MLQE-PE : A Multilingual Quality Estimation and Post-Editing Dataset

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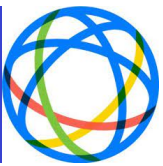
LREC, 2022









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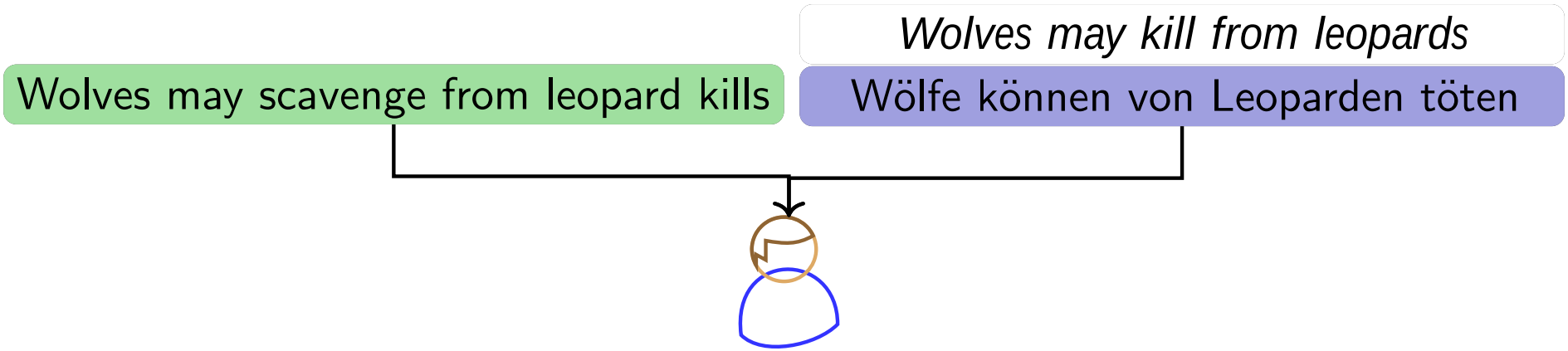

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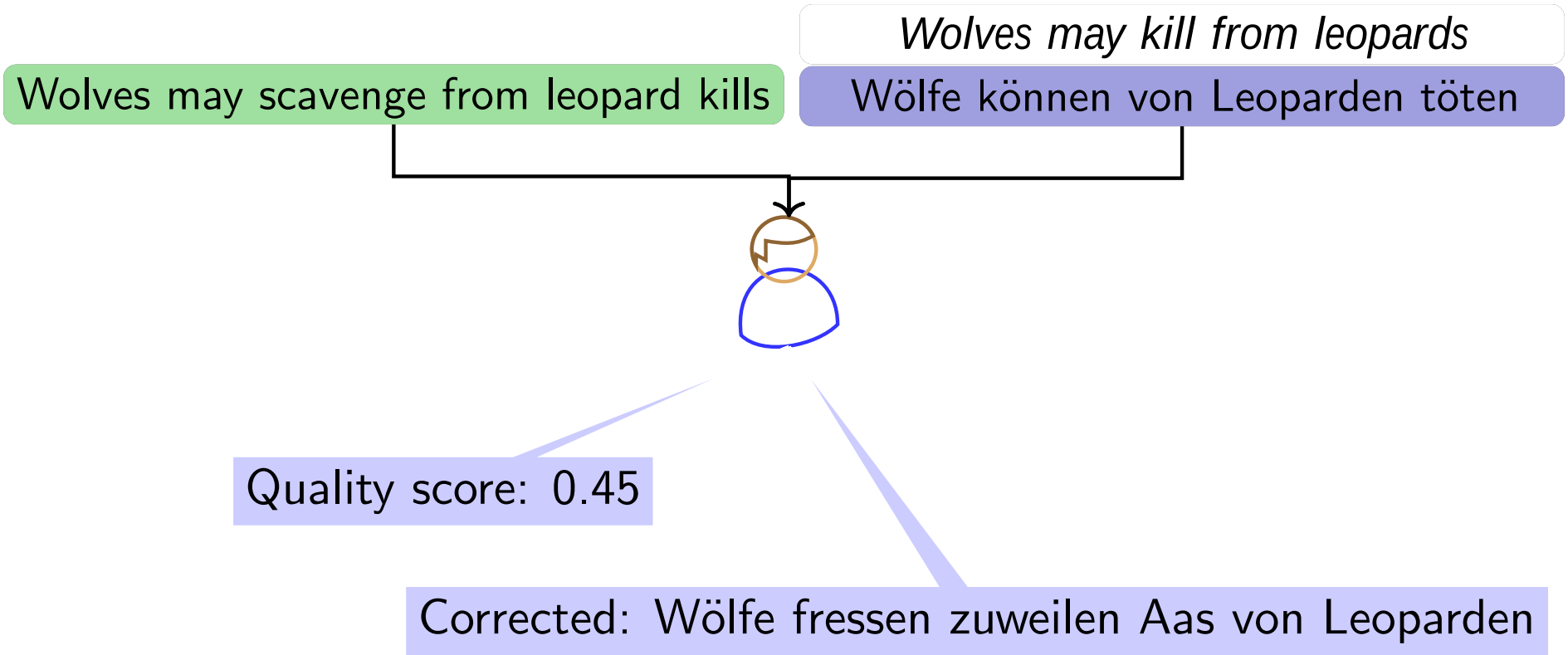

Why Quality Estimation?

Why Quality Estimation?

Wolves may scavenge from leopard kills

source sentence

Wölfe können von Leoparden töten

Wolves may kill from leopards

MT sentence

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Wolves sometimes eat carrion of leopards

human reference

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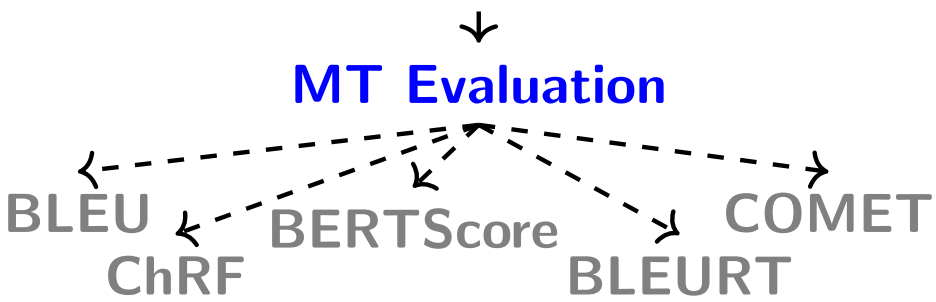

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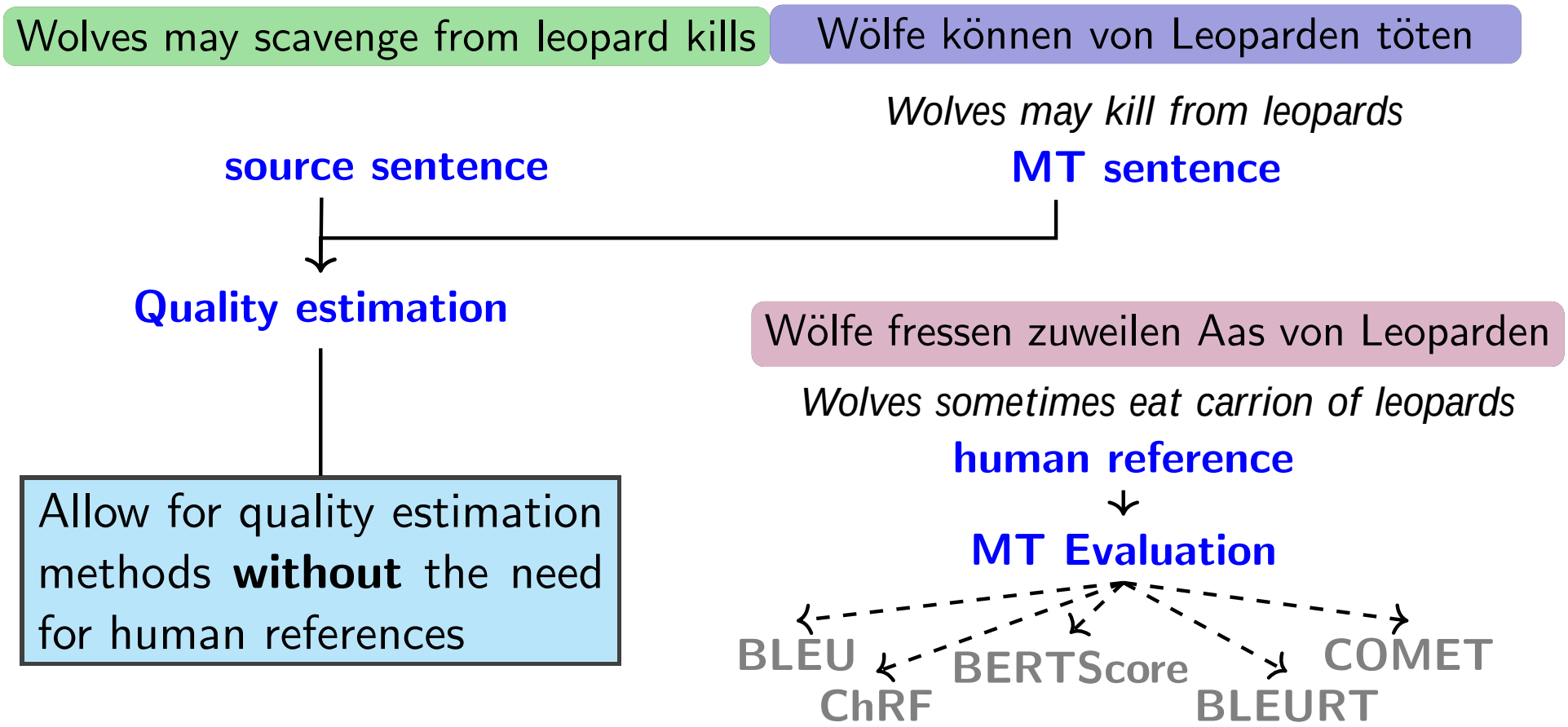

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MT Evaluation is not always possible/desired:

- Expensive and time consuming to obtain references
- On-the- y translation
  - Flag potentially critical errors
  - Decide which segments need human-editing
- Zero-shot applications:
  - Apply to low-resource languages
  - Adapt to domains without human references

MLQE-PE Quality Estimation Data Annotations

For each segment (source - MT sentence pair) we provide:

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  - 3 annotators per segment
  - mean z-score as final value
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  - Minimum number of edits needed to reach from the MT to the post-edited sentence
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Word level scores:

- Binary OK or BAD tags
  - On the target (MT) tokens: Wrong or irrelevant tokens
  - On the target gaps (between tokens): Missing tokens
  - On the source tokens: Mistranslated or non-translated tokens

Word-level tag extraction

How do we extract OK and BAD tags from post-edited sentences?

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How do we extract OK and BAD tags from post-edited sentences?

- Extract alignments between PE and MT, SRC
  - MT-PE ! Monolingual: TERcom
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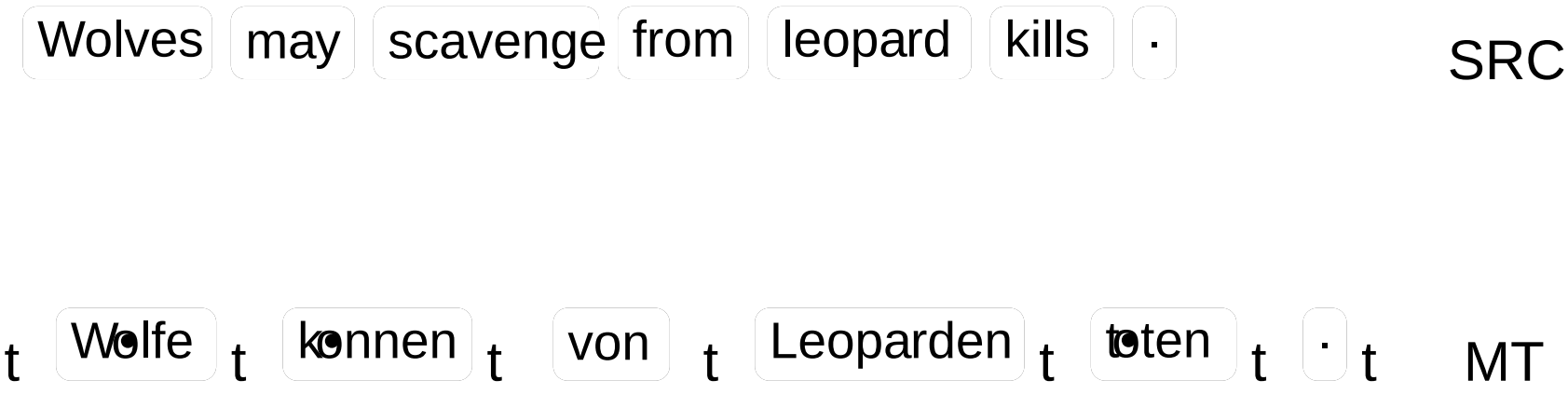

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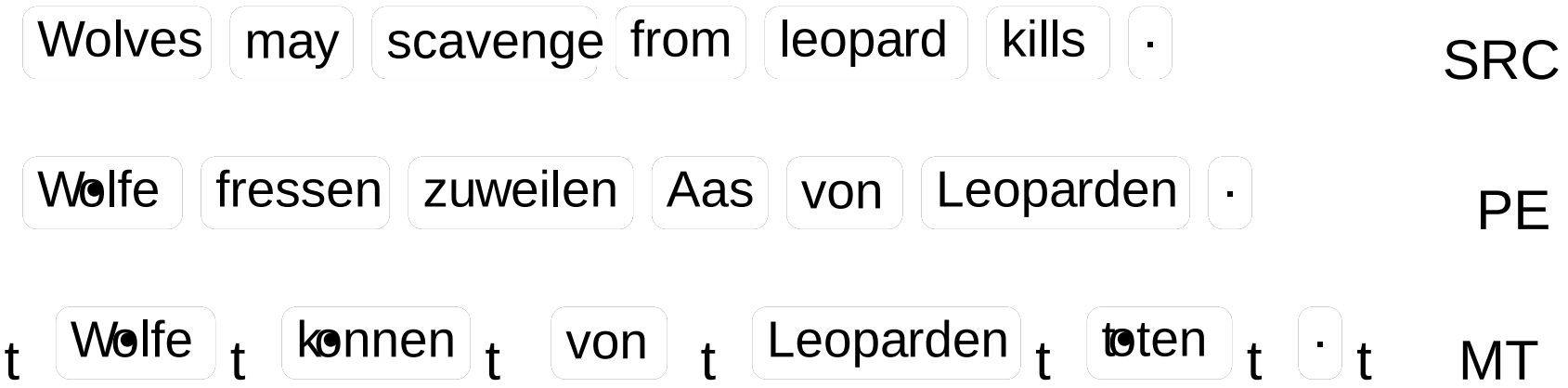

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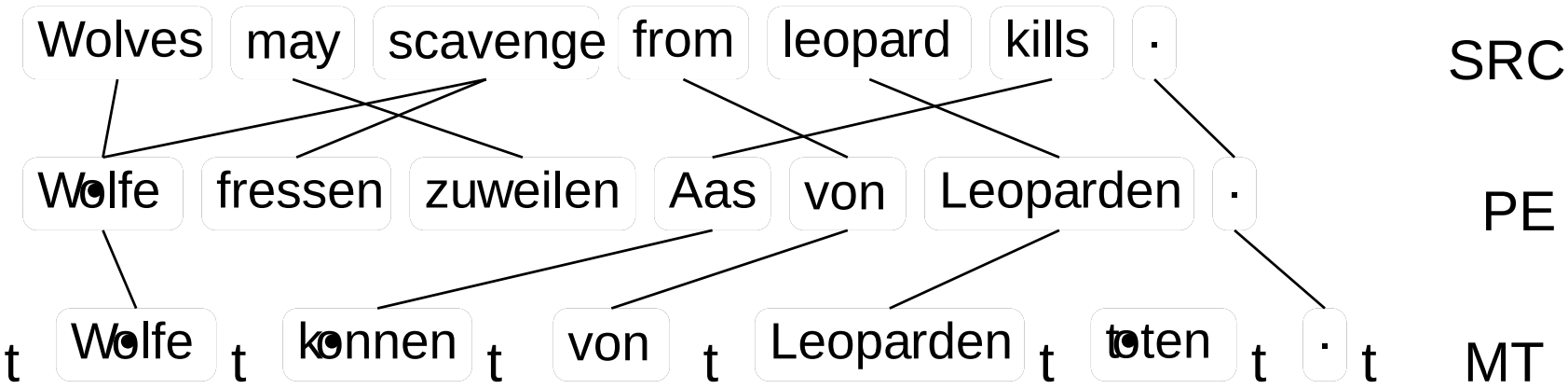

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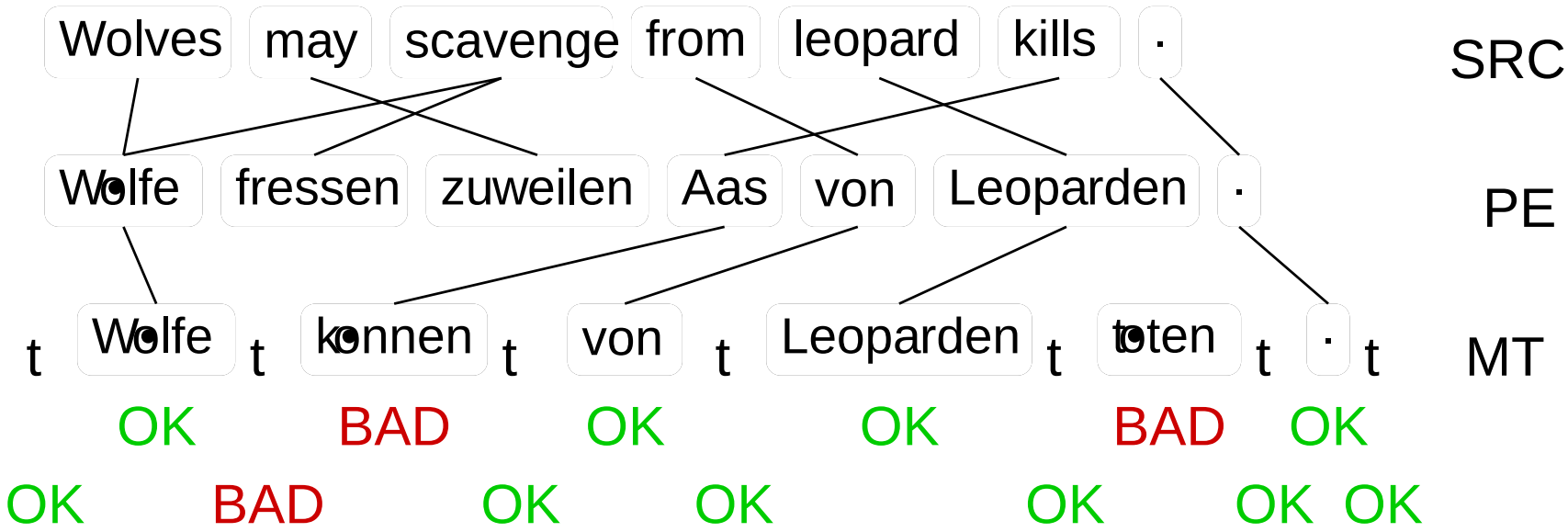

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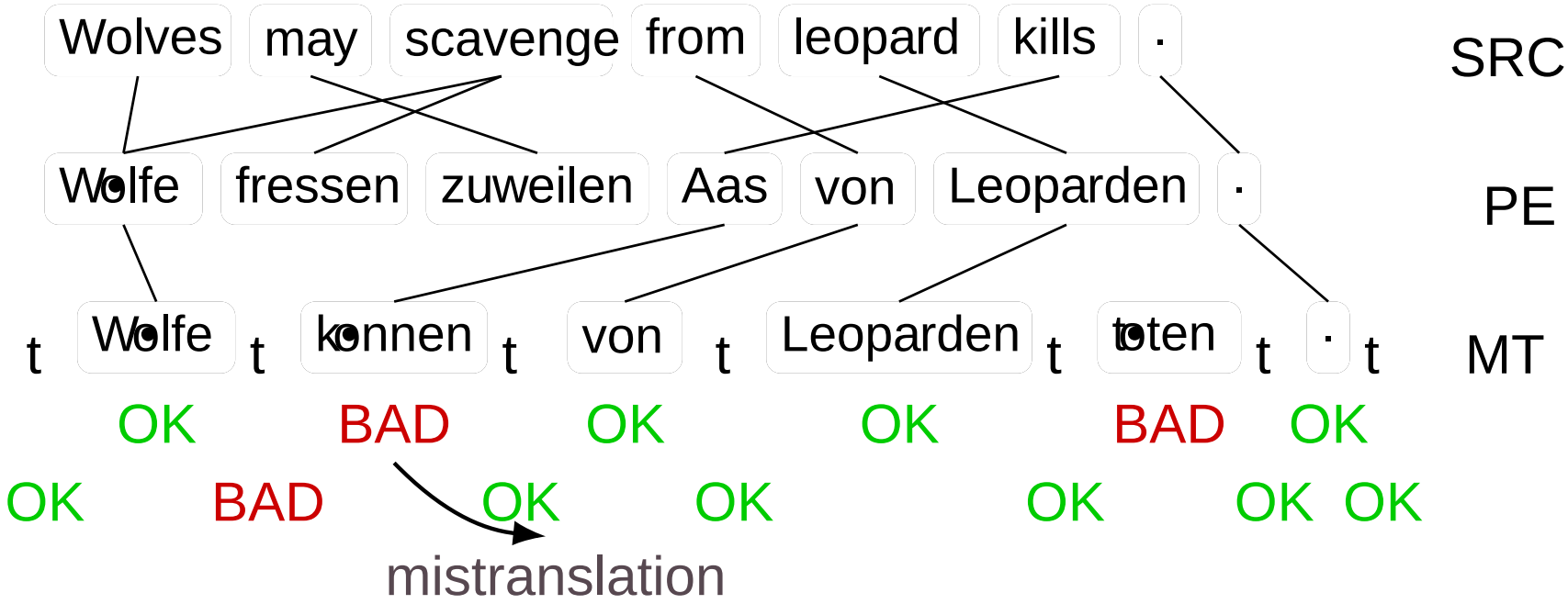

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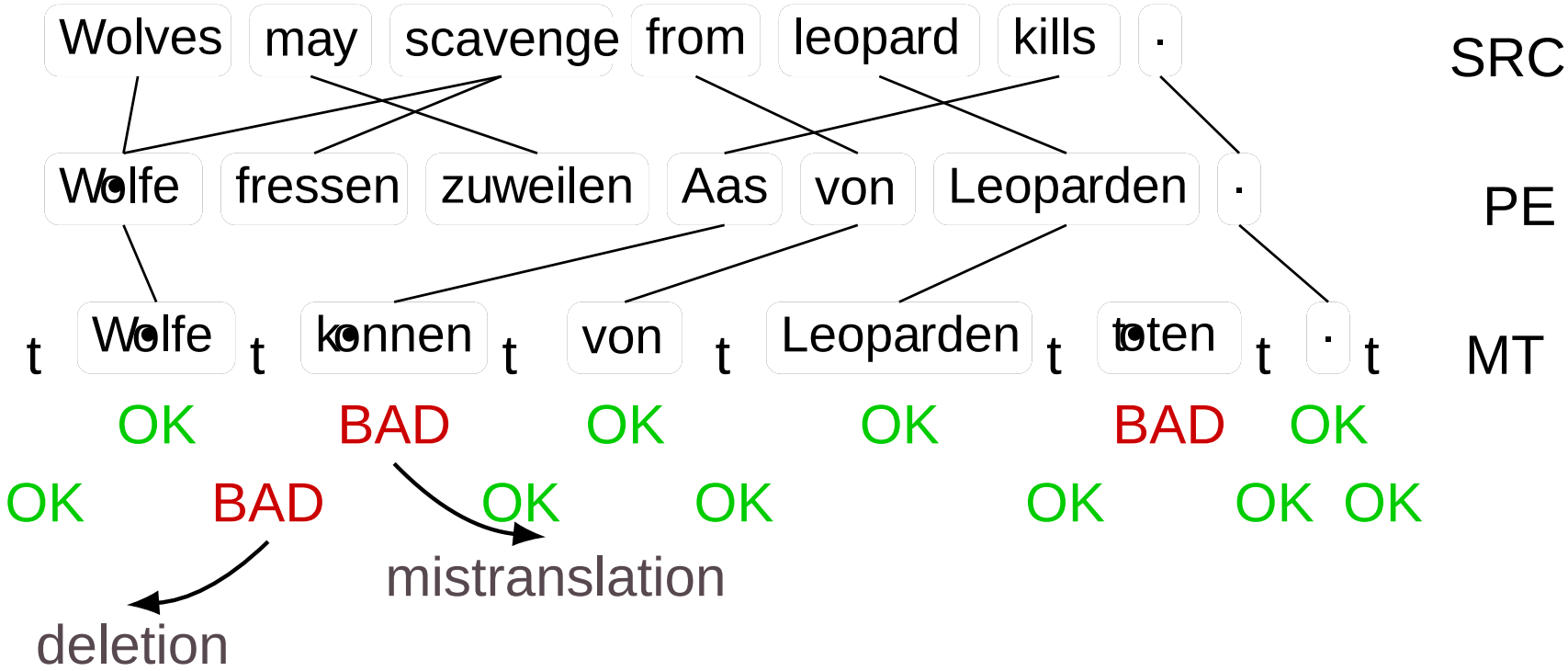

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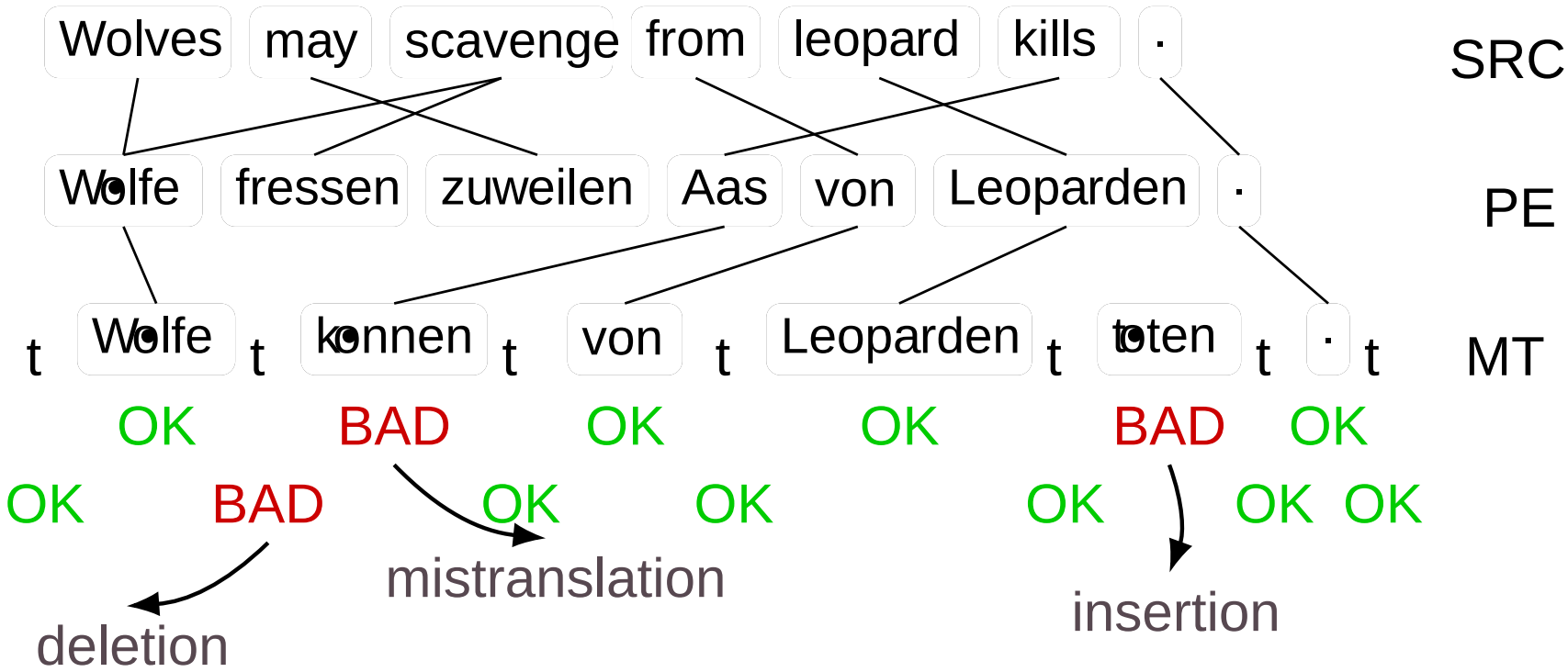

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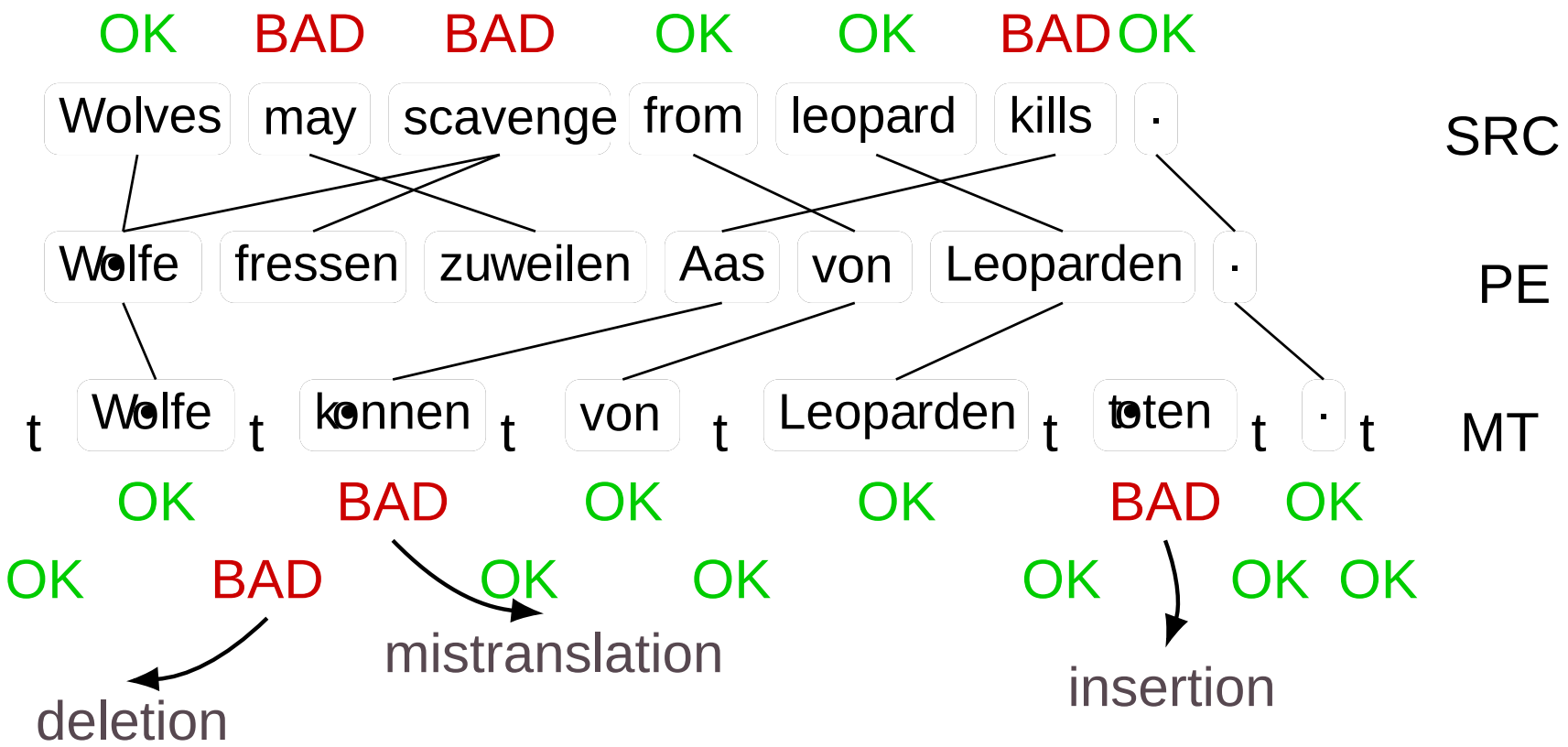

Annotations by language pair

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- Enable glass-box approaches
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→ motivate context aware approaches

X Useful features for quality estimation

DA-HTER score correlations

High-resource language pairs:

- Di erent score distributions
- HTER scores (horiz.) are skewed to zero
- Upper-left corner! high-quality translations

DA-HTER score correlations

Mid & Low resource language pairs:

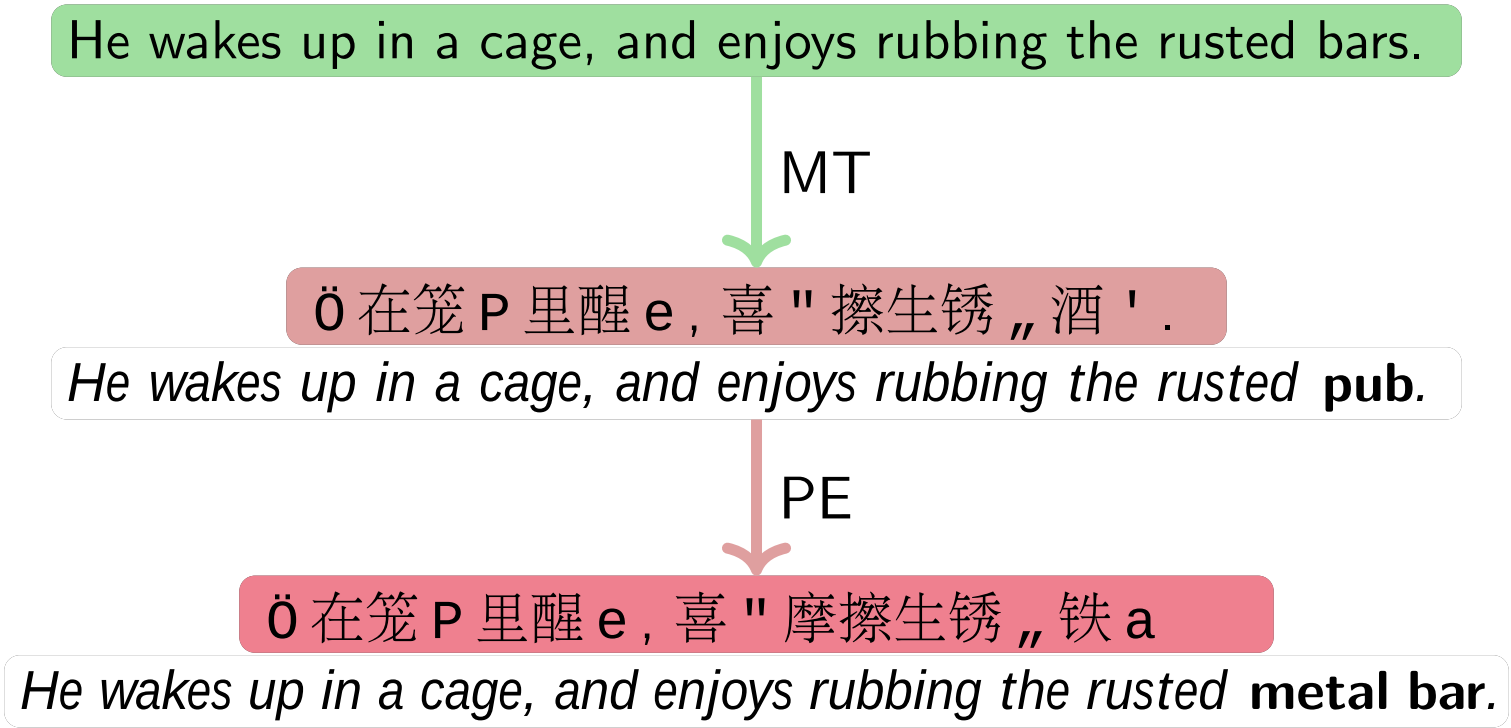
More on scores and correlations

	Avg. DA "	Avg. HTER #
En-De	82.61	0.18
Ro-En	69.18	0.24
En-Ja	67.96	0.36
En-Cs	66.94	0.26
En-Zh	62.86	0.23
Et-En	60.09	0.29
Ps-En	53.53	0.53
Si-En	51.42	0.59
Km-En	46.58	0.65
Ne-En	36.51	0.66
Ru-En	68.67	0.23

	Pearson	Spearman
En-De	-0.42	-0.48
Ro-En	-0.76	-0.71
En-Ja	-0.14	-0.11
En-Cs	-0.41	-0.46
En-Zh	-0.21	-0.16
Et-En	-0.61	-0.63
Ps-En	-0.71	-0.67
Si-En	-0.29	-0.28
Km-En	-0.49	-0.43
Ne-En	-0.54	-0.49
Ru-En	-0.51	-0.47

Discrepancies

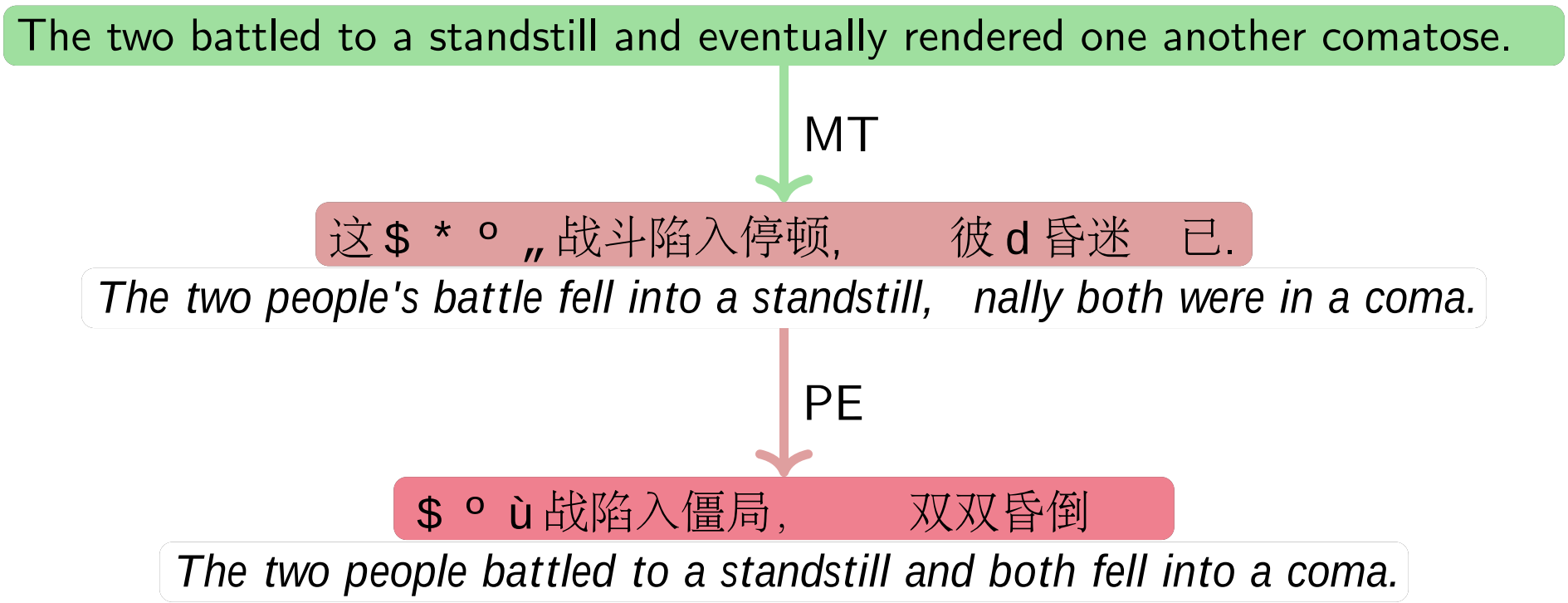
Case 1: Minimal post-editing



- Average DA score: 0.33 ! low quality
- HTER score from PE: 0.33 ! high quality

Discrepancies

Case 2: Heavy post-editing

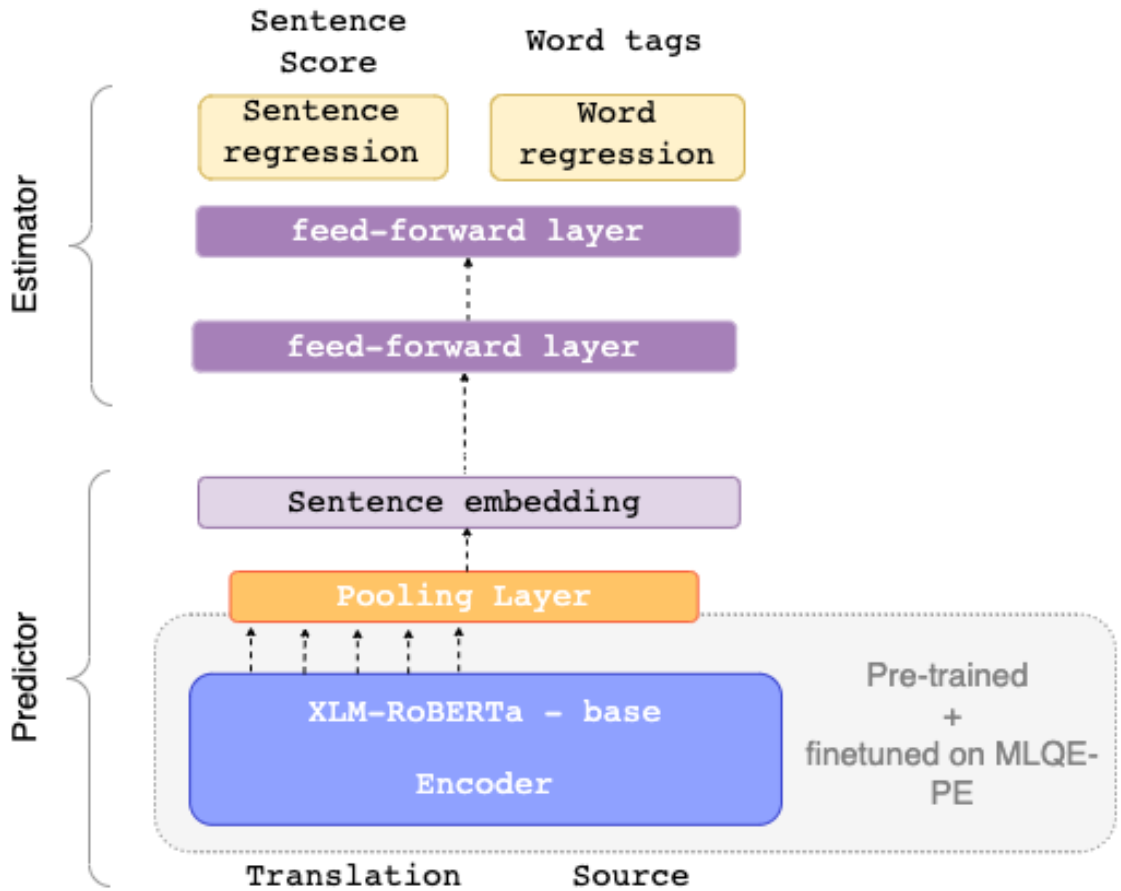


- Average DA score: 0.73 ! high quality
- HTER score from PE: 1.00 ! low quality

Baseline model

One of the main goals is to support the development of better QE models

- Predictor-Estimator architecture
  - Based on OpenKiwi
- Single head for sentence level DA
- Multitasking for:
  - Sentence-level HTER
  - Word-level tags



Baseline sentence-level results

Languages	Pearson r "	RMSE #
Direct Assessment		
En-De	0.403	0.433
En-Zh	0.525	0.534
Ru-En	0.677	0.492
Ro-En	0.818	0.408
Et-En	0.660	0.543
Ne-En	0.738	0.524
Si-En	0.513	0.626
En-Cs	0.352	0.686
En-Ja	0.230	0.617
Km-En	0.562	0.614
Ps-En	0.476	0.711
AVG	0.541	0.562

Languages	Pearson r "	RMSE #
HTER		
En-De	0.529	0.129
En-Zh	0.282	0.246
Ru-En	0.448	0.188
Ro-En	0.862	0.111
Et-En	0.714	0.149
Ne-En	0.626	0.160
Si-En	0.607	0.159
En-Cs	0.306	0.206
En-Ja	0.098	0.232
Km-En	0.576	0.196
Ps-En	0.503	0.290
AVG	0.502	0.188

Baseline word-level results

	Words in MT		Words in SRC	
Languages	MCC ″	F_1-Multi ″	MCC ″	F_1-Multi ″
En-De	0.370	0.415	0.322	0.363
En-Zh	0.247	0.308	0.241	0.295
Ru-En	0.256	0.319	0.251	0.292
Ro-En	0.536	0.553	0.511	0.539
Et-En	0.461	0.512	0.405	0.459
Ne-En	0.440	0.483	0.390	0.438
Si-En	0.425	0.456	0.335	0.379
En-Cs	0.273	0.372	0.224	0.312
En-Ja	0.131	0.217	0.175	0.272
Km-En	0.351	0.409	0.279	0.355
Ps-En	0.313	0.425	0.249	0.361
AVG	0.346	0.402	0.307	0.370

In practice

Already used:

In practice

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- X WMT Quality Estimation Shared Tasks
  - 2020 Edition: En-De, En-Zh, Et-En, Ne-En, Ro-En, Ru-En, Si-En
  - 2021 Edition: En-De, En-Zh, Et-En, Ne-En, Ro-En, Ru-En, Si-En, En-Cs, En-Ja, Km-En, Ps-En

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- X Eval4NLP Explainable Quality Estimation Task
  - 2021 Edition: Et-En, Ro-En

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Maybe also:

- I Catastrophic error detection
- I Active learning approaches
- I Context-aware quality estimation

That's not all

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- X Contribute resources:
  - New language pairs (especially low-resource)
  - New domains - challenge sets
  - Additional annotations - references
- X Use
  - New tasks
  - Compare performance on existing tasks
- X Provide feedback :)