Learning Machine Learning:
A Comparative Study of Industrial Design and Computer Science Students

Exploring the Role of STEM Backgrounds in Foundational ML Education

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1. Background

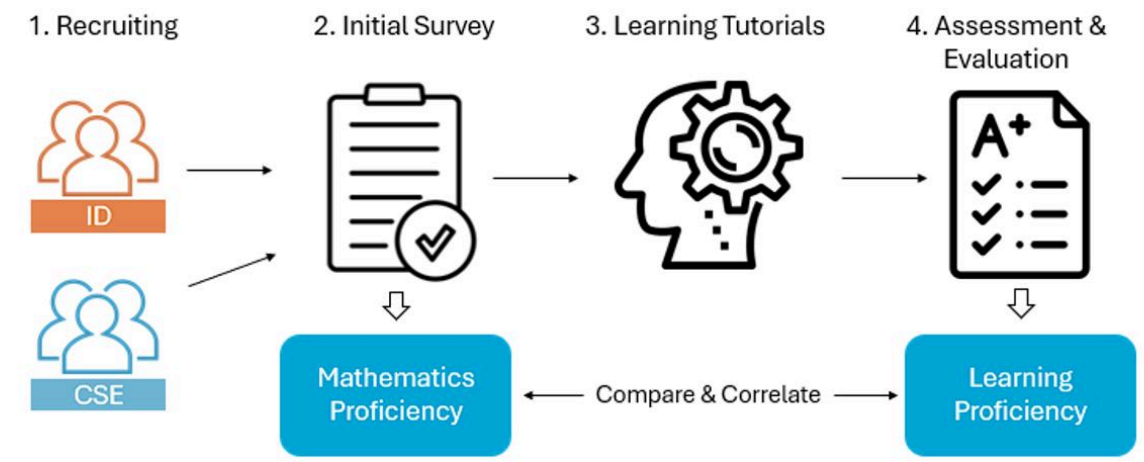
- Teaching machine learning is a challenge, especially for non-CS students. [1]
- Traditional ML education often assumes strong STEM backgrounds [1]
- Understanding how diverse academic backgrounds influence ML learning outcomes can help design more inclusive and effective teaching strategies [2], [3]

2. Research Question

- What are the **differences in learning outcomes** between **industrial design** and **computer science** students when introduced to **foundational machine learning topics?**
- How are these outcomes influenced by **prior mathematics knowledge**?

1. How do industrial design and computer science students differ in their prior knowledge in mathematics?
2. How does prior proficiency in mathematics correlate with performance on foundational ML topics?
3. How do students from these faculties perform on ML concepts with varying levels of relevance in mathematics?
4. What qualitative patterns emerge in the challenges students face while learning ML?

3. Methodology



The collected data are analyzed with:

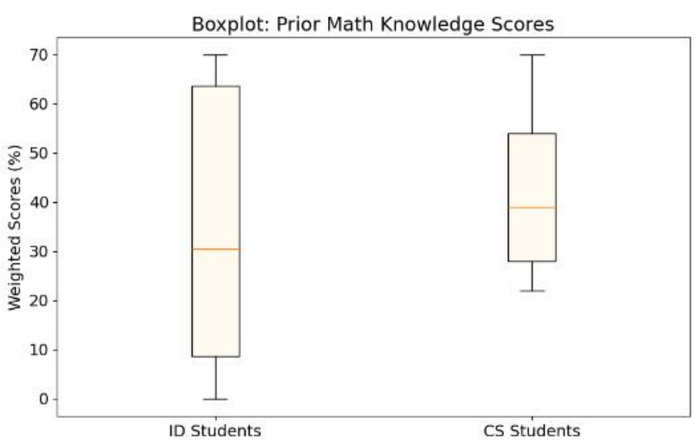
- **Mann-Whitney U Test** and **Kruskal-Wallis H Test** for comparing results
- **Pearson Correlation Analysis** for finding correlations
- **Thematic Analysis** for analyzing qualitative patterns

4. Results

1. Initial Mathematics Scores

CS students had a higher median score, but **no significant difference** in the scores was found with U-statistic of 53.00 and p-value of 0.4730.

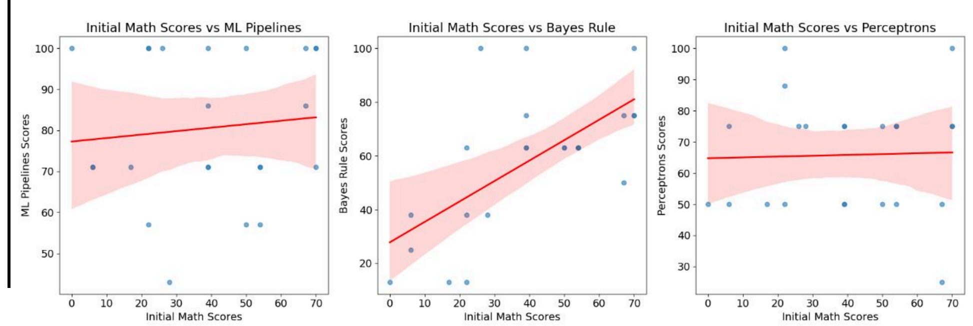
Group	Mean	Standard Deviation
ID	35.10	28.38
CS	43.08	16.04



2. Topic-Based Analysis

A **strong positive relationship** between the initial mathematics score and the performance on **Bayes' Rule** topic was found, but no significant relationship was found for other topics.

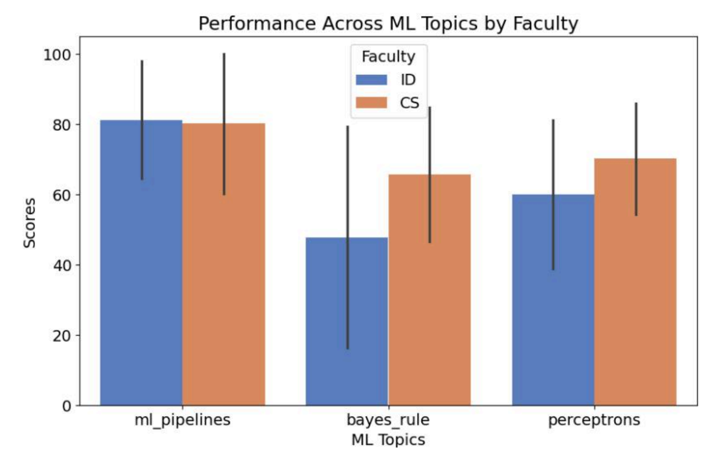
Topic	Pearson Coefficient (r)	P-value
ML Pipelines	0.10	0.6422
Bayes' Rule	0.64	0.0010
Perceptrons	0.03	0.8869



3. Faculty-Based Analysis

No significant differences in faculty performance for all topics.

Topic	H-statistic	P-value
ML Pipelines	0.01	0.9217
Bayes Rule	1.62	0.2026
Perceptrons	1.79	0.1807



4. Qualitative Patterns

Similarities:

- Found ML Pipelines topic easy
- Found Bayes' Rule topic difficult
- Visualization and real-life examples helped in the learning process

Differences:

- CS students found **Perceptrons** topic moderate, while ID students found it difficult
- CS students thought **programming** demos would be a good way to teach ML, while ID students thought interactive and **prototype-based** learning would work better

5. Conclusion

1. While prior **mathematics proficiency** significantly impacts performance on **math-intensive ML topics** such as Bayes' Rule, it has less influence on less math-relevant topics like ML pipelines.
2. Although CS students generally performed better on quantitative topics, consistent with their stronger mathematical backgrounds, ID students demonstrated **comparable proficiency** on less mathematics-intensive topics, highlighting their adaptability and potential to learn ML through interdisciplinary approaches.
3. Qualitative responses underscored the value of **interactive and visual teaching methods**, particularly for ID students, who emphasized creativity and practical application.

6. Future Work

- Increasing the number of participants to increase the generalisability of the result
- Including students from various faculties to uncover broader trends
- Tracking student performance over a longer period of time to incorporate more advanced contents
- Exploring a wider range of ML topics
- Designing and testing teaching methods specifically adapted for non-majors to provide actionable points for educators

References

[1] A. J. Ko. We need to learn how to teach machine learning. Bits and Behavior, 2017.
[2] Y. M. Banadaki. Enhancing the role of machine learning in stem disciplines through supervised undergraduate re-search experiences. Infonomics Society, 2020.
[3] N. Cheong. Machine learning algorithms for recommendation of learning cs courses in e-learning systems. In Proceedings of the 5th International Conference on Learning Analytics and Knowledge. ACM, 2022.