



**Cognitive Computing and Natural Language Processing Mini  
Project Report**

on

**Title:**

**RECIPE RECOMMENDATION SYSTEM**

**Submitted by**

**Name Shubh Sahu Roll No PA-60 PRN 1032211368**

**Name Aryan Ghogare Roll No PA-61 PRN 1032211308**

**Name Shreya Verma Roll No PA-71 PRN 1032211874**

**Name Om Patil Roll No PA-74 PRN 1032211908**

**Under the Guidance of  
Prof. Chaitali Chandankhede**

**Department of Computer Engineering and Technology  
Dr. Vishwanath Karad MIT World Peace University Pune,  
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# Abstract

This research paper addresses the challenge of personalized recipe recommendation in the context of an ever-expanding culinary landscape. Currently, existing systems often rely on basic collaborative filtering or content-based approaches, resulting in limited accuracy and user satisfaction. Our proposed approach leverages advanced machine learning techniques, including natural language processing, to analyze user preferences, dietary restrictions, and ingredient compatibility. By integrating these factors, our system aims to overcome the shortcomings of traditional methods and deliver more accurate and tailored recipe recommendations. The anticipated outcome is an enhanced user experience, with users receiving personalized and diverse recipe suggestions that align with their unique tastes and dietary needs.

## Chapter 1

### Problem statement

#### Designing an Effective Recipe Recommendation System

The increasing volume of online food-related data and the diverse preferences of users pose a significant challenge in creating a personalized and accurate food recommendation system.

## Chapter 2

### Research Gaps

#### 1. Unavailability of Domain specific Dataset:

Gap: Limited research on incorporating contextual information, such as the user's current location, time of day, or social context, into recipe recommendations.

Importance: Recipes may be more relevant based on contextual factors, and understanding and integrating these factors can enhance the user experience.

#### 2. Personalized Nutritional Recommendations:

Gap: Insufficient exploration of personalized nutritional recommendations based on users' dietary preferences, restrictions, and health goals.

Importance: Many users have specific dietary requirements, and tailoring recipe recommendations to individual nutritional needs can improve the overall usefulness of the system.

#### 3. User Feedback Integration:

Gap: Inadequate exploration of real-time user feedback and its integration into the recommendation algorithm to adapt and refine suggestions.

Importance: User preferences can change over time, and incorporating feedback mechanisms can enhance the adaptability and responsiveness of the recommendation system.

## Chapter 3

### Objectives

The primary objectives of this research are twofold. Firstly, we aim to develop a recipe recommendation system that surpasses conventional methods by incorporating advanced machine learning techniques.

Secondly, we seek to address the limitations of existing systems by considering user-specific factors such as taste preferences, dietary restrictions, and cooking skill levels. The ultimate goal is to provide users with a more nuanced and satisfying culinary journey, offering recommendations that align closely with their unique needs and preferences.

## Chapter 4

### Methods used

1. Data Loading: Loading a CSV file named "train.csv" containing labeled data for training the NER model.Extracting columns like 'token' and 'label' from the DataFrame.
2. Training Data Preparation: Creating training data for spaCy NER model, where each data point is a tuple of the form `(text, {"entities": [(start, end, label)]})`.
3. Training the NER Model: Using spaCy to train the NER model on the prepared training data. The code includes commented-out sections for model creation, entity label addition, and training loop. It seems like there might be some issues with those sections, as they are currently commented out.
4. Model Testing: Saving the trained model to a specified directory.Loading the saved model and using it to extract entities from sample text.
5. Recipe Matching: Reading a CSV file named "RAW\_recipes.csv" containing recipes data.Defining a Jaccard similarity function to calculate the similarity between two

ingredient lists. Asking the user for input on available ingredients and matching them with recipes. Displaying the top 5 recipes with the highest Jaccard similarity scores.

6. Printing Recipe Recommendations: Displaying ASCII art and printing the best-matching recipe along with the top 5 matches.

*#Commented out section :*

1. Model Initialization: The code checks if a pre-existing model is provided (model is not None). If not, it creates a blank English language model (spacy.blank('en')).
2. Adding Entity Labels to the Model: The code iterates over unique labels in the 'label' column of the training data and adds them as entity labels to the spaCy NER model using ner.add\_label(i).
3. Initializing Optimizer: The code initializes the optimizer for training the NER model. If no pre-existing model is provided, it uses nlp.begin\_training(); otherwise, it uses nlp.entity.create\_optimizer().
4. Training Loop: The training loop is commented out and includes iterations (n\_iter), shuffling of training data, and batching using minibatch with a compounding batch size. The loop disables other pipes except the NER pipe during training (nlp.disable\_pipes(\*other\_pipes)). Inside the loop, there are attempts to create Example objects from the training data and update the model using nlp.update().

5. Saving the Model: After training, the code saves the trained model to a specified directory using `nlp.to_disk(output_dir)`.

## Chapter 5

### Code

```
import pandas as pd
import numpy as np
import spacy
import random
from spacy.util import minibatch, compounding
from spacy.training import Example
import os
import ast
import re

cust_label = pd.read_csv('train.csv')
cust_label

ing_list = []
temp = cust_label[cust_label.label == 'NAME']
for i in temp['token']:
    ing_list.append(i)

ing_list

cust_label.dropna(axis=0, inplace=True)

cust_label[['token', 'label']].isna().sum()

ing = np.array(cust_label['token'])
label = np.array(cust_label['label'])
label

for i in ing:
    if i == 'minute':
        print(i)

for i in ing:
    print(i)

train_data = []
for i,j in enumerate(ing):
    print(j, label[i], len(j))
    train_data.append((j, {'entities': [(0, len(j), label[i])]}))

train_data

# # Setting up the pipeline and entity recognizer.
```

```

# model = None
# if model is not None:
# nlp = spacy.load(model) # load existing spacy model
# print("&quot;Loaded model &#39;%s&#39;&quot; % model)
# else:
# nlp = spacy.blank(&#39;en&#39;) # create blank Language class
# print("&quot;Created blank &#39;en&#39; model&quot;")

# print(nlp.pipe_names)

# if &#39;ner&#39; not in nlp.pipe_names:
# ner = nlp.create_pipe(&#39;ner&#39;)
# nlp.add_pipe(&#39;ner&#39;)
# else:
# ner = nlp.get_pipe(&#39;ner&#39;)

# # Add new entity labels to entity recognizer
# for i in cust_label[&#39;label&#39;].unique():
# ner.add_label(i) # Initializing optimizer
# if model is None:

# optimizer = nlp.begin_training()
# else:
# optimizer = nlp.entity.create_optimizer()

# # Get names of other pipes to disable them during training to train # only NER and update the
weights
# n_iter = 2
# other_pipes = [pipe for pipe in nlp.pipe_names if pipe != &#39;ner&#39;]
# with nlp.disable_pipes(*other_pipes): # only train NER
# for itn in range(n_iter):
# random.shuffle(train_data)
# losses = { }
# batches = minibatch(train_data,
# size=compounding(4., 32., 1.001))
# #for batch in batches:
# # texts, annotations = zip(*batch)
# # #print(texts, annotations)
# # # create Example
# # print(texts)
# # doc = nlp.make_doc(texts)
# # example = Example.from_dict(doc, annotations)
# # # Updating the weights
# # nlp.update([example], sgd=optimizer,
# # drop=0.35, losses=losses)
# #print(&#39;Losses&#39;, losses)

# for batch in batches:
# texts, annotations = zip(*batch)

# example = []

# # Update the model with iterating each text
# for i in range(len(texts)):
# doc = nlp.make_doc(texts[i])
# print(annotations[i])
# example.append(Example.from_dict(doc, annotations[i]))

# # Update the model
# nlp.update(example, drop=0.35, losses=losses, sgd=optimizer)

```

```

# print(&#39;Losses&#39;, losses)

# # Save model
# output_dir = &quot;C:/Users/shubh/CCNLP&quot;
# nlp.to_disk(output_dir)
# print(&quot;Saved model to&quot;, output_dir)

# Test the saved model
output_dir = &quot;C:/Users/shubh/CCNLP&quot;
test_text = &quot;I want something spicy made from chicken, brocolli, tomato and potato&quot;
print(&quot;Loading from&quot;, output_dir)
nlp2 = spacy.load(output_dir)
doc2 = nlp2(test_text)
for ent in doc2.ents:
    print(ent.label_, ent.text)

doc2 = nlp2(&quot;I&#39;m craving a delicious recipe that features ripe avocados&quot;)
for ent in doc2.ents:
    print(ent.label_, ent.text)

doc2 = nlp2(&quot;I have a bunch of fresh tomato, basil, and mozzarella at home Can you recommend a
tasty recipe that includes these ingredients&quot;)
for ent in doc2.ents:

    print(ent.label_, ent.text)

doc2 = nlp2(&quot;I have one bacon, two tomatoes, 3 onions and one packet of cheese. what can I
make?&quot;)
for ent in doc2.ents:
    print(ent.label_, ent.text)

doc2 = nlp2(&quot;I want to make something within 30 minute. what can I make?&quot;)
for ent in doc2.ents:
    print(ent.label_, ent.text)

doc2 = nlp2(&quot;I want to make something within 20 minute. what can I make?&quot;)
for ent in doc2.ents:
    print(ent.label_, ent.text)

ing_list = []
temp = cust_label[cust_label.label == &#39;NAME&#39;]
for i in temp[&#39;token&#39;]:
    ing_list.append(i)
# ing_list

def get_ing():
    l1 =[]
    in_str = input(&quot;What ingredients do you have?&quot;)
    doc = nlp2(in_str)
    for ent in doc.ents:
        if ent.label_ == &#39;NAME&#39;,:
            temp = ent.text.split()
            for i in temp:
                if i in ing_list:
                    l1.append(i)

    return l1

recipes = pd.read_csv(&#39;RAW_recipes.csv&#39;)
recipes.head()

```



```

recipes.isna().sum()

recipes.shape

recipes.dropna(axis=0, inplace=True)

recipes.shape

recipes.isna().sum()

ingredients_compare = []
for i in recipes.ingredients:
    ingredients_compare.append(ast.literal_eval(i))

recipes['ingredients_compare'] = ingredients_compare

steps_list = []
for i in recipes.steps:
    steps_list.append(ast.literal_eval(i))
#print(steps_list[0])

recipes['steps_new'] = steps_list

recipes.head()

recipes.ingredients[42]

# Function to calculate Jaccard similarity
def jaccard_similarity(list1, list2):
    intersection = len(set(list1) & set(list2))
    union = len(set(list1) | set(list2))
    return intersection / union if union != 0 else 0

def get_recipes():
    temp = get_ing()
    # Use apply along with a lambda function to compare each element in the lists
    recipes['Match'] = recipes['ingredients'].apply(lambda x: all(item in x for item in temp))
    temp2 = recipes[recipes['Match']==True]
    #print(len(temp2))
    if len(temp2) != 0:
        temp2['Similarity'] = temp2['ingredients_compare'].apply(lambda x:
            jaccard_similarity(x, temp))
        # Find the row with the highest similarity
        best_match_row = temp2.loc[temp2['Similarity'].idxmax()]
        top_5_matches = temp2.nlargest(5, 'Similarity')
        top_5_matches.reset_index()
    else: # This case runs when theres no complete match of ingredients
        recipes['Similarity'] = recipes['ingredients_compare'].apply(lambda x:
            jaccard_similarity(x,
            temp))
        # Find the row with the highest similarity
        best_match_row = recipes.loc[recipes['Similarity'].idxmax()]
        top_5_matches = recipes.nlargest(5, 'Similarity')
        top_5_matches.reset_index()

# Print the DataFrame with the similarity scores
#print("\nBest Matching List:")
#print(best_match_row['ingredients'])

```

```

#print("&quot;Jaccard Similarity:&quot;,, best_match_row[&#39;Similarity&#39;])
#print(temp)
#print("&quot;Top 5: &quot;,,top_5_matches[[&#39;ingredients&#39;,, &#39;Similarity&#39;]])
ascii_art = "&quot;&quot;&quot;
#####
# # # # #
# # # # #
#####
# # # # #
# # # # #
#####
# # # # #
# # # # #
#####
&quot;&quot;&quot;

print(ascii_art)

print("&quot;Here are some of the recipes that might be relevant for you: &quot;)
#print(top_5_matches.iloc[1])
for i in range(5):
    t = top_5_matches.iloc[i]
    print("&#39;Name of dish: &#39;,, recipes[&#39;name&#39;][t.name])
    print(f"&#39;Ingredients required: {t.ingredients}&#39;")
    #print(t.steps)
    c = 1
    for i in t.steps_new:
        print(f"&#39;step {c}: {i}&#39;")
        c+=1
    print("&quot;\n\n&quot;)

get_recipes()

```

## Chapter 6

### Output

What ingredients do you have?I have chicken, cheese and bread

```

#####
# # # # #
# # # # #
#####
# # # # #
# # # # #
#####
# # # # #
# # # # #
#####

```

Here are some of the recipes that might be relevant for you:

```

Name of dish: turkey or chicken sandwich
Ingredients required: ['chicken', 'swiss cheese', 'catalina dressing', 'bread']
step 1: put the turkey / chicken on your bottom piece of bread
step 2: place / sprinkle your cheese over the top
step 3: if you are dipping , go ahead and put your top slice on top of the cheese
step 4: microwave this for about 30 seconds
step 5: cut your sandwich diagonallyand pour your dressing into a bowl
step 6: dip in your sandwich into the dressing and enjoy !

```

```

Name of dish: chicken parmigiana jaffle
Ingredients required: ['chicken breasts', 'tomato paste', 'bread', 'cheese', 'ham', 'butter']
step 1: plug in the sandwich maker to heat up
step 2: in a small frypan fry chicken until cooked
step 3: cut chicken into slices
step 4: spread butter onto one side of the bread and tomato paste onto the other
step 5: place 2 of these bread slices into the jaffle maker , butter side down
step 6: top with chicken , cheese and ham
step 7: place remaining slices of bread on top , paste side facing into the chicken filling
step 8: cook in jaffle maker until browned to your liking

```

The output appears to be a formatted display of the best recipe recommendation based on the provided ingredients ("chicken," "cheese," and "bread"). The recommended recipes are "Turkey or Chicken Sandwich" and "Chicken Parmigiana Jaffle." Each recipe includes the name of the dish, a list of required ingredients, and a set of step-by-step instructions for preparation. The formatting includes a visual representation of the dish using '#' characters and provides a clear structure for the user to follow when making the recommended recipes.

## Chapter 7

### Conclusion

In conclusion, the Recipe Recommendation System successfully leverages NLP techniques to provide accurate and relevant recipe suggestions based on user-input ingredients. The inclusion of a user interface and robust handling of potential issues contribute to an overall effective and user-friendly system. Ongoing improvements and refinements can further enhance the system's capabilities for a more seamless user experience.

### References:

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