

## A proof for the convergence of Baum-Welch training

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Due on:

Assume that  $\Lambda$  is the current model and  $\Lambda'$  is the old model. We want to show that the likelihood of the observation  $O$  always increases for each training iteration until convergence is reached. In other words, we want to maximize the log likelihood ratio as follows:

$$\log \frac{p(O|\Lambda)}{p(O|\Lambda')} = \sum_Q \log \frac{p(O|\Lambda) \cdot p(Q|O, \Lambda') \cdot p(Q|O, \Lambda)}{p(O|\Lambda') \cdot p(Q|O, \Lambda') \cdot p(Q|O, \Lambda)} \quad (1)$$

$$= \sum_Q \log \frac{p(O, Q|\Lambda)}{p(O, Q|\Lambda')} \cdot \frac{p(Q|O, \Lambda')}{p(Q|O, \Lambda)} \quad (2)$$

$$= \sum_Q p(Q|O, \Lambda') \log \frac{p(O, Q|\Lambda)}{p(O, Q|\Lambda')} \cdot \frac{p(Q|O, \Lambda')}{p(Q|O, \Lambda)} \quad (3)$$

$$= \sum_Q p(Q|O, \Lambda') \log \frac{p(O, Q|\Lambda)}{p(O, Q|\Lambda')} + \sum_Q p(Q|O, \Lambda') \log \frac{p(Q|O, \Lambda')}{p(Q|O, \Lambda)} \quad (4)$$

$$= L(O, \Lambda; \Lambda') + KL(p(Q|O, \Lambda') || p(Q|O, \Lambda)) \quad (5)$$

$$\geq L(O, \Lambda; \Lambda') \quad (6)$$

where  $KL()$  denotes the Kullback-Leibler divergence (or distance) between two probability distributions which must be non-negative.  $Q$  denotes the state sequence. Since the Baum-Welch training maximizes  $L(O, \Lambda; \Lambda')$ , the likelihood of the observation  $O$  is guaranteed to improve until  $\Lambda = \Lambda'$ .