Bayesian Networks for Operational Risk Management, Compliant with Basel II

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Riassunto: Ogni attività, in qualunque settore, è soggetta a rischi operativi. Nel campo bancario, il Comitato di Basilea per la Vigilanza Bancaria ha formulato negli ultimi anni delle raccomandazioni, note come Basilea II, per la gestione dei rischi; in particolare, delinea approcci interni avanzati (AMA) per i rischi operativi. In questo contesto, è possibile applicare un modello di reti bayesiane per gestirli, vale a dire determinare il capitale regolamentare attraverso l’Op VaR, identificare gli eventi che influiscono maggiormente sulle perdite e controllarli. L’obiettivo è delineare una metodologia di rete bayesiana che consenta di integrare diverse fonti di dati, limitare l’allocazione del capitale attraverso l’impiego della propagazione dell’evidenza e di migliorare la gestione dei rischi tenendo presente l’attività dei controlli interni ed esterni.

Keywords: Operational Risk Management, Bayesian Network, Basel II, Op VaR, Loss Data Collection, Self and Risk Assessment, Capital Requirement.


The aim of this paper is to provide a Bayesian model which allows to manage operational risk (OR) and measure internally capital requirement, compliant with Advanced Measurement Approach (AMA) recommended by Basel Committee on Banking Supervision (Basel II) for internationally active banks (see e.g. Basel Committee on Banking Supervision, 2003). In fact, the rising interest of the supervisors and the banking industry, in the recent years, for operational risk is due to the growth of e-commerce, large scale mergers and acquisitions and the use of more highly automated technology which test integrated system and provoke a number of situations which increase OR. In “The New Basel Capital Accord” (Basel II), published by the Basel Committee, operational risk is defined as “the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events”, including legal risk but not strategic and reputational risk. The Accord asks a minimum capital requirement ($K$) which has to be detected against credit risk, market risk and operational risk$^1$; it has also stated a figure of 12% of minimum capital requirement for OR$^2$ and, at

$^1$ The amount of capital charge has to cover also other types of risk, defined as “other risk”.

$^2$
the same time, it allows three different calculation approaches for the regulatory capital, rising in complexity and decreasing in capital requirements. Using the so called “Basic Indicator Approach” (BIA) the capital charge will be calculated as product of Gross Income and Alpha Factor\(^3\). The “Standardised Approach” (TSA) is built on the BIA by dividing a bank’s activities into a number of standardized business lines\(^4\). Within each business line, the capital charge is the same indicator GI of OR times a fixed percentage (beta factor, different for each business line). The “Advanced Measurement Approach” (AMA) provides discretion to individual banks on the use of internal loss data, while the method to calculate the required capital is internally set and verified by supervisors.

2. Using Bayesian networks for AMA

In general, the objective is to estimate a loss distribution and to derive functions of interest from it (such as the Value at Risk, VaR); in particular, losses in operational risk are realisations of a convolution between a counting process (frequency) and a number of continuous processes (severities). The lack of an appropriate historical database makes difficult to apply statistical inference techniques without resorting to simulations. For a review of statistical models for operational risk management see e.g. Cruz (2002), King (2001) or Alexander (2003).

Bayesian networks for operational risk have been proposed by Cornalba and Giudici (2004). They offer a solution to banks seeking to combine both qualitative and quantitative data and also to meet the requirements of the AMA to measuring operational risk. In fact, the Bayesian statistical approach (see e.g. Cifarelli and Muliere, 1989) allows to integrate, via Bayes theorem, different sources of information coming from loss data collection, self assessment opinions and external data. This allows a unified knowledge which allows to manage operational risk (i.e. through identification, assessment, monitoring and control/mitigation) and, at the same time, to determine minimum capital requirements better through the Op VaR, a percentile defined by Basel Committee. The latter is the risk measure used for regulatory capital purposes and reflects a holding period of one-year and a confidence level of 99.9 percent. Bayesian networks give us more then the Op VaR calculation: we can also consider the correlation between losses of different business lines and risk types and we can evaluate the impact of “causal” factors, such as the internal/external audit process, control system or other key risk indicators (on people, IT and processes).

3. The model

A Bayesian network can be described by a set of nodes representing random variables and a set of arrows connecting these nodes in an acyclic manner (for a more precise

\(^{2}\) This requirement would produce a capital amount in line with the OR actually faced by large and complex banking organizations.

\(^{3}\) It is established, as Beta Factor, by Basel Committee.

\(^{4}\) In “The New Basel Capital Accord” OR exposures and losses have been broken into a series of standardised business unit (called business line, which are 8) and into a group of operational risk losses according to the nature of the underlying operational risk event (called event type, which are 7).
definition see e.g. Jensen, 1996, or Giudici, 2003). Each node has assigned a conditional probability that describes how the states of node depend on the parents of the node itself. The topology of the graph defines the (probabilistic) dependences between the variables, through a set of conditional distributions.

In the OR context we are interested to quantify the capital charge and search the influence of several risk factors, including internal and external controls. Therefore, the graphical model we propose contains three types of node: losses, internal and external controls (CI and CE). Each node is a discrete random variable that is measured for each statistical unit, defined by the crossing Company/Business line/Event type/Process. More precisely, the loss variable is compiled by expert on the basis of the predicted losses for next period (year) and the effectiveness of the internal and the external controls (CI and CE) formulated on the basis of expert’s opinion which gives information about the quality of the internal and external control system of the organisation. Expert opinions are usually obtained through an internal procedure of risk and control self assessment, which is periodically done through questionnaires, submitted to risk manager (process owners, expert of different processes of the bank).

Initially, the bayesian network is learned with the expert opinions (qualitative learning) coming self assessment. This means a network topology is learned initially from the expert opinion. Since process owners don’t know the links between nodes and their direction, the network learns them from the joint opinions. Therefore, the graphical model is a good instrument to represent prior knowledge (self assessment opinions) and the data (losses).

**Figure 1:** Example of a network structure learned only with prior opinions.

Once the network is initialised, loss data is inserted daily. Each day leads to one data point, corresponding to the observed severities of the occurred losses. Figure 1 gives the result of structural learning on a sample of nodes, using the software Hugin 6.3. Once data are initiated, structural learning leads to determining the graphical description of the dependencies (the links between nodes) induced by the expert’s opinions and the data. In other words, the aim is to obtain edges (arrows) that link a child node $X$ to their parents, if there is conditional dependence of $X$ on them.

After structural learning, we have performed quantitative learning, i.e. we learned the conditional probability distribution, or local distribution, $P(X|\Pi X)$, for each variable $X$, given its parents $\Pi X$. Marginal distributions for each node of the network can be obtained from such local distributions, i.e. for each variable $X$ given each combination of states of its parents $P$. Figure 2 gives one of such marginal distribution.
From marginal distribution it is possible to calculate the Op VaR. We know that, while the previous results are based on daily data; Basel II requires an annual holding period. In order to calculate the required capital coverage for the correct holding period, it is necessary to simulate total losses from each marginal loss distribution (by summing over days). Below (table 1), we present the result of the simulation we have implemented, for the node 1/3/7/91 (Firm/ Retail Banking/Execution, delivery & process management/Process) according to different simulation sizes (scenarios).

Table 1: Results of simulation for the node 1/3/7/91.

<table>
<thead>
<tr>
<th>VaR OP (€)</th>
<th>scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.324.612,310</td>
<td>with 10000</td>
</tr>
<tr>
<td>1.379.085,286</td>
<td>with 25000</td>
</tr>
<tr>
<td>1.377.908,000</td>
<td>with 25000</td>
</tr>
<tr>
<td>1.357.427,000</td>
<td>with 50000</td>
</tr>
<tr>
<td>1.357.430,072</td>
<td>with 50000</td>
</tr>
<tr>
<td>1.360.500,435</td>
<td>with 60000</td>
</tr>
</tbody>
</table>

From table 1 note the results for the simulation on probabilistic distribution. The Op VaR compulsory to the risk is about 1.360.500 €. The overall Op VaR, determined by summing all Firm/Business line/Event Type/Process Op VaRs, represents the capital charge required to satisfy Basel II requests for operational risk.

References