

MealMaster: A Recipe Bot Recommendation System

Group7

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1. Problem Formulation:

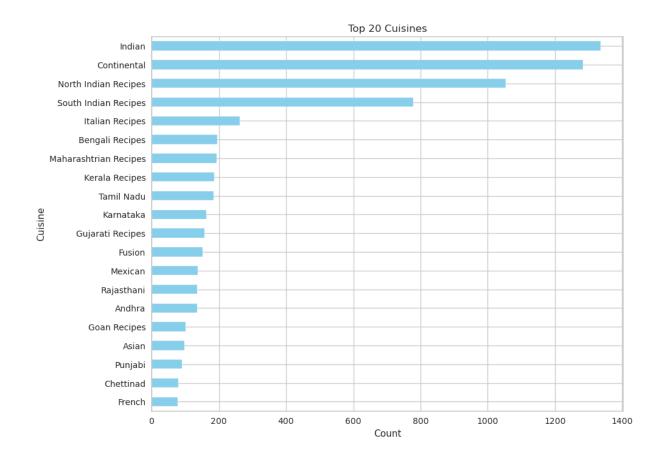
Our project aims to develop a chatbot that provides personalized recipe recommendations. This chatbot will use two crucial factors to generate suggestions: the user's preferred cuisine and available ingredients. To accomplish this, we will utilize clustering to categorize similar recipes and classification to identify the most suitable category based on the user's preferences. All this will be part of a chatbot that's easy and convenient for users to find new recipes.

2. Data and Data Preprocessing:

Our project uses a dataset from Kaggle, which has over 8,000 recipes, most of them being Indian dishes. This dataset gives us many details about each recipe, like how to cook it, the ingredients needed, how long it takes, who wrote the recipe, and how it's rated. We can use this information to compare different recipes, and group similar ones together.

We began our project by performing an initial analysis of the dataset, examining the distribution and frequency of each feature as depicted in (*Figure 1*).

We saw that some types of cuisines didn't have many recipes, and there was a lot more data for 'Indian' cuisine than for other types of cuisine. This means our data was not balanced.



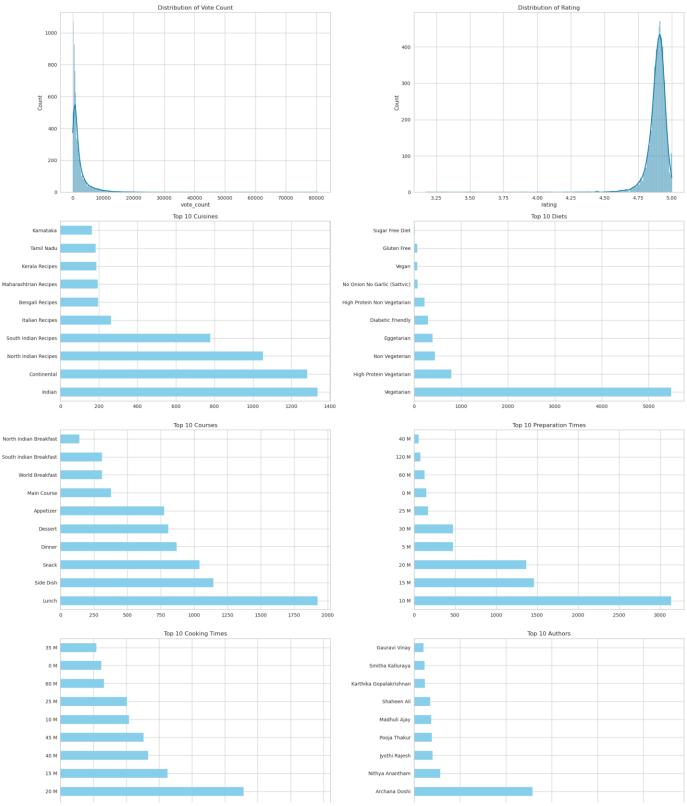
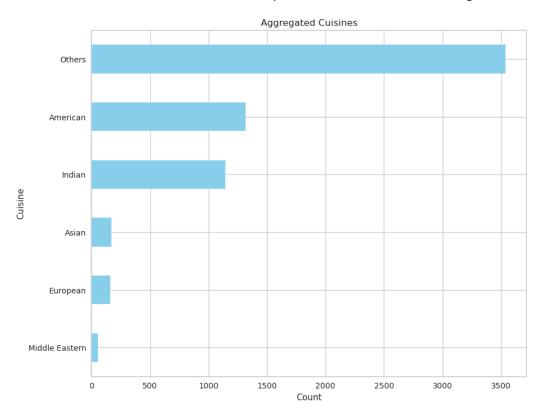


Figure 1

Merging Cuisines:

To make things easier, we put cuisines into bigger groups. We also had some missing information in our data. To handle this, we removed the parts of the data that had missing info and we also



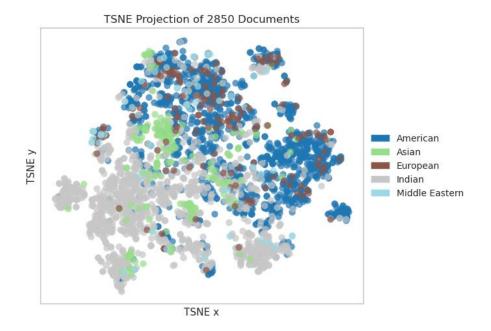
removed the "Others" from the Data.

3. Feature Engineering:

To transform our data for effective modeling, we utilized TF-IDF (Term Frequency-Inverse Document Frequency) and Word2Vec. These strategies convert textual information into numerical vectors.

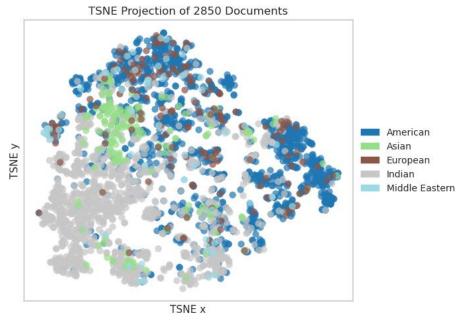
1. TF-IDF:

In our project, we employed TF-IDF this technique evaluates the importance of a word in a document relative to a corpus, allowing us to discern the key ingredients and processes in each recipe and use this information in our recommendation system.



2. Word2Vec:

In addition to TF-IDF, we also used Word2Vec, a method that creates word embeddings by analyzing the context in which words appear. This technique allows us to capture semantic relationships between words.

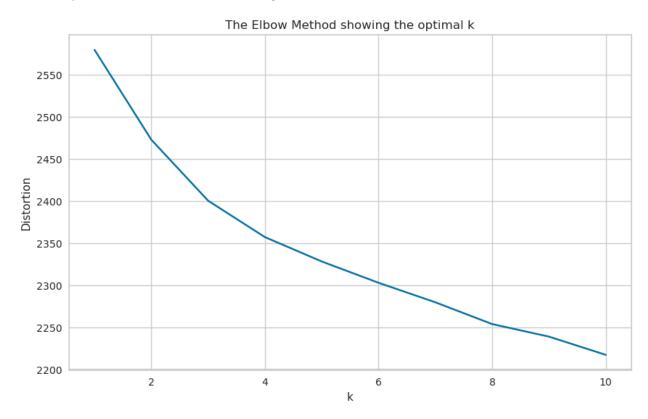


We noticed that TF-IDF provided a clearer separation of our data compared to Word2Vec. While Word2Vec captures semantic relationships and is excellent for understanding context, it was the TF-IDF method that excelled in distinguishing and categorizing our cuisines more distinctly.

4. Modeling and Model Evaluation:

1. Clustering:

We used the k-means clustering algorithm to group our recipes, specifically focusing on their ingredient profiles. This approach allowed us to identify and categorize similar recipes, offering a structured way to make recipe recommendations based on ingredient similarities.



By using the elbow method, we found that the best way to group them was into four main clusters.

3. Recommendation System:

Procedure:

- 1- Recipe Profiling:
- Features Utilized: Cuisine type, course, diet, and ingredients.
- Data Transformation: One-hot encoding is applied to categorical metadata like cuisine type, course, and diet. The ingredients are vectorized using Term Frequency-Inverse Document Frequency (TF-IDF) to capture their importance.
- Profile Creation: The one-hot encoded and TF-IDF vectorized features are horizontally stacked to create a comprehensive profile for each recipe.
- 2- Data Preparation:
- The DataFrame's index is reset to ensure a sequential order, which is essential for accurate indexing and retrieval of recipes.

- 3- Similarity Computation:
- Method: Cosine similarity, a metric that measures the cosine of the angle between two nonzero vectors, is computed between the recipe profiles. A value closer to 1 indicates a higher similarity.
- Outcome: A matrix of cosine similarities between recipes is generated.
- 4- Recommendation Algorithm:
- A function, recommend recipes content based, is designed to recommend similar recipes:
 - The provided recipe title is standardized (converted to lowercase and stripped of white spaces).
 - o The index of the specified recipe in the DataFrame is identified.
 - o Cosine similarities for the given recipe against all others are retrieved.
 - o Recipes are sorted based on their similarity scores.
 - The cluster or category (e.g., dessert, main course) of the given recipe is identified.
 This acts as an additional filtering criterion.
 - The function recommends recipes that belong to the same cluster as the input and excludes the input recipe itself from the recommendations.
 - The recommended recipes are then returned in the form of a DataFrame.

5- Test Case:

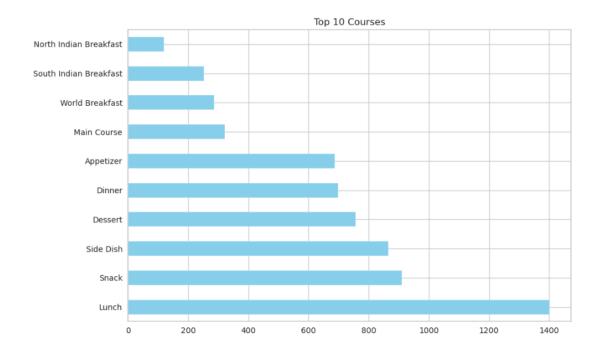
• The recommendation system is tested with the recipe titled "Pineapple Upside Down Cake Recipe". The system successfully recommends five similar recipes from the dataset.

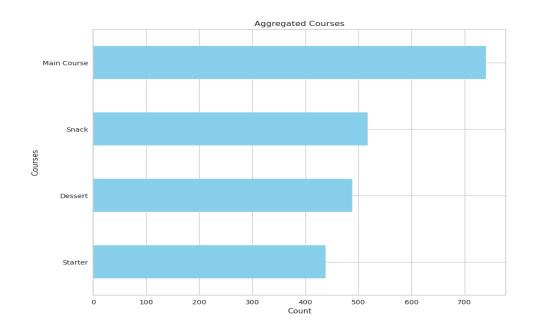
| j | | recipe_title | description | cuisine | course | diet | prep_time | cook_time | ingredients | instructions | category | cuisine_agg | course_agg | ingredients_cleaned | cluster_ingredients |
|---|------|---|---|-------------|---------|------------|-----------|-----------|---|--|--------------------|-------------|------------|---|---------------------|
| | 21 | Eggless Chocolate Mug Cake Recipe - Instant Mi | Chocolate Mug Cake Recipe is a quick-fix, inst | continental | Dessert | Vegetarian | 10 | 1 | butter unsalted/cocoa powder/sugar/all purpose | To begin making the Eggless Chocolate Mug Cake | Cake Recipes | American | Dessert | butter unsaltedcocoa powdersugarali purpose fl | 0 |
| | 940 | Chocolate Cherry Cake Recipe | Chocolate Cherry Cake Recipe is from Scratch a | continental | Dessert | Vegetarian | 45 | 15 | whole eggs all purpose flour maida cocoa powde | To begin with the Chocolate Cherry Cake From | Cake Recipes | American | Dessert | whole eggsall purpose flour maidacocoa powderm | 0 |
| | 1324 | Carrot Cake Parfait With Custard And Strawberr | Moist chunks of carrot cake (with whole wheat) | continental | Dessert | Vegetarian | 10 | 40 | sugar brown sugar demerara sugar sunflower oil | To begin making the Carrot Cake Parfait With C | Dessert Recipes | American | Dessert | sugarbrown sugar demerara sugarsunflower oilwh | 0 |
| | 1986 | Eggless Lemon Pound Cake Recipe | The Old Fashioned is a buttery cake perfec | continental | Dessert | Vegetarian | 5 | 45 | butter unsalted caster sugar all purpose flour | To begin preparing the Lemon Pound Cake, prehe | Cake Recipes | American | Dessert | butter unsaltedcaster sugarall purpose flour m | |
| | 2054 | Delicious Strawberry Tea Cake Recipe | The Wholesome Strawberry Cake is just the kind | continental | Dessert | Vegetarian | 20 | 50 | butter salted brown sugar demerara sugar whole | To begin making the 50% Whole- Wheat Strawberry | Cake Recipes | American | Dessert | butter saltedbrown sugar demerara sugarwhole w | |

4. Classification:

In our project, we tried three methods to make our Recipe Bot work best: Support Vector Machines (SVM), Logistic Regression, and Random Forest (RF). We tested each one to see which gave the best recipe suggestions.

Before we started predicting with methods like SVM, Logistic Regression, and Random Forest, we grouped similar recipes together. This made our Recipe Bot give better and more accurate suggestions.





In evaluating the performance of our models, we obtained the following accuracy scores:

1. Logistic Regression: 60.96%

2. Support Vector Machines (SVM): 59.13%

3. Random Forest: 58%

Among the three models, Logistic Regression yielded the highest accuracy, closely followed by SVM, with Random Forest slightly lagging behind.

5. Error Analysis:

1. Logistic Regression:

Accuracy: 61%

Pros: Achieved the highest accuracy among the three. Consistently good performance across all classes, especially for Class 0.

Cons: Some challenges with Classes 2 and 3, but still relatively strong.

2. **SVM** (Support Vector Machines):

Accuracy: 59.13%

Pros: Good performance, also for Class 0. Close in accuracy to Logistic Regression.

Cons: Faced challenges with Classes 2 and 3, particularly in recall.

3. Random Forest:

Accuracy: 58%

Cons: Achieved the lowest accuracy among the three models. Had difficulties with Class 3 in both precision and recall.

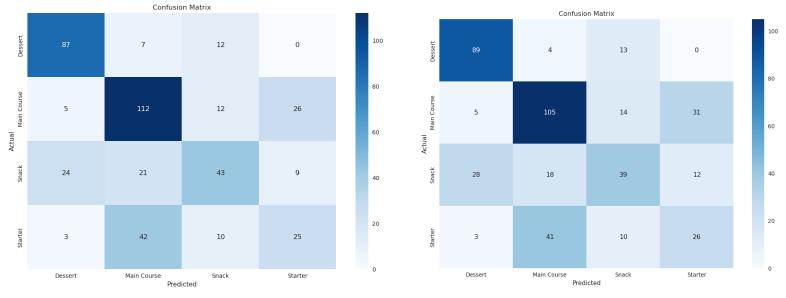
Logistic Regression is the best model for this dataset. It achieved the highest accuracy and showed consistently good performance across all classes. While SVM and Random Forest were competitive, they lagged slightly behind in terms of overall accuracy and faced more pronounced challenges with certain classes.

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Dessert | 0.73 | 0.82 | 0.77 | 106 |
| Main Course | 0.62 | 0.72 | 0.66 | 155 |
| Snack | 0.56 | 0.44 | 0.49 | 97 |
| Starter | 0.42 | 0.31 | 0.36 | 80 |
| | | | | |
| accuracy | | | 0.61 | 438 |
| macro avg | 0.58 | 0.57 | 0.57 | 438 |
| weighted avg | 0.59 | 0.61 | 0.60 | 438 |
| | | | | |

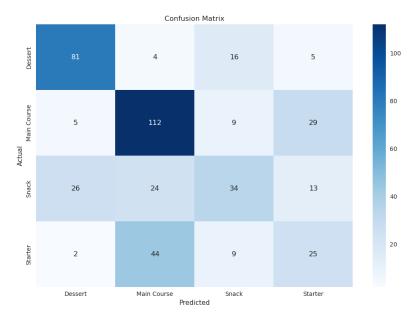
Logistic Regression

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Dessert | 0.71 | 0.84 | 0.77 | 106 |
| Main Course | 0.62 | 0.68 | 0.65 | 155 |
| Snack | 0.51 | 0.40 | 0.45 | 97 |
| Starter | 0.38 | 0.33 | 0.35 | 80 |
| | | | | |
| accuracy | | | 0.59 | 438 |
| macro avg | 0.56 | 0.56 | 0.56 | 438 |
| | precision | recall | f1-score | support |
| Dessert | 0.71 | 0.76 | 0.74 | 106 |
| Main Course | 0.61 | 0.72 | 0.66 | 155 |
| Snack | 0.50 | 0.35 | 0.41 | 97 |
| Starter | 0.35 | 0.31 | 0.33 | 80 |
| | | | | |
| accuracy | | | 0.58 | 438 |
| macro avg | 0.54 | 0.54 | 0.53 | 438 |
| weighted avg | 0.56 | 0.58 | 0.56 | 438 |

Random Forrest







Random Forest

Examples of the performance differences between models:

| | ingredients | Actual Course | Predicted Course |
|-----|--|---------------|------------------|
| 2 | butter unsalted caster sugar whole eggs all pu | Dessert | Snack |
| 6 | mango ripe tomato onion rajma large kidney bea | Snack | Main Course |
| 7 | black eyed beans lobia rice carrots gajjar gre | Starter | Main Course |
| 15 | potatoes aloo garlic fresh thyme leaves salt | Snack | Dessert |
| 16 | chicken onion tomato green chillies bay leaves | Snack | Main Course |
| | | | |
| 428 | all purpose flour maida red chilli powder ging | Snack | Main Course |
| 429 | sabudana tapioca pearls milk sugar cardamom po | Main Course | Snack |
| 431 | mango ripe fresh cream milk condensed milk | Snack | Main Course |
| 435 | spinach leaves palak coriander dhania leaves p | Main Course | Starter |
| 436 | brown sugar demerara sugar cocoa powder milk m | Snack | Dessert |

Logistic Regression

| | ingredients | Actual Course | Predicted Course |
|-----|--|---------------|------------------|
| 2 | butter unsalted caster sugar whole eggs all pu | Dessert | Snack |
| 6 | mango ripe tomato onion rajma large kidney bea | Snack | Main Course |
| 7 | black eyed beans lobia rice carrots gajjar gre | Starter | Main Course |
| 15 | potatoes aloo garlic fresh thyme leaves salt | Snack | Dessert |
| 16 | chicken onion tomato green chillies bay leaves | Snack | Main Course |
| | | | |
| 430 | tortillas iceberg lettuce onion tomato green b | Snack | Starter |
| 431 | mango ripe fresh cream milk condensed milk | Snack | Main Course |
| 434 | bermuda grass powder ginger salt black pepper | Starter | Main Course |
| 435 | spinach leaves palak coriander dhania leaves p | Main Course | Starter |
| 436 | brown sugar demerara sugar cocoa powder milk m | Snack | Dessert |

SVM

| | ingredients | Actual Course | Predicted Course |
|-----|--|---------------|------------------|
| 2 | butter unsalted caster sugar whole eggs all pu | Dessert | Snack |
| 4 | shrimps butter salted orange color lemon juice | Main Course | Dessert |
| 10 | sabudana tapioca pearls shallots mixed vegetab | Snack | Starter |
| 15 | potatoes aloo garlic fresh thyme leaves salt | Snack | Dessert |
| 16 | chicken onion tomato green chillies bay leaves | Snack | Main Course |
| | | | <u></u> |
| 429 | sabudana tapioca pearls milk sugar cardamom po | Main Course | Snack |
| 430 | tortillas iceberg lettuce onion tomato green b | Snack | Main Course |
| 431 | mango ripe fresh cream milk condensed milk | Snack | Main Course |
| 435 | spinach leaves palak coriander dhania leaves p | Main Course | Starter |
| | | | |

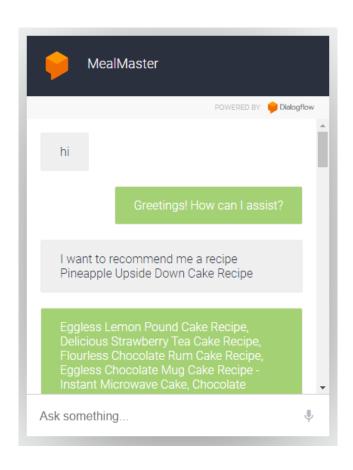
Random Forrest

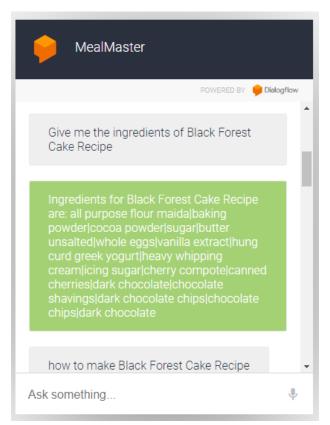
Conclusion:

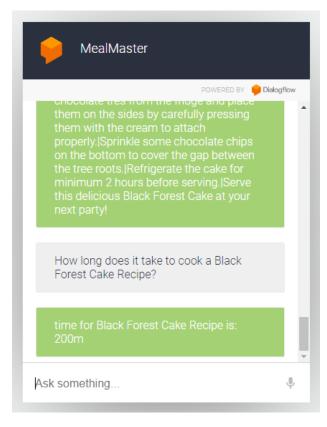
- 1. **Challenges with Class 3**: All three models struggled to accurately predict Class 3, as evidenced by both low precision and recall values. This suggests that Class 3 instances might be hard to distinguish from other classes, possibly due to overlapping features or insufficient training data.
- 2. **Class Imbalance Impact**: The varying 'support' values (number of instances) for each class is because of an imbalanced dataset. When there's a class imbalance, models tend to favor the majority class, which can lead to poorer performance on minority classes. This could be a reason why certain classes, especially Class 3, are not being predicted as effectively.
- Bad Recall for Certain Classes: Besides Class 3, some models also had difficulty with Class 2. This
 means that a significant number of true instances for these classes were being missed or
 wrongly classified.
- 4. **Precision Challenges**: While some classes had decent recall, their precision was lacking. This means that while the models were capturing a good number of true positive instances, they were also misclassifying other instances into these classes, leading to false positives.
- 5. **Overall Accuracy**: The models didn't reach 65% accuracy, so there's more work to do. Even though we improved the data features, tweaking model settings and looking at dataset issues might help boost results.

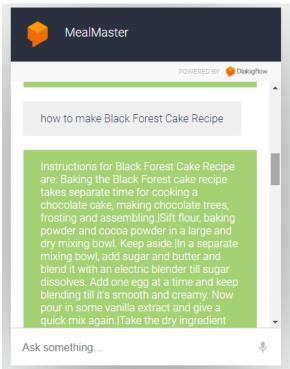
6. Chatbot:

These are screenshots from our chatbot.









The weakness of the chatbot is that we should enter the exact recipe name, and any misspelling lead to the recipe not found.