# Predicting Avocado Prices with Different Models

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## Predicting Avocado Prices with Different Models

#### 9 The outcome variable

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##

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\$ 4770

Across the entire United States, avocados are being sold everyday despite their
fluctuating price. Our goal for this project was to create a machine learning model capable
of accurately predicting a given state's avocado price over time across states based on.
Avocado prices vary based on type (i.e., conventional vs. organic).

We will be answering the research question: What is the strongest predictor of
avocado prices in the United States? Thus, our goal is to find the feature that most
strongly predicts the price of avocados in the United States. The purpose of this project is
to provide consumers, local grocers, and farmer's markets with a tool to predict avocado
prices.

## Description of the Data

#### 20 Core features and descriptive statistics

We analyzed the avocado prices dataset retrieved from Kaggle and compiled by the
Hass Avocado Board. The dataset consists of approximately 18,000 records over 4 years
(2015 - 2018). The dataset contains information about avocado prices by type (organic or
conventional), region purchased in the United States, total volume sold, and date sold.

```
## tibble [18,249 x 14] (S3: tbl df/tbl/data.frame)
  ##
       $ ...1
                      : num [1:18249] 0 1 2 3 4 5 6 7 8 9 ...
26
       $ Date
                      : Date[1:18249], format: "2015-12-27" "2015-12-20" ...
  ##
       $ AveragePrice: num [1:18249] 1.33 1.35 0.93 1.08 1.28 1.26 0.99 0.98 1.02 1.07 ...
  ##
28
       $ Total Volume: num [1:18249] 64237 54877 118220 78992 51040 ...
  ##
       $ 4046
                      : num [1:18249] 1037 674 795 1132 941 ...
  ##
                           [1:18249] 54455 44639 109150 71976 43838 ...
       $ 4225
  ##
31
```

: num [1:18249] 48.2 58.3 130.5 72.6 75.8 ...

52

```
: num [1:18249] 8697 9506 8145 5811 6184 ...
       $ Total Bags
  ##
33
                     : num [1:18249] 8604 9408 8042 5677 5986 ...
       $ Small Bags
  ##
34
       $ Large Bags
                     : num [1:18249] 93.2 97.5 103.1 133.8 197.7 ...
  ##
35
       $ XLarge Bags : num [1:18249] 0 0 0 0 0 0 0 0 0 ...
  ##
36
                      : chr [1:18249] "conventional" "conventional" "conventional" "conventi
  ##
       $ type
37
       $ year
                      : num [1:18249] 2015 2015 2015 2015 2015 ...
  ##
38
                      : chr [1:18249] "Albany" "Albany" "Albany" "Albany" ...
       $ region
  ##
39
  ## # A tibble: 6 x 14
                          average ~1 total~2 x4046 x4225 x4770 total~3 small~4 large~5
  ##
           x1 date
  ##
        <dbl> <date>
                               <dbl>
                                        <dbl> <dbl>
                                                    <dbl> <dbl>
                                                                    <dbl>
                                                                             <dbl>
                                                                                     <dbl>
  ## 1
            0 2015-12-27
                                1.33
                                      64237. 1037. 5.45e4 48.2
                                                                    8697.
                                                                             8604.
                                                                                      93.2
  ## 2
            1 2015-12-20
                                1.35
                                      54877.
                                               674. 4.46e4 58.3
                                                                    9506.
                                                                                      97.5
                                                                             9408.
  ## 3
            2 2015-12-13
                                0.93 118220.
                                               795. 1.09e5 130.
                                                                    8145.
                                                                             8042.
                                                                                     103.
            3 2015-12-06
                                      78992. 1132 7.20e4
  ## 4
                                1.08
                                                            72.6
                                                                             5677.
                                                                                     134.
                                                                    5811.
            4 2015-11-29
  ## 5
                                1.28
                                      51040. 941. 4.38e4
                                                             75.8
                                                                             5986.
                                                                                     198.
                                                                    6184.
  ## 6
            5 2015-11-22
                                1.26
                                      55980. 1184. 4.81e4 43.6
                                                                    6684.
                                                                             6556.
                                                                                     127.
48
        ... with 4 more variables: x large bags <dbl>, type <chr>, year <dbl>,
49
  ## #
          region <chr>, and abbreviated variable names 1: average price,
50
          2: total_volume, 3: total_bags, 4: small_bags, 5: large_bags
51
```

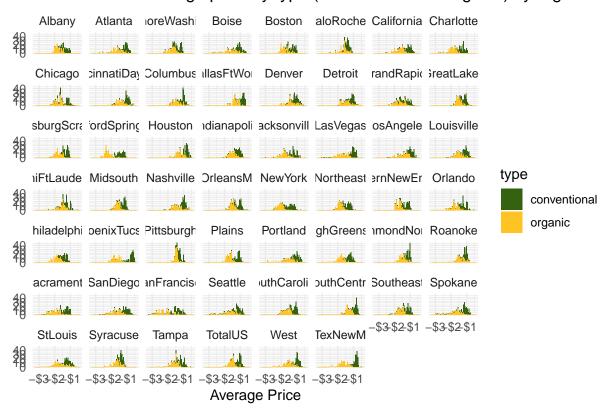
#### Frequencies and distribution of data

First, we subsetted the variables of interest from the dataset. From the histogram below, we can see that our outcome variable, average price, is normally distributed. Mean price across data was \$1.41 (SD = \$0.4). The highest average price for organic avocados was in San Francisco, CA in 2016 for \$3.25 and the lowest average price was in Cincinnati, OH in 2017 for \$0.44.

Table 1
Frequencies of the data

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurt
date	1	18249	NaN	NA	NA	NaN	NA	Inf	-Inf	-Inf	NA	
type*	2	18249	1.50	0.50	1.00	1.50	0.00	1.00	2.00	1.00	0.00	-2
average_price	3	18249	1.41	0.40	1.37	1.38	0.42	0.44	3.25	2.81	0.58	(
$total\_volume$	4	18249	850644.01	3453545.36	107376.76	232479.38	152652.16	84.56	62505646.52	62505561.96	9.01	92
region*	5	18249	27.50	15.58	27.00	27.50	19.27	1.00	54.00	53.00	0.00	-1

## Distribution of average price by type (conventional vs. organic) by region



## Missing data check

60	##	x1	date	average_price	total_volume	x4046
61	##	0	0	0	0	0
62	##	x4225	x4770	total_bags	small_bags	large_bags
63	##	0	0	0	0	0
64	##	x_large_bags	type	year	region	

65 ## 0 0 0

No missingness was found for the variables in the dataset.

## Description of the models

Three different modeling approaches will be used to predict avocado price from sale features, including: Linear Regression, Decision Trees, and Random Forest. Since the purpose of this project is to provide consumers, local grocers, and farmer's markets with a tool to predict avocado prices, we want to examine the predictive power of several features that contribute to avocado price. Thus, we first examined the effect of all predictors in a linear regression model to compare with the advanced models. Next, we added more complexity to the model by growing and pruning decision tree regression models to predict avocado price. Finally, we used a random forest to reduce the variance to get a more accurate prediction.

Model Fits

## 78 Preparation

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The dataset is split into training and test set with the following code. The training set has 14,599 observations, and the test set has 4,650 observations. We examined which model has the optimal fit to predict avocado price (RMSE, MAE, and R-squared).

```
require(recipes)
loc <- sample(1:nrow(df), round(nrow(df) * 0.8))
df_train <- df[loc, ]
df_test <- df[-loc, ]

#dim(df_train)
#dim(df_test)</pre>
```

## Model 1: Linear Regression Model with Cross Validation

To obtain a general understanding of how our predictor variables fit our data, we
first fitted a linear regression model without regularization. The equation generated by the
linear model is then applied to predict outcome of new unseen data. Our criteria for
evaluation of model fit will be the root mean square error (RMSE). We used 10-fold cross
validation to determine the optimal value for the complexity penalization factor, alpha.

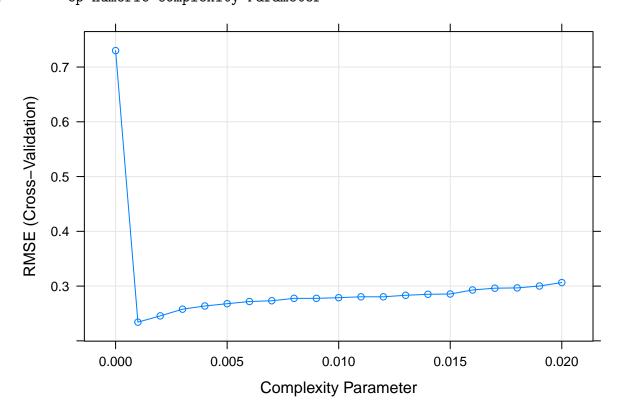
\*\* ## intercept RMSE Rsquared MAE RMSESD RsquaredSD MAESD

\*\* ## 1 TRUE 0.2633607 0.5689546 0.1988435 0.007748081 0.026833 0.005724263

#### 90 Model 2: Decision Trees

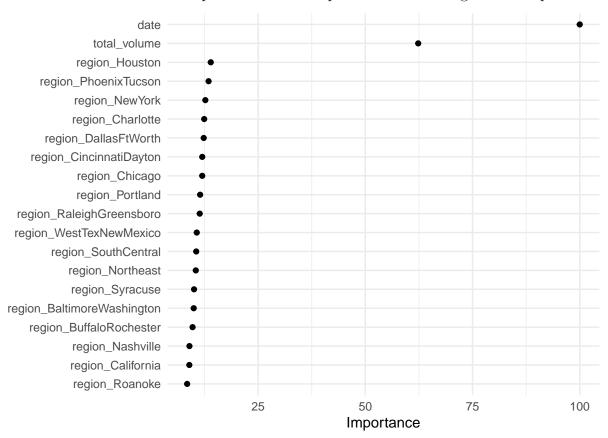
Next, we fitted decision tree regression model with cross validation to get a better estimate of the generalization error on new unseen data..

93 ## parameter class label 94 ## 1 cp numeric Complexity Parameter



```
96 ## cp
97 ## 2 0.001
```

We examined the complexity parameters for the model and found that date sold and total volume sold were the most important factors as predictors for average avocado price.



#### 101 Model 3: Random Forest

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Finally, we fitted a random forest regression model. According to the random forest regression, the top predictor of avocado prices is type (i.e. whether the avocado is organic or conventional). This result aligned with our expectations, as our preliminary data analyses depicted differences in distributions between organic and conventional avocado prices.

```
## mtry splitrule min.node.size
## 1 25 variance 2
```

```
## Growing trees.. Progress: 95%. Estimated remaining time: 1 seconds.

## Growing trees.. Progress: 93%. Estimated remaining time: 2 seconds.

## Growing trees.. Progress: 100%. Estimated remaining time: 0 seconds.

## Growing trees.. Progress: 98%. Estimated remaining time: 0 seconds.

## Growing trees.. Progress: 83%. Estimated remaining time: 6 seconds.
```

## [1] 1.219530 1.189503 1.236844 1.242663 1.259437 1.222274

#### 14 Comparing Models

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Examining the predictions we can see that the random forest model outperformed the linear and decision tree models. This is because it has the highest R<sup>2</sup> and the least error. Thus, we can assume that random forest models can be trusted to predict avocado prices.

Model	Rsquare	RMSE	MAE	
Linear Regression	0.5548706	0.2729584	0.2042162	
Decision Trees	0.7022162	0.2233039	0.1709096	
Random Forest	0.9136772	0.1221203	0.0857799	

**Data Visualization** 

Figure 1: Avocado Prices and total volume sold by type with regression
lie lines. We examined our variables of interest visually with several plots. First we
log-transformed the total volume sold to examine its relationship with average price. We
can see that more conventional type avocados were sold at a lower price than organic
avocados.

# Relationship between avocado prices and total volume sold by coventional vs. organic type

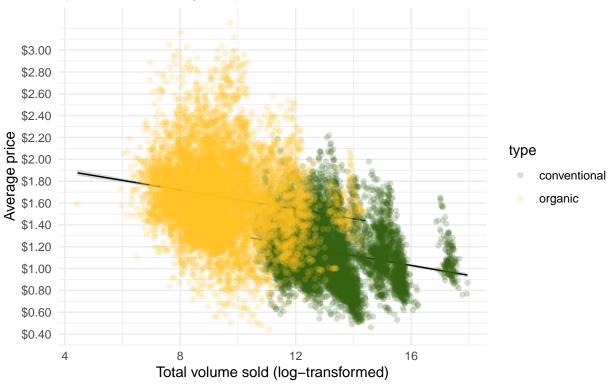
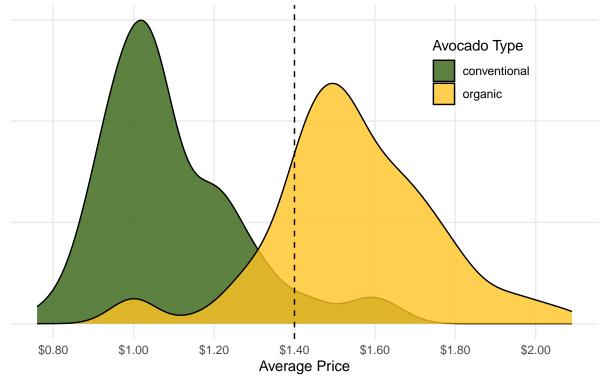


Figure 2: Distribution of avocado prices by type.

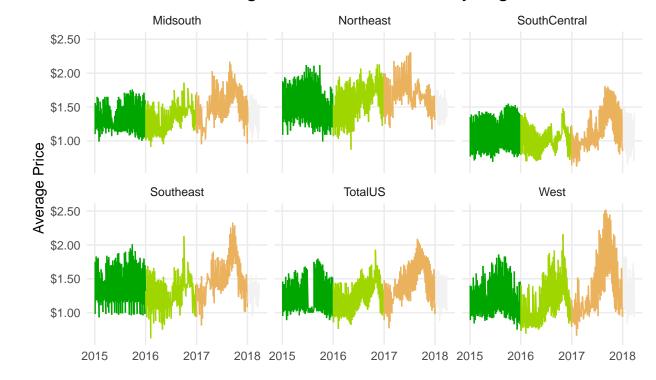
Distribution of Organic & Conventional Avocado Prices



Data: Hass Avocado Board

Figure 3: Regional avocado prices change over time.

Average Price of avocados by region



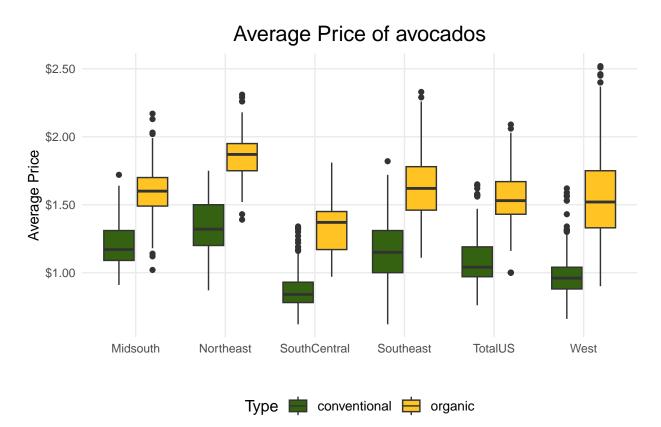
Data: Haas Avocado Board

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Figure 4: Boxplots of average price of avocados by region compared with total US.



Data: Haas Avocado Board

Discussion

#### 135 Conclusion

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We optimized three models to predict average avocado prices and we found that the test scores for our predictive models were overall high. For the random forest regression model, the total variance explained was 91% and the decision tree model explained 69% of the variance.

We discovered some interesting findings from the models. The decision tree regression model predicted that date sold and total volume sold are the most important features for predicting avocado price.

The region where the avocado was sold was an important feature in the pricing of avocados. For instance, regions such as Baltimore/Washington and Houston were the third and fourth most important predictors of average avocado price.

146 References

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