On the robustness of event detection evaluation: a case study

Matthias Feys, Thomas Demeester, Blaz Fortuna, Johannes Deleu, Chris Develder
Ghent University - iMinds, Belgium
firstname.lastname@intec.ugent.be

ABSTRACT
Research on evaluation of IR systems has led to the insight that a robust evaluation strategy requires tests on a large number of events/queries. However, especially for event detection, the number of manually labeled events may be limited. In this paper we investigate how to optimize the evaluation strategy in those cases to maximize robustness. We also introduce two new vector space models for event detection that aim to incorporate bursty information of terms and compare these with existing models. Experiments show that exploiting graded relevance levels reduces the impact of subjectivity and ambiguity of event detection evaluation. We also show that although user disagreement is significant, it has no real impact on result ranking.

Categories and Subject Descriptors
H.2.8 [Information Systems]: Database applications - Data mining; H.3.3 [Information Search and Retrieval]: Information filtering

Keywords
Event Detection, Evaluation, Vector Space Models

1. INTRODUCTION AND BACKGROUND
Research in the area of event detection deals with discovering events that are described in collections of unstructured texts, such as news data or social media streams, and related tasks such as assigning new content to event streams, or extracting information about entities that play a role in an event. We focus on the subtask of retrospective event detection, where the goal is to discover events in a historical news archive. A popular approach for retrospective event detection is to use the so-called burstiness of terms, i.e., sudden increases in term frequencies. BurstVSM, a method proposed by Zhao et al., uses these bursts to define a burst-based Vector Space Model (VSM) and clusters the articles based on this burst-based representation to define the events. We will compare this method with clustering based on tf-idf vectors and two new variants inspired by boosting: increasing the weights of terms that are temporally important.

In contrast to typical evaluation of event detection algorithms, using binary relevance levels and basic metrics such as precision and recall, we will leverage the work of the general IR community and introduce the use of graded relevance levels for this task. We will analyse some robustness issues, ambiguity and subjectivity, of event detection evaluation, and show how graded relevance levels and related metrics can help to reduce the impact of these issues.

2. EXPERIMENTAL SETUP
2.1 Data Collections
We perform experiments on two separate annotated datasets. The first contains the Chinese articles and annotations used in, spanning news related web-articles from 2000 to 2009. The second dataset is constructed to test the impact of graded relevance levels and contains Flemish news articles spanning the year 2011. In both datasets the annotated data comprises a list of events (target events) and their corresponding lists of related articles. The latter are constructed by starting from a list of seed events, created by extensive and highly recall-oriented queries, and manually annotating the resulting articles.

2.1.1 Chinese dataset
Since some preprocessing steps could not be reproduced, we were not able to use an exact copy of the set described in. Our version of the dataset contains over 12,000,000 articles and more than 600,000 unique tokens (after filtering out infrequent (df < 10) tokens, and using IKAnalyzer for tokenization). The labels per document are binary (a document is either related to the event or not), obtained by using a majority vote of the labels from three different students. In total we have 129 labelled events. As in the original paper, we split the set of events into three partitions based on the number of articles related to each event. The resulting

3We like to thank Xin Zhao for sharing his data and code.
4Provided by Mediargus (www.mediargus.be)
52012 version of https://code.google.com/p/ik-analyzer/
6In [5], only 100 were mentioned.
The article is in no way related to the event mentioned in another context), but only long before or afterwards (e.g., the event is just Distant (D): necessarily completely, and contains little essential information.

Strong (S): The article is strongly and entirely related to the event, either describing it completely, or focusing on a particular aspect. Weak (W): The article is related to the event, but not necessarily completely, and contains little essential information. Distant (D): The article is remotely related to the event, but only long before or afterwards (e.g., the event is just mentioned in another context). No: The article is in no way related to the event.

All 19 events were annotated at least once (spanning almost 12,000 annotated documents in total). For 12 of these events, double judgments were gathered. With $U_1$ we will refer to the annotators that provided the first judgment for all events, while $U_2$ provided the second judgment for 12 events. All annotated were experienced and paid students.

2.2 Event-oriented Document Representations

We will compare four vector space models (VSMs) as document representation for event detection: tf-idf, BurstVSM [5], and two new models, their respective boosted counterparts, denoted as B-tf-idf and B-BurstVSM. All methods rely on term features $f(w)$ (i.e., tf-idf) as feature weights.

This boosting is achieved by taking burst information for each term into account. For each term $w$ we identified the corresponding bursts $\beta_i$ and the burst durations $\Delta_{\beta_i}$ (number of days the term is in a bursty state, $q_1$). We also calculated the daily emission costs $\sigma(q_0,w,q_1)$ for each term and day $t$, considering the state (bursty $q_1$ vs. non-bursty $q_0$) of this term. This emission cost measures the discrepancy between actual and expected term frequency, given the state, as defined in [5]. The boosting for each term is achieved by multiplying the respective static feature weights $f(w)$ with the boosting factor $b^{\beta_i,w,t}$, defined as:

$$b^{\beta_i,w,t} = \log \left[ \Delta_{\beta_i} \cdot \max_t \left( \sigma(q_0,w,q_1,t) - \sigma(q_1,w,t) \right) \right]$$

(1)

Where the $\max_x(\cdot)$ defines the maximum possible gain in daily emission cost by being in a bursty state ($q_1$). For all VSMs, the events are subsequently retrieved by grouping the articles based on their respective vector representations.

The annotated Flemish corpus can be made available to researchers upon signing an NDA with Mediargus.

<table>
<thead>
<tr>
<th>MAP ± stdev</th>
<th>Chinese</th>
<th>Flemish</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>moderate</td>
<td>large</td>
</tr>
<tr>
<td>tf-idf</td>
<td>0.50±0.25</td>
<td>0.35±0.24</td>
</tr>
<tr>
<td>BurstVSM</td>
<td>0.54±0.21</td>
<td>0.46±0.20</td>
</tr>
<tr>
<td>B-BurstVSM</td>
<td>0.59±0.18*</td>
<td>0.53±0.21*</td>
</tr>
<tr>
<td>B-tf-idf</td>
<td>0.60±0.21*</td>
<td>0.53±0.22*</td>
</tr>
</tbody>
</table>

Table 1: MAP for the different VSMs for the different event sets (see Section 2.1). The best results are in bold, the new VSMs in italic. The systems that significantly outperform tf-idf (p-value <0.05) are indicated with an asterisk.

We used the same clustering tool, CLUTO[6] for all methods. The performance of these methods on the Chinese and Flemish dataset can be found in Table 1. We used Mean Average Precision (MAP) for evaluating the retrieved events (considering only strong articles as relevant for the Flemish dataset, and for which the ordering of the articles is based on the distance from the centroid), which enables a natural transition to the graded counterpart, mean graded average precision (GAP). On both datasets we observe that the boosted VSMs outperform their non-boosted counterparts.

Large values for the standard deviation (calculated over all the events) on the metrics are observed on all event sets. We see that on the Chinese dataset, both boosted VSMs significantly outperform the basic tf-idf method, especially for the large events. Note that on the Flemish dataset, the tf-idf method performs better than BurstVSM. Furthermore, none of the observed differences appeared significant at the 0.05 level on this dataset, due to the small number of test events.

3. ANALYSIS OF EVALUATION ISSUES

In this section we take a closer look at the event detection evaluation methodology, focusing on three aspects: (1) the definition of the events, (2) the impact of subjectivity, e.g., by modeling user disagreement, and (3) the impact of the annotation coverage. All experiments are performed on the Flemish dataset.

3.1 Event Definition

To analyse the impact of the event definition on the evaluation results, we consider two aspects. First, we analyse the impact of the relevance definition, i.e., we use binary relevance, but consider different cut-off levels (the relevance categories defined in Section 2.1.2). Secondly, we consider two types of events, homogeneous and heterogeneous, and analyse if the selected event type has an influence on the evaluation results.

Table 2 shows the MAP for three relevance definitions, $S$: only documents labeled strong are considered relevant, $S+W$: both strong and weak are relevant, and $S+W+D$, including the distant documents as well. The results show that the broader $S+W$ definition of event relevance as compared to the $S$ case, leads to improved MAP values for the temporal

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5The annotated Flemish corpus can be made available to researchers upon signing an NDA with Mediargus.
6The difference in effectiveness of the BurstVSM method with respect to [5] is due to the fact that its authors performed a manual preprocessing step in filtering out documents, which was not documented and could not be reconstructed.

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Table 2: MAP values on the Flemish newswire corpus with different relevance cut-off levels. The systems that significantly outperform tf-idf (p-value < 0.05) are indicated with an asterisk. Best VSM in bold.

<table>
<thead>
<tr>
<th></th>
<th>S</th>
<th>S+W</th>
<th>S+W+D</th>
</tr>
</thead>
<tbody>
<tr>
<td>tf-idf</td>
<td>0.24±0.22</td>
<td>0.23±0.21</td>
<td>0.19±0.18</td>
</tr>
<tr>
<td>B-tf-idf</td>
<td>0.29±0.21</td>
<td>0.37±0.23*</td>
<td>0.35±0.22*</td>
</tr>
<tr>
<td>BurstVSM</td>
<td>0.22±0.20</td>
<td>0.30±0.23</td>
<td>0.29±0.22</td>
</tr>
<tr>
<td>B-BurstVSM</td>
<td>0.24±0.20</td>
<td>0.32±0.23</td>
<td>0.31±0.23</td>
</tr>
</tbody>
</table>

Table 3: MAP values on the Flemish corpus for two types of events (binary relevance cut-off at the S level).

<table>
<thead>
<tr>
<th></th>
<th>homogeneous</th>
<th>heterogeneous</th>
</tr>
</thead>
<tbody>
<tr>
<td>tf-idf</td>
<td>0.30±0.22</td>
<td>0.19±0.24</td>
</tr>
<tr>
<td>B-BurstVSM</td>
<td>0.15±0.13</td>
<td>0.34±0.23</td>
</tr>
<tr>
<td>BurstVSM</td>
<td>0.12±0.13</td>
<td>0.33±0.21</td>
</tr>
<tr>
<td>B-tf-idf</td>
<td>0.26±0.21</td>
<td>0.33±0.22</td>
</tr>
</tbody>
</table>

Table 4: MAP and GAP with the annotations of U_2 as the retrieved set (binary relevance; relevance definitions as in Table 2). U_1 annotations are used as reference.

<table>
<thead>
<tr>
<th></th>
<th>MAP</th>
<th>GAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>U_2 (S)</td>
<td>0.45±0.12</td>
<td>0.44±0.10</td>
</tr>
<tr>
<td>U_2 (S+W)</td>
<td>0.58±0.13</td>
<td>0.63±0.06</td>
</tr>
<tr>
<td>U_2 (S+W+D)</td>
<td>0.62±0.16</td>
<td>0.73±0.08</td>
</tr>
</tbody>
</table>

Table 3.2.1 User Disagreement Model

The User Disagreement Model (UDM) [1] allows estimating the parameters \( P_{T_i}^{M/N} \), the probability that at least \( M \) out of a set of \( N \) annotators assign a certain document the relevance label \( T \) if one observed annotator gave this document the label \( i \). These probabilities are estimated from a small subset of documents annotated by two different annotators, and are subsequently used as relevance weights in the GAP metric. For the calculations of \( P_{T_i}^{1/2} \) (based on two annotators), we used micro-averaging over the different events similar to [1]. An important property of the UDM is that it allows evaluation on the highest level of relevance, compensating for those results with a lower relevance that another user might consider as top relevant. This way we can incorporate user disagreement in our evaluation.

3.2.2 Reducing impact of subjectivity with GAP and UDM

We will test if GAP (using the calculated UDM parameters \( P_{T_i}^{1/2} \) as the relevance weights, more precisely, 0.21 for the weakly relevant articles, and 0.11 for distant relevant) is more robust to subjectivity (user disagreement) than MAP. We will test this hypothesis with two experiments. First, we will calculate the performance of user \( U_2 \), when we consider the annotations of \( U_1 \) as reference annotations, using MAP vs. GAP. Next, we will measure the performance of each VSM and calculate the average difference between the performance by using the annotations of user \( U_1 \) vs. the annotations of \( U_2 \) as reference for both metrics.

The results of the first experiment are shown in Table 5. Since both MAP and GAP require a ranked list of results and the sets of annotations only contain the annotated relevance levels, we calculate both metrics by averaging over 1000 random document orderings within each relevance level. The lower standard deviation on the GAP and the mostly higher absolute values show that using graded relevance levels and the GAP metric leads to a more robust evaluation (w.r.t. user disagreement), especially when event algorithms would output a ranking of all candidate documents in decreasing order of relevance to the event, rather than returning a smaller subset of results for each event, e.g., \((S+W+(D))\) instead of \(S\), although the effect is rather limited. Table 5 shows the results of the second experiment. This demonstrates that GAP reduces the mean difference
3.2.3 Impact of user disagreement on system rankings

Finally, we compared the ranking of the different VSMs by using user $U_1$ vs. $U_2$ as reference. The system rankings (averaged over all events) are the same for both annotation sets. This shows that the strong user disagreement (cf. Jaccard coefficient of 0.47 when considering only $S$ articles for the comparison of the annotations of $U_1$ vs. $U_2$) has little impact on the actual system comparisons. However, by considering the rank correlation of the ranking of the systems for each event individually between the users, averaged over all events, the mean rank correlation increases from 0.53 with MAP, to a mean rank correlation of 0.72 for GAP, again showing the higher robustness of GAP.

3.3 Annotation coverage

In this section we will analyse how many articles of each event we need to annotate in order to make reliable conclusions. Figure 1 shows the mean rank correlation, (and standard deviation) for different levels of annotation coverage using GAP. The rank correlation is defined as the kendall $\tau$'s rank correlation between the global ranking (averaged over all events) of systems and the individual system ranking per event, averaged over all events. The mean and standard deviation of the rank correlation for each annotation coverage level are obtained by averaging the rank correlation over 500 random samples (with the given annotation coverage) of the “annotated” articles. The ignored articles are completely re-considered 

<table>
<thead>
<tr>
<th>VSM</th>
<th>$\Delta_{MAP}^{U_1,U_2}$</th>
<th>$\Delta_{GAP}^{U_1,U_2}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>tf-idf</td>
<td>0.07±0.07</td>
<td>0.04±0.04</td>
</tr>
<tr>
<td>B-tf-idf</td>
<td>0.16±0.12</td>
<td>0.09±0.07</td>
</tr>
<tr>
<td>BurstVSM</td>
<td>0.10±0.09</td>
<td>0.05±0.04</td>
</tr>
<tr>
<td>B-BurstVSM</td>
<td>0.13±0.11</td>
<td>0.06±0.06</td>
</tr>
</tbody>
</table>

Table 5: Robustness of evaluation using MAP vs. GAP. The mean and standard deviation of the difference between the results obtained by using the two different reference annotations for all techniques are shown.

between the results obtained by using two different reference annotations. Furthermore, it shows that the temporal VSMs are more susceptible to user disagreement than tf-idf.

4. CONCLUSION

We analysed the impact of the ambiguity of the event definition, annotation subjectivity, and annotation coverage on the evaluation of event detection systems. We also introduced two new boosted VSMs that outperform their non-boosted counterparts. Our experiments show that an unambiguous definition of events (specifying the event types


\cite{3} W. Zhao, R. Chen, K. Fan, H. Yan, and X. Li. A novel burst-based text representation model for scalable event detection. In ACL, pages 43–47, 2012.

Note that the number of annotations may depend on, e.g., the event type (large vs. small).

Figure 1: Mean rank correlation for GAP in function of annotation coverage. The mean rank correlations are obtained by sampling 500 times for each annotation coverage point, and the relevance level between article and event) is critical for comparing between systems. Without precisely defining the required relevance level or choosing a specific type of event, the resulting systems ranking cannot be determined unambiguously. Graded relevance levels can reduce the ambiguity of relevance assessments and hence increase the robustness of the evaluation. The impact of subjectivity of the annotations on the system performance can also be reduced by considering graded relevance levels and using GAP with UDM. Although the user disagreement is large, we showed that it has little impact on the ranking of our systems. This suggests that we do not need to prioritize the problem of user disagreement. However, we need to test this hypothesis on more systems, and in a setting with a larger pool of judged test events, in order to make reliable conclusions. Also, the noticeable influence of the heterogeneity of events needs to be further investigated. Finally, we showed that we can significantly reduce the collection size with little impact on system rankings, opening up the way to larger numbers of annotated test events.

5. ACKNOWLEDGMENTS

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6. REFERENCES


