Zero-Shot Continual Learning

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Modern CL techniques

Modern CL techniques can be divided into three types:

- Regularization-based ([4], [1], etc): detect the weights which are important for previous tasks and do not change them much in the future.
- Replay-based ([2], [6], etc): store a part of previous data to replay it in the future.
- Component-based ([5], [3], etc): allocate different parts of the network to different tasks.

All of them has the loss in the form:

$$\mathcal{L}(\theta) = L_{\text{current task}} + L_{\text{forgetting}}$$

But what if we'll try to improve the performance on future tasks?

$$\mathcal{L}(\theta) = L_{\text{current task}} + L_{\text{forgetting}} + L_{\text{future transfer}}$$

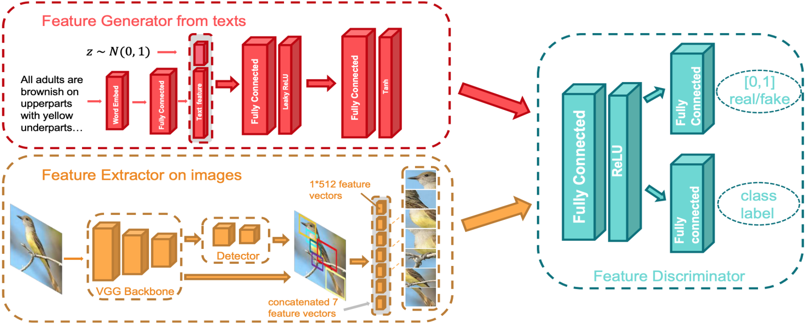
Zero-Shot Learning (ZSL)

- For each class $y \in \mathcal{Y}$ associate an attribute vector a_c which describes its characteristics.
- All the data is divided into two parts: seen $D^s = \{X^\mathrm{s}, Y^\mathrm{s}, A^\mathrm{s}\}$ and unseen $D^u = \{X^\mathrm{u}, Y^\mathrm{u}, A^\mathrm{u}\}$.
- First, we train on seen data D^s using class attributes and then validate the performance on unseen data D^u (or on both $D^s \cup D^u$).
- Using information from class descriptions we can detect classes that we have not seen during training.
- It can be used to improve future transfer for CL models.

Generative Adversarial Zero-Shot Learning [7]

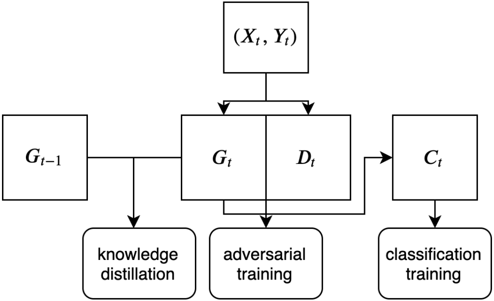
GAZSL approach for ZSL:

- Train a conditional GAN model to generate samples from class descriptions.
- Train a classifier to predict a class from the generated sample.
- At test time, generate unseen samples, compute a class prototype and compare test images to synthetic prototypes.



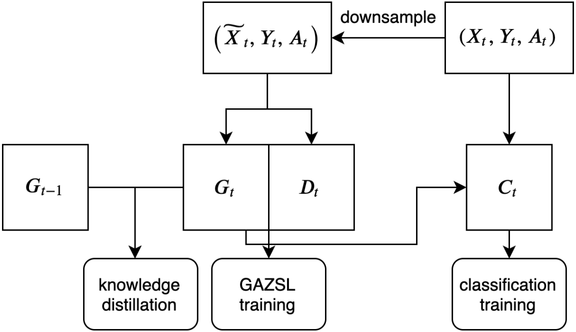
Generative Memory for Continual Learning [6]

- For task t, train a conditional GAN model (G_t, D_t) to save current dataset.
- Distill the knowledge of previous generator G_{t-1} into G_t so not to forget previous data.
- Train a classifier C_t on top of G_t.



Zero-Shot Continual Learning

- Merge two approaches: GAZSL + MeRGAN to improve future transfer.
- Since GAN model is difficult to train in high-scale image space, one can train it in either low-scale image space or latent space.



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