Problem Set 3

Jungwoong Yoon (jy8963)

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1 Exercise 1

- 1. All possible hidden state sequences: (1 2 3 4), (1 1 3 4), (1 3 3 4)
- 2. The best hidden sequence: $(1\ 3\ 3\ 4)$
- 3. $P(HTT|\lambda) = \frac{5}{32}$
- 4. $\alpha_2(1) = \frac{1}{16}$

2 Exercise 2

2.1 Computing class likelihoods

```
HMM.list = [fee_HMM, pea_HMM , rock_HMM, burt_HMM, see_HMM]
wav_list = ["fee_wav", "pea_wav" , "rock.wav", "burt.wav", "see_wav", "she_wav"]

for wav in wav_list:
    print("Using {}".format(wav))

    for hmm in HMM_list:
        forward_result = hmm.forward(compute_phone_likelihoods(model, load_audio_to_melspec_tensor(wav)))

# viterb1_result = hmm.viterb1(compute_phone_likelihoods(model, load_audio_to_melspec_tensor(wav)))
        print("{}: likelihood = {}".format(name, forward_result))

print()
```

2.2 Implementing the Forward Algorithm

```
def forward(self, state_likelihoods):
    # state_likelihoods.shape is assumed to be (N_timesteps, 48)
    # TOOO: fill in
    time = state_likelihoods.shape[0]
    alpha = np.zeros((time, self.N_states))

for t in range(time - 1):
    # Initialization
    if t == 0:
        for i in range(self.N_states):
            alpha[t, i] = state_likelihoods[t, self.labels[i]] + self.pi[i]

# Induction
    for i in range(self.N_states):
        cur = [alpha[t, j] + self.A[j, i] for j in range(self.N_states)]
        alpha[t+1, i] = logsumexp(cur) + state_likelihoods[t+1, self.labels[i]]

# Termination (alpha_{T}(N))
return alpha[-1, -1]
```

2.3 Implementing the Viterbi Decoding Algorithm

```
def viterbi(self, state_likelihoods):
    # state_likelihoods.shape is assumed to be (N_timesteps, 48)
    # TODO: fill in
    time = state_likelihoods.shape[0]
    delta = np.zeros((time, self.N_states))
    psi = np.zeros((time, self.N_states), dtype=int)
    q_star = np.zeros(time, dtype=int)

for t in range(time):
    if t == 0:
        # Initialization
        for i in range(self.N_states):
            delta[t, i] = state_likelihoods[t, self.labels[i]] + self.pi[i]
    else:
        # Induction
        for i in range(self.N_states):
            prev = [delta[t-1, j] + self.A[j, i] for j in range(self.N_states)]
            psi[t, i] = np.argmax(prev)
            delta[t, i] = prev[psi[t, i]] + state_likelihoods[t, self.labels[i]]

# Termination
    q_star[-1] = np.argmax(delta[-1])

# Backtrace
for t in range(time-1, 0, -1):
    q_star[t - 1] = psi[t, q_star[t]]

return q_star
```

2.4 Implementing Viterbi Training

```
def viterbi_transition_update(self, state_likelihoods):
    # state_likelihoods.shape is assumed to be (N_timesteps, 48)
# TODO: fill in
    q_star = self.viterbi_state_likelihoods]
print(np.exp(self.A))

for i in range(self.A.shape[0]):
    tau = 0
    gamma = 0

for t in range(len(q_star) - 1):
        cur_state = q_star[t]
        next_state = q_star[t+1]

    if cur_state == i:
        gamma += 1

for j in range(self.A.shape[1]):
    for t in range(len(q_star) - 1):
        cur_state = q_star[t]
        next_state = q_star[t]
        next_state = q_star[t+1]

    if cur_state == i and next_state == j:
        tau += 1

    self.A[i, j] = tau / gamma

self.A = np.log(self.A + self.eps)
print(np.exp(self.A))
```

2.5 Likelihood computation

	fee HMM	pea HMM	rock HMM	burt HMM	see HMM	she HMM
fee	212.22	178.08	-94.74	-88.53	188.32	188.97
pea	252.19	270.26	12.14	75.10	238.91	237.35
rock	-61.38	-3.84	156.74	65.48	-60.25	-62.19
burt	-59.64	-17.15	114.60	218.39	-71.04	-95.40
see	76.37	78.22	-173.40	-155.18	233.89	132.22
she	77.35	91.23	-210.63	-190.74	124.16	283.93

All of the words were correctly recognized.

2.6 Optimal state sequence

2.7 Viterbi Update

New likelihood for "rock": 168.82 (The likelihood increased.)

Updated transition matrix (after exponentiation):

```
[9.3e - 001]
             1.0e + 000
                          1.0e + 000
                                      1.0e + 000
                                                  1.0e + 000
                                                              1.0e + 000
1.0e-200
            9.17e - 001
                          1.0e + 000
                                      1.0e + 000
                                                  1.0e + 000
                                                              1.0e + 000
1.0e - 200
             1.0e-200
                          9.3e - 001
                                      1.0e + 000
                                                  1.0e + 000
                                                              1.0e + 000
1.0e-200
            1.00e - 200
                          1.0e - 200
                                      9.1e-001
                                                  1.0e+000
                                                              1.0e + 000
1.0e-200
             1.0e-200
                          1.0e - 200
                                      1.0e-200
                                                  7.5e - 001
                                                              1.0e + 000
1.0e - 200
             1.0e-200
                          1.0e - 200
                                      1.0e - 200
                                                  1.0e - 200
                                                              1.0e + 000
```

The original transition matrix had all $a_{ij} = 0$ (before adding eps), except for those where i = j. The updated matrix is similar to the original, but for a_{ij} where i = j, its $a_{ij+1}...a_{iN}$ have probability of 1.