



Predicting Brand Preferences With Demographic Data and Machine Learning Algorithms

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Goal: Predict Customer Preference for Brand of Laptop Based on Other Demographic Data

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- 1) Provided a complete set of customer demographic data and laptop brand preference.
- 2) Build, cross-validate, and refine classification models on the complete dataset.
- 3) Test the refined classification models on hold-out data.
- 4) Apply the best model to new demographic data and predict customer preference for a certain brand of laptop (Acer or Sony).



Demographic Data Included Customer Age, Annual Salary, Education, Primary Car, and US Region

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[10,000 x 7] data matrix, ARFF format

Retailer Provided Data

age (20-80), annual salary (\$20-150k), education level (HS-PhD), primary car (20 types), US region (8 options), available credit (\$0-500k), and laptop brand preference (Acer or Sony)



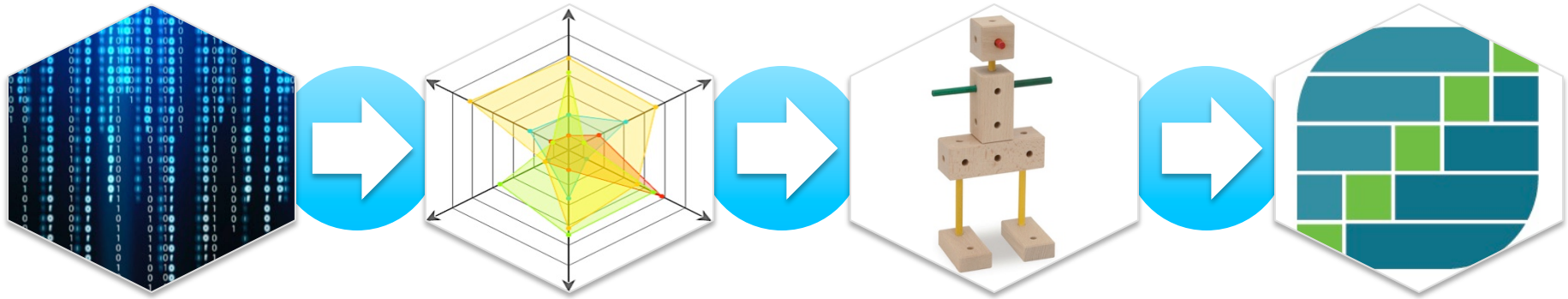
Approach

70,000 data points

5 analyses

Conducted Analysis with R and Employed Machine Learning Algorithms

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1 Import

R Language

Clean Data

2 Analyze

R Language

Plot Data

3 Model

R Language

Machine Learning

4 Predict

R Language

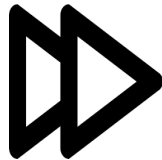
Report

Cleaned Data: Transformed Columns to Numeric and Factors and Removed NULL Values

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Retailer provided data

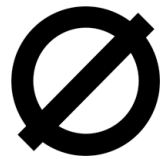
Fairly clean, but required some additional cleaning to facilitate analysis



`R as.numeric() or as.factor()`

Values to Numeric or Factor

Applied to: All



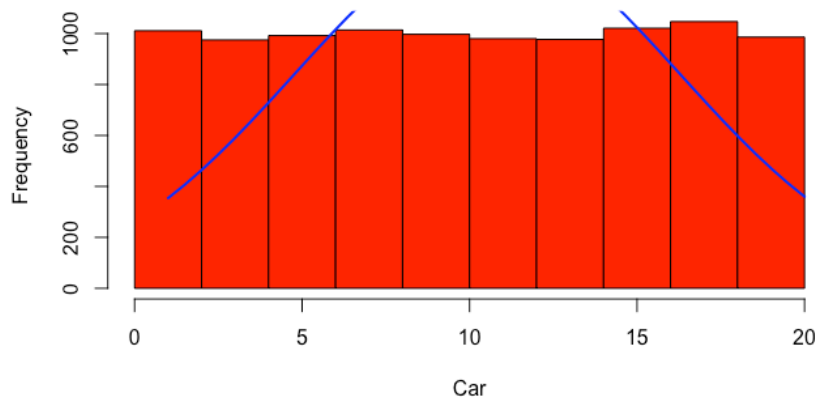
`R na.exclude()`

Removed NULL Values

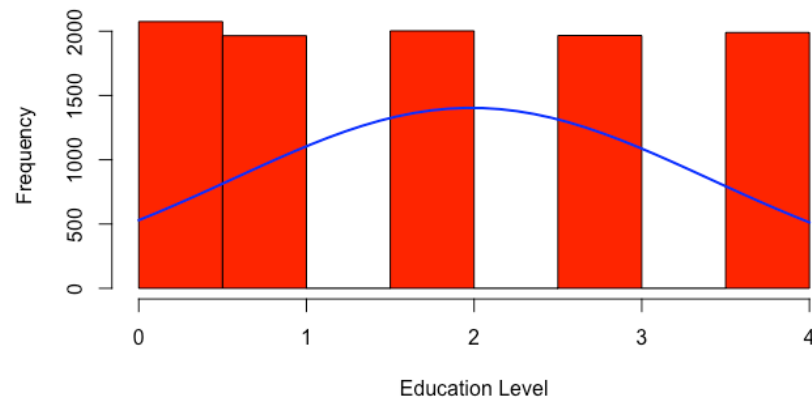
Applied to: All

Plotting the Cleaned Data Revealed a Reasonable Distribution of Features – No Dominant Values

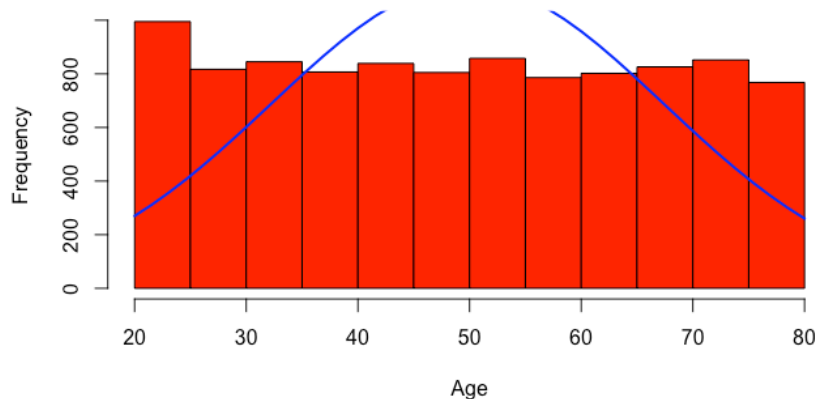
Histogram with Normal Curve



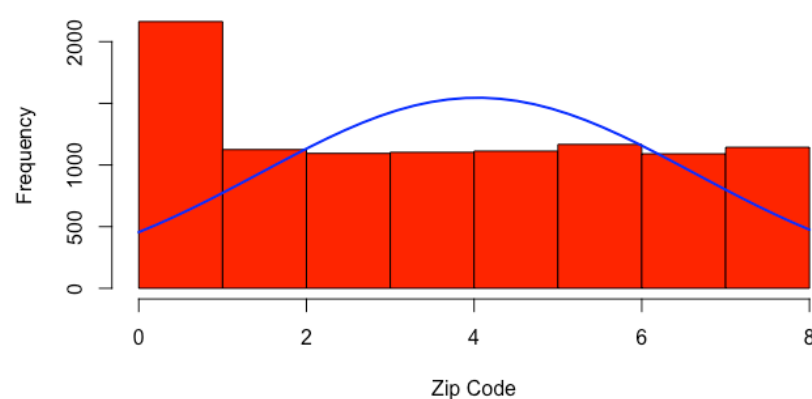
Histogram with Normal Curve



Histogram with Normal Curve

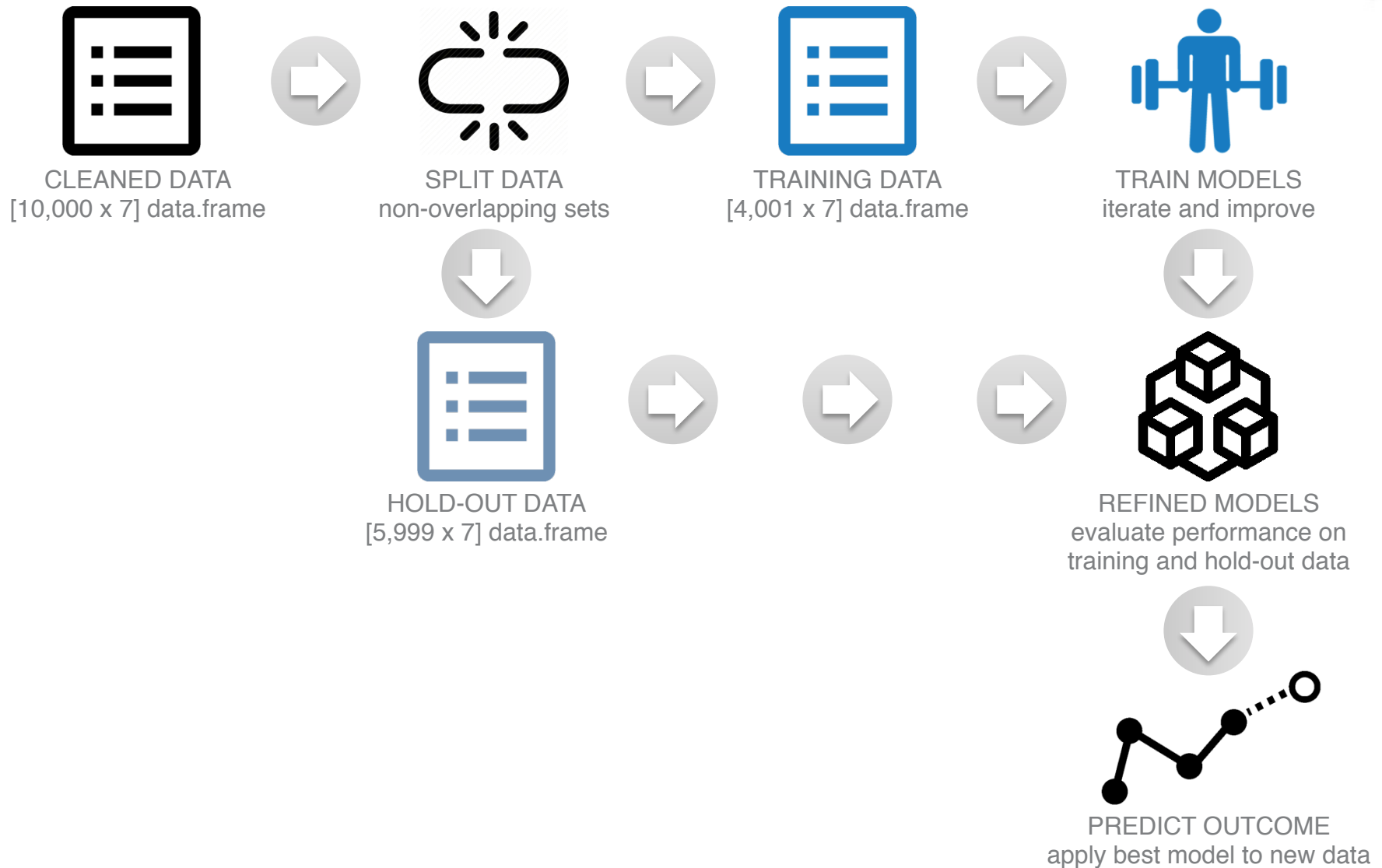


Histogram with Normal Curve



Split the Data Into Two Sets: Training and Hold-Out – Optimized on Training, Evaluated Models Against Both

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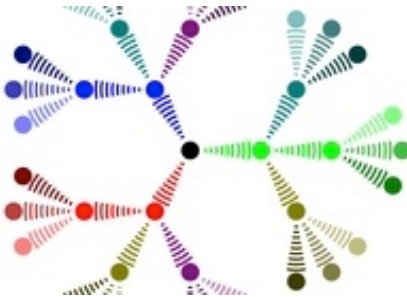
Employed Four Different Machine Learning Algorithms; Optimized Accuracy of Each on the Training Data

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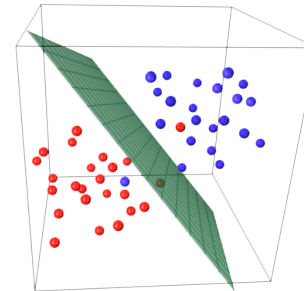
RandomForest Classifier

```
R RFfit <- train(brand ~., data = training,  
method = "rf", metric = "Accuracy", trControl =  
fitControl, ntree = 500, tuneGrid = rfGrid6,  
importance = TRUE)
```



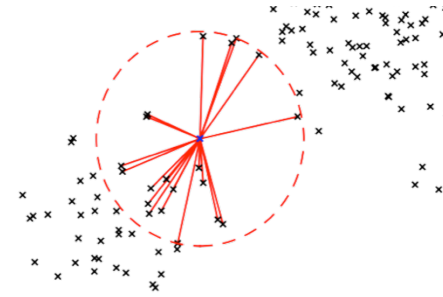
c5.0 Statistical Classifier

```
R c50fit <- train(brand ~., data = training,  
metric = "Accuracy", trControl = fitControl,  
method = "C5.0", tuneLength = 10, verbose =  
FALSE)
```



e1071 Support Vector Classifier

```
R e1071SVMopt <- tune.svm(brand ~ ., data =  
training, metric = "Accuracy", gamma =  
svm5Grid, cost = svm5Grid, kernel = "radial",  
trControl = fitControl)
```



kNN Nearest-Neighbor Classifier

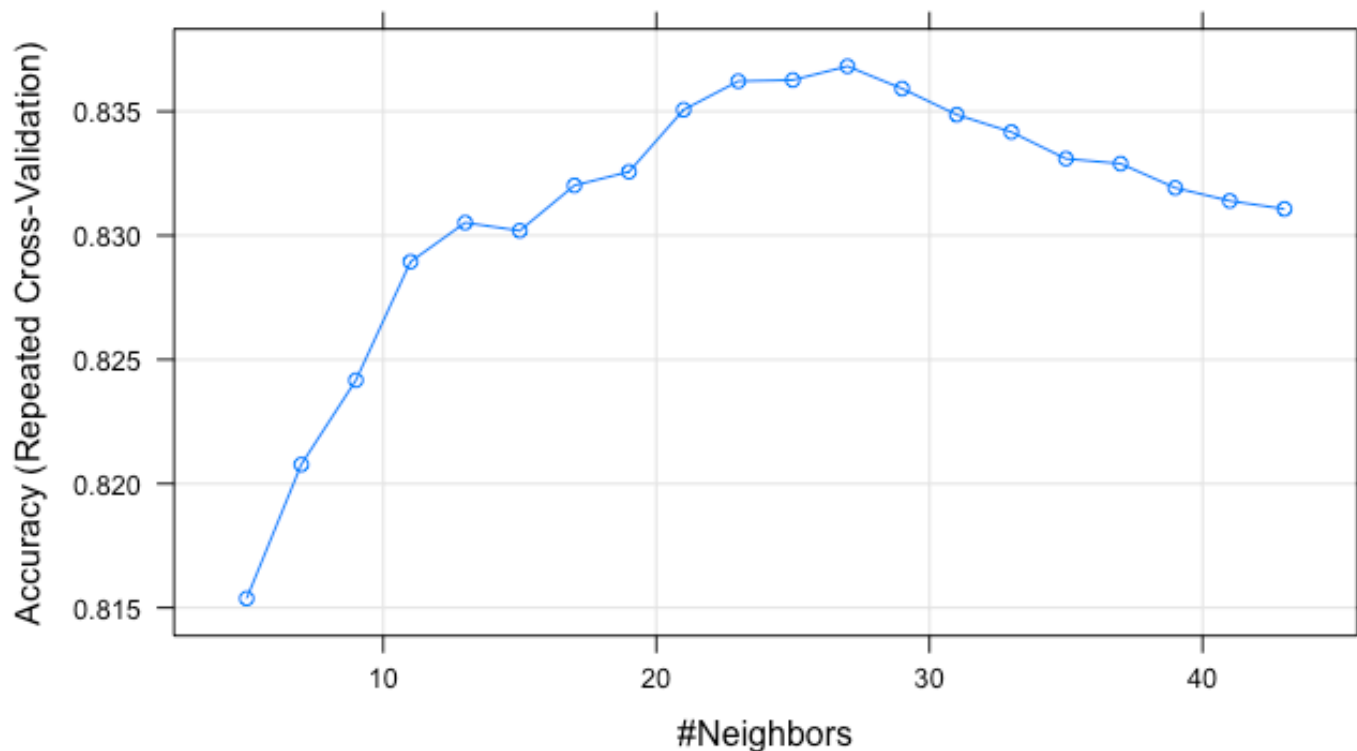
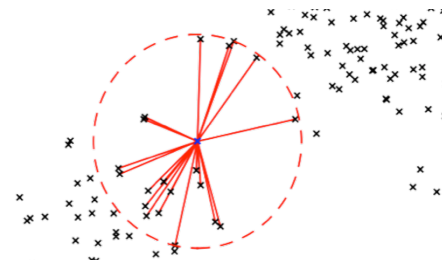
```
R kNNfit <- train(brand ~., data = training,  
method = "knn", metric = "Accuracy", trControl =  
fitControl, tuneLength = 20, preProc =  
c("range"))
```

Nearest-Neighbor Model Illustrates the Refinement Process to Optimize the Accuracy of the Model

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kNN Nearest-Neighbor Classifier

```
R kNNfit <- train(brand ~., data = training, method =  
"knn", metric = "Accuracy", trControl = fitControl,  
tuneLength = 20, preProc = c("range"))
```



Optimized Accuracy of Classifier Models on Training Data, Used 10-fold Cross-Validation to Limit Overfitting

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Calculated Classification Model Metrics of Predicted Values vs. Actual Training Set Values For All Approaches

| Model Name | Accuracy | Precision | Recall | Sensitivity | Specificity |
|------------------|----------|-----------|--------|-------------|-------------|
| RandomForest | 1 | 1 | 1 | 1 | 1 |
| c5.0 | 0.93 | 0.92 | 0.90 | 0.90 | 0.95 |
| e1071 SVM radial | 0.91 | 0.85 | 0.92 | 0.92 | 0.90 |
| kNN | 0.86 | 0.83 | 0.81 | 0.81 | 0.90 |
| e1071 SVM poly | 0.69 | 0.78 | 0.24 | 0.24 | 0.96 |

Values derived from Confusion Matrix for each model, comparing predicted vs. training values

Accuracy = correctly categorized

Precision = fraction of predicted that are actually in that class

Recall = fraction of actual that detected by the model

Sensitivity = true-positive rate

Specificity = true-negative rate

Even With 10-fold Cross-Validation to Limit Overfitting it Appears RandomForest and c5.0 May Still Overfit

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Further validating models against hold-out data will examine if certain models overfit the training data

RandomForest and c5.0 Classification Models Performed Very Well on Hold-Out Data – Not Overfit

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Calculated Classification Model Metrics of Predicted Values vs. Training and Hold-Out Values For All Approaches

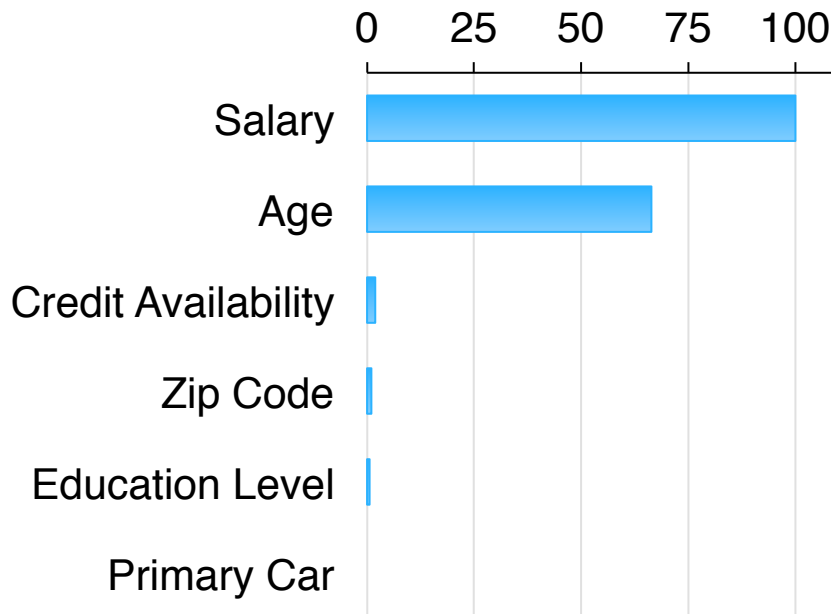
| Model Name (dataset) | Accuracy | Precision | Recall | Sensitivity | Specificity |
|-----------------------------|----------|-----------|--------|-------------|-------------|
| RandomForest (train) | 1 | 1 | 1 | 1 | 1 |
| RandomForest (hold-out) | 0.92 | 0.90 | 0.89 | 0.89 | 0.94 |
| c5.0 (train) | 0.93 | 0.92 | 0.90 | 0.90 | 0.95 |
| c5.0 (hold-out) | 0.92 | 0.91 | 0.88 | 0.88 | 0.95 |
| e1071 SVM radial (train) | 0.91 | 0.85 | 0.92 | 0.92 | 0.90 |
| e1071 SVM radial (hold-out) | 0.86 | 0.80 | 0.86 | 0.86 | 0.87 |
| kNN (train) | 0.86 | 0.83 | 0.81 | 0.81 | 0.90 |
| kNN (hold-out) | 0.84 | 0.80 | 0.77 | 0.77 | 0.88 |
| e1071 SVM poly (train) | 0.69 | 0.78 | 0.24 | 0.24 | 0.96 |
| e1071 SVM poly (hold-out) | 0.67 | 0.72 | 0.19 | 0.19 | 0.95 |

Salary and Age of Customers Were the Most Influential Fields in the RandomForest and c5.0 Models

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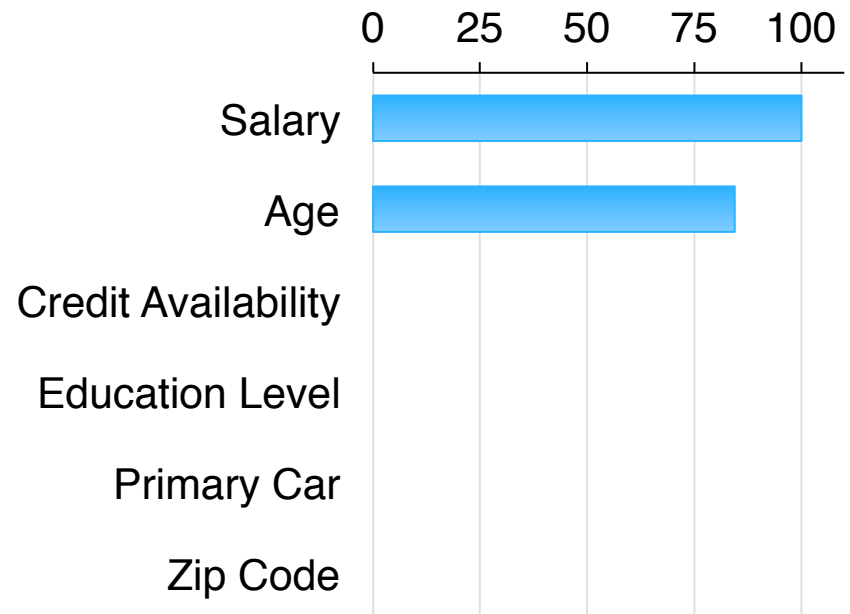
Influential RandomForest Fields

Salary and Age were the most influential in the model – all values are normalized to 100.



Influential c5.0 Fields

Only Salary and Age were used by the model – all values are normalized to 100.

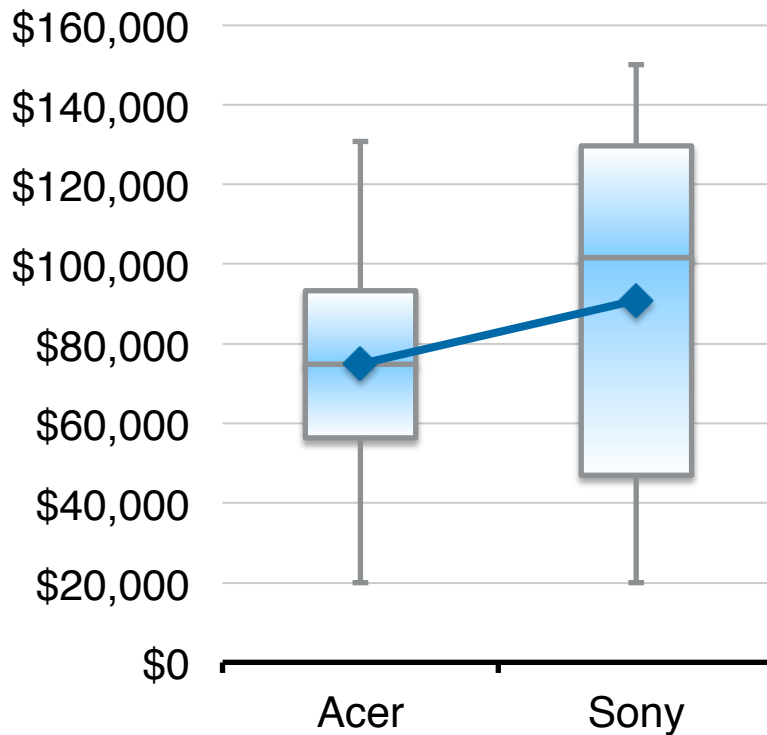


Field Dependencies of the RF and c5.0 Models Were Not Obvious as Data Had Very Subtle Age Correlation

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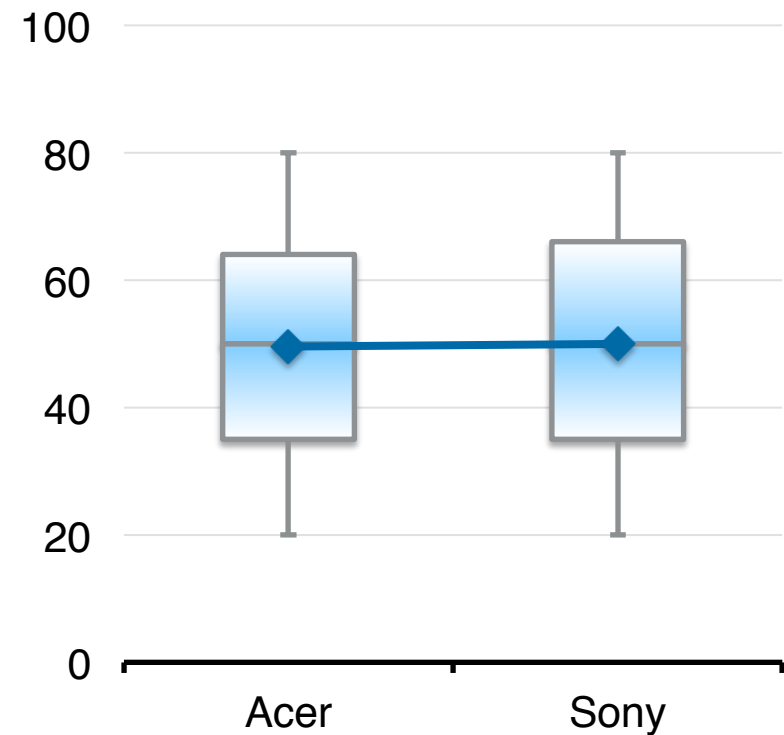
Salary vs. Brand Preference

Sony customers had higher mean, median, and max salaries than Acer customers in the Cleaned Data.



Age vs. Brand Preference

All age statistics were nearly identical for the Acer and Sony customer groups in the Cleaned Data.

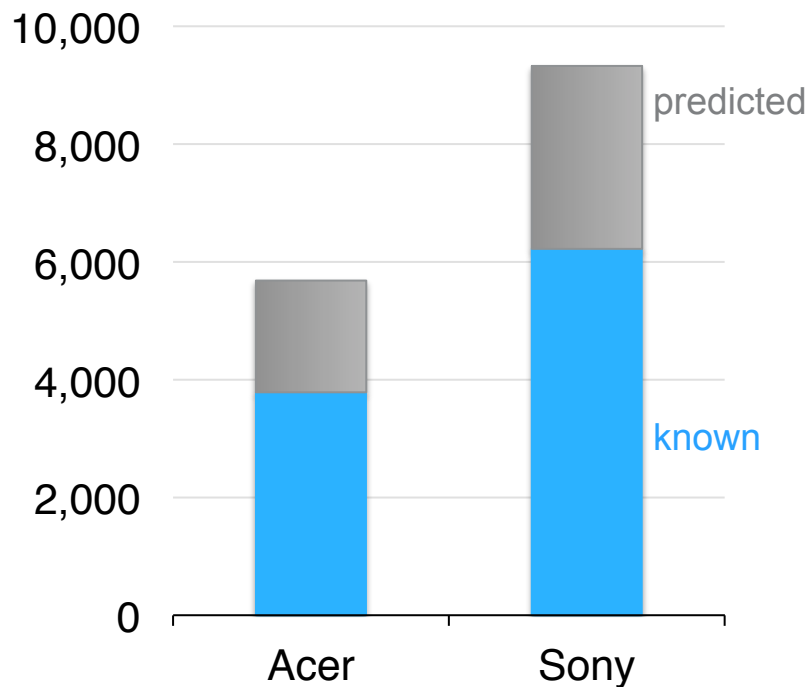


Applied Validated RandomForest and c5.0 Models to New Data to Predict Customer Brand Preferences

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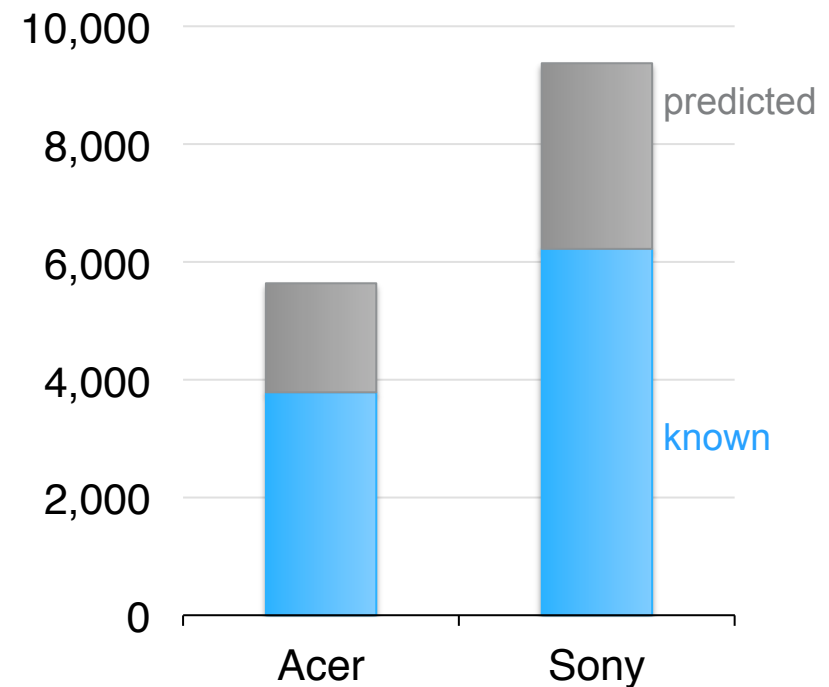
RF Model Brand Prediction

Application of model to new data shows preference for Sony over Acer.



c5.0 Model Brand Prediction

Application of model to new data shows preference for Sony over Acer.



All results show a strong brand preference for Sony

Recommendations for Future Data Collection Campaigns to Inform Customer Brand Preferences

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- 1) Future data collection campaigns should gather the customer age and salary as the first questions (most important fields in current analyses).
- 2) Continue to collect additional customer information such as Credit Availability, Zip Code (US Region), and Education Level as it may be important in other brand preference analyses.
- 3) Important to collect some information on customer brand preferences in future surveys to validate future demographic data and survey models (allows for creation of future training and hold-out datasets).
- 4) Primary car was not an important feature in the top two models – might consider making this a later question or dropping this question/field.



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<https://github.com/BFauber>