Appendix for "Generalized Class Incremental Learning"

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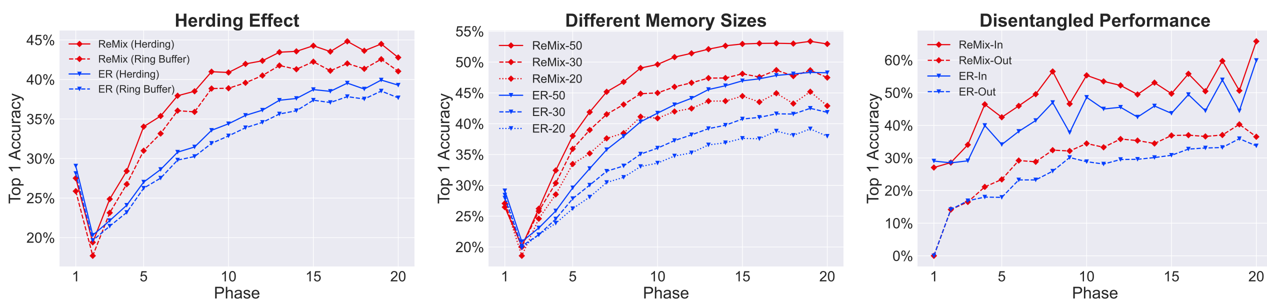

Figure 1. **Left**: Herding v.s. ring buffer to select exemplars for *ReMix* and *ER*. **Middle**: Performance of *ReMix* and *ER* with varying exemplar sizes. **Right**: Disentangled performance comparing *ReMix* with *ER*.

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 $K_t \sim \mathcal{U}(1, 100)$, $\mathbf{W}_t^1 = \text{UNIFORM}$, $\mathbf{W}_t^2 = \text{TASK-VARIED}$.

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.

A.3. Disentangled performance.

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.

*Equal contribution