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November 18, 2023

1 HW7_Handling_Longer_Sequences_Class_Imbalance: 20 Points

Homework 7 Instructions In this assignment, you'll work with the StackExchange dataset from HW5, focusing on `basic_cleaned_text` and `Tag_Number_final`. Changes from HW5 1. Data Filtering: Select rows from `basic_cleaned_text` with a word count > 400 (about 4000 samples). 2. Custom Collate Function: Develop a function for handling longer sequences. Break the document into smaller chunks (sub-parts). 3. Subclass Trainer: - Modify the `custom_loss` function for longer sequences and class imbalance. - For calculating loss, take the log probabilities for each chunk and average them to get document-level log probabilities, which should be used in your loss function. 4. Aggregation Function: Create a function for aggregating predictions. - Similar to the loss function, make predictions based on aggregated log probabilities from chunks. 5. Evaluation Method: With the implementation of chunking, Trainer.Predict will become incompatible. Write your own function for evaluations. Reference Files: Use `2_MultiClass_imbalanced_custom_Trainer.ipynb` and `4_imdb_bert_longer_seq_sliding_window_detailed.ipynb` from the `Final_files` in Lecture 10 folder.

[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 -U -qq
    base_folder = Path("/content/drive/MyDrive/NLP")
else:
    base_folder = Path("/home/harpreet/Insync/google_drive_shaannoor/data")


from transformers import AutoConfig, AutoModelForSequenceClassification,␣
↪AutoTokenizer, Trainer, TrainingArguments
from transformers import AutoTokenizer, DataCollatorWithPadding, pipeline
from datasets import load_dataset, DatasetDict, Dataset, ClassLabel
import evaluate

from collections import Counter
import torch
from torch.utils.data import DataLoader
```

```python
from scipy.special import softmax
from scipy.special import logsumexp

import wandb
import pandas as pd

# import functional from torch as F
import torch.nn.functional as F
from functools import partial
import gc


import numpy as np
from sklearn.metrics import ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import random

import textwrap
```

```
Mounted at /content/drive
                              521.2/521.2

kB 8.0 MB/s eta 0:00:00
                              84.1/84.1 kB
14.4 MB/s eta 0:00:00
                              2.1/2.1 MB
53.1 MB/s eta 0:00:00
                              261.4/261.4

kB 39.7 MB/s eta 0:00:00
                              115.3/115.3

kB 18.9 MB/s eta 0:00:00
                              134.8/134.8

kB 22.0 MB/s eta 0:00:00
                              190.6/190.6

kB 25.9 MB/s eta 0:00:00
                              248.6/248.6

kB 34.2 MB/s eta 0:00:00
                              62.7/62.7 kB
9.9 MB/s eta 0:00:00
```

[2]:
```python
# CHANGE FOLDERS TO WHERE YOU WANT TO SAVE DATA AND MODELS
data_folder = base_folder/'datasets/Classification_HW/csv_files'
model_folder = base_folder/'models/nlp_spring_2023/HW7'
model_folder.mkdir(exist_ok=True)
```

[3]:
```python
def print_wrap(text, d):
    # Wrap the text to limit the width to 'd'
    wrapped_text = textwrap.fill(text, width=d)

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

1.1 Exploring and Understanding Dataset

1.2 Stack Exchange MultiClass Dataset

- In this HW, you will identify tags for stack exchange Questions.
- This data is a subset of data available in a Kaggle Competition.
- The given dataset has different questions asked in the StackExchange website for various technical domains.
- We have fetched only those questions that contain the top 10 individual tags.
- **Each question has only one tag. This means that this is a multi-class classification problem.**
- These are the ten categories for tags in the data.

Index	Tag
0	C#
1	java
2	php
3	javascript
4	android
5	jquery
6	c++
7	python
8	iphone
9	asp.net

1.3 Load Data set

[4]:
```python
# The file 'multiclass_hw_basic_clean.csv' is availaible on e-Learning␣
↪0_data_Folder
# Make sure that you specify the correct path
# The file name need to be in the string, thaat is why we have used␣
↪str(file_path)
# We loaded imdb dataset from huggingface
# in this case we are creating a hugginmgface dataset from csv file
stack_dataset = load_dataset('csv', data_files= str(data_folder /
↪'multiclass_hw_basic_clean.csv'))
```

```
Downloading data files:   0%|          | 0/1 [00:00<?, ?it/s]

Extracting data files:   0%|          | 0/1 [00:00<?, ?it/s]
```

```
Generating train split: 0 examples [00:00, ? examples/s]
```

1.4 Understanding your data

[5]:
```python
print(stack_dataset)
```

```
DatasetDict({
    train: Dataset({
        features: ['Unnamed: 0.1', 'Unnamed: 0', 'Title', 'Body',
'cleaned_text', 'Tags', 'Tag_Number_final', 'combined_text',
'basic_cleaned_text'],
        num_rows: 188878
    })
})
```

1.5 Understanding the datatype of columns

[6]:
```python
stack_dataset['train'].features
```

[6]:
```
{'Unnamed: 0.1': Value(dtype='int64', id=None),
 'Unnamed: 0': Value(dtype='int64', id=None),
 'Title': Value(dtype='string', id=None),
 'Body': Value(dtype='string', id=None),
 'cleaned_text': Value(dtype='string', id=None),
 'Tags': Value(dtype='string', id=None),
 'Tag_Number_final': Value(dtype='int64', id=None),
 'combined_text': Value(dtype='string', id=None),
 'basic_cleaned_text': Value(dtype='string', id=None)}
```

- As you can see the dataset has lot of faeatures. However they are not all useful.
- Title is the title of the stack exchange post
- Body is the main text of the post
- combined_text is Title and Body combined with no pre-processing
- basic_cleaned_text is Title and Body combined with basic preprocessing (remove html tags, urls, emails).
- cleaned_text - Here we have combined Body and Text and has done some motre pre-propcessing in addition to basic (removing stopwords, lammetization)
- Tags - names of programming language to which the post belongs
- Tag_Number_final - index corresponding to Tags
- **Your goal in this HW is to predict Tags given Body and Title of the post**
- **You will use Tag_Number_final and basic_cleaned_text for this HW**

1.6 Acess indivdual element

[7]:
```
# Assuming 'stack_dataset' is a huggingface dataset
# Select only the desired columns and rename them
selected_columns = {
    'text': stack_dataset['train']['basic_cleaned_text'],
    'label': stack_dataset['train']['Tag_Number_final']
}

# Create a new dataset with the selected columns
stack_selected_columns = Dataset.from_dict(selected_columns)
```

[8]:
```
stack_selected_columns
```

[8]:
```
Dataset({
    features: ['text', 'label'],
    num_rows: 188878
})
```

[9]:
```
stack_selected_columns.features
```

[9]:
```
{'text': Value(dtype='string', id=None),
 'label': Value(dtype='int64', id=None)}
```

[10]:
```
stack_selected_columns['label'][:10]
```

[10]:
```
[8, 4, 3, 9, 4, 0, 3, 2, 0, 7]
```

[11]:
```
print_wrap(stack_selected_columns['text'][0], 80)
```

```
detail disclosure indicator on UIButton Is there a simple way to place a detail
disclosure icon on a UIButton? I'm using a navigation controller and I want a
button press to push a new view on the stack, so I thought a detail disclosure
icon would be appropriate, but I haven't found a straightforward way to do that
yet. What I have in mind is something like the "When Timer Ends" button in the
Timer subview of the Clock app.
```

[12]:
```
stack_selected_columns
```

[12]:
```
Dataset({
    features: ['text', 'label'],
    num_rows: 188878
})
```

1.7 Filtering Larger Reviews

[13]:
```
# Filter samples with more than 400 words
def filter_long_samples(example):

    return example['text'] is not None and len(example['text'].split()) > 400

stack_selected_columns = stack_selected_columns.filter(filter_long_samples)
```

```
Filter:   0%|          | 0/188878 [00:00<?, ? examples/s]
```

1.8 Exploratory Data Analysis (EDA)

1.8.1 Change dataset format to Pandas

[14]:
```
# Set the format to Pandas
# CODE HERE

stack_selected_columns.set_format(type='pandas')
```

[15]:
```
# get all rows the dataset
df = stack_selected_columns[:]
```

[16]:
```
df.head()
```

[16]:

	text	label
0	NullPointerException in OnCreate of inherited …	4
1	List View OnitemClick Animation I did a list v…	4
2	uploading video file through ftp in android Hi…	4
3	C++ alternatives to preprocessor macro code ge…	6
4	Reading null values in a byte array c# I am tr…	0

[17]:
```
# DO NOT RUN THIS CELL
```

[18]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4772 entries, 0 to 4771
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   text    4772 non-null   object
 1   label   4772 non-null   int64
dtypes: int64(1), object(1)
memory usage: 74.7+ KB
```

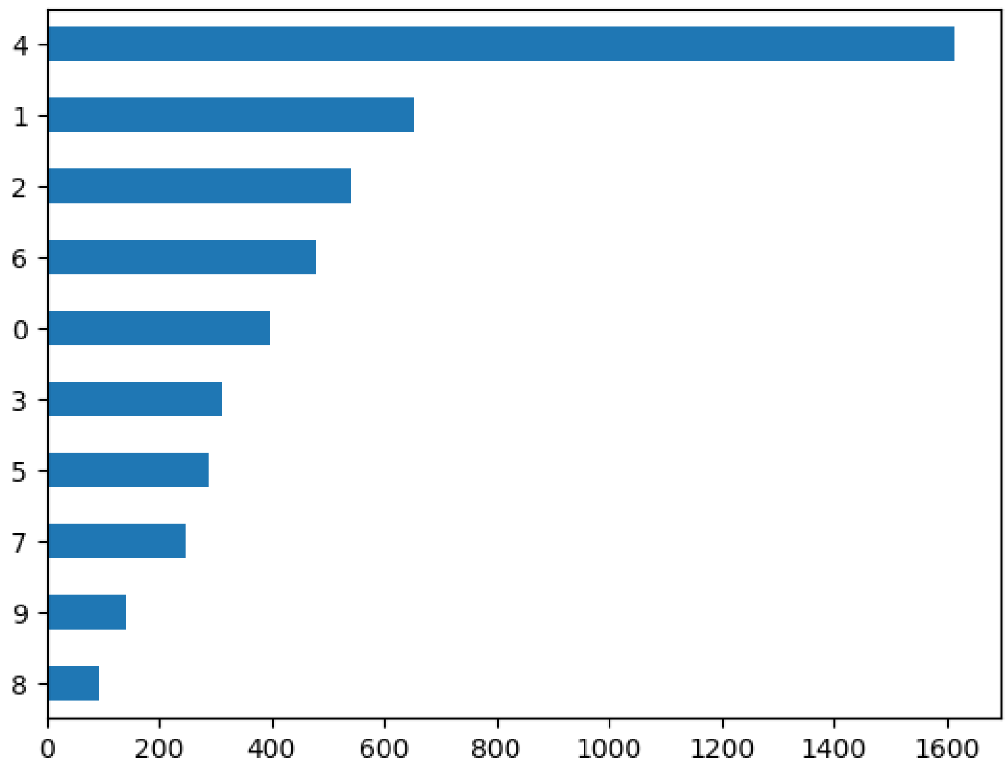
[19]:
```
# DO NOT RUN THIS CELL
```

1.8.2 Visualize distribution of class labels

It is important to undetrstand the distribution of the class labels to check if there is any imbalance among the categories.

[20]:
```
# Plot a horizontal bar chart showing the count of each unique value in the
↪'label' column of the dataframe 'df'.
# The counts are displayed in ascending order for better visualization of the
↪distribution.
# CODE HERE
# check distribution of class labels in training dataset
df['label'].value_counts(ascending=True).plot.barh()
```

[20]: <Axes: >



[21]:
```
# DO NOT RUN THIS CELL
```

Conclusions:

From the above figure, we can clearly see the imbalance between labels. The most of the questions are of 'Android' Language and least from 'asp.net'

1.8.3 Calculate Class Weights

[22]:
```
# 1. Compute the class frequencies:
class_weights = df['label'].value_counts(normalize=True, sort=False)

print(class_weights)

# 2. Sort weights by index (i.e., by label):
class_weights = class_weights.sort_index()

# 3. Compute the inverse of the class frequencies:
class_weights = 1/class_weights

# 4. Normalize the weights so they sum up to 1 (this step is optional but can␣
↪be useful):
class_weights = class_weights / class_weights.sum()

# 5. Convert the weights to a PyTorch tensor:
class_tensor_weights = torch.tensor(class_weights.values, dtype=torch.float)
```

```
4    0.338433
6    0.100587
0    0.083403
2    0.113789
3    0.065381
1    0.137469
8    0.019279
7    0.051551
5    0.060142
9    0.029966
Name: label, dtype: float64
```

[23]:
```
class_tensor_weights
```

[23]:
```
tensor([0.0675, 0.0410, 0.0495, 0.0862, 0.0166, 0.0937, 0.0560, 0.1093, 0.2922,
        0.1880])
```

[24]:
```
sum(class_tensor_weights)
```

[24]:
```
tensor(1.)
```

[24]:
```

```

1.8.4 Check length of the reviews

[25]:
```
# Add empty strings for rows that do not have any text
df['text'] = df['text'].fillna('')
```

[26]:
```
# Add a new column to the dataframe 'df' named 'words_per_review'.
# This column computes the number of words in each review in the 'text' column␣
↪by splitting the text on spaces and counting the resulting words.
df['words_per_review'] = df['text'].apply(lambda x : len(x.split(' '))) # CODEE␣
↪HERE
```

[27]:
```
df.head()
```

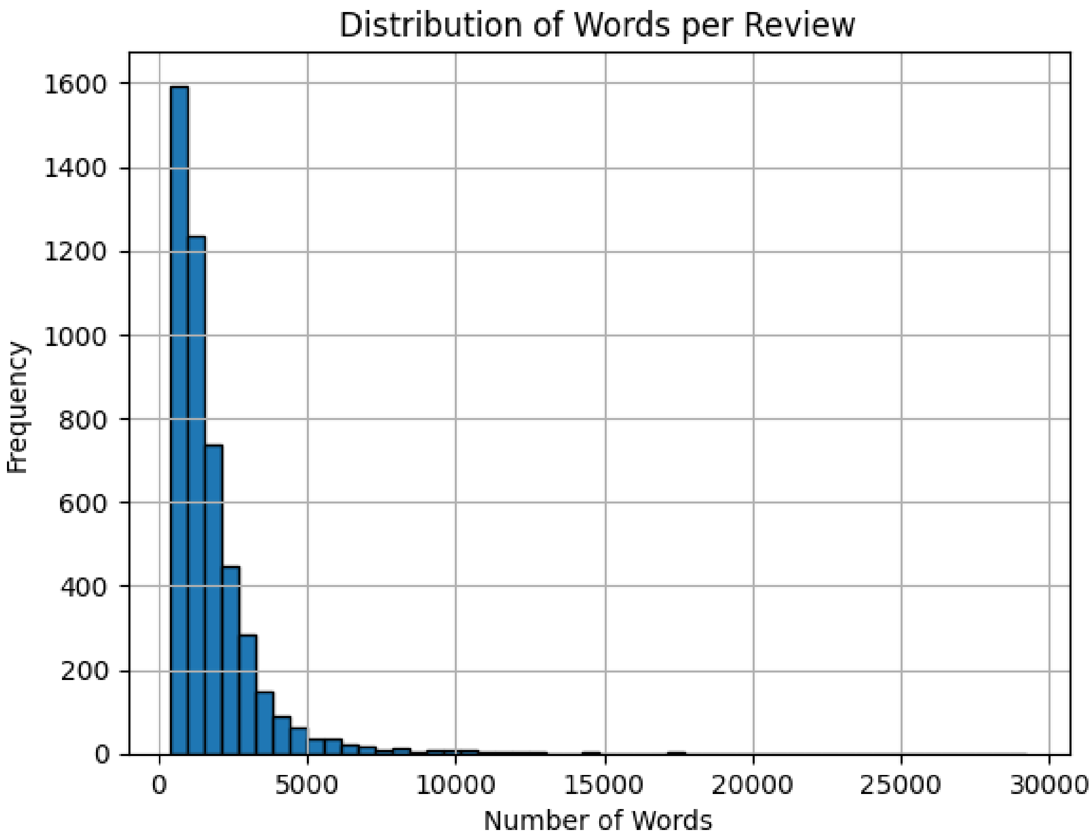
[27]:

	text	label	words_per_review
0	NullPointerException in OnCreate of inherited …	4	1235
1	List View OnitemClick Animation I did a list v…	4	2875
2	uploading video file through ftp in android Hi…	4	2215
3	C++ alternatives to preprocessor macro code ge…	6	739
4	Reading null values in a byte array c# I am tr…	0	1400

[28]:
```
# DO NOT RUN THIS CELL
```

Plot the distribution of review length

[29]:
```
# Plot a histogram of the 'words_per_review' column
df['words_per_review'].hist(bins=50, edgecolor='black')

# Adding labels and a title for clarity
plt.xlabel('Number of Words')
plt.ylabel('Frequency')
plt.title('Distribution of Words per Review')

# Display the plot
plt.show()
```



[30]:
```
# The model we are going to use has token (subwords) limit of 512.
# Let us check how many reviews has more than 500 words

count = (df['words_per_review'] > 500).sum()
print(f"Number of reviews with more than 500 words: {count}")
```

```
Number of reviews with more than 500 words: 4559
```

[31]:
```
# count the rows that do not have any text
count = (df['words_per_review'] ==0).sum()
print(f"Number of reviews with no text words: {count}")
```

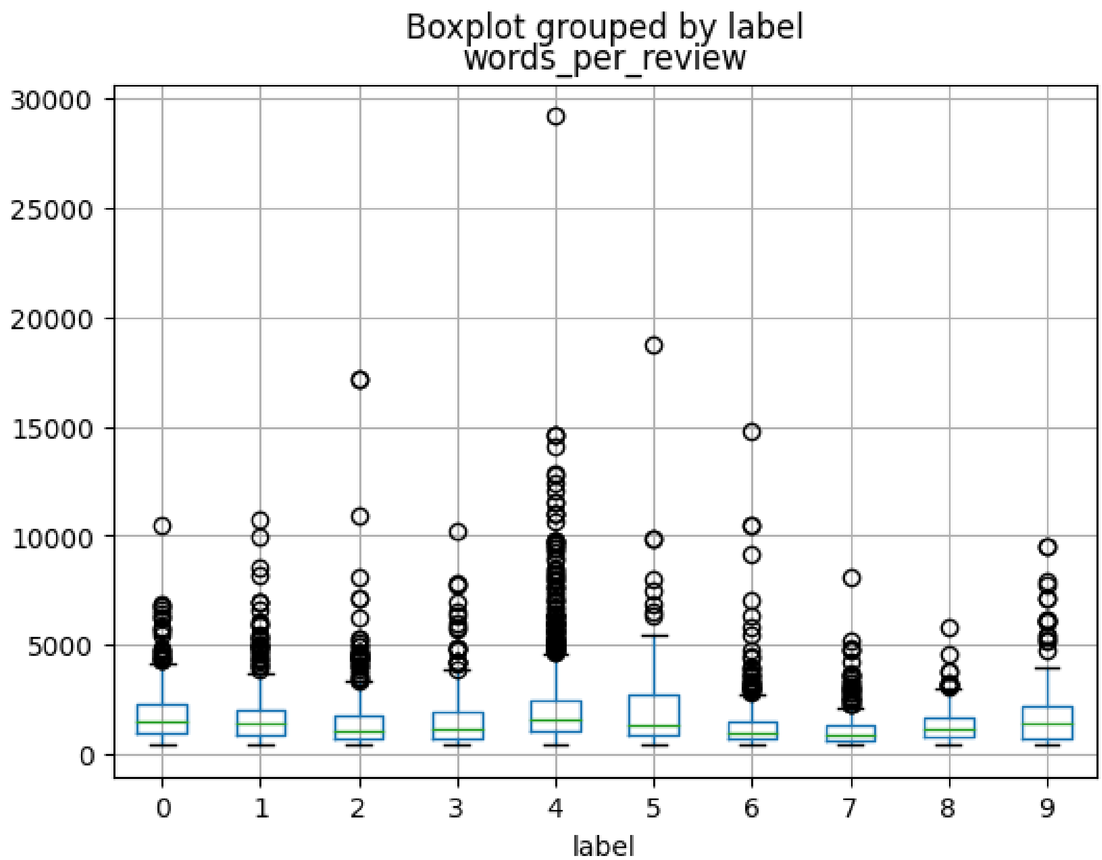
```
Number of reviews with no text words: 0
```

[32]:
```
# check the rows that have less than 20 words
count = (df['words_per_review'] <20).sum()
print(f"Number of reviews with less than 20 words: {count}")
```

```
Number of reviews with less than 20 words: 0
```

[33]:
```
# distribution of number of words for each class label
df.boxplot('words_per_review', by='label')
```

[33]: `<Axes: title={'center': 'words_per_review'}, xlabel='label'>`



- From the above graph, it seems that the distribution of number of words is similar for all the classes.
- Most models have max sequence length of 512. We have less than 1% observatins that have more than 512 words.

1.8.5 Reset dataset format

[34]:
```
# reset the format back to huggingface dataset
stack_selected_columns.reset_format()
# CODE HERE
```

1.9 Data Pre-processing

1.9.1 Create train, valid, test splits

[35]:
```
# We know this information from how we created this dataset
class_names = ['c#', 'java', 'php','javascript', 'android', 'jquery', 'c++', ␣
↪'python', 'iphone', 'asp.net']
```

[36]:
```
# Cast the 'label' column of stack_selected_columns to the ClassLabel type with␣
↪specified class names from class_names.
stack_selected_columns = stack_selected_columns.cast_column('label',␣
↪ClassLabel(names = class_names))
```

```
Casting the dataset:   0%|          | 0/4772 [00:00<?, ? examples/s]
```

The code above modifies the label column of the stack_selected_columns data structure to represent categorical data using the class names provided in class_names. This will help us to keep the index and names mapping together.

[37]:
```
stack_selected_columns.features
```

[37]:
```
{'text': Value(dtype='string', id=None),
 'label': ClassLabel(names=['c#', 'java', 'php', 'javascript', 'android',
'jquery', 'c++', 'python', 'iphone', 'asp.net'], id=None)}
```

[38]:
```
stack_selected_columns
```

[38]:
```
Dataset({
    features: ['text', 'label'],
    num_rows: 4772
})
```

[39]:
```
# Split the 'stack_selected_columns' dataset into training, validation, and␣
↪test sets.
# The aim is to have 60% for training, 20% for validation, and 20% for testing.

# First, split the dataset into a 60% training set and a 40% temporary set (to␣
↪be further split).
# Use stratified sampling based on the 'label' column to ensure that each split␣
↪has a similar distribution of labels.
test_val_splits = stack_selected_columns.train_test_split(test_size= 0.4,␣
↪seed=21, stratify_by_column='label') # CODE HERE

# Extract the 60% training dataset.
train_split = test_val_splits["train"] #CODE HERE
```

```
# Split the 40% temporary set into two equal parts: validation (20%) and test␣
↪(20%).
# Again, use stratified sampling based on the 'label' column.
test_val_splits =  test_val_splits["test"].train_test_split(test_size= 0.5,␣
↪seed=21, stratify_by_column='label') #CODE HERE

# Extract the validation and test datasets.
val_split = test_val_splits['train']# CODE HERE
test_split = test_val_splits['test'] # CODE HERE
```

[40]:
```
stack_selected_columns_dict = DatasetDict({'train': train_split, 'val':␣
↪val_split, 'test': test_split})
```

[41]:
```
# combine train, val splits into one dataset
train_val_subset= DatasetDict({'train': train_split, 'val': val_split})

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

1.9.2 Create subset for experimentation

[42]:
```
train_split_small = train_split.shuffle(seed=42).select(range(10))
val_split_small = val_split.shuffle(seed=42).select(range(10))
test_split_small = test_split.shuffle(seed=42).select(range(10))
```

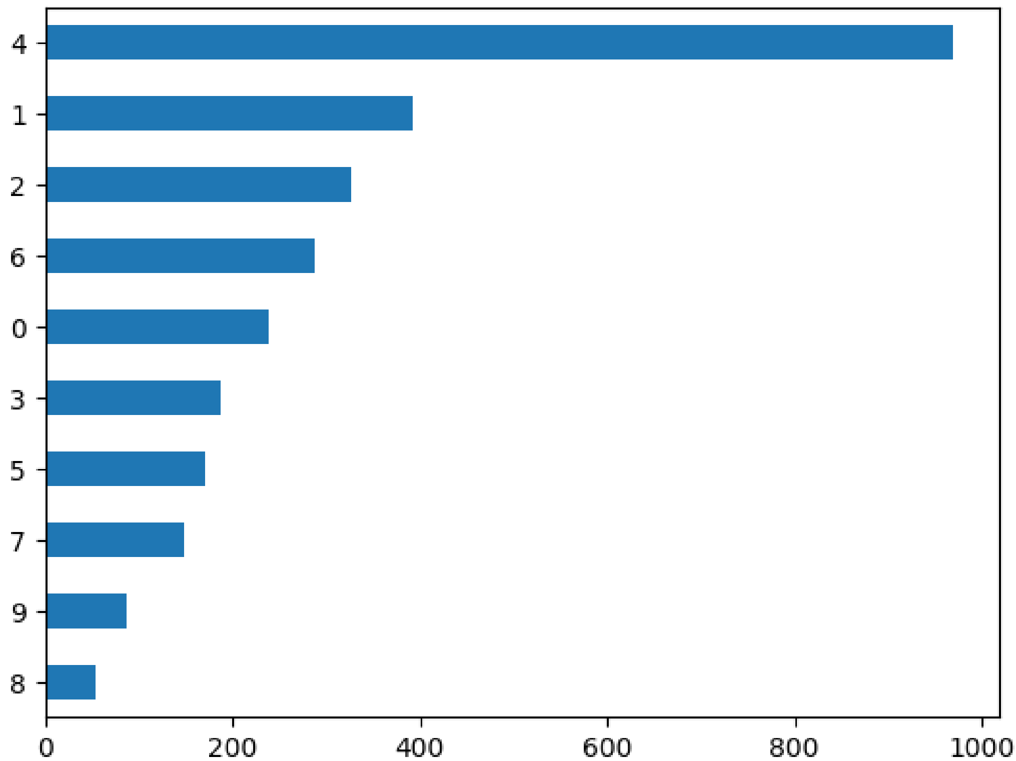
[43]:
```
# combine train, val splits into one dataset
train_val_small= DatasetDict({'train': train_split_small, 'val':␣
↪val_split_small})

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

[44]:
```
train_val_subset.set_format(type='pandas')
```

[45]:
```
df_train = train_val_subset['train'][:]
```

[46]:
```
# check ditsribution of class labels in training dataset
df_train['label'].value_counts(ascending=True).plot.barh()
```

[46]:
```
<Axes: >
```



[47]:
```
# Reset the format of train_val_subset to its original huggingface format
train_val_subset.reset_format()
```

[48]:
```
# Retrieve the feature structures (data types and associated details) of the␣
↪'train' split from train_val_subset.
train_val_subset['train'].features
```

[48]:
```
{'text': Value(dtype='string', id=None),
 'label': ClassLabel(names=['c#', 'java', 'php', 'javascript', 'android',
'jquery', 'c++', 'python', 'iphone', 'asp.net'], id=None)}
```

[49]:
```
# Cast the 'label' column of the entire train_val_subset to the ClassLabel type␣
↪using the provided class names from class_names.
train_val_subset = train_val_subset.cast_column('label', ClassLabel(names =␣
↪class_names)) # CODE HERE
```

```
Casting the dataset:   0%|          | 0/2863 [00:00<?, ? examples/s]

Casting the dataset:   0%|          | 0/954 [00:00<?, ? examples/s]
```

[50]:
```
train_val_subset['train'].features
```

[50]:
```
{'text': Value(dtype='string', id=None),
 'label': ClassLabel(names=['c#', 'java', 'php', 'javascript', 'android',
'jquery', 'c++', 'python', 'iphone', 'asp.net'], id=None)}
```

1.10 Create Custom_Collate function

[51]:
```
def collate_function(batch, tokenizer, max_length, stride):


    text_batch = [item['text'] for item in batch]

    # Check if any of the batch items has 'label', if so process labels.
    if all('label' in item for item in batch):
        label_batch = [item['label'] for item in batch]
        doc_labels = torch.tensor(label_batch, dtype=torch.long)
    else:
        doc_labels = None


    # Tokenize the batch of texts
    tokenized = tokenizer(text_batch,
                          padding='longest',
                          truncation=True,
                          return_tensors='pt',
                          max_length=max_length,
                          return_overflowing_tokens=True,
                          stride=stride)

    # Flatten the chunks if necessary using overflow_to_sample_mapping
    overflow_to_sample_mapping = tokenized.get("overflow_to_sample_mapping",␣
 ↪None)

    result = {
        **tokenized,
        "overflow_to_sample_mapping": overflow_to_sample_mapping,
    }

    # Repeat labels for the chunks based on overflow_to_sample_mapping, only if␣
 ↪labels are present
    if doc_labels is not None and overflow_to_sample_mapping is not None:
        labels = doc_labels[overflow_to_sample_mapping]
        result["labels"] = labels
        result["doc_labels"] = doc_labels

    return result
```

[52]:
```python
from collections import Counter
import torch

def cal_class_weights(input_tensor):
    # Convert the tensor to a list
    input_list = input_tensor.cpu().detach().numpy().tolist()

    counts = Counter(input_list)
    total = sum(counts.values())

    for key, value in counts.items():
        counts[key] = value / total

    # Convert counts dictionary to a Pandas Series
    import pandas as pd
    sd = pd.Series(counts).sort_index()

    class_weights = 1 / sd
    class_weights = class_weights / class_weights.sum()

    class_tensor_weights = torch.tensor(class_weights.values, dtype=torch.float)

    return class_tensor_weights
```

1.11 Function to initialize model

[53]:
```python
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 = AutoModelForSequenceClassification.from_pretrained(checkpoint,␣
 ↪config=config)

    return model, config
```

1.12 Aggregate Predictions

[54]:
```python
def stable_log_softmax(x):
    # Subtract the max for numerical stability along the last axis (axis=-1)
    x_max = np.max(x, axis=-1, keepdims=True)
    # Use logsumexp for better numerical stability
    log_softmax = x - x_max - logsumexp(x - x_max, axis=-1, keepdims=True)
    return log_softmax



def aggregate_predictions(logits, aggregation_method,␣
↪overflow_to_sample_mapping):

    probabilities = softmax(logits, axis=-1)
    log_probabilities = stable_log_softmax(logits)

    # print('log_probs', log_probabilities.shape)
    # print('overflow_to_sample_mapping', overflow_to_sample_mapping.shape)

    # Get unique documents

    unique_docs, inverse_indices = np.unique(overflow_to_sample_mapping,␣
↪return_inverse=True)
    num_docs = unique_docs.size

    # Create a mask for documents
    mask = overflow_to_sample_mapping[:, None] == unique_docs[None, :]

    # Initialize the aggregated_predictions variable
    aggregated_predictions = None

    if aggregation_method == "average_log_probs":
        # Compute average probabilities using NumPy
        avg_log_probs = (log_probabilities[:, None, :] * mask[:, :, None].
↪astype(float)).sum(axis=0) / mask.sum(axis=0, keepdims=True).transpose((1,␣
↪0))
        aggregated_predictions = np.argmax(avg_log_probs, axis=-1)
        scores = np.exp(avg_log_probs.max(axis=-1))

    elif aggregation_method == "average_probs":
        # Compute average probabilities using NumPy
        avg_probs = (probabilities[:, None, :] * mask[:, :, None].
↪astype(float)).sum(axis=0) / mask.sum(axis=0, keepdims=True).transpose((1,␣
↪0))
        aggregated_predictions = np.argmax(avg_probs, axis=-1)
        scores  = avg_probs.max(axis=-1)
```

```
    elif aggregation_method == "max_probs":
        # Compute max probabilities per document
        max_values = np.where(mask[:, :, None], log_probabilities[:, None, :],␣
↪float('-inf'))
        max_log_probs = np.max(max_values, axis=0)
        aggregated_predictions = np.argmax(max_log_probs, axis=-1)
        scores = np.exp(max_log_probs.max(axis=-1))

    elif aggregation_method == "majority_vote":
        # Convert logits to actual predictions before voting
        predictions = np.argmax(logits, axis=1)
        # Tally the votes for each document
        vote_tally = np.zeros((num_docs, logits.shape[-1]), dtype=int)
        np.add.at(vote_tally, overflow_to_sample_mapping, np.eye(logits.
↪shape[-1], dtype=int)[predictions])
        # Determine the majority vote for each document
        aggregated_predictions = np.argmax(vote_tally, axis=1)
        scores = vote_tally.max(axis=-1) / vote_tally.sum(axis=-1)
    else:
        raise ValueError(f"Unsupported aggregation_method:␣
↪{aggregation_method}")

    # # Calculate evaluation metrics using document-level labels
    # metrics = evaluate.combine([
    #     evaluate.load("accuracy"),
    #     evaluate.load("f1", average="macro")
    # ])
    # evaluations = metrics.compute(predictions=aggregated_predictions,␣
↪references=doc_labels)

    # return evaluations

    return aggregated_predictions, scores
```

1.13 Custom Trainer

[55]:
```
from transformers import Trainer
import torch
import torch.nn as nn
from transformers.trainer_utils import EvalPrediction


class CustomTrainer(Trainer):
    def __init__(self, *args, loss_type="average_log_probs", **kwargs):
        super(CustomTrainer, self).__init__(*args, **kwargs)
```

```
        self.loss_type = loss_type



    def compute_loss(self, model, inputs, return_outputs=False):

        labels = inputs["labels"]
        overflow_to_sample_mapping = inputs.pop("overflow_to_sample_mapping",␣
↪None)
        doc_labels = inputs.pop("doc_labels", None)
        logits = model(**inputs).logits

        # convert logits to log probabilities, probabilities
        log_probabilities = F.log_softmax(logits, dim=-1)
        probabilities = F.softmax(logits, dim=-1)


        # Number of unique documents and chunks
        num_docs = doc_labels.size(0)
        num_chunks = overflow_to_sample_mapping.size(0)

        # Ensure overflow_to_sample_mapping is on the same device as doc_labels
        overflow_to_sample_mapping = overflow_to_sample_mapping.to(doc_labels.
↪device)

        # Create a tensor representing each unique doc
        unique_docs = torch.arange(num_docs).to(doc_labels.device)

        # Create the mask
        mask = overflow_to_sample_mapping[:, None] == unique_docs[None, :]

        loss_fn = nn.NLLLoss(weight = class_tensor_weights.to(model.device))

        #loss_fn = self.nll_loss(weight = cal_class_weights(labels).to(model.
↪device))


        if self.loss_type == "average_log_probs":
            avg_log_probs = (log_probabilities[:, None, :] * mask.unsqueeze(-1).
↪float()).sum(0) / mask.sum(0, keepdim=True).T

            # print('avg_log_probs_shape', avg_log_probs.shape)
            loss = loss_fn( avg_log_probs, doc_labels)
            # print(loss)

        elif self.loss_type == "average_probs":
```

```python
            avg_probs = (probabilities[:, None, :] * mask.unsqueeze(-1).
↪float()).sum(0) / mask.sum(0, keepdim=True).T

            avg_log_probs = torch.log(avg_probs)
            # print('avg_log_probs_shape', avg_log_probs.shape)
            loss = loss_fn(avg_log_probs, doc_labels)
            # print(loss)

        elif self.loss_type == "max":
            max_values = torch.where(mask.unsqueeze(-1), log_probabilities[:,␣
↪None, :], torch.tensor(float('-inf'), device=log_probabilities.device))
            max_log_probs = max_values.max(dim=0).values
            # print('max_log_probs_shape', max_log_probs.shape)
            loss = loss_fn(max_log_probs, doc_labels)
            # print(loss)

        elif self.loss_type == "loss_per_chunk":
            # print('log_probs_shape', log_probabilities.shape)
            loss = loss_fn(log_probabilities, labels.view(-1))
            # print(loss)

        else:
            raise ValueError(f"Unsupported loss_type: {self.loss_type}")


        return (loss, logits) if return_outputs else loss
```

1.13.1 Plot Confusion Matrix

[56]:
```python
def log_and_plot_confusion_matrix(filtered_labels,  filtered_predictions,␣
↪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.
    # # 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()
```

1.14 Set up Logger for experiments

1.14.1 Function to set Trainer

[57]:
```
def get_trainer(model, training_args, train_dataset, eval_dataset, loss_type,␣
↪tokenizer, data_collator):
    trainer = CustomTrainer(
    loss_type = loss_type,
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=eval_dataset,
    data_collator=data_collator,
    tokenizer=tokenizer,

)
    return trainer
```

1.14.2 Function to tokenize dataset and, train and eval models

1.14.3 Evaluation

[58]:
```
from torch.utils.data import DataLoader
from transformers import PreTrainedModel
from evaluate import load

def evaluate_model(dataloader: DataLoader, model: PreTrainedModel, metric_only:
 ↪bool = True, aggregation_method: str ='average_log_probs'):
    # Load the accuracy metric
    accuracy_metric = load("accuracy")
    device = 'cuda' if torch.cuda.is_available() else 'cpu'
    predictions = []
    all_doc_labels = []

    # Loop over batches
    for batch in dataloader:
        model.eval()
        doc_labels = batch.pop("doc_labels", None).cpu().numpy()
        overflow_to_sample_mapping = batch.pop("overflow_to_sample_mapping",
 ↪None).cpu().numpy()
        batch = {k: v.to(device) for k, v in batch.items()}

        with torch.no_grad():
            outputs = model(**batch)
            logits = outputs.logits.cpu().numpy()
            aggregated_predictions, scores =
 ↪aggregate_predictions(logits=logits,

 ↪aggregation_method=aggregation_method,

 ↪overflow_to_sample_mapping=overflow_to_sample_mapping)

            accuracy_metric.add_batch(predictions=aggregated_predictions,
 ↪references=doc_labels)
            if not metric_only:
                predictions.extend(aggregated_predictions)
                all_doc_labels.extend(doc_labels)

    # Calculate and return the final accuracy.
    final_accuracy = accuracy_metric.compute()['accuracy']

    if metric_only:
        return final_accuracy
    else:
        return final_accuracy, predictions, all_doc_labels
```

[59]:
```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()
```

[91]:
```python
def tokenize_train_evaluate_log(training_args, checkpoint, base_folder,
                                class_names, train_val_subset, loss_type):
    # 1. Free memory
    free_memory()

    # 2. Setup wandb
    wandb.login()
    %env WANDB_PROJECT = nlp_course_fall_2023-HW7-PartB

    ######################## 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/HW7"/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
    collate_fn = partial(collate_function, tokenizer=tokenizer,max_length =␣
↪512, stride = 128)
```

```
    trainer = get_trainer(model, training_args, train_val_subset['train'],␣
↪train_val_subset['val'], loss_type, tokenizer, collate_fn)

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

    # 7. Log Metrics and Plot


    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}.")

    path = 'checkpoint-'+ str(best_model_checkpoint_step)
    checkpoint = str(model_folder/path)
    model = AutoModelForSequenceClassification.from_pretrained(checkpoint)

    # Make sure to use 'cuda' if a GPU is available.
    device = 'cuda' if torch.cuda.is_available() else 'cpu'

    model = model.to(device=device)


    val_accuracy, val_predictions, val_labels = evaluate_model(trainer.
↪get_test_dataloader(train_val_subset['val']), model, metric_only=False)

    print(f"Validation accuracy: {val_accuracy}")

    wandb.log({"val_accuracy": val_accuracy})

    log_and_plot_confusion_matrix(val_labels, val_predictions , class_names)

    wandb.finish()



    return best_model_checkpoint_step
```

2 Experiment 1

2.1 Hyperparameters and Checkpointing

[83]:
```
from transformers import TrainingArguments

# Define the directory where model checkpoints will be saved
model_folder = base_folder / "models"/"nlp_spring_2023/HW7/bert-base-uncased/"
# 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=1,  # Total number of training epochs
    # Number of samples per training batch for each device
    per_device_train_batch_size=8,
    # Number of samples per evaluation batch for each device
    per_device_eval_batch_size=8,
    gradient_checkpointing=True,  # Use gradient checkpointing to reduce memory␣
 ↪usage
    gradient_accumulation_steps=2,
    weight_decay=0.01,  # Apply L2 regularization to prevent overfitting
    learning_rate=1e-5,  # Step size for the optimizer during training
    optim='adamw_torch',  # Optimizer,
    fp16= True, # Use mixed precision training for memroy optimization
    # argument for EvalPred to include inputs and outputs
    remove_unused_columns=False,

    # 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 20 training steps
    save_strategy="steps",  # Save model checkpoint at specified step intervals
    save_steps=20,  # Save a model checkpoint every 20 training steps
    load_best_model_at_end=True,  # Reload the best model at the end of training
    save_total_limit=1,  # Retain only the best and the most recent model␣
 ↪checkpoints


    # 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='stack_HW7_2',  # Experiment name for Weights & Biases
)
```

2.2 Initialize Trainer

[84]:
```
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(
```

[85]:
```
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 ,
                              loss_type = 'average_log_probs')
```

```
wandb: WARNING Calling wandb.login() after wandb.init()
has no effect.
```

```
env: WANDB_PROJECT=nlp_course_fall_2023-HW7-PartA
```

```
Some weights of BertForSequenceClassification 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.
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
  warnings.warn(
```

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

```
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
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UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
```
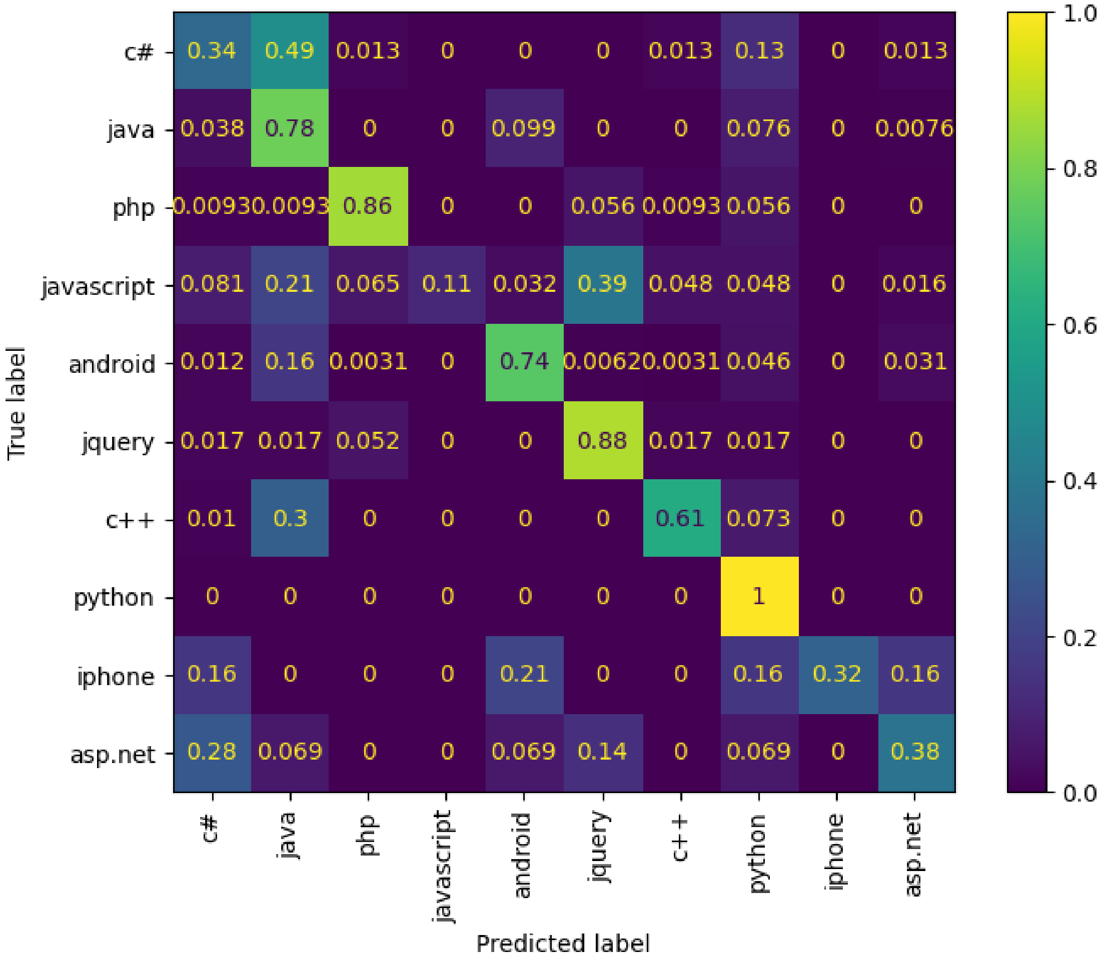

```
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
  warnings.warn(
```

```
The best model was saved at step 160.
```

```
Downloading builder script:   0%|          | 0.00/4.20k [00:00<?, ?B/s]
```




```
VBox(children=(Label(value='0.007 MB of 0.007 MB uploaded\r'),␣
↪FloatProgress(value=1.0, max=1.0)))
```

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

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

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

[87]:
```
path = 'checkpoint-'+ str(best_model)
checkpoint = str(model_folder/path)
model = AutoModelForSequenceClassification.from_pretrained(checkpoint)
# Make sure to use 'cuda' if a GPU is available.
device = 'cuda' if torch.cuda.is_available() else 'cpu'

model = model.to(device=device)

tokenizer = AutoTokenizer.from_pretrained(checkpoint)
```

```
# 5. Initialize Trainer
collate_fn = partial(collate_function, tokenizer=tokenizer,max_length = 512,␣
↪stride = 16)

trainer = get_trainer(model, training_args, train_val_subset['train'],␣
↪train_val_subset['val'], 'average_log_probs', tokenizer, collate_fn)




val_accuracy, val_predictions, val_labels = evaluate_model(trainer.
↪get_test_dataloader(train_val_subset['val']), model, metric_only=False)
```

[ ]:
```
log_and_plot_confusion_matrix(val_labels, val_predictions , class_names)
```

[88]:
```
val_accuracy
```

[88]: 0.6708595387840671

[90]:
```
```

3 Experiment 2

3.1 Hyperparameters and Checkpointing

[92]:
```
from transformers import TrainingArguments

# Define the directory where model checkpoints will be saved
model_folder = base_folder / "models"/"nlp_spring_2023/HW7/bert-base-uncased/"
# 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=1,  # Total number of training epochs
    # Number of samples per training batch for each device
    per_device_train_batch_size=8,
    # Number of samples per evaluation batch for each device
    per_device_eval_batch_size=8,
    gradient_checkpointing=True,  # Use gradient checkpointing to reduce memory␣
↪usage
    gradient_accumulation_steps=4,
    weight_decay=0.01,  # Apply L2 regularization to prevent overfitting
    learning_rate=1e-5,  # Step size for the optimizer during training
```

```
    optim='adamw_torch',  # Optimizer,
    fp16= True, # Use mixed precision training for memroy optimization
    # argument for EvalPred to include inputs and outputs
    remove_unused_columns=False,

    # 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 20 training steps
    save_strategy="steps",  # Save model checkpoint at specified step intervals
    save_steps=20,  # Save a model checkpoint every 20 training steps
    load_best_model_at_end=True,  # Reload the best model at the end of training
    save_total_limit=1,  # Retain only the best and the most recent model␣
 ↪checkpoints


    # 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='stack_HW7_2_2',  # Experiment name for Weights & Biases
)
```

3.2 Initialize Trainer

[93]:
```
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(
```

[94]:
```
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 ,
                             loss_type = 'average_log_probs')
```

```
env: WANDB_PROJECT=nlp_course_fall_2023-HW7-PartB
```

```
Some weights of BertForSequenceClassification 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>
```

```
<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>
```

```
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
  warnings.warn(
```

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

```
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
UserWarning: torch.utils.checkpoint: please pass in use_reentrant=True or
use_reentrant=False explicitly. The default value of use_reentrant will be
updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
docs for more details on the differences between the two variants.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/torch/utils/checkpoint.py:429:
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updated to be False in the future. To maintain current behavior, pass
use_reentrant=True. It is recommended that you use use_reentrant=False. Refer to
```
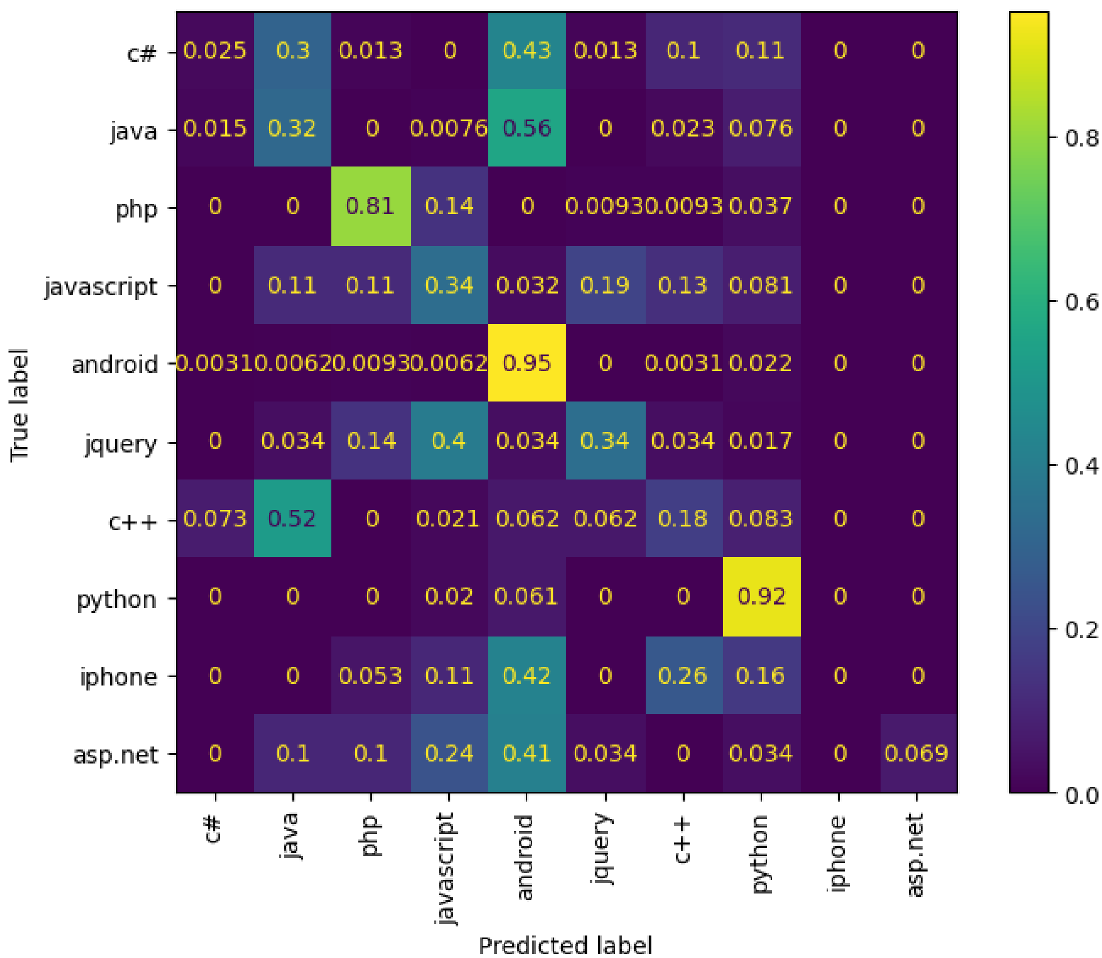

```
docs for more details on the differences between the two variants.
  warnings.warn(
```

```
The best model was saved at step 80.
Validation accuracy: 0.5691823899371069
```




```
VBox(children=(Label(value='0.007 MB of 0.007 MB uploaded\r'),␣
↪FloatProgress(value=1.0, max=1.0)))
```

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

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

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

3.3 Pipeline Experimentation

[118]:
```python
from transformers import Pipeline

class LongDocumentClassificationPipeline(Pipeline):

    def __init__(self, *args, max_length=512, stride=100,␣
↪aggregation_method='average_log_probs', **kwargs):
        self.max_length = max_length
        self.stride = stride
        self.aggregation_method = aggregation_method
        super().__init__(*args, **kwargs)

    def __call__(self, documents=None, **kwargs):

        if isinstance(documents, str):
            documents = [{'text': str(documents)}]
        elif isinstance(documents, list) and all(isinstance(doc, str) for doc␣
↪in documents):
            documents = [{'text': doc} for doc in documents]

        elif isinstance(documents, list) and all(isinstance(doc, dict) and␣
↪'text' in doc for doc in documents):
            # Input is already in the expected format, no action needed.
            pass

        # If the input doesn't match any of the above types, raise an error.
        else:
            raise TypeError("Input not supported. Expected a string, a list of␣
↪strings, or a list of dicts with a 'text' key.")
        # Debug: print the type and content of documents before calling the␣
↪parent method


        return super().__call__(inputs=[documents], **kwargs)

    def _sanitize_parameters(self, **kwargs):
      # Update kwargs with max_length, stride, and aggregation_method if␣
↪provided
        self.max_length = kwargs.pop('max_length', self.max_length)
        self.stride = kwargs.pop('stride', self.stride)
        self.aggregation_method = kwargs.pop('aggregation_method', self.
↪aggregation_method)
        return kwargs, {}, {}


    def preprocess(self, inputs=None):
```

```python
        # Use the custom collate function to prepare the inputs
        tokenized = collate_function(inputs, tokenizer =self.tokenizer, max_length = self.max_length, stride = self.stride)
        model_inputs = {k: v.to(self.device) for k, v in tokenized.items()}
        return model_inputs

    def _forward(self, model_inputs):
        # Remove keys that are not needed by the model's forward method
        if 'doc_labels' in model_inputs:
            self.doc_labels = model_inputs.pop('doc_labels').cpu().numpy()
        if 'overflow_to_sample_mapping' in model_inputs:
            self.overflow_to_sample_mapping = model_inputs.pop('overflow_to_sample_mapping').cpu().numpy()

        # Call the model's forward method with the cleaned inputs
        self.model = self.model.to(self.device)
        self.model.eval()
        with torch.no_grad():
            outputs = self.model(**model_inputs)

        return outputs

    def postprocess(self, model_outputs, **kwargs):
        logits = model_outputs.logits
        # Convert to numpy and calculate probabilities
        logits = logits.cpu().numpy()  # Ensure logits are on CPU for NumPy operations

        # print("Logits shape:", logits.shape)
        # print("Overflow to sample mapping:", self.overflow_to_sample_mapping)


        aggregated_predictions, scores  = aggregate_predictions(logits, self.aggregation_method, self.overflow_to_sample_mapping)
        # print("Aggregated Predictions:", aggregated_predictions)
        # Convert the aggregated predictions to labels and scores
        results = []
        for (pred, score) in zip(aggregated_predictions, scores):
            # print('preds', pred)
            label_name = self.model.config.id2label[pred]
            # print(self.model.config.id2label)
            # print('label_name', label_name)
            #results.append({"label": label_name, "score": score})
            results.append(pred)

        return results
```

[139]:
```
custom_pipeline = LongDocumentClassificationPipeline(model = model, tokenizer =␣
↪tokenizer, device = 0)
sample = test_split_small['text'][:4]
```

[140]:
```
test_split
```

[140]:
```
Dataset({
    features: ['text', 'label'],
    num_rows: 955
})
```

[151]:
```
preds = custom_pipeline(test_split['text'][:10])
preds
```

[151]:
```
[[6, 1, 0, 7, 1, 7, 1, 1, 1, 2]]
```

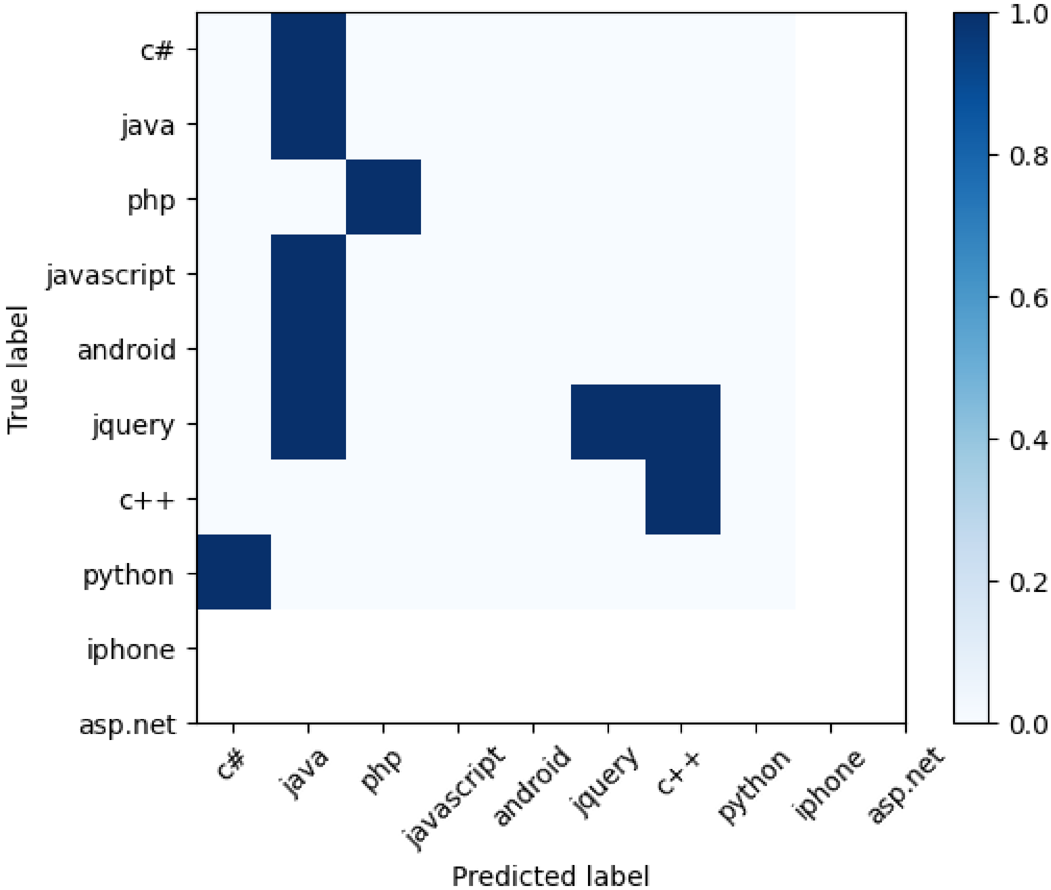
[143]:
```
preds[:][0]
```

[143]:
```
[5, 7, 1, 4, 7, 1, 1, 7, 1, 1]
```

[153]:
```
test_split['label'][:10]
```

[153]:
```
[6, 6, 9, 6, 1, 7, 3, 0, 4, 2]
```

[154]:
```
# prompt: plot confusion matrix for multi class classification with predictions␣
↪and labels


from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt

# Create a confusion matrix
cm = confusion_matrix(test_split['label'][:10], preds[0])

# Plot the confusion matrix
plt.imshow(cm, cmap=plt.cm.Blues)
plt.colorbar()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names, rotation=45)
plt.yticks(tick_marks, class_names)
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.show()
```



c#
java
php
javascript
android
jquery
c++
python
iphone
asp.net
True label
Predicted label
1.0
0.8
0.6
0.4
0.2
0.0


```
[ ]:
```