Towards Climate Awareness in NLP Research

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Abstract

The climate impact of AI, and NLP research in particular, has become a serious issue given the enormous amount of energy that is increasingly being used for training and running computational models. Consequently, increasing focus is placed on efficient NLP. However, this important initiative lacks simple guidelines that would allow for systematic climate reporting of NLP research. We argue that this deficiency is one of the reasons why very few publications in NLP report key figures that would allow a more thorough examination of environmental impact. As a remedy, we propose a climate performance model card with the primary purpose of being practically usable with only limited information about experiments and the underlying computer hardware. We describe why this step is essential to increase awareness about the environmental impact of NLP research and, thereby, paving the way for more thorough discussions.

1 Introduction

As Artificial Intelligence (AI), and specifically Natural Language Processing (NLP), scale up to require more computational resources and thereby more energy, there is an increasing focus on efficiency and sustainability (Strubell et al., 2019; Schwartz et al., 2020). For example, training a single BERT base model (Devlin et al., 2019) requires as much energy as a trans-American flight (Strubell et al., 2019). While newer models are arguable more efficient (Fedus et al., 2021; Borgeaud et al., 2022; So et al., 2022), they are also an order of magnitude larger, raising environmental concerns (Bender et al., 2021). The problem will only worsen with time, as compute requirements double every 10 months (Sevilla et al., 2022).

A group of NLP researchers has recently proposed a policy document\(^1\) of recommendations for efficient NLP, aiming to minimize the greenhouse gas (GHG) emissions\(^2\) resulting from experiments done as part of the research. This proposal is part of a research stream aiming towards Green NLP and Green AI (Schwartz et al., 2020), which refers to “AI research that yields novel results while taking into account the computational cost, encouraging a reduction in resources spent.”

While branding NLP and AI research as green increases awareness of the environmental impact, there is a risk that the current framing, which exclusively addresses efficiency, will be perceived as the solution to the problem. However, we claim that climate awareness is essential enough to be promoted in mainstream NLP (rather than only as a niche field) and that positive impact must be an inherent part of the discussion (Rolnick et al., 2019; Stede

\(^{1}\)https://www.aclweb.org/portal/content/efficient-nlp-policy-document

\(^{2}\)GHG, CO2, and carbon are used interchangeably in this paper. CO2eq (or CO2e), i.e., carbon dioxide equivalent translates GHG other than CO2 into CO2 equivalents based on the global warming potential (Brander and Davis, 2012).
and Patz, 2021). Of course, we attribute benevolent motives to the authors of the proposed policy document. Nevertheless, we would like to avoid a situation analogous to a common phenomenon in the financial field, where companies brand themselves as green or sustainable for branding or financial reasons, without implementing proportional measures in practice to mitigate the negative impact on the environment. This malpractice is analogous to greenwashing. While this is a general term, one aspect of greenwashing is “a claim suggesting that a product is green based on a narrow set of attributes without attention to other important environmental issues” (TerraChoice, 2010).3 Our motivation is in line with the EU Commission’s initiative to “require companies to substantiate claims they make about the environmental footprint of their products/services by using standard methods for quantifying them. The aim is to make the claims reliable, comparable and verifiable across the EU – reducing ‘greenwashing’ (companies giving a false impression of their environmental impact).”4

The implied notion that more efficient NLP is sufficient for sustainability is misleading and even harmful: regardless of the extent of reduction, resources are still consumed, and GHGs are still emitted, among other negative effects. The current mindset aims, at best, to prolong the duration of this process, which is, however, one-sided and has one goal in mind: scaling up the performance of AI to satisfy the increasing demands from consumers given its novel capabilities. Concepts such as reciprocity with the environment or positive impact on it, which are central in some indigenous worldviews (Kimmerer, 2013), are excluded from the discourse: the aforementioned proposed policy document explicitly states that conference tracks and areas established as part of the initiative are “not meant for submissions which use NLP for positive impact on the environment, e.g., to mitigate climate change, but rather on efficient solutions for NLP. Moreover, like other general tracks, such as machine learning for NLP, this track is not dedicated to a particular application, but rather focuses on the methods for making models more efficient.”

Furthermore, the perception that carbon neutrality can be achieved by compensating for emissions by financial contributions, a practice referred to as carbon offsets. However, following such an approach is problematic because of a controversial and often misleading debate about this concept and the level of carbon prices required to achieve climate goals. The Intergovernmental Panel on Climate Change (IPCC) and various international organizations like the International Energy Agency (IEA) clearly state that mitigation activities are essential. Compensation activities will be necessary for hard-to-abate-sectors, once all other technological solutions have been implemented, and where mitigation is not (yet) feasible.5 Moreover, economic dynamic efficiency requires investments in decarbonization technologies to keep the climate targets within reach. Compensation activities, especially in the afforestation area, delay the needed investments. This delay might exacerbate the likelihood of crossing climate tipping points and/or yields to a disorderly transition to a decarbonized economy (European Systemic Risk Board, 2016).

Another research stream (see §4.1) provides researchers with software tools to measure carbon footprint while training models, and report it in their manuscripts (Lacoste et al., 2019; Henderson et al., 2020; Anthony et al., 2020; Lottick et al., 2019). While these proposed tools are very helpful, our literature survey (§2) shows that adaption by the community is limited. We argue that this results from technical issues that limit the application to standard systems. More importantly, we argue that the limited usage of these tools is caused by a lack of awareness about the topic of carbon footprint in NLP.

In contrast, we aim to simplify climate performance reporting. This work contributes to the field of NLP in the following ways:

- We conduct a survey of environmental impact statements in NLP literature published in the past six years (§2). This survey is conducted across five dimensions that directly influence the environmental impact.

3Paper, for example, is not necessarily environmentally preferable just because it comes from a sustainably harvested forest. Other important environmental issues in the papermaking process, such as greenhouse gas emissions or chlorine use in bleaching, may be equally important. Other examples are energy, utilities, and gasoline corporations that advertise about the benefits of new sources of energy while some are drilling into unexplored areas to source oil and thus destroying natural habitats and losing biodiversity, disguising the imbued hidden impacts (de Freitas Netto et al., 2020).


• We delineate the different notions of “efficiency” common in the literature, proposing a taxonomy to facilitate transparent reporting, and identify ten simple dimensions across which researchers can describe the environmental impact resulted by their research (§3).

• We propose a climate performance model card (§4) with the main purpose of being practically usable with only limited information about experiments and the underlying computer hardware (see Figure 1).

2 Survey of Climate Discussion in NLP

The issue of environmental impact is more general and not limited to NLP, but relevant to the entire field of AI: Schwartz et al. (2020) surveyed papers from ACL, NeurIPS, and CVP. They noted whether authors claim their main contribution to improving accuracy or some related measure, an improvement to efficiency, both, or other. In all the conferences they considered, a large majority of the papers target accuracy. However, we claim that the issue is more complex, and it is not sufficient to consider only the “main contribution.” Every paper should ideally have a positive impact or provide sufficient information to discuss meaningful options to reduce and mitigate negative impacts.

We conduct a similar survey of papers in *ACL venues from 2016-2021. However, instead of focusing on the main contribution, we look for any discussions on climate-related issues. We identify five dimensions in our study sample and create a regex pattern for each.6 These dimensions are public model weights, duration of model training or optimization, energy consumption, the location where computations are performed, and GHG emissions. If the regex pattern matches the text of a paper at least once,7 we consider that paper as discussing the corresponding category. We derive the proportions of papers by dividing the number of papers discussing a category by the number of deep learning-related papers. We only consider deep learning-related papers, as for these papers, climate-related issues are of much higher relevance than for those using other machine learning algorithms. While our approach with regex patterns is not perfect, we argue that it is sufficient to get a sense of the development of climate-related discussions in the literature. In addition, we get a much broader picture than with a manual analysis.

Figure 2 shows our findings. In general, researchers discuss climate-related issues more and more in their work. For instance, the proportion of papers that publish their model weights has almost quadrupled from about 1% in 2017 to 4% in 2021. We also find an increase in the proportion of papers that provide information on emissions or energy consumption. Nevertheless, the proportion for these categories, in particular, remains at a low level. This highlights the need to raise awareness of climate-related issues further and find a simple but effective way to report them transparently.

3 Towards Actionable Awareness

Efficiency (alongside accuracy) has been one of the main objectives in NLP (and computer science in general) long before its environmental aspects have been widely considered. In general, it refers to the amount of resources consumed (input) in order to achieve a given goal, such as a specific computation or accuracy in a task (output). Different definitions of efficiency correspond to different concepts of input and output. It is crucial to (1) understand the different concepts, (2) be aware of their differences and consequently their climate impact, and (3) converge towards a set of efficiency measures that will be applied for comparable climate performance evaluation in NLP research.
Schwartz et al. (2020) sets out to compare several efficiency measures in AI. They focus on input or resource consumption measures: CO2eq emissions, electricity usage, elapsed real time, number of parameters, and FPO (floating-point operations). They suggest FPO as a concrete, reliable measure for climate-related efficiency that does not depend on the underlying hardware, local electricity infrastructure, or algorithmic details. Additionally, they suggest measuring efficiency as a trade-off between performance and training set size to enable comparisons with small training budgets.

Henderson et al. (2020) show that FPOs can be misleading: “while FPOs are useful for measuring relative ordering within architecture classes, they are not adequate on their own to measure energy or even runtime efficiency.” They, therefore, recommend reporting various key figures, and they also provide a tool, experiment-impact-tracker for reporting this information automatically.

### 3.1 Climate Performance Reporting

The Greenhouse Gas Protocol⁸ is a widely used reporting framework for corporates. However, this standard does not foresee, so far, an explicit ICT (information and communications technology) component. We build on the general principles of the GHG Protocol (relevance, completeness, consistency, transparency, and accuracy) to propose principles for improving climate-related performance reporting of AI. While the Greenhouse Gas Protocol focuses on GHG emissions, we propose a more general framework corresponding to the different concepts of efficiency. We, therefore, replace the term GHG emissions with the term climate-related performance assessments. All adaptions and further refinements of the GHG Protocol are written in *italics*.

**Relevance** Ensure the *climate-related performance assessment* appropriately reflects the *climate-related performance of training, evaluation and deployment*, and serves the decision-making needs of users—both internal and external to the research group. Consider both factors inherent to the model (e.g., number of parameters) and model-external factors (e.g., energy mix).

**Completeness** Account for and report on all *relevant climate-related performance assessment* items, using standardized model cards (see §4) to ensure accessibility to relevant information. Disclose and justify any specific exclusions or missing information, and explain which data input would be required to provide it. State how you will deal with the missing information in the future to reduce information gaps.

**Consistency** Use consistent methodologies to make meaningful comparisons of reported emissions over time. Transparently document any changes to the data, inventory boundary, methods, or other relevant factors in the time series. Use readily-available emission calculation tools to ease comparison with other models. If you decide not to use available tools, explain why you deviate from available tools and report your assumptions about the energy mix, the conversion factors, and further assumptions required to calculate model-related emissions.

**Transparency** Address all relevant issues factually and coherently. Disclose any relevant assumptions and refer to the accounting and calculation methodologies and data sources used.

**Accuracy of reporting** Achieve sufficient accuracy of the quantification of climate-related performance to enable users to make decisions with reasonable assurance as to the integrity of the reported information. *Ensure that you report on the climate-related performance, even if you are in doubt about the accuracy. If in doubt, state the level of confidence.*

### 3.2 Actions Towards Improvement

Reporting climate-related performance is not a goal on its own. Instead, it should be a means to raise awareness and translate it into actionable climate-related performance improvements when training and deploying a model. In addition, climate-aware model performance evaluations should ensure that downstream users of the technology can use the model in a climate-constrained future. Researchers should aim for climate-resilient NLP and algorithms to unlock long-term positive impacts. How to future-proof AI and NLP models should become an essential consideration in setting up any project.

The overall process of integrating these considerations would use enhanced transparency to unlock actionable awareness. Reporting on climate-related performance...
model performance should put researchers in a position to reflect on their setup and take immediate action when training the next model. To support this reflection for the researchers, the following proposes our climate performance model card.

## 4 Climate Performance Model Cards

Since 2020, NeurIPS requires all research papers to submit broader impact statements (Castelvecchi et al., 2021; Gibney, 2020). NLP conferences followed suit and introduced optional ethical and impact statements, starting with ACL in 2021. Leins et al. (2020) discuss what an ethics assessment for ACL should look like but focus solely on political and societal issues. Tucker et al. (2020) analyze the implications of improved data efficiency in AI but only discuss the societal aspect of access in research and industry, leaving environmental issues unexplored. Mitchell et al. (2019) introduced model cards to increase transparency about data use in AI, similarly due to societal issues. We propose extending impact statements and model cards to include information about the climate-related performance of the development and training of the model, improvements compared to alternative solutions, measures undertaken to mitigate negative impact, and importantly, about the expected climate-related performance of reusing the model for research and deployment.

Our proposed model card also includes any positive impact on the environment. A large direct negative impact does not rule out net positive impact due to contribution to downstream environmental efforts. While net impact cannot be measured objectively, since it depends on priorities and projections on the future use of the technology, we can set a framework for discussing this complex issue, providing researchers with the best practices to inform future researchers and practitioners.

Table 1 shows our proposed sustainability model card, structured into a minimum card and an extended card. The minimum card contains very basic information about the distribution of the model, its purpose for the community, and roughly the computational work that has been put into the optimization of the models. The extended card then includes the energy mix to compute the CO2eq emissions. In total, our sustainability model card contains eleven elements:

1. **Publicly available.** In recent years, NLP researchers often make their final model available for the public. This trend came up to increase the transparency of research, yet, at the same time, it avoids the necessity to train frequently used models multiple times across the community. Thus, by publishing model (weights), computational resources and thereby CO2eq emissions can be reduced.

2. **Duration—training of final model.** This field denotes the time it took to train the final model (in minutes/hours/days/weeks). In case, there are multiple final models, this field asks for the training time of the model which has been trained the longest.

3. **Duration of all computations.** The duration of all computations required to produce the results of the research project is strongly correlated with the CO2eq emissions. Thus, we want to motivate NLP researchers to vary model types and hyperparameters reasonably.

4. **Energy consumption.** Besides the duration for training, the power consumption is the driving factor for CO2eq emissions. Based on the type of research, the majority of energy can be consumed by CPUs or GPUs. We ask the researchers to report the energy consumption in watt for the main hardware being used to optimize the model. For simplicity, we also

### Table 1: Proposed climate performance model card.

<table>
<thead>
<tr>
<th>Information</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Is the resulting model publicly available?</td>
<td>Yes/No</td>
</tr>
<tr>
<td>2. How much time does the training of the final model take?</td>
<td>Time</td>
</tr>
<tr>
<td>3. How much time did all experiments take (incl. hyperparameter search)?</td>
<td>Time</td>
</tr>
<tr>
<td>4. What was the energy consumption (GPU/CPU)?</td>
<td>Watt</td>
</tr>
<tr>
<td>5. At which geo location were the computations performed?</td>
<td>Location</td>
</tr>
<tr>
<td>6. What was the energy mix at the geo location?</td>
<td>gCO2eq/kgWh</td>
</tr>
<tr>
<td>7. How much CO2eq was emitted to train the final model?</td>
<td>kg</td>
</tr>
<tr>
<td>8. How much CO2eq was emitted for all experiments?</td>
<td>kg</td>
</tr>
<tr>
<td>9. What is the average CO2eq emission for the inference of one sample?</td>
<td>kg</td>
</tr>
<tr>
<td>10. Which positive environmental impact can be expected from this work?</td>
<td>Notes</td>
</tr>
<tr>
<td>11. Comments</td>
<td>Notes</td>
</tr>
</tbody>
</table>
ask to report the peak energy consumption of the hardware. We want to underline again, that this model card’s objective is not to have the most precise information but rather to have a rough estimate about the energy consumption.

5. **Geographical location.** The energy mix (the CO2eq emissions per watt consumed) depends on the geographical location. Thus, it is important to report where the model was trained.

6. **Energy mix at geographical location.** To compute the exact CO2eq emissions, the energy mix at the geographical location is required. Organizations such as the European Environment Agency⁹ report these numbers.

7. **CO2eq emissions final model.** This field describes an estimation for the emitted CO2eq. Given the time for the computation (see item 3.), the energy consumption and the energy mix, the total CO2eq emissions for the research can be calculated by

\[
\text{ComputationTime} \times \frac{\text{EnergyConsumption (kW) \times EnergyMix (gCO2eq/kWh)}}{1} = \text{gCO2eq}.
\]

8. **Total CO2eq emissions.** Similar to the previous item, this field describes the total CO2eq emitted during the training of all models. The calculation is equivalent to item 8.

9. **CO2eq emissions for inference.** Given that a model might be deployed in the future, the expected CO2eq emissions in use of the model can be of value. To assure comparison between models, we ask the authors to report the average CO2eq emission for the inference of one sample. For a dataset of \(n\) samples, it can be calculated by

\[
\frac{1}{n} \times \text{InferenceTime} \times \frac{\text{EnergyConsumption (kW) \times EnergyMix(gCO2eq/kWh)}}{1} = \text{gCO2eq}.
\]

10. **Positive environmental impact.** NLP technologies begin to mature to the point where they could have an even broader impact and support to address major problems such as climate change. In this field, authors can state the expected positive impact resulting from their research. In case that the underlying work is not likely to have a direct positive impact, authors can also categorize their work into “fundamental theories”, “building block tools”, “applicable tools”, or “deployed applications” (Jin et al., 2021), and discuss why their work could set the basis for future work with a positive environmental impact.

11. **Comments.** The objective of this climate performance model card is to collect the most relevant information about the computational resources, energy consumed, and CO2eq emitted that were the result of the conducted research. Comments can include information about whether a number is likely over- or underestimated. In addition, this field can be used to provide the reader with indications of possible improvements in terms of energy consumption and CO2eq emissions.

### 4.1 Automating Reporting

Several tools automate measurement and reporting of energy usage and emissions in ML. Lacoste et al. (2019) introduced a simple online calculator¹⁰ to estimate the amount of carbon emissions produced by training ML models. It can estimate the carbon footprint of GPU compute by manually specifying hardware type, hours used, cloud provider, and region. Henderson et al. (2020) presented a Python package¹¹ for consistent, easy, and more accurate reporting of energy, compute, and carbon impacts of ML systems by estimating them and generating standardized “Carbon Impact Statements.” Anthony et al. (2020) proposed a Python package¹² that also has predictive capabilities, and allows proactive and intervention-driven reduction of carbon emissions. Model training can be stopped, at the user’s discretion, if the predicted environmental cost is exceeded. Lottick et al. (2019) actively maintain a Python package¹³ that, besides estimating impact and generating reports, shows developers how they can lessen emissions by optimizing

⁹See [https://www.eea.europa.eu/](https://www.eea.europa.eu/).

¹⁰[https://mlco2.github.io/impact/](https://mlco2.github.io/impact/)


¹²[https://github.com/lfwa/carbontracker](https://github.com/lfwa/carbontracker)

¹³[https://codecarbon.io](https://codecarbon.io)
their code or by using cloud infrastructure in geographical regions with renewable energy sources.

We encourage the use of automated tools to facilitate reporting, but we claim they are not a substitute for awareness by all actors involved.

5 Discussion

AI and NLP research are behind in incorporating sustainability discourse in the discussion. In the field of finance, an increasing amount of companies worldwide are soon required to state their environmental and broader sustainability-related impacts and/or commitments in their annual reports, mostly following the recommendations laid out by the Task Force on Climate-related Financial Disclosures (TCFD; Financial Stability Board, 2017).  

Of course, significant differences exist between annual reports and research papers: while companies are increasingly asked to take responsibility for their actions and are held accountable to their commitments by stakeholders, researchers can shake off responsibility by transferring it to practitioners who use the technology based on their research. Researchers are thus never held responsible for committing to reducing negative environmental impact unless they choose to submit their work to specific workshops or conference tracks on sustainable and efficient NLP. However, there are no best practices on what they can do to help those who are responsible for committing to sustainability—what information is necessary for accurate reporting and informed decision making?

The quantification of indirect impact during reuse and deployment of artifacts developed in research is complex and can only be estimated. We, therefore, expect that this discussion in environmental impact statements will be more abstract and harder to assess. As a framework, we propose borrowing the notion of scopes from corporate GHG accounting, according to who is responsible at each scope:

1. experiments in writing the paper,
2. impact on other researchers and practitioners in reducing emissions while using of the technology, and
3. the use of the technology for reducing emissions or other positive impact.

Table 2: Extended model performance evaluation.

<table>
<thead>
<tr>
<th>Standard</th>
<th>Model performance (i.e., model out-put accuracy)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emerging</td>
<td>Climate-related performance (i.e., CO2eq emissions generated by training, deploying and using the model)</td>
</tr>
<tr>
<td>Future</td>
<td>Climate-related efficiency performance (i.e., marginal accuracy improvements relative to marginal input requirements)</td>
</tr>
</tbody>
</table>

Similarly, model performance should not only be assessed in terms of output. Instead, the inputs required to obtain a certain performance outcome should be equally assessed. Based on this principle, we argue that future model performance evaluation should be based on model performance and climate performance (cf. Table 2).

Perhaps the most relevant to our work is the paper by Henderson et al. (2020), calling for systematic reporting of the energy and carbon footprints of machine learning. We focus on NLP, raising several issues specific to the technical but also socio-political situation the field is situated in within the broader AI community.

NLP is relevant in several aspects to the UN sustainable development goals (Vinuesa et al., 2020; Conforti et al., 2020). Jin et al. (2021) defined a framework for the social impacts of NLP, of which environmental impacts are a special case. They define an impact stack consisting of four stages, from (1) fundamental theory to (2) building block tools and (3) applicable tools, and finally to (4) deployed applications. Furthermore, they identify questions related to sustainable development goals for which NLP is relevant. They categorize Green NLP as relevant only to the particular goal of “mitigating problems brought by NLP,” by minimizing direct impact as part of technology development. However, we claim that Green NLP must be viewed more broadly. For example, Rolnick et al. (2019) discuss how machine learning can be used to tackle climate change, listing several fields with identified potential. For NLP, they mention the impact on the future of cities, on crisis management, individual action (understanding personal footprints, facilitating behavior change), informing policy for collective decision-making, education, and finance. Stede and Patz (2021) note that the topic of climate change has received little attention in the NLP community and propose applying NLP to analyze the

For instance, in the United Kingdom a new legislation will require firms to disclose climate-related financial information, with rules set to come into force from April 2022.
climate change discourse, predict its evolution and respond accordingly. The ACL workshop on NLP for Positive Impact (Field et al., 2021) is a relevant focused venue for publishing such research.

6 Impact and Limitations

As pointed out by Schwartz et al. (2020), a comparison between researchers and practitioners from various locations and with various prerequisites can be difficult. Therefore, we want to point out Do’s and Don’t’s that, in our opinion, should be followed by the authors of papers, as well as from reviewers who assess the quality thereof.

Do increase transparency. With our climate performance model card, we aim to provide guidelines that give concrete ideas on how to report energy consumption and CO2eq emissions. Our model card, on purpose, still allows for flexibility so that authors can change it to their respective setup. In case of high CPU usage, the authors can simplify their energy consumption by only looking at the CPU energy consumption; in the case of the GPU, it can simply be based on the GPU. Our main goal is transparency for users and increased awareness for modelers and researchers. Hence, transparency is to be weighted over accuracy.

Do use the model cards to enable research institutions and practitioners to report on their climate performance and GHG emissions. An increasing number of first-moving research labs and institutes have started to account for their GHG emissions from direct energy use and flying, and intend to include their ICT emissions (e.g., ETH Zurich, 2021; UZH Zurich, 2021). However, harmonized approaches are still lacking. Use the model cards to road-test how far they could support your institutions’ GHG and climate impact reporting.

Don’t use this model card for assessing the research quality. The value of research is often only clear months or years after publication. Thus, the ratio between emitted CO2eq and contribution to the NLP community cannot be measured accurately. Additionally, the emitted CO2eq depends on the hardware used for the computations. Researchers working with less energy-efficient hardware would have a disadvantage if the emitted CO2eq were being used for assessing the quality.

However, considering the energy efficiency of model performance might indirectly reduce a Global North–South bias, given that access to computational power is not evenly distributed across the World. Hence, targeting energy efficiency and reducing the computational power required to train and run models might mitigate some concerns on the inequality of research opportunities.

Don’t report your voluntary financial climate protection contributions as emission offsetting. While emission offsetting used to be hailed as an efficient way to reduce global greenhouse gas emissions, this notion had to be revised with updated climate science consensus, at the latest with the IPCC’s Special Report on Global Warming of 1.5C from 2018 (Masson-Delmotte et al., 2018). Related to this aspect, do not communicate relative (efficiency-related) improvements as absolute climate-related performance improvements.

Don’t use this model card to assess net climate-related impacts. AI as an enabler for higher-order effects, for example, for climate-neutral economies and societies, is an important topic, which is, however, not in our scope. Instead, our approach aims to increase transparency about every model’s first order effects, be the model designed for societal change (or any other higher-order effect) or not.

7 Conclusion

We argued that branding efficient methods in NLP as green or sustainable is insufficient and that due to the importance of the issue, climate awareness must be promoted in mainstream NLP rather than only in niche areas. We conducted a survey of climate discussion in NLP papers and found that climate-related issues are increasingly being discussed but are still uncommon. We proposed actionable measures to increase climate awareness based on experience from the finance domain and finally proposed a model card focusing on reporting climate performance transparently, which we encourage NLP researchers to use in any paper.

While our discussion, survey, and recommendations are aimed towards the NLP community, much is applicable to other AI fields. Indeed, specific recommendations have been made for machine learning (Patterson et al., 2022) and medical image analysis (Selvan et al., 2022), for example. However, our focus on NLP enabled us to be more specific about relevant modeling components in our model card, as they are commonly used in NLP work. Furthermore, framing our arguments within the discourse initiated in the NLP community allowed us to address the specific points raised in this discussion so far.
References


David Patterson, Joseph Gonzalez, Urs Hölzle, Quoc Hung Le, Chen Liang, Lluis-Miquel Munguia, Daniel Rothchild, David So, Maud Texier, and Jeffrey Dean. 2022. The Carbon Footprint of Machine Learning Training Will Plateau, Then Shrink.


A Example for sustainability model card

In the following, we give an example of a filled out climate performance model card. We describe this based on ClimateBert, a language model which was finetuned on climate-related text (Webersinke et al., 2021).

1. All weights of the final model are publicly available.

2. The paper proposes a fine-tuned language model on climate-related text. Thus, the proposed models are specific to a field and not task agnostic.

3. The duration for optimizing the final model was around 8 hours. Note, that the paper proposes four final models but this field should only mention the optimization time for one model.

4. In total, we estimate the duration for all computations to be 12 days (=288 hours). This estimation is likely pessimistic, i.e., the duration for all computations was likely lower. However, we want to point out again that this model card values transparency over accuracy.

5. The main hardware used for training were 2 x NVIDIA RTX A5000 with each GPU taking 230 watts. We add another 120 watts for the remaining hardware which would not be required by our model card.

6. The models were all trained on servers in Germany.

7. The energy mix is roughly 470 gCO2eq/kWh (according to umweltbundesamt.de/publikationen/entwicklung-der-spezifischen-kohlendioxid-7).

8. Calculating
   
   \[
   8 \text{ hours} \times 0.7 \text{ kW} \times 470 \text{ gCO2eq/kWh}
   \]
   
   leads to 2.63 kg CO2eq emissions.

9. Calculating
   
   \[
   288 \text{ hours} \times 0.7 \text{ kW} \times 470 \text{ gCO2eq/kWh}
   \]
   
   leads to 94.75 kg CO2eq emissions.

10. A pass of 100,000 samples through the proposed model took 0.187 hours on the same server (using a batch size of 512). We then calculate

   \[
   \frac{0.187}{100,000} \times 0.7 \text{ kW} \times 470 \text{ gCO2eq/kWh} = 0.62 \text{ mgCO2eq}
   \]

   as the emission for the inference of one sample.

11. The proposed language model on its own does not directly have a positive environmental impact. However, it can be used to train more accurate NLP models on climate-related downstream tasks. For instance, question-answering systems for climate-related topics or greenwashing detectors could benefit from this pretrained language model.

12. Block pruning is a method which drops a large number of attention heads in transformer models while only decreasing model performance slightly. Thus, the number of weights after block-pruning is decreased considerably which, in turn, decreases the CO2eq emissions. Very likely, this method would show the same effect on the proposed ClimateBert model.

B Development of NLP models over time

Figure 3 shows the computational power that was put into the development of the major NLP models (Sevilla et al., 2022). With few exceptions, the training compute for NLP models has steadily increased over the past decade. Although progress has also been made in terms of more energy efficient hardware (e.g., 19.5 GFLOPS/watt in a 2013 GTX Titan to 168.3 GFLOPS/watt in a 2021 RTX A6000), the increase in terms of required FLOPs is substantially larger. Exemplary, going from GPT (in 2018) to GPT-3 175B (in 2020), the training compute increase from 1.1E19 to 3.14E23 FLOPs — an increase by a factor larger than 25,000.

C GHG Protocol information requirements for companies

Whilst the GHG Protocol does not provide an ICT sector tool, it provides emission factors by fuel source to calculate GHG emissions based on the energy consumption. The emission factors reflect...
the scientific climate consensus, based on the report of the Intergovernmental Panel on Climate Changes’ latest Assessment Report (for now the IPCC’s AR5, AR6 will be released soon). In terms of specific information to be disclosed, the GHG protocol guidance states the following items, which serve to build our model card approach. The items that can be used for our approach are the following:

- **DESCRIPTION OF THE COMPANY AND INVENTORY BOUNDARY**
  - An outline of the organizational boundaries chosen, including the chosen consolidation approach
  - An outline of the operational boundaries chosen, and if scope 3 is included, a list specifying which types of activities are covered.

- **INFORMATION ON EMISSIONS**
  - Total scope 1 and 2 emissions independent of any GHG trades such as sales, purchases, transfers, or banking of allowances.
  - Emissions data separately for each scope.
  - Methodologies used to calculate or measure emissions, providing a reference or link to any calculation tools used.
  - Any specific exclusions of sources, facilities, and / or operations.

- **INFORMATION ON EMISSIONS AND PERFORMANCE**
  - Emissions data from relevant scope 3 emissions activities for which reliable data can be obtained.
  - Emissions data further subdivided, where this aids transparency, by business units/facilities, country, source types, and activity types
  - Relevant ratio performance indicators (e.g. emissions per kilowatt-hour generated, tonne of material production, or sales).
  - An outline of any GHG management/reduction programs or strategies.
  - An outline of any external assurance provided and a copy of any verification statement, if applicable, of the reported emissions data.
  - Information on the quality of the inventory (e.g., information on the causes and magnitude of uncertainties in emission estimates) and an outline of policies in place to improve inventory quality.

- **INFORMATION ON OFFSETS**
  - Information on offsets that have been purchased or developed outside the inventory boundary, subdivided by GHG
## Minimum card

<table>
<thead>
<tr>
<th>Information</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Is the resulting model publicly available?</td>
<td>Yes</td>
</tr>
<tr>
<td>2. How much time does the training of the final model take?</td>
<td>8 hours</td>
</tr>
<tr>
<td>3. How much time did all experiments take (incl. hyperparameter search)?</td>
<td>288 hours</td>
</tr>
<tr>
<td>4. What was the energy consumption (GPU/CPU)?</td>
<td>0.7 kW</td>
</tr>
<tr>
<td>5. At which geo location were the computations performed?</td>
<td>Germany</td>
</tr>
</tbody>
</table>

## Extended card

<table>
<thead>
<tr>
<th>Information</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>6. What was the energy mix at the geo location?</td>
<td>470 gCO2eq/kWh</td>
</tr>
<tr>
<td>7. How much CO2eq was emitted to train the final model?</td>
<td>2.63 kg</td>
</tr>
<tr>
<td>8. How much CO2eq was emitted for all experiments?</td>
<td>94.75 kg</td>
</tr>
<tr>
<td>9. What is the average CO2eq emission for the inference of one sample?</td>
<td>0.62 mg</td>
</tr>
<tr>
<td>10. Which positive environmental impact can be expected from this work?</td>
<td>This work can be categorized as a “building block tools” following Jin et al. (2021). It supports the training of NLP models in the field of climate change and, thereby, have a positive environmental impact in the future.</td>
</tr>
<tr>
<td>11. Comments</td>
<td>Block pruning could decrease CO2eq emissions (Lagunas et al., 2021).</td>
</tr>
</tbody>
</table>

Table 3: Climate performance model card: Filled in example for ClimateBert (Webersinke et al., 2021).