Describing the Information Seeking Behavior:

An Investigation on Comparing Learning Models Using Experimental Data Sets

DESCRIPTION DU COMPORTEMENT DE LA RECHERCHE D'INFORMATION :

UNE INVESTIGATION SUR LA COMPARAISON DES MODÈLES D'APPRENTISSAGE EN UTILISANT L'ENSEMBLE DE DONNÉES EXPÉRIMENTALES

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Abstract: The purpose of this paper is to investigate the rule and characteristics of ACADEMIC users' information seeking behavior, as well as primary factors which influencing satisfaction and behavior outcomes as consequences of the value of information seeking. To examine the users' behavior, several learning models were adopted, such as Bush-Mosteller model, Bayesian model,, fictitious play and EWA model.

Here we employ both qualitative and quantitative approaches to examine the phenomenon of information seeking. We tried to compare the consistence of different models on the basis of experimental data. In Nanjing University of Science and Technology, 120 students were randomly assigned to three different teams and provided different communicating environment according to different learning models when seeking same assign for two hour.

The result of a series of confirmatory factor analyses reveals that users' satisfaction and behavior outcomes had correlated factors with moderate to good reliability. The findings from model analyses showed that EWA are more adapted to the others.
Key words: learning model, information seeking, academic user

Résumé: Le présent article vise à étudier les règles et caractéristiques du comportement de la recherche d'information des utilisateurs académiques, et les facteurs essentiels influant sur les résultats de satisfaction et de comportement en raison de la valeur de la recherche d'information. Afin d'examiner le comportement des utilisateurs, plusieurs modèles d'apprentissage ont été adoptés, tels que modèle Bush-Mosteller, modèle Bayesian, jeu fictif et modèle EWA.

Nous employons ici à la fois les approches qualitatives et quantitatives pour étudier le phénomène de la recherche d'information. On tente de comparer la cohérence de différents modèles sur la base des données expérimentales. A l'Université de Sciences et Technologie de Nanjing, 120 étudiants distribués au hasard dans 3 groupes ont offert, pour les mêmes tâches de recherche de 2 heures, de différents environnements de communication en vertu des modèles d'apprentissage distincts.

Le résultat d'une série d'analyses sur les facteurs confirmatoires montre que les résultats de satisfaction et de comportement ont corrélation avec la moyenne et la grande fiabilité. Les résultats des analyses de modèles indiquent que EWA s'adapte mieux à d'autres.
Mots-Clés: modèle d'apprentissage, recherche d'information, utilisateur académique

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1. INTRODUCTION

More and more database companies pay attention to academic users and it is becoming an important issue. As for database companies, in order to attract more users, they have to put in tremendous effort to concerning their needs and preference. Because of the importance of that problem, this paper investigated academic users' information seeking behavior from the learning behavior perspective and also concerned the consistence of learning models.

Generally speaking, learning is an universal phenomenon in the world. It is a process that all kinds of animals obtain individual behavior experience. Narrowly speaking, learning only mean the human learning behavior. Mainly through language as intermediary to master social experience and it is a positive process. Psychologists started to study learning processes extensively approximately 100 years ago. At that time, psychology was dominated by the view that processes within the brain cannot be studied and that explanations of behavior should be based purely on observable variables. In the 1950s psychologists started a new line of research into learning processes. They studied the impact of social interaction and observation on learning and divided learning only into two fundamentally different ways(Thomas Brenner, 2005). First, humans share with other animals a simple way of learning, which is usually called reinforcement learning. This kind of learning seems to be biologically fixed. It does not involve any conscious reflection on the situation. Hence, people are not always aware that they are learning. In addition to reinforcement learning, people are able to reflect on their actions and consequences. We are able to understand the mechanisms that govern our surrounding and life; and we are able to give names to objects and establish causal relations that describe their interaction and nature. Nowadays, this is mainly studied in psychology under the label of learning and is referred to as cognitive learning. We introduce both reinforcement leaning and cognitive learning in this paper.

The paper organizes as follows. Section 2 briefly introduces 4 learning models, that is Bush-Mosteller model, fictitious play, Bayesian learning and EWA. We also analysis the feasibility of learning models to describe academic users' information seeking behavior. Section 3 describes the experimental procedure. Section 4 describes the results and section 5 concludes.

2. LEARNING MODELS

In the past few years, there has been a tremendous increase in the number of learning models used in many kinds of fields. As for different model building purposes, the performance of the same model is varying widely in different areas. We choose the most prominent models——Bush-Mosteller model, fictitious play, Bayesian learning and EWA——to investigate the characters of academic users' information seeking behavior.

2.1 Bush-Mosteller model

Bush-Mosteller model is based on the considerations of Estes who took the first steps towards a mathematical formulation of reinforcement learning(Bush and Mosteller, 1955). The probability vector $p(t)$ changes during the learning process according to the theory of reinforcement. Bush and Mosteller distinguished only between rewarding and punishing outcomes, but not within both classes. The change in the probability $p(a,t)$ of the individual to realize action a is given by

$$p(a,t+1)=p(a,t)+\begin{cases} v\cdot\Pi(t)\cdot(1-p(a,t)) & a=a(t)\wedge\Pi(t)\geq 0\\ v\cdot\Pi(t)\cdot p(a,t) & a=a(t)\wedge\Pi(t)<0\\ -v\cdot\Pi(t)\cdot p(a,t) & a\neq a(t)\wedge\Pi(t)\geq 0\\ -v\cdot\Pi(t)\cdot\dfrac{p(a,t)\cdot p(a(t),t)}{1-p(a(t),t)} & a\neq a(t)\wedge\Pi(t)<0 \end{cases}$$

$\Pi(t)$ is reinforcement strength.

In the process of information seeking, the strategy which would be adopted is usually according to users past searching experience. Generally, they would choose the seeking strategies that are usually used. If one strategy improves user's seeking satisfaction, he would choose the strategy in the next time. Otherwise it would be abandoned. Actually, it is represented by a frequent distribution of behavior patterns. Then there is reinforcement learning phenomenon when academic users' information seeking and adopt this model to investigate users' behavior character is reasonable.

2.2 Fictitious play

Fictitious play is one of cognitive learning(Brown, 1951). It assumes that individuals in a game mentally record all previous moves of their opponents. The individuals are assumed to memorize all previous behaviors of all other individuals. Thus, they are able to calculate the frequency of occurrence for each action profile a_{i-}. They assume that their opponents' actions will occur with the same probability in the future. Consequently, the expected probability $p(a_{i-}, t)$ for each action profile a_{i-} realized by the other individuals is given by

$$E(p(a_{-i}, t)) = \frac{1}{t}\sum_{\tau=0}^{t-1} \delta(a_{i-}(\tau) = a_{i-})$$

$$\text{where } \delta(a_{i-}(\tau) = a_{i-}) = \begin{cases} 1 & a_{i-}(\tau) = a_{i-} \\ 0 & a_{i-}(\tau) \neq a_{i-} \end{cases}$$

$$E(\Pi_i(a_i, t)) = \sum_{a_{i-}} \Pi_i(a_i, a_{i-}) \cdot E(p(a_{i-}, t))$$

In fact, when information seeking, academic users, especial the freshman, obtain experience not only from their experience, but also from other individuals. Generally speaking, users would choose the strategies which were preferable used by formers, so users' cognitive learning phenomenon is obvious.

2.3 Bayesian learning

Bayesian learning is the oldest and most prominent 'optimal' learning model. Individuals are assumed to act rationally considering all available information and maximizing their own profit on the basis of this information. The basic mechanisms of this learning model are in line with the psychological notion of cognitive learning: People develop hypotheses/beliefs about the world according to their observations. The model is given by

$$p(\theta = \theta_i | x) = \frac{\pi(\theta = \theta_i) p(x|\theta = \theta_i)}{\sum_{j=1}^{n} \pi(\theta = \theta_j) p(x|\theta = \theta_j)}$$

$$E(\theta = \theta_i | x) = \sum \theta_i \cdot p(\theta_i | x)$$

Where $\pi(\theta)$ is prior distribution, $p(\theta|x)$ is posterior probability distribution, $p(x|\theta)$ is the conditional probability distribution of the model parameter given the data.

Academic users would consider all available information before information seeking, which form prior knowledge. During the seeking process, according to the searching experience, they would form new cognitive of the strategies, and then the prior knowledge and the new cognitive jointly form posterior knowledge. Subsequently, users might decide in such a way that they maximize their expected utility. Then using Bayesian learning model to investigate uses' information seeking behavior is reasonable.

2.4 EWA

EWA is short of experience-weighted attraction model(Anderson and Camerer, 2000). In this model, it is argued that two fundamental types of learning processes exist: reinforcement learning and belief learning. The model is designed such that it describes these two learning processes as border cases for specific choices of the models parameters. The model is described by two equations that determine the process of updating in the light of new experience:

$$N(t) = \rho \cdot N(t-1) + 1$$

$$A_i^j(t) = \frac{\phi \cdot N(t-1) \cdot A_i^j(t-1) + [\delta + (1-\delta) \cdot I(s_i^j, s_i(t))] \cdot \pi_i(s_i^j, s_{-i}(t))}{N(t)}$$

A logit response function is used to map attractions into probabilities:

$$P_i^{\,j}(t+1) = \frac{e^{\lambda \cdot A_i^j(t)}}{\sum_{k=1}^{m_i} e^{\lambda \cdot A_i^k(t)}}$$

$N(t)$ is called the experience weight and $A_i^j(t)$ is called the attraction if strategy j for individual i. $I(s_i^j, s_i(t))$ is indicator function. The parameter δ is the weight placed on foregone payoffs. The parameter ϕ reflects decay of previous attractions due to forgetting or to deliberate ignorance of old experience when the learning environment is changing. The parameter ρ controls the rate at which attractions grow.

According to former analysis, both reinforcement learning and cognitive learning exist during the information seeking process. Then, we choose the combined model to make data consistence and hope that the result would be satisfied.

3. EXPERIMENTAL PROCEDURE

In order to make comparison research of different models, we organized the control experiments at the library of Nanjing University of Science and Technology. The experiment lasted for about two hours. A ￥5 participation fee and subsequent earnings for correct decisions were paid in private at the end of the experiment. Throughout the experiment, we assured anonymity and an effective isolation of subjects in order to minimize any external interpersonal factors that might have caused a tendency towards uniform behavior. And then extract data from observation of kinescope. **Figure 1** summarizes our experimental design and procedures.

1st. 120 participants, senior college students or graduate students who had similar information seeking experience were recruited from all kinds of specialties.

2nd. Divide all participants into three teams(team A, team B, team C) randomly.

3rd. In first stage of the experiment, team A finished self-reinforcement process (the assignment was brought by themselves, was not appointed by us). Team B finished advance training (finish the same kind of assignment as in the second stage). Team C had no any assignment and they entered the second stage of the experiment directly.

4th. In second stage of the experiment, all participate finished 9 periods assignments. All participants read the instructions before experiment; they were also read aloud by an experimental administrator. If the participant success finished one assignment, he would earn ￥8, and nothing otherwise.

4. RESULTS

We only extract data from the second stage of experiment. First examine the model consistence and then compare the difference among teams.

4.1 Model consistence

In order to examine the consistence of different learning models, we use the first period data for model computation and compare the computed result with participants' real action in the second period. And then use the first and second period data for model computation and also compare the computed result with participants' real action in the third period. Repeat the same computation process until the last period. **Figure 2** summaries the computation process.

Figure 3 is the percentage plotting of consistence of the four model. From the figure, we observe that EWA performance better than other three. And the discrepancy among Bush-Mosteller、fictitious play and Bayesian learning is not obvious.

Table 1 is the normal test of the 4 models. From the test results, we could see all the consistence proportions accords with normal distribution, except EWA. Then when EWA compares with other models for significant test, we need to adopt Wilcoxon 2-sample test. And test any two among other three, we could use T test. The test results are listed in **Table 2**. From the table, we could see the probability of nonparametric test between Bush-Mosteller learning and EWA is 0.0114, which is smaller than 0.05. Then we thinking the consistence effect between the two models be different is reasonable. Similarly, there are different consistence effect between EWA and fictitious play, EWA and Bayesian leaning. Summing up, the consistence effect of EWA is the best among the four models and the effect between the other three is similar.

4.2 Comparison among teams

In order to test whether different stimulation would cause different information seeking behavior, we also use the method described in **Figure 2.** And separately calculate the models consistence proportions of three teams. From **Figure 4,** we could see

1st. Totally, the consistence proportions increases with the experiment period increases.

2nd. As for fictitious play and Bayesian learning, the consistence of team A and B is obviously better than team C, while the discrepancy of consistence proportions of Bush-Mosteller and EWA could not obtain from the picture.

3rd. EWA performances best of the four models. In several periods, the computation results are 100% consistent with the real choice.

Table 3 lists test result of any two teams. From the table, we observe that the behavior performance of team A and B is distinctly different with team C, which means model is consistence better to self-reinforcement and advance training team.

5. CONCLUSIONS

1st. Model consistence performs well for the four learning model. At least 50% computation results are consistent with participants' real choice. Then it is feasible to use the four learning model to investigate academic users' information seeking behavior.

2nd. EWA performs best in the four models, which means both reinforcement learning and cognitive learning exist during the information seeking process. Then the learning model which only considers one kind of learning would decrease consistence effect.

3rd. There is obvious discrepancy between self-reinforcement team and no self-reinforcement team; also there is obvious discrepancy between advance training team and no advance training team. That means that the ability of academic users' self-study is very well. If database companies pay more attention to the wieldy of the web interface, more and more users would be loyal, because they would learn how to use the database efficiently by self-reinforcement. On the other hand, user training is also an important method to help them improve their ability of using database. So the companies could pay more attention to the users training.

4th. For the future, we hope that more empirical and experimental tests are conducted for the various learning models. This would help to develop a clear picture of the condition for different learning process of academic uses' to occur and the accurate ways to model them.

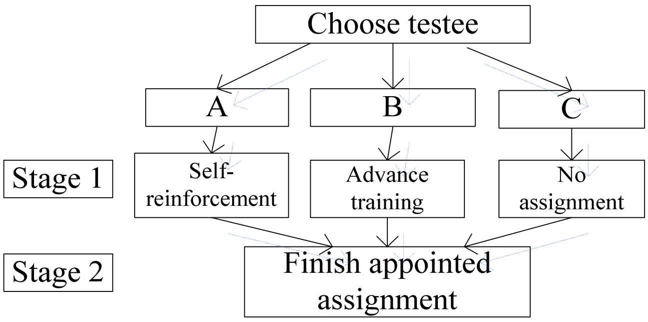


Figure 1 Experimental design and procedure

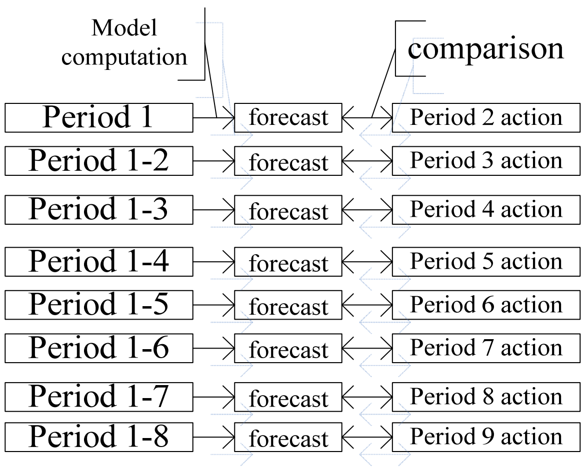


Figure 2 Computation process

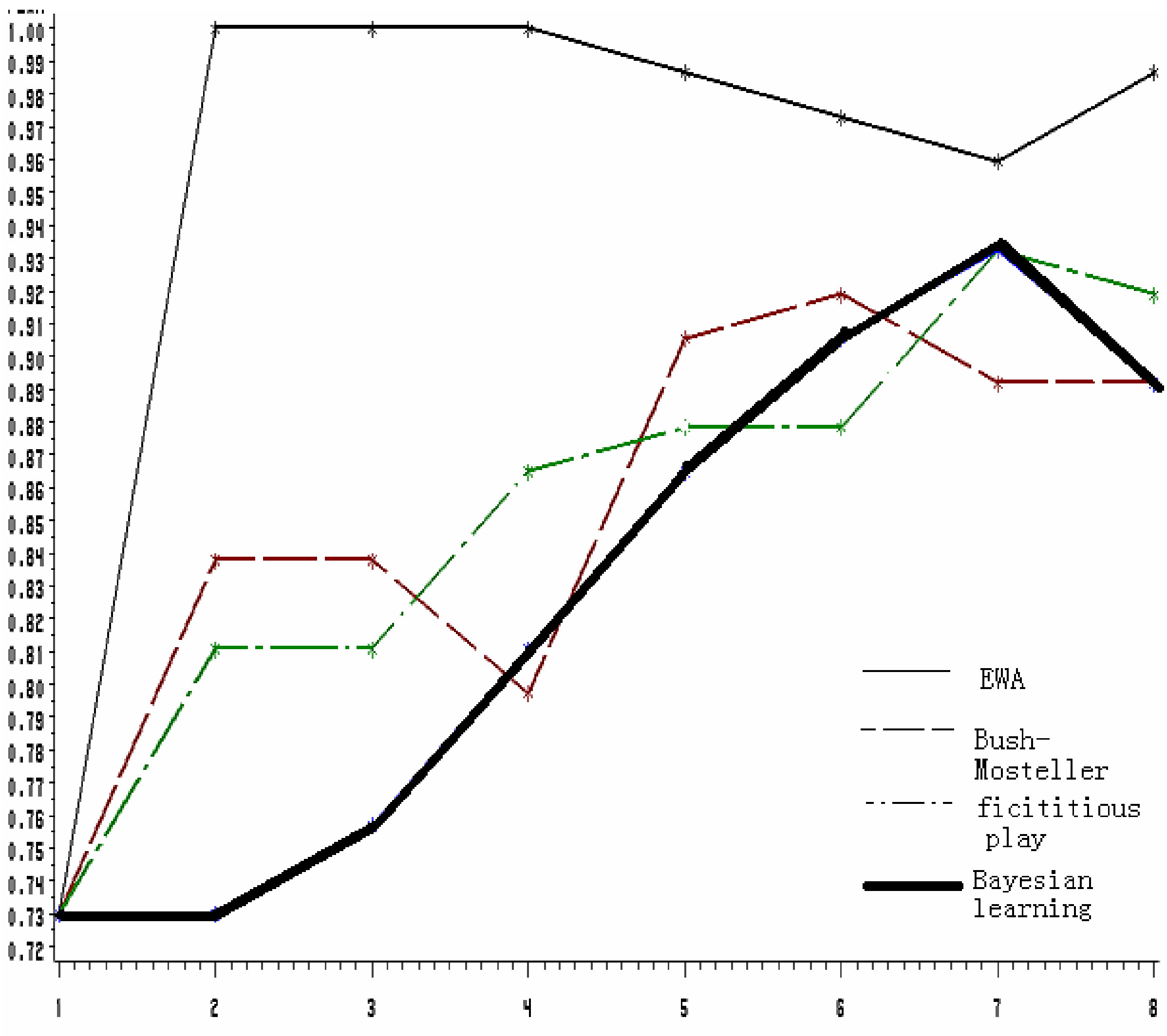
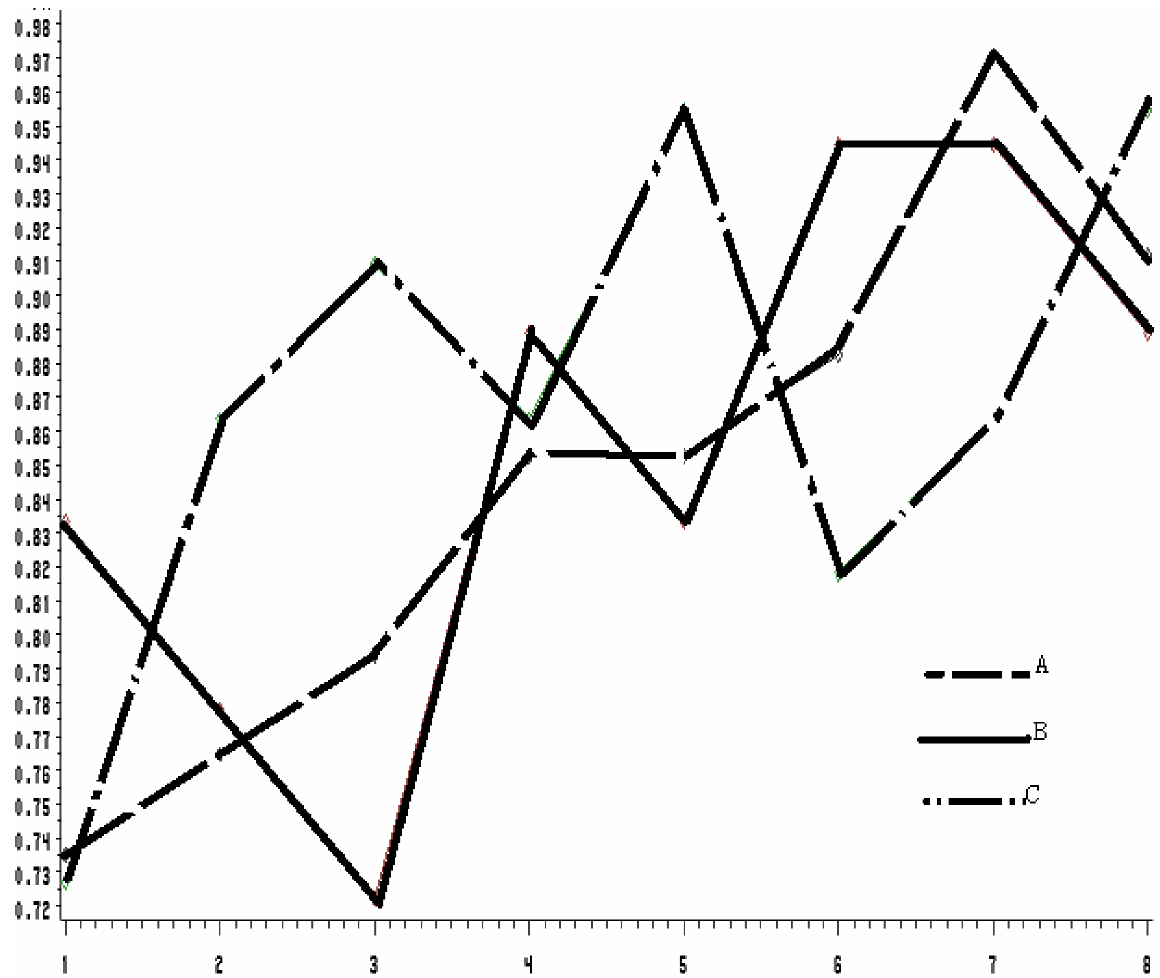
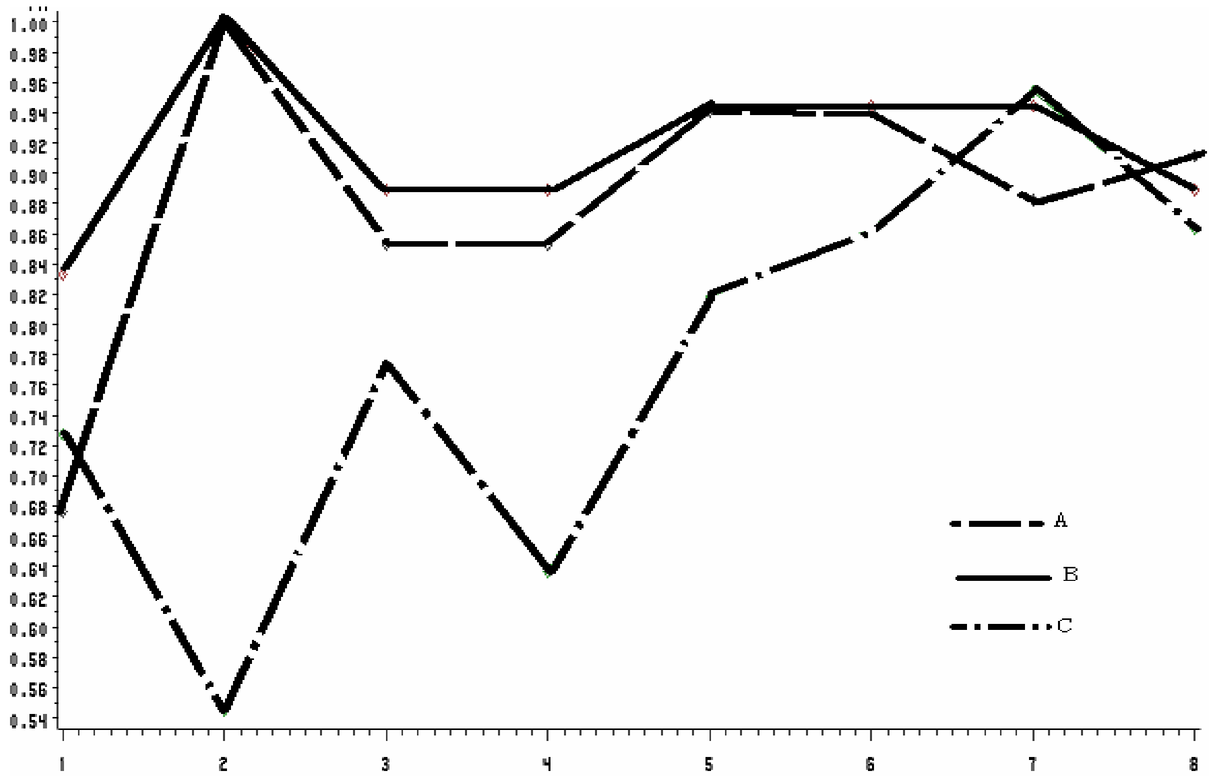


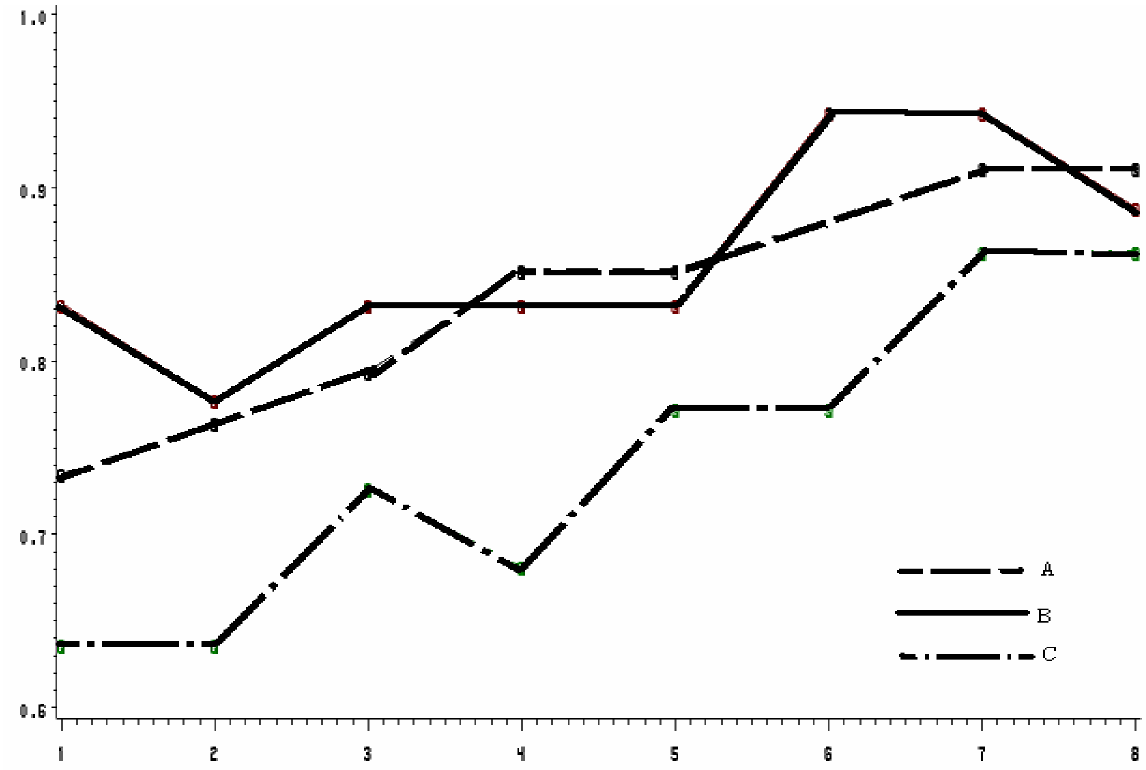
Figure 3 Percentages plotting of consistence effect



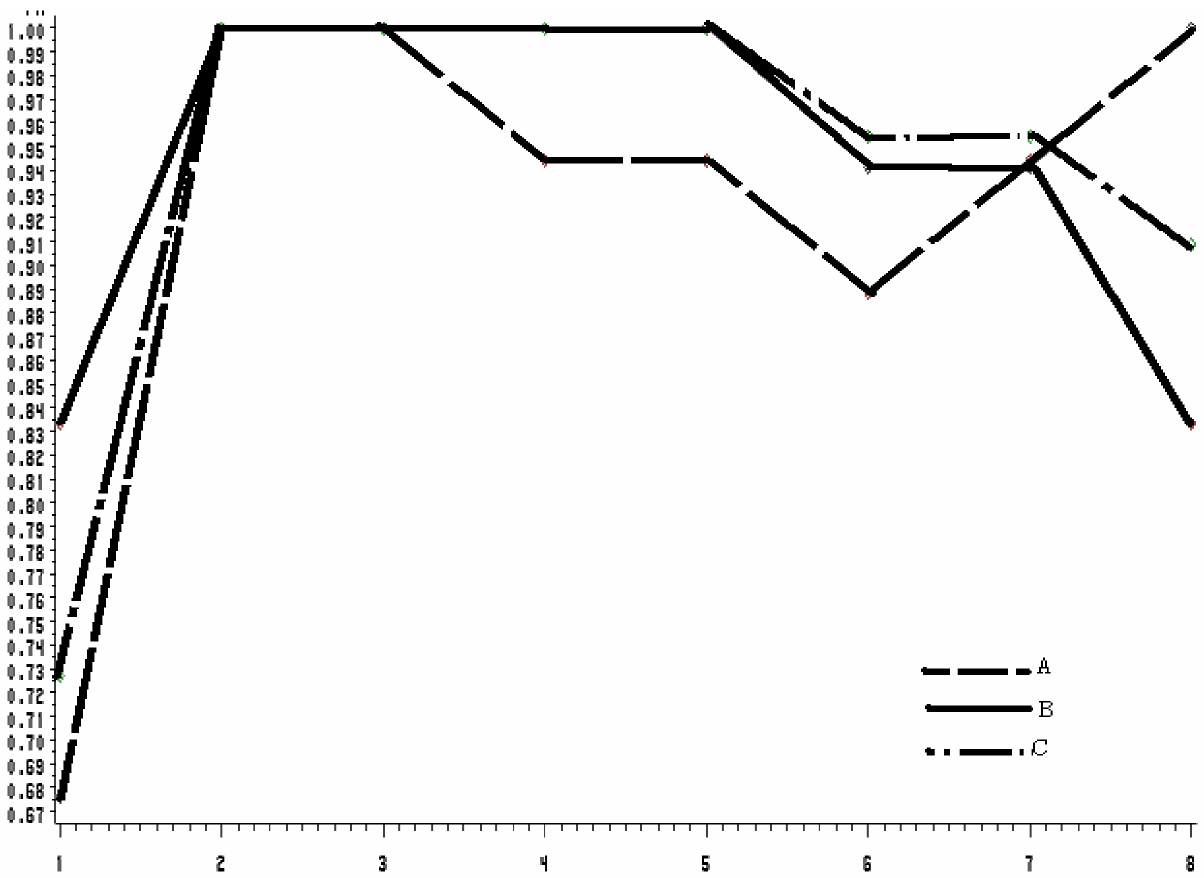
(I) Bush-Mosteller model



(II) Fictitious play



(III) Bayesian learning



(IV) EWA

Figure 4 Percentages plotting of consistence effect

Table 1 Normal test

	Normal test	
	W: Normal	Pr<W
(I)Bush-Mosteller learning	0.9492	0.7051
(II)fictitious play	0.8684	0.1438
(III)Bayesian learning	0.8487	0.0947
(IV)EWA	0.5531	0.0001

Table 2 T test and Wilcoxon test

	T test		Wilcoxon 2-sample Test	
	T: Mean=0	Pr>T	Z	Prob>Z
I&II	-0.7107	0.4890	——	——
I&III	0.5713	0.5772	——	——
I&IV	——	——	2.5317	**0.0114**
II&III	-1.1960	0.2518	——	——
II&IV	——	——	2.5354	**0.0112**
III&IV	——	——	2.5921	**0.0095**

Table 3 T test or Wilcoxon test

model		Normal test		T test/ Wilcoxon test	
		W: Normal	Pr<W	T: Mean=0/Z	Pr>T/Z
Bush-Mostell model	A-B	0.8330	0.0656	-1.7245(T)	0.1283
	A-C	0.8889	0.2328	1.8575(T)	**0.0456**
	B-C	0.8561	0.1120	2.7575(T)	**0.0282**
Fictitious play	A-B	0.9676	0.8765	-0.4419(T)	0.6719
	A-C	0.9270	0.4944	-0.8245(T)	0.4369
	B-C	0.9331	0.5492	-0.3702(T)	0.7222
Bayesian learning	A-B	0.9141	0.3888	-1.4816(T)	0.1820
	A-C	0.9372	0.5880	6.2781(T)	**0.0004**
	B-C	0.9733	0.9192	5.6178(T)	**0.0008**
EWA	A-B	0.8920	0.2481	3.3758(T)	**0.0001**
	A-C	0.7602	0.0114	3.3888(Z)	**0.0007**
	B-C	0.8349	0.0685	-2.7674(Z)	**0.0057**

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