Levenshtein Training for Word-level Quality Estimation

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Problem Definition

source	Impfungen beenden die Pandemie											
target	Vaccinations	␣	put	␣	ends	␣	to	␣	the	␣	pandemic	
labels	**OK**	**OK**	**OK**	**BAD**	**BAD**	**OK**	**OK**	**OK**	**OK**	**OK**	**OK**	

- **Word-level Quality Estimation (QE)**
  - Generate **binary quality tags** for each **word** and the **gaps** between every two words
  - **BAD** on **word** indicates deletion/substitution
  - **BAD** on **gap** indicates insertion

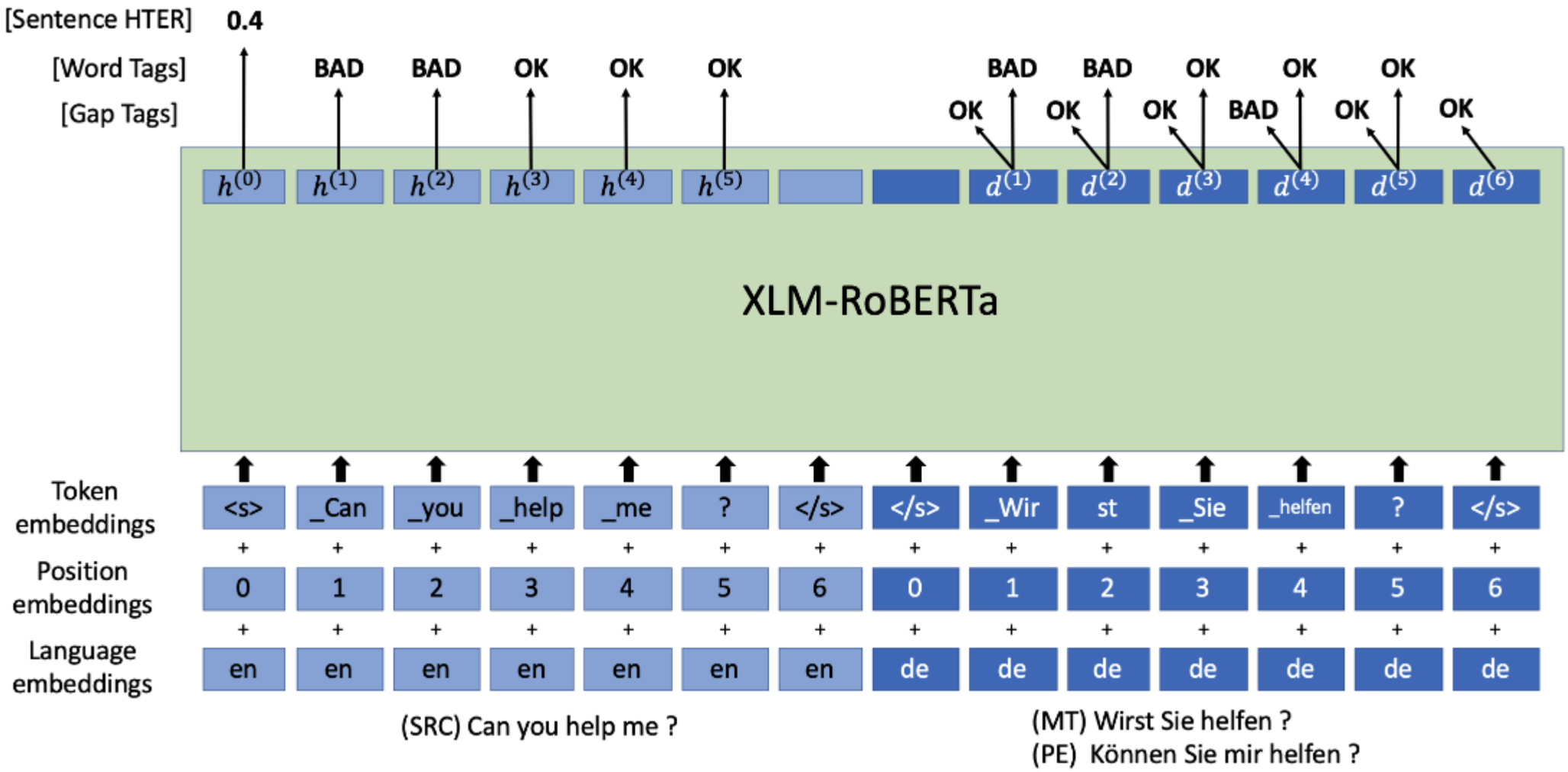
http://statmt.org/wmt21/quality-estimation-task.html

Evaluation

	OK	**OK**	**OK**	**BAD**	**BAD**	**OK**	**OK**	**OK**	**OK**	**OK**	**OK**
target	Vaccinations	␣	put	␣	ends	␣	to	␣	the	␣	pandemic
post-edit	Vaccinations	␣	put	an	end	␣	to	␣	the	␣	pandemic

- Ask **humans** to **post-edit** system translation
- Generate word-level references by computing **TER**

Predictor-Estimator



Picture from Lee (2020)

Translation Probability?

- Problems:
  - **Left-context only**, while bidirectional available
  - Cannot predict **gap labels**

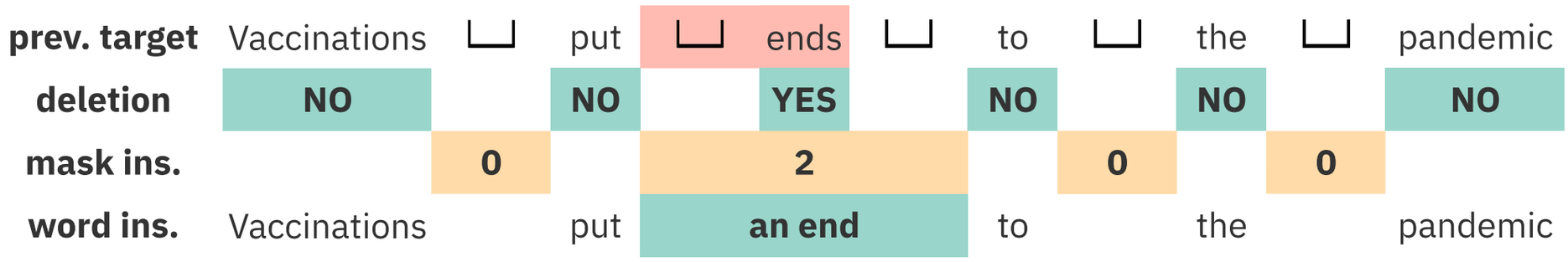
Can we do better?

- **Levenshtein Transformer!**

- A non-autoregressive translation model that performs decoding iteratively

Gu, Wang and Zhao (2019)

Why LevT?



- Solves both weaknesses:
  - **Mask prediction** -> can predict **gap labels**
  - **Iterative decoding** -> access to **bidirectional** context

Training Process

(Optional) Stage 0
Pre-train Encoder/Decoder

Stage 1
Levenshtein Pre-training

Stage 2
Pseudo Translation Triplet Fine-tune

Stage 3
Human Translation Triplet Fine-tune

Training Process

- Training a LevT for **translation**
- **Knowledge distillation** (KD) is often necessary
- (Optionally) **Initialize** the transformer blocks of encoder/decoder with pretrained model

What's Left?

- Iterative decoder:
  - **Noised target** -> **Subword-level Edit Tags**
- QE decoder:
  - **MT target** -> **Word-level Edit Tags**
- Not great. Should minimize this mismatch.

Training Process

(Optional) Stage 0
Pre-train Encoder/Decoder

Stage 1
Levenshtein Pre-training

Stage 2
Pseudo Translation Triplet Fine-tune

Stage 3
Human Translation Triplet Fine-tune

- Fine-tune with **pseudo translation triplets** (src, tgt, pe)

Training Process

(Optional) Stage 0
Pre-train Encoder/Decoder

Stage 1
Levenshtein Pre-training

Stage 2
Pseudo Translation Triplet Fine-tune

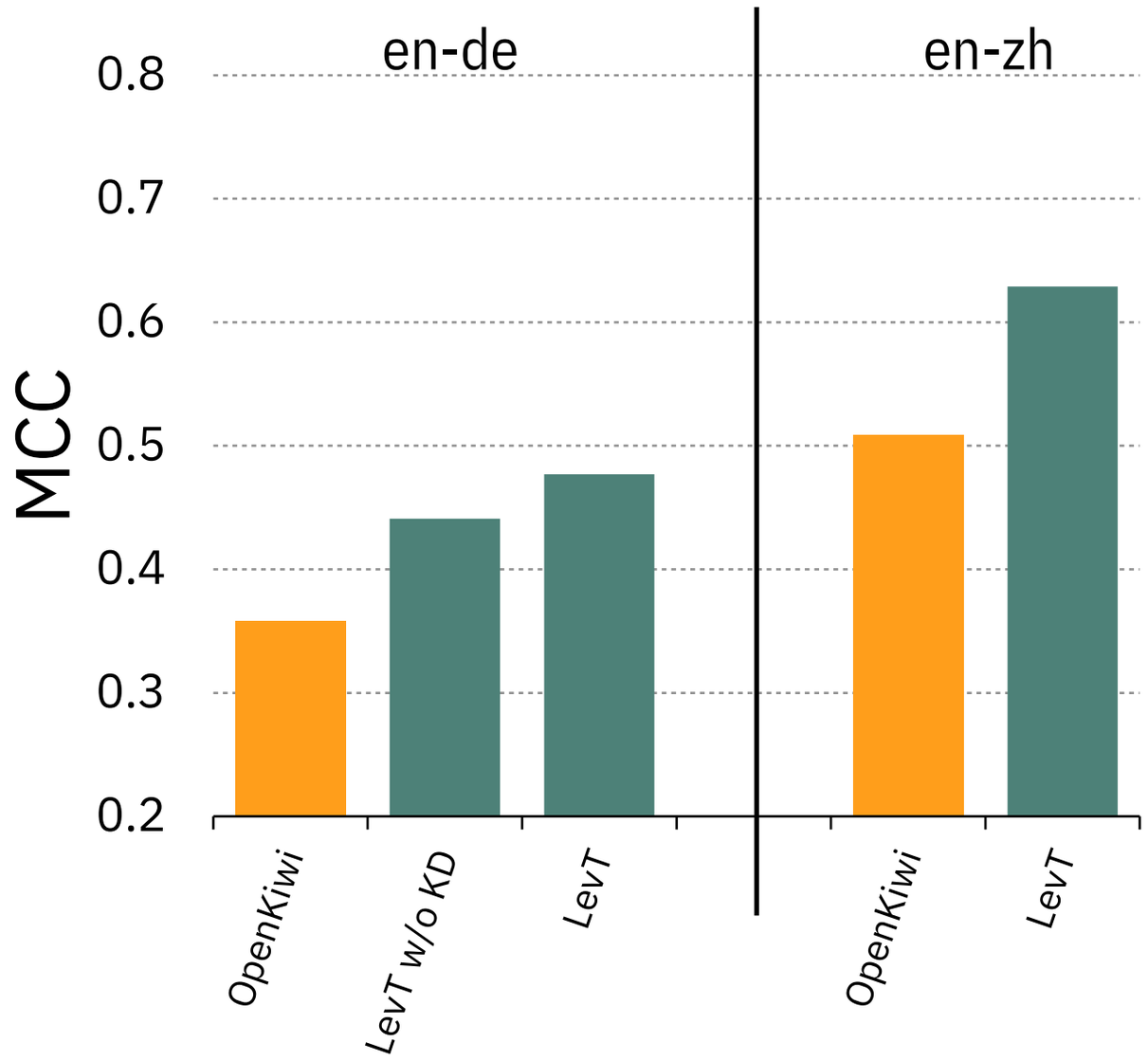
Stage 3
Human Translation Triplet Fine-tune

- Fine-tune with the actual **human post-edited translation triplet**
- (7k triplets)

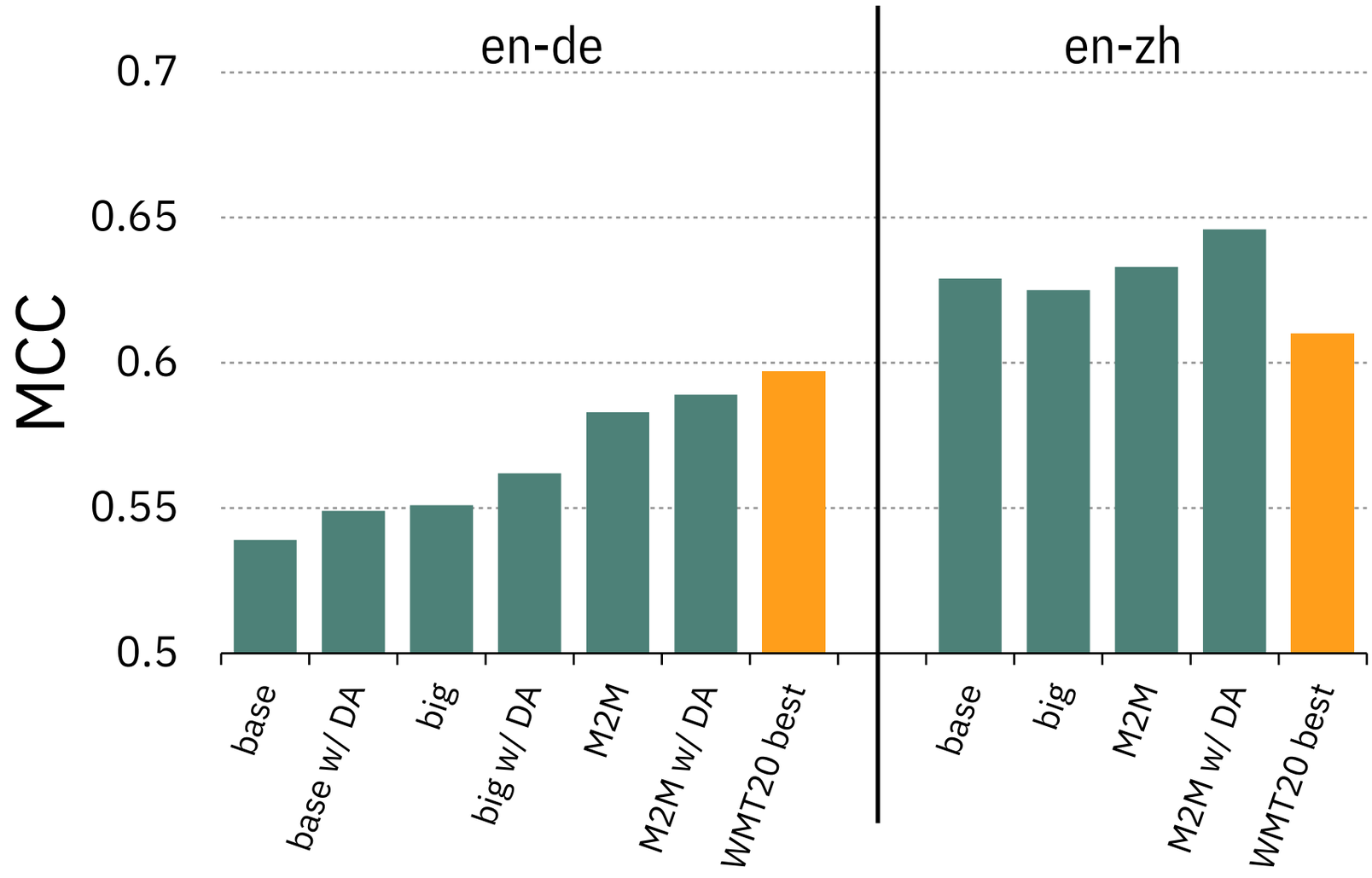
Experiments

- We evaluate under the WMT20 shared task setup
  - **En-De** and **En-Zh** language pairs
- Metric: Matthews Correlation Coefficient (**MCC**)
  - **higher is better**

Constrained Setting



Unconstrained Setting



Conclusion

- We propose to use **Levenshtein Transformer** for the task of **word-level QE**
- We propose a series of **fine-tuning procedures** to adapt the LevT model to match the input/output format of the word-level QE
- **Data-efficient**
- **Competitive result**

WMT21 QE Shared Task

- LevT-QE participated in **WMT21 QE shared task**
- Results are competitive, achieving the **1st place** in Word-MCC metric for en-de
- System paper: *The JHU-Microsoft Submission for WMT21 Quality Estimation Shared Task*
- **Thursday, Nov 11th, 10:30a – 12:00p AST**

Thanks!
Jobs@NYC?

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paper & code