Embarrassingly Easy Document-Level MT Metrics: How to Convert Any Pretrained Metric Into a Document-Level Metric

IST & Unbabel seminar

EPFL

Amazon AI

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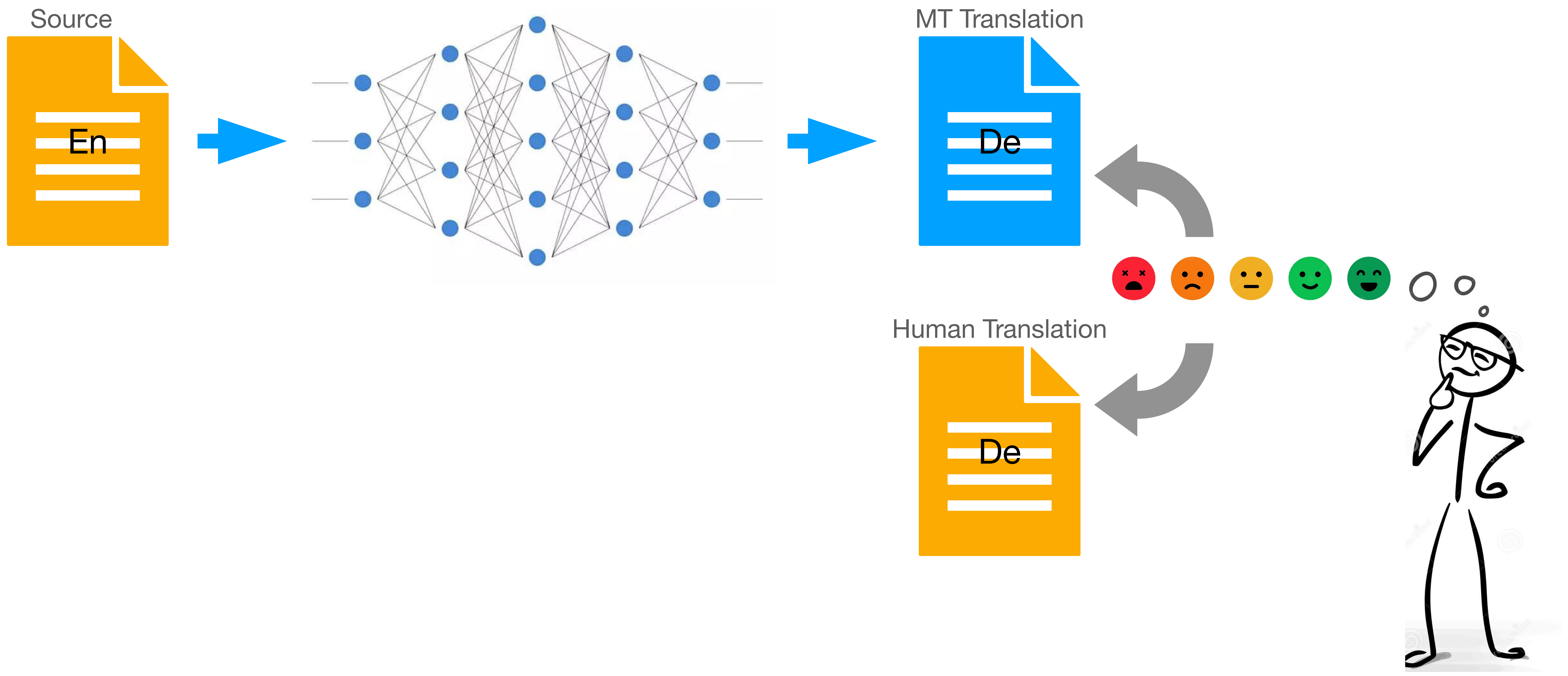
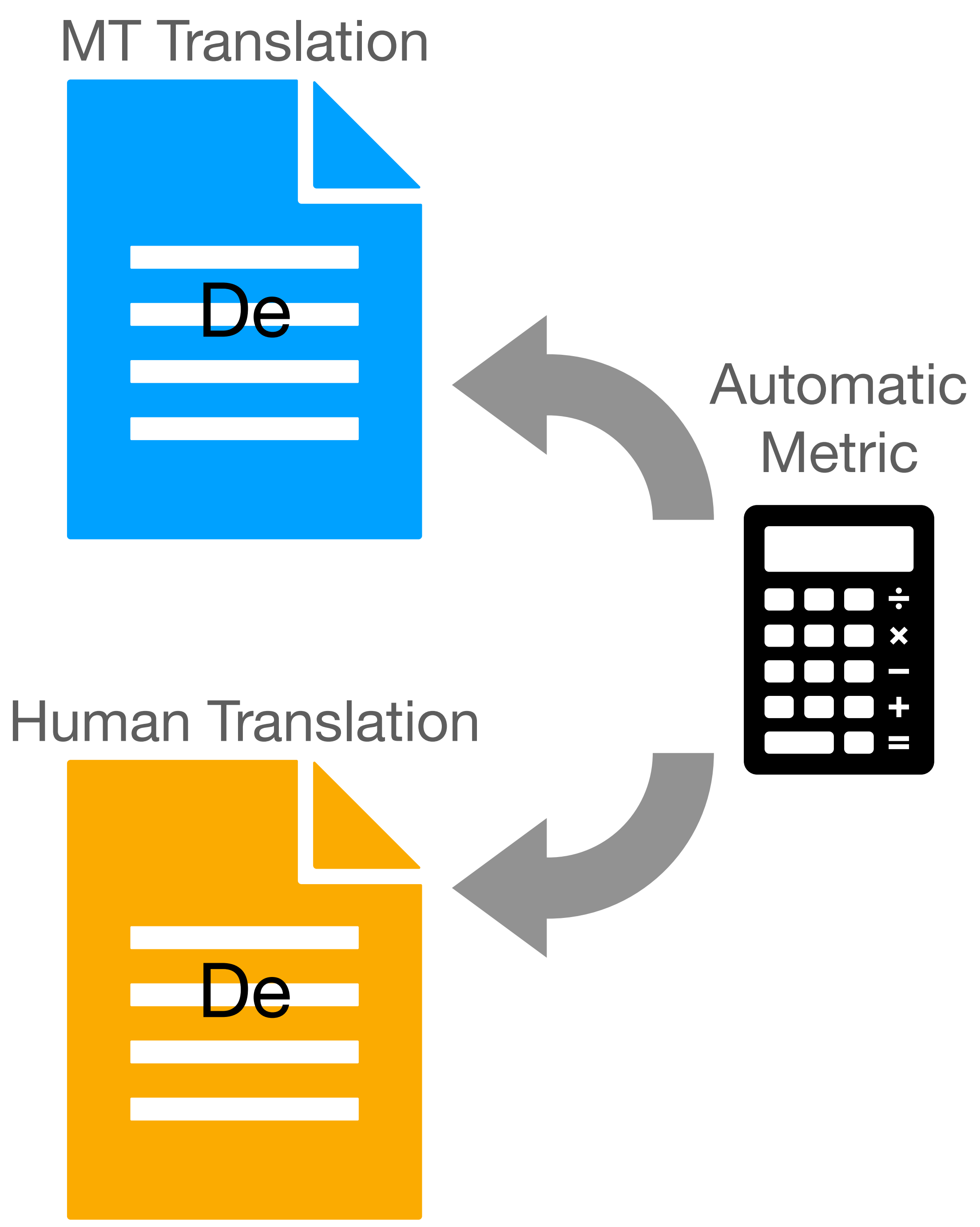
Evaluation of Machine Translation



Evaluation of Machine Translation

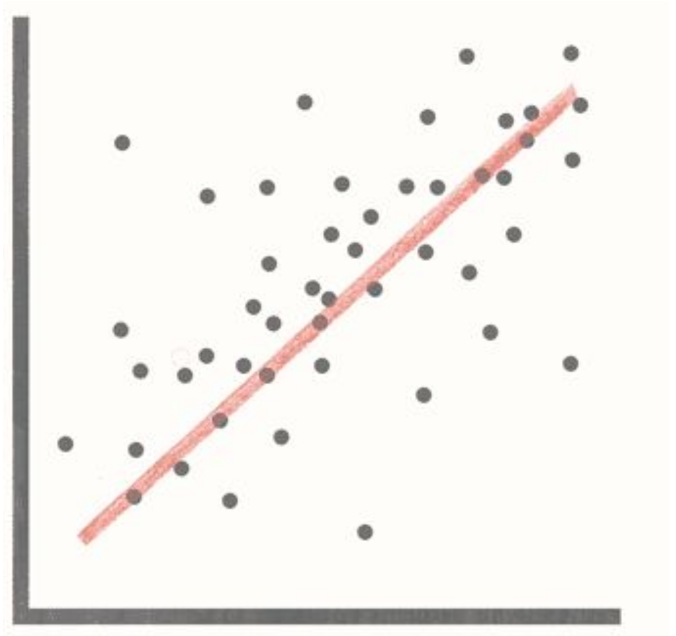


- Classic, n-gram matching metrics: BLEU[1], ChrF[2], TER[3]

- Recent, learnable metrics: BERTScore[4], COMET[5], Prism[6]

Evaluation of Evaluation of Machine Translation

	Human Score (↑)	Metric Score (↑)
Brand in französischem Chemiewerk gelöscht		
Fire extinguished in French chemical plant		
Fire extinguished at French chemical plant	0.57	37.99
Fire at French chemical plant extinguished	0.65	53.73
Brand in French chemistry	-1.83	19.38



Evaluation of Evaluation of Machine Translation

Fire extinguished in French chemical plant

Brand in French chemistry

BLEU
ChrF
TER

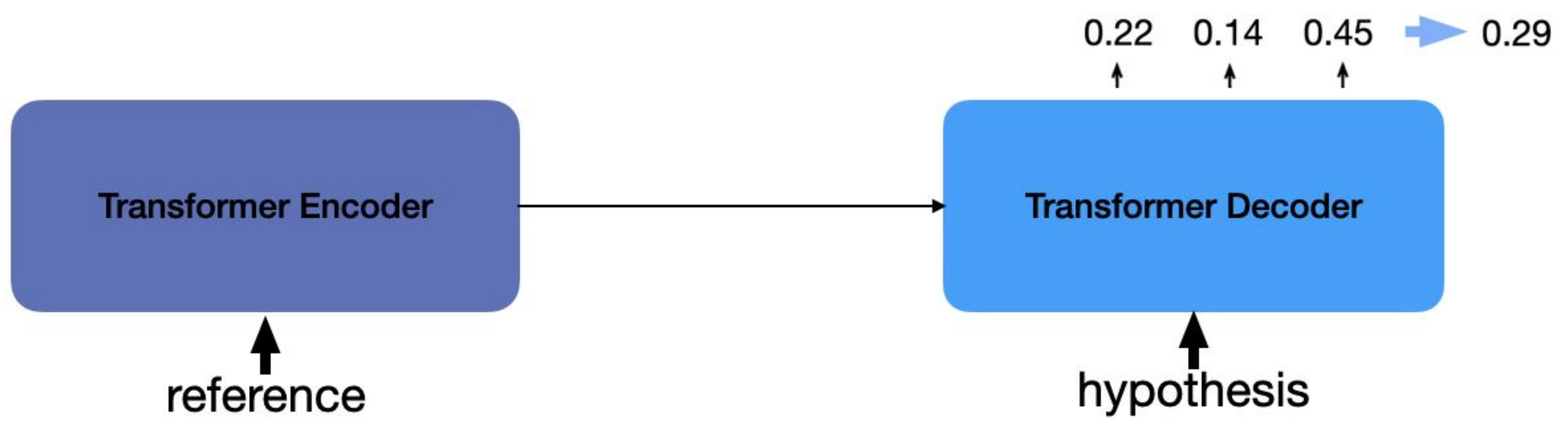
Why do we need all these metrics ???

Traditional metrics like BLEU demonstrate poor correlation with human judgements that can even be negative when looking at the top *k* systems[7].

Evaluation of Evaluation of Machine Translation

State-of-the-art metrics use representations from pretrained Language Models or MT systems to evaluate MT outputs

Prism



BERTScore

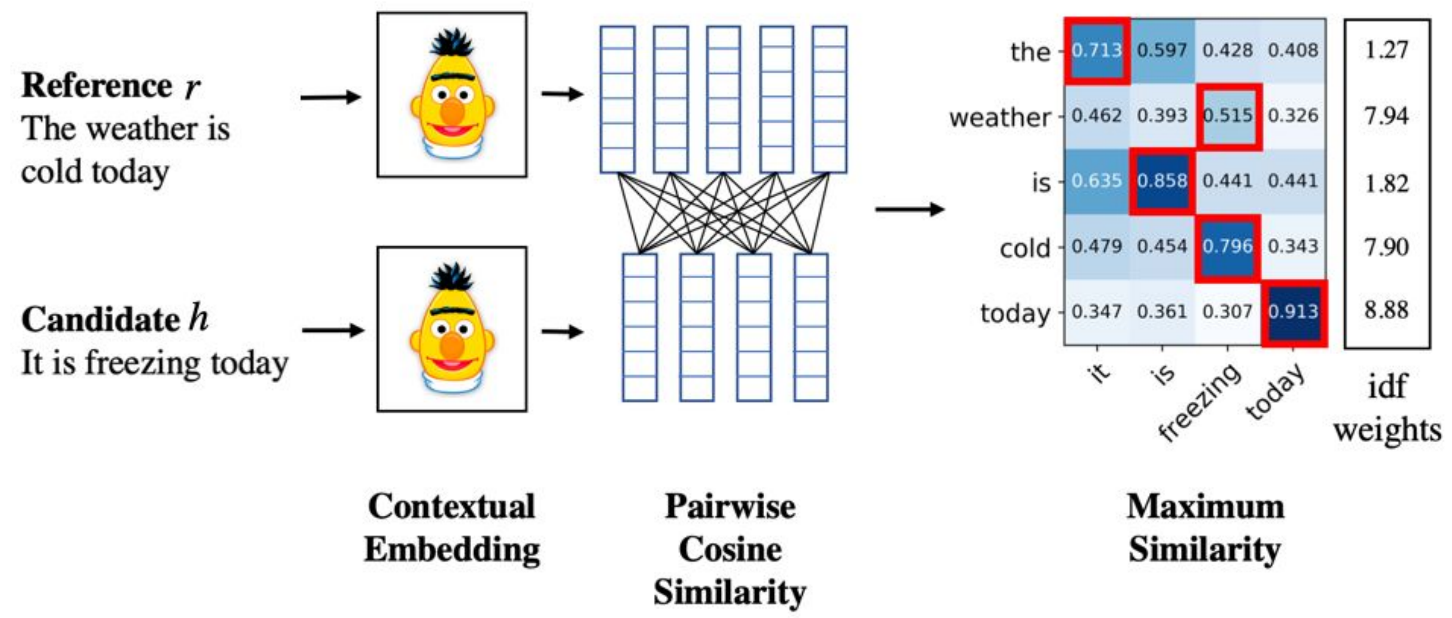


Figure from [4].

COMET(-QE)

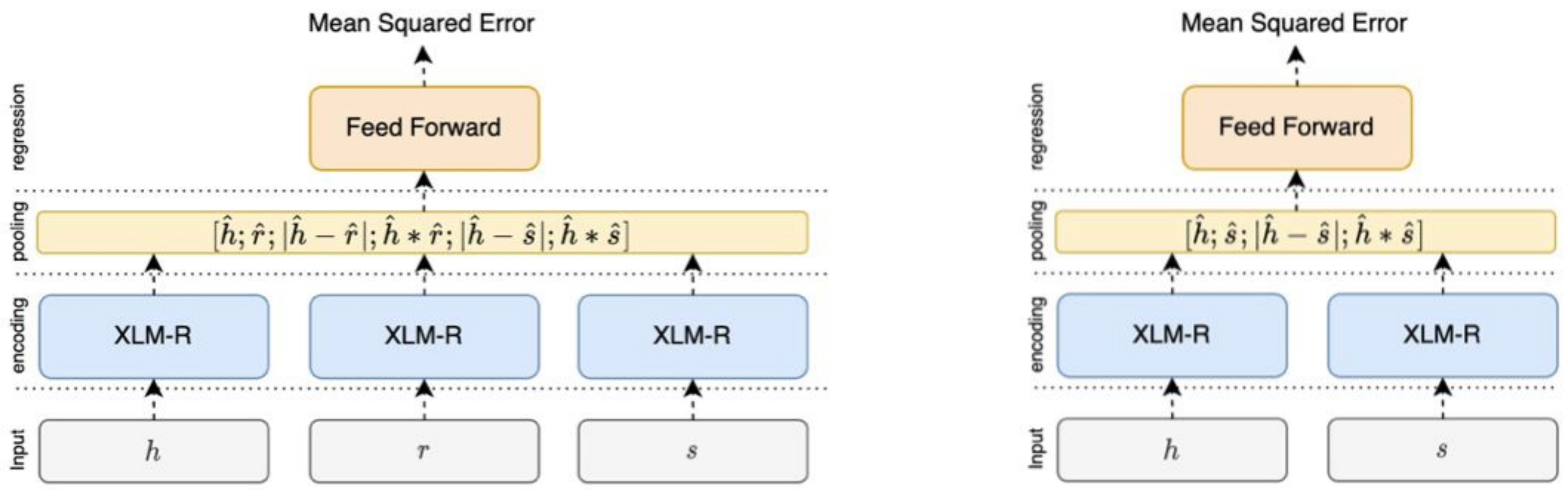


Figure from [5].

Evaluation of Evaluation of Machine Translation

Fire extinguished in French chemical plant

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Prism
BERTScore
COMET

Why do we need all these metrics ???

Metrics that use contextual representations from neural networks have been shown to correlate better with humans[7]!

What is still missing ???

Problem Formulation

Sentences can be ambiguous when judged in isolation !

source-based evaluation

pronoun translation

sent1	I put it in my car.	what is "it"?
+1 pr.	What did you do with the suitcase? I put it in my car.	it=SUITCASE

Figure from [8].

disambiguation

sent2	Yes, she did.	main verb?
+1 pr.	Did she give you any? Yes, she did.	main verb=GIVE what is "any"?
+2 pr.	So you went to your wife for money. Did she give you any? Yes, she did.	main verb=GIVE any=MONEY

Figure from [8].

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Figure from [8].

reference-based evaluation

~~pronoun translation~~

disambiguation

system	translation
human	There are too many bugs.
system1	There are too many **insects**.
system2	There are too many **flaws**.
system3	There are too many **hidden microphones**.

Problem Formulation

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Figure from [8].

reference-based evaluation

~~pronoun translation~~

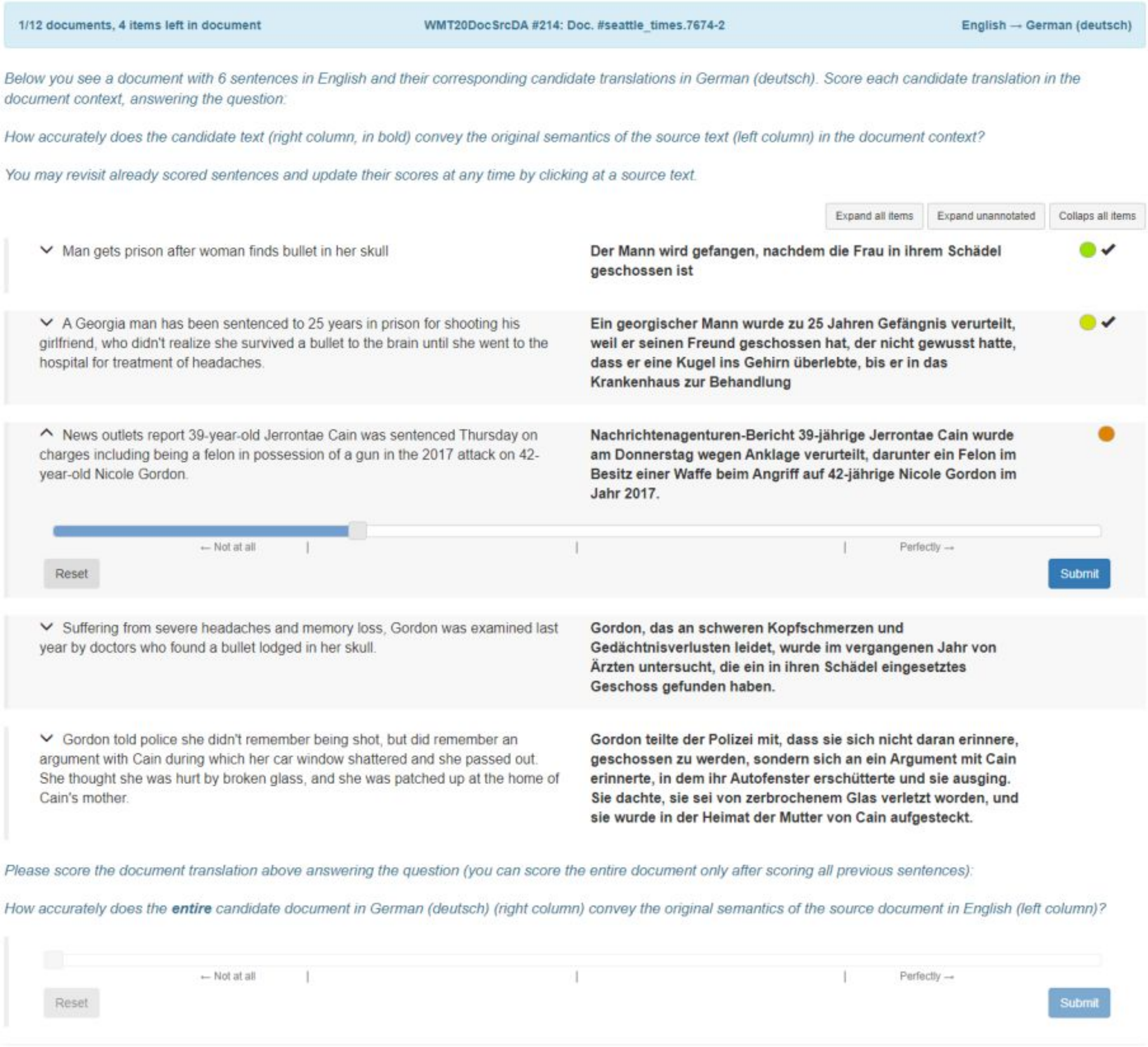
disambiguation

system	translation		
human	There are too many bugs.	+1 pr	Do you ever clean this house?
system1	There are too many **insects**.	✓	
system2	There are too many **flaws**.	✗	
system3	There are too many **hidden microphones**.	✗	

Problem Formulation

Evaluating at the sentence level is **misleading**: MT systems appear to perform better and even reach human parity[10]

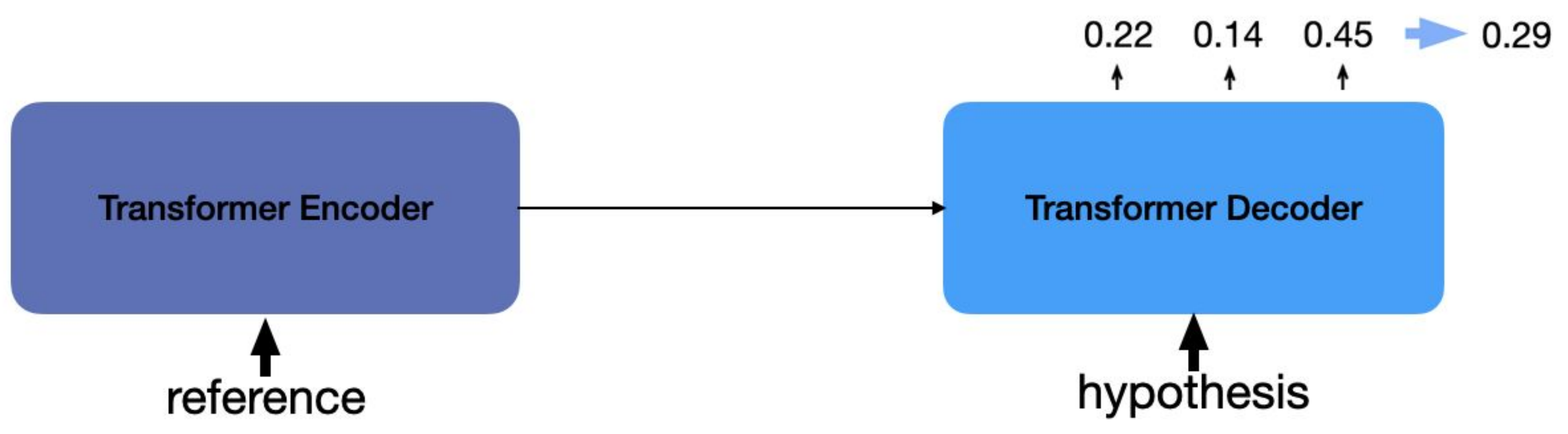
Best practices for human evaluation of MT have been revised and now annotators are <u>strongly advised</u> to take context into account[11]!

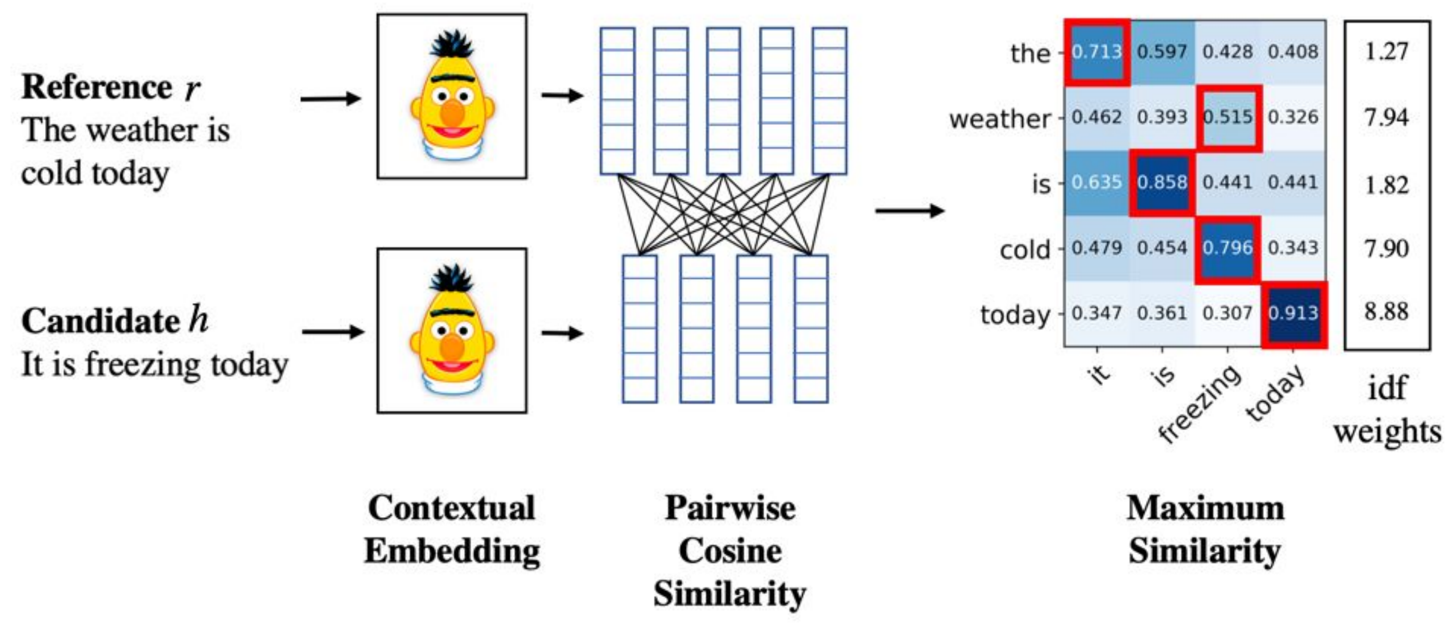


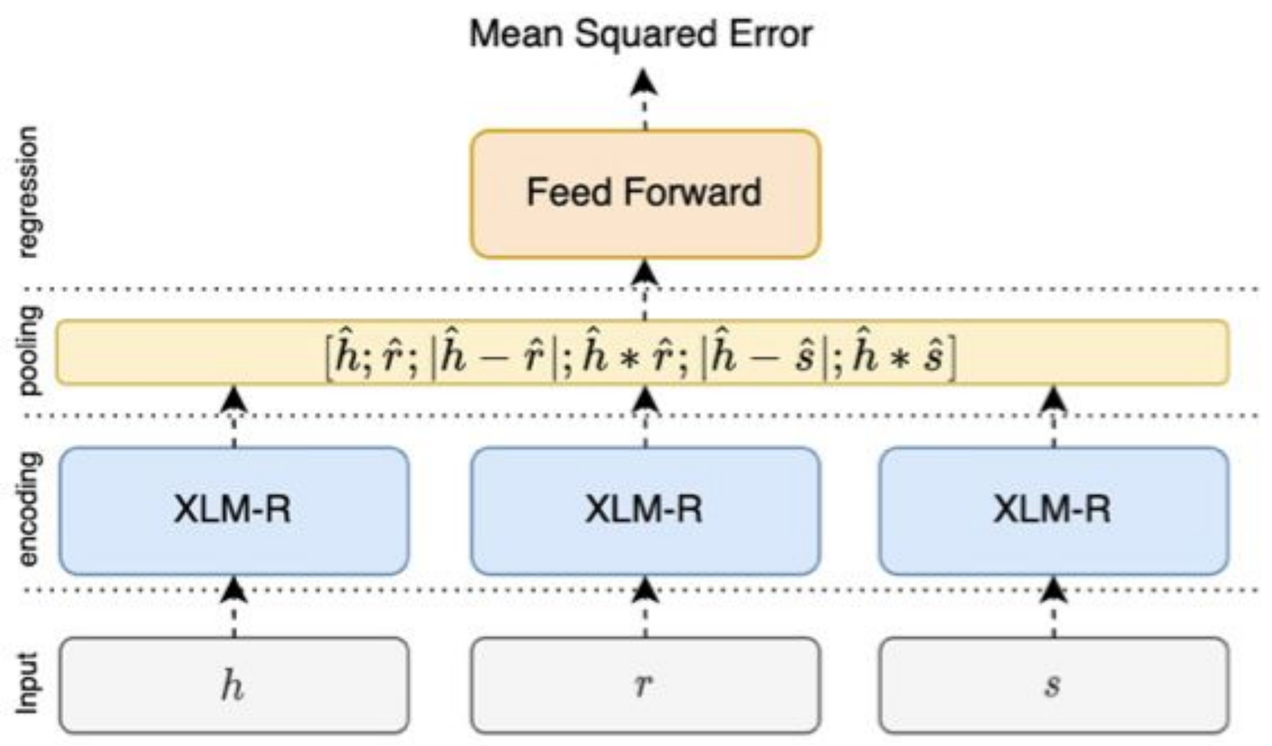
Appraise interface from [9].

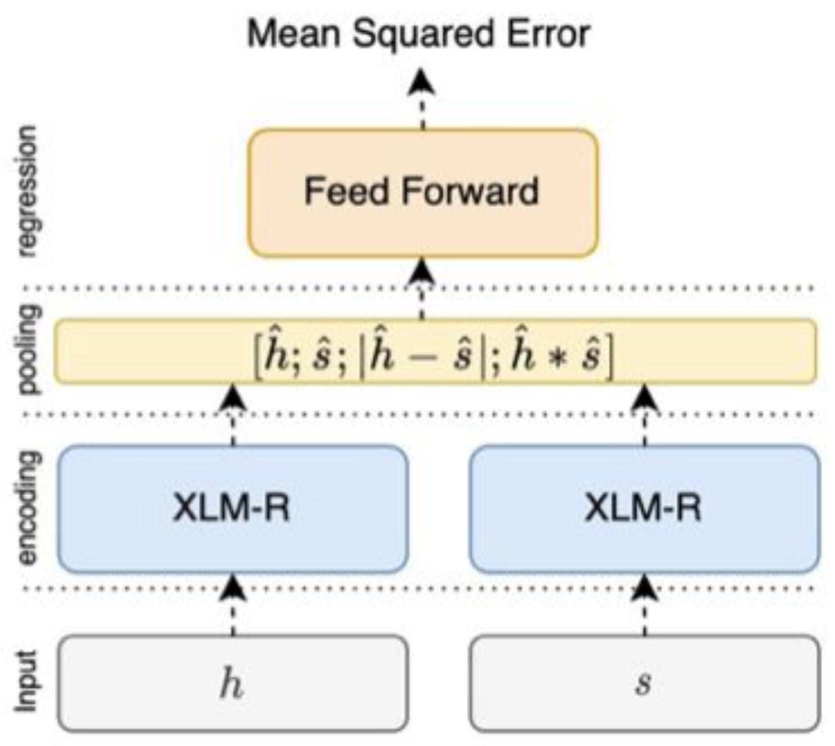
Problem Formulation

Overlap-based and learned metrics still operate on the **sentence-level**









How can we incorporate context into learned metrics?

Related Work

Document-level context has also been proven useful for MT systems

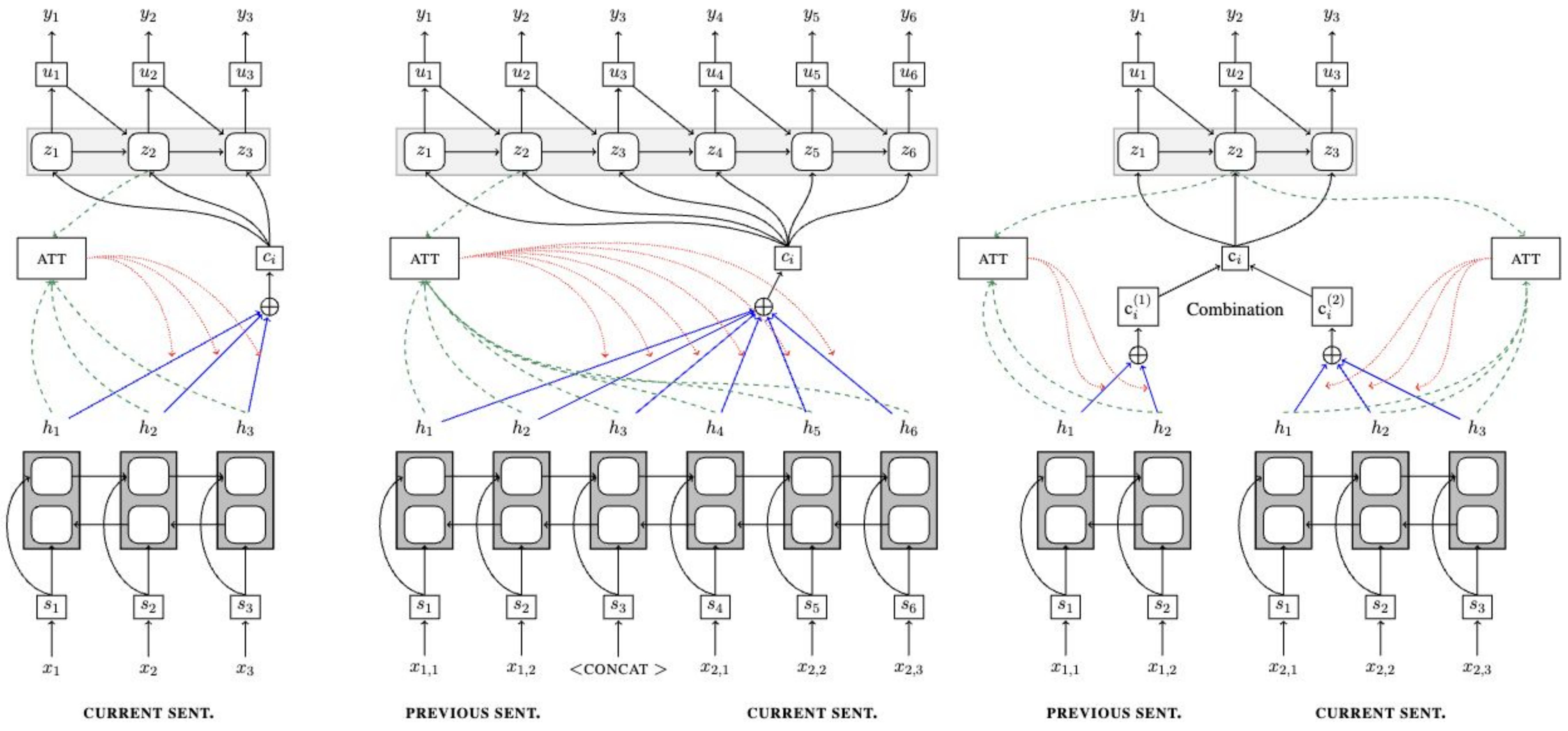


Figure from [12].

- Different ways to encode context: concatenation, encoders, gating
- Unclear if translation quality improves: human evaluation or targeted datasets[14]

Related Work

Context usage is mostly <u>unexplored</u> in automatic MT metrics

		ENTITY $\mathcal{E}$	TENSE $\mathcal{V}$	PRONOUN $\mathcal{P}$	DM $\mathcal{M}$
SRC	a) 小乔(Qiao) 看着(*look*) 相片回忆(*recall*) 起了二十年前。 b) 那个满脸胡须的男人(man) 正是(*be*)她(she) 的新婚丈夫。 c) 那却是(*be*) 他们之间初次见面(*meet*)。 d) 小乔(Qiao)一见到他(he) 心里就咯噔(*jolt*) 了一下，噌的站(*stand*) 起来。	⟦Qiao⟧	[VBD, VBZ]	[masculine, feminine, epicene, neuter]	[contigency, temporal, expansion, comparison]
REF	a) **Qiao** ***looked*** at the photo and ***recalled*** twenty years ago.	[1]	[2, 0]	[0, 0, 0, 0]	-
	b) This bearded **man** ***was*** **her** newlywed **husband**,	[0]	[1, 0]	[0, 1, 0, 0]	[0, 0, 0, 0]
	c) ⟦yet⟧ this ***was*** the first time they ***were meeting*** with each other.	[0]	[2, 0]	[0, 0, 1, 0]	[0, 0, 0, 1]
	d) ⟦So⟧ **Qiao**'s heart ***jolted*** as soon as ⟦she⟧ saw **him**, and ⟦she⟧ quickly ***stood*** up.	[1]	[2, 0]	[1, 2, 0, 0]	[1, 0, 0, 0]
MTA	a) **Qiao** ***looked*** at the photo and ***recalled*** twenty years ago.	[1]	[2, 0]	[0, 0, 0, 0]	-
	b) This bearded **man** ***is*** **her** newlywed **husband**.	[0]	[0, 1]	[0, 1, 0, 0]	[0, 0, 0, 0]
	c) This ***is*** the first time they ***meet*** with each other.	[0]	[0, 2]	[0, 0, 1, 0]	[0, 0, 0, 0]
	d) **Joe**'s heart ***is*** squeaky as soon as ⟦he⟧ saw **him**, and ⟦he⟧ quickly ***stands*** up.	[0]	[0, 2]	[3, 1, 0, 0]	[0, 0, 0, 0]
MTB	a) **Qiao** ***looked*** at the photo and ***recalled*** the past twenty years ago.	[1]	[2, 0]	[0, 0, 0, 0]	-
	b) This **man** with the beard ***was*** **her** newly-wed **husband**.	[0]	[1, 0]	[0, 1, 1, 0]	[0, 0, 0, 0]
	c) ⟦However⟧, that was the first time they *met*.	[0]	[2, 0]	[0, 0, 1, 0]	[0, 0, 0, 1]
	d) ⟦So⟧ as soon as **Qiao** saw **him**, ⟦her⟧ heart ***became*** squeaky, and ⟦she⟧ swiftly ***stood*** up.	[1]	[2, 0]	[1, 2, 0, 0]	[1, 0, 0, 0]

BlonDe: an overlap-based document-level MT metric for English that focuses on discourse phenomena[15]

Document-level MT Metrics

Simple and **effective** approach -> add context during inference:

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Instead of just using source hypothesis and reference
concatenate source, hypothesis and reference context

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- No retraining
- No document-level human annotations

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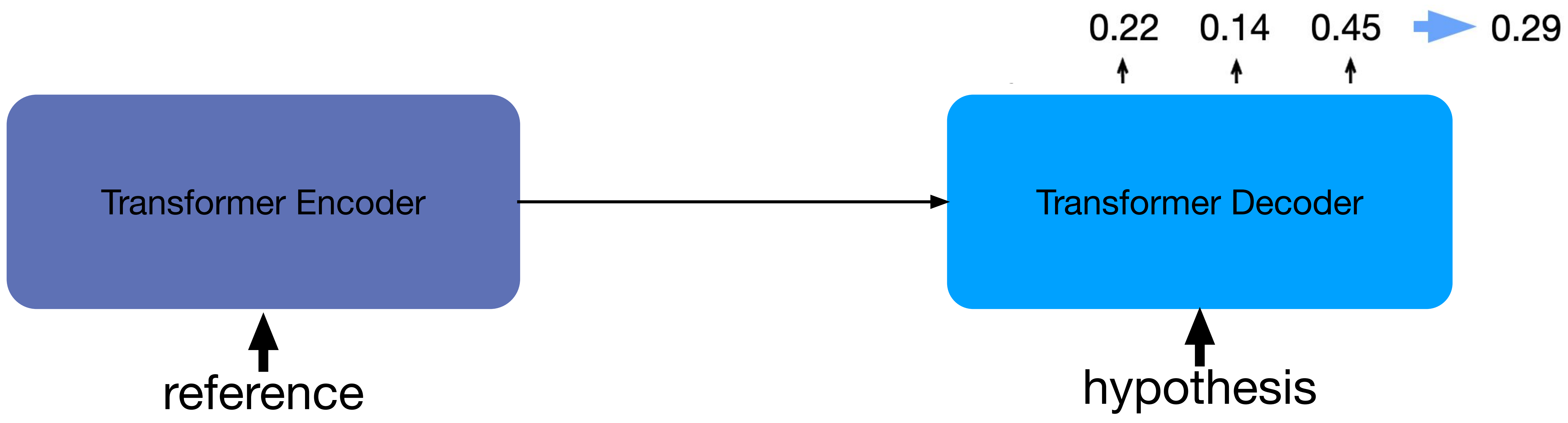
Score one sentence at a time using document-level context

Document-level MT Metrics

Simple and **effective** approach -> add context during inference:

Prism

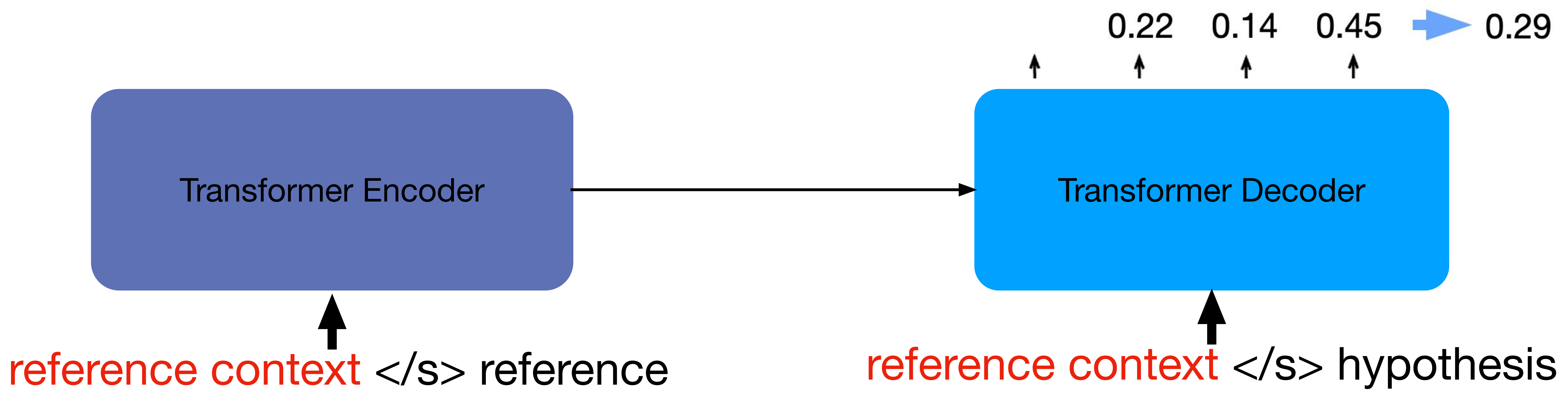


- Test whether the hypothesis is a paraphrase of the reference and vice versa
- A multilingual MT model that was trained at the sentence level as the paraphrase model (m39v1)

Document-level MT Metrics

Simple and **effective** approach -> add context during inference:

Document-level **Prism**

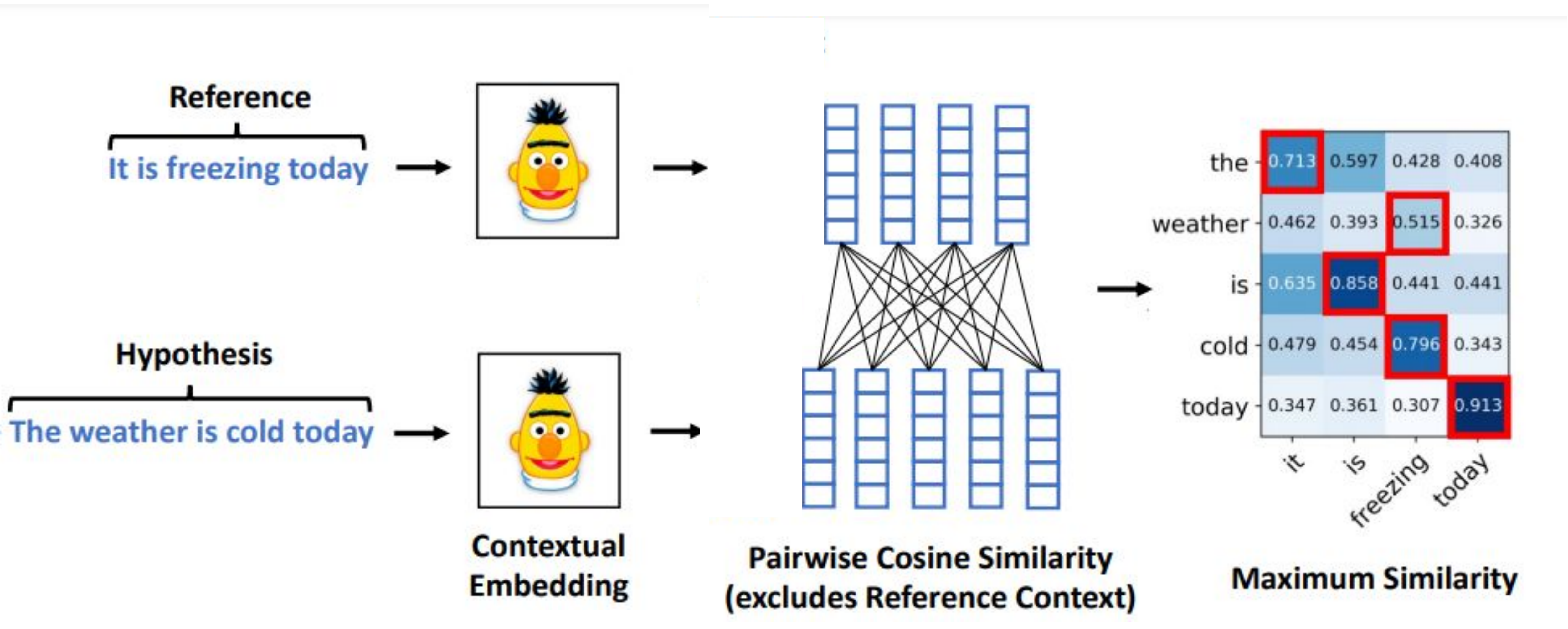


- We use mBART-50[16] a multilingual LM that was trained at the document level as the paraphrase model
- We concatenate the reference context to both the encoder and decoder
- We only compute token-level probabilities for the sentence we want to score

Document-level MT Metrics

Simple and **effective** approach -> add context during inference:

BERTScore

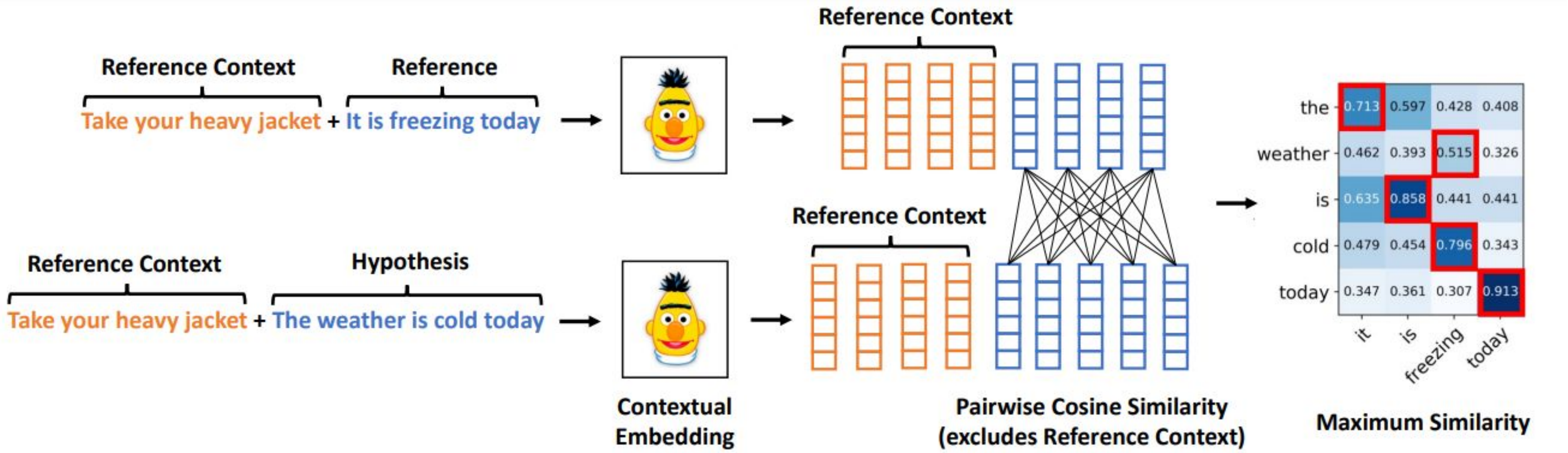


- Contextual embeddings from BERT
- Soft-alignment between words
- Greedy matching from matrix to calculate precision, recall and F1

Document-level MT Metrics

Simple and **effective** approach -> add context during inference:

Document-level **BERTScore**



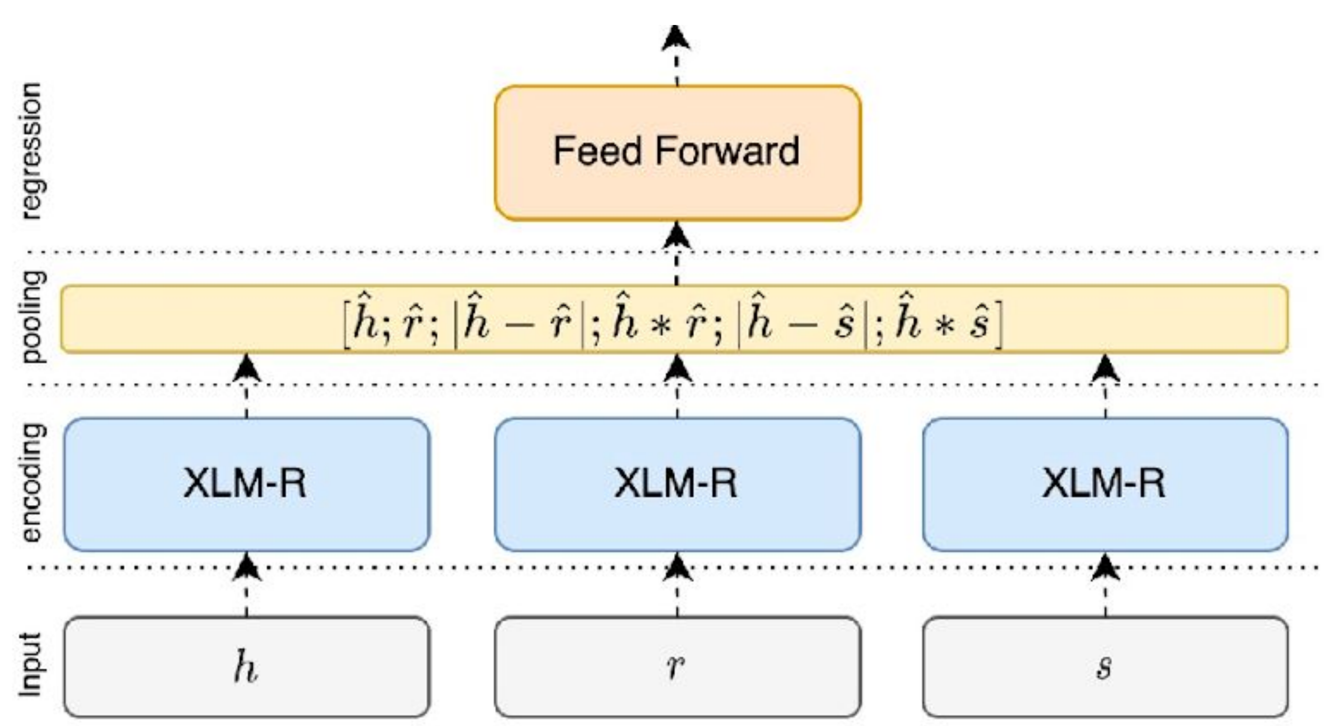
- We concatenate the reference context when encoding the reference or the hypothesis with the LM
- We only align the tokens of the current sentence by setting all the other similarity scores to zero
- BERT is pretrained on chunks of text (512 tokens)

Document-level MT Metrics

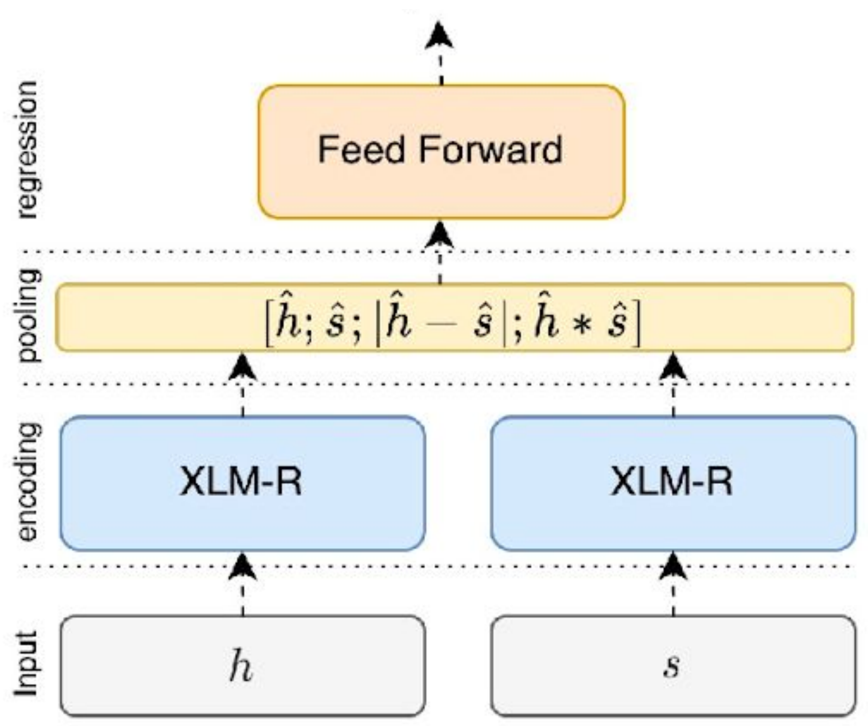
Simple and **effective** approach -> add context during inference:

COMET

COMET



COMET-QE

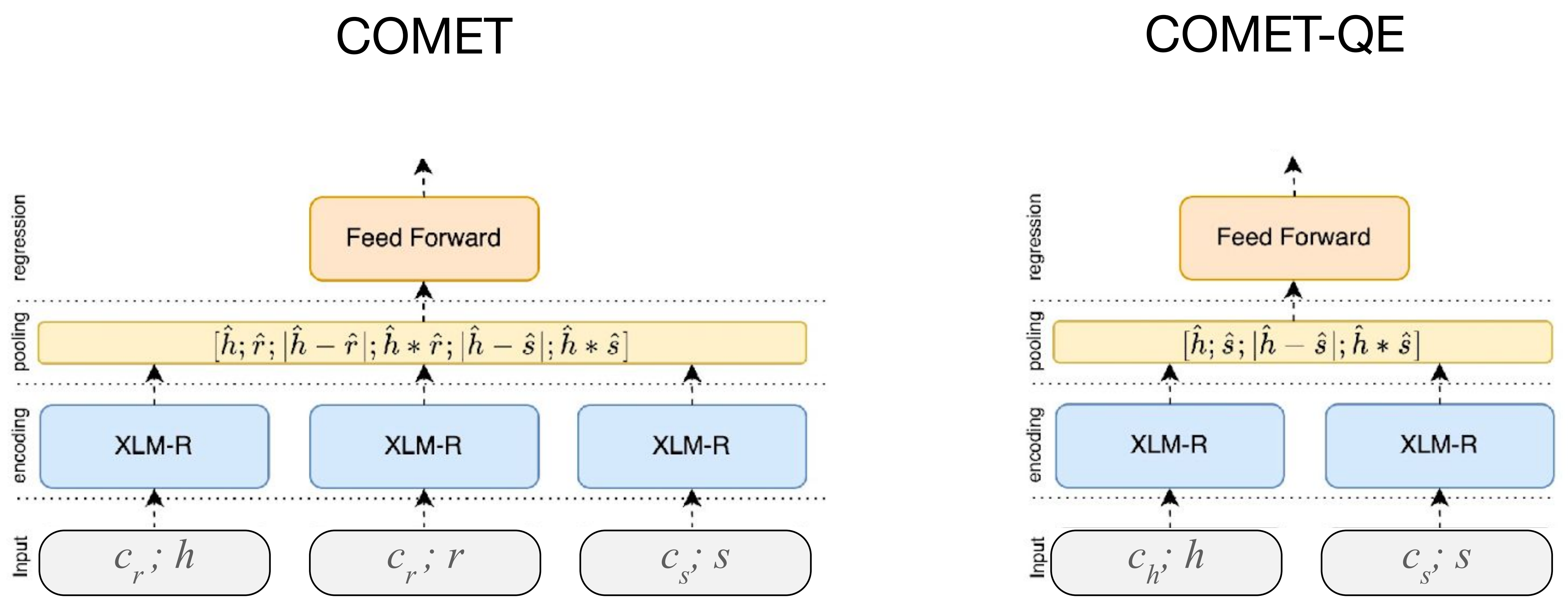


- Contextual embeddings from XLM-R[16] for source, candidate and reference
- Average pooling of output token embeddings
- Model is trained to predict human scores

Document-level MT Metrics

Simple and **effective** approach -> add context during inference:

Document-level **COMET**



- We concatenate source and reference context with the source and reference sentences in the encoder
- We average the embeddings of the current sentence only
- XLM-R is pretrained on chunks of text

Experiments

We evaluate our approach on the MQM annotations of WMT21 Metrics Task[18]:

- MQM guidelines strongly advise annotators to take context into account[11]
- Two different domains, News (articles, long sentences) and TED talks (transcribed speech, shorter sentences, contextual phenomena)

All our models can handle <u>more than one sentence</u> as input.

We use the *two previous sentences* as context.

We substitute the hypothesis context, c_h, with the reference context, c_r, when available to avoid propagation of errors.

Results

Model	Input	TED talks			News		
		En→De	En→Ru	Zh→En	En→De	En→Ru	Zh→En
BlonDe	$\langle c_h, h, c_r, r\rangle$	-	-	-0.232	-	-	0.212
Prism (m39v1)	$\langle h, r\rangle$	0.656	0.867	0.272	0.841	0.799	0.558
Prism (mBART-50)	$\langle h, r\rangle$	0.486	0.845	0.240	0.661	0.710	0.363
Doc-Prism (mBART-50)	$\langle c_r; h, c_r; r\rangle$	**0.692**	**0.852**	**0.372**	**0.825***	**0.777**	**0.374**
BERTScore	$\langle h, r\rangle$	0.506	0.831	0.293	0.930	**0.629**	**0.575***
Doc-BERTScore	$\langle c_r; h, c_r; r\rangle$	**0.613***	**0.836**	**0.344***	**0.948***	0.622	0.535
COMET	$\langle s, h, r\rangle$	**0.818**	0.841	0.266	0.772	0.659	**0.628**
Doc-COMET	$\langle c_s; s, c_r; h, c_r; r\rangle$	0.816	**0.849**	**0.297**	**0.802***	**0.676**	0.513
COMET-QE	$\langle s, h\rangle$	0.694	0.818	**-0.209**	0.711	0.688	**0.529**
Doc-COMET-QE	$\langle c_s; s, c_h; h\rangle$	**0.724**	**0.830**	-0.255	**0.733**	**0.733***	0.462

System-level Pearson correlation with WMT21 MQM annotations for the news domain and TED talks.
Results for baselines and trained metrics with (Doc-*) and without context.

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System-level Pearson correlation with WMT21 MQM annotations for the news domain and TED talks.
Results for baselines and trained metrics with (Doc-*) and without context.

- Significantly outperform document-level metric baseline
- Improved correlation for TED talks across metrics and language pairs
- Improvements on news for 2/3 pairs.
  Zh->En reference is of lower quality (MQM score 4.2, best MT 4.47)[19]

Results

Q: *Do the gains of our approach come from contextual phenomena?*

We use contrastive sets (ContraPro[20], DiscEvalMT[12]) used to evaluate document-level MT models.

source:	*It could get tangled in your hair.*
reference:	***Sie** könnte sich in deinem Haar verfangen.*
contrastive:	***Er** könnte sich in deinem Haar verfangen.*
contrastive:	***Es** könnte sich in deinem Haar verfangen.*

We consider the original and contrastive references as outputs of different MT systems.

We only test reference-free metrics (COMET-QE), otherwise the task is trivial.

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Model	En → De			En → Fr				
	Intra	Inter	Total	Intra	Inter	Total	Anaphora	Disambiguation
Doc-MT (Lopes et al., 2020)	-	-	70.8	-	-	83.2	82.5	55.0
COMET-QE	78.2	40.9	48.4	76.3	76.6	76.5	50.0	50.0
Doc-COMET-QE (this work)	**80.5**	**72.6**	**74.2**	**88.7**	**88.0**	**88.3**	**83.5**	**68.0**

Accuracy (%) for targeted evaluation of contextual phenomena.

- Consistent and significant improvements using context
- Our approach outperforms document-level MT systems
- Gains even when the antecedent is in the current sentence (Intra)

Results

Q: *Do the gains of our approach come from contextual phenomena?*
A: *YES*

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Analysis

Q: *Does context quality play an important role?*

We substitute the hypothesis context, c_h, with the reference context, c_r, in all metrics but COMET-QE.

	Context	Doc-Prism	Doc-BERTScore	Doc-COMET
hypothesis	$\langle c_s; s, c_r; r, c_h; h\rangle$	0.595	0.624	0.630
reference	$\langle c_s; s, c_r; r, c_r; h\rangle$	**0.649**	**0.650**	**0.659**

Average correlation for all domains and language pairs using hypothesis vs reference context.

- Hypothesis context leads indeed to worse correlation
- Conditioning on low-quality context has diminishing results (e.g. Zh->En)

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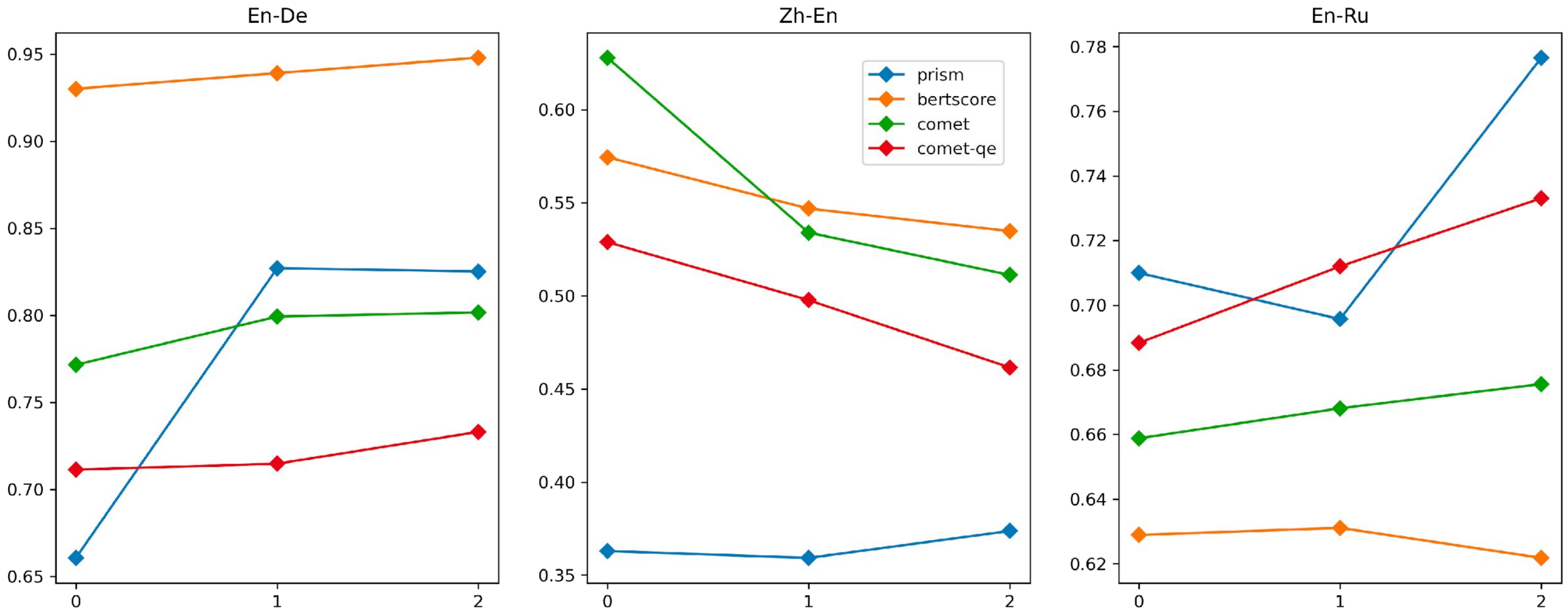
Average correlation for all domains and language pairs using hypothesis vs reference context.

- <u>Hypothesis context</u> leads indeed to <u>worse</u> correlation
- Conditioning on low-quality context has diminishing results (e.g. Zh->En)

Analysis

Q: *How much context should be used in document-level MT metrics?*



Correlation vs. amount of context for news articles.

- Adding more context helps for 2/3 pairs
- For Zh->En using less context helps, due to low quality of the reference

Conclusion

- **Simple and effective** approach towards document-level MT metrics
- **No retraining or additional data** needed
- Consistent **improvements** across all metrics (TED talks)
- Gains come from **better context utilization**

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Limitations

- Not fully **document-level** : consistency, fluency
- **Context** might be **redundant** in some cases

Future Work

- Explore other ways of integrating context (e.g. gating)
- Retrain/Adapt metrics on document-level annotations

Thank you! Questions?

COMET PR (work in progress)

Scoring MT outputs:

Command Line usage:

To score using the original, sentence-level COMET/COMET-QE models:

```
comet-score -s src.de -t hyp1.en -r ref.en --model wmt21-comet-mqm
comet-score -s src.de -t hyp1.en --model wmt21-comet-qe-mqm
```

To score using the document-level COMET/COMET-QE simply add the `--doc` flag:

```
comet-score -s src.de -t hyp1.en -r ref.en --doc --model wmt21-comet-mqm
comet-score -s src.de -t hyp1.en --doc --model wmt21-comet-qe-mqm
```

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