Revisiting Checkpoint Averaging for Neural Machine Translation

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Abstract

Checkpoint averaging is a simple and effective method to boost the performance of converged neural machine translation models. The calculation is cheap to perform and the fact that the translation improvement almost comes for free, makes it widely adopted in neural machine translation research. Despite the popularity, the method itself simply takes the mean of the model parameters from several checkpoints, the selection of which is mostly based on empirical recipes without many justifications. In this work, we revisit the concept of checkpoint averaging and consider several extensions. Specifically, we experiment with ideas such as using different checkpoint selection strategies, calculating weighted average instead of simple mean, making use of gradient information and fine-tuning the interpolation weights on development data. Our results confirm the necessity of applying checkpoint averaging for optimal performance, but also suggest that the landscape between the converged checkpoints is rather flat and not much further improvement compared to simple averaging is to be obtained.

1 Introduction

Checkpoint averaging is a simple method to improve model performance at low computational cost. The procedure is straightforward: select some model checkpoints, average the model parameters, and obtain a better model. Because of its simplicity and effectiveness, it is widely used in neural machine translation (NMT), e.g. in the original Transformer paper (Vaswani et al., 2017), in systems participating in public machine translation (MT) evaluations such as Conference on Machine Translation (WMT) (Barrault et al., 2021) and the International Conference on Spoken Language Translation (IWSLT) (Anastasopoulos et al., 2022); Barrault et al. (2021); Erdmann et al. (2021); Li et al. (2021); Subramanian et al. (2021); Tran et al. (2021); Wang et al. (2021b); Wei et al. (2021); Di Gangi et al. (2019); Li et al. (2022), and in numerous MT research papers (Junczys-Dowmunt et al., 2016; Shaw et al., 2018; Liu et al., 2018; Zhao et al., 2019; Kim et al., 2021). Apart from NMT, checkpoint averaging also finds applications in Transformer-based automatic speech recognition models (Karita et al., 2019; Dong et al., 2018; Higuchi et al., 2020; Tian et al., 2020; Wang et al., 2020). Despite the popularity of the method, the recipes in each work are rather empirical and do not differ much except in how many and exactly which checkpoints are averaged.

In this work, we revisit the concept of checkpoint averaging and consider several extensions. We examine the straightforward hyperparameters like the number of checkpoints to average, the checkpoint selection strategy and the mean calculation itself. Because the gradient information is often available at the time of checkpointing, we also explore the idea of using this piece of information. Additionally, we experiment with the idea of fine-tuning the interpolation weights of the checkpoints on development data. As reported in countless works, we confirm that the translation performance improvement can be robustly obtained with checkpoint averaging. However, our results suggest that the landscape between the converged checkpoints is rather flat, and it is hard to squeeze out further performance improvements with advanced tricks.

2 Related Work

The idea of combining multiple models for more stable and potentially better prediction is not new in statistical learning ( Dietterich, 2000; Dong et al., 2020). In NMT, ensembling, more specifically, ensembling systems with different architectures is shown to be helpful (Stahlberg et al., 2019; Rosendahl et al., 2019; Zhang and van Genabith, 2019). In contrary, checkpoint averaging uses checkpoints from the same training run with the same neural network (NN) architecture. Compared
3 Methodology

In this section, we discuss extensions to checkpoint averaging considered in this work. An intuitive illustration is shown in Fig.1.  

3.1 Extending Vanilla Checkpoint Averaging

The vanilla checkpointing is straightforward and can be expressed as in Eq.1. Here, \( \theta \) denotes the model parameters and \( \hat{\theta} \) is the averaged parameters. \( k \) is a running index in number of checkpoints \( K \), and \( S \), where \( |S| = K \), is a set of checkpoint indices selected by some specific strategy, e.g. top-\( K \) or last-\( K \). In the vanilla case, \( w_k = \frac{1}{K} \), i.e. uniform weights are used.

\[
\hat{\theta} = \sum_{k \in S} w_k \theta_k
\] (1)

As shown in Eq.2, we further consider non-uniform weights and propose to use softmax-normalized logarithm of development set perplexities (DEVPPL) with temperature \( \tau \) as interpolation weights. We define \( w \) in this way such that it is in the probability space.

\[
w_k = \frac{\exp(-\tau \log \text{DEVPPL}_k)}{\sum_{k' \in S} \exp(-\tau \log \text{DEVPPL}_{k'})}
\] (2)

3.2 Making Use of Gradient Information

Nowadays, NMT models are commonly trained with stated optimizers like Adam (Kingma and Ba, 2015). To provide the "continue-training" utility, the gradients of the most recent batch are therefore also saved. Shown in Eq.3, we can therefore take a further step in the parameter space during checkpoint averaging to make use of this information. Here, \( \eta \) is the step size and \( \frac{1}{K} \sum_{k \in S} \nabla_\theta L(\theta_k) \) is the mean of the gradients stored in the checkpoints.

\[
\hat{\theta} = \sum_{k \in S} w_k \theta_k - \eta \frac{1}{K} \sum_{k \in S} \nabla_\theta L(\theta_k)
\] (3)
3.3 Optimization on Development Data

In addition to using DEVppl, one can optimize the interpolation weights directly on the development data. Specifically, to ensure normalization, we re-parameterize the model with the logits $g_k$ in a softmax function, initialized at zero and updated via one-step gradient descent, with step size $\eta$, on development data to avoid overfitting. As shown in Eq. 4, $w_k$ is the normalized interpolation weights. Note that we refrain from updating the raw model parameters $\theta_k$ from each checkpoint but only update the logits $g_k$. Here, $L$ refers to the cross entropy loss of the re-parametrized NN on the development data.

$$
w_k = \frac{\exp g_k}{\sum_{k' \in S} \exp g_{k'}}
$$

$$g_{k,0} = 0, \quad g_{k,1} = -\eta \nabla_{g_k} L(g_k; \theta_1, ..., \theta_K)$$

(4)

4 Experiments

We re-implement Transformer (Vaswani et al., 2017) using PyTorch (Paszke et al., 2019) and experiment on IWSLT14 German-, Russian-, and Spanish-to-English (de-en, ru-en, es-en), and WMT16 English-to-Romanian, WMT14 English-to-German, WMT19 Chinese-to-English (en-ro, en-de, zh-en) datasets. Due to limited length, we only present representative results on de-en in this section. Results on other language pairs can be found in the appendix and the trends are similar to that reported in this section. Note that, in the experiments below, the test BLEU scores are under consideration. However, we argue that it is not critical because checkpoint averaging is a vetted trick to boost system performance and our goal is to better understand the parameter space and not to obtain "the state-of-the-art" in some public scoreboard.

In Fig. 2, we plot the BLEU (Papineni et al., 2002) scores versus increasing $K$, where the previous $K$ checkpoints starting from the best checkpoint (in terms of DEVppl) are selected. As can be seen, initial BLEU improvements are obtained but as worse and worse checkpoints are included, the BLEU score drops as expected.

In Fig. 3, ranking all checkpoints by their DEVppl, the top-$K$ checkpoints are selected for averaging. Notice that up to $K = 40$, the DEVppl is still around 5, whereas in the last-$K$ case, significantly worse checkpoints (the early checkpoints) are already included in the interpolation. It can be seen that the final BLEU score is much less sensitive to the choice of $K$ in this case. Of course the final performance also relies on the checkpointing settings (e.g. the checkpointing frequency) but it is clear from the comparison that one should prefer to include checkpoints with better DEVppl.

In Fig. 4, we plot the BLEU scores against the temperature $\tau$ in Eq. 2. Here, we select last-$K$ checkpoints as in Fig. 2 to artificially include some bad-performing checkpoints. Two sanity checks can be done here. When $\tau$ is very small, uniform weights are used and the performance is close to the vanilla last-40 case. When $\tau$ is very large, one-hot weights are used and the performance is close to that of the best checkpoint. We observe that using the DEVppl-dependent weights results in similar performance increase compared to the vanilla case, meaning that the checkpoint selections can be automated by selecting a proper $\tau$.

Next, we study how the system performance changes with the step size used in the one-shot gradient update (Fig. 1b and Eq. 3). As shown in Fig. 5, we interpolate three systems selecting top-$K$ checkpoints with $K = 2$, $K = 5$ and $K = 10$, respectively. Here, temperature $\tau = 100$. In line
with the results in Fig.2 and Fig.3, the models with $K = 5$ and $K = 10$ are slightly better than the model with $K = 2$. However, as the step size $\eta$ increases, the BLEU score quickly drops as the averaged model diverges further away from the initial mean. It is clear from the figure that nothing is gained in terms of BLEU during the $\eta$ scan. In other words, these results suggest a very flat surface along the direction of averaged gradients.

To investigate if optimization on the development data would work, we implement Eq.4 and sweep over step size $\eta$. As shown in Fig.6, the gradient update on the weights move the model towards the best checkpoint ($\theta_0$ here), and $w_0$ increases to 1.0 with large enough $\eta$. There is, however, little improvement to be obtained along the path. Note that this is the restricted case (Eq.4) where only interpolation weights are allowed to change and model parameters are not updated.

Given the results so far, it is clear that although a small boost of BLEU score can be robustly obtained in various checkpoint averaging settings, it is hard to squeeze out any further improvement with the extensions considered here. We therefore perform a grid search over the interpolation weights $w_k$ with $K = 3$, to examine the landscape between the checkpoints. Shown in Fig.7, is the intersection of $w_1 + w_2 + w_3 = 1, 0 \leq w_k \leq 1$ in the space of the interpolation weights. From the figure, except when really close to the vertices, i.e. $(w_1, w_2, w_3) = (1, 0, 0)$ or $(0, 1, 0)$ or $(0, 0, 1)$, the surface is rather flat with small fluctuations here and there. Considered together with the previous results, this suggests that the gradient direction in the flat area may be unreliable and not much improvement is to be gained by further tuning the interpolation weights. Of course one could argue that in higher dimensions the surface could look different by moving off of the $\sum_{k \in S} w_k = 1$ hyperplain, but we think it is unlikely to be helpful as Fig.5 is a counter-evidence at hand.

![Figure 4: Last-40 weighted sum on de-en.](image)

![Figure 5: One-shot gradient update of top-K weighted sum with $\tau = 100$ on de-en.](image)

![Figure 6: Optimization of interpolation weights $w_k$ on development data with $K = 2$ on de-en.](image)

![Figure 7: Neighborhood of the top-3 checkpoints on de-en. The hexagons are artifacts from plotting because a denser grid of points is used in the plot than in checkpoint averaging and the dots are colored by querying the nearest neighbor in the checkpoint averaging grid.](image)

5 Conclusion

We consider checkpoint averaging, a simple and effective method in neural machine translation to boost system performance. Specifically, we examine different checkpoint selection strategies, calcu-
late weighted average, make use of gradient information and optimize the interpolation weights. We confirm the robust improvements from checkpoint averaging and that the checkpoint selection can be automated with the weighted average scheme. However, by closely looking at the landscape between the checkpoints, we find the surface to be rather flat and conclude that tuning in the space of the interpolation weights may not be a meaningful direction to squeeze out further improvements.

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Appendix A  Additional Results

As mentioned, only results on de-en are reported in Sec. 4. In this section, further results on the other datasets are shown.

The data statistics are summarized in Tab. 1.

| dataset | vocab | train pairs | test pairs |
|---------|-------|-------------|------------|
| ru-en   | 10k   | 150k        | 5.5k       |
| de-en   | 10k   | 160k        | 6.8k       |
| es-en   | 10k   | 170k        | 5.6k       |
| en-ro   | 20k   | 0.6M        | 2.0k       |
| en-de   | 44k   | 4.0M        | 3.0k       |
| zh-en   | 47k   | 17.0M       | 4.0k       |

Table 1: Statistics of the datasets.

Fig. 8 shows the last-\( K \) simple mean BLEU and DEVPL curves on ru-en. As can be seen, the degradation of the interpolated models starts to happen when checkpoints with worse perplexities are included into the mixture.

In Fig. 11, we plot the neighborhood of three checkpoints on en-de. Here, one good checkpoint and two relatively worse checkpoints are included to show the difference compared with Fig. 7. As can be seen, the area near the good checkpoint is overall brighter and the region closer to the two worse checkpoints is darker. Although noise is visible from the plot, it is clear that there is not a specific optima where the BLEU score of the checkpoint-averaged model is significantly better.

Earlier in Fig. 4, we select last-40 checkpoints to include some bad-performing checkpoints. Here, the top-10 checkpoints are selected and it is clear from the figure that there is not much to be gained when tuning the interpolation weight via the temperature hyperparameter \( \tau \).
In Fig. 12, we further plot the neighborhood of three checkpoints on zh-en. Here, two good checkpoint and one relatively worse checkpoint are included to show the difference compared with Fig. 7. From the figure, it can be seen that, overall, the interpolation closer to the two good checkpoints is better than when the worse checkpoint has a larger weight. Although +0.4% absolute BLEU score improvement is possible, there is no further improvement to be gained when tuning the interpolation weights.

Figure 12: Neighborhood of three checkpoints on zh-en. Two good checkpoint and one relatively worse checkpoint are included to show the difference compared with Fig. 7. The hexagons are artifacts from plotting because a denser grid of points is used in the plot than in checkpoint averaging and the dots are colored by querying the nearest neighbor in the checkpoint averaging grid.