Eco-Friendly Product Recommendation System Using Large Language Model Lllama-2

Chinmayee Bondgulwar[1], Sakshi Jagtap[2], Sarthak Shelar[3], Pratiksha Shevatekar[4]
[1,2,3]*Student, Dr. D.Y. Patil Institute of Engineering, Management and Research, Akurdi*
[4]*Head Of Department- Computer, Dr. D.Y. Patil Institute of Engineering, Management and Research, Akurdi*

***Abstract*—Product Recommendation is a vital part of any ecommerce platform. It acts as a window for the users to surf through new products and for the sellers to market these products. It plays a crucial role in increasing sales and engagement of the ecommerce platform. These ecommerce platforms prioritize product recommendations based on sponsored listings, popularity and sales, while they do profit the organization the new age opts for recommendation of more sustainable products. Using eco-friendly products have innumerable benefits viz environmental protection, sustainable sourcing, healthier choices. Using ecommerce platforms that are considerably always in use in day-to-day life of every individual, to promote such eco-friendly products can be profitable both for the organization and the environment. Traditionally the systems would use collaborative filtering, content-based filtering to generate product recommendations. These systems have some disadvantages like cold start problem and problem in providing complex user preferences. The Large Language Models (LLM) are known to handle massive datasets of text and learn to generate human language at high level. This makes them beneficial for activities like product recommendation as they have the potential to amplify user preferences and understand product description. In this paper we propose an eco-friendly product recommendation system that uses Llama-2 LLM. Our system works by generating personalized user embedding for each user. The previous interactions with the system are taken into accord by this embedding for user preferences. The system uses this embedding to generate eco-friendly recommendations ranked highly on the list of recommended products for the user. Our results show that our system outperforms the traditional approaches on metrics like purchase rate and click-through rate. It also happens to be beneficial for promoting environmentally responsible products and creating a demand in the market for the users, eventually increasing supply of carbon-neutral products.**

***Index Terms*—Generative AI, Large Language Models, Ecommerce, Eco-friendly.**

I. INTRODUCTION

Personalized recommendation systems have emerged as an essential way to enhance business and magnify user experience by offering tailored product suggestions. These systems traditionally were dependent upon collaborative filtering, content-based methods to predict user preferences. The system has found its way to be an integral part of the online shopping experience too. It has provided the business industry with a transformative way of using vast seas of user data. The traditional methods of collaborative filtering and content-based recommendations have been overcome with the emergence of deep learning in the digital era. Deep learning has evolved into a tool inspired by the working of the human brain. It is an advanced part of machine learning which has opened doors for an unparalleled approach to data interpretation. When deep learning is implemented into product recommendations, it provides us with more sophisticated and meticulous understandings of the user preferences, demeanor, and intentions. Instead of solely relying on the user interactions or static content attributes, recommendation systems enriched by deep learning also take into consideration the user intent and the details that were previously spurned. This way of deeply understanding the user's objective can aid in building a system which is more precise, personalized and helps in captivating the user’s interest and amplifying their experience. The advancement in machine learning has introduced an evolution in technology. Llama-2 Large Language Models (LLM) as they are called are the new reformers in recommendation mechanisms. The Llama-2 LLM gives us with its extensive knowledge repository and convoluted understanding of the connotations. Its recent headway in the field of healthcare, sentiment analysis has cut across the past large language models. When utilized for recommendation, the model ensures the ability to not only understand the user's intent but also understand the reason behind the intent. It does so by exploring the user's determination, sentiment and context. Taking into consideration the expanse in which the Llama-2 can be used, a business can strive by offering more eco-friendly recommendations. This can promote another use case of Llama-2 LLM and revolutionaries the ecommerce market by initiating an approach to contribute to saving the environment. The profound understanding done by Llama-2 LLM-based recommendation system is at the rim of ecommerce and digital content creation. The embodiment of Llama-2 LLM with the recommendation system can redefine the standard of user satisfaction and engagement. In this exploration, we delve into the subtleties of the product recommendation system enhanced by the Llama-2 Large Language Model, revealing the exciting prospect of integrating the recommendation system with the Llama-2 LLM and discovering its new potential. The notion of eco-friendly recommendation system only makes it more enticing to encourage ourselves in reforming a new touch in the world of recommendation systems. To our understanding, this research represents the deep dive into LLM-driven product recommendations using Instacart data.

II. LITERATURE SURVEY

Recommender systems play a crucial role in modern digital services, particularly in e-commerce platforms where user preferences heavily influence purchasing decisions. By leveraging AI models, these systems enhance user engagement and satisfaction by offering personalized product suggestions. Traditional recommender systems commonly rely on collaborative filtering or content-based filtering. Collaborative filtering predicts user preferences based on the behavior of similar users, while content-based filtering recommends items by analyzing a user's past interactions. Despite their success, these approaches face notable challenges. Collaborative filtering often suffers from the cold start problem, were insufficient data on new users or items limits recommendation accuracy. Content-based filtering, on the other hand, may struggle to grasp complex user preferences accurately. Recent advancements in recommendation techniques have introduced new approaches to address these challenges: Matrix Factorization Techniques: Koren et al. [1] introduced matrix factorization techniques, effectively decomposing user-item interaction data to capture latent features that improve recommendation accuracy. Deep Learning Approaches: Zhang et al. [2] proposed a multi-view deep neural network that integrates content data with collaborative information, showcasing the strength of deep learning models in enhancing recommendation performance. Hybrid Methods: Burke [3] introduced hybrid recommendation systems that combine collaborative filtering, content-based filtering, and demographic insights to improve overall accuracy and mitigate individual model limitations. Sustainability-aware Recommendations: Spillo et al. [4] explored the balance between algorithm performance and environmental impact in their sustainability-aware recommender system, emphasizing the need for energy-efficient solutions without compromising recommendation quality. Eco-Friendly Consumer Goods Categorization: Larranaga and Valor [5] provided an integrative review on eco-friendly consumer product classification, highlighting how consumer perception plays a key role in sustainable product adoption. Adaptive Green Marketing Systems: Lee and Huang [6] proposed a specialized recommender system architecture designed for adaptive green marketing, ensuring that eco-friendly products are effectively highlighted in personalized suggestions. Sustainable E-Commerce Strategies: Stalidis et al. [7] reviewed sustainable marketing strategies in ecommerce, emphasizing recommendation techniques that promote environmentally conscious choices among consumers. Cold-start Problem Solutions: Schein et al. [8] proposed strategies for handling the cold start problem by incorporating contextual data and leveraging domain-specific insights to improve recommendation outcomes for new users or items. LLMs in Recommendations: Roumeliotis et al. [9] conducted a comparative analysis of GPT and Llama models in product review evaluation, illustrating how LLMs enhance recommendation performance by interpreting detailed product descriptions and user feedback. Consumer Behavior in Eco-friendly Product Selection: Sarmad et al. [10] explored the impact of information asymmetry and online reviews on consumer behavior when selecting eco-friendly products, underscoring the importance of transparency in sustainable marketing. Future Prospects: Emerging trends such as explainable AI, multi-objective recommendations, and real-time data processing continue to shape the landscape of recommendation systems. Incorporating large language models (LLMs) like LLaMA-2 offers promising advancements in improving recommendation accuracy, scalability, and the ability to address cold start scenarios. Incorporating LLMs in sustainable product recommendations offers personalized insights, improved user engagement, and a scalable solution for enhancing eco-friendly shopping experiences. By leveraging the strengths of both traditional recommendation approaches and modern LLMs, developers can build robust, efficient, and environmentally conscious recommendation systems for diverse digital platforms.

III. INTEGRATING LLM INTO RECOMMENDATION SYSTEM

A. Semantic-Based Recommendations Llama-2 applies advanced NLP capabilities to understand contextual meaning behind user queries and feedback. More accurate recommendations of eco-friendly products can then be addressed in line with user preference and intent, hence making sustainable and conscious choices.

B. Cold-Start Problem Solution Traditional recommendation systems face challenges in new users or products because there is no interaction history. Llama-2 mitigates this problem by using the textual inputs provided by users, such as preferences and concerns about sustainability, to generate preliminary recommendations even without prior interactions.

C. Real-Time Dynamic Interaction Using its generative capabilities, Llama-2 allows for interactive and adaptive recommendations. Users can refine their preferences through real-time feedback, which the system uses to continuously improve ecofriendly product suggestions, enhancing personalization and user engagement.

Challenges in LLM-based Recommendation Systems:

D. Computational Challenges Llama-2 is a large and complex model that requires substantial computational resources; hence, its real-time use for eco-friendly product recommendations could be challenging.

E. Sometimes, AI-generated recommendations may carry biases or inaccuracies. Ethically sound and reliable eco-friendly product suggestions are a must.

F. Limitations of Text-Based Analysis Solely relying on Llama-2 for text-based recommendations may lead to overlooking important nontextual user interactions and may miss significant insights for recommending sustainable products.

IV. METHODOLOGIES

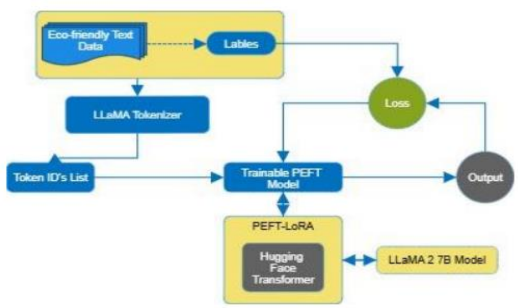
System Architecture:

The product recommendation system is implemented on a multi-layer architecture that keeps frontend and backend components distinct. The frontend user interface is a dynamic web application that allows customers to search for products, filter them, and view personalized recommendations. The backend services, as embodied by the RainforestClient implementation, are responsible for data extraction from Amazon's product database through the Rainforest API. Supporting services include currency conversion for consistent pricing across regions, implemented through the CurrencyConverter class. Error handling middleware includes retry strategies with exponential backoff, thus improving system resilience. The architecture uses the Llama-2 large language model as the main recommendation engine, which takes natural language queries and translates them into suitable product suggestions.

Data Collection and Processing:

Data is collected systematically by the RainforestClient service that makes API calls for fetching product details from Amazon India. The client supports general product search as well as fetching rich product information in terms of ASIN identifiers. Handling of pagination ensures complete coverage of products even for large result sets. For uniform financial comparison, the system provides multi-currency support through the CurrencyConverter class that converts all prices to

Indian Rupees (INR). The conversion is done using exchange rate APIs with error handling for unsuccessful conversions. Data preprocessing involves parsing JSON responses, missing value handling, normalization of product attributes, and feature extraction appropriate for the recommendation model.



Recommendation Algorithm:
The recommendation engine begins with sophisticated query processing based on Llama-2's natural language processing. This involves query expansion, as well as intent classification to determine whether the user is comparing or looking for specific products, and entity extraction to find brand names or product categories. Product matching is achieved through relevance scoring, determining the similarity of query terms to product descriptions, as well as through price-based filtering and rating-based ranking. The system learns user preferences by monitoring behavioral patterns, such as searches, clicks, and purchases, thus building individual preference profiles that change over time. The Llama-2 model has been finetuned for the e-commerce domain to maximize its recommendation ability.

Error Handling and Resilience:
One of the essential characteristics of the system is robust error handling, and this is implemented by specific error classes such as RainforestAPIError and CurrencyConversionError. The handle_api_errors function utilizes the decorator pattern to offer uniform error handling with automatic retries on the occurrence of transient failure. The strategy features exponential backoff on failed requests, hence respecting API rate limits. The system further incorporates strategies for graceful degradation, which provide partial functionality on the occurrence of service failure through the use of caching on temporary failures and conducting health checks to monitor service status. The employed error handling strategy offers feedback to the user regardless of whether the underlying services are failing. Assessment Indicators System analysis employs various complementary measures to quantify performance end-to-end. Recommendation accuracy is quantified in terms of precision (recommended items out of recommended items), recall (recommended relevant items out of all relevant items), and derived measures such as F1- score. System latency monitoring is accomplished through end-to-end response time measurement and component-by-component performance profiling. User satisfaction is quantified both through explicit feedback mechanisms such as ratings and surveys, and implicit measures such as click-through rate and time spent looking at recommendations. Conversion metrics quantify how recommendations are driving purchases, e.g., click-through rate, add-to-cart rate, and purchase completion rate, with revenue attribution to individual recommendation sources. Experimental Design The test environment is tightly controlled to achieve reproducibility of results. The testing applies standardized hardware setups with uniform software environments, as outlined in the project's dependency management plan. The benchmarking process generates baseline models employing non-LLM recommendation methods for comparison. Proven ground truth test sets permit cross-validation protocols and statistical significance testing. An A/B testing infrastructure enables real-time testing by user segmentation, with well-defined metrics for comparison and sample size calculation to enable statistical reliability. The analysis of results uses confidence intervals to determine the reliability of differences between the LLM-based method and baseline methods.

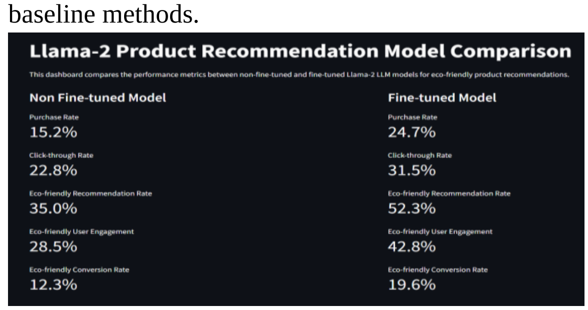


Fig-2. Model Results

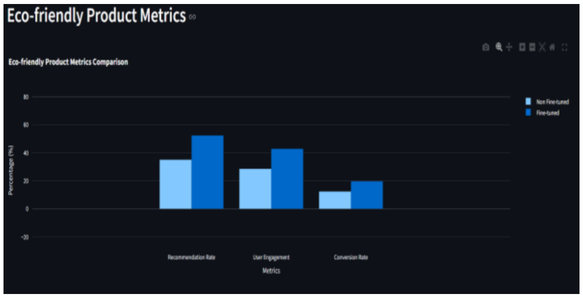


Fig-3. Eco-Friendly Metrics

V. TESTING AND EVALUATION OF FINE-TUNED LLAMA 2

Here, we use the already-trained Llama 2. A 7 billion parameter model, fine-tuned on text data. categorization tasks. This model, and its other Llama 2 counterparts, effectively based on the auto-regressive transformer design. The inherent weightings of the Llama 2 7B model transform to align with the Hugging Face Transformer architecture makes it possible to deploy Hugging. Face's fine-tuning ability. After being transformed, the model is embedded in the PEFT-LoRA model, a mechanism that enforces the Low-Rank Adaptation (LoRA) method, on the Parameter-Efficient Fine-Tuning (PEFT) repository. In Fig.2 we can see the result of the non-finetuned model does not give product recommendations. It gives links and wrong values. Fig.3. illustrates correct recommendation after fine tuning.

VI. CONCLUSION

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