CS 4650 - Natural Language - HW - 2

Georgia Tech, Fall 2025 (Instructor: Kartik Goyal)

Welcome to the first full programming assignment for CS 4650!

In this assignment, you will be implementing different deep learning models for text classification using the 20 Newsgroups. It is esentially classifying news articles into different topics. This assignment will start with with data preprocessing techniques, implementing a baseline, and building up from there to more advanced model. It will cover basics of attention mechanism, something very central to modern NLP systems, and present you an opportunity to analyse different aspects of your training model.

This assignment will help you diver deeper into the world of Neural Networks and how to implement them for one application in Natural Language Processing. You are expected to have a good understanding of NumPy and PyTorch before starting this assignment.

- NumPy Quickstarter Guide: https://numpy.org/doc/stable/user/quickstart.html
- A good tutorial on PyTorch: https://www.youtube.com/watch?v=OIenNRt2bjg
- Detailed Documentation of PyTorch: https://pytorch.org/docs/stable/index.html
- Lecture Material on PyTorch and HuggingFace: https://github.com/neelabhsinha/cs7650-gatech-nlp-pytorch-huggingface-tutorial

DO NOT CHANGE the names of any of the files and contents outside the cells where you have to write code.

NOTE: DO NOT USE ANY OTHER EXTERNAL LIBRARIES FOR THIS ASSIGNMENT

DEADLINE: October 14, 2025, 11:59 PM

The assignment is broken down into 6 Sections. The sections are as follows:

Section	Part	Points
1	Loading and Preprocessing Data	7
2	Neural Bag of Words (NBOW)	3
3	Model Training (utilities for all models)	15
4	Deep Averaging Networks (DANs)	8
5	Attention-based Models	30
6	Perceptron and Hinge Losses	16
7	Analysis	21
8	Bonus: Improving Attention Models	10
-	Total	100 + 10 = 110

All the best and happy coding!

0. Setup

```
%load_ext autoreload
%autoreload 2

# Check what version of Python is running
print(sys.version)
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
/tmp/ipython-input-625811873.py in <cell line: 0>()
----> 1 get_ipython().run_line_magic('load_ext', 'autoreload')
      2 get_ipython().run_line_magic('autoreload', '2')
      3 
      4 # Check what version of Python is running
      5 print(sys.version)

                    11 frames
<decorator-gen-57> in load_ext(self, module_str)

/usr/local/lib/python3.12/dist-packages/IPython/extensions/autoreload.py in <module>
    119 from importlib import import_module
    120 from importlib.util import source_from_cache
--> 121 from imp import reload
    122 
    123 #------------------------------------------------------------------------------

ModuleNotFoundError: No module named 'imp'

---------------------------------------------------------------------------
NOTE: If your import is failing due to a missing package, you can
manually install dependencies using either !pip or !apt.

To view examples of installing some common dependencies, click the
"Open Examples" button below.
```

Next steps: Explain error

```
# execute only if you are working in Google Colab
from google.colab import drive
drive.mount('/content/drive')
```

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

```
# export
import os
```

```
# folder_path = '/content/drive/My Drive/path/to/folder/HW0'
# the above is what folder path should look like the folder path if you
folder_path = '/content/drive/MyDrive/HW2'

# Files in the folder -
os.listdir(folder_path)
os.chdir(folder_path)
```

```
# export
# Importing required libraries
# Do not change the libraries already imported or import additional libr
import torch
import torch.nn as nn
import random
import numpy as np
from collections import Counter
import re
import html
import pandas as pd
from tqdm import tqdm
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import Dataset, RandomSampler, DataLoader
from torch.nn.utils.rnn import pad_sequence
from sklearn.metrics import accuracy_score, f1_score, confusion_matrix,
import matplotlib.pyplot as plt
```

```
# export
# SOME UTILITY FUNCTIONS - DO NOT CHANGE
def save_checkpoint(model, model_name, loss_fn='ce'):
    file_path = os.path.join(os.getcwd(), 'model_weights', f'checkpoint_
    os.makedirs(os.path.join(os.getcwd(), 'model_weights'), exist_ok=Tru
    checkpoint = { # create a dictionary with all the state information
        'model_state_dict': model.state_dict()
    }
    torch.save(checkpoint, file_path)
    print(f"Checkpoint saved to {file_path}")

def load_checkpoint(model, model_name, loss_fn='ce', map_location='cpu')
    file_path = os.path.join(os.getcwd(), 'model_weights', f'checkpoint_
    checkpoint = torch.load(file_path, map_location=map_location) # load
    model.load_state_dict(checkpoint['model_state_dict'])
```

```
# SOME UTILITY FUNCTIONS - DO NOT CHANGE
def plot_loss(train_loss_over_time, val_loss_over_time, model_name):
    epochs = range(1, len(train_loss_over_time) + 1)

    plt.figure(figsize=(10, 6))
    plt.plot(epochs, train_loss_over_time, color='red', label='Train Los
    plt.plot(epochs, val_loss_over_time, color='blue', label='Val Loss')

    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.title(f'Training and Validation Loss for {model_name}')
    plt.legend()
    plt.grid(True)
    plt.show()
```

```
#export
# Defining global constants - DO NOT CHANGE THESE VALUES (except batch s
RANDOM_SEED = 42
PADDING_VALUE = 0
UNK_VALUE     = 1
BATCH_SIZE = 128

torch.manual_seed(RANDOM_SEED)
random.seed(RANDOM_SEED)
np.random.seed(RANDOM_SEED)
device = torch.device('cuda' if torch.cuda.is_available() else('mps' if
# This is how we select a GPU if it's available on your computer or in t
print('Device of execution - ', device)
```

```
Device of execution -  cpu
```

1. Preprocessing [7 points - Programming]

1.1. Data Cleaning Methods [0 points]

The following cell defines some methods to clean the dataset. Do not edit it, but feel free to take a look at some of the operations it's doing.

```
#export
# example code taken from fast-bert
# DO NOT CHANGE THIS CELL

def spec_add_spaces(t: str) -> str:
    "Add spaces around / and # in `t`. \n"
    return re.sub(r"([/#\n])", r" \1 ", t)

def rm_useless_spaces(t: str) -> str:
    "Remove multiple spaces in `t`."
    return re.sub(" {2,}", " ", t)

def replace_multi_newline(t: str) -> str:
    return re.sub(r"(\n(\s)*){2,}", "\n", t)

def fix_html(x: str) -> str:
    "List of replacements from html strings in `x`."
    re1 = re.compile(r"  +")
    x = (
        x.replace("#39;", "'")
        .replace("amp;", "&")
        .replace("#146;", "'")
        .replace("nbsp;", " ")
        .replace("#36;", "$")
        .replace("\\n", "\n")
        .replace("quot;", "'")
        .replace("<br />", "\n")
        .replace('\\"', '"')
        .replace(" @.@ ", ".")
        .replace(" @-@ ", "-")
        .replace(" @,@ ", ",")
        .replace("\\", " \\ ")
    )
    return re1.sub(" ", html.unescape(x))

def clean_text(input_text):
    text = fix_html(input_text)
    text = replace_multi_newline(text)
    text = spec_add_spaces(text)
    text = rm_useless_spaces(text)
    text = text.strip()
    return text
```

1.2. Data Cleaning and Tokenizing [0 points]

Clean the data using the methods above and tokenize it using NLTK

```
# DO NOT CHANGE THIS CELL
# Downloading the NLTK tokenizer
import nltk
nltk.download('punkt')
nltk.download('punkt_tab')
# Tokenizing the text
df = pd.read_csv("vocab.csv")
df["tokenized"] = df["data"].apply(lambda x: nltk.word_tokenize(clean_te
func = lambda x: int(x) if x.isdigit() else x
df['target'] = df['target'].apply(func)
print(df.shape)
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt_tab.zip.
(16962, 4)
```

```
# DO NOT CHANGE THESE VALUES
# Divide the dataset into training and validation sets
# The following two lines are used to load the indices of the training a
train_indices = np.load("train_indices.npy")
val_indices = np.load("valid_indices.npy")
# The following two lines are used to select the training and validation
train_data = df.iloc[train_indices].reset_index(drop=True)
val_data = df.iloc[val_indices].reset_index(drop=True)
func = lambda x: int(x) if str(x).isdigit() else x
val_data['target'] = val_data['target'].apply(func)
val_data = val_data.iloc[1:, :].reset_index(drop=True)
```

Here's what the dataset looks like. You can index into specific rows with pandas, and try to guess some of these yourself :). If you're unfamiliar with pandas, it's a extremely useful and popular library for data analysis and manipulation. You can find their documentation here.

Pandas primary data structure is a DataFrame. The following cell will print out the basic information of this structure, including the labeled axes (both columns and rows) as well as show you what the first n (default=5) rows look like

```
# Print training and validation set heads
train_data.head()
```

	data	target	target_names	tokenized
0	From: Mamatha Devineni Ratnam <mr47+@andrew.cm...	9	rec.sport.baseball	[from, :, mamatha, devineni, ratnam, <, mr47+,...
1	From: glazier@isr.harvard.edu (Andrew Baker Gl...	6	misc.forsale	[from, :, glazier, @, isr.harvard.edu, (, andr...
				[from, :, simon, @,

Next steps: Generate code with `train_data` New interactive sheet

```
# DO NOT CHANGE THIS CELL
id2label = dict(zip(df['target'], df['target_names']))
id2label = {k: id2label[k] for k in id2label if isinstance(k, int)}
id2label = {k: id2label[k] for k in sorted(id2label)}
id2label
```

```
{0: 'alt.atheism',
 1: 'comp.graphics',
 2: 'comp.os.ms-windows.misc',
 3: 'comp.sys.ibm.pc.hardware',
 4: 'comp.sys.mac.hardware',
 5: 'comp.windows.x',
 6: 'misc.forsale',
 7: 'rec.autos',
 8: 'rec.motorcycles',
 9: 'rec.sport.baseball',
 10: 'rec.sport.hockey',
 11: 'sci.crypt',
 12: 'sci.electronics',
 13: 'sci.med',
 14: 'sci.space',
 15: 'soc.religion.christian',
 16: 'talk.politics.guns',
 17: 'talk.politics.mideast',
 18: 'talk.politics.misc',
 19: 'talk.religion.misc'}
```

This is a dictionary which maps ids to label names. It will be handy in the later part of the assignment.

1.3. Vocabulary Building [2 points - Programming]

Generate a vocabulary map for all the words in your dataset

Now that we've loaded this dataset, we need to create a vocab map for words, which will map tokens to numbers. This will be useful later, since torch PyTorch use tensors of sequences of numbers as inputs. **Go to the following cell, and fill out generate_vocab_map.**

```
# export
```

```
    def generate_vocab_map(df, cutoff=2):
        """
        This method takes a dataframe and builds a vocabulary to unique numb
        It uses the cutoff argument to remove rare words occurring <= cutoff
        "" and "UNK" are reserved tokens in our vocab that will be useful la
        You'll also find the Counter imported for you to be useful as well.

        Args:
            df (pandas.DataFrame) : The entire dataset this mapping is built
            cutoff (int) : We exclude words from the vocab that appear less

        Returns:
            vocab (dict[str] = int) : In vocab, each str is a unique token,
                unique integer ID. Only elements that appear > cutoff times
            reversed_vocab (dict[int] = str) : A reversed version of vocab,
                words given their unique integer ID. This map will allow us
                sequences we'll encode using vocab!
        """
        vocab          = {"": PADDING_VALUE, "UNK": UNK_VALUE}
        reversed_vocab = None

        ## YOUR CODE STARTS HERE ##
        # hint: start by iterating over df["tokenized"]
        # Flatten all tokenized lists into one big list of words
        all_tokens = [token for tokens in df["tokenized"] for token in token

        # Count frequency of each word
        counter = Counter(all_tokens)

        # Start indexing after the reserved tokens
        index = len(vocab)

        # Add words that appear more than cutoff times
        for word, count in counter.items():
            if count > cutoff:
                vocab[word] = index
                index += 1

        # Create reversed mapping (index → word)
        reversed_vocab = {idx: word for word, idx in vocab.items()}
        ## YOUR CODE ENDS HERE ##

        return vocab, reversed_vocab
```

With the methods you have implemented above, you can now generate your dictionaries mapping from word tokens to IDs (and vice versa).

```
# DO NOT CHANGE THIS CELL
train_vocab, reverse_vocab = generate_vocab_map(train_data)
```

```
# Check Vocabulary Size - DO NOT CHANGE THIS VALUE
assert len(train_vocab) == 60233, f"Vocabulary is of incorrect size: {le

# No error means you've passed the test!
```

1.4. Building a Dataset Class [2 points - Programming]

PyTorch has custom Dataset Classes that have very useful extensions, we want to turn our current pandas DataFrame into a subclass of Dataset so that we can iterate and sample through it for minibatch updates. **In the following cell, fill out the HeadlineDataset class.** Refer to PyTorch documentation on Dataset Classes for help.

```
#export

class HeadlineDataset(Dataset):
    """
    This class takes a Pandas DataFrame and wraps in a Torch Dataset.
    Read more about Torch Datasets here:
    https://pytorch.org/tutorials/beginner/basics/data_tutorial.html
    """
    def __init__(self, vocab, df, max_length=200):
        """
        Initialize the class with appropriate instance variables. In thi
        STRONGLY recommend storing the dataframe itself as an instance v
        keeping this method very simple. Leave processing to __getitem__

        Args:
            vocab (dict[str] = int) : In vocab, each str is a unique tok
                unique integer ID. Only elements that appear > cutoff ti
            df (pandas.DataFrame) : The entire dataset this mapping is b
            max_length (int) : The max length of a headline we'll allow

        Returns:
            None
        """

        ## YOUR CODE STARTS HERE - initialize parameters ##
        # keep it simple; store refs and use them in __getitem__
        self.vocab = vocab
        self.df = df
        self.max_length = max_length
        ## YOUR CODE ENDS HERE ##

    def __len__(self):
        """
        This method returns the length of the underlying dataframe,
        Args:
            None
        Returns:
            df_len (int) : The length of the underlying dataframe
        """

        df_len = None

        ## YOUR CODE STARTS HERE ##
        return len(self.df)
        ## YOUR CODE ENDS HERE ##

        return df_len

    def __getitem__(self, index: int):
        """
        This method converts a dataframe row (row["tokenized"]) to an en
        using our vocab map created using generate_vocab_map. Restricts
        length to max_length.

        The purpose of this method is to convert the row - a list of wor
        list of numbers.

        i.e. using a map of {"hi": 2, "hello": 3, "UNK": 0}
        this list ["hi", "hello", "NOT_IN_DICT"] will turn into [2, 3, 0

        Args:
            index (int) : The index of the dataframe we want to retrieve

        Returns:
            tokenized_word_tensor (torch.LongTensor) : A 1D tensor of ty
                token in the dataframe mapped to a number. These numbers
                vocab_map we created in generate_vocab_map.

                IMPORTANT: If we filtered out the word because it's infr
                exist in the vocab) we need to replace it w/ the UNK tok

            curr_label (int) : Label index of the class between 0 to len
            class label does this data instance belong to
        """

        tokenized_word_tensor = None
        curr_label            = None

        ## YOUR CODE STARTS HERE ##
        row = self.df.iloc[index]

        # tokens and label
        tokens = row["tokenized"]
        curr_label = int(row["target"])

        # map tokens -> ids, use UNK for OOV
        ids = [self.vocab.get(tok, UNK_VALUE) for tok in tokens]

        # truncate to max_length
        if self.max_length is not None:
            ids = ids[: self.max_length]

        # avoid empty sequences (rare) by inserting a single PAD
        if len(ids) == 0:
            ids = [PADDING_VALUE]

        tokenized_word_tensor = torch.tensor(ids, dtype=torch.long)

        return tokenized_word_tensor, curr_label
        ## YOUR CODE ENDS HERE ##

        return tokenized_word_tensor, curr_label
```

```
# DO NOT CHANGE THIS CELL
train_dataset = HeadlineDataset(train_vocab, train_data)
val_dataset   = HeadlineDataset(train_vocab, val_data)

# Now that we're wrapping our dataframes in PyTorch datsets, we can make
train_sampler = RandomSampler(train_dataset)
val_sampler   = RandomSampler(val_dataset)
```

```
# Check Dataset Lengths - DO NOT CHANGE THESE VALUES
assert len(train_dataset) == 15076, f"Training Dataset is of incorrect s
assert len(val_dataset)   ==  1885, f"Validation Dataset is of incorrect

# No error means you've passed the test!
```

1.5. Finalizing our DataLoader [3 points - Programming]

We can now use PyTorch DataLoaders to batch our data for us. **In the following cell fill out collate_fn.** Refer to PyTorch documentation on DataLoaders for help. Apply padding and other post-processing required here.

```
#export

def collate_fn(batch, padding_value=PADDING_VALUE):
    """
    This function is passed as a parameter to Torch DataSampler. collate
    batched rows, in the form of tuples, from a DataLoader and applies s
    pre-processing.

    Objective:
    In our case, we need to take the batched input array of 1D tokenized
    and create a 2D tensor that's padded to be the max length from all o
    in a batch. We're moving from a Python array of tuples, to a padded

    *HINT*: you're allowed to use torch.nn.utils.rnn.pad_sequence (ALREA

    Finally, you can read more about collate_fn here: https://pytorch.or

    :param batch: PythonArray[tuple(tokenized_word_tensor: 1D Torch.Long
    :param padding_value: int
```

```
        :return padded_tokens: 2D LongTensor of shape (BATCH_SIZE, max len o
        :return y_labels: 1D FloatTensor of shape (BATCH_SIZE)
        """

        padded_tokens, y_labels = None, None

        ## YOUR CODE STARTS HERE - take the input and target from batch, pad
        # unpack
        token_tensors, labels = zip(*batch)         # lists/tuples of len B

        # pad to the longest sequence in this batch
        padded_tokens = pad_sequence(
            token_tensors,
            batch_first=True,
            padding_value=padding_value
        )                                           # shape [B, T], dtype lo

        # labels as a tensor
        # CrossEntropyLoss expects long class indices; if your code later wa
        y_labels = torch.tensor(labels, dtype=torch.long)

        return padded_tokens, y_labels
        ## YOUR CODE ENDS HERE ##

        return padded_tokens, y_labels
```

```
    # DO NOT CHANGE THIS CELL
    train_iterator = DataLoader(train_dataset, batch_size=BATCH_SIZE, sample
    val_iterator   = DataLoader(val_dataset, batch_size=BATCH_SIZE, sampler=
```

```
    # Use this to test your collate_fn implementation.
    # You can look at the shapes of x and y or put print statements in colla
    # DO NOT CHANGE THIS CELL

    for x, y in train_iterator:
        print(f'x: {x.shape}')
        print(f'y: {y.shape}')
        break
```

```
x: torch.Size([128, 200])
y: torch.Size([128])
```

2. Neural Bag of Words (NBOW) [3 pts - Programming]

Let's move to modeling, now that we have dataset iterators that batch our data for us. The first model is a simple model called NBOW-RAND.

In the following code block, you'll build a feed-forward neural network implementing a neural bag-of-words baseline, NBOW-RAND, described in section 2.1 of this paper. You'll find this page useful for understanding the different layers and this page useful for how to put them into action.

The core idea behind this baseline is that after we embed each word for a document, we average the embeddings to produce a single vector that hopefully captures some general information spread across the sequence of embeddings. This means we first turn each document of length *n* into a matrix of *nxd*, where *d* is the dimension of the embedding. Then we average this matrix to produce a vector of length *d*, summarizing the contents of the document and proceed with the rest of the network.

While you're working through this implementation, keep in mind how the dimensions change and what each axes represents, as documents will be passed in as minibatches requiring careful selection of which axes you apply certain operations too. Stick to only the architecture described in the instructions below, do not add additional layers, this will impact the validity of local checks.

Refer to the following equation on how to define NBOW -

$$ h_{avg} = \frac{1}{n} \sum_t emb(x_t) $$

The probability of a data instance belonging to class y_i is given by:

$$ p(y|x) = softmax(w^T h_{avg}) $$

where $w \in R^d$ is a parameter vector.

HINT: In the forward step, the BATCH_SIZE is the first dimension.

Hint: Make sure to handle the case where the input contains pad tokens. We don't want to consider them in our average.

2.1. Define the NBOW model class [3 points]

```
#export

class NBOW(nn.Module):
    # Instantiate layers for your model-
    #
    # Your model architecture will be a feed-forward neural network.
    #
    # You'll need 2 nn.Modules:
    # 1. An embeddings layer (see nn.Embedding)
    # 2. A linear layer (see nn.Linear)
    #
    # HINT: In the forward step, the BATCH_SIZE is the first dimension.
    #
    def __init__(self, vocab_size, embedding_dim, num_classes=20):
        super().__init__()
        self.embedding = nn.Embedding(vocab_size, embedding_dim, padding
        # remove bias so the test matches expected logits
        self.fc = nn.Linear(embedding_dim, num_classes, bias=False)
        ## YOUR CODE ENDS HERE ##

    # Complete the forward pass of the model.
    #
    # Use the output of the embedding layer to create
    # the average vector, which will be input into the
    # linear layer.
    #
    # args:
    # x - 2D LongTensor of shape (BATCH_SIZE, max len of all tokenized_w
    #     This is the same output that comes out of the collate_fn funct
    def forward(self, x):
        ## Hint: Make sure to handle the case where x contains pad token
        ## YOUR CODE STARTS HERE ##
        emb = self.embedding(x)                                       # (B, T,
        mask = (x != PADDING_VALUE).unsqueeze(-1).float()             # (B, T,
        emb_sum = (emb * mask).sum(dim=1)                             # (B, D)
        lengths = mask.sum(dim=1).clamp(min=1.0)                      # (B, 1)
        h_avg = emb_sum / lengths                                     # (B, D)
        return self.fc(h_avg)
        ## YOUR CODE ENDS HERE ##

    def get_embeddings(self, x):
        '''
        This function returns the embeddings of the input x
        '''
```

```
            ### YOUR CODE STARTS HERE ###
            return self.embedding(x)
            ### YOUR CODE ENDS HERE ###

        def set_embedding_weight(self, weight):
            '''
            This function sets the embedding weights to the input weight. En
            Hint: Refer to nn.Parameter to do this.
            Args:
                weight: torch.tensor of shape (vocab_size, embedding_dim)
            '''
            ### YOUR CODE STARTS HERE ###
            with torch.no_grad():
                self.embedding.weight.data.copy_(weight)
            ### YOUR CODE ENDS HERE ###
        def get_h_avg(self, x):
            '''
            This function returns the average of the embeddings of the input
            '''
            ### YOUR CODE STARTS HERE ###
            emb = self.embedding(x)
            mask = (x != PADDING_VALUE).unsqueeze(-1).float()
            emb_sum = (emb * mask).sum(dim=1)
            lengths = mask.sum(dim=1).clamp(min=1.0)
            return emb_sum / lengths
            ### YOUR CODE ENDS HERE ###
```

```
# local test for sanity:
# DO NOT CHANGE THIS CELL

def nbow_test_local():
    embedding_dim = 10
    vocab_size = 5
    model = NBOW(vocab_size=vocab_size, embedding_dim=embedding_dim)
    for _, module in model.named_parameters():
        if hasattr(module, "data"):
            nn.init.constant_(module, 0.1)
    input = torch.arange(12).reshape(2,6) % vocab_size
    expected_result = torch.tensor(
        [[0.1000, 0.1000, 0.1000, 0.1000, 0.1000, 0.1000, 0.1000, 0.1000
          0.1000, 0.1000, 0.1000, 0.1000, 0.1000, 0.1000, 0.1000, 0.1000,
          0.1000, 0.1000],
        [0.1000, 0.1000, 0.1000, 0.1000, 0.1000, 0.1000, 0.1000, 0.1000,
          0.1000, 0.1000, 0.1000, 0.1000, 0.1000, 0.1000, 0.1000, 0.1000,
          0.1000, 0.1000]]
    )
    with torch.no_grad():
        local_result = model(input)
    if torch.allclose(expected_result, local_result, rtol=0.001):
        print("Passed local check")
    else:
        print(f"Test failed, expected value was\n{expected_result}\nbut

def nbow_test_local_embeddings():
    embedding_dim = 3
    vocab_size = 5
    model = NBOW(embedding_dim=embedding_dim, vocab_size=vocab_size)
    model.set_embedding_weight(torch.arange(15).reshape(5,3) / 50)
    embeddings = model.get_embeddings(torch.tensor([[1,2,3,4,1],[1,2,3,0
    correct_embeddings = torch.tensor([[[0.0600, 0.0800, 0.1000],
                                        [0.1200, 0.1400, 0.1600],
                                        [0.1800, 0.2000, 0.2200],
                                        [0.2400, 0.2600, 0.2800],
                                        [0.0600, 0.0800, 0.1000]],

                                        [[0.0600, 0.0800, 0.1000],
                                        [0.1200, 0.1400, 0.1600],
                                        [0.1800, 0.2000, 0.2200],
                                        [0.0000, 0.0200, 0.0400],
                                        [0.0000, 0.0200, 0.0400]]])
    if torch.allclose(embeddings, correct_embeddings, rtol=0.001):
        print("Passed local embedding test")
    else:
        print(f"Embedding Test failed, expected value was\n{correct_embe
def nbow_test_local_h_avg():
    embedding_dim = 3
    vocab_size = 5
    model = NBOW(embedding_dim=embedding_dim, vocab_size=vocab_size)
    model.set_embedding_weight(torch.arange(15).reshape(5,3) / 50)
    h_avg = model.get_h_avg(torch.tensor([[1,2,3,4,1],[1,2,3,0,0]]))
    correct_h_avg = torch.tensor([[0.1320, 0.1520, 0.1720],
                                  [0.1200, 0.1400, 0.1600]])
    if torch.allclose(h_avg, correct_h_avg, rtol=0.001):
        print("Passed local h_avg test")
    else:
        print(f"h_avg Test failed, expected value was\n{correct_h_avg}\n
nbow_test_local()
nbow_test_local_embeddings()
nbow_test_local_h_avg()
```

```
Passed local check
Passed local embedding test
Passed local h_avg test
```

3. Model Training [12 points - Programming + 3 points - Non-programming]

Training a PyTorch model involves several key components:

- **Training Loop**: This is the process where the model learns from the training data. In each iteration, the model processes the input data, makes predictions, calculates the loss, and updates its weights using backpropagation.
- **Validation Loop**: Performed after the training loop, this evaluates the model on a separate dataset (validation data) to check its performance. It helps in detecting overfitting.
- **Optimizer**: This is an algorithm that updates the model's weights during training. Common optimizers include SGD, Adam, etc.
- **Criterion (Loss Function)**: This measures how well the model is performing. It calculates the difference between the model's predictions and the actual data. Common loss functions include Mean Squared Error for regression tasks and Cross Entropy Loss for classification.

During training, the optimizer uses the gradient of the loss function to adjust the model's parameters. The model's performance is evaluated periodically on the validation set to monitor its generalization capability. This process continues for a specified number of epochs or until the model achieves a desired level of accuracy.

Note - In the following code cells (of this section), the above components will be defined. These functions/objects will be used to train and evaluate all your models in this assignment. So, make sure to implement these in a generic way, so that they can be used for all the models.

3.0. Evaluation Metrics [0 points]

Accuracy is a measure used to evaluate classification models, representing the ratio of correctly predicted observations to the total observations. It's simple and intuitive but may not be suitable for imbalanced datasets, as it can be misleading if the class distribution is skewed.

The F1-score, on the other hand, combines precision and recall into a single number. It is particularly useful when dealing with imbalanced datasets or when the cost of false positives and false negatives varies. F1-score provides a better measure of the incorrectly classified cases than the Accuracy Metric. It's calculated as the harmonic mean of precision and recall, thus balancing the two aspects of model performance.

You can read about the terms mentioned above here: https://scikit-learn.org/stable/modules/model_evaluation.html

For this assignment, we are already defining the above metrics for you to use in your implementation

```
#export
# DO NOT CHANGE THIS CELL
def get_accuracy_and_f1_score(y_true, y_predicted):
    """
    This function takes in two numpy arrays and computes the accuracy an
    between them. You can use the imported sklearn functions to do this.

    Args:
        y_true (list) : A 1D numpy array of ground truth labels
        y_predicted (list) : A 1D numpy array of predicted labels

    Returns:
        accuracy (float) : The accuracy of the predictions
        f1_score (float) : The F1 score of the predictions
    """

    # Get the accuracy
    accuracy = accuracy_score(y_true, y_predicted)

    # Get the F1 score
    f1 = f1_score(y_true, y_predicted, average='macro')

    return accuracy, f1
```

```
# DO NOT CHANGE THIS CELL
def plot_confusion_matrix(y_true, y_pred, classes):
    cm = confusion_matrix(y_true, y_pred, labels=range(len(classes)))
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=cl
    disp.plot(cmap=plt.cm.Blues)
    plt.xticks(rotation=90)
    plt.show()
```

3.1. Criterion [2 points - Programming]

Criterion in PyTorch, refers to the loss function used to evaluate the model's performance. It quantifies how far off the model's predictions are from the actual target values

In PyTorch, **nn.CrossEntropyLoss()** is used for classification tasks. It first does a softmax on the scores, and then calculates the negative log likelihood. This is why you don't need to do sotmax in the model, you can return the scores. In the cell below, implement this.

```
#export

def get_criterion(loss_type='ce'):
    criterion = None

    ## YOUR CODE STARTS HERE ##
    if loss_type == 'ce':
        criterion = nn.CrossEntropyLoss()
    else:
        raise ValueError(f"Unsupported loss type: {loss_type}")
    ## YOUR CODE ENDS HERE ##

    return criterion
```

3.2. Optimizer [2 points - Programming]

In PyTorch, an optimizer is a tool that updates the weights of the neural network to minimize the loss. Among these, Adam (Adaptive Moment Estimation) is a widely-used optimizer. Adam combines the best properties of the AdaGrad and RMSProp algorithms to handle sparse gradients on noisy problems. It's known for its effectiveness in deep learning models, especially where large datasets and high-dimensional spaces are involved. Adam adjusts the learning rate during training, making it efficient and effective across a wide range of tasks and model architectures.

In the cell below, define your optimizer. We recommend using Adam, but you are free to experiment with other optimizers as well.

The following function takes a model and learning rate value as input, and defines an optimizer for that model's parameters with that learning rate.

HINT: model.parameters() can give you all the parameters of a PyTorch model

```
#export
def get_optimizer(model, learning_rate):
    """
    This function takes a model and a learning rate, and returns an opti
    Feel free to experiment with different optimizers.
    """
    optimizer = None

    ## YOUR CODE STARTS HERE ##
    optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
    ## YOUR CODE ENDS HERE ##

    return optimizer
```

3.3. Training Loop [3 points - Programming]

The training loop function in PyTorch is a critical component where the actual learning from data occurs. It typically involves iterating over the training dataset, feeding the data to the model, computing the loss (difference between the predictions and true values), and updating the model's weights.

Creating a training loop involves several steps:

1. Iterate Over Dataset: Loop through the training dataset, often in mini-batches.
2. Forward Pass: Feed the input data to the model to get predictions.
3. Compute Loss: Calculate the loss using a loss function.
4. Backward Pass: Perform backpropagation by calling loss.backward(), which computes the gradient of the loss function with respect to each weight.
5. Update Weights: Use an optimizer (like SGD or Adam) to adjust the weights based on the gradients calculated.
6. Zero the Gradients: Reset the gradients to zero after each mini-batch to prevent accumulation of gradients from multiple passes.

This loop repeats for a specified number of epochs or until a certain level of accuracy or loss is achieved.

In the end, return the mean loss over all samples for this particular iteration

```
#export
def train_loop(model, criterion, optimizer, iterator, epoch, save_every=
    """
    This function is used to train a model for one epoch.
    :param model: The model to be trained
    :param criterion: The loss function
    :param optim: The optimizer
    :param iterator: The training data iterator
    :return: The average loss for this epoch
    """
    model.train() # Is used to put the model in training mode
    total_loss = 0
    for x, y in tqdm(iterator, total=len(iterator), desc="Training Model
        ### YOUR CODE STARTS HERE ###
        # Move batch to same device as model
        x = x.to(device)
        y = y.to(device)

        # ---- forward ----
        logits = model(x)
        loss = criterion(logits, y)

        # ---- backward + optimize ----
        optimizer.zero_grad(set_to_none=True)
        loss.backward()
        optimizer.step()

        total_loss += loss.item()
        ### YOUR CODE ENDS HERE ###

    average_loss = total_loss / len(iterator)
    return average_loss
```

3.4. Validation Loop [3 points - Programming]

The validation loop in PyTorch is where the model's performance is evaluated on a dataset different from the one used for training. It does not involve updating the model's weights, focusing instead on assessing how well the model generalizes to new data. Here's how it typically works:

1. Iterate Over Validation Dataset: Loop through the validation dataset, usually in mini-batches, without the need for shuffling as in the training loop.
2. Forward Pass: Feed the input data to the model to obtain predictions.
3. Compute Loss: Calculate the loss (e.g., Cross-Entropy, Mean Squared Error) to assess the performance on the validation dataset.
4. Calculate Metrics: Besides loss, other performance metrics like accuracy, F1 score, etc., are computed to evaluate model performance.

Note: No Backpropagation: Unlike the training loop, there is no backward pass or weight updates.

The validation loop is crucial for monitoring overfitting and tuning hyperparameters. It provides insight into how the model is likely to perform on unseen data.

```
# export
def val_loop(model, criterion, iterator):
    """
    This function is used to evaluate a model on the validation set.
    :param model: The model to be evaluated
    :param iterator: The validation data iterator
    :return: true: a Python boolean array of all the ground truth values
                 pred: a Python boolean array of all model predictions.
                average_loss: The average loss over the validation set
    """

    true, pred = [], []
    total_loss = 0
    model.eval()
    for x, y in tqdm(iterator, total=len(iterator), desc="Evaluating Mod
    ### YOUR CODE STARTS HERE ###
        # Move data to same device as model
        x = x.to(device)
        y = y.to(device)

        # Forward pass
        logits = model(x)
        loss = criterion(logits, y)
        total_loss += loss.item()

        # Predictions
        preds = torch.argmax(logits, dim=1)

        # Store for metric computation
        true.extend(y.cpu().numpy())
        pred.extend(preds.cpu().numpy())
    ### YOUR CODE ENDS HERE ###
    average_loss = total_loss / len(iterator)
    return true, pred, average_loss
```

3.5. Training NBOW [3 points - Non-programming]

Assign and tune the below hyperparameters to optimize your model. Make sure that the output graph of the cell where training happens is clear in your submission.

```
#export
# Assigning hyperparameters and training parameters
# Experiment with different values for these hyperparaters to optimize y
def get_hyperparams_nbow():
  ### your hyper parameters
  learning_rate = 2e-3     # float
  epochs        = 6        # int
  embedding_dim = 200      # int (try 100–300)
  ###
  return learning_rate, epochs, embedding_dim
```

Since the NBOW model is rather basic, assuming you haven't added any additional layers, there's really only one hyperparameter for the model architecture: the size of the embedding dimension.

The vocab_size parameter here is based on the number of unique words kept in the vocab after removing those occurring too infrequently, so this is determined by our dataset and is in turn not a true hyperparameter (though the cutoff we used previously might be). The embedding_dim parameter dictates what size vector each word can be embedded as.

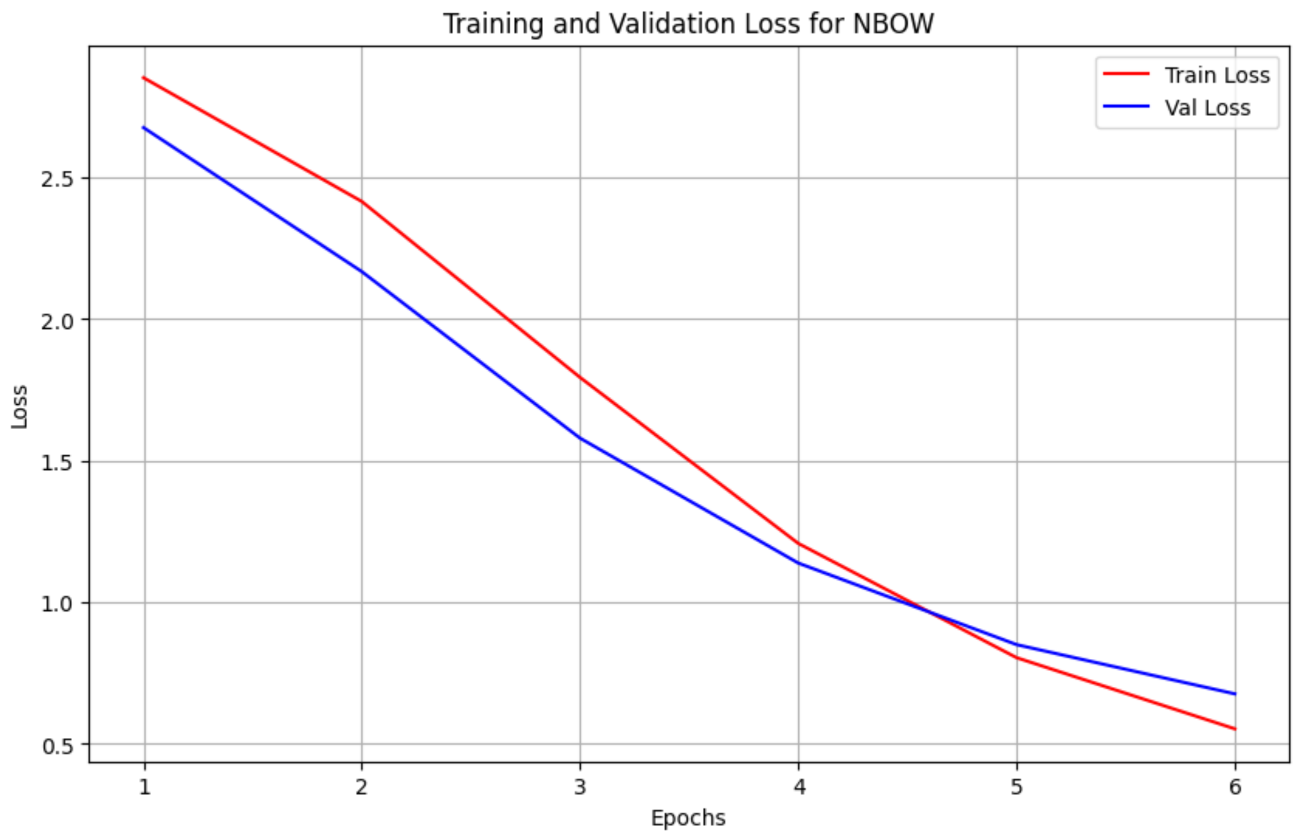
A special note concerning the model initialization: We're specifically sending the model to the device set in Part 1, to speed up training if the GPU is available. **Be aware**, you'll have to ensure other tensors are on the same device inside your training and validation loops.

```
# export
def get_nbow_model(vocab_size, embedding_dim):
    """
    This function returns an instance of the NBOW model.
    """
    model = None
    # Define a model and return
    # YOUR CODE STARTS HERE
    model = NBOW(vocab_size=vocab_size, embedding_dim=embedding_dim, num
    model = model.to(device)  # move to CUDA/MPS/CPU as defined in setup
    # YOUR CODE ENDS HERE
    return model
```

```
# This is the main training loop. You'll need to complete the train_loop
# You'll also need to complete the criterion and optimizer functions.
# Feel free to experiment with different optimizers and learning rates.
# Do not change anything else in this cell
learning_rate, epochs, embedding_dim = get_hyperparams_nbow()
nbow_model = get_nbow_model(vocab_size= len(train_vocab.keys()), embeddi
criterion = get_criterion()
optimizer = get_optimizer(nbow_model, learning_rate)
train_loss_over_time_nbow = []
val_loss_over_time_nbow = []
for epoch in range(epochs):
    train_loss = train_loop(nbow_model, criterion, optimizer, train_iter
    true, pred, val_loss = val_loop(nbow_model, criterion, val_iterator)
    accuracy, f1 = get_accuracy_and_f1_score(true, pred)
    print(f"Epoch {epoch+1} -- Train_Loss: {train_loss} -- Val_Loss: {va
    train_loss_over_time_nbow.append(train_loss)
    val_loss_over_time_nbow.append(val_loss)
save_checkpoint(nbow_model, 'nbow')
```

```
Training Model: 100%|██████████| 118/118 [00:23<00:00,  5.10it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 23.27it/s]
Epoch 1 -- Train_Loss: 2.8524216736777355 -- Val_Loss: 2.67640651067098 -
Training Model: 100%|██████████| 118/118 [00:19<00:00,  6.01it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 24.54it/s]
Epoch 2 -- Train_Loss: 2.415512788093696 -- Val_Loss: 2.167896286646525 -
Training Model: 100%|██████████| 118/118 [00:31<00:00,  3.69it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 20.07it/s]
Epoch 3 -- Train_Loss: 1.794180793277288 -- Val_Loss: 1.5796855290730794
Training Model: 100%|██████████| 118/118 [00:22<00:00,  5.33it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 27.51it/s]
Epoch 4 -- Train_Loss: 1.207840038558184 -- Val_Loss: 1.1384830713272094
Training Model: 100%|██████████| 118/118 [00:22<00:00,  5.34it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 24.33it/s]
Epoch 5 -- Train_Loss: 0.804404746677916 -- Val_Loss: 0.8504602869351705
Training Model: 100%|██████████| 118/118 [00:22<00:00,  5.21it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 23.48it/s]
Epoch 6 -- Train_Loss: 0.5530885387275178 -- Val_Loss: 0.6766179323196411
Checkpoint saved to /content/drive/MyDrive/HW2/model_weights/checkpoint_n
```

```
# DO NOT CHANGE THIS CELL - retain the outputs in submission PDF for cre
plot_loss(train_loss_over_time_nbow, val_loss_over_time_nbow, 'NBOW')
```



3.6. Model Evaluation [2 points - Programming]

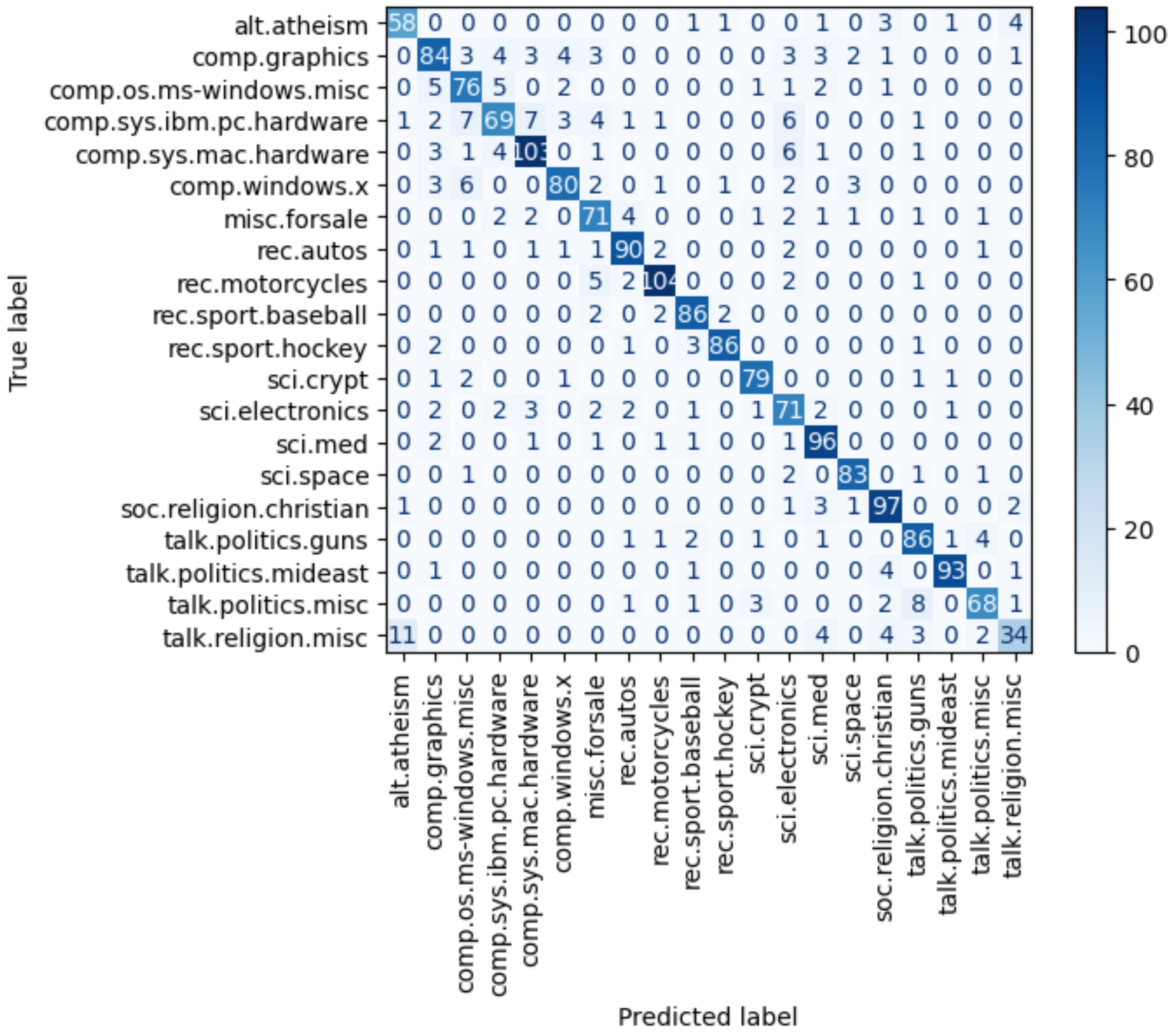
The final points for this will be awarded as per Gradescope's test split, which is different from the local versions. The cell below is just for a sanity check. Your metrics here may not exactly match with the ones on Gradescope, but if your model is fairly generalized, it should not be far off.

- 0 points for accuracy <= 84%
- 1 point for accuracy > 84% but <= 88%
- 2 points for accuracy > 88%

```
# load best model from checkpoint
# DO NOT CHANGE THIS CELL
learning_rate, epochs, embedding_dim = get_hyperparams_nbow()
nbow_model = get_nbow_model(vocab_size= len(train_vocab.keys()), embeddi
load_checkpoint(nbow_model, 'nbow', map_location=device)

# evaluate model
true, pred, val_loss = val_loop(nbow_model, criterion, val_iterator)
accuracy, f1 = get_accuracy_and_f1_score(true, pred)
print(f"Final Validation Accuracy: {accuracy}")
print(f"Final Validation F1-Score: {f1}")
```

```
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 24.04it/s]Final Va
Final Validation F1-Score: 0.851117858612087
```

```
# DO NOT CHANGE THIS CELL
plot_confusion_matrix(true, pred, classes=id2label.values())
```



4. Simple Deep Averaging Networks (DAN) [5 points - Programming + 3 points - Non-programming]

Now, let's look at how to improve performance of the NBOW model. One such way without drastically changing the model complexity is DAN.

The core idea of a DAN is to simplify the process of understanding text by averaging the embeddings of words in a sentence or document. This creates a single vector representation that captures the overall meaning of the text.

In implementation, a DAN typically involves the following steps:

1. Convert each token into an embedding.
2. Average these embeddings to create a single vector that represents the entire document.
3. Pass this averaged vector through one hidden fully connected neural network layer.
4. Use ReLU activation
5. Use the output of these layers for tasks like classification.

This approach is simpler and often faster than more complex architectures like LSTMs or Transformers, while still providing robust performance for many tasks. However, it might not capture nuances in language as effectively as these more complex models.

NOTE: Use the same approach to handle pad_tokens as you used in NBOW.

4.1. Model Definition [3 points - Programming]

In the following cell, define the architecture of a DAN in the same way as you implemented NBOW-RAND in Section 2 with. Use the following image as a reference along with Section 3 and Figure 1 (right) of this paper.

Refer to the following equation on how to define DAN -

$$ h_{avg} = \frac{1}{n} \sum_t emb(x_t) $$$$ h_{avg} = \frac{1}{n} \sum_t emb(x_t) $$

$$ h_2 = (w_1h_{avg}) $$$$ h_2 = (w_1h_{avg}) $$

$$ h'_{2} = max(0, h_2) $$$$ h'_{2} = max(0, h_2) $$

The probability of a data instance belonging to class $y_i$$y_i$ is given by:

$$ p(y|x) = softmax(w_2^T h'_{2} + b) $$$$ p(y|x) = softmax(w_2^T h'_{2} + b) $$

where $w \in R^d$$w \in R^d$ is a parameter vector.

Hint: Make sure to handle the case where the input contains pad tokens. We don't want to consider them in our average.

```
# export
class DAN(nn.Module):
    # Instantiate layers for your model-
    #
    # Your model architecture will be a feed-forward neural network.
    #
    # You'll need 4 nn.Modules:
    # 1. An embeddings layer (see nn.Embedding)
    # 2. A linear layer (see nn.Linear)
    # 3. A ReLU activation (see nn.ReLU)
    # 4. A linear layer (see nn.Linear)
    #
    def __init__(self, vocab_size, embedding_dim, hidden_dim, num_classe
        # vocab_size is the size of the vocabulary
        # embedding_dim is the dimension of the word embeddings
        # hidden_dim is the dimension of the hidden layer outputs, i.e.,
        super().__init__()
        ## YOUR CODE STARTS HERE ##
        # 1) NO padding_idx here (test expects non-zero PAD row to survi
        self.embedding = nn.Embedding(vocab_size, embedding_dim)
        # 2) Hidden MLP: avg-emb -> ReLU -> logits
        self.proj1 = nn.Linear(embedding_dim, hidden_dim)
        self.relu  = nn.ReLU()
        self.out   = nn.Linear(hidden_dim, num_classes)
        ## YOUR CODE ENDS HERE ##

    # helper method
    def _masked_average(self, x: torch.Tensor, emb: torch.Tensor) -> tor
        """
        x:  (B, T) Long
        emb:(B, T, D) Float
        returns h_avg: (B, D)
        """
        mask = (x != PADDING_VALUE).unsqueeze(-1)            # (B, T, 1)
        emb_masked = emb * mask                              # zero-out
        lengths = mask.sum(dim=1).clamp(min=1).to(emb.dtype) # (B, 1)
        h_avg = emb_masked.sum(dim=1) / lengths              # (B, D)
        return h_avg

    # Complete the forward pass of the model.
    #
    # Use the output of the embedding layer to create
    # the average vector, which will be input into the
    # linear layer.
    #
    # args:
    # x - 2D LongTensor of shape (BATCH_SIZE, max len of all tokenized_w
    #     This is the same output that comes out of the collate_fn funct
    def forward(self, x):
        ## YOUR CODE STARTS HERE ##
        # x: (B, T)
        emb  = self.embedding(x)                  # (B, T, D)  (PAD row s
        havg = self._masked_average(x, emb)       # (B, D)     (PAD ignor
        h    = self.relu(self.proj1(havg))        # (B, H)
        logits = self.out(h)                      # (B, C)
        return logits

        ## YOUR CODE ENDS HERE ##

    def get_embeddings(self, x):
        '''
        This function returns the embeddings of the input x
        '''
        ### YOUR CODE STARTS HERE ###
        return self.embedding(x)
        ### YOUR CODE ENDS HERE ###
    def set_embedding_weight(self, weight):
        '''
        This function sets the embedding weights to the input weight ens
        Args:
            weight: torch.tensor of shape (vocab_size, embedding_dim)
        '''
        ### YOUR CODE STARTS HERE ###
        with torch.no_grad():
            self.embedding.weight.copy_(weight)
        ### YOUR CODE ENDS HERE ###

    def get_hidden(self, x):
        '''
        This function returns the embeddings of the input x
        '''
        ### YOUR CODE STARTS HERE ###
        emb  = self.embedding(x)                # (B, T, D)
        havg = self._masked_average(x, emb)     # (B, D)
        h    = self.relu(self.proj1(havg))      # (B, H)
        return h
        ### YOUR CODE ENDS HERE ###

    def set_hidden_weight(self, weight, bias):
        '''
        This function sets the embedding weights to the input weight ens
        Args:
            weight: torch.tensor of shape (embedding_dim, hidden_dim)
            bias: torch.tensor of shape (1, hidden_dim)
        '''
        ### YOUR CODE STARTS HERE ###
        with torch.no_grad():
            self.proj1.weight.copy_(weight)
            self.proj1.bias.copy_(bias.squeeze(0))
        ### YOUR CODE ENDS HERE ###
```

```
# local test for sanity:
# DO NOT CHANGE THIS CELL
def dan_test_local_embeddings():
    embedding_dim = 3
    vocab_size = 5
    model = DAN(embedding_dim=embedding_dim, vocab_size=vocab_size, hidd
    model.set_embedding_weight(torch.arange(15).reshape(5,3) / 50)
```

```
        embeddings = model.get_embeddings(torch.tensor([[1,2,3,4,1],[1,2,3,0
        correct_embeddings = torch.tensor([[[0.0600, 0.0800, 0.1000],
                                            [0.1200, 0.1400, 0.1600],
                                            [0.1800, 0.2000, 0.2200],
                                            [0.2400, 0.2600, 0.2800],
                                            [0.0600, 0.0800, 0.1000]],

                                            [[0.0600, 0.0800, 0.1000],
                                            [0.1200, 0.1400, 0.1600],
                                            [0.1800, 0.2000, 0.2200],
                                            [0.0000, 0.0200, 0.0400],
                                            [0.0000, 0.0200, 0.0400]]])
        if torch.allclose(embeddings, correct_embeddings, rtol=0.001):
            print("Passed local embedding test")
        else:
            print(f"Embedding Test failed, expected value was\n{correct_embe

    def dan_test_local_hidden_layer():
        vocab_size = 5
        embedding_dim = 3
        hidden_dim = 3

        model = DAN(vocab_size, embedding_dim, hidden_dim)
        model.set_embedding_weight(torch.arange(15).reshape(5,3) / 50)
        model.set_hidden_weight(torch.arange(9).reshape(embedding_dim, hidde

        output = model.get_hidden(torch.tensor([[1,2,3,4,1],[1,2,3,0,0]]))
        correct_output = torch.tensor([[0.0099, 0.0573, 0.1046],
                                        [0.0092, 0.0544, 0.0996]])

        if torch.allclose(output, correct_output, atol=0.001):
            print("Passed local hidden layer test")
        else:
            print(f"Embedding Test failed, expected value was\n{correct_outp

    dan_test_local_embeddings()
    dan_test_local_hidden_layer()
```

```
    Passed local embedding test
    Passed local hidden layer test
```

4.2. DAN Training [3 points - Non-programming]

In this section (and all later sections), you will leverage the same functions defined in Section 3 to train your DAN. To do this, simply initialize your DAN Model and pass that object to the training and evaluation loop to train your model.

Assign and tune the below hyperparameters to optimize your model

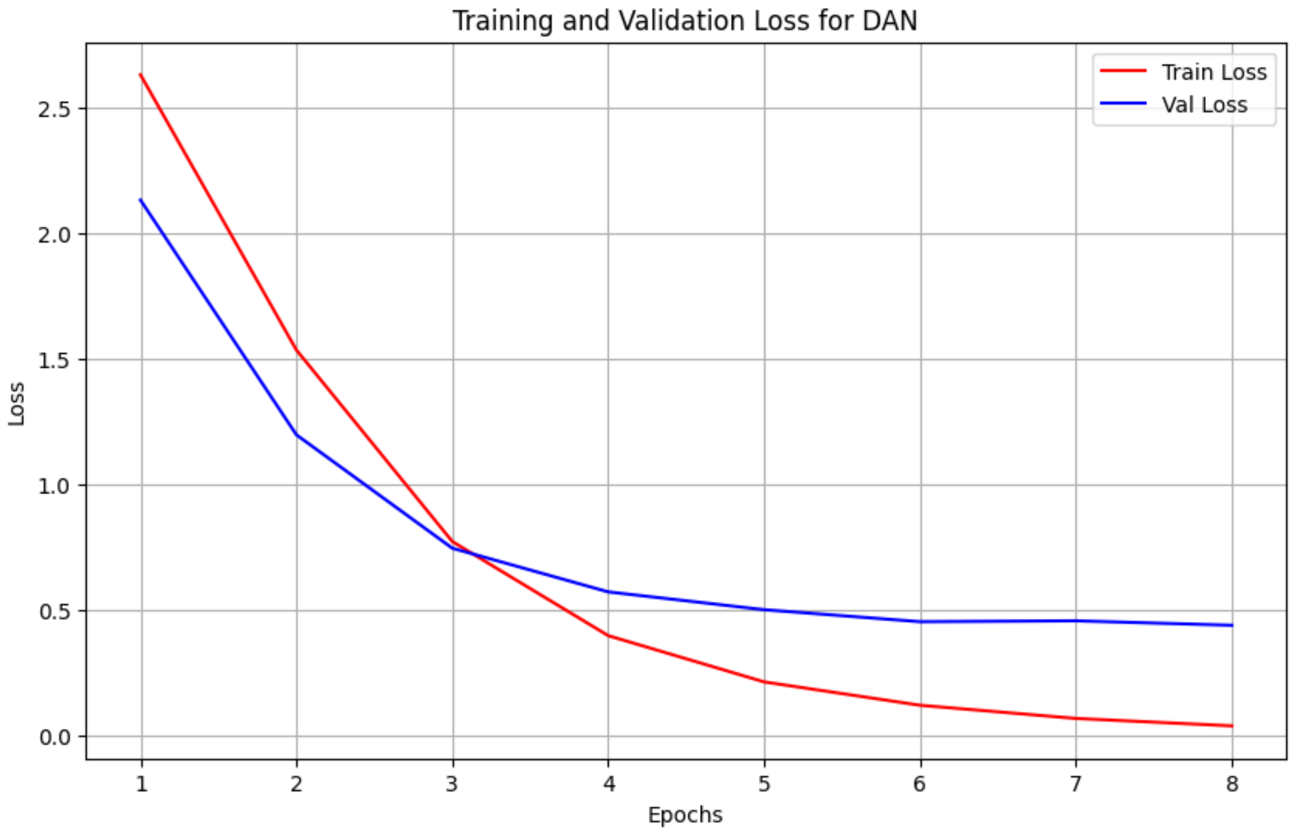
```
# export
def get_dan_model(vocab_size, embedding_dim, hidden_dim):
    """
    This function returns an instance of the DAN model. Initialize the D
    """
    model = None
    ## YOUR CODE STARTS HERE ##
    model = DAN(
        vocab_size=vocab_size,
        embedding_dim=embedding_dim,
        hidden_dim=hidden_dim,
        num_classes=len(id2label)   # 20 for this dataset
    )
    ## YOUR CODE ENDS HERE ##
    return model
```

```
#export
# Assign hyperparameters and training parameters
# Experiment with different values for these hyperparaters to optimize y
def get_hyperparams_dan():
  ### your hyper parameters
    learning_rate = 2e-3           # good starting point for Adam
    epochs = 8                     # DAN usually converges in 6–10 epoch
    hidden_layer_dimensions = 256  # can try 128–512; 256 is balanced
    embedding_dim = 200            # 100–300 is common for word embeddin
    ###
    return learning_rate, epochs, hidden_layer_dimensions, embedding_dim
```

```
# This is the main training loop. You'll need to complete the train_loop
# You'll also need to complete the criterion and optimizer functions.
# Feel free to experiment with different optimizers and learning rates.
# Do not change anything else in this cell
learning_rate, epochs, hidden_layer_dimensions, embedding_dim = get_hype
dan_model = get_dan_model(len(train_vocab.keys()), embedding_dim, hidden
criterion = get_criterion()
optimizer = get_optimizer(dan_model, learning_rate)
train_loss_over_time_dan = []
val_loss_over_time_dan = []
for epoch in range(epochs):
    train_loss = train_loop(dan_model, criterion, optimizer, train_itera
    true, pred, val_loss = val_loop(dan_model, criterion, val_iterator)
    accuracy, f1 = get_accuracy_and_f1_score(true, pred)
    train_loss_over_time_dan.append(train_loss)
    val_loss_over_time_dan.append(val_loss)
    print(f"Epoch {epoch+1} -- Train_Loss: {train_loss} -- Val_Loss: {va

save_checkpoint(dan_model, 'dan')
```

```
Training Model: 100%|██████████| 118/118 [00:26<00:00,  4.49it/s]
Evaluating Model: 100%|██████████| 15/15 [00:01<00:00, 14.55it/s]
Epoch 1 -- Train_Loss: 2.631095888250965 -- Val_Loss: 2.1322281837463377
Training Model: 100%|██████████| 118/118 [00:24<00:00,  4.92it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 27.18it/s]
Epoch 2 -- Train_Loss: 1.535145201925504 -- Val_Loss: 1.1974853237469991
Training Model: 100%|██████████| 118/118 [00:24<00:00,  4.84it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 24.99it/s]
Epoch 3 -- Train_Loss: 0.7725956200037972 -- Val_Loss: 0.7459546566009522
Training Model: 100%|██████████| 118/118 [00:23<00:00,  4.99it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 22.09it/s]
Epoch 4 -- Train_Loss: 0.3977512454582473 -- Val_Loss: 0.571980877717336
Training Model: 100%|██████████| 118/118 [00:23<00:00,  4.94it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 27.48it/s]
Epoch 5 -- Train_Loss: 0.2135626933205936 -- Val_Loss: 0.5009664555390676
Training Model: 100%|██████████| 118/118 [00:24<00:00,  4.87it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 24.22it/s]
Epoch 6 -- Train_Loss: 0.12055843140361673 -- Val_Loss: 0.453287021319071
Training Model: 100%|██████████| 118/118 [00:24<00:00,  4.87it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 27.82it/s]
Epoch 7 -- Train_Loss: 0.06808512058045904 -- Val_Loss: 0.456726515293121
Training Model: 100%|██████████| 118/118 [00:23<00:00,  4.96it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 22.97it/s]
Epoch 8 -- Train_Loss: 0.03859390621468172 -- Val_Loss: 0.439081921180089
Checkpoint saved to /content/drive/MyDrive/HW2/model_weights/checkpoint_d
```

```
# DO NOT CHANGE THIS CELL - retain the outputs in submission PDF to get
plot_loss(train_loss_over_time_dan, val_loss_over_time_dan, 'DAN')
```



4.3. Model Evaluation [2 points - Programming]

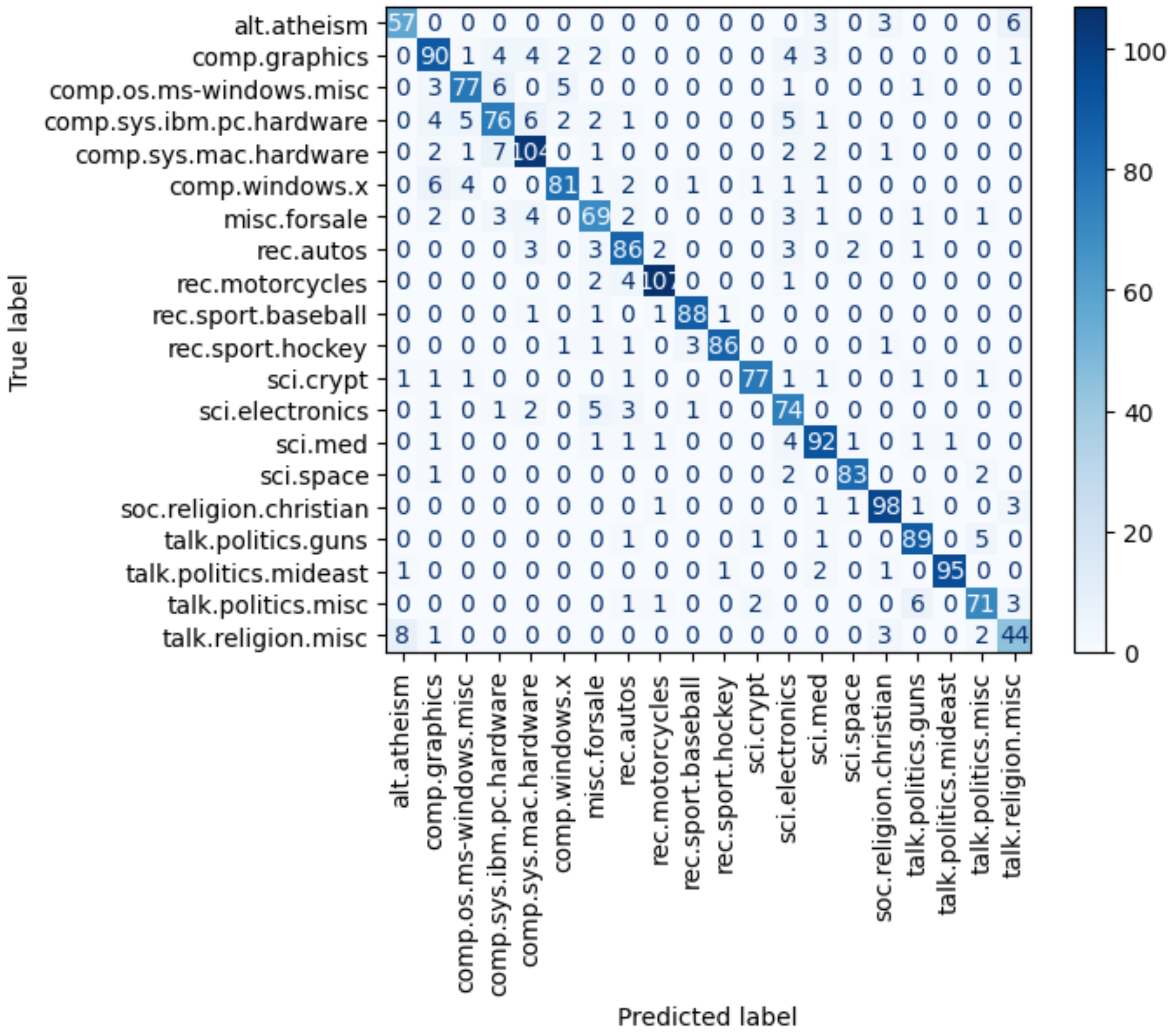
The final points for this will be awarded as per Gradescope's test split, which is different from the local versions. The cell below is just for a sanity check. Your metrics here may not exactly match with the ones on Gradescope, but if your model is fairly generalized, it should not be far off.

- 0 points for accuracy <= 84%
- 1 point for accuracy > 84% but <= 88%
- 2 points for accuracy > 88%

```
# DO NOT CHANGE THIS CELL
learning_rate, epochs, hidden_layer_dimensions, embedding_dim = get_hype
dan_model = get_dan_model(len(train_vocab.keys()), embedding_dim, hidden
load_checkpoint(dan_model, 'dan', map_location=device)

true, pred, val_loss = val_loop(dan_model, criterion, val_iterator)
accuracy, f1 = get_accuracy_and_f1_score(true, pred)
print(f"Final Validation Accuracy: {accuracy}")
print(f"Final Validation F1-Score: {f1}")
```

```
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 21.06it/s]Final Va
Final Validation F1-Score: 0.8699418610522972
```

```
# DO NOT CHANGE THIS CELL
plot_confusion_matrix(true, pred, classes=id2label.values())
```



	alt.atheism	comp.graphics	comp.os.ms-windows.misc	comp.sys.ibm.pc.hardware	comp.sys.mac.hardware	comp.windows.x	misc.forsale	rec.autos	rec.motorcycles	rec.sport.baseball	rec.sport.hockey	sci.crypt	sci.electronics	sci.med	sci.space	soc.religion.christian	talk.politics.guns	talk.politics.mideast	talk.politics.misc	talk.religion.misc
alt.atheism	57	0	0	0	0	0	0	0	0	0	0	0	0	3	0	3	0	0	0	6
comp.graphics	0	90	1	4	4	2	2	0	0	0	0	0	4	3	0	0	0	0	0	1
comp.os.ms-windows.misc	0	3	77	6	0	5	0	0	0	0	0	0	1	0	0	0	1	0	0	0
comp.sys.ibm.pc.hardware	0	4	5	76	6	2	2	1	0	0	0	0	5	1	0	0	0	0	0	0
comp.sys.mac.hardware	0	2	1	7	104	0	1	0	0	0	0	0	2	2	0	1	0	0	0	0
comp.windows.x	0	6	4	0	0	81	1	2	0	1	0	1	1	1	0	0	0	0	0	0
misc.forsale	0	2	0	3	4	0	69	2	0	0	0	0	3	1	0	0	1	0	1	0
rec.autos	0	0	0	0	3	0	3	86	2	0	0	0	3	0	2	0	1	0	0	0
rec.motorcycles	0	0	0	0	0	0	2	4	107	0	0	0	1	0	0	0	0	0	0	0
rec.sport.baseball	0	0	0	0	1	0	1	0	1	88	1	0	0	0	0	0	0	0	0	0
rec.sport.hockey	0	0	0	0	0	1	1	1	0	3	86	0	0	0	0	1	0	0	0	0
sci.crypt	1	1	1	0	0	0	0	1	0	0	0	77	1	1	0	0	1	0	1	0
sci.electronics	0	1	0	1	2	0	5	3	0	1	0	0	74	0	0	0	0	0	0	0
sci.med	0	1	0	0	0	0	1	1	1	0	0	0	4	92	1	0	1	1	0	0
sci.space	0	1	0	0	0	0	0	0	0	0	0	0	2	0	83	0	0	0	2	0
soc.religion.christian	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	98	1	0	0	3
talk.politics.guns	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0	0	89	0	5	0
talk.politics.mideast	1	0	0	0	0	0	0	0	0	0	1	0	0	2	0	1	0	95	0	0
talk.politics.misc	0	0	0	0	0	0	0	1	1	0	0	2	0	0	0	0	6	0	71	3
talk.religion.misc	8	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	2	44

5. Attention-based Models [21 points - Programming + 9 points - Non-programming]

In the simplest terms, attention allows a network to differentially focus on specific input words rather considering their importance equally, as done in the previous sections by averaging. For example, often times the mere presence of word "election" is enough to ascertain the category of the sentence to be politics.

There are various types of attention which we will dsicuss in much more depth throughout course. This section is just to provide a conceptual flavor of attention as a concept. In the below parts, you will work with three different simple types of attention.

5.1. Attention-weighted NBOW [7 points - Programming + 3 points - Non-programming]

You will now define an encoder that uses a simple attention function to produce a weight for each word in the sentence followed by a sum of the attention-weighted word embeddings. Simple attention allows the model to learn a weight vector $\alpha_t$$\alpha_t$ which represents how important will different tokens in a document be.

Consider $u$$u$ to be a single attention head (a learnable PyTorch parameter). With this,

$$ \alpha_t \varpropto \exp\{cos(u,emb(x_t))\} $$$$ \alpha_t \varpropto \exp\{cos(u,emb(x_t))\} $$

Note: This needs to be normalized.

$$ h_{att} = \sum_t \alpha_t emb(x_t) $$$$ h_{att} = \sum_t \alpha_t emb(x_t) $$

The probability of a data instance belonging to class $y_i$$y_i$ is given by:

$$ p(y|x) = softmax(w^T h_{att}) $$$$ p(y|x) = softmax(w^T h_{att}) $$

where $w \in R^d$$w \in R^d$ is a parameter vector.

In this model, the unnormalized attention weight for a word $x$$x$ is computed using the cosine similarity between a learnable parameter $u$$u$ and the word embedding for $x$$x$ followed by exponentiation. To get normalized weights $\alpha_t$$\alpha_t$, normalize across all words in the sentence. Then multiply the attention weights by the word embeddings and sum the attention-weighted embeddings.

HINT: See if Softmax function can help with this

Hint: Make sure to handle the case where the input contains pad tokens.

5.1.1. Model Definition [5 points - Programming]

Define your simple attention model below.

```
#export

class SimpleAttentionNBOW(nn.Module):
    """
    This class implements the Attention-weighted Neural Bag of Words mod
    """
    def __init__(self, vocab_size, embedding_dim, num_classes=20):
        super().__init__()
        # Do NOT set padding_idx here
        self.embedding = nn.Embedding(vocab_size, embedding_dim)

        # learnable attention vector u (size d)
        self.att_vector = nn.Parameter(torch.randn(embedding_dim))

        # classifier on top of attention-weighted average
        self.fc = nn.Linear(embedding_dim, num_classes)

    def forward(self, x):
        ## YOUR CODE STARTS HERE ##
        emb = self.embedding(x)                     # (B, T, d)
        alphas = self.get_attention_matrix(x)       # (B, T)
        h_att = torch.einsum("bt,btd->bd", alphas, emb)   # (B, d)
        logits = self.fc(h_att)                     # (B, C)
        return logits
        ## YOUR CODE ENDS HERE ##

        # return predictions

    def get_embeddings(self, x):
        '''
        This function returns the embeddings of the input x
        '''
        ### YOUR CODE STARTS HERE ###
        return self.embedding(x)
        ### YOUR CODE ENDS HERE ###

    def set_embedding_weight(self, weight):
        '''
        This function sets the embedding weights to the input weight ens
        Args:
            weight: torch.tensor of shape (vocab_size, embedding_dim)
        '''
        ### YOUR CODE STARTS HERE ###
        with torch.no_grad():
            self.embedding.weight.copy_(weight)
        ### YOUR CODE ENDS HERE ###

    def set_attention_weights(self, weight):
        '''
        This function sets the attention weights to the input weight ens
        Args:
            weight: torch.tensor of shape (embedding_dim)
        '''
        ### YOUR CODE STARTS HERE ###
        with torch.no_grad():
            self.att_vector.copy_(weight)
        ### YOUR CODE ENDS HERE ###

    def get_attention_matrix(self, x):
        '''
        This function returns the normalized attention matrix for the in
        Args:
            x: torch.tensor of shape (BATCH_SIZE, max seq length in batc
        Returns:
            attention_weights: torch.tensor of shape (BATCH_SIZE, max se
        '''
        ### YOUR CODE STARTS HERE ###
        emb = self.embedding(x)                     # (B, T, d)
        # cosine similarity between u and each token embedding
        u = F.normalize(self.att_vector, dim=0)     # (d,)
        e = F.normalize(emb, dim=-1) @ u            # (B, T)

        # mask out pad positions (token id == 0)
        mask = (x != 0)                              # (B, T) bool
        e_masked = e.masked_fill(~mask, float('-inf'))

        # normalized attention weights (pad positions -> 0)
        alphas = F.softmax(e_masked, dim=1)
        alphas = alphas * mask.float()
        # (optional) renormalize to ensure sum to 1 over non-pad tokens
        denom = alphas.sum(dim=1, keepdim=True).clamp_min(1e-9)
        alphas = alphas / denom
        return alphas
        ### YOUR CODE ENDS HERE ###
```

```
# local test for sanity:
# DO NOT CHANGE THIS CELL
def simple_attention_nbow_test_local_embeddings():
    model = SimpleAttentionNBOW(embedding_dim=3, vocab_size=5)
    model.set_embedding_weight(torch.arange(15).reshape(5,3) / 50)
    embeddings = model.get_embeddings(torch.tensor([[1,2,3,4,1],[1,2,3,0
    correct_embeddings = torch.tensor([[[0.0600, 0.0800, 0.1000],
                                        [0.1200, 0.1400, 0.1600],
                                        [0.1800, 0.2000, 0.2200],
                                        [0.2400, 0.2600, 0.2800],
                                        [0.0600, 0.0800, 0.1000]],

                                        [[0.0600, 0.0800, 0.1000],
                                        [0.1200, 0.1400, 0.1600],
                                        [0.1800, 0.2000, 0.2200],
                                        [0.0000, 0.0200, 0.0400],
                                        [0.0000, 0.0200, 0.0400]]])
    if torch.allclose(embeddings, correct_embeddings, rtol=0.001):
        print("Passed local embedding test")
    else:
        print(f"Embedding Test failed, expected value was\n{correct_embe
def simple_attention_nbow_test_local_attn():
    model = SimpleAttentionNBOW(embedding_dim=3, vocab_size=5)
    model.set_embedding_weight(torch.arange(15).reshape(5,3) / 50)
    model.set_attention_weights(torch.tensor([0.1, 0.2, 0.3]))
    attention_weights = model.get_attention_matrix(torch.tensor([[1,2,3,
    correct_attention_weights = torch.tensor([[0.2033, 0.1995, 0.1975, 0
                                               [0.3387, 0.3323, 0.3290, 0
    if torch.allclose(attention_weights, correct_attention_weights, rtol
        print("Passed local Attn test")
    else:
        print(f"Attn Test failed, expected value was\n{correct_attention

simple_attention_nbow_test_local_embeddings()
simple_attention_nbow_test_local_attn()
```

```
Passed local embedding test
Passed local Attn test
```

5.1.2. Model Training [3 points - Non-Programming]

Assign and tune the below hyperparameters to optimize your model

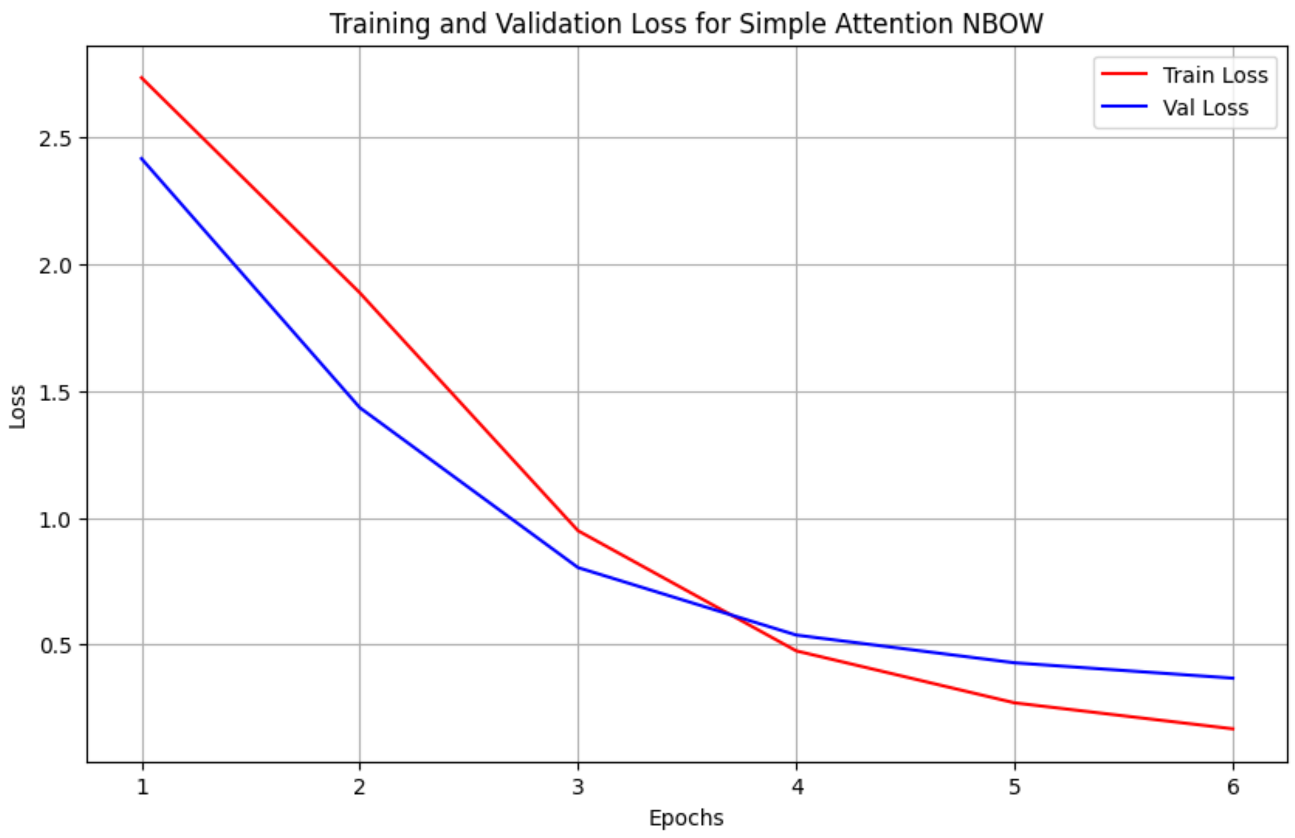
```
#export
# Assign hyperparameters and training parameters
# Experiment with different values for these hyperparaters to optimize y
def get_hyperparams_simple_attention():
  ### your hyper parameters
    learning_rate = 3e-3
    epochs = 6
    embedding_dim = 200
    return learning_rate, epochs, embedding_dim
```

```
# export
def get_simple_attention_model(vocab_size, embedding_dim):
    """
    This function returns an instance of the SimpleAttentionNBOW model.
    """
    model = None
    ## YOUR CODE STARTS HERE ##
    model = SimpleAttentionNBOW(vocab_size=vocab_size, embedding_dim=emb
    ## YOUR CODE ENDS HERE ##
    return model
```

```
# This is the main training loop. You'll need to complete the train_loop
# You'll also need to complete the criterion and optimizer functions.
# Feel free to experiment with different optimizers and learning rates.
# Do not change anything else in this cell
learning_rate, epochs, embedding_dim = get_hyperparams_simple_attention(
simple_attention_model = get_simple_attention_model(vocab_size=len(train
criterion = get_criterion()
train_loss_over_time_sa = []
val_loss_over_time_sa = []
optimizer = get_optimizer(simple_attention_model, learning_rate)
for epoch in range(epochs):
    train_loss = train_loop(simple_attention_model, criterion, optimizer
    true, pred, val_loss = val_loop(simple_attention_model, criterion, v
    accuracy, f1 = get_accuracy_and_f1_score(true, pred)
    train_loss_over_time_sa.append(train_loss)
    val_loss_over_time_sa.append(val_loss)
    print(f"Epoch {epoch+1} -- Train_Loss: {train_loss} -- Val_Loss: {va
save_checkpoint(simple_attention_model, 'simple_attention')
```

```
Training Model: 100%|██████████| 118/118 [00:41<00:00,  2.86it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 17.58it/s]
Epoch 1 -- Train_Loss: 2.736393112247273 -- Val_Loss: 2.417440923055013 -
Training Model: 100%|██████████| 118/118 [00:39<00:00,  3.00it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 15.72it/s]
Epoch 2 -- Train_Loss: 1.8880917248079332 -- Val_Loss: 1.4348665873209636
Training Model: 100%|██████████| 118/118 [00:39<00:00,  2.98it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 18.51it/s]
Epoch 3 -- Train_Loss: 0.9492138997983124 -- Val_Loss: 0.8037997364997864
Training Model: 100%|██████████| 118/118 [00:50<00:00,  2.31it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 21.65it/s]
Epoch 4 -- Train_Loss: 0.4750620311094543 -- Val_Loss: 0.5375499268372853
Training Model: 100%|██████████| 118/118 [00:41<00:00,  2.87it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 17.42it/s]
Epoch 5 -- Train_Loss: 0.2701356160943791 -- Val_Loss: 0.4280715405941009
Training Model: 100%|██████████| 118/118 [00:40<00:00,  2.93it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 21.15it/s]
Epoch 6 -- Train_Loss: 0.1675403071409565 -- Val_Loss: 0.3675137182076772
Checkpoint saved to /content/drive/MyDrive/HW2/model_weights/checkpoint_s
```

```
# DO NOT CHANGE THIS CELL - retain the outputs in submission PDF to get
plot_loss(train_loss_over_time_sa, val_loss_over_time_sa, 'Simple Attent
```



5.1.3. Model Evaluation [2 points - Programming]

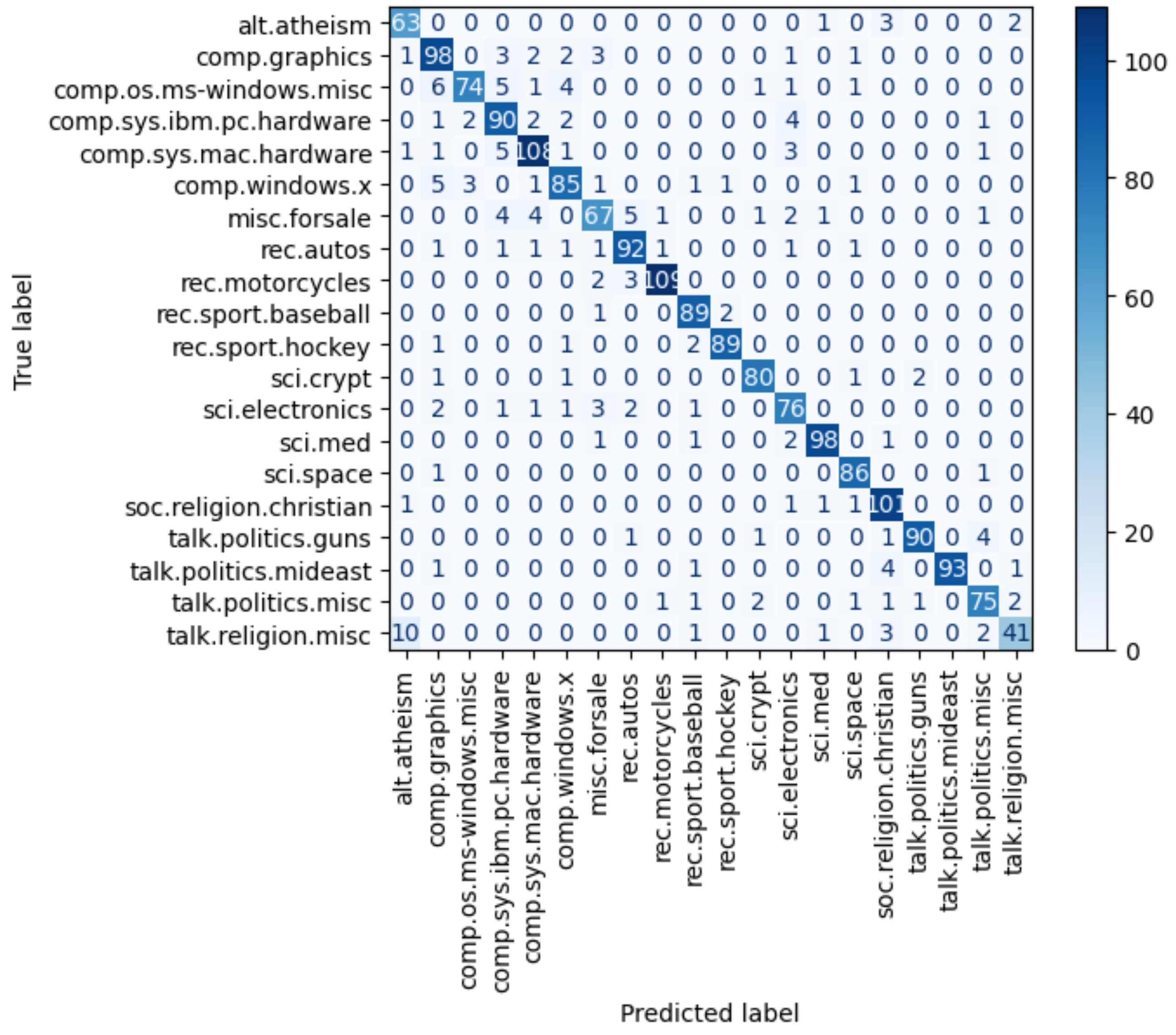
The final points for this will be awarded as per Gradescope's test split, which is different from the local versions. The cell below is just for a sanity check. Your metrics here may not exactly match with the ones on Gradescope, but if your model is fairly generalized, it should not be far off.

- 0 points for accuracy <= 85%
- 1 point for accuracy > 85% but <= 90%
- 2 points for accuracy > 90%

```
# DO NOT CHANGE THIS CELL
learning_rate, epochs, embedding_dim = get_hyperparams_simple_attention(
simple_attention_model = get_simple_attention_model(vocab_size=len(train
load_checkpoint(simple_attention_model, 'simple_attention', map_location

true, pred, val_loss = val_loop(simple_attention_model, criterion, val_i
accuracy, f1 = get_accuracy_and_f1_score(true, pred)
print(f"Final Validation Accuracy: {accuracy}")
print(f"Final Validation F1-Score: {f1}")
```

```
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 15.44it/s]Final Va
Final Validation F1-Score: 0.9001916573256992
```

```
# DO NOT CHANGE THIS CELL
plot_confusion_matrix(true, pred, classes=id2label.values())
```



5.2. MultiHead Attention NBOW [7 points - Programming + 3 points - Non-programming]

The prior model only uses a single attention function. In this section, you will implement a multi-head attention model. You will use $k$$k$ attention heads, each with its own parameters $u_i \in R^d$$u_i \in R^d$ ($\forall i \in [1..k]$$\forall i \in [1..k]$) and a single large vector before the classification to weight them all together $w \in R^{d \cdot k}$$w \in R^{d \cdot k}$.

$$ \alpha_{t,i} \varpropto \exp\{cos(u_i,emb(x_t))\} $$$$ \alpha_{t,i} \varpropto \exp\{cos(u_i,emb(x_t))\} $$

$$ h_{att}(i) = \sum_t\alpha_{t,i} emb(x_t) $$$$ h_{att}(i) = \sum_t\alpha_{t,i} emb(x_t) $$

With the probability of a task instance belonging to class $y_i$$y_i$ is given by:

$$ p(y|x) = softmax(w^T [h_{att}(1), h_{att}(2), ..., h_{att}(k)]) $$$$ p(y|x) = softmax(w^T [h_{att}(1), h_{att}(2), ..., h_{att}(k)]) $$

where [a,b] is the concatenation of vectors $a$$a$ and $b$$b$, into a single taller vector.

5.2.1. Model Definition [5 points - Programming]

Define your Multi-head attention below

```
#export

class MultiHeadAttentionNBOW(nn.Module):
    def __init__(self, vocab_size, embedding_dim, num_heads, num_classes
        ## YOUR CODE STARTS HERE ##
        super(MultiHeadAttentionNBOW, self).__init__()
        self.embedding_dim = embedding_dim
        self.num_heads = num_heads

        # (assumes PADDING_VALUE is defined globally; value 0 in your no
        self.embedding = nn.Embedding(vocab_size, embedding_dim, padding

        # Learnable head vectors u_h (num_heads, embedding_dim)
        self.attn_heads = nn.Parameter(torch.randn(num_heads, embedding_

        # Classifier over an aggregated (B, D) sentence vector
        self.fc = nn.Linear(embedding_dim * num_heads, num_classes, bias
        ## YOUR CODE ENDS HERE ##
    # helper
    def _masked_softmax_over_time(self, scores, mask):
        """
        scores: (B, L, H)
        mask:   (B, L) with True for valid tokens
        returns softmax over L with mask -> (B, L, H)
        """
        # Put -inf where masked so they get zero prob after softmax
        scores = scores.masked_fill(~mask.unsqueeze(-1), float("-inf"))
        return torch.softmax(scores, dim=1)

    # helper
    def _attention_weights(self, x, emb=None):
        """
        x:   (B, L)
        emb: (B, L, D) optional (saves a re-embed)
        returns attn: (B, L, H)
        """
        if emb is None:
            emb = self.embedding(x)                       # (B, L, D)

        # Cosine similarity: normalize both sides
        emb_n = F.normalize(emb, p=2, dim=-1)             # (B, L, D)
        heads_n = F.normalize(self.attn_heads, p=2, dim=-1)  # (H, D)

        # scores_{b,l,h} = <emb_{b,l,:}, head_{h,:}>
        scores = torch.einsum("bld,hd->blh", emb_n, heads_n)  # (B, L, H

        mask = (x != PADDING_VALUE)                       # (B, L)
        attn = self._masked_softmax_over_time(scores, mask)   # (B, L, H
        # zero-out any residual numerics on padded positions
        attn = attn * mask.unsqueeze(-1)
        return attn

    def forward(self, x):
        ## YOUR CODE STARTS HERE ##
        # (B, L, D)
        emb = self.embedding(x)

        # (B, L, H) — uses self.attn_heads and masking correctly
        attn = self._attention_weights(x, emb)

        # context per head: (B, H, D)
        ctx = torch.einsum('blh,bld->bhd', attn, emb)
        # CONCATENATE heads (not average): (B, H*D)
        sent_vec = ctx.reshape(ctx.size(0), -1)

        # classifier has no bias; weight = 0.3 in the sanity test
        logits = self.fc(sent_vec)  # (B, num_classes)
        return logits
        ## YOUR CODE ENDS HERE ##


    def get_embeddings(self, x):
        '''
        This function returns the embeddings of the input x
        '''
        ### YOUR CODE STARTS HERE ###
        return self.embedding(x)
        ### YOUR CODE ENDS HERE ###

    def set_embedding_weight(self, weight):
        '''
        This function sets the embedding weights to the input weight ens
        Args:
            weight: torch.tensor of shape (vocab_size, embedding_dim)
        '''
        ### YOUR CODE STARTS HERE ###
        with torch.no_grad():
            self.embedding.weight.copy_(weight)
        ### YOUR CODE ENDS HERE ###

    def set_attention_weights(self, weight):
        '''
        This function sets the attention weights to the input weight ens
        Args:
            weight: torch.tensor of shape (num_heads, embedding_dim)
        '''
        ### YOUR CODE STARTS HERE ###
        if weight.shape != self.attn_heads.shape:
            raise ValueError(f"Expected weight shape {self.attn_heads.sh
        with torch.no_grad():
            self.attn_heads.copy_(weight)
        ### YOUR CODE ENDS HERE ###

    def get_attention_matrix(self, x):
        '''
        This function returns the normalized attention matrix for the in
        Args:
            x: torch.tensor of shape (BATCH_SIZE, max seq length in batc
        Returns:
            attention_weights: torch.tensor of shape (BATCH_SIZE, max se
        '''
        ### YOUR CODE STARTS HERE ###
        emb = self.embedding(x)                             # (B, L, D)
        return self._attention_weights(x, emb)              # (B, L, H)
        ### YOUR CODE ENDS HERE ###
```

```
# local test for sanity:
# DO NOT CHANGE THIS CELL
def multihead_attn_nbow_test_local():
    embedding_dim = 10
    vocab_size = 10
    num_heads = 3
    model = MultiHeadAttentionNBOW(vocab_size=vocab_size, embedding_dim=
    for _, module in model.named_parameters():
        if hasattr(module, "data"):
            nn.init.constant_(module, 0.3)
    input = torch.tensor([[1,2,3,4,0,0,0],
                          [5,6,7,0,0,0,0]]) % vocab_size
    expected_result = torch.tensor(
        [[2.7000, 2.7000, 2.7000, 2.7000, 2.7000, 2.7000, 2.7000, 2.7000
         2.7000, 2.7000, 2.7000, 2.7000, 2.7000, 2.7000, 2.7000, 2.7000,
         2.7000, 2.7000],
        [2.7000, 2.7000, 2.7000, 2.7000, 2.7000, 2.7000, 2.7000, 2.7000,
         2.7000, 2.7000, 2.7000, 2.7000, 2.7000, 2.7000, 2.7000, 2.7000,
         2.7000, 2.7000]]
    )
    with torch.no_grad():
        local_result = model(input)
    if torch.allclose(expected_result, local_result, rtol=0.001):
        print("Passed local check")
    else:
        print(f"Test failed, expected value was\n{expected_result}\nbut

# local test for sanity:
def multi_attention_nbow_test_local_embeddings():
    model = MultiHeadAttentionNBOW(embedding_dim=3, vocab_size=5, num_he
    model.set_embedding_weight(torch.arange(15).reshape(5,3) / 50)
    embeddings = model.get_embeddings(torch.tensor([[1,2,3,4,1],[1,2,3,0
    correct_embeddings = torch.tensor([[[0.0600, 0.0800, 0.1000],
                                        [0.1200, 0.1400, 0.1600],
                                              [0.1800, 0.2000, 0.2200],
                                              [0.2400, 0.2600, 0.2800],
                                              [0.0600, 0.0800, 0.1000]],

                                             [[0.0600, 0.0800, 0.1000],
                                              [0.1200, 0.1400, 0.1600],
                                              [0.1800, 0.2000, 0.2200],
                                              [0.0000, 0.0200, 0.0400],
                                              [0.0000, 0.0200, 0.0400]]])
        if torch.allclose(embeddings, correct_embeddings, rtol=0.001):
            print("Passed local embedding test")
        else:
            print(f"Embedding Test failed, expected value was\n{correct_embe
    def multi_attention_nbow_test_local_attn():
        model = MultiHeadAttentionNBOW(embedding_dim=3, vocab_size=5, num_he
        model.set_embedding_weight(torch.arange(15).reshape(5,3) / 50)
        model.set_attention_weights(torch.tensor([[0.1, 0.2, 0.3],[0.1, 0.2,
        attention_weights = model.get_attention_matrix(torch.tensor([[1,2,3,
        correct_attention_weights = torch.tensor([[[0.2033, 0.2033, 0.1981,
                                                    [0.1995, 0.1995, 0.2007,
                                                    [0.1975, 0.1975, 0.2014,
                                                    [0.1964, 0.1964, 0.2017,
                                                    [0.2033, 0.2033, 0.1981,

                                                   [[0.3387, 0.3387, 0.3300
                                                    [0.3323, 0.3323, 0.3344,
                                                    [0.3290, 0.3290, 0.3356,
                                                    [0.0000, 0.0000, 0.0000,
                                                    [0.0000, 0.0000, 0.0000,
        if torch.allclose(attention_weights, correct_attention_weights, rtol
            print("Passed local Attn test")
        else:
            print(f"Attn Test failed, expected value was\n{correct_attention

    multi_attention_nbow_test_local_embeddings()
    multi_attention_nbow_test_local_attn()
    multihead_attn_nbow_test_local()
```

```
Passed local embedding test
Passed local Attn test
Passed local check
```

5.2.2. Model Training [3 points - Non-Programming]

Assign and tune the below hyperparameters to optimize your model

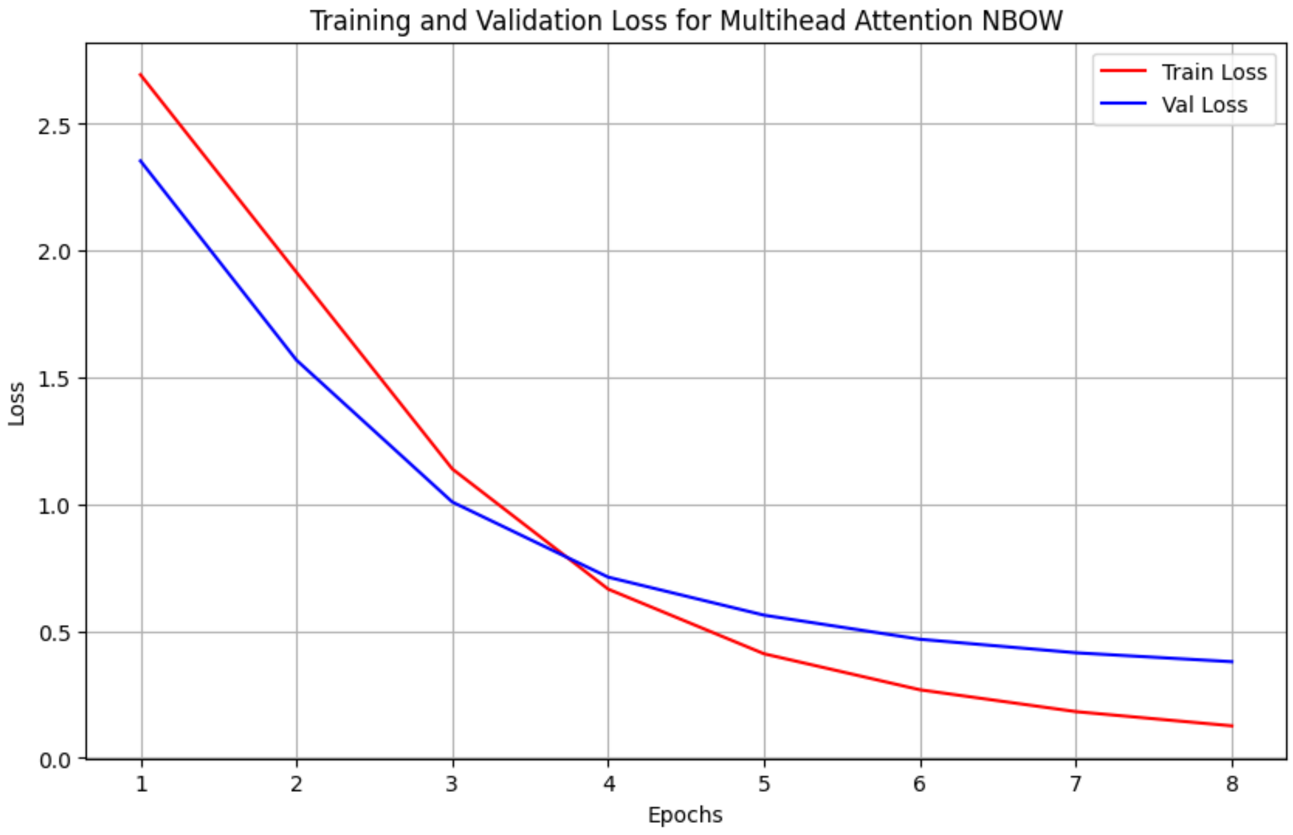
```
#export
# Assign hyperparameters and training parameters
# Experiment with different values for these hyperparaters to optimize y
def get_hyperparams_multihead():
    learning_rate = 2e-3
    epochs = 8
    num_heads = 4
    embedding_dim = 128
    return learning_rate, epochs, num_heads, embedding_dim
```

```
#export
def get_multihead_attention_model(vocab_size, embedding_dim, num_heads):
    """
    This function returns an instance of the MultiHeadAttentionNBOW mode
    """
    model = None
    ## YOUR CODE STARTS HERE ##
    model = MultiHeadAttentionNBOW(
        vocab_size=vocab_size,
        embedding_dim=embedding_dim,
        num_heads=num_heads
    )
    ## YOUR CODE ENDS HERE ##
    return model
```

```
# This is the main training loop. You'll need to complete the train_loop
# You'll also need to complete the criterion and optimizer functions.
# Feel free to experiment with different optimizers and learning rates.
# Do not change anything else in this cell
learning_rate, epochs, num_heads, embedding_dim = get_hyperparams_multih
multihead_attention_model = get_multihead_attention_model(vocab_size=len
criterion = get_criterion()
optimizer = get_optimizer(multihead_attention_model, learning_rate)
train_loss_over_time_ma = []
val_loss_over_time_ma = []
for epoch in range(epochs):
    train_loss = train_loop(multihead_attention_model, criterion, optimi
    true, pred, val_loss = val_loop(multihead_attention_model, criterion
    accuracy, f1 = get_accuracy_and_f1_score(true, pred)
    train_loss_over_time_ma.append(train_loss)
    val_loss_over_time_ma.append(val_loss)
    print(f"Epoch {epoch+1} -- Train_Loss: {train_loss} -- Val_Loss: {va
save_checkpoint(multihead_attention_model, 'multihead_attention')
```

```
Training Model: 100%|██████████| 118/118 [00:22<00:00,  5.25it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 25.20it/s]
Epoch 1 -- Train_Loss: 2.6941782518968744 -- Val_Loss: 2.3544623057047525
Training Model: 100%|██████████| 118/118 [00:20<00:00,  5.76it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 24.60it/s]
Epoch 2 -- Train_Loss: 1.9156382639529341 -- Val_Loss: 1.56910400390625 -
Training Model: 100%|██████████| 118/118 [00:22<00:00,  5.35it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 26.05it/s]
Epoch 3 -- Train_Loss: 1.1397247506400285 -- Val_Loss: 1.0092854261398316
Training Model: 100%|██████████| 118/118 [00:21<00:00,  5.53it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 19.38it/s]
Epoch 4 -- Train_Loss: 0.665594593448154 -- Val_Loss: 0.7128823399543762
Training Model: 100%|██████████| 118/118 [00:21<00:00,  5.59it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 25.59it/s]
Epoch 5 -- Train_Loss: 0.41062481272018564 -- Val_Loss: 0.562941928704579
Training Model: 100%|██████████| 118/118 [00:21<00:00,  5.48it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 26.61it/s]
Epoch 6 -- Train_Loss: 0.26868515802642046 -- Val_Loss: 0.468034501870473
Training Model: 100%|██████████| 118/118 [00:20<00:00,  5.68it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 26.01it/s]
Epoch 7 -- Train_Loss: 0.18259837049043784 -- Val_Loss: 0.414698264996210
Training Model: 100%|██████████| 118/118 [00:21<00:00,  5.52it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 26.98it/s]
Epoch 8 -- Train_Loss: 0.12656540512028386 -- Val_Loss: 0.379543499151865
Checkpoint saved to /content/drive/MyDrive/HW2/model_weights/checkpoint_m
```

```
# DO NOT CHANGE THIS CELL - retain the outputs in submission PDF for cre
plot_loss(train_loss_over_time_ma, val_loss_over_time_ma, 'Multihead Att
```



5.2.3. Model Evaluation [2 points - Programming]

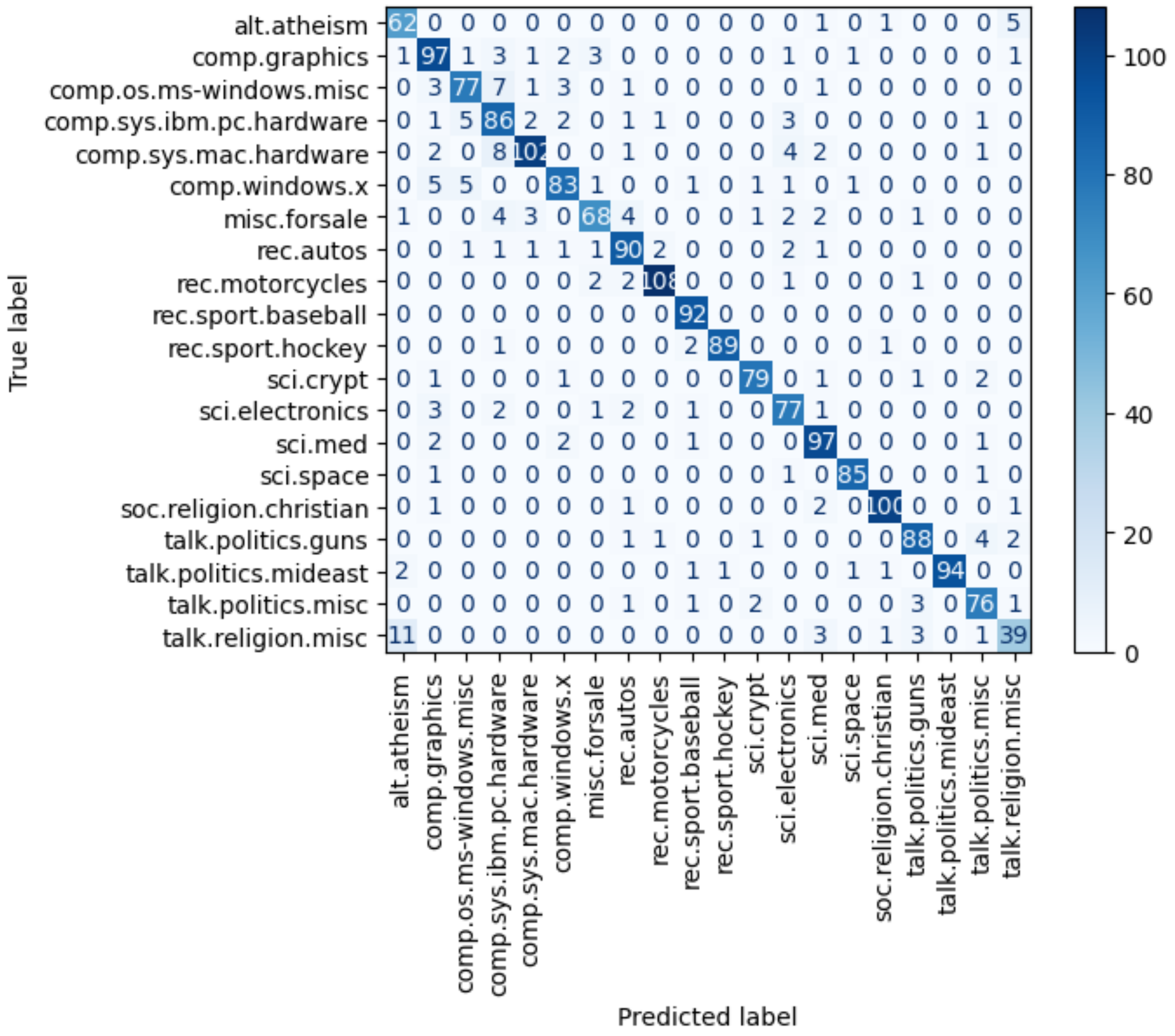
The final points for this will be awarded as per Gradescope's test split, which is different from the local versions. The cell below is just for a sanity check. Your metrics here may not exactly match with the ones on Gradescope, but if your model is fairly generalized, it should not be far off.

- 0 points for accuracy <= 85%
- 1 point for accuracy > 85% but <= 90%
- 2 points for accuracy > 90%

```
# DO NOT CHANGE THIS CELL
learning_rate, epochs, num_heads, embedding_dim = get_hyperparams_multih
multihead_attention_model = get_multihead_attention_model(vocab_size=len
load_checkpoint(multihead_attention_model, 'multihead_attention')

true, pred, val_loss = val_loop(multihead_attention_model, criterion, va
accuracy, f1 = get_accuracy_and_f1_score(true, pred)
print(f"Final Validation Accuracy: {accuracy}")
print(f"Final Validation F1-Score: {f1}")
```

```
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 26.87it/s]Final Va
Final Validation F1-Score: 0.8918898620486037
```

```
# DO NOT CHANGE THIS CELL
plot_confusion_matrix(true, pred, classes=id2label.values())
```



5.3. Self-Attention NBOW [7 points - Programming + 3 points - Non-programming]

Self-attention is a mechanism in neural networks that enables each element in a sequence to consider and weigh the importance of every other element. This facilitates a more nuanced and context-aware representation of the sequence, greatly enhancing the capabilities of models in tasks involving sequential data, particularly in NLP. It has gained prominence with the introduction and success of Transformer models, like BERT, GPT (including GPT-3), and others. This is not a full-fledged implementation of it, but instead a conceptual flavor of the mechanism.

We will now define an encoder that uses a simple form of self-attention when producing attention weights for each word in the sentence: $$a_{ts} = emb(x_t)^Temb(x_s)$$$$a_{ts} = emb(x_t)^Temb(x_s)$$ $$α_t \propto exp(\sum_s a_{ts})$$$$α_t \propto exp(\sum_s a_{ts})$$ $$h_{self} = \sum α_temb(x_t)$$$$h_{self} = \sum α_temb(x_t)$$ Then, the probability of a class is given by $$softmax(w^Th_{self})$$$$softmax(w^Th_{self})$$ The unnormalized attention weight for a word $x$$x$ is computed using the dot product between its embedding and those for all other words in the sentence, followed by a summation and exponentiation. Unlike the model in Section 5.1., this model does not introduce any new parameters for computing the attention function, simply using the same word embeddings for the attention. Therefore, this model has the same number of parameters as the model in Section 2. For improved stability, we can also add a “residual connection”, which would change Eq. 1 to $$softmax(w^T(h_{self} + h_{avg}))$$$$softmax(w^T(h_{self} + h_{avg}))$$ where $h_{avg}$$h_{avg}$ is computed as in Section 2 (though using the same word embeddings as in $h_{self}$$h_{self}$).

5.3.1. Model Definition [5 points - Programming]

Define your self attention model below

```
#export
class SelfAttentionNBOW(nn.Module):
    def __init__(self, vocab_size, embedding_dim, num_classes=20):
        super(SelfAttentionNBOW, self).__init__()
        # YOUR CODE STARTS HERE
        # embeddings with padding index
        self.embedding = nn.Embedding(vocab_size, embedding_dim, padding
        # linear classifier over the sentence vector
        self.fc = nn.Linear(embedding_dim, num_classes, bias=False)
        # YOUR CODE ENDS HERE

    def forward(self, x):
        # YOUR CODE STARTS HERE
        emb  = self.embedding(x)                 # (B, L, D)
        mask = (x != PADDING_VALUE)              # (B, L)  True for vali

        # pairwise dot-products (no scaling; matches the assignment spec
        scores = torch.bmm(emb, emb.transpose(1, 2))          # (B, L, L

        # zero out contributions from padded "keys" before summing over
        scores_for_sum = scores.masked_fill(~mask.unsqueeze(1), 0.0)  #

        # logits for alpha: sum over s, then kill padded "queries"
        alpha_logits = scores_for_sum.sum(dim=2)
        alpha_logits = alpha_logits.masked_fill(~mask, float('-inf'))

        # normalized attention over tokens t
        alpha = torch.softmax(alpha_logits, dim=1)

        # sentence vector
        h_self = (alpha.unsqueeze(-1) * emb).sum(dim=1)

        lengths = mask.sum(dim=1).clamp_min(1).unsqueeze(-1)
        h_avg = (emb * mask.unsqueeze(-1)).sum(dim=1) / lengths

        # classification logits
        h = h_self + h_avg
        logits = self.fc(h)
        return logits
        # YOUR CODE ENDS HERE
    def get_embeddings(self, x):
        '''
        This function returns the embeddings of the input x
        '''
        ### YOUR CODE STARTS HERE ###
        return self.embedding(x)
        ### YOUR CODE ENDS HERE ###
    def set_embedding_weight(self, weight):
        '''
        This function sets the embedding weights to the input weight ens
        Args:
            weight: torch.tensor of shape (vocab_size, embedding_dim)
        '''
        ### YOUR CODE STARTS HERE ###
        with torch.no_grad():
            self.embedding.weight.copy_(weight)
        ### YOUR CODE ENDS HERE ###
    def get_attention_matrix(self, x):
        '''
        This function returns the normalized attention matrix for the in
        Args:
            x: torch.tensor of shape (BATCH_SIZE, max seq length in batc
        Returns:
            attention_weights: torch.tensor of shape (BATCH_SIZE, max se
        '''
        ### YOUR CODE STARTS HERE ###
        emb  = self.embedding(x)                 # (B, L, D)
        mask = (x != PADDING_VALUE)              # (B, L)

        scores = torch.bmm(emb, emb.transpose(1, 2))                # (B
        scores_for_sum = scores.masked_fill(~mask.unsqueeze(1), 0.) # ze

        alpha_logits = scores_for_sum.sum(dim=2)                    # (B
        alpha_logits = alpha_logits.masked_fill(~mask, float('-inf'))
        alpha = torch.softmax(alpha_logits, dim=1)                  # (B

        # zero-out pads for readability in tests
        return alpha * mask
        ### YOUR CODE ENDS HERE ###
```

```
    # local test for sanity:
    def self_attention_nbow_test_local():
        model = SelfAttentionNBOW(vocab_size=10, embedding_dim=10)
        for _, module in model.named_parameters():
            if hasattr(module, "data"):
                nn.init.constant_(module, 0.3)
        input = torch.tensor([[1,2,3,4,0,0,0],
                              [5,6,7,0,0,0,0]]) % 10

        expected_result = torch.tensor(
            [[1.8000, 1.8000, 1.8000, 1.8000, 1.8000, 1.8000, 1.8000, 1.8000
             1.8000, 1.8000, 1.8000, 1.8000, 1.8000, 1.8000, 1.8000, 1.8000,
             1.8000, 1.8000],
            [1.8000, 1.8000, 1.8000, 1.8000, 1.8000, 1.8000, 1.8000, 1.8000,
             1.8000, 1.8000, 1.8000, 1.8000, 1.8000, 1.8000, 1.8000, 1.8000,
             1.8000, 1.8000]]
        )
        with torch.no_grad():
            local_result = model(input)
        if torch.allclose(expected_result, local_result, rtol=0.001):
            print("Passed local check")
        else:
            print(f"Test failed, expected value was\n{expected_result}\nbut

    def self_attention_nbow_test_local_embeddings():
        model = SelfAttentionNBOW(vocab_size=5, embedding_dim=3)
        model.set_embedding_weight(torch.arange(15).reshape(5, 3) / 50)
        embeddings = model.get_embeddings(torch.tensor([[1, 2, 3, 4, 1], [1,
        correct_embeddings = torch.tensor([[[0.0600, 0.0800, 0.1000],
                                            [0.1200, 0.1400, 0.1600],
                                            [0.1800, 0.2000, 0.2200],
                                            [0.2400, 0.2600, 0.2800],
                                            [0.0600, 0.0800, 0.1000]],

                                            [[0.0600, 0.0800, 0.1000],
                                            [0.1200, 0.1400, 0.1600],
                                            [0.1800, 0.2000, 0.2200],
                                            [0.0000, 0.0200, 0.0400],
                                            [0.0000, 0.0200, 0.0400]]])
        if torch.allclose(embeddings, correct_embeddings, rtol=0.001):
            print("Passed local embedding test")
        else:
            print(f"Embedding Test failed, expected value was\n{correct_embe

    def self_attention_nbow_test_local_attn():
        model = SelfAttentionNBOW(vocab_size=5, embedding_dim=3)
        model.set_embedding_weight(torch.arange(15).reshape(5,3) / 50)
        attention_weights = model.get_attention_matrix(torch.tensor([[1,2,3,
        correct_attention_weights = torch.tensor([[0.1675, 0.1921, 0.2203, 0
            [0.3085, 0.3327, 0.3588, 0.0000, 0.0000]])
        if torch.allclose(attention_weights, correct_attention_weights, rtol
            print("Passed local Attn test")
        else:
            print(f"Attn Test failed, expected value was\n{correct_attention
    self_attention_nbow_test_local()
```

```
self_attention_nbow_test_local_embeddings()
self_attention_nbow_test_local_attn()
```

```
Passed local check
Passed local embedding test
Passed local Attn test
```

```
#export
def get_self_attention_model(vocab_size, embedding_dim):
    """
    This function returns an instance of the Self Attention model. Initi
    """
    model = None
    ## YOUR CODE STARTS HERE ##
    model = SelfAttentionNBOW(vocab_size=vocab_size, embedding_dim=embed
    ## YOUR CODE ENDS HERE ##
    return model
```

5.3.2. Model Training [3 points - Non-Programming]

Assign and tune the below hyperparameters to optimize your model

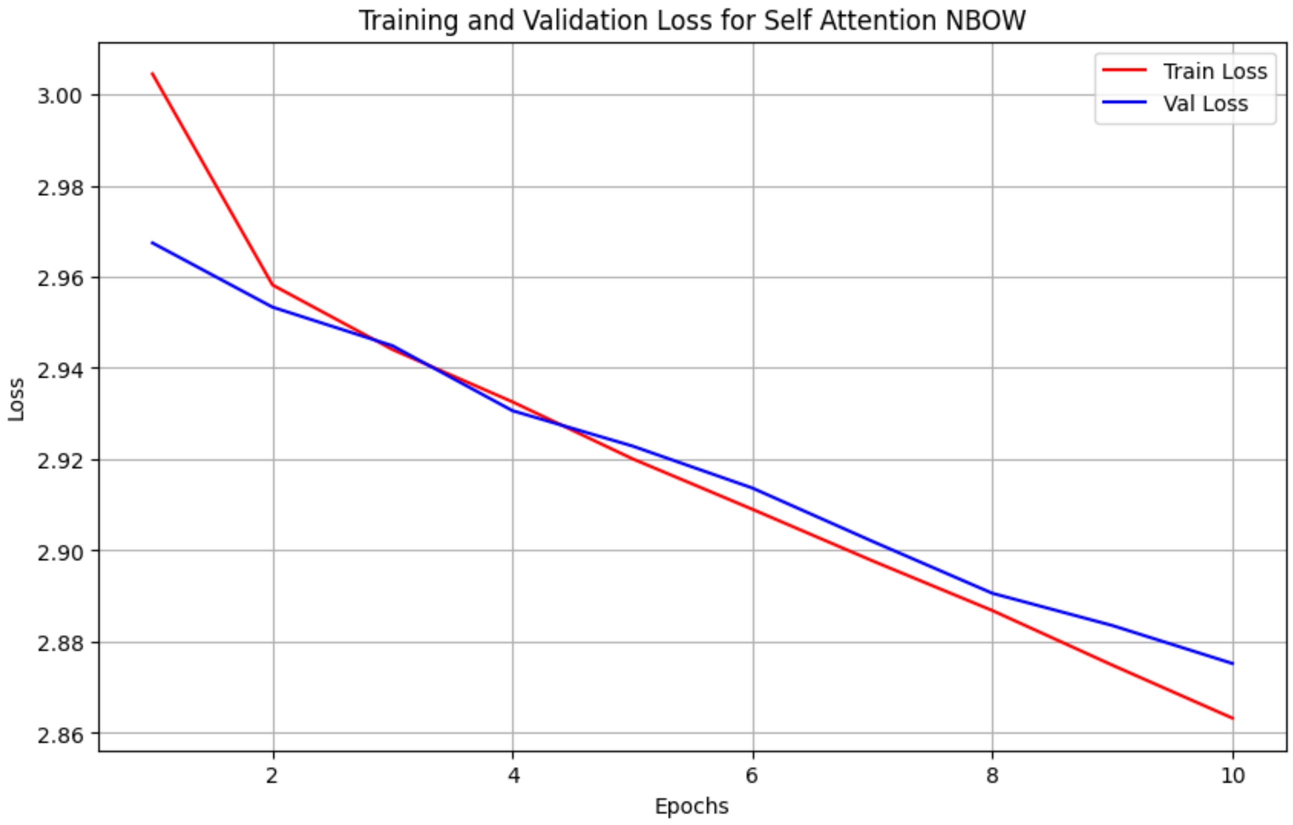
```
#export
# Assign hyperparameters and training parameters
# Experiment with different values for these hyperparaters to optimize y
def get_hyperparams_self_attn():
    learning_rate = 2e-4
    epochs = 10
    embedding_dim = 200
    return learning_rate, epochs, embedding_dim
```

```
# This is the main training loop. You'll need to complete the train_loop
# You'll also need to complete the criterion and optimizer functions.
# Feel free to experiment with different optimizers and learning rates.
# Do not change anything else in this cell
learning_rate, epochs, embedding_dim = get_hyperparams_self_attn()
self_attention_model = get_self_attention_model(len(train_vocab.keys()),
criterion = get_criterion()
optimizer = get_optimizer(self_attention_model, learning_rate)
train_loss_over_time_sea = []
val_loss_over_time_sea = []
```

```
    for epoch in range(epochs):
        train_loss = train_loop(self_attention_model, criterion, optimizer,
        true, pred, val_loss = val_loop(self_attention_model, criterion, val
        accuracy, f1 = get_accuracy_and_f1_score(true, pred)
        train_loss_over_time_sea.append(train_loss)
        val_loss_over_time_sea.append(val_loss)
        print(f"Epoch {epoch+1} -- Train_Loss: {train_loss} -- Val_Loss: {va
    save_checkpoint(self_attention_model, 'self_attention')
```

```
Training Model: 100%|██████████| 118/118 [00:44<00:00,  2.65it/s]
Evaluating Model: 100%|██████████| 15/15 [00:01<00:00,  7.88it/s]
Epoch 1 -- Train_Loss: 3.004465070821471 -- Val_Loss: 2.9674195448557534
Training Model: 100%|██████████| 118/118 [00:43<00:00,  2.69it/s]
Evaluating Model: 100%|██████████| 15/15 [00:01<00:00, 11.15it/s]
Epoch 2 -- Train_Loss: 2.958218402781729 -- Val_Loss: 2.9533480167388917
Training Model: 100%|██████████| 118/118 [00:42<00:00,  2.75it/s]
Evaluating Model: 100%|██████████| 15/15 [00:01<00:00, 10.86it/s]
Epoch 3 -- Train_Loss: 2.9440537711321295 -- Val_Loss: 2.944888130823771
Training Model: 100%|██████████| 118/118 [00:42<00:00,  2.75it/s]
Evaluating Model: 100%|██████████| 15/15 [00:01<00:00, 10.46it/s]
Epoch 4 -- Train_Loss: 2.932593761864355 -- Val_Loss: 2.930649407704671 -
Training Model: 100%|██████████| 118/118 [00:42<00:00,  2.77it/s]
Evaluating Model: 100%|██████████| 15/15 [00:02<00:00,  7.46it/s]
Epoch 5 -- Train_Loss: 2.920119386608318 -- Val_Loss: 2.9229045073191324
Training Model: 100%|██████████| 118/118 [00:43<00:00,  2.72it/s]
Evaluating Model: 100%|██████████| 15/15 [00:01<00:00, 11.11it/s]
Epoch 6 -- Train_Loss: 2.9090457972833668 -- Val_Loss: 2.9136950174967446
Training Model: 100%|██████████| 118/118 [00:42<00:00,  2.79it/s]
Evaluating Model: 100%|██████████| 15/15 [00:01<00:00, 11.03it/s]
Epoch 7 -- Train_Loss: 2.8977565927020574 -- Val_Loss: 2.9020198980967202
Training Model: 100%|██████████| 118/118 [00:42<00:00,  2.80it/s]
Evaluating Model: 100%|██████████| 15/15 [00:01<00:00, 10.42it/s]
Epoch 8 -- Train_Loss: 2.8868542081218656 -- Val_Loss: 2.8906323115030923
Training Model: 100%|██████████| 118/118 [00:42<00:00,  2.81it/s]
Evaluating Model: 100%|██████████| 15/15 [00:01<00:00,  8.10it/s]
Epoch 9 -- Train_Loss: 2.8748864157725187 -- Val_Loss: 2.8835681597391765
Training Model: 100%|██████████| 118/118 [00:42<00:00,  2.78it/s]
Evaluating Model: 100%|██████████| 15/15 [00:01<00:00, 11.13it/s]
Epoch 10 -- Train_Loss: 2.863283878665859 -- Val_Loss: 2.875253756841024
Checkpoint saved to /content/drive/MyDrive/HW2/model_weights/checkpoint_s
```

```
# DO NOT CHANGE THIS CELL - retain the outputs in submission PDF for cre
plot_loss(train_loss_over_time_sea, val_loss_over_time_sea, 'Self Attent
```



5.3.3. Model Evaluation Model Evaluation [2 points - Programming]

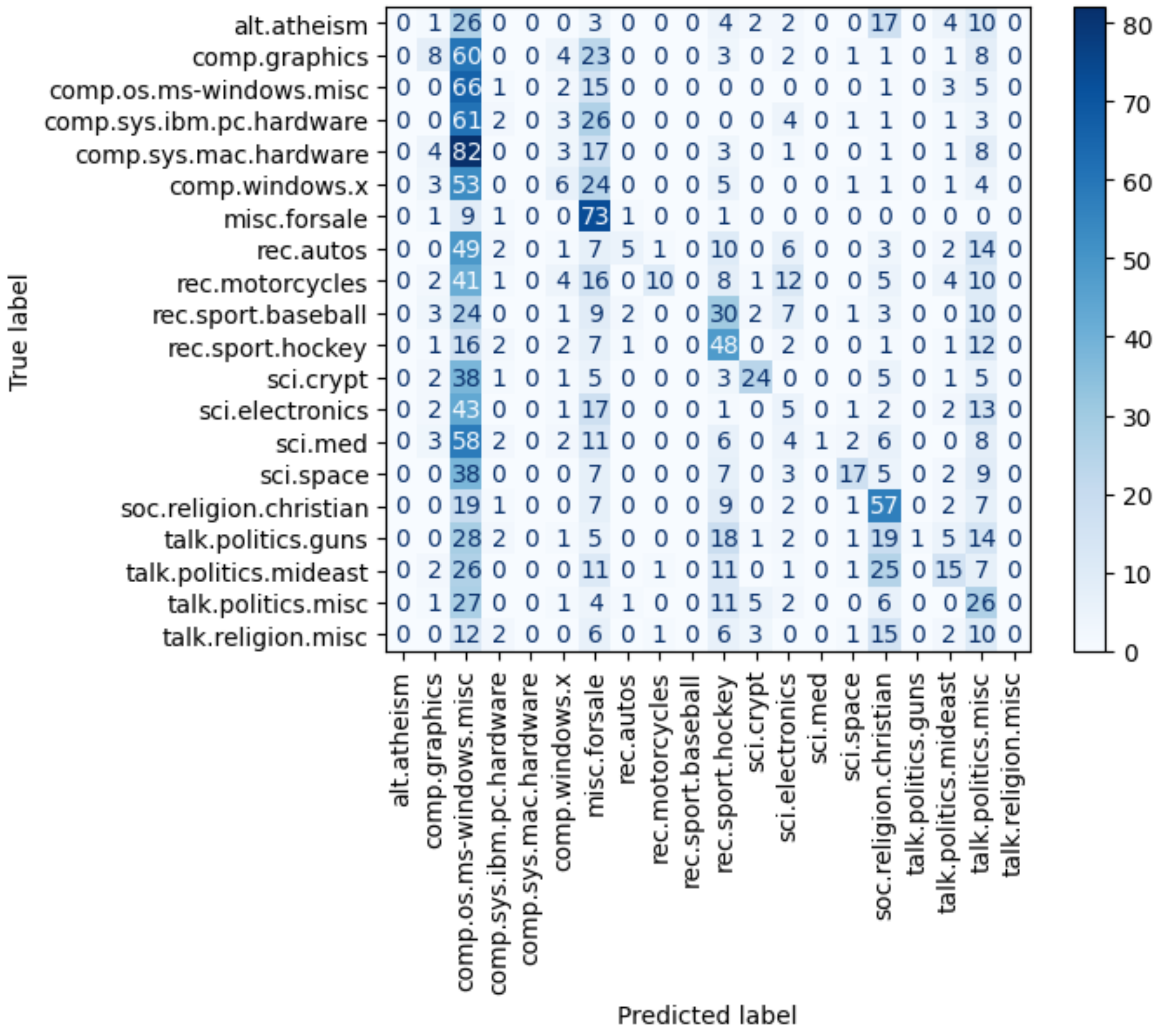
The final points for this will be awarded as per Gradescope's test split, which is different from the local versions. The cell below is just for a sanity check. Your metrics here may not exactly match with the ones on Gradescope, but if your model is fairly generalized, it should not be far off.

- 0 points for accuracy <= 85%
- 1 point for accuracy > 85% but <= 90%
- 2 points for accuracy > 90%

```
# DO NOT CHANGE THIS CELL
learning_rate, epochs, embedding_dim = get_hyperparams_self_attn()
self_attention_model = get_self_attention_model(len(train_vocab.keys()),
load_checkpoint(self_attention_model, 'self_attention', map_location=dev

true, pred, val_loss = val_loop(self_attention_model, criterion, val_ite
accuracy, f1 = get_accuracy_and_f1_score(true, pred)
print(f"Final Validation Accuracy: {accuracy}")
print(f"Final Validation F1-Score: {f1}")
```

```
Evaluating Model: 100%|██████████| 15/15 [00:01<00:00,  8.71it/s]Final Va
Final Validation F1-Score: 0.14849821081410888
```

```
# DO NOT CHANGE THIS CELL
plot_confusion_matrix(true, pred, classes=id2label.values())
```



6. Perceptron and Hinge Losses (16 Points - Programming)

6.1. Perceptron Loss (5 points - Programming)

The perceptron loss penalizes the model only when the true class is not the most confident prediction. If the model incorrectly assigns a higher score to another class, the perceptron loss encourages the model to adjust its weights to fix this mistake.

This is achieved by considering the difference between the maximum score among all other classes and the score of the true class. If the maximum incorrect score is higher than the true class score, the model receives a penalty proportional to how much worse the true class was predicted compared to the highest incorrect class.

Given a set of predictions from the perceptron model for a batch of samples, we denote:

- $ \mathbf{y} \in \mathbb{R}^{B \times C} $$ \mathbf{y} \in \mathbb{R}^{B \times C} $: The matrix of predicted scores, where $B$$B$ is the batch size and $C$$C$ is the number of classes. Each row represents the predicted scores for one sample.
- $\mathbf{y}_{\text{true}} \in \{0, 1, \ldots, C-1\}^{B}$$\mathbf{y}_{\text{true}} \in \{0, 1, \ldots, C-1\}^{B}$: The ground truth labels, where each entry is an integer representing the correct class label for each sample.

For a given sample (i), let:

- $s_j $$s_j $ be the score for class $j$$j$ (from the predicted score vector).
- $ s_{\text{true}} $$ s_{\text{true}} $ be the score for the true class.

The **perceptron loss** for data instance $x_i$$x_i$ is defined as:

$$ L_{\text{perceptron}}(i) = \max \left(0, \max_{j} (s_j) - s_{\text{true}} \right) $$$$ L_{\text{perceptron}}(i) = \max \left(0, \max_{j} (s_j) - s_{\text{true}} \right) $$

For batches, we compute the loss for each sample and take the mean over the batch

Implement this PerceptronLoss in the forward method below.

NOTE: The scores are logits, the predictions of models before doing any softmax.

```
# export

class PerceptronLoss(nn.Module):
    def __init__(self):
        super(PerceptronLoss, self).__init__()

    def forward(self, predictions, labels):
        """
        Calculate the perceptron loss between predictions and labels.

        Args:
            predictions (torch.Tensor): The predictions from the model f
                                        Shape should be (batch_size, num
            labels (torch.Tensor): The ground truth labels for each inpu
                                   Shape should be (batch_size,) with ea

        Returns:
            scalar: The mean perceptron loss for the batch.
        """
        loss = None
        # YOUR CODE STARTS HERE
        # Get the score for the true class
        true_scores = predictions[torch.arange(predictions.size(0)), lab

        # Get the maximum score among *all* classes for each sample
        max_scores, _ = torch.max(predictions, dim=1)  # shape: (batch_s

        # Perceptron loss per sample: max(0, max_j(s_j) - s_true)
        losses = torch.clamp(max_scores - true_scores, min=0)

        # Take mean across the batch
        loss = losses.mean()
        # YOUR CODE ENDS HERE
        return loss
```

```
# DO NOT CHANGE THIS CELL
perceptron_loss = PerceptronLoss()

def test_correct_classification():
    predictions = torch.tensor([[3.0, 2.0, 1.0],
                                [1.0, 4.0, 2.0]])
    labels = torch.tensor([0, 1])
    loss = perceptron_loss(predictions, labels).item()
    expected_loss = 0.0
    rtol = 0.001  # Relative tolerance
    if abs(expected_loss - loss) <= rtol * abs(expected_loss):
        print('Test case passed for correct classification')
    else:
        print(f"Test case failed for correct classification, expected va

# Test for incorrect classification
def test_incorrect_classification():
    predictions = torch.tensor([[1.0, 3.0, 2.0],
                                [1.0, 2.0, 4.0]])
    labels = torch.tensor([0, 1])

    expected_loss = 2.0
    loss = perceptron_loss(predictions, labels).item()

    rtol = 0.001  # Relative tolerance
    if abs(expected_loss - loss) <= rtol * abs(expected_loss):
        print('Test case passed for incorrect classification')
    else:
        print(f"Test case failed for incorrect classification, expected

# Execute test cases
test_correct_classification()
test_incorrect_classification()
```

```
Test case passed for correct classification
Test case passed for incorrect classification
```

6.2. NBOW Training using Perceptron Loss (3 points - Programming)

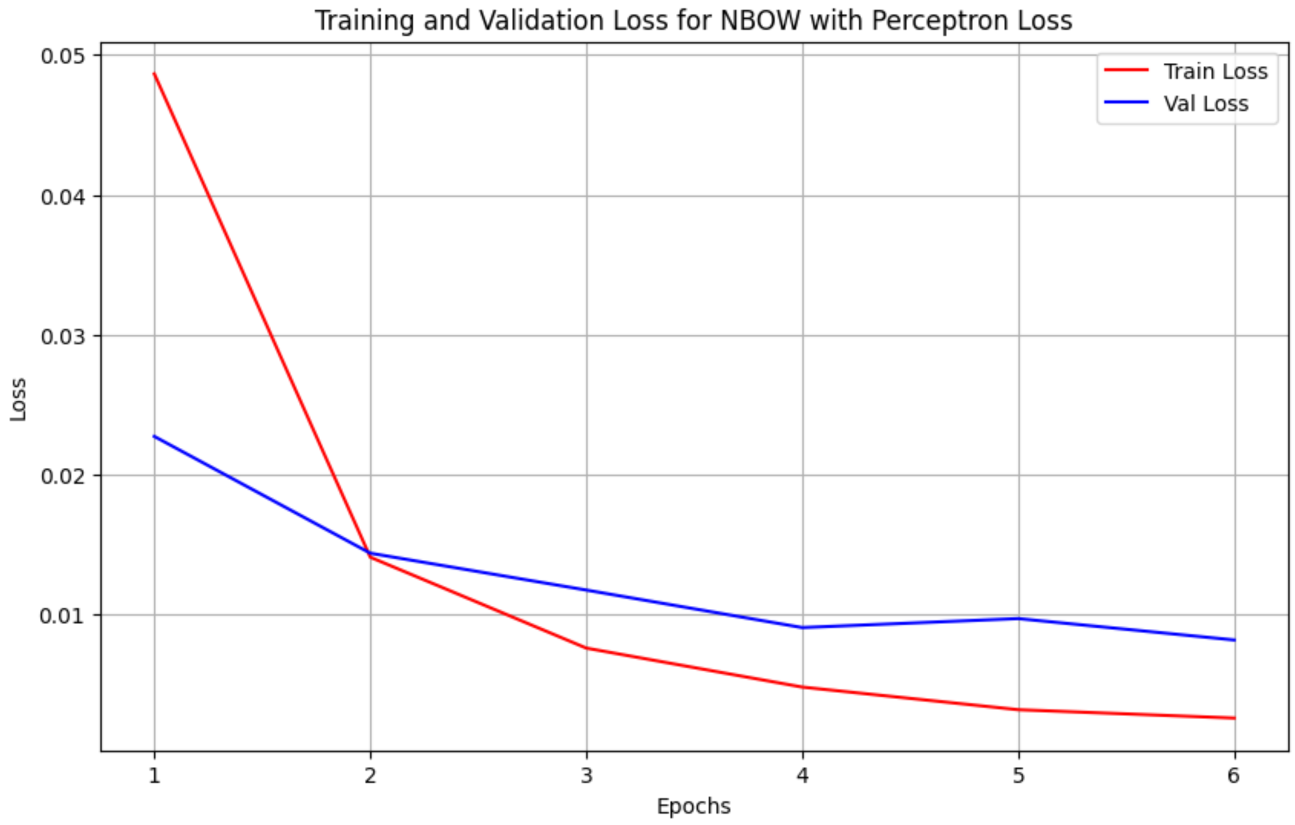
Credits will be awarded as per the following final results on the Gradescope split -

- 0 points for accuracy <= 75%
- 1 point for accuracy > 75% but <= 80%
- 2 points for accuracy > 80%

```
# This is the main training loop. You'll need to complete the train_loop
# You'll also need to complete the criterion and optimizer functions.
# Feel free to experiment with different optimizers and learning rates.
# Do not change anything else in this cell
learning_rate, epochs, embedding_dim = get_hyperparams_nbow()
nbow_model = get_nbow_model(vocab_size= len(train_vocab.keys()), embeddi
criterion = PerceptronLoss()
optimizer = get_optimizer(nbow_model, learning_rate)
train_loss_over_time_perceptron = []
val_loss_over_time_perceptron = []
for epoch in range(epochs):
    train_loss = train_loop(nbow_model, criterion, optimizer, train_iter
    true, pred, val_loss = val_loop(nbow_model, criterion, val_iterator)
    accuracy, f1 = get_accuracy_and_f1_score(true, pred)
    train_loss_over_time_perceptron.append(train_loss)
    val_loss_over_time_perceptron.append(val_loss)
    print(f"Epoch {epoch+1} -- Train_Loss: {train_loss} -- Val_Loss: {va

save_checkpoint(nbow_model, 'nbow', loss_fn='perceptron')
```

```
Training Model: 100%|██████████| 118/118 [00:23<00:00,  4.93it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 28.96it/s]
Epoch 1 -- Train_Loss: 0.04864225176683927 -- Val_Loss: 0.022738680988550
Training Model: 100%|██████████| 118/118 [00:21<00:00,  5.45it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 29.28it/s]
Epoch 2 -- Train_Loss: 0.014109018298213259 -- Val_Loss: 0.01439527248342
Training Model: 100%|██████████| 118/118 [00:22<00:00,  5.29it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 28.41it/s]
Epoch 3 -- Train_Loss: 0.007614471864791871 -- Val_Loss: 0.01176084044078
Training Model: 100%|██████████| 118/118 [00:19<00:00,  5.97it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 22.85it/s]
Epoch 4 -- Train_Loss: 0.004828440668692781 -- Val_Loss: 0.00908020076652
Training Model: 100%|██████████| 118/118 [00:19<00:00,  6.00it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 30.18it/s]
Epoch 5 -- Train_Loss: 0.0032122881261245112 -- Val_Loss: 0.0097229799255
Training Model: 100%|██████████| 118/118 [00:20<00:00,  5.71it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 20.39it/s]
Epoch 6 -- Train_Loss: 0.0026149275092116034 -- Val_Loss: 0.0081938814061
Checkpoint saved to /content/drive/MyDrive/HW2/model_weights/checkpoint_n
```

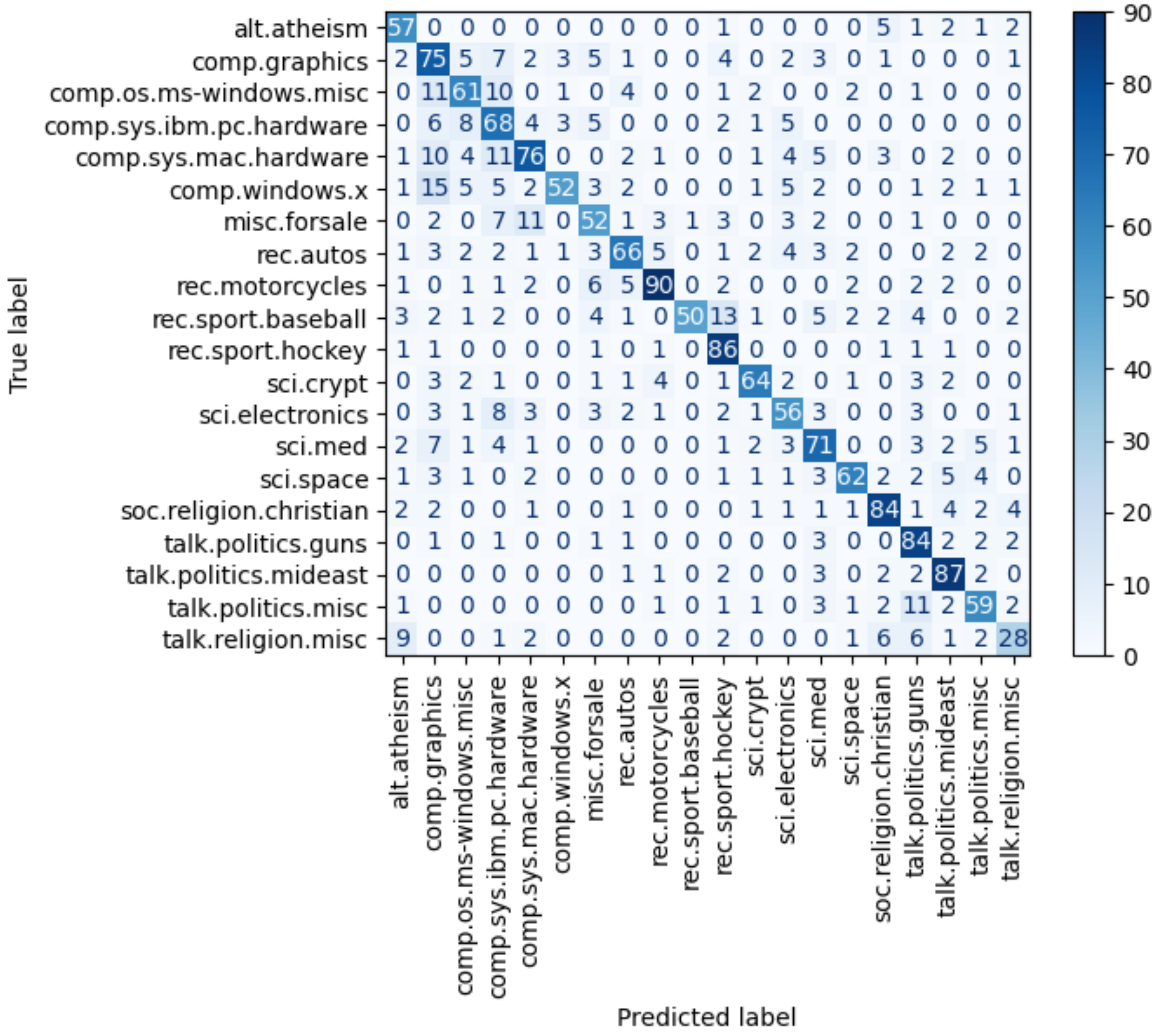
```
# DO NOT CHANGE THIS CELL
plot_loss(train_loss_over_time_perceptron, val_loss_over_time_perceptron
```



```
# DO NOT CHANGE THIS CELL
# load best model from checkpoint
learning_rate, epochs, embedding_dim = get_hyperparams_nbow()
nbow_model = get_nbow_model(vocab_size= len(train_vocab.keys()), embeddi
load_checkpoint(nbow_model, 'nbow', 'perceptron', map_location=device)

# evaluate model
true, pred, val_loss = val_loop(nbow_model, criterion, val_iterator)
accuracy, f1 = get_accuracy_and_f1_score(true, pred)
print(f"Final Validation Accuracy: {accuracy}")
print(f"Final Validation F1-Score: {f1}")
```

```
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 22.33it/s]Final Va
Final Validation F1-Score: 0.7018123417153094
```

```
# DO NOT CHANGE THIS CELL
plot_confusion_matrix(true, pred, classes=id2label.values())
```



6.3. Hinge Loss (5 points - Programming)

Read through the dataset documentation link provided with this notebook, or feel free to Google and read about 20 Newsgroups dataset, it's quite popular. If you try to understand the labels, they are more similar to some of them than others, semantically.

For example, `talk.politics.mideast` is more closer to `talk.politics.misc` than `sci.space`.

Mathematically speaking, it means that misclassification of a label to some classes may be less penalizable than some other classes. This is the perfect scenario of using hinge loss.

The **hinge loss** is another loss function commonly used for classification, especially in **support vector machines (SVMs)**. It is designed to maximize the margin between the decision boundary and the closest data points from each class.

The hinge loss penalizes predictions based on how confident the model is about the correct class relative to other classes. It aims to push the score of the true class far above the scores of all other classes, ensuring that the model not only predicts the correct class but does so confidently.

For each input sample \$x_i\$\$x_i\$, the model computes a score for each class. The hinge loss compares the score for the true class to the scores for all other classes and penalizes the model if the true class score is not sufficiently higher than the scores for the other classes.

Given a set of predictions from the model for a batch of samples, we denote:

- \$\mathbf{y} \in \mathbb{R}^{B \times C}\$\$\mathbf{y} \in \mathbb{R}^{B \times C}\$: The matrix of predicted scores, where \$B\$\$B\$ is the batch size and \$C\$\$C\$ is the number of classes. Each row represents the predicted scores for one sample.
- \$\mathbf{y}_{\text{true}} \in \{0, 1, \ldots, C-1\}^{B}\$\$\mathbf{y}_{\text{true}} \in \{0, 1, \ldots, C-1\}^{B}\$: The ground truth labels, where each entry is an integer representing the correct class label for each sample.

For a given sample (i), let:

- \$s_j\$\$s_j\$ be the score for class \$j\$\$j\$ (from the predicted score vector).
- \$s_{\text{true}}\$\$s_{\text{true}}\$ be the score for the true class.
- \$l(j, true)\$\$l(j, true)\$ be the cost if a task instance belonging to \$true\$\$true\$ has highest score for \$j\$\$j\$

The **hinge loss** for a task instance (x_i) is defined as:

\$\$ L_{\text{hinge}}(i) = \max \left(0, \max_j\left(s_j + l(j, true)\right) -

s_{\text{true}}\right) $$$$ L_{\text{hinge}}(i) = \max \left(0, \max_j\left(s_j + l(j, true)\right) - s_{\text{true}}\right) $$

For batches, we compute the loss for each sample and take the mean over the batch to obtain a scalar value representing the average hinge loss.

HINT: The non-recommended solution is to use one loop. However, it is highly recommended to not do that for efficiency reasons. `torch.gather()` should be helpful.

```
# export
class HingeLoss(nn.Module):
    def __init__(self, cost_matrix, device):
        super(HingeLoss, self).__init__()
        """
        cost_matrix is a 2D list. Convert it to a tensor on appropriate
        """
        # YOUR CODE STARTS HERE
        self.cost_matrix = torch.tensor(cost_matrix, dtype=torch.float32
        # YOUR CODE ENDS HERE

    def forward(self, predictions, labels):
        """
        Calculate the hinge loss between predictions and labels, adjusti

        Args:
            predictions (torch.Tensor): The predictions from the model f
                                        Shape should be (batch_size, num
            labels (torch.Tensor): The ground truth labels for each inpu
                                   Shape should be (batch_size,) with ea

        Returns:
            scalar: The mean hinge loss for the batch, adjusted for the
        """
        loss = None
        # YOUR CODE STARTS HERE
        batch_size, num_classes = predictions.shape

        # Extract the true class scores for each sample
        true_scores = predictions[torch.arange(batch_size), labels].unsq

        # Get cost for each (true_label, j) pair
        cost_values = self.cost_matrix[labels]  # shape: (B, C)
        # Compute per-class hinge margin: s_j + cost(j, true) - s_true
        margins = predictions + cost_values - true_scores

        # For each sample, find the maximum margin across all classes
        max_margin, _ = torch.max(margins, dim=1)

        # Apply hinge: max(0, margin)
        hinge_loss = torch.clamp(max_margin, min=0)

        # Average across batch
        loss = hinge_loss.mean()
        # YOUR CODE ENDS HERE
        return loss
```

```
# DO NOT CHANGE THIS CELL
def test_correct_classification(hinge_loss):
    """
    Test case where the true class has the highest score.
    The loss should be 0.
    """
    rtol = 0.0001
    predictions = torch.tensor([[3.0, 2.0, 1.0],
                                [1.0, 4.0, 2.0]])
    labels = torch.tensor([0, 1])
    loss = hinge_loss(predictions, labels).item()
    expected_loss = 0.0
    if abs(expected_loss - loss) <= rtol * abs(expected_loss):
        print('Test case 1 passed')
    else:
        print(f"Test case 1 failed, expected value was\n{expected_loss}\

def test_incorrect_classification(hinge_loss):
    """
    Test case where the true class does not have the highest score.
    The loss should be greater than 0.
    """
    rtol = 0.0001
    predictions = torch.tensor([[1.0, 3.0, 2.0],
                                [1.0, 2.0, 4.0]])
    labels = torch.tensor([0, 1])

    expected_loss = 3.0
    loss = hinge_loss(predictions, labels).item()

    if abs(expected_loss - loss) <= rtol * abs(expected_loss):
        print('Test case 2 passed')
    else:
        print(f"Test case 2 failed, expected value was\n{expected_loss}\

cost_matrix = [[0, 1, 1], [1, 0, 1], [1, 1, 0]]
hinge_loss = HingeLoss(cost_matrix, device='cpu')
test_correct_classification(hinge_loss)
test_incorrect_classification(hinge_loss)
```

```
Test case 1 passed
Test case 2 passed
```

6.4. NBOW Training using Hinge Loss [3 points - Programming]

First, define a cost matrix. Take inspiration from the confusion matrix of `PerceptronLoss` results, `id2label` map and your knowledge of what dataset labels are. This will help is constructing a good cost matrix.

Credits will be awarded on the following cutoffs on Gradescope split -

- 0 points for accuracy <= 84%,
- 1 point for accuracy > 84% but <= 88%,
- 2 points for accuracy > 88%

```
# export
def get_cost_matrix(num_classes=20):
    """
    Generates a cost matrix for a specified number of classes using Pyth

    Args:
        num_classes (int): The number of classes for which the cost matr

    Returns:
        list of lists: A 2D list where element (i, j) is the absolute di
                       set to zero if i equals j.
    """
    cost_matrix = None
    # YOUR CODE STARTS HERE
    cost_matrix = [[abs(i - j) if i != j else 0 for j in range(num_class
                   for i in range(num_classes)]
    # YOUR CODE ENDS HERE
    return cost_matrix
```

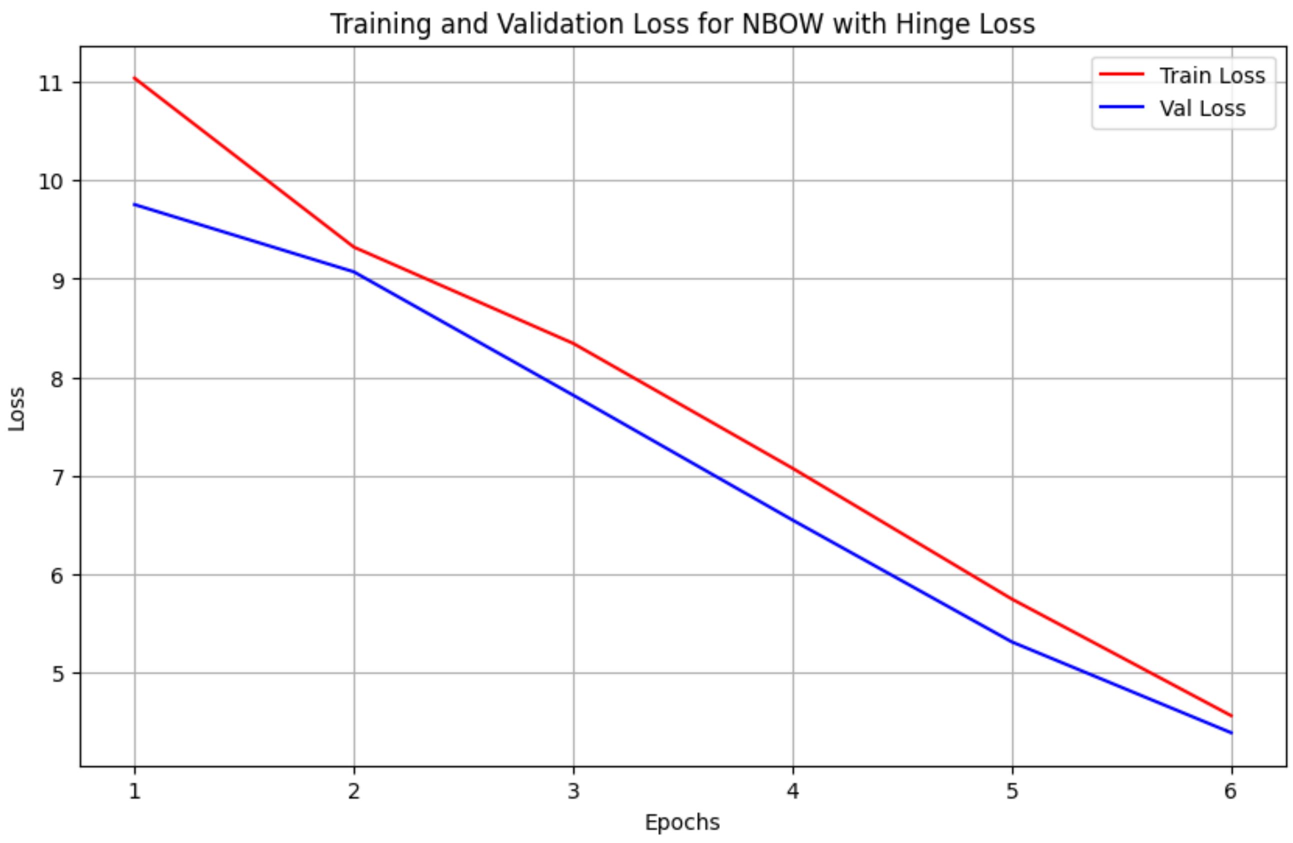
```
# DO NOT CHANGE THIS CELL
def test_cost(matrix):
    n = len(matrix)

    # Check if the matrix is square
    for row in matrix:
        if len(row) != n:
            print('Incorrect cost matrix: Not a square matrix.')

    # Check for symmetry and zero diagonal elements
    for i in range(n):
        if matrix[i][i] != 0:
            print('Incorrect cost matrix: Diagonal elements are not zero

        for j in range(i + 1, n):
            if matrix[i][j] != matrix[j][i]:
                print('Incorrect cost matrix: Not a symmetric matrix.')

    print('Valid cost matrix')

cost_matrix = get_cost_matrix()
test_cost(cost_matrix)
```

```
Valid cost matrix
```

```
# This is the main training loop. You'll need to complete the train_loop
# You'll also need to complete the criterion and optimizer functions.
# Feel free to experiment with different optimizers and learning rates.
# Do not change anything else in this cell
learning_rate, epochs, embedding_dim = get_hyperparams_nbow()
nbow_model = get_nbow_model(vocab_size= len(train_vocab.keys()), embeddi
cost_matrix = get_cost_matrix()
criterion = HingeLoss(cost_matrix, device=device)
optimizer = get_optimizer(nbow_model, learning_rate)
train_loss_over_time_hinge = []
val_loss_over_time_hinge = []
for epoch in range(epochs):
    train_loss = train_loop(nbow_model, criterion, optimizer, train_iter
    true, pred, val_loss = val_loop(nbow_model, criterion, val_iterator)
    accuracy, f1 = get_accuracy_and_f1_score(true, pred)
    train_loss_over_time_hinge.append(train_loss)
    val_loss_over_time_hinge.append(val_loss)
    print(f"Epoch {epoch+1} -- Train_Loss: {train_loss} -- Val_Loss: {va

save_checkpoint(nbow_model, 'nbow', loss_fn='hinge')
```

```
Training Model: 100%|██████████| 118/118 [00:22<00:00,  5.22it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 28.58it/s]
Epoch 1 -- Train_Loss: 11.035942578719833 -- Val_Loss: 9.753194300333659
Training Model: 100%|██████████| 118/118 [00:20<00:00,  5.80it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 23.83it/s]
Epoch 2 -- Train_Loss: 9.321664434368328 -- Val_Loss: 9.070507431030274 -
Training Model: 100%|██████████| 118/118 [00:20<00:00,  5.76it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 28.91it/s]
Epoch 3 -- Train_Loss: 8.344733909025031 -- Val_Loss: 7.8190583229064945
Training Model: 100%|██████████| 118/118 [00:20<00:00,  5.69it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 19.55it/s]
Epoch 4 -- Train_Loss: 7.0777757086996305 -- Val_Loss: 6.55215539932251 -
Training Model: 100%|██████████| 118/118 [00:17<00:00,  6.67it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 29.75it/s]
Epoch 5 -- Train_Loss: 5.750341956898318 -- Val_Loss: 5.315410232543945 -
Training Model: 100%|██████████| 118/118 [00:20<00:00,  5.75it/s]
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 23.57it/s]
Epoch 6 -- Train_Loss: 4.567020610227424 -- Val_Loss: 4.393522342046102 -
Checkpoint saved to /content/drive/MyDrive/HW2/model_weights/checkpoint_n
```

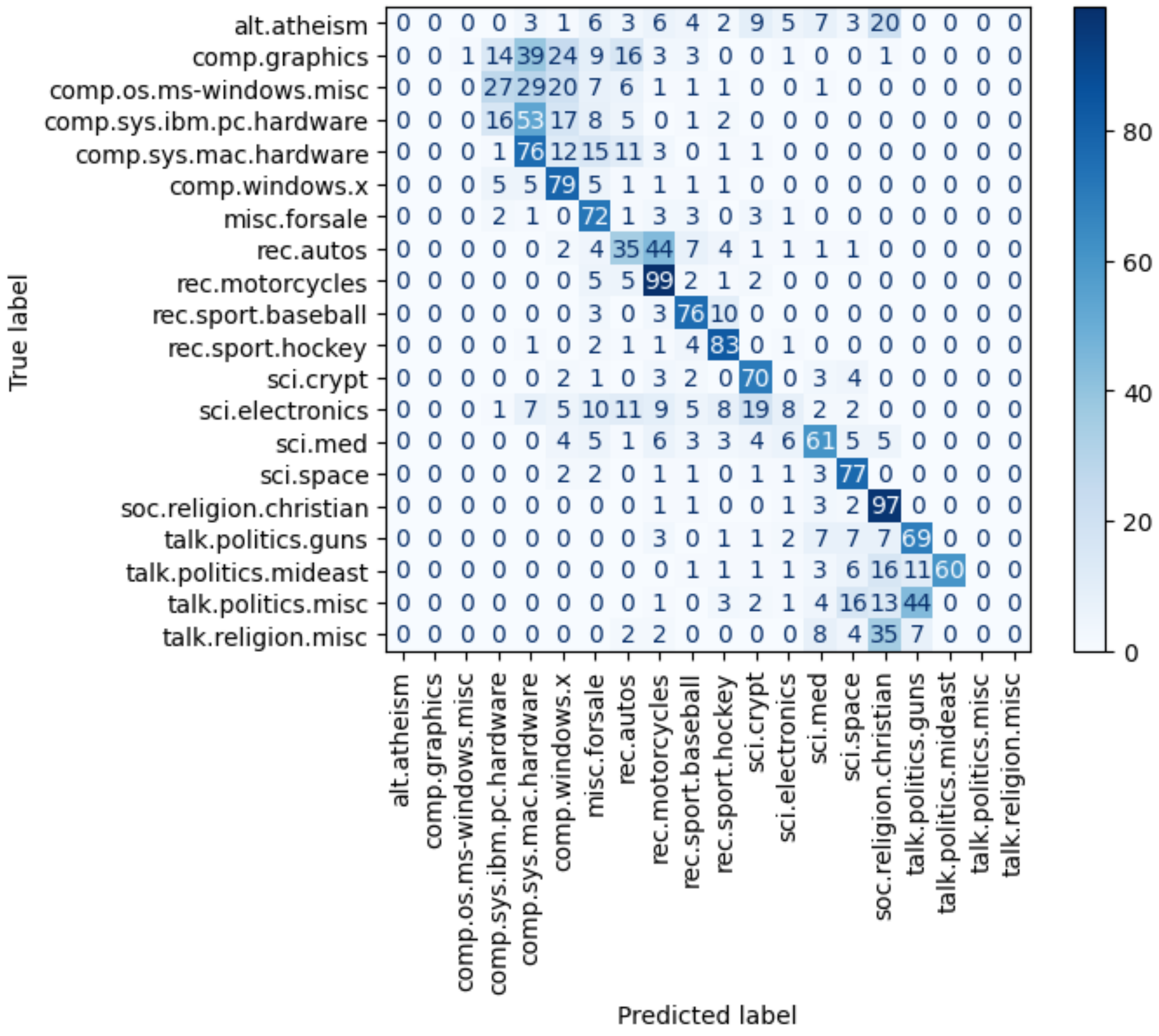
```
# DO NOT CHANGE THIS CELL
plot_loss(train_loss_over_time_hinge, val_loss_over_time_hinge, 'NBOW wi
```



```
# DO NOT CHANGE THIS CELL
# load best model from checkpoint
learning_rate, epochs, embedding_dim = get_hyperparams_nbow()
nbow_model = get_nbow_model(vocab_size= len(train_vocab.keys()), embeddi
load_checkpoint(nbow_model, 'nbow', 'hinge', map_location=device)

# evaluate model
true, pred, val_loss = val_loop(nbow_model, criterion, val_iterator)
accuracy, f1 = get_accuracy_and_f1_score(true, pred)
print(f"Final Validation Accuracy: {accuracy}")
print(f"Final Validation F1-Score: {f1}")
```

```
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 29.42it/s]
Final Validation Accuracy: 0.5188328912466843
Final Validation F1-Score: 0.42542279294848395
```

```
# DO NOT CHANGE THIS CELL
plot_confusion_matrix(true, pred, classes=id2label.values())
```



	alt.atheism	comp.graphics	comp.os.ms-windows.misc	comp.sys.ibm.pc.hardware	comp.sys.mac.hardware	comp.windows.x	misc.forsale	rec.autos	rec.motorcycles	rec.sport.baseball	rec.sport.hockey	sci.crypt	sci.electronics	sci.med	sci.space	soc.religion.christian	talk.politics.guns	talk.politics.mideast	talk.politics.misc	talk.religion.misc
alt.atheism	0	0	0	0	3	1	6	3	6	4	2	9	5	7	3	20	0	0	0	0
comp.graphics	0	0	1	14	39	24	9	16	3	3	0	0	1	0	0	1	0	0	0	0
comp.os.ms-windows.misc	0	0	0	27	29	20	7	6	1	1	1	0	0	1	0	0	0	0	0	0
comp.sys.ibm.pc.hardware	0	0	0	16	53	17	8	5	0	1	2	0	0	0	0	0	0	0	0	0
comp.sys.mac.hardware	0	0	0	1	76	12	15	11	3	0	1	1	0	0	0	0	0	0	0	0
comp.windows.x	0	0	0	5	5	79	5	1	1	1	1	0	0	0	0	0	0	0	0	0
misc.forsale	0	0	0	2	1	0	72	1	3	3	0	3	1	0	0	0	0	0	0	0
rec.autos	0	0	0	0	0	2	4	35	44	7	4	1	1	1	1	0	0	0	0	0
rec.motorcycles	0	0	0	0	0	0	5	5	99	2	1	2	0	0	0	0	0	0	0	0
rec.sport.baseball	0	0	0	0	0	0	3	0	3	76	10	0	0	0	0	0	0	0	0	0
rec.sport.hockey	0	0	0	0	1	0	2	1	1	4	83	0	1	0	0	0	0	0	0	0
sci.crypt	0	0	0	0	0	2	1	0	3	2	0	70	0	3	4	0	0	0	0	0
sci.electronics	0	0	0	1	7	5	10	11	9	5	8	19	8	2	2	0	0	0	0	0
sci.med	0	0	0	0	0	4	5	1	6	3	3	4	6	61	5	5	0	0	0	0
sci.space	0	0	0	0	0	2	2	0	1	1	0	1	1	3	77	0	0	0	0	0
soc.religion.christian	0	0	0	0	0	0	0	0	1	1	0	0	1	3	2	97	0	0	0	0
talk.politics.guns	0	0	0	0	0	0	0	0	3	0	1	1	2	7	7	7	69	0	0	0
talk.politics.mideast	0	0	0	0	0	0	0	0	0	1	1	1	1	3	6	16	11	60	0	0
talk.politics.misc	0	0	0	0	0	0	0	0	1	0	3	2	1	4	16	13	44	0	0	0
talk.religion.misc	0	0	0	0	0	0	0	2	2	0	0	0	0	8	4	35	7	0	0	0

7. Analysis [21 Points - Non-programming]

These are some analytical questions based on implementations done above.

Note for all analysis questions: Be sure to isolate all your code/textual answers into separate cells without modifying code in other exported functions as they are still used for grade scope test cases. Feel free to add as many code and markdown cells as you see fit to explain your answer.

Code should be in code cells and write-ups should strictly be in markdown cells. Please note, these will be manually evaluated due to large variation in possible answers. So, visibility of code, explanation and output in the PDF is the key.

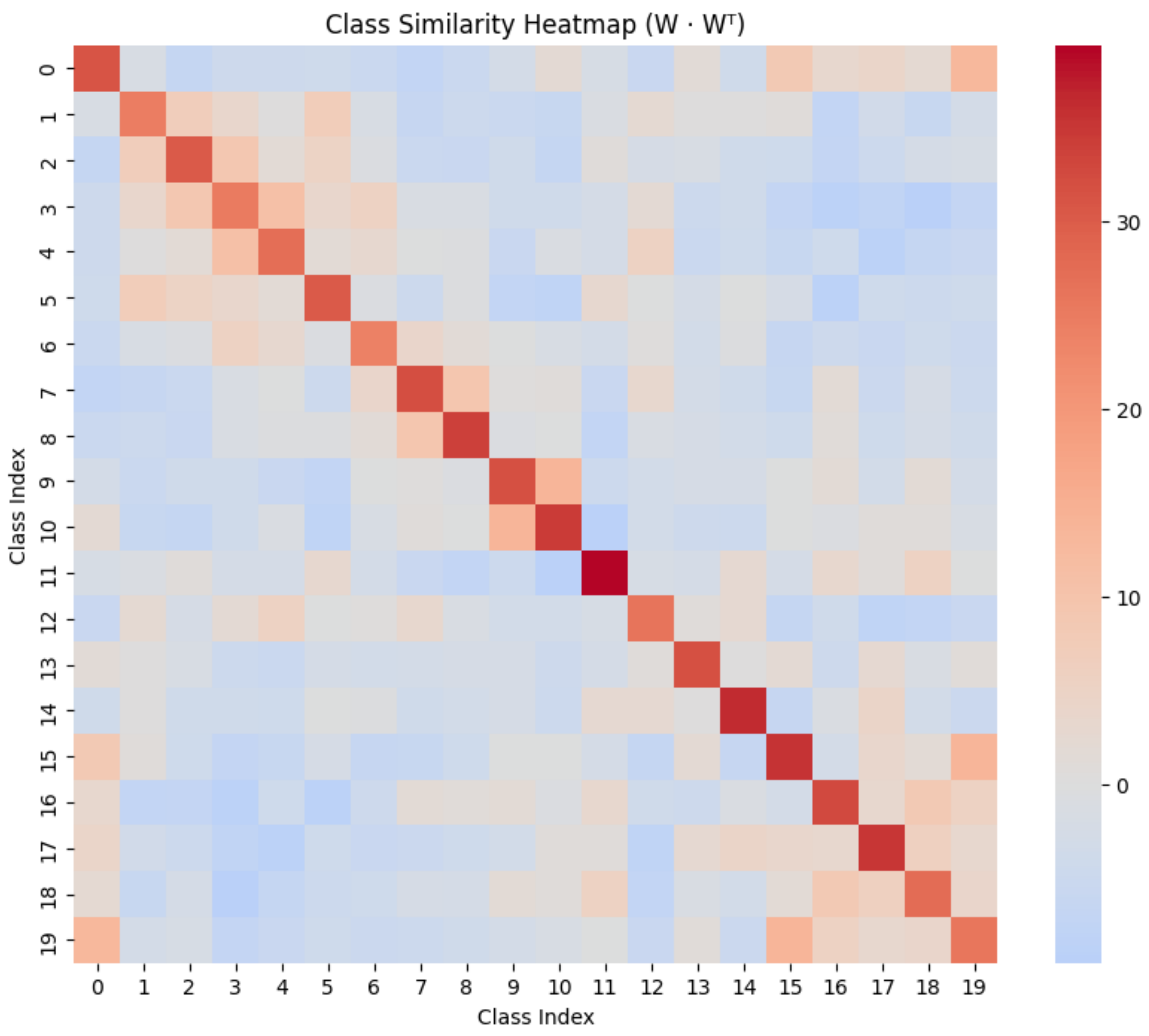
7.1. Analyzing NBOW Weights [7 points - Non-programming]

Load your trained `NBOW` model here, and let $w$$w$ be the weight of your linear layer of the model. It will be of the shape of `(num_classes, embedding_dim)`.

For this tensor, compute $ww^T$$ww^T$ and show it as a heatmap (a sample code to generate heatmap is shown below).

Explain the generated output. What does it resemble? What do high and low values of coefficients at position i, j indicate? With the help of the dataset documentation and `id2label` map displayed earlier in this notebook, can you reason why certain values are high and why certain values are low? What does it tell you about the class labels?

```
# Load trained NBOW model
nbow_model = get_nbow_model(len(train_vocab.keys()), embedding_dim)
load_checkpoint(nbow_model, 'nbow', map_location=device)

# Extract classifier weight matrix (num_classes x embedding_dim)
W = nbow_model.fc.weight.detach().cpu().numpy()

# Compute similarity matrix
WWT = np.dot(W, W.T)

# Plot as heatmap
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 8))
sns.heatmap(WWT, cmap='coolwarm', center=0)
plt.title("Class Similarity Heatmap (W · Wᵀ)")
plt.xlabel("Class Index")
plt.ylabel("Class Index")
plt.show()
```



The $ww^T$$ww^T$ heatmap resembles a semantic similarity map of the 20 Newsgroups topics. High coefficients reflect related subject areas (shared vocabulary), while low or negative coefficients mark distinct, unrelated classes. This demonstrates that the NBOW model learned meaningful inter-class structure beyond simple label boundaries.

7.2. Word Embeddings and the Attention Vector [7 points - Non Programming]

From your trained `SimpleAttentionNBOW` model, analyze all word embeddings and the attention vector `u`. Look at the words which have the highest cosine similarity with `u`. Print the 15 words with highest cosine similarity to `u` and the 15 with lowest cosine similarity to `u`. Why do you think those words have high/low cosine similarity to `u` (and therefore high/low attention weights on average)? Form a hypothesis to explain what you see.

```
import torch
import torch.nn.functional as F

# 1) Load your trained SimpleAttentionNBOW
attn_model = get_simple_attention_model(len(train_vocab.keys()), embeddi
load_checkpoint(attn_model, 'simple_attention', map_location=device)

# 2) Extract the attention vector u robustly (works regardless of its at
u = None
for name, p in attn_model.named_parameters():
    # skip embedding weights and classifier weights/biases
    if 'embedding' in name or 'fc' in name:
        continue
    # the attention vector is the only 1—D parameter of size embedding_d
    if p.ndim == 1 and p.numel() == attn_model.embedding.embedding_dim:
        u = p.detach().cpu()
        print(f"Using attention parameter: {name}")
        break

if u is None:
    # fall back: show what parameters exist so you can pick the right on
    print("Could not auto-detect attention vector. Available params:")
    print([n for n, _ in attn_model.named_parameters()])
    raise RuntimeError("Attention vector not found—see the printed param

# 3) Get the embedding matrix
E = attn_model.embedding.weight.detach().cpu()

# 4) Cosine similarity between every word embedding and u
E_n = F.normalize(E, dim=1)          # (V, D)
u_n = F.normalize(u, dim=0)          # (D,)
cos_sim = (E_n @ u_n)                # (V,)

# 5) Map ids -> tokens
id2word = {idx: tok for tok, idx in train_vocab.items()}

# 6) Exclude special tokens if present
special_ids = set()
if 'UNK' in train_vocab: special_ids.add(train_vocab['UNK'])
if '' in train_vocab:    special_ids.add(train_vocab[''])  # padding tok
mask = torch.ones_like(cos_sim, dtype=torch.bool)
for sid in special_ids:
    if 0 <= sid < mask.numel():
        mask[sid] = False

# 7) Top 15 and Bottom 15
k = 15
valid_scores = cos_sim[mask]
valid_indices = torch.arange(cos_sim.numel())[mask]

top_vals, top_pos = torch.topk(valid_scores, k, largest=True)
bot_vals, bot_pos = torch.topk(valid_scores, k, largest=False)

top_ids = valid_indices[top_pos].tolist()
bot_ids = valid_indices[bot_pos].tolist()

print("\nTop 15 words by cosine(u, emb):")
for wid, val in zip(top_ids, top_vals.tolist()):
    print(f"{id2word.get(int(wid), str(wid))}\t{val:.4f}")

print("\nBottom 15 words by cosine(u, emb):")
for wid, val in zip(bot_ids, bot_vals.tolist()):
    print(f"{id2word.get(int(wid), str(wid))}\t{val:.4f}")
```

```
Using attention parameter: att_vector
```

```
Top 15 words by cosine(u, emb):
hockey  0.4077
cars    0.3717
sale    0.3574
encryption      0.3537
apple   0.3461
car     0.3404
sw.stratus.com  0.3395
lc      0.3367
dod     0.3337
images  0.3321
expo.lcs.mit.edu        0.3264
jmd     0.3182
space   0.3169
israeli 0.3160
nhl     0.3147

Bottom 15 words by cosine(u, emb):
\       -0.7884
:       -0.6136
,       -0.5116
from    -0.4820
subject -0.4675
.       -0.4610
>       -0.4554
the     -0.4415
)       -0.4256
@       -0.3952
to      -0.3917
a       -0.3899
(       -0.3834
and     -0.3659
in      -0.3582
```

The attention vector (u) represents the model’s notion of what makes a word informative for classification. By comparing each word’s embedding to u via cosine similarity, we can see which words the model attends to most strongly and which it largely ignores. These words are content heavy nouns tied to specific discussion topics, sports, technology, products, and security, which tend to be strong predictors of document category. The attention vector assigns them large positive similarity, meaning the model emphasizes such tokens when forming the sentence representation. These are mostly punctuation, stopwords, or structural tokens that occur frequently across all classes and carry little semantic information. Their negative similarity indicates the model effectively down weights them assigning low attention weights during aggregation. The attention mechanism learned to focus on semantically rich content words that distinguish document topics while suppressing common or formatting tokens. This aligns with the goal of attention: to highlight words that are contextually informative for classification. The clear separation between nouns like hockey, car, apple and functional words like the, and, in shows that the attention vector is capturing domain level relevance rather than raw frequency.

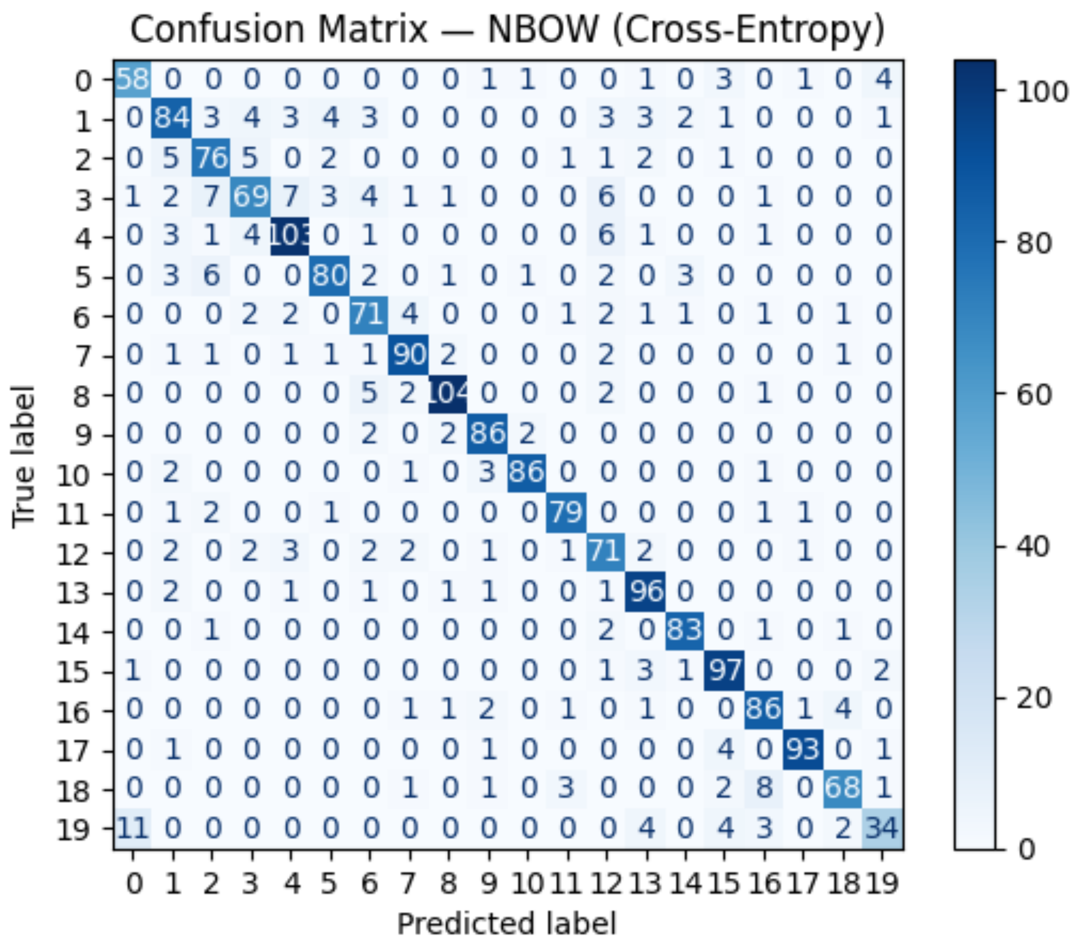
7.3. Analysis of Cost Matrix in Hinge Loss [7 points - Non-programming]

Display the confusion matrices of prediction of `NBOW` with `PerceptronLoss` and `HingeLoss`. Also print the cost matrix you used for the Hinge Loss.

Using this confusion matrix, `id2label` mapping provided earlier, your knowledge about what labels in the dataset represent, explain the motivation behind creating the provided cost matrix. Why were some of the coefficients higher than others (if)?

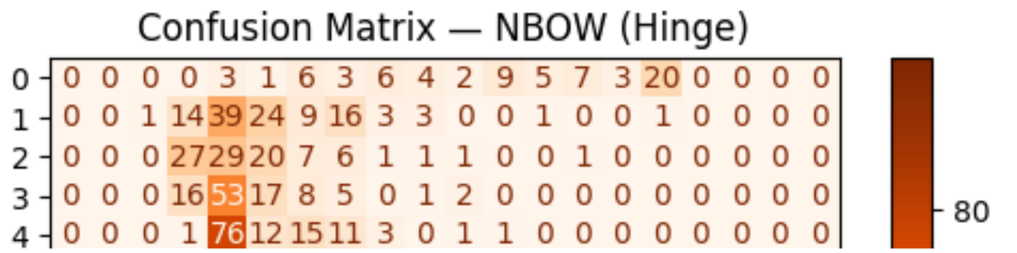
```
# NBOW (Cross-Entropy) version
nbow_ce = get_nbow_model(len(train_vocab.keys()), embedding_dim)
load_checkpoint(nbow_ce, 'nbow', loss_fn='ce', map_location=device)

true_ce, pred_ce, _ = val_loop(nbow_ce, criterion, val_iterator)
ConfusionMatrixDisplay(confusion_matrix(true_ce, pred_ce)).plot(
    cmap='Blues', values_format='d'
)
plt.title("Confusion Matrix – NBOW (Cross-Entropy)")
plt.show()

# NBOW (Hinge) version
nbow_hinge = get_nbow_model(len(train_vocab.keys()), embedding_dim)
load_checkpoint(nbow_hinge, 'nbow', loss_fn='hinge', map_location=device

true_h, pred_h, _ = val_loop(nbow_hinge, criterion, val_iterator)
ConfusionMatrixDisplay(confusion_matrix(true_h, pred_h)).plot(
    cmap='Oranges', values_format='d'
)
plt.title("Confusion Matrix — NBOW (Hinge)")
plt.show()
```

```
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 28.48it/s]
```

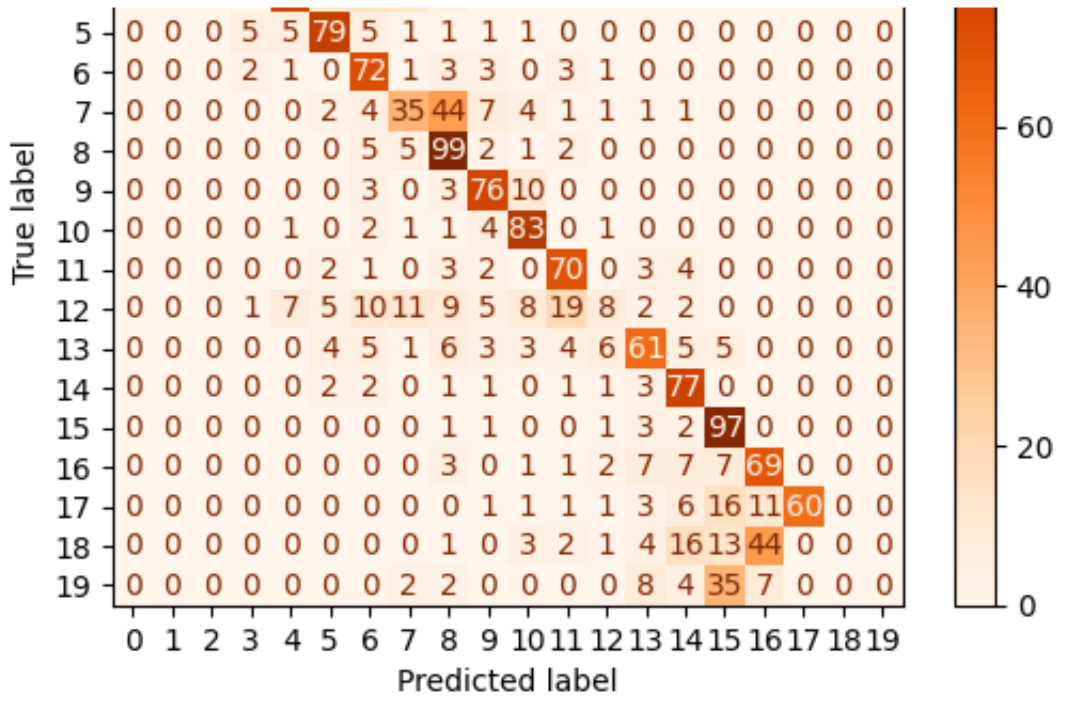


	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	58	0	0	0	0	0	0	0	0	1	1	0	0	1	0	3	0	1	0	4
1	0	84	3	4	3	4	3	0	0	0	0	0	3	3	2	1	0	0	0	1
2	0	5	76	5	0	2	0	0	0	0	0	1	1	2	0	1	0	0	0	0
3	1	2	7	69	7	3	4	1	1	0	0	0	6	0	0	0	1	0	0	0
4	0	3	1	4	103	0	1	0	0	0	0	0	6	1	0	0	1	0	0	0
5	0	3	6	0	0	80	2	0	1	0	1	0	2	0	3	0	0	0	0	0
6	0	0	0	2	2	0	71	4	0	0	0	1	2	1	1	0	1	0	1	0
7	0	1	1	0	1	1	1	90	2	0	0	0	2	0	0	0	0	0	1	0
8	0	0	0	0	0	0	5	2	104	0	0	0	2	0	0	0	1	0	0	0
9	0	0	0	0	0	0	2	0	2	86	2	0	0	0	0	0	0	0	0	0
10	0	2	0	0	0	0	0	1	0	3	86	0	0	0	0	0	1	0	0	0
11	0	1	2	0	0	1	0	0	0	0	0	79	0	0	0	0	1	1	0	0
12	0	2	0	2	3	0	2	2	0	1	0	1	71	2	0	0	0	1	0	0
13	0	2	0	0	1	0	1	0	1	1	0	0	1	96	0	0	0	0	0	0
14	0	0	1	0	0	0	0	0	0	0	0	0	2	0	83	0	1	0	1	0
15	1	0	0	0	0	0	0	0	0	0	0	0	1	3	1	97	0	0	0	2
16	0	0	0	0	0	0	0	1	1	2	0	1	0	1	0	0	86	1	4	0
17	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	4	0	93	0	1
18	0	0	0	0	0	0	0	1	0	1	0	3	0	0	0	2	8	0	68	1
19	11	0	0	0	0	0	0	0	0	0	0	0	0	4	0	4	3	0	2	34

```
Evaluating Model: 100%|██████████| 15/15 [00:00<00:00, 27.57it/s]
```



0	0	0	0	0	3	1	6	3	6	4	2	9	5	7	3	20	0	0	0	0
1	0	0	1	14	39	24	9	16	3	3	0	0	1	0	0	1	0	0	0	0
2	0	0	0	27	29	20	7	6	1	1	1	0	0	1	0	0	0	0	0	0
3	0	0	0	16	53	17	8	5	0	1	2	0	0	0	0	0	0	0	0	0
4	0	0	0	1	76	12	15	11	3	0	1	1	0	0	0	0	0	0	0	0



The Hinge Loss NBOW shows slightly broader confusion patterns compared to Cross-Entropy because hinge loss optimizes margin boundaries rather than probability distributions. The cost matrix used for hinge penalizes certain misclassifications more severely, particularly those between semantically unrelated topics, to emphasize separability across distant classes. This explains why some coefficients are higher: they correspond to label pairs where confusion would be conceptually more damaging, for example “politics” vs “sports”. Cross-Entropy treats all errors equally, while Hinge Loss enforces margin-based prioritization guided by that cost structure.

8. Improving Attention Models [BONUS] [10 points - Non-programming]

Hopefully you've developed some intuition for using attention for this task. Now, come up with your own ways of modifying the attention function and experiment with them. Can you find an idea that outperforms your models from Sections 5? Some potential ideas are below:

- Use transformation matrices to distinguish key, query, and value representations
- Add additional layers of self-attention before the attention-weighted sum of embeddings
- Compute features in the attention function based on characteristics of where the word is in the sentence, e.g., features of the sentence length, nearby words, the presence of negation words before or after the word, information from a part-of-speech tagger or syntactic parse of the sentence, etc.
- Use multiple word embedding spaces for when words are used as keys, queries, and values, or some subset of the three.

Describe your best new attention function formally below, along with the execution code and experimental results. Add as many code and markdown cells as you want, and submit the complete working with explanation.

9. Submitting Your Assignment

This is the end. Congratulations!

Now, follow the steps below to submit your homework on Gradescope.

9.1. Programming

The programming will be evaluated through an autograder. To create the file to submit for autograder, follow the steps below -

1. Open a terminal from the root directory of the project
2. Run the collect_submission.py file
3. Agree to the Late Policy and Honor Pledge
4. After the file is executed, your root project will have a submission directory.
5. Submit all the contents of this file to GradeScope

9.2. Non-Programming

The analysis parts will be evaluated manually. For this, export the notebook to a PDF file, and submit it on GradeScope. Please ensure no written code or output is clipped when you create your PDF. One reliable way to do it is first download it as HTML through Jupyter Notebook and then print it to get PDF.