

# Naver Labs Europe’s Systems for the WMT19 Machine Translation Robustness Task

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## Abstract

This paper describes the systems that we submitted to the WMT19 Machine Translation robustness task. This task aims to improve MT’s robustness to noise found on social media, like informal language, spelling mistakes and other orthographic variations. The organizers provide parallel data extracted from a social media website<sup>1</sup> in two language pairs: French-English and Japanese-English (in both translation directions). The goal is to obtain the best scores on unseen test sets from the same source, according to automatic metrics (BLEU) and human evaluation. We proposed one single and one ensemble system for each translation direction. Our ensemble models ranked first in all language pairs, according to BLEU evaluation. We discuss the pre-processing choices that we made, and present our solutions for robustness to noise and domain adaptation.

## 1 Introduction

Neural Machine Translation (NMT) has achieved impressive results in recent years, especially on high-resource language pairs (Vaswani et al., 2017; Edunov et al., 2018), and has even lead to some claims of human parity (Hassan et al., 2018).<sup>2</sup>

However, Belinkov and Bisk (2018) show that NMT is brittle, and very sensitive to simple character-level perturbations like letter swaps or keyboard typos. They show that one can make an MT system more robust to these types of synthetic noise, by introducing similar noise on the source side of the training corpus. Sperber et al. (2017) do similar data augmentation, but at the word level and so as to make an MT model more robust to Automatic Speech Recognition errors (within a speech translation pipeline). Cheng et al.

(2018) propose an adversarial training approach to make an encoder invariant to word-level noise. Karpukhin et al. (2019) propose to inject aggressive synthetic noise on the source side of training corpora (with random char-level operations: deletion, insertion, substitution and swap), and show that this is helpful to deal with natural errors found in Wikipedia edit logs, in several language pairs.

Michel and Neubig (2018) release MTNT, a real-world noisy corpus, to help researchers develop MT systems that are robust to natural noise found on social media. The same authors co-organized this task (Li et al., 2019), in which MTNT is the primary resource. Vaibhav et al. (2019) show that back-translation (with a model trained on MTNT) and synthetic noise (that emulates errors found in MTNT) are useful to make NMT models more robust to MTNT noise.

This task aims at improving MT’s robustness to noise found on social media, like informal language, spelling mistakes and other orthographic variations. We present the task in more detail in Section 2. Then, we describe our baseline models and pre-processing in Section 3. We extend these baseline models with robustness and domain adaptation techniques that are presented in Section 4. Finally, in Section 5, we present and discuss the results of our systems on this task.

## 2 Task description

The goal of the task is to make NMT systems that are robust to noisy text found on Reddit, a social media, in two language pairs (French-English and Japanese-English) and both translation directions. The evaluation will be performed on a blind test set (obtained from the same source), using automatic metrics and human evaluation. We present our final BLEU scores in Section 5, while the human evaluation results are given in the shared task overview paper (Li et al., 2019).

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

<sup>2</sup>These claims were discussed at WMT by Toral et al. (2018).

**MTNT** Michel and Neubig (2018) crawled monolingual data from Reddit in three languages: English, French and Japanese, which they filtered to keep only the “noisiest” comments (containing unknown words or with low LM scores).

Then, they tasked professional translators to translate part of the English data to French, and part of it to Japanese. The Japanese and French data was translated to English. The resulting parallel corpora were split into train, valid and test sets (see Table 1). The test sets were manually filtered so as to keep only good quality translations. The data that was not translated is made available as monolingual corpora (see Table 3).

**Other data** In addition to the provided in-domain training and evaluation data, we are allowed to use larger parallel and monolingual corpora (see Tables 2 and 3). For FR↔EN, any parallel or monolingual data from the WMT15 news translation task<sup>3</sup> is authorized. For JA↔EN, we are allowed the same data that was used by Michel and Neubig (2018): KFTT, TED and JESC.

**Challenges** Michel and Neubig (2018) identified a number of challenges for Machine Translation of MTNT data, which warrant the study of MT robustness. Here is an abbreviated version of their taxonomy:

- Spelling and grammar mistakes: e.g., their/they’re, have/of.
- Spoken language and internet slang: e.g., lol, mdr, lmao, etc.
- Named entities: many Reddit posts link to recent news articles and evoke celebrities or politicians. There are also many references to movies, TV shows and video games.
- Code switching: for instance, Japanese text on Reddit contains many English words.
- Reddit jargon: words like “downvote”, “upvote” and “cross-post”,<sup>4</sup> and many acronyms like TIL (Today I Learned), OP (Original Poster), etc.
- Reddit markdown: characters like “~”, “\*” and “” are extensively used for formatting.
- Emojis and emoticons (“;-”).

<sup>3</sup><http://www.statmt.org/wmt15/translation-task.html>

<sup>4</sup>The French-speaking Reddit community sometimes uses funny literal translations of these: “bas-vote”, “haut-vote” and “croix-poteau”.

Lang pair	Lines	Words	
		Source	Target
JA→EN	6 506	160k	155k
EN→JA	5 775	339k	493k
FR→EN	19 161	794k	763k
EN→FR	36 058	1 014k	1 152k

Table 1: Size of the MTNT training corpora. Word counts by Moses (fr/en) and Kytea (ja) tokenizers.

Lang pair	Lines	Words	
		Source	Target
JA↔EN	3.90M	48.42M	42.63M
FR↔EN	40.86M	1 392M	1 172M

Table 2: Size of the authorized out-of-domain parallel corpora in constrained submissions.

- Inconsistent capitalization: missing capital letters on proper names, capitalization for emphasis or “shouting”, etc.
- Inconsistent punctuation.

**Evaluation** Automatic evaluation is performed with cased BLEU (Papineni et al., 2002), using SacreBLEU (Post, 2018).<sup>5</sup> For English and French, the latter takes as input detokenized MT outputs and untokenized reference data. For Japanese, MT outputs and reference are first tokenized with Kytea<sup>6</sup> (Neubig et al., 2011) before being processed by SacreBLEU (because it does not know how to tokenize Japanese). The organizers will also collect subjective judgments from human annotators, and rank participants accordingly.

Language	Corpus	Lines
Japanese	MTNT	32 042
	MTNT	26 485
French	news-discuss	3.84M
	news-crawl	42.1M
English	MTNT	81 631
	news-discuss	57.8M
	news-crawl	118.3M

Table 3: Authorized monolingual data.

### 3 Baseline models

This section describes the pre-processing and hyper parameters of our baseline models. We will

<sup>5</sup>BLEU+case.mixed+numrefs.1+smooth.exp+tok.13a+version.1.3.1

<sup>6</sup>kytea -model share/kytea/model.bin -out tok (v0.4.7)

then detail the techniques that we applied for robustness and domain adaptation.

### 3.1 Pre-processing

**CommonCrawl filtering** We first spent efforts on filtering and cleaning the WMT data (in particular CommonCrawl).

We observed two types of catastrophic failures when training FR→EN models: source sentence copy, and total hallucinations.

The first type of error (copy) is due to having sentence pairs in the training data whose reference “translation” is a copy of the source sentence. [Khayrallah and Koehn \(2018\)](#) show that even a small amount of this type of noise can have catastrophic effects on BLEU. We solve this problem by using a language identifier (`langid.py`, [Lui and Baldwin, 2012](#)) to remove any sentence pair whose source or target language is not right.

Then, we observed that most of the hallucinations produced by our models were variants of the same phrases (see [Table 5](#) for an example). We looked for the origin of these phrases in the training data, and found that they all come from CommonCrawl ([Smith et al., 2013](#)).

We tried several approaches to eliminate hallucinations, whose corresponding scores are shown in [Table 4](#):

1. Length filtering (removing any sentence pair whose length ratio is greater than 1.8, or 1.5 for CommonCrawl): removes most hallucinations and gives the best BLEU score (when combined with LID filtering). This type of filtering is common in MT pipelines ([Koehn et al., 2007](#)).
2. Excluding CommonCrawl from the training data: removes all hallucinations, but gives worse BLEU scores, suggesting that, albeit noisy, CommonCrawl is useful to this task.<sup>7</sup>
3. Attention-based filtering: we observed that when hallucinating, an NMT model produces a peculiar attention matrix (see [Figure 1](#)), where almost all the probability mass is concentrated on the source EOS token. A similar matrix is produced during the forward pass of training when facing a misaligned sentence pair. We filtered CommonCrawl as follows: we trained a baseline FR→EN model on WMT without

<sup>7</sup>And yet, CommonCrawl represents only 7.9% of all lines and 6.5% of all words in WMT.

LID	Len	CC	Att	FR	Hallu.	BLEU
		✓		126	46	34.4
				0	12	34.8
✓	✓			0	0	35.2
✓		✓		0	29	37.7
✓	✓	✓	✓	0	0	38.7
✓	✓	✓		0	10	39.6

Table 4: Number of hallucinations and French-language outputs (according to `langid.py`) when translating MTNT-test (FR→EN). LID: language identifier, Len: length filtering, CC: training data includes CommonCrawl, Att: attention-based filtering.

SRC	T’as trouvé un champion on dirait !
REF	You got yourself a champion it seems !
MT	I’ve never seen videos that SEXY !!!

Table 5: Example of hallucination by a FR→EN Transformer trained on WMT15 data without filtering.

filtering, then translated CommonCrawl while forcing the MT output to be the actual reference, and extracted the corresponding attention matrices. We computed statistics on these attention matrices: their entropy and proportion of French words with a total attention mass lower than 0.2, 0.3, 0.4 and 0.5. Then, we manually looked for thresholds to filter out most of the misalignments, while removing as little correctly aligned data as possible.

A combination of LID, length-based and attention-based filtering removed all hallucinations in the MT outputs, while obtaining excellent BLEU scores. The resulting corpus has 12% fewer lines.<sup>8</sup> We use this filtered data for both FR→EN and EN→FR. As the JA↔EN training data seemed much cleaner, we only did a LID filtering step.

**SentencePiece** We use SentencePiece ([Kudo and Richardson, 2018](#)) for segmentation into subword units.

An advantage of SentencePiece is that it does not require a prior tokenization step (it does its own coarse tokenization, based on whitespaces and changes of unicode categories). It also escapes all whitespaces (by replacing them with a meta symbol), so that its tokenization is fully reversible. This is convenient for emoticons, which

<sup>8</sup>LID: -5%, length filtering: -6.7%, attention filtering: -0.5%.

	!	,	ve	never	seen	videos	that	5	EX	y	!	!	!	EOS	
!_T	11	1	0	4	3	3	0	0	0	0	0	0	0	1	
,	0	1	0	0	0	0	0	0	0	0	0	0	0	0	
as	1	0	1	1	0	0	0	0	0	0	0	0	0	0	
_trouvé	1	1	0	12	2	0	0	0	0	0	0	0	0	0	
_un	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
_champion	1	0	0	2	1	1	0	0	0	0	0	0	0	0	
_on	1	0	0	0	1	0	0	0	0	0	0	0	0	0	
_di	0	0	0	1	1	0	0	0	0	0	0	0	0	0	
rait	0	0	0	1	0	0	0	0	0	0	0	0	0	0	
_	1	0	0	0	0	0	0	0	0	0	1	0	0	0	
!	1	0	0	0	0	1	2	0	0	0	3	8	5	5	
EOS	76	90	94	71	85	92	95	96	97	97	93	89	92	91	94

Figure 1: Attention matrix of a French (left) → English (top) Transformer when hallucinating. This is the average of the attention heads of the last decoder layer over the last encoder layer.

Moses-style tokenization tends to break apart irreversibly.

SentencePiece also normalizes unicode characters using the NFKC rules (e.g.,  $\frac{1}{2} \rightarrow 1/2$ ). It is useful for Japanese, which sometimes uses double-width variants of the ASCII punctuation symbols (e.g., “fullwidth question mark” in unicode table).

We tried different settings of SentencePiece, and settled with the BPE algorithm (Sennrich et al., 2016b),<sup>9</sup> with a joined model of 32k tokens for FR↔EN (with a vocabulary threshold of 100), and two separate models of size 16k for JA↔EN.

**Japanese tokenization** SentencePiece’s tokenization is based mostly on whitespaces, which are very rare in Japanese. For this reason, a pre-tokenization step may be useful (as a way to enforce some linguistic bias and consistency in the BPE segmentation).

We tested several tokenizers for Japanese: MeCab (with IPA and Juman dictionaries),<sup>10</sup> Juman++,<sup>11</sup> and Kytea.<sup>12</sup> MeCab and KyTea gave comparable results, slightly better than when using no pre-tokenization (especially when Japanese is the target language), and Juman++ gave worse results. We settled with Kytea, which is the official tokenizer used on the EN→JA task.<sup>13</sup>

<sup>9</sup>SentencePiece also implements ULM (Kudo, 2018).

<sup>10</sup><http://taku910.github.io/mecab/>

<sup>11</sup><https://github.com/ku-nlp/jumanpp>

<sup>12</sup><http://www.phontron.com/kytea/>

<sup>13</sup>We use the default model shipped with KyTea.

## 3.2 Model and hyper-parameters

We use Transformer Big for FR↔EN and JA→EN, and Transformer Base for EN→JA. We work with Fairseq, with essentially the same hyper-parameters as Ott et al. (2018).

For FR↔EN, we fit up to 3500 tokens in each batch, while training on 8 GPUs (with synchronous SGD). We accumulate gradients over 10 batches before updating the weights. This gives a theoretical maximum batch size of 280k tokens. These models are trained for 15 epochs, with a checkpoint every 2500 updates. We set the dropout rate to 0.1. The source and target embedding matrices are shared and tied with the last layer.

For JA↔EN, we fit 4000 tokens in each batch, and train on 8 GPUs without delayed updates, for 100 epochs with one checkpoint every epoch. We set the dropout rate to 0.3.

For both language pairs, we train with Adam (Kingma and Ba, 2015), with a max learning rate of 0.0005, and the same learning rate schedule as Ott et al. (2018); Vaswani et al. (2017). We also do label smoothing with a 0.1 weight. We average the 5 best checkpoints of each model according to their perplexity on the validation set. We do half precision training, resulting in a 3× speedup on V100 GPUs (Ott et al., 2018).

## 4 Robustness techniques

We now describe the techniques that we applied to our baseline models to make them more robust to the noise found in MTNT.

### 4.1 Case handling

One of the sources of noise in the MTNT data is capital letters. On the Web, capital letters are often used for emphasis (to stress one particular word, or for “shouting”). However, NMT models treat uppercase words or subwords as completely different entities than their lowercase counterparts. BPE even tends to over-segment capitalized words that were not seen in its training data.

One solution, used by Levin et al. (2017) is to do factored machine translation (Sennrich and Hadrow, 2016; Garcia-Martinez et al., 2016), where words (or subwords) are set to lowercase and their case is considered as an additional feature.

In this work, we use a simpler technique that we call “inline casing”, which consists in using special tokens to denote uppercase (<U>) or title

case subwords (<T>), and including these tokens within the sequence right after the corresponding (lowercase) subword. For instance, They were SO TASTY!!  $\rightarrow$  they <T> \_were \_so <U> \_tas <U> ty <U> !!. SentencePiece is trained and applied on lowercase text and the case tokens are added after the BPE segmentation. We also force SentencePiece to split mixed-case words (e.g., MacDonalds  $\rightarrow$  \_mac <T> donalds <T>).

## 4.2 Placeholders

MTNT contains emojis, which our baseline MT models cannot handle (unicode defines over 3 000 unique emojis). We simply replace all emojis in the training and test data with a special <emoji> token. Models trained with this data are able to recopy <emoji> placeholders at the correct position.<sup>14</sup> At test time, we replace target-side placeholders with source-side emojis in the same order.

We use the same solution to deal with Reddit user names (e.g., /u/frenchperson) and subreddit names (e.g., /r/france). MT models sometimes fail to recopy them (e.g., /u/français). For this reason, we identify such names with regular expressions (robust to small variations: without leading / or with extra spaces), and replace them with <user> and <reddit> placeholders.

## 4.3 Natural noise

We extract noisy variants of known words from the MTNT monolingual data, thanks to French and English lexicons and an extended edit distance (allowing letter swaps and letter repetitions). We also manually build a list of noise rules, with the most common spelling errors in English (e.g., your/you’re, it/it’s) and French (e.g., ça/sa, à/a), punctuation substitutions, letter swaps, spaces around punctuation and accent removal. Then we randomly replace words with noisy variants and apply these noise rules on the source side of MTNT-train, CommonCrawl and News Commentary (MTNT-train, TED and KFTT for EN $\rightarrow$ JA), and concatenate these noised versions to the clean training corpus.

## 4.4 Back-translation

Back-translation (Sennrich et al., 2016a; Edunov et al., 2018) is a way to take advantage of large

<sup>14</sup>We ensure that there is always the same number of placeholders on both sides of the training corpus.

amounts of monolingual data. This is particularly useful for domain adaptation (when the parallel data is not in the right domain), or for low-resource MT (when parallel data is scarce).

In this task, we hope that back-translation can help on JA $\rightarrow$ EN, where we have less parallel data, and on FR $\leftrightarrow$ EN to expand vocabulary coverage (in particular w.r.t. recent named entities and news topics which are often evoked on Reddit).

Table 3 describes the monolingual data which is available for constrained submissions. News-discuss (user comments on the Web about news articles) is probably more useful than news-crawl as it is closer to the domain. We use our baseline models presented in Section 3 to back-translate the monolingual data. Following Edunov et al. (2018), we do sampling instead of beam search, with a softmax temperature of  $\frac{1}{0.9}$ .

In all language pairs, we back-translate the target-language MTNT monolingual data, with one different sampling for each epoch. We also back-translate the following data:

- JA $\rightarrow$ EN:  $\frac{1}{20}$ <sup>th</sup> of *news-discuss.en* per epoch (with rotation at the 21<sup>th</sup> epoch).
- FR $\rightarrow$ EN:  $\frac{1}{5}$ <sup>th</sup> of *news-discuss.en* per epoch (with rotation at the 6<sup>th</sup> epoch).
- EN $\rightarrow$ FR: *news-discuss.fr* with one different sampling for each epoch and  $\frac{1}{5}$ <sup>th</sup> of *news-crawl.fr* (with rotation at the 6<sup>th</sup> epoch).

## 4.5 Tags

We insert a tag at the beginning of each source sentence, specifying its type: <BT> for back-translations, <noise> for natural noise, <real> for real data, and <rev> for MTNT data in the reverse direction (e.g., for JA $\rightarrow$ EN MT, we concatenate MTNT JA $\rightarrow$ EN and “reversed” MTNT EN $\rightarrow$ JA). We found that “isolating” the back-translated data with a different source-side tag gave better BLEU scores. At test time, we always use the <real> tag.

Like Kobus et al. (2017), we also use tags for domain adaptation. We prepend a tag to all source sentences specifying their corpus. For instance, sentences from MTNT get the <MTNT> tag and those from Europarl get the <europarl> tag. These “corpus” tags are used in conjunction with the “type” tags (e.g., MTNT back-translated sentences begin with <MTNT> <BT>). At test time, we use <MTNT> to translate MTNT-domain text, and no corpus tag to translate out-of-domain text.

Model	Test	Valid	Blind
MTNT	6.7 <sup>†</sup>	–	5.8
MTNT fine-tuned	9.8 <sup>†</sup>	–	–
Transformer base + tags	13.5	11.2	13.7
+ Back-Translation (BT)	15.0	12.8	14.1
+ Trans. big architecture **	15.5	12.4	14.7
+ Ensemble of 4 *	<b>16.6</b>	<b>13.7</b>	<b>16.4</b>

Table 6: BLEU scores of the JA→EN models on MTNT-test, MTNT-valid and MTNT-blind.

Model	Test	Valid	Blind
MTNT	9.0 <sup>†</sup>	–	8.4
MTNT fine-tuned	12.5 <sup>†</sup>	–	–
Transformer base + tags	19.5	19.0	16.4
+ BT + natural noise **	19.4	19.4	16.5
+ Ensemble of 6 *	<b>20.7</b>	<b>21.2</b>	<b>17.7</b>

Table 7: BLEU scores of the EN→JA models.

We found that this method is roughly as good for domain adaptation as fine-tuning. We settle with corpus tags (rather than fine-tuning), as it is more flexible, less tricky to configure and has better properties on out-of-domain text.

## 5 Results

Tables 6, 7, 8 and 9 give the BLEU scores of our models on the MTNT-valid, MTNT-test and MTNT-blind sets (i.e., final results of the task). For FR↔EN we also give BLEU scores on news-test 2014, to compare with the literature, and to measure general-domain translation quality after domain adaptation. For news-test, we use Moses’ `normalize-punctuation.perl` on the MT outputs before evaluation.

“MTNT” and “MTNT fine-tuned” are the baseline models of the task organizers (Michel and Neubig, 2018). The models marked \* and \*\* were submitted respectively to the competition as primary and secondary systems. Our primary ensemble models ranked first in all translation directions (with +0.7 up to +3.1 BLEU compared to the next best result). † means that different SacreBLEU parameters were used (namely “intl” tokenization).

The “robustness” techniques like inline casing, emoji/Reddit placeholders and natural noise had little to no impact on BLEU scores. They solve problems that are too rare to be accurately measured by BLEU. For instance, we counted 5 emojis and 36 “exceptionally” capitalized words in MTNT-test. Improvements could be mea-

Model	Test	News	Blind
MTNT	23.3 <sup>†</sup>	–	25.6
MTNT fine-tuned	30.3 <sup>†</sup>	–	–
Transformer big	39.1	39.3	40.9
+ MTNT + tags	43.1	39.2	45.0
+ BT + natural noise **	44.3	40.2	47.0
+ Ensemble of 4 *	<b>45.7</b>	<b>40.9</b>	<b>47.9</b>

Table 8: BLEU scores of the FR→EN models on MTNT-test, news-test 2014 and MTNT-blind.

Model	Test	News	Blind
MTNT	21.8 <sup>†</sup>	–	22.1
MTNT fine-tuned	29.7 <sup>†</sup>	–	–
Transformer big	33.1	40.7	37.0
+ MTNT + tags	38.8	40.2	39.0
+ BT + natural noise **	40.5	42.3	41.0
+ Ensemble of 4 *	<b>41.0</b>	<b>42.9</b>	<b>41.4</b>

Table 9: BLEU scores of the EN→FR models.

sured with BLEU on test sets where these phenomena have been artificially increased: e.g., an all-uppercase test set, or the natural noise of Karpukhin et al. (2019).

Most of the BLEU gains were obtained thanks to careful data filtering and pre-processing, and thanks to domain adaptation: back-translation and integration of in-domain data with corpus tags.

**Punctuation fixes** We looked at the translation samples on the submission website, and observed that the French references used apostrophes and angle quotes. This is inconsistent with the training data (including MTNT), which contains mostly ASCII single quotes and double quotes. A simple post-processing step to replace quotes led to a BLEU increase of 5 points for EN→FR.<sup>15</sup>

## 6 Conclusion

We presented our submissions to the WMT Robustness Task. The goal of this task was to build Machine Translation systems that are robust to the types of noise found on social media, in two language pairs (French-English and Japanese-English). Thanks to careful pre-processing and data filtering, and to a combination of several domain adaptation and robustness techniques (special handling of capital letters and emojis, natural noise injection, corpus tags and back-translation), our systems ranked first in the BLEU evaluation in all translation directions.

<sup>15</sup>The organizers and participants were informed of this.

## References

- Yonatan Belinkov and Yonatan Bisk. 2018. [Synthetic and Natural Noise Both Break Neural Machine Translation](#). In *ICLR*.
- Yong Cheng, Zhaopeng Tu, Fandong Meng, Junjie Zhai, and Yang Liu. 2018. [Towards Robust Neural Machine Translation](#). In *ACL*.
- Sergey Edunov, Myle Ott, Michael Auli, and David Grangier. 2018. [Understanding Back-Translation at Scale](#). In *EMNLP*.
- Mercedes Garcia-Martinez, Loic Barrault, and Fethi Bougares. 2016. [Factored Neural Machine Translation Architectures](#). In *IWSLT*.
- Hany Hassan, Anthony Aue, Chang Chen, Vishal Chowdhary, Jonathan Clark, Christian Federmann, Xuedong Huang, Marcin Junczys-Dowmunt, William Lewis, Mu Li, Shujie Liu, Tie-Yan Liu, Renqian Luo, Arul Menezes, Tao Qin, Frank Seide, Xu Tan, Fei Tian, Lijun Wu, Shuangzhi Wu, Yingce Xia, Dongdong Zhang, Zhirui Zhang, and Ming Zhou. 2018. [Achieving Human Parity on Automatic Chinese to English News Translation](#). *arXiv*.
- Vladimir Karpukhin, Omer Levy, Jacob Eisenstein, and Marjan Ghazvininejad. 2019. [Training on Synthetic Noise Improves Robustness to Natural Noise in Machine Translation](#). *arXiv*.
- Huda Khayrallah and Philipp Koehn. 2018. [On the Impact of Various Types of Noise on Neural Machine Translation](#). In *Proceedings of the Second Workshop on Neural Machine Translation and Generation (WNMT)*.
- Diederik Kingma and Jimmy Ba. 2015. [Adam: A Method for Stochastic Optimization](#). In *ICLR*.
- Catherine Kobus, Josep Crego, and Jean Senellart. 2017. [Domain Control for Neural Machine Translation](#). In *RANLP*.
- Philipp Koehn, Hieu Hoang, Alexandra Birch, Chris Callison-Burch, Marcello Federico, Nicola Bertoldi, Brooke Cowan, Wade Shen, Christine Moran, Richard Zens, Chris Dyer, Ondrej Bojar, Alexandra Constantin, and Evan Herbst. 2007. [Moses: Open Source Toolkit for Statistical Machine Translation](#). In *ACL*.
- Taku Kudo. 2018. [Subword Regularization: Improving Neural Network Translation Models with Multiple Subword Candidates](#). In *ACL*.
- Taku Kudo and John Richardson. 2018. [SentencePiece: A simple and language independent subword tokenizer and detokenizer for Neural Text Processing](#). In *EMNLP*.
- Pavel Levin, Nishikant Dhanuka, and Maxim Khalilov. 2017. [Machine Translation at Booking.com: Journey and Lessons Learned](#). In *EAMT*.
- Xian Li, Paul Michel, Antonios Anastasopoulos, Yonatan Belinkov, Nadir K. Durrani, Orhan Firat, Philipp Koehn, Graham Neubig, Juan M. Pino, and Hassan Sajjad. 2019. [Findings of the First Shared Task on Machine Translation Robustness](#). In *WMT*.
- Marco Lui and Timothy Baldwin. 2012. [langid.py: An Off-the-shelf Language Identification Tool](#). In *ACL*.
- Paul Michel and Graham Neubig. 2018. [MTNT: A Testbed for Machine Translation of Noisy Text](#). In *EMNLP*.
- Graham Neubig, Yosuke Nakata, and Shinsuke Mori. 2011. [Pointwise Prediction for Robust, Adaptable Japanese Morphological Analysis](#). In *ACL-HLT*.
- Myle Ott, Sergey Edunov, David Grangier, and Michael Auli. 2018. [Scaling Neural Machine Translation](#). In *WMT*.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wj Zhu. 2002. [BLEU: a Method for Automatic Evaluation of Machine Translation](#). In *ACL*.
- Matt Post. 2018. [A Call for Clarity in Reporting BLEU Scores](#). In *WMT*.
- Rico Sennrich and Barry Haddow. 2016. [Linguistic Input Features Improve Neural Machine Translation](#). In *WMT*.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016a. [Improving Neural Machine Translation Models with Monolingual Data](#). In *ACL*.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016b. [Neural Machine Translation of Rare Words with Subword Units](#). In *ACL*.
- Jason R Smith, Herve Saint-Amand, Magdalena Plamada, Philipp Koehn, Chris Callison-Burch, and Adam Lopez. 2013. [Dirt Cheap Web-Scale Parallel Text from the Common Crawl](#). In *ACL*.
- Matthias Sperber, Jan Niehues, and Alex Waibel. 2017. [Toward Robust Neural Machine Translation for Noisy Input Sequences](#). In *IWSLT*.
- Antonio Toral, Sheila Castilho, Ke Hu, and Andy Way. 2018. [Attaining the Unattainable? Reassessing Claims of Human Parity in Neural Machine Translation](#). In *WMT*.
- Vaibhav, Sumeet Singh, Craig Stewart, and Graham Neubig. 2019. [Improving Robustness of Machine Translation with Synthetic Noise](#). In *NAACL*.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, ukasz Kaiser, and Illia Polosukhin. 2017. [Attention Is All You Need](#). In *NIPS*.