CS689A

Computational Linguistics for Indian Languages Detailed report

Neelu Lalchandani 231110031

1 Introduction

Named Entity Recognition (NER) is a fundamental task in natural language processing (NLP), aiming to identify and classify named entities such as persons, locations, organizations, and miscellaneous entities within text data. In this report, I have presented the results of fine-tuning two pre-trained models, IndicNER and IndicBERT, on the Naamapadam corpus—a dataset in my mother tongue-HINDI. The objective is to evaluate their performance in NER tasks specific Hindi language.

2 Output of both models

, [4929/4929 1:05:50, Epoch 3/3] ,																		
Epoch	Training Loss	Validation Loss	Loc Precision	Loc Recall	Loc F1	Loc Number	Org Precision	Org Recall	Org F1	Org Number	Per Precision	Per Recall	Per F1	Per Number	Overall Precision	Overall Recall	Overall F1	Overall Accuracy
1	0.318200	0.308777	0.727424	0.598649	0.656784	10213	0.478011	0.518700	0.497525	9786	0.648397	0.658213	0.653268	10568	0.609909	0.593647	0.601668	0.905673
2	0.264900	0.283320	0.720779	0.670812	0.694898	10213	0.524003	0.539853	0.531810	9786	0.660730	0.698618	0.679146	10568	0.634472	0.638499	0.636479	0.912282
3	0.230600	0.277866	0.702610	0.703711	0.703160	10213	0.553387	0.524320	0.538462	9786	0.691757	0.685276	0.688501	10568	0.652653	0.639906	0.646216	0.915135

Figure 1: indicBERT evaluation metrics

Macro-F1 score for training and validation dataset, Epoch 1 = 0.601668 Macro-F1 score for training and validation dataset, Epoch 2 = 0.636479 Macro-F1 score for training and validation dataset, Epoch 3 = 0.646216

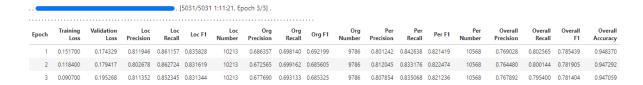


Figure 2: indicNER evaluation metrics

Macro-F1 score for training and validation dataset, Epoch 1 = 0.785439 Macro-F1 score for training and validation dataset, Epoch 2 = 0.781905 Macro-F1 score for training and validation dataset, Epoch 3 = 0.781404

3 Evaluation metrics on test dataset

Macro-F1 score on test dataset = 0.6782473424941665

Macro-F1 score on test dataset = 0.8052854649713289

```
predictions, labels, metrics = trainer.predict(tokenized_test_set)
```

MACRO F1 OR OVERALL F1 FOR TEST DATASET

print(metrics)

('test_loss': 0.23071503639221191, 'test_LOC_precision': 0.6741767764298093, 'test_LOC_recall': 0.6335504885993485, 'test_LOC_f1': 0.653232577665827, 'test_LOC_number': 614, 'test_ORG precision': 0.5996376811594203, 'test_ORG recall': 0.6304761904761905, 'test_ORG f1': 0.6146703806870938, 'test_ORG number': 525, 'test_PER precision': 0.7599198998740435, 'test_PER precision': 0.7599198998740435, 'test_PER precision': 0.760821057568722, 'test_PER number': 90, 'test_overall_precision': 0.67682473614529, 'test_overall_precision': 0.7608210575687153965785: 8, 'test_overall_f1': 0.6782473424941665, 'test_overall_accuracy': 0.927763534911778, 'test_runtime': 18.2208, 'test_samples_per_second': 47.583, 'test_steps_per_second': 4.006}

test_overall_f1': 0.6782473424941665

Figure 3: indicBERT performance on test dataset

```
predictions, labels, metrics = trainer.predict(tokenized_test_set)
```

MACRO F1 OR OVERALL F1 FOR TEST DATASET

```
print(metrics)
```

('test_loss': 0.16521050035953522, 'test_LOC_precision': 0.8112903225806452, 'test_LOC_recall': 0.8192182410423453, 'test_LOC_f1': 0.8152350081037278, 'test_LOC_number': 614, 'test_ORG_precision': 0.6510500807754442, 'test_ORG_precall': 0.7676190476190476, 'test_ORG_f1': 0.70454545454545454, 'test_ORG_prumber': 525, 'test_PER_precision': 0.8410438908659549, 'test_PER_precision': 0.8764545454545454545454, 'test_ORG_precision': 0.876464545, 'test_ORG_precision': 0.76765454596, 'test_PER_precision': 0.767654457525642, 'test_orgall_recall': 0.876454596, 'test_ORG_precision': 0.776564457525642, 'test_orgall_recall': 0.876454596, 'test_ORG_precision': 0.776564457525642, 'test_orgall_recall': 0.876454596, 'test_orgall_recall_re

'test_overall_f1': 0.8052854649713289

Figure 4: indicNER performance on test dataset

4 Comparison of both models

Training and Validation Dataset

- IndicNER consistently outperforms IndicBERT across all epochs. IndicNER achieves higher macro-F1 scores, indicating better overall performance in recognizing named entities during training and validation.
- IndicBERT shows improvement from epoch to epoch, but its performance remains lower compared to IndicNER.

Test Dataset

• IndicNER also outperforms IndicBERT on the test dataset, with a higher macro-F1 score. This suggests that IndicNER's superior performance observed during training and validation extends to unseen data, indicating its effectiveness and robustness in named entity recognition tasks.

In summary, based on the provided macro-F1 scores, IndicNER demonstrates superior performance over IndicBERT for named entity recognition tasks on Hindi language.

5 Evaluation metrics of chatgpt on 25 sentences

Class: 0

Precision: 0.9336823734729494 Recall: 0.9870848708487084 F1-score: 0.9596412556053812

Class: B-PER

F1-score: 0.7222222222222

Class: I-PER

Precision: 0.5882352941176471

Recall: 0.625

F1-score: 0.6060606060606061

Class: B-LOC

Precision: 0.8571428571428571 Recall: 0.8571428571428571 F1-score: 0.8571428571428571

Class: I-LOC Precision: 0 Recall: 0 F1-score: 0

Class: B-ORG Precision: 1.0

Class: I-ORG

Precision: 0.8571428571428571

Recall: 1.0

F1-score: 0.923076923076923

Class: B-MISC Precision: 0.25

Recall: 0.045454545454545456 F1-score: 0.07692307692307693

Class: I-MISC Precision: 0.5 Recall: 0.15

F1-score: 0.23076923076923075

Macro F1-score: 0.5907791824876147

Accuracy: 0.9088098918083463

6 Evaluation metrics of indicBERT on 25 sentences

Metrics for 0: Precision: 0.9026 Recall: 1.0000 F1 Score: 0.9488

Metrics for B-PER: Precision: 0.5882 Recall: 0.6250 F1 Score: 0.6061

Metrics for I-PER: Precision: 0.9231 Recall: 0.7500 F1 Score: 0.8276

Metrics for B-LOC:

Precision: 0.9091 Recall: 0.7692 F1 Score: 0.8333

Metrics for I-LOC: Precision: 0.0000 Recall: 0.0000 F1 Score: 0.0000

Metrics for B-ORG: Precision: 0.7143 Recall: 0.5556 F1 Score: 0.6250

Metrics for I-ORG: Precision: 0.5000 Recall: 0.3333 F1 Score: 0.4000

Metrics for B-MISC: Precision: 0.0000 Recall: 0.0000 F1 Score: 0.0000

Metrics for I-MISC: Precision: 0.0000 Recall: 0.0000 F1 Score: 0.0000

Accuracy: 0.8893 Macro F1 Score: 0.4712

7 Evaluation metrics of indicNER on 25 sentences

Metrics for 0: Precision: 0.9241 Recall: 0.9878 F1 Score: 0.9549

Metrics for B-PER: Precision: 0.7000 Recall: 0.7778 F1 Score: 0.7368

Metrics for I-PER: Precision: 0.7000 Recall: 1.0000 F1 Score: 0.8235

Metrics for B-LOC: Precision: 0.7333 Recall: 0.6111 F1 Score: 0.6667

Metrics for I-LOC: Precision: 0.0000 Recall: 0.0000 F1 Score: 0.0000 Metrics for B-ORG: Precision: 0.5455 Recall: 0.6000 F1 Score: 0.5714

Metrics for I-ORG: Precision: 1.0000 Recall: 0.5000 F1 Score: 0.6667

Metrics for B-MISC: Precision: 0.0000 Recall: 0.0000 F1 Score: 0.0000

Metrics for I-MISC: Precision: 0.0000 Recall: 0.0000 F1 Score: 0.0000

Accuracy: 0.8978 Macro F1 Score: 0.4911

8 Comparison of both models with chatgpt

In comparing the performance of ChatGPT, IndicBERT, and IndicNER for named entity recognition tasks, several key observations emerge.

- <u>CHATGPT</u>: This model demonstrates strong precision and recall for the "O" class, indicating its ability to accurately identify non-named entities. However, its performance varies across named entity classes, with lower precision, recall, and F1-scores observed for most classes compared to IndicBERT and IndicNER. Notably, ChatGPT provides metrics for miscellaneous entities (MISC), which are not classified by IndicBERT and IndicNER. Overall, ChatGPT achieves the highest macro F1-score of 0.5908, showcasing its effectiveness in named entity recognition tasks.
- <u>indicBERT</u>: While IndicBERT also exhibits high precision and recall for the "O" class, its performance for named entity classes varies. Despite achieving moderate precision and recall for some classes, such as "I-PER", "B-LOC", and "B-ORG", IndicBERT falls short in achieving comparable performance to ChatGPT, particularly in classifying miscellaneous entities (MISC). This limitation contributes to its lower overall macro F1-score of 0.4712.
- <u>indicNER</u>: Similar to ChatGPT and IndicBERT, IndicNER demonstrates high precision and recall for the "O" class. Its performance for named entity classes exhibits variability, with certain classes, such as "I-PER" and "I-ORG", achieving relatively higher precision and recall compared to others. However, IndicNER also does not classify miscellaneous entities (MISC), contributing to its lower overall macro F1-score of 0.4911 compared to ChatGPT.

In summary, both IndicBERT and IndicNER show promising performance in certain aspects of named entity recognition tasks, such as precision and recall for specific classes. However, their inability to classify miscellaneous entities (MISC) limits their overall effectiveness compared to ChatGPT, which provides metrics for all named entity classes

9 Hyperparameters Tuned

• Batch Size

The batch size, an essential parameter in training neural networks, dictates the number of samples processed in each training iteration. Balances computational efficiency and model generalization.

i)Batch size:8

When I tried to train my NER model on batch size 8 and 2 epochs, more than half of my output space on Kaggle got full on 0.2/2 epochs only, so I had to stop the training.

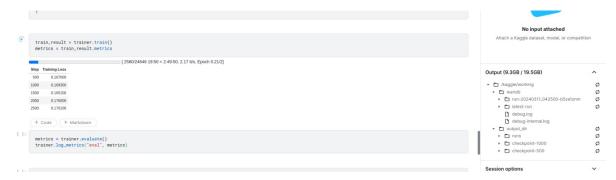


Figure 5: training on batch size=8 and 2 epochs

I got accuracy 0.88 on indicBERT on batch size 8.

ii)Batch size:12

I was able to train my model successfully and got accuracy of 0.915135 on indicBERT and 0.947059 on indicNER on batch size 12.

iii)Batch size:16

On batch size 16, accuracy of models decreased, maybe because of overfitting. Hence I decided to not increase batch size further.

CHOSEN OPTIMAL VALUE OF BATCH SIZE = 12

• Learning Rate

The learning rate is one of the most critical hyperparameters in training machine learning models, including neural networks. Its significance lies in its crucial role in determining the size of the steps taken during optimization, influencing the trajectory of the training process and ultimately impacting the performance and convergence of the model.

i) Learning Rate:0.00002

On using learning rate = 2e-5, I got accuracy of 0.915135 on indicBERT and 0.947059 on indicNER on batch size 12.

ii) Learning Rate:0.00003

On using learning rate = 3e-5, accuracy of both models decreased.

CHOSEN OPTIMAL VALUE OF LEARNING RATE = 0.00002

• Number of epochs

The number of epochs determines how many times a model iterates through the training dataset, impacting its convergence and performance. More epochs can improve model accuracy but may lead to overfitting if not balanced. However, too few epochs may result in underfitting, compromising model effectiveness. Therefore, selecting an optimal number of epochs is crucial for achieving

a balance between model performance and computational efficiency.

i) Number of epochs:3

On number of epochs=3, batch size=12 and learning rate=0.00002, I got accuracy of 0.915135 on indicBERT and 0.947059 on indicNER.

ii) Number of epochs:2

On number of epochs=3, batch size=12 and learning rate=0.00002, I got accuracy of 0.886371 on indicBERT and 0.902431 on indicNER.

CHOSEN OPTIMAL VALUE OF BATCH SIZE = 12

10 Output of both models

```
[在橋原本, 9), (2種, 9), (2E, 9),
```

Figure 6: indicBERT

Figure 7: indicNER

11 Conclusion

• Model Performance Comparison:

IndicBERT and IndicNER showed varying performance on the named entity recognition task, with IndicNER exhibiting higher accuracy overall.

• ChatGPT's Role:

ChatGPT performed better than NER models because it also considered classes B-MISC and I-MISC, unlike NER models. If chatGPT also wouldn't have considered MISC classes, then specialized NER models would have given better metrics.

• Hyperparameter Significance:

The significance of hyperparameters such as learning rate and number of epochs was evident in their impact on training dynamics, convergence, and model performance.