A Decision Management Approach to Basel II Compliant Credit Risk Management[1]

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ABSTRACT

In this paper we highlight some high level requirements for Basel II compliant credit risk management and share a decision management approach to this problem as a case example of a real world business data mining application.

Keywords

Credit risk management, scoring models, decisioning, predictive analytics, monitoring, Basel II

1. INTRODUCTION

The new Basel Accord (Basel II) aims to make regulatory capital requirements more sensitive to risk to improve the overall stability of the financial market. Basel II covers credit, market and operational risk. For calculating and managing credit risk, banks can follow the so-called Internal Ratings-Based approach (IRB), which allows calculation of risk ratings based on predictive models developed by the bank on its own data [1,2]. As such, predictive data mining has a huge business impact on this application area.

This paper is a position paper and its goal is to present Basel II and credit risk management in general as an interesting application area for predictive data mining applications and research, and to identify challenges and opportunities. Data mining research often focuses on the core model development step in the KDD process, however we claim that other steps are also of key importance for credit risk management, such as integrating predictions with business rules, policies and strategies, safe deployment and the monitoring of business performance, decisions and predictive models.

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1.1 Outline of the paper

The procedures for developing, deploying and monitoring models must meet certain requirements, some of which are specified explicitly by Basel II regulations and some of which are implied by it. In section 2 we will highlight a selection of these requirements. Next, we will share the Chordiant Decision Management approach as a case example of a state of the art industry solution for implementing a managed Basel II credit risk management process and outline opportunities for data mining research (section 3). In addition we identify some opportunities that are related to Basel II, beyond mere compliancy (section 4). Section 5 concludes the paper.

2. The Internal Ratings Based Approach

The Internal Ratings Based (IRB) approach depends on so-called risk components to calculate the expected loss for each exposure, which in turn sum up to the total credit risk. Basel II dictates that the capital requirements are not only based on the expected losses but also on the sophistication of the methods used to estimate these losses. The more advanced the methods used, the better a bank can do in reducing the minimum capital requirements, which in turn allows banks to free up capital to be used for other purposes such as investments. Estimates of exactly how much can be freed up vary from 7% for large international banks (‘Group 1 Banks’) to 27% (small and midsize banks) and 50% (high quality mortgage portfolios) [3,4].

2.1 Requirements

As discussed a central requirement is to calculate the expected loss for an exposure, it is defined as:

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$$EL= PD \times LGD \times EAD \times M \quad (1)$$

with PD the probability of default (not paying back a loan or equivalent completely), LGD the loss given default, EAD the exposure at default and M the maturity of the exposure.

Typically, under the so-called IRB Foundation approach, banks provide their own estimates of PD and use supervisory estimates for other risk components – in the Advanced IRB approach all components are estimated by the bank itself.

Basel compliant ratings must be calculated on the basis of at least two years of data, so the availability of historical data over that period is a must have.

The data must be analyzed to calculate ratings that properly reflect the risk in a portfolio. Traditionally, classical statistical methods like regression are used for estimating risk components. However, the Basel II standard does not require a specific modeling algorithm to be used, rather the modeling process must meet a number of criteria.

Merely being predictive is not good enough. The models must be proven to be stable under varying economic conditions and over various points in time. A priori risk assessment knowledge that may improve the bottom-up risk models must be made explicit and incorporated where possible. A safe and auditable process must be followed to develop, deploy and monitor credit models and strategies.

3. A Decision Management Approach

In this section we would like to outline the various steps involved in managing the Basel II credit risk management process, present our decision management approach as an example of real world application of data mining and discuss various challenges and opportunities.

Historically, the focus of our tools and methodology was purely on predictive model development for credit risk management using genetic algorithms [10]. Later it evolved into a full decision management platform for optimizing the overall customer relationship, across issues like risk, cross sell, service and attrition (‘next best action’ or ‘next best activity’).

Decision Management provides managed process support for the steps after a model has been developed: linking models with business rules into a decision logic (strategy management), batch and real-time decision logic deployment and monitoring of decisions and models [3,4,6,7].

3.1 Risks and Losses Datamarts

As discussed Basel II requires that at least two years of risk and losses data is available. As usually data is out there somewhere in the company, getting reliable access to it is generally the issue.

However, it is generally less of a problem than for other business areas because banks have been obliged to keep a lot of risk related records for financial or accounting regulations. Furthermore, periodical snapshots of a simple flattened customer table are usually sufficient, and explorative predictive analytics can be used to guide the search for relevant risk indicators that should be stored on an ongoing basis in the risk data mart.

Risk management is an area where everyone is aware of the risk and reality of poor data quality. From a data mining research point of view it could be interesting to adapt algorithms specifically for mining ‘dirty’ data or further develop methods that continuously monitor data quality or detect anomalies [5,9].

3.2 Safe Model Development Process

Basel II requires that best practices for developing rating models are followed, to minimize the scope for errors and ensure consistent quality. In our opinion, the best and safest way to ensure this is to hardcode this process in the model development tool and to provide automated support where possible, without sacrificing user control. This should not be limited to the core model algorithms, but also include project definition, data preparation and model evaluation. Because of this model factory approach, model accuracy, -robustness and process compliancy are optimized and a full audit trail to the development process can be provided. As core modeling algorithms, logistic regression, additive scorecards, decision trees and genetic algorithms are used, to cover the whole spectrum between simple, understandable models and more powerful, complex models.

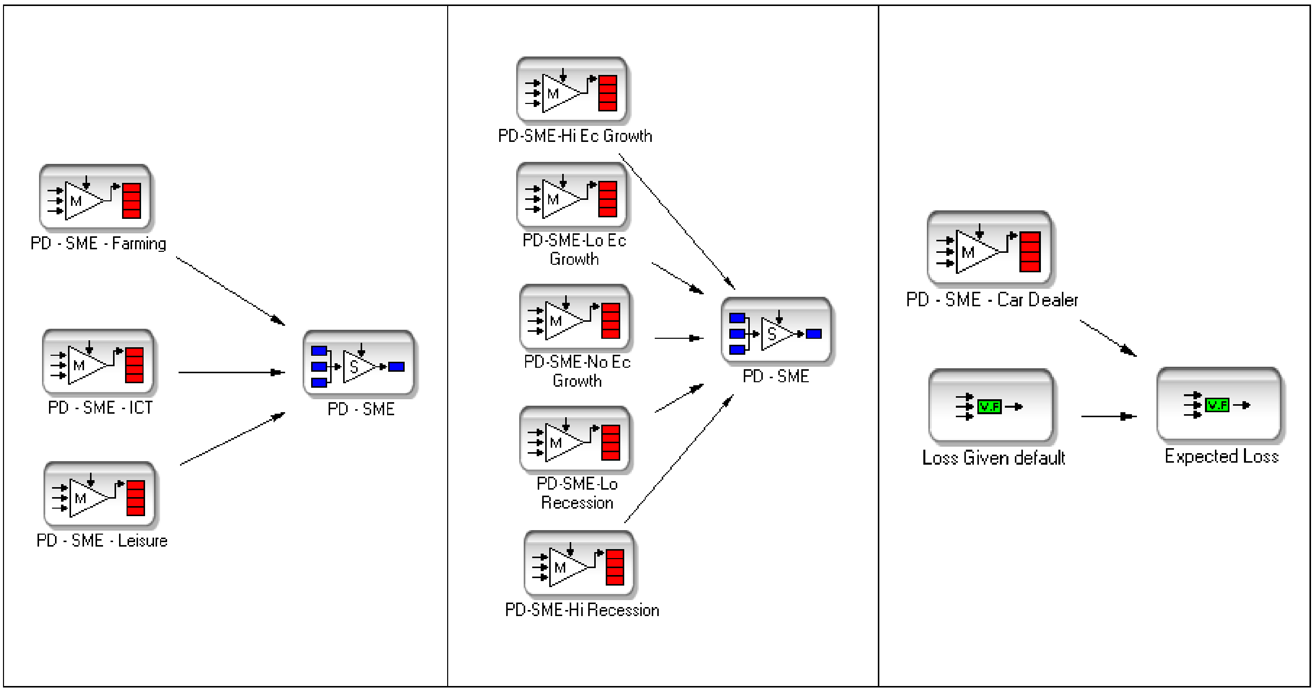

Figure 1: Decision logic examples: combining models for subpopulations, logic aware of the economic cycle, logic implementing the core IRB formula**.**

There are various interesting opportunities for data mining research. Of course there will always be a need for better scoring algorithms, especially if these allow to reduce the variance error which is generally a major source of error in real world problems (see also [8]). However as discussed above providing more (semi)-automated support for the entire model development process may have even more impact.

For instance, evaluation of scoring models is an topic of its own. Simple measures such as accuracy do not suffice because of the relatively low default rates. For instance measures such as area under the ROC curve are more useful. In addition usually extensive testing needs to take place to demonstrate the stability of these models on different samples and over time periods ('back testing'). Often simulations are used as well to check under what conditions models may break down, by generating inputs over a range of distributions and studying the behavior of the model, for instance through Monte Carlo simulations.

3.3 Business Policies, Rules and Strategies

The core idea of the decision management approach is that often not just a prediction is needed, but rather a decision. In our approach we allow rating models to be complemented by decision rules. This facility is typically used to express risk assessment knowledge based on information that is out of scope of the model. Examples are exceptions that lead to an increase or decrease in rating or simply the implementation of core IRB formulae. Another use case would be a comprehensive rating system that requires multiple rating models. An example would be a system that rates small and medium enterprises based on several sector specific rating models, or a rating logic that combines models for different economic cycles (figure 1). These are relatively simple examples; a real world decision logic generally contains tens to hundreds of decision components or more.

The marriage between models and rules is an area that could deserve more attention in data mining research. At least in AI data mining and knowledge based systems are usually quite separate areas. Also it is often claimed that integration of models into applications is specific for each application and doesn't allow the development of generic methods. The decision management approach of combining rules and models can be seen as a counter example to this claim. The same methodology is also used for marketing (real time next best activity, marketing campaigns) and medical applications (implementing decision support and medical protocols).

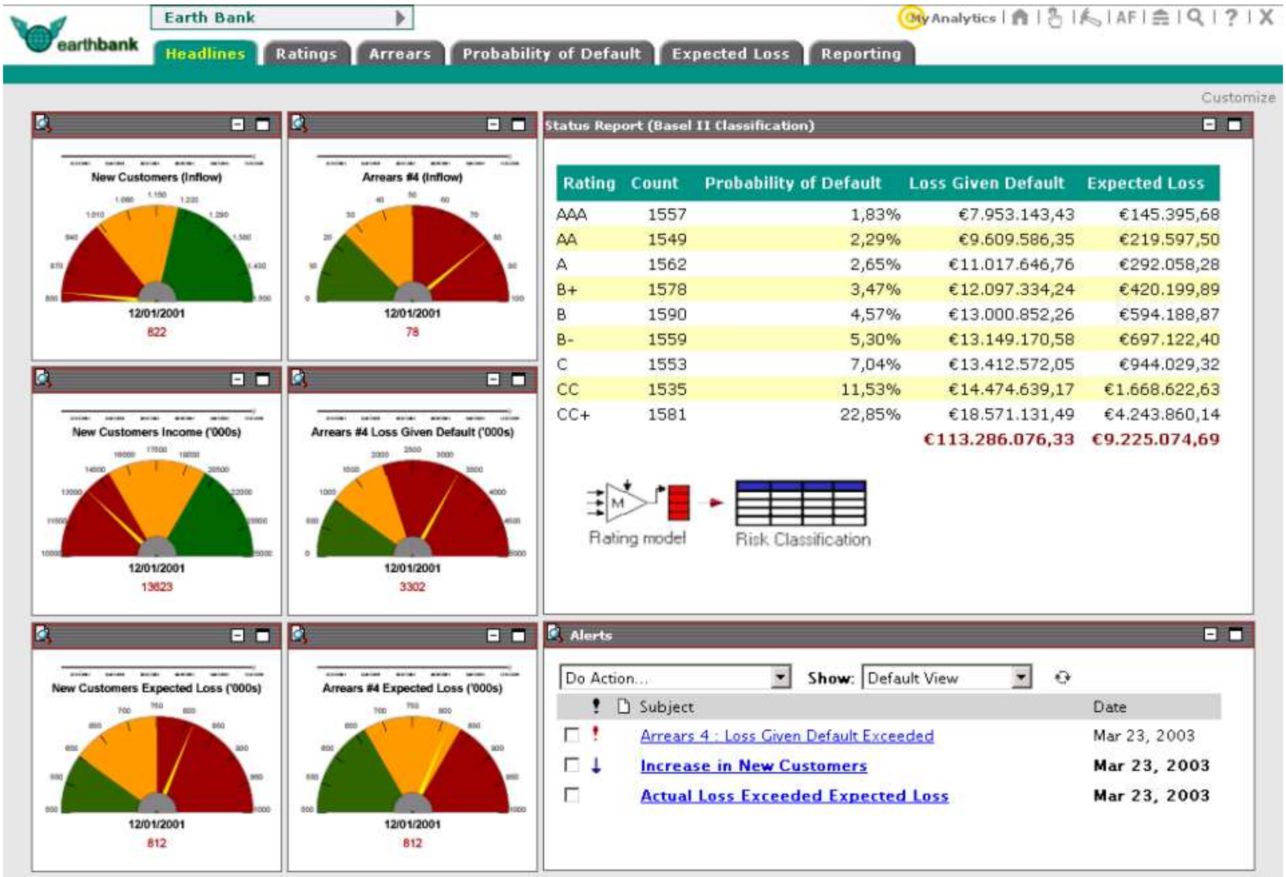

Figure 2: Example of a monitoring dashboard

3.4 Monitoring

To be Basel II compliant. product & customer portfolios, rating logic and models must be monitored continuously and consistently. Example analyses include calculation of rating and score distributions, comparisons of predicted and actual defaults and losses, and population drift. This is achieved without the need to actually design or build a dedicated data mart or equivalent repository. Again, this is a feature of process automation. In model development all expectations are stored within the model and in model deployment all the produced ratings along with the input are written away to the monitoring data mart, which contains a unified Basel II data model. Obviously, cost of the data mart is not an issue from a regulatory perspective; however the automated approach again minimizes the risk of errors (figure 2).

The monitoring of models (and decisions) is another topic that is very useful but also interesting (and under studied) from a data mining research point of view. For instance how can be detected that a model is getting 'tired' and needs to be replaced. Or what are methods to discover the root cause of a change in score distributions? Did the portfolio change or are the models no longer valid? How can we detect a sudden external change in the environment? How could we use a set of credit models and strategies and adaptively use the best ones given the current environment, or in other words how can we use monitoring to adaptively steer the rating environment in a safe manner?

4. Basel II Related Applications

Banks that have implemented an IRB compliant process will be rewarded considerably. Changes in capital requirements of only a couple per cent will have significant impact on the bottom line. However, Basel II is not just an exercise in compliancy, but also an opportunity to build on the rating environment and implement or improve related applications.

The first candidate applications to profit from a Basel II infrastructure are other credit risk management applications. Examples are loan acceptance models (for new clients), behavioral models (during client lifetime) and collection models (after arrears or default). This is actually not limited to the banking industry, but will be relevant for non-Basel sectors like telecommunications, insurance and retail as well. Note that these application areas lead to interesting new research problems as well. For instance in application scoring outcome information (loan repayed) is missing for a non random sample (the rejected applicants). This is known as the ‘reject inference’ or ‘outcome inference’ problem.

Secondly, the risk dimension may be included in any situation where the right offer has to be made to the right client, i.e. integrate risk as one of the dimensions when deciding the next best action for a given customer. Customer relationship management should become risk sensitive, so that high risk clients are not targeted, or offers for a client are configured so that both risk and revenue are optimized. An example is risk based pricing, which allows a bank to accept customers that would normally be rejected. From a client perspective, the communication channel or customer touch point should not necessarily influence the treatment, offers and value he gets, so the client rating must be done both offline (batch scoring for outbound marketing campaigns for example) or online (contacts through inbound call centers or web site visits).

5. Conclusion

In this paper we have discussed Basel II compliant credit risk management as an interesting area as an interesting application of data mining. We have presented the decision management approach to credit risk management that puts heavy emphasis on the steps and processes beyond the core modeling step. In our view this opens up new areas for data mining research as well.

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