CS224W Course Project Proposal: A survey of Network Alignment

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Abstract

This document is a project proposal for the CS231A open course project. It details our plans for contributing to current research in real-time object tracking. Possible datasets, algorithms, readings and evaluation methods are reviewed.

1 Problem Statement

2 Algorithms

3 Data and Evaluation

We will use the data from three large online social networks in our experiments: Twitter, Flickr and Foursquare. On these social networks, the data of user profiles and friendship connections are all public and accessable by crawlers or APIs.

The first graph is the "following" relationships on the Twitter[1], a microblogging service, which has 500 million users (200 million active).

The second graph is the "contact" relationship on Flickr[2], a photo-sharing service, which has 51 million registered members and 6 billion images on Jan 19, 2012.

The third graph is the "Friends" relationships on Foursquare[3], a location-based social network, which has 22 million global users on March 2, 2012.

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SNS Twitter Flickr Foursquare

Social structure data Profile data

Foursquare

3.1 Ground truth

To verify our de-anonymizing results , we have to determine the ground truth, i.e., the true mapping between the users of the online social networks. Actually, we do not need to label the mapping of all users since the ground truth as a test set can be far smaller than the complete network data.

[1]http://www.twitter.com
[2]http://www.flickr.com
[3]http://www.foursquare.com

Instead of labeling the user mapping by human editors, there are several sources to get the ground truth.

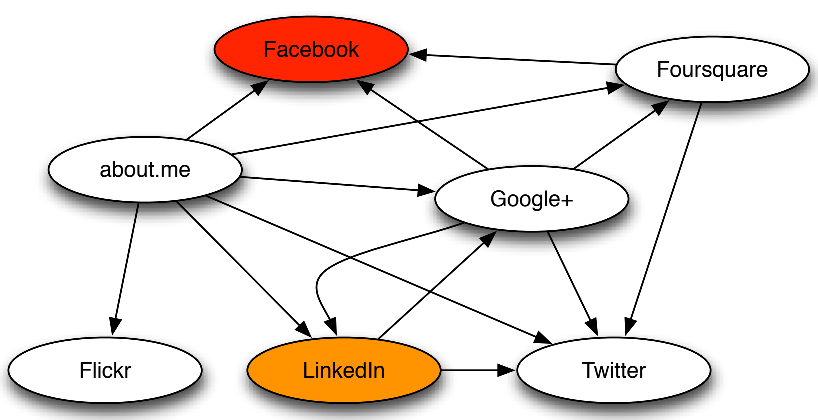
3.1.1 Single-source ground truth

About.me[4] is a personal web hosting service, which had at least 1 million users on October, 2011 [5]. The site offers registered users a simple platform from which to link multiple online identities, relevant external sites, and popular social networking websites such as Google+, Twitter, Facebook, LinkedIn, Flickr, YouTube, Foursquare. These links on user profile is naturally human-labelled mapping by the user itself, which can be seen as a zero-error ground truth. We picked a random sample of the mappings and verified by human inspection that the most of about.me users have Twitter accounts and at least one of Flickr and Foursquare accounts. About.me also provides simple APIs to list user directory and view the links on user profile without the strict crawling limitation. Therefore, we will mainly adopt the data from about.me to be our ground truth in this project.

3.1.2 Inferred multiple-source Ground truth

The links of the user profile page of the social networking websites are another great sources for ground truth, which is also generated by the user itself. Usually, a single user has many accounts for different social networking website. On the user profile page, there might be links to this user's accounts in the other popular social networking webiste. Especially, nowadays, for the most the social networking website, the user logs in with the connection to his/her Twitter or Facebook account, and that website may show the user's Twitter and Facebook account in the user profile. For example, the figure 1 shows how the links connects to other social networking website on the user profile page among the famous large social networking website: LinkedIn publicly shows the users' linked Twitter account and Gmail/Google+ account; and public Google+ profile reveals the user's Facebook and Twitter account; and Foursquare will show the user's login Twitter or Facebook account information.

Figure 1: Links on the user profile page of serveral social networking website



Fortunately, on these famous social networking webiste in the figure 1, the most of user's profile

[4]http://about.me

[5]http://techcrunch.com/2011/10/17/about-mes-ceo-on-how-to-hit-a-million-users-in-300-days-figure-out-who-your-entourage-is/

pages are publicly accessbile. A crawler can easily follow these links on the profile page, discover all linked accounts about one user, and even retrieve the user's real name and affiliation from the profile on the real-name social networking website, such as LinkedIn and Facebook (colorred in orange and red in figure 1. Thus, we can build a ground truth by exploring all linked accounts of each user.

3.2 Evaluation

Since we have a ground truth, correct matches

We will compare Network Alignment [24] and Simulated Annealling [19].

Belief Propagation

4 Deliverable

We will Ultimately, we hope to create a

nal report which summarizes the various corre- lations between sentiment content and popularity, which also provides a detailed picture of the way in which quote variants with the same informational content vary over time as function of sentiment. Central to our project is the examination of the causal eect of sentiment upon popularity and we want to build a story which best tests this theory. On a more conceptual level, we would like to use these results to comment on the fundamental nature of the news; shifting the focus away from its traditional conception as either an objective or even manipulative source of information, to more of a community of self-replicating entities whose properties arise out of internal features of sentiment, such as emotional variation and selection.

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5 Appendix