FACULTY
OF MATHEMATICS
AND PHYSICS
Charles University

MASTER THESIS

Bohdan Ihnatchenko

Multi-Target Machine Translation

Institute of Formal and Applied Linguistics

Supervisor of the master thesis: doc. RNDr. Bojar Ondřej, Ph.D.
Study programme: Computer Science
Study branch: Artificial Intelligence

Prague 2020

This is not a part of the electronic version of the thesis, do not scan!

I declare that I carried out this master thesis independently, and only with the cited sources, literature and other professional sources. It has not been used to obtain another or the same degree.

I understand that my work relates to the rights and obligations under the Act No. 121/2000 Sb., the Copyright Act, as amended, in particular the fact that the Charles University has the right to conclude a license agreement on the use of this work as a school work pursuant to Section 60 subsection 1 of the Copyright Act.

In .... date ....

Author's signature

Dedication.

Title: Multi-Target Machine Translation

Author: Bohdan Ihnatchenko

Institute: Institute of Formal and Applied Linguistics

Supervisor: doc. RNDr. Bojar Ondřej, Ph.D., Institute of Formal and Applied Linguistics

Abstract: Abstract.

Keywords: Machine translation words

Contents

Introduction

With increasing availability of computational resources and enormous amount of publicly available corpora it is now possible to obtain a machine translation (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

In this chapter, we go through the theory of methods which are used in the work.

1.1 XXX TODO: History of machine translation

XXX TODO: rephrase Han [2016]

1.2 XXX TODO: 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, recurrent neural network (RNN) and convolutional neural network (CNN) architectures 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 long short-term memory (LSTM) and gated recurrent unit (GRU) cells were used, as their structure allowed to pass the internal state on longer distances due to selective forgetting.

Transformer model uses the *self attention* mechanism to encode contextual information in each word position. *Position encoding* allows passing the position information without explicit sequential connections as in RNN. Architecture of the *Transformer* model is shown on Figure 1.1. For tasks involving very long sequences autors also proposed *restricted* self-attention, which considers only a neighborhood of size r in the input sequence centered around the respective output position. As was stated by *Transformer*'s authors, there are three main points why self-attention mechanism should be preferred (which are compared with RNN and CNN in Table 1.1):

- 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 XXX TODO: Preprocessing: BPE

XXX TODO: models for the big UN corpus were trained with SentencePiece, not BPE

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.

1.4 Translation evaluation

1.4.1 History

In 1966 first machine translation evaluation methods were proposed by the Automatic Language Processing Advisory Committee (ALPAC). The proposed metrics were "intelligibility" and "fidelity" [ALPAC, 1966, p 67]. Trained human raters were needed to measure the metrics.

Later, after years of using manual evaluation, automatical evaluation metrics were created, such as word error rate (WER) Su et al. [1992], translation edit rate (TER) Snover et al. [2006], etc. Nowadays the most popular metric is bilingual evaluation understudy (BLEU) which is described in the next section.

1.4.2 BLEU - bilingual evaluation understudy

In Papineni et al. [2002] a nowel method of automatic machine translation evaluation was introduced - bilingual evaluation understudy (BLEU). Its advantages are the high speed and low cost of evaluation, language independence and high correlation with judgements of highly skilled human raters.

Shortly, BLEU score consists of modified n-gram precision scores corrected by brevity penalty, which ensures the produced translation lenght is close to the reference one. BLEU score is computed for the whole test corpus.

Modified *n*-gram precision score

The main element of the metric is the *precision* measure. It is computed in the following way: the number of candidate translation words (unigrams) that are present in any reference translation is divided by the total number of words in the candidate translation. This approach leads to overrating candidate translation which consists of only one or a couple of words that occur in reference translations, as can be seen in Example 1.4.1.

Intuitively, after a word from the reference translation has occurred, it should not be considered in the calculation anymore. This intuition is formalized as the *modified unigram precision*. It is computed in the following way:

1. count the maximum number of occurrences of a word in any reference translation;

2. clip the total count of every candidate word by the maximum reference count;

3. sum the clipped counts;

4. divide this sum by the total (not clipped) number of candidate words.

As a result, the sentence which may receive a high precision score will receive more realistic evaluation measured by modified precision score, as can be seen in Example 1.4.1.

> Candidate: <u>of</u> <u>of</u> <u>of</u> of of of of of of of
> Reference: London is the capital <u>of</u> England and <u>of</u> the United Kingdom <u>of</u> Great Britain and Northern Ireland.
> Precision: $10/10 = 1.0$
> Modified unigram precision: $3/10 = 0.3$
>
> **Example 1.4.1.** Precision and modified unigram precision. Similarly is computed modified n-gram precision score for any n, but n-gram counts are collected instead.

Sentence length

A produced translation should not be too short or too long. It is usually done by pairing precision with *recall*. However, in BLEU, multiple reference sentences can be used for one source sentence, so recalling all possible translations from every reference is not what is needed. BLEU authors introduced the *brevity penalty* factor for this purpose. In short, it penalizes produced translations that are shorter than the references. To avoid excessive penalization of shorter sentences, the *brevity penalty* is computed on the whole translated set. In the equation below, r is the test corpus' effective reference length and c is the total length of the candidate translation corpus. To compute r the best match lengths for each candidate sentence in the corpus are added.

$$BP = \begin{cases} 1, & \text{if } c > r; \\ e^{1-r/c}, & \text{otherwise} \end{cases} \tag{1.1}$$

Equation

Combining all the above, the metric works in this way (Equation (1.2)):

1. compute the geometric mean of the modified n-gram precisions (p_n), using n-grams up to length N and positive weights (w_n) summing to one.

2. compute *brevity penalty* as in Equation (1.1).

3. multiply results of steps 1. and 2.

Authors proposed to use $N = 4$ and uniform weights $w_i = 1/4$.

The metric value is in a range from 0 to 1. However, popular implementations such as SacreBLEU [Post, 2018] report it in percentage points from 0 to 100.

$$BLEU = BP \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right) \tag{1.2}$$

1.5 Multi-target machine translation

In this section, we have a closer look at an area in MT, which this thesis is dedicated to – multi-target MT. First, we talk about multi-lingual MT in general: multi-way, multi-source and multi-target. Later we describe the specific approach from multi-lingual MT – complete sharing of model parameters, which we are using in this work.

1.5.1 Multi-lingual machine translation

With constant improvement of neural MT systems performance, researchers started to experiment with incorporating multiple source languages, or target languages, or both, into one model, and the results are promising:

- having L1→L2 and L2→L3 non-parallel corpora allows to train a model that can produce L1→L3 translation of decent quality XXX FIX: cite some paper;
- having a high-resource L1 and low-resource L2 from the same language group helps increase Source→L2 translation quality with pretraining on Source→L1 data XXX FIX: cite the paper.

Even if the concept of combining multiple languages into one model and possible outcomes of such combination may seem intuitive, there exist multiple approaches of how exactly this might be performed. As for current time, Dabre et al. [2019] categorizes MNMT (multi-lingual neural machine translation) in the following way (Figure 1.2):

Multi-Way Translation. The goal is constructing a single NMT system for one-to-many, many-to-one or many-to-many translation using parallel corpora for more than one language pair.

Low or Zero-Resource Translation. Large amounts of parallel texts of high quality are available for most of European languages. However, it is not true for most of other languages in the world. Three main directions have been studied for these cases. *Transfer learning*: Transferring translation knowledge from a high-resource language pair to improve the translation of a low-resource language pair. *Pivot translation*: Using a high-resource language (usually English) as a pivot to translate between a language pair. *Zero-shot translation*: Translating between language pairs without parallel corpora.

Multi-Source Translation. Having the source side represented by multiple languages may increase translation quality in general or help to remove ambiguities present in one or another source language (e.g. cases, noun genders, etc.).

1.5.2 Massively multi-lingual machine translation XXX TODO: with complete sharing

Johnson et al. [2017] proposed a way to build a multi-lingual machine translation model without any changes to the *Transformer* architecture. The only change was performed on the input data. To make the *Transformer* model process multi-lingual data, they added the desired target language tag 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 the 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 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.

In one of the experiments, they varied the number of languages in the model and measured the model's performance on the specified set of translation directions. They started with a 5-to-5 model with English, Arabic, French, Russian, and Ukrainian selected. Given that the dataset was English-centric, they trained the 5-to-5 model to translate in En→{Ar, Fr, Ru, Uk} and {Ar, Fr, Ru, Uk}→En directions. Therefore, name 5-to-5 refers to the model's ability to accept source sentence in 5 languages and to translate into the same five languages. For 25-to-25 model they added 20 more randomly selected languages to the 5-to-5 setup. In all the cases they trained a large Transformer model with 473.7M parameters. As can be seen in Table 1.2, the quality of translation is significantly worse when a model is trained to translate more languages.

1.6 Conclusion

In this chapter we introduced theoretical and historical background for this work. Firstly, we took a short walk through the history of machine translation. Then we described the most used type of NMT models – self-attention *Transformer* model. After that we went over the history of translation evaluation in general and the most used method of automatic evaluation – BLEU – in particular. In the end, multi-lingual neural machine translation was reviewed with more detailed view into 'complete sharing' scheme.

	En-Ar	En-Fr	En-Ru	En-Uk
5-to-5	**12.42**	**37.30**	**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	20.70	14.59
103-to-103	10.25	34.42	19.90	13.89

Table 1.2: **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.

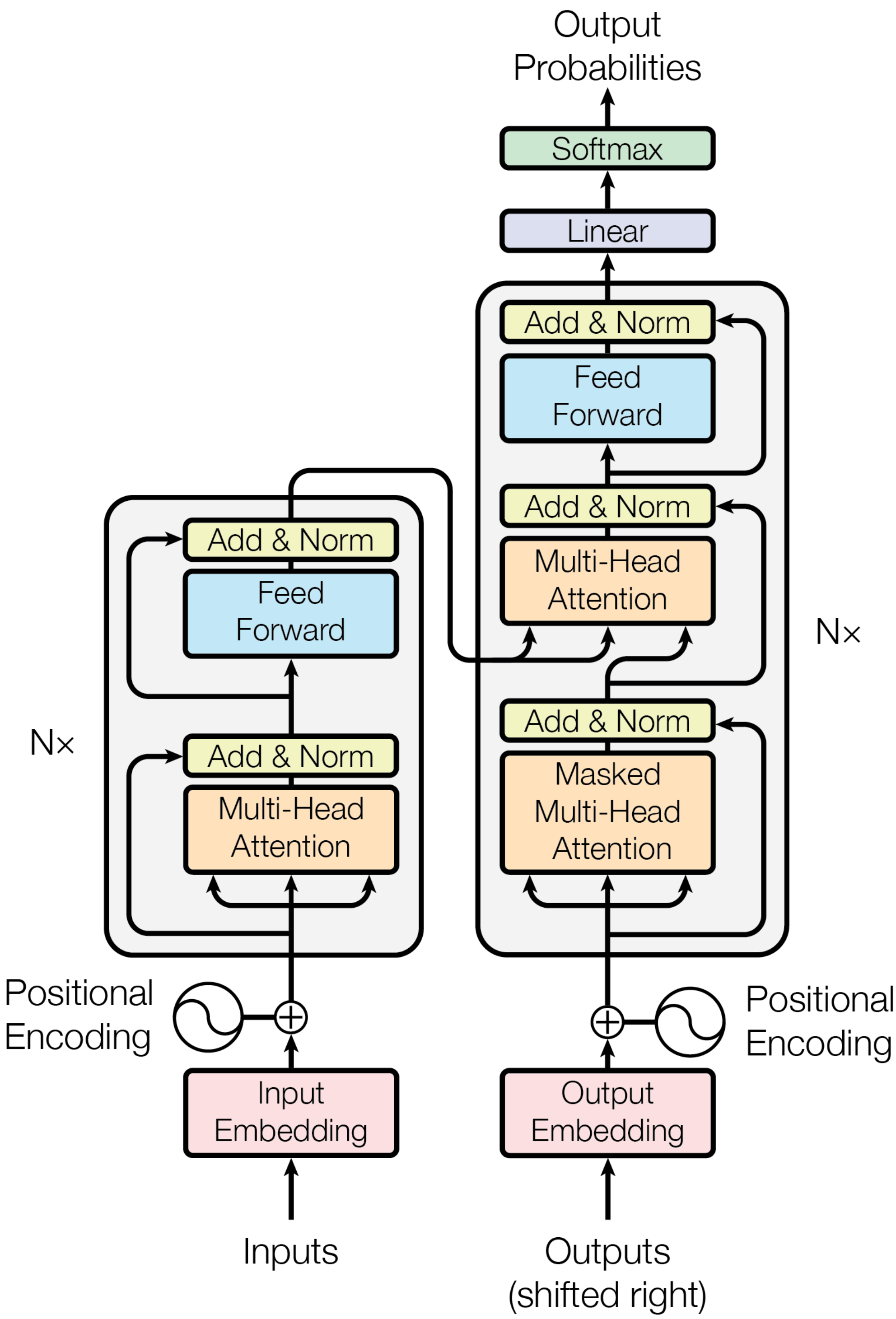


Figure 1.1: **Transformer model architecture.**

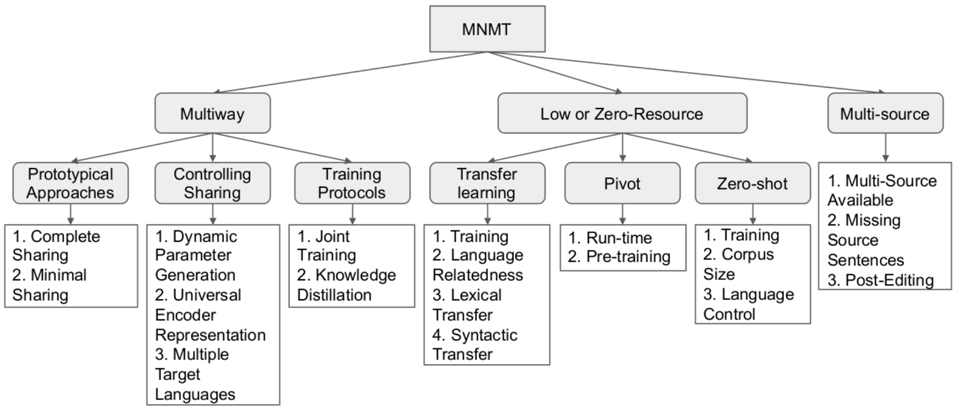


Figure 1.2: **MNMT research categorized.** According to resource scenarios and underlying modeling principles. By Dabre et al. [2019]

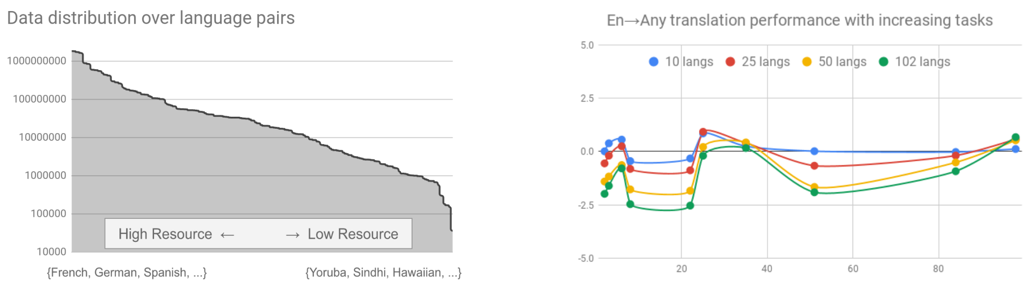


Figure 1.3: **Tranlsation performance for 102 languages from Arivazhagan et al. [2019].** Axis X is shared between left and right plot. On axis X there are languages sorted by amount of training data. Left: amount of training data (axis Y) for a language. Right (best viewed in color): Effect of increasing 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.

2. Experiment setup

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

2.1 XXX TODO: Questions and constraints

Constraints:

> Translation quality for multi-lingual system is better or insignificantly worse than for mono-lingual one-to-one tranlsation system.
>
> Maximum possible target languages are combined in one model.

Questions:

> How, *on average*, does adding one more randomly selected target language to the multitarget model affect its En→De performance?
>
> How is it different if we add a linguistically similar, not a randomly selected language?
>
> How does adding one more language from the same language family or group *on average* affect translation performance for a selected language pair (e.g. En→De)?

2.2 Experiments

2.2.1 Starting point

The approach described in Section 1.5.2 with combining multiple translation directions into the standart *Transformer* model can be also used to train just multi-target models, i.e. with one source language and multiple target languages. The following papers (Arivazhagan et al. [2019], Aharoni et al. [2019]), which further develop the approach, describe and try many different interesting cases. However, in each setting there is usually only one model of each kind considered. For example, when in Aharoni et al. [2019] compares 5-to-5, 25-to-25, 50-to-50, etc. models, there is only one 5-to-5 model, one 25-to-25, etc.

To conduct our experiments, we use this approach, but with the following differences:

- We fix English as a source language, as we are exploring the multi-target experiments only, .
- For every translation direction and every setting we train multiple models. E.g. for the En→De translation direction and 1-to-5 setting there are couple of En→{De + 4 randomly selected targets} models.
- We use only up to 5 target languages in the model because of:
  - limited resources;
  - our selected datasets (which will be described in the next section) do not contain more than 5-6 languages of the same language group.

2.2.2 Proposed experiments

Bilingual baseline

Bilingual models. The purpose is to have a reference point to be able to reason how does every additional target language affects the model's performance. Siddhant et al. [2019] shows that using target language tags results in the same model efficiency as separately encoding the target. Therefore, we use target tags in this setting too, so that we can use the same training pipeline.

Multi-lingual baselines (RANDOM)

Multilingual models with a random set of target 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 (SIMILAR)

Multilingual models with a set of target languages from the same language group. Due to shared parts of vocabulary and linguistic properties we expect to see better results than for multi-lingual baselines. Ideally the results could be comparable with bilingual baselines.

2.3 Dataset(s)

2.3.1 TO EDIT: 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.

Given the list of target languages in this dataset (see full list in Appendix A.2.2), we decided to select these two groups of languages for the SIMILAR experiment:

- Germanic group: da, de, is, no, nl, sv.
- Slavic with cyrillic script: bg, mk, ru, uk.

We made use of the sampling and splitting of the data created by the ELITR project.[2] For each of the language pairs and each sub-dataset the data was split 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. XXX FIX: To be more explicit that the sampling is directed towards certain domains. This is

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

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

somewhat unclear. Firstly, if available, the sentences were taken from Europarl, then EUbooks, OpenSubtitles, and then all remaining sub-datasets. The same procedure was used to sample XXX TODO: check 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 we found an overlap in the source side of different language pairs. 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 number of sentence pairs to 0.85-0.95 millions per language pair. XXX TODO: describe the figure with stats XXX TODO: describe the table with groups of sub-datasets XXX TODO: group 4: open folder, save file XXX TODO: group 5: Tanzil - completely different domain, Books of 18th cent.- dated vocabulary Wikipedia - automaticaly aligned sentences.

group	subdataset names	description
1	Europarl/vx, DGT, MultiUN, EUbookshop, JRC-Acquis, ECB, EMEA	Proceedings and documents from Europarl, UN, etc.
2	NewsCommentary, GlobalVoices, WMT-News	News articles and commentaries
3	OpenSubtitles, Tatoeba	Short sentences, human speech, general domain
4	OpenOffice, PHP, KDE4, Gnome	Software documentation or interface elements
5	Tanzil, Books, Wikipedia	Other

Table 2.1: **Groups of subdatasets in OPUS.**

2.3.2 XXX TODO: UN parallel corpus: English to 5 languages

XXX TODO: as I show en-to-5 results in RANDOM section, this DS should be here Eisele and Chen [2010]

2.4 Method

In this section we describe how the models are trained, which metrics are collected and how are they analyzed.

2.4.1 XXX TODO: Training

For example, let us take En→{Fr, De} setup, which means that the model to be trained should take a source sentence in English and produce translation either in French or in German. The language of model's output depends on the target tag at the beginning of the input sentence, i.e. <2fr> tag in source sentence leads to French target.

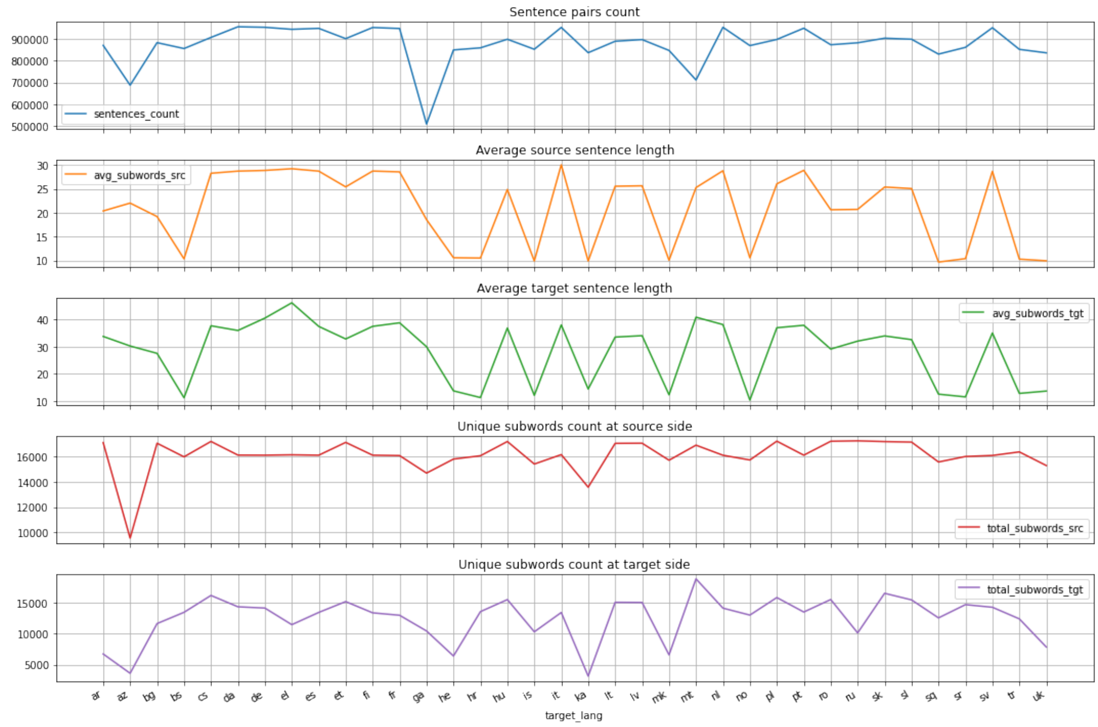


Figure 2.1: **Training data language statistics.** Languages are on the X axis sorted as in Appendix A.2.2. From top to bottom: total number of sentence pairs in training set per language, average number of subwords per sentence on the source side, the same on the target side, total number of unique subwords for this target language on the source side, the same on the target side.

To train such a model, only related sentence pairs are subsampled from the whole training set. In this case, from the whole training set we select only those sentence pairs which source side starts with tags <2fr> or <2de>. Such subsampled dataset is then used to train the model.

During the training procedure, once per specified number of updates occurs the checkpointing of the model. The model weights are saved to the disk and number of measurements are logged.

Those measurements are:

- training loss value (mean value for all updates since last checkpoint)
- learning rate value
- training speed (processed words per second)
- training time since last checkpoint
- number of updates happened from the beginning till this checkpoint

Hardware usage should also be recorded if possible:

- GPU usage
- CPU usage
- memory usage
- disk I/O
- network I/O

The hardware metrics are not important for model's evaluation but may help early spot mistakes like underuse of GPU or CPU, lack of RAM, etc. This is why they could possibly be recorded continuously. XXX TODO: link to this point from wandb section

2.4.2 TO EDIT: Validation

The validation set is used to track model's performance during the training on an unseen set of data and to perform early stopping. These measurements are only used during the training and not for the evaluation.

Once per specified number of steps the validation occurs: validation metrics are recorded, for any metric which value was improved current model weights are saved as best model by this metric. If early stopping condition occurred then the training process is stopped.

For any model the validation set is constructed from the big validation set by selecting only relevant sentence pairs in the same way as the training set, i.e. pairs with the target in one of the examined languages. For the example setup from above, En→{De,Fr}, the validation set consists of an equal amount of En→De and En→Fr sentence pairs. E.g. if in the complete validation set there are 1000 sentence pairs for each of possible target languages, then for En→{De,Fr} model the validation set will contain 2000 sentence pairs, and for En→{De,Es,Fr} it will contain 3000 sentence pairs.

For the validation set, we collect not only the loss function value but also the metric of interest, which is BLEU score. However, this BLEU scores are not used for the model's evaluation but only during the training process. The BLEU of the whole model's validation set is not something we are interested in. For the discussed example we collect validation bleu:fr and bleu:de scores which represent BLEU scores for French and German parts of validation set. E.g., to compute bleu:fr we select only En→Fr sentence pairs from the validation set.

Also, an aggregated value of the bleu:xx scores, i.e. the mean of BLEU scores over all target languages of the current model, is also recorded and may be used for early stopping: ending the training process when the metric is not improved during last N validation steps.

Altogether, the following validation metrics are recorded after the validation step:

- loss function value
- bleu:xx which is BLEU score for each of model's target languages
- aggregated value of all bleu:xx values
- translation time of the model's validation set

2.4.3 XXX TODO: Finishing the training

When should we stop the training? It is not possible to say precisely when did the model acquire its best performance because of stochastic nature of the training algorightm (SGD). Because of that we need to use some method to decide when training process should be stopped.

Number of epochs

XXX TODO: First occurence of a term to be italic The easiest approach is to specify the number of epochs after which the training is stopped. This could be a good solution for the case when all models that will be compared are trained on the same amount of data from the same domain. But in our case, adding one more target language adds a constant amount of sentence pairs to the training set. Roughly, if the number of epochs is specified as a stop condition, a bilingual En→De model will see the German training data x times, when multilingual En→De, Fr, Es will only see the German training data $x/3$ times.

Early stopping

Early stopping is a regularization technique used to avoid possible overfitting of a model on the training data. In general, it works in the following way: after every validation step it checks if the metric value improved during last N validations. The metric to be controlled and number of validation steps N are the parameters of this method (see Figure 2.2).

Another situation is even more probable in the area of NMT with generally large training datasets: model's validation performance is either stalled or slightly improved (see Figure 2.3). In this case early stopping helps to avoid unnecessary spendings on computational resources.

In our case we could use early stopping to ensure more equal conditions for models with different sizes of training data. A suitable number N could be found experimentaly, but which metric should be used?

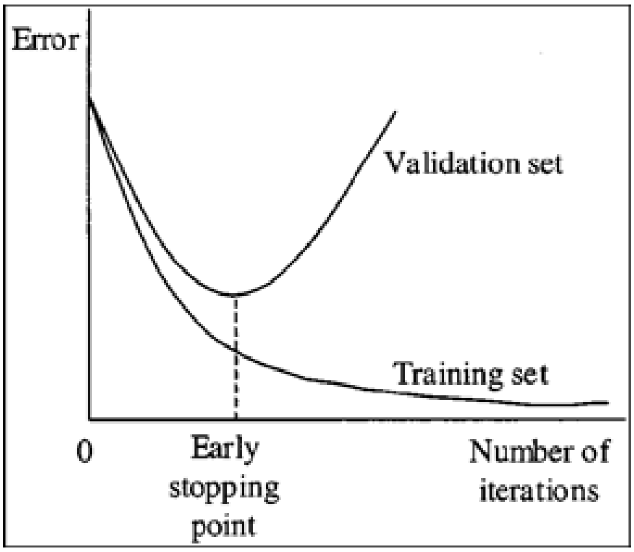


Figure 2.2: **Early stopping to prevent overfitting.** At the 'early stopping' point the model's performance on unseen validation set of data does not improve anymore. Further training leads to poorer performance on unseen data. Stopping the training at this point results in better model's performance on unseen data.

XXX TODO: cross-entropy, perplexity; they may not represent the model's performance, what about BLEU

Given that the task is to train a model that is as good as possible in **every** of its target directions, the BLEU score of the whole translated validation set for this set of languages does not say anything about the model's performance in each specified translation direction.

Aggregated value of BLEU scores

Therefore, we should use separate BLEU scores which represent model's performance in each of translation directions. The most intuitive and naive way is to compare BLEU scores for each target language.

However, most of frameworks and toolkits can monitor only one metric for the early stopping. Considering that different validation BLEU scores are computed for different parts of the validation set and in which are in different languages, they cannot be directly compared and may have different scale.

For example, a model for the En→{De,Fr} direction is being trained. Before the moment, an En→De model has already been trained and had the best BLEU score of 25 on the German part of the validation set. A En→Fr model has also been trained, and its result on the French part of the validation score is 35. So for the currently training En→{De,Fr}, one percentage point change for the En→De direction is not equal to the same change for the En→Fr direction.

Geometric mean is known to be good for aggregating multiple metrics with different scale (see Equation (2.1)).

XXX initially I wanted to achieve what was in the removed paragraph, but it did not happen (in some cases one of BLEU scores goes a bit down), so I have

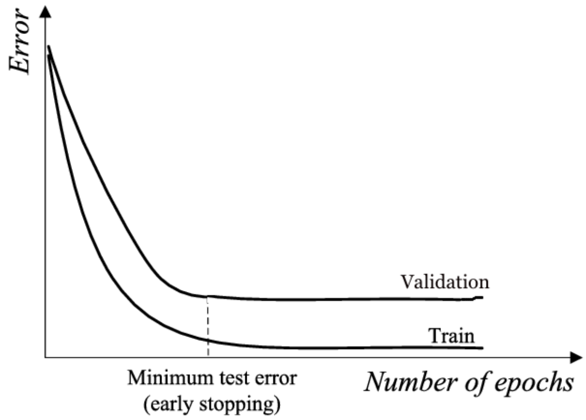


Figure 2.3: **Early stopping as the model is not improving.** Even though the metric value on the training set is still slowly improving, the its value on the unseen validation set is stalled. Further spending of computational resources is unjustified.

replaced it with this version

$$geometric\_mean = \left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}} = \sqrt[n]{x_1 x_2 \cdots x_n} \tag{2.1}$$

2.4.4 TO EDIT: Testing

After the training is finished, the received models should be evaluated on unseen test data. For experiments with en-to-5 dataset (Section 2.3.2) the test sets are created in the same way as validation sets. For en-to-36 dataset (Section 2.3.1) the test set is divided on subsets by the source dataset. It means, that each of source datasets (like OpenSubtitles/v11, Europarl/v7, etc.) there exists a separate test set. So after translating the test set for each of target directions of the model the following record is created:

- model name
- source language
- target languages
- tested target language
- BLEU score for this part of translation
- metric, based on which the best model was saved
- dataset name (for en-to-36)

Let us return to the example setup is En→{De, Fr} and suppose the reported validation metrics are the mean loss function value on test set and 'translation' (geometric mean of all reported BLEU scores, see Section 2.4.2). After the training is finished, there will be two models: best by loss value and best by 'translation'. For each of those two records are created: for En→Fr translation and for En→Es. In total, 4 results are recorded.

If the model was trained and tested on en-to-36 dataset, than 4 times n records are created, where n is number of OPUS subdatasets from which the data was sampled.

2.4.5 XXX TODO: Analysis

After required set of models is trained and their test metrics are collected, data should be analysed.

2.5 Training tools

In the following section we describe the tools that are uset to implement what was shown in Section 2.4.

2.5.1 Toolkits

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 help it is possible to construct any of today's state-of-the-art NMT models; prebuilt 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]

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

- 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.

2.5.2 Computational cluster

In the experiments proposed above the expected number of models to be trained is quite big. First of all, there should be 36 models for *mono-target baseline* for En→36 dataset. For *multi-target random* experiment the number is much bigger. For example, let us consider a case with En→3 models - each model translates from English to 3 target languages. Specifying that each of 36 target languages from En→36 dataset should appear at least in 3 En→3 models, series of random generation of En→3 setups gave the smallest amount of such setups equal to 44. For En→5 case with 5 target languages in each model and with the same restriction of minimum occurance the same procedure gave the minimum amount of needed models equal to 34.

To be able to train large number of models in a reasonable amount of time we needed to use computational cluster with GPU cards. The computational clusters available at the institution are operating under SGE[12] scheduling software and are equipped with GPU cards with minimum CUDA *compute capability* 6.1.

Considering data storage quota limitation and high utilization of computational resources by the cluster's users, the following training pipeline was designed:

- Prepare task list
- Iterate over the list working with at most N tasks in parallel
- For each task
  - Subsample the dataset taking only those sentence pairs with target languages specified in the task
  - Run the training procedure for limited amount of time (e.g. for one hour only) starting with previous checkpoint if it already exists
  - Regularly compute metrics on the developement set and report them
  - On the event of evaluation on the developenemt set save the best model for each metric
  - After time is out the training is stopped and subsampled datasets are removed
- If for next selected task the model is already trained then select next task from the list
- If for next selected task the model is currently being trained then decrease the number N of tasks processed in parallel

[10] `https://github.com/tensorflow/tensor2tensor`
[11] Junczys-Dowmunt et al. [2018]
[12] `https://arc.liv.ac.uk/trac/SGE`

2.5.3 Inspecting the training process

As the number of models trained and being trained is growing, monitoring of the training process becomes more and more complicated. If the experiments are also being run on different computational clusters it becomes very possible that a parameter mistakenly set up to different value or a corrupted dataset, or even hardware version may lead to an unexpected difference in results.

To address these and other issues that may occur during the training process we use Weights&Biases[13] experiment tracking tool. Its main features that are useful in this prospective are following:

- Metric visualization
  - Training and validation loss curves (Figure 2.4 left subplot)
  - Scatter plots (Figures 2.5 and 2.4 middle subplot)
- Artifact storage
  - Model checkpoints storage
    - stores 'heavy' model files which cannot be stored in *git*
    - along with *git* it makes possible to move training to the different computational cluster system
  - Sample translations of validation set
    - helps to observe improvements of translation quality in time
    - lets verify that model is actually produces meaningfull translation
- Customizable reports
- Hardware utilization

2.5.4 XXX TODO: 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.

Tuning early stopping on early runs

The initial early stopping setting was that after 5 consecutive validation steps without improvement of validation loss value the training process stopped. However, during the training of first couple of bilingual models the following situation have happened quite often. Further improving performance on validation set by couple of tenths of BLEU points took as much time as reaching the optimal state.

On the Figure 2.6 can be seen that path from the beginning of training to optimal point B (26.9 BLEU) took as much time as its further improvement by

[13] Biewald [2020]

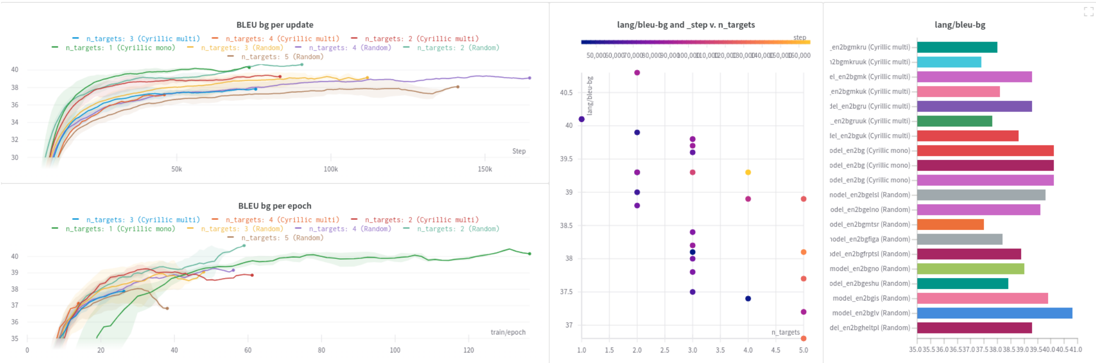


Figure 2.4: **Single language results visualization: models other target languages are randomly selected vs. those selected from similar group of languages.** XXX TODO: split it in print-friendly way Here is a part of interactive report for 'slavic languages with cyrillic script vs. random' experiment. In this specific case models' performace on Bulgarian part of validation set is compared.
Left: BLEU score for En→Bg translation direction is monitored with training step on X axis (top) and training epoch (bottom). Each curve represents mean value (line) and its min/max value (range) at the point of time of multiple models' results. Models are grouped by number of target languages and experiment subgroup (En→Bg, En→Slavic and En→Random).
Middle: Number of targets (axis X) vs. BLEU on En→Bg validation set (axis Y) vs. update steps (colos with scale at the top).
Right: Individual models' En→Bg validation BLEU scores.

0.2 BLEU at point D (27.1 BLEU). However, there were certain models with a bit bigger improvement after a much longer time, e.g. 0.8 BLEU points on Figure 2.7.

Possible situations of this kind were discussed in Section 2.4.3. After considering also some of preliminary multilingual runs the 'patience' parameter of early stopping was set to 15. After 15 consequent validation steps without metric improvement the training process is stopped.

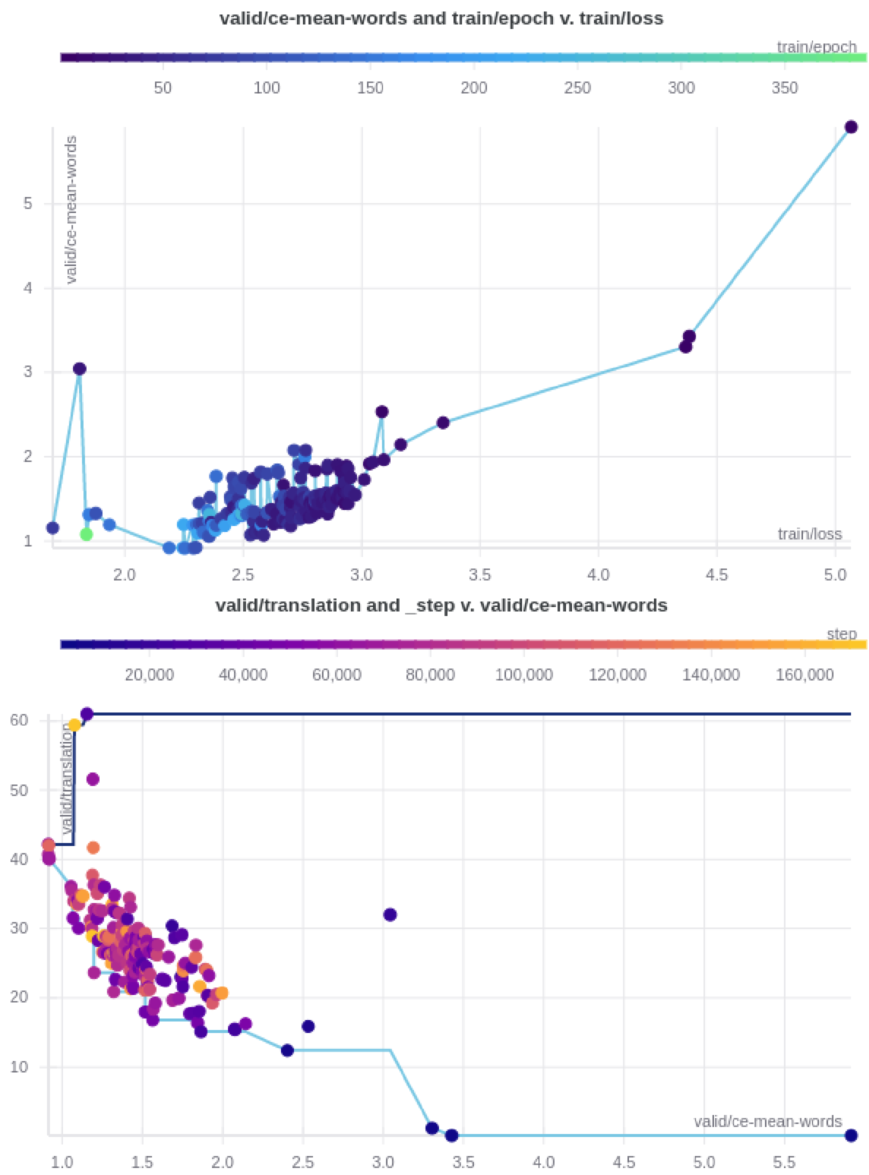


Figure 2.5: **Overall model convergence dashboard.** On these two interactive graphs each point represents one model. Models that are currently training are visualized here together with completely converged models and those which training process is currently on hold.
Left: axis X represents the training loss value, axis Y represents the value for the same loss function calculated on the validation set. The color of each point represents current training epoch for the model. Normally for any model the point moves from top right part of this graph to the bottom left part, representing both training and validation loss being gradually decreased during the training procedure. The point that moves to the middle left part of the graph may signalize about either overfitting of the model on training set, or difference in data distribution in training and validation set, or else some mistake in training settings.
Right: on this plot loss value on the validation set (axis X) is compared with geometric mean of BLEU scores for each of target languages. For any model during the training procedure its point usually moves from bottom right corner into the cluster of other points. Model which point 'arrives' to any other location than the cluster may need special attention.

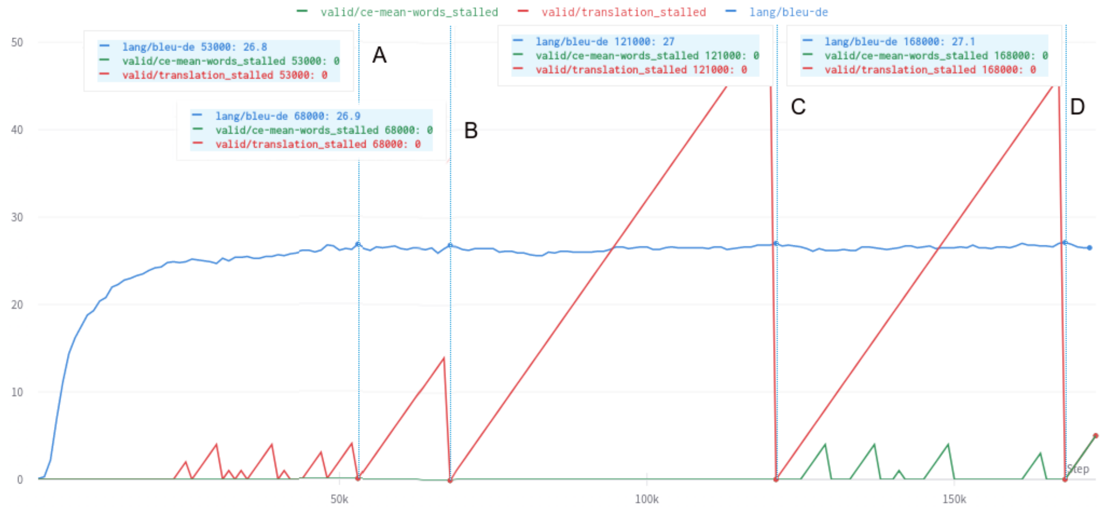


Figure 2.6: **Example change of model's performance on validation set in time.** Preliminary En→De model.
Blue: validation metric (value on the left axis in BLEU)
Red: validation metric (BLEU) stalled. Each consecutive validation step when the metric is not improved this value is incremented by 1. When the metric is improved this value is reset to 0.
Green: loss function value on validation set is stalled. Same logic as for *Red*.
BLEU score values at the points of improvement: *A* – 26.8, *B* – 26.9, *C* – 27.0, *D* – 27.1.

Figure 2.7: **Small improvement during long training.** In this case (En→Fi) the difference is a bit more visible: 21.3 at the first point and 21.9 at the best. Colors and scales are the same as at Figure 2.6.

3. Bilingual and multi-lingual baselines

In this chapter, we describe the baseline experiments. Bilingual baselines are needed to specify the starting point: how good can a model perform on a specific translation direction for each test set.

After bilingual results are collected and inspected, it is time for multi-lingual baselines. For this purpouse, we trained models with randomly selected sets of target languages. This way we can see how much adding more target languages to the model changes its performance on the same specific translation direction.

Most of experiments are done on the en-to-36 dataset with couple of additional experiments on the en-to-5 dataset.

3.1 XXX TODO: Bilingual baseline

We trained bilingual models on the en-to-36 dataset and received a number of values for each translation direction. Test results for relevant target directions (i.e. languages from 'Germanic' and 'Slavic with Cyrillic script' from Section 2.2.2) are shown in Table A.1. For example, for En→De direction we trained a bilingual model. After that, we evaluated the model on the test set and received BLEU scores for each sub-dataset, as shown in Figure 3.1. Later, when an En→{De, others} model will be trained and evaluated on the same test set, its En→De performance on each sub-dataset will be compared with these values.

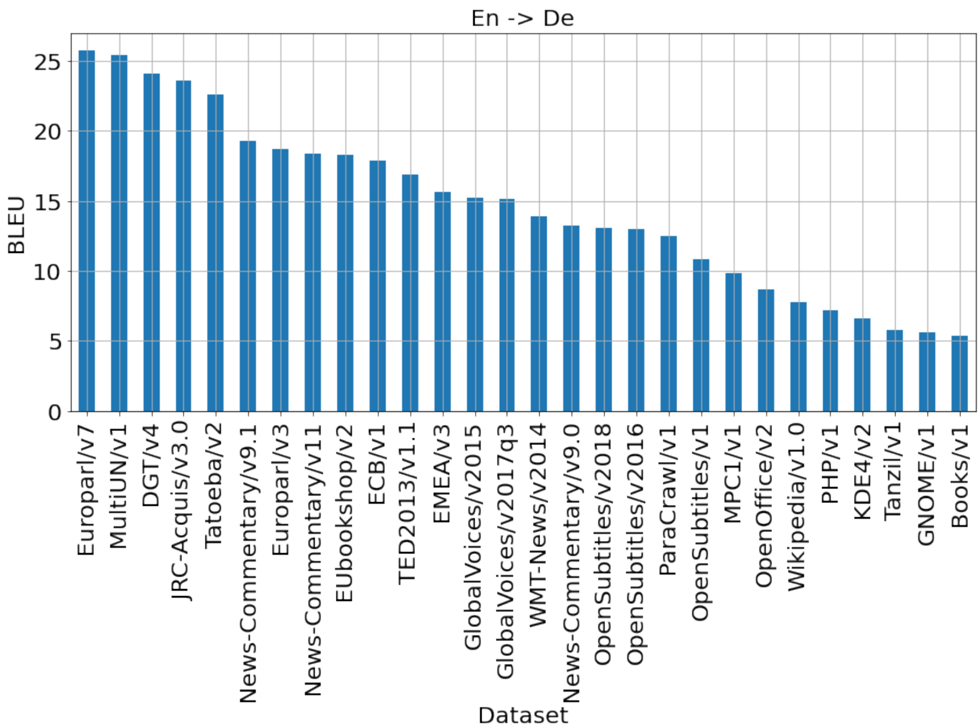


Figure 3.1: **En→De bilingual results.** Datasets on the X axis are sorted by declining BLEU score.

In Figure 3.1 we can see that BLEU scores for datasets in group 1 (Table 2.1), i.e. Europarl/v7, MultiUN/v1, DGT/v4 and JRC-Acquis/v3.0 are the highest; the lowest it is for sub-datasets from groups 4 and 5, such as PHP/v1, KDE/v4, Tanzil/v1, GNOME/v1, and Books/v1.

BLEU score values for different test sets cannot be compared directly. However, too big or too small value can give us some insight about the data.

Let us look closer at some example translations from different sub-datasets of the En→De test set. In Example 3.1.1 we can see a translation produced by our bilingual En→De model compared with the reference translation and two unnamed online translation systems. The sentence pair is from the Europarl/v7 sub-dataset of En→De test set. As was stated in Section 2.3.1, Europarl/v7 was a prioritized source of data to be sampled to the training set. Even though our translation has different wording comparing to the reference one, the sense is preserved. Interestingly, at the same time, our translation is much closer to the ones produced by online MT systems.

> **Source (En):** <2de> Finally, I fully support the compromise agreement reached by our committee on Article 5 (4).
> **Reference translation (De):** Ich unterstütze ohne jede Einschränkung die von unserem Ausschuss zu Artikel 5 Absatz 4 erzielte Kompromissvereinbarung.
> **Our bilingual En→De:** Schließlich unterstütze ich die von unserem Ausschuss erzielte Kompromiss zu Artikel 5 Absatz 4 voll und ganz.
> **OMT-G:** Schließlich unterstütze ich voll und ganz die Kompromissvereinbarung, die unser Ausschuss zu Artikel 5 Absatz 4 getroffen hat.
> **OMT-D:** Schließlich unterstütze ich voll und ganz die von unserem Ausschuss erzielte Kompromissvereinbarung zu Artikel 5 Absatz 4.
>
> **Example 3.1.1.** Bilingual En→De model's output of test set sentence translation (from Europarl/v7 sub-dataset) compared with the reference one and online translation systems OMT-G and OMT-D. Here and further for the online translation system, the target tag is omitted and the target language is selected directly in the system. For our system, the following sentence is firstly preprocessed. XXX TODO: add link to preprocessing section; add short section about bpe

Next prioritized sources for sampling training data were Eurobookshop and OpenSubtitles. The first dataset has domain and vocabulary similar to the Europarl dataset. But OpenSubtitles dataset has data of a different domain: transcribed human speech from films and series. It has much shorter sentences and the speech of different register.

In Example 3.1.2 we can see an issue of another kind that might happen: short sentence might not have all the needed information. Here English 'you' in the reference translation is translated as 'ihr' (2. person, plural), and in our translation as 'Sie' (3. person, plural) which refers to a polite form of 'you'. One of the online MT systems translates it as 'du' (2. person, singular). The difference in exact translation of 'you' affects the translation of 'know', because in German the verb has different conjugation for each person and case, comparing to English, where s/es are only added to the verb for 3. person, singular.

Source (En): <2de> Do you know it?
Reference translation (De): Kennt ihr das?
Our bilingual En→De: Wissen Sie das?
OMT-G: Weißt du es?
OMT-D: Kennen Sie es?

Example 3.1.2. Example sentence from OpenSubtitles/v2018 sub-dataset of the En→De test set.

3.2 XXX TODO: Multilingual baseline

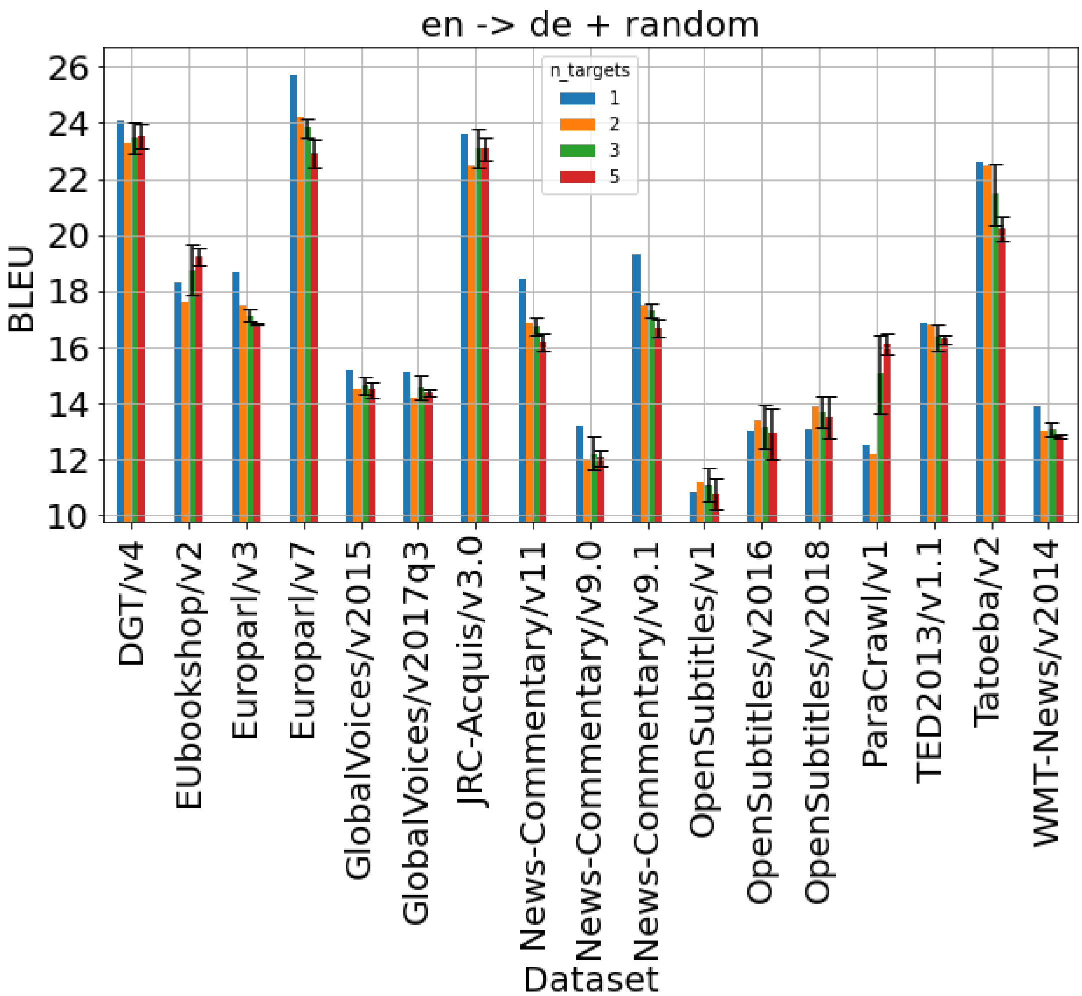


Figure 3.2: **En→De monolingual baseline results (RANDOM).** Datasets with BLEU lower than 10 are removed

En→De,Fr, En→De, Az, En→De, Bg En→Bg, Az models provide us with 3 results for En→De direction 2-target baseline, as well as one value for En→Fr, two values for En→Bg and two for En→Az. These aggregated En→De, X results will be later compared with aggregated En→$De, X1, X2$ for 3 target languages, En→$De, X1, X2, X3$ for 4 target languages, where X1, ... Xi are randomly selected languages. Also in the next chapters these results will serve as a baseline for aggregated En→$De, Y1, Y2...$ results of N target languages for languages Yi being from some group of languages similar to De.

3.3 Expected results

As we have seen in section 1.5.2, models with more languages in the mix usually perform slightly or significantly worse than bilingual ones. Also, for bilingual baselines no significant change in performace is expected with adding the target language tags.

However, there might be different unexpected effects due to slight domain-wise differences in corpora content for different target languages.

3.4 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.

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 3.1: **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)

3.5 Performance decrease on richer data sets

1 to 3, 4, 5 on UN corpus (much more sentence pairs per target language)

model	BLEU
m.esfrru t.ru	40.35
m.esru t.ru	42.16
m.frru t.ru	41.95
m.ru t.ru	44.20
m.esfrru t.fr	45.03
m.esfr t.fr	46.84
m.frru t.fr	45.66
m.fr t.fr	48.64
m.esfrru t.es	56.33
m.esfr t.es	57.94
m.esru t.es	57.31
m.es t.es	59.94

4. Group by language groups

4.1 Language groups

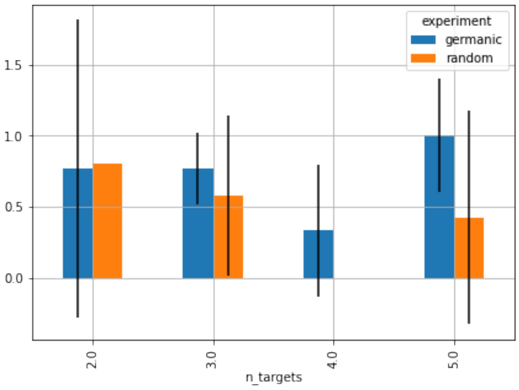
1 to 2, 3, 4, 5, etc. models on en-to-36 dataset (0.9 mil. sentences per target language) compared with random runs

4.1.1 Germanic group

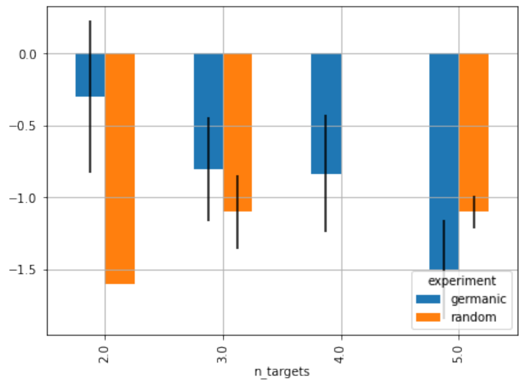
Here Germanic group consists of German, Dutch, Swedish, Danish, Norwegian and Islandic. Models En→Germanic are compared to En→non-Germanic, where non-Germanic consists of any langauge except from the Germanic group. On Figures 4.1 and 4.2 some selected results are visualized along with vocabulary changes. 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:

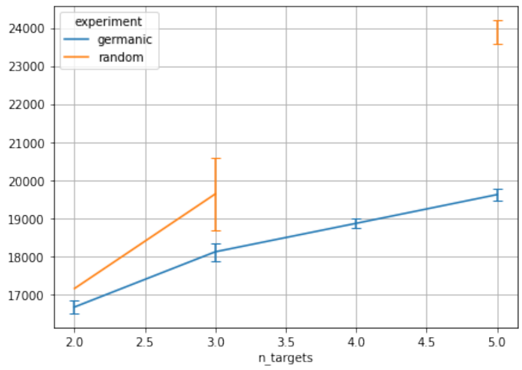
- For test sets with lower bilingual BLEU score adding more target languages to the model improves the score; adding related target languages improves it even more
- Adding more target languages improves translation result on test sets from spontaneous speech domain but worsenes it for prepared speech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



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

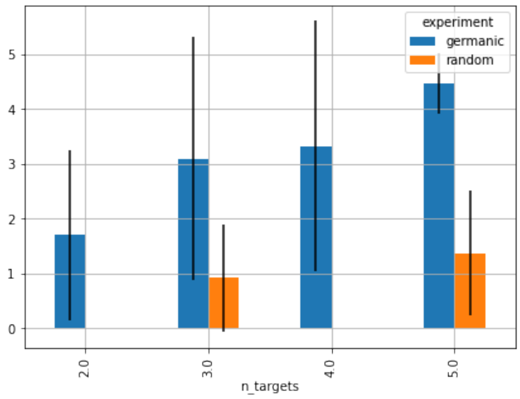


(b) MultiUn, bilingual score: 25.4 BLEU

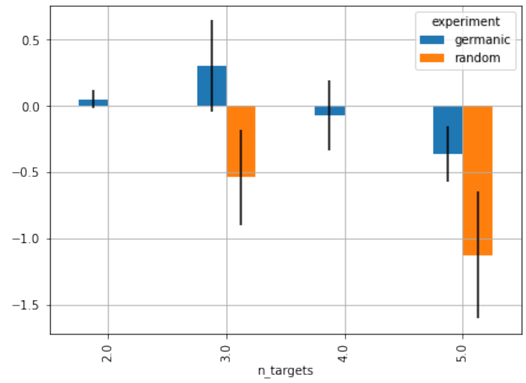


(c) Subword dictionary size used for target side

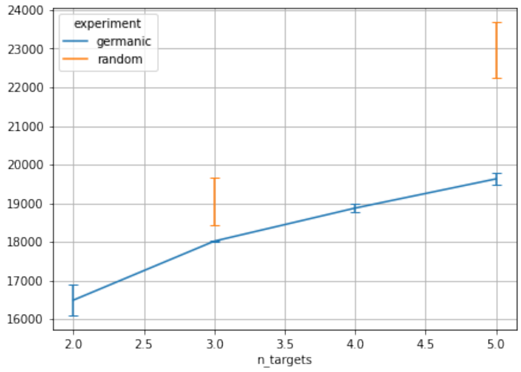
Figure 4.1: **En→De BLEU score difference: Random vs. Germanic.** On X axis - number of target languages. On Y axis - difference score comparing with monolingual BLEU. Black vertical lines show standard deviation. (a) Adding random target language as well as a related one slightly improves German translation 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



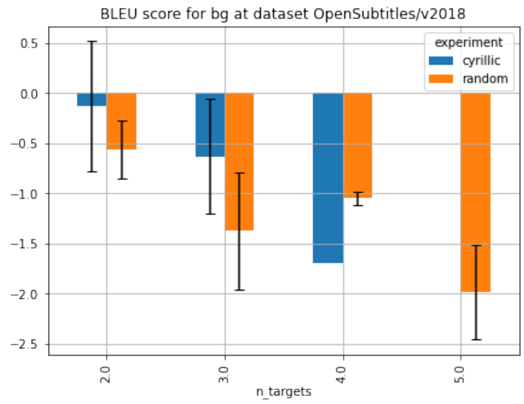
(c) Subword dictionary size used for target side

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

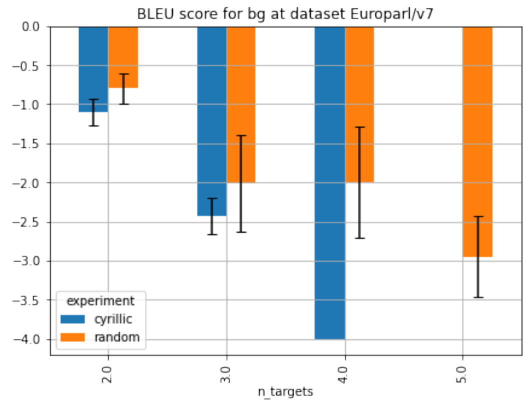
4.1.2 Slavic with cyrillic script

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.

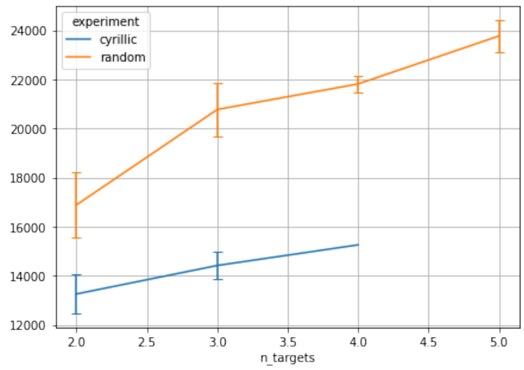
From the two opposite observations of 4.1.1 in this case the second one is observed: low results are getting slightly better, good results are getting slightly or significantly worse.



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

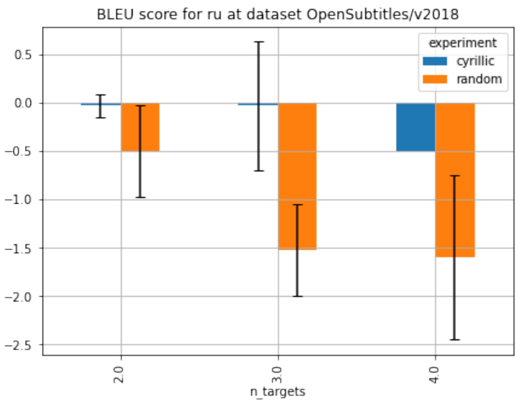


(b) Europarl/v3, bilingual score: 41.4 BLEU

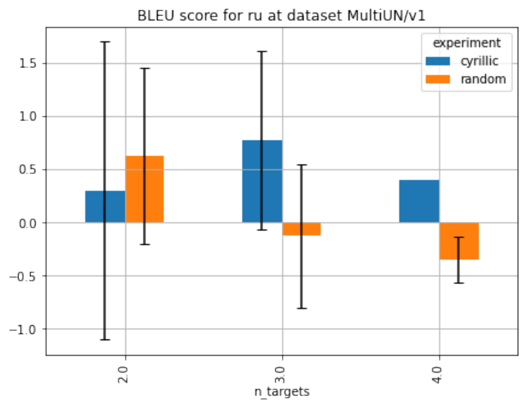


(c) Subword dictionary size used for target side

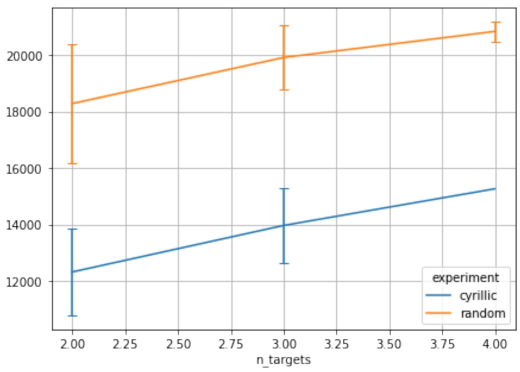
Figure 4.3: **En→Bg BLEU score difference: Random vs. Slavic with cyrillic script.** Axis are same as for Figures 4.2 and 4.1. There is not any data for Cyrillic and 5 targets as there are only 4 such languages in the en-to-36 dataset. Both (a) and (b) show significant decrease in translation quality. 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

Bibliography

Roee Aharoni, Melvin Johnson, and Orhan Firat. Massively Multilingual Neural Machine Translation. In *Proceedings of the 2019 Conference of the North {A}merican Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 3874–3884, Minneapolis, Minnesota, 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1388. URL `https://www.aclweb.org/anthology/N19-1388`.

ALPAC. *Language and Machines.* National Academies Press, Washington, D.C., jan 1966. ISBN 978-0-309-57056-5. doi: 10.17226/9547. URL `http://www.nap.edu/catalog/9547`.

Naveen Arivazhagan, Ankur Bapna, Orhan Firat, Dmitry Lepikhin, Melvin Johnson, Maxim Krikun, Mia Xu Chen, Yuan Cao, George Foster, Colin Cherry, Wolfgang Macherey, Zhifeng Chen, and Yonghui Wu. Massively Multilingual Neural Machine Translation in the Wild: Findings and Challenges. jul 2019. URL `http://arxiv.org/abs/1907.05019`.

Loïc Barrault, Ondřej Bojar, Marta R Costa-jussà, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Matthias Huck, Philipp Koehn, Shervin Malmasi, Christof Monz, Mathias Müller, Santanu Pal, Matt Post, and Marcos Zampieri. Findings of the 2019 Conference on Machine Translation (WMT19). In *Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1)*, pages 1–61, Stroudsburg, PA, USA, 2019. Association for Computational Linguistics. doi: 10.18653/v1/W19-5301. URL `http://www.aclweb.org/anthology/W19-5301https://www.aclweb.org/anthology/W19-5301`.

Lukas Biewald. Experiment tracking with weights and biases, 2020. URL `https://www.wandb.com/`. Software available from wandb.com.

Ondřej Bojar, Christian Federmann, Mark Fishel, Yvette Graham, Barry Haddow, Philipp Koehn, and Christof Monz. Findings of the 2018 conference on machine translation (WMT18). In *Proceedings of the Third Conference on Machine Translation: Shared Task Papers*, pages 272–303, Belgium, Brussels, October 2018. Association for Computational Linguistics. doi: 10.18653/v1/W18-6401. URL `https://www.aclweb.org/anthology/W18-6401`.

Raj Dabre, Chenhui Chu, and Anoop Kunchukuttan. A Brief Survey of Multilingual Neural Machine Translation. may 2019. URL `http://arxiv.org/abs/1905.05395`.

Andreas Eisele and Yu Chen. {M}ulti{UN}: A Multilingual Corpus from United Nation Documents. In *Proceedings of the Seventh International Conference on Language Resources and Evaluation ({LREC}'10)*, Valletta, Malta, 2010. European Language Resources Association (ELRA). URL `http://www.lrec-conf.org/proceedings/lrec2010/pdf/686{_}Paper.pdf`.

Lifeng Han. Machine Translation Evaluation Resources and Methods: A Survey. 2018, 2016. URL `http://arxiv.org/abs/1605.04515`.

Melvin Johnson, Mike Schuster, Quoc V Le, Maxim Krikun, Yonghui Wu, Zhifeng Chen, Nikhil Thorat, Fernanda Viégas, Martin Wattenberg, Greg Corrado, Macduff Hughes, and Jeffrey Dean. Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation. *Transactions of the Association for Computational Linguistics*, 5:339–351, 2017. doi: 10.1162/tacl_a_00065. URL `https://www.aclweb.org/anthology/Q17-1024`.

Marcin Junczys-Dowmunt, Roman Grundkiewicz, Tomasz Dwojak, Hieu Hoang, Kenneth Heafield, Tom Neckermann, Frank Seide, Ulrich Germann, Alham Fikri Aji, Nikolay Bogoychev, André F T Martins, and Alexandra Birch. Marian: Fast Neural Machine Translation in {C++}. In *Proceedings of ACL 2018, System Demonstrations*, Melbourne, Australia, 2018. URL `https://arxiv.org/abs/1804.00344`.

Philipp Koehn. *Neural Machine Translation*. Cambridge University Press, 2020.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei jing Zhu. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting on association for computational linguistics*, pages 311–318. Association for Computational Linguistics, 2002.

Martin Popel and Ondřej Bojar. Training tips for the transformer model. *The Prague Bulletin of Mathematical Linguistics*, 110, 03 2018. doi: 10.2478/pralin-2018-0002.

Matt Post. A call for clarity in reporting BLEU scores. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 186–191, Brussels, Belgium, October 2018. Association for Computational Linguistics. doi: 10.18653/v1/W18-6319. URL `https://www.aclweb.org/anthology/W18-6319`.

Aditya Siddhant, Melvin Johnson, Henry Tsai, Naveen Arivazhagan, Jason Riesa, Ankur Bapna, Orhan Firat, and Karthik Raman. Evaluating the Cross-Lingual Effectiveness of Massively Multilingual Neural Machine Translation. sep 2019. URL `http://arxiv.org/abs/1909.00437`.

Matthew Snover, Bonnie J. Dorr, Richard H. Schwartz, and Linnea Micciulla. A study of translation edit rate with targeted human annotation. 2006.

Keh-Yih Su, Ming-Wen Wu, and Jing-Shin Chang. A new quantitative quality measure for machine translation systems. In *Proceedings of the 14th Conference on Computational Linguistics - Volume 2*, COLING '92, page 433–439, USA, 1992. Association for Computational Linguistics. doi: 10.3115/992133.992137. URL `https://doi.org/10.3115/992133.992137`.

Jörg Tiedemann. Parallel data, tools and interfaces in opus. In Nicoletta Calzolari (Conference Chair), Khalid Choukri, Thierry Declerck, Mehmet Ugur Dogan, Bente Maegaard, Joseph Mariani, Jan Odijk, and Stelios Piperidis, editors, *Proceedings of the Eight International Conference on Language Resources* *and Evaluation (LREC'12)*, Istanbul, Turkey, may 2012. European Language Resources Association (ELRA). ISBN 978-2-9517408-7-7.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is All you Need. In I Guyon, U V Luxburg, S Bengio, H Wallach, R Fergus, S Vishwanathan, and R Garnett, editors, *Advances in Neural Information Processing Systems 30*, pages 5998–6008. Curran Associates, Inc., 2017. URL `http://papers.nips.cc/paper/7181-attention-is-all-you-need.pdf`.

List of Figures

List of Tables

Abbreviations

ALPAC Automatic Language Processing Advisory Committee. 5

BLEU bilingual evaluation understudy. 1, 5, 6, 8, 9, 13, 16–19, 22–24, 26, 27, 29, 31–35, 41, 42

BPE byte pair encoding. 1, 4

CNN convolutional neural network. 4

GRU gated recurrent unit. 4

LSTM long short-term memory. 4

MT machine translation. 3, 7, 27

NMT neural machine translation. 7, 8

RNN recurrent neural network. 4

SGD stochastic gradient descent. 17

Glossary

baseline In machine learning this term refers to a simple or naïve initial solution, which efficiency it then taken as a reference point and later improved. . 13

early stopping Regularization technique to avoid model overfit. Usualy consists of stopping the training process when the value of some selected metric on the validation set is not improved for last number of validation steps. . 17–19, 22, 23, 41

en-to-36 The dataset with source sentences in English and target sentences in 36 languages, described in Section 2.3.1 . 2, 19, 20, 26, 47

en-to-5 The dataset created from UN parallel corpus, with source sentences in English and target sentences in one of following 5 languages: Spanish, French, Russian, Arabic and Chinese; described in Section 2.3.2 . 2, 19, 26, 47

epoch Refers to one pass of full training dataset to the learning algorightm . 17

loss Loss function, also often called 'objective function' and 'error function'. It is optimized during the training process. In our experiments it is mean word cross-entropy score.. 22

overfitting Occurs when the model's performance on unseen validation set stops improving while on the training set it still improves. . 17, 24

A. Attachments

A.1 Additional tables

A.1.1 Bilingual results

target dataset	bg	da	de	is	mk	nl	no	ru	sv	uk
Books/v1	—	—	5.4	—	—	4.8	—	8.3	—	—
DGT/v4	33.1	27.4	24.1	—	—	25.9	—	—	28.9	—
ECB/v1	—	20.9	17.9	—	—	21.2	—	—	—	—
EMEA/v3	15.1	16.4	15.6	—	—	15.8	—	—	17.6	—
EUbookshop/v2	38.2	24.1	18.3	—	—	18.9	—	—	24.7	—
Europarl/v3	—	24.6	18.7	—	—	23.4	—	—	23.6	—
Europarl/v7	41.4	32.5	25.7	—	—	26.0	—	—	33.3	—
GNOME/v1	—	—	5.6	2.4	—	8.9	—	—	—	—
GlobalVoices/v2015	—	—	15.2	—	10.6	18.6	—	13.2	—	—
GlobalVoices/v2017q3	—	—	15.1	—	10.7	19.1	—	14.4	—	—
JRC-Acquis/v3.0	30.8	27.3	23.6	—	—	25.7	—	—	29.1	—
KDE4/v2	6.9	8.5	6.6	4.2	4.8	8.1	—	4.1	8.4	1.3
MPC1/v1	—	—	9.8	—	—	—	—	—	—	—
MultiUN/v1	—	—	25.4	—	—	—	—	14.6	—	—
News-Commentary/v11	—	—	18.4	—	—	19.2	—	23.9	—	—
News-Commentary/v9.0	—	—	13.2	—	—	—	—	18.2	—	—
News-Commentary/v9.1	—	—	19.3	—	—	—	—	22.1	—	—
OpenOffice/v2	—	—	8.7	—	—	—	—	—	8.6	—
OpenSubtitles/v1	19.3	17.1	10.8	—	—	12.5	23.1	16.2	13.4	—
OpenSubtitles/v2016	23.2	14.8	13.0	24.3	24.3	13.7	27.0	19.5	14.8	11.2
OpenSubtitles/v2018	23.7	15.6	13.1	23.1	24.6	13.4	29.6	19.2	15.3	12.2
PHP/v1	—	—	7.2	—	—	12.6	—	3.3	8.9	—
ParaCrawl/v1	—	—	12.5	—	—	17.9	—	11.1	—	—
SETIMES/v1	23.2	—	—	—	6.4	—	—	—	—	—
SETIMES/v2	27.5	—	—	—	10.4	—	—	—	—	—
TED2013/v1.1	—	—	16.9	—	—	19.1	—	14.7	—	—
Tanzil/v1	5.7	—	5.8	—	—	4.6	6.1	2.4	4.4	—
Tatoeba/v2	—	—	22.6	—	—	28.9	—	27.7	—	13.3
UN/v20090831	—	—	—	—	—	—	—	9.9	—	—
Ubuntu/v14.10	—	—	—	—	—	8.6	—	—	—	—
WMT-News/v2014	—	—	13.9	—	—	—	—	—	—	—
WikiSource/v1	—	—	—	—	—	—	—	—	5.3	—
Wikipedia/v1.0	11.7	—	7.8	—	—	9.6	—	10.6	—	—

Table A.1: BLEU scores for bilingual models

A.2 Language lists

The source language is always the same:
en - English
In the following sections there are lists of *target* languages.

A.2.1 Languages from en-to-5

ar - Arabic
fr - French
es - Spanish
ru - Russian
zh - Chinese

A.2.2 Languages from en-to-36

XXX TODO: list with names
XXX TODO: two language groups used in the experiments