

Few-Shot Class-Incremental Learning via Entropy-Regularized Data-Free Replay (Supplementary Material)

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A Overall Algorithm

Algorithm 1 Entropy-regularized Data-free FSCIL

Require: $\mathcal{T}_i(\cdot; \theta_i)$, $\mathcal{A}_i(\cdot; \theta_{A_i})$, $\mathcal{G}_i(\cdot; \theta_{G_i})$: models

Require: $\alpha, \beta, \lambda_1, \lambda_2$: learning rates

Require: $\{\mathcal{D}_{train}^0, \mathcal{D}_{train}^1, \dots, \mathcal{D}_{train}^N\}$: datasets

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1: Base training of  $\mathcal{T}_0(\cdot; \theta_0)$  on  $\mathcal{D}_{train}^0$  ▷ Session 0.
2: for  $i = 1, \dots, N$  do ▷ Loop through all the sessions.
3:   1. Training Generator using entropy regularization.
4:   while not converge do
5:      $z \sim \mathcal{N}(0, I)$  ▷ Sampling noise vector.
6:     for k iterations do
7:        $\theta_{G_i} \leftarrow \theta_{G_i} - \alpha \frac{\partial \mathcal{L}_G^*}{\partial \theta_{G_i}}$  ▷ Update generator.
8:     end for
9:      $\theta_{A_i} \leftarrow \theta_{A_i} - \beta \frac{\partial \mathcal{L}_A}{\partial \theta_{A_i}}$  ▷ Update auxiliary model.
10:  end while
11:  2. Learning incrementally with uncertain data.
12:  initialize  $\mathcal{T}_i(\cdot; \theta_i)$  by  $\mathcal{T}_{i-1}(\cdot; \theta_{i-1})$ 
13:  while not converge do
14:     $x^* \leftarrow \mathcal{G}_i(z; \theta_{G_i})$  ▷ Generate data for replaying.
15:     $y^* \leftarrow \operatorname{argmax}(\mathcal{T}_{i-1}(x^*))$  ▷ labeling  $x^*$  by old model’s activation.
16:     $\mathcal{D}_{train}^{i*} \leftarrow \mathcal{D}_{train}^i \cup \{x^*, y^*\}$  ▷ Update dataset.
17:    Sample  $\{x, y\}$  from  $\mathcal{D}_{train}^{i*}$ 
18:     $\{\theta_{i-1}^b, \theta_{i-1}^l\} = \{\theta_{i-1}^b, \theta_{i-1}^l\} - \lambda_1 \frac{\partial \mathcal{L}_{CE}}{\partial \{\theta_{i-1}^b, \theta_{i-1}^l\}}$  ▷ Fine-tuning old parameters.
19:     $\theta_i^{l*} = \theta_i^{l*} - \lambda_2 \frac{\partial \mathcal{L}_{CE}}{\partial \theta_i^{l*}}$  ▷ Update new parameters.
20:  end while
21:   $\theta_i = \{\theta_i^b, \theta_i^l\}$ , where  $\theta_i^l = \{\theta_{i-1}^l, \theta_i^{l*}\}$ 
22: end for
23: return  $\mathcal{T}_N(\cdot; \theta_N)$ 

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In this section, we demonstrate the overall algorithm for a better understanding of our proposed method. At the beginning of each session, we first train a generator given the old model from the previous session. After the training of the generator, we then conduct incremental learning following Section 4.2, where we form a new dataset by combining the novel data with the relabeled replayed data and only use the cross-entropy loss to learn novel classes and avoid forgetting of old classes.