The Social Media Genome: Modeling Individual Topic-Specific Behavior in Social Media

Petko Bogdanov
Ambuj K. Singh
UCSB, Comp. Sci.

Michael Busch
Jeff Moehlis

Boleslaw K. Szymanski
RPI, Comp. Sci.

Michael Busch
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User Model: Motivation

- Predict influence on neighbors
- Dependent user behavior
  - Behavior adopted from neighbors (ex. Hashtags)
- Evolutionary descriptions (i.e., genetics)
  - How do behaviors change in time? (future work)
Definition: Genotype

(1) a per-user entity that summarizes *observable behavior* of the user w.r.t different *topics*.

(2) an allele that the user introduces to the process of message propagation through a network.

User Model: Genotype

Genotype Network
Twitter Data

Proof of concept using Twitter messages containing hashtags:

SNAP data set from 2009 (Leskovec)
CRAWL data set from 2012 (our lab)

<table>
<thead>
<tr>
<th>Topic</th>
<th>SNAP (users=42M,tweets=467M)</th>
<th>CRAWL (users=9K,tweets=14.5M)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Business</td>
<td>27 Hashtags, 20k Users, 1,155 Uses/HT</td>
<td>19 Hashtags, 1,493 Users, 88 Uses/HT</td>
</tr>
<tr>
<td>Celebrities</td>
<td>32 Hashtags, 26k Users, 1,009 Uses/HT</td>
<td>- Hashtags, - Users, - Uses/HT</td>
</tr>
<tr>
<td>Politics</td>
<td>485 Hashtags, 349k Users, 2,020 Uses/HT</td>
<td>121 Hashtags, 5,480 Users, 49 Uses/HT</td>
</tr>
<tr>
<td>Sci/Tech</td>
<td>33 Hashtags, 415k Users, 6,889 Uses/HT</td>
<td>63 Hashtags, 4,982 Users, 100 Uses/HT</td>
</tr>
<tr>
<td>Sports</td>
<td>98 Hashtags, 76k Users, 3,274 Uses/HT</td>
<td>24 Hashtags, 320 Users, 14 Uses/HT</td>
</tr>
</tbody>
</table>

TABLE: Statistics of the SNAP and CRAWL data sets.
Users are consistent in how they respond to a topic.

HT metrics for each user:

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>Randomly pick topic for HT. Proportional to prior distribution.</td>
</tr>
<tr>
<td>F-PAR</td>
<td>Fraction of parents who used HT.</td>
</tr>
<tr>
<td>LAT</td>
<td>Inverse of number of posts b/n first HT use of parent and user.</td>
</tr>
<tr>
<td>LOG-LAT</td>
<td>Log-normalized version of LAT.</td>
</tr>
<tr>
<td>N-USES</td>
<td>Number of HT uses.</td>
</tr>
<tr>
<td>TIME</td>
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</tr>
</tbody>
</table>

Fig. 1: Training and testing accuracy of leave-one-out Linear Discriminant (LD) classification.
Network HT classifier

Observations:
(a) Accuracy improves with # of HT users
(b) LOG-LAT filters out avg. behavior, performs best

Table III: Error rates of the Naive-Bayes (NB) consensus topic classification.

<table>
<thead>
<tr>
<th></th>
<th>Bus</th>
<th>Celeb</th>
<th>Pol</th>
<th>Sci./Tech</th>
<th>Sport</th>
<th>E[x]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rand.</td>
<td>0.96</td>
<td>0.95</td>
<td>0.28</td>
<td>0.85</td>
<td>0.95</td>
<td>0.45</td>
</tr>
<tr>
<td>F-PAR</td>
<td>0.50</td>
<td>0.88</td>
<td>0.61</td>
<td>0.15</td>
<td>0.09</td>
<td>0.41</td>
</tr>
<tr>
<td>LAT</td>
<td>0.09</td>
<td>0.46</td>
<td>0.18</td>
<td>0.19</td>
<td>0.25</td>
<td>0.21</td>
</tr>
<tr>
<td>LOG-LAT</td>
<td>0.05</td>
<td>0.13</td>
<td>0.19</td>
<td>0.12</td>
<td>0.03</td>
<td>0.13</td>
</tr>
<tr>
<td>N-PAR</td>
<td>0.09</td>
<td>0.50</td>
<td>0.88</td>
<td>0.09</td>
<td>0.03</td>
<td>0.40</td>
</tr>
<tr>
<td>N-USES</td>
<td>0.45</td>
<td>0.42</td>
<td>0.90</td>
<td>0.22</td>
<td>0.56</td>
<td>0.54</td>
</tr>
<tr>
<td>TIME</td>
<td>1.0</td>
<td>1.0</td>
<td>0.01</td>
<td>0.92</td>
<td>0.88</td>
<td>0.61</td>
</tr>
</tbody>
</table>

Fig. 2: Accuracy of the network classification as a function of the number of weak (local) classifiers.
Influence Backbones

- **Influence Edge** = directed edge connecting a user of a HT to all of his followers who use the same HT at a later time.

- **Influence Network** (Backbone) = a subset of the follower network, made of influence edges.
  - When sorted by topic: influence edge weights are proportional to number of HT influence edges of same topic.

Fig. 3: Overlap among topic influence and corresponding follower subnetworks (SNAP).
Influence Backbones

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- Relatively small SCC of influence networks supports the existence of influential root nodes.

- Kendall-tau rank correlations show that backbone rank is dissimilar to other ranks.

Fig. 4:
(Top) Largest weakly and strongly connected component sizes as a fraction of the network size.
(Bottom) Kendall-tau rank correlation of node importance measures between influence and follower networks.
Application: Influence Prediction

- Activity-based (genotype) predictors perform 20% better than structural predictors.
- Genotype + Backbone structure outperforms all others.

- Structural Predictors:
  - # of Followees
  - # of Followers
  - # of reciprocal links

- Activity-based predictors:
  - Act = same HT history
  - Topic Act = same topic history
  - RW+Act = Backbone centrality + Act

Fig. 5: Influential followee and adopter prediction accuracy for both SNAP and CRAWL data sets.
Application: Network Latency Minimization

- 40% latency reduction by targeting 1% of the network.
- Latency minimization requires both genotype and influence backbone.

Fig. 6: Comparison of three heuristics for Latency Minimization in the SNAP dataset.
Ongoing and Future Work

- Data sparsity: use urls, sentiment, etc. in addition to HTs.
- Drift of genotypes over long time periods.
- Apply evolution opinion dynamics models to genotypes.
- Estimate exposure rates and size of informed populations using non-linear Kalman Filters.
Media Coverage

WHICH-50

MIT Technology Review

What’s Your Social-Media Genotype?

Your pattern of behaviour on Twitter can be defined by a simple “genotype” and used to predict your future behaviour, say network researchers.

THE CONVERSATION

30 July 2013, 11.40pm AEST

Algorithms can predict how tweets spread

AUTHOR

Boleslaw Szymanski

Professor of Computer Science atPennsylvania State University
Invariant behavior

On an individual basis, users tend to be consistent in how they respond to a topic.

For each user:

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Fig. 1: Training and testing accuracy of leave-one-out Linear Discriminant (LD) classification. MALLET framework text classifier provided HT topic ground truth.

LD:
Application: Influence Prediction

Goal: *Determine which followees are likely to influence a given user to adopt a hashtag of a certain topic, and, analogously which followers are likely to adopt a hashtag.*

Strategy:
1. Look at the local network structure of a novel hashtag user.
2. Rank that user’s set of Topical Influence Network followers based on their propensity to adopt the novel hashtag.
3. Propensities are determined by follower’s local network structure, and activity features (genotype).
4. Compare predictions to actual hashtag usage.
Goal: *Determine which nodes in the topic influence backbone should be targeted for latency reductions, so as to reduce the average minimum latency over the network.*

Strategy:
1. Compute TIME measure of genotype for each node.
2. Discover the backbone for a desired topic.
3. Compute minimum path latencies (sum of TIMEs) between each node.
4. Solve k-LatMin problem (NP-hard) for desired number of target nodes. Set target node latency to zero.