Predicting Customer Preferences With Demographic Data and Machine Learning Algorithms

Benjamin P. Fauber, Ph.D.
Austin, Texas USA

September 13, 2016

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

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

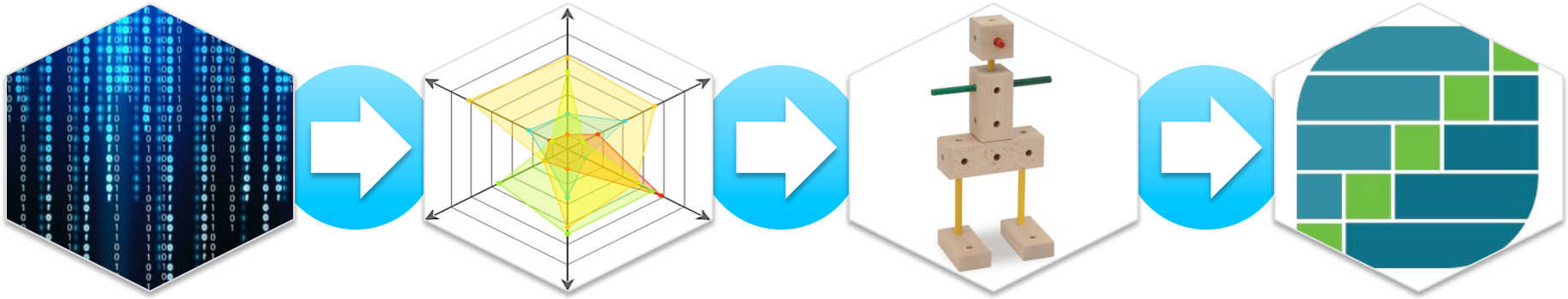
[10,000 x 7] data matrix, ARFF format

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



1 Import

R Language

Clean Data

2 Analyze

R Language

Plot Data

3 Model

R Language

Machine Learning

4 Predict

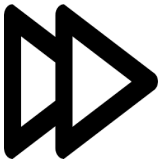
R Language

Report

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

Retailer provided data

Fairly clean, but required some additional cleaning to facilitate analysis



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

Values to Numeric or Factor

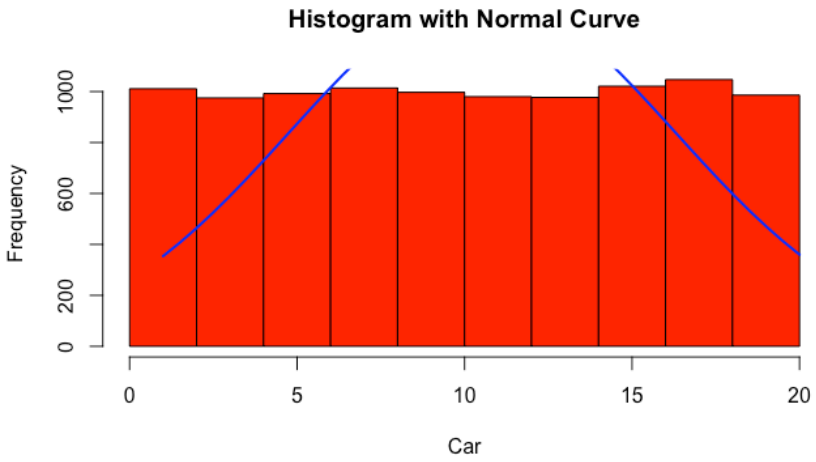
Applied to: All

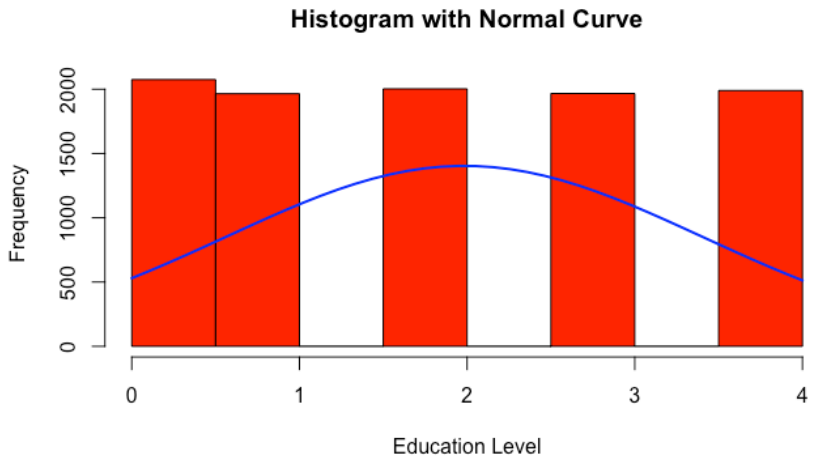
R `na.exclude()`

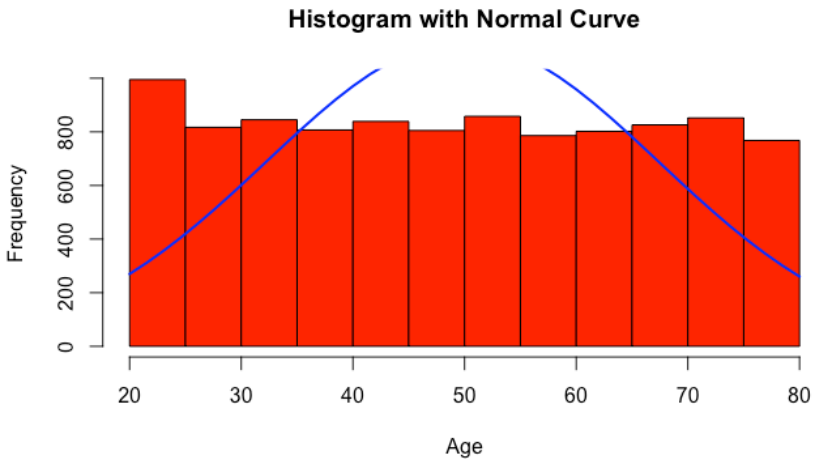
Removed NULL Values

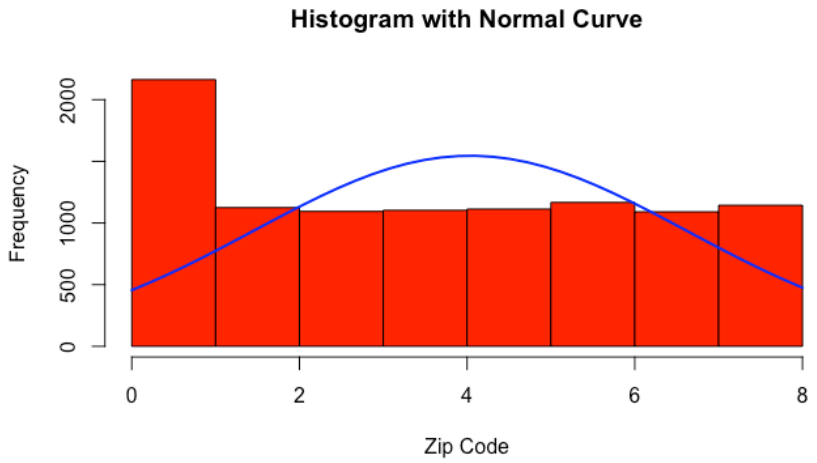
Applied to: All

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









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

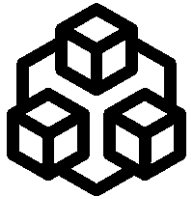
CLEANED DATA
[10,000 x 7] data.frame

SPLIT DATA
non-overlapping sets

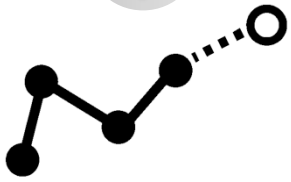
TRAINING DATA
[4,001 x 7] data.frame

TRAIN MODELS
iterate and improve

HOLD-OUT DATA
[5,999 x 7] data.frame



REFINED MODELS
evaluate performance on
training and hold-out data

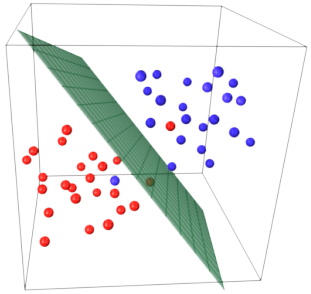


PREDICT OUTCOME
apply best model to new data

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

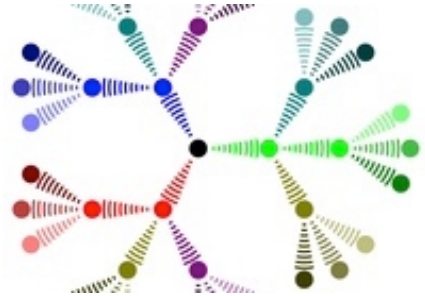
RandomForest Classifier

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



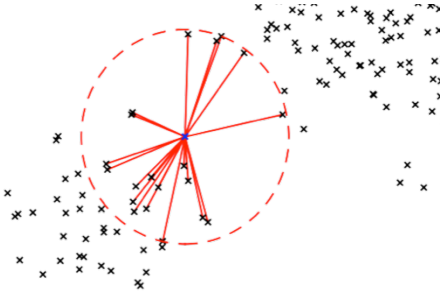
e1071 Support Vector Classifier

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



c5.0 Statistical Classifier

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



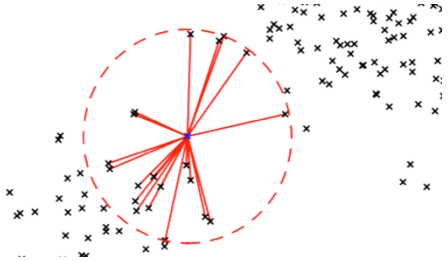
kNN Nearest-Neighbor Classifier

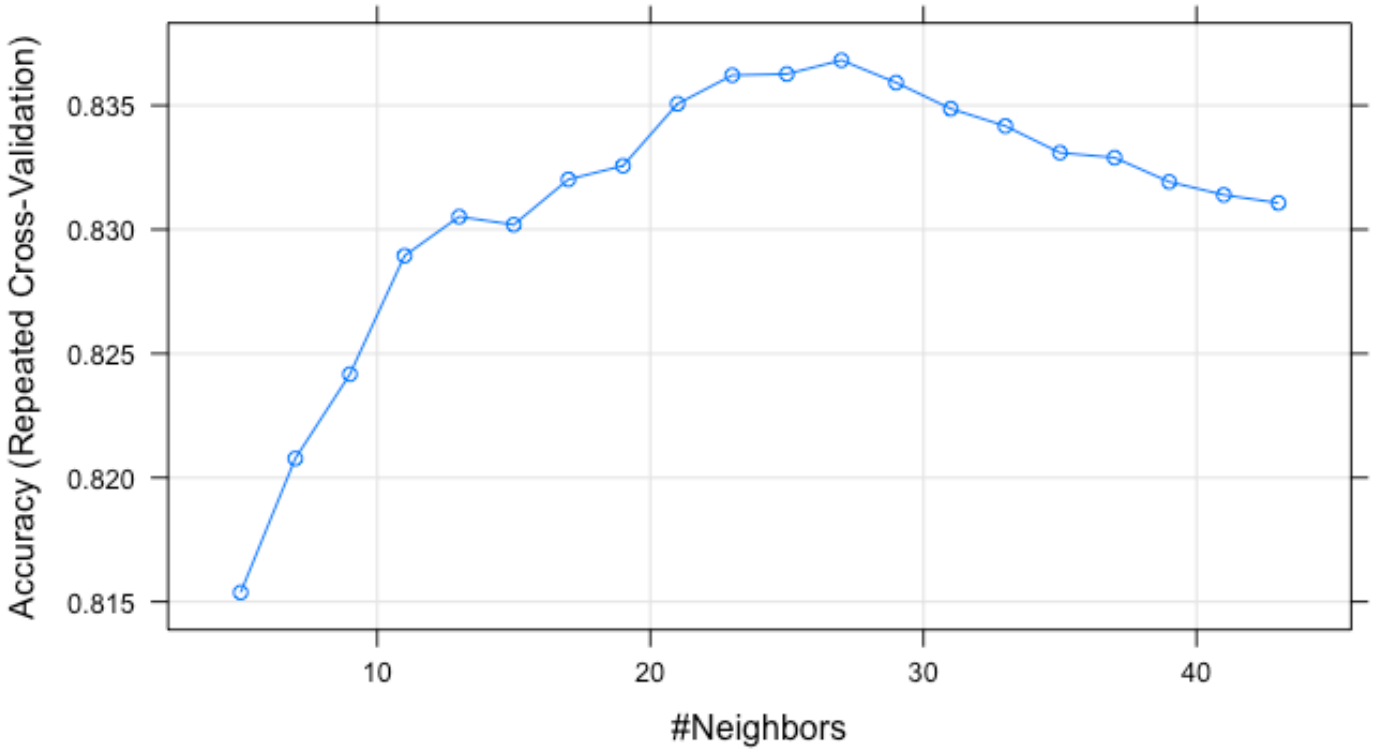
```
R kNNfit <- train(brand ~., data = training,
method = "knn", metric = "Accuracy", trControl
= fitControl, tuneLength = 20, preProc =
c("range"))
```

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

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

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

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

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

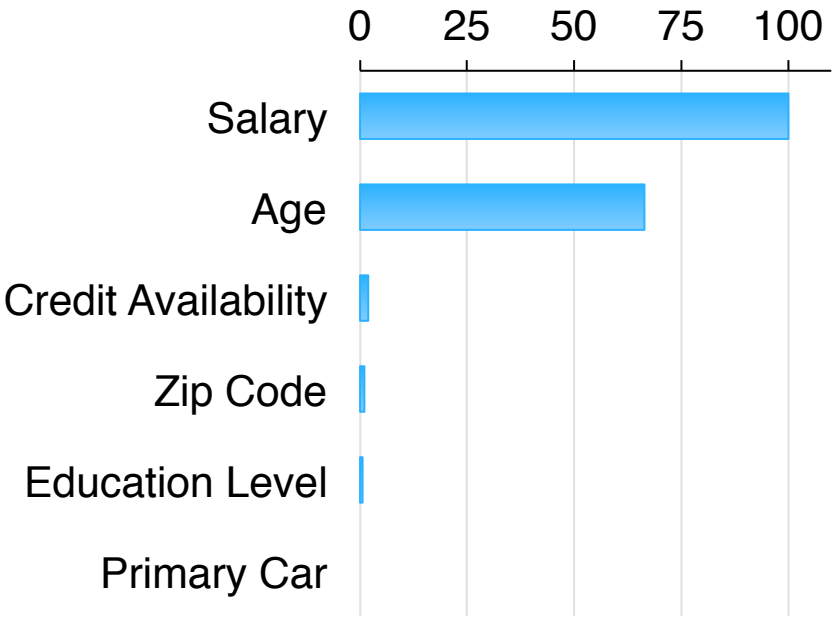
Calculated Classification Model Metrics of Predicted Values vs. Training and Hold-Out Values For All Approaches

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

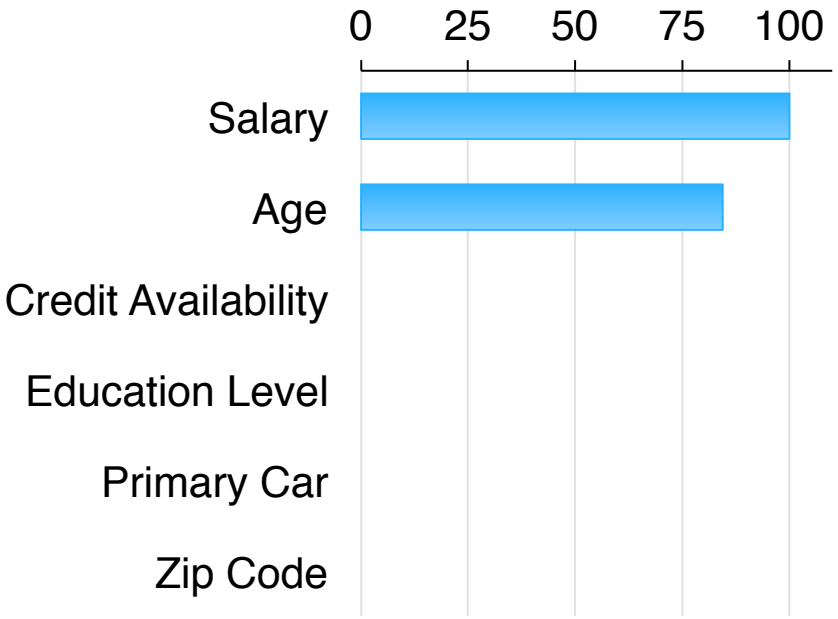
Influential RandomForest Fields

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



Influential c5.0 Fields

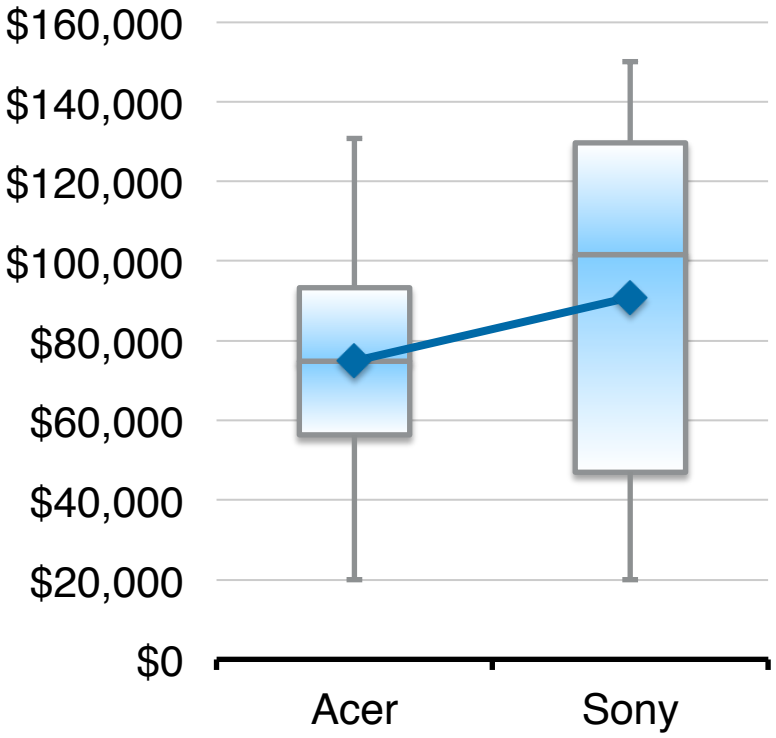
Only Salary and Age were used by the model – all values are normalized to 100.



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

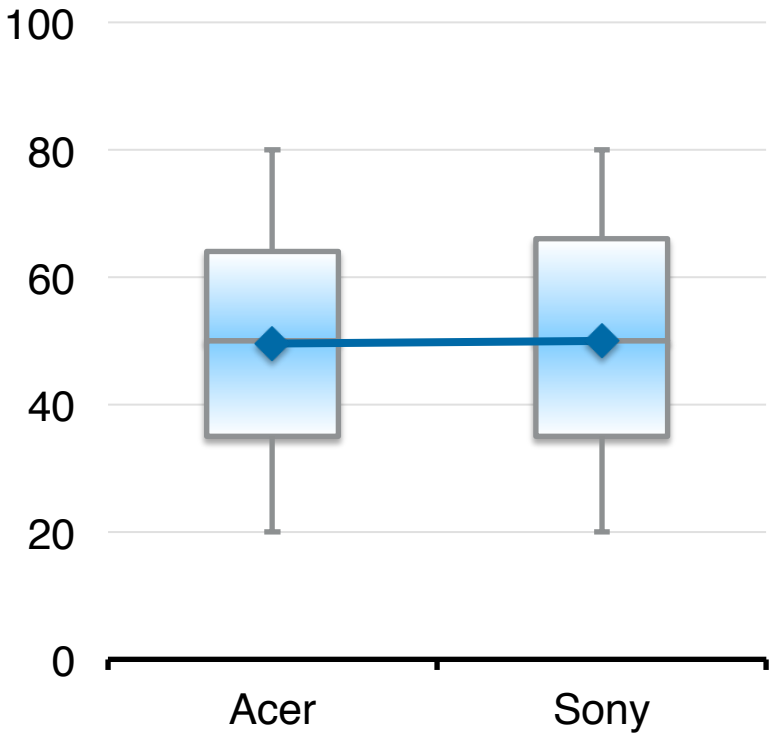
Salary vs. Brand Preference

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


```
srIncomp # new data, 5000 x 7 dataframe, missing brand preferences

# RF model
class6new <- data.frame(predict(class6fit, srIncomp,
interval="predict", level=0.95, na.action=na.omit))

# c5.0 model
class2new <- data.frame(predict(class2fit, srIncomp, interval =
"predict", level =0.95, na.action=na.omit))

#list the predictor column names and summarize the models

# RF model

predictors(class6fit) # salary, age, elevel, car, zipcode, credit
print(class6fit$bestTune) # mtry = 3, ntree = 500

# c5.0 model

predictors(class2fit) # salary, age
print(class2fit$bestTune) # trials = 10, model = tree, winnow = T
```

Recommendations for Future Data Collection Campaigns to Inform Customer Brand Preferences

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.

Benjamin P. Fauber, Ph.D.
Austin, Texas USA

https://github.com/BFauber