

Lifelong Learning

Study Guide

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Chapter 26 of "The NeuroAI Handbook"

How brains keep old memories while learning new ones, and the AI tricks that borrow the idea.

One-sentence thesis. Forgetting is not a failure of capacity but of interference, new learning overwriting old, so every real solution, biological or artificial, is a policy for deciding what to protect.

PART 1: The Stability-Plasticity Dilemma

The Tension at the Heart of Learning

Start with the bind, not the algorithm. A learner that never changes learns nothing new; a learner that changes freely erases what it already knew. Intelligence lives in the narrow band between those failures. This is the **stability-plasticity dilemma**: *plasticity* is the ability to absorb new information quickly, *stability* is the ability to keep old knowledge intact, and the two pull in opposite directions. Too plastic and yesterday's skill is gone by tomorrow; too stable and the system is a fossil.

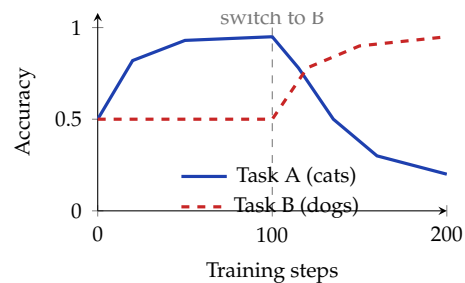
Humans manage this so effortlessly we forget it is hard. You can learn a colleague's name today without deleting your childhood address. Modern deep networks cannot, because they are extremely plastic and almost nothing anchors them to the past.

Catastrophic Forgetting

The failure mode has a name. Train a standard network to recognize cats, then train the same network to recognize dogs, and it will typically forget cats almost completely, its accuracy on the first task collapsing

toward chance. This is **catastrophic forgetting** (McCloskey and Cohen, 1989), and it is the single biggest barrier to AI that learns in the real world.

The mechanism is plain once you see it. Gradient descent adjusts *shared* weights to reduce error on whatever data is in front of it right now, with no term in the loss that says "and keep the old task working." The weights that encoded cats are simply overwritten to fit dogs. **Watch out.** This is not a bug in one architecture, it is the default behavior of any network trained on tasks in sequence without a countermeasure.



The moment training switches to Task B, accuracy on Task A falls off a cliff.

Two Systems, Two Speeds

The brain faces the identical dilemma and solved it not by finding one perfect learning rate but by using **two** memory systems at once. This is **complementary learning systems** theory (McClelland, McNaughton, and O'Reilly, 1995; Kumaran, Hassabis, and McClelland, 2016). The **hippocampus** learns fast, stores specific episodes, and is highly plastic. The **neocortex** learns slowly, stores generalized knowledge, and is stable. New experience lands first in the fast system; only gradually, and carefully, does it migrate into the slow one.

ANALOGY

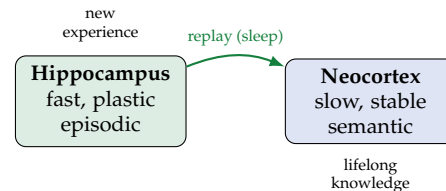
A sculptor's studio and a grand library. The hippocampus is the studio, fast and messy, shaping each day's experience into a fresh sculpture. The neocortex is the library, slow and permanent. Each night the librarian reviews the day's best pieces and painstakingly casts a few in marble for the permanent collection, leaving the archive stable and organized.

Sleep Replay Does the Consolidation

The migration is not passive. During sleep the hippocampus literally **replays** the day's experience, reactivating the same neural sequences seen during

waking, sped up ten to twenty times, packaged into brief high-frequency bursts called **sharp-wave ripples**. Each replay is a training example handed to the neocortex, so the slow system learns the new pattern gradually, interleaved with old knowledge, without a sudden overwrite. Consolidation runs over hours to years: a fresh memory is hippocampus-dependent, an ancient one lives distributed in cortex.

Two further biological details matter. **Selectivity, not volume.** The brain does not replay everything; salient and rewarding experiences are prioritized. And **synaptic tagging** (Frey and Morris, 1997) shows the molecular version: a strongly stimulated synapse triggers protein synthesis, and only recently "tagged" synapses can capture those proteins to become permanent, so what gets consolidated is decided locally and competitively.



Fast episodic capture, then slow, interleaved consolidation into the stable store.

If Forgetting Is Overwriting, There Are Only Three Moves

Once you see forgetting as interference in shared weights, the space of fixes is small: **rehearse** the past so it is never fully absent, **protect** the weights that encode it, or **grow** new capacity so nothing has to be overwritten. Every continual-learning method is a version of one of these three.

Replay, Rehearse the Past

The most direct fix is also the most biological: keep a buffer of old examples and mix them into new training. This **experience replay** is the engineering twin of hippocampal replay, and on standard benchmarks it is the most effective single method, storing even a small slice of old data prevents most forgetting. Its cost is memory and, sometimes, privacy, you have to keep the old data around.

Regularization, Protect What Matters

You do not always have the old data. **Elastic Weight Consolidation** (EWC; Kirkpatrick et al., 2017) instead asks which *weights* mattered for the old task and anchors those in place. Importance is measured by the **Fisher information**, essentially the curvature of the old-task loss around its optimum: a weight in a steep valley is critical, a weight on a flat plateau is free to move.

In symbols, learning task B minimizes the new loss plus a Fisher-weighted penalty pulling each weight back toward its old value $\theta_{A,i}^*$:

$$\mathcal{L}(\theta) = \mathcal{L}_B(\theta) + \frac{\lambda}{2} \sum_i F_i (\theta_i - \theta_{A,i}^*)^2$$

ANALOGY

Tie each weight to its old value with a spring. The spring's stiffness is that weight's Fisher information, so important weights are held tightly while unimportant ones stretch freely to fit the new task. The knob λ tunes all the springs at once: too loose and old knowledge drifts away, too tight and nothing new can be learned.

Synaptic Intelligence and Memory Aware Synapses are cousins that estimate importance differently, and the brain analog is real, **synaptic consolidation** makes important synapses physically resistant to change.

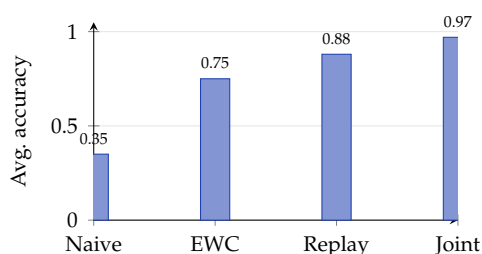
Architecture, Grow New Capacity

The third move refuses to share weights at all. **Progressive Neural Networks** (Rusu et al., 2016) freeze the entire old network and add a fresh "column" for each new task, wired to the old columns by **lateral connections** so new tasks can reuse old features. The result is **zero forgetting** plus positive forward transfer, paid for with memory and compute that grow with the number of tasks. Two lighter variants round out the toolbox: **Learning without Forgetting** preserves the old input-output behavior by distillation instead of storing data, and **meta-learning** (MAML, Reptile) hunts for an initialization that adapts to any new task in a few steps, echoing the brain's *metaplasticity*, the plasticity of plasticity itself.

Method	Core idea	Forgetting	Cost	Brain analog
Fine-tuning	Just train on each task in turn (baseline)	Severe	$O(1)$	none
Replay	Rehearse a buffer of stored old examples	Low	buffer memory	hippocampal replay
EWC	Anchor high-Fisher weights near old values	Moderate	$2 \times$ params	synaptic consolidation
Progressive Nets	Freeze old, add a column per task	Zero	$O(T)$ params + compute	cortical expansion / routing
LwF	Distill old behavior, no old data kept	Low-Mod	old-model copy	functional preservation

The Split-MNIST Verdict

Put the methods on the same benchmark, five sequential digit tasks, and the ranking is clear. Naive fine-tuning drops from about **95 percent** to roughly **20 percent** on the earliest tasks, textbook catastrophic forgetting. Replay recovers most of that. EWC lands in between, a good middle ground when old data cannot be kept. Joint training on all tasks at once is the upper bound nobody can beat online. The metrics that matter are **average accuracy**, **forgetting** (a task's drop from peak to final score), and **forward/backward transfer** (whether learning one task helps others).



Average accuracy over all five tasks; Joint training is the offline upper bound.

The Foundation-Model Shortcut

The newest twist changes the game. Take a large pretrained model, freeze it, and adapt to each new task with a tiny set of added parameters, prompts, adapters, or **LoRA** low-rank updates, typically **0.1 to 1 percent** of the weights per task. Because the base never changes, forgetting of its core knowledge is zero, and the rich pretrained features transfer to almost everything. It is efficient and popular, but it leans on an expensive pretrained model and can struggle on domains far from what that model saw.

What the Brain Still Does Better

Even the best methods are missing pieces of the biological recipe. AI trains continuously; the brain has dedicated **offline** consolidation phases (sleep). AI replay usually samples uniformly; the brain replays **selectively**, prioritizing what matters. And over long sequences, networks can suffer **catastrophic plasticity loss**, becoming too rigid to learn anything new, the mirror image of forgetting. Task-free settings and true backward transfer, where new learning actually improves old skills, remain largely open.

Quick Self-Test

1. In a network trained on cats then dogs, what specifically gets destroyed, and why does plain gradient descent do it?
2. Name the brain's two complementary learning systems and state what each contributes to avoiding forgetting.
3. In EWC, what does the Fisher information measure, and how exactly does it change the loss function?
4. Progressive Networks guarantee zero forgetting. What is the price, and why does it grow with the number of tasks?
5. Give one thing sleep-based consolidation does that experience replay in current AI systems does not.

If You Remember One Thing

Forgetting is interference, and every solution is a policy for what to protect. The brain protects by consolidating its most important memories into a separate, stable store while it sleeps; AI protects by rehearsing old data, anchoring important weights, or freezing them, and none yet matches the brain's selective, offline consolidation.