Topical Anomaly Detection from Twitter Streams

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Topical Anomaly Detection from Twitter Streams

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Propagation of off-topic tweets under the subterfuge of trending topics is a common form of abuse in high throughput streams such as Twitter. Such tweets can be detected using the inconsistency between the “claimed” topic (as captured by the hashtags) and the “content” as evidenced by the pages pointed to by the URLs in the tweet.

Existing works
(a) Fail to detect tweets with relevant keywords but containing off-topic links; (b) May get misled by prominent author or account; and (c) Need event-specific training samples and classifier threshold.

Our Approach
(i) Analyzes the content referred to by the URLs in a tweet, (ii) Against documents collected from reliable sources gleaned from the URL prefix in a tweet, (iii) With threshold determined experimentally and dynamically. Thus, it is robust, scalable, and adaptive.

Evaluation
We use the confusion matrix metric.

Table 1. Baseline approach

<table>
<thead>
<tr>
<th>Event</th>
<th>on-topic</th>
<th>off-topic</th>
<th>classified on-topic</th>
<th>classified off-topic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Egypt Crisis</td>
<td>145</td>
<td>19</td>
<td>132</td>
<td>132</td>
</tr>
<tr>
<td>Japan Earthquake</td>
<td>120</td>
<td>12</td>
<td>100</td>
<td>12</td>
</tr>
<tr>
<td>Osama Death</td>
<td>342</td>
<td>27</td>
<td>315</td>
<td>27</td>
</tr>
</tbody>
</table>

Table 2. Our approach

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<tr>
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The goal is to spot topically anomalous tweets from Twitter streams.

Algorithm:
For each document from a trusted source, the Sim_{avg} is updated.
For document from an un-known source, Sim_{max} is compared with Sim_{avg}.

Table 3. Sample tweets tagged as anomalous by our system