# Visualization of Students' Solutions as a Sequential Network

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***Abstract*—It is known that timely and personalized feedback is vital to the learning process, and because of increasing enrollment, instructors can find it harder to provide that feedback. Learning analytics presents a solution to this problem. The growth in popularity of online education systems better enables learning analytics by providing additional educational data. This work focuses on the analysis of students' incorrect short answers and their pathways to correct solutions. By considering student submissions as sequences, this work uses a dimension called "distance" which can be used to predict how far off a student's incorrect answer is from a correct one. This distance metric can be used for recognizing students who may need help, understanding which concepts students struggle with, evaluating assessment questions, and improving multiple-choice answers.**

**This paper discusses the methods, relevant learning scenarios, and applications of the learning analytics system. It features the results and analysis of a usability test conducted on 56 faculty members.**

***Index Terms*—network, learning analytics, data visualization**

## I. Introduction

Today's instructors face a growing problem: connecting with their students. Because of trends in higher education funding and enrollment, recent world events, and new implementations of teaching tools and strategies, the distance between instructors and students has grown.

Increasing enrollment and dwindling funding have encouraged many universities to consider offering more hybrid classes [1]. Due to the recent COVID-19 pandemic, universities were forced to migrate to emergency remote learning. This showed the potential benefits of hybrid and online classes, but it also presented challenges with student motivation as well as student-faculty interaction [2], [3].

A pronounced rise in engineering enrollment [4], [5] has partially led instructors to seek and implement new educational methods. Learning management systems have seen more use recently [6], and the use of automatic grading systems has risen as well [7]–[9]. These systems have been shown to improve student learning because of their timely feedback, objective grading, and more relaxed environment.

With these changes, instructors can find it more difficult to gather and analyze information from the classroom. Hybridized online learning provides instructors with fewer opportunities to directly observe student learning, obscuring how students approach problems and which concepts they struggle with. When using automated grading systems, instructors may not gain intuition about their assessments that they would through conventional grading. Additionally, larger class sizes make it harder to identify students that may need more help.

The goal of this research is to provide a novel web-based visualization application to support instructors with learning analytics insights. Learning analytics is the use of educational data to optimise classroom learning. Leveraging learning analytics is a natural choice as it benefits from the trends in education mentioned earlier: more students, digitized learning, and automated graders all can give rise to more educational data for input to learning analytics tools. To assist instructors with analyzing student thinking, improving assessment, and recognizing intervention opportunities, a learning analytics tool would:

1) Provide an intuitive interface for instructors to help visualize how students are approaching problems.
2) Define and display metrics to help assess students' learning.
3) Aggregate those metrics in an interactive view to help identify groups or individuals who have difficulties.

The remainder of this paper is organized as follows. Section II reviews prior related research. Section III introduces the features of our tool. Section IV presents the survey conducted on faculty members. Section V describes potential uses of our tool. Finally, Section VI presents our conclusion and future directions.

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## II. Related Works

The goal of this research is to enable educators to note trends in student data at a high level but still draw fine-grain conclusions through close inspection. This is distinct from approaches such as the Error Quotient [10], the WatWin measure [11], the Normalized Programming State Model [12], and machine learning approaches [13], [14] in that these works do most of the analysis for instructors. In contrast, the work presented in this paper seeks to provide educators with the means to explore their data and discover students' learning trajectories, rather than analyze data for them.

This paper attempts to meet this need through the development of a visualization model that presents learning traces in a network format. A single learning trace is a sequence of a student's attempted answers for a fill-in-the-blank or short answer question. The use of a network to visualize students in learning analytics is not a new concept on its own. For example, studies have modeled how students navigate online courses using networks [15], [16]. Prior research has also explored representing causal relations between abstract concepts [17] as well as the associations between learned concepts [18].

Furthermore, recent educational research has shown that incorrect answers can provide additional insights into students' learning as well as behavior. Several models have been applied to online assessments in programming and math: 1) binary information (correct/incorrect), 2) manual mapping of wrong answers into categories, such as "typing errors", "misconceptions", "numerical errors", 3) automatic classification into "common" and "uncommon" answers, 4) clustering and community detection [19]–[21]. These studies point to a common issue with the skewness in the distribution of wrong answers, where there is a large gap between high-performing and low-performing students. This work hopes to enable instructors to explore this gap. Response time has been used as a measurement of student performance. However, it often requires aggregated data, hindering the understanding of individual learning [22].

This research is novel in three ways. First, it models students in a smaller scope than most learning analytics tools: instead of analyzing concepts and events within courses, it analyzes answers within individual questions. Second, it applies a new metric to compare incorrect answers. Finally, it presents information in a dynamic and interactive visual format. As shown by a review of visual learning analytics literature [23], most tools only use simple and static models.

## III. Methods

This paper presents a novel visualization scheme that represents students' answers as nodes in a network. When solving a problem, students may propose many intermediate incorrect answers before arriving at a correct solution. We have developed a visualization tool that takes a sequence of answers proposed by not one student, but all the sequences generated by a group of students (e.g., a class's worth of students) while attempting to solve a particular problem. In this way, the focus is on how students progress between answers, which can provide insight into students' thinking processes. The visualization can be applied in learning scenarios that fulfill these criteria:

1) Students attempt to answer a question and repeat until they input a correct answer.
2) The state space of reasonable answers is limited. Applicable formats include fill-in-the-blank, multiple-choice, or calculations.

The data required by this visualization tool are sequences of chronologically ordered answers given by students when attempting to answer a question. This is why the first criterion is required: the sequences of responses can occur in a formative assessment that allows for multiple attempts. The tool focuses on how students' answers develop as they attempt to answer questions. Previous research [24] has found that students' understanding of a problem develops as they make multiple attempts to answer questions.

For example, suppose a student is asked to provide the chemical formula for acetic acid. This question has multiple correct answers; one possible correct answer is $C_2H_4O_2$. For the purposes of formative assessment, a student may input any number of incorrect answers before arriving at a correct answer. An example sequence entered by a fictional student "Abe" might be HFl, $C_2H_3O_3$, $C_2H_4O_2$. In this sequence, Abe entered two incorrect answers before entering a correct answer. This visualization tool utilizes this sequence of answers from Abe along with the sequences of answers from the remaining students to generate a network. An example of an input data set can be found in Table I.

TABLE I
SYNTHETIC RAW DATA

| Student Identifier | Student's Attempt | Attempt Correct? |
|---|---|---|
| Abe | HFl | Incorrect |
| Abe | $C_2H_3O_3$ | Incorrect |
| Abe | $C_2H_4O_2$ | Correct |
| Olivia | $C_2H_3O_3$ | Incorrect |
| Olivia | $HC_2H_3O_2$ | Correct |
| ... | ... | ... |
| Kelly | $HC_2H_3O_2$ | Correct |

Fig. 1 shows the network visualization generated from the data in Table I. Each node in the network represents an answer that at least one student attempted while trying to solve the problem. Every node's size is proportional to how many times all students input the answer associated with the node, meaning more common answers stand out compared to less common ones. Red nodes represent incorrect answers and green nodes represent correct answers.

The edges of the network are generated as follows: When a student inputs her first answer "A", a directed edge is created from the white "Start" node to the node representing answer "A". If the attempt was incorrect, the student tries again, making an edge from "A" to "B". This process is continued until she inputs a correct answer or she exits the system

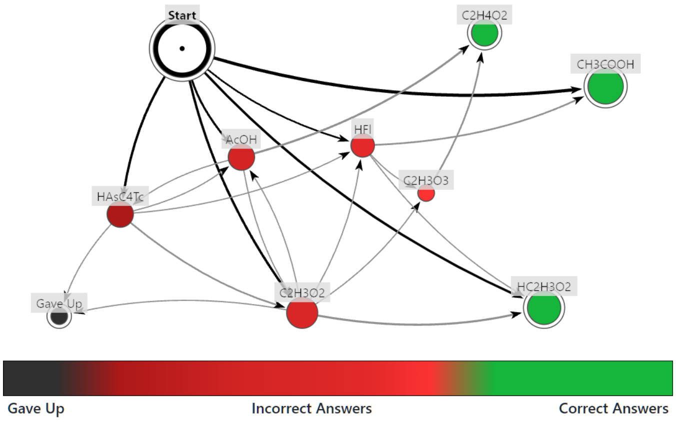



Fig. 1. An example network populated from synthetic data representing a class's answers to the question "What is the formula of acetic acid?".

without completing the question. In the second case, an edge is drawn from the student's last attempted answer to the black "Gave Up" node. As multiple students take the same path between two nodes, the edge grows wider, providing visual feedback as to how many times this edge was traversed, and the node grows larger indicating the answer associated with the node was input multiple times. All students' paths through the network begin at the "Start" node, and end either at a correct answer or at the "Gave Up" node. In accordance with finite state machines, the beginning and ending points of the network have a ring around them.

The horizontal positioning of nodes is another feature of the visualization. Correct answers are on the right side of the network, and the "Gave Up" node is on the left. The remaining nodes are positioned according to their "distance" from the correct answers. Each node's distance metric is calculated as the arithmetic mean of how many more attempts students tried after leaving a node representing an incorrect answer before coming to a correct answer. Nodes that have higher distances are positioned on the left side of the network, which is farther away from the correct answers. Their color is also slightly darkened to visually indicate that after students input answers represented by these darker nodes, they took more attempts to arrive at a correct answer.

The network in Fig. 1 is only a static screenshot of the online tool. The network is a dynamic physics simulation powered by `D3.js` [25]. The simulation pulls connected nodes closer together and pushes unconnected nodes apart. Users can click and drag nodes in the network to arrange it how they see fit as well as activate a red-green color blindness mode that changes the color scheme from red-green to yellow-blue.

The tool offers options and filters that allow educators to dynamically configure the visualization. When a user clicks on a node, the tool shows the node's calculated distance from the correct answers, how many students answered the question correctly immediately following their input of the selected attempt, and a list of the students that input the answer. Users can direct the tool to filter by students to show only a subset of the classroom's paths through the network. An example of student filtering can be found in Fig. 2. In this example, a single student's path stands out because all other paths and nodes have been dimmed. A user can also combine nodes through drag-and-drop, which allows the user to simplify the network by aggregating similar answers together by their concepts.

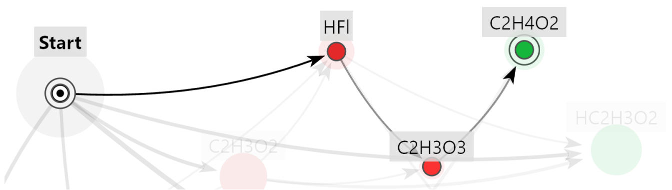
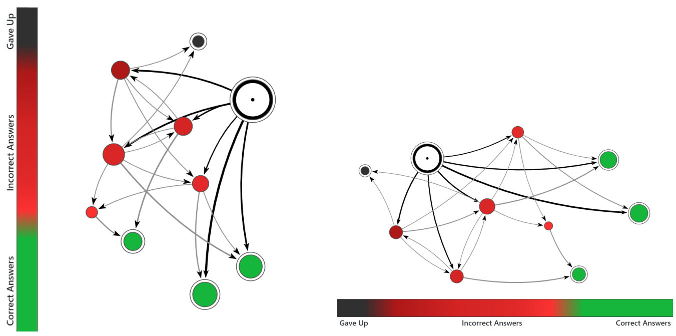



Fig. 2. A single student's path through the network.

## IV. Survey

Faculty from 10 STEM departments and a Humanities and Arts department were invited to complete an anonymous survey to evaluate our interactive visualization tool in terms of its usability and utility. The survey served three purposes. First, it measured the tool's usability by asking faculty to answer questions using the dashboard. Second, half of the respondents were shown a vertical layout of the network as in Fig. 3a, and the other half were shown a horizontal layout as in Fig. 3b. At the end of the survey, the respondents were shown both layouts and answered which layout they found more intuitive. Third, we asked the respondents to describe the ways they might use the tool, getting feedback from educators' perspectives.




(a) Vertical (b) Horizontal

Fig. 3. Vertical and horizontal layouts.

We received 56 responses, with 50 of them coming from STEM faculty and the remaining 6 from Humanities and Arts faculty. All participants stated that they were familiar with graphs, and 12 participants indicated that they had previously taken a seminar, course, or training session on visualization.

Of the 56 respondents, 54 completed all 5 usability questions on the survey. The usability section showed an example network generated by the tool and asked respondents to answer multiple-choice questions based on the networks. For example, respondents were given the prompt "From the dashboard in

Fig. 1, you can see that there are three correct answers (marked by green circles) in this specific question. How many of the three correct answers were reached by a student on their first try (i.e., a student that did not input any incorrect answers)?". Respondents were shown Fig. 4, and provided five choices: 0, 1, 2, 3, and "It cannot be determined". Out of the 54 respondents that completed all the usability questions, 46 of them correctly answered 2.

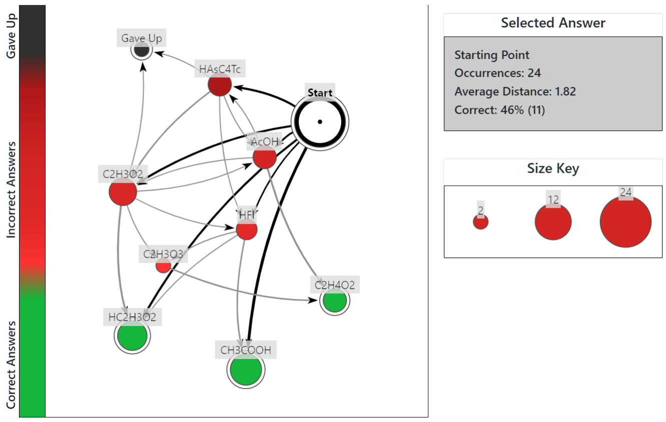



Fig. 4. Image of network provided to respondents to answer usability question.

Across all five usability questions, the respondents answered correctly 91.5% of the time. We see this result as satisfactory, as the respondents were only given a brief description of how the tool worked. Of the 23 incorrect answers given, 15 of them were "It cannot be determined". This means only 8 out of the 270 total answers (3.0%) were a result of respondents misinterpreting the tool. These results are summarized in Table II. Respondents that were shown vertical network layouts scored higher on average: 94.3% compared to the horizontal cohort's 88.5%.

TABLE II
USABILITY RESULTS

| | Correct | Not sure | Incorrect |
|---|---|---|---|
| Count | 247 | 15 | 8 |
| Percentage | 91.5% | 5.5% | 3.0% |

At the end of the usability test, participants were shown an example of both the horizontal and vertical layouts. Of the 56 respondents, 58.9% preferred the horizontal layout, 12.5% preferred vertical, and 28.6% stated they had no preference. When asked to provide reasons why, respondents that preferred the horizontal layout stated they were "used to thinking about graphs with time on the x-axis" and that "left to right feels more like progressing from start to finish". Respondents that were initially shown the vertical layout were less likely to prefer the horizontal layout, with only 46.4% of the cohort preferring the horizontal layout.

## V. APPLICATIONS

The tool can be applied to a broad range of learning analyses. First, users can filter by student to investigate how individual students' understanding changes over time. Second, users can analyze the incorrect answers that students gave to understand which concepts students struggle with. Third, users can evaluate their questions and use the tool to generate future multiple-choice options.

One application of the tool is analyzing individual students' thinking on questions. Users can filter the network by student, dimming the other students' paths. This shows the student's sequence of attempted answers in the larger context of the classroom's performance. A respondent commented "[the tool] helps indicate how the student was classifying the information in their head". Instructors could identify students that are thinking differently than others by examining how many other students shared the student's answers.

The tool can also be used to investigate student thinking by comparing answers. A respondent said that the tool could help "elucidate the students' thought patterns" by examining the incorrect answers given by students. For example, the tool can help differentiate between incorrect answers that were commonly given initially and those that students gave later in their sequences. The incorrect answers tried by students at the start might be due to misreading or misunderstanding the question, and incorrect answers tried later are more likely to be due to misconceptions about the material. The tool shows this through its arrows. Thick arrows leading from the "Start" node to another node indicate that many students attempted that node as their first answer. A respondent commented that "arrows of common paths from wrong answers might help me understand common misconceptions that I should address while teaching". A large red node that has a thick arrow coming from the "Start" node shows that many students shared the same initial misconception. Instructors can analyze the connections a node has to develop a hypothesis about why students might be tempted to respond with a particular answer. In response, instructors can clarify their question or adjust their instructional material to better cover the common misconception.

Respondents also identified ways that they could use the distance metric in learning analytics. One commented "if a student chose a node with really high distance, it suggests they have a very basic misunderstanding, while if they choose nodes with lower distances they might have more minor misunderstandings about the info". If a user is interested in a specific answer, she or he can select that answer in the network and click a button to highlight the group of students that input that answer, dimming out the others. This can be especially effective on incorrect answers with a high distance from correct answers, as it may reveal that the students who input the highlighted answer also shared other answers. A synthetic example of this is in Fig. 5, where highlighting the students that answered AcOH shows that they also shared multiple other answers. Users can use that information to better understand what concept the selected group of students is struggling with. Instructors can then reinforce the concept in later lectures or with additional instructional materials.

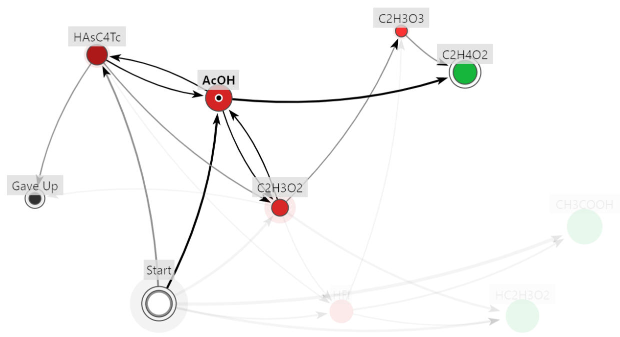



Fig. 5. Selecting a group of students that input the same incorrect answer.

The tool can be used to examine questions as well. An ideal question would be challenging enough where some incorrect answers would be expected, but still not be unnecessarily difficult. A question that is too challenging can lead students to give up, or to guess answers, eventually coming across the correct answer through "brute force". The tool can provide insight into this, as a network of a question where students primarily guessed will be made up of many small red nodes because students did not try similar answers. In contrast, a question where students were more thoughtful in their answers would generate a comparatively fewer amount of larger red nodes, as the students would overlap with their incorrect answers. Fig. 6 shows an example of what a network would look like where students primarily guessed. One respondent commented "You could see when students are guessing and checking/struggling and flailing on which problems. You'll get the chance to see a rough idea of why they're guessing what they're guessing". After identifying that students may have been guessing, users can investigate individual student paths to identify the strategies students employed at a more fine-grain level.

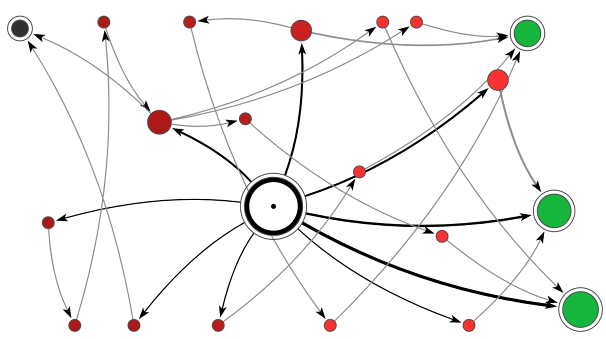


Fig. 6. A large number of small incorrect answers can indicate that students employed guessing.

The tool's distance metric can be used to predict students' future performance. Since the distance of each incorrect answer is defined to be the average number of attempts before students reached a correct answer, the metric could be used to predict that a student who just input a high-distance answer is likely to take many more answers until they reach a correct answer. A respondent said "This could be a very interesting tool, especially if it updates and can be used in real-time in a classroom during an active learning activity". Using the data from a previous session, instructors could be notified in real-time on how students are performing, and could even be warned when a student inputs a high distance answer. Identifying students that are likely to struggle on a question could provide instructors with a chance to intervene during active learning activities, assisting where needed.

Work has been done in developing systematic methods to develop quality distractors (plausible but incorrect options) for multiple-choice questions. Some of this work [26] has used natural language processing and machine learning techniques to analyze a large corpus of written responses to identify categories of student misconceptions. The tool could be applied to serve a similar purpose, as the largest red nodes represent the most common incorrect answers given by students. We believe that the larger red nodes in our network will correspond to misconception categories, and verifying this conjecture is included as one of our options for future work.

## VI. Conclusion

In this paper, we presented a novel web-based learning analytics tool that used a network to model students' sequences of attempted answers. Educators could use the tool to visualize how students' understanding of problems develops, identify trends in correct and incorrect answers, and measure how different thinking strategies affect learning. We conducted a user study of 56 faculty members, 50 of which were STEM faculty. The respondents scored an average of 91.5% on our usability test. We described various ways to use the tool to analyze students, answers, and questions.

It should be noted that this work's scope is limited, as the tool can only be applied to specific learning environments. It requires that students make attempts to answer a question until they get it correct and that the amount of possible answers is reasonably limited. This means that the tool cannot be applied to questions requiring long textual responses. However, this tool is often applicable to online formats, which have become more popular due to recent trends in education.

In Section V we noted that the larger red nodes in one of our networks might correspond to categories of misconceptions held by students. If this conjecture can be verified, our networks might be leveraged by instructors for more quickly developing plausible distractors for multiple-choice questions.

Applying the tool to various educational domains is appealing. Preliminary piloting of the tool has been conducted with data from the introductory computer science courses where sequences of responses have come from students asked to determine the values of variables after a few lines of code have been executed. More recently, we have been in discussions with a faculty member in electrical engineering about using the tool to analyze sequences of answers provided to questions concerning digital signal processing filters.

In a formative assessment setting, we have collected a sequence of student responses to a prompt. One might think of these as taking snapshots of the student's thinking as she or he moves toward a correct answer. Another area for future work would be to expand the analysis of student performance from one question at a time to a string of questions. We believe there might be detectable trends across multiple questions. For example, analyzing multiple questions at once can help instructors more confidently identify groups of students that are struggling.

Another area of interest is to utilize the tool to identify various groups of students, like those that employ guessing strategies or those that could benefit from additional instruction. We could utilize this information to select students for think-aloud problem-solving sessions. During these think-alouds, we would have the students verbalize their thought processes when providing a sequence of answers. By analyzing these think-alouds, we might better pin down their problem-solving processes and create interventions. The tool in this sense would help us reduce the number of students needed to participate in a very time-consuming think-aloud process.

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