Literature Review Team-C
Introduction to Carbon Footprinting and the Role of Large Language Models (LLMs)

1 Introduction

The pressing need to address climate change has made carbon footprint accounting (CFA) a critical practice for quantifying greenhouse gas (GHG) emissions [1]. Traditional methods, particularly Life Cycle Assessment (LCA), are essential for measuring a product's environmental impact, including GHG emissions. LCA involves analyzing emissions from raw material extraction through disposal. However, these methods are often complex, time-consuming, and require significant manual analysis by domain experts, hindering scalability and real-time updates.

This is where Large Language Models (LLMs) come in. LLMs have demonstrated remarkable abilities in natural language understanding and generation. They can process and analyze unstructured data, such as policy documents, scientific literature, and industry reports [2]. This capability makes LLMs valuable for automating various tasks in the carbon footprinting process, including [3].

- Mapping business activities to appropriate emission factors (EFs) [4]
- Analyzing product descriptions and other textual data [5]
- Retrieving relevant information from vast databases [**policy˙perspective˙2024**]

The use of LLMs in CFA can significantly reduce the time and effort required for data collection and analysis, improving the efficiency and scalability of the process.

2 Key Challenges in Traditional Carbon Footprinting

Manual carbon footprinting has several limitations:

- **Complexity and Time Consumption**: LCA is a complex process that involves tracking emissions across the entire product lifecycle, from raw material extraction to disposal. This process requires extensive data collection and analysis, which can be very time-consuming [6].
- **Reliance on Human Expertise**: Traditional methods heavily depend on domain experts to track emissions, select appropriate EFs, and interpret data, making it difficult to scale [7].
- **Data Gaps and Inconsistencies**: Accessing granular supply chain data is often challenging, and EF databases can be incomplete. This leads to uncertainties and inconsistencies in carbon footprint estimates [4].
- **Difficulty with Real-Time Updates**: Traditional methods struggle to incorporate real-time data and policy changes [8].

These challenges highlight the need for automated and more efficient methods for carbon footprint assessment, which LLMs can help to address.

3 LLM-Based Approaches for Carbon Footprint Assessment

Several studies explore how LLMs can enhance carbon footprinting:

3.1 Automated Emission Factor (EF) Matching

- **Parakeet**: Leverages LLMs to analyze business activity descriptions and recommend appropriate EFs, offering human-readable justifications [7].
- **Flamingo**: Employs neural language models to automatically identify suitable EFs given text descriptions of products. It uses industry sector classification to determine when no good match exists in the database, achieving a precision of 75% in EF matching [4].

3.2 Economic Input-Output LCA (EIO-LCA) Automation

- **CaML**: Uses semantic text similarity to match products with industry sectors, a key step in EIO-LCA, which estimates emissions per dollar at an industry level. By using SBERT, CaML outperforms manual methods and achieves a MAPE of 22% [5].

3.3 End-to-End Carbon Footprint Modeling

- **LLM Carbon**: An end-to-end model designed to predict the carbon footprint of both dense and Mixture-of-Experts (MoE) LLMs during their training, inference, experimentation, and storage phases. It considers various LLM, hardware, and data center parameters [6].

3.4 Real-Time Carbon Footprint Accounting

- The **LLMs-RAG-CFA** method integrates LLMs with Retrieval-Augmented Generation (RAG) technology to provide real-time carbon footprint analysis. By using RAG, the system can access up-to-date data from diverse sources [**naics˙2024**].

3.5 Real-Time Carbon Footprint Accounting

- **LLMs-RAG-CFA** integrates LLMs with Retrieval-Augmented Generation (RAG) technology to provide real-time carbon footprint analysis [1].

4 Addressing the Carbon Footprint of AI Itself

While LLMs offer solutions for assessing carbon emissions, it is important to recognize that they can also contribute significantly to carbon footprints. Studies are now addressing how to reduce the carbon footprint of AI systems themselves:

4.1 Carbon-Aware LLM Inference

- **SPROUT**: Focuses on reducing the carbon footprint of LLM inference by using generation directives to guide the model to provide concise responses. By employing a strategic optimizer for directive assignment and a novel offline quality evaluator, SPROUT can reduce carbon emissions by more than 40% [2].

4.2 Operational and Embodied Carbon Footprints

The carbon footprint of LLMs encompasses operational carbon (from electricity consumption) and embodied carbon (from the production of hardware).

- **LLM Carbon**: Can be used to model both these types of carbon footprints, offering a holistic view of the environmental impacts of LLMs [6].

5 Evaluation Metrics

Several metrics are used to evaluate the performance of LLM-based carbon footprinting systems:

- **Mean Absolute Percentage Error (MAPE)**: Measures the accuracy of the predicted carbon emissions compared to actual values.
- **Information Retrieval Rate (IRR)**: Measures the ability of the system to retrieve relevant carbon footprint data from various data sources.
- **Information Deviation (ID)**: Quantifies the difference between the retrieved information and the true or actual data.

6 Conclusion

The literature shows that LLMs, combined with techniques like RAG, offer significant potential for automating and improving carbon footprint assessment across various sectors. These technologies can lead to more efficient, accurate, and scalable carbon footprinting processes. Further research should explore how to optimize these methods, address data limitations, and further reduce the carbon footprint of AI systems themselves. The ongoing research in this domain is crucial for advancing environmental sustainability by enabling organizations to better manage and reduce their carbon emissions.

References

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