Small-Group Learning, with Application to Neural Architecture Search

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Abstract
Small-group learning is a broadly used methodology in human learning and shows great effectiveness in improving learning outcomes: a small group of students work together towards the same learning objective, where they express their understanding of a topic to their peers, compare their ideas, and help each other to trouble-shoot problems. We are interested in investigating whether this powerful learning technique can be borrowed from humans to improve the learning abilities of machines. We propose a novel learning approach called small-group learning (SGL). In our approach, each learner uses its intermediately trained model to generate a pseudo-labeled dataset and re-trains its model using pseudo-labeled datasets generated by other learners. We propose a multi-level optimization framework to formulate SGL which involves three learning stages: learners train their network weights independently; learners train their network weights collaboratively via mutual pseudo-labeling; learners improve their architectures by minimizing validation losses. We develop an efficient algorithm to solve the SGL problem. We apply our approach to neural architecture search and achieve significant improvement on CIFAR-100, CIFAR-10, and ImageNet.

1. Introduction
In human learning, an effective and widely used methodology for improving learning outcome is small group learning (SGL). In SGL, a small group of students work together towards the same learning objective, where they express their understanding of a topic to their peers, compare their ideas, and help each other to trouble-shoot problems. SGL can effectively facilitate deeper and more meaningful learning.

Inspired by this collaboration-driven learning technique of humans, we are interested in investigating whether this methodology is helpful for improving machine learning as well. We propose a novel learning framework – small-group learning (SGL). In this framework, there are a group of learner models. They solve the same learning task $T$. Without loss of generality, we assume $T$ is classification while noting that our framework can be applied to other tasks as well. Each learner $k$ has a learnable neural architecture $A_k$ and two sets of network weights $W_k$ and $V_k$. The architectures and network weights of different learners are different. All learners share the same training dataset and validation dataset. These learners help each other to learn, in the following way: given an unlabeled dataset, each learner uses its intermediately trained model (including architecture and network weights)
to generate pseudo-labels on this dataset and each learners leverages the pseudo-labeled datasets generated by other peers to re-train its model. In this framework, there are three learning stages. In the first stage, each learner \( k \) trains its network weights \( V_k \) on the training dataset, with its architecture \( A_k \) fixed. In the second stage, each learner \( k \) uses its optimally trained \( V_k^* \) in the first stage to make predictions on the unlabeled dataset and generates a pseudo-labeled dataset; then each learner \( k \) trains its second set of network weights \( V_k \) using the pseudo-labeled datasets generated by other learners and the human-labeled training dataset. In the third stage, each learner \( k \) updates its architecture \( A_k \) by minimizing the prediction losses on the validation dataset. The three stages are performed jointly end-to-end in a multi-level optimization framework, where different stages influence each other. We apply our method for neural architecture search in image classification tasks on CIFAR-100, CIFAR-10, and ImageNet (Deng et al., 2009). Our method achieves significantly better accuracy than state-of-the-art baselines.

The major contributions of this paper is as follows:

- Inspired by the small-group learning technique of humans, we propose a novel machine learning approach called small-group learning (SGL). In our approach, each learner uses its intermediately trained model to generate a pseudo-labeled dataset and re-trains its model using pseudo-labeled datasets generated by other learners.

- We propose a multi-level optimization framework to formulate SGL which involves three learning stages: learners learn independently; learners learn collaboratively; learners validate themselves.

- We develop an efficient algorithm to solve the SGL problem.

- We apply our approach for neural architecture search on CIFAR-100, CIFAR-10, and ImageNet. The results demonstrate the effectiveness of our method.

The rest of the paper is organized as follows. Section 2 and 3 present the method and experiments respectively. Section 4 reviews related works. Section 5 concludes the paper.

2. Methods

In this section, we propose a framework for small-group learning (SGL) and develop an optimization for solving the SGL problem.

2.1. Small-Group Learning

In our framework, there are a set of \( K \) learners, all of which learn to solve the same target task. Without loss of generality, we assume the task is classification. Each learner \( k \) has a learnable architecture \( A_k \) and two sets of learnable network weights \( V_k \) and \( W_k \). All learners share the same training dataset \( D^{(tr)} \), the same validation dataset \( D^{(val)} \), and an unlabeled dataset \( D^{(u)} \). The \( K \) learners perform learning in three stages. In the first stage, each learner \( k \) trains its weights \( V_k \), with its architecture \( A_k \) fixed:

\[
V_k^*(A_k) = \min_{V_k} L(V_k, A_k, D^{(tr)}).
\]
The architecture $A_k$ is used to define the training loss. But it is not updated at this stage. If $A_k$ is learned by minimizing this training loss, a trivial solution will be yielded where $A_k$ is very large and complex that it can perfectly overfit the training data but will generalize poorly on unseen data. Note that the optimally trained weights $V^*_k(A_k)$ is a function of $A_k$ since $V^*_k(A_k)$ is a function of $L(V_k, A_k, D^{(tr)})$ and $L(V_k, A_k, D^{(tr)})$ is a function of $A_k$.

In the second stage, each learner $k$ uses its optimal model $V^*_k(A_k)$ learned in the first stage to make predictions on the unlabeled dataset $D^{(u)} = \{x_i\}_{i=1}^N$ and generates a pseudo-labeled dataset $D^{(pl)}_k(D^{(u)}, V^*_k(A_k)) = \{(x_i, f(x_i; V^*_k(A_k)))\}_{i=1}^N$ where $f(\cdot; V^*_k(A_k))$ is the network parameterized by $V^*_k(A_k)$. $f(x_i; V^*_k(A_k))$ is a $J$-dimensional vector where $J$ is the number of classes and the $j$-th element of $f(x_i; V^*_k(A_k))$ indicates the probability that $x_i$ belongs to the $j$-th class. The sum of all elements in $f(x_i; V^*_k(A_k))$ is one. Meanwhile, each learner $k$ uses the pseudo-labeled datasets $\{D^{(pl)}_j\}^K_{j=k}$ produced by other learners as well as the human-labeled dataset $D^{(tr)}$ to train its network weights $W_k$

$$W_k^*(A_k, \{V^*_j(A_j)\}^K_{j\neq k}) = \min_{W_k} L(W_k, A_k, D^{(tr)}) + \lambda \sum_{j \neq k} L(W_k, A_k, D^{(pl)}_j(D^{(u)}, V^*_j(A_j)))$$

where the first loss term $L(W_k, A_k, D^{(tr)})$ in the objective is defined on the human-labeled training dataset and the second loss term is defined on the pseudo-labeled datasets produced by other learners. Both losses are cross-entropy losses. $\lambda$ is a tradeoff parameter. Note that $W_k^*(A_k, \{V^*_j(A_j)\}^K_{j\neq k})$ is a function of $A_k$ and $\{V^*_j(A_j)\}^K_{j\neq k}$ since $W_k^*(A_k, \{V^*_j(A_j)\}^K_{j\neq k})$ is a function of $L(W_k, A_k, D^{(tr)}) + \lambda \sum_{j \neq k} L(W_k, A_k, D^{(pl)}_j(D^{(u)}, V^*_j(A_j)))$ which is a function of $A_k$ and $\{V^*_j(A_j)\}^K_{j\neq k}$. In the third stage, each learner validates its network weights $W_k^*(A_k, \{V^*_j(A_j)\}^K_{j\neq k})$ on the validation set $D^{(val)}$. The learners optimize their architectures by minimizing the validation losses:

$$\min_{\{A_k\}^K_{k=1}} \sum_{k=1}^K L(W_k^*(A_k, \{V^*_j(A_j)\}^K_{j\neq k}), A_k, D^{(val)}).$$

The three stages are mutually dependent: $\{V^*_k(A_k)\}^K_{k=1}$ learned in the first stage are used to define the objective function in the second stage; $\{W_k^*(A_k, \{V^*_j(A_j)\}^K_{j\neq k})\}^K_{k=1}$ learned in the second stage are used to define the objective in the third stage; the updated $\{A_k\}^K_{k=1}$ in the third stage in turn change the objective functions in the first stage, which subsequently render $\{V^*_k(A_k)\}^K_{k=1}$ to be changed.

Putting these pieces together, we have the following SGL framework, which is a three-level optimization problem:

$$\min_{\{A_k\}^K_{k=1}} \sum_{k=1}^K L(W_k^*(A_k, \{V^*_j(A_j)\}^K_{j\neq k}), A_k, D^{(val)})$$

s.t. $\{W_k^*(A_k, \{V^*_j(A_j)\}^K_{j\neq k})\}^K_{k=1} = \min_{\{W_k\}^K_{k=1}} \sum_{k=1}^K L(W_k, A_k, D^{(tr)})$

$$+ \lambda \sum_{j \neq k} L(W_k, A_k, D^{(pl)}_j(D^{(u)}, V^*_j(A_j)))$$

$$\{V^*_k(A_k)\}^K_{k=1} = \min_{\{V_k\}^K_{k=1}} \sum_{k=1}^K L(V_k, A_k, D^{(tr)})$$

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Figure 1: Illustration of small-group learning. The solid arrows denote the process of making predictions and calculating losses. The dotted arrows denote the process of updating learnable parameters by minimizing corresponding losses. For simplicity, we assume there are two learners in the group. Extension to multiple learners is straightforward.

This formulation nests three optimization problems. On the constraints of the outer optimization problem are two inner optimization problems corresponding to the first and second learning stage respectively. The objective function of the outer optimization problem corresponds to the third learning stage.

Similar to (Liu et al., 2019), we represent the architecture $A$ of the learner in a differentiable way. The search space of $A$ is composed of a large number of building blocks. The output of each block is associated with a variable $a$ indicating how important this block is. After learning, blocks whose $a$ is among the largest are retained to form the final architecture. In this end, architecture search amounts to optimizing the set of architecture variables $A = \{a\}$.
In this section, we derive an optimization algorithm to solve the SGL problem defined in Eq. (4). Inspired by (Liu et al., 2019), we approximate $V^*_k(A_k)$ using one-step gradient descent update of $V_k$ with respect to $L(V_k, A_k, D^{(tr)})$. We plug the approximation $\{V_j^*(A_j)\}_{j=1}^K$ into $\sum_{k=1}^K L(W_k, A_k, D^{(tr)}) + \lambda \sum_{j \neq k}^K L(W_k, A_k, D_j^{(pl)}(D^{(u)}, V_j^*(A_j)))$ and obtain an approximated objective $\sum_{k=1}^K O^w_k$. Then we approximate $W'_k(A_k, \{V_j^*(A_j)\}_{j \neq k}^K)$ using one-step gradient descent update of $W_k$ with respect to $O^w_k$. Finally, we plug the approximation $\{W'_j\}_{j=1}^K$ of $\{W^*_k(A_k, \{V_j^*(A_j)\}_{j \neq k}^K)\}$ into $\sum_{k=1}^K L(W'_k(A_k, \{V_j^*(A_j)\}_{j \neq k}^K), A_k, D^{(val)})$ and perform gradient-descent update of $\{A_k\}_{k=1}^K$ with respect to this approximated objective. In the sequel, we use $\nabla^2_{X,Y} f(X, Y)$ to denote $\frac{\partial f(X, Y)}{\partial X \partial Y}$.

We approximate $V'_k(A_k)$ using

$$V'_k = V_k - \xi_u \nabla V_k L(V_k, A_k, D^{(tr)})$$

(5)

where $\xi_u$ is a learning rate. Plugging $\{V_j^*(A_j)\}_{j=1}^K$ into $\sum_{k=1}^K L(W_k, A_k, D^{(tr)}) + \lambda \sum_{j \neq k}^K L(W_k, A_k, D_j^{(pl)}(D^{(u)}, V_j^*(A_j)))$, we obtain an approximated objective $\sum_{k=1}^K O^w_k$ where $O^w_k = L(W_k, A_k, D^{(tr)}) + \lambda \sum_{j \neq k}^K L(W_k, A_k, D_j^{(pl)}(D^{(u)}, V_j^*))$. Then we approximate $W'_k(A_k, \{V_j^*(A_j)\}_{j \neq k}^K)$ using one-step gradient descent update of $W_k$ with respect to $O^w_k$:

$$W'_k = W_k - \xi_u \nabla W_k L(W_k, A_k, D^{(tr)}) + \lambda \sum_{j \neq k}^K L(W_k, A_k, D_j^{(pl)}(D^{(u)}, V_j^*))$$

(6)

Finally, we plug $\{W'_j\}_{j=1}^K$ into $\sum_{k=1}^K L(W'_k(A_k, \{V_j^*(A_j)\}_{j \neq k}^K), A_k, D^{(val)})$ and get $\sum_{j=1}^K L(W'_j, A_j, D^{(val)})$. We can update the architecture $A_k$ of learner $k$ by descending the gradient of $\sum_{j=1}^K L(W'_j, A_j, D^{(val)})$ w.r.t $A_k$:

$$A_k \leftarrow A_k - \eta_A (\nabla A_k L(W'_j, A_j, D^{(val)}) + \sum_{j \neq k}^K \nabla A_k L(W'_j, A_j, D^{(val)}))$$

(7)

where

$$\nabla A_k L(W'_j, A_k, D^{(val)}) =$$

$$\nabla A_k L(W_k - \xi_w \nabla W_k L(W_k, A_k, D^{(tr)}) + \lambda \sum_{j \neq k}^K L(W_k, A_k, D_j^{(pl)}(D^{(u)}, V_j^*)), A_k, D^{(val)}) =$$

$$\nabla A_k L(W'_k, A_k, D^{(val)}) - \xi_u \nabla^2_{A_k, W_k} L(W_k, A_k, D^{(tr)}) +$$

$$\lambda \sum_{j \neq k}^K L(W_k, A_k, D_j^{(pl)}(D^{(u)}, V_j^*)) \nabla W'_k L(W'_k, A_k, D^{(val)})$$

(8)
we split the original 50K training set into a new 25K training set and a 25K validation set. Following (Liu et al., 2019), we first perform architecture search which finds out an optimal cell, then perform architecture evaluation which composes multiple copies of the searched cell into a large network, trains it from scratch, and evaluates the trained model on the test set.

### 3. Experiments

We apply SGL for neural architecture search in image classification tasks. Following (Liu et al., 2019), we first perform architecture search which finds out an optimal cell, then perform architecture evaluation which composes multiple copies of the searched cell into a large network, trains it from scratch, and evaluates the trained model on the test set.

#### 3.1. Datasets

We used three datasets in the experiments: CIFAR-10, CIFAR-100, and ImageNet (Deng et al., 2009). The CIFAR-10 dataset contains 50K training images and 10K testing images, from 10 classes (the number of images in each class is equal). Following (Liu et al., 2019), we split the original 50K training set into a new 25K training set and a 25K validation set.
In the sequel, when we mention “training set”, it always refers to the new 25K training set. During architecture search, the training set is used as $D^{(tr)}$ in SGL. The validation set is used as $D^{(val)}$ in SGL. During architecture evaluation, the combination of the training data and validation data is used to train the large network stacking multiple copies of the searched cell. The CIFAR-100 dataset contains 50K training images and 10K testing images, from 100 classes (the number of images in each class is equal). Similar to CIFAR-100, the 50K training images are split into a 25K training set and 25K validation set. The usage of the new training set and validation set is the same as that for CIFAR-10. The ImageNet dataset contains a training set of 1.2M images and a validation set of 50K images, from 1000 object classes. The validation set is used as a test set for architecture evaluation. Following (Liu et al., 2019), we evaluate the architectures searched using CIFAR-10 and CIFAR-100 on ImageNet: given a cell searched using CIFAR-10 and CIFAR-100, multiple copies of it compose a large network, which is then trained on the 1.2M training data of ImageNet and evaluated on the 50K test data. In SGL, when searching architectures on CIFAR-10, the input images (without labels) in CIFAR-100 are used as the unlabeled dataset; vice versa.

3.2. Experimental Settings

Our framework is a general one that can be used together with any differentiable search method. Specifically, we apply our framework to the following NAS methods: 1) DARTS (Liu et al., 2019), 2) P-DARTS (Chen et al., 2019), 3) PC-DARTS, and 4) DARTS$^-$ (Chu et al., 2020a). The search space in these methods are similar. The candidate operations include: $3 \times 3$ and $5 \times 5$ separable convolutions, $3 \times 3$ and $5 \times 5$ dilated separable convolutions, $3 \times 3$ max pooling, $3 \times 3$ average pooling, identity, and zero. In SGL, the network of each learner is a stack of multiple cells, each consisting of 7 nodes. $\lambda$ is set to 0.1.

For CIFAR-10 and CIFAR-100, during architecture search, each learner’s network is a stack of 8 cells, with the initial channel number set to 16. The search is performed for 50 epochs, with a batch size of 64. The hyperparameters for each learner’s architecture and weights are set in the same way as DARTS, P-DARTS, PC-DARTS, and DARTS$^-$. The network weights are optimized using SGD with a momentum of 0.9 and a weight decay of 3e-4. The initial learning rate is set to 0.025 with a cosine decay scheduler. The architecture variables are optimized with the Adam (Kingma and Ba, 2014) optimizer with a learning rate of 3e-4 and a weight decay of 1e-3. During architecture evaluation, 20 copies of the searched cell are stacked to form each learner’s network, with the initial channel number set to 36. The network is trained for 600 epochs with a batch size of 96 (for both CIFAR-10 and CIFAR-100). The experiments are performed on a single Tesla v100. For ImageNet, following (Liu et al., 2019), we take the architecture searched on CIFAR-10 and evaluate it on ImageNet. We stack 14 cells (searched on CIFAR-10) to form a large network and set the initial channel number as 48. The network is trained for 250 epochs with a batch size of 1024 on 8 Tesla v100s. Each experiment on SGL is repeated for ten times with the random seed to be from 1 to 10. We report the mean and standard deviation of results obtained from the 10 runs.
| Method                      | Error(%) | Param(M) | Cost   |
|-----------------------------|----------|----------|--------|
| *ResNet (He et al., 2016)  | 22.10    | 1.7      | -      |
| *DenseNet (Huang et al., 2017) | 17.18   | 25.6     | -      |
| *PNAS (Liu et al., 2018a)  | 19.53    | 3.2      | 150    |
| *ENAS (Pham et al., 2018)  | 19.43    | 4.6      | 0.5    |
| *AmoebaNet (Real et al., 2019) | 18.93   | 3.1      | 3150   |
| *DARTS-2nd (Liu et al., 2019) | 20.58±0.44 | 1.8     | 1.5    |
| *GDAS (Dong and Yang, 2019) | 18.38    | 3.4      | 0.2    |
| *R-DARTS (Zela et al., 2020) | 18.01±0.26 | -       | 1.6    |
| ∆DARTS⁺ (Liang et al., 2019) | 17.11±0.43 | 3.8     | 0.2    |
| *DropNAS (Hong et al., 2020) | 16.39    | 4.4      | 0.7    |
| †DARTS-1st (Liu et al., 2019) | 20.52±0.31 | 1.8     | 0.4    |
| SGL-DARTS-1st (ours)       | 18.54±0.21 | 2.2     | 1.2    |
| *DARTS⁻ (Chu et al., 2020a) | 17.51±0.25 | 3.3     | 0.4    |
| †DARTS⁻ (Chu et al., 2020a) | 18.97±0.16 | 3.1     | 0.4    |
| SGL-DARTS⁻ (ours)          | 16.90±0.10 | 3.5     | 2.0    |
| *P-DARTS (Chen et al., 2019) | 17.49    | 3.6      | 0.3    |
| SGL-P-DARTS (ours)         | 16.58±0.18 | 3.6     | 2.1    |
| †PC-DARTS (Xu et al., 2020) | 17.01±0.06 | 4.0     | 0.1    |
| SGL-PC-DARTS (ours)        | 16.34±0.11 | 4.1     | 0.5    |

Table 2: Results on CIFAR-100, including classification error (%) on the test set, number of parameters (millions) in the searched architecture, and search cost (GPU days). SGL-DARTS-1st denotes that our method SGL is applied to the search space of DARTS. Similar meanings hold for other notations in such a format. DARTS-1st and DARTS-2nd denotes that first order and second order approximation is used in DARTS. * means the results are taken from DARTS⁻ (Chu et al., 2020a). † means we re-ran this method for 10 times. The search cost is measured by GPU days on a Tesla v100.

3.3. Results

Table 2 shows the classification error (%), number of weight parameters (millions), and search cost (GPU days) of different NAS methods on CIFAR-100. From this table, we make the following observations. First, when our method SGL is applied to different NAS baselines including DARTS-1st (first order approximation), DARTS⁻, P-DARTS, and PC-DARTS, the classification errors of these baselines can be significantly reduced. For example, applying our method to DARTS-1st, the error reduces from 20.52% to 18.54%. Applying our method to P-DARTS, the error reduces from 17.49% to 16.58%. This demonstrates the effectiveness of our method in searching for a better architecture. In our method, learners with different architectures collaboratively solve the same task. They provide pseudo-labeled datasets to each other to help each other train better models. In single-learner NAS, there is a risk that the searched architecture gets stuck in a local optimal.
| Method                        | Error(%)  | Param(M) | Cost |
|------------------------------|-----------|----------|------|
| *DenseNet (Huang et al., 2017) | 3.46      | 25.6     | -    |
| *HierEvol (Liu et al., 2018b)  | 3.75±0.12 | 15.7     | 300  |
| *NAONet-WS (Luo et al., 2018)  | 3.53      | 3.1      | 0.4  |
| *PNAS (Liu et al., 2018a)      | 3.41±0.09 | 3.2      | 225  |
| *ENAS (Pham et al., 2018)      | 2.89      | 4.6      | 0.5  |
| *NASNet-A (Zoph et al., 2018)  | 2.65      | 3.3      | 1800 |
| *AmoebaNet-B (Real et al., 2019)| 2.55±0.05 | 2.8      | 3150 |
| *R-DARTS (Zela et al., 2020)   | 2.95±0.21 | -        | 1.6  |
| *GDAS (Dong and Yang, 2019)    | 2.93      | 3.4      | 0.2  |
| *SNAS (Xie et al., 2019)       | 2.85      | 2.8      | 1.5  |
| △DARTS+ (Liang et al., 2019)   | 2.83±0.05 | 3.7      | 0.4  |
| *BayesNAS (Zhou et al., 2019)  | 2.81±0.04 | 3.4      | 0.2  |
| *DARTS-2nd (Liu et al., 2019)  | 2.76±0.09 | 3.3      | 1.5  |
| *MergeNAS (Wang et al., 2020)  | 2.73±0.02 | 2.9      | 0.2  |
| *NoisyDARTS (Chu et al., 2020b)| 2.70±0.23 | 3.3      | 0.4  |
| *ASAP (Noy et al., 2020)       | 2.68±0.11 | 2.5      | 0.2  |
| *SDARTS (Chen and Hsieh, 2020)| 2.61±0.02 | 3.3      | 1.3  |
| *DropNAS (Hong et al., 2020)   | 2.58±0.14 | 4.1      | 0.6  |
| *FairDARTS (Chu et al., 2019)  | 2.54      | 3.3      | 0.4  |
| *DrNAS (Chen et al., 2020)     | 2.54±0.03 | 4.0      | 0.4  |
| *DARTS-1st (Liu et al., 2019)  | 3.00±0.14 | 3.3      | 0.4  |
| SGL-DARTS-1st (ours)           | 2.41±0.06 | 3.7      | 1.2  |
| *DARTS− (Chu et al., 2020a)    | 2.59±0.08 | 3.5      | 0.4  |
| SGL-DARTS− (ours)              | 2.60±0.07 | 3.1      | 2.0  |
| *P-DARTS (Chen et al., 2019)   | 2.50      | 3.4      | 0.3  |
| SGL-P-DARTS (ours)             | 2.47±0.10 | 3.6      | 2.1  |
| *PC-DARTS (Xu et al., 2020)    | 2.57±0.07 | 3.6      | 0.1  |
| SGL-PC-DARTS (ours)            | 2.60±0.12 | 3.5      | 0.5  |

Table 3: Results on CIFAR-10. * means the results are taken from DARTS− (Chu et al., 2020a), NoisyDARTS (Chu et al., 2020b), and DrNAS (Chen et al., 2020). The rest notations are the same as those in Table 2.

Group-learning can significantly reduce this risk. If one learner is stuck in a local optimal, other learners can help it escape the local optimal via knowledge transfer based on pseudo-labeling. **Second**, our method SGL-PC-DARTS achieves the best performance among all methods, which further demonstrates the effectiveness of SGL in driving the frontiers of neural architecture search forward. **Third**, the number of weight parameters and search costs corresponding to our methods are on par with those in differentiable NAS baselines. This shows that SGL is able to search better-performing architectures without significantly increasing network size and search cost. A few additional remarks: 1) On CIFAR-100,
| Method                                      | Top-1 Error (%) | Top-5 Error (%) | Param (M) | Cost (GPU days) |
|---------------------------------------------|-----------------|-----------------|-----------|-----------------|
| *Inception-v1 (Szegedy et al., 2015)        | 30.2            | 10.1            | 6.6       | -               |
| *MobileNet (Howard et al., 2017)            | 29.4            | 10.5            | 4.2       | -               |
| *ShuffleNet 2× (v1) (Zhang et al., 2018)    | 26.4            | 10.2            | 5.4       | -               |
| *ShuffleNet 2× (v2) (Ma et al., 2018)       | 25.1            | 7.6             | 7.4       | -               |
| *NASNet-A (Zoph et al., 2018)               | 26.0            | 8.4             | 5.3       | 1800            |
| *PNAS (Liu et al., 2018a)                   | 25.8            | 8.1             | 5.1       | 225             |
| *MnasNet-92 (Tan et al., 2019)              | 25.2            | 8.0             | 4.4       | 1667            |
| *AmoebaNet-C (Real et al., 2019)            | 24.3            | 7.6             | 6.4       | 3150            |
| *SNAS-CIFAR10 (Xie et al., 2019)            | 27.3            | 9.2             | 4.3       | 1.5             |
| *BayesNAS-CIFAR10 (Zhou et al., 2019)       | 26.5            | 8.9             | 3.9       | 0.2             |
| *PARSEC-CIFAR10 (Casale et al., 2019)       | 26.0            | 8.4             | 5.6       | 1.0             |
| *GDAS-CIFAR10 (Dong and Yang, 2019)         | 26.0            | 8.5             | 5.3       | 0.2             |
| *DSNAS-ImageNet (Hu et al., 2020)           | 25.7            | 8.1             | -         | -               |
| *SDARTS-ADV-CIFAR10 (Chen and Hsieh, 2020)  | 25.2            | 7.8             | 5.4       | 1.3             |
| *PC-DARTS-CIFAR10 (Xu et al., 2020)         | 25.1            | 7.8             | 5.3       | 0.1             |
| *ProxylessNAS-ImageNet (Cai et al., 2019)   | 24.9            | 7.5             | 7.1       | 8.3             |
| *FairDARTS-CIFAR10 (Chu et al., 2019)       | 24.9            | 7.5             | 4.8       | 0.4             |
| *FairDARTS-ImageNet (Chu et al., 2019)      | 24.4            | 7.4             | 4.3       | 3.0             |
| *DrNAS-ImageNet (Chen et al., 2020)         | 24.2            | 7.3             | 5.2       | 3.9             |
| *DARTS⁺-ImageNet (Liang et al., 2019)       | 23.9            | 7.4             | 5.1       | 6.8             |
| *DARTS⁻-ImageNet (Chu et al., 2020a)        | 23.8            | 7.0             | 4.9       | 4.5             |
| *DARTS⁺-CIFAR100 (Liang et al., 2019)       | 23.7            | 7.2             | 5.1       | 0.2             |
| *DARTS-2nd-CIFAR10 (Liu et al., 2019)       | 26.7            | 8.7             | 4.7       | 4.0             |
| SGL-DARTS-1st-CIFAR10 (ours)                | 24.9            | 7.7             | 5.2       | 4.0             |
| *P-DARTS-CIFAR10 (Chen et al., 2019)        | 24.4            | 7.4             | 4.9       | 0.3             |
| SGL-P-DARTS-CIFAR10 (ours)                  | 24.3            | 7.2             | 5.1       | 0.3             |
| *P-DARTS-CIFAR100 (Chen et al., 2019)       | 24.7            | 7.5             | 5.1       | 0.3             |
| SGL-P-DARTS-CIFAR100 (ours)                 | 23.9            | 7.2             | 5.3       | 0.3             |

Table 4: Results on ImageNet, including top-1 and top-5 classification errors on the test set, number of weight parameters (millions), and search cost (GPU days). * means the results are taken from DARTS⁻ (Chu et al., 2020a) and DrNAS (Chen et al., 2020). The rest notations are the same as those in Table 2. The first row block shows networks designed by humans manually. The second row block shows non-gradient based search methods. The third block shows gradient-based methods.

DARTS-2nd with second-order approximation in the optimization algorithm is not advantageous compared with DARTS-1st which uses first-order approximation; 2) In our run of DARTS⁻, the performance reported in (Chu et al., 2020a) cannot be achieved.

Table 3 shows the classification error (%), number of weight parameters (millions), and search cost (GPU days) of different NAS methods on CIFAR-10. As can be seen, applying our proposed SGL method to DARTS-1st, †DARTS⁻ (our re-run), and P-DARTS reduces the errors of these baselines. Especially on DARTS-1st, with the usage of SGL, the error is reduced from 3.00% to 2.41%, which is the best among all methods in this table. This further
demonstrates the efficacy of our method in searching better-performing architectures, by letting a group of learners mutually help each other to train better models. Table 4 shows the results on ImageNet, including top-1 and top-5 classification errors on the test set, number of weight parameters (millions), and search costs (GPU days). Following (Liu et al., 2019), we take the architectures searched by SGL-DARTS-1st on CIFAR-10, by SGL-P-DARTS on CIFAR-10, by SGL-P-DARTS on CIFAR-100, and evaluate them on ImageNet. As can be seen, applying our SGL method to DARTS, P-DARTS, and PC-DARTS, the top-1 and top-5 errors are both reduced significantly. This further demonstrates the effectiveness of our method.

4. Related Works

Neural architecture search (NAS) has achieved remarkable progress recently, which aims at searching for the optimal architecture of neural networks to achieve the best predictive performance. In general, there are three paradigms of methods in NAS: reinforcement learning (RL) approaches (Zoph and Le, 2017; Pham et al., 2018; Zoph et al., 2018), evolutionary learning approaches (Liu et al., 2018b; Real et al., 2019), and differentiable approaches (Cai et al., 2019; Liu et al., 2019; Xie et al., 2019). In RL-based approaches, a policy is learned to iteratively generate new architectures by maximizing a reward which is the accuracy on the validation set. Evolutionary learning approaches represent the architectures as individuals in a population. Individuals with high fitness scores (validation accuracy) have the privilege to generate offspring, which replaces individuals with low fitness scores. Differentiable approaches adopt a network pruning strategy. On top of an over-parameterized network, the weights of connections between nodes are learned using gradient descent. Then weights close to zero are later pruned. There have been many efforts devoted to improving differentiable NAS methods. In P-DARTS (Chen et al., 2019), the depth of searched architectures is allowed to grow progressively during the training process. Search space approximation and regularization approaches are developed to reduce computational overheads and improve search stability. PC-DARTS (Xu et al., 2020) reduces the redundancy in exploring the search space by sampling a small portion of a super network. Operation search is performed in a subset of channels with the held out part bypassed in a shortcut. Our proposed SGL framework can be applied to any differentiable NAS methods.

5. Conclusions

In this paper, we propose a new machine learning approach – small-group learning (SGL), inspired by the small-group cooperative learning technique of humans. In SGL, a set of learners help each other to learn better: each learner uses its intermediatively trained model to make predictions on unlabeled data examples and generates a pseudo-labeled dataset; meanwhile, each learner uses pseudo-labeled datasets generated by other learners to retrain and improve its model. We propose a multi-level optimization framework to formalize SGL which involves three learning stages: each learner trains an initial model separately; all learners retrain their models collaboratively by mutually performing pseudo-labeling; all learners improve their neural architectures based on the feedback obtained during model
validation. Our framework is applied for neural architecture search and achieves significant improvement on CIFAR-100, CIFAR-10, and ImageNet.

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