Appendix for “Generalized Class Incremental Learning”

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Figure 1. Left: Herding v.s. ring buffer to select exemplars for ReMix and ER. Middle: Performance of ReMix and ER with varying exemplar sizes. Right: Disentangled performance comparing ReMix with ER.

A. Detailed analysis on ReMix

In this section, we provide detailed analysis of ReMix to understand its success in GCIL settings. As a case study, we limit our discussion within the setup where \( K_t \sim U(1, 100) \), \( W^1_t = \text{UNIFORM} \), \( W^2_t = \text{TASK-VARIED} \).

A.1. Herding is effective.

In this experiment, we test another exemplar management scheme which employs a Ring Buffer to store exemplars for each class. The performance comparison of these two exemplar management schemes used in ER and ReMix is presented in Figure 1 (Left). We can see that Herding is consistently better than Ring Buffer across all incremental training phases for both ReMix and ER.

A.2. Different memory sizes.

In Figure 1 (Middle), we show the effects of different sizes of exemplars (20, 30, 50) per class used by Herding. The increased exemplar size improves both ER and ReMix. Nevertheless, ReMix is consistently superior to ER with different exemplar sizes.


In Figure 1 (Right), we show the performance on classes in the current phase (in-phase classes) and not in the current phase (out-phase classes) separately. Improvements on out-phase classes demonstrate that ReMix further alleviates catastrophic forgetting classes not in the current phase. Improvements on in-phase classes show that ReMix improves sample efficiency to quickly learn classes in the phase.

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