Thesis Project Plan

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1 Introduction

Food waste is a global challenge, especially in households, often due to poor meal planning[1]. Most of the recipe recommendation systems prioritize popular or healthy recipes [2]. While health aware, they often don't take into consideration sustainability (i.e minimizing waste).

My system addresses the above mentioned shortcomings of traditional recipe recommender systems, taking into consideration the users ingredient inventory, their allergies, and prioritizing ingredients that are soon to expire, in order to reduce food waste. Additionally, I plan on expanding this system to further recommend user's a sequence of meals, to propagate leftovers, and in turn, further reducing food waste.

I propose using a knowledge graph-augmented LLM framework. The structured representation of data in KG enables modeling of complex relationship between entities, enhancing contextual understanding; improving the accuracy of generated LLM responses [3]. By considering cooking constraints (pantry states, expiry dates) in a knowledge graph and leveraging LLMs for natural interaction, the system aims to reduce household food waste by prioritizing soon-to-expire ingredients and leftover-driven meal planning.

1.1 Research Questions

– How can a knowledge graph model dynamic pantry states/ingredient inventory to minimize waste?

2 Related Works

Several studies leverage KGs to enhance recipe recommendations by modeling structured relationships between ingredients, recipes, and nutritional attributes.

The paper "Health-guided recipe recommendation over Knowledge graphs" [4], prioritizes recipe healthiness by modeling nutritional constraints and ingredient relationships. Builds a food KG linking recipes, ingredients, and nutrients and uses graph traversal algorithms to find recipes meeting user-specified health goals (e.g., providing "low-carb" recipes).

The paper "Personalized Food Recommendation as Constrained Question Answering over a Large-scale Food Knowledge Graph" [2] also prioritizes health based recipes' but uses a different method. They propose to treat the task of personalized recipe recommendation as a constrained question answering over a food KG. Specifically, recommendation is conducted in a Knowledge Base Question Answering(KBQA) setting where the system takes as input a user query, such as -"what is a good breakfast that contains bread?" and retrieves all recipes from the KG that satisfies this query. This approach further offers recommendations that take into consideration personalized user requirements, that includes their allergies, nutritional needs and even their food logs.

Hybrid KG-LLM Method
Recent efforts integrate LLMs for richer personalization. "KERL: Knowledge-enhanced personalized recipe recommendation using LLM's" [5] combines food KG's with LLM's to provide personalized food recommendations and recipes with nutritional information. Given a natural language question, KERL extracts entities, retrieves subgraphs from the KG, which are then fed into the LLM as context to select the recipes that satisfy the constraints.

While the above methods prioritize health-aware recommendations, and some systems do enable pantry-driven queries by matching users input ingredients to recipes, they don't integrate expiry-aware reasoning to prioritize the soon-to-expire ingredients. I addresses this by modeling pantry inventories with expiry timelines in the KG to optimize recommendations for reducing waste.

3 Methodology

The proposed system integrates a Knowledge Graph (KG) with a Large Language Model (LLM) to deliver personalized, waste-reducing recipe recommendations. The methodology consists of three parts:

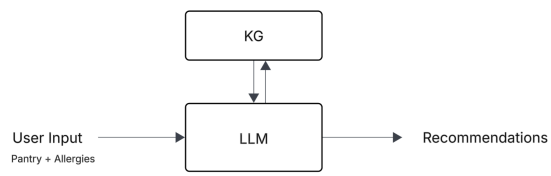
Dataset and KG construction

The system begins by aggregating structured data about ingredients, recipes, and user-specific pantry states. A Neo4j-based Knowledge Graph serves as the backbone, modeling relationships between ingredients (e.g., shelf life, nutritional properties) and recipes. Ingredient perishability is explicitly represented using temporal edges. User constraints (allergies, dietary preferences) are linked to their respective pantry profiles, enabling constraint-aware querying.

LLM with RAG

I use simulated pantry data of users (e.g., "I have tomatoes expiring tomorrow and chicken") or respond to targeted prompts (e.g., "List ingredients expiring soon"). Relevant recipes are fetched from the KG based on ingredient expiry and constraints.
Recommendation

Finally, the system generates recipe recommendations using a Retrieval-Augmented Generation (RAG) pipeline and presents them to the users.



4 Experimental Setup

To evaluate this system, I employ automated LLM-as-judge metrics [6], to evaluate my systems recommendations. It works by defining evaluation prompts based on certain criterias, and asking the LLM to assign scores to the recommendations my system generates.

The following are the criteria on which I'll be evaluating my system-

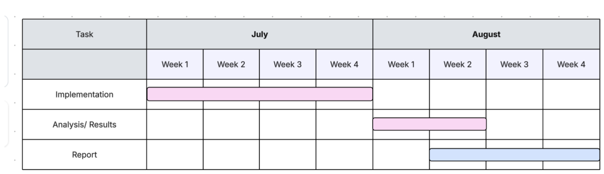
- **User constraint adherence**: This measures how well recommendations adhere to users dietary restrictions like allergies or other dietary needs. Eg prompt-

"Check if Recipe X violates [user constraints: e.g., vegan, nut-free]."

Manual Evaluation

- **Waste Reduction**: Tracking the system's ability to prioritize expiring ingredients. I simulate pantry states with perishable items and manually calculate the percentage of soon-to-expire ingredients consumed by recommended recipes.

5 Estimated Timeline



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