SHARE OR NOT? LEARNING TO SCHEDULE LANGUAGE-SPECIFIC CAPACITY FOR MULTILINGUAL TRANSLATION

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ABSTRACT

Using a mix of shared and language-specific (LS) parameters has shown promise in multilingual neural machine translation (MNMT), but the question of when and where LS capacity matters most is still under-studied. We offer such a study by proposing conditional language-specific routing (CLSR). CLSR employs hard binary gates conditioned on token representations to dynamically select LS or shared paths. By manipulating these gates, it can schedule LS capacity across sub-layers in MNMT subject to the guidance of translation signals and budget constraints. Moreover, CLSR can easily scale up to massively multilingual settings. Experiments with Transformer on OPUS-100 and WMT datasets show that: 1) MNMT is sensitive to both the amount and the position of LS modeling: distributing 10%-30% LS computation to the top and/or bottom encoder/decoder layers delivers the best performance, surpassing several strong baselines; and 2) one-to-many translation benefits more from CLSR compared to many-to-one translation, particularly with unbalanced training data. Our study further verifies the trade-off between the shared capacity and LS capacity for multilingual translation. We corroborate our analysis by confirming the soundness of our findings as foundation of our improved multilingual Transformers. Source code and models will be released.

1 INTRODUCTION

Model architecture design injects inductive biases to neural network layouts, allowing a learning algorithm to favor certain representations over others, independent of the observed data (Mitchell, 1980). In multilingual neural machine translation (MNMT), where the learning objective is commonly cast as a multi-task learning problem (Firat et al., 2016a; Ha et al., 2016; Johnson et al., 2017), the inductive bias researchers usually study is deciding on which components of the neural network to share between tasks (languages), and which components to leave specific to the task or language. These components can be entire layer stacks, individual layers or even some sub-layers (Sachan & Neubig, 2018; Blackwood et al., 2018; Wang et al., 2019; Zhu et al., 2020). Noticeably, the search space of which parameters to share and at which granularity grows rapidly, as we make neural networks large or increase the number of tasks (languages). This rapid expansion of the search space prevents us from exhaustively exploring the choice of sharing patterns in MNMT.

The incapability of full-space exploration motivates methods relying on heuristics (Sachan & Neubig, 2018), that lack flexibility when more languages are covered, or meta-learning (Platanios et al., 2018), that are often hard to scale. These limitations hinder their generalization to large-scale multilingual models, which is the very focus of our study. In large scale multilingual models, also known as massively multilingual models (Aharoni et al., 2019; Arivazhagan et al., 2019; Zhang et al., 2020b), hundreds of languages with varying amounts of training data, difficulty and linguistic properties are jointly trained together in a multi-task setup. While the joint training enables positive transfer across languages, it also introduces task-interference between dissimilar languages (Arivazhagan et al., 2019; Wang et al., 2020) and a capacity bottleneck emerges due to the increased number of languages and data (Huang et al., 2019; Zhang et al., 2020b).

In this paper we adopt an end-to-end data driven approach (conditional language-specific routing, or CLSR) which permits directly probing a large section of the search space. We let the network

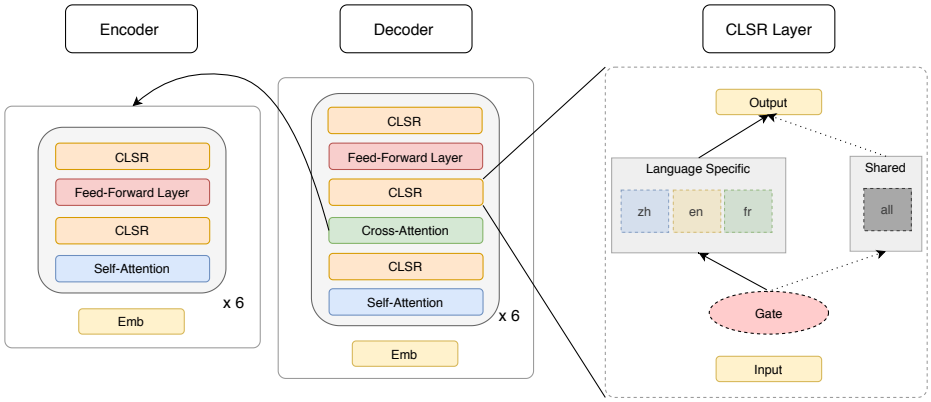


Figure 1: The model architecture used for our experiments. We introduce a CLSR layer after every transformer sub-layer in the encoder and the decoder. The gating layer learns to route every input through either the LS projection layer, or a shared projection layer. We analyze the outputs of the gating layers to develop a MNMT architecture with LS projections.

learn the sharing structure from the data itself, by learning to route between language-specific (LS) or shared pathways. These two routes determine the mode of operation for the network: when the LS branch is selected, the model is given access to a set of LS layers (implemented as simple projections per language) and when the shared branch is chosen, the computation is routed to a layer that is used by all languages. By guiding the (gating) decision process with token level activation information, the network flexibly learns to alternate between the two modes and naturally lends itself to a conditional computation approach for multilingual processing (Bengio et al., 2013; Davis & Arel, 2013; Bapna et al., 2020). The gate states are optimized towards maximizing translation quality, but regularized with a budget constraint to control the amount of LS capacity. Reducing the available budget results in fewer gates routing through the LS paths, enforcing CLSR to identify the most crucial sub-layers which allows us to observe and study the importance of each sub-layer for multilingual processing. Our approach is visually depicted in Figure 1.

We verify our proposal on WMT and the massively multilingual OPUS-100 dataset, with models building on the Transformer architecture (Vaswani et al., 2017). We explore target-specific and source-specific modeling for one-to-many[1] and many-to-one translation, respectively. To measure the degree of each sub-layer's tendency to be language-specific, we propose LSScore metric. Our results show that CLSR successfully navigates the trade-offs in LS modeling, outperforming several strong baselines. Our main findings are summarized below:

- Both the amount and the position of LS layers matter for MNMT. The best performance is achieved by distributing 10%-30% LS computation to the top and/or bottom encoder/decoder layers.
- Feed-forward sub-layers utilize more LS capacity compared to other sub-layers on one-to-many translation.
- One-to-many translation benefits more from CLSR (with target LS parameters) compared to many-to-one translation (with source LS parameters), particularly when the training data is imbalanced.
- The induced sharing pattern learned by CLSR is highly similar across languages.
- We can use the learned patterns to hard-code better parameter sharing strategies for multilingual Transformers.

2 Related Work

Our work closely relates to language-specific (LS) modeling for multilingual NMT and conditional computation for sequential data which we will recap both here. Early research on MNMT focused

[1]In a one-to-many machine translation setup, a single source side language (commonly English) is tasked to be translated into multiple target languages, one at a time.

on improving shared capacity for separate bilingual models to enhance cross-lingual transfer. These efforts included sharing encoders for one-to-many translation (Dong et al., 2015), sharing decoders for many-to-one translation (Zoph & Knight, 2016; Lee et al., 2017) and sharing sub-layers (attention) for many-to-many translation (Firat et al., 2016a;b). These studies corroborated the feasibility of accommodating multiple languages with shared NMT sub-components, motivating researchers to explore universal MNMT. Ha et al. (2016) and Johnson et al. (2017) proposed such an implementation that performs multilingual translation with a single monolithic NMT model where the entire network is shared across languages, thanks to a target language token informing the model which language to translate into. Although this paradigm shows great scalability (Aharoni et al., 2019), the language token alone affords little flexibility in handling language diversity with a rigid share-all layout. Follow-up studies thus resort to LS modeling in an attempt to seek a better trade-off between sharing and not sharing. Methods in this category involve specializing neural attentions (Blackwood et al., 2018; Sachan & Neubig, 2018; Wang et al., 2019), broadening encoder outputs and normalizations (Zhang et al., 2020b), decoupling multilingual encoders and/or decoders (Vázquez et al., 2019; Escolano et al., 2020), inserting lightweight adapters (Bapna & Firat, 2019) and separately modeling languages for different clusters (Tan et al., 2019), to name a few. Nevertheless, these methods heavily depend on heuristics, providing little evidence about how to optimally distribute LS capacity across the model.

By contrast, our proposed CLSR forces the model to learn LS behaviour. It can be treated as a simplified differentiable neural architecture search (NAS) model (Liu et al., 2019) with a search space defined by the presence/absence of LS projections after every transformer sub-layer. However, in contrast with NAS, we utilize conditional computation (Bengio et al., 2013) to make the choice of executing the shared or LS path conditional on the input representations. This allows us to compare and contrast the choice of LS vs shared paths on different inputs and languages. Conditional computation has previously been successfully applied to adapt the amount of computation to the input in recurrent models (Graves, 2016) and transformers (Dehghani et al., 2019; Elbayad et al., 2020), or to significantly scale up model capacity by utilizing sparsely-gated Mixture-of-Experts layers (Shazeer et al., 2017; Lepikhin et al., 2020). Zhang et al. (2020a) applied conditional computation to sparsify encoder outputs in sequence-to-sequence models in order to reduce attention costs, while Bapna et al. (2020) introduced conditional execution of Transformer sub-layers to control the amount of computation expended by the model at inference. Different from these studies, we explore conditional computation as an analysis tool to understand the ideal arrangement of LS capacity for MNMT. Utilizing conditional computation to search for better LS sharing patterns in multilingual translation, to the best of our knowledge, has never been investigated before.

3 BACKGROUND: MNMT

Given a source sentence $X' = \{x_1, x_2, \ldots, x_I\}$ and its target translation $Y = \{y_1, y_2, \ldots, y_J\}$, we follow Johnson et al. (2017) to reuse standard bilingual NMT models for multilingual translation by altering the source input with a language token *lang*, i.e. changing X' to $X = \{\textit{lang}, x_1, x_2, \ldots, x_I\}$. Note that *lang* denotes the target language in one-to-many translation but source language in many-to-one translation.

We model translation from X to Y with Transformer (Vaswani et al., 2017). Transformer relies on the following residual-normalization structure (He et al., 2015; Ba et al., 2016) to smooth information flow and avoid gradient vanishing and explosion:

$$\mathbf{z}^{l+1} = \mathrm{LN}\left(\mathbf{z}^l + f\left(\mathbf{z}^l\right)\right), \tag{1}$$

where l denotes layer depth and $\mathrm{LN}(\cdot)$ is layer normalization (Ba et al., 2016). Function $f(\cdot)$ represents the basic building block in Transformer, such as attention network or feed-forward network. The encoder in Transformer is a stack of L identical layers, with each layer involving a self-attention sub-layer (SAN) and a feed-forward sub-layer (FFN). The decoder uses a similar structure except for an extra cross-attention sub-layer (CAN) inserted in-between the above two sub-layers.

4 CONDITIONAL LANGUAGE-SPECIFIC ROUTING (CLSR)

The success of MNMT comes at the cost of expressivity and model's ability to capture language-specific characteristics. It has been empirically shown that the language signals from language

indicator tokens alone are not sufficient (Arivazhagan et al., 2019), making architectures dedicated to LS modeling a necessity (Blackwood et al., 2018; Sachan & Neubig, 2018; Zhang et al., 2020b). Nevertheless, the question when and where LS modeling matters most in MNMT still remains to be answered. To this end, we propose conditional language-specific routing (CLSR) which specializes $f(\cdot)$ and changes the formulation in Equation 1 as follows:

$$\mathbf{z}^{l+1} = \text{LN}\left(\mathbf{z}^l + \text{CLSR}\left(f\left(\mathbf{z}^l\right)\right)\right). \tag{2}$$

CLSR learns a hard binary (scalar-valued) gate $g(\cdot)$ for each input token based on its hidden representation $\mathbf{z}^l \in \mathbb{R}^d$. These gates endow each sub-layer in Transformer with the capability of routing information selectively through either LS path $\mathbf{h}^{lang}$ or shared path $\mathbf{h}^{shared}$:

$$\text{CLSR}\left(f\left(\mathbf{z}^l\right)\right) = g(\mathbf{z}^l)\mathbf{h}^{lang} + (1 - g(\mathbf{z}^l))\mathbf{h}^{shared}, \tag{3}$$

$$\text{with} \quad \mathbf{h}^{lang} = f\left(\mathbf{z}^l\right)\mathbf{W}^{lang}, \quad \mathbf{h}^{shared} = f\left(\mathbf{z}^l\right)\mathbf{W}^{shared}, \tag{4}$$

where $\mathbf{W}^{shared}$ is a weight matrix shared across languages, while parameter $\mathbf{W}^{lang}$ is only used for modeling language *lang* which endows NMT with source or target LS modeling capacity.[2] Intuitively, a closed gate, corresponding to shared capacity, encourages maximal cross-lingual information transfer; an open gate, corresponding to LS capacity instead, improves language awareness for translation albeit it blocks knowledge transfer. CLSR balances between the two modes as controlled by the gates.

Following Bapna et al. (2020), we parameterize the gate $g(\cdot)$ with a two-layer feed-forward network $G(\cdot)$, and inject zero-mean Gaussian noise during training to discretize it (Chiu & Raffel, 2018) :

$$g(\mathbf{z}^l) = \sigma\left(G(\mathbf{z}^l) + \alpha(t)\mathcal{N}(0,1)\right), \quad G(\mathbf{z}^l) = \text{Relu}\left(\mathbf{z}^l\mathbf{W}_1 + \mathbf{b}\right)\mathbf{w}_2, \tag{5}$$

where $\sigma(\cdot)$ is the logistic-sigmoid function, d_g is the gating feed-forward hidden dimension, and $\mathbf{W}_1 \in \mathbb{R}^{d \times d_g}, \mathbf{w}_2 \in \mathbb{R}^{d_g}$ are trainable parameters. α is linearly increased along with training steps t. In this way, the gating parameters can be optimized with accurate gradients when α is small at the beginning so as to measure the degree to which each position in each sub-layer benefits from LS modeling. As training progresses, α grows larger, forcing the gating network to emit hard outputs. At inference time, we discretize the gate based on a simple decision rule: $g(\mathbf{z}^l) = \delta\left(G(\mathbf{z}^l) > 0\right)$, where $\delta(\cdot)$ is a Dirac measure.

We train the gates based on the standard maximum likelihood objective, along with an additional budget regularization term that enables control over the amount of LS capacity used for translation. Let the set of all CLSR layers in the encoder be $\mathcal{M}_{enc}$ and the decoder be $\mathcal{M}_{dec}$. Then the amount of LS computation utilized by a sentence pair (X, Y) is given by $G_{(X,Y)} = \sum_{x \in X}\sum_{m \in \mathcal{M}_{enc}} g_m(x) + \sum_{y \in Y}\sum_{m \in \mathcal{M}_{dec}} g_m(y)$. Given a budget constraint $p \in [0, 1]$ and a batch of sentence pairs, $\mathcal{B}$, the training loss function of CLSR is formulated below:

$$\mathcal{L}(\mathcal{B}) = \sum_{(X,Y)\in\mathcal{B}} \text{MLE}(X, Y) + \left| \frac{\sum_{(X,Y)\in\mathcal{B}} G_{(X,Y)}}{\sum_{(X,Y)\in\mathcal{B}}(|X||\mathcal{M}_{enc}| + |Y||\mathcal{M}_{dec}|)} - p \right|, \tag{6}$$

Intuitively, the budget constraint tries to regulate the amount of LS computation available to all tokens in the batch as a fraction p of the total LS computation in the model. Given that we make a binary decision for every input for every CLSR layer, this corresponds to a search space of $\mathcal{O}(2^{|X||\mathcal{M}_{enc}|+|Y||\mathcal{M}_{dec}|})$. This gating space not only grows with respect to the model depth and sub-layer types, but also is highly input dependent. This dependency makes it difficult to search the entire space using heuristic methods (Blackwood et al., 2018).

The constraint in Equation 6 is imposed upon the aggregated gates. As a consequence, the model can learn to trade-off LS capacity for certain layers and inputs for others. Decreasing the budget encourages gate closure, such that the LS path is chosen only in the critical sub-layers. Thus, a properly learned gating function reveals the activations of LS paths and helps gain insights into the model behavior.

[2]We maintain a set of language-specific weight matrices in order to compute $\mathbf{h}^{lang}$ for each language. To make the parameter number manageable, we share the set of LS matrices $\mathbf{W}^{lang}$ across all encoder or decoder sub-layers, but distinguish $\mathbf{W}^{lang}_{enc}$ and $\mathbf{W}^{lang}_{dec}$, LS matrices for the encoder and decoder, respectively.

5 EXPERIMENTS

Data and Evaluation We report results on two benchmarks: OPUS-100 (Zhang et al., 2020b) and WMT-14 (Barrault et al., 2019). OPUS-100 is a massively multilingual dataset collected from OPUS (Tiedemann, 2012), including 100 languages in total with 99 languages to-and-from English.[3] It consists of 55M training sentence pairs with up to 1M samples per language pair, and covers 94 dev/test language pairs, each with 2000 samples at most. WMT-14 is another multilingual English-centric dataset composed of 13 widely-used WMT benchmarks following Siddhant et al. (2020) but excluding Kazakh and Gujarati due to their poor parallel resource. Compared to OPUS-100, WMT-14 involves much fewer languages but its training data distribution is highly skewed across diverse language pairs, ranging from 0.2M (En-Tr) to 60M (En-Cs) training examples, thus posing severe challenges. We show more details about the train, dev and test data for WMT-14 in Appendix A.

We apply byte pair encoding (BPE) algorithm (Sennrich et al., 2016) using SentencePiece (Kudo & Richardson, 2018) to preprocess multilingual sentences with a vocabulary size of 64K. We use BLEU (Papineni et al., 2002), offered by SacreBLEU (Post, 2018)[4], for translation evaluation. Following Zhang et al. (2020b), we split the 94 test language pairs in OPUS-100 into three groups based on their training data size to ease model evaluation: high resource (>0.9M, 45 languages), low resource (<0.1M, 26 languages) and medium resource (others, 28 languages). Similarly, we split the 13 test language pairs in WMT-14 as follows: High (>10M, 5), Low (<1M, 5) and Med (others, 3).

We perform experiments for one-to-many translation (O2M) and many-to-one translation (M2O). In addition to using the original training data as is, we also report results with a temperature-based strategy to balance the training data distribution by over-sampling low-resource languages with a temperature of $T = 5$ (Arivazhagan et al., 2019).

We report average BLEU, and also show win ratio (Zhang et al., 2020b, WR), informing the proportion of language pairs on which our method beats our baseline. To evaluate how often each sub-layer is LS, we introduce a new metric, LSScore, formulated as follows:

$$\text{LSScore}_f(l, p) = \frac{1}{|\mathcal{P}|} \sum_{p \in \mathcal{P}} \tilde{g}^p_{l,f} - p, \tag{7}$$

where $\tilde{g}^p_{l,f}$ denotes the gating value averaged over all test tokens for the l-th sub-layer $f(\cdot)$ trained under a budget of p. Recall that we pose the budget constraint to the summed gate value instead of each individual gate, as in Equation 6. This gives CLSR the freedom to close more gates in some language-insensitive sub-layers (i.e. $\tilde{g}^p_{l,f} < p$) while preserve more for the others (i.e. $\tilde{g}^p_{l,f} > p$). A larger LSScore, > 0 in particular, indicates that this sub-layer utilizes more LS modeling.

Model Settings We adapt Transformer base for our experiments: $L = 6$, $d = 512$, 8 attention heads with FFN middle size of 2048. Dropout of rate 0.1 is applied to residual connections and attention weights. We optimize parameters using Adam (Kingma & Ba, 2015) ($\beta_1 = 0.9, \beta_2 = 0.98$) with label smoothing of 0.1. Learning rate is scheduled according to the inverse square root of running steps with a warmup step of 4K (Vaswani et al., 2017). We limit training sequence length to 100, and train all models with a batch size of 1920. We set the maximum running step to 500K and 600K for OPUS-100 and WMT-14, respectively. We perform beam search decoding with beam size of 4 and length penalty of 0.6. We average the last 5 checkpoints for evaluation. For CLSR, we set d_g to 128, and linearly increase α from 0 to 5 along training steps (Bapna et al., 2020).[5] We vary the budget p in the range of $\mathcal{P} = \{0.0, 0.1, 0.3, 0.5, 0.7, 0.9, 1.0\}$ to study its impact on model performance.

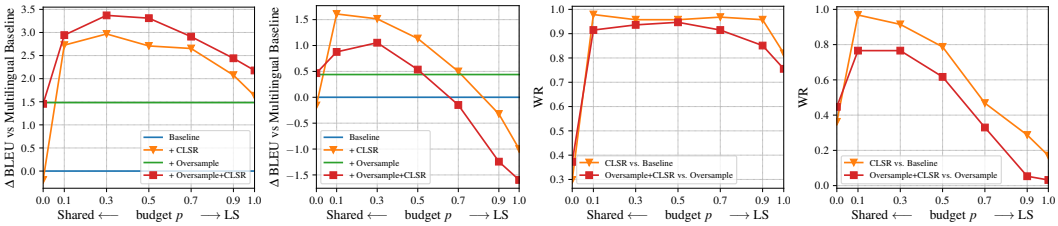
5.1 RESULTS ON OPUS-100

On the trade-off between shared and language-specific capacity. Using more LS modeling fails to deliver increasingly better translation performance, as shown in Figure 2(a) and 2(b) when

[3] http://opus.nlpl.eu/opus-100.php

[4] Signature: BLEU+case.mixed+numrefs.1+smooth.exp+tok.13a+version.1.4.10.

[5] Note that, there are 99×2 and 13×2 independent $\mathbf{W}^{lang}$ weight matrices when CLSR is used for OPUS-100 and WMT-14, respectively. This corresponds to each language having a weight matrix in the encoder and the decoder.

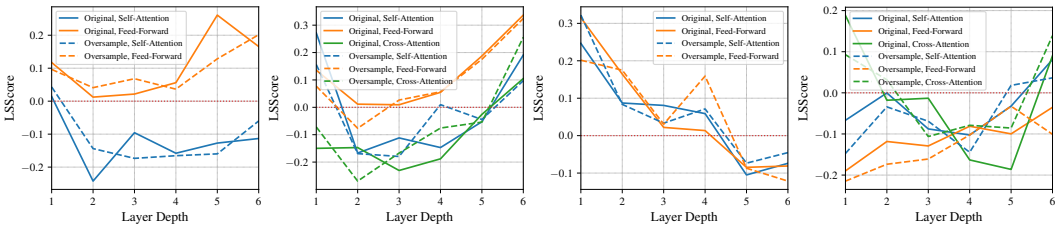


(a) BLEU for O2M (b) BLEU for M2O (c) Win Ratio for O2M (d) Win Ratio for M2O

Figure 2: Average BLEU 2(a),2(b) and win ratio 2(c),2(d) over all test language pairs for O2M and M2O on OPUS-100 when varying the budget p. *Baseline*: multilingual baseline on the original training data; *Oversample*: oversampling low-resource data with a temperature of 5.

p approaches 1.0. At the point of full LS capacity for Transformer, i.e. $p = 1.0$, CLSR even underperforms its corresponding multilingual baseline by a large margin of 1.0-2.0 BLEU on M2O, Figure 2(b). Similarly, sharing all model parameters across language pairs, $p \rightarrow 0.0$, also yields suboptimal performance with either original or oversampled training data. CLSR achieves its best translation quality at $p = 0.3$ (+2.0/3.0 BLEU) and $p = 0.1$ (+0.5/1.5 BLEU) for O2M and M2O, respectively. The win ratio curves in Figure 2(c) and 2(d) further confirm the robustness of these quality improvements, where properly scheduling LS capacity outperforms the baselines on $>\sim 80\%$ language pairs. These results clearly show the trade-off between these two kinds of capacity.

When does language-specific capacity matter for multilingual translation? Results in Figure 2 show that O2M favors more LS modeling and benefits more from it compared to M2O ($p = 0.3$ vs. $p = 0.1$, and +3.0 vs. +1.5 BLEU on the original training data). We conjecture that translations on M2O share the same target language (English), so information can be easily transferred through shared modeling; by contrast, MNMT has to handle languages of diverse typological features for O2M, demanding stronger capacity delivered to each translation direction. Results in Figure 2 also show that CLSR yields more aggressive improvements on the original training data, compared to the oversampled counterpart (+3.0 vs. +2.0 BLEU on O2M and +1.5 vs. +0.5 BLEU on M2O). Fine-grained analysis on each resource group, as shown in Figure 7 (Appendix B), reveals that CLSR yields more improvements for low-resource translation where the oversampling strategy partially offsets these improvements.



(a) Encoder, O2M (b) Decoder, O2M (c) Encoder, M2O (d) Decoder, M2O

Figure 3: LSScore of encoder and decoder sub-layers for O2M 3(a), 3(b) and M2O 3(c), 3(d) on OPUS-100. The solid lines correspond to models trained on the original data, while the dashed lines are on the oversampled data. We also include a red, dotted line to indicate the LSScore of 0.

Where should we add language-specific capacity in multilingual Transformer? Figure 2 suggests that CLSR uses 10-30% LS capacity to reach its best performance. We next study how CLSR schedules this capacity across all Transformer sub-layers, in order to determine the ideal arrangement of LS layers for translation. Figure 3 shows the results. Regardless of layer types, CLSR schedules more LS capacity to the top and/or bottom encoder/decoder layers rather than the middle ones. We find that more LS capacity is allocated to feed-forward sub-layers for O2M (both encoder Figure 3(a) and decoder Figure 3(b)), while the cross-attention sub-layers use more LS capacity for M2O (decoder, Figure 3(d)). Regarding the encoder for M2O, we observe no significant LSScore difference among different sub-layers as in Figure 3(c). Overall, CLSR tends to make the "M" side more LS, i.e. the encoder side of M2O (Figure 3(c)) and the decoder side of O2M (Figure 3(b)).

Data Setting	Model	O2M					M2O				
		High	Med	Low	All	WR	High	Med	Low	All	WR
Original	Baseline	21.39	22.36	18.02	20.93	-	28.55	30.10	29.71	29.27	-
	LS$^\diamond$	+0.75	+1.83	+3.96	+1.79	94.68	-0.54	-0.16	-0.46	-0.41	32.98
	CLSR-S	+0.06	-0.09	-0.34	-0.08	41.49	-0.14	-0.06	+0.02	-0.08	37.23
	CLSR-L	+0.39	+1.54	+4.37	+1.62	84.04	-1.13	-0.47	-0.46	-0.78	21.28
	CLSR*	**+1.45**	**+2.83**	+6.40	**+2.97**	95.74	**+0.65**	**+1.52**	**+3.79**	**+1.61**	**96.81**
	Top-Bottom	+1.27	+2.71	**+6.60**	+2.89	96.81	+0.38	+1.16	+3.06	+1.21	78.72
	Dedicated	+1.35	+2.75	+6.46	+2.90	**97.87**	+0.61	+1.50	+2.85	+1.38	89.36
Over Sample	Baseline	19.95	24.22	25.27	22.41	-	26.98	30.69	**34.26**	29.71	-
	LS$^\diamond$	+0.99	+1.30	+0.94	+1.07	90.43	-0.55	-0.61	-3.96	-1.33	12.77
	CLSR-S	+0.02	+0.13	+0.30	+0.11	44.68	-0.04	+0.06	-0.84	-0.19	35.11
	CLSR-L	+0.62	+0.60	+0.34	+0.55	69.15	-1.02	-1.11	-4.56	-1.84	7.45
	CLSR*	+1.76	**+2.04**	+1.94	+1.89	93.62	+0.82	+0.84	-0.13	**+0.62**	76.60
	Top-Bottom	+1.73	+1.91	+1.83	+1.81	**96.81**	+0.83	**+1.05**	-1.36	+0.41	73.40
	Dedicated	**+1.79**	+2.03	**+2.07**	**+1.92**	94.68	**+0.99**	+0.92	-0.88	+0.55	**77.66**

Table 1: Translation quality for O2M and M2O on OPUS-100 with the original and oversampled training data. We list average BLEU↑ for High, Med, Low and All language groups, as well as WR↑ over all language pairs. *Baseline*: the vanilla multilingual baseline; *LS$^\diamond$*: the LS model proposed by Zhang et al. (2020b); *CLSR-S*: CLSR but always using shared modeling, i.e. $g(\mathbf{z}^l) = 0$ for all inputs; *CLSR-L*: CLSR but always using LS modeling, i.e. $g(\mathbf{z}^l) = 1$ for all inputs; *CLSR**: the best CLSR model; *Top-Bottom*: applying LS modeling only to the top and bottom Transformer layers; *Dedicated*: dedicated model that allocates LS modeling based on LSScore distribution. Best results are highlighted in **bold**.

Does CLSR schedule language-specific capacity based on linguistic similarity? It is intriguing to explore how the capacity scheduled by CLSR is actualized, especially whether CLSR learns to organize LS capacity according to linguistic characteristics or not. The heatmap in Figure 6, Appendix B shows that the LSScore distribution over different sub-layers (y-axis) has only subtle difference across different language pairs (x-axis). This suggests that the capacity schedule has little to do with linguistic characteristics. More results in other settings are given in Figure 6, Appendix B, which reflect similar observation. In short, CLSR allocates LS capacity to specific sub-layers rather than specific languages.

On detailed results and comparison to other baselines. Table 1 summarizes our results. [6] Although LS$^\diamond$ improves O2M, it fails to surpass the vanilla Baseline on M2O, indicating that the position of its LS layer, i.e. on top of the encoder outputs (Zhang et al., 2020b), is sub-optimal for many-to-one translation. Compared to LS$^\diamond$, CLSR-S uses no LS modeling while CLSR-L injects LS projection into each sub-layer, both of which delivers inferior performance on O2M (against LS$^\diamond$ and Baseline) and M2O (against Baseline), echoing our findings from Figure 2. By contrast, CLSR* yield promising results, beating Baseline on O2M and M2O, underlining the importance of seeking balances between sharing and not sharing. Among all baselines, CLSR* offers the best flexibility in controlling the LS modeling, which achieves the best performance in all settings, on either original (+>1.61 BLEU (All) and +>95% WR against Baseline) or oversampled (+>0.62 BLEU (All) and +>76% WR against Baseline) training data, with better performance on O2M.

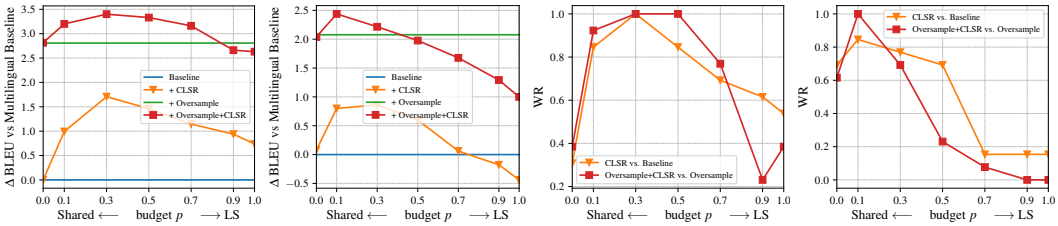
Can we use these insights to improve multilingual Transformer? We answer this question by transferring our findings from Figure 3 into the following two Transformer variants: one enhances the top and bottom encoder/decoder layers with LS projections (*Top-Bottom*), while the other makes high-LSScore sub-layers LS (*Dedicated*).[7] Results of these experiments, in Table 1, demonstrate that incorporating our findings into Transformer helps to improve translation performance. The dedicated model in particular recovers and even surpasses the performance of CLSR*.

5.2 Results on WMT-14

Figure 4 shows the capacity trade-off on WMT-14, reconfirming the ability of CLSR. One noticeable difference is that the relative improvements become smaller. We ascribe this to the smaller

[6] We list the number of trainable parameters for each model in Table 6, Appendix D.

[7] Detail about which sub-layers are specialized in Dedicated is given in Table 4, Appendix B.



(a) BLEU for O2M (b) BLEU for M2O (c) Win Ratio for O2M (d) Win Ratio for M2O

Figure 4: Average BLEU 4(a),4(b) and win ratio 4(c),4(d) over all test language pairs for O2M and M2O on WMT-14 when varying the budget p.

Data Setting	Model	O2M					M2O				
		High	Med	Low	All	WR	High	Med	Low	All	WR
Original	Baseline	27.24	16.27	8.72	17.58	-	30.64	24.37	18.66	24.58	-
	LS$^\diamond$	+0.06	+0.66	+1.68	+0.83	84.62	-0.06	-0.37	-0.92	-0.46	23.08
	CLSR-S	+0.00	+0.16	+0.20	+0.12	53.85	+0.04	+0.16	+0.28	+0.17	69.23
	CLSR-L	-0.52	+0.43	+2.06	+0.70	61.54	-0.82	-0.50	+0.00	-0.43	15.38
	CLSR*	**+0.46**	**+1.46**	**+3.10**	**+1.71**	**100.0**	**+0.12**	+0.73	+1.52	+0.80	**84.62**
	Top-Bottom	+0.10	+0.96	+2.78	+1.34	84.62	-0.08	+0.70	+1.26	+0.62	61.54
	Dedicated	+0.26	+1.00	+2.98	+1.48	92.31	+0.04	**+0.86**	**+1.90**	**+0.95**	**84.62**
Over Sample	Baseline	26.10	19.00	15.52	20.39	-	29.96	26.33	23.56	26.66	-
	LS$^\diamond$	+0.30	+0.60	+0.26	+0.36	84.62	-0.44	-0.56	-0.80	-0.61	00.00
	CLSR-S	-0.12	+0.03	+0.04	-0.02	46.15	+0.06	+0.04	-0.26	-0.07	46.15
	CLSR-L	-0.56	-0.10	-0.32	-0.36	7.69	-0.90	-1.00	-1.24	-1.05	00.00
	CLSR*	**+0.50**	**+0.67**	+0.64	**+0.59**	**100.0**	**+0.26**	**+0.30**	**+0.50**	**+0.36**	**100.0**
	Top-Bottom	+0.12	+0.40	+0.56	+0.36	84.62	-0.08	+0.00	-0.50	-0.22	30.77
	Dedicated	+0.46	+0.57	**+0.66**	+0.56	**100.0**	+0.16	+0.17	+0.22	+0.19	84.62

Table 2: Translation quality for O2M and M2O on WMT-14 with the original and oversampled training data.

number of language pairs in WMT-14, where the effect of introducing LS capacity into the model is smaller compared to the massively multilingual setting (Arivazhagan et al., 2019). Table 2 shows similar results as Table 1, where CLSR* delivers the best overall performance, and both Top-Bottom and Dedicated improve multilingual translation compared to Baseline (except for M2O with oversampling). More results are given in Appendix C. Our results demonstrate that the CLSR approach generalizes to different datasets, with varying number of languages and resource sizes. We provide additional experiments ablating different elements on CLSR in Table 7, Appendix E.

6 Conclusion and Future Work

Share or not? This is an open question when developing MNMT models. In this paper, we attempt to answer this question by proposing conditional language-specific routing (CLSR). Our empirical results demonstrate that CLSR learns to balancing between shared and LS paths across all NMT sub-layers, improving the quality of multilingual translation. Our analysis on OPUS-100 and WMT-14 suggest that both the position and the amount of LS capacity greatly affects MNMT. Scheduling 10%-30% LS layers to the top and/or bottom encoder/decoder layers reaches CLSR's peak performance. We also demonstrate how our findings can be leveraged to design a multilingual Transformer with an optimal sharing pattern. We believe that our work improves our understanding on the trade-off between sharing and not sharing, paving the way for better multilingual models.

In the future, we plan to extend our study to many-to-many translation as well as larger-capacity models. We also plan to adapt CLSR to other multilingual multi-task learning settings to better handle knowledge transfer among different tasks, especially for cross-lingual downstream transfer.

REFERENCES

Roee Aharoni, Melvin Johnson, and Orhan Firat. Massively multilingual neural machine translation. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 3874–3884, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1388. URL https://www.aclweb.org/anthology/N19-1388.

Naveen Arivazhagan, Ankur Bapna, Orhan Firat, Dmitry Lepikhin, Melvin Johnson, Maxim Krikun, Mia Xu Chen, Yuan Cao, George Foster, Colin Cherry, Wolfgang Macherey, Zhifeng Chen, and Yonghui Wu. Massively multilingual neural machine translation in the wild: Findings and challenges. *CoRR*, abs/1907.05019, 2019. URL http://arxiv.org/abs/1907.05019.

Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. Layer normalization. *arXiv preprint arXiv:1607.06450*, 2016.

Ankur Bapna and Orhan Firat. Simple, scalable adaptation for neural machine translation. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pp. 1538–1548, Hong Kong, China, November 2019. Association for Computational Linguistics. doi: 10.18653/v1/D19-1165. URL https://www.aclweb.org/anthology/D19-1165.

Ankur Bapna, Naveen Arivazhagan, and Orhan Firat. Controlling computation versus quality for neural sequence models. *arXiv preprint arXiv:2002.07106*, 2020.

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

Yoshua Bengio, Nicholas Léonard, and Aaron Courville. Estimating or propagating gradients through stochastic neurons for conditional computation. *arXiv preprint arXiv:1308.3432*, 2013.

Graeme Blackwood, Miguel Ballesteros, and Todd Ward. Multilingual neural machine translation with task-specific attention. In *Proceedings of the 27th International Conference on Computational Linguistics*, pp. 3112–3122, Santa Fe, New Mexico, USA, August 2018. Association for Computational Linguistics. URL https://www.aclweb.org/anthology/C18-1263.

Chung-Cheng Chiu and Colin Raffel. Monotonic chunkwise attention. In *International Conference on Learning Representations*, 2018. URL https://openreview.net/forum?id=Hko85plCW.

Andrew Davis and Itamar Arel. Low-rank approximations for conditional feedforward computation in deep neural networks, 2013.

Mostafa Dehghani, Stephan Gouws, Oriol Vinyals, Jakob Uszkoreit, and Lukasz Kaiser. Universal transformers. In *International Conference on Learning Representations*, 2019. URL https://openreview.net/forum?id=HyzdRiR9Y7.

Daxiang Dong, Hua Wu, Wei He, Dianhai Yu, and Haifeng Wang. Multi-task learning for multiple language translation. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pp. 1723–1732, Beijing, China, July 2015. Association for Computational Linguistics. doi: 10.3115/v1/P15-1166. URL https://www.aclweb.org/anthology/P15-1166.

Maha Elbayad, Jiatao Gu, Edouard Grave, and Michael Auli. Depth-adaptive transformer. In *International Conference on Learning Representations*, 2020. URL https://openreview.net/forum?id=SJg7KhVKPH.

Carlos Escolano, Marta R Costa-jussà, José AR Fonollosa, and Mikel Artetxe. Multilingual machine translation: Closing the gap between shared and language-specific encoder-decoders. *arXiv preprint arXiv:2004.06575*, 2020.

Orhan Firat, Kyunghyun Cho, and Yoshua Bengio. Multi-way, multilingual neural machine translation with a shared attention mechanism. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 866–875, San Diego, California, June 2016a. Association for Computational Linguistics. doi: 10.18653/v1/N16-1101. URL https://www.aclweb.org/anthology/N16-1101.

Orhan Firat, Baskaran Sankaran, Yaser Al-onaizan, Fatos T. Yarman Vural, and Kyunghyun Cho. Zero-resource translation with multi-lingual neural machine translation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pp. 268–277, Austin, Texas, November 2016b. Association for Computational Linguistics. doi: 10.18653/v1/D16-1026. URL https://www.aclweb.org/anthology/D16-1026.

Alex Graves. Adaptive computation time for recurrent neural networks. *arXiv preprint arXiv:1603.08983*, 2016.

Thanh-Le Ha, Jan Niehues, and Alexander Waibel. Toward multilingual neural machine translation with universal encoder and decoder. In *Proceedings of the 13th International Workshop on Spoken Language Translation (IWSLT)*, Seattle, USA, December 8-9 2016.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. *CoRR*, abs/1512.03385, 2015. URL http://arxiv.org/abs/1512.03385.

Yanping Huang, Youlong Cheng, Ankur Bapna, Orhan Firat, Dehao Chen, Mia Chen, HyoukJoong Lee, Jiquan Ngiam, Quoc V Le, Yonghui Wu, et al. Gpipe: Efficient training of giant neural networks using pipeline parallelism. In *Advances in neural information processing systems*, pp. 103–112, 2019.

Melvin Johnson, Mike Schuster, Quoc V. Le, Maxim Krikun, Yonghui Wu, Zhifeng Chen, Nikhil Thorat, Fernanda Viégas, Martin Wattenberg, Greg Corrado, Macduff Hughes, and Jeffrey Dean. Google's multilingual neural machine translation system: Enabling zero-shot translation. *Transactions of the Association for Computational Linguistics*, 5:339–351, 2017. doi: 10.1162/tacl_a_00065. URL https://www.aclweb.org/anthology/Q17-1024.

Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In *International Conference on Learning Representations*, 2015.

Taku Kudo and John Richardson. SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pp. 66–71, Brussels, Belgium, November 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-2012. URL https://www.aclweb.org/anthology/D18-2012.

Jason Lee, Kyunghyun Cho, and Thomas Hofmann. Fully character-level neural machine translation without explicit segmentation. *Transactions of the Association for Computational Linguistics*, 5:365–378, 2017. doi: 10.1162/tacl_a_00067. URL https://www.aclweb.org/anthology/Q17-1026.

Dmitry Lepikhin, HyoukJoong Lee, Yuanzhong Xu, Dehao Chen, Orhan Firat, Yanping Huang, Maxim Krikun, Noam Shazeer, and Zhifeng Chen. Gshard: Scaling giant models with conditional computation and automatic sharding. *arXiv preprint arXiv:2006.16668*, 2020.

Hanxiao Liu, Karen Simonyan, and Yiming Yang. DARTS: Differentiable architecture search. In *International Conference on Learning Representations*, 2019. URL https://openreview.net/forum?id=S1eYHoC5FX.

Tom M Mitchell. *The need for biases in learning generalizations*. Department of Computer Science, Laboratory for Computer Science Research . . . , 1980.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pp. 311–318, Philadelphia, Pennsylvania, USA, July 2002. Association for Computational Linguistics. doi: 10.3115/1073083.1073135. URL https://www.aclweb.org/anthology/P02-1040.

Emmanouil Antonios Platanios, Mrinmaya Sachan, Graham Neubig, and Tom Mitchell. Contextual parameter generation for universal neural machine translation. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pp. 425–435, Brussels, Belgium, October-November 2018. Association for Computational Linguistics. doi: 10.18653/v1/D18-1039. URL https://www.aclweb.org/anthology/D18-1039.

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

Devendra Sachan and Graham Neubig. Parameter sharing methods for multilingual self-attentional translation models. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pp. 261–271, Brussels, Belgium, October 2018. Association for Computational Linguistics. doi: 10.18653/v1/W18-6327. URL https://www.aclweb.org/anthology/W18-6327.

Rico Sennrich, Barry Haddow, and Alexandra Birch. Neural machine translation of rare words with subword units. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 1715–1725, Berlin, Germany, August 2016. Association for Computational Linguistics. doi: 10.18653/v1/P16-1162. URL https://www.aclweb.org/anthology/P16-1162.

Noam Shazeer, Azalia Mirhoseini, Krzysztof Maziarz, Andy Davis, Quoc Le, Geoffrey Hinton, and Jeff Dean. Outrageously large neural networks: The sparsely-gated mixture-of-experts layer. *arXiv preprint arXiv:1701.06538*, 2017.

Aditya Siddhant, Ankur Bapna, Yuan Cao, Orhan Firat, Mia Chen, Sneha Kudugunta, Naveen Arivazhagan, and Yonghui Wu. Leveraging monolingual data with self-supervision for multilingual neural machine translation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 2827–2835, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.252. URL https://www.aclweb.org/anthology/2020.acl-main.252.

Xu Tan, Jiale Chen, Di He, Yingce Xia, Tao QIN, and Tie-Yan Liu. Multilingual neural machine translation with language clustering. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pp. 963–973, Hong Kong, China, November 2019. Association for Computational Linguistics. doi: 10.18653/v1/D19-1089. URL https://www.aclweb.org/anthology/D19-1089.

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

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

Raúl Vázquez, Alessandro Raganato, Jörg Tiedemann, and Mathias Creutz. Multilingual NMT with a language-independent attention bridge. In *Proceedings of the 4th Workshop on Representation Learning for NLP (RepL4NLP-2019)*, pp. 33–39, Florence, Italy, August 2019. Association

for Computational Linguistics. doi: 10.18653/v1/W19-4305. URL https://www.aclweb.org/anthology/W19-4305.

Xinyi Wang, Yulia Tsvetkov, and Graham Neubig. Balancing training for multilingual neural machine translation. *arXiv preprint arXiv:2004.06748*, 2020.

Yining Wang, Long Zhou, Jiajun Zhang, Feifei Zhai, Jingfang Xu, and Chengqing Zong. A compact and language-sensitive multilingual translation method. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 1213–1223, Florence, Italy, July 2019. Association for Computational Linguistics. doi: 10.18653/v1/P19-1117. URL https://www.aclweb.org/anthology/P19-1117.

Biao Zhang, Ivan Titov, and Rico Sennrich. On sparsifying encoder outputs in sequence-to-sequence models. *arXiv preprint arXiv:2004.11854*, 2020a.

Biao Zhang, Philip Williams, Ivan Titov, and Rico Sennrich. Improving massively multilingual neural machine translation and zero-shot translation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 1628–1639, Online, July 2020b. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.148. URL https://www.aclweb.org/anthology/2020.acl-main.148.

Changfeng Zhu, Heng Yu, Shanbo Cheng, and Weihua Luo. Language-aware interlingua for multilingual neural machine translation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 1650–1655, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.150. URL https://www.aclweb.org/anthology/2020.acl-main.150.

Barret Zoph and Kevin Knight. Multi-source neural translation. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 30–34, San Diego, California, June 2016. Association for Computational Linguistics. doi: 10.18653/v1/N16-1004. URL https://www.aclweb.org/anthology/N16-1004.

A DATASET DETAILS

Table 3: Statistics of train, dev and test data for WMT-14.

Language Pair	Data Sources			# Samples		
	Train	Dev	Test	Train	Dev	Test
En-Cs	WMT19	WMT17	WMT18	64336053	3005	2983
En-Fr	WMT15	WMT13	WMT14	40449146	3000	3003
En-Ru	WMT19	WMT18	WMT19	38492126	3000	2000
En-Zh	WMT19	WMT18	WMT19	25986436	3981	2000
En-Es	WMT13	WMT13	WMT13	15182374	3004	3000
En-Fi	WMT19	WMT18	WMT19	6587448	3000	1996
En-De	WMT14	WMT13	WMT14	4508785	3000	3003
En-Et	WMT18	WMT18	WMT18	2175873	2000	2000
En-Lv	WMT17	WMT17	WMT17	637599	2003	2001
En-Lt	WMT19	WMT19	WMT19	635146	2000	1000
En-Ro	WMT16	WMT16	WMT16	610320	1999	1999
En-Hi	WMT14	WMT14	WMT14	313748	520	2507
En-Tr	WMT18	WMT17	WMT18	205756	3007	3000

Figure 5: Training data distribution over language pairs for OPUS-100 and WMT-14.

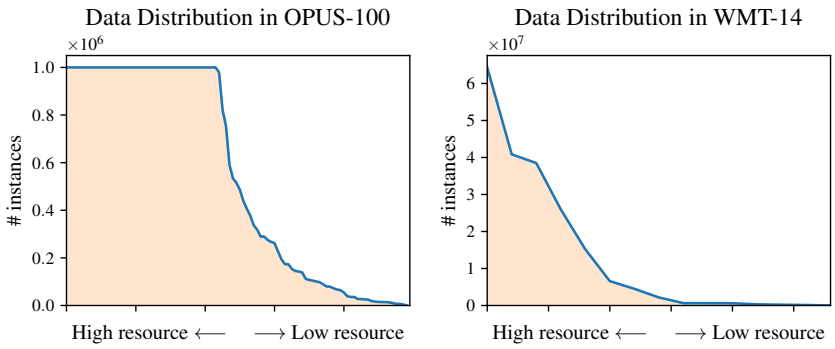


Table 3 lists the statistics for WMT-14. We collect these datasets following Siddhant et al. (2020). Figure 5 shows the training data distribution. Training data in WMT-14 is more imbalanced across different language pairs compared to OPUS-100.

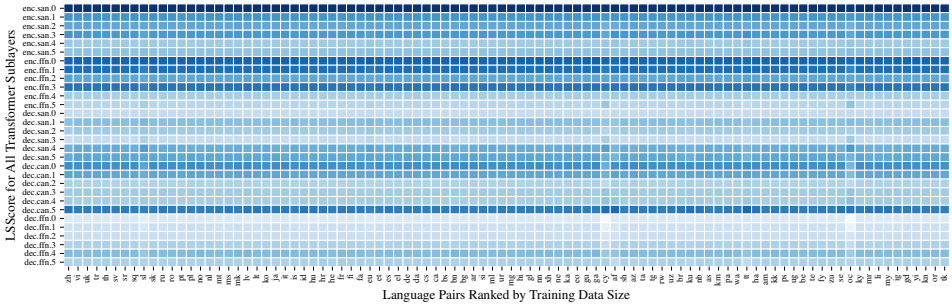
B MORE RESULTS ON OPUS-100

Table 4: Selected sub-layers by Dedicated on OPUS-100. *SAN/CAN*: self-/cross-attention; *FFN*: feed-forward.

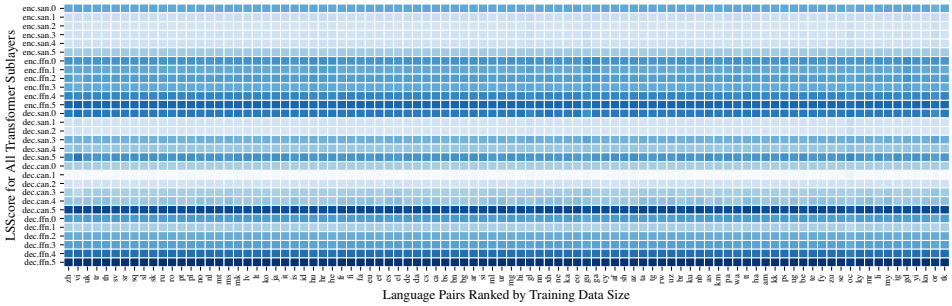
Data Setting	Encoder				Decoder					
	Bottom		Top		Bottom			Top		
	SAN	FFN	SAN	FFN	SAN	CAN	FFN	SAN	CAN	FFN
Original, O2M	✓	✓		✓	✓		✓	✓	✓	✓
Original, M2O	✓	✓							✓	✓
Oversample, O2M				✓	✓			✓	✓	✓
Oversample, M2O	✓								✓	

Figure 7 shows the translation performance of CLSR on each resource group when varying the budget p. We find that LS modeling greatly improves translation on low-resource settings, although

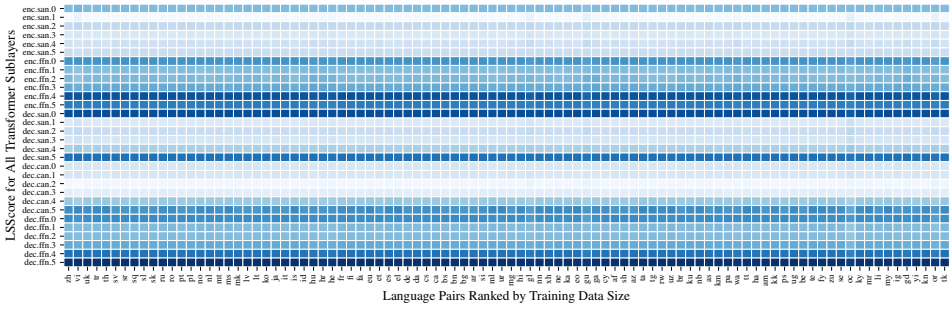
Figure 6: Heatmap of LSScore distribution on OPUS-100 trained w/ and w/o oversampling. X-axis denotes language pairs ranked by training data size, and y-axis denotes encoder (*enc*) and decoder (*dec*) sub-layers with a format of "enc/dec.layer types.layer index". Darker color indicates a larger LSScore.



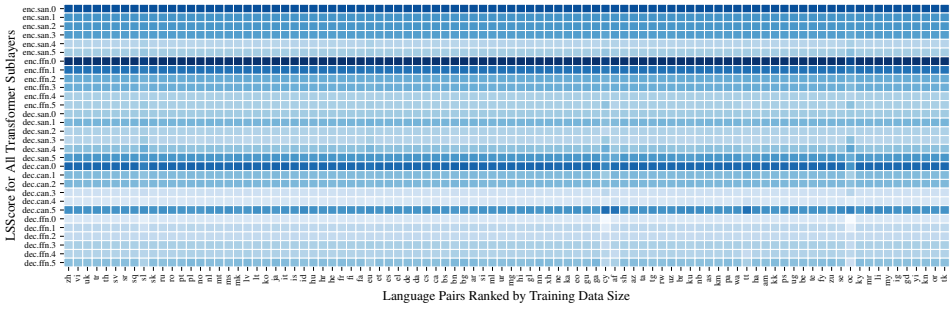
(a) Oversample, M2O



(b) Oversample, O2M



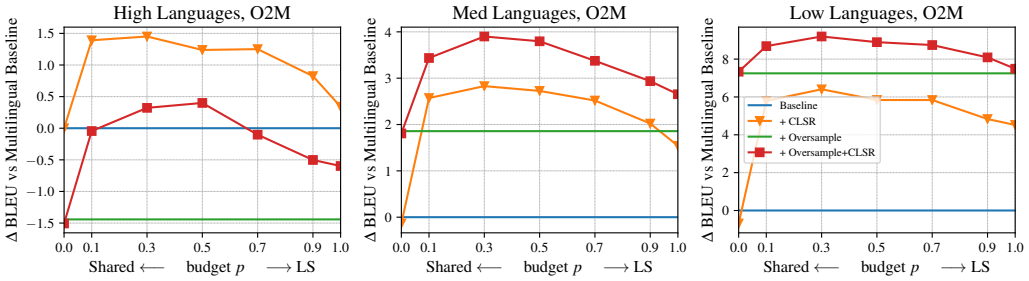
(c) Original, O2M



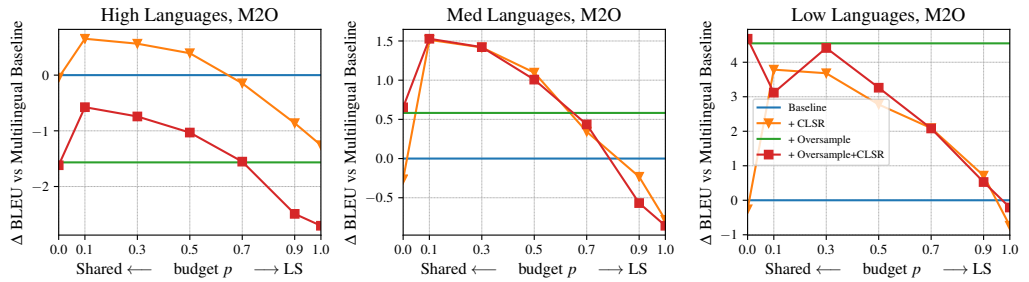
(d) Original, M2O

this improvement is partially offset by the oversampling strategy. We observe that the success of oversampling is built on top of sacrificing quality on high-resource languages, where CLSR largely narrows or even closes the performance gap against the multilingual baseline trained on the original

Figure 7: Impact of the budget p on average test BLEU for High/Med/Low-resource languages on OPUS-100.



(a) BLEU for O2M



(b) BLEU for M2O

data. In addition, we find no significant difference in term of the trade-off curve across resource groups compared to Figure 2.

Figure 6 shows the heatmaps for LSScore distribution. Regardless of translation directions (O2M or M2O) and data settings (Original or Oversample), there is no clear linguistic pattern behind these heatmaps. The learning of CLSR is not linguistic driven.

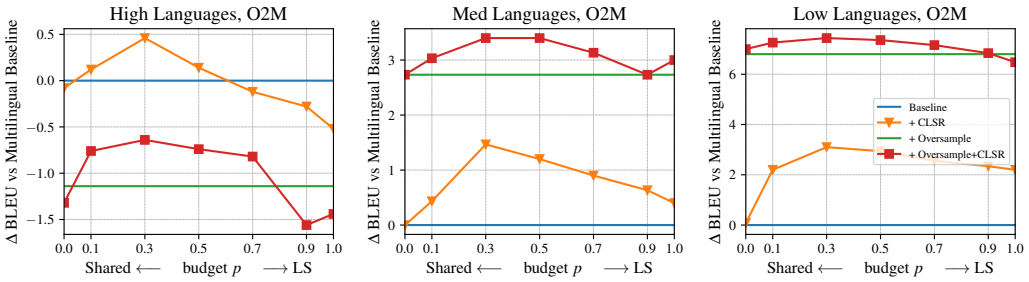
C More Results on WMT-14

Table 5: Selected sub-layers by Dedicated on WMT-14.

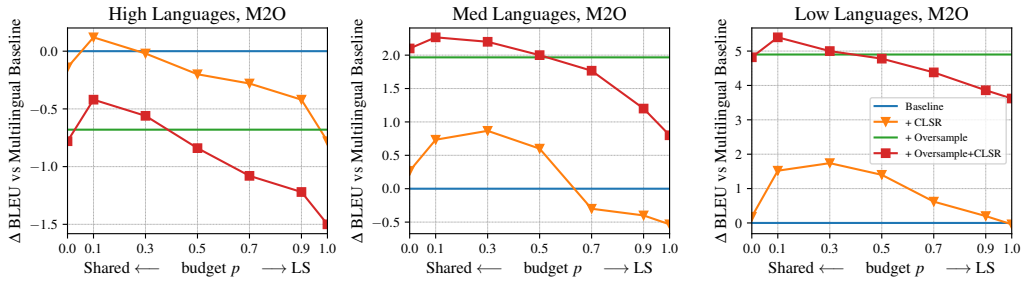
Data Setting	Encoder				Decoder					
	Bottom		Top		Bottom			Top		
	SAN	FFN	SAN	FFN	SAN	CAN	FFN	SAN	CAN	FFN
Original, O2M		✓		✓	✓		✓	✓	✓	✓
Original, M2O	✓	✓			✓	✓		✓		✓
Oversample, O2M		✓		✓	✓	✓		✓	✓	✓
Oversample, M2O	✓					✓		✓		✓

We show more results on WMT-14 here. Both heatmaps in Figure 9 and fine-grained trade-off curves in Figure 8 show a very similar story to the one on OPUS-100. In terms of LSScore distribution in Figure 10(d), we also have similar observation except that the cross-attention sub-layer in the decoder on M2O shows no clear LS preference.

These results suggest the high generalization of CLSR to different data settings.

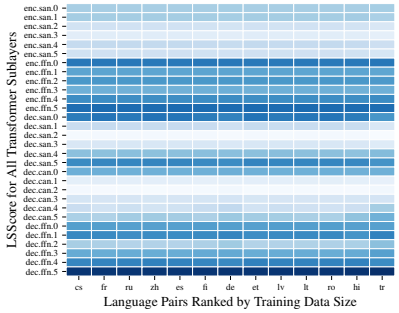


(c) BLEU for O2M

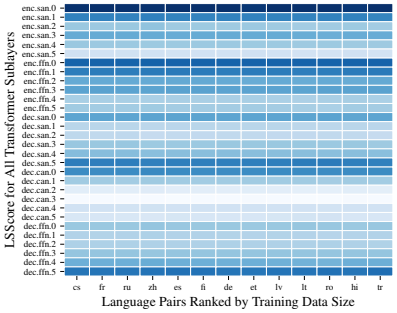


(d) BLEU for M2O

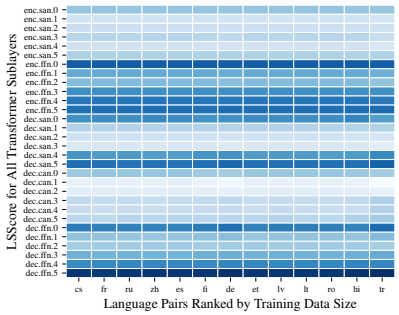
Figure 8: Impact of the budget p on average test BLEU for High/Med/Low-resource languages on WMT-14.



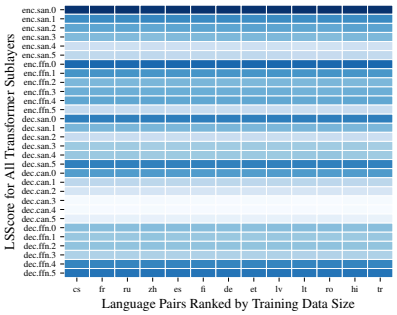
(a) Oversample, O2M



(b) Oversample, M2O

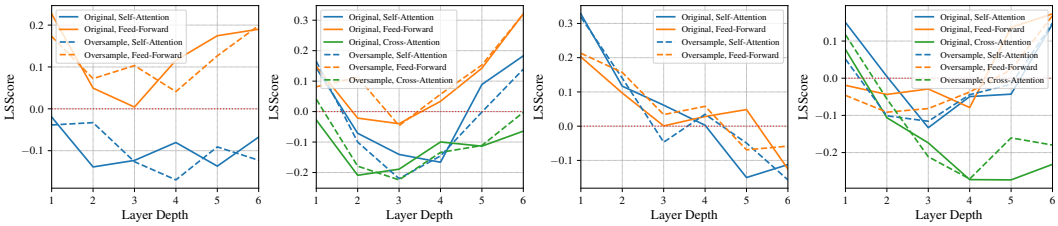


(c) Original, O2M



(d) Original, M2O

Figure 9: Heatmap of LSScore distribution on WMT-14.



(a) Encoder, O2M (b) Decoder, O2M (c) Encoder, M2O (d) Decoder, M2O

Figure 10: LSScore of encoder and decoder sub-layers for O2M 10(a), 10(b) and M2O 10(c), 10(d) on WMT-14.

Table 6: Number of parameters for each model on OPUS-100 and WMT-14.

Model	OPUS-100		WMT-14	
	O2M	M2O	O2M	M2O
Baseline	99M		106M	
LS$^\diamond$	129M		111M	
CLSR-S	102M		109M	
CLSR-L	148M		111M	
CLSR*	157M		121M	
Top-Bottom	153M		116M	
Dedicated (Original)	153M	154M	117M	117M
Dedicated (Oversample)	154M	155M	117M	117M

D Model Parameters

We list model parameters in Table 6. Note that the source/target vocabulary for O2M is the same as the target/source vocabulary for M2O, thus models for O2M and M2O have the same number of trainable parameters except for Dedicated where the network structure differs.

E Ablation Study

We provide two variants of CLSR for ablation. The first one examines whether CLSR could induce an optimal budget automatically by eschewing the budget constraint in Eq. 6 (CLSR w/o p); the second one further replaces the hard gating network with a vanilla soft gating network (CLSR-Gate).

Table 7 summarizes the translation results. Without the regularization term, CLSR w/o p yields an average gating value of 0.37/0.16 and 0.39/0.19 for O2M/M2O on OPUS-100 and WMT-14, respectively[8], resonating with our finding that O2M requires more LS capacity compared to M2O. Compared to CLSR*, CLSR w/o p produces more open gates, achieving comparable but overall worse performance in all data settings. This highlights the importance of the added regularization term, where without such regularization the model is likely spending extra learning cycles to automatically optimize for the budget as with CLSR w/o p. This in return hints the importance of optimization routines (learning) which we held constant in this study.

By contrast, switching to soft gating network, CLSR-Gate gains translation quality in most settings, although the quality gains are mostly less than 0.1 compared to CLSR*. Note that, CLSR-Gate relies on continuous gates, indicating a much higher flexibility in balancing parameter sharing patterns. However, we also notice that CLSR-Gate performs worse on M2O, even fails to beat the vanilla Baseline (All) on the oversampled WMT-14. Unlike CLSR-Gate, CLSR* uses hard binary gates which eases capacity analysis and achieves consistent improvements across data settings.

[8]We also average the gating value over the original and oversampled data settings.

Data Setting	Model	#Param	O2M					M2O				
			High	Med	Low	All	WR	High	Med	Low	All	WR
OPUS-100												
Original	Baseline	99M	21.39	22.36	18.02	20.93	-	28.55	30.10	29.71	29.27	-
	CLSR*	157M	+1.45	+2.83	**+6.40**	+2.97	95.74	+0.65	+1.52	**+3.79**	**+1.61**	**96.81**
	CLSR w/o p	157M	+1.37	+2.77	+6.28	+2.88	96.81	+0.53	+1.27	+3.17	+1.34	90.43
	CLSR-Gate	157M	**+1.55**	**+3.13**	+6.21	**+3.06**	**97.87**	**+0.74**	**+1.62**	+2.87	+1.48	93.62
Over Sample	Baseline	99M	19.95	24.22	25.27	22.41	-	26.98	30.69	**34.26**	29.71	-
	CLSR*	157M	+1.76	+2.04	+1.94	+1.89	93.62	+0.82	+0.84	-0.13	+0.62	76.60
	CLSR w/o p	157M	+1.72	+1.92	+2.06	+1.86	**97.87**	+0.73	+0.56	-1.10	+0.27	71.28
	CLSR-Gate	157M	**+2.00**	**+2.24**	**+2.35**	**+2.15**	**97.87**	**+1.12**	**+1.28**	-1.04	**+0.68**	**79.79**
WMT-14												
Original	Baseline	106M	27.24	16.27	8.72	17.58	-	30.64	24.37	18.66	24.58	-
	CLSR*	121M	**+0.46**	**+1.46**	+3.10	+1.71	**100.0**	**+0.12**	**+0.73**	+1.52	+0.80	**84.62**
	CLSR w/o p	121M	+0.32	+1.23	+3.00	+1.57	**100.0**	-0.04	+0.56	+1.72	+0.78	76.92
	CLSR-Gate	121M	**+0.46**	+1.43	**+3.14**	**+1.72**	**100.0**	+0.02	**+0.73**	**+1.68**	**+0.83**	**84.62**
Over Sample	Baseline	106M	26.10	19.00	15.52	20.39	-	29.96	26.33	23.56	26.66	-
	CLSR*	121M	+0.50	+0.67	+0.64	+0.59	**100.0**	**+0.26**	**+0.30**	**+0.50**	**+0.36**	**100.0**
	CLSR w/o p	121M	+0.48	+0.63	+0.66	+0.59	**100.0**	+0.02	+0.24	-0.12	+0.02	38.46
	CLSR-Gate	121M	**+0.52**	**+0.77**	**+0.78**	**+0.68**	**100.0**	+0.14	**+0.30**	-0.64	-0.12	61.54

Table 7: Translation quality for O2M and M2O on OPUS-100 and WMT-14 with the original and oversampled training data. *CLSR-Gate*: CLSR with $g(\mathbf{z}^l)$ a normal soft gating network; *CLSR w/o p*: CLSR trained without budget constraint.