Recipes for Adapting Pre-trained Monolingual and Multilingual Models to Machine Translation

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Abstract

There has been recent success in pre-training on monolingual data and fine-tuning on Machine Translation (MT), but it remains unclear how to best leverage a pre-trained model for a given MT task. This paper investigates the benefits and drawbacks of freezing parameters, and adding new ones, when fine-tuning a pre-trained model on MT. We focus on 1) Fine-tuning a model trained only on English monolingual data, BART. 2) Fine-tuning a model trained on monolingual data from 25 languages, mBART. For BART we get the best performance by freezing most of the model parameters, and adding extra positional embeddings. For mBART we match the performance of naive fine-tuning for most language pairs, and outperform it for Nepali to English (0.5 BLEU) and Czech to English (0.6 BLEU), all with a lower memory cost at training time. When constraining ourselves to an out-of-domain training set for Vietnamese to English we outperform the fine-tuning baseline by 0.9 BLEU.

1 Introduction

Machine Translation (MT) has recently seen significant advances, with improvements in modeling, especially since the advent of neural models (Sutskever et al., 2014; Bahdanau et al., 2015), and the availability of large parallel corpora for training such systems (Smith et al., 2013; Kocmi and Bojar, 2017; Tiedemann, 2012). However, often standard neural systems do not perform well on *low-resource* language pairs (Koehn and Knowles, 2017), especially when the language pairs are only distantly related. Since these languages are spoken by a large fraction of the worlds population, reducing the gap in performance between high and low-resource MT could have a large impact.

An explosion of interest in large-scale pretraining in Natural Language Processing has led to

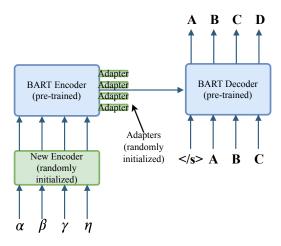


Figure 1: Schematic diagram showing the components of our system for adapting BART to MT. We learn a new encoder that takes as input the source language, with a potentially different vocabulary to the original BART system. We freeze most BART parameters (frozen model components are shown in blue).

increased performance on smaller datasets, by simple *fine-tuning* of large pre-trained models on downstream tasks. The typical approach is to train a large model as some form of denoising autoencoder on text from the web (for example English Wikipedia), with the most common approaches based on predicting masked out sections of an input sentence using the unmasked context. For Natural Language Generation (for example summarization of text), performance can be improved by pre-training a sequence-to-sequence model (Song et al., 2019; Lewis et al., 2019).

However previous work has shown that on NLP tasks such as Natural Language Inference, the relative performance of fine-tuning vs. keeping the pre-trained model frozen depends on the similarity of the pre-training and downstream tasks (Peters et al., 2019). We observe empirically that simple fine-tuning of a monolingual model for MT

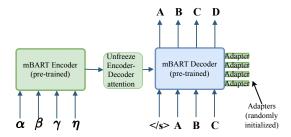


Figure 2: Schematic diagram showing one method of adapting mBART to MT, unfreezing the encoder and encoder-decoder attention, and adding adapters in the decoder. Model components colored blue are not updated during fine-tuning.

can result in worse performance than training from scratch (e.g. Table 1). For MT, our downstream task will always involve more than one language, and the more common monolingual (usually only English) pre-training (Peters et al., 2018; Radford et al., 2018; Devlin et al., 2019; Yang et al., 2019b; Liu et al., 2019) may be inadequate since when fine-tuning the input or output domain will be a non-English language.

Multi-lingual pre-training offers a solution, by modifying the pre-training objective to include many languages. Using a multi-lingual pre-trained model as an initialisation for MT has resulted in strong performance, especially on lower-resource language directions (Liu et al., 2020). However it is challenging to balance the training data so that higher-resource languages do not overwhelm lower-resource ones (Arivazhagan et al., 2019; Conneau et al., 2019). For a particular language it may be hard to source monolingual data, or it may be simply not included in training.

Even for multi-lingual pre-trained models, more challenging downstream tasks may pose problems. A task we consider is multilingual MT (training on many language pairs and sharing all or most model parameters), which can improve performance on low-resource language pairs by transfer from the other language pairs included in training. Previous work observed problems of performance degradation, often on high-resource languages, due to interference and constrained capacity (Johnson et al., 2017; Tan et al., 2019). And when initialising from a pre-trained model, we want to avoid 'catastrophic forgetting', where by fine-tuning on a particular language pair we lose the knowledge about another language pair that is stored in the model weights.

Previous work has explored how improve on sim-

ple fine-tuning, by freezing pre-trained model parameters (Peters et al., 2019; Houlsby et al., 2019) and using lightweight 'adapter modules' (Houlsby et al., 2019; Stickland and Murray, 2019) which are inserted between the layers of the pre-trained network. We aim to explore and improve on these approaches for both bilingual and multi-lingual MT (in contrast to previous work largely focusing on text classification). We explore freezing different subsections of the pre-trained model, and show that depending on the pre-trained model and target task, different freezing strategies are needed. We expect freezing to be particularly useful when the parallel data is of low quality, in which case naive fine-tuning may, for example, over-specify the pre-trained model to a particular domain.

Our main contributions are:

- Introducing a novel fine-tuning approach based on that of Lewis et al. (2019) but with adapter modules in the encoder of the pretrained sequence-to-sequence model and additional positional representations in the input module that feeds in the pre-trained encoder.
- Extensive experiments with fine-tuning a multi-lingual pre-trained model for MT showing the benefits and drawbacks of freezing various parameters. For example we find we should freeze the decoder but unfreeze the encoder-decoder attention when fine-tuning on $Xx \rightarrow En$ data, and in the other direction we should freeze the encoder but unfreeze the entire decoder.
- Results on fine-tuning a multi-lingual pretrained model for multi-lingual MT showing that freezing parameters improves performance on some, mostly distantly related, language directions.

2 Background and Related Work

BART and mBART We briefly describe the pre-trained models we focus on in this work. In order to perform machine translation with the minimum of modifications to the pre-trained model, we prefer models that can perform conditional sequence generation. We concentrate on the BART (Bidirectional and Auto-Regressive Transformer) model (Lewis et al., 2019) and the multilingual BART (mBART; Liu et al., 2020) model. BART and mBART are sequence-to-sequence models

with the standard transformer-based neural machine translation architecture, i.e. an encoder and autoregressive decoder. The pre-training task they are trained on is reconstructing a document from a noisy version of that document (so called 'denoising autoencoder'). Examples of noise added to the training data include randomly shuffling the order of the original sentences, randomly changing the start position of the document, and using a masking scheme where arbitrary length spans of text are replaced with a single mask token. BART and mBART are trained entirely on monolingual data from the web, with English data for BART and data form 25 different languages for mBART.

BART and mBART have almost identical architectures, with 12 encoder layers and 12 decoder layers with model dimension of 1024 and 16 attention heads. BART has a vocabulary of approximately 40k and \sim 428M parameters, whereas mBART has a larger vocabulary of size 250k and \sim 680M parameters.

Pre-trained Models for MT There has been much recent progress in pre-training for NLP applications (Peters et al., 2018; Radford et al., 2018; Devlin et al., 2019; Yang et al., 2019b; Liu et al., 2019), with the most relevant for our work focusing on text generation (Radford et al., 2019; Song et al., 2019; Dong et al., 2019; Raffel et al., 2019; Lewis et al., 2019) Specifically for MT, Ramachandran et al. (2017) proposed pre-training the encoder-decoder modules as two separate language models, and Yang et al. (2019a); Zhu et al. (2020) explored approaches incorporating BERT model weights into the usual seq-to-seq architecture.

Multilingual MT Multilingual translation (Firat et al., 2016; Viégas et al., 2016; Aharoni et al., 2019; Arivazhagan et al., 2019) aims to jointly train one translation model that translates multiple language directions, and shares representations to improve the translation performance on low-resource languages (Gu et al., 2018). Our freezing approach is similar in spirit to Sachan and Neubig (2018) who investigate which parameters are most useful to share for multi-lingual MT with transformer models. Our work differs in that we start from a multi-lingual pre-trained model, and decide between sharing or freezing parameters.

Transfer Learning for MT *Transfer learning* hopes to leverage a related task to perform well on a target task, for example by initialising the model

weights from those resulting from training on a related task. In the context of MT various approaches have been explored, with a common method training on one or more high-resource language and fine-tuning on a (possibly related) low-resource language (Neubig and Hu, 2018).

The most closely related work to ours is that of Bapna and Firat (2019), who introduce freezing and adapters (extra parameters inserted within the transformer) for domain adaption in MT. They take a sequence-to-sequence model trained on a large parallel corpus, and fine-tune on the same language pair in a different domain (e.g. legal text). We differ in that we start from a pre-trained model that has not been trained on parallel text, and study how our approach should change with different downstream tasks and pre-trained models.

Approaches based on freezing various model components have also been proposed in (Thompson et al., 2018; Zoph et al., 2016), but have focused on RNN based approaches where the pretrained model was trained with parallel data, unlike our transformer models pre-trained on monolingual data.

3 Methods

Because BART has been trained on only English input, we need to use different techniques when fine-tuning BART and mBART for MT, with a schematic overview shown in Figure 1 and Figure 2. BART and mBART are standard sequenceto-sequence models, where an encoder consumes a sequence of source-side tokens, and a decoder acts as a conditional language model, generating target tokens given a source sequence. Intuitively, we want the encoder and decoder to be performing roughly the same tasks during fine-tuning as they were during pre-training. For BART this means the input to the encoder should be similar to (embedding vectors of) noisy English text. Therefore when training on say, Vietnamese to English, we first transform the Vietnamese source sentence into a representation useful for BART. We introduce new parameters (the 'Input Module') that consume the source sentence and produce hidden vectors we can feed into the BART encoder. We describe the Input Module architecture in section 3.1.

mBART can be fine-tuned without modification since during pre-training it saw the languages it will be fine-tuned on. To increase flexibility when freezing parts of the network, we optionally add extra parameters to both BART and mBART described in section 3.2.

3.1 Input Adapter Architecture

We refer to the network that takes in the source language text and outputs hidden vectors useful for BART as an 'Input Module' or $\mathrm{IM}(\cdot)$. To improve performance on low-resource MT, we use smaller token embedding vectors on the source side of size $d_{\mathrm{s}}=512$, whereas BART uses hidden vectors of size $d_{\mathrm{BART}}=1024$. The full network is as follows, with $\{\mathbf{e}_t\}_{t=0}^l$ token embeddings for a source sentence with l tokens,

$$BART(IM(\{\mathbf{e}_t\}_{t=0}^l)), \tag{1}$$

where BART(·) is the full BART encoder-decoder model. Where we would normally input token embeddings to the BART model we use the outputs of the Input Module. The t-th element of $\mathrm{IM}(\{\mathbf{e}_t\}_{t=0}^l)$ as follows:

$$\alpha \text{LN}(\mathbf{W} \text{Transformer}(\{\mathbf{e}_t\}_{t=0}^l)_t)$$
 (2)

and where LN(·) is Layer-Norm, **W** is a matrix projecting up from d_s to d_{BART} , and Transformer(·) is the application of a series of Transformer layers (with learned positional embeddings). α is a scalar, in our case equal to $\sqrt{d_{BART}}$, which is required to insure the input to BART is on the same scale as the embedding vectors BART was trained on. If we remove LN(·), **W** and α , and set $d_s = d_{BART}$, we recover the method introduced by (Lewis et al., 2019) for fine-tuning BART on MT.

We found empirically that the details of positional embedding vectors are important for good performance (see Table 1), perhaps because of the need for the BART model to deal with different word order to that it was trained on. We optionally add a fixed sinusoidal positional embedding (Vaswani et al., 2017) vector \mathbf{p} , with $\mathbf{p}_i^l = \sin(l/10000^{i/(d_s/2-1)})$, if $0 \le i < d_s/2$, and $\mathbf{p}_i^l = \cos(l/10000^{(i-(d_s/2-1))/(d_s/2-1)})$ if $d_s/2 \le i < d_s$, where l indexes position and i indexes dimension.

We add these to the input of each transformer layer in $\mathrm{IM}(\cdot)$. Note that positional embedding are typically added only to the token embeddings, and not before each layer as we do, and note this means the network has access to both *learned positional embeddings* (only at the embedding layer), and *fixed sinusoidal* ones at the input to each layer.

3.2 Within-Network Adapter Architecture

When freezing parts of a pre-trained model (either BART or mBART in our case), we may want to add flexibility by modifying the pre-trained model architecture. One approach is to use 'adapters', introduced by Houlsby et al. (2019); Stickland and Murray (2019) which are newly-initialised neural network layers that can be 'slotted in' to the layers of the pre-trained model.

We only considered simple adapter architectures, essentially feed-forward networks, with one hidden layer, and a residual connection to the output. The dimension of the hidden layer can be much smaller than the model dimension to reduce computational cost and parameter count. We use one adapter per transformer layer, inserting them at the end of the layer (Stickland and Murray, 2019; Bapna and Firat, 2019). We use the following architectures, with h the hidden state of a particular token after the usual transformer layer, and h_{out} the hidden state of the token after the adapter layer:

$$\mathbf{z} = \text{gelu}(\mathbf{W}_d \mathbf{h})$$

$$\mathbf{h}_{\text{out}} = \tanh(\mathbf{W}_u \mathbf{z}) + \mathbf{h}$$
(3)

The tanh non-linearity helped with stability in early experiments, probably because it prevents the adapter output exploding by constraining it between -1 and 1.

We also considered a version of the adapter based on the 'gated linear unit' (GLU; Dauphin et al., 2016) architecture:

$$\mathbf{z} = 2\sigma(\mathbf{W}_g \mathbf{h}) \odot \text{gelu}(\mathbf{W}_d \mathbf{h})$$

$$\mathbf{h}_{\text{out}} = \tanh(\mathbf{W}_u \mathbf{z}) + \mathbf{h}.$$
(4)

We found the network was sensitive to changes in the magnitude of the hidden states the adapter produced, and therefore multiply the sigmoid gate by 2 so that it approximately leaves the magnitude of the hidden states unchanged.

3.3 Freezing Details

BART We freeze all parameters of BART except the weights and biases of the layer-norm modules (following Houlsby et al. (2019)), and additionally unfreeze the self-attention module of the first layer in the BART encoder, which is a small fraction of total BART parameters $(24 \cdot 2d_{\rm BART}$ from layer-norm parameters and $4d_{\rm BART}^2$ from the self-attention module). We freeze BART token embeddings (used in the softmax layer).

mBART In most of our experiments we unfreeze layer-norm parameters, positional and token embeddings, and either the entire encoder or decoder module (or the encoder and subsections of the decoder). We unfreeze the self-attention module of the first layer in the BART encoder and decoder.

4 Experimental Settings

We use the fairseq (Ott et al., 2019) library for all experiments. The final models are selected based on validation likelihood, except for multilingual fine-tuning where we evaluate the models after 9000 training steps. We use beam-search with beam size 5 for decoding, and evaluate all BLEU scores using the SacreBLEU (Post, 2018) software. We use ISO language codes in this work for convenience, listed in Table 10, and use the same parallel data as Liu et al. (2020), listed in Table 10.

We fine-tune frozen BART and an Input Module on a single pair of bi-text data, feeding the source language into the Input Module and decoding the target language. For mBART we feed the source language into the encoder and decode into the target language. For mBART we use the same hyper-parameters as Liu et al. (2020). When using adapters we use 0.1 dropout in the adapter bottleneck layer (z in section 3.2), and use a hidden dimension of either 128, or $\lfloor 2/3 \cdot 128 \rfloor$ when using a gated linear unit adapter. We use the Adam (Kingma and Ba, 2015) optimizer. Hyperparameters are listed in Appendix B.

4.1 Multi-lingual MT

We fine-tune mBART on a multi-lingual, many-toone $(Xx \rightarrow En)$ MT task. We train on all 25 languages present in mBART pre-training. Balancing the training schedule such that high-resource languages don't overwhelm low-resource languages and we don't overfit to the low-resource datasets is a challenging problem, but it is not the focus of this work. We chose a simple solution that performed well in practice: we used 'round-robin' training in which we cycle though all language pairs and perform one backwards pass on each one. We accumulate gradients for the entire cycle, i.e. we only update parameters once we have seen one minibatch from every language pair.

We train with a very large effective batch size, training on 32 GPUs with a per-GPU batch size of 4096 tokens, meaning our total batch size is $N \cdot 32 \cdot 4096$ tokens, where N is the number of

Languages	Vi-En
(1): BART + InputModule (unfreeze all)	9.5
(2): BART (frozen) + InputModule	27.9
(3): (2) + unfreeze layer-norm	28.4
(3) + sinusoidal positional embeddings	18.3
(1) + extra positional embeddings	22.0
(4): (3) + extra positional embeddings	29.0
(5): (3) + encoder adapters	28.9
(3) + decoder adapters	28.3
(6): (5) + extra positional embeddings	30.0
(7): (6) + GLU adapters	30.5

Table 1: Ablation study for various choices in the frozen BART method, with validation set BLEU score. We organise model settings by a number in brackets, (n), and define a new model configuration in bold as (n):. We use '+' to indicate the addition of new model settings on top of the previous ones. Method (2) is similar to the method introduced by (Lewis et al., 2019). Test set results are listed in Table 3 (as 'Frozen BART').

language pairs. We evaluate our model after 10000 training steps (amounting to $N \cdot 10000$ forwards-backwards passes through the model).

4.2 Vocabulary

BART uses the GPT-2 tokenizer, which operates on the byte level, not the more common character (or Unicode symbol) level, using the BPE (Sennrich et al., 2016) approach. BART could technically take any any Unicode string as input, regardless of language, however the BPE is learned on English text and is not ideal for other languages. When fine-tuning BART on machine translation we therefore learn a new BPE vocabulary (using the sentencepiece library¹) on the source data from the fine-tuning dataset, and can use a smaller vocabulary size of 5000, which empirically has performed better for low-resource MT (Guzmán et al., 2019; Sennrich and Zhang, 2019). We make no changes to the mBART tokenizer or vocabulary.

5 Results and Discussion

5.1 Frozen BART

Table 1 shows the effects of various choices we made in fine-tuning BART for MT. We see an 18.4 BLEU point improvement from fine-tuning a frozen BART model (with an Input Module) compared to an fine-tuning an unfrozen BART (again

¹https://github.com/google/sentencepiece

Languages	It-En	Si-En
(1): BART + InputModule + LN	34.1	5.1
(2): (1) + encoder adapters	35.0	7.3
(1) + decoder adapters	35.5	6.8
(3): (2) + extra pos. embeddings	36.3	8.7
(4) : (3) + GLU adapters	35.7	9.2

Table 2: Further Ablation study for key settings of the frozen BART method, with validation set BLEU score. Test set results are listed in Table 3 (as 'Frozen BART').

with an Input Module).

Adding extra flexibility with within-network adapters helps performance, especially when added to the BART encoder. It is important to use learned positional embeddings at the embedding layer in the Input Module, with an 10.1 BLEU score drop if we use fixed positional embeddings (at the embedding layer). We see consistent gains in Table 1 and Table 2 by adding additional, fixed sinusoidal positional embeddings to the input of every transformer layer of the Input Module, even when using an unfrozen BART. We hypothesize that the Input Module with extra fixed embeddings can more easily account for the different word order in the input language. We note an advantage over mBART is the smaller target vocabulary size (section 2). In the next section we compare these results to mBART and baselines.

5.2 Frozen mBART

In Table 3 and Table 4 we list results from freezing various parts of mBART. We get better performance than fine-tuning ('ft all' in Table 3) with our freeze decoder + fine-tune encoder-decoder attention method ('ft enc-dec' in Table 3) on Ne-En and Cs-En for $Xx \rightarrow En$, and mostly similar results to the baseline otherwise. If we constrain the training data to a random subset of 200k training examples from Ro-En (Table 6), the 'ft enc-dec' method outperforms simple fine-tuning. This effect generalises to an mBART variant that was pre-trained on only Ro and En monolingual data.

We believe a benefit to freezing, when fine-tuning on training data from a different domain to test data, will be avoiding specialising the pre-trained model to the fine-tuning train data domain. To test this we constructed a new Vi-En parallel dataset (Vi-En[†] in Table 3) using the some of the same sources as the Flores (Guzmán

et al., 2019) training data (the Si-En and Ne-En training sets used in this work), specifically GNOME/KDE/Ubuntu domain from the OPUS repository² and Bible translations from the bible-corpus³, and use the same test and validation sets as the IWSLT15 Vi-En dataset. By constraining ourselves to this out-of-domain training set we see the largest gains out of the language pairs we considered over the fine-tuning baseline (0.9 BLEU).

Table 3 shows the relative performance of frozen BART frozen mBART and baselines. Fine-tuning mBART gave consistently better results than frozen BART especially for distantly related languages. For Si, Ne and My the performance of frozen BART is roughly on par with a randomly initialised model (or much worse in the case of Ne-En). The parallel data for these languages is often lower quality, and the BART system has to learn about the non-English language from noisy or out-of-domain text (e.g. text from the Ubuntu manual for the En-Ne pair). For Vi and It, we have high quality parallel data, and the frozen BART method shows a large improvement over models trained from scratch, only approximately 1.5 BLEU points behind the best mBART results. However the frozen BART method is most useful when we do not have access to adequate monolingual data, and it is unlikely MT practitioners have both high quality parallel data and a lack of monolingual data. We note that we do not have exactly comparable models, because mBART was trained on more English data than BART and with different hyper-parameters in terms of the noising function used by each model.

5.3 What Should be Unfrozen?

For the $Xx \to En$ direction (Table 3) we can see that freezing the decoder always performs better than freezing the encoder (except for It-En where they perform roughly the same.) For the $En \to Xx$ direction (Table 4) we see slightly weaker evidence for the opposite trend, with the decoder more useful to fine-tune. There is a more English data in mBART pre-training than data in other languages, which may account for better results with a frozen encoder (when English is the source language) or decoder (when English is the target language). Adding flexibility with adapters in the frozen layers improves performances in all languages and directions, except for Nepali to English.

²http://opus.nlpl.eu/

³https://github.com/christos-c/bible-corpus/

Languages Size	Vi-En 133k	It-En 250k	Vi-En [†] 110k	Si-En 647k	Ne-En 564k	My-En 259k	Es-En 15M	Cs-En 11M
(1): Freeze decoder	30.0	36.5	12.1	13.6	11.0	27.4	34.1	26.6
Freeze encoder	29.7	36.6	12.0	12.3	8.8	25.2	33.8	25.6
(2): (1) + decoder adapters	30.0	36.7	12.2	14.2	10.8	27.7	34.4	27.4
(2) + ft enc-attn	30.6	37.0	12.3	14.9	11.4	29.0	35.1	27.0
(2) + ft self-attn	30.4	36.1	11.7	14.3	10.6	28.3	34.7	27.4
(2) + ft last 3 lyrs	30.6	36.6	12.1	14.7	11.5	28.1	34.9	27.6
Test (random init)	23.6	31.7	8.1	7.2	7.6	23.3	29.0	22.0
Test (frozen BART)	35.2	38.5		7.8	0.5	21.0		
Test (ft all)	36.7	39.8	14.1	14.0	14.1	27.6	34.5	29.2
Test (ft enc-attn)	36.4	39.4	14.9	14.1	14.6	27.9	34.4	29.8

Table 3: Validation BLEU score (unless stated otherwise) obtained by freezing various parts of the mBART and of adding adapters for $Xx \to En$. 'ft' refers to fine-tuning, i.e. unfreezing. Vi-En[†] refers to a new parallel, 'out-of-domain' dataset constructed similarly to the Flores (Guzmán et al., 2019) train sets (see section 5.2). 'Test (frozen BART)' indicates results from English-only BART with the best performing method from Table 2 or Table 1. Bold indicates the best test set score and all scores whose difference from the best is not statistically significant (with p-value less than 0.05). (Statistical significance is computed via bootstrapping (Koehn, 2004).)

Languages	En-Vi	En-It	En-Si	En-Ne	En-My	En-Es	En-Cs
Freeze decoder	29.7	32.2	2.1	5.8	35.0	35.4	17.7
(1): Freeze encoder	30.1	31.5	3.7	5.3	36.0	35.0	16.5
(2): (1) + encoder adapters	30.3	32.3	4.2	5.4	36.9	35.3	16.6
Test (ft all)	35.4	34.0	3.3	7.4	36.9	34.0	18.0
Test (freeze enc. + adapters)	35.0	34.3	3.3	6.9	35.9	32.5	16.7

Table 4: Validation BLEU score (unless stated otherwise) obtained by freezing various parts of the mBART and of adding adapters for for $En \rightarrow Xx$.

We explore more fine-grained unfreezing for the $Xx \to En$ direction (Table 3). We fine-tuned three equally sized subsets of the decoder: the encoder-decoder attention layers (approx. $12 \cdot 4d_{\rm BART}^2$ parameters), the self-attention layers in the decoder (approx. $12 \cdot 4d_{\rm BART}^2$ parameters), or the entire last three layers of the decoder (approx. $3 \cdot 16d_{\rm BART}^2$ parameters). We observe (in all language pairs except Nepali-English) that fine-tuning encoder-decoder attention performed best, with self-attention being the least useful to fine-tune. We hypothesize that this is because the pre-training task of mBART reconstructing noisy monolingual text, does not provide enough signal to align source and target text of different languages.

5.4 Memory Cost

Freezing parameters means we no longer need to allocate memory to storing their gradients. We

	Tokens per GPU
Finetune all	2304
(1): Freeze decoder	4096
Freeze encoder	3584
(2): (1) + decoder adapters	4096
(2) + ft enc-attn	3328

Table 5: Maximum number of tokens that would fit on one NVIDIA Volta GPU when fine-tuning mBART on the En-Vi training set. We evaluated batch sizes in increments of 256 tokens.

will obtain additional memory savings when using an optimizer that stores various other quantities (i.e. the Adam optimizer stores running averages of the first and second moments of gradients.). The memory savings allow for roughly 45-75% larger batches for the methods we consider in this work

Model	mBART	En-Ro mBART				
Languages (Size)	Ro-En (608k)	Ro-En (200k)	Ro-En (608k)	Ro-En (200k)		
Test (ft all)	37.8	36.4	38.5	37.7		
Test (ft enc-dec)	37.8	36.8	38.1	37.9		

Table 6: Validation set BLEU (unless stated otherwise) comparing freezing various parts of MBART and En-Ro MBART (pre-trained only on En and Ro data), fine-tuned on $Ro \rightarrow En$ parallel data. 'ft' referes to fine-tuning, i.e. unfreezing. 'Ro-En (200k)' refers to a random subset of the Ro-En training data of size 200k.

Src. Language	Ru	Fr	De	Zh	Es	Cs	Lv	Fi	Lt	Et	Hi	Si
Size	32M	29M	28M	25M	15M	11 M	4.5M	2.7M	2.1M	1.9M	788k	647k
Finetune all	33.6	39.0	33.1	20.2	33.7	29.9	21.1	29.0	22.8	28.6	25.4	16.9
Ft enc-dec attn	33.4	38.2	32.6	<u>20.2</u>	<u>34.0</u>	29.7	20.8	<u>29.1</u>	22.7	28.3	25.1	16.7
Src. Language	Ro	Ne	My	Ar	It	NI	Ko	Ja	Tr	Vi	Kk	Gu
Size	612k	563k	259k	251k	251k	237k	230k	223k	207k	133k	91k	12k
Finetune all	37.8	<u>20.7</u>	31.0	37.0	39.6	43.3	25.0	<u>18.7</u>	24.0	<u>37.4</u>	<u>14.6</u>	18.7
Ft enc-dec attn	37.9	20.8	30.5	36.9	39.3	43.0	24.2	18.8	23.7	37.5	15.0	18.3

Table 7: Test set BLEU score on many-to-one ($Xx \rightarrow En$) multilingual MT with a simple round-robin training schedule. 'Ft enc-dec attn' refers to fine-tuning the encoder, and fine-tuning the encoder-decoder attention module in every decoder layer, leaving the other decoder sub-modules frozen. The 'Ft enc-dec attn' model setting uses adapter modules in the decoder to increase flexibility after freezing parameters. Bold indicates the best score and all scores whose difference from the best is not statistically significant (with p-value less than 0.05). For clarity we underline language pairs where the 'Ft enc-dec attn' method matches or outperforms naive fine-tuning.

(see Table 5 for our mBART methods), but for larger pre-trained models the proportion of GPU memory freed up by freezing will increase. At inference time we no longer require gradients and we have the same memory cost.

5.5 Multilingual Fine-tuning of mBART

We explore freezing parts of the mBART model when fine-tuning on a challenging multi-lingual MT task. Table 7 lists results from a naive finetuning baseline, and results from freezing most of the decoder but unfreezing the encoder-decoder attention (when freezing we use GLU adapters in the decoder, see section 3.2). Freezing parameters hurts performance on some language pairs, and since freezing removes flexibility from the model and we have to adapt to 25 different directions this is perhaps not surprising. The language pairs where we match or improve on the baseline are Zh, Es, Fi, Ne, Ja, Vi and Kk. These are mostly (five out of seven) non-European languages, and distantly related to En. However since most of these results are not statistically significant further study is needed to verify this. Note we see a clear benefit over bilingual fine-tuning for some language pairs (e.g. compare our best Ne result from Table 3,

14.6 BLEU vs. 20.8 BLEU for multilingual finetuning). We leave to future work a more thorough investigation of the multilingual MT setting.

6 Conclusion

We recommend different strategies depending on downstream task and pre-trained model: For a language with high quality parallel data but without a pre-trained model trained on monolingual data from that language, using a frozen (Englsih-only) BART model with additional parameters at the source side improves performance compared to a randomly initialised baseline. For this approach it is important to give the model positional information, with learned positional embeddings at the embedding layer, and fixed ones at the input to each Input Module layer.

For a multilingual pre-trained model, we found performance improvements on some (mostly distantly related) languages for multilingual many-to-one fine-tuning, but most of these improvements were not statistically significant. For bilingual $En \rightarrow Xx$ fine-tuning we did not see any improvement, although the performance drops are small, and by freezing parameters we require less mem-

ory at training time compared to fine-tuning. For $Xx \to En$ bilingual fine-tuning it is important to unfreeze the encoder-decoder attention, and keep the rest of the decoder frozen. This approach can result in gains over simple fine-tuning, especially for distantly-related language pairs or those with out-of-domain training data.

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A Additional Ablation Study

In Table 8 we study the effect of unfreezing layer-norm parameters when fine-tuning mBART. Across all language pairs we see improvements from fine-tuning layer norm parameters over not fine-tuning them, and additional improvements from adding adapters, indicating both forms of adding flexibility are useful. In Table 9 we present additional results on the Ro-En pre-trained model (see section 5.2).

B Fine-tuning Hyper-parameters

For all experiments with bilingual datasets we use a batch size of 2048×16 tokens, i.e. 2048 tokens per GPU and 16 GPUs.

Frozen BART We train with 0.3 dropout for the frozen BART parameters, and 0.2 dropout for the Input Module parameters, 0.1 label smoothing, 0.2 dropout for the self-attention scores in the Input Module, 5000 warm-up steps, and 7e-4 maximum learning rate. We train for a maximum of 50K training updates for all low and medium resource pairs and 100K for high resource pairs.

Frozen mBART We train with 0.3 dropout, 0.2 label smoothing, 2500 warm-up steps, and 3e-5 maximum learning rate. Despite the adapter parameters being randomly initialised, the small learning rate did not affect performance (we performed a small sweep of larger learning rates and found only marginal gains, and so kept the same settings for simplicity). We use a maximum of 40K training updates for all low and medium resource pairs and 100K for high resource pairs (Es and Cs in our case).

Multi-lingual MT We train with 0.3 dropout, 0.1 dropout for self-attention scores, 4000 warm-up steps, and 1e-4 maximum learning rate.

Out-of-domain Vi-En Baseline To train a randomly initialised baseline for the out-of-domain Vi-En data (Vi-En[†] in Table 3) we used the same model architecture and training settings as those of Guzmán et al. (2019) use for training MT systems on similar data (but with Si or Ne source language). Specifically a seq2seq transformer with 5 encoder and decoder layers, hidden dimension 512. shared embeddings between the input and softmax layers, and strong regularisation (e.g. 0.4 dropout on hidden states, 0.2 dropout on attention scores, 0.2 label smoothing). We learn a BPE vocabulary (joint

	Vi-En	It-En	Si-En	Ne-En	My-En
Freeze decoder	26.6	35.1	13.1	10.3	26.6
Freeze encoder	29.4	36.1	12.1	8.7	24.1
(1): Freeze decoder + ft layer norm	30.0	36.5	13.6	11.0	27.4
Freeze encoder + ft layer norm	29.7	36.6	12.3	8.8	25.2
(1) + decoder adapters	30.0	36.7	14.2	10.8	27.7

Table 8: Validation BLEU score (unless stated otherwise) obtained by freezing various parts of the mBART and of adding adapters for $Xx \to En$. 'ft' refers to fine-tuning, i.e. unfreezing. We reproduce some rows from Table 3 for reference.

	mBART		En-Ro mBART	
	Ro-En (608k)	Ro-En (200k)	Ro-En (608k)	Ro-En (200k)
(1): Freeze decoder	38.8	37.9	40.4	39.9
Freeze encoder	39.1	38.3	40.0	39.2
(2): (1) + decoder adapters	39.3	38.0	40.6	40.0
(1) + ft enc-attn	39.8	39.0	40.5	40.5
(1) + ft self-attn	39.6	38.3	40.4	40.1
(1) + ft last 3 lyrs	39.6	38.6	40.5	40.3
Test (ft enc-dec)	37.8	36.8	38.1	37.9
Test (ft all)	37.8	36.4	38.5	37.7

Table 9: Validation set BLEU (unless stated otherwise) comparing freezing various parts of mBART and En-Ro mBART (pre-trained only on En and Ro data rather than 25 languages), fine-tuned on $Ro \rightarrow En$ parallel data. 'ft' referes to fine-tuning, i.e. unfreezing. 'Ro-En (200k)' refers to a random subset of the Ro-En training data of size 200k.

across source and target data) of size 5000 on the training data. For full details of hyper-parameters we refer the reader to Guzmán et al. (2019) and the associated GitHub repository⁴.

C Pre-training Languages

We reproduce in Table 10 the details from Liu et al. (2020) of the size of each pre-training language corpus for mBART.

⁴https://github.com/facebookresearch/flores

Code	Language	Tokens(M)	Size(GB)	Parallel data source
En	English	55608	300.8	
Ru	Russian	23408	278.0	WMT19
Vi	Vietnamese	24757	137.3	IWSLT15
Ja	Japanese	530 (*)	69.3	IWSLT17
De	German	10297	66.6	WMT19
Ro	Romanian	10354	61.4	WMT16
Fr	French	9780	56.8	WMT19
Fi	Finnish	6730	54.3	WMT17
Ko	Korean	5644	54.2	IWSLT17
Es	Spanish	9374	53.3	WMT19
Zh	Chinese (Sim)	259 (*)	46.9	WMT19
It	Italian	4983	30.2	IWSLT17
NI	Dutch	5025	29.3	IWSLT17
Ar	Arabic	2869	28.0	IWSLT17
Tr	Turkish	2736	20.9	IWSLT17
Hi	Hindi	1715	20.2	ITTB
Cs	Czech	2498	16.3	WMT19
Lt	Lithuanian	1835	13.7	WMT19
Lv	Latvian	1198	8.8	WMT17
Kk	Kazakh	476	6.4	WMT19
Et	Estonian	843	6.1	WMT18
Ne	Nepali	237	3.8	FLoRes
Si	Sinhala	243	3.6	FLoRes
Gu	Gujarati	140	1.9	WMT19
My	Burmese	56	1.6	WAT19

Table 10: Languages and Statistics of the CC25 Corpus. A list of the 25 languages used in mBART pretraining ranked with monolingual corpus size. (*) The Chinese and Japanese corpora are not segmented, so the token counts here are sentence counts.