As Little as Possible, as Much as Necessary: Detecting Over- and Undertranslations with Contrastive Conditioning

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Abstract

Omission and addition of content is a typical issue in neural machine translation. We propose a method for detecting such phenomena with off-the-shelf translation models. Using contrastive conditioning, we compare the likelihood of a full sequence under a translation model to the likelihood of its parts, given the corresponding source or target sequence. This allows to pinpoint superfluous words in the translation and untranslated words in the source even in the absence of a reference translation. The accuracy of our method is comparable to a supervised method that requires a custom quality estimation model.

1 Introduction

Neural machine translation (NMT) is susceptible to coverage errors such as the addition of superfluous target words or the omission of important source content. Previous approaches to detecting such errors make use of reference translations (Yang et al., 2018) or employ a separate quality estimation (QE) model trained on synthetic data for a language pair (Tuan et al., 2021; Zhou et al., 2021).

In this paper, we propose a reference-free algorithm based on hypothetical reasoning. Our premise is that a translation has optimal coverage if it uses *as little information as possible and as much information as necessary* to convey the source sequence. Therefore, an addition error means that the source would be better conveyed by a translation containing less information. Conversely, an omission error means that the translation would be more adequate for a less informative source sequence.

Inspired by contrastive conditioning (Vamvas and Sennrich, 2021), we use probability scores of NMT models to approximate this concept of coverage. We create parse trees for both the source sequence and the translation, and treat their constituents as units of information. Omission errors are detected by systematically deleting constituents from the source and by estimating the probability of the translation conditioned on such a partial source sequence. If the probability score is higher than when the translation is conditioned on the full source, the deleted constituent might have no counterpart in the translation (Figure 1). We apply the same principle to the detection of addition errors by swapping the source and the target sequence.

When comparing the detected errors to human annotations of coverage errors on the segment level (Freitag et al., 2021), our approach surpasses a supervised QE baseline that was trained on a large number of synthetic coverage errors. Human raters find that word-level precision is higher for omissions than additions, with 39% of predicted error spans being precise for English–German translations, and 20% for Chinese–English. False positives can occur if the translation has a different syntax than the source. We believe our algorithm could be a useful aid whenever humans remain in the loop, for example in a post-editing workflow.

We release the code and data to reproduce our findings, including a large-scale dataset of synthetic coverage errors in English–German and Chinese–English machine translations.

2 Related Work

Coverage errors in NMT Addition and omission of target words have been observed by human evaluation studies in various languages, with omission as the more frequent error type (Castilho et al., 2017; Zheng et al., 2018). They are included as typical translation issues in the Multidimensional Quality Metrics (MQM) framework (Lommel et al., 2014).[1] *Addition* is defined as an accuracy issue where the target text includes text not present in the source, and *omission* is defined as an accuracy issue where content is missing from the translation but

[1] http://qt21.eu/mqm-definition/

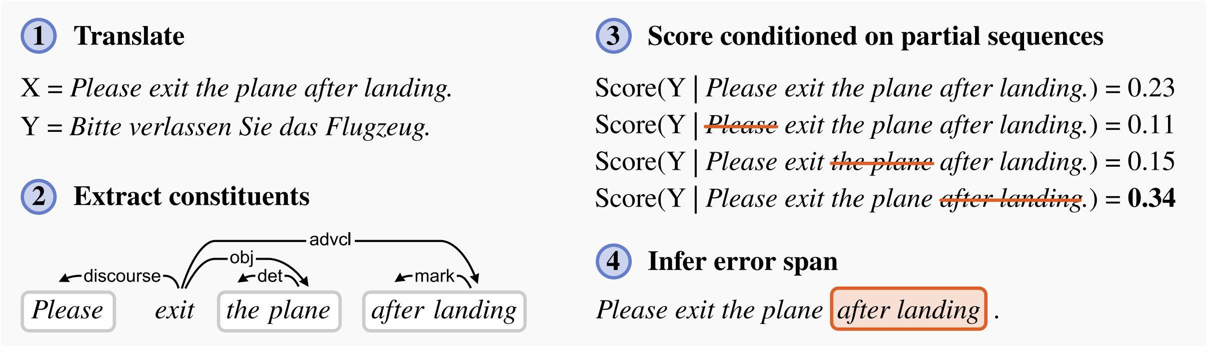

Figure 1: Example of how an omission error is detected. The German translation leaves *after landing* erroneously untranslated (Step 1). Potential error spans are derived from a parse tree (Step 2). An NMT model such as mBART50 assigns a higher probability score to Y conditioned on the source with *after landing* deleted than to Y conditioned on the full source (Step 3). This indicates that there is an omission error (Step 4).

is present in the source.[2] Freitag et al. (2021) used MQM to manually re-annotate English–German and Chinese–English machine translations submitted to the WMT 2020 news translation task (Barrault et al., 2020). Their findings confirm that state-of-the-art NMT systems still erroneously add and omit target words, and that omission occurs more often than addition. Similar patterns can be found in English–French machine translations that have been annotated with fine-grained MQM labels for the document-level QE shared task (Specia et al., 2018; Fonseca et al., 2019; Specia et al., 2020).

Detecting and reducing coverage errors While reference-based approaches include measuring the n-gram overlap to the reference (Yang et al., 2018) and analyzing word alignment to the source (Kong et al., 2019), this work focuses on the reference-free detection of coverage errors.

Previous work has employed custom QE models trained on labeled parallel data. For example, Zhou et al. (2021) insert synthetic hallucinations and train a Transformer to predict the inserted spans. Similarly, Tuan et al. (2021) train a QE model on synthetically noisy translations. In this paper, we propose a method that is based on off-the-shelf NMT models only.

Other related work has focused on improving coverage during decoding or training, for example via attention weights (Tu et al., 2016; Wu et al., 2016; Li et al., 2018; among others). More recently, Yang et al. (2019) found that contrastive fine-tuning on references with synthetic omissions reduces coverage errors produced by an NMT system.

[2]The terms *overtranslation* and *undertranslation* have been used in the literature as well. MQM reserves these terms for errors where the translation is too specific or too unspecific.

3 Approach

Contrastive Conditioning Properties of a translation can be inferred by estimating its probability conditioned on contrastive source sequences (Vamvas and Sennrich, 2021). For example, if a certain translation is more probable under the MT model when conditioned on a counterfactual source sequence, the translation might be inadequate.

Application to Omission Errors Figure 1 illustrates how contrastive conditioning can be directly applied to the detection of omission errors. We construct *partial source sequences* by systematically deleting constituents from the source. If the probability score of the translation (average token log-probability) is higher when conditioned on such a partial source, the deleted constituent is taken to be missing from the translation.

Application to Addition Errors We apply the same method to addition detection, but swap the source and target languages. Namely, we use an NMT model for the reverse translation direction, and we score the source sequence conditioned on the full translation and a set of partial translations.[3]

Potential Error Spans To keep our search space sub-quadratic to sequence length, we use a parser to enumerate potential error spans. We use universal dependency parsers (de Marneffe et al., 2021) given their broad availability. The set of constituents that we extract is defined as follows:[4]

[3]Another possibility would be to leave the translation direction unreversed and to score the partial translations conditioned on the source. However, the scores might be confounded by a lack of fluency in the partial translations.

[4]While we refer to the word spans as *constituents*, it should be noted that the word spans are not necessarily constituents

1. A constituent is a complete subtree.
2. It must cover a contiguous subsequence.
3. It contains a part of speech of interest.[5]

For every constituent extracted according to this definition, we create a partial sequence by deleting the constituent from the original sequence.

4 Experimental Setup

In this section we describe the data and tools that we use to implement and evaluate our approach.

Scoring model We use mBART50 (Tang et al., 2020), which is a sequence-to-sequence Transformer pre-trained on monolingual corpora in many languages using the BART objective (Lewis et al., 2020; Liu et al., 2020) that was fine-tuned on English-centric multilingual MT in 50 languages. Sequence-level probability scores are computed by averaging the log-probabilites of all target tokens.

Error spans We use Stanza (Qi et al., 2020) for dependency parsing, a neural pipeline for various languages trained on data from Universal Dependencies (de Marneffe et al., 2021). We make use of universal part-of-speech tags (UPOS) to define parts of speech that might constitute potential error spans. Specifically, we treat common nouns, proper nouns, main verbs, adjectives, numerals, adverbs, and interjections as relevant parts of speech.

Gold Standard Data We use state-of-the-art English–German and Chinese–English machine translations for evaluation, which have been annotated by Freitag et al. (2021) with translation errors.[6] We set aside translations by the system *Online-B* as a development set, and use the other systems as a test set, excluding translations by humans. The development set was used to identify typical UPOS tags of coverage error spans.

Synthetic Data We also create synthetic coverage errors, which we use for an evaluation study and for training a supervised baseline QE system. We propose a data creation process that is inspired by previous work (Yang et al., 2019; Zhou et al., 2021; Tuan et al., 2021) but is defined such that it works for both additions and omissions, and produces fluent translations.

We start from sentences in the source language and create *partial sources* by randomly deleting constituents. We machine-translate both, yielding *full* and *partial machine translations*. We retain only samples where the full machine translation is different from the partial one, and can be constructed by addition. This allows us to treat full machine translations as overtranslations of the partial sources, and the added words as addition errors. Conversely, partial machine translations are treated as undertranslations of the full sources. Negative examples are created by pairing the full sources with the full machine translations, and the partial sources with the partial machine translations.

Our synthetic data are based on monolingual news text released for WMT.[7] Partial sources are created by deleting each constituent with a probability of 15%. To train a supervised baseline QE system, we use 80k unique source segments per language pair. Statistics are reported in Table A3.

Supervised baseline system We follow the approach outlined by Moura et al. (2020). Implementation details are provided in Appendix A.

5 Evaluation

5.1 Segment-Level Comparison to Gold Data

The accuracy of our approach can be estimated based on the human ratings by Freitag et al. (2021).

Evaluation Design We use the MQM error types *Accuracy/Addition* and *Accuracy/Omission*, and ignore other types such as *Accuracy/Mistranslation*. We count a prediction as correct if any one of the human raters has marked the same error type anywhere in the segment.[8] We exclude segments from the evaluation that might have been incompletely annotated (because raters stopped after marking 5 errors). For ease of implementation, we also exclude segments that consist of multiple sentences.

Results The results of the gold-standard comparison are shown in Table 1. Our approach clearly surpasses the baseline in the detection of omission errors in both language pairs, and in the detection of addition errors in English–German translations. Both approaches recognize Chinese–English addition errors with low accuracy. We also note that the supervised baseline has low recall. Considering

in a strict sense according to phrase structure grammar.

[5]For example, a noun. In contrast, function words such as determiners or punctuation may be added/omitted for syntactic reasons, and such additions/omissions are not typically errors.

[6]https://github.com/google/wmt-mqm-human-evaluation

[7]http://data.statmt.org/news-crawl/

[8]We perform a segment-level evaluation and do not quantify word-level accuracy in this section since the dataset does not contain consistently annotated spans for coverage errors.

	Approach	Detection of additions			Detection of omissions		
		Precision	Recall	F1	Precision	Recall	F1
EN–DE	Supervised baseline	6.9±1.9	2.9±0.9	4.0±1.3	40.3±5.2	6.1±0.1	10.6±0.2
	Our approach	5.9	16.7	**8.7**	22.5	19.2	**20.7**
ZH–EN	Supervised baseline	4.3±0.6	4.7±0.7	4.5±0.6	49.6±0.6	9.4±1.0	15.9±1.4
	Our approach	2.3	41.6	4.4	26.5	62.3	**37.2**

Table 1: Segment-level comparison of coverage error detection methods on the gold dataset by Freitag et al. (2021). We average over three baseline models trained with different random seeds, reporting the standard deviation.

		EN–DE	ZH–EN
Target	Addition errors	2.3	1.2
	Any errors	7.4	12.0
Source	Omission errors	36.3	13.8
	Any errors	39.4	19.5

Table 2: Word-level precision of the spans highlighted by our approach according to a human evaluation.

its high performance on a synthetic test set (Table A1 in the Appendix), it seems that the model does not generalize well to real-world coverage errors, highlighting the challenges of training a supervised QE model on purely synthetic data.

5.2 Human Evaluation of Precision

We perform an additional word-level human evaluation to analyze the predictions obtained via our approach in more detail. Our human raters were presented segments that had been marked as true or false positives in the above evaluation, allowing us to quantify word-level precision.

Evaluation Design We employed two linguistic experts per language pair as raters.[9] Each rater was shown around 700 randomly sampled positive predictions across both types of coverage errors.

Raters were shown the source sequence, the machine translation, and the predicted error span. They were asked whether the highlighted span was indeed translated badly, and were asked to perform a fine-grained analysis based on a list of predefined answer options (Figures 2 and 3 in the Appendix).

A part of the samples were annotated by both raters. The agreement was moderate for the main question, with a Cohen's kappa of 0.54 for EN–DE and 0.45 for ZH–EN. Agreement on the more subjective follow-up question was lower (0.32 / 0.13).

Results The fine-grained answers allow to quantify the word-level precision of the spans highlighted by our approach, both with respect to coverage errors in particular and to translation errors in general (Table 2). Precision is higher than expected when detecting omission errors in English–German translations, but is still low for additions. The distribution of the detailed answers (Figures 2 and 3 in the Appendix) suggests that syntactical differences between the source and target language contribute to the false positives regarding additions. Some example predictions are provided in Appendix G.

Finally, Table 2 shows that many of the predicted error spans are in fact translation errors, but not coverage errors in a narrow sense. For example, more than 10% of the spans marked in Chinese–English translations were classified by our raters as a different type of accuracy error.

6 Conclusion

We have proposed a reference-free method to automatically detect coverage errors in translations. Derived from contrastive conditioning, our method relies on hypothetical reasoning over the likelihood of partial sequences. Since any off-the-shelf NMT model can be used to estimate conditional likelihood, no access to the original translation system or to an external quality estimation model is needed.

Segment-level evaluation based on real coverage errors shows that our approach generally outperforms a supervised quality estimation baseline trained on synthetic coverage errors. We believe that our method could be useful as an aid to translators and post-editors especially for the detection of omission errors, which according to our human evaluation are more reliably detected. Future work could address the low precision in the detection of addition errors, which are relatively rare in the datasets we used for evaluation.

[9] Raters were paid ca. USD 30 per hour.

References

Loïc Barrault, Magdalena Biesialska, Ondřej Bojar, Marta R. Costa-jussà, Christian Federmann, Yvette Graham, Roman Grundkiewicz, Barry Haddow, Matthias Huck, Eric Joanis, Tom Kocmi, Philipp Koehn, Chi-kiu Lo, Nikola Ljubešić, Christof Monz, Makoto Morishita, Masaaki Nagata, Toshiaki Nakazawa, Santanu Pal, Matt Post, and Marcos Zampieri. 2020. Findings of the 2020 conference on machine translation (WMT20). In *Proceedings of the Fifth Conference on Machine Translation*, pages 1–55, Online. Association for Computational Linguistics.

Sheila Castilho, Joss Moorkens, Federico Gaspari, Rico Sennrich, Vilelmini Sosoni, Yota Georgakopoulou, Pintu Lohar, Andy Way, Antonio Miceli Barone, and Maria Gialama. 2017. A comparative quality evaluation of PBSMT and NMT using professional translators. *16th Machine Translation Summit 2017*, pages 116–131.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised cross-lingual representation learning at scale. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8440–8451, Online. Association for Computational Linguistics.

Marie-Catherine de Marneffe, Christopher D. Manning, Joakim Nivre, and Daniel Zeman. 2021. Universal Dependencies. *Computational Linguistics*, 47(2):255–308.

Erick Fonseca, Lisa Yankovskaya, André F. T. Martins, Mark Fishel, and Christian Federmann. 2019. Findings of the WMT 2019 shared tasks on quality estimation. In *Proceedings of the Fourth Conference on Machine Translation (Volume 3: Shared Task Papers, Day 2)*, pages 1–10, Florence, Italy. Association for Computational Linguistics.

Markus Freitag, George Foster, David Grangier, Viresh Ratnakar, Qijun Tan, and Wolfgang Macherey. 2021. Experts, errors, and context: A large-scale study of human evaluation for machine translation. *arXiv preprint arXiv:2104.14478*.

Fabio Kepler, Jonay Trénous, Marcos Treviso, Miguel Vera, and André F. T. Martins. 2019. OpenKiwi: An open source framework for quality estimation. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 117–122, Florence, Italy. Association for Computational Linguistics.

Hyun Kim, Jong-Hyeok Lee, and Seung-Hoon Na. 2017. Predictor-estimator using multilevel task learning with stack propagation for neural quality estimation. In *Proceedings of the Second Conference on Machine Translation*, pages 562–568, Copenhagen, Denmark. Association for Computational Linguistics.

Philipp Koehn, Hieu Hoang, Alexandra Birch, Chris Callison-Burch, Marcello Federico, Nicola Bertoldi, Brooke Cowan, Wade Shen, Christine Moran, Richard Zens, Chris Dyer, Ondřej Bojar, Alexandra Constantin, and Evan Herbst. 2007. Moses: Open source toolkit for statistical machine translation. In *Proceedings of the 45th Annual Meeting of the ACL on Interactive Poster and Demonstration Sessions*, ACL '07, page 177–180, USA. Association for Computational Linguistics.

Xiang Kong, Zhaopeng Tu, Shuming Shi, Eduard Hovy, and Tong Zhang. 2019. Neural machine translation with adequacy-oriented learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 6618–6625.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics.

Yanyang Li, Tong Xiao, Yinqiao Li, Qiang Wang, Changming Xu, and Jingbo Zhu. 2018. A simple and effective approach to coverage-aware neural machine translation. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 292–297, Melbourne, Australia. Association for Computational Linguistics.

Yinhan Liu, Jiatao Gu, Naman Goyal, Xian Li, Sergey Edunov, Marjan Ghazvininejad, Mike Lewis, and Luke Zettlemoyer. 2020. Multilingual Denoising Pre-training for Neural Machine Translation. *Transactions of the Association for Computational Linguistics*, 8:726–742.

Arle Lommel, Hans Uszkoreit, and Aljoscha Burchardt. 2014. Multidimensional quality metrics (MQM): A framework for declaring and describing translation quality metrics. *Tradumàtica*, (12):0455–463.

Ilya Loshchilov and Frank Hutter. 2018. Decoupled weight decay regularization. In *International Conference on Learning Representations*.

João Moura, Miguel Vera, Daan van Stigt, Fabio Kepler, and André F. T. Martins. 2020. IST-unbabel participation in the WMT20 quality estimation shared task. In *Proceedings of the Fifth Conference on Machine Translation*, pages 1029–1036, Online. Association for Computational Linguistics.

Peng Qi, Yuhao Zhang, Yuhui Zhang, Jason Bolton, and Christopher D. Manning. 2020. Stanza: A python natural language processing toolkit for many human languages. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 101–108, Online. Association for Computational Linguistics.

Lucia Specia, Frédéric Blain, Marina Fomicheva, Erick Fonseca, Vishrav Chaudhary, Francisco Guzmán, and André F. T. Martins. 2020. Findings of the WMT 2020 shared task on quality estimation. In *Proceedings of the Fifth Conference on Machine Translation*, pages 743–764, Online. Association for Computational Linguistics.

Lucia Specia, Frédéric Blain, Varvara Logacheva, Ramón F. Astudillo, and André F. T. Martins. 2018. Findings of the WMT 2018 shared task on quality estimation. In *Proceedings of the Third Conference on Machine Translation: Shared Task Papers*, pages 689–709, Belgium, Brussels. Association for Computational Linguistics.

Yuqing Tang, Chau Tran, Xian Li, Peng-Jen Chen, Naman Goyal, Vishrav Chaudhary, Jiatao Gu, and Angela Fan. 2020. Multilingual translation with extensible multilingual pretraining and finetuning. *arXiv preprint arXiv:2008.00401*.

Zhaopeng Tu, Zhengdong Lu, Yang Liu, Xiaohua Liu, and Hang Li. 2016. Modeling coverage for neural machine translation. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 76–85, Berlin, Germany. Association for Computational Linguistics.

Yi-Lin Tuan, Ahmed El-Kishky, Adithya Renduchintala, Vishrav Chaudhary, Francisco Guzmán, and Lucia Specia. 2021. Quality estimation without human-labeled data. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 619–625, Online. Association for Computational Linguistics.

Jannis Vamvas and Rico Sennrich. 2021. Contrastive conditioning for assessing disambiguation in MT: A case study of distilled bias. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Association for Computational Linguistics.

Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. 2016. Google's neural machine translation system: Bridging the gap between human and machine translation. *arXiv preprint arXiv:1609.08144*.

Jing Yang, Biao Zhang, Yue Qin, Xiangwen Zhang, Qian Lin, and Jinsong Su. 2018. Otem&Utem: Over- and under-translation evaluation metric for NMT. In *Natural Language Processing and Chinese Computing*, pages 291–302, Cham. Springer International Publishing.

Zonghan Yang, Yong Cheng, Yang Liu, and Maosong Sun. 2019. Reducing word omission errors in neural machine translation: A contrastive learning approach. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 6191–6196, Florence, Italy. Association for Computational Linguistics.

Zaixiang Zheng, Hao Zhou, Shujian Huang, Lili Mou, Xinyu Dai, Jiajun Chen, and Zhaopeng Tu. 2018. Modeling Past and Future for Neural Machine Translation. *Transactions of the Association for Computational Linguistics*, 6:145–157.

Chunting Zhou, Graham Neubig, Jiatao Gu, Mona Diab, Francisco Guzmán, Luke Zettlemoyer, and Marjan Ghazvininejad. 2021. Detecting hallucinated content in conditional neural sequence generation. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 1393–1404, Online. Association for Computational Linguistics.

A Description of the Baseline System

We follow Moura et al. (2020) and use the OpenKiwi framework (Kepler et al., 2019) to train a separate Predictor-Estimator model (Kim et al., 2017) per language pair, based on XLM-Roberta (Conneau et al., 2020).

This supervised task can be described as token-level binary classification. Every token is classified as either `OK` or `BAD`, similar to the word-level labels used for the QE shared tasks (Specia et al., 2020). A source token is `BAD` if it is omitted in the translation, and a token in the translation is `BAD` if it is part of an addition error. For English and German, we use the Moses tokenizer (Koehn et al., 2007) to separate the text into labeled tokens; for Chinese we label the text on the character level.

Where suitable, we use the default settings of OpenKiwi. We fine-tune the large version of XLM-Roberta, which results in a model of similar parameter count as the mBART50 model we use for contrastive conditioning. We train for 10 epochs with a batch size of 32, with early stopping on the validation set. For token classification we train two linear layers, separately for source and target language. We use AdamW (Loshchilov and Hutter, 2018) with a learning rate of 1e-5, freezing the pretrained encoder for the first 1000 steps.

	Detection of additions				Detection of omissions			
	Prec.	*Recall*	*F1*	*MCC*	*Prec.*	*Recall*	*F1*	*MCC*
EN–DE								
Baseline	98.8±0.4	98.0±.2	**98.4**±.2	**96.8**±.1	94.0±1.3	96.6±0.4	**95.3**±.5	**90.5**±.2
Ours	78.1	88.3	82.9	76.7	79.6	98.4	88.0	77.9
ZH–EN								
Baseline	87.2±1.5	75.7±.6	**81.0**±.3	**72.6**±.6	67.3±1.3	68.0±1.2	**67.7**±.9	**53.8**±.3
Ours	33.0	86.9	47.9	22.7	28.3	98.4	43.9	40.4

Table A1: Segment-level and word-level (*MCC*) evaluation based on a test set with synthetic coverage errors.

	Short sentence pair			Long sentence pair		
	Additions	Omissions	Both	Additions	Omissions	Both
Baseline	-	-	23 ms	-	-	24 ms
Our approach	48 ms	49 ms	97 ms	177 ms	205 ms	383 ms
– excluding parser	22 ms	23 ms	46 ms	103 ms	156 ms	257 ms

Table A2: Average inference times when predicting on a short and a long sentence pair. We also report inference time without including the time needed for parsing, since we did not use a parser that is optimized for efficiency.

B Evaluation on Synthetic Errors

We used a test split held back from the synthetic data to perform an additional evaluation. On the segment level, we report Precision, Recall and F1-score. Like in Section 5.1, a prediction is treated as correct on the segment level if for a predicted coverage error there is indeed a coverage error of that type anywhere in the segment.

On the word level, we follow previous work on word-level QE (Specia et al., 2020) and report the Matthews correlation coefficient (MCC) across all the tokens in the test set.

Results Results are shown in Table A1. The supervised baseline has a high accuracy on English–German translations and a moderate accuracy on Chinese–English translations. In comparison, our approach performs clearly worse than the supervised baseline on the synthetic errors, but Table 2 shows that it outperforms the baseline in the detection of real-world MQM errors.

C Inference Time

Inference times are reported in Table A2. We measure the average inference time both for a short sentence pair and a long sentence pair. The short sentence pair is taken from Figure 1; the long sentence pair has 40 tokens in the source and 47 tokens in the target.

D Annotator Guidelines

You will be shown a series of source sentences and translations. One or several spans in the text are highlighted and it is claimed that the spans are translated badly. You are asked to determine whether the claim is true.

The highlighted spans can be either in the source sequence or in the translation. If a span is in the source sentence, check whether it has been correctly translated. If a span is in the translation, check whether it correctly conveys the source. Sometimes, multiple spans are highlighted. In that case, focus your answer on the span that is most problematic for the translation.

In a second step, you are asked to select an explanation. On the one hand, if you agree that the highlighted span is translated badly, please explain your reasoning by selecting your explanation. On the other hand, if you disagree and think that the span is well-translated, please select an explanation why the span might have been marked as badly translated in the first place. Should multiple explanations be equally plausible, select the first from the top.

E Dataset Statistics

Dataset split	Number of segments			Number of tokens			
	Total	W/ addition	W/ omission	Src. `OK`	Src. `BAD`	Tgt. `OK`	Tgt. `BAD`
EN–DE Train	135269	18423	18423	2185918	58378	2197843	53911
EN–DE Dev	16984	2328	2328	273311	7398	275156	6781
EN–DE Test	16984	2328	2328	273277	7701	275036	7032
ZH–EN Train	110195	10697	10697	2576135	62311	1866567	37730
ZH–EN Dev	14149	1383	1383	326743	7562	236685	4244
ZH–EN Test	14026	1342	1342	322000	7566	234757	4882

Table A3: Statistics for the dataset of synthetic coverage errors described in Section 4.

Dataset split	Number of segments		
	Total	With an addition error	With an omission error
EN–DE Dev	1418	77	187
EN–DE Test	8508	407	1057
– without excluded segments	4839	162	484
ZH–EN Dev	1999	69	516
ZH–EN Test	13995	329	3360
– without excluded segments	8851	149	1569

Table A4: Statistics for the gold dataset by Freitag et al. (2021).

F Examples of Synthetic Coverage Errors

English–German Example

Addition error

Partial source: But they haven't played.

Full machine translation: Aber sie haben nicht gegen ein Team wie uns gespielt.

Omission error

Full source: But they haven't played against a team like us.

Partial machine translation: Aber sie haben nicht gespielt.

Chinese–English Example

Addition error

Partial source: 医院和企业共同研发相关检测试剂盒，惠及更多患者。

Full translation: Hospitals and enterprises jointly develop related test kits to benefit more cancer patients.

Omission error

Full source: 医院和企业共同研发相关检测试剂盒，惠及更多肿瘤患者。

Partial translation: Hospitals and enterprises jointly develop related test kits to benefit more patients.

G Examples of Coverage Errors Predicted by Contrastive Conditioning

English–German Examples

Predicted addition error
Source: He added: "It's backfired on him now, though, that's the sad thing."
Machine translation: Er fügte **hinzu**: "Es ist jetzt auf ihn abgefeuert, aber das ist das Traurige."

Original MQM rating (Freitag et al., 2021): No related accuracy error marked by the three raters.

Answer by our human rater: The highlighted target span is not translated badly. It might have been highlighted because it is syntactically different from the source.

Meaning of highlighted span: hinzu = 'additionally'

Predicted omission error
Source: UK's medical **drug** supply still uncertain in no-deal Brexit
Machine translation: Die medizinische Versorgung Großbritanniens ist im No-Deal-Brexit noch ungewiss

Original MQM rating: No accuracy error marked by the three raters.

Answer by our human rater: The highlighted source span is indeed translated badly. It contains information that is missing in the translation but can be inferred or is trivial.

Predicted omission error
Source: The automaker is expected to report its quarterly vehicle deliveries in the next **few** days.
Machine translation: Der Autohersteller wird voraussichtlich in den nächsten Tagen seine vierteljährlichen Fahrzeugauslieferungen melden.

Original MQM rating: No related accuracy error marked by the three raters.

Answer by our human rater: The highlighted source span is not translated badly. The words in the span do not need to be translated.

Chinese–English Examples

Predicted addition error
Source: 美方指责伊朗制造了该袭击，并对伊朗实施新制裁。
Machine translation: The US accused Iran of causing the attack and imposed new sanctions **on Iran**.

Original MQM rating (Freitag et al., 2021): No related accuracy error marked by the three raters.

Answer by our human rater: The highlighted target span is not translated badly. No phenomenon that might have caused the prediction was identified.

Predicted omission error
Source: **目前**已收到来自俄罗斯农业企业的约50项申请。
Machine translation: About 50 applications have been received from Russian agricultural enterprises.

Original MQM rating: No accuracy error marked by the three raters.

Answer by our human rater: The highlighted source span is indeed translated badly. It contains information that is missing in the translation.

Meaning of highlighted span: 目前 = 'at present'

Predicted omission error
Source: 他说，该系统目前在世界上有很大需求，但俄罗斯军队也需要它，**其中**包括在北极地区。
Machine translation: He said that the system is currently in great demand in the world, but the Russian army also needs it, including in the Arctic.

Original MQM rating: No accuracy error marked by the three raters.

Answer by our human rater: The highlighted source span is not translated badly. The words in the span do not need to be translated.

Meaning of highlighted span: 其中 = 'among'

H Detailed Results of Human Evaluation

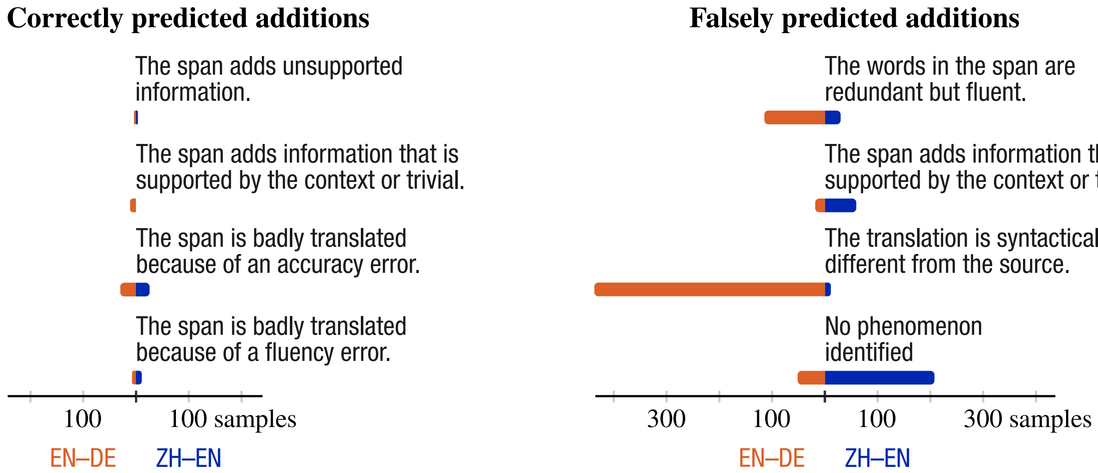

Figure 2: Results for the human evaluation of predicted addition errors. If human raters answered that the highlighted span in the translation was indeed badly translated, they were offered the four explanation options on the left. Otherwise they chose from the four options on the right.

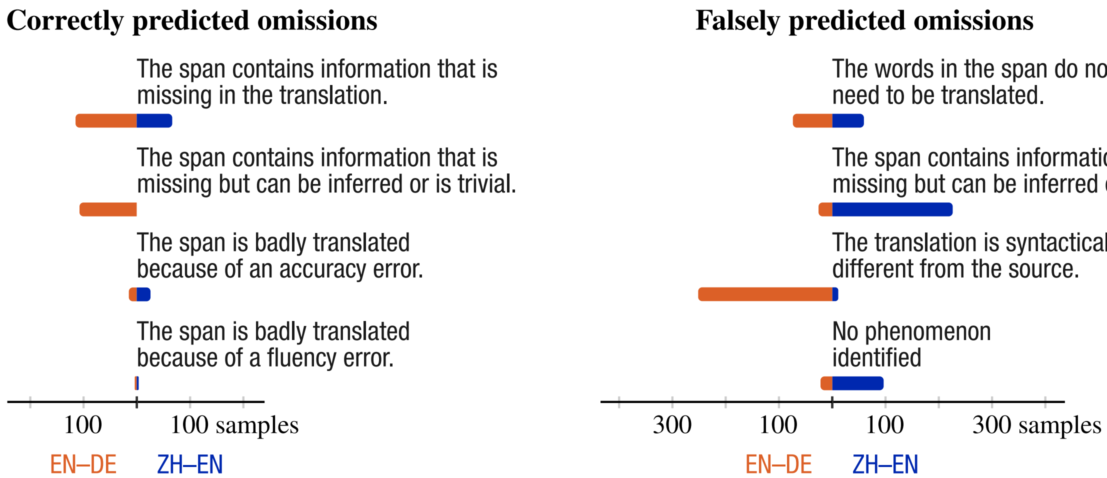

Figure 3: Results for the human evaluation of predicted omission errors. If human raters answered that the highlighted span in the source sequence was indeed badly translated, they were offered the four explanation options on the left. Otherwise they chose from the four options on the right.