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Selecting Valuable Mask Topic Stocks through Ontology Reasoning

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Abstract. Due to COVID-19, masks are in short supply. Accordingly, mask topic stocks have surged as well. However, faced with various mask topic stocks, plenty of individual investors can only blindly follow the trend, but lack of objective judgment. In light of this, an ontology-based stocks selection framework was proposed. Different from most prior methods, the proposed framework starts from fundamental analysis and combines qualitative knowledge and quantitative data. Concretely, qualitative knowledge refers to news, information of executives and industry chain partners, while quantitative data are the financial ratios from the financial statements of companies. Notably, supply chain information was also introduced to address the delay of statements disclosure. Moreover, with the risk preference coefficient, the proposed framework can adapt to investors with different risk preference. Lastly, the results of case study are basically consistent with the research results from four investment institutions, which proves the practicality and effectiveness of the proposed framework.

1. Introduction

For one thing, affected by COVID-19, the shortage of masks has become one of the biggest challenges in the prevention of the epidemic [1]. Taking one step further, between market demand and raw material costs, the profit margins of mask manufactures have been greatly expanded. Accordingly, in Chinese capital market, mask board has become hot as well. For another thing, in Chinese stock market, individual investors [2], accounting for a large proportion, are easily confused by massive information [2]. Therefore, individual investors urgently need an efficient method to handle multi-source information to select valuable mask topic stocks. Under the normal control of COVID-19, the mask market prospects are still quite good, but the opportunity is only for those who have real material mask manufacturers. For this, the main concern for individual investors is how to select the valuable mask topic stocks. Equally important, the selecting method for mask topic stocks should be sufficiently interpretable [3]. However, existing methods for stocks selection mainly focused on predicting stock prices or significant changes in stock price using machine learning. In fact, most relevant studies [3] adopt the deep learning algorithm, which is lack of interpretability. More importantly, its features are mostly technical indicators, which implies uncontrollable risks. In light of this, an effective stocks selection framework needs to satisfy the three requirements of interpretability, fundamental analysis and simplicity simultaneously. Luckily, ontology model has natural interpretability and reasoning ability [5, 6], which is very suitable for investment decision support.



To simultaneously address the investment risk, insufficient interpretability and inapplicability, an ontology-based selection framework for mask topic stocks was proposed. In this framework, cash flow was thought to be the core competence of mask manufactures. Furtherly, around cash flow, security, profitability, and growth become the main competency dimensions. Quantitatively, these abilities are evaluated by relevant financial ratios. Furthermore, to alleviate the delay of disclosure, the proposed framework also introduced the supply chain enterprises. In this way, with the analysis of supply chain enterprises, risks and perceived opportunities can be founded in advance. In addition, the risk preference coefficient and decision type evaluation were also considered to provide better personalized needs. Technically, the proposed framework mainly adopts OWL (*Ontology Web Language*) and SWRL (*Semantic Web Rule Language*) for ontology construction, and *Pellet* inference engine for ontology reasoning. To be specific, the proposed framework has five contributions:

1) Financial Analysis with Limited Risk. Different from technical analysis, the proposed framework started from fundamental analysis. Through fundamental analysis, the cash flow and four capabilities of enterprises can be analyzed quantitatively. In this way, major capabilities such as cash flow, security, profitability and growth were all included in the proposed framework. Therefore, the proposed framework can guarantee lower risk than previous technical analysis.

2) Ontology-based Framework with Adequate Interpretability and Operability. Ontology model not only has strong representation ability and reasoning ability, but also can be explainable and operable. This explanation and operability is very crucial for reliable selection of valuable stocks. Therefore, for the interpretability and operability, ontology model was chosen to be the basic model of the proposed framework.

3) Risk Preference Coefficient for Personalized Selection. To satisfy personalized risk preference of different investors, the risk preference coefficient was introduced to the proposed framework.

4) Combination of Qualitative Analysis and Quantitative Analysis. With data properties and object properties, quantitative and qualitative knowledge can be injected into one ontology model. Hence, the proposed framework can handle different types of information and provide more reliable results.

5) Prospective Mechanism based on Supply Chain. Aimed at the delay of financial statements disclosure, supply chain partners were innovatively introduced to the proposed framework. In the supply chain, the cost of manufactures is mainly paid to upstream suppliers, while sales revenue comes from downstream distributors. Because of this, the proposed framework has a prospective mechanism based on supply chain.

For illustration, the rest of the paper is structured as follows: Section 2 reviews some related work of ontology-based approaches for stocks selection; Section 3 briefly illustrates the ontology-based stocks selection framework; Section 4 introduces the construction of the stocks selection ontology, ontology evolution, and rule-based ontology reasoning; at last, Section 5 justifies the proposed framework through a case study of Chinese mask manufacture and Section 6 concludes the paper and presents some future work.

2. Related work

On the whole, the proposed framework involves many applications, which can be roughly divided into two research directions: information integration and intelligent reasoning.

2.1. Information integration

Information integration, mainly attempts to integrate multi-source information with the help of ontology model for retrieval and query. To integrate real-time financial data, [7] proposed an adaptive and real-time based architecture, where real-time financial data integration latency problems and semantic heterogeneity were resolved by combining a hybrid financial ontology. Furthermore, for XBRL (*Extensible Business Reporting Language*) filings and IFRS (*International Financial Reporting Standards*) standard, [9] and [10] respectively constructed XBRL filings (files) integration ontology

and the financial reporting ontology according to IFRS. However, the above ontology model mainly focuses on simple information integration and ignores the uneven quality of financial data. To improve the quality of online financial data, an ontology-based framework [11] was proposed, whose positive impact on the performance of financial decision-making was empirically demonstrated with asset valuation. However, there is a lack of timely news data to cope with the rapidly changing capital market. For this, several researches have also studied the ontology representation of financial news. For example, an ontology [12] was developed to represent financial headline news. The testing results [12] show that, 99% of headline news can be properly represented by the proposed ontology. In addition, a financial news recommendation algorithm based on ontology was also been proposed [13].

Undeniably, the above information sharing methods can effectively meet specific needs. But when it comes to stock selection for individual investors, these methods seem powerless, especially when it comes to controlling risk and operability.

2.2. Intelligent reasoning

Intelligent reasoning, refers to intelligent decision support based on ontology reasoning, which mainly involves financial reasoning, clinical support and intelligent manufacturing.

2.2.1. Financial reasoning.

Financial reasoning, mainly involves systemic financial risk prevention [14], financial statements fraud detection [15], bankruptcy prediction [16], insurance company activity modeling [17] and other applications [18, 19]. Aiming at systemic financial risk, [14] proposed to incorporate human factors into the ontology model to control risks. To detect financial statements fraud, [15] presented a knowledge-based detection system. Furthermore, for the bankruptcy risk, an effective ontology model [16] based on financial statements were proposed. Apart from risks prevention, ontology-based financial reasoning also involves opinion mining in financial news [20], which has achieved to semantically describe relations between concepts in the financial news domain.

2.2.2. Clinical support.

In knowledge engineering research, clinical support has always been an unavoidable topic [6]. Here, ontology-based disease diagnosis mainly refers to providing intelligent support for the selection of disease diagnosis and treatment scheme by means of ontology model [21]. Moreover, ontology-based diagnostic support mainly includes the diagnosis of diabetes [22], infectious disease [23] and universal multi-agent diagnostic systems [24]. Taking the diabetes diagnosis for example, a semantically interpretable FRBS (Fuzzy Rule-Based System) framework [22] for diabetes diagnosis was proposed and implemented. In terms of disease treatment, ontology-based decision support mainly focuses on cancer treatment [25] and antibiotic treatment [21, 26, 23]. Notably, [25] proposed to use Case-Based Reasoning (CBR) to provide physicians with treatment solutions from similar previous cases for reference.

2.2.3. Intelligent Manufacturing.

To address the uncertainly challenge in manufacturing and supply chain, a rule-based ontology model [27] has been constructed for enhancing supply chain resilience, through which the knowledge base of the ontology has also been created. Furthermore, to optimize the manufacturing process, [29] designed a knowledge-based multi-criteria decision support system to suggest candidate configurations and select a suitable configuration. Additionally, a rule-based ontology reasoning method [28] has also been proposed to support steel manufactures decision, whose effectivity has been justified through a case study in China's iron and steel industry.

The above related work, whether it is information integration or intelligent support, few ontologies have been used for individual investment support. In addition, existing research still mainly focuses on technical analysis and ignores the fundamental analysis of enterprises, which may mean excessive

risks. For this, an ontology-based method from fundamental analysis, was proposed to assist individual investment in mask topic stocks, which will be explained in more detail below.

3. Methodology

For the helpless individual investors, an interpretable and operational framework, which has with limited risk, was proposed to select valuable stocks. In the process, the proposed framework mainly includes two steps (Figure 1): knowledge representation and ontology-based decision support. According to the decision support process, the methodology for valuable stocks selection involves ontology representation, ontology evaluation and ontology reasoning. As shown in Figure 1, the results for stocks selection will be generated by ontology reasoning.

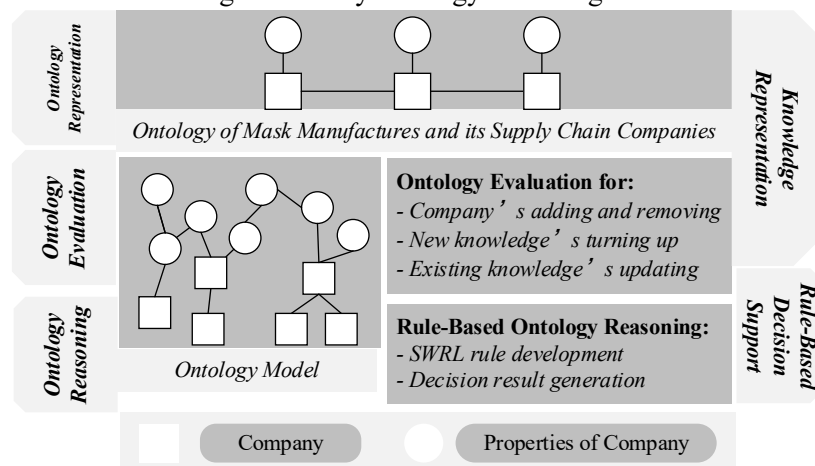


Figure 1. Steps of ontology-based investment decision support.

3.1. Ontology representation

According to [5], domain knowledge is the foundation of ontology model. Start from this, ten pieces of intuitions (Table 1) were adopted in the proposed ontology model. Notably, sentiment of news was also under consideration. Specifically, macro national policies, mesoscopic industry prospects and micro corporate news were all included. From this, ontology representation can be further divided into knowledge representation and formal representation.

Table 1. Major intuitions.

NO.	Content of Intuitions
1	The core competence of an enterprise is cash flow.
2	Around the cash flow, enterprise capacity mainly includes security, profitability and growth.
3	Cash flow capability, usually evaluated by free cash flow or free cash flow per share.
4	The solvency, can be measured by current ratio, quick ratio, equity ratio and debt-asset ratio.
5	The profitability can be reflected in the gross margin, net margin and return on equity.
6	Growth is mainly manifested in the growth of net margin, sales revenue and total assets.
7	The cost is paid to the upstream, while the revenue comes from the downstream.
8	Whether the chairman of an enterprise is composed of one person or not usually reflects the degree of centralization of the enterprise.
9	In the era of mobile Internet, public opinion can influence the life and death of an enterprise.
10	According to the scope of influence, public opinion can be divided into macro national policy and international situation, medium industry prospect and micro enterprise news.

Knowledge representation. In the proposed framework, cash flow was thought to be the core competence of mask manufactures. Furthermore (Figure 2), around cash flow, security, profitability, and growth become the main competency dimensions. More specifically, these capabilities are evaluated on the basis of financial ratios, which can be calculated by the financial statements items.

Besides, to mitigate the delay in financial disclosure, the framework also extends capacity evaluation to the upper and lower reaches of the supply chain. In the supply chain, the product flow and the capital flow are quietly flowing. Inspired by this observation, the upstream corresponds to the procurement cost, while the downstream corresponds to the sales revenue. In this way, based on the ability evaluation of upstream and downstream enterprises, risks and perceived opportunities can be prevented in advance. In addition, so as to better adapt to personalized investment needs, the proposed framework also introduced risk preference coefficient and decision type evaluation. Concretely, risk preference coefficient was used to adjust the threshold of financial ratios. Formally, the risk preference coefficient α has the following definition:

$$\alpha = \begin{cases} 0.5, \text{high risk averse} \\ 0.8, \text{low risk averse} \\ 1.0, \text{risk neutral} \\ 1.2, \text{low risk loving} \\ 1.5, \text{high risk loving} \end{cases} \quad (1)$$

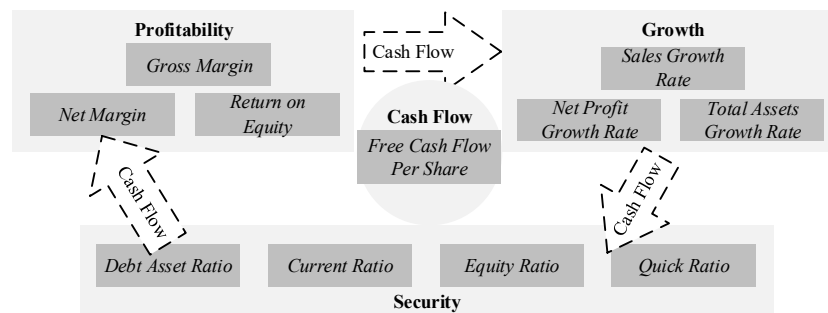


Figure 2. Major concern for cash flow.

Table 2. Introduction to relevant financial ratios.

Dimension	Financial Ratio	Implication	Ratio Definition
Cash Flow	<i>Free Cash Flow Per Share</i>	Cash actually held by a business that rewards shareholders	<i>Free Cash Flow / Shares</i>
Security	<i>Current Ratio</i>	The ability of an enterprise's current assets to be converted into cash and used to repay current liabilities	<i>Current Assets / Current Liabilities</i>
	<i>Quick Ratio</i>	The ability of a business to liquidate its current assets immediately to repay its current liabilities	<i>Quick Assets / Current Liabilities</i>
	<i>Equity Ratio</i>	When liquidation, the protection degree for the interests of creditors	<i>Total Liabilities / Total Owner's Equity</i>
	<i>Debt-Asset Ratio</i>	The proportion of total capital provided by creditors	<i>Total Liabilities / Total Assets</i>
Profitability	<i>Gross Margin</i>	The value added of a commodity after conversion from production	<i>Gross Profit / Sales</i>
	<i>Net Margin</i>	Net profit as a percentage of net sales or invested capital	<i>Net Profit / Sales</i>
Growth	<i>Return on Equity</i>	Income level of owner's equity	<i>Net Profit / Average</i>
	<i>Sales Growth Rate</i>	Compared with the last period, the percentage change of current sales	<i>(Sales of this year - Sales of last year) / Sales of last year</i>

<i>Net Profit Growth Rate</i>	Compared with the previous period, the percentage change of current net profit	$(\text{Net Profit of this year} - \text{Net Profit of last year}) / \text{Net Profit of last year}$
<i>Total Assets Growth Rate</i>	Compared with the previous period, the percentage change of current assets	$(\text{Total Assets of this year} - \text{Total Assets of last year}) / \text{Total Assets of last year}$

For example, if one individual investor is high risk averse, then the threshold of financial ratios will be adjusted to half of initial values. For simplicity, the risk preference coefficient of case was set to be 1. Taking one step further, the next question is financial ratios. For illustration, an introduction to financial ratios mentioned above was shown in Table 2.

3.1.1. Formal representation. Considering the presentation ability required by the investment decision support ontology model, the proposed framework mainly adopts OWL and SWRL for knowledge representation.

3.2. Ontology evaluation

In view of investment risk, interpretability and operability of the proposed framework, ontology evaluation would be carried out from two aspects: consistency check and completeness check.

Table 3. The axioms of consistency.

Axioms	Formal Definition
Axiom 1	$\text{SubClassOf}(C1, C2) \wedge \text{SubClassOf}(C2, C3) \rightarrow \text{SubClassOf}(C1, C3)$
Axiom 2	$\text{SubClassOf}(C1, C2) \wedge \dots \wedge \text{SubClassOf}(Ci, Ci+1) \dots \wedge \text{SubClassOf}(Cn, C1) = \text{False}$
Axiom 3	$\text{UnionOfRelation}(C1, C2) \wedge \text{UnionOfRelation}(C2, C3) \rightarrow \text{UnionOfRelation}(C1, C3)$
Axiom 4	$\text{UnionOfRelation}(C1, C2) \wedge \dots \wedge \text{UnionOfRelation}(Ci, Ci+1) \dots \wedge \text{UnionOfRelation}(Cn, C1) = \text{False}$
Axiom 5	$\text{EquivalentClass}(C1, C2) \wedge \text{EquivalentClass}(C2, C3) \rightarrow \text{EquivalentClass}(C1, C3)$
Axiom 6	$\text{SubClassOf}(C1, C2) \wedge \text{EquivalentClass}(C2, C3) \rightarrow \text{SubClassOf}(C1, C3)$
Axiom 7	$\text{SubClassOf}(C1, C3) \wedge \text{EquivalentClass}(C1, C2) \rightarrow \text{SubClassOf}(C2, C3)$
Axiom 8	$\text{DisjointWith}(C1, C2) \wedge (\text{SubClassOf}(C3, C1) \vee \text{EquivalentClass}(C3, C1)) \wedge (\text{SubClassOf}(C4, C2) \vee \text{EquivalentClass}(C4, C2)) \wedge \text{EquivalentClass}(C4, C2) \rightarrow \text{DisjointWith}(C3, C4)$

Where *SubClassOf*, *UnionOfRelation*, *EquivalentClass* and *DisjointWith* refer to the generic relationship between concepts, the whole and part relationship between concepts, the equivalent relationship between concepts and the disjoint relationship between concepts respectively.

3.2.1. Consistency check. Ontology consistency has three meanings in this paper: syntax consistency, semantic consistency and domain consistency. Syntax consistency, especially the grammatical rules of owl. Here, syntax consistency means that the description of an ontology conforms to the grammatical rules of the corresponding ontology description language (such as OWL). Generally speaking, syntax consistency needs to satisfy Axiom 1 to Axiom 7 in Table 3 at the same time. Semantic consistency, or logical consistency, refers to the logical basis of ontology description language. An example of the logic foundation of owl is Axiom 8 in Table 3. Domain consistency involves specific domain rules. Here, the value of total assets should be equal to the sum of total liabilities and owner's equity.

3.2.2. Completeness check. The completeness, refers to the completeness of knowledge needed to complete investment decision support. In other words, the domain knowledge introduced is complete, even a little redundant. Since there is no mature method for completeness check, the completeness check here is mainly based on the target task orientation. Specifically, whether the domain knowledge introduced is enough to complete the investment decision-making support of the mask topic stocks.

3.2.3. Ontology reasoning. Just using OWL is not sufficient to adequately represented the knowledge required for inference. With this in mind, SWRL was also adopted to represent rules. With added SWRL rules, inference engine can provide more results than sole OWL representation. Specifically, 29 SWRL rules were included in proposed ontology, which will be explained in detail in Case Study. In addition, considering ontology represented by OWL and SWRL, Pellet inference engine, which is based on Tableau algorithm [33], was used for ontology reasoning.

4. Case study

Affected by COVID-19, the stocks of masks have been highly sought after recently. Facing this unprecedented situation, a large number of individual investors seem to have no choice but to follow the trend. To better help plenty of individual investors, Company M, a famous Chinese mask manufacturer, was selected as the research object. Specifically, the data of Company M mainly comes from its disclosed financial statements. However, as a listed company, it is still difficult for us to know exactly the suppliers and distributors of Company M from its disclosed financial statements. Fortunately, the raw materials, equipment and main sales channels of masks are almost open. Based on this observation, the famous equipment supplier Company S1, the melt blown cloth supplier Company S2 and the widely distributed distributor Company D can be regarded as the substitutes of their supply chain partners. In this way, a specific industrial chain can be seen clearly.

4.1. Knowledge representation

Knowledge representation, here refers to the formal representation of class hierarchy, class properties and class axioms by OWL.

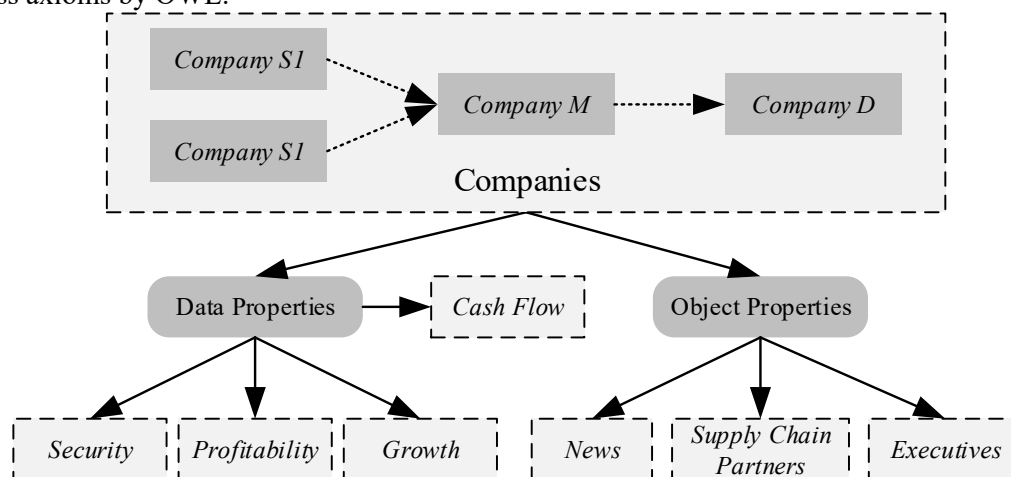


Figure 3. Class hierarchy of ontology model.

Table 4. Financial ratios of relevant companies in the first quarter.

Dimension	Financial Ratio	Company S1	Company S2	Company	Company
Cash Flow	Free Cash Flow Per Share	-154.72	-1.79	3.33	-1.93
Security	Debt Asset Ratio	34.61%	45.17%	42.66%	61.65%
	Current Ratio	1.61	1.51	1.7	0.97
	Quick Ratio	0.79	1.09	1.38	0.44
	Equity Ratio	0.53	0.87	0.75	1.79

Profitability	<i>Gross Profit Rate</i>	29.79%	42.12%	34.07%	33.08%
	<i>Net Margin</i>	9.58%	26.07%	16.70%	7.00%
	<i>Return on Equity</i>	1.47%	9.07%	8.36%	5.47%
Growth	<i>Net Profit</i>	146.60%	1545.49%	281.72%	23.01%
	<i>Growth Rate</i>				
	<i>Sales Growth Rate</i>	585.63%	30.04%	56.46%	20.34%
	<i>Total Assets Growth Rate</i>	37.09%	-5.99%	38.31%	19.16%

Table 5. Data properties and object properties.

Type of Properties	Level 1	Level 2	Domain
Data Properties	1.Cash Flow	<i>1.1 Cash Flow Per Share</i>	Company
		<i>2.1 Current Ratio</i>	Company
	2.Security	<i>2.2 Quick Ratio</i>	Company
		<i>2.3 Equity Ratio</i>	Company
		<i>2.4 Debt-Asset Ratio</i>	Company
		<i>3.1 Gross Margin</i>	Company
	3.Profitability	<i>3.2 Net Margin</i>	Company
		<i>3.3 Return on Equity</i>	Company
		<i>4.1 Sales Growth Rate</i>	Company
	4.Growth	<i>4.2 Net Profit Growth Rate</i>	Company
Object Properties	5.Properties of Executives	<i>5.1 Age</i>	Executives
		<i>5.2 Education</i>	Executives
		<i>5.3 Gender</i>	Executives
	6.withNews	<i>6.1 withMacro</i>	Company
		<i>6.2 withMeso</i>	Company
		<i>6.3 withMicro</i>	Company
	7.hasExecutives	<i>7.1 hasBoardChair-man</i>	Company
		<i>7.2 hasCEO</i>	Company
	8.SupplyChain	<i>8.1 hasSupplier</i>	Company
		<i>8.2 hasDistributor</i>	Company

Table 6. Equivalent class axioms.

Class	Equivalent Class Axioms
Cash Flow Good	<i>Company and (Free_Cash_Flow_Per_Share some xsd:float[>= -5.0f])</i>
Cash Flow Bad	<i>Company and (Free_Cash_Flow_Per_Share some xsd:float[< -5.0f])</i>
Security Good	<i>Company and ((Current_Ratio some xsd:float[>= 2.0f]) or (Debt_Asset_Ratio some xsd:float[<= 60.0f]) or (Equity_Ratio some xsd:float[<= 1.0f]) or (Quick_Ratio some xsd:float[>= 1.0f]))</i>
Security Bad	<i>Company and ((Current_Ratio some xsd:float[< 2.0f]) and (Debt_Asset_Ratio some xsd:float[> 60.0f]) and (Equity_Ratio some xsd:float[> 1.0f]) and (Quick_Ratio some xsd:float[< 1.0f]))</i>
Profitability Good	<i>Company and ((Gross_Margin some xsd:float[>= 3.0f]) or (Net_Margin some xsd:float[>= 2.0f]) or (Return_on_Equity some xsd:float[>= 1.0f]))</i>

Profitability Bad	<i>Company and ((Current_Ratio some xsd:float[< 2.0ff]) and (Debt_Asset_Ratio some xsd:float[> 60.0ff]) and (Equity_Ratio some xsd:float[> 1.0ff]) and (Quick_Ratio some xsd:float[< 1.0ff]))</i>
Growth Good	<i>Company and ((Net_Profit_Growth_Rate some xsd:float[>= 1.0ff]) or (Sales_Growth_Rate some xsd:float[>= 3.0ff]) or (Total_Assets_Growth_Rate some xsd:float[>= 1.0ff]))</i>
Growth Bad	<i>Company and ((Net_Profit_Growth_Rate some xsd:float[< 1.0ff]) and (Sales_Growth_Rate some xsd:float[< 3.0ff]) and (Total_Assets_Growth_Rate some xsd:float[< 1.0ff]))</i>

4.1.1. Class Hierarchy. On the whole, this case study covers the following areas of knowledge: news, executives and major financial ratios of Company M and its upstream and downstream enterprises (Company S1, Company S2 and Company D). Specifically, the main financial ratios disclosed by the four companies in the latest period (the first quarter of 2020) are shown in Table 4. Accordingly, a class hierarchy (Figure 3) can be formed by OWL. As shown in Figure 3, the data properties of the companies correspond to the quantitative evaluation of the four capabilities, while the object properties well represent its qualitative knowledge.

4.1.2. Properties. More specifically, properties of ontology were shown in Table 5. Among them, apart from Properties of Executive, all other properties were for class Company. In this way, except for the risk preference coefficient, the target company and its upstream and downstream partners and four major abilities evaluation were all included. Accordingly, a series of axioms of equivalent class, axioms of subclass and axioms of disjoint were derived. Notably, the risk preference coefficient was used to adjust the threshold of financial ratios. For simplicity, risk neutral was assumed in this case. That is, the risk preference coefficient of case was set to be 1.

4.1.3. Axioms. For example, the equivalence class axioms of this case mainly includes the equivalent class axioms shown in Table 6.

4.2. Rule-based stocks selection

Rules represented by SWRL are the important basis of ontology reasoning. Therefore, this part will be elaborated from SWRL rules and reasoning results respectively.

Table 7. Representative SWRL rules.

Rules	SWRL Representation
S1	<i>Company(?M) \wedge hasBoardChairman(?M, ?A) \wedge hasCEO(?M, ?B) \wedge differentFrom(?A, ?B) \rightarrow Decentralized(?M)</i>
S2	<i>Company(?M) \wedge hasBoardChairman(?M, ?A) \wedge hasCEO(?M, ?B) \wedge sameAs(?A, ?B) \rightarrow Centralized(?M)</i>
S3	<i>Company(?M) \wedge hasBoardChairman(?M, ?A) \wedge hasCEO(?M, ?B) \wedge differentFrom(?A, ?B) \wedge hasSupplier(?N, ?M) \rightarrow upDecentralized(?N)</i>
S4	<i>Company(?M) \wedge hasBoardChairman(?M, ?A) \wedge hasCEO(?M, ?B) \wedge sameAs(?A, ?B) \wedge hasDistributor(?N, ?M) \rightarrow downCentralized(?N)</i>
S5	<i>Company(?M) \wedge Free_Cash_Flow_Good(?M) \wedge hasSupplier(?N, ?M) \rightarrow upFree_Cash_Flow_Good(?N)</i>
S6	<i>Company(?M) \wedge Free_Cash_Flow_Bad(?M) \wedge hasDistributor(?N, ?M) \rightarrow downFree_Cash_Flow_Bad(?N)</i>
S7	<i>Company(?M) \wedge Growth_Bad(?M) \wedge hasSupplier(?N, ?M) \rightarrow upGrowth_Bad(?N)</i>
S8	<i>Company(?M) \wedge Growth_Good(?M) \wedge hasDistributor(?N, ?M) \rightarrow</i>

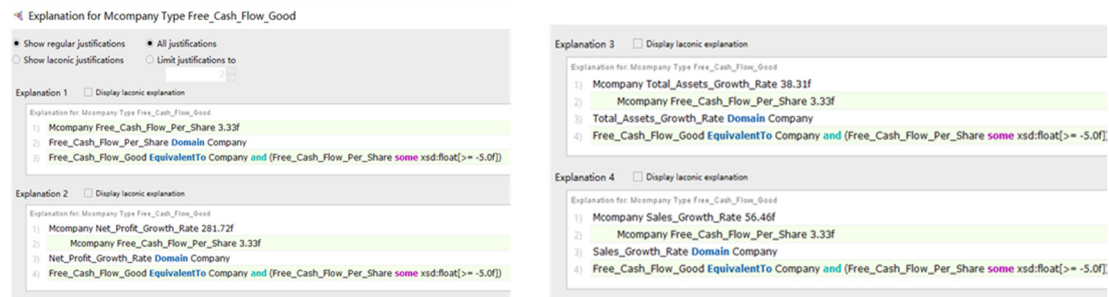
	<i>downGrowth_Good(?N)</i>
S9	<i>Company(?M) ∧ Security_Good(?M) ∧ hasSupplier(?N, ?M) → upSecurity_Good(?N)</i>
S10	<i>Company(?M) ∧ Security_Bad(?M) ∧ hasDistributor(?N, ?M) → downSecurity_Bad(?N)</i>
S11	<i>Company(?M) ∧ Profitability_Bad(?M) ∧ hasSupplier(?N, ?M) → upProfitability_Bad(?N)</i>
S12	<i>Company(?M) ∧ Profitability_Good(?M) ∧ hasDistributor(?N, ?M) → downProfitability_Good(?N)</i>
S13	<i>Company(?M) ∧ withMacro(?M, Positive) → Macro_Positive(?M)</i>
S14	<i>Company(?M) ∧ withMeso(?M, Netural) → Meso_Netural(?M)</i>
S15	<i>Company(?M) ∧ withMicro(?M, Negative) → Micro_Negative(?M)</i>

4.2.1. SWRL rules. In order to deduce the news, supply chain partners, power distribution and other aspects, 29 SWRL rules were also introduced into the case ontology. As shown in Table 7, 15 representative SWRL rules are listed. Taking S1 as an example, *Company(?M)* stands for Company M, While *hasBoardChairman(?M, ?A)* means that the board chairman of Company M is A. Similarly, *hasCEO(?M, ?B)* means that B is the CEO of Company M. Moreover, *differentFrom(?A, ?B)* indicates that A and B are two different individuals.

4.2.2. Reasoning results. Based on the ontology jointly represented by OWL and SWRL, the reasoning results of Figure 4 are given for Company M. As you can see, for risk neutral individual investors, Company M has a good investment value. Moreover, the result of this reasoning can well warn the risk. For example, the safety of the distributor of Company M in the first quarter is not very good, and it is expected that there will be some trouble in debt repayment in the future. In addition, ontology model is powerful and easy to explain. For example, Free Cash Flow Good of Company M has a series of explanations (Figure 5), which is very suitable for investment decision support. For example, the meaning of explanation 1 is that, because the domain of Free Cash Flow Per Share is Company, and the Free Cash Flow Per Share of Company M is 33, the Free Cash Flow of Company M is good.



Figure 4. Reasoning results of *Company M*.



a) Explanation 1 & Explanation 2

b) Explanation 3 & Explanation 4

Figure 5. Explanation for *Free Cash Flow Good* of *Company M*.Table 8. Performance prediction of *Company M* in 2020 from major investment institution.

	Number of Institutions	Minimum	Mean	Maximum	Industry Average
EPS	4	1.62 yuan	8.04 yuan	26.31 yuan	1.16 yuan
NP	4	3.57 billion yuan	18.45 billion yuan	60.95 billion yuan	9.88 billion yuan

Where **EPS** is short for *Earnings Per Share*, and **NP** is short for *Net Profit*.

As of May 29, 2020, a total of 4 institutions have predicted the annual performance of Company M in 2020 within 6 months. The forecast shows (Table 8) that, in 2020, Company M will have earnings per share of 1.89 yuan, a year-on-year growth of 107.6%, net profit of 421 million yuan, and a year-on-year growth of 136.1%¹. Such a conclusion is basically consistent with the result of ontological reasoning. This fully demonstrates the effectiveness of ontology-based stocks selection framework.

5. Conclusion

To simultaneously alleviate the problems of investment risk, insufficient interpretability and inapplicability, an ontology-based stocks selection framework was proposed. From the fundamental analysis, the proposed framework combines quantitative financial ratios analysis and qualitative news, executive and supply chain analysis, which can cover most information essential for stocks selection. In the case study, the results are basically consistent with the research reports of major investment institutions, which verifies the effectiveness and practicability of the proposed method. To be specific, our work involves five contributions: 1) fundamental analysis with limited risk; 2) ontology-based framework with adequate interpretability and operability; 3) risk preference coefficient for personalized selection; 4) combination of qualitative analysis and quantitative analysis; 5) prospective mechanism based on supply chain. However, there are still some limitations. For example, the introduce of news opinion need to be optimized, and the reasoning results needs to be further integrated for more convenient support, which will be our future work.

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¹ <http://stockpage.10jqka.com.cn/300677/worth/#stockreport>

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