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Curriculum Connectivity in Montclair State University's Undergraduate Mathematics Program

Ana G. Da Silva Jesus

Abstract

According to Piaget's cognitive development theory and the constructivism learning theory of education, real learning occurs when students establish long term connections between disciplines by either adapting or redefining previously acquired knowledge. These ideologies have important teaching and learning implications that directly influence curriculum development and the design of a course of study. This thesis explores the interconnectedness of the subjects required for the successful completion of an undergraduate math program at Montclair State University. More specifically, it models students' unique connections through a learning network and investigates the correlation between the interconnectivity of subjects and students' overall performance. Results from this project indicate that participants' GPA is significantly better when the number of connections between courses is higher. As a result, an integrated curriculum can provide students with more opportunities to make strong neural connections between courses and consequently improve their overall performance.

Keywords: connectivity, learning networks, education, mathematics, performance measuring

MONTCLAIR STATE UNIVERSITY

Curriculum Connectivity in Montclair State University's Undergraduate Mathematics Program

By

Ana G. Da Silva Jesus

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Thesis Committee

[redacted]

Dr. Jonathan Cutler
Committee Member

[redacted]

Dr. Mika Munakata
Committee Member

[redacted]

Dr. Ashwin Vaidya
Thesis Sponsor

CURRICULUM CONNECTIVITY IN MONTCLAIR STATE UNIVERSITY'S UNDERGRADUATE MATHEMATICS PROGRAM

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1. Introduction

Piaget's psychology development theory states that our brain is in constant 'cognitive conflict' as it struggles to make sense of new ideas and fits them into pre-existing knowledge structures [5]. Therefore, real learning occurs when students establish long term connections between disciplines by either adapting or redefining the knowledge they already possess. It makes sense then that curriculum development should be rooted in a constructivist approach that provides students with multiple opportunities to forge these connections. In order to understand the importance of mathematics in the real world, learners "need to be introduced to applications of mathematics in meaningful contexts" [8]. Still, students are constantly questioning the usefulness of mathematics and demanding a reason why it is part of college education. This suggests that undergraduate curricula at the university level are not portraying a high level of connectivity within subjects or providing students with opportunities to make meaningful connections. In this paper, I will be investigating how students perceive the interconnectedness of undergraduate math curricula using Piaget's developmental framework and the constructivist theory of education. I am interested in exploring students' unique learning networks to better understand how these connections play out in their overall understanding and appreciation of their education. I hypothesize that connectivity within subjects improves students' overall performance in undergraduate math programs and that the highest connected courses consist of prerequisite classes.

2. Literature Review

2.1 Psychological framework

To this day, Piaget's cognitive development theory continues to strongly influence educational practices and curriculum development. This theory of development has been essential in understanding how our brain constructs knowledge when presented with new ideas and how it makes meaning out of new information. Essentially, this approach is directly aligned to the constructivism learning theory, which describes learning as the unique and active process of linking ideas to pre-existing knowledge, to make meaning out of new situations [9]. Piaget claimed that new ideas create a state of disequilibrium in our brain and that to stabilize this state, learners can either accommodate the new information by adding to pre-existing mental structures; or assimilate the information by reconstructing old mental schema [3]. Hence, knowledge cannot be transferred from the instructor to the learner, instead; it is constructed by the learner based on personal experiences, perceptions and previously established structures [1]. Piaget's contributions gave rise to the decentralization of the teacher in classroom settings and to the incorporation of students' unique experiences, backgrounds and knowledge in the learning process. Multiple methodologies of teaching and learning have emerged from this theoretical framework with a focus on *discovery learning* and *unique meaning-making*. Project-based, problem-based, inquiry-based and experiential learning are all examples of student-centered techniques that introduce the teacher as the facilitator and allow learners to link new ideas to pre-existing brain structures. In mathematics, these models give students "the opportunity to explore their thoughts and knowledge, to be able to find their own concepts and formulas under the guidance of the teacher to make learning become meaningful" [11]. Since students are discovering and deriving the formulas themselves, they are naturally accommodating and/or assimilating new ideas into their brain; which makes the knowledge obtained through these experiences easy to transfer to other situations [11].

2.2 The connected curriculum

It is this easy transfer of knowledge within different subjects that is key in mathematics learning and should be taken into account in curriculum development. Since abstract mathematical concepts have no foundation or meaning unless they are connected to previously established knowledge structures, the enactment of curricula should account for how students construct knowledge. A curriculum focused on constructivism theory has been shown to improve students' knowledge and increase their critical thinking, reading and writing skills [19]. Holistic approaches at the K-12 level such as the *Montessori curriculum* and the *Integrated curriculum* are both examples of curricula that emphasize the interconnectedness of subjects and the incorporation of students' interest and personal experiences. The Montessori curriculum focuses on providing students with choices and encouraging students to explore their natural curiosity. It removes the teacher as the 'absolute authority' in the course material, and focuses on student-led learning [15]. A key feature of a Montessori school is that students are constantly learning all subjects at the same time as they discover disciplines and personal interests [15]. Hence, students' education becomes autonomous, interesting and relevant. Although not as self-directed, the integrated curriculum is focused on providing students with ample opportunities to connect to other disciplines at the same time they are developing 21st century skills. This research-based model is innovative for its connection to real world skills, and has been shown to match or surpass the academic success of students in traditional classrooms [6]. The interdisciplinary approach of an integrated curriculum not only leads to 'deep learning' but can also lead to "increased student engagement and motivation, less absenteeism, and better attitudes towards school" [6]. It focuses on transferring theoretical knowledge to the application of problems that are interdisciplinary and relevant for students' future. Regardless of the method used to offer students opportunities to make connections, both of these k-12 curriculum models highlight the interconnectedness of subjects as the main focus of their design.

A lot of effort and research has been placed on changing and improving k-12 curriculum resources but not as many proposals have been suggested for undergraduate math education. Due to the increased cognitive demand of courses at the college level, curricular changes have been less progressive and not many attempts have been made to improve college education. One interesting attempt however, introduced by Dilly Fung in her book *A Connected Curriculum for*

Higher Education aligns with the theoretical framework described in this paper [7]. Here, Fung presents a curriculum that is not only interdisciplinary, but also emphasizes the connections between students and researchers from all over the world and their collaboration on research topics of social relevance [7]. She believes that "if diverse students are empowered to collaborate actively in research and enquiry at every level of the curriculum, engaging others with their ideas and findings, both education and research will be able to contribute more effectively to the global common good" [7]. The third domain of her proposal concentrates on making connections within subjects and across other disciplines [7]. This domain resulted from the realization that many students narrow down their studies as soon as they begin a higher education program and are not provided with opportunities to connect to other subjects [7]. To improve the connectivity of undergraduate programs, Fung suggests the development of majors that are innovative and interdisciplinary, such as a Bachelors of Arts in Science or an Integrated Engineering program [7]. These programs will give students other disciplinary perspectives and will create stronger neural connections, which according to Piaget's cognitive learning theory comprises real learning. To analyze the effectiveness of a 'connected curriculum for higher education', we can model these neural connections through unique learning networks as described by students and measure the connectivity within subjects.

2.3 Concept maps and network modeling

Similarly to the mapping of courses in an undergraduate college program, a concept map defines the ideas or topics that should be learned in a course, and delineates possible paths within a network of concepts. It is a powerful tool often used by educators to improve and differentiate instruction based on sequencing and complexity. In a concept map, "links between concepts are shown by the hierarchical structure in which the lower concepts are subsumed beneath those which appear in higher levels, and the superordinate concepts are more general than the subsumed concepts" [13]. As a result, these maps identify relationships, commonalities and prerequisites within a module or course. Studies have found that when used to model connections between topics in science, this powerful tool has the potential to improve the science curriculum [12,13]. It enables "educators to better identify redundancy, omission, complexity, misconceptions and which items to assess" [12] and improves "both the process and the product of curriculum development" [13]. Concept maps have shown the importance of visualizing students' thinking and anticipating the learning paths students might follow. However, the structure of concept maps lacks the potential for analytical and statistical analysis which can provide very useful information when mapping an entire academic degree program.

Knowledge Space Theory (KST) is commonly used in research to support a more in-depth understanding of concept maps. "It provides a new way to assess students' cognitive organization of knowledge" and is often used by science educators in the classroom to analyze concept maps within a course [17,18]. This theory combines 'combinatorics and stochastic processes' to model a particular field of knowledge [13] and to identify possible learning paths. The learning networks derived from KST are not unique to the student since this approach defines and maps all important topics in a course. As a result, the network nodes representing concepts within a course are all the same. The only unique feature of KST is the students' learning paths. KST receives information about students' background knowledge and places learners in a specific knowledge state, which in turn is connected to other domains of knowledge. Then the algorithm finds the learning paths that students might take based on this placement. While this model can provide great insight about the process of learning a specific module in a course, its hierarchy structure is not ideal to model unique students' thinking or to model connections between courses in an undergraduate program.

Network modeling, on the other hand, allows for explicit representations of unique connections and "unlocks the ability to perform scalable analysis on the dataset such as a pathway analysis" for the courses that students are taking in an undergraduate program [16]. It consists of representing students' unique courses as nodes in a network and illustrating the transfer of information between these courses with directed edges. This model has been used to map the entire curriculum at MIT which led to interesting findings about the connectivity of subjects within each department. For example, it allowed researchers to analyze subgraphs of prerequisite courses within their network and gain insights about the maximum path length from one node to another [16]. This analysis had important implications for students' academic advice and curriculum writing.

In this thesis, I am interested in using a similar network model to map students' connections between courses at Montclair's undergraduate math program. I will use network modeling to facilitate the computation of statistical measures and will utilize Piaget's ideas from developmental psychology and the constructivism approach to education, to make predictions and conclusions about these networks. Finally, I will interpret the results for this analysis in terms of an ideal connected and integrated curriculum for undergraduate education.

3. Methodology

To measure the impact of current curriculum designs on students' ability to make connections within subjects and students' overall performance, I have analyzed participants' unique learning networks as perceived by them. In these networks, nodes represent courses students have taken during their undergraduate math program at Montclair State University (MSU), and edges illustrate connections that participants have made between these courses. Nodes can also be perceived as previously established schemas in participants' brains that have been altered and/or affected by incoming knowledge illustrated by connecting edges. This methodology draws both on Piaget's theory of cognitive development and on an ideal undergraduate curriculum that focuses on interconnectivity. Information for the analysis of these networks will be acquired through a survey, created in google sheets that is divided into two parts. The first part asks students to list the courses they have taken during their undergraduate math education and provides some details about their perceived performance and enjoyment. The second portion invites students to think about and list the connections that exist between all of their courses.

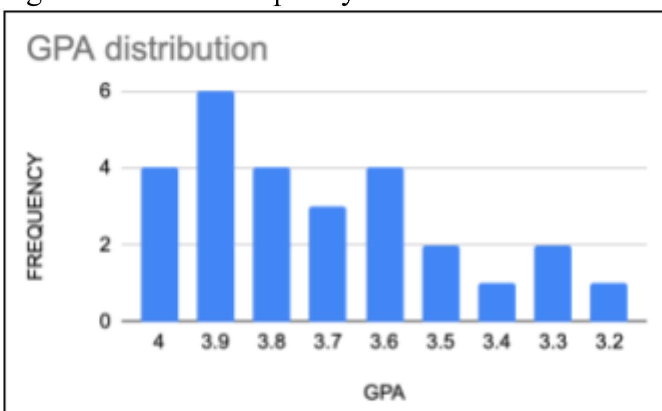
Participants are also asked to rate connection strengths and to classify such connections based on applicability, skills, prerequisite or other (see appendix for more details). Approval for this research and for the administration of this survey was received by the Institutional Review Board under research number IRB-FY20-21-2190.

3.1 Data Collection

All acquired data for this project was granted on a voluntary basis. As a result, data collection was a lengthy and effortful process. This research was introduced to students either by email or through a small in-person presentation. Students participating in this survey have all completed a consent form containing the project's description, instructions and details about privacy and confidentiality. All contributing participants have agreed to share their information for this study and make a contribution to research and development in education.

In total, this project received 35 participants. Although I have initially gathered information from different undergraduate majors, most students completing the survey were part of a math program. Consequently, some of the surveys that did not meet the criteria for undergraduate math majors have been dropped. In addition, two more surveys were dropped for incompleteness. This resulted in 29 data points consisting of 18 female students and 11 male students. On average, participants have taken 33 undergraduate courses and have made about 27 total connections between their courses. Their GPA ranges from 3.2 to 4.0 with fifty five percent of students having a GPA between 4.0 and 3.8 and the remaining students having a GPA between 3.7-3.2 (see figure 1 for details). Out of all participants, 38% of students had a double major or minor, either in education or in other stem related fields (see table 1 for details).

Figure 1: GPA vs frequency



Describes the frequency of each GPA for all 29 surveys collected.

Table 1: Participants' basic analysis

Average number of connections	27
Average GPA	3.6
Multiple majors	38%
Average number of courses	33

Provides a basic analysis for all 29 participants.

3.2 Network Analysis

After acquiring all the necessary data, I have performed a series of mathematical analyses to determine the Average Path Length (APL) and the Clustering Coefficient (CC) for each unique learning network. The APL estimates the average shortest path between any two nodes in the network and the CC measures the connectivity between the neighbors of any node. In these computations, loops have been removed since I am only measuring the connectivity within distinct subjects. In addition, repeated connections between any two courses have not been considered. These statistical measures were computed in MATLAB using the following mathematical formulas:

- $APL = \frac{\sum_{i \neq j} d(v_i, v_j)}{n(n-1)}$ where $d(v_i, v_j)$ is the shortest path length between any two nodes i and j; and n represents the number of nodes in the network. Since the average path length between a disjointed node and any other node is infinite, it was assumed that the average shortest path length between disjointed components equals the total number of nodes present in the original network. That is, $d(v_i, v_j) = n$ when i and j are disconnected. In the context of this project, this means that although the student did not find a connection between disjointed course i and course j, course i is still part of the undergraduate curriculum and therefore it would take traversing all courses before finding a meaningful connection between them. In other words, assuming that not all nodes are disjointed, then the students would need to revisit all n courses again to find a meaningful relationship.
- $CC = \frac{\sum c_i}{n}$ where $c_i = \frac{2N_v}{K_v(K_v - 1)}$ and N_v describes the number of links (edges) between neighbors of any vertex v, and K_v is the degree of vertex v. Since clustering coefficients estimate the connectivity between the neighbors of a node; isolated nodes, i.e. disconnected courses, have also been removed from these computations. This is without loss of generality since courses that are disconnected from the entire curriculum, do not have any clusters, and therefore do not add any information to our average clustering coefficient.

Following the assumptions listed above, a hub has been defined as any course that contains at least 4 distinct connections. Since most undergraduate math courses have at most 3 prerequisite courses, this guarantees the existence of at least one additional connection that is not a prerequisite for the course at hand. In addition, since most undergraduate math programs consist of about 33 classes, we are defining a Hub to be any course i that connects to at least 12% of the entire coursework for an undergraduate math degree. Hubs have been calculated for each independent network to provide insight about the highest connected courses.

3.3 Research questions

The aforementioned methodology and definitions permit the computation of statistical measures that can answer relevant questions for the improvement of undergraduate math curricula. In particular, I am interested in exploring the connection between a network's interconnectedness (through APL and CC), and students' overall performance in their undergraduate program. I will also investigate which courses have the highest degree, i.e. which classes have the largest number of unique connections; and how these relate to the undergraduate program. Lastly, I am interested in visualizing students' unique learning networks in the context of STEM and Humanity courses to look for emerging patterns. These results can provide a better insight about how students make meaning and forge long term connections within courses. In addition, results from this analysis will reveal if the curricular framework of a connected curriculum can influence the way students learn and perform at the undergraduate level.

4. Results

4.1 Network Images, APL & CC

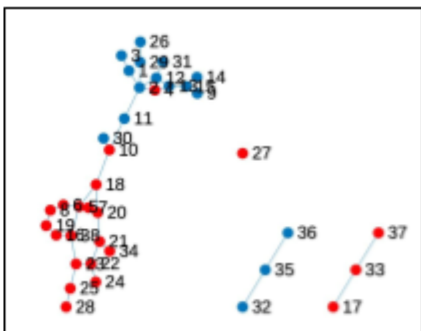
Presented below (figure 2) are the student's unique learning networks generated by MATLAB for all contributors to this project. The red nodes demonstrated on the graphs represent STEM courses and the blue nodes represent humanity courses. Following these graphs, is a summary of each participant's statistical measures. Since there is a variance in the number of courses that each students takes, NewAPL has been calculated using the following formula: APL/n where n represents the total amount of courses taken by each participant. NewAPL is a normalized statistical measure and its values range from 0 to 1. Consistent with my previous predictions, networks containing many disjointed courses have a larger APL while networks containing less isolated nodes travel a smaller average path to reach any other course. Another interesting fact results from the computation of clustering coefficients: Although some graphs might contain a reasonably small APL between courses, such as participants 1 and 33, this does not guarantee that there is a path between neighboring nodes. In fact, 62% of participants' clustering coefficient is zero. This indicates that most students are ranking courses in a hierarchical order, making their learning networks a concept map, and therefore are not creating paths between neighboring nodes.

4.2 STEM vs Humanity Courses

Through the classification of courses, I was also able to notice exciting patterns in students' learning networks. Such classification consists of labeling courses as STEM or Humanity classes and coloring them red and blue respectively. It is important to note that psychology was considered a STEM course but all other social science courses such as anthropology and sociology were characterized as humanities classes. In addition, economic related classes were incorporated into the STEM category but business courses were not. This classification allowed me to conclude that students' learning networks demonstrate a separation between the connections they make between STEM courses and the connections they make between non-STEM courses. Most students' networks, such as participants' 4,8,12,15,17,18,30 and 33 reveal that students are able to make connections between STEM disciplines but do not link any of these disciplines to humanity courses. Although there is an overlap of mathematical concepts in most math courses, this is not the case for humanities and these courses are also highly connected. As a result, this outcome can be attributed to a poor undergraduate math curriculum design, i.e. an unconnected curriculum, or simply because students were not given the opportunity to make connections between the topics they were learning in the classes. Other networks such as participants' 1, 14,16 and 34 illustrate a linkage between humanities and STEM courses but with a weak connection. With the exception of participant 16, the red and blue *trees* are either linked by 1 or 2 courses. In future research, this separation can be measured through the network's modularity.

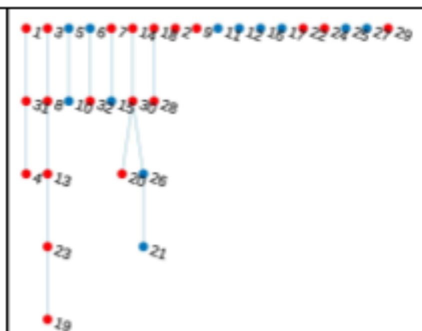
Figure 2: Students' unique learning networks, NewAPL and CC

Participant 1



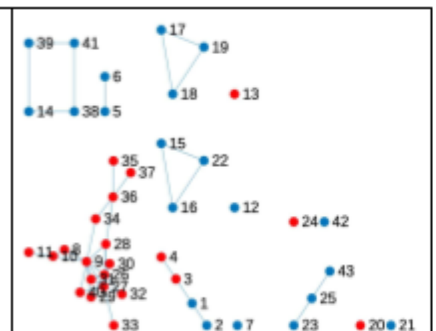
NewAPL	**0.42**
CC	**0**

Participant 3



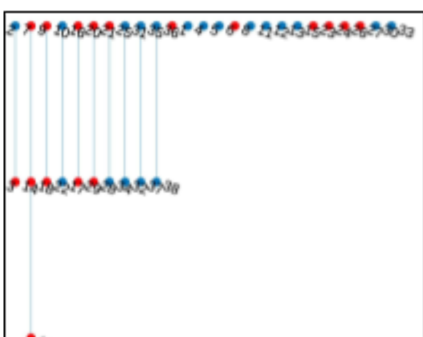
NewAPL	**0.95**
CC	**0**

Participant 4



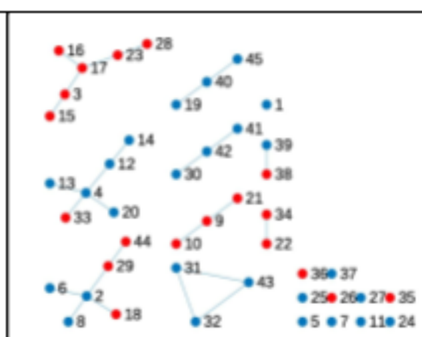
NewAPL	**0.83**
CC	**0.32**

Participant 5



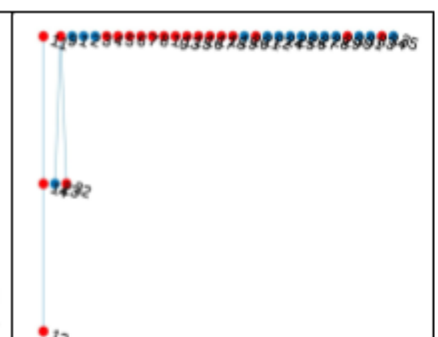
NewAPL	**0.98**
CC	**0**

Participant 6



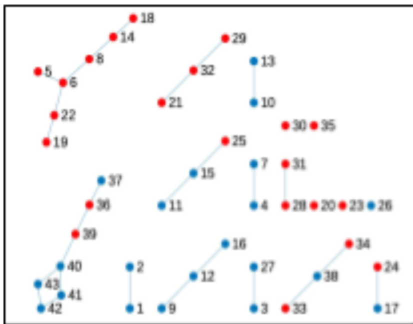
NewAPL	**0.94**
CC	**0.07**

Participant 7



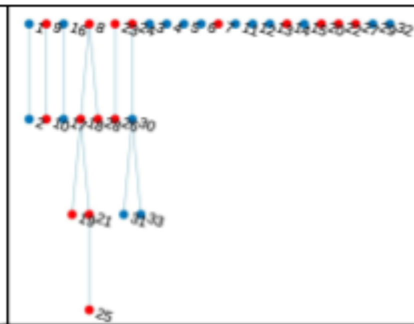
NewAPL	**0.82**
CC	**0.0**

Participant 8



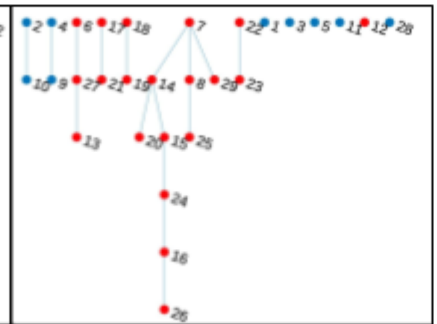
NewAPL	0.93
CC	0

Participant 9



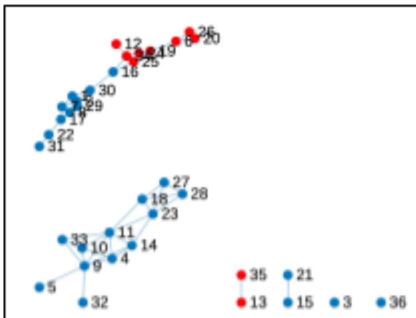
NewAPL	0.85
CC	0

Participant 12



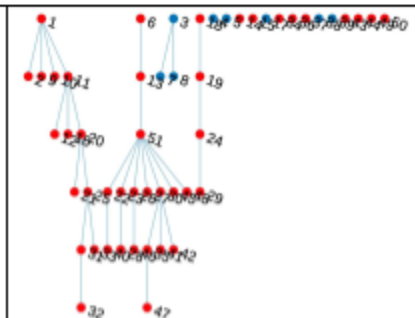
NewAPL	0.88
CC	0

Participant 14



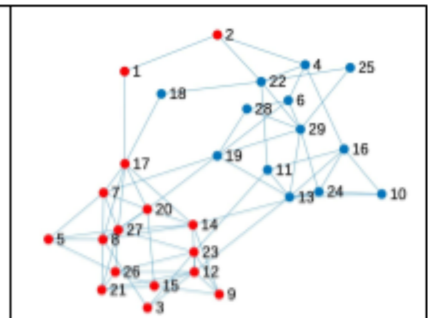
NewAPL	0.62
CC	0.45

Participant 15



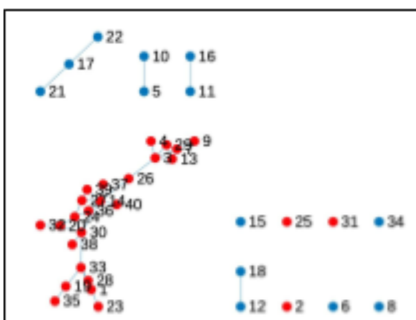
NewAPL	0.83
CC	0

Participant 16



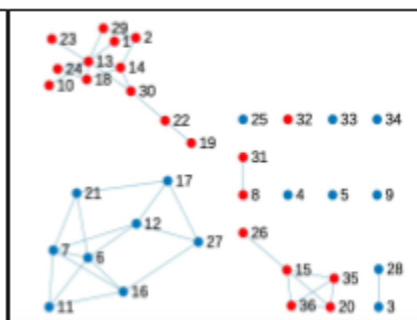
NewAPL	0.08
CC	0.42

Participant 17



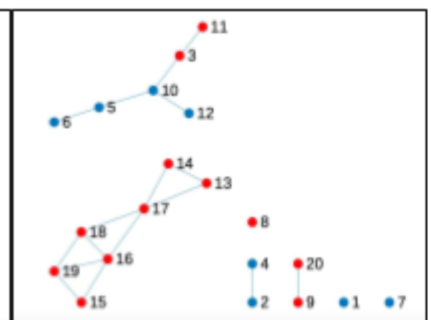
NewAPL	0.67
CC	0.15

Participant 18



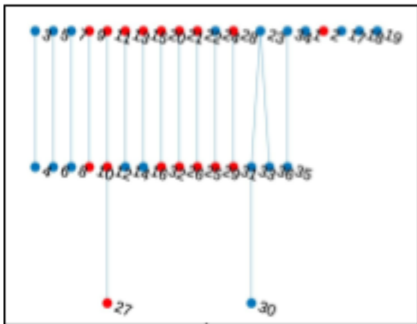
NewAPL	0.84
CC	0.27

Participant 19



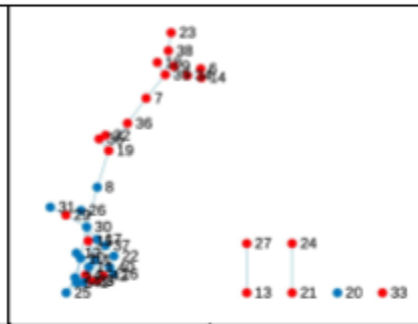
NewAPL	0.82
CC	0.26

Participant 21



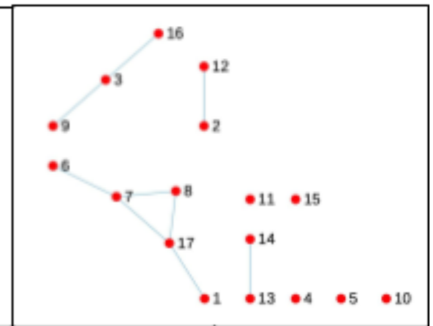
NewAPL	0.97
CC	0

Participant 22



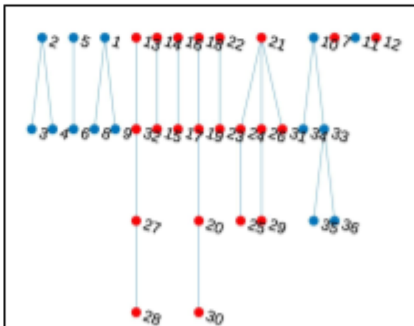
NewAPL	0.34
CC	0.28

Participant 23



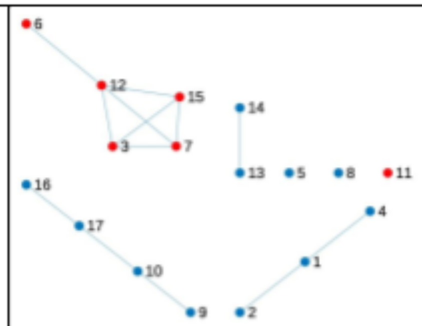
NewAPL	0.90
CC	0.10

Participant 24



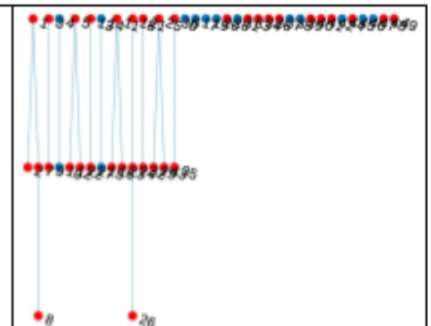
NewAPL	0.93
CC	0

Participant 25



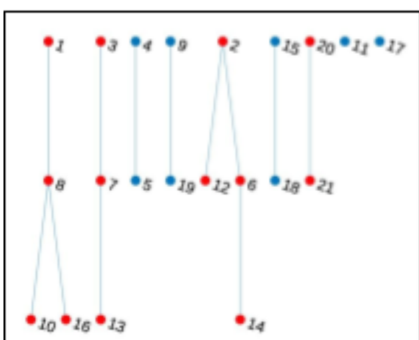
NewAPL	0.87
CC	0.21

Participant 26



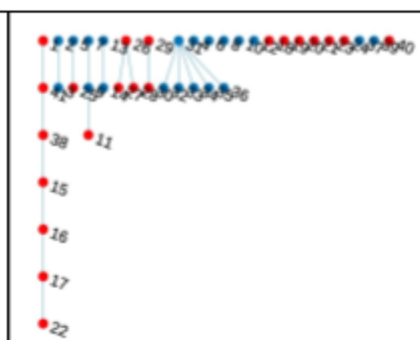
NewAPL	0.75
CC	0

Participant 28



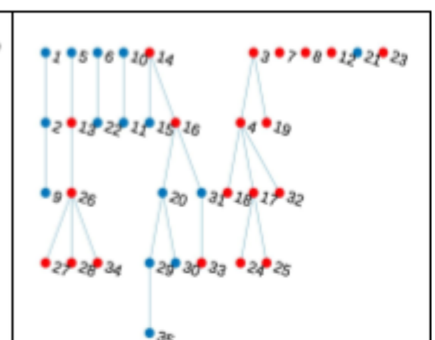
NewAPL	0.92
CC	0

Participant 29



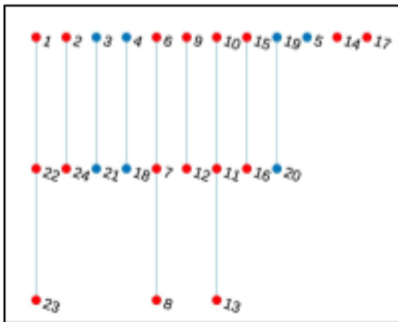
NewAPL	0.95
CC	0

Participant 30



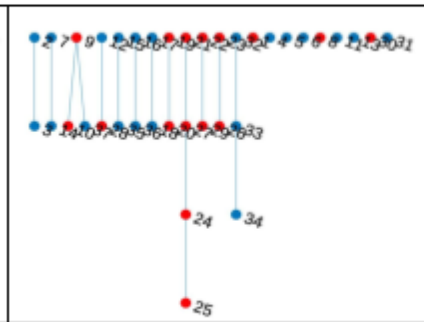
NewAPL	0.87
CC	0

Participant 31



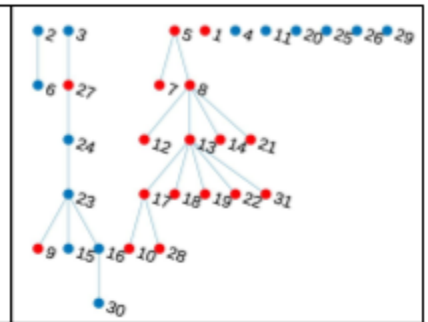
NewAPL	**0.95**
CC	**0**

Participant 32



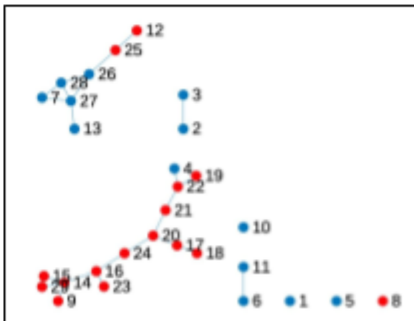
NewAPL	**0.97**
CC	**0**

Participant 33



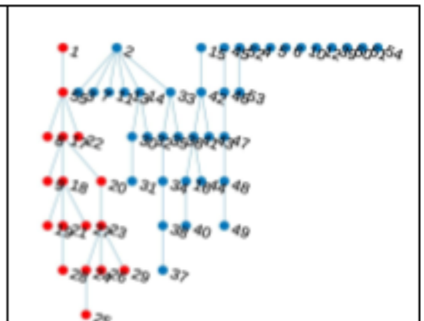
NewAPL	**0.76**
CC	**0**

Participant 34



NewAPL	**0.75**
CC	**0.16**

Participant 35



NewAPL	**0.83**
CC	**0**

Illustrates student's unique learning networks created in MATLAB and their corresponding NewAPL and CC. NewAPL has been calculated by dividing the average path length for the network divided by the number of courses students have taken during their undergraduate degree. Red nodes represent stem courses and blue nodes show all humanity courses.

4.3 Average number of connections

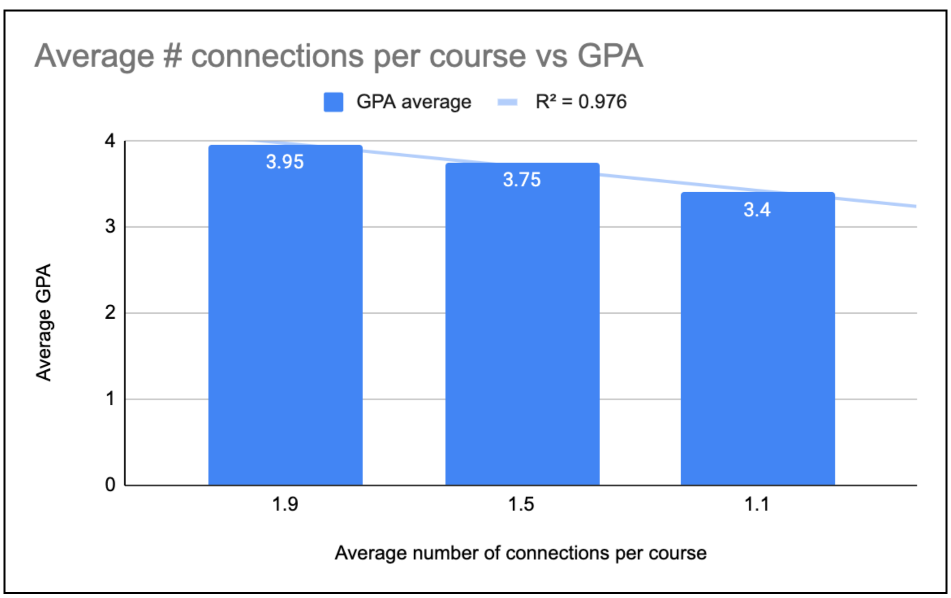
To generalize the results presented above and find average values that encompass all data, I have classified participants by their grade point average using the system described by table 2. This allowed me to create a fair distribution with an equal number of participants for each category.

Table 2: Student classification according to GPA

Bins	# of participants	Average GPA	Classification
1	10	3.95	Summa Cum Laude
2	10	3.75	Magna Cum Laude
3	9	3.4	Lowest performing

The top 10 performing participants averaged a GPA of 3.95 which falls under the category of Summa Cum Laude at MSU. The following 10 participants averaged a GPA of 3.75 and were labeled Summa Cum Laude. Lastly, the lowest 9 performing students averaged a GPA of 3.4 and were classified as the lowest performing. Creating these bins helped me explore students' average number of connections per course and their corresponding GPA. Below, we can see that there is negative linear relationship, with$r^2 = 0.98$, between students GPA and the average number of connections per class. This suggests that students that make less connections per course, are more likely to have a low GPA. We can also conclude from this graph that high performing students make on average 2 connections between each course in their program of study.

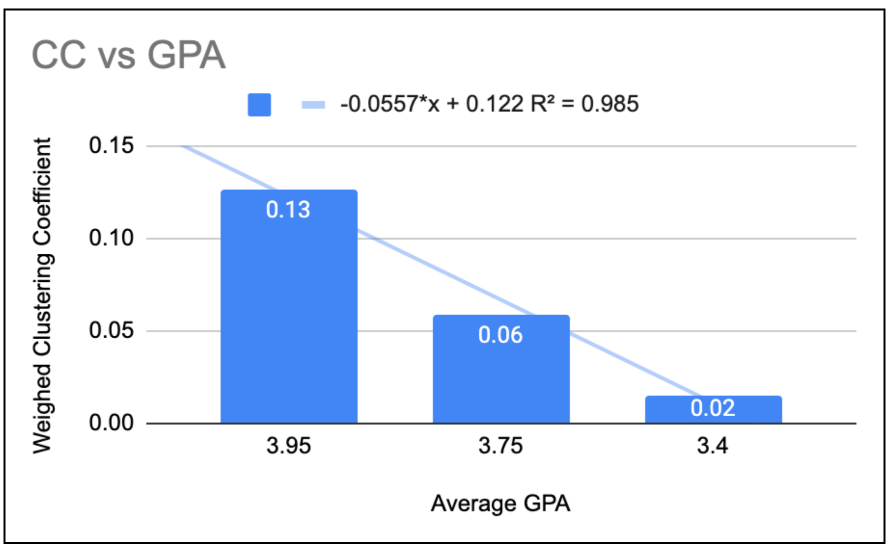
Figure 3: Average number of connections per course vs Average GPA



4.4 Clustering Coefficient

The clustering coefficient for these networks gives a deep understanding of how well information travels within students' neural structures and how quickly it can reach a neighboring course. In the context of this project, it helped me understand how likely it is that for any course A, connected to course B and C; there is also a connection between course B and C. In other words, the clustering coefficients averaged the number of triangles that can be formed within participants' learning networks. In general, the CC was very low or non-existent for most participants. Nevertheless, the few values obtained in this research show very conclusive results. Participants with an average GPA of 3.95 have a network with a higher clustering coefficient than students who fall in the other two categories. This means, they are able to make more triangular connections between courses than the others. Figure 4 clearly defines this relationship as negative and linear with $r^2 = 0.99$, which indicates that students with less triangular connections between courses perform worse than those that can link neighboring nodes. Finally, this analysis suggests that when information does not easily flow between adjacent courses, weaker connections are built.

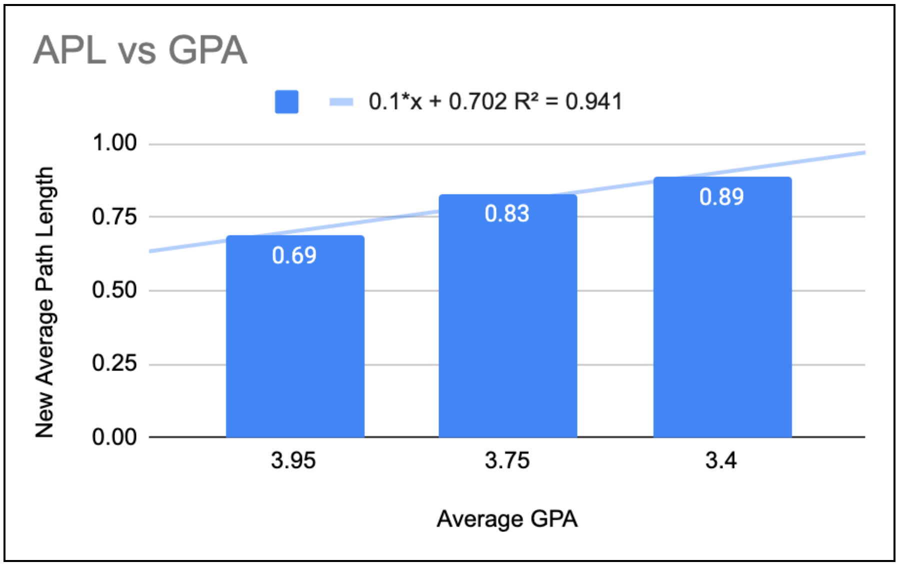
Figure 4: Clustering Coefficient vs Average GPA



4.5 Average Path Length

As theorized, the average path length for these networks also follows a linear trend. This interesting measure provides information about how quickly, on average, information travels from one course to another. Since the values have been normalized into NewAPL, they fall between zero and one, where 1 represents the longest path to reach a node, and 0 represents the shortest. Figure 5 compares the three GPA categories to the normalized average path length and reveals that students with a higher GPA demonstrate a higher connectivity within courses and therefore have a shorter average path length. On the other hand, lower performing students display a higher average path length since the average number of connections per course is also lower. APL analysis leads to the conclusion that students' ability to transfer information within courses is directly related to their GPA. As the APL between nodes increases, students' overall performance decreases.

Figure 5: Average path length vs Average GPA

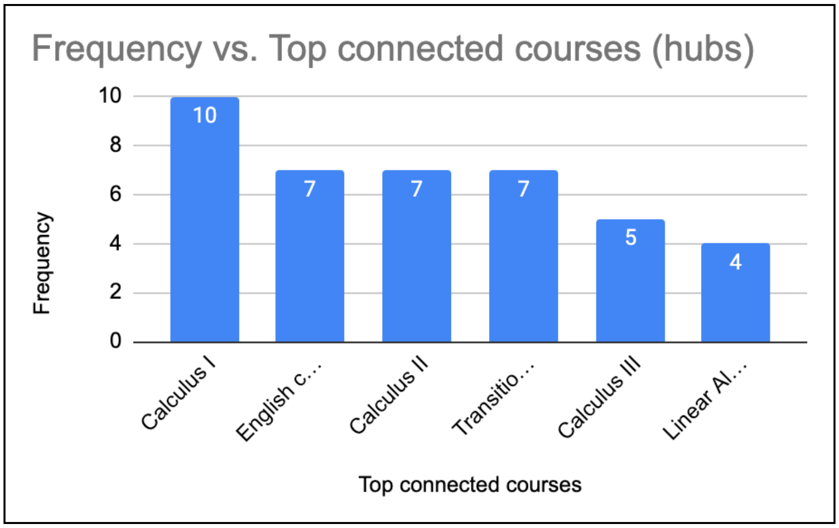


4.6 Hubs

Hubs have been defined as nodes of degree 4 or higher to represent the top connected courses in students' learning networks. To investigate hubs, I have analyzed each individual survey to identify the courses that have 4 or more edges connected to them. I then found how frequently these courses appear in students' surveys as top connected courses (see figure 6). For example, Calculus 1 is a hub (contains 4 or more connections) in 10 out of 29 surveys. Similarly, English Composition, Calculus 2 and Transition to Advanced Math are all high degree nodes in 7 out of 29 surveys. Finally, Calculus is a hub in 5 student's surveys and linear algebra is a highly connected course in 4 participants' networks. This analysis resulted in very interesting results about the nature of high degree nodes. Figure 6 displays top connected courses and how frequently they show up in this study, and suggests that hubs are mostly composed of courses that are prerequisites to more advanced classes. As expected in an undergraduate math program, 5 out of the 6 highly connected nodes below are major requirements with the exception of English Composition which is a foundational course. This indicates that the undergraduate math program at MSU provides ample opportunities for students to connect major courses but lacks interdisciplinary connectivity.

Although there is a clear relationship between students' GPA and their corresponding network's average path length, there seems to be no association between students' GPAs and the number of highly connected nodes. The average GPA for students that have described at least one hub in their network is 3.7 which is the same as the average GPA for students that did not establish any hub in their surveys. This result indicates that other factors, besides GPA, might influence the creation of highly connected nodes. It also shows that hubs can still exist in weakly connected networks.

Figure 6: Hubs vs frequency



Illustrates courses with highest degree and how frequent these courses show up in participants' learning networks

4.7 Curriculum Implications

The results described above have strong implications in curriculum development at the undergraduate level. Figure 3, 4 and 5 provide a clear understanding that participants' GPA is significantly better when the number of connections between courses is higher. On the curricular level, this means that students who are given more opportunities to make meaningful connections within courses are more likely to perform better. A connected curriculum as described by Fung, will not only provide students with more opportunities to make interdisciplinary connections, but will also address the problem of separation between STEM and Humanity courses. This is made possible by its emphasis on research and development and through the linking of interdisciplinary courses to relevant social causes. An integrated curriculum that provides students with opportunities to make more connections, allows for stronger neural connections, which according to the constructivism theory, comprises real learning. As suggested by Fung and supported by the results in this project, MSU and any higher education institution can benefit from the creation of more unique majors that bridge the gap between STEM and Humanity courses. This will improve the APL and CC of students' unique learning network as more opportunities to make meaningful connections will emerge.

5. Future Work & Considerations

To further develop this project, I plan on exploring the level of connectivity of individual courses required by Montclair's undergraduate math program, and how these connections affect other aspects of students' education such as enjoyment and perceived performance. It will also be interesting to explore how students classify their connections, based on applicability, prerequisites or important skills, and how this classification correlates to their enjoyment, perceived performance and overall GPA. Although the survey provided to students has been modified and optimized for time efficiency, it continues to require quite some time from its participants, and therefore recruitment for this project has been a great challenge. While I have narrowed the scope of participants' to math majors, I have not considered the effect of students' background and personal experiences on the number of connections they can make. In addition, some of the participants in this survey were transfer students and/or students double majoring. Hence, future work consists of applying the same statistical analysis and methods to a larger sample of students and narrowing the research to students who are not transferring from other universities or double majoring. To make sure students' exposure to courses is equally distributed, the next stage can also include the analysis of networks with the same number of nodes. Eventually, I plan on expanding this project to different majors within Montclair University to analyze students' unique learning networks based on their field of study and majors. Through this analysis, I can measure how connected or disconnected STEM and Humanity courses are within themselves and within the two distinct groups, and investigate how these connections influence students' GPA. This next phase will require the computation of networks' modularity which can be measured through Gephi and describes the strength of separation within the two groups.

6. Conclusion

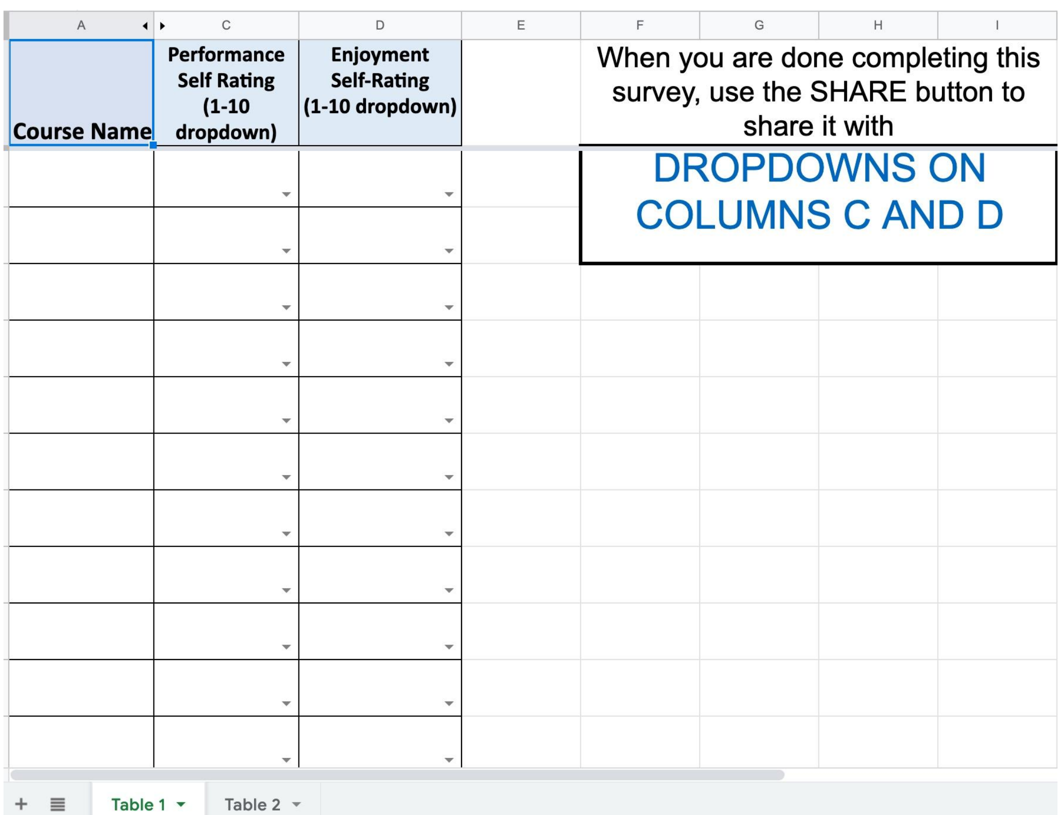
Despite its fixed structure, our brain is a complex system of interconnected areas that provide our body with multiple functions such as enabling action, perception and cognition [10]. As such, cognition models of learning are commonly associated with neural networks working together to transmit information, construct meaning and build stronger connections. In an attempt to simulate these complex systems, I have used network theory to build and analyze the unique learning structures of students' connections within courses. This analysis resulted in important insights about students' ability to make connections within subjects and their overall performance. It is clear that students who are provided with more opportunities to make connections within courses will perform better in their program of study. I have concluded that higher education institutions need to drastically improve the curriculum programs they offer their students to improve students' overall cognition and performance. Such changes need to take place at a small level, such as making sure that offered courses are meaningful and highly connected to other subjects; and at a larger scale, such as creating unique majors that connect STEM and humanities. The impactfulness of such changes might not be immediately noticeable but will certainly improve students' learning and information transfer as suggested by this research project.

Appendix

Below is a summary of the survey that was created to collect data about students' undergraduate educational experience:

Part 1 consists of an empty table with three columns labeled as "Course", "Performance self-rating " and "Enjoyment self-rating". Students begin by listing all the courses they have taken in their undergraduate coursework and by rating their performance (based on how much they believe they have learned) from 1-10 (1 being the lowest and 10 being the highest). They are also asked to recall the enjoyment of this course and rate them from 1-10 (1 being low enjoyment and 10 being high enjoyment).

Part 2 of the survey is easily accessible on a second tab of the same google sheet, and has already been coded to pre-fill the first and third column with the list of the courses students have entered on the first part of the survey. Hence, participants are asked to select a course from the first column and match it to a course from the third column if they believe there exists a connection between the two. They are also invited to rate the strength of such connection and to categorize the connection as: a prerequisite, application, important skill or other. If participants believe a course is not connected to any other subject, then it is considered an isolated node in the network with connection strength of zero.



Major: **GPA:**	**Note:** If a course is not related to anything and nothing is related to this course, list it under column A and select 'None' under column C. **USE THE DROPDOWN**	Use the dropdown to select a category that describes the type of connection between the two courses.	**Use the dropdown menu to tell us how strong you feel the connection is on a scale of 1-10, with 1 indicating a very weak connection and 10 indicating a very strong connection.**
Course Name	**Related Course**	**Why are these courses connected**	**Strength of Connection (1-10) 1-weak 10-strong**

Table 1 Table 2

Bibliography

[1] Ackermann, E. (2001). Piaget's constructivism, Papert's constructionism: What's the difference. Future of learning group publication, 5(3), 438.

[2] Beauchamp, G. A. (1968). Curriculum theory. Wilmette, Ill.: Kagg press.

[3] Blake, B. (2015). Developmental psychology: Incorporating Piaget's and Vygotsky's theories in classrooms.

[4] Chaplot, D. S., MacLellan, C., Salakhutdinov, R., & Koedinger, K. (2018, June). Learning cognitive models using neural networks. In International Conference on Artificial Intelligence in Education (pp. 43-56). Springer, Cham.

[5] Crossland, J. (2015). Is Piaget wrong. Primary Science, 137, 30-32.

[6] Drake, S. M., & Reid, J. L. (2018). Integrated curriculum as an effective way to teach 21st century capabilities. Asia Pacific Journal of Educational Research, 1(1), 31-50.

[7] Fung, D. (2017). A connected curriculum for higher education (p. 182). Ucl Press.

[8] Houghton, L. E., & Dawson-Threat, J. (1999). The American Undergraduate Math Curriculum: Maintaining a Connection with Application. The Journal of General Education, 48(1), 17-37.

[9] Naylor, S., & Keogh, B. (1999). Constructivism in classroom: Theory into practice. Journal of Science Teacher Education, 10(2), 93-106.

[10] Park, H. J., & Friston, K. (2013). Structural and functional brain networks: from connections to cognition. Science, 342(6158), 1238411.

[11] Sari, G., Gistituati, N., & Syarifuddin, H. (2019). The effect of guided discovery learning method toward students' ability in understanding math concept. International Journal of Educational Dynamics, 1(2), 54-60.

[12] Simon, J. (2010). Curriculum changes using concept maps. Accounting Education: an international journal, 19(3), 301-307.

[13] Stahl, C., & Hockemeyer, C. (2011). Knowledge space theory. 2008-06-18).[2009-12-23]. http://cran. r-project. org/web/packages/kst/vignettes/kst. Pdf.

[14] Starr, M. L., & Krajcik, J. S. (1990). Concept maps as a heuristic for science curriculum development: Toward improvement in process and product. Journal of research in science teaching, 27(10), 987-1000.

[15] Ültanir, E. (2012). An epistemological glance at the constructivist approach: Constructivist learning in Dewey, Piaget, and Montessori. *International journal of instruction*, *5*(2).

[16] Willcox, K. E., & Huang, L. (2017). Network models for mapping educational data. Design Science, 3.

[17] Taagepera, M., & Noori, S. (2000). Mapping students' thinking patterns in learning organic chemistry by the use of knowledge space theory. *Journal of Chemical Education*, *77*(9), 1224.

[18] Cathcart, L., Stieff, M., Marbach-Ad, G., Smith, A., & Frauwirth, K. (2010). Using knowledge space theory to analyze concept maps

[19] Terwel, J. (1999). Constructivism and its implications for curriculum theory and practice. *Journal of curriculum studies*, *31*(2), 195-199.

[20] John O'Meara and A. Vaidya, A Network Approach to Curriculum Design, Entropy (Complexity Section), 23(10), 1346, 2021.

[21] J. Keenan, M. Munakata, J. O'Meara, A. Vaidya and I. Wambacq, On the Impact of the Self in a Complex Knowledge Network, International Journal of Complexity in Education, 3(2), 2022, 53-78.