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Credit Card Risk Modelling Using Artificial Neural Network

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Agenda

Pages

Motivations

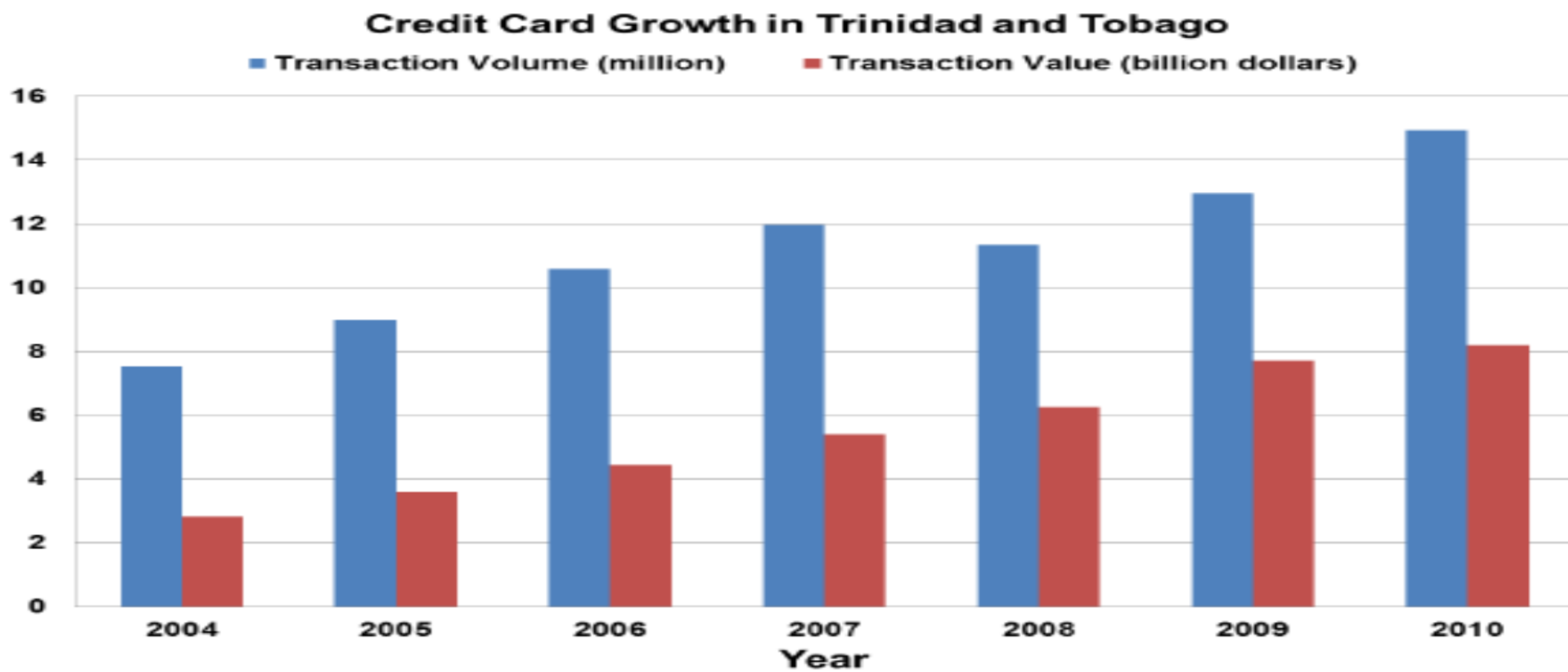
Rationale

- The pricing and management of credit risk in the banking book, as well as the **trading book** of financial institutions remain a major concern for regulators
  - Dodd-Frank Act (2010) removes mention of NRSROs for **ALL** financial regulations in United States
  - Basel III (codified in CRD IV in EU) contains provisions designed to reduce over-reliance on external ratings
- As a result, banks are forced strengthen their own-credit risk assessment and not to rely solely and mechanistically on external credit ratings
  - McBride (2013) notes that emphasis on internal credit risk models is as a result of the high levels of inaccurate credit ratings provided by external CRAs that contributed to the global financial crisis

Credit Risk in Trinidad & Tobago

Credit Exposure: Retail

- Central Bank of Trinidad and Tobago (2011)
  - Ratio of non-performing loans to total loans (as a %) increased from 0.7% in 2007 to 5.4% in 2012
  - Credit card spending increased by roughly 167% between 2004-2010 (TT$3 billion to TT$8 billion)



Retail Credit Risk Pricing

- Credit risk (expected loss):

$$\boldsymbol{CR = PD \times LGD \times EAD}$$

- Credit risk is not efficiently priced in the banking sector of Trinidad and Tobago
  - More or less all retail customers receive the same loan rate: everyone is "prime" customer!
  - No formal credit scoring of customers (default probability is not explicitly modelled)
- From a portfolio perspective, credit risk is also inefficiently managed
  - Banks manage individual exposure position and thus, their customers don't benefits from cross-subsidised loan pricing due to portfolio effects

Retail Credit Risk Pricing, cont'd

- Credit risk primarily managed through limit on exposure and collateralisation of loan
  - Actual loan rate is a lot higher than quoted once the level of collateralisation is taken into account and fairly priced
  - In many instances, loans are over collateralised and thus, banks technically are not expose to credit risk
- The heavy collateralisation of loans means that credit risk is largely modified and/ or substituted for other forms of risk:
  - <u>Operational risk</u>: failures in documentation and management of the collateral
  - <u>Market risk</u>: changes in the value of the collateral due to changes in market risk factors
  - <u>Liquidity risk</u>: the uncertainty of the liquidation cost of collateral once default occurs

Approaches to Credit Risk Modelling

Retail Credit Risk Models

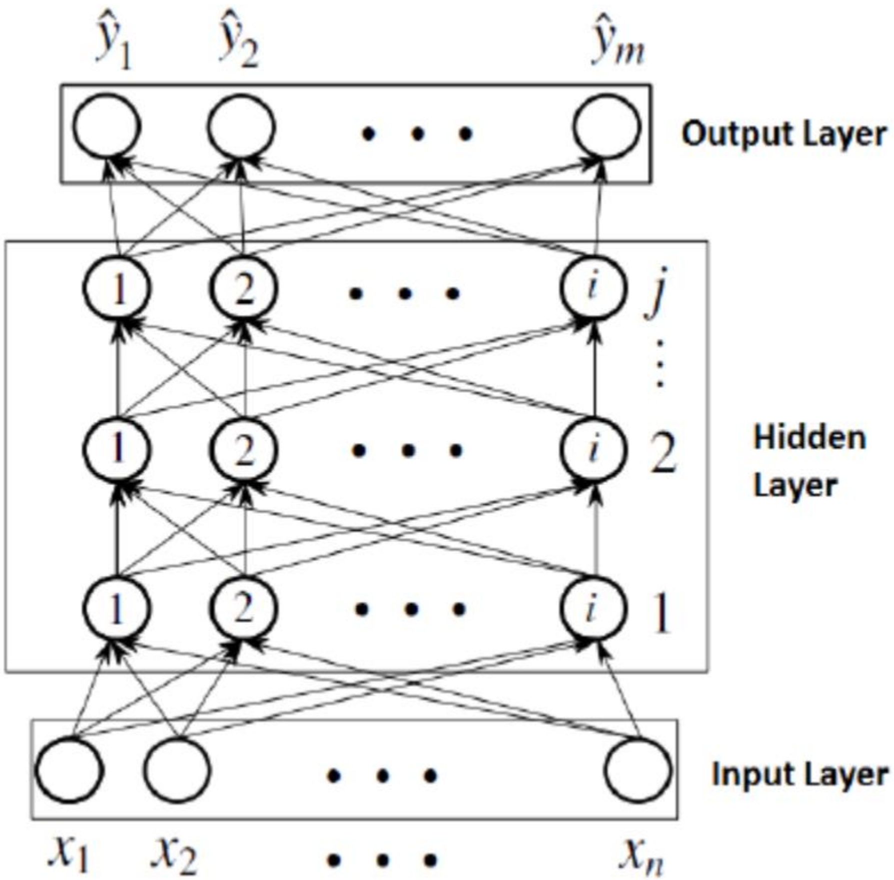
- Statistical discriminant analysis is one of the pioneering empirical models of credit risk (Altman 1968)
  - statistical limitations: independent variables must be normally distributed, and must be metric variables
- Logistic regression overcomes these restricted assumptions but still a linear methodology
- Machine-learning algorithms (supervised and unsupervised models)
  - availability of large amounts of data permits the use of more advanced models
- We use Artificial Neural Networks (ANNs) to model credit card default in Trinidad and Tobago
  - ANNs have shown to provide greater levels of accuracy in predicting defaults (Yu et al. 2008)

Introduction to ANNs

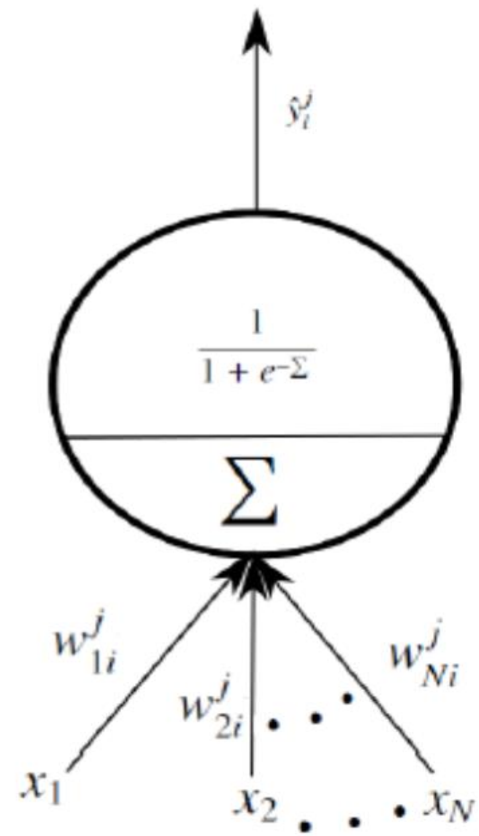
ANNs

- Inspired by biological neural networks (in the brain)
  - learn from and adapt to information represented by the data
  - operate as parallel-distribution processing models with various nodes and connections
  - different classes of ANN (FFNN, RBF, Recurrent Networks, Self-Organising Maps, etc.)
- Application to credit risk (credit scoring) modelling has enormous advantages over traditional approaches
  - better suited when the dependent and independent variables exhibit complex non-linear relationships
  - very tolerant of noisy and incomplete data sets
  - adaptive nature makes it quite useful in finance, where the environment is time-varying and dynamic
- In credit risk, the ANN that predominates is the FFNN

ANNs, cont'd



A general **Feed Forward Neural Network** (FFNN) with *j* hidden layers



A typical processing node from a FFNN

ANNs, cont'd

- The network learns by adjusting the weight values ($\boldsymbol{w}$) via a backpropagation learning algorithm

  1. data is fed through the network (with an initialised set of weights)
  2. the difference between the estimated and actual outputs is computed
  3. the error is then backpropaged though the network and used to update the weights
  4. a new set of training data is then fed through the network and the process is continued until training ends

$$E = \sum_{m=1}^{M} \left(\varepsilon^{(m)}\right)^2 = \sum_{m=1}^{M} \left(y_{output}^{(m)} - \hat{y}_{output}^{(m)}\right)^2 .$$

the optimal weighting vector, $\boldsymbol{w}$, that minimise the total error, $\boldsymbol{E}$. Alternatively, the root mean squared error (E_{RMS}) of the validation sample.

$$E_{RMS} = \sqrt{\frac{1}{M}\sum_{m=1}^{M} \left(\varepsilon^{(m)}\right)^2} ,$$

Data and Empirical Methodology

Credit Card Data Features

- Data from a major bank in Trinidad and Tobago
  - 1,300 credit cardholders (account opening date: 2/4/90 – 22/11/13)

Feature Name	**Type**	**Range**
Age bracket	Ordinal	1-10
Bank branch	Nominal	2-200
Length of time with the bank	Ordinal	1-6
Credit card product	Nominal	1-13
Number of dependents	Ordinal	1-5
Education level	Ordinal	1-5
Resident status	Binary	0 and 1 (=local)
Professional club member	Binary	0 and 1 (=yes)
Sex	Binary	0 and 1 (=male)

Data Pre-processing

- The data is normalised using the min-max normalisation method:

$$\frac{x_i - min\,(\mathbf{x})}{max\,(\mathbf{x}) - min\,(\mathbf{x})},$$

- Delinquency is defined as follows:

$$\left\{ \begin{array}{lcl} \text{Non-Delinquent} & \rightarrow & \text{Credit Card Payment} < 30 \text{ Days Past Due} \\ \text{Delinquent} & \rightarrow & \text{Credit Card Payment} \geq 30 \text{ Days Past Due} \end{array} \right\}$$

Empirical Methodology

- Split the data into three samples: training (700); validation (300); and testing (300)
- Single hidden layer, which still able to approximate any continuous function to any desired degree of accuracy (Brabazon & O'Neill 2006)
- Ten (10) different (random) initialising weighting vector, ***w***
- Vary the number of nodes (no optimal choice): 2-20
- The ANN that provides the highest accuracy (out-of-sample) is compared to the results from a logistic regression model

$$ln\left(\frac{p(y=1\,|\,\mathbf{x}_i)}{1-p(y=1\,|\,\mathbf{x}_i)}\right)=\sum_i \mathbf{x}_i\beta$$

where, we are modelling the probability of non-default

Empirical Methodology, cont'd

- Use a logistic (transfer) function

$$f(x) = \frac{1}{1+e^{-T}}.$$

  - common function use in classification and credit risk modelling

Empirical Results

Overall Predicted Accuracy

- The comparative accuracy from the **logistic regression** is **54.4%**

Number of Nodes	Mean Accuracy (%)	Standard Deviation (%)	Range of Accuracy (%)
2	**55.23**	2.18	[51.00, 58.00]
4	55.03	2.73	[49.33, 57.67]
6	55.20	1.91	[51.33, 58.00]
8	54.13	1.93	[50.67, 56.67]
10	53.33	2.68	[48.33, 57.33]
12	53.60	**1.14**	[51.67, 55.33]
14	53.37	2.71	[48.67, 57.00]
16	54.07	2.83	[50.00, **58.33**]

Partitioned Accuracy

The **ANN** (using the weights from 16 nodes ANN)

		Actual	
		Delinquent	Non-Delinquent
Predicted	Delinquent	30.00%	70.00%
	Non-Delinquent	20.00%	80.00%

Logistic regression model

		Actual	
		Delinquent	Non-Delinquent
Predicted	Delinquent	25.17%	74.83%
	Non-Delinquent	21.86%	78.14%

Significance of the Predictors

Logistic regression model

Feature Name	Coefficient	P-value
Age bracket	-0.005	0.918
Bank branch	0.000	0.987
Length of time with the Bank	-0.054	0.469
Credit card product	-0.007	0.791
Number of dependents	0.315	0.021
Education level	0.233	0.002
Resident status	-0.563	0.490
Professional club member	0.170	0.338
Sex	**0.459**	**0.004**

Plausible Explanations

- **Females are more likely to default than men**
  - Credit screening process is more favourably to women than men (e.g., car insurance premium)
  - The high proportion of single-mother families
    - Single-mother homes exceed 40% in several communities; up to 59% in Port of Spain (UNICEF 1995; Bernard 2003)
- **Positive relationship between the number of dependents and non-delinquency**
  - individuals with more dependents undergo more stringent screening
    - customers with more dependents are only ‘screened in’ if they are highly creditworthy
- We are unable to compare the financial position of the cardholders with their number of dependents or their gender

Conclusions

Key Findings

- We applied ANN to credit card data to predict default probability of cardholders and compare the results to those from a logistic model
- Our results revealed the following:
  - The neural network outperforms the logistic regression
  - Both tools are better at predicting non-delinquency
  - The gender of the cardholder is the most critical predictor of delinquency
    - **Men are less likely to default on their credit card payments**
  - Education level and number of dependents also important
    - Both exhibit positive relationships with non-delinquency

Q&A

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