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Green Machine Learning

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Abstract. Green machine learning refers to research that is more environmentally friendly and inclusive, not only by producing novel results without increasing the computational cost, but also by ensuring that any researcher with a laptop has the opportunity to perform high-quality research without the need to use expensive cloud servers. Efficient machine learning approaches (especially deep learning) are starting to receive some attention in the research community. This tutorial is concerned with the development of machine learning algorithms that optimize efficiency rather than only accuracy. We provide an overview of this recent field, together with a review of the novel contributions to the ESANN 2023 special session on Green Machine Learning.

1 Introduction

Over the past few years, Artificial Intelligence (AI) and Machine Learning (ML) have brought about a revolution in numerous industries. They have greatly enhanced efficiency and accuracy in sectors like healthcare, finance, transportation, education, and entertainment. To achieve higher performance, ML models have become increasingly complex, resulting in a larger number of parameters to estimate. However, these advancements come at a cost: the energy consumption required for training and running these models has risen significantly.

In the next coming years, this energy consumption is projected to multiply, potentially reaching over 30% of the world's total energy consumption by 2030. Large Language Models (LLMs), such as the recently launched ChatGPT with GPT-4 as backbone model, contribute to this trend with their substantial energy requirements. For instance, ChatGPT with GPT-3.5 allegedly consumed 1,287 megawatts and generated 552 metric tons of carbon dioxide emissions during its training, as reported by various sources. Not to mention that the more recent GPT-4 is estimated to be 10 times larger than its predecessor.

As the environmental impact of this disruptive technology grows almost exponentially, great concerns arise about its carbon footprint, and thus a new paradigm has emerged: Green machine learning. Green ML focuses on developing and implementing sustainable practices and techniques into the design, training, and deployment of the models so as to reduce AI systems' energy consumption and environmental footprint.

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Traditional ML algorithms often require large amounts of computational power and data, resulting in significant energy consumption from data centers and increasing greenhouse gas emissions. Green ML seeks to mitigate these environmental impacts by optimizing algorithms, improving hardware efficiency, and adopting sustainable data management practices. Thus, Green ML is characterized by low carbon footprints, small model sizes, low computational complexity, and logical transparency. It offers energy-effective solutions in cloud centers as well as mobile/edge devices. Green ML also provides a clear and logical decision-making process to gain people's trust.

This special session delves into the emerging field of Green ML, exploring the various approaches, methodologies, and innovations that aim to make AI and ML more environmentally sustainable, such as federated learning, transfer learning, etc. We will explore the key challenges and opportunities in reducing energy consumption, minimizing carbon emissions, and promoting ethical and responsible AI practices. The adoption of these approaches not only has those environmental advantages, essential for the future and mandatory in the UE [1], but also allows for cost savings and increased efficiency without compromising performance or accuracy.

2 Green Machine Learning

The binomial artificial intelligence and environment has a dual perspective. On the one hand, we have artificial intelligence as a new technology with the potential to move towards a green economy (green by AI), and on the other, AI as a polluting agent in need of the design of energy-efficient algorithms (green in AI).

According to the existing literature, green algorithms are usually defined as those algorithms capable of maximizing energy efficiency and reducing the environmental impact of AI models, while supporting the use of this technology to respond to different environmental challenges. In this way, two different types of algorithms are being referred to. On the one hand, those which use and training are energy efficient (systems that are themselves green, green by design). On the other hand, algorithms specifically created or used to help meet the environmental challenges set out, among others, in the Paris Agreement on climate change, in the United Nations Sustainable Development Goals[1], or in the most recent European Green Deal[2].

The debate revolves around the difference between red artificial intelligence, and green artificial intelligence [2]. In 2018 a study[3] revealed that the computational needs to train large ML models were doubling every 3.4 months since 2012 (deviating quite a bit from Moore's Law which states that this should happen every 18 months). In 2020, another paper [3] introduces the concept of red AI,

[1] `https://sdgs.un.org/goals`

[2] `https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en`

[3] `https://openai.com/research/ai-and-compute`

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which "buy" better results at the cost of using massive computational resources. Their authors analyzed more than 60 papers at the most prestigious conferences and concluded that the vast majority (between 75% and 90% depending on the conference) prioritized accuracy over efficiency.

However, the energy consumption of machine learning algorithms should not be seen as something impossible to reduce and does not have to be assumed as the cost of progress in this field. Green machine learning can be defined as machine learning research that produces novel results without increasing computational cost and, ideally, reducing it. In the specialized literature, we can find several strategies that can be carried out to reduce this consumption and will be following described.

- **Algorithmic optimization.** Making algorithms more efficient can have many benefits, in addition to reducing their environmental footprint. This is one of the most productive strategies and the focus of green algorithm development. One area that is quite active is making the inference process efficient, using quantization or energy-aware pruning [4].
- **Hardware optimization.** Choosing more computationally efficient hardware can also contribute to energy savings, as some GPUs have substantially higher efficiency in terms of floating point operations per second (FLOPS) per watt of power usage compared to others. Another important issue is in parallelization. One obvious way to reduce the training time of algorithms is to distribute the computations among several processing cores. Anthony et al. [5] showed that, for a given task, increasing the number of cores to 15 improved both execution time and greenhouse emissions. However, when the reduction in execution time is smaller than the relative increase in the number of cores, distributing the computation can worsen carbon emissions. They performed some experiments demonstrating how marginal improvements in runtime lead to disproportionately large emissions. Finally, edge computing is also a relevant strategy in this context, as the idea is to carry out the computation at the locations where the data is collected or used, thus avoiding the need of sending the data to a datacenter or to the cloud, at the same time that it takes advantage of the limited computational and energy resources of the IoT devices.
- **Choice of data center.** The carbon footprint is directly proportional to the efficiency of the data center and the carbon intensity of its location. The latter is perhaps the most important factor for the total carbon footprint due to the huge variation between countries, from less than 20 gCO2e kWh^{-1} in Norway and Switzerland to over 800 gCO2e kWh^{-1} in Australia, South Africa, and some US states.
- **Reducing the pragmatic scaling factor.** Limiting the number of times an algorithm is run, especially those that are computationally expensive, is surely the easiest way to reduce energy consumption. Another possible

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strategy is to limit the time spent on hyperparameter tuning, for example with less exhaustive searches [6, 7, 8].

Machine learning risks contributing significantly to climate change if it follows the energy consumption trend of large models. Therefore, if researchers and developers are aware of the energy and CO2 footprint they are causing, they are more likely to take measures to reduce it. This is why several tools for calculating and predicting energy consumption from artificial intelligence algorithms are emerging. Carbontracker[4] is one such tool, in particular for estimating the consumption of deep learning models (famously computationally and energy intensive). Another openly available tool is Green Algorithms[5], which can be easily integrated with computational processes as it requires a minimum amount of information and does not interfere with existing code.

3 Recent contributions

As an area of active research and development in recent years, there are a variety of recent contributions in Green ML that are focused on a variety of strategies:

- **Environmental Impact Assessment:** Beyond algorithmic advancements, researchers have also been working on frameworks and tools to assess the environmental impact of machine learning systems. Over the recent years, Yigitcanlar et al. [9] explored how cryptocurrency mining has led to increased energy consumption worldwide, concluding that Bitcoin miners are expected to consume approximately 130 terawatt hours of energy (TWh), which represents approximately 0.6% of global electricity consumption. This puts the bitcoin economy on par with the CO2 emissions of small developing countries such as Sri Lanka or Jordan. In the field of Natural Language Processing (NLP), Strubell et al. [10] raised the alarm when they discovered that training a widely used computational model emitted as much CO2 as five cars in their lifetime. More recently, George et al. [11] reported that language models like GPT-3 [12] or ChatGPT reportedly consumed over 700,000 liters of water during its training phase, which is equivalent to the amount of water used by an average American household in about 20 years.
- **Energy-Efficient Models:** Researchers have focused on designing optimization techniques that reduce the computational resources required, thus minimizing energy consumption. These approaches include sparse training methods [13, 14, 15], quantization techniques [16, 17, 18], and low-precision arithmetic operations [19, 20], which decrease both the memory footprint and the computational complexity of training models.
- **Hardware Acceleration:** Another area of focus in Green ML is the development of specialized hardware accelerators (like GPUs or TPUs [21])

[4] `https://carbontracker.org`
[5] `http://www.green-algorithms.org`

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tailored specifically for machine learning tasks, and the ability to customize machine learning models to be used in that specific hardware [22, 23]. For instance, works in edge computing [24, 25] suggest that we can achieve not only less-energy demanding algorithms but also privacy-preserving architectures that can be trained without sharing all of the data.

- **Data Center Optimization:** Researchers have developed algorithms and frameworks that dynamically manage server loads [26, 27], adjust cooling systems [28, 29], and optimize resource allocation to reduce energy consumption in data centers [30].
- **Energy-Efficient Structures:** Green ML contributes to making structures more energy-efficient. ML models can analyze sensor data from smart buildings [31, 32] and cities [33, 34] to optimize heating, ventilation, and air conditioning (HVAC) systems, lighting, and energy usage patterns, resulting in significant energy savings and reduced carbon emissions [35, 36].

Other important fields of study like climate change [37], sustainable agriculture [38, 39], renewable energy forecasting [40, 41] or waste management [42] are gaining special interest over the last years, increasing the scope of the use of machine learning in different green scenarios.

4 Contributions to the special session

The Green Machine Learning special session has garnered contributions from multiple research groups, showing methodologies that tackle both the theoretical and applied dimensions of the core subject matter. The subsequent section provides concise introductions to each accepted paper, highlighting their significance and relevance.

Two of the accepted papers propose more efficient methods in the field of feature selection. Feature selection (FS) is a fundamental task in machine learning, as it can help in reducing dimension and thus contributes to more understandable models. García-Castillo et al. [43], in particular, develop a novel and efficient method for feature selection in domain adaptation, a type of transfer learning where the source and target domains share the feature space and task but differ in their distributions. The researchers present an alternative method, Mutual Information Maximization (MIM), as opposed to the commonly used evolutionary algorithms in the field. MIM offers advantages such as eliminating the need for an iterative search process and being computationally less demanding. Through experiments conducted on two datasets, they demonstrate that their proposed method outperforms two previously suggested alternatives that rely on evolutionary algorithms: Sticky Binary Particle Swarm Optimization using classifiers or data complexity metrics. Specifically, their method shows superior efficiency, speed, and the capability to select a smaller subset of features, while still achieving competitive accuracy results in classification tasks.

In the work of Suárez-Marcote et al. [44], an efficient and green approach for feature selection is proposed, using principles from information theory. A key

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novelty of their method lies in employing logarithmic division and fixed-point precision techniques. The authors conducted experiments involving two popular information-theoretic filter methods, namely Mutual Information Maximization and Joint Mutual Information Maximization. The results of their study suggest that adopting low-precision representations has the potential to decrease energy consumption without compromising information content. Additionally, the use of logarithmic division provides an extra level of energy efficiency, which proves beneficial in resource-constrained environments. In terms of classification performance, the modified algorithms employing fixed-point representation and logarithmic division demonstrated comparable results to the baseline approaches, even when there were slight discrepancies in the obtained feature rankings.

Lourenço et al. [45] present a scalable and sustainable methodology for condition-based maintenance of wheel out-of-roundness. The methodology involves developing an anomaly detection model using locality-sensitive hashing to analyze extensive time series datasets generated by railway network sensors. The implementation leverages the Apache Spark framework for parallel processing, facilitating efficient data analysis across multiple clusters. The performance study conducted demonstrates the robustness and efficiency of the fault detection method, even when confronted with various wheel profiles, track irregularities, train speeds, sensor positions, and non-linear environmental factors that may introduce artificial noise and signal distortion.

Shumska et al. [46] introduce a novel and efficient approach, called block-diagonal dissimilarity extension, within the Generalized Matrix Learning Vector Quantization (GMLVQ) framework, and applied it to agricultural multispectral images. Their findings suggest that, for the Statlog dataset classification in Euclidean space, using the quadratic form yields the highest accuracy, while the full and block-diagonal configurations of GMLVQ matrices yield comparable results. Their models demonstrate similar accuracy levels as previously reported methods such as neural networks, support vector machines, and k-nearest neighbors, while offers the advantages of interpretability, reduced complexity, and the ability to visualize multispectral data.

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