




The Influence of Teacher Interactions on Sentiment Development in MOOC Discussion Forums

1st Ranjiraj Rajendran Nair
Faculty of Computer Science
Otto von Guericke University
Magdeburg, Germany
ranjiraj.nair@st.ovgu.de 

2nd Thomas Staubitz
Hasso Plattner Institute
University of Potsdam
Potsdam, Germany
thomas.staubitz@hpi.de 

3rd Christoph Meinel
Hasso Plattner Institute
University of Potsdam
Potsdam, Germany
christoph.meinel@hpi.de 

Abstract—

Massive Open Online Courses (MOOCs) are delivering rich learning content to a variety of audiences. Next to the learning material, the discussion forums play a major role in the success of MOOCs. A healthy climate in the discussions is of great importance for the motivation of the instructors and the participants. We have employed a sentiment analyzer to observe the development of the discussions in several of our courses. We expect to obtain a better understanding of the development in the discussions, the influence of the instructors' interventions on this behavior, and to some extent the dropout and course completion development.

I. MOTIVATION

During the recent years, MOOCs have developed to become a model for delivering rich learning content online to anyone, anywhere in the world [3]. Essentially, they provide a useful form of learning that complements traditional higher education [7]. Next to the delivery of learning material, such as videos, texts, interactive exercises, tests, and exams, the discussion forums often play a major role in the success of these courses. Most MOOC platforms offer a discussion forum that allows participants to become active contributors to a course. The majority of courses on our platform is offered in a semi-synchronous form. The content is delivered on a weekly basis throughout the active duration of the course, which can span over two, four, or six weeks. The exams and some of the exercises have deadlines, which often are scheduled at the end of a week. Within the weeks, however, the learners are free to access the material whenever they want. The discussion forums are mostly used as a communication tool among the learners and between the learners and the instructors. At the end of the course, the discussion forums are switched to *read-only* mode. The course material, except for the graded exams, as their deadlines have passed, stays available for everybody in archive mode. One of the tasks of the instructors and teaching teams on our MOOC platform is to maintain a good vibe in the discussion forums. Anecdotal observations of the teaching teams show that the development of the sentiment in the discussions influences the motivation of the teaching teams as well as the learners. To obtain a broader understanding of the mood development in the forums, its influence on the learners and their learning outcomes, and the influence of the instructor interventions on this development, we employed a

sentiment analyzer to measure these effects. Furthermore, we define and calculate various metrics to better estimate these learning behaviours, particularly, we propose a metric in the form of a polarity score to measure the impact of positive and negative discussions in the forum.

II. RELATED WORK

Learning analytics is the collection and analysis of data about learners and their learning context. Typically, this involves analyzing digital data, such as online material access, records, grades, and interactions. However, to get a more complete picture of the learning experience, emotional aspects should also be considered. The work from Suero Montero and Suhonen suggests analyzing non-structured text data, such as learning diaries, personal blogs, and chat communications, to identify emotions in online courses. They also discuss the role of negative emotions in learning, and ethical concerns related to using emotional data, and propose the use of automatic emotion detection and analysis to offer personalized feedback and support in online courses [9]. Gkontzis et al. used sentiment analysis techniques to extract emotional knowledge from student messages in forums and quizzes, focusing on a more educational data mining approach. They identify the polarity and emotion of messages and categorize them into positive, negative, or neutral [2]. *Discussion forums* allow participants to become active contributors on most MOOC platforms. Khalil and Ebner, examined 30 popular courses on 6 different MOOC platforms. According to this study, 80% of the examined MOOCs provided discussion groups [4]. Staubitz and Meinel, found evidence that courses with a high forum participation have better completion rates. But by far, not all course participants are active in the discussion forums. In the analysis of their platform, only 0.02% to 12% of the course participants are actively contributing to the discussions, whereas 12% to 52% are passively following them [8]. This aligns with observations on other MOOC platforms [1]. *Instructor interventions* in discussion forums have been categorized by Rossi et al. e.g. into answering questions, providing feedback, clarifying course concepts, encouraging discussion, and moderating forum interactions [6]. Wilson and Lipsey have analyzed the frequency and timing of instructor interventions to gain insights into the level of instructor

engagement and the effectiveness of the interventions [12]. Frequent and timely interactions indicate that the instructor is actively engaged with the forum and responsive to student needs. Wilkes and Bligh evaluated instructor interventions on the quality of the provided responses. Effective interventions are those that are relevant to the discussion, provide accurate information, and encourage further discussion or reflection among students [11]. The previously published work, shows that forum discussions are widely used in MOOCs and that the emotional development in these discussions as well as the influence of instructor interventions is worth further exploration. The paper at hand uses similar approaches and applies them on the large data set that we collected in our courses.

III. RESEARCH QUESTIONS

RQ1: *Can we establish a polarity score for the discussions in a course forum to determine the overall sentiment development throughout the course?* **RQ2:** *Is there any measurable correlation between the forum interaction and the course completion rates?* **RQ3:** *Is there a measurable effect of the instructors’ interventions on the forum activity, forum sentiment, or completion rates?*

IV. METHODOLOGY

Our basic data set consisted of the forum interactions in about 95 courses on our MOOC platform. It is historic data that was collected from 2012 to 2021. Our platform allows to export pseudonymized reports for different aspects of the courses such as access of course elements, results in exams and tests and the interactions in the discussion forums. Pseudonymized means that no personal data of the participants is contained in these reports and that the user ids are encrypted with a standard cryptographic algorithm (SHA-256). Courses on our platform that are particularly designed for the use in schools have been excluded before we exported the data as the forum interaction in these courses is generally very low. After an initial analysis of the remaining courses, we also excluded the programming courses, as a majority of the discussions there is strongly problem-focused and contains a high percentage of code examples, which impedes running a sentiment analysis. The most basic categorization of courses on our platform is technical (IT-related) courses vs. non-technical (mostly *Design Thinking*-related¹) courses. We selected five tech and six non-tech courses, with sufficiently large numbers of longer forum discussions to provide a sufficiently large text corpus for the sentiment analysis. Table I gives an overview on the selected courses. We have encoded the courses with upper case letters from A to L to identify them throughout the rest of the paper². Table II provides additional information about the selected courses, such as the number of participants, the course duration in weeks, the number of teaching team

¹“Design Thinking is an innovation method that uses an iterative process to deliver user- and customer-oriented results to solve complex problems.” [10]

²All the courses are offered on the platform <https://open.hpi.de/courses/> (A) sql, (B) intsec2016, (C) smarhome2017, (D) insights-2017, (E) linux2018, (F) ideas2018, (G) international-teams2019, (H) prototype2019, (I) design-thinking2019, (K) designthinkinginorganisations2020, (L) kieinstieg2020

Year	Lang.	Category	Topic	Code
2013	German	Tech.	Data management with SQL	A
2016	German	Tech.	Internet Security	B
2017	German	Tech.	Embedded Smart Home	C
	English	Non-tech.	A Course on Human-Centered Research	D
2018	German	Tech.	Linux for Everybody	E
	English	Non-tech.	From Synthesis to Creative Ideas	F
2019	English	Non-tech.	Building and Testing Prototypes	H
	English	Non-tech.	With Design Thinking to a Networked Culture	I
	English	Non-tech.	Remote Teamwork	G
2020	English	Non-tech.	Design Thinking in Organizations	K
	English	Tech.	Introduction to AI and Machine Learning	L

TABLE I: A representative cross section of technical and non-technical courses has been selected from the basic data set. An additional selection criterion was the availability of sufficiently long discussion threads.

Course	#Part.	Weeks	#TTM	#Posts	#Threads	Avg. l.
A	5,762	6	1	3,897	659	6
B	9,334	6	6	7,791	1,127	7
C	1,868	2	2	1,043	189	6
D	3,284	5	3	1,912	191	10
E	9,990	2	2	4,413	641	7
F	1,921	4	3	994	102	10
G	1,645	4	3	4,651	232	20
H	1,789	4	3	878	82	11
I	2,417	5	2	1,363	185	7
K	4,282	2	1	1,277	150	9
L	7,633	4	2	2,260	305	7

TABLE II: Number of participants, course duration in weeks, number of teaching team members who actively posted in the forum, number of posts and threads and average length of the threads in the discussion forums.

members who have been active in the discussion forums, the number of posts and threads and the average length of the threads in the forums. Generally, the weekly workload in the courses is calculated with five to eight hours, depending on the participants’ previous knowledge and the depth of their self-learning activities. A discussion forum in a course is organized in *threads*. *Threads* consist of a *question*, *answers*, and *comments*. In the following, we will summarize them as *posts*. We define the term *participants* as registered users of the MOOC platform who have enrolled in a course before the course deadline has passed **and** who have visited at least one learning item in the course. Basically, these requirements restrict the numbers to those users who have been technically

able to actively contribute to the discussions³. This number can significantly differ from the number of course enrollments. About 50-80%, of the enrolled users qualify as participants according to our definition. The discussion forum is generally open to all participants and there are only few discussions that are actively triggered by the instructors.

A. RQ1: Sentiment Polarity Score

We transformed the separate posts in the raw forum data export into a paragraph structure within a common corpus. We then machine-translated the discussions in German language into English language. This step was inevitable as the analysis produced unusable results for the texts in German language, but it might have introduced a certain amount of inaccuracy in the results as we only did quality checks on random samples.

This corpus consists of paragraphs $P \in \{p_1, p_2, \dots, p_p\}$. Each of these paragraphs consists of sentences from $p = 1$ to n ($p_p = \{s_1, s_2, \dots, s_s\}$) which consist of words ($s_{s,p} = \{w_1, w_2, \dots, w_t\}$), where w are the words within the sentences and $s_{s,p}$ is the s^{th} sentence of the p^{th} paragraph. Each sentence s_s is decomposed into an ordered bag-of-words model (BoW). The words in each sentence $w_{p,s,t}$ are looked up and compared to a vector of polarized words from a lexicon provided by Rinker [5]. This particular lexicon was chosen because sentences containing negations are treated separately. The *polarity of a word* is a measure of how positive or negative the word is rated. The words are marked as ($w_{p,s,t}^n$) negator, ($w_{p,s,t}^i$) intensifier, or ($w_{p,s,t}^d$) de-intensifier from the polarized word vectors (Figure 1). These polarized words ($p^{**}w$) form a context cluster ($c_{p,s,l}$), where l is the cluster index representing a subset of the sentence, i.e., ($c_{p,s,l} \subseteq s_{s,p}$). The context cluster ($c_{p,s,l}$) of words is pulled surrounding the polarized words ($p^{**}w$), which is fixed at 4 words previous to and 2 words next to $p^{**}w$. The estimation of n-words 'previous to' ($n * prev$) and n-words 'next to' ($n * next$) have been defined by us after several trials. Therefore, the context cluster can be represented as follows: ($c_{p,s,l} = p^{**}w_{p,s,t-(n**prev)}, \dots, p^{**}w_{p,s,t}, \dots, p^{**}w_{p,s,t+(n**next)}$). The words tagged by all the corresponding clusters ($c_{p,s,l}^\theta$) are added together as ($c_{p,s}^\theta$). Then the quantity is divided by taking the square root of the word count ($\sqrt{w_{p,s**t}}$) yielding, an averaged estimate from the polarity over all words as,

$$\Gamma_{\alpha_{p,s}} = \frac{\sum \alpha_{p,s}}{\bar{S}} \quad (1)$$

where $\alpha_{p,s} = \frac{c_{p,s}^\theta}{\sqrt{w_{p,s**t}}}$ and \bar{S} is the mean of all sentences ($s_{p,s}$) within a paragraph (p_p).

³There is a certain inaccuracy in this approach as our data did not allow for all courses, particularly the older ones, to reliably determine if the user actually had visited the required course item before the end of the course.

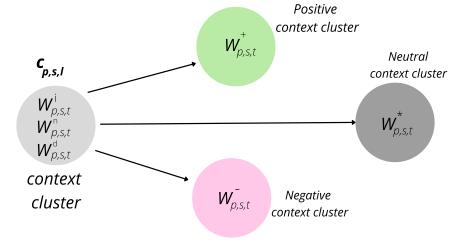


Fig. 1: An illustration of different types of context clusters. Clusters ($w_{p,s,t}^+$), ($w_{p,s,t}^-$) and ($w_{p,s,t}^*$) are created from the parent context cluster $c_{p,s,l}$.

B. RQ2: Forum Interaction and Course Completion

The completion rates of the courses are calculated as the ratio between the users who have earned a Record of Achievement (RoA) and the users who have been technically able to earn a RoA. Our definition for *users who are technically able to earn a RoA* is that they have to be enrolled before course end and have at least visited one course item. To earn a RoA, a participant has to earn at least 50% of all available points in the graded exams of a course.

We separately calculated the completion rates for **all course participants** and for the **course participants who actively contributed to the discussions**:

$$CR^{all} = \frac{RoA^{Participants}}{Participants} \quad (2)$$

and

$$CR^{active} = \frac{RoA_{activeinforum}^{Participants}}{Participants_{activeinforum}} \quad (3)$$

We then ran several regression tests to determine if there are any statistically significant correlations between the general forum activity, the overall sentiment in the forum, and the general completion rates or the completion rates of the participants who were active in the forums.

C. RQ3: Effect of Instructor Interventions

We calculated the instructors activity on the basis of the number of posts by the instructors and the number of total posts using the following equation:

$$\psi^C = \left(\frac{P_{instructor}^C}{PC - P_{instructor}^C} \right) \quad (4)$$

where ψ^C is the instructors activity for course C , P^C represents the total number of posts P for course C , and $P_{instructor}^C$ is the total number of posts by the instructors. Similar to the approach in RQ2, we ran regression tests to determine if there are any correlations the teaching teams' forum activity and the overall forum activity, sentiment in the forum, the general completion rates, or the completion rates of the participants who were active in the forums. We also attempt to visualize the development of the forum sentiment and the influence of the teacher interaction.

V. RESULTS

A. RQ1: Establishing a Sentiment Polarity Score

Figure 2 shows an excerpt from a processed discussion corpus. The original post is shown at the top in black. It is followed by the display of the overall polarity estimate for this corpus. The value can be interpreted as: this particular thread shifts the general polarity of the discussions in the course with a value of 0.164 towards an overall positive score. The sentences that are highlighted in ‘green’ have been evaluated as having a positive sentiment, while the sentences that are highlighted in ‘red’ have been evaluated as having a negative sentiment. The sentences that are not highlighted at all are considered to be neutral. The actual classification is done using the context clusters that have been introduced in Section IV, Figure 1. The 5-digit numbers in bold are the first five digits of the pseudonymized user ID, which are used to separate the posts.

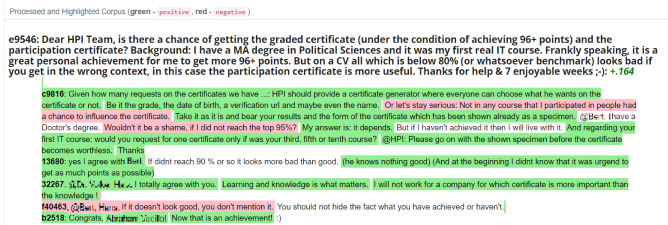


Fig. 2: Example for the sentiment classification.

Based on this, we have calculated a percentage of negative posts for each of the courses. These values are listed in Table III. With two exceptions, *D* (16%) and *H* (20%), the percentage of negative posts is around 10% in each of the courses. From the data we have so far, we cannot draw any conclusions about the reasons why the sentiment in these two courses was so much more negative. We also only have examined some random examples but have not yet conducted a structured review of the the sentiment analysis results to exclude the possibility that there are flaws in the analysis itself.

B. RQ2: Forum Interaction and Course Completion

The length of the courses ranges from two to six weeks. To properly compare the amount of posts within the courses, we calculated the average amount of posts per week. By this we can group the courses into *low activity* (in average less than 500 posts per week: *D*, *F*, *H*, *I*), *medium activity* (500 - 1000 posts per week: *A*, *C*, *L*, *K*) and *high activity* (more than 1000 posts per week: *B*, *E*, *G*). Interestingly, most of the Design Thinking courses, where we intuitively would have expected a particularly high forum activity, are located in the lowest interactivity group. On the other hand, as shown in Table III, the design thinking courses range amongst those with the highest percentage of active and passive forum participation among the course participants. We use the term active forum participation for participants who have written at least one

Course	P _{active}	P _{passive}	ψ	$\psi^{proactive}$	Neg.
A	10.78%	na	5%	1%	11.65%
B	9.94%	12.19%	11%	2%	12.20%
C	7.28%	25.59%	6%	2%	8.10%
D	23.39%	32.95%	22%	4%	15.53%
E	5.56%	27.37%	6%	3%	9.20%
F	27.23%	30.40%	20%	5%	11.55%
G	24.80%	55.93%	16%	9%	12.22%
H	21.19%	57.57%	28%	4%	19.63%
I	24.62%	66.20%	2%	18%	12.81%
K	10.70%	53.83%	2%	52%	12.10%
L	9.31%	58.06%	9%	4%	8.14%

TABLE III: Active(write) and passive(read) learner participation in the discussion forums, the percentage of teaching team activity(ψ) in the forum. $\psi^{proactive}$ shows the percentage of threads among the teaching team posts. The last column shows the percentage of posts that have been categorized as negative(Neg.) by the sentiment analysis.

post or (to a much lesser extent) who have up- or down-voted questions or answers. We use the term passive forum participation for participants who have accessed at least one discussion in a forum for reading.

The course *G* substantially differs from the other courses as it contained a project in which the participants had to work in teams. To support these teams, the platform provides a feature called *Collab Spaces*. These *Collab Spaces* provide each team with a private discussion forum. In *G* about 64% of the discussions took place within the teams. The *Collab Spaces* also are available in the other courses. Basically, every participant can create as many of them as they want. However, only in the course *E* the feature was actively used. Even here, only 0.02% of the discussions happened within the *Collab Spaces*. Table IV shows the different completion

Course	A	B	C	D	E	F
CR ^{all}	30%	41%	31%	25%	na	22%
CR ^{active}	77%	83%	80%	63%	na	47%

Course	G	H	I	K	L
CR ^{all}	20%	16%	na	81%	54%
CR ^{active}	45%	44%	na	89%	78%

TABLE IV: General completion rate vs. completion rate of participants who actively used the forum. The completion rate for passive forum participants is close to the active forum users. *Participants* are defined as enrolled users who have at least visited one course item before the end of the course. Active forum participants are participants who have also at least posted once in the forum. The completion rate is defined as the ratio of Records of Achievement(RoA) that have been earned by the participants or the active forum participants. *E* and *I* did not offer a RoA.

rates for all participants and those participants who actively contributed to the forums. The completion rate of the active forum participants, generally is at least twice as high as the completion rate amongst all participants. Obviously, there is

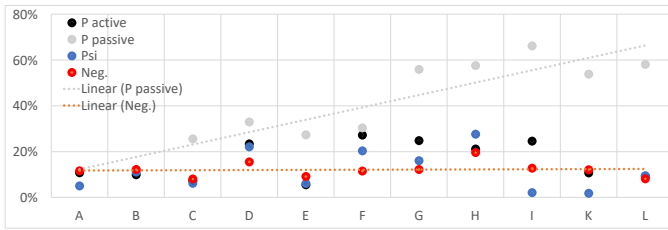


Fig. 3: Forum activity(Table III).

no direct causation between the activity of a user in the forum and their completion of the course. It is more likely to assume that more engaged users are more likely to both actively contribute to the forum and successfully complete the course. The regression tests showed that there is no statistically significant influence of the amount of negative posts on the completion rates. Neither overall nor for the active forum participants. There is also no correlation between negative posts and passive forum usage. We had expected a slightly negative effect here, as some users might be appalled by negative or rude language. However, there are also always participants who enjoy heated discussions to some extent. Furthermore, this effect is hard to measure, as in the moment when a participant might get appalled by rude language or negative sentiments, the reading event was already triggered and cannot be undone. The only observable effects here would be long term. There is some correlation, however, between negative posts and active forum participation. Again, it is hard to tell if there is also a causation and in which direction it might be. Negative posts often provoke other participants to answer and defend the courses or the platform. On the other hand, negative emotions often are the stronger triggers to stimulate the urge of using the forum than positive ones. Furthermore, the statistical significance for this effect is quite weak in the examined data ($p=0.06$) and needs to be validated in a broader data set. However, we can see a statistically significant negative influence of the active forum contribution on the course completion, particularly, among the active forum contributors ($p=0.0008$). This indicates that our second hypothesis (negative emotions are the stronger trigger) for the previous observation might be more likely. Neither the amount of active nor the amount of passive forum usage has a significant effect on the course completion.

C. RQ3: Effect of Instructor Interventions

Table III shows that both the learners' participation in the discussion forums and the teaching teams' activity in the forums differ substantially from course to course. Except from *I* and *K* we generally observe that the teaching teams in the non-tech courses interact stronger with the participants than in the tech courses. There is also a higher percentage of participants who are actively contributing to the forum. Both observations meet our expectations. Interestingly, the teaching teams of the two non-tech courses with the lowest forum interactivity, *I* and *K*, also have the highest percentage of proactive posts by the teaching team, while the teams in

the other courses mainly respond to questions that have been triggered by the participants. Figure 3 visualizes some of the data from Table III.

The regression tests reveal that there is a statistically significant higher amount of teaching team posts in courses that sport more posts with negative sentiment ($p=0.02$). In this case, we think it is quite safe to assume that the higher teaching team activity is caused by the more negative posts than the other way round. We have also observed that a higher teaching team activity in the forum has a statistically significant negative correlation with both the general course completion rate ($p=0.02$) and even more the completion rate of the active forum participants ($p=0.002$). Again, we strongly think that this is only a correlation and not at all a causality. We are very positive that there are other factors that are causing the development of both values.

Finally, we attempted to visualize the development of the sentiment within the discussion forums. So far, the visualization is only based on the timestamps and not the development within the threads. The discussions posts within a course are displayed in a row chart where each row represents a day within a course week, e.g. *W1D1* is the first day in week 1. The analysis differentiates between instructor posts and learner posts. The sentiment values for each group are color coded as defined in Figure 4c.

Unfortunately, the validation of the results revealed that the data source to determine if a certain post has been created by a teacher has not been read correctly and only shows the threads that have been created by teachers but not the answers and comments. This only affects the visualizations in Figure 4. All other data has been properly obtained and validated from separate data sources. Furthermore, it only affects the color coding of the posts—the decision if a post is made by a learner or an instructor—but not the general structure nor the sentiment analysis in these visualizations. We, therefore, decided to keep these visualizations as they help to show further issues of this approach, which will be discussed in Section VI.

VI. CONCLUSION & FUTURE WORK

We have established a way to determine the polarity of the forum discussions. At the current state, the results have been validated on random samples. Before developing this further, a more general structured validation is required. The initial interpretation and approximate validation of the results suggests that the approach is reasonable. However, since we only used a single sentiment analysis algorithm, we have not been able to perform statistical tests to check the quality and validity of our results. Next to that, the results need to be validated in more detail by a larger group of instructors to make sure that the results align with their experience during the course. We ran regression tests on the data to find correlations between the participants' activity in the forums, the teaching teams' activity in the forums, the polarity of the forum discussions, and the completion rates of the participants in general as well as the sub-population of participants who actively contributed

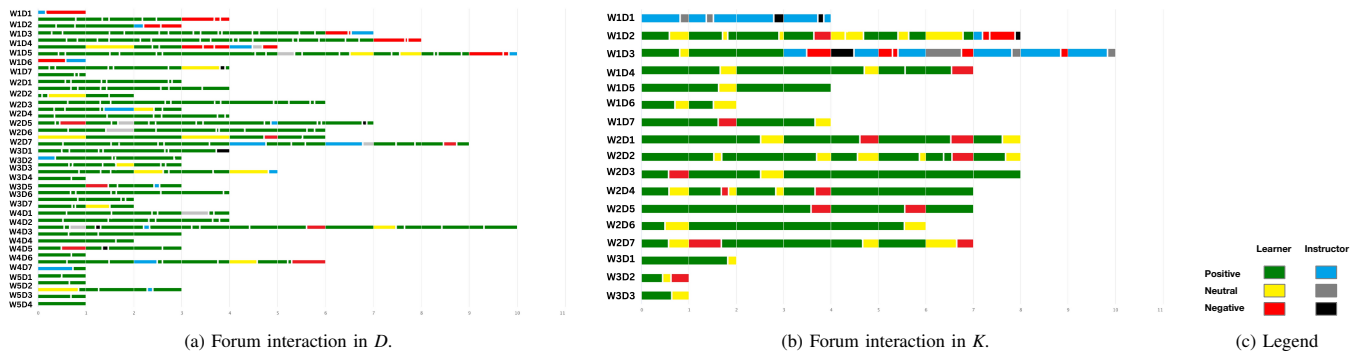


Fig. 4: Sentiment analysis visualization for selected courses

to the forum. Although the completion rate among the active participants in the forums is substantially higher than the general completion rates, it is unlikely that participants do better in the courses due to their forum activity. It is more likely that there is a third variable, such as the learner's general motivation and interest in the topic that causes both, the higher forum activity and the better learning outcome. The regression tests also show that there is basically no influence of neither the activity nor the sentiment development in the forums on the completion rates. However, it has to be mentioned that all examined teaching teams have been quite successful in keeping the negative sentiments in the forum on a low level and outbursts of negative sentiment in the forum are rare. Once the calculation for the polarity score is properly validated, it, nevertheless will be useful to re-run the analysis on a broader data set to confirm these results.

The basic idea was to determine if a visualization of the development in currently running courses would be helpful to support the course instructors and teaching teams in their daily work within these courses. Given the limited effect of the sentiment development on the completion rates the usefulness of such efforts remain questionable.

In conclusion, the research that we have summarized in the paper at hand, has, even in its current, incomplete state, significantly improved our understanding of the forum discussions and their influence on the course dynamics and learning outcomes.

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