Questions A

A1. HMMs and GMMs

- What is common in the concepts of GMMs and HMMs?
- What is the difference between the concepts of GMMs and HMMs?

A2. Structure

- Describe the basic functionality of a HMM using the diagram on slide 14.
- Which quantities determine the expected output length of a HMM?

A3. Mathematical definition

- Which two matrices determine the characteristics of the HMM in a unique way?
- How is the HMM model $\boldsymbol{\lambda}$ thus defined?
- In literature, often additionally an initial distribution $\boldsymbol{\pi}$ is given, which defines for each model state the probability that the HMM starts in this state. How does the vector $\boldsymbol{\pi}$ look like for a HMM definition in the style of this lecture?

Answers B

B1. Fundamental problems of HMMs

- Evaluation, decoding, and estimation: see slide 23
- Application examples:
  - Evaluation: Speech recognition. Using the evaluation, the probability that an HMM generates a given feature vector sequence (of an utterance) can be determined, i.e., how well the HMM matches the utterance.
  - Estimation: Model training; estimate the HMM parameters on the basis of a database of feature vector sequences.

B2. Forward algorithm

- The forward probability $f_i(n)$ is defined as the probability that after n time steps the HMM is in the state S_i and generated the feature sequence $\boldsymbol{X}^{(n)}$ on its way.
- The three steps are explained on slide 29.
- Yes, in order to solve the estimation problem, a backward algorithm will be introduced.

B3. Viterbi algorithm

- Initialization, recursion, and termination: ...
- In the variable $t_i(n)$, the information to backtrack the optimal path are stored. An illustration can be found on slide 44.

Questions B

B1. Fundamental problems of HMMs

- Describe the three problems / tasks of a HMM in your own words.
- Name the applications of these problems.

B2. Forward algorithm

- What is a forward probability?
- Describe the forward algorithm in a few words. Explain shortly the three main parts (initialization, recursion, termination) of the algorithm.
- Could the algorithm also be applied backwards?

B3. Viterbi algorithm

- Describe the Viterbi algorithm in your own words. You can refer to slide 32.
- What meaning does the variable $t_i(n)$ have?

Answers A

A1. HMMs and GMMs

- Both HMMs and GMMs model emission probabilities,
- but only the HMM also models a temporal behaviour.

A2. Structure

- States (S_0, S_1, S_2, S_3) with initial state S_0 and final state S_3; Transition probabilities $a_{i,j}$; Emission probabilities $b_i(\boldsymbol{x})$; see slide 14.
- If the transition probabilities to the final state (here: a_{13} and a_{23}) are close to 1, the expected output length is small.

A3. Mathematical definition

- The defining matrices are the transition matrix $\boldsymbol{A}$ and the emission matrix $\boldsymbol{B}$.
- The HMM can thus be defined by $\boldsymbol{\lambda} = (\boldsymbol{A}, \boldsymbol{B})$.
- Because in the context of this lecture, the HMM always starts in the dedicated initial state S_0, the initial distribution vector can be written as $\boldsymbol{\pi} = (1, 0, \ldots, 0)$.