Crowdsourcing-based Feedback Analysis on Educational Management

Mahuya Soe[1], Sujoy Chatterjee[2], Anirban Mukhopadhyay[1]

[1]Department of Computer Science and Engineering, University of Kalyani, India,
[2]Informatics Cluster, University of Petroleum and Energy Studies, India,

Abstract

COVID-19 had an immense effect on the majority of international industries. Education is the only industry that has completely gone online in the majority of countries around the globe. It is necessary to rethink students' life during COVID-19 and solicit significant proactivity from the community. Crowdsourcing, which entails having a group of people work together to solve a complex problem and then publicly share ideas, is one approach for gathering community input. To make various strategic decisions to understand the emerging problems faced by the different people a crowdsourcing-based open call is performed. This type of open questionnaire comprises the opinions of the crowd over various questions in numerical format. In addition to the numerical rating, the decision-makers solicit textual information to support their opinions. Now, this type of problem arises a new kind of decision-making problem, where both textual and numerical information is collected from the crowd. A limited amount of research has been performed to study this type of problem as subjective labeling is present there, hence, distinguishing spammers from the normal crowd is challenging. We proposed a variety of techniques to assemble public opinions in both the numerical and textual format and find some novel topics to aid the decision-makers to think about alternative strategies in the education sector. Experimental results from real-life datasets demonstrate the effectiveness of the proposed method.

Motivation and Background

The recent coronavirus Omicron (COVID-19) outbreak had affected the education sector to a great extent. To prevent the transmission of COVID-19 during this time many universities/colleges went for online learning. Although many institutes have provided their best to impart knowledge in online mode, still, there exist substantial challenges faced by the students. As a decision-maker, it is highly important to understand the inherent problems raised in online learning. However, understanding this type of educational problem to take up a new strategy from students' perspective is not easy, but rather a time-consuming job. Therefore, outsourcing this problem to a crowd (11; 13) is effective and it can solve the task easily. Here, the university or college students who are involved in their studies can be thought of as Crowd (1).

Recently, a study was conducted to evaluate students' views about mobile learning after the current pandemic in basic education colleges in Kuwait(6). The study concluded with a good impression from the student in utilizing mobile learning in higher education. This study reported that the e-learning mode is an advancement in education, but significant efforts are needed to improve online learning applications. Some researchers investigate challenges and obstacles in e-learning during COVID-19 according to the educational facilities provided by different institutes(7). The focus of this study is to identify university students' obstacles during the current global crisis and provide possible solutions that can improve the learners' performance (4; 5; 6). Although crowdsourcing in this aspect is beneficial, the students (i.e. crowd) may not provide their actual perspectives (3). Rather, to malfunction it they may intentionally provide the wrong feedback. Hence, it is very important to track the good crowd workers who are providing their real perspectives. To be best of our knowledge, no study is available that consider various voting strategies like utilizing test question (discussed in the next paragraph), along with numeric and textual information to understand the perceptiveness of the crowd (i.e., students) in the educational domain during COVID situation. Here, the opinions are from their perceptiveness, hence identifying the good or bad crowd workers is really challenging.

This study identified the real challenges faced by students in online learning during the pandemic. While collecting the responses we design a set of twisted-pair questions, where one question is mostly synonymous with the other question but in a different form. For example, the tested hypotheses with the test questionnaire are alike each other are: 1) Do the majority of the students are distracted while few are consistent all the time throughout the online class, thus creating negative effects on student learning behavior? 2) Do you find off-task media multitasking while online learning is dividing attention and students get distracted during learning? State the reason in two sentences.

Therefore, if someone provides a good rating for one question, then he must provide a good rating for another question of that set. However, aggregating all the numeric and text information obtained from the crowd is difficult. In this work, an attempt has been made to find the aggregated answer from all of these opinions. Besides it, this study can provide top k-most annotators' opinions as well as gener-

ate a few novel ideas. Here, the Latent Dirichlet Allocation (LDA) model is used to discover a user-specified number of topics shared by the crowd (12).

Problem Formulation

Let us formalize the strategic decision-making from the crowdsourced environment. We consider a finite set of questions $Q = \{q_1, q_2 \ldots, q_n\}$ that are the annotation task and a finite set of annotators $A = \{a_1, a_2, \ldots, a_m\}$ who are the crowd workers. The finite set of opinion vector O in numeric format $O = \{o_1, o_2, \ldots..o_k\}$, where, O ranges in 1 to 5. On the other hand, $T = \{t_1, t_2, \ldots, t_k\}$ be text information provided by them to support their reasoning for their corresponding rating.

An annotation process is a 6 tuple $\{$(Q,A,O,T,F_1,F_2)$\}$ consisting of (i) a set of questions Q, (ii) a set of annotators A, (iii) a set of numeric opinions O, (iv) a set of textual reasoning provided by each crowd worker T (v) a mapping function for numeric rating, F_1: $(Q \times A) \mapsto O$ and (vi) another mapping function for textual opinion, F_2: $(Q \times A) \mapsto T$. The objective is to obtain the aggregated decision from numeric and textual information from the annotators of all the questions in Q. Moreover, it is very important to quantify the good annotator compared with the other annotators, hence finding the accuracy from the textual and numeric information is required.

Proposed Method

The proposed method first aims to determine which annotator provides the real perceptiveness of his own. We find the accuracy of the crowd workers in two different ways based on textual as well as numeric information. Finally, these accuracies are employed to find the final decision for all the questions. The steps for computing this are written below.

- From the obtained opinion, based on the numeric rating, we first apply the majority voting algorithm. After that, we find the deviation of each crowd from the majority and compute the accuracy. This accuracy acts as a weight to find the aggregated decision from all the crowd.
- Using the twisted Pairwise Questionnaire, we find the accuracy of the crowd worker from the numeric information. The twisted pair-wise question is some questions where two same questions are presented in a different way such that the crowd cannot recognize them easily. Hence, if someone responds with a high rating (agree) on one question, he should not provide a low rating (disagree) for another question of the same set. Thus, from the deviation of the two opinions for this twisted pair question, the quality of the crowd workers can be identified. Here, such type of three twisted-pair questions has been used.
- As discussed above, from the textual information of the twisted pairwise set, we find the closeness between two textual contexts of the two sentences by applying the cosine similarity metric. The crowd worker having high cosine similarity means the crowd worker responded most similar text in the twisting pair. Hence, it can be concluded that crowd workers with the most similar responses is the most authentic crowd worker on the twisted pairwise questionnaire set.
- Finally, for both the accuracy obtained from the twisted pairwise questions (textual accuracy) and numeric rating (numeric accuracy), we obtain the final accuracy of the crowd worker by summing up both the accuracies. Henceforth, we obtain the top k most annotator based on the final accuracy. Finally, to find the aggregated decision of each question, these weights are employed.

  Moreover, we apply LDA for finding the important topics out of all the textual information. Here, from this analysis, Decision makers can be aware of the topic in which the majority is quite interested. Additionally, many abstract ideas which are have not been considered by the decision makers can also be identified easily using this crowdsourcing approach.

Experimental Analysis

In our experimental design, we conducted a study aiming to analyze the online education challenges by posting 13 questions to the online crowd. 25 students, having diverse demographic areas from the University of Kalyani, India, have responded to the questions. The three accuracies e.g., textual, numerical, and overall (summing up of textual and numeric) of various crowd workers are demonstrated in Fig. 1. It can be noticed that for a few crowd workers the textual accuracy is zero. On the other hand, a few crowd workers have an accuracy of more than 90%. Thus, we find the aggregated rating of each question by using the weights of the overall accuracy (numeric and text) of the crowd. In Fig. 2, the extracted topics regarding one question "Supportiveness of the teacher in an online class" is presented. In this situation, it has been noticed that the extracted topics 'Supportive', 'Yes', etc. mentioned by the majority have a positive sentiments. Hence, this way new topics are generated which will be beneficial for the decision-makers to design new policies.

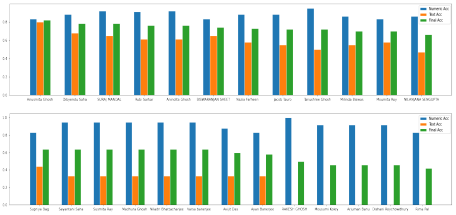

Figure 1: Snapshot of the annotators' accuracy based on twisted-pair questions ("Numeric rating" and "Text").

Figure 2: Snapshot of the extracted topic regarding "Supportiveness of the teacher in an online class".

Acknowledgment

A. Mukhopadhyay acknowledges the support received from the MATRICS project grant (MTR/2020/000326) of SERB, DST, Govt. of India. All the authors would like to thank the crowd contributors involved in this work.

References

[1] Chatterjee, Sujoy, Anirban Mukhopadhyay, and Malay Bhattacharyya (2019). *A review of judgment analysis algorithms for crowdsourced opinions*, IEEE Transactions on Knowledge and Data Engineering 32.7 (2019): 1234-1248.

[2] Chatterjee, Sujoy, Anirban Mukhopadhyay, and Malay Bhattacharyya(2017), *Smart city planning with constrained crowd judgment analysis*, In 2017 AAAI Spring Symposium Series. 2017.

[3] Day, Suzanne, et al. *Assessment of a Crowdsourcing open call for approaches to university community engagement and strategic planning during COVID-19*, JAMA network open 4.5 (2021): e2110090-e2110090.

[4] Ullah, Abaid, Mahmoona Ashraf, S. Ashraf, and S. Ahmed. *Challenges of online learning during the COVID-19 pandemic encountered by students in Pakistan*, Journal of Pedagogical Sociology and Psychology 3, no. 1 (2021): 36-44.

[5] Pham, Vu Phi Ho, and Thao Nguyen Da Vo, *"CALL in Asia during Covid-19 and Models of E-learning*, In 17th International Conference of the Asia Association of Computer-Assisted Language Learning (AsiaCALL 2021), pp. 1-10. Atlantis Press, 2021.

[6] Mahyoob, Mohammad. *Challenges of e-Learning during the COVID-19 Pandemic Experienced by EFL Learners*, Arab World English Journal (AWEJ) 11, no. 4 (2020).

[7] Kaisara, Godwin, and Kelvin Joseph Bwalya. *Investigating the E-learning challenges faced by students during COVID-19 in Namibia*, International Journal of Higher Education 10, no. 1 (2021): 308-318.

[8] Sawyer, E. A., Howard, C. (2007). *Online learning program strategic planning and execution: Considering goals, benefits, problems and communities of practice*. Journal of College Teaching Learning (TLC), 4(8).

[9] Liberman-Yaconi, Leonardo, Terrena Hooper, and Kate Hutchings. *Toward a model of understanding strategic decision-making in micro-firms: exploring the Australian information technology sector*, In Journal of Small Business Management 48, no. 1 (2010): 70-95.

[10] Divjak, Blaženka, and Nina Begicevic Redep. *Strategic Decision Making Cycle in Higher Education: Case Study of E-Learning*, International Association for Development of the Information Society (2015).

[11] Ipeirotis, P. G.; Provost, F.; and Wang, J. *Quality management on amazon mechanical turk*. In KDDWorkshop on Human Computation (HCOMP). 89. (2010)

[12] Ekinci, Ekin, and Sevinç İlhan Omurca. "Concept-LDA: Incorporating Babelfy into LDA for aspect extraction." Journal of Information Science 46, no. 3 (2020): 406-418.

[13] Alonso, O.; Rose, D.; and Stewart, B. *Crowdsourcing for relevance evaluation*. ACM SIGIR Forum 42(2):9–15, (2010)