Applying connectivism? Does the connectivity of concepts make a difference for learning and assessment?

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Abstract—The society is in a state where learning has no limits and starts to overlap with technological developments. The recent advent of a connectivistic learning theory promises to shed light on how we learn in environments of interconnected knowledge and how the connectivity of concepts can guide the learning and conceptualization. This paper will have a look at a domain ontology-based approach to learning and assessment and investigate if the connectivity of the stored concepts, measured by a selected set of centrality measures, can provide a prediction of the assessment performance. The analysis will be conducted on a real world application with 247 students in the field of business informatics.

I. INTRODUCTION

It is natural that well connected concepts are usually judged as prominent and important to understand a given domain. The concept of a car can be understood but not fully mastered without the basic knowledge on how an engine is working and the idea of a car cannot be fully grasped without understanding how the concept of the engine modifies the car’s appearance and functionality.

Connectivism is a learning theory which accounts, among other aspects, for the value of connectivity and the importance to see a domain to learn in the context of its connected concepts. Yet – is it mandatory to master a central “well connected” concept to master connected knowledge? And further – is the assumption observable in a specific real world application?

To tackle the answer this paper will introduce the STUDIO environment as an application platform providing a concept map for learning and assessment, implemented as a Domain Ontology. To investigate the correlation between the connectivity of concepts and the learner’s performance, centrality measures from the field of network analysis will be applied to the structure of the STUDIO domain ontology. Finally a correlation analysis will be conducted, while two experimental performance measures are proposed and applied in a study with students in the field of business informatics: the “neighbourhood” performance and the “next node” performance.

Section II of this paper will summarize the implications for a technology enhanced solution for learning from the learning theory of connectivism. Section III introduces the STUDIO environment for blended learning, that is used to conduct the experiment. Section IV will describe the centrality measures, which are adopted to express the importance of domain concepts, in line with the idea of connectivism. Section V summarizes the findings and highlights limitations.1

II. ON CONNECTIVISM

Connectivism - which goes back to the seminal work of Downes and Siemens [1], [2] – is a technology oriented learning theory, focusing on the connectivity and reachability of information, while fostering the decisive power to differentiate between important and unimportant information as part of the learning. As Siemens addresses [1] - the majority of learning theories conclude that learning occurs only inside a person and fail to address learning outside of learners like technology enhanced learning. Additionally, existing theories do not tackle personal and organizational learning within organizations and neglect to assert the value of what is being learned.

Within the digital age, learning cannot rely on personal experience anymore but rather is derived as a competence from forming connections. Facing the speed and need of the technology enhanced society, the learner cannot experience every situation and borrows the experience from other people as their collected knowledge.

Connectivism strengthens the view that learning is motivated by connectivity, connecting experiences but also external information, residing in external, interconnected sources. Learning occurs in environments with shifting core elements – potentially outside of the learner’s control – that connect specialized information sets. Connections which offer the learner to learn more, are more important than the current state of knowledge. In this regard connectivism reveals that decisions are based on changing foundations and stresses the importance of the ability to differentiate between important and unimportant information. Accordingly, Siemens formulates eight principles of connectivism [1]:

1. Learning and knowledge rests in diversity of opinions.
2. Learning is a process of connecting specialized nodes or information sources.
3. Learning may reside in non-human appliances.

1 The authors acknowledge the financial support of the Eduworks Marie Curie Initial Training Network Project (PITN-GA-2013-608311) of the European Commission’s 7th Framework Program.
4. Capacity to know more is more critical than what is currently known.
5. Nurturing and maintaining connections is needed to facilitate continual learning.
6. Ability to see connections between fields, ideas, and concepts is a core skill.
7. Currency (accurate, up-to-date knowledge) is the intent of all connectivist learning activities.
8. Decision-making is itself a learning process. Choosing what to learn and the meaning of incoming information is seen through the lens of a shifting reality. […]

Following the concept of the connectivistic learning theory, new publications are emerging in the breach between technology enhanced learning and information systems, in line with the work of Downes “An Introduction to Connective Knowledge” [2]. Connectivism appeals especially in situations of informal learning and technology enhanced working environments, where learning in constantly changing situations and requirements cannot be explained anymore by traditional learning theories..

Yet, connectivism received a variety of critiques, especially in more traditional publications, as the concept of connectivism is being weakly rooted in existing literature. Furthermore, the initial ideas are still incomplete and weak regarding the criteria of learning, categorized in the classification system of learning and instructional design by Schunk [3]. Additionally, Van Plon Verhagen criticizes that the concept of connectivism has a curriculum level focus, instead of being an instructional level theory, since it tackles “what is learned” and “why” and not “how learning takes place” [4], as needed for a complete learning theory.

Independent of existing critiques, connectivism offers a new concept of learning and in this regard presents how a blend of concepts of existing learning theories is possible. E.g., it is showing in parts similarities to other aspects of the traditional theory, by acknowledging connected experiences similar to the view of constructivism.

III. AN ONTOLOGY ENHANCED APPROACH FOR BLENDED LEARNING

A. The STUDIO Learning and Assessment Environment

The STUDIO learning environment supports organizations in situations of non-formal and informal learning, in applying and evaluating knowledge, in adapting changes to their own context quickly, and in translating learning into action. The concept of STUDIO is that learning is supported by a sustainable cycle of assessment, learning and reflection, in which mastered concepts are set into a context and learning content is explored step by step. STUDIO is a well-explored solution and based on the domain ontology concept of Vas [5]–[7]. It is an extensible and domain independent learning environment that models the relevant domain concepts and their relations by ontological entities around which learning, knowledge management and assessment tasks are carried out.

The ontology-based domain models are at the core of the system as they drive the creation, storage, validation and search for relevant knowledge elements. Accordingly, the structure of content is also determined by the ontology in STUDIO, meaning that every piece of content (learning material or a test question) is connected to one (and only one) specific concept of the Domain Ontology. On a conceptual level, the system is divided into three logical entities, the Domain Ontology, a Knowledge Repository and a Knowledge Retrieval Engine.

Learning material is stored in the Content Repository, while test questions are stored in the Test Item Repository, from which items are loaded on demand by the Adaptive Test Engine. The Content Presentation module is entitled to present and visualize the stored content pieces (adaptive tests, test results, ontology visualization and learning materials) to the end users. STUDIO operates in case of every predesigned domain in three circular steps, as visualized in Figure 1:

1. Assessment: The process starts with a guided self-assessment test that has to define the knowledge gaps of the learner. The Test Engine passes questions one by one to the learner, evaluates the progress on the fly and selects new questions based on the previously provided answers and the modeled graph structure of the domain.
2. Reflection: Upon completion of the test, an overview of the mastered and failed concepts within the domain is provided for the learner, visualized on a graph of the domain ontology. The learner can reflect on the results in a connected and contextualized way and develops a conceptualization of the required knowledge.
3. Learning: Based on the concepts which the learner could explore through the assessment (the assessment will stop if a learner continues to fail concerning a concept), the learner gets access to multimedia learning material, which offers a background to the explored knowledge and additionally outbound links to external resources, fitting to the logic of connectivism.

Figure 1: Three stages learning cycle in STUDIO.

B. The Connective Nature of STUDIO

When a learning and assessment unit needs to be created to support a given domain of learning in an organization, e.g. “car design”, the instructional designer selects the relevant concepts from the domain ontology in a guided design process. The selection of concepts for learning creates a domain subset which groups related concepts based on the structure of the domain ontology.
The resulting subset captures extracted information about concepts and relations based on the ontology model [5], but foremost it resembles a graph of the target learning domain. A detailed description of the extraction and composition process is provided in [7].

Based on the graph and the coded information, the testing algorithm can select appropriate concepts for the learner to be assessed on, and, within the result visualization frontend, gives the possibility to see the tested concepts in the context of related concepts. This structure of concepts, extracted from the domain ontology, pictures in a very well structured and well connected way a learning map which follows the fundamental idea of connectivism.

C. Bottom-up Assessment

The Adaptive Test Engine – as the key application in STUDIO – exploits the advantages of the ontological descriptions. In the course of testing the Testing Engine “walks through” the ontology structure and asks questions concerning each affected ontology concept.

The STUDIO environment offers a variety of assessment algorithms with different rationales of adaptivity. The strategy on how to explore a domain of learning is connected to learning and instructional design considerations and needs a careful planning under supervision and support of learning theories. For a STUDIO focused discussion on learning theories see [8]. For this study a bottom-up approach was used.

The bottom-up assessment is based on the assumption that learners know and learn initial details about the represented domain first, even if they cannot answer questions to more abstract, higher level concepts yet – a view that correlates with a behavioristic learning approach [9].

Fig. 2 shows a structure, extracted from the domain ontology. To explore the structure within the assessment, while following the logic of a behavioristic bottom-up approach, the testing algorithm has to follow a set of rules. The assumption for the testing is that detailed knowledge is tested first. Further, a specific concept has to be seen in the context of the highest level concept of the structure. E.g. if the domain explores the knowledge around the functionality of a car, the concept of tires and the laws of physics to make them move would be detailed concepts.

Linking connectivity to the assessment algorithm, the algorithm will select detailed nodes with the highest distance to the top level concept. Distance can be expressed here as the lowest count of edges which have to be passed to reach the highest level. The sum of “paths” from detailed to abstract concepts creates a tree, where the main concept is the top node. As edges within the domain ontology capture directed semantic directions, e.g. “relates to” or “requires”, the resulting tree is a directed graph.

Each node can have multiple connections, but in the logic of the structure, detailed concepts are regarded as children, while higher concepts are regarded as parents. The system requires the learner to pass a threshold of direct children of a parent-node to be eligible for the question of the parent-node.

A node or concept is considered as passed, if the question for the node itself has been passed and at least a required pass-threshold is reached for the direct children. This way the algorithm follows a clear exploration path from the bottom to the top. The profit is the tight connection to the behavioristic logic. Yet, as addressed later, this introduces on one hand a strong trend for the exploration and on the other hand may limit a later test analysis, as the system will stop when a student fails often and also will stop to test specific branches if a failed node blocks the entrance.

The overall domain ontology is a directed graph, defining relations with semantic from one concept to other concepts. This property is also given to each extracted graph and the algorithm uses the relation direction to prevent loops in the directed graph by black-listing visited nodes and paths which cannot be walked when vital concepts were failed and no other alternative path is open. In the following analysis the algorithm will select most detailed nodes, shown as outer circle concepts in Fig. 2, and explore the structure to the top. It finishes a path if a node and its children are not sufficiently passed and finishes the test if no path is left to walk.

IV. ANALYZING THE CONNECTIVITY AND ITS INFLUENCE ON THE CONCEPT KNOWLEDGE OF STUDENTS

The rationale of this study is to investigate if there is a relationship between the connectivity of a graph structure of concepts of a given domain of learning, and the performance of learners who learn and are assessed based on the same concept structure. If a connection is evident, it will underline the meaning of connectivism for practical solutions for assessment and learning.

To conduct the investigation, the connectivity will be measured by centrality measures. Centrality measures are going back to social science research to measure the relationship in networks of people [10] and continuously find application in new types of networks as project portfolio networks [11], text analysis [12] or protein networks [13]. For this study a selection of centrality measures is done and introduced in the next section and will be used and compared within the analysis.

A. Measures of Connectivity

Networks, or “graphs” are used in variety of different disciplines to visualize, explain and reason on systems behavior, and can be explained full or in parts by entities and their relations. Graphs can have different structures, being undirected or directed and enhanced with weights and contextual information. In contrast to purely structural measures, centrality measures strafe to attach an importance to the connectivity of nodes, which is conceptually near to the expression of connection importance in the frame of connectivism.

A node could have inbound and outbound connections. For the calculation of the centrality of nodes in this study we assume, except for the Katz-centrality, in a simplification the directed graph as undirected.
The equations for centrality in the next sections are in line with the formalization of [10]. The following selection is designed to cover initial centrality measures which quantify the connectivity (degree), the flow of information (betweenness, closeness) and the node importance (eigenvector, Katz).

1) Degree-Centrality

The most straightforward indicator for centrality is the degree centrality. Degree-centrality captures the number of edges connected to a vertex or node k.

For a node j with a neighborhood of n direct connected nodes, the degree-centrality for the complete graph can be captured by an adjacency matrix as:

\[ k_i = \sum_{j=1}^{n} A_{ij} \]  

(1)

2) Eigenvector-Centrality

As an extension to the idea of the degree-centrality, the eigenvector-centrality takes into account the centrality of other connected nodes. In this regard the eigenvector-centrality accounts for the centrality-based importance of other nodes. So even for neighborhoods with a low number of connected nodes, a connected node will be judged as important if itself is connected to other important nodes.

Calculating the eigenvector-centrality is an iterative process, where each iteration improves the centrality till the graph converges. The Eigenvector-centrality \( x_i \) of all nodes i is calculated with:

\[ x_i = \frac{1}{\alpha} \sum_j A_{ij} x_j \]  

(2)

3) Katz-Centrality

The Katz-centrality extends the eigenvector-centrality and additionally introduces parameters to modify the centrality for a given graph. The parameter \( \alpha \) scales the centrality, while the parameter \( \beta \) defines a baseline, so that e.g. for any value of \( \beta \) greater than zero, the centrality for a node will be also always greater than zero and add additional importance to the surrounding nodes. The Katz-centrality is defined as:

\[ x_i = \alpha \sum_j A_{ij} x_j + \beta \]  

(3)

4) Betweenness-Centrality

The Betweenness-centrality measures how strong a given node is part of a shortest paths between nodes and models the flow of information within a network. As pointed out by [10], nodes with a high degree of betweenness may indicate a high control of a single node in a network over the flow. For a node i on the shortest path between s and t, while \( n_{st}^{ij} \) is 1 if the node is on the shortest path, the betweenness is given by:

\[ n_{st}^{ij} = \sum_{st} n_{st}^{ij} \]  

(4)

5) Closeness-Centrality

For measuring how “close” a node is to other nodes in the network, the closeness-centrality measures for a node i the mean across all shortest paths to all other nodes j within the graph, with:

\[ \ell_i = \frac{1}{n} \sum_j d_{ij} \]  

(5)

B. The Study Design

The data of this study is based on the use of the STUDIO system in a higher education learning environment. The data were collected throughout a bachelor’s level course on Business Informatics at the Corvinus University of Budapest. Within the course, 247 students accessed the system throughout a period of 20 days to get prepared for the final exam. Throughout the period, students passed altogether through 1161 assessment and learning cycles, receiving - with repetition - 73654 questions out of a pool of 165 distinct questions, for overall 61 different concepts, which are the nodes within the underlying domain graph.

The result of each test is depending on the knowledge of the student and on the bottom-up evaluation logic, evaluating the performance on the fly and selecting in an adaptive way the next question to assess. As such, measuring the overall performance may not be fully independent of the rationale of evaluation. To break through this dependency this study will focus on a local performance. To do so we conduct a two-stage experiment.

Within the first stage we are focusing on a local “node neighborhood” performance, where only direct connected neighbors of a node are taken into account. Here the performance measure indicates how many surrounding nodes are passed if the node in focus is passed. In the second stage the focus is narrowed and for a given passed node only the node which is asked next is investigated and therefore a more detailed and direct impact is measured as a “next node” performance.

The nodes which are selected for investigation are selected based on their centrality and both experiments are repeated for each centrality measure. Both experiments include a final step where all passed nodes in the dataset are selected, to analyze the neighborhood and the next node performance. The idea is that if the centrality measures are good candidates to select nodes which predict the passing of surrounding nodes based on their centrality, then the average pass-rate of neighboring nodes or the next node has to be significantly different from the average pass-rate of the complete set of nodes.

<table>
<thead>
<tr>
<th>Centrality</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Var.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Katz-centrality</td>
<td>0.05</td>
<td>0.21</td>
<td>0.12</td>
<td>0.0367</td>
<td>0.001</td>
</tr>
<tr>
<td>Degree-centrality</td>
<td>1</td>
<td>7</td>
<td>2.33</td>
<td>1.578</td>
<td>2.491</td>
</tr>
<tr>
<td>Betweenness-centrality</td>
<td>0.00</td>
<td>0.57</td>
<td>0.07</td>
<td>0.1138</td>
<td>0.013</td>
</tr>
<tr>
<td>Eigenvector-centrality</td>
<td>0.01</td>
<td>0.39</td>
<td>0.09</td>
<td>0.0899</td>
<td>0.008</td>
</tr>
<tr>
<td>Closeness-centrality</td>
<td>0.16</td>
<td>0.32</td>
<td>0.21</td>
<td>0.0385</td>
<td>0.001</td>
</tr>
</tbody>
</table>

To prepare the dataset we implemented an extraction and transformation algorithm in the Python programming language (v3.5.1) [14]. For each analysis we created one initial dataset, where we calculate – for every taken assessment test and assessed node – the direct connected nodes and store if they were passed or not, while for the...
second experiment we specifically store if the next assessed node were passed or not.

For both sets we calculated and integrated all five centrality measures, using the graph specialized Python library NetworkX (v1.11) [15]. A short summary of the calculated measures is given in Tab. 1 and an example for the calculated Katz-centrality (KC) and degree-centrality (DC) is visible in Fig. 2.

C. Experiment I: The "Neighborhood" Performance

The first experiment targets to collect the direct neighborhood of selected nodes, to compare if it is passed considerably higher when the selected central node is passed. The initially selected nodes are selected based on their calculated centrality measure. For comparability we call these central nodes “CNodes”.

To account for the intuition “the higher the centrality, the higher the local neighborhood performance” we filtered the dataset of the experiment to all cases where CNodes were passed. We then grouped the data for each respective centrality measure into classes with the same centrality value. These classes were sorted by the centrality measure and we added, from the highest to the lowest class, centrality value classes into the analysis dataset, till the new dataset accounted for 20% of the passed CNodes.

We repeated this selection for each single centrality measure and created five analysis datasets, to which we added a sixth set which includes all passed CNodes. This sixth group is the comparison group. Tab. I shows the resulting borders for each centrality measure to split the dataset of the experiment into an 80%/20% ratio. For each of the created centrality-datasets we conducted basic descriptive statistics and derived the mean pass-rate for the direct connected neighbors (NHPassrate) of the passed CNodes. Finally, we compared the mean pass-rates.

While the observation is generally supporting a “the higher, the higher” trend, the comparison to the “all CNodes” comparison group, with a similar 76.87% mean, makes evident that this detected trend is universal for the passing of nodes in the neighborhood of passed nodes, and therefore underlines no expected “better” trend for a high centrality measure, backing specifically the selected CNodes. So – surprisingly – the basic descriptive statistic indicates no room for a positive trend correlation.

D. Experiment II: The “Next Node” Performance

Following the preparation logic of the first experiment (select passed CNodes, replicate the set for each centrality measure and keep in each set only the rows which account for 20% or less of the highest centrality value bins), we again selected all passed nodes as central nodes (CNodes) but in contrast we observed the node which were assessed next (NextNodePassed) by the adaptive assessment algorithm, if, and only if this next node still has a direct connection to the selected CNode. This framing is required as the assessment algorithm may jump within the structure from one path to another, if the earlier path were completely assessed.

For the resulting datasets we calculated again the mean of the performance - this time for the next direct connected and assessed node. The summary is shown in Tab. IV. Again the different centrality measures are on a comparable level for passed CNodes. Yet, in this experiment, the average mean across the centrality measures is 89.38% which is an 8.51% increase against the “all CNodes” comparison group, while especially the degree-centrality shows an increase with 10.46%.

### Table II.

<table>
<thead>
<tr>
<th>Katz-centrality</th>
<th>Degree-centrality</th>
<th>Betweenness-centrality</th>
<th>Eigenvector-centrality</th>
<th>Closeness-centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt; 0.14</td>
<td>&gt; 3</td>
<td>&gt; 0.10</td>
<td>&gt; 0.13</td>
<td>&gt; 0.24</td>
</tr>
</tbody>
</table>

Based on the summary in Tab. III we can see that the mean NHPassrate is very closely centered around a mean pass-rate of 75.81% for all five observed centrality measures, with a similar close std. deviation.

### Table III.

<table>
<thead>
<tr>
<th>Katz-centrality &gt; 0.14</th>
<th>Degree-centrality &gt; 3</th>
<th>Betweenness-centrality &gt; 0.10</th>
<th>Eigenvector-centrality &gt; 0.13</th>
<th>Closeness-centrality &gt; 0.24</th>
<th>All CNodes</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>Min</td>
<td>Max</td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Var.</td>
</tr>
<tr>
<td>13647</td>
<td>0</td>
<td>100</td>
<td>77.11</td>
<td>32.3658</td>
<td>1047.546</td>
</tr>
<tr>
<td>8985</td>
<td>0</td>
<td>100</td>
<td>76.85</td>
<td>24.9339</td>
<td>621.699</td>
</tr>
<tr>
<td>9046</td>
<td>0</td>
<td>100</td>
<td>75.94</td>
<td>26.6452</td>
<td>709.968</td>
</tr>
<tr>
<td>9154</td>
<td>0</td>
<td>100</td>
<td>74.34</td>
<td>29.1131</td>
<td>847.570</td>
</tr>
<tr>
<td>8238</td>
<td>0</td>
<td>100</td>
<td>74.82</td>
<td>28.9576</td>
<td>838.542</td>
</tr>
<tr>
<td>48711</td>
<td>0</td>
<td>100</td>
<td>76.87</td>
<td>35.0058</td>
<td>1225.407</td>
</tr>
</tbody>
</table>

![Figure 3: Mean “NextNodePassed” in percentage against an “AllCNodes” mean baseline. The x-axis is cumulative with NextNodePassed intervals of: [1], [2], [3], [4], [5], [6].](image)

![Figure 3](image)

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In Fig. 3, we take a closer look at the degree-centrality against the “All CNodes” baseline. The graph plots a repetition of the experiment with different degree-centrality borders. The highest mean percentage of NextNodePassed is reached for a degree-centrality > 4, while the percentage drops again when only more than 5 relations are taken into account. With 92.08%, > 4 is showing an enhancement of 11.79% against the overall mean.

E. Pearson Correlations for Observed Variables

Tab. V shows the correlations between the observed variables. For NextNodePassed, the positive correlations of the centrality measures indicate the results of the second experiment. For NHPassed the centrality measures show a weak negative correlation.

If we assume that experiment II shows a valid positive trend, then the negative correlation of the measures in experiment I can be explained by the dominant prequisite of the assessment algorithm to sufficiently pass a rate of child nodes to be eligible to receive a question for the parent. This leads to a situation where a number of parent nodes may have potentially had been in the ability of the learner to pass, but weren’t asked based on the assessment logic. While these cases are implicitly excluded by the criteria to take only passed CNodes into account for the experiment, the Pearson correlation includes these cases, which may tip the scale towards a negative correlation.

V. CONCLUSION AND LIMITATIONS

We tackled the question if, in the sense of connectivism, the connectivity of concepts can have an importance for assessment and learning and influence the observed performance of a learner. This study was conducted within the STUDIO learning and assessment environment and the analyzed data was based on a real world test with 247 bachelor level students, preparing for an examination in the domain of business informatics.

The STUDIO domain ontology provided us with a graph based representation of the concepts of the learning domain and we used centrality measures to quantify different concepts of connectivity and importance and compared them to a local learner performance.

Within two experiments we have shown that a higher centrality measure for a given concept can play a role in predicting the passing of the next assessed, connected concept. In a broader neighborhood this trend couldn’t be traced.

Especially the later analysis has a strong overlap with the rationale of the bottom-up assessment logic to fail general nodes based on previous detailing nodes. Furthermore the structure and rational of the used ontology will have an influence on the results and tests with other sub-domains of the ontology and an alternative ontology is recommended. Both, the influence of the testing algorithm and the specific ontology have to be investigated in future studies.

The good message is that we can show tender indications that the connectivistic learning theory may indeed link a connectivity importance for concepts to real learning implications. But, a wider range of analysis in different applications will have to separate the wheat from the chaff.

REFERENCES