

# What is full-duplex SLM?

A system that can listen and speak “simultaneously”

- **Modular full-duplex**

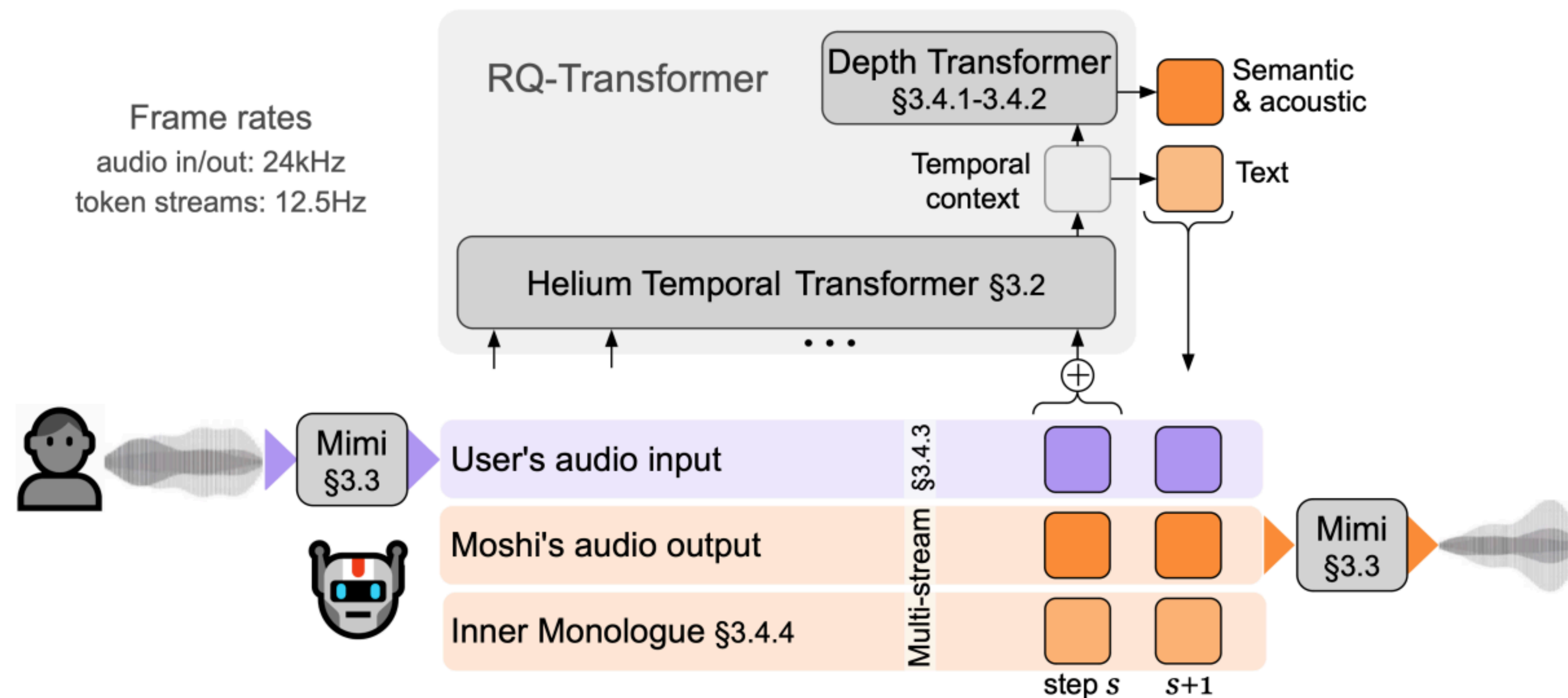
- Using an external orchestrator: FlexDuo, Semantic VAD, etc.
- Using internal state prediction: FreezeOmni, NeuralFSM, etc.

- **End-to-end full-duplex**

- Single-stream modeling: SyncLLM, OmniFlatten, SALM-Omni, etc.
- Multi-stream modeling: dGSLM, **Moshi**, Voila, etc.

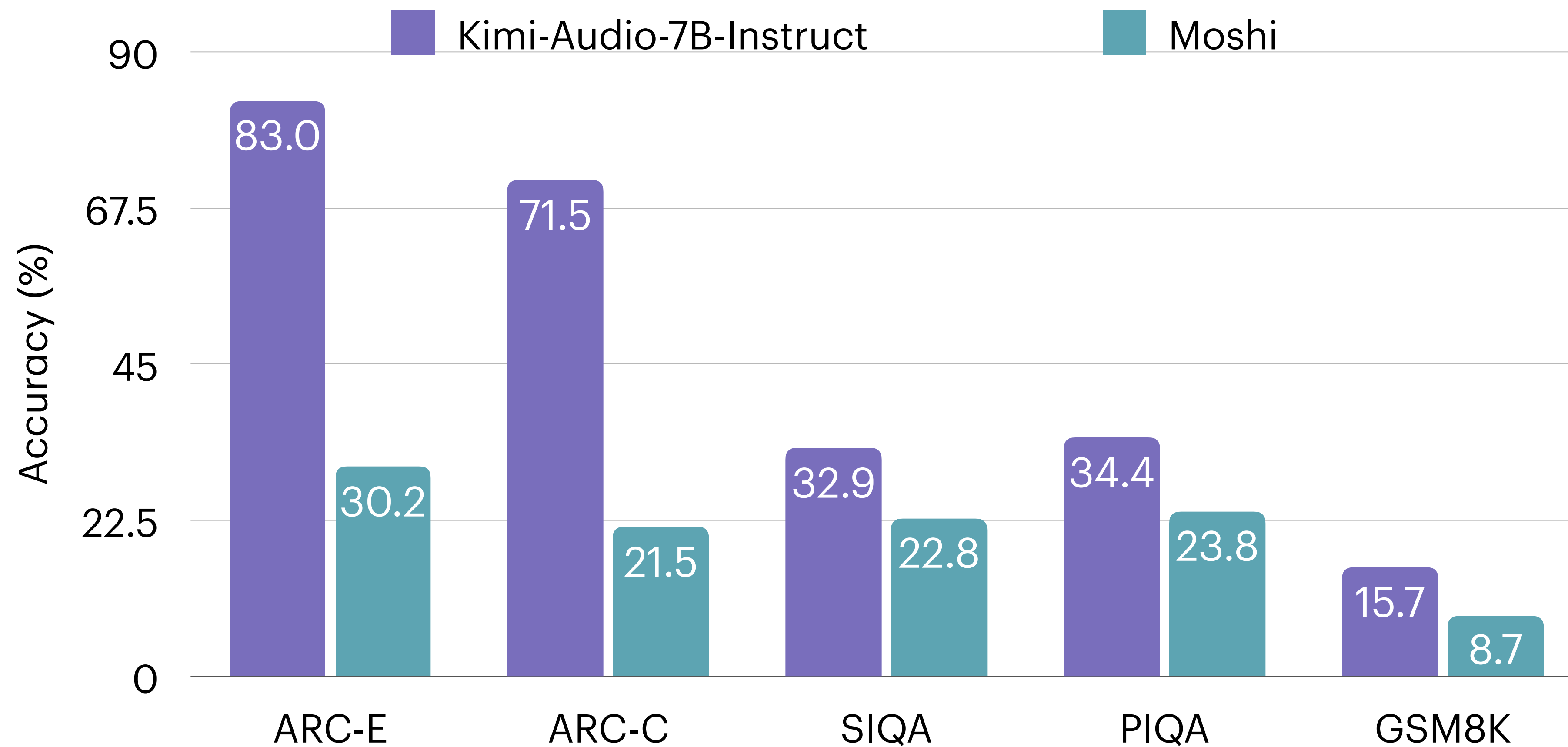
# Moshi

Open-source FD model by Kyutai



D'efosse, Alexandre et al. "Moshi: a speech-text foundation model for real-time dialogue." *ArXiv*.

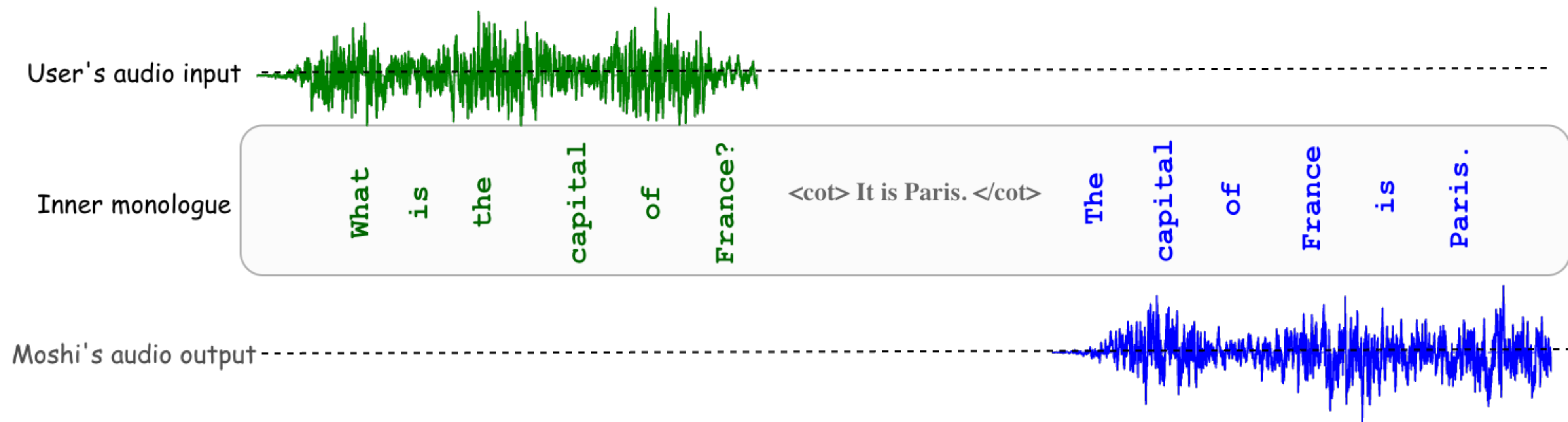
# Moshi performs poorly on spoken reasoning tasks



# CoT fine-tuning for Moshi

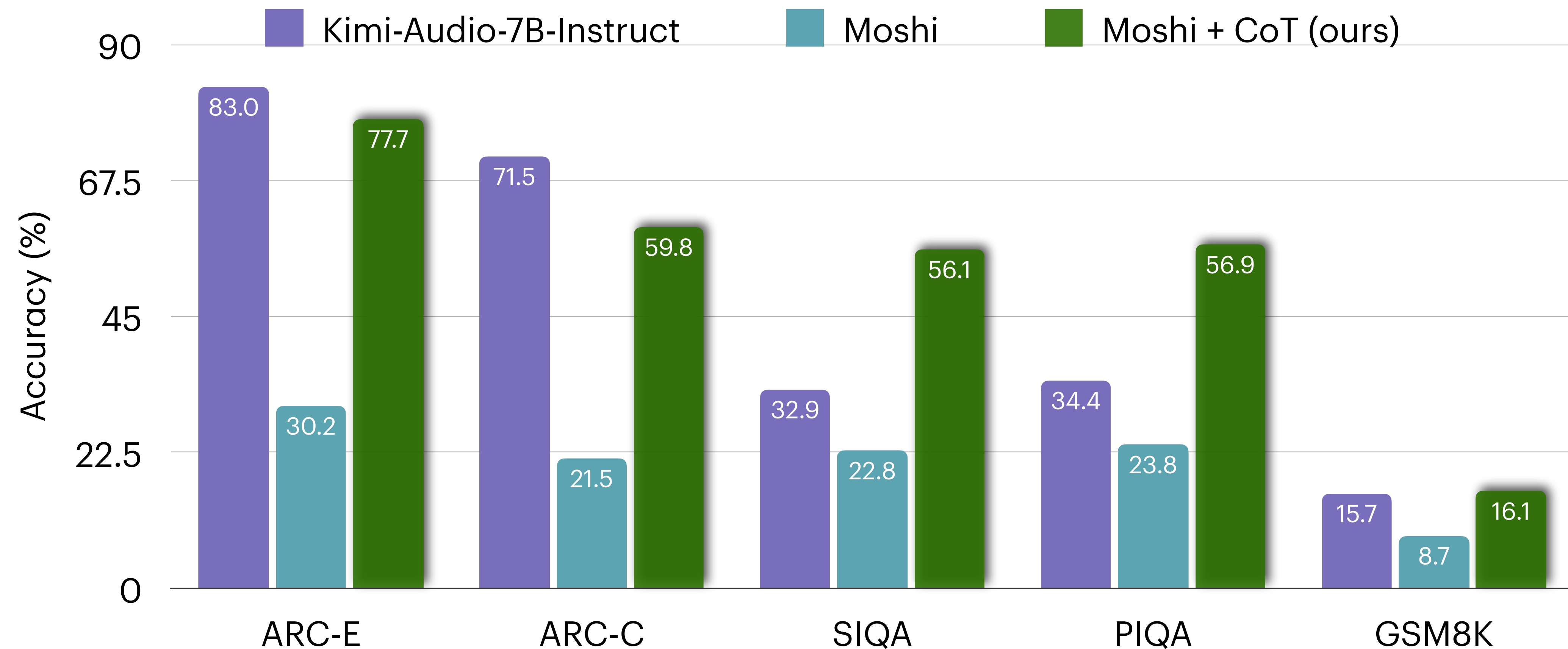
CoT = chain-of-thought

- Fine-tune the model to additionally generate the following on the text monologue channel:
  - **Streaming user audio transcripts**
  - **Chain of thought** (reasoning) between `<cot>` and `</cot>`

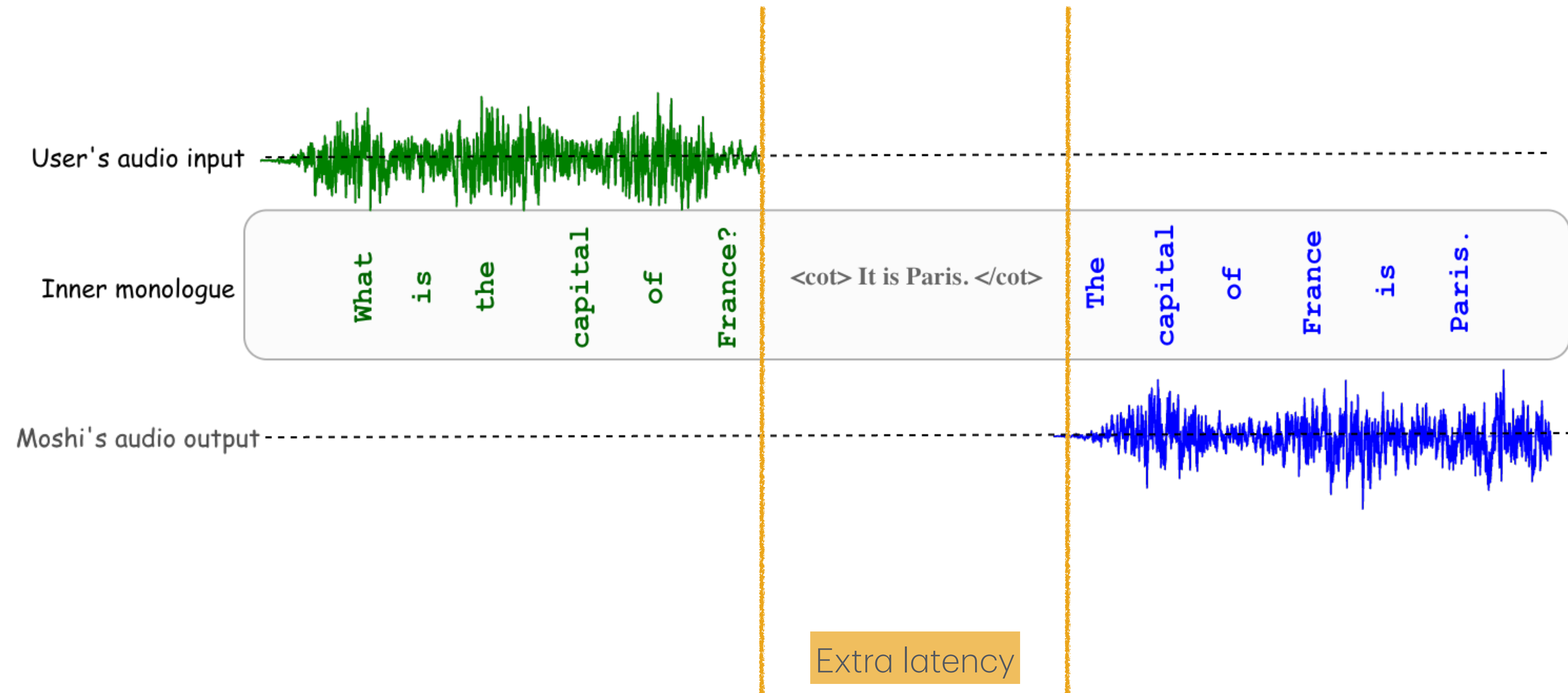


# CoT improves reasoning by 2-3x...

We use synthesized CoT-Collection training data



# ...but it increases response latency!



# How can we reduce this latency?

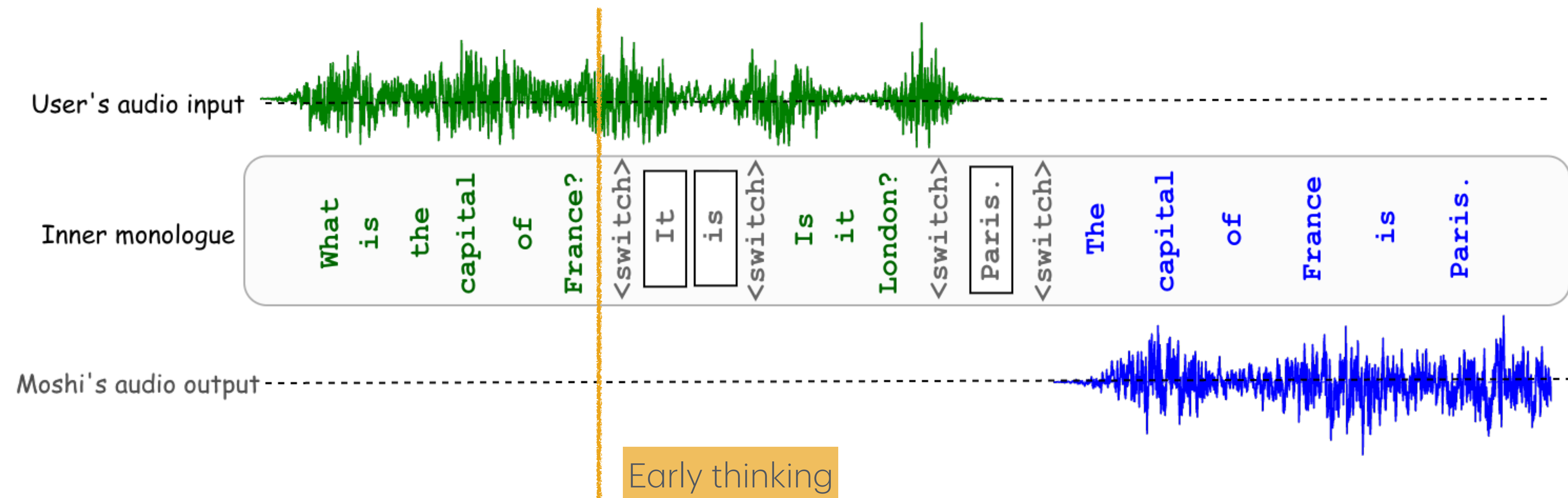
- Two possible approaches:
  1. **Thinking while speaking**: interleave thinking with response generation, e.g. Mini-Omni-Reasoner (Xie et al.)
  2. **Thinking while listening**: start reasoning early during user's question!



# We train the model to start reasoning early

## CoT fine-tuning with left shifted tokens

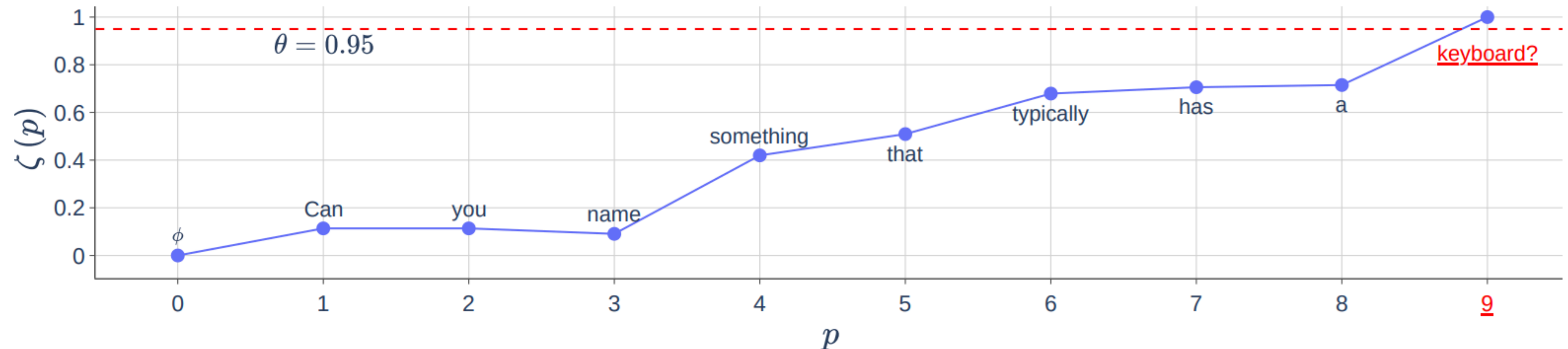
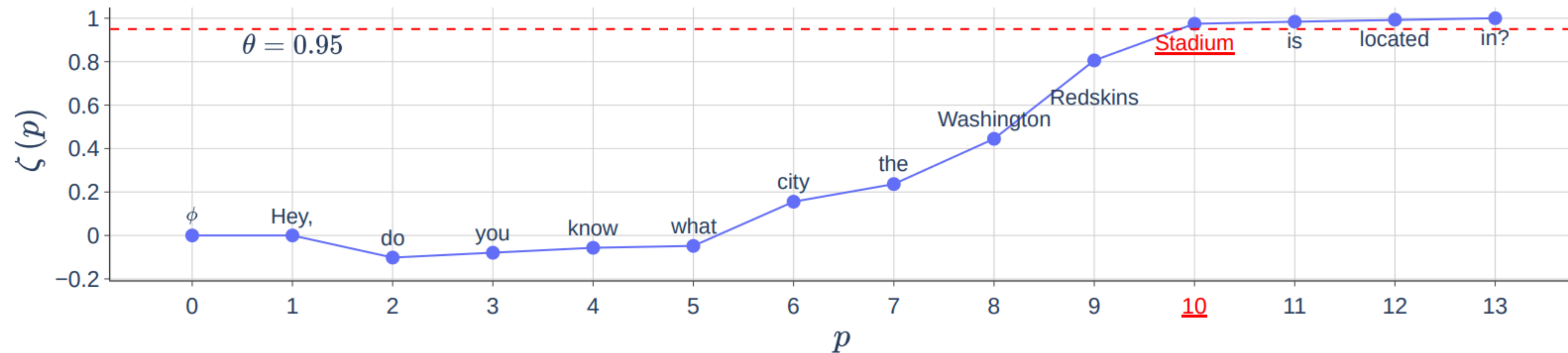
- We use special `<switch>` tokens to interleave the ASR and reasoning tokens.





# How much should we shift?

We want to identify an *inflection point* in the question



# Question Completeness (QC)

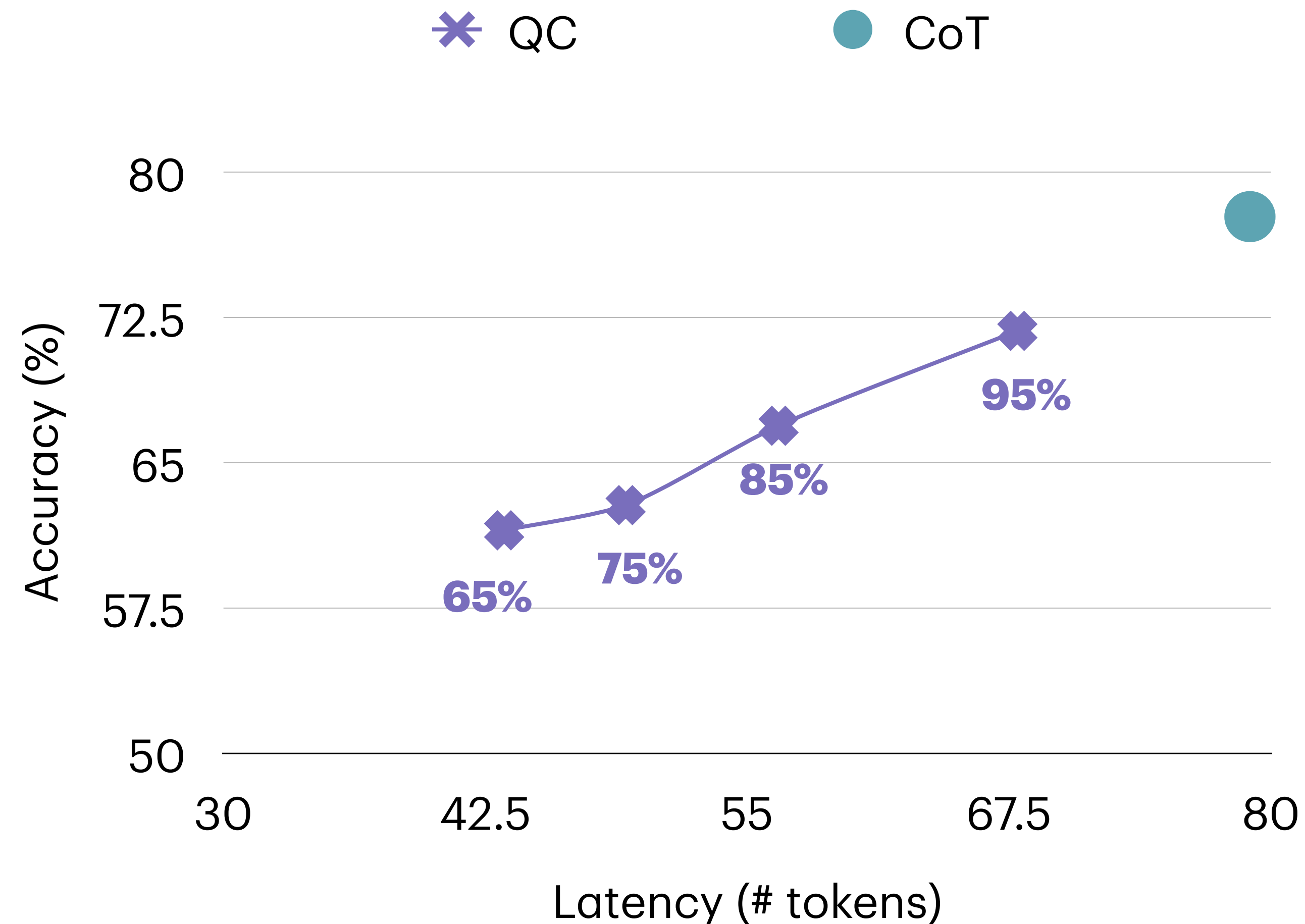
- We use an external LLM (LLaMA3-8B-Chat) to get the probability of the reasoning (**R**) + answer (**A**) after each word of the question, and then compute the **Question Completeness**  $\zeta(p)$ :

$$\zeta(p) = 1 - \frac{\mathcal{D}_{\text{KL}}(\mathbf{X}_N || \mathbf{X}_p)}{\mathcal{D}_{\text{KL}}(\mathbf{X}_N || \mathbf{X}_0)}, \quad \text{where } \mathbf{X}_p = \Pr(\mathbf{R}, \mathbf{A} | \mathbf{Q}_{0:p})$$

- This quantity measures how “complete” is the question at word  $p$  from the point-of-view of generating **R** and **A**.
- The QC curve is monotonically increasing in  $p$ .

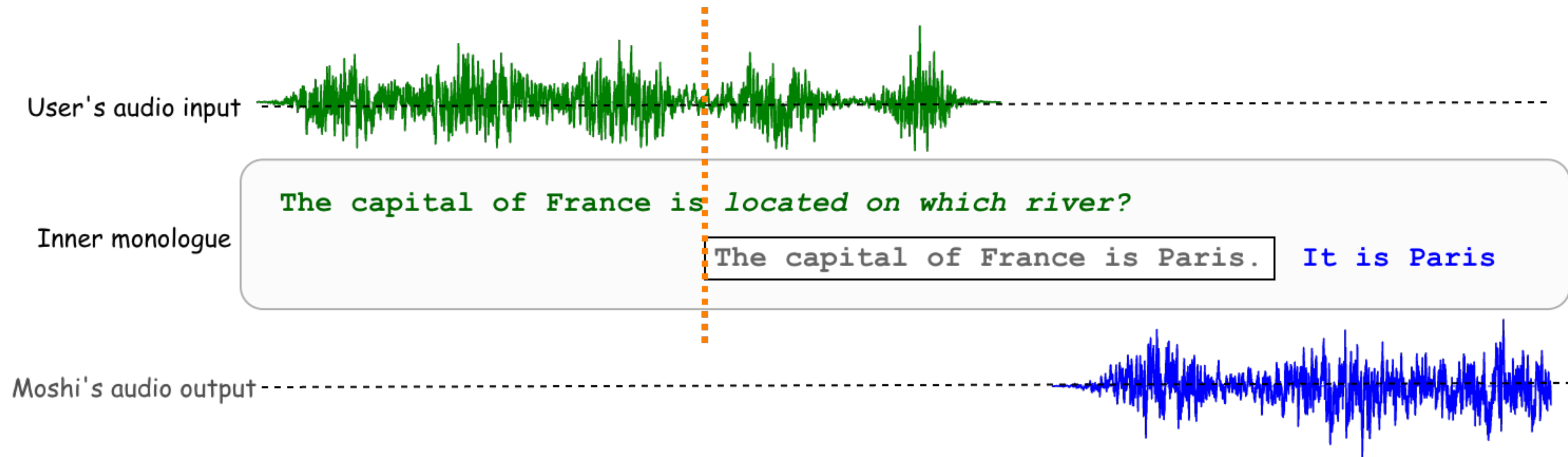
# Training with different QC thresholds

Accuracy v/s latency on ARC-E



# Why does accuracy degrade?

- The model is not trained to consider new incoming information after it starts reasoning!



# We use DPO to teach *adaptive* reasoning

Preference pairs are created using rejection sampling

$$\mathcal{L}_{\text{DPO}}(\pi_{\theta}) = -\mathbb{E}_{(x, y^+, y^-) \sim \mathcal{D}} \left[ \log \sigma \left( \beta \left[ \log \frac{\pi_{\theta}(y^+ | x)}{\pi_{\text{ref}}(y^+ | x)} - \log \frac{\pi_{\theta}(y^- | x)}{\pi_{\text{ref}}(y^- | x)} \right] \right) \right]$$

1. Train SFT model  $\pi_{\text{ref}}$  with QC = 75%.
2. Generate 10 outputs per prompt ( $x$ ), where we force the model to decode `<start_cot>` at QC = 75%.
3. Select a response with correct answer as  $y^+$ , and one with wrong answer as  $y^-$ .

# Accuracy improves significantly after DPO

