BLED 2013 Proceedings BLED Proceedings

7-2013

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26th Bled eConference

eInnovations:
Challenges and Impacts for Individuals, Organizations and Society

June 9, 2013 – June 13, 2013; Bled, Slovenia

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Abstract

The emergence of online financial information channels, such as web portals and financial blogs, eases the challenge process for scammers of publishing fraudulent contents in order to manipulate share prices. To maintain market integrity, financial market surveillance authorities monitor these different information channels to detect suspicious behaviour. However, as the available amount of online information increases, analyses become more costly and time-consuming. In order to support related decisions, we have developed a model to identify fraudulent situations. Based on interviews with domain experts, we first identified the factors determining suspicious situations and then applied a qualitative multi-attribute modelling technique. Thereby, our resulting model builds upon valuable knowledge of domain experts and provides means to address the challenge of information based market manipulation.

Keywords: Market Manipulation, Market Surveillance, Qualitative Modelling, Decision Support

1 Introduction

With an increasing number of market manipulation cases observed in recent years, financial market surveillance has gained increased attention in both practice and academia. In one recent case1, a prominent US-celebrity published a recommendation for a penny stock investment on Twitter of which he held a significant position. Generally, such stock

1 Chris Barth, Forbes staff: http://www.forbes.com/sites/chrisbarth/2011/01/11/get-rich-or-die-tweetin/

promotions, if distributed to a large audience, can lead to significant price effects for the respective penny stock, causing abnormally high returns. After these returns are realized, the promoter sells his stocks and since there was no significant change of the company's real value, the other investors run the risk of losing their money due to falling stock prices. Many private investors lack the necessary financial knowledge to judge this situation and are thus particularly vulnerable to such fraudulent stock promotions that make up these so-called "Pump and Dump" (P&D) market manipulation schemes2.

In order to address such market integrity threats, surveillance authorities need to gain insights into the manipulative behaviour of market participants. However, being aware of different information channels and diverse manipulation activities, this task remains cost-intensive and requires a lot of effort. As the available budget of market surveillance authorities is limited (Aggarwal & Wu, 2003), decision support systems may therefore contribute within this context.

This research contributes to the on-going discussion of how to support financial market surveillance authorities by analysing data published in several web-based social networks and portals. Based on expert interviews, during several iterations, we derive the essential indicators for the decision regarding whether a certain financial instrument is suspected of manipulation by a P&D scheme.

We present our research contribution in the form of an IT artefact, developed within a multinational design science research project. In doing so, we present a qualitative model that can support users in the decision-making process. We apply a qualitative multi-attribute modelling method to develop a corresponding model, which belongs to the hierarchical decision-making models being suitable for unstructured decision problems (Aggarwal & Wu, 2003), (Ou, Cao, Yu, & Zhang, 2007).

This paper is organized as follows: In the next section, we provide a review of the related work followed by a description our methodology. In the subsequent sections, we present our design principles, the model and the experimental results. Finally, we conclude and provide an outlook on future work.

2 Related Work

In the financial domain, there exists a variety of different market manipulation schemes. An overview and classification of these schemes is provided by (Allen & Gale, 1992), (Bagnoli & Lipman, 1996), (Aggarwal & Wu, 2003), (Mei, Wu, & Zhou, 2004), covering action-based, trade-based, and information-based manipulation schemes. Trade-based manipulation is defined as the action of buying and then selling, whereas information-based manipulation is defined as the publication of false information or false rumours. Thus, action-based manipulation is defined as the actions which are non-trade-based and non-information-based actions.

2 The U. S. Securities and Exchange Commission (SEC): P&D Schemes, http://www.sec.gov/answers/pumpdump.htm

Related to price and volume manipulation, a variety of schemes exists: For example, ramping/gouging, where the broker bluffs the enthusiastic in a specific stock. Another scheme is so called pre-arranged trading, where the participants enters identical price and volume orders at the same time. The next scheme is P&D manipulation scheme. P&D manipulations aims at manipulating the share price by disseminating untrue information in order to make profit from an increased price level ((Cumming, Zhan, & Aitken, 2012), (Aggarwal & Wu, 2003)). If P&D manipulation is defined as a kind of information-based manipulation, we can thus argue that 50-Cent's behaviour can be classified as information-based market manipulation due the following reasons: First, faulty and misleading information was spread in a persuasive manner, such as "You can double your money right now. Just get what you can afford". Second, the information was spread over his Twitter account, where it was received by his 3.8 million followers. Finally, he promoted a company whose shares he owns. Taken together, this behaviour caused an artificial increase of the stock price, which, when shares were sold at the end of the day, resulted in a breath-taking profit of 8.7 Mio$. Helpful insights on how to address such manipulation schemes from a market surveillance perspective are presented by (Aggarwal & Wu, 2003). Based on structured data such as the time series, the authors explore how market manipulation affects market efficiency. They show that prices rise during the manipulation phase, only to fall when the manipulation concludes. As noted by (Kirkos, Spathis, & Manolopoulos, 2007) there is little research that utilizes the rich universe of unstructured (i.e. textual) data to support market surveillance activities.

Other research scrutinizes the real-time detection of fraudulent activities (Mukherjee, Diwan, Bhattacharjee, Mukherjee, & Misra, 2010). The authors present an information system (IS) for compliance offices for monitoring investment staff by detecting outliers and by performing evaluations along predefined rules. The predefined rules for example assess significant trading volumes observed. With the objective to utilize both structured and unstructured data sources, qualitative multi-attribute model may serve as a basis to address this challenge.

Qualitative multi-attribute models utilize data and values proposed by decision makers, usually domain experts, in order to analyse and address a situation. The qualitative models thus remain highly suitable for unstructured decision problems where approximate judgment prevails over precise numerical calculations (Bohanec, 2003). In previous academic research, qualitative multi-attribute modelling was successfully applied in different domains, including e-learning and ecology (Arh & Blažič, 2007). While we observe a high grade of specialisation in the financial domain, there is little research applying qualitative multi-attribute models to build upon the extensive knowledge of domain experts, especially in the field of market surveillance. Thus, in this research, we aim to contribute to the knowledge base and apply the qualitative multi-attribute modelling approach in the market surveillance domain. Therefore, we have developed a qualitative multi-attribute model, which aims at detecting information-based market manipulation in the form of P&D schemes utilizing both structured and unstructured data.

3 Methodology

3.1 Design Science Research Approach

Design science research is one of the prominent research paradigms that has driven a research stream in information systems discipline, with the goal of making contributions to the knowledge base on the basis of developed IT Artefacts (Hevner, March, Park, & Ram, 2004). According to the authors, four different types exist: constructs, models, methods, and instantiations. Constructs provide a language for the definition and the communication of the problem and its solution. Models represent the relationships between the constructs. Methods represent procedures to perform specific tasks. Finally, instantiations are based on constructs, models, and methods expressing the implementation in working systems. Because, our research effort aims on providing a set of steps for a specific problem solution, therefore, our artefact belongs to the group of the model artefacts.

As illustrated by (Vaishnavi & Kuechler, 2008), typical design science research projects follows a series of steps:

I. Awareness of the problem: The first step aims at identifying the problem by conducting the literature review. Within the same step, a drill-down into the problem is required in order to explore the user needs.
II. Suggestion: After the user needs are explored, potential decision alternatives can be suggested. In this step, the complexity of the whole problem is decomposed to problems of lower complexity.
III. Development: The aim of the third step is to deliver an artefact, which in our case is a qualitative multi-attribute model.
IV. Evaluation: After the artefact is being developed, the evaluation aims at exploring its functionalities and performance.
V. Conclusion: The design cycle ends by providing judgements on the developed artefact.

In our research efforts, we adapt these general process steps to guide our development of the artefact.

3.2 Qualitative Multi-Attribute Modelling Methodology

Within the development phase III, we aim to develop a qualitative multi-attribute model to assess decision alternatives. The models can be developed in several different ways; the most common is via expert modelling. The model is developed on the basis of interviews with experts. Qualitative multi-attribute modelling is being conducted in a series of four steps (Bohanec, 2003):

1. Identifying attributes: Aims at identifying the important attributes of the decision problem.
2. Structuring attributes: Aims at composing the attributes into hierarchical groups, and enabling decomposing into smaller and possibly more manageable sub-problems.

Thus, in this step, we are able to present our model. The model is refined within of the following two steps of defining scales and rules.

3. Defining attribute scales: aims at describing the scales of each attribute (e.g. very-low, low, medium, high, very-high).
4. Defining aggregation rules: based on the step before, the scales are evaluated individually and then aggregated by the model into an overall utility: The higher the utility, the appropriate alternative.

Once developed, qualitative models specify a working method of the evaluation of "objects", which can be easily embedded into software systems such as a decision support system. For the development and the experimental evaluation of our qualitative multi-attribute model, we use the DEXi software (Bohanec & Rajkovič, 1990).

3.3 Proposed Research Design

In our research, we combine the general design process cycle of design science research (Vaishnavi & Kuechler, 2008) and the qualitative multi-attribute modelling methodology (Bohanec, 2003) to guide our model development. Our resulting research approach is represented in Figure 1.

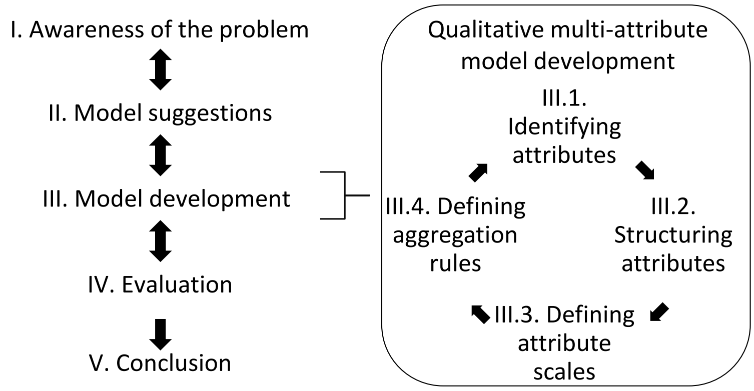

Figure 1: Research approach based on (Vaishnavi & Kuechler, 2008) and (Bohanec, 2003)

In the subsequent section, we explain the development of our artefact. Here, we follow design step I, II as suggested by (Vaishnavi & Kuechler, 2008); step III constitutes the development of our qualitative model; steps IV and V are presented thereafter.

4 Problem Definition

The goal of the first process step is to generate problem awareness through identification and definition of the specific decision problem. We conduct this step by means of both a survey of related academic literature exploring the problem and an investigation of the user-specific needs. We initially agree with the definition of financial surveillance as stated by (Heping, 2006), namely that such surveillance "[…] refers to a comprehensive non-stop process of a fully automated or interactive intelligent financial system(s) for continuous monitoring of the target markets." (p. 2/15). Furthermore, we use the definition of P&D schemes as stated by (Kyle & Viswanathan, 2008), that "In a pump-and-dump manipulation scheme, the perpetrator first acquires a large long position, then publishes false information to induce market participants to push prices up by buying the asset, and finally liquidates his own long position at a profit”, (p. 276).

Due to the fact that the amount of information published in different online media is increasing continuously, our study focuses on the detection of P&D market manipulation scenarios like the ‘50 Cent’ example. To fully understand the problem at hand, we identified four people working in a market surveillance context who have both substantial knowledge about various market manipulation schemes and experience with systems for detecting financial market manipulations. One expert has 20 years of experience as a decision maker, another two with approx. 10 years’ experience in developing market surveillance solutions. The fourth one is an expert of a European financial regulatory authority. In several interviews, the experts were asked to explain typical factors for P&D market manipulations. The questions posed to them are grouped into three categories (Table 1).

Category	Explanation
Problem description	Precisely define the problem. What do we access? What is the decision about? Is the multi-attribute modelling a suitable approach to the problem? Who are the actors? Who is affected and who is responsible for the decision?
Requirements description	What are the goals and functionalities of an appropriate problem solution?
Relevant inputs for addressing requirements	What are the characteristics of typical pump-and-dump scenarios? How can P&D be detected, what parameters/variables need to be observed? What are the parameters/variables and their meanings? Which factors/aspects must one take into account when scanning the market by hand in order to detect market manipulation? Can those factors/aspects be measured? Are ordinal qualitative scales of measurement appropriate (e.g., high, low, medium)? What could an entity-relationship-model look like? What are the relations between them? What kind of data do we require?

Table 1: Interview structure for problem definition

5 Decision Model Suggestion

In the interviews, one of the main requirements identified is the generation of a market surveillance indicator, i.e., an alert. Such a surveillance indicator would support the decision of the compliance officer (e.g., regulatory authority) which is decomposed into investigating the suspicious trading behaviour, then communicating the suspicious behaviour with the source before escalating the situation and taking further steps if necessary. The detection of suspicious market behaviour appears to be a complex problem in the means of deciding which of the observed patterns are suspicious and which are not. Therefore, we aimed at developing a qualitative multi-attribute decision model to support decision alternatives by assessing suspicious or non- suspicious market situations.

6 Qualitative Multi-Attribute Model Development

6.1 Attribute Identification

In the interview context, the experts stated that a main determinant of P&D manipulations is "The publication of untrue information within different news channels". Furthermore, the experts stated that this kind of news covers certain financial instruments, which are issued by certain companies. Consequently, the P&D problem is divided into these main attributes: news, financial instruments and companies. Thereafter, in telephone interviews and further face-to-face meetings, the lists of attributes have been refined. Thus, the detection of suspicious situations is based on the following considerations:

- Company: Previous research shows that companies whose stocks are recommended in P&D market manipulation schemes mostly lack prospect business (Rockness & Williams, 1988). In order to determine whether a company is suspicious, the experts consider two possibilities. First, if a company has already been part of such a manipulation. As one of the experts stated: "Financial regulators frequently issue warnings or litigation releases, and the company is put on a blacklist of suspicious firms". Second, the history of the company is taken into account. The experts state that: "Market manipulators usually target new companies or companies that have been bankrupt". An examination into the company's history can uncover aspects of company's past practices which could justify doubts regarding the reliability of its market activity. Accordingly, the attribute 'Company' is refined by attributes 'Blacklists' and 'History'.
- Financial Instrument: The financial instrument also needs to be assessed in order to detect potentially suspicious situations. In this case, the experts focus on the question of whether the financial instrument is listed in a suspicious market segment, i.e., "…in a segment with low regulatory requirements, it is easier to published manipulated information in the form of corporate disclosures, among other things". Furthermore, the experts state: "low market capitalization" is seen as an "additional indicator of a suspicious financial instrument" since corresponding stock prices can adjust on the basis of lower trading volumes, (as opposed to large-capitalized stocks). Finally, a significant change in trading volume or trading behaviour can also be seen as suspicious. Accordingly, the attribute 'Financial Instrument' is refined by attributes 'Market Segment' and 'Market Capitalization'.
- The Attribute 'News' estimates the suspiciousness of published news based on following criteria:
    - Content: Covers, as stated by one of the experts: "Whether the web publication includes specific content, e.g. increase in revenue, new product development". The sub-model assesses suspiciousness according to content considered over predefined periods of time.

- Sentiment: Incorporates the sentiment expressed within the news source. In this respect, the experts state that "A positive significant change in sentiment could indicate a suspicious situation". Therefore, the sub-model assesses the suspiciousness of estimated sentiments over a predefined period and compares it with the sentiments of a longer period.

6.2 Attribute Structure

As a result of the conducted interviews, the model was extended. In this context, the interrelations between the attributes have been defined. Hereafter, three main groups of attributes were identified as illustrated in Figure 2:

Company:
- History
  - Age
  - Bankrupt
- Blacklist
  - Country black list
  - Industry black list
  - Company black list

Financial Instrument:
- Market
  - Segment
  - Capitalization
- Trading
  - Volume
  - Number of trades

News:
- Content
- Sentiment

Figure 2: Structured attributes for assessment of P&D cases

On the basis of further interviews, we developed an attribute structure in the form a hierarchical tree. The model is refined into attributes which can be structured and measured so that finally the attributes can be represented as tree of attributes (Bohanec, 2003). In the model, the problem is decomposed into various components, namely:

- Root node, as the target attribute, representing an indicator which determines whether a suspicious market situation prevails.
- Internal set of aggregated attributes (e.g. 'History'), which is used to structure the attributes relevant to the decision.
- Final set of basic attributes (e.g. 'Country Blacklist'), representing attributes that can be measured, e.g. by means of data analysis.

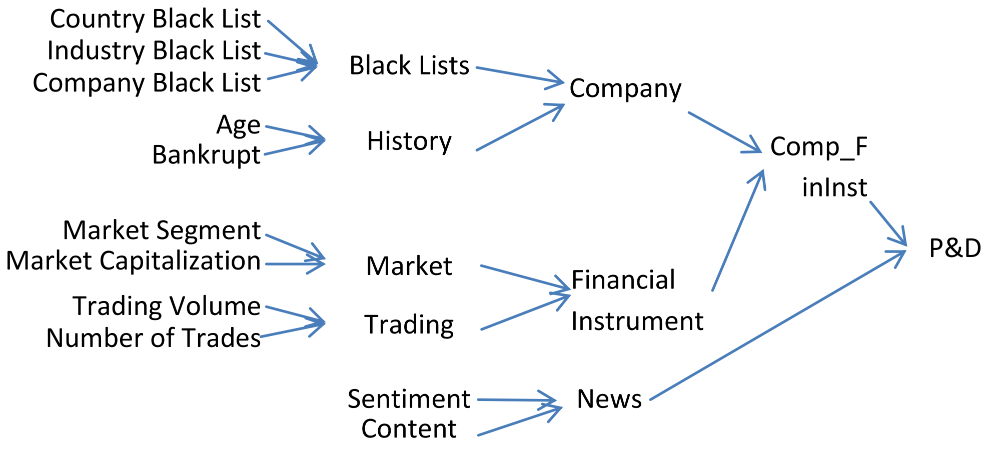

Figure 3: Model of attribute structure

Error! Reference source not found. represents the tree structure of the proposed model. We derive two sub trees: A sub tree for the news, and a sub tree for the company and the related financial instrument.

6.3 Attribute Scales

The value scales for each attribute are set in cooperation with the domain experts. Each attribute can take values from the corresponding scale. Most scales are ordered from 'good' values (non-suspicious situation) to 'bad' (indicating a highly suspicious situation). For example, the attribute 'CountryBlackList' can either be 'yes' or 'no'. If a company originates from a country which is black-listed, the corresponding value will be set to 'yes'. Such country blacklists are provided by regulatory authorities. The complex aggregated attributes (Comp_FinInst, Company, Black Lists, History, Financial Instrument, Market, Trading, and News), are dependent upon the lower level attributes (Country-, Industry-, Company Black List, Age, Bankrupt, Market Segment, Market Capitalization, Trading Volume, Number of Trades, Sentiment, and Content). The scales then consist of three to five values:

- P&D: The high level attribute is an aggregated attribute. It indicates the suspiciousness of P&D situations. The values v-high, high, med, low, v-low indicate the suspiciousness.
- Comp_FinInst: The aggregated attribute. It detects the suspiciousness for the attributes Company and Financial Instrument, and is labelled as v-high, high, med, low or v-low.
- Company: The aggregated attribute of Black Lists and History. Assess the potential suspiciousness of the company as v-high, high, med, low or v-low
- Black Lists: If the company appear in any of the blacklist, then the aggregated attribute is labelled as low, medium or high.
- Country-, Company- , and Industry blacklists: The values are either yes, indicating the appearance in the list, or no.

  - Country Blacklist: Countries which do not rely on the global international standard (FATF – The Financial Action Task Force) to combat money laundry and terrorism. The current lists can be accessed via the FATF3.
  - Industry black list: There is no black list predefined by a reputable organisation such as a regulatory authority. However, it became apparent that suspicious financial instruments are oftentimes issued by companies for which it is not clear in which industry they are operating in. The experts state that, if this information is available from data vendors for financial instruments and the issuing companies, then it is considered to be reputable. In Contrast, missing industry type data can be seen as suspicious.
  - Company black list: Companies who are either not approved by a regulatory body or are involved in stock fraud, can be found on e.g. the SEC list4.
- History: The aggregated value indicates the suspiciousness as low, medium or high.
  - Age: The low level attribute indicates the suspiciousness as old, med or new. Where old stands for older companies. In our case, the experts define old >10 years.
  - Bankrupt: If the company was insolvent/bankrupt in its history, the low level attribute can be labelled as was, no or is.
  - Financial Instrument: The aggregate attribute, which assess the potential suspiciousness of the financial instrument, is labelled as v-high, high, med, low or v-low.
- Market: The aggregated attribute assess the potential suspiciousness of the market with the labels low, med or high.
  - Market Segment: If the market segment is potentially suspicious then, the label ‘yes’ appears. Otherwise, the label ‘no’.
  - Market Capitalization: Small capitalization is labelled ‘low’. In our case, according to the experts, small capitalization appears to be less than 5Mio$. High capitalization is defined as more than 30 Mio$. The range between 5 and 30 Mio$ is labelled as ‘med’.
- Trading: The aggregated attribute assesses the potential suspiciousness of the trading behaviour and is labelled low, med, and high.
  - Trading Volume: Recent changes in the market volume are labelled low, med or high.
  - Number of Trades: Recent changes of number of trades are labelled low, med or high.

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3 http://www.fatf-gafi.org/topics/high-riskandnon-cooperativejurisdictions/documents/fatfpublicstatement-16february2012.htm
4 http://www.sec.gov/litigation/suspensions/2012/34-66980.pdf

- News: Aggregates the attributes Sentiment and Content. Assesses the potential suspiciousness of a news, and is labelled as v-high, high, med, low or v-low
    - Sentiment: Assessment of the long and short term sentiment. Indicates the change between long and short term sentiment, and is labelled as v-high, high, med, low or v-low.
    - Content: Assessment of the long and short content. Indicates the change between long and short term content. Assess the recent changes in the suspiciousness of the news, and is labelled as v-high, high, med, low or v-low.

6.4 Aggregation Rules

In qualitative models, decision rules serve as the aggregation of values from the basic to the root attribute. For each aggregate attribute in the model, a table of rules specifying the values of the said attributes for all combinations of values in the lower-level attributes is defined by the interviewed domain experts. The root attribute 'P&D', for example, depends on the lower-level attributes 'Comp_FinInst' and 'News'. The corresponding decision rules have been defined as shown in Figure 4. Rules 24, and 25 illustrate situations of very high suspiciousness, which occur whenever 'News' and 'Comp_FinInst' are either high or very-high. Rule 1, however, demonstrates that the suspiciousness of a situation is very low only when the attributes 'News' and 'Comp_FinInst' are both of very low suspiciousness.

	Comp_FinInst	News	P&D
1	v-low	v-low	**v-low**
2	v-low	low	**low**
3	v-low	med	**low**
4	v-low	high	**med**
5	v-low	v-high	**high**
6	low	v-low	**low**
7	low	low	**low**
8	low	med	**med**
9	low	high	**med**
10	low	v-high	**high**
11	med	v-low	**low**
12	med	low	**med**
13	med	med	**med**
14	med	high	**high**
15	med	v-high	**high**
16	high	v-low	**med**
17	high	low	**med**
18	high	med	**high**
19	high	high	**high**
20	high	v-high	**v-high**
21	v-high	v-low	**high**
22	v-high	low	**high**
23	v-high	med	**high**
24	v-high	high	**v-high**
25	v-high	v-high	**v-high**

Figure 4: Decision rules for P&D attribute

7 Experimental Evaluation of the Qualitative Multi-Attribute Model

In order to demonstrate the validity of the developed model, we go along with (Hevner et al., 2004)'s suggested experimental evaluation. Following the approach by using the evaluation functionality of the DEXi software, we are able to evaluate the behaviour of the model. In the following paragraphs, we explain the functional experiment.

The proposed model is implemented with DEXi software and used for the evaluation and analysis of suspicious situations. The evaluation is designed to reveal the different levels of suspiciousness in potential P&D cases. Figure 5 shows the input data and results of the evaluations of five hypothetical situations.

The first of these situations appears not suspicious given the specific attribute values. The consequent evaluation yields only low and very low values with all the aggregate attributes. In contrast, the last two situations are assessed as high and v-high suspicious, as an inspection of the internal model variables reveals. The fourth and fifth situations are suspicious, the former due to the high volume of highly positive news and the latter as a result of several elements, among them, the company's appearance on the black list, it's recent entry into the market, its unusually high trading volume of the financial instrument. In the last situation, there is also an indication that short-term sentiment in the news is perhaps too positive.

Once complete, the results of this evaluation can be presented to the domain experts in order to appraise the decision rules of the model. Although these results are based on those decision rules developed in cooperation with the same domain experts, these exemplary results can lead to further reflections on the model and a further adjustment or refinement of its components.

Attribute	V-low susp.	Low susp.	Med. susp.	High susp.	V-high susp.
P&D	v-low	low	med	high	v-high
├**Comp_FinInst**	v-low	low	med	med	high
│├**Company**	v-low	low	high	high	high
││├**BlackLists**	low	med	high	high	high
│││├CountryBlackList	no	no	no	no	yes
│││├IndustryBlackList	no	yes	yes	yes	yes
│││└CompanyBlackList	no	no	yes	yes	yes
││└**History**	low	low	low	med	med
││ ├Age	old	med	med	new	new
││ └Bankrupt	no	no	no	no	no
│└**FinancialInstrument**	v-low	low	low	low	high
│ ├**Market**	low	low	low	low	med
│ │├MarketSegment	no	no	no	no	no
│ │└MarketCapitalization	high	med	med	med	low
│ └**Trading**	low	med	med	med	high
│ ├TradingVolume	low	med	med	med	high
│ └NumberOfTrades	low	med	med	med	high
└**News**	v-low	low	med	high	v-high
├Sentiment	v-low	low	med	high	v-high
└Content	v-low	low	med	high	v-high

Figure 5: Evaluation examples

Within our expert interviews as well as during the regular project meetings, the outcomes of these evaluations have been presented and discussed with both domain experts as well with a representative of a European national financial supervisory authority. Feedback has been used to refine the decision rules, which finally brought us a stable set of these rules.

8 Conclusion

The fraudulent behaviour of market participants represents a topic that has gained increased importance within financial markets. Market surveillance combined with decision support systems enable appropriate analyses of large amounts of data to support decision making in this field. One severe market manipulation scenario is P&D schemes, where manipulators aim to increase stock prices by dissemination positive but false information in order to sell these stocks at a profit. Within our research, we experienced that detecting related market manipulations requires a great amount of expert knowledge. Therefore we applied qualitative multi-attribute modelling in order to derive a decision model from expert interviews that includes the different factors influencing whether or not a financial instrument is affected by a P&D scheme. The proposed model is developed by means of the DEXi software.

From a theoretical perspective, we contribute to the literature on financial market surveillance, especially with regard to the explanation of what factors characterize P&D market manipulations. Based on expert interviews, we find that company and financial instrument characteristics, as well as news-related characteristics like sentiment and content, play a crucial role in identifying P&D market manipulations. Furthermore, the qualitative model also provides insight as to how these different factors are interconnected. From a practical point of view, we provide a decision model that can be included in decision support systems to assist surveillance authorities in identifying suspicious market situations.

With further research, we plan to extend the evaluation of our model with both real and artificial data. Our intention is to acquire fraudulent cases from market surveillance authorities that can be used to evaluate the decision model; however, we are aware that related information is not easy to obtain and that a consequent evaluation with artificial data would be more appropriate. For this purpose, we will generate different attribute values for the input parameters and consider the decision models' output. As a next step, we will evaluate whether the domain experts agree with the models' classifications. The model at hand, however, already provides valuable insights into which factors are essential to assess whether a certain financial instrument is suspected of manipulation by a P&D schema.

Acknowledgement

The research leading to these results has received funding from the European Community's Seventh Framework Programme (FP7/2007-2013) within the context of the Project FIRST, Large scale information extraction and integration infrastructure for supporting financial decision making, under grant agreement n. 257928.

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