Restaurant Menu Dish Recommendation using Content and/or Collaborative Filtering

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tAIsty is a restaurant menu recommendation system that uses both collaborative and content-based filtering to suggest dishes to users. The system employs machine learning algorithms like Approximate Nearest Neighbors (ANN) and a vector database to efficiently match users with similar tastes and recommend dishes based on their past orders and preferences. By storing dish attributes such as ingredients and cuisine types, the system can also suggest dishes similar to a user's current selection. The system also incorporates features such as allergy filtering to further personalize recommendations. In addition to this, in order to highlight the quality of ingredients, their expiry dates are notified to restaurants, and in turn, end users are recommended these dishes, thereby reducing food wastage. This recommendation system can be incorporated into digital menus of restaurants.

Keywords: Recommendation systems, Collaborative filtering, Content-based filtering, Vector databases, Food recommendation

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1 Introduction

Recommendation systems have revolutionized the face of many industries, especially e-commerce and streaming services, where recommendations can spearhead decision-making.

With the food industry expanding, especially the restaurant industry and a larger variety of options with diet plans available, there is a growing need for customized menus. Along with a larger menu and the option of diets presented to the customer, the burden of the choice can result in decision fatigue that negatively affects the satisfaction levels of customers and bottom lines of restaurants. This motivated us to build a recommendation systems developed based on individual preferences for favorite dishes with the help of machine learning, known as tAIsty. The system relies on collaborative filtering, but its approach ensures content-based filtering through ingredients, cuisine, and dietary restrictions, keeping in view the behavior and historical interaction of users. This recommendation system can be integrated into the digital menus of restaurants which are nowadays becoming commonplace.

This project fills that gap by developing an elastic recommendation framework that is designed to improve the dining experience in the restaurant industry. tAIsty will leverage Nearest Neighbor Algorithms to provide restaurants with highly accurate recommendations of dishes that maximize customer interaction and help restaurants display dishes that match both the available inventory and customers' desires. The question of building a good recommendation system is addressing each user's need. For instance, new users or dishes are in a ”cold start” problem in the provision of recommendations. Traditional collaborative filtering cannot recommend without enough user data, while content-based filtering may not take the behavior of a user into consideration, making it rely on recent activity and becoming less relevant to other behaviors or times. Thus, tAIsty uses a hybrid approach that combines the benefits of both elements, such that suggestions will remain relevant even in cases of sparse user activity history.

The project benefits from the success of hybrid recommendation systems applied in multiple domains. It will accommodate user preferences on top of that, but it promotes the idea in the interest of the freshness factor; recommendations are made in consideration of quality and the fresh availability as well. The following sections describe the tAIsty design and implementation, recommendation algorithms, data processing methodologies, and system architecture. The proposed system also accounts for suggestions made as 'Today's specials' based on the features like expiry date of ingredients used in dishes, the date when it was brought in, the freshness of that product etc. Aiming towards the reduction and management of the food items, leading to lesser food wastage. Scalability and future enhancement considerations included surveying how tAIsty could use customer reviews or even be in real-time regarding dish availability to enhance recommendations. With these strategies, tAIsty then showcases exactly how machine learning can be used to give meaningful and adaptive recommendations toward better service for the diner and provides restaurants tools to optimize the utilization of their resources in a better way.

2 Literature Review

2.1 Introduction

Recommender systems are information filtering techniques used to predict user preferences and offer tailored suggestions. In recent years, food recommender systems have gained significant attention, addressing the challenge of navigating diverse culinary options and promoting healthy eating habits. This literature review explores the landscape of food recommender system research, examining key arguments, findings, and their relevance to developing robust and personalized food recommendation platforms.

2.2 Filtering Techniques and Hybrid Approaches

The foundation of food recommender systems lies in **collaborative filtering** and **content-based filtering** methods. Singh and Dwivedi developed a food recommendation system combining these techniques [1]. Their system uses the k-nearest neighbors algorithm to recommend food items based on user preferences and ratings from similar users. Similarly, Srinivasa and Pattekar designed a restaurant food recommendation system utilizing collaborative filtering, content-based filtering, and **association rule mining** using the Apriori algorithm. This system leverages a user's previous orders and taste preferences to suggest similar items or those frequently purchased together. These studies highlight the effectiveness of combining filtering techniques to create more comprehensive and accurate recommendation systems.

Hybrid systems, which integrate multiple recommendation approaches, have emerged as a promising direction in food recommendation research. Melese argued that hybrid systems can overcome the limitations of individual methods, providing more accurate and diverse recommendations. Their research explored a hybrid system that incorporates both content-based and collaborative filtering, highlighting the potential of combining user preferences with item attributes to generate personalized suggestions.

2.3 Sentiment Analysis and User Preferences

Asani, Vahdat-Nejad, and Sadri explored the potential of **sentiment analysis** to understand user preferences from online reviews. Their research demonstrated that analyzing user-generated content can offer valuable insights into dining experiences, facilitating the identification of popular dish choices and restaurants that align with user preferences. The incorporation of sentiment analysis could enhance recommendation accuracy by providing a deeper understanding of user opinions and satisfaction levels.

2.4 Nutritional Information and Health-Conscious Dining

With a growing emphasis on healthy eating habits, incorporating **nutritional information** and **dietary constraints** has become crucial for food recommender systems. Toledo, Alzahrani, and Martínez focused on integrating these aspects into their recommendation system, arguing for the development of systems that promote healthier food choices. They proposed a system that considers users' nutritional requirements and preferences, suggesting dishes aligned with their dietary goals.

2.5 Time-Aware Recommendations and Deep Learning

Recognizing the dynamic nature of user preferences, Rostami et al. developed a **time-aware** food recommender system using **deep learning** and graph clustering techniques. Their system addresses the evolving nature of taste preferences over time, incorporating **time stamps** to track changes in user behavior and provide recommendations relevant to the current context. Time-awareness is an essential aspect of personalized food recommendations as it accounts for the temporal dynamics of preferences and ensures the relevance of suggestions.

2.6 Knowledge Graphs and Future Directions

The use of **knowledge graphs** in food recommender systems has gained momentum in recent years. Melese highlighted the importance of incorporating knowledge graphs to capture complex relationships between food items, ingredients, and user preferences, offering a more structured representation of food-related information. This approach has the potential to enhance recommendation accuracy by providing a richer understanding of the culinary domain.

Trattner and Elsweiler outlined various challenges in food recommender system research, including the **cold start problem** and **data sparsity**. They advocated for the exploration of innovative techniques to address these challenges, such as leveraging external knowledge sources, incorporating user demographics and preferences, and developing advanced hybrid approaches. Future research should also focus on evaluating systems in real-world settings to assess user engagement and satisfaction levels.

Table 1: Literature Review Summary

Author(s)	**Contribution**
Singh & Dwivedi [1]	Used k-NN with collaborative and content-based filtering for food recommendations
Srinivasa & Pattekar [2]	Combined collaborative filtering, content-based filtering, and Apriori for restaurant recommendations
Melese [3]	Explored hybrid models integrating multiple recommendation techniques
Asani, Vahdat-Nejad [4]& Sadri	Applied sentiment analysis on reviews to enhance recommendations
Toledo, Alzahrani & Martínez [5]	Incorporated nutritional data for health-conscious recommendations
Rostami et al. [6]	Developed a time-aware system using deep learning and graph clustering
Trattner & Elsweiler [7]	Addressed cold start and data sparsity issues in food recommendation

3 Basic Terms

- **Content-Based Filtering**: This method recommends items similar to what a user has liked in the past. It analyses the characteristics of items (e.g., ingredients, cuisine type, dietary tags) and recommends similar one based on a number of metrics such as cosine distance.
- **Collaborative Filtering**: This approach leverages the preferences of similar users to make recommendations. It analyses patterns in user ratings and suggests items liked by users with similar tastes. For instance, if several users who like pizza also enjoy pasta, the system might recommend pasta to a user who likes pizza.

- **Cold Start Problem**: This challenge arises when the system has limited information about a new user or a new item, making it difficult to generate accurate recommendations. Addressing the cold start problem often involves gathering initial preferences or using hybrid techniques to leverage any available information.
- **Evaluation Metrics**: These measures assess the performance of recommender systems, quantifying their accuracy, relevance, and user satisfaction. Common metrics for recommendation systems include CTR(Click through rate), Precision@K, Recall@K and MAP@K
- **Vector Database (VectorDB)**: A database optimized for storing and querying high-dimensional vector embeddings. In food recommender systems, VectorDBs (e.g., MongoDB Atlas Vector Search) are used to store embeddings of dish features and user profiles, facilitating fast and scalable similarity-based retrievals.
- **Approximate Nearest Neighbors (ANN)**: An efficient search technique to quickly find items that are close in feature space to a query item. HNSW and NNDescent are some of the various ANN algorithms used across a plethora of applications

4 Methodology

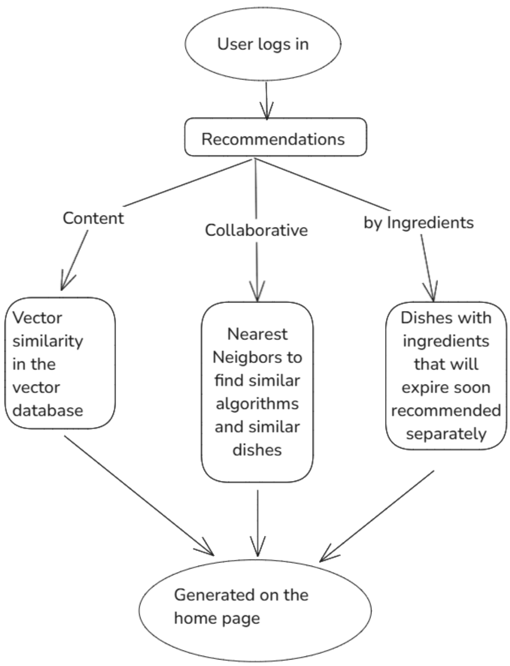

Figure 1: Recommendation Processes

tAIsty consists of a combination of three recommendation techniques:

4.1 Content-Based Filtering

Utilizes vector similarity in the vector database to find dishes similar to those in the user's order history. The user can also find dishes similar to a particular dish when they interact with them.

4.2 Collaborative Filtering

Based on the number of orders for each dish by each user, a user-item matrix can be generated. Thus nearest neighbors algorithms can be run to find similar users or similar food items if the transpose is considered.

4.3 Ingredient-Based Filtering

Recommends dishes containing ingredients that will expire quickly, thereby optimizing the usage of the inventory.
All three recommendation streams converge to generate personalized recommendations that are displayed on the home page.

To evaluate the performance of the recommendation system, the following metrics are used:

4.4 Precision at k

Precision@k (P@k) measures the proportion of relevant recommendations in the top-k results.

$$\text{Precision@k} = \frac{\text{Number of relevant items in k}}{k} \tag{3.1}$$

4.5 Recall at k

Recall@k (R@k) evaluates how many relevant items are retrieved out of all possible relevant items.

$$\text{Recall@k} = \frac{\text{Number of relevant items in k}}{\text{Total Number of Relevant Items}} \tag{3.2}$$

4.6 Click-Through Rate (CTR)

Click-Through Rate (CTR) reflects user engagement by measuring the ratio of clicks to total impressions.

$$\text{CTR} = \frac{\text{Number of clicks}}{\text{Number of impressions}} \times 100 \tag{3.3}$$

4.7 Content Similarity / Distance Metric

For content-based filtering, the cosine similarity between the user preference vector $\vec{u}$ and item feature vector $\vec{i}$ is calculated as:

$$\text{Cos}(\vec{u}, \vec{i}) = \frac{\vec{u} \cdot \vec{i}}{||\vec{u}|| \times ||\vec{i}||} = \frac{\sum_{j=1}^{n} u_j i_j}{\sqrt{\sum_{j=1}^{n} u_j^2} \times \sqrt{\sum_{j=1}^{n} i_j^2}} \tag{3.4}$$

Vector databases such as Weaviate use cosine distance to calculate distances between embeddings.

5 Proposed Architecture

The proposed architecture for tAIsty is designed to deliver personalized food recommendations by leveraging a hybrid recommendation system that combines content-based filtering and collaborative filtering, supported by a vector database and approximate nearest neighbor (ANN) search techniques.

The system begins with data ingestion from multiple sources, including web-scraped data collected through BeautifulSoup (BS4) or Selenium, manually curated synthetic data and survey responses, and publicly available downloaded datasets. This data is stored centrally in a database, ensuring efficient handling of both raw and processed information. Additionally, a separate file structure is used to manage ingredients and their expiry dates, keeping shelf life independent from the ingredient data.

Once the data is collected, a preprocessing pipeline refines and selects relevant features for recommendation. The system extracts two key types of attributes: content-based features such as cuisine, dish name, and allergen information, and collaborative filtering features, which include user order history, food IDs, and customer IDs. These features drive two complementary recommendation approaches.

For content-based filtering, the system converts dish attributes into vector embeddings, enabling similarity-based retrieval. This is achieved using Vector search, which efficiently identifies dishes with similar characteristics. This method ensures that even first-time users receive relevant recommendations based on the inherent properties of menu items.

The collaborative filtering component leverages user interaction data to make recommendations based on shared preferences. A Customer-Food-Rating Matrix is constructed, where user-item interactions (e.g., order history) are processed using techniques such as matrix factorization (ALS, SVD) and nearest neighbor-based methods (HNSW with PyNNDescent). Unlike traditional rating-based collaborative filtering, this approach places greater emphasis on actual order counts to generate more reliable recommendations.

The retrieval and recommendation process is seamlessly integrated into the user interface. Without logging in, users receive content-based recommendations. Once logged in, they benefit from collaborative filtering-driven personalization. Additionally, selecting a dish triggers an immediate display of similar items. A feedback system could be implemented to refine their recommendations by clicking 'like' or 'dislike,' which adjusts the underlying recommendation weights dynamically.

Future enhancements include integrating LLM-based personalized re-ranking, which would further refine recommendations based on contextual understanding, and implementing user clustering to suggest dishes based on community-driven preferences. The system is also designed with scalability in mind, allowing for cloud deployment to support real-time recommendation updates.

By combining content-based similarity, collaborative filtering-driven personalization, and ANN-based retrieval, tAIsty offers a robust and scalable approach to menu dish recommendations, ensuring that users receive highly relevant and personalized suggestions in real time.

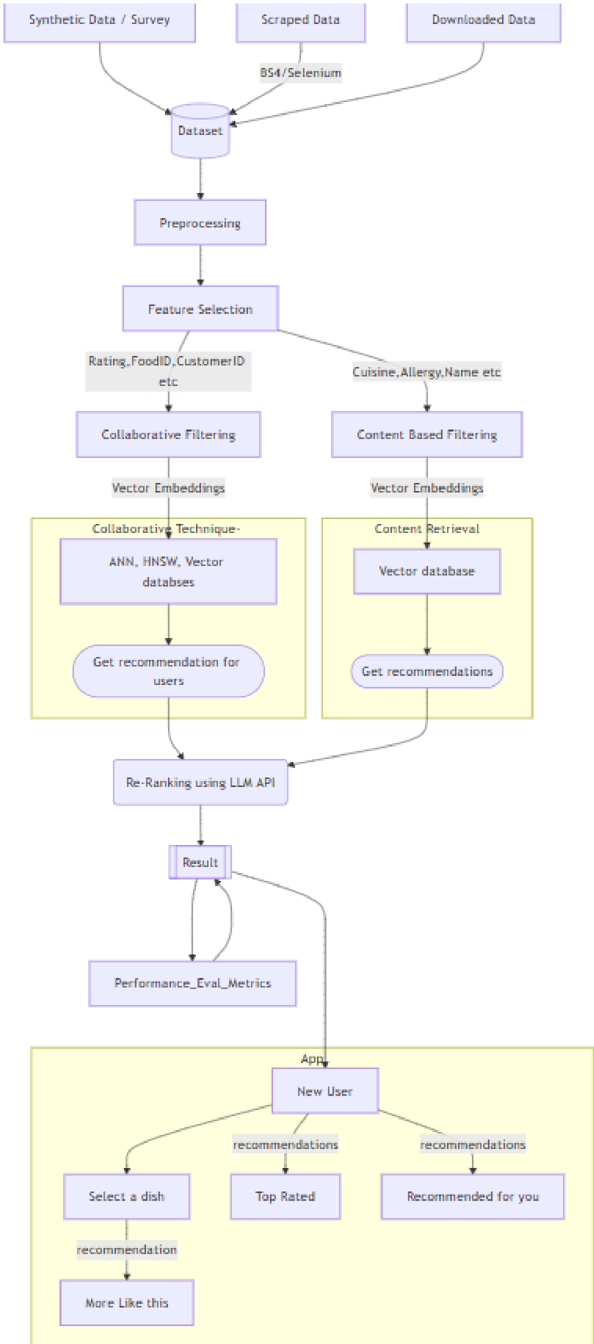

Figure 2: Proposed System Architecture

6 Comparison of tAIsty with relevant platforms

6.1 Personalization and Accuracy of Suggestions

- **tAIsty**: This system can be integrated with the digital menu of each restaurant and could be scaled for chains of restaurants. The approach aims to provide dish suggestions that are more pertinent and specific to the different needs of individual users.
- **Zomato and Swiggy**: Zomato leverages recommendation systems to recommend restaurants and cuisines and dishes based on personalized profiles.

Hybrid Approach: The algorithms used by tAIsty could provide more relevant recommendations compared to basic collaborative or content-based methods used by other platforms.

6.2 Management of Allergies and Dietary Limitations

- **tAIsty**: Provides a clear allergy filtering function that allows users to specify their allergies, ensuring that dishes containing those allergens are omitted from suggestions. This emphasis on user safety and adherence to dietary requirements enhances trust and improves user experience.
- **Zomato/Swiggy**: Zomato has recently implemented veg mode and provides allergy filtering options in the orders, but not in the recommendation system itself.

Advantage: The proactive approach of tAIsty in handling allergy cases makes it a strong contender in this niche market by offering a safer and more personalized experience.

6.3 Solution to the Cold Start Problem

- **tAIsty**:
  - **Hybrid Approach**: Uses both collaborative and content-based filtering to generate recommendations even when user data is sparse.
  - **Fallback Methods**: Defaults to popularity-based recommendations and allows new users to define their preferences for initial suggestions.
- **Zomato/Swiggy**: Zomato and Swiggy provide a questionnaire when a user first signs in, to understand user preferences

Advantage: tAIsty's approach to handling new users and sparse data could lead to more relevant recommendations from the start, fostering user engagement and platform adoption.

6.4 Reduction of Food Waste

- **tAIsty**: Designed to minimize food waste by prioritizing dishes with ingredients nearing expiration. Additionally, it analyzes past data to predict demand and optimize ingredient usage.
- **Zomato and Swiggy**: No specific feature or initiative aimed at reducing food waste has been identified.

Advantage: Sustainability-focused features could make tAIsty appealing to environmentally conscious users and restaurants, setting it apart from existing platforms.

6.5 User Interface and Experience

- **tAIsty**: Features an intuitive user interface that provides personalized recommendations upon login, while also offering content-based suggestions for users who do not log in.
- **Zomato/Swiggy**: Both platforms have well-designed interfaces, but the effectiveness of their recommendation systems compared to tAIsty remains unknown.

Potential Advantage: While further evaluation is needed, tAIsty's emphasis on personalized recommendations and user-friendly design may enhance user engagement and satisfaction.

6.6 Key Considerations

- **Limited Information on Zomato and Swiggy**: The analysis is primarily based on tAIsty, with minimal publicly available details on the algorithms and features of Zomato and Swiggy.
- **Empirical Effectiveness**: The actual effectiveness and user satisfaction of tAIsty compared to Zomato and Swiggy need to be verified through empirical data and user reviews, which are currently unavailable.

6.7 Comparison with a website-based digital menu

While comparing the proposed system's features and approach with an already existing digital menu designed and deployed in a restaurant, we found out a few features that they were lacking:

- **Allergy and dietary restriction management**:
  - **tAIsty**: Includes allergy filtering function, allowing the users to specify their allergies, ensuring dishes containing specified allergens are excluded from the recommendations, prioritizing user safety and strictly catering to the dietary needs.
  - **Restaurant's platform**: Offers menus accessible via QR codes. However, doesn't prominently feature functionalities that allow users to filter out dishes based on the allergens or dietary restrictions.
- **Personalization and recommendation engine**:
  - **tAIsty**: Makes use of a hybrid recommendation system that combines collaborative filtering with content-based filtering (focusing on dish attributes like ingredients and cuisine). This approach aim towards offering features dish suggestions tailored to individual user preferences, enhancing the dining experience.
  - **Restaurant platform**: Provides a digital platform for menu browsing and ordering. While it offers features like QR code-based digital menus and online ordering, it doesn't emphasize personalized dish recommendations based on user behavior or preferences.
- **Addressing cold start problem**:

  - **tAIsty**: Makes use of:
    * Hybrid Approach: Combining collaborative and content-based filtering to generate recommendations even with sparse user data.
    * Fallback Methods: Utilizing popularity-based recommendations and allowing new users to define their preferences to guide initial suggestions.
  - **Restaurant platform**: Doesn't specifically address strategies for personalized recommendations for new users with limited or no interaction history.
- **Sustainability and Food Waste Reduction**:
  - **tAIsty**: Aims to prevent food waste by:
    * Suggesting dishes with ingredients nearing expiration.
    * Analyzing past data to predict dish demand, helping avoid overstocking.
    * Balancing ingredient usage with customer preferences to optimize inventory.
  - **Restaurant platform**: Lacks focus on features aimed at reducing food waste through inventory or ingredient management.
- **User Interface and Experience**:
  - **tAIsty**: Designed with an intuitive and easy-to-use interface offering personalized recommendations upon user login and content-specific suggestions even without logging in, enhancing user engagement.
  - **Restaurant platform**: Designed with a straightforward interface that allows customers to scan QR codes to access digital menus and place orders. While effective for browsing and ordering, it doesn't emphasize personalized user experiences or recommendations.

7 Conclusion

tAIsty can be integrated into digital restaurants' menus. Thus each restaurant could have its own menu and users and consequently their own version of tAIsty. Additionally, recommendation of dishes whose ingredients would expire could be facilitated with the integration of an inventory management system. However, tAIsty can be scaled for restaurants chains, where the menu is generally the same, thus user profiles can be retained across various locations. Thus, the hardware requirements that could handle concurrent requests of all the customers present in a restaurant at a particular time would be necessary.

1. **Enhanced Personalization and Relevance**: tAIsty's hybrid recommendation system contains collaborative and content-based filtering, together with ANN and vector database integration, to provide more accurate, personalized suggestions aligned with user preferences.

2. **Management of Allergy and Dietary Limitations**: tAIsty is unique for its specific allergy filtering feature, allowing users to avoid dishes containing allergens, thus ensuring a safe experience for people with dietary restrictions. Zomato and Swiggy have not prominently addressed allergy management, which may limit their usability for individuals with dietary sensitivities.

3. **Cold Start Problem Solution**: tAIsty addresses the cold start problem with fallback strategies, including popularity-based and user-defined preferences, to enhance engagement with new users from the beginning. It remains unclear whether Zomato and Swiggy have any dedicated solutions for this issue, potentially impacting their ability to attract and retain new users effectively.

4. **Sustainability and Reduction of Food Waste**: tAIsty includes planned waste-reduction features, such as serving dishes with ingredients nearing expiration, and balanced ingredient use, which highlight its commitment to sustainability. Since neither Zomato nor Swiggy has implemented similar food waste reduction initiatives, tAIsty could appeal to environmentally conscious users and restaurants.

5. **User Interface and Experience**: tAIsty focuses on a customer-friendly, personalized interface designed to support both logged-in and guest users, potentially boosting user satisfaction and engagement. Although Zomato and Swiggy have well-designed interfaces, the extent of their personalization capabilities remains unclear.

6. **Empirical Validation and User Satisfaction**: While tAIsty's features offer notable advantages, real-world validation through empirical data and user feedback is essential to confirm these benefits. Further research and user testing would help substantiate tAIsty's potential to outperform Zomato and Swiggy across various metrics, including personalization, dietary safety, sustainability, and user satisfaction.

In summary, tAIsty presents a promising alternative to existing food recommendation platforms, with its emphasis on personalization, dietary management, solutions for the cold start problem, and sustainability. These factors suggest that tAIsty could become a preferred choice for users seeking a more tailored, safe, and eco-conscious dining experience.

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