Frame-Level Speech Recognition

GOAL:

Given data which consists of melspectrograms, and phoneme labels for each 28-dimensional vector in the melspectrogram. The task is to predict the label of a particular 28-dimensional vector in an utterance (plus optional context) using a Feed Forward Deep Neural Network (FF-DNN or MLP).

OBJECTIVES:

- The main goal here is to explore neural networks for speech recognition, mainly focusing on phoneme state labelling.
- Speech recognition is an important field in deep learning with multiple applications. Speech is a fundamental form of human communication.
- Speech recognition involves converting spoken language into written text or data that could be understood by machines.
- Speech data refers to audio recordings of human speech, while phonemes represent the smallest units of sound that can convey a different meaning(bake, take: b,t).
- Spectrograms are visual representations of the acoustic properties of speech signals, i.e. captures the changes in the frequency over time.

DATASET DETAILS

- Dataset contains audio recordings (utterances) and their phoneme state (subphoneme) labels.
- The data comes from articles published in the Wall Street Journal (WSJ) that are read aloud and labelled using the original text.
- The dataset provided has speech data in the form of Mel spectrograms.
- The data comprises of:
  - Speech recordings (raw mel spectrogram frames)
  - Frame-level phoneme state labels
- Training data have around 28539 samples

Phonemes and Phoneme States

- As letters are the atomic elements of written language, phonemes are the atomic elements of speech.
- It is crucial for us to have a means to distinguish different sounds in speech that may or may not represent the same letter or combinations of letters in the written alphabet.
- In the dataset, we will consider a total of 40 phonemes in this language.
- A powerful technique in speech recognition is to model speech as a markov process with unobserved states.
- This model considers observed speech to be dependent on unobserved state transitions. We refer to these unobserved states as phoneme states or subphonemes. For each phoneme, there are 3 respective phoneme states. The transition graph of the phoneme states for a given phoneme is as follows:
- Example: [”+BREATH+”, ”+COUGH+”, ”+NOISE+”, ”+SMACK+”, ”+UH+”, ”+UM+”, "AA”, ”AE”, ”AH”, ”AO”, ”AW”, ”AY”, ”B”, ”CH”, ”D”, ”DH”, ”EH”, ”ER”, ”EY”, ”F”, ”G”, ”HH”, ”IH”, ”IY”, ”JH”, ”K”, ”L”, ”M”, ”N”, ”NG”, ”OW”, ”OY”, ”P”, ”R”, ”S”, ”SH”, ”SIL”, ”T”, ”TH”, ”UH”, ”UW”, ”V”, ”W”, ”Y”, ”Z”, ”ZH”]
- Hidden Markov Models (HMMs) estimate the parameters of this unobserved markov process (transition and emission probabilities) that maximize the likelihood of the observed speech data.
- We will take model-free approach and classify mel spectrogram frames using a neural network that takes a frame (plus optional context) and outputs class probabilities for all 40 phoneme states. The training data has the corresponding phonemes for this data and we need to train an MLP for predicting. We will be building a multilayer perceptron(MLP) that can effectively recognize and label the phoneme states in the training data. An MLP is a type of neural network that comprises multiple layers of perceptrons, that help it capture the features and patterns of the data.

Speech Representation

- Raw speech signal (also known as the speech waveform) is stored simply as a sequence of numbers that represent the amplitude of the sound wave at each time step. This signal is typically composed of sound waves of several different frequencies overlaid on top of one another. For human speech, these frequencies represent the frequencies at which the vocal tract vibrates when we speak and produce sound. Since this signal is not very useful for speech recognition if used directly as a waveform, we convert it into a more useful representation called a "melspectrogram" in the feature extraction stage.
- The variation with time of the frequencies present in a particular speech sample are very useful in determining the phoneme being spoken. In order to separate out all the individual

frequencies present in the signal, we perform a variant of the Fourier Transform, called the Short-Time Fourier Transform (STFT) on small, overlapping segments (called frames, each of 25ms) of the waveform. A single vector is produced as the result of this transform. Since we use a stride of 10ms between each frame, we end up with 100 vectors per second of speech. Finally, we convert each vector into a 28-dimensional vector (for further readings https://haythamfayek.com/2016/04/21/speech-processing-for-machine-learning.html). For an utterance T seconds long, this leaves us with a matrix of shape (100*T, 28) known as the melspectrogram. Note that in the dataset provided to you, we have already done all of this pre-processing and provided the final (*, 28) shaped melspectrograms to you. The data provided consists of these melspectrograms, and phoneme labels for each 28-dimensional vector in the melspectrogram. The task is to predict the label of a particular 28-dimensional vector in an utterance.

PERFORMANCE METRIC

- Accuracy
- Confusion Matrix
- Precision and Recall

EXPERIMENT

- Build FF-DNN only without any batchnorm or dropout
- Different right and left context are added so that capture more variability in the speaker utterances smoothing
- Sparse MLP is created using the loss function
    - Reference: https://ieeexplore.ieee.org/document/5734801
- No Augmentation
- No hyper-parameter tuning however used our past knowledge to set hyper-paramters
- Advanced weight initialization, Label smoothing in loss function, gradient clipping and scheduler are used.

```
! ls /content/
```

```
!pip install torch-summary --quiet
```

```
import torch
import numpy as np
import sklearn
import gc
```

```
import zipfile
import pandas as pd
from tqdm.auto import tqdm
import os
import datetime
import torchsummary
device = 'cuda' if torch.cuda.is_available() else 'cpu'
print("Device: ", device)
```

```
Device:  cuda
```

```
# # using colab for including google drive to save model ch
# from google.colab import drive
# drive.mount('/content/drive')
```

```
!pip install --upgrade --force-reinstall --no-deps kaggle==
!mkdir -p /root/.kaggle
```

```
Collecting kaggle==1.5.8
  Downloading kaggle-1.5.8.tar.gz (59 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 59.2/59.2 kB 2.7 MB/s eta 0:00:
  Preparing metadata (setup.py) ... done
Building wheels for collected packages: kaggle
  Building wheel for kaggle (setup.py) ... done
  Created wheel for kaggle: filename=kaggle-1.5.8-py3-none-any.whl size=73249
  Stored in directory: /root/.cache/pip/wheels/b5/23/bd/d33cbf399584fa44fa049
Successfully built kaggle
Installing collected packages: kaggle
  Attempting uninstall: kaggle
    Found existing installation: kaggle 1.7.4.2
    Uninstalling kaggle-1.7.4.2:
      Successfully uninstalled kaggle-1.7.4.2
Successfully installed kaggle-1.5.8
```

```
with open("/root/.kaggle/kaggle.json", "w+") as f:
    f.write('{"username":"dineshbuswala","key":"a67fefaecac

!chmod 600 /root/.kaggle/kaggle.json
```

```
# commands to download data from kaggle

!kaggle competitions download -c 11785-hw1p2-f23 --force
!mkdir -p '/content/data'

# !unzip -qo /content/11785-hw1p2-f23.zip -d '/content/data
```

```
Downloading 11785-hw1p2-f23.zip to /kaggle/working
100%|██████████████████████████████| 3.97G/3.99G [00:24<00:00, 195MB
100%|██████████████████████████████| 3.99G/3.99G [00:24<00:00, 173MB
```

```
!unzip -qo /kaggle/working/11785-hw1p2-f23.zip -d '/content
```

```
! rm -r /content/data/11-785-f23-hw1p2/test-clean
! rm -r /content/11785-hw1p2-f23.zip
```

```
! ls /content/data/11-785-f23-hw1p2/train-clean-100/mfcc/ |
```

```
28539
```

```
### configuration variables
EPOCHS                                = 4
BATCH_SIZE                            = 2048 * 2
LEFT_CONTEXT                          = 7
RIGHT_CONTEXT                         = 7
INITIAL_LEARNING_RATE                 = 1e-3
L2_PENALTY                            = 1e-5
STEP_SIZE                             = 2
GAMMA                                 = 0.1
BASE_DIRECTORY                        = '/content/data/11-785-f23
TRAINING_DATA                         = BASE_DIRECTORY + 'train-c
EVALUATION_DATA                       = BASE_DIRECTORY + 'dev-cle
PHONEMES                              = ['[SIL]',   'AA',    'AE'
                                          'B',     'CH',    'D',
                                          'F',     'G',     'HH',
                                          'L',     'M',     'N',
                                          'R',     'S',     'SH',
                                          'V',     'W',     'Y',
PHONEMES_TO_INDEX                      = {phoneme: idx for idx, p
NUMBER_OF_NEURONS                      = [2048, 2048, 1024, 1024,
MODEL_DIR                              = "/content"
CLIP_VALUE                             = 1.0
LABEL_SMOOTHING                        = 0.01
```

```
class AudioDataset(torch.utils.data.Dataset):
    def __init__(self, root, phonemes = PHONEMES_TO_INDEX,
                 left_context = LEFT_CONTEXT,
                 right_context = RIGHT_CONTEXT):

        self.left_context = left_context
        self.right_context = right_context
        self.phonemes_mapping = phonemes

```

```
        self.mfcc_dir = os.path.join(root, 'mfcc')
        self.transcript_dir = os.path.join(root, 'transcri

        # List and sort mfcc and transcript files
        mfcc_names = sorted(os.listdir(self.mfcc_dir))
        transcript_names = sorted(os.listdir(self.transcri

        # Sanity check
        assert len(mfcc_names) == len(transcript_names), "

        total_frames = 0

        for i in range(len(mfcc_names)):
            mfcc_path = os.path.join(self.mfcc_dir, mfcc_n

            mfcc = np.load(mfcc_path,
                           allow_pickle = False,
                           mmap_mode='r')
            total_frames += mfcc.shape[0]
            del mfcc

        sample_mfcc = np.load(os.path.join(self.mfcc_dir,
        self.mfcc_dim = sample_mfcc.shape[1]
        ### Right Padding is added here automatically
        self.mfccs = np.zeros((total_frames + right_contex
        self.transcripts = [None] * (total_frames + right_
        ### Release memory
        del sample_mfcc, total_frames
        gc.collect()

        index = 0
        for i in range(len(mfcc_names)):
            mfcc = np.load(os.path.join(self.mfcc_dir, mfc
                           allow_pickle = False,
                           mmap_mode = 'r')

            mfcc = (mfcc - mfcc.mean(axis = 1, keepdims =

            transcript = np.load(os.path.join(self.transcr
                                 allow_pickle = False,
                                 mmap_mode='r')[1:-1]

            self.mfccs[index: index + mfcc.shape[0]] = mfc
            self.transcripts[index: index + len(transcript
            index += mfcc.shape[0]
```

```
            del mfcc, transcript

            if i % 1000 == 0:
                gc.collect() ### Release memory

        # Save original dataset length (before adding righ
        self.length = len(self.mfccs) - right_context

        # Map transcript phonemes to indices
        self.transcripts = [self.phonemes_mapping.get(p, -

        ### Release memory
        del mfcc_names, transcript_names
        gc.collect()

    def __len__(self):
        return self.length

    def __getitem__(self, ind):
        if ind < self.left_context:  # index is less than
            # zeros need to prepend with it
            padding = []
            for _ in range(self.left_context - ind):
                padding.append(np.zeros((1, self.mfcc_dim)

            for i in range(ind):
                padding.append(self.mfccs[i][None, :])

            # Include current and right context frames
            current = self.mfccs[ind][None, :]  # Ensure s
            right_context = [self.mfccs[i][None, :] for i
            frames = np.concatenate(padding + [current] +

        else:  # when index is greater than or equal to le
            left_context_frames = self.mfccs[ind - self.le
            current = self.mfccs[ind][None, :]  # Ensure s
            right_context_frames = self.mfccs[ind + 1: ind

            frames = np.concatenate([left_context_frames,

        frames = frames.flatten()  # Flatten to get 1D dat
        frames = torch.FloatTensor(frames)  # Convert to t
        phonemes = torch.tensor(self.transcripts[ind], dty

```

```
# Create a dataset object using the AudioDataset class for
train_data = AudioDataset(TRAINING_DATA)

# Create a dataset object using the AudioDataset class for
val_data = AudioDataset(EVALUATION_DATA)

```

```
train_loader = torch.utils.data.DataLoader(
    dataset     = train_data,
    num_workers = 2,
    batch_size  = BATCH_SIZE,
    pin_memory  = True,
    shuffle     = True
)

val_loader = torch.utils.data.DataLoader(
    dataset     = val_data,
    num_workers = 1,
    batch_size  = BATCH_SIZE,
    pin_memory  = True,
    shuffle     = False
)

print("Train dataset samples = {}, batches = {}".format(tra
print("Validation dataset samples = {}, batches = {}".forma
```

```
Train dataset samples = 36091157, batches = 8812
Validation dataset samples = 1928204, batches = 471
```

```
# # Testing code to check if data loaders are working as ex
# total_batches = len(train_loader)

# for i, (frames, phoneme) in enumerate(train_loader):
#     if i < 10 or i >= total_batches - 10:
#         print(f"Batch {i + 1}/{total_batches}")
#         print("Frames:", frames)
#         print("Phoneme:", phoneme)
#         print("-" * 50)

```

```
class Network(torch.nn.Module):
    def __init__(self, input_size):
        super(Network, self).__init__()

```

```
        # Neurons in each layer: input -> hidden(s) -> outp
        self.neurons = [input_size] + NUMBER_OF_NEURONS + [

        layers = []
        for in_features, out_features in zip(self.neurons[:
            layers.append(torch.nn.Linear(in_features, out_
            layers.append(torch.nn.ReLU())

        # Final layer (no activation)
        layers.append(torch.nn.Linear(self.neurons[-2], sel

        # Combine all into a sequential model
        self.model = torch.nn.Sequential(*layers)

        # Apply weight initialization
        self._initialize_weights()

    def _initialize_weights(self):
        print('Initialization of weights using Kaiming')
        for m in self.model:
            if isinstance(m, torch.nn.Linear):
                # Kaiming initialization for weights
                torch.nn.init.kaiming_uniform_(m.weight, no


    def forward(self, x):
        out = self.model(x)
        return out

```

```
INPUT_SIZE = (LEFT_CONTEXT + RIGHT_CONTEXT + 1) * 28
model = Network(INPUT_SIZE).to(device)
# Pass the input size as a tuple, without the batch dimensi
torchsummary.summary(model, (INPUT_SIZE,))
```

```
Initialization of weights using Kaiming
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                 [-1, 2048]         862,208
              ReLU-2                 [-1, 2048]               0
            Linear-3                 [-1, 2048]       4,196,352
              ReLU-4                 [-1, 2048]               0
            Linear-5                 [-1, 1024]       2,098,176
              ReLU-6                 [-1, 1024]               0
            Linear-7                 [-1, 1024]       1,049,600
              ReLU-8                 [-1, 1024]               0
            Linear-9                  [-1, 512]         524,800
```

```
          ReLU-10                  [-1, 512]               0
        Linear-11                  [-1, 256]         131,328
          ReLU-12                  [-1, 256]               0
        Linear-13                  [-1, 256]          65,792
          ReLU-14                  [-1, 256]               0
        Linear-15                   [-1, 40]          10,280
================================================================
Total params: 8,938,536
Trainable params: 8,938,536
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 0.11
Params size (MB): 34.10
Estimated Total Size (MB): 34.21
----------------------------------------------------------------
```

```python
class SparseLoss(torch.nn.Module):
    def __init__(self, model, lambda_l1=1e-4):
        super(SparseLoss, self).__init__()
        self.ce_criterion = torch.nn.CrossEntropyLoss(label
        self.lambda_l1 = lambda_l1
        self.model = model

        # Collect indices of Linear layers, skipping first
        self.linear_layer_indices = [
            i for i, layer in enumerate(self.model.model[1:
            if isinstance(layer, torch.nn.Linear)
        ]

    def forward(self, logits, targets):
        ce_loss = self.ce_criterion(logits, targets)

        sparse_loss = 0.0
        for i in self.linear_layer_indices:
            weight = self.model.model[i].weight  # [out_fea

            # Neuron-wise aggregation: sum inputs per neuro
            neuron_weights = weight.sum(dim=1)  # [out_feat

            # sum(log(1 + (neuron)^2))
            sparse_loss += torch.log1p(neuron_weights.pow(2

        total_loss = ce_loss + self.lambda_l1 * sparse_loss
        return total_loss

```

```python
# criterion = torch.nn.CrossEntropyLoss(label_smoothing = L
```

```
# We use CE because the task is multi-class classification
criterion = SparseLoss(model, lambda_l1 = 1e-4)
optimizer = torch.optim.Adam(model.parameters(),
                             lr = INITIAL_LEARNING_RATE,
                             weight_decay = L2_PENALTY) #De
scheduler = torch.optim.lr_scheduler.StepLR(
    optimizer, step_size = STEP_SIZE, gamma = GAMMA
)
# Refer - https://pytorch.org/docs/stable/notes/amp_example
```

```
torch.cuda.empty_cache()
gc.collect()
```

```
101
```

```
def train(model, dataloader, optimizer, criterion):

    model.train()
    tloss, tacc = 0, 0 # Monitoring loss and accuracy
    batch_bar   = tqdm(total=len(train_loader), dynamic_nco

    for i, (frames, phonemes) in enumerate(dataloader):

        ### Initialize Gradients
        optimizer.zero_grad()

        ### Move Data to Device (Ideally GPU)
        frames      = frames.to(device)
        phonemes    = phonemes.to(device)

        ### Forward Propagation
        logits  = model(frames)

        ### Loss Calculation
        loss    = criterion(logits, phonemes)

        ### Backward Propagation
        loss.backward()

        ### Clip gradients
        torch.nn.utils.clip_grad_norm_(model.parameters(),

        ### Gradient Descent
        optimizer.step()

```

```
        tloss   += loss.item()
        tacc    += torch.sum(torch.argmax(logits, dim= 1) =

        batch_bar.set_postfix(loss="{:.04f}".format(float(t
                              acc="{:.04f}%".format(float(t
        batch_bar.update()

        ### Release memory
        del frames, phonemes, logits
        torch.cuda.empty_cache()

    batch_bar.close()
    tloss   /= len(train_loader)
    tacc    /= len(train_loader)

    return tloss, tacc
```

```
def eval(model, dataloader):

    model.eval() # set model in evaluation mode
    vloss, vacc = 0, 0 # Monitoring loss and accuracy
    batch_bar   = tqdm(total=len(val_loader), dynamic_ncols

    for i, (frames, phonemes) in enumerate(dataloader):

        ### Move data to device (ideally GPU)
        frames      = frames.to(device)
        phonemes    = phonemes.to(device)

        # makes sure that there are no gradients computed a
        with torch.inference_mode():
            ### Forward Propagation
            logits  = model(frames)
            ### Loss Calculation
            loss    = criterion(logits, phonemes)

        vloss   += loss.item()
        vacc    += torch.sum(torch.argmax(logits, dim= 1) =


        batch_bar.set_postfix(loss="{:.04f}".format(float(v
                              acc="{:.04f}%".format(float(v
        batch_bar.update()

        ### Release memory
```

```
        del frames, phonemes, logits
        torch.cuda.empty_cache()

    batch_bar.close()
    vloss   /= len(val_loader)
    vacc    /= len(val_loader)

    return vloss, vacc
```

```
best_model_path = os.path.join(MODEL_DIR, "best_model.pt")
best_acc = -np.inf
for epoch in range(EPOCHS):
    ### clean up memory before computation
    torch.cuda.empty_cache()
    gc.collect()

    print(f"\nEpoch {epoch + 1}/{EPOCHS}")

    curr_lr = float(optimizer.param_groups[0]['lr'])
    train_loss, train_acc = train(model, train_loader, opti
    val_loss, val_acc = eval(model, val_loader)

    print(f"\tTrain Acc: {train_acc*100:.2f}%\tTrain Loss:
    print(f"\tVal   Acc: {val_acc*100:.2f}%\tVal   Loss: {v

    # Save model at every epoch
    epoch_model_path = os.path.join(MODEL_DIR, f"model_at_e
    torch.save(model.state_dict(), epoch_model_path)

    # Save best model
    if val_acc > best_acc:
        best_acc = val_acc
        torch.save(model.state_dict(), best_model_path)
        print(f"Updated Best Model at: {best_model_path}")

    ### take step in adjusting the learning rate
    scheduler.step()


```

```
Epoch 1/4
Train:   0%|          | 0/8812 [00:00<?, ?it/s]
Val:   0%|          | 0/471 [00:00<?, ?it/s]
        Train Acc: 70.53%       Train Loss: 1.0100      LR: 0.0010000
        Val   Acc: 70.38%       Val   Loss: 1.0031
Updated Best Model at: /content/best_model.pt

Epoch 2/4
Train:   0%|          | 0/8812 [00:00<?, ?it/s]
Val:   0%|          | 0/471 [00:00<?, ?it/s]
        Train Acc: 75.57%       Train Loss: 0.8290      LR: 0.0010000
        Val   Acc: 71.77%       Val   Loss: 0.9586
Updated Best Model at: /content/best_model.pt

Epoch 3/4
Train:   0%|          | 0/8812 [00:00<?, ?it/s]
Val:   0%|          | 0/471 [00:00<?, ?it/s]
        Train Acc: 79.85%       Train Loss: 0.6779      LR: 0.0001000
        Val   Acc: 74.03%       Val   Loss: 0.8763
Updated Best Model at: /content/best_model.pt
```

```
gc.collect()
```

```
83
Val:   0%|          | 0/471 [00:00<?, ?it/s]
        Train Acc: 81.11%       Train Loss: 0.6383      LR: 0.0001000
        Val   Acc: 73.92%       Val   Loss: 0.8873
```

```
# Load best model after training
model.load_state_dict(torch.load('/content/best_model.pt'))
```

```
<All keys matched successfully>
```

```
from sklearn.metrics import classification_report, confusio
model.eval()  # Set model in evaluation mode
predicted = []
groundtruth = []

for frames, phonemes in val_loader:

    # Move data to device
    frames = frames.to(device)
    phonemes = phonemes.to(device)

    # Disable gradient calculation
    with torch.inference_mode():
        logits = model(frames)

    predict = torch.argmax(logits, dim = 1)

    # Detach and move to CPU for evaluation
    predicted.extend(predict.detach().cpu().tolist())
```

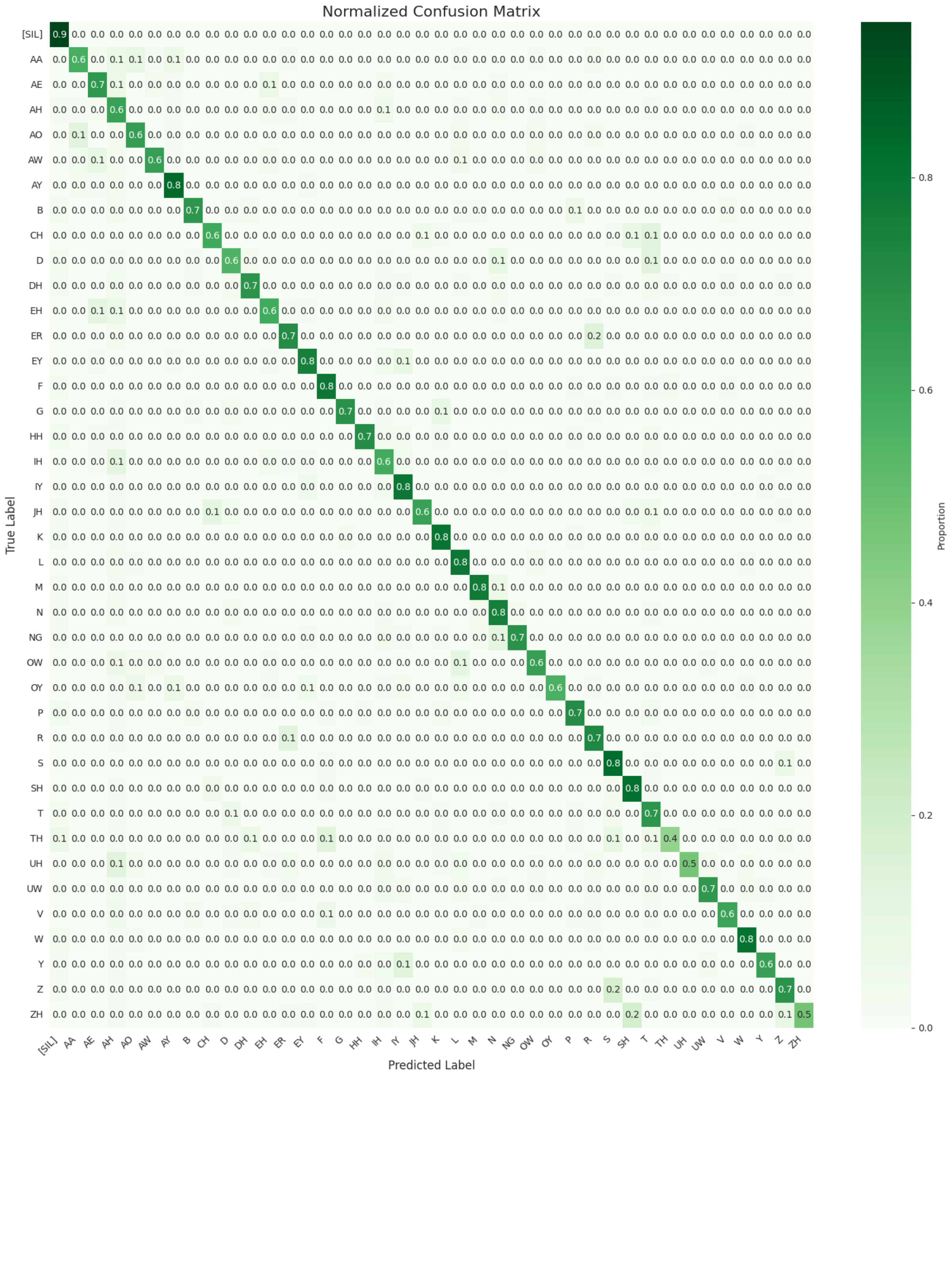
```
    groundtruth.extend(phonemes.detach().cpu().tolist())

    # Release memory
    del frames, phonemes, logits, predict
    torch.cuda.empty_cache()

# Print classification report
print(classification_report(
    groundtruth,
    predicted,
    target_names = PHONEMES  # Skipping SOS and EOS tokens
))
```

	precision	recall	f1-score	support
[SIL]	0.93	0.95	0.94	319908
AA	0.59	0.58	0.58	29688
AE	0.64	0.66	0.65	49298
AH	0.62	0.63	0.62	123734
AO	0.65	0.64	0.65	29340
AW	0.69	0.64	0.66	20274
AY	0.77	0.83	0.80	49332
B	0.68	0.67	0.68	23607
CH	0.65	0.60	0.62	12644
D	0.66	0.56	0.60	62763
DH	0.69	0.68	0.68	37100
EH	0.60	0.59	0.60	47112
ER	0.67	0.71	0.69	54928
EY	0.73	0.76	0.74	36184
F	0.71	0.79	0.75	37562
G	0.73	0.69	0.71	13541
HH	0.73	0.70	0.71	34813
IH	0.62	0.59	0.60	74887
IY	0.77	0.78	0.78	70861
JH	0.67	0.63	0.65	8730
K	0.76	0.80	0.78	47016
L	0.75	0.78	0.76	65902
M	0.76	0.77	0.77	44728
N	0.74	0.76	0.75	94541
NG	0.70	0.69	0.69	19327
OW	0.68	0.63	0.65	30755
OY	0.69	0.57	0.63	3861
P	0.71	0.71	0.71	34131
R	0.69	0.73	0.71	62686
S	0.80	0.82	0.81	101184
SH	0.79	0.82	0.80	17628
T	0.68	0.67	0.68	97390
TH	0.45	0.39	0.42	9247
UH	0.64	0.47	0.54	6286
UW	0.73	0.66	0.69	26691
V	0.70	0.62	0.66	27440
W	0.79	0.80	0.80	37697
Y	0.68	0.63	0.66	9669
Z	0.72	0.68	0.70	54850
ZH	0.74	0.48	0.58	869

```
    accuracy                           0.74   1928204
   macro avg       0.70      0.68      0.69   1928204
weighted avg       0.74      0.74      0.74   1928204
```

```
import seaborn as sns
import matplotlib.pyplot as plt
sns.set_style("darkgrid")
```

```
# Compute confusion matrix
cm = confusion_matrix(groundtruth, predicted)

# Normalize confusion matrix by row (i.e., by true labels)
cm_normalized = cm.astype('float') / cm.sum(axis = 1, keepd

# Replace NaNs (from division by zero, if any row sum is 0)
cm_normalized = np.nan_to_num(cm_normalized)

# Plot
plt.figure(figsize=(15, 16))
sns.heatmap(cm_normalized,
            annot=True,
            fmt=".1f",
            cmap="Greens",
            xticklabels=PHONEMES,
            yticklabels=PHONEMES,
            cbar_kws={'label': 'Proportion'})

plt.title('Normalized Confusion Matrix', fontsize=16)
plt.xlabel('Predicted Label', fontsize=12)
plt.ylabel('True Label', fontsize=12)
plt.xticks(rotation=45, ha='right', fontsize=10)
plt.yticks(rotation=0, fontsize=10)
plt.tight_layout()
plt.show()

```


Normalized Confusion Matrix
True Label
Predicted Label
Proportion
[SIL] AA AE AH AO AW AY B CH D DH EH ER EY F G HH IH IY JH K L M N NG OW OY P R S SH T TH UH UW V W Y Z ZH
0.0 0.2 0.4 0.6 0.8

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