Social Shopping

Rebecca Anderson

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Social Shopping

by

Rebecca Anderson

A thesis submitted in partial fulfillment
of requirements for the degree of
Master of Science
Department of Information Systems and Decisions Sciences
College of Business Administration
University of South Florida

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Date of Approval:
April 27, 2009

Keywords:  Social Pricing, Recommender Systems, Social Networks, E-Commerce, Trust

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Table of Contents

List of Tables ii
List of Figures iii
Abstract iv
Chapter 1: Social Shopping on the Internet 1
  1.1 What is Social Shopping? 1
  1.2 Matrix of Social Shopping Websites 3
  1.3 Sites in the Matrix 8
  1.4 What is Social Shopping on the Internet? 19
  1.5 Scoring/Social Index 20
Chapter 2: Survey of Research in Social Shopping 22
  2.1 Online Purchase Decisions 22
  2.2 Impact of User Reviews 24
  2.3 Impact of Recommender Systems 26
  2.4 Impact of Social Networks 28
Chapter 3: Pricing Mechanisms and Social Shopping: A Case for Demand Aggregation 31
Chapter 4: A Social Recommendation Algorithm 34
  4.1 Examining Collaborative Filtering 34
  4.2 Examining Amazon.com 36
  4.3 Examining SNACK 38
  4.4 Utilizing the Social Network 40
Chapter 5: Conclusion 43
References Cited 44
List of Tables

Table 1-A  Matrix of Social Shopping Websites  4
Table 1-B  Matrix of Social Shopping Websites  5
Table 2    Social Index  20
Table 3    Weighted Social Index  21
Table 4    Collaborative Filtering  34
Table 5    Item-to-Item Collaborative Filtering  .36
Table 6    Customer Interest Level in Movies by Genre  41
List of Figures

| Figure 1. | Woot | 11 |
| Figure 2. | Kaboodle | 11 |
| Figure 3. | Zebo | 12 |
| Figure 4. | ThisNext | 12 |
| Figure 5. | StyleHive | 13 |
| Figure 6. | StyleFeeder | 13 |
| Figure 7. | ShopStyle | 14 |
| Figure 8. | Amazon | 14 |
| Figure 9. | Walmart | 15 |
| Figure 10. | Target | 15 |
| Figure 11. | JC Penney | 16 |
| Figure 12. | QVC | 16 |
| Figure 13. | Sears | 17 |
| Figure 14. | Overstock | 17 |
| Figure 15. | Kohls | 18 |
| Figure 16. | Macy’s | 18 |
| Figure 17. | Network Classification Model | 29 |
| Figure 18. | SNACK Network Nodes | 39 |
Social Shopping

Rebecca Anderson

ABSTRACT

Social shopping is one of the latest trends on the Internet. Websites dedicated to social networking with a focus on shopping have been emerging on the web for a few years. The basic idea is that consumers are looking for product information on the Internet and social shopping sites provide a place for consumers to find this information from other consumers. These sites provide a place for their users to engage in socialization and shopping simultaneously, sometimes following recommendations of premier users, who are labeled from other users. However, purchases aren’t made through these sites. So, there may still be something missing from the experience. For these sites, social pricing mechanisms may be implemented to provide revenue. Major e-commerce websites have begun focusing on increasing social features throughout the transaction process. For example, more websites are including ratings, reviews and recommendations of products and services by other consumers. However, pure e-commerce websites do not provide functionality that allows consumers to communicate in real time. Hence, there are some features missing from the social experience. Also, the social functionality included in pure e-commerce websites, tends to be utilized for the benefit of the Web site, as opposed to the consumers. Both social shopping sites and e-commerce sites have seen independently successful though few sites have been able to truly integrate these together at this point. It may be more beneficial to the end user if these sites could work in unison. This thesis is an exploratory study of the emerging social shopping phenomenon. The contributions of this work include analysis of the social shopping phenomenon and identifying metrics and Web sites that incorporate social shopping, a survey of academic literature related to social shopping and social pricing and a review of current recommender system algorithms with a discussion on
how to incorporate social networking data into the algorithms to improve recommendations. Improvement suggestions include incorporating customer purchase history with social networking information. Potential future research ideas are included.
Chapter 1: Social Shopping on the Internet

The popularity of social networking sites has steadily increased over the past few years. This is important for businesses because it means that large groups of people are congregating and communicating in the same place online on a consistent basis. Ideally businesses should harness the buying power of the social networks, but this is not always easy. Gaining the trust of many social network users is a difficult task. Social websites are places where people go to interact with friends and meet new people. This is often not the atmosphere in which users want to interact with businesses or be bombarded with advertising. A possible solution is social shopping websites.

Essentially, social shopping encompasses various types of viral marketing. Businesses are increasingly paying attention to this. People who participate on these websites have already identified themselves as buyers and have indicated which products they are interested in. Further, users readily give up information about themselves, such as location and hobbies and they have a group of friends with similar interests. Given the extent of explicitly revealed information these sites are potential gold mines for companies in terms of learning about customers. With social shopping sites, businesses can more easily find and target future customers.

1.1 What is Social Shopping?

There are many definitions for social shopping. Wikipedia defines it as “a method of e-commerce and of traditional shopping in which consumers shop in a social networking environment similar to MySpace.” Entrepeneur.com defines it as “the intriguing offspring of social networking and online shopping.” The New York Times calls it “a new category of e-commerce that tries to combine two favorite online activities: shopping and social networking.” About.com describes it as “the combination of social media and e-commerce. In essence, it is taking all the key aspects of the social web – friends,
groups, voting, comments, discussions – and focusing them on the world’s favorite activity: shopping.” GetElastic describes it as “a mashup that resembles social bookmarking, social networking and comparison shopping in a blender.” Inc.com calls it “services [that] combine the networking power of MySpace with the data-crunching power of Google and in the process bring a little more humanity to the act of shopping online.” The LATimes.com wrote that it is “combine[s] two of the Web’s most prominent activities: engaging in commerce and chatting with like-minded folk.”

Hitwise finds social shopping to be “a group of websites… that center around the users creating customized wish lists to share with friends or people with similar tastes, rather than aggregating content around the product or retailer.” TechCrunch calls it “a strange grab-bag of sites all trying to crack the nut of how to monetize social networking around shopping, which is most social when it is real-world, not virtual.”

These definitions are limiting as they force the definition around e-commerce, as opposed to all forms of commerce. Only TechCrunch and Answers.com reference the idea that social shopping could extend beyond the web. What is social shopping really?

In this thesis we define social shopping as shopping in which a customer’s purchasing process is in part affected by communication between the customer and others who are not affiliated with a product. For example, when two friends are shopping at a department store, one friend may make a comment about an item and the other friend makes a purchase based, at least in part, on that comment.

This concept includes a wide spectrum of communication and shopping scenarios. Some environments create more sociability than others. For instance, shopping malls tend to provide a more social environment than stand alone stores. This is because shopping malls include activities other than shopping that promote social activities, such as dining, movie theaters and arcades. Also, shopping malls play host to a variety of retail stores which allows shoppers to complete multiple tasks in one outing and compare prices and selections between similar items. All these characteristics combine to make shopping malls highly social in nature. Stand alone stores do not provide the same social environment that shopping malls do. It is less likely to see dining or other activities offered in these stores. Also, the shopper is unable to complete as many tasks and is
unable to comparison shop. Stand alone stores do not prohibit social behavior; they simply do not create a social environment. The goal of the stand alone store is product driven, while the goal of the shopping mall is socially driven.

Social shopping can also occur through other forms of commerce, such as shopping using the television. This is most commonly done with companies HSN and QVC that have their own cable television networks. Shopping in this form occurs when viewers purchase an item seen on television by calling a phone number during the program. This form of shopping is not social in nature, but can become social when two or more people are communicating about a product as the sale is happening. For instance, two people could be together in a room, talking over the phone, chatting on the Internet, etc. while watching the television broadcast.

Auctions are a form of shopping that can be social in nature. Shopping in this form occurs when many people bid up the price of an item and the person with the highest bid gets the item. As large groups of people form to bid on products, conversations between individuals are likely and result in social shopping. Shopping over the Internet, or e-commerce, is also popular and can be social in nature. E-commerce began as an individual activity, but with the advent of social networking sites, has increasingly become a social activity. These can be split such as brick and mortar stores into concepts of shopping malls and stand alone stores. There are social networking sites themed around shopping, such a Kaboodle.com, which correlates to the shopping mall. There are product driven sites with social elements that translate to the stand alone store, such as Amazon.com, which most people are accustomed to. E-commerce also takes place in the form of auctions through sites such as eBay.com

1.2 Matrix of Social Shopping Websites

Below is a matrix of the top eight social shopping websites in the United States according to Alexa.com, and the top ten e-commerce websites (excluding eBay Express, since that has since shut down) according to HitWise. There are a total of fourteen prominent social features, displayed below in two separate tables.
### Table 1-A Matrix of Social Shopping Websites

<table>
<thead>
<tr>
<th>Website</th>
<th>Rating</th>
<th>Review</th>
<th>Poll</th>
<th>Profile</th>
<th>Comment Wall</th>
<th>Forum</th>
<th>Email</th>
</tr>
</thead>
<tbody>
<tr>
<td>Woot</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kaboodle</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Zebo</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>ThisNext</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>StyleHive</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>StyleFeeder</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ShopStyle</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Amazon</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Walmart</td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Target</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JC Penney</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>QVC</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sears</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overstock</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Kohls</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Macy’s</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
</tbody>
</table>
Table 1-B Matrix of Social Shopping Sites

<table>
<thead>
<tr>
<th></th>
<th>Blog</th>
<th>Games/Quizzes</th>
<th>Share on Other Sites</th>
<th>Social Network Support</th>
<th>Social Pricing</th>
<th>Recs</th>
<th>Social Recs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Woot</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Kaboodle</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zebo</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ThisNext</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>StyleHive</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>StyleFeeder</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ShopStyle</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amazon</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Walmart</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>N</td>
<td></td>
</tr>
<tr>
<td>Target</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JC Penney</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>QVC</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Sears</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overstock</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Kohls</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Macy’s</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>N</td>
</tr>
</tbody>
</table>

The categories in the columns were chosen because they allow for communication between at least two people.

- When customers rate products, as seen in figure 16, they quickly communicate about the value, usefulness or other measurement to other potential customers.
- Reviews, as seen in figure 3 and figure 9, are similar except that customers have the ability to offer more information about a product than a rating. Ratings and reviews are common across both socially driven and product driven websites.
- Polls, as seen in figure 2, allow people to ask others for their choice among specific products. So, if someone is interested in buying a pair of jeans and is looking at different brands or styles, that person can post a poll requesting others to vote for the best pair.

- Profiles, as seen in figure 7, give people the opportunity to, not only broadcast information about themselves, but search through profiles to find others like them. Profiles allow people with similar tastes and interests to find and connect with one another.

- Comment walls, as seen in figure 6, allow people to write personalized messages to others.

- Forums, as seen in figure 1, provide a space for people to discuss products, brands or anything else as a group.

- Many sites provide an email feature, as seen in figures 11 and 15, which allows someone to send information about a specific product to another person.

- Blogs, as seen in figures 5 and 14, are similar to reviews in that they allow people to write, in as much detail as they wish, about any aspect of a product or brand.

- Some people post games and quizzes, as seen in figure 5, which allows other people to interact with different products.

- Another common feature is the ability to share product information from one site on any other site, as seen in figure 8. This allows one person to communicate with multiple people in various places from one medium.

- Social network support, as seen in figure 4, lets users use existing social networks formed on popular social networking sites, such as Facebook, explicitly.

- Social pricing occurs when users get financial incentives or different product prices based on the degree of their social involvement in the site.

- Recommendations are system generated and often based on proprietary algorithms. Social recommendations are also system generated based on algorithms that generate recommendations specifically for a user but based on other users’ data.
There are few conclusive studies that show which of these particular features influences a purchasing decision and it is also possible that the effects of these features can vary based on the site. However, all the listed features have the potential to influence decisions as they give people the opportunity to interact with the product and communicate with others in the shopping process.

As the matrix shows, recommendations are the most popular of the social features, while social pricing is rare. The matrix can also be viewed as a brief summary of the features that the Internet shopping population is looking for today. Online shoppers want an easy way to sort through all the available choices and they prefer recommendations from people like themselves, or social recommendations. Recommendations are also an easy way to aggregate opinions. With technologies like instant messaging a user can only contact other users one at a time. With recommendations, users can quickly see many opinions at once. The advantage that instant messaging has is that the conversations occur in real time and with someone that the user is already familiar with. Familiarity is helpful because there is already a trust in the taste and opinion of the person giving the recommendation. Amazon, attempts to alleviate the concern in trusting a recommendation by allowing users to review the recommendations. In other words, customers that have utilized a recommendation in a purchase decision can then give a rating about the helpfulness of the recommendation. Amazon sorts recommendations by rating, so new customers first see what other customers found to be helpful. It would be interesting for Amazon to allow users to create taste based profiles and append this information to the recommendations.

There is clearly potential for new social technologies to emerge in this space as well. Real time video messaging and voice communications would be natural since they are technologies already being utilized on the web. These kinds of technologies would increase direct communication between two people already known to one another. Since people prefer recommendations from others that they trust, these technologies have the potential to increase purchases. However, they decrease communication to many people at once, which is what social shopping is founded on. Perhaps the next generation in
social shopping will come full circle back to the people already known to us, as opposed to strangers on the Internet.

In terms of comparing specific e-commerce sites today, based on the matrix Overstock offers the most social features of the e-commerce sites and Woot offers the fewest social features of the social shopping sites. This shows that there is a wide range of sociability on many different types of retail websites. It is difficult to know which features are the most useful at various points in the decision process. It is also difficult to know whether it is more beneficial for product sites to integrate more social features or for social sites to sell an actual product.

1.3 Sites in the Matrix

Figure 1 through figure 16 illustrates how specific social features are usually provided in e-commerce sites. Below are brief descriptions of the sites in the matrix.

Woot.com sells one product a day and every day is therefore “a different product”. There is a forum on the site where members discuss the daily product, post any reviews they have found on it and what it retails for on other sites. Also, Woot.com shows the community real time statistics about how many items have been sold, where the purchases are coming from across the country, the percentage of people who bought multiple items and more.

Kaboodle.com does not actually sell anything. This is primarily a social networking site with a focus on shopping. Users create profiles and shopping lists and interact with other users with similar shopping tastes. The items in the shopping lists are from third party e-commerce sites and not sold directly by Kaboodle. Currently Kaboodle is one of the most popular social shopping websites.

Zebo.com is also a social networking site geared toward shopping, but also allows users to buy and sell items through the site. This makes sellers buyers and vice versa all in the same place. Also, this site is a little more competitive in that users are ranked based on how much they own, or which brands they own. Revenue comes from people selling items on the site and from paid advertisements.
ThisNext.com has all the social networking elements of a social shopping site. It allows users to make widgets to showcase products they like on other sites. It also has mavens, which are users that have reached celebrity status on the site by many other users following their recommendations and purchases. The site further categorizes mavens by the regions and product categories they are most popular in. Mavens also play a role in the site’s marketing efforts. Revenue comes from referrals based on reviews on the site.

StyleHive.com is a social shopping site that focuses on fashion. The site allows users to tag trends found across the Internet and also posts information on shopping deals and discounts. Users of the site then promote high end fashion, so it is targeted specifically to a certain segment. Further, the site allows retailers and designers to introduce their products through various features, such as the blogs or communities.

StyleFeeder.com is a social bookmarking site. Users bookmark various products across the Internet that interests them. StyleFeeder creates a kind of personalized shopping engine for users based on the items that they’ve bookmarked. StyleFeeder has also created widgets that allow users to post their personal stylefeed on other sites across the web.

ShopStyle.com is a social networking site focused completely on fashion and accessories. Users can browse through multiple retailers through the site and create their own look based on products found on the site. Users can also sign up to have sales on their favorite brands emailed to them from the site. The brands featured on this site tend to be high end and high priced.

Amazon.com is one of the oldest e-commerce websites. This site carries almost anything a user could want to purchase online from highly recognizable brands and products to some of the most obscure. The site features a reputed recommendation system that matches users to potential products. It is also widely used for getting detailed and very useful customer reviews for products.

Walmart.com is the online presence of one of the largest retailers in the world. The site features close out prices on all products, just as the brick and mortar stores do. It offers products across multiple categories and highlights coupons and savings on the site.
Target.com carries products across multiple categories. Most products carried are also available in brick and mortar stores except a bridal fashion line only available online. It also offers an online deal of the week.

JC Penney.com carries the same products as the brick and mortar department store, with a few additional items only found online. Users can rate and review online items, which are popular social features.

QVC.com offers the same products as on television, but they are always available, until they are sold out, on the site. Users can also watch the televised item in real time while on the site and can check program guides for future televised item sales.

Sears.com offers the same product lines as the brick and mortar store. They try to market the site through email newsletters and incent users to sign up for them by offering $10 in coupons. Users can also find outlet items on the site.

Overstock.com is an e-commerce site that offers low prices on products across multiple categories. It also has auction, auto and real estate sections. Overstock offers users recommendations based on items they’ve looked at or purchased in the past.

Kohls.com offers the same product line that is found in the brick and mortar store. It appears to have the fewest social features of all the sites listed based on the metrics listed here.

Macy’s.com features the same product line as the brick and mortar stores, though occasionally offers discounts only available online. It offers an application to be downloaded to the desktop that shows products offers personalized to the user. It also has few social features compared to others discussed here.
Figure 1 Woot

Figure 2 Kaboodle
Figure 3 Zebo

Figure 4 ThisNext
Figure 5 StyleHive

Figure 6 StyleFeeder
Figure 7 ShopStyle

Figure 8 Amazon
Figure 9 Walmart

Figure 10 Target
Figure 11 JC Penney

Figure 12 QVC
Figure 13 Sears

Figure 14 Overstock
Figure 15 Kohls

Figure 16 Macy’s
1.4 What is Social Shopping on the Internet?

Sites like Amazon.com were in existence even prior to the dot com boom in the 2000-2001 periods. What is becoming increasingly popular is combining e-commerce with social features to create social shopping. Currently, social shopping sites are product driven and the kinds of products that usually show up on these sites are personal products, such as clothing, home décor, music and music accessories and gadgets. Further, the newest and trendiest items on the market are generally quick to be found and discussed in these networks. Often, the sites do not actually sell anything. To purchase any of the products seen, the user must return to the product provider’s site. These kinds of sites aggregate data by allowing users to tag products on other sites using a browser plug-in or by uploading information about a product straight to the site. The users that generally frequent the social shopping sites today are predominantly younger and technology savvy.

A feature of some of the most social sites is the “premier shopper”. Essentially, site users can reach celebrity status by being “followed” by other site users. The recommendations of the premier users carry more weight than those of other users. They become premier users through their reputation of promoting products that are well liked by other users. Reputation systems are employed in order for users to rate one another. Also, the websites promote their premier users, further increasing the celebrity status.

When shopping in a mall, there are a finite number of items from which to choose. A potential customer can see, touch and interact with the item. Potential customers can also compare similar items and see other people interacting with and purchasing items of interest. On the Internet, these things are not as easy to do and the processes, such as in comparing similar items, can be overwhelming. Also, on the Internet the number of possible items from which to choose is often very large. Social shopping sites offer a solution to this problem by providing a place online for customers to review and recommend products and for potential customers to easily find and utilize this information. The sites also allow users to add other users with similar interests and tastes to their networks. This allows users to have connections with one person who shares
their taste in music, another who shares their taste in interior design, a third with a shared taste in clothing and so on.

Social shopping sites give online shoppers the ability to create a profile, specifying their tastes in various products and to network with others with similar tastes. Users provide the content for the site and users set the product trends, often leading to viral marketing for various products. The future of these sites as standalone destinations will depend on how these business models thrive. However the social features incorporated on these sites and the technologies used to enable user interactions may gradually be incorporated into most e-commerce sites.

1.5 Scoring/Social Index

The sites in the matrix above were scored based on which social features were present. A simple rating score comprised on the number of social features present is used to rank the sites in Table 2.

Table 2 Social Index

<table>
<thead>
<tr>
<th>Rating</th>
<th>Site</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>StyleHive</td>
</tr>
<tr>
<td>8</td>
<td>ThisNext</td>
</tr>
<tr>
<td>7</td>
<td>Kaboodle</td>
</tr>
<tr>
<td>7</td>
<td>Zebo</td>
</tr>
<tr>
<td>7</td>
<td>Overstock</td>
</tr>
<tr>
<td>5</td>
<td>ShopStyle</td>
</tr>
<tr>
<td>5</td>
<td>StyleFeeder</td>
</tr>
<tr>
<td>5</td>
<td>QVC</td>
</tr>
<tr>
<td>4</td>
<td>Amazon</td>
</tr>
<tr>
<td>4</td>
<td>JC Penney</td>
</tr>
<tr>
<td>3</td>
<td>Macy’s</td>
</tr>
<tr>
<td>3</td>
<td>Woot</td>
</tr>
<tr>
<td>2</td>
<td>Sears</td>
</tr>
<tr>
<td>2</td>
<td>Target</td>
</tr>
<tr>
<td>2</td>
<td>Walmart</td>
</tr>
<tr>
<td>1</td>
<td>Kohls</td>
</tr>
</tbody>
</table>
An interesting observation is that Overstock actually has more social features than some of the social sites, whereas Woot is less social than some of the e-commerce sites. It might be more useful to weight some of the social features as more important than the others. Social features that promote a communication to a single person may be more effective than communication directed at a group of people. Such features are comment walls, polls, social recommendations and email. A weighting that rates these twice as heavily as others is used in Table 2. The changes to the table are minor, with effects to only two sites, Kaboodle and Kohls.

Table 3 Weighted Social Index

<table>
<thead>
<tr>
<th>Rating</th>
<th>Site</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>StyleHive</td>
</tr>
<tr>
<td>10</td>
<td>Kaboodle</td>
</tr>
<tr>
<td>10</td>
<td>ThisNext</td>
</tr>
<tr>
<td>9</td>
<td>Zebo</td>
</tr>
<tr>
<td>9</td>
<td>Overstock</td>
</tr>
<tr>
<td>6</td>
<td>ShopStyle</td>
</tr>
<tr>
<td>6</td>
<td>StyleFeeder</td>
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<tr>
<td>6</td>
<td>QVC</td>
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<tr>
<td>6</td>
<td>JC Penney</td>
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<tr>
<td>5</td>
<td>Amazon</td>
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<tr>
<td>4</td>
<td>Macy’s</td>
</tr>
<tr>
<td>3</td>
<td>Sears</td>
</tr>
<tr>
<td>3</td>
<td>Woot</td>
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<tr>
<td>2</td>
<td>Kohls</td>
</tr>
<tr>
<td>2</td>
<td>Target</td>
</tr>
<tr>
<td>2</td>
<td>Walmart</td>
</tr>
</tbody>
</table>
Chapter 2: Survey of Research in Social Shopping

Given that the social shopping phenomenon is recent there is little work that has studied this area directly. However there are bodies of work in related topics such as factors influencing online purchase decisions, the impact of user reviews in e-commerce, the impact of online recommender systems and the interaction between social networks and e-commerce. In this chapter we survey work in these related areas.

2.1 Online Purchase Decisions

Multiple factors influence a customer’s online purchase decision. Two major factors are trust and reputation and these are greatly influenced through site design, security and social factors (Yoon 2002). Social influence affects trust and reputation as users recommendations tend to increase these factors when the site is unknown to users. Also, users tend to perceive a site as being valuable when other people have used it or made purchases from it in the past. Non-social factors are also important in increasing trust and reputation. A site should have the capability to secure users’ personal information. Further, when a site is poorly designed it increases frustration and dissatisfaction, which is linked to a decrease in reputation.

There are two main trust definitions: Reliability and Decision (Jøsang et al 2006). Reliability Trust is reliability in somebody or something. Decision Trust is the extent to which one party is willing to depend on someone or something in a given situation with a feeling of relative security, even though there could be negative consequences. In other words, reliability trust equates to having faith in someone or something. Decision trust equates to having faith in someone in a given situation with some level of risk.

An e-commerce site must have certain features in place to establish trust. These include security and privacy. Consumers will not consider any other aspects of the site unless security and privacy have been established (Chen and Barnes 2007). These are
hence absolutely necessary. This is because consumers want to be sure that any transaction made on the site is safe, meaning there is no chance of someone stealing credit card information during or after the process. Privacy concerns surround how personal information is used after the transaction and shipment of the product. Some simple ways to create a secure site are to utilize SSL certificates. In terms of privacy, listing an easily accessible privacy policy on the site is important.

Website usability is also linked to trust (Egger 2000). This refers to how easy it is to use the site. Consistency in information architecture and navigational schemes are important in terms of decreasing confusion and frustration for users. Using common metaphors throughout the site also help. This includes placing the navigation scheme at the top or left side of the page and placing the call to action at the upper right corner of the page. Utilize white space throughout the site to draw attention to the main content. Give the user the ability to get to the important information within one or two mouse clicks. Further, using language and terminology the user is familiar with increases website usability. The easier it is to use the site, the more the user will trust the site.

Usability is closely related to perceived usefulness. Perceived usefulness is the idea the site will provide a value to the user (Chen and Barnes 2007). This not only occurs by a website having a given product. This also occurs through functionality available on the site, such as search and sort modules, shopping cart software, streamlined check out processes and so forth. Also, the site should provide simple facilitation between the vendor and the consumer (Egger 2000), particularly sites that act as storefronts, such as Amazon. Essentially this consists of anything the user believes will make their experience simple, therefore increasing the user’s belief in the usefulness of the site.

Reputation is another necessity in new users establishing trust in a website. Reputation can be considered a collective measure of trust (Jøsang et al 2006). So, e-commerce websites need to garner a positive reputation to gain new users. Personal experience is generally more important than reputation, but when personal experience is absent than trust often has to be based on reputation (Jøsang et al 2006). So, how is reputation established? One way is by observing the actions of others. People will do
what other people have already done. When a new user on an e-commerce site can see that other people have used the site and found it useful, that new user’s trust in the site is increased. Online there are many ways of providing information that will influence reputation. Some types of reputation influencers are: rating, reviews, sales volumes and recommendations.

Ratings are shown (Chen 2007) to have a positive impact on reputation as are sales volumes. These are both indicators that other people, not only find the site to be useful, but have enough trust in the site to make a purchase. These tend to be displayed graphically. Also, these tend to be greatly useful to users of the website because it is simple and quick to leave a rating.

Experts and consumers both leave product reviews, but which opinion matters more? Consumers tend to trust the reviews of other consumers more than experts (Chen 2007). There may be a level of skepticism when accepting the recommendation of an expert since an expert could have been incented to speak on behalf of the product. However, a group of consumers are not likely to have the same incentive motivation to recommend a product. This is also true of recommendations from a recommender system as opposed to recommendations from a website owner. Consumers tend to trust the recommender system over the website owner (Chen 2007).

### 2.2 Impact of User Reviews

Online user reviews positively affect purchase decisions on e-commerce websites (Duan et al. 2008). However, reviews are more influential in terms of creating awareness, than in actually persuading a user to purchase a product. Further, as mentioned in the previous section, reviews are successful in establishing trust in an e-commerce site for new users. The type of user making the review is also important as consumer reviews tend to carry more weight than expert reviews.

Online reviews influence consumers in two ways. First, reviews are influential in perception of product quality, generally through a detailed review (Duan et al 2008). Second, reviews are influential in increasing product awareness, generally when
dispersed through online communities (Duan et al 2008). What appears to happen is that users are influenced by awareness more than by persuasion. For example, when a new iPhone is released user reviews abound throughout the Internet on product sites, blogs, social networks, etc. The more information there is about the product, the more aware a new user is about the product. Greater awareness has a larger influence on purchase decisions than persuasion. This is probably because people are not willing to take the time to read many reviews. However, if there are many reviews, then many people must have an interest in the product. The more reviews are dispersed throughout the Internet, the greater affect it will have (Duan et al 2008) on purchase decisions.

Other studies suggest that consumer reviews do have an effect on persuasion. Reviews on a website also have an effect on herd behavior, which is the concept that people will do what other people have already done. In fact, reviews can actually be more effective than ratings in this sense. When new users saw reviews by consumers that contradicted ratings they change their choices (Chen 2007). It could be the case that reviews can change opinions at the time of purchase, which would mean the decision to buy has already been made. In this case, intent becomes important. Also, the reviews are located on an e-commerce site at influential points during the transaction process. However, if the purchase decision has not been made, reviews may not persuade a consumer to purchase, but awareness of the product may aid in coming to the decision.

The herd behavior concept also applies in terms of who has left the review, as mentioned in the previous section. Consumers tend to influence other consumers more than experts do (Chen 2007). Consumers also tend not to be influenced by reviews of website owners. This is because the owner has something to gain, in terms of revenue, by leaving a review or making a recommendation. A review like this can seem more like a sales pitch. Consumers leaving reviews have nothing to gain, as they have already purchased and are utilizing the product or service. Consumers simply find value in the product and wish to inform others about it.
2.3 Impact of Recommender Systems

Recommender systems, or system generated recommendations, are becoming ubiquitous across e-commerce websites mostly because they are viewed as more influential than user reviews in the online purchase decision. How recommender systems are implemented varies by website. There are four distinct types of systems: collaborative filtering, content based, recommendation support system and social data mining (Terveen and Hill 2001). In collaborative filtering systems recommendations for a user are collaborative in that they are based on purchases made by “similar” users. The more user purchase data the better the system is at giving product recommendations. Content based systems are based on the content of the item viewed. For instance, a content based system may recommend other comedies to users who viewed a comedy film. Support systems do not actually make recommendations. Instead they support users in making recommendations for and finding recommendations from other users. Social data mining systems mine preferences from social interactions with other users. These systems require no input directly from the user in making recommendations. Some sites use one specific system while others combine tools from various systems to guide user purchase decisions.

Recommendations provided through recommender systems are more influential than recommendations provided by human experts (Senecal and Nantel 2004). Further, recommendations provided through recommender systems are actually judged more valuable than recommendations provided by friends (Sinha and Swearingen 2001). A part of the reason for this is that recommender systems offer a level of personalization because recommendations are based off previous purchases and other customers similar to the user. Human experts are merely giving a review of a product, not necessarily specified for any individual user. Friends, most likely, have a better idea of a user’s tastes, but may not have a complete idea of purchase history in all domains. Further, users do not mind spending some time rating items, if this provides them with useful recommendations from the system. The only request the user has is to provide enough information about the product for him to make a purchase decision. The problem is defining how much information is enough, since this will generally vary by user.
A newer area of study in terms of recommender systems involves incorporating social information data along with purchase data in providing recommendations (Kim and Srivastava 2007). This information could come from the number of nodes between people in a social network, information garnered from products between people in a network, for instance, using the Tell A Friend email feature, data mining social information communicated through profiles, comments and blogs, etc. SNACK (Lam 2004) is an example of this kind of recommender system. SNACK provides a weight to recommendations based on closeness between people in a social network (Lam 2004). Kim and Srivastava (2007) suggest an approach based on encouraging users to recommend a product to a friend and capturing the data between the two people (also, capture purchase and product from data from online communities as well as reviews). With enough data a fairly substantial representation of user taste can be built out which will enable valuable recommendations. However, transparency in data collection would have to be present for this model to work. Otherwise users may feel their privacy has been invaded.

Incorporating context into recommendations could add value to recommender systems. For example, in the service industry recommendations for a business lunch would be different than recommendations for a dinner date (Bonhard and Sasse 2006). So, incorporating event or situational context could improve recommendations made by recommender systems. The question is how to get this information and when to present it. Bonard and Sasse (2006) found that two situations had to be met for a user to trust a contextual recommendation. First, the advice seeker knows they have taste overlap with the recommender. Second, the advice seeker and recommender know each other well enough and have enough mutual taste that the recommender has a high likelihood of providing a valuable recommendation. To apply this to a recommender system, it would make sense to incorporate taste in terms of rated or selected products when making recommendations. To do this the system should provide information regarding profile similarity and overlap in ratings and reviews of items complementary to the product being recommended (Bonhard et al 2006). Interestingly, familiarity with the profile does
2.4 Impact of Social Networks

Word of mouth has a positive impact on online purchase decisions (Dellarocas 2003), as does profile similarity between advice seekers and recommenders. Most word of mouth actually takes place implicitly. In other words, users endorse products by using them as opposed to talking about them. There is explicit communication, which occurs when a user discusses satisfaction in a product. This often comes in the form of user reviews, which can be found on an e-commerce website or a weblog (blog). Further, there are programs to target influence maximizers within a network, sometimes called network targeting (Kempe et al. 2003). Influence maximizers are users in a social network who have the ability to impact many other users within their own networks. By targeting only the maximizers the message will be sent more efficiently than by targeting the whole network.

Network targeting is becoming more prevalent as online communities continue to flourish on the web. There are many people searching for content and network targeting seeks to get the right content in front of the right people. According to Hill et al (2006), one model of network targeting is the network classification model. This model uses knowledge of the links between entities in a network to estimate quantity of interest. Typically, users are most influenced by other users closest to them in a network. For instance consider figure 17 below.
Using this model, Person 1 would be most influenced by Person 2 and Person 3 because they are closest to him in the network. Person 1 would be less influenced by Person 4, Person 5 and Person 6 because they are furthest away from him in the network. However, taste becomes important as well. It is possible for people far away in terms of network nodes to share similar taste in Product X than people in the closest nodes. Closeness does not necessarily imply taste similarity.

Intent of the online community becomes relevant here. The intentions of users in a community like Myspace or Facebook is mostly sociability, the intention is not to make a purchase. So nodes, in terms of closeness, in a network like this may not have similar purchase histories or similar product tastes. The intentions of users in a community like Kaboodle or ThisNext is to find and purchase products. For example, it is like going to a shopping mall with a group of friends. So nodes, in terms of closeness, in a network like this would be more likely to have similarity in purchase histories and product tastes. Essentially, the community from which this information is gathered is important.

One model of getting information and recommendations into a network is the Push-Poll recommender system. This approach seeds a item into a social network (Push), then queries adjacent users about whether the item should be recommended for the current user (Poll) (Webster and Vassileva 2007). The process would begin with analysis and classification of content found in the network and user rating of content. Then an
item determined to be relevant to the network would be pushed through. Some advantages to this model are utilizing social networks to create recommendations as opposed to setting rules (Webster and Vassileva 2007). Also, new items can be introduced with minimum analysis (Webster and Vassileva 2007), since the network is actually making the recommendation of the item. This may increase efficiency in terms of computation of the algorithm.
Chapter 3: Pricing Mechanisms and Social Shopping: The Case of Demand Aggregation

Can online users efficiently form (electronic) communities that might be able to receive or negotiate better prices? If an online mechanism existed for easy participation within a group purchase would buyers avail themselves of this opportunity? What products or services might this work for? When and why would retailers – who are profit maximizers and often averse to discounting - want to participate in such a mechanism?

Indeed these questions are important and timely. Some early firms, such as Mercata and Mobshop, who were in the business of facilitating retail group-buying online, have failed and shut down operations. There are some insights from recent academic work that has studied this (relatively new) pricing mechanism.

So why did some early group-buying attempts fail? One proposed factor is the purchase uncertainty (Tan et al 2007) that might come from a group-buying consortium. For instance, in some ways in which this is implemented, prospective buyers may not know how long they might have to wait to receive the product (Cook 2001), or what they might eventually have to pay for the product (Tan et al. 2007). It has also been proposed that the concept may be “too difficult” (Cook 2001) for retail buyers. This type of purchasing works best when placed at the right place in the supply, though it may be difficult to know what the “right place” is. For retailers, this type of purchasing may not always make sense because they are last in the supply chain, meaning they would have to sacrifice some of their profits to make it work. However, products at the beginning or end of their lifecycles might fit well into a group-buying mechanism.

To an extent, these issues can be addressed by better system transparency, where buyers can see all the other orders, and price-conditional orders, in which a buyer places an order at a maximum price at which it can be, executed (Tan et al. 2007). Indeed in such a mechanism it has been shown (Chen 2002) that the optimal bid price for a prospective buyer is influenced mainly by her reservation prices and not by when the
buyer comes into the market or what other prospective buyers do. Still, to date, it has not been shown if making these changes resulted in any successful retail group-buying market. However, they stand as independent design suggestions worthy of greater exploration.

There has also been case-study research that looked at a variety of firms (Kauffman and Wang 2002). In this work some additional conjectures as to why early online retail group-buying did not work include (1) The critical mass effect – perhaps early group buying implementations online did not each have enough transaction volume to better compete with larger retail wholesalers who do better with bulk discounting (2) The product variety issue – perhaps there was too much product variety in online retail, leading to order fragmentation, making it harder to “group” similar orders (3) The product lifetime effect - perhaps group buying may work for “newer” products that attract many customers, suggesting that this may be a pricing mechanism that may be used once early in the lifetime of a product and (4) The search cost effects - perhaps current search (engine) options favor fixed price mechanisms since there is no way of determining the final price for an ongoing group purchase offer until the price discovery process is completed. Many of the above are also echoed in Tang (2008) where many failed group-buying schemes in the US are compared to an emerging group-buying scheme in China called “tuangou”.

So when exactly can this be superior to the traditional posted fixed-price offers in the retail space? There have been two attempts to address this, coming from different perspectives.

Anand and Aron (2003) as well as Chen (2004) study this from a seller’s perspective. Under various stylized assumptions both these papers study analytical models that compare group buying to the traditional fixed price mechanism. Anand and Aron (2003) argue that group buying in retail may be superior to fixed price mechanisms when one of two different factors come in. First, if there is sufficient demand uncertainty then sellers may benefit from using a group buying mechanism. Demand uncertainty is usually rare for a common product that is well-understood, hence this again suggests that there may be specific markets where the mechanism might better work in. Second, a
combination of economies of scale and production postponement matter. Specifically, if the seller realized scale economies and can wait until demand aggregation occurs before production then group buying can be superior. Chen (2004) extend these insights and argue that the seller’s penchant for risk matters as well, with higher risk favoring the group buying outcome. In their work, Chen (2004) characterizes higher risk as a greater preference for selling higher volumes.

What if, from a seller’s perspective, demand uncertainty and the ability to postpone production do not exist? Can there still be conditions under which the seller might benefit from a group buying mechanism online? This is an important question that needs to be examined in future research.

A totally different take on this has been from the buyer’s side, where research has looked at how buyers can be efficiently grouped to make group-buying work. Hyodo (2003) and Li (2004) study mechanism design for coalition formation – i.e. how can groups be formed efficiently? Using a game theoretic perspective Li (2004) show the difficulty in designing efficient mechanisms, arguing that an incentive compatible mechanism that induces buyers to reveal the truth may be elusive in some situations. On the other hand, using a very different computational approach, Hyodo (2003) show how Genetic Algorithm-based simulations can be used to optimally group buyers into clusters for specific product categories. To an extent this shows that research into the dynamics of social behavior can play a role in determining when and how this pricing mechanism will work online.
Chapter 4: A Social Recommendation Algorithm

This chapter examines recommendation algorithms and discusses how to enhance recommender systems by utilizing social data.

4.1 Examining Collaborative Filtering

Collaborative filtering systems are one of the most popular types of recommender systems. It works by representing a customer as an item vector (Linden et al 2003). This system then finds customers most similar to a given user to make item recommendations. See Table 4 as an example.

Table 4 Collaborative Filtering

<table>
<thead>
<tr>
<th></th>
<th>Item 1</th>
<th>Item 2</th>
<th>Item 3</th>
<th>Item 4</th>
<th>Item 5</th>
<th>Item 6</th>
<th>Item 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer 1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Customer 2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Customer 3</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Customer 4</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Customer 5</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Customer 6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Customer 7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

The recommendations are made based on similarity between customers, where 1 represents a purchase. The system uses the cosine measure (Linden et al 2003) to find a similarity coefficient between 0 and 1 where zero equates to no similarity and one equates to 100% similarity. These similarity numbers may then be used to identify similar customers.

As an example, based on the Table 4, data similarity between Customer 1 and the other Customers are listed below.

34
Customer 1’s Similarity to:

- Customer 2 Similarity = 0.5
- Customer 3 Similarity = 0
- Customer 4 Similarity = 0.4
- Customer 5 Similarity = 0.4
- Customer 6 Similarity = 0.6
- Customer 7 Similarity = 0.3

Therefore, the order of relevance for Customer 1 is:
<Customer 6, Customer 2, Customer 4, Customer 5, Customer 7, Customer 3>.

Similarly, Customer 6’s similarities to others may be calculated as:

Customer 6’s similarity to:

- Customer 1 Similarity = 0.6
- Customer 2 Similarity = 0.3
- Customer 3 Similarity = 0.4
- Customer 4 Similarity = 0.4
- Customer 5 Similarity = 0.2
- Customer 7 Similarity = 0.3

Therefore the order of relevance for Customer 6 is:
<Customer 1, Customer 3, Customer 4, Customer 2, Customer 7, Customer 5>

Collaborative filtering is commonly used, but technically cumbersome (Linden et al. 2003). Similarity between customers tends to be sparse, so the system churns through data looking for customers to compare. This lengthens the time to provide a recommendation. Also, customers have to rate or purchase an item before a recommendation can be made, since comparisons are between customers. Further, customers have to be “signed in” before any recommendations can be made.
4.2 Examining Amazon.com

A method used by Amazon.com (Linden et al. 2003) takes the transpose of the collaborative filtering matrix, previously discussed. This means that Amazon represents items as a dimensional vector of customers (Linden et al. 2003). In other words, the system finds items that are most similar to items being viewed by a user to make item recommendations. See Table 5 as an example.

Table 5 Item-to-Item Collaborative Filtering

<table>
<thead>
<tr>
<th></th>
<th>Customer 1</th>
<th>Customer 2</th>
<th>Customer 3</th>
<th>Customer 4</th>
<th>Customer 5</th>
<th>Customer 6</th>
<th>Customer 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Item 1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Item 2</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Item 3</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Item 4</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Item 5</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Item 6</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Item 7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

The recommender system is looking for similar items, where 1 represents a purchase, instead of similar customers. By flipping the vector the algorithm can quickly identify which items have been purchased together, correlating these as similar items (Linden et al. 2003). The reason Amazon does this is to increase speed in making a recommendation. The data in a collaborative filtering system can be slow to search through because it is based on customers as opposed to items. Customer purchases tend to be sparse when compared with items. However, searching by items that have been purchased is less tenuous since most items have been purchased at least once. Most rows
in the inverted matrix are likely to have a significantly larger number of ones than in the original matrix.

In this system each item receives a similarity coefficient between 0 and 1, zero being no similarity at all and one being 100% similar using the same cosine metric (Linden et al. 2003). As an example, item similarity for items 1 and 3 are listed below:

Item 1’s similarities to:
- Item 2: Similarity = 0.4
- Item 3: Similarity = 0.3
- Item 4: Similarity = 0.8
- Item 5: Similarity = 0.3
- Item 6: Similarity = 0
- Item 7: Similarity = 0.3

Therefore the order of relevance for Item 1 is:
<Item 4, Item 2, Item 3, Item 5, Item 7, Item 6>

Item 3’s similarities to:
- Item 1: Similarity = 0.3
- Item 2: Similarity = 0.7
- Item 4: Similarity = 0
- Item 5: Similarity = 0.2
- Item 6: Similarity = 0.7
- Item 7: Similarity = 0.4

Therefore the order of relevance for Item 3 is:
<Item 2, Item 6, Item 7, Item 1, Item 5, Item 4>

An item that a user has purchased, rated or is currently viewing is matched to similar items in the table to provide recommendations to the customer. Consider a couple examples.
First, Customer 5 visits Amazon.com. The system has a record of this customer’s purchase history. Since Customer 5 has already purchased item 1 and item 3, but has not purchased item 4 or item 6, the system recommends item 4 and item 6 as soon as the customer enters the website. Item 4 and Item 6 are recommended because they are the closest in similarity to the previous purchases made by customer 5.

Second, an anonymous user comes to Amazon.com. No recommendations can be provided until that user views a product, since there is no available purchase history. However, if this user views item 1, the recommender system will recommend item 4 to the user. If this user views item 3, the system will recommend item 6. Even though there is no purchase history, viewing an item shows a level of interest. Since Amazon has already rated item similarity from purchases of previous users, the system is able to make recommendations.

Amazon.com’s recommender system is valuable to all users on the website. However, a critical mass is needed for this recommender algorithm to succeed. This means that the site has to have a large number of products and a large number of customers. If the website has few product and/or few customers, the recommendations will most likely not be valuable. Is there a way to utilize a recommender system without having a critical mass? A site could pull an XML feed from a product database, like that of Best Buy to gain a large number of products. If the site could gather a large number of products, then customers could be pulled from sites that have a critical mass of users. Perhaps, information from a social network could be utilized in this situation.

4.3 Examining SNACK

The SNACK (Social Network in Automated Collaborative-filtering of Knowledge) begins with the collaborative filtering algorithm (refer to table 4), then incorporates information from the advice seeker’s social network, utilizing multiple nodes beyond the first ones (refer to figure 17). SNACK gives a weight to the similar customers provided by the collaborative filtering system, based on closeness in nodes to the user (Lam 2004). Let us examine the collaborative filtering example provided above.
Customer 1’s closest customers: <Customer 6, Customer 2, Customer 4, Customer 5, Customer 7, Customer 3>
Customer 6’s closest customers: <Customer 1, Customer 3, Customer 4, Customer 2, Customer 7, Customer 5>

Now, let us include social network information.

![SNACK Network Nodes](image)

Since there are five levels within the network, let us provide a weight of 0.4 to the first level, 0.3 to the second level, 0.2 to the third level, 0.1 to the fourth level and 0 to the fifth level.

That means Customer 1’s customer similarity profile will change in the following manner:

Customer 1’s modified similarities to:

- Customer 2 Similarity = 0.5 + 0.4 = 0.9
- Customer 3 Similarity = 0 + 0.3 = 0.3
- Customer 4 Similarity = 0.4 + 0.3 = 0.7
- Customer 5 Similarity = 0.4 + 0.4 = 0.8
- Customer 6 Similarity = 0.6 + 0.3 = 0.9
• Customer 7 Similarity = 0.3 + 0.2 = 0.5

Therefore the order of relevance for Customer 1 changes to:
Customer 1’s closest customers: <Customer 2, Customer 6, Customer 5, Customer 4, Customer 7, Customer 3>

In a similar manner, Customer 6’s customer similarity profile will change:

Customer 6’s changed similarities to:
• Customer 1 Similarity = 0.6 + 0.3 = 0.9
• Customer 2 Similarity = 0.3 + 0.2 = 0.5
• Customer 3 Similarity = 0.4 + 0.1 = 0.5
• Customer 4 Similarity = 0.4 + 0.1 = 0.5
• Customer 5 Similarity = 0.2 + 0.4 = 0.6
• Customer 7 Similarity = 0.3 + 0.4 = 0.7

Therefore the order of relevance for Customer 6 changes to:
Customer 6’s closest customers: <Customer 1, Customer 7, Customer 5, Customer 2, Customer 3, Customer 4>

Customer 1 had slight variations when the social weight was added. Customer 6 had more drastic variations. In this model, Customers 3 and 4 flipped places with Customers 7 and 5 from the collaborative filtering model.

4.4 Utilizing the Social Network

The Amazon recommender system finds similarity between products and the SNACK recommender system weights customer similarity based on nodes in a social network. Is this the best there is? There is such an abundance of information all over the Internet, that it seems recommender systems are missing potentially important data points. The first thing to do is identify a community whose intention is focused on
making a purchase decision. This will provide a network of people with similar taste profiles and a plethora of data mining opportunities to look match products with users.

In any given social network a user creates a profile that generally includes information on taste, such as favorite books, movies, music, etc. There is also textual information left in comment walls, blogs and reviews that can be mined. Also, there are connections between individual people that can be utilized and connections between individuals and a user group that can be utilized.

Any algorithm for a social recommender system should categorize a user’s tastes. So, given the information available for collection, the system should categorize available products, such as Horror Films and Romantic Comedies. Then assign each user a weight, based on taste, for each category. An example is given in table 6.

Table 6 Customer Interest Level in Movies by Genre

<table>
<thead>
<tr>
<th>Genre</th>
<th>Customer 1</th>
<th>Customer 2</th>
<th>Customer 3</th>
<th>Customer 4</th>
<th>Customer 5</th>
<th>Customer 6</th>
<th>Customer 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horror</td>
<td>0.1</td>
<td>0.2</td>
<td>0.9</td>
<td>0.2</td>
<td>0.3</td>
<td>0.1</td>
<td>0.7</td>
</tr>
<tr>
<td>Action</td>
<td>0.5</td>
<td>0.1</td>
<td>0.3</td>
<td>0.1</td>
<td>0.5</td>
<td>0.6</td>
<td>0.2</td>
</tr>
<tr>
<td>Drama</td>
<td>0.3</td>
<td>0.7</td>
<td>0.6</td>
<td>0.7</td>
<td>0</td>
<td>0.4</td>
<td>0.5</td>
</tr>
<tr>
<td>Comedy</td>
<td>0.8</td>
<td>0.3</td>
<td>0</td>
<td>0.3</td>
<td>0.9</td>
<td>0.8</td>
<td>1</td>
</tr>
<tr>
<td>Romantic Comedy</td>
<td>0</td>
<td>0.5</td>
<td>0.2</td>
<td>0.6</td>
<td>0.4</td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td>Sci-Fi</td>
<td>0.7</td>
<td>1</td>
<td>0.5</td>
<td>0.8</td>
<td>0.7</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>Children</td>
<td>0.4</td>
<td>0.6</td>
<td>0.1</td>
<td>0.5</td>
<td>0.6</td>
<td>1</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Based on this information the system knows that Customer 2 and Customer 4 have very similar tastes in terms of movies. However, when the two customers are compared by taste in clothing, there is little similarity. So, using taste categorization allows the system to make very specific recommendation.

Closeness in user network nodes and user group when making a recommendation should also be considered. The SNACK algorithm does a good job of weighting users in terms of closeness (refer to figure 18). However, the nodes should not be considered unless the users match in taste categories. So, the system already knows that Customer 2 and Customer 4 are similar in terms of movie taste. If they are also close in terms of
network nodes or they are the same user group in a community, the system should give them weight when providing a recommendation.

Essentially, the system needs to a viable social network in order to provide valuable recommendations. Then the system needs to incorporate categorized taste recommendations that are weighted if users are close in the network or are both in a taste based user group.
Chapter 5: Conclusion

This thesis is an exploratory study on online social shopping, which is an emerging phenomenon in e-commerce. We discussed current industry trends, social features, academic research, social pricing and recommender algorithms. There are a myriad of questions that need to be answered related to this phenomenon in future work.

- Will sites that have high social capital, but do not generate revenue outside of advertising be able to succeed long term?
- Could sites with brick and mortar stores benefit from adding social features and if so how exactly?
- Which social features influence purchasing decisions and by how much?
- At what point in the purchase decision does the user utilize social features?
- Does a communal focus create purchase conversions better than an individual focus?
- How easy is it for users to find other users with similar taste profiles?
- Should the system aid in connecting people with similar profiles?
- Under what circumstances could demand aggregation succeed?
- What factors need to be included to successfully implement social recommendation algorithms?

In conclusion, the popularity of social shopping websites is clearly increasing. In industry, at least, it seems that there is a belief that social communication has a positive effect on purchase decisions. More research needs to be done to validate this hypothesis and to determine long term viability of the social shopping sites that exist today. Also, more research needs to be done to determine how to utilize social information to improve recommendations made by recommender systems.
References Cited


Bonhard, P. and Sasse, M.A. 2006. ‘Knowing me, knowing you’ - Using profiles and social networking to improve recommender systems. BT Technology Journal Vol 24 No 3.


