Novel Recipe Generation : Cuisine Constraint

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Student's Declaration

We hereby declare that the work presented in the report entitled **"Novel Recipe Generation : Cuisine Constraint"** submitted by us for the partial fulfillment of the requirements for the degrees of *Bachelor of Technology* in *Computer Science & Engineering* at Indraprastha Institute of Information Technology, Delhi, is an authentic record of our work carried out under the guidance of **Dr. Ganesh Bagler**. Due acknowledgments have been given in the report for all material used. This work has not been submitted anywhere else for the reward of any other degree.

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This is to certify that the above statement made by the candidates is correct to the best of our knowledge.

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Place & Date: IIIT Delhi, 29^{th} *Nov,* 2023

Dr. Ganesh Bagler

Abstract

In this project, we ventured into computational gastronomy to craft AI-generated recipes that embody diverse regional cooking styles. Our methodology initially centered on a novel tokenization approach, using the GPT-2-based AI model Ratatouille and integrating cuisine-specific tokens within the comprehensive RecipeDB and later into a method for recipe categorization based on TF-IDF analysis and machine learning models. The aim is to understand the relevance of ingredients across various cuisines by quantifying their significance within a corpus of recipes. This strategy yielded decent results in reflecting regional culinary styles. However, recognizing the potential for enhancement, we shifted our focus toward advanced recipe encoding methods. Our challenge was to capture the unique culinary essence of various regions, a task with no straightforward solution. Utilizing the comprehensive RecipeDB and the AI model Ratatouille, based on GPT-2, we experimented with different recipe encoding methods. These included both semantic and contextual models to generate 'embeddings' – numerical representations of recipes that computers can analyze. The effectiveness of these embeddings was vital in assessing mirroring distinct regional flavors, drawing from language processing research to represent diverse cooking styles.

Acknowledgments

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Contents

Chapter 1

Introduction

This project represents an innovative fusion of culinary arts and artificial intelligence, aiming to redefine traditional recipe generation. Our methodology combines the fine-tuning of the GPT- 2-based model, Ratatouille, with unique region-specific tokens, and the investigation of various embedding models like Word2Vec, FastText, and BERTSequentialClassifier for deeper culinary insights.

The essence of the challenge lies in creating a system that not only blends ingredients in novel ways but also faithfully represents specific regional cooking styles, giving each recipe a sense of authenticity and cultural depth. Utilizing the extensive RecipeDB, we have fine-tuned Rata- touille to recognize and incorporate regional culinary nuances, guided by the added tokens.

The second approach is more exploratory, where we delve into the potential of various embedding models like Word2Vec, FastText, and BERTSequentialClassifier. These models are designed to encode recipes into embeddings, which we then analyze using cosine similarity and clustering methods. The goal is to discover if these embeddings can reveal any inherent patterns or styles characteristic of different regional cuisines.

Chapter 2

Literature Review

This chapter presents a review of key studies in the field of computational gastronomy, each contributing valuable insights into various aspects of recipe modeling, cuisine classification, and novel recipe generation.

2.1 A Named Entity Based Approach to Model Recipes (2022)[2]

This study offers a novel approach to modeling recipes by focusing on the structure and semantics of recipe texts. By analyzing the ingredients, utensils, and cooking processes, and representing them as tuples, the research provides a computable format for recipes. This method addresses challenges in ingredient identification, such as the evolving nature of recipes, homographs, and variations in lexical structures. The study employs Named Entity Recognition (NER) mod- els for tagging ingredient phrases and identifies key attributes like quantity, temperature, and processing state. This structured approach is significant for tasks like translation, similarity determination, and novel recipe generation.

2.2 Classification of Cuisines from Sequentially Structured Recipes (2022)[5]

This paper addresses the challenge of accurately classifying cuisines based on culinary features like ingredients, cooking processes, and utensils. It emphasizes the significance of cooking tech- niques and their order in the structure of a recipe. Using the RecipeDB dataset, the study implemented various classification models, including RoBERTa, Logistic Regression, and Naive Bayes, achieving the highest accuracy with RoBERTa. This research highlights the importance of treating recipes as sequential data and the impact of feature selection on cuisine classification accuracy.

2.3 RecipeDB: A Resource for Exploring Recipes (2020)[1]

RecipeDB is a structured database that integrates recipes, ingredients, cooking techniques, and nutritional profiles with flavor profiles and health associations. It covers a broad spectrum of cuisines globally, categorizing ingredients into 29 exclusive groups and labeling recipes with dietary styles. The database facilitates scientific explorations of the culinary space, linking culinary attributes to taste and health impacts. It also provides an interactive web interface for easy access and navigation, offering a comprehensive resource for culinary research.

2.4 Ratatouille: A Tool for Novel Recipe Generation (2022)[3]

This study explores novel recipe generation as a Natural Language Processing task, employing deep learning models like LSTMs and GPT-2. Ratatouille, a web-based application, generates new recipes from given ingredients, addressing the challenge of structuring semi-structured text data like recipes. The research evaluates various models for their ability to generate contextually relevant and structured recipes. It highlights the limitations of existing models in generating well-structured recipes and proposes using special tokens to improve the generation process, aiming for efficiency and accuracy in recipe generation.

Chapter 3

Dataset

RecipeDB provides a structured compilation of recipes, making it an ideal resource for exploring the culinary space. The dataset includes a wide variety of recipes, with 118,171 recipes from cuisines across the globe, incorporating 6 continents, 26 geo-cultural regions, and 74 countries. It features a rich assortment of over 20,262 ingredients and describes 268 cooking processes. These recipes are further linked to their flavor profiles, nutritional information, and health associations, providing a comprehensive resource for our analysis.

For the purpose of addressing the cuisine constraint problem in our study, we focus on the top five cuisines by recipe count within the RecipeDB. This approach is not only driven by simplicity but also by the substantial volume of data available for these cuisines, which ensures a robust set of recipes to work with.

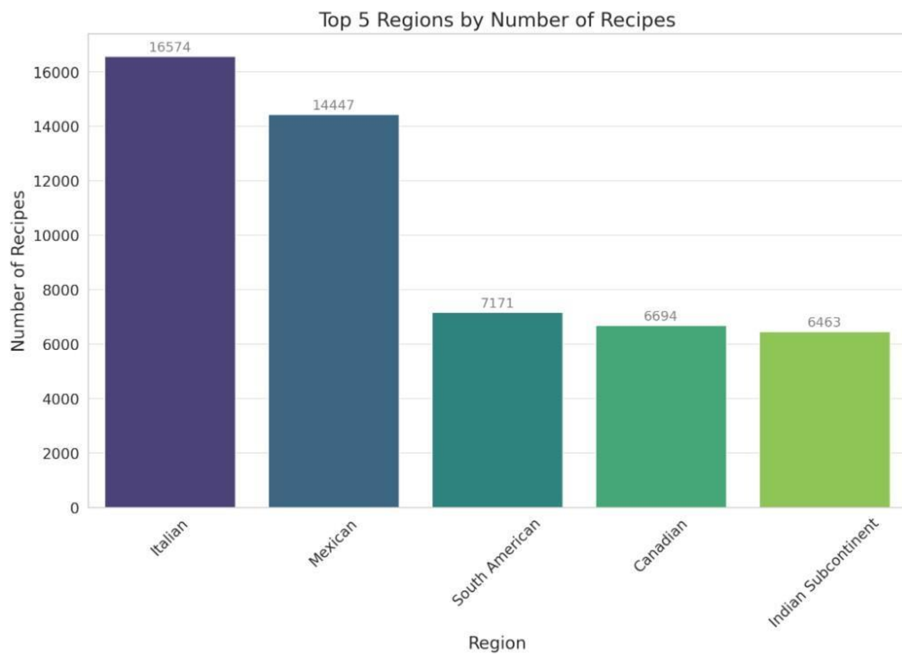

Figure 3.1: Visualization of the Top 5 Cuisines by Recipe Count in RecipeDB

As shown in Figure 3.1, the distribution of recipes in the top five cuisines illustrates the diversity and richness of the dataset.

3.1 Data Preprocessing

Prior to training our model, the RecipeDB dataset underwent a preprocessing phase. This was necessary to refine the dataset and tailor it to our research needs. We removed any incomplete or redundant entries and standardized the length of the recipes to 2000 characters to conform to the most common recipe length in the dataset. The recipes were formatted to include three main components: the title, a list of ingredients, and the cooking instructions.

Chapter 4

Models for Embedding Generation

In our project, we have employed various embedding models such as Word2Vec, FastText (both standard and pre-trained forms), and BERTSequentialClassifier, each chosen for their potential to capture the nuances of regional cooking styles. The study ”Learning Personal Food Pref- erences via Food Logs Embedding” [4] offers insights relevant to our approach, particularly in the context of identifying food preferences and categories, which can be analogous to discerning regional cooking styles.

4.1 Word2Vec

Word2Vec has been effectively used in food computing to capture relationships between different ingredients and concepts. This model’s ability to generate embeddings that reflect these rela- tionships is crucial for our task. By analyzing food logs, Word2Vec can help identify commonly eaten foods or preferred ingredients, a process similar to distinguishing ingredients characteristic of specific regional cuisines.

4.2 Food Embeddings and Labeling

The study emphasizes the use of food embeddings for labeling food categories, a process integral to our goal of understanding and encoding regional cooking styles. Food embeddings, created using models like Word2Vec, enable the identification of parent food categories, which can be likened to recognizing the distinctive elements of different regional cuisines.

4.3 Performance Evaluation of Embedding Methods

The performance evaluation of embedding methods as discussed in the study highlights the importance of context in embedding generation. This aligns with our approach, where understanding the context in which ingredients are used is key to capturing regional cooking styles.

The study’s results show that certain methods, particularly those removing generic food-related words, are more effective. This insight is valuable for our project, as it underlines the need to focus on embeddings that capture the unique context of regional cuisines.

4.4 BERT and Contextual Embeddings

The study suggests that improved embeddings, such as those generated using BERT, could lead to better performance. BERT’s ability to incorporate context into embeddings is particularly relevant for our project. It can help overcome dataset limitations and accurately label food entries, which is analogous to our task of distinguishing and categorizing regional cooking styles based on ingredient use and cooking methods.

4.5 Support Vector Classification

The selection of a linear SVC model was based on its scalability to accommodate a number of samples. Also, it is effective for both dense and sparse inputs, particularly considering the sparse nature of our TF-IDF matrix. Moreover, the model's built-in support for multi-class classification, utilizing a one-vs-the-rest scheme, provided a structured approach to handle diverse class distinctions within the dataset.

4.6 K-Nearest Neighbor

KNN was implemented to identify the k training vectors closest to the test data vectors, employing Euclidean distance and cosine similarity as proximity measures. The latter exhibited marginally superior performance.

Chapter 5

Methodology

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5.1 Model Training with Cuisine Tokens

The crux of our first approach lies in training a GPT-2 model, specifically tailored to generate recipes. A novel aspect of our training involved the integration of cuisine-specific tokens. These tokens are unique identifiers representing five major cuisines:

- <CUISINE_ITALIAN>
- <CUISINE_MEXICAN>
- <CUISINE_SOUTH AMERICAN>
- <CUISINE_CANADIAN>
- <CUISINE_INDIAN SUBCONTINENT>

These tokens were embedded within the training data, enabling the model to recognize and generate recipes that align with the culinary attributes of these specific cuisines.

5.1.1 Recipe Generation Mechanism

For generating recipes, the model takes a set of ingredients and a chosen cuisine token as input. It then crafts a complete recipe text, encompassing a title, a list of ingredients, and cooking instructions. The format of the input plays a vital role, as the inclusion of a specific cuisine token guides the model in generating a recipe consistent with the culinary practices of that cuisine.

5.1.2 Ensuring Novelty and Diversity

A significant feature of our methodology is the emphasis on novelty and diversity. The model is designed to create unique and varied recipes based on the ingredients and cuisine tokens provided. This is achieved by incorporating randomness in ingredient selection and relying on the trained model's capability to craft inventive recipes from these inputs.

5.1.3 Evaluation of Generated Recipes

To ascertain the quality and novelty of the recipes generated, we employed both qualitative and quantitative evaluation methods. One such quantitative measure was the BLEU score, a standard metric in natural language processing used to compare the machine-generated text against a reference corpus. This provided an objective assessment of the linguistic quality and novelty of the recipes.

5.2 Embedding Generation

5.2.1 Selection and Preprocessing of Data

For embedding generation, we focused on the title, ingredients, and cooking instructions of each recipe. The data was again preprocessed to remove irrelevant information, ensuring that the embeddings would be representative of the culinary style.

5.2.2 Formatting for Each Model

The formatting of data varied based on the requirements of each embedding model (Word2Vec, FastText, BERTSequentialClassifier). This ensured that each model could optimally learn from the recipe data.

5.2.3 Embedding Generation

After preprocessing, embeddings were generated for each recipe, creating numerical representations that could be analyzed computationally.

5.2.4 Evaluation of Embeddings

To assess the quality and effectiveness of the generated embeddings, we employed two evaluation methods: cosine similarity and unsupervised clustering with k-means.

Cosine Similarity

We used cosine similarity to evaluate the embeddings. This involved averaging the embeddings of recipes for each of the top five regions (based on the number of recipes in the dataset) and then calculating the cosine similarity between these averaged embeddings. This step was crucial to determine how well the embeddings captured the distinct culinary styles of each region.

Unsupervised Clustering with K-Means

Additionally, we performed unsupervised clustering using the k-means algorithm to create clus- ters (10 and 5 clusters for each model). This clustering helped us understand the grouping of recipes based on their embeddings and to see the distribution of recipes from each region within these clusters. The percentages of each region's recipes' embeddings in the clusters were analyzed. This analysis provided insights into how well the models could differentiate between the cooking styles of different regions.

5.3 Employing a TF-IDF matrix

To construct the matrix, we compute the product of Term Frequency and Inverse Document Frequency.
For TF, we follow the formula. Number of times an ingredient occurs in a recipe upon a number of ingredients in the recipe.
For IDF, we take the log of a number of recipes in the corpus upon a number of recipes containing that ingredient.
To mitigate the dominating effect of common ingredients we multiply them to calculate the TF-IDF matrix.

5.3.1 Preprocessing of recipe data

Since the data was raw and not processed, we applied various pre-processing techniques.
Like lemmatization, removing duplicate recipe IDs. Then perform ingredients merging and combining titles, regions and instructions together into a single dataframe.
Then we remove punctuation, capitals, and extra space after every instruction.
Then we removed all of the stop words, I added a few stop words of my own that weren't contributing to cuisine classification such as salt, sugar, tablespoon, cut, cup, slice etc.

We removed cuisines with very less examples as that would lead to false positives, and cuisines with more than 4000 recipes were taken.

5.3.2 Evaluation

The following models were taken with configurations given below to evaluate the performance.

Algorithm	Ngram model	K-value	C
Linear SVC:	Unigram	-	0.9
KNN	Unigram	4	

Chapter 6

Results

6.1 Evaluation of Generated Novel Recipes

Our primary objective was to generate novel recipes that exhibit creativity and uniqueness while aligning with specific cuisines. To assess the quality and novelty of the AI-generated recipes, we used BLEU scores. BLEU (Bilingual Evaluation Understudy) is a widely used metric in natural language processing to measure the similarity between a generated text and a reference text. In our context, the reference text is the original recipe dataset, and the generated text represents the AI-generated recipes.

Here are the BLEU scores for the generated novel recipes in different cuisines:

- **Chinese Cuisine:** BLEU Score = 4.621967646086874e-12
- **Indian Cuisine:** BLEU Score = 1.8546376311654376e-11
- **Italian Cuisine:** BLEU Score = 2.6844903311191096e-12
- **Mexican Cuisine:** BLEU Score = 8.975555254625472e-09
- **Southern Cuisine:** BLEU Score = 1.1008823788114727e-18

The BLEU scores for the generated novel recipes across different cuisines are extremely low, indicating a high level of novelty and creativity in the recipes.

6.2 Example Generated Recipes

As examples of the AI-generated recipes, we present two recipes generated for Indian and Italian cuisines:

Indian Cuisine

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.

Italian Cuisine

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 AI's ability to generate unique and creative recipes while staying true to the essence of Indian and Italian cuisines.

6.3 Embedding Results

1. Region cosine similarity: This is the cosine similarity of the average of all the recipe embeddings for each region, creating ”region embeddings”.
2. Average cosine similarity: This is the average of the cosine similarities of each randomly sub-sampled recipe from each region.

3. 10 Clusters plot: Plot showing the distribution of each region's recipes in 10 different clusters.
4. 5 Clusters plot: Plot showing the distribution of each region's recipes in 5 different clusters.

6.3.1 BERT Embeddings

1. Region cosine similarity:

Table 6.1: Cosine Similarity Matrix for BERT

	Italian	Mexican	South American	Canadian	Indian Subcontinent
Italian	1.0000	0.9999	0.9999	0.9999	0.9999
Mexican	0.9999	1.0000	0.9999	0.9999	0.9999
South American	0.9999	0.9999	1.0000	0.9999	0.9999
Canadian	0.9999	0.9999	0.9999	1.0000	0.9999
Indian Subcontinent	0.9999	0.9999	0.9999	0.9999	1.0000

2. Average cosine similarity:

Table 6.2: Average Cosine Similarity Among Recipe Embeddings for BERT

	Italian	Mexican	South American	Canadian	Indian Subcontinent
Italian	1.0000	0.9890	0.9895	0.9902	0.9893
Mexican	0.9890	1.0000	0.9897	0.9902	0.9895
South American	0.9895	0.9897	1.0000	0.9908	0.9902
Canadian	0.9902	0.9902	0.9908	1.0000	0.9907
Indian Subcontinent	0.9893	0.9895	0.9902	0.9907	1.0000

3. 10 Clusters plot:

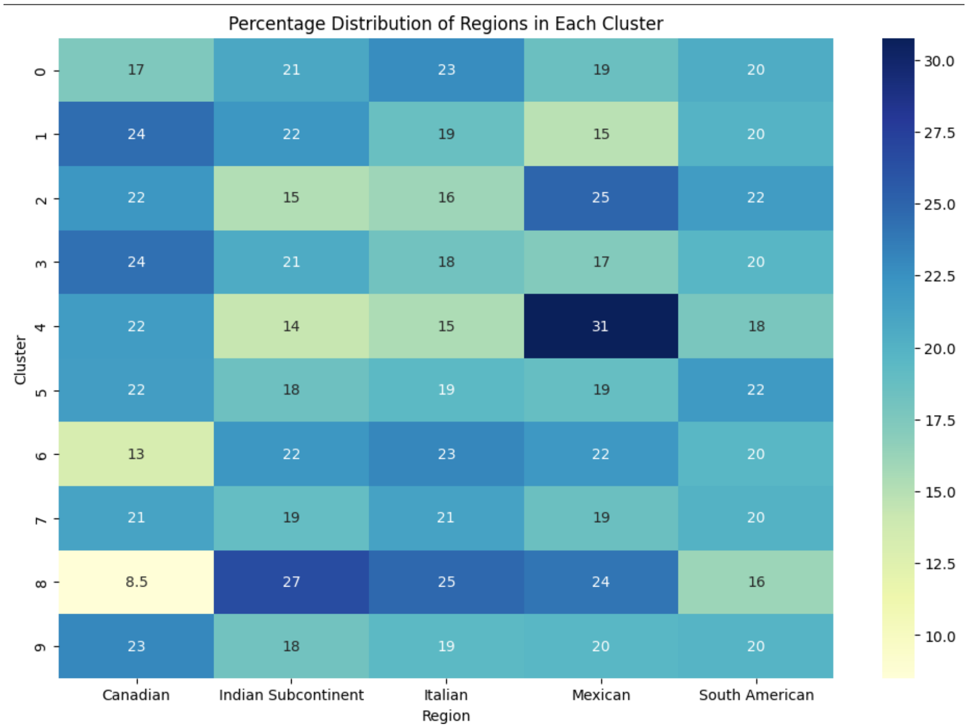


Figure 6.1: BERT with 10 clusters.

4. 5 Clusters plot:

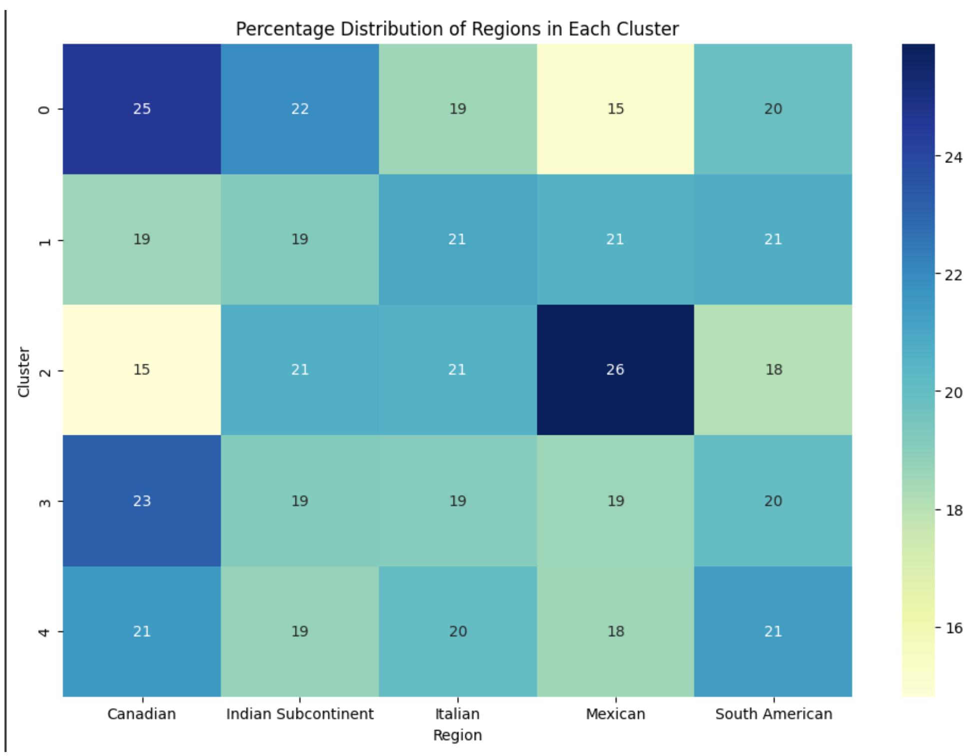


Figure 6.2: BERT with 5 clusters.

6.3.2 Word2Vec Embeddings

1. Region cosine similarity:

Table 6.3: Cosine Similarity Matrix for Word2Vec

	Indian Subcontinent	Mexican	South American	Italian	Canadian
Indian Subcontinent	1.0000	0.7820	0.7130	0.7588	0.8024
Mexican	0.7820	1.0000	0.7867	0.8439	0.8226
South American	0.7130	0.7867	1.0000	0.8029	0.7775
Italian	0.7588	0.8439	0.8029	1.0000	0.8482
Canadian	0.8024	0.8226	0.7775	0.8482	1.0000

2. Average cosine similarity:

Table 6.4: Average Cosine Similarity Among Recipe Embeddings for Word2Vec

	Italian	Mexican	South American	Canadian	Indian Subcontinent
Italian	1.0000	0.1537	0.1631	0.1236	0.1524
Mexican	0.1537	1.0000	0.1552	0.1085	0.1564
South American	0.1631	0.1552	1.0000	0.1346	0.1608
Canadian	0.1236	0.1085	0.1346	1.0000	0.1256
Indian Subcontinent	0.1524	0.1564	0.1608	0.1256	1.0000

3. 10 Clusters plot:

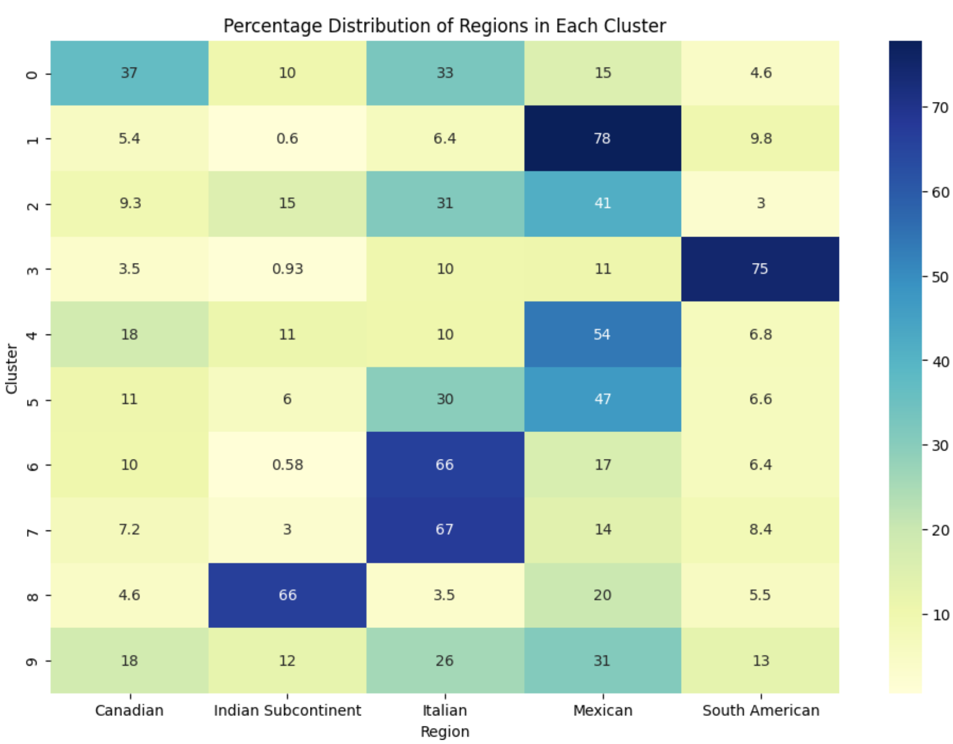


Figure 6.3: Word2Vec with 10 clusters.

4. 5 Clusters plot:

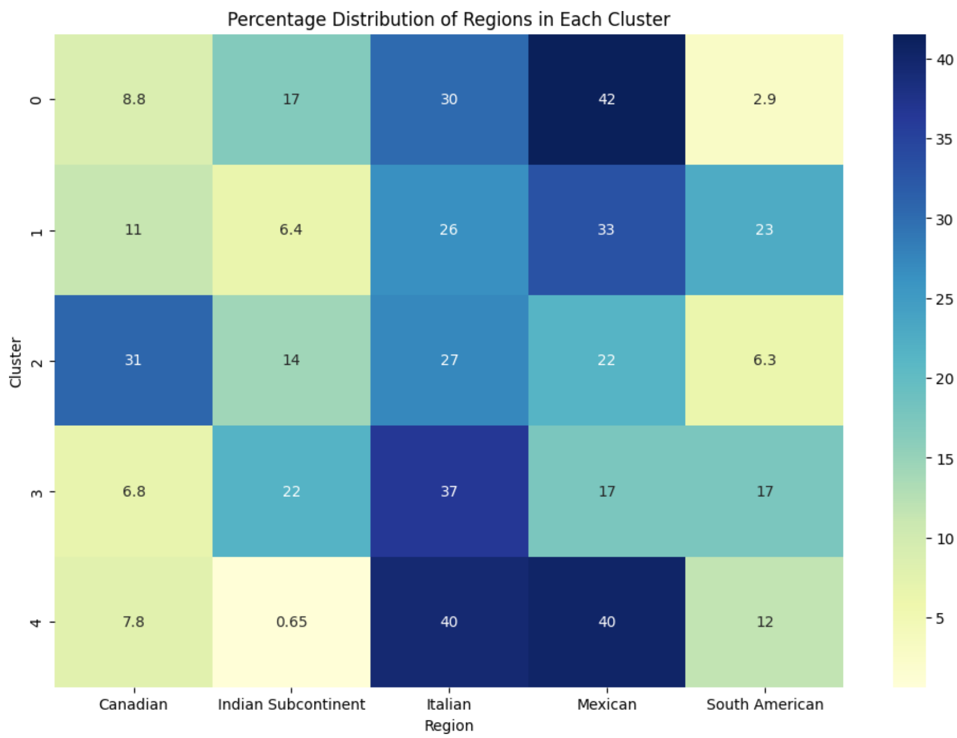


Figure 6.4: Word2Vec with 5 clusters.

6.3.3 FastText Embeddings

1. Region cosine similarity:

Table 6.5: Cosine Similarity Matrix for FastText

	Indian Subcontinent	Mexican	South American	Italian	Canadian
Indian Subcontinent	1.0000	0.8854	0.8147	0.8830	0.8771
Mexican	0.8854	1.0000	0.8453	0.9034	0.9086
South American	0.8147	0.8453	1.0000	0.8452	0.8267
Italian	0.8830	0.9034	0.8452	1.0000	0.9213
Canadian	0.8771	0.9086	0.8267	0.9213	1.0000

2. Average cosine similarity:

Table 6.6: Average Cosine Similarity Among Recipe Embeddings for FastText

	Italian	Mexican	South American	Canadian	Indian Subcontinent
Italian	1.0000	0.2354	0.2650	0.2238	0.2632
Mexican	0.2354	1.0000	0.2453	0.2148	0.2529
South American	0.2650	0.2453	1.0000	0.2243	0.2653
Canadian	0.2238	0.2148	0.2243	1.0000	0.2273
Indian Subcontinent	0.2632	0.2529	0.2653	0.2273	1.0000

3. 10 Clusters plot:

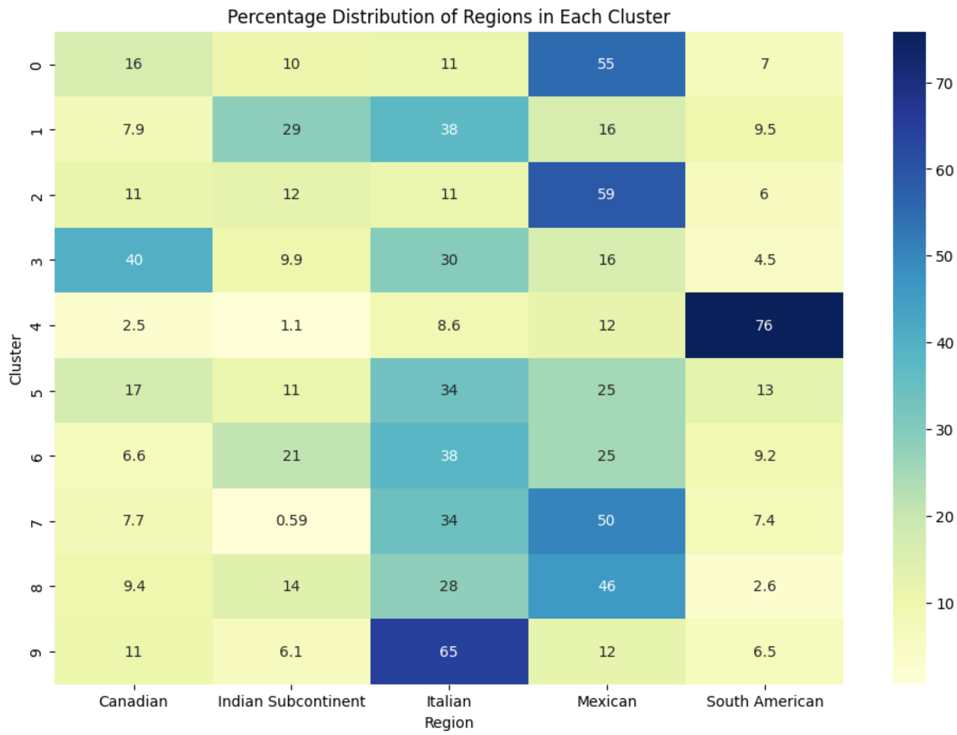


Figure 6.5: FastText with 10 clusters.

4. 5 Clusters plot:

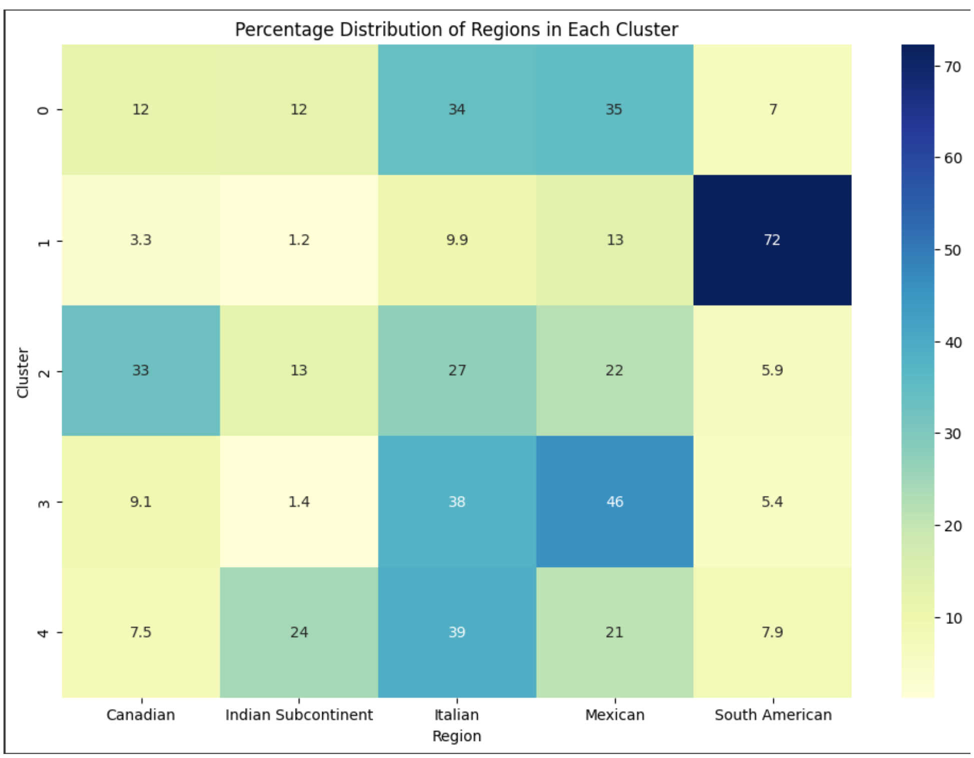


Figure 6.6: FastText with 5 clusters.

The region cosine similarity matrices show the cosine similarity between different regions, indicating how similar the regional embeddings are in the respective embedding models (Word2Vec, FastText, and BERT).

The average cosine similarity matrices show the average cosine similarity between recipes from different regions, providing insights into how recipes within the same region are similar or dis- similar in the embedding space.

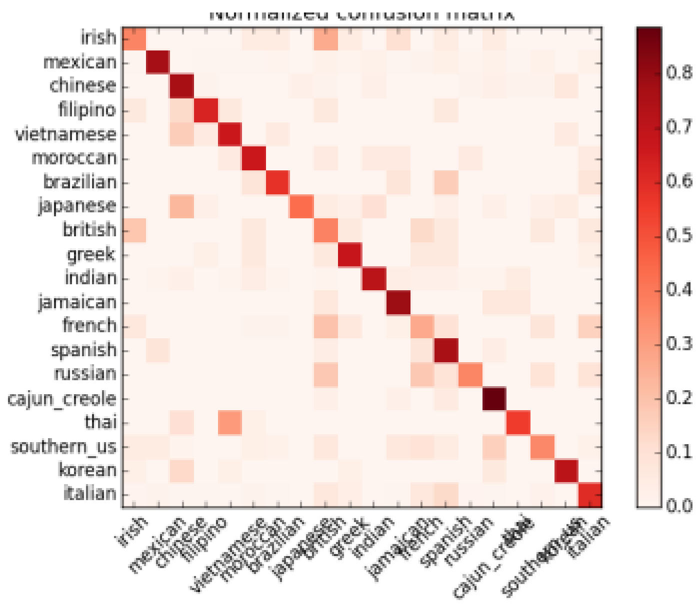
The percentage of recipes from each region within each cluster was then plotted, revealing the distribution of regional recipes across the clusters. This visualization can offer valuable insights into several aspects:

- Regional Similarity: It can demonstrate whether recipes from the same region tend to cluster together, indicating a higher degree of similarity in their embeddings. This insight can validate the effectiveness of the embedding models in capturing regional cooking styles.
- Cross-Regional Patterns: The plots can reveal if certain clusters contain recipes from multiple regions. This may suggest the existence of common cooking elements or shared ingredients across different cuisines.
- Outliers: Clusters with a low percentage of recipes from any specific region may represent outliers or recipes that do not conform to the typical cooking style of any region. This could lead to further investigations into these outlier recipes.
- Model Performance: The distribution of recipes in clusters can serve as an indirect measure of how well the embedding models differentiate between regional cooking styles. Models that perform well would result in clearer distinctions between clusters.

Further investigations could explore the anisotropic nature of contextual embeddings, where most vectors fall within a narrow cone, resulting in high cosine similarities. This observation may suggest that contextual embeddings capture certain common features or patterns in recipes that lead to high similarity scores.

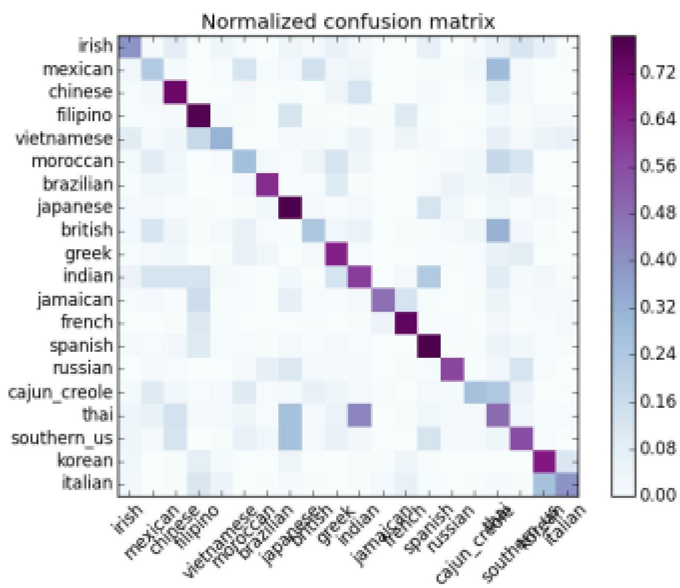
6.4 SVC Results

The accuracy we got for this method on the validation set is 0.5326.



6.5 KNN

The accuracy we got for KNN classification is 0.619. Here we checked with 4-nearest neighbors.



Chapter 7

Future Work

This chapter outlines potential directions for extending the work presented in this thesis. The aim is to build upon the foundations laid by this research and to explore novel applications and improvements in the field of computational gastronomy.

7.1 Advanced Ingredient Embedding Models

- Explore the development of more complex neural network architectures to enhance ingre- dient embeddings, capturing deeper relationships between ingredients, cooking methods, and regional flavors.
- Investigate the application of graph neural networks to effectively model the complex interactions between ingredients and cooking techniques.

7.2 Cuisine-Specific Model Fine-Tuning

- Fine-tune models on a larger subset of region-specific recipes to increase the accuracy and authenticity of cuisine representation.
- Develop specialized generative models, such as GPT variants, for each cuisine to generate recipes that faithfully represent traditional and contemporary culinary practices.

7.3 Cross-Cuisine Recipe Adaptation

- Develop machine learning algorithms capable of adapting recipes from one cuisine to an- other, focusing on ingredient substitutions that maintain the original dish's intent while fitting into another cuisine's flavor profile.

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