Subjective versus Objective Questions: Perception of Question Subjectivity in Social Q&A

Zhe Liu(✉) and Bernard J. Jansen

College of Information Sciences and Technology, The Pennsylvania State University, University Park, PA 16802, USA
zul112@ist.psu.edu, jjansen@acm.org

Abstract. Recent research has indicated that social networking sites are being adopted as venues for online information-seeking. In order to understand questioner's intention in social Q&A environments and to better facilitate such behaviors, we define two types of questions: subjective information-seeking questions and objective information seeking ones. To enable automatic detection on question subjectivity, we propose a predictive model that can accurately distinguish between the two classes of questions. By applying the classifier on a larger dataset, we present a comprehensive analysis to compare questions with subjective and objective orientations, in terms of their length, response speed, as well as the characteristics of their respondents. We find that the two types of questions exhibited very different characteristics. Also, we noticed that question subjectivity plays a significant role in attracting responses from strangers. Our results validate the expected benefits of differentiating questions according to their subjectivity orientations, and provide valuable insights for future design and development of tools that can assist the information seeking process under social context.

Keywords: Social Q&A · Social search · Information seeking · Social network · Twitter

1 Introduction

As understanding the information needs of users is crucial for designing and developing tools to support their social question and answering (social Q&A) behaviors, many of the past studies analyzed the topics and types of questions asked on social platforms [1-3]. With a similar aim in view, in this work, we also study the intentions of questioners in social Q&A, but we focus more specifically on identifying the subjectivity orientation of a question. In other words, we build a framework to differentiate the objective questions from the subjective ones. We believe this kind of subjectivity analysis can be very important in social Q&A due to several reasons: First, as previous studies suggested that both factual and recommendation/opinion seeking questions were asked on social platforms, our study allows people to automatically detect the underlying user intent behind any question, and thus provide more appropriate answers. More specifically, we assume that objective questions focus more on

N. Agarwal et al. (Eds.): SBP 2015, LNCS 9021, pp. 131–140, 2015.
DOI: 10.1007/978-3-319-16268-3_14

the accuracy of their responses, while subjective questions require more diverse replies that rely on opinion and experience. Second, we believe that our work can serve as the first step in implementing an automatic question routing system in social context. By automatically distinguishing subjective questions from the objective ones, we could ultimately build a question routing mechanism that can direct a question to its potential answerers according to its underlying intent. For instance, given a subjective question, we could route it to someone who shares about the same experience or knows the context well to provide more personalized responses, while for an objective question, we could contact a selected set of strangers based on their expertise or could submit it to submit it to search engines.

From the above viewpoint, we carry out our subjective analysis on Twitter. We implement and evaluate multiple classification algorithms with the combination of lexical, part-of-speech tagging, contextual and Twitter-specific features. With the classifier on question subjectivity, we also conduct a comprehensive analysis on how subjective and objective question differs in terms of their length, posting time, response speed, as well as the characteristics of their respondents. We show that subjective questions contain more contextual information, and are being asked more during working hours. Compared to the subjective information-seeking tweets, objective questions tend to experience a shorter time-lag between posting and receiving responses. Moreover, we also notice that subjective questions attract more responses from strangers than objective ones.

2 Related Work

As an emerging concept, social Q&A has been given very high expectations due to its potential as an alternative to traditional information-seeking tools. Jansen et al. [4] in their work examining Twitter as a mechanism for word-of-mouth advertising reported that 11.1% of the brand-related tweets were information-providing, while 18.1% were information-seeking . Morris et al. [1] manually labeled a set of questions posted on social networking platforms and identified 8 question types in social Q&A, including: recommendation, opinion, factual knowledge rhetorical, invitation, favor, social connection and offer. Zhao and Mei [5] classified question tweets into two categories: tweets conveying information needs and tweets not conveying information needs. Harper et al. [6] automatically classified questions into conversational and informational, and reached an accuracy of 89.7% in their experiments.

As for the task of question subjectivity identification, Li et al. [7] explored a supervised learning algorithm utilizing features from both the perspectives of questions and answers to predict the subjectivity of a question. Zhou et al. [8] automatically collect training data based on social signals, such as like, vote, answer number, etc, in CQA sites. Chen et al. [9] built a predictive model based on both textual and meta features, and co-training them to classify questions into: subjective, objective, and social. Aikawa et al. [10] employed a supervised approach in detecting Japanese subjective questions in Yahoo!Chiebukuro and evaluated the classification results using weighed accuracy which reflected the confidence of annotation.

Although a number of works exist on question subjectivity detection, none of them are conducted within social context. Considering the social nature of Q&A on SNS, we present this study, focusing on comparing objective and subjective questions in social Q&A, and propose the overarching research question of this study:

How subjective and objective information-seeking questions differ in the way they are being asked and answered?

To measure the difference, we first propose an approach which can automatically distinguish objective questions from subjective ones using machine learning techniques. In addition, we introduce metrics to examine each type of question.

3 Annotation Method

To guide the annotation process, we in this section present the annotation criteria adopted for identifying the subjective and objective questions in social context.

Subjective Information-Seeking Tweet: The intent of a subjective information-seeking tweet is to receive responses reflecting the answerer's personal opinions, advices, preferences, or experiences. A subjective information-seeking tweet is usually with a "survey" purpose, which encourages the audience to provide their personal answers.

Objective Information-Seeking Tweet: The intent of an objective information-seeking tweet is to receive answers based on some factual knowledge or common experiences. The purpose of an objective question is to receive one or more correct answers, instead of responses based on the answerer's personal experience.

Considering that not all questions on Twitter are of information-seeking purpose, in our annotation criteria we also adopted the taxonomy of information-seeking and non-information-seeking tweets from [10], although differentiating these two types are not of our interest in this study.

To better illustrate our annotation criteria used in this study, in Table 1 we listed a number of sample questions with subjective, objective or non- information-seeking intents.

Table 1. Subjectivity categories used for annotation

Question Type	Sample Questions
Subjective	• Can anyone recommend a decent electric toothbrush? • How does the rest of the first season compare to the pilot? Same? Better? Worse?
Objective	• When is the debate on UK time? • Mac question. If I want to print a doc to a color printer but in B&W how do I do it?
Non-information	• Why is school so early in the mornings? • There are 853 licensed gun dealers in Phoenix alone. Does that sound like Obama's taking away gun rights?

Given the low percentage of information-seeking questions on Twitter [11], to save our annotator's time and effort, in this study, we crawled question tweets from Replyz (www.replyz.com). Replyz is a very popular Twitter-based Q&A site, which searches through Twitter in real time looking for posts that contain questions based on their own algorithm (Replyz has been shut down on 31 July, 2014). By collecting questions through Replyz, we filtered out a large number of non-interrogative tweets.

For our data collection, we employed a snowball sampling approach. To be more specific, we started with the top 10 contributors who have signed in Replyz with their Twitter account as listed on Replyz's leaderboard. For each of these users, we crawled all the question tweets that they have answered in the past from their Replyz profile. Then, we identified the individuals who posted those collected questions and went to their profile to crawl all the interrogative tweets that they have ever responded. We repeated this process until each "seed" user yielded at least 1,000 other unique accounts. After removing non-Twitter questioners in our collection, in total, we crawled 25,697 question tweets and 271,821 answers from 10,101 unique questioners and 148,639 unique answerers.

We randomly sampled 3,000 English questions from our collection and recruited two human annotators to work on the labeling task based on our annotation criteria on subjective, objective and non-information-seeking tweets. Finally, 2,588 out of 3,000 questions (86.27%) received agreement on their subjectivity orientation from the two coders. Among the 2,588 interrogative tweets, 24 (0.93%) were labeled as with mix intent, 1,303 (50.35%) were annotated as non-information seeking, 536 (20.71%) as subjective information seeking, and the rest 725 (28.01%) as objective information seeking. Our Cohen's kappa is quite high at 0.75.

4 Question Subjectivity Detection

4.1 Feature Engineering

In this section, features extracted for the purpose of question subjectivity detection are introduced. In total, we have identified features from four different aspects, including: lexical, POS tagging, context and Twitter-specific features.

Lexical Features: we adopted word-level n-gram features. We counted the frequencies of all unigram, bigram, and trigram tokens that appeared in the training data. Before feature extraction, we lowercase and stemmed all the tokens using the Porter stemmer [12].

POS Tagging Features: In addition to the lexical features, we also believed that POS tagging can add more context to the words used in the interrogative tweets. To tag the POS of each tweet, we used the Stanford tagger [13].

Syntactic Features: The syntactic features describe the format or the context of a subjective or objective information-seeking tweet. The syntactic features that we adopted in this study include: the length of the tweet, number of clauses/sentences in the tweet, whether or not there is a question mark in the middle of the tweet, whether or not there are consecutive capital letters in the tweet.

Contextual Features: We assume that contextual features, such as URL, hashtag, etc., can provide extra signals for determining whether a question is subjective or objective. The contextual features that we adopted in this study are: whether or not a question tweet contains a hashtag, a mention, a URL, and an emoticon.

For both lexical and POS tagging features, we discarded rare terms with observed frequencies of less than 5 to reduce the sparsity of the data.

4.2 Classification Evaluation

We next built a binary classifier to automatically label subjective and objective information-seeking questions. We tested our model using a number of classification algorithms implemented in Weka, including: Naïve Bayes, LibSVM, and SMO, using 10-fold cross-validation. We only reported the best results obtained.

First, we evaluated the classification accuracies along with the number of features selected using the algorithm of information gain as mentioned above. We noticed that all three algorithms attained high accuracies when the number of features selected equaled to about 200. Next, based on the 200 features selected, we accessed the classification performances based on the evaluation metrics provided by Weka, including accuracy, precision, recall, and F-measure. The majority induction algorithm, which simply predicts the majority class, was applied to determine the baseline performance of our classifier. Table 2 demonstrated the classification results.

Table 2. Classification results using the top 500 selected features

Method	Accuracy	Precision	Recall	F1
NaïveBayes	80.12	83.46	22.16	35.02
LibSVM	76.17	90.58	43.47	58.75
SMO	81.65	87.66	26.63	40.85

5 Impact of Question Subjectivity on User Behavior

In this section, we address our research goal by understanding the impact of question subjectivity on individual's asking and answering behaviors in social Q&A. In order to do that, we first need to identify the subjectivity orientation of all 25,697 collected questions. However, as we built our classification model as a further step of providing subjectivity indication only after a question has been predetermined as informational, we can't directly apply it to the entire data set. So, to solve this challenge, we adopted the text classifier as proposed in [5] and [11] to eliminated all non-information-seeking tweets first. With the adopted method, we achieved a classification accuracy of 81.66%. We believe this result reasonable comparing to the 86.6% accuracy reported in [5], as Replyz has already removed a huge number of non-informational questions based on some obvious features, such as whether or not the question contains a linketc. We presented the overall statistics of our classified data set in Table 3.

5.1 Characterizing the Subjective and Objective Questions

Given the positive correlation reported between question length and degree of personalization in [14], we assume that subjective information-seeking questions on Twitter are longer than the objective ones. To examine the difference, we conducted Mann–Whitney U test across the question types on character and word scales.

Table 3. Classification results using the top 500 selected features

Question Type	Non-informational	Informational	
		Subjective	Objective
Questions	15, 311	3,984	6,402
Questioners	4,762	2,267	3,072
Answers	169,690	44,636	57,495
Answerers	87,331	28,190	33,118

In our data set, information-seeking questions asked on Twitter had an average length of 81.47 characters and 14.78 words. With the empirical cumulative distribution function (ECDF) of the question length plotted in Figure 1, we noticed that both the number of characters and words differ across question subjectivity categories. Consistent with our hypothesis, in general subjective information-seeking tweets (M_c = 87, M_w = 15.95) contain more characters and words than the objective ones (M_c = 73, Mn_w = 14.05). Mann–Whitney U test further proofed our findings with statistically significant p-values less than 0.05 (z_c = -17.39, p_c = 0.00 < 0.05; z_w = -15.75, p_w = 0.00 < 0.05). Through our further investigation on the content of questions, we noted that subjective questions tended to use more words to provide additional contextual information about the questioner's information needs. Examples of such questions include: *"So after listening to @wittertainment and the Herzog interview I need to see more of his work but where to start? Some help @KermodeMovie ?", and "Thinking about doing a local book launch in #ymm any of my tweeps got any ideas?"*

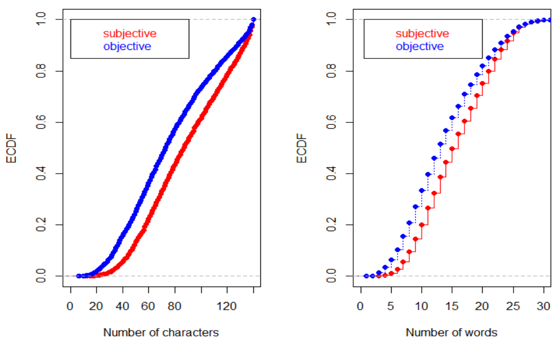

Fig. 1. Distribution of question length on character and word levels

5.2 Characterizing the Subjective and Objective Answers

So far, we have only examined the characteristics of subjective and objective information-seeking questions posted on Twitter. In this subsection, we presented how the subjectivity orientation of a question can affect its response.

Response Speed

Considering the real time nature of social Q&A, we first looked at how quickly subjective and objective information-seeking questions receive their responses. We adopted two metrics in this study to measure the response speed: the time elapsed until receiving the first answer, and the time elapsed until receiving the last answer. In Figure 2, we plotted the empirical cumulative distribution of response time in minutes using both measurements. We log transformed the response time given its logarithmic distribution.

In our data set, more than 80% of questions posted on Twitter received their first answer in 10 minutes or less, no matter their question types (84.60% objective questions and 83.09% subjective ones). Around 95% of questions got their first answer in an hour, and almost all questions were answered within a day. From Figure 5, we noticed that it took slightly longer for individuals to answer subjective questions than the objective ones. The t-test result also revealed significant difference on the arrival time of the first answer between question types ($t = -3.08$, $p < 0.05$), with subjective questions on average being answered in 4.60 minutes after the question was posted and objective questions being answered in 4.24 minutes. We assumed that this might because subjective questions were mainly posted during working hours, whereas, respondents were more active during free time hours [14].

In addition to the first reply, we also adopted the arrival time of the last answer to imply the temporality of each question. Define in [15], question temporality is "a measure of how long the answers provided on a question are expected to be valuable". Overall, 67.79% of subjective and 69.49% objective questions received their last answer in an hour. More than 96% of questions of both types closed in a day (96.68% objective questions and 96.16% subjective ones). Again, the t-test result demonstrated significant between-group difference on the arrival time of the last answer ($t = 3.76$, $p < 0.05$), with subjective questions on average being last answered in 44 minutes after the question was posted and objective questions being answered in 38 minutes. Examples of objective questions with short temporal durations include: *"Hey, does anyone know if Staples & No Frills are open today?"* and "*When is LFC v Valarenga?"*

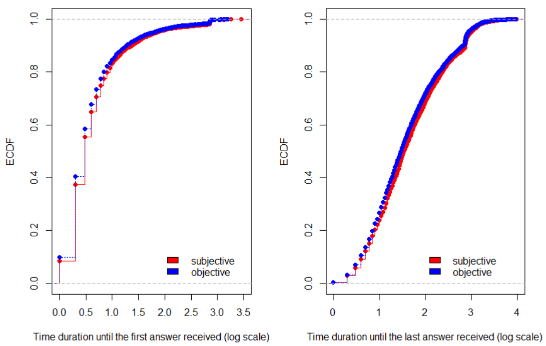

Fig. 2. Distribution of question response time in minutes

Characteristics of Respondents

In addition to the response speed, we were also interested in understanding whether the characteristics of a respondent affect his/her tendency to answer a subjective or objective question on Twitter. In order to do so, we proposed a number of profile-based factors, including: the number of followers, the number of friends, daily tweet volume, which is measured as the ratio of the total count of status to the total number of days on Twitter, and the friendship between the questioner and the respondent. Here, we only categorized questioner-answerer pairs with reciprocal follow relations as "friends", while the rest as "strangers".

We crawled the profile information of all respondent in our dataset, as well as their friendships with the corresponding questioners via Twitter API. Since our data set spanned from March 2010 to February 2014, 2,998 out of 59,856 unique users in our collection have either deleted their Twitter accounts or have their accounts set as private. So, we were only able to collect the follow relationship between 95% (78,697) of the unique questioner-answer pairs in our data set.

We used logistic regression to test whether any of our proposed factors were independently associated with the respondent's behavior of answering subjective or objective questions on Twitter. The results of our logistic regression analysis were shown in Table 4.

Table 4. Logistic regression analysis of variables associated with subjective or objective question answering behavior

Predictor	Odds Ratio	p-value
Number of followers	1.00	0.24
Number of friends	1.00	0.07
Daily tweet volume	0.99	0.00*
Friendship	1.04	0.03*

From Table 4, we noticed that among all four variables, the respondent's daily tweet volume and friendship with the questioner were significantly associated with his/her choice of answering subjective or objective questions in social Q&A. To better understand those associations, we further performed post hoc analyses on those significant factors.

First, as for the friendship between the questioner and the respondent, among all 78,697 questioner-answerer pairs in our data set, 22,220 (28.23%) of the follow relations were reciprocal, 24,601 (31.26%) were one-way and 31,871 (40.51%) were not following each other. The number of reciprocal following relations in our collection is relatively low, comparing to the 70%-80% and the 36% rates as reported in [16, 17] .We think this is because Replyz has created another venue for people to answer other's questions, even if they were not following each other on Twitter, and this enabled us to better understand how strangers in social Q&A select and answer questions.

Besides the overall patterns described, we also conducted chi-square test to examine the dependency between the questioner-respondent friendship and the answered question type. As shown in Table 5, the chi-square cross-tabulations revealed a significant trend between the two variables ($\chi^2 = 13.96$, $p = 0.00 < 0.05$). We found that in real-world settings, "strangers" were more likely to answer subjective questions than "friends". This was unexpected given previous work [1] showed that people claimed in survey that they prefer to ask subjective questions to their friends for tailored responds. One reason for this could be that compared to objective questions, subjective questions require less expertise and time investment, so that could be a better option for strangers to offer their help.

Table 5. Answered question type by questioner-answerer friendship

Question Type	Friendship Type	
	Friends	Strangers
Subjective	23.9% (n = 6359)	25.3% (n = 20229)
Objective	76.1% (n = 8234)	74.7% (n = 24355)

In addition in order to examine the relationship between the respondent's daily tweet volume and his/her answered question type, a Mann–Whitney U test was performed. The result was significant ($z = -7.87$, $p = 0.00 < 0.05$), with respondents to the subjective questions having more tweets posted per day ($M = 15.07$) than the respondents of the subjective questions ($M = 13.24$). This result further proved our presumption in the previous paragraph that individuals with more time spent in social platforms are more willing to answer more time consuming questions, in our case, the objective ones.

6 Discussion and Conclusion

In this work, we distinguished and analyzed 6,402 objective and 3,984 subjective questions. First, we found that contextual restrictions were imposed more often on subjective questions, and thus made them normally longer in length than the objective ones. In addition, our results revealed that subjective questions experienced longer time-lags in getting their initial answers. Furthermore, we also noticed that it took shorter time for the objective questions to receive all their responses. One interpretation of this finding could be that many of the objective questions asked on Twitter were about real-time content (e.g. when will a game start? where to watch the election debates, etc.) and were sensitive to real world events [5], so answers to those questions tended to expire in shorter durations[15]. Another possible explanation was that, since answers to the objective questions were supposed to be less diverse, individuals would quickly stop providing responses after they saw a satisfactory number of answers already exist to those questions. Of course, both speculations need support from future detailed case studies. At last, in assessing the preferences of friends and strangers on answering subjective or objective questions, we demonstrated that even though individuals prefer to ask subjective questions to their friends for tailored responds [1], it turned out that, in reality, subjective questions were being responded more by strangers. We thought this gap between the ideal and reality imposed a design challenge in maximizing the personalization benefits from strangers in social Q&A.

In terms of design implications, we believe that our work contributes to the social Q&A field in two ways: First, our predictive model on question subjectivity enables automatic detection of subjective and objective information-seeking questions posted on Twitter and can be used to facilitate future studies on large scales. Second, our analysis results allow the practitioners to understand the distinct intentions behind subjective and objective questions, and to build corresponding tools or systems to better enhance the collaboration among individuals in supporting social Q&A activities. For instance, we believe that given the survey nature of subjective questions and stranger's interests in answering them, one could develop an algorithm to route those subjective questions to appropriate respondents based on their locations and past experiences. In contrast, considering the factorial nature and short duration of objective questions, they could be routed to either search engines or individuals with equivalent expertise or availability. In summary, our work is of good value to both research community and industrial practice.

References

1. Morris, M.R., Teevan, J., Panovich, K.: What do people ask their social networks, and why?: A survey study of status message Q & A behavior. In: SIGCHI (2010)
2. Lampe, C., et al.: Help is on the way: patterns of responses to resource requests on facebook. In: CSCW (2014)
3. Liu, Z., Jansen, B.J.: Almighty twitter, what are people asking for? In: ASIS & T (2012)
4. Jansen, B.J., et al.: Twitter Power: Tweets as Electronic Word of Mouth. Journal of the American Society for Information Science and Technology **60**(11), 2169–2188 (2009)
5. Zhao, Z., Mei, Q.: Questions about questions: An empirical analysis of information needs on twitter. In: WWW (2013)
6. Harper, F.M., Moy, D., Konstan, J.A.: Facts or friends?: distinguishing informational and conversational questions in social Q & A sites. In: SIGCHI (2009)
7. Li, B., et al.: Exploring question subjectivity prediction in community QA. In: SIGIR (2008)
8. Zhou, T.C., Si, X., Chang, Y.E., King, I., Lyu, M.R.: A data-driven approach to question subjectivity identification in community question answering. In: AAAI (2012)
9. Chen, L., Zhang, D., Mark, L.: Understanding user intent in community question answering. In: WWW (2012)
10. Aikawa, N., Sakai, T., Yamana, H.: Community qa question classification: Is the asker looking for subjective answers or not. IPSJ Online Transactions **4**, 160–168 (2011)
11. Li, B., et al.: Question identification on twitter. In: CIKM (2011)
12. Porter, M.F.: An Algorithm for Suffix Stripping. Program: Electronic Library and Information Systems **14**(3), 130–137 (1980)
13. Toutanova, K., et al.: Feature-rich part-of-speech tagging with a cyclic dependency network. In: NAACL2013-Volume 1
14. Liu, Z., Jansen, B.J.: Factors influencing the response rate in social question and answering behavior. In: CSCW (2013)
15. Pal, A., Margatan, J., Konstan, J.: Question temporality: identification and uses. In: CSCW (2012)
16. Paul, S.A., Hong, L., Chi, E.H.: Is twitter a good place for asking questions? a characterization study. In: ICWSM (2011)
17. Zhang, P.: Information seeking through microblog questions: The impact of social capital and relationships. In: ASIS & T (2012)