The effect of Product Ratings on Viral Marketing

CS224W Project proposal

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In network-based marketing, social influence is considered in order to optimize marketing strategies. Social influence in e-commerce has been studied for more than one and a half decades, to a large extent in the context of product endorsements and chains of recommendations. We propose to study friends’ influence in social networks exerted through reviews that include rankings, which means that a review can be anything from a recommendation to disapproval.

I. Introduction

An important economic issue for companies is the desire to minimize costs of marketing while maximizing expected profits. Different types of marketing tactics are usually considered, including mass marketing, direct marketing, and network-based marketing. For mass marketing, products are promoted indiscriminately to all potential customers. In contrast, for direct marketing, products are promoted to customers which are likely to be profitable, based on characteristics of individual people. This approach is particularly useful for advertising niche products which, somewhat surprisingly, collectively constitute a significant online sales volume. Finally, for network-based marketing, social influence is considered. In this case, customers themselves are leveraged to perform most of promotional effort. Network-based marketing is a more recent and very active field of research. It exhibits similarities to the spread of diseases and is therefore often also referred to as viral marketing. Successful viral marketing is related to the problem of maximizing the spread of influence on a social network, a topic which has been discussed extensively in the course, and which we propose to examine further.

II. Reaction paper

We are discussing three papers in the field of viral marketing in this report, spanning a time frame of one and a half decades. The oldest paper we consider was authored by Domingos and Richardson in 2001, entitled Mining the network value of customers [1]. It is one of the first works to quantify network effects in customer valuation models. Before their pioneering work, it was presumed that consumers make their purchasing decisions individually, independent of other customers and word of mouth. We then consider the paper by Leskovec, Adamic, and Huberman, entitled The dynamics of viral marketing, published in 2007 [3]. It builds on the work by Domingos et al. and presents an analysis of a person-to-person recommendation network with 4 million people. Finally, we discuss the paper by Vidmer, Medo, and Zhang, entitled Unbiased metrics of friends’ influence in multi-level networks, published in 2015 [5]. It critiques the paper by Leskovec et al. and points out that large differences in item popularities can cloud the analysis of the influence of friends. We will now summarize these three papers and critique them.

A. Summaries

The expected value of marketing to a potential customer has two components: The intrinsic value, which is the expected profit from sales directly to him/her, and the network value, which is the expected profit from sales to other customers that are directly or indirectly influenced by him/her.

1. Domingos et al., Mining the network value of customers [1]

Domingos et al. put the goal of finding the best viral marketing strategy on a more solid foundation by being the first to attempt to quantify the network value of a customer. With this information, they answer the fundamental algorithmic question as to which individuals should be targeted to trigger large cascades of product adoption. Domingos et al. propose to
model social networks as Markov random fields, where each customer’s probability of purchasing a product is a function of both the intrinsic desirability of the product for the customer and the influence of other customers [1]. A second major part of the paper deals with the construction of a framework to mine the required network information. They take a collaborative filtering database as an example for a data source used for mining influence networks.

2. Leskovec et al., The dynamics of viral marketing [3]

Leskovec et al. study the application of disease contagion models to recommender systems. They analyze a person-to-person recommendation network and, for the first time, directly quantify how influential person-to-person recommendations really are by empirically studying an online retailer’s incentivized viral marketing program. This incentive program works by allowing customers that purchase a product to send email advertisements (called recommendations in the paper) to their friends. The first person to purchase the same product through such a referral within a week earns a 10% discount, while the recommender obtains a 10% credit on their purchase.

The authors are able to draw several important conclusions: First, the number of additional purchases due to recommendations is generally small, suggesting that viral marketing is not as epidemic as vendors have hoped. Further, the likelihood that a product is purchased by a customer increases with the number of recommendations. However, this is true for only the first few recommendations and then quickly saturates at a relatively low probability. This is inconsistent with traditional epidemic and innovation diffusion models. Also, when the number of recommendations between two customers increases, the recommendations are more likely to be ignored (diminishing returns). This means that high-degree nodes tend not to be effective recommenders. Finally, they observe homophily, which is the tendency of similar customers to purchase similar products.

In addition to this analysis, Leskovec et al. propose a model to identify products for which viral marketing is likely to be effective. The model predicts the general tendency that recommendation chains are relatively short, and that only a few larger cascades occur.


Vidmer et al. show that currently-used measures for the influence of friends are biased when very popular products are present. They propose three metrics to better measure the influence of friends in networks:

1. A normalized exposure to better distinguish the influence of friends from preferential attachment,

2. a normalized contagion count to correct contagion count for highly-active users, and

3. a spreading coefficient to measure topological features of item spreading.

Vidmer et al. proceed to apply these three metrics to datasets from Yelp and Digg.com. To assess the usefulness of these metrics in measuring the influence of friends, they compare their values in actual graphs with values obtained in randomized graphs for which the influence of friends, supposedly, has been removed. They find that their proposed metrics perform better at distinguishing original and randomized networks than conventional metrics.

To further drive home this point, Vidmer et al. develop a simple artificial network model based on preferential attachment which allows setting the degree of friends’ influence explicitly. Again, they are able to demonstrate the superiority of their new metrics compared to conventional metrics to assess the influence of friends.

B. Critique

1. Domingos et al., Mining the network value of customers

The influential paper by Domingo et al. (1735 citations) is the first systematic attempt to understand and influence viral marketing to optimize market decisions, and so it has sparked
a whole new field of research. Of course, being a pioneering paper, it does not have the space to discuss numerous related aspects that have been picked up by other researchers later on. This includes the benefit of considering the time dependence of the processes and adapting the marketing strategy as the network evolves. Also, it can be very helpful to combine different sources of information into a single network. Finally, malicious manipulation of the network by users has to be avoided.

By the time Domingos et al. published their research, collaborative filtering had been used routinely already at e-commerce sites, motivating their opportunistic approach of constructing an implicit influence network from collaboration systems. They showed that this network can still be used effectively to locate and interpret influential people. However, this is not a social network in the purest sense since it does not consider actual acquaintances, friendships, or at least common geography. Instead, it is assumed that users influence each other solely based on their ratings, even though customers may be affected in many other ways, for example by people that are not even part of the network.

An important challenge to the approach by Domingos et al. is scalability to larger networks. Kempe et al. have shown that the problem is computationally expensive due to intractability of the General Threshold model, which is NP-hard [2]. Domingos et al. recognized this and proposed to segment large networks into more tractable smaller communities. In their later 2002 work, they achieved results with smaller computational costs [4].

2. Leskovec et al., The dynamics of viral marketing

Leskovec et al. offer deep insights into the spread of knowledge and effectiveness of influence, thereby providing important tools for vendors to apply viral marketing strategies to boost sales, including for niche products. This will become increasingly important as customers continue to embrace digital social networks. The discovered inconsistency with traditional epidemic and innovation diffusion models stresses the need for new influence mechanisms congruous with the data in recommendation networks.

This important study has, however, some limitations. For example, it does not really treat word-of-mouth (recommender) advertisement because recommendations are sent out before a customer receives the product and can test it. Also, the nature of the discount incentive program casts shadows of doubt on the motives for the recommendation – is the email an actual recommendation or just an attempt to benefit from a discount? It is also problematic that the automated form-email recommendation potentially looks like spam and might get ignored.

Further, this study measures only online viral activity. We do not really know the extent of influence by the recommendations because friends could be inclined to purchase the recommended product somewhere else.

In addition, their approach does not shine light on the structure of the influence network in any detail. Their model predicts communities, products, and pricing categories for which viral marketing could be effective, but, for a given product, it does not provide a recipe for avoiding recommendation chains to terminate early.

Finally, the study limits itself by allowing only purchasers to initiate and carry on recommendation chains. There are other ways to initiate and enable an epidemic of product sales, for example through potential spontaneous product endorsements by socially influential people, such as celebrities, which do not purchase the product and so are not part of the network.

3. Vidmer et al., Unbiased metrics of friends’ influence in multi-level networks

Vidmer et al. use recommendations from the Yelp dataset to study spreading of products. Every review is taken as a new step in a chain of spreading a contagion. The problem is that not all reviews are recommendations because they can be anywhere from positive to neutral to negative. Treating all these reviews the same does not seem sensible as one would expect that a positive review is much more likely to motivate customers to purchase a product and to spark longer chains of reviews than a negative one.
The other dataset that Vidmer et al. are using originates from Digg.net. It is of limited value since it is strongly biased: It contains only the most popular items. Items of average or lower popularity, for which the new metrics were supposed to be particularly helpful, are not included.

Further, their normalized metrics are prone to noise for small normalization constants, and so they introduce *ad-hoc* lower limits for item degrees (number of reviews) and number of friends. Unfortunately, many items have only a small number of reviews, and many users have only a small number of friends, so this approach makes only limited used of the available network data.

Finally, the benefit of applying the new metrics to the original and to the randomized data is not always obvious. For example, it is somewhat of an over statement that all three curves in Figure 3 (a) of their paper [5] shows the same pattern, thereby weakening their argument.

## III. Project proposal

### A. Problem statement

None of the papers that we have discussed considers the nature of the influence explicitly, i.e. whether a customer endorses a product or not. Neither Domingos et al. nor Leskovec et al. have a measure for consumer satisfaction; customers do not rank their purchases, and so it is not clear if they really recommend a product to their friends. Domingos et al. derived a network from collaborative filtering without ranking products, and Leskovec et al. base their endorsement on an incentive program which strongly biases the recommender to promote a product to his/her friends, even if the product has not even been received yet. The Yelp dataset used by Vidmer et al. contains ranking information but the authors chose to ignore it. Clearly, a negative review is not likely to ensue a cascade of purchases. Therefore, a promising further research question, which we propose to explore, is to consider the degree of enthusiasm in recommendations and reviews and to determine how they affect the network value of a customer.

If time allows, we will take this idea a step further and consider that it is likely that friends’ influences are different in different regions and/or in different cultures. To analyze this concept, we will break up large social networks geographically, analyze friends’ influences locally, and compare their effectiveness.

### B. Dataset

We propose to use the data from the recent Round 8 Yelp Dataset Challenge [6] as it is particularly suitable for this work. It features a user-user social network with friendship edges. In addition, it provides a list of businesses as well as reviews written by the users, from which a user-business bipartite graph can be constructed. In this graph, users and businesses form the nodes, and the reviews are the edges. The reviews include one-to-five-stars ratings of the businesses.

The original dataset contains 2.7M reviews, 687K users, and 86K businesses, along with 566K business attributes. The original friends network contains 687K users and 4.2M social edges. We retain only users with at least one friend and only businesses with at least one review. Also, for uniformity, we limit our analysis to restaurant businesses, which constitute the vast majority. This results in 1.1M reviews, 219K users, and 26K businesses. The modified friends network contains 219K users and 1.6M social edges.

### C. Work plan

We will start out by studying basic network characteristics. For the user-user network, this includes computing distributions of degrees, clustering coefficients, and sizes of weakly-connected components. In extension to the work by Vidmer et al., we will group the businesses according to their average rating (e.g. positive, neutral, and negative), creating several different bipartite user-business networks. For each of these networks, we will determine the distributions of ratings and degree distributions.

We will then apply the analysis proposed by Vidmer et al. to quantify the influence of friends as a function of the average business rating, which we consider a major improvement of their
analysis. In particular, we will compare normalized exposures, normalized contagion counts, and spreading concentrations for these three networks, and also compare them to randomized networks for which friendship influence has been removed and with model network data which allows various degrees of friends’ influence.

If time permits, we will break up the graphs geographically into cities or communities, taking advantage of the provided longitudinal and lateral position of each business. We then assign users to a city or community if he/she has reviewed a business in that city. This implies that users are potentially members of multiple cities as visitors. We will only analyze cities or communities with a sufficient amount of data. We will then proceed and study the effect of cultural differences on the friendship influence. This may include considering additional business information provided by the business data and in the reviews.

D. Algorithms, techniques, and models

We will use data randomization techniques to verify the degree to which the influence of friends matters. We will use the configuration model to randomize the user-business network while keeping the user-user network the same. This means that the set of businesses that a user reviews is randomized while the degrees of both the items and the users stay unchanged. This way, the influence of friends has been removed from the network.

Vidmer et al. proposed a model in which the friends’ influence can be varied continuously. It keeps the original Yelp user-user network but generates an artificial user-business network by creating global and local (friend) review links stochastically. We will fit this model to the Yelp user-business networks, separated by review ratings, to match user and business degree distributions. Comparisons of the model fitting parameter values might provide further insight into the user-business network. This artificial network model can be used to determine the performance of the new metrics for friends’ influence.

E. Evaluation and conclusions

Intuitively we expect that the length of recommendation chains decreases with decreasing star rating because users are less likely to try a restaurant with a low rating. Our work will show if the Yelp network follows this intuition, and if not, we hope that the acquired analysis data will allow us to explain potential surprises. Further, comparing old and new metrics for these graphs will show if Vidmer’s conclusions still hold when the actual ratings are considered.