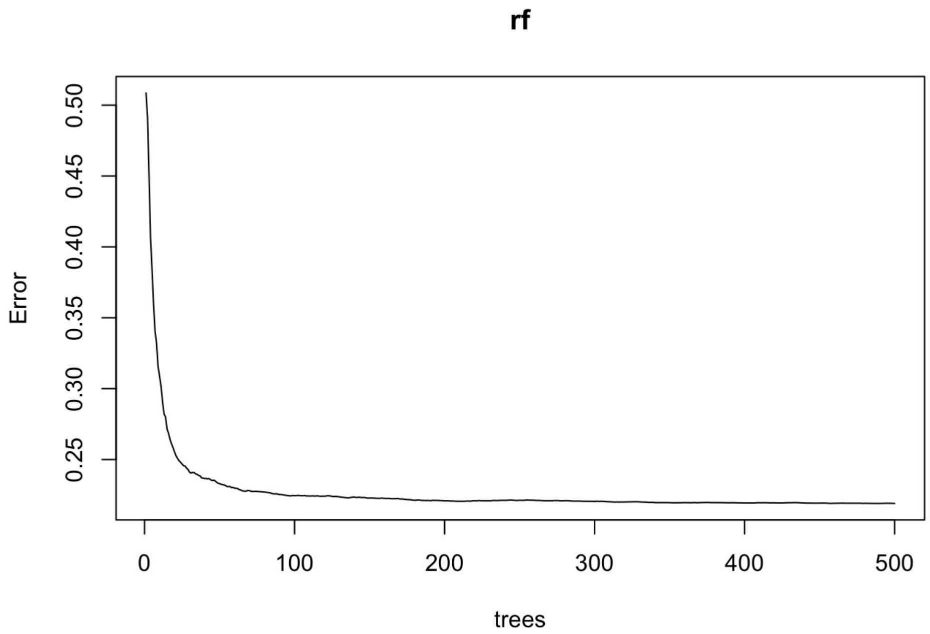
Bagging

- Feature importance:
- The Region name, bathrooms and rooms seem to have a stronger effect on the price of a house.



Random Forests

Random Forests

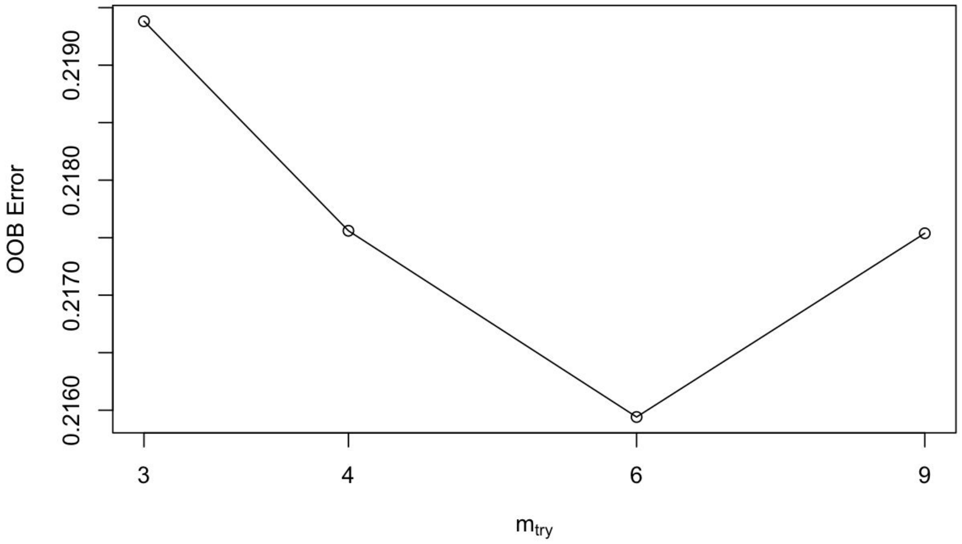


- Set ntree=500, mtry=4 (default)
- Test MSE: 0.2127

Optimal mtry Parameter

- tuneRF() function

```
##    mtry  OOBError
## 3     3 0.2193815
## 4     4 0.2175599
## 6     6 0.2159408
## 9     9 0.2175382
```



Tune Using The Optimal mtry

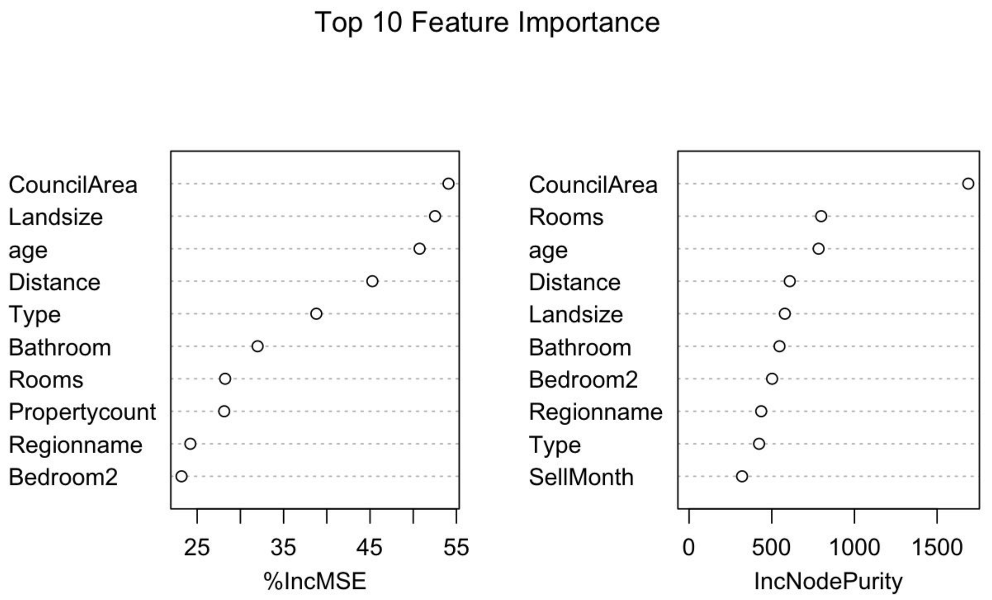
- Set ntree=500, mtry=6
- Test MSE: 0.2115

# of Trees	# of variables at each split	Test MSE
ntree=500	mtry=4	0.2127
ntree=500	mtry=6	0.2115

```
## Call:
##  randomForest(formula = Price ~ ., data = train, mtry = 6, importance = TRUE)
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 6
##
##           Mean of squared residuals: 0.2160597
##                     % Var explained: 78.05
```

Feature Importance

	%IncMSE	IncNodePurity
Rooms	28.236506717	798.97720
Type	38.787836662	423.32872
Method	4.032808757	100.24231
Distance	45.273557453	608.95794
Bedroom2	23.188694391	501.99143
Bathroom	31.994683968	546.87787
Car	17.492084776	110.68837
Landsize	52.524638732	579.17912
CouncilArea	54.084471377	1688.40411
Regionname	24.208334041	436.28853
Propertycount	28.126708567	194.95971
SellYear	6.586972312	47.35067
SellMonth	-0.002773935	320.56163
age	50.737487069	783.28740

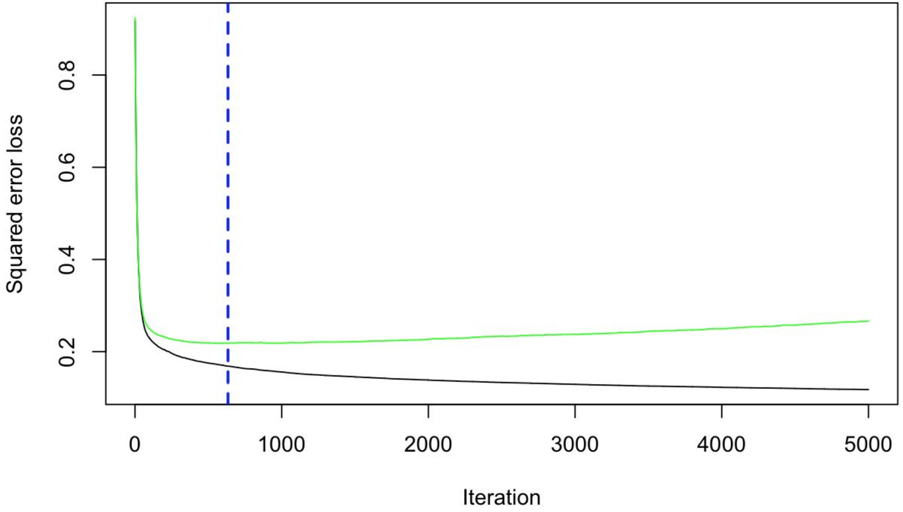


Boosting

Tune Manually

	# of Trees	shrinkage(learning rate)	Test MSE
boost1	n.trees=100	shrinkage=0.1	0.2525
boost2	n.trees=500	shrinkage=0.1	0.2072
boost3	n.trees=1000	shrinkage=0.1	0.2003
boost4	n.trees=5000	shrinkage=0.1	0.2014
boost5	n.trees=1000	shrinkage=0.2	0.2060

Optimal Iteration




```
relative.influence(boost6)
```

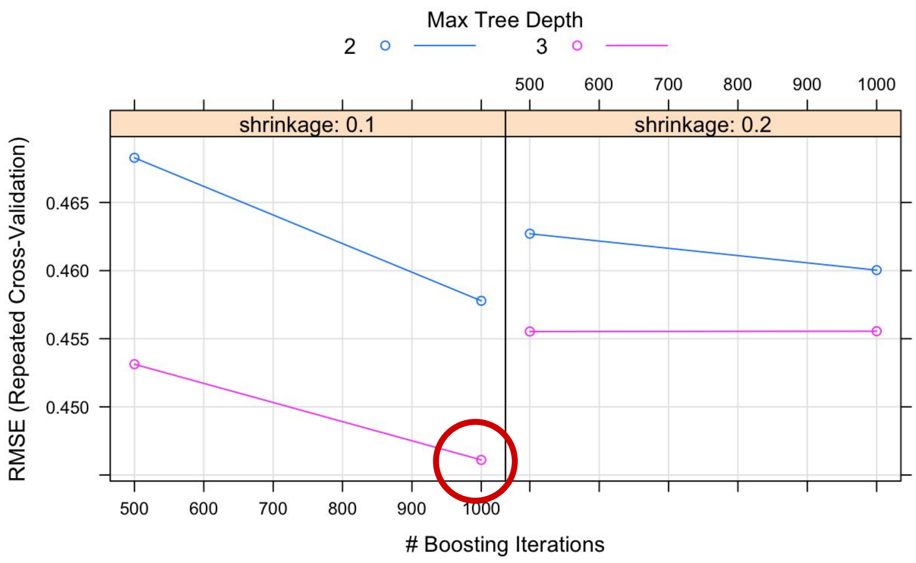
```
## n.trees not given. Using 634 trees.
```

```
##          Rooms         Type       Method     Distance     Bedroom2
##     2340.20033   1801.52152     76.13334   1320.24155    994.75387
##       Bathroom          Car     Landsize  CouncilArea   Regionname
##     2437.03614    308.81701    941.37716   6009.39939    146.72703
## Propertycount     SellYear    SellMonth          age
##      249.87518     40.39025    224.18286   2188.69709
```

Tune Using Grid Search

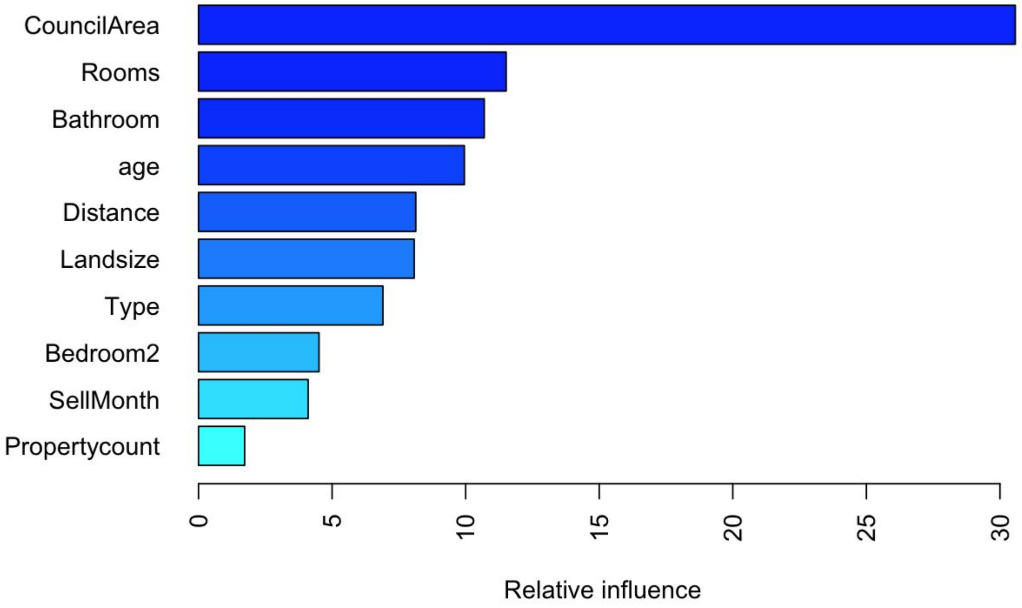
- hyper_grid:
  - n.trees = 500, 1000
  - interaction.depth = 2, 3
  - shrinkage = 0.1, 0.2
  - n.minobsinnode = 10

shrinkage	interaction.depth	n.trees	RMSE
0.1	2	500	0.4682779
0.1	2	1000	0.4577827
0.1	3	500	0.4531315
0.1	3	1000	0.4461076
0.2	2	500	0.4627059
0.2	2	1000	0.4600345
0.2	3	500	0.4555301
0.2	3	1000	0.4555548

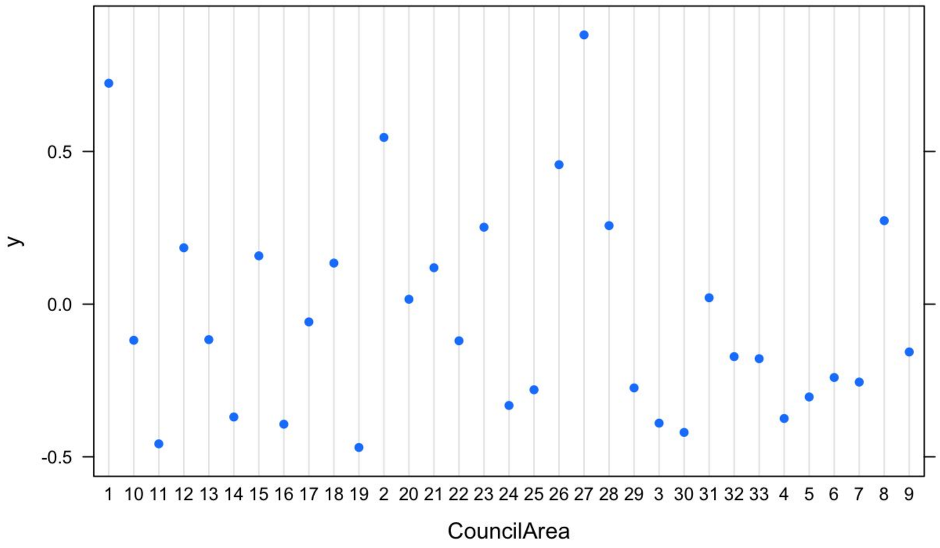


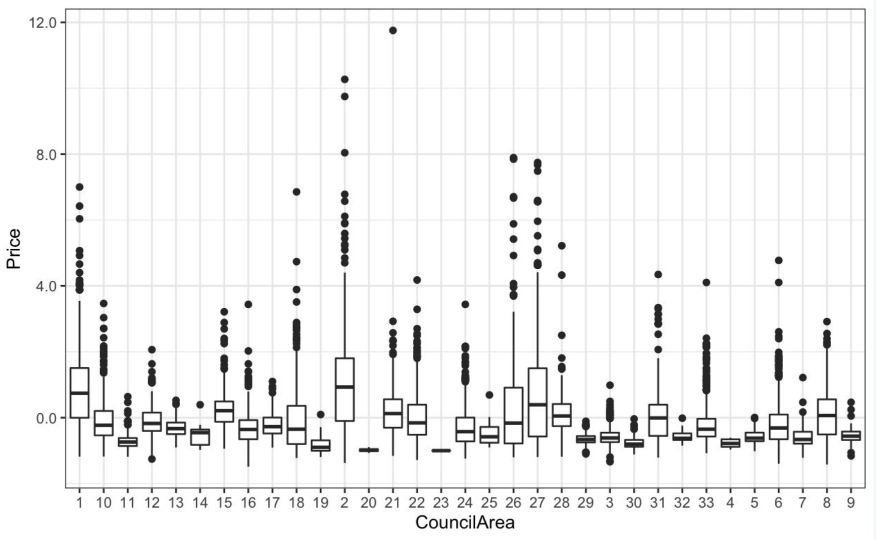
Feature Importance

- 10-fold cross validation
- Using tuned parameters:
  - n.trees = 1000
  - interaction.depth = 3
  - shrinkage = 0.1
- Test MSE: 0.1990



CouncilArea v.s. Price





- #1: Bayside City Council
- #2: Boroondara City Council
- #27: Stonnington City Council

Summary

Feature Importance:

CouncilArea

Model	Test MSE
Ridge Regression	0.3611925
Lasso Regression	0.3562078
Linear Regression	0.3560723
Regression Trees	0.4011495
Bagging	0.3956213
Random Forests	0.2115062
Boosting	0.1942090

Q&A