Master Thesis

Twitter User Classification Based on Specificity of their Information Dissemination Target

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Abstract

This guide gives instructions for writing your B.E. or M.E. theses following the standard of the Department of Information Science. The standard includes the structure and format which you must obey on writing your theses.

This guide also explains how to use a LaTeX style file for theses, named `kuisthesis`, with which you can easily produce well-formatted results. Since this guide itself is produced with the style file, it will help you to refer its source file `eguide.tex` as an example.

Note for graduate students: This document is written for students of old graduate school of information science, not for graudate school of informatics. Writers of master thesis belonging to graduate school of informatics must obey rules given by each department.

情報発信の対象限定性に基づく Twitter ユーザの分類

竹村 光

内容梗概

この手引では，特別研究報告書および修士論文をどのような構成とするか，またどのような形式で作成するかを説明したものである。また，当教室で定めた形式に則った論文を日本語 LaTeX を用いて作成するためのスタイル・ファイルである，kuisthesis の使い方についても説明している。なお，この手引自体も kuisthesis を用い，定められた形式に従って作成されているので，必要に応じてソース・ファイル eguide.tex を参照されたい。

Twitter User Classification Based on Specificity of their Information Dissemination Target

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Chapter 1 Introduction

With widespread use of social medias, such as blogging services or social network services (SNS), today we have become able to publish information on the Web more easily than previously. Especially recently, microblogging services have been growing explosively.

Microblogs are a new type of services which have both characteristics of blogs and SNS. In microblogs, users can post short messages more easily and rapidly than in conventional blogs or SNS. Microblogs are not necessarily regarded as a medium for publishing useful information to the public, so users of microblogs post messages more casually than that of conventional blogs or SNS. Because of these characteristics, a large number of messages are posted on microblogs every day, and the messages contain various types of contents, from personal notes or life logs to useful information or discussion on specific topics. Furthermore, messages describing current situations especially characterize microblogs among various types of messages. This type of message is much more frequent than in conventional blogs or SNS, so a large number of microblogging messages include real-time information.

Among many microblogs, Twitter[1)] is especially growing rapidly. As of 2012 December, Twitter has over 200 million active users in the world[1], and as of June, more than 400 million messages are posted on it per day[2]. In Twitter, users can post short messages with at most 140 characters, which are called tweets. By this limitation, Twitter makes information publishing more easily and rapidly than conventional blogs or SNSs. The most distinctive feature of Twitter is its mechanism of *"follow"*. In Twitter, if a user follow other users, all tweets by these followee users are retrieved in real time, and are shown in a list sorted in the reverse chronological order, as shown in Figure 1. This list is called the *"timeline"* of the follower users. The mechanism of follow is more casual than user-linking functions in ordinary SNS; it does not require the permission by the followee, and does not necessarily imply reciprocal relationship. Another important function in Twitter is the *"reply"* function, by which a user can post

1) `http://twitter.com/`

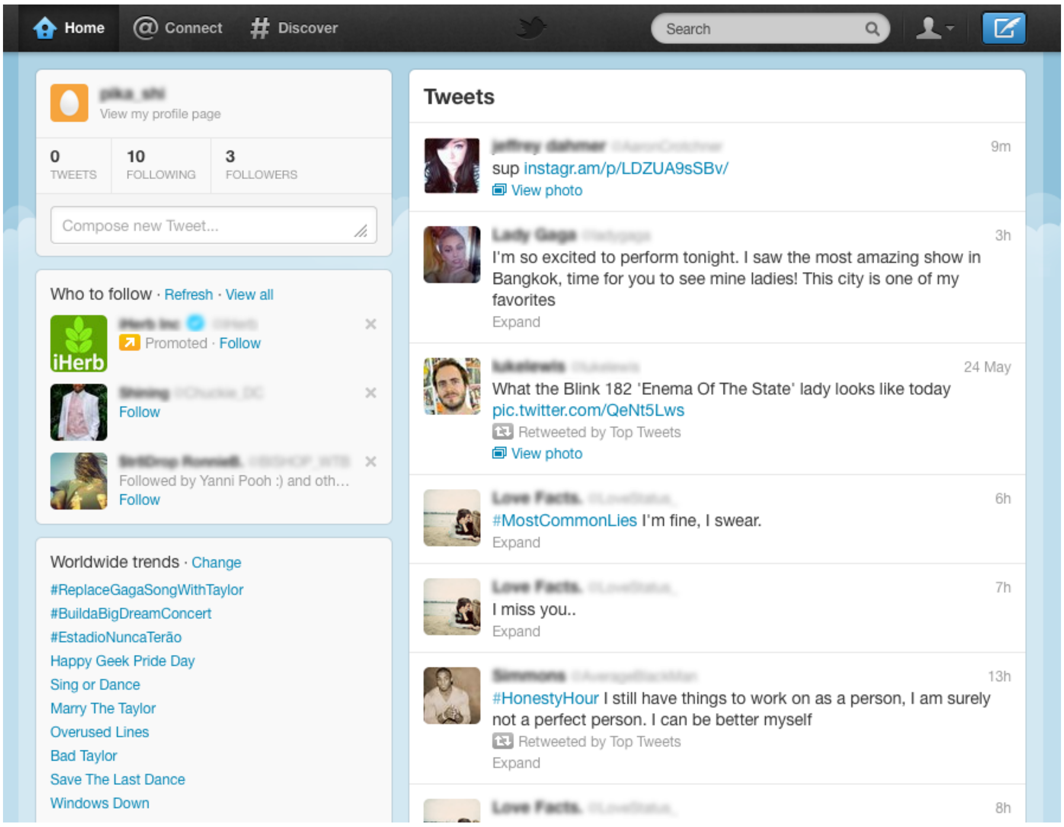

Figure 1: An example of a user's timeline in Twitter

a message as a reply to another user. By using this function, users can use Twitter for conversation, as in instant messaging services.

Twitter has many characteristics of conventional social medias, so it is used for many purposes. Some publish information to the public widely, some publish information specified for certain topics, and some communicate with their friends or others. Because of this characteristic, Twitter has attracted great attention as a new type of social media.

As explained above, Twitter is used for various purposes. As a result, the wideness of target scope of information publishing varies greatly among users. So, in this study, we propose a method to classify Twitter users from the point of view of how widely target scope of their information publishing is, i.e., whether they publish information to the public widely or publish information specified in certain users. In this study, we call the former *"target specificity is low"*, and the latter *"target specificity is high"*. In this method, we focus on the followers of the user, and we classify him/her whether his/her followers are consistent in some noticeable characters or not. If his/her followers are consistent in some noticeable characters, it suggests that he/she publishes information in which particular users are interested. On the other hand, if they are not consistent in any noticeable characters, there is a high probability that the user is followed by a wide variety of users and it suggests that he/she publishes information in which the public, i.e., almost all users, is interested.

In addition, in this study, we focus on Twitter users classified into "target specificity is high" by the above, and we propose the method to determine what causes their target specificity, i.e., why their target scope of information publishing is specified to certain users. In a large number of Twitter users, their target scope are specified to certain users, and the causes vary from user to user. For example, users publishing technical information about programming is supposed to publish information to unspecified users, but their target specificity is considered high because the topic of their publishing information is specified to certain users, who are interested in programming. And also, users communicating with their friends or who announces to club members is supposed to publish information to the users specified extensionally. So their target specificity is supposed to be high, regardless of contents of their publishing information. In this method, first, we roughly classify causes of the target specificity into two categories: (1) because they publish information specified for certain topics, and (2) because they publish information to the users specified extensionally. Then we construct classifiers which determine whether users only belong to the category (1), only belong to the category (2), or belong to both (1) and (2), based on various features which correlate with each category. Figure 2 shows the overall flow of our methods.

On the Web, it is hard to know what kinds of users each Web page targets to. But in Twitter, we can know what kind of users each user target to by their follow relationships. By using this relationships, we can classify users based on the target specificity of their information publishing.

Twitter user classification of this study is supppsed to apply to Twitter search. In current Twitter search, we input a search word in the search box

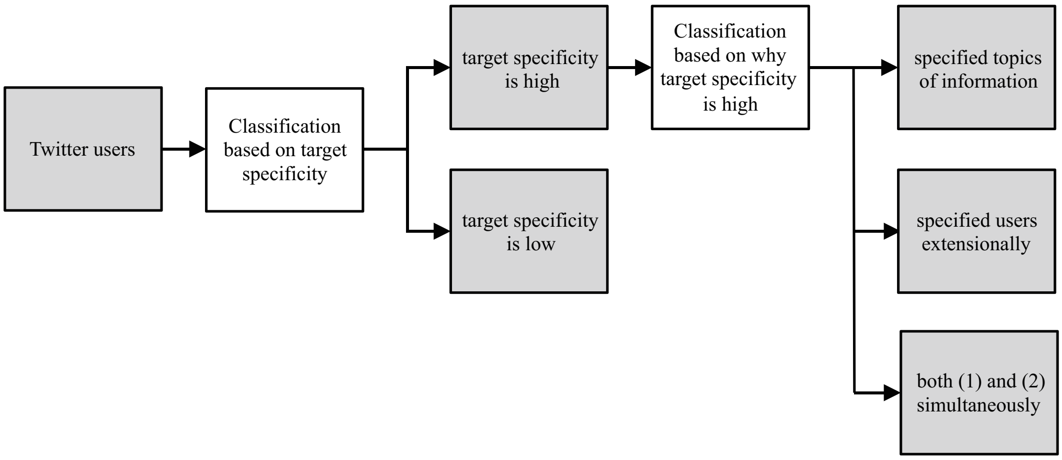

Figure 2: Overall flow of our methods

and receive messages including the word. But with this method, messages in search results have various target scope of information publishing. So it frequency happens that messages of certain target scope we need are buried in many other messages. For example, when we search in Twitter with the word “MacBook Air”, what kinds of messages we needs depends on the situation of that time, e.g., we may need public news about MacBook Air, we may need technical information about it, or we may need users’ reviews of it to refer when we buy new one. But in current Twitter search, these information is mixed up in search results. At that time, by using the classification of this study, we can search messages based on what kinds of users they target to. In this way, we can prevent messages we need from being buried in many other messages and find messages we need easily.

The contribution of this paper is summarized as follows.

- We propose a new classification scheme of Twitter users’ target specificity of information publishing.
- We show a method of classifying users based on above scheme.
- In regard to users classified into “target specificity is high”, we show a method of determining why their taiget specificity is high.

The rest of this paper is organized as follows. Next section explains some related work and makes the position of this study clear. Then we define Twitter users’ target specificity of information publishing and formulate our problem, and we discuss why their target specificity is high in Chapter 3. In Chapter 4, we explain the method of classifying Twitter users based on their target specificity of information publishing. In addition, in regards to Twitter users classified into "target specificity is high" by the above method, we explain the method of determining why their target specificity is high in Chapter 5. Then in Chapter 6, we presents the results obtained from experiments we conducted to evaluate our methods. Chapter 7 concludes the paper.

Chapter 2 Related Work

With explosive widespread use of microbloggs, studies about them have recently become frequently performed. There are various studies of microblogs, e.g., studies of the classification microblogging messages from various point of view[3], studies of ranking microblogging messages by the content relevance and so on[10], or studies of focusing on real-time nature of migroblogs[26, 22].

In this study, we focus on the fact that Twitter is used for various purposes. We attempt to classify Twitter users based on the wideness of target scope of their information publishing, and apply this classification scheme on Twitter search and so on. We explain the following previous studies: studies about the purpose of use of microbloggs in 2.1, studies of classifying Twitter users and measuring their influence in 2.2, studies useful for finding microblogging messages related to only certain Twitter users in 2.3, and studies about Twitter search in 2.4. We make the position of this study clear by introducing these studies.

2.1 Purpose of Use of Microblogs

There has been many studies about the purpose of use of microblogs. Java et al.[15] analyzed the topological and geographical structure of Twitter's social network and attempted to understand the user intentions and community structure in microblogging services. As a result, they found that the main types of user intentions are daily chatter, conversation, sharing information and reporting news. Kwak et al.[17] reported that Twitter is used both as a social network service and as a media for disseminating or gathering information, and in its follower-following topology analysis they have found a non-power-law follower distribution, a short effective diameter, and low reciprocity, which all mark a deviation from known characteristics of human social networks. There are many more studies about the purpose of use of microbloggs[29, 31].

Ehrlich et al.[11] conducted a content analysis and examined the use of public microbloggs (Twitter) for public and private use by comparing internal microblogs (in the workspace). As a result, there were significant differences in content. The internal microblogs were generally used to solicit technical assistance or as part of a conservation. The public microblogs were used for status updates and to share general information.

In recent years, Twitter, one of public microblogs, is often used for not only publishing information to the public but also having a relationship to only a certain community. It is able to be said that this study focuses on the fact that we use Twitter for various purposes.

2.2 Classification of Twitter Users and Measuring their Influence

There are many studies focusing on Twitter users, e.g., studies of classification them from various point of view, and studies which measure their influence.

Studies focusing on the classification of Twitter users are performed frequently and they have a wide variety of classification schemes, e.g., the classification based on their attributes such as political orientation or ethnicity by leveraging observable information such as the user behavior, network structure, and linguistic content of their posting messages[25], the classification into spam users or not by extracting observable features from the collected candidate spam profiles, e.g., number of friends, text on the profile, age, and so on[18], and the classification into human users, bots, and cyborgs using entropy measures, machine learning, and so on[9]. Bots refer to automated programs posting on Twitter, and cyborgs refer to either bot-assisted humans or human-assisted bots, i.e., interweave characteristics of both humans and bots.

The classification scheme proposed by Yan et al.[30] deeply relates to ours. They proposed methods to classify Twitter users into open accounts and closed accounts. An open account is the account with a purpose for advertising or spreading information such as a shop, a singer, a news agency, and so on. On the other hand, a closed account is the account with a purpose for making friends or communication such as a user who publishes messages about daily log, feeling show, and so on. This classification scheme is close to ours, but does not coincide with ours because open accounts don't often publish information to the public widely. For example, a user who publishes very technical information about programming to unspecified users is an open account though he is a target user.

In microblogs like Twitter or other social network services like Facebook, users correspond to nodes in social network graphs. As well as the classification of users, i.e., nodes in the graphs, the classification of edges, i.e., relationship between a user and his followers, is related to our study. Leskovec et al.[19, 20] classified edges in SNS into positive edges such as friendship, and negative edges such as antagonism. Kunegis et al.[16] also use positive edges and negative edges in Slashdot, a message board service, in order to rank the users. Cheng et al.[8] and Hopcroft et al.[13] studied the problem of predicting reciprocity between two given Twitter users.

There are also studies focusing on measuring influence of Twitter users. Jianshu et al.[28] focused on the problem of identifying influential users of microblogs. Cha et al.[7] analyzed the influence of them by employing three measures that capture different perspectives: indegree, retweets, and mentions. Then they measured the dynamics of influence across topic and time. If target specificity of Twitter users defined in this study is high, there is a high probability that they have a big influence on Twitter, but how low target specificity of a user is does not necessarily coincide with how big his influence is.

2.3 Find Messages Related to Some Twitter Users

There are also studies useful for finding of microblogging messages related to only a part of Twitter users.

Sakaki et al.[12] proposed a method of monitoring messages in Twitter and detecting occurrences of a specific kind of event in the real world, such as earthquakes or typhoons. They produced a probabilistic spatiotemporal model for the target event that can find the center and the trajectory of the event location. Ikawa et al.[14] attempt to discover the location where a message was generated by using its textual content. They learned associations between a location and relevant keywords from past messages, and guessed where a new message came from. It is able to be said that these studies are useful for finding messages in Twitter related to certain geographical areas.

Sriram et al.[6] proposed approach effectively classifies the message to a predefined set of generic classes such as News, Events, Opinions, Deals, and Private Messages. They proposed to use a small set of domain-specific features extracted from the user's profile and text. Nishida et al.[24] proposed a method that uses data compression for classifying an unseen tweet as being related to an interesting topic or not. It is able to be said that these studies are useful for finding messages in Twitter specified to certain topics.

As mentioned above, there are many studies useful for finding microblogging messages related to only a part of Twitter users in various points of view. But these points of view exist in great number, so it is not an efficient approach to find these messages from each point of view. Thus in this study, we attempted to measure Twitter users' target specificity of information publishing in an integrated way. In addition, we roughly classified various causes of target specificity into two categories.

2.4 Twitter Search

The characteristic of search on microblogs is different from that of Web search[4] in that search on microblogging services can get information in real time[5] and not only information published by the mass media but also much casual information published by individuals[15]. Thus, a purpose of use of search on microblogs often becomes a subject of study.

Teevan et al.[27] observed that people use Twitter search to find temporally relevant information, e.g., breaking news, real-time content, and popular trends, and information related to people, e.g., content directed at the searcher, information about people of interest, and general sentiment and opinion. Furthermore, they compared Twitter search with Web search and found that search results on Twitter included more social chatter and social events, and those on the Web included more basic fact and navigation content. Massoudi et al.[21] proposed a retrieval model for searching messages on microblogs for a given topic of interest and a dynamic query expansion model for messages retrieval. And Nagamoti et al.[23] described several strategies for ranking messages of microblogging services in a real-time search engine.

As mentioned above, there are many studies about search on microblogs, and contents of them are greatly various. In this study, we focus on the purpose of use of microblogs, and attempt to apply it to Twitter Search. It is able to be said that this study also focuses on search on microblogs just like studies explained above, but there has not been studies based on Twitter user's target specificity of information publishing so far.

Chapter 3 Target Specificity of Twitter Users

In this chapter, we discuss the target specificity of Twitter users, the measure of to what degree target scope of their information publishing is specified, and define it. Then we also discuss why target scope of their information publishing is specified.

3.1 Definition of Target Specificity

In this study, we consider target specificity of Twitter users, as the measure of to what degree target scope of their information publishing is specified. More formally, we define *target specificity* of a Twitter user as to what degree the user set supposed to be included in target scope of his information publishing is inclining to a part of all Twitter users, i.e., to what extent this user set deviates from the user set randomly sampled from all Twitter users. In this paper, we express target specificity of the Twitter user u as $\mathit{TargetSpecificity}(u)$. This formula takes a range of $[0, 1]$.

For example, a user mainly publishing technical information about programming is supposed to publish information to programmers. So users who are interested in this information are inclining toward a part of Twitter users. Thus, it is supposed that target specificity of the user is high.

On the other hand, a user publishing information about world news publishes information useful for the public widely. So the public is supposed to be interested in this information, and the deviation between users who are interested in this information and users randomly sampled from all Twitter users may be very small. Thus, it is supposed that target specificity of the user is low.

As mentioned above, target specificity of Twitter users is defined as to what extent the user set supposed to be included in target scope of his information publishing deviates from the user set randomly sampled from all Twitter users. Thus, the fact that target specificity of a user is high does not necessarily coincide with the fact that there is high similarity between users supposed to be included in target scope of his information publishing each other. For example, users supposed to be included in target scope of information publishing of a user publishing information about earthquake in a certain area are probably consistent in the area they live in, and so his/her target specificity is supposed to be high. But their other characteristics, e.g., age, sex, interests, communities they belong to, and so on, vary from user to user. Thus it is not be able to be said that they have high similarity each other. In other words, even if there are various types of users in target scope of his information publishing, we consider that target specificity of the user is high as long as the majority of users in the target scope are consistent in at least one attribute.

In this paper, we determine a threshold δ. If target specificity of a user is higher than δ, we call him a *target user*, and if lower, we call him a *non target user*. More formally, we define them as follows:

$$\begin{cases} u \text{ is a } \textit{target user}, & \text{if } \textit{TargetSpecificity}(u) > \delta \\ u \text{ is a } \textit{non target user}, & \text{otherwise.} \end{cases}$$

3.2 Why Target Specificity is High

In this subchapter, we discuss what causes target specificity of a user, i.e., why target scope of his information publishing is specified. As a result of our analysis, this is roughly classified into two causes: (1) because he publish information specified for certain topics, and (2) bacause he publish information to the users specified extentionally. We discuss their two causes of the target specificity in the follow.

(1) Specified topics of information extensionally

The first cause of target specificity of a user is because he publishes information specified to a few topics extensionally, whether he publishes information to the users specified extentionally or not. For example, a user mainly publishing technical information about programming is supposed to publish information to unspecified users, but it is considered that target scope of his information publishing is specified because he specifies the topic of information, i.e., programming. Furthermore, a user mainly publishing information about a certain conference is supposed to publish information to the users who attend the conference or are interested in it. Thus it is considered that target scope of his information publishing is specified.

The way to specify topics of information is roughly classified into two cases. In the first case, a user specifies topics based on demographic data, e.g., age, settled areas, sex, occupation, career, and so on. It is able to be said that a user publishing weather information in a certain area specifies topics based on demographic data. In the second case, a user specifies topics based on psychographic data e.g., taste, hobby, values, and so on. It is able to be said that a user publishing information about cooking specifies topics based on psychographic data.

(2) Specified target users extensionally

The second cause of target specificity of a user is because he publishes information specified to some users extensionally whether he specifies topics of his publishing information or not. For example, a user communicating with his friends publishes various contents of information, but it is considered that target scope of hisher information publishing is specified because heshe specifies users extensionally, i.e., he publishes information to the closed users, i.e., his friends. Furthermore, a user mainly getting in touch with members of a certain club publishes information to the closed users specified extensionally, i.e., the club members. Thus it is considered that target scope of his information publishing is specified.

Sometimes, both (1) and (2) simultaneously cause the target specificity of a user. For example, a user who publishing information to the members of the artist's fan club publishes information specified not only users of his information publishing, i.e., the members of the artist's fan club, but also the topic of information, i.e., the latest news about the artist and so on. Furthermore, it is also true in case of a user notifying students in a certain university of the news toward them because he publishes information specified extensionally, i.e., students of the university, and the topics of information, i.e., the news toward them. In addition, some users use Twitter for the both purpose of publishing information of a certain topic and communicating with their friends. It is able to be said that such users are also an example of the case that both (1) and (2) simultaneously cause the target specificity of a Twitter user.

Chapter 4 Classifying Users Based on Target Specificity

In this chapter, we explain the method of classifying Twitter users based on target specificity of their information publishing defined in Chapter 3.

4.1 Assumptions and Outline of the Method

In this study, we assume that a follower set of a user is the user set randomly sampled from users included in target scope of his information publishing. Thus, we focus on the follower set of a user we intend to classify.

A user publishing information to the public widely, e.g., a user publishing information about world news, is supposed to be followed by various types of users. On the other hand, followers of a user publishing information specified in certain users are supposed to be consistent in a certain noticeable character. For example, a user publishing technical information about programming is supposed to be mainly followed by programmers, and a user communicating with his friends is supposed to be mainly followed by his friends.

Based on the above, we classify a user whether his followers are consistent in a certain noticeable character and difficult to suppose to be randomly sampled from all Twitter users, or his followers are not consistent in any noticeable characters. Figure 3 (a) shows the case of followers of a user being consistent in the noticeable character A. In such a case, his followers are supposed to incline toward a part of all Twitter users, thus we consider that the more consistent his followers are in a certain noticeable character, the higher his target specificity is.

In addition to this parameter: whether followers of a user are consistent in a certain noticeable character or not, we consider whether his follower set are covered with consistency subsets which cover intermediately widely. Here, *a consistency subset* denotes a subset which have consistency in a certain noticeable character. As show in Figure 3 (b), in regard to followers of a user, when half of them are consistent in the noticeable character A and the others are consistent in the character noticeable B. It is not able to be said that they are

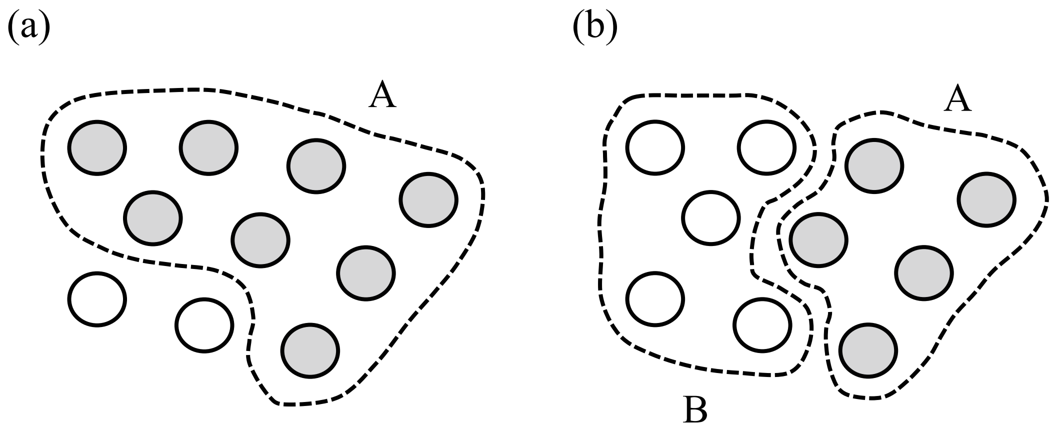

Figure 3: Two examples of high target specificity

consistent in one noticeable character, but his follower set are covered with two consistency subsets cobering the set intermediately widely. In such a case, we consider that his target specificity is high.

These two parameters are summarized as follows:

(a) The more consistent followers of a user are in a certain noticeable character, the higher his target specificity is, and

(b) The more covered his follower set is with consistency subsets covering the set intermediately widely, the higher his target specificity is.

Target specificity of a user is quite high when his followers are consistent in one noticeable character, and it becomes lower as they do not become consistent in any noticeable characters.

4.2 Classification Algorithm

In this subchapter, we explain the algorithm of computing a score of target specificity of a user u based on the outline mentioned in the above subchapter.

First, we collect all consistency subsets included in F_u, the follower set of u. Then, in regard to each subset S_{F_uc}, which is consistent in the character c included in F_u, we compute $SubsetScore(S_{F_uc})$ which denotes to what degree users in S_{F_uc} are consistent in c. We will propose two models computing $SubsetScore(S_{F_uc})$ in 4.3.

Second, in the descending order of $SubsetScore(S_{F_uc})$, we give this score to

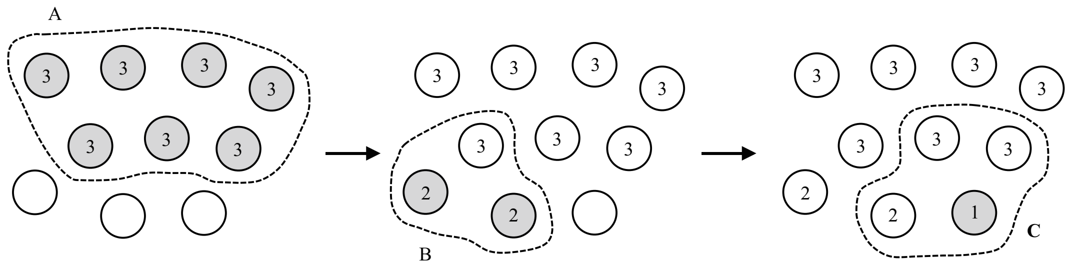

Figure 4: A case of the algorithm flow

each follower f in $S_{F_u c}$ as $UserScore_{att}(f)$, where att means a attribute measuring consistency, and we will explain two attributes in 4.4. Here, we do not give a score to f if he/she already has a score. Then, we repeat this step over all $SubsetScore(S_{F_u c})$. In regard to users who are not given a score after the above repeat, we set 0 to them. In other words, in regard to each f of u, we give $UserScore_{att}(f)$ to the largest $SubsetScore(S_{F_u c})$ of $S_{F_u c}$ in which f is included, as follows:

$$UserScore_{att}(f) = \max_{S_{F_u c} \in F_u} \{SubsetScore(S_{F_u c}) | \ f \in S_{F_u c}\}.$$

Then, we take average of all $UserScore_{att}(f)$ for $SpecificityScore_{att}(u)$, a score of target specificity of u using the attribute att, as follows:

$$SpecificityScore_{att}(u) = \frac{1}{|F_u|} \sum_{f \in F_u} UserScore_{att}(f).$$

For example, suppose the case shown in Figure 4. We assume that a follower set of a user u have three consistency subsets: A, B, and C, and $SubsetScore(A)$, $SubsetScore(B)$, and $SubsetScore(C)$ are 3, 2, and 1 respectively. In the descending order of $SubsetScore(S_{F_u c})$, i.e., in order of A, B, and C, we give scores to each follower f as $UserScore_{att}(f)$ as shown in Figure 4. Finally, we compute average of $UserScore_{att}(f)$ and take 2.6 for $SpecificityScore_{att}(u)$.

This is how we compute a score of target specificity of u using the attribute att. Below is a summary of the algorithm:

1. we collect all consistency subsets included in the follower set,

2. we score each consistency subset based on to what extent users in it are consistent in a certain noticeable character,

3. in the descending order of the above scores, we repeatedly give the score to each user in the subset, and

4. we take average of scores for a score of target specificity.

4.3 Scoring Models of Consistency Subsets

In this subchapter, we explain a couple of models in the follow: the probabilistic model and the subtracting model which compute $SubsetScore(S_{F_uc})$ mentioned in 4.2

4.3.1 Probablistic Model

In this model, in regard to the consistency subset S_{F_uc} being consistent in the character c in the follower set F_u, we consider that how low the probability that the user set of the same size as F_u randomly sampled from all Twitter users includes the subset being consistent in c and whose size is $|S_{F_uc}|$ and over. The lowness of the probability means that S_{F_u} is inclining to a part of all Twitter users, so it is able to be said that S_{F_uc} has consistency in a noticeable character if the probability is low. Thus, the lower the probability is, the higher score we give. On the other hand, if the probability is not so low, the deviation between S_{F_uc} and the user set randomly sampled from all Twitter users may be small, and it is difficult to say that S_{F_uc} has consistency in a noticeable character. Thus, we give a low score in this case.

In addition to this parameter: how low the probability mentioned above is, we consider the covering rate of S_{F_uc} to F_u. The higher the covering rate of S_{F_uc} to F_u is, the higher score we give. Based on these two parameters, we compute $SubsetScore(S_{F_uc})$.

These two parameters are summarized as follows.

- The lower the probability that the user set of the same size as F_u randomly sampled from all Twitter users includes the subset being consistent in the same character as the character of S_{F_uc} and whose size is $|S_{F_uc}|$ and over, the higher score we give.
- The higher the covering rate of S_{F_uc} to F_u is, the higher score we give.

Then, we define this model more formally. First, we compute $P(S_{F_uc})$, the probability that the user set of the size of $|F_u|$ randomly sampled from the set of all Twitter users includes the subset being consistent in c and whose size is $|S_{F_u c}|$ and over, by the formula below:

$$P(S_{F_u c}) = \int_{|S_{F_u c}|}^{n} \binom{n}{x} p^x (1-p)^{n-x} dx, \qquad n = |F_u|, \qquad p = \frac{|S_{Ac}|}{|A|}$$

where A is the set of all Twitter users, and S_{Ac} is the subset which is consistent c in the character included in A. The parameter x in the above formula is based on a binomial distribution.

In addition, by adding the covering rate of $S_{F_u c}$ to F_u to the above parameter, we compute $\mathit{SubsetScore}(S_{F_u c})$. However, there is some possibility that $P(S_{F_u c})$ is excessively low because $S_{F_u c}$ has a remarkable character, e.g., the character only a few users of all users have, in spite of the size of $S_{F_u c}$ is very small. In this model, we expect that the consistency subset covers the follower set at least intermediately widely. So in such a case, we do not give any scores to $S_{F_u c}$. More formally, we determine a threshold γ which cuts down the above case.

Then, we compute $\mathit{SubsetScore}(S_{F_u c})$ by the formula below:

$$\mathit{SubsetScore}(S_{F_u c}) = \begin{cases} \dfrac{|S_{F_u c}|}{|F_u|} \log(1 - P(S_{F_u c})) & \text{if } \dfrac{|S_{F_u c}|}{|F_u|} > \gamma, \\ 0 & \text{otherwise.} \end{cases}$$

This is how we compute $\mathit{SubsetScore}(S_{F_u c})$ by using the probabilistic technique.

4.3.2 Subtracting Model

In this model, in regard to the consistency subset $S_{F_u c}$, we consider a covering rate of $S_{F_u c}$ to F_u in comparison to a covering rate of the subset which is consistent in the character c to the set of all Twitter users. We call the former *a local rate* and the latter *a global rate*. The fact that a local rate is high and a global rate is low means $S_{F_u c}$ has consistency in a noticeable character and is including toward a part of all Twitter users. If a local rate is low or a global rate is high, it is difficult to say that $S_{F_u c}$ has consistency in a noticeable character. Based on the above, we compute $\mathit{SubsetScore}(S_{F_u c})$ by the formula below:

$$SubsetScore(S_{F_u c}) = \max\{\frac{|S_{F_u c}|}{|F_u|} - \frac{|S_A c|}{|A|}, 0\}.$$

In summary, we give a high score in the case of having the two features simultaneously as follows:

- a covering rate of $S_{F_u c}$ to F_u is high, and
- a covering rate of the subset being consistent in the same character as the character of $S_{F_u c}$ to the set of all Twitter users is low.

This is how we compute $SubsetScore(S_{F_u c})$by using the subtracting technique.

4.4 Attributes for Extracting Consistency Subsets

In this subchapter, we explain a couple of attributes measuring consistency: common terms in profiles and location information, and common followees. By using these attributes, we extract consistency subsets from the follower set of a user. We explain these two attributes in the follow.

4.4.1 Common Terms in Profiles and Location Information

As the first attribute measuring consistency, we consider common terms included in profiles and local information of followers.

There is a high possibility that users belonging to the same community or having the same interest have the same term in their profiles or location information in common. Thus, we extract such terms for measuring consistency. Here, we extract only noun phrases, which characterize their profiles or location information strongly.

Based on the above, we define the method of extracting consistency subsets more formally. We compute the consistency subset $S_{F_u t}$ which is consistent in the term t in F_u by the formula below:

$$S_{F_u t} = \sum_{f \in F_u} \{f |\ t \in Demography(f)\}$$

where $Demography(f)$ is the profile and location information of f. This is how we extract consistency subsets by using common terms in profiles and location information.

4.4.2 Common Followees

As the second attribute measuring consistency, we consider common followees of followers.

Users being consistent in a certain noticeable character often have the common tendency of the follow. Users belonging to the same community are dense on the social graph, so there is a high possibility that they follow common users in the community. In addition, followers of a user publishing technical information about programming is supposed to follow another user publishing useful information about programming in common. Thus, we focus on the tendency of the follow and extract such followees for measuring consistency.

Based on the above, we define the method of extracting consistency subsets more formally. We compute the consistency subset $S_{F_u e}$ which is consistent in the followee e in F_u by the formula below:

$$S_{F_u e} = \sum_{f \in F_u} \{f | \ e \in E_f\}$$

where E_f is the followee set of f. This is how we extract consistency subsets by using common followees.

4.5 Final Classification Based on Target Specificity

In this subchapter, we explain the method of computing target specificity of a user by using scores computed up to this point. In addition, based on target specificity, we also explain the method of classifying users.

The $\mathit{SpecificityScore}_{att}(u)$ computed in 4.2 is higher in the cases that

- the more consistent followers of a user are in a noticeable character, or
- the more covered his follower set are with consistency subsets covering it intermediately widely.

Then, we compute a score of target specificity of u. We first compute $\mathit{SpecificityScore}_{term}(u)$, which is using common terms in profiles and location information as an attribute measuring consistency mentioned in 4.4.1, and $\mathit{SpecificityScore}_{followee}(u)$, which is using common followees mentioned in 4.4.2.

Next, we propose a couple of approaches computing target specificity of u by using the above two scores in the follow.

(1) Average and maximum of two scores

In the first approach, we take the average and the maximum scores of two scores. For comparison of two scores, we first normalize them by computing the deviation values.

Then, we take the average score of two scores for target specificity of u by the formula below:

$$\mathit{TargetSpecificity}(u) = \mathrm{avg}\{\mathit{SpecificityScore}_{term}(u), \mathit{SpecificityScore}_{followee}(u)\}$$

In addition to the average score, we also take the larger one of two scores for target specificity of u, because the larger one is supposed to characterize target specificity more strongly than the other. More formally, we compute $\mathit{TargetSpecificity}(u)$ by the formula below:

$$\mathit{TargetSpecificity}(u) = \max\{\mathit{SpecificityScore}_{term}(u), \mathit{SpecificityScore}_{followee}(u)\}$$

This is how we compute a score of target specificity of u using the approach taking the average and the maximum of two scores.

(2) Binary classifier with the features of two scores

In the second approach, we construct a binary classifier with the feature of two scores. If target specificity of u is high, we set $\mathit{TargetSpecificity}(u)$ to 1, and otherwise we set it to 0. We adopt SVM and decision tree as a classifier.

Then we classify users based on target specificity. We determine a threshold δ which can classify target users and non target users accurately the most, and we classify them by δ. More formally, we classify them as follows:

$$\begin{cases} u \text{ is a } \mathit{target\ user}, & \text{if } \mathit{TargetSpecificity}(u) > \delta \\ u \text{ is a } \mathit{non\ target\ user}, & \text{otherwise.} \end{cases}$$

This is how we classify users into target users and non target users based on target specificity.

Chapter 5 Classifying Users of High Target Specificity

In this chapter, in regards to Twitter users classified into "the target specificity is high" by the method mentioned in the above chapter, we explain the method of determining why their target specificities are high based on the result of our analysis mentioned in 3.2.

5.1 Architecture of the Classifiers

Here, we focus on the two causes of the high target specificity mentioned in 3.2 as follows:

(1) because they publish information specified for certain topics, and

(2) because they publish information to the users specified extensionally,

and we determine whether a user we intend to classify correlates with each cause mentioned above.

We first determine various features of the user which potentially correlate with each cause. Then, based on these features, we construct the classification method which classifies users into three categories: (1) their target specificity is high because they publish information specified for certain topics, (2) because they publish information to the users specified extensionally, and (3) in the cause of both (1) and (2). By classifying users with the above classifiers, we determine why their target specificities are high.

We adopted SVM and decision tree as a classifier. Next, we propose a couple of approaches to classify users into three categories.

5.1.1 3-class Classifier

In the first approach, we construct a single 3-class classifier using one-against-one method. Each result class corresponds to each category: (1), (2), and (3). Figure 5 (a) shows architecture of a 3-class classifier.

5.1.2 2 Binary Classifiers

In the second approach, we construct two binary classifiers, each of which determines (i) whether users publish information specified for certain topics, amd (ii) whether users publish information to the users specified extensionally, re-

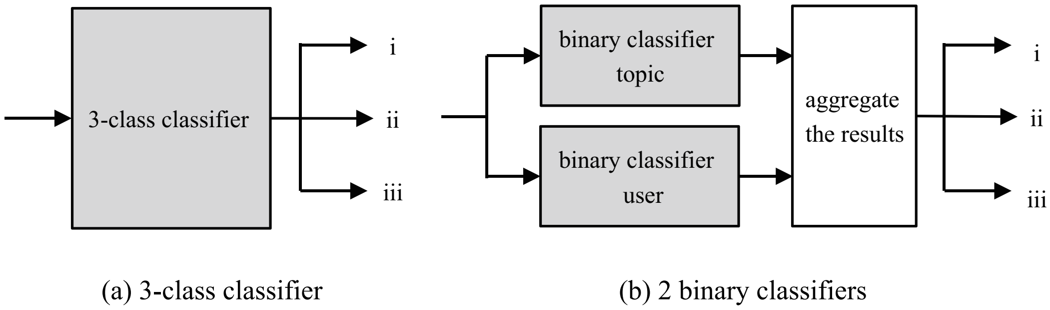

Figure 5: Architecture of a couple of classifiers: (a) 3-class classifier and (b) 2 binary classifiers

spectively. When the results of two classifiers are *yes* and *no* respectively, we classify them into the category (1): their target specificity is high because they publish information specified for certain topics. When *no* and *yes*, we classify them into the category (2): because they publish information to the users specified extensionally, and when *yes* and *yes*, we classify them into the category (3): in the cause of both (1) and (2). Figure 5 (b) shows architecture of 2 binary classifiers.

5.2 Features Used for the Classification

In this subchapter, we explain what features of users we used for the classification. All the feature values shown below were normalized to values between 0 and 1.

(i) numbers of followees and followers, and their ratio

If the user publishes information to unspecified users, there is high probability that a number of his/her followers is quite large or a number of his/her followees is quite small. So in such a case, a ratio of a number of his/her followees to a number of his/her followers is supposed to be very small. Furthermore, if the user publishes information to the closed users, i.e., his/her friends, his/her club members, and so on, there is high probability that numbers of his/her followers and followees are very close because the user is supposed to have a reciprocal connection with them. Thus, numbers of followees and followers, and their ratio are expected to be useful for determining why their target specificities are high.

We take a logarithm of numbers of followers and followees because the difference of large numbers of followers and followees are not as important as the difference of small numbers of followers and followees.

(ii) mutual follow ratio

There is high probability that the user publishing information to the closed users has a large mutual follow ratio, i.e., a number of users with whom one follows one another is large, because the user is supposed to have a reciprocal connection with them. Therefore, a mutual follow ratio is expected to be useful for determining why their target specificities are high.

(iii) frequency of replies by "@"

There is high probability that the user publishing information to the closed users has a high frequency of replies by "@", i.e., the user replies to his/her followers frequently. In regard to a mutual follow ratio mentioned in (ii), there are some users publishing information to unspecified users in spite of a large mutual follow ratio, but in regard to a frequency of replies by "@", there is high probability that the user publish information to the closed users. This is because a high frequency of replies by "@" demonstrates that the user is supposed to have a reciprocal connection with them. Therefore, a frequency of replies by "@" is expected to be useful for determining why their target specificities are high.

(iv) partialness of topics in messages

In regard to a user publishing information specified for certain topics, topics in his/her messages are often partial. Thus, we use the partialness of topics in his/her messages as a feature for the classification.

Then, we explain how to compute a partialness of topics in messages of u. We first collect up to 200 messages in order of newness. Second, we extract noun phrases from them and we use their phrases as a corpus. We extract only noun phrases bacause they characterize contents of the messages strongly. Then, we determine the topic of each message by using Latent Dirichlet Allocation (LDA), which is a generative probabilistic model for collections of discrete data such as text corpora, by using the above corpus. Finally, we compute partialness of topics in messages $partialness(u)$ as follows:

$$partialness(u) = -\sum_{t \in T_u} p_t \log p_t, \qquad p_t = \frac{|\{m|\ m \in M_u,\ topic(m) = t\}|}{|M_u|}$$

where M_u is a message set of u, T_u is the topic set we use for computing this feature, and $topic(m)$ is the topic of a message m. The partialness of topics $partialness(u)$ is the entropy of M_u on the topic. This is how we compute a partialness of topics in messages.

Chapter 6 Experiments and Discussion

In this chapter, we conduct experiments to evaluate our methods proposed in Chapter 4 and Chapter 5, and present the results obtained from them. In addition, we discuss our methods based on the results.

6.1 Data Set

We collected the data set from the real Twitter data by using Twitter API.

We first randomly selected 1,000 Twitter users whose timezone is Japan. At this time, we omitted users who are followed from nobody and who post no tweet in order to select only active users. Then, we divided them in two sets equally, i.e., each of which include 500 users.

Second, we had 6 experienced Twitter users as participants, all of whom are male graduate students in engineering, from 23 to 25 years old. We assigned each set to 3 participants, and we asked each participant to determine one of the following categories each user in the assigned set is supposed to be in:

(i) the user publishes information to the public widely,

(ii) the user publishes information specified for certain topics,

(iii) the user publishes information to the users specified extensionally, and

(iv) the user publishes information (ii) specified for certain topics (iii) to the users specified extensionally.

These categories correspond to the category (b), (1), (2), (3) in Figure 2 respectively.

Then, we selected users whose category at least 2 out of 3 participants coincide with, and as a result, we were able to collect 93, 320, 375, and 30 users in the category (i), (ii), (iii), and (iv). We randomly selected 90 users from the category (i), and 30 users from (ii), (iii), and (iv) respectively. We collected these 180 users in total, and we used them as the data set. Table 1 shows the breakdown of the data set: average and standard deviation of numbers of followers, followees, and tweets in each category.

Then, for each user, we collected at most 1,000 followers of the user, and in regard to the followers who follow at most 1,000 users, we also collected their

Table 1: Breakdown of data set: average and standard deviation of numbers of followers, followees, and tweets in each category shown in the format of *Average (SD)*

category	follower	followee	tweet
i	475,679 (535,894)	11,274 (37,906)	9,763 (14,607)
ii	58,142 (171,784)	3,353 (7,218)	9,992 (23,572)
iii	573 (1,389)	598 (1,545)	8,829 (29,505)
iv	82,942 (262,161)	1,568 (3,594)	5,677 (6,600)

followees. We used them in order to evaluate our methods.

6.2 Experimental Settings and Libraries

First, we conducted the experiments evaluating the method of classifying Twitter users based on the target specificity of their information publishing mentioned in Chapter 4. We used 90 users classified into the category (i) as target users, and 90 users classified into the category (ii), (iii), and (iv) as non target users. We first computed $\mathit{SpecificityScore}_{term}(u)$ and $\mathit{SpecificityScore}_{followee}(u)$ for each user u, and computed the precision of the classification of target users and non target users using a couple of attributes separately. Next, we computed $\mathit{TargetSpecificity}(u)$ based on the above scores. Then, we determined a threshold δ which can classifies target users and non target users accurately the most, and evaluated the classification results with δ. When computing $\mathit{TargetSpecificity}(u)$, we used two models: the probabilistic model and the subtracting model mentioned in 4.3, and compared them.

Second, we conducted the experiments evaluating the method of determing why the target specificity of the user is high in regard to the target user mentioned in Chapter 5. We extracted users from the category (ii), (iii), and (iv) by 30 users, and used 90 users in total. We first extracted features mentioned in Chapter 5 from the user, which are normalized to a value between 0 and 1. Then, based on these features, we constructed two types of classifiers: a single 3-class classifier and two binary classifiers, which classify users into three categories: (ii), (iii), and (iv), and evaluated the classification results using 3-fold cross validation. We used two learning algorithms: SVM and the decision tree as classifiers, and compared them. For SVM, we used LIBSVM[1], which is a popular SVM library, with the Gaussian kernel, which using one-against-one method for multiclass classification. For the decision tree, we used scikit-learn [2].

We used twpro search API[3] in order to get a number of users who have a certain term in their profiles. We also used MeCab[4] for morphological analysis of Japanese sentences in profiles, local information, and tweets of users. Furthermore, we used gensim[5] for using Latent Dirichlet Allocation (LDA).

6.3 Results and Evaluation of Classifying Users Based on Target Specificity

In this subchapter, we show the results of the experiments classifiying users based on target specificity of their information publishing.

We first show the precision of the classification of target users and non target users using a couple of attributes measuring consistency, i.e., common term and common followers, separately. We also used a couple of models mentioned in 4.3, i.e., the probablistic model and the subtracting model, which compute $SubsetScore(S_{F_u c})$. In regard to the probablistic model, we take 0.01, 0.03, 0.05 for γ, the threshold which cuts down the case that a local rate is very small, and compared them. The second and third rows of Table 2 show the precision of the classification using common terms and common followees as attributes, respectively. For each attribute, a bold number shows when the precision becomes the highest.

In each case of using common terms and common followees as attributes, we achieved the highest precision when we used the probablistic model with $\gamma = 0.01$ and the subtracting model respectively. In regard to the probablistic

1) `http://www.csie.ntu.edu.tw/~cjlin/libsvm/`

2) `http://scikit-learn.org/stable/modules/tree.html`

3) `http://twpro.jp/doc/api/search`

4) `http://mecab.sourceforge.net/`

5) `http://radimrehurek.com/gensim/`

Table 2: Precision of the classification of target users and non target users using a couple of attributes measuring consistency separately

attributes	Probablistic Model			Subtracting Model
	$\gamma = 0.01$	$\gamma = 0.03$	$\gamma = 0.05$	
common terms	**0.861**	0.850	0,839	0.850
common followees	0.828	0.828	0.817	**0.833**

model, we can see that the smaller γ is, thecharacterize target users though the covering rate of $S_{F_u c}$ to F_u is not high, and can contribute the classification of target users and non target users. But for both attributes, the difference between the precision of the probablistic model and that of the subtracting model is not so big. So it is considered that these two models are about the same effect.

In addition, the precision using common terms as attributes is higher than that using common followees regardless of models. This suggests that common terms in profiles and location information are useful for extracting consistency subsets than common followees. This is supposed to be because not only target users but also non target users sometimes have common followees in their followers, in contrast with common terms. For example, a user publishing information about world news, one of non target users, sometimes have common followees publishing world news in his/her followers. But the global rate of such followers is usually large, so there is no necessity for us to notice about them in most cases.

Now for each attribute, we use the highest precision of these models, i.e., that of the probablistic model with $\gamma = 0.01$ for common terms and the subtracting model for common followees. Figure 6 shows the histogram of specificity scores of each attribute on target users and non target users. In the case of using common terms as attiributes, specificity scores of most non target users are very small, with the average 0.004. On the othe hand, those of most target users are large, and even the average, 0.065, is as same as the maximum score for non target users, i.e., 0.067. A similar trend is apparent in the case of using

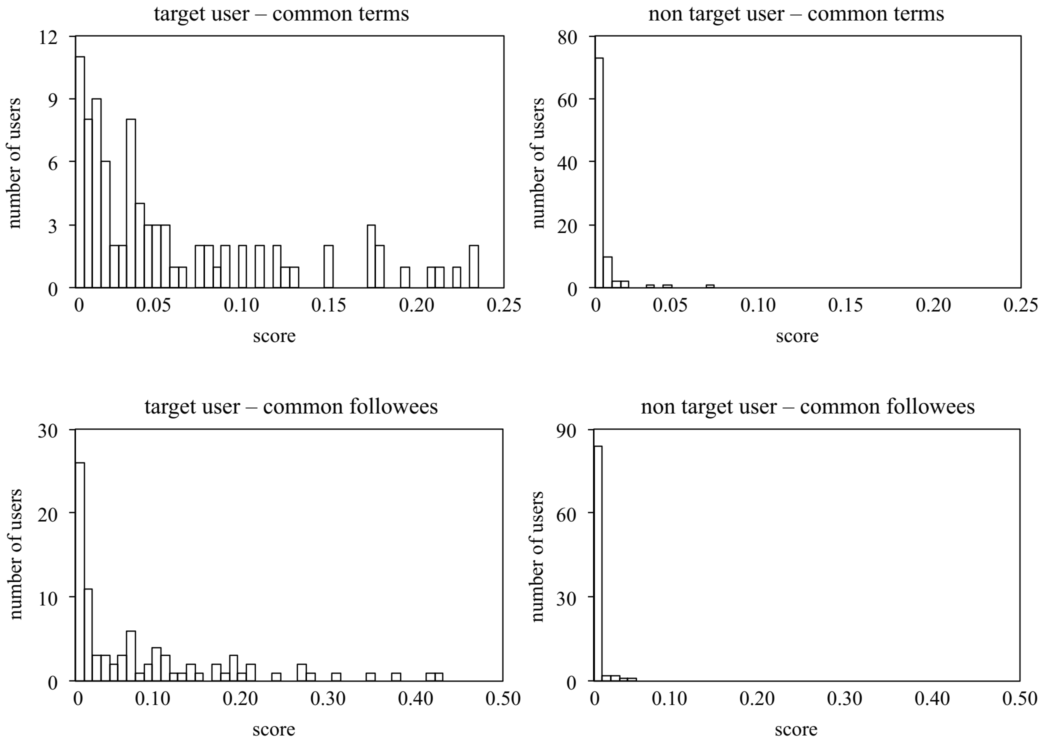

Figure 6: The histogram of specificity scores of each attribute on target users and non target users

common followees as attributes: even the median for target users, i.e., 0.050, is larger than the maximam score for non target users, i.e., 0.043.

Figure 7 shows the cumulative histogram of specificity scores of each attribute on target users and non target users. More and more target users cumulate as scores become smaller, and more and more non target users cumulate as scores become larger. Therefore, the score on which the sum of numbers of target users and non target users is the largest is the score which can classifies target users and non taraget users accurately the most, and we set this score to the threshold δ. In each case of using common terms and common followees as attributes, we take δ for 0.009 and 0.012 respectively.

Next, we show the relationship between two attributes, i.e., common tersm and common followees. Figure 8 shows a scatter diagram based on specificity scores of these two attributes on target users and non target users. On target users, points of scores of these attributes are widely distributed and have weak

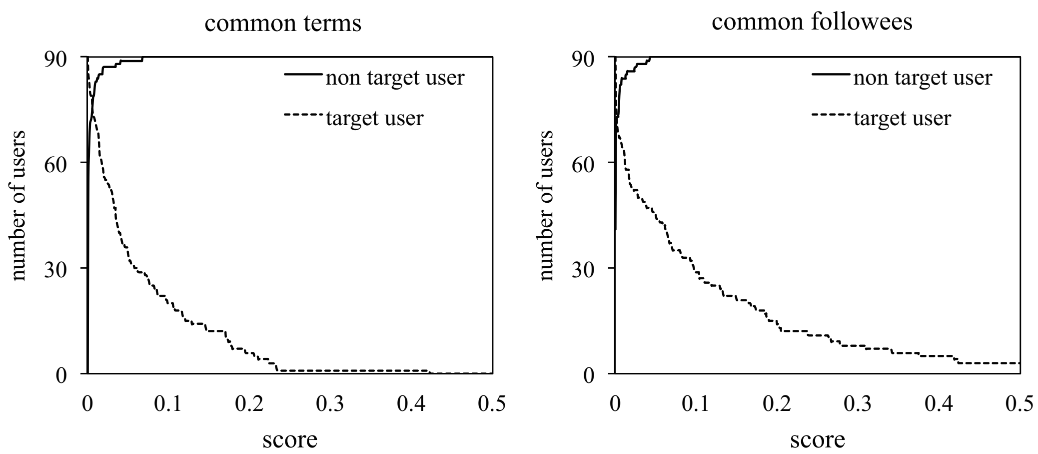

Figure 7: The cumulative histogram of specificity scores of each attribute on target users and non target users

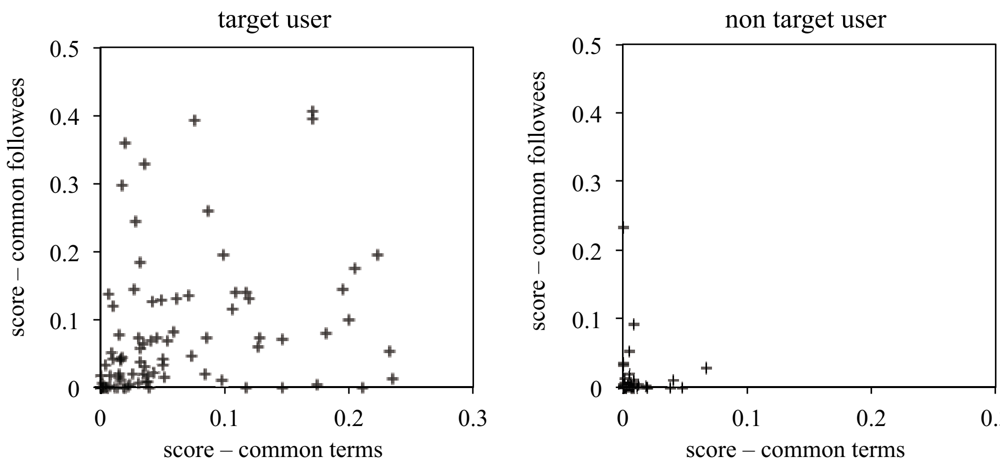

Figure 8: A scatter diagram based on specificity scores of a couple of attributes, common terms and common followees, on target users and non target users

positive correlation, with the correlation coefficient 0.507. That is, there is high possibility that the higher one score is, the higher the other score is. Of course, as shown in Figure 8, there are some outliers, i.e., one score is high and the other score is low. On the othe hand, points of scores of these attributes concentrate on the point $(0, 0)$ on no target users, and have no correlation, with the correlation coefficient 0.232.

Then, we show the precision of the final classification of target users and

Table 3: Precision of the final classification of target users and non target users

Baseline		Proposed Method			
follower	SVM	max	avg	SVM	decision tree
0.878	0.828	0.856	0.872	**0.944**	0.906

non target users. The second and third columns of Table 3 shows the precision of a couple of baselines: a follower method, i.e., numbers of followers arranged in the descending order, and a simple SVM method, respectively. The precision of the follower method achieved 0.878, which suggests that target specificities are mainly related to numbers of followers. This precision is quite high for a baseline, but notice that our final goal is classifying outliers: target users who have many followers or non target users who have a few followers, with high precision. While the precision of the simple SVM method was 0.828.

The following columns show the precision of four types of proposed methods: the maximum and the average scores of a couple of attributes, and the methods using SVM and decision tree as classifiers with the features of these two scores, respectively. The precision of the maximum score was 0.856, which was lower than the precision using only common terms as attributes, i.e., 0.861. This suggests that some non target users may have a high score in either attribute, and it is able to be a noise for the classification. The precision of the average score was 0.872, which was higher than the precision using only common terms or common followees as attributes, but lower than the follower method, i.e., 0.878. The precision of the methods using SVM and decision tree as classifiers achieved 0.944 and 0.906 respectively, and the former was the highest precision of four proposed methods, 0.66 point higher than the follower method. This suggest that the method using SVM is also able to classify users who is difficult to classify by only numbers of followers: target users who have many followers or non target users who have a few followers with high precision, with a certain degree of high precision.

Finally, we show the details of the results of a part of users. Upper and

Table 4: Details of the results of a part of users

target user	**term & followee**	*local rate*	*global rate*	*SubsetScore*	*SpecificityScore*
@MCstaff_Fukuoka	Fukuoka	0.563	0.047	0.390	0.235
	music	0.114	0.096	0.076	
	Hakata	0.095	0.003	0.076	
	@fukuoka_yokane	0.069	0.023	0.046	0.010
	@f_sunpalace	0.063	0.023	0.040	
	@mbc_o2_eiji	0.059	0.028	0.031	
@Jars0830	Arashi	0.439	0.039	0.304	0.233
	participation	0.190	0.026	0.131	
	line	0.130	0.045	0.090	
	@Yamnos5	0.249	0.004	0.246	0.067
	@ars_762	0.109	0.072	0.037	
	@nino_xoxo_	0.070	0.033	0.037	
@pa_ko065	piano	0.528	0.009	0.366	0.223
	music	0.250	0.096	0.173	
	Sapporo	0.139	0.022	0.096	
	@mofu_co	0.500	0.001	0.499	0.277
	@miko3535	0.500	0.003	0.497	
	@shimagaraneko	0.472	0.002	0.470	
non target user	**term & followee**	*local rate*	*global rate*	*SubsetScore*	*SpecificityScore*
@tenkijp	Tokyo	0.033	0.196	0	2.51e-5
	hobby	0.022	0.095	9.28e-16	
	music	0.021	0.096	1.18e-15	
	@tenkijp_jishin	0.421	10.4	0	0
	@Kantei_Saigai	0.358	14.8	0	
	@bouei_saigai	0.277	6.31	0	
@masason	fan	0.059	0.676	2.62e-17	1.20e-12
	Tokyo	0.027	0.196	0	
	music	0.024	0.096	1.34e-15	
	@shigeruishiba	0.050	0.939	0	0
	@WSJJapan	0.066	3.56	0	
	@HeizoTakenaka	0.05	3.62	0	
@Kantei_Saigai	Tokyo	0.034	0.196	0	3.52e-9
	hobby	0.027	0.095	1.14e-15	
	movie	0.019	0.043	1.85e-7	
	@MofaJapan_ITPR	0.056	0.597	0	0.001
	@CAO_BOUSAI	0.203	0.834	0	
	@MofaJapan_jp	0.062	0.950	0	

lower half of Table 4 show details of the results of target users and non target users respectively, i.e., their screen names, noticeable terms and followees extracted for measuring consistency, their local rates, global rates, and scores of consistency subsets, and specificity scores of each attribute.

The first rows of upper half show the details of the results of the target user @MCstaff_Fukuoka, the account publishing information about the concert hall in Fukuoka. In regard to common terms in profiles and location information, our method extracted terms related to the account, e.g., Fukuoka, music, Hakata, and so on. In tegard to common followees, our method also extracted followers related to the account as with common terms, e.g., @fukuoka_yokane, the account publishing information about the CD shop in Fukuoka, @f_sunpalace, the other account publishing information about the same concert hall, and so on. These terms and followees have the high local rate in spite of the low global rate, so the scores of consistency subset become high. As a result, the specificity score of each attribute on this account is high. The other target users, @Jars0830 and @pa_ko065, are just alike.

The first rows of lower half show the details of the results of the non target user @tenkijp, the account publishing weather information in Japan. In regard to common terms in profiles and location information, our method extracted terms, which is not rare, e.g., Tokyo, hobby, music, and so on. In tegard to common followees, our method also extracted followees, who is not rare, i.e., who have a large number of followers, as with common terms, e.g., @tenkijp_jishin, the account publishing earthquake information, @Kantei_Saigai, the account publishing disaster information, and so on. These terms and followees have the high local rate to a certain degrrees, but they have the global score much higher than the local score, so the scores of consistency subset become very small. As a result, the specificity score of each attribute on this account is small. The other non target users, @masason and @Kantei_Saigai, are just alike.

Table 5: Precision of the classification of target users

SVM		decision tree	
3-class	2 binary	3-class	2 binary
0.678	**0.689**	0.556	0.533

Table 6: Precision of SVMs without each feature

Removed Feature	3-class	2 binary	-user	-topic
with all	0.678	0.689	0.856	0.833
i	**0.644**	**0.656**	**0.811**	0.844
ii	0.722	0.711	0.867	0.844
iii	0.678	0.678	0.844	0.833
iv	0.655	0.678	0.844	**0.822**

6.4 Results and Evaluation of Classifying Users of High Target Specificity

In this subchapter, we show the results of the experiments classifiying target users. Table 5 shows the precision of four types of classification methods: a combination of two approaches and two classifiers, i.e., a 3-class SVM, 2 binary SVMs, a 3-class decision tree, and 2 binary decision trees, with all features mentioned in Chapter 5 into three categories. The precision of classification methods using SVMs as classifiers are more than 10 points higher than that using decision trees. When using SVMs as classifiers, the precision of 2 binary classifiers are a little higher than that of a 3-class classifier, and it is the opposite when using decision trees. But for both methods using SVMs and decision trees, the difference between the precision of 2 binary classifiers and that of a 3-class classifier is not so big, which suggests that the two causes of the high target specificity mentioned in 3.2 are highly independent of each other.

Next, we show the details of the results of classification methods using SVMs as classifiers. The second column of Table 6 shows the precision of each classification method with all features, and the following columns show the precision

Table 7: A part of topics extracted by LDA

id	words
1	news, program, broadcast, morning, night, tonight
2	update, blog, picture, smart phone, weather
3	worst, typhoon, Sea of Japan, electricity
4	earthquake, observation, focus, concern, teacher

when we remove each feature from the data. Each feature of i, ii, iii, and iv correspond to those in Chapter 5 respectively. For each method, a bold number shows when the precision becomes the lowest.

The socond and third rows show the precision of a 3-class SVM and 2 binary SVMs respectively. For each method, the precision became the lowest when we removed the feature (i): numbers of followees and followers, and their ratio. It is able to be said that numbers of followees and followers, and their ratio are mainly useful for determining the cause of high target specificity. The precision also became lower to some extent when we removed the feature (iv): partialness of topics in messages. This suggests that partialness of topics in messages is related to high target specificity. Table 7 shows a part of topics out of 20 extracted by LDA. We were able to extract topics about news programs, disasters, and so on. On the other hand, the precision became higher when we removed the feature (ii): mutual follow ratio. This suggests that mutual follow ratio and whether the user publishes information to the closed users are not necessarily correlating.

The fourth and fifth rows show the precision of each binary SVM used for the method of 2 binary SVMs: a SVM determining whether users publish information specified for certain topics or not, and that determining users publish information to the users specified extensionally, respectively. The precision of the former became the lowest when we removed the feature (i): numbers of followees and followers, and their ratio, and that of the latter became the lowest when we removed the feature (iv): partialness of topics in messages, which is the noticeable metter. This suggests that partialness of topics is more useful for determing whether users publish information to the users specified extensionally or not than whether users publish information specified for certain topics or not.

Chapter 7 Conclusion

In this study, we focus on the fact that the wideness of target scope of information publishing varies greatly among users bacause Twitter is used for various purpose, we proposed the method to classify Twitter users from the point of view of how widely the target scope of their information publishing is, i.e., whether they publish information to the public widely or publish information specified in certain users.

First, we defined the target specificity of the Twitter user, as the measure of how much target scope of their information publishing is specified. Second, based on this definition, we proposed the algorithm of computing a score of the target specificity. In this algorithm, we focused on the two parameters: (a) whether followers of the user are consistent in a certain noticeable character or not, and (b) whether the follower set of the user is covered with consistency subsets which cover intermediately widely or not. For computing the score, we proposed a couple of models computing a score of the consistency subset: the probabilistic model and the subtracting model, and we compared the above two models. Furthermore, we proposed a couple of attributes for extracting consistency subsets from the follower set of the user: common terms in profiles and location information and common followees. Then, we finally proposed the method of classifying Twitter users based on the score. We conducted the experiment and our experimental results confirmed that these two techniques improve the precision.

In addition, in this study, in regard to Twitter users classified into "he target specificity is high ""y thehe above method, we proposed thy the above method, we proposed the method of determining why their target specificities are high. We analysed the causes of high target specificity, and based on them, we classified the user into three categories: (1) they publish information specified for certain topics, (2) they publish information to the users specified extensionally, and (3) in the cause of both (1) and (2). In this method, we constructed 3-class classifiers which classify a user into the above three categories based on various features of the user which potentially correlate with each cause, and we determined why the target specificity is high by using them.

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References

[1] Brian, M.: Twitter now has 200 million monthly active users, up 60 million in 9 months, http://thenextweb.com/twitter/2012/12/18/twitter-now-has-200-million-monthly-active-users-up-60-million-in-9-months/ (2012).

[2] McGee, M.: With 400 Million Tweets Per Day, Twitter Spending "Inordinate Resources" On Improving Content Discovery, http://marketingland.com/twitter-400-million-tweets-daily-improving-content-discovery-13581 (2012).

[3] Irani, D., Webb, S., Pu, C. and Li, K.: Study of trend-stuffing on twitter through text classification, *Collaboration, Electronic messaging, Anti-Abuse and Spam Conference (CEAS)* (2010).

[4] Broder, A.: A taxonomy of web search, *ACM Sigir forum*, Vol. 36, No. 2, ACM, pp. 3–10 (2002).

[5] Busch, M., Gade, K., Larson, B., Lok, P., Luckenbill, S. and Lin, J.: Earlybird: Real-time search at twitter, *Data Engineering (ICDE), 2012 IEEE 28th International Conference on*, IEEE, pp. 1360–1369 (2012).

[6] Sriram, B., Fuhry, D., Demir, E., Ferhatosmanoglu, H. and Demirbas, M.: Short text classification in twitter to improve information filtering, *Proceeding of the 33rd international ACM SIGIR conference on research and development in information retrieval*, ACM, pp. 841–842 (2010).

[7] Cha, M., Haddadi, H., Benevenuto, F. and Gummadi, K.: Measuring user influence in twitter: The million follower fallacy, *4th international aaai conference on weblogs and social media (icwsm)*, Vol. 14, No. 1, p. 8 (2010).

[8] Cheng, J., Romero, D. M., Meeder, B. and Kleinberg, J.: Predicting reciprocity in social networks, *Privacy, security, risk and trust (passat), 2011 ieee third international conference on and 2011 ieee third international conference on social computing (socialcom)*, IEEE, pp. 49–56 (2011).

[9] Chu, Z., Gianvecchio, S., Wang, H. and Jajodia, S.: Who is tweeting on twitter: human, bot, or cyborg?, *Proceedings of the 26th Annual Computer Security Applications Conference*, ACM, pp. 21–30 (2010).

[10] Duan, Y., Jiang, L., Qin, T., Zhou, M. and Shum, H.: An empirical study on learning to rank of tweets, *Proceedings of the 23rd International Con-*

ference on Computational Linguistics, Association for Computational Linguistics, pp. 295–303 (2010).

[11] Ehrlich, K. and Shami, N.: Microblogging inside and outside the workplace, *Proc. ICWSM*, Vol. 10 (2010).

[12] Sakaki, T., Okazaki, M. and Matsuo, Y.: Earthquake shakes Twitter users: real-time event detection by social sensors, *Proceedings of the 19th international conference on World wide web*, ACM, pp. 851–860 (2010).

[13] Hopcroft, J., Lou, T. and Tang, J.: Who will follow you back?: reciprocal relationship prediction, *Proceedings of the 20th ACM international conference on Information and knowledge management*, ACM, pp. 1137–1146 (2011).

[14] Ikawa, Y., Enoki, M. and Tatsubori, M.: Location inference using microblog messages, *Proceedings of the 21st international conference companion on World Wide Web*, ACM, pp. 687–690 (2012).

[15] Java, A., Song, X., Finin, T. and Tseng, B.: Why we twitter: understanding microblogging usage and communities, *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 workshop on Web mining and social network analysis*, ACM, pp. 56–65 (2007).

[16] Kunegis, J., Lommatzsch, A. and Bauckhage, C.: The slashdot zoo: mining a social network with negative edges, *Proceedings of the 18th international conference on World wide web*, ACM, pp. 741–750 (2009).

[17] Kwak, H., Lee, C., Park, H. and Moon, S.: What is Twitter, a social network or a news media?, *Proceedings of the 19th international conference on World wide web*, ACM, pp. 591–600 (2010).

[18] Lee, K., Caverlee, J. and Webb, S.: The social honeypot project: protecting online communities from spammers, *Proceedings of the 19th international conference on World wide web*, ACM, pp. 1139–1140 (2010).

[19] Leskovec, J., Huttenlocher, D. and Kleinberg, J.: Predicting positive and negative links in online social networks, *Proceedings of the 19th international conference on World wide web*, ACM, pp. 641–650 (2010).

[20] Leskovec, J., Huttenlocher, D. and Kleinberg, J.: Signed networks in social media, *Proceedings of the SIGCHI Conference on Human Factors in*

Computing Systems, ACM, pp. 1361–1370 (2010).

[21] Massoudi, K., Tsagkias, M., de Rijke, M. and Weerkamp, W.: Incorporating query expansion and quality indicators in searching microblog posts, *Advances in Information Retrieval*, Springer, pp. 362–367 (2011).

[22] Mathioudakis, M. and Koudas, N.: Twittermonitor: trend detection over the twitter stream, *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data*, ACM, pp. 1155–1158 (2010).

[23] Nagmoti, R., Teredesai, A., De Cock, M. et al.: Ranking approaches for microblog search, IEEE Computer Society (2010).

[24] Nishida, K., Banno, R., Fujimura, K. and Hoshide, T.: Tweet classification by data compression, *Proceedings of the 2011 international workshop on DETecting and Exploiting Cultural diversiTy on the social web*, ACM, pp. 29–34 (2011).

[25] Pennacchiotti, M. and Popescu, A.: A machine learning approach to twitter user classification, *Fifth International AAAI Conference on Weblogs and Social Media (ICWSM)* (2011).

[26] Takemura, H. and Tajima, K.: Tweet Classification Based on Their Lifetime Duration, *Proceedings of the 21st International Conference on Information and Knowledge Management (CIKM)*, ACM, pp. 2367–2370 (2012).

[27] Teevan, J., Ramage, D. and Morris, M.: # TwitterSearch: a comparison of microblog search and web search, *Proceedings of the fourth ACM international conference on Web search and data mining*, ACM, pp. 35–44 (2011).

[28] Weng, J., Lim, E.-P., Jiang, J. and He, Q.: Twitterrank: finding topic-sensitive influential twitterers, *Proceedings of the third ACM international conference on Web search and data mining*, ACM, pp. 261–270 (2010).

[29] Wu, S., Hofman, J. M., Mason, W. A. and Watts, D. J.: Who says what to whom on twitter, *Proceedings of the 20th international conference on World wide web*, ACM, pp. 705–714 (2011).

[30] Yan, L., Ma, Q. and Yoshikawa, M.: Classifying Twitter Users Based on User Profile and Followers Distribution, *Database and Expert Systems Ap-*

plications, Springer, pp. 396–403 (2013).

[31] Zhao, D. and Rosson, M. B.: How and why people Twitter: the role that micro-blogging plays in informal communication at work, *Proceedings of the ACM 2009 international conference on Supporting group work*, ACM, pp. 243–252 (2009).