Machine Learning in Finance

Overview

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Classification Problem with Big Data: Churn, Part I

Classification Problem with Big Data: Churn, Part I

- We will put neural network classification against a **Random Forest** for predicting Churn (percentage of customers who drop their cell-phone service)..
- The Random Forest is an effective classifier.
- It is a development of the .631 Bootstrap.
- When we look at big data, data sets can be big in two ways: a large number of data observations and a large number of classifiers.
- The number of classifiers, of course, can be further expanded if we take interaction terms or polynomial expansions in the regression model

Classification Problem with Big Data: Churn, Part I

- The Random Forest bootstraps on the data: it takes randomly chosen subsets of the data (with replacement) for estimation, multiple times.
- It then examines the predictive or out-of-sample performance with the “left-out” data sets for each bootstrap.
- But the Random Forest also selects subsets of the classifiers randomly out of the full set of classifiers or covariates and builds large numbers of “trees”
- From the various trees, with different combinations of classifiers, it selects the best based on the median out-of-sample performance of its prediction errors.
- Of course Random Forests can be used for simple forecasting as well as classification. But they work best for classification.

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Classification Problem with Big Data: Churn, Part II

Classification Problem with Big Data: Churn, Part II

- Acme Telephonica (AT) is a mobile phone operator that has customers across every state of the U.S.A.
- AT struggles with customer churn prediction—customers leaving AT for other mobile phone operators.
- In 2010 AT hired a predictive data analytics specialist, to take a new approach to reducing customer churn.
- This case study describes the work carried out by the specialist after a took AT s to develop a predictive data analytics solution to this business problem.
- We have a data set of 32 covariates, with Chun as the Target, 10,000 observations. Mix of categorical and continuous data.
- Statistics on the next two tables.

Classification Problem with Big Data: Churn, Part II

	Median	Std Dev		Median	Std Dev
age	34.00	22.16	**avgOverBundleMins**	3.00	106.37
occupation	0.00	1.80	**avgRoamCalls**	0.00	6.05
regionType	2.00	2.38	**callMinutesChangePct**	-0.10	5.23
marriageStatus	1.00	0.77	**billAmountChangePct**	-0.01	0.76
children	0.00	0.43	**avgReceivedMins**	52.54	169.98
income	5.00	3.14	**avgOutCalls**	13.33	35.67
numHandsets	1.00	1.35	**avgInCalls**	2.00	17.68
handsetAge	339.00	257.08	**peakOffPeakRatio**	1.40	3.88

Classification Problem with Big Data: Churn, Part II

	Median	Std Dev		Median	Std Dev
smartPhone	1.00	0.30	**peakOffPeakRatioChangePct**	0.01	9.97
HandPrice	0.00	57.07	**avgDroppedCalls**	5.33	14.86
creditRating	1.00	1.57	**lifeTime**	17.00	9.61
homeOwner	0.00	0.47	**lastMonthCustomerCareCalls**	0.00	5.75
creditCard	4.00	1.41	**numRetentionCalls**	0.00	0.23
avgBill	49.21	43.89	**numRetentionOffersAccepted**	0.00	0.16
avgMins	359.63	540.44	**newFrequentNumbers**	0.00	0.64
Charge	44.99	23.96	**churn**	0.50	0.50

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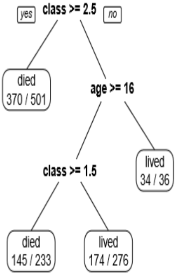
- Random Forests is based on **CART** (Classification and Regression Trees)
- To better understand how Random Forests work, we can look at a classifier system from the Titanic survival data
- This is a simple example based on two covariates: age and class of service, for the [0,1] survival probability.
- Trees of course, can built over many more characteristics.

Who survived the Titantic?



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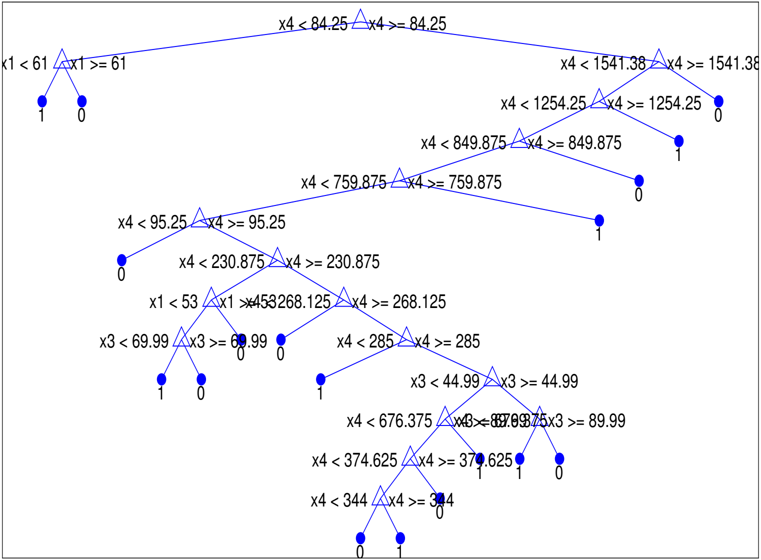
Random Forests: Theory and Design, Part II

- For the Churn example, we can draw a tree based on four covariates [children no, roaming calls, average call minute, home owner]
- As becomes clear, the classification trees become wider and deeper
- We can start several classification trees starting with different variables.


x4 < 84.25
x4 >= 84.25
x1 < 61
x1 >= 61
x4 < 1541.38
x4 >= 1541.38
x4 < 1254.25
x4 >= 1254.25
x4 < 849.875
x4 >= 849.875
x4 < 759.875
x4 >= 759.875
x4 < 95.25
x4 >= 95.25
x4 < 230.875
x4 >= 230.875
x1 < 53
x4 < 268.125
x4 >= 268.125
x3 < 69.99
x3 >= 69.99
x4 < 285
x4 >= 285
x3 < 44.99
x3 >= 44.99
x4 < 676.375
x3 >= 89.99
x4 < 374.625
x4 >= 374.625
x4 < 344
x4 >= 344

Random Forests: Theory and Design, Part II

- As noted by Kelleher, MacNamee, and D'Arcy (2020) in Machine Learning for Predictive Data Analytic s, "data understanding" is a key first step.
- In their data set, the researcher sampled data over a period of 5 years.
- The final data set of 10000 randomly sampled customers was split evenly between those who churned and those who did not.
- In the full data set the ratio is about one in ten, but 50-50 in a balanced **ABT (**Analytic Base Table).
- We first estimate the full sample without and with cross-validation. Then we estimate 75% of the data set (randomly sampled) and evaluate the predictive performance with the left-out data. We repeat this 500 times and evaluate the predictive accuracy.

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Random Forests: Predicting Churn, Part I

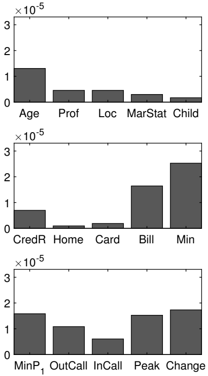
Random Forests: Predicting Churn, Part I

- Let's first look at the in-sample performance of the Churn Estimation.
- The total percentage of wrong decisions, both false positives and false negatives, is less than 10%.

Confusion Matrix		
	State of World	
Decision:	Churn=1	Churn=0
Churn=1	.461	.037
Churn=0	.038	..462

Random Forests: Predicting Churn, Part I

- For the Decision Tree, we can assess the relative importance of each of the 31 covariates: Age of phone is most important.



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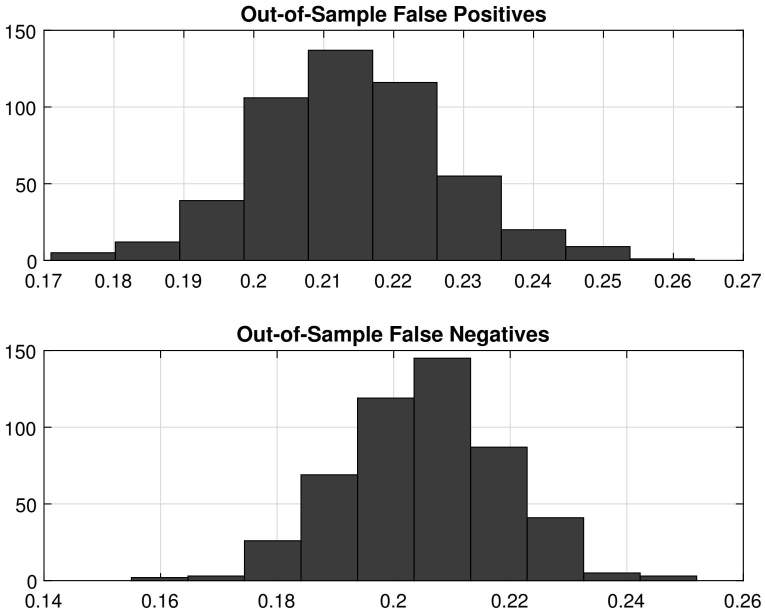
Random Forests: Predicting Churn, Part II

Random Forests: Predicting Churn, Part II

- We see that the hand phone age, not surprisingly, is the biggest predictor of Churn
- The amount of the bill and total minutes are also important predictors
- While this information is interesting we want to know how the model does with out-oi-sample data.
- The ABT had a 50-50 split of Churn and Non-Churn results. In reality the Churn rate is 10%
- Lets try random selections of 9000 for estimation with the remaining 1000 for prediction, and repeat this 500 times.

Random Forests: Predicting Churn, Part II



Random Forests: Predicting Churn, Part II

- We see that the error rates are much larger when we move to out-of-sample or test-set evaluation.
- Given the presence of outliers, it is recommended that one use the median values of the percentage errors rather than the mean.
- Total accuracy: .580; False Positive: .214; False Positive: .206
- Results are better than a 50-50 coin flip.

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Churn Prediction with Neural Nets, Part I

Churn Prediction with Neural Nets, Part I

- Let's see if a neural network can beat a Random Forest, both for in-sample and out-of-sample accuracy.
- We will first try a complex neural network of many hidden layers, with the following structure: [20 15 10 5]
- We will estimate the network for the full sample and then evaluate its performance on the basis of bootstrapping.
- We randomly select 9000 observations for estimation and evaluate the out-of-sample performance for the remaining 1000.

Churn Prediction with Neural Nets, Part I

- To evaluate the network we will look at the accuracy and the importance of the variables.
- However with the nonlinear network, we have to do a numerical perturbation from the median values of each covariate.
- We first obtain the network prediction, $\hat{y}{=}f(x^{median})$
- For each of the covariates, $i = 1,....31$, we calculate $x^{i^*} = x^{median}{+}.00001$,for $i == i^*$, else $x^{i^*}{=}\, x^{median}$ for $i \neq i^*$
- We then calculate $y^{i^*} = f(x^{i*})$ and obtain the differences $(y{-}y^{i^i})/.00001$

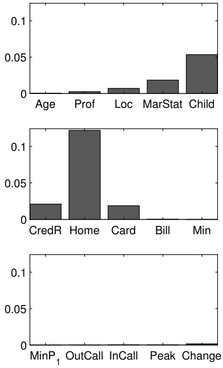
Churn Prediction with Neural Nets, Part I

- In-sample performance of complex network: Overall Accuracy Rate: .560. OK better than flipping a fair coin.

Confusion Matrix		
	State of World	
Decision:	Churn=1	Churn=0
Churn=1	.2902	.229
Churn=0	.2098	..2705

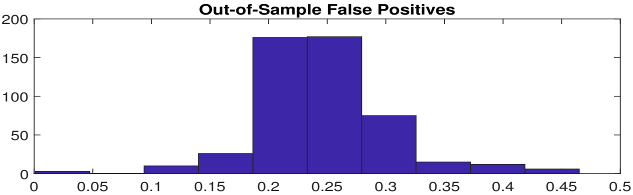
Churn Prediction with Neural Nets, Part I

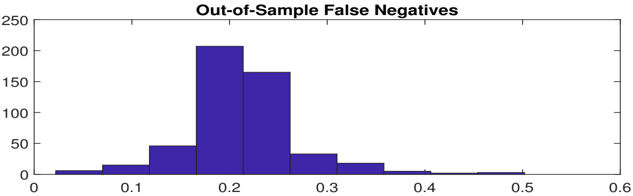
- The network gives another picture of the relative importance with Smartphone, home and children playing a bigger role as predictors of likelihood of churn



Churn Prediction with Neural Nets, Part I

- We see that the out-of-sample accuracy of the net is better than that of the Random Forest. Well slightly better!





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Churn Prediction with Neural Nets, Part II

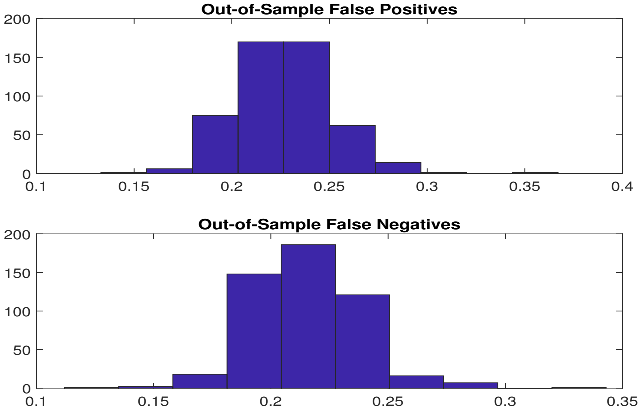
Churn Prediction with Neural Nets, Part II

- Let's try a **simple net** with just one layer of 31 neurons.
- Accuracy rate is .58. Performance is better in-sample than that of the deep net.

Confusion Matrix		
	State of World	
Decision:	Churn=1	Churn=0
Churn=1	.278	.194
Churn=0	.202	..305

Chun Prediction with Neural Nets, Part II

- Out-of-sample prediction errors are worse than the more complex net.



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