Patent Analysis for Supporting Merger and Acquisition (M&A) Prediction: A Data Mining Approach

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Abstract. M&A plays an increasingly important role in the contemporary business environment. Companies usually conduct M&A to pursue complementarity from other companies for preserving and/or extending their competitive advantages. For the given bidder company, a critical first step to the success of M&A activities is the appropriate selection of target companies. However, existing studies on M&A prediction incur several limitations, such as the exclusion of technological variables in M&A prediction models and the omission of the profile of the respective bidder company and its compatibility with candidate target companies. In response to these limitations, we propose an M&A prediction technique which not only encompasses technological variables derived from patent analysis as prediction indictors but also takes into account the profiles of both bidder and candidate target companies when building an M&A prediction model. We collect a set of real-world M&A cases to evaluate the proposed technique. The evaluation results are encouraging and will serve as a basis for future studies.

Keywords: Merger and Acquisition (M&A), M&A Prediction, Patent Analysis, Data Mining, Ensemble Learning.

1 Introduction

Merger and Acquisition (M&A) refers to the process of merging or acquiring all or parts of other companies' property rights under certain conditions in order to have the controlling rights [17], and is a critical business behavior to pursue complementarity between companies from different dimensions such as resource, channel, brand, and technology [2], [9], [19], [20]. Proper M&A behavior has the benefit of changing the market structure and increasing market power, generating economies of scale and other synergies, having tax advantage, or serving managerial ambitions [6]. M&A plays an increasingly important role in the highly competitive business environment and is a major tool that companies adopt to sustain or even extend their competitive advantages. According to the report conducted by Thomson Financial[1], the volume of

[1] http://www.tfsd.com/marketing/banker_r2/HomeWelcome.asp

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worldwide announced M&As during 2007 reached US$4.5 trillion, a 24.2% increase over the previous record set in 2006. Even the volume of completed M&As reached a 23.9% increase from US$3.0 trillion to US$3.8 trillion between 2006 and 2007.

The motivation of M&A can be diverse but the goals are similar, i.e., to assist companies to strengthen their weaknesses and to consolidate their strengths. However, in contrast with the intended goals, M&A frequently results in market-share losses, skimpier profits, and in long term, loss money for shareholders [20]. For example, according to a study of 150 mergers with values greater than US$500 million in the 1990s by Mercer Management, 50% of M&A cases were failures judged by their effect on stockholders wealth after three years. Another study by Sirower [16] found that of 168 deals analyzed, roughly two-thirds of M&As destroyed value for shareholders [16]. To increase the success of M&A activities, the critical first step for a bidder company is to identify suitable target companies that have resources complementary to those of the bidder company.

Given a bidder company, M&A prediction deals with the selection of target companies that have resources complementary to those of the bidder company. As mentioned, it is the critical first step of an M&A activity because an inappropriate selection likely leads to the failure of this M&A activity. M&A prediction is also important from the perspective of possible target companies (i.e., those companies that are possible to be acquired or merged by bidder companies). For example, M&A prediction can help startup companies assess their possibility of being acquired or merged and who are the possible bidder companies. Such assessment will facilitate startup companies to develop appropriate strategies for improving their possibility of being acquired or merged and/or increasing economic benefits to the shareholders of the startup companies obtained from future M&A activities. In addition, M&A prediction can also be valuable for venture capitals to hunt for investment targets. For venture capitals, the first-rate investment targets are those who have the potential for growing rapidly in the very near future. An important indicator for evaluating the growing potential of a company is the probability of being merged or acquired, because M&A targets are generally those that have unique resources or superior solutions for emerging techniques.

M&A prediction has received much research attention [1], [6], [10], [13], [15], [17]. Most of prior studies mainly employ financial and managerial variables as indicators on constructing their M&A prediction models. However, prior studies incur some limitations. First, the absence of including technological variables may limit the scenarios where M&A prediction can be applied. M&A activities are especially critical for those high-tech industries, because they often use M&As to acquire state-of-the-art technologies or rapidly expand their R&D capabilities. Thus, most of the existing M&A prediction studies may not effectively be applied to high-tech industries in which the technological-oriented competitive strategy prevails. Second, most of existing studies concentrate on identifying candidate M&A targets without considering the profile of the bidder company under discussion [7]. Such M&A prediction can support the assessment of the probability of a company being acquired or merged, but who are likely to be bidder companies is not a concern in the assessment. Consequently, M&A prediction models developed by prior studies may not be effective because the profile of the respective bidder company and its compatibility with a candidate target company are not taken into consideration.

In response to the aforementioned limitations of existing M&A prediction studies, we propose an M&A prediction technique that not only incorporates technological variables as prediction indicators but also takes into account the profiles of two companies (where one being the possible bidder company and another being the candidate target company) and their compatibility. Specifically, in this study, we employ patent analysis to derive technological variables for M&A prediction. Due to the properties of novelty and exclusion of patents, we believe that patents are an excellent source for evaluating the technological capability of a company. The remainder of the paper is organized as follows. Section 2 reviews literature relevant to this study. In Section 3, we depict the detailed design of our proposed patent-based M&A prediction technique. Subsequently, we describe our experimental design and discuss important evaluation results in Section 4. Finally, we conclude in Section 5 with a summary and some future research directions.

2 Literature Review

In this section, we review existing studies on M&A prediction. Several prior studies have concentrated on M&A prediction and most of them adopt financial and managerial variables as indicators for M&A prediction. Common financial variables employed include firm size [1], [6], [10], [13], [17], market to book value ratio (or Tobin's Q) [6], [10], [15], [17], cash flow [1], [6], [15], [17], debt to equity ratio [6], [15], [17], and price to earning ratio [10], [17]. Other financial variables, such as cost to income ratio [13], net loans to total asset ratio [13], capital expenditures to total asset ratio [15], growth [13], outperformance [6], return on average asset [13], and tax shield effect [17], are also used in some prior studies. Besides the financial variables, managerial variables, such as management inefficiency [1], [10], resource richness [10], industry variations [10], and relevance degree of the business boundaries [17], represent another category of indicators adopted by existing M&A prediction studies.

As for the analysis methods applied to learn an M&A prediction model, logistic regression is the most common one [1], [6], [10], [13], [15]. Discriminant analysis and rule induction can also be found in some prior studies [15].

The results of existing M&A prediction studies are promising and beneficial for M&A research and practices. However, there are some limitations that may degrade the effectiveness or restrict the applicability of the prior studies. First, most of existing M&A prediction studies consider only financial and/or managerial variables. Given the growing importance of technology and innovation to strategic competitiveness, it is essential for bidder companies to pay attention to technological issues in their M&A decision making [9]. Appropriate assessment of the technological capabilities of bidder and target companies in an M&A activity not only helps to avoid costly errors and reduce the failure rate but also helps the bidder company to better realize the value of the technological assets acquired [9]. Although few studies utilizing technological information to perform the M&A prediction (e.g., [1]) employ patent information of target companies to help select M&A candidates for a bidder company, only very limited technological information (e.g., whether a firm has any granted or applied patents and the number of granted or applied patents) is employed. The exclusion or limited use of technological variables for M&A prediction limits the scenarios where M&A prediction can be applied. M&A activities are especially critical for those high-tech industries (e.g., information and communication technology, electronics, bio-technology, pharmaceutical), because they often use M&As to acquire state-of-the-art technologies or rapidly expand their R&D capabilities. Thus, most of the existing M&A prediction studies may not effectively be applied to high-tech industries in which the technological-oriented competitive strategy prevails. As a result, there is a pressing need to develop an alternative approach that employs comprehensive technological variables for M&A prediction.

Second, most of existing studies induce the M&A prediction model depending solely on the information of candidate target companies (i.e., without considering the profile of the bidder company under discussion). Such M&A prediction can support the assessment of the probability of a company being acquired or merged, but who are likely to be bidder companies is not a concern in this assessment. Accordingly, most of prior studies are not practicable in some important application scenarios. For example, for venture capitals, the described M&A prediction provides insufficient information for hunting investment targets because the growth potential of a company that is likely to be acquired or merged depends on who the potential bidder company is (e.g., whether the potential bidder company is the industry leader). In addition, prior studies may not produce effective M&A prediction models because the profile of the respective bidder company and its compatibility with a candidate target company are not taken into consideration.

3 Patent Analysis for M&A Prediction

In this study, we formulate the M&A prediction problem as follows: given a bidder company and a candidate target company, M&A prediction is to predict whether the candidate target company will be acquired or merged by the bidder company. That is, we consider M&A prediction as a classification problem with two possible decision categories: M&A (i.e., the candidate target company will be acquired or merged by the bidder company) and non-M&A (i.e., the candidate target company will not be acquired or merged by the bidder company). In this section, we first define and describe the technological variables (derived from patent analysis) employed in our proposed M&A prediction technique. Subsequently, we depict the ensemble learning algorithm developed for our proposed technique.

3.1 Variables for M&A Prediction

A patent is a collection of exclusive rights that protect an inventor's new machine, process, article, or any new improvement theory for a fixed period of time. Due to its properties of novelty and exclusion, patent is an excellent source for evaluating the capability of technology or innovation of a company. Patent analysis has been widely applied to many application domains, such as the estimation of stock performance [5], M&A analysis [1], [3], [4], evaluation of R&D collaboration [18], and analysis of corporate strategy [12]. Patent analysis is mainly based on the statistic and citation information of patents. For example, a commonly adopted statistic variable for patent analysis is the number of patents [1], [3], [4], [5], [12]. When citation information is considered, variables, such as impact of patent [3], [5], technology strength [3], [4],

[8], [12], [14], science link [3], [4], [5], [8], technology cycle time [3], [4], [5], [12], [14], and concentration rate [12], [18], are usually employed. The idea behind patent citation analysis is that patents cited by many later patents tend to contain important ideas upon which many later inventions are built [3]. As a result, a company with a large number of frequently cited patents is likely to possess technological and competitive advantages in that specific domain.

According to the review of the existing patent analysis studies, we summarize and develop five categories of variables, namely *technological quantity*, *technological quality*, *technological innovation*, *technological diversity*, and *technological compatibility*, for building the patent-based M&A prediction model. Specifically, thirteen variables, which cover the first four categories of technological variables, are estimated to measure individual technological capability of the given bidder company (f_b) and the given candidate target company (f_c), respectively. In addition, seventeen variables are included to measure the technological compatibility between f_b and f_c. As a result, a total of forty-three variables are employed for M&A prediction in this study.

For each company involved in the target M&A prediction (i.e., f_b or f_c), we measure the company's ***technological quantity*** as follows:

- Number of Patents (*NP*): *NP* measures the number of patents granted to a company under discussion and is an indicator of the technological capability of the company [3], [5], [14]. If a company has a higher number of patents, the company is likely to have better technological capability. For a company i (f_b or f_c), $NP_i = |P_i|$ where P_i is the set of patents granted to company i.
- Number of Recent Patents (*NRP*): *NP* measures the overall technological capability of a company from its establishment. However, for a company with a long history, *NP* may not be an effective measure of the company's technological capability because its patents may be granted long time ago. Thus, we adopt another measure *NRP* to estimate the recent technological capability of the company [3]. Specifically, *NRP* considers the patents granted within three years only. For a company i (f_b or f_c), $NRP_i = \underset{j \in P_i \text{ and } age(j) \leq 3}{\text{count}}(j)$, where $age(j)$ returns the number of years between the year when the patent j was granted and the current year (or more specifically, the year when the target M&A is concerned).

For each company (i.e., f_b or f_c), we measure its ***technological quality*** as follows:

- Impact of Patents (*IP*): *IP* measures the impact of patents of a company based on the number of forward citations to these patents [8]. However, it is common that earlier patents tend to have higher number of forward citations. To avoid this possible bias due to the ages of patents, we employ the *novel citation index* (*NCI*) to estimate the *IP* of a company. The NCI of a patent j (i.e., NCI_j) is calculated as: $NCI_j = \alpha \times (Y_c - Y_j + 1)^{\sigma} \times C_j$, where Y_c is the current year, Y_j is the published year of the patent j, C_j is the number of forward citations received by patent j, and α and σ are constant variables to adjust the weight. Accordingly, the impact of patents of a company i (f_b or f_c) is then estimated by averaging the *NCIs* across all patents of the company. Specifically, $IP_i = \frac{\sum_{j \in P_i} NCI_j}{|P_i|}$.

- Technology Strength (TS): TS is another measure of the impact of a company's patents and is typically estimated by the average current impact index (CII) of a company's patents within a specific technological field [3], [14]. The CII of a company i in technological field d is defined as: $CII_{id} = \frac{C_{id} / K_{id}}{C_d / K_d}$, where C_{id} is the total number of forward citations received by the patents of company i in technological field d in the current year, K_{id} is the number of patents of company i in technological field d, C_d is the total number of forward citations received in the current year by all patents in technological field d, and K_d is the number of patents in technological field d. Accordingly, the overall technology strength of a company i (f_b or f_c) is then estimated by averaging the CII values across all the technological fields covered by the company. That is, $TS_i = \frac{\sum_{d \in F_i} CII_{id}}{|F_i|}$, where F_i is the set of technological fields covered by company i.

  In this study, the technological field of a patent is determined by the patent classification system (i.e., IPC classification system [21]). An IPC class of a patent can be specified at four levels: section, class, subclass, and subgroup. For example, given a patent with an IPC class as A01B/01, its technological field at section, class, subclass, and subgroup levels are 'A', 'A01', 'A01B', and 'A01B/01' respectively. To consider the impacts of different classification levels when estimating TS of a company, we further differentiate TS into four variables according to their classification levels. That is, for the bidder company f_b, $TS\text{-}S_b$ (for the section level), $TS\text{-}C_b$ (for the class level), $TS\text{-}SC_b$ (for the subclass level), and $TS\text{-}G_b$ (for the subgroup level) are used for M&A prediction. Likewise, four variables are developed for the candidate target company f_c: $TS\text{-}S_c$, $TS\text{-}C_c$, $TS\text{-}SC_c$, and $TS\text{-}G_c$.

For each company (i.e., f_b or f_c), we measure its ***technological innovation*** as follows:

- Link to Science (LS): The link between patents and scientific articles reveals the extent to which a company is building on scientific research and is often used to measure the degree of technological innovation of a company [4], [8], [12]. Let ls_j be the number of links to scientific articles in patent j. Accordingly, the link to science of company i (f_b or f_c) is calculated as the average link to scientific articles across all patents of the company: $LS_i = \frac{\sum_{j \in P_i} ls_j}{|P_i|}$.
- Technology Cycle Time (TCT): TCT measures the average median year of the patents cited by the patents of a company [4], [12], [14]. Companies whose patents cite relatively recent patents are likely to be innovating faster than those whose patents cite older patents. Given a patent j with k citations and the ordered published years of references cited by patent j (i.e., $<y_1, y_2, \ldots, y_k>$, where $y_h \leq y_{h+1}$ for all h where $1 \leq h < k$). We determine the technology cycle time of a patent j as: $tct_j = y_{(k+1)/2}$ if k is an odd number and $tct_j = \frac{y_{k/2} + y_{(k/2)+1}}{2}$ if k is an even

number. Subsequently, the TCT of company i (f_b or f_c) is then computed as: $TCT_i = \frac{\sum_{j \in P_i} tct_j}{|P_i|}$.

For each company (i.e., f_b or f_c), we measure its ***technological diversity*** as follows:

- Concentration Rate (CR): CR measures the concentration of patents of a company across all technological fields covered by the patents of the company [18]. Accordingly, for a company i (f_b or f_c), $CR_i = \frac{\sum_{d \in F_i} \left(\frac{K_{id}}{K_i} \times \log_2 \frac{K_{id}}{K_i} \right)}{\log_2 |F_i|}$. Evidently, if a company concentrates only in one technological field, its respective CR value will be 0 (i.e., no diversity). However, if a company's patents are evenly distributed across different technological fields, its CR value will approach to 1.

  As with technology strength, the technological field of a patent is determined by the IPC classification system. Correspondingly, when estimating CR for a company, we differentiate CR into four variables by considering the impacts of different classification levels. That is, $CR\text{-}S_b$ (for the section level), $CR\text{-}C_b$ (for the class level), $CR\text{-}SC_b$ (for the subclass level), and $CR\text{-}G_b$ (for the subgroup level) are included to measure the concentration rate of f_b. Similarly, $CR\text{-}S_c$, $CR\text{-}C_c$, $CR\text{-}SC_c$, and $CR\text{-}G_c$ are employed for f_c.

Subsequently, we describe the seventeen variables employed to measure the ***technological compatibility*** between the bidder company (f_b) and the candidate target company (f_c).

- Compatibility of Technological Fields (CTF): CTF measures the cosine similarity of percentages of patents of f_b and f_c across all technological fields covered by the two companies. Specifically, $CTF_{bc} = \frac{\sum_{d \in F_{bc}} R_{bd} \times R_{cd}}{\sqrt{\sum_{d \in F_{bc}} R_{bd}} \times \sqrt{\sum_{d \in F_{bc}} R_{cd}}}$, where R_{id} is the percentage of patents of company i in technological field d (i.e., $R_{id} = \frac{K_{id}}{|P_i|}$) and F_{bc} is the union of the technological fields covered by f_b and those covered by f_c.

  According to the IPC classification system, we also consider four possible levels of technological fields and use four variables to measure the CTF between f_b and f_c. That is, $CTF\text{-}S_{bc}$ (at the section level), $CTF\text{-}C_{bc}$ (at the class level), $CTF\text{-}SC_{bc}$ (at the subclass level), and $CTF\text{-}G_{bc}$ (at the subgroup level) are included.
- Relative Strength of Technological Quantity: The relative strength of technological quantity calculates the ratio of each of the two technological quantity measures defined previously (i.e., number of patents and number of recent patents) between f_b and f_c. Specifically, the relative strength in number of patents (NP) is defined as: $RNP_{bc} = \frac{NP_b}{NP_c}$, and the relative strength in number of recent patents (NRP) is $RNRP_{bc} = \frac{NRP_b + 0.5}{NRP_c + 0.5}$. The constant 0.5 is added to avoid the situation when the denominator is zero.

- Relative Strength of Technological Quality: The relative strength of technological quality calculates the ratio of each of the two technological quality measures defined previously (i.e., impact of patents and technology strength) between f_b and f_c. Specifically, the relative strength in impact of patents (IP) is measured as: $RIP_{bc} = \frac{IP_b + 0.5}{IP_c + 0.5}$. For the technology strength (TS), four variables are defined for different IPC classification levels: $RTS\text{-}S_{bc} = \frac{TS\text{-}S_b + 0.5}{TS\text{-}S_c + 0.5}$ (for the section level), $RTS\text{-}C_{bc} = \frac{TS\text{-}C_b + 0.5}{TS\text{-}C_c + 0.5}$ (for the class level), $RTS\text{-}SC_{bc} = \frac{TS\text{-}SC_b + 0.5}{TS\text{-}SC_c + 0.5}$ (for the subclass level), and $RTS\text{-}G_{bc} = \frac{TS\text{-}G_b + 0.5}{TS\text{-}G_c + 0.5}$ (for the subgroup level).
- Relative Strength of Technological Innovation: The relative strength of technological innovation calculates the ratio of each of the two technological innovation measures defined previously (i.e., link to science and technology cycle time) between f_b and f_c. Specifically, the relative strength in link to science (LS) is measured as: $RLS_{bc} = \frac{LS_b + 0.5}{LS_c + 0.5}$, and the relative strength in technology cycle time (TCT) is defined as: $RTCT_{bc} = \frac{TCT_b}{TCT_c}$.
- Relative Strength of Technological Diversity: The relative strength of technological diversity calculates the ratio of concentration rate (CR) between f_b and f_c. Specifically, four variables are defined according to the IPC classification levels: $RCR\text{-}S_{bc} = \frac{CR\text{-}S_b + 0.5}{CR\text{-}S_c + 0.5}$ (for the section level), $RCR\text{-}C_{bc} = \frac{CR\text{-}C_b + 0.5}{CR\text{-}C_c + 0.5}$ (for the class level), $RCR\text{-}SC_{bc} = \frac{CR\text{-}SC_b + 0.5}{CR\text{-}SC_c + 0.5}$ (for the subclass level), and $RCR\text{-}G_{bc} = \frac{CR\text{-}G_b + 0.5}{CR\text{-}G_c + 0.5}$ (for the subgroup level).

3.2 Ensemble Learning Algorithm

As mentioned, we formulate M&A prediction as a classification problem with two possible decision categories: M&A and non-M&A. To learn an M&A prediction model, we need to prepare a set of training examples of the two categories. Because it is easier to obtain non-M&A cases than M&A cases, a set of training examples tends to be highly asymmetric or skewed in the two categories. To deal with such skewness in a training set, we develop an ensemble approach for learning. Given a training set, the basic idea of our ensemble learning algorithm is that we sample k training subsets from the training set for training k base classifiers. Assume that we have n M&A cases and m non-M&A cases (where $n < m$) in the training set. Each training subset will comprise all of the n M&A cases and $\alpha \times n$ randomly sampled non-M&A cases, where α is used to adjust the ratio of non-M&A and M&A cases in a training subset. Subsequently, an induction learning algorithm (specifically, Naïve Bayes classifier [11] in this study) is applied to build a base classifier for each training subset.

To predict a new (unseen) case (i.e., a pair of a bidder company and a candidate target company), each base classifier will produce the probability that the case belongs to the M&A category. We can employ the average method by averaging the probability predicted by each base classier to arrive at the overall probability. Consequently, if the overall probability is equal to or greater than 0.5, the case will be predicted as in the M&A category; otherwise, the non-M&A category. Alternatively, we can adopt the weighted average method to obtain an overall probability, where the weight of a base classifier depends on its prediction accuracy on the training set.

4 Empirical Evaluation

In this section, we describe our data collection and evaluation design, and then discuss some important evaluation results of the proposed patent-based M&A prediction technique.

4.1 Data Collection

The M&A cases from January 1, 1997 to May 27, 2008 are collected from the SDC Platinum database[2] for our evaluation purpose. We limit the M&A cases to companies in certain industries in Japan. The procedure of data collection and filtering is illustrated in Fig. 1. We apply four filtering rules to form the M&A cases in our dataset. We first search each M&A case in which both the bidder and the target are from the same country (i.e., Japan) from the SDC Platinum database. The bidders and targets in SDC Platinum Database could be companies or departments of companies. It is possible that the bidder and target are different departments in the same company or the bidder and target are departments from different companies. Because the analysis unit of this study is at the company level, the first filtering rule filters out those M&A cases retrieved from the SDC Platinum database that the bidder or target is a department rather than a company.

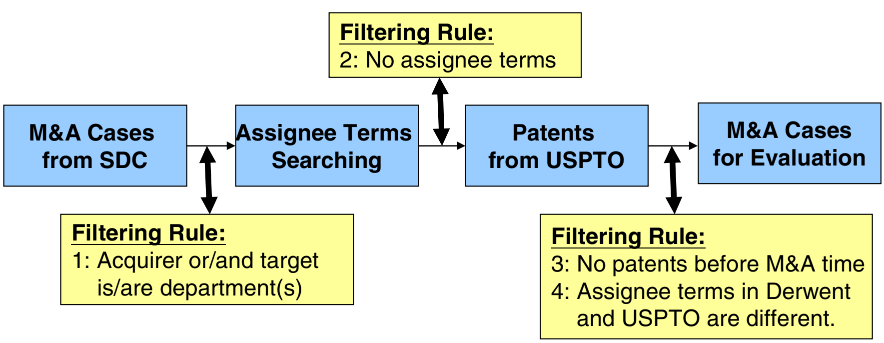

Fig. 1. Procedure of Data Collection and Filtering

[2] http://www.thomsonreuters.com/products_services/financial/sdc

Table 1. Summary of M&A Cases in Japan Dataset

Industry	Original#	After†	Industry	Original	After
Electronics	592	38	Machinery	548	6
Communication	83	4	Prepackaged Software	571	3
Computer Equipment	106	5	Chemical	494	5
Total Number of Usable M&A cases: 61 out of 2394 original cases					

#: Number of M&A cases retrieved from the SDC Platinum database.

†: Number of M&A cases retained after the filtering process.

Subsequently, we submit the name of each company that passes through the first filtering rule to the Derwent Innovation Index database[3] to search for their assignee terms in the USPTO database[4]. The purpose of assignee term search is to find alternative names of a company and allow us to search for all the patents granted to this specific company. For example, the company name of the "Taiwan Semiconductor Manufacturing Company Ltd." in the SDC Platinum database is "Taiwan Semiconductor Mnfr Co." It has three possible assignee terms according to the Derwent Innovation Index database, namely "Taiwan Semiconductor Mfg Co Ltd," "Taiwan Semiconductor Mfg Co," and "Taiwan Semiconductor Mfg Corp Ltd." After finding all alternative names for each company appearing in our dataset, the second filtering rule is then applied to eliminate those cases without having any assignee terms. A company without any assignee terms implies that it does not have any issued patents and thus should be removed from our dataset.

Subsequently, M&A cases with corresponding assignees terms are employed to search for patent documents from the USPTO database, which will then be used to derive the values for the forty-three variables depicted in Section 3.1. In this stage, the third filtering rule is applied to remove these cases that do not have any issued patents before the year of the corresponding M&A case. In addition, the fourth filtering rule, which filters out cases whose assignee terms in the Derwent Innovation Index database are different from those in the USPTO database, is executed forthwith. The remaining M&A cases are then used for our empirical evaluation purposes. After the data filtering process, 61 useable M&A cases are retained our dataset. The summary of our dataset is provided in Table 1.

Following the collection of M&A cases, we have to generate non-M&A cases to serve as negative examples. We believe that representative non-M&A cases should be those having the opportunity for being M&A cases. From the technological complementarity perspective, a non-M&A case whose bidder and target companies come from different industries may not make much sense. As a result, our non-M&A case generation process is performed intra-industrially and based on 3 assumptions. First, bidder companies are usually large companies and, thus, have less chance to be acquired or merged. Second, a target company acquired or merged by a bidder company at a specific time has no chance to be the target of another company before the known M&A case. Third, a target company acquired or merged by a bidder company at a specific time will never be a target again afterward. We use an example to illustrate our non-M&A case generation process. Assume that there are three M&A cases in the

[3] http://scientific.thomsonreuters.com/products/dii/

[4] http://www.uspto.gov/main/patents.htm

same industry: *A* acquired *B* on time t_1, *C* acquired *D* on time t_2, and *E* acquired *F* on time t_3. Moreover, assume that t_1 is earlier than t_2 and t_2 is earlier than t_3. Consequently, we can generate three non-M&A cases including *A* did not acquire *D* and *A* did not acquire *F* on time t_1, and *C* did not acquire *F* on time t_2. Following this non-M&A case generation process, we create 523 non-M&A cases from the 61 M&A cases for our Japan dataset.

4.2 Evaluation Design

To evaluate the effectiveness of the proposed patent-based M&A prediction technique, we design two evaluation experiments. The first experiment is to evaluate the prediction power of the proposed technique. The second experiment examines the effect of different decision combination methods (i.e., average and weighted average) in our ensemble learning algorithm.

In all experiments, a tenfold cross-validation strategy is employed to estimate the learning effectiveness. That is, given a dataset, we divide all cases in the dataset randomly into ten mutually exclusive subsets of approximately equal size. In turn, we designate each subset as the testing examples while the others serve as training examples. To minimize the potential sampling biases, we perform the tenfold cross-validation process three times and the overall effectiveness is estimated by averaging the performance estimates obtained from the 30 individual trials. In addition, we set the number of base classifiers (k) in our ensemble learning algorithm as 30.

4.3 Effectiveness of the Proposed M&A Prediction Technique

In this experiment, we employ the average method for decision combination in our ensemble learning algorithm and investigate the effectiveness of the proposed M&A prediction technique across different values for α (the ratio of non-M&A cases and M&A cases in a training set), ranging from 1 to 3 in increment of 1. As Table 2 shows, an increase of α improves prediction accuracy, precision rate for the M&A category, and recall rate for the non-M&A category. Because the increase of α means the inclusion of more non-M&A cases into each training set. As a result, the M&A prediction model induced with more non-M&A cases will favor the majority category (i.e., having the tendency of predicting the non-M&A category); thus, decreasing recall rate for the M&A category and precision rate for the non-M&A category. Overall, a smaller value for α is more desired, because it improves recall rate for the M&A category, which is the major concern of this study. Specifically, when setting α as 1,

Table 2. M&A Prediction Results in the Japan Dataset

		M&A Category		**Non-M&A Category**	
α	**Accuracy**	**Recall**	**Precision**	**Recall**	**Precision**
1	88.16%	46.43%	42.93%	92.97%	93.83%
2	88.43%	45.90%	44.00%	93.27%	93.80%
3	88.78%	44.30%	45.30%	93.87%	93.60%

Table 3. M&A Prediction Results with Different Weighting Methods in the Japan Dataset

Decision Combination Method	Accuracy	M&A Category Recall	M&A Category Precision	Non-M&A Category Recall	Non-M&A Category Precision
Average	88.16%	46.43%	42.93%	92.97%	93.83%
Weighted Average	87.94%	45.37%	41.97%	92.80%	93.67%

the recall and precision rates for the M&A category are 46.43% and 42.93%, respectively. Given the complexity of M&A decision, the prediction effectiveness attained by our M&A prediction technique is considered satisfactory. We believe that the expansion of the size of the dataset should further improve the effectiveness of the proposed technique.

4.4 Effects of Decision Combination Methods

As mentioned, we propose two different decision combination methods (i.e., average and weighted average) in the ensemble learning algorithm. We conduct this experiment to empirically investigate their effects on the effectiveness of the proposed M&A prediction technique. According to the evaluation result suggested by the previous experiment, we set α as 1. As Table 3 illustrates, the average method outperforms the weighted average one in all measures examined. Especially, the performance differentials of recall and precision for the M&A category (i.e., 1.06% and 0.96%, respectively) are greater than those of recall and precision for the non-M&A category (i.e., 0.17% and 0.16%, respectively). This result suggests that the weighted average method (weighted by the accuracy of each base classifier) appears to favor the prediction of the non-M&A category and thus sacrifice the recall and precision for the M&A category.

5 Conclusion and Future Research Direction

M&A plays an increasingly important role in the modern business environment. Companies usually conduct M&A to pursue complementarity from other companies for preserving and/or extending their competitive advantages. Appropriate selection (prediction) of M&A targets for a given bidder company is a critical first step to the success of the M&A activity. However, most of existing studies apply only financial and managerial as indicators on constructing M&A prediction model and select candidate target companies without considering the profile of the respective bidder company and its compatibility with candidate target companies. These limitations greatly limit the applicability of the prior studies. To overcome these limitations, we propose an M&A prediction technique that not only encompasses technological variables as prediction indictors but also takes into account the profiles of both bidder and candidate target companies when building an M&A prediction model. Forty-three technological variables are derived from patent analysis and an ensemble learning algorithm is developed for our proposed patent-based M&A prediction technique. We collect a set of real-world M&A cases to evaluate the proposed technique. The evaluation results are encouraging and will serve as a basis for future studies.

Some ongoing and future research directions are summarized as follows. First, in this study, we only examine the effectiveness of the proposed technique in one dataset (i.e., Japan). It is essential to collect additional datasets to empirically evaluate the proposed M&A prediction technique. Second, this study only includes technological variables in the M&A prediction model. Incorporating other types of variables (e.g., financial and managerial) into the M&A prediction model is desirable and should further improve the prediction effectiveness reported in this study. Last but not least, there is still room for improving the effectiveness (especially recall and precision rates for the M&A category) of our proposed technique. One direction is to include additional technological measures and the other is to further extend the ensemble learning algorithm proposed in this study.

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