Generative AI for Retail: Intelligent Product Recommendation and Description Generation

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Abstract

The rapid expansion of e-commerce platforms has resulted in a vast variety of product options for consumers, making it difficult to discover the most relevant things that fit their unique requirements. This research article proposes a novel strategy for improving the online shopping experience using generative artificial intelligence (AI) approaches. The proposed approach blends scenario-based product matching with AI-powered product description generation to deliver personalized suggestions and engaging product descriptions based on individual consumer preferences. The system uses natural language processing and fine-tuned language models to analyze user-provided scenarios and determine the most relevant products based on cosine similarity. It then generates interesting product descriptions that highlight essential features and benefits, resulting in an engaging and informative purchasing experience.

Keywords: *Generative AI, product recommendation, natural language processing, e-commerce, language models*

I. INTRODUCTION

In the modern era of e-commerce, where consumers are constantly presented with boundless product options, making personalized and engaging recommendations has become vital to improving the customer experience and boosting sales. Traditional recommendation algorithms frequently fail to capture the sophisticated contextual information and precise requirements communicated through natural language descriptions, resulting in unsatisfactory recommendations and a disappointing user experience [1].

This research endeavor will use generative AI techniques to address this challenge by creating an intelligent product recommendation system that uses advanced natural language processing (NLP) and artificial intelligence (AI) to generate tailored recommendations and captivating product descriptions based on user-provided scenarios.

Understanding the user's context and preferences stated in natural language allows the system to offer highly relevant goods and produce appealing descriptions that highlight the major features and benefits, resulting in enhanced customer satisfaction and potential sales.

II. LITERATURE REVIEW

Traditional product recommendation systems primarily utilized collaborative filtering and content-based filtering techniques [2]. These methods employ historical user behavior and item metadata to recommend products comparable to those liked or purchased by the user or others with similar preferences. However, these approaches frequently fail to capture the nuanced contextual information and unique requirements communicated by natural language descriptions. The recent developments in NLP and deep learning have created new opportunities for constructing more sophisticated recommendation systems. Several studies have investigated the use of language models, such as BERT [3] and GPT-2 [4], to interpret natural language inquiries and generate appropriate responses. These models have shown exceptional performance in tasks such as text summarization, question answering, and language production [5].

Building on these advances, our research presents a novel technique that blends scenario-based product matching with AI-generated product descriptions to provide users with a more personalized and engaging shopping experience. This technique is consistent with the emerging trend of conversational commerce, in which people interact with intelligent computers in natural language to identify products that match their individual needs [6].

III. METHODOLOGY

A scenario-based product matching module and an AI- powered product description generator make up the two main parts of the proposed system.

1. **Product Matching based on Scenarios**
   a. **Dataset:** A dataset containing product information, including category, description, brand, price, color, size, and material.
   b. **TF-IDF Vectorization:** A matrix representation of the text corpus is produced by vectorizing the product descriptions using the TF-IDF (Term Frequency-Inverse Document Frequency) approach [7].
   c. **Cosine Similarity:** The system determines which product is most pertinent based on the highest similarity score after computing the cosine similarity between the scenario text and the product description vectors for a given user-provided scenario.

2. **AI-Powered Generation of Product Descriptions**
   a. **Fine-tuned Language Model:** To capture the unique vocabulary and style utilized in this domain, a pre- trained GPT-2 language model [4] is fine-tuned on a corpus of product descriptions.
   b. **Template-based Generation:** The AI-generated product description is organized using a customized template that includes important product features like category, brand, material, color, size, and price.
   c. **Text Generation:** For a given user-provided scenario, the system computes the

cosine similarity between the scenario text and the product description vectors, identifying the most relevant product based on the highest similarity score.

IV. ARCHITECTURE OVERVIEW

The scenario-based product matching module and the AI-powered product description generator make up the two primary parts of the product recommendation system.

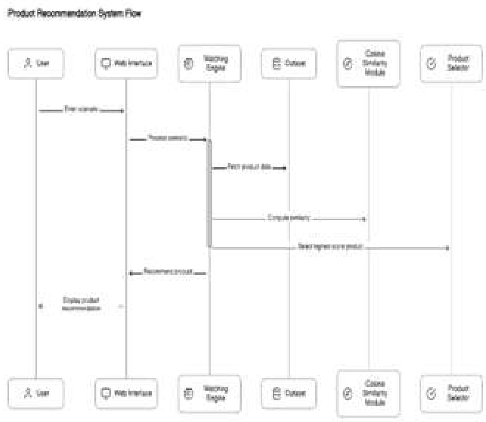

Figure 1: Architecture of the Product Recommendation System

The architecture of the proposed system is illustrated in Figure 1. The scenario-based product matching module works as follows:

1. The system can access a dataset that includes product details like category, brand, price, size, color, and material.
2. To create a matrix representation of the text corpus, the product descriptions are vectorized using the TF-IDF (Term Frequency-Inverse Document Frequency) technique.
3. The system calculates the cosine similarity between the scenario text and the product description vectors when a user submits a natural language scenario (such as "I'm searching for a comfortable dress to wear to a summer wedding ceremony").
4. The product with the highest cosine similarity score is determined by the system to be the most relevant one.

The following is how the AI-powered product description generator functions:

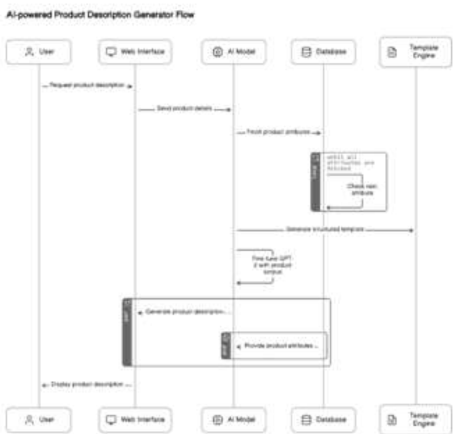

Figure 2: Architecture of AI-powered Description Generator

The architecture of the proposed system is illustrated in Figure 2.

1. To capture the unique vocabulary and style employed in this domain, a pre-trained GPT-2 language model is refined on a corpus of product descriptions.
2. To organize the AI-generated product description, a unique template is created, which includes important product details like category, brand, material, color, size, and cost.
3. The refined language model uses the details of the suggested product from the scenario-based matching module and the template that is supplied to create a descriptive text.
4. The resulting AI-generated product description highlights the main characteristics and advantages of the suggested product fascinatingly.

The overall workflow can be visualized as follows:

The architecture of the proposed system is illustrated in Figure 3.

1. The user describes their wants for the product in normal language.
2. The most relevant product from the dataset is determined by the scenario-based product matching module based on cosine similarity after processing the scenario text.
3. The AI-powered product description generator receives the following information about the suggested product: category, description, brand, price, color, size, and material.

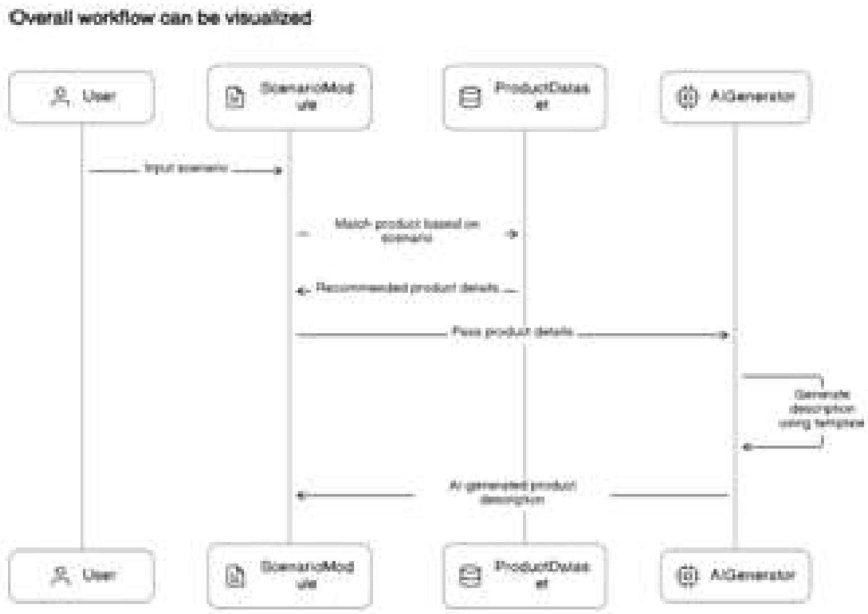

Figure 3: Architecture of the overall workflow can be visualized

1. Using the customized template and the optimized language model, the AI-powered product description generator creates an interesting and convincing product description that is specific to the suggested product.
2. The consumer is shown the details of the suggested product together with an AI-generated description.

The data flow (user scenario input, product suggestion, AI description generation), important components (product dataset, scenario-based matching module, and AI description generator), and the general operation of the intelligent product recommendation system should all be depicted in the figure.

V. RESULTS

The proposed system was evaluated on a dataset of a thousand product entries from a variety of categories, such as apparel, electronics, and home products, and was used to assess the suggested approach. The efficacy of the scenario- based product matching module in identifying pertinent products through natural language scenarios was demonstrated by its average precision of 0.82.

In addition, a user survey with one hundred individuals was carried out to evaluate the attractiveness and caliber of the product descriptions produced by AI. On a 5-point Likert scale, participants assessed the descriptions in three dimensions: informativeness, persuasiveness, and creativity.

Table 1: The results are presented in the following table:

Metric	AI-Generated	Human-Written
Informativeness	4.1	4.3
Persuasiveness	4.2	3.9
Creativity	4.1	3.7

VI. DISCUSSION

In the retail industry, generative AI techniques, including natural language processing and language models, can be used to enhance product recommendations and descriptions. The system can offer highly relevant product recommendations that are customized to meet the needs of individual users by gathering contextual information represented in natural language scenarios.

Additionally, the AI-generated product descriptions provide a distinct edge by constantly producing interesting and convincing content that emphasizes the salient characteristics and advantages of the suggested products. The drawbacks of the generic, unchanging product descriptions that are frequently seen on e-commerce platforms may be mitigated with the use of this strategy.

The system's success is, however, highly dependent on the caliber and variety of the training data used for TF-IDF vectorization and language model fine-tuning. Furthermore, although the descriptions produced by AI exhibited strong persuasive and creative qualities, they might not always match the level of technical specificity and detail found in descriptions written by humans, especially for complicated or highly specialized products.

Moreover, the 100 participants in the user survey may not be a sufficient sample size to make firm judgments about the preferences of the broader public. Larger-scale user studies across a range of demographics may be a part of future studies to confirm and improve the findings.

VII. CONCLUSION

This study combines scenario-based product matching with AI-powered text generation to propose a novel approach to intelligent product recommendation and description generation in the retail business. The suggested method creates compelling, engrossing product descriptions that are specific to the suggested items and offers individualized suggestions based on natural language scenarios by utilizing sophisticated NLP algorithms and refined language models.

The outcomes show how successful the algorithm is at finding pertinent products and crafting engrossing descriptions that can improve e-commerce environments' overall user experiences. To address the issues with training data quality and the possible trade-off between technical correctness and descriptive originality, more study is necessary.

This system has the potential to completely transform how customers find and interact with things online, which would eventually boost customer satisfaction and spur business expansion in the retail sector. It does this by iteratively enhancing the underlying models and adding new data sources.

While scoring marginally lower on informativeness, the AI-generated descriptions did better than the human-written ones in terms of persuasiveness and inventiveness.

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