DECISION SUPPORT MODEL FOR THE ASSESSMENT OF BANK REPUTATIONAL RISK

Marko Bohanec[1,*], *Giorgio Aprile*[3], *Maria Costante*[2], *Morena Foti*[2], *Nejc Trdin*[1],
[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.

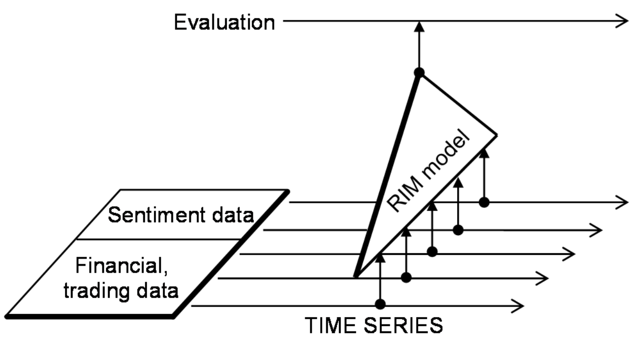

Figure 1: *Basic operational scheme of RIM.*

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.

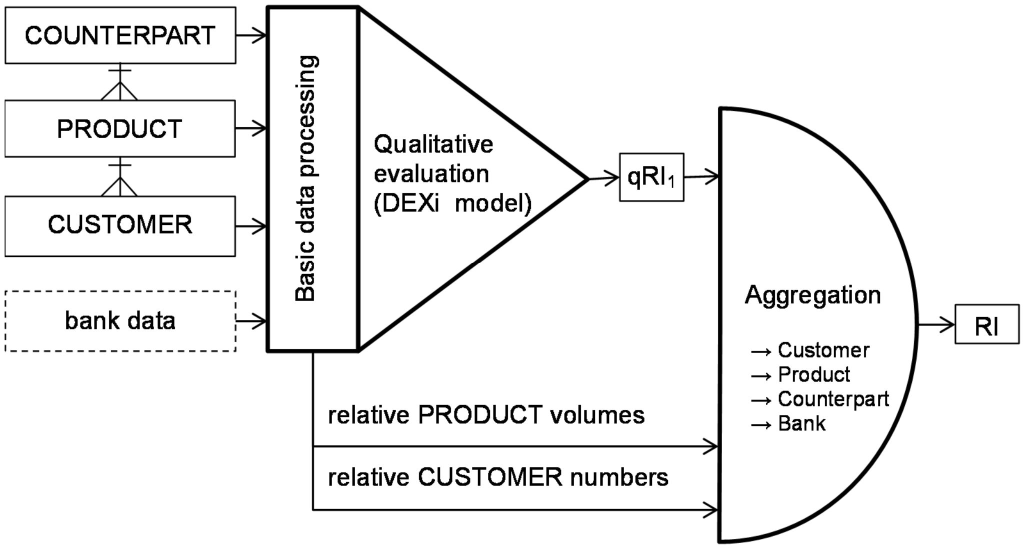

Figure 2: *Architecture and components of RIM.*

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.

Attribute	Scale
qRI1	*low*; *medium-low*; medium; high; very-high
├qS	*neutral*; *low-neg*; med-neg; high-neg; very-neg
├**qPM**	*in-line*; *low*; medium; high; very-high
│ ├qP	*in-line*; *low*; medium; high; very-high
│ └qM	*in-line*; *low*; medium; high; very-high
└qRV1c	*low*; *medium-low*; medium; high; very-high

Figure 3: *Structure and scales of qualitative evaluation attributes.*

The aggregation is implemented as a qualitative multi-attribute model developed according to methodology DEX (Bohanec et al., 2013). This means that all variables in the model are discrete and can take values from small symbolic value scales (Figure 3), and that the aggregation of values in the model is carried out according to expert-defined decision rules. Figure 4 shows an example of rules that aggregate input attributes qP and qM into an internal attribute qPM. For all rules, see FIRST D6.3 (2013).
The final risk qRI_1 is expressed on the five-valued scale: low, medium-low, medium, high, very-high.

	qP	qM	qPM
1	<=*low*	*in-line*	*in-line*
2	*in-line*	*low*:medium	*low*
3	<=medium	*low*	*low*
4	medium	<=*low*	*low*
5	>=medium	*in-line*	*low*
6	*in-line*	high	medium
7	*low*:medium	medium	medium
8	>=high	*low*	medium
9	<=*low*	very-high	high
10	*low*	>=high	high
11	*low*:high	high	high
12	high	medium:high	high
13	>=high	medium	high
14	>=medium	very-high	very-high
15	very-high	>=high	very-high

Figure 4: *Rules for aggregating qP and qM into qPM.*

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 → Product → Counterpart → 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 $RI_i, i = 1,2, \dots, g$, 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

Bohanec, M., Rajkovič, V., Bratko, I., Zupan, B., Žnidaršič, M. (2013): DEX methodology: Three decades of qualitative multi-attribute modelling. *Informatica* 37, 49–54.

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.

FSS (2013). *First Sentiment Service*. http://zabica.ijs.si/FirstSentimentService2/Service.asmx.

JDEXi (2012). *Open-source DEXi Java Library*. http://kt.ijs.si/MarkoBohanec/jdexi.html.

Liu, B. (2010). Sentiment Analysis and Subjectivity. In: *Handbook of Natural Language Processing*, 2nd Edition (eds. N. Indurkhya, F. J. Damerau), Boca Raton: CRC Press.

Settlements, B. f. (2009). *Enhancements to the Basel II Framework.* Basel: BIS committee, July 2009.

Date	RI	Level	RNp%	RVp%	Counterpart	RI	Contr%	Product	RI	Contr%
2013-04-22	2.38	v-high	1.9753	0.3277	CTP 24	2.43	37.36	PROD 0435	2.63	4.09
					CTP 33	1.13	25.02	PROD 0476	2.54	2.77
					CTP 06	1.06	16.05	PROD 0479	2.49	2.18
					CTP 25	1.11	12.68	PROD 0133	2.30	1.71
					CTP 32	1.06	7.04	PROD 0478	2.55	1.66
2013-04-23	1.08	low	1.9750	0.3277	CTP 24	1.22	37.35	PROD 0435	1.38	4.09
					CTP 33	1.13	25.01	PROD 0476	1.00	2.77
					CTP 06	1.06	16.04	PROD 0479	1.03	2.18
					CTP 25	1.11	12.67	PROD 0133	1.39	1.71
					CTP 32	1.06	7.04	PROD 0478	1.00	1.66
2013-04-24	1.08	low	1.9755	0.3278	CTP 24	1.22	37.34	PROD 0435	1.38	4.09
					CTP 33	1.13	25.01	PROD 0476	1.00	2.77
					CTP 06	1.06	16.03	PROD 0479	1.03	2.18
					CTP 25	1.11	12.68	PROD 0133	1.38	1.71
					CTP 32	1.06	7.05	PROD 0478	1.00	1.66
2013-04-25	1.08	low	1.9276	0.3253	CTP 24	1.22	37.80	PROD 0435	1.38	4.09
					CTP 33	1.13	23.70	PROD 0476	1.00	2.77
					CTP 06	1.06	16.26	PROD 0479	1.03	2.18
					CTP 25	1.11	13.07	PROD 0133	1.39	1.71
					CTP 32	1.06	7.24	PROD 0478	1.00	1.66
2013-04-26	1.05	low	1.9283	0.3253	CTP 24	1.20	37.79	PROD 0435	1.23	4.09
					CTP 33	1.13	23.71	PROD 0476	1.00	2.77
					CTP 06	1.06	16.26	PROD 0479	1.01	2.18
					CTP 25	1.11	13.06	PROD 0133	1.27	1.71
					CTP 32	1.07	7.24	PROD 0478	1.00	1.66
2013-04-29	2.39	v-high	1.8710	0.3302	CTP 24	2.43	38.32	PROD 0435	2.62	4.14
					CTP 33	1.14	27.37	PROD 0476	2.54	2.78
					CTP 06	1.07	13.90	PROD 0479	2.48	2.19
					CTP 25	1.10	13.18	PROD 0133	2.36	1.77
					CTP 32	1.07	5.29	PROD 0478	2.55	1.66

Figure 5: *Bank-level RIM report. Counterparts (CTP) and financial products (PROD) are anonymised.*

Zbornik 16. mednarodne multikonference

INFORMACIJSKA DRUŽBA – IS 2013

Zvezek A

Proceedings of the 16th International Multiconference

INFORMATION SOCIETY – IS 2013

Volume A

Uredili / Edited by

Matjaž Gams, Rok Piltaver, Dunja Mladenić, Marko Grobelnik, Franc Novak, Bojan Blažica, Ciril Bohak, Luka Čehovin, Marjan Heričko, Urban Kordeš, Zala Kurinčič, Katarina Marjanovič, Toma Strle, Vladimir A. Fomichov, Olga S. Fomichova, Vladislav Rajkovič, Tanja Urbančič, Mojca Bernik, Andrej Brodnik

7.–11. oktober 2013 / October 7th–11th, 2013

Ljubljana, Slovenia

Zbornik 16. mednarodne multikonference

INFORMACIJSKA DRUŽBA – IS 2013

Zvezek A

Proceedings of the 16th International Multiconference

INFORMATION SOCIETY – IS 2013

Volume A

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

Matjaž Gams, Rok Piltaver, Dunja Mladenić, Marko Grobelnik, Franc Novak, Bojan Blažica, Ciril Bohak, Luka Čehovin, Marjan Heričko, Urban Kordeš, Zala Kurinčič, Katarina Marjanovič, Toma Strle, Vladimir A. Fomichov, Olga S. Fomichova, Vladislav Rajkovič, Tanja Urbančič, Mojca Bernik, Andrej Brodnik

http://is.ijs.si

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

Uredniki:

prof. dr. Matjaž Gams
Rok Piltaver

prof. dr. Dunja Mladenić
Marko Grobelnik

prof. dr. Franc Novak
Bojan Blažica
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

Zbornik 16. mednarodne multikonference

INFORMACIJSKA DRUŽBA – IS 2013

Proceedings of the 16th International Multiconference

INFORMATION SOCIETY – IS 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