Extracting User's Hidden Profile on Twitter

Dong Wang, Mohan Yang, Yuchen Liu

Department of Computer Science
University of California, Los Angeles

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Extracting User's Hidden Profile on Twitter

Introduction

Tiwtter 101

- A world of 140 characters
- Following, follower & non-reciprocal relationship
- A short biography of 160 characters, plaintext
  - Difficult to know a user's profile, including affiliation, occupation, interests etc.
  - 27.2% of users have a bio less than 5 characters, 43.9% of users have a bio less than 10 characters

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Benefit of complete user profile

- Recommendation system - related users, news and services
- Advertisement delivery
- Search result relevance

Introduction

Observations

A user is studying at UCLA, but he might not explicitly write this fact in his biography.

- In his followings and followers, there might be a considerate amount of users who is explicitly indicating they are students at UCLA.
- In his tweets, he might post about something related to UCLA. He could also retweet tweets containing such information.

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Try to predict whether a user belongs to a category (e.g., studying at UCLA) using the information from

- Followings & followers
- Tweets, location & biography

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Problem Formulation

- A directed graph $G = (V, E)$
- A node $u \in V = \{1, 2, \cdots, n\}$ represents a user in twitter
- A directed edge $(u, v) \in E$ indicates user u is following user v
- Sets $follower(u)$ and $following(u)$
- Size of set is $|follower(u)|$, and $|following(u)|$

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- A category $\mathcal{C}$, we want to identify all users that belong to $\mathcal{C}$
- Prior knowledge, $V = \mathcal{A} + \mathcal{B}$
  - Users in $\mathcal{A}$ belong to $\mathcal{C}$
  - The results for users in $\mathcal{B}$ are unknown
- A relevance score s_u for $u \in \mathcal{B}$, rank users in $\mathcal{B}$ based on s_u

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Snowball Algorithm

- The probability of a user u belonging to $\mathcal{C}$ is determined by the relevance score s_u
- Assume the probability of u publishing a tweet belonging to $\mathcal{C}$ is also s_u, and each user publishes the same number (k) of tweets
- The probability of receiving a tweet in $\mathcal{C}$ by u is

$$\frac{\sum_{v \in following(u)} s_v k}{|following(u)| k} = \sum_{v \in following(u)} \frac{s_v}{|following(u)|}$$

- Further assume that a user publishes exactly what he receives, then the probability of publishing a tweet in $\mathcal{C}$ by u is

$$s_u = \sum_{v \in following(u)} \frac{s_v}{|following(u)|}$$

Bidirectional Snowball Algorithm

- Snowball - tweets propagation from user to his followers
- Inverse direction - tweets propagation from user to his followings
- A user in $\mathcal{C}$ tends to follow many users in $\mathcal{C}$, while a user followed by many users in $\mathcal{C}$ tends to belong to $\mathcal{C}$

$$
\begin{aligned}
p_u &= \sum_{v \in following(u)} \frac{p_v}{|following(u)|} \\
q_u &= \sum_{v \in follower(u)} \frac{q_v}{|follower(u)|}
\end{aligned}
$$

- Users are ranked according to the relevance score $s_u = p_u q_u$, which is a combination of relevance to category $\mathcal{C}$ from both following and follower directions

Naive Bayes Algorithm

- Users in $\mathcal{A}$ ($\mathcal{B}$) are positive (negative) training examples
- T_u is the collection of u's tweets, location and biography
- $W = \{w_1, \cdots, w_m\}$ is the word set for corpus $\bigcup_{u=1}^{n} T_u$
- $\mathbf{1}_{T_u}(w_i)$ is the indicator function of T_u

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- $\mathbf{1}_{T_u}(w_i)$ is the indicator function of T_u
- The naive Bayes classifier finds $i \in \{0, 1\}$ which maximizes

$$p(c = i | w_1 = \mathbf{1}_{T_u}(w_1), \cdots, w_m = \mathbf{1}_{T_u}(w_m)),$$

- or equivalently maximizes

$$p(c = i) \prod_{j=1}^{m} p(w_j = \mathbf{1}_{T_u}(w_j) | c = i).$$

- It is equivalent to determining the sign for s_u

$$\begin{aligned} s_u &= \log(p(c = 1)) - \log(p(c = 0)) \\ &+ \sum_{j=1}^{m} (p(w_j = \mathbf{1}_{T_u}(w_j) | c = 1) - p(w_j = \mathbf{1}_{T_u}(w_j) | c = 0)). \end{aligned}$$

Co-training Algorithm

Perspective of previous algorithms

- Bidirectional snowball algorithm - network structure level
- Naive Bayes algorithm - tweets information level

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Co-training algorithm combines the two algorithms together, iteratively reinforce the result of one algorithm by the result of the other algorithm.

Co-training Algorithm

Algorithm 1 CO-TRAINING

Input: Category $\mathcal{C}$, two disjoint sets $\mathcal{A}$ and $\mathcal{B}$, parameter k and l
Output: An array *rank* containing users in $\mathcal{B}$ ranked on the probability of belonging to $\mathcal{C}$

```
repeat
    rank' ← bidirectional snowball algorithm(𝒜, ℬ)
    rank ← naive Bayes algorithm(𝒜, ℬ)
    𝒜 ← 𝒜 + {top l users in rank'}
    𝒜 ← 𝒜 + {top l users in rank}
until Top k users in rank' and rank are the same
return rank
```

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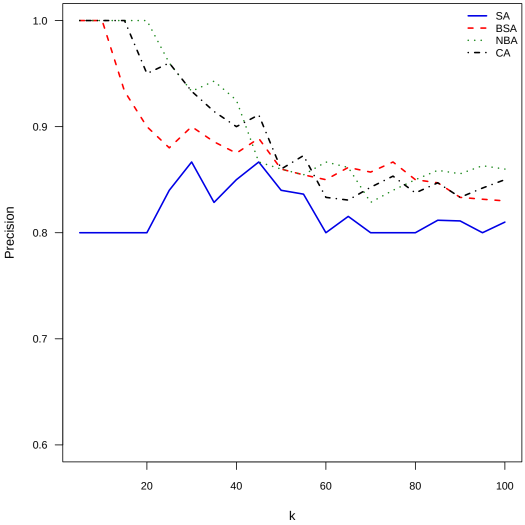
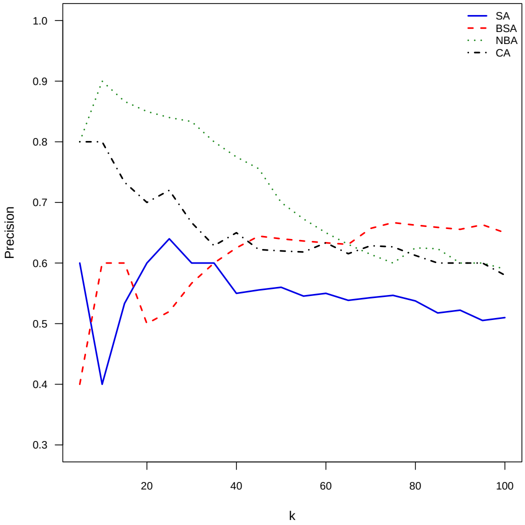
Experiment Setup

- Data collection
  - Seed users from UCLA, USC, Stanford and MIT, two-level breadth first traversal starting from seed user
  - $540,000$ users, $15,321,508$ tweets, $3,143,115$ different words
  - Filter out less frequent words(occurrance < 100) $=>$ about $20,000$ words
- Category $\mathcal{C}$ and keyword $z_{\mathcal{C}} => V = \mathcal{A} + \mathcal{B}$
  - $\mathcal{C} =$ "users in UCLA", $z_{\mathcal{C}} =$ "UCLA"
- Randomly select 20% from $\mathcal{A}$, remove the bigoraphy and move them to $\mathcal{B}$
- Manually label top 100 results of different methods for UCLA category

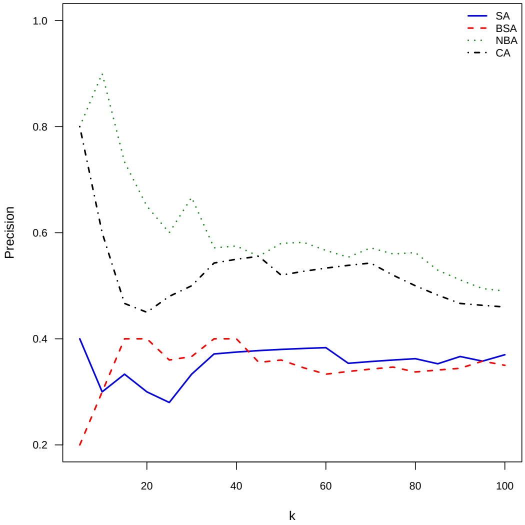
Precision@k for UCLA Category



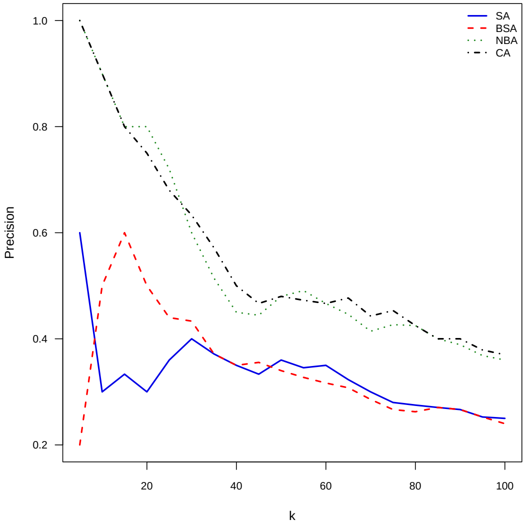
Precision@k for USC Category



Precision@k for Stanford Category

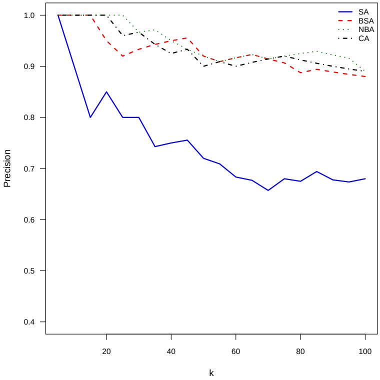


Precision@*k* for MIT Category

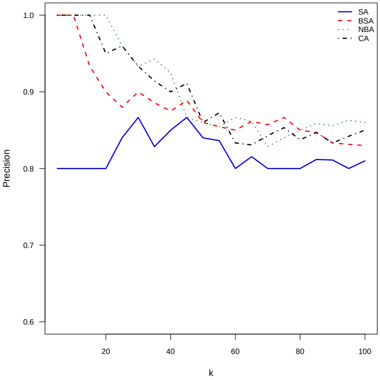


3rd Ranking User from Snowball Algorithm for UCLA Category

Human Labeled Data Vs. Automatic Evaluation

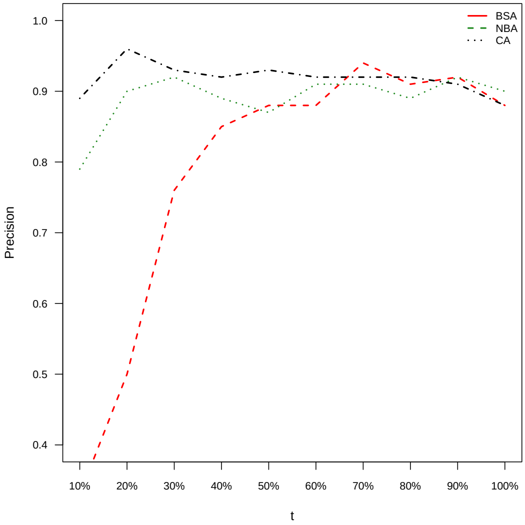


Precision@k for UCLA category on human labeled data



Precision@k for UCLA category with automatic evaluation

Precision@*k* for UCLA Category With Loss of Information



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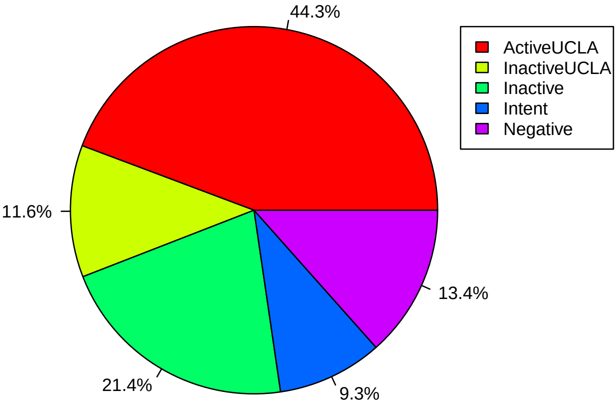
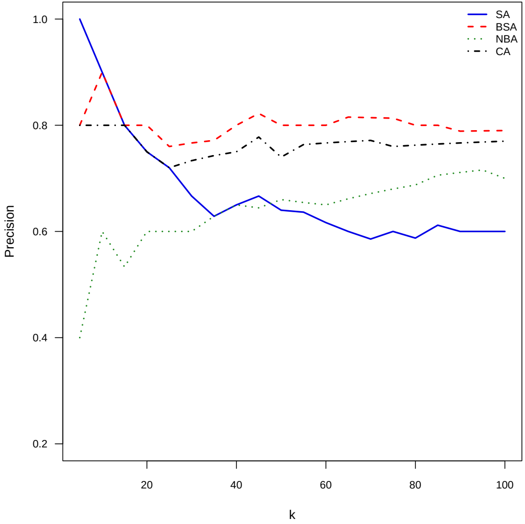
User Classification



Precision@k of Active Users in UCLA Category



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Conclusion

- Three simple algorithms and a co-training algorithm to rank the users based on the relevance score to a given category
- These simple algorithms perform very well on twitter data
- Co-training algorithm can be applied to many other problems that require learning to rank the nodes in a graph

Future work

- Different weights for users based on the importance and activity in the network
- Apply co-training algorithm to friend recommendation system

Thanks!