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An Ontology for Investment in Chinese Steel Company

Liming Chen, Baoxin Xiu, Zhaoyun Ding, Bin Liu, Xianqiang Zhu

Abstract**—**In the era of big data, public investors are faced with more complicated information related to investment decisions than ever before. To survive in the fierce competition, it has become increasingly urgent for investors to combine multi-source knowledge and evaluate the companies' true value efficiently. For this, a rule-based ontology reasoning method is proposed to support steel companies' value assessment. Considering the delay in financial disclosure and based on cost-benefit analysis, this paper introduces the supply chain enterprises financial analysis and constructs the ontology model used to value the value of steel company. In addition, domain knowledge is formally expressed with the help of Web Ontology Language (OWL) language and SWRL (Semantic Web Rule Language) rules. Finally, a case study on a steel company in China proved the effectiveness of the method we proposed.

Keywords**—**Financial ontology, steel company, supply chain, ontology reasoning.

I. Introduction

WITH the rapid development of information technology, public investors have access to various information related to investment. However, due to the lack of professional experience and enough knowledge, they are easily confused by massive information. Therefore, public investors urgently need an efficient method to handle multi-source information to assess companies' value accurately. In view of this, the aim of the paper is to present the application of ontology in companies' value assessment based on cost-benefit analysis to support investment decision.

Specifically, the paper's method is mainly oriented towards the steel industry. Many researchers believe that the steel industry is at a breaking point for the difficult global economic situation and pollution [1]. This has also led to a lack of financial ontology research in the iron and steel industry. However, this paper believes that steel, whether as a building material or as a raw material for equipment and home appliances, will not decline at least in near future. In addition, the steel industry itself is a capital-intensive industry which depends on large capital investment. Thus, this paper believes that it is of great practical and theoretical significance to study the financial ontology of steel companies.

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II. Related Work

On the definition of ontology, there are several different opinions in academia [2]-[5]. The definition of "explicit definition of a particular concept" [6] is adopted here. That is, ontology is the formal expression of a specific domain knowledge. On the whole, there is relatively little research on the investment ontology of steel companies in academia, which mainly includes two directions: steel ontology and investment ontology [7].

Relevant researches on investment ontology mainly focus on the sub-directions of viewpoint mining (emotion analysis) in financial news [8], fraud detection based on financial statements [9], ontology representation of financial reports [10], bankruptcy prediction [11], risk management in financial field [12], [13], and formal representation of financial news headlines [14]. Specifically, relevant technologies are mainly applied as follows: (1) extract knowledge from massive data by using data mining algorithms such as decision tree [9] and association rule mining [15]; (2) carry out formal expression of financial news (information) [7], [10], [16] and emotional semantic analysis [8]; (3) fraud detection [9], risk early warning [11], [12], crisis prevention [13], etc., are carried out by means of knowledge reasoning of ontology model. However, there are few studies on enterprise investment value evaluation based on ontology model and knowledge reasoning. In other words, there is almost no research on investment ontology modeling (framework) which is directly oriented to the evaluation of enterprise investment value.

The research on steel ontology mainly focuses on the production decision based on supply chain [17], intelligent manufacturing [17], steel manufacturing process [18] and other aspects. That is, the study of steel ontology can be divided into two major directions: knowledge management system in the field of steel and intelligent manufacturing in steel enterprises. The knowledge management system in the field of steel is mainly based on the perspective of the industrial chain [17], which is committed to comprehensively integrating various internal and external knowledge of steel companies, improving the interoperability of information systems, and providing as much and as appropriate knowledge as possible for decision-making of production and operation. On the other hand, the direction of intelligent manufacturing based on steel ontology can achieve the seamless connection of knowledge between different departments by breaking through the knowledge boundary of production and manufacturing process [18], thus facilitating the promotion of intelligent manufacturing in the iron and steel industry.

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III. Ontology-Based Decision Support Process

Faced with massive information, numerous public investors are easily caught in analysis and collation of data, which may be quite hard for public investors who is lack of professional training and knowledge. In view of this, an ontology-based investment decision support process (Fig. 1) is proposed and explained as follows.

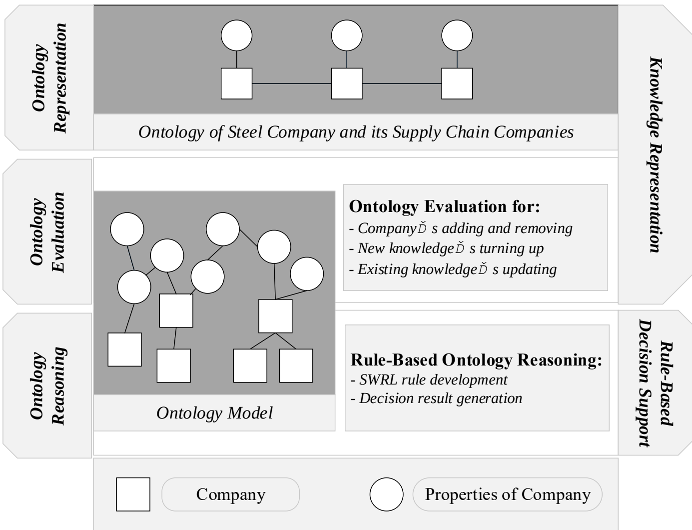

Fig. 1 Ontology-Based Decision Support Process

A. Knowledge Preparation

In order to obtain the greatest possible return on investment, value assessment of companies is essential. For this, we introduced cost-benefit analysis (Value = Benefit – Cost) and supply chain analysis (Fig. 2) to assess the value of companies.

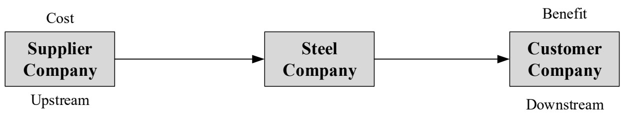

Fig. 2 Ontology-Based Decision Support Process

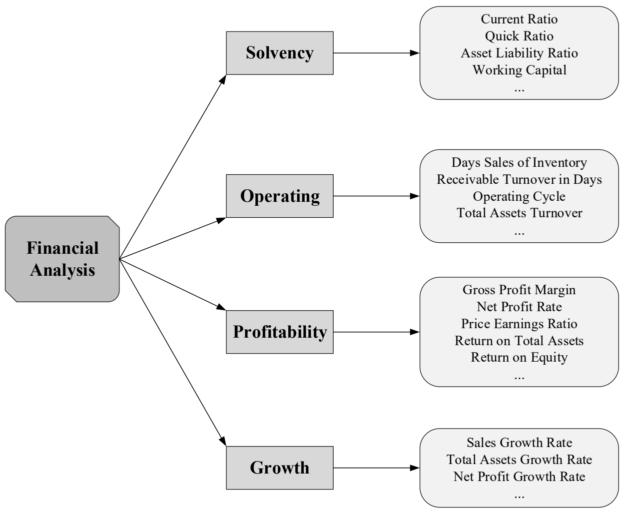

Fig. 3 Financial Analysis

Specifically, we introduce traditional financial analysis (Fig. 3), which uses a series of indicators to evaluate an enterprise's solvency, operating, profitability and growth capabilities. On the whole, based on the financial analysis of iron and steel enterprises and their upstream and downstream enterprises, this paper assists the decision of value investment. Therefore, we need to prepare knowledge related to the financial analysis of steel companies, upstream and downstream companies. Moreover, for qualitative analysis, we also add some information about the companies’ location and executives. In general, we need the supply chain information, the financial statements, and basic information of steel companies and its supply chain cooperative companies. Here are 15 intuitions (Table I) used for our ontology model.

B. Rule-Based Decision Support

Simple formal expression of relevant information does not assist in decision-making. To get knowledge useful for investment decision, rules are essential. With rules and inference engine, we can add more types of knowledge into ontology model, and more valuable knowledge can be provided. In this ontology model, reasoning results include decision mechanism and financial analysis of relevant companies.

IV. Methodology

In this section, the ontology-based investment decision method in China’s iron and steel company is proposed. It is on the basis of ontology representation of steel companies, upstream and downstream companies and SWRL rules.

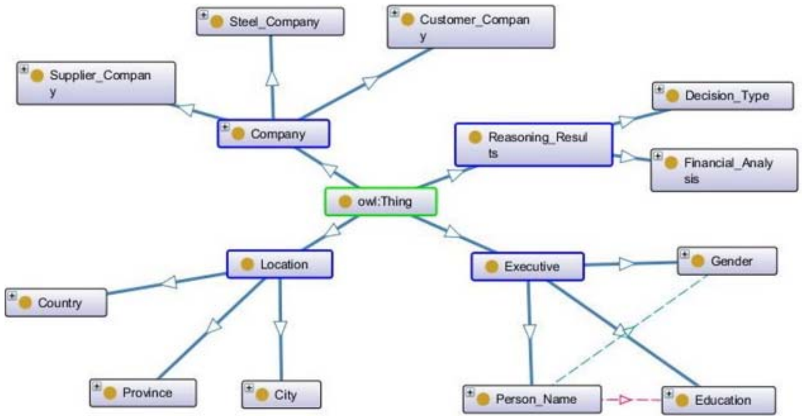

Fig. 4 Major Classes

TABLE I
RELEVANT INTUITIONS

Intuition	Content
Intuition 1	In economics, cost-benefit analysis can reflect the investment prospects of a company well.
Intuition 2	The cost of a company is mainly paid to upstream suppliers, and the revenue is mainly from downstream customers.
Intuition 3	For intuition 2, analysis based on the supply chain can better predict the investment prospects of a company.
Intuition 4	Traditional financial analysis theory believes that analyzing a company should from four aspects: solvency, operational capability, profitability, and growth ability.
Intuition 5	Depending on the time span, solvency can be divided into short-term solvency and long-term solvency.
Intuition 6	Short-term solvency is mainly analyzed by *operating cash*, *current ratio* and *quick ratio*, while long-term solvency is mainly represented by *asset-liability ratio*.
Intuition 7	The operational capacity is mainly reflected in the three aspects of inventory, accounts receivable and total assets, which correspond to three indicators: i*nventory turnover days*, *accounts receivable turnover days* and *total asset turnover rate*.
Intuition 8	The evaluation of corporate profitability mainly relies on four indicators: *gross profit margin*, *net interest rate*, *return on net assets*, and *return on total assets*.
Intuition 9	The development potential of a company is mainly reflected in *asset growth rate*, *sales growth rate* and *profit growth rate*.
Intuition 10	Whether it is an upstream enterprise or a downstream enterprise of a steel enterprise, once its four major capabilities are in crisis, it is worthy of attention from steel companies.
Intuition 11	When a company's chairman and general manager are part-time, the company is usually a centralized enterprise. Otherwise, it is a decentralized enterprise.
Intuition 12	The upstream enterprises of iron and steel enterprises mainly include coke enterprises, iron ore enterprises and electric power enterprises.
Intuition 13	The downstream enterprises of iron and steel enterprises mainly include construction enterprises, equipment manufacturing enterprises and home appliance enterprises.
Intuition 14	The main executives of steel companies include legal representatives, chairman, general manager, secretary of the board of directors and chief financial officer.
Intuition 15	The stock market is risky, and investment needs to be cautious.

A. Ontology Representation

As shown in Fig. 4, four major classes are considered in the ontology: Company, Executive, Location and Reasoning Results.

The Company class includes steel company, supplier company, and customer company, which correspond to supply chain. The Executive class describes Company's executive information, including name, gender and education. The Location class describes the location information of company. For example, *Steel Company A* is located in Paris, France. The Reasoning Results class is used to store the reasoning results from inference engine. It includes decision type and financial analysis. Among them, the Financial Analysis class is come from traditional financial analysis and supply chain analysis with OWL and SWRL rules.

B. The Evaluation of Ontology

As Fig. 5 shows, the *Company* class and the *Reasoning Results* class form the two main classes of the ontology model. The Executive class and the Location class are designed to build two main class object properties. With the addition of non-trivial instances and the HermiT inference engine, we have also obtained an example of Reasoning Classes while completing the consistency of reasoning verification.

It is obvious that nearly every steel company has its supplier (upstream) company and customer (downstream) company. Moreover, the four capabilities of financial analysis and executive properties are suitable for every steel company in China. So our ontology model is robust. In addition, the *supplier company* class and *customer company* class has its own subclass, which is aimed at iron and steel company. What's more, our threshold standard for assessing the company's ability is formulated according to the characteristics of Chinese steel industry. So it is suitable for value assessment of steel companies in China.

In summary, the ontology model proposed is flexible for adding or deleting individuals and knowledge and suitable for value investment decision support.

C. Rule-Based Ontology Reasoning

A single OWL ontology model is not sufficient to adequately express the knowledge required for inference. With this in mind, this paper also adopts SWRL for Rule representation, which is very helpful for reasoning. Specifically, 26 SWRL rules are included in the ontology model. Table II shows the 8 representative SWRL rules. With these SWRL rules, inference engine can provide more results than sole OWL representation, which is helpful for value assessment of steel company. And so the method in this paper is called rule-based ontology reasoning.

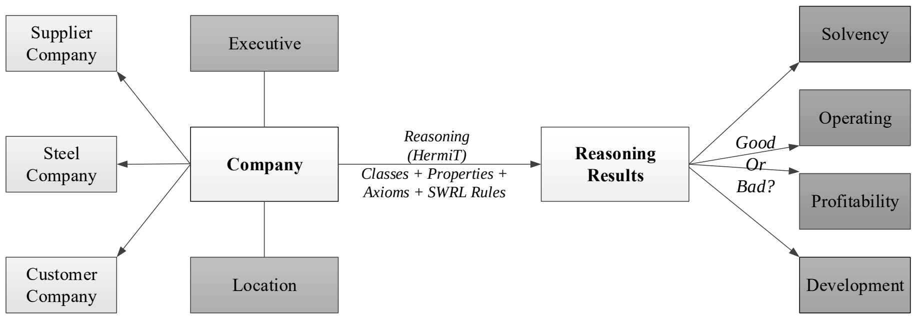

Fig. 5 Class Hierarchy

TABLE II
SWRL RULES

SWRL rule	Content
S1	*lightsteel: City(?M) ^ lightsteel: Located_in(?M,?Z) -> lightsteel: Country(?Z)*
S2	*lightsteel: Company(?M) ^ lightsteel: Located_in(?M,?Z) -> lightsteel: City (?Z)*
S3	*lightsteel: Chairman (?M,?Z) ^ lightsteel: CEO(?M,?Z) ^ sameAs(?Z, ?Z) -> lightsteel: Centralized (?M)*
S4	*lightsteel: CEO(?M,?B) ^ lightsteel: Chairman(?M,?A) ^ differentFrom(?A, ?B) -> lightsteel: Decentralized(?M)*
S5	*lightsteel: Supplier(?A,?B) ^ lightsteel:Solvency_Good(?B) -> lightsteel: Supplier_Solvency_Good(?A)*
S6	*lightsteel: Supplier(?A,?B) ^ lightsteel:Solvency_Bad(?B) -> lightsteel: Supplier_Solvency_Bad(?A)*
S7	*lightsteel: Chairman(?M,?A) ^ lightsteel:Iron_Steel_Firms(?M) ^ lightsteel: CEO(?M,?B) ^ sameAs(?A,?B) -> lightsteel: Centralized(?M)*
S8	*lightsteel: CEO(?M,?B) ^ lightsteel: Steel_Company(?M) ^ lightsteel: Chairman(?M,?A) ^ differentFrom(?A,?B) -> lightsteel: Decentralized (?M)*

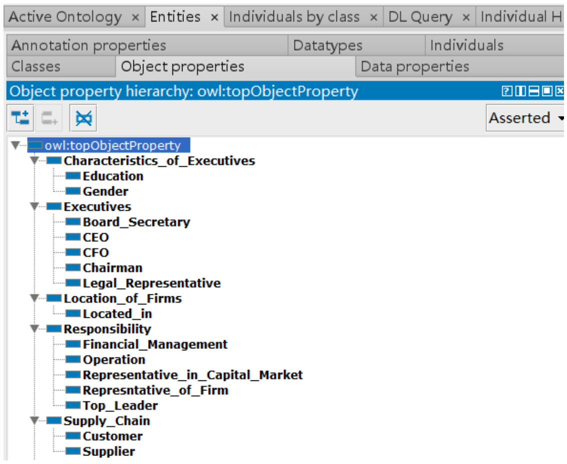

Fig. 6 Object Properties

V. CASE STUDY

For explicitly, this paper chose Steel Company A, a famous Chinese steel company, as example. In addition to the SWRL rules and ontology levels mentioned above, we also added some properties and axioms.

A. Properties

Properties are divided into object properties and data properties, which correspond to qualitative analysis and quantitative analysis.

The object properties of this research (Fig. 6) mainly include three categories: executive properties, supply chain properties and geographical properties mainly used for qualitative analysis of firms. It is worth mentioning that the supply chain properties can reflect the supplier and customer relationships among steel companies, upstream companies, and downstream companies.

The data properties (Fig. 7) are divided into two categories: age properties and four major capabilities' properties. In addition to the age corresponding to the quantitative analysis of executives, the remaining four major data properties are mainly used to quantitatively assess the investment prospects of companies.

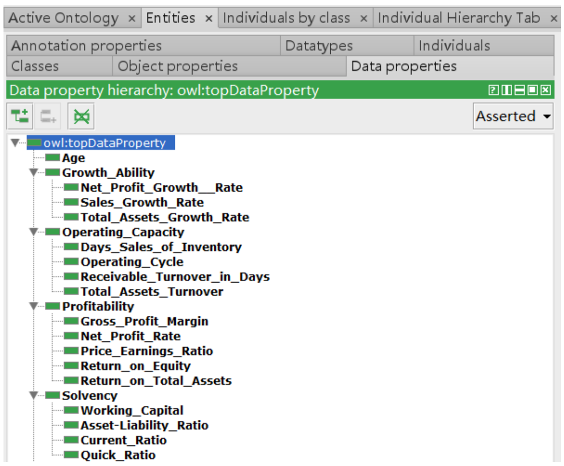

Fig. 7 Data Properties

B. Axioms

Our ontology model contains a total of 891 axioms. Among them, the largest number is the individual axiom and the 455 individual axioms, including 91 class assertions, 186 object property assertions, and 178 data property assertions. The following will focus on class axioms. The 77 class axioms include 8 equivalence class axioms, 55 subclass axioms, 6 disjoint axioms and 8 hidden GCI. Fig. 8 shows the equivalence class axioms, subclass axioms, and disjoint axioms of the *Solvency_Good* class.

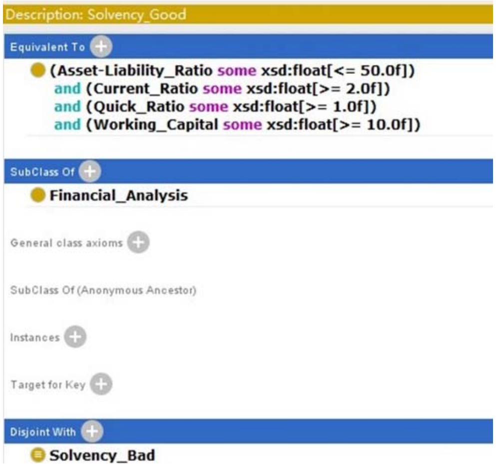

Fig. 8 Equivalence Class, Subclass and Disjoint Axioms

C. Reasoning Results

The case study is mainly done by adding 91 non-trivial instances related to *Steel Company A*, with the help of a *HermiT* inference engine. Fig. 9 shows the reasoning results of *Steel Company A*.

Taking solvency good of *Steel Company A* for example, the explanation (Fig. 10) is that the *current ratio*, *quick ratio*, *working capital* and *asset-liability ratio* have reached the *solvency good* equivalence class.

VI. Conclusion and Future Work

As Fig. 11 shows, our ontology model is based on cost-benefit analysis, combining supply chain analysis and financial analysis methods to consider comprehensive. On the one hand, the ontology model achieves a combination of qualitative and quantitative by means of both object and data attributes. On the other hand, we have also considered the reality of upstream cost pilots and downstream revenue pilots, and achieved a clever combination of historical summaries and future prospects.

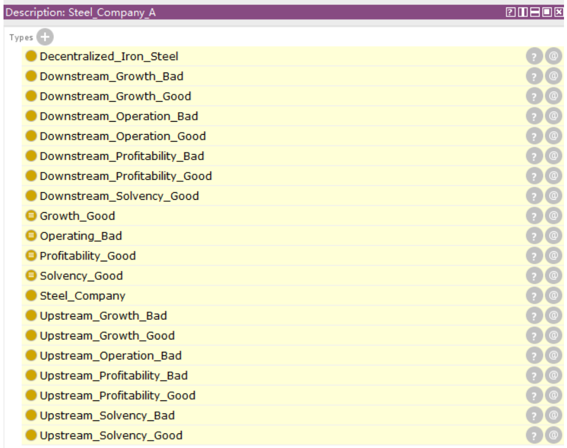

Fig. 9 Reasoning Results

The actual demand and research shortage of the steel company value assessment financial ontology model gave birth to the construction of this ontology model. According to the cost-benefit analysis (Fig. 12), this study constructs the ontology model of steel company investment combined the supply chain and the four capability evaluation indicators of financial analysis. Based on the non-trivial examples added, the results of *HermiT* reasoning and theoretical analysis show that the consistency and completeness of the model are tested. Lastly, taking Steel Company A as example, the case study proves the efficiency of the model we constructed. However, the model in this paper still has some shortcomings. For example, the internal analysis of the company is not deep enough and supply chain analysis does not include competitor analysis and policies analysis, which could be our future work.

Fig. 10 Explanation for *Steel Company A* Solvency Good

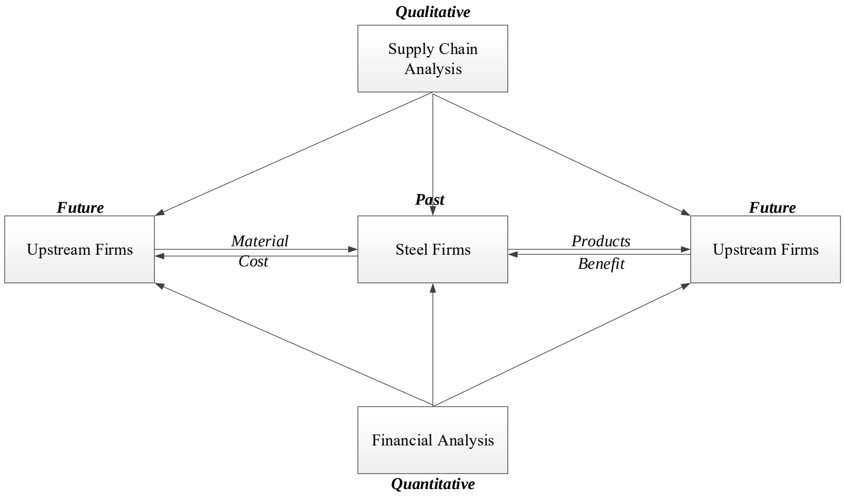

Fig. 11 Completeness Proof

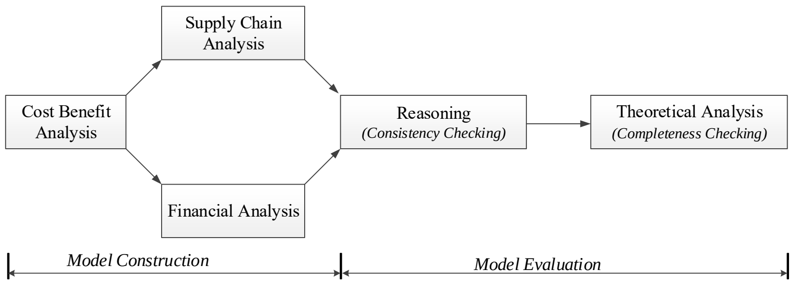

Fig. 12 Research Process

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