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Collaborative knowledge construction during computational lab activities in Financial Mathematics

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Abstract

Nowadays, there is a growing interest in including some aspects of computation and computational thinking within science subjects, in particular Mathematics. Moreover, the COVID pandemic has increased the opportunities for remote-based work across economies, including education. This implies that workers and students should be able to collaborate remotely using collaborative technologies. In this paper, we show how tailored student-led computational practices designed for a Computational Finance module provide opportunities for the co-creation of knowledge in Financial Mathematics in a Computer-Supported Collaborative Learning environment. We analyzed students' answers to a weekly survey using Gunawardena et al. (1997) Interaction Analysis Model for collaborative knowledge construction. The results show that, in a large number of discussions, the highest levels of the collaborative learning process were achieved.

Keywords: *Collaborative knowledge construction; computational thinking; computer supported collaborative learning; inclusive computational practices; interaction analysis model; financial mathematics.*

1. Introduction

Nowadays, there has been growing interest in including some aspects of computation and computational thinking within science subjects, in particular in Maths pathways. The use of computation can deepen the learning and experience of Mathematics; at the same time, Mathematics also provides a meaningful context which computational thinking can be applied to (Lockwood et. al., 2019). In this setting, Computational Finance is a new and highly interdisciplinary Math subject, relevant to master Financial Mathematics and computational thinking and fundamental for high-level quantitative finance jobs. Despite the incredible growth of Financial Mathematics programs in the last few years, it is worthy to notice that the Computational Finance curriculum is under-researched. Moreover, the COVID pandemic has caused a rapid increase in the demand from employers for remote-based work across economies (World Economic Forum, 2020). The same happened in the education sector. This implies that workers and students should be able to collaborate remotely, using digital tools for communication and shared workspace.

In this paper, we show how tailored student-led computational practices designed for a Computational Finance module delivered at University College Dublin provide opportunities for the co-creation of knowledge in Financial Mathematics in a Computer-Supported Collaborative Learning environment (CSCL). We analyzed the students' responses to weekly surveys to address the following research question: do the activities designed for the Computational Finance module allow students to create shared knowledge in financial Mathematics?

2. Theoretical framework

CSCL is a field of research, emerging in the '90s, focused on how technology can facilitate the sharing and creation of knowledge and expertise through peer interaction and group learning processes (Resta & Laferrière, 2007). CSCL grounds on socio-constructivist theories, where learning is seen as a construction process performed by communities of practice, social units participating in a common situation with a shared goal. Communities of practice are built through the coordinated use of collaborative technologies, tools that enable individuals to jointly participate in the construction of a shared knowledge (Roschelle & Teasley, 1995). The design of CSCL environments is crucial to promote the process of collaborative knowledge construction. Donnely et al. (2014) identified four features that should be considered when creating CSCL activities: (1) tasks should be meaningful to engage students in exploration and relevant problem solving activities; (2) simulations and dynamic visualizations can create emerging conditions for collaborative learning; (3) students need to be encouraged to collaborate in their work; (4) it is important to cultivate the use of metacognitive strategies over time, to enhance students' capacity to self and coregulate themselves in socio-cultural environments. An example of similar CSCL for Mathematics can be found in (Barana & Marchisio, 2016).

The “inclusive computational practices” definition (Caballero & Hjorth-Jensen, 2018) is perfectly aligned with the above description. In fact, this definition includes a wide range of high-level coding activities like having students work in groups with simulations to understand the main characteristics of a mathematical model; giving students pieces of code to complete or modify in order to adapt them to a different problem; critically inspecting and judging computational inputs and outputs; advising students on open-ended group projects where they write code from scratch. Inclusive computational practices have been heavily used to design physics undergraduates’ modules in Michigan State University and Georgia Tech (Caballero et al., 2012; Caballero & Hjorth-Jensen, 2018). Here computation and computational thinking are a central element and not a tool in the design process.

The process and outcomes of collaboration can be analyzed using different frameworks. This study adopts the Interaction Analysis Model (IAM) for collaborative knowledge construction designed by Gunawardena et al. (1997). According to Lucas et al. (2014), interaction is “the process through which negotiation of meaning and co-creation of knowledge occurs and should be viewed as the totality of interconnected and mutually responsive messages, an entire gestalt formed by the online communications among participants”. Thus, the co-creation of knowledge is conveyed by interaction. Based on this definition, Gunawardena et al. (1997) developed a IAM oriented at capturing the knowledge construction process when a community of practice learns using collaborative technologies. It is composed of 5 phases: (1) sharing and comparing of information; (2) discovering and exploring dissonance or inconsistency among ideas or statements; (3) negotiation of meaning/co-construction of knowledge; (4) testing and modification of proposed synthesis or co-construction; (5) agreement statement(s)/applications of newly constructed meaning.

This model was originally created to analyze the interactions during an online debate among researchers and education professionals, i.e. with peer experts within an asynchronous setting where the technology is a communication tool. Gunawardena et al. (1997) themselves argued (and encouraged) that the same method could be applied also with non-experts (such as students) and in different CSCL settings. Recently, the IAM has been used to analyze face-to-face interactions of students working in synchronous settings with peer non-experts and using technology as a cognitive tool (see for example Zabolotna et al., 2023). In this paper, we show how tailored inclusive computational practices may provide opportunities for the co-creation of knowledge in Computational Finance in a CSCL environment.

3. Research methodology: setting, data collection and analysis

This research study has been conducted in the AY 2020/2021 in the Computational Finance module ACM30070, core for the stage 3 of the BSc in Financial Mathematics (FM), School of Mathematics and Statistics, UCD. The module is also optional for stage 3 of the BSc in Applied and Computational Mathematics (ACM). In 2020/2021, 50 students attended the module, with 35 FM and 15 ACM. This module was offered as a pilot in 2016/2017. Then, it was redesigned and improved to include labs including computational practices and group activities in a CSCL environment where students actively participate in the co-creation of their knowledge. Those practices are structured to reciprocally use computational thinking to enrich the mastery of FM and the theory of FM to enrich students' computational thinking. An extensive description of the module design and lab activities can be found in (Perrotta, 2021) and (Perrotta & Dolphin, 2021). To facilitate students' learning and ensure engagement and participation, a tutor and a teaching assistant moderated the labs, actively intervening only if needed or required by students. Each lab lasted 2h. During the first hour, students worked in groups on computational modeling, pseudo-coding, data analysis and other related computer-based activities. In the second hour, each group chose a representative to present the group outcomes to the whole class. The tutor guided groups in presenting their results and encouraged dialogue between groups in order to come to a conclusion. The class was divided into 7 groups (6 of 7 students and 1 of 8), which stayed the same for the whole term. Students were grouped according to: their GPA, (homogeneous, i.e. similar GPA on AVG), their pathway (5 FM and 2 ACM), and gender balance (at least 2 women per group). To positively set students' expectation in view of co-creation of knowledge, students were made aware of their similar GPA, so that they were all expected to be able to contribute in the same way within their group. After each lab, students were invited to fill out a Google Form survey to critically reflect on the activities done in class. Each student completed 10 surveys (1 per week). The survey contains qualitative and quantitative questions, their answers constitute the dataset for this research study. In this paper, we analyze the (open-ended) answers to the following questions:

1. Were the expected outcomes and goals of today's lab clear to you? If yes, please list which are, in your opinion, the key concepts of today's class. If not, please state what was unclear to you.
2. Can you describe in detail in your own words how peer feedback and discussions have or have not helped you in supporting your learning today? Please refer explicitly to the exercises we have covered and make examples.
3. How useful do you think the computational part was for improving your understanding today? Please refer explicitly to the exercises we have covered and make examples.

The Survey was filled out individually and it stayed open for one week, so this activity can be classified as an individual, asynchronous, computer-mediated one. We highlight that the dataset refers to the Jan-May 2020 period. Before March 2020, lab activities took place f2f, in Active Learning rooms. When restrictions were put in place, labs were live-streamed on Zoom, with groups working in breakout rooms with shared screens in the first hour.

For the analysis of this pilot study, we selected 6 students out of 50, who worked in 6 different groups. The selection was made in order to represent three different proficiency levels: two high-level students, two medium achievers and two low-level students. There are 5 males and 1 female in the sub-sample. We analyzed the 6 students' answers to the 10 weekly surveys for the question listed in section 3 using the IAM framework. For each student and each survey, one phase of knowledge co-construction was selected, namely the highest phase that could be inferred from all the answers to the questions of the survey. The goal of our analysis was identifying which was the highest phase reached by the groups during one lab, in order to infer the level of knowledge co-construction achieved by that group during the lab. Since the complete discussions were not available and knowledge co-construction is a progressive process, when one phase was identified from the survey's answers, we deduced that the lower phases were covered during the discussion. So, when more than one phase was detected, we chose the highest one. In case of doubts between two or more phases, we chose the lowest one. The analyses were performed independently by the authors, so that all answers were analyzed by two researchers, and then discussed by all the authors altogether. Then, the phases' frequencies in the 10 labs were computed.

4. Results and discussion

Table 1 shows the frequencies of the highest phases occurred during the discussions that we identified from the answers of the three questions listed in Section 3.

Table 1. Phases of knowledge construction reached during the lab discussions.

Phase	Frequency	Percentage
1	20	35.1%
2	11	19.3%
3	13	22.8%
4	2	3.5%
5	12	19.3%

From these results, we can notice that all the phases of knowledge co-construction described in the IAM occurred during the discussions. Phase 1 is the most frequent, which is in line with similar studies. We assigned to phase 1 those answers which simply show that students compared their solutions or ideas without moving to a deeper discussion. One example of phase 1 is the following, where it seems that during the lab time the group discussion was limited to sharing different points of views.

"As mentioned above, my classmates helped me get a better grasp of the delta of an option. It was helpful to hear their points of view and their thoughts [...] "

Phases 2, 3 and 5 have a similar frequency. We assigned to phase 2 those answers which allowed us to detect disagreement or discussion about different emerging ideas. One example of phase 2 is the following, where it seems that during lab time there was discussion about different ideas and approaches, but students did not reach a common solution:

"Peer feedback was good this week, especially with question 8, where multiple different people brought up differences between the two techniques, so we all learned of differences we wouldn't have thought of. However, with question 7, we were all quite confused [...] and did not get the answer out."

Phase 3 was identified when there was evidence of common knowledge or an agreed solution achieved through collaborative work or discussion after a deep reflection. One example is the following, where the transition from phase 2 (identification of disagreement) to phase 3 (agreement of an explanation) is clearly visible.

"In Q3, we discussed the different possible parameters and variables. Some said that volatility should be a variable, others said a parameter. We agreed that in the real world, it is of course varying constantly but in the BS model it is treated as a parameter."

Phase 4 is the least common, maybe due to the fact that many groups that reached phase 4 then moved to phase 5, and therefore they are included in the number of answers assigned to phase 5. The following answer provides an explicit example of phase 4, since we can observe how the students of this group used the technologies to test and find a confirmation of the knowledge shared during the previous discussion:

"We were able to discuss more things about the model. We actually plotted a comparison of the binomial price and the Black-Scholes price for different values of n and saw that as n got larger the binomial price (which is only an approximation) came much closer. We also plotted the error and observed that the binomial price eventually seemed to converge to the binomial price."

Phase 5 was detected when there was evidence of modification of individual understanding as a consequence of the interaction, such as in the following answer:

"[…] *the computational aspect that we focused on was the implementation of Fincad. [...]. The most educational part for me was to notice he vast difference in options prices when the* *time to maturity and the spot price is 10 euro above the strike price. The call price was roughly 1 euro and the put price was so small it is almost negligible and can be rounded to 0. This prompted much speculation and debate in our group as to the reason why (We believe it's because the price of the share at maturity was unlikely to fall below the strike price, resulting in most likely a loss). We also used Fincad to evaluate the put-call parity with a time to maturity of two years now. By calculating the respective put and call prices using Fincad, we were able to see this was roughly true to approximately 0.362 of a difference between the two sides of the equation. This computational aspect allowed me […] to solidify the truth of the put call parity."*

This answer perfectly shows all the collaborative knowledge construction process occurred, from phase 1 to phase 5. We can see how the group passed through phases 1 and 2 (comparing and contrasting different ideas on why they found a difference between call and put prices), then moved to phase 3 (agreeing on a hypothesis on why the phenomenon occurred), then 4 (testing the shared solution with Fincad) and lastly to phase 5 (applying the new knowledge that the discussion helped them gain, reaching a more solid comprehension of the theory).

5. Conclusions and future improvements

We performed a pilot study to investigate the effectiveness of tailored inclusive computational practices in providing opportunities for the co-creation of knowledge in Computational Finance in a CSCL environment. We selected 6 students out of 50 and we analyzed the answers to the weekly survey questions listed in section 3 through the IAM framework. The results are shown in Table 1 and are in line with the available literature using the same framework in different CSCL environments. From these results, we can notice that all the phases of knowledge co-construction described in the IAM occurred during the discussions. Despite phase 1 being the most frequent (35.1%), which is in line with previous studies (Lucas et al., 2014), relevant number of discussions which developed beyond phase 3: 3.5% stopped at phase 4, the 19.3% reached phase 5. This result improves the available literature and lets us conclude that the proposed activities have been successful in activating the highest level of co-construction of knowledge. The technology and computation used in this module had a key role, since they mediated and fostered the whole learning process. This result supports Donnely et al.'s (2012) thesis: the collaboration within specific problem-solving and computational thinking activities creates suitable conditions for co-learning construction in CSCL environments. We are now planning to extend the analysis to the entire dataset to further investigate how computation intended as combined with a collaborative learning environment fostered the whole learning process. Another possible development of our research is focusing on the impact of group composition in the co-construction of knowledge: indeed, we noticed groups constituted by students with lower GPAs collaborated more than students with higher GPAs, and this was reflected in the attainment of higher phases. This study has a limitation: we have analyzed students' answers instead of recorded conversations, so students may have reached higher phases but without being able to express this in words. For this reason, we are planning to collect a new dataset based on video-recordings of activities and analyze discussions transcripts with the IAM framework.

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