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SIMPLIFYING LAPTOP SELECTION FOR NON-TECH SAVVY INDIVIDUALS: CHATBOT BASED RECOMMENDATION SYSTEM

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ABSTRACT

In the current era of technology, recommendation systems are commonly used to assist individuals in sorting through extensive information and making well-informed choices. Although recommendation systems have been utilized in various fields, such as movies, skincare, and education, there is a lack of research on recommending products for laptops, even though they are crucial in daily activities. Many non-tech-savvy individuals have difficulty selecting the right laptop for their needs, even though laptops are essential for students, professionals, and home users. This study explores how intelligent chatbots can streamline decision making by offering customized laptop suggestions tailored to individual preferences, including budget, usage, and technical requirements. The proposed system uses a combination of Natural Language Processing (NLP) and web scraping to provide current product information during interaction. Information gathered from an Internet survey is utilized to enhance the system's recommendation algorithm, with a specific focus on important factors such as processors, storage, and graphics cards. This system helps people who are not comfortable with technology to overcome difficulties, enabling them to make better decisions when buying laptops. In the future, this recommendation system could broaden its range to include more types of electronic devices.

Keywords: Laptops, Chatbot, Recommendation System, Non-Tech Savvy.

I. INTRODUCTION

In today's highly competitive electronics market, successfully meeting user demands and preferences is critical for any product to stand out. Recommendation systems have emerged as powerful tools for solving the problem of information overload by providing personalized suggestions based on users' interests and requirements. These systems, commonly employed by platforms like Amazon and Netflix, analyse user behaviour and preferences to predict the most relevant products. However, traditional recommendation systems often fall short when it comes to helping users select highly personalized products, such as laptops, especially for individuals who lack technical expertise.

Choosing the right laptop is particularly challenging for non-tech-savvy individuals, given the increasing complexity of hardware and software specifications. With a vast array of options available on e-commerce platforms and the frequent use of technical jargon, many users struggle to make well-informed decisions about essential features like processors, operating systems, RAM, and graphics cards. Online reviews are often insufficient or too generalized, adding to the confusion.

To address these challenges, this study proposes a chatbot-based Laptop Recommendation System designed to simplify the laptop selection process for the general public, particularly individuals who are not well-versed in technical details. The chatbot interacts with users through a conversational interface, asking simple questions about their usage preferences and key technical requirements. It then recommends laptops based on important factors such as operating system (Windows, Linux, macOS, Chrome OS), processor (Intel, AMD), memory (RAM), and graphics card (integrated or discrete). By focusing on these key specifications, the system aims to provide personalized and accurate laptop recommendations that match users' needs.

Furthermore, this system eliminates the need for users to browse through multiple websites or rely solely on generalized online reviews, which often lead to confusion. Leveraging AI-driven chatbots and up-to-date product data, this study offers a streamlined and user-friendly solution to the laptop selection problem for a diverse range of consumers.

II. LITERATURE REVIEW

Recommendation systems have become an integral part of various industries, particularly e-commerce and digital platforms. The ability to suggest relevant products or services based on user preferences has increased the user experience and business efficiency. In recent years, various methods have been explored for building robust recommendation systems, from collaborative filtering to machine-learning-based solutions. This review focuses on product recommendation systems, particularly in the context of laptop selection for non-tech-savvy users using chatbots, machine learning, and natural language processing (NLP).

Evolution of Recommendation Systems

The early stages of recommendation systems relied heavily on content-based and collaborative filtering approaches. These methods are highly effective for structured data, such as movie or book recommendations, but lack adaptability when user input or feedback is sparse, which is known as the "cold start" problem. Traditional content-based systems use attributes of the items (e.g., genre for movies, processor for laptops) to recommend similar products, whereas collaborative filtering relies on user interactions with items to suggest what others with similar preferences liked.

However, these systems often require significant user data or specific knowledge of the technical parameters (e.g., RAM, processor type, and GPU). As noted in research on hybrid laptop recommendation systems, conventional recommendation methods, particularly for technical products such as laptops, pose challenges for users unfamiliar with jargon. Thus, for non-tech-savvy users, a more intuitive interface, such as chatbots driven by NLP, could simplify the interaction by avoiding technical details and focusing on user-friendly queries.

Cold Start Problem and Hybrid Approaches

One of the most significant challenges in recommendation systems is the cold start problem. This occurs when the system has little to no data about a user or product, making it difficult to suggest relevant recommendations. To address this, hybrid recommendation systems combine various techniques, such as content-based and collaborative filtering, with machine learning to improve the prediction accuracy.

For example, in the field of laptop recommendation, a hybrid approach that combines collaborative filtering (based on past user behavior) with machine-learning models can help capture product features and predict user preferences more effectively. In addition, methods such as Naive Bayes Classifiers (NBC) and the Analytical Hierarchical Process (AHP) have been used to address cold start issues by comparing product alternatives and associating features with products without relying on past user history. These approaches ensure that recommendations remain accurate, even for new users.

In the chatbot model, leveraging hybrid machine learning techniques would allow the system to balance analyzing user inputs (via NLP) and scraping relevant data from the web to generate personalized recommendations for laptops without technical jargon.

Machine Learning for Product Classification

Recent advances in machine learning (ML) have enabled recommendation systems to classify and predict user preferences with higher precision. For laptop recommendations, classification algorithms such as Support Vector Machines (SVM), Decision Trees, and Artificial Neural Networks (ANN) are often used to segment products into categories such as budgets, midranges, and flagships.

These classifiers work by learning from a dataset that includes product features (price, brand, and specifications) and user preferences. SVMs, for example, are known for their excellent performance in classification tasks, achieving a high accuracy in classifying laptop products into different categories. Decision Trees, on the other hand, offer an intuitive way to map user decisions based on simpler attributes, which could be useful in a chatbot that interacts with non-technical users.

However, for users who may not be familiar with these technical parameters, integrating these classifiers into an NLP-based chatbot allows the system to translate complex machine-learning outputs into more digestible insights. For instance, instead of asking users to specify the RAM or processor, the chatbot could ask about their typical usage (e.g., gaming, graphic design, and office work) and map these inputs to the most relevant laptop features using ML classifiers in the background.

Chatbots and Natural Language Processing (NLP)

Chatbots have become increasingly popular in applications requiring human-computer interaction from customer service to e-learning environments. Natural Language Processing (NLP) is the cornerstone of these systems, allowing chatbots to interpret and understand user input in a conversational manner. The use of NLP not only facilitates interaction with non-tech-savvy users, but also allows for customization and personalization of responses.

In recommendation systems, NLP enables the chatbot to translate user requirements into actionable data points for machine-learning models. For example, instead of expecting users to specify the technical aspects of a laptop, the chatbot can use simple questions like, "Do you need a laptop for gaming, professional use, or everyday tasks?" to infer the important specifications. This removes the technical language barrier and allows for more user-friendly interactions.

In addition, studies have shown that NLP-based chatbots improve user engagement and satisfaction by providing real-time responses based on individual needs. By incorporating sentiment and user behavior analyses, these systems can refine their recommendations over time, offering more accurate suggestions for each interaction. This aligns with the proposed chatbot model, where NLP is used to interpret user requirements and provide suitable laptop recommendations while scraping updated product data from the web.

Data Scraping and Real-Time Updates

For a recommendation system to remain effective, especially in rapidly evolving markets, such as electronics, it is essential to have real-time data on product availability, pricing, and features. Web scraping allows recommendation systems to gather up-to-date information from e-commerce platforms, ensuring that the recommendations are relevant and current.

In the context of your chatbot, web scraping can be employed to continuously update the product database using the latest laptops and their specifications. This real-time integration ensures that users receive recommendations reflecting the latest market trends and pricing structures. Research indicates that web scraping combined with NLP and machine learning can significantly enhance the accuracy and timeliness of recommendations by constantly refreshing the data pool.

Additionally, the integration of scraping technologies can help bridge the gap between user inputs and product availability, ensuring that the chatbot can recommend products that meet user needs and are currently available for purchase.

Personalization and User-Centric Design

One of the primary goals of modern recommendation systems is to provide personalized experience for each user. In the context of chatbots recommending laptops, personalization involves understanding the unique needs of each user, such as budget constraints, design preferences, and intended use. Studies have shown that personalization significantly improves user satisfaction as recommendations are tailored to individual preferences.

By leveraging machine learning, NLP, and web scraping, chatbots can provide a highly personalized user experience. The system can collect data from users through simple, non-technical questions, and use this information to recommend laptops that fit their specific needs. Furthermore, by analyzing user feedback and interactions, chatbots can refine their recommendations over time, thereby improving their accuracy and relevance.

III. METHODOLOGY

The development of Simplifying Laptop Selection for Non-Tech Savvy Individuals: Chatbot-based Recommendation System follows a structured methodology to ensure that the recommendations are accurate, personalized, and easy to understand for non-technical users. The methodology is divided into several key stages: data collection, data processing, natural language processing (NLP) for user interaction, machine learning

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models for recommendation, and user interface development. Each step is designed to create an effective and user-friendly system.

Data Collection

To provide meaningful laptop recommendations, the system requires comprehensive and up-to-date data on various laptops and their specifications. This data is gathered through **web scraping**:

- **Web Scraping**: Automated web scraping tools such as BeautifulSoup, Scrapy, and Selenium are employed to extract details from online retailers, manufacturers, and e-commerce websites. The scraped data includes vital technical specifications like processor types, GPU models, RAM, storage capacities, battery life, and pricing information. This ensures that the recommendation system has access to the latest laptops available in the market.
- **Benchmark Scores and Component Data**: To determine the performance of each laptop, the system collects benchmark scores for key components such as processors, GPUs, and storage devices. These benchmarks, sourced from established online platforms, help the system evaluate the real-world performance of different laptops. By using these scores, the system can accurately recommend laptops that meet the user's performance needs.
- **API Integration**: In addition to web scraping, the system may integrate with third-party APIs (if available) to fetch data in a more structured format. This helps cross-verify the scraped data and maintain accuracy in the recommendations.

Data Storage and Processing

The data collected is stored and processed in a structured manner to ensure efficient retrieval and analysis:

- **Database Management**: The system uses a combination of relational databases (such as MySQL or PostgreSQL) and NoSQL databases (like MongoDB) to store the scraped data. This ensures scalability and flexibility in handling both structured and semi-structured data. Relational databases store laptop specifications, while NoSQL databases handle unstructured data such as customer reviews or feedback.
- **Data Cleaning and Preprocessing**: The raw data collected is cleaned to remove duplicates, handle missing values, and correct structural errors. This ensures that only high-quality data is used in the recommendation process. Libraries such as Pandas and NumPy are used for data cleaning and preprocessing, making the dataset ready for analysis.

Natural Language Processing (NLP) for User Interaction

The system's chatbot interface allows users to interact with the recommendation engine through natural language queries. This is achieved through advanced NLP techniques:

- **NLP Models**: Pre-trained models like BERT (Bidirectional Encoder Representations from Transformers) or GPT (Generative Pre-trained Transformer) are used to interpret user inputs. These models allow the system to understand natural language queries such as "I need a laptop for office work under $800" or "I want a laptop with a long battery life for travel." Libraries like **spaCy** and **NLTK** are employed to handle NLP tasks.
- **Extracting User Preferences**: The chatbot extracts important details from the user's input, such as budget, intended use (e.g., gaming, work, travel), and specific preferences (e.g., lightweight design, high-performance GPU). This allows the system to tailor the recommendations based on the user's needs without requiring technical knowledge.
- **Context Understanding and Sentiment Analysis**: Sentiment analysis is also employed to gauge the user's satisfaction with the chatbot's responses. If the system detects confusion or dissatisfaction, it adapts its responses to provide clearer, more helpful recommendations.

Machine Learning Model for Laptop Recommendation

The recommendation system employs machine learning techniques to process user inputs and provide personalized laptop suggestions:

- **Classifier Model**: A classifier model processes the user's inputs and matches them with the best-suited laptops. The system is trained using historical data, including laptop specifications, benchmark scores, and user preferences. Machine learning algorithms such as **random forests**, **decision trees**, or **support vector machines (SVM)** are used to classify and rank laptops based on how well they meet the user's criteria.

- **Weighted Scoring System**: Each laptop is scored based on how well its specifications align with the user's stated preferences. A weighted scoring system is applied to ensure that the most important factors (e.g., processor speed, battery life) receive higher priority in the recommendation process. This ensures that users receive recommendations tailored to their specific needs.
- **Adaptive Learning**: The recommendation system is designed to improve over time through adaptive learning. User feedback, such as whether a recommended laptop was purchased or met their expectations, is used to adjust the model and refine future recommendations. This feedback loop helps the system continuously evolve and become more accurate.

User Interface (UI) and Interaction Design

The chatbot interface is designed to be intuitive and accessible, allowing non-tech-savvy users to easily interact with the system:

- **Chatbot Interface:** The primary user interaction occurs through a chatbot, which provides a conversational experience. Users can either type their queries or use voice commands. The chatbot is built using platforms like **Rasa** or **DialogFlow**, which enable smooth natural language interaction.
- **Frontend Development**: The user interface is developed using modern web technologies such as **React**, **Vue.js**, or **Angular** to create a responsive and user-friendly design. The interface is designed to be accessible across different devices, including desktops, tablets, and smartphones.
- **Cross-Platform Integration**: The system can be integrated with popular messaging platforms such as WhatsApp, Facebook Messenger, or a dedicated web interface, allowing users to access the chatbot from various channels.

Recommendation Output

Once the user's preferences are analysed, the system generates a list of laptops that best match their criteria:

- **Personalized Recommendations**: The system provides a recommendation of laptop from a ranked list of laptops based on the user's input. The recommendation includes a detailed explanation of why the laptop was chosen, highlighting key specifications such as processor performance, battery life, and price. This transparency helps users understand how the recommendations align with their needs.

Testing and Evaluation

To ensure the system functions correctly and delivers accurate recommendations, thorough testing and evaluation are conducted:

- **User Testing**: The system is tested with a variety of users, especially those who have limited technical knowledge. This helps to ensure that the chatbot interface is easy to use and that the recommendations are appropriate. User feedback is collected to identify any issues in the interaction process or with the recommendations themselves.
- **Performance Evaluation**: The machine learning model is evaluated for its accuracy and performance using metrics such as precision, recall, and F1-score. Additionally, the speed of the system in providing recommendations is tested to ensure that users receive timely responses. The system's ability to adapt and improve through feedback is also closely monitored to ensure continuous improvement.

IV. CONCLUSION

The proposed chatbot model for laptop recommendations is designed to assist non-tech-savvy individuals in selecting the right laptop without needing to understand technical specifications. By asking simple, non-technical questions about user needs, such as their primary use (e.g., work, entertainment, portability), the chatbot can recommend suitable laptop models using machine learning algorithms. This model simplifies the decision-making process, making it accessible to a wider range of users who may not be familiar with technical terms like RAM or processor speed.

However, the current model has limitations. The data used for this project is based on a specific set of user interactions and preferences. Therefore, the recommendations generated may not fully account for the wide variety of user needs across different demographics, professional fields, or geographic regions.

To improve the accuracy and personalization of the chatbot in the future, additional factors should be incorporated. These could include user preferences related to design, portability, and price range, along with non-technical priorities like battery life or durability. By gathering data from a broader user base and analysing trends across various use cases, the model could provide more tailored and accurate recommendations.

Future research could explore advanced Natural Language Processing (NLP) techniques to enhance user interactions. NLP could analyse online reviews and customer feedback to identify trends and preferences in laptop features, helping to refine the recommendations further. By incorporating data from web-scraped reviews, the chatbot could provide recommendations based on real user experiences rather than just product specifications.

Additionally, integrating chatbot functionality with NLP would enhance the overall user experience by enabling conversational interactions. The chatbot could ask simple, non-technical questions to understand user preferences, such as "Do you need a laptop for gaming or general use?" or "How important is battery life for you?" This conversational approach would create a more engaging and personalized experience, empowering users to make confident decisions without needing to delve into technical details.

In conclusion, the integration of machine learning, web scraping, and NLP provides a strong foundation for developing a chatbot capable of making informed laptop recommendations to non-technical users. Future improvements and expansions of the model will enhance its applicability, ensuring that users from diverse backgrounds can easily find laptops that suit their unique needs.

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