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A Social Choice Force Model for Estimating Collective Action Manipulation

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Abstract: For e-commerce websites collective actions have significant influence on the behaviors and decisions of individual customers. In this work, we propose a dynamic utility model for customers in e-commerce by considering a "social choice force" (SCF) effect on utility functions of agents. We apply the Artificial societies, Computational experiments, and Parallel execution (ACP) approach to investigate the short-term efforts of collective action manipulation. Experimental results show that the proposed agent model and algorithm outperform the baseline prediction algorithm and illustrate the effect of collective action manipulation in a group buying directory website.

Keywords: Cyber Space, Collective Actions, E-Commerce, Agent Modeling, Manipulation, Neural Networks.

1. INTRODUCTION

With the rapid development of cyber space, e-commerce is widely accepted all over the world because of its convenience for customers. In online stores, e-commerce directories and e-commerce search engines, the websites present static attributes of products such as prices and brands, and dynamic attributes, i.e. outcomes generated by collective actions by customers such as sales volume, clicks volume and praise volume. Those two kinds of attributes will affect customers' clicking and buying behaviors. Thus, in e-commerce websites, a customer can influence other people by making small change to the collective outcome. Meanwhile, collective actions (Waytz, 2012) (Edmond, 2011) can be exploited to manipulate to affect customers choice (e.g. by a mass of sponsored advertising or fraud clicks), if the effect is larger than regular promotion methods such as advertising and price-off. Hence, there is necessarily a need for further research in collective actions in e-commerce environments.

Collective actions can be formally defined as "all activity involving two or more individuals contributing to a collective effort on the basis of mutual interests and the possibility of benefits from coordinated actions" (G. Marwell, 1993) (A. Hemetsberger, 2006). Over the past few years, research in collective actions modeling has made great progress, and drawn great attention from different disciplines, including information science, social sciences as well as economics (Oliver, 2013) (Miller, 2013) (Wang, 2010) (Wang, 2011) (Sawada, 2013). López-Pintado and Watts (López-Pintado, 2008) classified the existing collective action modeling methods about decision making into two main categories: utility models and heuristic models. Utility models emphasize the psychological and economic considerations along the decision making process, while heuristic models address how individuals make decisions under the influence of social connections. When modeling collective actions in cyber space, existed works pay more attention to the interact mechanism between agents(Nemiche, 2012), the impact of information content to collective behaviors(Margetts, 2012), or the control of trust during social network evolution(Taddei, 2013). Those research works focus on the influence of social networks.

In e-commerce websites, modeling customer influenced by collective action and predicting the effect of collective action manipulation are still facing with many challenges. On one hand, in e-commerce websites, modeling customers will result in a large variance and inaccurate estimation of users actions because the user behavior patterns change frequently with the impact of collective actions. We call this kind of customers mobilizable agents for convenient. On the other hand, for e-commerce websites (especially for small and medium enterprises), the distribution of customer types is not stable and hard to estimate the collective actions considering the information cascade. For the former problem, we consider utility methods to model users' action objective, while an agent's utility function will change with the collective action, namely a social choice force model. For the latter one, the Artificial societies, Computational Experiments, and Parallel execution (ACP) approach (Wang (2007), Duan (2013)) is a promising way to combine real-world problems with computational experiments based on agent modeling. We build artificial societies using real-world data and the proposed

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SCF model, then design computational experiments for different scenarios to verify and compare the effect of different kinds of promotion policies including collective action manipulation and price-off promotion.

The contributions of this work can be summarized as follows: (1) An agent model considering collective action in e-commerce websites is proposed to discuss decision making and behavior prediction for building artificial societies. (2) We design computational experiments to analyze the effect of collective action manipulation. (3) We conduct real-world experiments to verify our assumptions and models on an e-commerce directory website.

The rest of this paper is organized as follows. In section 2, we state the decision making scenarios of agents in e-commerce websites, and the research problems. In section 3, we present a social choice force model for mobilizable agents. Section 4 provides an ACP approach to estimate collective action manipulation in a real-world e-commerce website. We conclude this work in Section 5.

2. PROBLEM STATEMENT AND ANALYSIS

In e-commerce environments, customers check for the product list according to recommendation or query results, and then click their favorite products according to the detailed informations provided by websites (e.g. the website will provide a list of products to the customer). Those informations can be summarized into two types, basic informations of the products and output of collective actions performed by all the customers. Basic informations of products are almost constant generally and controlled by the vendors, while the collective outputs are changing over time with the development of customer actions. User clicks, comments, and special events such as "like" will emerge certain collective outcome according to the mechanism of the website to the customers(e.g. total user clicks volume). However, strategic vendors would try to utilize big amount of sponsored advertising or fraud clicks to change the collective output. Those manipulation behaviors would result in the change of the collective outcome instantly, in turn the psychological biases and mobilization of some of the customers to click their products, promoting the rank in the e-commerce search engines. How to estimate the effect of collective action manipulation becomes an emergent problem in mechanism design of e-commerce service providers.

User behavior models are needed for predicting the favorite alternative selection. We consider the user click process in an e-commerce website as a series of decision problems. Without the influence of collective actions, a customer would take an optimal action to maximize his utility function according to his preference. However, field experiments show that there are big amount of mobilizable agents, whose actions are not optimizing the original utility functions but varied with the collective outcome.

This study focuses on estimating the effect of collective action manipulation in e-commerce environments. Specifically, given the collective action manipulation policy, we want to know how a specific customer will make his choice among the presented product list, and moreover how many customers will be influenced by the policy in a short period.

Table 1. List of notations

Notation	Definition
$\mathcal{X}$	feature vector space of agents
$x \in \mathcal{X}$	the feature vector of an alternative
N	the volume of agents
$\mathcal{Y}$	feature vector space of alternatives
$y \in \mathcal{Y}$	the feature vector of an alternative
M	the volume of alternatives
$s \in S \subset \mathbb{R}^m$	collective outcome
$A \subset \mathcal{Y}$	agents' action space
$a_j^* \in A$	agent j's action
Ω	agents' utility function space
$u \in \Omega$	the utility function
$F_s : \Omega \to \Omega$	social choice force mapping
$T(s, i, j)$	transformation matrix of SCF

The notations used in this paper are listed in Table 1. A customer agent with feature vector $x \in \mathcal{X}$ will choose his favorite product with feature vector $y \in \mathcal{Y}$ among a list of product $A \subset \mathcal{Y}$, given the outcome $s \in S$ of collective actions. A vendor's policy can be modifying the price of a product (i.e. change y to y') or collective action manipulation (i.e. change s to s'). We aim to predict an customer's favorite product given the vendor's policy and find the most effective promotion policy.

3. A SOCIAL CHOICE FORCE MODEL FOR MOBILIZABLE AGENTS

We take efforts to model mobilizable agents and predict customers' product clicking behavior. In this section, we firstly model customers' product clicking behavior using utility functions. Then, the dynamic of utilities is modeled by state transformation processes, thus a mobilizable agent's utility function will change with the collective actions. In the proposed social choice force model, a mobilizable agent will first determine his utility function for product clicking objective according to the collective outcome. Then, he will make the optimal decision to maximize his utility function.

3.1 Modeling Product Clicking Behaviors

We model a customer's product clicking behavior as finding the product which maximizing the customer's utility function given a set of products and the collective outcome. Considering vector s be current output of customers' collective actions, an agent's utility function is denoted by $u(s, x, a)$, where x is the feature vector of the agent, $a \in A$ is the agent's choice. Although the agent's real action is to click on an alternative in pages of the e-commerce website (e.g. products or categories to be clicked), we use the feature vector $a \in A \subset \mathcal{Y}$ of the selected alternative to represent his choice where $\mathcal{Y}$ is the feature vector space of all possible alternatives, because in real world scenarios each product's feature vector is generally unique. x, s and A form all the input information when an agent is making his click decision. x includes his stable basic features such as age, gender, place of residence, etc, s summarizes the outcome of all the customers' actions, while A is provided by the website by predicting best-matching alternatives according to the agent's feature vector. If we can predict an agent's utility function $u(s, x, a)$, his favorite choice can be calculated by finding the maximum value of his utility function.

Next, we focus on the transformation process of agents' utility functions, and provide a social choice force (SCF) model to describe and predict the actions of mobilizable agents. In this model, we assume an agent's utility function will change according to the current collective outcome, and then make the decision by optimizing his utility. Given the collective outcome s, a mapping $F_s : \Omega \to \Omega$ transforms an agent's original utility function $u \in \Omega$ to $u^{'} = F_s(u) \in \Omega$. He performs action $a^* = \mathrm{argmax}_{a \in A}\, u^{'}(s, x, a)$ to maximize his utility, where A is his set of alternatives. Then all the action aggregate the new collective outcome $s^{'} = G(s, a_1^*, \ldots, a_N^*)$, where G is designed by the website. In our case, G is defined as

$$G_j(s, a_1^*, \ldots, a_N^*) = s_j + \sum_{i=1}^{N} 1_{a_i^* = y_j}, j = 1, 2, \ldots, M, \quad (1)$$

$$G = (G_1, \ldots, G_M)^T \quad (2)$$

We summarize the SCF model as:

Model 1. (Social Choice Force Model).

$$u_i^{'} = F_s(u_i), \quad i = 1, 2, \ldots, N. \quad (3)$$

$$a_i^* = \underset{a \in A}{\mathrm{argmax}}\, u^{'}(s, x_i, a_i), \quad i = 1, 2, \ldots, N. \quad (4)$$

$$s^{'} = G(s, a_1^*, \ldots, a_N^*). \quad (5)$$

3.2 Numerical Approach

In this section, we propose approximation algorithms to train the SCF F_s and to predict agent's actions.

For each agent i, we extract action sequence from the log and get triples (s^t, x_i, a_i^t), $t = 1, 2, \ldots$. Utilizing back-propagation algorithm to train neural networks with input s^t, x_i and output a_i^t for each agent i, we can get approximation functions $a = f_i(s, x)$. Let $u_i(s, x, a) = -|f_i(s, x) - a|^2$, we have the initial set of utility function $\overline{\Omega}$. Then, we cluster $\overline{\Omega}$ into k sets. In each of them we choose a center and form the utility space $\Omega = \{\beta_1, \ldots, \beta_k\}$.

Now, we compute the transition matrix $T(s, i, j)$, which indicates when the collective outcome is s, the probability an agent with original utility function β_i will change his utility function to β_j. Thus, $\beta_j = F_s(\beta_i)$. The utility function of an agent is find by $u^* = \mathrm{argmax}_{u \in \Omega} \sum_{t=T-l}^{T} |\, \mathrm{argmax}_a\, u(s^t, x, a) - a^t|^2$. Thus, the transition matrix can be calculated by statistics. The training algorithm is summarized in Algorithm 1.

When predicting a customer's action, given a mobilizable customer's recent action and state sequence (s^t, x_i, a_i^t), we start with estimating his recent utility function u by finding the minimal mean squire error (MSE) through all the base functions in $\beta_1, \ldots, \beta_k$. Then a predictive utility function given the collective outcome s can be estimated by selecting the most-likely utility after the social choice force transformation $u^{'} = T_s(u)$. Hence, we can estimate the agent's click by maximizing his current utility function.

Algorithm 1

procedure TRAINING SCF(s, x, a)
  for $i \leftarrow 1, N$ **do**
    train neural networks $f_i(s, x)$
    $u_i(s, x, a) = -|f_i(s, x) - a|^2$
  end for
  $\Omega_0 = \{u_1, \ldots, u_N\}$
  $\Omega = \{\beta_1, \ldots, \beta_k\} \leftarrow$ cluster Ω_0
  repeat for (s^t, x_i, a_i^t)
    $u = \mathrm{argmax} \sum_{t=0}^{T} |a^t - \mathrm{argmax}_a\, u(s^t, x, a)|^2$
    $u^{'} = \mathrm{argmax} \sum_{t=T-l}^{T} |a^t - \mathrm{argmax}_a\, u(s^t, x, a)|^2$
    $T(s, i, j) \leftarrow T(s, i, j) + 1$, if $u = \beta_i$, $u^{'} = \beta_j$.
  until
  normalize $T(s, i, j)$
end procedure

3.3 Experiments for Customer Behavior Prediction

We collect real-world data including detailed user browsing operations with collective outcomes (recent click amount of certain alternative, i.e. a set of products, on the websites) from a practical group buying directory website (http://www.tuan515.com) during the period from Oct. 2012 to Oct. 2013. From these data, we can extract information about collective outcome s, relevant alternative's features y (including source website of group buying products, deal price, origin price, categories, start date, etc.), and customer features x extracted from user profiles and historical logs. Parameters for user features and alternative features can be statistically obtained from historical logs of user behaviors and database of the website. In addition, we do some approximate treatments on the data in order to provide intelligible experimental settings. For instance, we assign scores range 0 to 1 to source websites based on historical user clicks to evaluate those websites and get normalized value. We use MSE between feature vector of the predicted user clicks a^* and the real user clicks to measure the accuracy of prediction.

In this section, we design comparison experiments to verify the proposed social choice force model, with real-world datasets generated from historical user click logs. We identify the influence of social choice force on customer behaviors and evaluate the prediction accuracy by comparing methods of SCF model and a baseline prediction method based on back propagation neural networks.

In the implementation of SCF model, 80 percent of the data are used to train the model. We train 3-layer back-propagation neural networks for each agent, each of which employ 94 customer features as inputs, 4 alternatives features as outputs, and 100 logistic neurons as the hidden layer. Then, the social choice force is calculated using Algorithm 1. The remaining 20 percent data are used to verify the performance of the SCF model. In order to reduce noise of collective outcomes, we cluster the collective outcomes into discrete value.

For comparison purposes, we implement a baseline strategy used in our practical e-commerce website utilizing neural networks. The baseline algorithm predicts user behaviors applying neural network method based on the same customer features, alternative features and collective outcomes as in SCF model. Customer features and collective outcomes are treated as input of the neural networks, while alternative features are outputs. We also use 80 percent data as training data and the remaining 20 percent as testing data. The experiment results (the mean square error between the real user click and the predicted value) are shown in Figure 1. The x-ray is cluster number of collective outcomes, while the y-ray is the accuracy.

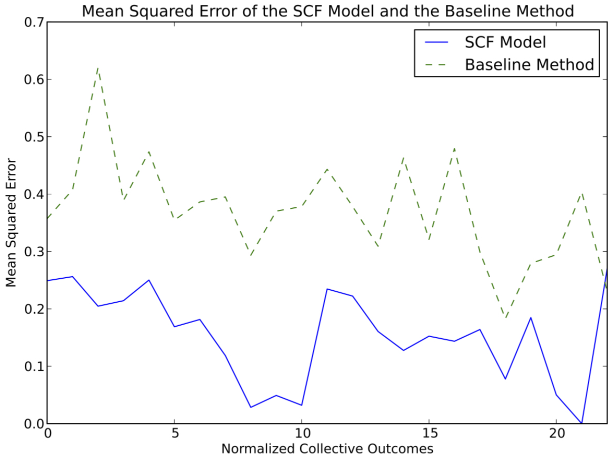

Fig. 1. Influence of Social Choice Force to Single Agents

From Figure 1, we can draw conclusions as follows,

(1) Both the SCF method and the baseline method converge well.
(2) The average resulting MSE error of the prediction accuracy using SCF model is about 0.15 over 4, which indicates the SCF model performs well for customer behavior predicting under the specific e-commerce environment.
(3) The resulting MSE error of the SCF model is significantly smaller than the benchmark method in most situations.

4. ACP APPROACH TO ESTIMATE COLLECTIVE ACTION MANIPULATION

In the next, we propose ACP approach to estimate collective action manipulation. The framework is shown in Figure 2. Firstly, we construct agent based artificial societies and update agent models with real-world data. Then, computational experiments are designed to evaluate policies with different scenarios. Lastly, best policy selected in computational experiments is performed in e-commerce systems to verify the policy in real-world environment.

4.1 Artificial Societies

We build artificial societies to simulate vendors' promotion strategies and customers' clicking behaviors. Agent models in artificial societies are updated using historical and real-time data from the real-world e-commerce website. Agent models, parameters and distributions constitute the scenario, which is generated with different purposes in computational experiments. In our approach, there are four kinds of agents: products, vendors, customers and a SCF (i.e. the outcome of collective actions).

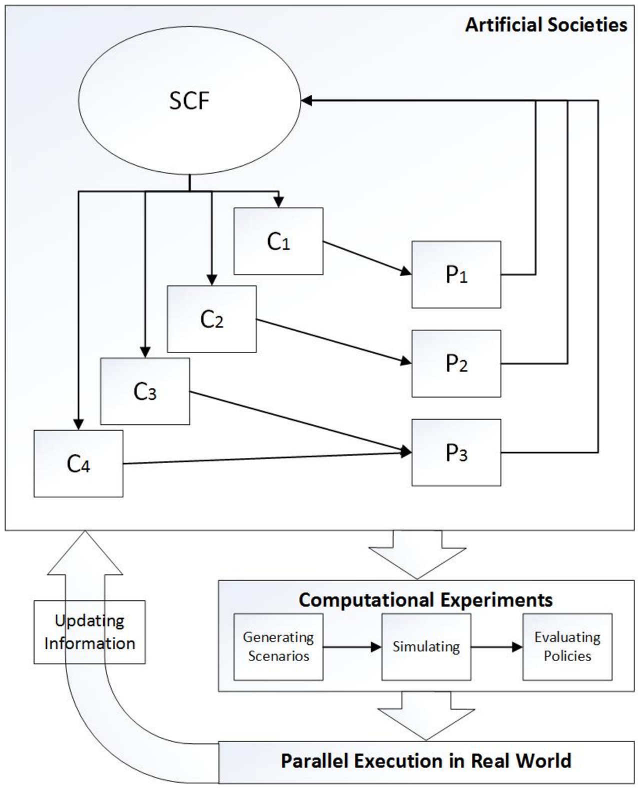

Fig. 2. Framework of ACP Approach for Estimating Collective Action Manipulation

A product agent has a feature vector $y \in \mathcal{Y}$, which presents static attributes such as prices, brands and vendors. A product agent's price can be modified by it's vendor.

A strategic agent can perform different promotion activities on his products. In this work, we assume there are two kinds of promotion: price-off and collective action manipulation, both with multiple levels.

A customer agent with feature vector $x \in \mathcal{X}$ will randomly visit the direction or search service of the e-commerce website to get a list of products. In order to simulate the real-world scenarios, we assume a customer agent will first estimte the utility u_j of each product $j \in A$ according to the proposed SCF model, then choose a product randomly according to the distribution:

$$P(j) = \frac{u_j}{\sum_{l \in A} u_l}. \tag{6}$$

Note that, the expected prediction is still the product with maximal utility. Actions of customer agents change the SCF instantly according to equation 5 and his set of products $A^{'} = A - \{a^*\}$ (Because the website do not count the revisit clicks.).

SCF is a virtual agent. It stores collective outcome $s \in S$ such as sales volume, clicks volume and praise volume of recent customer activities.

4.2 Computational Experiments

We design computational experiments to estimate the effect of collective action manipulation. In this work, we will compare the following 3 policies for promotion of alternative-0 with lower clicks. "Do-Nothing", do nothing. "Collective-Action-Manipulation", manipulate 100% more recent clicks. "Price-Off", perform 20% discount on the price.

Firstly, 40 scenarios with $|\Omega| = 36$ are randomly generated according to the agent models in the previous section. In each scenario, agent distributions are updated from the real-world e-commerce website. Then, policies are performed in scenarios at 50-th time slot (which is the half of the simulation) of each artificial societies. After 100 iterations, the results of computational experiments are illustrated in the following figures. The x-ray is the simulated ticks, while the y-ray indicates the normalized click number in each experiments. We draw the upper bounds, the lower bounds and the mean values of the simulated results.

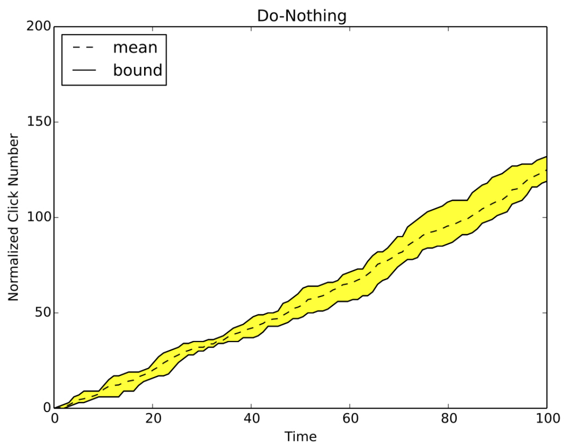

Fig. 3. Computational Experiments without promotion

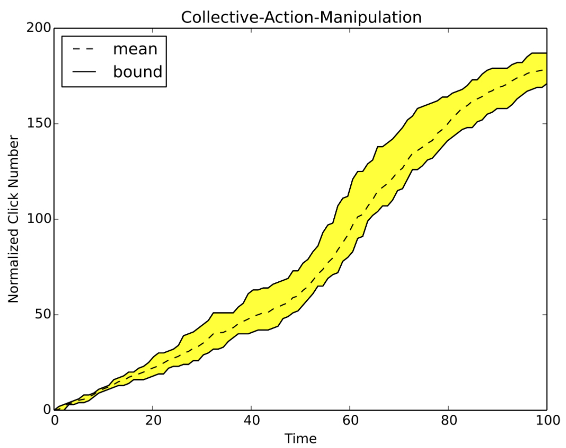

Fig. 4. Computational Experiments with Collective-Action-Manipulation

As is shown in the results, we can see that,

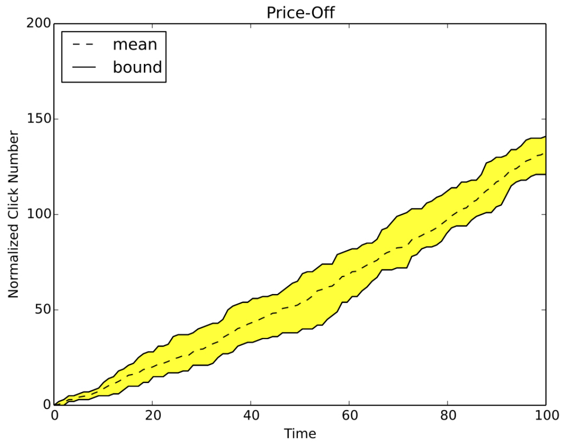

Fig. 5. Computational Experiments with Price-Off

(1) Both the "Collective-Action-Manipulation" policy and the "Price-Off" policy bring additional clicks.
(2) Collective action manipulation is more guaranteed than price-off promotion in the generated scenarios.
(3) Although not quite notable, in Figure 3 and Figure 5, the "mean" curves are convex. It shows that collective action will encourage customers' clicking behaviors.
(4) In Figure 4, the slope of the curve is decreasing after about 74 ticks. This is because the volume of customers is small in the proposed scenarios and after 74 ticks most of the customer agents who are interested in the alternative have already clicked it. Hence, higher collective outcomes do not guarantee the convexity of the click-time curve if the volume of customer is small.

4.3 Real-world Effects of Collective Action Manipulation

The aim of this experiment is to find how real-world customers can be influenced through certain collective action manipulation, and observe how many agents will follow the conducted manipulation. To change the collective action in a real-world website is with great risk to both the customers and the website. So we limit our operation to only one time, with a moderate modification of collective outputs (we adopt the policy "Collective-Action-Manipulation" to double the user clicks of an obscure alternative, namely "alternative-0"). Certain announcements are also published in the resulting page to customers in order to reduce the real influence. Then we observe the short-term effect (within a day) of the conducted collective action manipulation.

We compare customers' predicted mobilized actions and real actions collected from our website after the collective action manipulation. The overall predicting precision of the short-term effect over all the agents is acceptable (81% agents' MSE of behaviors are less than $\epsilon = 0.3$), although it is less than the precision of the prediction without the manipulation in the first experiment.

The final effects of collective action manipulation is shown in Figure 6. The x-ray is the time in a day, while the y-ray indicates the normalized click number we collected in the website. As we can see, the "alternative-0" attracts much

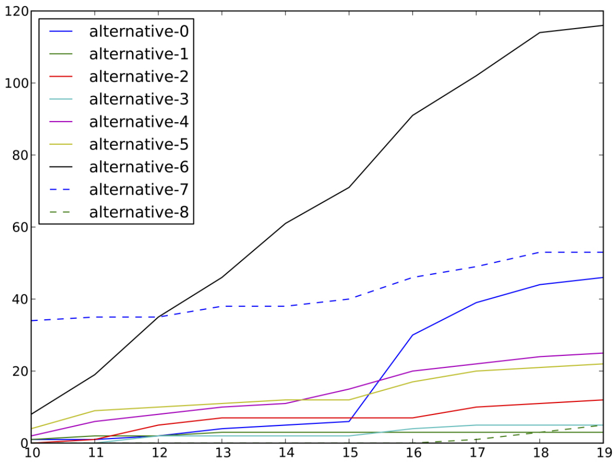

Fig. 6. Effects of Collective Action Manipulation in a Real-world E-Commerce Website

customers to click after the collective action manipulation. But the increasing speed is slow down after a period. It verifies the analysis in the computational experiments.

4.4 Analysis

From the experimental results above, we can see that the proposed social choice force model works well for prediction of agent preference variation in a real-world e-commerce website. Assumptions such as the dynamic of the utility functions and mobilizable agents might be valid from the experiment results, although we have not prove them directly.

Collective actions play an important role in e-commerce environments. The collective action manipulation experiment shows a great influence on real-world customers in group buying websites.

5. CONCLUSION

In this work, we investigate influence of collective actions on the behaviors and decisions of individual customers in e-commerce webistes. Agent models and algorithms are proposed and verified in computational experiments and field experiments. In an ongoing work, we utilize the SCF model to optimize advertizing effects in RTB auctions. Another interesting but challenging perspective is to explore influence of collective actions in socialized e-commerce websites, thus to increase the user experience for customers.

REFERENCES

Fei-Yue, Wang, et al. "A study of the human flesh search engine: crowd-powered expansion of online knowledge." Computer (2010): 45-53.

Marwell, Gerald, and Pamela Oliver. The critical mass in collective action. Cambridge University Press, 1993.

Hemetsberger, A. "Understanding consumers collective action on the Internet: a conceptualization and empirical investigation of the free-and open-source movement." Research Synopsis, Cumulative Habilitation at the University of Innsbruck (2006).

Fei-Yue, Wang. "Study on cyber-enabled social movement organizations based on social computing and parallel systems." Journal of University of Shanghai for Science and Technology 33.1 (2011): 8-17.

Oliver, Pamela. "Collective Action (Collective Behavior)." The Wiley-Blackwell Encyclopedia of Social and Political Movements (2013).

Miller, Noam, et al. "Both information and social cohesion determine collective decisions in animal groups." Proceedings of the National Academy of Sciences 110.13 (2013): 5263-5268.

Sawada, Yasuyuki, et al. "Modes of collective action in village economies: Evidence from natural and artefactual field experiments in a developing country." South Asia 93.H41 (2013): H54.

López-Pintado, Dunia, and Duncan J. Watts. "Social influence, binary decisions and collective dynamics." Rationality and Society 20.4 (2008): 399-443.

Nemiche, Mohamed, Vicent Cavero, and Rafael Pla Lopez. "Understanding social behavior evolutions through agent-based modeling." Multimedia Computing and Systems (ICMCS), 2012 International Conference on. IEEE, 2012.

Margetts, Helen, et al. "Social influence and collective action: An experiment investigating the effects of visibility and social information moderated by personality." Under review, available on SSRN (2012).

Taddei, Stefano, and Bastianina Contena. "Privacy, trust and control: Which relationships with online self-disclosure?." Computers in Human Behavior 29.3 (2013): 821-826.

Waytz, Adam, and Liane Young. "The Group-Member Mind Trade-Off Attributing Mind to Groups Versus Group Members." Psychological Science 23.1 (2012): 77-85.

Edmond, Chris. Information manipulation, coordination, and regime change. No. w17395. National Bureau of Economic Research, 2011.

Wang, F. Y. (2007). Toward a paradigm shift in social computing: the ACP approach. Intelligent Systems, IEEE, 22(5), 65-67.

Duan, W., Cao, Z., Wang, Y., Zhu, B., Zeng, D., Wang, F. Y., Song, H., Wang, Y. (2013). An ACP Approach to Public Health Emergency Management: Using a Campus Outbreak of H1N1 Influenza as a Case Study. Systems, Man, and Cybernetics: Systems, IEEE Transactions on, 43(5), 1028-1041.