

The Ability of Technical Students to Think Realistically About Machine Learning

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Machine learning (ML) has a strong presence in our society. It is highly applicable in varied tasks, from image recognition to recommendation engines [4]. We can assume that ML will be used for various purposes beyond our imagination. Therefore, new ML applications' creators must understand its capabilities and data requirements, in order to properly consider user perspectives on data privacy and intrusiveness.

Previous research indicates that current UX designers are often unable to work with ML in new applications, and treating ML as a form of magic [1]. This means they hold unrealistic views about ML, leading to inaccurate expectations about its capabilities. Therefore, designers encounter difficulties in properly considering the user experience when creating a ML product [5]. We contribute to previous research by exploring whether such knowledge gap also exists for current technical students, and what could be improved.

RESEARCH QUESTION:

To what extent are current technical students able to realistically consider the capabilities, data requirements and application of machine learning, when trying to apply this by designing for an innovative and highly social context like a smart closet?

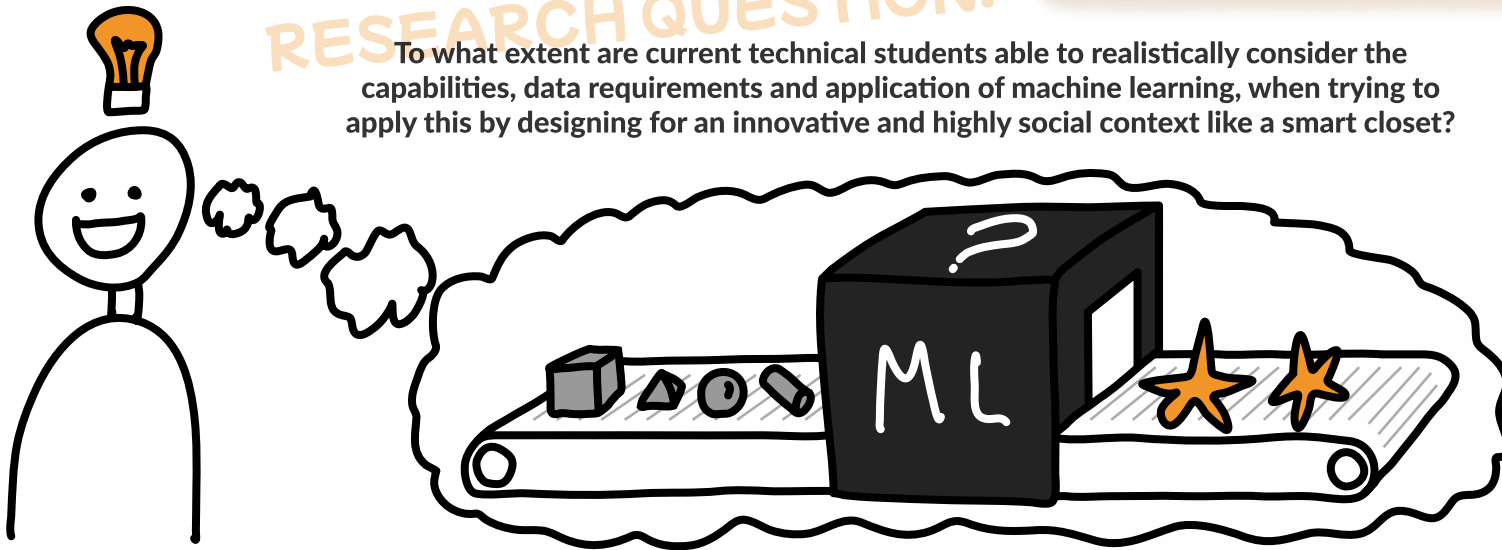


Figure 1: Machine learning is often treated as a form of magic, capable of anything, which is unrealistic

BACKGROUND

Our research goal is towards designing new and innovative ML applications with a highly social context, because we expect that ML in such context will require more personal data from users. Therefore, we decided to create a smart closet which can generate outfits. We view outfit generation as highly socialized, because an outfit can modify personal perceptions about someone [2,3].



Figure 3: Setup of co-design session

Through co-design sessions, we explored how well technical students can think about ML in a new and innovative concept like a smart closet. After presenting our UI prototype, the students were asked to determine features they would like in a smart closet, what data would be needed for those features, and how they would feel about the feature and its data requirements from a user perspective.

This method allows us to determine how accurate their expectations about ML capabilities and its data requirements actually are, and what needs to improve.

STUDY METHOD

First, we underwent a design process to determine the features of a smart closet, and the data needed for these features. Besides serving as a useful research artifact for our study, this process also generated knowledge and experience about crucial aspects when designing for ML.

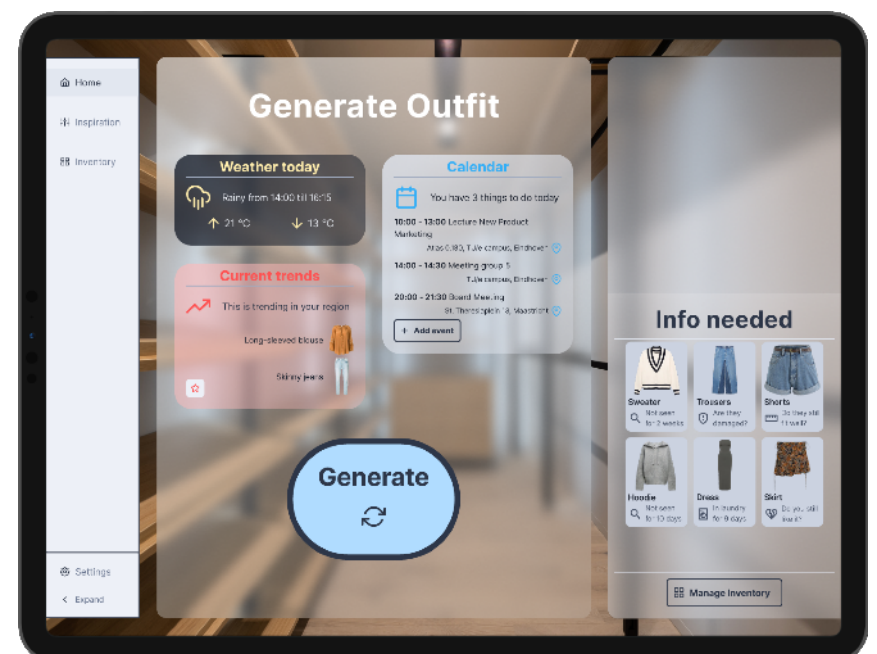


Figure 2: Our UI prototype for a smart closet, show features and data

Qualitative Results:

Of the required data for each feature written down by our participants, there were either too little datapoints for the feature to work, or many datapoints actually resembled features or functionalities instead of raw data. When reviewing the participants' features, many are not expected to function properly with only the data written down.

Quantitative Results:

Most participants considered the proposed features as worthy, acceptable, and non-intrusive. 76% of the responses to statements were in agreement with the features and the data collection required, which is an unrealistically high number in a highly social context like this one.

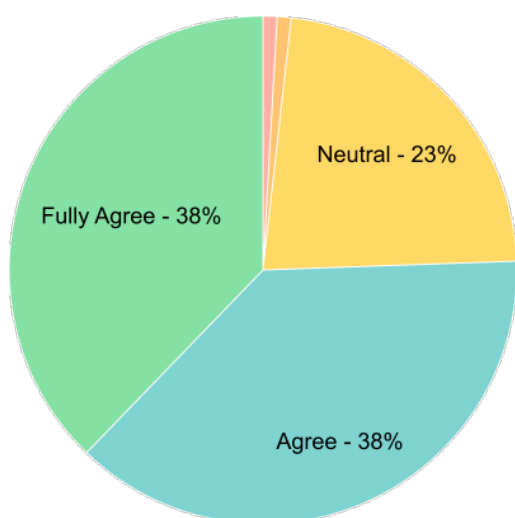


Figure 4: Distribution of participants' answers to statements regarding features and needed data, agree = positive

DISCUSSION

As shown in both the qualitative and quantitative results, participants demonstrated misconceptions and a general lack of understanding about ML. They were unrealistic about its capabilities, data requirements, and potential consequences when trying to implement it in a new and innovative concept. Such result aligns with previous literature stating that UX designers without previous education in ML often feel like it is magic [1].

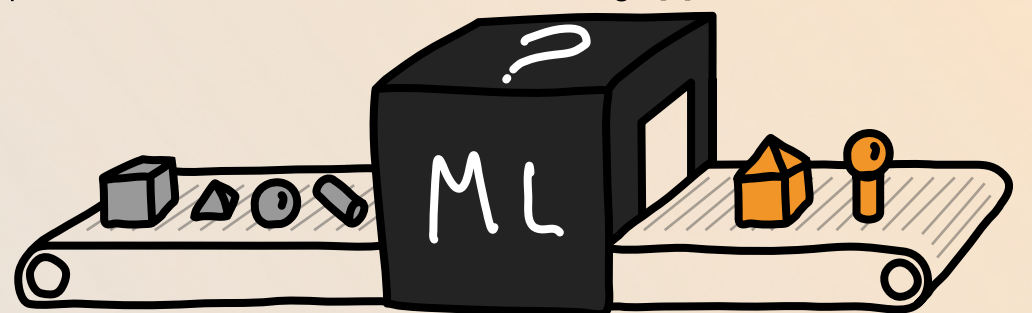


Figure 5: No need to learn how to program ML, only what it can do and what it needs

This research reveals that technical students may lack a realistic understanding of ML and its implications when applying it to a new concept in a highly social context. Since ML is applicable in various fields, we advocate for increased ML education in ML-applicable studies outside of computer sciences and data science. They don't need to learn exactly how to make it, only what it can do and what it would need.

[1] Graham Dove, Kim Halskov, Jodi Forlizzi, and John Zimmerman. 2017. UX Design Innovation: Challenges for Working with Machine Learning as a Design Material. In Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17), Association for Computing Machinery, New York, NY, USA, 278–288. DOI: <https://doi.org/10.1145/3025453.3025739>

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[5] Qian Yang, Aaron Steinfeld, Carolyn Rosé, and John Zimmerman. 2020. Re-examining Whether, Why, and How Human-AI Interaction Is Uniquely Difficult to Design. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20), Association for Computing Machinery, New York, NY, USA, 1–13. DOI: <https://doi.org/10.1145/3313831.3376301>