DECISION SUPPORT MODEL FOR THE ASSESSMENT OF BANK REPUTATIONAL RISK

Marko Bohanec1,*, Giorgio Aprile3, Maria Costante2, Morena Foti2, Nejc Trdin1,
1 Jožef Stefan Institute, Department of Knowledge Technologies, Jamova 39, SI-1000 Ljubljana, Slovenia
2 MPS, Risk Management Division, V.le Mazzini 23, Siena, Italy
3 Aon, Principal Consultant, 8 DevonShire Square, London
* e-mail: marko.bohanec@ijs.si

ABSTRACT
This paper presents a decision support model aimed at the assessment of reputational risks associated with bank operation. The innovative aspect of the model is that it combines different types and sources of information: structured and unstructured, quantitative and qualitative, internal and external. Unstructured, qualitative and external aspects are represented by sentiment of news and blogs about bank counterpart organisations. The model is multi-attribute and hierarchical, and is composed of three modules: basic data processing, qualitative evaluation, aggregation; these are presented in detail. The paper also presents a prototype implementation of the model and illustrates its application on real-life data.

1 INTRODUCTION
The current financial crisis has dramatically changed the risk profile associated to the production and distribution of investment products and services by banks and other financial institutions. Reputational risk is defined as “the risk arising from negative perception on the part of customers, counterparties, shareholders, investors, debt-holders, market analysts, other relevant parties or regulators that can adversely affect a bank’s ability to maintain existing, or establish new, business relationships and continued access to sources of funding” (Settlements, July 2009). It has become vital for banks to measure, monitor, assess and mitigate their reputational risks.

The reputational risk model (RIM for short) presented in this paper is aimed at estimating bank reputational risk as a means to supporting risk managers. The model builds on structured data, which is readily available in a bank, and supplements it with information extracted from external unstructured data, mostly blogs, online newspapers and financial documents available on the web. Specifically, external information is assessed in form of sentiment, that is, a positive or negative view, attitude, emotion or appraisal on the studied object from a document author or actor (Liu, 2010).

RIM has been developed in the context of the EU project FIRST (2010-2013). FIRST addresses the challenges of dealing in real-time with massive amounts of heterogeneous data and information in financial markets, and provides infrastructure for collecting and processing this data. One of the services developed in FIRST provides a daily sentiment related to a given financial organisation (FSS, 2013); RIM uses this service as one source of input data. The other source is composed of structured data, provided by a bank that carries out reputational risk analysis. In FIRST, the bank is represented by the project partner Banca Monte dei Paschi di Siena, Italy (MPS).

2 BASIC CONCEPTS
The basic operational scheme of RIM is shown in Figure 1. Input data consists of several time series, coming from two primary sources:
(1) sentiment data, provided by the FIRST infrastructure, based on an analysis of unstructured external data;
(2) data about financial product performance, provided by the bank, based on structured internal data.
All time series are typically sampled on a daily basis.

Figure 1: Basic operational scheme of RIM.

Time series data taken at a particular point in time represent a situation that has to be assessed for reputational risk. The assessment is carried out by a hierarchical multi-attribute model, which is denoted by a triangle in Figure 1 and described in detail in section 3.
The result of evaluating a single situation is expressed in terms of reputation risk index (RI), a number from 1 to 5, where the higher number represents a higher risk. Applying the model in each time point, we obtain a time series of RI’s. In addition, since RIM is a hierarchical model and therefore contains internal variables, we also obtain time series of all internal variables; this is useful for the explanation of obtained results and aids model transparency.

3 MODEL STRUCTURE AND COMPONENTS

The basic function of RIM is to assess RI corresponding to a given financial product and a given customer at some given point in time. Therefore, the assessment is based on input data of two main entities: PRODUCT and CUSTOMER (Figure 2). The third entity is COUNTERPART, that is, a producer of PRODUCT, which is an object of sentiment assessment. The relations between COUNTERPARTs, PRODUCTS, and CUSTOMERs are all ‘one-to-many’: a COUNTERPART produces one or more PRODUCTS, and each PRODUCT can be sold to one or more CUSTOMERs of the bank.

Time series processed by RIM contain data about these three entities. The fourth data source is the bank itself (MPS), which provides data on volumes and benchmark performance of specific groups of products.

RIM processes this input data using three main components (Figure 2): (1) basic data processing, (2) qualitative evaluation, and (3) aggregation.

3.1 Basic Data Processing

The basic data processing part of RIM takes input data about PRODUCTS, CUSTOMERs and COUNTERPARTs and transforms them into a form suitable for further use in the qualitative evaluation and aggregation components. The following variables are produced by the module:

Sentiment indicator $S$: Sentiment measured on text sources referring to the counterpart. $S = w_{SP}S_{SP} + w_{LP}S_{LP}$, where $S_{SP}$ and $S_{LP}$ are short-term (last day) and long-term (30-days average) of counterpart’s sentiment, and $w_{SP}$ and $w_{LP}$ are the associated weights, by default set to 30% and 70%, respectively. $S_{SP}$ and $S_{LP}$ are represented as numbers on the interval $[-1, +1]$ and are obtained from FSS (2013).

Performance indicator $P$: A measure to which extent the financial product is performing in line with customer expectations. $P = PP + 0.1(PP - BP)$, where $PP$ is an absolute product performance measured since the customer bought the product, and $BP$ is benchmark performance of similar products. Both $PP$ and $BP$ are defined by the bank for each customer and product pair.

Mismatching indicator $M$: Defined as a difference between the risk profile of the customer and the risk profile of its portfolio for each product. This indicator measures the extent to which the customer’s portfolio is still in line with their risk investment profile, which is defined in the contract between the bank and the customer. The risk profile of the product is a composite measure that is already in place in MPS.

Relative product and customer volumes: The higher the volume of some product held by some customer, and the higher the number of users holding some product, the higher the effect of this customer and product to potential reputational risk. For this purpose, the basic data processing module calculates a number of quantities representing relative shares of product volumes in total bank assets, and relative numbers of customers holding some product or group of products. These quantities typically serve as weights in further processing.

Discretized variables $qS$, $qP$, $qM$ and $qRV_{1C}$: Finally, all numerical indicators that enter the qualitative evaluation (section 3.2), that is $S$, $P$, $M$ and $RV_{1C}$ (relative volumes of a given product in the total assets of customer $C$), are discretized according to rules defined by MPS reputational risk experts. For more details on discretization, the reader is referred to FIRST D6.3 (2013).
3.2 Qualitative Evaluation

The function of the qualitative evaluation model is to produce the value of \( qRI_1 \), i.e., qualitative assessment of \( RI \) for a given customer/product pair. This is achieved through qualitative aggregation of \( qS, qP, qM \) and \( qRV_{1c} \), according to the hierarchical scheme presented in Figure 3.

![Figure 3: Structure and scales of qualitative evaluation attributes.](image)

The aggregation is implemented as a qualitative multi-value scales (Figure 3), and that the aggregation of values in the model are discrete and can take values from small symbolic attribute model developed according to methodology DEX input attributes as a numerical value in the range \([1,5]\). The range medium-low, medium, high, very-high.

![Figure 4: Rules for aggregating \( qP \) and \( qM \) into \( qPM \).](image)

3.3 Aggregation

In the part described so far, RIM assesses reputational risk only for a given customer/product pair in a given point in time. The role of the aggregation component is to determine \( RI \) for groups of customers and/or products (in the same point in time). For each of the studied groups \( G \) (customers, products, counterparts, bank), the aggregation produces a corresponding reputational index \( RI_G \), which is represented as a numerical value in the range \([1,5]\). The range corresponds to the five qualitative risk classes, therefore \( RI = 1 \) corresponds to the case without reputational risk, and \( RI = 5 \) denotes the highest risk.

The aggregation of \( RI \) is hierarchical by the levels: Customer \( \rightarrow \) Product \( \rightarrow \) Counterpart \( \rightarrow \) Bank. This means that individual customers’ assessments \( qRI_1 \) are first aggregated into product reputational indices \( RI_P \) for all products \( P \). These are then grouped by counterparts \( T \) into \( RI_T \), and finally aggregated into a single synthetic reputational index \( RI \) at the bank level.

Furthermore, \( RI \) reflects the fact that some products influence reputational risk more than others. Particularly important are products that have high volumes and are held by many bank customers. Therefore, a collective \( RI_G \) of some group \( G \), whose individual indices are \( RI_i, i = 1, 2, ..., g \), is defined as the weighted average:

\[
RI_G = \frac{\sum_{i=1}^{g} w_i RI_i}{\sum_{i=1}^{g} w_i}
\]

Each weight \( w_i \) consists of two components, \( w_{V,i} \) and \( w_{N,i} \), so that \( w_i = 60w_{V,i} + 40w_{N,i} \). Both \( w_{V,i} \) and \( w_{N,i} \) depend on some group of products \( P_i \) and reflect the relative share of corresponding product volumes and customer numbers in the bank, respectively. Thus, \( w_{V,i} \) is defined as the share of volumes of \( P_i \) in total assets \( TA \) of the bank:

\[
w_{V,i} = \frac{1}{TA} \sum_{p \in P_i} V_p
\]

Here, \( V_p \) represents the total volume of product \( p \). Similarly, \( w_{N,i} \) takes into account the number of customers holding \( P_i \) with respect to the total number of bank customers \( TN \):

\[
w_{N,i} = \frac{1}{TN} \sum_{p \in P_i} N_p
\]

Here, \( N_p \) is the number of customers holding product \( p \).

4 IMPLEMENTATION

At present, RIM is implemented as prototype software called RIMstream. At input, RIMstream takes time series of data provided by the bank, then it queries FSS (2013) for the corresponding sentiment data, calculates \( RI \) for all customer/product pairs in all given points in time, and performs the hierarchical aggregation of \( RI \) for products, counterparts and whole bank in the same points in time. At output, it generates a series of HTML reports for the user at all four levels of aggregation. RIMstream is implemented in Java and uses JDEXi (2012), an open-source Java library for the evaluation of DEX models.

5 EXAMPLE APPLICATION

Because of space limitations, we illustrate the application of RIMstream only with a single report (Figure 5). The report was obtained on a realistic and fairly big input data stream prepared by MPS, which contained about 1.9 million data items from the period April 13 to May 24, 2013, involving 11 counterparts, 985 products, 130565 customers and 327826 different customer/product pairs. At output, 997 reports were obtained for the bank, counterpart and product level. For more detailed examples of these, see FIRST D6.3 (2013).
The highest-level report is called the “bank-level report” (Figure 5) and presents an overall aggregation of reputational-risk analysis. The left hand side shows the reputational index on each date in terms of average ($RI$), discrete level, and the corresponding relative volume and number shares. It is evident that on most days $RI$ was relatively low (1.05 or 1.08), with two exceptions on April 22 and 29, when the risk increased to 2.38 and 2.39, respectively. Reasons for this are partly revealed on the right hand side of Figure 5, which displays five counterparts and five products that contributed most to $RI$. It is apparent that high risks were induced due to problems with the reputation of counterpart “CTP 24”. Lower-level reports (not shown here) provide further details to explain this assessment and reasons for it.

### 6 CONCLUSION

RIM is a novel reputational risk assessment model, whose distinguishing characteristic is that it combines internal structured information, which is readily available in banks, with sentiment assessments, obtained by analysis of external and unstructured text documents. The latter are provided through information infrastructure developed in the project FIRST. RIM is a multi-attribute and hierarchical model that contains both quantitative and qualitative evaluation components.

At present, RIM is implemented as prototype software, which still requires substantial verification and validation, particularly by financial experts, reputation risk managers and other end-users. In the future, the prototype will be upgraded into a fully-featured decision support system, containing a database and a suitable user interface supporting on-line analytical data processing.

### REFERENCES


FIRST (2010-2013). Large scale information extraction and integration infrastructure for supporting financial decision making. EU project FP7-ICT-257928, http://project-first.eu/

FIRST D6.3 (2013): Highly Scalable Machine Learning and Qualitative Models v2. FIRST Deliverable D6.3.


<table>
<thead>
<tr>
<th>Date</th>
<th>RI</th>
<th>Level</th>
<th>$%NP$</th>
<th>$%VP$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013-04-22</td>
<td>2.96</td>
<td>v-high</td>
<td>1.9725</td>
<td>0.3272</td>
</tr>
<tr>
<td>2013-04-23</td>
<td>1.08</td>
<td>low</td>
<td>1.9750</td>
<td>0.3277</td>
</tr>
<tr>
<td>2013-04-24</td>
<td>1.08</td>
<td>low</td>
<td>1.9725</td>
<td>0.3278</td>
</tr>
<tr>
<td>2013-04-25</td>
<td>1.08</td>
<td>low</td>
<td>1.9276</td>
<td>0.3253</td>
</tr>
<tr>
<td>2013-04-26</td>
<td>1.05</td>
<td>low</td>
<td>1.9283</td>
<td>0.3253</td>
</tr>
<tr>
<td>2013-04-29</td>
<td>2.39</td>
<td>v-high</td>
<td>1.8710</td>
<td>0.3302</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Counterpart</th>
<th>RI</th>
<th>Cont%</th>
<th>Product</th>
<th>RI</th>
<th>Cont%</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTP 24</td>
<td>2.40</td>
<td>37.36</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 33</td>
<td>1.13</td>
<td>25.02</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 05</td>
<td>1.06</td>
<td>16.05</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 25</td>
<td>1.11</td>
<td>12.68</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 15</td>
<td>1.06</td>
<td>7.04</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 24</td>
<td>1.22</td>
<td>37.35</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 33</td>
<td>1.13</td>
<td>25.01</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 05</td>
<td>1.06</td>
<td>16.04</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 25</td>
<td>1.11</td>
<td>12.97</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 32</td>
<td>1.06</td>
<td>7.04</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 24</td>
<td>1.22</td>
<td>37.34</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 05</td>
<td>1.13</td>
<td>25.01</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 25</td>
<td>1.11</td>
<td>12.68</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 15</td>
<td>1.06</td>
<td>7.05</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 24</td>
<td>1.22</td>
<td>37.80</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 33</td>
<td>1.13</td>
<td>23.70</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 05</td>
<td>1.06</td>
<td>16.26</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 25</td>
<td>1.11</td>
<td>15.07</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 32</td>
<td>1.06</td>
<td>7.24</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 24</td>
<td>1.20</td>
<td>37.79</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 33</td>
<td>1.13</td>
<td>23.71</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 05</td>
<td>1.06</td>
<td>16.26</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 25</td>
<td>1.11</td>
<td>15.06</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 32</td>
<td>1.07</td>
<td>7.24</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 24</td>
<td>2.43</td>
<td>38.32</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 33</td>
<td>1.24</td>
<td>27.37</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 05</td>
<td>1.07</td>
<td>15.90</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 25</td>
<td>1.10</td>
<td>15.18</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTP 32</td>
<td>1.07</td>
<td>5.29</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 5: Bank-level RIM report. Counterparts (CTP) and financial products (PROD) are anonymised.
Proceedings of the 16th International Multiconference
INFORMATION SOCIETY – IS 2013
Volume A

Uredili / Edited by

7.–11. oktober 2013 / October 7th–11th, 2013
Ljubljana, Slovenia
Inteligentni sistemi
Izkopavanje znanja in podatkovna skladišča (SiKDD 2013)
Interakcija človek-računalnik v informacijski družbi
Sodelovanje, programska oprema in storitve v informacijski družbi
Kognitivna znanost
Kognitonika
Vzgoja in izobraževanje v informacijski družbi
Srednjeevropska konferenca o uporabnem teoretičnem računalništvu
(MATCOS 2013)

Intelligent Systems
Data Mining and Data Warehouses (SiKDD 2013)
Human-Computer Interaction in Information Society
Collaboration, Software and Services in Information Society
Cognitive Science
Cognitonics
Education in Information Society
Middle-European Conference on Applied Theoretical Computer Science
(MATCOS 2013)

Uredili / Edited by


http://is.ijs.si

7.–11. oktober 2013 / October 7th–11th, 2013
Ljubljana, Slovenia
Uredniki:

prof. dr. Matjaž Gams
Rok Piltaver

prof. dr. Dunja Mladenič
Marko Grobelnik

prof. dr. Franc Novak
Bojan Blažiča
Ciril Bohak
Luka Čehovin

prof. dr. Marjan Heričko

dr. Urban Kordeš
Zala Kurinčič
Katarina Marjanovič
Toma Strle

prof. dr. Vladimir A. Fomichov
prof. dr. Olga S. Fomichova

prof. dr. Vladislav Rajkovič
prof. dr. Tanja Urbančič

dr. Mojca Bernik

prof. dr. Andrej Brodnik

Založnik: Institut »Jožef Stefan«, Ljubljana
Priprava zbornika: Vedrana Vidulin, Mitja Lasič, Vesna Lasič
Oblikovanje naslovnice: Vesna Lasič, Mitja Lasič, Mitja Luštrek

Ljubljana, oktober 2013
Inteligentni sistemi

Intelligent Systems

Uredila / Edited by
Matjaž Gams, Rok Piltaver

http://is.ijs.si

8. in 9. oktober 2013 / October 8th and 9th 2013
Ljubljana, Slovenia