Scoring Models

Application Scorecard For SME Bank Loan

Issues & Objectives

- To develop application scoring model for SME lending for a bank in Indonesia
- The SME portfolio was new to this bank which had been recently acquired by a multinational bank headquartered in Australia
- The scoring model would be used for SME loan origination decisions
- Critical component in the plan for scaling up operations in accordance with Indonesian government directive

Solution

- Bootstrapping was used to overcome the limitation of a small sample.
- Reject rates were taken as a surrogate for default rate.
- Model Gini = 66.74* & Model KS = 53.85** indicating high quality scorecard

Challenges

- The number of data points was very small ≈ 400 making it difficult to obtain reliable results through predictive modeling
- Such sparsity of data is not uncommon in Asia
- The SME portfolio was new so the history of defaults had not been well established.

Benefits

- Process Automation
- Ensures Consistency in decision making
- Predictive modeling replaces gut feel
- Scores recalibrated with default data after sometime

Moral Risk

- Company Reputation
- Management Experience
- Reference
- New / Existing Clients

Business Risk

- Type of Business
- Location / Property
- Years Trading
- Utilization
- Loan Objective

Financial Risk

- Financial index – Trend and Forecast
- Liquidity Ratio
- Leverage Ratio
- Profitability Ratio

*Gini > 55 indicates a high quality scorecard
**KS > 45 indicates a high quality scorecard

Calibration of Expert Scorecard by ML Methods

Issues & Objectives

- For the first time in India, a scorecard was developed for the client to keep vigil on the listed companies to avoid potential financial disaster
- Scorecard was based on financial as well nonfinancial events such as auditors, board of directors, litigation, news etc
- The task was to refine expert scorecard with ML methods

Challenges

- Listed and unlisted flag was incomplete in the database
- Many companies had large number of missing data
- Frequent modification of event logic
- Running ML models and processing score with new weights took several hours posing a challenge to multiple iteration

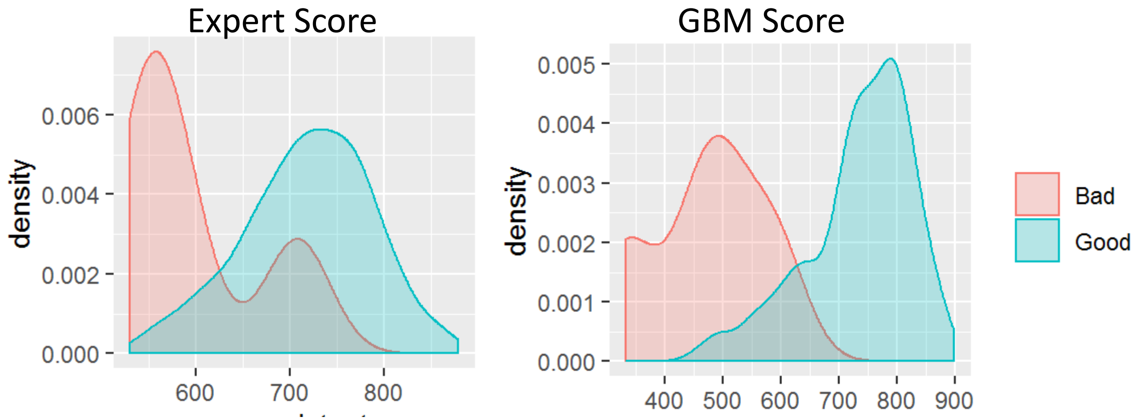
Benefits

- Discriminatory power of the calibrate scorecard was found to be higher than the expert scorecard
- Apply a decision overlay which enhanced the predictive power of the scorecard
- Better separation between GOOD and BAD companies in modelled score

Solution

- Decision tree, Random forest and Gradient boosting were used to obtain weights of the events
- ML methods were run in h2o
- Models for listed and unlisted companies were built
- Separate weights for listed and unlisted companies were used to arrive at the consolidated score of parent companies

	Expert	DT	RF	GBM
AUC	.88	.96	.96	.97
KS	.71	.91	.92	.91
GINI	.76	.92	.92	.94



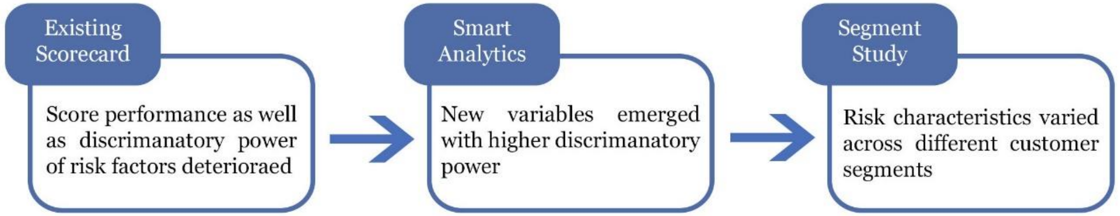
Application Scorecard For Auto Loan

Issues & Objectives

Application scorecard for sub-prime customers
- Review and recalibrate scorecard
- Use insight data to improve alignment between underwriting rules and scores

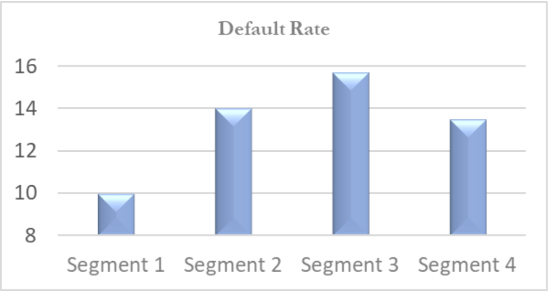
Challenges

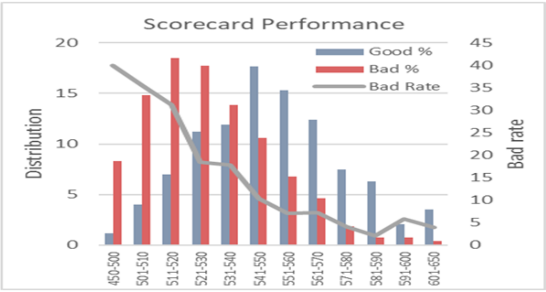
- Methodology for current scorecard not well documented
- Scores not aligned with underwriting rules
- Data in batches – Credit history, product information, loan terms in different files from different time periods
- Performance available only for 8% TTD population who take up loan from 55% approval



Solution

- Data collation to align all variables from same time-period was carried out using R for analysis
- Customers classification using domain knowledge and statistical methods – Decision tree and cluster analysis.
- Multiple scorecards each with superior performance than existing scorecard
- All scorecards rescaled to have similar odds
- Scorecard as a linear function for easy integration with loan origination system
- Reviewed underwriting rule and corporate reporting system and recommended changes





Application Scorecard For Auto Loan & Subsequent Analysis

Issues & Objectives

- After a span of 4 years, retro comparison of two bureau data in terms of coverage and quality with a view to change scorecard

Challenges

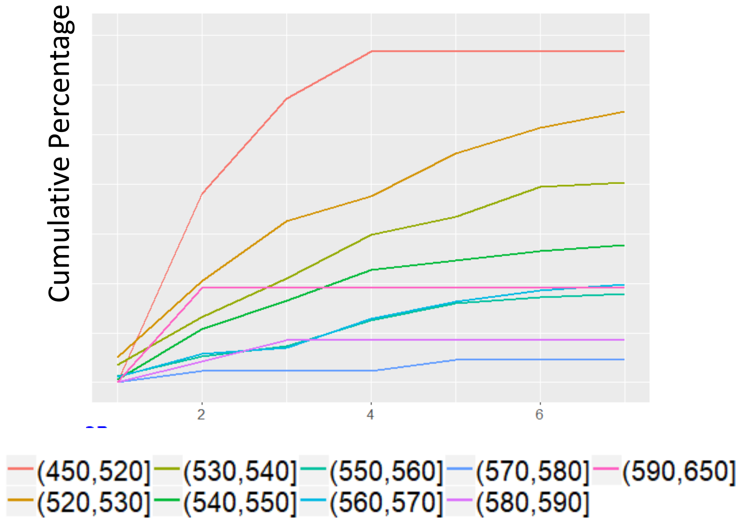
- During the process of creating scorecard
  - Methodology for existing scorecard not well organized
  - Credit history, product information, loan terms all data scattered
  - Performance available for 8% TTD among 55% approval
- During subsequent analysis
  - Payment behaviour KPI was not structured
  - Underwriting rule was not well documented
- Bureau data for same time period for like for like comparison

Benefits

- Discriminatory power of the multiple scorecards was found to be higher than the single scorecard
- Scorecard was implemented and is operational for 4 years
- Better understanding of payment on KPI
- Recommendation on underwriting rule - same characteristics considered in model as well as by underwriters thus causing double penalty
- Clear understanding of coverage and potential for scorecards built from both

Solution

- Data processing and analysis was done with R
- Customer classification to obtain homogeneous segments (Decision tree and cluster analysis)
- Multiple scorecards all scaled to have same odds
- Scorecard as a linear function for easy integration with LOS
- Cohort-wise analysis of payment bahaviour of arrear and upto date customers as well as various loan instruments
- Analysis of characteristics to obtain the ones possibly affecting underwriter decisions - made recommendations
- Statistical comparison of bureau data as well as quick scorecards using both



Credit Scoring for Leasing Company

Issues & Objectives

- A large company in UK finances lease of office equipment, primarily to small and medium companies with ticket size less than £10K
- Leased items depreciates rapidly and seizure of collateral does not recover the debt
- The company currently cherry picks customers who seldom go bad
- They want to expand customer base while controlling risk
- For this they want a scorecard to replace rule driven underwriting for better screening

Solution

- Model developed by R program
- 2 scorecards with and without credit bureau ratings were delivered
- Discriminatory power of the scorecards were high as seen from high KS and GINI

Challenges

- Company book identified only 2.5% bad lease – payment history data was fraught with inconsistent figures
- After incorporating liquidation/insolvency/dissolution status and rating from credit bureau record, the incidence was boosted to 12%. The process classified non takers of loan to Good and Bad by a logical method and not by reject inference

Benefits

- Scorecard developed by Statistical method
- Scrutiny restricted to high scorers reducing manual work by a factor of 5 -10

	Model with Credit Rating		**Model without Credit Rating**	
	Training	Test	Training	Test
KS	47	53	46	53
GINI	63	67	61	65

Credit Scoring for Leasing Company Subsequent Analysis

Issues & Objectives

Two and half years after implementation of scorecard the client approached with the following requirements

- Performance review of scorecard
- Two separate scorecards for companies with full financial records and micro entities who are exempt from filling full records
- Best process to incorporate business sector in the model
- Ways to increase approval for intermediate customers
- Explore a different bureau data

Challenges

- Company book identified only 2.5% bad lease – a very small sample for model
- Payment history data for the large number of customers whose lease was brokered by the client was fraught with inconsistent figures
- Many financial fields had large number of missing data

Benefits

- Scorecard developed by Statistical method replacing purely rule based method
- Discriminatory power of the scorecards were high as seen from high KS and GINI
- Facilitated work of underwriters by restricting scrutiny of limited proposals
- Comparison of different bureau data by a neutral company

Solution

- Scorecard development
  - Model developed by R program
  - After incorporating liquidation/insolvency/dissolution status and rating from credit bureau record, the incidence was boosted to 12%. The process classified non takers of loan to Good and Bad by a logical method and not by reject inference
  - 2 scorecards with and without credit bureau ratings were delivered
- Subsequent analysis
  - 4 definitions of defaults are considered
  - Variable importance computed for each of the defaults for full account companies and micro entities
  - Use various modelling technique to differentiate between Good, Probable Bad and Definite Bad

	Model with Credit Rating		Model without Credit Rating	
	Training	Test	Training	Test
KS	47	53	46	53
GINI	63	67	61	65

Fraud Scoring for Insurance Claims

Issues & Objectives

- A major insurance company in Singapore used to manually examine each travel insurance claim to identify potentially fraudulent one
- Suspicious claims were subject to a more detailed investigation
- This involved considerable manual effort & inconsistent processes
- The project objective was to develop a score to identify potentially fraudulent claims which would be subject to greater scrutiny.

Solution

- Gradient Boosting – a powerful machine learning algorithm was used for detecting potentially fraudulent cases
- Substantial lift demonstrated. – on the client test data set it sufficed to examine 7.75% of all claims to identify 91.67% of all fraudulent claims

Challenges

- Data included 77,445 claim records of which only 120 had been determined to be potentially fraudulent
- So identified potentially fraudulent claims are rare events (0.15%) and therefore hard to detect
- It was however expected that there could be a large number of undetected fraudulent claims

Benefits

- Process automation, ensuring consistency, cost saving and increased accuracy
- Scrutiny restricted to high scorers reducing manual work by a factor of 5 -10

Score (Probability of Claim being Fraudulent)	Potentially Fraudulent	Not Fraudulent	Cumulative (Potentially Fraudulent)	Cumulative (Total)
>50%	0	1	0.00%	0.00%
40-50%	0	19	0.00%	0.09%
30-40%	4	163	33.33%	0.83%
20-30%	7	1,551	91.67%	7.75%
10-20%	1	12,536	100.00%	63.41%
0-10%	0	8,243	100.00%	100.00%

Credit Scoring for Micro Finance Provider

Issues & Objectives

- A Multi-finance company providing financing facilities for small and medium enterprises in Indonesia.
- The objective was to develop multiple portfolios for different loan types.
- Link the scorecard to core banking system to produce instant score at the time of application

Solution

- The whole process is automated with Smart proprietary software, ACreS
- 4 portfolios were built one each for Retail SME, Corporate SME, Retail Vehicle Loan and Corporate Vehicle Loan.
- In absence of core banking system, webservice is created to input data and receive instant score
- Newly entered data is stored in a database

Challenges

- On account of data security, the company developed the model in-house. No data was shared with Smart
- Most of the data fields are in local language
- Smart guided the whole process remotely with only one on-site visit and many hours of online consulting. This involved detailed analysis of numerous variables for each scorecard

Benefits

- Process automation, ensured consistency, decreased manual work and increased accuracy.
- Generation of scorecards in real time with performance measures
- Variable transformations are automatically accounted in scoring population
- Deployment of the model and scorecard for scoring new applicants.
- Easy monitoring of score with the help of interactive reports

Score distribution

score_bin	BAD	GOOD	BAD_rate	GOOD_Rate	Cum_BAD_Rate	Approval_Rate	TPR	FPR	Acc	Lift
(513, Inf]	2	98	2.00	98.00	2.00	10.00	0.22	0.05	0.73	2.22
(511,513]	3	97	3.00	97.00	2.50	20.00	0.42	0.10	0.75	2.11
(509,511]	17	83	17.00	83.00	7.33	30.00	0.61	0.17	0.77	2.03
(507,509]	12	88	12.00	88.00	8.50	40.00	0.71	0.26	0.73	1.79
(504,507]	20	80	20.00	80.00	10.80	50.00	0.82	0.36	0.69	1.64
(501,504]	32	68	32.00	68.00	14.33	60.00	0.89	0.48	0.63	1.48
(498,501]	31	69	31.00	69.00	16.71	70.00	0.93	0.60	0.56	1.33
(495,498]	56	44	56.00	44.00	21.62	80.00	0.98	0.72	0.49	1.23
(492,495]	60	40	60.00	40.00	25.89	90.00	0.99	0.86	0.40	1.10
(-Inf,492]	67	33	67.00	33.00	30.00	100.00	1.00	1.00	0.30	1.00

Notes:

1. Rows under *_Rate columns add to 100%. This gives marginal rates; i.e. percentage of cases in that score band which lie in one or the other outcome category.
2. Cum_*_Rate in a row gives the cumulative rate of undesired outcome for all applications with score greater than the min row score.
3. Approval rate gives the percentage of applicants scoring above the min row score
4. TPR & FPR reported at upper limit of the score bins

Scoring Return of COD Consignments

Issues & Objectives

- To develop a scoring model to identify consignments likely to be returned, in case of Cash on Delivery (CoD) payments for one of the largest e-tailer distributors.

Solution

- Univariate analysis to identify significant variables
- Clustered clients based on number of orders from a specific vendor
- Developed various models and recommended the most suitable one

Challenges

- Extremely large data – Over 2.5 million records
- Data inconsistencies
- Traffic variation at different time of the day

Benefits

Training Data	Test Data	Gini **	K-S *
Jul 14 – Sep 14	Oct 14	42%	38%
Aug 14 –Oct 14	Nov 14	44%	40%
Sep 14 – Nov 14	Dec 14	44%	41%
Oct 14 – Dec 14	Jan 15	45%	42%

*K-S 36 – 45High separation for application scorecard
**Gini36 – 45Average separation, definitely useful