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Adaptive Personalized Network Relationships in the CHUNK Learning Environment

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***Abstract*—How can learner profiles support personalized online learning? Our current research analyzes a personalized adaptive system for education called CHUNK Learning. The CHUNK Learning system builds on a network of modules, and a learner profile, both tagged with keywords. CHUNK Learning currently utilizes simple keyword relationships to suggest a tailored, personalized, adaptive learning plan guiding the learner through the network of modules. However, supervised machine learning methods may be more suitable to enable the implementation of an iterative algorithm for refined learning plans. In this paper, we investigate the relationship between learner profile and adaptive learning plans. Learners first create a profile in CHUNK Learning which establishes their baseline learning plan. Then, as learners begin to interact with the learning environment, the CHUNK Learning system updates the learning plan based on learner activities (learned, viewed, tested), keyword searches, and content ratings by increasing or reducing the strength of the connection between the learner profile and activities. Additionally, we demonstrate that by connecting all learners within an academic program, we create a stronger bond between learners, which results in a reduced path between activities. We conclude that by reducing the path length between activities, we strengthen connections in the CHUNK Learning environment resulting in a more concise academic plan for learners.**

***Keywords*—education; adaptive learning; learning systems; network theory (graphs); adaptive algorithms.**

I. Introduction and Motivation

Institutions design current educational experiences in a manner which presents learning material to students through a very formal and rigid structure. This structure forces all students, regardless of personal academic backgrounds or capabilities, through an academic pipeline where they must complete topics in a sequential order to move forward to the next topic. At the Naval Postgraduate School in Monterey, California, USA, a web-based software application known as CHUNK Learning explores potential methods to relieve some of the rigor of this standard academic environment [1].

The Curated Heuristic Using a Network of Knowledge for Continuum of Learning (CHUNK Learning) environment is an educational platform that draws information from a learner profile to recommend a tailored educational experience for them [1]. The CHUNK Learning environment (Fig. 1) consists of courses, CHUNKs, CHUNKlets, and activities. Courses are generally added by instructors and typically align with a course offered in the academic curriculum. A CHUNK is a topic within a course, equivalent to a section in a textbook. A CHUNK is divided into smaller pieces called CHUNKlets. CHUNKlets are recommended experiences to maximize learning comprehension for each learner, within a particular CHUNK. Finally, activities are the base level of interaction within the CHUNKlets. Activities are the final link to videos, PowerPoint presentations, and other media which may be accessed by the learner. Throughout the paper, “user” and “learner” are used interchangeably.

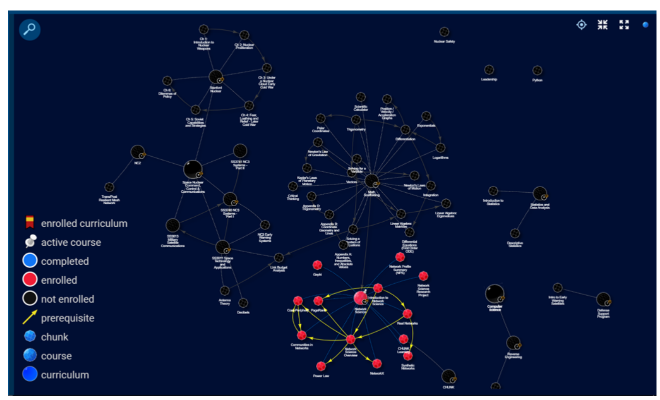

Fig. 1. A Snapshot of the CHUNK Learning Environment.

We desire to implement a web-based program which recommends educational experiences to learners. Our motivation in conducting this research is to analyze links within the learner profile to develop an adaptive network that recommends activities to the learners based on their recent keyword searches, content ratings, and common connections between them. The desired end state is to have refined algorithms in the CHUNK Learning environment to provide recommendations similar to methods currently used in industry. For example, if someone conducts a search engine inquiry regarding a potential product purchase, then commercial services like Amazon will take that information and return not only suggestions for that product, but also additional items which are closely related to the original search [2]. This method has been proven to generate additional revenue in sales, and in our research we would apply the same concept to translate commercial potential into increased academic potential.

To develop the relationship between learners and activities, CHUNK Learning analyzes learner profiles and links activities with the learner based on a simplistic count of keyword matches. Profile information includes information such as military branch of service, course enrollments, prior education, and experience. To conduct our research, we develop a network model linking learners to activities using adaptive keyword weighting based on CHUNK Learning use (viewed, tested, liked) data. As the CHUNK Learning environment does not currently contain this network model, we compare the network relationships for the initial static profile and an adaptive profile to determine overall impacts on the learner's educational experience.

We organize the remainder of this paper as follows. Section II provides an overview of related work. We then establish the definition of our network model and introduce the methodology for comparing and contrasting the existing CHUNK Learning structure to a novel one in Section III. In Section IV, we present the experimental setup, followed by the results and interpretation in Section V. Finally, we conclude and present recommendations for future research in Section VI.

II. Related Work

Existing recent approaches to a personalized adaptive learning methodology include research using web-based services [3]–[6], personalized learning models [7]–[9], the creation of e-learning environments combined with web-based services [10]–[12] and the creation of user interfaces based on user behavior episode identification [13]–[16]. While all methodologies have benefits and limitations, we narrow our focus towards the creation of a user interface based on episode identification, analysis of user feedback, and the creation of an adaptive learner profile.

Prior CHUNK Learning research at the Naval Postgraduate School by MAJ Jan-Daniel Cleven (German Army) introduces a multi-layer network model relating classes to learners through interests [17]. The nodes represent classes and learners in the Operations Research curriculum and the edges represent keyword relationships between the classes and learners. This model incorporates learner feedback by weighting the connection between the nodes. Course syllabi are filtered by metadata tagging to extract the top ten relevant keywords for each course offered, assigned to the nodes. The system uses weighted feedback to provide recommendations for the learner's future coursework. This feedback diminishes the presence of unfavorable courses and brings preferred courses to the top of the recommended list. We are particularly interested in the feedback component of this research and its inclusion in our experiment as a feedback methodology.

Previous research on adaptive user interfaces is of particular interest to our area of study. The approach taken by Jiming Liu, Chi Kuen Wong, and Ka Keung [16] is a design that reacts to different situations and requirements, then records user's behavior. Their approach is based on Episodes Identification and Association (EIA), which recognizes the learner's patterns by tracing the learner's action sequences. The episodes can be thought of as a record of learner behavior used to predict the best educational experience. One of the limitations of this approach is the possibility of losing data due to limitations in the types of recorded events. For example, a user could initiate typing in a search bar, but then select an auto-generated recommendation without recording that search in the action sequence. The goal of their interface is to help learners according to adaptive learning plans. The authors recognized the need to develop learner profiles to enable personalized interactions. Their approach discovers rules that can best describe and predict learner's behavior by finding frequently occurring episodes in the learner's action sequences. They distinguish two types of interface events: text input events and mouse click events. We believe that focusing on both text input events and mouse click events to update an adaptive keyword list will be valuable to improving our network model of an adaptive educational environment.

Another existing approach to personalized learning published by KK Thyagharajan and Ratnamanjar Nayak [5] involves implementing a web-service to ensure the residual validity of learning content. The authors use dynamic methods based on the learner's needs and preferences to fulfill learning objectives. Systems such as Intelligent Tutoring Systems (ITS) [13] and Adaptive Hypermedia (AH) [11] are also possible solutions to personalize the learning experience for the student. Such systems may tailor the educational offerings to the learner's objectives, prior knowledge, learning style, experience, and many other characteristics. The downfall is that these existing systems remain criticized for believing that the embedding of expert knowledge is sufficient for efficient learning to occur. Although beneficial, our model does not include this approach. We do, however, recommend it for consideration in future research.

In our study, we focus on an adaptive network science methodology to propose an improved learner experience in the CHUNK Learning environment. The aim is to improve the educational experience recommendations to the learner through a dynamic profile. The adaptive network studies the effect of a learner feedback loop as well as learner profile updates based on his/her behavior in the CHUNK Learning environment, similar to the study completed by Liu, Wong and Keung [16]. Additionally, we focus on connecting learners based on academic curricula to determine effects to the individual learner in the educational environment.

III. Network Model & Methodology

In this research, we develop a network model for an adaptive, personalized educational environment for CHUNK Learning tailored to enhance each student's educational experience. Our network model includes two elements: nodes and edges. The nodes are learner profiles and activities, while the edges are tuples consisting of keywords from a learner's profile that link him/her to an activity.

Our methodology focuses on comparing and contrasting the existing structure of user-to-activity connections based on static keywords within CHUNK Learning, to a more dynamic structure that updates a keyword list within a learner profile based on his/her CHUNK Learning use. In the existing structure, the learner's profile has a static and adaptive component. The static profile consists of keywords derived from initial data input when each learner establishes his/her initial profile. The keyword tuples in the static profile do not change, unless the learner manually edits the profile. In contrast, the learner's adaptive profile consists of a profile where the keyword tuples dynamically update by capturing data from learner's use of the CHUNK Learning environment. We focus on one adaptive category, activities, which are one level below a CHUNKlet in the CHUNK Learning network, to determine the effectiveness of the keyword relationships. This dynamic network process can be iterated multiple times to further refine the keyword relationships.

The baseline methodology uses the existing structure of the CHUNK Learning curriculum. That is, the nodes in the network are learners and activities. The edges in this network connect learners to activities through keyword matches found in the learner's initial profile. Based on a weighted sum of keywords, the learning system presents the learner with activities that match keywords from their profile. In order to model this network, we develop a small sample of five learner profiles generated with pseudo-random keywords from the available keywords list. We then use this information to generate a network model for the initial static network.

We then modify the simulated learner profiles in such a way as to replicate the effects that an adaptive, personalized education environment may have on a learner. We apply this adaptive concept to generate our second network model, taking into account the new adaptive profile data. The nodes still represent the learners and the activities, and the edges are still the keywords linking the learners to an activity, but now the methodology focuses on an adaptive profile approach. The combination of the initial static profile with randomly updated keyword relationships generates the new adaptive network. Using this method, we expect that edges between activities and learners will evolve based on the learners perceived quality of the available activities. Some activities may become disconnected as lower valued edges diminish, while other activities may gain relevance as they accumulate stronger connections.

In addition to an adaptive learner profile based on keyword updates, we update the adaptive network to include additional edges that connect learners with similar academic curricula in order to analyze the effectiveness of connecting learners sharing similar characteristics within their profiles. These relationships form a completely connected sub-network between learners with similar academic backgrounds. This sub-network shows learners with similar academic curricula having a shared relationship with activities which are prevalent in their academic field. These improved relationships reduce the distance between the learner and content that is relevant to their peers, and additionally, they can be used to pre-compile future learner profiles as new learners begin using the CHUNK Learning system.

Lastly, we analyze the effects that a feedback loop could have on the personalized learning environment. Utilizing the adaptive network model that we create, we use an average learner rating to determine whether or not an activity should be available within the learner environment. We expect our simulation to show the effects of feedback, such as learner activity rating, on the learner's experiences within CHUNK Learning.

Our methodology of comparing and contrasting the effects of two different learning experiences should offer us valuable information on the type of educational environment that is more beneficial to a user.

IV. Experimental Set Up

In order to set up our experiment, we first analyze existing CHUNK Learning data to find data that links learners to activities through keywords. The initial set of keyword relationships from the current database resulted in more than 4200 potential relationships for sources and targets. In order to see the effects on the individual learner, we pare down this available data to create five virtual learner profiles. The decision to create only five learner profiles provides us with a potential advantage. Five is a small number, but still significant in our case, allowing us to visually see changes that we would expect to happen given a larger pool of profiles. We use the sources and targets to generate and investigate a directed network in both R-project [18] and Gephi [19].

We model the five virtual learners with a list of keywords and activities for both the static and adaptive networks. The learners are the same for each network. Only the list of keywords change in the adaptive version. In our static network model, each learner begins with between three to five randomly selected activities each with between one to five keywords for a total of seven to ten total entries. Multiple keywords matching to the same activity provides an integer value for weighted edges.

In order to set up our adaptive profile network simulation, we set some parameters. First, we limit a learner's keyword list to their top eight keywords. Our goal is to strengthen learner connections to activities without creating a network overpopulated with activities due to a long list of keywords.

Also, a long list of keywords could potentially provide too many recommendations to a learner, therefore lessening the benefit of a personalized learning environment. Although the number of keywords is adjustable, we maintain the keyword list to a maximum of eight for our simulation. Another defining parameter is that a learner's established connection to activities is through a minimum of two keywords. The purpose of this parameter is to, once again, strengthen the link between learners and activities. In the static version of the network, these parameters do not exist. There are some edges of weight one, linking a learner to activities by one keyword such as "video". However, the keyword "video", provides no information as to the content most relevant to the learner. Therefore, in order to improve the learner experience, we implement the minimum of two keywords to link a learner to an activity. We update the learner keywords at random to simulate word searches related to their academic activities. We update all learners similarly, each gaining one new keyword. If the learner's keyword list exceeds eight, the simulation removes a keyword from the list at random until the learner profile reaches the number eight. We do not provide a ranking for keywords in our simulation.

We run this experiment in both Gephi and R in order to provide multiple visualizations. As no network visualization is the same, we analyze different things about our two networks by looking at them from different perspectives. We believe that analysis from multiple viewpoints is valuable to this experiment.

After running our initial experiment, we continue working with the adaptive network. The first experiment we conduct connects learners based on their academic curriculum in the adaptive network. Of our five learners, we select two different academic curricula. We assign two learners to the "math" curriculum and two learners to the "operations research" curriculum. We then assign one learner to two curricula as a "double major," in both "math" and "operations research". The experiment connecting learners allows us to analyze a path to an activity that does not exist without the learner-to-learner connection. In addition to path length, the learner connection allows us to analyze the impact of certain learners on the centrality of the overall network.

The last evaluation conducted for this experiment is a feedback simulation. Although we do not create a feedback loop, we want to see possible effects of learner ratings on activities. Therefore, we set a minimum average activity rating within the system. For an activity to be available to a learner, the minimum rating is three. However, sensitivity can be modified to change the weight of feedback at any time. We randomly assign activity ratings to each activity. If an activity has an average rating of less than three, it does not populate the network simulation. We use the results of this simulation to analyze the impacts and effectiveness of a feedback loop in an adaptive, personalized learning environment.

After completing the simulations of our network experiment, we compare and contrast the initial static profile model against the adaptive profile model, without learner connections. Each simulation provides us unique and different information regarding edge weights, number of nodes, number of edges, average out degree, path length, and centralities. We then use this information to analyze our network.

V. Results and Analysis

After completing our experiment by running simulations of our static and adaptive networks in R and Gephi, we review and analyze our results. Our results focus on structural elements, specifically path lengths, path diameters, and network centralities, as well as how suitable a node is for spreading information.

A. Graph Composition

The following figures and tables include the results from the incremental changes in our CHUNK Learning environment simulations. Fig. 2 and Table I demonstrate the results from the baseline, static network which models the existing methods of the CHUNK Learning system.

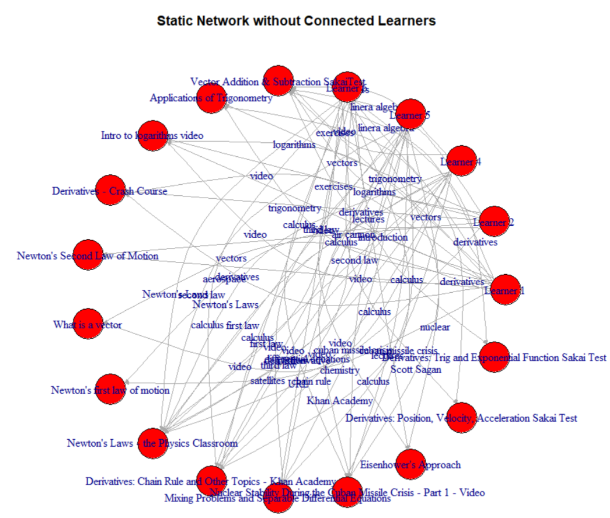

Fig. 2. Initial Static Network without Connected Learners

TABLE I. Static Network Results.

Number of Vertices	19
Number of Edges	59
Average Path Length	3.321
Diameter Length	6

In Fig. 3, learners are connected to activities through a list of keywords and to each other. This model is our baseline, which we use to compare to the adaptive network model simulations. As can be seen in Table II, connecting the learners reduces the average path length between learners and activities immediately.

Fig. 4 is our adaptive profile network simulation. This network shows what would happen if each of our five

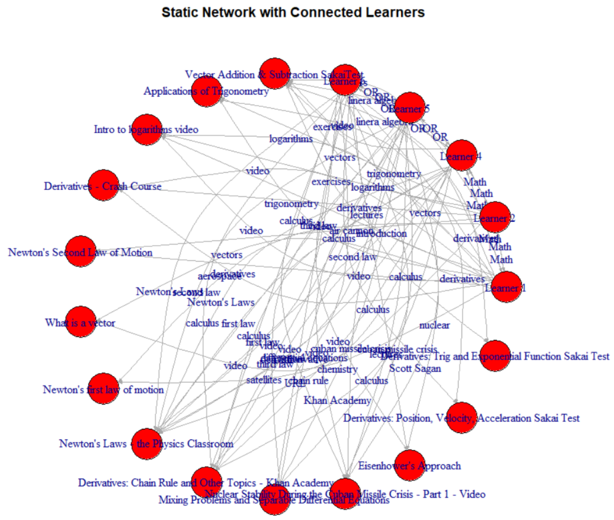

Fig. 3. Initial Static Network with Connected Learners

TABLE II. STATIC NETWORK RESULTS - CONNECTED LEARNERS.

Number of Vertices	19
Number of Edges	71
Average Path Length	2.397
Diameter Length	4

simulated Learners had their keyword lists updated with one new keyword, their keyword lists restricted to eight keywords, and a minimum of two keywords required to link a learner to an activity. Through this change in the simulation, the updated keyword list generated new edges, linking learners to new activities with the addition of one new keyword (Table III). As expected, these new connections increased the total number of nodes in the network. The number of learners did not change, but new activities populated based on their updated keyword lists. We found it valuable to determine if the average out-degree of a learner changed when comparing the static profile to the adaptive profile network. The average out-degree increased by two in the adaptive model. We expected this result as we added the requirement for a minimum of two keywords to connect a learner to an activity. These results tell us that the small changes made have enhanced the educational experience for the learner. The more edges linking a learner to an activity strengthens the learner's experience in this educational environment.

TABLE III. ADAPTIVE NETWORK RESULTS.

Number of Vertices	24
Number of Edges	67
Average Path Length	4.06
Diameter Length	8

Fig. 5 depicts the simulation which connects learners to each other through academic disciplines such as "Mathematics" and "Operations Research." This simulation increased the number of edges in the overall network, and we analyze this a bit further by focusing on path lengths. Fig. 6 and

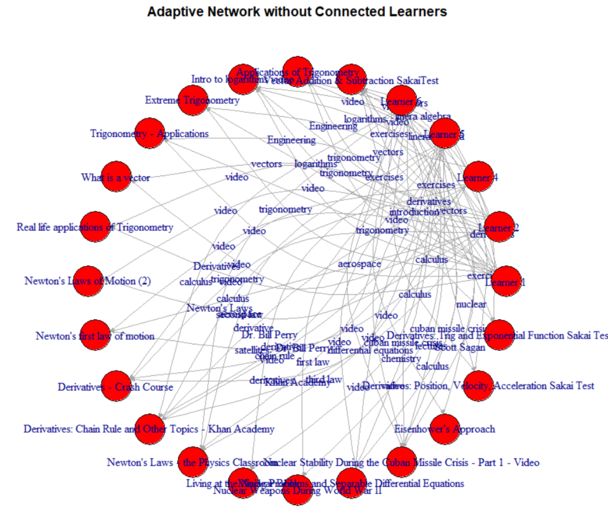

Fig. 4. Adaptive Network without Connected Learners.

Fig. 7 present the results of this analysis and next we discuss the conclusions drawn from our analysis in more detail.

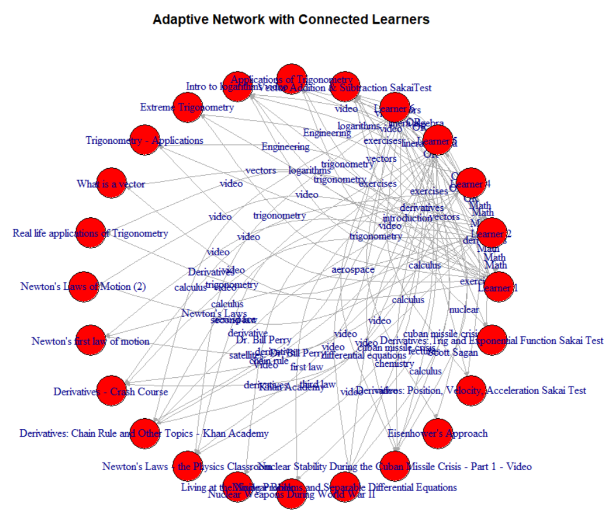

Fig. 5. Adaptive Network with Connected Learners.

TABLE IV. ADAPTIVE NETWORK RESULTS - CONNECTED LEARNERS.

Number of Vertices	24
Number of Edges	79
Average Path Length	2.452
Diameter Length	4

Fig. 6 again shows us the adaptive network without connected learners. This time we highlight the path a user would have to take to arrive at a non-recommended activity. In order for Learner 6 to get to the highlighted course not recommended to him/her, he/she would have a path of length three to get to that course. After reviewing these results, we predict that this path would shorten if we connected learners.

Fig. 7 depicts an alternate view of the adaptive profile network with connected learners. We connect the learners

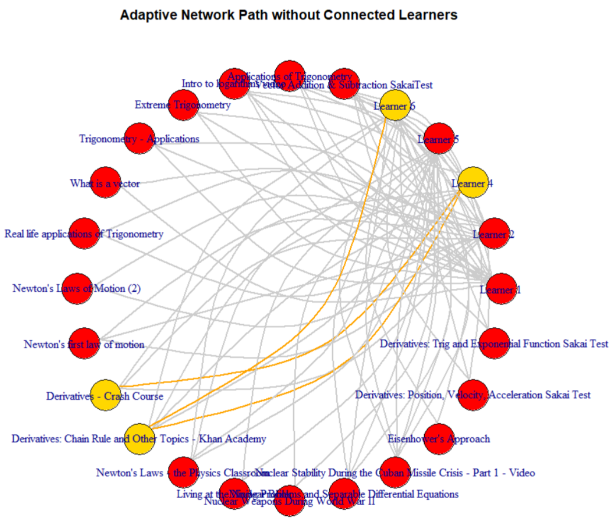

Fig. 6. Adaptive Network Path Showing Disconnected Learners.

through academic disciplines such as mathematics and operations research. What we find is that the minimum path Learner 6 requires to get to the same highlighted course as in Fig. 6, shortens due to the inter-learner connectivity. Therefore, we find it valuable to the educational environment to connect learners with similar qualities. This connection makes activities available to the learner even though they may not have in their profile keywords related to such activities.

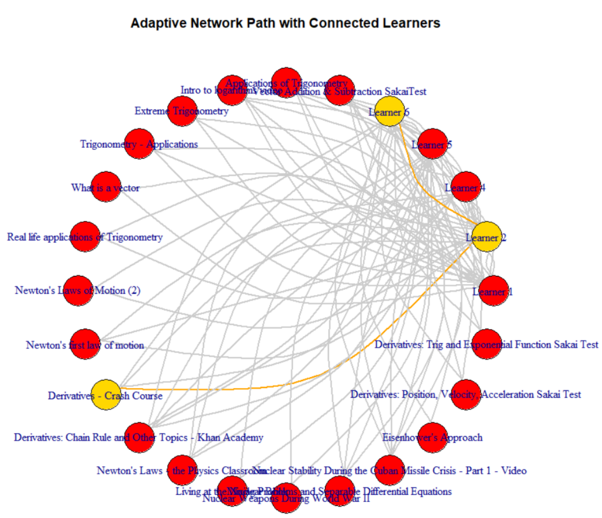

Fig. 7. Adaptive Network Path Showing Connected Learners.

This concept is similar to what Amazon.com users see when shopping on Amazon's App or website. After a user purchases item "W", Amazon connects users who brought item "W" then shows additional items through a section called "Customers who bought item "W" also bought "Y", "X", and "Z"." The adaptive concept offers predictive options given past user behavior. In the CHUNK Learning environment, students may see Learners who completed activity "A" also completed activity "B".

The final incremental change we make to our CHUNK Learning environment network simulation includes analyzing the effects of feedback. We perform this analysis through a simulated activity rating. We randomly assign average ratings to each activity. If the rating is less than three, the activity becomes no longer available in the learner's educational environment.

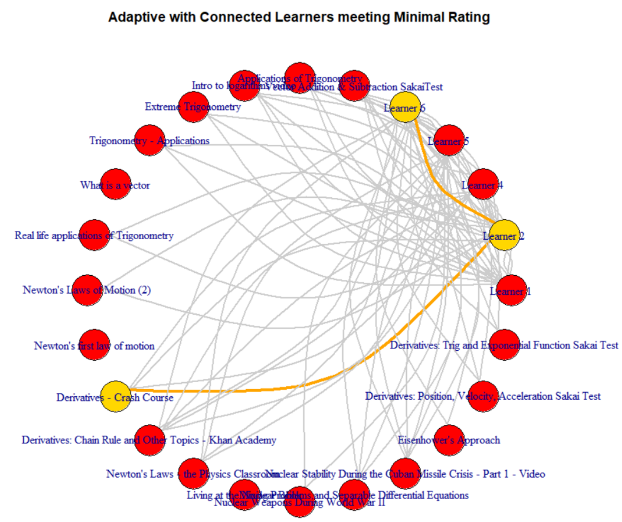

Fig. 8. Path Connecting Learners to Activities Meeting Minimal Ratings.

Fig. 8 is an example of the network with the same path length as found in Fig. 7. As shown in Fig. 8, however, activities with average learner feedback of less than three are no longer present. Since the path from Learner 2 to "Derivatives–Crash Course" meets the required minimum rating value, the connection holds. We find this simulation valuable as feedback provides the CHUNK Learning environment with the ability to continually monitor and update its content to provide the best educational environment for individual learners, concluding that a feedback loop, in the form of average activity rating, enhances a learner's educational experience in the CHUNK Learning environment.

In Fig. 8, three activities fail to meet the rating threshold. As a result, the adaptive simulation disconnects the activity from the network but does not delete the activity from the CHUNK Learning environment. Activities may continue to hold educational value after review and remain within the system. Disconnecting activities from the network inside the CHUNK Learning environment may signal the activity needs maintenance due to a faulty hyperlink, or the delivery of the material fails to resonate with learners. In other words, the activity may be "boring" or the instructor "uninteresting" and the activity should be revamped. Moreover, merely deleting the activity would prevent the analysis of trends for poorly rated content and inhibit overall CHUNK Learning environment improvement and growth.

This concept is similar to Amazon's product review. In the CHUNK Learning environment, learners provide direct feedback for each activity. Amazon rarely offers its shoppers poorly rated products. In turn, CHUNK Learning users would only see exceptional-to-average rated learning activities.

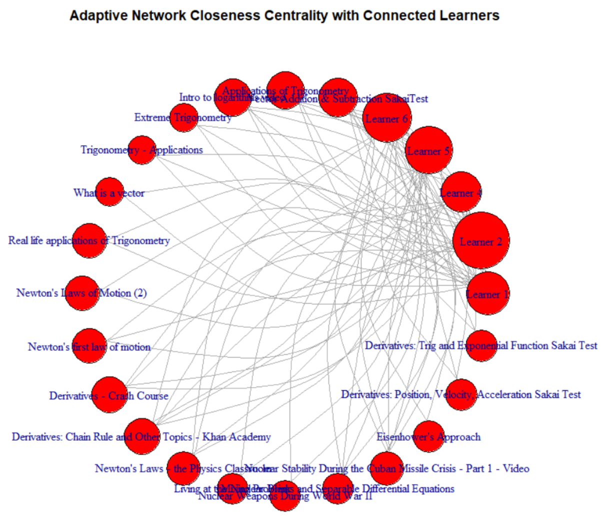

Fig. 9. Normalized Closeness Centrality Network with Unconnected Learner.

B. *Network Centralities*

Lastly, after running all of our simulations, we find it valuable to analyze centralities on our network. The closeness centrality and eigenvector centrality help measure the effectiveness of node information dissemination. By examining centralities, different node characteristics come into play. These node characteristics are essential when determining how to improve the CHUNK Learning experience.

The network simulations shown in Fig. 9 and Fig. 10 depict the closeness centrality of the adaptive graph without and with learner connections, respectively. While differences exist, the differences yield no significant results which can drastically improve the CHUNK Learning environment.

Fig. 11 depicts the eigenvector centrality of the adaptive network, while Fig. 12 shows the eigenvector centrality of the adaptive network with connected Learners. As expected, Fig. 12 is more densely connected. Our findings indicate that the learner connected adaptive network has advantages over the unconnected network.

Significant to the eigenvector centralities is the shuffle of Learner eigenvalues rankings once learners were connected within the network. The learners' eigenvalues are ranked in Table V.

TABLE V. LEARNER EIGENVALUES.

Unconnected Learner Eigenvalues		Connected Learner Eigenvalues	
Learner 1	1.0000	Learner 2	1.0000
Learner 2	0.7540	Learner 1	0.8370
Learner 4	0.4003	Learner 4	0.6612
Learner 6	0.2206	Learner 5	0.6347
Learner 5	0.1831	Learner 6	0.6249

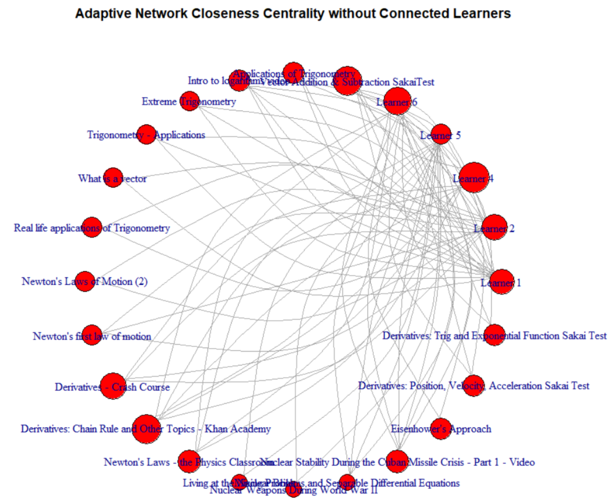

Fig. 10. Normalized Closeness Centrality Network with Connected Learners.

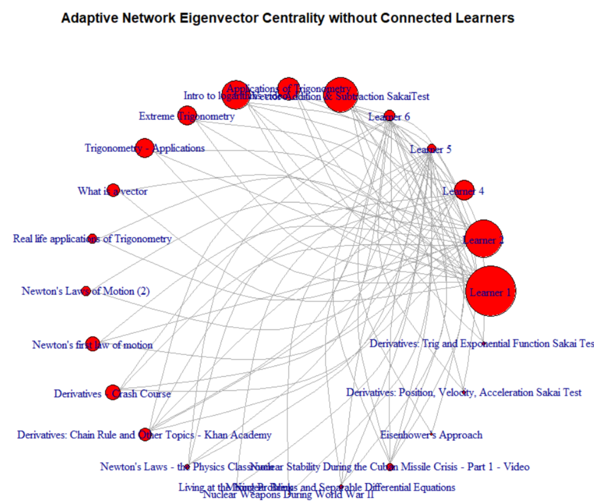

Fig. 11. Scaled Eigenvector Centrality Network with Unconnected Learner.

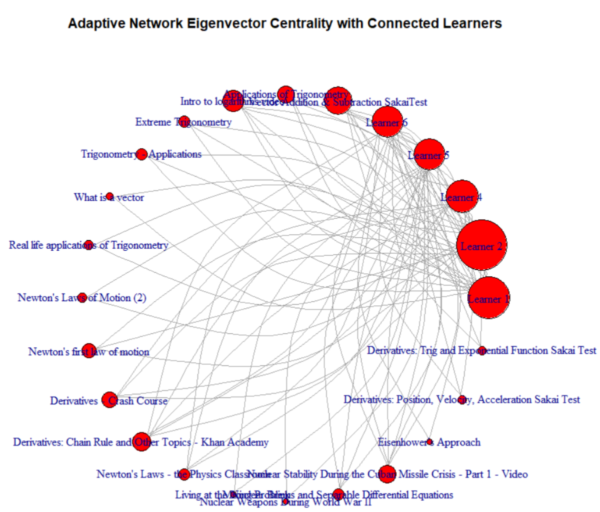

Fig. 12. Scaled Eigenvector Centrality Network with connected Learners.

Eigenvector centrality measures the impact that neighboring nodes have on one another. There are three significant results when comparing unconnected learners to connected learners using eigenvector centralities. First, all but one of the eigenvalues increase, meaning connecting learners results in a significant impact from the weight of the neighboring learner and activity. Second, the re-ranking of eigenvalues showing a learner's individual network connections is imperative during analysis. Learners who connect to other active Learners connect to more information. Moreover, and lastly, by design Learner 2 is a "double major" in Mathematics and Operations Research. Between Learner 2's connected activities and it's neighbors connected activities, Learner 2 is only a maximum of three moves away from any Mathematical or Operational Research activity in the simulated CHUNK Learning environment. This "double major" concept could be applied to a variety of adaptive network characteristics such as learner personal interest, undergraduate degree information, or favorite instructional video.

VI. Conclusions and Future Directions

After reviewing and analyzing the results of the network simulations, we believe more work can be done to enhance the personalized educational experience in the CHUNK Learning environment. Limitations to our experiment were scaling and iterating. We based our analysis on a small sample of randomly simulated learners. To further improve results and provide additional justification for a personalized learning environment, experiments should focus on a much larger scale with real data. Iterating the process over time would also show the effects on learning in the educational environment. Knowing these limitations led to a list of recommendations for future work.

First, feedback is essential to an adaptive, personalized learning environment. A learner rating from one to five could provide a measurable weight to the adaptive list of keywords in a learner's profile. Although a learner may search a particular keyword or use a specific activity, it is possible they may not have an interest in that topic. Therefore, the feedback loop would be a valuable tool to keep the keyword list weighted and updated based on learner ratings.

In addition to a learner activity rating, another area for future work would be to implement statistics in the form of a dashboard within a learner profile. This dashboard will allow the learner to see the derivation of recommendations for certain activities as well as the progress they are making on completing their academic goals.

While we found that connecting learners can be valuable by providing a shortened path to an activity, in the future, it would be useful to analyze the possibility of learner's sharing keywords through their connections. This sharing of information can provide a direct path from a learner to activities through a shared keyword or keywords.

While there is still much work to be done, the results of small scale simulations in an adaptive, personalized educational environment provide valuable insight. An adaptive network within the CHUNK Learning environment would enhance the learner's educational experience by recommending activities most relevant and exciting to the user.

Acknowledgments

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