ESTIMATING TRAJECTORY HMM PARAMETERS USING MONTE CARLO EM WITH GIBBS SAMPLER

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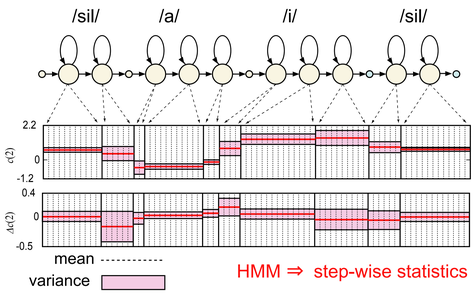
1. Background

Limitations of HMMs for modeling speech

- Constant statistics within a state
- Conditional independence assumption



Alternative approach

- Segment models (HDM, SSM, SLDS, etc.)

⇒ Increase #parameters and computational cost

- Use of dynamic features (Δ and ΔΔ coefficients)

⇒ Improper in the sense of statistical modeling

Trajectory HMM (Tokuda et. al, Eurospeech03)

- Impose relationships between static & dynamic

⇒ Reformulate an HMM as a trajectory model

- Overcome the above two limitations
- Viterbi-type training algorithm has been derived
- Lack of the EM-type training algorithm

⇓

2. Objective

EM-type algorithm for the trajectory HMM

- Temporal covariance matrix is generally full

⇒ Impossible to perform the exact EM algorithm

- Approximate training
  - Viterbi approximation
  - Variational EM
  - Monte Carlo EM (Sampling)

    ⇒ Obtain sub-optimal state sequences
- Evaluation in a speech recognition experiment

3. Definition of the trajectory HMM

Output probability of observation $\boldsymbol{c}$ from a trajectory HMM Λ

$$P(\boldsymbol{c} \mid \Lambda) = \sum_{\text{all } \boldsymbol{q}} P(\boldsymbol{c} \mid \boldsymbol{q}, \Lambda)\, P(\boldsymbol{q} \mid \Lambda)$$

$$P(\boldsymbol{c} \mid \boldsymbol{q}, \Lambda) = \mathcal{N}(\boldsymbol{c} \mid \bar{\boldsymbol{c}}_{\boldsymbol{q}}, \boldsymbol{P}_{\boldsymbol{q}})$$

$$P(\boldsymbol{q} \mid \Lambda) = \prod_{t=1}^{T} P(q_t \mid q_{t-1}, \Lambda)$$

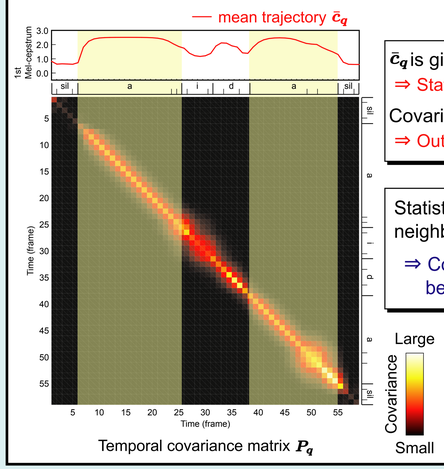
$\boldsymbol{c}$: static feature vector seq. ($MT \times 1$)

$\boldsymbol{q}$: state (mixture) seq.

$\bar{\boldsymbol{c}}_{\boldsymbol{q}}$: mean trajectory (vector) ($MT \times 1$)

$\boldsymbol{P}_{\boldsymbol{q}}$: temporal covariance mat. ($MT \times MT$)

M : #dim. of static feat. vec. (ex. MFCC)



$\bar{\boldsymbol{c}}_{\boldsymbol{q}}$ is given as a *smooth trajectory*

⇒ Statistics vary within a state

Covariance matrix $\boldsymbol{P}_{\boldsymbol{q}}$ is *full*

⇒ Output probs. depend on each other

Statistics vary according to their neighboring models

⇒ Coarticulation effect can naturally be captured

4. Estimating parameters of trajectory HMMs

Auxiliary function (hidden variable: state seq. $\boldsymbol{q}$)

$$\mathcal{Q}(\Lambda, \Lambda') = \sum_{\text{all } \boldsymbol{q}} P(\boldsymbol{q} \mid \boldsymbol{c}, \Lambda)\, \log P(\boldsymbol{c}, \boldsymbol{q} \mid \Lambda')$$

However, applying the exact EM algorithm is intactable... (>_<)
(Temporal covariance matrix is full)

⇒ Approximate training

- Viterbi approximation (Viterbi training) [Zen, et. al; ICASSP04]
- Markov Chain Monte Carlo (Monte Carlo EM; MCEM)

$$\mathcal{Q}(\Lambda, \Lambda') \approx \sum_{n=1}^{N} \frac{1}{N} \log P(\boldsymbol{c}, \boldsymbol{q}_n \mid \Lambda')$$

□□ - Approximate using N state (Gaussian) seqs.

□□ - Generating $\boldsymbol{q}$ ⇒ Gibbs sampling

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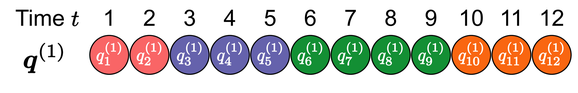
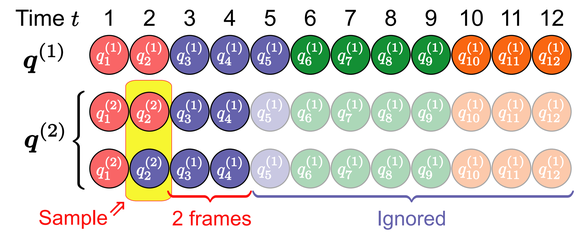
5. Generating state seqs. using Gibbs sampler

Step 1.



Initialized by the delayed decision Viterbi algorithm

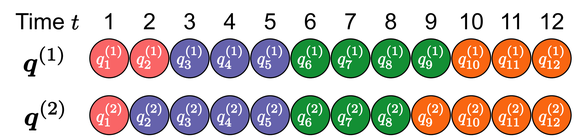
Step 2.



- Only consider states at the following J frames (ex. J=2)
- Generate random value using $P\left(q_2 \mid \boldsymbol{c}, q_1^{(2)}, q_3^{(1)}, q_4^{(1)}, \Lambda\right)$

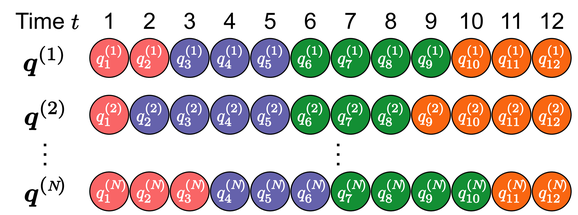
  ⇒ Choose $q_2^{(2)}$ according to generated random value
- Repeat until reaching the final frame

Step 3.



Final frame ⇒ 2nd state seq. sample is obtained

Step 4.



Repeat N times ⇒ N state seqs. can be sampled

Taking partial derivative of the approx. auxiliary function with respect to trajectory HMM parameters

□⇒ Parameter reestimation formulas

6. Speech recognition experiment

Conditions

Database	ATR Japanese continuous speech database b-set speaker MHT
Training data	450 utterances
Test data	53 utterances
Feature vector	0～18 order Mel-cepstral coefficients and its delta and delta delta
Model structure	3-state left-to-right monophone model with single Gaussian state output distribution

Training procedure

Estimate trajectory HMMs using baseline HMMs as their initial models

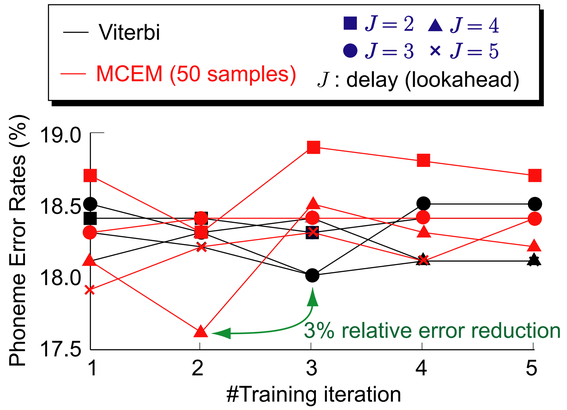
- Viterbi training × 5 iterations
- MCEM algorithm (50 samples) × 5 iterations

Recognition procedure

1. Generate 100-best hypotheses
2. Rescore using trajectory HMMs
   - Delayed decision Viterbi algorithm + beam search
   - Sampling was not performed during rescoring

Experimental results

HMM: 19.7% Best: 13.9% Worst: 27.4%



The performance of the MCEM-trained trajectory HMMs were relatively unstable (17.6%～18.9%)

- Mismatch between training and recognition?
- Sampling ⇒ Stochastic method?