ShritejShrikant_Chavan_HW6c

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0.1 Setup Environment and Install Libraries

[1]:
```
# CHANGE FOLDERS AS PER YOUR SETUP
from pathlib import Path
if 'google.colab' in str(get_ipython()):
    from google.colab import drive
    drive.mount("/content/drive")
    !pip install datasets transformers evaluate wandb accelerate seqeval -U -qq
    base_folder = Path("/content/drive/MyDrive/NLP")
else:
    base_folder = Path("/home/harpreet/Insync/google_drive_shaannoor/data")


from transformers import AutoConfig, AutoModelForTokenClassification,␣
↪AutoTokenizer, Trainer, TrainingArguments
from transformers import AutoTokenizer, DataCollatorForTokenClassification,␣
↪pipeline
from datasets import load_dataset, DatasetDict, Dataset, ClassLabel, Sequence
import evaluate


import wandb

import numpy as np
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
import torch
import gc

import textwrap
```

```
Mounted at /content/drive
                                        493.7/493.7
kB 7.5 MB/s eta 0:00:00
```

```
                           7.9/7.9 MB
20.2 MB/s eta 0:00:00
                           84.1/84.1 kB
12.5 MB/s eta 0:00:00
                           2.1/2.1 MB
55.8 MB/s eta 0:00:00
                           261.4/261.4

kB 28.7 MB/s eta 0:00:00
                           43.6/43.6 kB
5.7 MB/s eta 0:00:00
  Preparing metadata (setup.py) … done
                           115.3/115.3

kB 14.7 MB/s eta 0:00:00
                           134.8/134.8

kB 18.4 MB/s eta 0:00:00
                           302.0/302.0

kB 33.9 MB/s eta 0:00:00
                           3.8/3.8 MB
71.9 MB/s eta 0:00:00
                           1.3/1.3 MB
75.8 MB/s eta 0:00:00
                           190.6/190.6

kB 26.4 MB/s eta 0:00:00
                           243.9/243.9

kB 29.5 MB/s eta 0:00:00
  Preparing metadata (setup.py) … done
                           62.7/62.7 kB
9.1 MB/s eta 0:00:00
                           295.0/295.0

kB 35.2 MB/s eta 0:00:00
  Building wheel for seqeval (setup.py) … done
  Building wheel for pathtools (setup.py) … done
```

0.2 Specify Model & Data Path

[2]:
```python
# CHANGE FOLDERS TO WHERE YOU WANT TO SAVE DATA AND MODELS
data_folder = base_folder/'datasets/brown_corpus'
model_folder = base_folder/'models/nlp_spring_2023/ner'
model_folder.mkdir(exist_ok=True)
data_folder.mkdir(exist_ok=True)
```

0.3 Create Functions

[3]:
```
def print_wrap(text, d):
    # If the text is a list, convert it to a string
    if isinstance(text, list):
        # Convert None values to a default string (e.g., "None" or an empty␣
↪string)
        text = ' '.join(str(item) if item is not None else "None" for item in␣
↪text)

    # Wrap the text to limit the width to 'd'
    wrapped_text = textwrap.fill(text, width=d)

    # Print the wrapped text
    print(wrapped_text)
```

0.3.1 Load and Split Dataset

[4]:
```
def split_dataset(data = 'conll2003', train = 5000, val_test = 1000):
    conll_dataset = load_dataset(data)

    train_split_small = conll_dataset['train'].shuffle(seed=42).
↪select(range(train))
    val_split_small = conll_dataset['validation'].shuffle(seed=42).
↪select(range(val_test))
    test_split_small = conll_dataset['test'].shuffle(seed=42).
↪select(range(val_test))

    # combine train, val splits into one dataset
    train_val_subset = DatasetDict({'train': train_split_small, 'val':␣
↪val_split_small})

    # create test dataset from test split
    test_subset = DatasetDict({'test': test_split_small})

    class_names = conll_dataset['train'].features['ner_tags'].feature.names

    return train_val_subset, test_subset, class_names
```

0.3.2 Create function for Tokenizer

[5]:
```
def align_targets(labels, word_ids):

    aligned_labels = []

    previous_word_id = None

```

```
    b2i = {1:2, 3:4, 5:6, 7:8}

    for w in word_ids:

        if w is None:

            label = -100
        elif w != previous_word_id:
            label = labels[w]

        else:
            label = labels[w]

            if label in b2i:
                label = b2i[label]


        aligned_labels.append(label)

        previous_word_id = w

    return aligned_labels



# CODE HERE
```

0.3.3 Function for Tokenization

[6]:
```
def get_tokenized_dataset(checkpoint, dataset):
    tokenizer = AutoTokenizer.from_pretrained(checkpoint)

    def tokenize_fn(batch):
        """
        Tokenizes a batch of sequences and aligns the target labels with the␣
 ↪tokenized outputs.

        Args:
        - batch (dict): A dictionary containing:
            * 'tokens': A list of lists where each inner list contains tokens␣
 ↪of a sequence.
            * 'tags': A list of lists where each inner list contains POS tags␣
 ↪corresponding to the 'tokens'.

        Returns:
        - dict: A dictionary containing tokenized inputs and their␣
 ↪corresponding aligned labels.
```

```python
    """

    # Tokenize the 'tokens' from the batch. This returns various fields␣
↪like 'input_ids', 'attention_mask', etc.
    # 'is_split_into_words=True' indicates the input is already tokenized␣
↪into words.
    # 'truncation=True' ensures sequences longer than the model's max␣
↪length are truncated.
    tokenized_inputs = tokenizer(batch['tokens'], truncation=True,␣
↪is_split_into_words=True)

    # Extract the original labels/tags from the batch.
    labels_batch = batch['ner_tags']

    # This list will store the labels aligned with the tokenized input.
    aligned_labels_batch = []

    # Iterate over each example in the batch.
    for i, labels in enumerate(labels_batch):
        # Obtain the word IDs for the tokenized example. This helps in␣
↪aligning the original labels with the tokens.
        word_ids = tokenized_inputs.word_ids(i)

        # Align the original labels with the tokenized example and append␣
↪to the aligned_labels_batch list.
        aligned_labels_batch.append(align_targets(labels, word_ids))

    # The HuggingFace trainer expects the labels for token classification␣
↪tasks to be under the key 'labels'.
    # Store the aligned labels in the 'labels' key of the tokenized_inputs␣
↪dictionary.
    tokenized_inputs['labels'] = aligned_labels_batch

    return tokenized_inputs

  tokenized_dataset = dataset.map(tokenize_fn, batched=True)

  tokenized_dataset = tokenized_dataset.remove_columns(['tokens', 'ner_tags',␣
↪'pos_tags','chunk_tags', 'id'])

  tokenized_dataset.set_format(type='torch')

  return tokenized_dataset
```

0.3.4 Function to initialize model

[7]:
```
def initialize_model(checkpoint, class_names):
    config = AutoConfig.from_pretrained(checkpoint)
    id2label = {}
    for id_, label_ in enumerate(class_names):
        id2label[str(id_)] = label_

    label2id = {}
    for id_, label_ in enumerate(class_names):
        label2id[label_] = id_

    config.id2label = id2label
    config.label2id = label2id

    model = AutoModelForTokenClassification.from_pretrained(checkpoint,␣
↪config=config)

    return model, config
```

0.3.5 Function to compute metrics

[8]:
```
seqeval_metric = evaluate.load('seqeval')
def compute_metrics(logits_and_labels):
    """
    Compute sequence tagging metrics using the seqeval metric.

    Args:
    - logits_and_labels (tuple): A tuple containing model logits and true␣
↪labels.

    Returns:
    - dict: A dictionary containing precision, recall, f1-score, and accuracy.
    """

    # Separate logits and labels from the input tuple
    logits, true_labels = logits_and_labels

    # Obtain predicted label indices by selecting the label with the highest␣
↪logit value for each token
    predicted_indices = np.argmax(logits, axis=-1)  # Shape: (batch_size,␣
↪sequence_length)

    # Convert label indices to their string representation, ignoring special␣
↪tokens (label index = -100)
    string_true_labels = [[class_names[label_id] for label_id in sequence if␣
↪label_id != -100] for sequence in true_labels]
```

```
    # Convert predicted indices to their string representation, but only for␣
↪tokens where the true label isn't -100
    string_predictions = [
        [class_names[pred_id] for pred_id, true_label_id in zip(pred_sequence,␣
↪true_sequence) if true_label_id != -100]
        for pred_sequence, true_sequence in zip(predicted_indices, true_labels)
    ]

    # Compute the metrics using seqeval
    metrics_results = seqeval_metric.compute(predictions=string_predictions,␣
↪references=string_true_labels)

    return {
        'precision': metrics_results['overall_precision'],
        'recall': metrics_results['overall_recall'],
        'f1': metrics_results['overall_f1'],
        'accuracy': metrics_results['overall_accuracy']
    }

# CODE HERE
```

```
Downloading builder script:   0%|          | 0.00/6.34k [00:00<?, ?B/s]
```

0.3.6 Function to set Trainer

[9]:
```
def get_trainer(model, training_args, train_dataset, eval_dataset,␣
↪compute_metrics, tokenizer, data_collator):
    trainer = Trainer(
        model=model,
        args=training_args,
        train_dataset=train_dataset,
        eval_dataset=eval_dataset,
        compute_metrics=compute_metrics,
        tokenizer=tokenizer,
        data_collator= data_collator
    )
    return trainer
```

0.3.7 Plot Confusion Matrix

[10]:
```
def log_and_plot_confusion_matrix(trainer, tokenized_val_dataset, class_names):
    # Perform prediction using the trainer
    valid_output = trainer.predict(tokenized_val_dataset)

    # Convert the logits (raw prediction scores) from the valid_output object␣
↪into class predictions.
```

```python
    # For each input, pick the class with the highest logit as the predicted␣
↪class.
    # Also, extract the true label IDs from valid_output and store them as an␣
↪array for further analysis.
    valid_predictions = np.argmax(valid_output.predictions, axis=2)
    valid_labels = np.array(valid_output.label_ids)

    # 2. Filter out any tokens with label -100 (typically used for padding or␣
↪special tokens)
    mask = valid_labels != -100
    filtered_predictions = valid_predictions[mask]
    filtered_labels = valid_labels[mask]

        # log the Confusion Matrix to Wandb
    wandb.log({
        "conf_mat": wandb.plot.confusion_matrix(
            preds=filtered_predictions,        # Model's predicted class labels.
            y_true=filtered_labels,      # Actual labels from the validation␣
↪set.
            class_names=class_names   # Custom class names for display in the␣
↪confusion matrix.
        )
    })

    # Plot the confusion matrix using Matplotlib
    fig, ax = plt.subplots(figsize=(8, 6))
    ConfusionMatrixDisplay.from_predictions(
        y_true=filtered_labels,
        y_pred=filtered_predictions,
        ax=ax,
        normalize="true",
        display_labels=class_names,
        xticks_rotation=90
    )
    plt.show()
```

[11]:
```python
def free_memory():
    """
    Attempts to free up memory by deleting variables and running Python's␣
↪garbage collector.
    """
    gc.collect()
    for device_id in range(torch.cuda.device_count()):
        torch.cuda.set_device(device_id)
        torch.cuda.empty_cache()
    gc.collect()
```

0.3.8 Function to tokenize dataset and, train and eval models

[12]:
```
def tokenize_train_evaluate_log(training_args, checkpoint, base_folder,
                                class_names, train_val_subset, compute_metrics):
    # 1. Free memory
    free_memory()

    # 2. Setup wandb
    wandb.login()
    %env WANDB_PROJECT = nlp_course_fall_2023-HW6-PartC

    ######################## ALLOWED TO CHANGE THIS BLOCK␣
↪################################################

    # MAKE SURE THE BASE FOLDER IS SETUP CORRECTLY
    #  YOU CAN CHANGE THIS LINE IF YOU WANT TO SAVE IN A DIFFERENT FOLDER

    model_folder = base_folder / "models" / "nlp_spring_2023/ner"/checkpoint
    model_folder.mkdir(exist_ok=True, parents=True)

    ######################## ALLOWED TO CHANGE THIS BLOCK␣
↪################################################


    # 3. Get Tokenized Dataset and Data Collator
    train_val_tokenized_dataset = get_tokenized_dataset(checkpoint,␣
↪train_val_subset)

    # 4. Initialize Model and Tokenizer
    model, config = initialize_model(checkpoint, class_names)
    tokenizer = AutoTokenizer.from_pretrained(checkpoint)

    # 5. Initialize Trainer
    data_collator = DataCollatorForTokenClassification(tokenizer = tokenizer,
                                                       padding=True,
                                                       label_pad_token_id=-100,
                                                       return_tensors='pt') # CODE␣
↪HERE

    trainer = get_trainer(model, training_args,␣
↪train_val_tokenized_dataset['train'],
                          train_val_tokenized_dataset['val'], compute_metrics,␣
↪tokenizer, data_collator)

    # 6. Train and Evaluate
    trainer.train()
    trainer.evaluate(train_val_tokenized_dataset['val'])
```

```
    # 7. Log Metrics and Plot
    log_and_plot_confusion_matrix(trainer, train_val_tokenized_dataset['val'],␣
↪class_names)

    best_model_checkpoint_step = trainer.state.best_model_checkpoint.
↪split('-')[-1]
    wandb.log({"best_model_checkpoint_step": best_model_checkpoint_step})
    print(f"The best model was saved at step {best_model_checkpoint_step}.")

    wandb.finish()

    return best_model_checkpoint_step
```

0.4 Experiments

0.4.1 Experiment 1 - BERT base uncased and Choosing F1 as evaluation metric

[13]:
```
# Define the directory where model checkpoints will be saved
model_folder = base_folder / "models"/"nlp_spring_2023/ner"
# Create the directory if it doesn't exist
model_folder.mkdir(exist_ok=True, parents=True)

# Configure training parameters
training_args = TrainingArguments(
    # Training-specific configurations
    num_train_epochs=2,  # Total number of training epochs
    # Number of samples per training batch for each device
    per_device_train_batch_size=16,
    # Number of samples per evaluation batch for each device
    per_device_eval_batch_size=16,
    weight_decay=0.01,  # Apply L2 regularization to prevent overfitting
    learning_rate=2e-5,  # Step size for the optimizer during training
    optim='adamw_torch',  # Optimizer,

    # Checkpoint saving and model evaluation settings
    output_dir=str(model_folder),  # Directory to save model checkpoints
    evaluation_strategy='steps',  # Evaluate model at specified step intervals
    eval_steps=20,  # Perform evaluation every 10 training steps
    save_strategy="steps",  # Save model checkpoint at specified step intervals
    save_steps=20,  # Save a model checkpoint every 10 training steps
    load_best_model_at_end=True,  # Reload the best model at the end of training
    save_total_limit=2,  # Retain only the best and the most recent model␣
↪checkpoints
    # Use 'accuracy' as the metric to determine the best model
    metric_for_best_model="f1",
    greater_is_better=True,  # A model is 'better' if its accuracy is higher
```

```
    # Experiment logging configurations (commented out in this example)
    logging_strategy='steps',
    logging_steps=20,
    report_to='wandb',  # Log metrics and results to Weights & Biases platform
    run_name= 'ner_exp1',  # Experiment name for Weights & Biases
)
```

[14]:
```
train_val_subset, test_subset, class_names = split_dataset()
```

```
Downloading builder script:   0%|          | 0.00/9.57k [00:00<?, ?B/s]

Downloading metadata:   0%|          | 0.00/3.73k [00:00<?, ?B/s]

Downloading readme:   0%|          | 0.00/12.3k [00:00<?, ?B/s]

Downloading data:   0%|          | 0.00/983k [00:00<?, ?B/s]

Generating train split:   0%|          | 0/14041 [00:00<?, ? examples/s]

Generating validation split:   0%|          | 0/3250 [00:00<?, ? examples/s]

Generating test split:   0%|          | 0/3453 [00:00<?, ? examples/s]
```

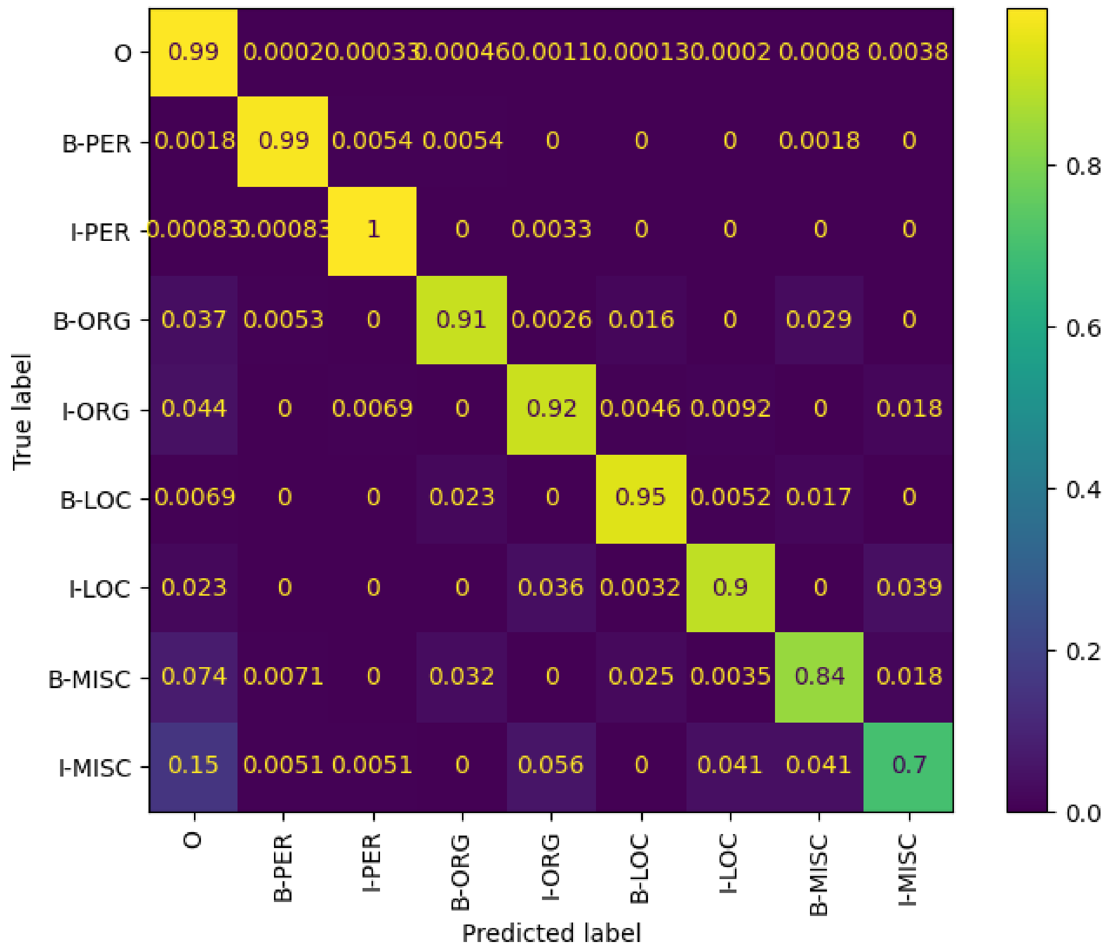
[15]:
```
checkpoint = 'bert-base-uncased' # CODE HERE
training_args_dict = training_args.to_dict() # Convert TrainingArguments to␣
 ↪dictionary
training_args_dict['run_name'] = f'{checkpoint}' # Update the run_name
new_training_args = TrainingArguments(**training_args_dict)
```

```
/usr/local/lib/python3.10/dist-packages/transformers/training_args.py:1697:
FutureWarning: `--push_to_hub_token` is deprecated and will be removed in
version 5 of  Transformers. Use `--hub_token` instead.
  warnings.warn(
```

[16]:
```
best_model = tokenize_train_evaluate_log(training_args= new_training_args,␣
 ↪checkpoint=checkpoint, base_folder=base_folder,
                             class_names=class_names,␣
 ↪train_val_subset=train_val_subset,
                             compute_metrics=compute_metrics)
```

```
<IPython.core.display.Javascript object>

wandb: Appending key for api.wandb.ai to your netrc file:
/root/.netrc

env: WANDB_PROJECT=nlp_course_fall_2023-HW6-PartC

Downloading (…)okenizer_config.json:   0%|          | 0.00/28.0 [00:00<?, ?B/s]

Downloading (…)lve/main/config.json:   0%|          | 0.00/570 [00:00<?, ?B/s]
```

```
Downloading (…)solve/main/vocab.txt:   0%|          | 0.00/232k [00:00<?, ?B/s]

Downloading (…)/main/tokenizer.json:   0%|          | 0.00/466k [00:00<?, ?B/s]

Map:   0%|          | 0/5000 [00:00<?, ? examples/s]

Map:   0%|          | 0/1000 [00:00<?, ? examples/s]

Downloading model.safetensors:   0%|          | 0.00/440M [00:00<?, ?B/s]

Some weights of BertForTokenClassification were not initialized from the model
checkpoint at bert-base-uncased and are newly initialized: ['classifier.weight',
'classifier.bias']
You should probably TRAIN this model on a down-stream task to be able to use it
for predictions and inference.

<IPython.core.display.HTML object>

wandb: Currently logged in as: shritej24c
(redeem_team). Use `wandb login --relogin` to force relogin

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

You're using a BertTokenizerFast tokenizer. Please note that with a fast
tokenizer, using the `__call__` method is faster than using a method to encode
the text followed by a call to the `pad` method to get a padded encoding.

<IPython.core.display.HTML object>

/usr/local/lib/python3.10/dist-packages/seqeval/metrics/v1.py:57:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/seqeval/metrics/v1.py:57:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 due to no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, msg_start, len(result))

<IPython.core.display.HTML object>
```



<IPython.core.display.HTML object>

The best model was saved at step 480.

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

[18]:
```
from transformers import AutoModelForTokenClassification, AutoTokenizer


test_subset_tokenized = get_tokenized_dataset(checkpoint, test_subset)

tokenizer = AutoTokenizer.from_pretrained(checkpoint)

# 5. Initialize Trainer
data_collator = DataCollatorForTokenClassification(tokenizer = tokenizer,
```

```
                                                  padding=True,
                                                  label_pad_token_id=-100,
                                                  return_tensors='pt') # CODE HERE


checkpoint = str(model_folder / "checkpoint-{}".format(best_model))


tokenizer = AutoTokenizer.from_pretrained(checkpoint)
model = AutoModelForTokenClassification.from_pretrained(checkpoint)

from transformers import TrainingArguments

training_args = TrainingArguments(
    output_dir="./results",
    per_device_eval_batch_size=16,  # adjust based on your GPU memory
    do_train = False,
    do_eval=True,
    report_to=[]  # disable logging
)



trainer = Trainer(
    model=model,
    args=training_args,
    eval_dataset=test_subset_tokenized['test'],  # Make sure this dataset is␣
 ↪tokenized!
    tokenizer=tokenizer,
    data_collator=data_collator,
    compute_metrics=compute_metrics,
)

results = trainer.evaluate()
```

```
You're using a BertTokenizerFast tokenizer. Please note that with a fast
tokenizer, using the `__call__` method is faster than using a method to encode
the text followed by a call to the `pad` method to get a padded encoding.
```

```
<IPython.core.display.HTML object>
```

[19]:
```
results
```

[19]:
```
{'eval_loss': 0.11766493320465088,
 'eval_precision': 0.836027713625866,
 'eval_recall': 0.8850855745721271,
 'eval_f1': 0.8598574821852731,
 'eval_accuracy': 0.9703125,
```

```
 'eval_runtime': 1.5092,
 'eval_samples_per_second': 662.598,
 'eval_steps_per_second': 41.744}
```

0.4.2 Experiment 2 - Changing Subset of the training Data from 5k to 10k and val & test from 1k to 2k & Choosing F1 as evaluation metric

[20]:
```
# Define the directory where model checkpoints will be saved
model_folder = base_folder / "models"/"nlp_spring_2023/ner"
# Create the directory if it doesn't exist
model_folder.mkdir(exist_ok=True, parents=True)

# Configure training parameters
training_args = TrainingArguments(
    # Training-specific configurations
    num_train_epochs=2,  # Total number of training epochs
    # Number of samples per training batch for each device
    per_device_train_batch_size=16,
    # Number of samples per evaluation batch for each device
    per_device_eval_batch_size=16,
    weight_decay=0.01,  # Apply L2 regularization to prevent overfitting
    learning_rate=2e-5,  # Step size for the optimizer during training
    optim='adamw_torch',  # Optimizer,

    # Checkpoint saving and model evaluation settings
    output_dir=str(model_folder),  # Directory to save model checkpoints
    evaluation_strategy='steps',  # Evaluate model at specified step intervals
    eval_steps=20,  # Perform evaluation every 10 training steps
    save_strategy="steps",  # Save model checkpoint at specified step intervals
    save_steps=20,  # Save a model checkpoint every 10 training steps
    load_best_model_at_end=True,  # Reload the best model at the end of training
    save_total_limit=2,  # Retain only the best and the most recent model␣
 ↪checkpoints
    # Use 'accuracy' as the metric to determine the best model
    metric_for_best_model="f1",
    greater_is_better=True,  # A model is 'better' if its accuracy is higher


    # Experiment logging configurations (commented out in this example)
    logging_strategy='steps',
    logging_steps=20,
    report_to='wandb',  # Log metrics and results to Weights & Biases platform
    run_name= 'ner_exp1',  # Experiment name for Weights & Biases
)
```

[21]:
```
train_val_subset, test_subset, class_names = split_dataset(train = 10000,␣
 ↪val_test = 2000)
```

[22]:
```
checkpoint = 'distilbert-base-uncased' # CODE HERE
training_args_dict = training_args.to_dict() # Convert TrainingArguments to␣
↪dictionary
training_args_dict['run_name'] = f'{checkpoint}' # Update the run_name
new_training_args = TrainingArguments(**training_args_dict)
```

```
/usr/local/lib/python3.10/dist-packages/transformers/training_args.py:1697:
FutureWarning: `--push_to_hub_token` is deprecated and will be removed in
version 5 of  Transformers. Use `--hub_token` instead.
  warnings.warn(
```

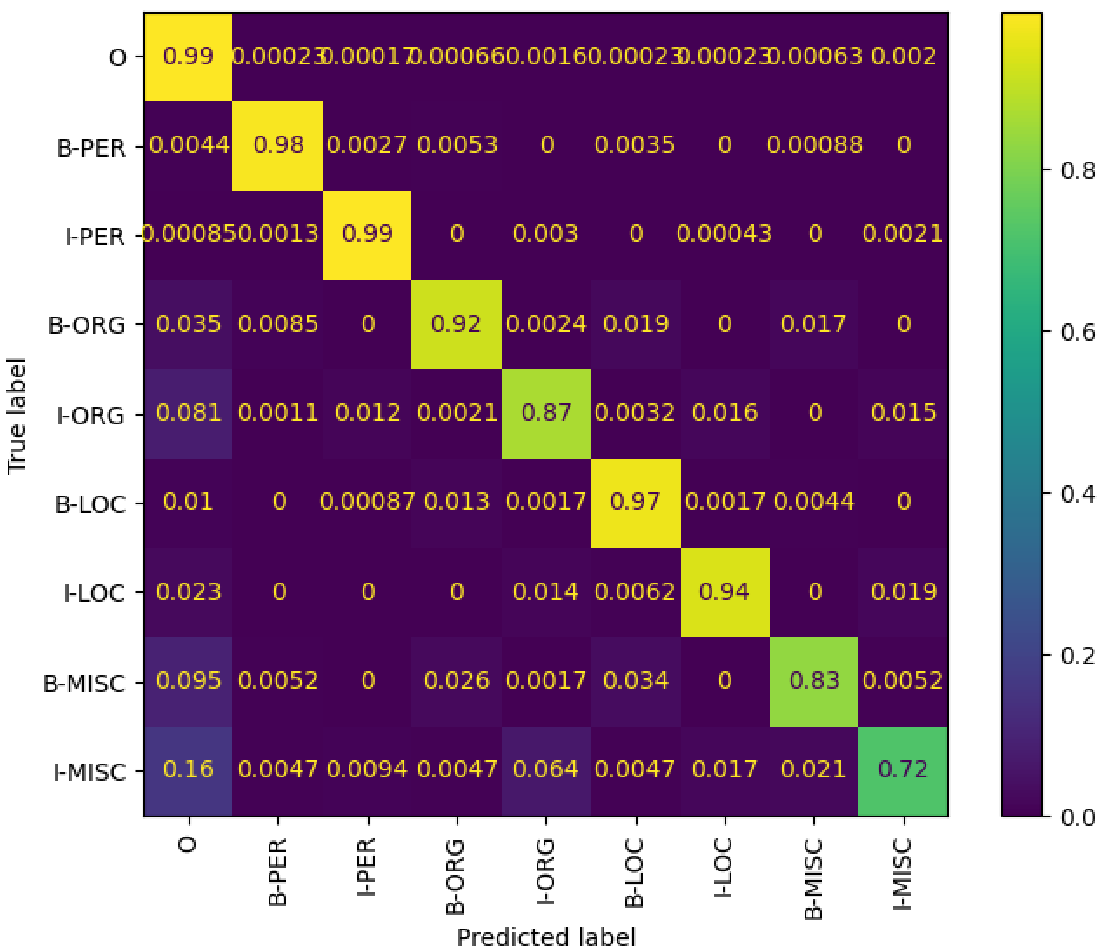
[23]:
```
best_model = tokenize_train_evaluate_log(training_args= new_training_args,␣
↪checkpoint=checkpoint, base_folder=base_folder,
                              class_names=class_names,␣
↪train_val_subset=train_val_subset,
                              compute_metrics=compute_metrics)
```

```
env: WANDB_PROJECT=nlp_course_fall_2023-HW6-PartC

Downloading (…)okenizer_config.json:   0%|          | 0.00/28.0 [00:00<?, ?B/s]

Downloading (…)lve/main/config.json:   0%|          | 0.00/483 [00:00<?, ?B/s]

Downloading (…)solve/main/vocab.txt:   0%|          | 0.00/232k [00:00<?, ?B/s]

Downloading (…)/main/tokenizer.json:   0%|          | 0.00/466k [00:00<?, ?B/s]

Map:   0%|          | 0/10000 [00:00<?, ? examples/s]

Map:   0%|          | 0/2000 [00:00<?, ? examples/s]

Downloading model.safetensors:   0%|          | 0.00/268M [00:00<?, ?B/s]

Some weights of DistilBertForTokenClassification were not initialized from the
model checkpoint at distilbert-base-uncased and are newly initialized:
['classifier.weight', 'classifier.bias']
You should probably TRAIN this model on a down-stream task to be able to use it
for predictions and inference.

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

You're using a DistilBertTokenizerFast tokenizer. Please note that with a fast
tokenizer, using the `__call__` method is faster than using a method to encode
the text followed by a call to the `pad` method to get a padded encoding.
```

```
<IPython.core.display.HTML object>
```

```
/usr/local/lib/python3.10/dist-packages/seqeval/metrics/v1.py:57:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/seqeval/metrics/v1.py:57:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 due to no predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/seqeval/metrics/v1.py:57:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
<IPython.core.display.HTML object>
```



```
The best model was saved at step 1000.
```

```
<IPython.core.display.HTML object>
```

```
VBox(children=(Label(value='0.006 MB of 0.006 MB uploaded (0.000 MB␣
↪deduped)\r'), FloatProgress(value=1.0, max…
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.HTML object>
```

[24]:

```
tokenizer = AutoTokenizer.from_pretrained(checkpoint)

# 5. Initialize Trainer
data_collator = DataCollatorForTokenClassification(tokenizer = tokenizer,
                                                   padding=True,
                                                   label_pad_token_id=-100,
                                                   return_tensors='pt') # CODE HERE


checkpoint = str(model_folder / "checkpoint-{}".format(best_model))


tokenizer = AutoTokenizer.from_pretrained(checkpoint)
model = AutoModelForTokenClassification.from_pretrained(checkpoint)

from transformers import TrainingArguments

training_args = TrainingArguments(
    output_dir="./results",
    per_device_eval_batch_size=16,  # adjust based on your GPU memory
    do_train = False,
    do_eval=True,
    report_to=[]  # disable logging
)



trainer = Trainer(
    model=model,
    args=training_args,
    eval_dataset=test_subset_tokenized['test'],  # Make sure this dataset is␣
↪tokenized!
    tokenizer=tokenizer,
    data_collator=data_collator,
    compute_metrics=compute_metrics,
```

```
)

results = trainer.evaluate()

results
```

```
You're using a DistilBertTokenizerFast tokenizer. Please note that with a fast
tokenizer, using the `__call__` method is faster than using a method to encode
the text followed by a call to the `pad` method to get a padded encoding.
```

```
<IPython.core.display.HTML object>
```

[24]:
```
{'eval_loss': 0.10696234554052353,
 'eval_precision': 0.8479154433352907,
 'eval_recall': 0.882640586797066,
 'eval_f1': 0.8649296196466009,
 'eval_accuracy': 0.9718149038461539,
 'eval_runtime': 1.1845,
 'eval_samples_per_second': 844.219,
 'eval_steps_per_second': 53.186}
```

For NER classification I have tried 2 experiments

1. Using more complex model BERT over DistillBERT and changing the evaluation metric to F1 and got Test F1-score = 0.85986 and Accuracy = 0.9703 over the previous model of DistillBERT F1-score = 0.8319 and Accuracy = 0.9651
2. Here I used the 2x the subset of the data than our previous model and used F-1 evaluation metric and got Evaluation F1-score = 0.86493 and Accuracy = 0.97181 over the previous model of DistillBERT and lesser subset of data with F1-score = 0.8319 and Accuracy = 0.9651

We can conclude that using larger model, proper metric and more data will definitely yeild better results on Test Data set

[ ]:
```

```