KDD Cup 2009 presentation: University of Melbourne

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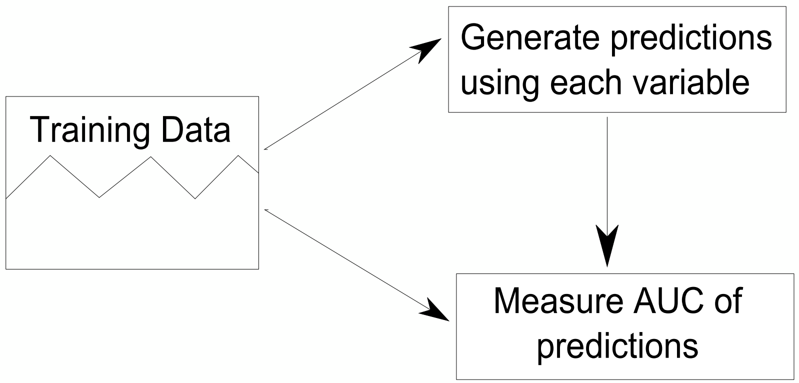
Challenge Introduction

Some of the main features of the data that needed consideration:

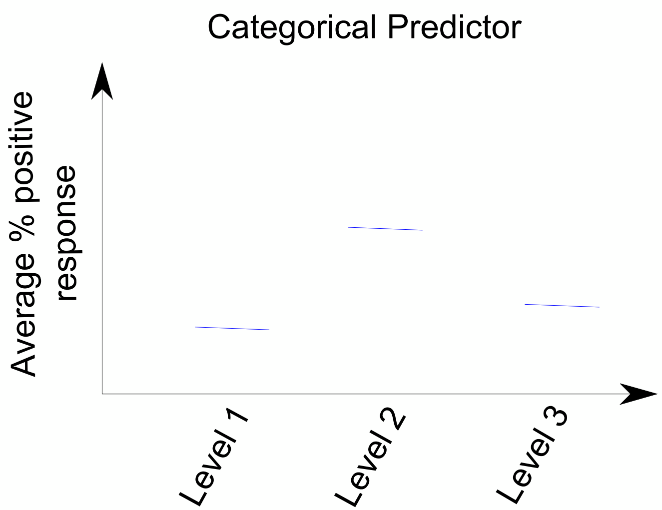
- Large number of observations
- Large number of predictors, many of limited value
- Continuous and categorical values
- “Messy” data
- Variable interactions
- Class imbalances

Feature selection

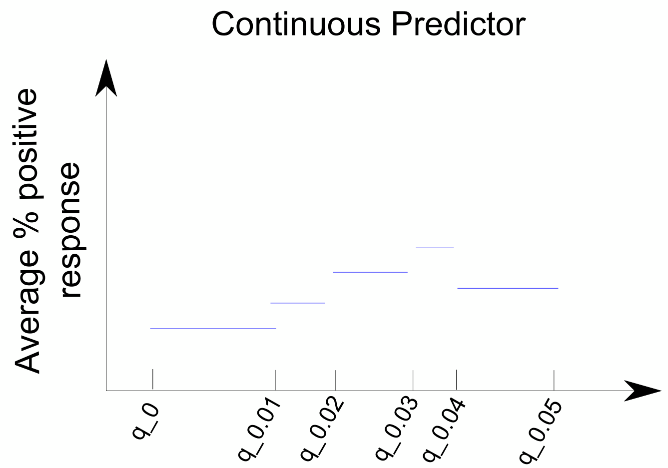
Our approach required a substantial reduction in dimensionality.
We ranked the predictors for each of the three responses.



Feature selection



Feature selection



Feature selection

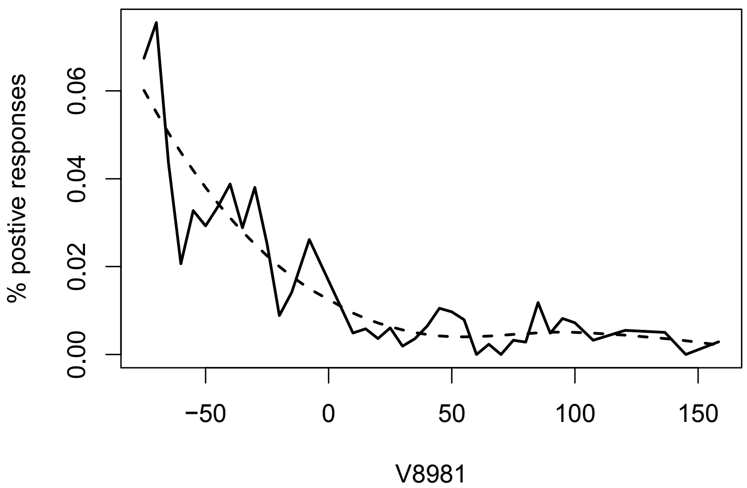
The approach was very simple, but had the following advantages:

- Speed
- Stability with respect to scale
- Comparability between categorical and continuous variables
- Ability to detect nonlinear relationships

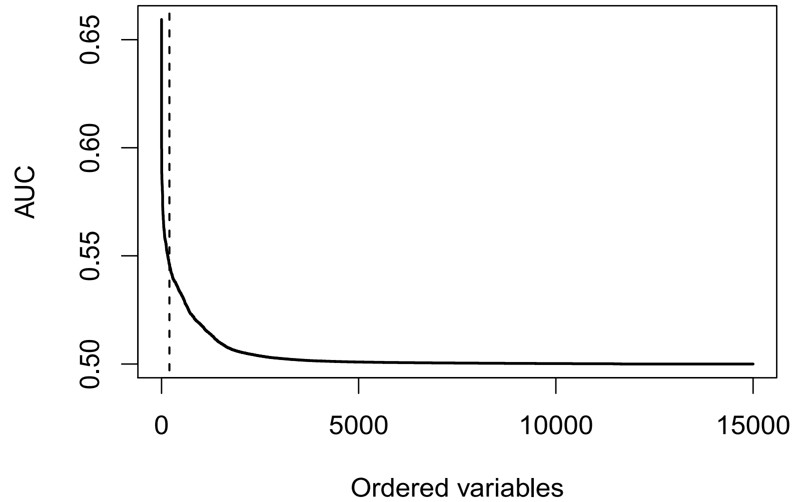
Appetency and Churn feature selections produced good results. Upselling was more variable.

Feature selection

Figure shows the quantile fit for the most important variable in the Churn model.



AUC scores for predictors in Churn model



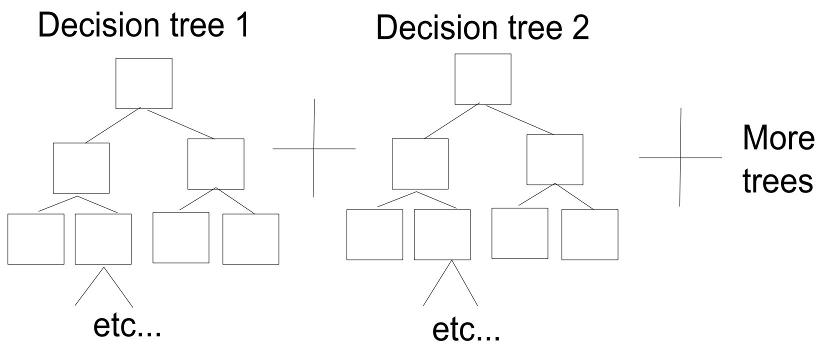
Treatment of categorical variables

Having categorical variables with a large number of levels proved highly undesirable. We attempted to aggregate the levels.If a categorical variable had > 25 levels, we replaced it:

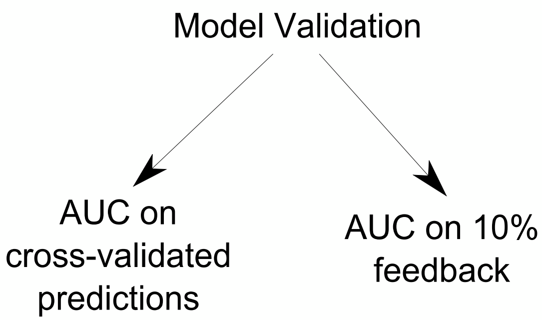
- kept any levels with > 1000 observations worth of exposure.
- aggregating any levels with exposure between 500-999 together
- aggregating any levels with exposure between 250-499 together
- aggregating any levels with exposure between 1-250 together.

Producing final models

For each response we built a gradient boosting machine, using decision trees as the based learner, with shrinkage



Producing final models



Producing final models

Decision trees have a number of features that make them suitable for this year's competition

- Handling of missing values.
- Robustness against extreme values.
- Handling categorical and continuous variables.
- Models interactions between predictors.
- Can model nonlinear dependencies.

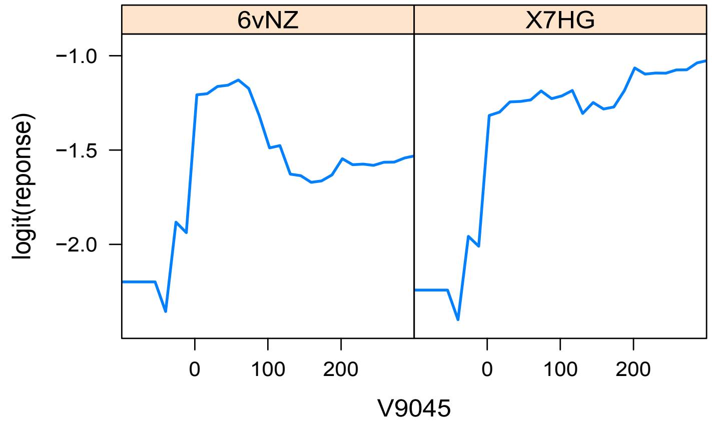
Some model parameters

	Model		
	Churn	Appetency	Upselling
Number of variables	198	196	201
Class weight	12	20	12
Shrinkage parameter	0.01	0.01	0.01
Number of trees	1300	1300	3000
Tree depth	5	3	5

Table: Model parameters for boosted tree models

Interaction example

Partial expectation plot of the logit transform of the probability of a positive response, by V9045 across two levels of V14990.



Relative variable importance

Rank	Churn		Appetency		Upselling	
	Name	Rel. Inf.	Name	Rel. Inf.	Name	Rel. Inf.
1	V8981	20.13	V9045	23.78	V9045	45.52
2	V14990	10.25	V8032	13.56	V14990	7.86
3	V10533	4.65	V14995	10.79	V8981	5.32
4	V14970	4.60	V14990	6.07	V12507	4.96
5	V5331	2.36	V5826	3.72	V6808	4.65
6	V14995	2.19	V8981	3.23	V1194	2.58
7	V14822	2.10	V10256	3.03	V14970	2.16
8	V9045	2.00	V12641	2.72	V14871	1.33
9	V2570	2.00	V14772	1.72	V1782	1.15
10	V14923	1.88	V14939	1.68	V10256	1.05
11	V14765	1.19	V14867	1.62	V5026	0.96
12	V14904	1.14	V14970	1.42	V8032	0.91
13	V5702	1.13	V11781	1.14	V14786	0.81
14	V11047	1.12	V14871	0.89	V7476	0.62
15	V14778	0.97	V14788	0.86	V11781	0.59

Computational resources