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AI models for Carbon Footprinting

Comparison of Models

Introduction

Carbon accounting has become a major concern for organizations in recent years. To address this, several models are available on the market. In this report, we will review three models—Parakeet, Flamingo, and CaML used for recommendations on carbon footprinting. These models have revolutionized the intensive process of Emission Factor (EF) recommendations, which is a crucial component of Life Cycle Assessment (LCA).

Brief about the Models

The Parakeet Model is developed by Amazon Science and used for recommending EFs by leveraging LLMs to parse activity descriptions. It also provides human-understandable justifications for the EFs recommended and has Precision@1 (Top Recommendation Accuracy) of 86.91%.

The Flamingo Model is also developed by Amazon Science to address the challenge of incomplete Environmental Impact Factor (EIF). It maps product descriptions to standardized industry codes (e.g., NAICS or ISIC) to identify gaps in these datasets.

The CaML Model (Carbon Footprinting using Machine Learning) tackles the limitations of manual Economic Input-Output Life Cycle Assessment (EIO-LCA), where people misclassify the products into overly broad industry categories. It computes semantic similarity between product descriptions and sector definitions, ranking the top five matching for human verification. This approach efficiently bridges the gap between domain expertise and scalability, making organizations capable of conducting large-scale EIO-LCA with the least human effort and intervention.

Methodology

In this section, we will be discussing the working and core objectives of all the models.

- Parakeet Model:
    a. Its primary objective is to automate the EF selection for both pLCA and EEIO-LCA through semantic text-matching and text-generations using LLMs (Large Language Models) for EF (Emission Factor) mapping.
    b. Methodology:
        i. Paraphrases unstructured inputs into standardized activity descriptions.
        ii. Sentence Transformers generate semantic embeddings for cosine similarity matching against EF databases.
        iii. The final LLM pass selects the desired EF from top candidates and generates human-interpretable justifications.
- Flamingo Model:
    a. Its primary objective is to address EF databases' incompleteness by mapping products to industry sectors and recommending proxy EFs.
    b. Methodology:
        i. Classifies product descriptions into sectoral hierarchies.
        ii. Identify gaps and recommend proxies from the parent-child sector.
        iii. Prioritizes regionalized EFs when available.
- CaML Model:
    a. Its primary objective is to reduce categorization errors in EIO-LCA through semantic similarity.
    b. Methodology:
        i. Calculates cosine similarity between descriptions and sector definitions using a pre-trained sentence transformer.
        ii. Ranks top matches for human validation.
        iii. Integrates with EEIO databases to calculate carbon intensity per sector match.

Methodological Frameworks Supporting AI Models

1. Environmentally Extended Input-Output Analysis (EEIOA): It provides the macroeconomic framework to AI-driven tools estimating emissions embedded in supply chains. It links economic transaction data between the sectors that enable models.

2. Process Life Cycle Assessment (pLCA): It provides a granular analysis of emissions from raw material extraction, production, and disposal.

3. Product Carbon Footprint (PCF) Standards: These standards (e.g, ISO 14067) provide crucial guidance for AI models by defining system boundaries, allocation methods and reporting formats. These standards ensure consistency in EF selections by incorporating metadata like temporal validity and geographical applicability which helps Parakeet and Flamingo with recommendations.

Comparison between Parakeet, Flamingo, and CaML Models

- **Performance Benchmarks:**

Metric	Parakeet	Flamingo	CaML
Precision@1 (EEIO-LCA)	**92.3%**	**75.0%**	**N/A**
Precision@1 (pLCA)	**78.1%**	**N/A**	**N/A**
MAPE Reduction	**N/A**	**N/A**	**55% -> 22%**
Multilingual Support	**65 Languages**	**7 Languages**	**English Only**
Human Override Rate	**4.2% (EEIO), 15.7% (pLCA)**	**18.9%**	**9.5%**
Processing Speed	**12.7s/query**	**4.2s/query**	**2.8s/query**

- **Strengths and Limitations**

Parakeet:

1. Strengths:
    a. High precision in the case of EEIO-LCA due to generative justifications.
    b. Handles noise and multilingual inputs through paraphrasing.
    c. LLM-generated justification outputs

2. Limitations:
    a. Slower Processing
    b. Struggles with Novel Materials

Flamingo:

1. Strengths:
    a. Handles incomplete EIF datasets via sectoral fallbacks
    b. Faster execution
    c. Effective for macroeconomic analyses and policy-making

2. Limitations:
    a. Lacks Granularity for pLCA
    b. Limited multilingual support

CaML:

1. Strengths:
    a. Superior EIO-LCA accuracy through semantic disambiguation
    b. Minimal Human Intervention
    c. Lightweight architecture and rapid processing

2. Limitations:
    a. Designed for EIO-LCA
    b. Limits in Novel Sector Handling

- **Integration Architecture:**

Component	**Parakeet**	**Flamingo**	**CaML**
LLM Backbone	Claude 3	ROBERTa-large	BERT-base
VectorDB	FAISS	Elasticsearch	Annoy
Sector Classifier	Custom CNN	XGBoost	N/A
Output Format	JSON + Natural Language	CSV	CSV/API