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WIP: Vectorized Interdisciplinary Overlap between STEM Domains using the MIDFIELD Dataset

Dr. Tim Ransom, Clemson University

Computer Science Lecturer, PhD Engineering and Science Education

Stephanie A Damas, Clemson University

Stephanie Ashley Damas is currently a graduate student at Clemson University studying to get her Ph.D. in Engineering and Science Education. Her area of interest is Diversity and Inclusion in Engineering. She holds a bachelorâ€™s degree in electrical engi

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Dr. Tim Ransom* Dr. Stephanie Damas†

Abstract

This work in progress applies multiple similarity metrics to course enrollment vectors derived from the MIDFIELD dataset to characterize relationships between undergraduate STEM programs. We employ five complementary measures—Jaccard, TF-IDF Cosine, Overlap Coefficient, PMI, and Kulczynski—to distinguish curricular width, specialized identity, subset relations, signature course bonds, and mutual resemblance. Three relationship categories emerge from the metric analysis: *nested* relationships, where one program's coursework is largely contained within another; *parallel* relationships, where programs share a common curricular base but diverge in specialization; and *convergent* relationships, where programs share both general and specialized content at high levels. Applied to computing, engineering, science, and cross-domain STEM groupings, the approach surfaces non-obvious pairings such as Aerospace and Industrial Engineering—a convergent pair with the highest specialized technical similarity (~45% TF-IDF Cosine) in the engineering group despite occupying different traditional sub-disciplines. We address the research question: *What types of curricular relationships have emerged between undergraduate STEM programs as evidenced by student enrollment patterns?* Preliminary results and implications for curriculum design are discussed.

Keywords: Interdisciplinary Education, Curriculum Analysis, MIDFIELD, Similarity Metrics

1 Introduction

Students often have a level of agency in the courses they take on their paths to graduation, opting to take courses that may not be housed in their declared major's department. Such cross-departmental enrollment indicates that students acquire knowledge, skills, or attitudes (KSAs) from several disciplines and are, to some degree, interdisciplinary in their education. Courses frequently chosen by students in a given domain indicate a trend that we interpret as overlap between programs.

Interdisciplinary studies integrate concepts, theories, and methods from multiple disciplines [1]. In interdisciplinary majors, there is a deliberate effort to create a new perspective or approach that is not limited to any single discipline, resulting in a deeper understanding of complex issues. Interdisciplinary majors create space for solutions that would be impossible within the confines of

*Clemson University, tsranso@clemson.edu
†University of Michigan, damas@umich.edu

a single discipline. While multidisciplinary approaches also draw on multiple fields, interdisciplinary programs combine tools and methods from distinct disciplines into an integrated whole [1].

Several STEM domains have been historically interdisciplinary. The computing domain has created new interdisciplinary programs as it engages with other knowledge branches such as human-centered computing and bioinformatics [2]. These specialized programs offer a targeted approach to solving complex issues and act as a point of attraction for students to enroll in one university or department over another. The curricula of these interdisciplinary programs often include courses from their broader source fields. For example, a bioinformatics curriculum draws courses from both computer science and biology departments, and its coursework may be largely nested within either parent field's catalog. Specialized courses are also often created in the narrower field to meet the needs of interdisciplinary students. Many engineering programs include a general engineering component that gives a shared set of KSAs to all engineering students, creating parallel relationships where programs share a common base but diverge in specialization.

Interdisciplinary programs can make STEM more attractive to students with marginalized identities who seek to bridge the gap between their lived experiences and technical fundamentals [3]. Franco et al. demonstrated that interdisciplinary quantitative initiatives can broaden participation in data-intensive fields [4]. Identifying the courses and academic choices that facilitate cross-domain applicability is therefore both a curricular design concern and an equity concern. The National Science Foundation has identified convergence research as one of its top 10 BIG Ideas, arguing that the nation's grand challenges "will not be solved by one discipline alone" [5]. To prepare students to address these challenges, we must evaluate how curricula facilitate interdisciplinary study. In our analysis, we use the term "convergent" to describe a specific metric pattern where two programs share both general and specialized content at high levels—programs that may be natural sites for the kind of convergence research the NSF envisions.

This work analyzes undergraduate navigation through STEM domains using the Multiple-Institution Database for Investigating Engineering Longitudinal Development (MIDFIELD) [6]. We use student enrollment in courses as a proxy for curricular overlap between programs, acknowledging that enrollment patterns reflect a combination of student interest, degree requirements, prerequisite structures, and scheduling constraints. By applying multiple similarity metrics to the same enrollment data, we classify relationships between STEM programs into three categories—*nested*, *parallel*, and *convergent*—defined by their metric signatures (see Methodology). We address the research question: *What types of curricular relationships have emerged between undergraduate STEM programs as evidenced by student enrollment patterns?*

These classifications have practical implications at multiple levels. Academic advisors can guide students toward cross-domain courses that enrollment patterns show are commonly taken by peers in related programs. Curriculum committees can identify where undocumented collaboration between departments already exists. And at the university level, program pairs with high curricular overlap indicate existing demand for interdisciplinary certificates, cross-listed courses, or dual-degree pathways.

2 Positioning Within Prior Work

While existing research has explored engineering student pathways, interdisciplinary education, and curricular structure, these efforts have primarily addressed these areas in isolation. We draw on all three areas but approach them using a different unit of analysis: relationships between degree programs, drawn from observed enrollment behavior. This section situates our work within prior research on the MIDFIELD dataset, interdisciplinary engineering education, and curricular analytics, and identifies how our approach extends beyond existing uses of these research areas.

2.1 MIDFIELD Literature

Prior work using the MIDFIELD dataset has primarily focused on student persistence, migration between majors, and longitudinal academic trajectories [6–9]. These studies have established MIDFIELD as a powerful tool for understanding how students move through engineering pathways over time. However, the dataset has been used less frequently to characterize relationships between programs themselves [10]. We position majors as structured collections of curricular experiences and examine how those structures relate to one another, shifting the unit of analysis from student pathways to program relationships.

2.2 Interdisciplinarity Literature

Research on interdisciplinary engineering education has largely examined program design, student identity development, or institutional initiatives that intentionally combine fields [11–14]. Such work typically defines interdisciplinarity administratively through degree labels, departmental collaborations, or curricular intentions. In contrast, we operationalize interdisciplinarity behaviorally, using observed course-taking patterns to detect when programs function as subsets, parallels, or convergent domains regardless of institutional labeling. This approach identifies interdisciplinary structure even where no formal interdisciplinary program exists.

2.3 Curricular Analytics Literature

Recent curricular analytics approaches model curricula using prerequisite networks or course dependency graphs to evaluate complexity and progression, some of which have leveraged the MIDFIELD data set [10, 15–17]. These methods characterize structure within a single degree program but do not typically quantify relationships across programs. Our multi-metric vectorized approach extends curricular analytics across disciplinary boundaries by distinguishing shared breadth, specialized identity, subset containment, and statistically significant co-enrollment. The resulting taxonomy provides a cross-program structural interpretation rather than a within-program sequencing interpretation.

2.4 Explicit contribution

Together, these distinctions position our work as a bridge between student-trajectory research and curricular structure research. By applying complementary similarity metrics to enrollment vectors, we identify latent structural relationships between degree programs that are not visible from catalog requirements or departmental organization alone. Our contribution is therefore not simply measuring overlap [18], but defining interpretable relationship types—nested, parallel, and convergent—that provide actionable information for advising, curriculum design, and interdisciplinary program development.

3 Methodology

We use the MIDFIELD dataset to collect records of courses that students were enrolled in during their education. Student paths to graduation are analyzed to determine curricular overlap between STEM domains. We extend our prior work that relied on binary course presence (enabling only Jaccard indices) by incorporating course frequency data, which enables a suite of complementary similarity metrics that each reveal a different facet of the relationship between programs.

3.1 Data Source

The MIDFIELD dataset provides academic records of over 98,000 students from eighteen universities in the USA going back several decades. We filter to data from 2000 onward to address the potential overrepresentation of older degree curricula and to better engage with curricula that are likely to represent a contemporary student's experience.

3.2 Data Analysis

For each CIP code (Classification of Instructional Programs [19]) in the MIDFIELD dataset, a set of courses is identified that any student who completed that degree took while progressing toward graduation. These sets include every course students took: general education courses, courses in and out of their declared major, courses that were begun but not completed, and courses that were both required and elective. Each course set is then augmented with the frequency of each course's presence in the dataset to create a vector. These vectors represent the domains in a many-dimensional space that enables the metrics interpreted in the next section. By incorporating course frequency rather than binary presence alone, we can apply multiple similarity metrics to the same vectorized data, enabling distinctions among subset containment, specialized identity, and statistically surprising co-enrollment that a single metric cannot capture.

3.3 Metric Selection Rationale

A single similarity metric cannot distinguish between programs that share a broad general-education base and programs that share specialized technical content. We select metrics that each address a specific analytical limitation, as summarized below. Together, the suite separates curricular width from specialized identity, detects subset containment, and identifies statistically surprising co-enrollment bonds.

3.3.1 Jaccard Index (Curricular Width)

The Jaccard index [20] serves as our baseline. It measures the proportion of courses shared across the union of two programs' course sets. Because it treats every course taken by even one student as a set member, it can be diluted by rare electives, often resulting in lower scores for very large or diverse programs. It answers: *How much total curricular territory do two programs share?*

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

3.3.2 TF-IDF Cosine (Specialized Identity)

Where Jaccard treats all courses equally, TF-IDF [21, 22] weights courses by their specificity. A course like *Calculus I* (taken by many majors) gets low weight, while *Advanced Microcontrollers* (unique to a few) gets high weight. The cosine of the resulting TF-IDF vectors measures whether two programs share identity-defining coursework rather than generic prerequisites. This metric is resistant to differences in program size because it uses normalized frequencies. It answers: *Do two programs share the specialized courses that define their identities?*

$$\text{Cosine Similarity} = \frac{\mathbf{v}_A \cdot \mathbf{v}_B}{\|\mathbf{v}_A\| \|\mathbf{v}_B\|}$$

3.3.3 Overlap Coefficient (Subset Detection)

The Overlap Coefficient [23, 24] divides the intersection size by the size of the smaller set. A high Overlap Coefficient paired with a low Jaccard index is the signature of a nested relationship: the smaller program's coursework is largely contained within the larger one. For example, if Software Engineering students take almost everything Computer Science students take, but CS students have a much broader elective set, the Overlap Coefficient remains high while the Jaccard score drops. It answers: *Is one program's curriculum largely a subset of another's?*

$$\text{Overlap}(A, B) = \frac{|A \cap B|}{\min(|A|, |B|)}$$

3.3.4 PMI Similarity (Signature Bonds)

Pointwise Mutual Information [25] measures whether a course-major pairing occurs more often than would be expected if they were independent. A high PMI value indicates courses that are characteristic of a specific pair of programs and unlikely to appear together by chance. We use Positive PMI (clamping negative values to zero) and compute cosine similarity over the resulting vectors. It answers: *Do two programs share courses that are statistically surprising for both?*

$$\text{PMI}(m, c) = \log\left(\frac{p(m, c)}{p(m)p(c)}\right)$$

3.3.5 Kulczynski Similarity (Mutual Resemblance)

There is a large imbalance in program representation in the data: large engineering programs have significantly more enrollment data simply because more students have been through those curricula. The Kulczynski metric [26] addresses this by averaging the overlap proportions from each program's perspective individually, making it more robust when comparing a very large program to a small, specialized one. It answers: *On average, how well would a student from one program fit in the other?*

$$\text{Kulczynski}(A, B) = \frac{1}{2}\left(\frac{|A \cap B|}{|A|} + \frac{|A \cap B|}{|B|}\right)$$

4 Preliminary Results

Applying these metrics across Engineering, Science, Computing, and broader STEM domains reveals three recurring relationship types, summarized in Table 1. Each type is characterized by a distinct metric signature that a single metric alone cannot identify. We note that the specific percentage values are less important than the relative differences between domain pairs within the same metric and the dendrogram clustering patterns.

Table 1: Metric signatures for three curricular relationship types. High/Low are relative to other pairs within the same domain.

Type	Jaccard	TF-IDF	Overlap	PMI	Example
Nested	Low	Low	High	Var.	IT $\subset$ CS
Parallel	Med	Low	Med	Low	EE $\parallel$ Civil Eng
Convergent	High	High	High	High	Aero $\approx$ Ind Eng

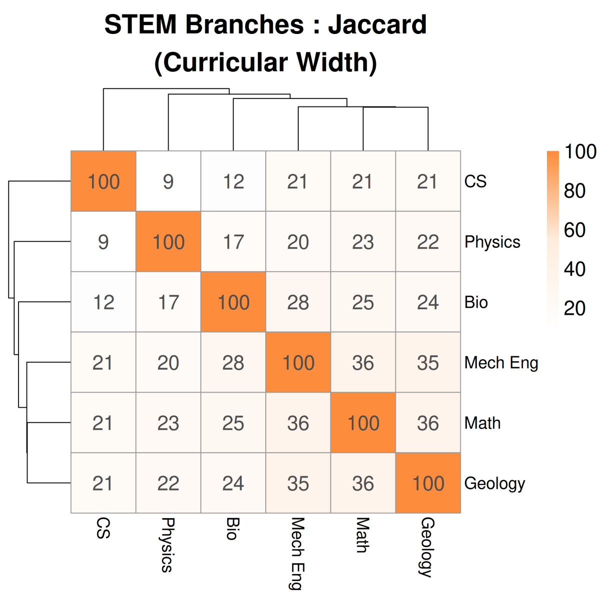
A **nested** relationship exists when the Overlap Coefficient between two programs is high while the Jaccard index is comparatively low, indicating that the smaller program functions as a specialized subset of the larger one. The high Overlap score shows that most of the smaller program's coursework is contained within the larger program, while the low Jaccard reflects the larger program's broader curricular territory that dilutes the intersection relative to the union.

A **parallel** relationship exists when two programs share a substantial common base (high Jaccard or Kulczynski) but diverge in their specialized content (low TF-IDF Cosine). This pattern arises when programs share prerequisites or a common core curriculum but develop distinct specializations beyond that base.

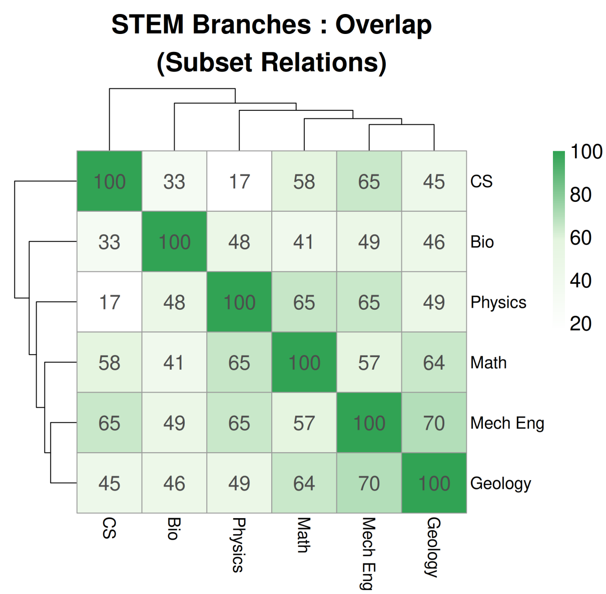
A **convergent** relationship exists when two programs score high across all metrics—sharing both general coursework and specialized technical content—suggesting deep curricular alignment that may not be reflected in departmental organization. Convergent pairs are candidates for cross-listed courses, interdisciplinary certificates, or dual-degree pathways.

4.1 STEM Overview

At the broadest level, representative STEM fields show expected patterns that validate the approach. Mathematics emerges as a central bridge (Figure 1a), sharing significant coursework with Mechanical Engineering (~36% Jaccard), Physics (~23%), and Computer Science (~21%).



(a) Jaccard Similarity



(b) Overlap Coefficient

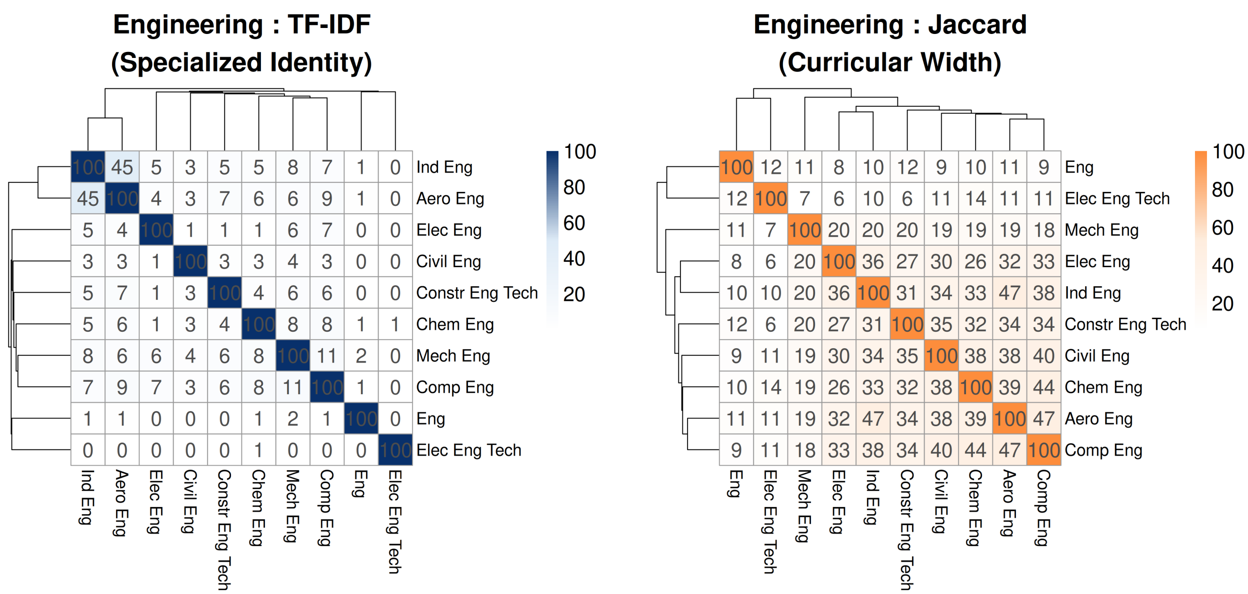
Figure 1: Similarity in Interdisciplinary STEM Degrees

Physics is more curricularly similar to Mechanical Engineering (~20% Jaccard) than to Computer Science (~9% Jaccard). Comparing Figures 1a and 1b illustrates the nested pattern: the Overlap Coefficient between Physics and Mechanical Engineering (~65%) is notably higher than the Jaccard score, indicating a nested dynamic: a large portion of a Physics major's coursework—particularly the foundational physical science and mathematics sequences—is required for or commonly taken by Mechanical Engineering students. Zooming into individual domains reveals less expected structures.

4.2 Engineering

TF-IDF analysis is particularly informative for engineering curricula because the many courses shared across sub-disciplines can inflate simpler metrics; TF-IDF downweights these ubiquitous courses to isolate specialized content. Figure 2a shows the TF-IDF metric applied to the top engineering majors by enrollment. While Jaccard indices between engineering disciplines are generally high due to shared mathematics and physics prerequisites (Figure 2b; e.g., Electrical Engineering and Computer Engineering share ~33% Jaccard similarity), the TF-IDF metric separates those generic relationships from specific ones. The high TF-IDF similarity between computing-related and electrical engineering programs indicates that these curricula share specialized technical content beyond the common engineering core. Several MIDFIELD institutions house merged "Electrical and Computer Engineering" departments, and the analysis detects this structural relationship.

The overall TF-IDF similarity between engineering programs is typically low (median ~3%), indicating that the specialized courses distinguishing each program constitute a small fraction of the overall curriculum. The general engineering model—a shared base of courses across sub-



(a) TF-IDF Similarity

(b) Jaccard Similarity

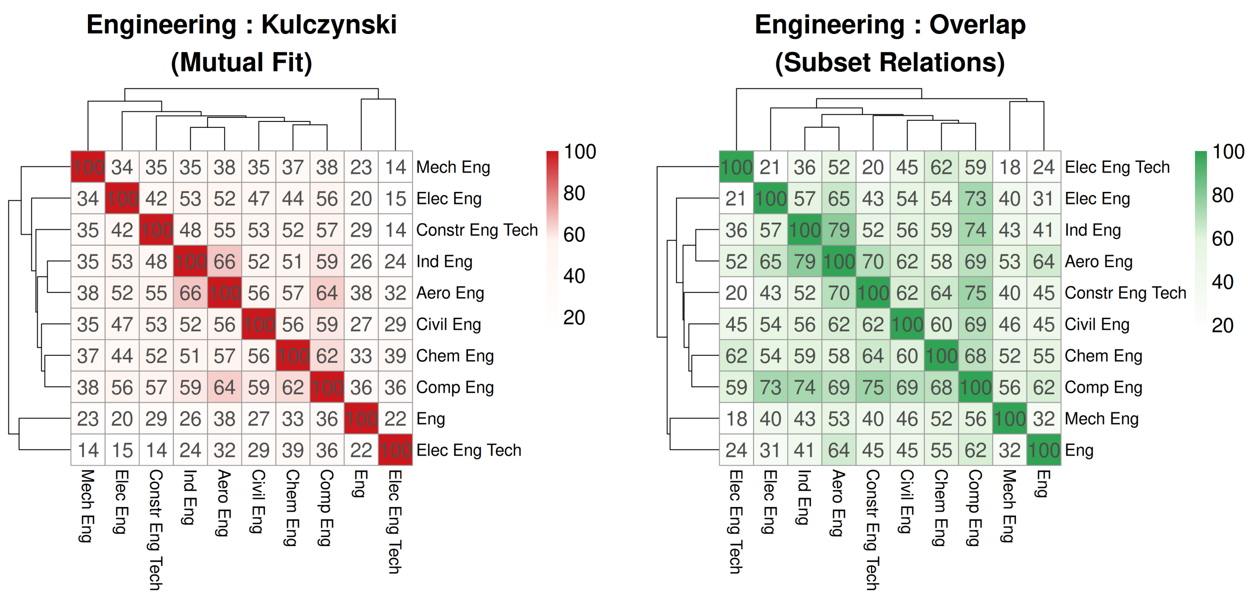
Figure 2: Specialized vs. Broad Similarity in Engineering Degrees

disciplines—is the dominant pattern, which supports the parallel characterization.

The most striking result is the similarity between Aerospace Engineering and Industrial Engineering. This pair produces the highest or near-highest score on every metric: TF-IDF (~45%, Figure 2a), Jaccard (~47%, Figure 2b), Kulczynski (~66%, Figure 3a), and Overlap (~79%, Figure 3b). The TF-IDF score is more than four times higher than the next strongest engineering pair, indicating that Aerospace and Industrial Engineering share a substantial core of specialized courses that do not appear broadly across other engineering fields. The specific shared content likely includes areas common to both programs' accreditation requirements [27], such as systems-level analysis and applied statistics, though identifying the individual courses driving this similarity is a target of future work. The Kulczynski metric (Figure 3a) further confirms this: the Aerospace-Industrial pairing is the strongest in the engineering group, while most other engineering programs show moderate mutual resemblance consistent with the shared general engineering core.

4.3 Sciences

The science disciplines provide a useful contrast to engineering's shared-core structure. The immense variation between science fields means that cross-departmental enrollment is more likely to reflect elective choices rather than shared requirements. The PMI metric is well suited here because it identifies course-major pairings that occur more often than chance would predict. In Figure 4a, the strongest cluster connects Animal Sciences (CIP 01, Agriculture), Biochemistry, and Animal Biology, with the Animal Sciences-Biochemistry pair producing the highest PMI in the entire science matrix (~23%). This is followed by Animal Sciences-Animal Biology (~20%) and Biochemistry-Animal Biology (~18%). This triangle of programs shares statistically surprising co-enrollment that crosses CIP family boundaries: Animal Sciences is classified under Agri-



(a) Kulczynski Similarity

(b) Overlap Coefficient

Figure 3: Mutual Resemblance and Subset Relations in Engineering Degrees

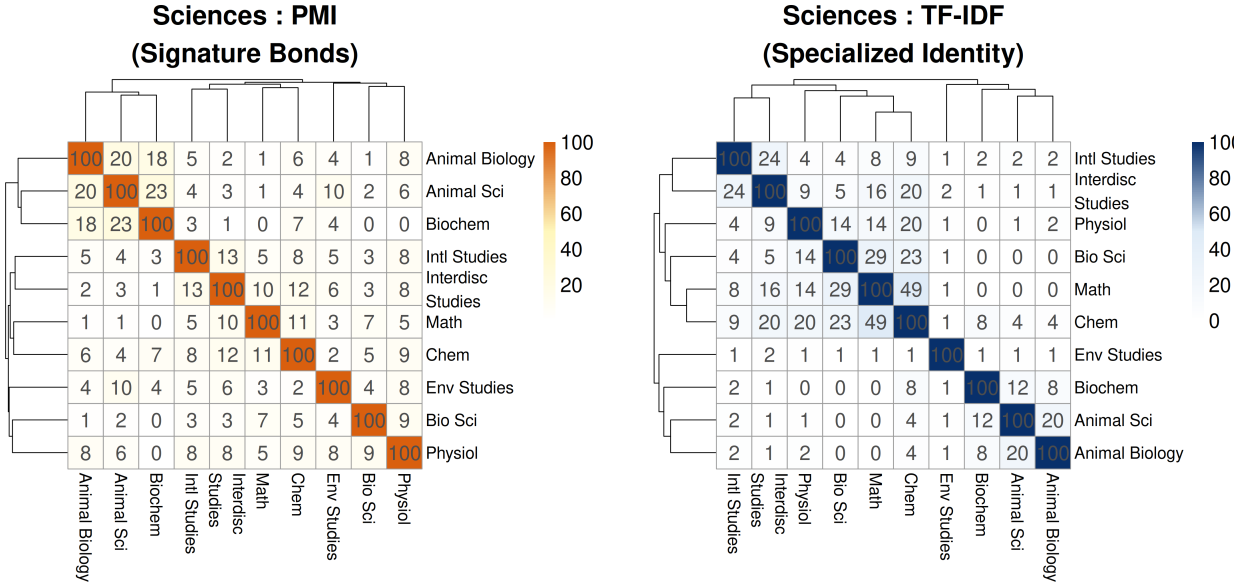
culture (CIP 01), while Biochemistry and Animal Biology fall under Biological Sciences (CIP 26). The clustering suggests that students in these programs take specialized courses in each other's departments at rates well above what chance would predict.

Mathematics acts as a generalist connector, with moderate PMI values across many science programs—its strongest bonds are with Chemistry (~11%) and Interdisciplinary Studies (~10%). The Mathematics-Chemistry relationship is particularly notable: their TF-IDF similarity (~49%, Figure 4b) is the highest specialized-content pair in the entire science matrix, indicating that these programs share identity-defining coursework beyond common prerequisites. Biological Sciences, despite being the largest science program by enrollment, shows relatively weak PMI connections to most other fields (strongest: Physiology at ~9%), suggesting that its broad curriculum does not generate the statistically surprising co-enrollment patterns that smaller, more focused programs produce.

4.4 Computing

In the computing domain, the multi-metric analysis highlights structural differences between related majors. The relationship between Computer Science (CS) and Computer Engineering (CompE) exhibits a moderate Jaccard index (~25%, Figure 5b) but a notably higher Overlap Coefficient (~52%, Figure 5a), indicating that CompE's coursework is partially nested within the CS curriculum even though CS has a broader elective set that dilutes the Jaccard score. The TF-IDF score for this pair (~29%, Figure 6) is also among the highest computing pairings, confirming that the shared courses are specific technical courses central to the identity of both programs rather than general education requirements. CS and CompE thus exhibit a mix of nested and convergent characteristics.

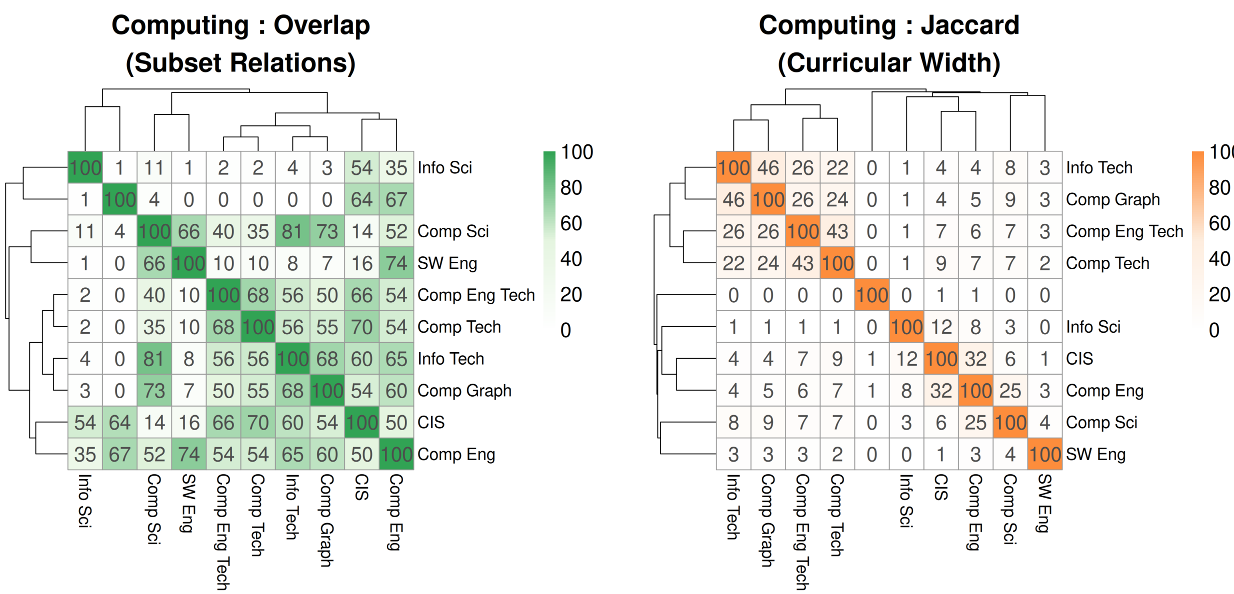
The cleanest nested relationship in the computing domain is between Information Technology and



(a) PMI Similarity

(b) TF-IDF Similarity

Figure 4: Similarity in Science Degrees



(a) Overlap Coefficient

(b) Jaccard Similarity

Figure 5: Subset Relations and Curricular Width in Computing Degrees

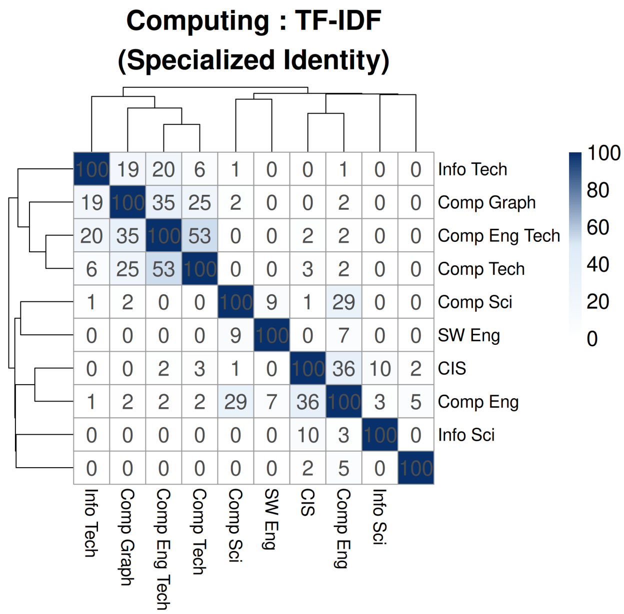


Figure 6: TF-IDF Similarity in Computing Degrees

Computer Science. IT shares a very high Overlap Coefficient (~80%, Figure 5a) with CS but a much lower Jaccard score (~8.5%, Figure 5b)—the largest divergence between these two metrics in the entire dataset. Nearly all IT coursework overlaps with CS, but IT students also take a distinct set of courses (e.g., networking, systems administration) that CS students largely do not. A single-metric analysis using only Jaccard would classify IT and CS as barely related; the Overlap Coefficient reveals that IT functions as a specialized subset of CS.

5 Discussion

The results reveal that STEM domains are not uniformly interdisciplinary—they are interdisciplinary in structurally different ways. Engineering is dominated by parallel relationships: a shared core with sharp specialization divergence, and rare convergent exceptions like the Aerospace-Industrial pair. Computing is organized as nested hierarchies branching from a common ancestor. The sciences share the least curricular territory overall but produce the most statistically surprising cross-boundary clusters. These structural differences mean that interdisciplinary initiatives cannot be designed uniformly across STEM; the appropriate intervention depends on the relationship type that dominates a given domain.

The combined application of these metrics to the MIDFIELD data produces actionable distinctions for curriculum designers at each relationship type. For **nested** relationships (e.g., IT within CS), academic advisors can guide students in the smaller program toward the broader parent field's electives, and departments can identify courses in the larger program that serve as de facto requirements for the smaller one. For **parallel** relationships (e.g., most engineering sub-disciplines), collaboration should focus on coordinating shared prerequisite sections across departments to ensure consistent preparation. For **convergent** relationships (e.g., Aerospace-Industrial Engineering), the deep curricular alignment suggests concrete opportunities for cross-listed courses, interdisciplinary certificates, or dual-degree pathways that their departmental separation might otherwise obscure.

5.1 Limitations

Our analysis measures curricular overlap through student enrollment patterns, which is a necessary but not sufficient indicator of interdisciplinary engagement. Course enrollment reflects a combination of student interest, degree requirements, prerequisite chains, scheduling convenience, and institutional policies. We cannot fully disaggregate these factors in the current analysis. Consequently, our results identify where programs share common ground in student course-taking behavior, but should not be interpreted as direct evidence of interdisciplinary knowledge integration [1]. Future work incorporating course-level requirement data from institutional catalogs could help isolate elective choices from required overlap.

Additionally, our analysis aggregates data across eighteen universities and over two decades (2000–present). Curricula change over time, and institutional contexts vary: a high similarity score for a given pair could be driven disproportionately by a few large institutions or by older curricula that have since diverged. We cannot currently distinguish between a relationship that holds universally and one that is an artifact of a specific institution's departmental structure. Disaggregating results by institution and time period is a priority for future work.

6 Conclusion & Future Directions

This work demonstrates how existing curricular overlap between STEM programs can be characterized through student enrollment patterns. By applying multiple similarity metrics to the MIDFIELD dataset, we distinguish between parallel programs that share a broad common base but diverge in specialization, nested programs where one is a specialized subset of another, and convergent programs that share both general and specialized content at high levels. These distinctions move beyond what a single metric can reveal and provide actionable information for curriculum designers at multiple institutional levels.

Future work will focus on: (1) disaggregating required coursework from elective enrollment to isolate student choice from degree structure; (2) applying these metrics across time windows to detect whether programs are becoming more or less similar over time (e.g., whether Biology is becoming more computational); (3) validating detected relationships against known interdisciplinary programs and expert assessments at MIDFIELD institutions; and (4) analyzing whether these patterns hold across all universities or if specific institutions have unique interdisciplinary characteristics.

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