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Machine learning approach for finding business partners and building reciprocal relationships

Junichiro Mori *, Yuya Kajikawa, Hisashi Kashima, Ichiro Sakata

The University of Tokyo, 7-3-1, Hongo, Bunkyo-ku, Tokyo 113-8656, Japan

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ABSTRACT

Business development is vital for any firms. However, globalization and the rapid development of technologies have made it difficult to find appropriate business partners such as suppliers and customers, and build reciprocal relationships among them, while it simultaneously offers many opportunities. In this contribution, we propose AI-based approach to find plausible candidates of business partners using firm profiles and transactional relationships among them. We employ machine learning techniques to build a prediction model of customer–supplier relationships. We applied our approach to the large amount of actual business data. The results showed that our approach successfully found potential business partners with *F*-values of about 84% and reciprocity among them with *F*-values of about 77%. Using our method, we also developed the Web-based system that helps people in actual businesses to find their new business partners. These contribute to developing one's own business in the complicated, specialized and rapidly changing business environments of recent years.

1. Introduction

Business development is a perdurable issue for any firms pursuing sustainable development. In particular, organizational relationships among firms such as customer–supplier relationships and strategic alliance have an significant effect to develop business because they can work as a source of innovation. Firms in a cooperation network can utilize their network in a variety of ways. They not only share the costs and risks of their activities but also obtain access to new markets and technologies, make use of complementary skills, and share knowledge capabilities, and finally influence firm performance (Dyer & Singh, 1998, 2000; Eisenhardt & Schoonhoven, 1996; Nishiguchi, 1994; Powell, Koput, & Smith-Doerr, 1996; Uzzi, 1996).

Firms must seek new business partners to acquire new opportunities and also to activate existing relationships, while long-term and dedicated relationships with trust is the vital source of innovation. But such an activity is laborious, time-consuming, and subjective. Traditional stakeholder theories and frameworks can enhance our understandings in the roles of business partners, but cannot serve as a guidance to find new partners and to keep reciprocity among them. And current experts employ a manual approach to selection of business partners and do not scale up to accommodate the rapid pace of change in business environment and market.

Several studies have addressed to evaluate selected business partners by financial strength. In the previous literatures, attributional features such as financial data, product and service quality, and technological capabilities/compatibilities are utilized in the analysis to evaluate suppliers (Guo, Yuan, & Tian, 2009; Hsu, Chang, & Huang, 2007; Tseng, Huang, Jiang, & Ho, 2006; Wang, Zhong, & Zhang, 2004) by introducing the implications of previous literatures in supply chain management (Cusumano & Takeishi, 1991; Chaudhry, Frost, & Zydiak, 1993; Choi & Hartley, 1996; Dickson, 1966; Lee, Ha, & Kim, 2001; Muralidharan, Anantharaman, & Deshmukh, 2002; Swift, 1995; Weber & Current, 1993).

However, it is not easy to obtain such data in advance before actual transactions is contracted and launched. On the other hands, we can easily obtain explicit data of firms such as the number of employee and date of foundation from the Web or commercial databases. Therein, one of important questions with a computational approach to find business partners is how to deal with the vast amount of firm data which is available from several data sources and therefore how to identify meaningful features among the data.

To exploit the opportunities acquired by partnerships, it is also crucial to establish reciprocal relationships in addition to finding new business partners. Business reciprocity is the term to describe business dealings between independent firms whereby they make mutual concessions designed to promote the business interests of each (Stocking & Mueller, 1957). Although researchers have studied the origin of business reciprocity from a point of buying power and profitability of customer (Kelly & Gosman, 2000), the current business situation is more complex and the understanding on the

* Corresponding author.
E-mail addresses: jmori@ipr-ctr.t.u-tokyo.ac.jp (J. Mori), kaji@ipr-ctr.t.u-tokyo.ac.jp (Y. Kajikawa), kashima@mist.i.u-tokyo.ac.jp (H. Kashima), isakata@ipr-ctr.t.u.-tokyo.ac.jp (I. Sakata).

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reciprocity is not enough. Therefore, for supporting to find business partners and build reciprocal relationships computationally, it is also important to understand characteristics of firms building reciprocal relationships based on the actual data. Johnson and Sohi argued that reciprocity comes from the cross-managerial level between firms (Johnson & Sohi, 2000), however, the origin of such a managerial strategy and characteristics of those firms building reciprocal relationships are obscure.

The aim of this paper is to find new business partners such as suppliers and customers, and build reciprocal relationships among them with the help of Artificial Intelligence (AI) systems. To this aim, we propose a machine learning approach to model and predict customer–supplier relationships based on explicitly available profiles of firms and their transactional relationships. With the available firm data, we design several features that characterize customer–supplier relationships. We employ those features, which are represented with a very large dimensional vector, with the support vector machine (SVM) to learn a model of customer–supplier relationships. Consequently, our method can automatically predict potential business partners given firm profiles and its existing transactional relationships. We applied our approach to the vast amount of actual business data. Our results showed that our approach successfully found plausible candidates of business partners with *F*-values of about 84% and reciprocity among them with *F*-values of about 77%. Based on the results in our experiment, we develop the Web-based system that helps people in actual businesses to find their new business partners and develop their business. Our contributions in this paper are two folds. First, we design and examine meaningful features of explicit firm data for modeling business relationships using a machine learning approach. Second, we integrate our method into the Web-based system and demonstrate the applicability to practical services. These would lead to help find new and reciprocal business relationships in both theoretical and practical ways.

This paper is organized as follows. In the next section, we describe related work. We illustrate the methodology and data in Section 3. Then, we show the results of our analysis and discuss the determinants of customer–supplier relationships in Section 4. We show the application of our method as the Web-based system in Section 5. And finally, we conclude our paper in Section 6.

2. Method

2.1. Business Partner Selection as a machine learning problem

Currently, business intelligence boosted by AI technologies have gained increasing attention. In particular, machine learning and data mining have been used for business data in finance, marketing, and scheduling (Aytug, Bhattacharyya, Koehler, & Snowdon, 1994; Bose & Mahapatra, 2001; Bose & Chen, 2009; Kumar & Ravi, 2007). However, accurate prediction, though essential, is often hindered by complex relationships between predictor and target variables.

Several applications have employed the support vector machine (SVM) (Vapnik, 1995) which is a semi-parametric and supervised machine learning technique to deal with such complex relationships. The superior performances of SVM can be seen in various applications such as pattern recognition, regression estimation, time series predication and text classification. Application of SVM in the context of business data mining can be seen only in the recent literatures such as analysis of marketing data (Cui & Curry, 2005), consumers' credit scoring (Huang, Chen, & Wang, 2007), forecasting of demand load in supply chain (Carbonneau, Laframboise, & Vahidov, 2008), supplier evaluation (Guo et al., 2009; Hsu et al., 2007; Tseng et al., 2006; Wang et al., 2004), default prediction of SMEs (Kim & Sohn, 2010), and bankruptcy prediction (Min & Lee, 2005; Yeh, Chi, & Hsu, 2010).

Several studies have addressed a problem of customer/supplier selection using a machine learning approach including SVM (Chou & Chang, 2008; Guosheng & Guohong, 2008). In the previous literatures, attributional features such as financial data, product and service quality, and technological capabilities/compatibilities are employed in the analysis to evaluate suppliers (Guo et al., 2009; Hsu et al., 2007; Tseng et al., 2006; Wang et al., 2004). However, it is often difficult obtain such information in advance. In contrast, we use explicitly available data of firms to design features. Additionally, previous works typically use a small corpus whose size is around 100. We use the large size whose size is larger than the previous works by the order of two. And we deal with a large dimensional vector of various features on top of the vast amount of data.

Moreover, in this paper we utilize customer–supplier relationships to predict the focal relationship. There is less studies utilizing such relational features in business data mining. Therefore, the issue tackled in this paper is closely related to the link-prediction problem. In the link-prediction problem, utilization of relational features intrinsic to the network itself can offer meaningful inferences from observed network data (Liben-Nowell & Kleinberg, 2007).

2.2. Basic concepts

We regard selection of business partners such as supplier and customer as one of machine learning problems. As the machine learning problem, we try to learn a model to predict whether there exists a customer–supplier relation between a firm X_c and a firm X_s given a firm pair (X_c, X_s).

More formally, let denote by

$$(X_c, X_s) := x_{c1}, \ldots, x_{cl}, \ldots x_{s1}, \ldots, x_{sm}, \ldots, x_{cs1}, \ldots, x_{csn}$$

the l attributes where each x_c represents the attribute about a customer X_c, the m attributes where each x_s represents the attribute about a supplier X_s, and the n attributes where each x_{cs} represents the relational attribute between the X_c and the X_s. Then, let denote by $Y := y$ the customer–supplier relation, where y takes a value either of +1 (which indicates "relation") or -1 (which indicates "non relation").

Our goal is to build a model f which relates the firm pair instances of (X_c, X_s) to their customer–supplier relations, i.e., $Y = f(X_c, X_s)$. Several methods to build such models have been developed in the field of machine learning. In our study, we employ SVM which is one of the state-of-the-art predictive models. The SVM is well-known for its high predictive performance, and has been applied in numerous application areas.

The SVM assumes the following linear model:

$$y := sign(f(x)) := sign(w^T x) := sign(w_1 x_1 + w_2 x_2 + \ldots + w_d x_d),$$

where $x = (x_1, x_2, \ldots, x_d)$ is a d-dimensional feature vector and $w = (w_1, w_2, \ldots, w_d)$ is the parameter vector of the same dimension which specifies the model. A positive value of w_j indicates the jth feature x_j positively contributes to the prediction, while a negative value contributes to it negatively. The *sign* function returns +1 when its argument is positive, and returns -1 otherwise. Given the data set X and Y, the SVM learning algorithm finds the optimal parameter w^* which minimizes the following objective function:

$$\Sigma_i \max\{1 - y_i f(x_i), 0\} + c\|w\|_2^2,$$

where the first term is the loss function which penalizes misclassifications, and the second term is the regularization term which

Table 1
Manufacturing industrial categories.

Fiber, Lumber, Furniture, Pulp, Publishing/Printing, Chemical, Oil/Coal, Rubber, Leather, Ceramic, Steel, Metallic, Mechanics, Electronics

Table 2
Firm attributes.

Capital, Number of employee, Date of foundation, Number of competitors, Ranking, Address, CEO's native prefecture, CEO's old school, Industrial categories, Bankers, Suppliers, Customers

Table 3
Features.

	Feature	Number of features
Customer's or supplier's	Capital	1
	Number of employee	1
	Date of foundation	1
	Number of competitors (nation)	1
	Ranking (nation)	1
	Number of competitors (prefecture)	1
	Ranking (prefecture)	1
	Address	47
	CEO's native prefecture	47
	CEO's old school	415
	Industrial categories	868
	Bankers	7197
Customer's	Suppliers	30,660
	Customers	30,660
	Industrial categories of suppliers	868
	Industrial categories of customers	868
Supplier's	Suppliers	30,660
	Customers	30,660
	Industrial categories of suppliers	868
	Industrial categories of customers	868
Relation (common)	Address (prefecture)	47
	CEO's native prefecture	47
	CEO's old school	415
	Industrial categories	868
	Bankers	7197
	Suppliers	30,660
	Customers	30,660
	Industrial categories of suppliers	868
	Industrial categories of customers	868

avoids over-fitting to the given data set. c is a small constant which balances the two terms.

The regularization term $\|w\|_2^2 := w_1^2 + w_2^2 + \cdots + w_d^2$ penalizes the parameter vector being too large, and it is known to work well when we predict with data outside the given data set. When the dimensionality of the feature vector is extremely large compared to the number of data, the problem called over-fitting arises. As shown in our experiment, our model comprises very high dimensional feature vectors. The regularization term plays a role for avoiding the over-fitting problem. As the regularization term, we employ $\|w\|_2^2$ (called L_2-regularization) and $|w|_1$ (called L_1-regularization). The L_1-regularization term defined as $|w|_1 := |w_1| + |w_2| + \cdots + |w_d|$ tends to suppress many of the parameters to zero, which results in a small amount of parameters selected. In our experiment, we examine selected parameters in a model and identify which particular features are meaningful for predicting potential business partners and reciprocal relationships.

2.3. Firm data and feature design

In our experiment, we focus on manufacturing firms in the Tokyo area which is the largest economic block in Japan. We select 30,660 firms on manufacturing industrial categories (Table 1) and obtain the data for each firm from commercial business databases.[1] The firm data includes attributes described in Table 2. The number of competitors shows how many other firms (nation-wide or prefecture-wide) exist in one's industrial category. Ranking shows the rank order of one's sales (nation-wide or prefecture-wide). Although profit data is available, we exclude profit from the attributes because we use profit data to evaluate reciprocal customer–supplier relationships as described in our experimental settings.

Using the firm data, we design features of a customer–supplier relation as shown in Table 3. The features showed in the row of "Customer's or Supplier's" describe basic attributes. The features of "Customer's (Supplier's)" describe customer (supplier)-specific attributes. Relational features are based on commonly shared attributes between a customer and a supplier. As a result, one learning instance which is a supplier and customer pair is represented with 41 kinds of features and a 214,904 high dimensional vector.

3. Experiment

3.1. Ex.1: Predicting customer–supplier relationships

We conducted a first experiment with existing 34,441 supplier and customer pairs from our data set. The goal of this experiment is to learn a model to predict customer–supplier relationships in our data set. We used the pairs as positive instances. As negative instances, we randomly selected the same number of a firm pair that does not have any customer–supplier relationships. We created 5 set of the training data with 5 different set of negative instances.

With the data set, we compared the performance of following learners by using fivefold cross validation. As the performance measures, we employed *Precision*, *Recall*, and *F*-value. The optimal parameter for the regularization was chosen with a greedy search.

- L_2 and L_1 regularization SVM.
- L_2 and L_1 regularization logistic regression.

Our preliminary experiment showed that the L_2 regularization SVM performed well, which we employed in our evaluation.

3.2. Ex.2: Predicting reciprocal customer–supplier relationships

We next conducted an experiment to learn a model to predict more reciprocal customer–supplier relationships. Therein, we regard a reciprocal relationship as such that both supplier's and customer's profit rates rank in the top N% of respective industrial categories.

We obtained 10,245 supplier and customer pairs as N = 50% from our data set, 3799 pairs (N = 30%), and 358 pairs (N = 10%). As negative instances, we randomly selected the same number of a customer–supplier pair for each data such that the supplier and the customer's profit rates do not rank in the top N% of respective industrial categories. We created 5 set of the training data with 5 different set of negative instances. With the data set, we compared the performance of a learner by using fivefold cross validation.

[1] http://www.tdb.co.jp/english/.

Table 4
F-value (*precision*/*recall*) of predicting customer–supplier relationships.

	Data1	Data2	Data3	Data4	Data5
Ex.1	84.85 (84.20/85.51)	84.88 (84.57/85.20)	84.90 (84.62/85.19)	84.73 (84.04/85.42)	84.92 (84.49/85.36)
Ex.2					
($N = 50$)	77.95 (74.89/81.27)	77.92 (74.82/81.28)	78.15 (74.89/81.71)	77.68 (74.38/81.28)	78.11 (75.31/81.13)
($N = 30$)	76.37 (72.61/80.54)	76.17 (72.26/80.52)	76.58 (73.10/80.41)	77.05 (73.69/80.73)	76.99 (73.36/80.99)
($N = 10$)	77.46 (78.12/76.81)	77.84 (79.19/76.53)	79.56 (78.16/81.00)	78.34 (77.38/79.32)	75.40 (72.30/78.77)

4. Results and discussions

4.1. Accuracy of modeling of business relationships

The performance of predicting customer–supplier relationships is shown with *Precision*, *Recall*, and *F*-value in Table 4. On average, the *F*-value of predicting customer–supplier relationships is about 84.8%. The *F*-value of predicting reciprocal customer–supplier relationships is about 75–79%. Depending on *N*, the performance varies as much as 1–3 points. Intuitively, it is more difficult to model superior reciprocity like top 10% relationships than that of top 30 % or 50%. However, there is no significant difference between *N* in terms of the *F*-value while the *Recall* is slightly decreasing as *N* becomes smaller. This indicates that our approach successfully find plausible candidates of business partners and reciprocity among them with high accuracy.

Table 5
Weight of positive features for predicting customer–supplier relationships (Ex.1).

Feature	Average weight
Customer's number of employee	2.80
Supplier's number of employee	1.74
Customer's ranking (nation-wide)	1.13
Common address	0.95
Common industrial categories	0.77
Supplier's ranking (nation-wide)	0.93
Supplier's date of foundation	0.80
Customer's date of foundation	0.74
Customer's ranting (prefecture-wide)	0.70
Common industrial categories of suppliers	0.69

Table 6
Weight of positive features for predicting reciprocal customer–supplier relationships (Ex.2).

Feature	Average weight (rank order)		
	$N = 50$	$N = 30$	$N = 10$
Customer's ranking (nation-wide)	1.23 (2)	0.36 (4)	0.05 (5)
Supplier's ranking (nation-wide)	1.34 (1)	0.20 (8)	0.06 (4)
Customer's ranking (prefecture-wide)	0.51 (6)	0.31 (6)	0.12 (2)
Supplier's ranking (prefecture-wide)	0.22 (8)	0.23 (7)	0.03 (6)
Customer's number of competitors (nation-wide)	0.26 (7)	0.46 (3)	0.01 (8)
Supplier's number of competitors (nation-wide)	0.66 (3)	0.55 (1)	0.10 (3)
Customer's capital	0.62 (4)	0.53 (2)	–
Supplier's capital	0.56 (5)	0.35 (5)	–
Customer's date of foundation	0.17 (9)	0.10 (10)	0.02 (7)
Supplier's date of foundation	0.15 (10)	0.13 (9)	0.14 (1)

Table 7
Weight of positive relational features for predicting reciprocal customer–supplier relationships (Ex.2).

Feature	Average weight		
	$N = 50$	$N = 30$	$N = 10$
Common address	0.040	0.025	–
Common CEO's native address	–	0.002	0.012
Common CEO's old school	0.021	0.017	0.004
Common bankers	0.004	0.003	–

4.2. Features affecting the existence of business relationships

To identify meaningful features for our prediction, we closely examined our learning model. The averaged weights of positive features for predicting customer–supplier relationships (Ex.1) are shown in Table 5. Overall, both customer's and supplier's *number of employee* and *ranking* strongly contribute to the prediction of customer–supplier relationships. It indicates that relatively large firms have more opportunities to find business chances than other firms. *common address* also has meaningful impact, which means that firms tend to select business partners which are located in physical proximity.

In our case, *date of foundation* is also another important factor. Positive weight of this feature implies that old firms have more business relationships. This is partly because of their trust and reputation. On the other hand, young firms have difficulty in finding

Fig. 1. Screenshot of Web system for finding business partners.

their business partners. This phenomenon is explained with the term "liability of newness". It says that the higher rate of failure among young firms, which he attributed to the difficulties new firms have in securing the resources they need for survival (Stinchcombe, 1965). This liability arises at least in part because young firms have less of the legitimacy needed to gain trust and support from other actors (Singh, Tucker, & House, 1986).

These results seem to show that large and old firms have more business partners especially when they are located in physical proximity than ventures and small and medium sized firms. However, the existence of customer–supplier relationship does not mean the existence of reciprocal relationship between them. In the next, we examine which particular features are affecting the reciprocity of business relationships.

4.3. Features affecting the reciprocity of business relationships

The averaged weights of positive features for predicting reciprocal customer–supplier relationships (Ex.2) are shown in Table 6. The features having large weight and therefore affecting the prediction of business relationships much differ between Ex.1 and Ex.2. For the prediction of reciprocal relationships, *ranking*, *number of competitors*, *capital*, and *date of foundation* are good indicators, while they are dependent on N.

Although *ranking* and *date of foundation* has meaningful and positive weight both Ex.1 and Ex.2, the high weight of *ranking* and *number of competitor* is distinctive for Ex.2. *ranking* shows the rank order of one's sales and *number of competitors* shows how many other firms exist in one's industrial category. Both features can be considered as indicators of competitive circumstance of business environment and competitive advantage of the focal firms, which leads to reciprocal relationships both for supplier and customer.

Capital is another unique feature for Ex.2. This might be interpreted that business models requiring large investment in factory and machinery requires long-term relationships with their business partners to recover their initial investment, and therefore it requires reciprocal business model.

Table 7 shows the averaged weights of relational features for predicting reciprocal customer–supplier relationships. Comparing the features in each N of Ex.2, we can see the different effect of physical proximity (i.e., *common address* and *common bankers*). For $N = 50$, *common address* and *common bankers* have relatively meaningful impact among relational features. The effect disappears for $N = 10$. Instead, for $N = 10$, *common CEO's native prefecture* and *common CEO's old school* are relatively meaningful relational features. This might indicate that informal personal network and trust fermented in that network is important especially for high reciprocity of business relationships.

Since our results are based on the data of firms in Japan, we can speculate that firm data from different social and cultural backgrounds might result in different meaningful features. However, our method itself is general enough to apply to other firm data.

5. Applications

Our proposed method can be utilized for people in business to find their potential business partners. To demonstrate this, we integrated our method into the Web system. Fig. 1 shows the screenshot of the Web system. In the system, firm data including the information to be used for modeling business relationships are automatically collected from the Web and several dabatases. A user can search for firms according his or her interests. And the system automatically recommends a list of potential business partners of a target firm with their tag crowd which is a list of keywords. The recommended business partners are also visualized on top of existing customer–supplier networks so that the user can easily find potential business partners.

In case a user cannot find a firm of interest, she can register the information of a new firm and then the system automatically updates the learning model. The user feedbacks such as explicit rating and implicit click log of recommendations are also used to update the model. The system is currently being integrated with the Web site of a government-supported organization which promotes collaboration within industries, and will be publicly available.

6. Conclusions and future work

As the complexity and the change of speed of business environment increases, there is an increasing interest and need for AI technologies to analyze business data. In this paper, we showed that the learner of L_2 regularization SVM performs well to model a customer–supplier relationship with F-values of about 84% and reciprocity among them with F-values of about 77%, which showed that our approach can successfully find plausible candidates of business partners.

Our results showed that *number of employee*, *ranking*, *date of foundation* are the major determinants of the existence of customer–supplier relationships. On the other hand, competitive circumstance of business environment and competitive advantage of the focal firms are important characteristics of reciprocal relationships among firms. And informal personal network and trust fermented in that network is also important especially for high reciprocity of business relationships.

Our approach can be utilized to find new business partners, and therefore to develop one's own business under the complicated, specialized and rapidly changing business environments. To demonstrate this, we integrated our method into the Web system and provided an actual service. Future studies will explore the possibilities of including more semantically rich features such as keywords which represent firms' activities, products, and technologies.

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