Frame Level Classification of Speech

In this challenge you will take your knowledge of feedforward neural networks and apply it to a more useful task than recognizing handwritten digits: speech recognition. You are provided a dataset of 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. If you have not encountered speech data before or have not heard of phonemes or spectrograms, we will clarify the problem further.

The training data comprises of:

1. Speech recordings (raw mel spectrogram frames)
2. Frame-level phoneme state labels

The test data comprises of:

1. Speech recordings (raw mel spectrogram frames)
2. Phoneme state labels are not given

Your job is to identify the phoneme state label for each frame in the test data set. It is important to note that utterances are of variable length. We are providing you code to load and parse the raw files into the expected format. You can find that code here.

Phonemes and Phoneme States

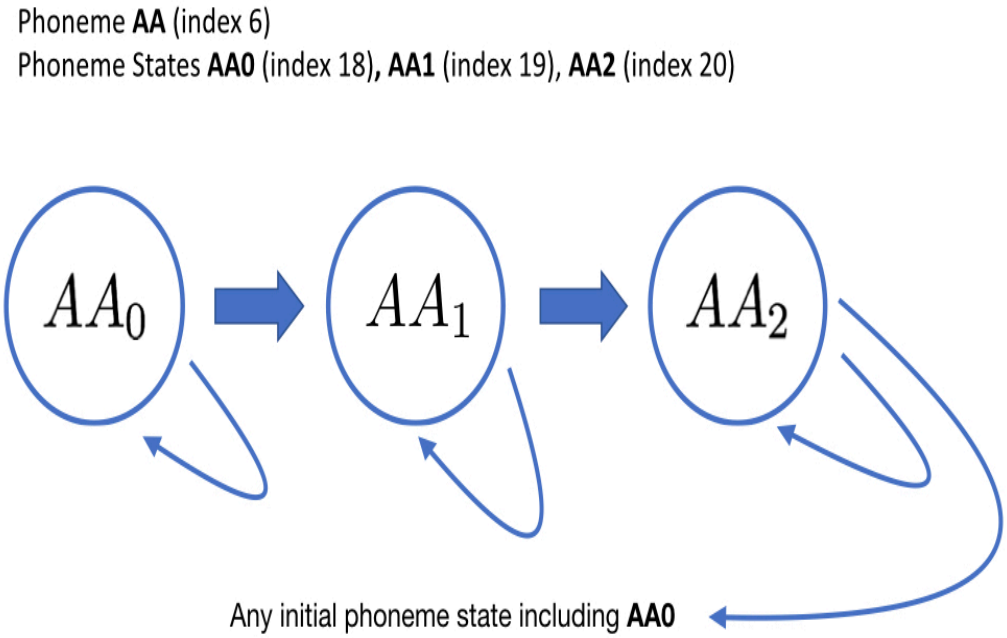
As letters are the atomic elements of written language, phonemes are

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.

For this challenge we will consider 46 phonemes in the english language.

["+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"]

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. Therefore for our 46 phonemes, there exist 138 respective phoneme states. The transition graph of the phoneme states for a given phoneme is as follows:



Hidden Markov Models (HMMs) estimate the parameters of this unobserved markov process (transition and emission probabilities) that maximize the likelyhood of the observed speech data. Your task is to instead take a 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 138 phoneme states. Performance on the task will be measured by classification accuracy on a held out set of labelled mel spectrogram frames. Training/dev labels are provided as integers [0-137].

Speech Representation

As a first step, the speech (audio file) must be converted into a feature representation (matrix form) that can be fed into the network.

In our representation, utterances have been converted to "mel-spectrograms" (you do not have to convert anything, just use the given mel-spectrograms), which are pictorial representations that characterize how the frequency content of the signal varies with time. The frequency domain of the audio signal provides more useful features for distinguishing phonemes.

For a more intuitive understanding, consider attempting to determine which instruments are playing in an orchestra given an audio recording of a performance. By looking only at the amplitude of the signal of the orchestra over time, it is nearly impossible to distinguish one source from another. But if the signal is transformed into the frequency domain, we can use our knowledge that flutes produce higher frequency sounds and bassoons produce lower frequency sounds. In speech, a similar phenomenon is observed when the vocal tract produces sounds at varying frequencies.

To convert the speech to a mel-spectrogram, it is segmented into little "frames", each 25ms wide, where the "stride" between adjacent frames is 10ms. Thus we get 100 such frames per second of speech.

From each frame, we compute a single "mel spectral" vector, where the components of the vector represent the (log) energy in the signal in different frequency bands. In the data we have given you, we have 40-dimensional mel-spectral vectors, i.e. we have computed energies in 40 frequency bands.

Thus, we get 100 40-dimensional mel spectral (row) vectors per second of speech in the recording. Each one of these vectors is referred to as a frame. The details of how mel spectrograms are computed from speech is explained here.

Thus, for a T-second recording, the entire spectrogram is a 100*T x 40

matrix, comprising 100*T 40- dimensional vectors (at 100 vectors (frames) per second).

Data Files

You can find the training and test data under the 'Data' tab

Optional Readings

Read the Implementation Details section for some tips and advice on building your classifier.

Go through this link to understand how Mel-Spectrograms are generated

Evaluation Metric

The evaluation metric for this competition is frame-level accuracy. There are a total of 169,656 frames in the test set. You will be ranked by unweighted accuracy on those phoneme state labels.

Submission Format

Submission files should contain two columns: Id and Label.

- **Id**: the 0-based index of the frame in the test set [0-169,655]
- **Label**: the predicted label of the phoneme [0-137]

Id=0 is the first frame in the first utterance. Id=169,656 is the last

frame in the last utterance. A sample submission file is available on the Data page.

Rules

Your model **MUST** use an MLP (no RNNs or ConvNets). We will check your code to make sure this is the case. However, you are free to use auto-differentiation libraries like PyTorch or Tensorflow.

(Note: Support will most likely only be provided for PyTorch.)

Implementation Tips

Network Architecture

Your MUST use MLP (e.g. no RNN or CNN)

Feel free to experiment with different architectures. The simplest approach is to build a feedforward network that takes in a single frame (input size 40) and outputs probabilities across phoneme states using a softmax output to normalize the logits.

(Hint1: Rolling in the deep.)

(Hint2: What have you learned from part 1?)

Context

Temporal context is important for distinguishing elements of speech and you can experiment with adding context to your ANN model. For example, you can try concatenating k mel spectrogram frames around the current time step. This technique would make the size of the input vector 40 * (2k + 1). You will need to adjust your data preprocessing and batching logic to adapt for frame context. Writing code that will let you experiment with variable context sizes easily is recommended.

Intuition: Since each mel spectrogram frame is only 25ms of the speech audio data, a single frame is unlikely to represent a complete phoneme. Concatenating nearby "k" frames will thus be helpful. Here "k" can be viewed as a hyperparameter for you to try out.

(Hint: This is the key to boost your score!)

Data Batching

It is important to consider that the data is provided in the form of utterance samples and not frame samples. The property of mini-batch SGD that gradients over all batches in an epoch approximate the true gradient only holds if each batch is IID (Independent and Identically Distributed). If we sample uniformly over utterances and also sample uniformly over frames within the utterance, our batches will surely not be IID. For example, different utterances will have considerably different numbers of phoneme instances. Sampling uniformly biases the training data by over-representing phonemes in the utterance with fewer phonemes (and therefore its phoneme states). You can try a different sampling technique to batch your training data to mitigate this issue.

Many approaches are possible. See what can get you to the top of the leaderboard!

Tentative Kaggle Leaderboard Cut-Off Score

- A - 0.64
- B - 0.55 [Baseline]
- C - 0.45 [Random Prediction]
- D - 0.02

(Note1: Cut-off score is subject to change.)

(Note2: The score is based on private leaderboard, which will be released after competition deadline.)

(Note3: Try not to overfit the scores on public leaderboard, since it only contains 30% of the test set.)

Grading

These numeric grades are **upper bounds**, the actual score will be interpolated based on your ranking of private leaderboard.

- A+: 105/100, Upper bound for top ranking of private leaderboard.
- A: 100/100, Upper bound for passing cut-off score for A.
- B: 80/100, Upper bound for passing cut-off score for B.
- C: 60/100, Upper bound for passing cut-off score for C.
- D: 40/100, Upper bound for passing cut-off score for D.