Visual Progression Analysis of Student Records Data

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Abstract

University curriculum, both on a campus level and on a per-major level, are affected in a complex way by many decisions of many administrators and faculty over time. As universities across the United States share an urgency to significantly improve student success and success retention, there is a pressing need to better understand how the student population is progressing through the curriculum, and how to provide better supporting infrastructure and refine the curriculum for the purpose of improving student outcomes. This work has developed a visual knowledge discovery system called eCamp that pulls together a variety of population-scale data products, including student grades, major descriptions, and graduation records. These datasets were previously disconnected and only available to and maintained by independent campus offices. The framework models and analyzes the multi-level relationships hidden within these data products, and visualizes the student flow patterns through individual majors as well as through a hierarchy of majors. These results support analytical tasks involving student outcomes, student retention, and curriculum design. It is shown how eCamp has revealed student progression information that was previously unavailable.

1 Introduction

College is often known as the “best 4 years of your life”. Not all students can graduate successfully, however, many may end up dropping out. The attrition comes with significant pedagogical, economic, and societal costs. The related concerns have been growing year over year, especially during the past decade in the United States [6,17]. Even though quite a few universities have invested substantially in programs designed to increase student retention and success, the success rate has not improved very much [18,19].

In universities, there are sophisticated designs of how students are expected to progress through the curricula; and there are mechanisms put in place to support and foster the process so that the intended outcomes are achieved for the students. The designs involve many decisions about student advising, curriculum design, overlaps between majors, and what choices students can make at different times about their college affiliation and degree programs.

Those design decisions are made cumulatively by many people involved, sometimes based on theories, sometimes based on convenience, and sometimes based on subjective “lore” or “feel” that is derived from years of accumulated experience. It is important for all people involved to have a clear and complete view of the intrinsics in student progression processes.

Graph is a standard model to represent student progression processes. For example, course prerequisite relationships are often displayed as graphs. These graphs however, do not show how students actually progress, succeed or fail throughout their studies but rather give hints to what paths they should take. Graph models that show true progression are not always constructed and evaluated explicitly. In part, this is because campus administrative offices’ view of the entire process is limited to their specific functions only. In part, that’s also because of not knowing how the student population would make choices when they are allowed choices. As the associate provost of the authors’ university acknowledged - “no one has the full picture”.

In order to gain insights about student progression, student success, and student retention, a data science approach should examine the real world progression of students, as opposed to the hypothetical progression codified in the course catalog, graduation requirements, and advising guidelines. This real world information exists in the form of population-scale student records data that are available to university administrators, but are typically spread amongst independent offices. The data includes course grades, student schedules, major information, and university withdrawal rates.

In this work, we have developed a visual analysis system, eCamp, to integrate these sources and model student progression patterns based on electronic records from about 145,000 students collected over the course of 16 years. At a high level suited for campus administrators and based on major similarities, eCamp constructs and visualizes a university-wide major-graph. The major-graph shows how a student population start together with general education courses as freshmen, and then diverge into more advanced and specialized parts of their curricula as they progress through their majors. eCamp also shows student drop-out occurrences in the overall major-graph to better understand which majors are struggling in student retention. At a more detailed level, suited for department heads and faculty, eCamp constructs a set of course-graphs for over 400 majors on campus. These course-graphs capture the curriculum structure of each discipline on a per-major basis by modeling course-course relationships. Through these graphs, administrators can see the real-world structures that are formed. Additionally, they can see how students progress or fail through these structures.

When enabled by data, the Provost’s office was interested in answering questions about how the support infrastructure, which includes advising, tutoring, and supplemental assistance, was impacting student success. For example, it wondered how this infrastructure impacted student progression through their major. Many new students may wish to explore different majors to discover their true passion. But this exploration process cannot be unlimited in time if the students are to graduate in a reasonable amount of time. To facilitate students’ exploration and progress, it is important to know when and where are the time points for each student to make critical decisions about their major path. There are clearly gaps in the current way of providing advising services (both on a campus level and on a department level). But where are the gaps?

At the department level, questions from administrators revolved around whether the curriculum is working as designed. For example, are the general education courses preparing students for success in their major? Are gate keeping courses serving their functions? As students progress through the major, which courses play a central or peripheral role, and which courses are bottlenecks? Are there critical time points where diversity and/or retention drop off?

Our visualizations help university staff to think of such questions. Additionally, it empowers them to formulate hypotheses about curriculum design and student outcomes that were not previously possible to accurately articulate.

The rest of this paper is organized as follows. Section 2 provides
a discussion of related work. Section 3 describes the motivation for this work and the needs of university administrators. Section 4 explains how student records are used to model student behaviors. Section 5 explains the visualizations created to facilitate interaction with the model and how these visualizations meet the needs established in Section 3. Domain expert feedbacks are presented in Section 6, and the paper is concluded in Section 7.

2 RELATED WORK

2.1 Application Background

Many tools for analyzing university databases exist [2,3,7,10–13,15]. For example, DynMap visualizes student learning in a course by offering an ability to visually inspect students’ understanding and performance in a concept map as well as display the overall structure of the course topics and their dependencies [15]. Similarly, CourseVis visualizes student tracking data for a course management system, WebCT, for the purpose of analyzing student progress within a course, targeting distance learning settings [12]. CourseVis helped instructors see social, cognitive, and behavioral aspects of their students through visualizations of web log data from course management systems [13]. These systems tend to limit the scope of study to student progress in an individual course.

Some works go beyond course boundaries and focus on course-course relationships. They can show student course progression as prescribed by the catalog [16] or show student course grades based on the actual semesters in which students took the courses [5].

In contrast, eCamp focuses on visualizing student progression patterns through the curricula of all majors in a university. Whereas the largest granularity of data for previous work was typically a course or smaller, the smallest granularity of data is a course. To our knowledge, there are no existing works on visualizing student progression patterns of an institution-wide student population.

2.2 Technical Background

In order to extract student flow patterns, relationships among academic entities such as students, courses, and majors are analyzed. The first relationship modeled is major similarity. Over time, as the courses that students take become more specific, the possibility of switching majors declines. This creates a hierarchy of majors based on how similar they are. eCamp uses hierarchical clustering to exploit this temporal hierarchy of majors.

Hierarchies have been visualized in many ways. Dendrograms and TreeMaps [9] are two traditional ways of visualizing hierarchical structures. However, hierarchies with a temporal aspect cannot be adequately represented by these traditional schemes. One alternative in such cases is using Radial trees. Radial trees have been used in visualizing phylogenetic trees to show how biological species evolve over time [8,22]. However, they are unable to depict the proportion of elements that go through the hierarchy. Alternatively, sunburst graphs have been used to show how a population divides, going from one level of a hierarchy to another. PathRings uses sunburst graphs to show biological pathways [23]. One important aspect of sunburst graphs, however, is that they do not convey flow. Temporal flow is often visualized using Sankey diagrams [14] or Sankey-like structures [20,21]. Inspired by these techniques, eCamp uses a variation of a radial tree that visualizes student progression with Sankey-like edges to better convey the flow of students through time.

The second such relationship is the correlation of student success, represented as grades between courses. The course-course correlation is measured by Pearson’s coefficient. The graph formed by all courses of each major is a standard graph, which we render as a node-link diagram [14], as typically done in the field.

3 DRIVING APPLICATION

3.1 Overview

Our aim in this work is to develop an analytical framework that shows how the student population as a whole achieves its ultimate goal, graduation in a major of each individual’s choice, while exercising free will despite being given a choreographed script for its actions, the catalog. The outcome of the work provides new insight into university administration, and causes faculty and administrators to question how the system has been designed and whether the effects seen in the student population data are intended or not.

3.2 The Data

Like most organizations, universities collect and maintain their data assets independently by each campus office or department for their own purposes. Our data has come from multiple campus offices, all of which maintain the data in the campus wide ERP system called Banner. After processing, there are three main categories of data as shown in Table 1. These data include records from 144,798 students and over 400 majors over a period of 16 years.

| Category                 | Number of Entries | Size (MB) |
|--------------------------|-------------------|-----------|
| Graduation Records       | 100,239           | 33        |
| Student Grades           | 4,723,835         | 461       |
| Major Information        | 436               | <1        |

Graduation records provide information on which major students graduated in. Student grades provide information on when students took courses and what their grades in those courses were. Major codes is a unique identifier of a major in the database. Major information provides the ability to connect major codes used in the graduation records with major names. The names are not necessarily unique. This can happen when a major gets revamped significantly and receives a new major code for instance. For analysis, we use the unique identifier. However, however, for user-friendly reasons, the visualizations still use major names as text labels.

3.3 Analytics Needs

To better understand the needs of faculty and administrators, the authors have met with faculty, and administrators at the department level and in the Provost’s office.

The Provost’s office pointed to a need for analytics to help them evaluate how advising programs are affecting student retention and time-to-graduation, on a campus level, college level, and specific to individual majors, especially those with a large student population. In particular, they noted that a current gap in knowledge across the nation is identifying how success in general education courses may affect a student’s success in different majors. Furthermore, when a student transitions from one intended degree program to another, what kind of transitional advising can be provided before, during and after the change? These questions cannot be approached feasibly unless there are tools to reveal the underlying patterns, missing links, and problem areas.

Similar to the campus level desire for improvements, department heads need to better understand student progression patterns through their majors. They want to know which courses play a central role in student success, and whether the curriculum is working as designed (e.g., are the gate keeping courses serving their intended purpose). Furthermore, in relation to student progression, departments want a better understanding of student success, retention, and diversity issues from freshman year to the senior year.

Based on these needs, we identified three classes of curricular information to extract from the dataset: (i) student flow through university wide curriculum and progress patterns (i.e., graduation vs.
We summarize the overall architecture of eCamp in Figure 1. The steps to perform visual analysis of student flow are described in Section 5. The analytical tasks from the perspective of university administrators are in Section 6.

As shown in Figure 1, our data sources include information about three academic entities—majors, courses, and students. A major is comprised of both courses and students, and a course is comprised of students. With this population-scale student data, there are a variety of relationships that can be studied.

First, by analyzing how courses are shared among majors, data-driven relationships among all of the majors that students can choose from can be found. This knowledge on the major-major level depends on knowledge on the course-major level, which in turn depends on the course-course level and fundamentally the student-course level relationship. This observation of the multi-level nature of the relationships drove the design of eCamp’s modeling, visualization and analytics components.

Second, how courses relate to each other by the empirical order in which students take these courses can be identified, and by the correlations in grades achieved by the student cohort. Previously, the only way to identify such course-course relationships at scale was to resort to the pre-requisite or co-requisite relationships defined in catalogs. However, it is desirable to observe if students progress through the catalog the way it was intended by the university.

4 Modeling Multi-Level Relationships

We summarize the overall architecture of eCamp in Figure 1. The steps to perform major-major relationships and course-course relationships are described in this section. After the models are constructed, the steps to perform visual analysis of student flow are described in Section 5. The analytical tasks from the perspective of university administrators are in Section 6.

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4.1 Major-Major Relationship

Many courses that students take through their studies are often shared between a set of majors. This means that majors have an overlapping relationship with one another. As students take more courses that are specific to their own major, it becomes less possible and less probable for them to switch majors. We calculate this overlapping relationship based on the student records from those who graduate in those majors and the set of courses that they have taken.

4.1.1 M-Value

Calculating major-major relationships begins by estimating the degree to which students in a single major will take a set of courses. Given a major A and a set of courses, C, the estimate, $\text{MA}$, is

$$\text{MA} = \sum_{c_{i} \in C} \frac{s_{c_{i}}}{|S_{c_{i}}|^{2} |A|}$$

where $s_{c_{i}}$ is the number of students in major A in the course $c_{i}$, $|A|$ is the total student population of major A, $S_{c_{i}} = [s_{m_{1}}, s_{m_{2}}, \ldots, s_{m_{n}}]$ is a vector of counts of students in $c_{i}$ from all of the n different majors, $|S_{c_{i}}|^{2}$ is the Euclidean norm of the vector $S_{c_{i}}$, and is computed as $|S_{c_{i}}|^{2} = \sum_{k=1}^{n} s_{m_{k}}^{2}$.

In Equation (1), $\text{MA}$ corresponds to the probability that students in major A take course $c_{i}$. The per-course scores are then tallied up across the whole set of courses to form the overall M-Value for the major.

Some courses are taken by a much broader group of students than others. For example, introductory English courses have very little specificity in terms of majors, because they are shared by the entire student population. The additional term $|S_{c_{i}}|^{2}$ is introduced to reduce the weight of those general courses. This means that the final M-Value metric will be weighted towards courses which are shared between small sets of majors. A high M-Value means the given course set Courses has a high specificity to a major. If the students in a major are not taking the courses in Courses, the M-Value will be low.

The M-Value essentially measures the affinity between a major and a set of courses. In other words, on the basis of a fixed set of courses, C, one can compute the affinity measure of all of the majors on campus with that set of courses, C. For example, if the course set C consists entirely of bio-engineering courses, the M-Values computed for each major can help to rank the similarities of all of the majors on campus with bio-engineering.

4.1.2 Major-Major Relationship Graph

Using the M-Value, we can capture the similarity between all majors on campus. This similarity for two majors, A and B is calculated as:

$$M_{A,B} = \frac{M'_{A} + M'_{B}}{2}$$

where $M'_{A}$ is calculated for major A according to Equation (1) but using the course set taken only by students in major B. $M'_{B}$ is calculated for major B, but using the course set taken only by students in major A.

Suppose major A is computer science and major B is math. Then $M'_{A}$ measures the affinity between the major of computer science and the math major’s courses. $M'_{B}$ measures the affinity between the major of math and the computer science major’s courses. $M_{A,B}$ is an average of those two metrics and is the same value as $M_{B,A}$.

One can now gain a more precise control of the model by controlling which set of courses are used to compute the M-Values. For example, one can make major-major comparisons based on stages of a student’s education, by including in the course set, C, only those courses taken typically by the student population during the corresponding stage (such as freshman year vs. sophomore year or later). The resulting major-major similarities computed using M-Values will then vary from freshmen, sophomore, junior to senior year.
4.1.3 Student Dropout Patterns
While junior and senior students usually have a “declared” major, they can still change their major without going to the registrar’s office to update their records. In addition, although freshman and sophomore students may also have a “declared major”, many of them are in an exploration stage of their studies and they may be taking preparation courses that can lead to a few different majors. Effectively, their final major is unclear at that point.

Both of these situations can cause significant data quality issues if we analyze solely based on their “declared” majors. When it comes to analyzing for patterns of student dropouts, we need to make best-effort estimates of a student’s intended major based on the data available.

For this, we look at the courses that the students have taken and measure the amount of overlap between those courses and the courses of each potential major. The higher this overlap ratio is for a major, the more likely it is that they were pursuing that major.

Counting the number of estimated dropouts for a major can introduce uncertainties. For example, the intention of a student that has only taken two courses are more unclear than a student that drops out after having taken ten courses. Another potential caveat with this approach is a scenario where a student has changed major without updating his/her major in the university records, and then dropped out. By the data, it is difficult to not count the dropout as the previous major.

We do recognize these potential issues, and we account for this by showing the average overlap ratio for each major in a tooltip. The tooltip is shown when a user hovers over a major.

In Table 2, we show the top-5 majors in the database by number of graduates, and the average degree of overlap between courses taken by dropouts vs. the full curriculum of the best-matched major. If the average overlap is high, then these are more likely to have intended to graduate from that major. If the average shows low overlap, then very likely these are students dropping out early in their studies. This could hint that general education courses are causing the dropout rather than specialty courses of academic departments.

The total number of estimated dropouts for each major is shown in the major-major graph using a red and gray bar. The percentage of the red bar over the gray bar represents the dropout percentage.

4.2 Course-Course Relationships
Diving into a more detailed view, we look at student success and student progression at a departmental level. In academic departments, student progression is typically represented by pre-requisite relationships in course catalogs. However, many courses do not have pre-requisites. Additionally, some pre-requisite rules are not always enforced. Therefore, the actual progression of students cannot be captured effectively. In our available data, we found that students grades are the closest variable that when combined with temporal information about courses, can represent progression and success in a major. Specifically, we quantify how the courses taken by students in a major are structured with respect to when courses are taken by the students, as well as how courses are correlated in terms of student grades. With this knowledge, per-major curriculum structures can be determined. We believe other variables, such as instruction style, grading practices, rigor, etc. can help make the measure of student progression more accurate. However, these variables were not available.

For this purpose, we first calculate course-to-course correlation of student success. We then take these correlations and determine which courses are most-highly correlated with all other courses and at what point in time each course is being taken.

4.2.1 C-Value
The approach for determining course correlations is the C-Value metric. The C-Value, informally, measures the similarity between
two sets of grades, while accounting for the size of these sets. To begin the formal discussion, the C-Value is heavily based upon the Pearson Correlation Coefficient (PCC), which is commonly used for studying linear correlation between variables.

Let $X$ be a collection of grades for course $A$, and $Y$ be the collection of grades for course $B$. For these sample populations the PCC, $r_{A,B}$, can be described as the sample covariance of $X$ and $Y$ divided by the product of the sample variance of $X$ and the sample variance $Y$. This yields

$$r_{A,B} = \frac{\sum_{i=1}^{N_{A,B}} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{N_{A,B}} (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^{N_{A,B}} (Y_i - \bar{Y})^2}}$$

where $\bar{X}$ and $\bar{Y}$ are the sample means for $X$ and $Y$, respectively, $N_{A,B}$ is the number of students who took both course $A$ and course $B$, and $X_i, Y_i$ are specific student grades.

By using PCC, one can see the correlation between courses based upon how students performed within both of these courses. However, in this use case, PCC is insufficient without a final step. Consider a situation where only five people took a course typically unrelated to a major and then all went on to do well academically in the major. One might incorrectly determine that this course is highly correlated with success in the major. To correct for this, the final correlation metric, the C-Value, is scaled by $N_{A,B}$, producing

$$C_{A,B} = N_{A,B} \cdot r_{A,B}$$

Using the pairwise C-Value, one can calculate correlations between all courses within a major, and capture their similarity in terms of grades.

### 4.2.2 Per-Major Course-Course Relationship Graph

Calculating pairwise C-Value results in a similarity matrix, which can alternatively be thought of as an undirected, fully-connected, edge-weighted graph (shown in Figure 3). In this graph, each node is a single course and each edge weight corresponds to the C-Value between two courses.

The graph helps capture success progression through a major in two stages. First, courses that represent overall success in a major can be defined as those that correlate most with all other courses of the major. With this in mind, we can sort courses based on how representative they are of success in a particular major. We call the most representative courses, “core courses”. Returning to the similarity matrix notion of the C-Value results, this is done by finding the rows/columns with the highest sum. Second, we can calculate where a course fits temporally in the real-world curriculum. This is done by determining the average time, or semester, during which students take the course. Looking at core courses and their correlations, administrators can see if in practice the courses exhibit the logical organization that they had intended for them. A visualization of this model is presented in Section 5.3.

Additionally, in extracting these core courses, it becomes possible to fill a hole in the data source—the major being pursued by students who withdrew from the university is not known. Using each major’s core courses and the set of courses that each student took, what major the student was pursuing at the time of withdrawal can be predicted. This is owing to the fact that core courses are more representative of a major than other courses. The approach for determining a student’s intended major is to, for each major, measure the percentage of core courses that the student took. The more core courses a student takes, the narrower their options of switching majors would be. Therefore, the higher that percentage is for a major, the more probable it would have been for that student to graduate in that major. The intended majors for student withdrawals are included in the university-wide student flow visualization described in Section 5.1.

### 5 Analytical Tasks

The course-major and temporal hierarchy models described in Section 4.1 can be used to develop visualizations of student flow through the curriculum on a per-major basis and student flow through the temporal hierarchy of majors on a university-wide basis. The university-wide student flow visualization (Section 5.1) employs the temporal major hierarchies and the per-major student flow visualization (Section 5.2) employs the course-major models.

Using these two visualizations, a series of results which demonstrate the system’s use for analytics purposes is presented in Section 5.3.

For ease of deployment and for enabling a crowd-sourced way of using a visual knowledge discovery system, eCamp’s user interface is fully web-based. The web-based visualization is fully interactive and is created using D3.js and a PHP backend. The data processing and modeling the multi-level relationships are implemented in Python and take less than 5 minutes to compute on a regular desktop.

#### 5.1 University-Wide Student Flow

Figure 2 shows the university-wide student flow visualization. For this, the primary aim is to show similarities between majors in terms of how students progress towards graduation. Specifically, the goal is to show points in time where students encounter critical decisions with regards to which courses they take. At these critical decision points, the courses students take may significantly limit their future options.

The visualization is based on the temporal hierarchy of majors constructed in Section 4.1.2. The center of the visualization is the root of the tree of majors. It is the starting point for all students: before their first semester on campus when they have the whole set of more than 400 majors from which to choose.

In this hierarchy, each leaf node is a major, and each level of the hierarchy corresponds to a single semester. The paths show a flow of students from the root to a leaf node. Every step along the path reduces the student’s choice of potential majors, and eventually when reaching a leaf node, a student’s coursework will be virtually exclusive to major-specific courses for that major. The width of the path corresponds to the size of the remaining student population at logarithmic scale.

A secondary goal with this visualization is to show dropout patterns. When a student drops out, the student’s intended major can be predicted using the method based on core courses as described in

| Major Name | Number of Graduates | Estimated Number of Dropouts | Average Overlap |
|------------|---------------------|------------------------------|-----------------|
| Psychology | 3092                | 159                          | 63.71%          |
| Political Science | 1263            | 52                           | 61.40%          |
| Journalism & Electronic Media | 1094        | 51                           | 72.79%          |
| Communication Studies | 1012        | 59                           | 70.93%          |
| Biochemistry & Cellular and Molecular Biology | 826         | 12                           | 75.70%          |
Figure 3: Per-major curriculum diagram. Thicker edges between courses signify higher correlation between student grades in these courses. The major shown is computer science. The “core courses” are MATH 300, COSC 302, MATH 251, COSC 311, COSC 360, and COSC 380. The size of the nodes corresponds to the percentage of students failing the class. Inside each node, the red portion corresponds to the ratio of female students, while the blue shows the ratio of male students in the class.

Section 4.2.2 Each blue node on the path signifies that the subgroup has “traveled” together through the major hierarchy and reached a new milestone, a new semester. The grey and red line segments shown for each major represent the percentage of students who have dropped out of their intended major. When the red line segment equals the grey line segment in length, it means 100% dropout. Correspondingly, when the red line segment is half of the grey line’s length, it means 50% dropout. When the user hovers over a major, a popup tooltip displays the actual number of students that have graduated or dropped out, as well as the confidence percentage for the dropout estimation. The opacity of the red dropout bars also reflects the confidence value.

5.2 Per-Major Student Flow
The per-major student flow visualization shows for each course which courses it is strongly correlated with and when it is typically taken by students. An example of this visualization with the computer science major at the university is shown in Figure 3. The primary design goal with this visualization is to cleanly show correlations between courses. Accordingly, a node-link diagram was chosen for use, where each node is a course and each link represents a grade correlation between two courses. To allow users to quickly identify strong links, the thickness of each link is scaled, where thicker lines correspond to higher C-Values.

Since there is a C-Value between all course pairs, this has the potential to introduce significant visual clutter. To avoid this, the user is allowed to specify a C-Value threshold, below which links between courses are not shown.

The secondary design goals were to allow users to quickly identify “core courses” and show when the courses were typically being taken. To incorporate these goals, these two pieces of information are encoded into the courses' horizontal and vertical positions in the diagram. The horizontal position of a node indicates the average time at which the course is taken by the student population. The vertical position of a node indicates whether a course is core or peripheral to the major, and is determined by a course’s total correlation to all other courses in the major. The “core courses” are placed at the center of the diagram, with peripheral courses being further away from the center. The number of “core courses” is a user-controllable parameter. Since it is possible that nodes could occupy the same position with this approach, a spring-force approach is used to force nodes occupying the same position to have sufficient spacing.

Additionally, each node provides gender information as a pie chart, and the size of each node represents the normalized percentage of failures in that course. For example, Figure 3 shows that math courses tend to be the bottleneck for students. Auxiliary information such as the exact number of students taking the course, and grade distributions are shown to users as they click on the nodes.

Using this visualization, how students are moving through a major’s curriculum can be seen and whether the student population is progressing through the major’s curriculum in the way the faculty intended can be determined.

5.3 Analytics Results
With these two visualizations, eCamp is able to provide insight into the issues raised by the users. The following subsections present results showing how eCamp can enable users to form hypotheses regarding these issues.

Figure 4: This branch of the radial graph contains the university’s computer and electrical engineering majors. These majors split apart from most other majors by the end of the 1st semester.

5.3.1 Major Exploration Advising
Students who wish to explore different options before choosing a major must be made aware of how the courses they choose to take limit their options of which majors they may pursue. Figure 4 shows that students who are potentially interested in electrical engineering have a very limited time in which to commit to it, or they risk delaying their graduation. On the other hand, Figure 5 shows that students have five semesters to choose between industrial engineering and mechanical engineering, if they want to graduate on time. This calls into question the university’s policy of requiring a student to declare a major after 45 credit hours, as a student’s interests may affect how long they have to commit to a major.

5.3.2 Major Mobility Advising
Another common advising task is to help students who wish to change majors. Consider a third-semester computer engineering
student who comes to the advisor and expresses a desire to change majors due to a lack of interest in continuing computer engineering. Rather than simply relying upon experience, the advisor uses the radial tree to determine which majors would be a good fit for the student.

First, the advisor locates the path from the root node to the node of depth 3 that contains computer engineering. This path can be seen in Figure 4. Then, the advisor records each of the child majors from this node, and presents them to the student. Since at this point none of these majors exhibit highly specified coursework, the student should have little difficulty switching to any of them.

What if the student had not lost interest in computer engineering, but instead failed the physics course in the second semester? In this case, it is likely in the student’s best interests to change majors. While the temporal major hierarchy can again be used to determine which majors would be a good fit for the student, the advisor must now also consider that the major being switched to shouldn’t have the same physics course as an core course. Using the per-major curriculum diagrams for each of the majors identified, the advisor notices that in the sociology major the physics course is not close to the core courses, and recommends to the student that he or she consider switching to it. Alternatively, the advisor could use the ability to control the color saturation to show the similarity of all majors to computer engineering. Majors which exhibit a high similarity with it, but that are in different branches of the tree, such as computer science, are good recommendations to the student.

5.3.3 Course Correlations

eCamp’s ability to show course correlations has led to discovering a surprising result in the curriculum. Figure 6 shows that there is no correlation between Calculus I (MATH 141) and the introductory programming course (COSC 102) at the university. For a long time students have been told to take these courses concurrently and recently the faculty has formalized this advice by making them co-requisites. However, seeing the lack of correlation between the two courses calls into question whether or not this should remain the case (actually there is a very weak negative correlation between the two courses).

Despite this surprising result, it is seen in Figure 7 that the Calculus sequence as a whole does demonstrate correlation with two of the computer science core courses, Linear Algebra (MATH 251) and Discrete Mathematics (COSC 311). When seeing general education sequences that affect student success in a major, the authors feel that it presents a good opportunity to encourage collaborations between the major-level and university-level student support infrastructures. As noted in the introduction, whether these courses should be core courses in the CS curriculum is an interesting retention question, since they do not correlate with student success in non-theoretical CS courses, and many CS graduates will not engage in tasks requiring theoretical CS knowledge in their eventual jobs.

6 DOMAIN EXPERT FEEDBACK

In this section, more detailed observations that two of our domain experts derived from eCamp, as well as feedback about potential improvements are presented. The first was our department head, who is intimately familiar with the per-major curricula for the Electrical Engineering major. The second is a faculty member who formerly served as Vice Provost of the university, whose priorities are improving student retention and time-to-graduation. Both began to ask questions regarding both the per-major and university-wide curriculum that they had not previously considered.

Our department head examined the node-link diagram for Electrical Engineering, and saw both patterns that he had expected and patterns that he had not. One finding was that some of the courses showing strong grade correlations had the same instructor. He expressed a preference that course success be independent of instructors and instead be driven by the course’s material. Additionally, he expressed surprise that the courses meant to serve as gatekeeping courses for Electrical Engineering did not show strong correlation with success in most of the remaining curriculum, which led him to wonder why that was the case.

The former Vice Provost felt that the node-link diagrams are
useful for evaluating majors in terms of how welcoming they are to students switching to them. For example, she mentioned that Classical Civilization is typically considered a found major, where students who graduate with this major did not enter the university planning on doing so. In such a major, the core courses would ideally be very late in the student curriculum, which was the case for Classical Civilization. On the other hand, engineering departments would prefer for students to commit very early, so it would be best for their core courses to be much earlier in the curriculum.

She thought that the radial graph was interesting to university-wide administrators as it showed major branches of study available in the university. Specifically, she saw four main arms of majors and noted that the number of students graduating from each of these arms was very uneven. This led her to ask questions regarding how the university is distributing resources, and whether or not this distribution matched the goals of the university.

She also felt that first-year advisors’ work would benefit from access to the radial graph visualization. Specifically, she saw that the Journalism and Communications majors maintained shared curricula until very late in the student career. This means that students are likely to choose one of these majors before they have taken courses which would help them determine which major is best suited to their interests. Hence, it is important for first-year advisors to make sure that students are informed that they should keep an open mind about which major they like the most, as it should still remain possible to switch between these majors very late into the curriculum.

Regarding improvements to eCamp, the former Vice Provost noted that it would be useful to see how flow differs between students with different financial backgrounds. She noted that students from low-income backgrounds are considered to be at higher risk of not graduating, and it would be interesting to be able to see where these students are typically struggling. Additionally, she suggested building a data science tool to predict when students are changing majors and what majors they are changing to, as this could hint at why so many students take longer than 4 years to graduate.

7 Conclusion

This paper has taken a data science approach to integrate and make sense of previously disparate electronic student records, using a framework that models relationships that span multiple levels of entities: students, courses and majors. The prototype system, eCamp, enables university personnel to leverage the information hidden in these datasets to form questions and hypotheses about their curricula. eCamp has been made available to several administrators at the authors’ university, and a selection of analytical questions that eCamp helped to raise about student progression and retention are presented. In future works, we’d like to incorporate new data sources (e.g. student financial information) into our analysis.

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