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Multi-Target Machine Translation

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Dedication.

Title: Multi-Target Machine Translation

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Introduction

With increasing availability of computational resources and enormous amount of publicly available corpora it is now possible to obtain a MT system which produces translations of acceptable quality. But in the use cases similar to conferences, where one speech is translated into multiple target languages, the same amount of models needs to be deployed. Another option is to use multilingual MT system for all needed languages together, which may lead to a decreased quality of translations.

1. Background

1.1 History of machine translation

Han 2018, beginning

1.2 Transformer model

Introduced in Vaswani et al. [2017] Transformer model is used as a base for numerous state-of-the-art systems as can be seen for example in WMT18 [Bojar et al., 2018] and WMT19 [Barrault et al., 2019] results.

Prior to invention of the *Transformer* model, RNN's and CNN's were used to encode source side of the sentence pair and to decode it into the target sentence. Various window lengths in CNN architectures allowed to capture long range relations as well as short range ones; still the range was limited by the maximum window length. In RNN-like architectures LSTM and GRU cells were used, as their structure allowed to pass the internal state on longer distances due to selective forgetting.

Transformer model uses *self attention* mechanism to encode contextual information in each word position. *Position encoding* allows passing the position information without explisit sequential connections as in RNNs. As was stated by *Transformer*'s authors, there are three main points why self-attention mechanism should be preferred:

- total computational complexity per layer;
- the amount of computation that can be parallelized;
- the path length between long-range dependencies in the network.

1.3 Translation evaluation

Han 2018 - history Papineni et al. [2002] - BLEU paper

Layer type	Complexity per layer	Sequential operations	Maximum path length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

Table 1.1: **Maximum path lengths, per-layer complexity and minimum number of sequential operations for different layer types.** n is the sequence length, d is the representation dimension, k is the kernel size of convolutions and r the size of the neighborhood in restricted self-attention.

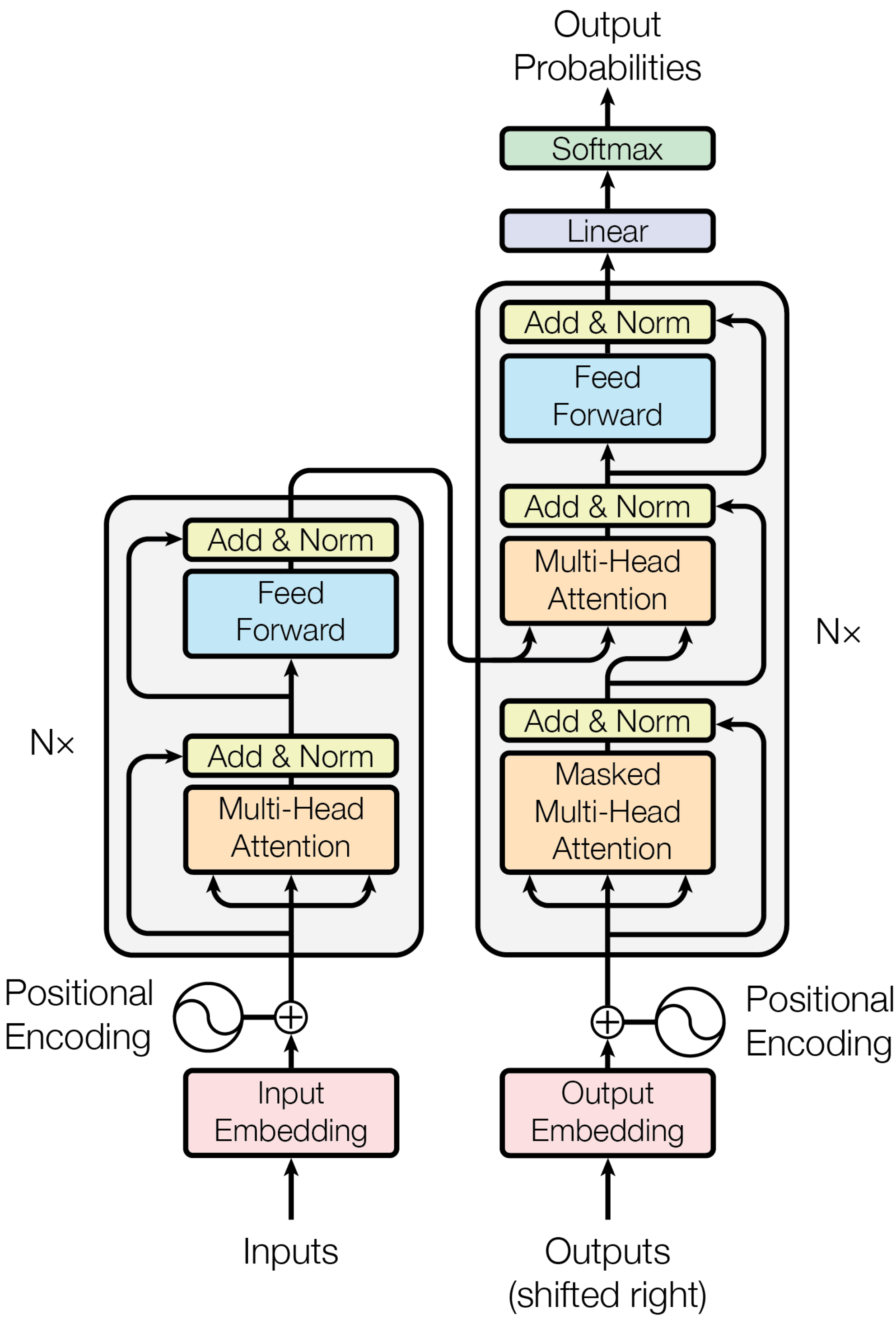


Figure 1.1: **Transformer model architecture.**

2. Experiment setup

In this chapter we describe the data used for experiments, training setup and In this chapter we describe the data, training setup and experiments that were run to answer the questions asked in this thesis.

2.1 Questions and constraints

XXX TODO: Limited resources, reasonable quality is still needed
Constraints:

Translation quality for multi-lingual system is insignificantly worse than for mono-lingual one-to-one tranlsation system.

Maximum possible target languages are combined in one model.

Questions:

How *in average* adding one more randomly selected target language to the multitarget model affects its En→De performance?

How is it different if we add a linguistically similar, not randomly selected language?

How is adding one more language from the same language family or group *in average* affects tranlsation performance for selected language pair (e.g. En→De)?

2.2 Experiments

2.2.1 Starting point

In Johnson et al. [2017] autors proposed a way to build a multi-lingual machine tranlsation model without any changes to the *Transformer* architecture. In fact, the only change should be performed on the input data. To make the *Transformer* model process multi-lingual data the language tag is added to the source sentence. For example, the following En→Cz sentence pair:

Hello world! → Ahoj světe!

is modified to:

<2cs> Hello world! → Ahoj světe!

With given method it is possible to produce translations in multiple languages using the same model just by altering the prepended target language tag. It was also demonstrated that this method slightly improves translation quality for low resource languages when compared to monolingual translation model.

In this and the following (Arivazhagan et al. [2019], Aharoni et al. [2019]) papers from Google many different cases are tried and described. However, in each setting there is usually only one model of each kind considered. For example, when in [Aharoni et al., 2019] authors compare 5-to-5, 25-to-25, 50-to-50, etc. models, there is only one 5-to-5 model, one 25-to-25, etc.

2.2.2 Proposed experiments

Monolingual baseline

Target language tags do not affect BLEU: Siddhant et al. [2020]. mNMT models en-to-4 and 4-to-en trained; 1) <2xx> added to the source; 2) target language encoded separately. BLEU scores are comparable using both approaches.

n-lingual baselines (random)

Multilingual models with random set of languages. The purpouse is twofold: to show BLEU score decrease with increasing number of target languages and to serve as a baseline for multitarget models with target languages grouped by in non-random way, e.g. by language group or linguistic similarity.

Group by language group

If all target languages are from one language group we expect to observe better translation quality comparing to multilingual baseline results with randomly selected target languages. This is expected due to shared parts of vocabulary (todo: expand with examples) and linguistic properties (again, expand with examples). Germanic group: da, de, is, no, nl, sv. Slavic with cyrillic script: bg, mk, ru, uk. Slavic: bg, cs, hr, mk, pl, ru, sk, sl, sr, uk

Group by linguistic similarity

From Siddhant et al. [2020] follows that languages' script and similarly the amount of shared vocabulary is not so important for XX→En translation direction. Example with Serbian and Croatian, with the same vocabulary but in different scripts.

2.3 Dataset(s)

2.3.1 English to 36 languages

To observe effects of linguistic similarity of target languages it is important to examine enough possible variations of those. The OPUS dataset (Tiedemann [2012]) is an open and free collection of texts that covers more than 90 languages with data from several domains.[1]

For our experiments the source language is English only.

Sampling and splitting of the data is the one used for ELITR project.[2] For each of language pairs and each sub-dataset the data was splitted to training, validation and testing sets. For each of the two latter sets 2000 random sentences were selected and the rest of the data remained for the training set. In cases where the sub-dataset contained less than 16000 sentence pairs no data went to the validation set. Later for each language pair there were 1000000 sentence pairs sampled from all training sub-sets. Firstly, if available, the sentences were

[1] Available at `http://opus.nlpl.eu/`

[2] `https://elitr.eu/wp-content/uploads/2019/07/D11.FINAL_.pdf`

taken from Europarl, then EUbooks, OpenSubtitles, and then all remaining sub-datasets. The same procedure was used to sample x000 of validation set sentences per each language pair. The test sets were left separate, so that the result on each domain would be observable.

Later an overlap in the source side of different language pairs was found. Although this would not directly lead to unfair increase of the test score, such sentence pairs were removed from the training sets. This filtering decreased the amound of sentence pairs to 0.85-0.95 millions per language pair.

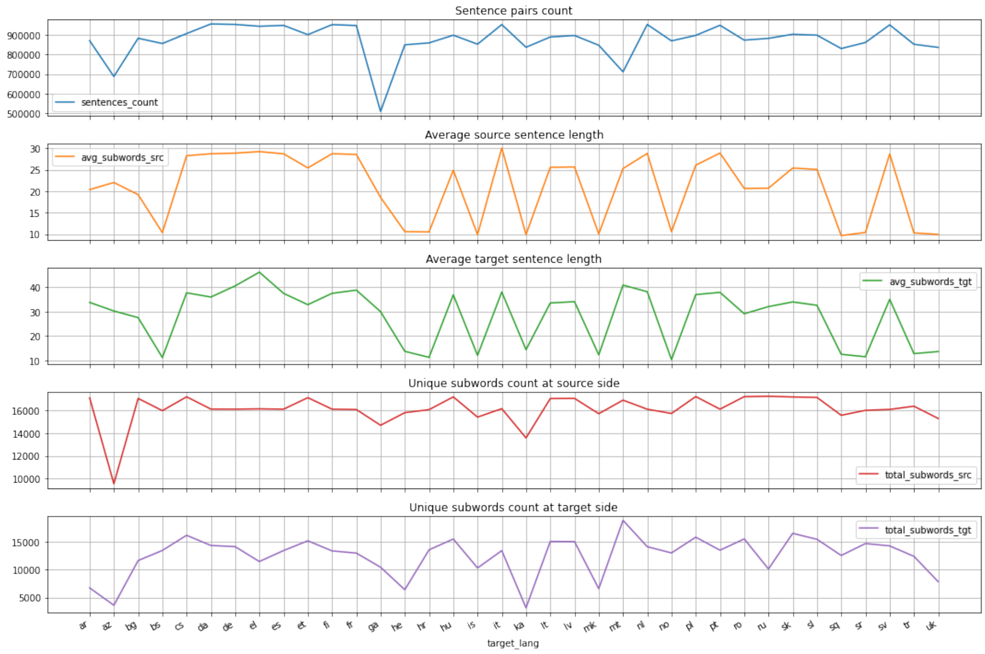


Figure 2.1: **Training data language statistics.** Languages are on the X axis sorted as in appendix. From top to bottom: total number of sentence pairs in training set per language, average amount of subwords per sentence on the source side, the same on the target side, total amount of unique subwords for this target language on the source side, the same on the target side.

To train a model on a specific subset of target languages, only related sentence pairs are subsampled. For example, to prepare data for En→{Fr, De} setup only sentences which source side starts with tags <2fr> or <2de> are selected to the training set. Development set is selected in the same way.

2.4 Training

2.4.1 Tool kits

There exists a number of different tools that can be used for training a NMT model. General purpouse deep learning programming libraries like Tensorflow[3] and PyTorch[4] are most popular for deep learning related research. With their

[3]https://tensorflow.org/
[4]https://pytorch.org/

help it is possible to construct any of today's state-of-the-art NMT models; pre-built and pre-trained models are initially present in such frameworks, but it is also possible to describe a model from scratch.

Another option is presented by specialized NMT tool kits. They usually contain efficient and tested implementations of NMT models as well as some of usefull preprocessing tools. For the experiments described in 2.2 there is a need to train significant amount of models with the same architecture and settings but different datasets. Due to that fact, in this work the use of specialized NMT tool kit is more suitable. Let us consider the foolowing list of broadly used tool kits as for year 2020, presented in Koehn [2020]:

- OpenNMT (based on Torch/pyTorch)[5]
- Sockeye (based on MXNet)[6]
- Fairseq (based on pyTorch)[7]
- Marian (stand-alone implementation in C++)[8]
- Google's Transformer (based on Tensorflow)[9]
- Tensor2Tensor (based on Tensorflow) [10]

We chose *MARIAN-NMT* tool kit[11] as a fast solution with stable and efficient *Transformer* Vaswani et al. [2017] implementation, minimum of third-party dependencies, and ability to train models on multiple GPU units in parallel.

2.4.2 Computational cluster

Many computations - cluster used.

Resourses are used by other people, disc quota is limited – parallel launching of experiments, switching to the next each 2 hours, saving only best models and the last one, removing subsampled datasets

2.4.3 Model settings

The initial parameter selection is made with respect to Popel and Bojar [2018]. First of all, the hyperparameters of MT model are tuned on couple of language pairs from one dataset. The parameters leading to the same result in shorter time were preferred. Then the selected parameters were used on all experimends with the dataset.

[5] `https://opennmt.net`
[6] `https://github.com/awslabs/sockeye`
[7] `https://github.com/pytorch/fairseq`
[8] `marian-nmt.github.io`
[9] `https://github.com/tensorflow/models/tree/master/official/transformer`
[10] `https://github.com/tensorflow/tensor2tensor`
[11] Junczys-Dowmunt et al. [2018]

3. Random choise of target languages

3.1 Overview

In this chapter we explore the effect of increasing number of target languages on the model performance in general. Multiple possible outcomes can be expected at this experiment: either performance drop due to the increased amount of languages to be processed by the model of the same size, or the opposite - performance increase due to shared knowledge gained by the model from bigger and varying dataset. Also, either of these options can be true for different target languages in different scale.

First of all, performance drop is expected. Considering that the size of the model is fixed, so is its capacity. At some moment adding more target languages should lead to the decrease in translation quality for each of every target language

3.2 Performance drop on massively multilingual setup

1-to-3, 5, 7, etc. models on en-to-36 dataset (0.9 mil. sentences per target language)

When the size of the model is fixed, adding more translation directions usually causes worsening of its performance. Multiple studies have shown this to be truth for many-to-many setup.

In Aharoni et al. [2019] models with up to 103 languages were tested. English centric in-house dataset was used to train En→Any and Any→En multilingual models. The average number of examples per language pair is 940k: for 13 out of the 102 pairs there were less than one million examples available. All languages from 5-to-5 model are present in 25-to-25, same is true for all languages from 25-to-25 with respect to 50-to-50 and so forth. In all cases they trained large Transformer model with 473.7M parameters. As can be seen on Table 3.1, the quality of translation is significantly worse when model is trained to translate more languages. However, it is worth reminding that this many-to-many experiment may have different reasons due to many-to-one direction present in it.

The decrease of model's performance with adding more target langueges is clearly shown in Aharoni et al. [2019].

3.3 Performance decrease on richer data sets

1 to 3, 4, 5 on UN corpus (much more sentence pairs per target language) Eisele and Chen [2010]

	En-Ar	En-Fr	En-Ru	En-Uk
5-to-5	**12.42**	**37.3**	**24.86**	16.48
25-to-25	11.77	36.79	23.24	**17.17**
50-to-50	11.65	35.83	21.95	15.32
75-to-75	10.69	34.35	20.7	14.59
103-to-103	10.25	34.42	19.9	13.89

Table 3.1: **BLEU scores for translation in one direction (part of Table 7 from [Aharoni et al., 2019]) .** Model trained on 5-to-5 English centric dataset (English to any and any to English) scores 12.42 BLEU for English-Arabic test set. Every language from 5 languages of 5-to-5 data set is included into 25-to-25 set, as well as every language from 25-to-25 data set is included into 50-to-50 and so forth.

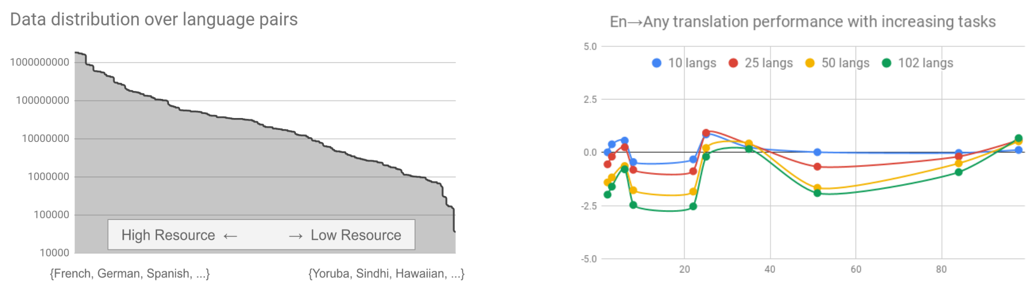


Figure 3.1: **Tranlsation performance for 102 languages from Arivazhagan et al. [2019] .** Axis X is shared between left and right plot. On axis X there are languages sorted by amount of training data. Left: amount of training data (axis Y) for a language. Right (best viewed in color): Effect of increasing the number of languages on the translation quality. On the axis X the languages are sorted the same way as on the left plot. The points visualized are 10 languages that are present in all setups from En $\leftrightarrow$ 10 to En $\leftrightarrow$ 102.

n_targets	mean	std	count
1	41.40	—	1
2	40.60	0.20	3
3	39.39	0.62	8
4	39.40	0.71	2
5	38.45	0.52	6

(a) En→Bg for *Europarl/v7* dataset.

n_targets	mean	count	std
1	19.50	1	–
2	18.88	4	0.39
3	17.45	4	0.52
4	17.80	2	0.42

(b) En→Ru for *OpenSubtitles/v2016* dataset.

Table 3.2: **BLEU score change with adding target languages.** (a) First row: for mono-lingual En→Bg model test BLEU score is 41.40. Second row: for 3 (column *count*) En→Any models with two target languages (column *n_targets*) one of which is Bulgarian the mean BLEU score is 40.60 with standard deviation 0.20. (b): same way as (a)

4. Group by language groups

4.1 Language groups

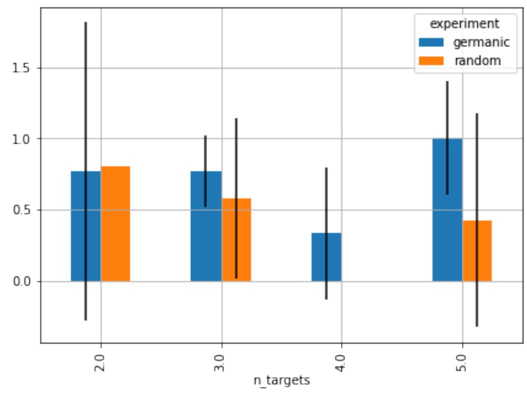
1 to 2, 3, 4, 5, etc. models on en-to-36 dataset (0.9 mil. sentences per target language) compared with random runs

4.1.1 Germanic group

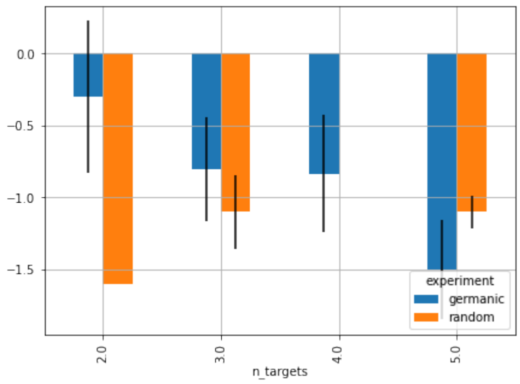
Here Germanic group consists of German, Dutch, Swedish, Danish, Norwegian and Islandic. Models En→Germanic are compared to En→non-Germanic, where non-Germanic consists of any langauge except from the Germanic group. On Figures 4.1 and 4.2 some selected results are visualized along with vocabulary changes. Results for OpenSubtitles/v2018 mean the BLEU score on test set part sampled from OpenSubtitles/v2018. On both figures the subfigure (a) shows the result on spontaneous or pseudo-spontaneous speech transcripts, sub-figure (b) shows the result for prepared speeches or documents from Europarl or UN meetings.

In this case observations are twofold:

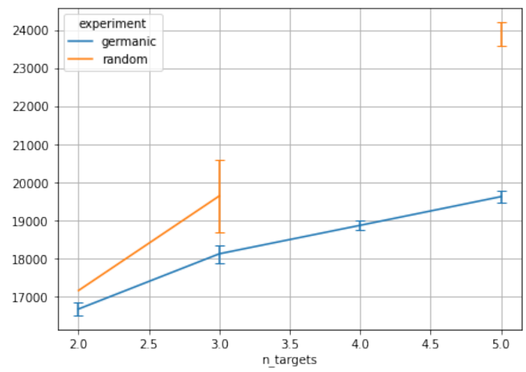
- For test sets with lower bilingual BLEU score adding more target languages to the model improves the score; adding related target languages improves it even more
- Adding more target languages improves translation result on test sets from spontaneous speech domain but worsenes it for prepared speech or documents.



(a) OpenSubtitles/v2018, bilingual score: 13.1 BLEU

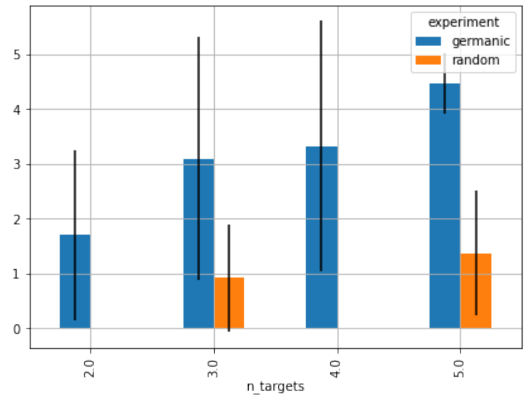


(b) MultiUn, bilingual score: 25.4 BLEU

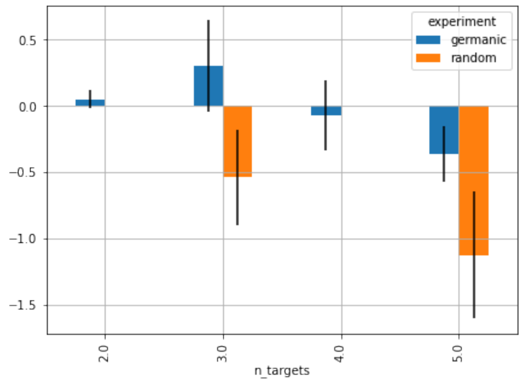


(c) Subword dictionary size used for target side

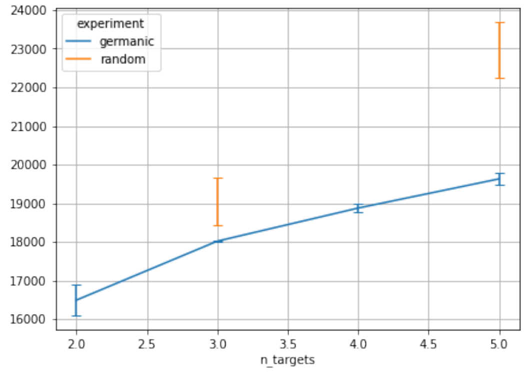
Figure 4.1: **En→De BLEU score difference: Random vs. Germanic.** On X axis - number of target languages. On Y axis - difference score comparing with monolingual BLEU. Black vertical lines show standard deviation. (a) Adding random target language as well as a related one slightly improves German translation score on speech transcript. (b) Adding neither a random nor a related target language helps with prepared speeches transcripts and documents in German. (c) Adding a related target language into the mix introduces less new unique subwords.



(a) OpenSubtitles/v2018, bilingual score: 15.6 BLEU



(b) Europarl/v3, bilingual score: 24.6 BLEU



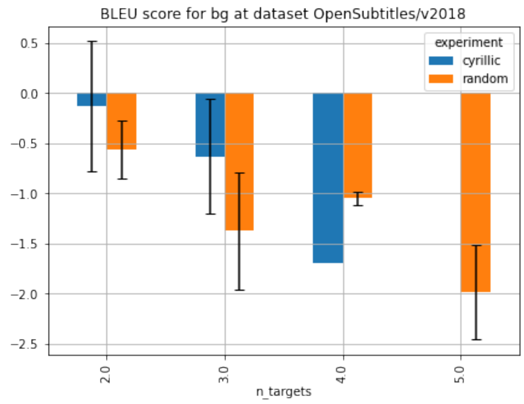
(c) Subword dictionary size used for target side

Figure 4.2: **En→Da BLEU score difference: Random vs. Germanic.** Axis are same as above. (a) For OpenSubtitles test set which which consists of human speech transcripts adding similar target language to the mix significantly imporves the result. (b) For Europarl/v3 which consists of prepared speeches transcripts and documents adding more germanic languages to the mix did not worsened Danish translation quality unlike the case with German. (c) Adding random target language to the mix adds more subwords to the target subword dictionary

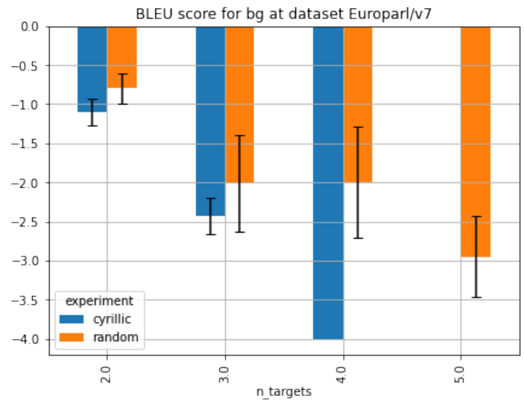
4.1.2 Slavic with cyrillic script

Here *Slavic with cyrillic script* group consists of Bulgarian, Macedonian, Russian and Ukrainian. Models En→Cyrillic are compared to En→non-Cyrillic, where non-Cyrillic consists of any langauge except from those from the group above. On Figures 4.3 and 4.4 some selected results are visualized along with vocabulary changes. Test sets for subfigures (a) and (b) selected the same way as in 4.1.1.

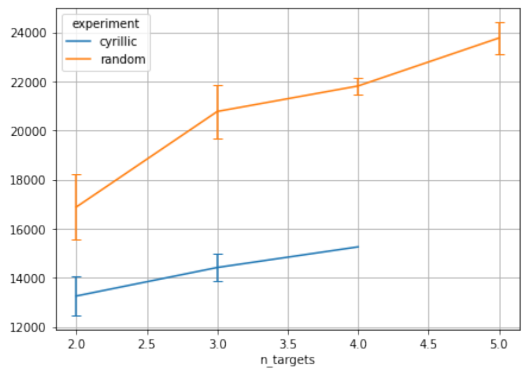
From the two opposite observations of 4.1.1 in this case the second one is observed: low results are getting slightly better, good results are getting slightly or significantly worse.



(a) OpenSubtitles/v2018, bilingual score: 23.7 BLEU

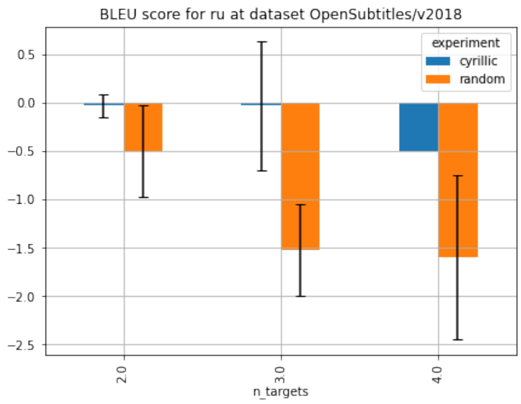


(b) Europarl/v3, bilingual score: 41.4 BLEU

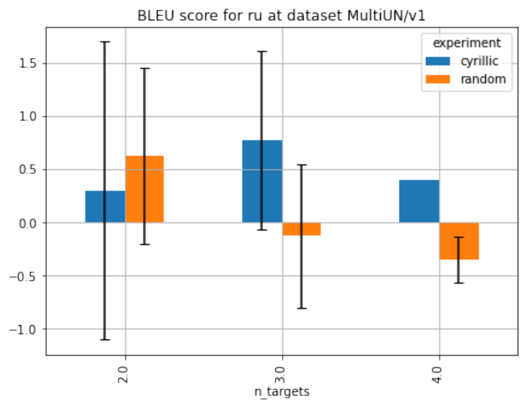


(c) Subword dictionary size used for target side

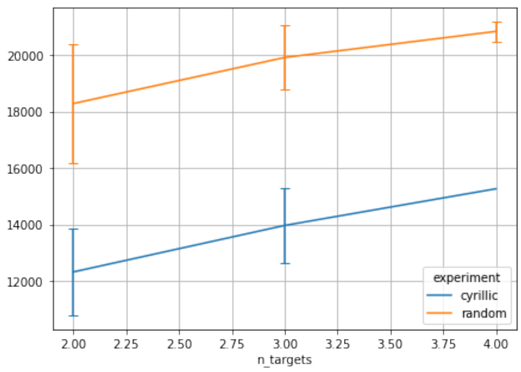
Figure 4.3: **En→Bg BLEU score difference: Random vs. Slavic with cyrillic script.** Axis are same as for Figures 4.2 and 4.1. There is not any data for Cyrillic and 5 targets as there are only 4 such languages in the en-to-36 dataset. Both (a) and (b) show significant decrease in translation quality. On (c) it is clearly visible how adding a random language with non-cyrillic script increases target subword vocabulary size.



(a) OpenSubtitles/v2018, bilingual score: 19.2 BLEU



(b) MultiUN, bilingual score: 14.6 BLEU



(c) Subword dictionary size used for target side

Figure 4.4: **En→Ru BLEU score difference: Random vs. Slavic with cyrillic script.** Axis are same as for Figures 4.2, 4.1 and 4.3. There is not any data for Cyrillic and 5 targets as there are only 4 such languages in the en-to-36 dataset. Both (a) and (b) show significant decrease in translation quality. On (c) it is clearly visible how adding a random language with non-cyrillic script increases target subword vocabulary size.

5. Discussion

5.1 Results

More languages in the mix: - share word ordering patterns - share vocabulary

More training data illustrates the properties of distribution better (some words are rare, some are often used)

5.2 Further work

Conclusion

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