Ontology of Bankruptcy Diffusion through Trade Credit Channel

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It is widely believed that the whole economic system has exhibited an increasingly intertwined nature in the context of economic globalization and regional integration. With the increasing interactions among trading partners in a supply network, bankruptcy of a member firm may make others get into distressed situations. This kind of phenomena is called bankruptcy diffusion or bankruptcy contagion.

In this paper, we focus on the bankruptcy diffusion in supply network through trade credit channel, which describes the phenomenon that the distressed customer’s default on its trade credit will make the financial crisis transmitted to suppliers. We have proposed a knowledge framework situated in the intelligent investment risk monitoring background. The knowledge framework is present to help shareholders, policy makers, and portfolio managers to identify candidate firms affected by a financially distressed firm. It consists of two components: 1) a formal ontology to represent static domain knowledge of bankruptcy diffusion phenomenon triggered by bankruptcy announcements; and 2) semantic rules to extend inference capability and enable automation of problem solving. An example is used to illustrate the ontological knowledge design for providing a preliminary evaluation. We believe that our approach may contribute to the literature in the following aspects: 1) at the conceptual level, we develop a formal, shared conceptualization utilizing ontology approach. The ontology provides structured representation of bankruptcy diffusion domain knowledge and lays a solid foundation for the analysis, design and deployment for future system development; and 2) at the implementation level, we represent the ontology using formal language Ontology

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Web Language (OWL) and develop semantic rules with Web Semantic Rule Language (SWRL) for enhancing logical inference and computable tractability.

Keywords: Ontology; Conceptual Modeling; OWL; SWRL; Bankruptcy Diffusion

ACM Classification: I 2.11 (Distributed Artificial Intelligence)

1. Introduction

Corporate bankruptcy occurs when a firm is faced with chronic and serious losses or becomes insolvent with liabilities which are disproportionate to asset liabilities (Xu et al., 2010). The volume of bankruptcy filings has significantly increased in recent years. According to the Administrative Office of the US Courts, bankruptcy cases of the fiscal year 2009 have totaled 1,402,816, up 34.5 percent over the 1,042,993 filings in the previous year. Traditionally, bankruptcy is attributed to a firm’s own poor management, difficulties in operating successfully in the market, or autocratic leadership (Ryu and Yue, 2005). However, in the network economy, with the intensifying inter-dependencies and interactions in the supply network, bankruptcy of a supply network member may cause other member firms getting into financial distress situations. This phenomenon is termed bankruptcy diffusion or financial contagion (Delli Gatti et al., 2009; Battiston et al., 2007). In this situation, not only the strong negative effect on the value of the filing firm’s stock is evident, but also the magnitude of indirect cost or impairment caused by this distressing situation is difficult to estimate. On 1 June 2009, a major American car manufacturer (aCar Corp) sought protection from its creditors when it filed for Chapter 11 bankruptcy. While there was a possibility that creditors would recover most of their investments, the majority of the stakeholders experienced significant losses. The stock price, then trading at $0.75 per share, had fallen 95.74% over the previous year. In addition to the direct impact felt at aCar Corp, the losses have extended to firms having various kinds of relationships with aCar Corp. Especially, those key suppliers relying on aCar Corp for a significant portion of their business and extending large trade credit to aCar Corp suffered a lot. For example, automotive parts supplier Lear (manufacturer of car seats and electronics) filed for bankruptcy a few weeks later.

An intuitive explanation of bankruptcy diffusion is the avalanches of trade credit chain among members in the supply network (Boissay, 2006). Nowadays, companies spare no efforts to engage in collaboration to gain competencies. Trade credit, as a common form of capital interaction, is widely used in business. It is an important source of financing tool for intermediate purchasing of goods and services. The accounts receivable created by trade credit sales constitutes a large portion of the total assets for some corporations. As a result, the firm facing customers’ defaults on trade credit is more likely to default themselves. The 2008 sub-prime mortgage crisis is a good example of widespread contagion because of a mass liquidity crisis. The phenomenon of bankruptcy diffusion is not uncommon and has attracted considerable attention in academic research. Recent studies in finance have provided evidence that bankruptcy filings have significant repercussions for both the bankrupt firms and a variety of associated shareholders. The empirical work by Bardos and Stili (Bardos and Stili, 2007) has studied defaults on trade credit and the risk contagion phenomenon in finance, i.e., how borrowers’ risk is transmitted to lenders. They demonstrate the pattern necessary for risk contagion and find that risk transmission occurs when receivables represent a significant portion of total assets. Despite the fact that bankruptcy diffusion is widely studied in finance, there is relatively little formal understanding about how these contagion effects can be utilized in intelligent risk monitoring and management.
filed. This conclusion is reached by doing a brief literature review in intelligent investment modeling and system development. In recent years, apart from quantitative information such as performance histories and risk indicators (for instance, beta value), text information has been found to have a visible impact on a security’s price (Chen and Liu, 2009). In intelligent investment field, online news is widely recognized as an important source to complement quantitative data (Chen, Wang and Lai, 2011; Schumaker and Chen, 2009; Wang et al, 2011). However, one common drawback of these studies is they only pay attention to one specific firm’s news events without considering the interdependencies among members may cause bankruptcy contagion effects. For example, a sudden financial emergency in a company could cause significant losses to its suppliers due to its inability to pay off its debts. When making a decision of an individual firm in their portfolio, investors should not be oblivious of the peculiarities of the various trading partners relating to that particular stock. Therefore, we assume that the ignorance of emphasis on ripple effects in intelligent financial investment illustrate a great need for a formal and fundamental understanding of this diffusion mechanism.

A supply network is a network of entities interacting to transform raw material into finished product for customers. Since interdependencies among supply network members on material, information, and finance are becoming increasingly intensive, financial status of one firm not only depends on its own management, but also on the performance and behaviours of other members. Therefore, understanding the financial flows variability and the material interactions is a key to quantify the risk of a firm. Due to the complex structure and dynamic interactions of modern supply networks, there are some difficulties faced by pure analysis approaches in analyzing financial status of the supply network members and the high degree of nonlinear interactions between them. Mathematical and operation research models usually do not function very well for this kind of financial decision making. These models always start with many assumptions and have difficulties modeling such complex systems that include many entities, relationships, features, parameters, and constraints. In addition, traditional modeling and analysis tools lack the ability to predict the impact of a specific event on the performance of the entire supply network. Current financial data analysis with large volumes of structure data cannot offer the full picture and intrinsic insights into the risk nature of a company. Motivated by the literature gap in risk monitoring in investment background and limitations of analysis approaches for handling bankruptcy contagion phenomenon, we propose an ontological approach to present a formal, shared conceptualization of this domain knowledge.

The word “ontology” is taken from philosophy, in which it means a systematic explanation of being. During the last decade, ontology has become a relevant word for the knowledge engineering community, as it refers to the shared understanding of some domain of interest which can be used as a unifying framework to represent selected phenomena. Ontology is a suitable and powerful tool for conceptual modeling. According to John Mylopoulos’ (Mylopoulos, 1992) definition, conceptual modeling is “the activity of formally describing some aspects of the physical and social world around us for the purposes of understanding and communication”. The fundamental problem of conceptual modeling is the development of an expressive presentation notation with which to represent knowledge (concepts and relationships between them). The conceptual model attempts to clarify the meaning of various, usually ambiguous terms, and ensure consistency. A standardized terminology needs to be semantically consistent across users and system developers, since the communication aspects of information require that communicating parties have the same understanding of the meaning of the exchanged
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information. Ontology, the most popular modeling representation tool, would normally be the first choice. Once the domain concepts have been established, the model becomes a stable basis for subsequent development of applications, which is the physical design or implementation with specific coding techniques (Corcho et al., 2003). In this paper, we aim to propose a knowledge framework for investigating bankruptcy diffusion phenomenon in the investment background. According to Schreiber et al. (1994), “the control knowledge and the domain knowledge are highly dependent”, one cannot define the domain knowledge without knowing what the task is going to be, and vice versa. Control knowledge is also called task solving ontology, where domain knowledge represents static aspects for employing the task solving ontology. For this part, we complement the static domain ontology by adding semantic rules for describing dynamic logic to get the computable results. At the implementation level, Ontology Web Language (OWL) is used to represent the static taxonomies and axioms of the static domain knowledge. OWL is based on description logic, which provides sound and decidable reasoning abilities. However, OWL is insufficient for describing task solving knowledge and enabling its automatic execution. Such explicit representation of implications is provided by program logics, such as rules. Semantic Web Rule Language (SWRL) is utilized for complementing the domain ontology and supporting more complex rule-based inference.

The rest of the paper is organized as follows: An introduction to the related work is given in the next section. In Section 3, the ontology engineering process and methods is described. In Section 4, the ontology for bankruptcy diffusion through trade credit channel in the supply network is firstly developed and represented at the conceptual level. In Section 5, at the implementation level, OWL is utilized to formally represent the domain knowledge and SWRL is employed to develop some task solving rules. In Section 6, a case study is utilized as a preliminary evaluation of our approach. Lastly, implications and discussions are presented, leading finally to the conclusion in Section 7.

2. Related Work
2.1 Bankruptcy Diffusion

Corporate bankruptcy occurs when a firm becomes insolvent with the liabilities that are disproportionate to assets and thus cannot meet its short term commitment (i.e., it is insufficient in cash flows to continue its operations) (Xu et al., 2010). In a network economy, however, when a firm goes bankruptcy or becomes financially distressed, the probabilities of bankruptcies in connected firms increase. In financial management and economics, tremendous research has been conducted to investigate the phenomena of financial contagion in financial systems and bankruptcy contagion in network economy. Usually, financial contagion is a term used specifically for the credit risk transmission between financial institutions; while bankruptcy contagion is more often used to indicate trade credit risk propagation in production network context. Their histories will be explained in detail in the following paragraphs.

Financial contagion has its origins in banking systems. By modeling financial contagion as an equilibrium phenomenon, Allen and Carletti (2006), for instance, emphasize the role of interbank credit in determining financial contagion. They propose the complete structure of interregional claims for preventing crisis diffusion. Van Rijckeghem and Weder (2001) support with this view that spillovers through common bank lenders are important in transmitting currency crisis. These researches mainly have focused on the causes of contagion effects among financial institutions.
Since trade credit is an important part of the network of business credit, the research of financial contagion has also been extended from banking systems to general inter-firm situations, especially in the supply network. Hertzel et al (2008) provide the direct evidence on how a financially distressed or bankruptcy firm affects its suppliers or customers. Their research offers a more comprehensive understanding about the overall wealth effects associated with financial distress and bankruptcy. Boyssay (2006) also emphasizes the role of trade credit by developing a theoretical model that bankruptcy propagates through a network of firms linked by trade credit. They conduct simulation experiments with US annual data to quantify the specific probability of diffusion.

Trade credit plays an important role as a propagation mechanism. It is extended by one firm to another through direct interaction which assumes the form of coordination mechanisms. The contagion phenomena are partly due to the presence of delayed payments (or defaults of trade credit) and corresponding increasing costs of the creditor. Although this kind of contagion phenomenon is widely studied in finance literature, it is not well utilized in the risk monitoring field especially in research focusing on intelligent investment modeling and system development. A great body of research has focused on utilizing financial news reports as an important tool offering multiple and dynamic perspective in stock market prediction (Schumaker and Chen, 2009), portfolio risk investment (Sycara et al, 1998), and financial risk monitoring (Wang et al, 2002). However, most of these studies have been limited to monitoring the news of one specific company of interest, neglecting analyzing indirect influence from other member firms in the supply network. Actually, a more likely scenario of exposure to distressed situations is that the investment portfolio includes securities affected by their customers' financial crisis or bankruptcy event. In this situation, identifying the candidate affected firms in the supply network is of great significance for risk monitoring in portfolio management.

2.2 Ontology

The word “ontology” is taken from Philosophy, where it means a systematic explanation of being. According to the most commonly cited definition, ontology is an explicit specification of a shared conceptualization (Gruber, 1993). Guarino (1998) clarifies Gruber’s definition by adding that the AI (Artificial Intelligence) usage of the term refers to “an engineering artifact, constituted by a specific vocabulary words”. Ontology is thus engineered by members of a domain for explicating a reality as a set of agreed terms and logically founded constraints on their use. The research of ontology has attracted a great deal of interest and has been applied in conceptual modeling, knowledge engineering, semantic web and so on. The common thread is the need for sharing the meanings of the terms in a given domain, which is a central role of the ontology. Ontology necessarily entails or embodies some sort of world view with respect to a given domain. The world review, referred as a conceptualization, is often conceived as a set of concepts (e.g. entities, attributes, and processes), their definitions, and their inter-relationships (Weber, 2003).

In conceptual modeling, ontology research has been used as a tool to better understand the domain of interest and a unifying framework to represent selected phenomena (Wand and Weber, 2002). For example, Ye et al (2009) have proposed three kinds of ontologies to further deepen the understanding of crisis contagion management in financial institutions and enhance knowledge sharing from static, dynamic, and social perspectives. In their study, static ontology is used to represent the static structure of financial market and define the basic concepts in crisis contagion management. Dynamic ontology deals with knowledge regarding the crisis contagion process.
Social ontology represents the social aspect of financial institutions, i.e. crisis contagion channels. Wang et al. (2008) use ontology to understand the knowledge about news and in building trading models on news in financial instrument markets. With the development of ontological domain knowledge, it is helpful to build trading models based on news in the financial instrument markets and facilitate design and implementation in this domain. Ontology is also very useful in agent-based modeling and systems. Guan and Zhu (2004) have proposed a new approach to facilitate ontology exchange among e-commerce agents. Specifically, through elaborating on the exchange model and the detailed design and implementation of product-brokering agents, they developed an evolutionary agent structure with hierarchical knowledge base. Furthermore, ontology could be used to support agent-based systems or Web service, such as ontology-supported website models, which will increase the level of automation in service discovery, invocation, composition, and interoperation (McIlraith et al., 2001).

3. Ontological Engineering Process
Ontology building is a nontrivial knowledge intensive process. It could be treated as a type of knowledge engineering, which includes several successive processes of knowledge acquisition, modeling and representation (Noy and Hafner, 1997). In this section, we describe the development process of our knowledge framework in detail. Through this process, we aim to develop the knowledge framework by utilizing ontological technologies for analyzing the bankruptcy diffusion phenomenon in investment background. This formal, shared ontology provides a better understanding of how the impairment of one firm may ripple through other layers of member firms in the supply network. The whole development is composed of four successive processes, as depicted in Figure 1.

1. Developing Conceptual Model – A conceptual model may take a variety of forms, but necessarily it includes a vocabulary of terms, and some specifications of their meanings. This includes a definition and indication of how concepts are inter-related, which collectively imposes a structure on the domain and constrains the possible interpretations of terms (Uschold and Gruninger, 1996). Hence, this phase is responsible for identifying main entities and creating the connections among these entities required to capture the domain knowledge. The model is created following an elaborate and thorough literature review that elicited various aspects of trade credit contagion in a customer-supplier relationship. For example, the
triggering concept underlying this model is the BankruptcyEvent, which is a structured representation of financial news announcements of the bankruptcy events. The interrelationships between different domain concepts are defined by Relations and Refineables, which will be given in detail in the following section.

2. **Symbolic Representation** – The contents of the ontological model must be made computable by using machine-readable language. In order to achieve this object, we utilize Ontology Web Language (OWL) as an ontology representation language. It allows the specification of a terminological hierarchy using a restricted set of first-order logical formulae and provides important logical requirements. These requirements include concept satisfiability, class subsumption, class consistency checking, etc. In order to support task solving knowledge inference based on the structured conceptualization, we also add some semantic rules. Although OWL provides considerable expressive power, it has limitations in computations and decidable reasoning capability, particularly concerning how to express properties and relationship inference. Semantic Web Rule Language (SWRL) is an emerging technology developed to address the above-mentioned difficulties. SWRL extends the set of OWL axioms to include Horn-like rules and enables the integration of SWRL rules with OWL knowledge base. In particular, SWRL is well suitable for transferring object properties and getting the new instances of OWL classes by inference. After extending semantic rules on the domain knowledge, an initial knowledge base is created as a result of this phase.

3. **Factual Knowledge Insertion** – The ontology is used to capture the semantic-based knowledge in a generic way that provides a common agreed structure. For example, the main entities in the bankruptcy contagion domain such as EconomicResource, BankruptcyEvent, EconomicEvent are abstracted in the upper level of the whole conceptual schema. At the bottom level, some specific instances and the values of relating attributes must be filled for each case operation. In our application, for instance, not only is the car manufacturer's name extracted from news as an instance of the Firm class, but its relevant attributes such as revenue, debt, and other information must be inserted as the right properties.

4. **Inference** – Once all three previous steps are completed, the ontological knowledge base is created. For reasoning with ontology and rules, the process is assisted by SWRLJESSTab plug-in in Protégé. Using SWRLJESSTab, it can infer new knowledge from the initial ontological knowledge base, resulting in a run-time knowledge base. For the specific mechanism behind this plug-in, please refer Golbreich (2004) for more details.

**4. Conceptual Modeling**

Conceptual modeling is the activity of formally describing some aspects of the physical and social world around us for the purpose of understanding and communication (Mylopoulos, 1992). According to this definition, the fundamental task of conceptual modeling is the development of an expressive presentation notation with which to represent knowledge (concepts and relationships between them). Once the domain concepts have been established, the model becomes a stable basis for subsequent development of applications in the domain. Therefore, it is necessary to select a suitable modeling tool for our conceptual model development. Ontology, the most popular modeling representation and modeling tool, would normally be the first choice. The knowledge representation scheme used to inform our knowledge model is based on Telos, a knowledge representation language developed at the University of Toronto (Mylopoulos et al., 1990). The Telos knowledge representation language adopts a representational framework which...
includes structuring mechanisms analogous to those offered by semantic networks and semantic data models, namely classification (inverse instantiation), aggregation (inverse decomposition) and generalization (inverse specialization).

As shown in Figure 2, a partial semantic structure of the conceptual model is present to give a graphical overview of the domain concepts and the relationships among them. Although Telos abolished completely the distinction between nodes/entities and links/relationships by denoting everything in the knowledge base as a proposition, we use two different diagrammatic notations: eclipse and rectangles. Eclipse in Figure 2 represents objects, while rectangle denotes the relationships between them. In addition, we use the following abstractions to represent properties and relationships between entities:

- **Refineables**: This abstraction is used to explicitly define the set of properties belonging to each entity. For instance, the supplier entity has the refineable `net_worth`, and the commercial contract entity has the refineable `hasFirstParty`. The refineables are organized hierarchically. A refineable may be assigned a value. For instance, the Refineable `DateOfIssue` may be assigned the data value 1 June, 2009.

- **Relations**: This abstraction is used to describe the relations existing between two entities, i.e. Entity-Entity relation. Example of this kind Relations is the relationships (`hasExtendCreditTo` and `hasSuppliedGoodsTo`) between customer and supplier entities.

Within Figure 2, the thick closed arrows represent Telos’ ISA links (subclass/class relations); the open arrows represent Telos’ In links (instance/parent class relations); the thin arrows present the Relations; and the arrows with diamond head represent the Refineables. The whole conceptual
model is demonstrated at three levels, namely, the Meta-class level, the Simple Class level and the Token level:

1. **Meta-Class Level**
   At the Meta-Class level, we have identified five basic concepts in the application domains represented with five meta-classes (see Table 1 for detail definitions). These five fundamental concepts are: `EconomicResource`, `EconomicAgent`, `EconomicEvent`, `Commitment`, and `NewsInformation`. The last concept is outside the scope of a supply network member, an external triggering source of the whole bankruptcy contagion phenomenon. The other four meta-classes are mainly responsible for describing enterprise operation relating to material, information, and financial flows. These five concepts are the ontological primitives upon which domain axioms are defined. The detailed definitions in Table 1 are adapted from the business-oriented Resource-Event-Agent ontology (Geerts and McCarthy, 2000). We further define and name a number of Refineables for each concept and Relations between the basic concepts. For instance, `EconomicResource` are associated with the `EconomicEvent` by the Relation `StockFlow` (inflow or outflow). In real life situations, it is easy to understand that economic events such as purchasing always result in outflows (case disbursements); at the same time, they also add more production materials into inventory which is an inflow process. An example of Relations is `hasParticipateIn`, which identifies the interaction mechanism among the economic agents involved in economic events. At last, a commitment will eventually be related to an economic event by a fulfillment Relation. In Telos, we can carry classification/generalization operation much further: to generalize common characteristics of Simple Class into the Meta-Class level objects.

<table>
<thead>
<tr>
<th>Meta-Class</th>
<th>Definitions</th>
</tr>
</thead>
<tbody>
<tr>
<td>EconomicResource</td>
<td>A thing that is scarce and has utility for economic agents; something users of business applications want to plan, monitor and control.</td>
</tr>
<tr>
<td>EconomicAgent</td>
<td>An organization or member in the network economy; capable of having control over economic resources and interacting with other organizations. Besides, outside information will have an impact on its stock valuation.</td>
</tr>
<tr>
<td>EconomicEvent</td>
<td>A change in the value of economic resources that are under control and operated among the enterprises</td>
</tr>
<tr>
<td>Commitment</td>
<td>A promise or obligations of economic agents to perform an economic event in the future</td>
</tr>
<tr>
<td>NewsInformation</td>
<td>On line news from information media, such as Bloomberg (<a href="http://www.bloomberg.com/">http://www.bloomberg.com/</a> )</td>
</tr>
</tbody>
</table>

**Table 1: Definitions of basic Meta-Class concepts**

2. **Simple Class Level**
   At the Simple Class level, the specialization of concepts at the Meta-Class level is given as well as the relationships between them. As a matter of fact, this kind of classification is very useful in many conceptual modeling applications. Economic agents are further divided into two
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different roles as customers and suppliers with Simple Class concept Firm. Our focus is on trade credit relationships among suppliers and customers since we mainly examine the bankruptcy diffusion effect caused by the interaction through trader-credit channel. The different roles are connected with two different Relations: 1) hasSuppliedGoodsTo Relation; the output of a supplier firm is the input for a customer firm; 2) hasExtendCreditTo Relation: in business context, most suppliers extend trade credit to customers through agreements of contracts. As far as the EconomicResource is concerned, it can be categorized into two groups: Product class and FinancialAsset class, representing physical flow and financial flow separately. Product structures and relations are basic clues for identifying customer-supplier relations in the supply network; meanwhile, the activities of enterprise operation are closely related with financial assets. On the one hand, the financial status of a company will exert great constraints on activities such as purchasing; on the other hand, the trade credit term specified in the contract will change the inflow/outflow of the relating financial resources. The financial statement is the basis for understanding financial health and evaluating the performance of business operations. The financial statement summarizes a company’s assets, liabilities, and shareholders’ equities at a specific point of time. A balance sheet, comprising of assets, liabilities, and owners’ equities, is a snapshot of the financial condition of the business. In order to use financial ratio for bankruptcy prediction, every financial ration is a Simple Class.

3. Token Level

All entities at the Token level correspond to the domain instances. These instances and their relationships do not exist at the current place but will be filled as case facts or obtained as inference results. For instance, NIVA VAZ 213 is an instance of the domain class Automobile, which groups all the similar objects under the common generic description. Because of the complexity of the whole conceptual model, many links between entities are omitted. For example, the Customer-Supplier binary relation between Delphi and aCar Corp at the Token level is an instance of a Simple Class level Relation concept hasSuppliedGoodsTo and hasExtendCreditTo, which are also instances of a Meta-Class Relation interactWith. With this conceptual modeling, it gives a hierarchal structure of the domain knowledge for bankruptcy diffusion phenomenon. The whole ontology provides a solid framework to represent identifiable business ties among market participants.

5. Knowledge Representation

5.1 Static Knowledge Implementation in OWL

5.1.1 Ontology Web Language

Ontology Web Language (OWL) is a recent development in standard ontology language advocated by the World Wide Web Consortium (W3C). OWL is developed for ontology modeling. Through building hierarchies of classes, it describes concepts in a domain and relates the classes to each other using properties. The main advantages of OWL are efficient reasoning support, sufficient expressive power, and convenient expression (Hsu and Kao, 2005). Knowledge models represented by OWL consist of Classes, Properties, Individuals (members of Classes), and Restrictions. Restrictions specify facts that must be satisfied by an individual for it to be a member of the Class. OWL employs a rich set of operators, e.g., intersection, union, and negation. OWL offers three sub-languages: OWL Lite; OWL DL; and OWL Full. Among these three languages, OWL Full provides the maximum expressiveness and the syntactic freedom. Although
OWL Full allows an ontology to augment the meaning of the pre-defined (RDF OR OWL) vocabulary, the RDF base does not have computational guarantees in OWL Full and it is unlikely that any reasoning software will be able to support complete reasoning for every feature of OWL Full (http://www.w3.org/TR/owl-features/). OWL Lite provides a quick migration path for the taxonomies. It only permits cardinality values of 0 or 1 (http://www.w3.org/TR/owl-features/) and OWL Lite supports those users primarily needing a classification hierarchy and simple constrains.

OWL DL (Description Logic) supports those users who want maximum expressiveness while retaining computational completeness and decidability (Rubin, 2008; Temal et al, 2008). Therefore, in our study, OWL DL is the most suitable since it has enough expressiveness in representing the varieties of classes as well as relationships between them, and also provides the decidability results from its logical inference. The basic elements of DL include (Beimel and Peleg, 2011):

- Concepts – unary predicates/formulae with one free variables (e.g. Person, Company, Activity);
- Roles – binary predicates/formulae with two free variables (e.g. hasParent);
- Individuals – constants (e.g. Catherine, Mike); and
- Operators – for forming restricted concepts and roles;

The smallest propositionally closed DL consists of:

- Concepts constructed using Booleans: \( \cap \), \( \cup \), \( \neg \) (i.e. Intersection, union, and compliment) and restricted quantifiers: \( \forall \), \( \exists \) (i.e. All-Values-From, Some-Values-From)
- Only atomic roles

One of the key features of OWL-DL is that it can be processed by a DL reasoner. A DL reasoner provides a set of Description-Logics inference services, such as:

- Consistency checking: ensuring that a knowledge model does not contain any contradictory facts;
- Classification: computing the superclass-subclass relation to create a complete class hierarchy;
- Realization: finding the most specific classes that an individual is a member of.

### 5.1.2 Knowledge Representation and Formalization

The purpose of the implementation task is to map the knowledge model at the conceptual level into a formal representation in a machine-readable format (i.e. the intended users are machines, not humans). We chose OWL as a representation language. One of our design concerns is the nature of the inference method. Our first thought is to identify candidate affected companies caused by bankruptcy diffusion through trade credit channel. The triggering event is usually a bankruptcy news announcement. In our case, for example, an instance of BankruptcyEvent class transmits the following information: company A files for bankruptcy on 2011.08.28. The questions here are how to 1). Identify possible affected firms (direct and indirect suppliers and creditors); and 2). Infer the valuation effects (hasGreatImpact or hasMinorImpact). Hence, the problem of analyzing the impact or contagion strength regarding coming news turns out to be a Classification problem.

The conceptual model implemented with OWL is firstly about to represent relating entities and their relationships through class hierarchies. Then, based on these static ontological classes, we demonstrate an inference method that formulates an incoming bankruptcy event as an individual of BankruptcyEvent class. Through rule development and inference, it will automatically produce a “GreatImpact/MinorImpact” response. The designed principles by which we develop the knowledge framework can be summarized as follows:
1. We formalize the conceptual model into an OWL-based ontology using Protégé (version 3.4.4). Within the ontology, we define basic classes to represent the model abstractions: Entities, Refineables, and Relations.

2. Besides the basic classes, we created additional classes to represent the bankruptcy news event. We name this class BankruptcyEvent class. The triggering bankruptcy event, which is the source of whole inference process, has to be formalized too. We structure it as an individual of the BankruptcyEvent class, and name the news GMaCar_News in response to our case. At the initial knowledge model building process, the GMaCar_News has no values for some attributes. For instance, among various attributes of GMaCar_News, some R2R_Relations will be got in the run-time knowledge as intermediate results of inference. To infer this kind of new knowledge, we set SWRL rules that define how to get meaningful and logical knowledge by chains of properties.

The OWL based ontology consists of “class”, “property” and “individual”, which roughly correspond to conceptual model members such as concept, attributes and instances. In the OWL DL definition, the subClassOf keyword shows the inheritance hierarchies of domain concepts. A property defines a directed relationship from a resource to another resource or literal. OWL distinguishes two kinds of properties: 1) an “object property” linking a resource to a resource, and 2) a “data-type property” linking a resource to a literal.

In the process of mapping the conceptual model into the formal OWL-ontology, we list several important steps as following:

1. We define the three basic abstractions as super-classes in the ontology. The respective defined super-classes are: Entity, Refineable, and Relation.

2. We define the four entities as subclasses of the super-class Entity: Firm, Commitment, Economic_Event, and EconomicResource.

3. NewsInformation is constructed outside Entity super-class since we assume this kind of news information is external source outside the enterprise scope.

4. We define the refineables as subclass of the Refineable super-class, which are organized hierarchically and associated with entities via OWL properties. Consequently, some refineables are associated with their respective entities via object properties (e.g., hasRelatingEntity), while others are associated via data-type properties (e.g., hasDateOfIssue). The following are examples of defined OWL properties and their respective domain entities (for an overview of the class hierarchies, see Figure 3):

   - For BankruptcyEvent class: hasRelatingEntity, hasContagionImpact, hasDateOfIssue, and hasContent;
   - For Firm class: hasName, hasFinancialLeverage, bankruptcyIndex and isBankruptcyState. For the bankruptcyIndex attribute, its value is a weighted combination of different financial statement ratios used for checking financial status of a firm. Bankruptcy prediction has drawn a lot of research interests in previous literature, with the most original models coming from statistical methods. In the late 1960s, discriminant analysis (DA) was introduced to create a composite empirical indicator of financial ratio. Using financial ratios, Beaver (1966) has developed an indicator that best differentiated between failed and non-failed companies using univariate analysis. The univariate approach is later improved and extended to multivariate analysis by Altman (1968) and Altman et al (1977). The Altman’s ZETA model is a formula that predicts whether a company will go bankrupt
within one year. Extensive testing has found this formula to be very accurate, as high as 90% in some cases. It works by weighting various aspects of a company’s assets and earnings in order to generate a final score. The original model was designed for certain manufacturing companies, but now it has expanded to cover other areas. The high accuracy in assessing bankruptcy risk of corporations makes it a useful tool in many applications such as credit worthiness analysis of firms, and identification of undesirable investment risk for portfolio managers and individual investors. Therefore, it is also a suitable method to provide a good indicator in our applications.

Specifically, we adopt the following formula to calculate this index:

\[ Z = 0.012Z_1 + 0.014Z_2 + 0.033Z_3 + 0.006Z_4 + 0.999Z_5 \]

where

- \( Z_1 = \) working capital/total assets;
- \( Z_2 = \) retained earnings/total assets;
- \( Z_3 = \) earnings before interests and taxes/ total assets;
- \( Z_4 = \) market value equity/book value of total liabilities;
- \( Z_5 = \) sales/total assets

\( Z \) is the overall index

A score of \( Z \) less than 2.675 indicates that a firm has a 95% percent chance of becoming bankrupt within one year.

5. A refineable may be assigned an Allowed Value. In this ontology, one possible way of allowed values is enumerated individuals (instances) of their corresponding refineable. For example, the two options of company financial status (bankruptcy and not bankruptcy) are defined as individuals of \( \text{BankruptcyState} \) class. Besides Allowed Values, some conditions must be added for defining classes. The typical conditions for the Firm class are given in Figure 4.
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6. In accordance with the conceptual model constructed in Section 4, the various relations are defined with OWL as subclasses of the Relation super-class. The relations are grouped into two main subclasses: 1) EntityToEntityRelation (E2E_Relation for short). The following are examples as subclasses of E2E_Relation: a) hasExtendCreditTo and b) hasSuppliedGoodsTo. Here, we list several examples of OWL-DL coding paragraphs exported from Protégé. Table 2 shows an example of the OWL-DL definition of the Class SecurityClass. Table 3 and Table 4 show the examples of the OWL-DL definitions of object property and data-type property. Within the conceptual model, we created the NewsInformation class to represent the generic concept of announcements that are daily published on electronic sources such as Reuters Bloomberg.

```
<owl:Class rdf:about="#Firm">
  <rdfs:subClassOf rdf:resource="#EconomicAgent"/>
  <owl:equivalentClass>
    <owl:Restriction>
      <owl:someValuesFrom rdf:resource="#Product"/>
    </owl:onProperty>
    <owl:Restriction>
      <owl:onProperty>
        <owl:ObjectProperty rdf:ID="hasProduced"/>
      </owl:onProperty>
    </owl:Restriction>
  </owl:equivalentClass>
</owl:Class>
```

Table 2: The OWL-DL definition of Class Firm

```
<owl:ObjectProperty rdf:ID="hasSuppliesGoodsTo">
  <rdfs:domain rdf:resource="#Firm"/>
  <rdfs:subPropertyOf rdf:resource="#interactWith"/>
  <rdfs:range rdf:resource="#Firm"/>
</owl:ObjectProperty>
```

Table 3: The OWL-DL definition of ObjectProperty hasSuppliedGoodsTo
This class could be further classified into more specific events such as merger and acquisition event, bankruptcy event and CEO changing. Since our focus here is bankruptcy diffusion phenomenon, all the specific bankruptcy filings are formalized via the BankruptcyEvent class with additional unique restrictions for expressing scenario characteristics. The following is a list of design principles, primarily for its reasoning requirements:

1. Following the definitions of conceptual model abstractions, the BankruptcyEvent class is related to Firm class via object property: hasInfluenceOn. Specifically, we start the formalization process by assuming the focus company in the bankruptcy announcement is playing the role as a customer in a trade transaction. Therefore, the BankruptcyEvent class may also be related to the Firm class via object property hasIndirectInfluenceOn by going through several production layers in the supply network. It is this kind of customer-supplier relationship transmission leading to the credit risk propagation in the supply network. Obviously, the property hasIndirectInfluenceOn is an instance of object property hasInfluenceOn.

2. The set of BankruptcyEvent class serves the inference method that analyzed an incoming bankruptcy announcement. The incoming news is represented as an individual (“instance” in OWL) of the most generic NewsInformation class.

5.2 Dynamic Task Solving Knowledge Implementation in SWRL
5.2.1 Semantic Web Rule Language

Task solving needs computational functions and inference with typical solutions through providing logics or rules. Since OWL provides limited deductive reasoning capabilities, some researches have concentrated on adding rules to handle this problem. Semantic Web Rule Language (SWRL) allows the user to write Horn-like rules (Horrocks et al., 2004) that can be expressed in terms of OWL classes and support reasoning about OWL individuals. A SWRL rule contains an antecedent part, which is referred to as the body; and a consequent part, which is referred to as the head. Both the body and the head consist of positive conjunctions of atoms. Atoms in these rules can be of the form C(x), P(x, y), sameAs(x, y), differentFrom(x, y), where C is an OWL class; P is an OWL property; and x/y can by variables, OWL individuals or OWL data values. SWRL offers deductive reasoning capabilities that can infer new knowledge from an existing OWL knowledge base. SWRL rule can also use arithmetic operators and compute the desired behaviour based on the context of individual, which may be a dynamic context with multiple components. The following is a SWRL rule expressing the inference that a person with a male sibling has a brother:

**Rule 1:**

\[
\text{Person}(p) \land \text{hasSibling}(p, s) \land \text{Man}(s) \rightarrow \text{hasBrother}(p, s)
\]

During our ontology engineering process, we use Protégé, a free open source ontology editor and knowledge acquisition system to define the knowledge model. We adopted the SWRLJESSTab
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plug-in to generate SWRL rules and run the inference through JESS rule engine. In our study, OWL and SWRL rules combined together to create an ontological knowledge base for the purpose of: 1) describing static structured knowledge relating with entities, properties, and relationships between them from financial, production, and information perspectives, and 2) developing dynamic rules as problem solving for targeting the contagion firm members in the supply network.

5.2.2 Rule Development

Once the static domain knowledge is semantically represented and structures, it is necessary to gain benefit by ontology-based reasoning and inference mechanisms. An ad hoc inference mechanism can be designed for a specific ontology in order to address specific problems and requirements of the domain (Meditskos and Bassiliades, 2008). Hence, machine-readable logical rules are developed in SWRL as the common behaviour pattern in identifying candidate affected firms. This study started collecting and editing semantic rules by consulting experts, case studies, and literature analysis. We give some examples as illustrated by the following details:

1. Rule 1 is used mainly to identify customer-supplier relationship between two entities by checking the product’s component.

   Rule 1

   \[ \text{Firm}(?, x) \land \text{Firm}(?, y) \land \text{Pr\,oduct}(?, p1) \land \text{Pr\,oduct}(?, p2) \land \text{has\,Pr\,oducts}(?, x, ?, p1) \land \text{has\,Pr\,oducts}(?, y, ?, p2) \land \text{has\,Product\,Component}(?, p1, ?, p2) \rightarrow \text{is\,Supplier\,Of}(?, y, ?, x) \]

2. By fixing a certain threshold, we assume that a supplier adopting great financial leverage may be more vulnerable and fragile faced with a distress situation of its customer. The higher financial leverage usually means a large amount of trade credit. The financial leverage is calculated by the trade credit divided by equity level at book value (the values of the individuals are asserted into knowledge base when triggering inference).

   Rule 2

   \[ \text{Firm}(?, x) \land \text{has\,Financial\,Leverage}(?, x, ?, \text{leverage}) \land \text{swrlb:\,greater\,Than}(?, \text{leverage}, 70\%) \rightarrow \text{has\,Great\,Firm\,Leverage}(?, x, l) \]

Once Rule 2 and Rule 3 assert that in the context of the high degree of credit interdependence, the contagion effect is manifested as bankruptcy diffusion effect. A score of bankruptcy index less than 2.675 indicates that a firm has a 95% percent chance of becoming bankrupt.

Rule 3

\[ \text{Bankruptcy\,Event}(?, e) \land \text{has\,Relationship}(?, e, ?, x) \rightarrow \text{is\,Bankruptcy\,State}(?, x, l) \]

Rule 4

\[ \text{is\,Supplier\,Of}(?, y, ?, x) \land \text{is\,Bankruptcy\,State}(?, x, l) \land \text{has\,Bankruptcy\,Index}(?, y, ?, b) \land \text{swrlb:\,less\,Than}(?, b, 2.675) \land \text{has\,Great\,Firm\,Leverage}(?, x, l) \rightarrow \text{has\,Bankruptcy\,Probability}(?, y, ?, \text{prob}) \land \text{swrlb:\,greater\,Than}(?, \text{prob}, 95\%) \]
Rule 5

\[ \text{Firm}(?, y) \land \text{hasBankruptcyProbability}(?, y, \text{prob}) \land \text{swrlb:greaterThan}(?, \text{prob}, 95\%) \]
\[ \rightarrow \text{hasContagionImpact}(Great) \]

Protégé software provides a SWRL rule editor using SWRLJESSTab plug in. A rule inference engine Java Expert System Shell (JESS) can be embedded into Protégé to perform SWRL rules. As shown in Figure 5, the SWRL editor in Protégé-OWL integrates two parts: rule editor and inference control panels. The top frame allows users to edit rules completely as text. It also allows users to select OWL entities from a current loaded knowledge base and insert them into the rule being edited. The bottom frame is a runtime interface that launches JESS and other relevant functions. Consequently, performing rules can help ontology-based systems infer more implicit new knowledge.

6. Case Study

Case study is widely used as an effective method to demonstrate the applicability of the ontological approach in different domains (Vorobiev and Bekmamedova, 2010; Perkowitz and Etzioni, 2000). In this section, we illustrate the implications of the ontological knowledge framework by a specific example in the American automobile industry – the case of car manufacturer’s Chapter 11 bankruptcy filing. In this case study, we put emphasis on investigating the bankruptcy diffusion effect through the trade credit channel in the supply network. This study is used to generally demonstrate how the static domain ontology combined with problem solving task (represented by semantic rules) work together. We firstly obtain some newly updated facts about the main participants in the American automobile industry from Yahoo Finance. After the data is entered into the Protégé knowledge base, the JESS engine is triggered to perform the inference.
6.1 Step 1: Fill Facts into the Knowledge Base

We could fill in different instances for each different case. In our example, we name the specific news announcement Car_News. The structuring of the Car_News goes through two steps:

a) Constructing the specific Car_News from the news resource in the form of an XML document. The original file consists of a set of data items collecting from the online news database (e.g., the information distributor, the issuing data, and the focus company, etc).

b) Creating all possible supply network members and all E2E_Relations as well as E2R_Relations, which are based on the values of attributes of the focus company: the value of hasRelatingEntity. The set of these individuals and properties are required for the completion of the knowledge base. Without this factual information, DL reasoner cannot begin its inference. In this case, some basic firms like TRW Automotive, American Axle, Lear, and Delphi are filled in as instance of the domain level class Firm Class in Protégé. From the contents' source of viewpoint, the ontology property contains “asserted property” and “inferred property”.

Firstly, we fill the facts of relevant entities (values of asserted property) into the columns of “asserted property”. In this simplified network of the US automotive industry, we have taken several firms as representatives of the overall structure. The contents of “inferred property” fields are the intermediates or last reasoning results after running the JESS rule engine.

6.2 Step 2: Operation

6.2.1 Find Direct and Indirect Suppliers of aCar Corp

For the properties whose contents are unknown or implicit during the initial stage, these contents will be produced by the computations using known facts. Finding potentially affected firm caused by a bankruptcy event can be achieved by deducing the content of some inferred properties. Semantic rules are fired to accomplish inference.

As parts suppliers extend trade credits to car manufacturers, the failure to fulfill debt commitments by a customer may hamper the solvency of the parts supplier. Worse still, the parts suppliers may become unable to pay their own suppliers located in the upper level, leading to a chain of similar failures (bankruptcy diffusion effect) and result in bankruptcy avalanches in extreme cases. Therefore, finding direct and indirect suppliers of aCar Corp is a key step.

Rule I is iteratively implemented when the rule engine feeds more facts into the system. Qualified suppliers are assigned into the isPartsSupplier property and customer-supplier relationship and customer-supplier relationship is identified between firms. To further clarify the cooperation of the rules, Figure 6 shows the details of successive changes in implementing inference. In Figure 6, blocks I, II, and III roughly represent different layers of the supply network. The filled rectangle inside each block represents the Firm; the small circle represents properties of a class; and the arrow line denotes the sequence of inference. From the first block, instance of Firm class aCar Corp has its product NIVA VAZ 2123. The product (NIVA VAZ 2123) needs some components (seat cushions) manufactured by aSeat Corp. After the first round of inference, aCar Corp obtains its supplier aSeat Corp.

The second block continues performing the same rule. aSeat Corp. Obtains a chemistry company aChem Corp as its upstream supplier this time. aChem Corp is an enterprise with main areas in selling paint and engineering poly-meters to the auto industry. In a similar scenario in the third block, E2 finds a supplier E3. Since we define isSupplierOf property as transitive property, the inference can be extended to higher layers until all facts are addressed. Although no chemical
firms are in the list of major suppliers or credits in the bankruptcy filing, computation results find DuPont aChem Corp is also inferred as an indirect supplier of aCar Corp.

6.2.2 Find Possible Affected Firms by Constraints
Many firms are connected with aCar Corp by the customer-supplier relationships; however, not all of them will suffer a stock depreciation effect as a result of the aCar Corp bankruptcy event. Firms are identified with a high possibility of a distressed situation among the suppliers must meet two criteria: 1) aCar Corp is their main customers and the financial leverage is higher than 70% (i.e., the sale of their product is greatly dependent on aCar Corp and extending great trade credit to aCar Corp); 2) cash liquidity: the score of bankruptcy index less than 2.675 indicating that a firm has a 95 percent chance of becoming bankrupt.

6.2.3 Wealth Effects on Affected Firms
After the execution of all the rules with filled facts, each inferred item is then assigned into the corresponding property “hasBankruptcyProbability” with varying values as its content. The most vulnerable suppliers include TRW Automotive, American Axle, Lear, Delphi, Hewlett Packard and Continental. Our reasoning results are in accordance with these quotes reported later.
example, aSeat Corp. (Tier-1 supplier) has a bleak future. Both aCar Corp’s and aSeat Corp.’s stock shares continue to get hammered. aCar Corp stock shares traded as low as $1.40 on Friday morning and aSeat Corp has dropped from 7 cents to 2 cents on Tuesday. aCar Corp’s price is the lowest since 23 May, 1933 and the price for aSeat Corp is also so low that the NYSE (New York Stock Exchange) has delisted it.

7. Conclusion

Compared to other news-based risk monitoring and management models omitting interdependence among economic entities, we have proposed a knowledge framework focusing on the bankruptcy diffusion phenomenon through trade credit channel. It provides a conceptual understanding for the analysis, design, development and implementation of intelligent investment applications, which are important for helping analysts and investors identify firms affected by a financially distressed member. This ontological approach offers a solid, mature, and reliable formal knowledge representation mechanism by means of accurate conceptualization, shared understanding and logical reasoning. At the conceptual level, domain knowledge is represented by Telos graphical notation; at the implementation level, the conceptual model is implemented in OWL and SWRL, in which SWRL is mainly used for problem solving and computable results. A preliminary verification and validation of the overall approach is presented by aCar Corp bankruptcy event. The case study shows that the approach can be applied to a real world example to identify candidate affected firms.

Through offering shared and formal understanding of bankruptcy diffusion phenomenon, the knowledge framework suggests a number of insights for various agents in the economy. Firstly, company manager should be especially cautious when selecting customers as trading partners in the supply network. For those who may delay their payments or default at their trade credit, administrations should prepare enough cash buffer in order to avoid such diffusion or contagion risk. Secondly, banks should calculate risk premia depending not only on the characteristics of a firm, but also those of its customers’ customers. Finally, policy makers may want to impose limits on trade credit agreements, which may exacerbate the upstream amplification of risk. The authority is also responsible for alerting the various decision makers involved about the possibility of risk propagation and amplification. In general, we believe our knowledge framework lays a solid foundation for decision support systems that can be applied broadly. In particular, this ontological approach of bankruptcy diffusion through trade credit channel contributes to the literature in the following aspects:

- At the conceptual level: by creating a conceptual ontology structure, ontology based fundamental domain conceptualization is constructed. This domain ontology provides a fundamental shared understanding of the domain of bankruptcy diffusion through trade credit channel to disclose the real and dynamic exposures from investment perspectives.
- At the implementation level: we implement the abstract conceptual model by using semantic techniques (OWL and SWRL) for extending computability and reasoning support.

Finally, we envisage a number of future research aspects that will be considered in the short term. Firstly, although the application has already been validated by a real life case, the evaluation of case study is only a rough measure. More quantitative data from experiments or simulation results are needed to verify the scalability of the model. Secondly, we will increasingly extend our OWL ontological knowledge base and develop the semantic rules to benefit from expressivity and inference capability of the ever-growing semantic web techniques and software.
References


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