出國報告　　(出國類別：國際會議)

跨學科的商業研究討論會

The SIBR 2015 Osaka Conference on Interdisciplinary Business & Economics Research

服務機關：國立暨南國際大學國際企業學系

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派赴國家：日本大阪

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摘要

本次國際會議名稱為「跨學科的商業研究討論會」，研討會為期二天，會議的主題是「跨學科知識進步：過去的經驗和未來的議程」。該 SIBR 會議匯集了學術和來自不同的商業和經濟學科的專業人員跨學科交流最新研究成果和集體討論新的研究思路。鼓勵採用理論，定量，定性的研究論文，或混合方法的方法，提升使用跨學科的各式研究方法、想法。

本篇文章主要目的是找出旅館及旅遊業關鍵財務困境屬性，提出了對酒店和旅遊公司預警模型。預警模型是基於神經網絡，利用它沒有滿足嚴格的統計限制，達到卓越的性能預測。實驗結果表明，我們提出的預測模型，結合「連續浮動前向選擇」和「神經網絡的質量預測」，能提供更精準的數據訊息。

目次

壹、　目的

本篇文章主要目的是找出關鍵財務困境屬性，提出了對酒店和旅遊公司預警模型。本文作者為王昶勝博士候選人（第一作者，以下稱本人）與王銘杰博士共同著作，發表議題為「A financial distress pre-warning model for hospitality and tourism firms」，由本人上臺以英文簡報說明。並借由文章的發表與國際學者接軌。

貳、 過程

一、 研討會投稿過程

1. 2015/03/7，完成投稿。
2. 2015/03/14 收到通過確認通知信件
3. 2015/06/19 確認場次時間
4. 2015/06/30 出發。
5. 2015/07/04 返回臺灣

會議相關資訊網址：

http://sibresearch.org/sibr-osaka-conference-call.html

二、 研討會參與過程

1. 發表場次為 07/03 實證金融&計量經濟學（Empirical Finance & Econometrics）場次

參、　　文章暨簡報內容

一、投稿文章

A financial distress pre-warning model for hospitality and tourism firms

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ABSTRACT

The hospitality and tourism firms have been facing a severe challenge because of recent financial tsunamis and accounting scandals. With the volume of financially distressed hospitality and tourism firms increasing, it is essential to find out which firms are most exposed to the risk of financial distress, because realizing a potentially distressed firms and point out its inherent problems that enhance the possibility of firms to survive in the highly competitive environment and yield the chance for decision makers to make an appropriate actions to turn the firm around. Thus, the primary objective of this study is to identify the key financial distress attributes and proposed a pre-warning model for hospitality and tourism firms. The key financial distress attributes can be determined by sequential floating forward selection, one sort of feature selection techniques. The original data undergone the feature selection process not only can eliminate the computational burden, but also increase the forecasting performance. The pre-warning model was based on neural network, one kind of artificial intelligence techniques which can reach superior outstanding forecasting performance without satisfying strict statistical limitation. The experimental result shows that our proposed forecasting model which incorporated sequential floating forward selection and neural network achieve outstanding forecasting quality and provide a more concise knowledge of the data.

Keywords: Hospitality and tourism risk prediction, Artificial intelligence, Decision making, Knowledge visualization

I. Introduction

In highly competitive financial environments, the mechanisms for risk warning have become important key instruments to guarantee the stability of the financial market because of their potential to prevent huge economic losses for related parties (e.g., creditors, bankers, investors, stockholders, and managers). Numerous firms falling into a financial crisis status during the same time period could cause another financial tsunami in the capital markets (Cao et al. 2011). Thus, helping firms effectively forecast a financial crisis is becoming much more essential in order to avoid the global economy going into a depression.

Compared with well-established research domains (financial crisis prediction, credit scoring, etc.), little work has been done on forecasting a warning for those firms falling into the decline stage, which is the inevitable stage before a financial crisis occurs. The corporate life-cycle theory views the corporation from the longitudinal perspective, by which the corporation might move through a justly predictable sequence of developmental stages. A widely utilized corporate life cycle basically consists of four or five stages: start-up, growth, maturity, decline, and death (Cao et al. 2011). Among these stages, the decline stage is much more important to recognize than the others. After going through the start-up, quick growth, and relatively stable maturity stages, numerous firms fall into the decline stage and encounter many aspects of crises. If managers can modify the capital structure of their firms in the decline stage, then the firms will have a higher possibility of surviving in an extremely competitive market rather than falling into the death stage.

The effectiveness of a multi-agent mechanism depends on two elements: preciseness and diversity of the base instrument/model. Among the artificial intelligence techniques, decision tree (DT) is widely utilized for various reasons: (1) its forecasting outcome can be easily attained for a decision maker, (2) the forecasting model construction by DT has no pre-defined assumption about the underlying distribution, and (3) the forecasting model construction by DT is faster than other artificial intelligence techniques. Thus, we select DT with its superior generalization ability as a base classifier. How to generate a diverse outcome is another critical task that can be solved by the technique called the random subspace method (RSM) (Ho, 1998). The utilization of dissimilar space for multi-agent mechanism establishment has been extensive in recent research. Ho (1998) indicated that RSM is able to facilitate forecasting accuracy and decreases the generalization error. The basic idea of RSM, rooted in the theory of stochastic discrimination (Kleinberg, 2000), has some points that are the same a bagging, but instead of sampling examples it samples subspaces (Skurichina and Duin, 2001; Garcia-Pedrajas and Ortiz-Boyer, 2008). It has been successfully implemented on numerous research domains.

The rest of the paper is structured as follows. Section 2 introduces the methodologies used in this study. Section 3 presents a review of the data from our empirical work and the experimental decisions. Finally, section 4 offers conclusions.

II. Methodologies

The most commonly implemented artificial intelligence (AI) technique in the category of data mining and machine learning is decision trees (DT) and it can be used to handle two main types of problems: one is the regression problem and the other is the classification problem. Due to the nature of easy-to-implement and comprehension, it has become gradually more popular than other AI techniques. Kim and Uoneja (2014) stated that C4.5, one of the popular types for constructing a DT model, generates DT by an assessing criteria namely information gain (IG) or by partitioning the tree at a specific stage. This technique starts with a minimal tress and evaluates the attributes that provides the most useful partition of the training cases. The mathematical format of gain ratio was represented in Eq. (1) and it is the assessing criteria for splitting in the C4.5 DT technique.

$$G(a_g) = \left[\sum_{h=1}^{k} -(\frac{B_{Y_h}^{(u)}}{B^{(u)}}) \log(\frac{B_{Y_h}^{(u)}}{B^{(u)}}) \right] - \left[\sum_{s=1}^{s} (\frac{B^{(s)}}{B^{(u)}}) \sum_{h=1}^{k} -(\frac{B_{Y_h}^{(s)}}{B^{(s)}}) \log(\frac{B_{Y_h}^{(s)}}{B^{(s)}}) \right], \tag{1}$$

where the first term and the second term in the formula represent the entropy at the parent node and the entropy at the child node, respectively. The difference between the two expresses the information and attributes that generate the gain ratio, and the largest gain ratio among all gain ratios is used to handle the partition task. Each child node is treated again as a new tree, and the process repeats until there is no misclassification in the training data (Kim and Upneja, 2014).

III. Empirical results

To examine the effectiveness of the multi-agent structure and feature selection approach DA, the study presents the outcomes under two scenarios: (1) with and without multi-agent structure; and (2) with and without feature selection. The experimental results are in Tables 1-2. To ensure that the outcomes do not happen by chance, we examine the significance of the prediction outcomes by means of the independent sample t-test, with the statistical outcomes in Table 3. According to our research finding, the multi-agent structure outperforms the singular structure. The finding is in response to prior research done by Sharkey (1996). The merit of the multi-agent structure complements any error made by the singular model. The model with the feature selection procedure not only can increase forecasting accuracy, but also can decrease both types of errors.

Table 1. The results of scenario 1.

Condition	With and without multi-agent structure (RSM+DA+DT v.s. DT)		
	Accuracy	Type I errors	Type II errors
CV-1	90.44 ***v.s.*** 83.22	9.51 ***v.s.*** 16.79	10.00 ***v.s.*** 16.67
CV-2	90.11 ***v.s.*** 78.33	10.12 ***v.s.*** 21.98	7.78 ***v.s.*** 18.89
CV-3	91.67 ***v.s.*** 80.44	8.40 ***v.s.*** 19.63	7.78 ***v.s.*** 18.89
CV-4	90.22 ***v.s***. 79.67	9.88 ***v.s.*** 20.12	8.89 ***v.s***. 22.22
CV-5	91.33 ***v.s.***79.89	9.01 ***v.s.*** 20.49	5.56 ***v.s.***16.67
AVG.	90.76 ***v.s.***80.31	9.38 ***v.s.*** 19.80	8.00 ***v.s.*** 18.67

Table 2. The results of scenario 2.

Condition	With and without feature selection (RSM+DA+DT v.s. RSM+DT)		
	Accuracy	Type I errors	Type II errors
CV-1	90.44 ***v.s.*** 87.56	9.51 ***v.s.*** 12.35	10.00 ***v.s.*** 13.33
CV-2	90.11 ***v.s.*** 86.11	10.12 ***v.s.*** 13.83	7.78 ***v.s.*** 14.44
CV-3	91.67 ***v.s.*** 84.89	8.40 ***v.s.*** 15.80	7.78 ***v.s.*** 8.89
CV-4	90.22 ***v.s***. 81.33	9.88 ***v.s.*** 19.26	8.89 ***v.s***. 13.33
CV-5	91.33 ***v.s.***82.67	9.01 ***v.s.*** 18.02	5.56 ***v.s.***11.11
AVG.	90.76 ***v.s.***84.51	9.38 ***v.s.*** 15.85	8.00 ***v.s.*** 12.22

Table 3. The statistic result under two dissimilar scenarios.

Condition	Scenario 1 (RSM+DA+DT v.s. DT)		
	Accuracy	100-Type I errors	100-Type II errors
AVG.	90.76 ***v.s.***80.31	90.62 ***v.s.***80.20	92.00 ***v.s.***81.33
Statistic	p-value= 0.00	p-value= 0.00	p-value=0.00
Condition	Scenario 2 (RSM+DA+DT v.s. RSM+DT)		
	Accuracy	100-Type I errors	100-Type II errors

AVG.	90.76 ***v.s.***84.51	90.62 ***v.s.***84.12	92.00 ***v.s.***87.78
Statistic	p-value=0.00	p-value=0.00	p-value=0.00

IV. Conclusions

The prediction of corporate financial distress is an important and challenging issue that has served as an impetus for many academic research studies over the past decades. While intangible assets are widely acknowledged to be essential elements when forecasting a corporate financial crisis, they are usually excluded from prior related early warning models. The objective of this study is to utilize the attributes of intangible assets as predictive variables and to propose a multi-agent hybrid mechanism, MAHM, to increase preciseness in the prediction of corporate financial distress. The introduced MAHM is grounded on the hybrid model that integrates multiple dissimilar base instruments into an aggregated outcome and has proved its superior forecasting performance. The fundamental idea behind the hybrid model is to complement the error made by a singular model.

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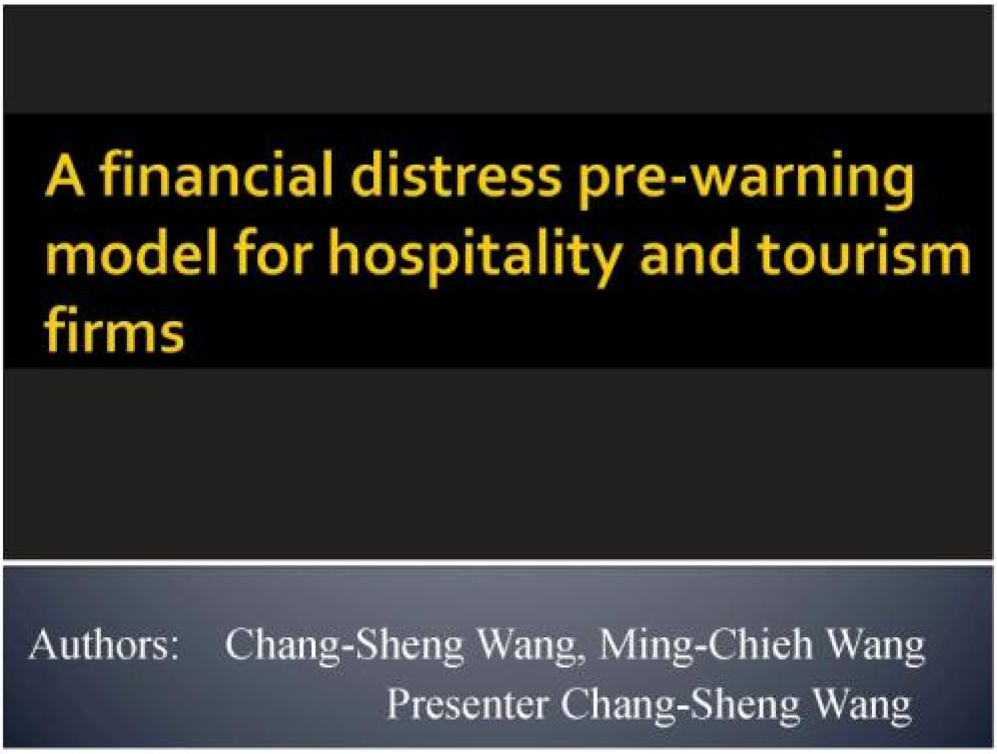
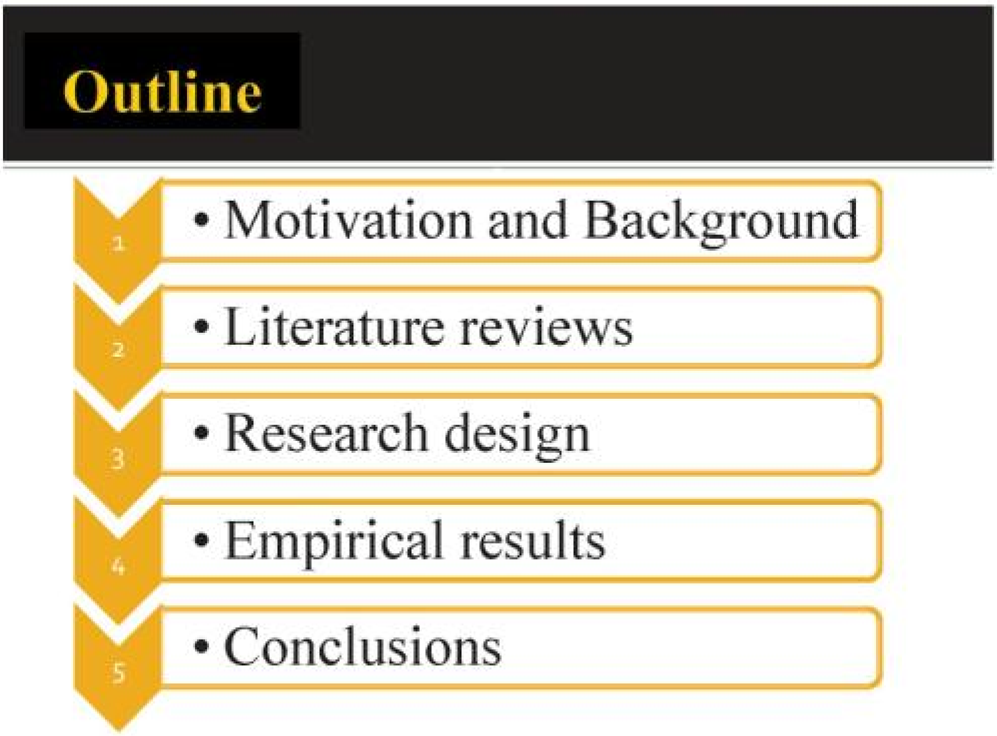
二、簡報


A financial distress pre-warning model for hospitality and tourism firms
Authors: Chang-Sheng Wang, Ming-Chieh Wang
Presenter Chang-Sheng Wang


Outline
1
• Motivation and Background
2
• Literature reviews
3
• Research design
4
• Empirical results
5
• Conclusions

Motivation and Background

Problems

- Financial crisis (Listed companies, investors, and even the overall economy of a country)

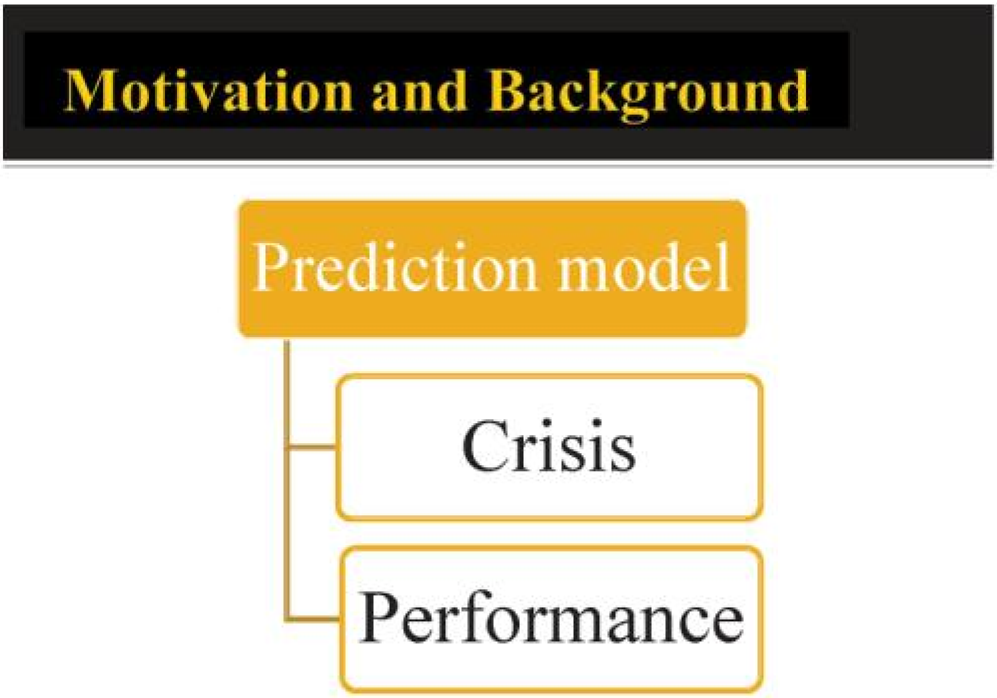
Solutions

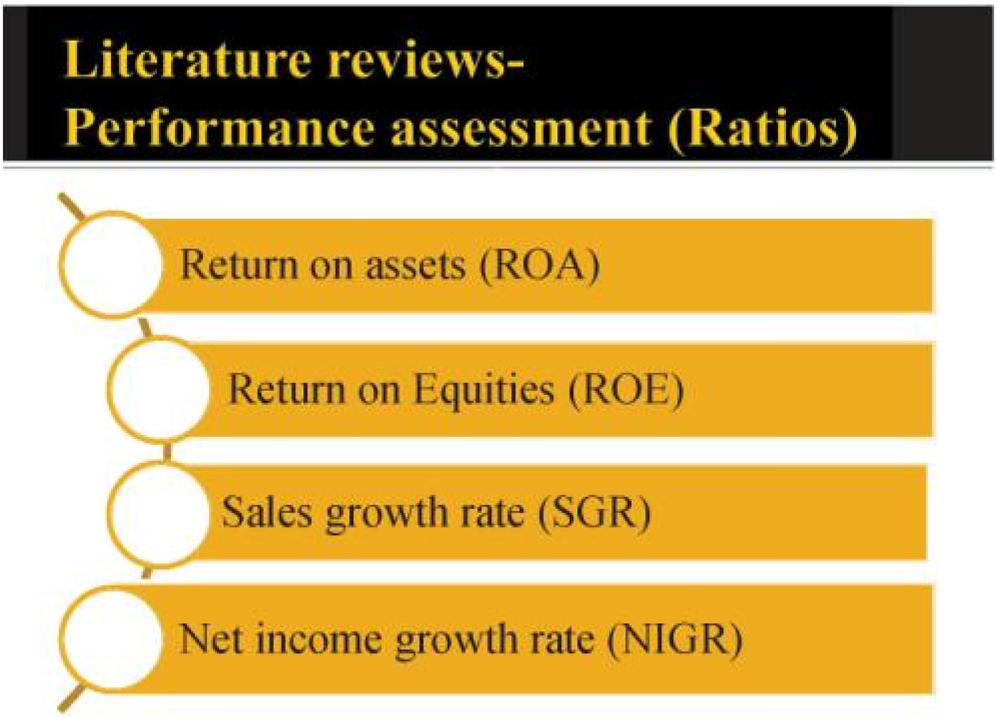
- Financial crisis prediction model construction

Motivation and Background

Idea

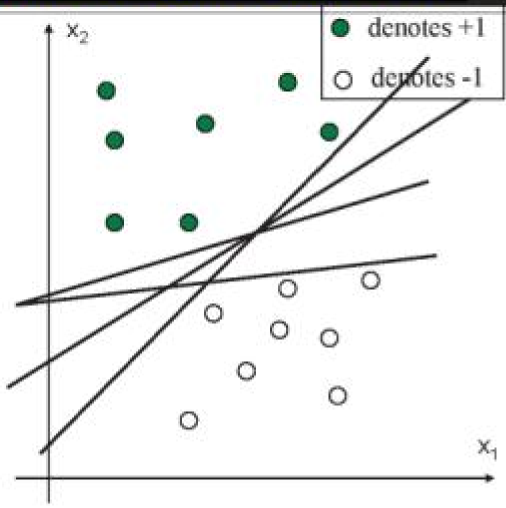
If the prediction of a financial crisis is reliable or reachable, then top corporate managers can initiate remedial procedures to prevent any serious deterioration in firm performance before the crisis bursts out, while investors can adjust their investment strategies and allocate their scarce economic resources to help scale down or even decrease anticipated investment related losses.


Motivation and Background
Prediction model
Crisis
Performance


Literature reviews-
Performance assessment (Ratios)
Return on assets (ROA)
Return on Equities (ROE)
Sales growth rate (SGR)
Net income growth rate (NIGR)

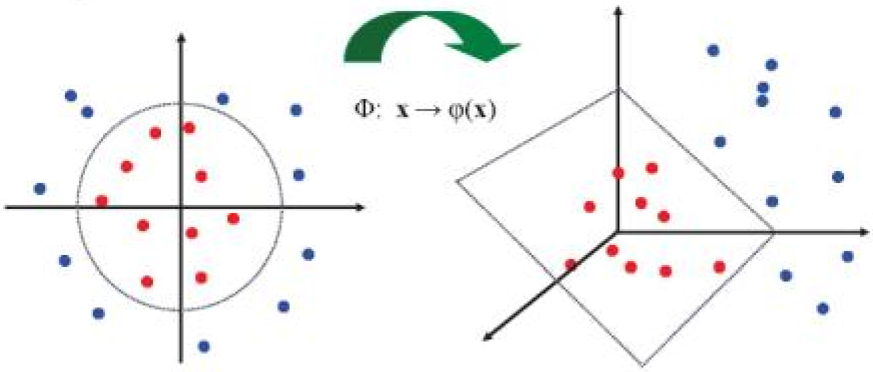
Research design-Support Vector Machine-Linear Discriminant Function

- How would you classify these points using a linear discriminant function in order to minimize the error rate?
- Infinite number of answers!
- Which one is the best?



Non-linear SVMs: Feature Space

- General idea: the original input space can be mapped to some higher-dimensional feature space where the training set is separable:



Empirical results

Ratios	Illustration
R1: WC/TA	Working capital to total assets
R2: TD/TA	Total debts to total assets
R3: CA/CL	Current assets to current liabilities
R4: QA/CL	Quick assets to current liabilities
R5: OI/TA	Operating income to total assets
R6: NI/TA	Net income to total assets
R7: C/TA	Cash to total assets
R8: I/S	Inventory to sales
R9: S/TA	Sales to total assets
R10: CA/S	Current assets to sales
R11: CF/TD	Cash flow to total debts
R12: QA/CL	Quick assets to current liabilities
R13: NI/(TA-TL)	Net income to (total assets-total liabilities)
R14: LTD/TA	Long-term debt to total assets
R15: CF/S	Cash flow to sales
R16: AE	Advertisement expenditure
R17: R&D	Research and development expenditure

Empirical results

Condition	Assessing criterion: Total accuracy (TA)			
	SVM	RF	BPNN	BN
CV-1	87.50	82.50	77.00	76.25
CV-2	88.75	82.25	78.00	72.25
CV-3	89.50	86.00	79.25	75.00
CV-4	89.25	84.00	77.00	81.75
CV-5	89.25	85.00	82.00	77.25
AVG	88.85	83.95	78.65	76.50

Empirical results

Condition	Assessing criterion: Sensitivity (SEN)			
	SVM	RF	BPNN	BN
CV-1	86.50	81.50	76.50	77.00
CV-2	89.50	82.50	78.00	73.00
CV-3	90.50	86.50	75.50	72.50
CV-4	88.00	85.50	78.00	83.00
CV-5	87.50	86.50	80.50	77.00
AVG	88.40	84.50	77.70	76.50

Empirical results

Condition	Assessing criterion: Specificity (SPE)			
CV-1	88.50	83.50	77.50	75.50
CV-2	88.00	82.00	78.00	71.50
CV-3	88.50	85.50	83.00	77.50
CV-4	90.50	82.50	76.00	80.50
CV-5	91.00	83.50	83.50	77.50
AVG	89.30	83.40	79.60	76.50

Empirical results

Condition	Assessing criterion: F-Score (FS)			
CV-1	87.37	82.32	76.88	76.43
CV-2	88.83	82.29	78.00	72.46
CV-3	89.60	86.07	78.44	74.36
CV-4	89.11	84.24	77.23	81.98
CV-5	89.06	85.22	81.73	77.19
AVG	88.80	84.03	78.46	76.48

Empirical results-Robustness check

Criterion	Model comparison	Hypothesis	z-value (p-value)
TA	SVM v.s. RF	$H_0: Med_{dF} = 0$ $H_1: Med_{dF} \neq 0$	Z=-2.023 (p=0.043)
	SVM v.s. BPNN		Z=-2.023 (p=0.043)
	SVM v.s. BN		Z=-2.023 (p=0.043)
SEN	SVM v.s. RF	$H_0: Med_{dF} = 0$ $H_1: Med_{dF} \neq 0$	Z=-2.023 (p=0.043)
	SVM v.s. BPNN		Z=-2.023 (p=0.043)
	SVM v.s. BN		Z=-2.023 (p=0.043)
SPE	SVM v.s. RF	$H_0: Med_{dF} = 0$ $H_1: Med_{dF} \neq 0$	Z=-2.023 (p=0.043)
	SVM v.s. BPNN		Z=-2.023 (p=0.043)
	SVM v.s. BN		Z=-2.023 (p=0.043)
FS	SVM v.s. RF	$H_0: Med_{dF} = 0$ $H_1: Med_{dF} \neq 0$	Z=-2.023 (p=0.043)
	SVM v.s. BPNN		Z=-2.023 (p=0.043)
	SVM v.s. BN		Z=-2.023 (p=0.043)

Conclusions

- We developed a general model based on statistical learning and manifold learning theories to predict the corporate financial crisis.
- A real case was executed to examine the feasibility of the proposed model.
- The results reveals that the proposed model is a promising alternative forecasting model for corporate financial crisis

Conclusions

- A real case was executed to examine the feasibility of the proposed model.
- The results reveals that the proposed model is a promising alternative forecasting model for corporate operating performance.

[redacted]

Thank you for your attention !!

三、中文概述

酒店和旅遊企業一直面臨著因為最近的金融海嘯和會計醜聞的一個嚴峻的挑戰。由於財務困難的熱情好客和旅遊企業的數量不斷增加，有必要找出哪些公司最容易受到財務困境的風險，因為實現一個潛在的不良企業，並指出其固有的問題，提高企業的生存可能性在激烈競爭的環境，並得到機會決策者做出適當的行動，以扭轉公司周圍。因此，本研究的主要目的是找出關鍵財務困境的屬性，並提出了對酒店和旅遊企業預警模型。關鍵財務困境屬性可以通過連續浮動前向選擇確定，某種類型的特徵選擇技術。原始資料經過特徵選擇過程中不僅可以消除計算負擔，同時也增加了預測的性能。預警模型是基於神經網路，一種人工智慧技術而沒有滿足嚴格的統計限制可以達到卓越出色的預測效果。實驗結果表明，我們提出的預測模型其中納入順序浮動前向選擇和神經網路實現卓越的品質預測和提供資料的更簡潔的知識。

最通常實現的人工智能（AI）技術在數據挖掘和機器學習的類別是樹木（DT）的決定，它可用來處理兩種主要類型的問題：一個是回歸問題，另一個是分類問題。由於易於實現和理解的性質，它已成為逐漸比其他人工智能技術更受歡迎。 Kim & Uoneja（2014）指出，C4.5，流行的類型構建 DT 機型之一，產生 DT 由評估標準，即信息增益（IG)，或通過分割樹在特定的階段。該技術始於一個最小的發束，並評估其提供的訓練的情況下最有用的分區的屬性。增益比值的數學形式的代表參加方程式。 （1)，它是用於分離在 C4.5 DT 技術的評估標準。其中第一項和第二項的公式中代表在父節點和子節點，分別。該兩篇報導的信息和產生的增益比的屬性，以及所有增益比之間的最大增益比之間的差被用來處理該分區的任務。每個子節點再次被視為一個新的樹，這個過程重複進行，直到有一個在訓練數據，沒有錯誤分類。（Kim & Upneja，2014 年）

要檢查的多智能體結構和功能的選擇方法 DA 的成效，研究提出在兩種情況下的結果：（1）有和沒有多智能體結構和（2）有和沒有特徵選擇。實驗結果如表 1-2。以確保該結果不偶然發生，我們研究該預測結果的由獨立樣本 t 檢驗的方法的意義，與在表 3 的統計結果根據我們的研究發現，多劑結構優於奇異的結構。這一發現是在回應夏基（1996 年）之前完成研究。多主體結構的優點彌補了單一模式的任何錯誤。與特徵選擇過程中的模型不僅可以提高預測精度，而且還可以減少這兩種類型的錯誤。

企業財務困境預測的是，曾作為動力，在過去幾十年來許多學術研究研究的重要和具有挑戰性的問題。而無形資產被公認為一個預測企業財務危機的時候是至關重要的因素，他們通常不包括在之前的相關預警模式。這項研究的目的是利用無形資產的屬性作為預測變數，並提出了多劑混合機制，MAHM，加大嚴謹的企業財務困境的預測。引進的 MAHM 接地上，集成了多個不同的基礎工具為聚集的結果，並證明了其卓越的性能預測的混合模式。混合模型背後的基本思想是，以補充由奇異模型所取得的錯誤。

肆、　交流說明

1. 本場次主要安排五篇文章發表，其中不乏傳統的計量模型或較為深的時間序列模型，主要的目的都是找出最適結果，看著各位學者的發表，自己才深深的覺得不論是何種資料，當遇到好伯樂時，它就是一篇好文章。
2. 在會中問題時，主席對於本篇文章所探討議題非常感到興趣，尤其就方法而言，主席就結果而言是一篇非常有趣的文章。而主席所發表的文章就是以匯率為主，但主席還是很欣賞本文的架構編排。
3. 普遍認為，以類神經如此新的研究方式來針對大陸旅館業的財報分析，著實兼具學術與實務。
4. 翻開大會所準備這次所有發表的文章名稱後，不難發現到研究領域之寬廣，與會的每位學者其研究的深度著實讓人敬佩，更可知在這條研究的道路還有很多可以讓人學習的地方。

伍、 心得與建議

本場次的參與人員層次及水平極高，包含泰國農業大學經濟系教授、臺灣清華大學經濟系副教授、韓國梨花女子大學工商管理系教授、印度銀行高層人員等，其中，清大老師的文章亦為本次研討會「最佳文章」之一。旁聽者人數相當多，在每一次報告後，臺上臺下討論相當熱烈。另外，主持人的主持能力相當出色，更有機會觀察到國際研討會議中主持人的表現與氛圍的掌控。本場次多以實證為主，主題都相當生活化，讓學術與生活應用連結性更強，也更確認自已以實務方式研究的方向無誤。透過主持人的穿針引線與臺上臺下的互動，也使得研究與方向更生活化，著實為一場相關精彩的研討會。此次參與該國際研討會，此次能夠親臨具有國際水準的研討會，收穫相當豐碩，並了解到其他國家相關領域學者在研究上所關注的課題與焦點。

附件：

	
研討會各場次表	研討會資料
	
SIBR 研討會會場	本人報告（右為主席）
 與會主席與人員	 研討會發表證明書