

## Assignment 1: Decision Tree analysis -- German Credit Data

Due: Sept 27<sup>th</sup>

The German Credit dataset has data on 1000 past credit applicants, described by 30 variables. Each applicant is also rated as “Good” or “Bad” credit (encoded as 1 and 0 respectively in the Response variable). The GermanCredit.xls file contains the variable descriptions and the data. New applicants for credit can be evaluated on these 30 variables. We would like to develop a credit scoring rule that can be used to help determine whether a new applicant presents a good or bad credit risk. Here, we will attempt to obtain a decision tree based model to determine if new applicants present a good or bad credit risk.

The original data has been transformed to ease analysis in this initial assignment. It is informative to compare the original and transformed data descriptions to see how different variables have been transformed. The original variables are given below.

### Assignment questions:

1. Explore the data: What is the proportion of “Good” to “Bad” cases? Are there any missing values – how do you handle these? Obtain descriptions of the predictor (independent) variables – mean, standard deviations, etc. for real-values attributes, frequencies of different category values. Examine variable plots.  
Do you notice ‘bad’ credit cases to be more prevalent in certain value-ranges of specific variables, and is this what one might expect (or is it more of a surprise)?  
What are certain interesting variables and relationships (why ‘interesting’)?  
From the data exploration, which variables do you think will be most relevant for the outcome of interest, and why?
2. We will first focus on a descriptive model – i.e. assume we are not interested in prediction.
  - (a) Develop a decision tree on the full data. What decision tree node parameters do you use to get a good model (and why?)
  - (b) Which variables are important to differentiate “good” from “bad” cases – and how do you determine these? Does this match your expectations (from the your response in Question 1)?
  - (c) What levels of accuracy/error are obtained? What is the accuracy on the “good” and “bad” cases? Obtain and interpret the lift chart.  
Do you think this is a reliable (robust?) description, and why.

We next consider developing a model for prediction. For this, we should divide the data into Training and Validation sets.

- (a) Consider a partition of the data into 50% for Training and 50% for Test. What model performance do you obtain? Consider performance based on overall accuracy/error and on the ‘good’ and ‘bad’ credit cases – explain which performance measures, like recall, precision, sensitivity, etc. you use and why. Also consider lift.  
Is the model reliable (why or why not)?

In developing the models above, change decision tree options as you find reasonable (for example, the minimum number of cases for split and at a leaf node, the split criteria, etc.) - explain which parameters you experiment with and why. Report on if and how different

parameters affect performance. Also, does pruning give a better model – please explain why or why not?

Which decision tree parameter values do you find to be useful for developing a good model. Are they the same for different training-test partitions?

(b) Consider two other type of decision tree operators – for example, CART, J48 – experiment with the parameters till you get a ‘good’ model. Summarize the parameters and performance you obtain (using tables can be helpful for this) from the different decision tree operators.

Does performance differ across different types of decision tree learners? Compare models using accuracy, sensitivity, precision, recall, etc (as you find reasonable – you answer to Questions (a) above should clarify which performance measures you use and why). Also compare performance on lift, ROC curves and AUC.

How do the models obtained from these decision tree learners differ?

(c) Decision tree models are referred to as ‘unstable’ – in the sense that small differences in training data can give very different models. Examine the models and performance for different samples of the training/test data (by changing the random seed). Do you find your models to be unstable -- explain?

(d) Consider partitions of the data into 70% for Training and 30% for Test, and 80% for Training and 20% for Test and report on model and performance comparisons (for the decision tree learners considered above).

In the earlier question, you had determined a set of decision tree parameters to work well. Do the same parameters give ‘best’ models across the 50-50, 70-30, 80-20 training-test splits?

Are there similarities among the different models ...in, say, the upper part of the tree – and what does this indicate?

Is there any specific model you would prefer for implementation?

3. Consider the net profit (on average) of credit decisions as:

Accept applicant decision for an Actual “Good” case: 100DM, and

Accept applicant decision for an Actual “Bad” case: -500DM

This information can be used to determine the following costs for misclassification:

		Predicted	
Actual		Good	Bad
	Good	0	100DM
	Bad	500DM	0

Use the misclassification costs to assess performance of a chosen model from Q 2 above.

Examine how different cutoff values for classification threshold make a difference – what do you find?

4. Let’s examine your ‘best’ decision tree model obtained. (a) What is the tree depth? And how many nodes does it have? What are the variables towards the ‘top’ of the tree, and are they similar to what you found in Question 2?

(b) Identify two relatively pure leaf nodes. What are the ‘probabilities for ‘Good’ and ‘Bad’ in these nodes?

(c) The tree can be used to obtain rules – give two sample rules obtained from the tree.  
(Rules will be of the form IF condition AND condition AND.... THEN classification).

5. The predicted probabilities can be used to determine how the model may be implemented. We can sort the data from high to low on predicted probability of “good” credit risk. Then, going down the cases from high to low probabilities, one may be able to determine an appropriate cutoff probability – values above this can be considered acceptable credit risk. The use of cost figures given above can help in this analysis.

For this, first sort the validation data on predicted probability. Then, for each validation case, calculate the actual cost/benefit of extending credit. Add a separate column for the cumulative net cost/benefit.

How far into the validation data would you go to get maximum net benefit? In using this model to score future credit applicants, what cutoff value for predicted probability would you recommend? Provide appropriate performance values to back up your recommendation.

## B. Data description

Var. #	Variable Name	Description	Variable Type	Description
1.	OBS#	Observation No.	Categorical	
2.	CHK_ACCT	Checking account status	Categorical	0 : < 0 DM 1: 0 < ... < 200 DM 2 : => 200 DM 3: no checking account
3.	DURATION	Duration of credit in months	Numerical	
4.	HISTORY	Credit history	Categorical	0: no credits taken 1: all credits at this bank paid back duly 2: existing credits paid back duly till now 3: delay in paying off in the past 4: critical account
5.	NEW_CAR	Purpose of credit	Binary	car (new) 0: No, 1: Yes
6.	USED_CAR	Purpose of credit	Binary	car (used) 0: No, 1: Yes
7.	FURNITURE	Purpose of credit	Binary	furniture/equipment 0: No, 1: Yes
8.	RADIO/TV	Purpose of credit	Binary	radio/television 0: No, 1: Yes
9.	EDUCATION	Purpose of credit	Binary	education 0: No, 1: Yes
10.	RETRAINING	Purpose of credit	Binary	retraining 0: No, 1: Yes
11.	AMOUNT	Credit amount	Numerical	
12.	SAV_ACCT	Average balance in savings account	Categorical	0 : < 100 DM 1 : 100<= ... < 500 DM 2 : 500<= ... < 1000 DM 3 : =>1000 DM 4 : unknown/ no savings account
13.	EMPLOYMENT	Present employment since	Categorical	0 : unemployed 1: < 1 year 2 : 1 <= ... < 4 years 3 : 4 <= ... < 7 years 4 : >= 7 years
14.	INSTALL_RATE	Installment rate as % of disposable income	Numerical	
15.	MALE_DIV	Applicant is male and divorced	Binary	0: No, 1: Yes
16.	MALE_SINGLE	Applicant is male and single	Binary	0: No, 1: Yes
17.	MALE_MAR_WID	Applicant is male and married or a widower	Binary	0: No, 1: Yes
18.	CO-APPLICANT	Application has a co-applicant	Binary	0: No, 1: Yes
19.	GUARANTOR	Applicant has a guarantor	Binary	0: No, 1: Yes
20.	PRESENT_RESIDENT	Present resident since - years	Categorical	0: <= 1 year 1<...<=2 years 2<...<=3 years 3:>4years
21.	REAL_ESTATE	Applicant owns real estate	Binary	0: No, 1: Yes
22.	PROP_UNKN_NONE	Applicant owns no property (or unknown)	Binary	0: No, 1: Yes
23.	AGE	Age in years	Numerical	
24.	OTHER_INSTALL	Applicant has other installment plan	Binary	0: No, 1: Yes

		credit		
25.	RENT	Applicant rents	Binary	0: No, 1: Yes
26.	OWN_RES	Applicant owns residence	Binary	0: No, 1: Yes
27.	NUM_CREDITS	Number of existing credits at this bank	Numerical	
28.	JOB	Nature of job	Categorical	0 : unemployed/ unskilled - non-resident 1 : unskilled - resident 2 : skilled employee / official 3 : management/ self-employed/highly qualified employee/ officer
29.	NUM_DEPENDENTS	Number of people for whom liable to provide maintenance	Numerical	
30.	TELEPHONE	Applicant has phone in his or her name	Binary	0: No, 1: Yes
31.	FOREIGN	Foreign worker	Binary	0: No, 1: Yes
32	RESPONSE	Credit rating is good	Binary	0: No, 1: Yes

\*\*\*\*\*

## C. ORIGINAL DATA DESCRIPTION

Description of the German credit dataset.

1. Title: German Credit data

2. Source Information

Professor Dr. Hans Hofmann  
Institut f"ur Statistik und "Okonometrie  
Universit"at Hamburg  
FB Wirtschaftswissenschaften  
Von-Melle-Park 5  
2000 Hamburg 13

3. Number of Instances: 1000

Two datasets are provided. the original dataset, in the form provided by Prof. Hofmann, contains categorical/symbolic attributes and is in the file "german.data".

For algorithms that need numerical attributes, Strathclyde University produced the file "german.data-numeric". This file has been edited and several indicator variables added to make it suitable for algorithms which cannot cope with categorical variables. Several attributes that are ordered categorical (such as attribute 17) have been coded as integer. This was the form used by StatLog.

6. Number of Attributes german: 20 (7 numerical, 13 categorical)  
Number of Attributes german.numer: 24 (24 numerical)

7. Attribute description for german

Attribute 1: (qualitative)  
Status of existing checking account  
A11 : ... < 0 DM  
A12 : 0 <= ... < 200 DM  
A13 : ... >= 200 DM /  
salary assignments for at least 1 year  
A14 : no checking account

Attribute 2: (numerical)  
Duration in month

Attribute 3: (qualitative)  
Credit history  
A30 : no credits taken/  
all credits paid back duly  
A31 : all credits at this bank paid back duly  
A32 : existing credits paid back duly till now  
A33 : delay in paying off in the past  
A34 : critical account/  
other credits existing (not at this bank)

Attribute 4: (qualitative)  
 Purpose  
 A40 : car (new)  
 A41 : car (used)  
 A42 : furniture/equipment  
 A43 : radio/television  
 A44 : domestic appliances  
 A45 : repairs  
 A46 : education  
 A47 : (vacation - does not exist?)  
 A48 : retraining  
 A49 : business  
 A410 : others

Attribute 5: (numerical)  
 Credit amount

Attribute 6: (qualitative)  
 Savings account/bonds  
 A61 : ... < 100 DM  
 A62 : 100 <= ... < 500 DM  
 A63 : 500 <= ... < 1000 DM  
 A64 : .. >= 1000 DM  
 A65 : unknown/ no savings account

Attribute 7: (qualitative)  
 Present employment since  
 A71 : unemployed  
 A72 : ... < 1 year  
 A73 : 1 <= ... < 4 years  
 A74 : 4 <= ... < 7 years  
 A75 : .. >= 7 years

Attribute 8: (numerical)  
 Installment rate in percentage of disposable income

Attribute 9: (qualitative)  
 Personal status and sex  
 A91 : male : divorced/separated  
 A92 : female : divorced/separated/married  
 A93 : male : single  
 A94 : male : married/widowed  
 A95 : female : single

Attribute 10: (qualitative)  
 Other debtors / guarantors  
 A101 : none  
 A102 : co-applicant  
 A103 : guarantor

Attribute 11: (numerical)  
 Present residence since

Attribute 12: (qualitative)  
 Property  
 A121 : real estate

A122 : if not A121 : building society savings agreement/  
           life insurance  
 A123 : if not A121/A122 : car or other, not in attribute 6  
 A124 : unknown / no property

Attribute 13: (numerical)  
     Age in years

Attribute 14: (qualitative)  
     Other installment plans  
     A141 : bank  
     A142 : stores  
     A143 : none

Attribute 15: (qualitative)  
     Housing  
     A151 : rent  
     A152 : own  
     A153 : for free

Attribute 16: (numerical)  
     Number of existing credits at this bank

Attribute 17: (qualitative)  
     Job  
     A171 : unemployed/ unskilled - non-resident  
     A172 : unskilled - resident  
     A173 : skilled employee / official  
     A174 : management/ self-employed/  
             highly qualified employee/ officer

Attribute 18: (numerical)  
     Number of people being liable to provide maintenance for

Attribute 19: (qualitative)  
     Telephone  
     A191 : none  
     A192 : yes, registered under the customers name

Attribute 20: (qualitative)  
     foreign worker  
     A201 : yes  
     A202 : no

\*\*\*\*\*