Predicting the Product Success Rate using Ant miner Algorithm

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***Abstract* - In the epoch of social commerce, users usually connect from e-commerce websites to social networking venues such as Facebook and Twitter. However, there have been few efforts on understanding the correlations between users' social media profiles and their e-commerce behaviors. In the real world there are millions of products are entering into the market. In those some of them make unsuccessfully and some of them are success. This paper presents a system for predicting the product success rate on e-commerce web sites from the user's social media profile by using Ant-Miner algorithm. We specifically aim at understanding if the user's profile information in a social network can be leveraged to predict what categories of products the user will buy from online websites. And whatever the product entering into the market that product will suggest to the users who are interested on that particular product. This can very useful for the manufactures because they can easily analyze which category of products mostly purchased by the users.**

***Index Terms* - Component, formatting, style, styling, insert.**

I. INTRODUCTION

All Human foraging behavior always seeks to approach an integrated set of information and to discover relationships between phenomena for the explanation of these phenomena and the prediction of their behaviors [2]. These attempts extended to purchase behavior field and have induced researchers to discover relationships among the online social network users. One of the techniques introduced is the application of Ant Colony Optimization in detecting the communities in the complex networks (Caihong Mu, 2014). This model was initially proposed by Dorigo (1992) to solve the Traveling Salesman Problem (TSP) (Dorigo and Stutzle, 2004). Thereafter, researches tended to benchmark this model to solve similar optimization problems in their field of study. The researchers of the computer science field were also to test this model in order to find out a solution for computational problems in the real world.

In recent years, many e-commerce companies such as Amazon and eBay have been moving into the social media space by allowing users to connect to social networking sites (e.g. Facebook and Twitter). The main strategic goal for social media interaction is to provide users with a more engaging and social experience, thus increasing user retention and adoption. More importantly, social media is often seen as a means to rejuvenate the user base and attract younger users. Classic Characteristics unlatched by social media include the possibility of sharing purchase activities with friends. When users connect from an e-commerce site to social media for the first time, they frequently concur to communicate with the e-commerce company basic information such as their demographics and personal interests (e.g. Facebook \likes"). However, e-commerce companies have not fully developed technologies to leverage this information to improve important features such as success rate prediction and product recommendation. When a new product entering into the market, we predict the success rate of that particular product based on the e-commerce websites by using the Ant-Miner algorithm,

In this paper we claim that social media information provides sufficient knowledge to predict, to a certain extent, the product success rate. For example, a new cosmetic item is entering into the market, the people who are interested to that particular category of products those people give more likes by online social networks than the others.

Ants Behavior

In real world ants run more or less at random around their colony to search for food. Ants deposit a chemical substance called pheromone along the travelled paths (Dorigo and Caro, 1999). After rainfall, these paths get white and become visible. Other ants upon finding these paths would follow the series. Then, if they find food place they will return back to the nest and deposit another path along with the existing one, and will be strengthened the before path.

When it turns to select a path, ants will prefer one containing high density of pheromone, i.e. paths on which more ants have travelled. Pheromone is slowly vanished. This evaporation is useful for three reasons: First, It makes the next series less attractive for following ants. Ants mostly take shorter paths; hence, the shorter path between nest and food source is highly strengthened and any farther path is less become strong. Second, unless pheromone did not vanished at all, the paths having been passed number of times would become so attractive that the random searching for food would be highly limited. Third, when food finished at the end of path, vanishing of the remaining paths would not mislead ants in their searching for that track leading to food source.

Therefore, when an ant finds a shorter (optimal) path from nest to food source, other ants will more likely follow the same path and, over time, the continuous strengthening of the path and the evaporation of other trails will make all ants become unidirectional (Dorigo and Colorni, 1996).

This behavior in ants has a kind of swarm intelligence having been recently considered by scientists. But it should be meassured that there is a major difference between swarm intelligence and social intelligence. In social intelligence the agents have a degree of intelligence. But, in swarm intelligence the agents have random behavior and there is no direct relationship between them and they are in indirect contact with each other by signals.It was referred to as Stigmergy which is a particular form of indirect communication used by social insects to coordinate their activities via changes made in the local environment (Dorigo et.al, 2000).

Ant Behavior System

Ant Colony System was initially proposed by Dorigo and Caro to solve the Traveling Salesman Problem (TSP) and with benchmarking of ants behavior he designed a powerful algorithm for solving optimization problems. In TSP the aim is to discover a closed tour of optimal path connecting n cities (Dorigo and Stutzle, 2004). Therefore, the path in TSP is a directional graph, also referred to as Hamilton cycle. An optimal path in weighted directional graph means a path with minimal length. Thus, the TSP is, in fact, discovering an optimal path for a weighted directional graph. Also, the length of optimal tour does not depend on the selection of Start vertex.

II. RELATED WORK

Product Prediction and Recommendation

Recommender systems have been widely studied in the past [10, 7, 9, 8] and applied to various domains. Ecommerce is a typical application for these systems, where they are used to predict or recommend product purchases. Two main techniques are most used: collaborative filtering and content-based. Collaborative Filtering Methods. The underlying assumption of collaborative filtering methods is that users who carry similar characteristics will tend to like similar products. Users are typically represented in a vector space which summarizes their characteristics (e.g. demographics, purchased products, review scores assigned to products). These systems suggest new products to a user by selecting a set of products that similar users have bought or reviewed in the past, but the user has not. Sarwar et al. [11] apply nearest neighbor collaborative filtering for recommending purchases and predicting movie ratings, showing that dimensionality reduction techniques solve scaling issues on large-data without losing accuracy

Item-Item collaborative filtering, on the other hand, makes product recommendations directly based on users' past behaviors on e-commerce websites. Sarwar et al. [12] propose a system that models item to item relationships and demonstrate that such systems deliver good quality recommendations in sparse data situations. The item-item method is also promising for incremental modelling and has big performance gain over user-user modelling.

Content-based Methods. In contrast to collaborative filtering methods, content-based methods often utilize the vast overload of information on the web, such as product reviews, customer opinions, and social media (e.g. blogs, tweets) to directly make product recommendations. In recent years, such systems have become more popular. Wietsma and Ricci [13] propose a system that structures product reviews to help rate and recommend products in a mobile decision aid scenario. Sen et al. [14] use users' tag preferences to predict movie preferences and demonstrate that such content-based systems are more effective than collaborative filtering methods.

Recommendation on Social Media

Recommendation on social media is a fairly new topic. Most work focuses on suggesting interesting content items (e.g. URLs, pictures, posts) or new friends. Social media recommender systems differ from classical ones in that they often leverage existing social relations to boost the recommendations. Two main techniques are most used: content based and community-based. Content-based methods are most popular even though some interest has focused on collaborative filtering. These systems assume that the content that users share on the social network reflects their own interests, thus endorse new products that are similar to their own shared content. Abel et al. [15] represent users by a frequency vector of the hashtags and entities that they mention in their tweets. A similar vector is built for URLs shared in Twitter by analyzing the content of their links. Users are then recommended URLs whose vector is most similar to theirs.

Community-based methods make the assumption that the content coming from a user's friends or authoritative users is more likely to be interesting for a user than the rest. Jiang et al [16]. Community-based systems show better performance with respect to purely content-based and collaborative filtering methods.

Social Networks and Purchase behaviors

Some research has investigated the broader topic of how social network influences users in their purchases. Bhatt et al [17] empirically demonstrate that a user’s friends exercise “peer pressure”: If friends widely adopt a product, the user is more likely to buy it. Guo et al [18] study the trading dynamics on the e-commerce social networks Taobao. They show that buyers are more likely to purchase from sellers that friends in their network have already bought from (information passing). They prove that when a buyer has to decide from which seller to buy a product the social network has a bigger influence on the decision than the seller’s rating and the price of the product.

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III. PURCHASE BEHAVIOR PREDICTION

Based on the activities performed by the online social network users we predict the purchase behavior of the users. Like In his section we explore strong if that information is strong enough to predict the purchase behavior.

Experimental Results

The results of the Ant-miner algorithm using the complete set of features (product categories, likes, purchases) with feature selection. And here we gave comparison among different classification algorithms like Logistic Regression, SVM, Navie Bayesian, Ant-miner algorithms. Among those Ant-miner algorithm gives the optimal results than the remaining algorithms.

Ant miner Algorithm

The goal of the Ant-miner is to extract the Classification rules from data. The Pseudo Code of Ant-miner is illustrated in Figure1.

```
Training set= all training cases;
WHILE (No. of uncovered cases in the Training set > max Uncovered cases
        I=0;
        REPEAT
                I=i+1;
                Ant incrementally constructs a Classification rule;
                Prune the just constructed rule;
                Update the Pheromone of the trail followed by the Ant_i;
        UNTIL (i>= No_of_Ants) or
                (Ant_i constructed the same rule as the previous No_of_rules Converge-1 Ants)
        Select the best rule among all Constructed rules;
        Remove the cases correctly covered by the selected rule from training set;
END WHILE
```

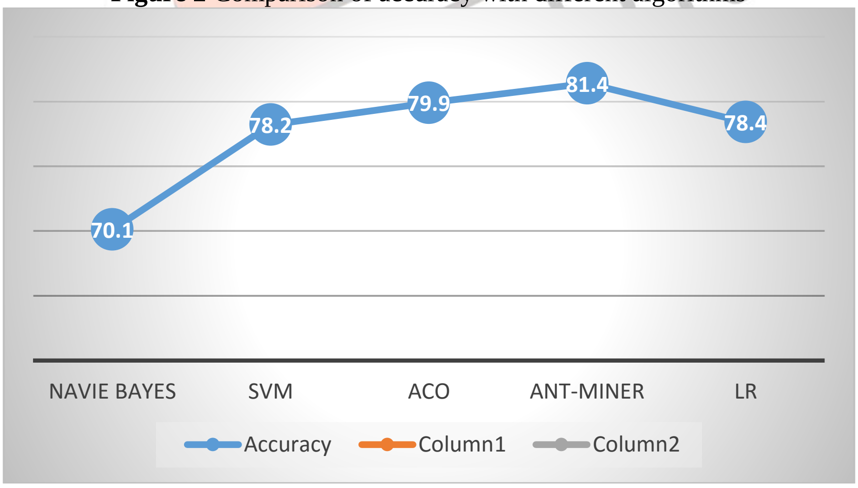
Figure 1: Pseudo code of Ant-miner

Table 1 Experimental Results of Different algorithms using various features

Algorithm	**Accuracy**
Navie Bayes	0.701
Logistic Regression	0.784
SVM	0.782
ACO	0.799
Ant-miner	0.804

Overall, the results suggest that ACO and Ant-miner algorithms gave the better results than the others.

Figure 2 Comparison of accuracy with different algorithms



In Fig.1 It shows the comparison of Ant-miner algorithm with different algorithms like Naive Bayes, SVM, Logistic Regression, ACO algorithms. Among those Ant-miner algorithm gives high accuracy and optimal results than the remaining algorithms.

IV. CONCLUSION

In this paper, we study the interactions and relationships between social media profiles and purchase behaviors on e-commerce websites. We classify the social network users based on the purchase behavior issue. When compared to the remaining all algorithms Ant-miner gives the accurate and optimal results.

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