# NTT Neural Machine Translation Systems at WAT 2017

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Innovative R&D by NTT

## General Settings

Attentional NMT based on Luong et al.
Byte Pair Encoding (vocab: 16k)
2 layers encoder-decoder
- Embed, Hidden, Attention = 512 units

Epochs: 20
SGD (Learning rate = 1.0, decay after 13 epochs)
Minibatch: 128 sentences
Japanese side tokenizer: KyTea
English side tokenizer: Moses tokenizer

## Our Implementation

https://github.com/nttcslab-nlp/wat2017

Try it!

## ASPEC (Scientific Paper)

### English-to-Japanese

| System | Training data | BLEU | Pairwise | Adequacy |
|---|---|---|---|---|
| Single | 3.0M (original) | 37.15 | – | – |
| Single | 2.0M (original) | 37.90 | – | – |
| Single | 2.0M (original) + 1.0M synthetic | 38.87 | – | – |
| 8 Ensemble | 2.0M (original) | 39.80 | 72.250 | |
| 8 Ensemble | 2.0M (original) + 1.0M synthetic | **40.32** | **75.750** | **4.41** |

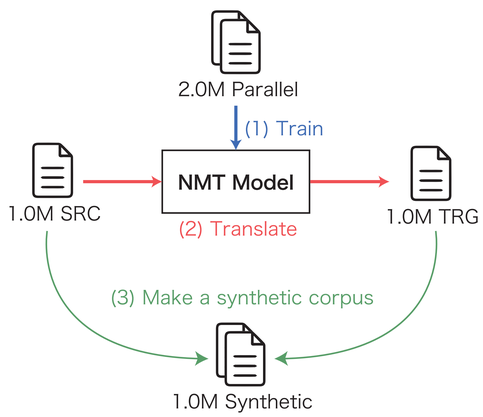
### Japanese-to-English

| System | Training data | BLEU | Pairwise | Adequacy |
|---|---|---|---|---|
| Single | 3.0M (original) | 26.07 | – | – |
| Single | 2.0M (original) | 27.43 | 75.000 | – |
| Single | 2.0M (original) + 1.0M synthetic | 27.62 | – | – |
| 8 Ensemble | 2.0M (original) | **28.36** | **77.250** | **4.14** |
| 8 Ensemble | 2.0M (original) + 1.0M synthetic | 28.15 | – | – |

### Noisy part on the corpus

**Q** Should we use the whole corpus?

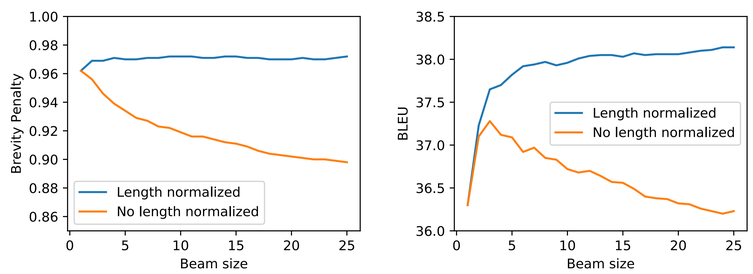
**A** No! The latter side is noisy.
We only need first 2.0M sentences.
Make synthetic corpus for the latter side.




### Length-based score normalization

Beam search with a large beam size tends to select shorter sentences. To rescore the scores, use the following formula proposed by Cromieres et al.

$$\hat{t} = \arg\max_{t \in \boldsymbol{t}} \left\{ \frac{p(t)}{|t|} \right\}$$




Length-based score normalization works well.
With this normalization, we can use larger beam size with keeping the length of the sentence.

Refs: Improving Neural Machine Translation Models with Monolingual Data, Sennrich et al., ACL 2016
Kyoto University Participation to WAT 2016, Cromieres et al., WAT 2016

## JIJI Corpus (Newspaper)

| Direction | System | BLEU | Pairwise | Adequacy |
|---|---|---|---|---|
| En→Ja | Single | 19.13 | 14.500 | – |
| | 8 Ensemble | **20.37** | **17.750** | **2.03** |
| Ja→En | Single | 19.44 | **32.000** | **2.05** |
| | 8 Ensemble | **20.90** | 26.750 | – |

### Difficulties on newspaper domain

| Direction | System | BLEU | Pairwise |
|---|---|---|---|
| En→Ja | Online-A | 11.29 | **69.750** |
| | RBMT-A | 5.31 | 31.250 |
| | NTT | **20.37** | 17.750 |

**Q** We achieved the highest BLEU score, but lower on the human evaluaion. Why?

**A** It's due to the noise on the corpus.

| | |
|---|---|
| Source | The two leaders initially planned to only send messages, without attending the events. |
| Target (Original) | 韓国の朴槿恵大統領も２２日のソウルでの祝賀行事出席を見送る方針を示していた。<br>(Korean President Park Geun-hye also indicated that she will not be presenting celebratory events in Seoul on the 22nd.) |

There are a lot of incorrect aligned sentence pairs.
- NMT model tries to fit these data, leading to drop the human evaluation score.
- We may need to consider how to train a model with noisy parallel corpus like this.