A (personal) view of statistical issues in (mainly retail) credit risk assessment

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Introduction

Risk management starts with risk assessment
that is, risk measurement

Measuring risk is a statistical estimation/inference problem

Statistical estimation/inference rely on adequate data

Different kinds of risk ➔ different kinds of model

Classic ***risk*** taxonomy:

- market risk
- operational risk
- credit risk
- etc

But also a ***statistical*** risk modelling taxonomy:

- structural models
- reduced form default models (int rates; risk ratings)
- reduced form mark-to-market models
- empirical models

Structural models: model based on financial ‘theory’

... iconic, mechanistic, phenomenological ...

Example: Merton structural model for PD

$$PD = \Phi\left(-\frac{\ln\left(A_0/F\right)}{\sigma_A\sqrt{T}} + \frac{\sigma_A\sqrt{T}}{2} \right)$$

Empirical models: based on observed relationships in (large) data sets

... descriptive,

Example: Credit scoring

Logistic regression

Neural networks

Random forests

Logistic regression tree

Broadly speaking

structural models in the corporate sector

empirical models in the retail sector

Note: earliest work in corporate sector was empirical

e.g. Altman’s linear discriminant analysis to predict company default

Good reasons for the difference:

Different sorts of data available

Corporate default models vs consumer default models

Corporate default models	Consumer default models
Small volume, large loans	Large volume, small loans
Hierarchy of approval: Senior managers approve large complex loans	Hierarchy of approval: Senior managers approve credit products
Audited corporate financial statements	Limited financial data on customers
Corporate payment records available	Credit history, usually incomplete
Close account management and review on loan-by-loan basis	Portfolio management by aggregate statistics performance
Market valuation	Monitor behaviour of individuals over time

Retail characterised by large data sets

Possibly billions of data points

And high dimensions

Credit card data:

- Transaction ID
- Transaction type
- Date and time of transaction (to nearest second)
- Amount
- Currency
- Local currency amount
- Merchant category
- Card issuer ID
- ATM ID
- POS type
- Cheque account prefix
- Savings account prefix
- Acquiring institution ID
- Transaction authorisation code
- Online authorisation performed
- New card
- Transaction exceeds floor limit
- Number of times chip has been accessed
- Merchant city name
- Chip terminal capability
- Chip card verification result

Condense past transactions on a credit line into a number of attributes which summarise behaviour

Combine attributes across credit lines

Example: Experian’s over 440 ‘STAGGs’
http://www.experian.com/products/attributetoolbox.html

Another example: fraud detection

US Patent 5,819,226 (see USPTO website) on *Fraud detection and modeling*, (HNC Software in 1992) lists the following variables:

Customer usage pattern profiles representing time-of-day and day-of-week profiles;
Expiration date for the credit card;
Dollar amount spent in each SIC (Standard Industrial Classification) merchant group category during the current day;
Percentage of dollars spent by a customer in each SIC merchant group category during the current day;
Number of transactions in each SIC merchant group category during the current day;
Percentage of number of transactions in each SIC merchant group category during the current day;
Categorization of SIC merchant group categories by fraud rate (high, medium, or low risk);
Categorization of SIC merchant group categories by customer types (groups of customers that most frequently use certain SIC categories);
Categorization of geographic regions by fraud rate (high, medium, or low risk);
Categorization of geographic regions by customer types;
Mean number of days between transactions;
Variance of number of days between transactions;
Mean time between transactions in one day;
Variance of time between transactions in one day;
Number of multiple transaction declines at same merchant;
Number of out-of-state transactions;
Mean number of transaction declines;
Year-to-date high balance;
Transaction amount;
Transaction date and time;
Transaction type.

“Additional fraud-related variables which may also be considered are listed below”

Current Day Cardholder Fraud Related Variables bweekend current day boolean indicating current datetime considered weekend cavapvdl current day mean dollar amount for an approval cavapvdl current day mean dollar amount for an approval cavaudl current day mean dollars per auth across day ccoscdoni current day cosine of the day of month i.e. cos(day ((datepart(cst.sub.-- dt) * &TWOPI)/30)); ccoscdow current day cosine of the day of week i.e. cos(weekday ((datepart(cst.sub.-- dt) * &TWOPI)/7)); ccoscmoy current day cosine of the month of year i.e. cos(month ((datepart(cst.sub.-- dt) * &TWOPI)/12)); cdom current day day of month cdow current day day of week chdzip current cardholder zip chibal current day high balance chidcapv current day highest dollar amt on a single cash approve chidcdec current day highest dollar amt on a single cash decline chidmapv current day highest dollar amt on a single merch approve chidmdec current day highest dollar amt on a single merch decline chidsapv 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mchgbks Merchant Charge-backs received mrtrvs Merchant Retrievals received (per SIC, merchant, etc.). The issuer pays for a retrieval. macqrat Merchant Acquirer risk managment rate (in Europe one merchant can have multiple acquires, but they dont have records about how many or who.) mprevrsk Merchant Previous risk management at this merchant? Yes or No mtyprsk Merchant Type of previous risk management (counterfeit, multiple imprint, lost/stolen/not received) msicrat Merchant SIC risk management rate mpctaut Merchant Percent of transactions authorized

Properties of the different approaches

Structural

- good if theory is right
    - needs less data to estimate
- bias if theory is wrong
    - special danger at extremes, or beyond data

Empirical

- unbiased if sufficiently flexible (e.g. ANNs)
- approximations if less flexible (e.g. logreg)
- cliff-edge effect? (models built in benign conditions?)
- low variance if large data sets

Built on years of experience!

Empirical model performance criteria

- likelihood
- AUC
- sum of squared EAD prediction errors?
- . . . .

Mismatch with business objectives?

A dynamic area

- the whole area is undergoing constant development

Examples:

- better theory in structural models

  e.g. replace log normal distributions

- dynamic adaptive empirical models
- include other variables in empirical models
  - econometric data
  - product data
  - vintage data
  - try to allow for changes in policy

But will never be perfect: competitive environment

How do we avoid the model misspecification problem?

Some cautionary comments about statistical risk models

1) population drift
   - and reactive population drift

2) poor choice of performance criterion

3) selectivity bias

4) data quality

5) non-statistical constraints on statistical models

1) Population drift

Characteristics of distributions of customers change:

- technological changes
- changing customer expectation
- changing financial products
- competitive changes
  - debt consolidation companies
- economic changes
  - higher default risks
  - people less willing to take on large loans

Example:

'*All lenders know that new customers are riskier than old ones*.'

David Lawrence, Citicorp

The old ones have undergone a selection process, with the poorer ones being dropped

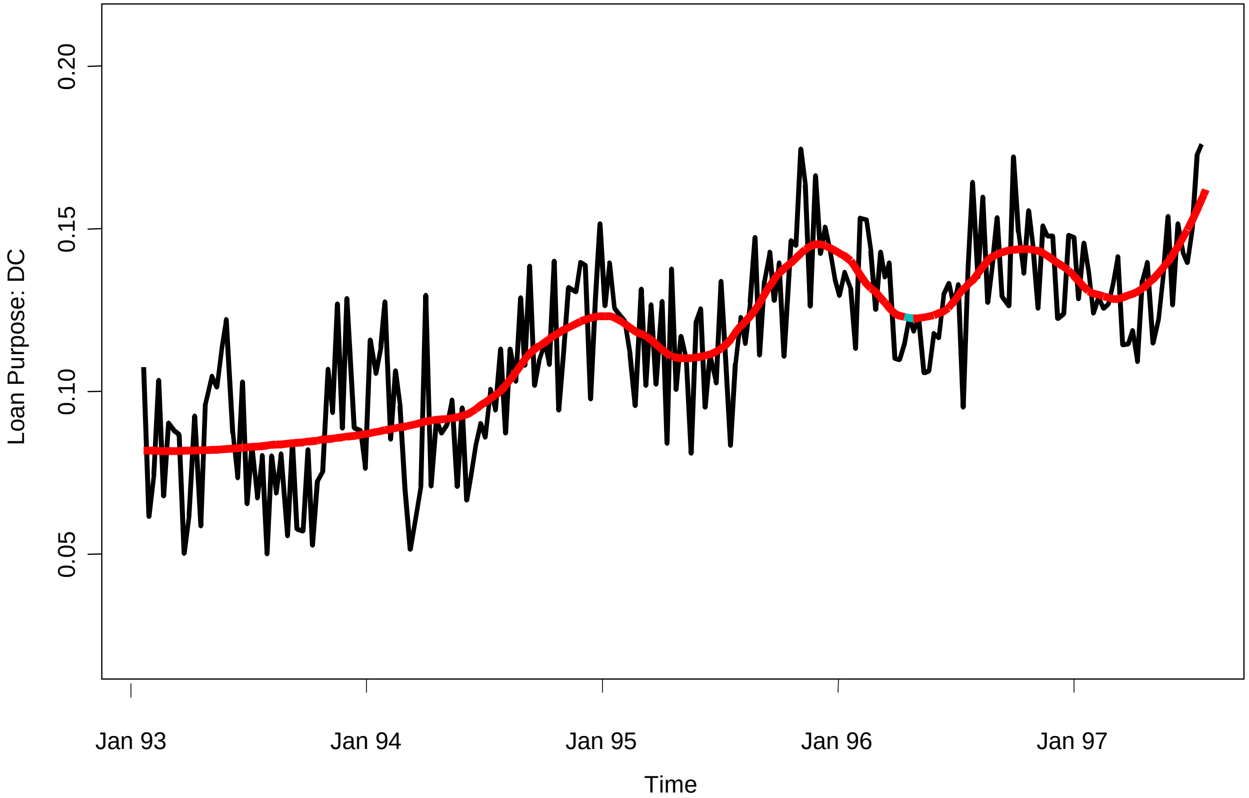
e.g. Citibank had a normal credit card write-off percentage of about 2%. But, when it increased its credit card business by over 500% in two years, the write-off level jumped to 7%

But this depends on the financial product and the market

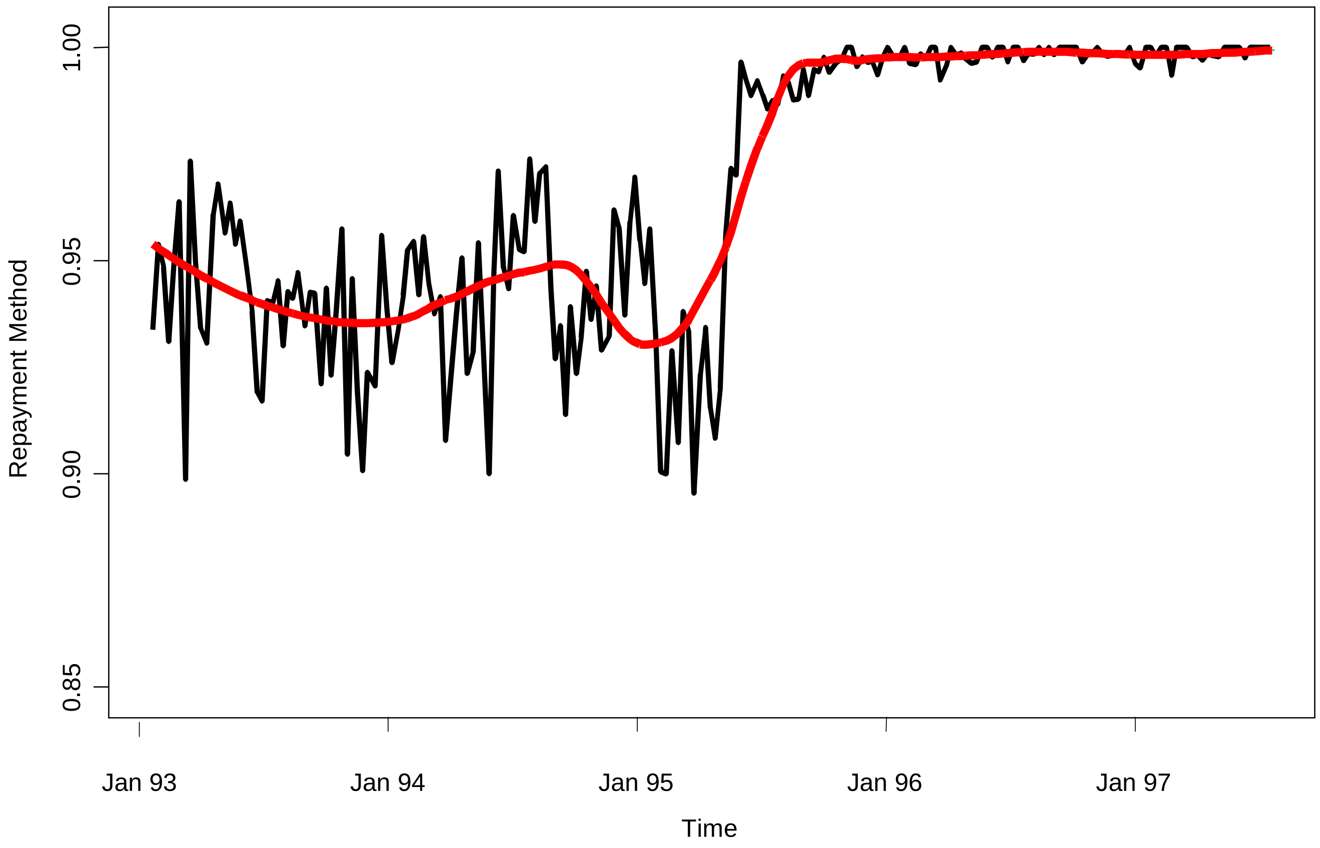
Nowadays, perhaps the ‘old’ customers are simply those who cannot get a better deal elsewhere

This has been observed in the mortgage market

Seasonal changes in types of customer
Trend in types of customer



Marketing initiatives changing type of customer

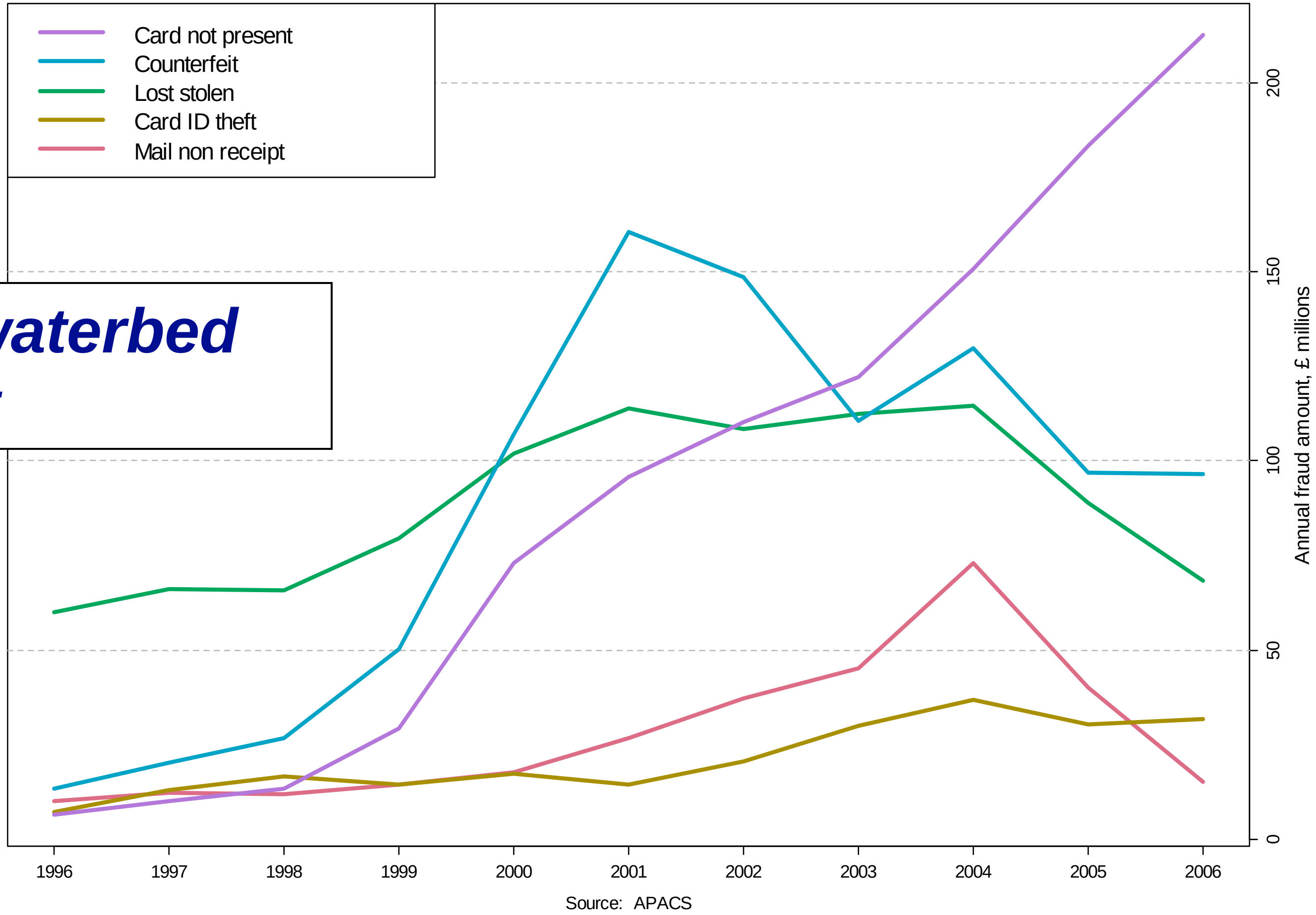


Reactive population drift

In all areas of retail risk modelling

- After all, the aim is not to predict for the fun of it
  - But in order to choose an optimal action

Example: fraud detection



The waterbed effect

Reactive population drift example: *Chip and PIN*

Chip and PIN intended/predicted to end card fraud

After UK rollout on 14 Feb 06, UK CC fraud declined
How much was a consequence of the publicity?

but

- Lloyds TSB observed increase in fraudulent use of UK cards in Europe (no C&P – mag stripe counterfeited)
- observed increase in ATM and cardholder not present fraud

2) Poor choice of performance criterion

Evaluation of models

- statistical metrics, quick and easy, miss the point?
- business metrics, hard to define

Choice of appropriate metrics

e.g. Basel II: PDxPGDxEAD

i) estimate components separately

ii) justified using assumption of independence. Is this valid?

iii) even if it is, is it the right thing to do? The metric ought to be sum of losses (not sum of squared losses, etc).

Different measures suit different objectives

Many objectives, many performance criteria:
- recipe for confusion

Many standard measures:

- $Gini = 2 \times \int B(s)\, g(s)\, ds - 1$
- $KS = \max_{s} \left| B(s) - G(s) \right|$
- $t = (\mu_G - \mu_B)/\sigma$
- $IV = \int \{ g(s) - b(s) \} \log g(s)/b(s)\, ds$

Different situations require different peformance measures

Application scorecards

Initial decision about an applicant

e.g. score 'creditworthiness' using application form information (perhaps supplemented by other, e.g. bureau)

Behavioural scorecards

Modelling customer behaviour over time

e.g. transaction patterns, repayment patterns, etc.

Behavioural scoring as a component of adaptive control systems

Example 1: Timeliness in fraud detection

		True class	
Predicted class		Fraud	Legitimate
	Fraud	a	b
	Legitimate	c	d

A very well known consumer credit organisation evaluates fraud using the two ratios

$$R_1 = a/(a+c)$$

$$R_2 = b/(a+b)$$

In itself, this would appear to be fine

But in fact, the units of assessment used are ***accounts***

An account is flagged as potentially fraudulent if ***at least one transaction is so flagged***

Problem 1: This means that one can make the probability of flagging an account as fraudulent as near to 1 as one wishes by examining enough transactions

Problem 2: Fails to include *timeliness* in the measure

A superior measure

An ***epoch*** is a transaction sequence ending with either

(i) a *fraud flag* on a true fraud

Or

(ii) or end of observed sequence

n n n n f n n f n n **n** n n f n n n n n **n** n n n n n n **f**

<table>
<tr><td></td><td></td><td colspan="2">True class</td></tr>
<tr><td rowspan="3">Predicted class</td><td></td><td>Fraud</td><td>Legitimate</td></tr>
<tr><td>Fraud</td><td>a</td><td>b</td></tr>
<tr><td>Legitimate</td><td>c</td><td>d</td></tr>
</table>

n n n n f n n f n n **n** n n f n n n n n **n** n n n n n n **f**

		True class	
Predicted class		Fraud	Legitimate
	Fraud	1	2
	Legitimate	3	21

This matrix includes ***timeliness*** in the count *c*

		True class	
Predicted class		Fraud	Legitimate
	Fraud	a	b
	Legitimate	c	d

Overall performance measure for given threshold:

$$T_1 = (a+b+kc) \Big/ \big(k(a+c)+b+d\big)$$

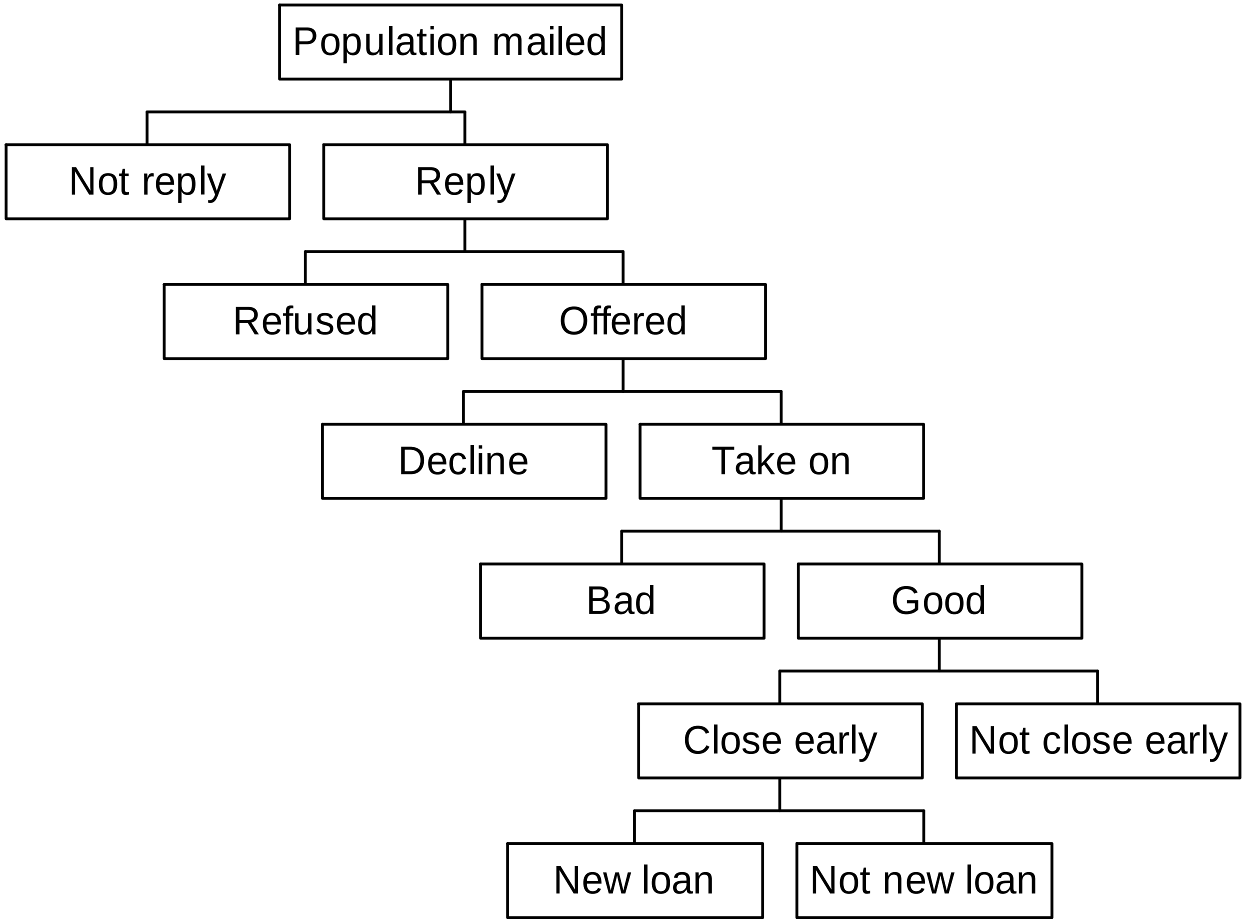
where *k* is the estimated relative cost of misclassifying a fraud as legitimate compared to converse

Or, if the bank can afford to investigate *C* cases

T_2: minimise *c* subject to $a+b=C$

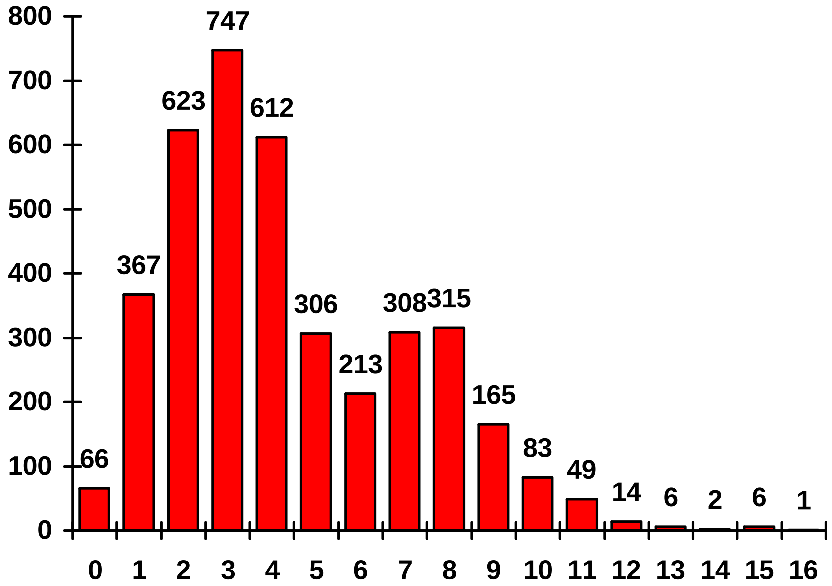
3) Selectivity bias

Sample selectivity problems:



4) Data quality

Missing fields   e.g. *n*=3884, *p*=25



Number of missing values

5 characteristics had no missing values and 2 had over 2000 missing values

In just one data UPL set:

- tiny outstanding amounts unpaid - coded as ‘bad debt’
- negative values in amount owed
- 12 month loans still active after 24 months
- outstanding balance drops to zero, then goes positive
- balances which are always zero
- numbers of months in arrears increasing by more than a single month in one step

One characteristic not being recorded for *any* of the applicants in a particular year (recorded as 'not given')

Leading to a difference of several points on the scorecard values for *all* applicants in that year

5) Non-statistical constraints on statistical models

Excluded characteristics

Aim: avoid discrimination on grounds unrelated to risk?

Approach: exclude gender, religion, age, marital status etc from retail risk models

Is the regulation missing the point?

1) If aim is to obtain most accurate estimates of probability of default

- include all characteristics in models

2) If aim is to obtain most accurate estimates of probability of default which can be obtained from information unrelated to excluded characteristics

- include all in model, and make decisions in subspace orthogonal to excluded characteristics

Predict *y* from

allowed characteristic x_1 and *excluded characteristic* x_2

Take truth to be $y = \alpha + \beta_1 x_1 + \beta_2 x_2$

(interactions can easily be added)

Current legislation:

$$y = \alpha + \gamma_1 x_1$$

Treat x_2 classes ***equally***:

$$y = \alpha + \beta_1 x_1$$

Treat x_2 classes ***fairly*** (best estimate of *y*):

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2$$

$$\gamma_1 = \beta_1 + \beta_2 \delta_{12}$$

Interpretability

Front end

- direct interface with customer
- legal and other requirements for ease of explanation
- feeling of ownership

$\Rightarrow$ - models linear in the customer characteristics

- recursive partitioning models

Back end

- classification performance is all

$\Rightarrow$ highly sophisticated and advanced methods

- neural networks
- SVMs

Special problems in particular areas

e.g. fraud

- the economic imperative
- the Pareto principle
- invisibility of fraud; visibility of detection
- delay in labelling
- mislabelled classes

An example of a possible initial structural alternative to empirical models for retail risk assessment

It's not obvious that structural models for portfolios or for the corporate sector are relevant to retail

But other structural ideas?

Insights from behavioural finance?

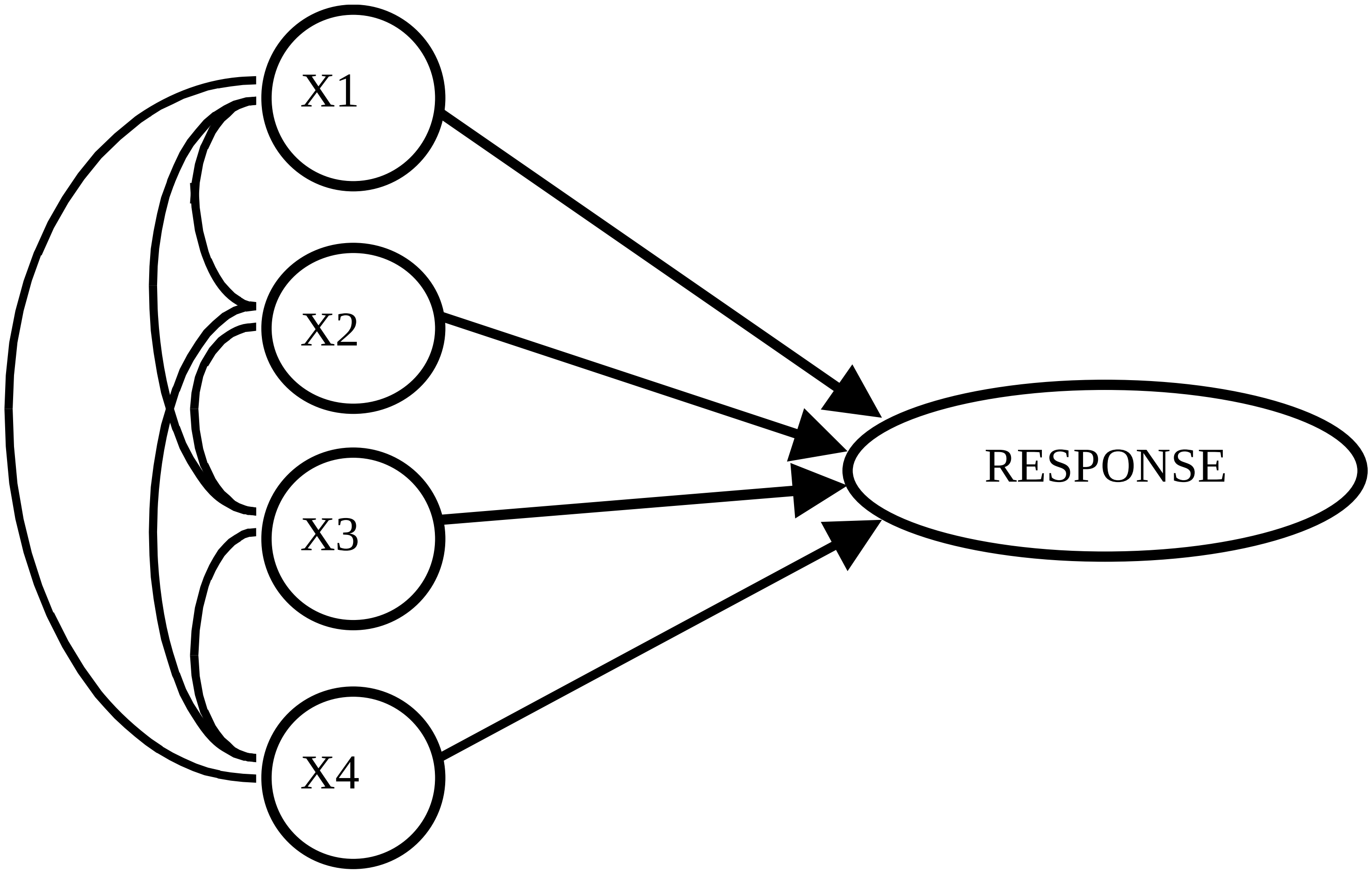
Collaborations with psychologists?

Example: The CQS model

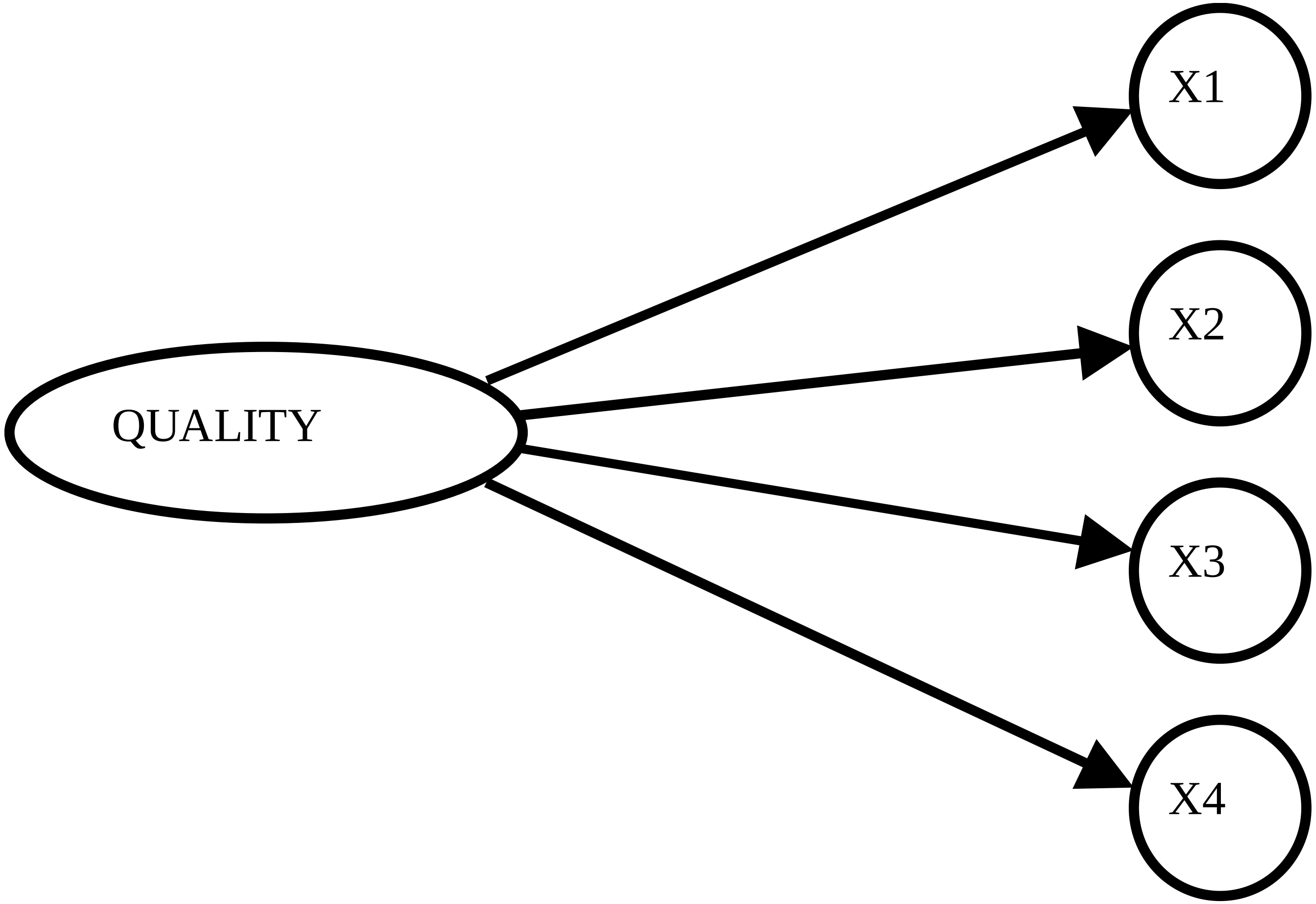
Model based on latent concepts in retail credit

- Character
- Collateral
- Capacity
- Capital
- Condition

Or create others according to expertise or formal model simplification

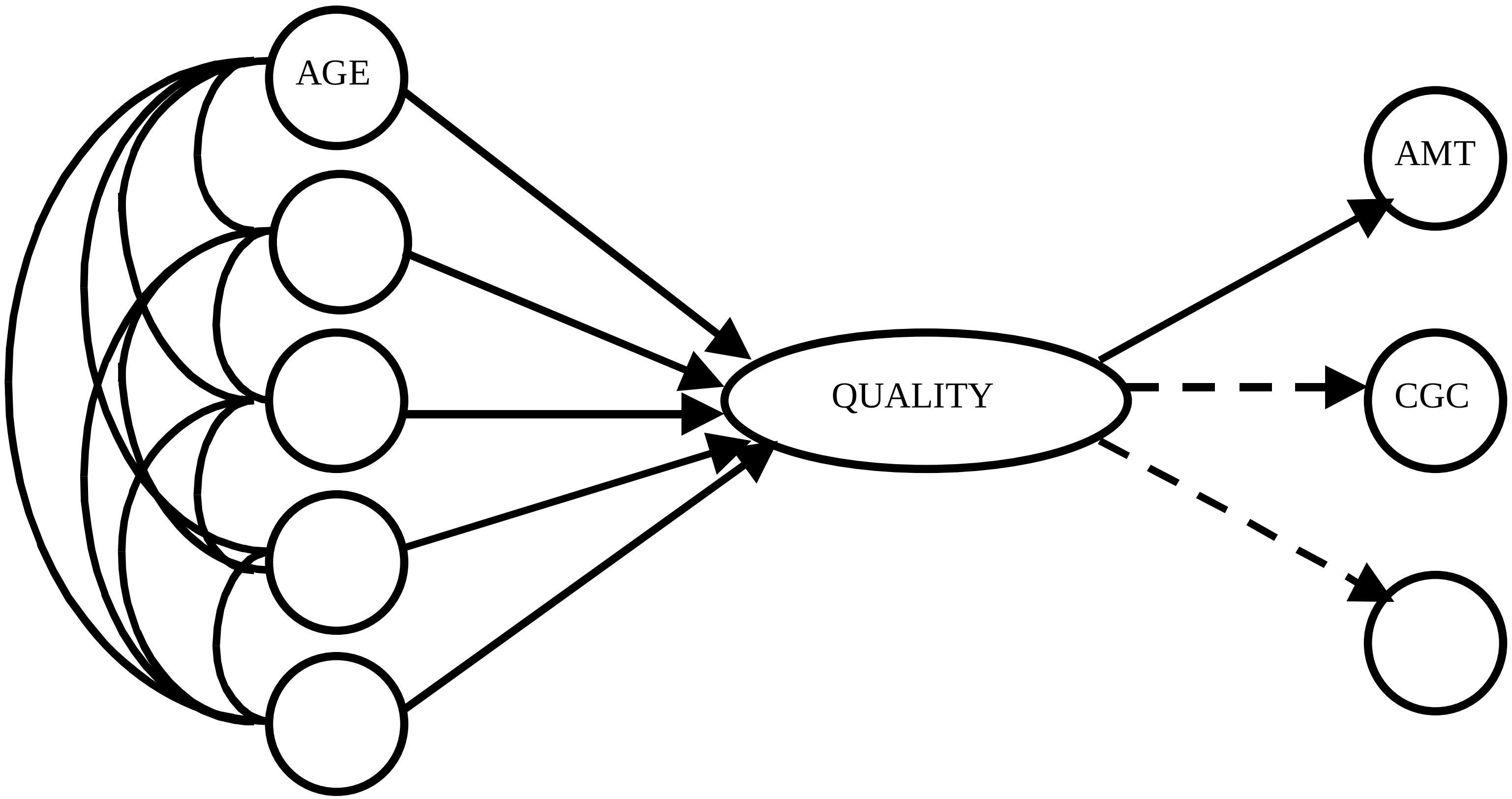


Age, income, other loans,....



CCJs, defaults, months in arrears, parking tickets, speeding fines,....

CQS model



Conclusions

Low level statistical credit risk models are good
But this does not protect against systemic problems

Clever risk evaluation models won't help if embedded in a process of disguising risk and handing it on

If banks shift focus from credit to equity growth

No matter how accurately one can assess the probability that someone or some corporation will default, if circumstances stay as they are, this does not help when:

- a new deal mortgage programme aimed at subprime is introduced
- regulations change making it tougher for Fannie May and Freddie Mac, so that
- banks grasp opportunity, invade Freddie and Fannie territory
- banks shift from credit to equity, growth driven models
- increase in subprime leverage
- Basel II creates an arbitrage opportunity and encourages off balance sheet vehicles
- SEC policy shift encourages greater debt to equity ratio

Future challenges and opportunities

- modern data capture; file merging
- very large data sets
- data streaming, dynamic, adaptive
- adverse selection bias and reject inference
- population drift
- reactive drift

END