# **Evaluating Decision Tree models** for credit

Data Analysis FGV – Winter School Raphael Ferreira



## **Problem**

Evaluating possible decision tree models for credit

**Target:** Creditability ("bad" or "good")

## **Database**

- ☐ German Credit Data (Statlog)
- 1000 instances
- 20 attributes (13 categorical, others integer)
- ☐ Year: 1994
- □ Source: UCI Machine Learning Repository (<a href="http://archive.ics.uci.edu/ml/datasets.html">http://archive.ics.uci.edu/ml/datasets.html</a>)

Attributes/Variables			
Duration in month			
Credit history			
Purpose			
Credit amount			
Savings account/bonds			
Present employment since			
Installment rate in percentage of disposable income			
Personal status and sex			
Other debtors / guarantors			
Present residence since			

Attributes/Variables			
Property			
Age in years			
Other installment plans			
Housing			
Number of existing credits at this bank			
Job			
Number of people being liable to provide maintenance for			
Telephone			
foreign worker	300 Bad		
Creditability	→ 700 Good		



## **Data Preparation**

- Changing categorical to numerical
- Database split in 60% training and 40% testing, randomly sorted

## **Watson Suggestion**

- Predictive strength was around **70**% for almost all variables, when it was in categorical format (Age was the first variable suggested)
- But predictive strength drop to 18% and variables chosen changed, when was formatted as numerical
- However, using numerical format, accuracy improved in this model
  - And data quality improved as well: from 69% to 74%



## **Models**

## Model 1: "All"

- "Supervised"
- Use all variables

## Model 5: "Watson Analytics"

- "Supervised"
- Use some variables
  - Duration In month
  - Installment Rate
  - Credit Amount
  - Credit History
  - Provide Maintenance For

#### Model 2: "Chosen"

- Supervised
- Use some variables
  - Duration in month
  - Credit Amount
  - Credit History
  - Present Employment Since
  - Job

## **Model 4: "Random Forest"**

- "Supervised"
- Use all variables



## **Results**

Considering this Cost/Ben. Matrix

	Cost/Ben. Matrix		Reference	
			Bad = 0	Good = 1
	Prediction	Bad = 0	0	-1
		Good = 1	-5	3

Model 1: "All"			
Confusion Matrix		Reference	
		Bad = 0	Good = 1
Prediction	Bad = 0	50	47
	Good = 1	62	241
# Nodes			17
Accuracy			0,7275
Balanced Accuracy			0,6416
AUC			0,7311
EV			366

Model 3: "Watson"				
Confusion Matrix		Reference		
		Bad = 0	Good = 1	
Prediction	Bad = 0	38	27	
	Good = 1	74	261	
# Nodes			5	
Accuracy			0,7475	
Balanced A	Accuracy		0,6228	
AUC			0,7165	
EV			386	

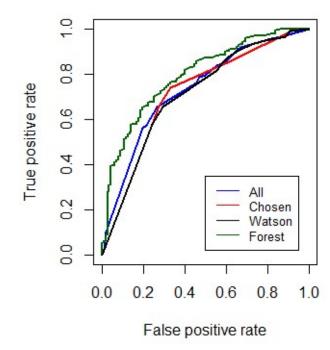
Model 2: "Chosen"				
Confusion Matrix		Reference		
		Bad = 0	Good = 1	
Prediction	Bad = 0	43	42	
	Good = 1	69	246	
# Nodes			7	
Accuracy			0,7225	
Balanced A	Accuracy		0,6190	
AUC			0,7165	
EV			351	

Model 4: "Random Forest"		
Confusion Matrix	Reference	
Confusion Matrix	Bad = 0	Good = 1
Prediction Bad = 0 Good = 1	45	31
Good = 1	67	257
# Trees		500
Accuracy		0,7550
Balanced Accuracy		0,6471
AUC		0,7930
EV		405



## **Performance**

- Random Forest presents the best performance in all indicators
- "Watson" is the second, and not so far from Random Forest (Accuracy, Balance Acc. and EV), and less complex
- "Chose" is the worst
- Important: EV depends on Cost/Benefit
  Matrix



## **Conclusions**

- Although Random Forest is the best model, it uses all variables, and some of them could lead to accountability problems (expected legal costs)
- Board should take in account these potential legal costs and expected profit from this model, and if potential costs are too high then..
- Watson Model is recommended!

