Predicting Popularity of Twitter Accounts through the Discovery of Link-Propagating Early Adopters

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BACKGROUND

In social media, such as Twitter,

- New useful users frequently appear.
- We want to detect such new useful users.
- Popularity-based methods, e.g., HITS and PageRank, do not work well for new users that have not established their reputation yet.

We propose a method of estimating prospective popularity of new users.
We first detect early adopters

※ Early adopters = The users who are good at finding new good information sources earlier than others.

- The new users followed by early adopters are probably good information sources even if they have few followers at this point.
- We can find good information sources by detecting early adopters.
OUR APPROACH

Information Source

S

EA

EA

EA

Early Adopters

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How do we detect early adopters?

Assumption

Early adopters

The users whose follow links are imitated by many followers.
DETECTION OF EARLY ADOPTERS

How do we detect early adopters?

Assumption

Early adopters

The users whose follow links are imitated by many followers.

We can detect early adopters based on the frequency of link imitation.
1. Detect links created through imitation.

2. Count number of link imitation.

3. Calculate *early adopter score* from the number of link imitation.
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4. Calculate *all users’* early adopter score.

5. Calculate *future popularity score* from followers’ early adopter score.
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ROADMAP

1. Detect links created through imitation.

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DETECTION OF LINK IMITATION

We cannot immediately know imitation of follow links.
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**Structures**

- triangle
- Non-reciprocity
DETECTION OF LINK IMITATION

We cannot immediately know imitation of follow links.

Structures
- triangle
- Non-reciprocity

This triangle is a trace that C imitated EA’s link to S.
DETECTION OF LINK IMITATION

We cannot immediately know imitation of follow links.

Structures

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DETECTION OF LINK IMITATION

We cannot immediately know imitation of follow links.

**Structures**
- triangle
- Non-reciprocity

It is important whether this link of triangle is reciprocal or non-reciprocal.
DETECTION OF LINK IMITATION

We cannot immediately know imitation of follow links.

- triangle
- Non-reciprocity

We only count triangles where the link is a non-reciprocal.
We cannot immediately know imitation of follow links.

**Structures**
- triangle
- Non-reciprocity

We can detect links created through imitation

**DETECTION OF LINK IMITATION**

Non-reciprocal follow links
WHEN THERE ARE MULTIPLE CANDIDATES

However, in the right figure, it is difficult to determine which was imitated by C, EA1 or EA2.
WHEN THERE ARE MULTIPLE CANDIDATES

However, in the right figure, it is difficult to determine which was imitated by C, EA1 or EA2

Each candidates are given a score equally.
1. Detect links created through imitation.

2. Count number of link imitation.

3. Calculate *early adopter score* from the number of link imitation.
HOW TO COUNT NUMBER OF IMITATION

Our method process all edges in the graph one by one.

Each follow link f in a graph

S

f

C
HOW TO COUNT NUMBER OF IMITATION

Our method process all edges in the graph one by one.

Intersection of S’s followers and C’s followees

Each follow link f in a graph
HOW TO COUNT NUMBER OF IMITATION

Our method process all edges in the graph one by one.

These intersection users are candidates of users whose links to S were imitated by C.
HOW TO COUNT NUMBER OF IMITATION

Our method process all edges in the graph one by one.

Accumulating the score for each candidate

Each follow link f in a graph

+0.5

EA2

EA1
HOW TO COUNT NUMBER OF IMITATION

Our method processes all edges in the graph one by one.

Accumulating the score for each candidate

EA1’s accumulated score = 0.5

Each follow link \( f \) in a graph

Our method processes all edges in the graph one by one.

Accumulating the score for each candidate

EA1’s accumulated score = 0.5

Each follow link \( f \) in a graph
HOW TO COUNT NUMBER OF IMITATION

Our method process all edges in the graph one by one.

Accumulating the score for each candidate

EA1’s accumulated score = 0.5 + 0.25 = 0.75
HOW TO COUNT NUMBER OF IMITATION

Our method process all edges in the graph one by one.

After processing all links in the graph, the scores accumulated to each user is the expected number of times that user has been imitated.
1. Detect links created through imitation.

2. Count number of link imitation.

3. Calculate *early adopter score* from the number of link imitation.
Early adopter score

\[
\text{Early adopter score} = \frac{\text{Number of link imitation}}{|\text{followees}| \times |\text{followers}|}
\]
Early adopter score

\[
\text{Early adopter score} = \frac{\text{Number of link imitation}}{|\text{followees}| \times |\text{followers}|}
\]

This denominator corresponds to the maximum number of times this user could be imitated.
EARLY ADOPTER SCORE

Early adopter score

\[
\text{Early adopter score} = \frac{\text{Number of link imitation}}{|\text{followees}| \times |\text{followers}|}
\]

This fraction corresponds to the imitation ratio of this user.
EARLY ADOPTER SCORE

Early adopter score

\[
\text{Early adopter score} = \frac{\text{Number of link imitation}}{\text{|followees| x |followers|}}
\]

\[
= \frac{2 \times 3}{3} = 6
\]
EARLY ADOPTER SCORE

Early adopter score

\[
\text{Early adopter score} = \frac{\text{Number of link imitation}}{|\text{followees}| \times |\text{followers}|}
\]

\[
= \frac{2}{2 \times 3} = \frac{2}{6}
\]

2 followees

3 followers

16/10/27

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EARLY ADOPTER SCORE

Early adopter score

\[
\text{Early adopter score} = \frac{\text{Number of link imitation}}{|\text{followees}| \times |\text{followers}|}
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\[
= \frac{2}{2 \times 3} = \frac{2}{6} = \frac{1}{3}
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4. Calculate *all users’* early adopter score.

5. Calculate *future popularity score* from followers’ early adopter score.
ROADMAP

4. Calculate *all users’* early adopter score.

5. Calculate *future popularity score* from followers’ early adopter score.
We call the estimated new user’s prospective popularity *future popularity score*. 
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Future popularity score is computed as *sum of early adopter scores* of the new user’s followers.
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Future popularity score is computed as *sum of early adopter scores* of the new user’s followers.

\[
S’\text{’s future popularity score} = 0.3 + 0.2 + 0.4 = 0.9
\]
OUR EXPERIMENT

• Dataset [Li et al., KDD 2012]
  – A sub-graph of Twitter crawled in 2011
  – About 20,000,000 users
  – About 300,000,000 follow links

• Target users
  – $T_n^w$: we select then-new users that are
    • within $w$ weeks after the creation, and
    • have more than $n$ followers
OUR EXPERIMENT

• Evaluation
  – We rank users in $T_n^w$ by our methods and baselines.
  – Ground truth: we rank users by their number of non-reciprocal followers as of 2015.
  – Compute Spearman’s $\rho$
OUR EXPERIMENT

• Baseline methods
  – FW: Number of followers in May 2011
  – PR_{nr}: PageRank scores on the graph consisting only of non-reciprocal links
  – HITS_{nr}: HITS scores on the graph consisting only of non-reciprocal links
  – AD: Adamic-Adar index

• Our methods
  – FPS: Feature popularity score
  – LR: The linear regression of FPS and some baselines
## OUR EXPERIMENT

<table>
<thead>
<tr>
<th>Method</th>
<th>( T^4_{10} )</th>
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<td>431</td>
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- **green**: best within baselines
- HITS works best in most cases.
- AD is the best in some cases.
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- FPS is the best in most cases among all the methods excluding LR.
- LR is the best for all cases. It means that FPS captures some aspects that are not captured by other methods.

**red**: best  
**blue**: best excluding LR
CONCLUSION

• We proposed a method of estimating prospective popularity of new users.
• Our method estimate it through the discovery of early adopters.
• Experiment by using sub-graph of Twitter.
• Our method outperforms baselines.