Identifying Entity Aspects in Microblog Posts

Spina, D.; Meij, E.; de Rijke, M.; Oghina, A.; Bui, M.T.; Breuss, M.

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ABSTRACT
Online reputation management is about monitoring and handling the public image of entities (such as companies) on the Web. An important task in this area is identifying aspects of the entity of interest (such as products, services, competitors, key people, etc.) given a stream of microblog posts referring to the entity. In this paper, we compare different IR techniques and opinion target identification methods for automatically identifying aspects and find that (i) simple statistical methods such as TF-IDF are a strong baseline for the task, significantly outperforming opinion-oriented methods, and (ii) only considering terms tagged as nouns improves the results for all the methods analyzed.

Categories and Subject Descriptors
H.3.1 [Information Storage and Retrieval]: Content Analysis and Indexing

Keywords
Microblog posts, entity profiling, aspects

1. INTRODUCTION
Online reputation management (ORM) deals with monitoring and handling the public image of entities such as people, products, organizations, companies, or brands on the Web. In the field of ORM, much of the effort is focused on analyzing mentions on social web streams (such as tweets) that are relevant to the entity of interest. An important task in this area is to identify not only posts that are relevant for a given entity, but also the specific aspects that people discuss.

Aspects refer to “hot” topics that people talk about in the context of an entity and are of particular interest for companies. Aspects can cover a wide range of issues and include (but are not limited to) company products, key people, other entities, services, and events. They are typically nouns, but can also be verbs, and (rarely) adjectives. They can change over time as public attention shifts from some aspects to others. For instance, for a company releasing its quarterly earnings report, its earnings can become a topic of discussion for a certain period of time and, hence, an aspect. Identifying aspects not only helps reputation analysts in determining what people say about an entity of interest, but it also facilitates a more fine-grained sentiment analysis than is typically possible, since opinions pertaining to aspects rather than to the entity can be identified [4]. Although aspects have been investigated in the context of, e.g., discussion fora [9], automatically determining aspects in streams of microblog posts remains an unsolved problem.

We study the following scenario. Given a stream of microblog posts related to a company [1,7], we are interested in a ranked list of aspects that are being discussed with respect to the company. We formulate our scenario as an information retrieval (IR) task, where the goal is to provide a ranking of terms, extracted from tweets that are relevant to the company. We compare different methods that address this task with three main goals: (i) to analyze how state-of-the-art IR approaches perform, (ii) to see how methods tailored specifically to identifying opinion targets perform, and (iii) to create a publicly available, humanly annotated dataset to facilitate follow-up research [8].

2. IDENTIFYING ENTITY ASPECTS
We evaluate four models for identifying aspects, given an entity and a stream of microblog posts related to that entity. All models work according to the same principle: comparing a pseudo-document built from entity-specific tweets with a background corpus C. This comparison allows us to score a term t using a function $s(t, D, C)$.

We compare four methods for identifying entity aspects: TF-IDF, the log-likelihood ratio (LLR) [2], parsimonious language models (PLM) [3] and an opinion-oriented method (OO) [5] that extracts targets of opinions to generate a topic-specific sentiment lexicon; we use the targets selected during the second step of this method. Table 1 describes how the scoring function is computed by each method. As usual, $if(t, D)$ denotes the term frequency of term t in pseudo-document D; $cf(t)$ denotes the term frequency in the collection C and $df(t)$ denotes the total number of pseudo-documents $D_i \in C$ in which the term t occurs at least once.

3. EXPERIMENTS
Determining aspects of an entity in streams of microblog posts involves two tasks. In the first task, tweets relevant to a given entity need to be identified; in the second, these tweets need to be analyzed in order to identify aspects. We focus on the second task and base our annotations on the data used for the WePS-3 ORM Task [1]. Here, the task that participating systems need to solve is to decide which tweets containing a company name are actually related to the company. In total, 99 companies are used for testing, with around 450 tweets (manually annotated for relevance) on average for each company. In our experiments, we only consider the tweets that are related to a company, adding up a total of 94 companies and 17,775 tweets with an average of 177 tweets per company.

\[^{1}\text{We only consider unigrams. When a unigram is an obvious constituent of a larger, relevant aspect it is considered relevant.}\]

\[^{2}\text{Available at }\text{http://bit.ly/profilingTwitter}\]
### Table 1: Scoring functions for identifying entity aspects.

<table>
<thead>
<tr>
<th>Method</th>
<th>Scoring function</th>
</tr>
</thead>
<tbody>
<tr>
<td>TF-IDF</td>
<td>( s(t, D, C) = \frac{tf(t, D) \cdot \log \frac{N}{df(t, D)}}{df(t)} )</td>
</tr>
<tr>
<td>LLR</td>
<td>( s(t, D, C) = 2 \cdot \left( t \cdot \log \left( \frac{N}{df(t, D)} \right) + b \cdot \log \left( \frac{N}{df(t)} \right) \right) )</td>
</tr>
<tr>
<td>PLM</td>
<td>( s(t, D, C) = \frac{P(t</td>
</tr>
<tr>
<td>OO</td>
<td>( s(t, D, C) = \chi^2(\text{target}(t, D), \text{target}(t, C)) )</td>
</tr>
</tbody>
</table>

We lowercase, remove punctuation, and tokenize the tweets. We do not perform stopword removal or stemming, but only keep terms occurring at least 5 times in the corpus to remove noisy terms.

We evaluate the methods for ranking aspects using a pooling methodology [10]; the 10 highest ranked terms from each method are considered and determine relevance in the context of the company; methodology [10]; the 10 highest ranked terms from each method occurring at least 5 times in the corpus to remove noisy terms.

We use the metrics for ranking aspects as described in [10]; the results when non-noun terms have been filtered out from the vocabulary. For all methods, MAP and precision values are slightly above 0.6, indicating a substantial agreement.

### Table 2: Aspect identification results. Best results in boldface; significant changes are w.r.t. the TF-IDF All words baseline.

<table>
<thead>
<tr>
<th>Method</th>
<th>MAP</th>
<th>PS</th>
<th>P10</th>
<th>MRR</th>
</tr>
</thead>
<tbody>
<tr>
<td>TF-IDF</td>
<td>0.3953</td>
<td>0.6957</td>
<td>0.6426</td>
<td>0.7908</td>
</tr>
<tr>
<td>PLM</td>
<td>0.3685</td>
<td>0.6723</td>
<td>0.6090</td>
<td>0.7979</td>
</tr>
<tr>
<td>OO</td>
<td>0.1537</td>
<td>0.4596</td>
<td>0.2915</td>
<td>0.7021</td>
</tr>
</tbody>
</table>

### 4. CONCLUSION

We addressed the task of identifying aspects that people discuss in a stream of microblog posts related to an entity, a task at the heart of online reputation management. We modeled this task as a ranking problem and compared IR techniques and opinion target identification methods for automatically identifying aspects. We used a pooling methodology to evaluate the methods. Simple statistical methods such as TF-IDF are a strong baseline for the task. Moreover, it is difficult to identify aspects by extracting opinion targets mainly because the language used in tweets is often non-standard, hampering the performance of such techniques. Future work includes considering n-grams as aspects and applying topic modeling techniques.

### 5. ACKNOWLEDGMENTS

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### References