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Analyzing Mergers and Acquisitions (M&A) in Japan Using AI methods

Bohua Shao[*1] Kimitaka Asatani[*1] Ichiro Sakata[*1]

[*1] School of Engineering, the University of Tokyo

If potential M&A cases can be detected automatically, this technology will improve the efficiency of M&A target recommendation and effectiveness of in-process M&A cases. However, in the past, M&A recommendation was impossible due to insufficient data and complexity of M&A. In this research, we provided a clustering method with cash flow features and company relationship features. From M&A clustering, we observed that M&A tend to concentrate in specific clusters. In order to improve the precision of M&A recommendation, we also analyzed the relationships between features from financial items and we extracted important features for identifying company relationships. The result of this research shows feasibility of recommending M&A from big data. In the future, we will design and select more features for analyzing M&A and we will associate results from AI with Management Science.

1. Introduction

Mergers and acquisitions (M&A), as we all know, are the transactions of the ownership of organizations. Historically, M&A in Japan showed a strong countercyclical trend. That is when the economy was prosperous, M&A were few while when the economy was not going well, M&A cases were prevailing. [Mehrotra 2011]

However, the “Financial Big Bang of Japan” from 1997 to 2006 changed this situation dramatically. Recently, according to the report of METI (Ministry of Economy, Trade and Industry) on 2018’s tax reform [METI 2017], the shareholders of acquirees can defer the tax on revenue during M&A. This reform helps promote M&A in Japan in the future.

Currently, M&A business is still conducted by huge human labor and scientific approaches are not prevailing for selecting suitable M&A partners. Actually, many M&A deals tend to be failures. In the financial engineering field, there are abundant AI approach research fruits. Hence, it is also possible to have M&A recommendations if sufficient data are provided.

This research is a part of the research project “Research on the feasibility of the M&A target recommendation for practical use”. The ultimate goal of this project is to provide companies with potential M&A target lists by an AI system. This work, aiming at understanding current M&A patterns and features in Japan, serves as a fundamental research for the project.

Previous literature about M&A preferred case studies and econometric methods. In this research, we used AI method, which was seldom used in M&A research field. By AI approach, in the future, we will be able to save labor work on M&A analysis a lot in the M&A business field. In this research, we also provided a new M&A clustering method, which is especially suitable for M&A in Japan in the past fifteen years.

2. Previous literature

Dickson argues about the relationship between the cash flow patterns and the firm life cycle. There are several stages in the firm life cycle and there are also corresponding cash flow patterns in each stage. [Dickinson 2011]

Shibayama *et al.* argued that M&A between firms of equal size is likely to result in difficulty in integration of knowledge base. [Shibayama 2006] Cloodt *et al.* had following statements. First, in order to increase innovative performance through M&A, companies have to target firms with moderately related knowledge base. Second, the author’s results clearly demonstrate that in high-tech industries, the M&A of a large absolute knowledge base only contribute to improved innovative performance during the first couple years after integration. Third, non-technology M&A in high-tech industries contribute less or negatively. [Cloodt 2006]

“Mastering the merger”, published by Bain & Company, Inc. in 2004, said M&A is a paradox for companies. Successful companies learn from M&A and authors recommend that companies should start from small M&A deals and then have large deals. [Harding and Rovit 2004]

In 2012, Mori *et al.* published a paper with the topic of predicting business partners by AI approach. In this paper, there are 3 feature types: suppliers’ features, customer’s features and their relationships’ features. The main method of this research is the support vector machine (SVM), which is a kind of supervised machine learning approach. In this paper, there are two experiments for predicting the business relationship. The latter experiment, which is designed to predict the reciprocal business relationships, is the elaborated version of the former one, which only predicts business relationships. The final achievement of this paper is developing a web system for recommending business partners. [Mori 2012]

3. Data

In this experiment, we are using the databases from UZABASE, Inc. In these databases, we have access to M&A information, company information and financial information.

In the M&A database, companies participating in M&A are divided into 4 roles. They are acquirer, ultimate acquirer, seller and target. The difference between acquirers and ultimate acquirers is that acquirers are ordinary companies while ultimate acquirers are mainly Private Equity funds and venture capital firms. The difference between targets and sellers is that targets are organizations for sale while sellers are the owners or

Contact: Bohua Shao, School of Engineering, the University of Tokyo, shaobohua6@gmail.com

shareholders of targets. In this paper, we only focused on "Acquirer" and "Target" because they are typical M&A roles.

There are 7 M&A types in the databases. They are "Merger of Equals", "Fund Buy-out", "Acquisition", "Minority Stake", "Joint Venture", "MBO" and "Demerger".

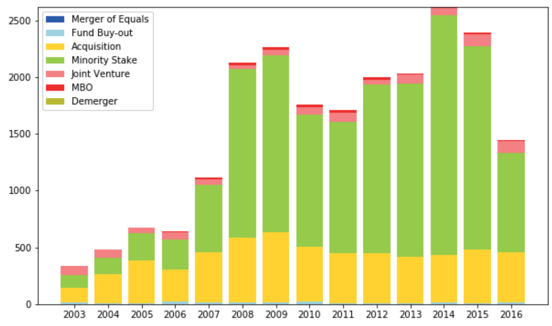

Figure 1. General information of M&A in Japan (2003-2016)

Figure 1 shows the number of M&A in each year in Japan, according to their types. From this figure, we find "Minority Stake", "Joint Venture" and "Acquisition" are prevailing in each year. In this research, we only focused on "Merger of Equals" and "Acquisition" because they are traditional understanding of M&A (M&A is the abbreviation of "Mergers and Acquisitions").

We have access to company information. In this paper, we focused only on 3692 Tokyo Stock Listed companies' information. They are labelled with the SPEEDA industrial classification codes. The SPEEDA code consists of 3 parts and 9 digits in total. The first 3 digits show the general classification, the second 3 digits show the medium classification and the last 3 digits show the detailed classification.

4. Experiments

4.1 Methods

In this research, we found M&A are very complex. In order to understand M&A patterns and phenomena, we used K-means [Shalev-Shwartz 2014] for our first trial.

Since we designed several features for analyzing M&A and we were interested in knowing which features are effective, we used Principal Component Analysis (PCA) [Shalev-Shwartz 2014].

4.2 Cash flow features

Before investigating M&A, we were interested in company behaviors. As mentioned in Chapter 2, the cash flow is a proxy for understanding company behaviors. We conducted such an investigation so as to have several basic knowledge for further research.

In this section, we used the following formula to calculate free cash flow:

$$\text{Free Cash Flow} = \text{Cash flow from operating activities} + \text{Cash flow from investing activities} \quad (1)$$

We designed 8 features shown in Table 1 for analyzing cash flow.

Table 1: 8 features

Name	Financial items
cfoa	Cash flow from operating activities
cfia	Cash flow from investing activities
cffa	Cash flow from financing activities
freecf	Free cash flow
plnetsales	Net sales
oprofit	Ordinary profit
cfb	Cash & Cash Equivalent - Beginning
cftd	Changes in cash flow

In this section, we focused on companies of all industries in Japan and we only focused on yearly financial reports. The cash flow data can be fetched from 1989, so we analyzed cash flow data from 1989 to now. We designed a vector with a length of 8, 8 dimensions. The 8 elements in a vector represent the financial data of 8 financial items of a company of a fiscal year. We also deleted vectors with data missing and finally we succeeded in generating about 70,000 vectors.

We used PCA for understanding the importance of each feature and we found that "Net sales" and "Cash & Cash Equivalent- Beginning" have high weights. Hence, these two features are important for cash flow analysis and will be fundamental knowledge for designing features and analyzing M&A further.

4.3 Features

In order to have M&A analysis, we will design 3 feature types: acquirers' features, targets' features and relationships' features. We plan to adopt the results from 4.2 and design features about financial items. As a first step, in this paper, we preferred to firstly investigate relationships' features.

We extracted M&A deal information from the M&A database. In this paper, we only focused on M&A between 3692 listed companies. According to the following statements, we made 3 features:

Dis3: If the acquirer and the target share the same general industrial classification (the first 3 digits in SPEEDA codes), the value is 1; otherwise: 0.

Hist3y: Value: 1: the acquirer had M&A experience in the period of three years in succession before the M&A announcement; 0: others.

Histbool: Value: 1: the acquirer had M&A experience before the M&A announcement; 0: others.

4.4 Evaluation

In order to have further understanding of M&A, we generated random samples for evaluation. For a fair evaluation, we again used the 3792 listed companies. We randomly make pairs from them and generated about 7,000,000 pairs by combination.

Next, we randomly selected 1,000 pairs from the nearly 7,000,000 pairs as random samples in this paper.

We deleted any data flaw and finally made 778 random sample vectors and 109 M&A case vectors. Then, we mixed up 778 random sample vectors and M&A vectors and applied K-means for clustering.

5. Results

We have three features and they are all valuing 0 or 1. Obviously, we should have 8 situations. However, there are 2 situations with “Hist3y” valuing 1 and “Histbool” valuing 0 are impossible. Hence, we decided to separate into 6 groups.

We had 6 clusters. The table below shows the number and proportion of M&A cases and random samples in each cluster. The very right column shows the ratio of M&A to random samples in each cluster.

Table 2: The number of M&A and random samples in clusters

Cluster id	M&A cases (%)	Random Samples (%)	Ratio of M&A to Random Samples
0	13 (11.93%)	399 (51.28%)	3.26%
1	7 (6.42%)	153 (19.67%)	4.58%
2	20 (18.35%)	59 (7.58%)	33.90%
3	37 (33.94%)	10 (1.29%)	370%
4	19 (17.43%)	128 (16.45%)	14.84%
5	13 (11.93%)	29 (3.73%)	44.83%
Total	109 (100.00%)	778 (100.00%)	Avg. 14.01%

From this Table 2, we find Cluster 0 has the lowest ratio of M&A cases to random samples while Cluster 3 does the highest. Hence, by only 3 features, we are able to find that M&A concentrate in a cluster. This phenomenon is interesting and we are interested in adopting other features in the future.

6. Summary

In this research, we attempted to analyze M&A with AI approaches. Results in Chapter 5 will help us design features for analyzing M&A in the future.

In the section 4.2, we analyzed cash flow. However, cash is strongly related with corporate governance and several reforms were conducted in Japan in the past years. In the future, we will associate the cash flow analysis with corporate governance.

We had only 109 M&A cases for Chapter 5 and it is far from enough. We will expand our research boundary from Japan to the whole world for our future research topic. We had only 3 features in this paper and in the future, we will adopt the results from cash flow analysis and design more features for further analysis.

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