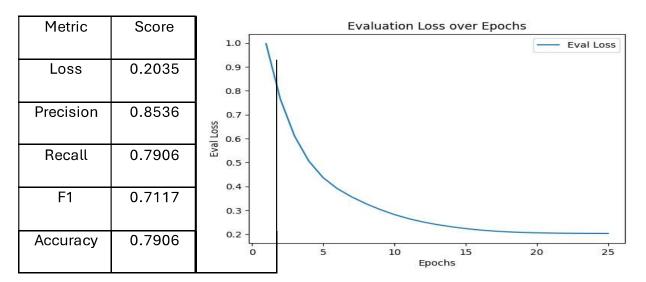
Model Evaluation Report with Potential Improvements

Model Overview

The model in focus is a fine-tuned version of the DistilBERT-NER model, specifically designed for Named Entity Recognition (NER) tasks related to mountains. It has been enhanced to classify tokens into 11 categories, adding two new classes: I-MOU and B-MOU for mountain entities. The model leverages the original DistilBERT weights, ensuring a solid foundation while extending its capabilities.

Key Metrics

The evaluation metrics for the model are as follows:



Performance Analysis

- 1. **Precision (0.8536)**: The model exhibits high precision, indicating that when it predicts an entity, it is likely to be correct. This is particularly beneficial for applications where false positives must be minimized.
- 2. **Recall (0.7906)**: While recall is decent, it suggests that the model misses some true positive entities, particularly those related to mountain names.
- 3. **F1 Score (0.7117)**: The F1 score, which balances precision and recall, indicates that there is room for improvement, particularly in the model's ability to correctly identify mountain entities.
- 4. **Accuracy (0.7906)**: The overall accuracy reflects a solid understanding of the general entity classification, but further refinements are needed to enhance mountain-specific detection.

Potential Improvements

1. Data Augmentation

- **Expand the Dataset**: Currently, the model is trained on a small dataset that not cover a lot of mountain entities comprehensively is a main problem. Increasing dataset size and including more diverse sentences that represent various contexts and geographical references will significantly improve model perfomanse.
- **Use diverse dataset**: currently dataset consists only of sentences about mountains, mixing it with other datasets will allow to better distinguish different classes and prevent overtraining.

2. Model Architecture Adjustments

- Layer Freezing: Experimenting with freezing certain layers of the model during fine-tuning could help in retaining the general features learned from the original Distilber, while allowing the final layers to adapt specifically for mountain-related entities.
- Class Weighting: Apply class weighting during training to give more importance to the new mountain classes (B-MOU and I-MOU), which might be underrepresented in the training data.

3. Hyperparameter Tuning

- **Learning Rate Optimization**: Fine-tuning the learning rate could lead to better convergence and improved model performance. Employing techniques like learning rate scheduling may also yield positive results.
- **Batch Size Experimentation**: Testing different batch sizes can affect the model's performance. A smaller batch size might enhance the model's ability to generalize.

4. Evaluation with Additional Metrics

- Analyze Confusion Matrix: Creating a confusion matrix to visualize misclassifications can provide insights into specific entities that are frequently misclassified, guiding further training and data refinement.
- **Cross-validation**: Implementing k-fold cross-validation during training can provide a better assessment of model stability and robustness.

Conclusion

train_test.ipynb	Training, evaluating and demo notebook
kner_dataset	Final dataset
model_train.py	Script for model training
inference_model.py	Script for model evaluating
dataset.txt	Dataset of raw text
create_dataset.ipynb	Notebook with all dataset creation tries and methods
BIO_Dataset.txt	Dataset of raw text, labeled sentences

The fine-tuned DistilBERT-NER model demonstrates commendable performance in recognizing mountain entities. However, due to lack of time, the dataset is small and of poor quality, which is the main problem . Due to dataset refinement, it will be possible to achieve 90%+ results of the original model in all metrics. And even more with adjusting the model architecture, tuning hyperparameters, implementing post-processing techniques, and evaluating with additional metrics,.