

From Priest to Doctor: Domain Adaptation for Low-Resource Neural Machine Translation

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Abstract

Many of the world’s languages have insufficient data to train high-performing general neural machine translation (NMT) models, let alone domain-specific models, and often the only available parallel data are small amounts of religious texts. Hence, domain adaptation (DA) is a crucial issue faced by contemporary NMT and has, so far, been underexplored for low-resource languages. In this paper, we evaluate a set of methods from both low-resource NMT and DA in a realistic setting, in which we aim to translate between a high-resource and a low-resource language with access to only: a) parallel Bible data, b) a bilingual dictionary, and c) a monolingual target-domain corpus in the high-resource language. Our results show that the effectiveness of the tested methods varies, with the simplest one, DALI, being most effective. We follow up with a small human evaluation of DALI, which shows that there is still a need for more careful investigation of how to accomplish DA for low-resource NMT.

1 Introduction

Neural machine translation (NMT) models have limited ability to deal with languages that lack large-scale monolingual and parallel corpora (Wang et al., 2021). Moreover, NMT systems face challenges when translating text from novel domains characterized by unique style or vocabulary (Koehn and Knowles, 2017; Saunders, 2022). Often, these issues co-occur, a scenario that has been neglected by researchers so far. Most of the world’s 7000+ languages are considered low-resource (Joshi et al., 2020), and existing data for them are in limited domains; the languages that could most benefit from domain adaptation (DA) are the ones left behind.

In this paper, we explore a realistic setting in which we aim to translate between a high-resource and a low-resource language and are restricted to the following commonly available resources: a)

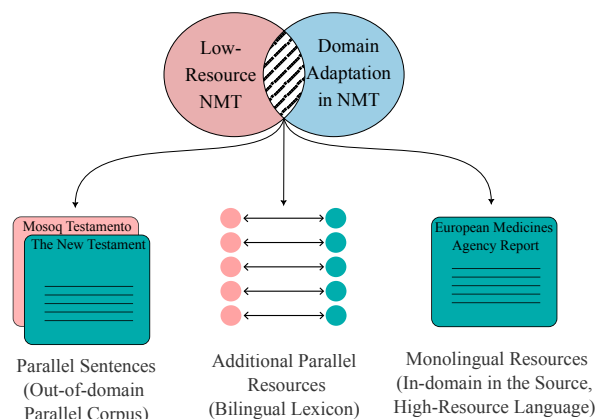


Figure 1: In our work, which looks at the (previously neglected) intersection of low-Resource NMT and domain adaptation in NMT, we consider only these commonly accessible resources.

Bible translations, i.e., a small parallel corpus in the source domain; b) monolingual target-domain texts in the high-resource language; and c) a bilingual dictionary for the two languages. To keep the setting generalizable, we assume neither access to a model pretrained on text in the low-resource language nor access to data in a related high-resource language, as for many truly low-resource languages, those are impossible to find.

We experiment with a set of four DA and low-resource NMT methods and aim to translate from English to a target language, simulating a low-resource setting. We use mBART (Liu et al., 2020) which has been fine-tuned on parallel Bible texts as our base model, and our goal is to adapt it to the target domains of government documents and medicine. The methods we investigate use the bilingual dictionaries in various ways.

Our experiments showcase the varying effectiveness of existing methods: the weakest approach results in models that perform *worse* than the base model, while the best approach – which, surprisingly, is also the simplest – results in a ChrF score

more than twice as high as the base model’s. However, as the best model only reaches a ChrF score of 42.47 and a BLEU score of 13.47 (on average), we also perform a small human evaluation, which confirms that there is still a need for the development of better DA methods for low-resource NMT. Our code is available on GitHub.¹

2 Related Work

Domain Adaptation in NMT As domains are defined by the characteristics of data (Saunders, 2022), many effective DA approaches focus on the data and, thus, can be applied to various underlying architectures. Some works focus on acquiring monolingual in-domain data, which is easier to find than in-domain parallel data. Back-translation uses monolingual target-domain data in the target language and produces artificial source sentences using a target-to-source NMT model (Poncelas et al., 2019; Jin et al., 2020). Chinea-Ríos et al. (2017) use monolingual source-side corpora and a source-to-target NMT model for forward-translation, where it is common to employ self-learning. With access to a small parallel corpus, extra training data can be created by introducing noise (Vaibhav et al., 2019). Synthetic parallel data can be acquired from an external source or generated using a predefined or induced lexicon. Hu et al. (2019) use a lexicon to back-translate target-side sentences. Peng et al. (2020) use a dictionary, injecting dictionary terms into out-of-domain texts to synthesize in-domain training data. Bergmanis and Pinnis (2021) augment the training data by annotating randomly selected source language words with their target language lemmas to integrate terms. Zhang et al. (2022) introduce lexical constraints into iterative back-translation.

Other approaches add parameters to the model, e.g., domain tags (Kobus et al., 2017; Stergiadis et al., 2021). Such a manipulation of the embeddings could extend to more terms in the vocabulary, beyond the tags (Pham et al., 2019; Sato et al., 2020; Man et al., 2023). With adapter-based methods, a domain-specific module is trained (Bapna and Firat, 2019). Chen et al. (2021) use a pointer-generator to copy suggestions from the input, which come from a domain-specific dictionary.

Low-Resource NMT Methods for low-resource MT show some overlap with DA methods. One

popular approach is data augmentation, which can be in the form of word or phrase replacement with the help of a bilingual lexicon (Nag et al., 2020). Back-translation, forward-translation, and data selection methods can also be applied (Sennrich et al., 2016; Fadaee and Monz, 2018; Dou et al., 2020). Transfer learning is a useful technique in low-resource NMT (Maimaiti et al., 2019; Kocmi and Bojar, 2020; Cooper Stickland et al., 2021). Liu et al. (2021) continue to pretrain mBART (Liu et al., 2020) on unseen languages, utilizing a bilingual dictionary. Although we do not inspect large language models (LLMs) in our experiments, some recent works explore the potential of LLMs for low-resource NMT. Robinson et al. (2023) observe that ChatGPT’s MT capabilities across the 204 languages of the FLORES-200 dataset (Costa-jussà et al., 2022) consistently lag behind traditional NMT models. Ghazvininejad et al. (2023) use dictionaries to suggest words to use in the output translation. Zhang et al. (2024) adopt different strategies for dictionary term lookup and the retrieval of examples for in-context learning. Siddhant et al. (2022); Ranathunga et al. (2023) note that, in the case of many low-resource languages, the problem is more severe since the only available parallel data are religious texts.

3 Data

Parallel Source-Domain Data In all experiments, the only *parallel* data we use for training come from the JHU Bible Corpus (McCarthy et al., 2020).

Target-Domain Data We explore adapting to two different domains, one at a time: government documents and medicine. The domain-specific data mostly come from past WMT translation tasks (Barraut et al., 2020; Akhbardeh et al., 2021; Kocmi et al., 2022, 2023). As we assume only *monolingual* in-domain training data (cf. Section 4), training and pretraining use only source-side sentences from these parallel data sets. Data availability varies across language/domain pairs, and we cap data set sizes to maintain comparability across languages. For **training** we use no more than 200K sentence pairs. If our setting requires **pretraining**, we use the same source-side sentences used for training. For **testing**, we use 1500 sentence pairs.

More details about the data used for each domain and language pair can be found in Appendix A.1.

¹https://github.com/alimrsn79/da_lr_nmt

Dictionaries The methods we investigate here call for source–target language dictionaries. To build dictionaries, for each language pair we extract the 5000 most frequent lemmas and their inflections from the monolingual training data and use the Google Translate API² to translate those words.³

We augment this dictionary with word pairs extracted from our small parallel corpora, using standard statistical approaches for lexicon induction. Specifically, we employ Fast Align (Dyer et al., 2013) on the Bible verses. The expansion of the dictionary with statistical methods follows previous work (Hu et al., 2019; Zhang et al., 2024).

Further information about the dictionaries is available in Appendix A.2.

Languages Because it is difficult to source domain-specific evaluation data in truly low-resource languages, we simulate a low-resource setting, selecting languages not seen during mBART’s pretraining. For the government domain, we experiment on **Croatian, Icelandic, Maltese, Polish, and Ukrainian**. For the medical domain, we use **Croatian, Icelandic, Maltese, and Polish**. In all cases, **English** is our high-resource language.

4 Experimental Setup

Our goal is to translate from English into our low-resource languages, one at a time. In this section, we describe the different approaches we investigate. All of them use mBART as the backbone model and are implemented using fairseq.⁴

mBART Baseline Our baseline is the pretrained mBART model, which has been trained on 25 languages and is said to generalize well to unseen languages (Liu et al., 2020).

DALI We adapt the method from Hu et al. (2019), who extract a lexicon by mapping word embeddings from the source to the target language. They then use this lexicon to back-translate from the target monolingual data, by word-for-word replacement. The resulting texts are the pseudo-parallel data that are used for training. We produce pseudo-parallel data using the same method, but use the dictionary described in Section 3. As we have access to monolingual texts in the *source* language, we do forward-translation instead of back-translation.

²<https://cloud.google.com/translate/>

³We expect performance might increase if we had domain-specific bilingual dictionaries for each language pair.

⁴<https://github.com/facebookresearch/fairseq>

LeCA Chen et al. (2021) append suggestions to the input to be used in the output. Their model uses a pointer-generator module to potentially copy from the input. Since the model updates just the probability of the next token by also considering copying from the input tokens, it is not a hard constraint. We match their DICTIONARY CONSTRAINT setting, where suggestions are made by looking up source-side terms in a given dictionary. We implement this on top of the base mBART model. Note that LeCA was not originally proposed for low-resource scenarios, and they do not use a pretrained model, instead training the base Transformer model from scratch.

CPT Liu et al. (2021) continue pretraining mBART on mixed-language text, modifying the pretraining scheme of the model. They corrupt the text by replacing some terms with their translation in the new language, and the model is trained to reconstruct the original text. In our setting, we must use source-side monolingual text only, matching their CPT w/ MLT (SRC) method. Note that in our experiments we translate from the high-resource language to the low-resource.

Combined We experiment with merging the above methods: first, we pretrain the model (CPT) and then train it with pseudo-parallel data (DALI) while using pointer-generators (LeCA).

Metrics We evaluate all methods on the test data described in Section 3, using BLEU (Papineni et al., 2002) and ChrF (Popović, 2015) as implemented by sacreBLEU (Post, 2018). We consider ChrF our main metric, as it focuses on characters and is more informative when translating into morphologically rich languages.

5 Results and Discussion

The results for all languages and domains appear in Table 1. On average, DALI performs best in the majority of the experiments. It is also the simplest of the methods to implement, as it is model-agnostic and only the training data is manipulated.

LeCA does not help in most cases, supporting Bafna et al. (2024), who observe that pointer-generators are not consistently helpful for low-resource NMT. LeCA was not initially devised for low-resource settings, and also the dictionary here includes just one translation per term, with no guarantee of matching the intended target side meaning. Since mBART was not pretrained on these

	Metric	Croatian		Icelandic		Maltese		Polish		Ukrainian	Average	
		Gov.	Med.	Gov.	Med.	Gov.	Med.	Gov.	Med.	Gov.	Gov.	Med.
mBART	BLEU	0.69	1.7	0.76	1.46	1.57	1.68	0.34	0.33	0.9	0.85	1.29
	ChrF	17.34	18.62	18.97	17.72	21.61	19.42	19.11	17.37	17.83	18.97	18.28
DALI	BLEU	<u>4.1</u>	<u>12.74</u>	<u>5.76</u>	<u>13.89</u>	<u>7.92</u>	16.68	<u>4.21</u>	10.57	<u>6.8</u>	<u>5.76</u>	<u>13.47</u>
	ChrF	38.87	43.32	36.02	41.07	49.55	48.77	36.33	36.73	37.51	39.66	42.47
LeCA	BLEU	0.65	1.68	0.98	0.24	1.41	1.5	0.35	0.41	0.79	0.84	0.96
	ChrF	17.48	18.23	19.24	15.97	20.6	18.56	17.6	17.11	18.74	18.73	17.47
CPT	BLEU	2.62	8.02	3.66	5.26	2.18	5.38	1.57	5.73	4.38	2.88	6.1
	ChrF	20.46	25.19	20.67	20.56	20.42	21.86	19.19	21.03	12.35	18.62	22.16
Combined	BLEU	3.87	12.21	5.63	13.4	7.14	<u>16.75</u>	3.82	<u>10.67</u>	6.69	5.43	13.26
	ChrF	39.93	42.11	36.33	40.56	48.17	48.88	35.72	36.11	36.46	39.32	41.92

Table 1: Performance on the all the test sets for the target domains government (Gov.) and medical (Med.) documents. Best BLEU score per column is underlined, while the best ChrF score is indicated in bold.

languages, its embeddings of words in the low-resource language might not as directly correspond to their source-side, high-resource counterparts; we hypothesize this may be another reason LeCA performs poorly for resource-constrained scenarios.

CPT is helpful in most of the experiments when compared to plain mBART, but not compared to DALI. After pretraining, the model is fine-tuned only on Bible data. In the pretraining, we reconstruct the source side, so the model only learns to output in the target language from the Bible verses. Pretraining helps the model get more familiar with the domain and establish connections between the embeddings of target words and their respective translations in the high-resource language.⁵

Combining the methods together shows some improvements over other individual methods, but generally fails to reach DALI’s performance. Note that the same dataset was used to both pretrain the model (the CPT part) and to then make pseudo-parallel data (the DALI part). Since LeCA is not helpful when added to the basic mBART, we also test performance of *Combined* without LeCA, on the medical domain. The results (Table 8) indicate that – when using the same dataset for both – adding pretraining on top of DALI can be detrimental, but removing LeCA increases performance on all languages for the medical domain.

LeCA only uses the dictionary in the final stage, and CPT uses the monolingual data during pretraining, before being fine-tuned on the bible data. DALI and *Combined* are the only methods that have access to source-side target-domain monolingual data during the final stage of training, which

could partially explain their superior performance. That a simple method like DALI – that mostly keeps the word order of the sentence language – should be the best performing method hints at the extensive room for growth in future work.

Figure 2 shows averaged sentence-level BLEU and ChrF scores plotted against their respective reference token lengths for DALI models. For length l , we average the scores of the models for different languages if the reference translation is of length l . We can see that generally the scores seem to get higher with longer sentences, especially for ChrF.

Example We see some interesting trends in the outputs. Table 2 showcases an example with the outputs of different methods for one sentence from the Maltese-medical test set, the language–domain pair with the most significant performance boost. *Warning: these outputs could include distressing language against women that may harm some readers.* Both mBART and LeCA translate in a religious tone. The same is true for CPT, which also tends to copy words from the input – as it was a part of the reconstruction procedure during pretraining. It is important to emphasize that Maltese is a morphologically rich language, and the inflections are mostly discarded in the outputs of DALI and *Combined*; for example the words are more likely to be disjoint in their outputs than they are in the target (the first “*il oħra*” vs “*l-oħra*” in the target), or they can be in different forms (“*huwa*” vs “*hija*”). Note that *ointment* was translated to *infusion* by DALI. Given the sensitivity of the domain, a translation like this can potentially be harmful.

Maltese at times has a different word order than that of English (“*il-mediċina tal-ġhajnejn*” is translated as “*ġhajn mediċina*”, which matches the order

⁵According to Liu et al. (2021), the performance boost is expected to increase if we have monolingual texts in the target language instead and can use them during pretraining.

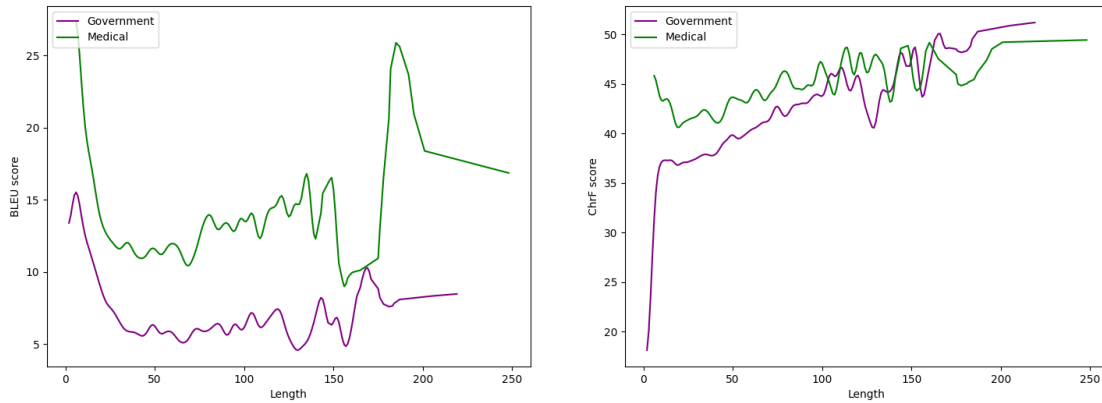


Figure 2: The trend of averaged sentence-level BLEU (left) and ChrF (right) scores against the token length of the reference translation for DALI models. The scores are averaged across all the model outputs of the same length – including averaging across languages, where relevant.

Source: if the other eye medicine is an eye ointment it should be used last			
mBART:	jekk il-mara l-ieħor hi ajn oħra , hi andha tinatalha l-aħħar fl-aħħar	LeCA:	inkella jekk il-mara l-ieħor hi ejt , tkun mamula l-aħħar
BT:	if the other woman is someone else, she should be punished in the end	BT:	otherwise if the other woman is a virgin, she will be the worst
DALI:	jekk il oħra għajn mediina huwa an għajn infużjoni dan għandu tkun użati l-aħħar	CPT:	jekk l-oħrajn ta ' l-ieħor hi ajnejja ointment , it should be used l-aħħar
BT:	If the other eye medicine is an eye infusion, this should be used last	BT:	Even though the other one is a ajnejja ointment, it should be used last
Combined:	jekk il oħra għajn mediina huwa an għajn ointment dan għandu tkun użati l-aħħar	Target:	jekk il-mediina tal-għajnejn l-oħra hija ingwent tal-għajnejn , dan għandu jintuża l-aħħar
BT:	If the other eye medicine is an eye ointment, this should be used last	BT:	Although the other eye medicine is an eye ointment, this should be used last

Table 2: **Warning: this table contains harmful language about women that may distress some readers.** An example of different model outputs for a Maltese sentence in the medical domain. For better comparison, the back-translations (BT) of the outputs to English are also included, done via Google Translate.

of its English counterpart “eye medicine”), and it is also more flexible. DALI and *Combined* produce word orders that closely follow the source language.

Human Evaluation Conducting a small-scale human evaluation of the Polish government translations of 25 source sentences, we find that, while DALI improves the communication of the overall semantics of the sentences, there is certainly room for improvement, especially when it comes to fluency and generating grammatical output. Additional model outputs and details of the human evaluation can be found in Appendix C.

6 Conclusion

This paper introduces a realistic setting that has been previously overlooked: DA for NMT into a low-resource from a high-resource language, with available resources restricted to limited parallel text, a dictionary, and monolingual texts in the high-resource language. The simplest approach – DALI – yields the best results, more than doubling baseline performance. A small-scale human evaluation indicates ample room for improvement, and we advocate for increased focus on this setting.

Limitations

It is important that these experiments be conducted for truly low-resource languages. The scope of this work was limited due to the availability of datasets in different domains for such resource-constrained languages; which was the main reason we resorted to experimenting on simulated low-resource languages. Limitations of finding domain-specific corpora for low-resource languages also extend to finding domain-specific dictionaries, and our dictionaries prepared with Google Translate only mimic target-domain dictionaries. In addition, we based our experiments on mBART only, and we leave the study of other multilingual pretrained models and LLMs (or even smaller, non-pretrained models like the base Transformer) in this setting for future work.

Ethics Statement

As our research shows that these methods do not sufficiently enhance performance for the models to be deemed useful, there are some caveats to be mindful of. Specifically, these methods should not be used for real-world MT in critical contexts involving low-resource languages; e.g. providing medical advice based on the translations produced by the model.

All the data used in the study is publicly available (see Appendix A.1).

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A Data

A.1 Datasets

Here are the details for the data used in training, testing and potential pretraining and pseudo data generation. All the datasets are lower-cased.

A.1.1 Parallel Data

The parallel data come from the New Testament verses from the Johns Hopkins University Bible Corpus (McCarthy et al., 2020). For all experiments, 8% of the verses are extracted to be used as validation data. The number of verses per language is in the range 7k-8k. The test dataset is of another domain, and it is discussed in A.1.2. The sizes of the train and validation datasets for different languages are shown in Table 3.

Language	Train	Validation
Croatian	7290	634
Icelandic	7167	624
Maltese	7122	620
Polish	7293	635
Ukrainian	6799	592

Table 3: Number of parallel Bible verses used in training and validation across different languages.

A.1.2 Pseudo-Parallel Data

We use the Tilde MODEL corpus (Rozis and Skadiņš, 2017) for the majority of our experiments, as it is listed as an available resource for many of WMT tasks during the last few years (Barrault et al., 2020; Akhbardeh et al., 2021; Kocmi et al., 2022, 2023). In all experiments, we retain 1500 sentence pairs for testing. This is the only portion for which we keep the target side, as we only manipulate the source side from the rest of them. In case there are more than 200K available pairs, we use seed = 42 to randomly choose 200K pairs from the dataset.

Government Domain

Croatian: We use EESC from the Tilde MODEL, that comprises document texts from the “European Economic and Social Committee” document portal. The full 200K sentence pairs are used for training and pretraining.

Icelandic: We use the concatenation of the following three datasets: “Government Offices in

Iceland - Reports”, “Government Offices in Iceland – Legislation and regulations”, and “Bilingual English-Icelandic parallel corpus from the official Nordic cooperation website” from the European Language Resource Coordination.⁶ This makes for a dataset of size 87233 that is used for both training and pretraining.

Maltese: As was the case with Croatian, we use the English-Maltese subsection of EESC, and we choose 200K sentence pairs from all available pairs.

Polish: We utilize RAPID from the Tilde MODEL, composed of the press releases of “Press Release Database of European Commission” released between 1975 and the end of 2016. 200K sentence pairs are extracted.

Ukrainian: We use “EU acts in Ukrainian” from the European Language Resource Coordination, resulting in 116,568 sentence pairs.

Medical Domain

For the four languages investigated (Croatian, Icelandic, Maltese, Polish), we use EMA from the Tilde MODEL. It is compiled from texts available via the European Medicines Agency document portal. All of these languages had more than 200K sentence pairs, from which 200K were extracted.

A.2 Dictionaries

The method with which the dictionaries are composed is described in 3. Since many of the lemmas might have several inflected forms that appear in the text, the dictionary sizes are larger than 5000, usually varying between 8k-10k. Here are the exact size of the dictionaries. In Table 4, the column ‘Bible’ denotes the number of terms extracted from the Bible and added to the *in-domain* terms that were drawn out from the monolingual source-side corpus. Note that if the term already exists in the in-domain dictionary, we do not replace it with the one from the Bible. The columns ‘Government’ and ‘Medical’ indicate the final size of the dictionary of their respective domains, including the new terms from the Bible.

B Training

The details of training are as follows. Each setting was trained once, and the experiments were done on NVIDIA A100 GPUs.

⁶https://language-data-space.ec.europa.eu/related-initiatives/elrc_en

	Bible	Government	Medical
Croatian	182	9948	8142
Icelandic	359	10004	8383
Maltese	319	10004	8309
Polish	417	10192	8337
Ukrainian	283	9437	-

Table 4: Sizes of different dictionaries used for different languages and domains.

Note that some of the experiments rely on others; for example, *Combined* has three stages of updating the model: 1) continual pretraining on the domain-specific texts, 2) training the model from step 1 on the Bible dataset (CPT), 3) training the model from step 2 on the pseudo parallel data + Bible (which is the DALI part). Some notable libraries we use include:

- fairseq v0.12.2 (which we modified to run our methods)
- torch v1.13.1
- sentencepiece v0.1.99
- transformers v4.30.2.

B.1 Training Hyperparameters

We implemented LeCA and CPT on fairseq for mBART, and had to change parts of the main library for compatibility. Since mBART needs a language id, we added new tokens for these new languages. We initialized their embeddings randomly (following the method for parameter initialization in Liu et al. (2020)). The fairseq hyperparameters used in pretraining and training are listed in Table 5.

B.2 Batches for experiments with DALI

In experiments containing DALI - DALI, *Combined* (and CPT + DALI which is done for medical domain experiments, as presented in Table 8) - batches are constructed in a particular way.

In each batch, we have the same number of instances from out-of-domain parallel data and in-domain pseudo-parallel data. Training batches do not contain overlapping in-domain pseudo-parallel data, but we do use the same out-of-domain parallel data in every batch, because we are limited to Bible verses for parallel data.

C Additional Outputs and Evaluation

Table 6 shows the model outputs for an example sentence from the Polish test set in the government

domain. We can see the same patterns of religious phrasing in mBART, LeCA and CPT. Some words have different translations than those used in the target translation; e.g. the model translates *banking* as “bankowość” while “bankowej” is used in the reference. Polish is also a morphologically rich language and it sometimes does not match English’s word order. Here, for example, *banking union* should be translated as “unii bankowej” while in DALI and *Combined* the phrase is translated as “bankowość unia”, in the same order as in the English sentence.

Human evaluation We conduct a small-scale human evaluation on a set of 25 randomly-selected sentences from the test set of Polish government data. A Polish native speaker annotator scored the translations for both communication of the **intended meaning** and the correctness of the overall **grammatical structure**, using a scale from 0 to 5. Only the translations of the original mBART (baseline) and DALI are compared. The average scores for **meaning** for baseline and DALI were 0.12 and 0.2, respectively. For the **grammar**, both models were given an average score close to 0. (Perhaps not surprising for a language with the morphological richness of Polish.) Of course, more in-depth study of the results is needed to draw any strong conclusions about usability.

Output statistics The average number of words, number of tokens, and number of characters of the outputs of different methods against the reference translations are presented in Table 7. For number of words, an output is split by white-spaces. For tokens, the mBART tokenizer is used. We average the results across languages. We report the averages because relative length patterns tend to be consistent across languages. The full table containing language specific statistic is available on the GitHub repository: https://github.com/alimrsn79/da_lr_nmt.

Hyperparameter	Pretraining	Training
arch		mbart_large
lr-scheduler		polynomial_decay
lr		3e-5
optimizer		adam
adam-eps		1e-06
adam-betas		(0.9, 0.98)
dropout		0.3
attention-dropout		0.1
bpe		sentencepiece
max-tokens		1024
save-interval		5
criterion		label_smoothed_cross_entropy
no-epoch-checkpoints		True
layernorm-embedding		True
encoder-normalize-before		True
decoder-normalize-before		True
share-decoder-input-output-embed		True
encoder-learned-pos		True
required-batch-size-multiple		1
label-smoothing		0.2
update-freq		2
seed		42
warmup-updates	2000	1000
min-epoch	20	75
min-epoch	60	150
patience	10	50
total-num-update	(number of steps in one epoch) * max-epoch	
task	denoising	translation_from_pretrained_bart
mask	0.35	-
tokens-per-sample	384	-
poisson-lambda	3.5	-
mask-length	span-poisson	-
replace-length	1	-
rotate	0	-
permute-sentences	0	-

Table 5: Pretraining and training hyperparameters

Source: in the banking union , those funds are pooled together gradually .

mBART:	przełoż zgrupował się wszystkie , które są w łodzi .	LeCA:	przełoż zgrupował one członki w lichwiarze .
DALI:	w the bankowość unia , te fundusze czy poszczepiony razem stopniowo .	CPT:	w banking union współ to zgromadziło , i nader to zgromadziło .
Combined:	w the bankowość unia , te fundusze czy pooled razem stopniowo .	Target:	fundusze te będą gromadzone stopniowo w ramach unii bankowej .

Table 6: An example of different model outputs for a Polish sentence in the government domain.

	Domain	Average		
		Words	Tokens	Characters
Reference	Gov.	23.51	44.65	154.55
	Med.	19.65	39.43	120.42
mBART	Gov.	25.12	49.25	132.7
	Med.	20.91	44.27	110.94
DALI	Gov.	26.83	43.99	155.28
	Med.	20.3	37.38	115.7
LeCA	Gov.	24.82	49.15	133.92
	Med.	22.94	46.02	117.94
CPT	Gov.	26.44	47.85	139.7
	Med.	20.5	38.23	109.46
Combined	Gov.	26.93	43.97	155.95
	Med.	20.31	37.41	116.09

Table 7: The average number of words, tokens, and characters of the outputs of different methods against the reference translation. The results are averaged over all the experiments.

	Metric	Croatian	Icelandic	Maltese	Polish	Average
DALI	BLEU	<u>12.74</u>	<u>13.89</u>	16.68	10.57	<u>13.47</u>
	ChrF	43.32	41.07	48.77	36.73	42.27
Combined	BLEU	12.21	13.4	16.75	10.67	13.26
	ChrF	42.11	40.56	48.88	36.11	41.92
CPT + DALI	BLEU	12.59	13.28	<u>17.03</u>	<u>10.88</u>	13.45
	ChrF	42.6	38.67	49.1	36.36	41.68

Table 8: Comparing CPT + DALI with DALI and *Combined* on the medical domain.

	Metric	Icelandic	
		Gov.	Med.
DALI	BLEU	5.76	13.89
	ChrF	36.02	41.07
Combined	BLEU	5.63	13.4
	ChrF	36.33	40.56
Full	BLEU	34.46	55.98
	ChrF	59.1	74.05

Table 9: Comparing the model trained on the full parallel dataset with DALI and *Combined* that only had access to the source side, for Icelandic. The full models were trained with the same hyperparameters as the training column in Table 5, but the training was done on the full in-domain parallel text instead of the Bible and pseudo-parallel sentences.