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Profiling social media users with selective self-disclosure behavior

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by

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Wei Gong

Abstract

Social media has become a popular platform for millions of users to share activities and thoughts. Many applications are now tapping on social media to disseminate information (e.g., news), to promote products (e.g., advertisements), to manage customer relationship (e.g., customer feedback), and to source for investment (e.g., crowdfunding). Many of these applications require user profile knowledge to select the target social media users or to personalize messages to users. Social media user profiling is a task of constructing user profiles such as demographical labels, interests, and opinions, etc., using social media data. Among the social media user profiling research works, many focus on analyzing posted content. These works could run into the danger of non-representative findings as users often withhold some information when posting content on social media. This behavior is called **selective self-disclosure**. The challenge of profiling users with selective self-disclosure behavior motivates this dissertation, which consists of three pieces of research works.

The first work is that of profiling silent users in social media. Silent users (or lurkers) are the users who choose not to disclose any information. In this work, we examined 18 weeks of tweets generated by two Twitter communities consisting of more than 110K and 114K users respectively. We find that there are many lurkers in the two communities. We also show that by leveraging lurkers' neighbor content, we are able to profile their attributes with accuracy comparable to that of profiling active users.

The second work is that of profiling users with selective topic disclosure. Social media users may choose not to post some of their interested topics. As a result, their posting and reading topics can be different. To better determine and profile social media users' topical interests, we conducted a user survey in

Twitter. In this survey, participants chose the topics they like to post (posting topics) and the topics they like to read (reading topics). We observe that users' posting topics differ from their reading topics significantly. We find that some topics such as "Religion", "Business" and "Politics" attract much more users to read than to post. With the ground truth data obtained from the survey, we show that predicting reading topics can be as accurate as predicting posting topics using features derived from posted content, received content and social networks.

The third work is that of profiling users with selective opinion disclosure. In social media, users may not disclose their opinions on a specific issue i even when they are interested in i. We call these users **issue-specific silent users** or i-silent users. This work investigates the opinions of i-silent users. We conducted an opinion survey on a set of users for two popular social media platforms, Twitter and Facebook. We analyzed the survey results together with their social media data. We find that more than half of our users who are interested in issue i are i-silent users in Twitter. The same has been observed for our Facebook users. The survey results also show that i-silent users have opinion distribution different from the users who post about i. With the ground truth user opinions from the survey, we show that predicting i-silent users' opinions can achieve reasonably good accuracy from user posted content that is *not* related to issue i, and achieve better accuracy when we utilize user opinions on other issues as features.

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Dedication

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Publications

This dissertation includes the following publications.

- Wei Gong, Ee-Peng Lim, Feida Zhu, Pei Hua Cher. On Unravelling Opinions of Issue Specific-Silent Users in Social Media. In *International AAAI Conference on Web and Social Media (ICWSM)*, 2016.

- Wei Gong, Ee-Peng Lim, Feida Zhu. Posting Topics Are Not Reading Topics: On Discovering Posting and Reading Topics in Social Media. In *International School and Conference on Network Science (NetSciX)*, 2016.

- Wei Gong, Ee-Peng Lim, Feida Zhu. Characterizing Silent Users in Social Media Communities. In *International AAAI Conference on Web and Social Media (ICWSM)*,2015.

Other publications that are not included to this dissertation.

- Wei Gong, Ee-Peng Lim, Feida Zhu, Palakorn Achananuparp, and David Lo. On Finding the Point Where There is No Return: Turning Point Mining on Game Data. In *SIAM: SIAM International Conference on Data Mining (SDM)*, 2014.

- Wei Gong, Ee-Peng Lim, Palakorn Achananuparp, Feida Zhu, David Lo and Freddy Chong Tat Chua. In-Game Action List Segmentation and Labeling in Real-Time Strategy Games. In *Computational Intelligence and Games (CIG)*, 2012.

Chapter 1

Introduction

Social media platforms such as Facebook and Twitter connect millions of users with very large online social networks where they share content from daily life to personal thoughts. The abundant user-generated content provides an unprecedented resource for *user profiling*, which seeks to determine user attributes such as their demographic attributes (e.g., age, gender and marital status) [109, 87, 68, 82], interests [114, 80, 22], preferences [67, 66], opinions [38], personalities [58, 43] and mental states [32, 33]. These user attributes characterize who the users are, what they like and what they think, and as such play a critical role in many applications such as viral marketing, recommendation systems and targeted advertising [71, 31, 125, 65, 39, 116, 104, 128, 2]. For example, knowing that a user is a 25 years old female interested in fashion allows a marketer to recommend her fashion magazines, fashion stores, and brands for young females.

User profiling can be challenging when considering social media user behaviors. We use three user behaviors for illustration, namely, (i) organizations as account owners, (ii) untruthfulness, and (iii) selective self-disclosure. Many organizations nowadays maintain social media accounts to engage customers and spread information [92, 77]. Content generated by these accounts and their behavior would be quite different from those of normal user accounts. Profiling human and organization accounts should therefore be treated differently. For example, we are interested in profiling human's personalities but organizations' marketing strategies. Consequently, profiling organizations requires different approaches.

Some users in social media do not post information truthfully [20, 93]. For example, in China, there are paid users, known as water army, posting fictitious articles, reviews, and comments in order to influence others' opinions on some social issues or products [20]. The content these paid users posted do not truly reveal their profiles such as opinions. Again, the usual way of profiling users based on content [129, 35, 94, 21, 58, 43] cannot be applied on them.

Social media users often select certain content to disclose. This behavior is known as *selective self-disclosure* [127, 29]. Specifically, when posting content in social media, users consciously or sub-consciously decide what content to share, to whom the content is shared with, and self-censor when selecting and crafting the content [8, 49, 29, 112]. As a result, the content users posted does not completely reveal their profiles such as interests. In this dissertation, we focus on profiling users with selective self-disclosure behavior.

Due to users' selective self-disclosure behavior, profiling them becomes a challenging task. In the extreme case, users may choose not to post any content and behave as audience. They are known as *lurkers*, or silent users [115, 45]. For this group of users, it is impossible to profile them by considering only their posted content. The immediate question is then *how do we profile silent users who do not post any content.*

Even for the users who post content online (we call them active users), they can still choose not to disclose some information. For instances, a user interested in business may never post business related content, and another user who never mentioned a mobile phone before may have some positive or negative opinion on it. *How do we know if a user is interested in a topic, if she never posted that topic? How do we know a user's opinion on a product,*

Target Users	Attributes to Profile
Silent users (who select not to disclose content)	Marital status, religion, and political orientation
Users with selective topic disclosure behavior	Posting topical interests and reading topical interests
Users with selective opinion disclosure behavior	Opinions

Table 1.1: Dissertation Overview.

an issue or an event, if she has not discussed it before?

To answer the aforementioned questions, this dissertation includes three works (see overview in Table 1.1), with each work focusing on users with a certain type of self-disclosure behavior and investigating how to profile certain attributes of them when they choose not to disclose some information. In the first work, we study silent users who choose not to disclose any information, and profile their attributes including marital status, religion and political orientation. In the second work, we study users with selective topic disclosure behavior and profile their posting and reading topical interests. In the third work, we study users with selective opinion disclosure behavior and profile their opinions on some social issues in Singapore. The details of these three works are introduced as follows.

1.1 Profiling Silent Users

In the first part of this dissertation, we study silent users (or called lurkers) who have none or little posted content and prefer to consume content or perform other non-content-generating activities quietly. We call this the *lurking* behavior which can be considered as a special case of selective self-disclosure behavior. As active users account for most of the social media content, existing social media research have focused on them but not the lurkers [50, 121, 87]. For example, when mining the topical interests and sentiments of users, one often does not consider lurkers as they do not generate sufficient content. This obviously leads to biased representation of topical interests and sentiments at the user population level.

In many applications, it is very important to identify the lurkers, and their demographic attributes, interests and opinions. Despite their online silence, lurkers (like active users) are individuals with interests and preferences. They pay attention to topics of interest to them and will seek for relevant content. They have preferences that can potentially be expressed as ratings and reviews on consumer products. They are also potential customers for targeted marketing. It is possible for lurkers to have different demographic and opinion distribution from active users. Failing to account for lurkers could therefore lead to the misjudgment of overall population-level demographic attribute distribution, interests and opinions. For example, Gayo-Avello [40] pointed out that one of the main reasons that has caused the low election prediction accuracy using social media (i.e., Twitter) data is that "*The silent majority is a huge problem. Very little has been studied in this regard and this should be another central part of future research*".

For the above reasons, we characterize silent users in Singapore and Indonesia Twitter communities and evaluate the accuracy of profiling their attributes including marital status, religion and political orientation by utilizing the content generated from their neighbors. This part of our research is covered in Chapter 3.

1.2 Profiling Users with Selective Topic Disclosure

In the second part of this dissertation, we study users' topical interests. With selective self-disclosure, users may not post some topics that they are interested in (i.e., selective topic disclosure). In contrast, when users read content online, because reading often does not generate any public data trace, users have less worries about how other people perceive them when reading online content. For example, a user interested in politics is likely to read political news and discussion, but may choose not to post political content to avoid unwanted disputes on some controversial issues. Therefore, we expect that users' posting topical interests (posting topics) can be different from reading topical interests (reading topics).

A number of previous studies have focused on predicting users' topic interests [114, 80, 22]. While these studies contribute to the understanding of *general* topic interests of users, they fail to distinguish between the posting and reading topics. In our research, we postulate that reading topics are as important as posting topics [46]. Posting topics are likely to capture only part of all topic interests of the user. The user's reading topics on the other hand reveal the additional content she is likely to pay attention to. If the purpose of user profiling is to discover topics that attract user attention, one should focus on users' reading topics. And if the purpose is to find topics that users are likely to share, one should focus on users' posting topics.

Given that user posting and reading topics can be different, we then aim to address the following important research questions. That is: (a) How different are users' posting and reading topics? (b) Are there topics that are more likely to be reading topics but not posting topics, and vice versa? (c) Is the difference between user posting and reading topics related to user personality? (d) Can we predict posting and reading topics accurately? and (e) Can we predict lurkers' reading topics accurately? This part of dissertation seeks to answer the above questions by conducting a user survey and exploring methods that profile user posting and reading topics separately. We present this work in Chapter 4.

1.3 Profiling Users with Selective Opinion Disclosure

In the third part of this dissertation, we focus on analyzing issue-specific silent users' opinions. Opinions of users are useful in many real world applications [76]. Retailers are keen to know how well consumer think of new products and in what product aspects. Political parties and analysts want to predict election outcome based on public opinions. Universities also rely on public ratings on their academic and research programs to secure good ranking. User opinion insights are important to organizations and governments. They allow decision makers to fine tune customer relationship services and government policies, and help individuals make decisions (e.g., which products to buy, which movies to watch or which politicians to vote).

With selective self-disclosure, users may choose not to disclose their opinions in social media (i.e., selective opinion disclosure). A user may choose to keep silent on an issue even when she is interested in it, or when she has opinions on it. For example, a user may not share her opinion online because she does not want to start an argument with others, she thinks the opinion is not appropriate to share in public, or she is afraid that many of her friends have different opinions [103, 49, 112].

User-generated content therefore includes opinions on an issue from only those who post about the issue. When we conduct opinion analysis on this content, we will likely derive a biased conclusion of what the public think about the issue. The main question here is then how can we obtain opinions on issues from a set of users who are interested in the issues but do not share their opinions in social media. These users are the issue-specific silent users or i-silent users [47]. For example, if a user is interested in issue "Healthcare Cost" but never posts about it, she is then considered a Healthcare Cost-silent user. We call the users who post about an issue the *issue-specific active* users or i-active users. It is important to note that i-silent users may still generate content unrelated to issue i. Hence, they may not be *overall silent users* who do not post anything or post only a little in a certain period time [115, 45]. On the other hand, an overall silent user is one who is i-silent for all issues.

This part of dissertation seeks to study to what extent i-silent users exist for different issues and whether their opinion distribution is similar or different from that of i-active users, and explore the methods that unravel the opinions of i-silent users. We cover this work in Chapter 5.

1.4 Contributions

In the following, we summarize the contributions of this dissertation under two main areas, namely (a) insights of selective self-disclosure behavior, and (b) user profiling methods and evaluation.

Insights of selective self-disclosure behavior in social media.

1. In our first work, we show that there are a significant number of lurkers in both Singapore and Indonesia Twitter communities. It shows that many users choose not to disclose information or disclose only a little information in social media. We derive several characteristics of lurkers in Twitter: Compared with active users, lurkers have much fewer followers and followees; Both active users and lurkers are more likely to connect with active users than lurkers; Lurkers break silence mainly to share information such as breaking news and updates of personal life.

2. In our second work, we show that the topics users like to post can be significantly different from the topics users like to read in social media. This finding verifies that social media users may choose to disclose only a subset of their interested topics. We also find that less extravert and less agreeable users are likely to have more differences in posting and reading topics. Thus personality is one possible explanation for users

posting and reading different topics. We also show that users appear to be indiscriminative when posting topics about "Gaming" and "Music". However, for topics such as "Religion", and "Politics", many users interested in reading them do not share them in Twitter. These findings suggest that to measure the popularity of a tweet or an event, we need to consider its topic. For example, if a tweet is about "Politics", then the number of users sharing it could possibly underestimate its popularity or influence.

3. In our third work, we examine two popular social media platforms, Twitter and Facebook, and conduct a survey to obtain users' opinions on seven social issues (Healthcare Cost, Retirement, Public Housing, Public Transport, Jobs, Education, and Population Growth) and to collect users' personal social media data. Our study shows that more than half of the users who are interested in issue i are i-silent users in both Twitter and Facebook, confirming that people not posting an issue does not imply that they do not have opinions on that issue. Hence, a large number of i-silent users' opinions will be overlooked if we consider i-active users' posts only. We also find that i-silent and i-active users may hold different opinion distributions. It suggests that to understand what the public think about an issue i, it is necessary to take i-silent users' opinions into account.

User profiling methods and evaluation.

1. In our first work, we propose to use the content from lurkers one-hop neighbors to profile lurkers. We demonstrate that profiling lurkers' marital status, religion and political orientation can be as accurate as profiling active users'. This result suggests that it is possible to infer other lurkers' latent attributes. This will also enable lurkers to enjoy personalized applications including search, recommendation systems and advertising.

2. In our second work, we profile posting and reading topics separately using different topic ranking strategies including *Popularity*, *Content* and *Followee-expertise*. We propose a model which learns to combine rankings from multiple ranking strategies. Although the content a user has read is not available, we demonstrate that we can still infer users' reading topics with promising performance. We also show that we can predict lurkers' reading topics using *Followee-expertise* with reasonable accuracy. The prediction of posting and reading topics can be useful in different practical scenarios. For example, users' posting topics can be used to predict whether they will share a topic specific event or speak up for a topic specific issue in the future. Users' reading topics can be used to predict whether they will click an advertisement related to these topics.

3. In our third work, we profile opinions for i-silent users as well as i-active users in Twitter and Facebook. We explore two types of features for opinion prediction task: the sentiment features extracted from users' content and the opinion features extracted from users' predicted opinions or ground truth opinions on other issues. We demonstrate the effectiveness of these features and show that although predicting i-active users' opinion yields better performance than that of i-silent users, it is still possible to predict i-silent users' opinions by leveraging on their i-unrelated content. We can achieve better performance if we make use of predicted i-silent users' opinions on other issues and achieve the best performance if we acquire the ground truth i-silent users' opinions on other issues. To be able to predict i-silent users' opinions will enable researchers to infer the opinion distribution in population level, and also have a better understanding of i-silent users.

1.5 Organization of the Dissertation

The rest of this dissertation is organized as follows. In Chapter 2, we review previous studies about selective self-disclosure behavior and user profiling. In Chapter 3, we characterize and profile lurkers. In Chapter 4, we study the difference between user posting and reading topics and profile user posting and reading topics separately. In Chapter 5, we profile the opinions of issue-specific silent users. Finally, we conclude this dissertation in Chapter 6.

Chapter 2

Literature Review

In this chapter, we review previous works on selective self-disclosure and user profiling in social media.

2.1 Selective Self-Disclosure

Self-disclosure, a process of sharing personal information with others, has been studied extensively in psychology [127, 28, 36, 34]. It is a 'cornerstone' of formating, developing and maintaining intimate social relationships [27], and it has been viewed as "both a sign and a cause of a healthy personality" [55, 54].

Selective self-disclosure refers to people *selecting* certain part of themselves to disclose. It happens both in face to face communication and in computer-mediated communication (CMC) [53, 10]. As social media, a popular CMC platform, attracts millions of users to share personal information and maintain relationships, the study of self-disclosure has been extended to social media [98, 105, 29].

Previous studies have shown that social media users would decide what content to post and to whom [8, 49, 29, 112]. For example, Hampton et al. [49] conducted a survey on 1,801 adults asking them how they react to an important public issue ("Edward Snowden's 2013 revelations of widespread government surveillance of Americans' phone and email records"). They found that people are less willing to discuss this issue in social media than in person, and that people are less likely to express their views online if they believe they have views different from others.

Some studies [29, 112] showed that when selecting and crafting the content, users may practice self-censorship. When censoring the content to be shared, users may finally decide not to disclose this content. Das and Kramer [29] examined 3.9 million Facebook users and found that 71% of users practise self-censorship on what content to share. In a qualitative study, Sleeper et al. [112] asked 18 Facebook users to report "all content they thought about sharing but decided not to share". The authors found that the reasons for self-censorship and deciding not to share include: (a) not wanting to start or continue an argument, (b) not wanting to offend others, (d) not wanting to bore others, and (d) not wanting to post content that might be inconsistent with their self images.

Lurking in Social Media. Lurking is a special case of selective self-disclosure behavior. When a user lurks, she selects not to disclose anything or disclose only a little information. Such a user is also known as a silent user or lurker. In traditional printed news media, lurking is almost the only possible activity as all news articles are written by professional journalists leaving very few selected reader comments to appear in special news columns. Social media, in contrast, depends largely on users to contribute and share content. A naive intuition may consider lurking on social media not a desired user behavior. Without enough users actively contributing content, the social media user community may shrink. In practice, however, lurking is a very common behavior found in many content providing sites [45, 83, 5, 11, 13]. Benevenuto el al. [11] in their work on user behavior in online social networks (e.g., Myspace and LinkedIn), concluded that browsing actions (i.e., lurking) constitute 92% of all user actions. Only very few users contributed content. Nonnecke and Preece [89] examined online discussion lists and showed 46% and 82% of users in health-support and software-support discussion lists respectively are lurkers. Muller et al. [83] showed that 72.2% of users are lurkers in an enterprise file-sharing service. All these studies conclude that lurking is a common behavior among online users.

As lurkers make up a significant proportion of users in online communities, several studies [90, 103, 63] have focused on the reasons for lurking. Preece et al. [103] conducted interviews and reported reasons such as (i) no need to post, (ii) personal privacy and safety concerns, (iii) shyness over public posting, and (iv) poor system usability. *No need to post* appears to be the top reason. In a survey conducted on a user-generated encyclopedia called Everything2.com, Lampe et al. [63] reported that many users choose to lurk because they are satisfied with "getting information", as opposed to "sharing information". Antin and Cheshire [5] found that Wikipedia users choose to lurk so as to learn enough about the site before they could actively contribute content. Similar findings of de-lurking behavior were also reported in other works [102, 107].

To summarize, with selective self-disclosure behavior, users only disclose part or even none of their activities, emotions, interests and opinions when posting in social media. As a result, it is challenging for researchers to have a complete understanding of individual social media users and user communities.

2.2 User Profiling

A user's profile is a description of the characteristics and preferences of the user [61, 81, 64]. It tells who the user is, what she likes and what kind of person she is. It can include the user's gender, age, marital status, religion, physical and mental conditions, interests, preferences, opinions, personalities, personal values, credits and many others. User profiling refers to the task of deriving user profiles by querying users or by performing predictions on the

Attributes	Representative Works
Demographic attributes	Age [109, 87, 68]; Gender [109, 73, 25]; Location [109, 74, 64]; Religion [88, 122]; Ethnicity [19]; Education [122, 82]
Interests and preferences	Topical interests [114, 80, 22, 130, 132, 129, 35]; Geo preferences [67, 66]
Opinions	Political affiliation [70, 109, 26]; Topics [38]
Personalities	Personalities [58, 43, 4, 7]; Personal values [21]
Mental states	Depression [32, 33]

Table 2.1: Related works on user profiling with social media data.

observed user data.

Many real world applications require profile information of their users. For example, doctors need patients' age, gender and medical history, etc. for diagnosis and treatment. Police profile criminals in order to narrow down possible suspects [120]. Banks decide whether to lend money to someone based on her credit history. Web applications also create new demands for user profiles. For example, video sharing websites and online shopping websites utilize user profiles to recommend videos and products respectively [71, 31, 2], social media sites offer news suggestions based on users' topical interests [99], and search engines return personalized results [39, 116].

Surveys and interviews are the traditional methods to obtain user profiles, but they involve much manual efforts, time and money. They are therefore not suitable for millions of users on social media platforms. On the other hand, the abundant data traces left by social media users create new opportunities for the much more scalable automated user profiling approaches [109, 64, 92]. In Table 2.1, we summarize the representative works on profiling users in social media. As shown in Table 2.1, social media data including user-generated content and user connections can be used to infer user profiles from basic demographic attributes such as age and gender to user personalities and depression states.

Due to the selective self-disclosure behavior, users do not fully disclose their information or sometimes do not disclose their information at all. Profiling such users can be challenging. For example, some users may be lurkers (i.e, never disclosed anything), and there is no content generated by them for user profiling. Can we still profile such users? If a user does not post 'Politics', do we know she is interested in Politics? If a user does not express her opinion on the current health care system, do we know that she holds positive or negative opinion on it? This dissertation aims to study lurker, users with selective topic disclosure, and users with selective opinion disclosure. We focus on profiling their demographic attributes, topical interests and opinions respectively. These attributes fall into the first three categories in Table 2.1. In the following three sections, we provide a more in-depth discussion on the related works on profiling users' demographic attributes, topical interests and opinions.

2.2.1 Demographic Attributes Profiling

Previous user profiling research has shown that users' latent demographic attributes can be inferred with reasonable accuracy based on user posted content and/or their social networks [109, 87]. For example, Liao et al. [68] and Nguyen et al. [87] inferred Twitter users' age based on their language use in tweets. Both works found that the words users use are associated with their age. Yang et al. [130] proposed a model to propagate item interests through users' friend links. Mislove et al. [82] utilized friend links to infer Facebook users' attributes such as their major. The authors proposed to detect communities in the networks, and then assign an identical attribute value to users in the same community. Li et al. [64] proposed to use both user posted content and social connections to profile user location.

Profiling lurkers' attributes. Many of these user profiling works often leave out the lurkers as they do not provide rich content features. Hence, we are not able to ascertain the accuracy of attribute profiling for lurkers, and whether the accuracy for lurkers and active users are very different.

Our proposed approach to profile lurkers is to utilize social links and neighbors' content [64, 131]. As shown in our data analysis, lurkers are likely to follow active users whose content are abundant. User profiling using neighbors' content has been shown to perform well for active users only in previous studies [131]. To the best of our knowledge, user profiling on lurkers and comparison between the profiling accuracy of lurkers and that of active users have not been studied earlier.

2.2.2 Topical Interests Discovery

To profile users' topical interests from their social media content, researchers often adopt supervised methods [114, 80, 22]. Michelson and Macskassy [80] infer Twitter user topic interests from named-entities in their posted tweets. The topics of these entities are then obtained through a knowledge base (i.e., Wikipedia). Unsupervised methods such as LDA [15] has been extended to infer user topic interests in Twitter [132, 129, 35]. Xu et al. [129] proposed a generative author-topic model extended from LDA. They assume that a tweet is generated either from the author's topic interests or from bursty events. Zhao et al. [132] proposed TwitterLDA (T-LDA) to generate topic distributions for Twitter users as well as topics for tweets. T-LDA assumes that every tweet has only one topic, as it is very short.

Profiling users with selective topic disclosure. The aforementioned studies contributed to discovery of topic interests by using posted content only. Nevertheless, they are good for inferring the topics that users disclose. However, due to users' selective self-disclosure behavior, users may read their interested topics but choose to post only part of their interested topics. In other words, we need to separate the profiling of user posting topical interest from that of reading topical interest. The existence of lurkers further add complexity to this profiling task. To the best of our knowledge, there are no other works addressing the above user profiling tasks so far.

2.2.3 Opinion Mining

Opinion mining is a classical text mining task to identify and extract "what people think" from textual content such as customer feedback emails, discussion forums, reviews and other social media postings [95, 72]. Understanding what people think using opinion mining is useful in product recommendation, product design, customer relationship management, and political sensing [95]. For example, users may buy products after reading opinions in product reviews. Companies improve product design and service delivery based on opinions in customers' feedback. Opinion mining has been intensively studied by the computational linguistics research community. The main focus is to determine whether a phrase, a sentence or a document is positive or negative, or to determine a user's view on certain issue, event or product [96, 30, 100, 126, 113].

Social media such as Twitter and Facebook has been a popular conduit for opinion mining [94, 119, 24, 111, 9, 59]. For example, the number and sentiments of related tweets can be used to predict overall election results such as German Federal Election in 2009 [119], US Senate special Election in Massachusetts 2010 [24], Dutch Senate Election in 2011 [110], Irish General Election in 2011 [12] and French Presidential and Legislative Elections in 2012 [17]. Other examples include the prediction of stock market by analyzing public mood and emotions in Twitter [16], movie box office prediction [6], and opinion shift over time modeling [69]. Opinion mining on social media data has also been used to predict individual users' opinions such as political orientation [70, 109, 26] and topics [38]. For example, Gao et al. [38] proposed a Matrix Factorization based model to predict user attitude toward controversial topics in social media.

Profiling users with selective opinion disclosure. All the aforementioned studies have shown that social media content can be used to effectively determine users' opinions. However, social media content is generated when users choose to disclose their thoughts [56, 48]. Thus the opinions of issue-specific silent users are not taken into account. (Remember that issue-specific silent users or i-silent users are the users who do not disclose their opinions on issue i even they are interested in i.) As a result, one may obtain a biased opinion profile of the entire user community [69, 40]. For example, Lin et al. [69] suggested that because of the self-reporting (i.e., selective self-disclosure) nature of social media, social media is a relatively poor tool for make population inferences. Gayo-Avello [40] also pointed out that failure to consider silent users has contributed to poor election prediction accuracy.

There are very little work focusing on i-silent users' opinions. Two big research questions linger around these users, namely: (a) Do the silent users share the same opinions as the active users? and (b) How can one predict the opinion of silent users? Mustafaraj et al. [84] compared the content generated by Twitter users who post very often and other users who post only once during the US Senate special Election in Massachusetts 2010. They found significant difference between the two groups of users' content. The result suggests that users who post none or only little content may hold opinions very different from very active users. It also suggests the importance of inferring i-silent users' opinions. As i-silent users do not post any content on the issue, inferring their opinions is challenging. To the best of our knowledge, our work is the first addressing this problem.

Chapter 3

Characterizing Silent Users in Social Media Communities

3.1 Introduction

Silent users choose to disclose very little or no information. They are also called the *lurkers*. Their behavior is called the lurking behavior, which is a special case of selective self-disclosure behavior. In this work, we call the other non-lurking users *active users*. As active users contribute most of the social media content, most of the existing social media research has focused on them but not the lurkers [50, 121, 87]. Just like active users, lurkers are individuals with interests and preferences. Although they choose not to disclose much information, they still pay attention to interesting topics and will seek for relevant content. They have preferences that can potentially be expressed as ratings and reviews on consumer products. They are also potential customers for targeted marketing. It is possible for lurkers to have different demographic and opinion distribution from active users. Failing to account for lurkers could therefore lead to the misjudgement of overall population-level conclusions.

We therefore study lurkers with the following two research goals. Our first goal is to define lurkers and characterize them in Twitter, which is chosen because it is where lurkers could most easily occur as a result of the ease of following others and, accordingly, the convenience of silent information consumption. We focus on 110,907 Twitter users from a Singapore-based community and 114,576 Twitter users from an Indonesia-based community. We examine the proportion of lurkers in these two Twitter communities, lurkers' social links with others and the motivations that may cause them to break silence. We identify the characteristics of lurkers by comparing them with active users. This gives us new insights into the lurking behavior and lurker's motivation of using Twitter. Note that this analysis is only possible with the availability of user tweets over a significant period of time as well as the follow relationships among the users. Therefore, we crawled all tweets posted by the users from the above two communities over 18 weeks and the follow links involving these users.

We define a lurker on Twitter as a user who is silent most of the time, i.e., he/she posts very few tweets during a given time interval. Using our Twitter datasets, we find that there are many lurkers in both communities. Compared with active users, lurkers have much fewer followers and followees. Both active users and lurkers are more likely to connect with active users. By sampling tweets and manually annotating them, we also found that a lurker breaks silence mainly to share information such as breaking news and updates of personal life.

Our second goal is to profile lurkers. Unlike many existing user profiling works that exclude lurkers from their empirical studies due to their inadequate content data [109, 87], we propose to utilize their neighbors' (their one-hop connected users) content to infer latent attributes including marital status, religion, and political orientation. We invest significant efforts in human annotation to obtain the ground truth labels. In our experiments, we compare the user profiling accuracy of lurkers with that of active users. The results show that using neighbors' content, we can predict lurkers' profile labels as accurate as active users' profile labels. It suggests that even lurkers do not generate much content, their profile attributes can still be uncovered from their neighbors. Therefore, it is indeed possible to personalize services for lurkers.

Chapter Outline. The rest of this chapter is organized as follows. In Section 3.2, we characterize lurkers in the Singapore and Indonesia Twitter communities. In Section 3.3, we present the results of profiling lurker's latent attributes. In Section 3.4, we conclude this work by discussing the implications of our findings, and pointing out the limitations and future works.

3.2 Characteristics of Lurkers in Twitter

In this section, we first describe the Twitter dataset used in this part of research. Secondly, we define lurkers and examine the extent of lurking behavior in our dataset. Thirdly, we study the difference between lurkers and active users in terms of their social links. Finally, we examine the motivations behind lurkers breaking silence.

3.2.1 Data

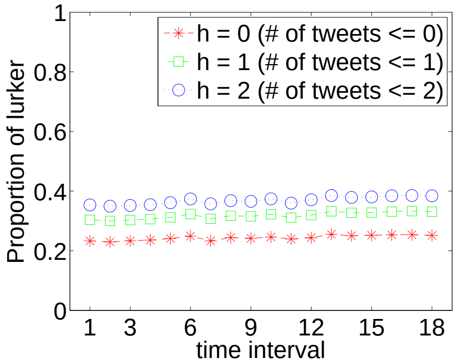
We focus on two communities in Twitter: a Singapore-based community and an Indonesia-based community. We crawled these two communities using the following strategy. We started the crawling process with 69 and 123 popular seed users from Singapore and Indonesia respectively. The seed users are known political figures, political candidates, political parties and organizations, activists, journalists and bloggers in Singapore/Indonesia. We then added users who are one hop and two hops away from the seed users. They are the seed users' followers and followees and the followers and followees of the seed users' followers and followees. Finally, we chose the users who declare Singapore (or Indonesia) as their locations in the biography fields and share their tweets and social links in the public domain. We then obtained 140,851 Singapore-based users and 126,047 Indonesia-based users. This research requires a full set of tweets generated by users during a target study period which is very different from many other research projects that were performed on sampled tweet data. We then crawled **all** their tweets generated during an 18-week period which our analysis will focus on. For Singapore users, we crawled from April 28th to August 31st, 2014. For Indonesia users, we crawled from June 16th to Oct 19th, 2014.

Removing churners. A limitation of the above dataset is that it may include lots of users who already left Twitter. These users are known as *churners* [91]. Churners do not post, and can be wrongly considered as lurkers. Since we only have limited access to Twitter users' data (e.g., their tweets and connections), it is impossible for us to know *exactly* who are the churners. To remove churners from our dataset, we crawled all the tweets that are posted by the 140,851 Singapore-based users and 126,047 Indonesia-based users for another 3 months after the 18-week period. If a user never posted during that 3 months, we consider him/her as a churner and remove him/her from our dataset. In this way, we make sure that the users we analyze are "alive" during the 18-week period time. After this churner removal step, we finally obtained **110,907 Singapore-based users** and **114,576 Indonesia-based users**.

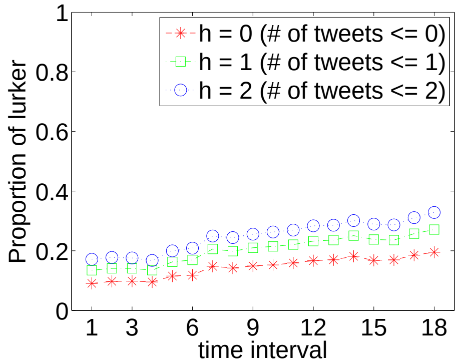
3.2.2 Lurkers in Twitter

Definition of lurker. We say a user is *lurking* or a user is a *lurker* during a time interval with duration d, if the number of tweets he/she posts in the time interval is not more than a *lurking threshold* h. This definition caters to the time duration covered by the observed data. By varying time interval duration d and lurking threshold h, we can examine different degrees of posting behavior (i.e., never post or post only a few tweets) over time.

Proportion of lurkers in Twitter communities. We empirically set d to be one week ($d = 1$ week) and vary h from 0 to 2, and derive the proportion



(a) Singapore

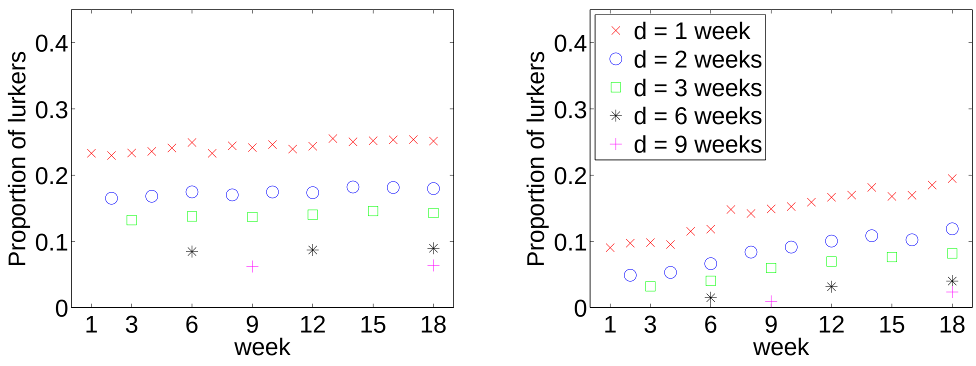


(b) Indonesia

Figure 3.1: Proportion of lurkers with $d = 1$ week.

of lurkers in the two communities across different disjoint time intervals over the 18 weeks. As shown in Figure 3.1(a), the proportion of lurkers in the Singapore community is very stable albeit a very small increasing trend. Every week, there are on average 24.4% of the users not posting any tweet (lurking threshold $h = 0$), 31.8% of the users posting no more than 1 tweet ($h = 1$), and 36.9% of the users posting no more than 2 tweets ($h = 2$). On the other hand, Figure 3.1(b) shows that the Indonesia community has smaller proportion of lurkers (e.g., on average 14.4% when $h = 0$), but the proportion increases steadily. Similar increasing trends are also observed when we use larger time interval duration d as shown in Figure 3.2. This figure shows that larger d has a smaller proportion of lurkers. Moreover, fewer users remain silent for longer time interval in both Twitter communities. It also implies that users may change their behavior from lurking to active between weeks.

Twitter users lurking behavior. To explain the above findings, we model Twitter user behavior changes overtime in the following way. We use L_t (or A_t) to denote a user is lurking (or active) at time interval t. We use $x_t = P(L_{t+1}|L_t)$ to represent the probability that a user maintains lurking behavior from time t to $t+1$. As a user who is lurking at t will either be lurking or active at $t+1$, we therefore have $1 - x_t = P(A_{t+1}|L_t)$. Similarly, we use $y_t = P(A_{t+1}|A_t)$ to represent the probability that a user maintains active behavior from time t to



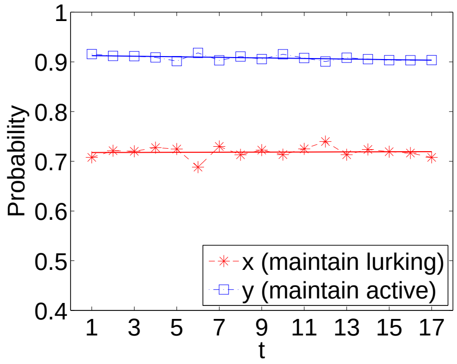
(a) Singapore (b) Indonesia

Figure 3.2: Proportion of lurkers with $h = 0$.

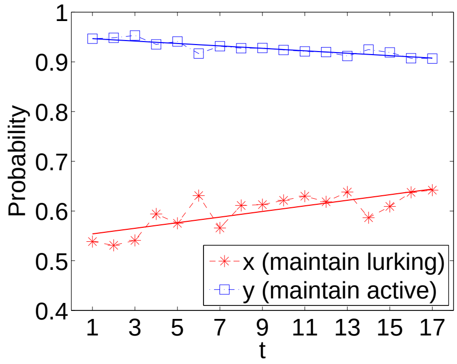
$t+1$, and $1 - y_t = P(L_{t+1}|A_t)$ to represent the probability of a user active at t but lurking at $t+1$.

Given a set of users U and their lurking and active behavior from time 1 to T, i.e., $D = \langle \{U_A^1, U_L^1\}, \ldots, \{U_A^T, U_L^T\} \rangle$ where U_A^t and U_L^t represents the set of active users and the set of lurkers at t respectively, we can estimate x_t and y_t by $x_t = P(L_{t+1}|L_t) = \frac{|U_L^t \cap U_L^{t+1}|}{|U_L^t|}$ and $y_t = P(A_{t+1}|A_t) = \frac{|U_A^t \cap U_A^{t+1}|}{|U_A^t|}$. With the time interval duration d as one week and $h = 0$, Figure 3.3 shows the probability of maintaining lurking ($x_t = P(L_{t+1}|L_t)$) and the probability of maintaining active ($y_t = P(A_{t+1}|A_t)$) from $t = 1$ to $t = 17$ in the two communities. We also plot the trend line of x_t and y_t. Note that we have consistent findings with different duration d and lurking threshold h settings.

The result suggests that generally lurkers are more likely to stay lurking and active users are also more likely to stay active (i.e., $x_t > 1 - x_t$ and $y_t > 1 - y_t$). There are users changing their behavior between weeks but with a small probability (e.g., $1-x_t < 0.5$ and $1-y_t < 0.1$ in Indonesia community). It is more likely for users go from lurking to active than from active to lurking as $1 - x_t > 1 - y_t$. This trend however may not continue forever for our two Twitter communities. In both communities, the probability of user maintaining lurking (x) has an increasing trend, and the probability of user maintaining active (y) has a decreasing trend. Comparing the two communities, we see the



(a) Singapore



(b) Indonesia

Figure 3.3: Probability of maintaining lurking and maintaining active.

probability of user maintaining lurking (x) from Indonesia community has a higher gradient (0.0001 for Singapore and 0.0056 for Indonesia), and the probability of user remaining active (y) from Indonesia also has a higher negative gradient (-0.0006 for Singapore and -0.0024 for Indonesia). This explains that we see the proportion of lurkers grows in both communities and the lurking behavior in Indonesia Twitter community shows a clear increasing trend in Figures 3.1 and 3.2.

In summary, we first observe there is a significant proportion of lurkers in our two Twitter user communities. Secondly, more users prefer to maintain their lurking or active behavior than to change their behavior. Finally, the proportions of lurkers in both communities are growing with different trends.

3.2.3 Lurker's Social Connections

A major difference between Twitter and other online community platforms such as Wikipedia is the presence of social connections among Twitter users. Lurkers in Twitter are therefore not entirely "invisible", as they may follow others or being followed by others. In Twitter, if user u follows another user v, we say u is v's follower, and v is u's followee. If v also follows u, we say they are friends with each other.

We first define the following social connection measures. User u's *in-reciprocity ratio* measures the proportion of u's followers who are followed back by u (i.e., $\frac{u\text{'s friend count}}{u\text{'s follower count}}$). User u's *out-reciprocity ratio* measures the proportion of u's followees who follow back u (i.e., $\frac{u\text{'s friend count}}{u\text{'s followee count}}$). User u's *lurker-follower ratio*, *lurker-followee ratio*, *lurker-friend ratio* measures the proportion of lurkers among u's followers, followees and friends respectively.

We then divide the two communities' users into lurkers and active users setting the time interval duration d as 18 weeks and $h = 5$. Thus we have 10,170 lurkers and 100,737 active users in the Singapore community, and 2,060 lurkers and 112,516 active users in the Indonesia community. We have tried other time interval durations and lurking thresholds and they do not affect the following findings.

Table 3.1 summarizes the lurkers and active users' social connections using different measures. The difference between lurkers and active users by every measure is statistically significant ($p < 0.05$ using Two-Sample t-test). We observe that lurkers are likely to have fewer followees and followers than active users. This suggests that lurkers are less interested in following others, and also are less attractive for others to follow. Despite this finding, lurkers have reasonable number of followees (median:85 in Singapore and median:145 in Indonesia) as they need to follow others to get information. We also notice that lurkers have followers (median:42 in Singapore and median:60 in Indonesia) although they do not post many tweets. One possible reason is that a lurker is followed by the users who know him/her offline. Another possible reason is that a lurker could be active before, and gained the followers during that time.

Reciprocity of social links is a very prevalent pattern in social networks. Kwak et al. [62] showed that link reciprocity ratio in Twitter is expected to be around 0.22. In other social networks (e.g., Flickr, Yahoo, etc.), the reciprocity ratio is much higher. In Table 3.1, our results show that the out- and in-reciprocity ratios are around 0.5 for the active users. These numbers are reasonable as we consider only follow links among users from the same community (Singapore or Indonesia). The findings on reciprocity ratio of lurkers

	User Group	Singapore Medium	Singapore Mean	Indonesia Medium	Indonesia Mean
Followee count	Lurker	85	189.6	145	266.3
	Active User	193	345.8	275	447.7
Follower count	Lurker	42	166.4	60	233.5
	Active User	167	875.1	299	2400.8
Out-reciprocity ratio	Lurker	0.25	0.31	0.21	0.29
	Active User	0.51	0.50	0.53	0.52
In-reciprocity ratio	Lurker	0.56	0.53	0.59	0.55
	Active User	0.63	0.57	0.52	0.50
Lurker-followee ratio	Lurker	0.04	0.1	0	0.01
	Active User	0.04	0.07	0	0.01
Lurker-follower ratio	Lurker	0	0.16	0	0.03
	Active User	0.06	0.11	0	0.02
Lurker-friend ratio	Lurker	0	0.12	0	0.02
	Active User	0.03	0.08	0	0.01

Table 3.1: Summary of social connections.

are on the other hand quite different.

The out-reciprocity ratio result shows it is much less likely for users to follow back to a lurker than an active user because lurkers offer little information and social interactions. For in-reciprocity, the Singapore lurkers are slightly less likely to follow back to their followers than active users. Lurkers from Indonesia community are slightly more likely to follow back. This result may be caused some culture difference between the two communities in following back behavior.

Finally, we also observe that the proportion of lurkers among both lurkers and active users' followers, followees and friends are very small. It reveals both lurkers and active users prefer to connect with active users.

3.2.4 Lurker's Motivations for Occasional Unlurking

Lurkers choose to remain silent and prefer to be an observer. However, although very infrequently, lurkers may be triggered to break silence. *What drives a user who prefers silent to speak out? Are the motivations to speak out different among the users with different activity levels (e.g., from lurkers,* *normal active users to very active users)?*

There are several studies about the reasons for posting in general. Java et al. [52] identified four reasons, namely (i) daily chatter (i.e., personal updates), (ii) conversations (i.e., interacting with people), (iii) information/URLs sharing, and (iv) news reporting. Naaman, Boase, and Lai [85] manually coded 400 tweets with nine category labels which include information sharing, self promotion, me now (i.e., personal activities), opinions/complaints, statements and random thoughts, and others. By analyzing 350 users and their posts (for each user, they randomly selected 10 posts without replies for analysis), they concluded that most users focus on personal updates. Alhadi, Staab, and Gottron [3] conducted a survey of tweeting reasons on 1000 randomly selected tweets using Amazons Mechanical Turk. They found that social interaction is the top reason, followed by emotion (which covers personal updates and me now in [85]).

Although the above studies identify the possible reasons for tweeting, they did not study the reasons for lurkers breaking silence and whether these reasons are any different from those of active users disclosing. We therefore would like to fill this gap by examining the motivations for lurkers posting tweets which may suggest new ways to encourage lurkers to generate more content. This part of study focused on Singapore users only as many Indonesia users do not write in English.

Motivations. Based on the theory of Use and Gratification (U&G) [97], we know that people like to contribute to a media product because it gratifies their needs. From this theory, Rafaeli et al. [108] derived three motivations for using and contributing to Wikipedia, i.e., information seeking, information sharing and entertainment.

In the case of Twitter, users can see it as a social platform and/or a media. They therefore use Twitter to get information such as current news and friends' updates, to interact with other Twitter accounts such as friends, celebrities and organizations, to share messages relating to personal activities or thoughts, to share information such as breaking news and interesting videos, books and games, etc., and to do advertisement. Among them, getting information is likely the main motivation (or need) for lurkers using Twitter [63]. In order to interact with people, share (personal or public) information, and perform advertisement, one needs to de-lurk.

Motivations	Resaons	Description
Information Sharing	News	Share latest news, or trending events
	General Information	Share alerts, knowledge, videos, jokes and games, etc.
Personal Update	Activity	Update activities and status
	Emotion	Express emotions and feelings towards self
	Opinion	Express opinions and feelings towards other things
	Thought	Express random thoughts and statements
Friend Interaction	Chat	Chat with friends
	Mention	Mention friends to get their attention
Public Interaction	Request	Queries or ask for feedback and advice
	Voice	Chat with celebrities, organizations or customers.
Advertisement	Commercial related.	Post commercial related advertisements and promotions
	Non-commercial related	Promote charitable institutions and political organizations, etc.

Table 3.2: Motivations of sending tweets.

Manual motivation labeling. To carefully determine the motivations for lurkers breaking silence, we first assign motivation labels to their tweets. For example, consider a tweet about a conversation between the tweet author and his/her friends *"@<User Name> Yea, see you tomorrow! Good night!"*. This is motivated by the need for social interaction. The questions now are therefore "what are the different motivation labels out there?" and "how these labels can be assigned to the lurker and non-lurker's tweets?"

Even with the tweet content at hand, assigning motivations to tweets is not an easy task. Nagarajan et al. [86] applied some simple heuristic rules to study user engagement in communities. For example, they defined a rule to assign conversational label to tweets that *"made references to other Twitter users utilizing the @user handle"*. The heuristic rule is however not always correct. For example, a tweet such as *"I love @<Celebrity Name>. She is doing great in the show!"* suggests that the user shares self opinions or thoughts rather than interacts with the celebrity. Therefore, most previous works [52, 85, 3, 118] that attempt to understand user intentions in writing tweets have resorted to manual effort to label tweets.

We manually assign motivations to tweets using a multiple-round approach mentioned in [85]. We first randomly selected 100 tweets. Then two coders (who are the author and another experienced social media researcher) independently labeled them with a set of motivation labels while writing down the reasons for choosing a certain motivation. Note that coders can assign multiple labels to one tweet. The two coders discussed and modified the set of motivation labels and the reasons of choosing them. We performed the above tasks three rounds (each round with a new set of 100 tweets) before finalizing the motivation label set and a common interpretation of the labels.

We measure the agreement of two coders using Jaccard Coefficient which is commonly used to measure similarity between two sets. Given a tweet i, if one coder assigns a set of motivation labels A, and the other coder assigns another set B, then the Jaccard Coefficient of this tweet is $J_i = \frac{|A \cap B|}{|A \cup B|}$. The agreement of two coders for a set of tweets I is then the average Jaccard Coefficient among all tweets, i.e., $J = \frac{\sum_{i \in I} J_i}{|I|}$. In the third round, the coders achieved 0.82 average Jaccard Coefficient. We believe this is a reasonable agreement and therefore finalized the set of motivation labels as shown in Table 3.2. The labels are *information sharing*, *personal update*, *friend interaction*, *public interaction* and *advertisement* and are described in the table. In this table, we use 'information sharing' label for sharing information that are not personal while 'personal update' label for sharing personal information.

We then recruited three coders (two of them are not authors of this work) to label a new and much larger set of tweets from users of different activity levels, namely, *lurkers, normal-low active users, normal-high active users and very active users*. They post $[1, 5]$, $[6, 200]$, $[201, 1000]$, and $[1001, +\infty]$ tweets respectively within our observed 18 weeks.

We sampled tweets to be labeled from the same time period (July 14 to July 27, 2014) in the following way. For users of each activity level, we first randomly selected 400 of them who published at least one tweet during the time period. Then for each user, we sampled one of his/her tweets. Among the 1600 tweets we sampled, 307 tweets are not written in English and were thus discarded. The agreements of every two out of three coders are 0.81, 0.83 and 0.81 respectively measured by average Jaccard Coefficient. We then use majority vote to determine the final motivation label(s) for each tweet, i.e., a label is assigned to a tweet if this label is agreed by at least two coders. We also discarded tweets (22 of them) that are assigned completely different labels. We were left with 326, 339, 303, and 303 tweets for lurkers, normal-low active users, normal-high active users and very active users respectively for motivation analysis.

Results. For a user type U, the proportion of tweets triggered by motivation label m is defined as $\frac{\text{No. of tweets from } U \text{ with label } m}{\text{Total No. of tweets from } U}$. As one tweet can have multiple labels, the sum of the proportion of tweets triggered by different motivations is greater than or equal to 1. Figure 3.4 shows the proportion of tweets assigned with different labels for each user activity level.

The result shows that information sharing and personal update are the top two motivations of speaking out across all user types. For lurkers and very active users, information sharing label is assigned to more tweets than personal update, whereas for normal-low and normal-high active users, personal update

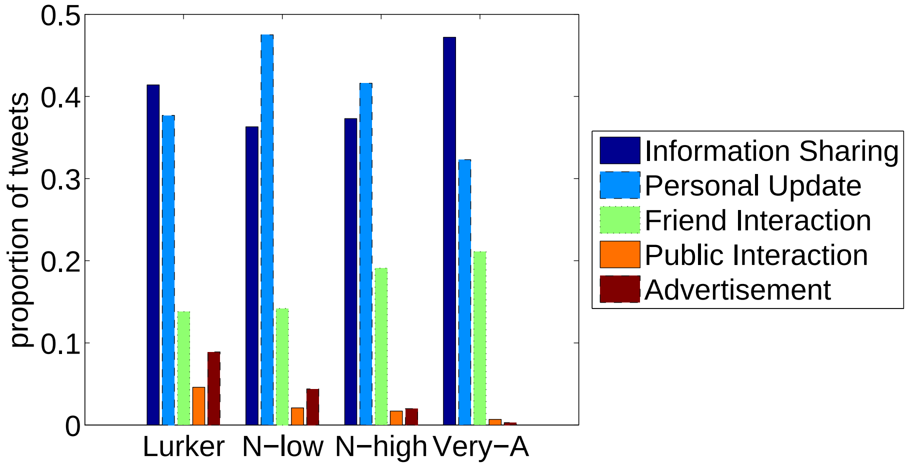


Figure 3.4: Proportion of tweets assigned with different motivation labels among lurkers (Lurker), normal-low active users (N-low), normal-high active users (N-high), and very active users (Very-A).

is assigned to slightly more tweets. Intuitively, a person is expected to have limited personal matter to update and limited number of friends to interact with. Tweets posted by very active users are therefore more likely motivated by information sharing than other motivations. For lurkers, the result suggests that lurkers are more likely to break silence when they encounter interesting matters and breaking news compared with other motivations.

Other than information sharing and personal update, the friend interaction label has been assigned to a significant proportion of tweets across all user types. Compared with active users, lurkers have the lowest proportion of tweets that are assigned with the friend interaction label. When users decide to post tweet, the active users are more likely to interact with friends.

Across all user types, public interaction and advertisement motivate the least proportion of tweets. Compare with active users, lurkers have the highest proportion of tweets that are labeled as public interaction. These are tweets for interacting with public figures, celebrities, or organizations which typically do not lead to further conversations. When users post tweets, compared with active users, lurkers are more likely to have conversations that do not enhance their social connectivity. Similarity, we also find that lurkers are more likely to post advertising tweets which again, typically do not enhance their social

Date	Top popular words from all lurkers' tweets	Top popular hashtags from all users' tweets
July 14th	#singapore, team, deco, unzipped, hoodie, messi	#ger, #worldcup, #sosingaporean, #cfcinbrazil, #cfc, #singapore
July 15th	#glendaph, game, typhoon, concert, ko, @abscbnnews	#cfc, #welcomediego, #notosofitel, #boycottsofitelph, #singapore, #freepalestine
July 16th	sa, po, @youtube, pl, @lovehindishows, #gerald987xijtpxhunterhayes	#cfc, #cfclive, #notosofitelday3, #boycottsofitelphday3, #singapore, #notosofitelday4
July 17th	**#mh17**, **mh17**, **malaysia**, **ukraine**, **airlines**, **plane**	**#mh17**, **#prayformh17**, **#ukraine**, **#malaysiaairlines**, #singapore, #prayforgaza
July 18th	**#mh17**, @youtube, **mh17**, sa, recruiting, @9vska	#cfc, **#mh17**, **#prayformh17**, #singapore, **#malaysiaairlines**, #gaza
July 19th	**#mh17**, inadh, **mh17**, chance, installed, battery	#mtvhottest, #cfclive, **#mh17**, #cfc, #zaynappreciationday, #singapore
July 20th	#prayforgaza, god, stats, @iam, #vaalutrailer, business	#mtvhottest, #liamappreciationday, #twitterpurge, **#mh17**, #sgxclusive, #singapore

Table 3.3: Top words from lurkers and top hashtags from all users. The words and hastags are ordered according to the number of users adopting them.

connectivity.

Popular topics among lurkers. The above findings show a major reason that lurkers break silence is to share something interesting and breaking. We now look into the topics in tweets generated by lurkers in large scale. The purpose is to have a deeper understanding of what events or topics that are likely to motivate many lurkers to break silence. We compare the top popular words (excluding the stop words) posted by all lurkers and top popular hashtags used by all users each day from July 14th to July 20th, 2014 (see Table 3.3). Hashtags (i.e., #some-keyword) on Twitter are used to mark topics in tweets for categorization purposes. Very popular hashtags are often trending topics. Therefore, the top popular hashtags used by all users are the topics that draw the most interest.

During the period July 14th to July 20th, 2014, we observed that there are

User group	Marital status Married	Single	Religion Christian	Muslim	Political orientation Opposition	Ruling party
0-MAX (All Users)	1329	1556	403	258	5002	2481
[0, 5] (Lurkers)	331	268	70	29	1110	427
[6, 50]	361	310	94	31	1136	362
[51, 200]	302	284	108	38	1171	431
[201, MAX]	335	694	131	160	1585	1261

Table 3.4: Label distribution in our datasets.

three common topics (or events) popular among both lurkers and all users. We marked them differently. The words in magenta also underlined are related to World Cup 2014 which ended on July 14th Singapore time (July 13rd in Brazil time). The words in blue and also **boldfaced** are related to a Malaysia airline crash tragedy on July 17th. And the words in red (also marked with boxes) are related to Gaza-Israel conflict 2014 which begins from July 8th. Hashtag #singapore is popular among Singapore Twitter users. We do not discuss it because it is often used for specifying the location of the events rather than describing topics.

The results show that when a global event such as the World Cup closing or Malaysia airline tragedy occurs, it becomes the top topic that triggers lurkers to break silence. In a normal day such as July 15th and 16th, lurkers do not follow general trends of hashtag adoption such as #cfc (the Chelsea football club). Gaza-Israel conflict 2014 as an event started about one week earlier was also popular among lurkers and other users, but in different dates. It suggests that this event was still globally aware but no longer "breaking".

3.3 Lurker Profiling

Another goal of this work is to profile lurkers and answer two questions: *How accurate are we able to profile lurkers? And are the performance of profiling lurkers and active users very different?* We choose to profile three attributes including marital status, religion, and political orientation. In this Section, we first describe the dataset used in each attribute profiling task. We then describe the methods of profiling lurkers. Finally we show the profiling performance.

3.3.1 Data

We use Singapore-based users with ground truth attribute labels in this part of research. To derive the ground truth of users' *marital status* and *religion*, we define several keywords and phrases related to the respective attribute label and use them to select the subsets of users for manual labeling [88]. For example, married users are likely to mention "wife", "husband", "my son", and "my daughter", while single users may mention "dating", "girlfriend", "my gf", "boyfriend", and "in a relationship". Christians are likely to mention "jesus", "christ", "protestant", "catholic", and "church", while Muslim users may often mention "allah", "muslim", "islam", and "mosque". We selected users whose biography field includes these keywords or phrases relevant to the marital status and religion and then assigned the attribute labels after manually reading the biographies. For religion attribute, we focus on profiling Christians and Muslim users, as much fewer Singapore Twitter users of other religions (e.g., Buddhists and Hindu, etc.) mention their religion beliefs in their biography fields.

The above approach unfortunately does not work well when determining the ground truth labels of users' *political orientation*. This is because very few Singapore Twitter users publicly declare their political orientation. We therefore adopt a similar method that was first introduced in [51] in which a few seed Twitter accounts owned by different political parties are used to propagate political affiliation labels. These seed accounts either belong to the *Ruling party* or the *Opposition*. If a user follows two or more seed political accounts and they all belong to only one party, we label the user with the respective political affiliation. Manual checks on a few labeled users verified that these assigned labels are accurate. In this way, we obtained the ground truth label of ruling party and opposition affiliated users.

Table 3.4 shows a summary of our datasets corresponding to the three attributes to be profiled. We obtained 2885, 661, and 7483 users with marital status, religion, and political labels respectively. To evaluate the accuracy of lurker profiling, we divide each set of labeled users into four groups according to their activity levels, i.e., the number of tweets they post during the 18 weeks from April 28, 2014 to August 31, 2014. For example, the lurker group is represented by the users who post no more than 5 tweets during the 18 weeks. We then have 331 married lurkers and 268 single lurkers.

As shown in Table 3.4, the distribution of users in different attribute classes is different for users with different activity levels. In the marital status dataset, among the most active users ([201, MAX]), there are much more single users than married users, whereas among the less active users ($[0, 5]$, $[6, 50]$, and $[51, 200]$), there are more married users. A similar situation also applies to the religion dataset. In the political orientation dataset, although opposition users are always the majority, they significantly outnumber the ruling party users in the less active user groups. This implies that lurkers may have very different profile composition compared with the active users.

3.3.2 Profiling Methods

We define four types of tweet content features to develop our profiling methods. These include the content of tweets posted by (a) the user, (b) the user's followees, (c) the user's followers and (d) the user's friends respectively. For lurkers, using their posted tweets is likely to give low accuracy. Our purpose is to evaluate methods using the tweets from the lurker's followees, followers or friends can help improve the profiling performance for lurkers. We also compare the accuracy of profiling lurkers against that of active users.

For each type of features, we apply Naive Bayes (NB) [75] and Support Vector Machine (SVM) to learn classifiers. For SVM, we use LIBSVM package [18] and TF-IDF of words in tweets as features. All the methods remove stop words from the tweets before training. We use F-score of the minority class to evaluate the profiling results since the datasets are skewed. In our

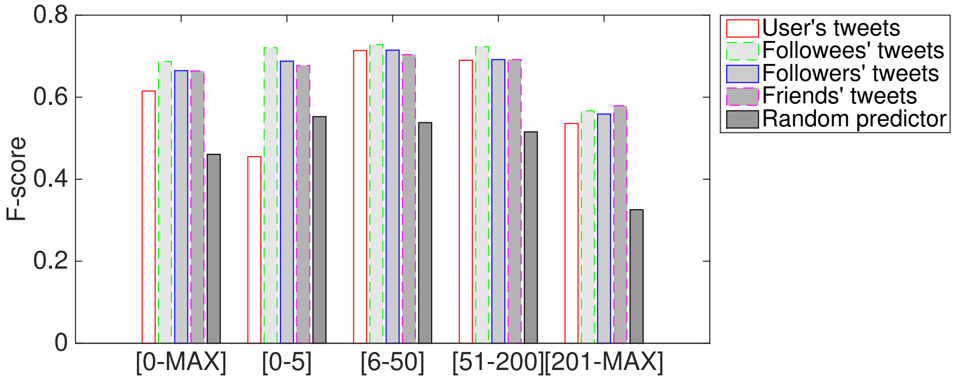


Figure 3.5: Marriage status prediction performance.

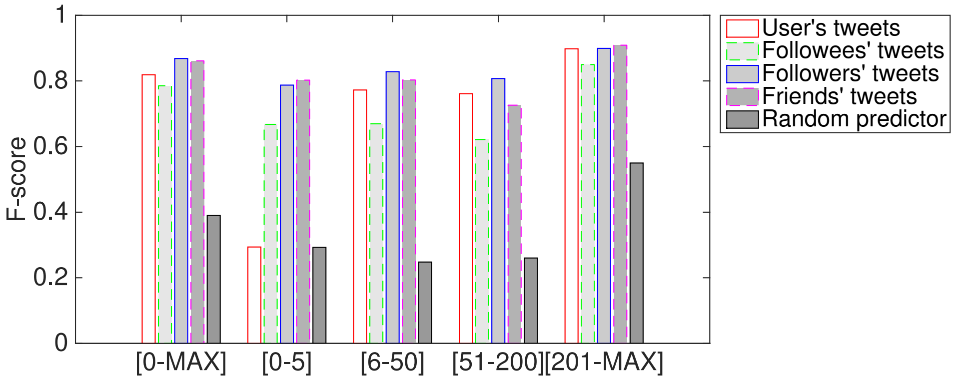


Figure 3.6: Religion prediction performance.

experiment, we apply 5-fold cross validation to derive the average F-score. At each round, we train a classifier, then apply this classifier to different activity levels of the users in the testing set. In this way, we obtain the profiling results for the users in $[0, 5], \ldots, [201, MAX]$ and $[0, MAX]$ group. We use a random predictor as baseline. The F-score for a random predictor is computed as $\frac{\text{number of samples in the minority class}}{\text{total number of samples}}$. The minority class is determined from the training datasets. They are the married, Muslim and ruling party classes for marital status, religion, and political orientation attributes respectively. For our datasets, we find that NB can achieve comparable and often better performance than SVM. Therefore, to ease of the comparison, we only show the results using NB as the classification algorithm.

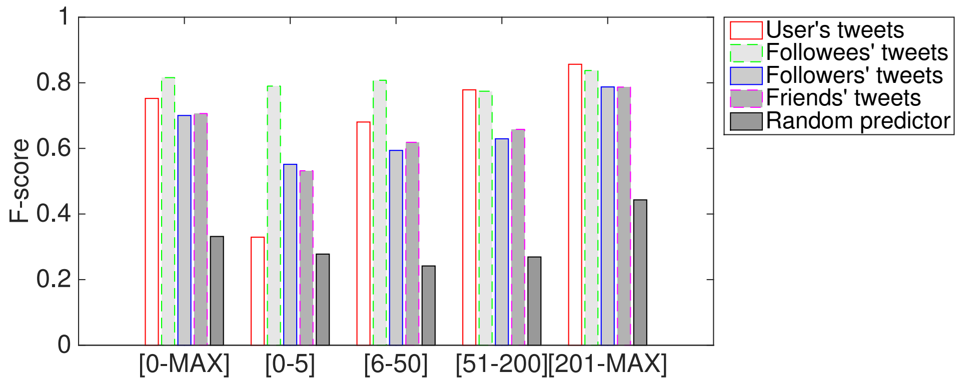


Figure 3.7: Politic orientation prediction performance.

3.3.3 Profiling Results

Figures 3.5, 3.6 and 3.7 show the prediction results for marital status, religion and political orientation respectively. We summarize the main findings as follows. First of all, as we expected, using users' tweets to predict attributes does not work well for the lurkers who do not post enough tweets (see performance on lurker group $[0, 5]$). Especially in the prediction of marital status, using users' tweets (F-score = 0.46) performs much worse than the random predictor (F-score = 0.55). However, we find using one-hop neighbors' (i.e., followees, followers or friends) tweets can achieve significantly better performance than using the random predictor and users' tweets in predicting lurkers' attributes. On the other hand, for active users who posted tweets in the range of $[6, 50]$, $[51, 200]$ and $[201, MAX]$, using users' tweets and user neighbors' tweets outperforms the random predictor significantly.

Secondly, we find the methods using followees' tweets usually outperform the methods using followers and friends' tweets when predicting marital status and political orientation. However, the methods that predict religion using followers and friends' tweets perform better than followees' tweets. Previous works often believe followees can better reveal a user's attribute as users can control who they follow but cannot control who follow them [131]. Our results show it is not always the case and suggest that we should also make use of the tweets generated by followers and mutual friends in the future.

Last but not least, we find that inferring lurkers' attributes is not always harder than active users. In our results, we see that using followees' tweets for marital status, followers and friends' tweets for religion, and followees' tweets for political status can achieve similar performance as profiling active users.

3.4 Discussion and Conclusion

In this section, we discuss our findings, the limitations of our work and the future directions.

Lurkers should not be neglected. The problem of *silent users* has been pointed out in a few previous works [84, 40, 69]. As a major function of social media is making social connections, we believe that it is meaningful to study the silent users in a community setting. From our analysis on Singapore and Indonesia user communities, we find that lurkers make up a significant proportion of users (see Figures 3.1 and 3.2). It suggests a large number of lurkers can be easily overlooked when inferring opinion, interest, attitude or preference at the population level by aggregating tweets. Furthermore, as the size of lurker group is growing (see Figure 3.3), it is crucial for a social media to keep lurkers interested in returning. In other words, a healthy social media should be able to attract audience. Thus it is important to create a pleasant and interesting space to draw lurkers' attention continuously. For example, in Google+ (plus.google.com), there are *What's Hot and Recommended* messages and people *You may know* in a user's timeline. While existing research often focuses on recommending content for active users [50, 121], it is also important to do the same for lurkers.

Lurker profiling. To prevent misrepresentation of lurkers, we are compelled to use features beyond user generated tweets to profile them. Our study shows that they are still connected with many active users (see Table 3.1). We demonstrate that it is possible to profile lurkers by leveraging the content generated by active users and the links between active users and lurkers. For attributes 'marital status', 'religion', and 'political orientation', we are able to profile lurkers with accuracy comparable to that of profiling active users. This result suggests it is possible to infer other lurkers' latent attributes and the techniques introduced in this work can be adopted. This will also enable lurkers to enjoy personalized services such as search, recommendation systems and advertising.

Considering 1) the size of lurker population is significant and growing, and 2) lurkers are the potential customers and audience, we suggest that future research could place more emphasis on understanding them so as to make social media a more desired place to keep lurkers engaged and possibly to make them active.

Limitations and future work. Our study has limitations which we hope can be addressed in the future research. Firstly, we do not differentiate the lurkers in different "lurking" levels. For example, some lurkers like to login Twitter and spend a lot of time reading, but some do not. Distinguishing them would be useful to the studies that aim to attract lurkers (i.e., audience) for a social media. For example, we could examine the factors that contribute to lurkers visiting Twitter often. Users' invisible activities such as login data and click history are needed in order to know users' "lurking" levels. However, collecting such data could lead to privacy concerns.

Secondly, our methods of profiling users' latent attributes are rudimentary. We infer lurkers attributes from the tweets generated by their one-hop neighbors. Future work could consider the network features of users to improve the lurker profiling accuracy.

Lastly, lurkers' behavior can be further explored in other aspects. For example, what makes a user become a lurker. Are lurkers born to be lurkers? If no, what causes active users to become lurkers? What are the differences between lurker and active user behavior outside of social media [124]?

Chapter 4

Posting Topics Are Not Reading Topics: On Discovering Posting and Reading Topics in Social Media

4.1 Introduction

Social media users make decisions about what content to post and read. As posted content is often visible to others, users self-censor the content to avoid inappropriate self-disclosure [29]. On the other hand, users have much more privacy space with reading social media content. As a result, social media users can show different topic interests when come to posting and reading content. In other words, users have different posting and reading topics.

A number of previous studies have focused on predicting users' topic interests [114, 80, 22]. While these studies contribute to the understanding of general topic interests of users, they do not distinguish between the posting and reading topics. However, reading topics are as important as posting topics [46]. Posting topics are likely to capture only part of all topic interests of the user. The user's reading topics on the other hand reveal some additional content she is likely to pay attention to. If we want to discover the topics that attract user attention, we should focus on profiling users' reading topics. If the purpose is to discover topics that users are likely to share with others (in the application of viral marketing, for example), one should focus on profiling the posting topics. For these reasons, we study to what extent that Twitter users posting topic interests are different from their reading topic interests. The insights will help to clarify why we need to profile social media users' posting and reading topics separately.

To assess the difference and better profile social media users' topic interests, we formulate the following two research goals. The first goal is to empirically study the posting and reading topics of Twitter users. In particular, we conduct a user survey involving 95 participants who are requested to declare their posting and reading topics. Our analysis of the survey data shows that the topics users like to post can be significantly different from the topics they like to read. There are some topics such as "Politics", "Religion" and "Business" that many users like to read them but do not like to post. We also show that a user's personality affects how different her posting and reading topics are.

The second goal of this work seeks to discover a user's posting and reading topics using historical content and following networks. We develop three different ranking strategies to rank user interested topics, namely: (a) *Popularity* which ranks by topic popularity, (b) *Content* which ranks topics by users' historical posted content and user received content, and (c) *Followee-Expertise* which ranks by topics that followees are well known for. We also propose a model which combines rankings from different ranking strategies. These methods are evaluated using the ground truth data obtained from our survey. The results show that the combined ranking achieves the best performance and using popularity or followees' expertise startegy performs significantly better than the content strategy. We also demonstrate that although predicting lurkers' reading topics is harder than predicting active users', Followee-Expertise is still able to predict lurkers' reading topics with promising performance.

Chapter Outline. The rest of this chapter is organized as follows. In Section 4.2, we assess the difference between user posting and reading topics. In Section 4.3, we profile users' posting and reading topics. In Section 4.4, we discuss and conclude this work.

4.2 Posting and Reading Topic Interests

In order to assess the difference between Twitter users' posting and reading topics, and obtain the ground truth for evaluating the methods of inferring users' posting and reading topics, a user survey is required. In this section, we first describe how to obtain a set of topics to focus in this work. Next, we describe the study procedure of this survey. Finally, we analyze the survey data and discuss the findings.

4.2.1 Topics in Tweets

We use the following method to obtain topics that are likely to cover all or most of the topics for our survey participants. We first crawled the tweets generated by a large number of users. We started our crawling process by randomly selecting 434 seed users from Singapore. We then crawled all their followees, who can be based anywhere. In this way, we obtained 93,312 users. Among them, 81,171 users have public accounts. We crawled the latest 200 tweets or whatever available from each public user using Twitter API. Next, we selected the tweets that are posted between Aug 25, 2014 and Nov 25, 2014, discarding tweets that are not written in English, stop words in tweets, and users with less than 10 tweets. Finally, we were left with 50,266 users and their more than 6.2 million tweets.

Next, we adopt T-LDA [132] to learn topics from these tweets. Zhao et

Topics	Some related keywords
Arts	art,artwork,@fineartamerica,artist
Adult Content	adult,porn,sex,pornography
Books	journal,book,poet,writer,author
Business, Finance	business,economy,finance,market, growth,estate,
Cars	f1,formula,driver,bmw,car
Deals	chance,deals,contest,cashback,win
Education	education,library,publish
Fitness, Health	fitness,health,workout,gym,weight, training,treatment
Food,Cooking	food,cook,recipe,restaurant,wine
Fashion, Style	fashion,#nyfw,collection,beauty,style
Gaming	game,xbox,ps4,gaming,dota,league
Jokes, Funny	funny,joke,humor,lol,humour,fun
Music	music,#mtvstars,concert,kpop,rock
Politics	politics,immigration,election,congress
Personal-Activity	eating,super,god,hell,moment,feeling, asleep,weather
Quotes	quote,success,happiness,positive
Religion	religion,lord,buddhism,islam,christain
Sports	sports,football,basketball,nba,nfl
Technology, Science	technology,tech,nasa,science,google, apple,ios,android
Twitter	twitter,follower,unfollowed,gained
TV & Films	tv,movie,trailer,plot,theater,imdb
Travel	travel,tour,vacation,hotel,holiday
Video	video,youtuber,youbube,viewer

Table 4.1: Topics and some related keywords.

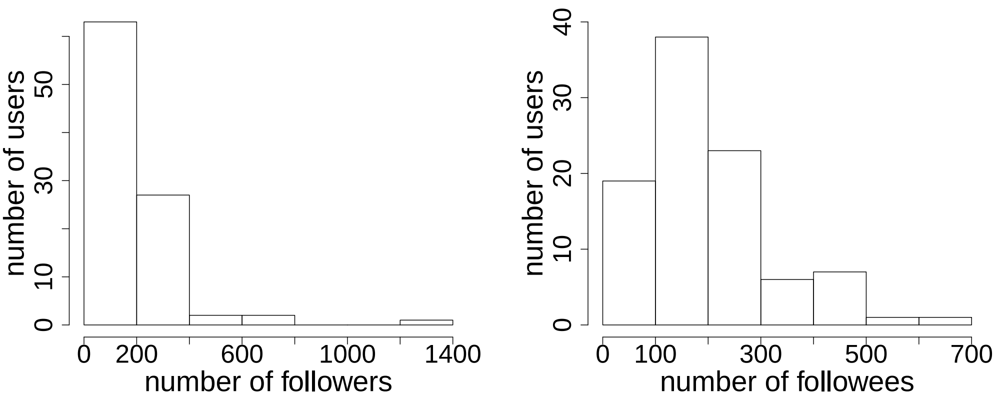
al. [132] showed that T-LDA can uncover topics in tweets better than several other LDA based methods. We call the topics generated by T-LDA the L-topics. In T-LDA, each L-topic is represented as a word distribution. We manually read the word distribution and then assigned a topic name to it. For example, a L-topic with top words: *collection*, *fashion*, *dress*, *wearing*, and *makeup* was assigned the topic name "Fashion". We manually checked all the L-topics generated with the number of L-topics $K' = 20, 30, 40, 50$ and 60. Note that multiple L-topics may be assigned with the same topic name and L-topics without clear topic may not be assigned with topic names. We finally obtained the 23 topics used in our survey, i.e., $Y = \{y_1, y_2, \ldots, y_T\}$ where $T = 23$. For each topic $y_t \in Y$, we manually selected a set of keywords γ_{y_t} from the top words in each of the L-topics that are assigned as y_t. Table 4.1 shows the 23 topics and some related keywords.

4.2.2 Survey Procedure

In this survey, we collect the following information. First, participants provide their Twitter accounts and Twitter usage pattern including how often they tweet and how many tweets they read. Second, participants rate the topics they *tweet* (or post) and the topics they *read* for each of the 23 topics we have identified as the common topics in local social media. The possible topic ratings are 'like', 'somewhat like', and 'do not like'. We will describe how we define this set of topics at the end of this section. Third, participants complete an IPIP 50-item questionnaire [1] [44], which is a widely used measure for the Five-Factor Model of personality. The Five-Factor Model is a broad classification of personality traits [78]. It divides human personality into 5 factors: (1) *extraversion*, which refers to the outgoing and sociability personality, (2) *agreeableness*, which refers to the tendency to be compassionate and cooperative towards others, (3) *conscientiousness*, which refers to the tendency to be efficient and organized in personality, (4) *neuroticism* (or emotional stability), which refers to the nervousness, anxiety, anger, depression prone personality, and (5) *openness to experience* (or intellect/imagination), which refers to the curiosity driven, adventurous, and sensitive to feeling personality. Using scoring instructions[2] for IPIP 50-item questionnaire, we can obtain participants' personality score in each of the five factors. The participants' personality scores will be used to assess if the difference between posting and reading topics is correlated with user personality.

Participants in the survey should have used Twitter for some time and have some social connections. We thus require that all participants have their accounts for at least 3 months and each participant at the point of survey follows at least 10 other accounts and is followed by at least 5 other accounts. We sent a recruitment email stating the above three criteria to all undergraduate students of a Singapore's public university. Previous research suggests that

[1] `http://ipip.ori.org/New_IPIP-50-item-scale.htm`
[2] `http://ipip.ori.org/newScoringInstructions.htm`



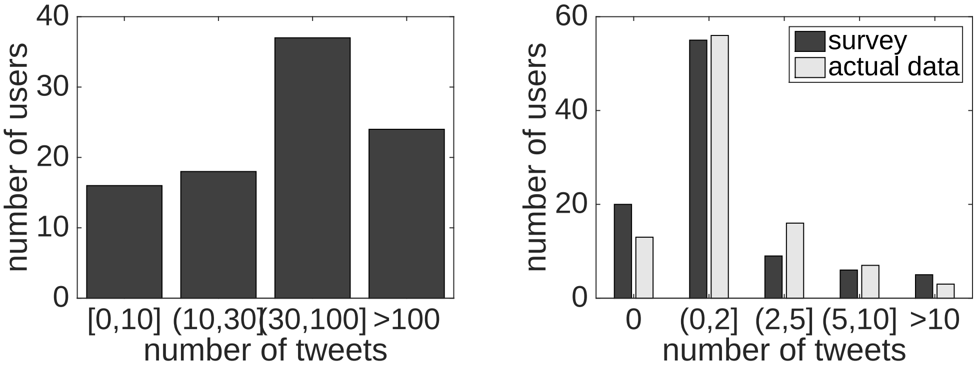
(a) Follower Count

(b) Followee Count

Figure 4.1: The survey participants' follower count and followee count distribution

university students are suitable for studies involving the Internet because they are more social media savvy [101]. We allow both lurkers and active users to participate in this survey. We then obtained survey results from 95 Twitter users including 49 protected accounts and 46 public accounts. All these participants received 10 Singapore dollars incentive for completing the survey. They comprise 33 males and 62 females with an average age of 21.6.

We then crawled all participants' tweets from March 1st to March 30th, 2015, their followers and followees using Twitter API. For the participants with public accounts, we can crawl their information directly. To collect the information of protected accounts, we created a special Twitter account to follow the protected accounts for a short time period. With this follower status, we can then crawl the protected accounts' tweets and social links. Figure 4.1 shows all the participants' follower count and followee count distribution. More than half of the participants have less than 200 followers and most of them have less than 300 followees. These participants are therefore not the celebrities, news media accounts, organizational accounts or advertisers. They are the ordinary Twitter users whom we want to focus on in this work.



(a) Reading

(b) Posting

Figure 4.2: Distribution of reading and posting frequency.

4.2.3 Survey Results and Findings

Twitter use. Figure 4.2 shows Twitter reading and posting frequency distribution among the 95 participants. In general, these participants read much more than they tweet. Most participants read 30 to 100 tweets and post less than 2 tweets per day. To verify the reliability of the survey data, we compare the user declared post volume with the actual tweet data from March 1st to March 30th, 2015. Figure 4.2(b) shows very similar distributions between survey data and tweet history data. Among the 95 users, 61 of them indicated the same posting frequency found in their tweet data, 29 of them stated their posting frequency bins slightly higher or lower than the actual posting frequency bin (e.g., the actual daily posting frequency is $(2, 5]$ while the participant declared frequency is $(0, 2]$ or $(5, 10]$), only 5 participants declared their posting frequency bins with more than one-bin difference from the exact frequency bins. It suggests that most of the participants provided information that tally with their actual behavior in Twitter.

Difference between posting and reading topics.

Next, we examine the difference between user posting and reading topics using our survey results. For clarity, we organize this analysis around four questions. The first question is: *What are the popular posting and reading topics?* Figure 4.3 plots the posting and reading topics' popularity among the partic-

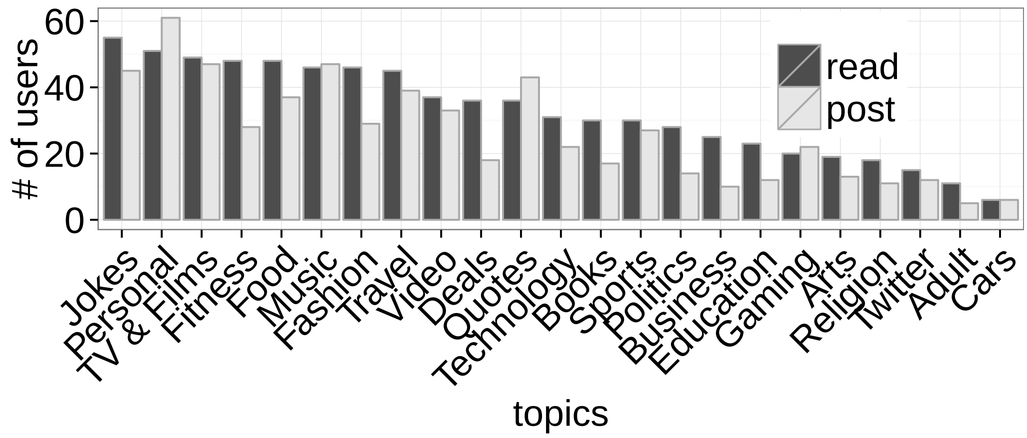
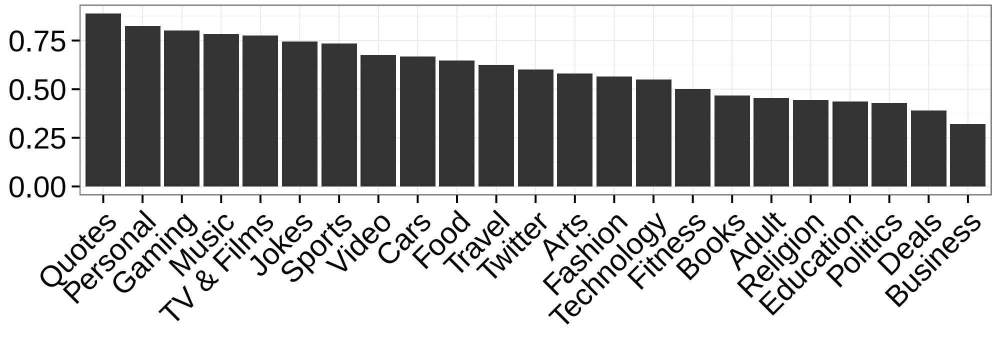


Figure 4.3: Popularity of posting and reading topics.

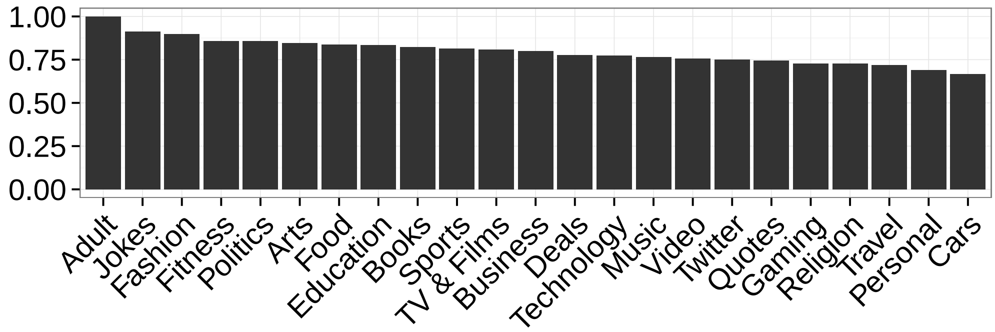
ipants. A posting (reading) topic's popularity is the number of participants who like to post (read) the topic. We observe that some topics are popular (or unpopular) for both posting and reading. For example, "TV & Films" and "Music" are among the popular topics, and "Cars" and "Gaming" are among the unpopular topics for both posting and reading. Some topics have significant popularity difference between posting and reading. For example, 48 participants like to read "Fitness" and only 28 participants like to post it. On the other hand, 43 participants like to post "Quotes" and 36 participants like to read it.

The second and third questions are: *Do Twitter users like to post a topic if they like to read it? And do Twitter users like to read a topic if they like to post it?* To answer them, we define the proportion of participants who like to post a topic y given that they like to read it by $P_y^p = \frac{|U_y^p \cap U_y^r|}{|U_y^r|}$, where U_y^p is the set of participants who like to post topic y, and U_y^r is the set of participants who like to read topic y. Similarly, the proportion of participants who like to read a topic y given that they like to post it is defined by $P_y^r = \frac{|U_y^p \cap U_y^r|}{|U_y^p|}$. Figures 4.4(a) and 4.4(b) show P_y^p and P_y^r respectively for the set of 23 topics.

Figure 4.4(a) shows that if a user likes to read a topic, on average, she would post it with 0.6 probability as $avg_y(P_y^p) = 0.6$. In contrast, the average probability of users liking to read topics which they like to post is significantly



(a) Proportion of posting participants among reading participants. (P_y^p)

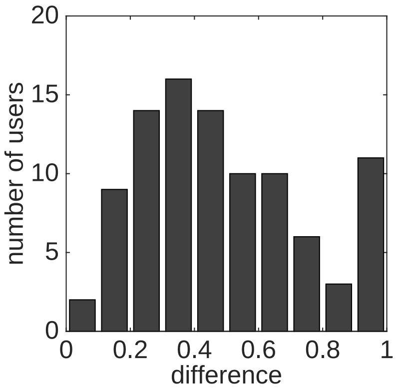


(b) Proportion of reading participants among posting participants. (P_y^r)

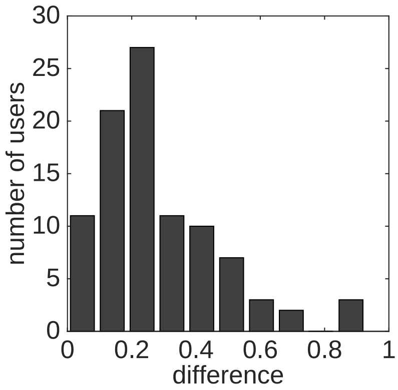
Figure 4.4: Proportion of users who like to post/read a topic out of those who like to read/post the same topic.

higher, with $avg_y(P_y^r) = 0.8$ (see Figure 4.4(b)). In addition, P_y^p varies largely between topics compared to P_y^r, as the standard deviations of P_y^p and P_y^r are 0.16 and 0.08 respectively. Particularly, only 32% of users who like to read "Business" also like to post it. Similarly, topics such as "Politics" and "Religion" also have low P_y^p (0.43 and 0.44). Topics such as "Gaming" and "Music" have much higher P_y^p (0.8 and 0.78). Such topics are more likely to be shared if users like to read them. These results reveal that there exist a number of topics that users are interested in reading but a significant proportion of these users choose not to disclose them.

Our fourth question asks: *how different are individual Twitter users' posting and reading topics?* Suppose a user declares a set of posting topics π^p and a set of reading topics π^r. We compute user posting and reading topic



(a) Like



(b) Like and Somewhat Like

Figure 4.5: Distribution of the differences between user posting and reading topics.

difference as $d = 1 - \frac{|\pi^p \cap \pi^r|}{|\pi^p \cup \pi^r|}$, where $\frac{|\pi^p \cap \pi^r|}{|\pi^p \cup \pi^r|}$ is the Jaccard coefficient of π^p and π^r. Jaccard coefficient is commonly used to measure the similarity of two sets. Hence d measures the difference between π^p and π^r. Both π^p and π^r can be defined by either topics that are liked with at least the "Like" or "Somewhat Like" rating.

Figure 4.5(a) shows the distribution of the differences between user's "Like" posting topics and reading topics. Figure 4.5(b) shows the distribution of the differences between user's "Like" and "Somewhat Like" posting topics and reading topics. As the mean differences of 0.5 and 0.28 are significantly larger than 0, we conclude that users have different topic interests in posting and reading.

Personality and topic interests. A number of studies have shown that users' personality traits affect how they use social media [4, 7]. For example, Amichai-Hamburger and Vinitzky [4] examined 237 Facebook users and found that users who are more extravert are likely to have more Facebook friends, neurotic users are more willing to share personally-identifying information, and people who are more open are more expressive on their Facebook profile, etc.. These studies suggest that personality affects user posting behavior. In this work, we hypothesize that a user's personality is associated with (a) her topic interests; and also (b) the difference between her posting and reading topics.

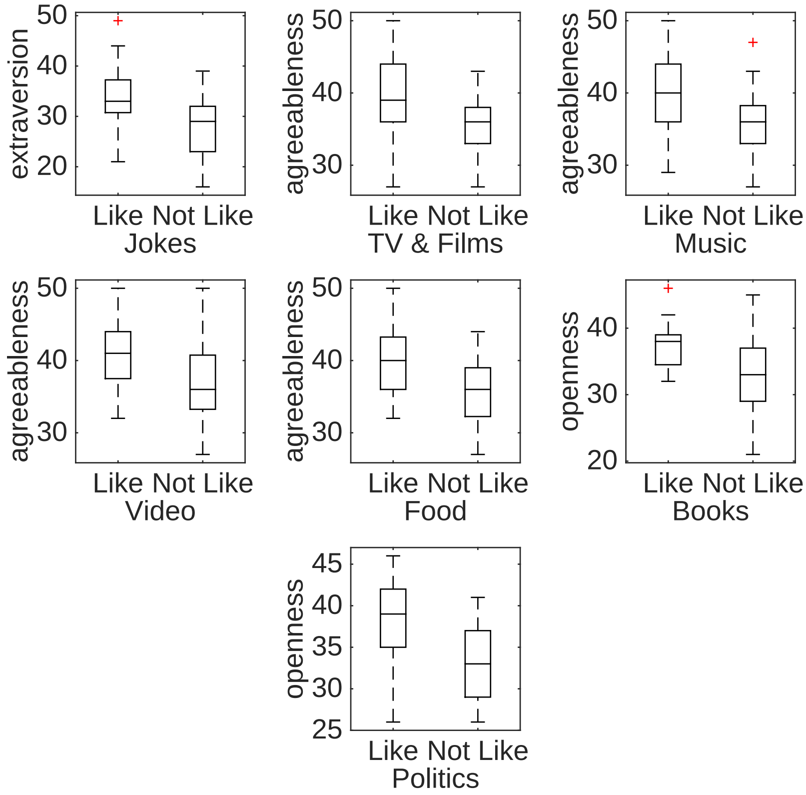


Figure 4.6: Personality and Posting behavior. Significance level is $p < 0.01$.

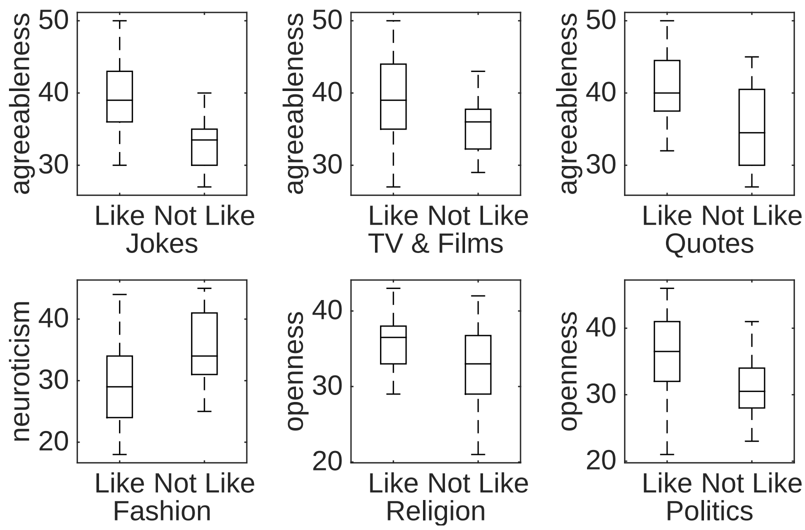
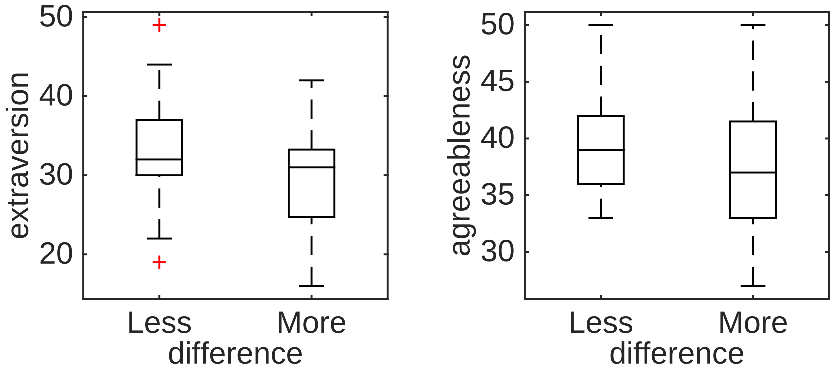


Figure 4.7: Personality and Reading behavior. Significance level is $p < 0.01$.

To test the first hypothesis, we conduct a significance test for the difference between the personality factor scores of users who like to read (or post) and those of users who do not like to read (or post) for all personality factor-topic combinations. This results in 5 (personality factors) $\times$ (23 (reading topics) +23 (posting topics)) = 230 significant tests. In Figure 4.6, we show those



(a) Extraversion (b) Agreeableness

Figure 4.8: Personality and the differences between user posting and reading topics. Significance level is $p < 0.05$.

test combinations with significant ($p < 0.01$) personality difference between the users who like to post a certain topic and the users who do not like to post the topic. We observe that users who like to post "Jokes,Funny" are more extravert (i.e., outgoing and expressive), those who like to post "Video", "Music", "TV & Films" and "Food,Cooking" are more agreeable (i.e., willing to agree with others), and those who like to post "Books" and "Politics" are more open to experience (i.e., curiosity driven, adventurous, and sensitive to feeling personality). Similarly, in Figure 4.7, we observe that (1) users who like to read "TV & Films", "Jokes,Funny" and "Quotes" are more agreeable than the users who do not like to read them, (2) users who like to read "Fashion,Style" are less emotionally stable, and (3) users who like to read "Politics" and "Religion" are more open to experience. The above findings suggest that users' personality are significantly related to several topics they like to post and read.

We then study if users' personality is correlated with their posting and reading topic difference. We first separate all participants into two groups. The 48 users in one group have larger posting and reading topic difference than the 49 users in the other group. We then test whether these two groups of users have different personality significantly. We find that two personality factors extraversion and agreeableness are negatively correlated with the posting and reading topic differences with significance level $p < 0.05$ (see Figure 4.8). It shows that less extravert and less agreeable users are likely to have more differences in posting and reading topics. Users' personality then provides a possible explanation for the differences between users' posting and reading topics.

4.3 Posting and Reading Topics Profiling

Another goal of this work is to discover Twitter users' posting and reading topics. We consider this problem as a form of ranking problem. In other words, to discover topic interests, we use ranking strategies to rank topics and aim to give user interested topics higher ranks and uninterested topics lower ranks. A ranking strategy takes certain information (e.g., content and following network) of a user as input and outputs a topic ranking for her. We define some notations first for later presentation. Let $Y = \{y_1, y_2, \ldots, y_T\}$ be the set of topics to be ranked. A ranking σ is a bijection from $\{y_1, y_2, \ldots, y_T\}$ to itself. We use $\sigma(y_t)$ to denote the rank given to topic y_t, $\sigma^{-1}(k)$ to denote the topic at the k-th position, $\sigma^{-1}(1...k)$ to denote the set of topics until the k-th position, and π to represent a set of ground truth posting or reading topics according to which type of topic interests we want to predict.

To evaluate a ranking strategy on a set of testing users U_{test}, we adopt *mean average precision at position n* (MAP@n) which is a common way to measure rankings. In our case, n represents the number of top ranking topics chosen as the predicted topics. For example, if $n = 5$, then we will use the top 5 topics in each user's ranking as the predicted topics for that user. To calculate MAP@n for U_{test}, we first calculate *average precision at position n* (ap@n) for each user in U_{test}: $ap@n = \frac{\sum_{k=1}^{n} P(k)}{n}$ where $P(k)$ represents the precision at the cut-off k topics in the ranking, i.e., $P(k) = \frac{|\sigma^{-1}(1..k) \cap \pi|}{k}$ if $\sigma^{-1}(k) \in \pi$, otherwise, $P(k) = 0$. The MAP@n for U_{test} is the average of the average precision of each user, i.e., MAP@$n = \frac{\sum_{u \in U_{test}} ap_u@n}{|U_{test}|}$.

The rest of this section is organized as follows. First, we present three different ranking strategies: Popularity, Content, and Followee-Expertise. Each ranking strategy takes different information of a user for topic discovery. Next, we propose a model that learns to combine rankings determined from different strategies. Finally, we show the performance of discovering user posting and reading topics.

4.3.1 Ranking Strategies

Popularity. Popularity ranks posting and reading topics according to their popularity. We call the Popularity strategy *Post-Popularity* (*Read-Popularity*) if we aim to discover posting topics (reading topics). The intuition of Popularity is that users are likely to be interested in popular topics. The popularity of each posting or reading topic is obtained from a set of training users U_{train}. Let $\pi^{(u)}$ be the set of ground truth topics for user u. For each topic $y \in Y$, we obtain its popularity measured by the number of training users interested in y, i.e., $|\{u|y \in \pi^{(u)}, u \in U_{train}\}|$. We then rank the topics by popularity. With Popularity ranking strategy, all users share the identical posting and reading topic rankings.

Content. A user's content can be tweets posted by herself or the tweets she received from her followees. The posted tweets are the content she likes to share. The received tweets include the content she likes to read. We therefore actually have two ranking strategies based on posted content and received content to infer a user's posting and reading topics respectively. They are called the *Posted-Content* and *Received-Content* strategies respectively. The intuition of Content ranking strategy is that users are likely to be interested in the topics that their posted or received content is associated with.

One main challenge in Content is to determine which part of the content can be associated with which ground truth (posting or reading) topics in Y

because the ground truth topics are directly declared by users without them marking up topics in their content. We therefore devise Content to generate user topic ranking as follows. We first obtain content from a set of users including the users whose topic interests we aim to infer and their followees. We then use T-LDA to generate all users' topic distributions from their content. To differentiate the topics learned by T-LDA from the topics to be ranked (Y), remember we call the former the *L-topics* $X = \{x_1, x_2, \ldots, x_K\}$.

Next, we map L-topics in X to topics in Y. For each topic $y_t \in Y$, we have defined a set of related keywords, i.e., γ_{y_t}. Each L-topic $x_k \in X$ is represented as a word distribution. We empirically use the top 30 words in the distribution as x_t's keywords, i.e., γ_{x_k}. We then find a topic y_{t_k} for x_k such that they share the most common keywords, i.e., $y_{t_k} = \arg\max_{y_t} |\gamma_{x_k} \cap \gamma_{y_t}|$. In this way, we can map every L-topic x_k to a topic y_{t_k}. It is possible to have multiple L-topics mapped to one topic in Y.

Finally, with the mapping from X to Y, we determine user topic distribution as follows. From T-LDA, each user is assigned a L-topic distribution, i.e., $\langle l_1, l_2, \ldots, l_K \rangle$ where l_k represents how likely the user is interested in x_k. For each $y_t \in Y$, we obtain the likelihood that the user is interested in y_t by summing up l_k for x_k's that are mapped to y_t, i.e., $z_t = \sum_{t_k=t} l_k$. Thus we obtain a topic distribution $\langle z_1, z_2, \ldots, z_T \rangle$ for this user. The Content ranking strategy returns the topics according to their topic ordering in $\langle z_1, z_2, \ldots, z_T \rangle$.

Followee-Expertise. A user's choice of following other users can reveal her reading topic interests. We particularly focus on followees who are well known to be associated with topics. These users are known as *topic experts* [41]. For example, if a Twitter account is well known to post content related to sports events, then this account is an expert in topic "Sports". The topic a user is well known to be associated with is her *topic expertise* or *expertise*. When a user has an expertise, it is likely to be followed by other users interested in that expertise. For example, if a user likes sports, she may follow sports news accounts or stars whose expertise is “Sports”. Thus, the intuition behind *Followee-Expertise* strategy is that a user is likely to be interested in reading a topic if many of her followees have expertise in that topic [14].

We adopt a method proposed in [41] to obtain followees with expertise. This method exploits the *List* feature of Twitter. In Twitter, users can create lists to organize their followees. Each list has a name given by the user who created this list. Some list names do not carry any meaning (e.g., “list #2”). Some list names show the social relationships of the members (e.g., “family”). There are also many list names that reveal the members' expertise (e.g., “music”).

We therefore make use of list names to obtain followees with expertise. First, we crawled the number of lists each followee is member of and the names of the lists. The users who are member of only very few lists are usually not well known and these lists are usually for social purpose. We therefore only included those followees who appear in at least 10 lists. For our survey participants, we obtained 15,395 followees. 8,601 of them are public users. Among the 8,601 followees, 43 percent of them appear in at least 10 lists. As Twitter API has rate limits, we collected at most 1000 lists per followee. Next, for each followee, we removed the stop words from the names of the lists she is member of and chose at most 20 top frequent words that appear in the names. We use $\beta^{(f)}$ to denote the chosen words for followee f.

Finally, to know f's expertise, we again utilize the keywords from each topic in Y: f's expertise is $y^{(f)} \in Y$ if $\beta^{(f)}$ and $y^{(f)}$'s related keyword set $\gamma_{y^{(f)}}$ share the most number of words, i.e., $y^{(f)} = \arg\max_y |\beta^{(f)} \cap \gamma_y|$. For example, for account @latimessports, we obtained $\beta^{(@latimessports)} = \{sports, news, media, lakers, nfl, baseball, \ldots\}$, and the topic expertise is “Sports”. For account @SoVeryBritish, the top words are $\{funny, comedy, humor, humour, fun, entertainment, \ldots\}$, we then associate this account with “Jokes,Funny”. For the current work, we assume each topic expert has one expertise. This assumption can be easily extended to an expert having multiple expertise topics.

For a user whose reading topics are to be predicted, we use the above way to derive a set of her followees with expertise, i.e, F^e. Each followee $f \in F^e$ has an expertise $y^{(f)}$. Followee-Expertise ranks topic $y \in Y$ in higher position than $y' \in Y$, if the number of followees with expertise y is larger than the number of followees with expertise y', i.e., $|\{f|y^{(f)} = y, f \in F^e\}| > |\{f|y^{(f)} = y', f \in F^e\}|$. For example, if a user follows 8 accounts with expertise "Sports", 4 accounts with "Politics" and 10 accounts with "Music", then the user's reading topic ranking is "Music", "Sports" and "Politics".

4.3.2 Learning to Combine Rankings

The above three ranking strategies utilize users' different information to infer their topic ranking, it is possible that different ranking strategies can complement each other so as to achieve better performance. We therefore propose a model that learns to combine rankings generated from multiple ranking strategies.

We are given a set of training users U_{train} that we wish to uncover their topic interests (posting or reading). For each user, we have a collection of rankings which are generated by different ranking strategies. We use $\sigma_i^{(u)}$ to represent the i-th ranking for user u. Remember that we use $\pi^{(u)}$ to denote the set of ground truth topics for user u. We have two ranking strategies, i.e., Posted-Content and Post-Popularity, for ranking posting topics, and Received-Content, Read-Popularity, and Followee-Expertise strategies for ranking reading topics.

For the i-th ranking strategy, we define a set of parameters $w_i = \{w_{i1}, w_{i2}, \ldots, w_{iT}\}$ where w_{it} represents how important the topic at position t is in the i-th ranking strategy and $0 < w_{it} < 1$. We then combine user u's rankings as follows: for each topic $y \in Y$, we obtain its overall (or combined) importance by summing up the topic y's importance in all ranking strategies, i.e., $\sum_i w_{i\sigma_i^{(u)}(y)}$ where $\sigma_i^{(u)}(y)$ represents the rank assigned to y by the i-th ranking for user u.

We then can re-rank all the topics based on their overall importance, and get a combined ranking $\phi^{(u)}$ for user u.

A good combined ranking $\phi^{(u)}$ should rank the topics from ground truth topics $\pi^{(u)}$ in front positions. Thus the topics in $\pi^{(u)}$ should be much more important than the other topics. This means we need $\frac{\sum_{y\in\pi^{(u)}}\sum_i w_{i\sigma_i^{(u)}(y)}}{\sum_{y\in Y}\sum_i w_{i\sigma_i^{(u)}(y)}}$ to be close to 1. In other words, we want the total importance of the user interested topics (the numerator) is close to the total importance of all topics (the denominator). We then can write our model as follows. We minimize the following function:

$$F(w) = \frac{1}{2|U_{train}|} \sum_{u\in U_{train}} (1 - \frac{\sum_{y\in\pi^{(u)}}\sum_i w_{i\sigma_i^{(u)}(y)}}{\sum_{y\in Y}\sum_i w_{i\sigma_i^{(u)}(y)}})^2 \tag{4.1}$$

To simplify the representation, we can rewrite $F(w)$ as:

$$F(w) = \frac{1}{2|U_{train}|} \sum_{u\in U_{train}} (1 - \frac{\sum_i\sum_t a_{it}^{(u)} w_{it}}{\sum_i\sum_t w_{it}})^2 \tag{4.2}$$

where $a_{it}^{(u)}$ equals to 1 if there exists a topic $y \in \pi^{(u)}$ such that $\sigma_i^{(u)}(y) = t$. Otherwise, $a_{it}^{(u)}$ equals to 0.

In order to make sure w_{it} falls in $(0, 1)$, we transform it using logistic function: $w_{it} = \frac{1}{1+e^{-\theta_{it}}}$. Thus, instead of learning w, we learn θ. To avoid overfitting, we add a regularization term to our objective function.

$$\begin{aligned} F(\theta) =& \frac{1}{2|U_{train}|} \sum_{u\in U_{train}} (1 - \frac{\sum_i\sum_t a_{it}^{(u)} w_{it}}{\sum_i\sum_t w_{it}})^2 \\ &+ \frac{\lambda}{2|U_{train}|} \sum_i\sum_t \theta_{it}^2 \end{aligned} \tag{4.3}$$

where $w_{it} = \frac{1}{1+e^{-\theta_{it}}}$ and λ is a control of the fitting parameters θ. As F is not convex, in order to improve the chances of finding a global minimum, a common strategy is to use gradient descent with random restart, which performs gradient descent many times with randomly chosen initial points, and selects the locally optimized point with the lowest F value. We write the derivative of F of θ_{jv}:

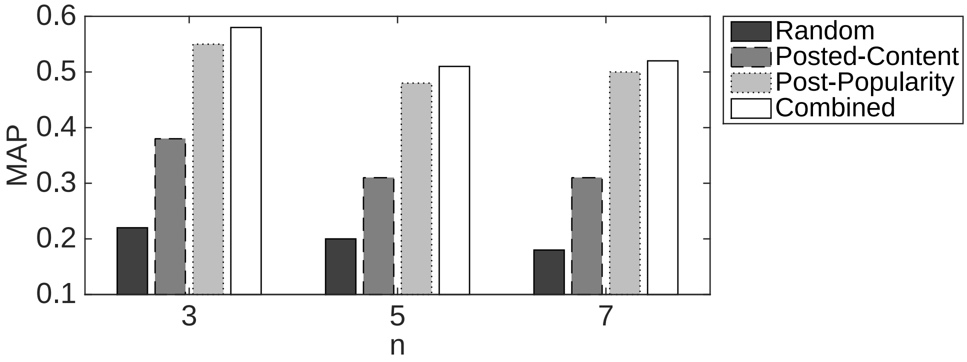
$$\begin{aligned}\frac{\partial}{\partial \theta_{jv}} F(\theta) = -\frac{1}{|U_{train}|} \sum_{u \in U_{train}} ((1 - \frac{\sum_i \sum_t a_{it}^{(u)} w_{it}}{\sum_i \sum_t w_{it}}) \\ \frac{a_{jv}^{(u)} \sum_i \sum_t w_{it} - \sum_i \sum_t a_{it}^{(u)} w_{it}}{(\sum_i \sum_t w_{it})^2} \\ \frac{e^{-\theta_{jv}}}{(1+e^{-\theta_{jv}})^2}) + \frac{\lambda}{|U_{train}|} \theta_{jv}\end{aligned} \tag{4.4}$$

The update rule is $\theta_{jv} := \theta_{jv} - \alpha \frac{\partial}{\partial \theta_{jv}} F(\theta)$, where α is the learning rate. After we learn θ and then obtain parameter w_i for each ranking strategy i, we can get the combined ranking for user u by computing the overall importance for each topic y_t using $\sum_i w_{i\sigma_i^{(u)}(y_t)}$.

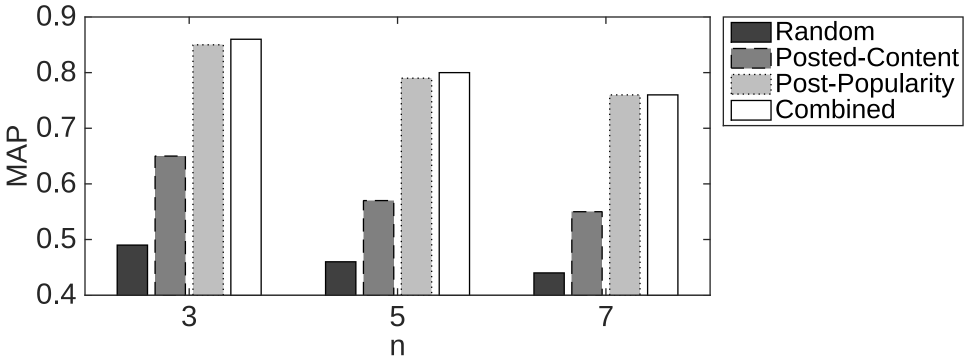
4.3.3 Results

We use the ground truth topics obtained from our survey to evaluate the ranking strategies and the combining method. All the following results are the average MAP by running experiments 10 times where each time we randomly select half number of users for training and the remaining users for testing. We empirically set $\lambda = 0.1$ and $\alpha = 20$.

Posting topic discovery. We use 69 participants who posted no less than 5 tweets from March 1st to March 30th, 2015 for this part of evaluation, and the remaining users are considered as lurkers who mainly focus on reading. We apply Posted-Content and Post-Popularity to predict user posting topics. Figure 4.9 shows the performance of these two ranking strategies and the performance of the combined rankings. To determine the significance of results, we use the randomly shuffled topics (i.e., the Random predictor) as baseline. In the Figure, x-axis n represents the number of topics that are chosen as the predicted topics. "Like" means that we use the topics that a user likes to post



(a) Like



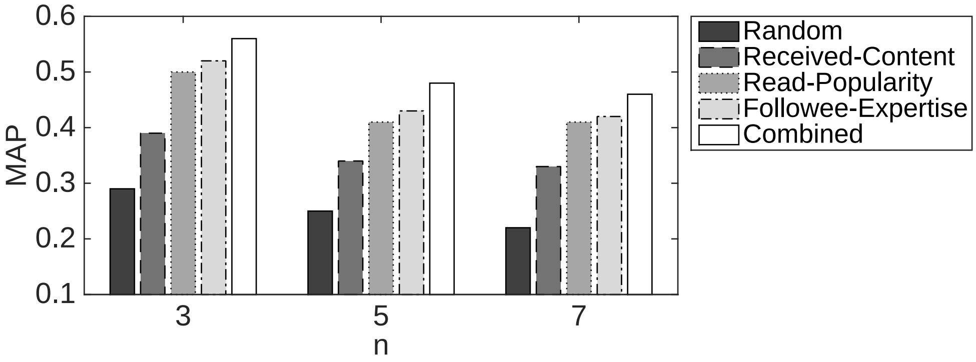
(b) Like and Somewhat Like

Figure 4.9: Results for posting topics.

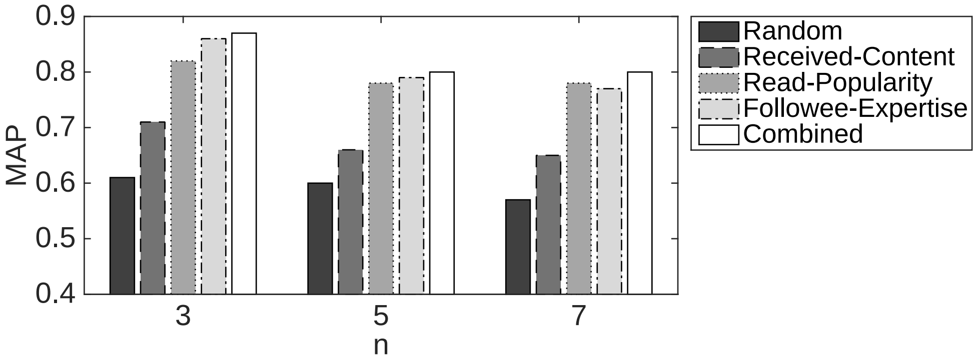
as the ground truth topics (Figure 4.9(a)), and "Like and Somewhat Like" means that we use the topics that a user selects "Like" or "Somewhat Like" as the ground truth topics (Figure 4.9(b)).

We have consistent findings with different n values from Figure 4.9(a) and Figure 4.9(b). We observe firstly that all our ranking strategies yield performance significantly better than Random. Secondly, Post-Popularity performs much better than Posted-Content. One possible reason is that inferring topics from tweets is still a challenging problem as tweets are short and people use many informal and idiosyncratic words in tweets [59]. The performance of Post-Popularity shows that there are some "universal" posting topics such as "TV & Films" and "Music". Finally, the combined ranking method achieves the best performance.

Reading topic discovery. We use all the survey participants in reading topic discovery evaluation. Figure 4.10 shows the performance of Received-Content,



(a) Like



(b) Like and Somewhat Like

Figure 4.10: Results for reading topics.

Read-Popularity and Followee-Expertise and the performance of their combined rankings. We summarize our observations as follows. First, all our ranking strategies perform significantly better than Random. Secondly, compared with Read-Popularity and Followee-Expertise, Received-Content does not predict user reading topics well. One possible reason is the difficulty of inferring topics in tweets. Another possible reason is that Twitter users are only interested in a subset of tweets they received. Thirdly, Followee-Expertise, an unsupervised method, mostly performs better than Read-Popularity. Fourthly, again, the combined ranking can achieve the best performance. Lastly, comparing Figures 4.9 and 4.10, we notice that reading topic discovery can achieve comparable performance as posting topic discovery, which suggests that although we do not have user reading behavior data traces, we can still predict user reading topics with reasonable accuracy.

Reading topic discovery for lurkers. In order to see how well we can

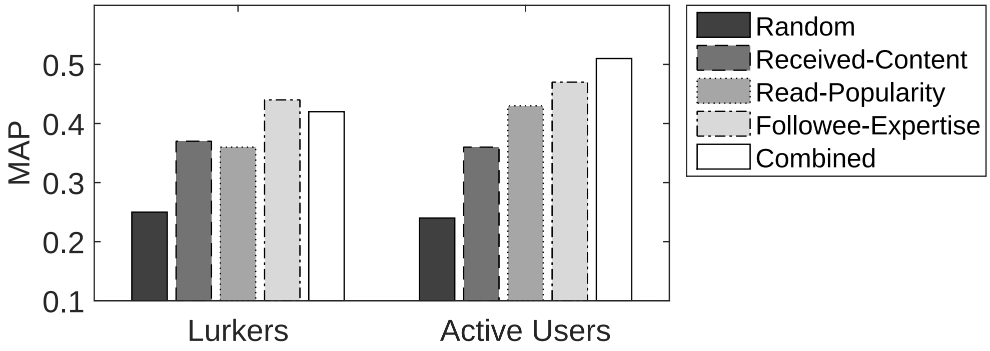


Figure 4.11: Reading topic prediction for lurkers and active users.

predict lurkers' reading topics, we divide the testing users into lurker group and active user group. The lurker group consists of the users who post less than 5 tweets from March 1st to March 30th, 2015 and the remaining users belong to the active user group. Figure 4.11 shows the performance of predicting reading topics for lurkers and active users. We set $n = 5$ and the ground truth topics are the "Like" topics. Other settings have consistent findings. We first observe that all our methods perform much better than Random for both lurker and active user groups. Secondly, overall, predicting active users' reading topics is easier than predicting lurkers'. Thirdly, Read-Popularity does not perform well for lurkers. It shows that compared with active users, lurkers are less likely to pay attention to the popular reading topics. Lastly, we find that Followee-Expertise performs best for the lurker group. Thus, using only this unsupervised method, we can achieve promising prediction results for lurkers.

4.4 Discussion and Conclusion

Selective topic disclosure. One of the main contributions of this work is to show that social media users' posting topics are different from their reading topics. This suggests that users are selective when choosing topics to disclose (i.e., post). We also confirm that topics are different in attracting people to post and read. For some topics, people like to both post and read, while for some other topics, people prefer to only read. Users seem to have less concerns when posting topics such as "Personal Activities", "Gaming" and "Music". However, for topics such as "Adult", "Religion", and "Politics", many users who are interested in reading them choose not to post them in Twitter. We also find that less extravert and less agreeable users are likely to have more differences in posting and reading topics. Users' personalities then correlate with the differences between users' posting and reading topics.

Our findings also suggest that to measure the popularity of a tweet or an event, we need to also consider its topic. For example, if a tweet is about "Politics", then the number of users sharing it could possibly underestimate its popularity or influence. Furthermore, as many users do not post controversial content, we need to keep in mind that users who express views or opinions in social media on an issue might not be the majority. In other words, the voices in social media are likely to be biased [40].

Posting and reading topic profiling. Our work also contributes to the prediction of users' posting and reading topics. We evaluate the prediction performance using different ranking strategies. We demonstrate that using popular topics or followees' expertise topics performs much better than using user posted content or received content. It is important to note that although the content a user has read is not available, we can predict users' reading topics with promising performance. We also show that we can predict lurkers' reading topics using the topic experts among their followees. The prediction of posting and reading topics can be useful in different practical scenarios. For example, users' posting topics can be used to predict whether they will share an event or speak up for an issue in the future. Users' reading topics can be used to predict whether they will click an advertisement.

Limitations and future work. We acknowledge that there are some limitations in this work: participants in our survey are undergraduates with similar ages, and our analysis is based on one social media platform. Nevertheless, our main finding, i.e., social media users' posting topics are different from their reading topics or social media users practise selective topic disclosure, is well-supported by previous studies and social psychology theory [49, 112, 29]. For example, users do not want to share "Adult", because "users do not want to post content that might be inconsistent with their self images". Users do not talk about "Religion" and "Politics" may be because "Users do not want to start or continue an argument" [112]. In our future work, we could study and compare the difference between posting and reading topics for a much larger user community and in other platforms such as Facebook.

Chapter 5

Opinion Mining for Issue-Specific Silent Users

5.1 Introduction

Nowadays, millions of users share content in social media. This abundant user-generated content provides an unprecedented resource for user opinion analysis. These user opinions are useful feedback for improving customer relationship services and government policies. They also help individuals make decisions on which products to buy, which movies to watch and which politicians to vote.

While many users share their opinions in social media, many others choose not to disclose theirs. With selective self-disclosure behavior, users can choose to keep silent on an issue even when they have some opinions on it (selective opinion disclosure). We call these users the *issue-specific silent* users or i-silent users. For example, if a user is interested in "Healthcare Cost" issue but never posts content related to it, we call her a Healthcare Cost-silent user. We call the users who post content related to an issue the *issue-specific active* users or i-active users. Note that i-silent users may still generate content unrelated to issue i. Hence, they may not be the *silent users* we discussed in Chapter 3. On the other hand, a silent user is one who is i-silent on all issues.

In social media, one can observe opinions from issue-specific active users only. When we conduct opinion analysis on issue related content, we will likely overlook the opinions of i-silent users and derive an opinion distribution biased by the i-active users. Therefore, in this work, we study the opinions of i-silent users in social media with two research goals. The first goal is to examine to what extent i-silent users exist for different issues and whether their opinion distribution is similar or different from that of i-active users. Achieving this goal is non trivial as ground truth opinions on issues are not in the observed social media data.

To obtain users' ground truth opinions, we conduct a user survey on a set of Singapore users who use Twitter and/or Facebook. In this survey, participants share their interests and opinions on seven social issues, and declare whether they discuss the issues in Twitter and Facebook. The issues include *Healthcare Cost*, *Retirement*, *Public Housing*, *Public Transport*, *Jobs*, *Education*, and *Population Growth*. As these are long-standing hot button social issues in Singapore, we expect the surveyed users to have opinions on them. Short term issues (e.g., events, news) are not included as they normally do not attract lasting public interests. Opinions on these short term issues are likely to be confined to only very small number of users.

We have derived a number of interesting findings from our survey results. We found that in both Twitter and Facebook, more than half of the users who are interested in issue i are i-silent users across all issues. i-active users are more likely to feel positive than i-silent users. These findings suggest the number of i-silent users can be large and they are likely to have opinion distribution different from that of i-active users. It is therefore necessary to consider i-silent users when profiling opinions of a user population.

The second goal of this work is to predict the opinions of i-silent users in Twitter and Facebook. Addressing this goal enables us to profile i-silent users even when they have no posted content about the issue. This opens up new opportunities to engage the i-silent users in various applications including product recommendation, personalized content filtering, and social media marketing. We propose two types of features for the prediction: (a) *sentiment features* extracted from users' content, and (b) *opinion features* extracted from users' predicted opinions or ground truth opinions on other issues. We demonstrate the effectiveness of our features and show that predicting i-silent users' opinions can achieve reasonably good accuracy from user posted content that is *not* related to issue i, and achieve better accuracy when we make use of user opinions on other issues.

Chapter Outline. We organize the rest of this chapter as follows. In Section 5.2, we describe our opinion survey and show the survey results. In Section 5.3, we profile i-silent users' opinions on the seven issues. Finally, we discuss our findings and conclude this work in Section 5.4.

5.2 i-Silent Users in Social Media

To study i-silent users in social media and to obtain their ground truth opinions, we conduct a social media user survey. In this section, we describe the survey procedure and present our findings.

5.2.1 Survey Procedure

The social media survey serves two purposes. It collects the ground truth opinions of users on topical issues. It also allows us to gather complete social media content of each users for opinion prediction. Since Twitter and Facebook are the two popular social media platforms, we focus on their users so as to allow us to compare the findings obtained from their users. We also confine the users to be from Singapore who are expected to be familiar with the same set of topical issues.

Our survey requires each Twitter participant to have created her Twitter account at least three months ago and have at least 10 followees and 5 followers. Similarly, each Facebook participant is required to have created her Facebook account at least three months ago and have at least 20 friends. This ensures that the survey will not involve inexperienced users. We recruited the participants from undergraduate students of three largest universities in Singapore by email and poster. The participants are also incentivized to invite friends to join the survey. Each participant received at least 10 Singapore dollars for completing the survey, inviting friends and sharing their social media data. Both the survey itself and the survey methodology were approved by the Institutional Review Board (IRB) of the authors' university.

The survey has two parts. The first part establishes some basic information and ground truth opinions about the users. The survey requires information about the user's gender and age. Each user also answers multiple choice questions for each of the seven issues (Healthcare Cost, Retirement, Public Housing, Public Transport, Jobs, Education, and Population Growth). They are: (1) Is the user interested in the issue? (i.e., does she have opinion on the issue?) (2) What is the user's opinion on the issue ([0-3]negative/[4-6]neutral/[7-10]positive)? (3) Does the user discuss this issue in Twitter if she is a Twitter user, or in Facebook if she is a Facebook user? And (4) What is her social media friends' opinions on the issue according to her perception?

The second part of the survey collects a complete set of social media data from the participants which includes both content and social connections. The social connections are follower and followee links for Twitter users, and friend links for Facebook users. We asked the Twitter users to provide their Twitter screen names so as to crawl their Twitter data including tweets, social connections and their public followers and followees' tweets using Twitter API. As we also allow protected Twitter users to participate in our survey, for these protected accounts, we created a special Twitter account to follow them for a short time period so as to crawl their data.

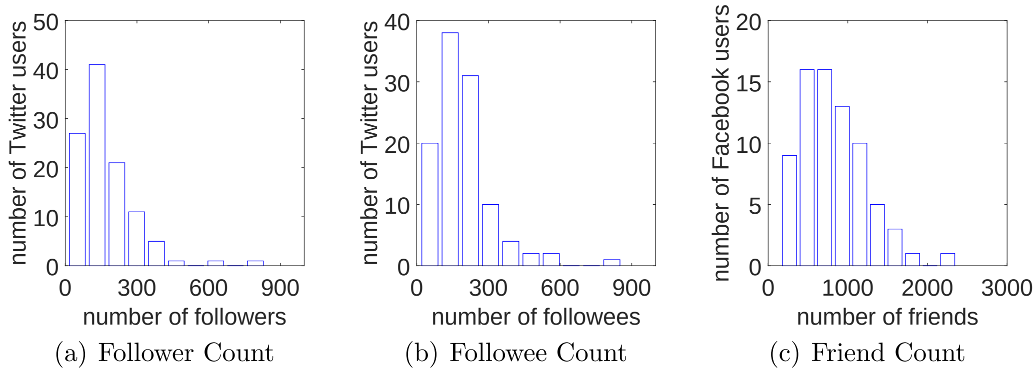


Figure 5.1: Twitter participants' follower count and followee count distribution and Facebook participants' friend count distribution.

To obtain Facebook users' data including friends and posts (i.e., statuses), we directly ask participants to provide us their Facebook data archives. Each Facebook archive includes almost all information in the user's account and we clearly stated this in the survey's informed consent form. Unfortunately, these archives exclude the friends' posts.

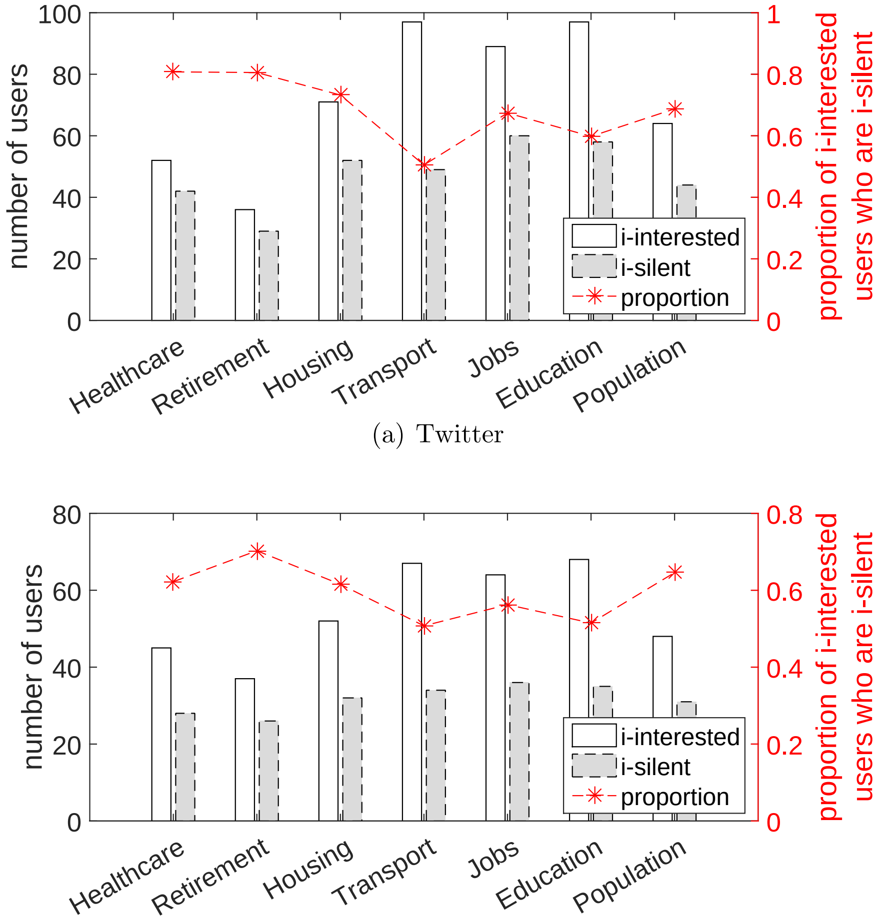
The survey was conducted from Sep 14, 2015 to Nov 12, 2015. We finally had 108 Twitter users and 74 Facebook users participated in the survey. Twitter users comprise 75 females and 33 males with an average age of 21.0. Facebook users comprise 48 females and 26 males with an average age of 21.3. Both users groups share very similar gender and age distributions. Figures 5.1(a), 5.1(b) and 5.1(c) show the Twitter users' follower count, followee count and the Facebook users' friend count distributions respectively. Our survey participants do not have very large number of followers or friends, thus they are "ordinary" users (not celebrities) whom we want to focus on in this research.

5.2.2 Survey Results and Findings

We analyze the survey results to answer the following questions:

1. To what extent do i-silent users exist in social media? Are females or males more likely to be i-silent users?

2. Do i-silent users have opinions different from i-active users?



(a) Twitter

(b) Facebook

Figure 5.2: The proportion of i-interested users who are silent on i.

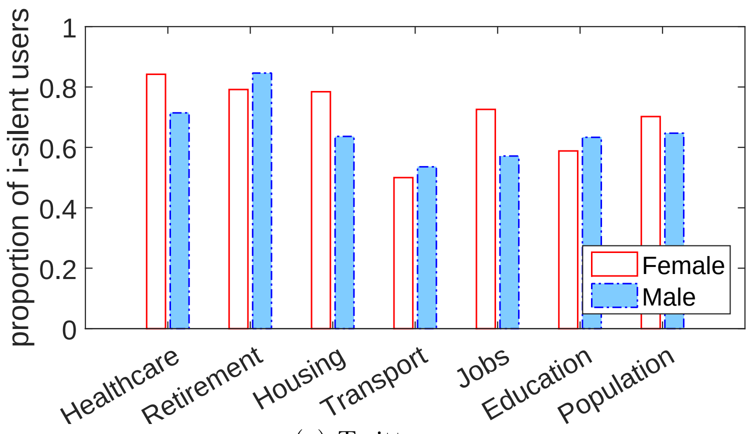
3. Do i-silent users believe that they have the same or opposite opinions with their friends? And how is it compared with i-active users' and their friends' opinions? Homophily is often observed among connected users. When a user's friends hold opinions (or perceived opinions) different from the user, it may prevent the user from expressing her opinion. We want to see if the effect exists in our survey and can explain the silent behavior.

Existence of i-Silent Users. Firstly, we examine to what extent i-silent users exist in social media for different issue i. Based on the survey results, i-silent users in Twitter are the users who declare their interest in issue i, but never post issue i content in Twitter. Similarly, i-silent users in Facebook are defined similarly. Figures 5.2(a) and 5.2(b) show, for each issue i, the number of i-silent users, the number of users who are interested in i (i.e., i-interested users), and the proportion of i-interested users who are silent on i in Twitter and Facebook respectively.

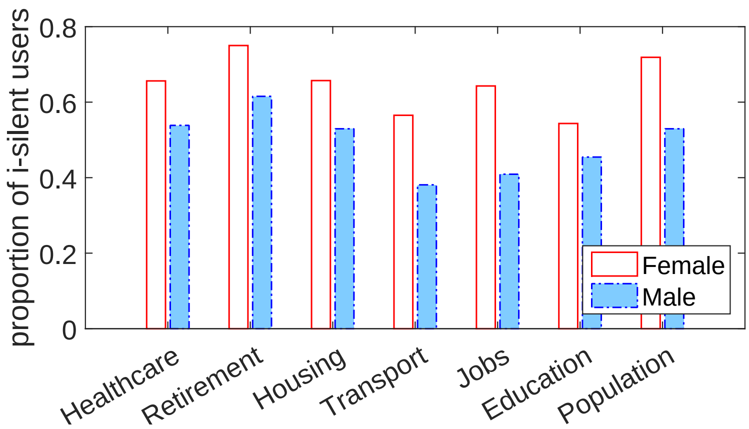
We observe that a significant proportion of i-interested users are i-silent users across all issues in both Twitter and Facebook. The proportion of i-interested users who are silent is above 0.5 for all issues. It suggests that many people do not speak up even when they are interested in an issue. We also observe that different issues attract different amount of people's interest. For example, many more participants are interested in Public Transport, Jobs and Education than Healthcare Cost and Retirement. This may be due to the young participants (with average age less than 22) who may not worry about healthcare and retirement. We may expect a different distribution for more senior people.

Gender difference among i-silent users. To answer whether females or males are more likely to be i-silent users, we compare the proportion of interested females who are i-silent users and likewise for the male users. Figure 5.3 shows that in Facebook, females are more likely to be silent on all issues than males (see Figure 5.3(b)). This result is consistent with findings in [123] which show that female users in Facebook share more personal topics (e.g., family and personal health) while male users share more public topics (e.g., politics, sports, etc.). On the other hand, females in Twitter are more likely to be silent than males on healthcare, housing, jobs and population issues. For other three issues, the females in Twitter are only marginally less silent than males.

i-Silent Users' and i-Active Users' Opinions. Next, we compare i-silent users and i-active users' opinions. i-active users are the users who are interested in issue i and post content about it. To ensure the significance of our results, we consider only the issues that have at least 20 i-silent users and 20 i-active users. Figures 5.4(a) and 5.4(b) show the proportion of i-silent users feeling negative, neutral and positive about issue i compared with the proportion of i-active users feeling negative, neutral and positive about i in Twitter and Facebook



(a) Twitter

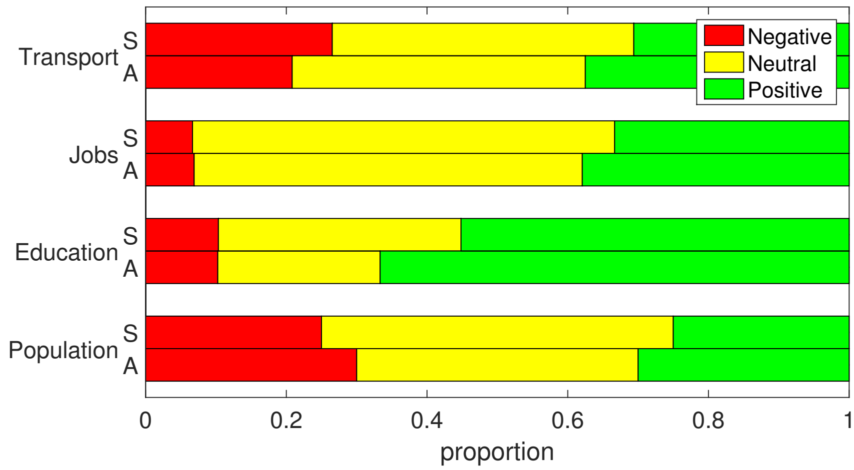


(b) Facebook

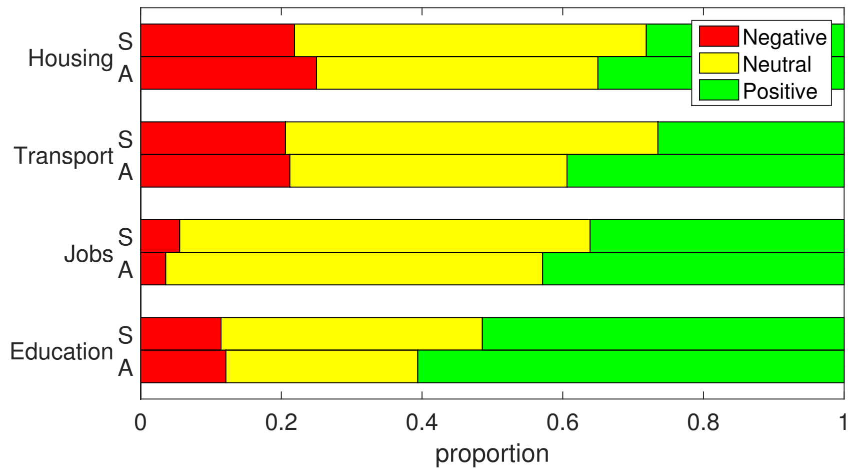
Figure 5.3: The proportion of interested females (males) who are i-silent users.

respectively. In each figure, the i-silent and i-active users are denoted by 'S' and 'A' respectively.

We observe that firstly, the proportion of i-silent users being positive is less than the proportion of i-active users being positive in both Twitter and Facebook (see the green bars on the right). For example, in Twitter, 30.6% of Public Transport-silent users are positive, and a larger proportion (37.5%) of Public Transport-active users are positive. It implies that i-active users are more likely to be positive. Secondly, the proportion of i-silent users being neutral is greater than the proportion of i-active users being neutral across all issues in both Twitter and Facebook (see the yellow bars in the middle), which shows that i-silent users are more likely to be neutral. It suggests that users who actively post about an issue are likely to have some positive or negative



(a) Twitter Participants

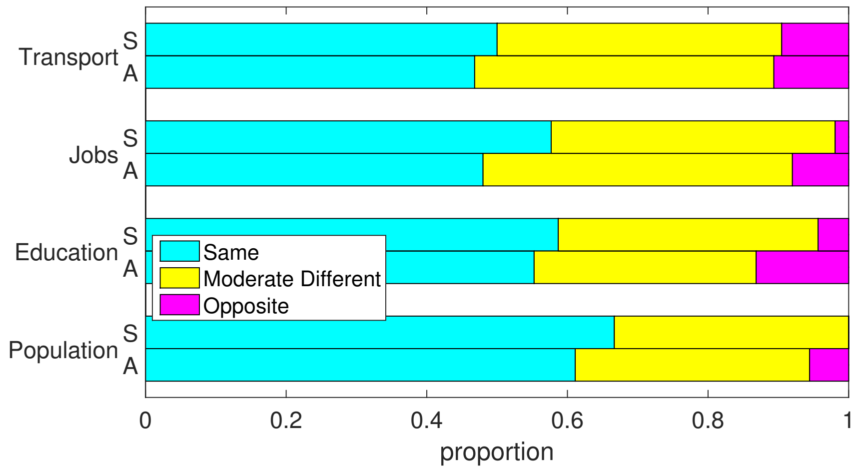


(b) Facebook Participants

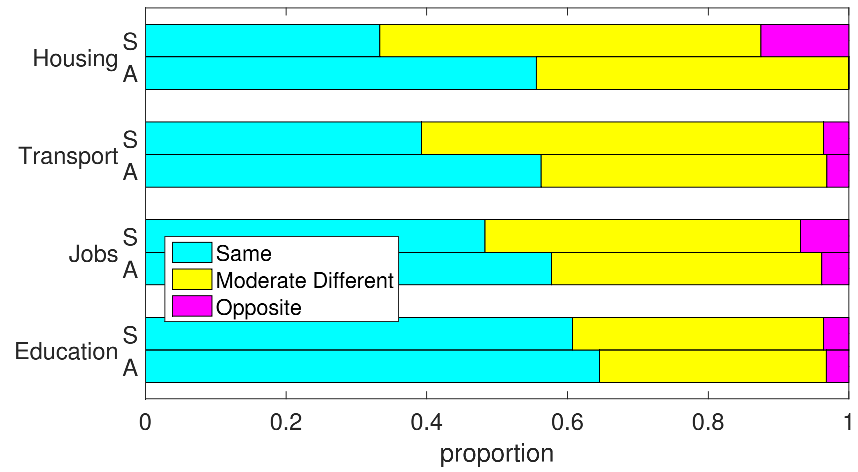
Figure 5.4: Comparison of i-silent users and i-active users' opinions. (S represents i-silent users and A represents i-active users.)

opinion on it. Thirdly, the difference between the proportion of i-silent users who are negative and the proportion of i-active users who are negative is not consistent across the issues and platforms. The above findings show that i-silent users are likely to have different opinion distribution from i-active users. It is therefore important to predict i-silent users' opinions separately from that of i-active users.

i-Silent Users' and Social Media Friends' Opinions. Finally, we examine if i-silent users believe that they have the same or opposite opinions with their social media friends, and how it is compared with i-active users and their friends' opinions. We note that social media friends are not all real friends



(a) Twitter Participants



(b) Facebook Participants

Figure 5.5: i-silent users and i-active users' opinions with their friends' opinions. (S represents i-silent users and A represents i-active users.)

of a user. Nevertheless, in the context of social media content sharing, it is reasonable to assume social media friends as an important social factor that affects content sharing decision, i.e., silent or active. In this analysis, the friends of a Twitter user refer to her followees from whom the user receives content.

For each issue i, we compute the proportions of i-silent users who believe having the same, moderate different and opposite opinions with their friends respectively. Suppose a user u's opinion on an issue is O_u, and she perceives that her friends' opinion is O_f, then u believes that she has the same opinion with her friends if O_u and O_f are both negative, neutral or positive, has moderate different opinion with her friends if one of O_u and O_f is neutral, and has opposite opinion with her friends if one of O_u and O_f is positive and the other is negative. We also compute the similar proportions for i-active users. Again, to ensure the significance of our results, we consider only the issues that have at least 20 i-silent users and 20 i-active users. Figures 5.5(a) and 5.5(b) depict the results among Twitter and Facebook participants respectively.

Firstly, we observe that both i-silent and i-active users believe some moderate difference existing between them and their online friends (see the yellow bars in the middle in Figure 5.5), but they are not likely to have opposite opinions with their friends (see the magenta bars on the right). The probability of users having opposite opinions with their social media friends is less than 0.13 for all issues in Twitter and Facebook. Thus, no matter users are silent or active on an issue, they perceive that the opinion differences with their social media friends are usually small.

Secondly, Figure 5.5(b) shows that compared with i-silent Facebook users, larger proportion of i-active Facebook users believe their having the same opinion with their online friends. For example, among Facebook users, 56.3% of Public Transport-active users believe their having the same opinion with their online friends, and the proportion is 39.3% for Public Transport-silent users. This phenomenon could be explained by that users are more likely to speak up when they believe their friends have similar opinions with them [49]. However, we have different observation from Twitter users. Compared with i-silent Twitter users, smaller proportion of i-active Twitter users perceive having the same opinion with their online friends. For example, among Twitter users, 46.8% of Public Transport-active users believe their having the same opinion with their online friends, and the proportion is 50.0% for Public Transport-silent users. The findings suggest that Facebook users are less interested to speak up when they have different opinions from their online friends, whereas Twitter users are more interested to speak up when they observe different opinions with their friends.

Why do i-silent users behave differently in the two platforms? A possible explanation is that although in both Twitter and Facebook, users can form connections and then get information from others, Facebook is used more as a private account for maintaining social connections with real life friends and family members [37]. People may not want to have arguments with their real life friends and family members online (i.e., in Facebook). On the other hand, Twitter is used more as an information channel where people connect with one another to get information that interests them [62]. Twitter users therefore have less personal connections with their friends, and thus more likely to express their differing opinions than Facebook users. Another possible explanation is that in general, our Facebook users have much more social connections than our Twitter participants (see Figure 5.1). Facebook users may want to be more "discreet" in sharing opinions with these friends.

To summarize, our survey results show that i-silent users exist across all the seven issues in Twitter and Facebook, and female Facebook users are more likely to be silent on these issues. We also show that in both Twitter and Facebook, i-active users are more likely to be positive than i-silent users, and both i-silent and i-active users think they do not have much opinion conflicts with their social media friends.

5.3 Opinion Prediction

In this section, we predict opinions on the seven issues for i-silent users as well as i-active users using their contributed social media posts. Figure 5.6 shows the process we used for predicting user opinion on an issue i. First, we classify posts into the posts that are related to i, i.e., i-related posts, and the posts that are not related to i, i.e., i-unrelated posts. Second, we obtain the posts' sentiments, i.e., positive, neutral, or negative. Next, we derive the features

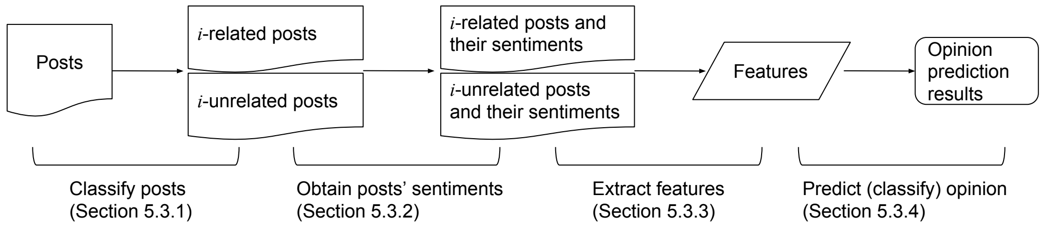


Figure 5.6: Opinion prediction process overview.

for opinion prediction based on user i-related posts' sentiments and user i-unrelated posts' sentiments. Finally, we use the features to build a classifier and obtain user opinion.

5.3.1 Issue Related and Unrelated Posts Classification

To separate posts to i-related and i-unrelated posts, a straightforward way is to manually label a number of i-related posts and i-unrelated posts, and train a classifier to find all i-related posts. However, as i-related posts are likely to only constitute a very small proportion, directly labeling posts will incur too much manual effort before we can assemble a reasonably sized i-related posts. For this reason, we focus on identifying highly issue specific-keywords (i.e., i-keywords) to distinguish i-related posts from other posts.

We obtained these keywords from a set of issue related news articles. In The Straits Times (www.straitstimes.com, the most widely circulated Singapore newspaper), news are categorized into local topical issues including five of our seven selected issues. They are Education, Public Housing, Public Transport, Healthcare Cost and Jobs[1]. We then crawled articles under these issues. By searching on The Straits Times website, we found the sets of news articles about the remaining two issues, Retirement and Population Growth[2]. All the collected articles have URL with prefix www.straitstimes.com/singapore to ensure that they are Singapore based. In this way, we collect at most 200 articles for each issue. We call the articles about issue i the i-articles.

[1] `www.straitstimes.com/singapore/education` (housing, transport, health, manpower)

[2] `www.straitstimes.com/search?searchkey=retirement` (population+growth)

From the i-articles, we extract discriminative phrases as keywords for issue i. To compute the discriminative power of a phrase p (unigram or bigram) for issue i denoted by $d_i^{(p)}$, we first define the relative frequency of p in i-articles, i.e., $f_i^{(p)} = \frac{\text{number of } i\text{-articles containing } p}{\text{number of } i\text{-articles}}$. We then define p's relative frequency in all articles, i.e., $f^{(p)} = \frac{\text{number of articles containing } p}{\text{number of articles}}$. The phrase p is discriminative in issue i if its relative frequency in i-articles is significantly larger than its relative frequency in all articles. Thus, we define the *discriminative power* of p by the difference of p's relative frequency in i-articles and all articles, i.e., $d_i^{(p)} = f_i^{(p)} - f^{(p)}$. We subsequently rank the phrases according to their $d_i^{(p)}$ in descending order, choose the top 30 phrases, and manually remove some duplicated phrases (for example, we remove 'a school' as we already have 'school' as a keyword for Education). Table 5.1 shows i-keyword examples for the seven issues.

Issue	Keywords
Healthcare Cost	health, patients, hospital, medical, treatment, amp, mind amp, disease, dr, body, blood, cancer, general hospital
Retirement	retirement, cpf, savings, provident, provident fund, central provident, fund, age, retire, payouts, income, cpf savings
Public Housing	housing, housing board, flat, flats, hdb, unites, room, order, resale, build, buyers, national development, property
Public Transport	transport, bus, lta, smrt, commuters, mrt, services, stations, train, transit, trains, buses, cars, sbs, passengers
Jobs	manpower, employers, companies, workers, skills, jobs, work, employment, mom, employees, hiring, career, job
Education	education, school, students, schools, student, learning, parents, children, university, teachers, programmes, academic
Population Growth	immigration, population, population growth, economic, foreign, immigrants, foreigners, ageing, birth rate

Table 5.1: Some keywords for each issue.

We then obtain the candidate i-related posts by selecting those containing any of the i-keywords. As our i-keywords are English words, the candidate i-related posts are likely written in English. We therefore do not perform further filtering to remove non-English posts. We call the set of candidate i-related posts S_i. However, not all posts in S_i are related to issue i. For example, post 'Let's train harder!' is not a Public Transport-related post although it contains keyword 'train'. Therefore, to further filter out the unrelated posts, we manually labeled 1000 randomly selected posts in S_i with 'related' and 'unrelated' labels, and then we use these labeled posts to build a Naive Bayes classifier and classify all the posts in S_i so as to get the final set of i-related posts. We can achieve at least 0.82 F-score for i-related posts across all the seven issues.

5.3.2 Sentiment Classification for Posts

To understand the sentiment of a post, we adopt the state-of-the-art Stanford sentiment analysis system proposed by Socher et al. [113]. This system uses a deep learning model, *Recursive Neural Tensor Network (RNTN)*, trained on Stanford sentiment treebank. The Stanford sentiment treebank is a dataset with 11,844 sentences from movie reviews and each sentence is a fully labeled parse tree. This dataset of trees (i.e., treebank) can be used to analyze the compositional effects of sentiment.

Although this Stanford sentiment analysis system achieves good results on movie reviews, it cannot be directly used on our problem. The first reason is that the system is trained using labeled movie reviews which are written in more formal way than posts in social media. Furthermore, the posts we have are posted by Singapore users, who use some regional slangs that do not appear in the Stanford sentiment treebank. For example, word 'sian' is used to express how bored and frustrated a person feels. Another reason is that the Stanford sentiment treebank does not include emojis (see Figure 5.7) and many emoticons (e.g., -.-, :D, :P, ^^)), which are frequently found in posts and are useful for predicting sentiment [1]. Emojis are represented using unicode [117]. For example, \U0001F60A is the unicode representation of a smile face.

For the aforementioned reasons, we create our own sentiment treebank by

Figure 5.7: Emoji examples in Twitter.

manually labeling 5,291 randomly selected issue related posts. We use post "Train is not so crowded. \U0001F60A ^^" as an example to explain how we label posts. This post contains emoji \U0001F60A and emoticon ^^. First, we encode emojis and emoticons[3] using unique codes. For example, we replace \U0001F60A to code 'U0001F60A' and ^^ to code 'emoticon0001'. The updated post is thus "Train is not so crowded. U0001F60A emoticon0001". Next, we use the Stanford Parser [57] to generate a parse tree for the updated post. The Stanford Parser considers our unique codes as noun words in the parse tree. We then replace the unique codes in the parse tree to the corresponding emojis and emoticons before the tree is manually assigned sentiment labels. Figure 5.8 shows the fully labeled parse tree for our example post. Note that each node in the parse tree is assigned one of the sentiment labels from very negative to very positive (−−, −, 0, +, ++). To label a node, we consider only the part of the sentence covered by the subtree rooted at the node. For example, to label the first node on the third level, we examine the phrase "is not so crowded." and assign a neutral label. Our labeling tool is built based on Stanford sentiment treebank labeling tool[4].

Our labeled posts include 1,421 negative (labeled as −− or −), 3,408 neutral (labeled as 0), and 462 positive (labeled as + or ++) posts. Less than 10% of our issue related posts are positive. This is in stark contrast with the surveyed user opinions in Figure 5.4 where we observe more positive users than negative users. It shows that although people may express many negative posts about an issue, their overall opinions on the issue can still be positive. For example, a user posting many times about crowded train may still feels

[3]The emoticons and emojis are found at: `https://en.wikipedia.org/wiki/List_of_emoticons`

[4]`http://nlp.stanford.edu:8080/sentiment/labeling.html`

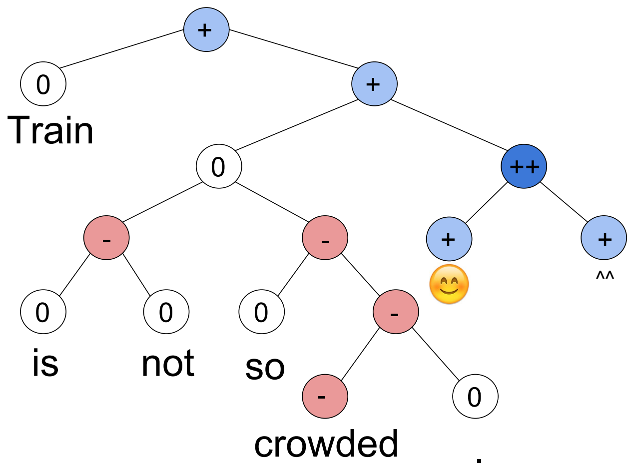


Figure 5.8: Labeled parse tree for "Train is not so crowded. \U0001F60A ^^".

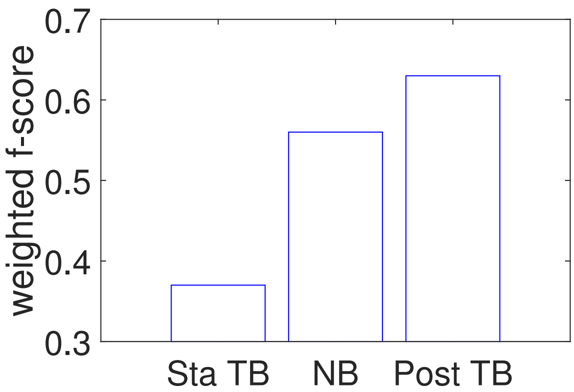


Figure 5.9: Classification results (weighted f-score) for issue related posts.

positive about the overall Public Transport service in Singapore.

We then train a RNTN model on our post sentiment treebank (Post TB) and compare with the same model trained on the Stanford sentiment treebank (Sta TB) and Naive Bayes (NB, which considers emojis and emoticons). We evaluate the three models using weighted f-score (i.e., sum of f-score of each sentiment class weighted by the proportion of posts of each class) and the results are obtained using 5-fold cross validation. According to Figure 5.9, Post TB outperforms Stanford TB and NB by 26% and 7% respectively. We subsequently use Post TB to predict sentiments of social media posts.

Sentiment of words. When labeling parse trees, we need to label sentiments of all individual words (including English words, emojis and emoticons) which appear as leaf nodes of the trees. A word may appear multiple times during the labeling process. From our post sentiment Treebank, we obtain the sentiment of a word by taking the majority vote of its sentiment labels. In total, we obtain 662 positive words, 905 negative words and 10,763 neutral words which will be used in deriving sentiment features for user opinion prediction.

5.3.3 Features for Opinion Prediction

With our extracted i-related posts, the post sentiment classifier and the sentiment of words, we extract two types of features for predicting opinion on issue i: (a) *sentiment features* extracted from posts, and (b) *opinion features* extracted from user opinions on other issues.

Sentiment features (SF). To construct sentiment features of a user, we use her statuses if she is a Facebook user, or her tweets and all her public followers' and followees' tweets if she is a Twitter user. Given a set of posts P (P can be statuses, or tweets), we define three sets of features for predicting user's opinion on issue i. Let P_i be the set of i-related posts, W be the set of words in all posts, W_i be the set of words in P_i, P^+ be the positive posts in P, P^0 be the neutral posts in P, P^- be the negative posts in P, W^+ be the positive words in W, W^0 be the neutral words in W, and W^- be the negative words in W. If a word never appeared in our sentiment treebank, we consider it neutral.

The first set of features are: the proportion of i-related posts that are positive, neutral, and negative, i.e., $\frac{|P_i^+|}{|P_i|}$, $\frac{|P_i^0|}{|P_i|}$, and $\frac{|P_i^-|}{|P_i|}$, and the proportion of words that are positive, neutral, and negative in i-related posts, i.e., $\frac{|W_i^+|}{|W_i|}$, $\frac{|W_i^0|}{|W_i|}$, and $\frac{|W_i^-|}{|W_i|}$. These features indicate if the user posts some positive, neutral, or negative content about the issue.

The second set of features are: the proportion of all posts that are positive, neutral and negative, i.e., $\frac{|P^+|}{|P|}$, $\frac{|P^0|}{|P|}$, $\frac{|P^-|}{|P|}$, and the proportion of words that are positive, neutral, and negative in all posts, i.e., $\frac{|W^+|}{|W|}$, $\frac{|W^0|}{|W|}$, $\frac{|W^-|}{|W|}$. This set of features tells if the user posts some positive, neutral, or negative content in general.

	Hea.	Ret.	Hou.	Tra.	Job.	Edu.	Pop.
Negative	6	8	14	23	6	10	17
Neutral	26	19	36	41	52	29	30
Positive	20	9	21	**33**	**31**	**58**	17
i-silent	42	29	52	**49**	**60**	**58**	44
i-active	10	7	19	**48**	**29**	**39**	20

Table 5.2: Class distribution for issues from Twitter users.

The third set of features are: the features from the first set divide by the features from the second set, i.e., $\frac{|P_i^+|}{|P_i|}/\frac{|P^+|}{|P|}$, $\frac{|P_i^0|}{|P_i|}/\frac{|P^0|}{|P|}$, $\frac{|P_i^-|}{|P_i|}/\frac{|P^-|}{|P|}$, $\frac{|W_i^+|}{|W_i|}/\frac{|W^+|}{|W|}$, $\frac{|W_i^0|}{|W_i|}/\frac{|W^0|}{|W|}$ and $\frac{|W_i^-|}{|W_i|}/\frac{|W^-|}{|W|}$. This set of features tells if the user is more positive, neutral, or negative when posting about the issue than when posting general content.

For i-silent users, the first and the third feature sets will have feature value 0, as they do not have i-related posts.

Opinion features (OF). We consider the user's opinions on other issues as the second type of features for opinion prediction. The intuition is that: (a) the user may have certain sentiment bias on all issues. For example, some users are more likely to be negative, but some are more likely to be positive; (b) the user's opinion on an issue may be correlated with or similar as her opinion on some other issue. For the above reasons, we attempt to predict the user's opinion on a target issue by making use of her opinions on other issues. To extract the opinion features, we consider two cases. The first case is when we have already acquired a user's ground truth opinions on other issues. This case could happen in some real applications. For instance, one may want to predict a user's interests by knowing her other interests, to predict a user's interests by knowing her gender, or to predict a user's age by knowing her interests. Another case is that we do not have the user's ground truth opinions on other issues. This case may be more common. For the first case, we directly use a user's ground truth opinions on other issues as features. For the second case, we first predict the user's opinions on other issues using only sentiment features from the content. We then use the predicted results as opinion features.

	Hea.	Ret.	Hou.	Tra.	Job.	Edu.	Pop.
Negative	5	8	12	14	3	8	9
Neutral	24	20	24	31	36	22	29
Positive	16	9	16	**22**	**25**	**38**	10
i-silent	28	26	32	**34**	**36**	**35**	31
i-active	17	11	20	**33**	**28**	**33**	17

Table 5.3: Class distribution for issues from Facebook users.

5.3.4 Opinion Prediction Results

With the above features, we train a SVM classifier to predict user opinion in Twitter and another classifier for Facebook. In our evaluation, we use 1000 posts (or less if the user does not post this number of posts) from each Twitter user or Facebook user. For a Twitter user, we also use at most 1000 tweets from each public followee or follower of the user. Tables 5.2 and 5.3 show the class distribution and the number of i-silent and i-active users for the seven issues for Twitter and Facebook users respectively. As the number of negative users in all issues are usually very small, to ensure the significance of our results, we show f-score for positive class with at least 20 users. The f-score is obtained with 5-fold cross validation. Again, we consider the issues that have at least 20 i-silent users and 20 i-active users. Finally, only Public Transport, Jobs, and Education issues meet our criteria in both Twitter and Facebook.

Tables 5.4 and 5.5 show the opinion prediction results for Twitter and Facebook users respectively. The baseline methods are a random predictor and a SVM classifier using unigrams from users' posts. Our methods include: (a) the sentiment features (SF) from user content, (b) the sentiment features from users' posts and opinion features (OF) from predicted user opinions on other issues, and (c) the sentiment features from users' posts plus the opinion features from ground truth user opinions on other issues. For Twitter users, there are three kinds of user content, namely: (a1) users' tweets, (a2) user public followees' tweets, and (a3) user public followers' tweets. For Facebook users, user content refers to Facebook statuses of the users.

We summarize our findings as follows. Firstly, for both Twitter and Face-

		Random	Unigrams-user tweets	SF-user tweets	SF-followee tweets	SF-follower tweets	SF-user tweets + OF-predicted opinion	SF-user tweets + OF-ground truth opinion
Public Transport	All users	0.34	0.43	0.51	0.49	0.50	0.51	**0.54**
	i-silent users	0.31	0.34	0.45	0.40	0.42	0.46	**0.50**
	i-active users	0.38	0.45	0.52	0.51	0.54	0.56	**0.58**
Jobs	All users	0.35	0.38	0.50	0.51	0.50	0.52	**0.55**
	i-silent users	0.33	0.41	0.49	0.51	0.52	0.50	**0.53**
	i-active users	0.38	0.31	0.50	0.51	0.47	0.52	**0.61**
Education	All users	0.60	0.66	**0.74**	0.71	0.66	**0.74**	**0.75**
	i-silent users	0.55	0.61	**0.72**	0.67	0.64	**0.71**	**0.71**
	i-active users	0.67	0.68	0.75	0.76	0.69	0.77	**0.80**

Table 5.4: Opinion prediction results (f-score for postive class) using SVM for Twitter users

		Random	Unigram-user statuses	SF-user statuses	SF-user statuses + OF-predicted opinion	SF-user statuses + OF-ground truth opinion
Public Transport	All users	0.33	0.33	0.48	0.49	**0.69**
	i-silent users	0.26	0.18	**0.41**	**0.41**	**0.42**
	i-active users	0.39	0.38	0.53	0.55	**0.82**
Jobs	All users	0.39	0.45	0.46	0.55	**0.69**
	i-silent users	0.36	0.34	0.40	0.52	**0.61**
	i-active users	0.43	0.54	0.54	0.60	**0.74**
Education	All users	0.56	0.63	0.70	**0.72**	**0.72**
	i-silent users	0.51	0.53	0.68	0.68	**0.71**
	i-active users	0.61	0.70	0.73	**0.75**	**0.74**

Table 5.5: Opinion prediction results (f-score for postive class) using SVM for Facebook users.

book users, all our methods outperform the baseline methods significantly for both *i*-silent users and *i*-active users. It suggests that considering the sentiment of posts and words can achieve better performance than considering the words alone. Secondly, for both Twitter and Facebook users, the prediction accuracy of i-active users' opinions is better than that of i-silent users. This findings is expected as i-active users contribute posts about issue i. Thirdly, we can predict i-silent users' opinions with reasonable accuracy although they do not post i-related posts. It implies that i-silent users' i-unrelated tweets can be used to predict their opinions on i. Fourthly, the sentiment features from user tweets, user followers' tweets and user followees' tweets yield similar performance. The findings imply that to predict a *overall* silent user's opinions, we may consider her neighbors' posts. Finally, combining the sentiment features and the opinion features from predicted user opinions on other issues usually yields better performance than using the sentiment features only, and furthermore, combining the sentiment features and the opinion features from ground truth user opinions on other issues achieves the best performance. It suggests that a user's opinions on other issues can help predict the user's opinion on this issue.

5.4 Discussion and Conclusion

Selective opinion disclosure. The main contributions of this work is to study the existence of issue-specific silent users and their opinions. We focus on two popular social media platforms, Twitter and Facebook, and conduct a survey to obtain users' opinions on seven different topical issues (Healthcare Cost, Retirement, Public Housing, Public Transport, Jobs, Education, and Population Growth) and to collect users' personal social media data. To our best knowledge, similar study was not conducted before. Our study has found that more than half of the users who are interested in issue i are i-silent users in both Twitter and Facebook, suggesting that users practise selective self-disclosure on opinions. It also suggests that when users not posting about an issue i does not imply that they are not interested in i. Hence, a large number of i-silent users' opinions will be overlooked if we only consider i-active users' posts only.

We also find that for the selected issues, i-active users are more likely to be positive than i-silent users. This finding suggests that i-silent and i-active users are likely to hold different opinion distributions. Thus, to profile the public opinion about an issue i, it is important to take i-silent users' opinions into account.

Opinion mining for i-silent users. Our work also contributes to the opinion prediction for i-silent users as well as i-active users in Twitter and Facebook. Opinion prediction for social media users is a challenging task, as we notice that people may give negative feedback about an issue but at the same time feeling overall positive about the issue. In other words, people may express unhappiness about one aspect of an issue but still feel positive for most other aspects.

We explore two types of features for opinion prediction task: the sentiment features extracted from users' content and the opinion features extracted from users' predicted opinions or ground truth opinions on other issues. We demonstrate the effectiveness of these features and show that although predicting i-active users' opinion yield better performance than that of i-silent users, it is still possible to predict i-silent users' opinions by leveraging on their i-unrelated content. We can have better performance if we make use of predicted i-silent users' opinions on other issues and achieve the best performance if we acquire the ground truth i-silent users' opinions on other issues. To be able to predict i-silent users' opinions will enable researchers to infer the opinion distribution in population level, and also have a better understanding of i-silent users.

Limitations and future work. As the first attempt to study issue-specific silent users, this work has been confined to a small user community and the survey conducted can be affected by selection bias. We therefore plan to study the opinions of issue-specific silent users for a much larger user community. Nevertheless, the possible selection bias does not prevent us drawing the conclusion that there is a significant proportion of i-silent users in social media or social media users practise selective opinion disclosure, since users self-censor when they talk publicly [29].

More research is clearly required to improve the accuracy of opinion prediction, particularly for the silent users. It is also interesting to find out the reasons for users to stay silent on an issue and for them to post after staying silent for some time. We can also consider other more controversial issues (such as abortion, affirmative action, gun control, etc.) in other country/region in the future work.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

In this dissertation, we study and profile social media users with selective self-disclosure behavior. With this behavior, users may choose not to post anything (i.e., lurking), not to post topics they are interested in (i.e., selective topic disclosure), or not to post opinions on their interested issues (i.e., selective opinion disclosure).

In Chapter 3, we focus our research on social media users' lurking behavior. We find that there are a significant number of lurkers in social media communities, suggesting many users do not want to disclose their information in social media at all. We also show that profiling lurkers' attributes can be as accurate as profiling active users. We emphasize that it is important to study lurkers in social media as they constitute a significant proportion of online social media user group, and it is possible to profile lurkers although they do not speak out.

In Chapter 4, we focus our research on social media users' selective topic disclosure behavior. We find that users post and read different topics, suggesting that users may not disclose some of their interested topics. We find that there are some topics such as "Politics" and "Religion" which many users who like to read do not like to post. We also explore the performance of predicting user posting and reading topics. We emphasize that to better understand a user's topic interests, we should consider both her posting and reading behavior.

In Chapter 5, we focus our research on social media users' selective opinion disclosure behavior. We find that more than half of the users who are interested in issue i are i-silent users in both Twitter and Facebook. It suggests that users may choose not to disclose all their opinions. We demonstrate that although predicting i-active users' opinion yields better performance than that of i-silent users, it is still possible to predict i-silent users' opinions by leveraging on their content that is not related to issue i. We can achieve better performance if we make use of predicted i-silent users' opinions on other issues and achieve the best performance if we acquire the ground truth i-silent users' opinions on other issues.

To summarize, in this dissertation, we study selective self-disclosure, a theory from social psychology, in the context of social media. We obtain interesting insights about social media users' selective self-disclosure behavior by analyzing both survey data and online user traces data. We also start works on user profiling that specifically concerns the selective self-disclosure behavior.

6.2 Future Work

User selective self-disclosure behavior in social media can be further studied considering user network effects. In terms of posting activity level, some users choose to disclose nothing, some disclose only a little over a long period of time, while others disclose a lot in a short period of time. In terms of topic choices, some users may like to share controversial topics such as politics and religion, while other users may share only non-controversial topics such as music and sports. In terms of emotions, some users may like to post positive content, while others may post mostly negative content.

What are the factors that affect users' choices in selecting what content to disclose? Personal values and personalities are possible intrinsic factors. Chen et al. [21] found that user personal values are significantly correlated with the use of some words in Reddit social network. For example, users with high hedonism (i.e., pursuit of pleasure and sensuous gratification) use more swear words and make more strong absolute statements. Our work in Chapter 4 shows that user personality traits are associated with user posting topics. For example, users who like to post politics are more open to experience.

Besides the above intrinsic factors, a user's posting content can also be affected by external factors such as the user's network, i.e., connections. Many studies have shown that users' networks exert different degrees of influence over their choices, opinions, feelings and behavior [79, 23, 130, 131, 60]. In particular, Hampton et al. [49] found that users are more likely to discuss controversial issues with close friends. Sleeper et al. [112] suggest that users self-censor their posts by considering the audience, i.e., their connections.

Despite the above results, we still have incomplete knowledge about how network affects user posting content in social media. How do the relationship types [106] between a user and her connections affect how she posts and what she posts? For example, if the user mostly connects with her family members, would she post frequently? What kind of content does she like to post? Is the content controversial or non-controversial? Positive or negative? What if the user mostly connects with classmates, colleagues, or strangers? Similarly, how does the closeness [42] between the user and her connections affect her posting content? And how does the embeddedness of the user in the network affect her posting content? Answering these questions will help us gain insights of user selective self-disclosure behavior from network aspect, which are important for social media services as their survival and growth highly depend on user self-disclosure.

Therefore, we plan analyze the associations between users' network factors (relationship types, closeness and embeddedness) and their posting behavior (posting frequency, posting topics and emotions). We plan to recruit users from Twitter and gather their relationship types with connections and closeness with connections through a survey. We would crawl their posts and links using Twitter API. We then can obtain the correlation between user network and posting behavior.

To strengthen our silent user study in Chapter 3, we plan to study silent users in other social network platforms such as Instagram which is for photo-sharing and video-sharing. We can explore if silent users behave similarly in Twitter and Instagram. We also want to improve our methods in user profiling tasks. One way is to obtain more ground truth data by manually labeling on larger number of users. Another possible way is to utilize unlabeled users' data for training with semi-supervised learning techniques.

We also plan to relate selective self-disclosure with social relationship development in social media. Previous research suggests that self-disclosure is critical for the development and maintenance of social relationships [34]. In offline face to face communication, usually a person discloses information particularly to another person (one to one disclosure). On the other hand, in social media, one's information can be disclosed to many others (one to many disclosure). Is there any difference between how one to one disclosure and one to many disclosure in affecting relationship development and maintenance? This could be another possible future work.

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