行政院國家科學委員會專題研究計畫 成果報告

決策學習模型的通用架構：尺度不變性與參數估計
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計畫參與人員：博士班研究生-兼任助理人員：陳淑萍

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行政院國家科學委員會專題研究計劃報告

決策學習模型的通用架構：

尺度不變性與參數估計

A general framework for decision-learning models: Dimensional invariance and parameter estimation

計畫編號：NSC 98-2410-H-194 -113

執行期限：98 年 8 月 1 日至 99 年 7 月 31 日

主持人：鄭中平　　中正大學心理學系

cpcheng@ccu.edu.tw

摘要

愛荷華賭博作業廣泛用在顯示不同群體在決策歷程中的差異，透過以量化的認知模型分析愛荷華賭博作業，由於模型中的參數分別對應愛荷華賭博作業心理歷程的成分，可進一步瞭解不同群體在決策歷程上的可能差異。除了常用的期望價值學習模型外，尚有近十個量化認知模型，企圖模擬愛荷華賭博作業的認知歷程。本研究首先建立一個通用的架構納入這些決策學習模型。其次，本研究針對此通用架構發展較具一般性的估計方式，以進行這些模型的參數估計。最後，透過通用架構進行這些模型的比對，瞭解模型的尺度不變性。

關鍵詞：愛荷華賭博作業、認知模擬、期望價值理論

Abstract

Iowa gambling task is a cognitive task designed for exploring the possible decision making deficit. By modeling this task, parameters of the expectancy-valence model may be correspondent to the components of psychological processes underlying the Iowa gambling task. Instead of often-cited expectancy-valence model, there are up to 10 quantitative decision-learning models aim to simulate Iowa gambling task. Firstly, the study proposed a general framework to incorporate most decision-learning models. Secondly, the study developed a comprehensive statistical routine for most decision-learning models under the framework. Finally, by comparing these models under the framework, we will explore the scale invariance issue.

Statement of the study

The study aims to develop a general framework to incorporate several decision choice models simulating the decision-making process of Iowa gambling task (IGT, Bechara, Damasio, Damasio, & Anderson, 1994). By doing so, we can implement one comprehensive parameter estimation procedure for several models. We will develop a comprehensive routine for all models, rather than develop several specific statistical routines for every single model. Simply put, the first aim of the study is to develop a general framework for IGT. The second aim of the study is to develop a routine for parameter estimation of these models. Third, we will check scale invariance properties under the general framework.

Iowa gambling task and Models

The Iowa gambling task was developed to simulate real-life decision making under uncertainty. IGT has 100 or more trials. In each trial, the participant should choose a card from four decks. Decks differ in their frequencies and values of gain and loss. Gains of some decks are higher, but their mathematical expectancies are negative. When the participant chooses a card, the gain and the loss will show. The participants are asked to maximize their outcome.

The task has been widely used to examine possible neuro-cognitive deficits in normal and clinical populations. IGT has been found to be useful in differentiating young and healthy subjects from other target groups such as elders (Wood, Busemeyer, Koling, Cox & Davis, 2005), substance abusers (Busemeyer, Stout, & Finn, 2007; Stout, Busemeyer, Lin Grant & Bonson, 2004; Verdejo-Garcia et al., 2007; Yechiam, Busemeyer, Stout & Bechara, 2005), patients with Huntington’s and/or Parkinson disease (Busemeyer & Stout, 2002), and patients with damage of orbital frontal cortex (Bechara et al., 1994; Busemeyer et al., 2007).

Busemeyer and Stout (2002) proposed the expectancy-valence learning model (EV model) to simulate cognitive process underling IGT. EV model consists of three parts. In the first part, the participant is supposed to calculate the valence in each trial, and then form the expectancy valence of every deck described in the second part. The last part described the participant's choice is based on the expectancy valence calculated during the trials. There are three parameters corresponding individual differences in the three parts in EV model including attention to the gain, attention to recent outcome and the change of sensitivity of response choice to expectancy valence across trials.

Parameters of the EV model may be interpreted in correspondence to the components of psychological processes underlying the task. Estimates of model parameters can then be used to compare healthy young adults against other target groups. For example, Busemeyer & Stout (2002) found higher learning rate parameter estimates for the Huntington group than that in healthy group; Cheng, Sheu, and Yen (2009) found that male adolescents pay more attention to gains than female adolescents. Among these, Yechiam et al. (2005) analyzed IGT data obtained from 10 different populations of participants based on the EV model, and mapped parameter estimates derived from each of the groups in the space of parameters.

Comparison of model parameter estimates on a map may reveal differences of decision making processes of distinct groups. If the differences of parameter estimates between groups are the main concern of the empirical studies undertaken, before comparing them, the adequacy of comparisons should be checked.

Instead of EV model, Ahn et al. (2008) proposed seven other models to simulate IGT. In each of the three parts of EV model, they consider an alternative for original description of every part, so there are eight IGT models including EV model. They evaluate eight models based on BIC (Bayesian Information Criterion) and generalization criterion method. According to the criteria they suggested, EV model is not the best among eight models. They concluded that switching to the other model in the future should be considered. However, as we shall see, the conclusion should be suspended because some models they compare are not scale invariant and comparisons of models which are not scale invariant may be problematic.

A General Framework for IGT Models

In the section, we proposed a general framework to incorporate Ahn’s eight models. By doing so, we can propose a general estimation routine and explore the scale invariance of eight models in a unified manner rather than check them individually. The general framework also consists of three parts, as followed:

$$v_t = (-\rho)^{I(wW_t - lL_t < 0)} | wW_t - lL_t |^{\alpha} \quad (1)$$

$$Ev_{t,k} = (1-((\delta_{t,k}+1)^{\beta}-1)a)Ev_{t-1,k} + \delta_{t,k}a^{\beta}v_k \quad (2)$$

$$P_{t+1,k} = \exp(\gamma t^c Ev_{t,k}) / \sum_{j=1}^{4} \exp(\gamma t^c Ev_{t,j}) \quad (3)$$

Because expectancy and prospect utility functions are combined into equation (1), it is a little more complicated. In equation (1), v_t, W_t and L_t denote the utility, win and loss at trial t. ρ, w, l and α are four parameters. $I(x)$ is a function which is 1 if statement x is true and is o if x is false. In equation (1), if we let $l = 1 - w$, $\alpha = \rho = 1$, then equation (1) will be the expectancy valence function in Ahn et al. (2008). If we let $l = w = 1$, then equation (1) will become to be prospect utility function.

In equation (2), $Ev_{k,t}$ is the expectancy utility of deck k at trial k. $\delta_{k,t}$ is the index variable to indicate whether deck k is chosen or not at trial t. At trial t, if the participant chooses deck k, $\delta_{k,t} = 1$, otherwise, $\delta_{k,t} = 0$. a and β are two parameters. If $\beta = 1$, equation (2) will be the delta learning rule It will be the decay reinforcement rule if $\beta = 0$.

Equation (3) describes the choice probability of deck k at trial t+1 $P_{t+1,k}$ is proportional to the expectancy utility of deck k at trial t. The expectancy utility is weighted by a function of trial t. γ and c are two parameters. If $\gamma = .1^{c}$, then it will be trial-dependent choice rule. If $c = 0$, it will be the trial-independent choice rule.

Parameter estimation of single subject

The second aim of the study is to develop a parameter estimation procedure for the general framework. We propose to estimate parameters of the general framework via maximum likelihood method and implement the estimation procedure by SAS.

Because equation (2) is defined recursively, we can combine all into a single equation as followed:

$$P_{t+1,k} = \exp(\gamma t^c \sum_{s=1}^{t} (1-a)^{\sum_{m=s}^{t} \delta_{k,m}^{\beta}} a^{\beta} \delta_{k,s} v_s) / \sum_{j=1}^{4} \exp(\gamma t^c \sum_{s=1}^{t} (1-a)^{\sum_{m=s}^{t} \delta_{j,m}^{\beta}} a^{\beta} \delta_{j,s} v_s)$$

(4)

In equation (4), the dependent variable is the deck the participant chooses at some trial t. The independent variables are all payoffs before the trial t. The framework can be seen as a special case of nonlinear regression models. For the dependent variable are categorical (the chosen deck), so the nonlinear regression may be some kind of multinomial logistic regression models. Parameters of multinomial logistic regression can be estimated with maximum likelihood method. SAS package NLMIXED is used in the study.

Parameter estimation of group data

Buesmeyer and Stout (2002) proposed a two-staged strategy to analyze group differences in parameters of EV model. First, estimates of model parameters are obtained separately from fitting the EV model to data of each individual. They estimated parameters of the EV model by the maximum likelihood method with Nelder-Mead simplex optimization (O’Neill, 1971). The values of these individual parameter estimates then serve as raw data for comparing group differences via standard parametric statistical procedures such as the Student’s t-test or analysis of variance.

The estimation procedure in the first stage is found to be susceptive to its start values during optimization and the two-stage procedure may lower the power to detect group difference (Cheng, Sheu, & Yen, 2009; Wetzels, Vandekerckhove, Tuerlinckx, & Wagenmakers, 2010). In order to overcome optimization problem and improve the power, Wetzels et al. suggested a Bayesian approach. Instead of Baysian approach, Cheng, Sheu, and Yen (2009) reparameterzied the EV model to overcome the optimization problem and suggested a mixed-effects model to improve the power.

In the same vain, we can easily extend the general framework to its mixed-effect version. All parameters in the framework will be seen as subject-specific random variables, and are assume to follow a multivariate normal distribution. Again, SAS package NLMIXED is used for its ability to handle mixed effect nonlinear regression.

Scale Invariance of the general framework

A model is scale invariant if we change the unit of scale of the model, we can find another set of values of parameters which make the same prediction. For a scale invariant model, if the value of parameter will not affected by the scale, we call it scale free. Otherwise, we call it scale dependent (Cudeck, 1989).

With the general framework for IGT models, we investigate scale invariance issue in the third study.

$$Let\ \mu = \lambda \nu,$$

$$(p_{k,t+1} \mid \mu) = \exp(\gamma\,' t^{c\,'} \sum_{l=1}^{t} s_{k,l,t-1}\mu_l) / \sum_{j=1}^{4} \exp(\gamma\,' t^{c\,'} \sum_{l=1}^{t} s_{j,l,t-1}\mu_l)$$

$$where\ s_{k,l,t} = (1-a)^{\sum_{m=l}^{t} D_{k,l}^{\beta}} a^{\beta} D_{k,l}$$

$$= \exp(\gamma^{'} t^{c^{'}} \lambda^{\alpha} \sum_{l=1}^{t} s_{k,l,t-1} v_l) / \sum_{j=1}^{4} \exp(\gamma^{'} t^{c^{'}} \lambda^{\alpha} \sum_{l=1}^{t} s_{j,l,t-1} v_l)$$

$$= \exp(\gamma^{'} t^{c} \sum_{l=1}^{t} s_{k,l,t-1} v_l) / \sum_{j=1}^{4} \exp(\gamma t^{c} \sum_{l=1}^{t} s_{j,l,t-1} v_l)$$

$$= (p_{k,t+1} \mid v) \quad by \;\; setting \; \gamma^{'} \lambda^{\alpha} = \gamma .$$

In summary, only models with trial-independent choice rule are scale invariant. Since some of eight models are not scale invariant, comparison based on BIC may be not proper. All parameters except sensitivity parameter in the models with trial-independent choice rule are scale independent. Comparison of sensitivity parameters across studies with different currency should be made with caution.

Conclusion and discussion

In the previous work, we found that several decision learning models share the same structure with EV model (Cheng & Sheu, 2008a,b). Besides the EV model, we found out that the Rescorla-Wagner model for conditioning (Rescorla & Wagner, 1972), Bush and Mosteller's model for avoidance learning (Bush & Mosteller,

1955) and a logistic regression model for avoidance learning (Gelman, Goegebeur, Tuerlinckx & Van Mechelen, 2000) can also be reformulated under the framework. Some properties can be easily observed under the learning-choice framework. For example, if we focus on the effect of trial t, we can observe that the logistic regression model is the only model whose learning rate depend on trial t. Its learning rate decreases as trials increase. And in EV model and logistic regression model, the probability of choice is a function of not only expectancy-valence but also trial t. That is, even if the expectancy valences of all options are the same at trial t1 and trial t2, EV model and logistic model will predict different choice probabilities. But for Rescorla-Wagner and Bush and Mosteller's models, the predictions are the same for t1 and t2, they have no memory.

With cognitive modeling, we can understand the different psychological processes in widely used IGT among populations assuming the model is appropriate. Previous studies show the benefit from taking mixed effect into account in cognitive modeling (e.g., Cheng, et, al, 2009; Rouder et. al., 2005). The study may provide some insight about the differences of psychological process under IGT indirectly by estimate the parameters more efficiently.

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出國報告

本次計畫中，前往荷蘭阿姆斯特丹，參與美國數學心理學學會（SMP）與歐洲數學心理學研究群（EMPG）聯合年會。美國數學心理學學會年會與歐洲數學心理學研究群年會是最大的兩個數學心理學方面會議，此次聯合舉辦，參與人數相當多。

會議總共舉行三天，會前一天尚有關於貝氏推論的工作坊。本次會議邀請 G. Logan 做主題演講，他回顧了他的注意力模型；另外還安排青年獎得主 S. Brown 分享研究成果與經驗，。除大會演講外，平行的口頭報告同時間有三場，議程相當緊湊。

我個人的報告是考慮模擬愛荷華賭局作業八種模型的尺度不變性，發現其中四種模型（包括常用的期望價值模型）不具尺度不變性，亦即，當改變模型中報酬（payoff）的單位時，模型的統計評估（AIC）與預測會隨之不同，但加入額外參數後此問題可獲解決。報告時，發展愛荷華賭局作業認知模擬的 Prof. Busemeyer 亦在場，他說明了當初發展期望價值模型時，原先考慮多一參數，但由於諸多原因而沒加入。本次會議除發表論文外，亦於會前參加一天的貝氏統計應用於認知模擬之工作坊，瞭解如何利用 winstep 結合 R 或 Matlab 之介面，以貝氏統計方式分析認知作業。

無衍生研發成果推廣資料

98 年度專題研究計畫研究成果彙整表

計畫主持人：鄭中平			計畫編號：98-2410-H-194-113-				
計畫名稱：決策學習模型的通用架構：尺度不變性與參數估計							
成果項目			量化			單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
			實際已達成數（被接受或已發表）	預期總達成數(含實際已達成數)	本計畫實際貢獻百分比		
國內	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	1	1	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（本國籍）	碩士生	0	0	100%	人次	
		博士生	1	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		
國外	論文著作	期刊論文	0	1	0%	篇	投稿中。
		研究報告/技術報告	0	0	100%		
		研討會論文	2	2	100%		
		專書	0	0	100%	章/本	
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（外國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		

其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	無

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

■達成目標

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說明：

2. 研究成果在學術期刊發表或申請專利等情形：

論文：□已發表 □未發表之文稿 ■撰寫中 □無

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With cognitive modeling, we can understand the different psychological processes in widely used IGT among populations assuming the model is appropriate. Although the often-cited EV model is questioned by its author, how to compare EV model with other possible models is still open. The study may provide some insight about the properties of decision- learning models for IGT and evaluates these models in a more appropriate manner.