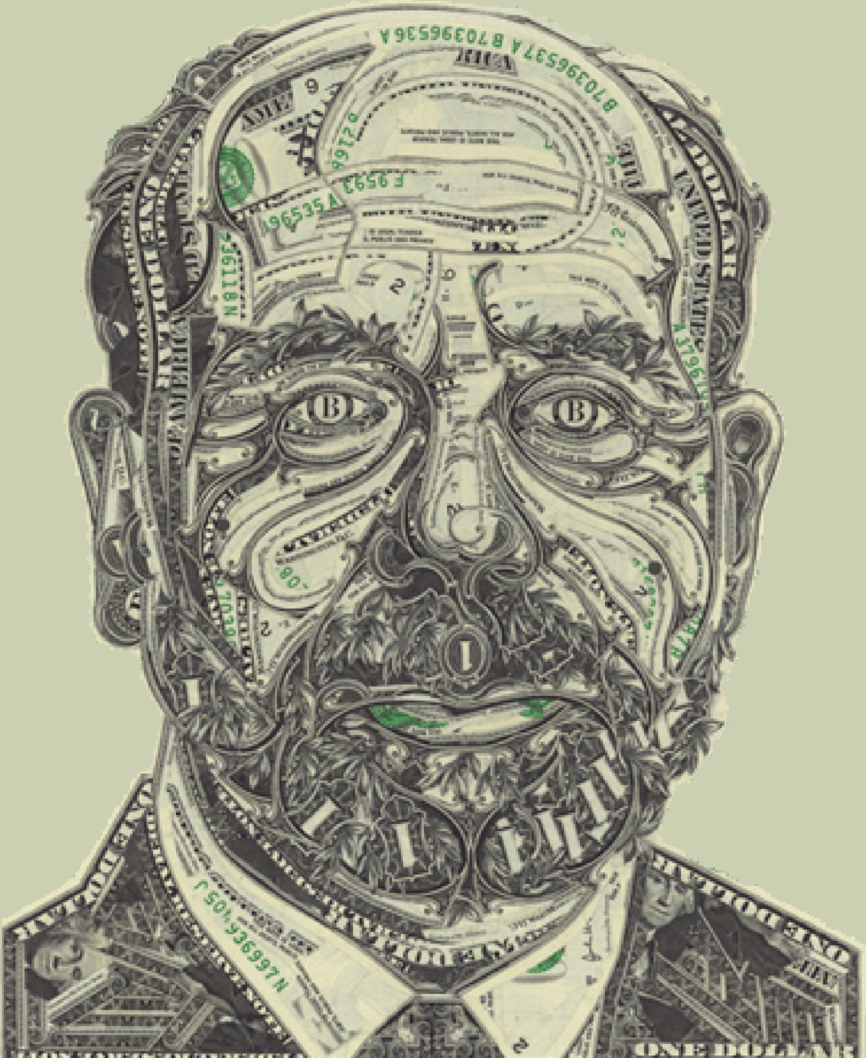
MAIN STREET QUANT



PRESENTS

PHILANTHROPIC ANALYTICS SHOWDOWN

BACKGROUND

- Expansion upon a graduate project / case competition
- Real life data: prominent veteran’s charity, 13M+ donors
- Data:
  - Sample for model development, 50/50 balanced response, 60/40 partition
  - Frequency, Recency, Worth, Demographics
  - Costs for each mail piece
- Problem: losing money on the ‘spray & pray’
  - Best expected response rate: 5.1%
- Benchmark logistic regression vs. classification tree in SAS JMP to predict likely donors
  - Maximize profit using classification under an asymmetric response
  - Generating the label printing list of likely donors

BACKGROUND

Journal of Machine Learning Research 15 (2014) 3133-3181 Submitted 11/13; Revised 4/14; Published 10/14

Do we Need Hundreds of Classifiers to Solve Real World Classification Problems?

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Editor: Russ Greiner

- Almost always parallel random forest (R/Caret), if not, then Gaussian SVM (libSVM)

- *"This is consistent with our experience running hundreds of Kaggle competitions: for most classification problems, some variation on ensembles decision trees (random forests, gradient boosted machines, etc.) performs the best."*

- Ben Hamner, Co-founder & CTO

NARRATIVE

- Imagine that YOU are the Executive Director of your favorite non-profit…
  - Education, health, faith, politics, social good, etc.
  - Maximize donations, minimize costs
- Do you have more than a $1M in your treasury?
  - University foundations
  - Political campaigns
  - Major national charities
- Do you have the means to hire a Fundraising Manager?
  - Not a programmer, uses point-and-click
- Do you have the means to hire a Data Scientist/Programmer?
  - Higher salary

NET PROFIT

	Baseline (No Sort)	
Role		
Projected Take	**$8,619,000**	
Mailer Costs ($0.68 Each)	**$8,840,000**	
Pieces to Send	**13,000,000**	
Expected Response Rate	**5.10%**	
Misclassification Rate	**94.90%**	
Gross Profit Lift		
Gross Profit	**-$221,000**	
Labor		
Burden (50%)		
Software		
Net Profit	**-$221,000**	

NET PROFIT

	Baseline (No Sort)	Logistic Regression (Excel)
Role		Consultant
Projected Take	$8,619,000	$3,967,760
Mailer Costs ($0.68 Each)	$8,840,000	3,130,948
Pieces to Send	13,000,000	1,0834
Expected Response Rate	5.10%	6.51%
Misclassification Rate	94.90%	35.99%
Gross Profit Lift		445.74%
Gross Profit	-$221,000	$764,080
Labor		$4,300
Burden (50%)		
Software		
Net Profit	-$221,000	$759,780

NET PROFIT

	Baseline (No Sort)	Logistic Regression (Excel)	Bootstrap Tree* (SAS JMP)
Role		Consultant	Fundraiser
Projected Take	$8,619,000	$3,967,760	$6,187,845
Mailer Costs ($0.68 Each)	$8,840,000	3,130,948	1,805,338
Pieces to Send	13,000,000	1,0834	6,247
Expected Response Rate	5.10%	6.51%	17.93%
Misclassificatio n Rate	94.90%	35.99%	17.63%
Gross Profit Lift		445.74%	2,083.04%
Gross Profit	-$221,000	$764,080	$4,382,507
Labor		$4,300	$48,500
Burden (50%)			$24,250
Software			$11,000
Net Profit	-$221,000	$759,780	$4,298,757

NET PROFIT

	Baseline (No Sort)	Logistic Regression (Excel)	Bootstrap Tree* (SAS JMP)	Radial SVM (R)
Role		**Consultant**	**Fundraiser**	**Programmer**
Projected Take	**$8,619,000**	**$3,967,760**	**$6,187,845**	**$8,558,011**
Mailer Costs ($0.68 Each)	**$8,840,000**	**3,130,948**	**1,805,338**	**517,586**
Pieces to Send	**13,000,000**	**1,0834**	**6,247**	**1,791**
Expected Response Rate	**5.10%**	**6.51%**	**17.93%**	**86.49%**
Misclassification Rate	**94.90%**	**35.99%**	**17.63%**	**0.83%**
Gross Profit Lift		**445.74%**	**2,083.04%**	**3,738.20%**
Gross Profit	**-$221,000**	**$764,080**	**$4,382,507**	**$8,040,425**
Labor		**$4,300**	**$48,500**	**$80,000**
Burden (50%)			**$24,250**	**$40,000**
Software			**$11,000**	
Net Profit	**-$221,000**	**$759,780**	**$4,298,757**	**$7,920,425**

NET PROFIT

	Baseline (No Sort)	Logistic Regression (Excel)	Bootstrap Tree* (SAS JMP)	Radial SVM (R)	Tuned Radial SVM (R)
Role		Consultant	Fundraiser	Programmer	
Projected Take	$8,619,000	$3,967,760	$6,187,845	$8,558,011	$8,618,785
Mailer Costs ($0.68 Each)	$8,840,000	3,130,948	1,805,338	517,586	$450,829
Pieces to Send	13,000,000	1,0834	6,247	1,791	1,560
Expected Response Rate	5.10%	6.51%	17.93%	86.49%	100%
Misclassificatio n Rate	94.90%	35.99%	17.63%	0.83%	0.00%
Gross Profit Lift		445.74%	2,083.04%	3,738.20%	3,795.91%
Gross Profit	-$221,000	$764,080	$4,382,507	$8,040,425	$8,167,956
Labor		$4,300	$48,500	$80,000	$80,000
Burden (50%)			$24,250	$40,000	$40,000
Software			$11,000		
Net Profit	-$221,000	$759,780	$4,298,757	$7,920,425	$8,047,956

COST/BENEFIT

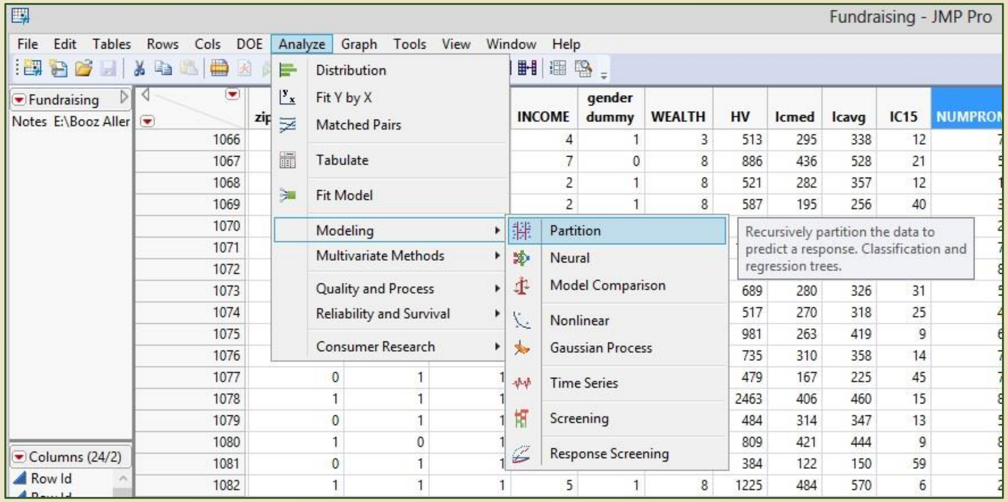
TAKE-AWAYS

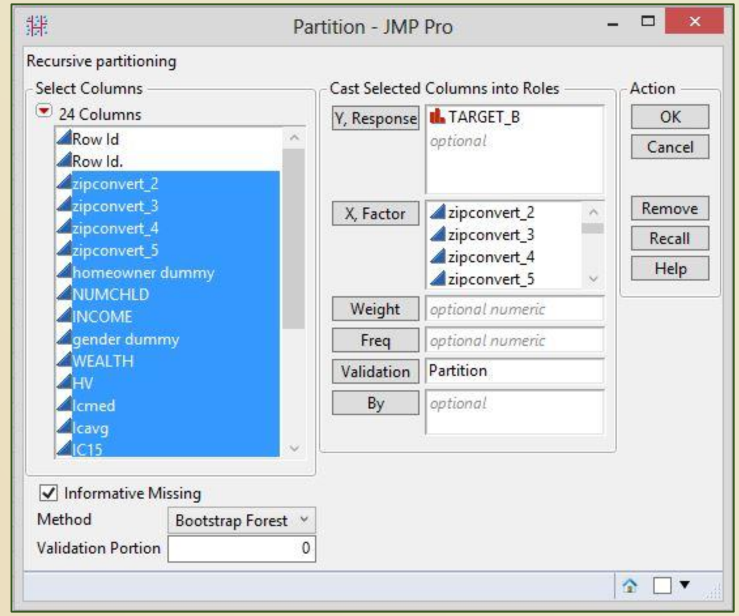
- Even small improvements in misclassification rates can lead to big financial gains.
- Expensive services do no necessarily yield the best results.
- Expensive software does not necessarily yield the best results.
- The world is attempting to automate and democratize statistical functions presently executed with programming:
  - Pro: Saves time and effort
  - Con: Greater use can lead to greater misuse. To wit:
    - Data Cleaning
    - Checking for Normality, Heteroskadcity, Multicolinearity, Endogeity, Variable Reduction
    - Drawing Statistical Inference from Machine Learning

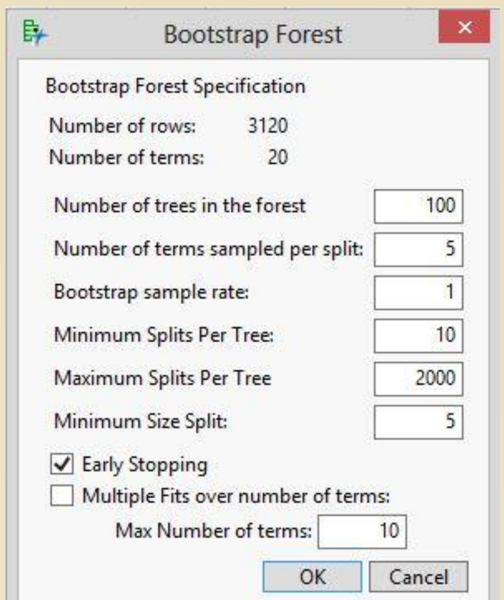
GITHUB REPO

https://github.com/JD-Freeman/Philanthropic-Analytics-Showdown

CLICK PATH - JMP







RESULTS - JMP

Bootstrap Forest for TARGET_B

Specifications

Target Column:	TARGET_B	Training rows:	3120
		Validation rows:	0
Number of trees in the forest:	100	Test rows:	0
Number of terms sampled per split:	5	Number of terms:	20
		Bootstrap samples:	3120
		Minimum Splits Per Tree:	10
		Minimum Size Split:	5

Overall Statistics

Measure	Training	Definition
Entropy RSquare	0.3183	1-Loglike(model)/Loglike(0)
Generalized RSquare	0.4757	(1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n))
Mean -Log p	0.4725	∑ -Log(ρ[j])/n
RMSE	0.3797	√ ∑(y[j]-ρ[j])²/n
Mean Abs Dev	0.3716	∑ |y[j]-ρ[j]|/n
Misclassification Rate	0.0564	∑ (ρ[j]≠ρMax)/n
N	3120	n

Column Contributions

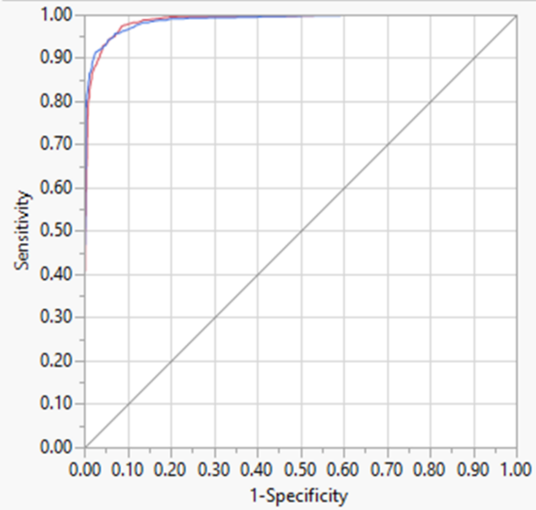
Term	Number of Splits	G^2	Portion
NUMPROM	2076	9510.49667	0.0851
AVGGIFT	1917	9059.63772	0.0810
RAMNTALL	1953	9043.14548	0.0809
HV	1946	9006.7556	0.0806
IC15	2045	8690.55212	0.0777
totalmonths	1977	8629.61547	0.0772
Icmed	1885	8557.62277	0.0766
Icavg	1809	8055.04086	0.0721
TIMELAG	1899	7643.88654	0.0684
LASTGIFT	1681	7397.7376	0.0662
MAXRAMNT	1672	7268.52299	0.0650
INCOME	1720	5626.2538	0.0503
WEALTH	1186	4077.8348	0.0365
gender dummy	1081	1996.14547	0.0179
homeowner dummy	790	1509.15954	0.0135
zipconvert_5	809	1477.9782	0.0132
zipconvert_2	645	1163.33475	0.0104
zipconvert_4	650	1131.61257	0.0101
zipconvert_3	603	1060.59827	0.0095
NUMCHLD	258	878.5888	0.0079

Confusion Matrix

Actual / Predicted

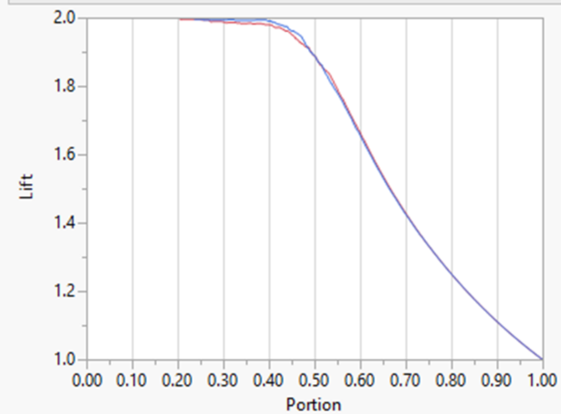
Training	0	1
0	1483	77
1	99	1461

Receiver Operating Characteristic



TARGET_B	Area
0	0.9889
1	0.9889

Lift Curve



R CODE

```
# This is the run of the parallel random forest. It did not beat SAS JMP bootstrap forest.

# Remember to set your working directory, install needed libraries, and set seed to 1.

> library("randomForest", lib.loc="~/R/win-library/3.1")
> library("foreach", lib.loc="~/R/win-library/3.1")
> library("doParallel", lib.loc="~/R/win-library/3.1")

> model <- read.csv("model.csv")
> response <- as.factor(model$TARGET_B)
> predictors <- read.csv('predictors.csv')
> MyRF <- train(predictors, response, method = "parRF")
> getTree(MyRF$finalModel)
> head(MyRF$finalModel$predicted)
> MyRFresult <- MyRF$finalModel$predicted
> write.csv(MyRFresult, file = "MyRFresult.csv", row.names = FALSE)

_____
# This is the run of the SVM and the tuned SVM

> library("e1071", lib.loc="~/R/win-library/3.1")
> dataframe <- data.frame(x=predictors, y=response)
> svmfit <- svm(y~., data=dataframe, kernel="radial", gamma=1, cost=1)
> str(svmfit)
> write.csv(svmresult, file = "svmresult.csv", row.names = FALSE)
> head(svmfit$fitted)
> svmresult <- svmfit$fitted
> tune.out=tune(svm, y~.,dat=dataframe, kernel="radial", ranges=list(cost=c(0.1,1,10,100,1000),gamma=c(0.5,1,2,3,4)))
> summary(tune.out)
 #best performance found is cost 100, gamma 0.5
> svmfit <- svm(y~., data=dataframe, kernel="radial", gamma=.5, cost=100)
> tunedsvmresult <- svmfit$fitted
> write.csv(tunedsvmresult, file = "tunedsvmresult.csv", row.names = FALSE)
```

MATRICES

Logistic Regression

Confusion Matrix

Actual		Predicted
Training	**0**	**1**
0	854	706
1	679	881

Reweighted:

		Predicted		
		0	1	
Actual	0	15891	13137	29,028
	1	679	881	1,560
		16570	14018	30,588

misclassification rate 0.45168

SAS JMP Bootstrap Forest*

Confusion Matrix

Actual		Predicted
Training	**0**	**1**
0	1483	77
1	99	1461

Reweighted:

		Predicted		
		0	1	
Actual	0	27595	1433	29,028
	1	99	1461	1,560
		27694	2894	30,588

misclassification rate 0.050085

R, Best of RF Runs

Confusion Matrix

	0	1	
0	867	693	1560
1	707	853	1560
	1574	1546	3120

Reweighted:

		0	1	
Actual	0	16,133	12895	29,028
	1	707	853	1560
		16,840	13748	30,588

Misclassification Rate: 0.445

R Support Vector Machine

Count of x	**Column Labels**			
Row Labels	**0**	**1**	**(blank)**	**Grand Total**
0	1547	13		1560
1	11	1549		1560
(blank)				
Grand Total	**1558**	**1562**		**3120**

Reweighted:

		0	1	
Actual	0	28,786	242	29,028
	1	11	1549	1560
		28,797	1791	30,588

Misclassification Rate: 0.0083

R Support Vector Machine Tuned

Count of Tuned	**Column Labels**			
Row Labels	**0**	**1**	**(blank)**	**Grand Total**
0	1560			1560
1		1560		1560
(blank)				
Grand Total	**1560**	**1560**		**3120**

Reweighted:

		0	1	
Actual	0	29,028	0	29,028
	1	0	1560	1560
		29,028	1560	30,588

Misclassification Rate: 0