Imputer:

Sequence Modeling via Imputation and Dynamic Programming

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Presenter: Desh Raj

Overview

- Preliminary: end-to-end ASR model types
- The Imputer model
  - Training scheme
  - Decoding policies
- Experimental results

Preliminary

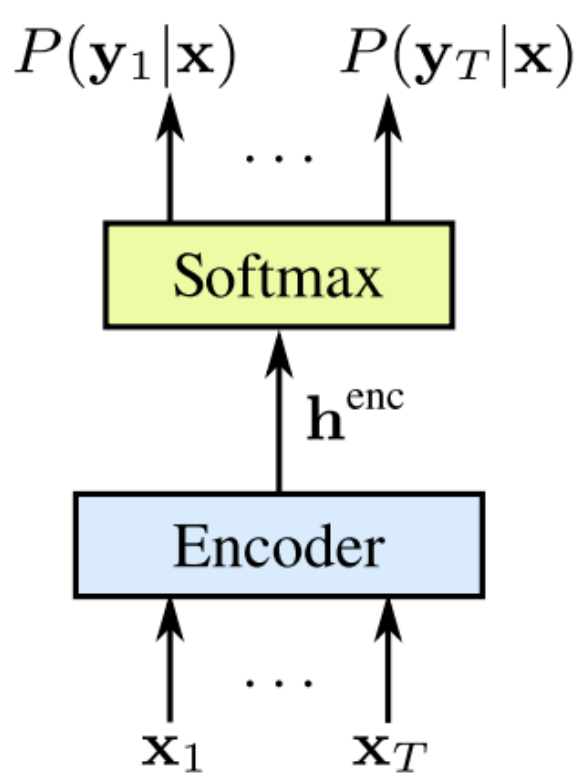
- 3 kinds of popular end-to-end ASR models:

    1. CTC-based

    2. RNN-Transducer

    3. Encoder-decoder (with attention)

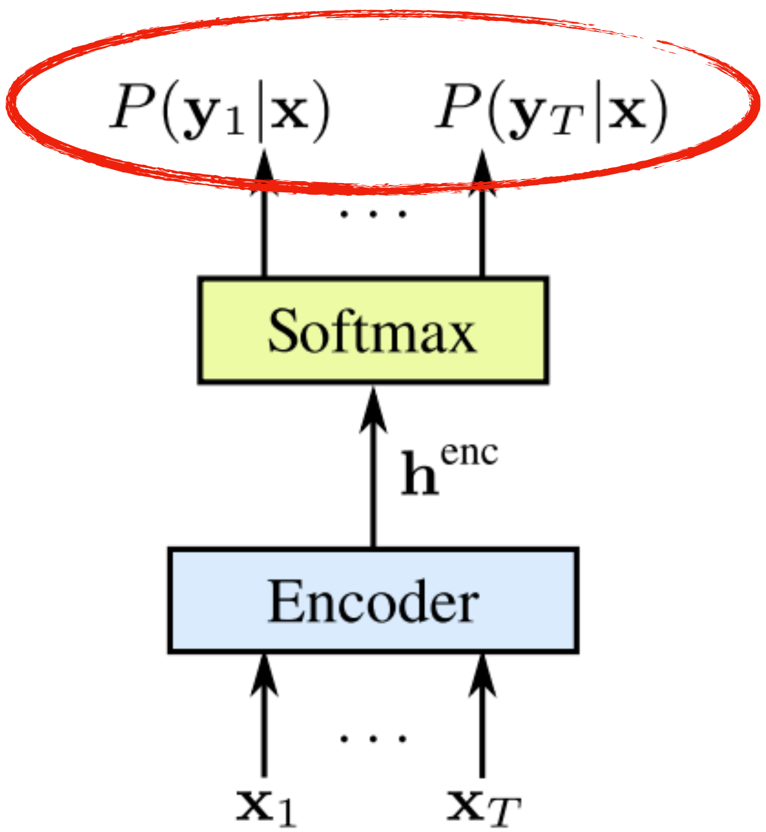
CTC



$$P(\mathbf{y}|\mathbf{x}) = \sum_{\hat{\mathbf{y}} \in \mathcal{B}(\mathbf{y},\mathbf{x})} \prod_{t=1}^{T} P(\hat{y}_t|\mathbf{x})$$

A comparison of sequence-to-sequence models for speech recognition. Prabhavalkar et al. Interspeech 2017.

CTC



Conditional independence assumption

So all tokens can be generated in parallel

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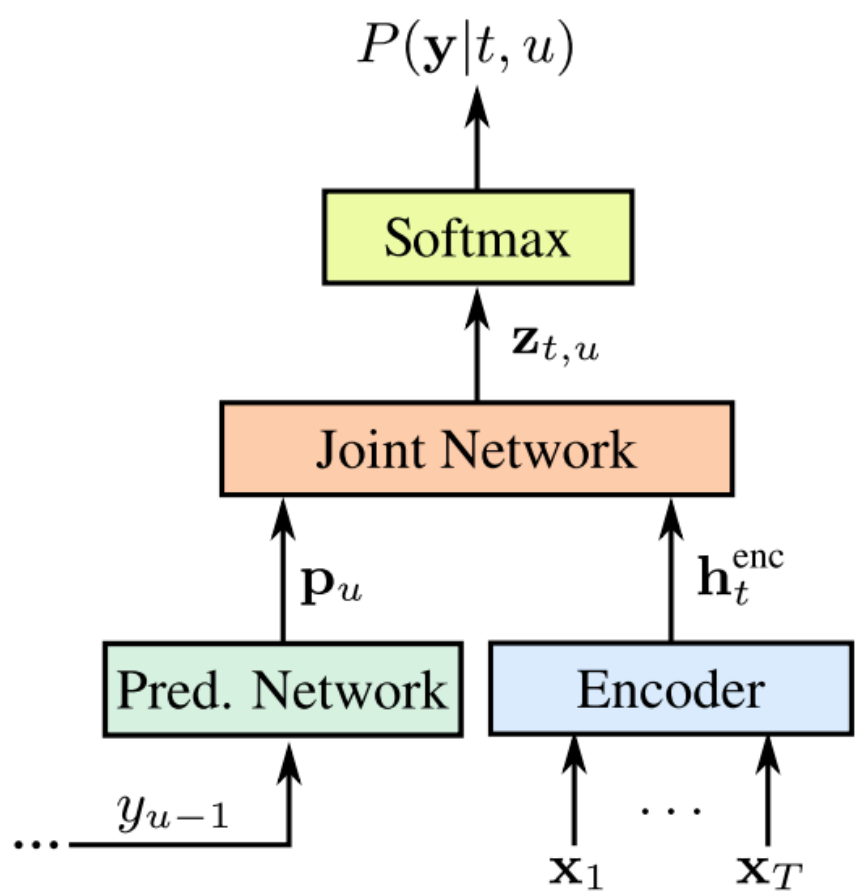
RNN-Transducer



$$\mathbf{h}_{t,u}^{\text{joint}} = \tanh(A\mathbf{h}_t^{\text{enc}} + B\mathbf{p}_u + b)$$

$$\mathbf{z}_{t,u} = D\mathbf{h}_{t,u}^{\text{joint}} + d$$

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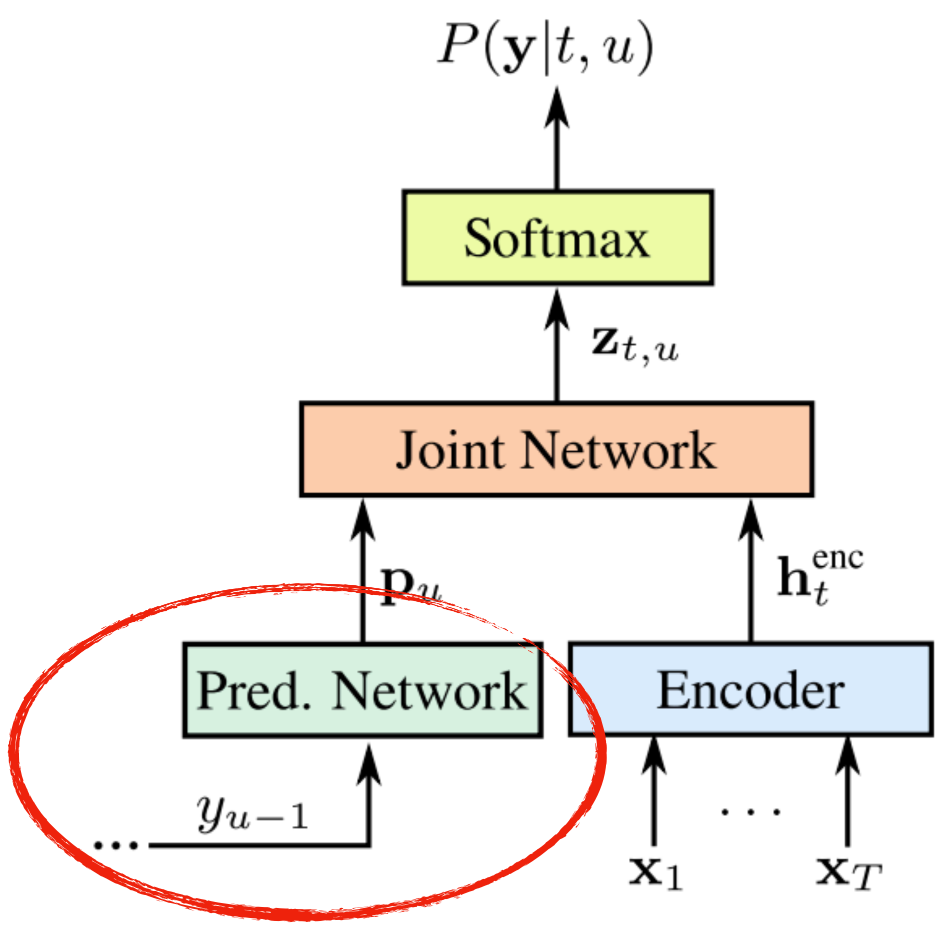
RNN-Transducer



Generated token depends on previous output

So have to generate sequentially

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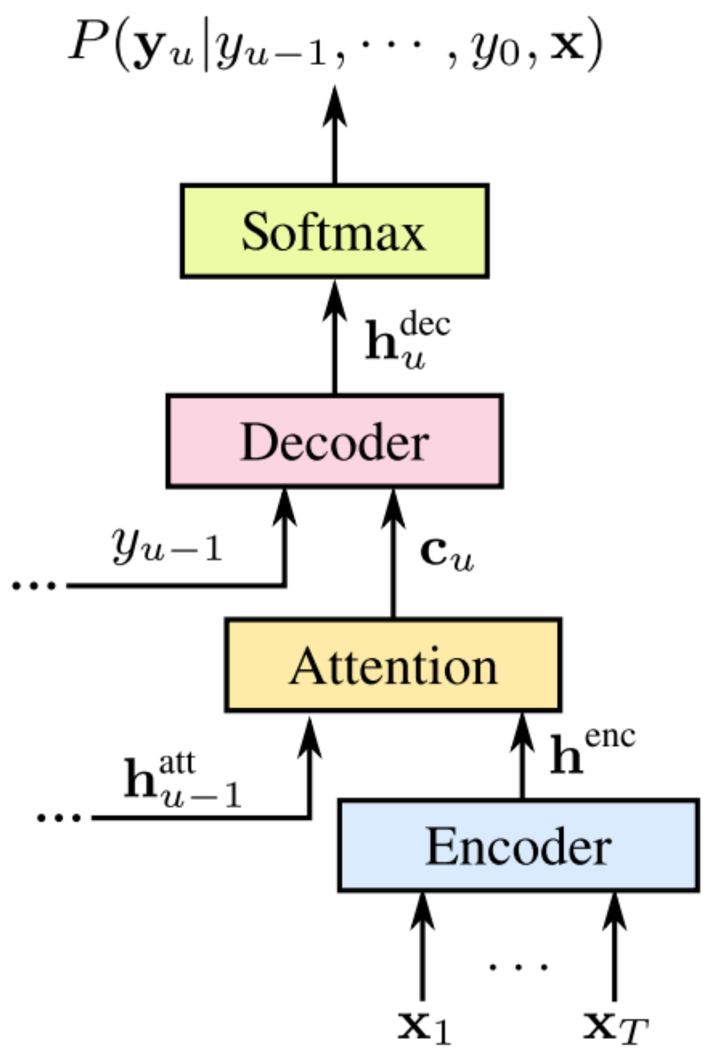
Encoder-decoder (with attention)



$$\beta_{t,u} = \langle \phi(\mathbf{h}_t^{\text{enc}}), \psi(\mathbf{h}_{u-1}^{\text{att}}) \rangle$$

$$\alpha_{t,u} = \frac{e^{\beta_{t,u}}}{\sum_{i=1}^{T} e^{\beta_{i,u}}}$$

$$\mathbf{c}_u = \sum_t \alpha_{t,u} \mathbf{h}_t^{\text{enc}}$$

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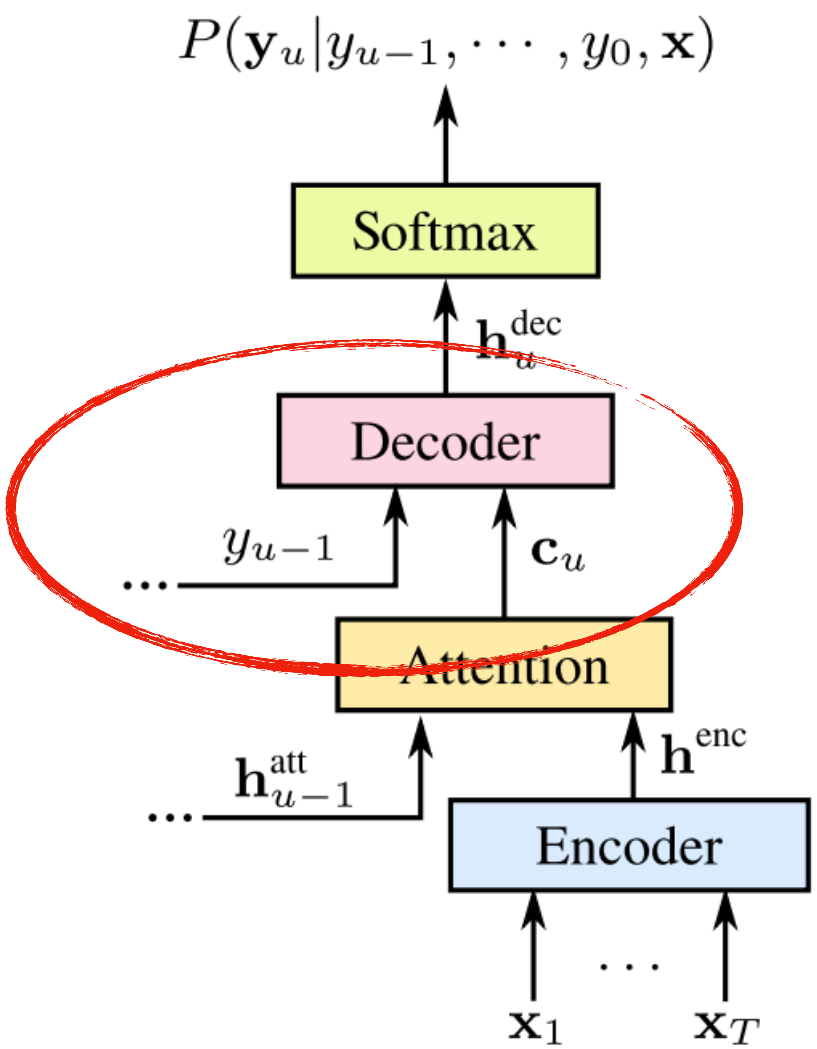

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Trade-off

- Speed vs. performance tradeoff
- For **faster inference**, sequence generation must be independent of previous tokens e.g. CTC
- But for **better performance**, conditionally dependent sequence generation is required e.g. RNN-T

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Autoregressive

Trade-off

- Speed vs. performance tradeoff

Non-autoregressive

- For **faster inference**, sequence generation must be independent of previous tokens e.g. CTC
- But for **better performance**, conditionally dependent sequence generation is required e.g. RNN-T

Autoregressive

Motivating Question

- Can we have something in between?
- A model which is not fully autoregressive (i.e. does not take O(n) steps during inference)
- But also does not have conditional independence assumptions

“Yes, we can.”

– Authors of the Imputer paper

A bit more on CTC

$$p(Y \mid X) = \sum_{A \in \mathcal{A}_{X,Y}} \prod_{t=1}^{T} p_t(a_t \mid X)$$

The CTC conditional **probability**

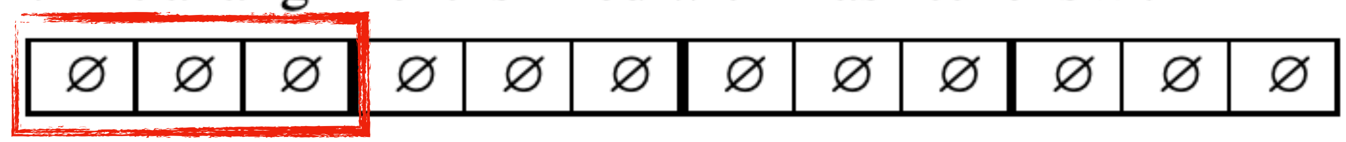
marginalizes over the set of valid alignments

computing the **probability** for a single alignment step-by-step.

Sequence modeling with CTC. Awni Hannun. https://distill.pub/2017/ctc/

The Imputer Decoding Model

1. Initial alignment is filled with mask tokens ∅.



Output sequence length = |x| is divided into blocks of size B

A block is generated independent of other blocks

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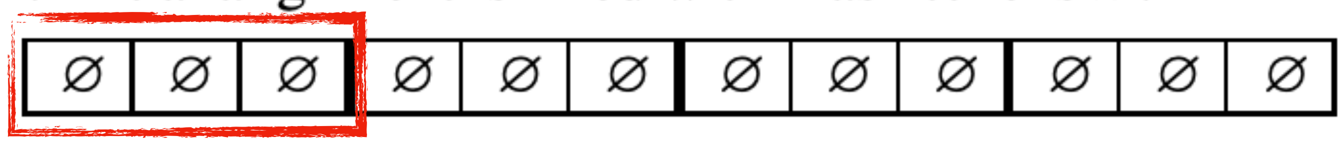

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B = 1 ?

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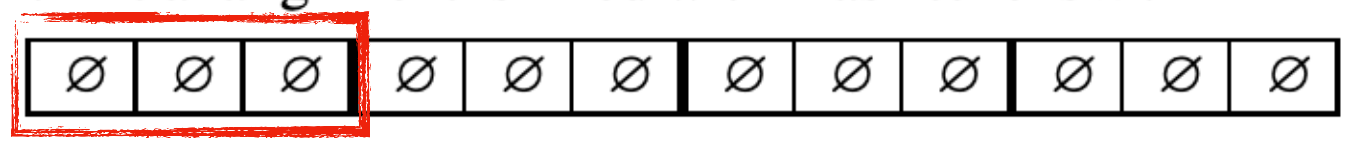

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B = |x| ?

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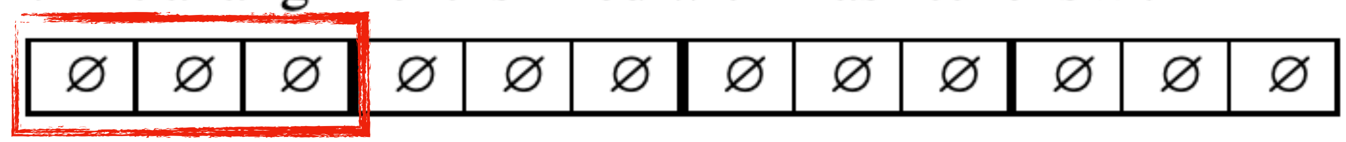


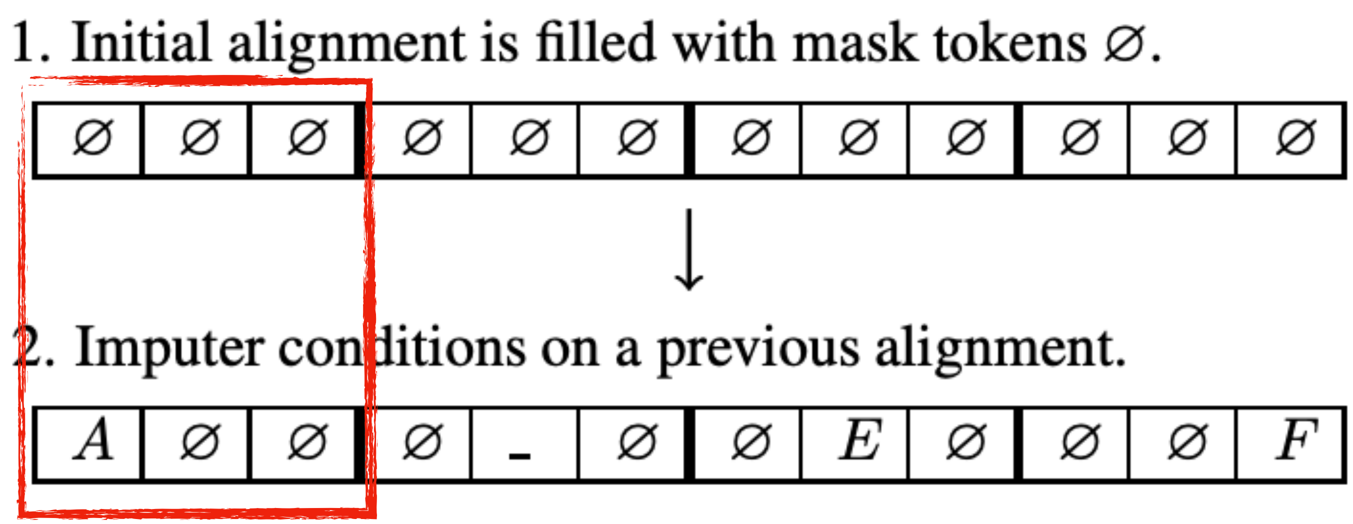
Output sequence length = |x| is divided into blocks of size B

A block is generated independent of other blocks

B = 1 ? **CTC**

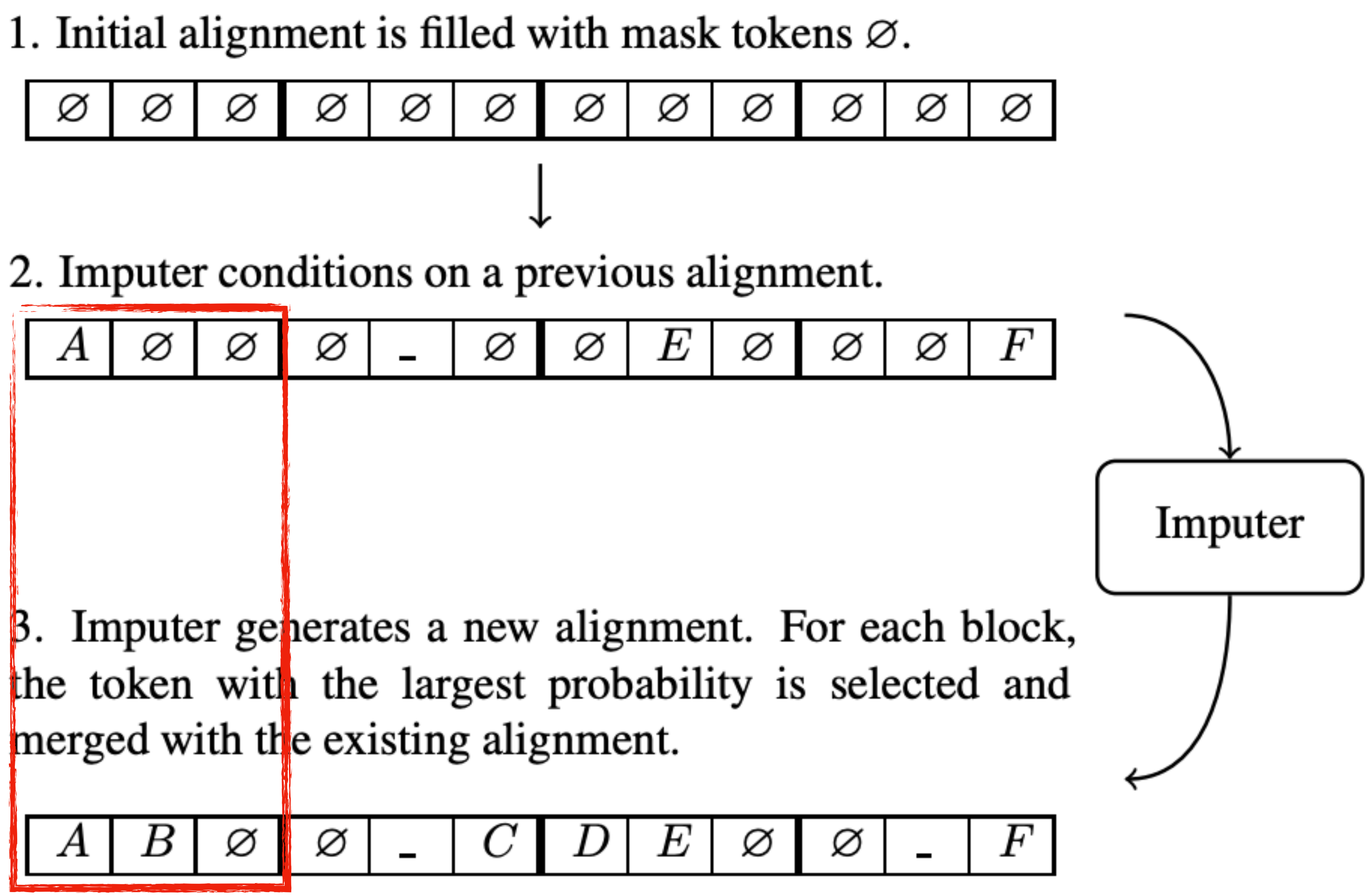
B = |x| ? **Fully autoregressive**

The Imputer Decoding Model



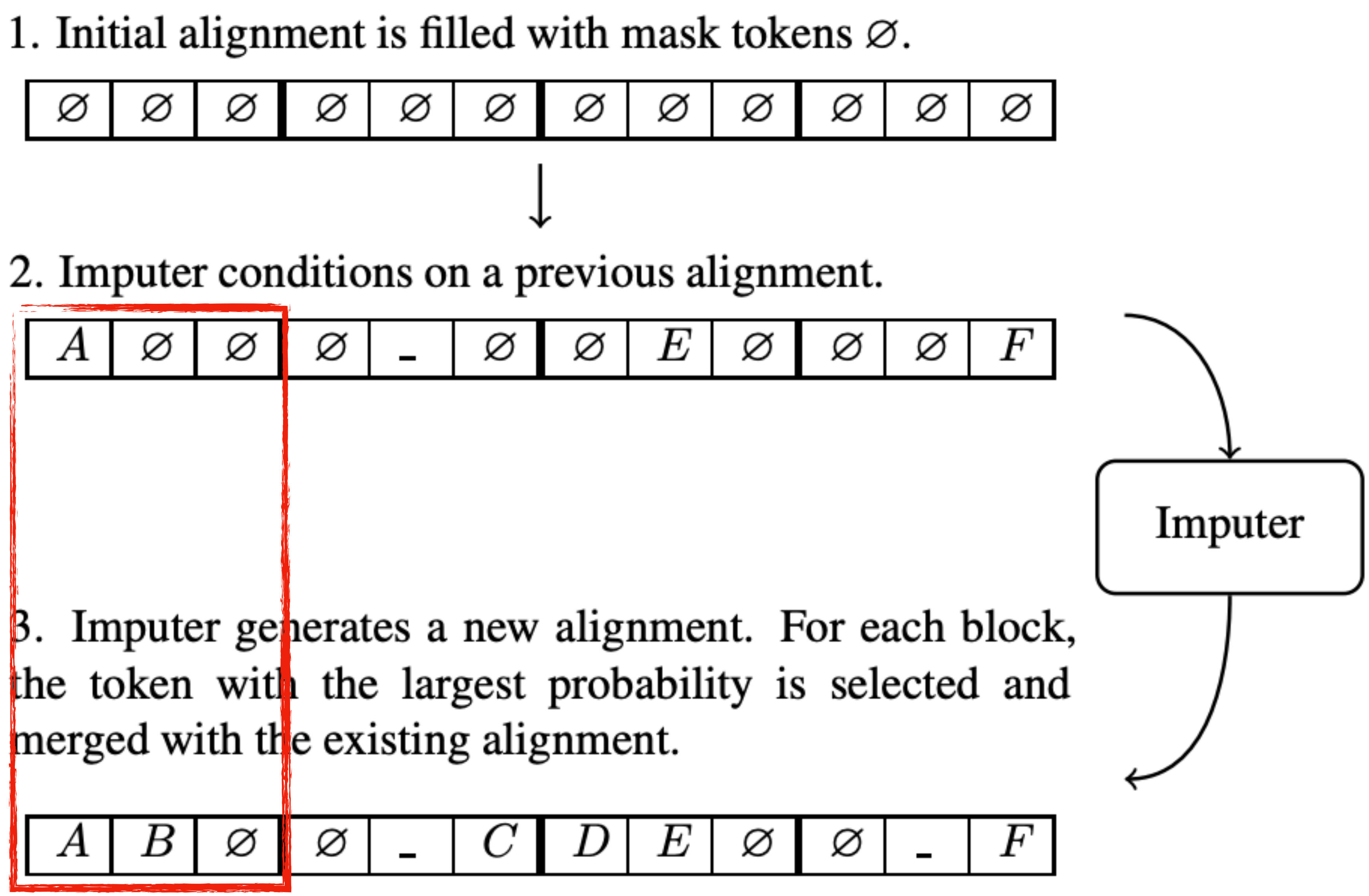
New alignment for the block is generated depending on input x and previous alignment

The Imputer Decoding Model



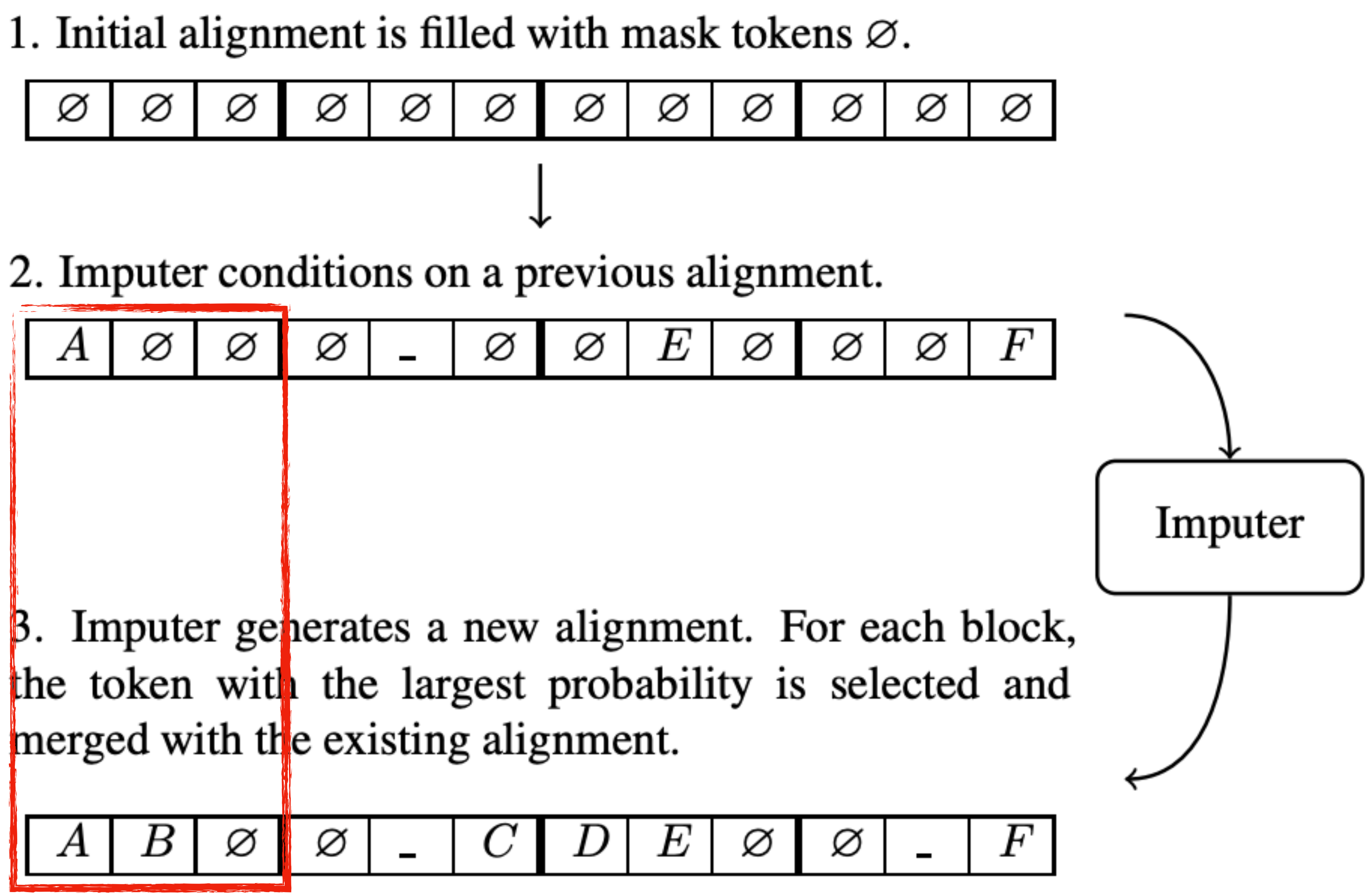
Keep the token with largest probability and merge with existing alignment

The Imputer Decoding Model



1 token "committed" in each step

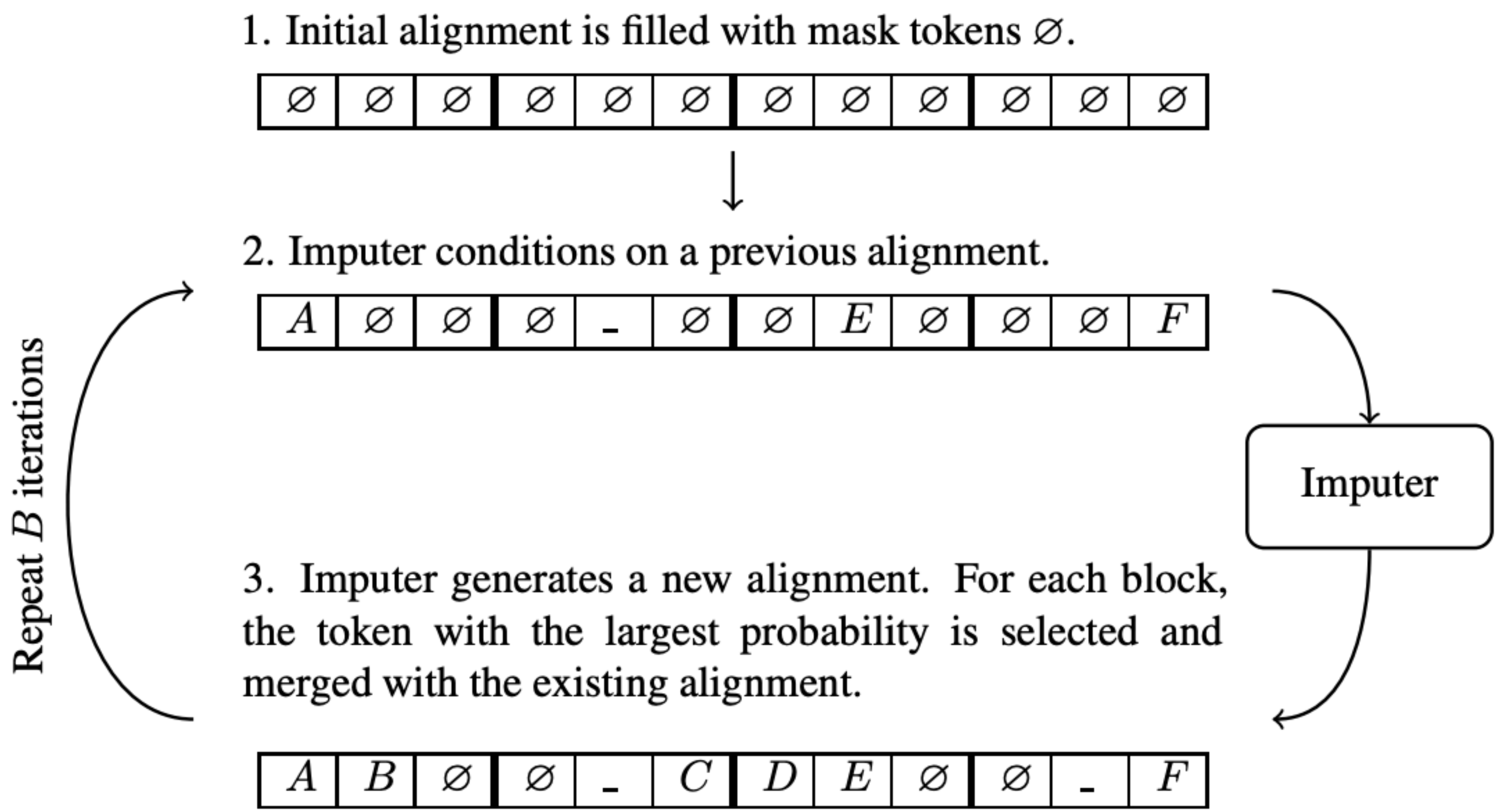
The Imputer Decoding Model



1 token "committed" in each step

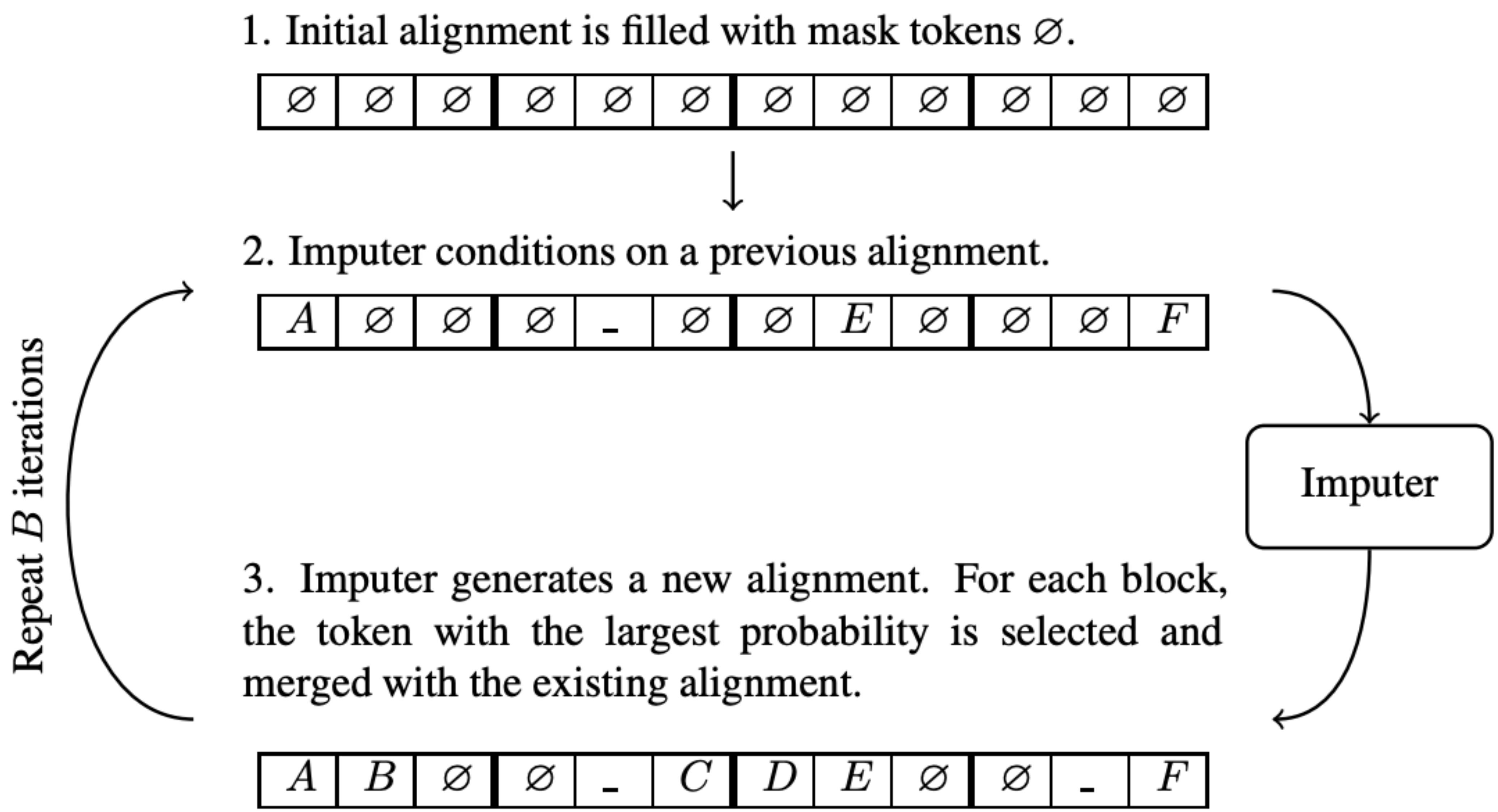
So how many steps would we need in total to get the sequence?

The Imputer Decoding Model



Sequence is generated in B steps

The Imputer Decoding Model



In a block, token generation is dependent on other tokens within the block

The model

$$p_\theta(a|\tilde{a}, x) = \prod_i p(a_i|\tilde{a}, x; \theta)$$

The model

$$p_\theta(a|\tilde{a}, x) = \prod_i p(a_i|\tilde{a}, x; \theta)$$

New alignment

Previous alignment

By conditioning on previous alignment, the tokens become conditioned on each other

Training objective

$$\log p_\theta(y|x) = \log \sum_{a \in \beta(y)} \sum_{\tilde{a} \in \gamma(a)} p_\theta(a|\tilde{a}, x)$$

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All alignments of y

All masking permutations

Training objective

$$J(\theta) = \mathbb{E}_{a\sim q}[\mathbb{E}_{\tilde{a}\sim r}[\log p_\theta(a|\tilde{a}, x)]]$$

All alignments of y

All masking permutations

Training objective

$$J(\theta) = \mathbb{E}_{a \sim q}[\mathbb{E}_{\tilde{a} \sim r}[\log p_\theta(a|\tilde{a}, x)]]$$

1. **How to sample alignments from q?**
2. **How to sample masks from r?**

Alignment policy

- Suppose we have an “expert” model pretrained e.g. CTC
- **Method 1**: Get all alignments, store them offline, and sample from this.
- **Method 2**: Get best alignment and add noise

$$J(\theta) = \mathbb{E}_{a \sim q}[\mathbb{E}_{\tilde{a} \sim r}[\log p_\theta(a|\tilde{a}, x)]]$$

Masking policy

- **Method 1**: Uniform or Bernoulli distribution -> every block may have different number of masked tokens

- **Method 2**: Choose b in [0,B) and mask out b tokens in each block randomly

$$J(\theta) = \mathbb{E}_{a\sim q}[\mathbb{E}_{\tilde{a}\sim r}[\log p_\theta(a|\tilde{a}, x)]]$$

How to train your Imputer?

1. **Imitation learning**

- Simply learn to copy the expert CTC model

$$J_{\mathrm{IM}}(\theta) = \mathbb{E}_{a\sim q_{\phi'}}\left[\mathbb{E}_{\tilde{a}\sim r}\left[\log p_\theta(a|\tilde{a}, x)\right]\right]$$

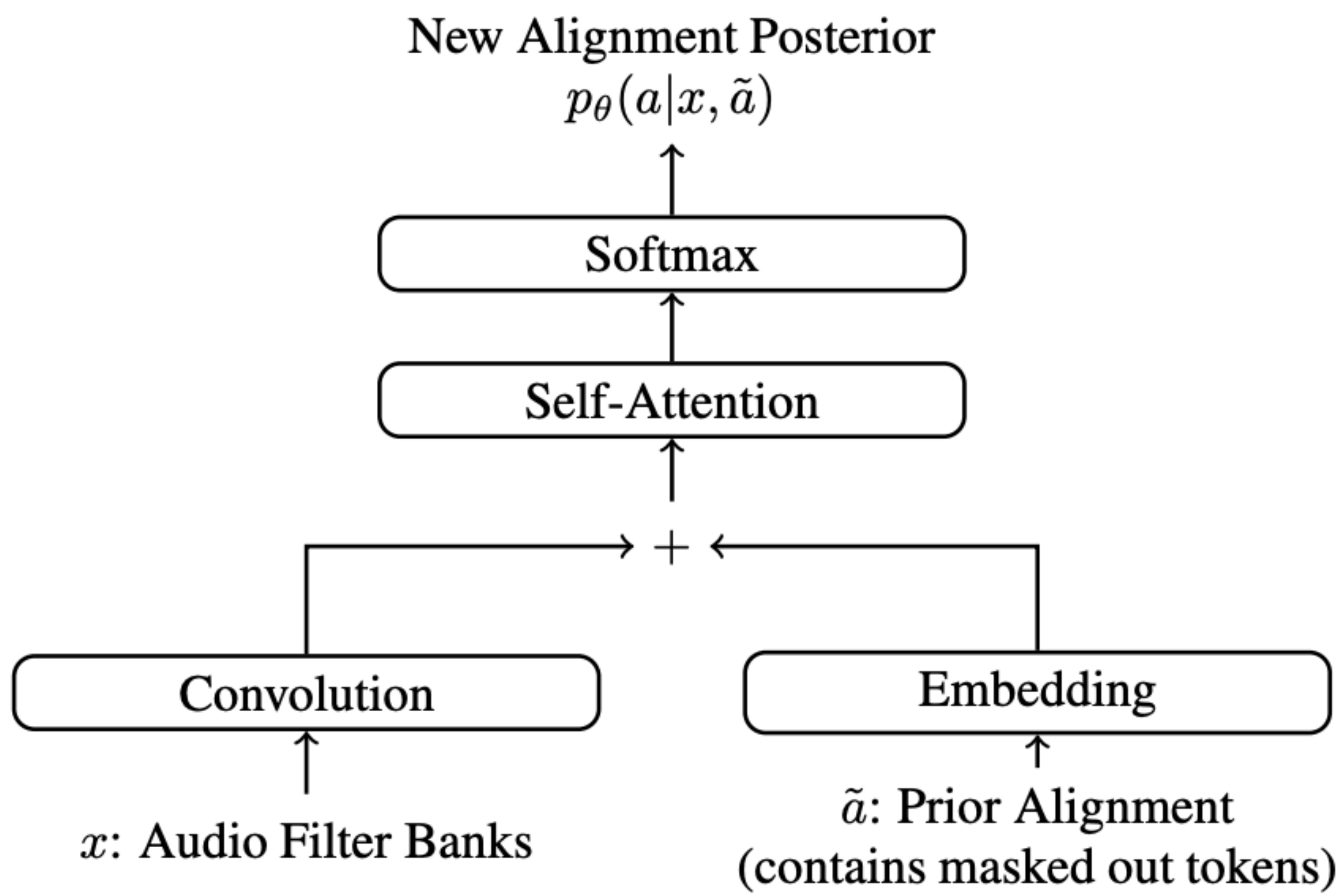
How to train your Imputer?

2. **Dynamic programming**

- Marginalize over all possible compatible alignments

$$J_{\mathrm{DP}}(\theta) = \mathbb{E}_{a \sim q_{\phi'}} \left[\mathbb{E}_{\tilde{a} \sim r} \left[\log \sum_{a' \in \beta'(\tilde{a}, a)} p_\theta(a' | \tilde{a}, x) \right] \right]$$

Model architecture


New Alignment Posterior
$p_\theta(a|x,\tilde{a})$
Softmax
Self-Attention
+
Convolution
Embedding
x: Audio Filter Banks
$\tilde{a}$: Prior Alignment
(contains masked out tokens)

Experimental results

WSJ - 82h

Table 1. Wall Street Journal Character Error Rate (CER) and Word Error Rate (WER).

Model	CER	WER	Iterations
seq2seq			
Bahdanau et al. (2016a)	6.4	18.6	n
Bahdanau et al. (2016b)	5.9	18.0	n
Chorowski & Jaitly (2017)	-	10.6	n
Zhang et al. (2017)	-	10.5	n
Chan et al. (2017)	-	9.6	n
Kim et al. (2017)	7.4	-	n
Serdyuk et al. (2018)	6.2	-	n
Tjandra et al. (2018)	6.1	-	n
Sabour et al. (2019)	3.1	9.3	n
CTC			
Graves & Jaitly (2014)	8.4	27.3	1
Liu et al. (2017)	-	16.7	1
CTC (Our Work)	5.6	15.2	1
Imputer (IM)	6.2	16.5	8
Imputer (DP)	4.9	12.7	8

Librispeech - 960h

Table 2. LibriSpeech test-clean and test-other Word Error Rate (WER).

Method	clean	other	Iterations
seq2seq			
Zeyer et al. (2018a)	4.9	15.4	n
Zeyer et al. (2018b)	4.7	15.2	n
Irie et al. (2019)	4.7	13.4	n
Sabour et al. (2019)	4.5	13.3	n
Luscher et al. (2019)	4.4	13.5	n
Park et al. (2019)	4.1	12.5	n
ASG/CTC			
Collobert et al. (2016)	7.2	-	1
Liptchinsky et al. (2017)	6.7	-	1
CTC (Our Work)	4.6	13.0	1
Imputer (IM)	5.5	14.6	8
Imputer (DP)	4.0	11.1	8

Some other stuff

- Block size 8 found to be best for training and inference
- Too large blocks can cause training issues
- All masking policies (Bernoulli, Uniform, Block) perform similar

Stuff which did not work :)

- Training with stale model samples instead of CTC expert
- Greedy decoding, simulated annealing decoding

Key takeaways

- Want something between CTC and fully autoregressive models
- Inference in constant time (B steps) + works better than both
- How to make things non-autoregressive? Use MASKING. (see BERT, Mask-Predict etc.)


thank you
gracias
merci
danke
obrigado
謝謝
ngiyabonga
teşekkür ederim
рахмат
Баярлалаа
спасибо
bedankt
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감사합니다
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