

Exploiting Bi-LSTM for Named Entity Recognition in Indian Culinary Science

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Outline:

- Objective
- Related Work
- Data Preprocessing
- Data Annotation
- Proposed Architecture
- Results
- Conclusion & Future Work

Objective:

- There is no dearth for Indian Recipes on the Internet.
- However, finding such information in an organized manner is a problem.
- Thus, the goal of our project is create a dataset in an untapped domain so that it can stimulate further research.
- We used deep learning model to tag the named entities in the Recipes.

Related Work:

- Timothy used a method that involved Conditional Random Fields which learnt the structures of sentences using an undirected model. The dataset used was a set of Tweets and they achieved an F1 score of 49.88.
- An approach that used Bi- Directional LSTMs with Orthographic Sequence Generators yielded an F1 score of 52.41 as proposed by Collier
- Chiu used a Bi-LSTM with character level CNN on the Brown Corpus for NER and achieved an F1 score of 85.53.

Data Preprocessing:

- Removal of extraneous, unnecessary characters that were inadvertently included as part of the dataset during scraping.
- Punctuations, especially commas, were highly improper and proved to be erroneous while handling the dataset as a CSV file.
- Spelling variations led to tagging of different ingredients as separate entities which is undesired.

Data Annotation:

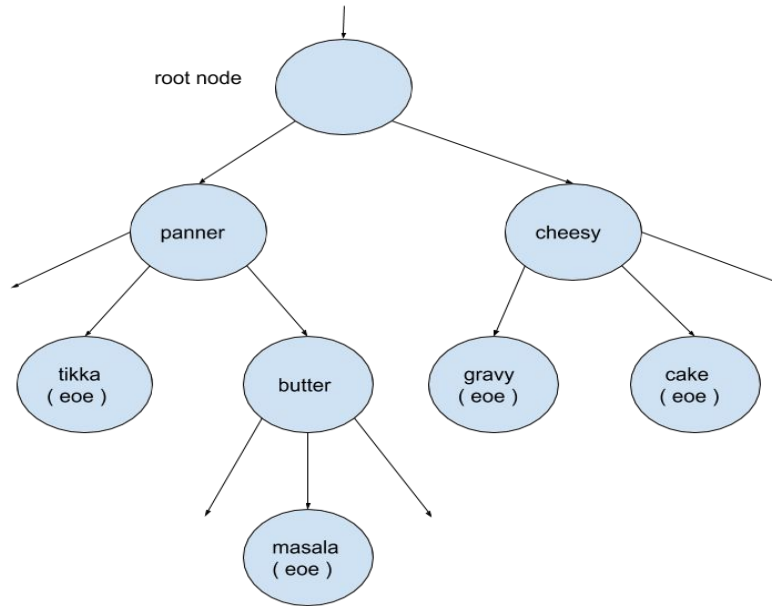


Fig 1: Trie of Words of Named Entities

Proposed Architecture:

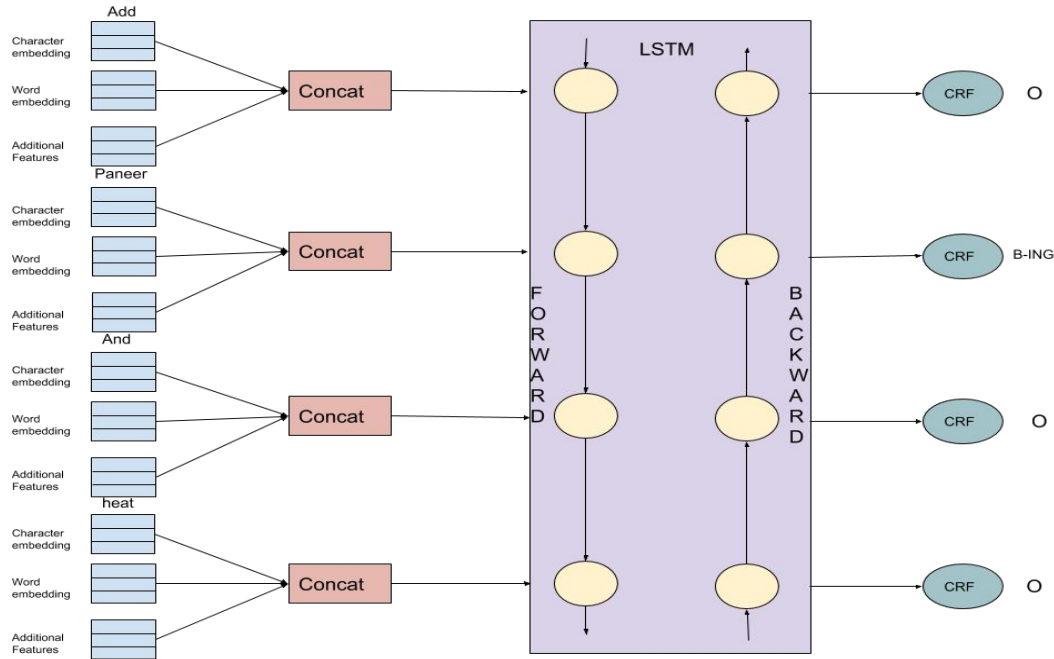


Fig 2: Overall Architecture of the model

Evaluation Metrics:

Precision:

$$\textit{precision} = \frac{\textit{true positives}}{\textit{true positives} + \textit{false positives}}$$

Mean Average Precision:

$$\textit{mean average precision} = \frac{\sum_{i=1}^{i=n} \textit{precision}_i}{n}$$

Recall:

$$\textit{recall} = \frac{\textit{true positives}}{\textit{true positives} + \textit{false negatives}}$$

Mean Average Recall:

$$\textit{mean average recall} = \frac{\sum_{i=1}^{i=n} \textit{recall}_i}{n}$$

F1 Score:

$$\textit{F1 score} = \frac{2 \cdot \textit{precision} \cdot \textit{recall}}{\textit{precision} + \textit{recall}}$$

Evaluation Metrics:

Mean F1 Score:

$$\text{mean average F1 Score} = \frac{\sum_{i=1}^{i=n} \text{F1 Score}_i}{n}$$

where, n = no of folds of validation used.

Results:

Version 1:

Train Sentences: 13,682

Dev Sentences: 5,145

Test Sentences: 5,071

Embeddings: Glove [7] 50 dims word embeddings.

Dataset: Not cleaned.

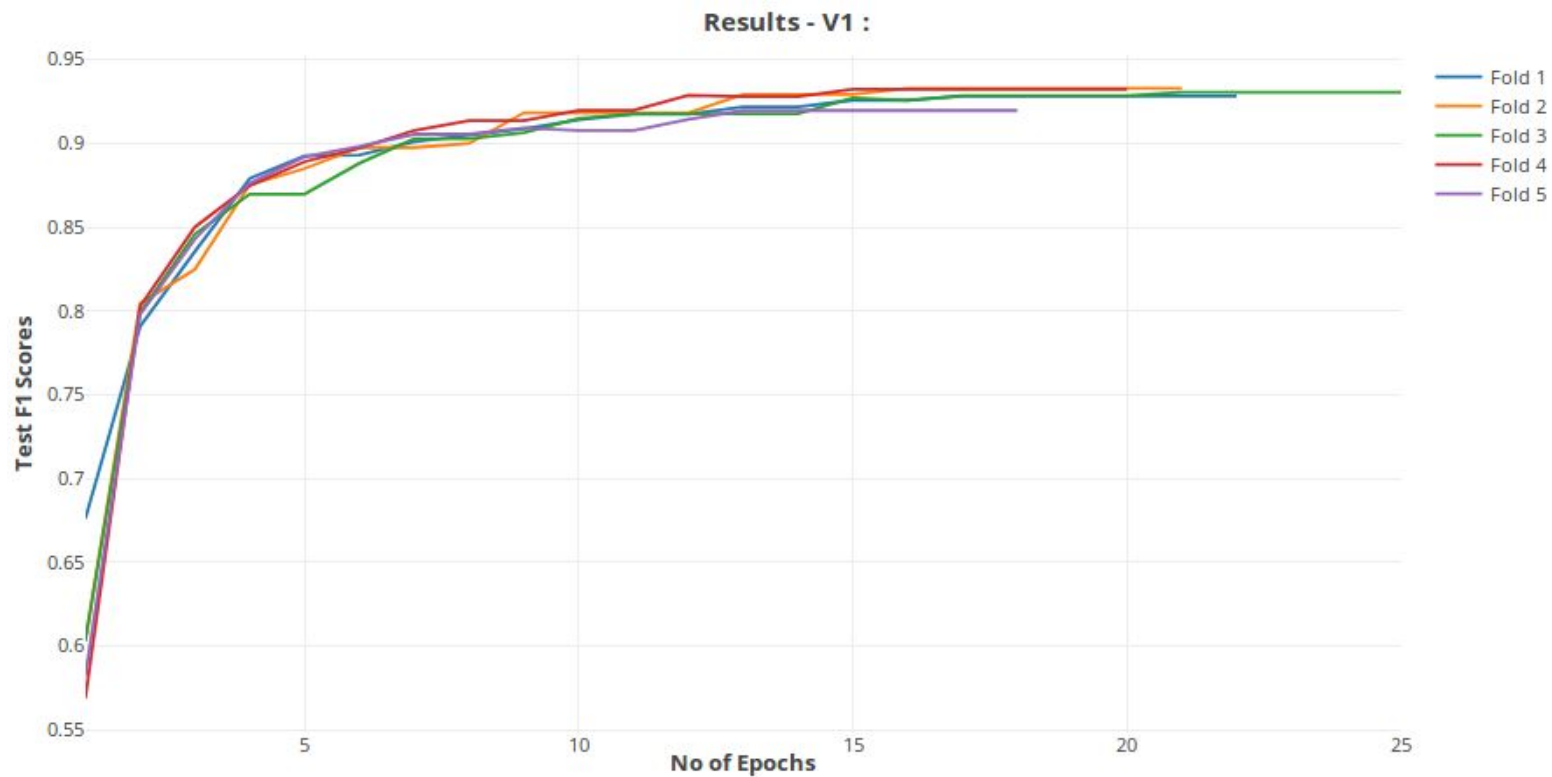
No of Folds of Validation: 5

Mean Average Precision (Test data) = 0.9205

Mean Average Recall (Test data) = 0.9371

Mean F1 Score (Test data) = 0.9287

Results:



Results:

Version 2:

Train Sentences: 14,323

Dev Sentences: 4869

Test Sentences: 4733

Embeddings: Glove[7] 200 dims word embeddings.

Dataset: Cleaned.

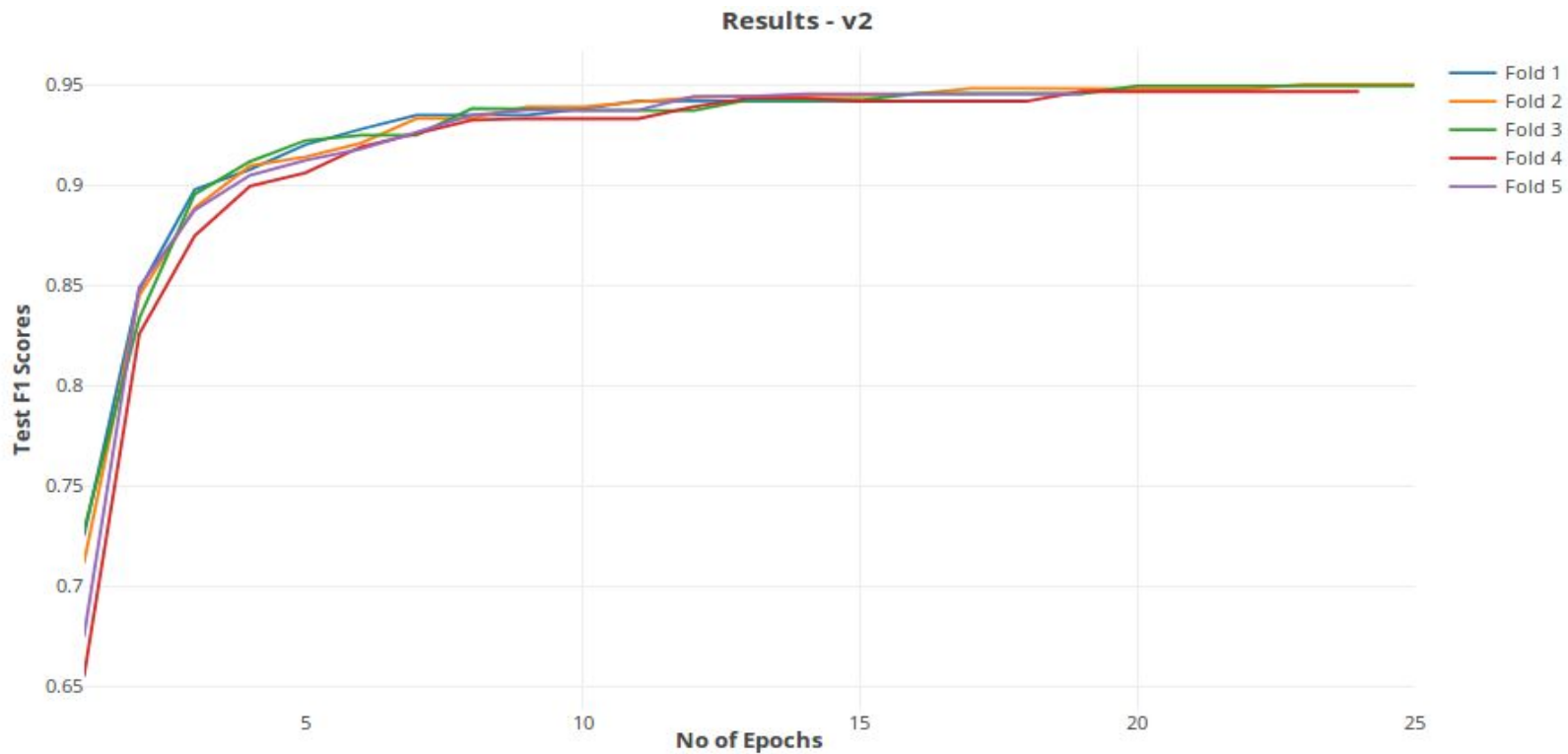
No of Folds of Validation: 5

Mean Average Precision (Test data) = 0.9403

Mean Average Recall (Test data) = 0.9530

Mean F1 Score (Test data) = 0.9466

Results:



Sample Output:

1. Add
2. two
3. tbsp
4. **onion B-ING**
5. and
6. two
7. tbsp
8. **tomato B-ING**
9. to
10. the
11. **ginger B-ING**
12. **paste I-ING**
13. along
14. with
15. few
16. amount
17. of
18. **salt B-ING**
19. .

Conclusion & Future Work:

- The data set can be utilized for further research in Culinary domain.
- Other NLP tasks such as breaking of a complex sentence, performing the coreference resolution in culinary science dataset can be performed.

Thank you!

