Detecting Action Items in Email

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Detecting Action-Items in E-mail

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1. INTRODUCTION

E-mail users have a difficult time managing their inboxes in the face of mounting challenges. These include prioritizing e-mails from a variety of senders, filtering junk e-mail, and quickly taking action on items that demand the user’s attention. Automated action-item detection targets the third of these problems by detecting e-mails which require an action or response, and within those e-mails, highlighting the specific text that indicates the request.

In contrast to action-item detection which aims at locating exactly where the action item requests are contained within the email body, typical text categorization (TC) merely assigns a topic label to the entire message — whether that label corresponds to an e-mail folder or an indexing vocabulary [8]. In further contrast to TC, action-item detection attempts to recover the sender’s intent, i.e. whether she means to elicit response or action on the part of the receiver. Whereas TC by topic [5, 6, 9], TDT [1], and even genre-classification [7] work well using just individual words as features, we believe that action-item detection is the first TC task where we clearly must move beyond bag-of-words — albeit not too far, as bag-of-n-grams seems to suffice.

The current schedule for the visit by the GRTY group looks like this:
+ 10:30 a.m. Individual Meetings (Break for Lunch)
+ 2:00 p.m. Sales Pitch
To prepare, I need each of your parts for the presentation by Wednesday. Keep up the good work!
–Henry

Figure 1: An E-mail with emphasized Action-Item

2. RELATED WORK

While Cohen et al. [3] describe an ontology of “speech acts” that subsumes action-items, their methods only make use of human judgments at the document-level. In contrast, we consider whether accuracy can be increased by using finer-grained human judgments that mark the specific sentences and phrases of interest. Corston-Oliver et al. [4] consider detecting items in e-mail for a “To-Do List” using a single classifier; however, they do not explicitly compare what if any benefits finer-grained judgments offer.

In contrast to previous work, we focus on the benefits that finer-grained (more costly) sentence-level human judgments offer over coarse-grained document-level judgments. Additionally, we consider multiple standard text classification approaches and analyze the differences of a document-level vs. a sentence-level approach.

3. PROBLEM DEFINITION & APPROACH

To provide better end-user benefit, a system would both detect an action-item document and indicate the specific sentences which contain the action-items. Therefore, there are three basic problems: document detection, document ranking, and sentence detection.

The labeled data can come in one of two forms: a document-labeling provides a yes/no label for each document as to whether it contains an action-item; a phrase-labeling provides a yes label for each action-item. Obviously, it is straightforward to generate a document-labeling consistent with a phrase-labeling by labeling a document “yes” if and only if it contains at least one “yes” phrase.

To train classifiers, we can take one of two approaches related to the form of the labeled data. The document-level view treats each e-mail as a learning instance with a class-label. In the sentence-level view, after automatic sentence-segmentation, each sentence is treated as a learning instance with an associated class-label.

Representation and Implementation Overview

For this study, only the body of each e-mail message was used. We compare a standard bag-of-words or unigram representation to a bag of n-grams. We also retain sentence-ending punctuation as a token. For the bag of n-grams, beginning-of-sentence and end-of-sentence markers are included. Finally, for the sentence-level classifiers using n-grams, we also code the position of the sentence relative to the e-mail in octiles. For feature selection, we use chi-squared and choose the number of features that yield the optimal document-level F1 for that classifier during nested cross-validation.

In order to compare the document-level to the sentence-level approach, we compare predictions at the document-level. We use the RASP parser [2] to automatically segment the text of the e-mail, and then treat any sentence that contains at least 30% of a marked action-item segment as an action-item.

We applied a variety of standard TC algorithms: k-NN (s-cut), multinomial naive Bayes, and SVMs. Once a sentence-level classifier makes a prediction for each sentence, we combine these predictions into a document-level prediction and a document-level score. We use the simple policy of predicting positive when any of the sentences is predicted positive. For ranking, the document score is the length normalized sum of the sentence scores above threshold.

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ACM 1-59593-034-5/05/0008.
To compare the performance of the classification methods, we use F1 and accuracy. We perform standard 10-fold cross-validation on the set of documents. For the sentence-level approach, all sentences in a document are either entirely in the training set or entirely in the test set for each fold. For significance tests, we use a two-tailed t-test to compare the values obtained during each cross-validation fold with a p-value of 0.05.

Our corpus consists of e-mails obtained from volunteers at our university. After eliminating duplicate e-mails, the corpus contains 744 e-mail messages. To balance cognitive load in the user studies (omitted here) and prevent chronological taints of cross-validation, the studies reported here are performed with a version of the corpus after quoted material is removed by hand.

Two human annotators labeled all the messages and identified each segment of the e-mail which contained action-items. At the document-level, the kappa statistic for inter-annotator agreement is 0.85 and 0.82 at the sentence-level. After reconciling the judgments there are 328 e-mails containing action-items.

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Table 1: Average Document-Detection performance with best performance per classifier in bold.

<table>
<thead>
<tr>
<th>Classifiers</th>
<th>Document Unigram</th>
<th>Document Ngram</th>
<th>Sentence Unigram</th>
<th>Sentence Ngram</th>
</tr>
</thead>
<tbody>
<tr>
<td>kNN</td>
<td>0.6670</td>
<td>0.7108</td>
<td>0.7615</td>
<td>0.7790</td>
</tr>
<tr>
<td>naïve Bayes</td>
<td>0.6572</td>
<td>0.6484</td>
<td>0.7715</td>
<td>0.7777</td>
</tr>
<tr>
<td>SVM</td>
<td>0.6904</td>
<td>0.7428</td>
<td>0.7282</td>
<td>0.7682</td>
</tr>
</tbody>
</table>

To compare the performance of the classification methods, we use F1 and accuracy. We perform standard 10-fold cross-validation on the set of documents. For the sentence-level approach, all sentences in a document are either entirely in the training set or entirely in the test set for each fold. For significance tests, we use a two-tailed t-test to compare the values obtained during each cross-validation fold with a p-value of 0.05.

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Table 2: Summary for n-grams versus unigrams (left) and sentence-level classifiers vs. document-level classifiers (right).

<table>
<thead>
<tr>
<th></th>
<th>Doc Winner</th>
<th>Sent Winner</th>
<th>F1</th>
<th>Acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>kNN</td>
<td>Unigram</td>
<td>Ngram</td>
<td>F1</td>
<td>Acc</td>
</tr>
<tr>
<td>naïve Bayes</td>
<td>Unigram</td>
<td>Ngram</td>
<td>F1</td>
<td>Acc</td>
</tr>
<tr>
<td>SVM</td>
<td>Ngram¹</td>
<td>Ngram</td>
<td>F1</td>
<td>Acc</td>
</tr>
</tbody>
</table>

Table 3: Performance for Sentence Detection.

<table>
<thead>
<tr>
<th></th>
<th>Unigram</th>
<th>Ngram</th>
<th>Unigram</th>
<th>Ngram</th>
</tr>
</thead>
<tbody>
<tr>
<td>kNN</td>
<td>0.9519</td>
<td>0.9536</td>
<td>0.6540</td>
<td>0.6686</td>
</tr>
<tr>
<td>naïve Bayes</td>
<td>0.9419</td>
<td>0.9530</td>
<td>0.6176</td>
<td>0.6676</td>
</tr>
<tr>
<td>SVM</td>
<td>0.9359</td>
<td>0.9579</td>
<td>0.6271</td>
<td>0.6672</td>
</tr>
</tbody>
</table>

5. REFERENCES