From Lab to Lecture: Analysis of the Connection Between DTU Professors' Research and Course Content They Teach

Erik Wold Riise, s194633[a], Lukas Rasocha, s233498[a], and Zou Yong Nan Klaassen, s230351[a]

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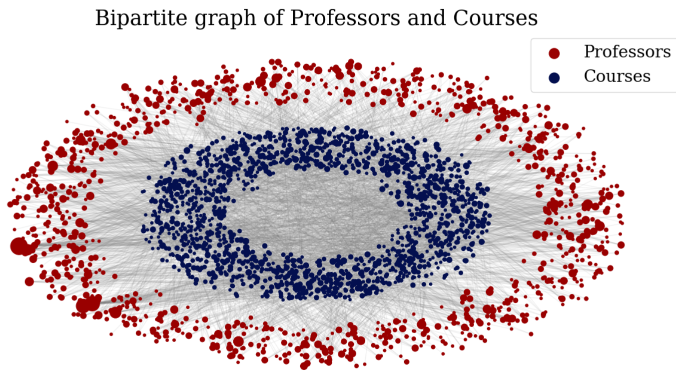

Fig. 1. Bipartite Graph of DTU Professors (in red) and Courses they teach (in blue) (sizes proportional to the degrees)

This study examines the alignment between professors' research expertise and the courses they teach at the Technical University of Denmark (DTU), addressing long-standing debates about the integration of research and teaching in higher education. By applying advanced natural language processing techniques, including transformer-based models and TF-IDF approaches, we analyzed data from 1,704 courses and 1,046 professors. Our findings reveal that professors are systematically assigned to courses aligned with their research areas, with some variation across disciplines. For example, Wind Energy showed the highest alignment, while Management and Economics exhibited lower alignment scores. However, we found no meaningful correlation between research-teaching alignment and student outcomes, such as grades and satisfaction. Finally, network analysis of cross-institute collaboration revealed clusters of interdisciplinary activity, particularly in life sciences and renewable energy, while computational disciplines showed potential for stronger integration. This work offers practical insights for optimizing academic organization and fostering collaboration, contributing to the broader discussion on how universities can effectively balance research and teaching responsibilities.

Research-teaching alignment | Natural Language Processing | Network Analysis | Higher Education | Interdisciplinary Collaboration

Introduction

"At the higher level, the teacher is not there for the sake of the student, both have their justification in the service of scholarship." With these words, Wilhelm von Humboldt articulated his vision in 1810 for a university model where teaching and research are inseparable. (1) In contrast, Cardinal Newman, writing in *"The Idea of the University"* proposed the opposite perspective, saying that *"to discover and to teach are distinct functions."* He stated that universities should be focused on teaching, while research should be conducted elsewhere. (2) These competing views have fueled centuries of debate about the relationship between teaching and research in higher education.

Currently, within academic institutions professors contribute to diverse research areas while simultaneously teaching course material to students. In some cases, professors teach courses closely related to their research topics, offering students unique insights drawn from their expertise. In other cases, the courses taught may diverge from their research focus. Understanding the degree to which professors' research aligns with the content and objectives of the courses they teach can offer

Significance Statement

Understanding how professors' research expertise aligns with their teaching responsibilities is crucial for modern universities striving to deliver high-quality education while maintaining research excellence. This study provides a data-driven analysis of research-teaching alignment at a major technical university using advanced natural language processing techniques. Our findings reveal patterns of interdisciplinary collaboration and identify opportunities for strengthening cross-institute research connections. These insights can guide universities in optimizing course assignments, aiding interdisciplinary collaboration, and balancing research and teaching responsibilities. The methodology developed here offers a framework for other institutions to evaluate and enhance their academic organization, ultimately contributing to more effective integration of research and teaching in higher education.

Author affiliations: [a]Technical University of Denmark

Lukas Rasocha: Data Collection - scraper of scholia topics and DTU Orbit, Initial EDA, Similarity approaches - NLP Methods: TFIDF, Transformer, Analysis for RQ 1, Contribution to the report
Erik Riise: Similarity approaches - Simple approach, Professor similarity network, Analysis for RQ 3, Report contribution
Zou Yong Nan Klaassen: Exploratory data analysis of the network, Analysis for RQ2, Report contribution

valuable insights into academic practices and their potential impact on student outcomes.

This study explores these dynamics within the Technical University of Denmark (DTU), focusing on three key research questions:

1. *How well do professors' research areas align with the content and objectives of the courses they teach, and how does this alignment vary across disciplines?*
2. *Does the alignment between professors' research and the courses they teach influence student satisfaction and performance (grades)?*
3. *How do research-teaching alignments between professors contribute to cross-institute collaboration, and what patterns of collaboration emerge across academic disciplines?*

To answer these questions, we employ natural language processing techniques to analyze course descriptions, learning objectives, and professors' research profiles. We also use network and statistical analyses to explore variations in alignment, their impact on student outcomes, and collaboration patterns across DTU's institutes.

Methods

Link to explainer notebook: https://github.com/yonnaklaassen/SocialGraphs/blob/main/final-project/main-final.ipynb

Data collection. The data for this study was gathered from three distinct sources. Course information, including descriptions, learning objectives, and additional attributes, was extracted from the DTU course base, available through a GitHub repository [*]. To obtain data about professors and their research activities, we developed a custom web scraper that collected details such as research profiles and areas of interest from DTU Orbit. Additionally, more granular research information was retrieved from the Scholia platform using its public API. [†]

The final dataset comprises two main components: the first, focused on courses, contains 6.44 MB of data across 1,704 courses and 225 variables; the second, focused on professors, contains 8.3 MB of data encompassing 1,046 professors and 6 variables.

Bipartite network. The graph was constructed as a bipartite network (Fig. 1) where an edge(c,p) indicates that course c is taught by professor p. The graph allows for an analysis of the relationship between professors and courses, offering insights into research areas and course content. The course nodes have the following node attributes: *course description, learning objectives, course content, average grade, rating average score, and study lines.* The professor nodes have attributes such as *profile description, keywords, research fingerprint,* and *scholia topics.*

Professor-course similarity. To investigate the alignment between professors' research areas and the courses they teach, we employed multiple methods to calculate similarity scores. These methods range from simple keyword recall calculations to advanced natural language processing (NLP) approaches using pre-trained transformer models. The resulting similarity matrices serve as the foundation for analyzing professor-course alignment.

Simple Approach (Recall). The simplest approach compares the keywords extracted from professors' research profiles to the aggregated course descriptions, learning objectives, and content of the courses they teach. This method calculates the recall of alignment, defined as the proportion of the professor's keywords that are found in the text of the associated courses:

$$\text{Recall} = \frac{|\text{Keywords}_p \cap \text{Tokens}_c|}{|\text{Keywords}_p|}$$

Here, Keywords_p represents the set of keywords associated with professor p, and Tokens_c represents the tokenized text of course c. Stop words, punctuation, and irrelevant terms are removed during preprocessing. While this approach provides a straightforward metric, it does not capture nuanced semantic relationships between words.

Bag of Words. In this approach, professor and course texts are represented as term-frequency vectors in a high-dimensional space. These vectors are constructed by counting occurrences of words after preprocessing. The similarity between a professor p and a course c is calculated using the cosine similarity:

$$\text{Cosine Similarity} = \frac{\mathbf{v}_p \cdot \mathbf{v}_c}{\|\mathbf{v}_p\|\|\mathbf{v}_c\|}$$

where $\mathbf{v}_p$ and $\mathbf{v}_c$ are the term-frequency vectors for professor p and course c, respectively. This method captures lexical overlap but does not account for the relative importance of terms or their contextual meaning.

TF-IDF-Based Approaches. The Term Frequency-Inverse Document Frequency method (3) improves on the Bag of Words approach by incorporating term importance. The weight $w_{t,c}$ of a term t in a course c is calculated as:

$$w_{t,c} = \text{TF}_{t,c} \cdot \log\left(\frac{N}{\text{DF}_t}\right)$$

where $\text{TF}_{t,c}$ is the term frequency of t in c, DF_t is the number of documents containing t, and N is the total number of documents. Both professor and course texts are represented as TF-IDF vectors, and cosine similarity is used to compute alignment scores. Three variations of this method were tested:

1. Unweighted TF-IDF: In this approach, the TF-IDF vectors for professors and courses are constructed without any additional weighting of terms.
2. Weighted TF-IDF: To enhance the representativeness of professors' profiles, weights are assigned to specific terms based on their relevance. Each term in the professor's dataset has an associated value of importance. These values are used to weight the terms so that the Term-Frequency is not based on the raw occurrence count, but rather on the weight of its importance. This approach gives greater importance to terms that are more reflective of a professor's research focus.
3. Weighted and Normalized TF-IDF: To ensure that the professor represented vector has a similar magnitude as the courses represented vectors , we normalized the term weights using Min-Max scaling.

[*] Github repository for the DTU course browser: https://github.com/JonatanRasmussen/dtu-course-browser

[†] Scholia: https://scholia.toolforge.org

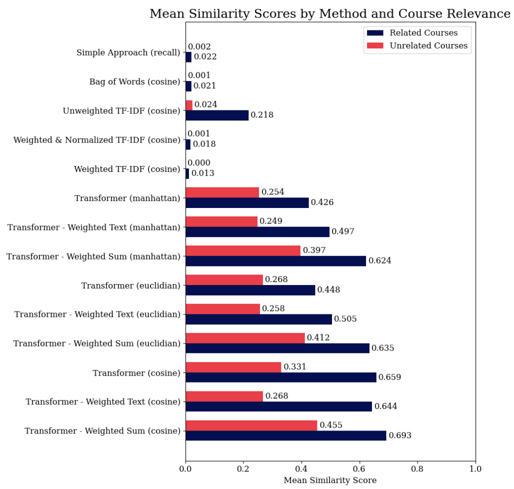

Fig. 2. The mean similarity scores obtained from various methods for courses categorized as related (blue) and unrelated (red) to specific professors' research areas. Non-transformer methods show similarity scores close to zero, suggesting they might not be the most optimal in order to capture meaningful scores. On the other hand, transformer-based approaches show a more clear distinction between related and unrelated courses, with the Transformer - Weighted Text (cosine) method achieving the most significant difference.

Transformer-Based Approaches. For a more nuanced understanding of professor-course alignment, we used a pre-trained transformer model. Encoder transformer models generate dense vector embeddings for textual inputs, which can effectively capture semantic meaning beyond simple word overlap (4). The specific model used was *Stella 400m* ‡ which is based on (5) and (6). While specific training details are unknown, the model is trained by Matryoshka Representation Learning (7).

Once again, we tried several variations:

1. Unweighted Transformer Embeddings: Embeddings were generated for raw professor and course texts, and cosine similarity was used to calculate alignment scores.
2. Weighted Text: Text inputs for the transformer model were augmented by repeating key terms proportional to their associated scores (e.g., normalized Scholia topic scores). This way we emphasized important research topics in the embedding process.
3. Weighted Sum of Embeddings: Instead of concatenating text, embeddings for each professor were created from individual embeddings of different components (e.g., profile descriptions, fingerprint concepts, Scholia topics) and combined using a weighted sum:

$$\mathbf{e}_p = \sum_{i=1}^{n} w_i \cdot \mathbf{e}_i$$

where $\mathbf{e}_i$ is the embedding of the i-th component and w_i is its weight. This approach again ensures that the research importance is reflected in the embedding space.

Distance-Based Metrics. In addition to cosine similarity, Euclidean and Manhattan distances were used to measure the alignment based on professor-course distances in the embedding space. These distance metrics were converted to similarity scores as follows:

‡ https://huggingface.co/dunzhang/stella_en_400M_v5

Table 1. Comparison of Network Construction Methods

Method	Edges	Density	Components	Communities	Modularity	Clustering
Fixed Threshold (0.7)	3,844	0.007	338	349	0.792	0.410
K-Nearest Neighbors (k=5)	3,856	0.007	2	18	0.777	0.398
Statistical (z-score ¿ 2)	18,262	0.033	1	9	0.645	0.421
Adaptive Threshold (90th)	54,499	0.100	1	6	0.467	0.400
MST Plus (95th)	27,329	0.050	1	8	0.554	0.494

$$\text{Similarity(c,p)} = \frac{1}{1 + d_{\text{measure}}(e_c, e_p)}$$

where measure $\in$ {manhattan, euclidean} and e_c is a course embedding and e_p is a professor embedding.

Professor-Professor similarity. In order to answer our third research question we also applied the transformer based similarity approach on a professor-to-professor basis. This resulted in a $N \times N$ matrix of similarities where N is the number of professors in our dataset.

Grade and satisfaction alignment. Once we obtained the professor-course similarity scores we went on to investigate whether the alignment has any effect on the student outcomes (grades and course rating), we calculated the Pearson correlation coefficient. This metric quantifies the strength and direction of the linear relationship between similarity scores and these variables, providing insight into the potential influence of research-teaching alignment on student performance and satisfaction. The score value ranges from -1 to 1. Other coefficient correlation methods were considered such as Kendall correlation and Spearman correlation, however using these methods made no difference in the result of the correlation scores, so we used Pearson as this is a more common method in most statistical libraries.

Cross-institute collaboration analysis. Taking advantage of the calculated similarity between professors, we constructed a network to examine cross-institutional collaboration at DTU.

Network Construction. We evaluated five methods of establishing links between professors based on cosine similarity scores s_{ij} between professors i and j: *fixed threshold, k-nearest neighbors (k-NN), statistical significance, adaptive threshold, and minimum spanning tree plus (MST+).*

We selected the k-NN approach ($k = 5$) for our final analysis (Tab. 1), as it provided the best balance of connectivity and community structure while maintaining network sparsity. Community detection was performed using the Louvain method (8), optimizing modularity:

$$Q = \frac{1}{2m} \sum_{ij} \left[w_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j)$$

Cross-Institute Analysis. For each professor p, their primary institute affiliation I_p was determined by:

$$I_p = \arg\max_i f_p(i)$$

where $f_p(i)$ is the frequency of teaching assignments in institute i. The cross-institute connection matrix C was constructed where c_{ij} represents network edges between institutes i and j:

$$c_{ij} = |\{(p, q) \in E : I_p = i \wedge I_q = j\}|$$

This institute-level network was analyzed using Louvain community detection to identify clusters of closely collaborating institutes.

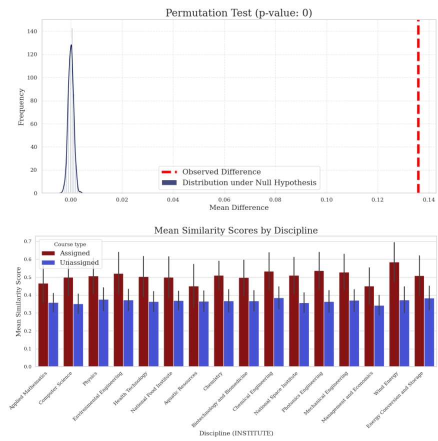

Fig. 3. Top: Permutation test comparing the observed difference in mean similarity scores between assigned and unassigned courses to the null distribution. The observed mean difference of 0.13 (red dashed line) is significantly greater than the differences generated under the null hypothesis (blue distribution), with a p-value of p = 0. This shows a strong evidence that professors are systematically assigned to courses that are more similar to them. Bottom: Mean similarity scores for assigned and unassigned courses across disciplines. Assigned courses consistently exhibit higher similarity scores compared to unassigned courses across all disciplines. The Wind Energy institute demonstrates the highest alignment between research and course content, while Management and Economics show the lowest alignment. Error bars represent standard deviations.

Results

Professor-course similarity (RQ 1).

Similarity methods. To evaluate the effectiveness of the various similarity approaches, we compared mean similarity scores for courses deemed related and unrelated to specific professors' research areas using our domain knowledge. The results are summarized in Fig. 2. While all methods consistently captured higher similarity scores for related courses compared to unrelated ones, the non-transformer methods produced values that were generally close to zero. This indicates that their vector representations might not be the best in order to adequately capture meaningful relationships between research and course content.

In contrast, transformer-based approaches showed significantly better performance. Among these, the Transformer method with weighted text achieved the largest difference in similarity scores between related and unrelated courses, and it was therefore selected as the method for subsequent analyses.

Discipline-specific alignment. To better understand the variation in professor-course alignment across disciplines, we analyzed the mean similarity scores of professors for assigned and unassigned courses within each institute (Fig. 3 (bottom)). We can see that across all disciplines, assigned courses consistently exhibited higher mean similarity scores compared to unassigned courses. The highest alignment of research and course content was observed in the Wind Energy institute, meaning that under our method this institute has the most professors who teach courses related to their research areas. In contrast, although still quite high, the Management and Economics institute and the Aquatic Resources institute exhibited the lowest alignment scores across all the institutes at DTU, indicating a less direct connection between research topics and teaching responsibilities in these fields.

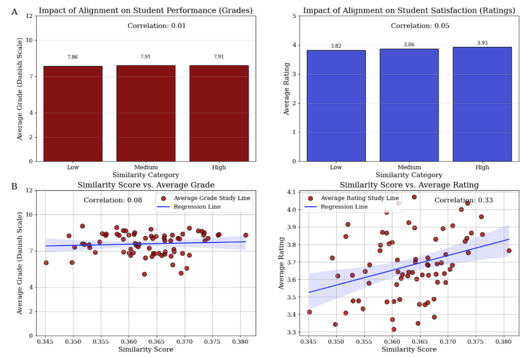

Fig. 4. Graphs showing the correlation coefficients between similarity scores (x-axis) and average grades/ratings (y-axis). (A) The data is binned into three categories based on similarity scores: low, medium, and high. The scores are calculated per course, not per category. Categorizations are for simpler data representation. (B) The red dots correspond to individual study lines (e.g. MSc. Computer Science, BSc. General Engineering). The blue regression line illustrates the relationship between the average grade/rating and similarity scores.

Statistical Test of Professor-Course alignment. To evaluate whether professors at DTU are systematically assigned courses more closely aligned with their research areas, we conducted a permutation test comparing similarity scores for assigned and unassigned courses. The observed mean difference in similarity scores was 0.13. Using 2,000 permutations, we generated a null distribution, as shown in Fig. 3 (top), alongside the observed difference. The observed mean difference was significantly higher than the null distribution, with a p-value of 0. We could therefore reject the null hypothesis and conclude that professors tend to be assigned courses that are more closely aligned with their research areas.

Grade and satisfaction alignment (RQ 2). A Pearson correlation analysis revealed no significant relationship between similarity scores and average student grades per course, see Fig. 4. The correlation coefficient of 0.01 indicates a negligible association. Similarly, the correlation between course similarity scores and course ratings was also very weak, with a score of 0.05, suggesting no meaningful relationship. Further exploration, considering the study lines, and calculating the correlation per study line, revealed no significant relationship between similarity scores and average student grades per study line. The correlation coefficient of 0.08, although slightly higher than the previous calculation (without considering study lines), still signifies a negligible association. The correlation between course similarity scores and course ratings per study line yielded a positive correlation coefficient of 0.33. Although stronger than the previous correlation without the study line, it still reflects a weak-to-negligible association.

Cross-institute collaboration analysis (RQ 3).

Network Structure. The k-NN ($k = 5$) professor similarity network comprises 1,046 nodes connected by 3,856 edges, resulting in a network density of 0.007. The network contains two connected components, with the Louvain algorithm detecting 18 distinct communities. The network has a high modularity score of 0.775 and an average clustering coefficient of 0.398.

Institute-Level Network. When analyzing collaboration at the institute level, the Louvain algorithm identified four distinct clusters of institutes. The first cluster consists of Applied Mathematics and Computer Science, representing quantitative and computational disciplines. The second cluster features seven institutes: Aquatic Resources, Biotechnology and Biomedicine, Chemical Engineering, Chemistry, Health Technology, KU - Copenhagen University, and the National Food Institute, primarily representing life sciences and biotechnology domains. The third cluster includes six institutes: BEng - Bachelor of Engineering, Environmental Engineering, Management and Economics, Mechanical Engineering and Wind Energy. The fourth cluster comprises Energy Conversion and Storage, National Space Institute, Photonics Engineering, and Physics, representing physical sciences and energy-related fields.

Cross-Institute Connections. The cross-institute connection matrix (Fig. 5) reveals varying levels of collaboration between institutes. The strongest cross-institute connection is observed between Mechanical Engineering and Environmental Engineering with 83 connections, followed by Mechanical Engineering and Wind Energy with 79 connections. Mechanical Engineering also shows the highest total number of external connections (476).

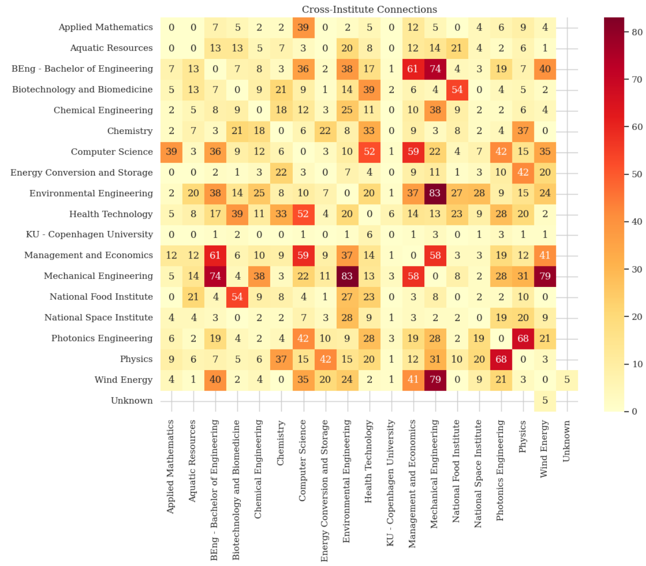

Fig. 5. Cross-institute connection matrix. Each cell (i, j) represents the number of connections between professors from institute i and institute j in the similarity network. Darker colors indicate higher numbers of connections.

Discussion

The findings of this study highlight the systematic alignment of professors' research areas with the courses they teach, the variability of this alignment across disciplines, and its implications for academic collaboration at DTU. The results for the first research question show strong evidence of intentional alignment, with professors assigned courses that closely reflect their research expertise. The statistical test demonstrated a significant observed difference in mean similarity scores between assigned and unassigned courses. This shows the university's efforts to leverage research expertise in teaching, which aligns with the broader goal of integrating research into education. While this alignment was consistent across all disciplines, the biggest differences were observed within the Wind Energy Institute achieving the highest alignment scores, while Management and Economics and Aquatic Resources showed comparably slightly lower alignment.

Interestingly, despite these efforts, the second research question revealed no significant correlation between research-teaching alignment and student outcomes, such as grades or satisfaction. This suggests that while aligning professors' research with their teaching assignments may enrich course content and offer students unique insights, it does not directly translate into measurable improvements in academic performance or satisfaction. Other factors, such as teaching methods, course design, and student workload, might play more influential roles. These findings open up avenues for further exploration, including examining the impact of alignment at finer levels of granularity, such as specific learning objectives or teaching styles.

The third research question highlighted the potential for cross-institute collaborations driven by shared research and teaching interests. Network analysis revealed that professors form distinct collaborative communities, with Mechanical Engineering playing a central role in fostering interdisciplinary integration, particularly with Environmental Engineering and Wind Energy. This emphasizes the potential of research-teaching alignment not only to enhance individual courses but also to facilitate broader institutional synergies. However, the relative isolation of computational disciplines like Applied Mathematics and Computer Science suggests opportunities for strengthening cross-disciplinary connections, which could enrich both teaching and research.

The overall findings of this study contribute to the ongoing discussion about the integration of research and teaching in higher education. While DTU demonstrates commendable alignment between professors' expertise and their teaching responsibilities, the results indicate that alignment alone is not all-important for improving student outcomes. Instead, it serves as a foundational element that, when combined with other pedagogical and institutional factors, can enhance the academic environment. These insights provide a framework for refining course assignment strategies and fostering interdisciplinary collaborations, not only at DTU but also at other institutions seeking to optimize the balance between research and teaching. Future research should aim to incorporate additional variables, such as publication data and qualitative insights, to provide a better understanding of these dynamics.

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