AlterSGD: Finding Flat Minima for Continual Learning by Alternative Training

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Abstract

Deep neural networks suffer from catastrophic forgetting when learning multiple knowledge sequentially, and a growing number of approaches have been proposed to mitigate this problem. Some of these methods achieved considerable performance by associating the flat local minima with forgetting mitigation in continual learning. However, they inevitably need (1) tedious hyperparameters tuning, and (2) additional computational cost. To alleviate these problems, in this paper, we propose a simple yet effective optimization method, called AlterSGD, to search for a flat minima in the loss landscape. In AlterSGD, we conduct gradient descent and ascent alternatively when the network tends to converge at each session of learning new knowledge. Moreover, we theoretically prove that such a strategy can encourage the optimization to converge to a flat minima. We verify AlterSGD on continual learning benchmark for semantic segmentation and the empirical results show that we can significantly mitigate the forgetting and outperform the state-of-the-art methods with a large margin under challenging continual learning protocols.

1. Introduction

Recently, deep neural networks (DNNs) became the dominant paradigm in various real-world applications, for example, image classification [12, 18, 17, 16, 19], semantic segmentation [43, 32, 27], object detection [39, 15, 38, 46, 35]. Typically, the DNN is trained offline by a huge data set sampled independently from the real-world, and it is commonly not feasible when we counter new data which is out-of-distribution with respect to the old data. Therefore, many areas in the Artificial Intelligence seek for the solution by learning new knowledge incrementally without forgetting the learned ones, also known as the continual learning (CL).

In this paper, we study the class continual learning (CCL), where we will incrementally update the DNN to learn a new set of classes disjointed with the learned classes. To reflect the sequential manner of the CCL, we use the term session to represent the learning step of each set of classes. For a new session, the corresponding training data is disjointed with all the previous one, which means the new dataset may not have any trained image from previous sessions. However, this is challenging for the DNN since it has intrinsic catastrophic forgetting problem when the DNN is updated incrementally, as pointed in [23]. In the CCL, the model is trained to learn a new session sequentially with new data which is not seen in previous sessions. At each session, the model needs to adapt to the changes from the new data’s distribution, which may potentially lead to the forgetting of the seen class.

Figure 1. Illustration of AlterSGD. After the normal training of current session tends to converge, AlterSGD conducts gradient descent and ascent alternatively. We show in Theorem 1 that AlterSGD is approximately equal to minimizing $\|\nabla_{\theta} L(\theta)\|^2_2$, where $L$ represents the loss function. The smaller gradient norm $\|\nabla_{\theta} L(\theta)\|^2_2$ represents flatter the region, e.g., region A has smaller gradient norm than region B. Therefore, AlterSGD tends to converge to a region with a flatter minima, e.g., region A.

*Equal contribution. ♣ Technical report.
On the other hand, in the non-continual learning scenario, i.e., learning all the classes at once, we know that when the batch size is too small, the distribution of each batch may extremely vary and cause the shifting of the loss landscape, leading to lousy generalization after training [22, 26]. One of the solutions for mitigating the distribution variation problem is to seek the flat-minimal region in the loss landscape [22, 11, 24, 21], as illustrated in Figure 2. Similarly, in the context of continual learning, such distribution variation will also happen because the training set of current session is disjoint with all the previous data. Hence, we attempt to search for the flat minima in order to potentially benefit the CL. Actually, there are some concurrent works also associating the flat local minimal with forgetting mitigation in CL from different viewpoints (e.g., in CPR [3] and stable SGD [31]). They both verify that maintaining flat local minima can further mitigate the forgetting issue in CL. However, these methods have the disadvantages as follows: (1) **Tedious hyperparameters tuning.** As they may include different regularization methods, it is unavoidable to finely tune the hyperparameter for different vision tasks (e.g., image classification, semantic segmentation) and different continual learning protocols. As pointed out in CPR, they need totally different hyperparameter even for different protocols in the same benchmark dataset (e.g., CIFAR100), which will be laborious and lack of principle to readily make the method work. (2) **Additional computational cost.** Since the additional regularization methods are existing throughout the new class training, it may inevitably introduce much more computation during training.

Therefore, in this paper, we propose method called AlterSGD: When the network tends to converge at each session, we alternate the gradient direction between descent and ascent such that we can search for the flat local minimal region before training on the next new session. Compared to the existing method, our method is efficient since the alternating of the gradient may not include additional computation and time. Moreover, we theoretically prove that such a strategy can encourage the optimization to converge to a flat minima.

Finally, we verify our method on class continual learning (CCL) for semantic segmentation and the empirical results show that we can significantly mitigate the forgetting of the classes learned in the initial session, and outperform the state-of-the-art (SOTA) for a large margin under challenging protocols. To summarize, the contributions of this paper include:

- We propose a simple and effective method to search for a flat local minimal region such that the forgetting of the learned class can be further mitigated on CCL.
- We provide the theoretical insight about why the AlterSGD may encourage the optimization to converge to the flat minima. We also conduct extensive experiments to verify the effectiveness of our method on CCL for semantic segmentation.

2. Related Works

2.1. Continual Learning

Aiming to mitigate the *Catastrophic Forgetting* problem, continual learning has been widely discussed on image classification [23, 7], which can be divided into replay methods, parameter isolation methods and regularization-based methods [8]. Replay methods [34, 20, 28] utilize data samples in the previous session as either the network inputs or the constraints for optimization in the new session. In parameter isolation methods [40, 29], model parameters are independent for each session, and one can freeze parameters for the previous session to avoid forgetting. Regularization-based methods [4, 25, 42, 23] mostly introduce an extra regularization term in the objective function, so as to strengthen the previously-learned knowledge when training on new session.

Another type of method is promoting wide local minima in continual learning. CPR [3] proves that maximizing the entropy of the output probability can also improve the accuracy for continual learning. In addition, motivated by the importance of learning stability, stable SGD [31] forms the suitable training regimes to widen the local minima in each learning session.

Despite the progress on image classification, recent works further investigate continual learning on object detection [37] and semantic segmentation [2] with knowledge distillation. In particular, the latter one introduces two novel loss terms to mitigate semantic distribution shift within the background.

2.2. Semantic Segmentation

With the advancement of Fully Convolution Network (FCN) [27], recent deep-learning-based approaches on se-
3. Proposed Method

In this section, we systematically introduce our proposed AlterSGD for continual learning as outlined in Section 1. The workflow of AlterSGD consists of two phases, the normal training and the alternative training. In the first phase, the model parameters are optimized by normal gradient descent for learning new classes while the second phase is to alternatively conduct gradient descent and ascent such that the optimizer searches for a flat local minima. We summarize our method in Algorithm 1.

We consider a continual learning problem with $S$ sessions. The empirical loss on the training set at the $s$th session is denoted by $L$. We denote $\theta_0$ as the model parameters from the previous session, i.e., $(s-1)$th session. Our objective is to learn new classes effectively and simultaneously mitigate forgetting the old classes. Let $T$ be the number of total iterations for parameter update and $p$ be the ratio for normal training. Now we introduce the training details for each phase as follows:

**Normal training phase.** In the first phase, the model is trained to learn the new classes at the current session. Therefore, the loss function $L$ is optimized by the normal gradient descent for the first $\lfloor pT \rfloor$ iterations, i.e.,

$$\theta_t = \theta_{t-1} - \eta \cdot \nabla_\theta L(\theta_{t-1}),$$

where $t = 1, 2, \ldots, \lfloor pT \rfloor$, $\lfloor \cdot \rfloor$ denotes the floor function which outputs the greatest integer less than or equal to the input, and $\eta$ is learning rate.

**Alternative training phase.** Though gradient descent converges to a local minima for learning a new session after the first phase, it may fall into the sharp minima which possibly aggravate catastrophic forgetting of previous sessions. In the second phase, the proposed AlterSGD utilizes the alternative gradient descent and ascent update rule for $T - \lfloor pT \rfloor$ iterations, i.e.,

$$\begin{align*}
\theta_t &= \theta_{t-1} - \eta \cdot \nabla_\theta L(\theta_{t-1}), \\
\theta_{t+1} &= \theta_t + \eta \cdot \nabla_\theta L(\theta_t),
\end{align*}$$

where $t = \lfloor pT \rfloor + 1, \lfloor pT \rfloor + 3, \ldots, T$.

Intuitively, the repeat oscillation by conducting gradient descent and ascent in the parameter space has potential to enable AlterSGD to escape the sharp local minima and approach an equilibrium state where the landscape of the loss function $L$ is relatively flat. In fact, we show in Theorem 1 that the update rule in Eq. (2) is approximately equal to minimizing $\|\nabla_\theta L(\theta)\|^2_2$, which means AlterSGD prefers a small norm of $\nabla_\theta L(\theta)$ during alternative training.

**Theorem 1.** The update rule of the alternative training in Eq. (2) is approximately equal to minimizing the square of $\nabla_\theta L(\theta)$, i.e., $\|\nabla_\theta L(\theta)\|^2_2$, by gradient descent with learning rate $\frac{\eta^2}{2}$.

**Proof.** From the update rule (2), we have

$$\begin{align*}
\theta_{t+1} &= \theta_t + \eta \cdot \nabla_\theta L(\theta_t) \\
&= \theta_{t-1} - \eta \nabla_\theta L(\theta_{t-1}) + \eta \nabla_\theta L(\theta_{t-1} - \eta \nabla_\theta L(\theta_{t-1})).
\end{align*}$$

Since $\eta$ is small, $\nabla_\theta L(\theta_{t-1} - \eta \nabla_\theta L(\theta_{t-1}))$ can be approximated by its Taylor expansion. Then we have

$$\begin{align*}
\theta_{t+1} &\approx \theta_{t-1} - \eta \nabla_\theta L(\theta_{t-1}) + \eta \nabla_\theta L(\theta_{t-1}) \\
&\quad - \eta \cdot \nabla^2_\theta L(\theta_{t-1}) \nabla_\theta L(\theta_{t-1}).
\end{align*}$$

By (4), $\theta_{t+1} \approx \theta_{t-1} - \frac{\eta^2}{2} \nabla_\theta L(\theta_{t-1})$, which indicates the update rule (2) is approximately equal to minimizing $\|\nabla_\theta L(\theta)\|^2_2$. \qed

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**Algorithm 1** AlterSGD training at the $s$th session

**Input:** The network parameters from the $(s-1)$th session, $\theta_0$; Loss function $L(\cdot)$; Learning rate $\eta$; The number of iterations $T$; The alternative ratio $p$.

**Output:** The network parameters at the $s$th session.

```
1: for $t$ from 1 to $\lfloor pT \rfloor$ do
2:   $\theta_t = \theta_{t-1} - \eta \cdot \nabla_\theta L(\theta_{t-1})$
3: end for
4: $\theta_{t+1} = \theta_t + \eta \cdot \nabla_\theta L(\theta_t)$
5: $\theta_T = \theta_{T-1} - \eta \cdot \nabla_\theta L(\theta_{T-1})$
6: $\theta_{T+1} = \theta_T + \eta \cdot \nabla_\theta L(\theta_T)$
7: return $\theta_T$
```

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Now we illustrate the behavior of AlterSGD using the conclusion of Theorem 1 and how it is related to our goal: As shown in Figure 1, both region A and B have a local minima but the local minima in region A is flatter than that in region B. Also, since the slope of region B is steeper than region A, the norm of gradient in region A is smaller than that in region B. Finally, AlterSGD tends to converge to region A, a flatter minima, where the norm of gradient is smaller.

4. Experiments

In this section, we demonstrate the effectiveness of our proposed AlterSGD as presented in Algorithm 1. The performance is evaluated on the continual class learning (CCL) in semantic segmentation. To compare with popular methods on CCL, we use the baselines as suggested in [30], including Elastic Weight Consolidation (EWC) [23], Path Integral (PI) [42], Riemannian Walks (RW) [4], Learning without Forgetting (LwF) [25], LwF-MC [34], ILT[30], and MiB [2]. To the best of our knowledge, MiB is the state-of-the-art (SOTA) technique on CCL in semantic segmentation, and we show that AlterSGD can even outperform MiB.

The regularization-based methods [22, 32, 4, 30, 2] mitigate forgetting by imposing a regularization to restrain the model parameters. At the $s$th session, we denote $D_s$ as the training set with $|D_s|$ samples and $\theta^s$ as the model parameters. The objective function of regularization-based methods can be formulated as,

$$\frac{1}{|D_s|} \sum_{(x,y^g) \in D_s} \left( \ell_{seg}^g(x, y^g) + \lambda_{reg} R^s(x) \right),$$

(5)

where $\ell_{seg}^g(\cdot)$ and $R^s(\cdot)$ represent the segmentation loss and the regularization term respectively, $y^g$ is the ground-truth segmentation map of the input image $x$, and $\lambda_{reg}$ is the regularization coefficient. In our experiments, we apply AlterSGD to Eq. (5) on the supervised loss term $\ell_{seg}^g(\cdot)$, which utilizes the update rule as follows,

$$\begin{align*}
\theta^s_t &= \theta^s_{t-1} - \eta \cdot \nabla_{\theta^s} \left[ \ell_{seg}^g \left( \theta^s_{t-1} \right) + \lambda_{reg} R^s \left( \theta^s_{t-1} \right) \right], \\
\theta^s_{t+1} &= \theta^s_t - \eta \cdot \nabla_{\theta^s} \left[ \ell_{seg}^g \left( \theta^s_t \right) + \lambda_{reg} R^s \left( \theta^s_t \right) \right]
\end{align*}$$

(6)

where $\ell_{seg}^g(\theta^s_t) = \frac{1}{|D_s|} \sum_{(x,y^g) \in D_s} \ell_{seg}^g(x, y^g)$, and $R^s(\theta^s_t) = \frac{1}{|D_s|} \sum_{(x,y^g) \in D_s} R^s(x)$.

Dataset & settings. We evaluate the performance on the benchmark dataset for semantic segmentation, PASCAL VOC 2012 [9]. PASCAL VOC contains 20 foreground semantic classes and a background class. For each experiment, we report the mean Intersection-over-Union (mIoU) in percentage on the validation set. The CCL experiments are conducted on 15-1 setting where the model is trained on first 15 classes in the initial session and then trained on another 5 classes sequentially. For each session, we only provide the label of the classes we will learn in the current session and the learned classes from the previous sessions will be masked as background. Following the settings in [2], in the initial session, the model is trained for 30 epochs with initial learning rate 0.01 to well-train the 15 classes; For the 5 continual sessions, the learning rate is changed to 0.001 and the model is still trained for 30 epochs in each session. We choose $\lambda_{reg}$ to be 100 according to [2] and choose $p = 25/30$. As the old data is not allowed to be accessed during new classes training, therefore we do not consider the replay method for comparison as they may store the old data.

Experimental results. Table 1 displays the result for the first 15 classes using different methods, and Table 2 presents the result of the last 5 classes and the overall results. To fairly compare our method with MiB [2], we use the same pretrained model obtained from the initial session, and use it to continually learn for five sessions under MiB [2] and our method respectively, reported in Table 1 and Table 2. In Table 1 and Table 2, the regularization-based methods, like EWC [23], PI [42], RW [4], LwF [25], LwF-MC [34], ILT[30] obtain the extremely poor results. The mIoU of both the first 15 classes and the last 5 classes are (closed to zero in most classes), which means that these methods are not directly effective in the continual learning for semantic segmentation, though they perform well on image classification.

Compared with MiB, AlterSGD achieves comparable results on the newly learned classes. Moreover, AlterSGD significantly outperforms MiB on the first 1-15 classes. On average over the first 15 classes, we improve the mIoU of MiB from 42.4 to 52.7, which means AlterSGD is capable of mitigating forgetting effectively. To sum up, the proposed AlterSGD is able to achieve satisfactory results on both newly learned session and mitigating forgetting.

In Figure 3, we show a qualitative analysis through visualizing the predicted segmentation map of the test images under MiB and our method respectively. Although MiB is the SOTA technique on CCL in semantic segmentation, from the visualization results we can observe that there is still a large segmentation error compared with ground-truth image, while this error can be significantly alleviated by the AlterSGD.

5. Analysis

5.1. Varying the alternative ratio $p$

In Algorithm 1, we use the hyperparameter $p$ to control the ratio of the length of normal training in each session. To study the appropriate $p$ for AlterSGD, we conduct CCL
Table 1. Per class mean IoU on 15-1 setting of PASCAL VOC for the first 15 classes for different continual learning methods.

| Method | aero | bike | bird | boat | bottle | bus | car | cat | chair | cow | table | dog | horse | mbike | person |
|--------|------|------|------|------|--------|-----|-----|-----|-------|-----|-------|-----|-------|-------|--------|
| FT     | 0.3  | 0.0  | 0.0  | 2.5  | 0.0    | 0.0 | 0.0 | 0.0 | 0.0   | 0.0 | 0.0   | 0.0 | 0.0   | 0.0   | 0.0    |
| PI     | 0.0  | 0.0  | 0.0  | 0.0  | 0.0    | 0.0 | 0.0 | 0.0 | 0.0   | 0.0 | 0.0   | 0.0 | 0.0   | 0.0   | 0.0    |
| EWC    | 0.0  | 0.0  | 0.0  | 1.0  | 0.0    | 0.0 | 0.0 | 0.0 | 0.0   | 0.0 | 0.0   | 0.0 | 0.0   | 3.6   | 0.0    |
| RW     | 0.0  | 0.0  | 0.0  | 0.2  | 0.0    | 0.0 | 0.0 | 0.0 | 0.0   | 0.0 | 0.0   | 0.0 | 0.0   | 2.2   | 0.0    |
| LwF    | 0.0  | 0.0  | 0.0  | 0.0  | 0.0    | 0.0 | 0.0 | 0.0 | 0.0   | 0.0 | 0.0   | 0.0 | 0.0   | 0.0   | 0.0    |
| LwF-MC | 0.0  | 0.0  | 0.0  | 0.0  | 0.0    | 0.0 | 0.0 | 0.0 | 0.0   | 0.0 | 0.0   | 0.0 | 0.0   | 0.0   | 0.0    |
| ILT    | 3.7  | 0.0  | 2.9  | 0.0  | 12.8   | 0.0 | 0.1 | 0.0 | 0.0   | 21.2| 0.1   | 0.4  | 0.6   | 13.6  |        |
| MiB    | 53.8 | 38.7 | 35.5 | 25.9 | 45.3   | 71.5| 71.5| 0.3 | 22.6  | 12.6 | 62.6  | 52.3 | 48.8  | 79.8  |        |
| Ours   | 64.6 | 39.4 | 44.5 | 39.1 | 56.4   | 78.5| 74.5| 2.4 | 51.7  | 14.2 | 66.2  | 60.2 | 62.5  | 78.6  |        |
| Joint  | 90.2 | 42.2 | 89.5 | 69.1 | 82.3   | 90.0| 94.2| 39.2| 87.6  | 56.4 | 91.2  | 86.8 | 88.0  | 86.8  |        |

Figure 3. Visualization results on the 15-1 setting of PASCAL VOC test set using MiB and AlterSGD (ours).

Table 2. Per class mean IoU for the last 5 classes.

| Method | plant | sheep | sofa | train | tv     | 1-15  | 16-20 | all     |
|--------|-------|-------|------|-------|--------|-------|-------|---------|
| FT     | 0.0   | 0.0   | 0.0  | 8.8   | 0.2    | 1.8   | 0.6   |         |
| PI     | 0.0   | 0.0   | 0.0  | 8.6   | 0.0    | 1.8   | 0.4   |         |
| EWC    | 0.0   | 0.0   | 7.4  | 7.4   | 0.3    | 1.3   |       |         |
| RW     | 0.0   | 0.0   | 8.2  | 8.2   | 0.2    | 1.5   |       |         |
| LwF    | 0.0   | 0.0   | 7.9  | 7.9   | 0.8    | 1.5   |       |         |
| LwF-MC | 0.0   | 0.0   | 11.9 | 11.0  | 4.5    | 5.2   |       |         |
| ILT    | 0.0   | 0.0   | 8.3  | 8.5   | 3.7    | 4.2   |       |         |
| MiB    | 30.9  | 11.4  | 11.8 | 26.1  | 30.0   |       |       |         |
| Ours   | 36.1  | 13.9  | 13.7 | 30.7  | 40.1   |       |       |         |
| Joint  | 36.3  | 13.9  | 13.7 | 30.7  | 40.1   |       |       |         |

Figure 4. Visualization results on 15-1 setting of PASCAL VOC test set using AlterSGD (ours).

Table 3. Mean IoUs of PASCAL VOC for different regularization coefficient $\lambda_{reg}$.

| $\lambda_{reg}$ | 1-15  | 16-20 | all   |
|-----------------|-------|-------|-------|
| MiB Ours        |       |       |       |
| $10^0$          | 30.9  | 11.4  | 11.8  |
| $10^1$          | 36.3  | 13.9  | 13.7  |
| $10^2$          | 42.4  | 12.6  | 12.9  |
| $10^3$          | 16.8  | 5.6   | 5.6   |

Table 3. Mean IoUs of PASCAL VOC for different regularization coefficient $\lambda_{reg}$.

| $\lambda_{reg}$ | 1-15  | 16-20 | all   |
|-----------------|-------|-------|-------|
| MiB Ours        |       |       |       |
| $10^0$          | 30.9  | 11.4  | 11.8  |
| $10^1$          | 36.3  | 13.9  | 13.7  |
| $10^2$          | 42.4  | 12.6  | 12.9  |
| $10^3$          | 16.8  | 5.6   | 5.6   |

on 15-1 setting of PASCAL VOC for different ratio $p$. The number of epoch is 30 for each session and we present the results of $p = 5/30, 10/30, \ldots, 30/30$ for conducting alternative training phase after the 5, 10, \ldots, 30 epoch respectively. When $p = 30/30$, AlterSGD only contains the normal training phase.

When $p$ is small (like $p = 5/30, 10/30$), the mIoUs of all 20 classes are almost zero. Besides, when $p = 15/30$, though mIoUs of the first 15 classes are 14.1, the mIoUs of the last 5 classes are still almost 0 (see Figure 4).

These phenomena reveal that $p$ should not be too small. This is because when $p$ is small, on one hand, the model...
does not have enough epochs to train the model in the normal training phase, which is not conducive to the learning of the current class. On the other hand, according to Theorem 1, the optimizer almost always searches for a relatively flat local minima, which affects finding a small enough local minima for the current class. Therefore, we suggest to start alternative training phase only after sufficient normal training, i.e., the training of the current class is close to convergence. Generally, \( p \) can be selected in \([0.8, 0.9]\).

### 5.2. Varying the penalty coefficient \( \lambda_{reg} \)

The regularization items \( R^{\delta p} (\cdot) \) in (6) are usually designed to maintain the performance of the old classes. The penalty coefficient \( \lambda_{reg} \) represents the intensity of the penalty, which has a great impact on the performance of regularization methods for continual learning [14]. In this section, we study the influence of \( \lambda_{reg} \) in AlterSGD. Table 3 displays results of \( \lambda_{reg} \) of different magnitude.

Since AlterSGD is applied to MiB, the trend of performance change of AlterSGD and MiB presented in Table 3 is consistent, i.e., the large mIoU of MiB, the larger mIoU of AlterSGD. Further, under different choose of \( \lambda_{reg} \), AlterSGD can consistently improve the performance. Specifically, AlterSGD significantly outperforms MiB on the first 15 classes and maintains the performance of last 5 classes.

| \( \lambda_a \) \( \lambda_b \) | 1-15 | 16-20 | all |
|---|---|---|---|
| 10^0 | 36.1 | 45.2 | 55.1 | 18.4 | 11.8 | 14.4 | 9.5 | 3.9 | 30.0 | 37.5 | 43.7 | 14.8 |
| 10^1 | 46.7 | 48.9 | 55.0 | 17.7 | 11.9 | 13.7 | 9.7 | 4.2 | 38.0 | 40.1 | 43.7 | 14.4 |
| 10^2 | 46.2 | 53.2 | 52.7 | 17.2 | 9.6 | 14.8 | 12.9 | 4.9 | 37.1 | 43.6 | 42.7 | 14.1 |
| 10^3 | 42.3 | 51.1 | 49.0 | 19.5 | 2.3 | 8.5 | 13.7 | 5.6 | 32.3 | 40.5 | 42.0 | 16.0 |

### 5.3. Varying \( \lambda_{reg} \) in the training phase

In our original setting in Eq. 6, \( \lambda_{reg} \) is the same for gradient descent and ascent. In this section, we explore the impact of using separately different \( \lambda_{reg} \) for gradient ascent and gradient descent. Eq. (6) can be rewritten as

\[
\begin{align*}
\theta_{t+1}^s &= \theta_{t}^s - \eta \cdot \nabla_{\theta} [ R(\theta_t^s) + \lambda_a R^a(\theta_{t-1}^s) ] , \\
\theta_{t+1}^b &= \theta_{t}^b - \eta \cdot \nabla_{\theta} [ R(\theta_t^b) + \lambda_b R^b(\theta_{t-1}^b) ] 
\end{align*}
\]

(7)

Table 4 shows the results of different combination of \( \lambda_a \) and \( \lambda_b \). The different combination of \( (\lambda_a, \lambda_b) \) for gradient ascent and gradient descent can indeed bring some performance improvements. However, compared with Table 3 where \( \lambda_a = \lambda_b \), the improvements are marginal. It suggests that we can keep the same \( \lambda_{reg} \) in AlterSGD when using gradient ascent and gradient descent alternatively.

### 6. Conclusion

In this paper, we study the class continual learning on semantic segmentation under the setting that the old data is inaccessible. In particular, we propose a simple and effective method to search for a flat local minimal region such that the forgetting problem of the learned class can be mitigated during the learning of new session. Moreover, we provide the theoretical insight to illustrate that our method can encourage the optimization to converge toward the flat minima. The extensive experiments verify the effectiveness of our method on CCL for semantic segmentation.

### References

[1] Vijay Badrinarayanan, Alex Kendall, and Roberto Cipolla. Segnet: A deep convolutional encoder-decoder architecture for image segmentation. *IEEE transactions on pattern analysis and machine intelligence*, 39(12):2481–2495, 2017.

[2] Fabio Cermelli, Massimiliano Mancini, Samuel Rota Bulò, Elisa Ricci, and Barbara Caputo. Modeling the background for incremental learning in semantic segmentation. In *Computer Vision and Pattern Recognition (CVPR)*, June 2020.
[3] Sungmin Cha, Hsiang Hsu, Taebaek Hwang, Flavio Calmon, and Taesup Moon. Classifier-projection regularization for continual learning. In International Conference on Learning Representations, 2021. 2

[4] Arslan Chaudhry, Puneet K Dokania, Thalaiyasingam Ajakan, and Philip HS Torr. Riemannian walk for incremental learning: Understanding forgetting and intransigence. In Proceedings of the European Conference on Computer Vision (ECCV), pages 532–547, 2018. 2, 4

[5] Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. IEEE transactions on pattern analysis and machine intelligence, 40(4):834–848, 2017. 3

[6] Liang-Chieh Chen, George Papandreou, Florian Schroff, and Hartwig Adam. Rethinking atrous convolution for semantic image segmentation. arXiv preprint arXiv:1706.05587, 2017. 3

[7] Matthias De Lange, Rahaf Aljundi, Marc Masana, Sarah Parisot, Xu Jia, Ales Leonardis, Gregory Slabaugh, and Tinne Tuytelaars. Continual learning: A comparative study on how to defy forgetting in classification tasks. arXiv preprint arXiv:1909.08383, 2(6), 2019. 2

[8] Matthias Delange, Rahaf Aljundi, Marc Masana, Sarah Parisot, Xu Jia, Ales Leonardis, Greg Slabaugh, and Tinne Tuytelaars. A continual learning survey: Defying forgetting in classification tasks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021. 2

[9] M. Everingham, S. M. A. Eslami, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman. The pascal visual object classes challenge: A retrospective. International Journal of Computer Vision, 111(1):98–136, Jan. 2015. 3, 4

[10] Jun Fu, Jing Liu, Jie Jiang, Yong Li, Yongjun Bao, and Hanqing Lu. Scene segmentation with dual relation-aware attention network. IEEE Transactions on Neural Networks and Learning Systems, 2020. 3

[11] Haowei He, Gao Huang, and Yang Yuan. Asymmetric valleys: Beyond sharp and flat local minima. arXiv preprint arXiv:1902.00744, 2019. 2

[12] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2016. 1

[13] Wei He, Meiqing Wu, Mingfu Liang, and Siew-Kei Lam. Cap: Context-aware pruning for semantic segmentation. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), pages 960–969, January 2021. 3

[14] Yen-Chang Hsu, Yen-Cheng Liu, Anita Ramasamy, and Zsolt Kira. Re-evaluating continual learning scenarios: A categorization and case for strong baselines. arXiv preprint arXiv:1810.12488, 2018. 6

[15] Han Hu, Jiayuan Gu, Zheng Zhang, Jifeng Dai, and Yichen Wei. Relation networks for object detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 3588–3597, 2018. 1

[16] Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 7132–7141, 2018. 1

[17] Zhongzhan Huang, Senwei Liang, Mingfu Liang, Wei He, and Haizhao Yang. Efficient attention network: Accelerate attention by searching where to plug. arXiv preprint arXiv:2011.14058, 2020. 1

[18] Zhongzhan Huang, Senwei Liang, Mingfu Liang, and Haizhao Yang. Dianet: Dense-and-implicit attention network. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 4206–4214, 2020. 1

[19] Zhongzhan Huang, Xinjiang Wang, and Ping Luo. Convolution-weight-distribution assumption: Rethinking the criteria of channel pruning. arXiv preprint arXiv:2004.11627, 2020. 1

[20] David Isele and Akansel Cosgun. Selective experience replay for lifelong learning. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 32, 2018. 2

[21] Zhiwei Jia and Hao Su. Information-theoretic local minima characterization and regularization. In International Conference on Machine Learning, pages 4773–4783. PMLR, 2020. 2

[22] Nitish Shirish Keskar, Dheevatsa Mudigere, Jorge Nocedal, Mikhail Smelyanskiy, and Ping Tak Peter Tang. On large-batch training for deep learning: Generalization gap and sharp minima. arXiv preprint arXiv:1609.04836, 2016. 2

[23] James Kirkpatrick, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, et al. Overcoming catastrophic forgetting in neural networks. Proceedings of the national academy of sciences, 2017. 1, 2, 4

[24] Bobby Kleinberg, Yuanzhi Li, and Yang Yuan. An alternative view: When does sgd escape local min-
ima? In *International Conference on Machine Learning*, pages 2698–2707. PMLR, 2018. 2

[25] Zhizhong Li and Derek Hoiem. Learning without forgetting. *IEEE transactions on pattern analysis and machine intelligence*, 40(12):2935–2947, 2017. 2, 4

[26] Senwei Liang, Zhongzhan Huang, Mingfu Liang, and Haizhao Yang. Instance enhancement batch normalization: An adaptive regulator of batch noise. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 4819–4827, 2020. 2

[27] Jonathan Long, Evan Shelhamer, and Trevor Darrell. Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3431–3440, 2015. 1, 2

[28] David Lopez-Paz and Marc’Aurelio Ranzato. Gradient episodic memory for continual learning. arXiv preprint arXiv:1706.08840, 2017. 2

[29] Arun Mallya, Dillon Davis, and Svetlana Lazebnik. Piggyback: Adapting a single network to multiple tasks by learning to mask weights. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 67–82, 2018. 2

[30] Umberto Michieli and Pietro Zanuttigh. Incremental learning techniques for semantic segmentation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops*, pages 0–0, 2019. 4

[31] Seyed Iman Mirzadeh, Mehrdad Furajtabar, Razvan Pascanu, and Hassan Ghasemzadeh. Understanding the role of training regimes in continual learning. In *Advances in Neural Information Processing Systems*, volume 33, pages 7308–7320, 2020. 2

[32] Hyeonwoo Noh, Seunghoon Hong, and Bohyung Han. Learning deconvolution network for semantic segmentation. In *Proceedings of the IEEE international conference on computer vision*, pages 1520–1528, 2015. 1

[33] Adam Paszke, Abhishek Chaurasia, Sangpil Kim, and Eugenio Culurciello. Enet: A deep neural network architecture for real-time semantic segmentation. arXiv preprint arXiv:1606.02147, 2016. 3

[34] Sylvestre-Alvise Rebuffi, Alexander Kolesnikov, Georg Sperl, and Christoph H Lampert. icarl: Incremental classifier and representation learning. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 2001–2010, 2017. 2, 4

[35] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 779–788, 2016. 1

[36] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015. 3

[37] Konstantin Shmelkov, Cordelia Schmid, and Karteek Alahari. Incremental learning of object detectors without catastrophic forgetting. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 3400–3409, 2017. 2

[38] Christian Szegedy, Alexander Toshev, and Dumitru Erhan. Deep neural networks for object detection. 2013. 1

[39] Paul Viola, Michael Jones, et al. Robust real-time object detection. *International journal of computer vision*, 4(34-47):4, 2001. 1

[40] Ju Xu and Zhanxing Zhu. Reinforced continual learning. arXiv preprint arXiv:1805.12369, 2018. 2

[41] Yuhui Yuan and Jingdong Wang. Ocnet: Object context network for scene parsing. 2018. 3

[42] Friedemann Zenke, Ben Poole, and Surya Ganguli. Continual learning through synaptic intelligence. In *International Conference on Machine Learning*, pages 3987–3995. PMLR, 2017. 2, 4

[43] Hang Zhang, Kristin Dana, Jianping Shi, Zhongyue Zhang, Xiaogang Wang, Ambrish Tyagi, and Amit Agrawal. Context encoding for semantic segmentation. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 7151–7160, 2018. 1

[44] Hengshuang Zhao, Xiaojuan Qi, Xiaoyong Shen, Jianping Shi, and Jiaya Jia. Icnet for real-time semantic segmentation on high-resolution images. In *ECCV*, 2018. 3

[45] Hengshuang Zhao, Jianping Shi, Xiaojuan Qi, Xiaogang Wang, and Jiaya Jia. Pyramid scene parsing network. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2881–2890, 2017. 3

[46] Zhong-Qiu Zhao, Peng Zheng, Shou-tao Xu, and Xindong Wu. Object detection with deep learning: A review. *IEEE transactions on neural networks and learning systems*, 30(11):3212–3232, 2019. 1

[47] Bolei Zhou, Hang Zhao, Xavier Puig, Sanja Fidler, Adela Barriuso, and Antonio Torralba. Scene parsing through ade20k dataset. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2017. 3