ASSESSING VALUE IN PRODUCT NETWORKS

Completed Research Paper

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Abstract

Traditionally, the value of a product is assessed according to its direct revenues. However, products do not exist in isolation but rather influence one another’s sales. Such influence is especially evident in eCommerce environments, where products are presented as a large-scale product network. We present the first attempt to use a systematic approach to estimate products’ true value to a firm in such settings. We separate a product’s value into its own intrinsic value, the value it receives from the network, and the value it contributes to the network.

Using data from the network of books on Amazon, we examine the relationship between revenue and the sources of value. We show that the value of low-sellers is underestimated when focusing on direct revenue, while the value of bestsellers is overestimated. We explore the sources of this discrepancy and discuss the implications for managing products in an environment of product networks.

Keywords: Product value, Electronic commerce, Recommendation systems, Networks, Long tail
Introduction

One of the interesting developments in retail in recent years is the emergence of online product networks, in which a large number of items are linked, mostly via online recommendation systems that use collaborative filtering algorithms. If one imagines the process of browsing an eCommerce site as being analogous to walking the aisles of a physical store, then the aisle structure of an online retailer consists not of a built physical system of shelves, but instead of the structure of interconnected hyperlinks among products. The placement of a product in this graph thus constitutes its virtual “shelf placement”. Amazon.com has created what is probably the best-known online product network: a co-purchase network, in which each product page shows prospective customers the other products that were purchased by buyers of the same product. This mechanism, which can substantially affect demand (Oestreicher-Singer and Sundararajan 2012), is increasingly used by diverse sellers such as Zappos.com, Hotels.com and Walmart.com to facilitate consumer navigation and to cross-sell products to customers, and thus enables such firms to more fully exploit the inherent relationships among products.

Here we highlight the issue of the assessment of the value of a product in such environments. Understanding the full value of a product (a category or a brand) can help managers to recognize which products to offer (or to stop offering) to customers, which products to promote, and how to better price different products. Traditionally, the value of a product or brand has been assessed according to the direct revenues the product creates. Yet, the true value generated by a product that is part of a network, which we label network value, should take cross-product effects into account. Specifically, it should consider both the revenue that an item generates by directing traffic to other items, and the revenues that an item is not “entitled” to due to traffic directed to it by other items.

Our aim here is thus twofold. First, we propose a method for assessing the network value of items in a given large-scale product network, using an approach that is in the spirit of the PageRank algorithm (Brin and Page 1998). For each item, we differentiate between the intrinsic value portion of its revenue, which is self-generated by the item, and the incoming value portion of its revenue, which is driven by the incoming recommendation links pointing from other items to the focal item. We assume that the incoming value of a given product “belongs” to the items that point to that product rather than to the product itself. Thus, we define a product’s network value (i.e., the value that takes into account its network relationship) as the sum of its intrinsic value and the value it generates for its neighbors via its outgoing links, which we label outgoing value. The approach we present here is applicable to large-scale databases and can be implemented in a relatively straightforward way, relying on observable data. This is of notable importance given that a product’s value is of interest not only to the retailer, but also to external parties such as product manufacturers whose access to such internal sales data may be limited.

Given the approach of value measurement in product networks, our second aim is to better understand the sources of network value, and specifically to examine how the network value of high selling items differs from that of low selling items. We apply our approach to a large product network of books collected from Amazon.com, and show that the value of low selling items is in fact underestimated compared to that of bestsellers: The network value of low sellers is higher than their revenue, while the network value of bestsellers is lower than their revenue. We find that while, because of their high sales, bestsellers contribute more traffic to the network compared with lower sellers (high outgoing value), on average the value they derive from the network is even greater than the value they contribute (high incoming value) due to three reasons: (a) they are recommended by more books, (b) the books that recommend them are higher sellers themselves and thus can send more traffic, and (c) the conversion rate of the incoming links for bestsellers is higher. In contrast, low sellers have much lower outgoing value as compared with bestsellers, but are also less frequently recommended, and thus their incoming value is even lower than their outgoing value. Additional data we collected from BarnesAndNoble.com support the ubiquity of this phenomenon.

This study contributes to current literature in a number of ways. First, it broadens the analysis of inter-product purchase effects, leveraging the new IT-enabled "store layout". Second, it highlights the need to consider the different means by which a product generates value for a firm. One can see an analogy to the case of social networks, where there is a growing understanding that a customer’s value to a firm stems not only from his purchases but also from his social influence, e.g., through word of mouth and imitation.
In the same spirit we aim to understand how the value items obtain from and provide to the network affects their overall value. This enables a new look at a firm’s product portfolio, based on the types of value that each product contributes and receives.

Third, we are better able to understand the magnitude and sources of value for a firm from different sales tiers. In particular, the importance of the larger number of low selling items known as the “long tail” of demand in electronic commerce and the ways in which the emergence of the long tail is driven by recommendation systems have been at the center of an ongoing discussion. We show that beyond facilitating the creation of the long tail, recommendation systems also enable the long-tail products to produce more value for the seller.

The paper continues as follows: After a background section, we introduce our theoretical model for computation of the network value of products. We then apply our model to data from Amazon.com, and, specifically, we examine its implications for the estimated value of the different sales tiers. We then discuss the implications of our results and directions for future work.

Background

A number of research streams relate to the work presented here. First, researchers have studied the interrelated effects of products. It is widely recognized that purchases across categories are correlated among consumer goods that are complements or substitutes for one another (Seetharaman et al. 2005; Niraj et al. 2008) and that such interrelated effects can be found in multiple cases, such as the effect of a “loss leader” (Hess and Gerstner 1987), software/hardware effects (Binken and Stremersch 2009) or cross-brand word of mouth (Libai et al. 2009).

In parallel, a group of studies have begun to explore product networks. One of the basic challenges in dealing with product networks is to show that the links can indeed create an effect beyond the underlying correlation between items. Two recent studies warrant specific mention, as they have demonstrated the effect of links: Stephen and Toubia (2010) established that links forming between sellers in an online social commerce network (such as eBay.com) affect sales; Oestreicher-Singer and Sundararajan (2012) looked at a book product network in Amazon, which is similar in nature to the data analyzed here. Oestreicher-Singer and Sundararajan (2012) controlled for alternative explanations for demand correlation using a variety of approaches, and showed that the explicit visibility of a co-purchase relationship does lead to a notable amplification of the influence that complementary products have on each other’s demand levels. Another interesting finding of their study, which we later discuss, is that bestsellers are better able to benefit from such links. That is, the visible incoming links of a bestseller create more sales than those of lower selling items.

Other research in this stream has demonstrated the effect of product network recommendations on search (Kim et al. 2010, 2011) and on sales (De et al. 2010) and has investigated how link design can affect the effectiveness of those recommendations (Bodapati 2008). The current research complements this stream by aiming to better understand how value is actually created at the item level: Given that recommendation links indeed affect consumption, how can we assess the different levels of value that an item contributes to and takes from the network, and how does this distribution of value differ for different items?

Finally, our work is related to growing efforts to understand the nature and significance of the “long tail” of demand in electronic commerce. The idea is that electronic commerce is composed of a relatively large proportion of sales of low-selling and even very-low-selling items, many of which are not sold in traditional stores (Anderson 2008). Previous literature has suggested that supply-side factors, such as broader product variety, and demand-side factors, such as reduced search costs, contribute to the emergence of the long tail (Brynjolfsson et al. 2003; Clemons et al. 2006; Cachon et al. 2008; Choi et al. 2010; Hinz et al. 2011; Brynjolfsson et al. 2011). Brynjolfsson et al. (2010), show that Amazon’s tail has grown longer since the year 2000. Yet, different studies have shown that easier search and observational learning effects can also increase the power of “superstars” in overall sales, and create in addition a “steep tail” (Elberse and Oberholzer-Gee 2007; Tucker and Zhang 2007). It has been argued that recommendation systems can increase the demand for long-tail products by making items that consumers might otherwise not have been aware of visible to them (Anderson 2008; Hervas-Drane 2009; Brynjolfsson et al. 2011), yet these systems may also reinforce the popularity of already popular products (Fleder and Hosanagar 2009; Oestreicher-Singer and Sundararajan 2011). We complement this literature
by looking at recommendation systems and the long tail from a different perspective: Rather than investigate how recommendation systems build the long tail, we explore how they allow the long tail (as well as other items) to provide value to other items. Thus, this work is consistent with recent calls in the marketing literature to better understand the profit impact of Internet recommendation systems and their effect on the value of the long tail (Hennig-Thurau et al. 2010).

Modeling Network Value of a Product

The Setting

We consider a large-scale network of interlinked products. The *outdegree* of a product *u* represents the number of links that originate from product *u* and point to other products, while the *indegree* is the number of links that point to *u* from other products. To help us demonstrate our approach, we will use the example of the recommendation product network of books on Amazon.com, and specifically the co-purchase network (“Customers who bought this item also bought …”). In that network, outdegree and indegree are determined by the links Amazon creates based on co-purchases of books.

The problem we analyze is of a firm that wants to understand the actual value contribution and the types of value generated by each product in the database. Note that our aim is not to analyze the optimal policy of the firm in shaping the network, an intriguing issue that is beyond the scope of this paper. Rather, we accept the structure of the network and the overall sum of revenue of all items as given. What we examine is how to redistribute this sum. Our approach is therefore applicable not only to retailers but also to external parties, such as product manufacturers (e.g., publishers of books in Amazon), who are not able to affect the links in the product network and must accept the network as given.

Revenue is a common measure for the value a product generates for the firm. We divide the revenue of a product into two parts, which we define as follows: (1) The *intrinsic value* portion of the revenue is self-generated by the item. One can think of it as the revenue that the product would be expected to yield on that website if it were not connected to others. (2) A product’s *incoming value* is driven by the recommendation links that point to that product from other products. Thus, for product *u*:

\[ \text{Revenue}(u) = \text{Intrinsic Value} (u) + \text{Incoming Value} (u) \]

It is important to stress that the intrinsic value of a product may depend on the specific website. While such value is clearly related to the inherent attractiveness of the item, intrinsic value may still differ between websites, as it is still affected by promotion, price, ratings and reviews, and the ease of reaching the item from within the website (for example using search tools available).

Our focus here is on the actual contribution of any focal product to the firm, which we label *network value*. Network value of a product stems from two sources, one of which is its intrinsic value. The other is the contribution of this product to the incoming values of products it recommends, which we label the *outgoing value* of the focal product.

\[ \text{Network Value} (u) = \text{Intrinsic Value} (u) + \text{Outgoing Value} (u) \]

This view is consistent with previous work aiming to assess the value of customers in a network by distinguishing between customers’ intrinsic value and the value they provide to the network (Domingos and Richardson 2001).

PageRank as a Benchmark

Our aim is to develop an approach that will re-allocate the value a product generates according to the full recommendation system that the product is a part of. Probably the best-known computational tool that allows a full network approach is *PageRank* (Brin and Page 1998), which is essentially an eigenvector centrality measure. This measure has been used for various applications involving ranking webpages. The best known application is Google's ranking system, but PageRank has also been used for various academic research purposes, for example, for understanding optimal advertising on the web (Katona and Sarvary 2008).

The original PageRank algorithm provides a ranking of the “importance” of a webpage in the hyperlinked structure of the web, based on the following mode:
A Product Network Value Model

The approach we use to determine product value is similar to PageRank, with a fundamental difference: We focus on the traffic (value) a product creates for other products, not only on the traffic it receives. Furthermore, similar to PageRank, we want to take into account the fact that different links (recommendations) generate different levels of traffic; thus, it is not enough to simply evaluate numbers of links. For example, in the context of Amazon, a link from Dan Brown’s bestseller *The Da Vinci Code* is likely to be a more fruitful recommendation compared with one from a lower-selling book.

We define *impressions* \( v \) as the number of people visiting product \( v \)'s page (also frequently referred to as page views) and observe its outgoing links. Clearly, not every link exposure leads to a purchase. We therefore define \( \alpha_{v-u} \) to be the Recommendation Conversion Rate (RCR), which represents the probability that a link exposure will result in a purchase. This probability is a combination of the probability that a link will be clicked on (frequently referred to as click-through rate), and the probability that the user’s visit to the next page will result in a purchase. Essentially, one could refer to the RCR as a “cross-selling conversion rate”.

We can now define the *incoming value* of the product, that is, the sales of the product that are attributed back to the network, as:

\[
(2) \quad \text{Incoming Value} (u) = \sum_{v \in \text{in}(u)} \alpha_{v-u} \cdot \text{impressions}(v) \cdot P(u),
\]

where \( P(u) \) is the price of product \( u \). Note that the greater the volume of traffic directed to the product from neighboring products (i.e., the greater the number of impressions of its neighbors or the link’s RCR), the larger the fraction of revenue that should be attributed to the incoming value of the product. For example, the incoming value of a book on Amazon that is recommended by many bestsellers should be greater than that of a book that earns similar revenue despite not getting many recommendations, or receiving recommendations from books that are not purchased often.

The remaining revenue generated by an item is by definition its *intrinsic value* (that is, the revenue portion that is not generated by incoming links from other items in the network):

\[
(3) \quad \text{Intrinsic Value}(u) = \text{Revenue}(u) - \text{Incoming Value}(u)
\]

= \( P(u) \cdot \left( Q(u) - \sum_{v \in \text{in}(u)} \alpha_{v-u} \cdot \text{impressions}(v) \right) \)

1. This model is often extended to include the possibility that a surfer might not follow one of the page’s links, but rather jump to a random page with probability \((1-d)\) (the “damping factor”); in this case
\[
\text{PageRank}(u) = \frac{(1-d)}{N} + d \sum_{v \in \text{in}(u)} \frac{\text{PageRank}(v)}{\text{OutDegree}(v)},
\]

where \( N \) is the number of pages on the web.
We can now attribute the respective portions of the incoming value to the items that originated these revenues. Therefore, the outgoing value of item $v$ is then the sum of all revenues that item $v$ generates by recommending other products:

$$\text{(4)} \quad \text{Outgoing Value}(v) = \sum_{u \in \text{Out}(v)} \alpha_{v \to u} \cdot \text{impressions}(v) \cdot P(u)$$

Adding the intrinsic value to the outgoing value of item $v$, we obtain an expression for $v$'s network value:

$$\text{(5)} \quad \text{Network Value}(v) = \text{Intrinsic Value}(v) + \text{Outgoing Value}(v)$$

$$= \left[ Q(v) - \sum_{u \in \text{In}(v)} \alpha_{u \to v} \cdot \text{impressions}(u) \right] \cdot P(v)$$

$$+ \sum_{u \in \text{Out}(v)} \alpha_{v \to u} \cdot \text{impressions}(v) \cdot P(u)$$

**Iterations and Convergence**

A fundamental question when exploring influence in networks is that of the "ripple" effect: To what extent can we assume that the network value created by an item spreads in a contagion-like way into the network, beyond the first degree of separation? We dealt with this issue by building an iterative process that enables the outgoing value of a given item to be “pushed” back to other items at higher degrees of separation. Owing to space constraints, we will not elaborate on this issue. Details are available upon request.

**Applying the Network Value Assessment Approach: The Issue of Profitability Tiers**

**The Amazon Co-purchase Network**

We created a database of product data including pricing, Sales Rank, rating and co-purchase network information for over 900,000 books sold on Amazon.com on a particular day in 2010. While Sales Rank is not an exact measure of sales, previous research has suggested methods of converting it into a sales measure. Thus, demand is computed based on the Sales Rank data provided by Amazon and following a log-linear conversion model suggested by Chevalier and Goolsbee (2003) and by Brynjolfsson et al. (2009) with the correction shown by Gabaix and Ibragimov (2009).

Amazon’s recommendation system is probably the best known among electronic retailers and has been widely used to demonstrate the role of recommender systems in general (Brynjolfsson et al. 2003; Fleder and Hosanagar 2009; Kim et al. 2011). Each product on Amazon.com has an associated webpage containing a set of “co-purchase links”, which are hyperlinks to products that were co-purchased most frequently with that product on Amazon.com (listed under the title, “Customers who bought this item also bought …”). In most online product networks that are based on a recommendation system, the number of recommended items is quite limited. On Amazon, for example, the co-purchase set for each webpage was limited to five items until relatively recently. Currently, more entries are allowed, but recommendations are effectively limited to no more than five for most users due to screen size.

The network was collected using a snowball sampling method, which started from a number of seed books and resulted in a large connected component.

**Ultimate Purchase Decision (UPD) data:** At the time the data were collected, another source of data was available to us that provided us with a richer representation of the effects in the product network (this source is no longer available). Near the bottom of each book’s page, Amazon presented a list titled “What Do Customers Ultimately Buy after Viewing This Item?”, which showed the books purchased by visitors to the page and the percentage of visitors who bought each book. As we will elaborate in what follows, this

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2. The Sales Rank is a number associated with each product on Amazon.com, which measures its demand relative to other products. The lower the number is, the higher the sales of that particular product.
information, which is a synthesis of Amazon’s click-through data, provided us with a proxy for the recommendation conversion rate for different items. UPD data were available for the vast majority of the books (764,769 books out of 916,944 of the books in the recommendation network), so the final network we use includes the connected books for which we have UPD data.

**Adjustments Made for the Empirical Dataset**

We adapted the data collected from Amazon to our model as follows.

The number of impressions, $\text{impressions}(v)$, is the number of Amazon buyers visiting product $v$’s page. Hence, the population we deal with consists solely of people who eventually purchased something. While this information was not directly available, the value of $\text{impressions}$ for each book could be calculated according to the UPD data and the demand for the book. That is, given the demand for book $v$, if $k$ percent of eventual buyers who viewed book $v$ purchased book $v$, then the number of impressions for book $v$ is:

$$\text{impressions}(v) = \frac{\text{Demand}(v)}{k_v}$$

The value of the recommendation conversion rate (RCR). A key parameter value needed to apply the model above is that of $\alpha_{v\leftrightarrow u}$: the RCR, or the probability that a recommendation link from book $v$ will convert into sales of book $u$. For a link between a given book $v$ and a given book $u$ in the recommendation network, we use the percentage of viewers of book $v$ who ultimately bought book $u$ as $\alpha_{v\leftrightarrow u}$. These values are available to us from the UPD data described above. (In cases in which recommended book $u$ was not included in the UPD data, the RCR was set to zero.)

Endogeneity issues in the Amazon network. Before we present the results, it is necessary to acknowledge endogeneity issues, which present challenges to the study of social networks (Manski 2000), and are also an issue in the case of product networks. Endogeneity largely stems from the fact that the product networks for retailers such as Amazon are created via the recommendation systems, and so network position is a function of past sales, which biases the study of the network’s influence on subsequent sales. While it has been shown that recommendation networks impact demand beyond alternative sources of correlation (Oestricher-Singer and Sundararajan 2012), it is still necessary to acknowledge that a person might have purchased the recommended book even in the absence of a recommendation, meaning that the real RCR values may be lower than those inferred from a straightforward measurement of purchases via clickstream data.

We took several steps to address this issue (see more following the data analysis). First, we repeated our analysis using RCR values (for each dyad of books) that were exogenously and randomly assigned on the basis of the distribution of RCR. That is, we assigned RCR values that were not the result of the true sales patterns. In this way we avoided measurement bias that stems from preexisting correlation among books. Second, we further varied the mean of the distribution of the simulated RCR to see how the fundamental results are affected by the mean level of influence in the network. As we later discuss, the substantive findings remain the same under different RCR levels. Finally, we note that in the following analysis our focus is on the differences among sales tiers, and not on measurement per-se for specific items. Thus, even if the RCRs that are attributed to the existence of the product network should be lower than the values used here, our essential results will still be relevant as long as the overall value distribution pattern characterizing the different tiers remains the same.

**Basic Results for Amazon**

We ran the iterative network value algorithm on the Amazon data, generating for each book measures of intrinsic value, incoming value and outgoing value. Consequently, we could compute the network value for each item. Columns 1 to 5 of Table 1 show summary statistics of our network value, incoming value, intrinsic value and outgoing value binned according to the revenue of the corresponding products. 3

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3. The binning of 20% follows the conversion when discussing demand distribution, and specifically the tail of the distribution.
A number of observations emerge from Table 1. First, books’ incoming value is considerably lower than their intrinsic value. That is, most value originates from the books themselves and not from recommendations. However, the ratio between books’ incoming value and their revenue varies across books in different revenue tiers. In the lowest selling tier—the bottom 20% in terms of revenue (“low sellers”)—books’ average incoming value is about 13.36% of their revenue. For the top selling tier—the top 20% in revenue (“bestsellers”)—this ratio is close to 22.74%. That is, the incoming value is relatively higher for bestsellers.

In terms of the outgoing value, the picture is somewhat different. Like incoming value, outgoing value is considerably lower than intrinsic value, yet in this case we observe a different trend. Looking at the ratio of the average outgoing value to revenue across tiers, we find that for low sellers the proportion of the outgoing value (3.03/6.21=48.75%) is higher than for other tiers. This proportion monotonically decreases as the revenue tier increases, culminating in a value of 15.67% for the bestsellers.

To better view the results, we define a measure that combines the different types of value for a given book, representing the difference between the value the item contributes to the network and the value it receives. We label this measure net influence.

\[
(7) \text{ Net influence} = \text{OutgoingValue} - \text{IncomingValue} = \text{NetworkValue} - \text{Revenue}. 
\]

It is straightforward to see that net influence is also the difference between the network value of an item and its revenue. Because this amount may depend on the sales level of the book, we can also consider the relative net influence of a book: net influence divided by revenue, which represents the portion of change between network value and revenue. Columns 6 and 7 of Table 1 show summary statistics of the net influence and the relative net influence, binned by revenue tiers.

Table 1 shows a clear and monotonic pattern: higher selling items contribute more to the network than lower selling items, yet benefit even more from it. This is apparent for the net influence, and the difference among tiers is even more vivid when the relative net influence is considered. Among low sellers (bottom 20%), relative net influence is 35.38%. Relative net influence monotonically decreases as revenue tier increases, so for the bestsellers, the relative net influence is -7.07%. That is, if one assesses a book’s value according to its revenue only, then the actual value that the seller derives from books in the tail may be underestimated, while the actual value derived from books in the head may be overestimated.

Using the demand conversions over our sample, we find that the value of the head of the distribution (top 20%) is overestimated by $1,166,683 a week, of which $292,645 are attributed to the tail of the distribution (lowest 20%). Of course, this does not mean that the books in the tail generate more absolute value than the books in the head. However, the value that low sellers generate is greater than the direct revenue they bring in, and therefore these books are underestimated.

The Sales Tier Effect: Why Are Bestsellers Overestimated?

We aim to explore the sources of the phenomena observed above. We identify a number of factors that together create the divergence among the sales tiers.

The number of incoming links. Consider Table 2, column 1, which presents information about the average indegree for books from different profitability tiers. Recall that the outdegree (the books that the focal
book recommends) is effectively limited in size, owing to the way that co-purchased products are presented on Amazon. The indegree, in contrast, varies substantially and is unlimited; yet we observe that that low selling books receive half the number of recommendations that bestselling books receive. This may not be surprising given that popular books are co-sold with more other books; yet this implies that low sellers may benefit less from the network (i.e., lower incoming value).

<table>
<thead>
<tr>
<th>Revenue Percentile</th>
<th>Average Indegree</th>
<th>Average units sold by the incoming link's books</th>
<th>Fraction of incoming links from books of the same revenue tier</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-20%</td>
<td>2.48</td>
<td>0.87</td>
<td>0.58</td>
</tr>
<tr>
<td>20-40%</td>
<td>3.24</td>
<td>1.03</td>
<td>0.33</td>
</tr>
<tr>
<td>40-60%</td>
<td>4.18</td>
<td>1.16</td>
<td>0.28</td>
</tr>
<tr>
<td>60-80%</td>
<td>5.38</td>
<td>1.33</td>
<td>0.29</td>
</tr>
<tr>
<td>80-100%</td>
<td>10.12</td>
<td>2.16</td>
<td>0.44</td>
</tr>
</tbody>
</table>

Table 2 – Revenue tiers and statistics about incoming links

The assortativity of demand. The next issue relates to the types of books that the products in each tier are connected to. We see from Table 2 (column 2) that books pointing at low sellers sold 0.87 units on average, whereas books pointing to bestsellers sold 2.16 units on average. Similarly, from column 3 we observe that books in a given revenue tier receive a large percentage of their recommendations from books in that same tier. That is, 58% of recommendations for low selling books come from low sellers, and 44% of the recommendations for bestsellers come from bestsellers. Thus, the product network is characterized by a high degree of network assortativity, a phenomenon frequently observed in social networks (Newman 2002) in which nodes in a network tend to be connected to nodes with similar attributes. In our context this means that high selling books get on average more traffic from the books they are connected to and thus benefit from a higher incoming value.

The average recommendation conversion rate (RCR). One other source of difference can stem from a differential RCR among books. To see the patterns in our data consider Table 3, which presents the average RCR from each tier to each of the others. Note that on average the conversion rate of recommendations from low sellers to bestsellers is 3.37%, while the RCR from bestsellers to low sellers is 1.48%. Looking at the average effects for each tier, two issues arise.

<table>
<thead>
<tr>
<th>From Tier</th>
<th>0-20%</th>
<th>20-40%</th>
<th>40-60%</th>
<th>60-80%</th>
<th>80-100%</th>
<th>Average outgoing RCR</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-20% - Low sellers</td>
<td>2.43%</td>
<td>3.52%</td>
<td>3.85%</td>
<td>3.87%</td>
<td>3.37%</td>
<td>3.41%</td>
</tr>
<tr>
<td>20-40%</td>
<td>2.16%</td>
<td>2.99%</td>
<td>3.44%</td>
<td>3.60%</td>
<td>3.44%</td>
<td>3.13%</td>
</tr>
<tr>
<td>40-60%</td>
<td>1.97%</td>
<td>2.49%</td>
<td>2.91%</td>
<td>3.27%</td>
<td>3.51%</td>
<td>2.83%</td>
</tr>
<tr>
<td>60-80%</td>
<td>1.83%</td>
<td>2.17%</td>
<td>2.51%</td>
<td>2.94%</td>
<td>3.49%</td>
<td>2.59%</td>
</tr>
<tr>
<td>80-100% - Bestsellers</td>
<td>1.48%</td>
<td>1.76%</td>
<td>1.96%</td>
<td>2.23%</td>
<td>3.01%</td>
<td>2.06%</td>
</tr>
<tr>
<td>Avg. incoming RCR</td>
<td>1.97%</td>
<td>1.76%</td>
<td>1.96%</td>
<td>2.23%</td>
<td>3.01%</td>
<td>2.06%</td>
</tr>
</tbody>
</table>

Table 3 – Average RCR among revenue tiers Incoming RCR.

We find that the average RCR of links pointing to bestsellers is higher than the RCRs of links pointing to lower sellers (e.g., 3.01% on average for bestsellers versus 1.97% for low sellers). This result is consistent with the findings of Oestreicher-Singer and Sundararajan (2012), who showed a similar pattern even after controlling for other sources of demand correlation between bestsellers and other books. In our case the implication is that the effective incoming value of bestsellers will be higher than that of lower sellers.

Outgoing RCR. The other observation is that the outgoing RCR of low sellers is higher than that of bestsellers. This increases the outgoing value created by low sellers. That is, people who visit the webpage of a bestseller are less likely to continue searching and to buy other items. Note, however, that even given this issue, the outgoing value of bestsellers is considerably higher than that of low sellers (see Table 1), because of the higher traffic to bestsellers’ pages. Therefore, while this phenomenon moderates the difference between low sellers and bestsellers, it does not refute the intuition that links from bestsellers will lead to more sales.
Overall, we find that bestsellers are recommended more frequently, the recommendations they receive are from higher selling books, and the conversion rates of their incoming links are higher. This results in a relatively high incoming value for high-selling products. While such products also generate more value (i.e., higher outgoing value), this value is not enough to “compensate” for the higher incoming value, and their overall network value is lower than their revenue.

Robustness Checks

In this section we examine the robustness of our results to two major changes in the environment we analyze: a simulated RCR that is not correlated with sales tier, and a network of a different seller.

A Simulated RCR

Since the RCRs we use are based on Amazon’s co-purchase data, and given the endogeneity issues discussed above, one question is what our results would look like if the RCR were independent of the network structure. One way to examine this is to randomly draw the RCR for each dyad from a predefined distribution of RCR values. Selecting RCR values in this way would help us to avoid any measurement bias that stems from correlation in items’ demand levels.

Thus, we re-ran the analysis with the same items and same network structure, but instead of using the empirical proxy for RCR, we drew RCR values from a normal distribution. We repeated this analysis using different mean values for the RCR distribution. The results for the main parameter of interest—the relative net influence—are presented in Table 4.

The picture that emerges is remarkably similar to that with the empirical RCR, and is consistent across all levels of average RCR. Low sellers (bottom 20% of books) are clearly undervalued. As the sales tier increases, the positive difference between network value and revenue becomes smaller, and for bestsellers (the top 20%) the difference becomes negative. As in the case of our original analysis (Table 1), bestsellers’ network value is lower on average than their revenue. Thus, the power of differential in degree and assortativity is enough to create the net influence pattern we witnessed.

<table>
<thead>
<tr>
<th>Revenue Percentile</th>
<th>RCR=1%</th>
<th>RCR=2%</th>
<th>RCR=3%</th>
<th>RCR=4%</th>
<th>RCR=5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-20%</td>
<td>4.96%</td>
<td>9.93%</td>
<td>14.98%</td>
<td>20.08%</td>
<td>25.23%</td>
</tr>
<tr>
<td>20-40%</td>
<td>2.69%</td>
<td>5.36%</td>
<td>8.07%</td>
<td>10.81%</td>
<td>13.54%</td>
</tr>
<tr>
<td>40-60%</td>
<td>1.41%</td>
<td>2.84%</td>
<td>4.26%</td>
<td>5.70%</td>
<td>7.14%</td>
</tr>
<tr>
<td>60-80%</td>
<td>0.77%</td>
<td>1.54%</td>
<td>2.32%</td>
<td>3.09%</td>
<td>3.88%</td>
</tr>
<tr>
<td>80-100%</td>
<td>-1.00%</td>
<td>-2.01%</td>
<td>-3.02%</td>
<td>-4.04%</td>
<td>-5.07%</td>
</tr>
</tbody>
</table>

Table 4 – Results of network value estimations using different mean RCR values (Amazon).

Comparing analyses using different average RCR values, the following picture emerges: The higher the average RCR: (a) the larger the incoming value; (b) the larger the outgoing value; and (c) the lower the intrinsic value. This pattern is observed for all revenue tiers. Recall that a higher RCR value suggests that people are more likely to click on a link on a product page and buy, which reflects more traffic through the network. We find that as consumers use the network more, items increasingly affect others and are affected more. Thus, the role of the intrinsic value of the item decreases. It should be noted, however, that even with an RCR value of 5%, intrinsic value is by far greater than incoming or outgoing value.

Applying the Model to BarnesandNoble.Com Data

While the prominent status of Amazon has made the website a source of analysis for numerous academic explorations of electronic commerce, an interesting question is, to what extent will the results reported here hold in other environments? To examine this point, we replicated the analysis using a second dataset of 257,000 books collected from the eCommerce website of BarnesAndNoble.com. The overall patterns of value distribution are consistent with those we identified above.
The data we were able to retrieve for BarnesAndNoble.com were far more limited than the data for Amazon: BarnesAndNoble.com did not report data similar to the UPD data in Amazon, and we were therefore unable to assess impressions and conversion rates. Hence, in what follows we use demand (units sold) as a proxy for impressions. We carried out a similar analysis for Amazon to be able to compare the two product networks. Based on the range of RCR values we observed for Amazon, for each dyad the RCR was chosen from a normal distribution $N(2\%, 0.4\%)$. Furthermore, to compare the two networks, we focused on a sub-network of 183,544 books that were present in both samples. Given that this is a subsample and not a complete network, the average outdegree is of course lower.

Results of the analysis for the Barnes and Noble data and for the restricted Amazon dataset are presented in Table 5.

<table>
<thead>
<tr>
<th>Revenue Percentile</th>
<th>Average Revenue ($)</th>
<th>Average Network value ($)</th>
<th>Average Incoming value ($)</th>
<th>Average Intrinsic value ($)</th>
<th>Average Outgoing value ($)</th>
<th>Average Net Influence</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Amazon.com</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-20%</td>
<td>5.83</td>
<td>6.19</td>
<td>0.33</td>
<td>5.50</td>
<td>0.70</td>
<td>6.29%</td>
</tr>
<tr>
<td>20-40%</td>
<td>11.20</td>
<td>11.56</td>
<td>0.75</td>
<td>10.45</td>
<td>1.12</td>
<td>3.26%</td>
</tr>
<tr>
<td>40-60%</td>
<td>17.28</td>
<td>17.56</td>
<td>1.31</td>
<td>15.97</td>
<td>1.60</td>
<td>1.66%</td>
</tr>
<tr>
<td>60-80%</td>
<td>28.78</td>
<td>29.02</td>
<td>2.29</td>
<td>26.49</td>
<td>2.53</td>
<td>0.82%</td>
</tr>
<tr>
<td>80-100%</td>
<td>105.18</td>
<td>103.64</td>
<td>9.90</td>
<td>95.29</td>
<td>8.36</td>
<td>-1.47%</td>
</tr>
<tr>
<td><strong>BarnesAndNoble.com</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-20%</td>
<td>10.20</td>
<td>10.81</td>
<td>0.64</td>
<td>9.56</td>
<td>1.24</td>
<td>5.95%</td>
</tr>
<tr>
<td>20-40%</td>
<td>18.75</td>
<td>19.50</td>
<td>1.17</td>
<td>17.58</td>
<td>1.91</td>
<td>3.97%</td>
</tr>
<tr>
<td>40-60%</td>
<td>28.07</td>
<td>28.86</td>
<td>1.88</td>
<td>26.19</td>
<td>2.68</td>
<td>2.82%</td>
</tr>
<tr>
<td>60-80%</td>
<td>44.64</td>
<td>45.37</td>
<td>3.29</td>
<td>41.35</td>
<td>4.02</td>
<td>1.64%</td>
</tr>
<tr>
<td>80-100%</td>
<td>150.85</td>
<td>148.51</td>
<td>13.71</td>
<td>137.14</td>
<td>11.37</td>
<td>-1.55%</td>
</tr>
</tbody>
</table>

Table 5 – Network value estimation results for Amazon and BarnesAndNoble.com using an average RCR of 2%.

Discussion

The emergence of online recommendation systems makes product networks a vivid reality for firms, and highlights the question of how managers can take advantage of product networks to enhance profitability. Here we focused on how product valuation can take the product network into account, presented an approach that enables marketers to adopt a network value view of products, and demonstrated its applicability for understanding the relationship between sources of value and revenue tiers in large-scale databases. In what follows, we focus on the implications and applications of the product network value approach.

Basic Measurement

The key to informed use of a product network is proper measurement of the effects, and especially the RCRs among dyads. There are two kinds of stakeholders we can consider: external users such as manufacturers and advertising agencies, and internal users, i.e., the eCommerce retailers (Amazon in our example). The external user has restricted access to the product network data. Still, to assess network value this user can do a number of things: a) use proxies, based on available online data, of the kind we used here to assess the product network parameters; b) purchase large-scale clickstream data from external service providers; and c) negotiate with internal users to obtain access to better data. Note that retailers who wish to carry out competitive benchmark analysis (e.g., Amazon analyzing the situation at BarnesAndNoble.com) are also limited in terms of their access to data and therefore would benefit from the ability to perform external analysis using limited data.

Looking at their own networks, retailers such as Amazon have access to much richer data compared with external users. For example, the retailer can use actual clickstream data in order to track how the links between items are activated, and thus to more precisely measure the recommendation conversion rate.
Yet, even given these data on link activation, a question of endogeneity remains: How many people who purchased items after following a link would have purchased those items without the existence of the product network? The advantage of a retailer is that it can conduct experiments to be better informed on this point. While it may not be practical to carry out continuous experiments for millions of items, an analysis of samples can help determine the answer. Approaches such the ones presented in Oestreicher-Singer and Sundararajan (2012a) can help eCommerce retailers to develop better capabilities in this regard.

Given the assessment of the RCR and the product network structure, managers can use the framework presented here to compute the different kinds of value that each item creates in the product network. Ideally, for each item, in addition to revenue, the firm can record outgoing, incoming and network value. This information can serve the firm in carrying out a dynamic analysis of the product network. A temporal, dynamic analysis of product networks is recommended for two reasons. First, product networks change with time: New products enter, the demand for certain items may saturate as a function of natural diffusion processes, and different trends affect demand. These processes may result in changes to the network value of the products in the network. The magnitude and range of such changes warrant exploration. A second issue is that dynamic changes present an opportunity to explore the effects in product networks, for example to get more accurate estimates for the RCR. This can happen when product networks are formed (Stephen and Toubia 2010) but also in the natural process in which links are formed and disappear over time. However, such analysis should be done carefully to control for exogenous events that happen during the intervals between observations (e.g., pricing or advertising changes) that can affect the intrinsic value of items and consequently the product network calculations.

A dynamic analysis can also help managers to think of how to build optimal product networks, an issue that is clearly of interest to online retailers. This requires further investigation beyond the scope of this study, which focused on re-allocating existing revenues and not on optimal ways to increase overall revenue. It should be also recalled that retailers such as Amazon claim that they do not try to manipulate the recommendation system in their favor, and thus any optimization effort should take into account the integrity of the recommendation system.

Managerial Use of the Product Network Knowledge

In recent years the use of recommendation systems has grown, alongside efforts to make these systems more effective. Yet much of the effort has focused on effective ways to build the recommendation systems, with little exploration of the profit implications (Hennig-Thurau et al. 2010). Managers can use the value-related measures presented here to obtain a better understanding of marketing in the presence of product networks in a number of ways:

Which products to keep. Companies increasingly aim to optimize their product and brand portfolios by considering the value each product generates, getting rid of items that do not provide enough value (Aaker 2004). Giving the possible discrepancy we demonstrated between revenue and network value, firms should see beyond revenue when making such decisions. This is similar to the transition in the customer management literature from viewing a customer’s value (and consequently the customer portfolio) as based solely on her purchases — to a broader view that also takes into account the customer’s effect on others via word of mouth (Kumar et al. 2010; Libai et al. 2010).

Our empirical analysis of the Amazon data is a good example. While firms may use revenue level to decide on the fate of products, in eCommerce sites the full value of the product should be taken into account. Our analysis suggests that the difference among revenue tiers may be somewhat smaller than that perceived based on revenues: In Amazon (and BarnesAndNoble.com) bestsellers may contributes less than perceived, and low sellers may contribute more. This should be taken into account in the decision of which products to keep.

In a broader sense, it is interesting to tie these results to literature on the “long tail” of demand in electronic commerce. This stream of literature is based on the idea that electronic commerce is composed of a relatively large proportion of sales of low-selling and even very-low-selling items, many of which are not sold in traditional stores, and that in fact these “long-tail” products provide an overall high value to sellers (Anderson 2008). Previous literature has suggested that supply-side factors, such as broader product variety, and demand-side factors, such as reduced search costs, contribute to the emergence of
the long tail (Brynjolfsson et al. 2003; Clemons et al. 2006; Hinz et al. 2011). Yet, different studies have shown that easier search and observational learning effects can also increase the power of "superstars" in overall sales, and create in addition a "steep tail" (Elberse and Oberholzer-Gee 2007; Tucker and Zhang 2007). It has been argued that recommendation systems can increase the demand for long-tail products by making items that consumers might otherwise not have been aware of visible to them (Anderson 2008), yet these systems may also reinforce the popularity of already popular products (Fleder and Hosanagar 2009; Östreicher-Singer and Sundararajan 2012b). The network value of products had not been taken into account in this stream to date. Our empirical analysis with the Amazon data suggests a clear need for future research using clickstream data to compare the RCRs of bestsellers with those of low sellers. Such research would facilitate further assessment of the real value of the long tail.

Marketing mix. Marketing mix decisions should clearly take into account how each product affects the other items connected to it. For example, additional intrinsic value created for an item via a promotion or low pricing may affect the outgoing value for other items that point to the focal product. The decision whether to place a product online or offline should also take into account incoming and outgoing value, value types that are not easily created in offline environments. Product network value analysis can thus help in achieving a more holistic understanding of the contribution of marketing mix actions.

Such issues are notable for advertising strategies. Many online environments use the pay-per-click (for example on search engines such as Google and Bing) or pay-per-purchase (for example in affiliate networks) advertising models. Often, keywords related to bestsellers have a higher bidding price than keywords related to low sellers, which makes the cost per click for the bestsellers' keywords higher than the cost per click for the low sellers' keywords. In order to take advantage of this difference, the advertiser should optimize his or advertising spending by looking at the network value of each of product instead of just its revenue. Similarly, in affiliate marketing, a commission is paid for each sale generated. In this case, in order to increase the number of sales and maximize the total network value, one can offer a higher commission percentage on the lower selling products.

Managing vertical relationships. An interesting implication of the product network value approach relates to the relationship between the eCommerce retailer and the manufacturers (e.g., the book publishers for Amazon). A product made by one manufacturer can generate recommendations for and receive recommendations from other products, which create a divergence between the value of the product to the retailer and the value to the producer. This discrepancy can affect the composition of the optimal product assortment and pricing, and in more general terms it can affect the balance of power in channels.

A straightforward way to look at this calculation is via the "net influence" measure. If the net influence of an item is positive, then the item gives the network more than it gets. The manufacturer may want to argue in such a case that it should receive a share of the total profits created by the item, rather than just a share of the revenue. When net influence is negative, the retailer may want to argue for paying the manufacturer a lower share.

In a general sense future research should further examine how the product network changes relationships in online channels. Recent research in this area has focused on the relationship between manufacturers and retailers and considered the optimal assortment the retailer should carry, and its price (Dragansk a, et al. 2009; Dukes, et al. 2009). Literature on slotting allowance, for example, has discussed the information asymmetry between the manufacturer and the retailer with regard to the true quality (and hence value) of the product (e.g., see Bloom, et al. 2000). Yet, none of these streams of literature has taken product network issues into account.

“Influencers” in Product Networks

It is interesting to compare the results we obtain regarding the flow of value in product networks to those obtained in research on social networks. Numerous studies have been devoted to the role of influencers in social networks, especially in the context of new product adoption (Katona et al. 2011, Iyengar et al. 2011). In many cases, influencers were identified on the basis of their connectivity to many others, or being a “hub” (Goldenberg et al. 2009). This was done under the assumption that higher connectivity leads an individual to influence more people, which also makes that individual an attractive target for seeding strategies (Hinz et al. 2011).
Who (or rather, which products) may be labeled “ influencers” in a product network? In most product networks the number of outgoing links is limited, so a straightforward comparison to social network hubs is not trivial. What is more essential to the effect on others is the amount of traffic an item can send via its existing links. The traffic that an item receives (and can subsequently divert onward) is captured here in the number of impressions on the item’s page. On the other hand, we should take into account the outgoing RCR from the item to other items, which is equivalent to persuasiveness in social networks. In the case of social networks, while per-link persuasiveness is often not available to researchers and thus often not considered, recent research suggests that, compared with less connected individuals, hubs may have a lower individual-level effect on each of their connections because of the limited attention the hub can give each connection (Katona et al. 2011). Here we also saw that the average RCR of outgoing links of bestsellers is lower than that of lower sellers (see Table 5); this may be due to higher quality or broader appeal of the focal book (e.g., lower tendency to keep searching).

To connect influence to revenue tiers, we define influencers as the top 10% in terms of outgoing value. The overall picture that emerges for the Amazon data (see also Table WF1 in Web Appendix F) is that the distribution of influence in the Amazon product network is spread across revenue tiers. While the majority (56%) of influencers are among the bestsellers (top 20% of revenue), the effect is still spread across revenue tiers.

Another issue is that of net influence. Here the comparison to social networks is limited, given that the research on the contribution of influencers in social networks has focused largely on the role of outgoing links, and not incoming ones. Nevertheless, it has been suggested that influencers in social networks have a higher-than-average indegree and thus are early adopters, which in turn contributes to their value (Goldenberg et al. 2009). Because the issue we investigate is not a contagion process, but valuation in existing product networks, in our context a product with a larger number of strong incoming links would have lower value relative to revenue, because some of its revenue actually comes from other items.

If we define influencers as the group of products with the top 10% of net influence, we find that bestsellers are again most likely to be influencers, but in this case they make up a smaller portion of the group (42%) as compared with influencers defined on the basis of outgoing value (see also Table WF1 in Web Appendix F). This result is particularly intriguing given that on average the net influence of this group is negative (see Table 3). It thus seems that there may be large differences among bestsellers in terms of net influence, which are driven by incoming value.

**Future Research and Limitations**

The analysis of value created in product networks raises many questions that are beyond the scope of this paper, and can be explored in further research. A few directions for future research are presented in what follows:

*Richer data.* We used the UPD database from Amazon to assess the RCRs between different products, yet rich large-scale clickstream data can help in fine-tuning this assessment. Such data also help to better analyze the factors that affect the RCR, for example, category popularity or web page design.

Another issue to further explore is the role of product complementarity. Choosing a specific camera may lead to the purchase of a lens, but it is not often that the purchase of a lens will lead to the purchase of a camera. Clickstream data should be carefully analyzed in such cases to ensure that the use of links by customers really creates a conversion effect.

The "goodness" of the recommended product. Clearly, if a link points to a product of high quality, the product is more likely to be purchased. Thus, future work may want incorporate the quality of the recommended product in the conversion rate, for example by assigning weights. However, given that in the simulation section, we randomly allocate the conversion rate, and the results are consistent across different values of RCR, we do not expect this to change our empirical findings significantly.

*Incremental revenue and dynamic analysis.* Our aim here was to re-distribute the value in an existing product network in which the overall revenue was fixed. Thus, in our framework if an item is taken out of the network, the disappearance of its outgoing value will result in a reduction of the incoming value of other items and consequently in an increase in their intrinsic value. Overall, no value will be lost.
One could build a system to examine how much value is added to the system when an item is lost or added. Towards this purpose a dynamic analysis of the product network over time is needed. However, such data are not always available. Another possibility is to examine a product network at different points in time. Yet, this analysis should be done very carefully to control for exogenous events that happen during the intervals between observations (e.g., pricing or advertising changes) that can affect the intrinsic value of items and consequently the product network calculations.

**Advertising-based revenue.** In this paper we focused on value created through sales of products. While this is still the major source of revenue for online retailers such as Amazon, advertising is an increasingly important source of revenue for websites. Note that in an advertising-based model, outgoing value can be created by the mere act of directing traffic to another product's page and does not necessarily depend on the conversion to sales. Hence, the actual “conversion rate” may be higher. However, the revenues per visitor may be lower. An extension of our work in this direction is an interesting avenue for future research.

**Implications for optimal behavior in the market.** Our analysis accepted the network as given and aimed to derive consequences in terms of products' network value. Retailers can theoretically affect the nature of the recommendation system, and thus use the method presented here to examine how the overall change may affect profits. While system design suggestions are outside the scope of this paper, the value framework we propose can be used to analyze the effectiveness of such systems.

**Other types of networks.** While online recommendation systems are natural candidates for product network analysis, product networks exist in various forms in many consumption situations, including offline ones. Items in a supermarket, products in a catalog, or stores in a mall can also be examples of product networks. One interesting observation in this context is that the pattern of interaction between interrelated products on shelves is different from that generated by the interconnected hyperlinks in an online store. The electronic product network is a complex graph, and hence its structure is very different from that of the three-dimensional brick and mortar store. For example, one important difference is that in the online product network links are not necessarily bidirectional. Another difference is that in the online product network the outdegree can be limited, but there is no limitation on the indegree. As a result, there are differences in the indegree and outdegree of products, and in the overall outdegree and indegree distribution. Figuring out the associations among products in offline settings may, however, be a larger challenge compared with the analysis of online recommendation systems. The market-basket analysis literature is a good reference for building association rules among products based on purchase data (Agrawal et al. 1993; Blattberg et al. 2008), and may be used as a starting point towards building product networks based on product associations.

**Conclusions**

Assessing the value of a product is central to informed marketing, including well-planned advertising, brand portfolio planning, channel placement, cross-selling initiatives, pricing, and compensation of marketing personnel. Understanding the true value of products is thus of essential importance for marketers. We present a systematic approach to estimate products' true value (the network value) to a firm in product networks and demonstrate our approach using data collected from the product network of books on Amazon.com. We show that the value of low sellers may be underestimated, while the value of best sellers may be overestimated when assessing the products value according to the direct revenues they create, the traditional method used so far.

As the share of online purchases increases, the ability of firms to measure and affect network value will rise. This study should therefore be only a first step towards a better understanding of this important concept.
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