The Demand Effect of Product Similarity Network

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The Demand Effect of Product Similarity Network

Research-in-Progress

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Abstract

With the increasing popularity of product assortments by recommendation system, how online seller manage the links of products seems important. As the similar products that are viewed together in product’s search pages, we study the economic effects of the similar products network. In this study, we construct the similarity network by using data from Taobao.com. We apply Cross-sectional data models to examine the spillover effect of reviews from the similar product, additionally how characters of network moderate this effect for three product categories. We find that the semantic similarity of similar product’s review has a negative impact on focal product’s sale. The more similar in context, the more substitutable of the product. Furthermore, the volume and price of similar product also have influence on the demand. From the view of network characteristics, we find that the in-degree of a product, clustering coefficient and density of the incoming network also has an impact on the demand.

Keywords: Product similar network, spillover effect, online review, semantic similarity

Introduction

Recommender systems (RS) are becoming essential for consumers to discover new products, which have a strong influence on what consumers view and buy. For instance, 35% of Amazon’s sales are attributed to recommendations. By the analysis in Netflix.com, Anderson (2006) found that with the usage of recommended system, the average monthly rent of seven DVD registered users is three times than that of traditional shops. Through an empirical study of Apple's iTunes music store, Fleder(2008) shows that the recommendation system expands the audience of the new product, which also enhances consumer’s relationships. Pathak (2010) analyze that product get more recommended from other goods, which will be more attractive for consumers, and the recommender systems increase sales from cross-selling. Lin z(2015) examine the impact of characters of recommended network on product demand.

Different from the network of co-view and co-purchase product recommendation system, this study analyze product network formed by product’s similar page. Firstly, we examine the spillover effect of reviews in the similar product’s network; additionally we calculate the cosine similarity of product’s review especially considering the semantic of text. Secondly, we construct the similarity network by
using data from Taobao.com, and analyze the characters of the entire networks; we also compare characters of different product's networks. Thirdly, we examine the demand effect of similar product's incoming-network, using the data of product's in-degree, network's density and clustering coefficient. Furthermore, different effects of search goods and experience goods are examined.

**Literature Review**

**Product similarity and product network**

Products seemed as similar when they perceived as substitutable as means for the same usage (Ratneshwar and Shocker 1991). In economic theory, the substitute of products has cross-price elasticity, if the price of one increase, the demand for the other will increase (Russell and Petersen 2000). In e-commerce, some studies have examined the effect of networks of co-views and co-purchases on demand. Oestreicher(2012) analyze the demand effect of recommendation networks in electronic markets. Zhang M, Bockstedt(2015) analyze the different effect of complementary and substitutable recommendation system. They observe a significant interaction effect between recommendation type and decision stage. This study constructs the network from similar product pages, where the similarity of product is calculated by Taobao.com.

This study related to the literatures on product networks. In e-commerce, online products are not isolated, because all kinds of recommendation systems make links between products, in the websites, products are nodes and the hyperlinks between products are edges of the network. Structural holes theory (Burt, 2002) acknowledges that people and other objective entities (firms, products) are in a better position to profit from their relationships with others. Stephen and Toubia (2010) indicates that recommending links from other vendors can increase sales’ probability of goods, because the product’s exposure probability is increased.Oestreicher, Sundararajan (2012) show that the co-purchase network has significant influence on the demand of complementary product. Oestreicher-Singer (2013) decomposes the revenue of product into intrinsic value and network value, where the network value is created by the recommendation’s links. Leem, Chun(2014) also study the effect of online recommendation network on online book demand. This study emphasize network-leveled point of view of the relation between all products.

**Online product reviews**

Through summarizing the research literature, there are two main aspects of online product review: the number of review and the ratings of review. Mayzlin (2006) finds that larger volume of reviews may give more information for consumers to reduce purchasing uncertainty. Higher grade means higher product’s quality, which can inspire much confidence for consumer. Ye (2009), Gong Shiyan (2012), Wang Kexi (2014) show that the relation between the volume of online reviews and sales is significant positive. They analyze the hotel rooms, books and tea brand respectively. Through the unconditional quantile regression, MEISEBERG (2016) conclude that the impact review on the sellers with low sales is higher than that with high sales. Cu T, Schneider (2016) show that volumes of post and UGC’s sentiment have a dynamic impact on the adoption rate of digital products. In addition, the research on review text is divided into two main aspects; one is to describe the attributes of product, while another is the users’ emotional judgment. Compared to the previous studies, we mainly analyze the impact of online reviews in the networks of similar product.

**Spillover effect of related product reviews**

Spillover effect of word-of-mouth refers to the extent to which a message influences beliefs, and the message related to attributes that are not contained in the product information (Ahlwalia et al. 2001).The authors find that when consumers are not familiar with a brand, the negative information spills over to the attributes, positive information does not. When consumers like the brand, a spillover occurs for the positive information as well. Libai et al.( 2009) show that consumer can adopt a brand as a result of an interaction with adopters of competing brands (cross-brand influence).Peres R, Van den Bulte(2014)find that a firm holding exclusivity cannot benefit from the positive word of WOM spillover generated by customers of other firms. Wang F, Chen L(2012) build product reviewers’ preference similarity network by mining product reviewers.

There are seldom academic articles on spillover effect of word-of-mouth considering the semantic similarity in context. In this study, we focus on the effect of reviews of similar products on the
individual’s purchase decision, especially considering the semantic similarity of reviews. Our hypotheses are as follow:

H1: The semantic similarity of similar review has a negative impact on focal product’s sales.
H2: The maximum quantity of similar review has a negative impact on focal product’s sales.
H3: The lowest price of the similar products has a positive impact on focal product’s sales.
H4: In-degree of the product in similarity networks has a positive impact on focal product’s sales.
H5: Clustering coefficient of product networks has a negative impact on focal product’s sales.
H6: Density of product networks has a positive impact on focal product’s sales.

**METHODOLOGY**

![Research framework](image)

In Figure 1, we present the process of constructing product similar network. We obtain data from Taobao.com, a China-based B2C e-commerce platform. We use a java_based crawler to get data on February 16, 2017. Our data including sales, volume of reviews, price, text of review from product’s similar pages. According to different product types (search goods and experience goods, our dataset is divided into three parts based on categories: (1) Beauty/Personal Care (2) Infant Food (3) Digital products.

**Cosine Similarity of Review**

Giving sentence T1, T2 of product review, the similarity is calculated by the following formula (Figure 2). As the review is Chinese, we use an open-source segmentation algorithm named Ansj which is based on the Chinese Dictionary. For semantic similarity computation, the TF-IDF algorithm is used to calculate the keyword’s inverse document frequency from reviews.

\[
\cos(T_1, T_2) = \frac{T_1 \cdot T_2}{\|T_1\| \cdot \|T_2\|}
\]

**Variable Construction**

Giving the similar networks of each product, we construct relevant variables. The dependent variable is sales, the product’s monthly sales recently. The key independent variable is simi_review, price, cos_simi_rev, low_simi_pri, lowp, indegree, net_cluster, net_density, while the volume of product...
reviews and the price of the product are treated as control variables. The detailed description of all variables is given in Table 1.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Descriptions</th>
<th>Variables</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>sales</td>
<td>the focal product’s monthly sales</td>
<td>price</td>
<td>price of focal product</td>
</tr>
<tr>
<td>review</td>
<td>The volume of focal product’s review</td>
<td>low_simi_pri</td>
<td>The lowest price of similar products</td>
</tr>
<tr>
<td>simi_review</td>
<td>The maximum volume of review from similar products</td>
<td>indegree</td>
<td>The focal product’s degree of in-network</td>
</tr>
<tr>
<td>cos_simi_rev</td>
<td>The cosine similarity of context, compared review of the focal product with review of similar product which has maximum comments</td>
<td>net_cluster</td>
<td>The clustering coefficient of similar product networks</td>
</tr>
<tr>
<td></td>
<td>net_density</td>
<td>The density of similar product networks</td>
<td></td>
</tr>
</tbody>
</table>

**Econometric Model**

We model the influence of similarity of product review, product’s in-degree and network density, network centrality on product demand. We specify the dependent variable in logarithmic form. To analyze the effect of similar product’s review, the cross-sectional linear model is specified in Equation [1],

\[
sales = \alpha + \beta_1 \text{review} + \beta_2 \text{simi_review} + \beta_3 \text{low_simi_pri} + \beta_4 \text{cos_simi_rev} + \beta_5 \text{indegree} - [1]
\]

To examine the entire network effect, we estimate a cross-sectional linear model shown in Equation [2]:

\[
sales = \alpha + \beta_0 \text{review} + \beta_1 \text{indegree} + \beta_2 \text{net_cluster} + \beta_3 \text{net_density} - [2]
\]

**Results**

In Table 2, we present the estimation results for the Beauty/Personal Care, Infant Food, Digital products (the observation we used is the product’s in-degree is greater than 10).

Firstly, we examine the spillover effect of word-of-mouth by calculating the cosine similarity of reviews. In the category of Infant Food, the coefficient of \( \text{cos_simi_rev} \) is -0.17 which is significant. It means the semantic similarity has a negative impact on sales. A 1% increase in the semantic similarity of review is associated with a 0.17% decrease in the product’s demand. Reviews of product always refer to product’s attribute (quality, features, etc.). When attributes of product’s in review context is more similar, it means that the stronger substitute effect of the review. While in the category of Beauty/Personal Care, the coefficient is 0.075, which is almost closing to zero. It is perhaps because the sample is not enough. Seen from the conclusions, the hypothesis H1 is only supported in category of Infant Food.

Secondly, we find that the hypothesis H2a is supported in Digital products and Infant Food, the coefficient of \( \text{simi_review} \) is negative in both category, but the coefficient in Beauty/Personal Care is positive. The volume of review in similar products has a significant substitute effect, especially considering the maximum quantity of review which represents the popularity of similar product. The more popular of similar product, the more substitutable of it. Coefficient in Infant Food is -0.792, and which in Digital products is -0.478. It seems the maximum quantity of similar review has a more significant influence on the experience goods than on search goods.

Thirdly, the coefficient of \( \text{low_simi_pri} \) is positive means that the lowest price of the similar products has a significant role of substitute. Hypothesis H3 is only supported in Beauty/Personal Care while is not supported in Digital products and Infant Food. Price substitution elasticity of similar product’s in

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Beauty/Personal Care is significant, one reason maybe the price of these product is more sensitive than others. We find that both the price and volume of similar product review have significant effect on the product’s sales. This result is consistent with the literature.

### Table 2. Results of Model[1]

<table>
<thead>
<tr>
<th>Variables</th>
<th>Digital products</th>
<th>Beauty Personal Care</th>
<th>Infant Food</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-2.546**</td>
<td>-1.366*</td>
<td>-0.614</td>
</tr>
<tr>
<td>review</td>
<td>0.537**</td>
<td>0.424**</td>
<td>0.423**</td>
</tr>
<tr>
<td>simi_review</td>
<td>-0.478**</td>
<td>0.282**</td>
<td></td>
</tr>
<tr>
<td>cos_simi_rev</td>
<td></td>
<td>0.075**</td>
<td>-0.157*</td>
</tr>
<tr>
<td>price</td>
<td></td>
<td>0.979**</td>
<td></td>
</tr>
<tr>
<td>low_simi_pri</td>
<td>-0.99**</td>
<td>0.764**</td>
<td>-0.933</td>
</tr>
<tr>
<td>indegree</td>
<td>0.91**</td>
<td>0.808**</td>
<td>0.698**</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.59</td>
<td>0.618</td>
<td>0.528</td>
</tr>
</tbody>
</table>

** p<0.05  * p<0.1, observations: Digital products (478), Beauty/Personal Care (173) Infant Food (328)

Furthermore, we can see that in the three categories the regression result support hypothesis H4, the coefficient of indegree is positive. It means In-degree of product in the incoming-network has a positive demand effect. It means that higher in-degree is associated with higher demand. The coefficient in Digital products is 0.91, which is highest. The lowest coefficient is in Infant Food, which is 0.457. It seems the role of position in the similar network is more important for search goods than for experience goods.

To examine the network factors’ economic effect at the entire network level, we compare Equationo and Equation1 (Table 3). When net_cluster and net_density are added into the regression equation, the R-squared increases from 0.448 to 0.532. It means the factors of net_cluster and net_density increase the explanatory ability of the regression equation. The coefficient of net_cluster is -0.792. The more clustering of similar product networks, the more centralized of links to seldom nodes, which will decrease the demand of the whole category’ level. The coefficient of net_density is 2.223. This result shows that if the density of similar product networks is greater, the links of the network is more uniform, which will increase product visibility and improve sale probability on category level. A 1% increase in the density of the incoming similar network is associated with a 2.223% increase in average demand. A 1% increase in the cluster of the incoming similar network is associated with a 0.792% decrease in average demand. In sum, these results support hypothesis H5 and H6.

### Table 3. Results of Model[2]

<table>
<thead>
<tr>
<th>Variables</th>
<th>Equation0</th>
<th>Equation1</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>1.318**</td>
<td>-4.629**</td>
</tr>
<tr>
<td>review</td>
<td>0.564**</td>
<td>0.517**</td>
</tr>
<tr>
<td>indegree</td>
<td>0.087**</td>
<td>0.084**</td>
</tr>
<tr>
<td>net_cluster</td>
<td></td>
<td>-0.792**</td>
</tr>
<tr>
<td>net_density</td>
<td></td>
<td>2.223**</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.448</td>
<td>0.532</td>
</tr>
</tbody>
</table>

Observations: 4289, ** p<0.05

### Conclusion

We find that the similar product reviews has spillover effect. The semantic similarity of similar product’s review has a negative role in the purchase of product. The more similar in semantic, the more substitutable of the product. A 1% increase in the semantic similarity of review is associated with a 0.17% decrease in the product’s demand. We also show that the price and reviews’ volume of similar product has significant effect on the sales. The effect has some different between search goods and experience goods. Furthermore, we construct the similarity network by using data from Taobao.com and calculate the characters of different product’s network. We examine the demand effect of the
incoming network. The in-degree, clustering coefficient and density of network also has influence on the demand. The structure of the entire similar product network is important to enhance the level of market performance. Our study contributes to the literature on online product reviews and product network. The result may give an insight to the manager of E-commerce, which also provide implications for recommendation-based product marketing and recommendation systems design.

References
Libai B, Muller E, Peres R. The role of within-brand and cross-brand communications in competitive growth[J]. *Journal of Marketing*, 2009, 73(3): 19-34.
Libai, B., E. Muller, R. Peres. 2009. The Role of Within-brand and Cross-brand Communications in Competitive Growth. *Journal of Marketing*, 73(3) 19-34.