Identifying Key Entities in Recipe Data-Report

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Executive Summary

This project focuses on identifying key entities, ingredients, quantities, and units, from unstructured recipe text using a sequence labeling approach. A Conditional Random Field (CRF) model was used to classify each token in a recipe sentence. The assignment involved preprocessing recipe data, engineering features, balancing classes, training a CRF model, and performing error analysis. The model performed well on structured patterns and offered insights into areas for improvement. The output supports applications like recipe parsers, grocery planners, or virtual kitchen assistants.

Problem Statement

Recipes contain structured information presented in unstructured text. Extracting the key components, ingredient names, measurement units, and quantities, is essential for many applications. This assignment formulates it as a Named Entity Recognition (NER) task, where each word (token) in a recipe is classified into one of the three categories.

Methodology

1. Data Loading and Validation:

- ➤ Loaded recipe data from a JSON file containing token-level POS labels.
- Cleaned and validated the data by ensuring that input_tokens and pos_tokens were aligned in length and structure.
- Dropped inconsistent rows and recalculated token lengths for reliability.



2. Exploratory Data Analysis (EDA):

- Visualized the most frequent ingredients and units using bar plots.
- Analyzed both training and validation datasets to identify distribution imbalances and label trends.

```
Top 10 most frequent ingredients in Training dataset:
powder: 129
Salt: 102
seeds: 89
Green: 85
chopped: 84
Oil: 83
Red: 81
Chilli: 77
Coriander: 71
Sunflower: 65
Top 10 most frequent units in Training dataset:
teaspoon: 162
cup: 136
tablespoon: 99
grams: 63
tablespoons: 61
inch: 52
cups: 50
sprig: 41
cloves: 39
teaspoons: 39
```

3. Feature Engineering:

- ➤ Designed a word2features function using spaCy for token-level features including:
 - Lexical (token, lemma, shape)
 - POS and dependency tags
 - Digit and punctuation flags
 - Quantity/unit detection using regex and keyword sets
 - Contextual features (previous and next tokens)

```
# print the length of train features and labels
print("Length of X_train_features:", len(X_train_features))
print("Length of y_train_labels:", len(y_train_labels))

Length of X_train_features: 196
Length of y_train_labels: 196

# print the length of validation features and labels
print("Length of X_val_features:", len(X_val_features))
print("Length of y_val_labels:", len(y_val_labels))

Length of X_val_features: 84
Length of y_val_labels: 84
```

4. Class Weighting:

Used inverse frequency to compute class weights, with additional penalization on 'ingredient' to address misclassification risk.

```
Label Counts: Counter({'ingredient': 5323, 'quantity': 980, 'unit': 811})
Total Samples: 7114
```

5. Model Building:

- ➤ Trained a CRF model with hyperparameters:
- ➤ algorithm='lbfgs', c1=0.5, c2=1.0, max_iterations=100, all_possible_transitions=True
- Used token-level feature dictionaries with embedded class weights during training.

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| ingredient | 1.00 | 1.00 | 1.00 | 5323 |
| quantity | 0.99 | 0.98 | 0.99 | 980 |
| unit | 0.98 | 0.99 | 0.98 | 811 |
| accuracy | | | 1.00 | 7114 |
| macro avg | 0.99 | 0.99 | 0.99 | 7114 |
| weighted avg | 1.00 | 1.00 | 1.00 | 7114 |

Visualizations and Key Insights

1. Training Performance:

- ➤ High accuracy for 'unit' and 'quantity' labels.
- ➤ Most misclassifications occurred in the 'ingredient' class due to semantic overlap and varied context.

2. Validation Metrics:

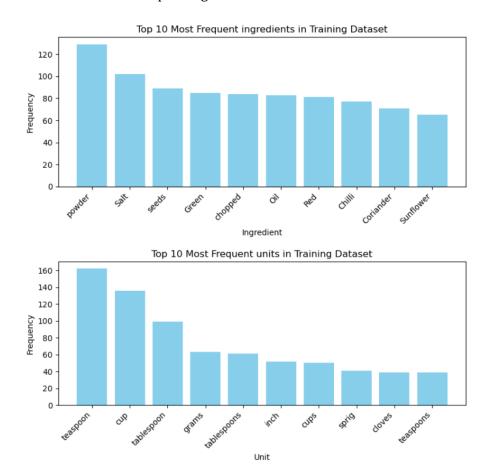
- > Flat classification report showed precision and recall scores across labels.
- Confusion matrix highlighted label confusions, particularly between 'ingredient' and 'unit'.

3. Error Analysis:

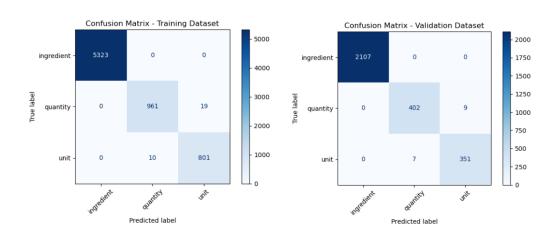
- Errors were logged when predicted labels did not match the true labels.
- ➤ Tokens like 'oil', 'milk', and 'salt' were often misclassified due to ambiguous context.
- Accuracy dropped when quantities were missing or sentence context was vague.
- ➤ A detailed error table was created with token, true label, predicted label, and surrounding context.

4. Sample Visualizations Included:

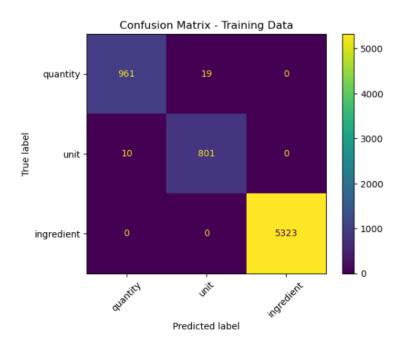
➤ Bar charts for top 10 ingredients and units.



Confusion matrices for both training and validation datasets.



> Confusion matrix training data.



> The table below shows error analysis with label-wise metrics and sample misclassifications from the validation set

> > cut into cm

1-1 2 tablespoon

powder 1/3 Water powder pinch Salt Salt 2 Instant

| Per-Label Error Analysis: | | | | | | | | |
|---------------------------|------------|----------|-----------|--------|---------|------------|---|--|
| | eight | class_w | accuracy | errors | total | label | | |
| | 7.26 | | 97.81 | 9 | 411 | quantity | 1 | |
| | 8.77 | | 98.04 | 7 | 358 | unit | 2 | |
| | 3.01 | | 100.00 | 0 | 2107 | ingredient | 0 | |
| context | pred_label | ue_label | _token tr | n next | ev_toke | token pro | | |
| powder 1/4 Salt | unit | quantity | Salt | er | powde | 1/4 | 0 | |
| French cut into | quantity | unit | into | h | Frenc | cut | 1 | |
| Pudina 6-8 Saffron | unit | quantity | Saffron | a | Pudin | 6-8 | 2 | |
| Oil cold pressed | quantity | unit | ressed | il p | 0 | cold | 3 | |
| pressed 1-1/2 Poppy | unit | quantity | Рорру | d | presse | 1-1/2 | 4 | |
| cut into cm | | | cm | | - | into | _ | |

1-1 tablespoon

Instant

1/3

quantity

quantity

Assumptions

- The 'input' and 'pos' sequences are pre-aligned and consistently tokenized.
- Quantity detection assumes common English fraction and decimal formats.
- Unit keywords are manually defined and may not cover all variations (e.g., 'dash', 'pinch').

Value & Benefits

- ✓ **Enhanced User Experience**: Automatically structuring recipe text enables voice assistants and mobile apps to guide users step-by-step, interpret ingredient lists, or convert units on the fly.
- ✓ **Smart Grocery Planning**: By extracting ingredients and quantities, apps can generate dynamic shopping lists, check pantry stock, or suggest meal prep based on available items.
- ✓ **Data Integration**: Structuring recipes allows integration with **nutrition APIs**, **meal tracking apps**, or **smart kitchen devices**, adding value across fitness, healthcare, and lifestyle sectors.
- ✓ E-commerce Enablement: Online retailers can link extracted ingredients to purchasable items, driving personalized product recommendations and increasing cart conversions.
- ✓ **Scalable Automation**: The CRF-based model is lightweight, interpretable, and deployable in resource-constrained environments like edge devices or mobile platforms.

Conclusion

The project achieved its objective of extracting structured information from recipe text using a CRF model with carefully engineered features and class weighting. The model performed strongly on consistent patterns like numeric quantities and units, and revealed areas for further improvement in handling context-heavy ingredient names. The work establishes a solid baseline for expanding this pipeline to real-world cooking assistants, shopping list generators, or voice-driven recipe platforms.