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Research Article

Network Visual Exploration for the Cooperation Map of Courses in Different Major Curricula *

Xiaojiao Chen[1]
Southeast University

Chengqi Xue[2]
Southeast University

Abstract

As the data science rising massive changes in many fields, effective visualization is urged for the huge amounts of data, also in the education industry is no exception. Education contains a great quantity of linked data whose key value lies in the connection. However, we do not know how different courses can carry out diversified cooperation in different major curricula. This paper proposes a network modelling approach to curriculum mapping depend on the 11 years' data of a university curriculum in the United States, using the network structure to study the curriculum connection from a network dynamic perspective, the network models present a visualize pattern with identify relationships and attributes around different courses. We also provide various descriptive statistics analysis data, such as density, average clustering, and number of nodes etc. Using complex network mapping the curriculum pattern of university education provide a gap analysis of a visualization pattern of educational curriculum research.

Keywords

Curriculum • Education • Complex Network • Data Visualization

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[1]School of Mechanical Engineering, Southeast University, Nanjing 211189, China. Email: chenxiaojiao@seu.edu.cn
[2]**Correspondence to:** Chengqi Xue (PhD), School of Mechanical Engineering, Southeast University, Nanjing 211189, China. Email: ipd_xcq@seu.edu.cn

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In recent years, rising demand and constrained resources enhanced by the recent technical, the excessive data resulting from information growth, researcher repeats a theme that rapid information growth is bring great benefits to a huge amount of collaborating on business, science, and public administration (Chen, Mao, & Liu, 2014). Big Data research is an emerging field of practice, drawing an extensive review of visualization, huge in volume, high in velocity, diverse in variety, exhaustive in scope, fine-grained in resolution and uniquely indexical in identification, relational in nature, flexible in holding the traits of extensionality, and scalability (Emani, Cullot, & Nicolle, 2015; Zicari *et al*., 2016; Zhang, & Hu, 2018). The mass of data need filtering and there is a deep correlation behind the data, more and more researcher realized huge amounts of data are needed to promote using effective visualization (Erevelles, Fukawa, & Swayne, 2016; Zeng, Li, & Wu, 2017; Mothe, & Rakotonirina, 2018; Hu, & Zhang, 2017; Chen, 2017; Shi, Xiao, Lu, & Yang, 2018; Clarke, 2016).

Focus on college education research, researchers had used a variety of visualization measures to determine a college education. The office of Digital Learning at MIT and Harvard Research Committee at Harvard University use two years' data of 68 open online course offered on edX to explore trends span, find that overall participation in their online course remain substantial and the average growth has been steady (Ho *et al*., 2015). Michail present booc.io, were formed in expert interviews, adapt a real-world course into booc.io, and perform introductory qualitative evaluation with students, which allows linear and non-linear presentation and navigation od education concepts and material (Schwab *et al*., 2017). Joseph provide a visualization tool mapping the relationships among learning outcome in the process of developing subject content (Seering, Huang, & Willcox, 2015).

For this paper, we built a visualization complex network of courses selection system, using the correlation of data to explore the curriculum pattern of major and the major progression from a network dynamic perspective. Why use complex network mapping the interdisciplinary pattern of major? Data always take the form of tables, where all but of the columns haven't give the relevant to the questions of interest, especially when the data analysis are bond by several hundred thousand or even millions of rows (Willcox, & Huang, 2017). Several studies have relied on measures the relationship of complex network, in which millions of members publicly articulate mutual "friendship" relations (Barabasi, & Oltvai, 2004; Kairam, Riche, Drucker, Fernandez & Heer, 2015; Zhao, Glueck, Chevalier, Wu, & Khan, 2016). In social sciences, where node-link depictions of social relations have been employed as an analytical tool since at least the 1930s (Ghani, Kwon, Lee, Yi, & Elmqvist, 2013; Mingers, & Leydesdorff, 2015). Linton Freeman documents the history of social network visualization within sociological research, it provided the color, size coding and shape can be used in visualization (Bernard, 2005). Upon a such node-link complex network is a best visualization layout how to contribute customized techniques for exploring connectivity in large graph structures, supporting visual search and analysis, and how to indentify and visualize community structures (Catalá-López *et al*., 2012; Chi, 2013). Complex Network as one good Topological data analysis turn out concept with data distance and data weight which can visualize and explore high dimension and complex real-word data community. (Offroy, & Duponchel, 2016)

Using complex network mapping the curriculum pattern of university education is the contributing of this paper, we want to provide a better visualization research on understanding and development of curriculum pattern in college education. Through mapping network, we can explore curriculum system, it explicitly various relationships among these different kinds of entities, such as subject title, the number of students who select the course, the disciplinary attributes, etc. How many and how these courses connect each other (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008), many effective information can be supported viewing by a network form. The proposed network modeling approach overcomes typically limitation through explicit modeling of the relationships in a graph structure, such a modeling approach is effective approach to conduct curriculum mapping in college education.

Methodology

In this paper, we mapping the curriculum network and using the curriculum arrangements structure to explore the degree of interdisciplinary. We got the data from an Institutional Research Office of the United States, all of the data are authentic, the data contains students' home department code, course of major, student-id, subject title and term-code, etc. In order to protect privacy, the students-id were hashed by the office.

Thousands of courses had been chosen by the students in a curriculum system, each course is represented as a node in the network graph, each link from one course to another forms a connection. Frist, we merge subject id and the student id data, present a matrix these 6234 courses to determine which pair of courses been selected by same person (Doreian, Lloyd, & Mrvar, 2013), all of data are processed by Python. Missing value were incomplete to work with in data cleansing. For example, duplicate Student-id information was deleted in case it will result in the value of correlation to be 1. After data aggregation, generate a distance matrices based on the number of students who selected the course. The subject id and the student id were merged, these are aggregated by the frequency of selective, the aggregated set is computationally efficient for the weight of the link.

Next, we map the network of course expressed by the community, algorithm reference from Ce´sar A. Hidalgo's methods of building Dynamic network (Hidalgo, Blumm, Barabási, & Christakis, 2009). Given the matrix data representing the number of common users between course 1 and course 2. Calculate the weight of the link and the correlation between course1 and course1 can be given by aggregated set (Ronen *et al.*, 2014). Then we use student's-test to assess the signification of these correlation and the p-value to definite the threshold of links.

Third, for every node we include other properties in JavaScript rendering such as the subject-id of the course, the website URL of the course, the number of how many students select the course, etc. here we concentrate on network pattern illustrating how different course connect with each other.

Results and Discussion

The Structure of curriculum network

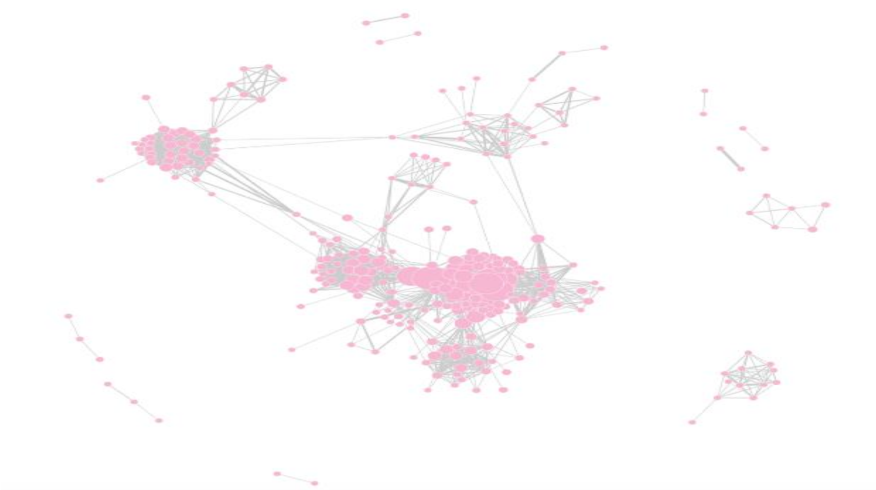

Figure 1. The curriculum network of a subject- Management

We can summarize the course arrangements follow Force-Directed Graph layout in the network drawing (Hidalgo, Blumm, Barabási, & Christakis, 2009), nodes are course identified by data base, each node represents a course, and node sizes are proportional to the number of student selection. Links show relationship according to the student selection, every link connect two courses, means a student choose the two courses, the weight of link show how many students choose the two courses. The network map the link of direct and indirect communication between course and course.

Figure 2. The curriculum network of a subject- SCM

The resulting network models represent the connectivity among different educational entitles, the attributes of the node- title and major, title which have rendering with a label in JavaScript when people click the node, it will appeared(Fig 2); Color is the major attribute, for a good visualization present we give the color coding to different subject; the number of nodes- how many courses in a major; the size of the node - the number of student who choose the course; the weight of link -the number of student who choose the course. Here we give the screen shot of curriculum network of subject Management (Fig 1) and subject SCM (Fig 2), more network will be details described in follow discussion.

We explore the curriculum network dynamics by asking the question: What are the research communities formed from its own internal unity collaborations in the curriculum network? We present these curriculum arrangements network of different subjects, introduced the data of diversity and clustering in relation to the subject own internal unity collaborations for the question. In order to give a clearly backbone and minimize these weak connections, we set a threshold of linkage strength greater than 0.2, presenting the network graph and sorting the data by grouping the value of density (Wagner *et al*., 2011).

Table 1 provides various descriptive statistics, list the top 8 subject (Density 0.5 < d ≤1) when ranked for number of nodes, the number of edges and average clustering. There are few courses in a subject network, but almost every course connected tightness in their own internal unity with Density 0.5 < d ≤1. The number of nodes shows that the share of subject 21 W-Writing, WKR-Wellesley Korean, CSB-Computation and Systems Biology, AS-Aerospace Studies, SCM-Supply Chain Management, EM-Engineering Management, HAP-H Public Health, EC-Edgerton Center, 21G-Global Studies and Languages are not particularly high in a whole network space, but the number of edges illustrates almost every courses of the subject connect with each other in their own internal unity. Density and average clustering data borne out the correctness of these courses interaction.

Drawing a circle scope to capture algorithmic layout scope visually in JavaScript render, used to analysis the distance of cluster-heart selection in network (Davenport, 2012; Shimbel, 1953). The node sizes are proportional to the number of students who select the course and the link weight are proportional to the number of students who select the two courses. Fig 3 present the curriculum network of subject 21 W-Writing, WKR-Wellesley Korean, CSB-Computation and Systems Biology, AS-Aerospace Studies, SCM-Supply Chain Management, EM-Engineering Management, HAP-H Public Health, EC-Edgerton Center, 21G-Global Studies and Languages, could be argued that the degree of intimacy is consistent with the data of statistics (Density 0.5 < d ≤1). Almost all of these subject network at the edge of whole network space, analyzed represented relatively weak links in the whole network but strong collaborate between in their own subject unity.

Table 1
Descriptive Statistics of Major Collaboration Networks

Rank	Subject ID	Subject	Number of nodes	Number of edges	Density	Average clustering
1	21W	Writing & Humanistic Studies	6	15	1	1
1	WKR	Wellesley, Korean	4	6	1	1
1	CSB	Computational & Systems Bio	5	10	1	1
1	AS	Aerospace Studies (ROTC)	6	15	1	1
5	SCM	Supply Chain Management	13	77	0.987179487	0.987179487
6	EM	Engineering Management	5	7	0.7	0.7
7	HAP	H, Public Health	11	36	0.654545455	0.82020202
8	21G	Global Studies and Languages	6	8	0.533333333	0.583333333

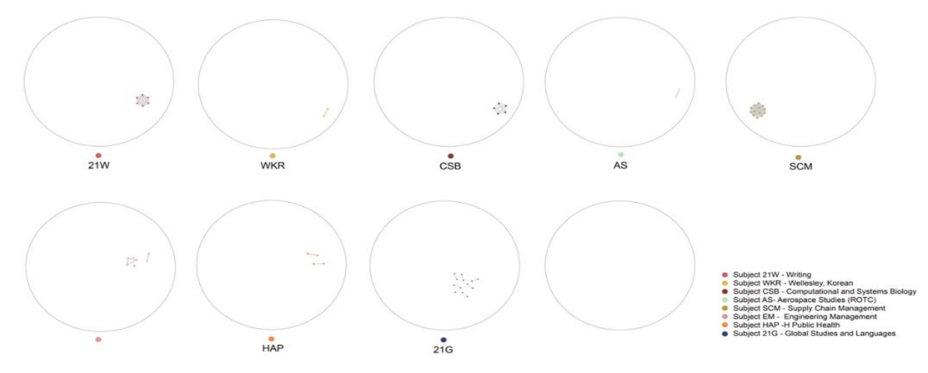

Figure 3. Density (0.5 < d ≤1)

In Table 2, there are 24 subject in this group (Density 0.1 < d ≤0.5), subject 20-Prog in Applied Biological Sci is the one with the highest density in the group, while ESD- Engineering Systems Division ranked the lowest density in the group. In terms of the number of nodes statistics, the number of nodes are increased correlated to density decreased, this transition seems also to have an initial effect on the density of the subject own internal unity. Furthermore, comparing the different subject network in the group, we found that the number of edges also effect on the degree of density, few nodes with more edges give a positive growth while more nodes with few edges give a negative growth. The value of density and average clustering borne out the correctness of these courses interaction.

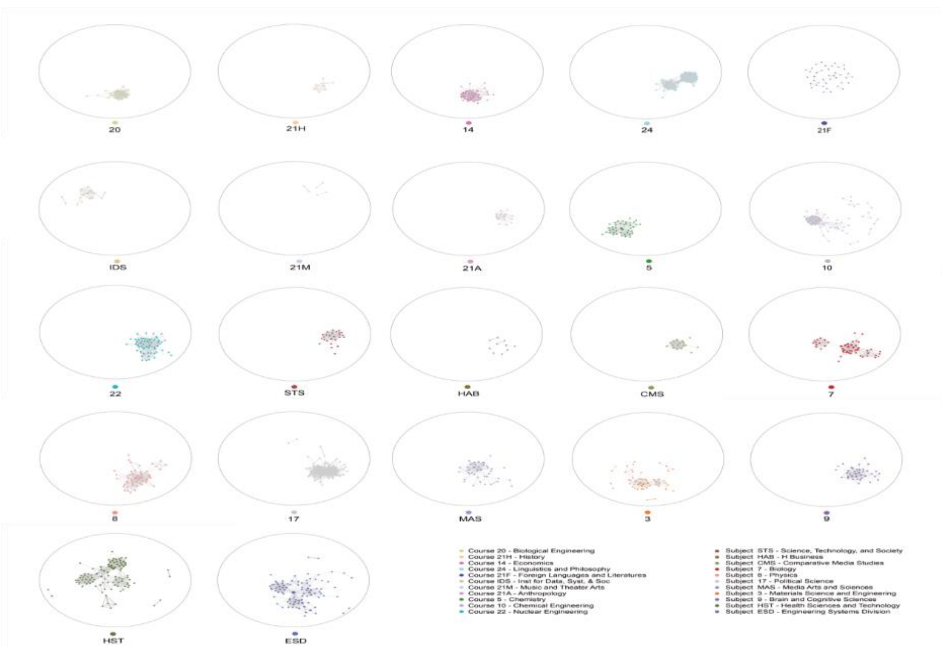

Figure 4. Density (0.1 < d <0.5)

This phenomenon also can be released in Fig 4, Fig 4 shows the map of 24 subjects network, subject 20-Prog in Applied Biological Sci, 21H-History, 14-Economics, 24-Linguistics and Philosophy, 21F-Foreign Languages/Literatures，IDS-Inst for Data, Syst, & Soc, 21M-Music and Theater Arts, 21A-Anthropology, 5-Chemistry, 10-Chemical Engineering, 22-Nuclear Engineering, STS- Science, Technology & Society, HAB-H, Business, CMS- Comparative Media Studies, 7- Biology, 8-Physics, 17- Political Science, MAS-Prog in Media Arts & Sciences, 3-Materials Science and Eng, 9-Brain & Cognitive Sciences, HST- Health Sciences & Technology, ESD-Engineering Systems Division.

A network of visualizations is thus possible with more nodes composed a larger network (Fig 4) and the lower density value left while positioned close to the central area of the map (Table 2).

Table 2
Descriptive Statistics of Major Collaboration Networks

Rank	Subject ID	Subject	Number of nodes	Number of edges	Density	Average clustering
1	20	Prog in Applied Biological Sci	24	128	0.463768116	0.697465066
2	21H	History	12	27	0.409090909	0.647222222
3	14	Economics	65	798	0.383653846	0.665055684
4	24	Linguistics and Philosophy	64	612	0.303571429	0.739820966
5	21F	Foreign Languages/Literatures	11	16	0.290909091	0.606060606
6	IDS	Inst for Data, Syst, & Soc	18	40	0.261437908	0.410229277
7	21M	Music and Theater Arts	9	9	0.25	0
8	21A	Anthropology	26	81	0.249230769	0.591899604
9	5	Chemistry	44	229	0.242071882	0.760739898
10	10	Chemical Engineering	57	338	0.211779449	0.602815348
11	22	Nuclear Engineering	63	399	0.204301075	0.608765917
12	STS	Science, Technology & Society	52	267	0.201357466	0.498608681
13	HAB	H, Business	13	15	0.192307692	0.176923077
14	CMS	Comparative Media Studies	34	105	0.187165775	0.405309723
15	7	Biology	58	304	0.183908046	0.757144997
17	8	Physics	58	275	0.166364186	0.61691153
18	17	Political Science	98	691	0.145381864	0.550226569
19	MAS	Prog in Media Arts & Sciences	44	132	0.139534884	0.539685643
20	3	Materials Science and Eng	53	183	0.132801161	0.587024048
21	9	Brain & Cognitive Sciences	60	219	0.123728814	0.476576972
22	HST	Health Sciences & Technology	130	932	0.111150865	0.638764586
24	ESD	Engineering Systems Division	96	460	0.100877193	0.59488348

Table 3
Descriptive Statistics of Major Collaboration Networks

Rank	Major ID	Major	Number of nodes	Number of edges	Density	Average clustering
1	18	Mathematics	100	475	0.095959596	0.449569948
2	HAE	H, Education	32	42	0.084677419	0.351339286
3	2	Mechanical Engineering	85	314	0.0830721	0.57599886
4	16	Aeronautics and Astronautics	60	139	0.078531073	0.556254209
5	15	Management	251	2072	0.066039841	0.707767983
6	12	Earth, Atmos, & Planetary Sci	188	967	0.055011947	0.500366367
7	4	Architecture	237	1508	0.05392262	0.510464822

Table 3 shows the descriptive statistics of 7 subjects (Density 0.05 < d <0.1), as the field increases in nodes number, the density of connectivity among the courses in a subject decrease, there is increasing range of the broader of these subject in Fig 3. The number of edges of subject 15-Mangement, 12- Earth, Atmos & Planetary Sci and 4-Architecture are significant compare with other subjects, such as subject 18-Mathematics, HAE-

Harvard, Education, 2-Mechanical Engineering, 16-Aeronautics and Astronautics. Subject 15, 12, 4 indicated as a central region among all the subject network (Fig 5), to be the important cluster dominate the structure of the network.

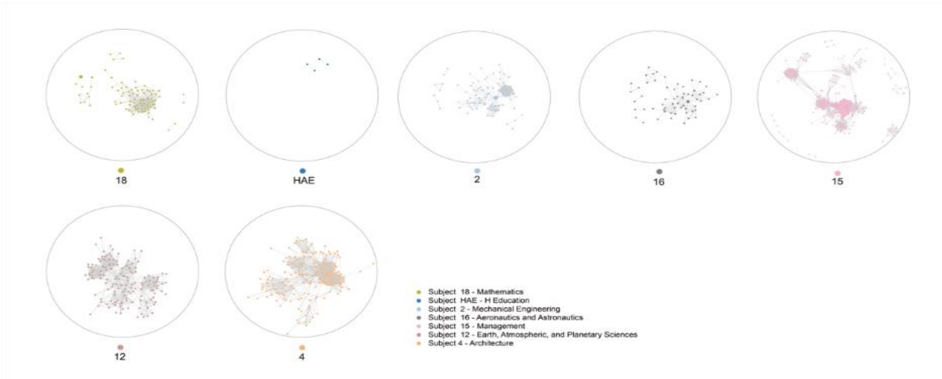

Figure 5. Density (0.05 < d <0.1)

The subject (density d < 0.05) 11-Urban Studies Planning, 6-Electrical Engineering, Computer Science, 1-Civil and Environmental Eng and HAA-H Arts and Sciences be divided into the last group. The number of nodes is large (but not maximum) with a massive number of edges, many courses leakage with each other or scattering around the central in a subject inter network, the structure of the network is clearly of maximum visual resolution (Fig 6), but minimum density (Table 4).

Table 4
Descriptive Statistics of Major Collaboration Networks

Rank	Major ID	Major	Number of nodes	Number of edges	Density	Average clustering
1	11	Urban Studies and Planning	176	761	0.049415584	0.444547371
2	6	Electrical Engineering and Computer Science	70	116	0.048033126	0.366283151
3	1	Civil and Environmental Eng	117	377		0.491223375
4	HAA	H, Arts and Sciences	199	407	0.02065885	0.552554704

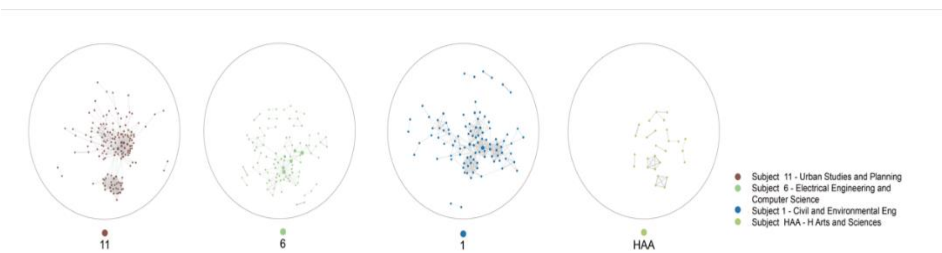

Figure 6. Density (d <0.05)

Conclusion and Future Research

This paper presented a scalable mathematical framework for education curriculum network, using curriculum network to study a major own internal unity collaborate relationship, exploring the major progression from a network dynamic perspective. The resulting network models represent the connectivity among different educational entitles, such as the title of courses, the attributes of the node and major, title which have rendering with a label in JavaScript when people click the node, it will appeared (Fig 2); Color is the major attribute, for a good visualization present we give the color coding to different subject; the number of nodes-how many courses in a major; the size of the node - the number of student who choose the course; the weight of link -the number of students who choose the course. All of the kinds of data have an excellent visualization in a map space, enable an effective visualization analytics, either using graph visualization analytics tools provides insight into learning the specific educational setting and research on the gap of curriculum pattern in forward.

For a research progress reasons, this paper had give a clearly curriculum structure of a disciplinary educational, we will explore the interaction between different disciplinary in the future, as we all known that a disciplinary major enterprise is affected not only by its own internal unity or intellectual justification, but also influenced by the connectivity of its components to other majors (Leydesdorff, & Rafols, 2012; Leydesdorff, Rafols, & Chen, 2013).

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