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Research in Progress

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Abstract

This paper studies the influence of observational learning and herding in networks of friends versus informants on consumer purchase decisions. We explore how people trade off their needs to belong and to be different by first developing an exponential random graph model to predict online purchasing decision while taking into considerations of product properties, consumer demographics, online rating, as well as consumer social networks. We test our model through collecting panel data on a leading social commerce site in Asia. Contrary to the popular belief that people tend to follow friends' choices, subjects in our context are more likely to diverge from the popular choice among their friends. As our study shows that the need to be different can dominate the need to be belong in certain contexts, we discuss managerial implications of our results for social media marketing.

Keywords: observational learning, herding, exponential random graph model

1   Introduction

The emergence of social commerce sites (SCSs) has tremendously changed the way users seek and share product information. The common belief behind social media marketing is the idea of information cascade: An information cascade occurs when it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information (Bikhchandani, Hirshleifer, & Welch, 1992). Recent evidence suggests that reviews in SCS have become increasingly important in consumer decision-making and consequently have an effect on the sale of products and services (Decker & Trusov, 2010; Ghasemaghaei & Hassanein, 2015; Ho-Dac, Carson, & Moore, 2013; Zhu & Zhang, 2010). As the information contained in SCS does not originate from producers, consumers usually consider such user-generated content more credible and influential than that generated by producers (Bickart & Schindler, 2001). Despite strong industry advocates and increasing scholarly interest (Yoganarasimhan, 2012), social commerce site has not yet proven to be effective at yielding high returns. As summarized in the industry report mentioned above, only 37% of marketers think that their Facebook efforts are effective. At the same time, a significant 89% of marketers state that increased exposure instead of social influence is the number-one benefit of social media marketing, a benefit that, in fact, is quite similar to that of traditional marketing. In this paper, we revisit the popular belief that people like to mimic others, in particular, their friends and informants. We argue that we have long known that humans need to be 'different' (Fromkin & Snyder, 1980) and there is no reason to believe that this need would always be subordinate to the need to fit into a wider social group. To gain a deeper understanding of the tradeoff between people's needs to be different and to belong, we build an exponential random graph model to predict online purchasing decision while taking into considerations of product properties, consumer demographics, online rating, as well as consumer social network.

Our findings stand in stark contrast to previous findings on behavioural convergence: our subjects are more likely to diverge from the choice that has high rating among their informants. In addition, we find that divergence usually happen among friends as subjects know that their choices were visible to their friends. Unless subjects observe their informants' actual actions (i.e., past purchase behavior), they are more likely to converge their choice. We believe the present work advances our knowledge in three perspectives. First, prior work has mainly focused on the influence of online friends' prior purchase or ratings on people's conformity behavior. The present work examines the influence of online social information from two sources – not only friends but also informants. Second, an extensive and growing literature documenting various influences of social relationships seems to imply that friends' behaviour should trigger individual's similar actions. Our findings show that this belief might not always be true. We argue that it is important to consider contextual factors when examining how users on social commerce sites trade off their psychological needs to belong and to be different. Finally, unlike many prior consumer online review studies that have analyzed the effects of online reviews either from the retailers' perspective (Decker & Trusov, 2010; Zhu & Zhang, 2010) or from consumers' perspective (Senecal & Nantel, 2004), we are among the first study to examine the effects by using social network analysis - exponential random graph model to predict online purchasing decision. From this angle, our findings offer a much more complete picture for policy makers, consumers, and retailers.

The reminder of this paper is structured as follows. First, we present the theoretical foundation of this research and review literature on observational learning and herding. We then build an exponential random graph model to predict online purchasing decision and present the results of data analysis. Finally, we conclude with the discussion as well as the limitations of our work.

2   Theoretical Background

2.1   Optimal Distinctiveness Theory

Optimal distinctiveness theory (ODT) suggests that people reconcile opposing needs for assimilation and differentiation through their group memberships (Brewer, 1991). ODT posits that individuals always look for equilibrium between extreme similarity to and extreme distinctiveness from others. According to ODT, individuals avoid self-construal that are either too personalized or too inclusive and instead define themselves in terms of distinctive category memberships. ODT relies on an assumption that individuals have two competing motivations in nature – a motivation to belong to others (Leary & Baumeister, 2017) and a motivation to be different from others (Fromkin & Snyder, 1980). Because of such conflicting nature of these two motivations, individuals cannot gratify one motivation much without sacrificing the other. Therefore, the best way of satisfying these two competing motivations at the same time is to maintain both of them at moderate levels. The uniqueness literature argues that people have a drive to be unique and that too much similarity leads to a negative emotional reaction (Fromkin & Snyder, 1980). However, there is little research on how the need to be different is trade off against the need to belong in online context, which is the main motivation of the current paper. We revisit the popular belief that people like to mimic others, in particular, their friends (i.e., friends tie) and informants (i.e., followings tie). We argue that humans need to be 'different' (Fromkin & Snyder, 1980), and there is no reason to believe that this need would always be subordinate to the need to fit into a wider social group. The general goal of this model is to gain a deeper understanding of interpersonal influences in social networks, the design of our model is tailored for investigating influence that is initiated by observing others' choices (i.e., informants' purchase and friends' purchase) and others' rating (i.e., informants' rating and friends' rating).

3   Modelling Framework

We develop a modelling framework for the simultaneous analysis of multiple relationships among a set of network actors.

3.1   Model Description

We use ERGM model to conduct social network analysis. The ERGM was first introduced by (Frank & Strauss, 1986; Wasserman & Pattison, 1996) and is well known for its capability in modeling the interdependence among links in social networks. ERGM is a stochastic network modeling method for deriving the likelihood of a network emerging from all the possible structures that could have been formed by a random assignment of ties across nodes in the network. Mein Goh, Gao, and Agarwal (2016) used ERGM revealed patterns of social support exchanged between users and the variations based on users' location. The model class is specified as

$$\Pr(X = x | R = r, F = f, C = c, P = p) \quad = \frac{1}{\kappa(\theta)} \exp \sum_{\theta_{\{\alpha, \beta, \gamma\}}} \{\theta_\alpha z_\alpha(x) + \theta_\beta z_\beta(x, c, p)$$
$$+ \theta_\gamma z_\gamma(x, r, f)\}$$

where the labels of the purchase, rating and following networks {X, R, F} become network random variables with their realizations labelled as {x, r, f}. The attribute variables of consumers and products, such as age and skin type, are represented by (C) and (P) respectively. $z_\alpha(x)$ are graph statistics, or counts of configurations only involving purchasing ties. z_β and z_γ are graph statistics representing the interaction among {X, R, F, C, P}. Each of the statistics has an associated parameter (θ) where a statistically significant parameter estimate indicates the corresponding configuration happens more (or

less depending on signs) than we would expect from random, and the represented social or behavior processes by those configurations may be concluded as drivers of the purchase network structure (X).

$\kappa(\theta)$ is a normalizing constant ensuring the model a proper probability distribution. The number of possible networks grows exponentially as the number of nodes increases, which makes $\kappa(\theta)$ in tractable. The maximum likelihood estimations of model parameters and their standard errors, and model goodness of fit (GOF) tests of ERGM, rely on Markov Chain Monte Carlo (MCMC) simulations (Snijders, 2002). We use the MPNet software for ERGM for multilevel networks (Wang et al., 2012) to model our empirical network, while building customized model specifications for our context

3.2   Data

3.2.1   Data collection

The data for this study were crawled during the month of December 2015 from a popular online beauty community (hereafter referred to as Community) in Asia, which provides a platform for members to learn about beauty products, to share their experience related to beauty products, and to interact with other beauty enthusiasts. The Community organizes beauty products by brands and provides basic information about each product. Members of the Community can post the experience that they have had with the use of any product (that is available at the Community), provide a rating (from 1 to 7) on the product, reply to other members' posts, recommend a member's post to others, and choose to "follow" other members on the community. They can also share the products that they have purchased by adding products to their "buy-lists".

The present study focuses on the discussion of branded products, which include all products under the same brand name. Individuals who have explicitly added a particular brand as their favorite brand are considered members of that brand community, and hence the unit of analysis for this study is a member of a brand community. We aim to explore how a member's purchase decision is influenced by other members' (i.e., friends and informants) product ratings and product choices in a brand community and how such influence is moderated by the social network tie in this brand community. We carefully choose one brand with 43 cosmetic products under the brand. There are 671 forum participants.

3.2.2   Social network structure in social commercial sites

We treat consumers and products of two different sets of nodes in a network, Figure 1 depicts the overall network structure. Products are represented by squares, and consumers by circles. The attributes of products (e.g. price) and the attributes of consumer (e.g. skin type) can be represented by the colors or sizes of the nodes. We label the purchasing network as (X) which is a collection of possible network ties {Xik} where Xik=1 if consumer i purchased product k, otherwise Xik=0. The Rating network is labelled as (R), ties within network (Rik) can be valued representing scores consumer i rated for product k. The rating scores can be represented by the widths of the rating ties. Both networks (X) and (R) are bipartite, or two-mode networks, where network ties are defined only between two distinct sets of nodes, that is, consumers and products, but not within each of the set of nodes. The following network among consumers, labelled as (F), is a one-mode network where only one set of nodes, are involved, i.e. the consumers. The following network is a directed network where (Fij=1) if consumer i follows consumer j, and Fij=Fji, if i and j are following each other reciprocally. We see reciprocal ties as much stronger forms of interpersonal ties, and interpret them as Friendship ties that are different from the weaker form of Following ties in just a single direction. From an ego user's perspective, we categorize ego's immediate network neighbors as:

Followers: who follows the ego by social ties. Large numbers of Followers may indicate the popularity of ego, and ego's behavior, e.g. rating, purchasing. Our model can test how ego's popularities may affect ego's own purchase.

Friends: who follows the ego, and being followed by the ego that forms a mutual network tie. Our model can test whether this stronger form of social tie can affect ego's purchasing behavior given the attributes, rating and purchase of ego's friends.

Informants: who are followed by the ego, and who may provide ego product information through their reviews and purchases.
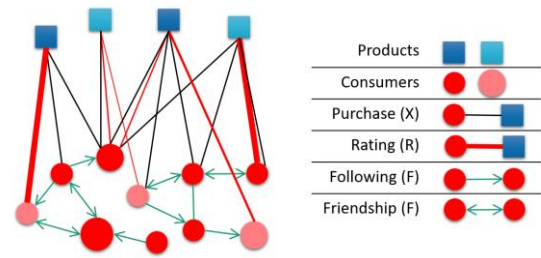

Figure 1 Social commercial sit as a networked system.

3.3   Results

Using ERGM we are able to test if the observed support network is random or if it is an outcome of exchange patterns proposed. Table 1 presents estimation results from a series of ERGM model. All significant results are marked in bold. Results showed that co-purchasing in informant networks is significant ($p<0.001$). The positive coefficient indicated that the more informants of an ego member purchase one product, the higher probability the ego member will purchase the product. The results showed that co-purchasing in friends network is not significant ($\beta=-0.425$, $p>0.1$). In addition, the results showed that ratings in informant network has negative effect ($\beta=-0.072$, $p<0.001$). The negative coefficient indicated that the more informants of an ego member provide high rating on a product, the less probability the ego member purchase the product. The results also showed that friends' rating doesn't show the significant effect on members' purchase behavior ($\beta=0.094$, $p>0.1$).

	Effects	Est.	Std. Err.
Purchasing	Density	**-12.168**	**0.796**
	Centralization	**0.148**	**0.023**
	Non-purchase	**-5.241**	**0.367**
	Product popularity	**1.975**	**0.361**
	Activity spread	**2.541**	**0.204**
	Customer sharing	**-0.106**	**0.051**
Consumer attributes	Combination skin	0.244	0.149
	Sensitive skin	**-0.471**	**0.201**
	Dry skin	0.174	0.147
	Age	**-0.010**	**0.004**
	Sensitive skin product sharing	**0.080**	**0.022**
Product attributes	Price	-0.012	0.014
	Received Intention	**-0.010**	**0.004**
Attributes interactions	Skin type match	0.268	0.188
	Activity within skin type	**-0.079**	**0.024**
Following and Purchasing	Receiver	-0.016	0.014
	Sender	0.018	0.010
	Co-purchasing	**0.259**	**0.083**
	Co-purchase (reciprocity)	-0.425	0.313
Rating, Following and Purchasing	Rating	**1.059**	**0.040**
	Sender's rating	**-0.030**	**0.011**
	Receiver's rating	-0.005	0.008
	Purchaser Rating and reciprocity	0.046	0.032
	Follow the rating	**-0.072**	**0.034**

	Rating and reciprocity	0.094	0.073

Table 1.   ERGM Results

4   Discussion and Conclusion

4.1   The influence of rating on consumer purchase decision

Influence among network members is typically initiated by herding, observations of others' choices, or both. Recent studies in marketing have explored many different aspects of word of mouth (WOM) such as its impact on adoption and sales (Chen & Xie, 2008; Chevalier & Mayzlin, 2006), and its dynamics (Godes & Silva, 2012), motivation (Moe & Schweidel, 2012) and manipulation (Anderson & Simester, 2014). In general, findings from this stream of the literature suggest that WOM is an important element in the modern marketing mix (Chen & Xie, 2008), with positive online ratings boosting products' online sales (Chevalier & Mayzlin, 2006). Table 1 illustrate the results of influence of herding (i.e., informants' rating and friends' rating) on consumer purchase decision. Contrary to previous literature, our results indicated that informants' rating has negative influence on consumer purchase decision. Friends' rating doesn't show any significant effect on consumer purchase decision. We identify the following result:

Proposition 1a. As more informants provide high rating to one product, individual is less likely to buy the product.

Proposition 1b: As more friends provide high rating on one product, individual will not converge to buy that product.

4.2   The influence of observational learning on consumer purchase decision

A handful of empirical papers have examined the mechanism of observational learning. juanjuan Zhang (2010) studied observational learning in the US kidney market. Chen, Wang, and Xie (2011) disentangled whether consumers' purchase decisions can be influenced by others' word of mouth or observational learning. Juanjuan Zhang and Liu (2012) examined whether observational learning is rational in the contexts of eBay. Cheung, Xiao, and Liu (2014) indicated that observational learning has more influence on consumer purchase decision compared with WOM. Consistent with previous literature, our results indicated that informants purchase behaviour will positively influence consumers' purchase decision. Interestingly, this effect will dilute by the social tie, which means friends' purchase behaviour will not influence consumers' purchase decision. We identify the following result:

Proposition 2a: As more informants purchase one product, individual is more likely to converge to buy the product.

Proposition 2b: As more friends purchase one product, individual will not converge to buy the product.

4.3   Limitations

There are a number of limitations to this research. First, given that online friends and opinion leaders might generate idiosyncratic ratings and purchase, which might confound the observed effect, lab experiments seem to better deal with the potential confounding. Researchers may collect data about the time consumers spend browsing content to quantify imitation behavior. An eye tracking technique can be used to measure the way users browse the content from friends and opinion leaders. Second, more variables of demographic information (i.e., age) should be considered in the future study. Third, this study collected data from a social commerce community, which focuses on fashion and beauty products, which are primarily hedonic. Thus, caution is advised in generalizing the results of this study to other online communities that focus on utilitarian products, such as notebooks.

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