Expert Systems with Applications 41 (2014) 1723–1729

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

An impact of online recommendation network on demand

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ARTICLE INFO

Keywords:
Social Network Analysis (SNA)
Centrality
Clustering coefficient
PageRank

ABSTRACT

This study proposes roles of online recommendation network on online book marketplace with social network perspective. Also this paper is to provide a new perspective on how Social Network Analysis (SNA) can be used to study the influence on demand by the recommendation network. We first built the books' recommendation network based on the co-purchasing data of customers and then computed the five network centralities and clustering coefficients using NodeXL. We also analyzed our research model by correlation and multiple regression analysis. The results of correlation analysis show a significant correlation between the six SNA measures – degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, PageRank centrality, and clustering coefficient-and demand, as well as the six SNA measures. The result of regression analysis demonstrates that five of six SNA measures in the recommendation network have a significant effect towards demand, and then the largest effect towards a book's demand is associated with degree centrality. According to our results, a book's position within this network affects its overall demand. Hence managers should build more effective and accurate recommendation network of books including data customers co-purchased, and in turn, position books with a high degree of centrality on the website.

1. Introduction

Through the rapid evolution of electronic commerce (e-commerce), large amount of information on Web sites present great challenges and opportunities to both customers and e-commerce firms. Most e-commerce firms are exploiting online product review and recommendation systems to attract customers' attentions. Some scholars examine the impact of online product reviews with regards to sales (Chevalier & Dina, 2006; Zhang & Dellarocas, 2006). Recently, other researches have begun to study the impact of recommendation networks (e.g. item-to-item, customer-to-customer, and item-to-customer) on demand or revenue using social network analysis (Goldenberg, Oestreicher-Singer, & Reichman, 2010; Oestreicher-Singer & Sundararajan, 2008; Susarla, Jeongha, & Yong, 2010; Xu et al., 2009).

This study places emphasis on the recommendation network built by customers' co-purchasing[2] books through online bookstores. Usually, this consists of nodes (books) and links (co-purchasing) and is made by "customers who bought this item also bought the following items" as shown in following Fig. 1. This is known as a "recommendation network" and has the social influence such as word-of-mouth (WOM) on electronic commerce.

Recent studies with regards to these kinds of networks are as follows: dual networks, including users, videos of Youtube (Goldenberg et al., 2010; Susarla et al., 2010), product recommendation networks by customers of e-bay or Amazon.com (Oestreicher-Singer & Sundararajan, 2008), blog networks (Mayzlin & Yoganarasimhan, 2008), and news networks (Dellarocas, Katona, & Rand, 2010).

Goldenberg et al. (2010) examined the impact of networks on customer satisfaction through dual networks, including videos, users, and subscriptions. They demonstrated that the betweenness centrality concerning user network is three times higher than that of other networks. This means users are shifting power to the edge of the network, allowing users to participate in innovation in such a way that would have been unthinkable just a decade ago. Oestreicher-Singer and Sundararajan (2008) studied the impact of visible social networks on customer preference through sharing of customer purchasing types. They discovered that PageRank is related to the Gini coefficient,[3] and the presence of a recommendation

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[1] Tel.: +82 51 640 3031.
[2] Co-purchase network is the same meaning as recommendation network.

[3] The Gini coefficient is a measure of the inequality of a distribution, a value of 0 expressing total equality and a value of 1 maximal inequality.

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http://dx.doi.org/10.1016/j.eswa.2013.08.071

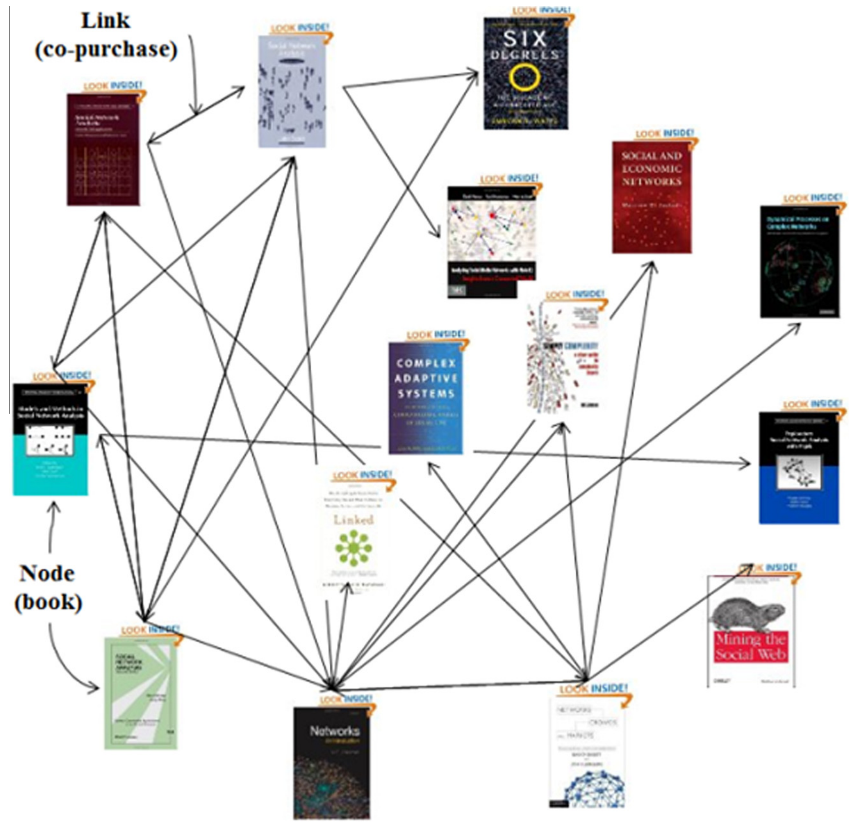

Fig. 1. Recommendation network created by co-purchasing books.

network will lower the Gini coefficient, or reduce the inequality in demand across products. Susarla et al. (2010) observed the impact of network structure and position on word of mouth concerning the early life stage of products. These observations demonstrated that the size and growth of a product's prestige was affected by an early buzz within the social network structure regarding the products.

Based on previous researches, we aim to discover whether the position of a book in a recommendation network affects the book's overall demand when it comes to online bookstores. For this study, we explore the following research questions:

(1) Which measures of SNA can be used to evaluate the effect of the recommendation network on demand?
(2) Is there a correlation between measures of SNA and a book's demand? If they are correlated, which measures of SNA have an impact on the book's demand?

The remainder of the paper is organized as follows: Section 2 reviews social network analysis measures. Section 3 proposes our research model and hypotheses. Section 4 describes the data resources and the research method applied to the data and our research model. Section 5 analyzes the impact of a recommendation

Table 1
Summary of SNA measures.

SNA measures	Formula
Degree centrality	$C_D(i) = \sum_{j=1}^{n} a_{ij}$ where element a_{ij} = 1 when a direct link exists between nodes i and j and a_{ij} = 0 otherwise
Closeness Centrality	$C_C(i) = \frac{n-1}{\sum_{v_j \in V, i \neq j} d_{ij}}$, where d_{ij} is distance from node i to all other nodes j in a given network
Betweenness centrality	$C_B(i) = \sum_{k \neq i \neq j \in N} \frac{\sigma_{kj}(i)}{\sigma_{kj}}$, where σ_{kj} is the sum of all shortest paths between nodes v_k and v_j, and $\sigma_{kj}(i)$ is the number of shortest paths that pass through v_k
Eigenvector centrality	$x_i = \frac{1}{\lambda}\sum_{j \in M(i)} x_j = \frac{1}{\lambda}\sum_{j=1}^{N} a_{ij} x_j$, where x_i is the average of the centralities of i's network neighbors and λ is a constant
PageRank centrality	$PageRank(i) = \frac{(1-\alpha)}{n} + \alpha \sum_{j \in G(i)} \frac{PageRank(j)}{OutDegree(j)}$, where $j \in G(i)$ if there is a link originating from product j to product i (meaning that product j is a network neighbor of product i) and OutDegree(j) is the total number of links originating from product j
Clustering coefficient	$C(i) = \frac{2E(i)}{k(i)k(i-1)}$, where $E(j)$ is the number of actual links, $k(i)$ is the number of actors (Watts & Strogatz, 1998)