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

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# Background

- **Twitter** is still the largest microblogging service which has 310M monthly active users.
- The most distinctive feature of Twitter is the mechanism of **follow**.

**follower**

**followee**

# Background

- 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**

# Background

- Twitter is used for various purposes.

**dissemination of latest news**

**publication of some messages**

**non-targeting accounts (to the general public)**

**communication with friends**

**announcements to some members**

**public discussion on specific topics**

**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**.

# Our Goal

- 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.

**non-targeting accounts**

CNN Breaking News

iPhone6s will be released in October!

**targeting accounts**

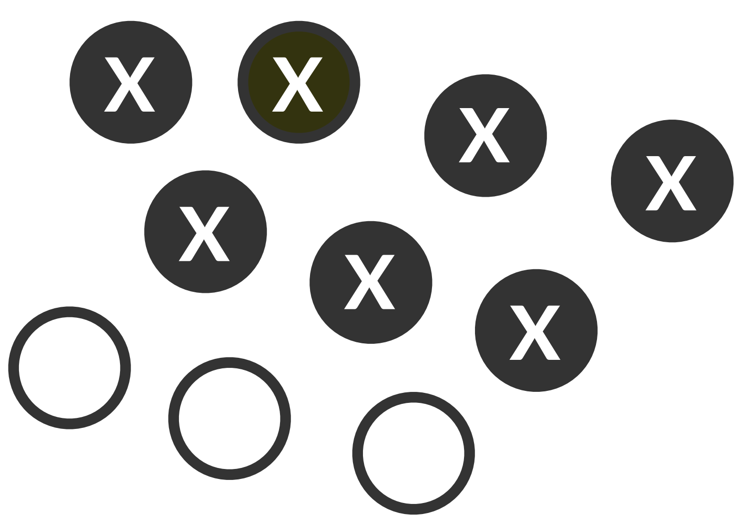
Support

Google map SDK is not working in iPhone6s.

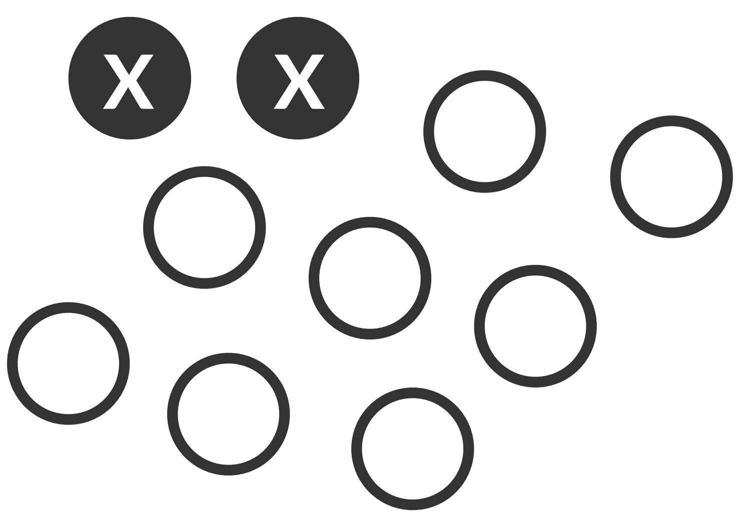
# Unusual Consistency

- 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.



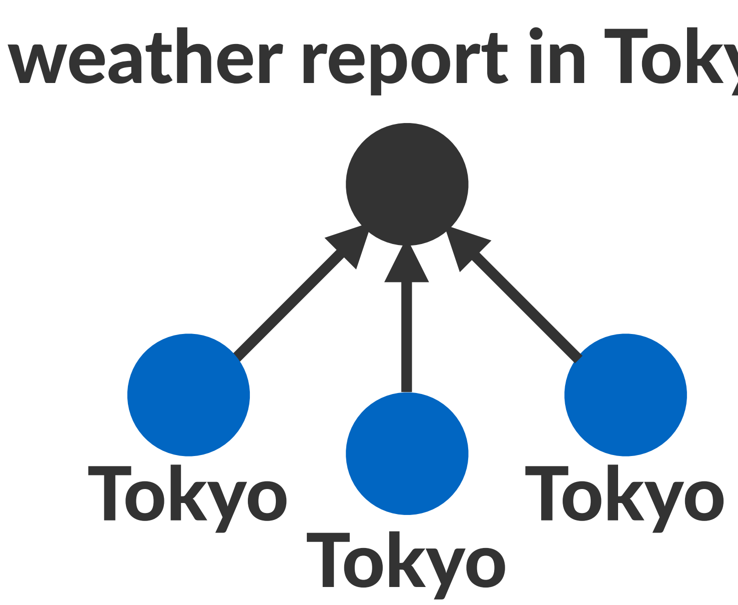

**the followers**

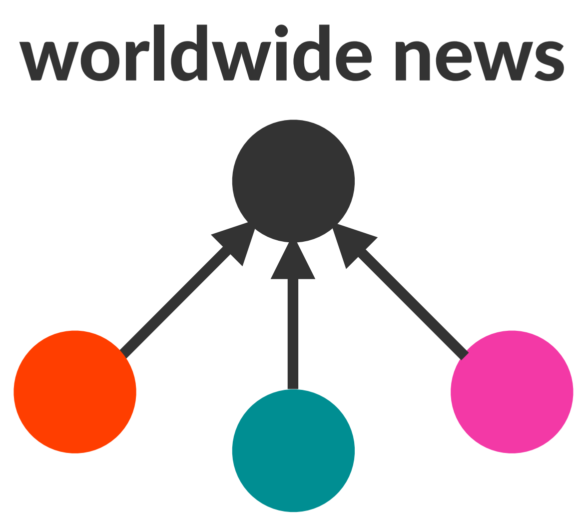



**a random sample from the given universe**

# Unusual Consistency

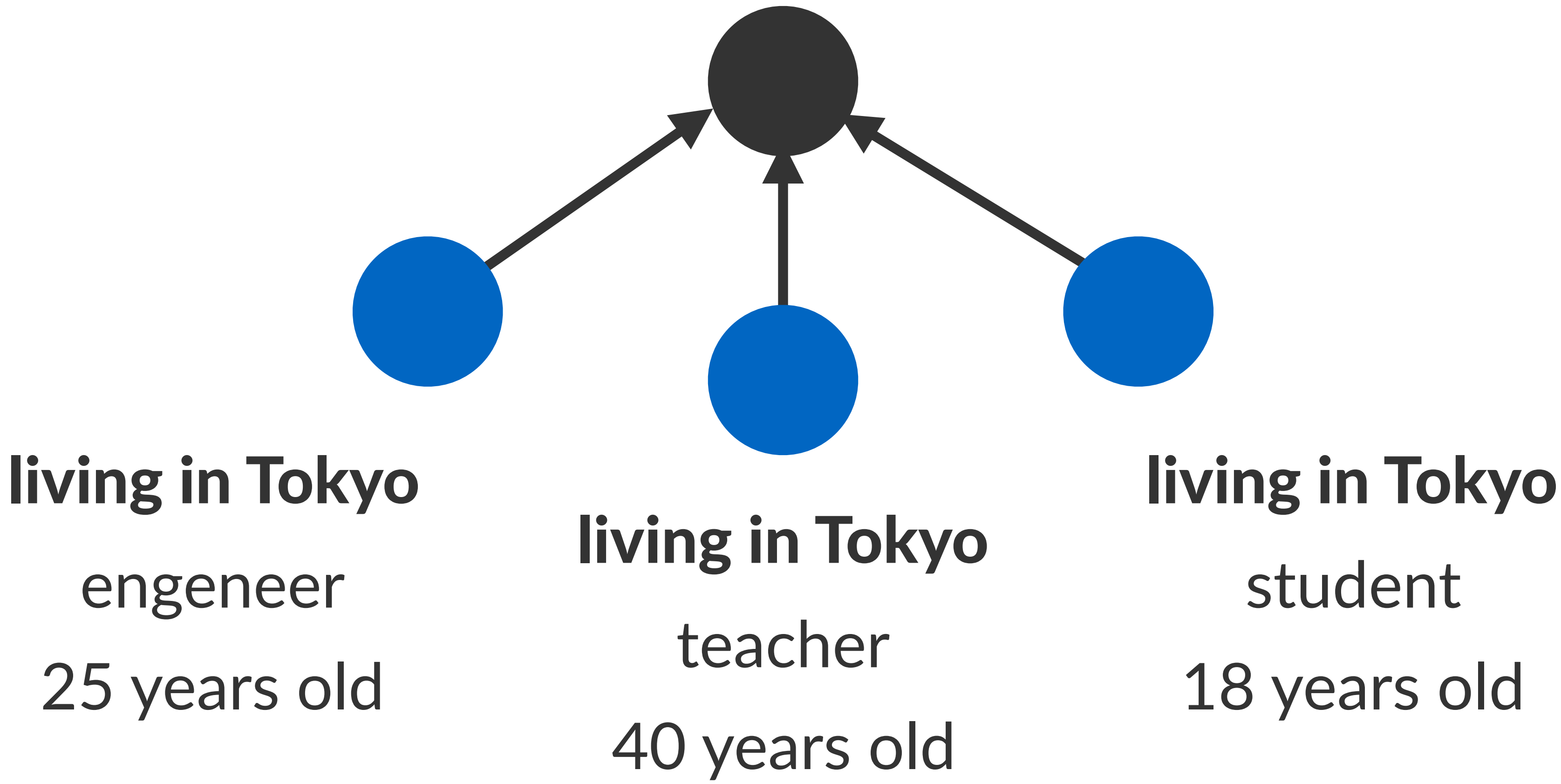
- E.g., an account disseminating **weather report in Tokyo**
  - The followers have a common property: **living in Tokyo**.
  - **Unusual consistency is high.**
- E.g., an account disseminating **worldwide news**
  - The followers have no unusually common properties.
  - **Unusual consistency is low.**



# 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.

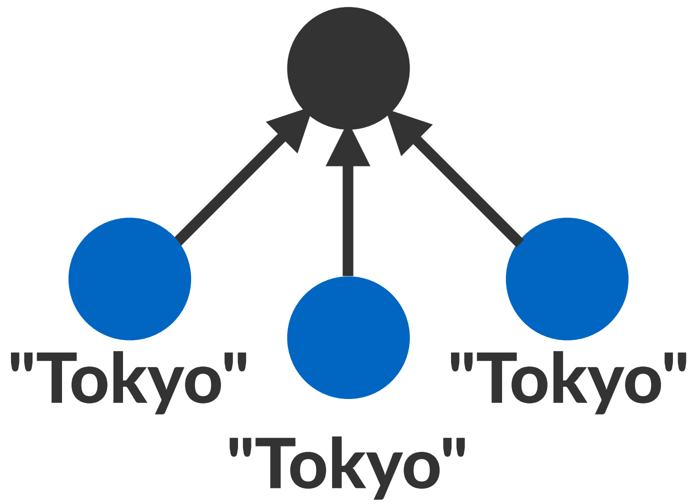


# Two Types of Properties

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

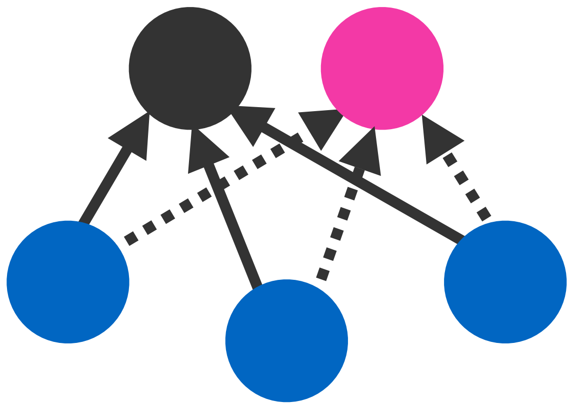
(1) example of common terms

**weather report in Tokyo**




(2) example of common followeers

**a member** **another member**



# Two Ways to Measure Consistency Scores

- For each **Sx: {** ***e*** $\in$ ***S*** **|** ***e has the property X*** **}**, we measure how unusual it is for ***S*** to include the subset that is as consistent as ***Sx*** 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 ***Sx***.

  - **Difference Model**: using the difference between the cover ratio of ***X*** in ***S*** and in the universe.

# Classify Accounts by Using Unusual Consistency

- Finally, we classify accounts into **targeting acocunts** 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

# Experimental Data Set

- We obtained 1,000 Twitter accounts whose timezone is Japan.
- We hired six Twitter users as assessors, and asked them to annonate **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

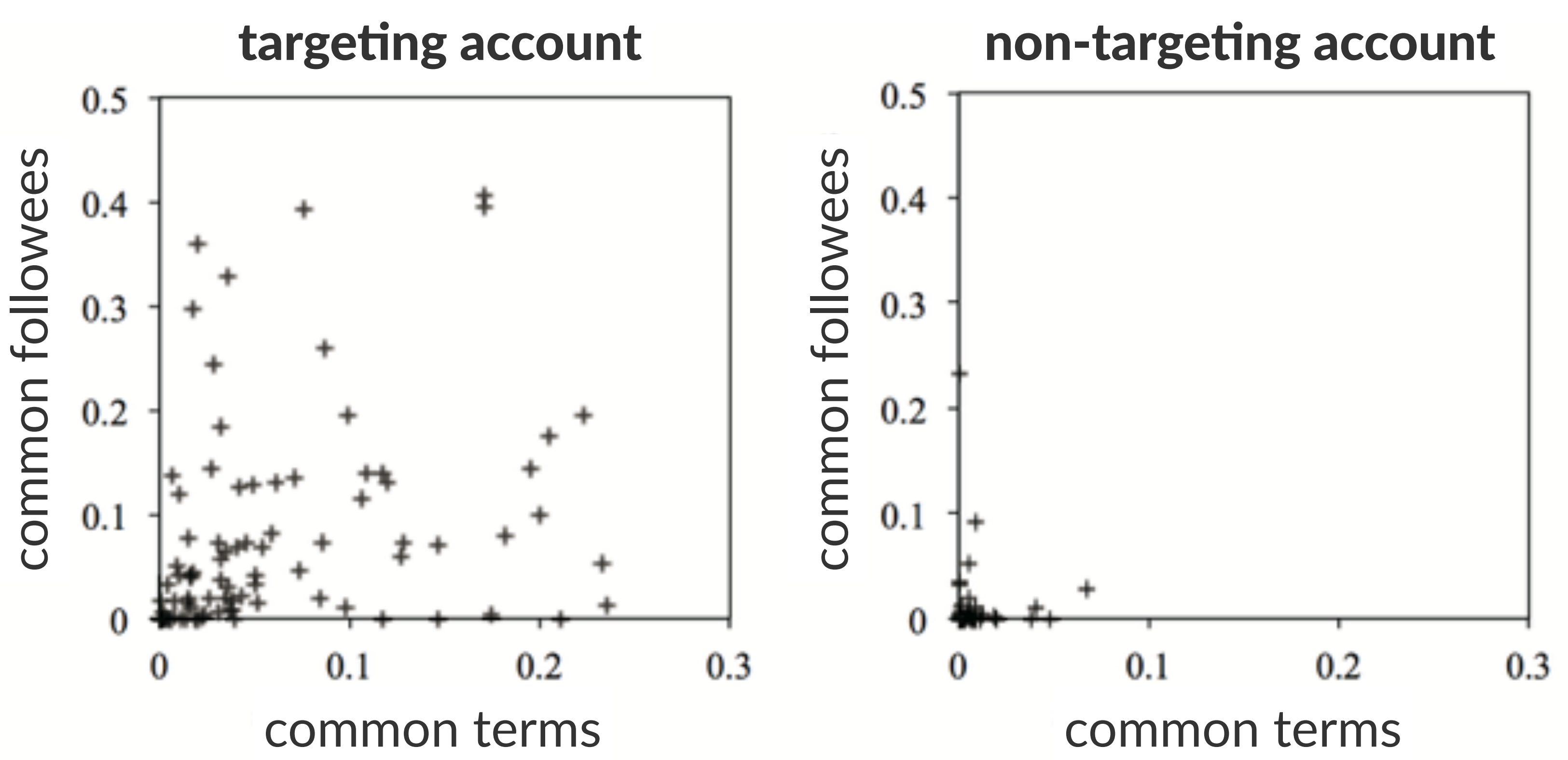
- Accuracy of our method only with either common terms or common followees

| | Probablistic Model | Difference Model |
|---|---|---|
| **common terms** | **0.861** | 0.850 |
| **common followees** | 0.828 | **0.833** |

- 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 θ
  - **SVM**: a binary SVM whose features are the maximum cover ratio of common terms and common followees

| **Baselines** | | **Proposed Methods** | | | |
|---|---|---|---|---|---|
| **follower** | **SVM** | **max** | **sum** | **SVM** | **decision tree** |
| 0.878 | 0.828 | 0.856 | 0.872 | **0.944** | **0.906** |

- The simple follower method achieves high accuracy 0.878.
- Two of our methods achieve even higher accuracy **0.944** and 0.906.

# Conclusion

- 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.