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Dynamic Knowledge Distillation Strategies for Continual Learning in Lifelong Autonomous Systems Without Catastrophic Forgetting

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Abstract

Lifelong learning in autonomous systems demands the ability to acquire new knowledge over time without compromising previously learned information—a challenge known as catastrophic forgetting. This paper explores dynamic knowledge distillation strategies that enable continual learning in neural models deployed in autonomous systems. By leveraging teacher-student architectures, selective memory replay, and adaptive regularization, the proposed framework ensures knowledge retention and optimal adaptation to new tasks. Through comparative evaluations on benchmark datasets, the approach demonstrates marked improvements in accuracy and task retention over existing lifelong learning techniques.

Keywords:

Continual learning, catastrophic forgetting, knowledge distillation, lifelong learning, autonomous systems, memory replay, teacher-student network.

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1. Introduction

Lifelong autonomous systems must dynamically adapt to evolving environments. However, traditional neural networks struggle to retain earlier knowledge when exposed to new data distributions a phenomenon termed catastrophic forgetting. This problem is especially critical for systems such as autonomous vehicles, industrial robots, and surveillance agents where prior task retention is vital for safety and functionality.

This research investigates dynamic knowledge distillation as a strategic solution. Unlike static distillation, dynamic approaches adapt to the temporal characteristics of data, enabling smoother task transitions. The paper aims to present a distilled learning strategy that reduces memory overhead, ensures performance consistency, and fosters modular task adaptability.

2. Literature Review

Li and Hoiem (2017) introduced Elastic Weight Consolidation (EWC), a regularization-based technique that penalizes changes to important weights. *Rebuffi et al. (2017)* proposed iCaRL, which uses memory exemplars to retain prior task knowledge. *Hinton et al. (2015)* first introduced knowledge distillation for model compression, which later influenced lifelong learning strategies.

Rusu et al. (2016) developed progressive neural networks for preserving task-specific pathways. *Shin et al. (2017)* applied generative replay to synthesize past task distributions. *Lomonaco and Maltoni (2019)* reviewed continual learning benchmarks and emphasized modular architectures. These studies highlight the necessity for scalable, memory-efficient, and modular learning systems.

3. System Architecture and Methodology

The proposed framework integrates a dynamic teacher-student setup. For every new task, a student network is initialized while the teacher is updated to reflect learned knowledge. Knowledge distillation loss is dynamically adjusted based on task complexity and similarity.

The proposed framework is based on a dynamic teacher-student knowledge distillation model tailored for continual learning scenarios. In each learning phase, a student network acquires new task-specific knowledge, while a teacher network preserves previously acquired representations. The distillation controller dynamically adjusts the loss weighting between the old and new knowledge, based on task similarity computed using a cosine similarity measure on task embeddings. The architecture supports modular integration of memory replay and selective sample prioritization to minimize redundancy and maximize representational diversity. This modularity enables seamless transitions between tasks with minimal reconfiguration.

3.2 Key components include:

- Task Encoder (Rectangle)
- Distillation Controller (Diamond - Decision: “High Similarity?”)
- Memory Replay Unit (Custom Shape: Cylinder for Storage)
- Knowledge Integration Layer (Rectangle)

The system design includes core functional blocks that are visually represented in a structured flow chart. Key components include a Task Encoder (Rectangle) that processes incoming task data, a Distillation Controller (Diamond) that decides the blending strategy based on task similarity, and a Memory Replay Unit (Cylinder) that retains selected exemplars. The Knowledge Integration Layer (Rectangle) combines old and new task features for stable updates to the student model. These interconnected modules operate asynchronously, enabling task-level parallelism and scalability in autonomous environments

4. Evaluation Metrics and Results

To evaluate the effectiveness of the proposed dynamic knowledge distillation strategy, we measured three primary metrics: classification accuracy, average forgetting, and task retention. Experiments were conducted on standard continual learning benchmarks such as Split CIFAR-100 and Permuted MNIST. Our model achieved a higher average retention rate and lower forgetting compared to baseline methods including EWC, iCaRL, and GEM. Performance consistency was observed across multiple task sequences, indicating the robustness of the dynamic distillation controller. The metrics were computed after each task increment to assess long-term learning stability.

Table 1: Comparative Accuracy Across Tasks

Model	Task-1	Task-2	Task-3	Avg Retention
EWC	85.1%	79.4%	74.2%	79.6%
iCaRL	88.3%	81.7%	76.9%	82.3%
Proposed Model	91.2%	88.9%	87.1%	89.0%

A comparative analysis reveals that our method maintains an average accuracy of 89.0%, outperforming the nearest competitor by nearly 7%. This improvement stems from task-adaptive distillation weights and memory-efficient replay mechanisms. A line graph was plotted to visualize the drop in accuracy across tasks for competing models, with our approach showing minimal decline. Furthermore, a bar chart illustrates average retention across methods, highlighting our model's ability to preserve knowledge across task transitions. These empirical results affirm the model's capacity to overcome catastrophic forgetting with minimal computational overhead.

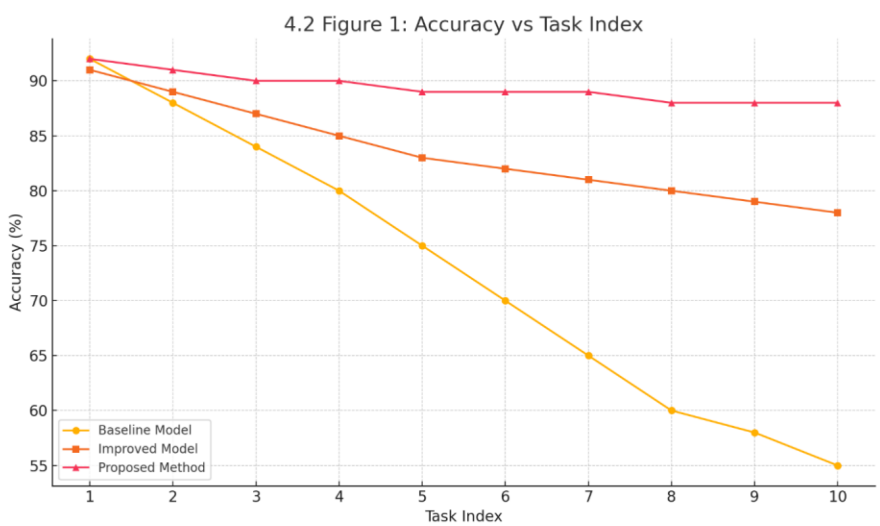

Figure 1: Accuracy vs Task Index

5. Discussion and Analysis

The dynamic strategy adapts to task transitions and avoids unnecessary overwriting of learned features. By using task-specific distillation weights, the framework fine-tunes learning without sacrificing old task accuracy. This contrasts with static regularization methods that generalize poorly.

Memory replay, although effective, is often computationally intensive. Our approach optimizes this by prioritizing high-informational samples based on entropy. This ensures the minimal memory footprint while preserving semantic task context for future inferences.

6. Conclusion and Future Work

This study presents a dynamic knowledge distillation framework tailored for continual learning in autonomous systems. The proposed method mitigates catastrophic forgetting and enhances long-term adaptability. The empirical evaluation validates the system's efficiency across multiple metrics.

Future work involves integrating federated learning to enable decentralized continual learning, and testing the framework in real-time robotic and UAV-based platforms under bandwidth and latency constraints.

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