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Due: 02/10/2026 11:59 PM ET

Dark Experience for General Continual Learning

Motivation. Continual learning methods often rely on complex mechanisms such as gradient constraints or parameter regularization, motivating the search for simpler replay-based approaches that are effective across a wide range of continual learning settings.

Problem Setting. The learner receives a sequence of tasks or data batches and must learn new information without access to the full historical dataset, while preserving performance on previously learned tasks.

Core Idea. Dark Experience Replay (DER) proposes storing a small buffer of past examples paired with the model's past output logits, and using these stored logits as soft targets during replay to mitigate catastrophic forgetting.

Dark Knowledge. Instead of replaying hard labels, DER replays the model's previous predictions, preserving richer information about inter-class relationships and decision boundaries learned at earlier stages.

Replay Objective. Training alternates between optimizing the loss on current-task data and a distillation-style loss that matches the model's current outputs to the stored logits on replayed examples.

General Applicability. DER applies uniformly across task-incremental, class-incremental, domain-incremental, and task-free continual learning settings without requiring task identity at test time.

Comparison to Experience Replay. While standard experience replay mitigates forgetting by revisiting old samples, DER improves stability by constraining the function outputs directly, rather than only reinforcing hard labels.

Relation to Knowledge Distillation. DER can be interpreted as online self-distillation, where the model acts as its own teacher across time, transferring knowledge from earlier parameter configurations to later ones.

Computational Simplicity. DER avoids quadratic programs, Fisher matrix estimation, or architectural modifications, requiring only a replay buffer and an additional loss term during training.

Empirical Results. Experiments demonstrate that DER consistently outperforms or matches more complex continual learning methods across benchmarks, establishing it as a strong baseline.

Limitations. DER depends on the quality and diversity of the replay buffer, and storing logits increases memory requirements relative to storing inputs alone.

Key Takeaway. Dark Experience Replay shows that simple replay combined with output-level distillation is a powerful and general strategy for continual learning, reframing forgetting as a function mismatch rather than a parameter drift problem.