A.XII. Scoring Procedures

Olivier Scaillet

University of Geneva and Swiss Finance Institute

Outline

Definition

The aim is to produce a score which enables to classify individuals according to their probability of default, to adopt one type of behavior or another, . . .

In particular, *Credit scoring* is the set of decision models and their underlying techniques that aid lenders in the granting of consumer credit.

These techniques decide who will get credit, how much credit they should get, and what operational strategies will enhance the profitability of the borrowers to the lenders.

History

Credit scoring is essentially a way to identify different groups in a population when one cannot see the characteristics that define the groups but only related ones.

Durand (1941) in research project for the US National Bureau of Economic Research (NBER) was the first to recognize that one could use that techniques proposed in statistics to discriminate between good and bad loans.

The first consultancy was formed in San Francisco by Bill Fair and Earl Isaac in the early 50s, and their clients were mainly finance houses, retailers, and mail-order firms.

History

The arrival of credit cards in the late 60s made the banks and other credit card issuers realize the usefulness of credit scoring.

The event that ensured the complete acceptance of credit scoring was the passage of the Equal Credit Opportunity Acts and its amendments in the US in 1975 and 1976.

These outlawed discrimination in the granting of credit unless the discrimination "was empirically derived and statistically valid".

In the 80s the success of credit scoring in credit cards meant that banks started using scoring for other products, like personal loans, home loans and small business loans.

How it Works

The potential borrower presents a proposition to the lender.

Previously, lenders (i.e., bankers) wove a magic wand which allowed them to gauge whether the risk was of an acceptably low level.

With scoring, the lender applies a formula to key elements of the proposition, and the output of this formula is usually a numeric quantification, the score, of the risk. Again the proposition will be accepted if the risk is suitably low.

Consider, for example, an application for a personal loan.

How it Works

Nowadays, the loan applicant will complete an application form. This could either be a paper form or on a computer screen (e.g. via internet or by a telesales operator).

Typically, the application data will be scored, but not all the application data are necessarily used in calculating a credit score.

To be concrete, let us consider a simple scoring operation.

Suppose that we have a scorecard with four variables (or characteristics): residential status, age, loan purpose, and value of county court judgments (CCJs).

How it Works - Simple Scorecard

Residential Status	Score		Age Range	Score
Owner	36		18-25	22
Tenant	10		26-35	25
Living with parents	14		36-43	34
Other specified	20		44-52	39
No response	16		53+	49

Loan Purpose	Score		Value of CCJs ($)	
New car	41		None	32
Second car	33		1-299	17
Home improvement	36		300-599	9
Holiday	19		600-1199	-2
Other	25		1200	-17

How it Works

A 20-year-old, living with his or her parents, who wishes to borrow money for a second-hand car and has never had a CCJ, will score 101 (14+22+33+32).

A 55-year-old house owner, who has had a $250 CCJ and wishes to borrow money for a daughter's wedding, would score 127 (36+49+25+17).

If the pass mark is 100, they will both be approved.

Qualitative Response Models

The main approach is based on

qualitative response models

If we face only two possibilities $\{0, 1\}$, they are called *binary response models* or *binary choice models*

$$P_t = P(Y_t = 1 \,|H_t) = E[Y_t \,|H_t]$$

where H_t denotes the information available at date t.

Obviously we cannot model the conditional expectation $E[Y_t \,|H_t]$ as in a regression by $X_t\beta$ since the probability should lie between 0 and 1.

Qualitative Response Models

Idea:
Use a transformation F which forces the linear combination of the explanatory variables to lie between 0 and 1:

$$E\left[Y_t \left| H_t\right.\right] = F\left(X_t \beta\right).$$

A good candidate is given by a cdf.

Probit model : normal cdf

$$F\left(x\right) = \Phi\left(x\right)$$

Logit model : logistic transform

$$F\left(x\right) = \frac{e^x}{1+e^x}$$

These models can be interpreted as *latent variable models*

Probit Model Example

Let Y_t^* be an unobserved or latent variable assumed to follow

$$Y_t^* = X_t\beta + u_t, u_t \sim N(0,1).$$

We observe only the sign of Y_t^* according to the relationship

$$Y_t = 1 \text{ if } Y_t^* > 0,$$

$$Y_t = 0 \text{ if } Y_t^* \leq 0.$$

In particular, Y_t^* may represent the utility from an action: (1) If the action yields a positive utility, it will be undertaken; (2) If the action yields a negative utility, it will not be.
Since we only observe whether action is undertaken or not, we only observe the *sign* of Y_t^*.

Probit Model Interpretation

Using

$$\begin{aligned} P(Y_t &= 1) = P\left(Y_t^* > 0\right) = P\left(X_t\beta + u_t > 0\right) \\ &= 1 - P\left(u_t \leq -X_t\beta\right) = 1 - \Phi(-X_t\beta) = \Phi(X_t\beta) \end{aligned}$$

we get the interpretation of a binary response model as a latent variable model.

In practice, Logit and Probit models tend to yield extremely similar results.

Estimation can be performed either by maximum likelihood or by nonlinear least squares.

General Qualitative Response Models

If we face three or more different values then we get the general case of

qualitative response models

We should distinguish between *ordered responses* and *unordered responses*

Examples:

- *Ordered*: Answer to a statement
  strongly agree, agree, indifferent, disagree, strongly disagree.
- *Unordered*: Answer to choice to commute
  walk, bus, bicycle, train, ...

Ordered Qualitative Response Models

Ordered qualitative response models can be based on either a Probit or a Logit specification.

Example: Probit model for three responses

$$
\begin{aligned}
Y_t^* =& X_t\beta + u_t, u_t \sim N(0,1),\\
Y_t =& 0 \text{ if } Y_t^* < \gamma_1,\\
Y_t =& 1 \text{ if } \gamma_1 \leq Y_t^* < \gamma_2,\\
Y_t =& 2 \text{ if } \gamma_2 \leq Y_t^*.
\end{aligned}
$$

The parameters are β and $\gamma = (\gamma_1, \gamma_2)'$. The thresholds $\gamma = (\gamma_1, \gamma_2)'$ determine what value of Y_t given value of Y_t^* will map into.

Ordered Qualitative Response Models

The number of elements in γ is always one fewer than the number of choices

When there are only two choices, this model is indistinguishable from an ordinary binary response model with the single element of γ playing the role of the constant term in the binary model.

This is equivalent to introducing a constant term in X_t and putting the first threshold equal to zero or not including a constant term and estimating γ_1.

Unordered Qualitative Response Models

Unordered models often correspond to

multinomial Logit models.

They are designed to handle $J+1$ responses

$$P(Y_t = 1) = \frac{1}{1+\sum_{j=1}^{J}\exp\left(X_t\beta^j\right)},$$

$$P(Y_t = l) = \frac{\exp\left(X_t\beta^l\right)}{1+\sum_{j=1}^{J}\exp\left(X_t\beta^j\right)} \text{ for } l = 2, ..., J+1$$

If $J = 1$, we get the ordinary logit model.

Qualitative Response Models - Applications

- INSEE survey concerning financial assets held by households

The holding of 0,1, . . . , or 4 assets is explained by age, revenue, education (university degree or not), address (small city or large city), . . .

- Granting of mortgages

Use Logit models to estimate the probability of defaulting, i.e. not paying back the mortgage.
According to answers given to a questionnaire, a score is established and the mortgage granted or not.

Qualitative Response Models - Applications

- Expertise scores for mutual funds

Ask to experts to simultaneously:

1. Answer a questionnaire concerning the factors they consider important in managing a fund, for example, presence of an asset selection committee, of risk management procedures, . . .
2. Give a note to the funds

Once scores are established, it allows mimicking expert behavior and give notes to new funds according to expert views.

It gives an automatic and quantitative way to rank funds according to some expertise.