Behavioral Models in Banking

Session held in the workshop “Machine Learning” and “Big Data”: basic concepts and applications
hosted by BPLIM, Banco de Portugal

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1. Introduction

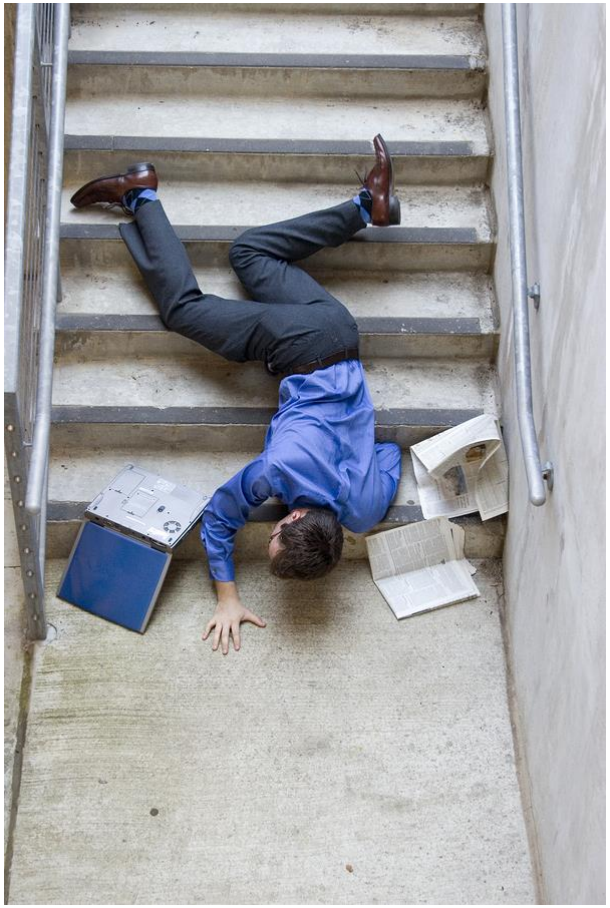
Credit risk management – The problem

Is this Person worthy for credit? How much is this Person worth?

Source: The New York Times Magazine. Photo illustration by Katherine Wolkoff. Models: COACD; FunnyFace Today.

1. Introduction

Credit risk management – The challenge



- **Will this Person default on credit obligations?**
- **For how long will this Person hold before defaulting?**
- **How much will I lose if this Person defaults?**

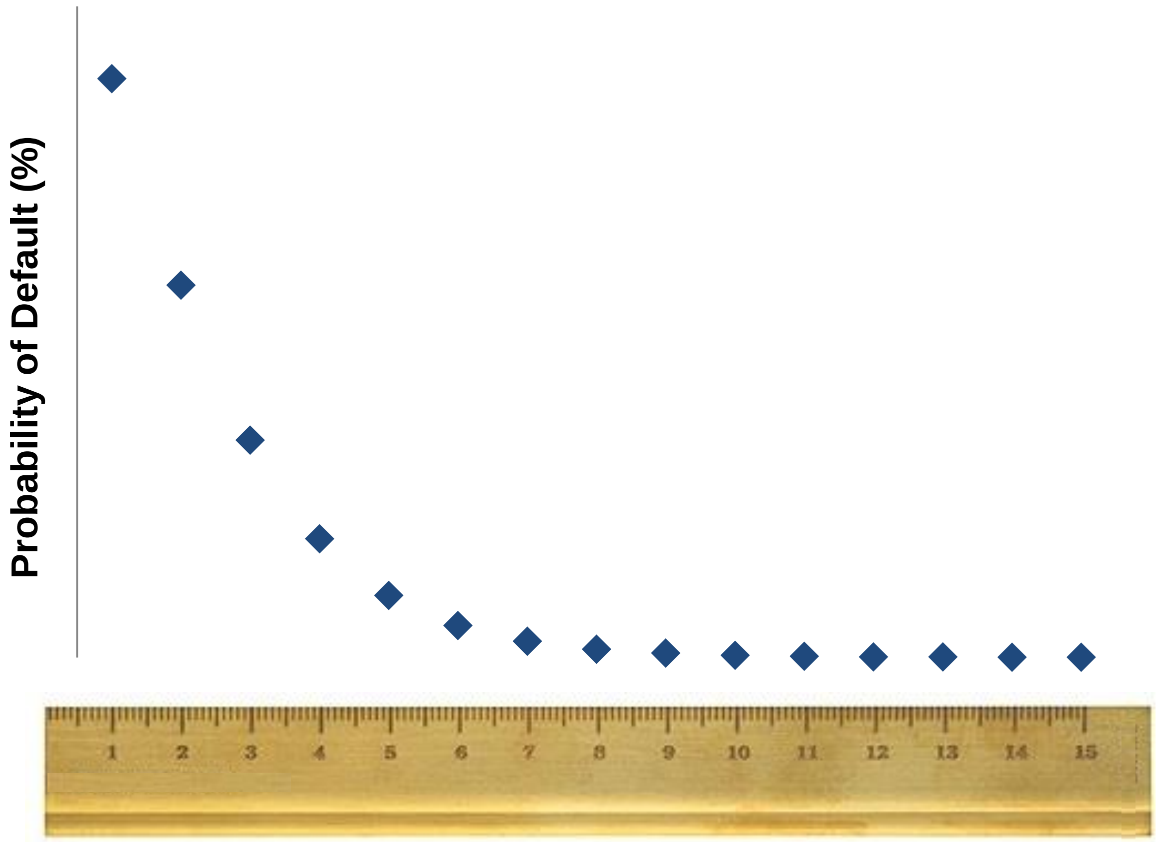
1. Introduction

Credit risk management – Magic ball

How to find the answers to these questions?

2. Credit risk management

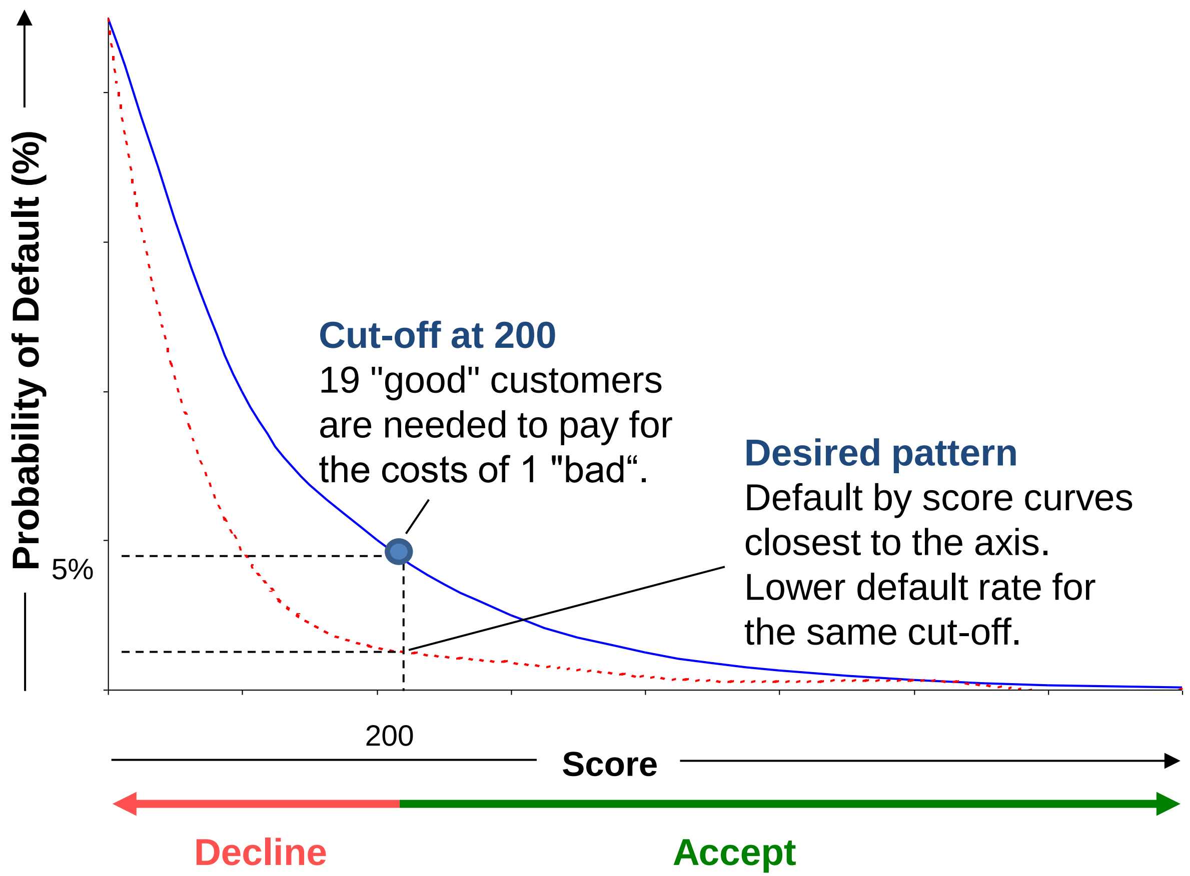
Behavioral credit scoring models



Behavioral models are at the cornerstone of modern banking, enabling to predict the probability of a borrower entering in default based on the behaviour of the individuals on their relation with their credit accounts.

2. Credit risk management

(Behavioral risk-based) decision making

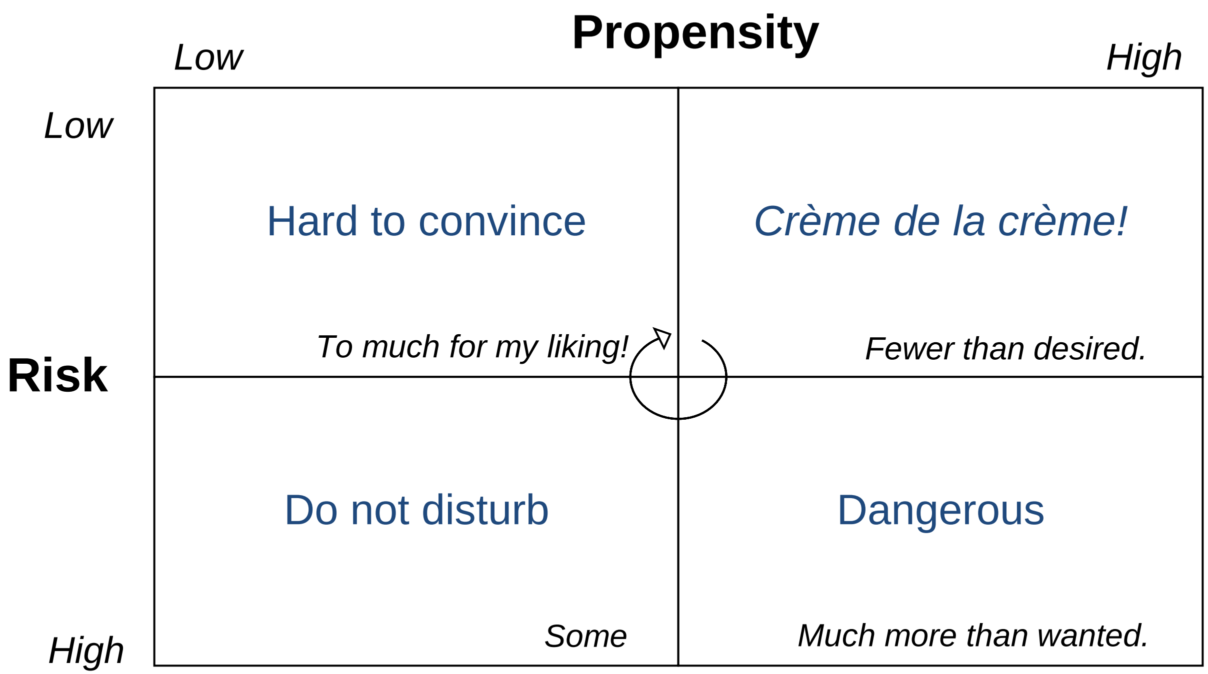


Cut-off is set to the score for a given targetted approval and default rates.
Approval and default rates are set by credit policies and regulatory boundaries.

Illustrative only. Illustration from the author.

2. Credit risk management

(Behavioral risk-based) business targetting

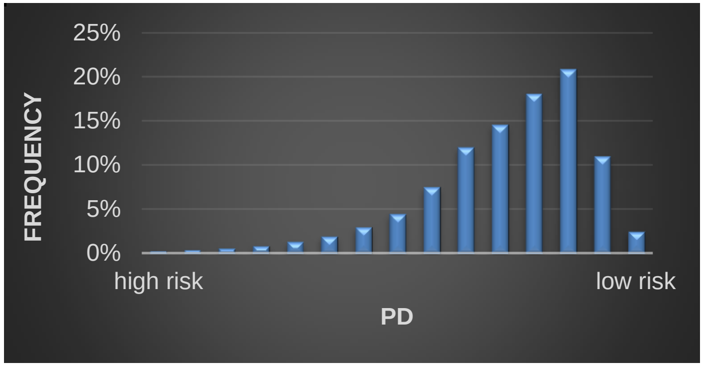


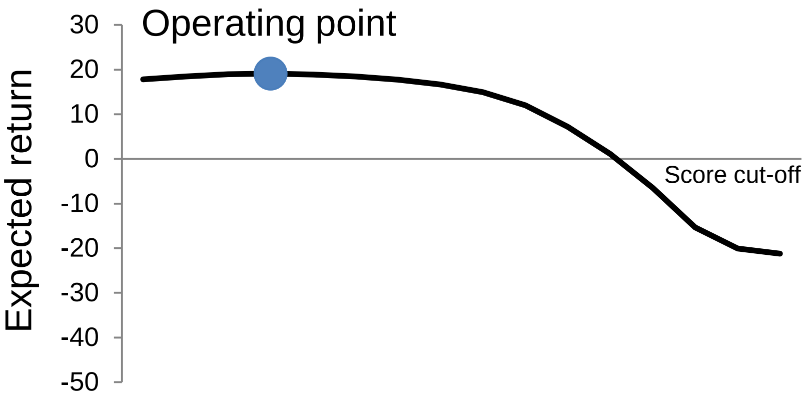
Propensity paradox. A never ending challenge!

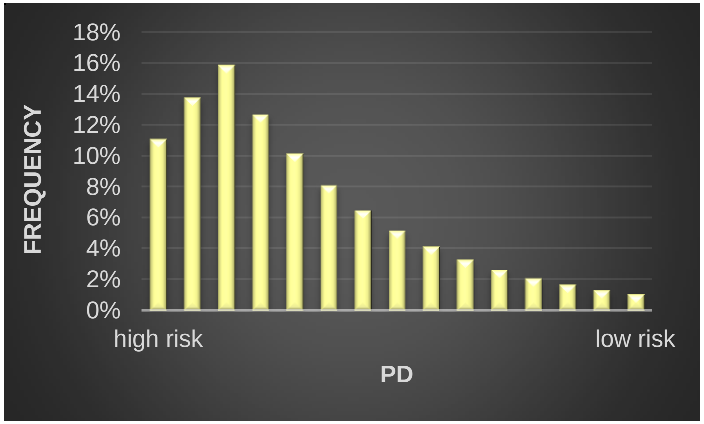
Adapted from McNab, Helen; Wynn, Anthea: Principles and Practice of Consumer Credit Risk Managment (2000).

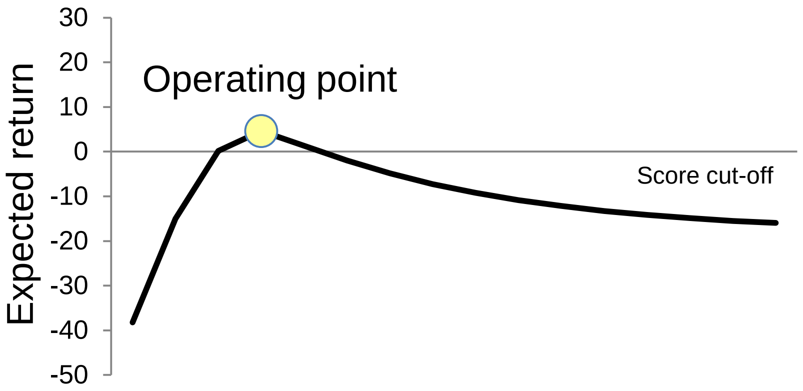
2. Credit risk management

(Behavioral risk-based) portfolio optimization









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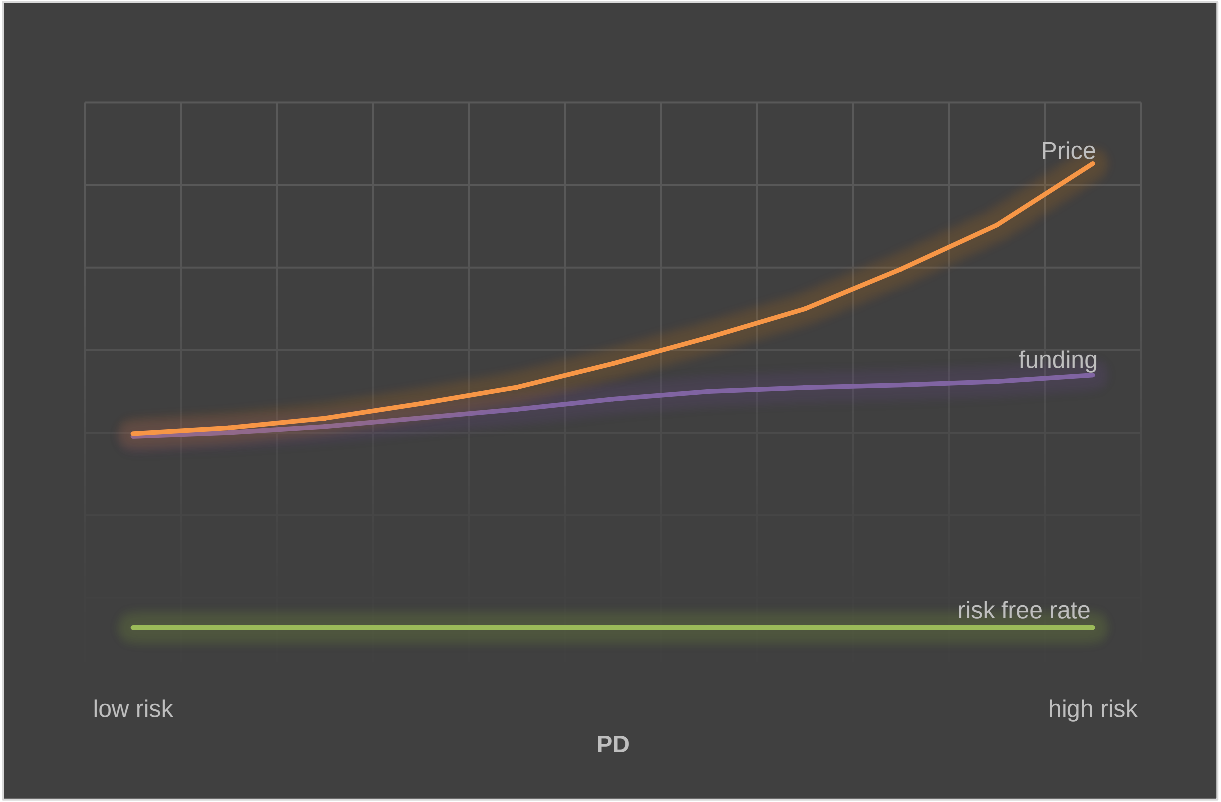
2. Credit risk management

(Behavioral risk-based) pricing



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3. Behavioral modelling

Risk factors - shopping patterns

3. Behavioral modelling

Risk factors - credit cards spending

3. Behavioral modelling

Risk factors - loans debt to service and payment history

Due Date	Computed Interest Due	Principal Due	Deferred Interest Balance	Principal Bal - Deferred Interest Bal	Outstanding Balance
02/01/2013	$1,080.92	$530.72	$0.00	$345,362.87	$345,362.87
03/01/2013	$1,079.26	$532.38	$0.00	$344,830.49	$344,830.49
04/01/2013	$1,077.60	$534.04	$0.00	$344,296.45	$344,296.45
05/01/2013	$1,075.93	$535.71	$0.00	$343,760.74	$343,760.74
06/01/2013	$1,074.25	$537.39	$0.00	$343,223.35	$343,223.35
07/01/2013	$1,072.57	$539.07	$0.00	$342,684.28	$342,684.28
08/01/2013	$1,070.89	$540.75	$0.00	$342,143.53	$342,143.53
09/01/2013	$1,069.20	$542.44	$0.00	$341,601.09	$341,601.09
10/01/2013	$1,067.50	$544.14	$0.00	$341,056.95	$341,056.95
11/01/2013	$1,065.80	$545.84	$0.00	$340,511.11	$340,511.11
12/01/2013	$1,064.10	$547.54	$0.00	$339,963.57	$339,963.57
01/01/2014	$1,062.39	$549.25	$0.00	$339,414.32	$339,414.32
02/01/2014	$1,060.67	$550.97	$0.00	$338,863.35	$338,863.35
03/01/2014	$1,058.95	$552.69	$0.00	$338,310.66	$338,310.66
04/01/2014	$1,057.22	$554.42	$0.00	$337,756.24	$337,756.24
05/01/2014	$1,055.49	$556.15	$0.00	$337,200.09	$337,200.09
06/01/2014	$1,053.75	$557.89	$0.00	$336,642.20	$336,642.20
07/01/2014	$1,052.01	$559.63	$0.00	$336,082.57	$336,082.57
08/01/2014	$1,050.26	$561.38	$0.00	$335,521.19	$335,521.19
09/01/2014	$1,048.50	$563.14	$0.00	$334,958.05	$334,958.05
10/01/2014	$1,046.74	$564.90	$0.00	$334,393.15	$334,393.15
11/01/2014	$1,044.98	$566.66	$0.00	$333,826.49	$333,826.49
12/01/2014	$1,043.21	$568.43	$0.00	$333,258.06	$333,258.06

Illustrative only.

3. Behavioral modelling

Risk factors - deposit accounts utilization

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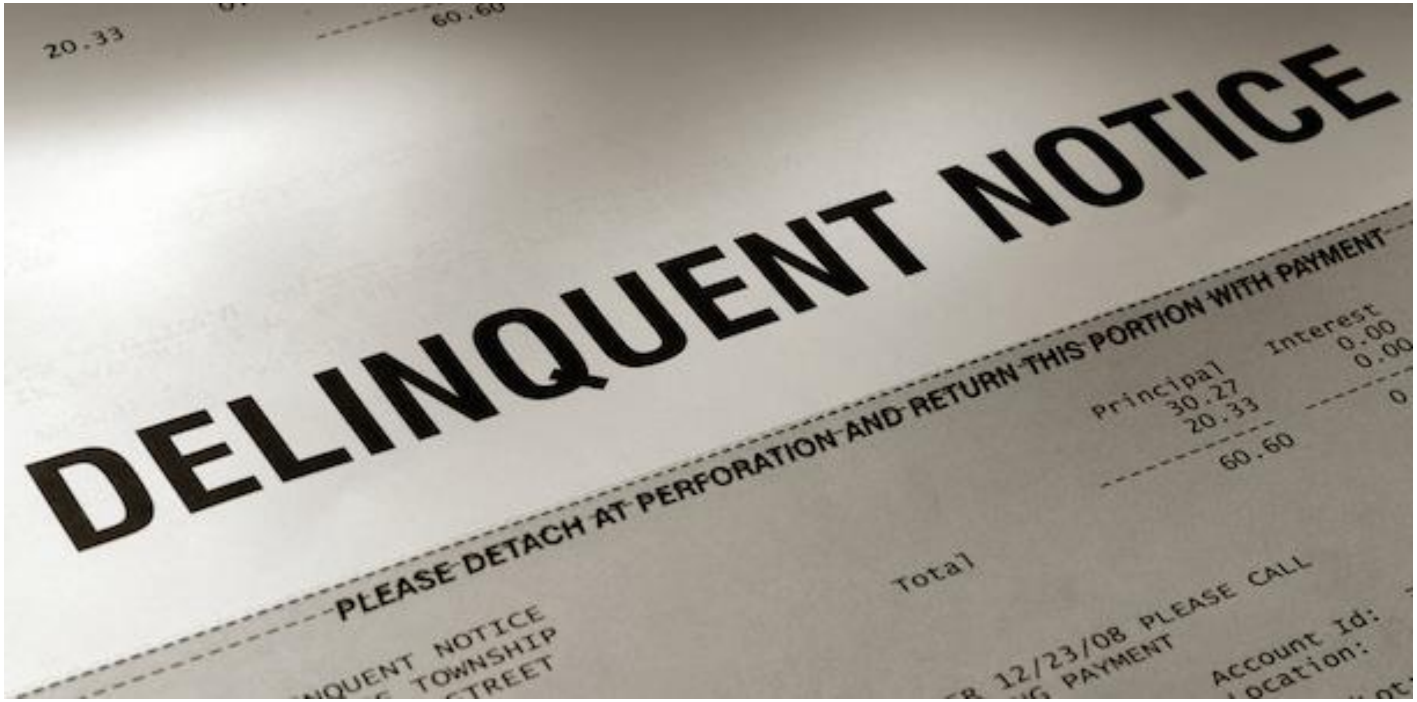
3. Behavioral modelling

Risk factors – money saving profile

3. Behavioral modelling

Risk factors – bankruptcy

3. Behavioral modelling
Outcome – Delinquency and default



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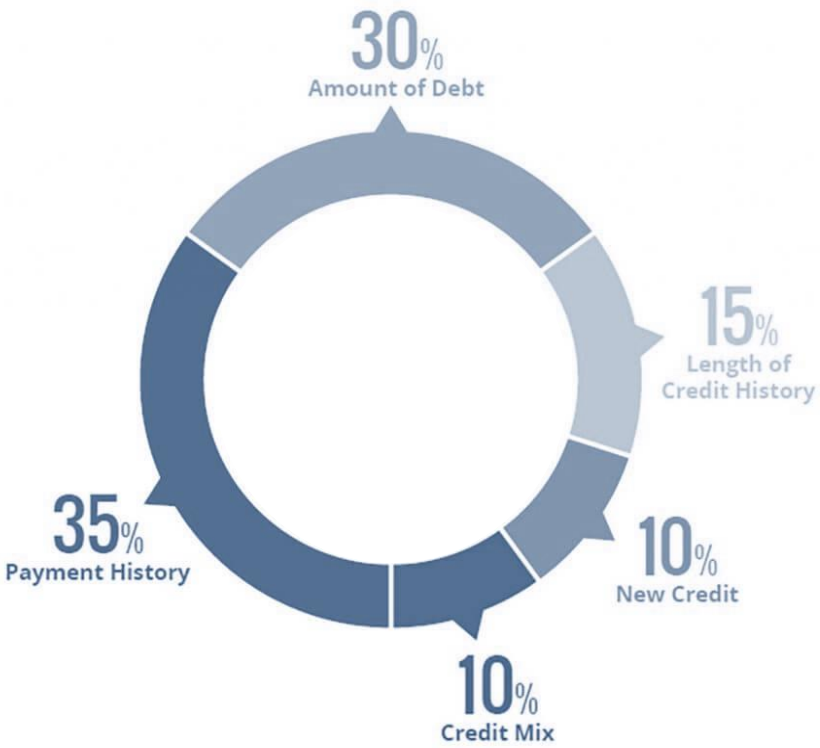
3. Behavioral modelling

A snapshot

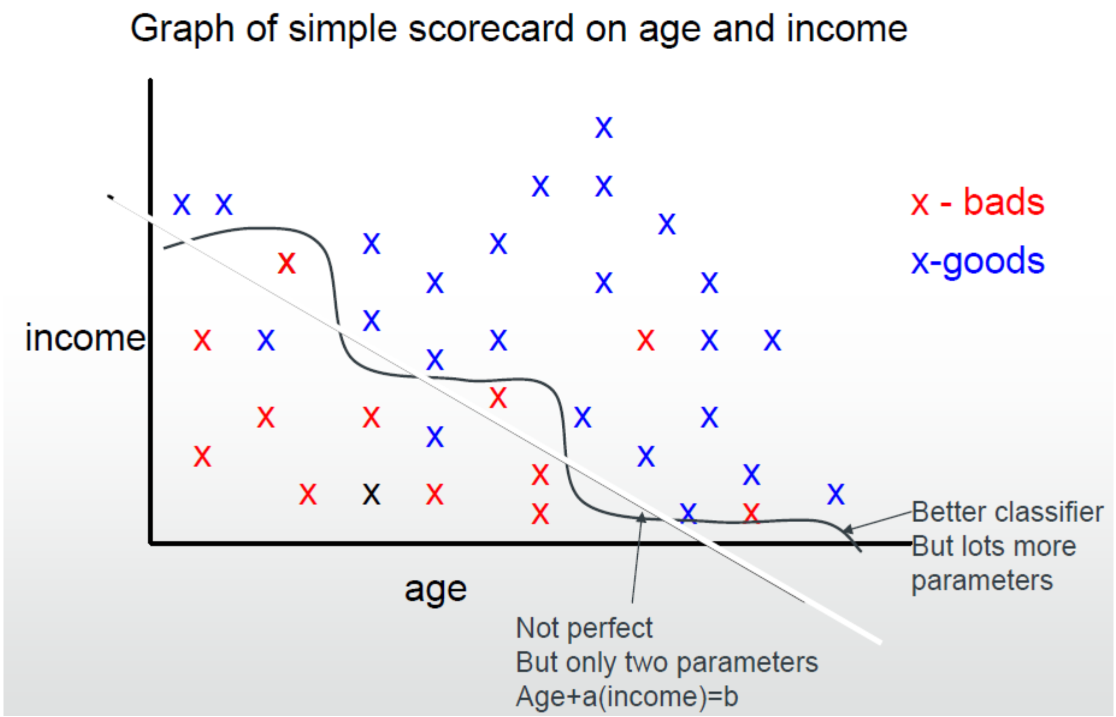


- Behavioral models arrived in 1960s. The revolution that wasn't!
- Use performance data, as well as application and credit bureau data: ratios over time, crossed variable characteristics, event counts, normalisations, trends, lagging.
- Pragmatic philosophy.
  - predict not explain, no causal modelling.
- One model; several updates.
- Legal considerations.
  - what cannot be used (race/gender/age?)
  - what must be used (e.g. debt to income and affordability).

FICO score sources of information used as an illustration.

3. Behavioral modelling

Classification problem with binary output



Find separation between “goods” and “bads” with a trade-off between performance ability and model complexity.

Source: Lyn Thomas, Credit Scoring - from risk assessment to pricing, profits and portfolios, Santiago de Chile.

3. Behavioral modelling

Models development recipe

- Take a sample of previous borrowers (qb).
- Enrich the dataset with a good set of behavioural risk drivers.
- Classify into “good” payers or “bad” (e.g. one year later).
- Keep apart cases where you are not sure about their performance: “indeterminate” (“didn’t defaulted, but not that good”).
- Exclude cases that will not be scored with the model (e.g. non recoverable, in legal, in recovery, special payment plan, non-risk bearing accounts and accounts inactive).
- Exclude cases were you cannot assign a performance class (e.g. deceased, balloon payments and grace periods).
- Use classification methods to find characteristics that best separate the two target classes.
- In future accept those with “good” characteristics; reject “bad”.

4. Classification methods

Some popular

- Existing credit scoring classification methods
  - discriminant analysis/ linear regression.
  - logistic regression.
  - classification trees, random forests.
  - linear programming.

- Developmental credit scoring approaches
  - expert systems - join the experts in a room and reach a consensus.
  - neural networks.
  - support vector machines.
  - genetic algorithms.
  - nearest neighbour methods.
  - bayesian learning network.
  - emsemble - combine classifiers outputs.

Source: Lyn Thomas, Credit Scoring - from risk assessment to pricing, profits and portfolios, Santiago de Chile.

4. Classification methods

Is there a best classification method?

- Logistic regression used to be an industry standard.
  - often used in conjunction with other approaches, such as classification trees, linear regression, linear programming.
- Segmented population: different scorecard in each segment.
  - system reasons (e.g. new accounts).
  - statistical reasons (way of dealing with interactions in variables).
  - strategic reasons (want to be able to deal differently with some groups).
- Other classification methods, such neural networks and support vector machines, have been piloted, though:
  - have missed to prove sufficient palatability or transparency, or;
  - haven't proved a great improvement in robustness.

4. Classification methods

Is there a best classification method?

- Regression approach allows statistical tests to say how important each characteristic is to classification.
  - gives lean/mean scorecards.
  - helps devise new application forms.
- Linear programming allows to set requirements on scores.
  - score (age <25) > score (age >60).
  - deals more easily with large numbers of application characteristics.
- Classification trees, neural nets, support vector machines pick up relationships between variables which may not be obvious.
- Ensemble: the error of the ensemble decreases, respecting to each individual classier, if and only if each individual classier has a performance better than a random choice.

4. Classification methods

Measuring performance – criteria and measures

- Discriminatory power: How good is the system at separating the two classes of goods and bads?
  - Divergence statistic.
  - H measure.
  - Mahalanobis distance.
  - Somer's D - concordance statistic.
  - Kolmogorov - Smirnov statistic.
  - ROC curve and Gini coefficient.

- Calibration of forecast: How well is performing my credit scoring adjusted by population odds? Not much used until the Basel requirements.
  - Chi-square (Hosmer-Lemeshow) test.
  - Binomial and normal tests.
  - Brier scores.
  - Traffic light approach (Dirk Tasche).

- Prediction error: How many bad decision I have made?
  (credit scoring adjusted by population odds, plus score or rating cut-off).
  - Error rates (ER) or percentage correctly classified (PCC).
  - Confusion matrix, swap sets, specificity, sensitivity.

4. Classification methods

Measuring performance – correlation of classifier rankings across measures

	AUC	PCC	BS	H	PG	KS
AUC	1.00					
PCC	.88	1.00				
BS	.54	.54	1.00			
H	.93	.91	.56	1.00		
PG	.79	.72	.51	.76	1.00	
KS	.92	.89	.54	.91	.79	1.00

Diverse measures, but judgment is quite alike.

Source: Lessmann, Stefan, et al. "Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research." *European Journal of Operational Research* 247.1 (2015): 124-136.

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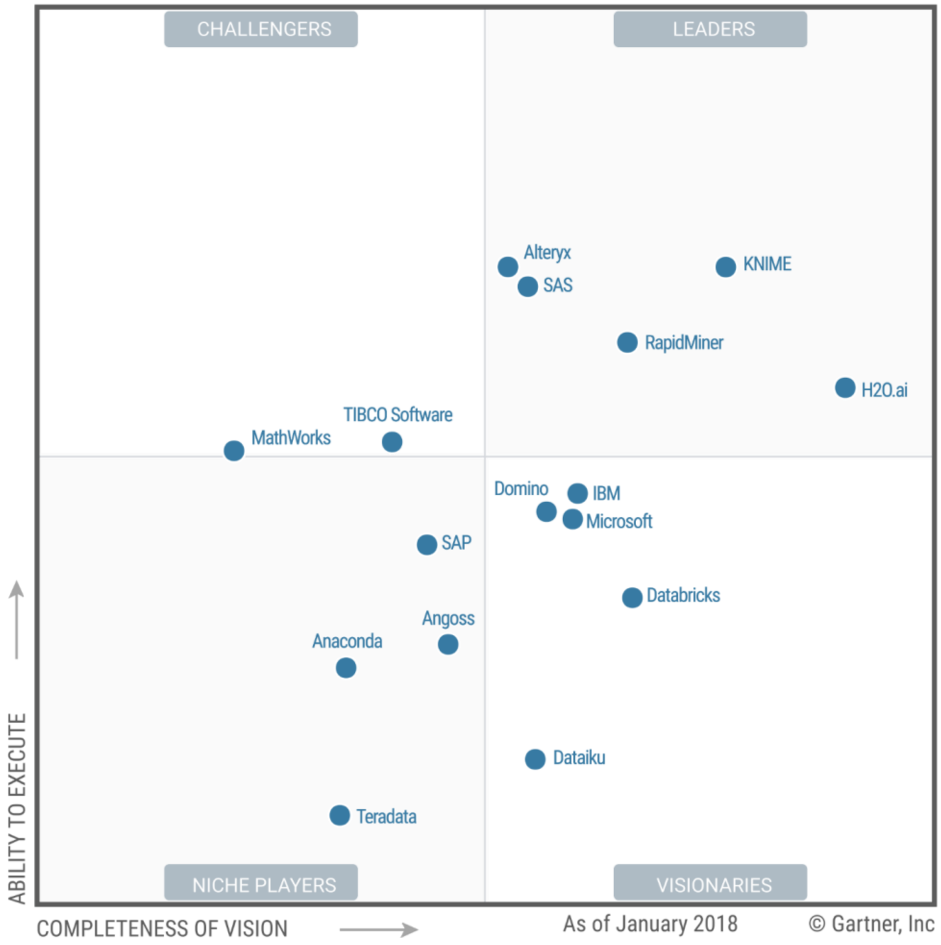
4. Classification methods

Magic Quadrant for Data Science Platforms



Source: Gartner 2018 Magic Quadrant for Data Science Platforms, as of January 2018.

4. Classification methods

Free software

Some of the top free

Orange, Weka, Rattle GUI, Apache Mahout, SCaViS, RapidMiner, R, ML-Flex, Databionic ESOM Tools, Natural Language Toolkit, SenticNet API, ELKI, UIMA, KNIME, Chemicalize.org , Vowpal Wabbit, GNU Octave, CMSR Data Miner, Mlpy, MALLET, Shogun, Scikit-learn, LIBSVM, LIBLINEAR, Lattice Miner, Dlib, Jubatus, KEEL, Gnome-datamine-tools, Python.

Some favourites

http://www.rcreditscoring.com/

Source: http://www.kluniversity.in/cse/skd1/about.html , as of 12nd October, 2016.

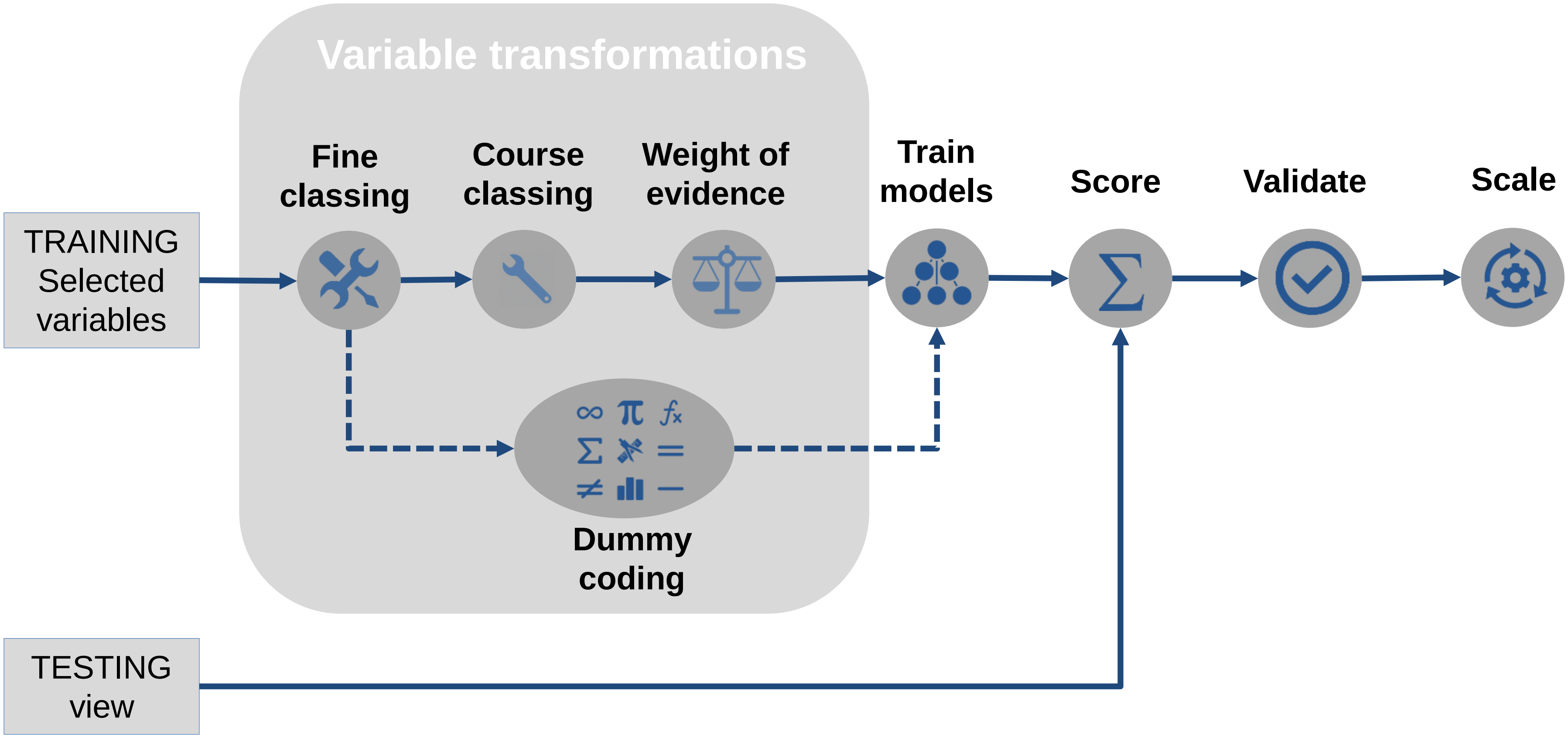
5. Hands-on modelling project

Gather raw material - Data, good data.

Garbage in, garbage out.

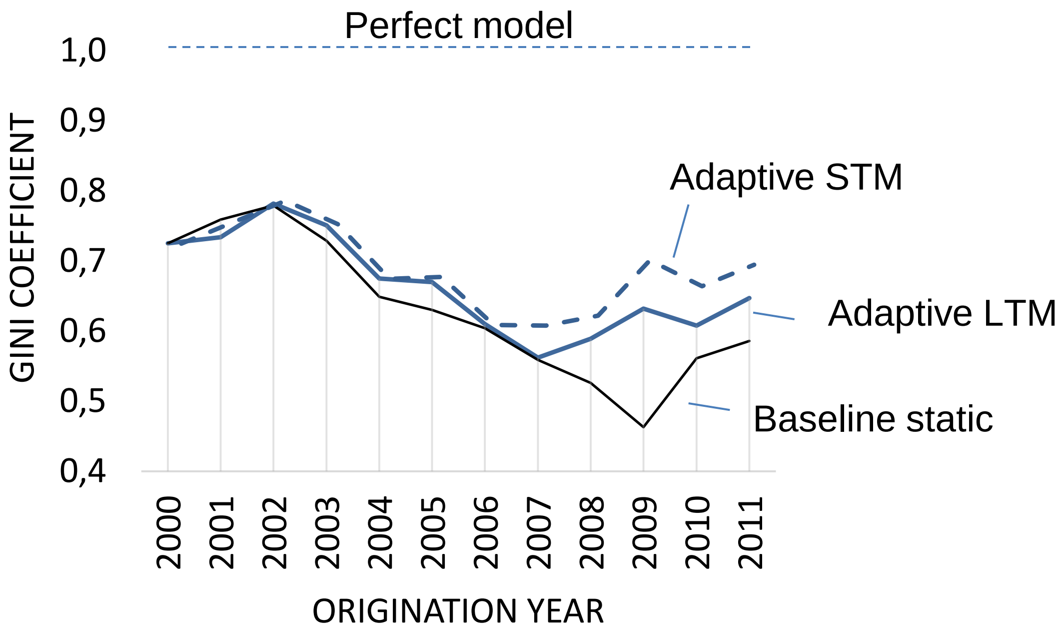
5. Hands-on analytics modelling

Development overview



5. Hands-on analytics modelling

The model is outdated at the very first day. Challenge it!



Newest data consistently improves forecasting accuracy.

Source: Sousa, M. R., Gama, J., & Brandão, E. (2016). Dynamic credit score modeling with short-term and long-term memories: the case of Freddie Mac's database. JOURNAL OF RISK MODEL VALIDATION, 10(1), 59-80.

6. Conclusions

Changing world claims for new methodologies

- Changes in objectives are more likely than a need for improved accuracy to force changes in methodology.
  - Move to assessing profitability not just default risk.
  - Need to estimate several events - default, cross selling, churn – and also when these events will occur.
- Survival analysis approaches.
  - Ask “when” events happen - default, early repayment, purchase, etc.
    - “How long customers survive before they default? “
    - “How long customers stay before they change companies? “
    - “How long until customer makes next purchase? “
    - “How long deteriorating systems survive before failure?”
- Big data analytics.
  - Improve the information for models by exploring new and unconventional data sources (e.g. new credit bureaus, new public databases, new virtual platforms, individuals/entities interactions, correlated risks, etc).
- Everything changes. So, dynamics must be promoted.
  - Markov chain models.
  - Incorporate economic/market effects.
  - Adaptive learning – self sensoring and self adjusting models.

Questions?

Thank you for your time!

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