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9B17M178

credit guarantee corporation: accommodating an expansion strategy—NOTE

Tuhin Sengupta and Shrestha Pratik wrote this technical note as an aid to instructors in the classroom use of the case Credit Guarantee Corporation: Accommodating an Expansion Strategy, No. 9B17M177. This technical note should not be used in any way that would prejudice the future use of the case.

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This technical note provides further explanation on the following important aspects of the teaching note analysis:

* Statistical models
* Scorecard model
* Decision tree
* Random forest model
* Neural network model
* Standard model (Basel II framework)
* Rete algorithm

Although these concepts will not be dealt with in detail, this note gives a glimpse into their inner workings. The following list of readings will help readers understand these concepts.

**RELEVANT READINGS**

* Iain Brown and Christophe Mues, “An Experimental Comparison of Classification Algorithms for Imbalanced Credit Scoring Data Sets,” *Expert Systems with Applications* 39, no. 3 (2012): 3446–3453.
* Jean-Paul Decamps, Jean-Charles Rochet, and Benoı̂t Roger, “The Three Pillars of Basel II: Optimizing the Mix,” *Journal of Financial Intermediation* 13, no. 2 (2004): 132–155.
* Charles L. Forgy, “Rete: A Fast Algorithm for the Many Pattern/Many Object Pattern Match Problem,” *Artificial Intelligence* 19, no. 1 (1982): 17–37.
* Ernest Friedman-Hill, *Jess in Action: Rule-Based Systems in Java* (Greenwich, CT: Manning Publications, 2003).
* Anil K. Jain and J. V. Moreau, “Bootstrap Technique in Cluster Analysis,” *Pattern Recognition* 20, no. 5 (1987): 547–568.
* James Taylor, *Decision Management Systems: A Practical Guide to Using Business Rules and Predictive Analytics* (Boston, MA: Pearson Education, 2012).
* David West, “Neural Network Credit Scoring Models,” *Computers & Operations Research* 27, no. 11 (2000): 1131–1152.

Statistical Models

A statistical model is a way to statistically find the characteristics that will most likely result in a final outcome. For example, suppose you want to predict the height of primary class students five years from now. A few characteristics to consider are the students’ present height, diet, and gender. These parameters form the characteristics of the model.

To make any statistical model accurate and predictive, two key inputs are required:

**Historical Data***—*With accurate and diverse historical data, one can predict the future with greater certainty. Consider the example where you want to predict the future height of a primary class student. Suppose you have a lot of historical data but the data are only about girls (female gender). The model might be highly accurate for female students, but the predictions from the data will be incorrect for male students. Hence, a diverse data set is important. It is also essential to have accurate data, as incorrect data can provide only incorrect predictions.

**Domain Expertise**—Domain expertise is a key aspect of making a highly accurate model. Continuing the previous example, suppose you have found that a student who eats a particular kind of sweet is more likely to grow taller than one who does not. For a non-expert in the field, this characteristic could mean there is a correlation between eating the sweet and the student’s future height. However, a domain expert might disagree on the same result. The expert might be able to shed more light on this characteristic by noting that the students who have this sweet all go to a sports club where they are given intense athletic training. Hence, a strong correlation can seem to be irrelevant data to a domain expert.

The following four models are the most widely used in the financial and banking industry to analyze risk for any asset.

Scorecard Model

A scorecard model is a predictive model, where we try to predict the future by getting a quantitative measure of each characteristic. This is done by dividing each characteristic into different ranges and assigning different scores to these ranges. This assignment is carried out after conducting data analysis and data crunching using software such as R and SAS. Special statistical and machine learning methods such as K-means clustering and bootstrap validation are used to get these scores. A final scorecard model will have the most important characteristics for different ranges along with their respective partial scores (as it is only for one characteristic). The sum of these partial scores forms a final score, used to assess the outcome. Returning to the example of predicting students’ height, assume that you found three important characteristics, as shown in Figure 1 below.

* Arm Span: What is the length of the stretch of the arm?
* Present Height: What is the present height of the student?
* Gender: Is the student male or female?

**Figure 1: Scorecard Model for Predicting Future Height**

|  |  |  |  |
| --- | --- | --- | --- |
| **Predicting Height Scorecard** | | | |
| **Bins** | **Range** | **Description** | **Score** |
| **Arm Span (a)** | | | |
| Small | 0 < = a < 0.5 | Less than 0.5 m | 20 |
| Medium | 0.5 < = a < 1 | Between 0.5 m and 1.0 m | 35 |
| Large | a > = 1 | Greater than 1 m | 45 |
| **Present Height (b)** | | | |
| Short | 0 < = b < 1 | Less than 1.0 m | 25 |
| Average | 1 < = b < 1.5 | Between 1.0 m and 1.5 m | 30 |
| Tall | b > = 1.5 | Greater than 1.5 m | 35 |
| **Female** | | | |
| Female | TRUE | FEMALE | 15 |
| Male | FALSE | MALE | 32 |

Source: Created by the authors.

As the figure shows, if the arm span for a particular student is between 0.5 and 1.0 metres (m), the partial score for the arm span characteristic is 35. Similarly, if the current height of the student is less than 1 m, the partial score for the present height characteristic is 25, and so on. For the final characteristic, assume that the student is a girl; her partial score would be 30.

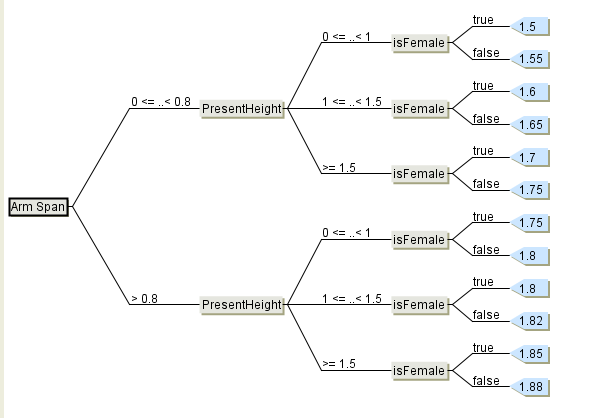
Summing the scores from all the characteristics gives a total score, which is indicative of the future height of the student. In the previous example, the total score for the student is 35 + 25 + 30 = 90, as found from the height-predicting score model. This score in itself is not significant, but if we compare it with another student’s scores, we can tell if this student will grow taller than the other student.

Decision Tree

A decision tree, unlike a score model, is a graphical representation of a predictive model using historical data. Here, each characteristic is a node on the branch of a tree, and the result can be found at the leaf (node with no further branching) of the tree. Unlike a score at the end, as in a scorecard, we get an actual predicting value.

Take the same example of finding the future height of students with the same three characteristics, and create a decision tree like the one shown in Figure 2. For example, consider a child who is female, with an arm span of 0.75 m (less than 0.80 m) and present height of 1.35 m (between 1.00 and 1.50 m). Her future height (five years from now), as predicted by the model, would be 1.60 m.

**Figure 2: Decision Tree**



Source: Created by the authors.

**Random Forest Model**

Random forests are groups of un-pruned classification or regression trees that are trained on bootstrap samples of the training data using random feature selection in the process of tree generation. After a large number of trees have been generated, each tree votes for the most popular class. These tree-voting procedures are collectively defined as random forests. For the random forest classification technique, two parameters require tuning: the number of trees and the number of attributes used to grow each tree. Random forests are basically an efficient estimation procedure in place of decision trees. Instructors and students can study these methodologies in detail using the academic literature listed in the Relevant Readings section.

**Neural Network Model**

The most commonly used neural network (NN) architecture in commercial applications, including credit- scoring models, is a multi-layer perceptron. However, there are other variants of NN architecture, such as mixture of experts, radial basis function, learning vector quantization, and fuzzy adaptive resonance. Therefore, one may expect different accuracy scores from different NN architectures. We can use different algorithms to estimate the unknown credit-scoring function and use different training methods to acquire information about the credit-scoring model. Instructors and students can study these methodologies in detail using the academic literature listed in the Relevant Readings section.

The next part of this note focuses on the most important part of credit-scoring models—implementing the BASEL II framework.

BASEL II FRAMEWORK[[1]](#footnote-1)

In June 2004, the Basel Committee on Banking Supervision issued a revised framework for International Convergence of Capital Measurement and Capital Standards to serve as a reference for the development and management of banking risks. This framework was intended for banks that moved to the internal ratings-based (IRB) approach. The IRB approach allows banks to devise their own internal measures of credit risk drivers, which are subjected to certain conditions and supervisory approval. As a result, banking institutions were allowed to determine the probability of default (PD), exposure at default (EAD), and loss given default (LGD) for borrowers using the IRB approach. These risk measures were then converted into risk weights, as specified by the Basel Committee.

This technical note does not cover the entire Basel framework in detail. Instead, it focuses on the relevant variables and definitions used in the case. First, it is important to understand the difference between expected losses and unexpected losses in the banking domain. Each year, the bank forecasts the average level of credit losses as reasonable, credible information for further analysis in the subsequent year. This calculated average credit loss is known as the expected losses (EL). The term “expected” has been used to highlight the randomness or the forecast error in the model. Losses that are incurred beyond this calculated EL are known as unexpected losses. The IRB framework, introduced previously, defined EL as a function of three variables: PD, EAD, and LGD. PD is defined as the randomness assigned by the bank to the expected proportion of defaulters. EAD is the defaulter’s outstanding amount at the time of default. The value of LGD depends on collaterals attached to different portfolios and the expected proceeds from the work-outs of the assets. The value is normally expressed as a percentage of EAD. In the teaching note, we have discussed briefly the ways of capturing these factors in the case.

EL is expressed mathematically as

Alternatively, as a percentage of EAD, we can express EL in the following manner:

We can now proceed to find the degree of the obligor’s exposure to the systematic risk factor. We need to calculate the asset correlation numbers. Asset correlation is defined as the association or relation between the sum of the asset value of a firm from one borrower and the asset value of another borrower. A high positive correlation indicates that the asset value of the borrower is directly linked to the economy of the region, as all borrowers are linked to a single risk factor. The asset correlation formula is presented below:

In the revised framework, the capital requirement, denoted by K, is expressed as a percentage of the exposure. Therefore, the variable K must be multiplied by EAD and the reciprocal of minimum capital ratio must be multiplied by a factor of (1 ÷ 8%) = 12.5 in order to derive the risk weighted assets.

Therefore, we have multiplied the minimum capital ratio of 8% to derive the minimum capital requirement, which is given below as

Rete Algorithm[[2]](#footnote-2)

The Rete algorithm was designed in 1974 by Charles L. Forgy. It is at the heart of all modern business rules management system tools. This algorithm is particularly well suited for handling complex situations where there are a lot of if-then-else conditions. A detailed explanation of the Rete algorithm is outside the scope of this note. However, this final section briefly describes the working process of the Rete algorithm and how it compares to a naïve implementation.

In the process of implementing rules, each rule is checked against the known input data. The implementation process is generally slow, and some rules need to be re-implemented if the triggering of any input data affects the conditions.

A Rete-based system builds a network of nodes, where each node is formed by a condition of a rule. Thus, a mesh or a tree structure is formed, where each rule is a path from the root (top) to the leaf (bottom most) node. If a similar condition for another rule is to be set up, the original node is reused; hence, the addition of any new rule would just mean the addition of new conditions to the existing structure.

This network of nodes is used to filter data as it propagates through it. The nodes at the top generally have many matches, but the number of matches gets reduced as we go down the network. At the bottom of the network are the terminal nodes, which trigger the action for the respective rule. Hence, the data to be evaluated would decide which rule is to be checked, and not every condition of every rule needs to be tested to give a correct response.

1. Basel Committee on Banking Supervision, “Basel II: Revised International Capital Framework,” Bank for International Settlements, accessed November 14, 2017, www.bis.org/publ/bcbsca.htm; Basel Committee on Banking Supervision, “An Explanatory Note on the Basel II IRB Risk Weight Functions,” Bank for International Settlements, 2005, accessed September 30, 2017, www.bis.org/bcbs/irbriskweight.htm. [↑](#footnote-ref-1)
2. Ernest Friedman-Hill, Jess in Action: Rule-Based Systems in Java (Greenwich, CT: Manning Publications, 2003). [↑](#footnote-ref-2)