Addressing Sustainable ML Life-cycles through Human-Centered Design

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Sustainability is a subject that has gained growing importance in the disciplines of human-computer interface (HCI) and machine learning (ML). While previous work has often focused on the end-user of a system or the system itself, we would like to emphasize the developer's role in making more sustainable decisions across the entire ML life-cycle. We outline selected articles briefly before moving on to discuss relevant aspects that developers should consider at each stage to make more sustainable decisions. With this paper we hope to contribute to a broader discussion on building and developing a more sustainable future.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**; • **Social and professional topics →** *Sustainability*.

Additional Key Words and Phrases: Sustainability, sustainable HCI, sustainable ML, Life-cycle management

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1 INTRODUCTION

Sustainability is becoming a more pressing issue in the human-computer interaction (HCI) [1] and machine learning (ML) [11] communities. The environmental impact of this constantly increasing growth in data, models, and systems becomes more relevant as ML approaches become more widely used [12]. Nevertheless, both communities often approach sustainability through different lenses. While many papers in sustainable HCI have taken on a more holistic view on the impact of systems on environmental, economic, and social aspects [1], sustainable ML has so far primarily focused on improving the training phases or algorithms [12]. In contrast, we aim to explore how human-centered design practices can be used to support more sustainable ML development throughout the entire life-cycle of systems, by defining the various impacts of ML systems and proposing strategies to mitigate these impacts, including data collection, model training, and recycling. Rather than solely focusing on optimizing algorithms, it is imperative to redefine the life-cycle of ML models to support sustainable actions through human-computer collaboration. Our objective is to create tools that help ML practitioners understand how a certain decision affects the environment and guide them in identifying suitable, more environmentally friendly models for their projects. By doing this, we intend to promote not only the use of more data- and energy-efficient training and optimization techniques for algorithms but also encourage more reuse and recycling of existing models, to reduce the overall power usage.

2 RELATED WORK

We start with briefly introducing current work in sustainable HCI and ML, as well as on ML life-cycle management.

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The perspective of Sustainable HCI: Sustainable HCI (SHCI) focused initially on individual behavior and follows a strategy based on how to the user aware about his actions [5]. DiSalvo and colleagues, for example, advocated for a persuasive strategy based on technology that uses eco-feedback to provide users with information about their energy consumption [3]. Many have objected to this approach on the grounds that users are rational consumers [1] and that methodologies commonly used in HCI, such as rapid prototyping, user involvement, and iterative design, can rather allow for early and increasing feedback when developing interactive systems [4]. In a recent review on existing work on sustainable HCI and its critiques, the authors concluded that the HCI community "should challenge the narrative that we can rely on technology to save us, just as we challenged the narrative that climate change is an individual behaviour change problem" [1]. Among the suggested directions emphasized by this review is that technology may give clarity to the complicated dynamics of multiple emission sources, including that of technology itself. In line with such work, we suggest using a human-centered approach we want to address a more holistic picture of sustainable development and the ML life-cycle. While the sustainable ML community frequently addresses sustainable development, we believe there is a major potential to apply such techniques to improve decisions made by developers when designing systems, such as the requirement for and utilization of data and the algorithms applied.

The perspective of Sustainable ML: Within the sustainable ML and artificial intelligence (AI) community there are two main branches of work: ML for sustainability and sustainability of ML [11]. The majority of work on ML for sustainable focuses on building ML models to predict the impact of technology, such as renewable energy [7] or electric cars [10], on the environment. On the other hand, sustainability of ML addresses how to enhance data collection, power sources, and infrastructures as well as how to quantify and lower the carbon footprint associated with developing and fine-tuning an algorithm [6]. Strubell et al.'s work [9] in particular has pushed the ML community to prioritize the carbon footprint of ML models on their research agenda. Their carbon footprint analysis of training their own models led them to the conclusion that we need to lower the carbon footprint of building and operating ML models, which received large echo throughout the community [12]. In line with this perspective, Wynsberghe in a recent article defined Sustainable AI/ML as:"a movement to foster change in the entire life-cycle of AI products (i.e. idea generation, training, re-tuning, implementation, governance) towards greater ecological integrity and social justice" [11]. He further emphasizes that sustaining environmental resources for present and future generations, societal economic models, and core societal values should all be compatible with developing ML systems. We see several overlaps in such a perspective with the previously outlined goals of sustainable HCI, and would like to highlight the role the HCI community may play in such an endeavor through our work.

Perspectives on ML Life-cycles: Our work aims to raise awareness of sustainable decisions and their consequences throughout the ML life-cycle. Among the first ML life-cycle model developed was the CRISP-DM in 1999 (Fig. 1.left) [8]. It is based on the premise that training and data management, in particular, significantly add to the overall carbon footprint of ML applications [13]. While it was primarily developed for Data Mining processes, it has gained wider acceptance for representing ML life-cycles in general [8].

It contains six distinct phases: The fundamental problem and user demands, as well as the project's objectives and requirements, are determined during the **Business understanding** phase. **Data understanding** refers to collecting data and identifying data quality issues. In the **Data preparation** phase the improved dataset is prepared, which often includes data analysis, data cleaning, and data transformation. In the **Monitoring** phase different modelling techniques

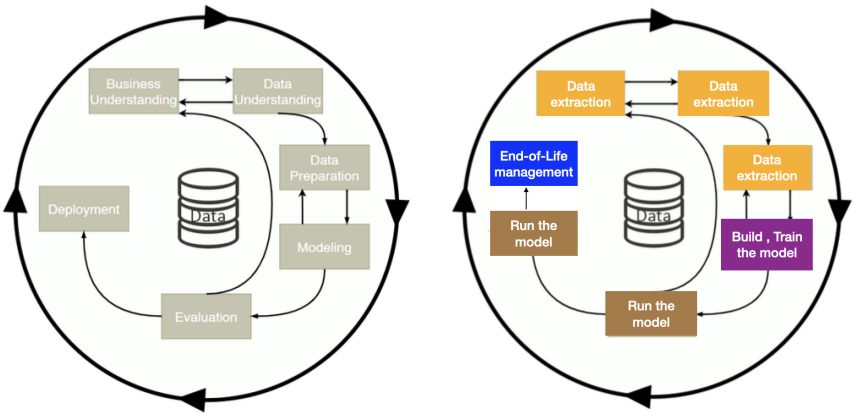

Fig. 1. The original CRISP-DM Life-cycle [8] (left), adapted Life-cycle from CRISP-DM (right)

are explored, selected and calibrated. The model is then examined during the **Evaluation** phase to ensure that it meets the established objectives. Finally, the resulting model is applied in the context of use during the **Deployment** phase.

Later work has adapted the CRISP-DM model [2] and reduced it to four phases (for comparison we marked these phases within the initial CRISP-DM model in Fig. 1.right). It contains a more general **Data extraction** phase, which covers the identification of the main problem, the collection of necessary data and the transformation into a dataset. The second **build and train the model** phase comprises selecting the appropriate algorithm and train it on the prepared data. The third **Run the model** phase involves all actions required to integrate the model into the production system. These may include evaluating parameters, interpreting the results, and identifying any areas for improvement. In the fourth **End-of-Life management** phase, different modelling techniques are tried out to reuse the final results, metrics and model's performance. We continue to discuss potential methods and approaches to assist developers at each stage of making more sustainable decisions.

3 SUPPORTING DECISION MAKING FOR SUSTAINABLE LIFE-CYCLES IN ML

Supporting more sustainable decision making for ML life-cycles entails a number of considerations, including ethical data collection, energy-efficient training and deployment, ongoing monitoring, and responsible retirement of models and data. From one step to the other during the ML life-cycle, the developer should be aware of the impact of their action in either the model building or using. This includes comparing model alternatives based on their impact on the environment and collecting only relevant data necessary for the task at hand.

Developing ML algorithms that prioritize sustainability as a key objective requires new approaches. Our focus is to develop tools that explain to ML practitioners how a given algorithm impacts the environment and assist them in identifying appropriate, more sustainable models for their projects. We hope that by doing so, we can encourage the use of more energy-efficient models, as well as more data-efficient training and optimization strategies for algorithms, thereby lowering overall power consumption. To illustrate our vision, we modified the previously mentioned ML life-cycles (Fig. 2) to address more sustainable concerns.

Project understanding: Describing desired ML model characteristics and expressing the project's goals, before choosing a model requires users to express possibly ambiguous or contradictory objectives. Therefore, developers usually depend on their own personal experience or on existing well-documented ML models and toolkits. As a result,

supporting developers to find more suitable, energy-efficient alternatives is critical to achieve more sustainable ML practice overall. We emphasize the importance for enabling developers to better compare project goals and constraints, such as maximum training time, amount of training data, or favoring speed over accuracy, in order to assess trade-offs. The HCI community has previously demonstrated in other domains how iterative processes can help users explore and narrow down their needs and ideas to achieve a specific goal. In a similar way, we intend to gather more information by focusing on the user's current understanding, knowledge, and perspective through interviews and observations in order to design products that allow them to iteratively express their needs. We suggest more research to identify the understanding of ML experts before selecting a model to build tools encouraging suitable and more sustainable models.

Data Extraction: Data management, which includes data storage, processing, and sharing of datasets can have a high impact on the environmental impact of a ML application. In order to avoid energy waste, developers need to be made aware of the minimum criteria for the collected data relevant to their current problem to avoid over-collection.Depending on the task, this could include the change from a deep learning approach to a model requiring less data or even a human-in-the-loop approach. This entails tools to aid developers to better understand the trade-off between accuracy, amount of data needed, and means to explore the quality of the data based on their current scenario. Further, sustainable data management also has to address potential issues with data ownership and governance. Addressing such issues early-on, requires redefining of what data quality means including the impact on the environment, as much as on the human and society it reflects. This could be addressed by developing new data visualization, data labeling, or data cleaning techniques that take into account ethical and societal concerns. In addition to addressing significant ethical issues, this could help guarantee that the data is both useable and effective for its intended users.

Building and Training the model: Using energy-efficient hardware, optimizing algorithms to reduce the number of iterations required, and using pre-trained models or transfer learning to reduce the amount of training required are all ways to optimize the training process to reduce energy consumption. However, ML experts may be unaware of such alternatives, and how to explain and visualize such differences remains an open question. Given the circular relationship between ML algorithm design, development, and deployment, it is critical to consider the re-usability and recyclability of hardware and infrastructure. Furthermore, the development of ML models that can be repurposed and adapted for different use cases. Using the prototyping concept, we see a need to create digital abstract models that represent the final ML algorithm. It enables developers to test and refine their ideas before finalizing the system by identifying reuse opportunities while also easier considering alternatives. In terms of technological systems, this is still a neglected topic in sustainability research.

Deployment: It is critical to better understand the needs and limitations of both users and stakeholders involved in the deployment process before deploying ML models. Conducting usability testing on the ML model and interface, for example, can assist in identifying any issues related to ease of use, user satisfaction, or efficiency. This may entail testing with a small group of users and incorporating feedback into the design before releasing models that would otherwise have to be retrained or adapted later due to incorrect configuration or interaction design.

Monitoring: Legacy software and hardware are a large source of energy waste. While most system monitoring observes and addresses errors, it ignores the potential of improving ML model performance. We believe that additional monitoring during the life of an algorithm, with a particular emphasis on energy reduction, can aid in identifying

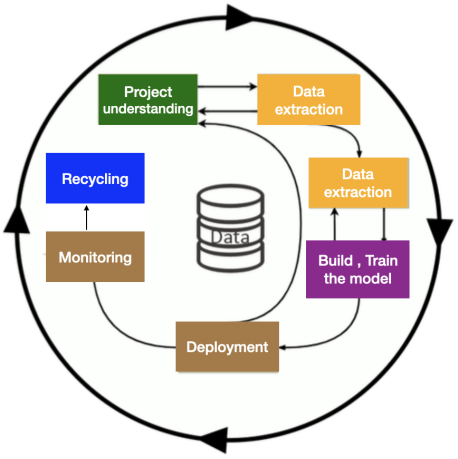

Fig. 2. Suggestion of a sustainable ML Life-cycle

issues or inefficiencies that may be affecting the overall sustainability in the long-term. Reducing the gap between ML model developers and users by collecting regular feedback on user needs as well as technological advancements allows existing models to remain relevant for longer while avoiding unnecessary re-runs of existing model solutions.

Recycling: We think it is important to consider several aspects in this phase: 1) Establish guidelines for retiring ML models that are transparent in terms of the system's purpose/use as well as any data related with these models, which should be handled responsibly. This may involve deleting data or securely storing it to prevent unauthorized access. 2) Enable the reuse of the results and the data of the previous running model to avoid unnecessary retraining and deployment.

4 DISCUSSION

So, why is it that current ML models are so unsustainable? To address current ML models' sustainability issues, we must reconsider our understanding, selection, and maintenance of these models. There is a number of common assumptions regarding successful ML models, which are (1) a model has to fit all possible cases; (2) more data equals more precision; and finally (3) higher precision and recall are always better. We see two major challenges with (1): developers and stakeholders are quite often unaware of a model's long-term use and application, and this ignores the constantly changing environments and needs of users, resulting in constant adaptation and retraining throughout the entire ML life cycle. Instead, focusing on a specific use case, including end-users during the development and allowing models to learn over time or connect to other models may help to avoid such wasteful efforts. The general drive for more data (2) has resulted in an increase in the amount of training data, which necessitates extensive computing resources and can have a significant carbon footprint. We believe that data quality and relevance should be prioritized, which necessitates a better understanding of the data source, for example, by investigating alternative approaches such as human-in-the-loop data labeling. Aiming for high precision and recall in ML models models (3) favors the use of complex and computationally intensive models that are difficult to scale and maintain. Instead, involving the user in model training may reduce the need for large amounts of data and computation. Overall, we think that it is not always necessary to create and train new models because improved recycling infrastructure may enable the reuse of models that have already been trained. Better documentation, explainability, and transparency during model development, on

the other hand, are required to enable such practice on a broad scale. To reduce the size and carbon footprint of ML models, some of the underlying assumptions and approaches that have traditionally guided ML development must be reconsidered. By focusing on more tailored, efficient, and sustainable approaches to ML development, we can help to reduce the environmental impact of these technologies.

Outlook: Supporting democratization of ML approaches

We hypothesise that taking a more iterative human-centered approach that helps developers express their goals, explore alternative models, and explains and guides developers through the ML development process and beyond has the potential to make ML models more accessible and easier to use overall. Such democratization of ML approaches refers to the idea of providing a broader community with access to knowledge, tools and resources.

This includes also promoting more ethical and responsible use of ML models. As ML becomes more widespread, we think that guiding such development in a more sustainable way and aiding user to better understand the limitations and potential biases of these models would benefit society overall. Increased understanding and accessibility would also enable users to recognize when and how to use ML models appropriately, as well as interpret and communicate the models' results to others. More research and development of new and innovative approaches to problem-solving and decision-making, however, is required to enable such future.

5 CONCLUSION

To create sustainable approaches for ML life-cycles, multidisciplinary collaboration and a multi-stakeholder strategy that considers the social, economic, and environmental implications of ML algorithms are required. As our understanding of sustainable ML approaches continues to develop, it is critical to integrate constant learning and adaptation in the ML life-cycles itself. This involves taking into account the energy efficiency of hardware and infrastructure as well as the carbon impact of ML algorithms. This also requires further effort to examine the environmental implications of decisions taken along the ML life-cycle, as well as to support the development of sustainable metrics and standards in this respect, which is in line with prior notions on "Green Policy Informatics" [1]. Finally, we must promote increased openness and accountability in the design and application of ML algorithms, ensuring that people and communities affected by these algorithms, through data or interaction, have a say in the processes of decision-making.

We believe there is a significant opportunity to develop more ethical and sustainable methods to addressing these issues through more human-centered approaches. Machines cannot understand the user requirements for a new ML-based system on their own. As a result, Human-AI collaboration can aid in balancing user needs in a sustainable manner. This paper offers a fresh look at the ML learning life-cycle in order to promote more sustainable action. I, the first author, am a first year PhD student with a strong technical background, and I am looking forward to extend my network among the HCI community focusing on Sustainable HCI. I hope my perspective can encourage interesting discussions among the workshop participants on how to restrict the environmental effects of ML algorithm during its life-cycle.

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