## **Recipe Recommendation System**

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### **Approach**

The primary objective of this project was to build a recommendation system for recipes based on user preferences, ingredients, and constraints such as time, dietary restrictions, and cuisine preferences. The system employs a hybrid recommendation strategy, combining Content-Based Filtering (CBF) and Collaborative Filtering (CF), enhanced with Natural Language Processing (NLP) for extracting user preferences from textual reviews.

**System Workflow**

**CBF with NLP:**

* Uses TF-to analyze the similarity between user-provided ingredients and the recipe database
* Filters for preparation time, dietary restrictions, and cuisine preferences extracted from recipe metadata manually.
* Enhanced by integrating review-based user preferences, where review text is vectorized and compared with vectorized (Description + tag) texts.
* The ingredient similarity and the review-description similarity are weighted and combined using the parameter **alpha.**

**CF:**

* Uses a pretrained SVD model to predict ratings for each recipe based on the user's past interactions with recipes
* The similarity score of CBF and CF are combined using parameter **beta**

**Hybridization:**

* Merge the similarity scores (CBF) and the CF scores using weights **alpha** and **beta** to create a unified final score.

**Output:**

* The system generates a final recipe recommendation score based on the weighted combination of ingredient-based, review-based, and user-behavior-based similarity measures.

**Challenges and their solutions**

| High computational cost of embedding textual data over 1M+ reviews | Opted for TF-IDF vectorization |
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| Balancing between the different recommendation techniques (CBF and CF). | Introduced a tunable parameter (α) to control the weightage of content-based and collaborative scores in the hybrid model. |
| Model selection | Experimented with different models and selected a hybrid approach to leverage strengths of both methods. |
| Finding the right fit for NLP | Used past reviews and compared with combined textual data of description and tags |
| Cold Start | Ingredient similarity and CF prediction |

### **Ideas for Improvement**

1. Using pretrained models for embedding textual data so as to get sophisticated semantic understanding
2. Adding more filters like Mood to correlate cravings or disposition. Sentiment analysis to keep it engaging.
3. Integrating Recipe bundles for complete meals.
4. Suggesting complimentary food items to enhance taste profile like Asian food with tea, Italian food with fine, Fast food with Carbonated drinks,etc
5. Match taste profile based on past interactions like spice,sweet,etc.
6. Introduce **“Tolerance meter”** to analyze user behaviour and preferences to certain flavours. Example: A user might enjoy very sweet dishes but have low tolerance to spices.
7. Utilizing nutrients data to promote healthier alternatives.
8. Including Reinforcement Learning for feedback loop.
9. Leveraging demographic data like age,location and time of day to construct target consumer clusters.
10. Room for Machine learning model to predict time constraints for preparation,cost of cooking,etc.
11. Integrating APIs for ingredient availability and prices through groceries stores nearby (or) display restaurants serving similar food items. (Yelp API or Places API)
12. Fine-tuned LLMs to engage with the users to provide insightful conversation until the user’s requirement is met.