LIG-CRIStAL System for the WMT17 Automatic Post-Editing Task

Alexandre Bérard **Olivier Pietquin***
Univ. Lille, CNRS, Centrale Lille, Inria, UMR 9189 CRIStAL
alexandre.berard@ed.univ-lille1.fr
olivier.pietquin@univ-lille1.fr

Laurent Besacier
LIG, Univ. Grenoble Alpes, CNRS
laurent.besacier@univ-grenoble-alpes.fr

Abstract

This paper presents the LIG-CRIStAL submission to the shared Automatic Post-Editing task of WMT 2017. We propose two neural post-editing models: a mono-source model with a task-specific attention mechanism, which performs particularly well in a low-resource scenario; and a chained architecture which makes use of the source sentence to provide extra context. This latter architecture manages to slightly improve our results when more training data is available. We present and discuss our results on two datasets (*en-de* and *de-en*) that are made available for the task.

1 Introduction

It has become quite common for human translators to use machine translation (MT) as a first step, and then to manually post-edit the translation hypothesis. This can result in a significant gain of time, compared to translating from scratch (Green et al., 2013). Such translation workflows can result in the production of new training data, that may be re-injected into the system in order to improve it. Common ways to do so are retraining, incremental training, translation memories, or automatic post-editing (Chatterjee et al., 2015).

In Automatic Post-Editing (APE), the MT system is usually considered as a blackbox: a separate APE system takes as input the outputs of this MT system, and tries to improve them. Statistical Post-Editing (SPE) was first proposed by Simard et al. (2007). It consists in training a Statistical Machine Translation (SMT) system (Koehn et al., 2007), to translate from translation hypotheses to a human post-edited version of those. Béchara et al. (2011) then proposed a way to integrate both the translation hypothesis and the original (source language) sentence. More recent contributions in the same vein are (Chatterjee et al., 2016; Pal et al., 2016).

When too little training data is available, one may resort to using synthetic corpora: with simulated PE (Potet et al., 2012), or round-trip translation (Junczys-Dowmunt and Grundkiewicz, 2016).

Recently, with the success of Neural Machine Translation (NMT) models (Sutskever et al., 2014; Bahdanau et al., 2015), new kinds of APE methods have been proposed that use encoder-decoder approaches (Junczys-Dowmunt and Grundkiewicz, 2016, 2017; Libovický et al., 2016; Pal et al., 2017; Hokamp, 2017), in which a Recurrent Neural Network (RNN) encodes the source sequence into a fixed size representation (encoder), and another RNN uses this representation to output a new sequence. These encoder-decoder models are generally enhanced with an attention mechanism, which learns to look at the entire sequence of encoder states (Bahdanau et al., 2015; Luong et al., 2016).

We present novel neural architectures for automatic post-editing. Our models learn to generate sequences of edit operations, and use a task-specific attention mechanism which gives information about the word being post-edited.

1.1 Predicting Edit Operations

We think that post-editing should be closer to spelling correction than machine translation. Our work is based on Libovický et al. (2016), who train a model to predict edit operations instead of words. We predict 4 types of operations: `KEEP`, `DEL`, `INS(word)`, and `EOS` (the end of sentence marker). This results in a vocabulary with three symbols plus as many symbols as there are possible insertions.

*now with DeepMind, London, UK

A benefit of this approach is that, even with little training data, it is very straightforward to learn to output the translation hypothesis as is (MT baseline). We want to avoid a scenario where the APE system is weaker than the original MT system and only degrades its output. However, this approach also has shortcomings, that we shall see in the remainder of this work.

Example If the MT sequence is "The cats is grey", and the output sequence of edit ops is "KEEP DEL INS(cat) KEEP KEEP INS(.)", this corresponds to doing the following sequence of operations: keep "The", delete "cats", insert "cat", keep "is", keep "grey", insert "." The final result is the post-edited sequence "The cat is grey ."

We preprocess the data to extract such edit sequences by following the shortest edit path (similar to a Levenshtein distance, without substitutions, or with a substitution cost of $+\infty$).

1.2 Forced Attention

State-of-the-art NMT systems (Bahdanau et al., 2015) learn a global attention model, which helps the decoder look at the relevant part of the input sequence each time it generates a new word. It is defined as follows:

$$attn_{global}(\mathrm{h}, s_t) = \sum_{i=1}^{A} a_i^t h_i \quad (1)$$

$$a_i^t = softmax(e_i^t) \quad (2)$$

$$e_i^t = v^T tanh(W_1 h_i + W_2 s_t + b_2) \quad (3)$$

where s_t is the current state of the decoder, h_i is the i$^{\text{th}}$ state of the encoder (corresponding to the i$^{\text{th}}$ input word). A is the length of the input sequence. W_1, W_2 and b_2 are learned parameters of the model. This attention vector is used to generate the next output symbol w_t and to compute the next state of the decoder s_{t+1}.

However, we don't predict words, but edit operations, which means that we can do stronger assumptions as to how the output symbols align with the input. Instead of a soft attention mechanism, which can look at the entire input and uses the current decoder state s_t to compute soft weights a_i; we use a hard attention mechanism which directly aligns t with i. The attention vector is then $attn_{forced}(h, s_t) = h_i$.

The $t \rightarrow i$ alignment is pretty straightforward: i is the number of KEEP and DEL symbols in the decoder's past output $(w_1, \ldots, w_{t-1})$ plus one.

Task	Train	Dev	Test 2016	Extra
en-de	23k (12k + 11k)	1000	2000	500k 4M
de-en	24k	1000	none	none

Table 1: Size of each available corpus (number of SRC, MT, PE sentence tuples).

Following the example presented earlier, if the decoder's past output is "KEEP DEL INS(cat)", the next token to generate is naturally aligned with the third input word ($i = 3$), i.e., we've kept "The" and replaced "cats" with "cat". Now, we want to decide whether we keep the third input word "is", delete it, or insert a new word before it.

If the output sequence is too short, i.e., the end of sentence marker EOS is generated before the pointer i reaches the end of the input sequence, we automatically pad with KEEP tokens. This means that to delete a word, there must always be a corresponding DEL symbol. This ensures that, even when unsure about the length of the output sequence, the decoder remains conservative with respect to the sequence to post-edit.

1.3 Chaining Encoders

The model we proposed does not make any use of the source side SRC. Making use of this information is not very straightforward in our framework. Indeed, we may consider using a multi-encoder architecture (Zoph and Knight, 2016; Junczys-Dowmunt and Grundkiewicz, 2017), but it does not make much sense to align an edit operation with the source sequence, and such a model struggles to learn a meaningful alignment.

We propose a chained architecture, which combines two encoder-decoder models (see fig. 1). A first model SRC $\rightarrow$ MT, with a global attention mechanism, tries to mimic the translation process that produced MT from SRC. The attention vectors of this first model summarize the part of the SRC sequence that led to the generation of each MT token. A second model MT $\rightarrow$ OP learns to post-edit and uses a forced attention over the MT sequence, as well as the attention vectors over SRC computed by the first system. Both models are trained jointly, by optimizing a sum of both losses.

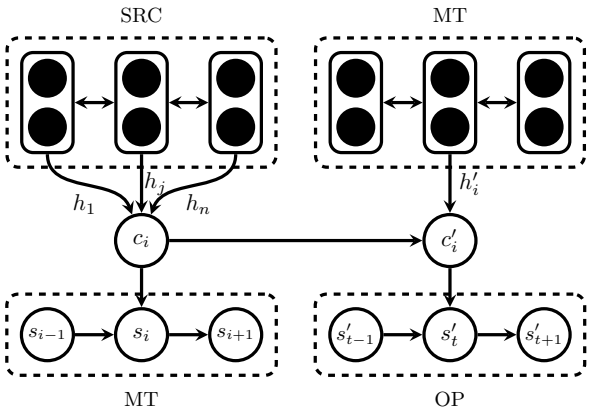


Figure 1: There are two bidirectional encoders that read the SRC and MT sequences. We maximize two training objectives: a translation objective (SRC $\rightarrow$ MT) and a post-editing objective (MT $\rightarrow$ OP). The OP decoder does a forced alignment with the MT encoder ($t \rightarrow i$), and uses the corresponding global attention context c_i over SRC: $c'_i = tanh(H_1 c_i + H_2 h'_i + b')$. The MT decoder and MT encoder share the same embeddings.

2 Experiments

This year's APE task consists in two sub-tasks: a task on English to German post-editing in the IT domain (*en-de*), and a task on German to English post-editing in the medical domain (*de-en*). Table 1 gives the size of each of the corpora available. The goal of both tasks is to minimize the HTER (Snover et al., 2006) between our automatic post-editing output, and the human post-editing output.

The *en-de 23k* training set is a concatenation of last year's *12k* dataset, and a newly released *11k* dataset. A synthetic corpus was built and used by the winner of last year's edition (Junczys-Dowmunt and Grundkiewicz, 2016), and is available this year as additional data (*500k* and *4M* corpora).

For the *en-de* task, we limit our use of external data to the 500k corpus. For the *de-en* task, we built our own synthetic corpus, using a technique similar to (Junczys-Dowmunt and Grundkiewicz, 2016).

2.1 Synthetic Data

Desiderata We used similar data selection techniques as Junczys-Dowmunt and Grundkiewicz (2016), applied to the *de-en* task. However, we are very reticent about using as much parallel data as the authors did. We think that access to such amounts of parallel data is rarely possible, and the round-trip translation method they used too cumbersome and unrealistic. To show a fair comparison, this paper should show APE scores when translating from scratch with an MT system trained with all this parallel data.

To mitigate this, we decided to limit our use of external data to monolingual English (*commoncrawl*). So, the only parallel data we use is the *de-en* APE corpus.

PE side Similarly to Junczys-Dowmunt and Grundkiewicz (2016) we first performed a coarse filtering of well-formed sentences of commoncrawl. After this filtering step, we obtained about 500M lines. Then, we estimated a trigram language model on the PE side of the APE corpus, and sorted the 500M lines according to their log-score divided by sentence length. We then kept the first 10M lines. This results in sentences that are mostly in the medical domain.

MT and SRC sides Using this English corpus, and assuming its relative closeness to the PE side of the APE corpus, we now need to generate SRC and MT sequences. This is where our approach differs from the original paper.

Instead of training two SMT systems PE $\rightarrow$ SRC and SRC $\rightarrow$ MT on huge amounts of parallel data, and doing a round-trip translation of the monolingual data, we train two small PE $\rightarrow$ SRC and PE $\rightarrow$ MT Neural Machine Translation systems on the APE data only.

An obvious advantage of this method is that we do not need external parallel data. The NMT systems are also fairly quick to train, and evaluation is very fast. Translating 10M lines with SMT can take a very long time, while NMT can translate dozens of sentences at once on a GPU.

However, there are strong disadvantages: for one, our SRC and MT sequences have a much poorer vocabulary as those obtained with round-trip translation (because we only get words that belong to the APE corpus). Yet, we hope that the richer target (PE) may help our models learn a better language model.

TER filtering Similarly to Junczys-Dowmunt and Grundkiewicz (2016), we also filter the triples to be close to the real PE distribution in terms of TER statistics. We build a corpus of the *500k* closest tuples. For each tuple in the real PE corpus,

Token	Count	Percentage
KEEP	326581	66.9%
DEL	76725	15.7%
"	5170	1.1%
,	3249	0.7%
die	2461	0.5%
der	1912	0.4%
zu	1877	0.4%
werden	1246	0.3%
KEEP	18367	90.4%
DEL	801	3.9%
"	199	1.0%
>	130	0.6%
,	93	0.5%
zu	63	0.3%
werden	37	0.2%
wird	30	0.1%

Table 2: Top 8 edit ops in the target side of the training set for *en-de* (top), and most generated edit ops by our primary (500k + 23k) system on dev set (bottom).

we select a random subset of *1000* tuples from the synthetic corpus and pick the tuple whose euclidean distance with the real PE tuple is the lowest. This tuple cannot be selected again. We loop over the real PE corpus until we obtain a filtered corpus of desirable size (*500k*).

2.2 Experimental settings

We trained mono-source forced models, as well as chained models for both APE tasks. We also trained mono-source models with a global attention mechanism, similar to (Libovický et al., 2016) as a measure of comparison to our forced models.

For *en-de*, we trained two sets of models (with the same configuration) on the 12k train set (to compare with 2016 competitors), and on the new (23k) train set.

The encoders are bidirectional LSTMs of size 128. The embeddings have a size of 128. The first state of the decoder is initialized with the last state of the forward encoder (after a non-linear transformation with dropout). Teacher forcing is used during training (instead of feeding the previous generated output to the decoder, we feed the ground truth). Like Bahdanau et al. (2015), there is a maxout layer before the final projection.

We train our models with pure SGD with a batch size of 32, and an initial learning rate of 1.0. We decay the learning rate by 0.8 every epoch for the models trained with real PE data, and by 0.5 every half epoch for the models that use additional synthetic data. The models are evaluated periodically on a *dev* set, and we save checkpoints for the best TER scores.

We manually stop training when TER scores on the dev set stop decreasing, and use the best checkpoint for evaluation on the test set (after about 50k steps for the small training sets, and 120k steps for the larger ones).

Unlike Junczys-Dowmunt and Grundkiewicz (2016), we do not use subword units, as we found them not to be beneficial when predicting edit operations. For the larger datasets, our vocabularies are limited to the 30,000 most frequent symbols.

Our implementation uses TensorFlow (Abadi et al., 2015), and runs on a single GPU.[1]

2.3 Results & Discussion

As shown in table 3, our *forced* (contrastive 1) system gets good results on the *en-de* task, in limited data conditions (*12k* or *23k*). It improves over the MT and SPE baselines, and over the global attention baseline (Libovický et al., 2016). The chained model, which also uses the source sentence, is able to harness larger volumes of data, to obtain yet better results (primary model). However, it lags behind large word-based models trained on larger amounts of data (Junczys-Dowmunt and Grundkiewicz, 2016, 2017; Hokamp, 2017).[2]

Figure 2 compares alignments performed by our attention models. We see that the global attention model struggles to learn a meaningful alignment on a small dataset (12k). When more training data is available (23k), it comes closer to our forced alignment.

We see that our good results on *en-de* do not transfer well to *de-en* (see table 4). The BLEU scores are already very high (about 16 points above those of the *en-de* data, and 10 points above the best APE outputs for *en-de*). This is probably due to the translation direction being reversed (because of its rich morphology, German is a much harder target that English). The results obtained with a vanilla SMT system (SPE) seem to confirm this difficulty.

[1] Our source code, and the configurations used in the experiments are available here: https://github.com/eske/seq2seq/tree/APE

[2] More results are published on the web page of the task: http://statmt.org/wmt17/ape-task.html

Model	PE attention	Data	dev	test 2016	test 2017		Steps
				TER		BLEU	
Baseline		none	24.81	24.76	24.48	62.49	
SPE		12k		24.64	24.69	62.97	
Best 2016 (AMU)		4M + 500k + 12k	21.46	21.52			
Best 2017 (FBK)		23k + ?			**19.60**	70.07	
Mono-source	global	12k	24.15	24.26			29000
	forced (contr. 1)		23.20	23.32	23.51	64.52	16600
Chained	forced (contr. 2)		23.40	23.30	23.66	64.46	23600
	forced (primary)	500k + 12k	22.77	**22.94**	**23.22**	65.12	119200
Mono-source	global	23k	23.60	23.55			47200
	forced (contr. 1)		23.07	22.89	23.08	65.57	38800
Chained	forced (contr. 2)		22.61	22.76	23.15	64.94	50400
	forced (primary)	500k + 23k	22.03	**22.49**	**22.81**	65.91	121200

Table 3: Results on the *en-de* task. The SPE results are those provided by the organizers of the task (SMT system). The AMU system is the winner of the 2016 APE task (Junczys-Dowmunt and Grundkiewicz, 2016). FBK is the winner of this year's edition. We evaluate our models on *dev* every 200 training steps, and take the model with the lowest TER. The *steps* column gives the corresponding training time (SGD updates). 500k + 12k is a concatenation of the 500k synthetic corpus with the 12k corpus oversampled 20 times. 500k + 23k is a concatenation of 500k with 23k oversampled 10 times.

The only reason why our *de-en* systems are able to not deteriorate the baseline, is that they only learned to do nothing, by producing arbitrarily long sequences of KEEP symbols. Furthermore, we see that the best results are obtained very early in training, before the models start to overfit and deteriorate the translation hypotheses on the dev set (see *steps* column).

The difference between our scores on the *de-en* dataset is not statistically significant, therefore we cannot draw conclusions as to which model is the best. Furthermore, it turns out that our models output almost only KEEP symbols, resulting in sequences almost identical to the MT input, which explains why the scores are so close to those of the baseline (see table 5).

Adding substitutions is not particularly useful as it leads to even more data sparsity: it doubles the vocabulary size, and results in less DEL symbols, and less training feedback for each individual insertion.

Future work One major problem when learning to predict edit ops instead of words, is the class imbalance. There are much more KEEP symbols in the training data as any other symbol (see tables 2 and 5). This results in models that are very good at predicting KEEP tokens (*do-nothing* scenario), but very cautious when producing other symbols. This also results in bad generalization as most symbols appear only a couple of times in the training data.

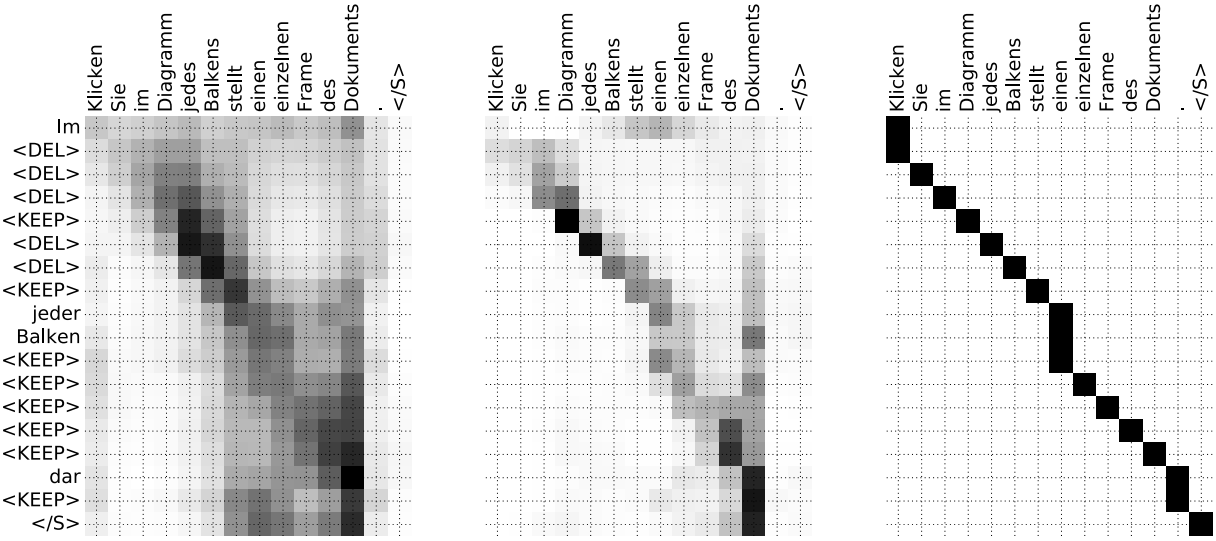
We are investigating ways to get a broader training signal when predicting KEEP symbols. This can be achieved either by weight sharing, or by multi-task training (Luong et al., 2016).

Another direction that we may investigate, is how we obtain sequences of edit operations (from PE data in another form). Our edit operations are extracted artificially by taking the shortest edit path between MT and PE. Yet, this does not necessarily correspond to a plausible sequence of operations done by a human. One way to obtain more realistic sequences of operations, would be to collect finer-grained data from human post-editors: key strokes, mouse movements and clicks could be used to reconstruct the 'true' sequence of edit operations.

Finally, we chose to work at the word level, when a human translator often works at the character level. If a word misses a letter, he won't delete the entire word and write it back. However, working with characters poses new challenges: longer sequences means longer training time, and more memory usage. Also, it is easier to learn semantics with words (a *character embedding* does less sense). Yet, using characters means more training data, and less sparse data, which could be very useful in a post-editing scenario.

Model	PE attention	Data	train-dev	dev	test 2017		Steps
			TER			BLEU	
Baseline		none	16.11	15.58	15.55	79.54	
SPE		24k			15.74	79.28	
Best 2017 (FBK)		24k + ?			**15.29**	79.82	
Mono-source	global	24k	16.06	15.55			5200
	forced (contr. 1)		16.05	15.57	15.62	79.48	3400
Chained	forced (contr. 2)		16.02	15.63	15.68	79.35	7000
	forced (primary)	500k + 24k	15.98	15.67	15.53	79.46	27200

Table 4: Results on the *de-en* task. Because the test set was not available before submission, we used a small part (1000 tuples) of the training set as a *train-dev* set. This set was used for selecting the best models, while the provided dev set was used for final evaluation of our models. The *500k + 24k* corpus is a concatenation of our synthetic corpus with the 24k corpus oversampled 10 times.



(a) Global attention 12k train set (b) Global attention 23k train set (c) Forced attention

Figure 2: Alignments of predicted edit operations (OP) with translation hypothesis (MT), on *en-de* dev set, obtained with different attention models.

Token	Count	Percentage
KEEP	382891	78.19%
DEL	51977	10.61%
the	2249	0.46%
,	1691	0.35%
of	1620	0.33%
to	1022	0.21%
a	952	0.19%
in	919	0.19%

Token	Count	Percentage
KEEP	17861	99.62%
DEL	52	0.29%
UNK	4	0.02%
:	3	0.02%
the	2	0.01%
Have	2	0.01%
A	1	0.01%
>	1	0.01%

Table 5: Top 8 edit ops in the target side of the training set for *de-en* (left), and most generated edit ops by our primary system on train-dev (right).

References

Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Łukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dan Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. 2015. TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems. Software available from `tensorflow.org`.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural Machine Translation by Jointly Learning to Align and Translate. In *ICLR 2015*. San Diego, California, USA, pages 3104–3112.

Hanna Béchara, Yanjun Ma, and Josef van Genabith. 2011. Statistical Post-Editing for a Statistical MT System. In *MT Summit XIII*. Xiamen, China, pages 308–315.

Rajen Chatterjee, José G. C. de Souza, Matteo Negri, and Marco Turchi. 2016. The FBK Participation in the WMT 2016 Automatic Post-Editing Shared Task. In *Proceedings of the First Conference on Machine Translation (WMT 2016)*. Association for Computational Linguistics, Berlin, Germany, pages 745–750.

Rajen Chatterjee, Marion Weller, Matteo Negri, and Marco Turchi. 2015. Exploring the Planet of the APEs: a Comparative Study of State-of-the-art Methods for MT Automatic Post-Editing. In *Association for Computational Linguistics*. pages 156–161.

Spence Green, Jeffrey Heer, and Christopher D Manning. 2013. The Efficacy of Human Post-Editing for Language Translation. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*. ACM, pages 439–448.

Chris Hokamp. 2017. Ensembling Factored Neural Machine Translation Models for Automatic Post-Editing and Quality Estimation. *arXiv preprint arXiv:1706.05083* .

Marcin Junczys-Dowmunt and Roman Grundkiewicz. 2016. Log-linear Combinations of Monolingual and Bilingual Neural Machine Translation Models for Automatic Post-Editing. In *Proceedings of the First Conference on Machine Translation (WMT 2016)*. Association for Computational Linguistics, Berlin, Germany, pages 751–758.

Marcin Junczys-Dowmunt and Roman Grundkiewicz. 2017. An Exploration of Neural Sequence-to-Sequence Architectures for Automatic Post-Editing. *arXiv preprint arXiv:1706.04138* .

Philipp Koehn, Hieu Hoang, Alexandra Birch, Chris Callison-Burch, Marcello Federico, Nicola Bertoldi, Brooke Cowan, Wade Shen, Christine Moran, Richard Zens, et al. 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*. Association for Computational Linguistics, pages 177–180.

Jindřich Libovický, Jindřich Helcl, Marek Tlustý, Ondřej Bojar, and Pavel Pecina. 2016. CUNI System for WMT16 Automatic Post-Editing and Multimodal Translation Tasks. In *Proceedings of the First Conference on Machine Translation (WMT 2016)*. Association for Computational Linguistics, Berlin, Germany, pages 646–654.

Minh-Thang Luong, Quoc V Le, Ilya Sutskever, Oriol Vinyals, and Łukasz Kaiser. 2016. Multi-task Sequence to Sequence Learning. In *ICLR 2016*. San Juan, Puerto Rico.

Santanu Pal, Sudip Kumar Naskar, Mihaela Vela, and Josef van Genabith. 2017. Neural Automatic Post-Editing Using Prior Alignment and Reranking. In *EACL 2017*. volume 2, pages 349–355.

Santanu Pal, Marcos Zampieri, and Josef van Genabith. 2016. USAAR: An Operation Sequential Model for Automatic Statistical Post-Editing. In *Proceedings of the First Conference on Machine Translation (WMT 2016)*. Association for Computational Linguistics, Berlin, Germany, pages 759–763.

Marion Potet, Laurent Besacier, Hervé Blanchon, and Marwen Azouzi. 2012. Towards a Better Understanding of Statistical Post-Edition Usefulness. In *IWSLT 2012*. Hong Kong, pages 284–291.

Michel Simard, Cyril Goutte, and Pierre Isabelle. 2007. Statistical Phrase-based Post-editing. In *NAACL-HLT 2007*. Rochester, New-York, USA, pages 508–515.

Matthew Snover, Bonnie Dorr, Richard Schwartz, Linnea Micciulla, and John Makhoul. 2006. A Study of Translation Edit Rate with Targeted Human Annotation. In *Proceedings of Association for Machine Translation in the Americas*. volume 200.

Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. Sequence to Sequence Learning with Neural Networks. In *Advances in Neural Information Processing Systems (NIPS 2014)*. Montral, Canada, pages 3104–3112.

Barret Zoph and Kevin Knight. 2016. Multi-Source Neural Translation. In *NAACL-HLT 2016*. Denver, Colorado, USA.