Automatically Predicting Peer-Review Helpfulness

Wenting Xiong
University of Pittsburgh
Department of Computer Science
Pittsburgh, PA, 15260
wex12@cs.pitt.edu

Diane Litman
University of Pittsburgh
Department of Computer Science &
Learning Research and Development Center
Pittsburgh, PA, 15260
litman@cs.pitt.edu

Abstract

Identifying peer-review helpfulness is an important task for improving the quality of feedback that students receive from their peers. As a first step towards enhancing existing peer-review systems with new functionality based on helpfulness detection, we examine whether standard product review analysis techniques also apply to our new context of peer reviews. In addition, we investigate the utility of incorporating additional specialized features tailored to peer review. Our preliminary results show that the structural features, review unigrams and meta-data combined are useful in modeling the helpfulness of both peer reviews and product reviews, while peer-review specific auxiliary features can further improve helpfulness prediction.

1 Introduction

Peer reviewing of student writing has been widely used in various academic fields. While existing web-based peer-review systems largely save instructors effort in setting up peer-review assignments and managing document assignment, there still remains the problem that the quality of peer reviews is often poor (Nelson and Schunn, 2009). Thus to enhance the effectiveness of existing peer-review systems, we propose to automatically predict the helpfulness of peer reviews.

In this paper, we examine prior techniques that have been used to successfully rank helpfulness for product reviews, and adapt them to the peer-review domain. In particular, we use an SVM regression algorithm to predict the helpfulness of peer reviews based on generic linguistic features automatically mined from peer reviews and students’ papers, plus specialized features based on existing knowledge about peer reviews. We not only demonstrate that prior techniques from product reviews can be successfully tailored to peer reviews, but also show the importance of peer-review specific features.

2 Related Work

Prior studies of peer review in the Natural Language Processing field have not focused on helpfulness prediction, but instead have been concerned with issues such as highlighting key sentences in papers (Sandor and Vorndran, 2009), detecting important feedback features in reviews (Cho, 2008; Xiong and Litman, 2010), and adapting peer-review assignment (Garcia, 2010). However, given some similarity between peer reviews and other review types, we hypothesize that techniques used to predict review helpfulness in other domains can also be applied to peer reviews. Kim et al. (2006) used regression to predict the helpfulness ranking of product reviews based on various classes of linguistic features. Ghose and Ipeirotis (2010) further examined the socio-economic impact of product reviews using a similar approach and suggested the usefulness of subjectivity analysis. Another study (Liu et al., 2008) of movie reviews showed that helpfulness depends on reviewers’ expertise, their writing style, and the timeliness of the review. Tsur and Rappoport (2009) proposed RevRank to select the most helpful book reviews in an unsupervised fashion based on review lexicons. However, studies of Amazon’s product reviews also show that the per-
ceived helpfulness of a review depends not only on its review content, but also on social effects such as product qualities, and individual bias in the presence of mixed opinion distribution (Danescu-Niculescu-Mizil et al., 2009).

Nonetheless, several properties distinguish our corpus of peer reviews from other types of reviews: 1) The helpfulness of our peer reviews is directly rated using a discrete scale from one to five instead of being defined as a function of binary votes (e.g. the percentage of “helpful” votes (Kim et al., 2006)); 2) Peer reviews frequently refer to the related students’ papers, thus review analysis needs to take into account paper topics; 3) Within the context of education, peer-review helpfulness often has a writing specific semantics, e.g. improving revision likelihood; 4) In general, peer-review corpora collected from classrooms are of a much smaller size compared to online product reviews. To tailor existing techniques to peer reviews, we will thus propose new specialized features to address these issues.

## 3 Data and Features

In this study, we use a previously annotated peer-review corpus (Nelson and Schunn, 2009; Patchan et al., 2009), collected using a freely available web-based peer-review system (Cho and Schunn, 2007) in an introductory college history class. The corpus consists of 16 papers (about six pages each) and 267 reviews (varying from twenty words to about two hundred words). Two experts (a writing instructor and a content instructor) (Patchan et al., 2009) were asked to rate the helpfulness of each peer review on a scale from one to five (Pearson correlation $r = 0.425$, $p < 0.01$). For our study, we consider the average ratings given by the two experts (which roughly follow a normal distribution) as the gold standard of review helpfulness. Two example rated peer reviews (shown verbatim) follow:

**A helpful peer review of average-rating 5:**

The support and explanation of the ideas could use some work. Broadening the explanations to include all groups could be useful. My concerns come from some of the claims that are put forth. Page 2 says that the 13th amendment ended the war. Is this true? Was there no more fighting or problems once this amendment was added?...

The arguments were sorted up into paragraphs, keeping the area of interest clear, but be careful about bringing up new things at the end and then simply leaving them there without elaboration (i.e. black sterilization at the end of the paragraph).

**An unhelpful peer review of average-rating 1:**

Your paper and its main points are easy to find and to follow.

As shown in Table 1, we first mine generic linguistic features from reviews and papers based on the results of syntactic analysis of the texts, aiming to replicate the feature sets used by Kim et al. (2006). While structural, lexical and syntactic features are created in the same way as suggested in their paper, we adapt the semantic and meta-data features to peer reviews by converting the mentions of product properties to mentions of the history topics and by using paper ratings assigned by peers instead of product scores.¹

| Class      | Label | Features                                                                 |
|------------|-------|--------------------------------------------------------------------------|
| Structural | STR   | review length in terms of tokens, number of sentences, percentage of sentences that end with question marks, number of exclamatory sentences. |
| Lexical    | UGR, BGR | $tf-idf$ statistics of review unigrams and bigrams.                       |
| Syntactic  | SYN   | percentage of tokens that are nouns, verbs, verbs conjugated in the first person, adjectives / adverbs and open classes, respectively. |
| Semantic   | TOP, posW, negW | counts of topic words, counts of positive and negative sentiment words. |
| Meta-data  | MET   | the overall ratings of papers assigned by reviewers, and the absolute difference between the rating and the average score given by all reviewers. |

Table 1: Generic features motivated by related work of product reviews (Kim et al., 2006).

¹We used MSTParser (McDonald et al., 2005) for syntactic analysis. Topic words are automatically extracted from all stu-
In addition, the following specialized features are motivated by an empirical study in cognitive science (Nelson and Schunn, 2009), which suggests that students' revision likelihood is significantly correlated with certain feedback features, and by our prior work (Xiong and Litman, 2010; Xiong et al., 2010) for detecting these cognitive science constructs automatically:

**Cognitive-science features (cogS):** For a given review, cognitive-science constructs that are significantly correlated with review implementation likelihood are manually coded for each idea unit (Nelson and Schunn, 2009) within the review. Note, however, that peer-review helpfulness is rated for the whole review, which can include multiple idea units. Therefore in our study, we calculate the distribution of feedbackType values (praise, problem, and summary) \((\text{Kappa} = .92)\), the percentage of problems that have problem localization — the presence of information indicating where the problem is localized in the related paper — \((\text{Kappa} = .69)\), and the percentage of problems that have a solution — the presence of a solution addressing the problem mentioned in the review — \((\text{Kappa} = .79)\) to model peer-review helpfulness. These kappa values (Nelson and Schunn, 2009) were calculated from a subset of the corpus for evaluating the reliability of human annotations. Consider the example of the helpful review presented in Section 3 which was manually separated into two idea units (each presented in a separate paragraph). As both ideas are coded as problem with the presence of problem localization and solution, the cognitive-science features of this review are praise\%=0, problem\%=1, summary\%=0, localization\%=1, and solution\%=1.

**Lexical category features (LEX2):** Ten categories of keyword lexicons developed for automatically detecting the previously manually annotated feedback types (Xiong et al., 2010). The categories are learned in a semi-supervised way based on syntactic and semantic functions, such as suggestion modal verbs (e.g. should, must, might, could, need), negations (e.g. not, don’t, doesn’t), positive and negative words, and so on. We first manually created a list of words that were specified as signal words for annotating feedbackType and problem localization in the coding manual; then we supplemented the list with words selected by a decision tree model learned using a Bag-of-Words representation of the peer reviews. These categories will also be helpful for reducing the feature space size as discussed below.

**Localization features (LOC):** Five features developed in our prior work (Xiong and Litman, 2010) for automatically identifying the manually coded problem localization tags, such as the percentage of problems in reviews that could be matched with a localization pattern (e.g. “on page 5”, “the section about”), the percentage of sentences in which topic words exist between the subject and object, etc.

## 4 Experiment and Results

Following Kim et al. (2006), we train our helpfulness model using SVM regression with a radial basis function kernel provided by SVMlight (Joachims, 1999). We first evaluate each feature type in isolation to investigate its predictive power of peer-review helpfulness; we then examine them together in various combinations to find the most useful feature set for modeling peer-review helpfulness. Performance is evaluated in 10-fold cross validation of our 267 peer reviews by predicting the absolute helpfulness scores (with Pearson correlation coefficient \(r\)) as well as by predicting helpfulness ranking (with Spearman rank correlation coefficient \(r_s\)). Although predicted helpfulness ranking could be directly used to compare the helpfulness of a given set of reviews, predicting helpfulness ranking is desirable in practice to compare helpfulness between existing reviews and new written ones without reranking all previously ranked reviews. Results are presented regarding the generic features and the specialized features respectively, with 95% confidence bounds.

### 4.1 Performance of Generic Features

Evaluation of the generic features is presented in Table 2, showing that all classes except syntactic (SYN) and meta-data (MET) features are sig-
significantly correlated with both helpfulness rating \((r)\) and helpfulness ranking \((r_s)\). Structural features (bolded) achieve the highest Pearson \((0.60)\) and Spearman correlation coefficients \((0.59)\) (although within the significant correlations, the difference among coefficients are insignificant). Note that in isolation, MET (paper ratings) are not significantly correlated with peer-review helpfulness, which is different from prior findings of product reviews (Kim et al., 2006) where product scores are significantly correlated with product-review helpfulness. However, when combined with other features, MET does appear to add value (last row).

When comparing the performance between predicting helpfulness ratings versus ranking, we observe \(r \approx r_s\) consistently for our peer reviews, while Kim et al. (2006) reported \(r < r_s\) for product reviews. Finally, we observed a similar feature redundancy effect as Kim et al. (2006) did, in that simply combining all features does not improve the model’s performance. Interestingly, our best feature combination (last row) is the same as theirs. In sum, our results verify our hypothesis that the effectiveness of generic features can be transferred to our peer-review domain for predicting review helpfulness.

| Features            | Pearson \(r \)   | Spearman \(r_s\) |
|---------------------|------------------|-------------------|
| STR                 | 0.60 ± 0.10*     | 0.59 ± 0.10*      |
| UGR                 | 0.53 ± 0.09*     | 0.54 ± 0.09*      |
| BGR                 | 0.58 ± 0.07*     | 0.57 ± 0.10*      |
| SYN                 | 0.36 ± 0.12      | 0.35 ± 0.11       |
| TOP                 | 0.55 ± 0.10*     | 0.54 ± 0.10*      |
| posW                | 0.57 ± 0.13*     | 0.53 ± 0.12*      |
| negW                | 0.49 ± 0.11*     | 0.46 ± 0.10*      |
| MET                 | 0.22 ± 0.15      | 0.23 ± 0.12       |
| All-combined        | 0.56 ± 0.07*     | 0.58 ± 0.09*      |
| STR+UGR+MET +TOP    | 0.61 ± 0.10*     | 0.61 ± 0.10*      |
| STR+UGR+MET         | 0.62 ± 0.10*     | 0.61 ± 0.10*      |

Table 2: Performance evaluation of the generic features for predicting peer-review helpfulness. Significant results are marked by * \((p \leq 0.05)\).

4.2 Analysis of the Specialized Features

Evaluation of the specialized features is shown in Table 3, where all features examined are signifi-

4The best performing single feature type reported (Kim et al., 2006) was review unigrams: \(r = 0.398\) and \(r_s = 0.593\).

5 Discussion

Despite the difference between peer reviews and other types of reviews as discussed in Section 2, our work demonstrates that many generic linguistic features are also effective in predicting peer-review helpfulness. The model’s performance can be alter-
Table 3: Evaluation of the model’s performance (all significant) after introducing the specialized features.

| Features       | Pearson r | Spearman r s |
|----------------|-----------|--------------|
| cogS           | 0.43 ± 0.09 | 0.46 ± 0.07  |
| LEX2           | 0.51 ± 0.11 | 0.50 ± 0.10  |
| LOC            | 0.45 ± 0.13 | 0.47 ± 0.11  |
| STR+MET+UGR   | 0.62 ± 0.10 | 0.61 ± 0.10  |
| STR+MET+LEX2   | 0.62 ± 0.10 | 0.61 ± 0.09  |
| STR+MET+LEX2+TOP | 0.65 ± 0.10 | 0.66 ± 0.08  |
| STR+MET+LEX2+TOP+cogS | 0.66 ± 0.09 | 0.66 ± 0.08  |
| STR+MET+LEX2+TOP+cogS+LOC | 0.67 ± 0.09 | 0.67 ± 0.08  |

6 Conclusions and Future Work

The contribution of our work is three-fold: 1) Our work successfully demonstrates that techniques used in predicting product review helpfulness ranking can be effectively adapted to the domain of peer reviews, with minor modifications to the semantic and metadata features. 2) Our qualitative comparison shows that the utility of generic features (e.g. meta-data features) in predicting review helpfulness varies between different review types. 3) We further show that prediction performance could be improved by incorporating specialized features that capture helpfulness information specific to peer reviews.

In the future, we would like to replace the manually coded peer-review specialized features (cogS) with their automatic predictions, since we have already shown in our prior work that some important cognitive-science constructs can be successfully identified automatically. Also, it is interesting to observe that the average helpfulness ratings assigned by experts (used as the gold standard in this study) differ from those given by students. Prior work on this corpus has already shown that feedback features of review comments differ not only between students and experts, but also between the writing and the content experts (Patchan et al., 2009). While Patchan et al. (2009) focused on the review comments, we hypothesize that there is also a difference in perceived peer-review helpfulness. Therefore, we are planning to investigate the impact of these different helpfulness ratings on the utilities of features used in modeling peer-review helpfulness. Finally, we would like to integrate our helpfulness model into a web-based peer-review system to improve the quality of both peer reviews and paper revisions.

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5The accuracy rate is 0.79 for predicting feedbackType, 0.78 for problem localization, and 0.81 for solution on the same history data set.
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