Classification of Twitter Accounts into Targeting Accounts and Non-targeting Accounts

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Twitter is still the largest microblogging service which has 310M monthly active users.

The most distinctive feature of Twitter is the mechanism of follow.
Twitter is used for various purposes.

- Dissemination of latest news
- Publication of some messages
- Communication with friends
- Announcements to some members
- Public discussion on specific topics
Twitter is used for various purposes. Dissemination of latest news or publication of some messages can be non-targeting accounts (to the general public). Communication with friends, announcements to some members, or public discussion on specific topics can be targeting accounts (to specific people).
Background

- The general public depends on the context.

- E.g., a Japanese news account is:
  - a non-targeting account when we assume "the general public" is the set of Twitter users in Japan.
  - a targeting account when we assume "the general public" is the set of all Twitter users in the world.
We propose a method for classifying Twitter accounts into **targeting accounts** and **non-targeting accounts**.

Our method can be useful in **tweet search systems**.
- e.g., The results of a query "iPhone6s" can be classified into public news and technical information.

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**Our Goal**

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  - **non-targeting accounts**
    - iPhone6s will be released in October!
  - **targeting accounts**
    - Google map SDK is not working in iPhone6s.
We measure **unusual consistency** of a set $S$.

$S$: a set of the followers of an account.

We find some common properties of the followers, and compute how much a user set with such a consistency **deviates from a random sample** from the given universe of Twitter users.

![Diagram]

- the followers
- a random sample from the given universe
Unusual Consistency

- E.g., an account disseminating **weather report in Tokyo**
  - The followers have a common property: **living in Tokyo**.
  - **Unusual consistency is high.**

- E.g., an account disseminating **worldwide news**
  - The followers have no unusually common properties.
  - **Unusual consistency is low.**
Unusual Consistency

- High unusual consistency does not imply that the followers are similar to each other in all respects.
- e.g., most followers of an account disseminating weather report in Tokyo have only one common property (living in Tokyo), but are dissimilar to each other in the other aspects.

![Diagram showing three nodes: one in the middle connected to three others. The middle node has properties: living in Tokyo, engineer, 25 years old. Each of the three connected nodes have properties: living in Tokyo, teacher, 40 years old; living in Tokyo, student, 18 years old.]
Two Types of Properties

- Two types of properties of the followers:
  1. **common terms** in their profiles or location information
  2. their **common followees**

(1) example of common terms (2) example of common followees

weather report in Tokyo

"Tokyo" "Tokyo"

a member another member
For each \( S_x: \{ e \in S \mid e \text{ has the property } X \} \), we measure how unusual it is for \( S \) to include the subset that is as consistent as \( S_x \) in two ways.

- **Probabilistic Model**: based on the probability that a set of the size \( |S| \) randomly sampled from the universe includes a subset that is as consistent as \( S_x \).

- **Difference Model**: using the difference between the cover ratio of \( X \) in \( S \) and in the universe.
Finally, we classify accounts into targeting accounts and non-targeting accounts by using $c_t(S)$ and $c_f(S)$.

$c_t(S)$: unusual consistency of $S$ computed by using common terms

$c_f(S)$: unusual consistency of $S$ computed by using common followees

We compared the following methods.

- compare $\max\{c_t(S), c_f(S)\}$ with $\theta$
- compare $c_t(S) + c_f(S)$ with $\theta$
- construct a SVM by using the two scores
- construct a decision tree by using the two scores
We obtained 1,000 Twitter accounts whose timezone is Japan.

We hired six Twitter users as assessors, and asked them to annotate whether the account is posting messages to the general public of Twitter users in Japan or not.

We classified the 1,000 accounts by the majority vote, and selected 90 accounts from each class as the data set.
Experimental Results

- Accuracy of our method only with either common terms or common followees

<table>
<thead>
<tr>
<th></th>
<th>Probabilistic Model</th>
<th>Difference Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>common terms</td>
<td>0.861</td>
<td>0.850</td>
</tr>
<tr>
<td>common followees</td>
<td>0.828</td>
<td>0.833</td>
</tr>
</tbody>
</table>

- In our method, common terms works better than common followees.
- From now on, we use
  - Probabilistic Model for common terms, and
  - Difference Model for common followees.
Experimental Results

- Distribution of two scores of targeting and non-targeting accounts

- Two scores of targeting accounts have only weak positive correlation.
Experimental Results

- Accuracy of four methods combining two scores
- Baselines
  - **follower**: compare the number of followers with $\theta$
  - **SVM**: a binary SVM whose features are the maximum cover ratio of common terms and common followees

<table>
<thead>
<tr>
<th>Baselines</th>
<th>Proposed Methods</th>
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<tbody>
<tr>
<td>follower</td>
<td>SVM</td>
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<tr>
<td>0.878</td>
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<td>max</td>
<td>sum</td>
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<td>0.856</td>
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<td>SVM</td>
<td>decision tree</td>
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<tr>
<td>0.944</td>
<td>0.906</td>
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</tbody>
</table>

- The simple follower method achieves high accuracy 0.878.
- Two of our methods achieve even higher accuracy **0.944** and 0.906.
We proposed a method for classifying Twitter accounts into targeting accounts and non-targeting accounts.

Our method found common properties of the followers, and calculated how much a user set with such a consistency deviates from a random sample from the given universe of Twitter users.

Our method using SVM achieved the highest accuracy 0.944.