Online Shoppers Purchasing Intention

Is it possible to predict whether a customer will buy a product from your website?

Agenda

- Define Business Problem
- Data Cleaning
- Machine Learning Models
 - o Principal Component Analysis
 - o Lasso
 - Classification Tree
 - Support Vector Machine
 - o Random Forest
 - Boosting
- Business Analytics

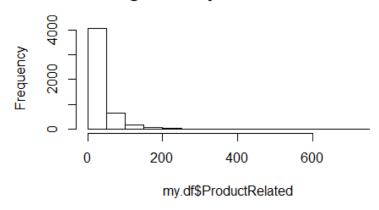
Dataset

- Source
 - UCI Machine Learning Repository
- Features
 - The dataset consists of feature vectors belonging to 12,330 sessions, 10 numerical and 8 categorical attributes.
 - The 'Revenue' attribute can be used as the class label.

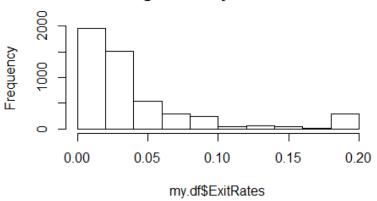
Histogram of Numeric Variables

Right-skewed

Histogram of my.df\$ProductRelated

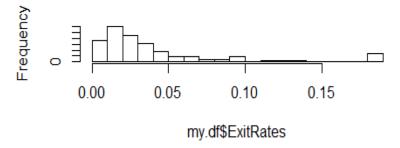


Histogram of my.df\$ExitRates

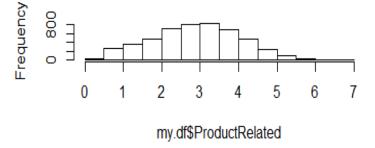


Log Transformation

Histogram of my.df\$ExitRates

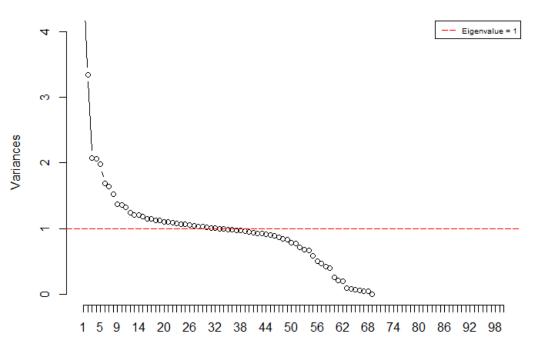


Histogram of my.df\$ProductRelated



Principal Component Analysis

First 100 Principal Components



Lasso

- Variables shrunk to o:
 - o Administrative, Administrative_Duration
 - o Informational, Information_Duration
 - ProductRelated_Duration
 - BounceRate
 - SpecialDay (!)
 - Weekend
- Test Error: 11.8%
- Type I Error Rate: 5.2%
- Type II Error Rate: 50.3%
- Power: 49.7%

Classification Tree

o Test Error: 10.9%

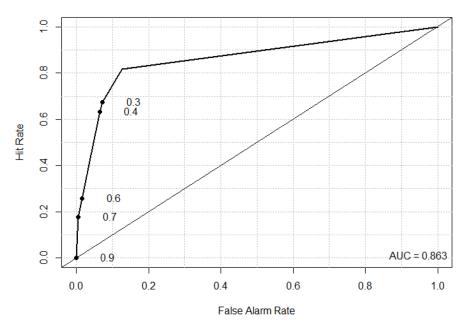
• Type I Error: 6.4%

o Type II Error: 36.7%

o Power: 63.3%

o AUC: 0.863

ROC Curve of Classification Tree

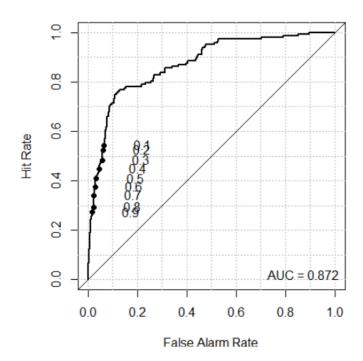


SVM - Linear Kernel

Tuning the model with multiple cost values

- o cost = 0.01, 0.1, 0.5, 1, 5, best at 1
- 915 support vectors(4000 observations in training set)
- o Type I: 7.03%
- o AUC: 0.8722396

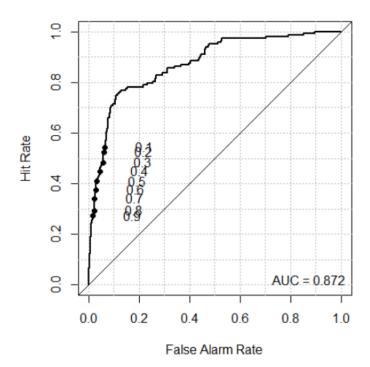
ROC Curve of Linear Kernel SVM



SVM - Radial Kernel

- Running extremely slow
- Tuning the model with multiple cost and gamma values
 - o cost =0.01, 0.1, 1, 5, best at 1
 - o gamma = 0.001, 0.01, 0.1, 0.5, 1, best at 0.1
 - o 1046 support vectors
 - o overall error rate: 11%
 - Type I: 5.6%
 - o AUC: 0.8722396

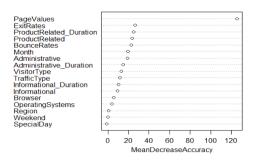
ROC Curve of Radial Kernel SVM

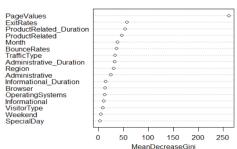


Random Forest

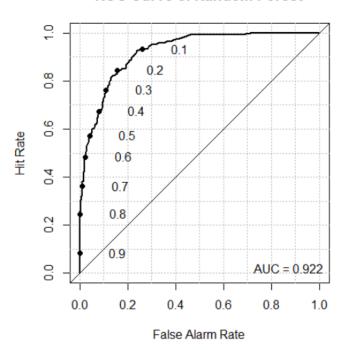
- Start with 500 trees
- Tuning the model with OOB error find the number of trees that produces the minimum OOB error rate
 - o 296 trees
- Rebuild the tree with the optimal number of trees
- Predict with the test set
- Type I Error: 4.22%
- AUC: 0.922327

Random Forest





ROC Curve of Random Forest

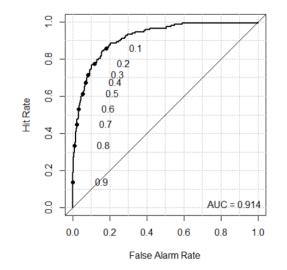


Gradient Boosting Machines

- Tuning the hyper parameters 81 combinations
- Rebuild the model based on the best parameters
- Type I error: 5.74%
- AUC: 0.9136062

```
hyper_grid <- expand.grid(
shrinkage = c(.01, .05, .1),
interaction.depth = c(3, 5, 7),
n.minobsinnode = c(5, 7, 10),
bag.fraction = c(.65, .8, 1),
optimal_trees = 0,
min_acc = 0</pre>
```

ROC Curve of GBM



Results

Model	Overall Error	Type I Error	Type II Error	AUC
Lasso	0.118	0.05158265	0.5034014	0.9015799
Logistic Regression	0.128	0.05627198	0.5442177	0.8856776
Classification Decision Tree	0.109	0.06447831	0.3673469	0.8630484
Linear SVM	0.121	0.07033998	0.414966	0.8722396
Radial SVM	0.11	0.05627198	0.4217687	0.8722396
Random Forest	0.099	0.04220399	0.4285714	0.922327
GBM	0.106	0.05744431	0.3877551	0.9136062

Summary

- Type I Error
 - We predict customers make a purchase, but they don't
- Type II Error
 - We predict customers don't make a purchase, but they do
- AUC
 - Overall prediction accuracy (combination of type I + type II)



Most Important Factors

1. Page Values

The average value for a web page that a user visited before completing an e-commerce transaction

2. Exit Rates

The percentage of all pageviews to the page

3. Product Related Duration

The total time the visitor spent on product related pages

4. Product Related

The number of product related pages visited during the session

5. Bounce Rate

The % of visitors who enter the site from that page and then leave without triggering any other requests to the analytics server during that session

Recommendation

- Page Value is the most important factor, keep customers clicking through the website
 - Create additional content for users to browse
 - Make sure website is easy to navigate
 - Create algorithm for blog posts/social content based on user navigation history
 - Helpful input for A/B testing and structure segments
- Reduce Exit Rates by incentivizing users to stay on the site (similar to Page Value)
- Continue to improve Product Recommendation algorithm

Bonus slides - Correlation Matrix

