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**Citation for published version:**

Libovický, J, Kasner, Z, Helcl, J & Dušek, O 2020, Expand and Filter: CUNI and LMU Systems for the WNGT 2020 Duolingo Shared Task. in *Proceedings of the Fourth Workshop on Neural Generation and Translation*. Association for Computational Linguistics, Online, pp. 153-160, The 4th Workshop on Neural Generation and Translation, Seattle, Washington, United States, 10/07/20.  
<https://doi.org/10.18653/v1/2020.ngt-1.18>

**Digital Object Identifier (DOI):**

[10.18653/v1/2020.ngt-1.18](https://doi.org/10.18653/v1/2020.ngt-1.18)

**Link:**

[Link to publication record in Edinburgh Research Explorer](#)

**Document Version:**

Publisher's PDF, also known as Version of record

**Published In:**

Proceedings of the Fourth Workshop on Neural Generation and Translation

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# Expand and Filter: CUNI and LMU Systems for the WNGT 2020 Duolingo Shared Task

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## Abstract

We present our submission to the Simultaneous Translation And Paraphrase for Language Education (STAPLE) challenge. We used a standard Transformer model for translation, with a crosslingual classifier predicting correct translations on the output  $n$ -best list. To increase the diversity of the outputs, we used additional data to train the translation model, and we trained a paraphrasing model based on the Levenshtein Transformer architecture to generate further synonymous translations. The paraphrasing results were again filtered using our classifier. While the use of additional data and our classifier filter were able to improve results, the paraphrasing model produced too many invalid outputs to further improve the output quality. Our model without the paraphrasing component finished in the middle of the field for the shared task, improving over the best baseline by a margin of 10–22% weighted F1 absolute.

## 1 Introduction

The usual goal of machine translation (MT) is to generate a single correct translation of a source sentence. Neural machine translation (NMT; Bahdanau et al., 2015; Vaswani et al., 2017) models a conditional distribution over possible target sentences given a source sentence, and uses beam-search decoding as a heuristic to get one or more translations. However, the number of *possible* correct translations is often vast in comparison (Bojar et al., 2013).

The STAPLE challenge (Mayhew et al., 2020) poses the problem of MT slightly differently. Here, the goal is to generate as many correct translations as possible. Knowing many correct translations can be useful e.g. for automatic scoring in tools for language education, such as Duolingo.<sup>1</sup> On

<sup>1</sup><https://www.duolingo.com>

one hand, the learners should be guided to use the more common formulations, on the other hand, they should not be penalized for providing a correct but unusual answer.

We present a pipeline of two systems in our submission to the STAPLE challenge. As the first step, we use a standard NMT model trained with additional, carefully filtered data. The NMT output  $n$ -best lists are filtered using a classifier. Second, we use a Levenshtein Transformer model (Gu et al., 2019) to generate paraphrases of the outputs of the first model. Again, the outputs of the Levenshtein Transformer are filtered using another classifier.

The paper is structured as follows. Our training datasets are described in detail in Section 2. We describe the two models in Sections 3 and 4 respectively. We conduct experiments with all five target languages in the challenge, i.e. Hungarian, Japanese, Korean, Vietnamese and Portuguese. The source language is English in all setups. The experiment settings are shown in Section 5. The results (Section 6) show that the Levenshtein Transformer paraphrase generator cannot easily improve on the filtered NMT output  $n$ -best list.

## 2 Data

### 2.1 STAPLE Dataset

The data in the STAPLE shared task comes from the Duolingo language learning platform. This represents a specific domain with a limited number of mostly simple sentences targeted at learners, using a limited vocabulary.

Each source (English) sentence comes with a list of valid translations in the target language, ranging from a few up to hundreds of paraphrases. All of the valid translations are further annotated with a probability score indicating how frequent a given variant is. Statistics of the data are given in Table 1.

We held out 200 source sentences with all their

Language	Prompts	Trans.	Avg. P/S
Hungarian	3,800	238,467	62.75
Korean	2,300	646,410	281.05
Japanese	2,300	788,591	342.87
Portuguese	3,800	503,839	132.59
Vietnamese	3,300	183,339	55.57

Table 1: STAPLE training data statistics (target language set, number of source sentences (prompts), number of paraphrases (translations), average number of paraphrases per source).

translations as our internal validation dataset. We use this dataset for validating the translation models and for estimating the filtering thresholds.

## 2.2 Additional data for MT

For training the translation model, we obtained out-of-domain parallel corpora from the OPUS collection (Tiedemann, 2012) for all target languages, ParaCrawl (Esplà et al., 2019) for Portuguese and Hungarian, and JParaCrawl (Morishita et al., 2019) for Japanese. We applied FastText language identifier (Joulin et al., 2016b,a) to clean the corpora. Furthermore, we filtered out sentence pairs with a length ratio that differs from the estimated mean ratio by more than 2.5 times the standard deviation.

As in-domain training data, we mix data from the STAPLE training dataset and the Tatoeba<sup>2</sup> corpus (part of the OPUS collection). To balance the underrepresentation of the in-domain data in the training dataset, we oversample both the STAPLE dataset (200×) and the Tatoeba dataset (10×).

We use the combined mixed-domain parallel corpora for training backtranslation models (Sennrich et al., 2016) and an XLM-R-based domain classifier. The classifier is trained to predict whether a target sentence came from the STAPLE training dataset, conditioning on the source sentence.

The monolingual data consists of Wikipedia, WMT NewsCrawl (Barrault et al., 2019) for Hungarian, Japanese and Portuguese, Leipzig Corpora NewsCrawl (Goldhahn et al., 2012) for all languages and the jpWaC corpus for Japanese (Erjavec et al., 2008).

We filtered both the monolingual and parallel data using the domain classifier. The classifier has over 99% accuracy on balanced data. We set a permissive threshold for keeping the sentence pair to  $10^{-5}$ .

<sup>2</sup><https://tatoeba.org/>

Based on preliminary experiments, we include only a single correct translation from the STAPLE training set into the machine translation training data. This had a slightly positive effect on translation quality. Also, the  $n$ -best lists obtained by machine-translating the STAPLE dataset are more representative and thus more suitable for training the classifier for  $n$ -best list filtering than if we included all translations from the training set.

## 3 Translation and Filtering Model

### 3.1 Translation Model

Our pipeline starts with the Transformer model (Vaswani et al., 2017) trained on the provided dataset enriched with additional data (see Section 2). This provides initial translations of the source sentence on the output  $n$ -best list, which are further filtered.

### 3.2 Filtering Classifier

We train a crosslingual classifier which predicts whether a translation in the MT output  $n$ -best list is correct (given the source sentence). Using the trained translation model, we first generate large  $n$ -best lists for all English sentences in the original training data. Next, we label each generated sentence whether it is a positive or a negative sample (based on the reference data). Finally, we create a balanced mix of negative and positive samples. Since the  $n$ -best lists contained much more incorrect translations, we oversample the list of correct translations.

We use XLM-RoBERTa as our sentence classifier model (XLM-R; Conneau et al., 2020), specifically the pretrained variant available in the HuggingFace Transformers library<sup>3</sup> (Wolf et al., 2019). We finetune this model on the balanced mix of the correct and incorrect translations for a given sentence.

During inference, we generate an  $n$ -best list for a given source sentence, and we apply the classifier to filter out the sentences which are labeled as incorrect using a threshold value. The  $n$ -best list size and the threshold are hyperparameters of the method.

## 4 Paraphrasing Model

As an additional step to increase the number of valid translations produced, we train a target-

<sup>3</sup><https://github.com/huggingface/transformers>

	All parallel	+ lang. & length filter	+ domain filtering	Monolingual	+ domain filtering	Total (unique)
Hungarian	56.1M	47.9 M	22.1M	54.3M	7.0M	27.1M
Japanese	14.7M	14.0 M	1.9M	44.2M	2.8M	4.7M
Korean	2.2M	2.0 M	0.6M	9.3M	0.8M	1.4M
Portuguese	63.5M	53.7 M	21.3M	30.0M	4.5M	25.8M
Vietnamese	3.9M	3.4 M	1.5M	9.7M	1.4M	2.8M

Table 2: Number of sentences in the parallel and monolingual data used for training the MT systems. The data in the second column were used for training the backtranslation systems, the last column corresponds to final translation systems.

language paraphrasing model. Rather than generating a translation directly from the source sentence, the model refines existing translations in order to produce new ones.

The model is based on the Levenshtein Transformer (LevT; Gu et al., 2019), which is a sequence generation model based on the Transformer (Vaswani et al., 2017) architecture. Instead of left-to-right autoregressive generation, LevT generates sequences in an arbitrary order using two basic operations – insertion and deletion. Using an initial sequence as a starting point, LevT is able to perform sequence refinement.

#### 4.1 Training

LevT iteratively applies three policies represented by fully-connected neural network layers on top of the last layer of a Transformer decoder:

1. *Deletion* policy  $\pi^{\text{del}}$  removes tokens from the sequence;
2. *Placeholder* policy  $\pi^{\text{plh}}$  inserts placeholders into the sequence;
3. *Insertion* policy  $\pi^{\text{ins}}$  replaces placeholders with tokens from the vocabulary.

The policies are trained to follow oracle policies. Given a source sequence  $X$  and a target sequence  $Y$ ,  $L(X, Y)$  is a minimum sequence of edit operations (delete and insert) that transform  $X$  to  $Y$ . Its length is equal to the Levenshtein distance (Levenshtein, 1966) between  $X$  and  $Y$ . The operations in  $L(X, Y)$  define oracle policies for  $\pi^{\text{del}}$ ,  $\pi^{\text{plh}}$  and  $\pi^{\text{ins}}$ .

There are two other possible training strategies: Either training the insertion policy to repair a target sentence with randomly dropped tokens, or training the deletion policy to refine the output from the insertion policy. However, we do not use these strategies for our model. In the first case, we did not find it beneficial for the model performance. In the

second case, the option does not fit together with our inference scheme as described in Section 4.2.

To train the model to gradually produce more diverse, but still valid paraphrases, we provided the model with training paraphrase pairs with minimum edit distance. We represent the set of paraphrases as a complete graph with edges weighted by the Levenshtein distance (see Figure 1). We construct a minimum spanning tree of this graph and use the sentence pairs from the spanning tree edges as training examples.

Formally, a training example for LevT is a tuple  $(E, X_0, X, Y)$  where  $E$  is the original English sentence,  $X_0$  is the gold translation,  $X$  is the source node and  $Y$  is the target node.  $(E, X_0)$  is processed by the encoder,  $X$  is used as the initial sequence for the decoder and  $Y$  acts as the ground truth. We do not use any additional data for LevT.

#### 4.2 Inference

In the original LevT formulation, inference is done by applying the model over the initial sequence for several iterations. This approach aims to produce a single output translation and the intermediate translations are deemed to be incorrect. We redefine the generation process as *state-space search*, considering translations in each step as potentially correct and accepting the translations based on the classifier score. We also repurpose the deletion policy as *paraphrasing policy*, which gives us the possibility to generate multiple translations in each step. Similarly to the original LevT architecture, the encoder output is grounding the translations in the source sentence throughout the inference process.

The process can start from an arbitrary number of initial translations – in our case, the initial translations are the filtered outputs from the MT system. We put all the initial translations in a queue. In each step, we pop a translation from the queue, and we let the deletion policy mark all tokens suitable for paraphrasing. To expand our search space, we gen-



et al., 2019). We replace the Transformer encoder with the pretrained XLM-R Base with 12 layers and 8 attention heads, keeping the vanilla Transformer decoder with 6 layers and 8 attention heads. We use the output layer of XLM-R as the decoder output layer and finetune it together with the last four layers of XLM-R (freezing the rest of XLM-R parameters). We train a separate decoder for each policy and employ the early exit as described by Gu et al. (2019) by using only the features from the third layer of the decoder for the deletion and placeholder policies.

The model is optimized using the Adam optimizer, with fixed learning rate  $10^{-5}$ , batch size 1,500 tokens, dropout rate 0.5 and label smoothing 0.1. We set the maximum number of placeholders for each position at 3 instead of 256.

We experiment with various decoding strategies. For deletion and placeholder policies, we introduce a penalty parameter preventing the policy from producing the zero (unchanged) outcome. This proved beneficial in particular for the deletion policy, as it frequently did not mark any tokens for deletion, thus limiting the search process. Alternatively, we force the policy to produce an outcome by selecting top  $k$  results with the highest score. In both cases, we find that limiting the number of placeholders generated at the same position to 1 helps to prevent excessive sentence length.

For the insertion policy, we give up the non-autoregressivity and replace the placeholders in the left-to-right order, re-running the decoder in each step. This acts as a supplement for the fact that the insertion policy cannot repeatedly interact with the deletion policy in a single state-space search step.

Our experiments show that it is difficult to find a set of decoding parameters which would consistently produce meaningful output. For generating paraphrases, we find it useful to use the *penalty* strategy described above and tune the penalty separately for each language. Producing less paraphrases generally leads to better results, as it tends to limit the amount of incorrect output. On the contrary, we use the *top-k* strategy for generating the classifier training data, as it produces negative samples more robustly.

## 6 Results

The results on the blind development and test data are shown in Table 3. Our translation model was able to bring considerable improvements over the

provided baseline models – 10–22% weighted F1 absolute due to increase in both precision and recall. We observed the highest improvements for Portuguese. Overall, our model tends to finish in the middle of the field.

Experiments with training data filtering showed that a smaller training set with better selected sentences leads to better translation quality than using a larger general domain corpus (see Table 4), although the general corpus was double in the number of sentences (see Table 2). The optimal beam size for filtering only roughly corresponds to the average number of paraphrases in the data (see Table 1). Figure 3 shows the effect of beam size on the output quality. Without filtering, the precision quickly drops with increasing beam size. The filtering can partially compensate for the precision loss, however, at the expense of decreasing recall, too.

Despite our extensive efforts, the paraphrasing model did not bring substantial improvements over the translation model. Increase in recall typically came with lower precision and lower weighted F1 score. Even with the specific classifier training and its overall accuracy over 99%, the LevT output was too noisy to be precisely filtered. The only improvement was achieved for Portuguese, where the final paraphrasing and filtering setting resulted in slightly higher precision and similar recall. However, the improvement was mostly influenced by the second round of filtering (on the paraphrasing output). Therefore, we did not include the paraphrasing output in our primary submission.

We suppose that the inefficiency of the LevT model is caused by a mismatch between model training criteria and its application: the individual policies are trained separately, but need to complement each other to achieve good results. Moreover, the loss computed independently for each paraphrase may prevent the model from learning to generate multiple paraphrases. The shortage of useful paraphrases may be also caused by the lack of additional training data.

## 7 Conclusions

We presented our submission to the 2020 STAPLE translation and paraphrasing shared task. Our model is based on the Transformer architecture, used additional carefully selected training data, a XLM-R-based classifier to filter MT output beams, and an optional paraphrasing component based on the Levenshtein Transformer approach. The MT

Target	System	Development						Test					
		Rk	Pre	W-R	W-F1	$\Delta_{base}$	$\Delta_{best}$	Rk	Pre	W-R	W-F1	$\Delta_{base}$	$\Delta_{best}$
Hungarian	MT	4/9	50.65	50.66	46.25	+16.40	-13.58	4/7	51.04	45.77	43.49	+15.39	-11.91
	+Para	-	49.73	50.57	45.75	+15.90	-14.08	-	49.91	45.66	43.01	+14.91	-12.39
Japanese	MT	5/10	39.02	19.36	21.50	+17.25	-10.09	5/8	36.70	19.93	21.28	+16.97	-10.49
	+Para	-	38.27	19.32	21.34	+17.09	-10.25	-	35.76	19.87	21.08	+16.77	-10.69
Korean	MT	4/8	40.05	21.57	22.21	+16.76	-19.16	4/6	38.94	19.35	20.58	+15.71	-19.77
	+Para	-	39.65	21.06	21.87	+16.42	-19.50	-	38.42	18.92	20.29	+15.42	-20.06
Portuguese	MT	8/14	49.75	46.78	42.74	+21.59	-13.00	6/10	49.88	43.81	40.84	+19.54	-14.26
	+Para	-	50.72	46.60	43.22	+22.07	-12.52	-	50.94	43.44	41.18	+19.88	-13.92
Vietnamese	MT	3/6	52.27	37.36	38.26	+11.47	-16.47	3/5	51.59	36.84	37.71	+12.32	-17.85
	+Para	-	53.17	36.39	37.68	+10.89	-17.05	-	52.09	36.35	37.34	+11.95	-18.22

Table 3: Results for both system variants and all languages. “MT” denotes the variant without paraphrasing (final official result), “+Para” is the system with paraphrasing. Metrics:  $Rk$  = official competition rank (with the number of valid submissions),  $Pre$  = precision (%),  $W-R$  = weighted recall (%),  $W-F1$  = weighted F1 (%),  $\Delta_{base}$  = weighted F1 difference w. r. t. the best baseline model (% absolute),  $\Delta_{best}$  = w. r. t. the overall winner (% absolute).

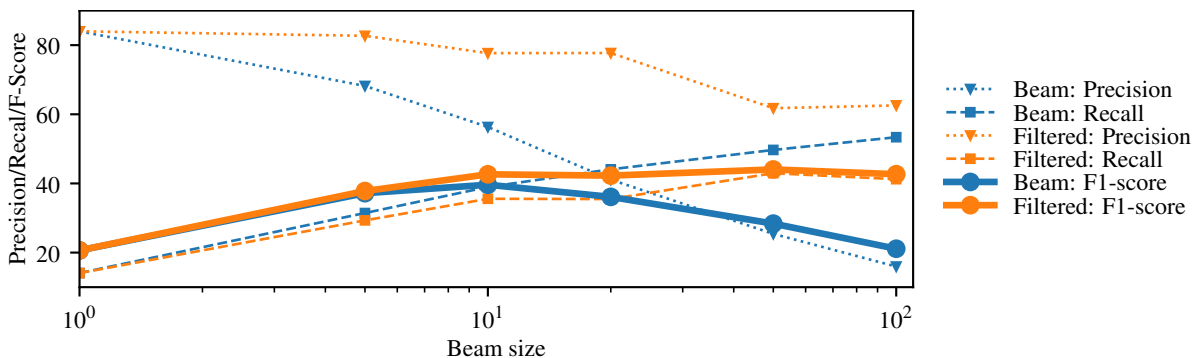


Figure 3: Precision, weighted recall and weighted F1 score for NMT decoding with different beam sizes and with and without beam filtering.

	AWS	Gen.	Dom.	Best	
Hungarian	29.2	27.4	40.2	49.1	100
Japanese	4.8	2.8	11.9	18.6	1000
Korean	4.9	6.5	11.5	22.0	1000
Portuguese	23.1	29.9	39.6	44.0	50
Vietnamese	20.3	33.0	38.5	42.1	5

Table 4: Translation quality measured by the weighted F1 score for general training (Gen.) data and domain-specific (Dom.) training data measured on our validation set with beam size 10 compared with the task baseline (AWS) and best filtered beam with beam size.

model with the filter was able to gain substantial increases over the baseline, but did not reach the top places in the challenge. The paraphrasing component’s output proved too noisy to bring any substantial benefits – we only observed minor improvements in Portuguese. Therefore, the paraphrasing was not included in our primary submission.

Improving the paraphrasing model could be an interesting direction of future work. The amount of incorrect output could be reduced by better ac-

counting for deletion and insertion policy interplay. However, computing the loss independently for each paraphrase may still hinder the ability of the model to generate multiple paraphrases for a single sentence. It may be thus necessary to rethink the training objective and tie it together with the inference process.

## Acknowledgements

Work conducted at LMU was supported by the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation programme (grant agreement No. 640550).

Work conducted at CUNI was supported by the Charles University grant No. 140320, the SVV project No. 260575, the European Union’s Horizon 2020 research and innovation programme under grant agreement No. 825303 (Bergamot), Czech Science Foundation grant No. 19-26934X (NEUREM3), and the Charles University project PRIMUS/19/SCI/10.

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