Choosing Business Collaborators Using Computing Intelligence Methods

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Abstract. Inter-firm collaboration has become a common feature of the developing international economy. Firms as well as the nations have more relationships with each other. Even relatively closed economies or industries are becoming more open, Australia and China are examples of this case. The benefits generated from collaboration and the motivations to form collaboration are investigated by some researchers. However, the widely studied relationships between collaboration and profits are based on tangible assets and turnovers whereas most intangible assets and benefits are neglected during the economic analysis. In the present paper, two methods, naive Bayes and neural network, from computing intelligence are used to study the benefits acquired from collaboration. These two methods are used to learn the relationship and make prediction for a specified collaboration. The proposed method has been applied to a practical case of WEMOSOFT, an independent development department under MOBOT. The predication accuracies are 87.18% and 92.31%, for neural network and naive Bayes, respectively. Experimental result demonstrates that the proposed method is an effective and efficient way to prediction the benefit of collaboration and choose the appropriate collaborator.

Keywords: Business Collaborators; Computing Intelligence; MOBOT.

1 Introduction

In recent years, the economic climate has fostered industrial cooperation more strongly than in the past. Cooperation has often proven superior to outright competition [1]. "Unless you've teamed up with someone, you become more vulnerable as barriers fall. The best way to eliminate your potential enemies is to form an alliance with them." [2].

Many researchers in different fields have decoded the principles of collaborating and cooperating. They have attempted to solve the problems and conflicts in collaborations and increase the benefits to all partners who participate in such collaborations. Countries, governments, firms, educators and even individuals benefited from their research.

Coase recognized the important role of Transaction Cost as well as the role of firms and argued that transaction costs were the reason why firms exist [3]. Arrow also contributed to the appreciation of the role of Transaction costs [4]. The main approach in Transaction Cost Economics is proposed in [5]. In addition, Williamson further categorised inter-firm transactions into competition (market transaction), governance (internal transaction), planning (contract), and promise (collaboration) [6]. Contractor et

D.-S. Huang et al. (Eds.): ICIC 2008, LNCS 5226, pp. 529–535, 2008.

al. believed that cooperation and competition provide alternative or simultaneous paths to success [1]. Much of the recent research is based on network cooperation, new technologies and multinational enterprises. For example: Hagedoorn's research on technology partnership [7] [8] [9]; Gilroy's work on the networking benefits for multinational enterprizes [10]; Roos's paper on the cooperating strategies for global business [11]; Kay's research on innovation and trust [12]; Chen and Shih's research on high-tech development [13]; Zhang and Dodgson's research on telecommunication cooperation in Asia [14].

These researchers recognized collaboration in different fields and industries. However, with globalization, the role and types of collaboration are changing rapidly. The risks facing different firms for collaboration have also changed due to emerging new technology and markets.

This paper discusses why firms collaborate; how they collaborate; and what are the main risks facing their collaborations. The motives for collaboration will be used to develop the questionnaire to collect data from firms and build the model. Different types of collaborations will help to identify the rapid changes in global market and collaboration. To increase the inter-firm collaboration, it is necessary to reduce or eliminate the risks associated with collaboration. Finally, the results of the case study will help in finding a new solution for inter-firm collaborations.

To understand better of collaboration, increased endeavor has been put into analysis and prediction of the result from collaboration. Conventionally, the analysis is based on manual, and thus exhaustive. In this paper, we propose to analyze the results of collaboration by using intelligent computing. Two models are proposed to develop the experience of collaboration, and are then used for predicting the result for future collaboration.

The remainder of this paper is organized as follows. Section 2 presents the motives, types and risks of collaboration. Computing intelligence methods for analyzing the results of collaboration are formulated in Section 3. Section 4 present the case study of WEMOSOFT. Section 5 is the conclusion, followed by future work.

2 The Motives, Types and Risks of Collaboration

The incentives for firms to collaborate may be external or internal. They all target the impact on final net profits or utilities, but with different business and political environments. Collaborations show great variety in their motivation. The external reasons or pressure that made firms collaborate may include: rapid economic and technological change; declining productivity growth and increasing competitive pressures; global interdependence; blurring of boundaries between business, overcoming government-mandated trade or investment barriers; labor; lack of financial resources; facilitating initial international expansion of inexperienced firms; and dissatisfaction with the judicial process for solving problems [1] [15] [16]. On the other hand, there are some benefits generated from collaborating, which may push firms that are chasing profits to collaborate: to access producers of information, new markets, benefits to the consumer;

lower coordination costs throughout the industry value chain; lower physical distribution costs; redistribution and potential reduction in total profits; reduction of innovation lead time; technological complementary; influencing market structure; rationalization of production; monitoring technological opportunities; specific national circumstances; basic R&D and vertical quasi-integration advantages of linking the complementary contributions of the partners in a ”value chain” [1] [16].

Pfeffer et al [17] and later Contractor et al [1] categorized the major types of cooperative as: Technical training and start-up assistance agreements; Production, assembly, and buy-back agreements; Patent licensing; Franchising; Know-how licensing; Management and marketing service agreement; Non equity cooperative agreements in Exploration, Research, partnership, Development, and co-production; and Equity joint venture.

Risk levels increase as the depth of cooperation increases: historical and ideological barriers; power disparities; societal-level dynamics creating obstacles to collaboration; differing perceptions of risk; technical complexity; political and institutional cultures; the role of management; the benefit distribution; and so on [15].

With the dynamic changes in global markets, it is hard to identify whether a company is safe when contributing to a new collaboration or not. Even the big companies can not category ”good” and ”bad” cooperators. The ”bad” cooperators here are interpreted as those cooperators that occupied some of resources but didn’t contributed any tangible and intangible benefit. The learning process is a huge work beyond one person’s ability. It needs thousands of real cases to clarify the blurred boundary from ”good” to ”bad”. One possible way to analyze these collaborations are to use the methods from computing intelligence, however, these are rarely reported when analyzing the results of collaboration. Motivated by the advanced learning and member ability, we propose to employ two methods, namely, naive Bayes and neural network for analyzing business collaboration.

3 Methods

To investigate the benefits from collaboration, we propose to use two models, namely, naive Bayes and neural networks [18]. Naive Bayes classifier is a simple probabilistic classifier based on applying Bayes’ theorem with naive independence assumptions. It is designed for use in supervised induction task, in which the performance goal is to accurately predict the class of test instances and in which the training instances include class information [19].

Aside from naive Bayes classifier, neural network (NN) is also employed for prediction because NN is used to simulate the network formed by neurons in brain. Specifically, We use multi layer perceptron (MLP), and train the MLP using backpropagation algorithm. The structure of the MLP is shown in Fig. 1.

To evaluate the performance of predication, the Leave-One-Out Cross-Validation (LOOCV) is conducted, and the predication accuracy is report based on LOOCV. The experiment is conducted using the Waikato Environment for Knowledge Analysis (WEKA) [20].

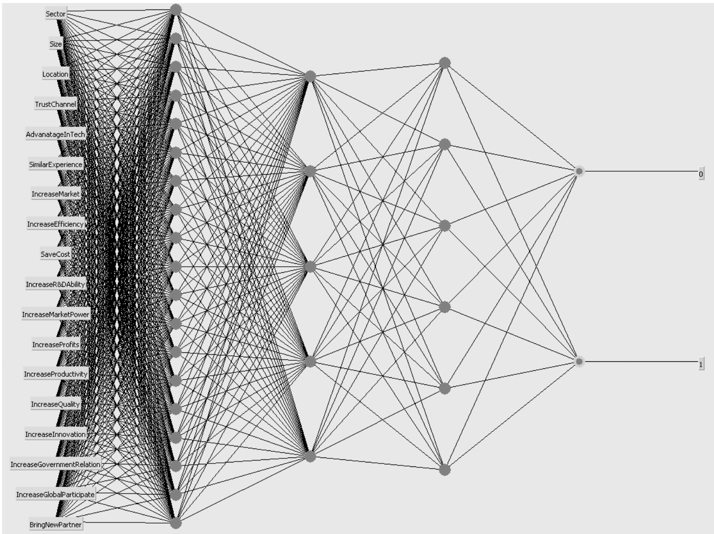

Fig. 1. The structure of the MLP for prediction of benefit from collaboration

4 Case Study

WEMOSOFT is an independent development group under Beijing MOBOT Software Technology Co., Ltd., which was established in 2005 and have successfully implemented more than ten projects in different fields. All the successful projects are based on good collaboration and cooperation. WEMOSOFT established its business network with more than one hundred telecommunication and software companies during 2005 to 2007. Some of them contributed directly to the successful projects and tangible profits, some contributed to its intangible benefits, but there are some firms didn't and seemingly won't contribute to any business operation. As a result, we separated all firms in the business network into three groups: tangible contributors, intangible contributors and none contributors. Due to the data analysis, there are about 1/10 tangible contributors and 1/3 intangible contributors in all business networks, which implies there are more than 2/3 none contributors but occupied most of the business resources and efforts. The purpose of this paper is how to use computer intelligence to reduce these costs and efforts in business operation.

4.1 Data Set Collection

The researched data was collected from WEMOSOFT, a Chinese company located in Beijing. WEMOSOFT was involved in business collaboration with its 39 collaborators from mid 2000 to the end of 2006. The researcher collected all the major features of its business collaboration via a designed questionnaire. All the data are analyzed based on the business collaboration categories included in part two and research conducted by the researchers.

There are 18 major determinants that will influence the success of business collaboration. They are: business sector, which described whether the collaborator is in the same or similar business sector of the researched company.

The determinants are defined as follow. Business size described the size similarity of WEMOSOFT and its collaborator. Business location is the geographic distance of the company, which also related to transaction costs for this collaboration. Business trust channel describes the level of trust before the collaboration. It depends on the business network and trust of WEMOSOFT, how it is known to the collaborator, how many layers of business relationship between it and its collaborator. This feature may be very complex, but all the data are virtualized into quantization for the convenience of research. The advantage in technology described the technical level of the collaborator, which is supposed to have a positive influence on the success of collaboration. Similar experience describes whether the collaborator had similar collaborating experience with another company before this collaboration. A positive relationship between a successful collaboration and increased market, increased efficiency, cost saving, increased R&D (research and development) ability, increased market power, increased profits, increased productivity, increased quality, increased innovation, improved government relationship, increased global participation, and bring new partners are expected.

The collected attributes are first normalized into the $[0, 1]$ interval according to the related influence, where $'0'$ indicates that this determinant has no contribution to the final result, $'1'$ indicates that this determinant has strong contribution to the final result. For class label, it is set to $'0'$ if the collaboration failed, otherwise, it is set to $'1'$. By doing so, we develop the data sets X with 39 rows and 18 columns, and Y with 39 rows and 1 column. For X, its ith row represents the ith sample with its class label represented in the ith row in Y.

4.2 Experimental Results

By using LOOCV, the prediction accuracy by using the naive Bayes classifier and MLP is 92.31% and 87.18%. The confusion matrix for naive Bayes and MLP are shown in Table 1 and Table 2, respectively. The confusion matrix indicated that both models achieved the same performance for predicting successful collaboration, whereas the naive Bayes classifier is superior to the MLP when classifing the failed collaborations.

Table 1. The confusion matrix of naive Bayes for predicting the benefit of collaboration

Collaboration Result	Success	Fail
Success	21	2
Fail	1	15
Accuracy	95.45%	88.24%

In summary, the proposed method achieved satisfactory performance for predicting the result of collaboration. As a consequence, this approach proved to be effective for analyzing the benefit of collaboration in the case study.

Table 2. The confusion matrix of MLP for predicting the benefit of collaboration

Collaboration Result	Success	Fail
Success	21	2
Fail	4	12
Accuracy	84%	85.71%

5 Conclusions

This paper proposes an alterative way to estimate the results of collaboration and cooperation based on computing intelligence, which plays an important role in the development of firms. Collaboration and cooperation is a way to generate more profits but also a vital strategy for most firms experiencing fast growth associated with globalization and international competition. Different firms in different circumstances may have varied motives in forming collaborations. With the development of the economic activities and variety of new firms as well as new markets, the type of collaboration is increasing and changing as well. Some examples are given to different types of collaboration. Firms as well as the institutions are searching for methods to reduce the risks from collaboration. It is more important for small and medium sized firms to plan and adopt collaboration strategies to survived fierce competition in the future. The proposed approach can be used to assist the analyze of making decision for collaboration.

6 Future Work

Future work will investigates the influence of each attribute on result of collaboration by using computing intelligence. By doing so, the key factors that lead to the success of collaboration can be identified. These factors can be use to improve the corresponding attributes of a firm for the success of collaboration with another firm. Moreover, advanced computing intelligence methods will also be developed for accurate prediction.

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