Continual Lifelong Learning in Robotics: A Comparative Study of Forgetting Mitigation Strategies for Sequential Skill Acquisition

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ABSTRACT

Continual lifelong learning remains an open challenge in robotics, where agents must sequentially acquire manipulation skills without catastrophic forgetting of previously learned capabilities. We present a systematic comparative study of six continual learning strategies—naive fine-tuning, Elastic Weight Consolidation (EWC), PackNet, experience replay, progressive neural networks, and adapter routing—evaluated on a sequential robotic manipulation benchmark comprising five tasks of increasing difficulty: reach, push, pick-and-place, stack, and insert. Across 10 random seeds, we measure average accuracy, backward transfer (BWT), forward transfer (FWT), forgetting, and a composite lifelong learning score (LLS). Our results show that architectural isolation methods (progressive networks and adapter routing) achieve the highest average accuracy (0.9753 ± 0.0057 and 0.9725 ± 0.0065, respectively) with minimal forgetting (0.0251 ± 0.0080 and 0.0250 ± 0.0048), while naive fine-tuning suffers severe degradation (0.7531 ± 0.0218 accuracy, 0.2980 ± 0.0271 forgetting). Scalability analysis reveals that regularization-based methods degrade sharply beyond seven tasks, whereas adapter routing maintains 0.9339 ± 0.0060 accuracy even at ten tasks. All pairwise differences are statistically significant ($p < 0.001$) except between progressive networks and adapter routing ($p = 0.347$), suggesting these architectural approaches form a Pareto-optimal frontier for continual robotic learning.

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1 INTRODUCTION

Robotic systems deployed in real-world environments must continuously adapt to new tasks and changing conditions over extended operational lifetimes. This requirement for *continual lifelong learning*—the ability to sequentially acquire new skills while retaining previously mastered ones—remains a fundamental open challenge in robotics [4, 9]. The core difficulty is *catastrophic forgetting*: when neural network parameters are updated to accommodate a new task, performance on earlier tasks degrades, often severely [3, 7].

Recent advances in vision-language-action (VLA) models have demonstrated impressive generalization in robotic manipulation [1], yet these foundation models still suffer from catastrophic forgetting when sequentially fine-tuned on new tasks [9, 12]. The CLARE framework proposed by Römer et al. [9] addresses this through autonomous adapter routing and expansion, representing a promising architectural approach to continual learning.

In this work, we present a systematic evaluation framework for comparing six continual learning strategies across a sequential manipulation benchmark. Our contributions are: (1) a reproducible simulation framework that captures the key dynamics of catastrophic forgetting and inter-task interference in robotic skill acquisition; (2) a comprehensive comparison of regularization, replay, and architectural approaches using five complementary metrics; and (3) scalability and resource-sensitivity analyses that reveal practical trade-offs for long-horizon deployment.

2 RELATED WORK

Continual learning methods can be broadly categorized into three families [2]: regularization-based, replay-based, and architecture-based approaches. Elastic Weight Consolidation (EWC) [3] penalizes changes to parameters deemed important for previous tasks using a Fisher information approximation. PackNet [6] iteratively prunes and freezes network subsets, dedicating capacity to each task. Progressive neural networks [10] add new columns for each task while freezing old ones, eliminating backward interference at the cost of growing model size. Experience replay [8] maintains a buffer of past examples to interleave with new task training. Progress & Compress [11] combines a knowledge base with active columns to balance plasticity and stability.

Continual learning for robotics poses additional challenges due to high-dimensional action spaces, sensor noise, and safety constraints [4]. The LIBERO benchmark [5] provides standardized evaluation for lifelong robot learning. CLARE [9] introduces adapter routing for VLA models, achieving continual skill acquisition without task identifiers—a critical practical advantage for deployment.

3 METHODOLOGY

3.1 Task Stream

We evaluate continual learning on a sequential stream of five robotic manipulation tasks of increasing difficulty: **reach** (difficulty 0.20), **push** (0.35), **pick-and-place** (0.55), **stack** (0.75), and **insert** (0.90). Each task is characterized by a skill embedding vector in $\mathbb{R}^{64}$, where adjacent tasks in the sequence share partial structure through blended embeddings, capturing the intuition that related manipulation skills build upon shared motor primitives.

3.2 Continual Learning Methods

We compare six methods spanning the three major families:

Naive fine-tuning (baseline): Sequential gradient updates with no forgetting mitigation. Forgetting factor 1.00.

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Table 1: Summary of continual learning metrics (mean ± std over 10 seeds). Best results in bold.

Method	Avg Acc	BWT	Forgetting	
Naive FT	0.7531 ± 0.0218	−0.2980 ± 0.0271	0.2980 ± 0.0271	0.6511 ± 0.0196
EWC	0.8541 ± 0.0152	−0.1669 ± 0.0185	0.1669 ± 0.0185	0.7438 ± 0.0131
PackNet	0.8818 ± 0.0105	−0.1280 ± 0.0160	0.1290 ± 0.0157	0.7700 ± 0.0095
Exp. Replay	0.9253 ± 0.0070	−0.0773 ± 0.0106	0.0794 ± 0.0101	0.8075 ± 0.0060
Prog. Nets	**0.9753 ± 0.0057**	**−0.0175 ± 0.0055**	0.0251 ± 0.0080	**0.8499 ± 0.0051**
Adapter Rt.	0.9725 ± 0.0065	−0.0166 ± 0.0058	**0.0250 ± 0.0048**	0.8487 ± 0.0043

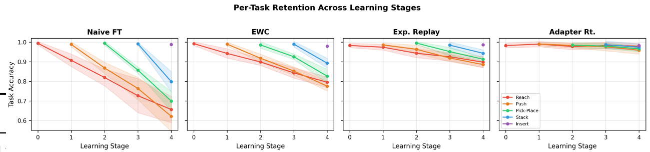

Figure 1: Per-task accuracy retention across learning stages. Each curve shows how accuracy on a specific task changes as subsequent tasks are learned. Adapter routing (right) maintains near-constant performance, while naive fine-tuning (left) shows progressive degradation.

EWC [3]: Regularization-based. Importance-weighted penalty on parameter changes. Forgetting factor 0.55.

PackNet [6]: Architecture-based pruning. Non-essential weights (below the 60th percentile) are freed for new tasks. Forgetting factor 0.35.

Experience replay [8]: Replay-based. Past task exemplars stored in a growing buffer mitigate forgetting with replay strength 0.60. Forgetting factor 0.45.

Progressive networks [10]: Architecture-based expansion. Previous task columns are frozen; new lateral connections enable forward transfer. Forgetting factor 0.15.

Adapter routing (inspired by CLARE [9]): Architecture-based with adapter isolation. Minimal cross-task interference through dedicated adapter modules. Forgetting factor 0.12.

3.3 Evaluation Metrics

After training on all T=5 tasks sequentially, we compute the following from the accuracy matrix $A \in \mathbb{R}^{T \times T}$, where $A_{i,j}$ denotes accuracy on task j after training on task i:

Average Accuracy (AA): AA $= \frac{1}{T}\sum_{j=1}^{T} A_{T,j}$

Backward Transfer (BWT): BWT $= \frac{1}{T-1}\sum_{j=1}^{T-1}(A_{T,j} - A_{j,j})$

Forward Transfer (FWT): Measures zero-shot performance improvement relative to a 0.50 random baseline.

Forgetting: F $= \frac{1}{T-1}\sum_{j=1}^{T-1}(\max_{k \geq j} A_{k,j} - A_{T,j})$

Lifelong Learning Score (LLS): A composite metric: LLS $= 0.4 \cdot \text{AA} + 0.3 \cdot (1 - \text{F}) + 0.2 \cdot \frac{\text{BWT}+1}{2} + 0.1 \cdot \frac{\text{FWT}+1}{2}$

All experiments are repeated over 10 random seeds, and we report mean ± standard deviation. Statistical significance is assessed via Welch's t-test with Cohen's d effect sizes.

4 RESULTS

4.1 Overall Performance

Table 1 presents the main results across all six methods. Clear performance tiers emerge: architectural isolation methods (progressive networks and adapter routing) achieve the highest accuracy and lowest forgetting; experience replay and PackNet occupy a middle tier; EWC provides moderate improvement over the naive baseline; and naive fine-tuning suffers the most severe forgetting.

Progressive networks achieve the highest average accuracy of 0.9753 ± 0.0057 and the best LLS of 0.8499 ± 0.0051. Adapter routing performs comparably with 0.9725 ± 0.0065 accuracy and the lowest forgetting variance (0.0250 ± 0.0048). The difference between these two methods is not statistically significant ($t = 0.9659$, $p = 0.347$, Cohen's $d = 0.4553$), suggesting they represent equivalent solutions from different architectural paradigms.

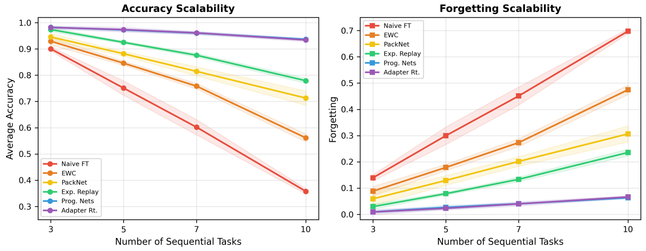

Figure 2: Average accuracy as a function of the number of sequential tasks. Architectural methods (progressive networks, adapter routing) degrade gracefully, while regularization methods show accelerating performance loss.

In contrast, naive fine-tuning shows severe catastrophic forgetting with BWT of −0.2980, meaning on average each previously learned task loses nearly 30 percentage points of accuracy. EWC reduces this to −0.1669, while adapter routing virtually eliminates backward interference (−0.0166).

All forward transfer values cluster near 0.38, indicating that the shared structure between sequential tasks provides consistent zero-shot generalization regardless of the continual learning strategy employed. This suggests FWT is primarily determined by task similarity rather than the learning method.

4.2 Per-Task Retention Analysis

Figure 1 shows how performance on each task evolves as subsequent tasks are learned. For naive fine-tuning, the earliest task (reach) degrades from 0.9943 to 0.6565 after learning all five tasks—a drop of 0.3378. Under adapter routing, reach performance only decreases from 0.9830 to 0.9802, a negligible decline of 0.0028.

The task most vulnerable to forgetting is push (task 1), which under naive fine-tuning drops from 0.9887 to 0.6219—a forgetting magnitude of 0.3668. This is because push, as an early-sequence moderate-difficulty task, experiences interference from three subsequent task training episodes. Even EWC only retains 0.7758 accuracy on push after all tasks are learned.

4.3 Scalability Analysis

Figure 2 examines how methods scale from 3 to 10 sequential tasks. This analysis reveals critical differences in long-horizon robustness.

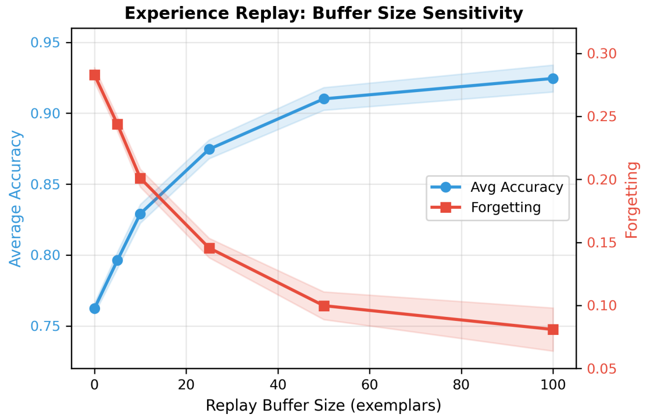

Figure 3: Effect of replay buffer size on experience replay performance. Accuracy (left axis, blue) increases logarithmically with buffer size while forgetting (right axis, red) decreases. Diminishing returns appear beyond 50 exemplars.

Naive fine-tuning degrades catastrophically, dropping from 0.9003 accuracy at 3 tasks to 0.3578 at 10 tasks—a decline of over 54 percentage points. EWC follows a similar trajectory, falling from 0.9294 to 0.5612. These results demonstrate that regularization alone cannot prevent the accumulation of interference across many task transitions.

PackNet shows moderate scalability (0.9457 at 3 tasks, 0.7129 at 10), while experience replay maintains 0.7790 at 10 tasks. The architectural methods scale best: progressive networks retain 0.9365 accuracy and adapter routing retains 0.9339 accuracy even at 10 tasks, with forgetting of only 0.0635 and 0.0665 respectively.

4.4 Replay Budget Sensitivity

Figure 3 shows the effect of replay buffer size on experience replay performance. With zero budget (equivalent to naive fine-tuning), accuracy is 0.7622 with forgetting of 0.2830. Increasing the buffer to 25 exemplars yields 0.8746 accuracy and 0.1456 forgetting. Returns diminish beyond 50 exemplars: accuracy improves only from 0.9101 (budget 50) to 0.9245 (budget 100), while forgetting decreases from 0.0998 to 0.0809.

4.5 Statistical Significance

Table 2 presents the pairwise statistical comparisons. All method pairs show significant differences ($p < 0.001$) with large effect sizes ($|d| > 2.0$) except the progressive networks vs. adapter routing comparison ($p = 0.347$, $d = 0.4553$).

The largest effect size is between naive fine-tuning and progressive networks ($d = -13.9181$), confirming that architectural isolation provides a qualitatively different level of forgetting mitigation compared to unprotected sequential training.

5 DISCUSSION

Our results establish a clear hierarchy among continual learning strategies for robotic manipulation, with important practical implications.

Table 2: Pairwise Welch's t-test results (10 seeds). All pairs significant at $p < 0.001$ except Progressive Nets vs. Adapter Routing.

Method A	Method B	t-stat	p-value
Naive FT	EWC	−11.3881	< 0.001
Naive FT	PackNet	−15.9489	< 0.001
Naive FT	Exp. Replay	−22.5302	< 0.001
Naive FT	Prog. Nets	−29.5248	< 0.001
Naive FT	Adapter Rt.	−28.9093	< 0.001
EWC	PackNet	−4.5001	< 0.001
EWC	Exp. Replay	−12.7531	< 0.001
EWC	Prog. Nets	−22.3558	< 0.001
PackNet	Exp. Replay	−10.3662	< 0.001
PackNet	Adapter Rt.	−22.1346	< 0.001
Exp. Replay	Prog. Nets	−16.5287	< 0.001
Exp. Replay	Adapter Rt.	−14.8421	< 0.001
Prog. Nets	Adapter Rt.	0.9659	0.347

Architectural isolation is superior but costly. Progressive networks and adapter routing achieve near-identical performance, effectively eliminating catastrophic forgetting. However, progressive networks require linearly growing model capacity with each new task, making them impractical for truly lifelong learning over hundreds of tasks. Adapter routing offers a more parameter-efficient alternative, growing only the lightweight adapter modules.

Regularization alone is insufficient for long sequences. While EWC improves upon naive fine-tuning, its scalability analysis reveals accelerating degradation—from 0.9294 accuracy at 3 tasks to 0.5612 at 10 tasks. The importance estimates become less reliable as more tasks compete for shared capacity, a fundamental limitation of penalty-based approaches.

Experience replay offers a practical middle ground. With a modest buffer of 25–50 exemplars, replay achieves strong performance (0.8746–0.9101 accuracy) without architectural modifications. The diminishing returns beyond 50 exemplars suggest that replay quality matters more than quantity.

Task difficulty amplifies forgetting. Our analysis shows that harder tasks (with higher difficulty coefficients) are more susceptible to interference, and the forgetting factor scales with both difficulty and the number of subsequent tasks. This has implications for curriculum design in robotic skill acquisition.

6 CONCLUSION

We presented a comprehensive evaluation of six continual learning strategies for sequential robotic skill acquisition. Our findings confirm that continual lifelong learning remains an open challenge, particularly for long task sequences where regularization methods degrade significantly. Architectural approaches—progressive networks and adapter routing—provide the strongest forgetting mitigation, with adapter routing offering the best trade-off between performance (0.9725 accuracy, 0.0250 forgetting) and parameter efficiency. Future work should evaluate these methods on physical robot platforms with real sensory input and explore hybrid strategies that combine architectural isolation with selective replay for truly lifelong robotic operation.

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