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Sustaining Continuous Collaborative Learning Flows in MOOCs: Orchestration Agent Approach

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Abstract: Collaborative learning spaces deployed in Massive Open Online Courses (MOOCs) provide productive social learning opportunities. However, sustaining collaboration in these spaces is challenging. This paper provides a classification of MOOCs participants based on their behavior in a structured collaborative learning space. This analysis leads to requirements for new technological interventions to orchestrate collaborative learning flows in MOOCs. The paper proposes the design of an intelligent agent to address these requirements and reports a study which shows that the intervention of the proposed orchestration agent in a MOOC facilitates to maintain continuous yet meaningful collaboration learning flows.

Keywords: Computer-Supported Collaborative Learning (CSCL), Intelligent Agents, Massive Open Online Courses (MOOCs), Collaborative Learning Flow Patterns (CLFPs)
Categories: H.5.0, I.2.0, K.3.1, L.2.0, L.3.6

1 Introduction

Massive Open Online Courses (MOOCs) have created learning opportunities towards a massive amount of students disregard their financial, educational and geographical boundaries. Within the concept of "education for all" MOOCs offer chances for millions of students to browse, pick and choose courses offered by well-recognized universities while students can follow their own agenda which was not feasible in earlier models of online education [Yang et al. 2013]. With the aim of offering opportunities for fruitful learning, at present many MOOCs provide social learning spaces and activities towards course participants [Manathunga et al. 2017]. However, sustaining learners' engagement in these collaborative spaces is challenging as levels of participation vary across learners and new cohorts of learners start course activities from week to week [Yang et al. 2013]. The problem is that for social learning opportunities to be fruitful, there need to be sufficient levels of active participation that keep meaningful flows in the collaborative activities [Rosé and Ferschke 2016].

In the field of Computer Supported Collaborative Learning (CSCL), carefully designed scripts aim to structure social interactions via different strategies i.e., defining roles, sequences of activities, etc. that can have positive effects in learning [Dillenbourg and Tchounikine 2007]. Collaborative Learning Flow Patterns (CLFPs) formulate the essence of script structures that have been proven effective in multiple educational situations [Hernández-Leo et al. 2010]. For example, the Pyramid CLFP proposes an activity flow in which learners start solving a task individually. Then learners form small groups to share their solution and agree on a common solution, to later form increasingly larger groups that further discuss and agree on common solutions. The Pyramid pattern facilitates opportunities for all learners to express and discuss their solutions and to learn and reflect on others' solutions. In a MOOC context, the Pyramid pattern also offer a scalable collaborative method, in that it keeps to a reasonable amount the number of solutions to be read and discussed by each individual learner (those solutions within each group in the Pyramid) and by the educators (if educators choose to monitor only the agreed solutions by Pyramid) [Manathunga and Hernández-Leo 2017]. CLFPs structure the flow of potentially fruitful collaborative learning activities, but the uncertainty of participation in these activities in MOOC contexts can hinder a meaningful progression in the flow of activities (e.g., inactive participants in a Pyramid group waiting for an agreement in order to join increasingly larger groups). A suitable real-time management (or orchestration [Dillenbourg and Tchounikine 2007]) of the learning scenario is vital for a successful collaboration flow that is uninterrupted and keeps the pedagogical method structure.

In this paper, we study the difficulties involved in maintaining continuous and meaningful flows of Pyramid activities and propose an experiment that incorporates intelligent agent technologies to address these difficulties. Data collected from an exploratory MOOC case, in which seven Pyramid activities are proposed, is used to identify the difficulties. A second MOOC case is designed and carried with twenty-eight Pyramid activities and Wizard of Oz (WOZ) integrated intelligent agents to overcome these difficulties. The evaluation of this second case focuses on studying whether the proposed intelligent agent can maintain an uninterrupted yet meaningful collaborative learning flow via monitoring and intervening to the flow when necessary.

This article is organized as follows. In section 2 we describe relevant literature considering social learning aspects in MOOCs, application of intelligent and adaptive techniques in educational systems and applicability of such techniques in MOOCs settings to foster collaboration. In section 3 a MOOC case study is presented in which we analyzed MOOC participants collaborative learning behavior in a Pyramid based collaborative learning scenario. Section 4 describes our empirical study which focused on design aspects of the intelligent agent to facilitate uninterrupted collaborative learning flows in MOOCs setting. The final section provides concluding remarks followed by future research directions.

2 Literature

2.1 Social Learning in MOOCs

CSCL is an effective pedagogical approach in which learners collaborate with peers to achieve learning goals while constructing shared knowledge and understanding [Fischer et al. 2007]. However, research has shown that learners do not collaborate spontaneously [Fischer et al. 2007]. On the other hand, maintaining a continuous collaborative learning flow becomes significantly important during collaborative script enactment, since these scripts consist a number of phases that occur one after the other in a consecutive manner [Hernández-Leo et al. 2010]. Failure to maintain desired collaborative learning behavior within phases negatively affects the flow of collaboration [Dillenbourg and Tchounikine 2007]. Achieving success in such collaborative settings heavily depends on the continuous and active participation of students.

In a Face to Face (F2F) classroom setting, in appropriately sized classes, student's collaborative learning behavior can be closely and continuously supervised by an educator [Pontes et al. 2010]. In such settings not only each individual student's engagement but also the behavior of a bunch of students as a group can be monitored by an educator to confirm that individuals and groups are actively involved in the collaborative learning task. However, even with the close guidance of an educator in a F2F setting maintaining a continuous collaborative learning flow is not easy. The passive behavior of some students can hamper collaboration [Vizcaíno 2005].

On the other hand, MOOCs have created opportunities to carry out course-related activities remotely from anywhere at any time and has gained social success. The history of MOOCs dated back to 2008 where George Siemens and Stephen Downes conducted the first MOOC titled 'Connectivism and Connective Knowledge' (CCK08) [Downes 2008]. Since then MOOCs evolved in different ways providing opportunities to plan, test and validate disruptive approaches to education [García-Peñalvo et al. 2017]. According to the underpinning pedagogical methodology, design, scope and management of resources and activities MOOCs have been categorized into two main types: cMOOCs and xMOOCs [García-Peñalvo et al. 2017]. Adapting from the connectivism learning theory cMOOCs (also known as the first-generation of MOOCs) are based on connectivist (that emphasizes social learning) while xMOOCs (also referred to as the second-generation of MOOCs) are based on instructionism and individualism [Fidalgo-Blanco et al. 2015]. Currently, many MOOC platforms adapt xMOOCs technologies e.g., Udacity, Coursera, edx [Fidalgo-Blanco et al. 2015] and have employed different social interaction spaces into the platform using different strategies. Although forum threads are the dominant channel [Brinton et al. 2014] through which teachers and students interact meet-ups at learning hubs introduced by Coursera and content-wide and course-wide cohorts on the edX platform [Manathunga et al. 2017] can be pointed out as some other instance for initiatives offering social and collaborative learning opportunities within MOOCs.

However, as it was pointed out earlier, deploying collaborative learning activities even in a synchronous F2F setting under the close guidance of an educator, poses difficulties i.e., maintaining a continuous flow of activities, student motivation, etc. Hence, deploying collaborative learning activities in MOOC settings can result in added complexity due to many reasons. Variability of learner's schedules, diverse individual characteristics and expectations, lack of educator influence, higher learner dropout rates and asynchronous nature of collaboration are to name a few. Coordination and management of group processes in such settings are a serious and a challenging task since learners are distributed both in time and space [Fidalgo-Blanco et al. 2015]. The continuous flow of collaboration can be easily interrupted in such settings due to aforementioned reasons, resulting unsavory learning experiences for motivated students [Tomar et al. 2016]. In light of this fact, it was observed that designing and implementing appropriate scaffolding strategies to maintain continuous collaborative learning flows become a need in MOOC settings. Exploration and deployment of new technological interventions that contribute to sustain collaborative learning activities can help to harness benefits of social learning in MOOC context [Rosé et al. 2014].

2.2 Adaptive and Intelligent Techniques in MOOCs

Recently a growing research interest towards incorporating adaptive and intelligent techniques into MOOCs have been observed. Existing literature has highlighted the need and the importance of incorporating adaptive techniques into MOOCs platforms in order to improve pedagogical effectiveness [Sonwalkar 2013] as well as to personalize and better adapt the learning process to the characteristics of students [Fidalgo-Blanco et al. 2015]. Different technological frameworks and innovative ways of supporting adaptivity in MOOCs have been proposed. For instance, [Sonwalkar 2013] have described the cloud computing architecture of an adaptive MOOC (aMOOC) platform that renders content adapting to five distinct learning strategies. [Leris et al. 2017] have identified and proposed six adaptive indicators (based on self-regulation and cooperation aspects of learning) that help to implement adaptivity within MOOCs context.

On the other hand, when considering intelligent techniques that are incorporated into MOOCs context intelligent agents play an important role. Different types of agents i.e., pedagogical agents, conversational agents have been deployed into MOOCs to keep learners motivated towards collaboration. As described in [Bendou et al. 2017] integration of animated pedagogical agents into online learning environments (LMS or MOOC) has helped to create natural human-machine interactions. Although pedagogical agents are not necessarily artificially intelligent these lifelike characters that appear on computer screens have helped to increase learner's motivation while decreasing dropouts [Bassi et al. 2014]. Ferschke et al. [2015] and Wen [2015] have described the integration of conversational agents into collaborative chat environments deployed in MOOCs. Agents facilitated to engage students in intensive discussions during collaboration.

However, it is worth mentioning that existing studies which incorporate intelligent assistance towards collaboration in MOOCs have mostly considered specific aspects of collaborations e.g., chat participation during a collaborative learning task. Most of these studies have taken for granted in one way or the other that continuous collaborations among participants occur automatically although less engagement of learner's participation in MOOCs is well-known. In a recent study carried out by [Fauvel and Yu 2016] has pointed out that intelligent agent techniques have not yet been applied to provide peer support in MOOCs context, although providing peer support in such settings is vital. Although Artificial Intelligent (AI) techniques can be integrated into almost every aspect of the MOOC ecosystem, only a few tools have been tested and deployed into the actual MOOCs context regardless of the fact that effective integration of these type of intelligent techniques could result in benefits [Bassi et al. 2014, Rosé and Ferschke 2016].

In a broader perspective, although technologies such as intelligent agents have proven to be effective in online education paradigms these technologies have not yet been fully leveraged within the MOOC context [Fauvel and Yu 2016]. Apart from being an animated character or a conversational partner, agents can be used to analyze data produced by the MOOC platform, in order to provide intelligent or mechanical assistance to improve design, delivery and assessment [Bassi et al. 2014].

3 An exploratory study of Pyramid collaborative learning activities in a MOOC

Research shows that identification of participants' profile differences in MOOCs facilitates to determine effective engagement mechanisms [Alario-Hoyos et al. 2014]. However, lack of attention towards analyzing participants' engagement differences in collaborative learning spaces deployed in MOOCs was observed. Inspired by the work already done in the field [Milligan et al. 2013, Alario-Hoyos et al. 2014] during this study we analyzed the behavior of learner's participation in a collaborative learning activity deployed in a MOOC course. The major objective of this case study was to determine how individual participation differences affect collaborative learning flows deployed in MOOC contexts. The exploratory MOOC case study was deployed in spring 2016, in the FutureLearn MOOC platform. A tool called 'PyramidApp' was used structure the collaborative enactment.

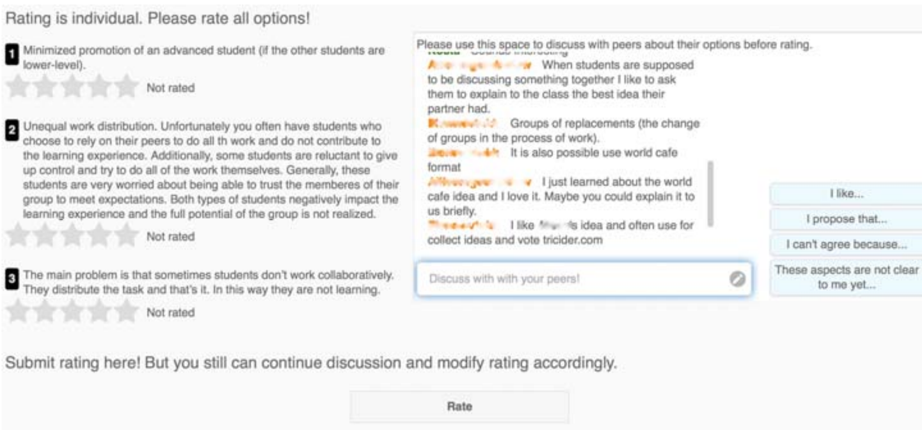


Figure 1: A screenshot of the PyramidApp showing rating space (left) and the negotiation space (right)

3.1 PyramidApp

PyramidApp [Manathunga and Hernández-Leo 2017] is a web-based application that implements flow orchestration of collaborative learning activities inspired by the Pyramid pattern [Hernández-Leo 2005]. A Pyramid flow is initiated with individual students solving a global task. Then, in a second level of the Pyramid, such individual solutions are discussed in small groups and agreed upon a common proposal. These small groups then form larger-groups iteratively and large group discussions will continue till a consensus is reached at the global level. PyramidApp implements an activity design tool for educators to author such collaborative activities with easy configurations such as the number of participants per Pyramid, number of rating submission stages, group size and timing configurations. Once a Pyramid flow activity is designed by the educator and published, it becomes accessible via a public URL. MOOC participants can then access the activity by logging to the PyramidApp tool using the given URL. Within a single Pyramid activity, each participant engages in the collaborative learning activity at two major levels including individual option submission stage and rating submission stages. Inbuilt discussion board of the tool provided a negotiation space for participants at group levels. Fig. 1 shows a sample screenshot of the PyramidApp as it is used in a MOOC setting. The social interactions facilitated by the PyramidApp in a MOOC context differentiates from other collaboration spaces with its structured accumulative collaborations that grow from individual level to small group discussions to large groups, promoting positive interdependence and negotiation skills that rather lacks in global forum discussions [Manathunga and Hernández-Leo 2017].

Week	**Pyramid flow abbrev.**	**No. of Pyramids**	**Pyramid abbrev.**
Week 1	Flow 1	1	W1F1P1
Week 1	Flow 2	1	W1F2P1
Week 1	Flow 3	2	W1F3P1 & W1F3P2
Week 2	Flow 1	2	W2F1P1 & W2F1P2
Week 3	Flow 1	1	W3F1P1

Table 1: Pyramid activities deployed in exploratory case study

3.2 Experimental Design

Within 3 consecutive weeks of the FutureLearn MOOC, we deployed 5 Pyramid flows (meaning 5 different tasks following a Pyramid flow), including 3 flows during the first week, 1 flow during the second week and 1 flow during the third week. Based on design configurations of the PyramidApp i.e., minimum number of learners allocated per Pyramid during a Pyramid flow, a number of Pyramids were instantiated allocating MOOC participants to Pyramids who logged into the system in different times. see [Tab. 1]. Initial design parameters of each Pyramid are given in Tab. 2. The first column in Tab. 2 indicates the abbreviation to identify each Pyramid. The second column indicates the minimum number of students required to create a Pyramid. The third column indicates the number of rating submission stages in each Pyramid. For instance, a number of Pyramid rating submission stages equal to 2 indicates that there are two rating submission stages, i.e., the first and the second rating submission stages. The fourth column indicates the number of students collaborated during the first rating submission stage. Since each Pyramid has only two rating stages this parameter refers to the size of each small group created during the first rating submission stage. In the second rating submission stage all participants were grouped together resulting four participants in each large group. Finally, the fifth and sixth columns indicate the time limits for initial option submission stage and subsequent rating stages (in hours). As this was a preliminary experiment using PyramidApp in a MOOC context, long timing durations were allocated for Pyramid phases to learn the participant behavior and structured collaborative learning feasibility in MOOC settings.

3.3 Subjects

Students enrolled in *3D graphics for Web Developers* MOOC course participated in the Pyramid activity deployed in the MOOC. The total number of students enrolled for the course was around 4300. Participants were informed that the activity was voluntary and that activity participation was part of a research experience and responses collected will be treated anonymously. Students were asked to use PyramidApp to share experiences and challenges faced when using novel 3D applications. Participants were assigned to Pyramid groups randomly. Based on PyramidApp log data, during the first week of the MOOC 76 participants accessed the Pyramid activity, while in the third week this number dropped to 15 and in the fifth week it dropped further until 8. In total 99 students have accessed the collaborative learning activity. The following section describes participants' collaborative activity enactment behaviour.

Pyramid abbrev.	**Min. students per Pyramid**	**No. of rating levels**	**Group size**	**Option sub. time limit**	**Rating sub. time limit**
W1F1P1	8	2	2	18 h	18 h
W1F2P1	8	2	2	18 h	18 h
W1F3P1	8	2	2	18 h	18 h
W1F3P2	8	2	2	18 h	18 h
W2F1P1	4	2	2	18 h	18 h
W2F1P2	4	2	2	18 h	18 h
W3F1P1	4	2	2	18 h	18 h

Table 2: Pyramid activity configurations

3.4 Results and analyses

PyramidApp log data was analyzed to determine collaborative learning behavior of MOOC participants. An overall activity participation analysis and an individual student level analysis was carried out.

Results of the overall activity participation analysis have shown that engagement in collaborative learning activity varied within weeks of the MOOC course, see [Fig. 2]. As it was described in section 3.3, not only the number of participants has become fewer in size, but also their overall engagement with the activity has decreased over-time. This observation also complies with the common attrition behavior of MOOC participants, in which they are highly active and engaged with the course in the first few weeks but degraded over the course progression [Sinha et al. 2014].

We then conducted an individual student level analysis in order to analyze how individual participation varied across different Pyramid stages. Results of the analysis revealed that some MOOC participants have participated in both initial and rating stages of the Pyramid activity, while some participants have escaped either initial option submission stage or subsequent rating stages. Further, some participants have only logged into the system but had not participated in the activity. Based on these behavioral differences we have categorized individual students into 5 major categories namely *Lurkers*, *Initiators*, *Contributors*, *Runners* and *Raters* which also complies with the participant categorizations proposed in previous work [Milligan et al. 2013, Alario-Hoyos et al. 2014].

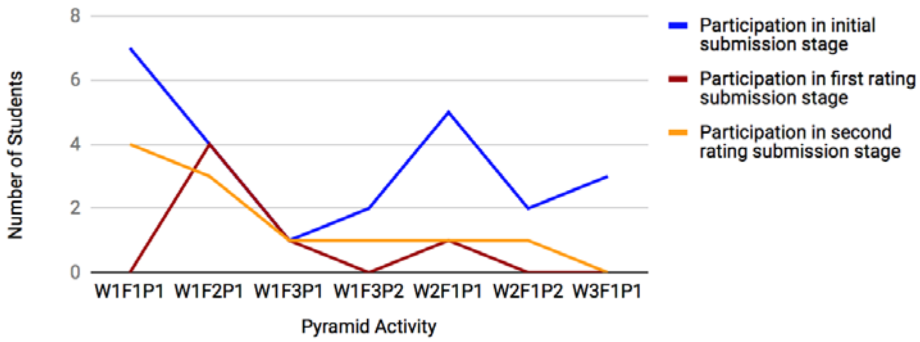


Figure 2: MOOC Pyramid activity participation

Lurkers are the MOOC participants who only logged into the PyramidApp but did not participate actively in any level of the collaborative learning activity. In other words, these participants do not add any contribution to the collaborative learning task. The opposite category of *Lurkers* was named as *Contributors* who have participated in all levels of the collaborative learning activity, contributing to reaching a group consensus. Other three categories namely *Initiators*, *Runners* and *Raters* have contributed to the collaborative learning activity in different levels. *Initiators* have participated only during the initial option submission stage. They have contributed to the collaborative learning activity providing their opinion about the question at hand. *Raters* are the participants who have not participated in the initial option submission stage but have participated only in rating levels. MOOC participants who have participated in initial level and at least one rating level i.e., first or second rating level were named as *Runners* since they contribute to maintain continuous collaborative learning flows. Fig. 3 summarizes the learner participation distribution according to aforementioned categorization across different Pyramid activities. Participants of the Pyramid W3F1P1 were excluded from this study since during that Pyramid participants only participated in the initial option submission level.

Apart from participation across different stages of Pyramids, we have also analyzed how each individual participated in the integrated chat of the PyramidApp. This chat environment facilitates small groups to collaboratively select the best option to rate via discussing their opinions. We have coded manually how many students have used the chat to discuss individual options submitted prior rating, via posting their opinion either as a question or a comment and how other students have collaborated via posting a response. Results of the analysis revealed that students have used chat to express their opinions only during the Pyramid activities occurred in the first week of the MOOC. Students have not used the chat during later weeks of the MOOC course.

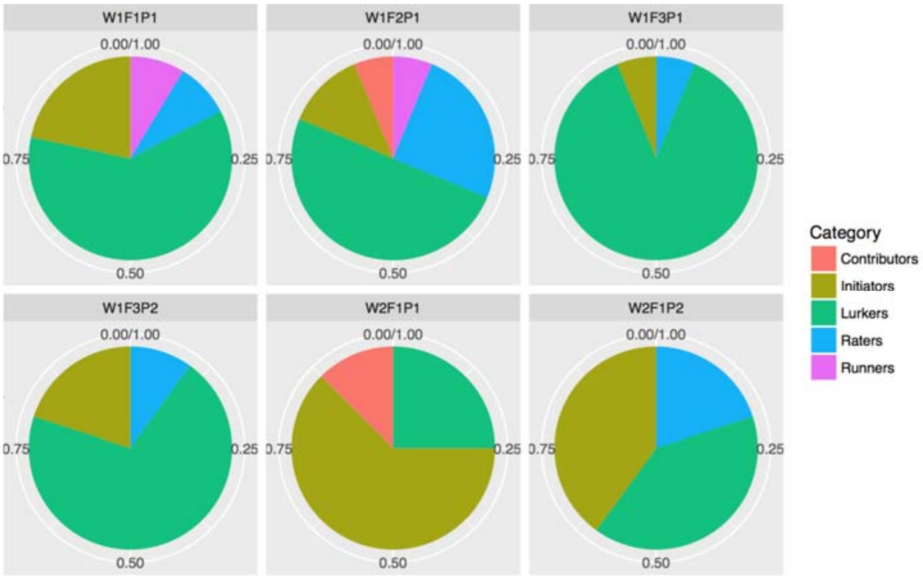


Figure 3: Individual student participation in different Pyramid activities

3.5 Difficulties identified

Based on the results of the analysis, it was seen that participants' overall engagement with the collaborative learning activity is fairly low. A majority of learners falls into the category of *Lurkers*. It was also noticed that a significant portion of the learners participated in the initial option submission level and some participated only during rating stages. When compared to *initiators* and *raters*, *runners* who have participated in both initial and rating submission stages were relatively low. Finally, the most important category the *contributors*, who participated in both initial submission level and rating levels, are very low which leads to unsuccessful Pyramid activity flows. Further, it was also observed that some students tried to collaborate with others seeking help to solve their doubts using chat. However, many questions left open without responses due to lack of activity engagement of the participants.

On the other hand, individual differences might have an influence on Pyramid activity participation. We have not conducted an analysis considering those aspects due to limitations in obtaining participants demographics details. However, based on the results of the analysis conducted it was determined that the choice of collaborative script design parameters can also have an impact towards different collaborative learning behaviours. As it was described earlier, design parameters such as the number of rating levels, time limits etc. has to be carefully selected. For instance, it was noticed that in some Pyramids, although individuals finished rating, the application wait until the predefined timer expires i.e., 18 hours, without progressing to the next levels. Lack of support towards dynamic script parameter changes in such situations resulting in increased waiting times can hinder learner's motivation towards the collaborative learning activity as activity progression is not visible even after a longer duration.

Apart from log data, we have also analyzed qualitative feedback obtained from activity participants. An online survey was used to obtain participants overall opinion about the activity. Some participants have commented that lack of participation of their group members have made them feel isolated. For instance "..no one replied to my questions at all.." and "..seeing one question per day felt inefficient..". Some participants have also commented that "..Time constraints rather tight for a FutureLearn course which can be done out of real-time..". Based on results of both quantitative and qualitative analysis it was seen that collaborative learning activities deployed in MOOCs context requires careful orchestration of script design parameters, and also continuous interaction and feedback generation towards questions that arise from collaborative learning environments, to maintain student's engagement and motivation towards a continuous collaborative learning flow.

4 Empirical study for the design of an Orchestration Agent for Pyramid activities in MOOCs

Based on our exploratory case study it was observed that sustaining continuous collaborative learning flows in MOOCs is challenging. Learner's continuous engagement with the activity is often hindered due to many reasons, damaging continuous flows of collaboration. Different participant behaviors and rigid script design parameters can have a major impact towards collaboration, see [Section 3.5]. These type of interruptions especially affect contributors who truly seek to enjoy benefits of collaborative participation. Hence it is important to look into technological interventions that would facilitate to maintain continuous flows of collaboration.

4.1 Orchestration Agent intervention in PyramidApp

With the motivation of creating collaborative learning opportunities towards motivated learners and by considering the work already done in the field, it was seen that incorporating intelligent agents into MOOCs could result in added advantages. Intelligent agents can assist to maintain continuous collaborative learning flows while monitoring interactions among learners eliciting the requirement of manual intervention of educators. However, due to the high cost associated with this type of agent implementations research suggests to adapt Wizard of Oz (WOZ) studies, to clarify design requirements [Maulsby et al. 1993]. Hence, to better identify design considerations of an intelligent agent, which will orchestrate collaborative learning activities while maintaining a continuous flow of collaboration, we conducted a WOZ experiment. The agent will be referred as *Orchestration Agent* hereafter. The experiment was carried out during a MOOC course named *Innovative collaborative learning with ICT* in February 2017 which was deployed in the Canvas Network Platform. The total number of students enrolled for the course was 1031. We determined different stages of the Pyramid activity in which agent intervention becomes important to maintain a continuous flow of collaboration as follows.

a. Pyramid Instantiating Phase: As it was mentioned earlier, in order to create a Pyramid a minimum number of students required to be logged into the system. Unlike in a classroom setting in which students log into the system as soon as they are given the URL, in a MOOC participants access the activity URL at different times. Due to this variability in login times students who accessed the system earlier requires to wait without being allocated to a Pyramid until the minimum number of students are logged into the system. Increased waiting times result in decreased motivation of learners towards the activity. Hence we decided that waiting time could be minimized if the orchestration agent logs into the system simulating student behavior after a predefined period of time e.g., 20 minutes after the first student accessed the URL.

b. Initial Option Submission Phase: Next, if the agent observes that none of the students have submitted an initial option during the initial option submission stage (before a predefined period, e.g., 2 minutes prior finishing initial option submission stage) we require the agent to post a model answer as an option. This intervention limits the progression of Pyramids which does not have options to rate in the subsequent rating stages.

c. Rating Submission Phases: During the rating submission stages, if the agent observes that a particular rating stage is frozen due to no ratings (before a predefined period, e.g., 2 minutes prior finishing each rating stage) we require the agent to provide a 3-star neutral rating to all options submitted by course participants. This action facilitated the groups to proceed to the next levels. Further, if the agent noticed that the options to rate include options submitted by the agent itself (due to the reason mentioned in *(b)*) those options should be given only a 1-star rating in order to degrade its own submissions while facilitating options submitted by students to be promoted to the next level. Fig. 4 summarizes agent actions.

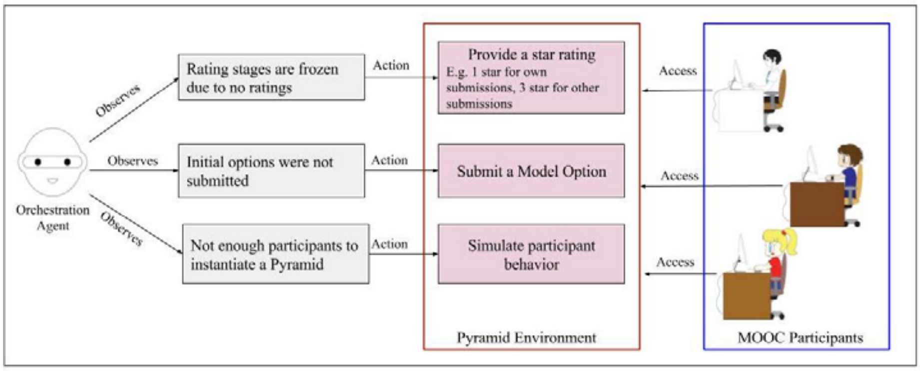


Figure 4: Orchestration Agent interventions in PyramidApp

4.2 Experimental Design

During the first and second week of the MOOC, we introduced collaborative learning activities using the PyramidApp in parallel to the course content. Initial design parameters of each Pyramid activity are given in Tab. 3. The first column in Tab. 3 indicates the activity type. We created four different types of Pyramid activities via differentiating the time allocated for each activity, namely *Very Rapid*, *Rapid*, *Long* and *Very Long*. The second column refers to the minimum number of students allocated for each Pyramid. We varied this attribute in the range of 4 to 6 during experiments in order to evaluate how different minimum sizes affect activity. However, we did not increase this attribute value more than 6 as we observed less number of participants during our previous collaborative learning activity. The third column refers to the number of Pyramid rating levels. We limited the value of this attribute to 2 in order to be consistent with the previous study. The fourth column refers to the number of students collaborated during the first rating submission stage. The fifth and sixth columns reflect the time allocated for initial option submission stage and subsequent rating stages based on the activity types described in the first column. Since we have categorized collaborative learning activities into four different categories based on time allocated for each activity the WOZ study also reflected how agent intervention requires being adapted according to different learning designs. However, it should be noted that due to limited time availability in MOOC it was not possible to carry out a balanced number of activities for each category. In summary we were able to carry out a total of 28 Pyramids, including 11 of *very rapid* type, 5 of *rapid* type, 10 of *long* type and 2 of *very long* type.

Activity type	**Min. students per Pyramid**	**Rating levels**	**Group size**	**Option sub. time limit**	**Rating sub. time limit**
Very Rapid	4 or 6	2	2	12 mints	12 mints
Rapid	4 or 6	2	2	47 mints.	47 mints.
Long	4 or 6	2	2	2 h	2 h
Very Long	4 or 6	2	2	6 h	6 h

Table 3: Configurations of Pyramid activities

4.3 Subjects

Students who were enrolled in *Innovative collaborative learning with ICT* MOOC course participated in the Pyramid collaborative learning activity deployed during the first and second week of the MOOC. Participants were informed that the activity participation was voluntary and that activity participation was part of a research experience and responses collected will be treated anonymously. Students were asked to use PyramidApp to discuss benefits and problems of CSCL until they reach a common group consensus to identify the most valuable benefit or the most popular problem. Participants were assigned to Pyramid groups randomly. During this empirical study, the role of the Orchestration Agent was enacted by the experimenter, the ‘Wizard’. Based on PyramidApp log data, 28 participants accessed the *very rapid* type Pyramid activities while 22 participants accessed the *rapid* type, 37 participants accessed the *long* type and only 5 participants accessed the *very long* type Pyramid activities. The following section describes results and analysis of the WOZ experiment.

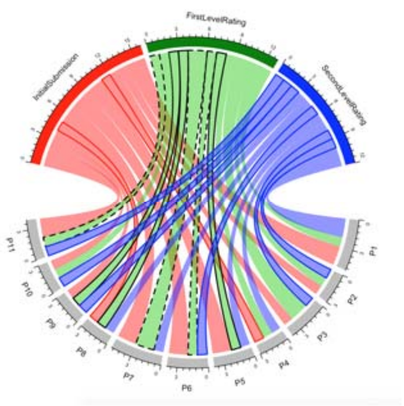
4.4 Results and analyses

PyramidApp log data was analyzed to determine collaborative learning behavior of MOOC participants and agent interventions. Chord diagrams were used to visualize learner's engagement in different levels of the Pyramid since these diagrams provide a compact way of representing information [Wei et al. 2016]. Log data was pre-processed to obtain input adjacency matrices for chord diagrams, in which the value in i^{th} row and j^{th} column represents the relation from object in the i^{th} row and the object in the j^{th} column while the absolute value measures the strength of the relation. R circlize package [1] was used to plot diagrams.

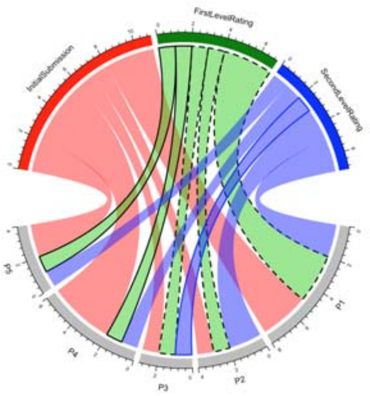
As can be seen in Fig. 5 (a), (b), (c), (d) each chord diagram consists of two sectors, namely the *Pyramid Sector* and *Submission Stage* sector. The Pyramid sector represents Pyramids that were created during each experimental activity. Pyramids were labeled starting from P1. The Submission stage sector represents different submission stages, i.e., initial option submission stage, first rating submission stage, second rating submission stage, which are colored in red, green and blue. Fig. 5(a) shows the chord diagram visualization for a total of 28 learners engagement in *very rapid* type Pyramid activities. Fig. 5(b) shows the visualization for a total of 22 learners engagement in *rapid* type Pyramid activities. Fig. 5(c) shows the visualization for a total of 37 learners engagement with *long* type Pyramid activities and finally Fig. 5(d) shows the visualization of 5 learners engagement with *very long* type Pyramid activities.

The width of each submission stage track represents the total number of submissions made for each submission stage by all participants allocated to different Pyramids. The width of each Pyramid sector denotes the total number of submissions made for all submission stages by participants in a particular Pyramid. Links between two sectors represent each submission stage engagement of participants who were allocated to different Pyramids. The thickness of each link is proportional to the number of submissions made by participants who were allocated to different Pyramids. Further, we have highlighted the links in order to emphasize the importance of orchestration agent participation in each Pyramid. For instance, a link with thick border denotes that the mandatory agent intervention was required for the Pyramid to proceed to the next levels, while a link with dashed border denotes that the agent participation was optional for the Pyramid to proceed to the next levels, but agent participation was required to create a meaningful collaborative learning scenario. This behavior of the agent became important during the first rating submission stage of each Pyramid activity, since only some small groups submitted ratings. Although lack of small group participation does not stop Pyramid from proceeding to the second rating submission stage, it is important that every small group participate in rating, as it affects the options which will be populated to the second (in this case the final) rating submission stage. We have emphasized this participation difference among small groups in first rating submission stage via thick and dashed border links. The following section describes the orchestration agent interventions in different Pyramid activities during the empirical study in detail.

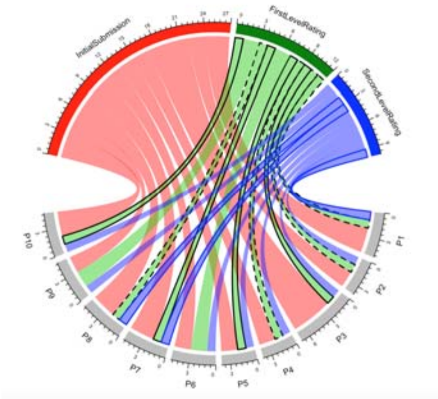
[1] https://cran.r-project.org/web/packages/circlize/index.html



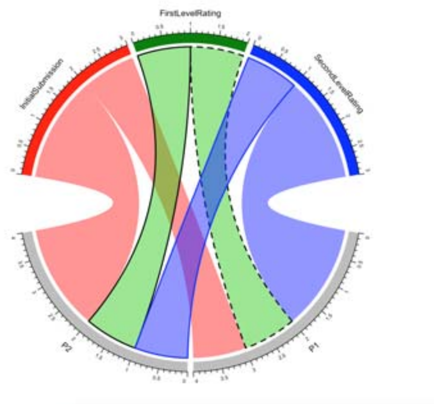
(a) Very Rapid



(b) Rapid



(c) Long



(d) Very Long

Figure 5: Patterns of engagement in different types of Pyramid activities

As it was mentioned earlier we have carried out 11 *very rapid* type Pyramid activities. It was observed that 7 out of 11 of these activities required orchestration agent to simulate student behavior to fulfil minimum student count requirement to generate a Pyramid within the allocated time frame. Also 10 out of 11 required agent intervention at least in one submission stage fully or partially due to lack of *contributors*. Not only lack of *contributors* but also lack of *initiators*, *runners* and *raters* have affected different submission stages. As it is denoted in Fig. 5(a), P4 and P8 Pyramids required mandatory agent intervention during initial option submission stage since there were no *initiators* or *runners*. Further, P5, P8 and P9 Pyramids required the mandatory intervention of the agent during first rating stage. However, in P6, P7 and P11 Pyramids agent participation were marked as optional because only one small group has participated in first rating submission stage. Hence, agent intervention was optionally required to create meaningful collaboration among small groups. Due to lack of *raters* and *runners*, P2, P3, P6, P9, P10 and P11 Pyramids also required agent mandatory intervention during second rating submission stage.

In *rapid* type activities only 1 Pyramid required orchestration agent to simulate student behavior to fulfil minimum student count requirement to generate a Pyramid. As denoted in Fig. 5(b), none of the Pyramids required mandatory agent intervention during the initial option submission stage, which indicated a strong presence of *initiators*. However, the same participation was not observed during the first rating submission stage. P1, P2 and P3 Pyramids required the optional participation of the agent while P4 and P5 Pyramids required mandatory participation of the agent to proceed to the next level. A higher student participation was also observed in the second rating submission stage. Mandatory agent intervention was only required during a single Pyramid P3.

In *long* type Pyramid activities 6 out of 10 Pyramids required orchestration agent to simulate student behavior to fulfil the minimum student count requirement to generate a Pyramid. As shown in Fig. 5(c) it can be seen that mandatory agent intervention during initial option submission stage was not required in any Pyramid. However, Pyramids P3, P5, P7 and P10 required mandatory agent intervention during the first rating submission stage to proceed to the next level while Pyramids P1, P2, P4 and P8 required optional agent intervention to create meaningful collaborations among small groups. Further, Pyramids P1, P7 and P8 required mandatory agent intervention during second rating submission stage. It should be noted that Pyramids P6 and P9 had a satisfactory participation of students in all Pyramid levels hence agent intervention was not required in any of the 3 submission stages. Finally, in very long type activities it was observed that both Pyramids required orchestration agent to simulate student behavior to fulfil the minimum student count requirement to generate a Pyramid. Further, as it is denoted in Fig. 5(d) agent mandatory intervention was required during both first and second rating submission stages of P2, while optional intervention during first rating submission stage was required in Pyramid P1.

4.5 Discussion

Results of the analysis revealed orchestration agent intervention to fulfil the minimum student count requirement to generate a Pyramid became important in 63.63% of *very rapid* activities, 20% of *rapid* activities, 60% of *long* activities and 100% of *very long* activities.

When considering different submission stages of the Pyramid it was observed that only *very rapid* activities required agent intervention in the initial submission stage (18.18%). In other 3 types of activities i.e., *rapid*, *long* and *very long* agent intervention was not required in the initial submission stage which indicated that learners have a higher engagement in the initial submission stage. However, it was observed that learner engagement with first rating submission stage and second rating submission stage varied. Mandatory agent intervention during first rating submission stage was required across all activity types including 27.27% in *very rapid* type activities, 40% in *rapid* type activities, 40% in *long* type activities and 50% in *very long* type activities. Optional agent intervention was also required across all activity types to create meaningful collaborations including 27.27% in *very rapid* type activities, 60% in *rapid* type activities, 40% in *long* activities and 50% in *very long* activities. Further, during the second rating submission stage it was observed that *very rapid* and *very long* activities required a higher intervention of the agent which was 54.55% and 50%. However, in *rapid* and *long* activities the requirement for agent intervention during the same stage was relatively low i.e. 20% and 30%.

In summary, based on the results of the analysis it became clearer that the orchestration agent participation in Pyramid activity becomes important in different stages in order to maintain an uninterrupted yet meaningful collaborative learning flows. Further, it was observed that orchestration agent intervention during Pyramid instantiating phase become also important in all activity types with the exception of rapid type activities.

5 Conclusions and Future Work

CSCL is a dynamic and an interdisciplinary field of research which mainly focuses on technological interventions towards education which could provide explicit or implicit support to facilitate the sharing and creation of knowledge through peer interactions and group learning processes. Working in groups create practical opportunities for students to resolve their doubts and to refine their knowledge on different learning aspects through discussions and rehearsals with peers. In the field of CSCL, CLFPs e.g., Pyramid essentially pre-structure the collaboration supporting practitioners to design learning tasks which will result in establishing productive interactions among learners. Deployment of such collaboration spaces scripted based on CLFPs creates productive yet meaningful collaboration opportunities towards MOOCs participants.

However, sustaining continuous yet meaningful collaborative learning flows in MOOCs are tedious due to many reasons. An exploratory MOOC case study carried out has shown that different participation behaviors and rigid script design parameters can have a major impact towards continuous collaboration. Findings of the exploratory MOOCs case study highlighted the requirement towards further investigations on technological interventions that facilitate to maintain continuous flows of collaboration, which will create collaborative learning opportunities towards motivated learners. Incorporation of intelligent agents was seen as a promising direction, as such techniques can be used to monitor interactions among learners eliciting the requirement of manual intervention of educators while facilitating the orchestration of collaboration. A WOZ study conducted in a MOOC has shown that intelligent agent intervention during collaboration enactment facilitates to sustain continuous yet meaningful collaboration learning flows, driving collaboration towards a productive state. Further, during the WOZ study, it became evident that only learning design parameter changes i.e., time allocation cannot drive collaboration towards a success, but it requires additional scaffolds. In the next steps of the research, it is of importance to investigate AI techniques which facilitates implementation of these agents, providing opportunities for its application and adaption in large-scale online learning settings.

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