Towards improving social presence in distributed online learning

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1 INTRODUCTION

For any online education community that currently has poor social network structures, a strategy for gradually building community among their students needs to be developed. Research in the area tends to focus on analysing an already successful model, leaving the process of evolution in a collaborative learning network unexplored. Social network theory gives us the tools to measure and study this evolution but there is a divide between social network theory and the promotion of effective learning outcomes.

Many claim that multi user virtual environments (MUVEs) do a good job at building collaborative learning networks (Liu et al., Kuznetcova and Glassman, Scavarelli, Arya, and Teather, Isbell, 2017, 2020, 2020, 2020, 202x). Other studies promote the use of peer feedback, discussion forums and student blogs (Berg, Admiraal, and Pilot, Guardado and Shi, Chang, Schillings et al., 2006, 2007, 2012, 2020). However providing a technology that has the affordances for facilitating the behaviour you desire does necessitate the technologies usage (Kreijns, Kirschner, and Jochems, 2003). Students need motivation to act collaboratively. So while the literature is clear that some platforms are better than others at promoting the growth of distributed learning networks, it is unclear why some approaches are successful, and some are not.

2 RELATED WORK

2.1 Problem Statement

Previous research from CS6460 stresses that OMSCS students struggle to find ways to socialise or build a sense of community. This is especially evident in Piazza, where communication is always task based and so students mainly interact with instructors and TAs, but not with each other. McVeigh-Schultz et al., 2020 found that, as of Fall '18, 71% of OMSCS students want more collaboration, 63% feel isolated and 70% know 2 or less people in the program. Students agreed that group formation is the most critical area for improvement. Sung, 2020 found that Piazza is a good way for students to communicate with instructors and TA's, but not for communication with other students as the vast majority of all interactions on the platform go through the instructors and TA's. This is not a problem restricted to OMSCS - Jiang, Fitzhugh, and Warschauer, Aldholay et al.,, 2018 among others have observed the same phenomenon in the general MOOC framework.

2.2 Social network analysis

Glassman et al., Kuznetcova, Lin, and Glassman, 2020, 2020 highlighted the rebel effect of giving students freedom to form close knit circles at the expense of the instructors authority. In general however, most studies reiterate that decentralised student networks are key in promoting long term engagement (Shih, Chang, and Chin, Jiang, Fitzhugh, and Warschauer, 2020,). Side effects include lower drop out rates, higher grades for those participating actively within the network and an organic dissemination of knowledge throughout the student population.

Kovanovic et al., 2014 revealed a crucial link between social network topology and social presence. This indicates that we can approximate social presence directly, without relying on user perception studies as most research has. Kim, Smirnov and Thurner, 2015, 2017 have shown how homophily (similarity) and expertise correlate with trust level and social presence in social networks. Furthermore, Kim, 2015 demonstrated the effects of various network topologies on the flow of knowledge through the network, and Cottica et al., 2017 gave us the tools to understand the knowledge embedded in these networks. These studies present an extensive toolbox for understanding social networks.

2.3 Social network leadership

The emergence of leaders in online learning networks has been well documented. Aldholay et al., 2018 quantitatively analysed the impact of teaching staff taking on transformational leadership roles in the learning network by helping small student groups individually. Jiang, Fitzhugh, and Warschauer, demonstrated how higher achieving students help lower achieving students in MOOC forums, and also how network centrality affects performance overall. Sutanto et al., 2011 explored the networking patterns that can predict which students act as leaders (namely degree and betweenness centrality). They found that if a leader changed their behaviour to be more of a mediator between other students than a director, they were twice as likely to be perceived as a leader.

3 METHODOLOGY

The Piazza API is used to scrape interactions between students across 4 different OMSCS classes for the 2020 spring and summer semesters. The social network is build such that nodes represent OMSCS students, and edges represent interactions on Piazza. An interaction is defined as either:

1. Leaving a followup on someone's post ('follower' relationship)
2. Leaving a comment on someone's followup ('commenter' relationship)

These are directed edges and commenters are always modelled as interacting with the follower, and not with other commenters on the same followup. This highlights a key limitation of Piazza; it limits users from conversing directly, and instead keeps all conversation public and task specific. To model the strength of connections, weights on an edge AB represent the total number of interactions that student A has sent to B. The sizes of each node represents its total number of interactions in the network (+10 for a post, + 2 for a followup and +1 for a comment). Furthermore, additional attributes are added to each node denoting its role in the course (instructor, TA, student).

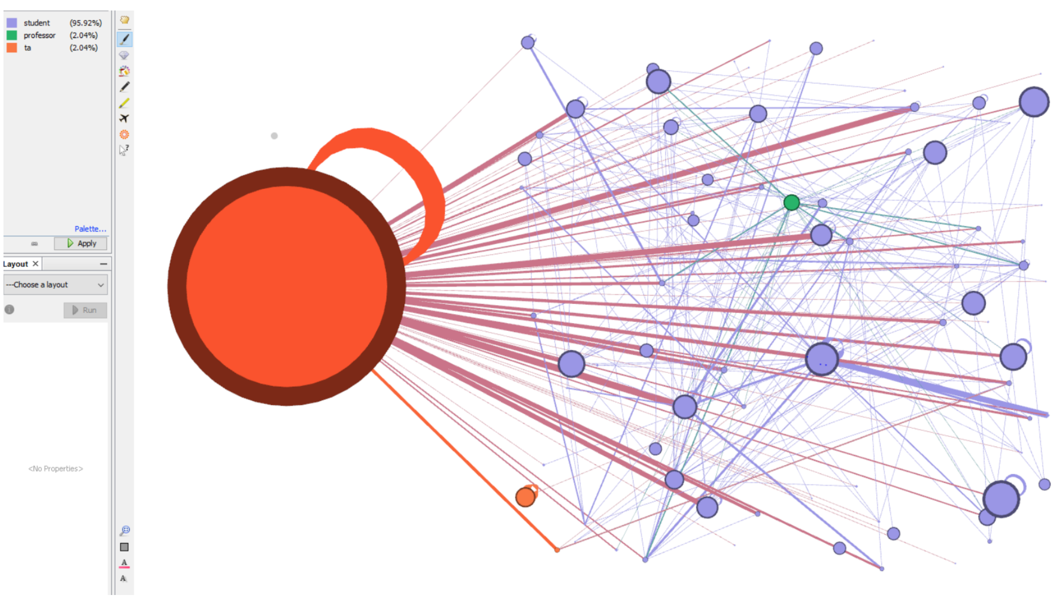

Figure 1—CS6460 network visualised in Gephi

Preliminary investigations were done in the Gephi visualisation tool **??**, before aggregated centrality scores were compared across each of the networks using networkx (Hagberg, Schult, and Swart, 2008) 2. All code involved is published on github. Formal definitions for each of the metrics can be found in the networkx documentation, they are described only briefly here:

1. *Degree centrality*: the fraction of all nodes that each node is connected to (node popularity)
2. *Betweenness Centrality*: how often a given node appears on the shortest path between the other nodes in the network (node importance)
3. *Closeness Centrality*: the reciprocal of the average shortest path distance from all other nodes to that node

We add one additional metric to this commonly used list, 'average weighted degree', which is simply the average of the sizes of each of the nodes (average number of interactions in the network).

Of these metrics, closeness is of particular interest, as it reflects the flow of information through the network:

> This measure is the inverse of the sum of all shortest paths to other vertices. Closeness can be regarded as a measure of how fast it will take to spread information to all other nodes. If a node has strong closeness centrality, it is in a position, with its relationships, to spread information quickly. These people (if nodes are people in the graph) can be important influencers of the network. (McKnight, 2013)

A high closeness centrality score is analogous to the 'small-world' network topology, which minimises the distance between all nodes (Cremonini and Casamassima, 2017). A low score is equivalent to the 'cave-people' topology, which is largely hierarchical and highly centralised.

Finally, a social presence survey (Arbaugh et al., 2008) was instrumented in an attempt to investigate whether centrality scores predict social presence and lend more evidence towards the claims made by Kovanovic et al., 2014. Unfortunately, only one class had significant participation levels and so those results are not analysed here.

4 RESULTS

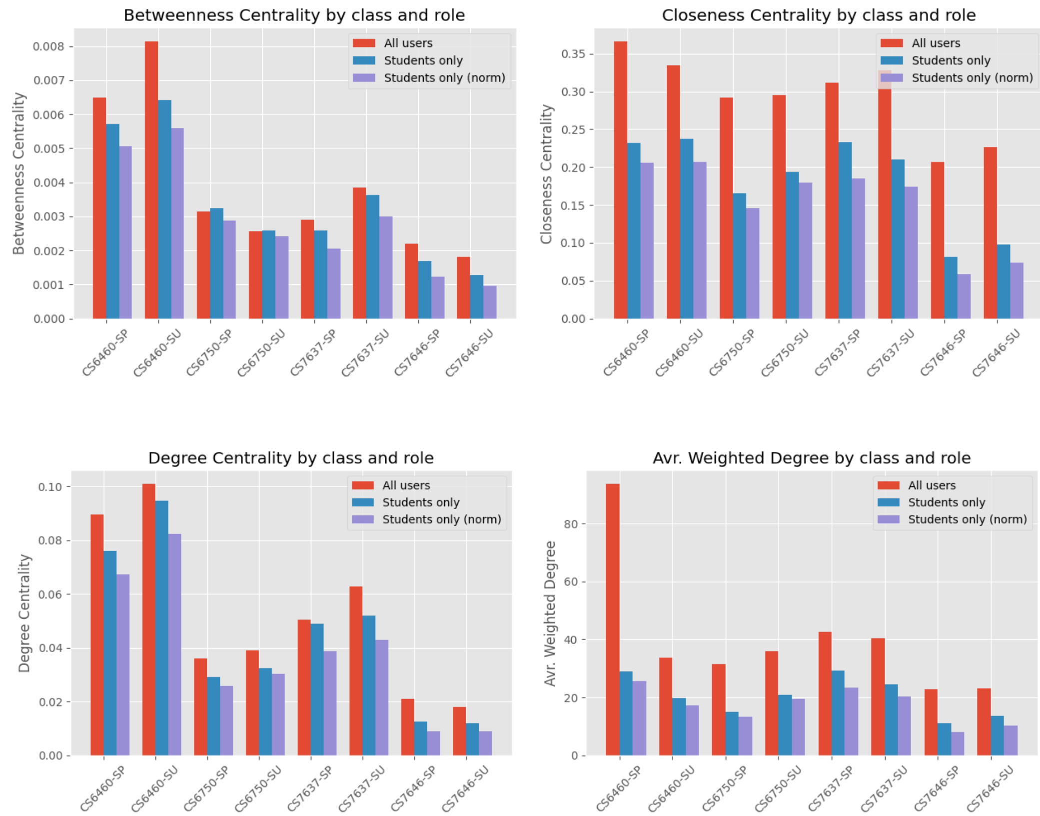

Figure 2—Centrality metrics by class and role

4.1 Comparing classes

What is evident from figure 2 is that each class as a clear trend - each of the metrics is stable between the summer ('SU' postfix) and spring ('SP' postfix) semester. We found that these differences are not correlated with simple attributes of the class such as class size (information that was manually queried from the OSCAR enrollment portal). Instead, we believe that the discrepancies between the classes reflect difference in how each class is operated. Unfortunately OMSCentral, a tool for OMS students to review courses they have completed, did not reveal any statistically significant differences bewteen the classes in terms of difficult, workload or enjoyment, so a set of key course attributes is suggested that might account for the variance seen in the centrality metrics. The table below 1 breaks down the different course attributes that are believed to enhance the connectedness of the Piazza networks.

Class	Peer feedback	Piazza Participation Points (PPs)	Common Test Suite	Group projects	Scheduled discourse	Avr. Degree Centrality
CS6460	Yes	Yes	N/A	Yes	Yes	0.8
CS7637	Yes	Yes	Yes	No	No	0.5
CS6750	Yes	Yes	No	No	No	0.3
CS7646	No	No	No	No	No	0.1

Table 1—Operational characteristics for each OMSCS course

These attributes are presented for context rather than to determine causality, which would require further investigation. That said, a need-finding survey that was instrumented to determine the perceived usefulness (Tokel and İsler, 2015) of the peer feedback tool for CS6460. It found that (n=21):

1. Behavioural intention was 70% (the intent to do more peer review for PPs)
2. Perceived enjoyment was 50%
3. Desire for further followup discussions was 64%
4. 64% agreed it enhanced communication with their peers

4.2 Comparing roles

Decentralised student networks that do not depend on intervention from TA's and instructors in order for students to collaborate are desirable (Kuznetcova, Glassman, and Lin, 2019). In figure 2, we also compare roles within each class. The 'all users' network consists of all nodes, whereas the 'Students only' is the same network with all TA & Instructor nodes removed.

Degree centrality is not largely impacted which is to say that the majority of connections in the network are between students. Betweenness centrality is seen to increase when removing TAs - as now shortest paths go through a greater % of nodes. Closeness takes the biggest hit because TAs tend to be the main connectors of the network. When you remove them, the shortest distance between students is dramatically increased and information flow through the network is likely to slow. This demonstrated a high degree of centralisation across all investigated OMSCS courses.

Note: the model considers student - student interactions on threads authored by instructors / TAs equal to those on student authored threads.

CS6460 is an anomaly in terms of average weighted degree as the sizes of instructor nodes are inflated 1. This is a result of how the network model weights the daily discourse threads posted by the instructors.

4.3 Centrality Distributions

So the question remains: are the observed differences between the classes significant? Do they reflect a noticeable difference in how each of the learning communities operates overall, or are these differences merely the result of a few outliers in each of the classes? To answer this, we look at the underlying distributions for the centrality metrics of the student-only networks.

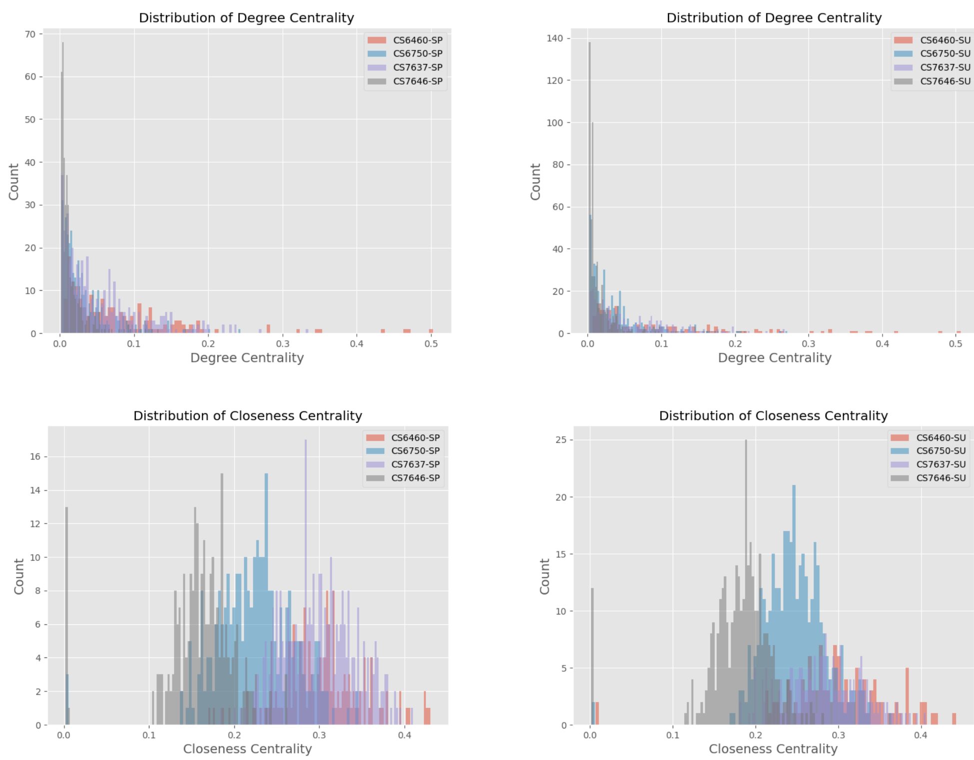

Figure 3—Centrality metric distributions: degree top, closeness bottom, spring left, summer right

In figure 2 there are few visible differences in the log-normal distributions of the degree centrality scores. This is the case for betweenness and avr. weighted degree as well. However, the distribution of closeness centralities is normally distributed for each course and each course appears to have a unique mean and standard deviation, suggesting that the Piazza experience is indeed unique per course. It suggests that rate at which knowledge is disseminated through the network is affected by the operational characteristics of the course (see table 1), however further investigation would need to be done to ensure this is not simply an effect of the central limit theorem.

5 LIMITATIONS

First and foremost, despite Kovanovic et al., 2014 showing centrality to be heavily correlated with social presence, it is noted that network centrality metrics remain weak indicators for causal inference (Dablander and Hinne, 2019). A link between course characteristics & closeness centrality could be strengthened by measuring social presence perception via surveys. Unfortunately, the attempt to do so was unsuccessful as there were not enough participants to provide evidence outside of CS6460.

Our network model was also limited to Piazza, despite Slack and the peer feedback tool being actively used by some courses. These were ignored so as not to introduce bias towards classes that chose to make use of those platforms.

There are also several features of Piazza as a platform, which limited the scope of the network model used:

1. It does not support-student interactions past a single semester of a shared course.
2. It does not encourage off-task communication, which is desirable for creating a resilient student driven network (Kreijns, Kirschner, and Jochems, 2003).
3. It doesn't allow students to create private groups to chat among themselves.

Regardless of the chosen platform, the network analytics approach employed here is subject to the obvious privacy restrictions: we cannot access interactions within private threads. This means that arguably the most important parts of the student social network will always be beyond reach. One remedy might be to request feedback from students on which peers they have formed closest connections with and compare these to the connections that have appeared in the network scrape.

Finally, the network model chosen is only one of many, and a different choice of model might show very different results. The most important decision made in this study is to create edges between commentor and follower for each comment, rather than between the other commentors to whom the given commentor may be replying. The reasoning for this choice is to reflect that the comment thread would not exist without the followup and so we consider the follower as the node responsible for connecting each of the commentors in the network hierarchy.

6 CONCLUSION

Figure 2 reveals distinct centrality trends for each course. This trend is further developed by considering the underlying distribution of closeness centralities in each network in 3. Here we see that closeness centrality is key to understanding which classes have more robust, decentralised student networks.

It was also found that the removal of TAs and instructors from the network has the largest impact on closeness centrality, indicating they are particularly important nodes when considering the flow of information through the network, as you would expect.

Suggestions could be made for further classes based on apparent correlations between the attributes listed in table 1 and the closeness centralities. However, since the claim is not yet strong enough, given the aforementioned limitations, we will leave such recommendations as the subject of future work.

Finally, 'leadership' qualities, as described by Aldholay et al., Sutanto et al., 2018, 2011 can be detected in the students that sit on the long tail of the degree centrality plots in figure 3. If a criteria were to be proposed for the automatic selection of TAs from students who had previously completed a course, this might be a useful heuristic. This is largely related to how emergent leaders are perceived as mediators rather than directors (Sutanto et al., 2011).

7 FUTURE WORK

During the execution of this project, I developed several hypothesis which remain interesting topics of research:

1. Network centrality predicts social presence. (Kovanovic et al., 2014) makes this claim already, but we can look to find further evidence towards it. As class centrality trends are apparent, we can compare previously obtained OMSCS social presence scores (Joyner et al., 2020) to the network centrality scores presented here to give further evidence to this claim.

2. Usage of the peer feedback tool accounts for a substantial proportion of the variance between classes in figure 2. It would be interesting to see, if you remove all edges in the graph common between CS6750 Piazza network & the corresponding peer feedback network, whether the closeness centrality distribution of the remaining CS6750 network would match that of CS7646, which does not make use of the peer feedback tool 3.
3. Perceived social presence & degree centrality are positively correlated behavioural intention (to finish OMSCS) and negatively correlated with dropout rate. *Note: gatech tableau service does not allow grouping by class, so we could not determine dropout rates per class.*

The conclusions in this study could be further enhanced by scraping more OMSCS classes, alongside investigations into the criteria outlined in table 1. It is suggested that a bot is added to all Piazza classes in future to expedite the process of retrieving network data for analysis. The SAMI project within DiLab is actively researching this area by introducing a social agent into OMSCS classes to encourage student - student interactions. This follows research that shows clustering students based on their interests and creating chat groups of similarly minded individuals will result in an increase in async student to student interactions (Kim, Shih, Chang, and Chin, Kapeller, Jäger, and Füllsack, Smirnov and Thurner, 2015, 2020, 2019, 2017).

Finally, despite reiterating the need for increased social presence in OMSCS, the need-finding survey revealed students were by and large not willing to schedule synchronous sessions to establish working relationships with their piers. This has been termed 'the Synchronicity Paradox' and has been previously documented by Joyner et al., 2020. Further investigation into platforms such as SyncEducate (Kutnick and Joyner, 2019) & Wooclap (Wooclap, 2018) is advised to attempt to overcome this.

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9 REFERENCES

[1] "A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda" (2020). In: *Computers Education* 147, p. 103778. ISSN: 0360-1315. DOI: https://doi.org/10.1016/j.compedu.2019.103778.

[2] Aldholay, Adnan H., Isaac, Osama, Abdullah, Zaini, and Ramayah, T. (2018). "The role of transformational leadership as a mediating variable in DeLone and McLean information system success model: The context of online learning usage in Yemen". In: *Telematics and Informatics* 35.5, pp. 1421–1437. ISSN: 0736-5853. DOI: https://doi.org/10.1016/j.tele.2018.03.012. URL: http://www.sciencedirect.com/science/article/pii/S0736585317308146.

[3] Arbaugh, J.B., Cleveland-Innes, Martha, Diaz, Sebastian R., Garrison, D. Randy, Ice, Philip, Richardson, Jennifer C., and Swan, Karen P. (2008). "Developing a community of inquiry instrument: Testing a measure of the Community of Inquiry framework using a multi-institutional sample". In: *The Internet and Higher Education* 11.3. Special Section of the AERA Education and World Wide Web Special Interest Group (EdWeb/SIG), pp. 133–136. ISSN: 1096-7516. DOI: https://doi.org/10.1016/j.iheduc.2008.06.003. URL: http://www.sciencedirect.com/science/article/pii/S1096751608000250.

[4] Berg, Ineke van den, Admiraal, Wilfried, and Pilot, Albert (2006). "Designing student peer assessment in higher education: analysis of written and oral peer feedback". In: *Teaching in Higher Education* 11.2, pp. 135–147. DOI: 10.1080/13562510500527685. eprint: https://doi.org/10.1080/13562510500527685. URL: https://doi.org/10.1080/13562510500527685.

[5] Chang, Ching-Fen (2012). "Peer Review via Three Modes in an EFL Writing Course". In: *Computers and Composition* 29.1, pp. 63–78. ISSN: 8755-4615. DOI: https://doi.org/10.1016/j.compcom.2012.01.001. URL: http://www.sciencedirect.com/science/article/pii/S8755461512000023.

[6] Cottica, Alberto, Hassoun, Amelia, Vallet, Jason, and Melançon, Guy (2017). "Semantic Social Networks: A New Approach to Scaling Digital Ethnography". In: *Internet Science*. Ed. by Ioannis Kompatsiaris, Jonathan Cave, Anna Satsiou, Georg Carle, Antonella Passani, Efstratios Kontopoulos, Sotiris

Diplaris, and Donald McMillan. Cham: Springer International Publishing, pp. 412–420. ISBN: 978-3-319-70284-1.

[7] Cremonini, Marco and Casamassima, Francesca (2017). “Controllability of social networks and the strategic use of random information”. In: *Computational Social Networks* 4. URL: https://api.semanticscholar.org/CorpusID:30538596.

[8] Dablander, Fabian and Hinne, Max (May 2019). “Node centrality measures are a poor substitute for causal inference”. In: *Scientific Reports* 9. DOI: 10.1038/s41598-019-43033-9.

[9] Glassman, Michael, Kuznetcova, Irina, Lin, Tzu-Jung, Tilak, Shantanu, Wang, Qiannan, and Walling, Amanda (2020). “Spaces of rebellion: the use of multi-user virtual environments in the development of learner epistemic identity”. In: *The Journal of Experimental Education* 0.0, pp. 1–18. DOI: 10.1080/00220973.2020.1712311. eprint: https://doi.org/10.1080/00220973.2020.1712311. URL: https://doi.org/10.1080/00220973.2020.1712311.

[10] Guardado, Martin and Shi, Ling (2007). “ESL students’ experiences of online peer feedback”. In: *Computers and Composition* 24.4, pp. 443–461. ISSN: 8755-4615. DOI: https://doi.org/10.1016/j.compcom.2007.03.002. URL: http://www.sciencedirect.com/science/article/pii/S8755461507000734.

[11] Hagberg, Aric A., Schult, Daniel A., and Swart, Pieter J. (2008). “Exploring Network Structure, Dynamics, and Function using NetworkX”. In: *Proceedings of the 7th Python in Science Conference*. Ed. by Gaël Varoquaux, Travis Vaught, and Jarrod Millman. Pasadena, CA USA, pp. 11–15.

[12] Isbell, David A. Joyner Charles (202x). *The Distributed Classroom*, pp. 261–283. ISBN: 000-000-00-0000-0. DOI: 00.0000/000-000-00-0000-0.

[13] Jiang, Suhang, Fitzhugh, Sean M, and Warschauer, Mark (n.d.). “Social positioning and performance in MOOCs”. In: *Workshop on Graph-Based Educational Data Mining*. Vol. 14. URL: http://ceur-ws.org/Vol-1183/gedm2014_proceedings.pdf#page=53.

[14] Joyner, David A., Wang, Qiaosi, Thakare, Suyash, Jing, Shan, Goel, Ashok, and MacIntyre, Blair (2020). “The Synchronicity Paradox in Online Education”. In: *Proceedings of the Seventh ACM Conference on Learning @ Scale*. L@S ’20. Virtual Event, USA: Association for Computing Machinery, pp. 15–

24. ISBN: 9781450379519. DOI: 10.1145/3386527.3405922. URL: https://doi.org/10.1145/3386527.3405922.

[15] Kapeller, Marie, Jäger, Georg, and Füllsack, Manfred (Dec. 2019). "Homophily in networked agent-based models: a method to generate homophilic attribute distributions to improve upon random distribution approaches". In: *Computational Social Networks* 6. DOI: 10.1186/s40649-019-0070-5.

[16] Kim, Young Ae (2015). "An enhanced trust propagation approach with expertise and homophily-based trust networks". In: *Knowledge-Based Systems* 82, pp. 20–28. ISSN: 0950-7051. DOI: https://doi.org/10.1016/j.knosys.2015.02.023. URL: http://www.sciencedirect.com/science/article/pii/S0950705115000775.

[17] Kovanovic, Vitomir, Joksimovic, Srecko, Gasevic, Dragan, and Hatala, Marek (2014). *What is the Source of Social Capital? The Association Between Social Network Position and Social Presence in Communities of Inquiry*. URL: http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.664.4492.

[18] Kreijns, K., Kirschner, P., and Jochems, W. (2003). "Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: a review of the research". In: *Comput. Hum. Behav.* 19, pp. 335–353. URL: http://dspace.library.uu.nl/bitstream/handle/1874/16872/kirschner_03_identifying_pitfalls_social_interaction_computer_supported.pdf?sequence=1.

[19] Kutnick, Denise and Joyner, David (June 2019). "Synchronous at Scale: Investigation and Implementation of a Semi-Synchronous Online Lecture Platform". In: pp. 1–4. ISBN: 978-1-4503-6804-9. DOI: 10.1145/3330430.3333653.

[20] Kuznetcova, Irina and Glassman, Michael (2020). "Rethinking the use of Multi-User Virtual Environments in education". In: *Technology, Pedagogy and Education* 29.4, pp. 389–405. DOI: 10.1080/1475939X.2020.1768141. eprint: https://doi.org/10.1080/1475939X.2020.1768141. URL: https://doi.org/10.1080/1475939X.2020.1768141.

[21] Kuznetcova, Irina, Glassman, Michael, and Lin, Tzu-Jung (2019). "Multi-user virtual environments as a pathway to distributed social networks in the classroom". In: *Computers Education* 130, pp. 26–39. ISSN: 0360-1315. DOI: https://doi.org/10.1016/j.compedu.2018.11.004. URL: http://www.sciencedirect.com/science/article/pii/S0360131518303014.

[22] Kuznetcova, Irina, Lin, Tzu-Jung, and Glassman, Michael (Mar. 2020). "Teacher Presence in a Different Light: Authority Shift in Multi-user Virtual Environments". In: *Technology, Knowledge and Learning*. DOI: 10.1007/s10758-020-09438-6.

[23] Liu, Dejian, Dede, Chris, Huang, Ronghuai, and Richards, John (Jan. 2017). *Virtual, Augmented, and Mixed Realities in Education*. ISBN: 978-981-10-5489-1. DOI: 10.1007/978-981-10-5490-7.

[24] McKnight, William (2013). *Information management: strategies for gaining a competitive advantage with data*. Newnes.

[25] McVeigh-Schultz, Joshua, Márquez Segura, Elena, Merrill, Nick, and Isbister, Katherine (Jan. 2020). "Enabling Effective Student Collaboration in MOOCs". In: DOI: CS6460ExemploraryPastProjects.

[26] Scavarelli, Anthony, Arya, Ali, and Teather, Robert J (2020). "Virtual reality and augmented reality in social learning spaces: a literature review". In: *VIRTUAL REALITY*. URL: https://link.springer.com/content/pdf/10.1007/s10055-020-00444-8.pdf.

[27] Schillings, Marlies, Roebertsen, Herma, Savelberg, Hans, Dijk, Anne van, and Dolmans, Diana (2020). "Improving the understanding of written peer feedback through face-to-face peer dialogue: students' perspective". In: *Higher Education Research & Development* 0.0, pp. 1–17. DOI: 10.1080/07294360.2020.1798889. eprint: https://doi.org/10.1080/07294360.2020.1798889. URL: https://doi.org/10.1080/07294360.2020.1798889.

[28] Shih, Yen-An, Chang, Ben, and Chin, Jonathan Y (2020). "Data-driven student homophily pattern analysis of online discussion in a social network learning environment". In: *Journal of Computers in Education* 7.3, pp. 373–394. ISSN: 2197-9987.

[29] Smirnov, Ivan and Thurner, Stefan (Aug. 2017). "Formation of homophily in academic performance: Students change their friends rather than performance". In: *PLOS ONE* 12.8, pp. 1–16. DOI: 10.1371/journal.pone.0183473. URL: https://doi.org/10.1371/journal.pone.0183473.

[30] Sung, Sohyun Sora (Jan. 2020). "Understanding Social Engagement Traits and Dynamics of Piazza Forum in the OMSCS courses". In: DOI: CS6460ExemploraryPastProjec

[31] Sutanto, Juliana, Tan, Chuan-Hoo, Battistini, Boris, and Phang, Chee Wei (2011). "Emergent Leadership in Virtual Collaboration Settings: A Social Network Analysis Approach". In: *Long Range Planning* 44.5. Social Software: Strategy, Technology, and Community, pp. 421–439. ISSN: 0024-6301.

DOI: https://doi.org/10.1016/j.lrp.2011.09.001. URL: http://www.sciencedirect.com/science/article/pii/S0024630111000422.

[32] Tokel, Saniye Tugba and İsler, Veysi (2015). "Acceptance of virtual worlds as learning space". In: *Innovations in Education and Teaching International* 52.3, pp. 254–264. DOI: 10.1080/14703297.2013.820139. eprint: https://doi.org/10.1080/14703297.2013.820139. URL: https://doi.org/10.1080/14703297.2013.820139.

[33] Wooclap (2018). "Wooclap". In: URL: https://www.wooclap.com/.