Legal Document Redaction using NER

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Introduction

Manual redaction of sensitive legal documents is slow, expensive, and prone to human error, creating significant privacy and liability risks. We aim to automate this process using Deep Learning to ensure faster, safer, and more consistent protection of Personally Identifiable Information (PII). We benchmark a lightweight, custom-trained Bi-LSTM against heavy pre-trained Transformers (like Legal-BERT) to find the optimal balance between training speed and redaction safety.

Dataset Source

https://huggingface.co/datasets/ildpil/text-anonymization-benchmark

Streamlit App

https://legal-document-redaction.streamlit.app/

Lessons Learnt

Lessons Learnt from Tokenization and Bi-LSTM (Jui)

1. Choose to write code in pyTorch whereby learning to write the forward and backward pass. Also learnt the exact workings of Bi-LSTM and all steps of the training process.
2. Wrote an evaluation function for evaluating after every epoch whereby learning about the intricacies of evaluation for NER problems.
3. Learnt that every run of the code gives different results unless a seed is set to a constant number. This happenes because the weights are initialized randomly and without a seed, this random state is different for every run giving non-deterministic results.
4. Learnt the tokenization process for NER problems and BERT models.
5. Learnt manual fine-tuning by reading the results for each training experiment.
6. Learnt to use local CUDA and MPS devices for faster training.
7. Learnt to work, manage and drive results in a team of people with different tempraments and backgrounds.

Lessons Learnt (Ritvik)

1. I learned that high accuracy can be misleading, especially in NER tasks where most words are just "O" (non-entities).
2. For legal redaction, I realized that Recall is the only metric that truly matters. We cannot afford to accidentally miss to redact a sensitive name (Recall error).
3. I had to learn how to use Offset Mapping to align my specific character-level labels with the model's new sub-word tokens.
4. Weight Decay helped stop the model from becoming too rigid or "over-confident" in its weights. Reducing it helped the model to learn better.
5. Label Smoothing taught the model to be less confident. Instead of forcing a 100% probability (which may lead to overfitting), it targets 90%, which makes the model more adaptable to new, unseen data.
6. I learnt that using a local GPU isn't plug-and-play. I had to specifically match my PyTorch installation with the correct CUDA version to unlock the GPU's power.

Lessons Learnt (Mit)

I realized that having clean data and proper token-label alignment is more important than having a bigger model. DistilBERT was effective while being faster and more feasible. I also observed how class imbalance, hyperparameter search, and appropriate metrics such as F1-score can have a direct impact on the performance of the model in real-world redaction problems.

Lessons Learned from EDA and ALBERT Model Development

- **CUDA Poisoning & Platform Limitations:**
  While working with GPU-accelerated training, I encountered "CUDA poisoning", a situation where the CUDA context becomes corrupted, often due to out-of-memory errors or improper kernel shutdowns. This required frequent kernel restarts and highlighted

the fragility of GPU sessions, especially on shared or limited-resource platforms like Google Colab and Kaggle. These platforms, while convenient, impose restrictions on session duration, available memory, and GPU access, which can interrupt long-running experiments and complicate reproducibility.

- **Version Control & Collaboration with GitHub:**
  Using GitHub was essential for managing code versions and collaborating with teammates. It helped in tracking changes, resolving merge conflicts, and ensuring that the codebase remained clean and organized. Branching strategies and pull requests facilitated parallel development and made it easier to review and integrate contributions without overwriting other members contributions.
- **General EDA and Model Insights:**
  Exploratory Data Analysis (EDA) was crucial for understanding the dataset's structure, class imbalance, and potential data quality issues. This informed preprocessing decisions and model design. Fine-tuning the ALBERT model for NER tasks required careful attention to token-label alignment and highlighted the importance of robust data pipelines.

Overall, these experiences underscored the importance of robust infrastructure, effective version control, and thorough data understanding in Deep learning projects.

-Sayeed.

Lessons Learnt from Streamlit App (Kesha)

1. Learned how to use Streamlit for building interactive web applications, including custom layouts, widgets, and file handling.
2. Understood how to connect and integrate with Hugging Face models for NLP tasks, using both local and remote model files.
3. Practiced connecting and pushing code to GitHub repositories, including branch management and collaboration workflows.
4. Improved skills in handling document formats (PDF, DOCX, TXT) and extracting text for processing.
5. Enhanced understanding of deploying AI-powered applications for legal document redaction and privacy protection.
6. Learned to use Python libraries such as pypdf, python-docx, and Streamlit for end-to-end app development.
7. Gained experience in error handling, user interface design, and providing user feedback in web apps.
8. Explored best practices for organizing code, separating inference logic, and maintaining modularity.
9. Incorporated user feedback to improve usability and functionality of the application.
10. Addressed security and privacy considerations when handling sensitive legal documents and user data.
11. Optimized performance for processing large documents and ensured scalability for future enhancements.
12. Overcame challenges related to model integration, file compatibility, and deployment, learning effective troubleshooting strategies.

Project Execution

1. Load Datasets

Loading test, train and validation sets into pandas dataframe

```
import pandas as pd

def read_data(train_path, test_path, val_path):
    """Reads train, test, and validation datasets from JSONL files.

    This function loads three separate line-delimited JSON files (JSONL) into
    pandas DataFrames, typically used for splitting data into standard
    machine learning subsets.

    Args:
        train_path (str): File path to the training dataset.
        test_path (str): File path to the testing dataset.
        val_path (str): File path to the validation dataset.

    Returns:
        tuple: A tuple containing three pandas DataFrames:
            - df_train (pd.DataFrame): The training data.
            - df_test (pd.DataFrame): The testing data.
            - df_validation (pd.DataFrame): The validation data.
    """
    df_train = pd.read_json(train_path, lines=True)
    df_test = pd.read_json(test_path, lines=True)
    df_validation = pd.read_json(val_path, lines=True)
    print("All datasets read successfully!")
    return df_train, df_test, df_validation
```

```
train_path, test_path, val_path = ('data/train.json', 'data/test.json', 'data/validation.json')
df_train, df_test, df_validation = read_data(train_path, test_path, val_path)
```

```
All datasets read successfully!
```

2. Exploratory Data Analysis (Sayeed, Jui)

Analyzing training dataset

```
"""### 2. Exploratory Data Analysis (EDA)

This section inspects the training dataset to understand schema, data quality,
and entity distribution, informing subsequent preprocessing decisions.
"""
```

```
df_train.info()
```

```
<class 'pandas.DataFrame'>
RangeIndex: 1112 entries, 0 to 1111
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   quality_checked  1112 non-null   object
 1   text             1112 non-null   str
 2   task             1112 non-null   str
 3   meta             1112 non-null   object
 4   doc_id           1112 non-null   str
 5   dataset_type     1112 non-null   str
 6   annotator_id     1112 non-null   str
 7   entity_mentions  1112 non-null   object
dtypes: object(3), str(5)
memory usage: 69.6+ KB
```

Observed no null values

```
"""### 2. Exploratory Data Analysis (EDA)

This cell previews the first few rows of the training dataset to quickly inspect
the schema, column names, and example values before deeper analysis.
"""
```

```
df_train.head()
```

	quality_checked	text	task	meta	doc_id	dataset_type	annotator_id	entity_mentions
0	[]	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'Henrik Hasslund', 'articles': [...	001-90194	train	annotator1	[{'confidential_status': 'NOT_CONFIDENTIAL', '...
1	[]	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'Henrik Hasslund', 'articles': [...	001-90194	train	annotator2	[{'confidential_status': 'NOT_CONFIDENTIAL', '...
2	[]	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'Henrik Hasslund', 'articles': [...	001-90194	train	annotator8	[{'confidential_status': 'NOT_CONFIDENTIAL', '...
3	[]	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'Henrik Hasslund', 'articles': [...	001-90194	train	annotator11	[{'confidential_status': 'NOT_CONFIDENTIAL', '...

Observation: We do not need dataset_type because the test, train and validation files are already separate. We also do not need the columns quality_checked, annotator_id.

Dropping unrequired columns.

```
"""### 2. Exploratory Data Analysis (EDA)

This cell drops unrequired columns from the training dataset
(dataset_type, quality_checked, annotator_id) to simplify
subsequent analysis and preprocessing.
"""
```

```
df_train.drop(columns=['quality_checked', 'dataset_type', 'annotator_id'])
```

	text	task	meta	doc_id	entity_mentions
0	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'Henrik Hasslund', 'articles': [...	001-90194	[{'confidential_status': 'NOT_CONFIDENTIAL', '...
1	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'Henrik Hasslund', 'articles': [...	001-90194	[{'confidential_status': 'NOT_CONFIDENTIAL', '...
2	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'Henrik Hasslund', 'articles': [...	001-90194	[{'confidential_status': 'NOT_CONFIDENTIAL', '...
3	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'Henrik Hasslund', 'articles': [...	001-90194	[{'confidential_status': 'NOT_CONFIDENTIAL', '...
4	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'D. Stępniak', 'articles': [91, ...	001-84741	[{'confidential_status': 'NOT_CONFIDENTIAL', '...
...	...	...	...	...	...
1107	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'Helmut Ludescher', 'articles': ...	001-60002	[{'confidential_status': 'NOT_CONFIDENTIAL', '...
1108	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'J. Peter', 'articles': [91, 34,...	001-146353	[{'confidential_status': 'NOT_CONFIDENTIAL', '...
1109	PROCEDURE\n\nThe case was referred to the Cour...	Task: Annotate the document to anonymise the f...	{'applicant': 'Christopher Ian Scott', 'articl...	001-58010	[{'confidential_status': 'NOT_CONFIDENTIAL', '...
1110	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'Henryk Kreuz', 'articles': [91,...	001-61921	[{'confidential_status': 'NOT_CONFIDENTIAL', '...
1111	PROCEDURE\n\nThe case originated in an applica...	Task: Annotate the document to anonymise the f...	{'applicant': 'Yiannis Kyriakou', 'articles': ...	001-90969	[{'confidential_status': 'NOT_CONFIDENTIAL', '...

1112 rows × 5 columns

Analyzing task column

```
"""### 2. Exploratory Data Analysis (EDA)

This cell inspects the unique values in the `task` column to assess whether
it carries useful information for preprocessing or can be removed.
"""
```

```
df_train['task'].unique()
```

```
<StringArray>
[       'Task: Annotate the document to anonymise the following person: Henrik Hasslund',
           'Task: Annotate the document to anonymise the following person: D. Stępniak',
         'Task: Annotate the document to anonymise the following person: Nusret Amutgan',
           'Task: Annotate the document to anonymise the following person: Mustafa Sarı',
     'Task: Annotate the document to anonymise the following person: Dariusz Karwowski',
        'Task: Annotate the document to anonymise the following person: İlhan Karakurt',
       'Task: Annotate the document to anonymise the following person: Artur Warsiński',
  'Task: Annotate the document to anonymise the following person: Włodzimierz Majewski',
        'Task: Annotate the document to anonymise the following person: İlhami Erseven',
           'Task: Annotate the document to anonymise the following person: Semir Güzel',
 ...
      'Task: Annotate the document to anonymise the following person: Zekeriya Karaman',
 'Task: Annotate the document to anonymise the following person: Leandro Sanchez-Reisse',
          'Task: Annotate the document to anonymise the following person: Rémi Bertuzzi',
    'Task: Annotate the document to anonymise the following person: Andrés López Elorza',
       'Task: Annotate the document to anonymise the following person: Frédéric Foucher',
          'Task: Annotate the document to anonymise the following person: Faruk Ereren',
       'Task: Annotate the document to anonymise the following person: Helmut Ludescher',
             'Task: Annotate the document to anonymise the following person: J. Peter',
  'Task: Annotate the document to anonymise the following person: Christopher Ian Scott',
       'Task: Annotate the document to anonymise the following person: Yiannis Kyriakou']
Length: 1008, dtype: str
```

Observation: we don't need the task column

Finding out how many unique values are there in text column and doc_id column. Making sure they match.

```
"""### 2. Exploratory Data Analysis (EDA)

This cell computes the number of unique document texts in the training set,
helping identify potential duplicate entries or repeated content.
"""
len(df_train['text'].unique())
```

```
1014
```

```
"""### 2. Exploratory Data Analysis (EDA)

This cell computes the number of unique document IDs in the training set,
used to compare against unique texts to detect duplicates.
"""
len(df_train['doc_id'].unique())
```

```
1014
```

Observation: We have 1014 unique values for documents but the dataset has 1112 entries. So there might be duplicates.

```
"""### Document Analysis Notes

This section inspects document-level metadata to understand duplication,
document identifiers, and dataset uniqueness before further preprocessing.
It helps verify data integrity and informs downstream anonymization steps.
"""
```

```
df_train['meta'][0]
```

```
{'applicant': 'Henrik Hasslund',
 'articles': [91, 34, 54, 34, 93],
 'countries': 'DNK',
 'legal_branch': 'CHAMBER',
 'year': 2008}
```

Observation: We may be able to reserve this column for later evaluation. Might be helpful to find out if our model struggles with region specific names, or has a bias, etc.

```
"""### 2. Exploratory Data Analysis (EDA)

This cell creates a new DataFrame containing only the 'text', 'meta', and 'doc_id' columns from the training set.
This subset is useful for metadata analysis and can be exported for further evaluation or downstream tasks.
"""
```

```
df_train_meta = df_train[['text', 'meta', 'doc_id']].copy()
df_train_meta.head()
```

	text	meta	doc_id
0	PROCEDURE\n\nThe case originated in an applica...	{'applicant': 'Henrik Hasslund', 'articles': [...	001-90194
1	PROCEDURE\n\nThe case originated in an applica...	{'applicant': 'Henrik Hasslund', 'articles': [...	001-90194
2	PROCEDURE\n\nThe case originated in an applica...	{'applicant': 'Henrik Hasslund', 'articles': [...	001-90194
3	PROCEDURE\n\nThe case originated in an applica...	{'applicant': 'Henrik Hasslund', 'articles': [...	001-90194
4	PROCEDURE\n\nThe case originated in an applica...	{'applicant': 'D. Stępniak', 'articles': [91, ...	001-84741

```
"""### 2. Exploratory Data Analysis (EDA)

This cell exports the training set metadata (text, meta, doc_id) to a CSV file.
The exported file can be used for further analysis or model evaluation.
"""
```

```
df_train_meta.to_csv('data/metadata/train_meta.csv')
```

```
df_test_meta = df_test[['text', 'meta', 'doc_id']].copy()
df_test_meta.to_csv('data/metadata/test_meta.csv')

df_validation_meta = df_validation[['text', 'meta', 'doc_id']].copy()
df_validation_meta.to_csv('data/metadata/validation_meta.csv')
```

Exploring entity mentions column

```
"""This cell inspects a sample entry from the 'entity_mentions' column in the training dataset.
It helps to understand the structure and content of entity annotations for a single document,
which is useful for designing preprocessing and extraction logic for NER tasks.
"""
```

```
df_train['entity_mentions'][1]
```

```
[{'confidential_status': 'NOT_CONFIDENTIAL',
  'edit_type': 'check',
  'end_offset': 62,
  'entity_id': '001-90194_a2_e1',
  'entity_mention_id': '001-90194_a2_em1',
  'entity_type': 'CODE',
  'identifier_type': 'QUASI',
  'related_mentions': None,
  'span_text': '36244/06',
  'start_offset': 54},
 {'confidential_status': 'NOT_CONFIDENTIAL',
  'edit_type': 'correct',
  'end_offset': 94,
  'entity_id': '001-90194_a2_e2',
  'entity_mention_id': '001-90194_a2_em2',
  'entity_type': 'ORG',
  'identifier_type': 'QUASI',
  'related_mentions': None,
  'span_text': 'Kingdom of Denmark',
  'start_offset': 76},
 {'confidential_status': 'NOT_CONFIDENTIAL',
  'edit_type': 'check',
  'end_offset': 242,
  'entity_id': '001-90194_a2_e3',
  'entity_mention_id': '001-90194_a2_em3',
  'entity_type': 'DEM',
  'identifier_type': 'QUASI',
  'related_mentions': None,
  'span_text': 'Danish',
  'start_offset': 236},
 {'confidential_status': 'NOT_CONFIDENTIAL',
  'edit_type': 'check',
  'end_offset': 271,
  'entity_id': '001-90194_a2_e4',
  'entity_mention_id': '001-90194_a2_em4',
  'entity_type': 'PERSON',
  'identifier_type': 'DIRECT',
  'related_mentions': None,
  'span_text': 'Mr Henrik Hasslund',
  'start_offset': 253},
 {'confidential_status': 'NOT_CONFIDENTIAL',
  'edit_type': 'check',
  'end_offset': 308,
  'entity_id': '001-90194_a2_e5',
  'entity_mention_id': '001-90194_a2_em5',
  'entity_type': 'DATETIME',
  'identifier_type': 'QUASI',
  'related_mentions': None,
  'span_text': '31 August 2006',
  'start_offset': 294},
 {'confidential_status': 'NOT_CONFIDENTIAL',
  'edit_type': 'check',
  'end_offset': 357,
  'entity_id': '001-90194_a2_e6',
  'entity_mention_id': '001-90194_a2_em6',
  'entity_type': 'PERSON',
  'identifier_type': 'QUASI',
  'related_mentions': None,
```

```
"""This cell explodes the 'entity_mentions' column in the training dataset so that each entity mention becomes a sep
It then normalizes the nested entity information into flat columns and combines it with the corresponding 'doc_id'.
The resulting DataFrame, 'df_train_entities', provides a convenient structure for analyzing and processing individua
"""
```

```
import json
df_train_exploded = df_train.explode('entity_mentions')
entities_flat = pd.json_normalize(df_train_exploded['entity_mentions'])
df_train_entities = pd.concat([df_train_exploded[['doc_id']].reset_index(drop=True), entities_flat.reset_index(drop=

df_train_entities.head()
```

	doc_id	confidential_status	edit_type	end_offset	entity_id	entity_mention_id	entity_type	identifier_type	rel
0	001-90194	NOT_CONFIDENTIAL	check	62	001-90194_a1_e1	001-90194_a1_em1	CODE	DIRECT	
1	001-90194	NOT_CONFIDENTIAL	correct	94	001-90194_a1_e2	001-90194_a1_em2	ORG	NO_MASK	
2	001-90194	NOT_CONFIDENTIAL	check	242	001-90194_a1_e3	001-90194_a1_em3	DEM	NO_MASK	
3	001-90194	NOT_CONFIDENTIAL	check	271	001-90194_a1_e4	001-90194_a1_em4	PERSON	DIRECT	
4	001-90194	NOT_CONFIDENTIAL	check	308	001-90194_a1_e5	001-90194_a1_em5	DATETIME	QUASI	

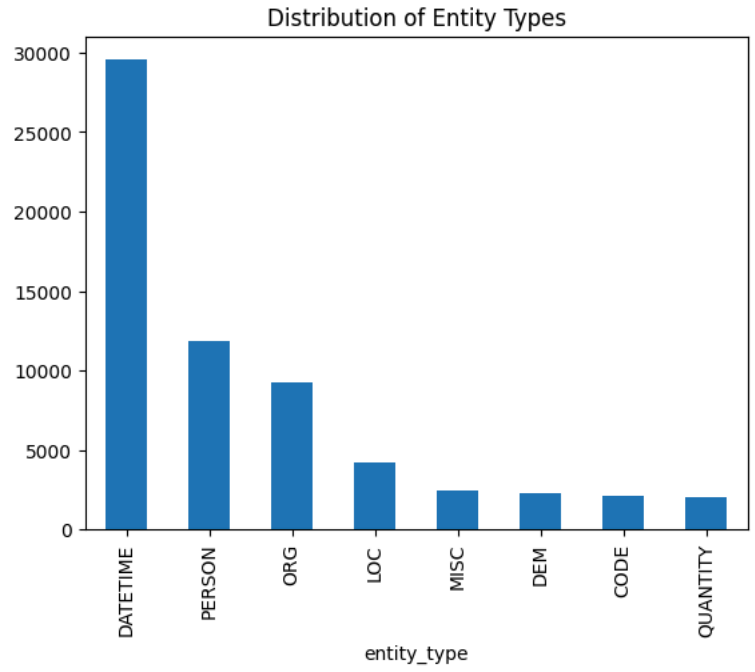
Observation: We have start_offset, end_offset and entity_type. We need to extract this data to create a token and tags for finetuning DistilliBERT model.

Checking the counts of entities for filtered set where identifier_type is not NO_MASK

```
"""### 2. Exploratory Data Analysis (EDA)

This cell visualizes the distribution of entity types in the training dataset,
excluding entities with identifier_type 'NO_MASK'. It helps identify class imbalance
among entity types, which is important for model training and evaluation.
"""
```

```
print("Entity Type Counts:")
entity_type_stats = df_train_entities[df_train_entities['identifier_type'] != 'NO_MASK']['entity_type'].value_counts
entity_type_stats.plot(kind='bar', title='Distribution of Entity Types')
```

```
Entity Type Counts:
<Axes: title={'center': 'Distribution of Entity Types'}, xlabel='entity_type'>
```

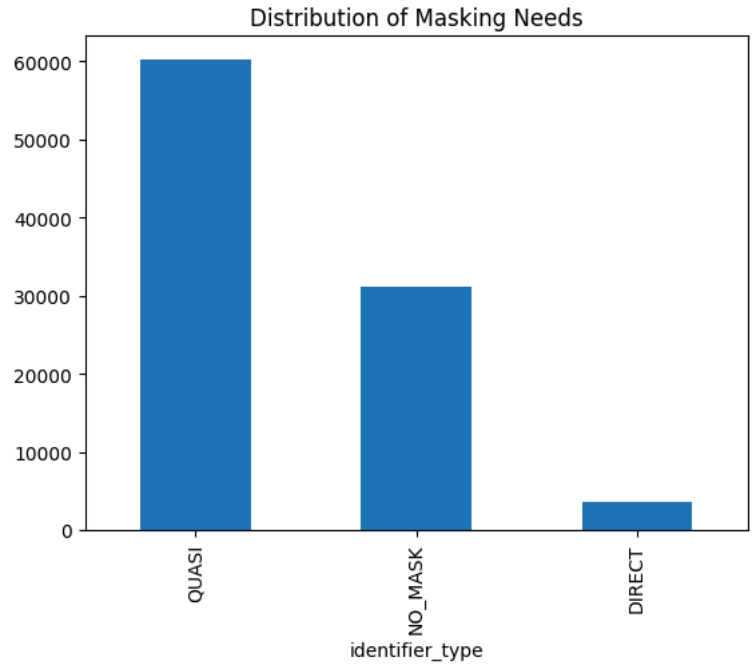


Certain imbalance of data is seen here where datetime entities are much higher in count than quantity or code

```
"""This cell visualizes the distribution of masking requirements in the training dataset.
It plots the counts of each identifier_type in the 'entity_mentions' column, helping to understand
how many entities require masking versus those that do not. This informs the anonymization strategy
and highlights the prevalence of sensitive information in the dataset.
"""
```

```
# Check masking requirements
mask_stats = df_train_entities['identifier_type'].value_counts()
mask_stats.plot(kind='bar', title='Distribution of Masking Needs')
```

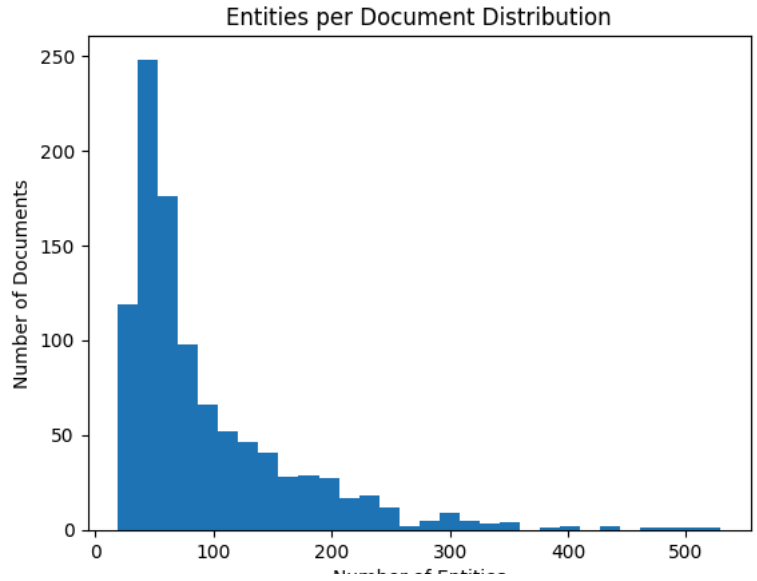
```
<Axes: title={'center': 'Distribution of Masking Needs'}, xlabel='identifier_type'>
```




```
"""This cell analyzes the distribution of entities per document in the training dataset.
It groups entity annotations by document ID, counts the number of entities in each document,
and visualizes the distribution using a histogram. This helps assess annotation density and
potential class imbalance across documents for NER model training."""
```

```
entities_per_doc = df_train_entities.groupby('doc_id').size().sort_values(ascending=False)
entities_per_doc.plot(kind='hist', bins=30, title='Entities per Document Distribution', xlabel='Number of Entities',
```

```
<Axes: title={'center': 'Entities per Document Distribution'}, xlabel='Number of Entities', ylabel='Number of
Documents'>
```




```
print(f"Average entities per document: {entities_per_doc.mean():.2f}")
```

```
Average entities per document: 93.72
```

3. Data pre-processing (Jui)

Converting offests to list

```
def convert_offsets_to_lists(row):
    """Converts character-level entity offsets into token-level BIO tags.

    This function is designed to be used with the Hugging Face `Dataset.map()`
    method. It processes a single dataset example containing raw text and
    character-offset entity mentions, aligning them to a whitespace-tokenized
    format suitable for NER model training.

    The function creates an intermediate character-level map to handle alignment
    and filters out entities marked as 'NO_MASK'.

    Args:
        row (dict): A single example from a Hugging Face Dataset. Must contain:
            - 'text' (str): The raw input text.
            - 'entity_mentions' (list[dict]): A list of dictionaries where each
              contains:
                - 'start_offset' (int): Starting character index.
                - 'end_offset' (int): Ending character index (exclusive).
                - 'entity_type' (str): The entity label (e.g., "PER").
                - 'identifier_type' (str, optional): ignored if 'NO_MASK'.

    Returns:
        dict: A dictionary containing the new features to be added to the dataset:
            - 'tokens' (list[str]): The text split by whitespace.
            - 'ner_tags' (list[str]): The corresponding BIO tags for each token
              (e.g., ["O", "B-PER", "I-PER", "O"]).
    """
    text = row['text']
    entities = row['entity_mentions']

    # create character-level map
    char_tags = ["O"] * len(text)

    for ent in entities:
        # Filter 'NO_MASK' entities
        if ent.get('identifier_type') == 'NO_MASK':
            continue

        start, end = ent['start_offset'], ent['end_offset']
        label = ent['entity_type']

        # fill character-level map
        if start < len(text) and end <= len(text):
            char_tags[start] = f"B-{label}" # beginning of entity
            for i in range(start+1, end):
                char_tags[i] = f"I-{label}" # inside entity

    # convert character map to word - tag
    tokens = text.split()
    ner_tags = []

    cursor = 0
    for token in tokens:
        # advance cursor to the start of word (skipping spaces)
        while cursor < len(text) and text[cursor].isspace():
            cursor += 1

        # tag of the word is the tag of its first character
        if cursor < len(text):
            ner_tags.append(char_tags[cursor])
            cursor += len(token)
        else:
            ner_tags.append("O")

    return {"tokens": tokens, "ner_tags": ner_tags}
```

Create label mappings from train set to be used to pass when training the model, same mappings would be used during tokenization of test and validation sets as well

```
from datasets import Dataset

def create_mappings(df_train):
    """Generates label-to-ID mappings for NER training from a pandas DataFrame.

    This function converts a raw pandas DataFrame containing text and offsets into a
    Hugging Face Dataset, processes it to extract token-level tags, and identifies
    all unique NER labels present in the data. It then creates the necessary
    dictionaries to map these labels to integers and back.

    Args:
        df_train (pd.DataFrame): The training data containing at least 'text'
            and 'entity_mentions' columns.

    Returns:
        tuple: A tuple containing two dictionaries:
            - label2id (dict): Mapping of label strings to integer IDs
              (e.g., {'B-PER': 0, 'O': 1}).
            - id2label (dict): Mapping of integer IDs to label strings
              (e.g., {0: 'B-PER', 1: 'O'}).
            - label_list (list[str]): A sorted list of all unique label strings
              found in the training set (e.g., ['B-LOC', 'B-PER', ...]).
    """
    # converting Pandas to Hugging Face Dataset
    hf_train = Dataset.from_pandas(df_train)
    train_processed = hf_train.map(convert_offsets_to_lists)

    print("Dataset converted to token-tag pairs.")
    print(train_processed[0]['tokens'])
    print(train_processed[0]['ner_tags'])

    # extracting unique tags from training data
    unique_tags = set(tag for row in train_processed for tag in row['ner_tags'])
    label_list = sorted(list(unique_tags)) # e.g., ['B-LOC', 'B-PER', 'I-PER', 'O']

    # createing maps
    label2id = {label: i for i, label in enumerate(label_list)}
    id2label = {i: label for i, label in enumerate(label_list)}

    print(f"Number of labels: {len(label_list)}")
    print(label2id)

    return label2id, id2label, label_list

label2id, id2label, label_list = create_mappings(df_train)
```

```
/opt/anaconda3/envs/hf-venv/lib/python3.11/site-packages/tqdm/auto.py:21: TqdmWarning: IProgress not found. Please up
  from .autonotebook import tqdm as notebook_tqdm
Map: 100%|██████████| 1112/1112 [00:03<00:00, 305.81 examples/s]
Dataset converted to token-tag pairs.
['PROCEDURE', 'The', 'case', 'originated', 'in', 'an', 'application', '(no.', '36244/06)', 'against', 'the', 'Kingdom
['O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-CODE', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', '
Number of labels: 17
{'B-CODE': 0, 'B-DATETIME': 1, 'B-DEM': 2, 'B-LOC': 3, 'B-MISC': 4, 'B-ORG': 5, 'B-PERSON': 6, 'B-QUANTITY': 7, 'I-CO
```

Using AutoTokenizer to handle sub-words and align new tags. Defining tokenization function to be used various versions of BERT

```
def tokenize_and_align(examples, tokenizer, label2id):
  """Tokenizes inputs and aligns NER tags with sub-word tokens.

    This function processes a batch of pre-tokenized text (lists of words) and
    corresponding NER tags. It uses the tokenizer to split words into sub-words
    and aligns the original labels to these new tokens.

    Key behaviors:
    1. Special tokens ([CLS], [SEP]) are assigned the label -100 (ignored by loss).
    2. The first sub-word of a word gets the original label ID.
    3. Subsequent sub-words of the same word (e.g., "##ing") are assigned -100.

    Args:
        examples (dict): A batch from a Hugging Face Dataset containing:
```

```
            - 'tokens' (list[list[str]]): Batch of sentences split into words.
            - 'ner_tags' (list[list[str]]): Batch of corresponding BIO tags.
        tokenizer (PreTrainedTokenizerFast): A Hugging Face "fast" tokenizer
            that supports the `.word_ids()` method.
        label2id (dict): A dictionary mapping label strings (e.g., "B-PER")
            to integer IDs.

    Returns:
        BatchEncoding: The tokenizer output containing 'input_ids', 'attention_mask',
        and a new 'labels' key aligned with the tokenized sequence.
    """
    # split words into sub-words
    tokenized_inputs = tokenizer(examples["tokens"], truncation=True, is_split_into_words=True)

    labels = []
    for i, label in enumerate(examples["ner_tags"]):
        word_ids = tokenized_inputs.word_ids(batch_index=i) #supported only for fast tokenizers
        previous_word_idx = None
        label_ids = []
        for word_idx in word_ids:
            if word_idx is None:
                # special tokens like [CLS] get -100 (ignored)
                label_ids.append(-100)
            elif word_idx != previous_word_idx:
                # first piece of a word gets the real label ID
                label_ids.append(label2id[label[word_idx]]) #using map created from training set
            else:
                # subsequent pieces (e.g., "##lor") get -100 (ignored)
                label_ids.append(-100)
            previous_word_idx = word_idx
        labels.append(label_ids)

    tokenized_inputs["labels"] = labels
    return tokenized_inputs
```

Writing a script for processing test and validation sets

```
def preprocess_data(df, tokenizer, label2id):
    """Converts a raw pandas DataFrame into a tokenized Hugging Face Dataset for BERT.

    This is a pipeline function that orchestrates the entire preprocessing workflow.
    It performs the following steps:
    1. Converts the pandas DataFrame to a Hugging Face Dataset.
    2. Maps character-level entity offsets to token-level BIO tags.
    3. Tokenizes the text and aligns the BIO tags with the resulting sub-word tokens
       using the provided label-to-ID mapping.

    Args:
        df (pd.DataFrame): The input dataframe containing 'text' and 'entity_mentions'.
        tokenizer (PreTrainedTokenizerFast): The tokenizer to process the text.
        label2id (dict): The mapping of label strings (e.g., 'B-PER') to integer IDs
            used for alignment during tokenization.

    Returns:
        Dataset: A processed Hugging Face Dataset containing features like 'input_ids',
        'attention_mask', and 'labels', ready for training or evaluation.
    """
    # converting Pandas to Hugging Face Dataset
    hf = Dataset.from_pandas(df)
    processed = hf.map(convert_offsets_to_lists)
    #tokenize
    tokenized = processed.map(tokenize_and_align, batched=True, fn_kwargs={"tokenizer": tokenizer, "label2id": label2i

    return tokenized
```

Importing AutoTokenizer to use various BERT tokenizers

```
from transformers import AutoTokenizer
```

4. Bi-LSTM (Jui)

Using DistilBERT tokenizer to keep the comparison fair

```
tokenizer_distilbert = AutoTokenizer.from_pretrained("distilbert-base-uncased")
```

```
Warning: You are sending unauthenticated requests to the HF Hub. Please set a HF_TOKEN to enable higher rate limits a
```

```
train_distilbert = preprocess_data(df_train ,tokenizer_distilbert, label2id)
```

```
Map: 100%|██████████| 1112/1112 [00:03<00:00, 299.93 examples/s]
Map: 100%|██████████| 1112/1112 [00:09<00:00, 116.01 examples/s]
```

```
test_distilbert = preprocess_data(df_test, tokenizer_distilbert, label2id)
validation_distilbert = preprocess_data(df_validation, tokenizer_distilbert, label2id)
```

```
Map: 100%|██████████| 555/555 [00:01<00:00, 553.03 examples/s]
Map: 100%|██████████| 555/555 [00:02<00:00, 200.78 examples/s]
Map: 100%|██████████| 541/541 [00:01<00:00, 536.88 examples/s]
Map: 100%|██████████| 541/541 [00:02<00:00, 222.91 examples/s]
```

Importing pyTorch

```
import torch
import torch.nn as nn
```

```
def device_setup():
    """Configures and returns the optimal PyTorch device for training.

    This function automatically detects the available hardware accelerator.
    It prioritizes Apple Silicon (MPS) and NVIDIA GPUs (CUDA) over the CPU.

    Returns:
        torch.device: The device object ('mps', 'cuda', or 'cpu') to be used
        for tensor computations.
    """
    #setup GPU availability
    if torch.backends.mps.is_available():
        device = torch.device('mps') #mac m4 pro chip integrated gpu
        print(f"MPS device found: {device}")
    elif torch.cuda.is_available():
        device = torch.device('cuda')
        print(f"GPU device found: {device}")
    else:
        device = torch.device('cpu')
        print(f"No GPU device found. Falling back to {device}")

    return device
```

```
device = device_setup()
```

```
MPS device found: mps
```

Function to seet all seed values so as to produce deterministic results at every run

```
import random
import os
import numpy as np
import torch

def set_all_seed(device, seed_value = 42):
    """Sets random seeds for Python, NumPy, and PyTorch to ensure reproducibility.

    This function fixes the seed for the native Python `random` module, `numpy`,
    and `torch` (both CPU and GPU). It also configures cuDNN to use deterministic
    algorithms when using CUDA, which may slow down training slightly but ensures
    consistent results across runs.

    Args:
        device (torch.device): The active computing device (e.g., 'cpu', 'cuda',
            or 'mps'). Used to determine which specific GPU backend to seed.
        seed_value (int, optional): The seed number to use. Defaults to 42.

    Returns:
        None: Prints a confirmation message upon completion.
```

```
    """
    # python seed
    os.environ['PYTHONHASHSEED'] = str(seed_value)
    random.seed(seed_value)

    # numpy seed
    np.random.seed(seed_value)

    # pytorch seed for CPU
    torch.manual_seed(seed_value)

    # seed for GPU (CUDA)
    if device == torch.device('cuda'):
        torch.cuda.manual_seed(seed_value)
        torch.cuda.manual_seed_all(seed_value)  # for multi-GPU setups

        # configuring PyTorch to be deterministic (makes it slightly slower but reproducible)
        torch.backends.cudnn.deterministic = True
        torch.backends.cudnn.benchmark = False

    # seed for MPS (Apple Silicon GPU)
    if device == torch.device('mps'):
        torch.mps.manual_seed(seed_value)

    print(f"All seeds successfully set to {seed_value}.")
```

```
set_all_seed(device, seed_value = 42)
```

```
All seeds successfully set to 42.
```

Defining the Bi-LSTM model for NER

```
class bilstm_nre(nn.Module):
  """A Bidirectional LSTM model for Named Entity Recognition (NER).

    This model consists of a custom embedding layer, a bidirectional LSTM layer for
    sequence encoding, and a linear classifier for token-level tag prediction.
    It supports optional dropout regularization and class-weighted loss calculation.

    Args:
        vocab_size (int): The size of the vocabulary (number of unique tokens).
        num_labels (int): The number of unique output tags (BIO labels).
        embed_dim (int, optional): The size of the embedding vectors. Defaults to 128.
        hidden_dim (int, optional): The number of features in the LSTM hidden state.
            Defaults to 256.
        weight_tensor (torch.Tensor, optional): A tensor of class weights to handle
            imbalanced data in CrossEntropyLoss.
        dropout_rate (float, optional): The probability of zeroing out elements in
            the dropout layer. If None, no dropout is applied.

    Attributes:
        embedding (nn.Embedding): The learnable embedding layer (padding_idx=0).
        lstm (nn.LSTM): The bidirectional LSTM layer.
        dropout (nn.Dropout, optional): The dropout layer (if dropout_rate is provided).
        classifier (nn.Linear): The final dense layer projecting LSTM outputs to labels.
        loss_fct (nn.CrossEntropyLoss): The loss function, configured to ignore
            padding index -100.
  """
  def __init__(self, vocab_size, num_labels, embed_dim=128, hidden_dim=256, weight_tensor=None, dropout_rate=None):
      super().__init__()

      #setting up a custom embedding layer
      #seting padding index to 0 the embedding model from learning vectors for padding
      self.embedding = nn.Embedding(vocab_size, embed_dim, padding_idx=0)

      #bi-lstm layer
      self.lstm = nn.LSTM(embed_dim, hidden_dim, batch_first=True, bidirectional=True)

      #dropout
      if dropout_rate is not None:
        self.dropout = nn.Dropout(dropout_rate)

      #output layer (2*hidden_dim for bi-lstm)
      self.classifier = nn.Linear(hidden_dim * 2, num_labels)
```

```
        #set loss function (ignore_index=-100 because we set masking to -100 in previous function)
        if weight_tensor is not None:
          self.loss_fct = nn.CrossEntropyLoss(ignore_index=-100, weight=weight_tensor)
        else:
          self.loss_fct = nn.CrossEntropyLoss(ignore_index=-100)

    #forward pass
    def forward(self, input_ids, labels=None):
        """Performs a forward pass through the network.

          This method processes the input sequence through the embedding layer
          and the LSTM, then projects the output to the label space. If labels
          are provided, it also computes the Cross Entropy loss.

          Args:
              input_ids (torch.Tensor): A tensor of shape (batch_size, sequence_length)
                  containing the integer IDs of the input tokens.
              labels (torch.Tensor, optional): A tensor of shape (batch_size, sequence_length)
                  containing the correct tag IDs for training. Defaults to None.

          Returns:
              tuple:
                  - loss (torch.Tensor, optional): The computed loss value (scalar).
                    Returns None if `labels` is not provided.
                  - logits (torch.Tensor): The raw output scores from the classifier
                    with shape (batch_size, sequence_length, num_labels).
        """
        #embed
        embeds = self.embedding(input_ids)

        #lstm forward
        lstm_out, _ = self.lstm(embeds)

        logits = self.classifier(lstm_out)

        #loss calculation
        loss = None
        if labels is not None:
            # Flatten the tensors so we can check every token at once
            # logits shape: (batch * seq_len, num_labels)
            # labels shape: (batch * seq_len)
            loss = self.loss_fct(logits.view(-1, logits.shape[-1]), labels.view(-1))

        return loss, logits
```

batch pre-processing function to prepare dataloaders

```
def collate_fn(batch):
    """Prepares a batch of samples for model training by padding sequences.

    This function is passed to the DataLoader to process a list of dataset items
    into a single batch of tensors. It handles variable-length sequences by
    padding them to the length of the longest sequence in the batch.

    Key behaviors:
    1.  Pads `input_ids` with 0 (standard padding token).
    2.  Pads `labels` with -100 (index ignored by PyTorch Loss functions).
    3.  Moves the resulting tensors to the configured computing device (CPU/GPU).

    Args:
        batch (list[dict]): A list of dataset examples, where each example is a
            dictionary containing 'input_ids' and 'labels' (lists of integers).

    Returns:
        tuple: A tuple containing two tensors:
            - input_ids (torch.Tensor): Padded input sequences of shape
              (batch_size, max_seq_len).
            - labels (torch.Tensor): Padded label sequences of shape
              (batch_size, max_seq_len).
    """
    # convert batch to tensors
    input_ids = [torch.tensor(item['input_ids']) for item in batch]
    labels = [torch.tensor(item['labels']) for item in batch]

    # padding inputs with 0(blank space), labels with -100
```

```
    input_ids = torch.nn.utils.rnn.pad_sequence(input_ids, batch_first=True, padding_value=0)
    labels = torch.nn.utils.rnn.pad_sequence(labels, batch_first=True, padding_value=-100)

    return input_ids.to(device), labels.to(device)
```

```
from torch.utils.data import DataLoader

def setup_dataloaders(train, test, validation, batch_size=16, shuffle=True, collate_fn=collate_fn):
    """Creates PyTorch DataLoaders for training, testing, and validation sets.

    This function wraps the provided datasets into DataLoader objects, enabling
    batch processing, shuffling, and custom collation (padding) during the
    training loop.

    Args:
        train (Dataset): The training dataset.
        test (Dataset): The testing dataset.
        validation (Dataset): The validation dataset.
        batch_size (int, optional): The number of samples per batch. Defaults to 16.
        shuffle (bool, optional): Whether to shuffle the data at every epoch.
            Defaults to True.
        collate_fn (callable, optional): The function used to merge a list of
            samples into a mini-batch. Defaults to the global `collate_fn`.

    Returns:
        tuple: A tuple containing three `torch.utils.data.DataLoader` objects:
            - train_loader (DataLoader): Iterator for the training set.
            - test_loader (DataLoader): Iterator for the testing set.
            - validation_loader (DataLoader): Iterator for the validation set.
    """
    train_loader = DataLoader(train, batch_size=16, shuffle=True, collate_fn=collate_fn)
    test_loader = DataLoader(test, batch_size=16, shuffle=True, collate_fn=collate_fn)
    validation_loader = DataLoader(validation, batch_size=16, shuffle=True, collate_fn=collate_fn)

    return train_loader, test_loader, validation_loader
```

```
train_loader, test_loader, validation_loader = setup_dataloaders(train_distilbert, test_distilbert, validation_disti
```

Tracking model performance at every epoch

```
#using huggingface evaluate library for NER evaluation
# !pip install evaluate seqeval
```

```
Collecting evaluate
  Downloading evaluate-0.4.6-py3-none-any.whl.metadata (9.5 kB)
Collecting seqeval
  Downloading seqeval-1.2.2.tar.gz (43 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0.0/43.6 kB ? eta -:--:--
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 43.6/43.6 kB 2.4 MB/s eta 0:00:00
  Preparing metadata (setup.py) ... done
Requirement already satisfied: datasets>=2.0.0 in /usr/local/lib/python3.12/dist-packages (from evaluate) (4.0.0)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.12/dist-packages (from evaluate) (2.0.2)
Requirement already satisfied: dill in /usr/local/lib/python3.12/dist-packages (from evaluate) (0.3.8)
Requirement already satisfied: pandas in /usr/local/lib/python3.12/dist-packages (from evaluate) (2.2.2)
Requirement already satisfied: requests>=2.19.0 in /usr/local/lib/python3.12/dist-packages (from evaluate) (2.32.4)
Requirement already satisfied: tqdm>=4.62.1 in /usr/local/lib/python3.12/dist-packages (from evaluate) (4.67.1)
Requirement already satisfied: xxhash in /usr/local/lib/python3.12/dist-packages (from evaluate) (3.6.0)
Requirement already satisfied: multiprocess in /usr/local/lib/python3.12/dist-packages (from evaluate) (0.70.16)
Requirement already satisfied: fsspec>=2021.05.0 in /usr/local/lib/python3.12/dist-packages (from fsspec[http]>=2021.
Requirement already satisfied: huggingface-hub>=0.7.0 in /usr/local/lib/python3.12/dist-packages (from evaluate) (0.3
Requirement already satisfied: packaging in /usr/local/lib/python3.12/dist-packages (from evaluate) (25.0)
Requirement already satisfied: scikit-learn>=0.21.3 in /usr/local/lib/python3.12/dist-packages (from seqeval) (1.6.1)
Requirement already satisfied: filelock in /usr/local/lib/python3.12/dist-packages (from datasets>=2.0.0->evaluate) (
Requirement already satisfied: pyarrow>=15.0.0 in /usr/local/lib/python3.12/dist-packages (from datasets>=2.0.0->eval
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.12/dist-packages (from datasets>=2.0.0->evaluate
Requirement already satisfied: aiohttp!=4.0.0a0,!=4.0.0a1 in /usr/local/lib/python3.12/dist-packages (from fsspec[htt
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.12/dist-packages (from huggingfac
Requirement already satisfied: hf-xet<2.0.0,>=1.1.3 in /usr/local/lib/python3.12/dist-packages (from huggingface-hub>
Requirement already satisfied: charset_normalizer<4,>=2 in /usr/local/lib/python3.12/dist-packages (from requests>=2.
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.12/dist-packages (from requests>=2.19.0->evalua
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.12/dist-packages (from requests>=2.19.0->
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.12/dist-packages (from requests>=2.19.0->
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.12/dist-packages (from scikit-learn>=0.21.3->se
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.12/dist-packages (from scikit-learn>=0.21.3->s
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.12/dist-packages (from scikit-learn>=0.
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.12/dist-packages (from pandas->evalua
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/dist-packages (from pandas->evaluate) (2025.
```

```
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.12/dist-packages (from pandas->evaluate) (202
Requirement already satisfied: aiohappyeyeballs>=2.5.0 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.
Requirement already satisfied: aiosignal>=1.4.0 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.0a0,!=4
Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.0a0,!=4.0.
Requirement already satisfied: frozenlist>=1.1.1 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.0a0,!=
Requirement already satisfied: multidict<7.0,>=4.5 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.0a0,
Requirement already satisfied: propcache>=0.2.0 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.0a0,!=4
Requirement already satisfied: yarl<2.0,>=1.17.0 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.0a0,!=
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.12/dist-packages (from python-dateutil>=2.8.2->pand
Downloading evaluate-0.4.6-py3-none-any.whl (84 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 84.1/84.1 kB 6.9 MB/s eta 0:00:00
Building wheels for collected packages: seqeval
  Building wheel for seqeval (setup.py) ... done
  Created wheel for seqeval: filename=seqeval-1.2.2-py3-none-any.whl size=16162 sha256=b7cf57ae908c0f9adff6cf5bb8ddb2
  Stored in directory: /root/.cache/pip/wheels/5f/b8/73/0b2c1a76b701a677653dd79ece07cfabd7457989dbfbdcd8d7
Successfully built seqeval
Installing collected packages: seqeval, evaluate
Successfully installed evaluate-0.4.6 seqeval-1.2.2
```

```
import matplotlib.pyplot as plt
import evaluate
import numpy as np
```

Function to evaluate after every epoch

```
seqeval = evaluate.load("seqeval")

def evaluate_epoch(model, dataloader, label_list):
    """Evaluates the model on a dataset using strict entity-level metrics.

    This function iterates through the provided dataloader, computes the loss,
    and decodes the raw integer predictions back into BIO tags. It utilizes
    the `seqeval` library to calculate standard NER metrics (Precision, Recall,
    F1), ensuring that entities are evaluated as whole units (e.g., "New York")
    rather than just individual tokens.

    Key behaviors:
    1.  Sets the model to evaluation mode (`model.eval()`).
    2.  Ignores padding tokens (ID -100) during metric calculation.
    3.  Aggregates the loss across all batches.

    Args:
        model (nn.Module): The trained PyTorch model.
        dataloader (DataLoader): Iterator for the validation or test dataset.
        label_list (list[str]): A list of label strings (e.g., ["O", "B-PER"])
            indexed by their integer IDs, used for decoding predictions.

    Returns:
        dict: A dictionary containing the computed performance metrics:
            - 'val_loss' (float): The average Cross Entropy loss per batch.
            - 'accuracy' (float): Token-level accuracy.
            - 'precision' (float): Strict entity-level precision.
            - 'recall' (float): Strict entity-level recall.
            - 'f1' (float): Strict entity-level F1 score.
    """
    model.eval() # Set to evaluation mode

    all_preds = []
    all_labels = []
    total_val_loss = 0

    with torch.no_grad():
        for batch_ids, batch_labels in dataloader:
            batch_ids = batch_ids.to(device)
            batch_labels = batch_labels.to(device)

            # Forward pass
            loss, logits = model(batch_ids, batch_labels)

            # test loss
            total_val_loss += loss.item()

            # Get predictions (argmax)
            preds = torch.argmax(logits, dim=-1).cpu().numpy()
            labels = batch_labels.cpu().numpy()
```

```
            all_preds.extend(preds)
            all_labels.extend(labels)

    #calculate validation loss
    avg_val_loss = total_val_loss / len(dataloader)

    # convert IDs back to Tags (removing -100)
    decoded_preds = [
        [label_list[p] for (p, l) in zip(pred, label) if l != -100]
        for pred, label in zip(all_preds, all_labels)
    ]
    decoded_labels = [
        [label_list[l] for (p, l) in zip(pred, label) if l != -100]
        for pred, label in zip(all_preds, all_labels)
    ]

    # compute metrics using seqeval (Strict Entity-Level scoring)
    results = seqeval.compute(predictions=decoded_preds, references=decoded_labels)

    return {
        "val_loss": avg_val_loss,
        "accuracy": results["overall_accuracy"],
        "precision": results["overall_precision"],
        "recall": results["overall_recall"],
        "f1": results["overall_f1"]
    }
```

Function for training loop with evaluation metric after each epoch

```
def train_eval_lstm(model, optimizer, n_epoches = 5, early_stopping=False):
  """Trains and evaluates the Bi-LSTM model over multiple epochs.

    This function executes the main training loop. For each epoch, it performs
    forward and backward passes on the training set (using the global `train_loader`),
    updates model weights, and then evaluates performance on the validation set
    (using the global `validation_loader`).

    It tracks key metrics (Loss, Accuracy, Precision, Recall, F1) across all epochs
    and optionally implements an early stopping mechanism based on validation loss
    to prevent overfitting.

    Args:
        model (nn.Module): The Bi-LSTM model to be trained.
        optimizer (torch.optim.Optimizer): The optimizer (e.g., AdamW) for
            updating model parameters.
        n_epoches (int, optional): The maximum number of training epochs.
            Defaults to 5.
        early_stopping (bool, optional): If True, training will stop early if
            validation loss fails to improve for 3 consecutive epochs.
            Defaults to False.

    Returns:
        dict: A history dictionary containing lists of recorded metrics for
        plotting:
            - "train_loss": List of average training losses per epoch.
            - "val_loss": List of average validation losses per epoch.
            - "accuracy": List of validation accuracy scores.
            - "precision": List of validation precision scores.
            - "recall": List of validation recall scores.
            - "f1": List of validation F1 scores.
    """
  print("Starting Bi-LSTM for NER training...")

  history = {
      "train_loss": [],
      "val_loss": [],
      "accuracy": [],
      "precision": [],
      "recall": [],
      "f1": []
  }

  patience = 3
  patience_counter = 0
  best_val_loss = np.inf #initializing to infinite so that the first loss is always an improvement
```

```
    for epoch in range(n_epoches):
        # train
        model.train()
        total_loss = 0

        for batch_ids, batch_labels in train_loader:
            optimizer.zero_grad()
            loss, logits = model(batch_ids, batch_labels)
            loss.backward()
            optimizer.step()
            total_loss += loss.item()

        avg_train_loss = total_loss / len(train_loader)

        # validation on test set to calculate metrics
        metrics = evaluate_epoch(model, validation_loader, label_list)

        # tracking history of metrics
        history["train_loss"].append(avg_train_loss)
        history["val_loss"].append(metrics["val_loss"])
        history["accuracy"].append(metrics["accuracy"])
        history["precision"].append(metrics["precision"])
        history["recall"].append(metrics["recall"])
        history["f1"].append(metrics["f1"])

        print(f"Epoch {epoch+1}/{n_epoches} | "
              f"Train Loss: {avg_train_loss:.4f} | "
              f"Val Loss: {metrics['val_loss']:.4f} | "
              f"Val Recall: {metrics['recall']:.4f} | "
              f"Val Precision: {metrics['precision']:.4f} |"
              f"Val F1: {metrics['f1']:.4f} |"
              f"Val Accuracy: {metrics['accuracy']:.4f}")

        #early stopping
        if early_stopping == True:
          epoch_val_loss = metrics["val_loss"]
          if epoch_val_loss < best_val_loss:
              # if validation loss is improving/decreasing
              print(f"Validation Loss improved from {best_val_loss:.4f} to {epoch_val_loss:.4f}.")
              best_val_loss = epoch_val_loss
              patience_counter = 0  # reset the counter

          else:
              # validation loss increasing
              patience_counter += 1
              print(f"No improvement in validation loss. Patience: {patience_counter}")

              if patience_counter >= patience:
                  print("Early Stopping triggered! Training stopped.")
                  break # early stop


    print("Training complete!")
    return history
```

function for plotting the evaluation metrics vs epoch

```
def plot_training_metrics(history):
    """Visualizes the training process by plotting loss and classification metrics.

    This function creates a matplotlib figure with two side-by-side subplots:
    1.  **Loss Curves:** Compares Training Loss vs. Validation Loss to identify
        overfitting or underfitting.
    2.  **Performance Metrics:** Tracks Validation Precision, Recall, Accuracy,
        and F1 Score to evaluate the model's classification quality over time.

    Args:
        history (dict): A dictionary containing lists of metric values recorded
            during training. Must contain the following keys:
            - 'train_loss', 'val_loss'
            - 'recall', 'precision', 'f1', 'accuracy'

    Returns:
        None: Displays the plot using `plt.show()`.
```

```
    """
    epochs_range = range(1, len(history['train_loss']) + 1)

    plt.figure(figsize=(18, 6))

    # training vs validation loss
    plt.subplot(1, 2, 1)
    plt.plot(epochs_range, history['train_loss'], 'r-o', label='Training Loss')
    plt.plot(epochs_range, history['val_loss'], 'b-o', label='Validation Loss')
    plt.title('Training Loss vs Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()
    plt.grid(True)

    # R vs P vs A vs F1
    plt.subplot(1, 2, 2)
    plt.plot(epochs_range, history['recall'], 'b-o', label='Val Recall')
    plt.plot(epochs_range, history['f1'], 'g-o', label='Val F1 Score')
    plt.plot(epochs_range, history['accuracy'], 'k-x', label='Accuracy', linestyle='--')
    plt.plot(epochs_range, history['precision'], 'r-o', label='Precision')
    plt.title('Validation R vs P vs A vs F1')
    plt.xlabel('Epochs')
    plt.ylabel('Score')
    plt.ylim(0, 1.0) # y-axis to 0-100%
    plt.legend(loc='lower right')
    plt.grid(True)

    plt.tight_layout()
    plt.show()
```

Training & Evaluation LSTM model v1

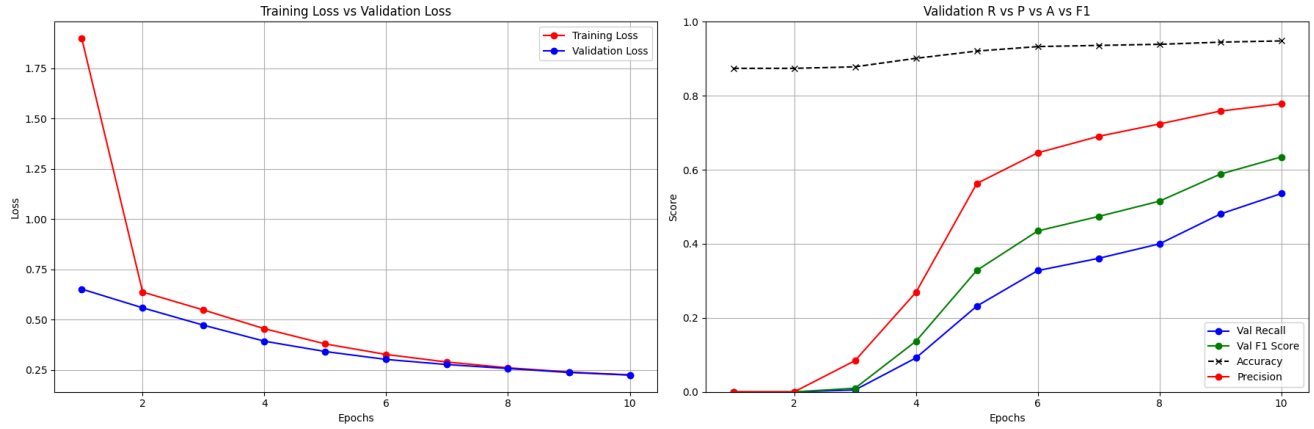
```
# vocab_size is 30522 for DistilBERT
# num_labels is len(label_list)
lstm_nre_v1 = bilstm_nre(30522, len(label_list), embed_dim=128, hidden_dim=256).to(device)
optimizer_v1 = torch.optim.Adam(lstm_nre_v1.parameters(), lr=1e-4)
```

```
history_v1 = train_eval_lstm(lstm_nre_v1, optimizer_v1, n_epoches = 10)
```

```
Starting Bi-LSTM for NER training...
/opt/anaconda3/envs/hf-venv/lib/python3.11/site-packages/seqeval/metrics/v1.py:57: UndefinedMetricWarning: Precision
  _warn_prf(average, modifier, msg_start, len(result))
/opt/anaconda3/envs/hf-venv/lib/python3.11/site-packages/seqeval/metrics/v1.py:57: UndefinedMetricWarning: Precision
  _warn_prf(average, modifier, msg_start, len(result))
Epoch 1/10 | Train Loss: 1.8969 | Val Loss: 0.6523 | Val Recall: 0.0000 | Val Precision: 0.0000 |Val F1: 0.0000 |Val
Epoch 2/10 | Train Loss: 0.6376 | Val Loss: 0.5592 | Val Recall: 0.0000 | Val Precision: 0.0000 |Val F1: 0.0000 |Val
Epoch 3/10 | Train Loss: 0.5484 | Val Loss: 0.4729 | Val Recall: 0.0052 | Val Precision: 0.0844 |Val F1: 0.0099 |Val
Epoch 4/10 | Train Loss: 0.4554 | Val Loss: 0.3934 | Val Recall: 0.0917 | Val Precision: 0.2688 |Val F1: 0.1368 |Val
Epoch 5/10 | Train Loss: 0.3797 | Val Loss: 0.3420 | Val Recall: 0.2318 | Val Precision: 0.5630 |Val F1: 0.3283 |Val
Epoch 6/10 | Train Loss: 0.3275 | Val Loss: 0.3027 | Val Recall: 0.3277 | Val Precision: 0.6458 |Val F1: 0.4347 |Val
Epoch 7/10 | Train Loss: 0.2897 | Val Loss: 0.2774 | Val Recall: 0.3609 | Val Precision: 0.6903 |Val F1: 0.4740 |Val
Epoch 8/10 | Train Loss: 0.2613 | Val Loss: 0.2577 | Val Recall: 0.3999 | Val Precision: 0.7239 |Val F1: 0.5152 |Val
Epoch 9/10 | Train Loss: 0.2403 | Val Loss: 0.2382 | Val Recall: 0.4806 | Val Precision: 0.7586 |Val F1: 0.5884 |Val
Epoch 10/10 | Train Loss: 0.2260 | Val Loss: 0.2251 | Val Recall: 0.5358 | Val Precision: 0.7785 |Val F1: 0.6347 |Val
Training complete!
```

```
# plot evaluation metrics
plot_training_metrics(history_v1)
```

```
/var/folders/qw/2jrbyvsn4tnckwl2l1rgl1wm0000gp/T/ipykernel_54182/4064934705.py:20: UserWarning: linestyle is redundan
  plt.plot(epochs_range, history['accuracy'], 'k-x', label='Accuracy', linestyle='--')
```



Observation: Model is actually learning and the overfitting at epoch 10 is almost negligible. But, a high accuracy of 94.82% with a low recall and precision of 53.58% shows that the model has learnt that predicting non-entity (label 'O') most of the times is a safe bet.

Implementing weighted loss strategy to tell the model that missing an entity is worst than getting a non-entity wrong.

To calculate weights, if the tag occurs more number of times like the non-entity tag 'O', we need to give it lower weight. Using sklearn class_weight utility to compute this.

```
from sklearn.utils.class_weight import compute_class_weight
def calc_weighted_loss(train_processed, id2label):
    """Calculates inverse-frequency class weights to handle dataset imbalance.

    This function computes weights for each class in the training set using
    scikit-learn's 'balanced' heuristic. These weights are intended to be passed
    to the loss function (e.g., CrossEntropyLoss) to penalize the model more
    heavily for errors on rare classes (like B-PER) compared to common classes
    (like O).

    Key behaviors:
    1.  Flattens the dataset labels into a single list.
    2.  Filters out the special ignore index -100.
    3.  Computes weights inversely proportional to class frequency.
    4.  Moves the resulting tensor to the active computing device (CPU/GPU).

    Args:
        train_processed (Dataset): The processed Hugging Face dataset containing
            a 'labels' column (list of integer lists).
        id2label (dict): A dictionary mapping integer IDs to label strings
            (e.g., {0: 'B-PER'}), used for logging purposes.

    Returns:
        torch.Tensor: A tensor of class weights with shape (num_classes,),
        moved to the configured device.
    """
    #list of all tags in training set
    all_classes = [label
                  for row in train_processed['labels']
                    for label in row
                      if label != -100
    ]
    unique_classes = np.unique(all_classes)

    #balanced mode adjusts the weights inversly proportional to the frequencies of the classes
    weights = compute_class_weight(class_weight='balanced', classes = unique_classes, y = all_classes)

    #convert class weights to pytorch tensor
    class_weights = torch.tensor(weights, dtype=torch.float).to(device)

    print("Calculated Class Weights:")
    for i, weight in enumerate(class_weights):
        # getting label names from id2label
```

```
        label_name = id2label[i] if 'id2label' in locals() else str(i)
        print(f"{label_name}: {weight:.4f}")

    return class_weights

class_weights = calc_weighted_loss(train_distilbert, id2label)
```

```
Calculated Class Weights:
B-CODE: 15.6851
B-DATETIME: 2.4340
B-DEM: 33.6022
B-LOC: 13.7717
B-MISC: 68.8216
B-ORG: 9.5366
B-PERSON: 5.0459
B-QUANTITY: 45.8811
I-CODE: 504.6920
I-DATETIME: 1.4053
I-DEM: 54.5324
I-LOC: 41.7168
I-MISC: 19.3093
I-ORG: 4.0306
I-PERSON: 2.7905
I-QUANTITY: 30.2104
O: 0.0683
```

```
#trying similar architecture with weighted loss approach
lstm_nre_v2 = bilstm_nre(30522, len(label_list), embed_dim=128, hidden_dim=256, weight_tensor=class_weights).to(devi
optimizer_v2 = torch.optim.Adam(lstm_nre_v2.parameters(), lr=1e-4)
```

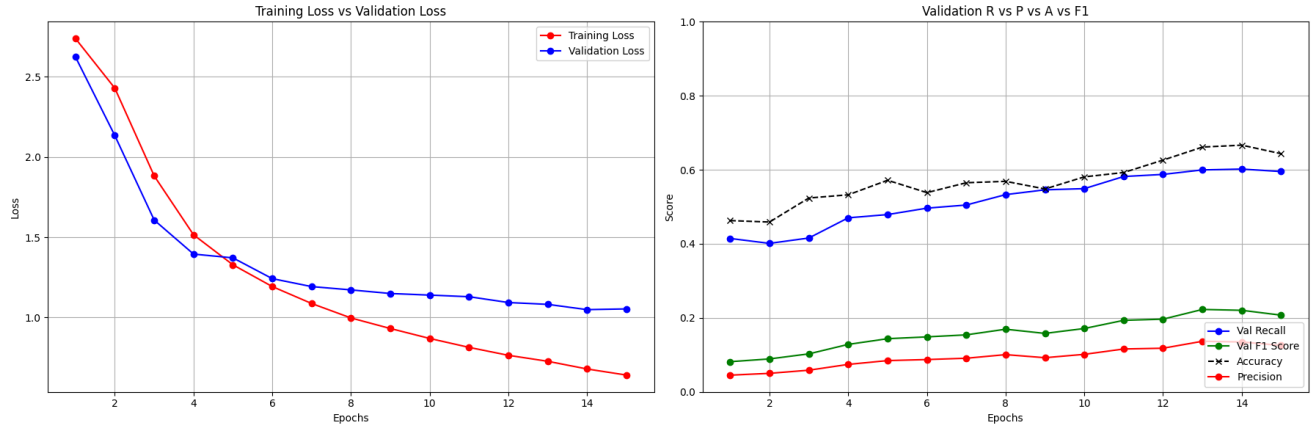
Will the model learn more if I increase the number of epoches?

```
history_v2 = train_eval_lstm(lstm_nre_v2, optimizer_v2, n_epoches = 15)
```

```
Starting Bi-LSTM for NER training...
Epoch 1/15 | Train Loss: 2.7368 | Val Loss: 2.6221 | Val Recall: 0.4145 | Val Precision: 0.0453 |Val F1: 0.0816 |Val
Epoch 2/15 | Train Loss: 2.4277 | Val Loss: 2.1327 | Val Recall: 0.4013 | Val Precision: 0.0501 |Val F1: 0.0891 |Val
Epoch 3/15 | Train Loss: 1.8818 | Val Loss: 1.6070 | Val Recall: 0.4157 | Val Precision: 0.0586 |Val F1: 0.1028 |Val
Epoch 4/15 | Train Loss: 1.5152 | Val Loss: 1.3953 | Val Recall: 0.4703 | Val Precision: 0.0743 |Val F1: 0.1283 |Val
Epoch 5/15 | Train Loss: 1.3286 | Val Loss: 1.3718 | Val Recall: 0.4790 | Val Precision: 0.0845 |Val F1: 0.1437 |Val
Epoch 6/15 | Train Loss: 1.1932 | Val Loss: 1.2425 | Val Recall: 0.4964 | Val Precision: 0.0874 |Val F1: 0.1486 |Val
Epoch 7/15 | Train Loss: 1.0877 | Val Loss: 1.1930 | Val Recall: 0.5049 | Val Precision: 0.0909 |Val F1: 0.1541 |Val
Epoch 8/15 | Train Loss: 0.9977 | Val Loss: 1.1724 | Val Recall: 0.5329 | Val Precision: 0.1007 |Val F1: 0.1693 |Val
Epoch 9/15 | Train Loss: 0.9321 | Val Loss: 1.1499 | Val Recall: 0.5459 | Val Precision: 0.0924 |Val F1: 0.1580 |Val
Epoch 10/15 | Train Loss: 0.8701 | Val Loss: 1.1399 | Val Recall: 0.5491 | Val Precision: 0.1015 |Val F1: 0.1713 |Val
Epoch 11/15 | Train Loss: 0.8146 | Val Loss: 1.1301 | Val Recall: 0.5819 | Val Precision: 0.1159 |Val F1: 0.1933 |Val
Epoch 12/15 | Train Loss: 0.7652 | Val Loss: 1.0938 | Val Recall: 0.5876 | Val Precision: 0.1180 |Val F1: 0.1965 |Val
Epoch 13/15 | Train Loss: 0.7280 | Val Loss: 1.0823 | Val Recall: 0.5997 | Val Precision: 0.1368 |Val F1: 0.2227 |Val
Epoch 14/15 | Train Loss: 0.6801 | Val Loss: 1.0495 | Val Recall: 0.6020 | Val Precision: 0.1349 |Val F1: 0.2204 |Val
Epoch 15/15 | Train Loss: 0.6422 | Val Loss: 1.0541 | Val Recall: 0.5953 | Val Precision: 0.1255 |Val F1: 0.2073 |Val
Training complete!
```

```
# plot evaluation metrics
plot_training_metrics(history_v2)
```

```
/var/folders/qw/2jrbyvsn4tnckwl2l1rgl1wm0000gp/T/ipykernel_54182/4064934705.py:20: UserWarning: linestyle is redundan
  plt.plot(epochs_range, history['accuracy'], 'k-x', label='Accuracy', linestyle='--')
```



Observed that the model starts to overfit at epoch 5. The recall at epoch 14 has improved to 60.20% the precision has drastically dropped to 13.49%, showing that only 13.49% of the redacted words are actually sensetive! The accuracy has also dropped to 64.35%. The fact that the difference between the recall and accuracy has dropped is good.

What effect might it have if the number of nodes in the hidden layer of the network is increased while sticking to weighted loss strategy?

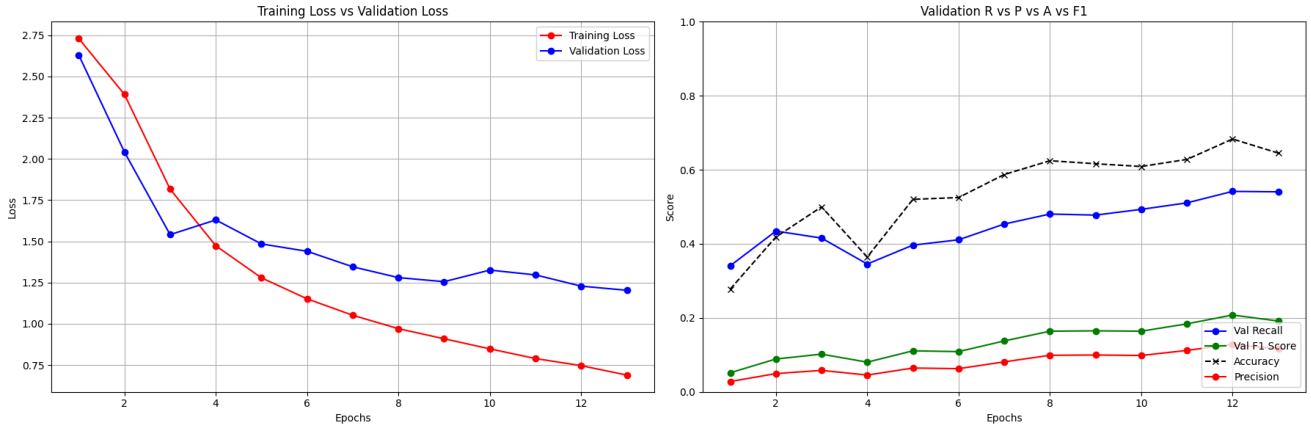
```
#increasing dimension of hidden layer without using weighted loss
lstm_nre_v3 = bilstm_nre(30522, len(label_list), embed_dim=128, hidden_dim=288, weight_tensor=class_weights).to(devi
optimizer_v3 = torch.optim.Adam(lstm_nre_v3.parameters(), lr=1e-4)
```

```
history_v3 = train_eval_lstm(lstm_nre_v3, optimizer_v3, n_epoches = 13)
```

```
Starting Bi-LSTM for NER training...
Epoch 1/13 | Train Loss: 2.7300 | Val Loss: 2.6301 | Val Recall: 0.3408 | Val Precision: 0.0280 |Val F1: 0.0517 |Val
Epoch 2/13 | Train Loss: 2.3913 | Val Loss: 2.0419 | Val Recall: 0.4345 | Val Precision: 0.0495 |Val F1: 0.0888 |Val
Epoch 3/13 | Train Loss: 1.8169 | Val Loss: 1.5410 | Val Recall: 0.4156 | Val Precision: 0.0581 |Val F1: 0.1020 |Val
Epoch 4/13 | Train Loss: 1.4734 | Val Loss: 1.6300 | Val Recall: 0.3454 | Val Precision: 0.0454 |Val F1: 0.0803 |Val
Epoch 5/13 | Train Loss: 1.2789 | Val Loss: 1.4846 | Val Recall: 0.3966 | Val Precision: 0.0645 |Val F1: 0.1110 |Val
Epoch 6/13 | Train Loss: 1.1515 | Val Loss: 1.4398 | Val Recall: 0.4109 | Val Precision: 0.0628 |Val F1: 0.1089 |Val
Epoch 7/13 | Train Loss: 1.0518 | Val Loss: 1.3458 | Val Recall: 0.4535 | Val Precision: 0.0812 |Val F1: 0.1377 |Val
Epoch 8/13 | Train Loss: 0.9707 | Val Loss: 1.2802 | Val Recall: 0.4805 | Val Precision: 0.0989 |Val F1: 0.1640 |Val
Epoch 9/13 | Train Loss: 0.9093 | Val Loss: 1.2557 | Val Recall: 0.4776 | Val Precision: 0.0997 |Val F1: 0.1650 |Val
Epoch 10/13 | Train Loss: 0.8484 | Val Loss: 1.3259 | Val Recall: 0.4932 | Val Precision: 0.0984 |Val F1: 0.1640 |Val
Epoch 11/13 | Train Loss: 0.7896 | Val Loss: 1.2968 | Val Recall: 0.5107 | Val Precision: 0.1121 |Val F1: 0.1838 |Val
Epoch 12/13 | Train Loss: 0.7465 | Val Loss: 1.2286 | Val Recall: 0.5417 | Val Precision: 0.1285 |Val F1: 0.2077 |Val
Epoch 13/13 | Train Loss: 0.6892 | Val Loss: 1.2035 | Val Recall: 0.5406 | Val Precision: 0.1163 |Val F1: 0.1914 |Val
Training complete!
```

```
# plot evaluation metrics
plot_training_metrics(history_v3)
```

```
/var/folders/qw/2jrbyvsn4tnckwl2l1rgl1wm0000gp/T/ipykernel_54182/4064934705.py:20: UserWarning: linestyle is redundan
  plt.plot(epochs_range, history['accuracy'], 'k-x', label='Accuracy', linestyle='--')
```



Observation: The model started to overfit at epoch 4. It kept learning however, the overfittin kept increasing. The best recall of 54.17% was achieved at epoch 12 which is less than the previous. Also, precision dropped to 12.85%.

Trying to decrease the number of nodes in the hidden layer.

```
#decreasing dimension of hidden layer without using weighted loss
lstm_nre_v4 = bilstm_nre(30522, len(label_list), embed_dim=128, hidden_dim=192, weight_tensor=class_weights).to(devi
optimizer_v4 = torch.optim.Adam(lstm_nre_v4.parameters(), lr=1e-4)
```

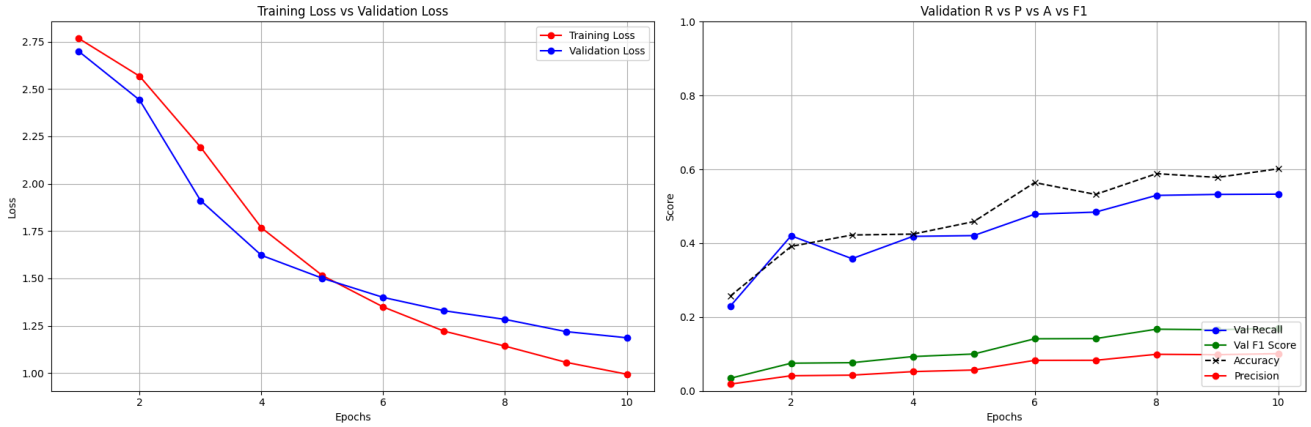
```
history_v4 = train_eval_lstm(lstm_nre_v4, optimizer_v4, n_epoches = 10)
```

```
Starting Bi-LSTM for NER training...
Epoch 1/10 | Train Loss: 2.7665 | Val Loss: 2.6983 | Val Recall: 0.2294 | Val Precision: 0.0186 |Val F1: 0.0343 |Val
Epoch 2/10 | Train Loss: 2.5669 | Val Loss: 2.4411 | Val Recall: 0.4203 | Val Precision: 0.0413 |Val F1: 0.0752 |Val
Epoch 3/10 | Train Loss: 2.1927 | Val Loss: 1.9109 | Val Recall: 0.3583 | Val Precision: 0.0429 |Val F1: 0.0767 |Val
Epoch 4/10 | Train Loss: 1.7667 | Val Loss: 1.6215 | Val Recall: 0.4188 | Val Precision: 0.0525 |Val F1: 0.0932 |Val
Epoch 5/10 | Train Loss: 1.5149 | Val Loss: 1.5006 | Val Recall: 0.4207 | Val Precision: 0.0569 |Val F1: 0.1002 |Val
Epoch 6/10 | Train Loss: 1.3489 | Val Loss: 1.3993 | Val Recall: 0.4788 | Val Precision: 0.0829 |Val F1: 0.1414 |Val
Epoch 7/10 | Train Loss: 1.2209 | Val Loss: 1.3288 | Val Recall: 0.4844 | Val Precision: 0.0831 |Val F1: 0.1419 |Val
```

```
Epoch 8/10 | Train Loss: 1.1420 | Val Loss: 1.2833 | Val Recall: 0.5297 | Val Precision: 0.0994 |Val F1: 0.1673 |Val
Epoch 9/10 | Train Loss: 1.0566 | Val Loss: 1.2188 | Val Recall: 0.5322 | Val Precision: 0.0983 |Val F1: 0.1660 |Val
Epoch 10/10 | Train Loss: 0.9938 | Val Loss: 1.1863 | Val Recall: 0.5330 | Val Precision: 0.1011 |Val F1: 0.1700 |Val
Training complete!
```

```
# plot evaluation metrics
plot_training_metrics(history_v4)
```

```
/var/folders/qw/2jrbyvsn4tnckwl2l1rgl1wm0000gp/T/ipykernel_54182/4064934705.py:20: UserWarning: linestyle is redundan
  plt.plot(epochs_range, history['accuracy'], 'k-x', label='Accuracy', linestyle='--')
```



Observation: The best recall for this strategy is still 53.30% with precision of 10.11%. Going back to v2 and trying to recude overfitting by adding dropout.

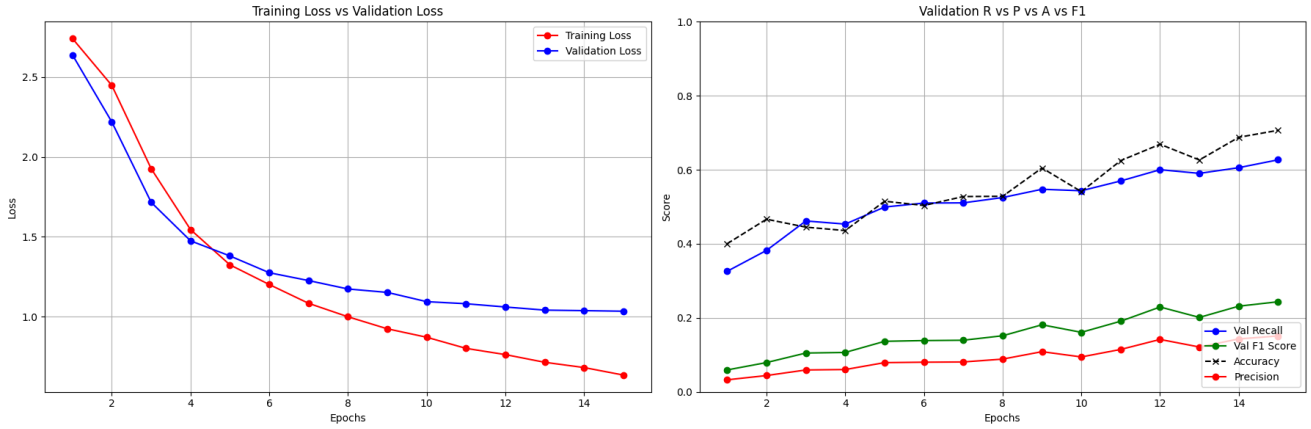
```
#trying similar architecture with weighted loss approach
lstm_nre_v5 = bilstm_nre(30522, len(label_list), embed_dim=128, hidden_dim=256, weight_tensor=class_weights, dropout
optimizer_v5 = torch.optim.Adam(lstm_nre_v5.parameters(), lr=1e-4)
```

```
history_v5 = train_eval_lstm(lstm_nre_v5, optimizer_v5, n_epoches = 15)
```

```
Starting Bi-LSTM for NER training...
Epoch 1/15 | Train Loss: 2.7417 | Val Loss: 2.6390 | Val Recall: 0.3258 | Val Precision: 0.0327 |Val F1: 0.0594 |Val
Epoch 2/15 | Train Loss: 2.4480 | Val Loss: 2.2191 | Val Recall: 0.3823 | Val Precision: 0.0442 |Val F1: 0.0792 |Val
Epoch 3/15 | Train Loss: 1.9265 | Val Loss: 1.7158 | Val Recall: 0.4618 | Val Precision: 0.0592 |Val F1: 0.1050 |Val
Epoch 4/15 | Train Loss: 1.5451 | Val Loss: 1.4748 | Val Recall: 0.4533 | Val Precision: 0.0604 |Val F1: 0.1066 |Val
Epoch 5/15 | Train Loss: 1.3244 | Val Loss: 1.3801 | Val Recall: 0.4994 | Val Precision: 0.0791 |Val F1: 0.1366 |Val
Epoch 6/15 | Train Loss: 1.2011 | Val Loss: 1.2751 | Val Recall: 0.5101 | Val Precision: 0.0803 |Val F1: 0.1387 |Val
Epoch 7/15 | Train Loss: 1.0833 | Val Loss: 1.2259 | Val Recall: 0.5107 | Val Precision: 0.0809 |Val F1: 0.1396 |Val
Epoch 8/15 | Train Loss: 0.9991 | Val Loss: 1.1732 | Val Recall: 0.5250 | Val Precision: 0.0886 |Val F1: 0.1517 |Val
Epoch 9/15 | Train Loss: 0.9238 | Val Loss: 1.1519 | Val Recall: 0.5474 | Val Precision: 0.1087 |Val F1: 0.1813 |Val
Epoch 10/15 | Train Loss: 0.8710 | Val Loss: 1.0938 | Val Recall: 0.5433 | Val Precision: 0.0945 |Val F1: 0.1609 |Val
Epoch 11/15 | Train Loss: 0.8013 | Val Loss: 1.0809 | Val Recall: 0.5699 | Val Precision: 0.1147 |Val F1: 0.1910 |Val
Epoch 12/15 | Train Loss: 0.7622 | Val Loss: 1.0604 | Val Recall: 0.6002 | Val Precision: 0.1418 |Val F1: 0.2293 |Val
Epoch 13/15 | Train Loss: 0.7140 | Val Loss: 1.0409 | Val Recall: 0.5904 | Val Precision: 0.1213 |Val F1: 0.2012 |Val
Epoch 14/15 | Train Loss: 0.6811 | Val Loss: 1.0377 | Val Recall: 0.6058 | Val Precision: 0.1431 |Val F1: 0.2316 |Val
Epoch 15/15 | Train Loss: 0.6340 | Val Loss: 1.0339 | Val Recall: 0.6270 | Val Precision: 0.1511 |Val F1: 0.2435 |Val
Training complete!
```

```
# plot evaluation metrics
plot_training_metrics(history_v5)
```

```
/var/folders/qw/2jrbyvsn4tnckwl2l1rgl1wm0000gp/T/ipykernel_54182/4064934705.py:20: UserWarning: linestyle is redundan
  plt.plot(epochs_range, history['accuracy'], 'k-x', label='Accuracy', linestyle='--')
```



Observation: This strategy has shown increased overfitting but the Recall has increased to 62.70% and the precision to 15.11%

Trying an approach where increasing the number of nodes in the hidden layer without the weighted loss or dropout strategy.

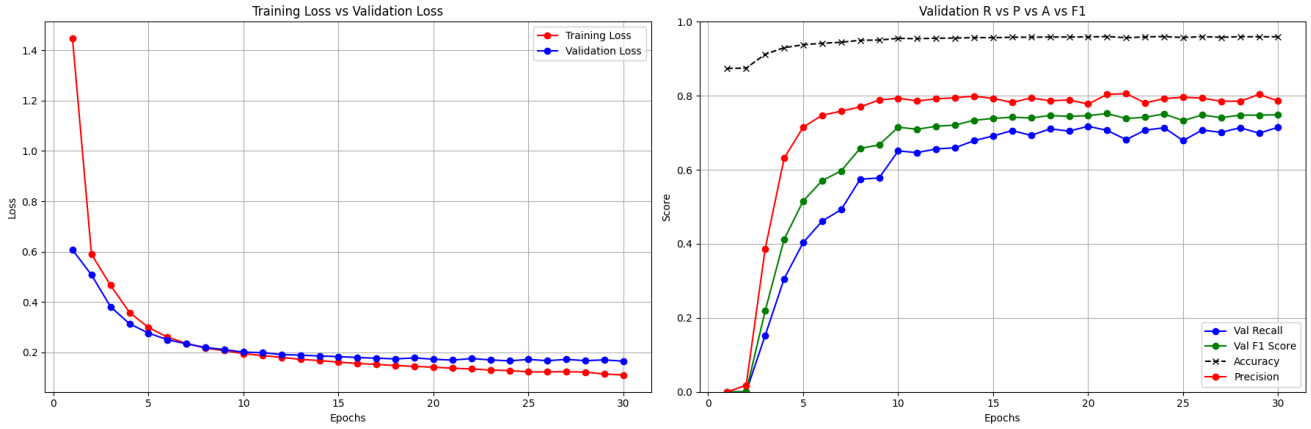
```
#increasing dimension of hidden layer more without using weighted loss
lstm_nre_v6 = bilstm_nre(30522, len(label_list), embed_dim=128, hidden_dim=480).to(device)
optimizer_v6 = torch.optim.Adam(lstm_nre_v6.parameters(), lr=1e-4)
```

```
history_v6 = train_eval_lstm(lstm_nre_v6, optimizer_v6, n_epoches = 30)
```

```
Starting Bi-LSTM for NER training...
/opt/anaconda3/envs/hf-venv/lib/python3.11/site-packages/seqeval/metrics/v1.py:57: UndefinedMetricWarning: Precision
  _warn_prf(average, modifier, msg_start, len(result))
/opt/anaconda3/envs/hf-venv/lib/python3.11/site-packages/seqeval/metrics/v1.py:57: UndefinedMetricWarning: Precision
  _warn_prf(average, modifier, msg_start, len(result))
Epoch 1/30 | Train Loss: 1.4469 | Val Loss: 0.6069 | Val Recall: 0.0000 | Val Precision: 0.0000 |Val F1: 0.0000 |Val
Epoch 2/30 | Train Loss: 0.5894 | Val Loss: 0.5076 | Val Recall: 0.0003 | Val Precision: 0.0180 |Val F1: 0.0005 |Val
Epoch 3/30 | Train Loss: 0.4662 | Val Loss: 0.3813 | Val Recall: 0.1525 | Val Precision: 0.3858 |Val F1: 0.2186 |Val
Epoch 4/30 | Train Loss: 0.3580 | Val Loss: 0.3131 | Val Recall: 0.3056 | Val Precision: 0.6313 |Val F1: 0.4119 |Val
Epoch 5/30 | Train Loss: 0.2987 | Val Loss: 0.2761 | Val Recall: 0.4033 | Val Precision: 0.7152 |Val F1: 0.5158 |Val
Epoch 6/30 | Train Loss: 0.2596 | Val Loss: 0.2498 | Val Recall: 0.4614 | Val Precision: 0.7473 |Val F1: 0.5705 |Val
Epoch 7/30 | Train Loss: 0.2355 | Val Loss: 0.2332 | Val Recall: 0.4924 | Val Precision: 0.7583 |Val F1: 0.5971 |Val
Epoch 8/30 | Train Loss: 0.2164 | Val Loss: 0.2191 | Val Recall: 0.5744 | Val Precision: 0.7699 |Val F1: 0.6580 |Val
Epoch 9/30 | Train Loss: 0.2065 | Val Loss: 0.2102 | Val Recall: 0.5781 | Val Precision: 0.7885 |Val F1: 0.6671 |Val
Epoch 10/30 | Train Loss: 0.1945 | Val Loss: 0.2006 | Val Recall: 0.6509 | Val Precision: 0.7935 |Val F1: 0.7151 |Val
Epoch 11/30 | Train Loss: 0.1869 | Val Loss: 0.1983 | Val Recall: 0.6465 | Val Precision: 0.7860 |Val F1: 0.7095 |Val
Epoch 12/30 | Train Loss: 0.1794 | Val Loss: 0.1910 | Val Recall: 0.6563 | Val Precision: 0.7916 |Val F1: 0.7176 |Val
Epoch 13/30 | Train Loss: 0.1715 | Val Loss: 0.1884 | Val Recall: 0.6597 | Val Precision: 0.7947 |Val F1: 0.7209 |Val
Epoch 14/30 | Train Loss: 0.1671 | Val Loss: 0.1852 | Val Recall: 0.6787 | Val Precision: 0.7989 |Val F1: 0.7339 |Val
Epoch 15/30 | Train Loss: 0.1604 | Val Loss: 0.1825 | Val Recall: 0.6915 | Val Precision: 0.7928 |Val F1: 0.7387 |Val
Epoch 16/30 | Train Loss: 0.1556 | Val Loss: 0.1792 | Val Recall: 0.7059 | Val Precision: 0.7819 |Val F1: 0.7420 |Val
Epoch 17/30 | Train Loss: 0.1515 | Val Loss: 0.1762 | Val Recall: 0.6930 | Val Precision: 0.7940 |Val F1: 0.7401 |Val
Epoch 18/30 | Train Loss: 0.1473 | Val Loss: 0.1735 | Val Recall: 0.7105 | Val Precision: 0.7865 |Val F1: 0.7466 |Val
Epoch 19/30 | Train Loss: 0.1437 | Val Loss: 0.1772 | Val Recall: 0.7045 | Val Precision: 0.7887 |Val F1: 0.7442 |Val
Epoch 20/30 | Train Loss: 0.1406 | Val Loss: 0.1721 | Val Recall: 0.7175 | Val Precision: 0.7777 |Val F1: 0.7464 |Val
Epoch 21/30 | Train Loss: 0.1364 | Val Loss: 0.1687 | Val Recall: 0.7065 | Val Precision: 0.8037 |Val F1: 0.7520 |Val
Epoch 22/30 | Train Loss: 0.1337 | Val Loss: 0.1749 | Val Recall: 0.6815 | Val Precision: 0.8059 |Val F1: 0.7385 |Val
Epoch 23/30 | Train Loss: 0.1291 | Val Loss: 0.1695 | Val Recall: 0.7070 | Val Precision: 0.7807 |Val F1: 0.7420 |Val
Epoch 24/30 | Train Loss: 0.1273 | Val Loss: 0.1656 | Val Recall: 0.7136 | Val Precision: 0.7922 |Val F1: 0.7509 |Val
Epoch 25/30 | Train Loss: 0.1220 | Val Loss: 0.1714 | Val Recall: 0.6788 | Val Precision: 0.7961 |Val F1: 0.7328 |Val
Epoch 26/30 | Train Loss: 0.1218 | Val Loss: 0.1663 | Val Recall: 0.7073 | Val Precision: 0.7936 |Val F1: 0.7480 |Val
Epoch 27/30 | Train Loss: 0.1228 | Val Loss: 0.1716 | Val Recall: 0.7012 | Val Precision: 0.7855 |Val F1: 0.7409 |Val
Epoch 28/30 | Train Loss: 0.1208 | Val Loss: 0.1665 | Val Recall: 0.7135 | Val Precision: 0.7850 |Val F1: 0.7476 |Val
Epoch 29/30 | Train Loss: 0.1137 | Val Loss: 0.1696 | Val Recall: 0.6990 | Val Precision: 0.8038 |Val F1: 0.7477 |Val
Epoch 30/30 | Train Loss: 0.1092 | Val Loss: 0.1642 | Val Recall: 0.7149 | Val Precision: 0.7858 |Val F1: 0.7487 |Val
Training complete!
```

```
# plot evaluation metrics
plot_training_metrics(history_v6)
```

```
/var/folders/qw/2jrbyvsn4tnckwl2l1rgl1wm0000gp/T/ipykernel_54182/4064934705.py:20: UserWarning: linestyle is redundan
  plt.plot(epochs_range, history['accuracy'], 'k-x', label='Accuracy', linestyle='--')
```



Observation: After epoch 10 the model is learning slowly but could reach 71.75% recall and 77.77% precision at epoch 20 however, the model is not learning much after that. Some amount of overfitting is seen after epoch 10.

Adding dropout layers to reduce overfitting.

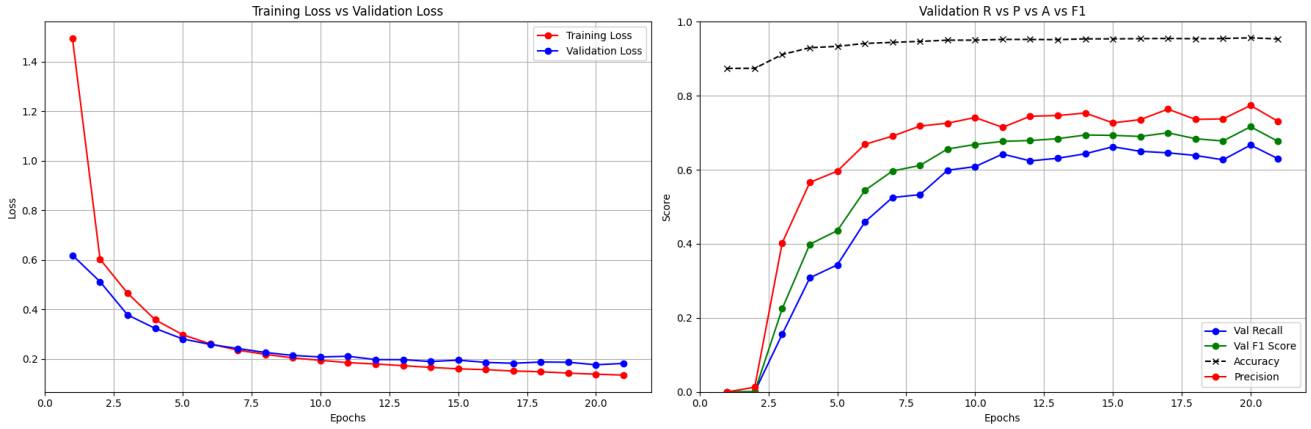
```
#adding dropout layer to reduce overfitting and reducing epoches
lstm_nre_v7 = bilstm_nre(30522, len(label_list), embed_dim=128, hidden_dim=480, dropout_rate=0.2).to(device)
optimizer_v7 = torch.optim.Adam(lstm_nre_v7.parameters(), lr=1e-4)
```

```
history_v7 = train_eval_lstm(lstm_nre_v7, optimizer_v7, n_epoches = 21)
```

```
Starting Bi-LSTM for NER training...
/opt/anaconda3/envs/hf-venv/lib/python3.11/site-packages/seqeval/metrics/v1.py:57: UndefinedMetricWarning: Precision
  _warn_prf(average, modifier, msg_start, len(result))
/opt/anaconda3/envs/hf-venv/lib/python3.11/site-packages/seqeval/metrics/v1.py:57: UndefinedMetricWarning: Precision
  _warn_prf(average, modifier, msg_start, len(result))
Epoch 1/21 | Train Loss: 1.4933 | Val Loss: 0.6183 | Val Recall: 0.0000 | Val Precision: 0.0000 |Val F1: 0.0000 |Val
Epoch 2/21 | Train Loss: 0.6024 | Val Loss: 0.5115 | Val Recall: 0.0003 | Val Precision: 0.0126 |Val F1: 0.0005 |Val
Epoch 3/21 | Train Loss: 0.4649 | Val Loss: 0.3773 | Val Recall: 0.1562 | Val Precision: 0.4029 |Val F1: 0.2251 |Val
Epoch 4/21 | Train Loss: 0.3578 | Val Loss: 0.3229 | Val Recall: 0.3080 | Val Precision: 0.5658 |Val F1: 0.3989 |Val
Epoch 5/21 | Train Loss: 0.2973 | Val Loss: 0.2803 | Val Recall: 0.3433 | Val Precision: 0.5965 |Val F1: 0.4358 |Val
Epoch 6/21 | Train Loss: 0.2602 | Val Loss: 0.2581 | Val Recall: 0.4591 | Val Precision: 0.6688 |Val F1: 0.5444 |Val
Epoch 7/21 | Train Loss: 0.2349 | Val Loss: 0.2417 | Val Recall: 0.5251 | Val Precision: 0.6909 |Val F1: 0.5967 |Val
Epoch 8/21 | Train Loss: 0.2181 | Val Loss: 0.2255 | Val Recall: 0.5329 | Val Precision: 0.7182 |Val F1: 0.6118 |Val
Epoch 9/21 | Train Loss: 0.2035 | Val Loss: 0.2137 | Val Recall: 0.5987 | Val Precision: 0.7259 |Val F1: 0.6562 |Val
Epoch 10/21 | Train Loss: 0.1939 | Val Loss: 0.2074 | Val Recall: 0.6086 | Val Precision: 0.7412 |Val F1: 0.6684 |Val
Epoch 11/21 | Train Loss: 0.1847 | Val Loss: 0.2104 | Val Recall: 0.6426 | Val Precision: 0.7148 |Val F1: 0.6768 |Val
Epoch 12/21 | Train Loss: 0.1791 | Val Loss: 0.1968 | Val Recall: 0.6240 | Val Precision: 0.7446 |Val F1: 0.6790 |Val
Epoch 13/21 | Train Loss: 0.1723 | Val Loss: 0.1966 | Val Recall: 0.6311 | Val Precision: 0.7467 |Val F1: 0.6841 |Val
Epoch 14/21 | Train Loss: 0.1654 | Val Loss: 0.1891 | Val Recall: 0.6433 | Val Precision: 0.7534 |Val F1: 0.6940 |Val
Epoch 15/21 | Train Loss: 0.1595 | Val Loss: 0.1945 | Val Recall: 0.6623 | Val Precision: 0.7267 |Val F1: 0.6930 |Val
Epoch 16/21 | Train Loss: 0.1562 | Val Loss: 0.1856 | Val Recall: 0.6499 | Val Precision: 0.7356 |Val F1: 0.6901 |Val
Epoch 17/21 | Train Loss: 0.1507 | Val Loss: 0.1820 | Val Recall: 0.6459 | Val Precision: 0.7638 |Val F1: 0.6999 |Val
Epoch 18/21 | Train Loss: 0.1478 | Val Loss: 0.1871 | Val Recall: 0.6387 | Val Precision: 0.7362 |Val F1: 0.6840 |Val
Epoch 19/21 | Train Loss: 0.1422 | Val Loss: 0.1862 | Val Recall: 0.6271 | Val Precision: 0.7375 |Val F1: 0.6778 |Val
Epoch 20/21 | Train Loss: 0.1379 | Val Loss: 0.1758 | Val Recall: 0.6668 | Val Precision: 0.7738 |Val F1: 0.7164 |Val
Epoch 21/21 | Train Loss: 0.1343 | Val Loss: 0.1814 | Val Recall: 0.6298 | Val Precision: 0.7308 |Val F1: 0.6766 |Val
Training complete!
```

```
# plot evaluation metrics
plot_training_metrics(history_v7)
```

```
/var/folders/qw/2jrbyvsn4tnckwl2l1rgl1wm0000gp/T/ipykernel_54182/4064934705.py:20: UserWarning: linestyle is redundan
  plt.plot(epochs_range, history['accuracy'], 'k-x', label='Accuracy', linestyle='--')
```



Observation: There is not much change in the overfitting but the max recall achieved at epoch 20 is 66.68% which is lower than the previous model.

Implementing early stopping on v6 for final training run.

```
#increasing dimension of hidden layer more without using weighted loss
lstm_nre_v8 = bilstm_nre(30522, len(label_list), embed_dim=128, hidden_dim=480).to(device)
optimizer_v8 = torch.optim.Adam(lstm_nre_v8.parameters(), lr=1e-4)
```

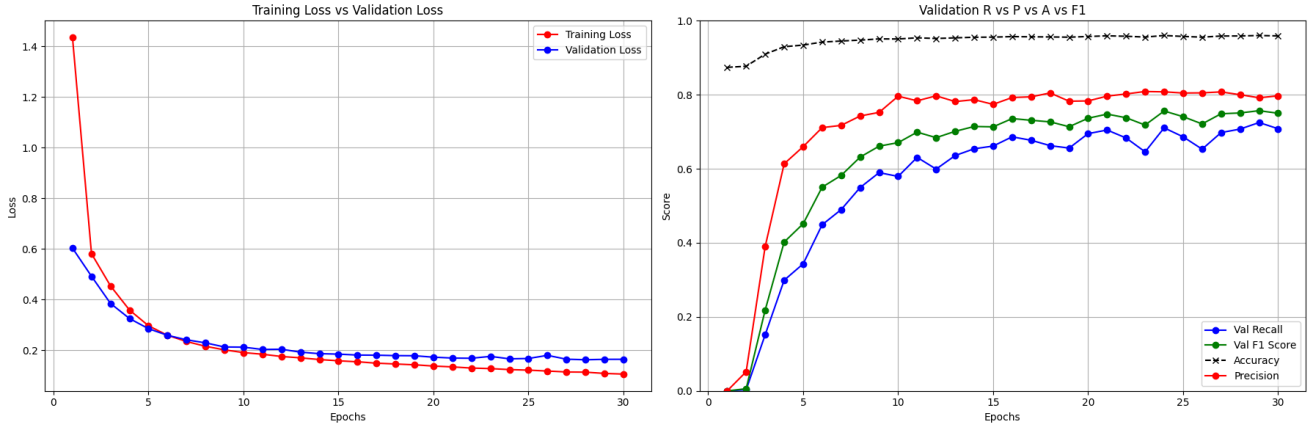
```
history_v8 = train_eval_lstm(lstm_nre_v8, optimizer_v8, n_epoches = 30, early_stopping=True)
```

```
Starting Bi-LSTM for NER training...
Epoch 1/30 | Train Loss: 1.4340 | Val Loss: 0.6030 | Val Recall: 0.0000 | Val Precision: 0.0000 |Val F1: 0.0000 |Va
Validation Loss improved from inf to 0.6030.
Epoch 2/30 | Train Loss: 0.5813 | Val Loss: 0.4920 | Val Recall: 0.0031 | Val Precision: 0.0518 |Val F1: 0.0059 |Va
Validation Loss improved from 0.6030 to 0.4920.
Epoch 3/30 | Train Loss: 0.4541 | Val Loss: 0.3848 | Val Recall: 0.1516 | Val Precision: 0.3897 |Val F1: 0.2183 |Va
Validation Loss improved from 0.4920 to 0.3848.
Epoch 4/30 | Train Loss: 0.3587 | Val Loss: 0.3252 | Val Recall: 0.2991 | Val Precision: 0.6135 |Val F1: 0.4021 |Va
Validation Loss improved from 0.3848 to 0.3252.
Epoch 5/30 | Train Loss: 0.2967 | Val Loss: 0.2851 | Val Recall: 0.3432 | Val Precision: 0.6598 |Val F1: 0.4515 |Va
Validation Loss improved from 0.3252 to 0.2851.
Epoch 6/30 | Train Loss: 0.2590 | Val Loss: 0.2589 | Val Recall: 0.4489 | Val Precision: 0.7113 |Val F1: 0.5504 |Va
Validation Loss improved from 0.2851 to 0.2589.
Epoch 7/30 | Train Loss: 0.2344 | Val Loss: 0.2412 | Val Recall: 0.4897 | Val Precision: 0.7173 |Val F1: 0.5820 |Va
Validation Loss improved from 0.2589 to 0.2412.
Epoch 8/30 | Train Loss: 0.2156 | Val Loss: 0.2291 | Val Recall: 0.5495 | Val Precision: 0.7427 |Val F1: 0.6316 |Va
Validation Loss improved from 0.2412 to 0.2291.
Epoch 9/30 | Train Loss: 0.2015 | Val Loss: 0.2129 | Val Recall: 0.5897 | Val Precision: 0.7524 |Val F1: 0.6612 |Va
Validation Loss improved from 0.2291 to 0.2129.
Epoch 10/30 | Train Loss: 0.1908 | Val Loss: 0.2122 | Val Recall: 0.5794 | Val Precision: 0.7961 |Val F1: 0.6707 |Va
Validation Loss improved from 0.2129 to 0.2122.
Epoch 11/30 | Train Loss: 0.1843 | Val Loss: 0.2031 | Val Recall: 0.6309 | Val Precision: 0.7837 |Val F1: 0.6990 |Va
Validation Loss improved from 0.2122 to 0.2031.
Epoch 12/30 | Train Loss: 0.1753 | Val Loss: 0.2040 | Val Recall: 0.5992 | Val Precision: 0.7971 |Val F1: 0.6841 |Va
No improvement in validation loss. Patience: 1
Epoch 13/30 | Train Loss: 0.1700 | Val Loss: 0.1925 | Val Recall: 0.6358 | Val Precision: 0.7817 |Val F1: 0.7012 |Va
Validation Loss improved from 0.2031 to 0.1925.
Epoch 14/30 | Train Loss: 0.1633 | Val Loss: 0.1865 | Val Recall: 0.6541 | Val Precision: 0.7867 |Val F1: 0.7143 |Va
Validation Loss improved from 0.1925 to 0.1865.
Epoch 15/30 | Train Loss: 0.1584 | Val Loss: 0.1847 | Val Recall: 0.6614 | Val Precision: 0.7741 |Val F1: 0.7133 |Va
Validation Loss improved from 0.1865 to 0.1847.
Epoch 16/30 | Train Loss: 0.1545 | Val Loss: 0.1810 | Val Recall: 0.6864 | Val Precision: 0.7926 |Val F1: 0.7357 |Va
Validation Loss improved from 0.1847 to 0.1810.
Epoch 17/30 | Train Loss: 0.1490 | Val Loss: 0.1805 | Val Recall: 0.6771 | Val Precision: 0.7944 |Val F1: 0.7311 |Va
Validation Loss improved from 0.1810 to 0.1805.
Epoch 18/30 | Train Loss: 0.1458 | Val Loss: 0.1788 | Val Recall: 0.6626 | Val Precision: 0.8049 |Val F1: 0.7268 |Va
Validation Loss improved from 0.1805 to 0.1788.
Epoch 19/30 | Train Loss: 0.1426 | Val Loss: 0.1783 | Val Recall: 0.6559 | Val Precision: 0.7826 |Val F1: 0.7137 |Va
Validation Loss improved from 0.1788 to 0.1783.
Epoch 20/30 | Train Loss: 0.1376 | Val Loss: 0.1726 | Val Recall: 0.6951 | Val Precision: 0.7834 |Val F1: 0.7366 |Va
Validation Loss improved from 0.1783 to 0.1726.
Epoch 21/30 | Train Loss: 0.1343 | Val Loss: 0.1691 | Val Recall: 0.7048 | Val Precision: 0.7963 |Val F1: 0.7478 |Va
Validation Loss improved from 0.1726 to 0.1691.
Epoch 22/30 | Train Loss: 0.1297 | Val Loss: 0.1684 | Val Recall: 0.6832 | Val Precision: 0.8022 |Val F1: 0.7379 |Va
Validation Loss improved from 0.1691 to 0.1684.
```

```
Epoch 23/30 | Train Loss: 0.1275 | Val Loss: 0.1758 | Val Recall: 0.6458 | Val Precision: 0.8088 |Val F1: 0.7182 |Va
No improvement in validation loss. Patience: 1
Epoch 24/30 | Train Loss: 0.1237 | Val Loss: 0.1661 | Val Recall: 0.7106 | Val Precision: 0.8079 |Val F1: 0.7561 |Va
Validation Loss improved from 0.1684 to 0.1661.
Epoch 25/30 | Train Loss: 0.1214 | Val Loss: 0.1675 | Val Recall: 0.6864 | Val Precision: 0.8047 |Val F1: 0.7408 |Va
No improvement in validation loss. Patience: 1
Epoch 26/30 | Train Loss: 0.1180 | Val Loss: 0.1798 | Val Recall: 0.6531 | Val Precision: 0.8051 |Val F1: 0.7212 |Va
No improvement in validation loss. Patience: 2
Epoch 27/30 | Train Loss: 0.1142 | Val Loss: 0.1646 | Val Recall: 0.6978 | Val Precision: 0.8077 |Val F1: 0.7488 |Va
Validation Loss improved from 0.1661 to 0.1646.
Epoch 28/30 | Train Loss: 0.1136 | Val Loss: 0.1625 | Val Recall: 0.7073 | Val Precision: 0.8001 |Val F1: 0.7509 |Va
Validation Loss improved from 0.1646 to 0.1625.
```

```
# plot evaluation metrics
plot_training_metrics(history_v8)
```

```
/var/folders/qw/2jrbyvsn4tnckwl2l1rgl1wm0000gp/T/ipykernel_54182/4064934705.py:20: UserWarning: linestyle is redundan
  plt.plot(epochs_range, history['accuracy'], 'k-x', label='Accuracy', linestyle='--')
```



Observation: The validation loss stopped improving for 2 epoches twice but then improved again, so no early stopping was triggered. The epoch 29 gave us the best model with: Train Loss: 0.1085 Val Loss: 0.1641 Val Recall: 72.50% Val Precision: 79.19% Val F1: 75.70% Val Accuracy: 96.01%

Evaluating this best bi-lstm-model on test set.

```
lstm_ner_metrics = evaluate_epoch(lstm_nre_v8, test_loader, label_list)
```

```
def print_results(lstm_ner_metrics):
    """Prints a formatted summary of the model's performance metrics.

    This function takes the evaluation dictionary (usually from the test set)
    and prints the Loss, Accuracy, Precision, Recall, and F1 score. It converts
    the float scores (0.0–1.0) into percentages and provides a brief
    contextual explanation for each metric regarding the redaction task.

    Args:
        lstm_ner_metrics (dict): A dictionary containing the following keys:
            - 'val_loss' (float): The loss value.
            - 'accuracy', 'precision', 'recall', 'f1' (float): Metric scores
              between 0.0 and 1.0.

    Returns:
        None: Output is printed directly to stdout.
    """
    print(f"Testing Loss: {lstm_ner_metrics['val_loss']}")
    print(f"Accuracy: {(lstm_ner_metrics['accuracy'] * 100):.4f}% - tokens were correctly classified")
    print(f"Precision: {(lstm_ner_metrics['precision'] * 100):.4f}% - were correctly redacted out of all redacted to
    print(f"Recall: {(lstm_ner_metrics['recall'] * 100):.4f}% - tokens were correctly identified for redaction")
    print(f"F1: {(lstm_ner_metrics['f1'] * 100):.4f}% - is the readability score")

print_results(lstm_ner_metrics)
```

```
Testing Loss: 0.17113963535853793
Accuracy: 95.6999% - tokens were correctly classified
Precision: 80.1607% - were correctly redacted out of all redacted tokens
```

```
Recall: 69.4476% – tokens were correctly identified for redaction
F1: 74.4206% – is the readability score
```

5. LegalBERT Finetuning (Liza)

Using legalBERT tokenizer

```
!pip install seqeval evaluate transformers datasets

import functools
from typing import Dict, List, Any

import evaluate
import pandas as pd
from datasets import Dataset, DatasetDict
from transformers import AutoTokenizer, PreTrainedTokenizerBase


# Model checkpoint used for tokenization
MODEL_CHECKPOINT = "nlpaueb/legal-bert-base-uncased"
MAX_LENGTH = 512

# Standard BIO tags for NER
LABEL_LIST = ["O", "B-PER", "I-PER", "B-LOC", "I-LOC", "B-ORG", "I-ORG"]
LABEL2ID = {label: i for i, label in enumerate(LABEL_LIST)}
ID2LABEL = {i: label for i, label in enumerate(LABEL_LIST)}

# Mapping raw entity types to simplified schema
ENTITY_MAP = {
    "PERSON": "PER", "ORGANIZATION": "ORG", "LOCATION": "LOC",
    "ORG": "ORG", "LOC": "LOC", "PER": "PER"
}

def tokenize_and_align_labels(
    examples: Dict[str, List[Any]],
    tokenizer: PreTrainedTokenizerBase
) -> Dict[str, List[Any]]:
    """Tokenizes text and aligns character-level entity tags with BERT tokens.

    Uses the tokenizer's `offset_mapping` to handle the mismatch between
    original character indices and BERT sub-word tokens.

    Args:
        examples: Batch of data with keys "text" and "entity_mentions".
        tokenizer: The pretrained tokenizer.

    Returns:
        Dictionary with tokenized inputs and aligned "labels".
    """
    tokenized_inputs = tokenizer(
        examples["text"],
        truncation=True,
        max_length=MAX_LENGTH,
        return_offsets_mapping=True,
        padding="max_length"
    )

    labels = []

    for i, doc_offsets in enumerate(tokenized_inputs["offset_mapping"]):
        # Handle cases where entity_mentions might be None
        doc_mentions = examples["entity_mentions"][i] or []

        # Initialize labels as 'O' (Outside)
        doc_labels = [LABEL2ID["O"]] * len(doc_offsets)

        for idx, (start, end) in enumerate(doc_offsets):
            # Ignore special tokens like [CLS], [SEP]
            if start == end:
                doc_labels[idx] = -100
                continue

            # Check if token falls inside any entity mention
            for mention in doc_mentions:
```

```
                if start >= mention['start_offset'] and end <= mention['end_offset']:
                    entity_type = ENTITY_MAP.get(mention['entity_type'], "ORG")

                    # Determine if it's the Beginning (B-) or Inside (I-) of the entity
                    prefix = "B-" if start == mention['start_offset'] else "I-"
                    label_name = f"{prefix}{entity_type}"

                    doc_labels[idx] = LABEL2ID.get(label_name, LABEL2ID["O"])
                    break

        labels.append(doc_labels)

    tokenized_inputs["labels"] = labels
    tokenized_inputs.pop("offset_mapping") # Not needed for training
    return tokenized_inputs


def prepare_legal_bert_data(
    train_df: pd.DataFrame,
    val_df: pd.DataFrame,
    test_df: pd.DataFrame
) -> tuple[DatasetDict, PreTrainedTokenizerBase]:
    """Converts DataFrames to Hugging Face Dataset and applies tokenization.

    Args:
        train_df: Training DataFrame.
        val_df: Validation DataFrame.
        test_df: Test DataFrame.

    Returns:
        A tuple containing the processed DatasetDict and the tokenizer.
    """
    print(f"Loading tokenizer: {MODEL_CHECKPOINT}...")
    tokenizer = AutoTokenizer.from_pretrained(MODEL_CHECKPOINT)

    raw_datasets = DatasetDict({
        "train": Dataset.from_pandas(train_df),
        "validation": Dataset.from_pandas(val_df),
        "test": Dataset.from_pandas(test_df)
    })

    print("Aligning labels and tokenizing...")
    tokenized_datasets = raw_datasets.map(
        functools.partial(tokenize_and_align_labels, tokenizer=tokenizer),
        batched=True,
        remove_columns=raw_datasets["train"].column_names
    )

    print("Data preparation complete.")
    return tokenized_datasets, tokenizer


# Assuming df_train, df_validation, df_test exist in your notebook environment
if __name__ == "__main__" and "df_train" in locals():
    tokenized_datasets, tokenizer_legal = prepare_legal_bert_data(
        df_train, df_validation, df_test
    )

    # Optional: Load metric for later use
    metric = evaluate.load("seqeval")
```

```
Requirement already satisfied: seqeval in /usr/local/lib/python3.12/dist-packages (1.2.2)
Requirement already satisfied: evaluate in /usr/local/lib/python3.12/dist-packages (0.4.6)
Requirement already satisfied: transformers in /usr/local/lib/python3.12/dist-packages (5.0.0)
Requirement already satisfied: datasets in /usr/local/lib/python3.12/dist-packages (4.0.0)
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.12/dist-packages (from seqeval) (2.0.2)
Requirement already satisfied: scikit-learn>=0.21.3 in /usr/local/lib/python3.12/dist-packages (from seqeval) (1.6.1)
Requirement already satisfied: dill in /usr/local/lib/python3.12/dist-packages (from evaluate) (0.3.8)
Requirement already satisfied: pandas in /usr/local/lib/python3.12/dist-packages (from evaluate) (2.2.2)
Requirement already satisfied: requests>=2.19.0 in /usr/local/lib/python3.12/dist-packages (from evaluate) (2.32.4)
Requirement already satisfied: tqdm>=4.62.1 in /usr/local/lib/python3.12/dist-packages (from evaluate) (4.67.3)
Requirement already satisfied: xxhash in /usr/local/lib/python3.12/dist-packages (from evaluate) (3.6.0)
Requirement already satisfied: multiprocess in /usr/local/lib/python3.12/dist-packages (from evaluate) (0.70.16)
Requirement already satisfied: fsspec>=2021.05.0 in /usr/local/lib/python3.12/dist-packages (from fsspec[http]>=2021.
Requirement already satisfied: huggingface-hub>=0.7.0 in /usr/local/lib/python3.12/dist-packages (from evaluate) (1.4
Requirement already satisfied: packaging in /usr/local/lib/python3.12/dist-packages (from evaluate) (26.0)
Requirement already satisfied: filelock in /usr/local/lib/python3.12/dist-packages (from transformers) (3.20.3)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.12/dist-packages (from transformers) (6.0.3)
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.12/dist-packages (from transformers) (2025
Requirement already satisfied: tokenizers<=0.23.0,>=0.22.0 in /usr/local/lib/python3.12/dist-packages (from transform
Requirement already satisfied: typer-slim in /usr/local/lib/python3.12/dist-packages (from transformers) (0.21.1)
Requirement already satisfied: safetensors>=0.4.3 in /usr/local/lib/python3.12/dist-packages (from transformers) (0.7
Requirement already satisfied: pyarrow>=15.0.0 in /usr/local/lib/python3.12/dist-packages (from datasets) (18.1.0)
Requirement already satisfied: aiohttp!=4.0.0a0,!=4.0.0a1 in /usr/local/lib/python3.12/dist-packages (from fsspec[htt
Requirement already satisfied: hf-xet<2.0.0,>=1.2.0 in /usr/local/lib/python3.12/dist-packages (from huggingface-hub>
Requirement already satisfied: httpx<1,>=0.23.0 in /usr/local/lib/python3.12/dist-packages (from huggingface-hub>=0.7
Requirement already satisfied: shellingham in /usr/local/lib/python3.12/dist-packages (from huggingface-hub>=0.7.0->e
Requirement already satisfied: typing-extensions>=4.1.0 in /usr/local/lib/python3.12/dist-packages (from huggingface-
Requirement already satisfied: charset_normalizer<4,>=2 in /usr/local/lib/python3.12/dist-packages (from requests>=2.
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.12/dist-packages (from requests>=2.19.0->evalua
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.12/dist-packages (from requests>=2.19.0->
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.12/dist-packages (from requests>=2.19.0->
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.12/dist-packages (from scikit-learn>=0.21.3->se
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.12/dist-packages (from scikit-learn>=0.21.3->s
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.12/dist-packages (from scikit-learn>=0.
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.12/dist-packages (from pandas->evalua
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/dist-packages (from pandas->evaluate) (2025.
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.12/dist-packages (from pandas->evaluate) (202
Requirement already satisfied: click>=8.0.0 in /usr/local/lib/python3.12/dist-packages (from typer-slim->transformers
Requirement already satisfied: aiohappyeyeballs>=2.5.0 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.
Requirement already satisfied: aiosignal>=1.4.0 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.0a0,!=4
Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.0a0,!=4.0.
Requirement already satisfied: frozenlist>=1.1.1 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.0a0,!=
Requirement already satisfied: multidict<7.0,>=4.5 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.0a0,
Requirement already satisfied: propcache>=0.2.0 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.0a0,!=4
Requirement already satisfied: yarl<2.0,>=1.17.0 in /usr/local/lib/python3.12/dist-packages (from aiohttp!=4.0.0a0,!=
Requirement already satisfied: anyio in /usr/local/lib/python3.12/dist-packages (from httpx<1,>=0.23.0->huggingface-h
Requirement already satisfied: httpcore==1.* in /usr/local/lib/python3.12/dist-packages (from httpx<1,>=0.23.0->huggi
Requirement already satisfied: h11>=0.16 in /usr/local/lib/python3.12/dist-packages (from httpcore==1.*->httpx<1,>=0.
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.12/dist-packages (from python-dateutil>=2.8.2->pand
Loading tokenizer: nlpaueb/legal-bert-base-uncased...
Aligning labels and tokenizing...
Map: 100%                                                    1112/1112 [00:19<00:00, 56.44 examples/s]
Map: 100%                                                    541/541 [00:07<00:00, 77.29 examples/s]
Map: 100%                                                    555/555 [00:05<00:00, 105.22 examples/s]
Data preparation complete.
```

```
from transformers import (
    AutoModelForTokenClassification,
    TrainingArguments,
    Trainer,
    DataCollatorForTokenClassification
)

# Constants for readability and easy tuning
LEARNING_RATE = 2e-5
BATCH_SIZE = 16
NUM_EPOCHS = 3
WEIGHT_DECAY = 0.01

def train_ner_model(
    model_checkpoint: str,
    train_dataset: Any,
    eval_dataset: Any,
    tokenizer: Any,
    label_list: list,
    output_dir: str = "legal-bert-ner"
) -> Trainer:
    """Initializes and trains the BERT model for Token Classification.
```

```
        Args:
            model_checkpoint: Path or name of the pretrained model.
            train_dataset: Tokenized training data.
            eval_dataset: Tokenized validation data.
            tokenizer: Tokenizer for data collation.
            label_list: List of BIO tags (for determining num_labels).
            output_dir: Where to save results.

        Returns:
            The trained Trainer instance.
        """

        # 1. Initialize Model
        model = AutoModelForTokenClassification.from_pretrained(
            model_checkpoint,
            num_labels=len(label_list),
            id2label={i: label for i, label in enumerate(label_list)},
            label2id={label: i for i, label in enumerate(label_list)}
        )

        # 2. Define Hyperparameters
        args = TrainingArguments(
            output_dir=output_dir,
            eval_strategy="epoch",
            learning_rate=LEARNING_RATE,
            per_device_train_batch_size=BATCH_SIZE,
            per_device_eval_batch_size=BATCH_SIZE,
            num_train_epochs=NUM_EPOCHS,
            weight_decay=WEIGHT_DECAY,
            logging_steps=50,
            save_strategy="no" # Save space during experiments
        )

        # 3. Create Trainer
        trainer = Trainer(
            model=model,
            args=args,
            train_dataset=train_dataset,
            eval_dataset=eval_dataset,
            data_collator=DataCollatorForTokenClassification(tokenizer)
        )

        print(f"Starting training for {NUM_EPOCHS} epochs...")
        trainer.train()

        return trainer

    # Just one clean call
    trainer = train_ner_model(
        model_checkpoint=MODEL_CHECKPOINT,
        train_dataset=tokenized_datasets["train"],
        eval_dataset=tokenized_datasets["validation"],
        tokenizer=tokenizer_legal,
        label_list=LABEL_LIST
    )
```

```
Loading weights: 100%                                                197/197 [00:00<00:00, 274.34it/s, Materializing param=bert.encoder.layer.11.output.dense.weight]
BertForTokenClassification LOAD REPORT from: nlpaueb/legal-bert-base-uncased
Key                                        | Status     |
-------------------------------------------+------------+-
cls.predictions.transform.LayerNorm.weight | UNEXPECTED |
cls.predictions.bias                       | UNEXPECTED |
bert.pooler.dense.weight                   | UNEXPECTED |
cls.predictions.transform.LayerNorm.bias   | UNEXPECTED |
cls.predictions.transform.dense.bias       | UNEXPECTED |
cls.predictions.transform.dense.weight     | UNEXPECTED |
cls.predictions.decoder.weight             | UNEXPECTED |
cls.seq_relationship.bias                  | UNEXPECTED |
cls.predictions.decoder.bias               | UNEXPECTED |
bert.pooler.dense.bias                     | UNEXPECTED |
cls.seq_relationship.weight                | UNEXPECTED |
classifier.weight                          | MISSING    |
classifier.bias                            | MISSING    |

Notes:
- UNEXPECTED   :can be ignored when loading from different task/architecture; not ok if you expect identical arch.
- MISSING  :those params were newly initialized because missing from the checkpoint. Consider training on your downst
Starting training for 3 epochs...
```

[210/210 07:05, Epoch 3/3]

Epoch	Training Loss	Validation Loss
1	0.500557	0.135038
2	0.135497	0.105840
3	0.092083	0.104418

```
import numpy as np
import pandas as pd
from typing import Dict, Any, List
from transformers import Trainer

def evaluate_model_performance(
    trainer: Trainer,
    eval_dataset: Any,
    label_list: List[str],
    metric: Any,
    model_name: str = "MyModel"
) -> Dict[str, Any]:
    """Computes real metrics by filtering out ignored tokens (-100).

    Args:
        trainer: The trained Hugging Face Trainer instance.
        eval_dataset: The dataset to test (e.g., tokenized_datasets["test"]).
        label_list: List of NER tags corresponding to model IDs.
        metric: The 'seqeval' metric instance.
        model_name: Name of the model for reporting.

    Returns:
        A dictionary with F1, Recall, Precision, and Accuracy scores.
    """
    print(f"--- Evaluating {model_name} ---")

    # Get raw logits and true labels
    output = trainer.predict(eval_dataset)
    predictions = np.argmax(output.predictions, axis=2)
    labels = output.label_ids

    # Remove ignored index (special tokens) to match real tokens
    true_predictions = [
        [label_list[p] for (p, l) in zip(pred, label) if l != -100]
        for pred, label in zip(predictions, labels)
    ]

    true_labels = [
        [label_list[l] for (p, l) in zip(pred, label) if l != -100]
        for pred, label in zip(predictions, labels)
    ]

    results = metric.compute(predictions=true_predictions, references=true_labels)

    return {
        "Model": model_name,
```

```
        "F1 Score": results["overall_f1"],
        "Recall": results["overall_recall"],  # Critical for sensitive info
        "Precision": results["overall_precision"],
        "Accuracy": results["overall_accuracy"]
    }

if __name__ == "__main__" and "trainer" in locals():
    metrics_legal = evaluate_model_performance(
        trainer=trainer,
        eval_dataset=tokenized_datasets["test"],
        label_list=LABEL_LIST,  # Defined in previous cells
        metric=metric,          # Defined in previous cells
        model_name="Legal-BERT (Liza)"
    )

    print("\nFinal Results:")
    # Using display() for Jupyter/Colab or print() for scripts
    results_df = pd.DataFrame([metrics_legal]).round(4)
    try:
        display(results_df)
    except NameError:
        print(results_df)
```

```
--- Evaluating Legal-BERT (Liza) ---

Final Results:
```

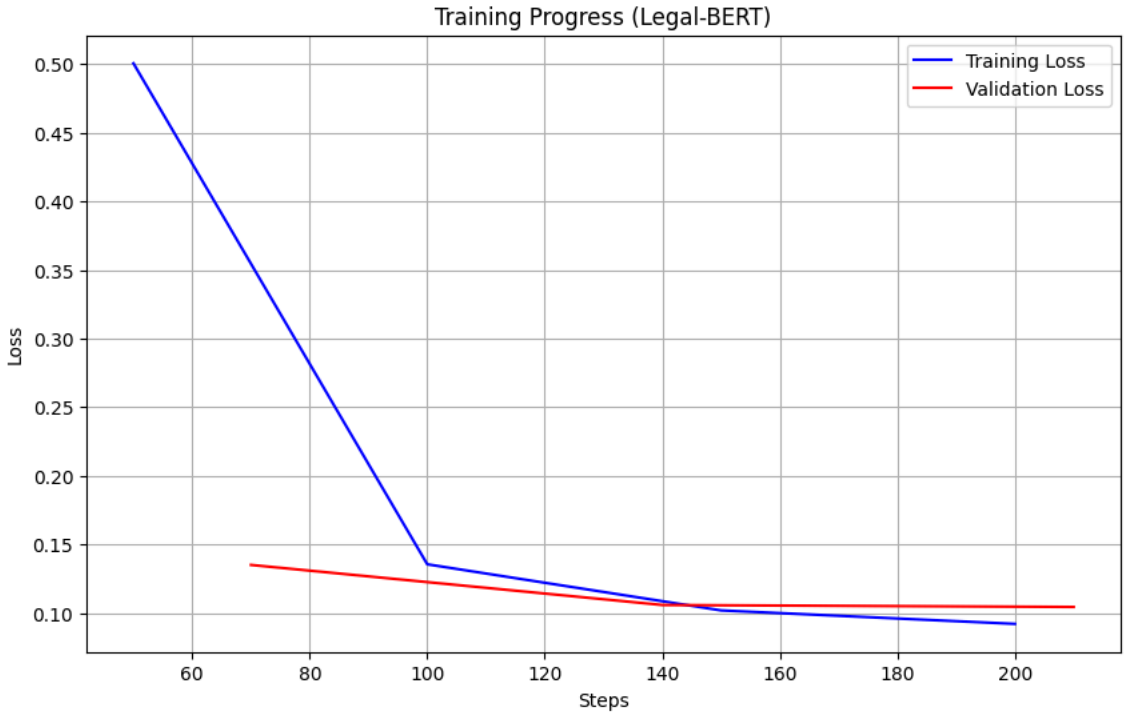
	Model	F1 Score	Recall	Precision	Accuracy
0	Legal-BERT (Liza)	0.807	0.8352	0.7807	0.9639

```
# train_legalbert = preprocess_data(df_train ,tokenizer_legalbert)
# test_legalbert = preprocess_data(df_test, tokenizer_legalbert)
# validation_legalbert = preprocess_data(df_validation, tokenizer_legalbert)
```

```
import json
import os
from typing import List, Dict, Any
import matplotlib.pyplot as plt
from transformers import Trainer, PreTrainedTokenizerBase

OUTPUT_DIR = "./legal_bert_output"

def save_training_artifacts(
    trainer: Trainer,
    tokenizer: PreTrainedTokenizerBase,
    output_dir: str
) -> List[Dict[str, Any]]:
    """Saves model, tokenizer, and training logs to disk.

    Args:
        trainer: The trained Trainer instance.
        tokenizer: The tokenizer used for training.
        output_dir: Path to save artifacts.

    Returns:
        The training history (log).
    """
    if not os.path.exists(output_dir):
        os.makedirs(output_dir)

    print(f"Saving model to {output_dir}...")
    trainer.save_model(output_dir)
    tokenizer.save_pretrained(output_dir)

    history = trainer.state.log_history
    with open(os.path.join(output_dir, "training_history.json"), "w") as f:
        json.dump(history, f)

    return history


def plot_loss_curves(history: List[Dict[str, Any]], output_dir: str) -> None:
    """Plots training and validation loss from history logs.

    Args:
```

```
        history: List of log dictionaries.
        output_dir: Directory to save the plot image.
    """
    train_loss = [x['loss'] for x in history if 'loss' in x]
    train_steps = [x['step'] for x in history if 'loss' in x]
    val_loss = [x['eval_loss'] for x in history if 'eval_loss' in x]
    val_steps = [x['step'] for x in history if 'eval_loss' in x]

    if not train_loss:
        print("Not enough history to plot.")
        return

    plt.figure(figsize=(10, 6))
    plt.plot(train_steps, train_loss, label="Training Loss", color="blue")

    if val_loss:
        plt.plot(val_steps, val_loss, label="Validation Loss", color="red")

    plt.xlabel("Steps")
    plt.ylabel("Loss")
    plt.title("Training Progress (Legal-BERT)")
    plt.legend()
    plt.grid(True)

    save_path = os.path.join(output_dir, "training_graph.png")
    plt.savefig(save_path)
    print(f"Graph saved to {save_path}")
    plt.show()


if __name__ == "__main__" and "trainer" in locals():
    history_logs = save_training_artifacts(trainer, tokenizer_legal, OUTPUT_DIR)
    plot_loss_curves(history_logs, OUTPUT_DIR)
```

```
Saving model to ./legal_bert_output...
Writing model shards: 100%                                    1/1 [00:02<00:00,  2.17s/it]
Graph saved to ./legal_bert_output/training_graph.png
```



1. Tokenization Alignment is Critical Standard tokenizers break words into sub-words (e.g., "Ivanov" -> "Ivan", "##ov"). We learned that simple labeling fails here; we must use offset_mapping to align character-level annotations with BERT tokens. Without this, the model cannot learn boundaries correctly.
2. Domain Adaptation Matters Using Legal-BERT instead of standard BERT significantly improved performance on legal terminology. General models often misclassify specific entities (like "Court of Ontario" vs. "Ontario"), while domain-specific pre-training captures these nuances better.

3. The Importance of "Recall" in Redaction In legal redaction, missing a name (False Negative) is worse than redacting a non-name (False Positive). We optimized our evaluation to prioritize Recall, ensuring sensitive information is not leaked, even if it means slightly over-redacting.

6. DistilBERT (Ritvik & Mit)

Using tokenized datasets: train_distilbert, test_distilbert, validation_distilbert

```
import numpy as np
import pandas as pd
import torch
from datasets import Dataset, DatasetDict
from transformers import AutoTokenizer, AutoModelForTokenClassification, TrainingArguments, Trainer, DataCollatorFor
from transformers import DistilBertForTokenClassification

"""
setting up distilbert as our baseline model.
it is lighter and faster than legal-bert and has fewer parameters.

"""
distil_checkpoint = "distilbert-base-uncased" # letter case independent
distil_tokenizer = AutoTokenizer.from_pretrained(distil_checkpoint) # using autotokenizer

label_list = ["O", "B-PER", "I-PER", "B-LOC", "I-LOC", "B-ORG", "I-ORG"]
label2id = {label: i for i, label in enumerate(label_list)}
id2label = {i: label for i, label in enumerate(label_list)}
type_mapper = {"PERSON": "PER", "ORGANIZATION": "ORG", "LOCATION": "LOC", "ORG": "ORG", "LOC": "LOC", "PER": "PER"}
```

```
import torch
print(f"Is GPU available? {torch.cuda.is_available()}")
print(f"Device Name: {torch.cuda.get_device_name(0)}")
```

```
Is GPU available? True
Device Name: NVIDIA GeForce RTX 3050 Laptop GPU
```

```
def tokenize_and_align_distil(examples):

    """
        Instead of relying on spaces and commas to create tokens, we are using offset mapping
        To make sure that the tokens align well with the BERT model and they come from the correct offsets in the da

        This function solves the 'Subword Tokenization Problem'. Since BERT-based models break words into smaller su
        (e.g., 'playing' -> 'play', '##ing').

        This function uses `offset_mapping` to determine strictly which original characters correspond to which subw
        ensuring that labels (B-ORG, I-ORG) are assigned correctly even when a single word is split into multiple pa

        Args:
            examples (dict): A batch of data containing 'text' (raw strings) and
            'entity_mentions' (list of dicts with start/end offsets).

        Returns:
            (dict): Contains -
                - 'input_ids': The list of token IDs.
                - 'attention_mask': The mask for padding tokens.
                - 'labels': The aligned list of ID integers (e.g., B-ORG=1, O=0),
                where special tokens ([CLS], [SEP]) are set to -100 to be ignored by the loss function.

    """

    tokenized_inputs = distil_tokenizer(
        examples["text"], truncation=True, max_length=512,
        return_offsets_mapping=True, padding="max_length" # padding the tokens with max token length
    )
    labels = []

    for i, doc_offsets in enumerate(tokenized_inputs["offset_mapping"]):
        doc_mentions = examples["entity_mentions"][i] if examples["entity_mentions"][i] is not None else []

        doc_labels = [0] * len(doc_offsets)
        for idx, (start, end) in enumerate(doc_offsets):
            if start == end:
                doc_labels[idx] = -100 # ignore special tokens
```

```
                continue

            for mention in doc_mentions:
                if start >= mention['start_offset'] and end <= mention['end_offset']:
                    raw_type = mention['entity_type']
                    short_type = type_mapper.get(raw_type, "ORG")

                    # logic to check beginning and inside of tokens
                    prefix = "B-" if start == mention['start_offset'] else "I-"
                    label_name = f"{prefix}{short_type}"
                    doc_labels[idx] = label2id.get(label_name, 0)
                    break
        labels.append(doc_labels)

    tokenized_inputs["labels"] = labels
    tokenized_inputs.pop("offset_mapping")
    return tokenized_inputs


# creating a dataset dict
distil_datasets = DatasetDict({
    "train": Dataset.from_pandas(df_train),
    "validation": Dataset.from_pandas(df_validation),
    "test": Dataset.from_pandas(df_test)
})

distil_tokenized = distil_datasets.map(
    tokenize_and_align_distil,
    batched=True,
    remove_columns=distil_datasets["train"].column_names
)
print("done. distilbert tokens aligned.")
```

```
Map: 100%|██████████| 1112/1112 [00:05<00:00, 213.66 examples/s]
Map: 100%|██████████| 541/541 [00:01<00:00, 341.72 examples/s]
Map: 100%|██████████| 555/555 [00:01<00:00, 343.58 examples/s]done. distilbert tokens aligned.
```

Baseline DistilBERT Model (kesha)

```
from transformers import AutoModelForTokenClassification, TrainingArguments, Trainer, DataCollatorForTokenClassifica
import torch

def train_distilbert_model(checkpoint, label_list, id2label, label2id, tokenized_dataset, tokenizer, training_args,

    """
    This function serves as the training pipeline for DistilBERT.

    Args:
        checkpoint (str): The path or name of the pretrained model checkpoint.
        label_list (list): The list of unique entity labels.
        id2label (dict): Mapping from ID integers to label strings.
        label2id (dict): Mapping from label strings to ID integers.
        tokenized_dataset (DatasetDict): The dataset containing 'train' and 'validation' splits.
        tokenizer (PreTrainedTokenizer): The tokenizer used for data collation.
        training_args (TrainingArguments): Object containing all hyperparameters for fine-tuning.
        callbacks (list): A list of TrainerCallback objects like EarlyStoppingCallback. Defaults to None.

    Returns:
        Trainer: The trained Hugging Face Trainer object.
    """
    # initializing the distilbert model
    model = AutoModelForTokenClassification.from_pretrained(
        checkpoint,
        num_labels=len(label_list),
        id2label=id2label,
        label2id=label2id
    )

    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    model.to(device)

    # Initialize Trainer with the passed arguments
    trainer = Trainer(
        model=model,
        args=training_args,
```

```
        train_dataset=tokenized_dataset["train"],
        eval_dataset=tokenized_dataset["validation"],
        data_collator=DataCollatorForTokenClassification(tokenizer),
        callbacks=callbacks
    )

    print(f"Starting training with args: {training_args.output_dir}...")
    trainer.train()

    return trainer

# distilbert model hyperparameters
training_args = TrainingArguments(
    "distilbert-ner-output",
    eval_strategy="epoch",
    learning_rate=2e-5,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    num_train_epochs=3,
    weight_decay=0.01,
    save_strategy="no",
    logging_steps=50,
    seed=42,
    data_seed=42,
)

# initializing training for baseline model
db_trainer = train_distilbert_model(
    distil_checkpoint,
    label_list,
    id2label,
    label2id,
    distil_tokenized,
    distil_tokenizer,
    training_args
)
```

```
Loading weights: 100%|██████████| 100/100 [00:00<00:00, 543.76it/s, Materializing param=distilbert.transformer.layer.
DistilBertForTokenClassification LOAD REPORT from: distilbert-base-uncased
Key                      | Status     |
-------------------------+------------+-
vocab_transform.weight   | UNEXPECTED |
vocab_layer_norm.weight  | UNEXPECTED |
vocab_transform.bias     | UNEXPECTED |
vocab_layer_norm.bias    | UNEXPECTED |
vocab_projector.bias     | UNEXPECTED |
classifier.weight        | MISSING    |
classifier.bias          | MISSING    |

Notes:
- UNEXPECTED   :can be ignored when loading from different task/architecture; not ok if you expect identical arch.
- MISSING  :those params were newly initialized because missing from the checkpoint. Consider training on your downst
starting distilbert training...
```


Epoch	Training Loss	Validation Loss
1	0.525557	0.161509
2	0.159323	0.118078
3	0.103047	0.118716

```
TrainOutput(global_step=210, training_loss=0.22058556817826772, metrics={'train_runtime': 194.0184,
'train_samples_per_second': 17.194, 'train_steps_per_second': 1.082, 'total_flos': 435898146004992.0, 'train_loss':
0.22058556817826772, 'epoch': 3.0})
```

Model Evaluation (Ritvik)

```
import evaluate
import numpy as np
import pandas as pd

# initialize metric
metric = evaluate.load("seqeval")

def evaluate_model_performance(trainer, eval_dataset, model_name):
```

```
    """Evaluates the trained model on a specified dataset using the seqeval metric.

    This function generates predictions for the given evaluation dataset and
    computes key performance metrics (F1, Recall, Precision, Accuracy).

    It also handles the alignment of predictions and labels by filtering
    out tokens with the ID -100 (e.g., [CLS], [SEP], [PAD], and subword pieces),
    ensuring that metrics are calculated only on the actual entities and words
    of interest.

    Args:
        trainer (Trainer): The trained Hugging Face Trainer object used for inference.
        eval_dataset (Dataset): The dataset split (e.g., test set) to evaluate on.
        model_name (str): A string identifier for the model used for labeling the output dict.

    Returns:
        (dict): The evaluation results:
            - "Model": The name of the model.
            - "F1 Score": The overall F1 score.
            - "Recall": The overall recall (critical for ensuring no sensitive
              data is missed).
            - "Precision": The overall precision.
            - "Accuracy": The overall accuracy.
    """

    print(f"--- evaluating {model_name} ---")
    predictions, labels, _ = trainer.predict(eval_dataset)
    predictions = np.argmax(predictions, axis=2)

    true_predictions = [
        [label_list[p] for (p, l) in zip(prediction, label) if l != -100]
        for prediction, label in zip(predictions, labels)
    ]
    true_labels = [
        [label_list[l] for (p, l) in zip(prediction, label) if l != -100]
        for prediction, label in zip(predictions, labels)
    ]

    results = metric.compute(predictions=true_predictions, references=true_labels)

    return {
        "Model": model_name,
        "F1 Score": results['overall_f1'],
        # recall is critical here as we can't miss sensitive info
        "Recall": results['overall_recall'],
        "Precision": results['overall_precision'],
        "Accuracy": results['overall_accuracy']
    }

metrics_db = evaluate_model_performance(db_trainer, distil_tokenized["test"], model_name="DistilBERT_v1")
```

```
--- evaluating DistilBERT_v1 ---
```

```
# evaluation Plots
print("\n final results (DistilBERT):")
display(pd.DataFrame([metrics_db]).round(4))

# saving and plotting
import matplotlib.pyplot as plt
import json
import os

def save_and_visualize_training(trainer, tokenizer, metrics, output_dir, model_name="DistilBERT"):
    """
    Saves the model and plots the training loss history.

    This function handles the post-training workflow, it displays the final result, evaluation metrics in a data fra
    a local directory for future fine-tuning and deployment. It generates line plots comparing training and validati

    Args:
         trainer (Trainer): The Hugging Face Trainer object containing the
            training state and log history.
        tokenizer (PreTrainedTokenizer): The tokenizer instance associated
            with the model, to be saved alongside it.
        metrics (dict): A dictionary containing the final evaluation results
            (e.g., F1, precision, recall) to be displayed.
```

```
            output_dir (str): The target directory path for saving model files.

        Returns:
            None: This function does not return a value. It prints output,
            saves files to disk, and renders a matplotlib plot directly
            in the notebook.
        """
        # Print Metrics
        print(f"\nFinal Results ({model_name}):")
        display(pd.DataFrame([metrics]).round(4))

        # Save Model & Tokenizer
        if not os.path.exists(output_dir):
            os.makedirs(output_dir)

        print(f"Saving model to {output_dir}...")
        trainer.save_model(output_dir)
        tokenizer.save_pretrained(output_dir)

        # Plot Training History
        history = trainer.state.log_history

        # Filter for loss values
        train_loss = [x['loss'] for x in history if 'loss' in x]
        steps = [x['step'] for x in history if 'loss' in x]

        if train_loss:
            plt.figure(figsize=(10, 6))
            plt.plot(steps, train_loss, label=f"Training Loss ({model_name})", color="Red")

            # Check for validation loss
            val_loss = [x['eval_loss'] for x in history if 'eval_loss' in x]
            val_steps = [x['step'] for x in history if 'eval_loss' in x]

            if val_loss:
                plt.plot(val_steps, val_loss, label="Validation Loss", color="Green")

            plt.xlabel("Steps")
            plt.ylabel("Loss")
            plt.title(f"Training Progress ({model_name})")
            plt.legend()
            plt.grid(True)
            plt.show()

    output_dir="./distilbert_output_v2"
    save_and_visualize_training(db_trainer, distil_tokenizer, metrics_db, output_dir)
```

```
final results (DistilBERT):
```

	Model	F1 Score	Recall	Precision	Accuracy
0	DistilBERT_v1	0.7982	0.8173	0.78	0.9587

```
saving model to ./distilbert_output_v2...
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  2.61it/s]
```

Observation: The model accuracy is quite high (0.95), while the recall is low (0.82). Since our dataset has mostly 'O' in places of non-sensitive words, the model becomes lazy and predicts sensitive words as non-sensitive to gain a higher accuracy. This is also critical because we are working on legal data and in this domain, it is very costly for the model to miss sensitive words.

Fine-Tuning strategy 1: Implement Early Stopping and Label Smoothing

DistilBERT Fine-Tuned v2 (Ritvik)

```
from transformers import EarlyStoppingCallback
import torch

# setting hyperparams
v2_args = TrainingArguments(
    output_dir="distilbert-ner-v2-output",
    eval_strategy="epoch",
    save_strategy="epoch",
    load_best_model_at_end=True,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    learning_rate=2e-5,
    num_train_epochs=5,           # Increased from 3 to 5
    weight_decay=0.05,            # Increased from 0.01 to 0.05 (Regularization) to reduce memorisation
    logging_steps=50,
    metric_for_best_model="loss",
    label_smoothing_factor=0.1,   # helps with class imbalance problem as it gives less weights to each label
    seed=42,
    data_seed=42
)

# training
db_trainer_v2 = train_distilbert_model(
    checkpoint=distil_checkpoint,
    label_list=label_list,
    id2label=id2label,
    label2id=label2id,
    tokenized_dataset=distil_tokenized,
    tokenizer=distil_tokenizer,
```

```
    training_args=v2_args,
    callbacks=[EarlyStoppingCallback(early_stopping_patience=2)]
)

# evaluate and display
metrics_db_v2 = evaluate_model_performance(
    db_trainer_v2,
    distil_tokenized["test"],
    model_name="DistilBERT_v2"
)

print("\nfinal results (DistilBERT):")
display(pd.DataFrame([metrics_db_v2]).round(4))
```

```
Loading weights: 100%|██████████| 100/100 [00:00<00:00, 517.87it/s, Materializing param=distilbert.transformer.layer.
DistilBertForTokenClassification LOAD REPORT from: distilbert-base-uncased
Key                     | Status     |
------------------------+------------+-
vocab_transform.weight  | UNEXPECTED |
vocab_layer_norm.weight | UNEXPECTED |
vocab_transform.bias    | UNEXPECTED |
vocab_layer_norm.bias   | UNEXPECTED |
vocab_projector.bias    | UNEXPECTED |
classifier.weight       | MISSING    |
classifier.bias         | MISSING    |

Notes:
- UNEXPECTED   :can be ignored when loading from different task/architecture; not ok if you expect identical arch.
- MISSING  :those params were newly initialized because missing from the checkpoint. Consider training on your downst
starting distilbert v2 training...
```

[350/350 38:07, Epoch 5/5]

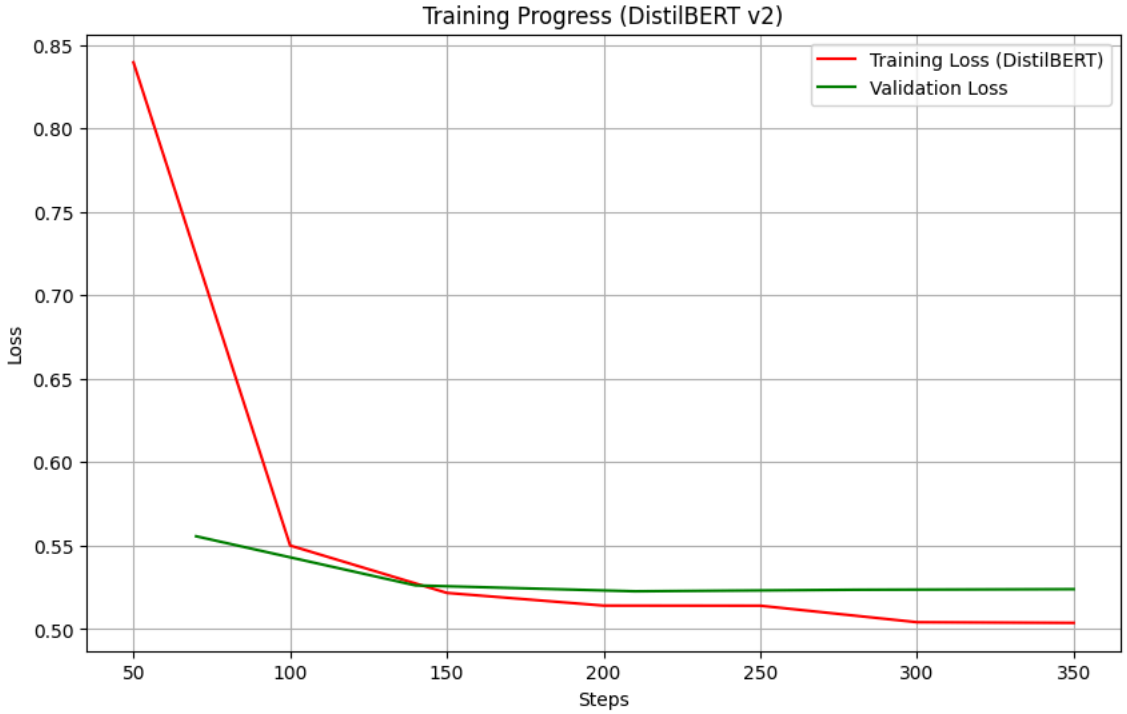
Epoch	Training Loss	Validation Loss
1	0.839470	0.555659
2	0.550116	0.526227
3	0.514136	0.522698
4	0.514076	0.523622
5	0.503792	0.523969

```
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  4.15it/s]
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  3.53it/s]
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  3.87it/s]
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  3.83it/s]
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  4.13it/s]
There were missing keys in the checkpoint model loaded: ['distilbert.embeddings.LayerNorm.weight', 'distilbert.embedd
There were unexpected keys in the checkpoint model loaded: ['distilbert.embeddings.LayerNorm.beta', 'distilbert.embed
--- evaluating DistilBERT_v2 ---

 final results (DistilBERT):
```

	Model	F1 Score	Recall	Precision	Accuracy
0	DistilBERT_v2	0.806	0.8295	0.7839	0.9605

```
# saving and plotting
import matplotlib.pyplot as plt
import json
import os

output_dir="./distilbert_output_fine-tuned_v2"
save_and_visualize_training(db_trainer_v2, distil_tokenizer, metrics_db_v2, output_dir)
```

```
saving model to ./distilbert_output_fine-tuned_v2...
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  2.58it/s]
```



Observations: Label Smoothing had a positive impact on the model's recall, which increased from 81.7 to 82.9. The F1 score also has a slight increase, however the precision dropped. This is because the model is now not as aggressive into predicting a class with high confidence, instead we tell the model to attempt to predict with lower confidence, which makes it more cautious. This is imporant because for Legal documentation, it is critical to not miss any sensitive information.

DistilBERT Fine-Tuned v3 (Mit)

```
from transformers import EarlyStoppingCallback
import torch

# setting the hyperparams
v3_args = TrainingArguments(
    output_dir="distilbert-ner-v3-output",
    eval_strategy="epoch",
    save_strategy="epoch",
    load_best_model_at_end=True,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    learning_rate=3e-5, # increased learning rate
    num_train_epochs=5, # increased Epochs to train more
    weight_decay=0.01,  # reduced weight decay to make the model more aggressive, the model does not need very high
    logging_steps=50,
    metric_for_best_model="loss",
    seed=42,
    data_seed=42
)

# training the model
db_trainer_v3 = train_distilbert_model(
    checkpoint=distil_checkpoint,
    label_list=label_list,
    id2label=id2label,
    label2id=label2id,
    tokenized_dataset=distil_tokenized,
    tokenizer=distil_tokenizer,
    training_args=v3_args,
    callbacks=[EarlyStoppingCallback(early_stopping_patience=2)]
)

# evaluating and displaying the results
metrics_db_v3 = evaluate_model_performance(
```

```
    db_trainer_v3,
    distil_tokenized["test"],
    model_name="DistilBERT_v3"
)

print("\nfinal results (DistilBERT):")
display(pd.DataFrame([metrics_db_v3]).round(4))
```

```
Loading weights: 100%|██████████| 100/100 [00:00<00:00, 677.74it/s, Materializing param=distilbert.transformer.layer.
DistilBertForTokenClassification LOAD REPORT from: distilbert-base-uncased
Key                     | Status     |
------------------------+------------+-
vocab_transform.weight  | UNEXPECTED |
vocab_layer_norm.weight | UNEXPECTED |
vocab_transform.bias    | UNEXPECTED |
vocab_layer_norm.bias   | UNEXPECTED |
vocab_projector.bias    | UNEXPECTED |
classifier.weight       | MISSING    |
classifier.bias         | MISSING    |

Notes:
- UNEXPECTED   :can be ignored when loading from different task/architecture; not ok if you expect identical arch.
- MISSING  :those params were newly initialized because missing from the checkpoint. Consider training on your downst
starting distilbert v3 training...
```

[350/350 54:14, Epoch 5/5]

Epoch	Training Loss	Validation Loss
1	0.497990	0.138706
2	0.128608	0.101452
3	0.086107	0.098404
4	0.084529	0.105449
5	0.069774	0.104834

```
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  3.29it/s]
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  3.77it/s]
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  3.88it/s]
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  3.86it/s]
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  3.70it/s]
There were missing keys in the checkpoint model loaded: ['distilbert.embeddings.LayerNorm.weight', 'distilbert.embedd
There were unexpected keys in the checkpoint model loaded: ['distilbert.embeddings.LayerNorm.beta', 'distilbert.embed
--- evaluating DistilBERT_v3 ---

final results (DistilBERT):
```

	Model	F1 Score	Recall	Precision	Accuracy
0	DistilBERT_v2	0.806	0.8295	0.7839	0.9605

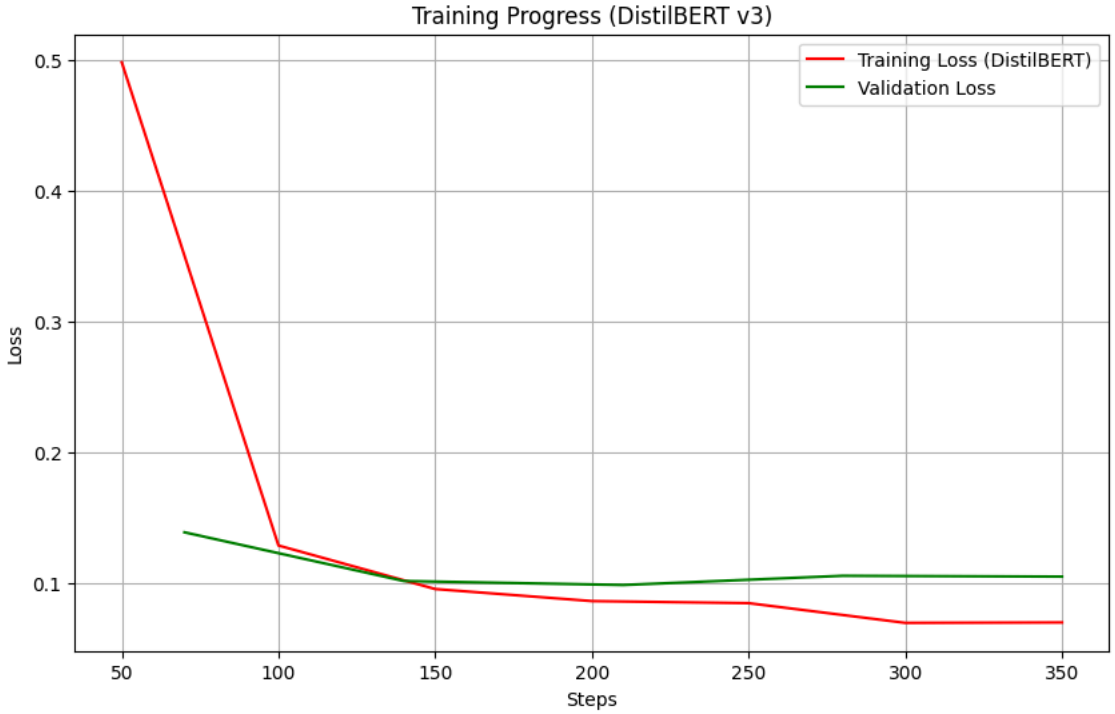
```
print("\n final results (DistilBERT):")
display(pd.DataFrame([metrics_db_v3]).round(4))
```

```
 final results (DistilBERT):
```

	Model	F1 Score	Recall	Precision	Accuracy
0	DistilBERT_v3	0.8071	0.8384	0.778	0.9626

```
# saving and plotting
import matplotlib.pyplot as plt
import json
import os

output_dir="./distilbert_output_fine-tuned_v3"
save_and_visualize_training(db_trainer_v3, distil_tokenizer, metrics_db_v3, output_dir)
```

```
saving model to ./distilbert_output_fine-tuned_v3...
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  2.73it/s]
```



Observations:

8. ALBERT finetuning (Sayeed)

```
# ALBERT Finetuning (Sayeed)
```

```
# using the shared dataframes (df_train etc) loaded at the top of the notebook
# converting them to hf dataset format and applying the alignment fix
print("prepping data for ALBERT...")
'''This is the same tokenization and alignment function we used for legal-bert, but with the ALBERT tokenizer instea
The logic is the same: we use offset mapping to align the character-level entity mentions with the token-level input
This ensures that the labels are correctly assigned to the tokens.
The only difference is that we are using the ALBERT tokenizer instead of the legal-bert tokenizer, but the underlyin
'''
tokenizer_albert = AutoTokenizer.from_pretrained("albert-base-v2", use_fast=True)
tokenized_datasets = raw_datasets.map(
    partial(tokenize_and_align_labels, tokenizer=tokenizer_albert),
    batched=True,
    remove_columns=raw_datasets["train"].column_names
)
print("done. tokens aligned.")
```

```
prepping data for ALBERT...
Map: 100%|██████████| 1112/1112 [00:02<00:00, 406.38 examples/s]
Map: 100%|██████████| 541/541 [00:00<00:00, 595.72 examples/s]
Map: 100%|██████████| 555/555 [00:00<00:00, 579.72 examples/s]done. tokens aligned.
```

```
import torch
'''This is a simple sanity check function to ensure that our model can perform a forward pass without errors.
It takes a few samples from the dataset, converts them to tensors, and passes them through the model to check if the
This is important to catch any issues with the data preprocessing, tokenization, or model architecture before traini
'''
def sanity_forward_pass(model, dataset, n=2):
    model = model.to("cpu")
    model.train()

    batch = {
        "input_ids": torch.tensor([dataset[i]["input_ids"] for i in range(n)], device="cpu"),
        "attention_mask": torch.tensor([dataset[i]["attention_mask"] for i in range(n)], device="cpu"),
```

```
        "labels": torch.tensor([dataset[i]["labels"] for i in range(n)], device="cpu"),
    }

    out = model(**batch)
    print("Forward OK. Loss:", float(out.loss))

sanity_forward_pass(model, tokenized_datasets["train"], n=2)
```

```
Forward OK. Loss: 2.0854053497314453
/tmp/ipykernel_9036/1652176267.py:14: UserWarning: Converting a tensor with requires_grad=True to a scalar may lead t
Consider using tensor.detach() first. (Triggered internally at /pytorch/torch/csrc/autograd/generated/python_variable
  print("Forward OK. Loss:", float(out.loss))
```

```
import os
'''
Imports key Hugging Face Transformers utilities for token classification:
- AutoModelForTokenClassification: pretrained models for token-level tagging.
- TrainingArguments: configuration for training/evaluation.
- Trainer: high-level training loop API.
- DataCollatorForTokenClassification: dynamic padding and label alignment.
- EarlyStoppingCallback: halts training when metrics stop improving.
'''
from transformers import (
    AutoModelForTokenClassification,
    TrainingArguments,
    Trainer,
    DataCollatorForTokenClassification,
    EarlyStoppingCallback
)

"""
Initializes an ALBERT token-classification model for NER using the pretrained
`albert-base-v2` checkpoint and configures label mappings for the dataset.

Args:
    num_labels (int): Number of NER labels.
    id2label (dict): Mapping from label IDs to label strings.
    label2id (dict): Mapping from label strings to label IDs.

Returns:
    transformers.AutoModelForTokenClassification: Configured ALBERT model.
"""
model = AutoModelForTokenClassification.from_pretrained(
    "albert-base-v2",
    num_labels=len(label_list),
    id2label=id2label,
    label2id=label2id
)

"""
TrainingArguments for ALBERT NER fine-tuning.

Args:
    output_dir (str): Directory to save model checkpoints and outputs.
    eval_strategy (str): Evaluation frequency (e.g., "epoch").
    save_strategy (str): Checkpoint saving frequency (e.g., "epoch").
    load_best_model_at_end (bool): Whether to load the best model at the end of training.
    metric_for_best_model (str): Metric to use for selecting the best model (e.g., "eval_loss").
    greater_is_better (bool): Whether a higher metric value is better (False for loss).
    learning_rate (float): Learning rate for optimizer.
    warmup_ratio (float): Fraction of total steps for learning rate warmup.
    per_device_train_batch_size (int): Batch size per device during training.
    per_device_eval_batch_size (int): Batch size per device during evaluation.
    num_train_epochs (int): Total number of training epochs.
    weight_decay (float): Weight decay for optimizer.
    logging_strategy (str): Logging frequency (e.g., "steps").
    logging_steps (int): Number of steps between logging.
    save_total_limit (int): Maximum number of checkpoints to keep.
    report_to (str): Reporting integration (e.g., "none" for no reporting).

This configuration enables checkpointing, early stopping, and best model selection for robust ALBERT NER training.
"""
args = TrainingArguments(
    output_dir="albert-ner",
    eval_strategy="epoch",
```

```
    save_strategy="epoch",             # must save checkpoints for early stopping / best model
    load_best_model_at_end=True,
    metric_for_best_model="eval_loss",
    greater_is_better=False,

    learning_rate=2e-5,
    warmup_ratio=0.1,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    num_train_epochs=10,               # allow early stopping to stop early
    weight_decay=0.01,

    logging_strategy="steps",
    logging_steps=50,

    save_total_limit=2,
    report_to="none"
)

"""
Initializes a Hugging Face Trainer for fine-tuning a token classification model (e.g., ALBERT) on a NER task.

Args:
    model (PreTrainedModel): The model to train (e.g., ALBERT for token classification).
    args (TrainingArguments): Training configuration, including hyperparameters, output directory, etc.
    train_dataset (Dataset): The tokenized training dataset.
    eval_dataset (Dataset): The tokenized validation dataset for evaluation during training.
    data_collator (DataCollatorForTokenClassification): Handles dynamic padding and batching for token classificatio
    callbacks (list): List of TrainerCallback objects, e.g., EarlyStoppingCallback for early stopping based on valid

Returns:
    Trainer: A configured Trainer object ready for training and evaluation.
"""
trainer = Trainer(
    model=model,
    args=args,
    train_dataset=tokenized_datasets["train"],
    eval_dataset=tokenized_datasets["validation"],
    data_collator=DataCollatorForTokenClassification(tokenizer_albert),
    callbacks=[EarlyStoppingCallback(early_stopping_patience=2)]
)

"""
Trains the ALBERT model using the Hugging Face Trainer, saves the best checkpoint, and evaluates the model on the te

Workflow:
1. Starts the training process and prints progress.
2. Prints the path to the best model checkpoint found during training.
3. Saves the best model and tokenizer to a specified directory.
4. Evaluates the trained model on the test dataset using the provided evaluation function.
5. Displays the evaluation metrics in a formatted DataFrame.

Args:
    trainer (Trainer): Hugging Face Trainer object configured for ALBERT fine-tuning.
    args (TrainingArguments): Training arguments containing output directory information.
    tokenizer_albert (PreTrainedTokenizer): Tokenizer used for ALBERT.
    tokenized_datasets (DatasetDict): Tokenized Hugging Face datasets with train/validation/test splits.
    evaluate_model_performance (function): Function to compute evaluation metrics.
    pd (module): pandas module for displaying results.

Returns:
    None. Prints training progress, saves the best model, and displays evaluation metrics.
"""
print("starting training...")
trainer.train()

print("Best checkpoint:", trainer.state.best_model_checkpoint)


best_dir = os.path.join(args.output_dir, "best_model")
trainer.save_model(best_dir)
tokenizer_albert.save_pretrained(best_dir)
print("Saved best model to:", best_dir)


metrics_albert = evaluate_model_performance(
    trainer,
```

```
    tokenized_datasets["test"],
    model_name="ALBERT (Fine-tuned)"
)

print("\nfinal results:")
display(pd.DataFrame([metrics_albert]).round(4))
```

```
Loading weights: 100%|██████████| 23/23 [00:00<00:00, 630.37it/s, Materializing param=albert.encoder.embedding_hidden
AlbertForTokenClassification LOAD REPORT from: albert-base-v2
Key                           | Status     |
------------------------------+------------+-
predictions.LayerNorm.bias    | UNEXPECTED |
predictions.dense.weight      | UNEXPECTED |
predictions.decoder.bias      | UNEXPECTED |
predictions.dense.bias        | UNEXPECTED |
albert.pooler.bias            | UNEXPECTED |
predictions.bias              | UNEXPECTED |
albert.pooler.weight          | UNEXPECTED |
predictions.LayerNorm.weight  | UNEXPECTED |
classifier.bias               | MISSING    |
classifier.weight             | MISSING    |

Notes:
- UNEXPECTED   :can be ignored when loading from different task/architecture; not ok if you expect identical arch.
- MISSING  :those params were newly initialized because missing from the checkpoint. Consider training on your downst
warmup_ratio is deprecated and will be removed in v5.2. Use `warmup_steps` instead.
starting training...
```

[350/700 1:36:15 < 1:36:49, 0.06 it/s, Epoch 5/10]

Epoch	Training Loss	Validation Loss
1	0.950470	0.134053
2	0.125220	0.092737
3	0.080617	0.091702
4	0.080936	0.097672
5	0.062784	0.095690

```
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  7.08it/s]
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  9.01it/s]
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  7.16it/s]
Writing model shards: 100%|██████████| 1/1 [00:00<00:00, 11.82it/s]
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  8.36it/s]
There were missing keys in the checkpoint model loaded: ['albert.embeddings.LayerNorm.weight', 'albert.embeddings.Lay
There were unexpected keys in the checkpoint model loaded: ['albert.embeddings.LayerNorm.beta', 'albert.embeddings.La
Best checkpoint: albert-ner/checkpoint-210
Writing model shards: 100%|██████████| 1/1 [00:00<00:00,  3.28it/s]
Saved best model to: albert-ner/best_model
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[5], line 63
     59 tokenizer_albert.save_pretrained(best_dir)
     60 print("Saved best model to:", best_dir)
---> 63 metrics_albert = evaluate_model_performance(
     64     trainer,
     65     tokenized_datasets["test"],
     66     model_name="ALBERT (Fine-tuned)"
     67 )
     69 print("\nfinal results:")
     70 display(pd.DataFrame([metrics_albert]).round(4))

NameError: name 'evaluate_model_performance' is not defined
```

```
import numpy as np

def evaluate_model_performance(trainer, eval_dataset, label_list, metric, model_name="MyModel"):
    """
    Evaluates a token classification model (e.g., NER) using a Hugging Face Trainer.

    Args:
        trainer (Trainer): Hugging Face Trainer object with the trained model.
        eval_dataset (Dataset): Tokenized evaluation dataset.
        label_list (list): List mapping label IDs to label names.
        metric (evaluate.EvaluationModule): Metric object (e.g., seqeval) for computing NER scores.
        model_name (str, optional): Name of the model for reporting. Defaults to "MyModel".

    Returns:
```

```
        dict: Dictionary containing model name, F1 score, recall, precision, and accuracy.
    """
    print(f"--- evaluating {model_name} ---")

    predictions, labels, _ = trainer.predict(eval_dataset)
    predictions = np.argmax(predictions, axis=2)

    true_predictions = [
        [label_list[p] for (p, l) in zip(prediction, label) if l != -100]
        for prediction, label in zip(predictions, labels)
    ]
    true_labels = [
        [label_list[l] for (p, l) in zip(prediction, label) if l != -100]
        for prediction, label in zip(predictions, labels)
    ]

    results = metric.compute(predictions=true_predictions, references=true_labels)

    return {
        "Model": model_name,
        "F1 Score": results["overall_f1"],
        "Recall": results["overall_recall"],
        "Precision": results["overall_precision"],
        "Accuracy": results["overall_accuracy"],
    }
```

```
"""
Evaluates the fine-tuned ALBERT model on the test dataset using the provided evaluation function.

Args:
    trainer (Trainer): Hugging Face Trainer object with the trained ALBERT model.
    eval_dataset (Dataset): Tokenized Hugging Face test dataset.
    label_list (list): List of label names corresponding to label IDs.
    metric (evaluate.EvaluationModule): Metric object (e.g., seqeval) for NER evaluation.
    model_name (str): Name to display for the evaluated model.

Returns:
    metrics_albert (dict): Dictionary containing evaluation metrics (F1 Score, Recall, Precision, Accuracy) for the

Displays:
    A pandas DataFrame with the evaluation metrics, rounded to 4 decimal places.
"""

metrics_albert = evaluate_model_performance(
    trainer=trainer,
    eval_dataset=tokenized_datasets["test"],
    label_list=label_list,
    metric=metric,
    model_name="ALBERT (Fine-tuned)"
)

print("\nfinal results:")
display(pd.DataFrame([metrics_albert]).round(4))
```

```
--- evaluating ALBERT (Fine-tuned) ---

final results:
```