Identifying Key Entities in Recipe Data

Business Objective: The goal of this assignment is to train a Named Entity Recognition (NER) model using Conditional Random Fields (CRF) to extract key entities from recipe data. The model will classify words into predefined categories such as ingredients, quantities and units, enabling the creation of a structured database of recipes and ingredients that can be used to power advanced features in recipe management systems, dietary tracking apps, or e-commerce platforms.

Problem Statement: The goal of this assignment is to identify and classify key entities in cooking recipe data using Named Entity Recognition (NER). Specifically, we aim to extract and correctly label entities such as 'ingredient', 'quantity', and 'unit' from textual recipe instructions. This task is vital for structuring and digitizing recipe data to make it searchable and usable in digital applications.

Assumptions Made:

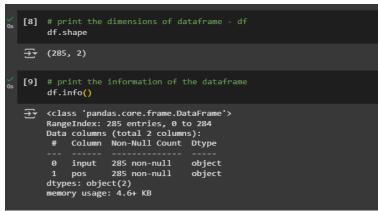
During the development of the Named Entity Recognition (NER) pipeline for identifying key entities in recipe data, several assumptions were made to simplify the modeling process and focus the scope of the problem. These assumptions influenced data preprocessing, feature extraction, and model design:

- Entity Classes Are Mutually Exclusive: Each token is assumed to belong to only one of the three entity classes: 'ingredient', 'quantity', or 'unit'. No overlapping or nested entities are considered.
- Labels Are Assigned at the Token Level: The model processes and assigns labels at the token level. Multi-word entities are expected to be captured by a sequence of token-level predictions.
- Context Is Limited to Neighboring Tokens: Feature engineering includes context from a fixed number of preceding and following tokens, without considering the entire sentence or paragraph.
- Class Weights Are Used to Address Imbalance: To address imbalance in the dataset (e.g., more 'ingredient' tokens), class weights are computed and used in the training process.
- No External Knowledge Base Is Used: The model relies solely on patterns learned from the training data, without referencing external databases or lexicons for ingredients or units.
- Evaluation Ignores Sentence-Level Entity Boundaries: Evaluation is based on token-level accuracy and confusion matrices. Span-level or partial entity recognition is not accounted for.
- **Noise and Misspellings Are Minimal:** The code assumes a clean dataset without significant typos, OCR errors, or noisy data entries.

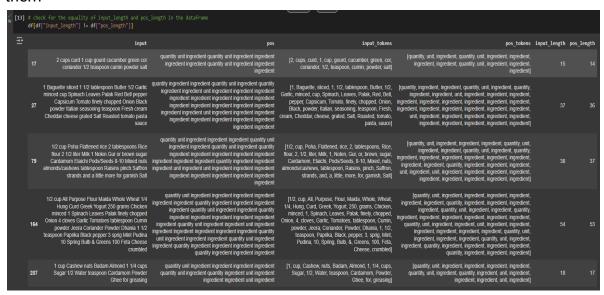
Methodology:

The approach involves preprocessing recipe texts, tokenizing them, and then applying NER to classify each token. Used traditional sequence labeling techniques along with feature engineering to build our models. The key stages in our methodology include:

- Importing necessary libraries
 - import sklearn_crfsuite # sklearn-crfsuite is a Py wrapper for CRFsuite (CRF implementation for sequence modeling)
 - import spacy # Library for advanced NLP tasks
 - from sklearn.model_selection import train_test_split
 - from sklearn_crfsuite import metrics # For evaluating CRF models
- Data Ingestion and Preparation
 - Read Recipe Data from Dataframe and prepare the data for analysis
 - o df.shape and df.info() DataFrame

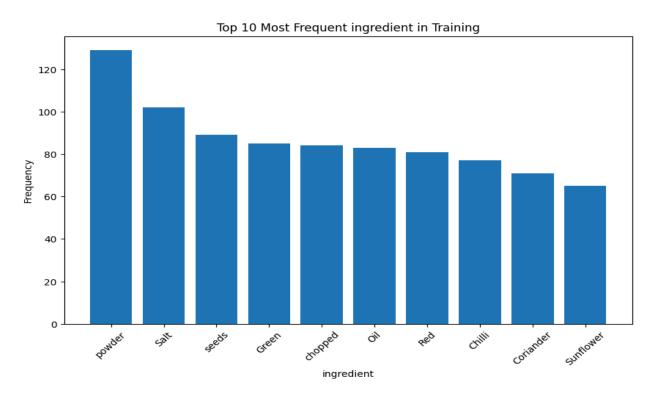


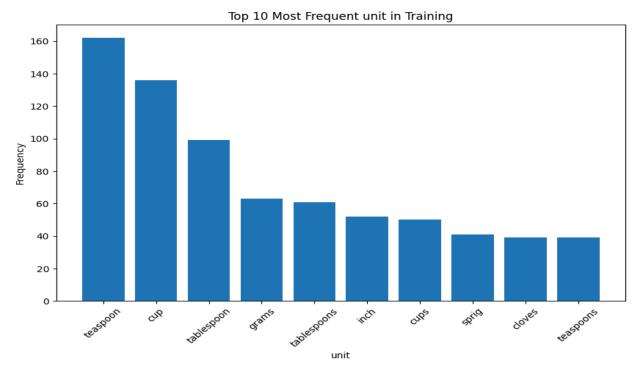
 Check for rows with unequal length of tokens in input and pos and remove them



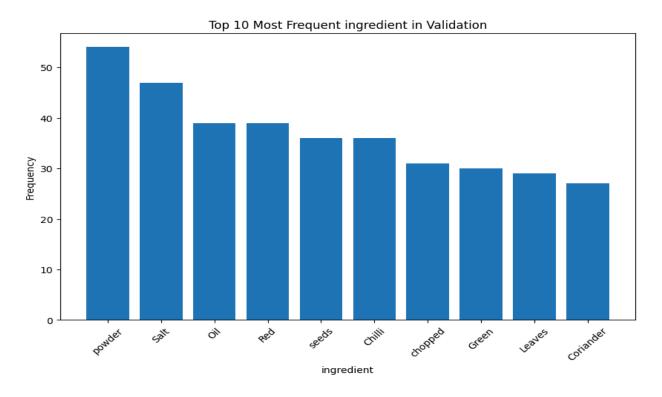
We can observe that we have only 3 unique pos labels in the recipe: {'unit', 'quantity', 'ingredient'}

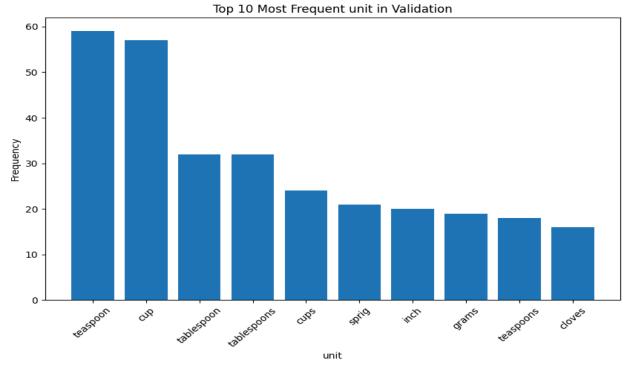
- Train-Validation Split
 - After splitting data into training (70%) and validation (30%) we have:
 Training samples: 196 and Validation samples: 84
- Exploratory Data Analysis on Training Data
 - o Categorizing tokens into labels (unit, ingredient, quantity)
 - o List top 10 frequent items in ingredient and unit lists for Training Data





- Exploratory Data Analysis on Validation Data
 - o Categorizing tokens into labels (unit, ingredient, quantity)
 - o List top 10 frequent items in ingredient and unit lists for Validation Data



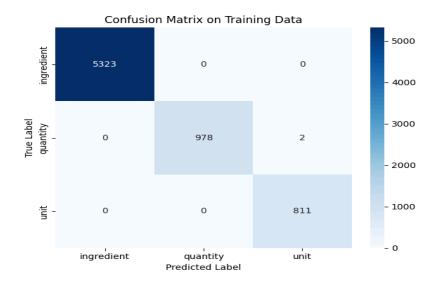


- Feature Extraction for CRF Model
 - Preform feature extraction to extract each token from recipe (word2features)
 - Applying weights to feature sets {'quantity': 2.4197 , 'unit': 2.9239 , 'ingredient': 0.4454}
 - Penalising ingredient label with 0.5 reducing weights_dict to {'quantity': 2.4197, 'unit': 2.9239, 'ingredient': 0.2227}
- Model Building and Training
 - Initializing CRF model with specified hyperparameters

- Prediction and Model Evaluation
 - Evaluate training data and print classification report

```
[61] # specify the flat classification report by using training data for evaluation
     print("Flat classification report by using training data for evaluation")
     print(metrics.flat_classification_report(y_train_labels, y_train_pred))
Flat classification report by using training data for evaluation
                  precision recall f1-score
                                                support
       ingredient
                      1.00
                                1.00
                                          1.00
                                                   5323
        quantity
                     1.00
                               1.00
                                        1.00
                                                    980
            unit
                     1.00
                                1.00
                                         1.00
                                                    811
                                                   7114
        accuracy
                                          1.00
                                                   7114
        macro avg
                      1.00
                                1.00
                                          1.00
     weighted avg
                      1.00
                                1.00
                                          1.00
                                                   7114
```

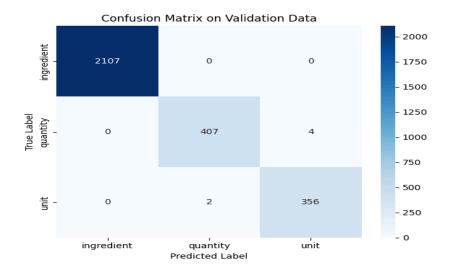
Display Confusion Matrix on Training Data



 Evaluate validation data and print classification report, from which we can draw that our model has performed incredibly well

```
[66] # specify flat classification report
     print("Flat Classification Report on Validation Data:")
     print(metrics.flat_classification_report(y_val_labels, y_val_pred))
     Flat Classification Report on Validation Data:
                    precision
                                 recall f1-score
                                                     support
       ingredient
                                   1.00
                         1.00
                                              1.00
                                                        2107
                         1.00
                                   0.99
                                              0.99
         quantity
                                                         411
             unit
                         0.99
                                   0.99
                                              0.99
                                                         358
         accuracy
                                              1.00
                                                        2876
        macro avg
                         0.99
                                   0.99
                                              0.99
                                                        2876
     weighted avg
                         1.00
                                   1.00
                                              1.00
                                                        2876
```

o Display Confusion Matrix on Validation Data



- Performing Error Analysis on Validation Data
 - Identify misclassified samples in validation dataset

```
Validation Error DataFrame:
   token true_label predicted_label prev_token next_token class_weight
     is quantity unit Pur 2 2.419728
                                   0il
                     unit
quantity
                                        kneading
     for quantity
                                                    2.419728
2
     to
            unit
                                   10 12
                                                    2.923962
                                 Haldi pinch
   a unit
pinch quantity
                      quantity
                                                    2.923962
                               Dal Asafoetida
                         unit
                                                    2.419728
5 cloves quantity
                         unit
                               Tomatoes
                                          Garlic
                                                    2.419728
```

- Ingredient label predictions are perfect, however its low class_weight indicates it's the most frequent label in the dataset, which might result in a biased model or overfitting for this class.
- Our model only made 4 errors in predicting quantity labels and 2 errors for unit labels. Despite their class_weights (2.42 and 2.87), helped the model learn to prioritize them.

Conclusion:

- With all classes achieving over 99% accuracy, the model demonstrates excellent performance and generalization on validation set
- For further analysis consider
 - Cross-validation for model's robustness
 - Monitoring performance when scaling to new recipes