

# Productionization

# Text Editing Advantages

Faithfulness

Constraining decoders in seq2seq is an active area of research

Control

We can control the word a model can add / remove.  
Can incorporate external knowledge (e.g., pronoun).

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Latency

Can be >10x faster inference.

Data efficient

Text Editing models need less training data.



Latency

# Case study: EdiT5 vs T5

- Two GEC models:
  - EdiT5 base (12-layer-encoder, 1-layer-decoder)
  - T5 base (12-layer-encoder, 12-layer-decoder)
- Profiles obtained on GPU
  - Profiles obtained with [Tensorflow Profiler](#)
  - PyTorch has [similar tools](#)

# GEC

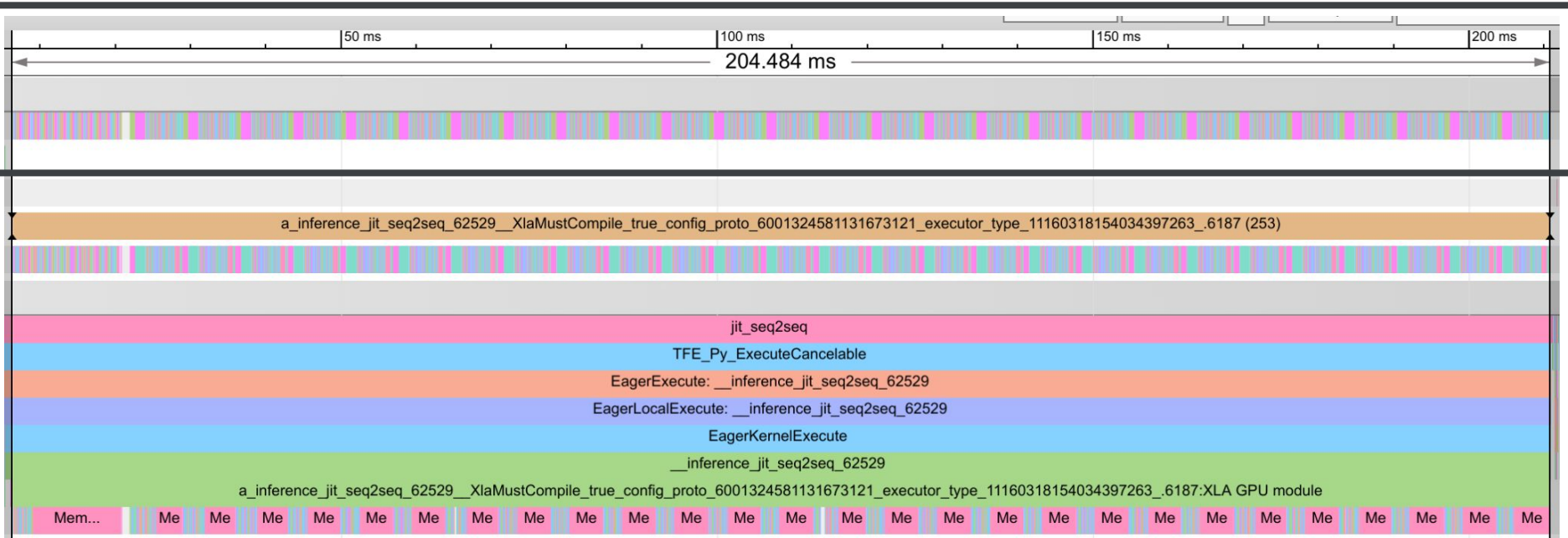
Input to correct (23 tokens):

*i was walking through the park when struck by bicycle ... my arm hurts a little now .*

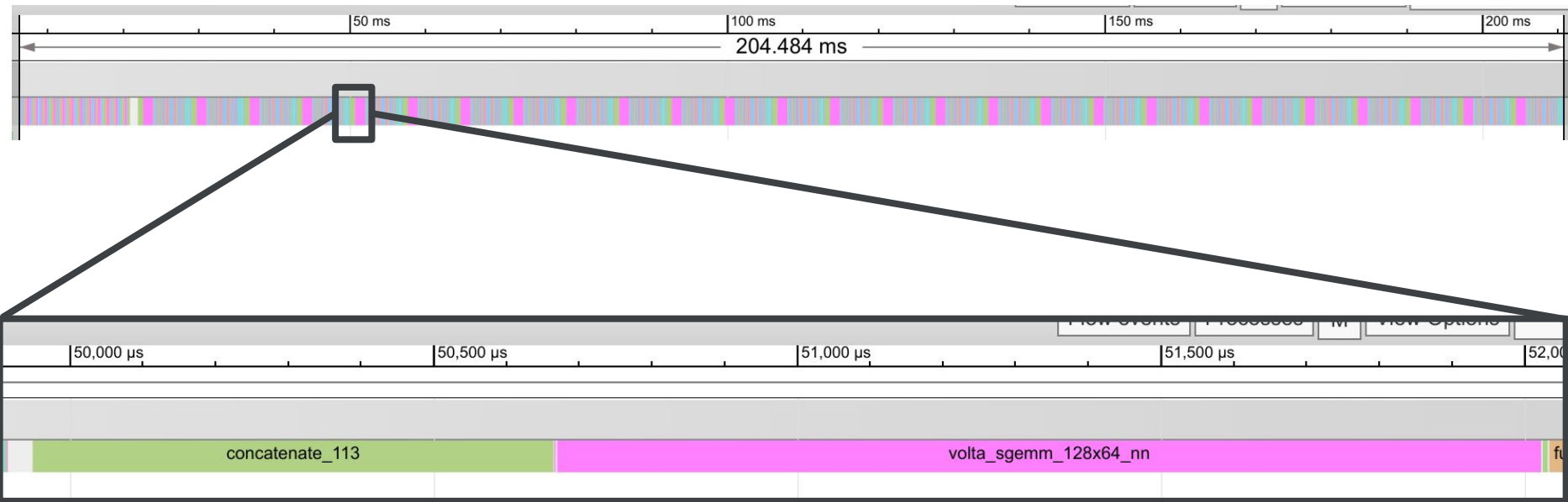
Decoder output Seq2seq (27 tokens):

**I** \_was \_walking \_through \_the \_park \_when **I \_was** \_struck \_by **a**  
\_bicycle \_ ... \_my \_arm \_hurt s \_ a \_little \_now \_ . </s>

# Seq2Seq



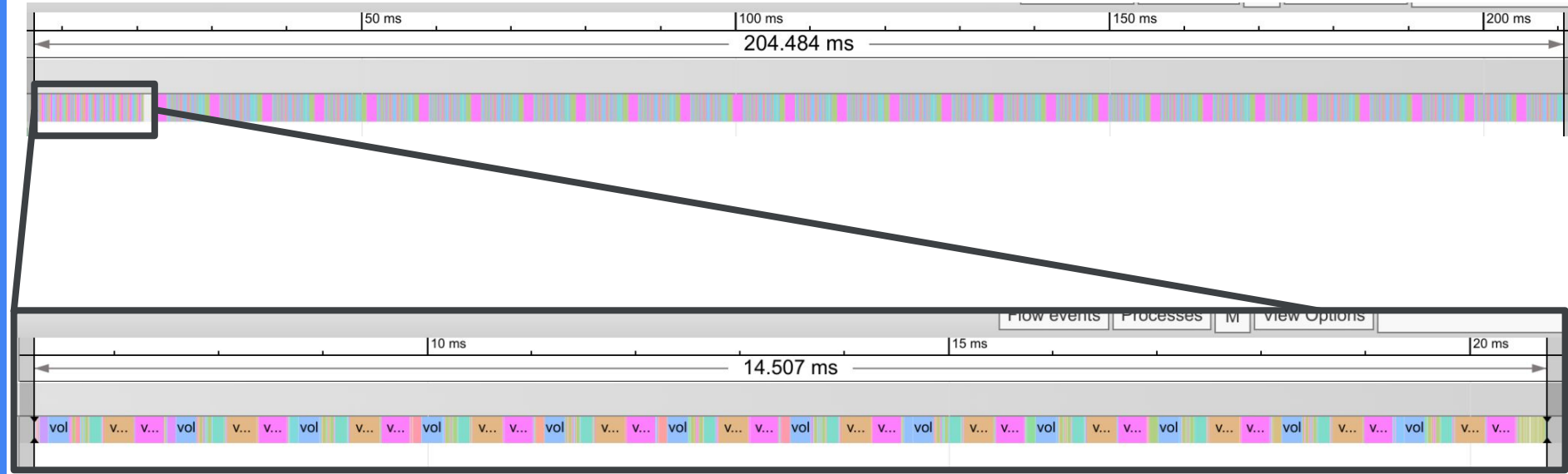
# Seq2Seq



- End-to-end latency: 204ms
- Compiled with [XLA](#)
- Disabling compilation will increase latency, but make the profile more readable

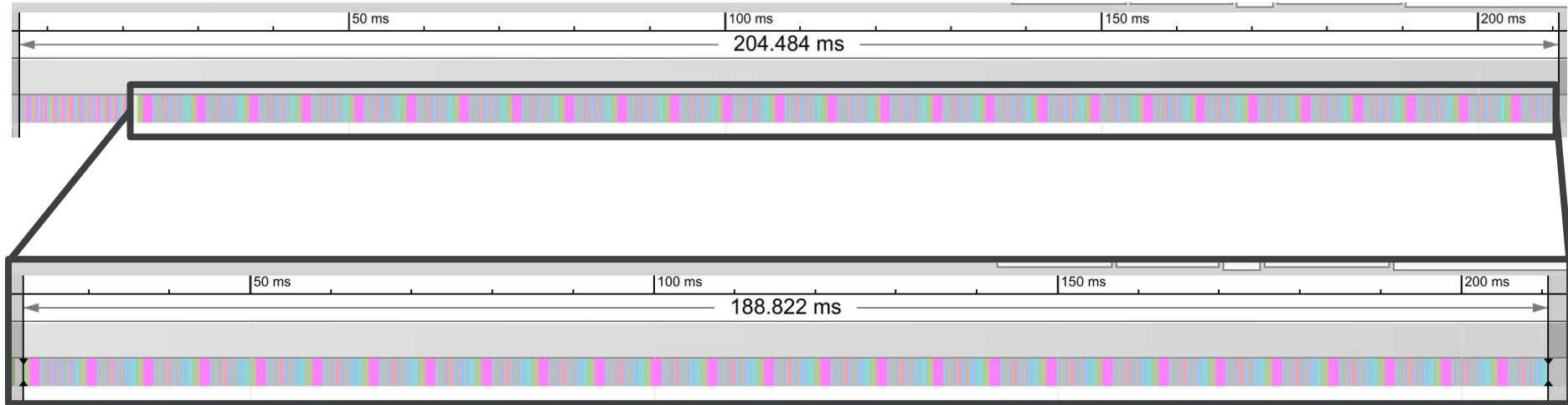


# Seq2Seq, encoder



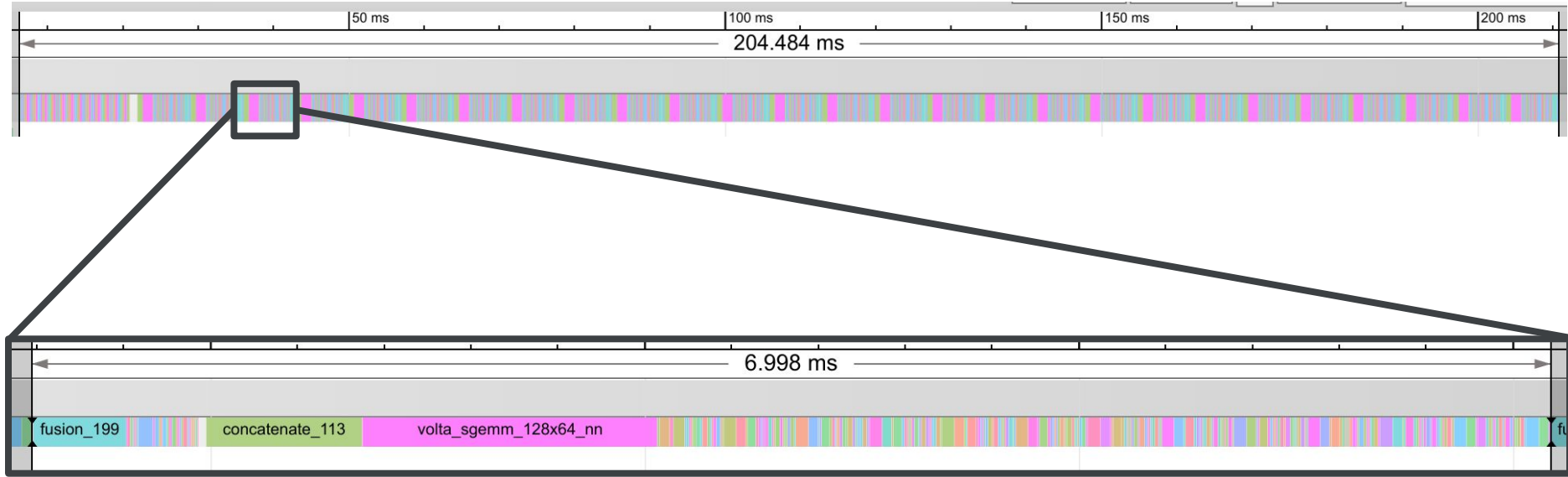
- Encoder takes 15ms

# Seq2Seq, decoder



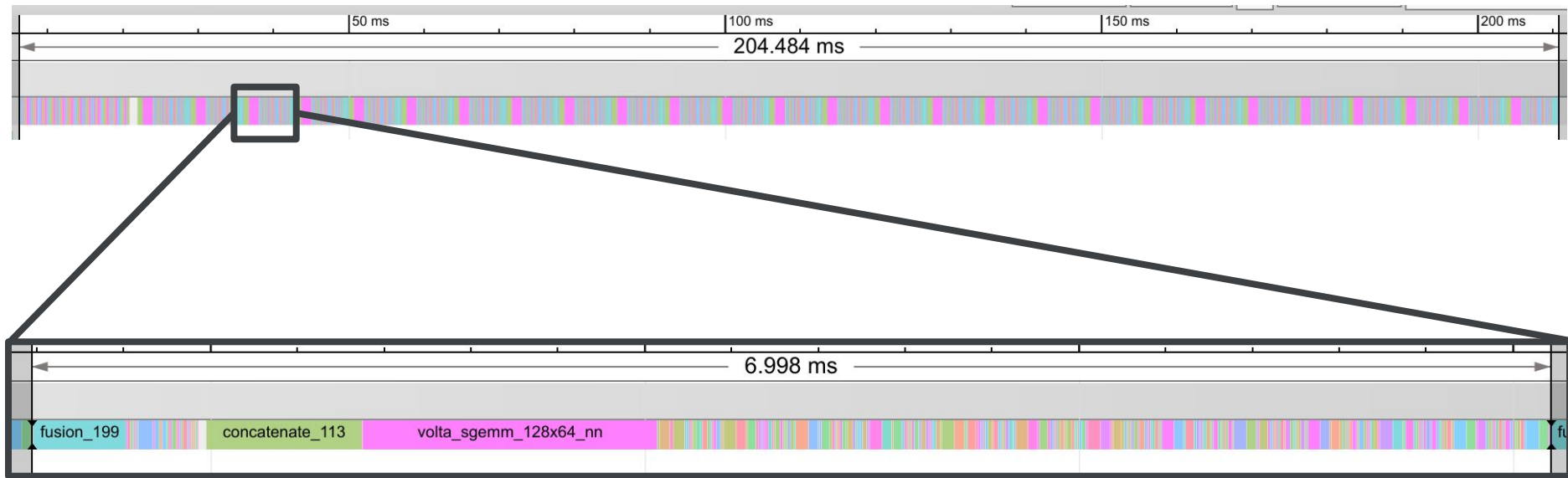
- Encoder takes 15ms
- Decoder takes 189ms

# Seq2Seq, decoder step



- Encoder takes 15ms
- Decoder takes 189ms
- Single decoder step takes 7ms
  - $7 \text{ [ms/step]} * 27 \text{ [steps]} = 189\text{ms}$

# Seq2Seq, conclusions



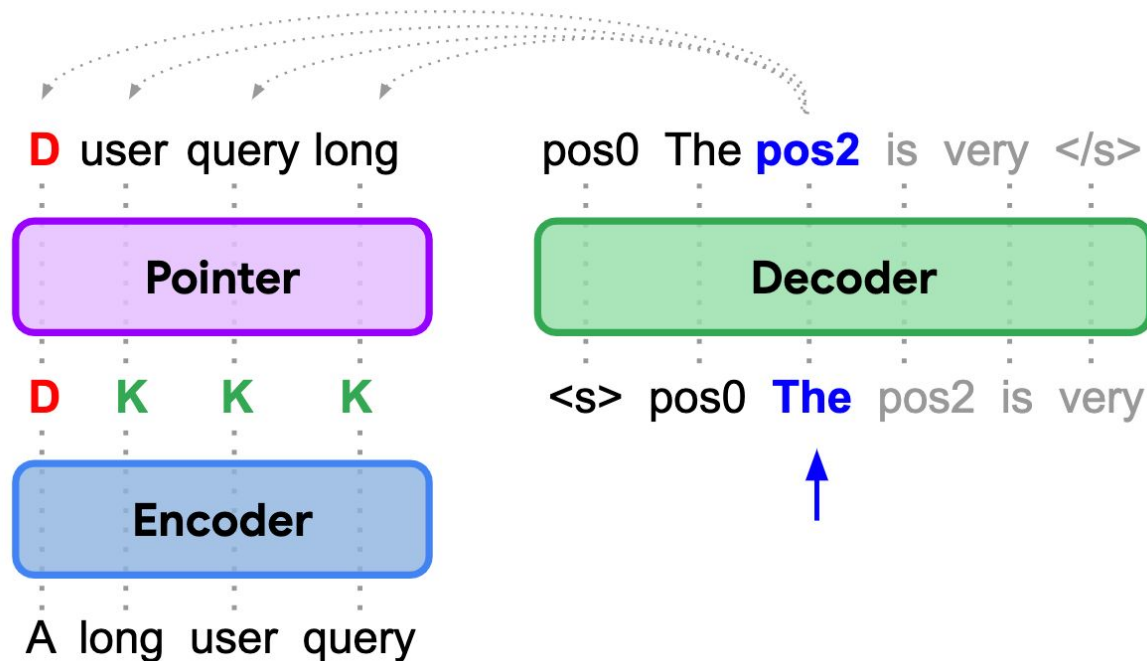
- Encoder takes 15ms
- Decoder takes 189ms
- Single decoder step takes 7ms
  - $7 \text{ [ms/step]} * 27 \text{ [steps]} = 189\text{ms}$

If we want to reduce latency, target the decoder:

- Reduce the number of steps.
- Reduce the latency per step.

# Refresher on EdiT5

Output: **The** user query **is very** long



# How does EdiT5 reduce latency?

- Use 1-layer decoder
  - Isn't limited to text-editing models
- It moves work into the encoder
  - Tagging, Reordering
- Limit use of autoregressive decoder

# GEC

Input to correct (21 tokens):

*i was walking through the park when struck by bicycle... my arm hurts a little now.*

Decoder output Seq2seq (27 tokens):

**I** \_was \_walking \_through \_the \_park \_when **I \_was** \_struck \_by **a**  
\_bicycle \_ ... \_my \_arm \_hurt s \_ a \_little \_now \_ . </s>

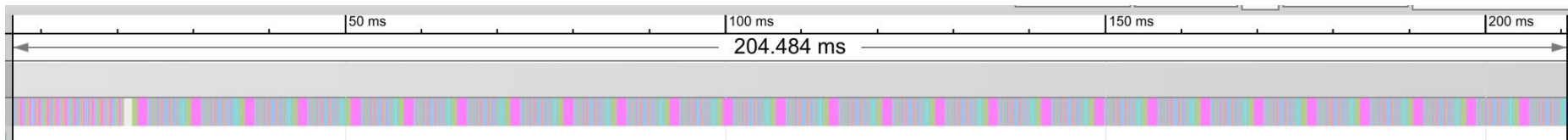
Decoder output EdiT5 (10 tokens)

<extra\_id\_1> **I** **\_was** <extra\_id\_6> **I \_was** <extra\_id\_8> **\_ a** </s>

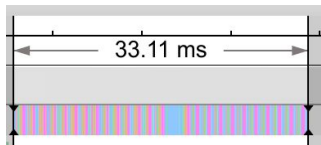
Note: extra ids are used to represent insertion positions.

# EdiT5 vs Seq2Seq

Seq2seq model:

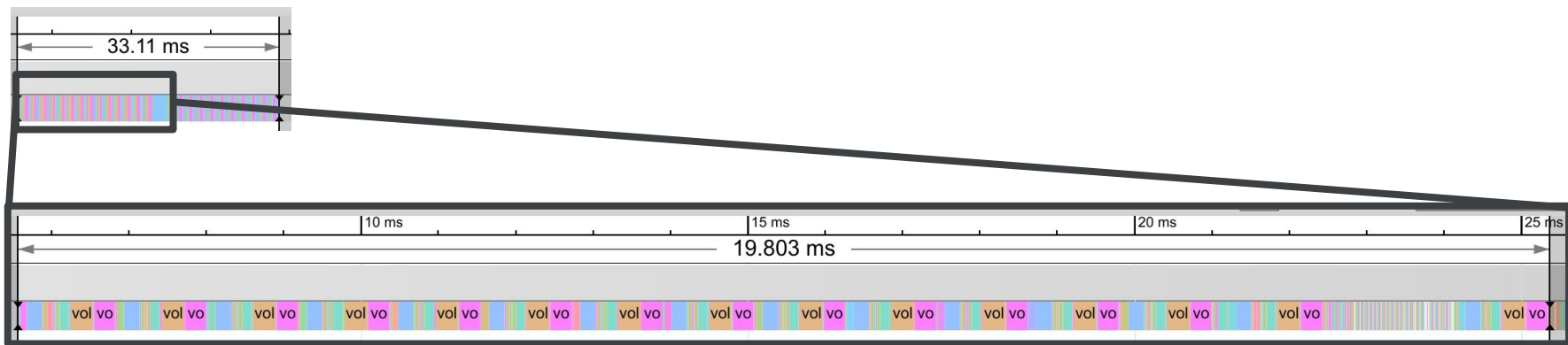


EdiT5 model:



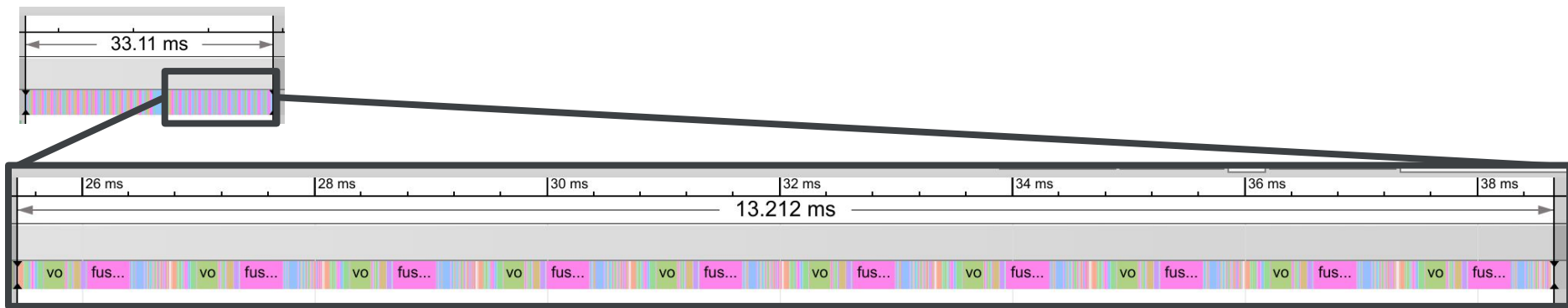


# EdiT5 encoder and overhead



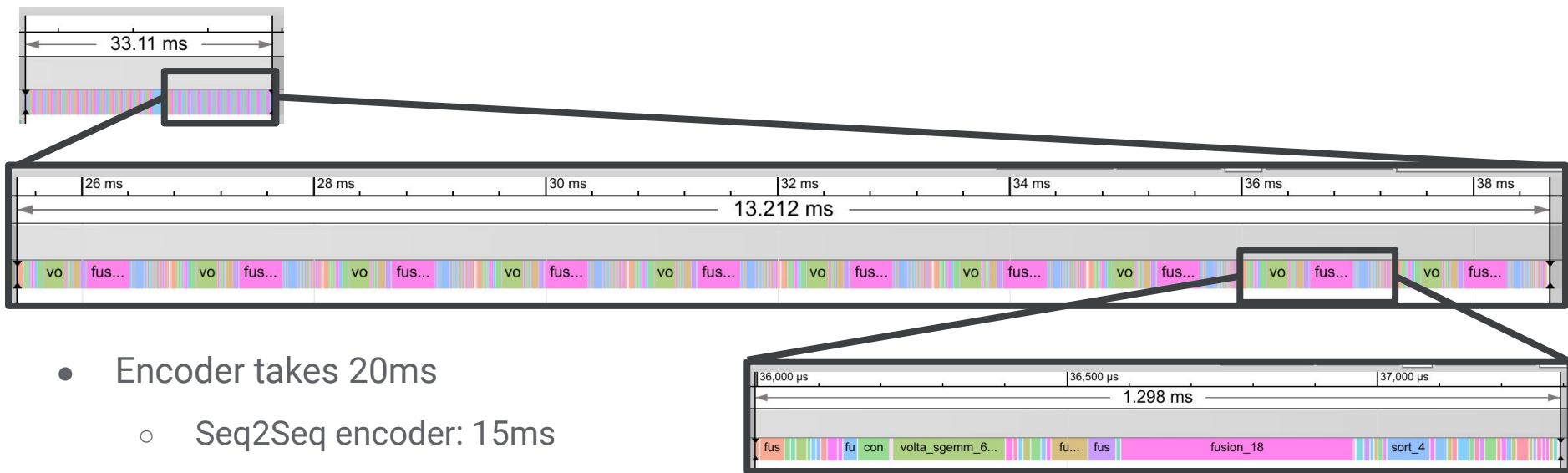
- Encoder takes 20ms
  - Seq2Seq encoder: 15ms
  - Pointing mechanism, extra layers

# EdiT5 decoder



- Encoder takes 20ms
  - Seq2Seq encoder: 15ms
  - Pointing mechanism, extra layers
- Decoder takes 13ms

# EdiT5 decoder step



- Encoder takes 20ms
  - Seq2Seq encoder: 15ms
  - Pointing mechanism, extra layers
- Decoder takes 13ms
  - Single step takes 1.3ms
  - Seq2Seq single step: 7ms

# How does EdiT5 reduce latency?

- Decoder step takes 1.3ms compared to 7ms
  - **5.4x** reduction
- There are 10 decoder steps, compared to 27
  - Another **2.7x** reduction

In summary: **14.5x** reduction in decoder latency compared to Seq2Seq, in exchange for **5ms** of overhead.

# Text editing for latency reduction

## Strategies:

- Parallel decoding
  - LaserTagger
- Iterative parallel decoding
  - GECToR, PIE, Levenshtein Transformer
- Semi-autoregression
  - Few-step decoder
    - Seq2Edits, EdiT5, others (e.g. [Chen et al., EMNLP 2020](#))
  - Combine with iterative decoding: Seq2Edits
- Pointing network for reordering: Felix, EdiT5

Iteration #	P	R	F <sub>0.5</sub>	# corr.
Iteration 1	72.3	38.6	61.5	787
Iteration 2	73.7	41.1	63.6	934
Iteration 3	74.0	41.5	64.0	956
Iteration 4	73.9	41.5	64.0	958

Table 4: Cumulative number of corrections and corresponding scores on CoNLL-2014 (test) w.r.t. number of iterations for our best single model.

[GECToR – Grammatical Error Correction: Tag, Not Rewrite \(Omelianchuk et al., BEA 2020\)](#)



Data efficiency

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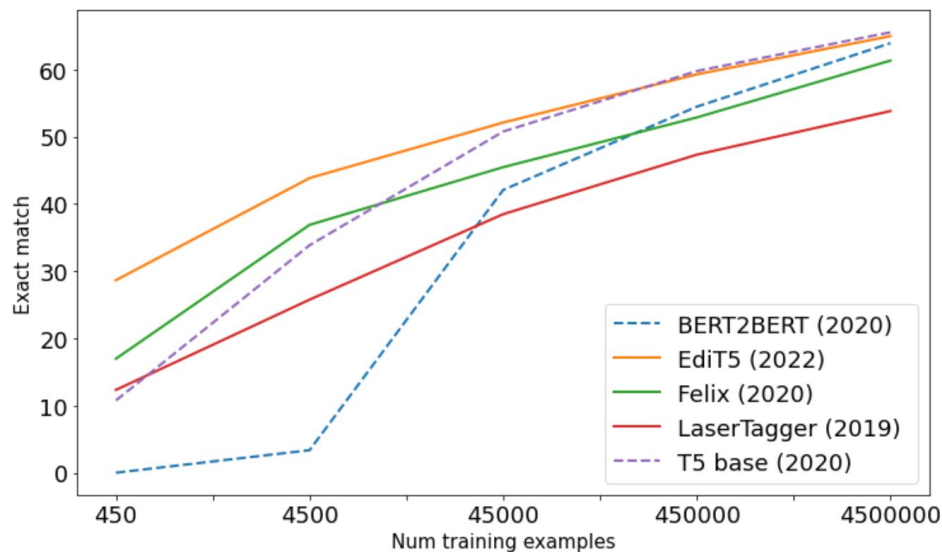
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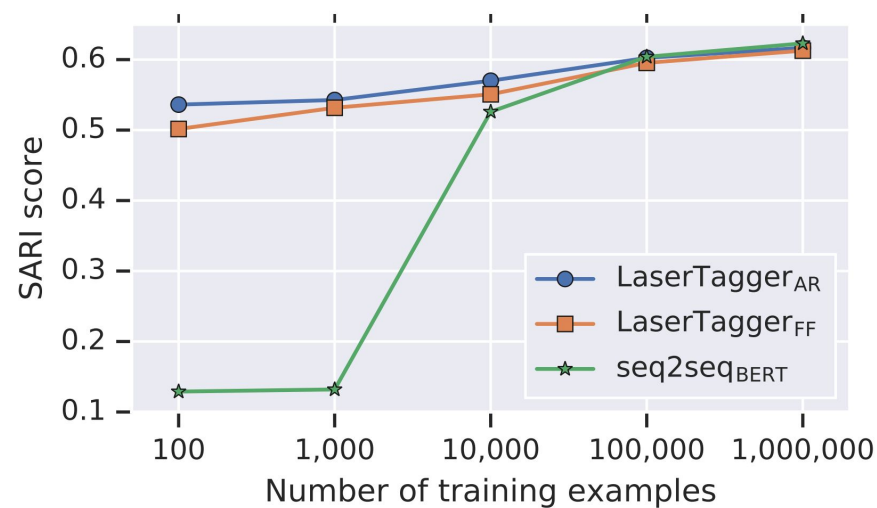
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# Text editing for low resource settings

## Sentence Fusion



## Sentence Splitting

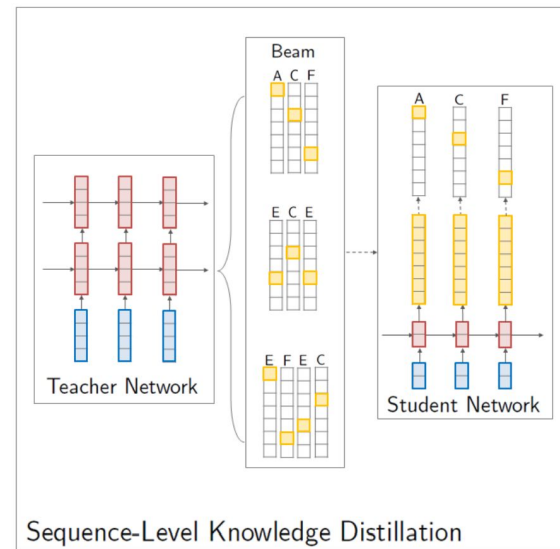


[Encode, Tag, Realize: High-Precision Text Editing \(Malmi et al., EMNLP 2019\)](#)



# Text editing models as distillation targets

- From seq2seq: Levenshtein Transformer
  - Text editing model to replicate oracle edits
  - Using seq2seq model instead of oracle improves scores
- From ensembles of text editing models: GECToR
  - Ensembles of GECToR models
  - [Tarnavskyi et al., ACL 2022](#)



[Sequence-Level Knowledge Distillation \(Kim & Rush, EMNLP 2016\)](#)

*Questions?*