Analogies for Machine Learning Loss Functions

An Empirical Study on Understanding and Motivation

1 - Introduction

- Machine learning is increasingly essential across all sectors – from healthcare to agriculture, and from cybersecurity to e-commerce [1].
- Yet, educational methods for teaching machine learning concepts remain underexplored [2].

"We need to learn how to teach machine learning." – Amy J. Ko

- Loss functions are the mechanism by which ML algorithms are evaluated to be accurate or not, therefore it is of great importance that they are understood correctly.

Research question:

How does the use of analogies in explaining loss functions of machine learning algorithms affect the conceptual understanding and motivation to learn in Computer Science students?

2 - Research method

Analogy creation

Analogies for 10 ML loss functions were generated using ChatGPT-4o, designed to map abstract ML concepts to relatable real-world scenarios.

Expert evaluation

ML-literate participants ($n = 15$) rated the analogies using a structured survey, evaluating concept coverage, mapping strength, and metaphoricity [3] for each analogy.

Student testing

An A/B study with 22 first-year CS students measured the impact of analogies on conceptual understanding and learning motivation through pre/post quizzes and the RIMMS survey [4].

3 - Example analogy

Reconstruction error analogy

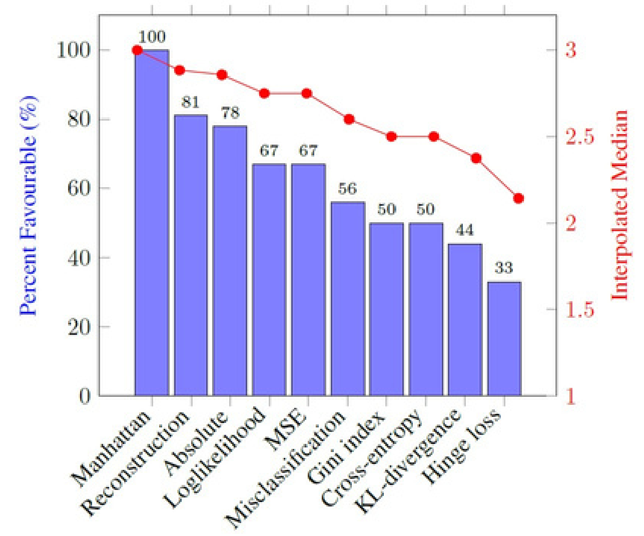
You saw a person and you're now describing them to a sketch artist who hasn't seen them. The sketch artist draws a portrait based on your description. Once finished, you compare the sketch to the real person. The more it differs, the higher the reconstruction error

4 - Research findings

Expert evaluations

Experts rated analogies for all 10 loss functions. The best-rated were those for Manhattan Distance and Reconstruction Error.

The agreement between raters was generally low across nearly every analogy.

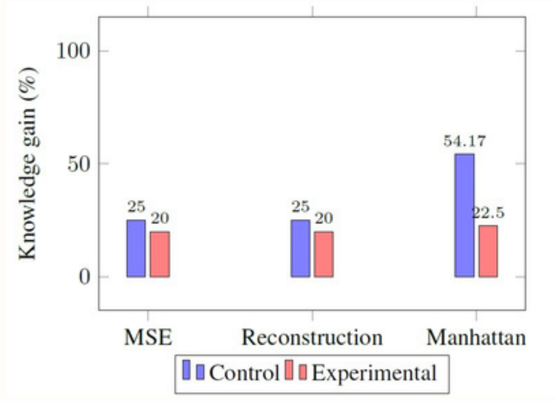


Student tests

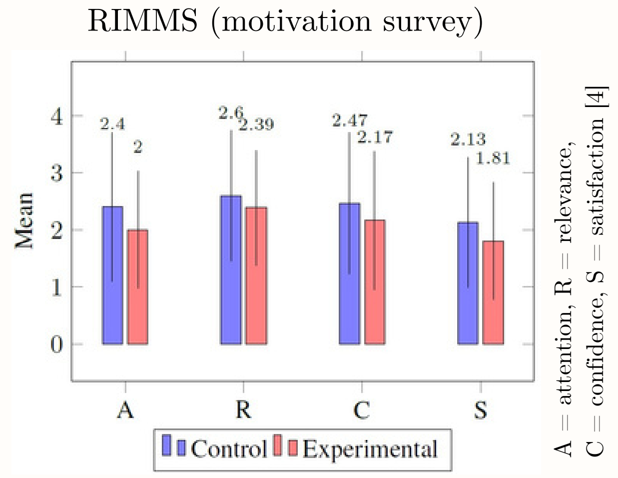
Knowledge gain:
Across the three tested analogies – MSE, Reconstruction, Manhattan Distance – no significant improvement in test scores was observed when analogies were included.

Motivation gain:
Students in the control group, having no analogies in their test, reported slightly higher motivation scores across all motivation categories, but differences were not statistically significant.

Knowledge gain across 3 analogies



RIMMS (motivation survey)



5 - Conclusion

- While the analogies were generally well-received by experts, student testing showed no conclusive improvement in either conceptual understanding or motivation to learn.
- Possible reasons for these results are: small sample sizes, increased cognitive load introduced by the analogies, or the analogies not being sufficient to increase the conceptual understanding or motivation of the students.
- The low inter-rater agreement could be attributed to the inherent subjectivity in rating analogies. Another reason could be the different educational backgrounds of the experts.
- Despite the inconclusive outcome, the study suggests further exploration, as analogies remain a promising tool in ML education. They have shown benefits in other, similar domains, like programming and computer science.
- This work contributes a reproducible framework for analogy evaluation and a set of 10 expert-rated and 3 student-tested analogies that can be adapted for future educational use.

Future work:
Future research should focus on the long-term effects of analogies on knowledge retention. Especially since loss functions are foundational concepts in machine learning, and will be required knowledge for any student in the field.

Scan the QR-code

For our website containing all analogies that this research project explored!

https://ml-teaching-analogies.github.io/

References

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