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Recent years have seen an exponential growth in the use of social networking systems, enabling their users to easily share information with their connections. A typical Facebook user, as an example, might have 300-400 connections that include relatives, friends, business associates and casual acquaintances. Sharing information with such a large and diverse set of people without violating social norms or privacy can be challenging. Allowing users to define groups and restrict information sharing by group reduces the problem but introduces new ones: managing groups and their members, relations and information sharing policies. This thesis addresses the problem of maintaining group membership. We describe a system that learns to classify a user's new connections into one or more existing groups based on the connection's attributes and relations. We demonstrate the approach using data collected from real Facebook users. The two major tasks are identifying the relevant features for the classification and selecting the learning mechanism that best suits the task. Hierarchical and overlapping groups pose another significant challenge. We show that our system classifies new connections into these groups with high accuracy even with only 10-20% of labeled data.

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ABSTRACT

Title of Document: GROUP RECOGNITION IN SOCIAL NETWORKS

Nagapradeep Chinnam, Master of Computer Science, 2011

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Recent years have seen an exponential growth in the use of social networking systems, enabling their users to easily share information with their connections. A typical Facebook user, as an example, might have 300-400 connections that include relatives, friends, business associates and casual acquaintances. Sharing information with such a large and diverse set of people without violating social norms or privacy can be challenging. Allowing users to define groups and restrict information sharing by group reduces the problem but introduces new ones: managing groups and their members, relations and information sharing policies. This thesis addresses the problem of maintaining group membership.

We describe a system that learns to classify a user's new connections into one or more existing groups based on the connection's attributes and relations. We demonstrate the approach using data collected from real Facebook users. The two major tasks are identifying the relevant features for the classification and selecting the learning mechanism that best suits the task. Hierarchical and overlapping groups pose another significant challenge. We show that our system classifies new connections into these groups with high accuracy even with only 10-20% of labeled data.

GROUP RECOMMENDATION IN SOCIAL NETWORKS

By

Nagapradeep Chinnam

Thesis submitted to the Faculty of the Graduate School of the
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Chapter 1
INTRODUCTION

In this chapter we present an introduction to the notion of social networks and the groups. We will discuss the need and motivation for classifying friends into groups and then present a formal thesis definition.

1.1 Social Networks and Groups

A social network is a structure made up of nodes, which may represent individuals, organizations and other real world entities, which are connected by relationships like friendship, kinship, interests etc.

Social networks have evolved into a virtual world where people are using them to connect to each other and to share updates in real time. There are hundreds of social web portals out there each tending different purposes and users varying from researchers to movie fans. Having a profile on one or the other social network has become a necessity for an average internet user. Social networks are even used for business promotions like organizing events and taking surveys etc. Consider for example, if you would like to conduct a survey it takes a lot of effort in terms of the promotion to reach out to the intended audience. Using social networks targeting the audience and reaching out has become very easy as the survey can spread virally from friend to friend getting it the maximum attention.

Table 1.1 List of social networking sites *Source: Wikipedia*

NAME	DESCRIPTION/FOCUS	NUMBER OF REGISTERED USERS
ACADEMIA.EDU	Social networking site for Academics/ Researchers	211,000
BADOO	General, Meet new people, Popular in Europe and Latin America	86,000,000
BLOGSTER	Blogging community	85,579
CLASSMATES.COM	School, college, work and the military	50,000,000
DELICIOUS	Social bookmarking allows users to locate and save websites that match their own interests	8,822,921
DOUBAN	Largest Chinese community providing user review and recommendation services for movies, books, and music. It also doubles up as the Chinese language book, movie and music database.	46,850,000
FACEBOOK	General	750,000,000+
FLIXSTER	Movies	32,000,000
FOURSQUARE	Location based mobile social network	2,000,000
IBIBO	Talent based social networking site that allows promoting one's self and also discovering new talent. Most popular in India	3,500,000
MEETUP.COM	General. Used to plan offline meetings for people interested in various activities	
ORKUT	General. Owned by Google Inc. Popular in India and Brazil	100,000,000

1.2 Motivation

One of the primary concerns in social networks is to maintain privacy in this virtual world while still staying connected with others. Striking balance between getting connected and maintaining privacy is becoming a crucial requirement to the end user. Consider the scenario, where you are planning to attend a base ball game featuring your favorite team on a weekday. You want to share it with your friends that you are watching a marquee game but at the same time don't want your colleagues at work don't know about your whereabouts. There are several privacy models that help the user in achieving this. One of these is a group based semantic model that clusters your friends into groups and the privacy settings can be fine tuned for each group depending on the user preferences.

Some statistics from Facebook, a famous social networking site:

- More than 500 million active users
- 50% of active users log on to Facebook in any given day
- People spend over 700 billion minutes per month on Facebook
- There are over 900 million objects that people interact with (pages, groups, events and community pages)
- More than 30 billion pieces of content (web links, news stories, blog posts, notes, photo albums, etc.) shared each month.

With so much information being generated and shared, groups are an essential entity of a social network, which makes sure that the information is shared only with the intended audience. Hence it is important to classify friends into different groups so that better privacy controls can be applied for each group while sharing

information. Groups provide private channels for communication in the social network.

Classifying friends into groups can be a tedious task. We believe that using machine learning, a model can be trained to accurately classify the friends into different groups. In this work, we would thus like to define a process that will classify a friend connection to a pre-defined group.

1.3 Thesis Contribution

The thesis contribution can be briefly stated as follows:

1. Understand how people group their friends in a social network and how they use them by taking a survey.
2. We determine the relevant features that are useful for classifying users into groups and then train a machine learning models for the classification.
3. We evaluate different approaches in machine learning to identify the best

Chapter 2

BACKGROUND AND RELATED WORK

In this chapter, we provide some background knowledge about SVMs and different versions of them and the external APIs we used to achieve our goal. We also describe some related work that has been pursued in the direction of grouping the friends in social networks like Facebook and LinkedIn.

2.1 SVMs

Support vector machines (SVMs) are a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. The standard SVM takes a set of input data and predicts, for each given input, which of two possible classes the input is a member of, which makes the SVM a non-probabilistic binary linear classifier.

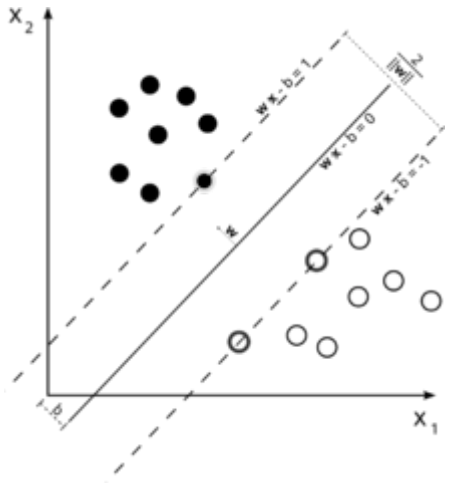
A SVM constructs a hyperplane or set of hyperplanes in a high or infinite dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data points of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

Given some training data $\mathcal{D}$, a set of *n* points of the form

$$\mathcal{D} = \{(\mathbf{x}_i, y_i) \mid \mathbf{x}_i \in \mathbb{R}^p,\ y_i \in \{-1, 1\}\}_{i=1}^{n}$$

where the y_i is either 1 or −1, indicating the class to which the point $\mathbf{x}_i$ belongs. Each $\mathbf{x}_i$ is a p-dimensional real vector. SVM finds the maximum-margin hyperplane that divides the points having $y_i = 1$ from those having $y_i = -1$[3].

Fig 2.1 Maximum-margin hyperplane and margins for an SVM trained with samples from two classes. *Source: Wikipedia*



Any hyperplane can be written as the set of points $\mathbf{x}$ satisfying

$$\mathbf{w} \cdot \mathbf{x} - b = 0,$$

where $\cdot$ denotes the dot product. The vector $\mathbf{w}$ is a normal vector: it is perpendicular to the hyperplane. The parameter $\frac{b}{\|\mathbf{w}\|}$ determines the offset of the hyperplane from the origin along the normal vector $\mathbf{w}$.

2.2 WEKA

Weka is a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset or can be called from the

Java code. Another advantage is portability, since it is fully implemented in the Java programming language and thus runs on almost any modern computing platform [1].

Weka is a comprehensive toolbench for machine learning and data mining. Its main strengths lie in the classification area, where all current ML approaches and quite a few older ones have been implemented within a clean, object-oriented Java class hierarchy. Regression, Association Rules and clustering algorithms have also been implemented. All of Weka's techniques are predicated on the assumption that the data is available as a single flat file or relation, where each data point is described by a fixed number of attributes.

2.3 Logistic Regression

Logistic regression or logit model is used for prediction of the probability of occurrence of an event by fitting data to a logit function logistic curve. It is a generalized linear model used for binomial regression. Like many forms of regression analysis, it makes use of several predictor variables that may be either numerical or categorical. Logistic regression is used extensively in the medical and social sciences fields, as well as marketing applications such as prediction of a customer's propensity to purchase a product or cease a subscription.

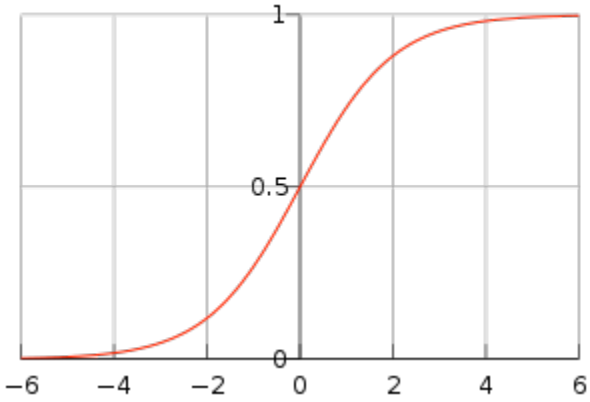
Logistic regression is a useful way of describing the relationship between one or more independent variables (e.g., age, sex, etc.) and a binary response variable, expressed as a probability, that has only two values, such as having cancer ("has cancer" or "doesn't have cancer").

A logistic function $f(z)$ for a given input z is given by

$$f(z) = \frac{e^z}{e^z + 1} = \frac{1}{1 + e^{-z}}$$

Fig 2.2 The logistic function with z on the horizontal axis and $f(z)$ on the vertical axis

Source: Wikipedia



The logistic function is useful because it can take as an input any value from negative infinity to positive infinity, whereas the output is confined to values between 0 and 1. The variable z represents the exposure to some set of independent variables, while $f(z)$ represents the probability of a particular outcome, given that set of explanatory variables. The variable z is a measure of the total contribution of all the independent variables used in the model and is known as the logit.

The variable z is usually defined as

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k,$$

where β_0 is called the "intercept" and β_1, β_2, β_3, and so on, are called the "regression coefficients" of x_1, x_2, x_3 respectively. Each of the regression coefficients describes the size of the contribution of that risk factor. A positive regression coefficient means that the explanatory variable increases the probability of the outcome, while a negative regression coefficient means that the variable decreases the probability of that outcome.

2.4 Facebook List Suggestions

Facebook has its own set of recommendation features. But from the examples we understood that it uses only the connections (mutual friends in a group) for suggestions. It ignores the other attributes. Also it seems to ignore the fact that groups might overlap.

2.5 InMaps

InMaps is a LinkedIn Labs experimental product that is an interactive visual representation of the LinkedIn user's professional universe and tries to identify the elusive hubs in the user's professional world. It is a great way to understand the relationships between you and your entire set of LinkedIn connections.

InMaps sifts through all of your connections, detects the relationships between them, and groups them into different network clusters. It color-codes and clumps these networks together so you can see the depth of your connections in one interface. By creating a network of interconnecting nodes representing each of your contacts, InMaps help you visualize clusters of your contacts based on how well they're

interconnected. User can then add labels to the groups of contacts, and zoom in and out of the map to discover trends or other details.

InMaps offers an insight into who the major connections, bridges and influencers are in the user's network. People with bigger dots and their names in larger fonts have more connections (and typically more sway) in specific clusters. For instance, by studying the interconnectedness of certain nodes, user can see who the 'bridge' in his relationships with groups of contacts. User can also see who knows the most people in a particular working sphere by how big their node is, which could be useful if you ever need to find a contact or someone with influence.

2.6 Facebook Applications on managing groups

There are several third party Facebook applications that try to automatically group people using various inputs.

2.6.1 Fellows

'Fellows' is a Facebook application which comes up with a way to automatically generate groups for your friends, using only the information "who knows who". By analyzing your Facebook connections, it presents the Facebook user with several groups. It tries to hide the burden of completely creating the groups from the user.

2.6.2 Social Flows

SocialFlows is a Facebook application to you by the Stanford Mobile & Social Computing Laboratory at Stanford University. It help you rediscover groups of

people that matter to you in your flows of life, without too much hassle on your part. It reveals user's important and closest social groups by analyzing tagged photos of the user and his friends. The discovered social groups can then be edited & refined using SocialFlows, and we can make the rediscovered social groups available to the user to share on Facebook as Facebook Friends Lists. Its goal is to help users protect their privacy by making it easy to create relevant personal social groups that users can safely share social information with. It also help users make sense of their ever growing social graph of friends by arranging them into groups that makes sense.

Chapter 3
UNDERSTANDING GROUPS

In a social network, grouping the connections into different lists helps the user to communicate effectively within the social graph targeting the intending audience. We have conducted a survey for Facebook users to understand how people use groups in the real life. This chapter apart from defining different types of groups also showcases the insights that we got from conducting the survey.

3.1 Why to group contacts?

Social network lets us connect and communicate with people that we are connected to in all kinds of ways like friends from school, family members, colleagues and people whom we know. In general, we don't have the same level of comfort with all of our friends in sharing updates or we might want to keep some updates private to a particular group or in some cases we might want to target specific set of our friends. This all leads to the creation of groups within our social network.

'Friend Lists' is a feature in Facebook that enables its users to group their friends. It allows to create named lists of friends that the user can use to organize their relationships whichever way works best for them. These private lists can be used to message people, send group or event invitations, and to filter updates from certain groups of friends. There are other uses that give the user more control over the information they share on Facebook and who they share it with.

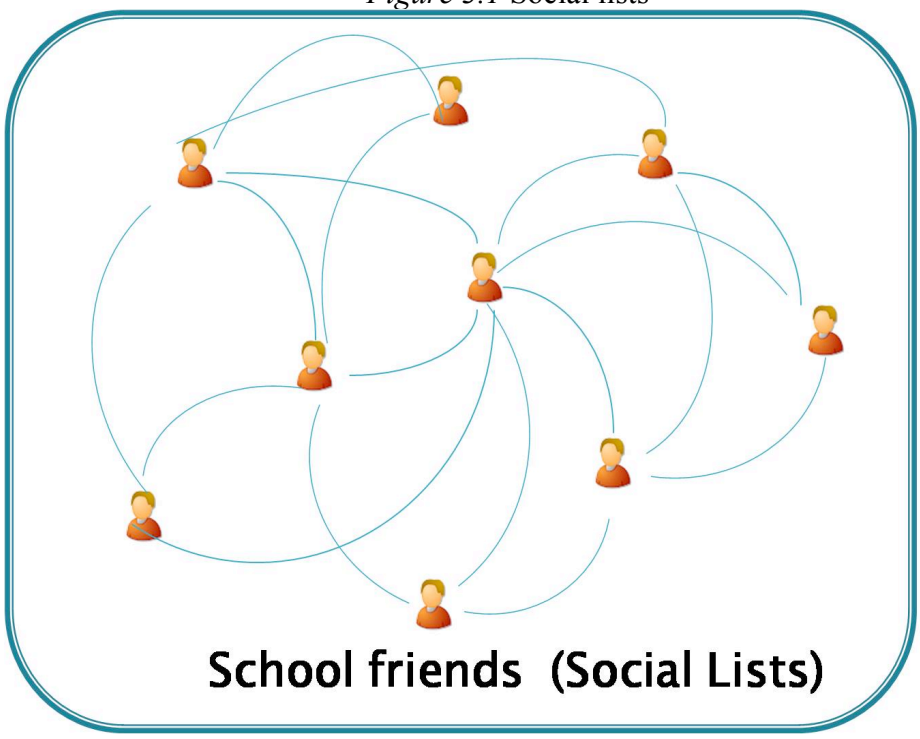
Facebook provides a more real-time model of keeping up with your friends' activities around the site and powerful way to filter your news feed. You can even use this as a marketing technique by grouping your friends related to their interests. When you have, you can send each group of friends emails related to what you think they'll enjoy. This is a very easy way to get the word out.

3.2 Types of groups

After observing the lists created by several users, we came up with these different types of groups.

3.2.1 Social Lists

Figure 3.1 Social lists

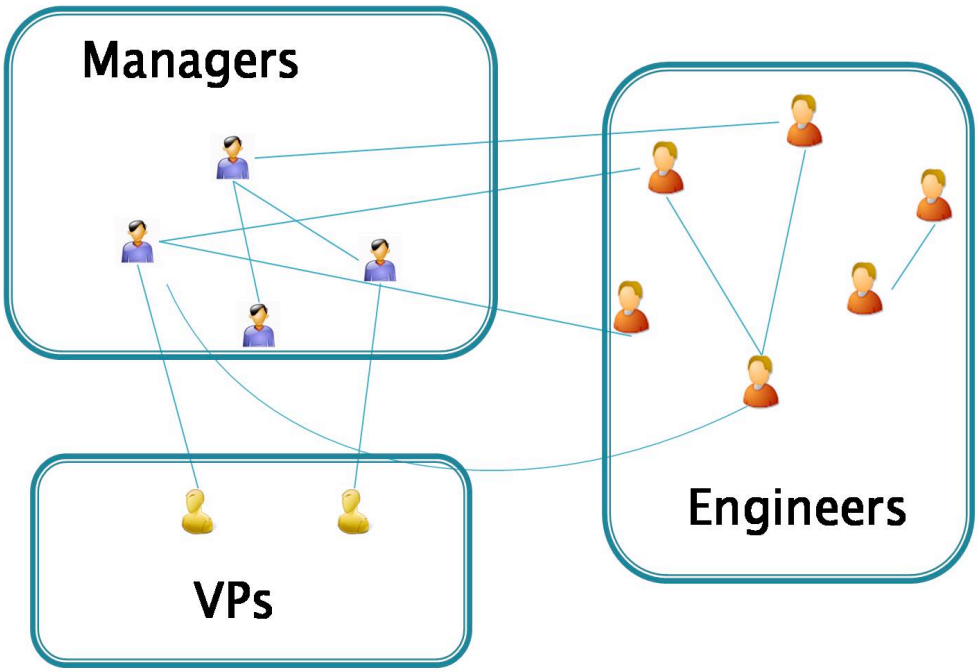


The members of these lists are strongly interconnected to one another. For a new member, the group membership is easily predictable by looking at the count of

friends he has in that group. Examples are groups like High school, Colleagues, Family etc.

3.2.2 Role based Lists

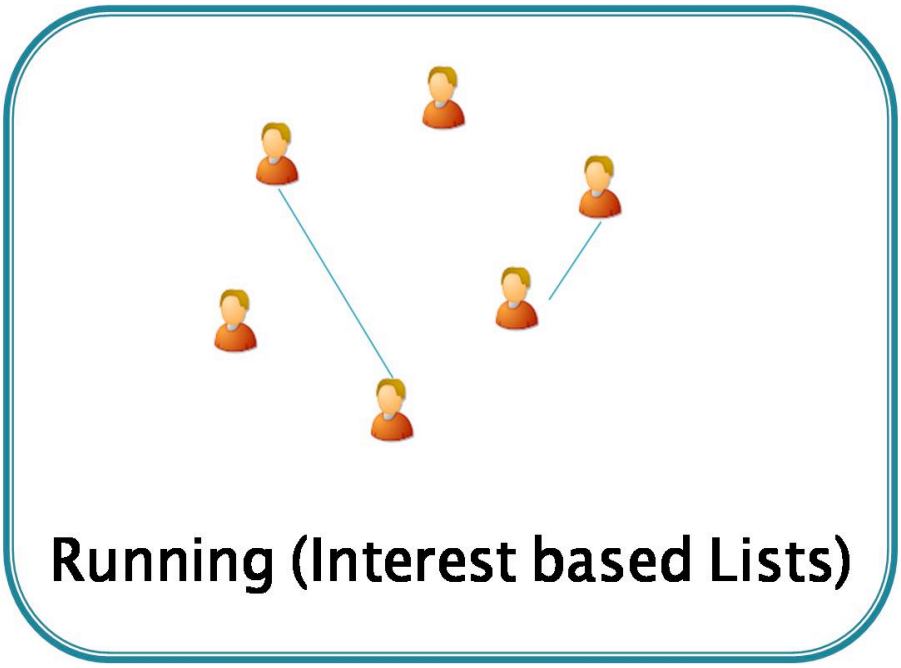
Figure 3.2 Role based lists



These lists are created based on their role in an organization or in one's personal life. The members of these lists may not be connected to each other, but from the user's (who created the lists) perspective these people share a common feature(s). Groups like Managers, Faculty are examples for this type of lists.

3.2.3 Interest based lists

Figure 3.3 Social lists



These lists are created to group the members who share common interest(s) with the user. Interest based lists differ from role based lists as the members of the later share a common property among themselves but in the former the members share a common interest/property with the user. The members in these lists may not be connected to each other.

3.2.4 Personal lists

These lists are created by the user based on the factors that are not captured by the social network. Factors may vary from personal reasons like how much they like them to the professional reasons. The model for these lists is tough to capture. Examples are groups like ‘best friends’ etc.

Table 3.1: Types of Lists

Lists Types	Is Strongly Connected	Shares Common Features Among Group Members	Shares Common Features With The User	Group Membership Recommendations
Social lists	Yes	Yes	Yes	Easy: based on connections
Role based lists	Need not be	Yes	Need not be	Easy: if information is available
Interest based lists	Need not be	Yes	Yes	Moderate: if information is available
Idiosyncratic lists	Need not be	Need not be	Need not be	Difficult

3.3 Survey

A survey has been conducted among Facebook users with a set of 12 objective questions. This survey is intended to understand how people use friend lists in Facebook. We got 128 responses from different age groups and varying professions. The results provided a great insight into the group dynamics in social networks.

3.3.1 Questionnaire:

1 What is your age?

A) <20 B) 20-30 C) 30-50 D) >50

2 How many hours do you spend every day on facebook?

A) <30 mins B) 1-2 hrs C) 2-4hrs D) i'm a facebook addict

3 What best describes your profession?

A) Student B) Working (IT related) C) Working (Non-IT) D) Retired

4 How many friends do you have in facebook?

A) <50 B)50-100 C)100-200 D) 200-500 E) 500-1000 F) >1000

5 I value my Facebook privacy?

A) Strongly disagree B) Disagree C) Neither agree nor disagree D) Agree E) Strongly Agree

6 What is your primary purpose for friend lists in Facebook?

A) Friend lists!! what are they? B) To organize my friends C) To share information in a controlled fashion D) Both B & C

7 How many friend lists have you created in Facebook?

A) None B)0-5 C) 6-10 D) >10

8 If possible what kind of privacy settings you would like to constrain using friend lists?

A) My status updates B) Likes & comments C) Photos and videos D) All

9 What kind of friend lists do you have or like to have?

A) Social lists (Almost everyone in these lists know each other Ex: Highschool, Colleagues, Family)

B) Role based lists (Ex: Managers, Faculty)

C) Interest based lists (Friends in these lists need not be connected Ex: Running)

10 Do you have any lists with overlapping friends?

A) No B) Just a few C) A lot

11 Do you like to have hierarchical lists (Ex: High school friends and High school best buddies)?

A) Yes B) No C) Don't care

12 What kind of analysis you would like to be done by a Facebook App on your friend lists?

A) Automatically create lists for me by looking at my friends information

B) Suggest friends to add to the lists that I have created

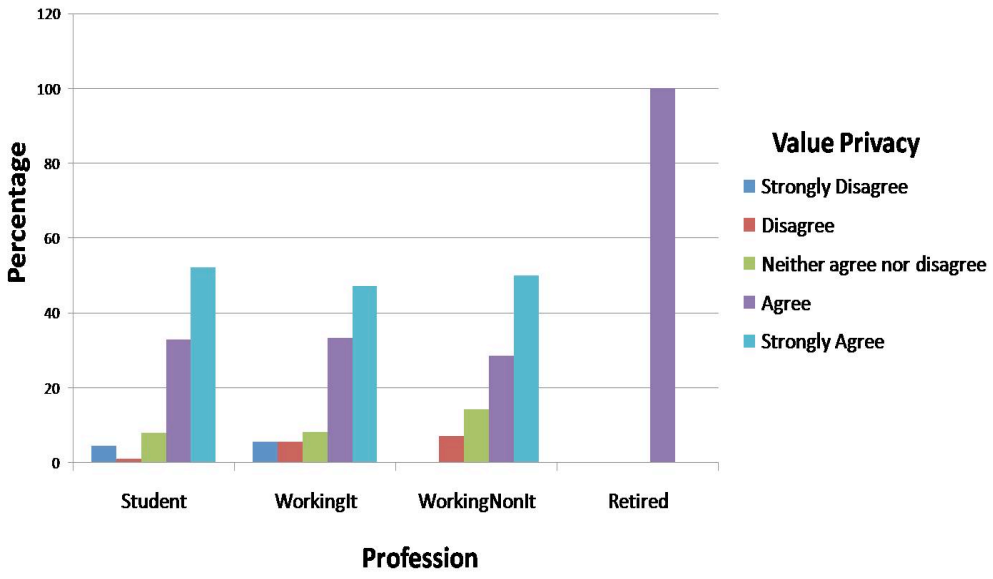
C) Data analysis over my friends profile information

3.3.2 Results:

From the questionnaire, we analyzed the relationships between privacy, groups and other attributes on 21 different data points. In the following section we present some of the findings that we find interesting.

3.3.2.1 Profession vs Privacy

Figure 3.4 Profession vs Privacy

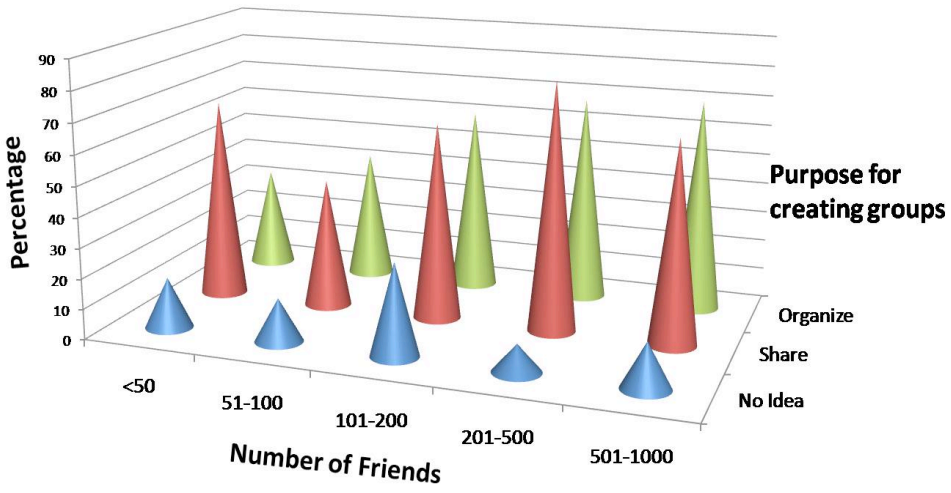


There is a general consensus among all the users irrespective of their profession about their privacy. Every one values it. To the statement 'They value their Facebook privacy' the percentage of users who agree and to the percentage of users who strongly agree to it is almost same. Users want privacy but they are not harsh about it. It shows that users don't want strong privacy policies that block them from the rest of the social network. They want policies that enable them to connect and share information in a secure way.

3.3.2.2 Number of friends vs Purpose for creating groups

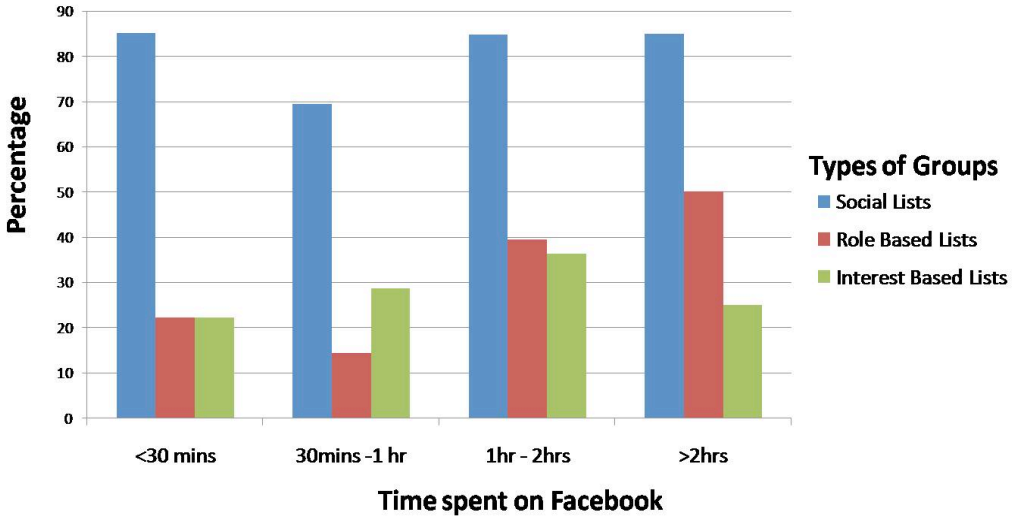
We tried to find out why users want to create groups. Is it to share information with their friends in a controlled fashion or to organize their friends? The results showed that both organizing friends and sharing information are equally important irrespective of the number of friends the user has.

Figure 3.5 Number of friends vs Purpose to create groups



3.3.2.3 Time spent on Facebook vs Types of groups

Figure 3.6 Time spent on Facebook vs Types of groups



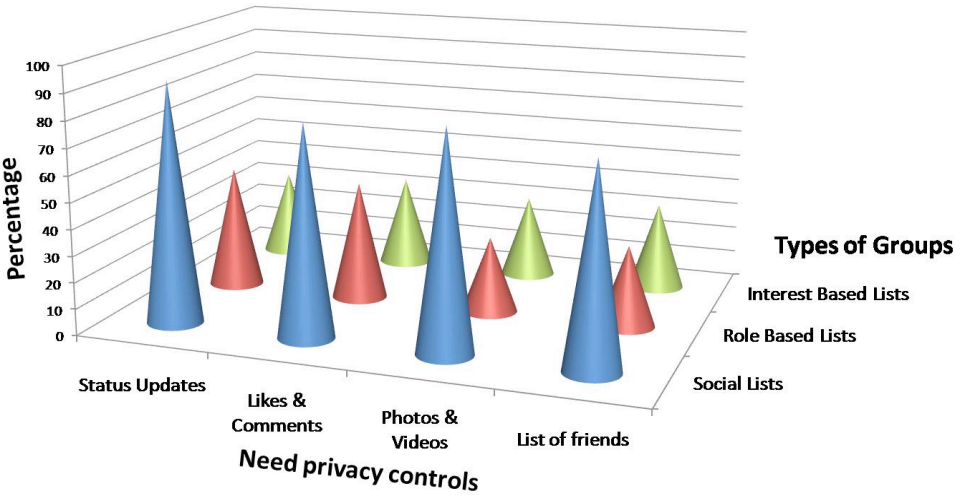
Social lists are popular among users irrespective of the time they spent on Facebook. Users who spend less time don't care much about the other kind of lists,

but as they spend more time there is an increase in the need of both Role based lists and Interest based lists.

3.3.2.4 Constraints vs Types of groups

Social lists are popular among the users and it is independent of the control on Facebook objects they wish to have. Role based lists are more popular among users who wish to constrain their status updates, likes and comments.

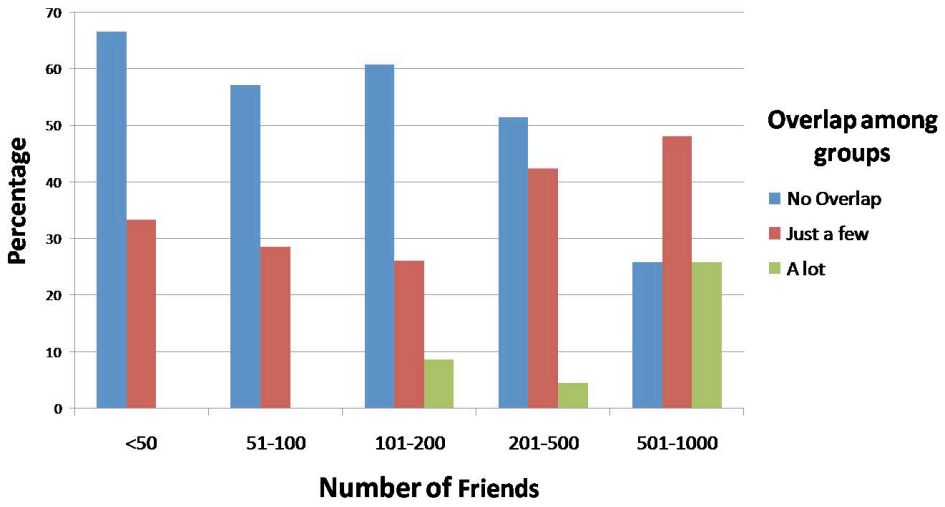
Figure 3.7 Constraints vs Group types



3.3.2.5 Number of friends vs Overlap in groups

As number of friends increases there is an increase in the overlap between the groups

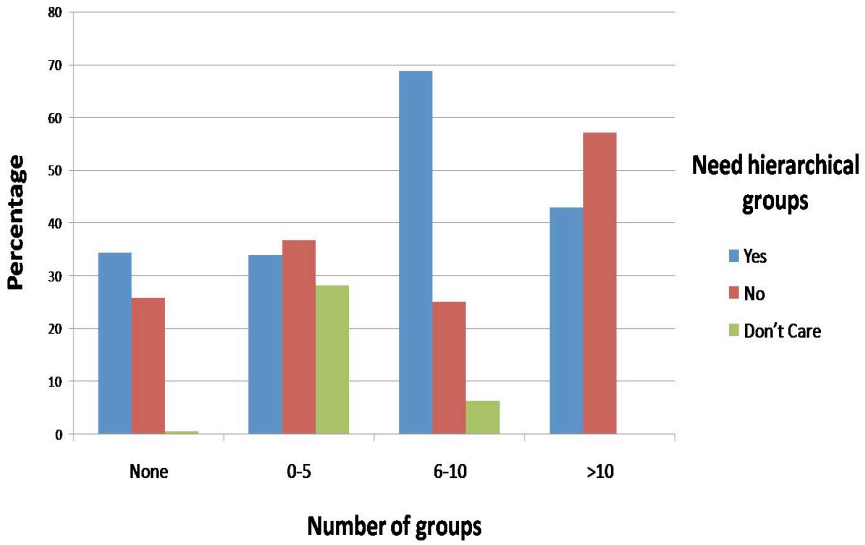
Figure 3.8 Number of Friends vs Overlap between groups



3.3.2.6 Number of lists vs Need for hierarchy in groups

As the size of the groups increases users felt the requirement of a hierarchical groups to organize them. Also the percentage of 'don't care' responses reduced to zero as the size of groups increases

Figure 3.9 Number of groups vs Hierarchy in groups



Chapter 4

SYSTEM DESIGN AND IMPLEMENTATION

In this chapter we will explain a high level design and implementation of our system. In the first section we explain the general architecture and the system components that have most direct influence on the system. We then describe the feature vector that we extracted from the datasets and the libraries and packages that we used to build this system.

4.1 System Architecture

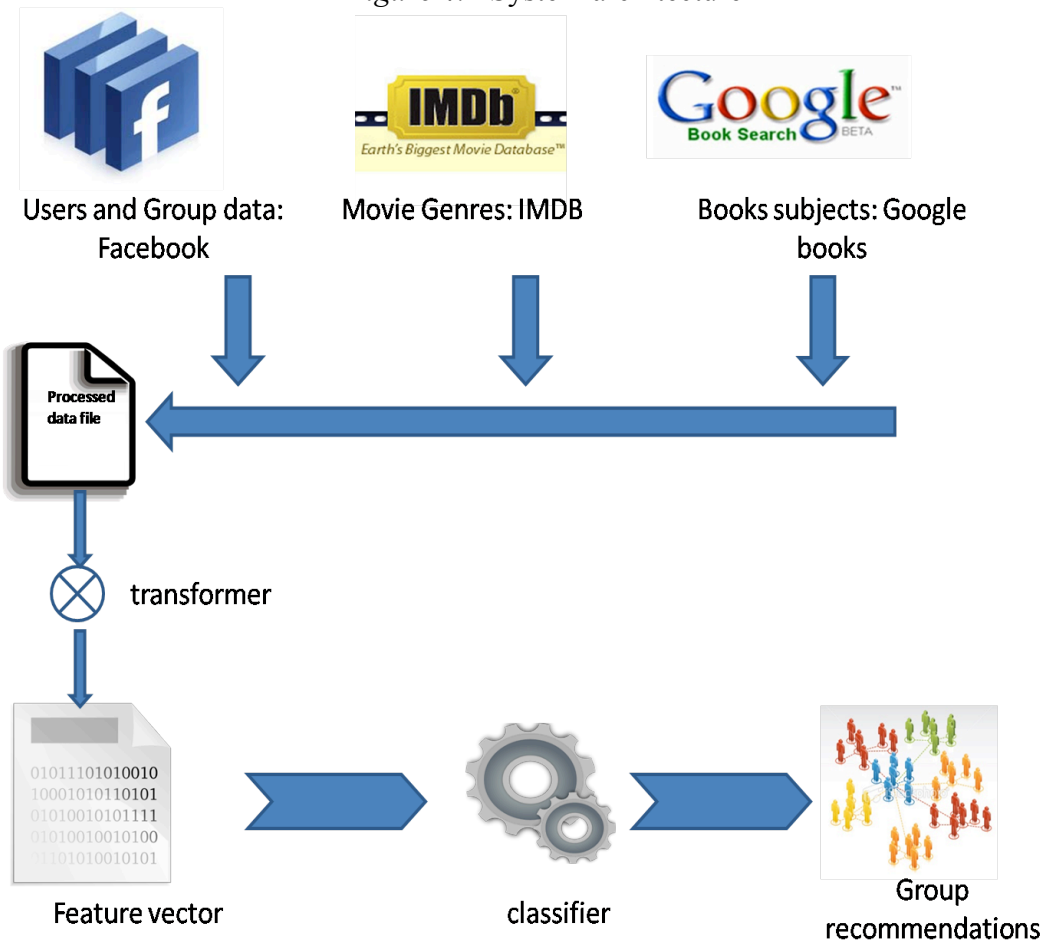
Figure 4.1 provides an architectural overview of our system.

The system architecture consists of 3 stages. In the first stage data is collected from Facebook using Graph API. It includes the data collected from each user about his friends and the lists (groups) that he has already created. This data is co-related with the inputs from IMDB (to identify the genres of the movies that the user has liked) and Google Books (to identify the subjects of the books that are liked by the user) to produce an intermediate file.

In the second stage, a transformer is used to produce a feature vector that is consistent with the classifier that is used in the next stage. Different classifiers use different input formats. Transformer takes the intermediate file and converts into the required format of the classifier.

The feature vector file that is produced is used as an input to the next stage where a classifier is trained to produce a model. This model is used to accurately predict the group assignments.

Figure 4.1 System architecture



4.2 Feature Vectors

The feature vector comprises of several features. Here is a comprehensive list of the features that are used as input for the classifier to come up with the recommendations for group assignments.

Table 4.2 shows all the relevant features extracted from the user's profile to create a feature vector file that trains the classifier.

4.2.1 General Information

Features like age, sex and languages are extracted from the basic information of the user profile. There are lots of groups that have same attribute values except that the groups are different in terms of the age of the members. Example: 'Family' and 'Kids' are two groups that might have same attribute values but differ in the age groups of its members. Another example can be 'UMBC CS Graduate Students' and 'UMBC CS Faculty'. These groups are usually part of a bigger group but are separated to achieve privacy. In cases like these, the 'age' attribute acts as a beacon to distinguish them from one another.

The languages section is processed using the bag-of-words model. The user's location is also captured in the feature vector. Most of the cities in Facebook are tagged along with their state and sometimes their country. The city and state information is mined from the user's location related features like 'current city' and 'home town'.

4.2.2 Education History

The user's education history provides a great insight into the social groups like 'high school', 'Graduate Friends' etc. Facebook provides an interface to collect good amount of information on the user's education background. We can extract fields like the name of the school, its type (college or graduate school or high school), degree the user has achieved and the concentration he majored in from the education

history of the user. This provides a comprehensive detail about the user, which includes all the schools/colleges that he has attended. From these fields bag of words are generated by removing the listed stop words.

4.2.3 Work History

Similar to the features extracted from the education history, attributes are captured from work history of the user. We are interested in the fields like name of the organization(s) the user worked for, position(s) he held, work city and work state along with other information like details of the project(s) for all places where the user has worked. From these fields bag of words are generated by removing the listed stop words.

Table 4.1. List of stop words used while processing text bag-of-words model

LIST OF STOP WORDS
AND, AT, FOR, IN, MY, OF, THE, &, !, -, ;

4.2.4 Is-A-Friend Relationship

Most of the members in social lists (almost everyone in these social lists knows each other Ex: High school, Colleagues, Family) are strongly connected. For a given person and a group, we can check how many 'friends' he has in that group. Based on the relationship 'is-a-friend' (is-connected), a mutual friend count is generated for the user's friend against each group. This count signifies how strongly a friend is connected to the rest of the friends in a group. A high number for a group

indicates a strong likelihood of that connection belonging to the group provided the group is a social list

This turned out to be a strong indicator in most of the groups to determine whether the membership of the user in that group. The count has to be normalized in order to consider the variance between memberships cardinality of different groups.

4.2.5 Movies, Television & Books

A person's favourite movies, television shows and the books he reads gives us good insight into the kind of person he is. These can be captured from the Facebook user's data.

Using the Netflix API[8], the genres of the movies and TV shows for which the user liked are identified. The summation of the count for each genre from all the movies and television shows is generated and is normalized to account the factor that some users might list more movies where as some might just list few. This count captures the user's interest in that genre.

Similarly for the books, Google book Data API is used to calculate the normalized count for each category the user is interested in.

4.2.6 Games, Sports, Activities & Interests

Facebook provides multiple fields like games, sports, activities, and interests to capture the user's extracurricular activities. These fields provide more information on the user interests and help our classifier to predict the interest-based groups more accurately.

A bag of words is generated using the fields like games, sports, favorite teams, favorite athletes, activities and interests of the user. These features try to capture the user's social life apart from education and work.

Table 4.2. Features extracted from different data collected from the Facebook user.

DATA COLLECTED	FEATURES EXTRACTED
BASIC PROFILE INFORMATION	Age, Sex, Home town, Home State, Current City, Current State, Languages
EDUCATION & WORK HISTORY	Bag of words from relevant features
MOVIES & TELEVISION	Normalized count of genres of the movies from the user interests using Netflix API
BOOKS	Normalized count of subjects of the books from the user interests using Google Data API
GAMES, SPORTS, ACTIVITIES & INTERESTS	Bag of words from relevant features
WHO KNOWS WHO (IS-CONNECTED)	Mutual friend count in each group

4.3 Libraries

4.3.1 Facebook Graph API

At Facebook's core is the social graph; people and the connections they have to everything they care about. The Graph API[6] presents a simple, consistent view of the Facebook social graph, uniformly representing objects in the graph (e.g., people, photos and pages) and the connections between them (e.g., friend relationships, shared content, and photo tags).

Every object in the social graph has a unique ID. You can access the properties of an object by requesting `https://graph.facebook.com/ID`

All of the objects in the Facebook social graph are connected to each other via relationships. Bret Taylor is a fan of the Coca-Cola page, and Bret Taylor and Arjun Banker are friends. We call those relationships *connections* in our API. You can examine the connections between objects using the URL structure `https://graph.facebook.com/ID/CONNECTION_TYPE`

Authorization:

The Graph API as such allows you to easily access all public information about an object. To get additional information about a user, you must first get their permission. At a high level, you need to get an *access token* for the Facebook user. After you obtain the access token for the user, you can perform authorized requests

on behalf of that user by including the access token in your Graph API requests. The Graph API uses OAuth 2.0 for authorization

```
https://graph.facebook.com/220439?access_token=...
```

Table 3.3 Data Permissions

USER PERMISSION	FRIENDS PERMISSION	DESCRIPTION
user_activities	friends_activities	Provides access to the user's list of activities as the activities connection
user_birthday	friends_birthday	Provides access to the birthday with year as the birthday_date property
user_education_history	friends_education_history	Provides access to education history as the education property
user_hometown	friends_hometown	Provides access to the user's hometown in the hometown property
user_interests	friends_interests	Provides access to the user's list of interests as the interests connection
user_location	friends_location	Provides access to the user's current location as the location property
user_work_history	friends_work_history	Provides access to work history as the work property
read_friendlists	manage_friendlists	Provides access to any friend lists the user created. All user's friends are provided as part of basic data, this extended permission grants access to the lists of friends a user has created, and should only be requested if your application utilizes lists of friends.

Access Token:

- Create a link to request necessary permissions from the user. The permissions are listed in the ‘scope’ parameter of the url

  ```
  https://graph.facebook.com/oauth/authorize?client_id=1010
  ```

```
48753299716&redirect_uri=http://ebiquity.umbc.edu/&scope=
.. &ext_perm=offline_access
```

- Once the user follows he above url and gives access permissions, he would be re-directed to the application website along with the 'code'.

```
http://ebiquity.umbc.edu/?code=..
```

- Use the code from the above URL to request the access token. To request the access token, construct the url along with the 'client id' and 'client secret' with the 'code' that we got from above url

```
https://graph.facebook.com/oauth/access_token?client_id=.
.&redirect_uri=http://ebiquity.umbc.edu/&client_secret=..
&code=..
```

- You will be redirected to a page where you can get the access token.

Calls to the Graph API:

- Get friend lists of the user

```
https://api.facebook.com/method/fql.query?query=SELECT
flid, name FROM friendlist WHERE owner=[facebook_id]
&access_token=[access_token] &format=JSON
```

- Get members in each friend list

```
https://api.facebook.com/method/fql.query?query=SELECT
flid,uid FROM friendlist_member WHERE flid IN (SELECT
flid FROM friendlist WHERE owner=[facebook_id])
&access_token=[access_token] &format=JSON
```

- To get the list of all the user's friends

  `https://graph.facebook.com/me/friends?access_token=[access_token]`

- To get the general information of each friend

  `https://graph.facebook.com/[friend id]?access_token=[access_token]`

- To get the data on the movies, books, music etc. of each user

  `https://graph.facebook.com/[friend id]/[movies/books/music]?access_token=[access_token]`

- To get the mutual friends in each list for a given user

  `https://api.facebook.com/method/friends.getMutualFriends?target_uid=[friend id]&access_token=[access_token]&format=JSON`

4.3.2 Netflix API

Netflix API is used to find out the genres of the movies that are liked by the user.

- Initializing Netflix API client

```
NetflixAPIClient apiClient = new
NetflixAPIClient(myConsumerKey, myConsumerSecret);
```

- Get the metadata of the movie title.

```
String uri = "http://api.netflix.com/catalog/titles";
HashMap<String, String> callParameters = new HashMap<String,
String>();
```

```
callParameters.put("term", movie);
NetflixAPIResponse response =
apiClient.makeConsumerSignedApiCall(uri, callParameters,
NetflixAPIClient.GET_METHOD_TYPE);
String results = response.getResponseBody();
```

The String ‘results’ will have the genre information encoded in it.

4.3.3 Google Books API

The To identify the subjects of the book, we use the Google Books Data API.

- Initiliaze ‘BooksService’ with the registered client name

```
BooksService service = new BooksService("ebiquity");
```

- Create an instance of ‘VolumeQuery’

```
VolumeQuery query = new VolumeQuery(new
URL("http://www.google.com/books/feeds/volumes"));
```

- Fetch the metadata for the book

```
query.setMinViewability(VolumeQuery.MinViewability.PARTIAL);
query.setFullTextQuery(book_name);
VolumeFeed volumeFeed = service.query(query, VolumeFeed.class);
List<VolumeEntry> vol = volumeFeed.getEntries();
```

‘VolumeEntry’ list will have the subject information of the book.

Chapter 5

EXPERIMENTAL ANALYSIS AND RESULTS

In this chapter we present the results of the experiments performed for classifying the 'friends' in Facebook into the groups created by the user. We define the datasets and the machine learning algorithms used for the classification. We also define the metrics used for the evaluation of our approach.

Coding and implementation was done in Java. Json library is used to parse the responses from Facebook and Weka java API is used for the classification.

5.1 Data Sets

For evaluating our model, we collected 18 different datasets from Facebook users. Each dataset comprises of the profile information and additional data of all the friends of the user. Here is a detailed distribution of the datasets.

Table 5.1 Distribtution of data sets

DATA SET #	NUMBER OF FRIENDS	NUMBER OF GROUP TAGS	NUMBER OF GROUPS	MAX & MIN NUMBER OF MEMBERS IN A GROUP
1	579	485	8	217,8
2	285	277	9	95,3
3	372	44	3	15,14
4	466	266	16	86,2
5	92	61	2	42,19
6	623	345	3	184,20
7	371	404	6	330,2

DATA SET #	NUMBER OF FRIENDS	NUMBER OF GROUP TAGS	NUMBER OF GROUPS	MAX & MIN NUMBER OF MEMBERS IN A GROUP
8	263	245	7	131,2
9	293	222	3	96,45
10	340	97	4	52,9
11	699	65	3	41,11
12	471	235	5	69,17
13	235	144	9	65,1
14	345	89	4	33,10
15	417	301	6	150,1

5.2 Machine Learning Algorithms

We used various machine learning algorithms to determine which approach suits our problem. For evaluating different methods, we used 10-fold cross validation. We started with Naïve Bayes classifier as a trial approach. Surprisingly it gave an accuracy of 84.3%. We then tried 'Decision trees'. As expected they proved to be a wrong approach and fared badly. The accuracy dropped to 71%. We then tried SVM Rank and then realized that it is not suitable for our problem. We then tried SVM Light. We created different models for each group of a user. Essentially we trained a binary classifier for each group. Although it gave very good results and gave accuracy up to 90%, the drawback was the difficulty in merging the results from different models and creating an ordered list of recommendations to the user.

Finally we zeroed up on linear regression, as it emits probabilities for each group which can be used for ordering the recommendations.

Table 5.2 Evaluation of various approaches

ALGORITHM	ACCURACY (10FOLD CROSS-VALIDATION)	SUITABLE APPROACH	DESCRIPTION
Naïve Bayes	79.25%	Yes	Used as a first trial.
Decision Trees	53.75%	No	Problem depends on many features and linear combinations of features is critical here
SVM Rank[4]	-	No	Is generally used for ranking similar items not for classification
SVM Light[3]	85.23%	Yes	Using it as a binary classifier, we have to generate n different models for n groups.
Logistic Regression	88.57%	Yes	Provides a good way of classification, also emits probabilities for each class which can be used for ordering them

5.3 Mean Average Precision

Precision and recall are single-value metrics based on the whole list of documents returned by the system. For systems that return a ranked sequence of documents, it is desirable to also consider the order in which the returned documents are presented. Average precision emphasizes ranking relevant documents higher. It is the average of precisions computed at the point of each of the relevant documents in the ranked sequence:

$$\text{AveP} = \frac{\sum_{r=1}^{N}(P(r) \times \text{rel}(r))}{\text{number of relevant documents}}$$

where *r* is the rank, *N* the number retrieved, *rel()* a binary function on the relevance of a given rank, and *P(r)* precision at a given cut-off rank:

$$\mathrm{P(r)} = \frac{|\{\text{relevant retrieved documents of rank r or less}\}|}{r}$$

This metric is also sometimes referred to geometrically as the area under the Precision-Recall curve. Note that the denominator (number of relevant documents) is the number of relevant documents in the entire collection, so that the metric reflects performance over all relevant documents, regardless of a retrieval cutoff.

Mean average precision for a set of queries is the mean of the average precision scores for each query.

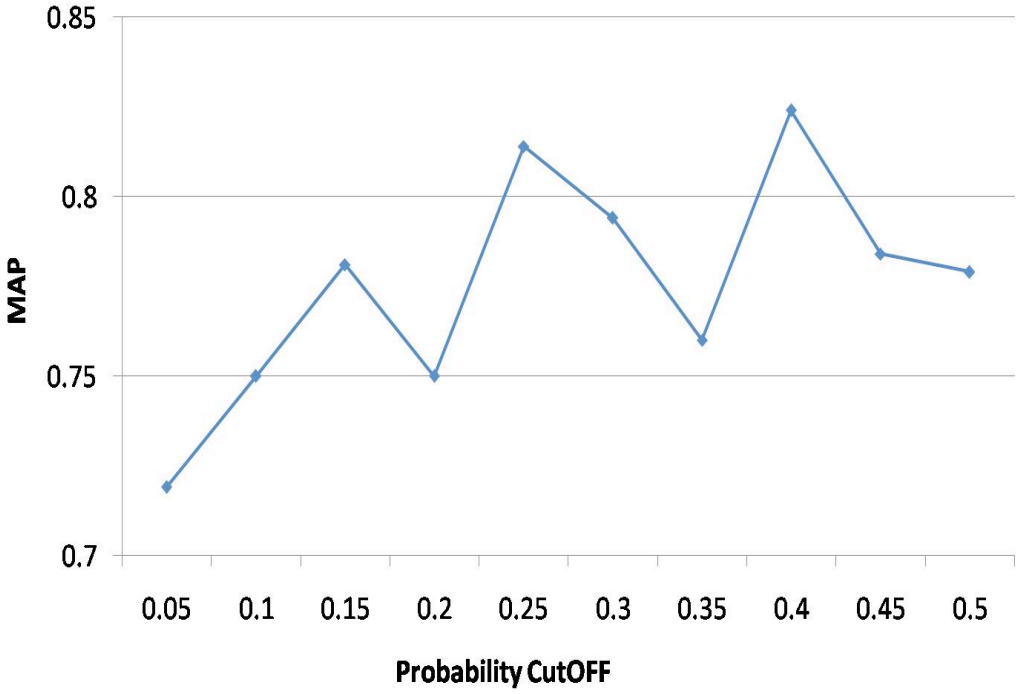
$$\mathrm{MAP} = \frac{\sum_{q=1}^{Q} \mathrm{AveP(q)}}{Q}$$

where *Q* is the number of queries.

5.4 Experiment 1: Optimize CutOff

While evaluating a test instance, logistic regression assigns probabilities to all the groups. To extract the result set out of these, we need to consider a threshold value such that the group would be relevant to the training instance if its probability crosses the threshold value. In order to find out the optimal value for this, we designed an experiment.

Figure 5.1 Optimizing Cut-off



While evaluating a test instance, logistic regression assigns probabilities to all the groups. To extract the result set out of these, we need to consider a threshold value such that the group would be relevant to the training instance if its probability crosses the threshold value. In order to find out the optimal value for this, we designed an experiment.

We divided the tagged data into 2 sets. One set with 66.67% of the data to train the model and the other with the remaining data to test the predictions of the model. We computed the 'Mean Average Precision' over all the data sets. We repeated this experiment with varying values of the cut-off.

We found that the system achieves maximum accuracy at levels 0.25 and 0.4. We have chosen the optimal value for cut-off as 2.5 because 0.4 is too high a probability for the results to ignore.

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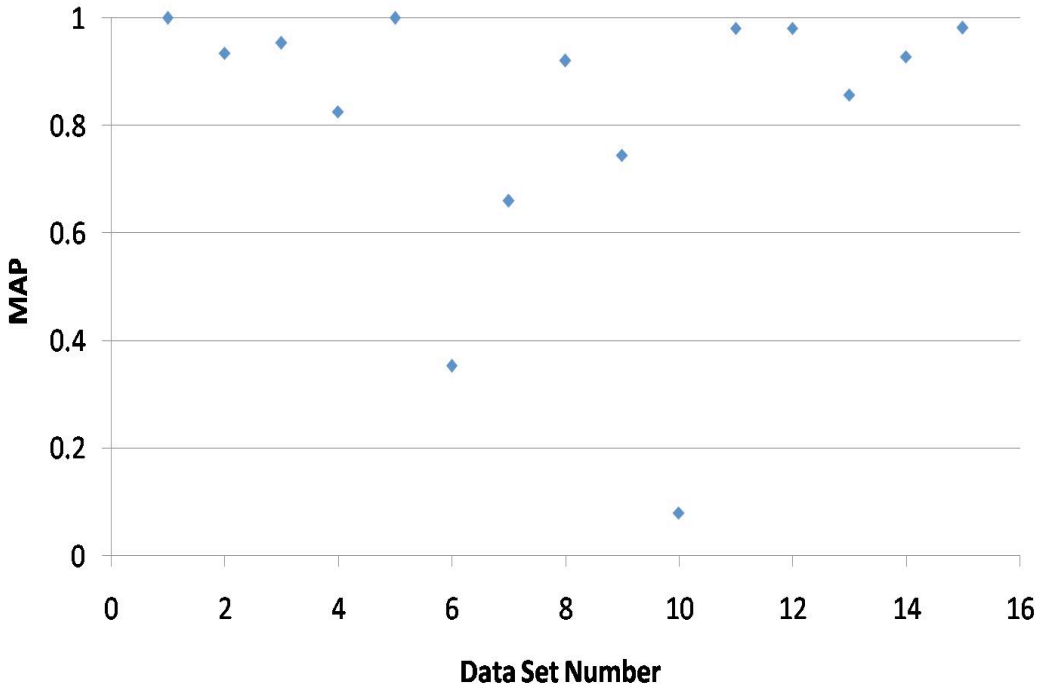
5.5 Experiment 2: Leave One Out

Figure 5.2 'Mean Average Precision' across data sets



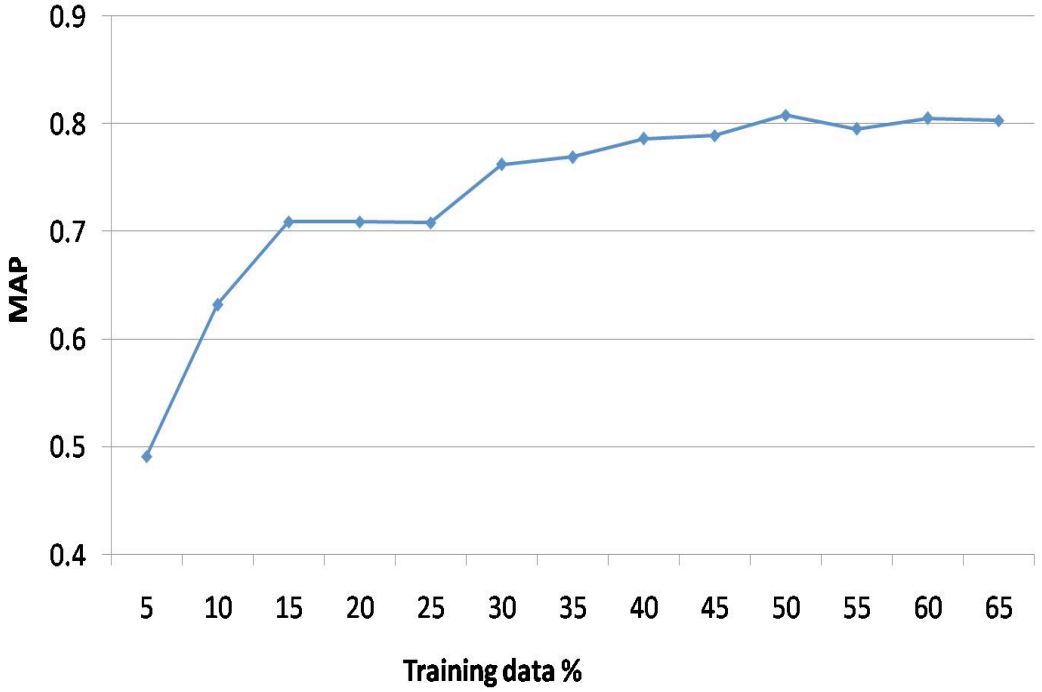
We designed this experiment to evaluate the accuracy of the classifier. From each data set we took a friend out and trained the classifier using the rest of the data. We then tried to predict the class labels for that friend. We computed the Average Precision for this result set and then computed MAP value for the entire data set.

For this experiment we fixed the value of the cut-off to 0.25. We got the MAP value as 0.813. There are couple of data sets for which our system performed poorly. Upon closely examining the group structures we found that they have 'Personal groups' which are tough to predict.

5.6 Experiment 3: Find Percentage of Minimum Training data required

After finding the accuracy of our system, we tried to find its limitations when the amount of training data available is very less compared to the unlabelled data. So we designed an experiment where we decreased the amount of training data to bare minimum. We started from 65% and lowered it till 5%. Our system showed high MAP values even the training data is just 15%.

Figure 5.3 Split on training data vs MAP



5.7 Experiment 4:Does size of the Group matters for accurately classification?

One of the questions that we came across while building the system is 'Whether the size of the group has any effect on the accuracy of the classifier?' We designed an experiment to address this issue. Using the same model as 'Leave one out' experiment, we removed a member from the group and then used the remaining data

to train the classifier and then tried to predict the class of the removed user. The figure below shows the MAP values against the group sizes.

Figure 5.4 Size of the groups vs MAP

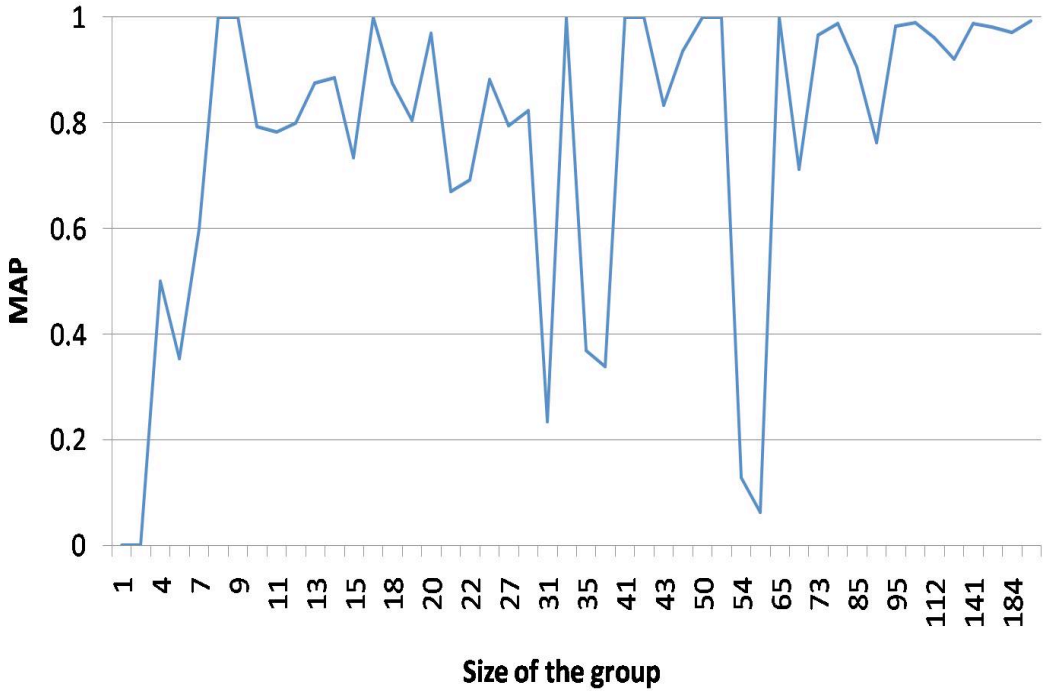
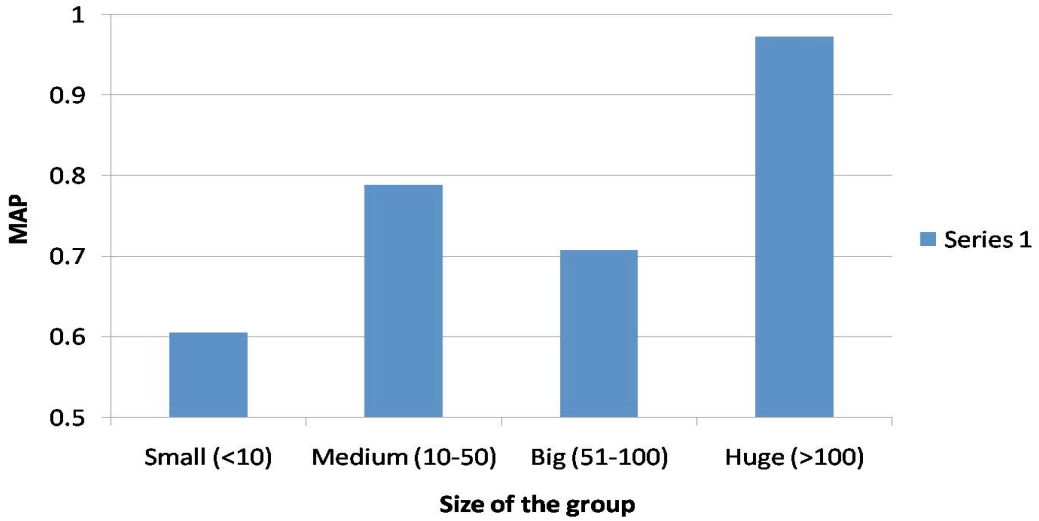


Figure 5.3 MAP vs Consolidated data sets



A consolidated graph on group sizes gives us a clear perspective on this problem. Clearly, as the group size increases it is easy to predict the class label.

Chapter 6
FUTURE WORK AND CONCLUSION

6.1 Conclusion

We proposed and described an approach to recommend groups for a user in social network. We analyzed the relationships between different attributes like age, profession, number of friends, number of groups, user's privacy concerns and different types of friend lists to gain a better understanding of group dynamics.
We tried several machine learning approaches and found the one that is optimal for the given problem. We analyzed different data points like minimum percentage of training data required to accurately classify the data, size of the group versus accuracy of the classifier and the optimal cut-off to use for a better MAP value of the approach.

Apart from coming up with the system to make recommendations for groups, we also found out several useful inferences some from the survey and some from our experiments. Overall we have a better understanding of group dynamics in social network.

6.2 Future Work

We observed that most of the users, apart from their general profile information usually don't update the features that are relevant to their interests. This accounts to more than 40% missing values which decrease the accuracy of the classifier. We would either like to predict their interests by looking at their entire social graph

including likes, comments or gather more information about the user from other systems. This helps in increasing the accuracy of the classifier.

Another add-on to our system can be a feature that automatically creates social lists like Family, High school, College, Workplace using clustering mechanisms. From our survey we found that 27% of the users did not have any friend lists and 55% of the users have created lists less than 5. We would like to have a cold start for that user base. There are already several approaches to identify these clusters on social lists like the LinkedIn's InMaps and Facebook application Fellows.

Also a Facebook App, for our system would be useful. It helps us to gather more data for analysis by connecting with Facebook users. The backend is developed completely in Java; we have to create a wrapper in php for the GUI of the application. For a Facebook application, we have to scale up our performance to meet the user needs.

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