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# *Amigo*: A Tool that Helps Consumer Decision Making in E-Commerce

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**Abstract**

The number of users who post opinions about products on the web grows every day. These reviews are either positive or negative and can possibly affect other users who are in doubt about buying the same product. When a possible buyer wants to use other buyers' reviews, s/he needs to spend a lot of time reading all these reviews. Besides, the user would prefer reading her/his friends' reviews instead of reading reviews from unknown users. To address this problem, this paper presents *Amigo* tool that searches on social networks for friends' reviews for a particular product and, using sentiment analysis, evaluates all these reviews to indicate whether or not the user would like the product, helping users in this complex decision-making process. *Amigo* tool was applied to suggest users sentiments about hotels and the preliminary results are presented.

## Introduction

More and more people are becoming online shoppers. Stores are making more products available for purchase through their websites. However, the huge volume of information on the Internet makes product search a complicated task. Several information search tasks are involved in a purchase process with an eCommerce Web site, such as, the search for information about the product, including product' reviews, the search for different brands/suppliers, and the comparison of the identified alternatives. This process requires substantial user effort, hence several information retrieval and data mining techniques have been developed.

There are systems, such as Red Opal (Scaffidi et al. 2007) which help users to locate products in a fast way based on features. However, this kind of system does not work when the user is not sure about the product. Recommender systems have helped users to search through the huge volume of information available on the Internet.

Recommender systems learn the user preferences using information gathering techniques and recommend relevant information or alternatives for the search being performed (Ricci et al. 2011). These systems provide easy and high-quality recommendations for a large user community (Jannach et al. 2010).



As shown in (Smith and Anderson 2016) eight in ten Americans are online shoppers. 74% of these online shoppers like to read reviews posted online by others users who have purchased the same item. Nowadays it is very easy to find different reviews on the Internet where users write about their experiences with purchased products. Sometimes, suppliers offer coupons or discounts to users who rate purchased products.

According to (Liu 2012) the choices we make are largely conditioned on how others see and evaluate the world and that is why when we need to make a decision we often seek out the opinions of others.

In the process of making a decision to buy or not a product, users first read several reviews about the product and then decide to buy it or not. However, reading all reviews available on the Internet is a difficult task for users. To facilitate this task, users could only read reviews of people they know. In social networks, for example, users may choose to read reviews of their friends.

Social networks have become one of the main channels where users post their satisfaction or frustration about a particular product. In fact, it is more common to see people complaining about some product than making compliments about it. It is very interesting that the opinions posted on social networks have a large impact on users and the comments from the experienced costumers provide important references to users who are trying to decide on a purchase. However, negative opinions have a more important role. They dominate discussions and participating users may have important consequences in democratic processes (Chmiel et al. 2011). Considering the huge volume of products' reviews available on social networks, users get stressed searching reviews on specific products they are interested.

One way of minimizing this problem is searching for reviews only in friends' profiles. In (Smith and Anderson 2016), authors show that 77% of the online shoppers think it is important to get advice from people they know. In addition, to reduce the search space, the user will probably rely more on friends' reviews than stranger's reviews. For example, when we are trying to book a hotel in Miami but we have never been there we need opinions. Users may go to *tripadivisor* to read what other users think about the hotels in

Miami. But they may find reviews of several hotels and still get confused. Users may decide considering the rank number, for instance, but if users found friends' reviews about a hotel, they would trust more in those reviews and it would certainly help in the decision by the hotel.

Considering this scenario, this paper presents *Amigo*: a tool that aims to help the user in her/his decision, without requiring the user to read all the reviews available on social networks. The tool checks the posts of the user's friends on *Facebook* and through sentiment analysis, it identifies the sentiments as positive or negative and suggests if the user would like a product or not.

In the following sections we present first some related work in sentiment analysis, recommender systems and social recommendation. Then we presents the *Amigo*tool and how it was implemented; we show some experiments done to evaluate the *Amigo* and finally we present our conclusions and some future work we have planned.

## Related Work

This section presents the main topics involved in this work.

### Sentiment analysis

Sentiment analysis is the computational study of sentiments, opinions and emotions expressed in text by users. Several companies have been used sentiment analysis to market their products, identifying new opportunities and managing their reputations. Through sentiment analysis is possible to estimate the product acceptance, determining strategies to improve product quality (Prabowo and Thelwall 2009).

The sentiment analysis process consists in identifying the trends or repercussion of a subject in texts that represent public opinion. Techniques of text mining and natural language processing may be applied to identify emotions in theses texts. The main goal is to understand the type of sentiment present in each text. A sentiment analysis task can be interpreted as a classification task where each category represents a sentiment (Prabowo and Thelwall 2009).

In the work presented in (Godbole, Srinivasaiah, and Skiena 2007), authors assigned scores indicating positive or negative opinion found in texts from newspapers and blogs. They expanded a candidate list of positive and negative words into a sentiment dictionary through a path-based analysis of synonyms and antonyms in WordNet.

As shown in (Unnamalai 2012), the sentiment of the user may be of three different types: explicit (the user likes reading about Artificial Intelligence), implicit (the user who bought books on Artificial Intelligence also bought science fiction books), and associative (users who like reading Artificial Intelligence also like to read about Star Wars movies).

Another approach that classifies the opinions as positive and negative was presented in (Dave, Lawrence, and Pennock 2003). Authors applied feature extraction based on scoring approach and training using machine learning methods.

In (Xia et al. 2007) authors proposed an opinion mining approach using the unified collocation framework (UCF) which incorporates attribute-sentiment and their syntactical features.

### Recommender Systems

As we already mentioned, several information search tasks are involved in a purchase process with an eCommerce Web site: the search for products' reviews, the search for different brands/suppliers, and the comparison of the identified alternatives. This process requires substantial user effort and Recommender Systems may deal with this information overload problem.

Recommender Systems learn the user preferences using information gathering techniques and recommend relevant information or alternatives for the search being performed (Ricci et al. 2011).

In (Mican, Mocean, and Tomai 2012), for instance, the authors developed a recommender system using social filtering, named WSNRS (Wise Social Network Recommender System). Considering the great amount of information published on social networks, the WSNRS presents a filter to show only relevant content, based on the relation between users and the number of interactions with the evaluated information. The content relevance is obtained by the collective intelligence analysis, originated from the users' interactions inside the network. This information is obtained and quantified by a data collector module. Though, this system needs at least some interaction among the users, losing precision when dealing with users that are not so active on the network. The WSNRS needs interaction among users to build its trust network, giving not so good recommendations when it does not happen.

Different recommendation techniques may be applied in recommender systems. The two main approaches used are the content-based filtering and the collaborative filtering (Melville and Sindhwani 2010), being this last one the most popular approach (Resnick et al. 1994). The content-based filtering analyses the attributes of items searched for or already acquired by the user, bringing results similar to those. The collaborative filtering, on the other hand, takes into consideration user data and searches for recommendation given to users with similar interests. Each of these approaches has positive and negative points depending on the context it is used. For example, a content-based filtering RS can be better in a web store where the user does not have a registration, compared to a social network, where the collaborative filtering can bring better results for the final user (Ricci et al. 2011).

### Social Recommendation

According to (Tang, Hu, and Liu 2013) social recommendation is any recommendation with online social relations as an additional input. Social relations can be trusted relations, friendships, memberships or following relations. Social relationships are enriched as social networks become more popular.

In *Facebook*, for instance, each day users have more interactions with friends and family. The higher the user's network of friends, the better will be the recommendations generated. Social recommender systems assume that users are correlated when they establish social relations (Tang, Hu, and Liu 2013).

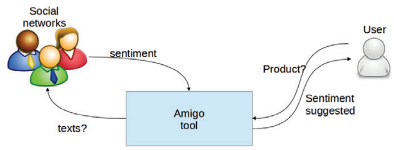


Figure 1: *Amigo* operation flow

In (Ma et al. 2008), authors presented *Sorec*, a factor analysis approach based on probabilistic matrix factorization, that solves the data sparsity and poor prediction accuracy problems by employing both users' social network information and rating records, based on the intuition that a person's social network affects personal behaviors on the Web.

## The *Amigo* tool

This section presents the developed tool and how it works. *Amigo*is a tool that reads friends' reviews posted on *Facebook*. It exploits all friends' reviews, available in the user's *Facebook* account, related to the product and it concludes if the user would have a negative or a positive sentiment about this product.

Figure 1 shows *Amigo*'s operation flow and how it can relate to a recommendation system. The initial step is to review the texts submitted in users' friends posts that are related to a specific product and then get a negative or positive feeling about that product. The main goal of *Amigo* is to analyze if the user would like a product, saving the user from the time consuming task of reading many reviews. Thus, the results of *Amigo* are very important to help recommender systems that help the user through personalized recommendations.

### Reading friends' captions pictures

Once the user is logged in his/her account, the tool retrieves all descriptions presented in his/her friends' posts. We use *Facebook Query Language* to query the *Facebook* database to retrieve information from the pictures' captions.

The tool then analyses the descriptions, post by post, following the interpretation process to classify sentiment presented in the picture's description. Although we trust our friends, in some cases we can rely on the recommendation from a friend to buy a TV, but we cannot rely on his recommendation to buy wine. In some products the taste of each person matters to decide. With this in mind, we decided to focus the tool on travel recommendations. Despite friends have different tastes, recommendations of hotels, for example, are more general.

In social networks, users post a lot of information about travels. They usually post on *Facebook* comments about vacations, such as, places, hotels or restaurants. Figure 2 shows an example where a user's friend made some comments about an hotel in Miami (USA). It is important to mention that initially we are interested in posts with description. Pictures that have no description are not considered.


Figure 2: Example of post about hotels

### The Process of Sentiment Analysis

The process of sentiment analysis in *Amigo* tool consists in identifying the repercussion of a product in *Facebook* posts. The final goal is to understand the type of sentiment presented in friends' posts, identifying one of two sentiments: a positive or a negative sentiment.

*Amigo* identifies the presence of one class in a text, distinguishing the main class from others. The process needs a list of predefined classes and indicators that helps to identify each class in the text. The indicators are terms (single words or expressions), each one associated with a numeric weight, representing the strength of the term for indicating the type of sentiment.

The process of reasoning about the presence of classes is based on probabilistic paradigms. The assumption is that many terms from different classes may be presented in a text. Thus, the process must distinguish what is the main class, by using mathematical formulas about numeric values that represent the strength of each term inside a class and the degree of importance of the term inside the text.

Algorithm 1 presents the algorithm for sentiment analysis of a given text. This algorithm was presented by (Loh et al. 2012). The first step is to identify indicators of classes in the text, that is, terms of the text that are associated with one or more classes in the task ontology. The weights (defined in the task ontology) of each term found in the text are summed separately for each class (sentiment). If a term appears more than once in a text, its strength for indicating the class is multiplied by its frequency in the text (the number of appearances).

The final result, if the text has a positive or a negative trend, depends on the numeric total for each class. The class with the greater value is the winner. If the result is tied (positive = negatives classes), the tool returns to a neutral answer. In this case, the tool assumes that is not possible to identify a dominant sentiment.

In many texts, it is possible to find positive and negative sentiments. For example, one user may publish his/her opinion about a product, reporting advantages or problems. In these cases, the tool tries to find the dominant sentiment, that is, the one with more presence or more emphatic.

### The ontology

The task ontology used was defined in (Loh et al. 2012) and it was composed by a list of words and expressions, where

**Algorithm 1** Algorithm for the Sentiment Analysis

```
for each occurrence of the word in the text do
    Search for the word in the ontology
    if the word is positive in the ontology then
        Sum the weight of the word in the ontology to the
        total positive weights
    end if
    if the word is negative in the ontology then
        Sum the weight of the word in the ontology to the
        total negative weights
    end if
end for
if total of positive weights > total of negative weights
then
    The text is classified as positive
end if
if total of positive weights < total of negative weights
then
    The text is classified as negative
end if
if total of positive weights = total of negative weights
then
    The text is classified as neutral
end if
```

each one is identified by the corresponding sentiment and a numeric weight. The weights are represented by integer numbers between 1 and 10, that represents the importance of the word to determine the sentiment presented in the text. A high weight means that the word indicates a sentiment without confusion.

The final list of emotional terms was created from the bases Affect and WordNet Affect and it was grouped in two classes (positive and negative). Some terms were disregarded, because it was not possible to classify the term as positive or negative. After that, the list of terms was combined with the list of terms from the machine learning stage and duplicities were removed.

The final phase was to determine the weight of each term to indicate the level of the sentiment. The weights were determined by a human expert (using a 1-10 scale), but using as parameter a numeric degree calculated by a text mining tool called Text Mining Suite (www.intext.com.br) in the machine learning step. This numeric degree is based on the frequency of the word inside each class (relative frequency inside each text and frequency in the texts of the training collection).

The final task ontology is composed by 3733 terms (single words and expressions), where 1160 are positives and 2573 are negative. This task ontology was used by *Amigo* in the process of searching for information in the friends' pictures. Table  shows an example of words presented in the final task ontology.

## Experiments

This section presents the experiments that were done to validate *Amigo* tool.

| Word | Weight | Type of sentiment |
|---|---|---|
| Anger | 10 | negative |
| Mad | 10 | negative |
| I Hated it | 10 | negative |
| Unsustainable | 10 | negative |
| Devastated | 10 | negative |
| Unfortunate | 10 | negative |
| Detrimental | 10 | negative |
| Damaged | 6 | negative |
| Futility | 5 | negative |
| Approved | 10 | positive |
| Magnificent | 10 | positive |
| I liked it | 10 | positive |
| Sympathize | 10 | positive |
| I loved it | 10 | positive |
| Congratulations | 10 | positive |
| Tolerant | 5 | positive |
| Proud | 5 | positive |

Table 1: Example of words presented in the ontology

| **Words** | **Number of Words** |
|---|---|
| Positive | 401 |
| Negative | 149 |

Table 2: Number of words to each type of sentiment

### Experiment Setup

In our experiment we did a partnership with a travel agency to have real passengers to validate the tool. Customers from this travel agency were invited to participate as volunteers of our experiment. The only requirement to be a volunteer was to have a *Facebook* account. In the period of one month we got 29 passengers volunteers.

We had 18 females and 11 males and their age were between 32 and 65. From all these volunteers, we observed that the average of friends in their account was 780.

Having the volunteers we then run a recommender system to get hotels' recommendations and asked users to evaluate the recommendations received. In this step we chose to use *Personal Tour*, an available multi-agent recommender system applied to the tourism domain that has already been validated in (Lorenzi, Loh, and Abel 2011).

For each volunteer we created a query in *Personal Tour* system to search for hotels in Miami. In *Personal Tour*, users may ask recommendations about travel (flight tickets, accommodations, attractions or the whole travel package) and agents work in a cooperative way to compose the recommendations. The recommendations are based on the agents' expertise. Each agent is an expert in a type of travel service (flights or accommodations, for instance).

*Personal Tour* returned a list with 4 different hotels:

- *Miami Beach Holiday Inn*
- *Courtyard Coconut Grove*
- *Loews Miami Beach*
- *Hyatt Regency Miami*

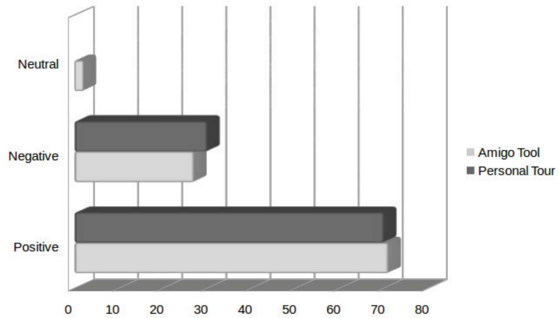


Figure 3: Evaluations: *Amigo* x *Personal Tour*

After receiving the hotel recommendations, the volunteers evaluated the hotels recommended, rating them using a 1-5 scale, being 5 the best rate and 1 the worst rate. The rates equal or greater than 3 were considered as *positive* rates and the rates 1 and 2 were considered as *negative* rates. These ratings were used to calculate the accuracy of the results obtained by *Amigo* tool.

We obtained 70% of postive rates, and 30% negative rates. These percentages will be compared with the percentages of positive and negative sentiments suggested by *Amigo* tool.

## Results from the experiments

With the list of hotels recommended by *personal tour* we then run *Amigo* tool for each volunteer in all his/her friends *Facebook* accounts with the goal of returning a positive or a negative sentiment about the recommended hotels.

Table  shows the number of words returned by *Amigo* that are related to the hotels. The tool found 401 positive words and 149 negative words. *Amigo* evaluated that 71% of the volunteers would have *positive* sentiments about the 4 hotels reviewed by their friends and 27% would have *negative* sentiments. However, 2% of the volunteers did not have information about hotels in Miami in their friends' posts and for this reason *Amigo* returned this number as *neutral*.

Usually in sentiment analysis, we need a dataset to evaluate the accuracy of the sentiments returned. However, in our experiment we did not have a dataset, we took advantage of the users' evaluations obtained from the recommender system. Then, in order to evaluate the accuracy of *Amigo*'s results we compared them with the evaluations obtained by *Personal Tour*.

Figure  3 shows the comparison of the results obtained in the experiment: 71% of positive sentiment (in *Amigo* tool) against 70% evaluations obtained by *Personal Tour*, and 27% of negative sentiment (*Amigo* tool) against 30% from *Personal Tour*. Both results are considered good.

Analyzing these presented results and each search done by *Amigo* tool we learned that:

- There is a compatibility between what the volunteer evaluated as positive and what the group of friends suggested as positive;
- It is possible to improve the accuracy of *Amigo* tool if we reduce the search space considering only closest friends. We saw that the volunteers' average friends are 780, but it is hard to believe that these 780 friends are really close to the volunteer. The weaker the relationship, the greater the probability of having less common tastes between users;
- In *Amigo* tool we had 2% of neutral sentiment. *Personal Tour* did not have this possibility due to the fact that users evaluate with rates from 1 to 5 and the rates may be negative (1 or 2) or positive (3, 4 or 5);
- *Personal Tour* and other recommender systems could deliver better recommendations if they have this search done by *Amigo* tool. This feature is a way to improve the user profile which means that the recommender system could know better about the user and thus improving its recommendations. The returned of negative sentiments would also help recommender systems. They could avoid to recommend the hotels that were suggested as *negative* by the user's friends.
- As negative point we learned that *Amigo* tool needs enough posts of friends about a specific hotel to be able to guess a sentiment. This could leads us to the cold start problem that could leave us with little to no data.

Other works had addressed the challenge of using sentiment analysis in recommender systems. In the work presented by (Aurchana, Iyyappan, and Periyasamy 2014), for instance, the authors developed a framework for sentiment analysis in the tourist domain. Four stages were created: stakeholder analysis, topical analysis, sentiment analysis and stock modelling. The sentiment analysis stage was built using tourism related web forum discussions.

Another interesting work was presented in (Gräbner et al. 2012) where authors proposed a lexicon-based approach to classify customer reviews of hotels by means of a sentiment analysis. In their first experiments only reviews for hotels located in New York were considered.

Our tool is different because it uses friends relations to select the comments for sentiment analysis, helping to minimize the problem of false recommendations or fake comments to push products.

## Conclusions and Future Work

This paper presented *Amigo* tool that is capable of helping users to decide about a specific product using users' friends reviews about the product. It reads information posted in user's friends *Facebook* account and through sentiment analysis, it returns if the user would have positive or negative sentiment about the product, avoiding the user to waste time reading all the available reviews.

Experiments were conducted in the tourism domain to test the efficiency of the tool where the goal was knowing if the user would have positive or negative sentiment about specific hotels. A real multi-agent recommender system (*Personal Tour*) was used in the experiments to recommended hotels. The evaluations done by the volunteers in the recommender system were compared with the results returned from *Amigo* tool. The results presented corroborate the idea that the proposed tool helps to minimize the hard work that the user would have to read all friends' reviews.

The *Amigo* tool could be improved if we consider the possibilities in the definition of thematic *Facebook* groups of friends. The user could define that s/he wants only the evaluations of a specific group such as family, work, friends, or a more oriented group such as a travel group (in which the friends have similar travel preferences or budget constraints). With this in mind, the user could receive evaluations from different groups of friends, with different tastes and evaluations to better decide what type of product s/he wants to buy.

As future work we want to consider into account all the user's preferences, context, and social aspects. Also, we are recruting more customers to have more data to new experiments. We are aware that having more customers the results of the experiments will be more robust.

To avoid the cold start problem we intent to integrate the tool with *Personal Tour* because it could bring recommendations based on experts agents in the cases where users have few friends who could give their opinion on a specific hotel.

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