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PERSONALIZED E-COMMERCE ASSISTANT USING GPT AND COLLABORATIVE FILTERING

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ABSTRACT

Shopping needs can be expressed intuitively by users thanks to PEA's deep learning architecture, which is trained using extensive customer data and product information.Enhancing customer satisfaction, PEA employs collaborative filtering and content-based recommendation algorithms to precisely align each product suggestion with a user's unique tastes and preferences. In order to enhance the shopping experience, PEA continuously adapts and evolves using a learning mechanism that reflects the changing preferences of users. Maintaining customer trust in the platform, PEA uses cutting-edge encryption and anonymization techniques to safeguard user information, thus ensuring data privacy. The proposed system consists of two primary components: a natural language processing (NLP) module powered by GPT and a recommendation engine based on collaborative filtering. The NLP module enables seamless and intuitive interactions between users and the e-commerce platform. Users can ask questions, seek product advice, or provide preferences in natural language, and GPT interprets and responds to their queries intelligently.

KEYWORDS : NLP, Collaborative filtering, Personalized e-commerce assistant

1.INTRODUCTION

With the modern digital era being widespread, e-commerce platforms are the primary channels for business owners to reach consumers. As the volume of products and services offered online continues to grow, the need for personalized shopping experiences has become crucial for boosting customer satisfaction and loyalty. One effective way to achieve this level of personalization is by combining the power of GPT (Generative Pre-trained Transformer) and Collaborative Filtering techniques to create a cutting-edge Personalized E-Commerce Assistant. By combining GPT with Collaborative Filtering, businesses can create a powerful and dynamic Personalized E-Commerce Assistant. The GPT API allows users to interact with the system using natural language, facilitating more nuanced and contextually aware conversations. This means users can express their preferences, desires, and needs in everyday language, eliminating the need for rigid keyword-based searches. The creation of a Personalized E-Commerce Assistant involves a multi-step process. Firstly, developers can integrate the GPT API into the platform to facilitate natural language interactions between users and the assistant. Users can communicate their preferences, desires, and requirements using conversational language, enabling the assistant to better understand their intent.Next, the system collects and analyses user behaviour data, such as purchase history, browsing patterns, and product feedback, to build a collaborative filtering model. product recommendations, ultimately driving customer satisfaction and business growth in the competitive e-commerce landscape.

2. RELATED WORKS

Yuhui Zhang , Hao Ding , Zeren Shui , Yifei Ma , James Zou , Anoop Deoras and Hao Wang "Language models as recommender systems", Pre-trained language models (PLMs) such as BERT and GPT learn general text representations and encode extensive world knowledge; thus, they can efficiently and accurately adapt to various downstream tasks which lead to the production of a system called Recommendation as Language Processing (RLP) , A unity pretrained and personalized prompt and prediction based algorithm(P5) . An arXiv premodel print called arXiv:2203.13366 was created based on the enhanced model and paradigm basis of the RLP . After studying the problem of personalized domain adaptation on graph neural networks with decentralized iteminteraction graphs and item features across different markets. One must obviate the need to centralize such data for domain adaptation by incorporating recent advances in personalized federated learning into GNNs, resulting in a personalized federated GNN framework.

Chenhao Hu, Shuhua Huang , Yansen Zhang and Yubao Liu [2022]" user implicit controversial recommender system" Conversational recommender frameworks has illustrated extraordinary victory. They can precisely capture a user's current nitty gritty inclination – through a multi-round interaction cycle – to successfully direct clients to a more personalized suggestion. However, conversational recommender frameworks can be tormented by the antagonistic impacts of predisposition, much like conventional recommenders. In this work, it is seen to contend for expanded consideration on the nearness of and strategies for checking predisposition in these developing frameworks.

2.1 Existing works

Building individualized e-commerce systems can be done using a number of current concepts and methods. These models use user preferences, behaviours, and historical data in order to deliver personalised recommendations and improve the user experience. The current scenario of e commerce systems has undergone drastic changes with the integration of AI along with deep learning techniques. Existing systems include machine learning models that employ the use of graph recommender techniques and user generated responses such as 'clicks', which can be improved upon definitely .

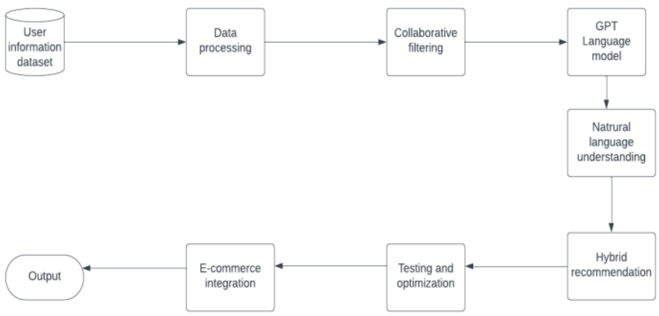
3.PROBLEM DESCRIPTION

Traditional e-commerce platforms rely on generic product recommendations, which reduces user engagement and results in lost sales opportunities. As these platforms struggle to correctly comprehend user queries, ineffective natural language processing frustrates users and produces inappropriate search results. These issues are addressed by the sophisticated ML model known as the customised E-commerce Assistant (PEA), which makes customised recommendations based on the preferences of certain customers. Users may communicate their shopping needs more naturally and get more relevant search results because to PEA's improved NLP capabilities. Continuous learning in PEA makes sure the model adjusts to shifting user preferences, improving client retention and providing recommendations that are up to current trends

3.1 Proposed work

In this current model Collaborative filtering and GPT (Generative Pre-trained Transformer) can be used to create a strong, tailored e-commerce system that uses user behavior and natural language processing data. Natural language processing and recommendation system knowledge are both necessary for integrating GPT and collaborative filtering.

4.SYSTEM ARCHITECTURE



The system architecture consists of several processes to be followed to execute the model that is proposed , it starts with data gathering and preprocessing which includes user data such as their browsing history and purchase history followed by the integration of collaborative filtering that filters the needs of the user accordingly , next we integrate gpt (Generative pre trained transformer) to help users identify things and make suggestions along with using natural language processing so the user can communicate with the system accordingly , the model is then carefully trained and tested before its deployment .

5.METHODOLOGY

A deliberate approach is required to integrate collaborative filtering and GPT (Generative Pre-trained Transformer) in an e-commerce environment in order to improve product recommendations and elevate customer experience. The procedure starts off with careful data preparation and gathering. To do this, historical user interaction data must be gathered and pre-processed to make sure it is suitable for training GPT and collaborative filtering models. This includes browsing history, purchases, and other related data. The preprocessed text data is used to train the GPT model after the data has been primed. This enables the model to discover patterns and connections from user feedback, reviews, and product descriptions. Then, based on text input, the GPT model is used to produce intelligent and persuading product summaries or recommendations. In parallel, algorithms for collaborative filtering, such as user-based or item-based collaborative filtering, are used to analyze user preferences and interactions. This makes it easier to create customised recommendations by taking into account either the tastes of people who are similar to them or products that have comparable traits.

A crucial step in combining the descriptive power of GPT with the unique insights from collaborative filtering is the combination of product summaries provided by GPT and recommendations from collaborative filtering. The tailored messages that go with the recommendations can be created by the GPT model, making them more engaging and instructive for users. A strong user involvement and feedback mechanism is set up in order to continuously improve the recommendation algorithm. Users are invited to comment on the suggestions, and this feedback loop is essential for fine-tuning the GPT model and collaborative filtering algorithms for increased accuracy and relevance over time.

5.1 Implementation

In order to use a machine learning model's predictive capabilities, it must be implemented into a functioning system or application. In order to facilitate effective storage and retrieval, the learned model is initially serialized into a portable format. During the initialization stage, this serialized model is then included into the application's code base or backend infrastructure. When input data is received, the necessary preprocessing is done to make sure it complies with the model's input specifications. We use the python programming language to implement the necessary dependencies and library to open the dataset , clean and fine tune the data and transformer model and calculate the accuracy and loss metrics.

6. RESULTS AND DISCUSSION

Fig 8.1 is the assessment of the proposed model’s approach performance after its training and fitting of data using actual data and contrast it with a number of representative methodologies that focus on diverse task families. The above table tells us how likely(probability) a related product is to be suggested to a user based on their user ratings and buying habits using unified "Pretrain, Personalized Prompt, and Predict Paradigm" through the performance comparison and ablation investigations.

In this graph of accuracy versus epoch,the training dataset's training epochs, or iterations, are represented on the x-axis. The accuracy of the model on a validation set (or training set) at each epoch is shown on the y-axis. Early epochs of training typically have a low accuracy because the model hasn't learned enough from the data. The accuracy typically rises as the model learns patterns and characteristics from the data throughout the training process.

In Fig 8.2 to quantify the mistake or difference between a model's anticipated outputs and the actual or true outputs, loss metrics (also known as loss functions) are used. A machine learning model is trained with the intention of minimizing this loss function, which aids in learning and improving the model's performance over time.

During the training process, loss measurements are generally shown as a graph to show how the loss evolves as the model iteratively updates its parameters. Typically, the loss metric value is plotted on the y-axis, with the number of training iterations or epochs plotted on the x-axis.

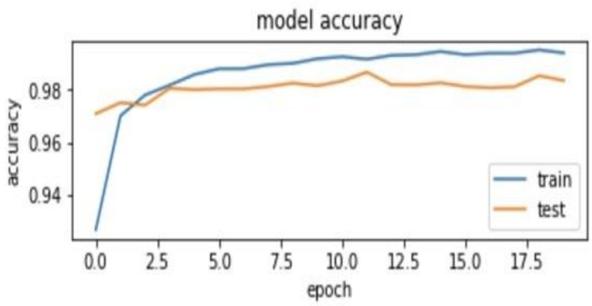


Fig 8.1 model accuracy metrics

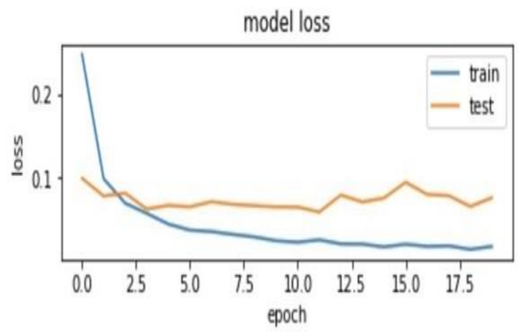


Fig 8.2 model loss metrics

7.CONCLUSION

The integration of GPT (Generative Pre-trained Transformer) and CF (Collaborative Filtering) into e-commerce platforms has the potential to greatly improve user experiences, increase sales, and personalize suggestions. While CF can make recommendations based on user behaviour and choices, GPT can produce product descriptions, reviews, and tailored content. E-commerce platforms may give customers a more enjoyable and customized purchasing experience by fusing these technologies.

8. FUTURE ENHANCEMENT :

Withstanding the done work , these are the following ways to improve the made model :

Fine tuning the model :The quality and relevance of generated material can be increased by customizing and fine-tuning GPT models expressly for e-commerce requirements. To improve the accuracy and informational value of the generated content, this can entail training the model using a dataset of e-commerce-related text.

Fairness and Bias: Efforts should be taken to reduce any biases that may exist in the recommendations or material that is generated.

Scalability and real-time integration: It's critical to create effective methods for integrating GPT and CF in real-time, especially for expansive e-commerce platforms. To handle a high amount of user interactions and provide timely and accurate recommendations, scalability is essential.

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