Zero-Shot and Unsupervised Machine Translation

Jonah Philion

April 3, 2018

Overview

1. Traditional Neural Machine Translation
2. Zero-Shot Translation (Johnson, 2017)
3. Unsupervised Neural Machine Translation (Artetxe, 2018)

Traditional Neural Machine Translation

Problem Given a sentence in language l, generate a sentence in language l' with the same meaning.

Problem Given a sentence in language l, generate a sentence in language l' with the same meaning.

Metrics

- BLEU - geometric mean of modified precision scores multiplied by a brevity penalty
- METEOR - harmonic mean of unigram precision and recall with recal weighted higher than precision. Stronger correlation with human judgement than BLEU but cited less often.

Traditional Neural Machine Translation with Attention

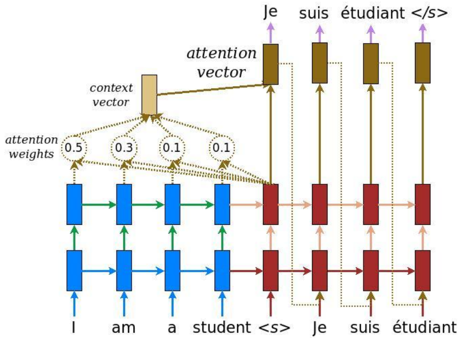


Figure: An NMT model with attention (Bahdanau, 2016).

Zero-Shot Translation (Johnson, 2017)

Motivation for Google Zero-Shot Translation (Johnson, 2017)

Problem

- Each pair of languages requires an encoder-decoder pair $\Rightarrow$ space is $O(n^2)$ in number of languages n.
- Google would like to support upwards of 100 languages with sometimes few to no sentence-to-sentence pairs.

Motivation for Google Zero-Shot Translation (Johnson, 2017)

Problem

- Each pair of languages requires an encoder-decoder pair $\Rightarrow$ space is $O(n^2)$ in number of languages n.
- Google would like to support upwards of 100 languages with sometimes few to no sentence-to-sentence pairs.

Solution

- Universal decoder and encoder for all language pairs.
- Add an artificial token to the input sequence to indicate the required target language.

Motivation for Google Zero-Shot Translation (Johnson, 2017)

Problem

- Each pair of languages requires an encoder-decoder pair $\Rightarrow$ space is $O(n^2)$ in number of languages n.
- Google would like to support upwards of 100 languages with sometimes few to no sentence-to-sentence pairs.

Solution

- Universal decoder and encoder for all language pairs.
- Add an artificial token to the input sequence to indicate the required target language.

```
Hello, how are you? -> Hola, ¿cómo estás?
```

```
<2es> Hello, how are you? -> Hola, ¿cómo estás?
```

Zero-Shot Architecture

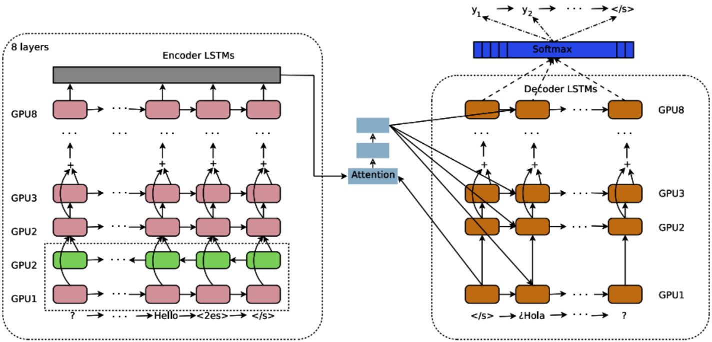


Figure: Google Zero-Shot Architecture (Johnson, 2017). Source sentence is reversed and prepended to the target language token.

Results

- On the many-to-many task, the model underperforms production translation models by 2.5%.

Table 4: Large-scale experiments: BLEU scores for single language pair and multilingual models.

Model	Single	Multi	Multi	Multi	Multi
#nodes	1024	1024	1280	1536	1792
#params	3B	255M	367M	499M	650M
Prod English→Japanese	23.66	21.10	21.17	21.72	21.70
Prod English→Korean	19.75	18.41	18.36	18.30	18.28
Prod Japanese→English	23.41	21.62	22.03	22.51	23.18
Prod Korean→English	25.42	22.87	23.46	24.00	24.67
Prod English→Spanish	34.50	34.25	34.40	34.77	34.70
Prod English→Portuguese	38.40	37.35	37.42	37.80	37.92
Prod Spanish→English	38.00	36.04	36.50	37.26	37.45
Prod Portuguese→English	44.40	42.53	42.82	43.64	43.87
Prod English→German	26.43	23.15	23.77	23.63	24.01
Prod English→French	35.37	34.00	34.19	34.91	34.81
Prod German→English	31.77	31.17	31.65	32.24	32.32
Prod French→English	36.47	34.40	34.56	35.35	35.52
ave diff	-	-1.72	-1.43	-0.95	-0.76
vs single	-	-5.6%	-4.7%	-3.1%	-2.5%

Figure: When trained on all pairs of three languages, the model achieves comparable BLEU scores. Since the simplest model has 255M instead of 3B parameters, this result is satisfying.

Zero-Shot

The model can translate between languages for which there was no parallel data during training.

Table 5: Portuguese→Spanish BLEU scores using various models.

	Model	Zero-shot	BLEU
(a)	PBMT bridged	no	28.99
(b)	NMT bridged	no	30.91
(c)	NMT Pt→Es	no	31.50
(d)	Model 1 (Pt→En, En→Es)	yes	21.62
(e)	Model 2 (En↔{Es, Pt})	yes	24.75
(f)	Model 2 + incremental training	no	31.77

Figure: PBMT is a phrase based translation system. NMT bridged is translation from Portuguese to Spanish going through English. NMT Pt→Es is a standard NMT model with attention trained on all available Portuguese to Spanish sentences. Model (f) is trained on a tenth of the data of model (c).

Interlingua

Source Language Code-Switching What if we mix languages in the source sentence?

- **Japanese:** 私は東京大学の学生です。 → I am a student at Tokyo University.
- **Korean:** 나는 도쿄 대학의 학생입니다. → I am a student at Tokyo University.
- **Mixed Japanese/Korean:** 私は東京大学학생입니다. → I am a student of Tokyo University.

Figure: The model handles mixed input language no problem.

Weighted Target Language Selection What if we feed linear combinations of target tokens?

Russian/Belarusian:	I wonder what they'll do next!
$w_{be} = 0.00$	Интересно, что они сделают дальше!
$w_{be} = 0.20$	Интересно, что они сделают дальше!
$w_{be} = 0.30$	Цікаво, что они будут делать дальше!
$w_{be} = 0.44$	Цікаво, що вони будуть робити далі!
$w_{be} = 0.46$	Цікаво, що вони будуть робити далі!
$w_{be} = 0.48$	Цікаво, што яны зробяць далей!
$w_{be} = 0.50$	Цікава, што яны будуць рабіць далей!
$w_{be} = 1.00$	Цікава, што яны будуць рабіць далей!

Figure: The model translates into Ukrainian in the process of translating to Russian and Belarusian.

Interlingua

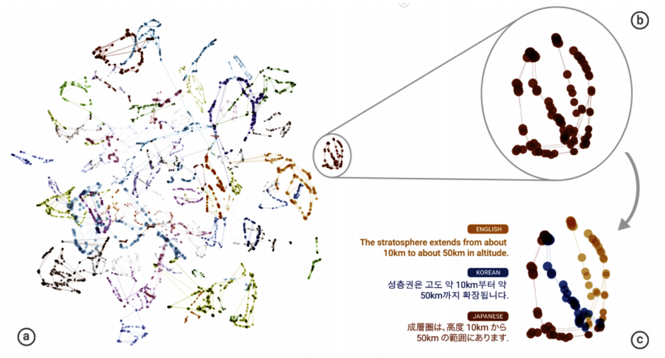


Figure 2: A t-SNE projection of the embedding of 74 semantically identical sentences translated across all 6 possible directions, yielding a total of 9,978 steps (dots in the image), from the model trained on English↔Japanese and English↔Korean examples. (a) A bird's-eye view of the embedding, coloring by the index of the semantic sentence. Well-defined clusters each having a single color are apparent. (b) A zoomed in view of one of the clusters with the same coloring. All of the sentences within this cluster are translations of "The stratosphere extends from about 10km to about 50km in altitude." (c) The same cluster colored by source language. All three source languages can be seen within this cluster.

Figure: Semantically identicle sentences have similar encodings.

Unsupervised Neural Machine Translation (Artetxe, 2018)

UNMT Motivation

- **Question** How well can we translate between language l_1 and l_2 given a corpus of text X_1 of language l_1 and a corpus of text X_2 of language l_2?

$\rightarrow$ Strong baseline for supervised NMT

$\rightarrow$ Translation in low-resource contexts

UNMT Motivation

- **Question** How well can we translate between language l_1 and l_2 given a corpus of text X_1 of language l_1 and a corpus of text X_2 of language l_2?

  $\rightarrow$ Strong baseline for supervised NMT

  $\rightarrow$ Translation in low-resource contexts

- **Solution** Train universal encoder and language-specific decoders to denoise and backtranslate.

UNMT Motivation

- **Question** How well can we translate between language l_1 and l_2 given a corpus of text X_1 of language l_1 and a corpus of text X_2 of language l_2?

  $\rightarrow$ Strong baseline for supervised NMT

  $\rightarrow$ Translation in low-resource contexts

- **Solution** Train universal encoder and language-specific decoders to denoise and backtranslate.
  This solution is one of many proposed solutions to this problem.

Model

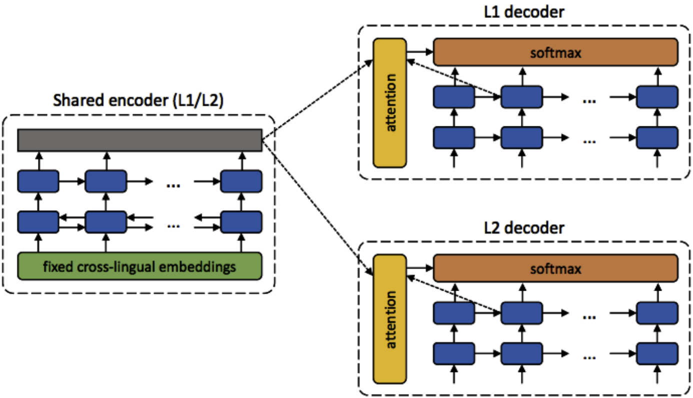


Figure: At test time, a sentence *src* from either l_1 or l_2 is fed to the encoder, and the target sentence decoder is used to predict a translation. At training time, the decoder used is the decoder associated with the language of *src*.

2 “Differences” from Standard NMT

2 "Differences" from Standard NMT

- **2-step training** Cross-lingual word embeddings are determined in an initial training step (Johnson, 2017). These embeddings are then frozen before training the encoder-decoder system.

2 “Differences” from Standard NMT

- **2-step training** Cross-lingual word embeddings are determined in an initial training step (Johnson, 2017). These embeddings are then frozen before training the encoder-decoder system.
- $\mathbf{L}_{denoise} + \mathbf{L}_{backtranslate}$ Training the ecoder-decoder consists of a loss associated with the ability to back-translate and a loss associated with the ability to denoise.

$L_{denoise}$

Loss
Given a sequence of length N, make $N/2$ transpositions iteratively. The model is trained with the standard word-by-word loss. Let $C(x)$ return our noise model applied to sentence x.

$$L_{denoise} = \mathbb{E}_{x \sim X_l, \hat{x} \sim d(e(C(x)), l)} \Delta(\hat{x}, x)$$

An example denoising case

```
this is example an sentence denoising for presentation my

-> this is an example denoising sentence for my presentation
```

$L_{backtranslate}$

Given an input sentence in one language, use the system in inference mode with greedy decoding to translate it to the other language. In this way, we obtain pseudo-parallel sentence pairs. Let $x' = d(e(x), l')$.

$$L_{backtranslate} = \mathbb{E}_{x \sim X_l, \hat{x} \sim d(e(x'), l)} \Delta(\hat{x}, x)$$

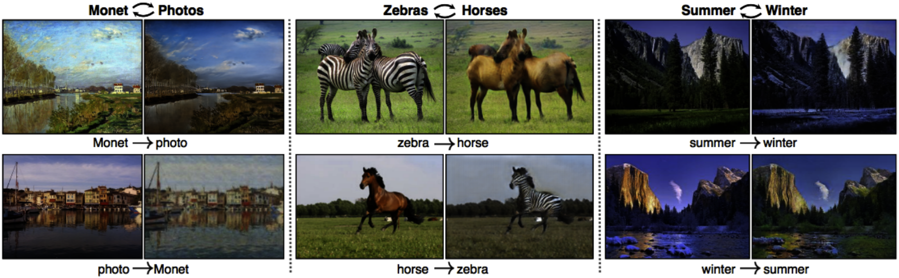
In the semi-supervised model, we also mix in parallel sentence examples to this loss. The above loss has had some success in unsupervised image-to-image translation (Zhu, 2018).

$L_{backtranslate}$

Given an input sentence in one language, use the system in inference mode with greedy decoding to translate it to the other language. In this way, we obtain pseudo-parallel sentence pairs. Let $x' = d(e(x), l')$.

$$L_{backtranslate} = \mathbb{E}_{x \sim X_l, \hat{x} \sim d(e(x'), l)} \Delta(\hat{x}, x)$$

In the semi-supervised model, we also mix in parallel sentence examples to this loss. The above loss has had some success in unsupervised image-to-image translation (Zhu, 2018).



Evaluation

Details

- French-English and German-English datasets from WMT 2014.

Evaluation

Details

- French-English and German-English datasets from WMT 2014.
- **Unsupervised model** trained on News Crawl corpus articles from 2007 to 2013.

Evaluation

Details

- French-English and German-English datasets from WMT 2014.
- **Unsupervised model** trained on News Crawl corpus articles from 2007 to 2013.
- **Semi-Supervised model** Additional 10k or 100k random sentence pairs from News Commentary.

Evaluation

Details

- French-English and German-English datasets from WMT 2014.
- **Unsupervised model** trained on News Crawl corpus articles from 2007 to 2013.
- **Semi-Supervised model** Additional 10k or 100k random sentence pairs from News Commentary.
- **Supervised model** WMT 2014 + UN and Gigaword corpus for French-English.

Evaluation

Details

- French-English and German-English datasets from WMT 2014.
- **Unsupervised model** trained on News Crawl corpus articles from 2007 to 2013.
- **Semi-Supervised model** Additional 10k or 100k random sentence pairs from News Commentary.
- **Supervised model** WMT 2014 + UN and Gigaword corpus for French-English.
- Spanish-English WMT data used for hyperparameter exploration.

Evaluation

Details

- French-English and German-English datasets from WMT 2014.
- **Unsupervised model** trained on News Crawl corpus articles from 2007 to 2013.
- **Semi-Supervised model** Additional 10k or 100k random sentence pairs from News Commentary.
- **Supervised model** WMT 2014 + UN and Gigaword corpus for French-English.
- Spanish-English WMT data used for hyperparameter exploration.
- Frozen cross-lingual embeddings from Artetxe (2017).

Results

Table 1: BLEU scores in newstest2014. Unsupervised systems are trained in the News Crawl monolingual corpus, semi-supervised systems are trained in the News Crawl monolingual corpus and a subset of the News Commentary parallel corpus, and supervised systems (provided for comparison) are trained in either these same subsets or the full parallel corpus, all from WMT 2014. For GNMT, we report the best single model scores from Wu et al. (2016).

		FR-EN	EN-FR	DE-EN	EN-DE
Unsupervised	1. Baseline (emb. nearest neighbor)	9.98	6.25	7.07	4.39
	2. Proposed (denoising)	7.28	5.33	3.64	2.40
	3. Proposed (+ backtranslation)	15.56	15.13	10.21	6.55
	4. Proposed (+ BPE)	15.56	14.36	10.16	6.89
Semi-supervised	5. Proposed (full) + 10k parallel	18.57	17.34	11.47	7.86
	6. Proposed (full) + 100k parallel	21.81	21.74	15.24	10.95
Supervised	7. Comparable NMT (10k parallel)	1.88	1.66	1.33	0.82
	8. Comparable NMT (100k parallel)	10.40	9.19	8.11	5.29
	9. Comparable NMT (full parallel)	20.48	19.89	15.04	11.05
	10. GNMT (Wu et al., 2016)	-	38.95	-	24.61

Figure: The model performs "surprisingly" well. However, there is discussion of whether this model is actually interesting given the lack of success of models 7., 8., and 9. in a fully supervised setting.

Evaluation

Table 2: Sample French→English translations from newstest2014 by the full proposed system with BPE. See text for comments.

Source	Reference	Proposed system (full)
Une fusillade a eu lieu à l'aéroport international de Los Angeles.	There was a shooting in Los Angeles International Airport.	A shooting occurred at Los Angeles International Airport.
Cette controverse croissante autour de l'agence a provoqué beaucoup de spéculations selon lesquelles l'incident de ce soir était le résultat d'une cyber-opération ciblée.	Such growing controversy surrounding the agency prompted early speculation that tonight's incident was the result of a targeted cyber operation.	This growing scandal around the agency has caused much speculation about how this incident was the outcome of a targeted cyber operation.
Le nombre total de morts en octobre est le plus élevé depuis avril 2008, quand 1 073 personnes avaient été tuées.	The total number of deaths in October is the highest since April 2008, when 1,073 people were killed.	The total number of deaths in May is the highest since April 2008, when 1 064 people had been killed.
À l'exception de l'opéra, la province reste le parent pauvre de la culture en France.	With the exception of opera, the provinces remain the poor relative of culture in France.	At an exception, opera remains of the state remains the poorest parent culture.

Figure: Example translations for the best unsupervised model. The model is a decent translator.

Extension Ideas AKA Pipe Dreams

We want to enforce that given a source sentence *src*, the translation $M(src)$ has the same meaning as *src* and is indistinguishable from sentences in the corpus of the target language.

Extension Ideas AKA Pipe Dreams

We want to enforce that given a source sentence *src*, the translation $M(src)$ has the same meaning as *src* and is indistinguishable from sentences in the corpus of the target language.

Problem Translations $M(x_{src})$ indistiguishable from corpus $x_i \sim X_{tgt}$

Extension Ideas AKA Pipe Dreams

We want to enforce that given a source sentence *src*, the translation $M(src)$ has the same meaning as *src* and is indistinguishable from sentences in the corpus of the target language.

Problem Translations $M(x_{src})$ indistiguishable from corpus $x_i \sim X_{tgt}$
$\Rightarrow$ $\mathbf{L}_{adversary}$ Force translations to fool a discriminator

Extension Ideas AKA Pipe Dreams

We want to enforce that given a source sentence *src*, the translation $M(src)$ has the same meaning as *src* and is indistinguishable from sentences in the corpus of the target language.

Problem Translations $M(x_{src})$ indistiguishable from corpus $x_i \sim X_{tgt}$
$\Rightarrow$ $\mathbf{L}_{adversary}$ Force translations to fool a discriminator

Problem Translations $M(x_{src})$ should capture the meaning of x_{src}

Extension Ideas AKA Pipe Dreams

We want to enforce that given a source sentence *src*, the translation $M(src)$ has the same meaning as *src* and is indistinguishable from sentences in the corpus of the target language.

Problem Translations $M(x_{src})$ indistiguishable from corpus $x_i \sim X_{tgt}$
$\Rightarrow$ $\mathbf{L}_{adversary}$ Force translations to fool a discriminator

Problem Translations $M(x_{src})$ should capture the meaning of x_{src}
$\Rightarrow$ $\mathbf{L}_{back^n translate}$ force invertibility of M over n cycles between l_{src} and l_{tgt}.

Extension Ideas AKA Pipe Dreams

We want to enforce that given a source sentence *src*, the translation $M(src)$ has the same meaning as *src* and is indistinguishable from sentences in the corpus of the target language.

Problem Translations $M(x_{src})$ indistiguishable from corpus $x_i \sim X_{tgt}$
$\Rightarrow \mathbf{L}_{adversary}$ Force translations to fool a discriminator

Problem Translations $M(x_{src})$ should capture the meaning of x_{src}
$\Rightarrow \mathbf{L}_{back^n translate}$ force invertibility of M over n cycles between l_{src} and l_{tgt}.

Problem Words aren't well defined for certain languages

Extension Ideas AKA Pipe Dreams

We want to enforce that given a source sentence *src*, the translation $M(src)$ has the same meaning as *src* and is indistinguishable from sentences in the corpus of the target language.

Problem Translations $M(x_{src})$ indistiguishable from corpus $x_i \sim X_{tgt}$
$\Rightarrow$ $\mathbf{L}_{adversary}$ Force translations to fool a discriminator

Problem Translations $M(x_{src})$ should capture the meaning of x_{src}
$\Rightarrow$ $\mathbf{L}_{back^n translate}$ force invertibility of M over n cycles between l_{src} and l_{tgt}.

Problem Words aren't well defined for certain languages
$\Rightarrow$ Add a language model loss with word-pieces to train end-to-end (Wu, 2016)

The End. Questions?