西安交通大學
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Class-Incremental Learning with Topological Schemas of Memory Spaces

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Regular session

Introduction

◆**Class-incremental learning (CIL)**

- CIL is fort the scenario where the classification model is exposed to a stream of new class training data while the old class training data is unavailable when learning for new classes.

◆**Problem:**

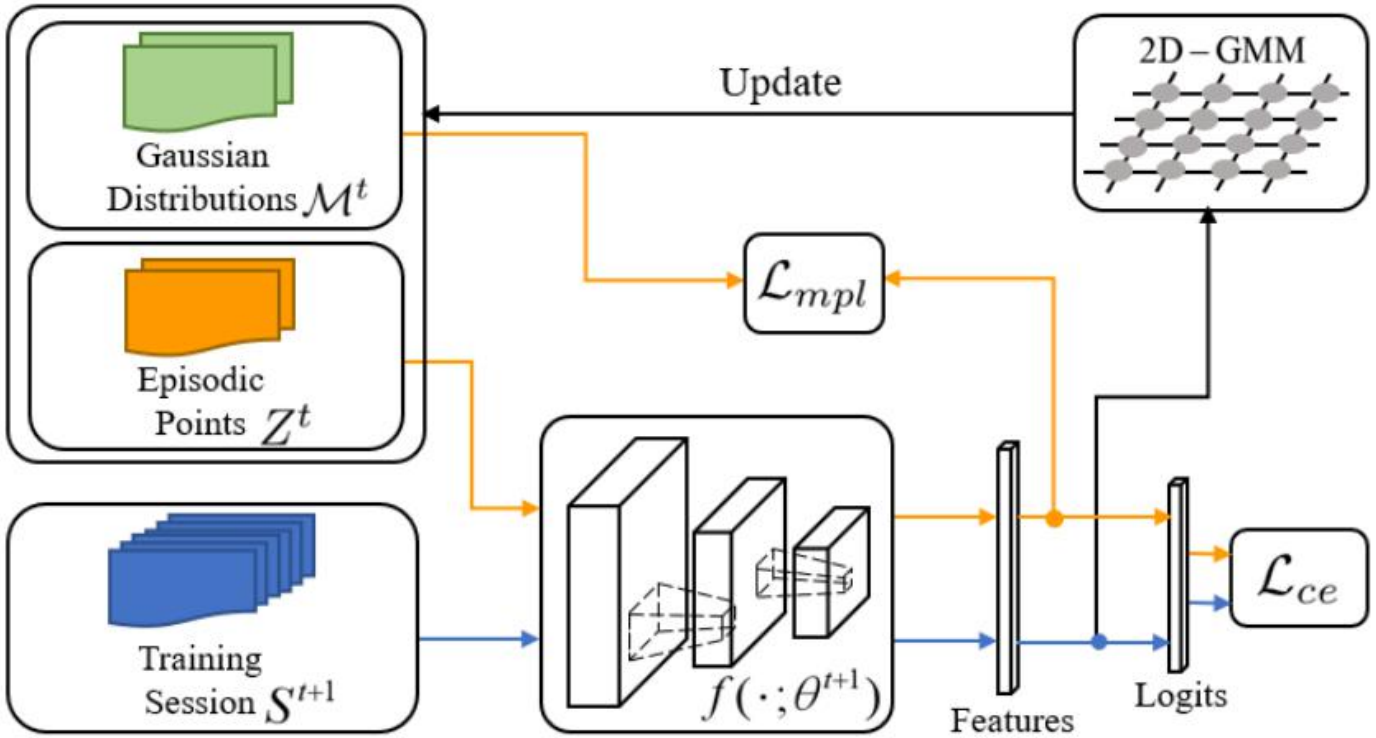
- A simple finetuning suffers from *catastrophic forgetting*, where the model's recognition performance on the old classes degrades severely once it learns for new classes.
- To address *catastrophic forgetting*, most CIL works adopt the distillation-based technique. Despite the distillation-based approach is claimed to be effective for CIL, it still has some critical issues as follows:
  - The quality of the exemplars is not guaranteed.
  - Model tends to overfit to the old class exemplars.
  - The CNN model also suffers from the 'bias' problem.

Motivation

we propose a novel CIL framework, named the *topological schemas model* (TSM).

- **2D-GMM**
  - A Gaussian mixture model arranged on 2D grids (2D-GMM) as the memory of the learned knowledge.
  - we develop a novel *competitive expectation-maximization* (CEM) method to train the 2D-GMM.
- **memory preservation loss (MPL)**
  - MPL preserves the distribution of 2D-GMM for old knowledge during incremental learning and alleviates catastrophic forgetting.

Overall framework



When learning the model at the $(t+1)$-th session, the cross-entropy loss term $\mathcal{L}_{ce}$ is applied to the output logits corresponding to S^{t+1} and Z^t. The memory preservation loss term $\mathcal{L}_{mpl}$ is applied to $\mathcal{M}^t$ and the output features of Z^t. After learning the model on S^{t+1}, the 2D-GMM is grown and updated.

2D-GMM Training

We develop a novel *competitive expectation-maximization* (CEM) method to train the 2D-GMM model, which contains two steps as follows:

- global *topology embedding* (TE) step
  - Using *Competitive Hebbian learning* (CHL) technique to update the parameters of 2D-GMM.

- local *expectation-maximization* (EM) finetuning step.
  - Using EM algorithm to finetune the parameters of 2D-GMM.

2D-GMM can represent the topological structure of the data manifold.

Mathematical form of the framework

The *memory preservation loss* (MPL) is defined as follows:

$$\mathcal{L}_{mpl}(Z^t, \mathcal{M}^t; \theta^{t+1}) = \sum_{k=1}^{M}\sum_{h=1}^{H}(f(z_k+\eta_h;\theta^{t+1})-\mu_k^t)^\top R_k(f(z_k+\eta_h;\theta^{t+1})-\mu_k^t)$$

Z^t denotes the episodic points. $Z^t = \{(z_k, \mu_k)\}_{k=1}^{M}$, μ_k denotes the mean vector of the k-th Gaussian distribution, z_k denotes the image whose feature is closest to μ_k. $\mathcal{M}^t$ denotes all the Gaussian distributions. $f(\cdot;\theta^t)$ denotes the feature extractor. η is the noise used to transform z_k. H is the number of noise types, M is the number of episodic points. R_k is the correlation coefficient matrix. Let $\Sigma = (c_{ij})_{d\times d}$ be the covariance matrix of k-th Gaussian component. R_k is defined as follows:

$$R_k = (r_{ij})_{d\times d} \qquad r_{ij} = \frac{c_{ij}}{\sqrt{c_{ii}\cdot c_{jj}}}$$

The overall loss function at stage $(t+1)$ is:

$$\mathcal{L}(S^{t+1}, Z^t, \mathcal{M}^t; \theta^{t+1}) = \mathcal{L}_{ce}(S^{t+1}\cup Z^t;\theta^{t+1}) + \lambda\mathcal{L}_{mpl}(Z^t, \mathcal{M}^t;\theta^{t+1})$$

The hyper-parameter λ is used to balance the strength of the MPL term.

Experiments

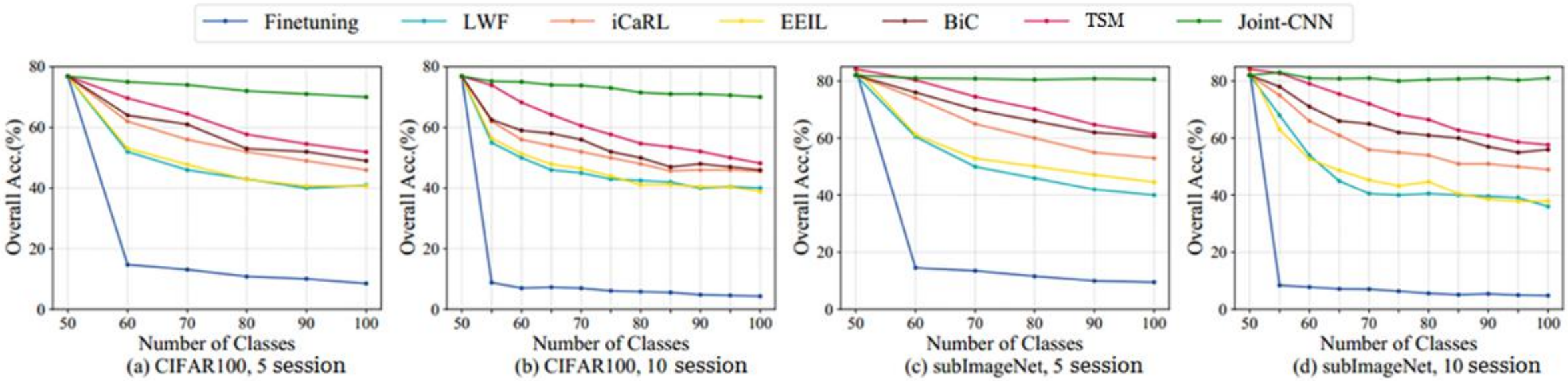
Datasets: CIFAR100, SubImageNet.

Protocol: We select half of the classes as the base classes, and then equally divide the rest classes into 5 or 10 incremental learning stages, where we use ‘5 session’ and ‘10 session’ to denote the corresponding settings.

Backbone network: ResNet32 for CIFAR100 and ResNet18 for SubImageNet.

Comparative methods: Finetuning, LWF, iCaRL, EEIL, BiC and Joint-CNN (upper-bound).

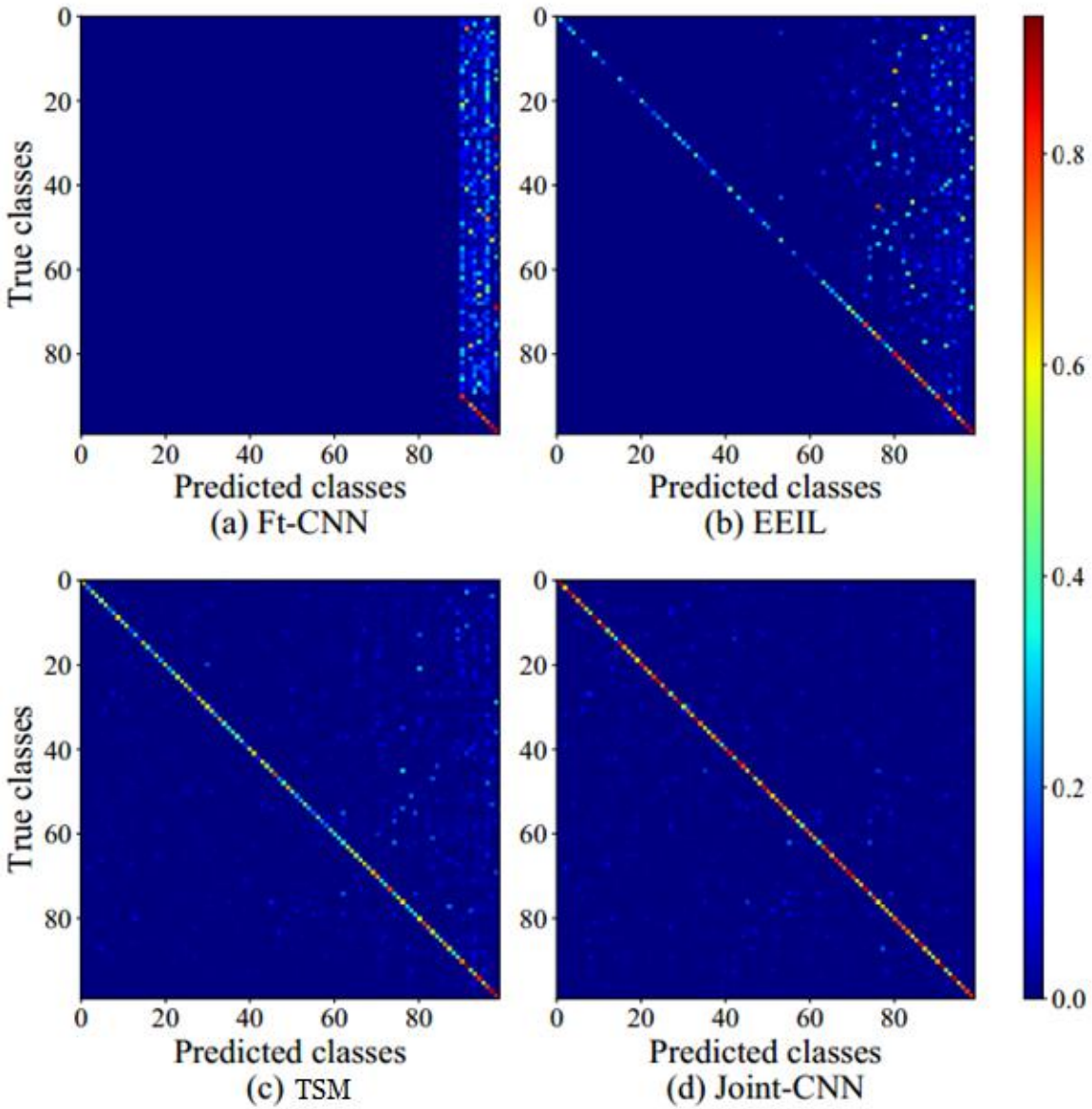
Results



Results on CIFAR100: Our method achieves the average accuracy of **62.52%** and **60.00%** under the 5 session and 10 session settings, respectively, while the state-of-the-art BiC achieves the average accuracy of 59.31% and 54.76%, correspondingly.

Results on SubImageNet: Our method achieves the average accuracy of **72.54%** and **69.83%** under the 5 session and 10 session settings, respectively. BiC achieves the average accuracy of 69.42% and 64.82%, correspondingly.

Visualization



The comparison of confusion matrices under the 5 session setting on CIFAR100.

The horizontal axis represents the predicted class, while the vertical one represents the ground-truth class.

The color bar on the right indicates the activation intensity corresponding to different colors.

Take Home Message

We propose a novel **TSM** framework to address the catastrophic forgetting problem for CIL

We propose a novel model **2D-GMM** as the memory of the learned knowledge. Meanwhile, a novel *competitive expectation-maximization* (**CEM**) method is proposed to train 2D-GMM.

We develop the *memory preservation loss* (**MPL**) that preserves the distribution of 2D-GMM for old knowledge.

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Thanks!

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