Recommendation as a Service in Mergers and Acquisitions Transactions

Yu-Chen Yang[1(✉)], Yi-Syuan Ke[1], Weiwei Wu[2], Keng-Pei Lin[1], and Yong Jin[2]

[1] National Sun Yat-Sen University, Kaohsiung, Taiwan
ycyang@mis.nsysu.edu.tw
[2] The Hong Kong Polytechnic University, Hung Hom, Hong Kong

Abstract. Mergers and acquisitions (M&A) happens frequently between corporations to combine and/or transfer their ownerships, operating units and assets. The purpose of the study is to develop a service that is able to recommend a feasible M&A deal. We integrate the support vector machine model with the kernel tricks to automatically determine M&A deals. In the end of the study, our proposed technique is empirically validated, and the results show the effectiveness of the recommendation service.

Keywords: Mergers and acquisitions · Machine learning · Support vector machine · Financial kernel · Recommendation service

1 Introduction

Mergers and acquisitions (abbreviated M&A) happens frequently between corporations to combine and/or transfer their ownerships, operating units and assets. The major objective of M&A is to improve companies' financial and operating performances with potential synergies, such as market share, profits, economies of scale, influence in the industry etc. Thomson Reuters reports that the value of worldwide M&A deals in the first nine months of 2018 reached $3.3 trillion, increased by 39% from 2017, and almost half of the deals worth more than $5 billion[1]. Thomson Reuters also shows that the largest M&A market is in the United States, following by Europe, Asia Pacific, Japan, and Africa-Middle East[2]. The volume of global M&A is continuing to grow rapidly, and M&A is one crucial trend of business behavior.

The purpose of the study is to develop a service that is able to recommend a feasible M&A deal. We propose the recommendation service integrating with the support vector machine (abbreviated SVM) model. Prior studies attempt to use various techniques of machine learning to evaluate a M&A firm, for example, logistic regressions (Meador et al. 1996; Pasiouras and Gaganis 2007), rule induction (Ragothaman et al. 2003), neural networks (An et al. 2006) and decision tree (Yang et al. 2014) etc. However, few studies implement the support vector machine (abbreviated SVM)

[1] https://www.ft.com/content/b7e67ba4-c28f-11e8-95b1-d36dfef1b89a.

[2] https://www.nytimes.com/2018/07/03/business/dealbook/mergers-record-levels.html.

F. F.-H. Nah and K. Siau (Eds.): HCII 2019, LNCS 11589, pp. 151–159, 2019.
https://doi.org/10.1007/978-3-030-22338-0_12

algorithm as M&A recommendation models. Comparing with the above models, the SVM model is very efficient for binary classification, including quickly finding hyperplanes to separate data and shorter training time (Cristianini and Shawe-Taylor 2000). Furthermore, our work incorporate three different kernels, including a Gaussian kernel, a polynomial kernel (Cristianini and Shawe-Taylor 2000) and a financial kernel (Cecchini et al. 2010). Finally, prior studies such as Yang et al. (2014) provide a novel technique to evaluate the M&A deals, but they only work on the Asia Pacific market, which may not be representative of the whole M&A markets. The study focuses on the major market, that is, the United States, and we will validate the proposed recommendation technique in M&A transactions in the U.S.

The remainder of the paper is organized as follows. Section 2 lists the related work to our study. Section 3 formulates the proposed M&A forecasting model based on the integration of SVM and kernels. Section 4 presents the evaluation of the proposed technique. Finally, the conclusions and possible directions for future research are provided in Sect. 5.

2 Related Work

We will present the two major related works in the section. First, we review the related studies of M&A recommendation techniques. Second, the SVM model and the kernel methods are introduced. The proposed service model is based on the combinations of SVM and kernels.

2.1 M&A Recommendation

The popular analysis techniques applied to developing M&A recommendations/predictions include logistic regression (Meador et al. 1996; Pasiouras and Gaganis 2007), rule induction (Ragothaman et al. 2003), and decision tree (Yang et al. 2014). First, logistic regression is the most common model. Meador et al. (1996) use logistic binary regression analysis to examine the accounting, financial, and market variables to predict the M&A target companies as well as horizontal and vertical subsamples of merged companies over the period 1981 to 1985. Their model shows the strongest predictive ability for horizontal acquisitions. Pasiouras and Gaganis (2007) also employ the model of logistic regression to examine the financial characteristics of Asian banks during the period of 1998 to 2004. They further indicate that high asset risky portfolios and high liquidity increase the probability of being involved in an acquisition. Ragothaman et al. (2003) apply the techniques of artificial intelligence (AI)-based rule induction to identify acquisitions targets. Decision tree is a new application in the section of M&A. Yang et al. (2014) propose a M&A prediction technique that incorporates a comprehensive set of technological indicators, the technological profiles of both the bidder firm and a candidate target firm. Different from prior studies, they derive some technological indicators derived via patent data analyses. The work of Yang et al. (2014) is the latest study that explores the M&A predictions so far. We will extend their work and the related indicators in the study.

2.2 Support Vector Machine and Financial Kernels

The support vector machine is a popular classification method created by Vapnik and colleagues (Boser et al. 1992; Cortes and Vapnik 1995; Cristianini and Shawe-Taylor 2000). Sometimes, we may have to deal with high-dimensional feature space. In order to reduce the dimensionality, some techniques can be employed, and one of the popular techniques is "kernel methods" – providing a powerful tool for learning non-linear relations with a linear machine. The basic philosophy is that a certain type of similarity measure, i.e. a kernel, maps the data set into a high-dimension feature space, in which linear methods are used for learning and estimation problems. We use the symbol K to represent a kernel matrix such that $K(\mathbf{u},\mathbf{v}) = \langle\phi(\mathbf{u}),\phi(\mathbf{v})\rangle$, where $\phi : X \to F$ means an implicit mapping ϕ from an input attribute space X onto some feature space F, and $\mathbf{u},\mathbf{v} \in X$. A kernel matrix K is required to satisfy these conditions: symmetric, positive semidefinite, and the Cauchy-Schwarz inequality (Cristianini and Shawe-Taylor 2000).

Several common types of kernel functions are listed in Cristianini et al. (2002) and the number is ever growing. One typical example is the polynomial kernel, which is defined as $K(\mathbf{u},\mathbf{v}) = (K_1(\mathbf{u},\mathbf{v}) + R)^d$, where $K_1(\mathbf{u},\mathbf{v})$ is the normal inner product kernel, d is a positive integer, and R is fixed. Another typical example is the Gaussian kernel (or called the radial basis function kernel): $K(\mathbf{u},\mathbf{v}) = \exp\left(\frac{\|\mathbf{u}-\mathbf{v}^2\|}{2\sigma^2}\right)$, where σ is a free parameter and determines the width of the kernel.

Cecchini et al. (2010) propose a useful financial kernel to determine management fraud. The financial kernel is denoted as $K_F(\mathbf{u},\mathbf{v})$ and computes all ratios of input attributes as well as year-over-year ratio. It begins with n attributes and produces $3n(n-1)$ features, which can be broken into six feature types. The mapping ϕ is represented as:

$$\phi(\mathbf{u}) = \left(\frac{u_{i1}}{u_{j1}},\frac{u_{j1}}{u_{i1}},\frac{u_{j2}}{u_{i2}},\frac{u_{i2}}{u_{j2}},\frac{u_{i1}u_{j2}}{u_{j1}u_{i2}},\frac{u_{j1}u_{i2}}{u_{i1}u_{j2}}\right)', i,j = 1,\ldots,n, \qquad i<j.$$

The financial kernel is also working on other financial analyses even though initially it is proposed for detecting management fraud. We are following the work of Cecchini et al. (2010) and apply the financial kernel into the M&A recommendation.

3 The Proposed Recommendation-as-a-Service Technique in M&A Transactions

In the section, we detail the design of our proposed recommendation-as-a-service technique in M&A transactions. Following the work of Yang et al. (2014), we replace the forecasting technique with the SVM model integrated with a Gaussian kernel, a polynomial kernel, or a financial kernel presented by Cecchini et al. (2010). Figure 1 shows the details of our proposed technique, where a training phase and a forecasting phase are involved.

The training phase involves two major steps: kernel mapping and inductive learning. First, we follow the previous studies and extract the values of the related

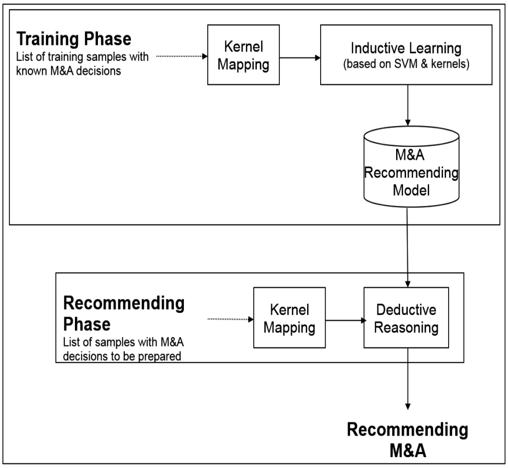

Fig. 1. Overall process of the proposed recommendation-as-a-service technique in M&A transactions

financial variables for each training sample (see Table 1). Then all the values of the financial variables will be mapped via a kernel function such as a polynomial kernel, a radial basis kernel or a financial kernel. Following kernel mapping is the inductive learning step, and we choose the R package "e1071" (Hornik et al. 2006; Dimitriadou et al. 2008), a supervised learning technique that provides computational efficiency and excellent interpretability. The package "e1071" offers a powerful function "svm()" with flexible parameter tuning methods. In the inductive learning step, we employ SVM integrated with a kernel to induce M&A recommending models from the set of training instances. In the recommending phase, we use the recommending model induced by SVM in the training phase to recommend an M&A candidate deal.

4 Empirical Evaluation

In this section, we express how we collect the data and design the evaluation. We then show the preliminary results from the evaluation of the proposed M&A recommendation service model.

4.1 Data Collection

The M&A cases are collected from the SDC Platinum database, which is available at https://financial.thomsonreuters.com/en/products/data-analytics/market-data/sdc-platinum-financial-securities.html. Totally 5,804 cases are collected, and the M&A cases are within 2000 and 2011 in technology-related industries of North America. These industries include hardware (with first-two-digit SIC code 35), software (with first-two-digit SIC code 36), and computer related business service (with first-three-digit SIC code 234). We further check whether these cases are available for our empirical evaluation purpose.

Table 1. Definitions of financial indicators of M&A

Indicator	Definition
3-year average dividend (DVT3)	A company's dividend payments to its shareholders over the last three years
Capital-expenditures-to-total-asset (CETA)	(Current assets – current liabilities)/(total assets)
Cash flow (CF)	Amount of money moving into and out of a business
Common shares traded divided by common shares outstanding (CSTRCSHO)	(Shares traded)/(shares outstanding)
Cost of goods sold (COGS)	Carrying value of goods sold during a particular period
Cost of goods sold divided by average inventory (COGSNI)	(Costs of goods sold)/inventory
Current ratio (CURRENTRATIO)	(Current assets)/(current liabilities)
Debt-to-assets ratio (DEBTTOASSETS)	(Sum of long-term and short-term debt)/(total assets)
Dividend (DVT)	A company's dividend
Debt-to-equity ratio (DEBTTOEQUITY)	(Sum of long-term and short-term debt)/(book value of equity)
Earnings before interest and taxes or operating income after depreciation (EBIT)	Revenue minus expenses, excluding tax and interest
Tobin's Q (Q)	(Sum of short-term and long-term debt)/(total assets)
Price-to-earning ratio (PE)	A company's share price to its per-share earnings
Profit margin (PROFITMAT)	Net income divided by revenue, or net profits divided by sales
Ratio of tangible (fixed) assets to total assets (TANGIBLEAT)	(Tangible assets)/(total assets)
Return on assets (ROA)	(Net income)/(total assets)
Return on equity (ROE)	(Net income)/(book value of equity)
Return on investment (ROI)	(Gain from investment – cost of investment)/(cost of investment)
Sales to total assets or asset turnover (ASSETTURNOVER)	(Net sales)/(total assets)
Tax shield effects (TAXSHIELD)	Taxable income reduces claiming deductions

If the M&A case is not likely technology-oriented, we remove it from the dataset. As a result, we end up with retaining a data set consist of 83 M&A cases and 680 non-M&A cases. The ratio between M&A cases and non M&A cases in the data set is 83/680 = 0: 12205.

For each case, the values of the corresponding financial variables (see Table 1) are collected from the Compustat database in the Wharton Research Data Services

(WRDS, available at https://wrdsweb.wharton.upenn.edu/wrds/). In order to transforming values taken from different sources into a consistent format, we further standardize the range of financial variables by this way:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)},$$

where x is an original value, and x' is the standardized value. Furthermore, the decision on M&A deal in a constantly changing business environment is usually dynamic and oscillated over time. We use lagged variables to incorporate feedback over time and capture the year-over-year effect. Hence, for each case, the values of 20 pairs financial variables are extracted from WRDS, and each pair of variables include one variable for the current year and one corresponding lagged variable for the previous year. Each M&A case (or each training instance) is expressed as:

$$(DVT3, DVT3_{lag}, DVT, DVT_{lag}, CETA, CETA_{lag}, CF, CF_{lag}, CSTRCSHO, CSTRCSHO_{lag}, COGS, COGS_{lag}, COGSNI, COGSNI_{lag}, CURRENTRATIO, CURRENTRATIO_{lag}, DEBTTOASSETS, DEBTTOASSETS_{lag}, DEBTTOQUITY, DEBTTOEQUITY_{lag}, EBIT, EBIT_{lag}, Q, Q_{lag}, PE, PE_{lag}, PROFITMAT, PROFITMAT_{lag}, TANGIBLEAT, TANGIBLEAT_{lag}, ROA, ROA_{lag}, ROE, ROE_{lag}, ROI, ROI_{lag}, ASSETTURNOVER, ASSETTURNOVER_{lag}, TAXSHIELD, TANGIBLEAT_{lag}).$$

4.2 Evaluation and Preliminary Results

In this section, we measure the effectiveness of our proposed M&A forecasting technique on the basis of the complete data set. The criteria used to measure the performance evaluation are "accuracy", "precision", "recall", and "F_1". We compare with different kernels in order to determine the optimal model based on the proposed M&A recommendation technique. Totally three different kernels are considered, including Gaussian, polynomial, and financial.

In order to determine the optimal model, we fine tune the parameters, measure the effectiveness, and compare the proposed technique with different kernels. Tables 2 and 3 show the tuning results of the technique integrated with the Gaussian kernel and the polynomial kernel, respectively. Apparently, the Gaussian kernel performs best as the parameter $\gamma = 0.5$, and the polynomial kernel is best with $\gamma = 0.5$ and 0.7. After detecting the proper parameter values, we further measure the performance of these three models, *i.e.*, the proposed technique with three different kernels: Gaussian ($\gamma = 0.5$), polynomial ($\gamma = 0.5$), and financial. The results are shown as Table 4. First, the Gaussian kernel beats the financial kernel. It shows higher accuracy (84:81% > 83:54%), higher precision (50% > 33:33%), higher recall (16:67% > 8:33%), and higher F1 (25% > 13:33%). Second, although the recall values are low, the Gaussian kernel's precision is 50%, much higher than the polynomial kernel's precision (23.53%). The result further indicates that the Gaussian kernel still has a 50% opportunity to correctly identify the M&A cases, while most predictions made with the polynomial kernel are incorrect (23.53%).

Table 2. Turning results of the proposed model with the Gaussian kernel

Gaussian kernel	Accuracy	Precision	Recall	F_1
$\gamma = 0.3$	83.54%	33.33%	8.33%	13.33%
$\gamma = 0.5$	84.81%	50.00%	16.67%	25.00%
$\gamma = 0.7$	84.81%	50.00%	8.33%	14.29%

Table 3. Turning results of the proposed model with the Polynomial kernel

Polynomial kernel	Accuracy	Precision	Recall	F_1
$\gamma = 0.3$	70.89%	21.05%	33.33%	25.81%
$\gamma = 0.5$	73.41%	23.53%	33.33%	27.59%
$\gamma = 0.7$	73.41%	23.53%	33.33%	27.59%

Table 4. Evaluation of different kernels

Kernel	Accuracy	Precision	Recall	F_1
Gaussian	84.81%	50.00%	16.67%	25.00%
Polynomial	73.41%	25.53%	33.33%	27.59%
Financial	83.54%	33.33%	8.33%	13.33%

5 Conclusion

M&A is a very common business activity and happens frequently in the high-technology industries because these IT companies are motivated for the speedy innovation and required to extend their resources and capabilities through the M&A transaction. In this study, we aim to provide a recommendation service that automatically determine a feasible M&A deal. We extend the work of Yang et al. (2014) and propose the M&A recommending technique on the basis of SVM. We also derive 40 financial variables and develop a training and recommending method for the technique. The M&A cases in the U.S. market are collected to validate the effectiveness of the proposed model.

However, the study is an initial exploration of the application of SVM in M&A recommending and forecasting. Our works still contains some limitations and may need to be improved in the future. First, we plan to show the performance of our proposed technique by incorporating other benchmark models, such as decision tree (C4.5), neural networks, or other machine learning techniques. Second, our proposed technique does not consider the possible negative outcomes, e.g. declining market shares and profits. Third, the study only focus on North America and only collect M&A cases from there. A generalized technique is still required although most M&A deals are made in North America. We plan to collect the M&A cases from other markets, including Europe and Asia Pacific to verify the generalization of our proposed technique.

Acknowledgement. This work is supported by the Ministry of Science and Technology of Taiwan (106-2410-H-110-082), and the Intelligent Electronic Commerce Research Center from the Featured Areas Research Center Program within the framework of the Higher Education Sprout Project by the Ministry of Education (MOE) in Taiwan.

Appendix

See Table 5.

Table 5. Reference of financial indicators

Indicator	Reference
3-year average dividend (DVT3)	Barnes (2000)
Capital-expenditures-to-total-asset (CETA)	Barnes (2000); Ragothaman et al. (2003)
Cash flow (CF)	Ragothaman et al. (2003); Ali-Yrkkö et al. (2005); Song et al. (2009)
Common shares traded divided by common shares outstanding (CSTRCSHO)	Meador et al. (1996)
Cost of goods sold (COGS)	Meador et al. (1996)
Cost of goods sold divided by average inventory (COGSNI)	Meador et al. (1996)
Current ratio (CURRENTRATIO)	Meador et al. (1996); Barnes (2000); Ragothaman et al. (2003); Tsagkanos et al. (2007)
Debt-to-assets ratio (DEBTTOASSETS)	Barnes (2000); Pasiouras and Gaganis (2007)
Dividend (DVT)	Barnes (2000)
Debt-to-equity ratio (DEBTTOEQUITY)	Meador et al. (1996); Ragothaman et al. (2003); Song et al. (2009)
Earnings before interest and taxes or operating income after depreciation (EBIT)	Meador et al. (1996)
Tobin's Q (Q)	Meador et al. (1996); Barnes (2000); Ragothaman et al. (2003); Song et al. (2009)
Price-to-earning ratio (PE)	Meador et al. (1996); Barnes (2000); Ragothaman et al. (2003); Song et al. (2009)
Profit margin (PROFITMAT)	Tsagkanos et al. (2007)
Ratio of tangible (fixed) assets to total assets (TANGIBLEAT)	Ali-Yrkkö et al. (2005)
Return on assets (ROA)	Meador et al. (1996); Pasiouras and Gaganis (2007)
Return on equity (ROE)	Meador et al. (1996); Barnes (2000); Tsagkanos et al. (2007)
Return on investment (ROI)	Ali-Yrkkö et al. (2005)
Sales to total assets or asset turnover (ASSETTURNOVER)	Meador et al. (1996); Barnes (2000); Tsagkanos et al. (2007)
Tax shield effects (TAXSHIELD)	Song et al. (2009)

References

Ali-Yrkkö, J., Hyytinen, A., Pajarinen, M.: Does patenting increase the probability of being acquired? evidence from cross-border and domestic acquisitions. Appl. Financ. Econ. **15**(14), 1007–1017 (2005)

An, S., He, Y., Zhao, Z., Sun, J.: Measurement of merger and acquisition performance based on artificial neural network. In: 2006 5th IEEE International Conference on Cognitive Informatics, pp. 502–506. IEEE, Beijing (2006)

Barnes, P.: The identification of UK takeover targets using published historical cost accounting data Some empirical evidence comparing logit with linear discriminant analysis and raw financial ratios with industry-relative ratios. Int. Rev. Financ. Anal. **9**(2), 147–162 (2000)

Boser, B.E., Guyon, I.M., Vapnik, V.N.: A training algorithm for optimal margin classifiers. In: Proceedings of the Fifth Annual Workshop on Computational Learning Theory, pp. 144–152. ACM, Pittsburgh (1992)

Cecchini, M., Aytug, H., Koehler, G.J., Pathak, P.: Detecting management fraud in public companies. Manag. Sci. **56**(7), 1146–1160 (2010)

Chapelle, O., Haffner, P., Vapnik, V.N.: Support vector machines for histogram-based image classification. IEEE Trans. Neural Netw. **10**(5), 1055–1064 (1999)

Cortes, C., Vapnik, V.: Support-vector networks. Mach. Learn. **20**(3), 273–297 (1995)

Cristianini, N., Shawe-Taylor, J.: An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods. Cambridge University Press, Cambridge (2000)

Cristianini, N., Shawe-Taylor, J., Lodhi, H.: Latent semantic kernels. J. Intell. Inf. Syst. **18**(2–3), 127–152 (2002)

Dimitriadou, E., Hornik, K., Leisch, F., Meyer, D., Weingessel, A.: Misc functions of the Department of Statistics (e1071), TU Wien. R package, 1, 5–24 (2008)

Hagedoorn, J., Duysters, G.: The effect of mergers and acquisitions on the technological performance of companies in a high-tech environment. Technol. Anal. Strat. Manag. **14**(1), 67–85 (2002)

Hornik, K., Meyer, D., Karatzoglou, A.: Support vector machines in R. J. Stat. Softw. **15**(9), 1–28 (2006)

Hu, X., Pan, Y.: Knowledge Discovery in Bioinformatics: Techniques, Methods, and Applications, vol. 5. Wiley, Hoboken (2007)

Hua, S., Sun, Z.: A novel method of protein secondary structure prediction with high segment overlap measure: support vector machine approach. J. Mol. Biol. **308**(2), 397–407 (2001)

King, D.R., Slotegraaf, R.J., Kesner, I.: Performance implications of firm resource interactions in the acquisition of R&D-intensive firms. Organ. Sci. **19**(2), 327–340 (2008)

Meador, A.L., Church, P.H., Rayburn, L.G.: Development of prediction models for horizontal and vertical mergers. J. Financ. Strat. Decis. **9**(1), 11–23 (1996)

Pasiouras, F., Gaganis, C.: Financial characteristics of banks involved in acquisitions: Evidence from Asia. Appl. Financ. Econ. **17**(4), 329–341 (2007)

Ragothaman, S., Naik, B., Ramakrishnan, K.: Predicting corporate acquisitions: an application of uncertain reasoning using rule induction. Inf. Syst. Front. **5**(4), 401–412 (2003)

Song, X.-L., Zhang, Q.-S., Chu, Y.-H., Song, E.-Z.: A study on financial strategy for determining the target enterprise of merger and acquisition. In: 2009 IEEE/INFORMS International Conference on Service Operations, Logistics and Informatics, SOLI 2009, pp. 477–480. IEEE, Chicago (2009)

Tsagkanos, A., Georgopoulos, A., Siriopoulos, C.: Predicting Greek mergers and acquisitions: a new approach. Int. J. Financ. Serv. Manag. **2**(4), 289–303 (2007)

Yang, C.-S., Wei, C.-P., Chiang, Y.-H.: Exploiting technological indicators for effective technology merger and acquisition (M&A) predictions. Decis. Sci. **45**(1), 147–174 (2014)