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A PRACTICAL RISK MANAGEMENT FRAMEWORK FOR INTELLIGENT INFORMATION SYSTEMS

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Abstract

This paper reports progress towards the development of a practical risk analysis and management framework for intelligent information systems based on the state-of-art techniques in uncertainty management. We provide an analysis of challenges raised by the need to manage risk and identify a set of key requirements for a practical framework that can support risk management in real environments that are open, complex and dynamic. We assess a number of relevant theories, approaches and techniques for their suitability in addressing the risk management challenges. Finally, we present our current multi-level risk analysis and modelling framework, and use benchmark problems in two entirely different domains to illustrate the broad range of our framework applicability.

Keywords: Knowledge management, Risk analysis, Risk modeling, Intelligent systems.

1 INTRODUCTION

Risk is inherent in almost every aspect of life, and as a result, being able to deal with risks rationally and effectively is crucially important for an intelligent information system (or agent) to perform its functions and achieve its objectives. For example, in foreign exchange markets, it is crucial for computerised treasury management systems to be able to respond to volatile market conditions and minimise various risks for many businesses to remain viable. Robotic soccer players are also intelligent agents (Kitano 1998) that need to respond to external environment and minimise risks such as interception by opponent robot during a ball passing operation. Unfortunately, the concept of risk usually carries different meanings in different domains, and there is no precise and generally accepted definition for risk. Furthermore, in the real world, we frequently operate in complex and dynamic environments where dealing with various risks in a consistent manner is very difficult and laborious. In this paper we show how utilising ideas and techniques from Artificial Intelligent (AI) research, we can develop intelligent systems and software tools that can assist us in dealing with risks. Even though managing risks has not been a main focus in AI research, there is a strong tradition and extensive work in dealing and modelling uncertain information in decision making. Our research aims to develop a formal and practical approach to risk modelling and management for information systems operate in *open*, *dynamic* and *complex* environments inspired by existing theories and techniques developed in the AI.

This paper demonstrates the ideas and significances of our current framework. Most of the technical details are omitted, i.e. theorems and formulae are not included, so that we can focus on the significance and innovation of the framework using only the level of details required to justify it. Readers interested in the technical details can find them in the references provided. The paper is organised as follows: we first give a short survey of definitions of risk from the research literature and present our own practical definition of risk. We will briefly discuss some of the important properties of risk that any risk management system must address. In section 3, we discuss what an open, dynamic and complex environment means and the requirements for our framework to be able to operate under such conditions. In section 4, we briefly survey several relevant theories and techniques developed in the AI research and discuss their applicability. In section 5, we present a three-level conceptual risk management framework and our own iterative risk analysis and modelling process. Finally, we conclude with a summary and brief discussion on the current progress. Throughout this paper we draw on two different but challenging domains: treasury risk management by businesses, and risk management by mobile robots.

2 A DEFINITION OF RISK

The concept of risk is complex and has not been precisely defined for general applications. Although people share a general notion of risk, it often carries different technical meanings in different domains and can be interpreted from different perspectives (Aven 2008; Tapiero 2004; Kaplan et al. 1981). In order to develop a framework for risk management for intelligent information systems that support or enact decisions, we develop a practical definition by combining common and essential notions of risk. Our risk model construction process is based upon this definition as given below:

Definition 1: A **risk** is a combination of the uncertainty of occurrence of a possible outcome from an initial event and the associated positive or negative payoff of the outcome on an intelligent (information) system with respect to achieving its goal(s).

Definition 2: A **scenario** is the possible outcome or event associated with a risk.

In this paper, we focus on the two properties of risk namely, uncertainty and consequences associated with possible scenarios. Both properties are strongly dependent on the task domain, system capabilities and the environment. Any useful risk modelling and management will require detailed analysis of the objectives, the domain, the environment, the system and the possible scenarios/outcome that may be encountered. We use two specific benchmark problems to further our discussions.

2.1 Benchmark Problems for Risk Modelling

Based on our definition of risk, we analyse and describe the benchmark problems in terms of *Task/Goal*, the *Environment*, the *Initial Event*, all possible *Scenarios* and all other *Associated Factors*. This simple domain analysis and problem description technique is significantly influenced by Aven (2008). Note that both benchmark problems as presented below have been simplified. We rely mostly on the first example for explanation and illustrate our framework; while using the second example to raise some interesting issues in developing a risk model.

2.1.1 Benchmark Problem 1 – Ball Passing Problem

For many years, RoboCup has been one of the driving forces behind advancing and applying theoretical ideas in AI to real world applications. One of the major challenges in robot soccer matches is ball passing between two robot teammates. There is still little deliberate ball passing between robots after many years of competitions. The ball passing problem presents a rich scenario which enables the exploration and analysis of various risk factors; events involved in passing a ball and building risk models of increasing sophistication. It is also an excellent benchmark risk management problem because it is a real world problem where empirical data and experimental results can be collected and the performance of risk modelling methods can be examined, compared, tested, and evaluated. We give a clear description of this problem in following format:

Task/Goal: Passing a ball between two NAO robots¹.

Environment: A RoboCup NAO soccer match with two opposing teams and each team is comprised of four identical robots.

Initial Event: One robot attempts to kick a ball towards one of its teammates, the receiver.

Scenarios: Final outcomes of the initial event are summarised in the Table 1. They are simplified scenarios, which allow us to highlight important features of our risk modelling approach.

SCENARIO	DESCRIPTION	PAYOFF
S_1	Ball kicked and caught by R_B .	1
S_2	Ball kicked and intercepted by an opposition robot.	-1
S_3	Failed to kick the ball.	-0.2

Table 1. A simplified analysis of possible scenarios for ball passing.

Associated Factors/Variables: Distance (D): Distance between R_A and R_B is 20 centimetres (in our example instance); Nearby Robots (NR): Any nearby robots (either friendly or hostile excluding R_B) could possibly intercept the ball.

2.1.2 Benchmark Problem 2 – Risk Management on Foreign Exchange (FX) Market

The Australian dollar is one of the most traded currencies on open foreign exchange markets. It is also one of the most volatile currencies in the market. It is crucial for many companies in the business of importing/exporting goods in Australia to manage their foreign exchange exposures carefully in order to minimise possible loss due to fluctuations in the exchange rate (Abbot 2009). A domain such as the foreign exchange market is extremely complex and dynamic. There are many macroeconomic and microeconomic factors influencing the Australia dollar exchange rate. Therefore, modelling and managing the risks is difficult task. We consider a simple risk modelling scenario from the perspective of an importer.

Task/Goal: Maintain a neutral foreign exchange position.

Environment: Australia-US dollar exchange rate fluctuates 0.5% on weekly basis. The firm imports large quantities of electronic goods that take one to two months to manufacture and two weeks for shipment. Payments for the goods is paid in single or multiple instalments.

Initial Event: The firm made a large order and the payment for the goods is made in two separate instalments.

SCENARIO	DESCRIPTION	PAYOFF
S_1	Oversee manufacturer willing to absorb the risk	0
S_2	No currency hedging. Financial losses due to lowing of AUD.	-1
S_3	No currency hedging. Minor financial gain due rise of AUD.	0.7
S_4	100 % currency hedging. No net losses and cost of hedging.	0.2

Table 2. A simplified analysis of possible scenarios for FX risk in Australian Dollars.

Associated Factors/Variables: Official Interest Rate (I); Global economic outlook (G); Currency hedging costs (CH); Current US dollar reserve within the company (R); and many more, some known and some unknown.

3 FRAMEWORK REQUIREMENTS

The key objective of our work is to develop a practical framework for risk analysis, modelling and management in real world domain/environments. Specifically, we require a framework that can accurately capture existing knowledge and relevant data of the domain. We adapt, extend and integrate well-established AI theories and techniques used to model uncertainty as a means to enable intelligent information systems to reach effective and optimal decisions. Before we can embark on the

¹ www.aldebaran-robotics.com/en

development of such a framework solution, we need to identify and analyse some aspects of the intrinsic nature of real-world domains and environments to which our framework will be applied. Unlike laboratory conditions, these environments possess three critical and challenging features:

Complexity: Many variables/risk factors are involved and interrelated in the task domain. Some variables are quantitative in nature; whereas others are qualitative or cannot be easily quantified. In our robot soccer match environment, we have quantitative variables such as distances between the robots, kicking distance (or power) of a robot; other variables such as ability of ball interception of opposing robot team are difficult to measure and quantify; whereas some of the soccer match rules are purely qualitative.

Openness: We may not know all of possible variables involved in the domain or we may not have sufficient amount of information for a variable. In the foreign exchange example, there are many hidden variables in the global currency exchange markets that are unknown to large number of market participants (Lyons 2001).

Dynamics: The environment evolves and changes with time. Relationships between variables may change and the number of variables in the domain may also change. Information available changes and new information may contradict existing knowledge. In the FX example, the Australia dollar is traditionally “tied” to the fortune in resource exports and global economic outlook. The global economic environment is constantly evolving. Ten years ago, China economic had little influence on the Australia dollar. In contrast, nowadays, current heavy investments in infrastructure in China have significant influence in the Australian exchange rate. Clearly, any risk models built ten years earlier need to be revised.

Therefore, risk analysis; knowledge capture and risk modelling processes must carefully address complexity, openness and environmental dynamics. Our approach takes the following design stance to the key requirements:

- Our framework makes no specific assumption that complete knowledge is available for the task domain; it is based on an Open World Assumption.
- Our modelling solution can handle both quantitative and qualitative domain information.
- Our modelling solution accommodates frequent update and revision of the existing knowledge base in order to accommodate changes in the domain environment.

Furthermore, our risk framework and model attempts to capture causal relationships among the domain variables to ensure the stability of the model and to support the development of appropriate treatments influence the desirable and undesirable variables in the system.

4 SURVEY OF RELEVANT AI THEORIES & TECHNIQUES

4.1 Classical Logic

Classical logic in AI is a formalism for declarative representation of knowledge together with sound and complete deductive reasoning mechanisms. The language of propositional logic is made of non-empty set of atoms (propositional signature) which consist of constant, variable, predicate symbols; connectives such as \perp (contradiction), \neg (not) and \wedge (and); truth values TRUE and FALSE. A predicate formula is in the form of a set of atoms connected by the connectives. An interpretation of a propositional language is a function that maps atoms into $\{\text{TRUE}, \text{FALSE}\}$. Semantics of a propositional formula is given by the truth value an interpretation maps the formula into. In the ball passing problem, we can represent the knowledge of “distance between Robot A (R_A) and Robot B (R_B) is Distance 20 centimetres and there are opposition robot nearby” as $\text{Distance}(R_A, R_B, 20) \wedge \text{OppositionNearby}(R_A, R_B)$. First-order logic is an extension of the propositional logic. Its signature becomes function constant and predicate constant; variable is an element in a finite sequence of symbols. First-order logic also introduces two qualifiers \forall (for all), \exists (exists) which are used to qualify formulas. The first-order logic has greater expressive power than the propositional logic. We use a form of first-order logic when we describe various algorithms for risk model construction and revision. For further details on both propositional and first-order logic, Lifschitz et al. (2008) gives an excellent account of classical logic in AI.

4.2 Non-monotonic Logics and Reasoning

The usefulness of classical logic is limited by its monotonic nature. That is, the logical consequences reached by classical logic reasoning cannot be invalidated or revised by new information. This kind of reasoning can be used to model information safely only in a closed static world. However, the environments for our risk modelling are neither closed nor static. Information systems typically possess incomplete information of the operational environment and often acquire new information that contradicts existing information. Consequently, the conclusions they previously reached may be

incompatible with incoming new information. Several classes of non-monotonic logic reasoning were developed to address this limitation in the classic logic such as Default Logic (Reiter 1980) and circumscription (McCarthy et al.). Their focus is on modifying the underlying inference mechanisms to create highly exotic inference behaviour. We prefer the alternative approach of Belief Revision (BR) that formalises the actual process of revising existing knowledge base which can be a simple classical logic. BR was first proposed as sets of logical postulates (AGM postulates) and three key change operators that govern knowledge expansion, contraction and revision on an existing knowledge base (Alchourron et al. 1985). Any belief change operators that satisfy the AGM postulates are guaranteed to respect the principle of minimal change and create a logically consistent knowledge base at the end of the process. Additional mechanisms such as Epistemic Entrenchment (Gärdenfors et al. 1988) and System of Spheres (Grove 1988) were developed to construct a unique contraction and revision operators respectively. Extensive follow-on works expanded original AGM framework so that BR can operate on belief base and operate iteratively over time (Spohn 1988; Williams 1994).

4.3 Bayesian Probabilistic Model

Both classical logic and standard non-monotonic logics only deal with qualitative data, they cannot handle numerical information usually required to represent uncertainty. The most common method of representing uncertainty is using probability. One of most popular probabilistic models in AI is the Bayesian Network (BN) (Pearl 1988). A Bayesian Network consists of a Direct Acyclic Graph (DAG) that uses nodes to represent domain variables and directed arcs between nodes represent dependencies between the variables. Mathematically, a BN is based on conditional probabilities and can be viewed as a joint probability distribution of variables and it handles numerical non-monotonic reasoning nicely. Numerous extensions and techniques for BN construction, network learning, refinement and inferences have been developed. Darwiche (2009) gives a comprehensive account of these developments. Despite its advantages, BNs still have major shortcomings for modelling risk. First, as a probabilistic model, BN rely on the Closed World Assumption (CWA). It assumes complete knowledge of the domain² and is unable to represent ignorance. Second, BN is restricted to probabilities as its inputs. Many domains may have no meaningful probabilities to work with. Third, construction (learning) and refinements of BNs require considerable amounts of meaningful data. In many domains, such as our ball passing, obtaining sufficient data is impractical. Fourth, it is difficult to directly and fully integrate classical logics with probabilistic model such as BNs, although some steps have been taken in that direction (Richardson et al. 2006).

4.4 Belief Function and Transferable Belief Model

One of the alternative methods for representing uncertainty is using the so-called belief function (Shafer 1990). Belief functions are based on the evidential theory and they provide for expressions of partial beliefs and even total ignorance. Belief functions can be used to capture domain experts' degree of belief of the state of affairs in a domain based on the currently available information. This is particularly useful when probabilistic data is difficult, expensive or impossible to obtain and when domain knowledge is incomplete. The Transferable Belief Model (TBM) models quantified beliefs (Smets et al. 1994) at two mental levels, the *credal* level where beliefs are entertained and the *pignistic* level where beliefs are used to make decisions³. At the credal level, a basic belief mass (BBM) is assigned to each element of a power set constructed from a set of atoms (frame of discernment Ω) that describes the domain. Ignorance is represented by the BBM assigned to Ω . Using the so-called pignistic transformation that is based on the expected utility theory (Smets 2005), beliefs expressed at the credal level can be transformed into probabilities for decision making.

5 A MULTI-LEVEL ITERATIVE RISK MANAGEMENT FRAMEWORK

From the short survey in the previous section, it is obvious that no single AI technology can provide an adequate solution to all of our framework requirements. A hybrid solution may provide a better answer to address the challenges in complex, open and dynamic environments. We adopt a multi-level approach and select appropriate AI methods depending on the nature of the available domain information, e.g. whether the information is qualitative or quantitative or both, for risk modelling and management. Another key feature of our framework is its iterative analysis and modelling process (e.g. Figure 1). We adapt existing methods such as belief revision and developed additional

² Modern BN can have hidden variables which handle unobserved data. However, hidden variables have already been incorporated in the model. BN cannot have *unknown* variables.

³ Both credal and pignistic are derived from Latin words 'credo' (I believe) and 'pignus', a bet.

mechanisms so that existing risk models can be revised iteratively while maintaining consistency. Table 3 gives a high level overview of the AI techniques used our three-level risk modelling framework. The table also provides a summary analysis of the nature of the risk model generated and the corresponding operational level should the modelling be used. Finally, inspired by the BN, our modelling framework produces an intuitive graphical model so that it can be more easily understood, interpreted and used by people as well as computers.

Abstraction Level	Theoretical Base for Modelling	Model Revision Method	Belief Value Type / Model Type	Causality Type	Application Level
High	Propositional Logic	Belief Revision	Qualitative	Deterministic	Strategic
Medium	TBM based model	Rank Revision	Semi-qualitative	Quasi-deterministic	Tactical management
Low	Bayesian Network	Model Selection	Quantitative	Probabilistic	Operational

Table 3. A high-level overview of the multi-level risk modelling framework.

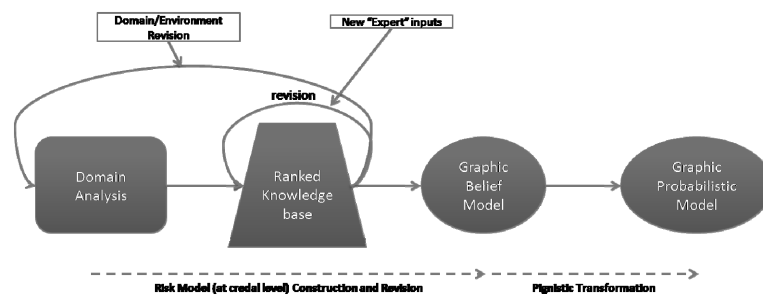


Figure 1. An overview of the iterative risk modelling process at medium level.

5.1 High Abstraction Level

At this level, we use classical propositional logic to capture the qualitative domain knowledge for the risk modelling. We introduce several predicates and axioms (omitted) to describe the relationships between the domain variables and capture some of the key intuitions from a risk modelling perspective.

Predicate	Meanings
InitEvent(A)	Initial event A occurs.
Scenario(A)	A possible scenario A occurs.
Factor(A)	A domain variable A occurs.
Lead(A, B)	A domain variable A leads to another domain variable or scenario B.

Table 4. Predicates for risk modelling.

We can describe a simple risk model for the ball passing problem as following:
InitEvent(IE). Factor(D). Scenario(S₁). Scenario(S₂). Lead(D, S₁). ¬Lead(D, S₂).

Graphically we present all possible risk models in a set of concentric structures which capture a natural ranking of information (Figure 2 a). Models with lower rank mean we have higher confidence that they correspond to the truth (or likely to be true). Specifically, we have the highest confidence (rank 0) in believing D leads to S₁ while ignorant of whether D will lead to S₂; we have less confidence (rank 1) in believing D leads to S₂ but not S₁ and even less sure (rank 2) that D leads to neither S₁ and S₂. When it is necessary to revise our current beliefs of the domain, we use belief revision to shuffle the models within the ranking and change our knowledge of the domain. A qualitative risk model developed at this level is used to represents the high-level structure knowledge for risk. Modelling risks at this strategic level may provide necessary information that will assist a company management setting the future direction for the firm.

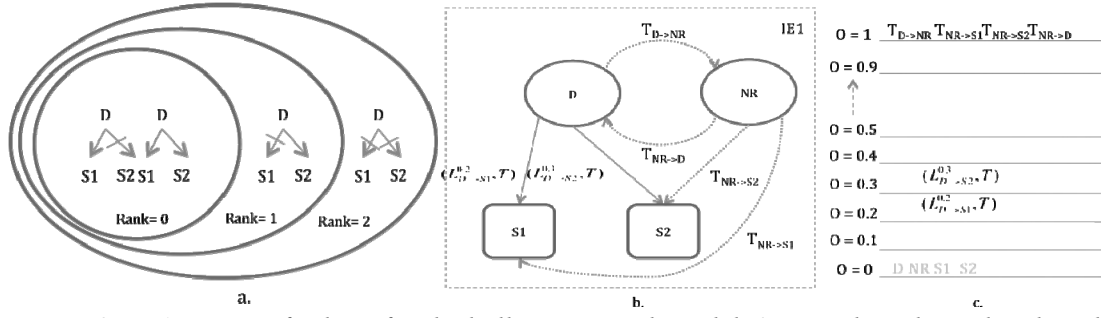


Figure 2. **a.** A system of sphere for the ball passing risk model; **b.** TBM based graphical model; **c.** Corresponding ranked structure for graphical model b.

5.2 Medium Abstraction Level

We developed an iterative modelling process (Figure 1) based on the ideas from the TBM. That is, we have a credal level and a pignistic level. At the credal level, we still use propositional logic to describe the domain variables. To describe the causal inference relations between the domain variables, we introduced a formal definition of lead based on the so-called Ramsey test (Lindstrom et al. 1998):

Definition 3: For a knowledge base K , let X and Y be two simple random variables. We accept a *lead* $L_{X→Y}$ if and only if Y is accepted with a belief value⁴ m in $K*X$, where $K*X$ denotes ‘ K revised by X ’.

This formal definition can be more easily understood, with the ball passing problem, through following questions: “Based on what you know about the soccer match (K), if robot A kicked the soccer ball towards robot B at distance D , will you accept the belief that the ball will be caught by B (S_1)?” If the answer is affirmative, then “How much weight (m) do you put on this belief?”. A lead $L_{D→S1}$ follows immediately with the answers. In fact, these two questions can be readily used to capture beliefs from domain experts. Noted, a lead $L_{X→Y}$ with $m = 1$ is semantically equivalent to have $\text{Lead}(X,Y)$ in the high level qualitative modelling whereas a lead $L_{X→Y}$ with $m = 0$ is (called vacuous lead, denoted as $T_{X→Y}$) is semantically equivalent to have $\text{Lead}(X,Y)$ and $\neg\text{Lead}(X,Y)$ in two separate equal-ranking models in the high level abstraction (see Figure 2 rank 0). It means we are ignorant of whether there is a causal inference relation from node X to Y . Furthermore, to capture “negative” belief (similar to $\neg\text{Lead}$), we use an additional diffidence component and construct a latent lead structure $(L_{X→Y}, L_{X→Y})$. For example, a lead structure $(L_{D→S1}^{0.8}, L_{D→S1}^{0.5})$ means that we have reasons to believe (with belief value 0.8) our distance will lead to scenario S_1 , and at the same time, we also have reasons to believe (with belief value 0.5) our distance will not lead to scenario S_1 . This is particularly useful, since we can fuse conflicting information from different sources.

All leads in a model are stored in a ranked knowledge base. The rank of a lead is calculated using an operator that transforms the lead latent structure into a rank number. We set up the ranking system from 0 to 1. Rank 0 is given to those sentences representing the inference relationship that are definitely plausible to our task domain⁵. Sentences that are the least plausible with respect to our domain, i.e. vacuous leads should always have the rank of 1. With this ranking structure, we have a clear picture of relative strengths of causal relationships between various risk factors and scenarios in our model.

Revision of the risk model comes in two categories:

- Revision of the domain and its environment. This usually means addition or removal of domain variables. Adding a new domain variable causes the implicit addition of vacuous leads that connect the new variable with the existing variables. Removal of a variable causes all leads that connect to that variable to also be removed.
- Revision of leads with new input information. New information of a lead is first fused with the existing knowledge of the lead. A new rank for the lead is then computed and the lead is shuffled with the rank structure in alignment with the expected degrees of belief.

When the risk model is ready to be used for decision making, we transform the model using the pignistic transformation. This risk modelling process works best when the domain knowledge is incomplete, available quantitative data is insufficient or information that is difficult to quantify as probability. It fills the modelling gap left between the higher level qualitative risk modelling and the low level quantitative risk modelling. More importantly, it provides the necessary transition route between the qualitative and quantitative model.

⁴ Technically, this belief value is the BBM from the Transferable Belief Model. The value is in range of $[0..1]$.

⁵ All nodes are also implicitly stored in the knowledge base with rank 0.

5.3 Low Abstraction Level

The key difference of risk modelling between this level and previous two levels is that we rely purely on numerical data and probability for building a risk model. This means, we cannot model ignorance and evidence with negative support at this level. Nevertheless, risk models developed here provide numerical computation of risks and it is ideal for operational level risk management. We utilise the popular Bayesian Network as the risk modelling and reasoning tool at this level. In fact, there are a number of existing works of using BN in risk management (Aven 2008; Rychlik et al. 2006).

6 CONCLUSIONS

In this paper, we have demonstrated the significance of our integrated and practical risk modelling and management framework and highlighted its key features. We gave a detailed account of where open, complex and dynamic real-world environments impact risk management and we gave a set of requirements that our risk management framework satisfies. We surveyed relevant theories, techniques and approaches of uncertainty management and proposed a three-level framework that adapts appropriate AI techniques to model risks under different decision making demands. Details of the framework and the use of benchmark problems demonstrate its broad applicability in addressing risk management challenges across a broad range of domains. In addition, this multi-level framework matches the structure of a typical organisation and therefore its implementation aligns with existing information systems architectures. We are also developing software implementation architecture to realise our framework in practice. To this end, we will use a multi-agent architecture since it matches nicely with our multi-level framework.

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