Facebook AI’s WMT20 News Translation Task Submission

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Abstract

This paper describes Facebook AI’s submission to WMT20 shared news translation task. We focus on the low resource setting and participate in two language pairs, Tamil ↔ English and Inuktitut ↔ English, where there are limited out-of-domain bitext and monolingual data. We approach the low resource problem using two main strategies, leveraging all available data and adapting the system to the target news domain. We explore techniques that leverage bitext and monolingual data from all languages, such as self-supervised model pre-training, multilingual models, data augmentation, and reranking. To better adapt the translation system to the test domain, we explore dataset tagging and fine-tuning on in-domain data. We observe that different techniques provide varied improvements based on the available data of the language pair. Based on the finding, we integrate these techniques into one training pipeline. For En → Ta, we explore an unconstrained setup with additional Tamil bitext and monolingual data and show that further improvement can be obtained. On the test set, our best submitted systems achieve 21.5 and 13.7 BLEU for Ta → En and En → Ta respectively, and 27.9 and 13.0 for Iu → En and En → Iu respectively.

1 Introduction

We participate in the WMT20 news translation task in two low resource language pairs (four directions), Tamil ↔ English (Ta → En and En → Ta) and Inuktitut ↔ English (Iu → En and En → Iu). These language pairs are challenging due to the lack of in-domain bitext training data and limited monolingual data. For Tamil, the available bitext corpora are from various sources; however, none of the sources is in the news domain, and each corpus is in limited size or noisy. Inuktitut encompasses the challenges present for Tamil, but is even more challenging because the quantity of available monolingual data is even less than the bitext data.

We explore techniques that leverage available data from all languages. First, we investigate supervised learning together with pre-training using mBART (Liu et al., 2020). Second, inspired by the recent success of improving low resource languages through multilingual models (Arivazhagan et al., 2019; Tang et al., 2020), we explore the utility of multilingual models, in the form of multilingual pretraining and subsequent fine-tuning. Third, we leverage the monolingual data of the source and target languages using data augmentation techniques, such as back-translation (Sennrich et al., 2015) and self-training (Ueffing, 2006; Zhang and Zong, 2016; He et al., 2019). Following Chen et al. (2019), we apply these techniques iteratively. Fourth, we use noisy-channel model reranking (Yee et al., 2019) to further boost performance. The reranking uses language modeling to select a more fluent hypothesis, which requires monolingual data in the target language.

Additionally, we investigate how adding substantially more unconstrained data can further improve the performance of En → Ta system. We incorporate data from bitext mining efforts such as CCMA-TRIX (Schwenk et al., 2019) and CCALIGNED (El-Kishky et al., 2019), as well as additional monolingual data from CCNET (Wenzek et al., 2019) curated from CommonCrawl. The additional data is used for iterative back-translation and to train stronger language models for noisy-channel reranking.

In a complementary direction, we investigate ways to adapt the translation system to the target domain. We explore controlled generation by adding dataset tags to indicate domain. Furthermore, we fine-tune our system on the in-domain data.

For all language directions, we obtain our final systems by fusing a combination of the tech-
niques mentioned above. We observe that the bulk of the improvements in our systems are from iterative back-translation and self-training, except the En $\rightarrow$ Iu system where we only have exceptionally limited quantities of Inuktitut monolingual data. Noisy-channel reranking provides further improvement on top of strong systems, especially for to-English directions where we have high-quality news-domain monolingual data to train a good language model. Each of the other techniques, including dataset tagging, fine-tuning on in-domain data, and ensembling also provides nice improvements.

2 Data

For the constrained track, we use monolingual data from all languages provided in WMT20 for mBART pre-training (Liu et al., 2020), and we use bitext data between English and other languages for training the system from scratch or fine-tuning the pretrained mBART models. We also require English, Tamil, and Inuktitut monolingual data for techniques such as back-translation, self-training, and creating language models for noisy-channel reranking. For low resource languages, Tamil and Inuktitut, we use all the available monolingual data, e.g. NewsCrawl + CommonCrawl + Wikipedia dumps for Tamil, and CommonCrawl for Inuktitut. For English, we only use NewsCrawl as the monolingual data because it is sufficiently large, high-quality, and in the news domain.

For the unconstrained track, we use Tamil monolingual data and Tamil-English mined bitext data from external sources based on CommonCrawl. The details are described in Section 2.2.

2.1 Data filtering

2.1.1 Bitext data

For each data source for each language pair, we remove duplicate sentence pairs and use fastText (Joulin et al., 2016a,b) language identification to remove sentence pairs where either the source or the target sentence is not predicted as the expected language. The resulting size of the bitext data of each language pair is shown in Appendix Table A.1.

2.1.2 Monolingual Data

We use monolingual data after fastText language identification filtering from all languages provided in WMT20 to train our mBART model. CommonCrawl contains a large quantity of data, but is also quite noisy as it is crawled from the web. Furthermore, the sentences are not in the news domain. To clean the data and select the sentences closer to the news domain, we apply the in-domain filtering method described in (Moore and Lewis, 2010) for languages that have NewsCrawl monolingual data. First, we train two n-gram language models (Heafield, 2011) on NewsCrawl and CommonCrawl respectively. Then, for each sentence from CommonCrawl, we obtain scores from these two language models, compute the difference between normalized log-probability, and we remove the lowest-scoring sentences. We heuristically examine the data and remove the bottom 30%-60% of sentences. Concretely, the scoring function is $H_{NC}(s) - H_{CC}(s)$, where $s$ is the sentence, $H_{NC}(s)$ and $H_{CC}(s)$ are the word-normalized cross entropy scores for sentence $s$ by n-gram language model trained on NewsCrawl and CommonCrawl data respectively.

We concatenate sentences from different sources and remove duplicate sentences for each language. We show the detailed dataset statistics in Appendix Table A.2.

2.2 Unconstrained setup for Tamil

In the unconstrained track, additional data can be used. We incorporate two additional sources of data: noisy bitext from data mining and monolingual data.

2.2.1 Mined bitext data

We use mined bitext data from cCMATRIX (Schwenk et al., 2019) and cCALIGNED (El-Kishky et al., 2019), two complementary mining strategies. Both approaches use the web data from unconstrained CommonCrawl to identify noisy bilingual matched pairs. cCMATRIX embeds monolingual sentences using LASER (Schwenk and Douze, 2017) multilingual sentence embeddings. To identify matching bitext pairs, the distance from each sentence to each other sentence is calculated based on the distance in the embedding space. For cCALIGNED, documents that could correspond to bitext pairs are aligned first at the document level, then at the paragraph level, and finally at the sentence level. In total, we include 2M aligned English-Tamil mined sentences.
2.2.2 Monolingual data
We used additional Tamil monolingual data from CommonCrawl snapshots between 2017-26 to 2020-10 extracted by ccNET (Wenzek et al., 2019). We break down the document-level structure from ccNET into sentences and apply further processing. We concatenate all the snapshots of the additional monolingual data, deduplicate the sentences, apply fastText language identification and remove sentences are not predicted as Tamil. The final data results in 125M sentences. Subsequently, we concatenate the unconstrained monolingual data with constrained monolingual data, and we use them for back-translation and training Tamil language model.

3 System overview
We use the Transformer (Vaswani et al., 2017) as our model architecture for all of our systems. To better train models with datasets in different sizes, we use random search to select the hyper-parameters that achieve the best BLEU score on the validation set. We use sentencepiece (Kudo and Richardson, 2018) to learn the subword units to tokenize the sentences. The details of selected hyper-parameters are listed in Appendix D. All our systems are trained with fairseq¹ (Ott et al., 2019).

3.1 Dataset tag
Training and decoding the model with an indication of domain (such as a specified dataset tag) (Kobus et al., 2016) is a technique that allows us to control the output domain of the trained system. Similarly, Caswell et al. (2019); Chen et al. (2019) show that adding specific tag to back-translated and self-translated data can improve model performance. We add dataset tags to all of our systems described in this paper, by pre-pending a domain specific tag to the source sentence during training. At test time, we sweep over all the possible tags that are used during training including “no tag”, and we choose the tag that achieves the best BLEU score on validation set. We find that when training with dataset tag, the supervised systems are 0.9 and 0.5 BLEU score higher than the system trained without dataset tag for Ta → En and En → Ta respectively. See results in Table 1.

3.2 Baseline systems
We investigate a variety of baseline approaches as the starting point for our models. For both Tamil and Inuktitut languages, we explore four different baseline systems, (1) bilingual supervised, (2) multilingual supervised, mBART pretraining with (3) bilingual and (4) multilingual fine-tuning. These systems are trained with constrained bitext and monolingual data. We will then improve these baseline models, as described in subsequent sections.

3.2.1 Bilingual supervised
To train the base bilingual systems, we pre-pend the dataset tag to the source sentence to differentiate data from different corpus and concatenate all data sources for that language.

3.2.2 Multilingual supervised
Arivazhagan et al. (2019) shows that multilingual model can improve the model performance of medium and low resource languages, as multilingual models are often trained on greater quantities of data compared to bitext models. Thus, we investigate if multilingual supervised models can be stronger starting points. We use all the bitext data between English and other languages provided in WMT20 to train many-to-one (XX → English) and one-to-many (English → XX) models. One challenge of multilingual training is different language directions have different quantities of data, and the high resource language can starve for capacity while low resource language can benefit from the transfer. To balance the trade-off between learning and transfer, we follow Arivazhagan et al. (2019) with a temperature-based strategy to sample sentences from different languages. Furthermore, for each direction, we optimize the transfer by selecting the best temperature and model checkpoint based on the BLEU score of the target language pair validation set.

3.2.3 mBART-pretraining with bilingual and multilingual fine-tuning
For mid and low resource languages, the quantity of available bitext may be low, but large resources of monolingual data exist. This monolingual data can be used in the form of pre-training, followed by subsequent fine-tuning into translation models. We use mBART (Liu et al., 2020) – a multilingual denoising pre-training approach – to pre-train our systems, which has shown substantial improvements com-

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¹https://github.com/pytorch/fairseq
pared to training the model from scratch. First, we
pre-train mBART across 13 languages (Cs, De, En,
Fr, Hi, Ja, Km, Pl, Ps, Ru, Ta, Zh) on all mono-
lingual data provided by WMT 20. For pretraining,
we used a batch size of 2048 sequences per batch
and trained the model for 240K steps. We learn
the SPM jointly on all languages. We sample the
same amount of sentences from monolingual data
of all languages to learn a vocabulary of 130,000
subwords. In the fine-tuning stage, we use exactly
the same data sources as the bilingual supervised
model and multilingual supervised model. For mul-
tilingual fine-tuning, previously people have built
bitext translation systems by fine-tuning pretrained
mBART models. Recent work Tang et al. (2020)
extended this to multilingual fine-tuning, which can
create multilingual translation models from multi-
lingual pre-trained models. Different from Tang
et al. (2020), we tune the temperature rate sepa-
rately for the four language directions we focus on.
In the multilingual fine-tuning stage, we use ran-
dom search to sweep over dropout, learning rate,
and temperature sampling factor, and we select the
model checkpoint based on the BLEU score evalu-
ated on the target language pair validation set.

3.3 Iterative back-translation (BT)

Back-translation (Sennrich et al., 2015) is an ef-
effective data augmentation technique to improve
model performance with target side monolingual
data. The method starts from training a target to
source translation system, which is subsequently
used to translate the monolingual data in the tar-
get language back to source language. Then the
synthetic back-translated dataset is concatenated
with the raw bitext data to train the source to tar-
get translation model. After the source to target
model is improved, the same technique can be ap-
plicated again to train the back-translation system in
the reversed direction. We repeat the process for
several iterations until no significant improvement
is obtained.

In all of our back-translation systems, we follow
Chen et al. (2019) to add dataset tags to both raw
bitext data and back-translated data. We upsample
the bitext data, and the upsampling ratio is selected
based on parameter sweeping and validating the
resulting improvement on the validation set. Beam
search with beam size 5 is used when generating
the synthetic sentences.

3.4 Noisy-channel reranking (NCD)

Reranking is a technique that uses a separate model
to score and better select hypotheses from the n-
best list generated by the the source to target model.
To rerank our system output, we use the noisy-
channel model (Yee et al., 2019) as the scoring
model (Ng et al., 2019; Chen et al., 2019). Given
a source and target sentence pair (x, y), the noisy-
channel model scores it with

\[
\log P(y|x) + \lambda_1 \log P(x|y) + \lambda_2 \log P(y)
\]

(1)

where \( \log P(y|x) \), \( \log P(x|y) \) and \( \log P(y) \) are
the forward model, backward model and language
model scores. The weights, \( \lambda_1 \) and \( \lambda_2 \), are tuned
through random search on the validation set. All
of our submitted test set hypotheses are ranked and
selected by noisy-channel reranking.

The language models used in noisy-channel
reranking are Transformers. For constrained track,
we use the monolingual data as described in Sec-
tion 2 to train the language models for English, Tamil.
For Inuktitut, we find that the monolin-
gual data is very limited and even smaller than
the size of bitext data, therefore we concatenate
the CommonCrawl data with the Inuktitut side of
the bitext data together to train the Inuktitut lan-
guage model. For unconstrained Tamil language
model, we train on the constrained data with the
additional unconstrained data extracted by ccNET
as described in Section 2.2. The SPM size, model
hyper-parameters, and evaluation of the language
models can be found in Appendix B.

3.5 Self-training (ST)

Self-training (Ueffing, 2006; Zhang and Zong,
2016; He et al., 2019) is a method that leverage
monolingual data in source language to improve
the system performance. We use the trained source
to target translation system to translate monolin-
gual data in source language to target language.
Similar to BT, the synthetic dataset can be concate-
nated with bitext data to train the source to target
model again. We follow Chen et al. (2019) and use
the noisy-channel model to select the top synthetic
sentence when decoding from monolingual data
into the source language. We inject the same types
of noise to the source side of synthetic data as He
et al. (2019).

Shen et al. (2019); Chen et al. (2019) both show
that self-training can provide complementary im-
provement in addition to back-translation, espe-
Table 1: Systems trained with and w/o dataset tags. The BLEU score is reported on validation set. We sweep all available dataset tags when decoding on validation set and report the best performing dataset tag. The BLEU scores of each dataset tag are reported in Appendix C.

| Model       | Ta → En | En → Ta | Iu → En | En → Iu |
|-------------|---------|---------|---------|---------|
| w/o tag     | 15.6    | 8.5     | 31.4    | 16.1    |
| with tag    | 16.5    | 9.0     | 31.3    | 16.1    |

Table 4.1 Baseline

We explore four different baseline approaches as described in Section 3.2 for each language direction in the constrained setup, Inuktitut ↔ English and Tamil ↔ English. The detailed results are shown in Table 2.

First, bilingual models are trained with bilingual bitext data. Next, we focus on multilingual training. The multilingual supervised models are trained with all the available bitext data provided by WMT20. We use the same SPM as described in Section 3.2.3. For both bilingual and multilingual models, we initialize the model weights either randomly or with pre-trained mBART model weights. Therefore, for each language direction, we have four combinations, bilingual supervised, multilingual supervised, mBART + bilingual fine-tuning and mBART + multilingual fine-tuning. We use dataset tags for all systems, and we sweep the tag that performs the best when decoding on the validation set. Additional details and hyper-parameters are provided in the Appendix D.

For to-English directions, both multilingual models and mBART pretraining can get better model performance than bilingual supervised model as shown in Table 2. For Ta → En direction, mBART + multilingual fine-tuning performs the best with 20.4 BLEU, which outperforms bilingual supervised system by 3.2 BLEU score. For the Iu → En direction, mBART + bilingual fine-tuning works the best and gets 32.9 BLEU score, which outperforms bilingual supervised baseline by 2.8 BLEU score. However, for from-English directions, we do not observe similar advantages with either multilingual model or mBART pretraining, and a properly tuned bilingual supervised model achieves the best results for both directions. We get 8.0 BLEU score for En → Ta direction, and we get 16.1 BLEU score for En → Iu direction.
ate back-translation data from English NewsCrawl data. We then train our first iteration back-translation system (“iter1-BT”) with upsampled bitext (upsampling ratio tuned on the validation set). Similarly, we train our second iteration back-translation system (“iter2-BT”) with upsampled bitext and back-translation data generated by En → Ta iter1-BT system (ensemble). The iter2-BT system (ensemble) is then used to generate ST data from Tamil NewsCrawl, CommonCrawl and Wiki data. We combine it with iter2-BT system’s data to train the iter2-BT+ST system. Finally, we fine-tune this system on the validation set and apply noisy-channel reranking to select the hypotheses. We explore Transformer models of different capacities and choose Transformer big (with 8K feed-forward dimension) for a good balance of performance and training speed. For the iter2-BT+ST system (and its ensemble/finetuned version), we further enlarge the encoder to 10 layers given higher data abundance.

We can see from Table 3 that our training pipeline improves model performance steadily (≥ 1.3 validation BLEU) after iterations, and in-domain fine-tuning as well as noisy-channel reranking are very helpful to alleviate the effects of train-test domain mismatch.

### 4.2.2 Constrained En → Ta system

For the En → Ta system, we first use the mBART+multi-FT baseline system for Ta → En to generate back-translation data from the monolingual data. We add different back-translation dataset tags based on the source of monolingual data and train our first iteration back-translation system (“iter1-BT”) by tuning upsampling ratios on the bitext and back-translation datasets. For the model architecture, we explore the options of training Transformers from scratch and fine-tuning a pretrained mBART model and find that the former performs better with ensembles. Doing one iteration of training with back-translation data gives 5.8 BLEU increase (Table 3). We further train the second iteration back-translation system (“iter2-BT”) with back-translation data generated from the best iter1-BT Ta → En system. As the gain from the second iteration is small (0.4 BLEU), we do not continue for the third iteration. Noisy-channel reranking is applied with the best systems from both language directions and the Tamil language model (Appendix B). We observe little gain (0.1 BLEU) and suspect it’s due to the high perplexity of the language model. Further fine-tuning the iter2-BT model on the validation set gives 4.1 BLEU score improvement on the validation holdout set.

| System | Ta → En | En → Ta |
|--------|---------|---------|
| baseline | 20.4 | 8.0 |
| + ensemble | 21.2 | 9.0 |
| iter1-BT | 23.4 | 13.8 |
| + ensemble | 24.8 | 14.1 |
| iter2-BT | 25.6 | 14.2 |
| + ensemble | 26.4 | 14.3 |
| + NCD | 28.5 | 14.4 |

Table 3: Results of Tamil systems. We report the BLEU scores on newsdev2020 validation set.

### 4.2.3 Unconstrained En → Ta system

For the unconstrained track, we first used the iteration1 + back-translation ensemble model to back-translate the additional monolingual data from CommonCrawl. Subsequently, we combined

| System | Ta → En | En → Ta |
|--------|---------|---------|
| NH | News | Combined |
| baseline | 42.4 | 19.2 | 32.9 |
| + ensemble | 42.4 | 19.4 | 32.9 |
| iter1-BT | 43.3 | 24.1 | 35.1 |
| + ensemble | 43.8 | 24.6 | 35.7 |

Table 4: Results of Iu → En systems. We report BLEU scores on both domain-split and the whole newsdev2020 validation set.

For the unconstrained track, we first used the iteration1 + back-translation ensemble model to back-translate the additional monolingual data from CommonCrawl. Subsequently, we combined
4.3 Inuktitut systems

The Inuktitut validation and test set are composed of data from two different domains, the proceeding of the Legislative Assembly of Nunavut from Nunavut Hansard (NH) and news. We find that the model can be further improved if we optimize our translation training pipeline for these two domains separately, and therefore we train and report BLEU score separately for each domain. The final domain-specific systems are ensembled from the fine-tuned models and followed by noisy-channel reranking. To use noisy-channel reranking for Nunavut Hansard domain, we fine-tune the English language model described in 3.4 on English side of the Nunavut Hansard 3.0 parallel corpus with noisy-channel reranking; however, we do not observe any improvement. The best result at the first iteration is from the back-translation system, which outperforms baseline system by 2.2 BLEU score (Table 4), where most of the gain comes from improvement on news domain.

We do not observe gains for doing the second iteration of back-translation for Iu → En system, and we suspect that it is due to lack of improvement for our En → Iu model from supervised approach to the first iteration. We then fine-tune the best iteration 1 Iu → En models on validation data for each domain. The final domain-specific systems are ensembled from the fine-tuned models and followed by noisy-channel reranking. To use noisy-channel reranking for Nunavut Hansard domain, we fine-tune the English language model described in 3.4 on English side of the Nunavut Hansard 3.0 training data provided in WMT20. The best Iu → En system we submit has 40.2 BLEU score on our validation holdout set.

4.3.2 Constrained En → Iu systems

We experiment with both self-training and back-translation with the best baseline systems reported in 4.1 to improve En → Iu system. For self-training,
we use ensembled supervised En → Iu model and beam decoding with beam size 5 to decode from English monolingual data. We decode from the English side of Nunavut Hansard 3.0 parallel corpus to train the model for Nunavut Hansard domain, and we decode from the English NewsCrawl data for news domain. However, we do not observe improvement for news domain, and there is only mild improvement (0.3 BLEU) for Nunavut Hansard domain as shown in Table 5. For back-translation, we use iteration 1 Iu → En news domain model from 4.3.1 to decode constrained Inuktitut CommonCrawl data. We get no improvement on Nunavut Hansard domain and mild improvement (0.2 BLEU) on news domain. We use self-training system for Nunavut Hansard domain and back-translation system for news domain, and it achieves 16.3 BLEU score on the validation set, which is merely 0.2 BLEU score improvement over baseline system. We then fine-tune the best systems we get on domain-specific validation set splits, followed by ensembling and noisy-channel reranking. The fine-tuning is very effective for the news domain, where we get 9.1 BLEU score improvement. This is expected because we do not have any training data from news domain. Our final submitted system achieves 22.0 on our validation holdout set.

| Submitted system | BLEU   |
|------------------|--------|
| Ta → En          | 21.5   |
| En → Ta          | 12.6   |
| En → Ta (unconst.) | 13.7   |
| Iu → En          | 27.9   |
| En → Iu          | 13.0   |

Table 6: Results of our best submitted systems of each direction. We report BLEU scores on newstest2020.

5 Conclusion

This paper describes Facebook AI’s Transformer based translation systems for the WMT20 news translation shared task. We focused on two low-resource languages pairs, Tamil ↔ English and Inuktitut ↔ English, and we explored the same set of techniques, including dataset tagging, mBART pretraining and fine-tuning, back-translation and self-training, fine-tuning on domain-specific data, ensembling, and noisy-channel reranking. We demonstrated strong improvements by stacking these techniques properly on three language directions, Ta → En , En → Ta , and Iu → En . The En → Iu direction is difficult to improve due to lack of target side monolingual data. Surprisingly, self-training does not work on En → Iu either even we have huge amounts of in-domain English side monolingual data. We are interested in continued exploration on how to better leverage source side monolingual data to improve En → Iu and other low resource languages where we do not have enough target side monolingual data.

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A Constrained data

In this section, we list the statistics for all the constrained datasets we use to build for our systems.

Bitext data Table A.1 shows the bitext data we used for multilingual systems. We use all bitext data between English and other 11 languages provided in WMT 20 except a couple of sources. We do not include the data back-translated by other system to avoid introducing bias. We do not include CzEng 2.0 for Czech nor CCMT for Chinese due to human mistake. We follow the filtering steps described in Section 2.1.1, and the size of dataset for each language pairs are listed in Table A.1.

Monolingual data Table A.2 shows the list of monolingual data we use for mBART-pretraining with 13 languages. We follow Section 2.1.2 to filter the monolingual data, and we list the amount of data before and after the filtering step.

B Language model used in noisy-channel reranking

Language model is required in the noisy-channel reranking system. We learn the BPE subwords with sentencepiece, and we train the Transformer based causal language models with fairseq in fp16 mode. The model size and hyper-parameters are tuned based on the perplexity of newsdev2020 validation sets per language. We describe the data and hyper-parameters of each language below, and we report the perplexities in Table B.1.

English language model We train our English language model with the high quality NewsCrawl data provided by WMT 20. We use the same filtering steps in Section 2.1.2 for NewsCrawl. We learn the BPE with 32K vocabulary size. We train the transformer-based model with 36 transformer layers, 1280 embedding dimension size, 5120 ffn dimension size, 20 attention heads and resulting in 749M parameters. The optimizer is Adam (Kingma and Ba, 2015) optimizer with beta1 = 0.9 and beta2 = 0.98. We use polynomial decay learning rate scheduler with 0.005 learning rate and 0.1 dropout rate. The maximum tokens are 4096 for each batch per GPU, and we train with 64 GPUs for 58K updates. As we show in Table B.1, this model achieves 23.3 perplexity on English side of Ta-En newsdev2020 set, 25.3 perplexity on news portion of Iu-En newsdev2020 set, and 29.7 perplexity on Nunavut Hansard portion of Iu-En newsdev2020 set. The perplexity on news validation sets are lower than none-news validation set. We use the English language model to rerank Ta → En system and news domain of Iu → En system.

To better rerank Iu → En hypotheses for Nunavut Hansard domain, we fine-tune the English language model on English side of Nunavut Hansard 3.0 parallel corpus. The perplexity on Nunavut Hansard portion of Iu-En newsdev2020 set is significantly improved from 29.7 to 8.1. We use the fine-tuned English language model to rerank the Nunavut Hansard domain of Iu → En system.

Tamil language model We train the Tamil language model for constrained En → Ta system with all the available Tamil monolingual data preprocessed in Section 2.1.2. The BPE vocabulary size is 32K. We train the transformer-based language model with 24 transformer layers, 1024 embedding size, 4096 ffn embedding size, 16 attention heads and resulting in 335M parameters. We use Adam optimizer with beta1 = 0.9 and beta2 = 0.98. We use polynomial decay learning rate scheduler with 0.005 learning rate and 0.1 dropout rate. The maximum tokens are 8192 for each batch per GPU, and we train with 16 GPUs for 46K updates. The model achieves 61.8 perplexity on Tamil side of Ta-En newsdev2020 set.

For unconstrained En → Ta system, we use both constrained Tamil monolingual data and the additional Tamil monolingual data described in Section 2.2. We share the same 32K BPE vocabulary as constrained Tamil language model. We use a larger transformer model with 32 transformer layers, 1024 embedding size, 4096 ffn embedding size, 8 attention heads. We use Adam optimizer with beta1 = 0.9 and beta2 = 0.98. We use cosine learning rate scheduler with 0.0001 learning rate and 0.3 dropout rate. The maximum tokens are 3072 for each batch per GPU, and we train with 32 GPUs for 69K updates. The model achieves 40.6 perplexity on Tamil side of Ta-En newsdev2020 set, which is better than the constrained Tamil language model.

Inuktitut language model The Inuktitut language model is trained with Inuktitut side of Nunavut Hansard 3.0 parallel corpus and the constrained Inuktitut monolingual data provided by WMT 20. The BPE vocabulary size is 5K. We train the transformer-based language model with
6 transformer layers, 512 embedding size, 4096 ffn embedding size, 8 attention heads and resulting in 34M parameters. We use Adam optimizer with $\text{beta}_1 = 0.9$ and $\text{beta}_2 = 0.98$. We use inverse square root learning rate scheduler with 0.0005 learning rate and 0.3 dropout rate. The maximum tokens 2048 for each batch per GPU, and we train with 8 GPUs for 89K updates. The model achieves 34.9 perplexity on Nunavut Hansard domain of Iu-En newsdev2020 set, and 81.69 perplexity on news portion of Iu-En newsdev2020 set.

C The effect of dataset tag at decoding time

We train our systems with dataset tag, and we sweep the dataset tags by add different tags to the same validation set and select the best performing tag. Table C.1 and C.2 show the system performance across different dataset tags.

First, we observe that sweeping the best performing dataset tag at decoding time is necessary. Using “no tag” to decode works the best for both Ta $\rightarrow$ En and En $\rightarrow$ Ta systems; however, using specific dataset tags works better for Iu $\rightarrow$ En and En $\rightarrow$ Iu systems. Second, the large BLEU score variations when decoding with different dataset tags show that the tags help the model to better adapt to different domains.

Overall, systems trained with dataset tags works better than trained without dataset tag as we show in Table 1.

D Hyper-Parameters

In this section, we report the hyper-parameters we use. For all of our translation systems, we use transformer based encoder-decoder model with shared embedding across encoder, decoder input and output embedding. We use Adam optimizer with $\text{beta}_1 = 0.9$ and $\text{beta}_2 = 0.98$, inversed square root learning rate scheduler, and 4000 warm-up steps with linearly increased rate. The loss is cross-entropy with label smoothing (Szegedy et al., 2016). We use the same batch sizes with maximum number of tokens 4096, and all models are trained with fp16. We sweep other hyper-parameters with random search, and we select the best performing system based on the evaluated BLEU scores on validation sets.

mBART pretraining We train the denoising mBART model with the constrained monolingual data from 13 languages described Section 2.1.2. We learn joint BPE across all languages with vocabulary size 130K. The transformer based encoder-decoder model has 12 encoder and decoder layers, 1024 embedding dimension, 4096 ffn embedding dimension and 16 attention heads, resulting in 487M parameters. We train the model with 0.0003 learning rate, 0.1 dropout rate, and no label-smoothing. We train the model with 256 GPUs for 240K updates.

Tamil systems For Ta $\rightarrow$ En, the best performing systems are mBART+multilingual fine-tuning model for baseline system, back-translation system for iteration 1 and BT+ST system for iteration 2. We report the hyper-parameters of the best performing system at each iteration in Table D.1.

For En $\rightarrow$ Ta, the best performing systems are bilingual supervised model for baseline system, back-translation system for iteration 1 and iteration 2. We report the hyper-parameters of the best performing system at each iteration, including the unconstrained system in Table D.2.

Inuktitut systems For Iu $\rightarrow$ En, the best baseline system is the mBART pretraining with bilingual fine-tuning. In iteration 1, we tune the model separately for Nunavut Hansard domain and news domain. The best Nunavut Hansard domain model is mBART pretraining with bilingual fine-tuning on bitext and news back-translated data, and the best news domain model is the back-translation model train from scratch. For En $\rightarrow$ Iu, the best baseline system is bilingual supervised model. Similar to Iu $\rightarrow$ En system, we tune the model separately for Nunavut Hansard domain and news domain in iteration 1. The best system for Nunavut Hansard domain is self-training model train from scratch, and the best system for news domain is the back-translation model train from scratch. We report the hyper-parameters of the best performing Iu $\rightarrow$ En and En $\rightarrow$ Iu systems at each iteration in Table D.3 and D.4.
### Table A.1: En-XX bitext data used for bilingual and multilingual systems. For each language pair, we use all available sources released in WMT20 except the datasets that are listed in the table.

| Language pair | # of sentences (M) | Missing datasets |
|---------------|-------------------|------------------|
| Cs-En         | 9.3               | 8.6              |
| De-En         | 45.9              | C2Eng2.0, back-translated news |
| Hi-En         | 1.27              |                  |
| Ja-En         | 16.2              |                  |
| Km-En         | 2.46              |                  |
| Pl-En         | 10.6              |                  |
| Ps-En         | 0.58              |                  |
| Ru-En         | 32.8              |                  |
| Tu-En         | 0.62              |                  |
| Zh-En         | 15.8              |                  |

### Table A.2: Monolingual data used for mBART pretraining and back-translation. The abbreviation in the sources column represent the following, CC: CommonCrawl, EP: Europarl, NC: NewsCommentary, NCL: NewsCrawl, ND: NewsDiscussions, Wiki: Wikipedia

| Target language | Training data | # of sentences | BPE size | PPL on newsdev2020 |
|-----------------|---------------|----------------|----------|--------------------|
| English         | NewsCrawl     | 190M           | 32K      | 23.3 29.7 25.3     |
|                 | + FT on       |                |          | 77.6 8.1 27.1      |
|                 | English side of NH |          |          |                    |
| Tamil           | CommonCrawl, NewsCrawl, Wikipedia | 30M | 32K | 61.8 - - |
| unconstr. Tamil | constrained Tamil data, CommonCrawl in Sec. 2.2 | 155M | 32K | 40.6 - - |
| Inuktitut       | Inuktitut side of Nunavut Harsand 3.0, CommonCrawl | 860K | 32K | 34.9 81.7 |

### Table B.1: Statistics of language models for each language.

| Tag          | Ta → En | En → Ta |
|--------------|---------|---------|
| None         | 16.5    | 9.0     |
| mkp          | 15.4    | 8.0     |
| nlp          | 15.6    | 6.8     |
| pib          | 15.5    | 8.6     |
| pmindia      | 15.5    | 8.7     |
| tanzil       | 11.9    | 0.6     |
| ufal         | 16.1    | 8.2     |
| wikimatrix   | 4.0     | 6.4     |
| wikititles   | 15.8    | 8.5     |

Table C.1: Tamil bilingual supervised single model performance when decoding on validation set with different dataset tags. The BLEU score is evaluated newsdev2020 validation set.
### Table C.2: Inuktitut bilingual supervised single model performance when decoding on validation set with different dataset tags. The BLEU score is evaluated on newsdev2020 validation set.

| Tag                          | Iu → En | En → Iu |
|------------------------------|---------|---------|
| None                         | 29.7    | 15.8    |
| Nunavut Hansard               | 31.3    | 16.0    |
| wikititles                   | 30.1    | 16.1    |

### Table D.1: Hyper-parameters of the best performing Ta → En systems.

| System                          | Subword (size) | # params | layers | embed size | fln embed size | attention heads | learning rate | dropout | label smoothing | # GPUs |
|---------------------------------|----------------|----------|--------|------------|----------------|-----------------|---------------|---------|----------------|--------|
| Baseline system (mBART+multi-FT) | BPE (130K)     | 487M     | 12     | 1024       | 4096           | 16              | 0.0001        | 0.2     | 0.2            | 16     |
| iter1 (BT)                      | Unigram (16384)| 293M     | 6      | 1024       | 8192           | 16              | 0.0005        | 0.1     | 0.1            | 8      |
| iter2 (BT+ST)                   | Unigram (16384)| 378M     | 10     | 1024       | 8192           | 16              | 0.001         | 0.2     | 0.2            | 64     |

### Table D.2: Hyper-parameters of the best performing En → Ta systems.

| System                          | Subword (size) | # params | layers | embed size | fln embed size | attention heads | learning rate | dropout | label smoothing | # GPUs |
|---------------------------------|----------------|----------|--------|------------|----------------|-----------------|---------------|---------|----------------|--------|
| Constrained Tamil               |                |          |        |            |                |                 |               |         |                |        |
| Baseline system (bilingual supervised) | Unigram (16384) | 31M     | 3      | 512        | 2048           | 8               | 0.0005        | 0.3     | 0.1            | 8      |
| iter1 (BT)                      | BPE (20K)      | 314M     | 10     | 1024       | 4096           | 16              | 0.0007        | 0.3     | 0.3            | 8      |
| iter2 (BT)                      | BPE (20K)      | 314M     | 10     | 1024       | 4096           | 16              | 0.0007        | 0.2     | 0.3            | 8      |
| Unconstrained Tamil             |                |          |        |            |                |                 |               |         |                |        |
| iter2 (BT)                      | BPE (20K)      | 1.2B     | 10     | 2048       | 8192           | 16              | 0.0001        | 0.3     | 0.1            | 8      |

### Table D.3: Hyper-parameters of the best performing Iu → En systems.

| System                          | Subword (size) | # params | layers | embed size | fln embed size | attention heads | learning rate | dropout | label smoothing | # GPUs |
|---------------------------------|----------------|----------|--------|------------|----------------|-----------------|---------------|---------|----------------|--------|
| Baseline system (mBART+bi-FT)   | BPE (130K)     | 487M     | 12     | 1024       | 4096           | 16              | 3e-5          | 0.1     | 0.1            | 16     |
| NH-domain: iter1-BT (mBART+bi-FT) | BPE (130K)     | 487M     | 12     | 1024       | 4096           | 16              | 1e-4          | 0.2     | 0.2            | 16     |
| news-domain: iter1-BT           | BPE (5K)       | 559M     | 12     | 1024       | 8192           | 16              | 0.001         | 0.2     | 0.2            | 64     |

### Table D.4: Hyper-parameters of the best performing En → Iu systems.

| System                          | Subword (size) | # params | layers | embed size | fln embed size | attention heads | learning rate | dropout | label smoothing | # GPUs |
|---------------------------------|----------------|----------|--------|------------|----------------|-----------------|---------------|---------|----------------|--------|
| Baseline system (bilingual supervised) | BPE (5K)       | 122M     | 4      | 1024       | 4096           | 8               | 0.001         | 0.3     | 0.3            | 4      |
| NH-domain: iter1-ST             | BPE (5K)       | 152M     | 5      | 1024       | 4096           | 16              | 0.0005        | 0.2     | 0.2            | 4      |
| news-domain: iter1-BT           | BPE (5K)       | 152M     | 5      | 1024       | 4096           | 16              | 0.001         | 0.2     | 0.2            | 4      |