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Projekt Report

AI Model Cards - a new concept to standardize environmental reporting for AI model

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1. Introduction

AI Models are on the rise - most prominently ChatGPT by OpenAI pushed into public perception when it was released in November 2022. Since then it showed an unprecedented rise in usership: compared to all other well-known internet services like Instagram, Spotify, Dropbox, not to mention Facebook, Twitter and Netflix, none has reached 1 Million users quicker than ChatGPT (Reuters 2023). While it has still to be seen how and where AI can be applied, it is without question that there is a high level of curiosity towards the future of AI.

Albeit humanity is not only facing the challenge of how to cope with AI, but also that of the climate crisis. Therefore all development and usage of AI has consequences towards reaching the Paris Agreement. Speaking of the environmental level of sustainability, it is also important to stress that AI can be used to improve that sustainability (or not), while keeping in mind that the development and the usage of AI has environmental implications by itself.

This report will give an overview over the current situation of AI, namely the publication of so-called AI model cards, which are non-standardized information sheets about how an AI is working. On the basis of two AI life cycle concepts, which show where environmental issues can occur, a Green AI Model Card is developed to give detailed insights into the sustainability of AI models and make them easily comparable.

2. Findings and Limitations

More than 35% of businesses worldwide use/deploy/integrate artificial intelligence (AI) technologies in their businesses presently (Forbes 2023). However, few AI companies have published Model Cards, and even fewer have incorporated environmental impact indicators (Github 2022). This section provides an overview of the research problem, the motivation behind the study, and the research objectives.

With approximately 35% of businesses worldwide utilizing AI, our research revealed a significant lack of published Model Cards, especially those addressing environmental concerns (Odeon 2023). Surprisingly, even renowned companies that participated in expert committees focused on measuring the environmental impacts of AI computing and applications, such as IBM and Nvidia, have failed to publish Model Cards with relevant environmental impact indicators (OECD 2022). This led us to explore the reasons behind this lack of transparency, considering factors like legal requirements and a limited understanding of sustainability indicators. To address this gap, we extensively reviewed the literature to identify suitable indicators to help assess AI models' environmental impacts. From our analysis, we identified a comprehensive set of around 60 indicators; however, due to time constraints, this report will focus on significant indicators classified as environmental impact indicators for the AI hardware lifecycle and AI software lifecycle.

To establish a foundation for our analysis, we conducted an extensive literature review focusing on existing research, publicly available data, and peer-reviewed academic papers. The review aimed to identify the current state of sustainability indicators in AI model documentation and explore the environmental impact indicators relevant to AI hardware and software lifecycles. The methodology we have used to gather data and identify the sustainability indicators is mainly a review of literature, scholarly articles, various published reports, and export committee findings on the environmental impact indicators of AI models.

The findings are presented in two sections: environmental impact indicators for the AI hardware lifecycle and environmental impact indicators for the AI software lifecycle. Each section provides a comprehensive analysis of the selected indicators, discussing their relevance, significance, and potential application in assessing the environmental impact of AI models. We emphasize the limited availability of standardized and validated data on the environmental impacts of AI computing, resulting in reliance on existing research and publicly available information.

The discussion section critically examines the findings and highlights the implications of the limited inclusion of environmental impact indicators in published Model Cards. It explores potential reasons for this deficiency, such as the absence of legal mandates and a limited understanding of appropriate indicators. Furthermore, it discusses the importance of enhancing transparency in AI model documentation to address the environmental concerns associated with AI technology.

Our study highlights a significant gap in including environmental impact indicators in AI company Model Cards. Despite the increasing adoption of AI technologies, most companies fail to publish Model Cards or include relevant sustainability indicators. By identifying about 60 potential indicators and presenting a focused analysis of significant indicators, this research lays the groundwork for future improvements in AI model documentation. We emphasize the need for standardized and validated data to enhance further understanding and assessment of the environmental impacts of AI computing and applications.

Based on the findings and discussion, the further section provides recommendations for AI companies, policymakers, and regulatory bodies to enhance the inclusion of sustainability indicators, specifically environmental impact indicators, in AI company Model Cards. The publication of sustainability indicators is essential to promoting transparency, accountability, and sustainability in AI technology.

Finally, we clearly felt the areas for future research, emphasizing the need for developing standardized frameworks for environmental impact assessment, exploring legal requirements and regulations pertaining to sustainability reporting in AI, and fostering industry-wide collaborations to address the identified gaps.

3. Sustainability indicators - AI Hardware Lifecycle

When looking at the Life-Cycle of an AI Hardware there are six stages in total which have various sustainability challenges that need to be addressed.

Production

The main sustainability challenge we have identified in the production process is the extraction of raw materials. To build new and more efficient chips as well as other technical elements, often new material is needed and especially rare materials are in high demand. The extraction process is a key source of emissions which is why the indicators we chose aim at capturing this issue. We suggest using the metric “Share of recycled raw materials” [%]. This metric would allow users to see whether new materials were extracted all over again or if a company instead chose to use recycled materials where possible, and therefore is contributing to the circular economy.

Transport

This stage is usually very difficult to capture and to isolate the sustainability effect from other stages. Nevertheless, in order to attempt to measure the emissions resulting from this stage we suggest using “Length of transportation route” [km] as a proxy from which approximate emissions can be calculated. The calculation would follow the standards set by the GHG Protocol by which the emissions factor needed for the calculation is determined by the fuel used for transportation as well as method of transportation.

Operation

During the operation process, multiple sustainability challenges can arise. Operating a datacenter usually requires a lot of energy and electricity and the datacenter has to be kept cool. To capture these two challenges in particular we suggest using “Power Usage Effectiveness (PUE)” as an indicator. As the name suggests PUE measures the effectiveness of a datacenter in using its energy. In addition, to also include the cooling process, we recommend using the indicator “Location of operation”. This is a particularly interesting one because the location of the datacenter and where it operates has a direct effect on its water consumption for cooling. Operating in climate zones known for high temperatures requires much more water to cool down the datacenter than operating on locations with cooler temperatures. For this reason, we argue that including this indicator in AI model cards is critical.

Further Development

Companies have incentives to continually improve their hardware to increase efficiency. At the same time, this continuous improvement directly causes more waste since old hardware becomes obsolete. Acknowledging the need of companies to desire more efficient hardware, we suggest the “climate-related efficiency” indicators as a way to measure the sustainability impact. This indicator measures how much materials will be needed as input and how much efficiency gains can be expected from the new hardware. The ideal scenario is that a small amount of new materials is needed for very large efficiency gains. This indicator will allow users and companies to evaluate whether the improvement of the hardware is justified when comparing input and output.

Beyond-Life
When looking at the final two stages of AI hardware Life-Cycle the main sustainability challenge is waste. Because AI hardware is not needed anymore because it has either been replaced by more efficient hardware or has malfunctioned and cannot be used anymore it becomes waste. Even though waste cannot always be prevented, how the waste is being treated and being disposed of can have huge environmental impacts. For the Beyond Life stage one of the indicators we recommend is “Electronics Disposal Efficiency (EDE)” [%] which measures how much of specifically electronic waste has been disposed of in environmentally appropriate ways. In addition, we also recommend asking for “Share of waste diverted” [%] which measures how much of the overall waste has been recycled or reused.

End of Life
As for End-of-Life one very simple and standard indicator which we also endorse is to ask for the “Total amount of waste generated” [t]. This measurement gives an overview in absolute number how much running an AI model causes in waste overall and allows for comparisons between models while also supplementing the percentage disclosures.

4. Sustainability Indicators - AI Software Lifecycle

In addition to the AI hardware-related criteria, several indicators exist that relate to the software of an AI system. In general, the “life cycle” of AI software comprises six main stages: data acquisition, model training, model deployment, model adaptation, beyond-life, and end-of-life.

Data Acquisition

In data acquisition, negative environmental impact is mainly caused by the amounts of data needed to create a performant AI model. More specifically, repercussions for the environment in this stage can arise from the data generation process itself, data storage, and data preprocessing, all of which require computational resources. Software-related indicators of the environmental footprint include the *dataset size* (Schwartz et al 2020) commonly measured in TB, which comprises the data used for experimenting, training, and testing. Another criterion is the *share of newly generated data* in percent, which measures what percentage of the dataset has been newly generated instead of “recycling” from existing open-source datasets, thereby requiring additional resources for data generation, storage, and preprocessing.

Model Training

Model training commonly includes multiple experiments to tune the hyperparameters of the model (Schwartz et al 2020). For each of the experiments, the energy cost measured in kWh is a crucial indicator of the environmental impact, yielding the total *training energy cost (TEC)* (Mehlin et al 2023) in sum. If determining the energy cost is too complex, the *total runtime* (ibid.) of each experiment can be measured and summed, serving as an indicator of the TEC if combined with the hardware-related criteria proposed in the preceding section. In addition, the indicator *accuracy per Joule* (ibid.) measured in 1/J assesses the accuracy, latency, and energy trade-offs between models. It quantifies how much energy is required per unit of accuracy and is, thus, particularly suited for normalized model comparisons. Similarly, *climate-related efficiency* (Hershcovich et al 2022) considers marginal accuracy improvements relative to marginal input requirements. Another indicator is the *number of parameters* (Mehlin et al 2023) of the final model, which is directly correlated with the complexity of the computations and can easily be determined.

Model Deployment

In model deployment, also referred to as model inference, negative impact on the environment can result from excessive model usage and long inference times. Relevant criteria include the *inference energy cost (IEC)* (ibid.), which is the energy required to use the model for a single inference. Another important criterion is the *model usage intensity (MUI)* (ibid.), which is defined as the (estimated) average number of inferences performed during a model life cycle. It is particularly meaningful when multiplied with the IEC. Especially for large, open-source models, the (estimated) *number of model users* can be a valuable indicator of the environmental footprint of an AI system. A metric for algorithmic efficiency that is nearly independent of hardware and software settings is the *number of floating-point operations (FLOPs)* (Schwartz et al 2020), which is defined as the number of operations required to execute a specific instance of a model.

Model Adaptation

The stage of model adaptation focuses on any operational steps that go beyond model deployment, e.g., model fine-tuning or retraining, which can cause additional environmental repercussions. Potential indicators include the (estimated) *retraining energy cost per year* in kWh/year, which captures additional energy costs resulting from retraining requirements. Moreover, fine-tuning a large model can be quite resource intensive. Therefore, it can make a large difference in terms of environmental footprint whether a model can be used out-of-the-box or whether it requires domain adaptation in the form of fine-tuning. This can be captured by specifying the *fine-tuning requirements* of a model.

Beyond-Life

Some indicators cannot be assigned to a single stage within the life cycle of AI software, e.g., indirect environmental impacts resulting from the application of an AI system in industry, or the long-term impact of an AI model on future systems. To capture these effects to some extent, model creators should state their intentions on *open sourcing the model and/or the training data* (Hershcovich et al 2022), thereby indicating potential resource savings for future researchers and practitioners. Furthermore, the *expected environmental impact* (Hershcovich et al 2022) of the model application should be reported – qualitatively for now, quantitatively as soon as sophisticated forecasting tools are available.

End-of-Life

Lastly, the end-of-life stage is concerned with data retention, i.e., what happens to the data used for model creation at the end of the life cycle. If the data is retained for (potential) future usage, storing the data requires additional resources. Potential indicators include the *share of data retained* in percent and the *total amount of data retained* in TB.

5. How a future model card could look like

Example Model		
Life Cycle Stage	**Indicator**	**Value**
Data acquisition	Dataset size [TB]	**45TB**
	Share of newly generated data [%]	**80%**
Model Training	Training energy cost (TEC) [kWh]	**200 kWh**
	Accuracy per Joule [1/J]	**0.001 1/J**
Beyond-Life (Hardware)	Share of waste diverted [%]	**60%**
	Electronics disposal efficiency [%]	**90%**
...	...	...

This Figure shows what a future model card could look like. On the left side, the Life Cycle Stages are displayed, in our case Data acquisition, Model Training and Beyond-Life. In the middle the model card shows the respective indicators for the stages like Data size which is in our case 45TB or Training energy cost. On the right side the values for the respective indicators are displayed. The critical values are marked red to show the importance of these indicators.

With this model card it will be easy to compare different AI models and have more transparency. It was important to us to make this model card as easy to understand as the cards in the card game we mentioned in the beginning. This way the model card can be easily read, understood and compared to other model cards.

The next step would be to look at ways to make this model card obligatory for companies which used AI. In order to achieve this and to change the status quo, decision makers would need to be involved and convinced of the importance of these model cards.

6. Conclusion

In conclusion, this work provides valuable insights into the current state of AI model documentation and the incorporation of sustainability indicators, particularly those related to environmental impact. The findings reveal a significant lack of published Model Cards and a limited understanding of appropriate indicators, despite the widespread use of AI technologies by businesses worldwide.

The proposed sustainability indicators for the AI hardware and software lifecycles offer a comprehensive framework for assessing the environmental impacts associated with AI technology. These indicators cover various stages, from production and transport to operation, further development, beyond-life, and end-of-life. They address critical sustainability challenges such as raw material extraction, transportation emissions, energy efficiency, waste management, and data retention.

The importance of enhancing transparency, accountability, and sustainability in AI model documentation is emphasized in our work. The inclusion of environmental impact indicators in Model Cards is crucial for promoting responsible AI practices and enabling comparisons between different models. However, the current lack of standardized and validated data on the environmental impacts of AI computing poses a challenge.

Finally, we outline the importance of future research and action, including the development of standardized frameworks for environmental impact assessment, exploration of legal requirements and regulations for sustainability reporting in AI, and fostering industry-wide collaboration. To drive change and make the model card obligatory for companies using AI, it is necessary to involve decision-makers and convince them of the importance of transparency and sustainability in AI technology.

Overall, the findings and recommendations presented in this work pave the way for advancements in AI model documentation, providing a foundation for future improvements and facilitating the integration of sustainability indicators. By addressing the identified gaps and embracing a collective effort, the AI community can work towards a more transparent, accountable, and environmentally conscious use of AI technology.

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