Tricks for Training Sparse Translation Models

Dheeru Dua hearts Shruti Bhosale hearts Vedanuj Goswami hearts James Cross hearts Mike Lewis hearts Angela Fan

University of California, Irvine, USA
Facebook AI
ddua@uci.edu

Abstract

Multi-task learning with an unbalanced data distribution skews model learning towards high resource tasks, especially when model capacity is fixed and fully shared across all tasks. Sparse scaling architectures, such as BASELayers, provide flexible mechanisms for different tasks to have a variable number of parameters, which can be useful to counterbalance skewed data distributions. We find that sparse architectures for multilingual machine translation can perform poorly out of the box, and propose two straightforward techniques to mitigate this — a temperature heating mechanism and dense pre-training. Overall, these methods improve performance on two multilingual translation benchmarks compared to standard BASELayers and Dense scaling baselines, and in combination, more than 2x model convergence speed.

1 Introduction

Training a universal model capable of handling many different tasks is a longstanding ambition in natural language processing (Collobert and Weston, 2008; Ruder, 2017; McCann et al., 2018), with recent progress driven by training transformer models on a wide range of tasks (Xue et al., 2020; Khashabi et al., 2020; Lu et al., 2020). A central challenge in multi-task learning is accounting for the dramatically varying amounts of training data available for different tasks, which can lead to overfitting on low-resource tasks whilst simultaneously underfitting on tasks with abundant training data.

In this work, we study multilingual machine translation as a multi-task learning problem (Dong et al., 2015; Domhan and Hieber, 2017), where a single model is trained to translate between many language pairs (Fan et al., 2021). Multilingual learning has the potential of cross-lingual transfer, allowing low-resource languages to benefit from high-resource data when trained together (Conneau et al., 2019). However, in practice, this positive transfer is often mitigated by interference between languages (Arivazhagan et al., 2019; Tan et al., 2019; Zhang et al., 2020). This is because all languages, irrespective of the amount of data, are trained with a fixed model capacity (Lepikhin et al., 2020), leading to insufficient specialized capacity.

Recent efforts have focused on sparse architectures (Shazeer et al., 2017; Lewis et al., 2021) to train very high capacity models — allowing high-resource languages sufficient specialization to reach stronger performance. However, these architectures can overfit to low-resource languages and often overall have worse performance than dense architectures (Fan et al., 2021; Tran et al., 2021), which utilize all of their parameters for each training example. We analyze the learning patterns of experts throughout training and identify a fundamental problem: experts specialize early on and rarely change specialization.

We propose two straightforward techniques to improve BASELayers-based sparse architectures (Lewis et al., 2021) for multitask learning: first, we slowly ramp the number of instances from low-resource tasks over epochs rather than having a fixed sampling ratio (Arivazhagan et al., 2019). This promotes cross-lingual transfer and reduces over-fitting as the model witnesses low-resource task instances in the later epochs. Second, we train a dense architecture before switching to sparse training. Intuitively, we learn a generalized representation that can transfer across all tasks first with a dense model and then gradually sparsify and specialize the experts to different tasks. Overall with these two modifications, we observe improvement in low-resource performance by 0.6 BLEU on WMT-15 benchmark and 1.1 BLEU on ML-50.
benchmark — whilst halving the training time.

2 Methods

We motivate the need for preventing early expert specialization and describe our proposed techniques to both circumvent this problem and more than double convergence speed.

2.1 Expert Utilization Rarely Changes

Sparse scaling schemes, such as BASELayers or Mixture-of-Experts, enable sparse computation by distributing model capacity across sets of experts. In each forward pass, only a small subset of experts are utilized, leading to incredibly compute-efficient scaling. The challenge, however, is the routing function — or how experts can be balanced so they actually specialize to learn different things (Kudugunta et al., 2020). When the routing mechanism is unbalanced, all the tasks degenerate to using only a single specific expert for all tasks (Lepikhin et al., 2020) — essentially wasting parameters. Often this problem is solved by penalizing the routing algorithm for un-utilized expert parameters via auxiliary losses. BASELayers (Lewis et al., 2021) employ a simple mechanism that learns a balanced routing without the need for additional auxiliary losses. In our work, we focus on BASELayers as it has straightforward and simple training and has previously been shown to have strong performance on language modeling tasks.

We observe that even though BASELayers leads to effective utilization of all parameters, it limits parameter sharing across tasks, which is crucial when the data distribution is unbalanced — if the number of tasks and experts are the same, all tasks end up using a different set of experts. As a result, when applied to multilingual machine translation, the performance is worse than a corresponding dense architecture. Figure 1 demonstrates that the main reason for limited parameter sharing is that expert assignment is fixed incredibly early on in training and rarely changes. Instead of learning how to better utilize capacity across high and low-resource languages over the training process, expert capacity is essentially frozen. We describe two strategies for more effective utilization of expert capacity, which can be easily applied to improve both low and high-resource translation performance.

![Figure 1: Expert distribution for Romanian and French as training progresses (10k, 30k and 50k updates) on WMT-15 benchmark, where Romanian is low-resource and French is high-resource.](image)

2.2 Balancing Low-Resource Tasks

Temperature Sampling: To ensure that low-resource tasks are well represented during model training, temperature sampling (Arivazhagan et al., 2019) is used to upsample low-resource tasks. If the data distribution across different tasks is $p$, then temperature sampling re-scales this distribution:

$$p \leftarrow \frac{p^{1/T}}{\sum_{n \in \text{tasks}} p^{1/T}}$$

As we increase temperature from 1 to $\infty$, the sampling distribution changes from the original data distribution (e.g. highly skewed) to a uniform distribution (e.g. tasks are equally represented).

Temperature Heating: Instead of sampling data for each task with a fixed temperature at every epoch, we propose slowly increasing the temperature over the learning schedule shown in Eq 2. We define a starting temperature $t_s$, which is gradually increased at each epoch $e$, with a square root factor defined over maximum number of epochs $C$.

The conduction coefficient $k$ determines the rate at which the temperature is increased.

$$t_{e+1} = \sqrt{1 + k \frac{e}{\sqrt{C}}} \times t_e^2$$

During the initial steps of training, this trains with lower temperatures, meaning high-resource tasks are better represented than low-resource tasks. As a result, the experts are more uniformly assigned across high-resource tasks. Upon
slowly introducing low-resource tasks by increasing temperature during the learning process, the gating mechanism learns to route low-resource tasks through experts which were initially trained with high-resource tasks. This promotes positive cross-lingual transfer from high-resource languages to linguistically similar low-resource languages.

2.3 Dense Pre-training

Architecturally, the sparsity in the output feed-forward layer of the transformer block can be viewed as a version of the same transformer on multiple GPUs with two main differences: the sparse feed-forward layers do not share parameters (have different initialization and gradients) and an additional gating mechanism decides which token should be routed to which expert. The alternative dense architecture would fully share parameters, so all parameters are utilized for each training example rather than routing to sparse parameters.

We propose first training a dense model for a fixed number of updates. Afterwards, we add a randomly initialized gating module and continue training the (output) feed-forward layers with sparsity, e.g. we do not average their gradients across compute nodes before back-propagating but update the weights individually in each node. As the sparse weights slowly diverge, they become more specialized towards specific tasks. Thus, models first learn a generalized representation when all parameters are fully shared, and then gradually specialize to handle different tasks. Training in this fashion not only improves the learning of specialized experts, but also increases convergence.

3 Experiments and Results

We demonstrate the advantages of our approach compared to BASELayers and dense baselines. We experiment with English → Many multitasking on two benchmarks, WMT-15\(^1\) and ML-50 (Tang et al., 2020) — the first includes 15 languages and the second 50 languages. We use a Transformer (Vaswani et al., 2017) sequence-to-sequence model with 6 encoder and decoder layers. We replace the final feed-forward layer of every alternate transformer block with a BASELayer. For ML50, we increase model capacity to 12 Transformer layers, following Tang et al. (2020). We implement our methods in fairseq (Ott et al., 2019) and evaluate performance with BLEU.

3.1 Effectiveness of Temperature Heating

On WMT-15, training with BASELayers as a baseline has worse low-resource performance compared to a similarly sized dense model, losing 0.6 BLEU. However, as we increase temperature, we recover the loss in low-resource task performance and also see improvements in the high-resource languages. The heating technique improves the overall BASELayers model performance by +0.7 BLEU (at \(t_s = 0.8\)) (see Table 1). We observe similar trends in ML-50, where adding heating improves low-resource performance by +1.4 BLEU. Furthermore, temperature heating improves convergence speed. Given fixed \(t_s\), the higher the \(k\), the faster the model converges. As shown in Figure 2, the model converges to same validation perplexity with \(k=3\) at 50k updates as 100k updates with \(k=1\).

\(^1\)http://www.statmt.org/wmt15/translation-task.html
Table 1: Average BLEU and wall clock training time (until convergence) for different starting temperatures with a fixed conduction coefficient, $k=1$. The baselines are from our best performing dense and BASELayers models.

| Model   | Low-Resource | High-Resource | All  |
|---------|--------------|---------------|------|
| WMT-15  |              |               |      |
| Dense   | 13.3         | 25.4          | 19.8 |
| BASELayers | 12.7       | 25.3          | 19.4 |
| + heating ($t_s=0.5$) | 13.1       | 26            | 20   |
| + heating ($t_s=0.8$) | 12.9       | 26.4          | 20.1 |
| + heating ($t_s=1.0$) | 13.2       | 26.1          | 20.1 |
| + heating ($t_s=1.5$) | 13.1       | 26.1          | 20.0 |
| + heating ($t_s=2.0$) | 13.3       | 25.5          | 19.8 |

| Model   | Low-Resource | Mid-Resource | High-Resource | All  |
|---------|--------------|-------------|---------------|------|
| ML-50   |              |             |               |      |
| Dense   | 10.71        | 23.65       | 24.70         | 22.53|
| BASELayers | 8.74       | 22.56       | 26.50         | 22.33|
| + heating ($t_s=0.8$) | 8.92       | 22.94       | 26.54         | 22.46|
| + heating ($t_s=1.0$) | 8.48       | 22.71       | 26.52         | 22.27|
| + heating ($t_s=1.5$) | 9.28       | 22.93       | 26.50         | 22.39|
| + heating ($t_s=2.0$) | 10.14      | 23.72       | 25.99         | 22.93|

3.2 Dense Pre-training with Heating

For the WMT-15 benchmark, Table 2 demonstrates that with dense pre-training, the best performing model improves by +0.75 BLEU over baseline BASELayers model but at the cost of 12% more computation time. To resolve this, we reduce computation time by introducing temperature heating, keeping the +0.7 BLEU improvement but reducing the computation time by $\sim$60%.

In the case of ML-50, results in Table 2 confirm a similar trend. By combining Dense Pre-training with temperature heating, we improve +0.5 BLEU over a baseline BASELayers configuration and improve convergence speed by 2.5x. However, temperature heating can also be applied to the baselines. In those cases, on both benchmarks, we find that utilizing Dense Pre-training in combination with heating still has slightly better performance with significantly faster convergence.

3.3 Effect on Expert Distribution

In standard BASELayer training, the learned expert distributions rarely change as the model trains (see Figure 1). This prevents expert capacity from being utilized more effectively, and contributes to low-resource overfitting. In contrast, with our proposed techniques, the expert distribution changes and learns over training. Figure 3 compares expert distribution between fixed temperature sampling and temperature heating over epochs for a low-resource language, demonstrating that temperature heating leads experts to change and learn over time.

In Figure 4, we show that by utilizing dense pre-training, we observe a high entropy in the expert distribution and increased expert sharing, indicating positive cross-lingual transfer from similar high to low-resource languages.

4 Related Work

Data Sampling Low-resource tasks are upsampled to balance their representation when pooled with high-resource tasks. Temperature sampling (Arivazhagan et al., 2019) upsamples the data distribution based on a fixed temperature. This simple technique can result in over-fitting if the data distribution is skewed. Active learning sampling (Gottumukkala et al., 2020) methods sample instances based on the current performance of task on dev set, which can be useful in case of catastrophic forgetting. Learned data sam-
|                  | Model                  | High-Resource | Low-Resource | All  | Walltime (min) |
|------------------|------------------------|---------------|--------------|------|---------------|
| **WMT-15**       | Dense                  | 25.2          | 12.7         | 19.4 | 76K           |
|                  | + heating              | 25.5          | 13.2         | 19.8 | 42K           |
|                  | BASELayers             | 25.2          | 12.9         | 19.5 | 77K           |
|                  | + heating              | 26.0          | 13.0         | 19.9 | 42K           |
|                  | Dense Pre-Train        | 26.3          | 13.3         | **20.2** | 86K           |
|                  | + heating              | 26.0          | 13.4         | **20.1** | **31K**       |
| **ML-50**        | Dense                  | 24.7          | 10.7         | 22.5 | 596K          |
|                  | + heating              | 25.9          | 10.5         | **22.7** | 173K          |
|                  | BASELayers             | 26.6          | 8.7          | 22.2 | 221K          |
|                  | + heating              | 26.5          | 9.3          | 22.4 | 151K          |
|                  | Dense Pre-Train        | 26.8          | 9.6          | 22.6 | 122K          |
|                  | + heating              | 26.7          | 9.8          | **22.7** | **87K**       |

Table 2: Average BLEU on test set of WMT-15 and ML-50, with increasing number of dense pre-training steps at a starting/fixed temperature of 1.5. Wall clock time is the total training time including dense pre-training and sparse fine-tuning until the model reaches validation perplexity of 5.99 for WMT-15 and 7.6 for ML-50.

plers (Wang et al., 2020) can choose better sampling schemes but are computationally expensive.

**Sparse Scaling** Sparsely-gated MoE models (Shazeer et al., 2017) were introduced to increase model capacity in a flexible and scalable manner via model parallelism. The routing mechanism that decides which tasks should be routed to which set of experts is the key element that governs effective (better representation) and efficient (balanced assignment) resource utilization. To promote a balanced assignment, routing techniques (Shazeer et al., 2017; Lepikhin et al., 2020; Fedus et al., 2021) add a number of auxiliary task that encourage the routing mechanism to use a diverse set of experts. BASELayers (Lewis et al., 2021) circumvents this problem by treating the routing mechanism as a linear expert-to-task assignment problem, without the need of auxiliary loss. Routing networks (Rosenbaum et al., 2017) learn better task representations by clustering and disentangling parameters conditioned on input.

5 Conclusion

We analyze the problem of balancing shared and specialized capacity in multitask learning, focusing on multilingual machine translation. We present two straightforward tricks to significantly increase convergence rate of mixture-of-expert models and improve their performance relative to dense baselines on two benchmarks.

References

Naveen Arivazhagan, Ankur Bapna, Orhan Firat, Dmitry Lepikhin, Melvin Johnson, Maxim Krikun, Mia Xu Chen, Yuan Cao, George Foster, Colin Cherry, et al. 2019. Massively multilingual neural machine translation in the wild: Findings and challenges. arXiv preprint arXiv:1907.05019.

Ronan Collobert and Jason Weston. 2008. A unified architecture for natural language processing: Deep neural networks with multitask learning. In Proceedings of the 25th international conference on Machine learning, pages 160–167.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Unsupervised cross-lingual representation learning at scale. arXiv preprint arXiv:1911.02116.

Tobias Domhan and Felix Hieber. 2017. Using target-side monolingual data for neural machine translation through multi-task learning. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 1500–1505.

Daxiang Dong, Hua Wu, Wei He, Dianhai Yu, and Haifeng Wang. 2015. 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), pages 1723–1732.

Angela Fan, Shruti Bhosale, Holger Schwenk, Zhiyi Ma, Ahmed El-Kishky, Siddharth Goyal, Mandeept Baines, Onur Celebi, Guillaume Wenzek, Vishrav Chaudhary, et al. 2021. Beyond english-centric multilingual machine translation. Journal of Machine Learning Research, 22(107):1–48.

William Fedus, Barret Zoph, and Noam Shazeer. 2021. Switch transformers: Scaling to trillion parameter models with simple and efficient sparsity. arXiv preprint arXiv:2101.03961.

Ananth Gottumukkala, Dheeru Dua, Sameer Singh, and Matt Gardner. 2020. Dynamic sampling strate-
gies for multi-task reading comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 920–924.

Daniel Khashabi, Sewon Min, Tushar Khot, Ashish Sabharwal, Oyvind Tafjord, Peter Clark, and Hannaneh Hajishirzi. 2020. Unifiedqa: Crossing format boundaries with a single qa system. arXiv preprint arXiv:2005.00700.

Sneha Kudugunta, Yanping Huang, Ankur Bapna, Maxim Krikun, Dmitry Lepikhin, Thang Luong, and Orhan Firat. 2020. Exploring routing strategies for multilingual mixture-of-experts models.

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

Mike Lewis, Shruti Bhosale, Tim Dettmers, Naman Goyal, and Luke Zettlemoyer. 2021. Base layers: Simplifying training of large, sparse models. arXiv preprint arXiv:2103.16716.

Jiasen Lu, Vedanuj Goswami, Marcus Rohrbach, Devi Parikh, and Stefan Lee. 2020. 12-in-1: Multi-task vision and language representation learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10437–10446.

Bryan McCann, Nitish Shirish Keskar, Caiming Xiong, and Richard Socher. 2018. The natural language decathlon: Multitask learning as question answering.

Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A fast, extensible toolkit for sequence modeling. arXiv preprint arXiv:1904.01038.

Clemens Rosenbaum, Tim Klinger, and Matthew Riemer. 2017. Routing networks: Adaptive selection of non-linear functions for multi-task learning. arXiv preprint arXiv:1711.01239.

Sebastian Ruder. 2017. An overview of multi-task learning in deep neural networks. arXiv preprint arXiv:1706.05098.

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

Xu Tan, Yi Ren, Di He, Tao Qin, Zhou Zhao, and Tie-Yan Liu. 2019. Multilingual neural machine translation with knowledge distillation. arXiv preprint arXiv:1902.10461.