

INCREMENTAL LEARNING AND FORGETTING IN STOCHASTIC TURN-TAKING MODELS



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Goals

1. Advance the state-of-the-art in stochastic turn-taking modeling:
 - ▶ history extension with model regularization
 - ▶ model re-estimation and/or adaptation
2. Enable quantitative social research into interactive conversational phenomena

Conclusions

- ▶ With respect to turn-taking, people are:
 1. generally **dissimilar**
 2. but **self-consistent**
 3. and **similar to their partner**
- ▶ Turn-taking is **not** 1st-order Markovian.

Impact

1. **Natural** turn timing now available to analytic and conversational agents.
2. Can now synthesize **emergent** behavior by composing dissimilar models.
3. Can now investigate how **prosody** may circumscribe chronogram cross entropy.

Minimizing Model Cross-Entropy for Speech/Non-Speech Chronograms

1. A **stochastic turn-taking model** Θ is a model which accounts for the distribution of speech \blacksquare and non-speech \square in time and across both participants.

$$P \left(\begin{array}{cccccc} & t-3 & t-2 & t-1 & t & t+1 \\ \dots & A & \square & \square & \blacksquare & \blacksquare & \square & \dots \\ & B & \blacksquare & \blacksquare & \square & \square & & \end{array} \right) = \dots \times P \left(\begin{array}{c} t-3 \\ A \square \dots \\ B \blacksquare \end{array} \right) \times P \left(\begin{array}{c} t-2 \\ A \square \dots \square A \\ B \blacksquare \dots \blacksquare B \end{array} \right) \times P \left(\begin{array}{c} t-1 \\ A \blacksquare \dots \square \square A \\ B \blacksquare \dots \blacksquare \blacksquare B \end{array} \right) \times P \left(\begin{array}{c} t \\ A \blacksquare \dots \square \square \blacksquare A \\ B \square \dots \blacksquare \blacksquare \blacksquare B \end{array} \right) \times \dots$$

2. Each factor can be further factored, by assuming that the \blacksquare/\square behavior of both participants is **independent**:

$$P \left(\begin{array}{c} t \\ A \blacksquare \dots \square \square \blacksquare A \\ B \square \dots \blacksquare \blacksquare \blacksquare B \end{array} \right) \doteq P \left(\begin{array}{c} t \\ A \blacksquare \dots \square \square \blacksquare A \\ \blacksquare \blacksquare \blacksquare B \end{array} \right) \times P \left(\begin{array}{c} t \\ B \square \dots \blacksquare \blacksquare \blacksquare B \\ \square \square \blacksquare A \end{array} \right) \quad \text{conditional independence (CI)}$$

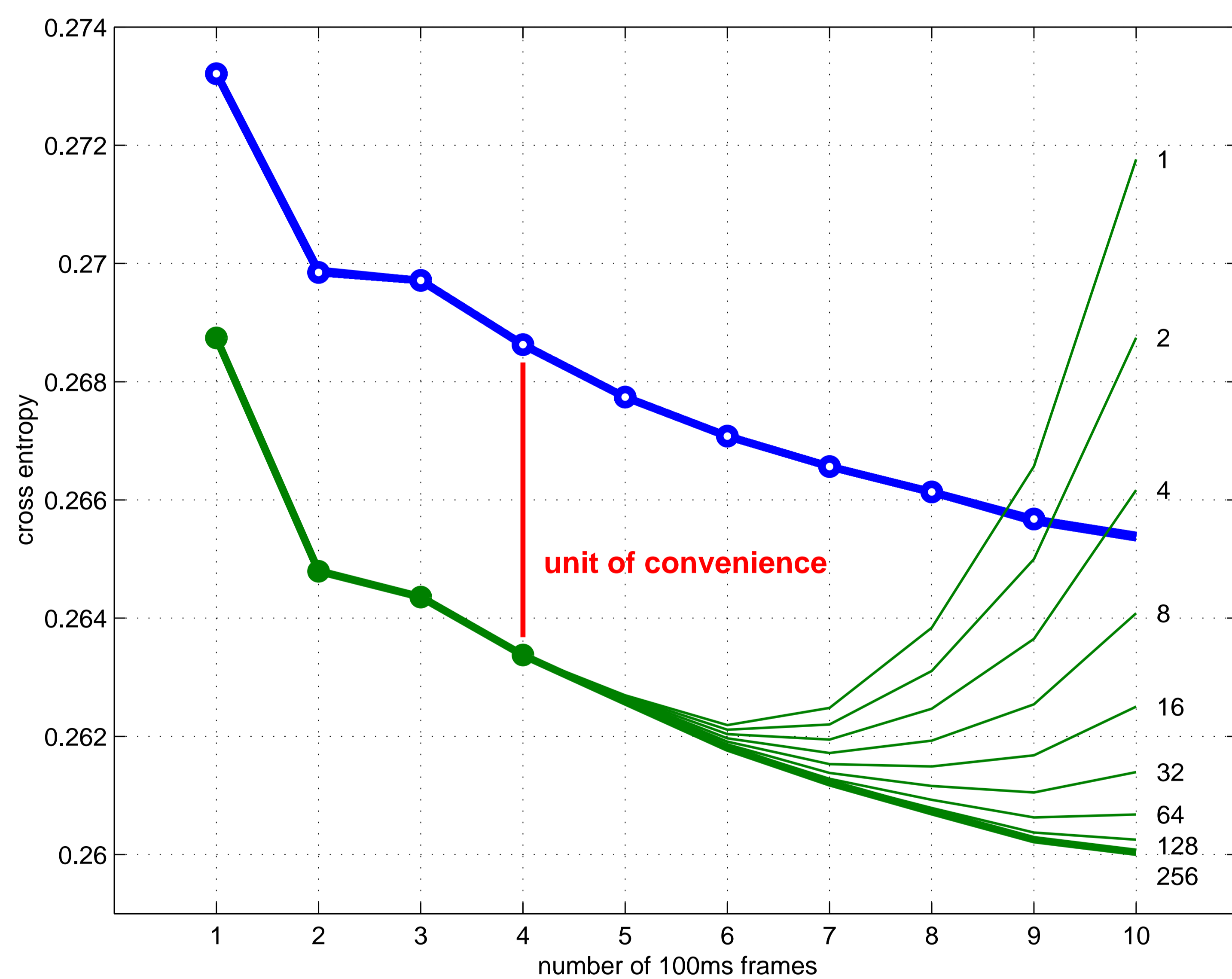
or

$$\doteq \underbrace{P \left(\begin{array}{c} t \\ A \blacksquare \dots \square \square \blacksquare A \end{array} \right)}_{\text{from A's point of view}} \times \underbrace{P \left(\begin{array}{c} t \\ B \square \dots \blacksquare \blacksquare \blacksquare B \end{array} \right)}_{\text{from B's point of view}} \quad \text{unconditional independence (UI)}$$

3. Train n -gram models with recursive Jelinek-Mercer interpolation.
4. Score using **normalized negative log-likelihood** \equiv **conditional cross entropy**.

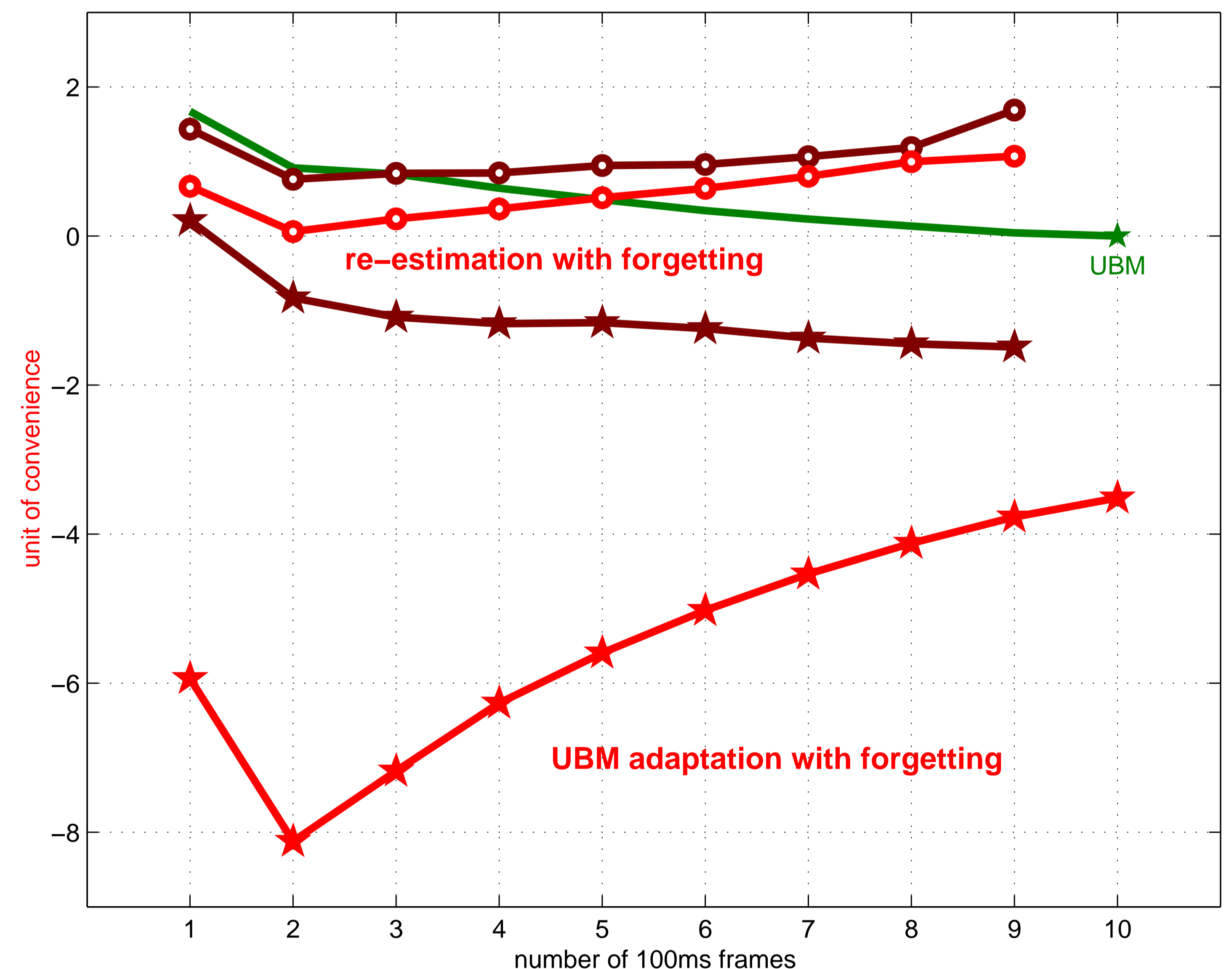
Question 1: Is one dialogue participant affected by the other?

If so, then for fixed history duration, conditioning on the other side should help: Θ_{CI} should be better than Θ_{UI} .



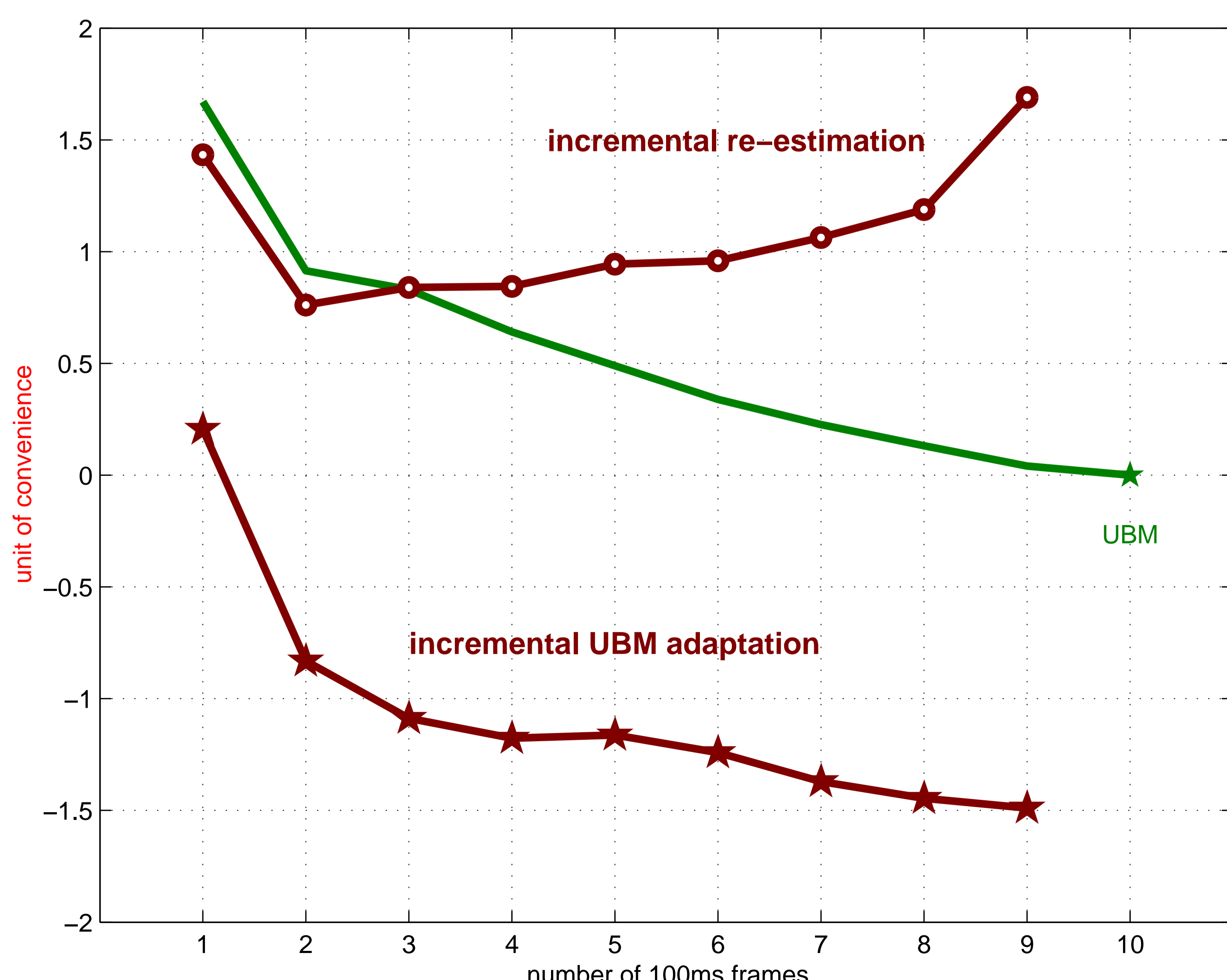
Question 3: Are turn-taking systematics time-dependent?

If so, then incremental training of Θ_{CI} should be accompanied by **"forgetting" the least-recent past**.



Question 2: Is there turn-taking variation within the population?

If so, then it may be better to estimate Θ_{CI} parameters using **tiny but matched data** than **large but mismatched data**.



Question 4: Is one dialogue participant similar to the other?

If so, then it may be better to estimate Θ_{CI} parameters using **tiny data from the other participant** than **large but mismatched data**.

