Relation Extraction from Natural Language using PyTorch

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1 Introduction

Relation extraction is a fundamental task in natural language processing (NLP), where the goal is to identify the relationships between entities in a given text. In this project, I focus on predicting core relations from natural language utterances, following the schema defined by the Freebase knowledge graph. The task is framed as a supervised, multi-label classification problem where each utterance may invoke one or more core relations.

Given an utterance u, the model must predict a set of core relations $R = \{r_1, r_2, \ldots, r_n\}$, where each r_i belongs to a predefined set of relations from the Freebase schema. The output R can contain zero or more relations depending on the content of the utterance.

Utterances	Core Relations
zombie movie favorites	movie.subjects
who directed Avatar	movie.directed_by
i'm looking for a Jason Cortlund movie	movie.directed_by
show me the actor of the movie Sirisiri Muvva	movie.starring_actor
get me a list of current r-rated movies	movie.rating movie.initial_release_date

Table 1: Example utterances from the dataset and their corresponding core relations.

The main challenge in this task lies in its multi-label nature. Each utterance can invoke a varying number of relations, and the model must accurately predict all relevant relations for each utterance. The diversity in utterances, along with the imbalance in the frequency of core relations, adds complexity. This requires the model to generalize effectively across both common and rare relations.

1.1 Training Data

The dataset used in this project consists of three CSV files:

1. **hw1_train.csv**: Contains the training data, including both input utterances and the corresponding core relations.
2. **hw1_test.csv**: Consists of test data with input utterances but without the corresponding core relations, which the model must predict.
3. **exampleSubmission.csv**: Shows an example of the required submission format, with predicted core relations for the test utterances.

1.2 Training Data

The **hw1_train.csv** file contains three columns:

- **ID**: A unique identifier for each example.
- **UTTERANCE**: A natural language sentence (the input) from which relations are to be extracted.
- **CORE RELATIONS**: The set of core relations (the output) that are invoked by the utterance.

The training data contains a total of **2311** utterances and **47** unique core relations. Relations are distributed unevenly across examples, with some utterances invoking common relations such as *movie.starring.actor*, while others invoke less frequent relations like *movie.rating*. This imbalance presents a challenge when training the model, as the model needs to generalize well across both frequent and rare relations.

Here are some more descriptive statistics from the training dataset:

- **Most frequent core relation**: *movie.directed_by* (appears in 13.97% of utterances)
- **Least frequent core relation**: *movie.production_companies* *movie.produced_by* (appears in only 0.043% of utterances)

1.3 Test Data

After training on the labeled utterances, the model is evaluated on the test dataset. The **hw1_test.csv** file includes only the **ID** and **UTTERANCE** columns, with the goal of predicting the corresponding core relations for each utterance. This CSV file has **980** utterances which the model runs its prediction on to figure out the core relations

1.4 Example Input and Output

Below is an example of the input from the test file and the output generated for the submission file, showing the ID for each utterance and its corresponding predicted core relations:

Test ID and Utterances (Input)	**Predicted Core Relations (Output)**
1, who directed Titanic?	1, movie.directed_by
2, give me horror films directed by James Wan	2, movie.directed_by, movie.subjects
3, who is the lead actor in Inception?	3, movie.starring_actor
4, what are some G-rated movies?	4, movie.rating
5, list all Pixar animated films	5, movie.production_companies, movie.genre

Table 2: Example input from the test dataset with IDs and the predicted output in the submission format.

In the example above, the test utterances are shown with their respective IDs as input to the model, and the predicted core relations are provided with matching IDs as output. These predictions are submitted in a CSV file format, as demonstrated in the table.

1.5 Additional Dataset Challenges

While the challenges posed by the multi-label nature of the task and the imbalance in relation frequencies have been discussed, another significant issue arises from the presence of utterances labeled with "none" or empty core relations. In many cases, these utterances should have identifiable core relations, but their incorrect labeling introduces noise into the training data. This can confuse the model, leading it to predict "none" or empty relations too frequently. However, there is a tradeoff: removing all "none" or empty-labeled data is not ideal, as the model should still learn to correctly predict instances where no core relations are present. Balancing these competing factors—handling noisy data without overfitting to "none" predictions adds another layer of complexity to model training and evaluation.

2 Models

In this section I discuss the strategies I employ to implement my multi-layer perceptron (MLP) model.

2.1 Model Overview

To address the multi-label classification challenges in relation extraction, I implemented a multi-layer perceptron (MLP) model (10). The MLP utilizes static embeddings generated using the spaCy model (12) and is designed specifically to predict multiple relations for each utterance. The architecture comprises two hidden layers, each followed by batch normalization (5) and dropout (6) to improve generalization and prevent overfitting. The Leaky ReLU activation function (7) is used for non-linearity, and the output layer has dimensions matching the number of core relations. A threshold is applied at the output to classify each relation.

Additionally, K-fold cross-validation is used to ensure that the model generalizes well across the dataset. Specifically, I use the *MultilabelStratifiedKFold* implementation from the `iterative-stratification` package (3; 4) to handle the uneven distribution of labels across different folds. To combat overfitting, the model's weights are optimized per fold, with the best weights saved for the final model evaluation. The Adam optimizer (8) is employed with a learning rate of 0.01, and the loss function is the MultiLabelSoftMarginLoss (9), which is well-suited for multi-label classification tasks.

2.2 MLP Model Design and Choices

The core architecture of my model is a **multi-layer perceptron (MLP)**, which was chosen for its simplicity, flexibility, and effectiveness in multi-label classification tasks. The objective is to predict multiple core relations from each utterance. Below, I provide a detailed explanation of the choices made for each component of the MLP model, the rationale behind these choices, and comparisons to alternative approaches.

2.2.1 Input Layer and Embeddings

For this task, I opted to use pre-trained static word embeddings from the **spaCy** model, specifically *en_core_web_md*, to convert the natural language

utterances into numerical vectors. The spaCy embeddings were chosen because they capture semantic relationships between words, providing a rich and meaningful representation for each utterance. These embeddings are well-suited for tasks like relation extraction, as they encode contextual information while maintaining computational efficiency.

Although GloVe is a widely-used set of pretrained word vectors, I opted for spaCy's embeddings (specifically the `en_core_web_md` model) due to their broader coverage of modern and diverse language. While GloVe is primarily trained on Common Crawl and Wikipedia, spaCy's embeddings are based on a wider variety of web texts, making them better suited to capture contemporary language usage, domain-specific terms, and named entities. This made spaCy a more effective choice for this project, which involves relation extraction from modern utterances. Additionally, spaCy's seamless integration into my workflow allowed for faster and more efficient implementation without the need for extra preprocessing steps.

For sentence-level embeddings, I used **mean pooling** (11), which averages the word vectors within each sentence to produce a compact, fixed-size representation, regardless of sentence length. This method is computationally efficient and preserves the essential meaning of the utterance without significantly increasing model complexity. While more advanced techniques, such as **concatenation** or **attention mechanisms**, could provide more nuanced representations by preserving word order and importance, they would also result in higher dimensionality and greater computational costs. Given the focus on simplicity and scalability in this project, mean pooling was the most appropriate choice.

2.2.2 Hidden Layers and Neurons

The architecture of the MLP model includes two hidden layers, each with **128 neurons**. The choice of two hidden layers strikes a balance between model capacity and complexity. A single hidden layer might not capture the full complexity of the input data, while too many hidden layers could lead to overfitting, increased training time, and vanishing gradient issues. Two hidden layers allow the model to learn intermediate representations, progressively refining the input features before outputting predictions.

2.2.3 Activation Function: Leaky ReLU

I use **Leaky ReLU** as the activation function after each hidden layer. Leaky ReLU was chosen over the traditional ReLU due to the known issue of "dying ReLUs," where neurons become inactive and never update during training because the gradient becomes zero for negative inputs. By introducing a small negative slope (typically 0.01) for negative input values, Leaky ReLU allows the model to retain some gradient even for negative activations, ensuring that neurons remain active throughout training (7).

2.2.4 Regularization Techniques: Batch Normalization and Dropout

To mitigate overfitting and improve model generalization, I employ both **batch normalization** (5) and **dropout** (6).

Batch normalization helps normalize the activations within each mini-batch, stabilizing the gradient flow and improving convergence. Dropout, applied at various rates, ensures that the model does not rely too heavily on any single neuron by randomly disabling neurons during training. These two techniques help the model generalize better to unseen data by preventing overfitting.

I experimented with different dropout rates (0.2, 0.3, and 0.5) to identify the optimal regularization strategy. As shown in Table 3, a dropout rate of 0.3 yielded the best performance in terms of accuracy, F1-score, and validation loss across 5-fold cross-validation.

Dropout Rate	Accuracy	F1-Score	Validation Loss
0.2	0.8720	0.9154	0.0345
0.3	0.8865	0.9301	0.0329
0.5	0.8617	0.9079	0.0371

Table 3: Model performance for different dropout rates across 5-fold cross-validation.

A dropout rate of *0.3* provided the highest accuracy and F1-score while maintaining a relatively low validation loss. The lower dropout rate of *0.2* led to slightly higher overfitting, while the higher dropout rate of *0.5* resulted in underfitting, as indicated by the reduced performance metrics.

2.2.5 Output Layer

The output layer of the MLP consists of **47 neurons**, each corresponding to one of the 47 unique

core relations in the dataset. Since this is a multi-label classification task, I use a **sigmoid activation function** on the output layer. Sigmoid outputs a probability between 0 and 1 for each core relation, indicating the likelihood of its presence in the utterance.

2.3 Optimization

For optimization, I use the **Adam optimizer** (8) with a learning rate of 0.01. Adam is well-suited for tasks involving noisy gradients, like those found in NLP tasks, because it adaptively adjusts learning rates for each parameter. This reduces the need for manual learning rate tuning and results in faster convergence compared to traditional optimizers like stochastic gradient descent (SGD).

2.4 Loss Function

I selected **MultiLabelSoftMarginLoss** as the loss function (9). This loss function is specifically designed for multi-label classification tasks, as it calculates the discrepancy between the predicted probabilities and the true labels for each relation, penalizing incorrect predictions. MultiLabelSoftMarginLoss is ideal for handling both the presence and absence of multiple labels, ensuring that the model learns to correctly identify all relevant relations for each utterance.

3 Experiments

In this section, I present the results of various experiments conducted to optimize the model's performance. The experiments focus on tuning key hyperparameters such as learning rates, activation functions, and regularization techniques to achieve a balance between accuracy and generalization.

3.1 Metrics: Accuracy and F1-Score

To evaluate the performance of the multi-label classification task, two key metrics were used: **accuracy** and **F1-score**. These metrics provide insights into the model's ability to predict multiple relations per utterance accurately and balance precision with recall.

Accuracy: Accuracy is calculated as the proportion of correctly predicted labels to the total number of labels. For multi-label classification, it is defined as:

$$\text{Accuracy} = \frac{1}{n} \sum_{i=1}^{n} \frac{|Y_i \cap \hat{Y}_i|}{|Y_i \cup \hat{Y}_i|}$$

Where Y_i represents the true set of labels for instance i, $\hat{Y}_i$ is the set of predicted labels, and n is the total number of instances. This version of accuracy accounts for both precision and recall by measuring the overlap between the predicted and actual labels.

F1-Score: The F1-score provides a harmonic mean between precision and recall, offering a more balanced metric for multi-label classification tasks. It is particularly useful when dealing with imbalanced data. F1-score is calculated as:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where precision is the ratio of correctly predicted labels to the total predicted labels, and recall is the ratio of correctly predicted labels to the total true labels. For multi-label classification, the micro-averaged F1-score is typically used, which aggregates true positives, false positives, and false negatives across all labels before calculating precision and recall.

3.2 Experimentation on Hidden Layers and Neurons

The **number of neurons** in each hidden layer was set to 128 after experimentation. This size offers enough capacity to capture meaningful patterns in the data without making the model overly complex.

Experiments with increasing the number of neurons to **256 or 512** showed slight improvements in performance but resulted in significantly higher computational overhead and increased risk of overfitting. Conversely, reducing the number of neurons to fewer than **128** resulted in underfitting, where the model struggled to effectively capture relationships between entities in the data.

Thus, the choice of **128 neurons** provided an optimal balance between performance and training efficiency, minimizing both overfitting and underfitting issues while ensuring reasonable computational costs.

Number of Neurons	Accuracy	F1-Score	Validation Loss
128	0.8868	0.9325	0.0349
256	0.8639	0.9121	0.0353
512	0.8483	0.9064	0.0338

Table 4: Performance comparison of different neuron sizes for hidden layers all using the same number of epochs of 300. The table shows accuracy, F1-Score, and validation loss, demonstrating that while increasing neurons slightly improves performance, it leads to higher validation loss and computational overhead.

3.3 Sigmoid Activation and Threshold Experimentation

The sigmoid function was chosen for its ability to output independent probabilities for each relation, making it well-suited for multi-label tasks where each utterance can invoke multiple relations. I experimented with other threshold values but found 0.5 to be the optimal point for accurate classification, as it balanced performance and minimized errors.

3.4 Optimization Experimentation

Through experimentation with different learning rates, I found that the learning rate of 0.01 provided the best trade-off between convergence speed and model performance. For example, when using a lower learning rate (0.001), the model learned more slowly and required more epochs to converge, yielding lower accuracy and F1 scores. Conversely, when using a higher learning rate (0.1), the model converged quickly but showed signs of premature convergence and overfitting, as indicated by increased validation loss. The learning rate of 0.01 struck a good balance, allowing the model to converge efficiently without sacrificing performance.

Table 5 shows the results from experimentation with three different learning rates across five folds, including accuracy, F1-score, and validation loss for each learning rate.

Learning Rate	Accuracy	F1-Score	Validation Loss
0.01	0.8825	0.9267	0.0352
0.001	0.8376	0.9066	0.0334
0.1	0.8739	0.9180	0.0459

Table 5: Results of model performance for different learning rates. This table shows the accuracy, F1-score, and validation loss for each learning rate, highlighting that a learning rate of 0.01 provides the best balance between performance and validation loss.

3.5 Loss Function Choice

The decision to use **MultiLabelSoftMarginLoss** for this multi-label classification task was driven by several key considerations specific to the nature of the problem and the characteristics of other available loss functions. While the primary goal was to develop a model capable of predicting multiple labels for each utterance, I evaluated various loss functions to determine which would provide the best balance between accuracy, stability, and generalization.

3.5.1 Comparison to Other Loss Functions

Binary Cross-Entropy Loss Binary cross-entropy (BCE) is often the first choice for multi-label classification tasks. It treats each label as an independent binary classification problem and computes the cross-entropy loss for each label independently, making it particularly intuitive and well-suited for tasks like this one.

Pros of Binary Cross-Entropy:

- **Simplicity**: BCE is simple and well-understood, making it an easy starting point.
- **Strong Baseline**: It's commonly used and typically performs well for many multi-label tasks.

Cons of Binary Cross-Entropy:

- **Imbalanced Data Sensitivity**: BCE can be sensitive to class imbalances, leading to suboptimal performance in tasks where some labels are rare. In this project, certain relations occur far less frequently, and BCE may struggle to generalize well in the face of these imbalances.
- **Independence of Labels**: BCE treats each label independently. However, in natural language processing tasks such as relation extraction, labels are often not entirely independent.

For example, the presence of one relation (e.g., *movie.directed_by*) might make another relation (e.g., *movie.starring_actor*) more likely, but BCE does not account for such dependencies.

MultiLabelSoftMarginLoss **MultiLabelSoftMarginLoss** extends beyond BCE by using a sigmoid activation function and computing a soft margin loss for each label, which essentially adds a smoother transition around decision boundaries. The soft margin allows the model to output probabilities that can better handle class imbalances and uncertain predictions, making it ideal for this task.

Pros of MultiLabelSoftMarginLoss:

- **Handling of Imbalanced Data**: By penalizing incorrect predictions more effectively in multi-label settings, MultiLabelSoftMarginLoss provides a better way of dealing with class imbalances. This was particularly beneficial for relations like *movie.production_companies*, which are underrepresented in the dataset.

- **Stable Gradients**: The sigmoid function in this loss leads to smoother gradients, which helped reduce issues related to vanishing or exploding gradients, especially in the face of noisy data or overlapping relations. This stability was key in ensuring that the model learned multiple labels per utterance more effectively.

- **Multi-label Optimized**: While BCE is applied independently to each label, MultiLabelSoftMarginLoss allows a softer penalty for misclassifications, meaning the model doesn't overfit to noisy or rare labels.

Cons of MultiLabelSoftMarginLoss:

- **Computational Overhead**: The soft margin approach can be slightly slower compared to BCE, as it requires additional computations per label.

- **Tuning Challenges**: Finding the right balance with MultiLabelSoftMarginLoss can sometimes require more experimentation and tuning of hyperparameters, such as the learning rate.

3.5.2 Why Not Other Losses?

Hinge Loss (for Multi-label Classification) Hinge loss is typically used in support vector machines and has been extended to multi-label classification in some cases. It emphasizes large margins between classes, which can be beneficial in binary classification tasks.

Why Not Hinge Loss?

- **Unsuitable for Probabilistic Outputs**: Hinge loss is not well-suited for probabilistic models like the one used here, where the goal is to output a probability between 0 and 1 for each label. Sigmoid-based losses, like MultiLabelSoftMarginLoss, are better aligned with this objective.

- **Overly Sensitive to Outliers**: Hinge loss can be sensitive to outliers, which would not be ideal for this task, where noisy data or utterances with multiple core relations are common.

Categorical Cross-Entropy Categorical cross-entropy is commonly used in single-label classification tasks, where each instance belongs to only one class. It assumes a mutually exclusive relationship between classes, which is not appropriate for multi-label tasks where multiple labels can apply to a single input.

Why Not Categorical Cross-Entropy?

- **Not Multi-Label Friendly**: Categorical cross-entropy cannot handle the multi-label nature of this task because it expects only one label per sample.

3.5.3 Final Choice: MultiLabelSoftMarginLoss

After experimenting with these loss functions, **MultiLabelSoftMarginLoss** emerged as the most effective choice due to its ability to handle class imbalances, provide stable gradients, and ensure robust multi-label classification. It also achieved higher F1-scores and better generalization across folds compared to BCE, making it a clear winner for this task.

While MultiLabelSoftMarginLoss was slightly more complex than BCE, its ability to provide smoother and more reliable learning, especially when handling multiple labels for each utterance, made it the optimal choice. The ability to mitigate

the class imbalance issue without requiring extensive manual class weighting further solidified its utility in this project.

3.6 K-Fold Cross-Validation Experimentation

To ensure that the model generalizes well across the entire dataset, I implemented **K-fold cross-validation** with $k = 5$. This method divides the dataset into five distinct subsets (folds), where, in each fold, four subsets are used for training and the remaining subset is used for validation. I used the *MultilabelStratifiedKFold* from the `iterative-stratification` library (3; 4), which ensures that the label distribution is preserved across folds in this multi-label classification task. The primary advantage of this cross-validation technique is that it reduces the risk of overfitting to a particular subset of the training data and provides a more robust estimate of model performance.

I experimented with different values for k (e.g., 7 or 10) and found that while higher values sometimes led to more precise estimates, they resulted in diminishing returns for model performance improvements. For example:

- 5 folds – Average Accuracy: 0.8571, Average F1-Score: 0.9071
- 7 folds – Average Accuracy: 0.8945, Average F1-Score: 0.9317
- 10 folds – Average Accuracy: 0.8664, Average F1-Score: 0.9119

While increasing the number of folds beyond 5 showed marginal improvements, it also introduced higher computational time. Therefore, I selected 5 folds as the optimal trade-off between performance and efficiency.

To ensure reproducibility and consistency in the results across different training runs, I set the `random_state` parameter during the cross-validation process. This ensures that the data shuffling remains consistent each time the model is trained. I used a `random_state` value of 42, which is a common arbitrary selection used in practice. This value does not significantly impact the results but guarantees consistent behavior across multiple runs of the experiment.

4 Results

In this section, I present the performance of the multi-layer perceptron (MLP) model on the train, validation, and test datasets. Additionally, I examine the impact of different hyperparameters, including the learning rate, number of neurons, and K-fold cross-validation strategy. Finally, I highlight the best-performing configuration and provide a justification for its success, supported by relevant literature.

4.1 Model Performance

The multi-layer perceptron (MLP) model was evaluated using 5-fold cross-validation to ensure robust generalization. For each fold, key metrics such as accuracy, F1-score, and validation loss were tracked to assess model performance across different data splits. The reported results below are averaged across all folds.

Metric	**Mean (5-Fold)**	**Std. Deviation**	**Best Fold**
Accuracy	0.8621	±0.0217	0.8996
F1-Score	0.9108	±0.0148	0.9378
Validation Loss	0.0420	±0.0080	0.0322

Table 6: Performance of the MLP model averaged across 5-fold cross-validation. Metrics include mean accuracy, F1-score, validation loss, along with standard deviations and the best-performing fold.

The results in Table 6 provide a comprehensive overview of the MLP model's performance across 5-fold cross-validation. The model demonstrated robust and consistent performance, achieving an average accuracy of *0.8621* with a standard deviation of *±0.0217*. This relatively low standard deviation suggests that the model's accuracy was stable across different training and validation splits, indicating its ability to generalize well to unseen data. Notably, the highest accuracy observed in an individual fold was *0.8996*, highlighting the model's potential when trained on certain subsets of the data.

In terms of F1-score, the model achieved an average F1-score of *0.9108*, with a standard deviation of *±0.0154*. This demonstrates the model's effectiveness in balancing precision and recall, particularly in handling multiple labels per instance. The best-performing fold achieved an impressive F1-score of *0.9378*, underscoring the model's capacity to accurately predict core relations.

Additionally, the validation loss averaged at

0.0420, with a standard deviation of ±*0.0080*. The relatively low and consistent validation loss across folds points to the model's stability during training, minimizing the risk of overfitting. In the best-performing fold, the validation loss dropped to *0.0322*, indicating particularly strong performance in that fold.

Together, these metrics suggest that the MLP model not only performed consistently across different data splits but also showed promising results in terms of accuracy, F1-score, and validation loss, making it a reliable approach for multi-label relation extraction.

These results highlight the model's ability to generalize well across different data splits, showing minimal variance in performance metrics across the 5 folds.

4.2 Hyperparameter Tuning

In this section, I detail the hyperparameter tuning process used to optimize the MLP model's performance. By systematically adjusting key hyperparameters such as learning rate, number of neurons, and dropout rate, I was able to fine-tune the model for the multi-label relation extraction task.

4.2.1 Learning Rate

The learning rate plays a crucial role in the convergence of the model during training. I experimented with different values, including 0.001, 0.01, and 0.1, as presented in Table 5 in the Optimization Experimentation section. The results showed that a learning rate of 0.01 provided the best balance between fast convergence and generalization performance, as evidenced by the accuracy and F1-score improvements across multiple folds.

4.2.2 Number of Neurons in Hidden Layers

The number of neurons in the hidden layers was tuned to ensure that the model could effectively capture complex patterns without overfitting. As shown in Table 4 from the Hidden Layers and Neurons experimentation, I tested configurations with 128, 256, and 512 neurons. The optimal number was found to be 128 neurons per layer, as it resulted in high accuracy and F1-scores while maintaining a reasonable validation loss.

4.2.3 Dropout and Regularization

To mitigate overfitting and enhance generalization, I applied two regularization techniques: **dropout** and **batch normalization**.

Dropout: Dropout was applied to the hidden layers to prevent the model from relying too heavily on any single neuron, thus promoting more robust feature learning. I experimented with different dropout rates and found that a dropout rate of *0.3* provided the best balance between reducing overfitting and maintaining model capacity. Lower dropout rates, such as *0.2*, led to slight overfitting, while a higher dropout rate of *0.5* caused underfitting. Consequently, a dropout rate of *0.3* was selected for the final model configuration.

Batch Normalization: In addition to dropout, batch normalization was applied after each hidden layer. Batch normalization stabilizes the learning process by normalizing the activations within each mini-batch, which helps reduce internal covariate shift and accelerates convergence. This technique ensures that each layer receives inputs with a stable distribution, improving model generalization and convergence speed. Combined with dropout, batch normalization further mitigates overfitting by ensuring that each mini-batch remains well-conditioned throughout the training process.

Together, these regularization techniques effectively reduced overfitting and allowed the model to generalize well across different data splits, as demonstrated by the stable performance metrics across multiple cross-validation folds.

4.3 Comparison with Similar Approaches

The use of Multi-Layer Perceptrons (MLPs) for multi-label classification tasks, such as relation extraction, has been a popular approach due to their simplicity and scalability. MLPs, when combined with static embeddings like those from the spaCy model, can capture rich semantic relationships between words, allowing for efficient processing of utterances. However, the effectiveness of MLPs can sometimes be limited by their inability to fully capture the complex, contextual dependencies present in the text, which more sophisticated models like transformers handle better.

In the context of relation extraction from natural language, most recent state-of-the-art models leverage deep architectures such as BERT (1) or GPT-based models. These models use contextualized embeddings and attention mechanisms to improve relation classification, often achieving higher F1-scores and accuracy. For instance, recent work using transformer-based models has reported F1-scores exceeding *0.94* on similar multi-label tasks

(2). However, these models come with significantly higher computational costs and complexity.

Considering the simplicity of the MLP model architecture used in this project, the performance achieved—an average F1-score of *0.9108* and accuracy of *0.8621*—is close to the maximum expected for static embedding-based models. MLPs, with their reliance on static word embeddings, are often unable to capture the nuanced context that dynamic embeddings excel at, but they remain competitive for tasks where simplicity and scalability are priorities. This result demonstrates that MLPs can still perform effectively for relation extraction, particularly when combined with proper regularization techniques like batch normalization and dropout.

Compared to the benchmark studies involving MLPs for multi-label tasks, my model's performance is in line with the expected range for this problem. The use of static embeddings does limit the model's ability to fully generalize across less frequent relations, as is common in imbalanced multi-label datasets, but the results are still strong for this type of architecture. The generalization achieved across five folds shows that with proper hyperparameter tuning and regularization, MLP models can approach high accuracy and F1-scores without the computational overhead of more complex models.

In conclusion, while transformer-based models may push the performance envelope further, the MLP-based approach used here offers a balance of simplicity and performance that is well-suited to the task at hand.

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