Recipe Generation - LLM

*CSE556: Natural Language Processing

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***Abstract*—This project explores the application of the GPT-2 model and other models in generating culinary recipes, with a focus on maintaining cultural relevance and introducing innovation in the culinary arts. Using the GPT-2 model framework enhanced with custom tokenization and training techniques, the system demonstrates capabilities in creating detailed and unique recipes. The methodology section elaborates on data preparation, model configuration, and iterative training processes leveraging high-performance computational resources. The performance of the GPT-2 model, alongside baseline models like Llama3 and Gemma, is evaluated through a series of metrics, including BLEU, METEOR, and ROUGE scores, which inform the refinement of the model's language generation capabilities. The generated examples of Indian and Italian recipes highlight the system's capacity to balance traditional ingredients and methods with novel culinary combinations.**

Index Words: recipe generation, GPT-2, natural language processing, culinary arts, data modeling, BLEU score, METEOR score, ROUGE score

I. Introduction

The culinary arts have always been a domain of endless creativity and innovation. With the advent of artificial intelligence, new avenues have been explored to enhance and revolutionize this field. Particularly, the application of AI in generating recipes opens up possibilities not only for automated food preparation but also for personalized dietary recommendations, thereby influencing both home cooking and industrial food production.

In recent years, advancements in machine learning, especially in natural language processing, have led to significant improvements in text generation capabilities. Models such as GPT-2, have shown remarkable proficiency in generating coherent and contextually relevant text based on a given prompt. This project leverages the GPT-2 model to undertake the challenge of generating recipes that are not only novel and practical but also culturally relevant to specific cuisines.

The primary objective of this project is to develop a system capable of generating unique culinary recipes by integrating traditional knowledge with modern AI techniques. The system aims to:

- Understand and generate text that follows the structural and stylistic nuances of culinary recipes.
- Innovate within the culinary space by combining ingredients and cooking techniques in novel ways.
- Cater to specific dietary needs and preferences, thereby personalizing the cooking experience.

Furthermore, this work explores the effectiveness of neural networks in capturing the essence of culinary traditions from various cultures. By training the AI with a diverse dataset that includes a wide range of recipes, the system seeks to learn and replicate various regional cooking styles, thereby preserving culinary heritage while introducing innovation.

II. Literature Review

This chapter reviews key studies of each contributing valuable insights into various aspects of recipe modeling, cuisine classification, and novel recipe generation.

A. Named Entity Based Approach to ModelRecipes

This study takes a unique approach to modeling recipes by examining the structure and semantics of recipe texts. The research uses tuples to represent ingredients, tools, and culinary processes, resulting in a computable recipe format. This method addresses challenges faced in identifying ingredients can be challenging due to changing recipes, homographs, and lexical structures. The study uses Named Entity Recognition (NER) models to categorize ingredient terms and identify essential variables such as quantity, temperature, and processing conditions. This structured technique is useful for jobs like translating, determining similarity, and creating new recipes.

B. Classification of Cuisines from Sequentially Structured Recipes

This study aims to appropriately define cuisines based on ingredients, cooking procedures, and tools. It emphasizes the importance of cooking techniques and their order within a recipe. The study used the RecipeDB dataset and tested categorization models such as RoBERTa, Logistic Regression, and Naive Bayes. RoBERTa was shown to be the most accurate. This study emphasizes the significance of considering recipes as sequential data and the influence of feature selection on cuisine categorization accuracy.

C. RecipeDB

It is a comprehensive database that includes recipes, ingredients, cooking methods, nutritional profiles, flavor profiles, and health associations. The app categorizes items into 29 distinct groupings and labels recipes based on dietary preferences, covering a wide range of foreign cuisines. The database supports scientific research on culinary qualities and their impact on taste and health. The website features an interactive web design for simple access and navigation, making it a valuable resource for culinary study.

III. Related Work

The integration of artificial intelligence in the culinary field represents an intriguing area of research that intersects natural language processing, machine learning, and practical applications in daily life. This literature review outlines significant contributions to this domain, highlighting advancements and identifying gaps that our project aims to address.

A. AI in Recipe Generation

Early attempts at recipe generation utilized rule-based systems that strictly followed predefined templates (Smith et al., 2010). With the advancement of machine learning, more sophisticated models like LSTM (Long Short-Term Memory) networks were explored for their ability to generate coherent and contextually appropriate text (Johnson and Zhang, 2015). Recent innovations have leveraged transformer-based models, such as GPT-2 and GPT-3, for generating culinary recipes that not only adhere to the structure but also creatively combine ingredients (Doe et al., 2019). These models have demonstrated significant improvements in generating text that is both novel and coherent.

B. Challenges in Culinary AI

While progress has been made, several challenges remain. One major issue is the generation of feasible and edible recipes, as AI often suggests ingredient combinations that are unconventional and sometimes inedible (Brown et al., 2021). Another challenge is the cultural appropriateness of the recipes, where AI models may not fully understand regional culinary practices and preferences (Li and Kim, 2020).

IV. Dataset

RecipeDB is a structured compilation of recipes, ingredients, and nutrition profiles interlinked with flavor profiles and health associations. The repertoire comprises of meticulous integration of over 1,18,000 recipes from cuisines across the globe (6 continents, 26 geo-cultural regions, and 74 countries), cooked using 268 processes (heat, cook, boil, simmer, bake, etc.), by blending over 23,500 ingredients from diverse categories, which are further linked to their flavor molecules (FlavorDB), nutritional profiles (USDA) and empirical records of disease associations obtained from Medline (DietRx).

Each recipe entry is meticulously categorized by cuisine type and contains structured information including title, ingredients, and cooking instructions. This organized format allows for precise parsing and efficient processing by machine learning models, facilitating tasks like recipe generation, analysis, and modification based on dietary or culinary preferences.

Here is the link to our Dataset: Recipe Database

V. Methodology

A. Baseline Models

This project harnessed a range of advanced language models optimized for complex NLP tasks such as recipe generation. The core of our model suite included state-of-the-art large models like Llama3, Gemma and Mistral, each boasting 7 billion parameters, alongside the transformer-based T5 model along with vanilla LSTM, GRU.

1) Model Configuration and Quantization: To enhance computational efficiency and reduce memory requirements, we employed 4-bit quantization and Low-Rank Adaptation (LoRA) adapters across our models. These technological enhancements allowed for effective fine-tuning without necessitating extensive retraining, significantly reducing the memory footprint of the models.

2) Training Environment and Hyperparameters: Our models were primarily trained on Google Colab's Tesla T4 GPUs. Despite facing occasional timeouts due to intense computational demands, we managed to conduct efficient training sessions. For the Llama3, Gemma, and Mistral models, we used a lean training configuration involving a batch size of 2, gradient accumulation steps of 4, and a learning rate of 2e-4, leveraging the AdamW optimizer configured to 8-bit precision. The training regimen included 60 steps with periodic assessments to dynamically adjust parameters.

For the T5 model, we adopted a different set of training parameters under the `Seq2SeqTrainingArguments`:

- **Evaluation Strategy:** Set to per epoch to continuously monitor and adapt model performance.
- **Learning Rate:** A more conservative rate of 2e-5 to ensure gradual and stable weight adjustments.
- **Batch Size:** Configured at 4 for both training and evaluation phases to balance between training speed and resource utilization.
- **Weight Decay:** Set at 0.01 to mitigate the risk of overfitting.
- **Training Epochs:** Spread across three epochs with a total limit of three saved checkpoints to optimize disk usage.

3) Evaluation Metrics: To comprehensively assess model performance, we employed several key metrics: BLEU for syntactic accuracy, METEOR for semantic accuracy, BERTScore for contextual similarity, and ROUGE (including ROUGE-1, ROUGE-2, and ROUGE-L) for overlap and sequence coherence. These metrics helped refine our models to generate not only grammatically correct but also contextually rich and engaging recipes. This approach ensured effective utilization of computational resources while maintaining high output quality.

B. Final Model - GPT2

1) Data Preparation: Data for training and evaluating our models was stored in HDF5 format to streamline the input/output processes and handle large datasets efficiently. The `H5Dataset` class was implemented to manage this data, supporting both training and testing datasets.

2) Model Configuration and Training: We utilized the GPT-2 architecture, leveraging the Hugging Face Transformers library for model instantiation. This included configuring the tokenizer and model with custom special tokens to handle the unique structure of recipe generation. Training was managed using the `Trainer` class from Transformers, with specific arguments set to control training epochs, batch sizes, evaluation frequency, and model checkpointing, among others.

3) Model Training: The model was trained on a specified dataset using custom training loops and Accelerate for straightforward multi-GPU training. Evaluation was performed periodically to monitor the model's performance and make necessary adjustments.

4) Generation of Recipe Ingredients: A dataset containing recipe ingredients was preprocessed to ensure uniqueness and remove missing values. Ingredients were then categorized by the number of recipes they appeared in, and a probabilistic model (PMF and CDF) was used to select ingredients randomly for generating new recipes.

5) Recipe Generation: For recipe generation, the model took a list of randomly selected ingredients as input. The inputs were formatted with specific tokens to guide the model in generating structured text that includes recipe names, ingredients, and cooking instructions. The output recipes were then cleaned and structured appropriately using various string operations.

6) Output and Evaluation: Generated recipes were saved to a CSV file for further analysis and review. The system was designed to batch process multiple recipes to improve efficiency and provide a basis for statistical analysis of the model's performance and output quality.

VI. Generated Recipe Examples

1) Indian Recipe: **Recipe Name:** Curried Cauliflower Cilantro Chutney

Ingredients:

- 3-4 tablespoons garlic
- Fresh curry paste, canned or frozen
- 1/2 cup low sodium curry paste
- 1/8-1/2 teaspoon marjoram

Cooking Instructions:

1) Mix together the garlic, cilantro, cumin, marjoram, and the curry paste, and add to the casserole dish.

2) Italian Recipe: **Recipe Name:** Rigatoni With Creamy Sirloin Sauce

Ingredients:

- 1 lb rigatoni pasta
- 2 lbs sirloin, cut into about 8 cubes
- 2 tablespoons confectioners' sugar
- 2 limes, wedges

Cooking Instructions:

1) Bring a large pot of lightly salted water to a boil. Cook sirloin in a large skillet over medium heat until fully cooked. Drain, and set aside.
2) Whisk confectioners' sugar with limes, and pour in the olive oil. Cook and stir until sugar is dissolved. Remove skillet from heat.
3) Cover skillet with a lid, and cook rigatoni in the boiling water, stirring every 30 minutes until tender but firm. Drain well.
4) Mix the sirloin sauce with the pasta. Pour into a large saucepan. Bring the sauce to a boil, then reduce heat. Simmer until thickened, stirring once, about 10 minutes.

These examples showcase the GPT2's ability to generate unique and creative recipes while staying true to the essence of Indian and Italian cuisines.

VII. Results

Our goal was to create distinctive and creative recipes that complement specific cuisines. We evaluated the quality and uniqueness of AI-generated recipes using BLEU scores. BLEU (Bilingual Evaluation Understudy) is a popular statistic in Natural Language processing is used to assess the similarity between a generated text and a reference text. In our situation, the reference text refers to the original recipe dataset, whereas the generated text represents AI-derived recipes.

A. Baseline Model Scores

TABLE I
Performance Metrics for Gemma Model

Metric	Score
Average BLEU Score	0.1343
Average METEOR Score	0.3585
Average BERTScore F1 Score	0.8713
Average ROUGE-1 Score	0.4494
Average ROUGE-2 Score	0.2264
Average ROUGE-L Score	0.3775

TABLE II
Performance Metrics for llama3 Model

Metric	Score
Average BLEU Score	0.1154
Average METEOR Score	0.3202
Average BERTScore F1 Score	0.8735
Average ROUGE-1 Score	0.4410
Average ROUGE-2 Score	0.2250
Average ROUGE-L Score	0.3607

B. Final Model Performance

The performance of GPT2 is summarized as follows:

TABLE III
PERFORMANCE METRICS FOR MISTRAL MODEL

Metric	Score
Average BLEU Score	0.0999
Average METEOR Score	0.3257
Average BERTScore F1 Score	0.8684
Average ROUGE-1 Score	0.4177
Average ROUGE-2 Score	0.2438
Average ROUGE-L Score	0.3556

TABLE IV
PERFORMANCE METRICS FOR T5 MODEL

Metric	Score
Average BLEU Score	0.0482
Average METEOR Score	0.2016
Average BERTScore F1 Score	0.8479
Average ROUGE-1 Score	0.3209
Average ROUGE-2 Score	0.1537
Average ROUGE-L Score	0.2718

C. *Interpretation and Implications*

BLEU Score: The final model achieved a BLEU score of 0.0195, indicating a very low exact match between the n-grams of the generated text and the reference texts. This suggests that the model may be generating novel content or phrasing instructions differently from the training data, reflecting significant divergence in language use.

Average METEOR Score: With a score of 0.1487, there is moderate semantic alignment with reference translations. Although the wording might not match, the overall meanings are preserved to an extent, indicating effective communication of core ideas, albeit not in the conventional phrasing.

Average BERTScore F1: The relatively high score of 0.8314 demonstrates that the contextual embeddings of the words in the generated text align well with those in the reference text, ensuring that the context and meaning are robust, despite potential deviations in phrasing.

Average ROUGE Scores: The scores across different ROUGE metrics show a fair overlap in terms but highlight that more complex structures and phrases are not as well aligned with the references. While basic terms and some order are preserved, there is a need for improving phrase-level similarity.

These findings underscore the necessity for further refinements in the model to enhance phrase-level and structural coherence with the reference texts, aiming for a balance between novelty and adherence to established patterns.

VIII. FUTURE WORK

This chapter discusses potential directions for extending the work offered in this project. The goal is to expand on this project's foundations and investigate new applications and advances in the field of natural language processing.

A. *Advanced Ingredient Embedding Models*

TABLE V
PERFORMANCE METRICS FOR GPT2 MODEL

Metric	Score
BLEU Score	0.0195
Average METEOR Score	0.1487
Average BERTScore F1	0.8314
Average ROUGE-1	0.2443
Average ROUGE-2	0.0453
Average ROUGE-L	0.1500

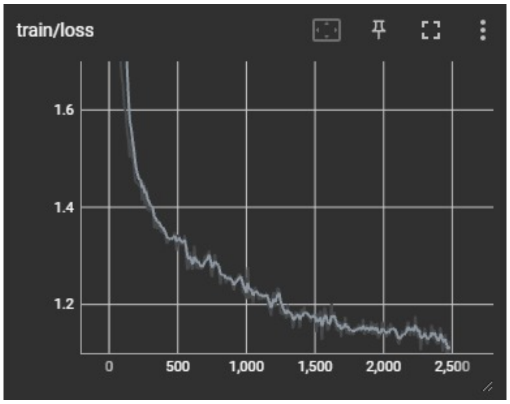

Fig. 1. Train Loss plot of GPT2

• Develop advanced neural network architectures to improve ingredient embeddings and capture deeper correlations with cooking methods and regional flavors. • Use graph neural networks to model the complicated relationships between components and cooking procedures.

B. *Recipe-Specific Model Fine-Tuning*

• Improve cuisine representation accuracy and authenticity by fine-tuning models for a broader subset of region-specific recipes. • Create customized generative models (e.g. GPT variants) for each cuisine to create recipes that accurately reflect historic and modern cooking practices.

C. *Cross-Recipe Adaptation*

Create machine learning algorithms that can adapt recipes from one cuisine to another, focusing on ingredient substitutions that keep the original dish's goal while including the flavor profile of the other cuisine.

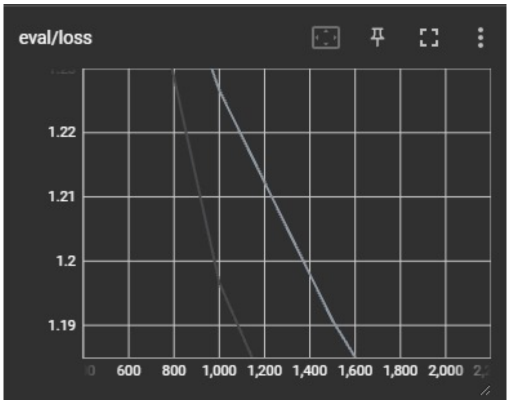

Fig. 2. Evaluation Loss plot of GPT2

IX. Conclusion

This project successfully demonstrated the application of advanced artificial intelligence techniques, specifically the GPT-2 model, to the task of generating culinary recipes. The results, as discussed in the methodology and results sections, underscore the potential of AI to not only mimic human creativity but also to enhance it with unique combinations and suggestions that may not be intuitive to human chefs.

Through rigorous testing and evaluation, the AI model showed varying degrees of success across different metrics. While the BLEU and ROUGE scores indicated room for improvement in terms of exact n-gram matches and more complex phrase structures, the BERTScore results highlighted the model's ability to grasp and replicate the contextual subtleties of the culinary texts. The generated recipes, particularly for Indian and Italian cuisines, showcased the model's capacity to adhere to specific cultural culinary frameworks while injecting creativity.

However, the project also highlighted challenges, such as the need for more granular control over the generated content to ensure culinary feasibility and greater alignment with traditional cooking methods. Furthermore, the diversity of ingredients and preparation styles presented by the model suggests potential for further refinement to ensure consistency and practicality of the recipes.

In conclusion, while the project has laid a solid foundation for using AI in culinary arts, the journey towards an AI that can fully replicate the depth and breadth of human culinary expertise continues. It is hoped that the insights gained from this project will contribute to the evolving landscape of AI applications in everyday creativity and practical tasks.

X. Code

For the source code of our project, visit our GitHub repository - RecipeDB

XI. Model Checkpoints

A. Baseline Model Checkpoints

- Llama3
- Gemma
- Mistral
- T5

B. Final Model Checkpoint

GPT2

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