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Article abstract

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Mapping Network Structure and Diversity of Interdisciplinary Knowledge in Recommended MOOC Offerings

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Abstract

In massive open online courses (MOOCs), recommendation relationships present a collection of associations that imply a new form of integration, such as an interdisciplinary synergy among diverse disciplines. This study took a computer science approach, using the susceptible-infected (SI) model to simulate the process of learners accessing courses within networks of MOOC offerings, and emphasized the potential effects of a network structure. The current low rate of access suggests that a ceiling effect influences learners' access to learning online, given that there are thousands of courses freely available. Interdisciplinary networks were created by adding recommended courses into four disciplinary networks. The diversity of interdisciplinarity was measured by three attributes, namely variety, balance, and disparity. The results attest to interesting changes in how the diversity of interdisciplinary knowledge grows. Particularly remarkable is the degree to which the diversity of interdisciplinarity increased when new recommended courses were first added. However, changing diversity implied that neighbouring disciplines were more likely to come to the forefront to attach to the interdisciplinarity of MOOC offerings, and that the pace of synergy among disparate disciplines slowed as time passed. In the absence of domain experts, expert knowledge is not sufficient to support interdisciplinary curriculum design. More evidence-based analytics studies showing how interdisciplinarity evolves in course offerings could help us to better design online courses that prepare learners with 21st-century skills.

*Keywords: d*istance education and online learning, informal learning, interdisciplinary projects, simulations

Introduction

Today, 21st-century skills demand ways of thinking that go beyond simple categories to include interconnections between disciplinary boundaries. Consequently, contemporary approaches to educating young people call for a new type of learning that incorporates interdisciplinary knowledge across the natural and social sciences, with the goal of solving real-world problems. However, integrating courses across disciplines in a conventional higher education setting is a demanding and challenging pursuit. Researchers (e.g., Holley, 2009; Jarmon et al., 2009; Meyers et al., 2013; Spector, 2015; Zhang, Burgos, & Dawson, 2019) have concluded that interdisciplinary learning to prepare learners with 21st-century skills demands new learning spaces that are no longer simply physical places, but also include an online environment that is supportive of informal learning.

Cormier and Siemens (2010, p. 32) argued that "online open courses allow for innovation in how educators prepare to teach, how learners negotiate knowledge from the information they are encountering, and how courses can have an impact on the broader field of study." Such online spaces are capable of accommodating different types of interaction that are open, flexible, and adaptable to new forms of knowledge integration (e.g., Gillet et al., 2005; Linn et al., 2003; Luo & Chea, 2020; Tucker & Morris, 2011). What has changed is not the knowledge itself in the current practice of online and flexible learning, but rather how the knowledge is delivered and re-constructed by the global body of learners (Maassen et al., 2018). Such learning environments allow learners to sustain interdisciplinary efforts in order to strengthen the relationships between what they have learned and other sources of knowledge and experience (Zhang, Burgos, & Dawson, 2019). Online learning, to some extent, resembles the interconnected world in which one lives and learns, and demonstrates how knowledge intersects and crosses borders (Anderson, 2008). Compared to conventional practices in higher education, the online space offers greater flexibility. It also allows knowledge to be recategorized or divided in much the same way as industry products are reconfigured to meet changing demands from rapidly developing society and digital technology (Adelman, 1999).

Nevertheless, we still do not know how this transformation occurs in the online delivery mode until it is carefully analysed. Nor will we understand how much online courses such as MOOC offerings have diversified and specialized until more courses are offered online, and data-driven research is available. This process of diversification and specialization is barely noticeable at first and then draws more attention from institutional management. Over time, the nature of MOOC offerings worldwide, and what we learn from them through analytic research, may have an impact on the current design of courses for knowledge acquisition in tertiary education. This will, in turn, contribute to preparing learners with 21st-century skills.

Network analysis enables us to make evidence-based decisions about the structural topology of current MOOC offerings. Identifying meaningful network structures among MOOC offerings provides an overall picture of the disciplinary knowledge in MOOCs. In this study, network analysis was used to explore the hidden topological knowledge structure of MOOCs on XuetangX (a widely recognized Chinese MOOC platform). The growing collection of MOOCs can be seen as a network of course nodes with links between the nodes. The linkage between any two courses came from XuetangX's recommendation mechanism. Using metrics developed in network science, this study investigated the network structures of disciplinary knowledge created in the MOOC space, and explored the extent to which such structures allowed for interdisciplinarity.

Problems of Disciplinary Structure in Conventional Higher Education

Our modern disciplinary structure has resulted in the diversification and specialization of labour and knowledge (Kockelmans, 1979). For centuries, disciplines have expanded, integrated, and scaled down; nevertheless, the main structure of higher education has not changed (Holley, 2017). The department is still arguably the dominant unit in which teaching and learning are designed and implemented for students (Trowler et al., 2003). Academic departments follow institute regulations to develop courses that address local issues and contexts (Higham, 2003), and a curriculum committee takes care of reviewing and approving the proposals for programmes and curricula (Massachusetts Institute of Technology [MIT], 2017). In this way, knowledge is, to a large extent, defined and compartmentalized based on institutional decisions. This is widely referred to as a traditional disciplinary approach to curricula (Venville, et al., 2012). This approach rests, however, on the assumption that there is a corpus of disciplinary knowledge (i.e., received wisdom that is beyond criticism; Kelly et al., 2008). “Curricula in higher education are to a large degree ‘hidden curricula’ . . . they take on certain patterns and relationships, but those patterns and relationships will be hidden from all concerned, except as they are experienced by the students” (Barnett, 2000, p. 260). Disciplinary knowledge is translated into curricula with reference to key criteria, standards, or educational outcomes that might be unintendedly weighted in favour of existing disciplinary capacity (West, 2018).

Given the increasing challenges facing educators in the 21st century, the process of how knowledge is produced today is global and diverse(Kahn & Agnew, 2017). There is an urgent demand for interdisciplinarity, a term commonly used to refer to the integration of knowledge from multiple disciplines (Choi & Pak, 2006). Nevertheless, the ethnocentric nature of disciplinary structures inevitably produces clusters of subject knowledge, thereby leaving gaps between them (Holley, 2017). Campbell (1969) proposed a famous fish-scale model of interdisciplinarity studies to criticize this kind of intuitional structure. Faculty are trained with respect to disciplinary norms, and interdisciplinary training is a complex endeavour for conventional higher education. Students continue to be increasingly trained within disciplinary domains, thus leaving epistemological gaps unexplored. Defining knowledge strictly in disciplinary domains has made it difficult to make potentially rich connections between various epistemological ideas (Holley, 2017). Following the arguments of the crisis of curriculum in the community (e.g., Priestley, 2011; Wheelahan, 2012), a number of researchers have agreed that higher education practices have yet to clearly define the problematic role and meaning of disciplinary knowledge that has existed for centuries (e.g., Graff, 2015; Trowler et al., 2012). Instead, most curricula are “fragmented . . . unconnected [and] rely on students’ efforts to make sense of the whole” (Hubbal & Gold, 2007, p. 8).

Large Repository of MOOCs Creates Opportunities for Analytics Studies

Educational researchers face a significant challenge preparing higher education to be proactive regarding these issues. There is no doubt that educational practices have undergone remarkable changes, but many practices remain rooted in 20th-century foundations of learning (Kahn & Agnew, 2017). The disruptive innovation of MOOCs attempt to change current practices while encountering contradictory demands for higher education in modern society. Currently, there are growing concerns about high dropout rates (Ang et al., 2020; Reich & Ruipérez-Valiente, 2019), lack of learner support (Gregori et al., 2018), as well as demand for better instructional design of MOOCs (Zawacki-Richter et al., 2018) and accountability regarding assessment of MOOCs (Suen, 2014). However, what is new in MOOCs is neither the innovative pedagogies nor the transformation of higher education, but rather an unnoticeable and slow process of the increasing specialization of MOOC offerings online (Schuwer et al., 2015). There are now over 163,000 MOOCs available in cyberspace, and trends indicate greater growth and differentiation (Shah, 2020).

As online learning is open and flexible, course offerings are less likely to follow compulsory requirements of university curricula (Brown et al., 2015). For instance, MOOCs are usually offered by experts in various areas from different universities or industries. As long as this is the case, MOOCs will continue to be offered in a bottom-up fashion without necessarily following any curricula or guidelines, which will inevitably create large repositories of courses from diverse disciplines. Traditionally, the course offering decisions that institutions make are governed by conventional disciplinary practices and advisement from programme directors within academic departments (MIT, 2017). However, none of these types of advice are available in the MOOC space.

Although MOOCs offer the opportunity to create something new, we lack the confidence to question why the content of courses bears a considerable resemblance to the face-to-face courses offered by schools and institutions. MOOCs, as an example of online educational practice, predominantly reflect what tertiary education produces (Zhang, Sziegat, et al., 2019). Disciplinary knowledge is commonly regarded as content knowledge. Online higher education preserves the tradition that the majority of such content knowledge is borrowed from conventional higher education (Naidu, 2017). As such, content knowledge has been criticized for decades, since content transfer implies behaviourist-type, old-fashioned approaches to learning (Eynon, 2017). Thus, there is an urgent call for educational researchers and practitioners to think outside the box, and to face the challenges of designing, planning, and implementing strategic changes to knowledge and curricula in the 21st century (Brown et al., 2015). The flexibility necessary for the design of interdisciplinary courses may be difficult to achieve and even harder to preserve in MOOCs. Nevertheless, as Gašević et al. (2014) argued, there is a need for "increased efforts towards enhancing interdisciplinarity" (p. 134) in MOOC research. One way to help interdisciplinary learning occur is by making sure that there is some disciplinary cohesion in the cohorts of MOOC offerings as well.

Since 2012, knowledge delivered online has worked its way up. MOOC offerings have produced a huge amount of data that allowed many analytic studies focused on learning processes, discussion, engagement, and self-regulation. Refer to Mangaroska and Giannakos (2018) and Tsai et al. (2020) for comprehensive reviews. A prominent trend of these studies is the use of an analytic approach to studying learners' behaviours through the exploration of engagement and dropouts, together with a careful examination of prediction and assessment. While such work has arguably illuminated our understanding of what contributes to quality learning and teaching online, the selection of disciplinary knowledge and its organization have often been neglected, as they have been deemed unimportant in this kind of analytic research into MOOCs. Network structures, while widely recognized in network science, have not been used to examine disciplinary knowledge created in the MOOC space. The structure of MOOC offerings reveals conceptual models of the different parts or components as well as course organization or structure. As more online courses are increasingly offered, making connections between different courses from different disciplines in a more synthesized way is an effective mechanism to support strategic institutional decisions on what MOOCs to offer in the future. Identifying the network structures of MOOC offerings could also provide insights into curriculum design for open and flexible learning. Such an approach to evidence-based decision making might discover important insights that would not have been identified through the conventional process of curriculum development (West, 2018). It is also critical for allowing truly interdisciplinary synergy that is not constrained by the unintended bias of a single discipline.

Methodology

This study sought to understand the network structure of MOOC offerings and the diversity of interdisciplinary knowledge offered by MOOCs by simulating the process of learners selecting recommended courses. In this study, we did not examine knowledge, as it has been explored in cognitive science. Instead, knowledge is only used as a result of a course, which is associated with a certain discipline. That is, the fact that a course is offered in a certain discipline is seen as contributing to a certain disciplinary knowledge, which is similar to bibliographic work or science of science research (e.g., Veletsianos & Shepherdson, 2015), in which journal articles are regarded as knowledge produced in certain disciplines. Our representation of disciplinary knowledge in relation to interdisciplinary knowledge was the product of network structures of recommended MOOCs offered on XuetangX.

The Case and Data Collection

XuetangX was selected as the case for this research study. As one of the top five MOOC providers worldwide, XuetangX hosts Chinese MOOCs, as well as courses from a consortium of leading universities worldwide. XuetangX, powered by the open-source platform edX, has expanded a number of features, such as recommendation systems, that are not found in many other MOOC platforms. Recommendations offered on MOOC platforms can play a useful hidden role in the selection of courses. On XuetangX, for each course, three recommended courses are provided on the right-hand side of the course page (as shown in Figure 1). While these current recommendations may not be intelligent enough to suggest that courses are related in any way, there might be an association of some kind that is worth exploring. For example, the fact that course A in engineering is recommended by course B in computer science implies not only that is there a relationship between course A and course B, but also that the knowledge bases of engineering and computer science are related. A collection of these kinds of individual associations offers a new form of integration, such as an interdisciplinary synergy between engineering and computer science. Identifying meaningful network structures of course offerings provides an overall picture of disciplinary knowledge (West, 2018).

Figure 1

Interface of a MOOC on XuetangX

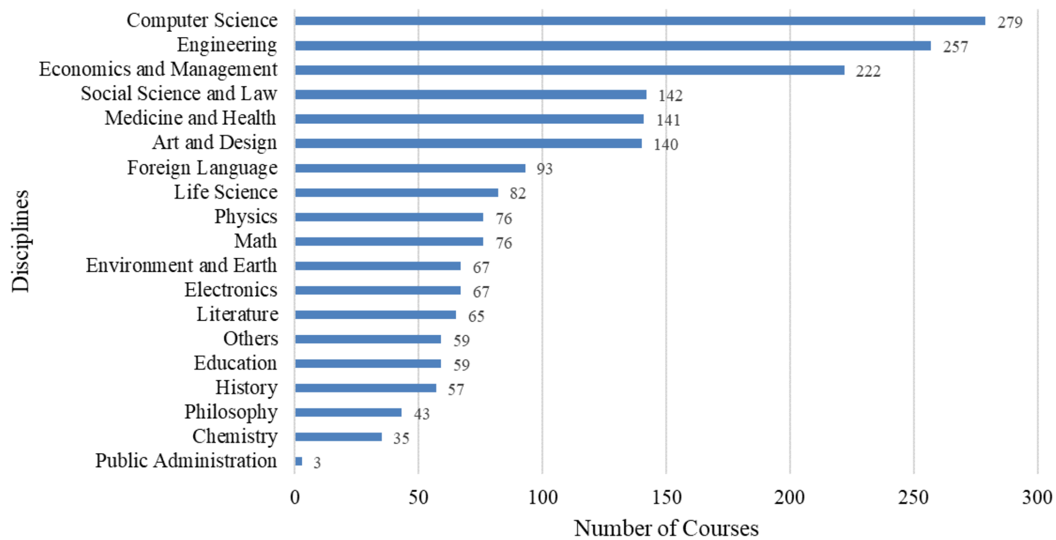
Note. Image captured from XuetangX website (*https://www.xuetangx.com/)*.

In the current study, a crawler programme written in Python was used to collect information about courses and the links recommending these courses from XuetangX. The data were collected until May 2019 from a total of 2,017 courses, among which 526 courses were exported from other MOOC platforms, such as edX. The disciplinary information of 1,990 courses was obtained from the original MOOC platform; 27 courses had no associated disciplinary labels. Each platform adopts different discipline categories to differentiate their courses. For example, 30 different disciplines are provided on edX, while only 21 different disciplines are available on XuetangX. In the present study, we followed XuetangX's discipline categories and merged the disciplines provided on edX into XuetangX's categories. For example, one discipline label—university prerequisite, containing 11 courses—was deleted, and another discipline, entrepreneurship, was merged into economics. By doing so, 19 final categories of disciplines were formed.

As 16 courses had no associated recommended courses (and were thus removed from XuetangX), a total of 1,963 courses were identified within 19 disciplines. As shown in Figure 2, the majority of the courses on XuetangX were within the disciplines of computer science, engineering, economics and management, and social sciences and law. Therefore, these top four disciplines that offer the majority of MOOCs were selected as the cases through which we explored the topological structure of their recommendation networks.

Figure 2

Number of Courses Within Each of the 19 Disciplines on XuetangX



Data Analysis

This study adopted computational and systems modelling, which uses simulation as a model to investigate complex systems, given that social and cultural perspectives of learning are interwoven with multiple levels of interactions (Janežič et al., 2018). As it seems that no researchers have collected learner behaviour data across different courses for a whole MOOC platform, it is impossible to use real learner behaviour data to create a disciplinary structure of MOOC offerings. Thus, we adopted the susceptible-infected (SI) model to illustrate how courses are accessed by learners in the recommended course network. We emphasized the potential effect induced by network structure rather than that from the learners' perspective. The SI model is used to simulate the spread of a disease in a population. It is a simple but common method of modelling the interaction of two populations in a network. In using this model, some assumptions are necessary. First, the size of the population is fixed, and we use N to represent it. Second, there are two classes of individuals in the population. S represents susceptible individuals who do not have the disease but are susceptible to it and I represents infective individuals who have the disease and are infectious; $S + I = N$ is always satisfied. Third, disease spreads through interactions between pairs of individuals—from infective individuals to susceptible individuals. Finally, an infectious rate between 0 and 1 is constant during the whole process (Allen, 1994).

In our research, we assumed that learners played the role of a disease in the SI model, and courses in the network act as individuals. Individuals are connected by recommendation links on Web pages, wherein the disease spreads through recommendation links. During the spreading process, there are only two classes of individuals (i.e., course resources)—S represents course resources not viewed and I represents course resources that have been viewed. The number of course resources in the network is fixed, and is equal to the sum of the unviewed and the viewed courses. Learners acquire neighbour resources moving through the recommendation links within a range of probability, and here, we assumed that the probability was constant.

Analysis of the Diversity of Interdisciplinary Knowledge

In this research, we explored how the degree of diversity changed using SI simulation for four interdisciplinary networks, namely engineering, social science, computer science, and economics and management. Evidence has indicated that the use of multiple metrics can reveal the differences between various bodies of disciplinary knowledge (Porter & Rafols, 2009). We measured the diversity of interdisciplinarity in networks comprising courses from different disciplines by three attributes, namely variety, balance, and disparity (Stirling, 2007). Combining these three metrics enabled us to measure the interdisciplinary knowledge of MOOCs to a level of detail that has been previously unexplored. The diversity of interdisciplinarity in networks comprising courses from different disciplines was measured by three attributes of variety, balance, and disparity/similarity (Stirling, 2007).

The variety attribute measured the number of distinct disciplines in which courses were offered—the greater the variety, the greater the diversity. We calculated variety by the ratio of the number of links that pointed to courses from different disciplines to the total links that pointed to all courses. Balance indicated the even distribution of these disciplines, analogous to statistical variance. The more even the balance, the greater the diversity. Entropy, proposed by Shannon (2001), has been widely used in thermodynamics; we used it as a metric to represent the balance of interdisciplinarity. The greater the entropy, the more even the balance. If an interdisciplinary network contained courses from a wide range of disciplines evenly, then the diversity level of this interdisciplinary network was high. Disparity illustrates the degree to which these disciplines differed. The Rao-Stirling index was used to measure disparities in interdisciplinarity.

Results

Topological Structure of Disciplinary Networks

As shown in Figure 3, the topological structures of the four selected disciplines varied greatly. All four disciplinary networks had significant community structures (Newman & Girvan, 2004), as the modularity values for all four disciplinary networks were greater than 0.3 (see Table 1). Moreover, we found that social sciences and law had the highest modularity value of 0.946. This shows that this disciplinary network had a better community structure than the other three networks.

Table 1

Summary of Statistical Properties of Four Disciplinary Networks

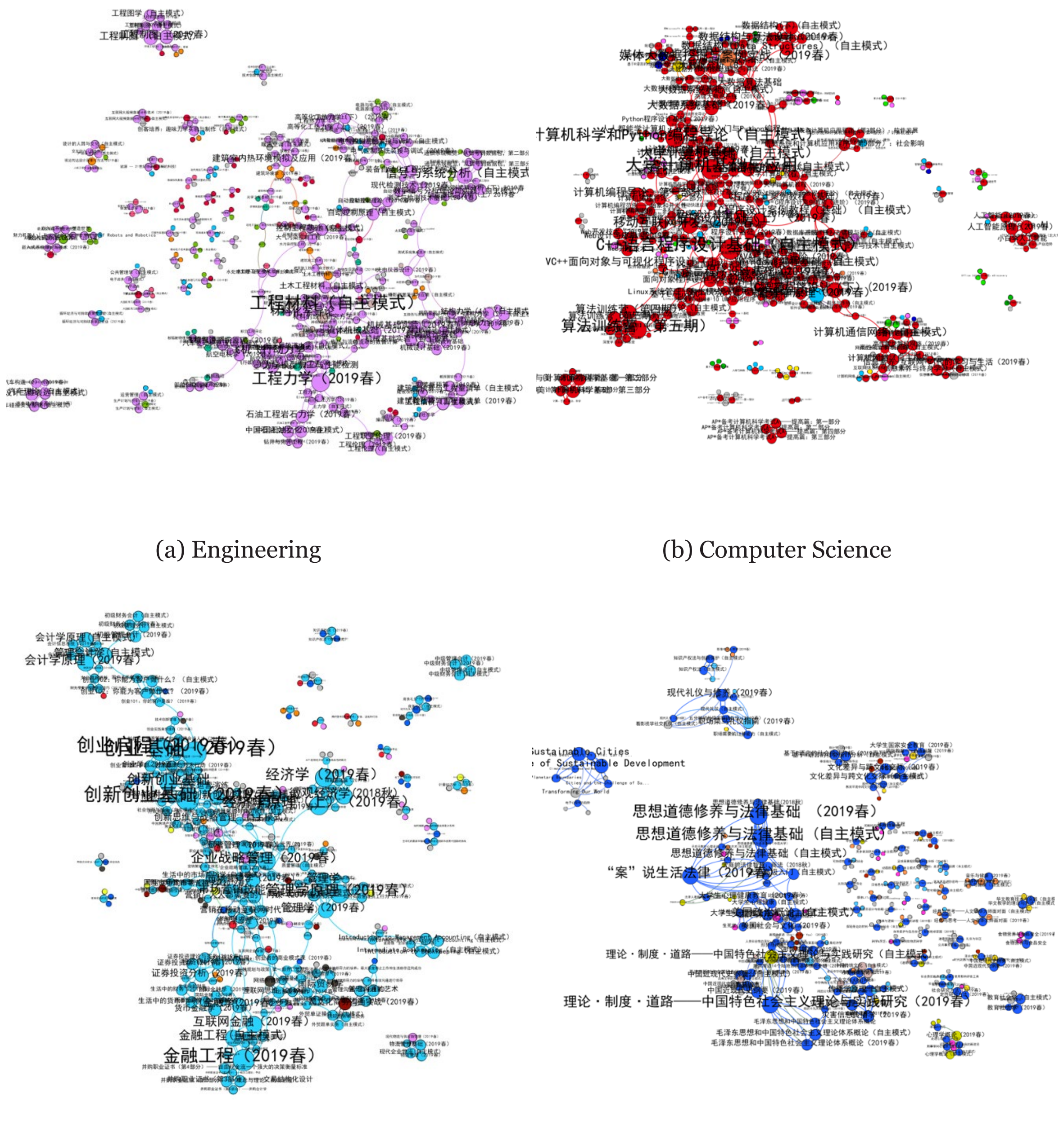
Network metrics	Computer science	Engineering	Economics and management	Social sciences and law	Entire network
Scale	407	451	323	315	1963
Edge	799	757	657	421	5715
Average degree (AD)	1.963	1.678	2.034	1.337	2.911
Diameter (D)	11	11	13	6	47
Average path length (APL)	3.403	2.913	2.842	1.685	10.856
Network density (ND)	0.005	0.004	0.006	0.004	0.001
Number of weakly connected components	19	32	16	45	6
Number of strongly connected components	311	352	246	279	1,076
Number of communities	35	45	29	49	39
Modularity	0.854	0.899	0.859	0.946	0.843

Different communities (represented in different colours in Figure 3) contained courses in different topics. The courses in the same community were very densely connected, which showed that the courses had similar themes. For example, in the subnetwork of computer science, Figure 3 (b), red represents one community. In this community, the courses were *Foundation of C*, *Foundation of C++*, *Advanced Course in C*, and so on. These courses belonged to the same theme: learning programming languages.

As shown in Figure 3, four disciplinary networks were not complete networks, but rather consisted of multiple independent subgraphs. The network of economics and management had the lowest degree of separation, with 16 subgraphs. The smallest subgraph had only three courses, while most of the remaining courses formed other complete subnetworks. The computer science network also has a similar distribution of subgraphs. The smaller subgraphs in computer science contain only two or three courses. There were some differences between the larger subgraphs and the smaller subgraphs. For example, in the computer science network, the theme of the smallest subgraph was electronics, but the theme of the largest subgraph was programming and engineering.

Figure 3

Recommendation Networks of Four Different Disciplines



(a) Engineering

(b) Computer Science

(c) Economics and Management

(d) Social Sciences and Law

Note. Colours represent detected communities (purple: engineering; green: EE; light blue: economics and management; red: computer science; dark blue: social sciences and law. The size of a node indicates the number of linkages.

As shown in Figure 3, the courses in economics and management were most densely interconnected. This structure can be measured by the average degree, a global description for all the nodes in the network, and used to measure the average number of neighbours the nodes have. The average degree of the economics and management network was 2.034, which was the largest value among the four disciplinary networks. On the other hand, the average degree of the social sciences and law network was only 1.337, the lowest value among all four disciplinary networks.

The information dissemination capability of a network can be measured by the network diameter (i.e., the maximum distance across the network), and the average path (i.e., the average of any distance between two nodes in the network; Lin, 2009). In the present study, a path length refers to the number of intermediate nodes that need to be communicated or exchanged between any two given courses. The network diameter and average path length for the social sciences and law subnetwork (D = 6, APL = 1.685) were shorter than those of the other three sub-networks (i.e., engineering: D = 11, APL = 2.913; computer science: D = 11, APL = 3.403; and economics and management: D = 13, APL = 2.842). These results indicated that learners in social sciences and law course networks took fewer steps to find other related courses in the same discipline. In this way, the knowledge structure of this discipline seems to be more conducive to learners' access.

In a directed graph, there are two kinds of connected components, namely strongly connected and weakly connected, depending on how we treat the directionality of links. In a strongly connected component, every node is reachable from every other node, while in a weakly connected component, every node is reachable from every other node, ignoring directions (Tabassum et al., 2018). Regarding the computer science discipline, the whole network contained 19 weakly connected components. Eight out of ten (79.85%) of the courses were bounded together in the largest connected component, which contained almost all of the total recommendation links (n = 694, 86.86%). It consisted predominantly of courses in the topics of programming and data analysis, which are the basic and fundamental courses in computer science. In this network, programming courses such as *C++ Programming* and *Computer Fundamentals and Applications* occupied central positions in the computer science recommendation network, in which we used the network metrics - in-degree - to measure the importance of a course.

Forming Interdisciplinary Networks of MOOCs

Interdisciplinary networks (i.e., extended disciplinary networks) were created by adding neighbour courses into the four disciplinary networks (as shown in Figure 4). We continued this process until no further course in the previous steps was added. Four interdisciplinary networks, one for each discipline, were created. For example, in the engineering discipline, in the first step, 194 courses that were recommended by the courses in engineering disciplines were added, of which most were courses in electronics, computer science, and economics. In the second step, using a similar mechanism, 158 courses were added, and this process was continued until step 12. After step 12, there were no courses available that had not been added in the previous steps. For three of the disciplinary networks, it took 12 to 13 steps to converge; however, economics and management required 22 steps to form an extended disciplinary network. For the extended computer science network, most of the newly added courses were from computer science, economics, and engineering. For the extended economics network, engineering and computer science made up most of the recommended courses. The social sciences and law network favoured courses from the disciplines of engineering, computer science, and economics.

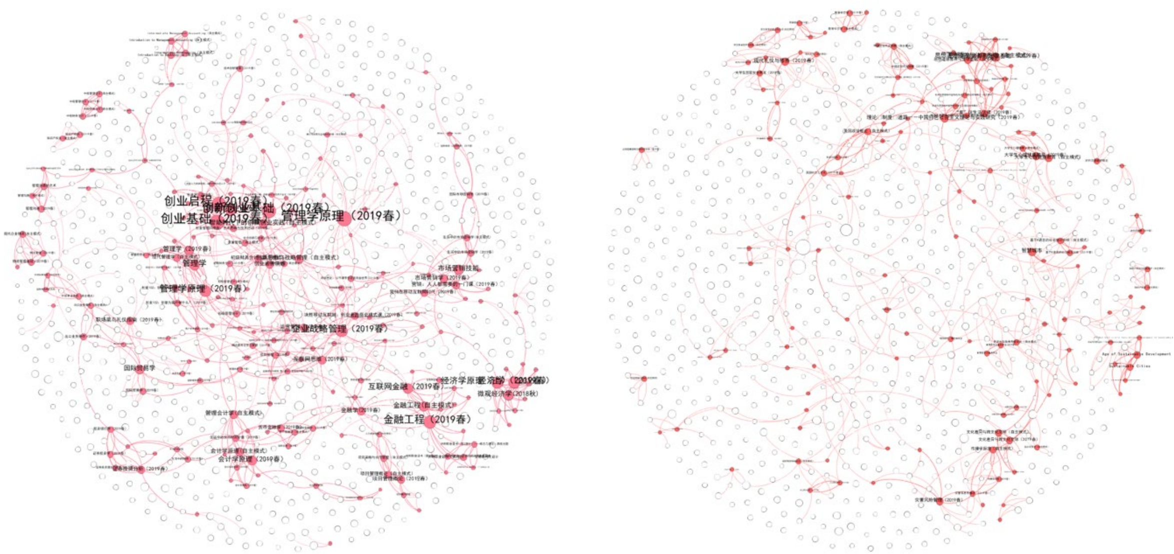
At the end of this process, for each of these connected interdisciplinary networks, there were approximately 857 to 917 courses. There was a large overlap among these four networks, with a total of 561 courses common to all four interdisciplinary networks. Between each pair of the two networks, at least 66% of the courses were the same, and approximately 563 courses belonged exclusively to only one network.

Interestingly, the strongest connected components across the four extended disciplinary networks were in the same network and included the same 30 courses. Among these courses, 15 were related to physics, 10 were related to engineering, and one was related to each of the environment and earth, computer science, history, and math. One course in the set was categorized as other.

Figure 4

The Four Interdisciplinary Networks

(a) Engineering (b) Computer Science



(c) Economics and Management (d) Social Sciences and Law

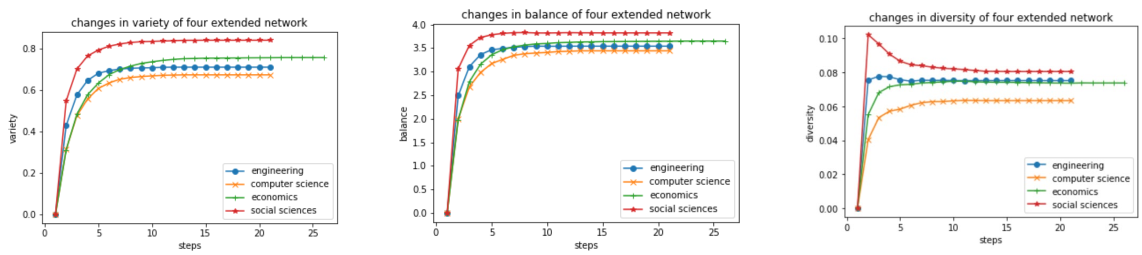
Note. Red nodes represent the courses within the same disciplines, and white nodes represent the courses from other disciplines.

The Diversity of The Interdisciplinary Networks

As shown in Figure 5 (left), while forming interdisciplinary networks by simulation, the variety of interdisciplinarity increased sharply first and then tended to stay steady. The variety of the extended social sciences and law network was relatively higher than that of the other three networks. In the first step, the variety of the extended social sciences and law network increased to 54.92% and then up to 84.19%. That is, learners who took courses in the social sciences and law were more likely to access courses from other disciplines. In the second simulation step, the disciplines that were added to the interdisciplinary networks increased sharply; courses recommended by the first cohort were likely to be those from different disciplines. This further implied that the first cohort of recommended courses to extend beyond the original disciplines were interdisciplinary and were likely to recommend further courses from different areas. As shown in Figure 5 (middle), the changes in balance in each interdisciplinary network followed the same pattern of variety. As shown in Figure 5 (right), the value of the Rao-Stirling index increased sharply while simulating the process of forming interdisciplinary networks. That is, the disparity of the interdisciplinary networks increased. This implied that when learners seek courses that extend beyond their own discipline, they were likely to access courses that are distinct from those they have previously studied.

Figure 5

Forming Interdisciplinary Networks Through Simulation



Note. Left-hand panel depicts variety, middle panel depicts balance, and right panel depicts disparity.

Figure 5 illustrates the use of variety, balance, and disparity to measure the diversity of interdisciplinarity networks. In our study, social sciences and law had the highest level of diversity, followed by engineering, economics, and computer science. The interdisciplinary network for social sciences and law evidenced more balance than that of computer science, which was dominated by its own courses. Additionally, computer science tended to take more steps to converge to a upper limit than did the other disciplines. That is, the recommended courses tended to stick to their own disciplines or neighbours.

While adding new courses to disciplinary networks, the variety, balance, and disparity all increased sharply at first and then tended to converge to a upper limit. It is worth noting that, for social sciences and law, disparity increased at first and then declined. Disparity measured how different disciplines were integrated when new courses were added step by step. During the first step of adding new recommended courses, the degree of difference between disciplines was very high. In other words, the recommended social sciences and law courses belonged to very different disciplines.

Information Diffusion Within Four Interdisciplinary networks

From Table 2, we see that although there were many courses available for the learners in different disciplinary networks, learners were limited to accessing all the recommended courses in the same discipline. For example, in the computer science network, students had access to an average of only 2.33% of the recommended courses, while the average increased to 5.42% to 7.51% for interdisciplinary network. This low information diffusion rate was because some courses did not recommend other courses even though they themselves had been recommended by them.

Table 2

Results of Information Diffusion of Eight Interdisciplinary Networks

Disciplinary network			Discipline	Extended disciplinary (interdisciplinary) network		
Minimum (%)	Maximum* (%)	Average (%)		Minimum (%)	Maximum* (%)	Average (%)
0.22 1 course	12.86 58 courses	1.42 6 courses	Engineering	0.11 1 course	52.53 468 courses	7.21 64 courses
0.25 1 course	12.78 52 courses	2.33 9 courses	Computer science	0.12 1 course	52.39 449 courses	7.51 64 courses
0.31 1 course	14.86 48 courses	2.61 8 courses	Economics and management	0.11 1 course	55.40 51 courses	5.42 50 courses
0.32 1 course	5.08 16 courses	0.93 3 courses	Social sciences and law	0.11 1 course	52.12 47 courses	6.65 60 courses

* The strongest connected component in the network reached the maximum capacity.

Using the SI model, the strongest connected component reached a high level of convergence. Nevertheless, the convergence only reached approximately 5.08% to 14.86% for any course, and belonged to the strongest connected component in the recommendation networks of four major disciplines. Learners needed to navigate approximately 62 to 122 times to access 5.08% to 14.86% of the courses on this particular recommendation network. In contrast, approximately 52.12% to 55.40% of courses could be accessed by navigating from any course belonging to this strongest connected component of the interdisciplinary networks. The remaining strongest connected components with a smaller number of courses were likely to reach low levels of convergence, with few exceptions. That is, the topological structures of these interdisciplinary networks tended to follow a large strongly connected component conducive to global information diffusion, while the remaining smaller strongly connected components supported local information diffusion.

Discussion

Network Structures of MOOCs Affect Access to Disciplinary Knowledge

In this research, MOOC recommendation relationships were used to create networks of MOOC offerings, and the topological structures of the recommended MOOC networks presented earlier were carefully examined to illustrate how the network structures of four disciplinary knowledge differed.

The four disciplinary networks had significant community structures, but the topological structures varied greatly. The disciplinary networks were not complete networks but they all demonstrated one large connected component and multiple smaller, independent subgraphs. In computer science, for example, eight out of ten of the courses were bounded together in the largest connected component, consisting predominantly of courses in the topics of programming and data analysis. The courses in economics and management were most densely interconnected. In contrast, the social sciences and law network was loosely connected, as indicated by the average degree. Nevertheless, social sciences and law had the shortest network diameter, which implied that these courses have a greater capability for information dissemination. These findings are important as they extended past research using bibliographic data to examine disciplinary knowledge.

The topological structures of interdisciplinary networks represent the intrinsic and potential constraints on the flow of information, which alters the online context in which interdisciplinary learning might occur. To understand how these structures influence information diffusion, the SI model was adopted to simulate how courses were accessed in four different disciplinary networks. This simulation helped us see how efficiently courses (representing disciplinary knowledge) were accessed, and how many courses were eventually acquired in forming respective networks of interdisciplinary knowledge. The process of disease (access to courses) spread started from each course in the network; we then calculated the average value of the proportion of accessed (infective) courses over time. For example, in the computer science network, students had access an average of only 2.33% of the recommended courses. One could argue that learners might not follow the recommended courses in regard to their learning, but as we argued earlier, recommendations for a course of study were examined as a mechanism for providing courses to learners, similar to courses suggested by tutors or institutions in conventional education. Such recommendations also implied a certain association between different disciplines or topics. This low rate of accessibility suggested that there was a ceiling effecting what learners could access or learn online, given that there are approximately 2,700 courses freely available. The concept of more is better might seem desirable in many circumstances that enable access to education, but these strategies, frequently used by industry, must be challenged by educational researchers (Sheail, 2018). Given the rate at which ever-increasing offerings of MOOCs are developed, the rate at which learners move around and select courses from different disciplines is actually very slow. The results of this study showed that the network structure of recommended courses served as a structure of disciplinary knowledge, and it affected how far and how quickly learners could approach all these courses. The results reported herein are consistent with studies that have emphasized how the network structure affects information diffusion in the knowledge management area (Arnaboldi et al., 2016; Lambiotte & Panzarasa, 2009; Reagans & McEvily, 2003).

Diversity of Interdisciplinary Knowledge in the Process of Knowledge Integration

In this study, interdisciplinary networks (i.e., extended disciplinary networks) were created by adding neighbour courses into the current four disciplinary networks. The findings shed light on the role that disciplinary knowledge plays in forming a new interdisciplinary network. Strong connections (i.e., the same 30 courses in the strong connect component shared by all four interdisciplinary networks) made up an important part of each interdisciplinary network, as such connections were conducive to learners accessing more courses in the whole network.

The disparity metric we used not only considered the number of disciplines added into the interdisciplinary network but also measured how distant the knowledge sources were, in other words, the disparity of disciplines (Porter & Rafols, 2009). To control the number of disciplines added to the network, it was very important to measure distance. Interdisciplinarity is often interpreted as inherent in a MOOC designed by experts from two or more disciplines, though this provides no basis for exploring the kinds of disciplines that should be integrated to create interdisciplinary knowledge.

The results of simulating the process of adding new recommended courses to the original networks attested to the interesting changes in how the diversity of interdisciplinary knowledge grew. Particularly remarkable is the degree to which the diversity of interdisciplinarity increased when first adding recommended new courses. All three metrics—variety, balance, and disparity—increased sharply. However, the changes in diversity implied that neighbouring disciplines were more likely to come to the forefront to attach to interdisciplinarity in MOOC offerings, and that the synergy between disparate disciplines proceeded at a much slower pace. This is mainly because when adding more recommended courses to the network, the added courses tended to be in a discipline that was not distant from or was the same as the previous ones; thus, they did not add as much interdisciplinarity. Moreover, for disciplines such as the social sciences and law, in which courses were loosely connected, the disparity level increased sharply when new recommended courses were first added. This implied that newly added courses belonged to disciplines that were distant from the previous ones.

It seems that the measures of interdisciplinarity in the studied networks indicated the considerable interchange of subject knowledge when learners considered moving out of their comfortable zone (i.e., their own discipline). By no means did the modern knowledge gap between different disciplines restrict learners from taking the initiative to select courses in another discipline, although the difficulty attached to doing so was beyond that which many of us anticipated.

In summary, knowledge integration, as evidenced by simulating the process of learners following recommendation links to access courses, drew mainly on neighbouring disciplines. The knowledge offered in such a MOOC space is arguably becoming more interdisciplinary but in a modest manner. Only a slow increase in the small segments of knowledge from more distant disciplines was observed, which is consistent with the findings from studies using journal articles to map the changes in interdisciplinary knowledge (Porter & Rafols, 2009).

Limitations and Future Work

Focusing on the question of how to prepare students to meet the 21st-century demand for skills led us to explore how delineating the structures of MOOC offerings allowed for knowledge integration using a simulation model. Similar to arguments by Fernández-Díaz et al. (2017) regarding the pedagogic architecture of a MOOC, we believe that the topological network structure of MOOC offering and the diversity of such networks influence learners' access to courses in the MOOC space. However, we are very conscious that an examination of the typological structure and diversity of interdisciplinary knowledge can perhaps only make an indirect contribution to the debates surrounding what online courses to offer in order to prepare students regarding 21st-century skills, and how these courses relate to each other. Nevertheless, this study offers an alternative approach to mapping interdisciplinary knowledge using network analysis, and it urges that analytics studies come to the forefront regarding using available course information to provide evidence in support of the design of online education. As we lack domain experts, expert knowledge is not sufficient to support interdisciplinary curriculum design, as argued earlier. More evidence-based analytics studies could help us by providing more evidence on how to increase access by a greater number of learners to respectively form interdisciplinary networks of knowledge (Rohs & Ganz, 2015).

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