Automatically Assessing the Post Quality in Online Discussions on Software

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Abstract

Assessing the quality of user generated content is an important problem for many web forums. While quality is currently assessed manually, we propose an algorithm to assess the quality of forum posts automatically and test it on data provided by Nabble.com. We use state-of-the-art classification techniques and experiment with five feature classes: Surface, Lexical, Syntactic, Forum specific and Similarity features. We achieve an accuracy of 89% on the task of automatically assessing post quality in the software domain using forum specific features. Without forum specific features, we achieve an accuracy of 82%.

1 Introduction

Web 2.0 leads to the proliferation of user generated content, such as blogs, wikis and forums. Key properties of user generated content are: low publication threshold and a lack of editorial control. Therefore, the quality of this content may vary. The end user has problems to navigate through large repositories of information and find information of high quality quickly. In order to address this problem, many forum hosting companies like Google Groups¹ and Nabble² introduce rating mechanisms, where users can rate the information manually on a scale from 1 (low quality) to 5 (high quality). The ratings have been shown to be consistent with the user community by Lampe and Resnick (2004). However, the

percentage of manually rated posts is very low (0.1% in Nabble).

Departing from this, the main idea explored in the present paper is to investigate the feasibility of automatically assessing the perceived quality of user generated content. We test this idea for online forum discussions in the domain of software. The *perceived quality* is not an objective measure. Rather, it models how the community at large perceives post quality. We choose a machine learning approach to automatically assess it.

Our main contributions are: (1) An algorithm for automatic quality assessment of forum posts that learns from human ratings. We evaluate the system on online discussions in the software domain. (2) An analysis of the usefulness of different classes of features for the prediction of post quality.

2 Related work

To the best of our knowledge, this is the first work which attempts to assess the quality of forum posts automatically. However, on the one hand work has been done on automatic assessment of other types of user generated content, such as essays and product reviews. On the other hand, student online discussions have been analyzed.

Automatic text quality assessment has been studied in the area of automatic essay scoring (Valenti et al., 2003; Chodorow and Burstein, 2004; Attali and Burstein, 2006). While there exist guidelines for writing and assessing essays, this is not the case for forum posts, as different users cast their rating with possibly different quality criteria in mind. The same argument applies to the automatic assessment of product review usefulness (Kim et al., 2006c):

¹http://groups.google.com

²http://www.nabble.com

| Stars | Label on the website | Number |
|--------|----------------------|--------|
| * | Poor Post | 1251 |
| ** | Below Average Post | 44 |
| *** | Average Post | 69 |
| * * ** | Above Average Post | 183 |
| ***** | Excellent Post | 421 |

Table 1: Categories and their usage frequency.

Readers of a review are asked "Was this review helpful to you?" with the answer choices Yes/No. This is very well defined compared to forum posts, which are typically rated on a five star scale that does not advertise a specific semantics.

Forums have been in the focus of another track of research. Kim et al. (2006b) found that the relation between a student's posting behavior and the grade obtained by that student can be assessed automatically. The main features used are the number of posts, the average post length and the average number of replies to posts of the student. Feng et al. (2006) and Kim et al. (2006a) describe a system to find the most authoritative answer in a forum thread. The latter add speech act analysis as a feature for this classification. Another feature is the author's trustworthiness, which could be computed based on the automatic quality classification scheme proposed in the present paper. Finding the most authoritative post could also be defined as a special case of the quality assessment. However, it is definitely different from the task studied in the present paper. We assess the perceived quality of a given post, based solely on its intrinsic features. Any discussion thread may contain an indefinite number of good posts, rather than a single authoritative one.

3 Experiments

We seek to develop a system that adapts to the quality standards existing in a certain user community by learning the relation between a set of features and the perceived quality of posts. We experimented with features from five classes described in table 2: *Surface, Lexical, Syntactic, Forum specific and Similarity features.*

We use forum discussions from the *Software* category of Nabble.com.⁵ The data consists of 1968 rated posts in 1788 threads from 497 forums. Posts can be rated by multiple users, but that happens

rarely. 1927 posts were rated by one, 40 by two and 1 post by three users. Table 1 shows the distribution of average ratings on a five star scale. From this statistics, it becomes evident that users at Nabble prefer extreme ratings. Therefore, we decided to treat the posts as being binary rated.: Posts with less than three stars are rated "bad". Posts with more than three stars are "good".

We removed 61 posts where all ratings are exactly three stars. We removed additional 14 posts because they had contradictory ratings on the binary scale. Those posts were mostly spam, which was voted high for commercial interests and voted down for being spam. Additionally, we removed 30 posts that did not contain any text but only attachments like pictures. Finally, we removed 331 non English posts using a simple heuristics: Posts that contained a certain percentage of words above a pre-defined threshold, which are non-English according to a dictionary, were considered to be non-English.

This way, we obtained 1532 binary classified posts: 947 good posts and 585 bad posts. For each post, we compiled a feature vector, and feature values were normalized to the range $[0.0, \ldots, 1.0]$.

We use support vector machines as a state-of-theart-algorithm for binary classification. For all experiments, we used a C-SVM with a gaussian RBF kernel as implemented by LibSVM in the YALE toolkit (Chang and Lin, 2001; Mierswa et al., 2006). Parameters were set to C = 10 and $\gamma = 0.1$. We performed stratified ten-fold cross validation⁶ to estimate the performance of our algorithm. We repeated several experiments according to the leave-one-out evaluation scheme and found comparable results to the ones reported in this paper.

4 Results and Analysis

We compared our algorithm to a majority class classifier as a baseline, which achieves an accuracy of 62%. As it is evident from table 3, most system configurations outperform the baseline system. The best performing single feature category are the Forum specific features. As we seek to build an adaptable system, analyzing the performance without these features is worthwhile: Using all other features, we

⁵http://www.nabble.com/Software-f94.html

⁶See (Witten and Frank, 2005), chapter 5.3 for an in-depth description.

| Surface FeaturesLength Question Frequency Exclamation Frequency Capital Word Frequency DifferenceThe number of tokens in a post. The percentage of sentences ending with "?".Lexical FeaturesSpelling Error Frequency Swear Word FrequencyThe percentage of sentences ending with "!".Information about the wording of the postsSwear Word Frequency Syntactic FeaturesThe percentage of words that are not spelled correctly. ³ Syntactic FeaturesSuggestion Sentences Syntactic FeaturesThe percentage of words that are not spelled correctly. ³ Porter SolutionSuggestion Sentences Syntactic FeaturesThe percentage of words that are not spelled correctly. ³ Porter SolutionSuggestion Sentences Suggestion SentencesThe percentage of words that are not spelled correctly. ³ Porter SolutionSuggestion Sentences Suggestion SentencesThe percentage of words that are not spelled correctly. ³ Syntactic FeaturesThe percentage of words that are not spelled correctly. ³ Properties of a postIsHTMLWhether or not a post contains HTML. In our data, this is encoded explicitly, but it can also be determined by regular expressions matching HTML tags.Properties of a postIsMailWhether or not a post has been copied from a mailing list. This is encoded explicitly in our data.Present in forum postingsQuote FractionThe fraction of characters that are inside quotes of other posts. These quotes are marked explicitly in our data.Similarity featuresForums are focussed on a topic. The relatedness of a post to the topic of the forum may influence post quality. We capture this relatedness by | Feature category | Feature name | Description |
|---|----------------------|--------------------------|---|
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| between the posts unigram vector and the unigram vector of the forum. | - | | forum may influence post quality. We capture this relatedness by the cosine |
| | | | between the posts unigram vector and the unigram vector of the forum. |

Table 2: Features used for the automatic quality assessment of posts.

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achieve an only slightly worse classification accuracy. Thus, the combination of all other features captures the quality of a post fairly well.

| SUF | LEX | SYN | FOR | SIM | Avg. accuracy |
|---------------|----------|--------------|-----|--------|---------------|
| | Baseline | | | 61.82% | |
| $\overline{}$ | | | | | 89.10% |
| $\overline{}$ | - | _ | _ | - | 61.82% |
| _ | | _ | _ | _ | 71.82% |
| _ | _ | | _ | _ | 82.64% |
| _ | _ | _ | | _ | 85.05% |
| _ | _ | _ | _ | | 62.01% |
| _ | | | | | 89.10% |
| | _ | | | | 89.36% |
| | | _ | | | 85.03% |
| | | | _ | | 82.90% |
| | | | | _ | 88.97% |
| _ | | | | - | 88.56% |
| | _ | _ | | _ | 85.12% |
| _ | - | \checkmark | | - | 88.74% |

Table 3: Accuracy with different feature sets. SUF: Surface, LEX: Lexical, SYN: Syntax, FOR: Forum specific, SIM: similarity. The *baseline* results from a majority class classifier.

We performed additional experiments to identify the most important features from the Forum specific ones. Table 4 shows that IsMail and Quote Fraction are the dominant features. This is noteworthy, as those features are not based on the domain of discussion. Thus, we believe that these features will perform well in future experiments on other data.

| ISM | ISH | QFR | URL | PAC | Avg. accuracy |
|---------------|-----|-----|-----|-----|---------------|
| $\overline{}$ | | | | | 85.05% |
| | _ | _ | _ | _ | 73.30% |
| _ | | _ | _ | _ | 61.82% |
| - | _ | | _ | _ | 73.76% |
| - | _ | - | | _ | 61.29% |
| _ | _ | _ | _ | | 61.82% |
| _ | | | | | 74.41% |
| | _ | | | | 85.05% |
| | | _ | | | 73.30% |
| | v | | _ | | 85.05% |
| | | | | - | 85.05% |
| | _ | | _ | _ | 84.99% |
| | | | - | - | 85.05% |

Table 4: Accuracy with different forum specific features. ISM: IsMail, ISH: IsHTML, QFR: QuoteFraction, URL: URL-Count, PAC: PathCount.

Error Analysis Table 5 shows the confusion matrix of the system using all features. Many posts that were misclassified as good ones show no apparent reason to be classified as bad posts to us. The understanding of their rating seems to require deep knowledge about the specific subject of discussion. The few remaining posts are either spam or rated negatively to signalize dissent with the opinion expressed in the post. Posts that were misclassified as bad ones often contain program code, digital signatures or other non-textual parts in the body. We plan to address these issues with better preprocessing in

| | true good | true bad | sum |
|------------|-----------|----------|------|
| pred. good | 490 | 72 | 562 |
| pred. bad | 95 | 875 | 970 |
| sum | 585 | 947 | 1532 |

Table 5: Confusion matrix for the system using all features.

the future. However, the relatively high accuracy already achieved shows that these issues are rare.

5 Conclusion and Future Work

Assessing post quality is an important problem for many forums on the web. Currently, most forums need their users to rate the posts manually, which is error prone, labour intensive and last but not least may lead to the problem of premature negative consent (Lampe and Resnick, 2004).

We proposed an algorithm that has shown to be able to assess the quality of forum posts. The algorithm applies state-of-the-art classification techniques using features such as *Surface, Lexical, Syntactic, Forum specific and Similarity features* to do so. Our best performing system configuration achieves an accuracy of 89.1%, which is significantly higher than the baseline of 61.82%. Our experiments show that forum specific features perform best. However, slightly worse but still satisfactory performance can be obtained even without those.

So far, we have not made use of the structural information in forum threads yet. We plan to perform experiments investigating speech act recognition in forums to improve the automatic quality assessment. We also plan to apply our system to further domains of forum discussion, such as the discussions among active Wikipedia users.

We believe that the proposed algorithm will support important applications beyond content filtering like automatic summarization systems and forum specific search.

Acknowledgments

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