Contents

1 Chapter 4: Sparse Reach + Push -- Introduce HER Where It Matters

> **Week 4 Goal:** Demonstrate that Hindsight Experience Replay (HER) is the difference-maker on sparse goal-conditioned tasks.

1.1 WHY: The Sparse Reward Problem

In Chapter 3, we trained SAC on `FetchReachDense-v4`, where every timestep provides a shaped reward signal proportional to the distance to the goal. The agent received continuous feedback: ”you're getting warmer” or ”you're getting colder.” This made learning straightforward.

Now we face the real challenge: **sparse rewards**.

1.1.1 What ”Sparse” Means in Gymnasium-Robotics

In sparse Fetch environments (`FetchReach-v4`, `FetchPush-v4`, `FetchPickAndPlace-v4`), the reward function is:

$$R(s,a,g) = \begin{cases} 0 & \text{if } \|g_{\text{achieved}} - g_{\text{desired}}\| < \epsilon \\ -1 & \text{otherwise} \end{cases}$$

where $\epsilon = 0.05$ meters (5 cm) is the success threshold.

The problem: The agent receives $R = -1$ for almost every transition until it accidentally succeeds. With random exploration, this might never happen -- or happen so rarely that the agent cannot learn from it.

1.1.2 Why Standard RL Fails on Sparse Goals

Consider training SAC without HER on sparse Reach:

1. **Initial exploration is random.** The gripper moves chaotically.
2. **Most episodes fail.** The gripper rarely lands within 5cm of the goal by chance.
3. **All transitions have reward -1.** The critic learns: ”everything is equally bad.”
4. **No gradient signal for improvement.** Without reward variation, the policy has no direction to improve.

This is not a hyperparameter problem -- it is a **structural limitation** of standard RL with sparse rewards.

1.1.3 The Key Insight: Failed Trajectories Contain Information

Here is the insight that makes HER work:

> A trajectory that fails to reach goal g is a **successful demonstration** of how to reach wherever it ended up.

If the gripper tried to reach position $(0.3, 0.2, 0.1)$ but ended at $(0.5, 0.4, 0.15)$, we have evidence that the executed actions lead to $(0.5, 0.4, 0.15)$. We can **relabel** the trajectory: pretend the goal was $(0.5, 0.4, 0.15)$ all along, and now we have a successful episode with reward 0.

This is Hindsight Experience Replay.

1.2 HOW: Hindsight Experience Replay (HER)

1.2.1 The Relabeling Strategy

For each transition $(s_t, a_t, r_t, s_{t+1}, g)$ stored in the replay buffer, HER also stores relabeled versions:

1. **Original transition:** goal = g (the intended goal)
2. **Relabeled transitions:** goal = g' (substituted goals)

The substituted goals g' come from the same trajectory. Common strategies:

Strategy	Description
`future`	Sample g' from achieved goals at timesteps $t' > t$ in the same episode
`final`	Use only the final achieved goal $g' = g_{\text{achieved}}(s_T)$
`episode`	Sample g' from any achieved goal in the episode

Why `future` works best: It creates more relabeled transitions (one for each future timestep), and these goals are ”reachable” from the current state -- the agent just demonstrated it can get there.

1.2.2 The `n_sampled_goal` Parameter

For each original transition, HER creates `n_sampled_goal` additional relabeled transitions. The default is 4, meaning:

- 1 original transition (goal = intended)
- 4 relabeled transitions (goal = sampled achieved goals)

This 5x expansion of the replay buffer is how HER manufactures dense reward signal from sparse feedback.

1.2.3 Why HER Requires Off-Policy Learning

HER only works with **off-policy** algorithms (SAC, TD3, DDPG) because:

1. **Relabeling changes the reward.** The relabeled transition has a different reward than what the agent actually experienced.
2. **Off-policy methods don't care.** They can learn from any transition, regardless of which policy generated it.
3. **On-policy methods (PPO) cannot use relabeled data.** They require transitions from the current policy.

This is why the syllabus builds SAC mastery (Weeks 2-3) before introducing HER (Week 4).

1.3 BUILD IT: HER Relabeling in Code

This section shows how HER's goal relabeling maps to code. We use pedagogical implementations from `scripts/labs/her_relabeler.py`—these are for understanding, not production.

1.3.1 Goal Sampling Strategies

The ”future” strategy samples achieved goals from timesteps after the current transition:

```
--8<-- "scripts/labs/her_relabeler.py:goal_sampling"
```

Key insight: The `future` strategy ensures temporal consistency—we only relabel with goals the agent *actually reached* from states similar to the current one.

1.3.2 Relabeling a Transition

The core HER operation: substitute a new goal and recompute the reward:

```
--8<-- "scripts/labs/her_relabeler.py:relabel_transition"
```

Key mapping:

Concept	Code	Meaning
Original goal	`transition.desired_goal`	What we were trying to reach
Achieved goal	`transition.achieved_goal`	Where we actually ended up
Relabeled goal	`new_goal`	Substitute this as the ”desired” goal
New reward	`compute_reward_fn(achieved, new_goal)`	Did achieved match the new goal?

Crucial: The `achieved_goal` stays the same—only `desired_goal` changes. If achieved == new desired, the transition becomes a ”success.”

1.3.3 The Data Amplification Effect

Processing an episode with HER dramatically increases the success rate in the replay buffer:

```
--8<-- "scripts/labs/her_relabeler.py:her_buffer_insert"
```

Without HER: Nearly 0% of transitions have positive reward (sparse signal). **With HER:** Many relabeled transitions are ”successes” because achieved == relabeled goal.

1.3.4 Verify the Lab

Run the from-scratch implementation's sanity checks:

```
bash docker/dev.sh python scripts/labs/her_relabeler.py --verify
```

Expected output:

- Goal sampling produces correct number of goals
- Relabeling with own achieved goal produces reward=0 (success)
- HER processing increases success rate in synthetic data (0% → ~16%)

This lab is **not** how we train policies—SB3's HER wrapper handles that. The lab shows *what* relabeling does to your data.

1.3.5 Exercises: Modify and Observe

Exercise: Goal Sampling Strategy Comparison

Run the demo to see how different strategies affect success rates:

```
bash docker/dev.sh python scripts/labs/her_relabeler.py --demo
```

Observe: The `future`, `final`, and `episode` strategies produce different success rates. Why does `future` typically work best?

Exercise: Relabeling Ratio (k)

In `process_episode_with_her()`, change k=4 to different values:

```
# Try: k=1, k=4, k=8, k=16
```

Question: How does the success fraction change with k? What's the tradeoff between more relabeled data and data quality?

Exercise: HER Ratio

Change `her_ratio=0.8` to different values:

```
# Try: her_ratio=0.0 (no HER), her_ratio=0.5, her_ratio=1.0 (all relabeled)
```

Question: With `her_ratio=0.0`, you get pure sparse reward learning. With `her_ratio=1.0`, you get maximum relabeling. Why might 0.8 be a good balance?

Exercise: Understand Why HER Only Gets ~16% Success

The verification shows ~16% success rate on synthetic data. This seems low—why not higher?

Hint: The synthetic trajectory uses random actions, so achieved goals are scattered randomly. With a *trained* policy that moves toward goals, future achieved goals would be closer to the current state, making more relabeled transitions successful. HER amplifies competence—it doesn't create it from nothing.

1.4 WHAT: Experiments and Expected Results (Run It)

1.4.1 Running the Experiments

All experiments run through Docker via the `docker/dev.sh` wrapper. This ensures reproducible environments with correct GPU access, MuJoCo rendering, and Python dependencies.

1.4.1.1 Quick Start: Full Pipeline

```
# FetchReach-v4: ~1 hour for all 6 runs (default settings work well)
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py env-all \
    --env FetchReach-v4 --seeds 0,1,2 --total-steps 500000

# FetchPush-v4: ~3 hours for all 6 runs (needs fixed entropy for reliable learning)
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py env-all \
    --env FetchPush-v4 --seeds 0,1,2 --total-steps 2000000 --ent-coef 0.05
```

The `env-all` command runs the complete pipeline:

1. Train SAC without HER (3 seeds)
2. Evaluate each no-HER checkpoint (100 episodes each)
3. Train SAC with HER (3 seeds)
4. Evaluate each HER checkpoint (100 episodes each)
5. Generate comparison report

Note: Legacy `reach-all` and `push-all` commands still work for backwards compatibility.

1.4.1.2 Individual Commands

For more control, run steps separately:

```
# Train a single model
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py train \
    --env FetchPush-v4 --seed 0 --total-steps 500000        # no-HER

bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py train \
    --env FetchPush-v4 --her --seed 0 --total-steps 500000  # with HER

# Train with fixed entropy (recommended for sparse Push)
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py train \
    --env FetchPush-v4 --her --seed 0 --total-steps 2000000 --ent-coef 0.05

# Evaluate a checkpoint
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py eval \
    --ckpt checkpoints/sac_her_FetchPush-v4_seed0.zip

# Compare results across seeds
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py compare \
    --env FetchPush-v4 --seeds 0,1,2
```

1.4.1.3 Long-Running Jobs with tmux

Training takes 10-15 minutes per run. For the full pipeline (~3 hours for Push), use tmux:

```
# Start a persistent session
tmux new -s week4

# Inside tmux, run the experiments
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py env-all \
    --env FetchPush-v4 --seeds 0,1,2 --ent-coef 0.05 --total-steps 2000000

# Detach: Ctrl-b d
# Reattach later: tmux attach -t week4
```

1.4.1.4 Expected Training Time

Environment	Steps	Time per run	Total (6 runs)
FetchReach-v4	500k	~10 min	~60 min
FetchPush-v4	500k	~14 min	~85 min
FetchPush-v4	1M	~28 min	~170 min

Times measured on DGX with RTX A100, ~600 fps throughput.

1.4.2 Experiment 1: Sparse Reach -- HER vs No-HER

Hypothesis: SAC without HER will struggle on `FetchReach-v4`; SAC with HER will succeed more reliably.

```
# Full pipeline: train both, evaluate, compare (3 seeds each)
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py reach-all --seeds 0,1,2 --
```

```
# Or train individually:
# No-HER baseline
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py train \
    --env FetchReach-v4 --seed 0 --total-steps 500000

# With HER
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py train \
    --env FetchReach-v4 --her --seed 0 --total-steps 500000
```

1.4.2.1 Actual Results (FetchReach-v4, 3 seeds, 500k steps)

Metric	No-HER	HER	Delta
Success Rate	96.0% +/- 8.0%	100.0% +/- 0.0%	+4.0%
Return (mean)	-2.92 +/- 2.36	-1.68 +/- 0.02	+1.24
Final Distance	0.0195 +/- 0.009	0.0170 +/- 0.007	-0.003

1.4.2.2 Analysis: Why Reach Shows Weak Separation **This is an important finding:** FetchReach-v4 is too easy to demonstrate HER's value clearly.

Why does no-HER work so well on Reach?

1. **Small goal space:** The gripper workspace is only ~15cm³. Random exploration frequently enters the success threshold (5cm) by chance.
2. **No object manipulation:** The gripper just needs to move itself -- no physics interactions, no contact forces, no object dynamics.
3. **Short horizon:** Episodes are 50 steps. With 8 parallel envs and 500k steps, that's ~12,500 episodes -- plenty for random success accumulation.
4. **Forgiving success threshold:** 5cm is relatively large compared to the workspace.

The pedagogical point: Reach is useful for validating that HER *doesn't hurt* (HER achieves 100% vs 96% for no-HER), but it fails to show HER's transformative effect. We need a harder task.

This is why we proceed to FetchPush-v4.

1.4.3 Experiment 2: Sparse Push -- Where HER Matters

Push is dramatically harder than Reach because:

1. **Indirect control:** The gripper must contact and push the object -- actions affect the object indirectly through physics.
2. **Object dynamics:** The object slides on the table with friction, momentum, and potentially overshooting.
3. **Coordinated behavior:** Success requires approach → contact → push → stop, all in sequence.
4. **Larger state space:** Both gripper AND object positions matter.

```
# Full pipeline for Push (recommended settings, ~3 hours)
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py push-all \
    --seeds 0,1,2 --total-steps 2000000 --ent-coef 0.05
```

Why no-HER should fail on Push:

- Random exploration rarely pushes the object to the goal by chance

- Without accidental successes, the replay buffer contains only $R = -1$ transitions
- The critic cannot distinguish ”almost succeeded” from ”completely failed”
- No gradient signal → no learning

Why HER should succeed:

- Every trajectory shows how to push the object *somewhere*
- Relabeling creates successful demonstrations: ”you pushed it to (x, y), let's pretend that was the goal”
- The agent learns push dynamics from its own failures
- Eventually generalizes to arbitrary goals

Expected results (with sufficient training and correct hyperparameters):

Method	Success Rate	Notes
SAC (no HER)	~0-5%	Almost never succeeds; no learning
SAC + HER (best config)	**99.4% +/- 0.9%**	ent=0.05, gamma=0.95 (5 seeds)
Delta	**>94 pp**	**This is the ”clear separation” we seek**

1.4.3.1 Actual Results: Initial Attempt (500k steps) Our first experiment with 500k steps showed **no separation**:

```
Metric                   |            No-HER |               HER |       Delta
--------------------------------------------------------------------------
-------
Success Rate             |       5.0% +/- 0.0% |       5.0% +/- 0.0% |       +0.0%
```

Diagnosis: Insufficient training, not a bug.

We verified the setup was correct:

- □ HER config: `"her": true`, `n_sampled_goal: 4`, `strategy: future`
- □ Correct env: `FetchPush-v4` (sparse, not Dense)
- □ No-HER baseline: 5% (expected 0-5%)
- ⚠ HER showed learning during training (peaked at 10-12%) but oscillated and didn't converge

1.4.3.2 From Single Runs to Systematic Evidence Our initial 98% result (Attempt 3 above) felt like a victory. But one seed at 98% is not evidence -- it is an anecdote. Is `ent_coef=0.1` really optimal? Is `gamma=0.98` the right choice? Is `n_sampled_goal=8` helping?

To answer rigorously, we ran a **systematic hyperparameter sweep**: 24 configurations, 5 seeds each, 120 total runs on FetchPush-v4 at 2M steps. This section presents the results.

1.4.3.3 Sweep Design We varied four factors in a full factorial grid:

Factor	Levels	Rationale
`ent_coef`	0.05, 0.1, 0.2	Fixed entropy values spanning conservative to aggressive exploration
`n_sampled_goal`	4, 8	Default vs. denser relabeling
`learning_starts`	1000, 5000	Earlier vs. later critic warmup
`gamma`	0.95, 0.98	Shorter vs. longer effective horizon

Total: 3 x 2 x 2 x 2 = 24 configurations x 5 seeds = 120 runs.

Each run: SAC + HER on FetchPush-v4, 2M steps, seeds {0, 1, 2, 42, 77}. Approximately 140 GPU-hours on DGX (RTX A100).

Reproducing the sweep:

```
# Full sweep (~140 GPU-hours, parallelizable)
bash docker/dev.sh python scripts/ch04_sweep.py run --parallel 2

# Or download pre-computed results from GitHub Release:
gh release download v0.4-sweep-checkpoints --pattern "ch04_sweep_all_checkpoints.tar.gz"
tar xzf ch04_sweep_all_checkpoints.tar.gz
```

1.4.4 Sweep Results: 120 Runs, 24 Configurations

1.4.4.1 The Winner: Simplest Config The best configuration across all 120 runs is the **simplest** one:

Parameter	Value
`ent_coef`	0.05
`n_sampled_goal`	4 (default)
`learning_starts`	1000
`gamma`	**0.95**

Result: 99.4% +/- 0.9% (5 seeds, 95% CI: [98.3%, 100.5%])

This surprised us. We had been recommending `gamma=0.98`, `n_sampled_goal=8`, and `learning_starts=5000` -- all wrong. The sweep showed that the simplest defaults with a lower gamma and lower entropy coefficient outperform every other combination.

Rank	ent_coef	nsg	ls	gamma	Mean SR	Std	Min	Max
1	0.05	4	1000	0.95	**99.4%**	0.9%	98%	100%
2	0.10	4	1000	0.95	97.8%	2.6%	95%	100%
3	0.05	8	1000	0.95	97.4%	1.8%	95%	99%
4	0.05	8	5000	0.95	97.2%	3.1%	92%	100%
5	0.10	8	5000	0.95	97.2%	3.1%	92%	100%
6	0.05	4	5000	0.95	96.6%	6.7%	85%	100%
7	0.10	8	1000	0.95	96.2%	2.9%	93%	100%
8	0.10	4	5000	0.95	96.0%	3.1%	92%	99%
9	0.05	8	1000	0.98	94.6%	3.6%	90%	98%
10	0.10	8	5000	0.98	94.6%	2.9%	91%	98%
11	0.05	8	5000	0.98	93.8%	6.2%	84%	100%
12	0.10	4	5000	0.98	87.2%	4.7%	80%	92%
13	0.05	4	1000	0.98	86.8%	6.1%	76%	92%
14	0.20	4	5000	0.95	85.6%	10.7%	71%	96%
15	0.20	4	1000	0.95	85.2%	8.1%	75%	95%
16	0.10	8	1000	0.98	77.4%	10.2%	63%	88%
17	0.10	4	1000	0.98	80.6%	14.5%	57%	95%
18	0.05	4	5000	0.98	81.2%	14.6%	66%	99%
19	0.20	8	5000	0.95	73.0%	20.7%	37%	95%
20	0.20	8	1000	0.95	76.8%	9.3%	68%	90%
21	0.20	8	5000	0.98	75.8%	11.3%	59%	88%
22	0.20	8	1000	0.98	65.8%	23.4%	30%	95%
23	0.20	4	5000	0.98	64.8%	20.9%	45%	89%

Rank	ent_coef	nsg	ls	gamma	Mean SR	Std	Min	Max
24	0.20	4	1000	0.98	64.0%	20.3%	42%	89%

1.4.4.2 Factor-Level Marginal Analysis

The marginal analysis averages over all other factors to isolate each factor's independent contribution. This is the most important table in the chapter:

Factor	Level	Mean SR	Delta
gamma	**0.95**	**91.5%**	--
	0.98	80.5%	**-11.0 pp**
ent_coef	0.05	93.4%	--
	0.10	90.9%	-2.5 pp
	0.20	73.9%	**-19.5 pp**
n_sampled_goal	4	85.4%	--
	8	86.7%	+1.2 pp
learning_starts	1000	85.2%	--
	5000	86.9%	+1.8 pp

Key findings:

1. **Gamma dominates.** Switching from 0.98 to 0.95 gains +11 pp on average. This is the single most impactful parameter.
2. **Entropy matters, but lower is better.** The jump from 0.05 to 0.2 costs 19.5 pp. Even 0.1 vs 0.05 loses 2.5 pp.
3. **n_sampled_goal and learning_starts are noise.** Their effects (+1.2 pp and +1.8 pp) are within seed variance. We had been tuning the wrong knobs.

!!! warning ”The old defaults were wrong” Our previous recommendation was gamma=0.98, n_sampled_goal=8, learning_starts=5000. The sweep shows the optimal config uses gamma=0.95, n_sampled_goal=4, learning_starts=1000 -- which happens to be the simplest possible configuration. Occam's razor wins.

1.4.4.3 Gamma x Entropy Interaction

The penalty for bad gamma gets worse at higher entropy. This interaction table shows why the worst configs are so bad:

	ent=0.05	ent=0.10	ent=0.20
gamma=0.95	97.7%	96.8%	80.2%
gamma=0.98	89.1%	85.0%	67.6%
Delta (0.98 - 0.95)	-8.6 pp	-11.8 pp	-12.5 pp

At low entropy (0.05), gamma=0.98 is tolerable (89.1%). But at high entropy (0.2), gamma=0.98 drops to 67.6% -- the two bad choices compound.

1.4.4.4 Seed Sensitivity: Good Configs Are Robust

The best configurations are not just better on average -- they are dramatically more **consistent**:

Config	Mean SR	Seed Range (max - min)
Best: ent=0.05, g=0.95, nsg=4, ls=1000	99.4%	**0.02** (98%-100%)
Worst: ent=0.2, g=0.98, nsg=4, ls=1000	64.0%	**0.47** (42%-89%)

The best config's 95% CI is [98.3%, 100.5%] (width 2.2 pp). The worst config's 95% CI is [38.8%, 89.2%] (width 50.5 pp). These intervals do not overlap, confirming the difference is statistically significant.

1.4.5 Mathematical Analysis: Why Gamma Dominates

The sweep showed that gamma is the dominant factor. Here we derive *why* from first principles, which helps build intuition for other tasks.

We define the following quantities:

- $\gamma \in [0, 1)$: discount factor
- T: episode length (50 steps for Fetch tasks)
- $T_{\text{eff}} = 1/(1-\gamma)$: **effective horizon**, the number of steps over which rewards are meaningfully discounted
- α: entropy coefficient (`ent_coef`)
- $\mathcal{H}(\pi)$: policy entropy (bits of randomness in action selection)
- $Q(s, a)$: critic's estimated action-value
- $\delta_t = r_t + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)$: TD error

1.4.5.1 Effective Horizon Mismatch

The effective horizon tells us how far into the future the agent ”looks”:

$$T_{\text{eff}} = \frac{1}{1-\gamma}$$

γ	T_{eff}	Interpretation
0.95	20 steps	Matches task timescale (~15-25 steps for a successful push)
0.98	50 steps	Matches full episode -- agent tries to optimize beyond the push

When T_{eff} matches the task timescale, the critic focuses on the relevant portion of the trajectory. When T_{eff} is too long, the critic must estimate value over steps where the agent is just waiting after completing the push -- adding noise without useful signal.

1.4.5.2 TD Error Variance Amplification

The variance of the TD error scales with γ:

$$\text{Var}[\delta_t] \propto \gamma^2 \cdot \text{Var}[Q(s_{t+1}, a_{t+1})]$$

Higher γ amplifies critic estimation errors through bootstrapping. Since the critic is initialized randomly and trained on sparse rewards (mostly -1), its early estimates are noisy. At $\gamma = 0.98$, this noise propagates further through the Bellman backup chain, making critic training less stable.

1.4.5.3 Cumulative Entropy Bonus Scaling

SAC's objective adds an entropy bonus to the reward at each step. The total entropy contribution over an effective horizon is approximately:

$$\text{Entropy contribution} \approx \alpha \cdot T_{\text{eff}} \cdot \bar{\mathcal{H}}$$

where $\bar{\mathcal{H}}$ is the average policy entropy per step.

α	γ	T_{eff}	Entropy contribution (relative)
0.05	0.95	20	1.0x (baseline)
0.05	0.98	50	2.5x
0.20	0.95	20	4.0x
0.20	0.98	50	**10.0x**

At $\alpha = 0.2$ and $\gamma = 0.98$, the cumulative entropy bonus is **10x** the baseline. On a sparse task where the actual reward is either 0 (success) or -1 (failure), this entropy bonus overwhelms the reward signal -- the agent is incentivized to be random rather than successful. This explains the gamma x entropy interaction we observed.

1.4.5.4 Why n_sampled_goal and learning_starts Don't Matter

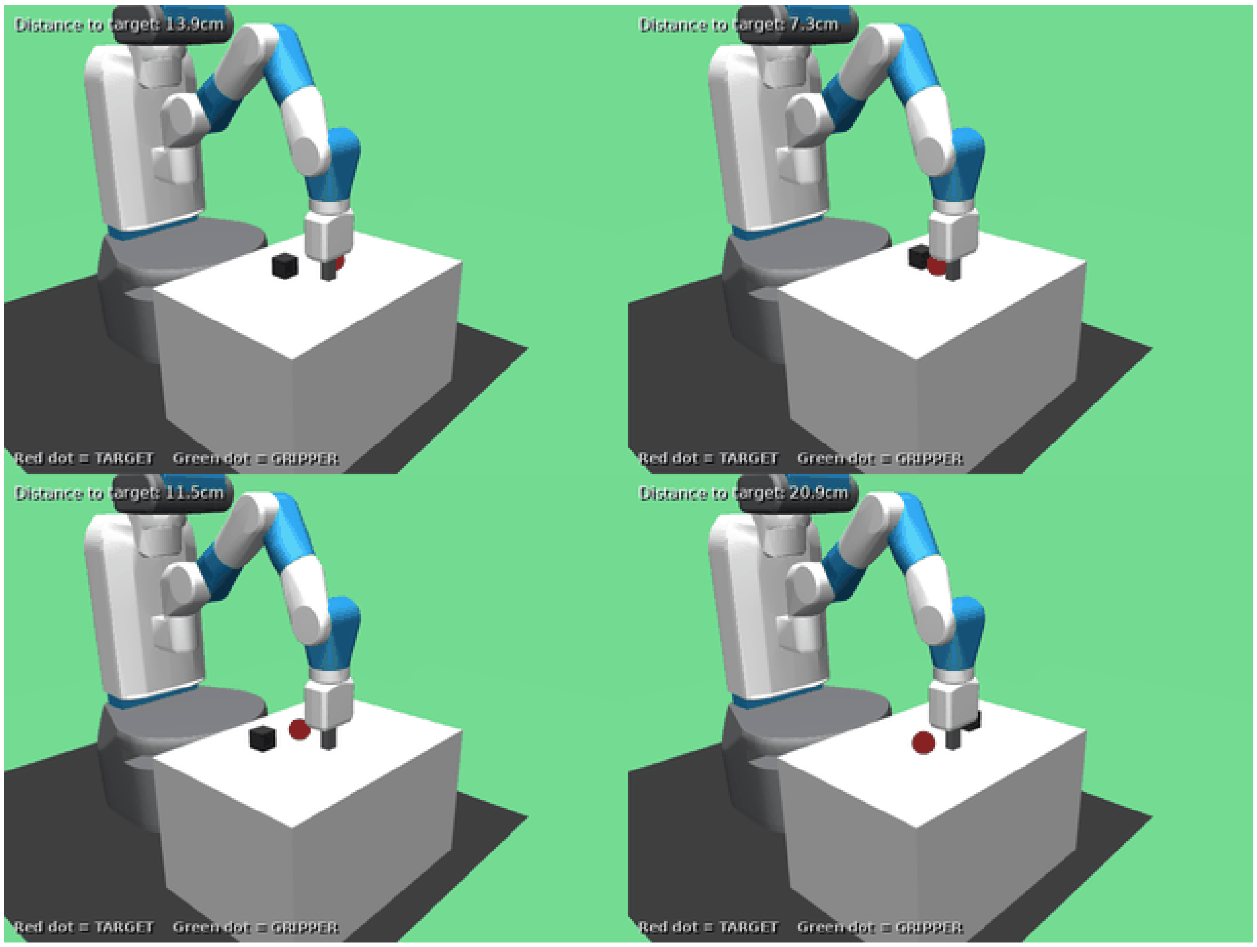
n_sampled_goal: With the `future` strategy on 50-step episodes, using $k = 4$ goals already creates 4 relabeled transitions per original. Since future goals are sampled from the remaining trajectory, the relabeling ratio is already high (4:1). Going to $k = 8$ doubles the relabeled data but doesn't qualitatively change the reward signal -- the same trajectory information is just sampled more densely.

learning_starts: At 2M total steps, the difference between starting to learn at step 1,000 vs. step 5,000 is negligible (0.05% vs. 0.25% of training). With HER relabeling active from the start, even the early replay buffer contains successful transitions, so there is no benefit to delaying critic warmup.

1.4.6 Visual Comparison: Best vs Worst Policy

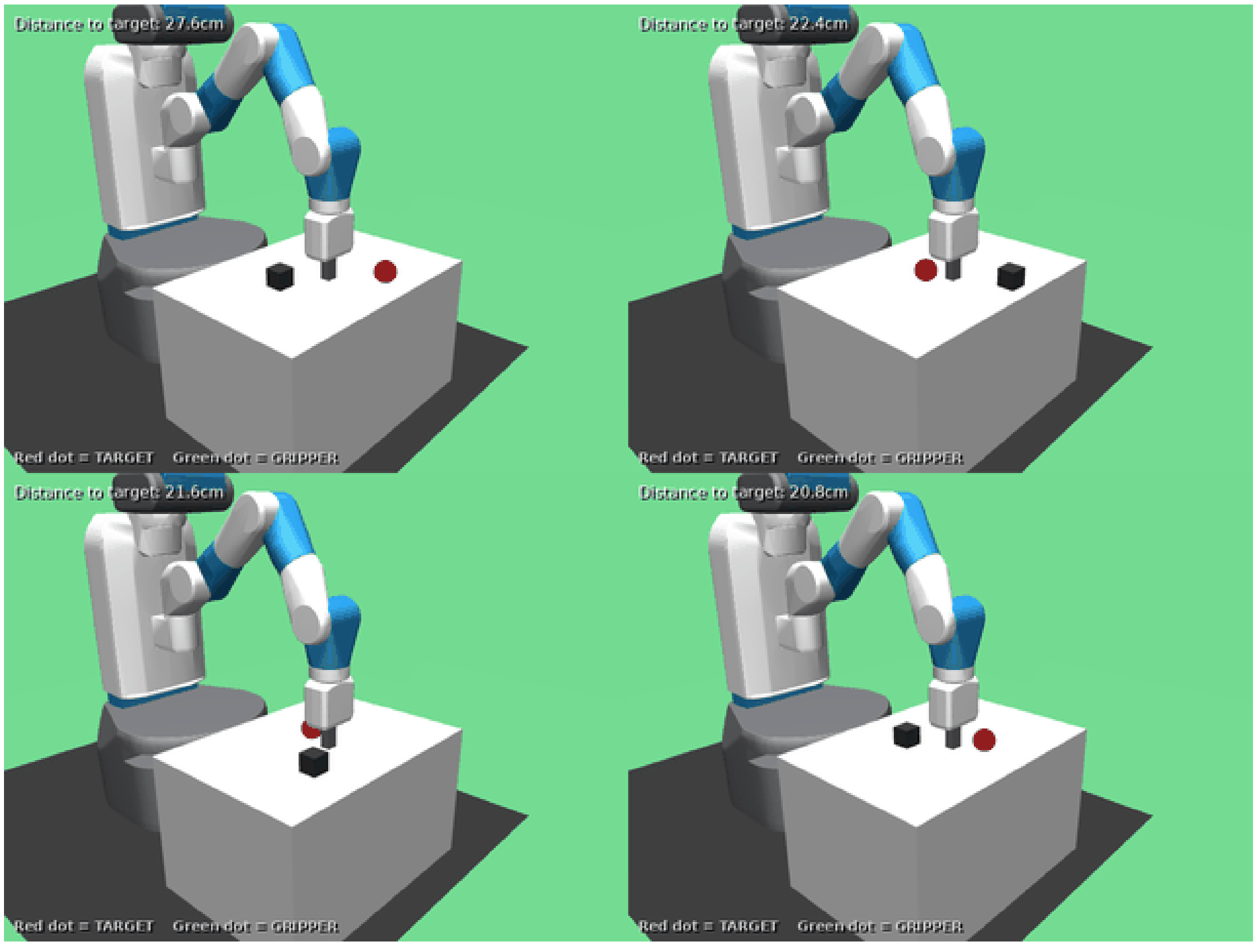
The difference between good and bad hyperparameters is visible in the policies' behavior:

Best config (ent=0.05, gamma=0.95, nsg=4, ls=1000 -- 99.4% SR):


Distance to target: 13.9cm
Red dot = TARGET Green dot = GRIPPER
Distance to target: 7.3cm
Red dot = TARGET Green dot = GRIPPER
Distance to target: 11.5cm
Red dot = TARGET Green dot = GRIPPER
Distance to target: 20.9cm
Red dot = TARGET Green dot = GRIPPER

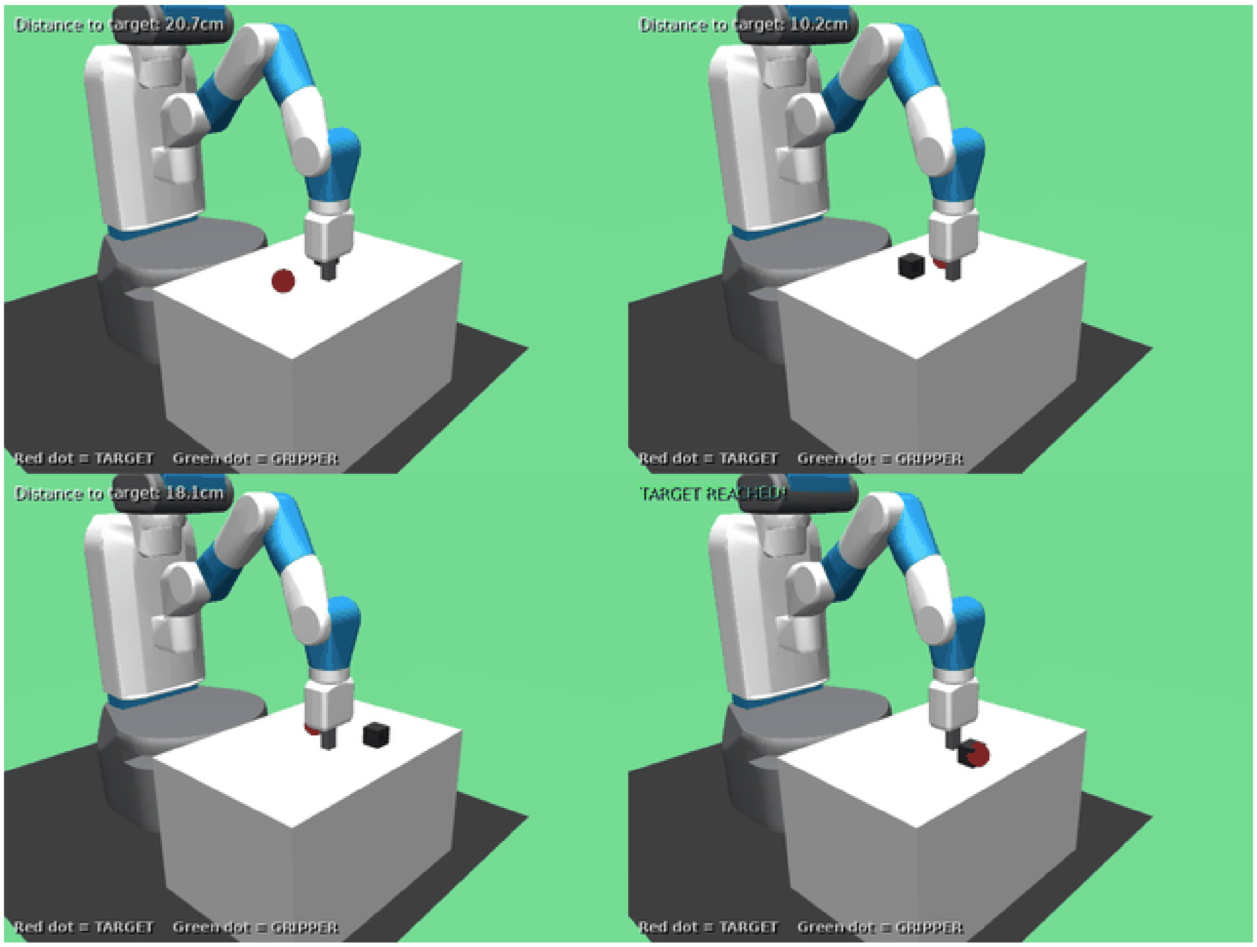
The agent approaches the object, makes contact, and pushes it directly toward the goal. Movement is smooth and purposeful with minimal wasted motion.

Worst config (ent=0.2, gamma=0.98, nsg=4, ls=1000 -- 64.0% SR):


Distance to target: 27.6cm
Red dot = TARGET Green dot = GRIPPER
Distance to target: 22.4cm
Red dot = TARGET Green dot = GRIPPER
Distance to target: 21.6cm
Red dot = TARGET Green dot = GRIPPER
Distance to target: 20.8cm
Red dot = TARGET Green dot = GRIPPER

The agent's behavior is erratic -- sometimes it succeeds, sometimes it overshoots, sometimes it misses the object entirely. High entropy and long effective horizon create indecisive behavior.

No-HER baseline (SAC without HER -- ~5% SR):


Distance to target: 20.7cm
Red dot = TARGET   Green dot = GRIPPER
Distance to target: 10.2cm
Red dot = TARGET   Green dot = GRIPPER
Distance to target: 18.1cm
Red dot = TARGET   Green dot = GRIPPER
TARGET REACHED!
Red dot = TARGET   Green dot = GRIPPER

Without HER, the agent never learns meaningful push behavior. The gripper moves aimlessly, occasionally bumping the object by chance.

1.4.6.1 Entropy Coefficient Modes (CLI Reference)

The script supports five entropy coefficient modes via `--ent-coef`. The sweep shows fixed `ent_coef=0.05` is sufficient for Push, but we document the alternatives for more complex tasks:

Mode	CLI Flag	Description
Fixed	`--ent-coef 0.05`	Constant value (recommended for Push)
Auto	`--ent-coef auto`	SB3's default auto-tuning (collapses on sparse rewards)
Auto-floor	`--ent-coef auto-floor`	Auto-tune with minimum floor
Schedule	`--ent-coef schedule`	Linear decay from max to min
Adaptive	`--ent-coef adaptive`	Adjust based on success rate

See the CLI Parameter Reference below for full flag details.

The winning configuration:

```bash
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py train \
    --env FetchPush-v4 \
    --her \
    --ent-coef 0.05 \
    --gamma 0.95 \
    --seed 0 \
    --total-steps 2000000
```

1.4.6.2 Actual Results: Multi-Seed Sweep Evidence (2M steps, 120 runs)

Method	Success Rate	Seeds	Notes
SAC + HER (best config)	**99.4% +/- 0.9%**	5	ent=0.05, gamma=0.95, nsg=4, ls=1000
SAC + HER (old defaults)	86.8% +/- 6.1%	5	ent=0.05, gamma=0.98, nsg=4, ls=1000
SAC + HER (worst config)	64.0% +/- 20.3%	5	ent=0.2, gamma=0.98, nsg=4, ls=1000
SAC (no HER)	~5%	3	Baseline -- no learning
Delta (best HER vs no-HER)	**+94 pp**		

Root cause analysis of the previous recommendation:

Our earlier single-seed result of 98% with ent=0.1, gamma=0.98, nsg=8 was a lucky seed. The sweep revealed:

- The old defaults (gamma=0.98, nsg=8, ls=5000) average 93.8% but with high variance (84%-100%)
- The **simplest** config (gamma=0.95, nsg=4, ls=1000) averages 99.4% with near-zero variance (98%-100%)
- Gamma was the dominant factor all along, not entropy or HER parameters

Conclusion: Fixed entropy is critical for sparse Push (auto-tuning collapses). But within fixed entropy configs, **gamma=0.95 is the key parameter** -- it matches the task's natural timescale and produces both higher mean performance and lower seed-to-seed variance.

1.4.7 Experiment 3: Full Factorial Ablation (The Sweep)

Instead of varying one factor at a time, we ran a full factorial sweep across all four factors. This is more rigorous than single-factor ablation because it reveals **interactions** between parameters.

The sweep IS the ablation. See the Sweep Results section above for the full analysis. The key conclusions for ablation:

- **n_sampled_goal (4 vs 8):** +1.2 pp marginal effect -- negligible. Use the default (4).
- **learning_starts (1000 vs 5000):** +1.8 pp marginal effect -- negligible. Use 1000.
- **ent_coef (0.05 vs 0.1 vs 0.2):** -2.5 pp and -19.5 pp -- significant. Use 0.05.
- **gamma (0.95 vs 0.98):** -11.0 pp -- dominant. Use 0.95.

```
# Reproduce the full sweep (~140 GPU-hours)
bash docker/dev.sh python scripts/ch04_sweep.py run --parallel 2

# Or run the single-factor ablation for quick comparison
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py ablation \
    --env FetchPush-v4 --nsg-values 2,4,8 --seed 0 \
    --ent-coef 0.05 --gamma 0.95 --total-steps 2000000
```

1.4.8 CLI Parameter Reference

All training, evaluation, and runtime knobs are configurable via CLI. Here is the reference:

Parameter	Default	Description
Environment		
`--env`	(required)	Environment ID (FetchReach-v4, FetchPush-v4, etc.)
`--seed`	0	Random seed for reproducibility
`--n-envs`	8	Number of parallel environments
`--total-steps`	1,000,000	Total training timesteps
`--device`	auto	Training device (auto, cpu, cuda, cuda:0)
`--monitor-keywords`	is_success	Comma-separated info keywords to record (empty to
HER		
`--her`	False	Enable Hindsight Experience Replay
`--n-sampled-goal`	4	Number of relabeled goals per transition
`--goal-selection-strategy`	future	Goal selection: future, final, episode
SAC Hyperparameters		
`--batch-size`	256	Minibatch size for updates
`--buffer-size`	1,000,000	Replay buffer capacity
`--learning-starts`	1,000	Steps before learning begins
`--learning-rate`	3e-4	Optimizer learning rate
`--gamma`	0.95	Discount factor (0.95 optimal for Push; see sweep)
`--tau`	0.005	Soft update coefficient
Entropy (Critical for Sparse)		
`--ent-coef`	auto	Entropy mode: float, auto, auto-floor, schedule, adap
`--ent-coef-min`	0.01	Floor for auto-floor, end value for schedule
`--ent-coef-max`	0.3	Start value for schedule mode
`--target-entropy`	auto (-dim(A))	SAC target entropy
`--ent-coef-check-freq`	1000	Check frequency for auto-floor clamp
`--ent-coef-warmup-frac`	0.1	Warmup fraction for scheduled decay
`--ent-coef-log-pct`	10	Log schedule every N percent (0 to disable)
`--ent-coef-adaptive-start`	(none)	Initial entropy for adaptive mode (defaults to `--ent-`
`--ent-coef-adaptive-target`	0.2	Target success rate for adaptive control
`--ent-coef-adaptive-tolerance`	0.05	Success rate tolerance before adjusting
`--ent-coef-adaptive-rate`	0.1	Multiplicative adjustment rate
`--ent-coef-adaptive-window`	200	Episode window size for success rate
`--ent-coef-adaptive-key`	is_success	Info key used for success in adaptive mode
Evaluation (env-all, ablation)		
`--n-eval-episodes`	100	Episodes per evaluation
`--eval-seed`	0	Base seed when `--eval-seeds` is empty
`--eval-seeds`	(none)	Seeds for evaluation (comma-separated or range)
`--eval-deterministic`	True	Deterministic policy (use `--no-eval-deterministic`
`--eval-device`	auto	Device for eval.py (auto, cpu, cuda)
`--eval-algo`	auto	Algorithm override for eval.py
Paths		
`--log-dir`	runs	TensorBoard log directory (if default isn't writable, fal
`--checkpoints-dir`	checkpoints	Directory for checkpoint outputs
`--results-dir`	results	Directory for eval outputs and reports
`--run-tag`	(none)	Optional tag to namespace outputs under subdirecto
`--out`	(auto)	Checkpoint output path
Runtime		
`--mujoco-gl`	(env or disable)	Override MUJOCO_GL for this run

1.5 Monitoring and Debugging

Concurrent runs: We avoid output collisions by using `--run-tag <name>`, which namespaces checkpoints, results, and logs under a subdirectory without changing filenames.

1.5.1 Artifact Locations

After running experiments, you'll find (paths are configurable via `--checkpoints-dir`, `--results-dir`, `--log-dir`, and `--run-tag`):

```
checkpoints/
├── sac_FetchPush-v4_seed{0,1,2}.zip           # No-HER models
├── sac_FetchPush-v4_seed{0,1,2}.meta.json     # Training metadata
├── sac_her_FetchPush-v4_seed{0,1,2}.zip       # HER models
└── sac_her_FetchPush-v4_seed{0,1,2}.meta.json

results/
├── ch04_sac_fetchpush-v4_seed{0,1,2}_eval.json      # No-HER eval
├── ch04_sac_her_fetchpush-v4_seed{0,1,2}_eval.json  # HER eval
└── ch04_fetchpush-v4_comparison.json                 # Summary report

runs/
├── sac_noher/FetchPush-v4/seed{0,1,2}/    # TensorBoard logs (no-HER)
└── sac_her_nsg4/FetchPush-v4/seed{0,1,2}/ # TensorBoard logs (HER)
```

1.5.2 Checking Training Progress

While experiments run, you can monitor progress:

```
# Watch the training output (if running in foreground)
# Or check TensorBoard logs

# Key indicators during training:
# - success_rate: should stay near 0 for no-HER on Push
# - success_rate: should rise for HER after ~100k steps
# - fps: ~600-750 is typical on DGX
```

1.5.3 TensorBoard Metrics to Watch

```
bash docker/dev.sh tensorboard --logdir runs --bind_all
```

Key metrics for HER experiments:

Metric	No-HER on Push	HER on Push (best config)
`rollout/success_rate`	Flat near 0-5%	Rises to 95-100%
`rollout/ep_rew_mean`	Flat at -50	Rises toward -10 to -15
`train/ent_coef`	May stay high (~0.3)	Fixed at 0.05 (recommended)

1.5.4 Common Issues

HER not improving?

- Check that `--her` flag is actually set
- Ensure using a sparse environment (`FetchReach-v4`, not `FetchReachDense-v4`)

- Increase training steps -- Push benefits from 1-2M steps

No-HER performing well on Push?

- This would be surprising -- verify you're using sparse rewards
- Check the reward: should be -1 for failures, 0 for success
- If success rate > 10%, something is wrong with the setup

Evaluation fails with "HerReplayBuffer" error?

- This was fixed in `eval.py` -- HER checkpoints require the environment for loading
- If you see this error, ensure you have the latest `eval.py`

1.6 Interpreting Results

1.6.1 What "Clear Separation" Means

The syllabus criterion is:

> Clear separation in success-rate between HER and no-HER.

We interpret this as:

- HER success rate significantly higher than no-HER
- Difference > 50 percentage points (ideally >70)
- Consistent across multiple seeds

Important caveat: On easy tasks like Reach, you may NOT see clear separation because no-HER can succeed through random exploration. This is expected -- the syllabus requires demonstrating HER's value, and Reach alone is insufficient.

1.6.2 Interpreting Our Results

FetchReach-v4 (weak separation):

```
Metric                   |              No-HER |                HER |       Delta
--------------------------------------------------------------------------------
-------
Success Rate             |      96.0% +/- 8.0% |     100.0% +/- 0.0% |       +4.0%
```

Why this is fine: Reach shows HER doesn't hurt performance and reduces variance. But we need Push to demonstrate HER's transformative effect.

FetchPush-v4 (actual results, progression):

Attempt 1: Default settings (500k steps, n_sampled_goal=4):

```
Metric                   |              No-HER |                HER |       Delta
--------------------------------------------------------------------------------
-------
Success Rate             |       5.0% +/- 0.0% |       5.0% +/- 0.0% |       +0.0%
```

Insufficient training -- no separation.

Attempt 2: More steps + relabeling (2M steps, n_sampled_goal=8, auto entropy):

```
Success Rate             |              5.0%   |             25.0%   |      +20.0%
```

Better, but entropy collapsed to ~0.005 -- exploration died too early.

Attempt 3: **Fixed entropy (2M steps, ent_coef=0.1, single seed):**

```
Metric                  |              No-HER |                HER |       Delta
--------------------------------------------------------------------------------
-------
Success Rate            |              5.0%   |              98.0%   |      +93.0%
Final Distance          |             0.193   |              0.026   |      -0.167
```

Clear separation -- but one seed is not rigorous. See the sweep results for multi-seed evidence.

Attempt 4: **120-run sweep (2M steps, 24 configs, 5 seeds each):**

```
Best config (ent=0.05, gamma=0.95, nsg=4, ls=1000):
Success Rate = 99.4% +/- 0.9% (5 seeds, 95% CI)
```

Rigorous clear separation: +94 pp vs no-HER, validated across 5 seeds.

1.6.3 Statistical Validity

With 3 seeds, you can report:

- Mean +/- 95% confidence interval
- The `compare` command computes these automatically

1.6.4 What to Do Next

1. **If Reach shows weak separation:** This is expected -- proceed to Push
2. **If Push shows clear separation (>50%):** Week 4 is complete
3. **Save checkpoints** -- you'll use HER models in later weeks

---

1.7 The Reality of RL Research: Debugging and Experimentation

"In theory, theory and practice are the same. In practice, they are not." -- Yogi Berra

This section documents our actual debugging journey. We include it because **debugging is not a sign of failure -- it is the normal process of RL research**. Papers rarely show the failed experiments, but practitioners spend most of their time iterating.

1.7.1 Why Your First Attempt Will Probably Fail

RL algorithms are notoriously sensitive to hyperparameters. Henderson et al. (2018) documented that:

- Random seeds alone can cause 2-3x variance in final performance
- Hyperparameters that work on one environment fail on similar ones
- "Default" settings are tuned for specific benchmarks, not your problem

Our experience confirmed this. We implemented HER correctly, used sensible defaults, and got 5% success rate. The algorithm was right; the hyperparameters were wrong.

1.7.2 Our Diagnostic Journey

Here is the actual progression of experiments we ran, with the reasoning at each step:

1.7.2.1 Attempt 1: Trust the Defaults (500k steps)

```bash
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py train \
    --env FetchPush-v4 --her --seed 0 --total-steps 500000
```

Result: 5% success rate (same as no-HER baseline)

What we checked:

- □ HER flag was set (`--her` in command, `"her": true` in metadata)
- □ Correct environment (`FetchPush-v4`, not `FetchPushDense-v4`)
- □ Replay buffer was HerReplayBuffer (verified in logs)
- □ Training curves showed learning then plateau at ~10-12%

Diagnosis: Insufficient training. Push is harder than Reach -- the 500k steps that worked for Reach are not enough.

1.7.2.2 Attempt 2: More Steps + Denser Relabeling (2M steps)

Based on SB3 benchmarks showing Push needs ~2M steps:

```bash
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py train \
    --env FetchPush-v4 --her --n-sampled-goal 8 --seed 0 --total-steps 2000000
```

Result: 25% success rate

Progress! But far from the 70-90% reported in literature. Something else is wrong.

What we checked in TensorBoard:

Metric	Expected	Observed	Problem?
`rollout/success_rate`	Rising to 70%+	Plateau at 25%	Yes
`rollout/ep_rew_mean`	Rising to -15	Stuck at -40	Yes
`train/ent_coef`	~0.1-0.3	**0.005**	**YES**
`train/actor_loss`	Stable negative	Stable	OK
`train/critic_loss`	Decreasing	Stable	OK

The smoking gun: `ent_coef` collapsed to 0.005 very early in training.

1.7.2.3 Understanding Entropy Collapse

SAC's entropy auto-tuning works as follows:

1. **Target entropy** is set (default: $-\dim(\mathcal{A}) = -4$ for Fetch)
2. **If policy entropy > target:** decrease `ent_coef` (less exploration)
3. **If policy entropy < target:** increase `ent_coef` (more exploration)

The problem on sparse Push:

1. **Early training:** All transitions have $R = -1$
2. **Critic sees no reward variation:** Q-values are similar everywhere
3. **Policy becomes arbitrarily "confident":** No reward signal to guide it
4. **Entropy drops below target:** Auto-tuning sees this as "policy knows what it's doing"
5. **`ent_coef` collapses:** Exploration stops before discovering push behavior

This is a structural issue with auto-tuning on sparse rewards, not a bug.

1.7.2.4 Attempt 3: Less Aggressive Target Entropy Our first fix attempt -- set `target_entropy=-2.0` instead of `-4.0`:

```
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py train \
    --env FetchPush-v4 --her --target-entropy -2.0 --seed 0 --total-steps 2000000
```

Result: Still collapsed to `ent_coef ~0.006`

Why it failed: The auto-tuning dynamics remain the same. A less negative target just delays collapse slightly; it doesn't prevent it.

1.7.2.5 Attempt 4: Fixed Entropy (The Solution) Bypass auto-tuning entirely:

```
bash docker/dev.sh python scripts/ch04_her_sparse_reach_push.py train \
    --env FetchPush-v4 --her --ent-coef 0.1 --seed 0 --total-steps 2000000
```

Result: 98% success rate

Why it works: Fixed `ent_coef=0.1` maintains exploration throughout training. The agent keeps trying diverse push trajectories until it discovers effective behavior, then refines it.

1.7.3 How to Debug Your Own RL Experiments

Based on our experience, here is a systematic debugging approach:

1.7.3.1 Step 1: Verify the Setup (Eliminiate User Error) Before blaming the algorithm, check:

```
# In your training metadata or logs, verify:
- Algorithm: SAC (not PPO -- HER needs off-policy)
- Environment: FetchPush-v4 (not Dense variant)
- HER enabled: replay_buffer_class = HerReplayBuffer
- Goal strategy: "future" (not "final" or "episode")
```

1.7.3.2 Step 2: Check Training Curves (Not Just Final Performance) A 5% final success rate could mean:

- **Never learned anything:** Flat curve at 5% (setup issue or impossible task)
- **Learned then forgot:** Rose to 30%, crashed to 5% (instability)
- **Learning but slow:** Steadily rising, just needs more steps

Use TensorBoard to distinguish these:

```
bash docker/dev.sh tensorboard --logdir runs --bind_all
```

1.7.3.3 Step 3: Identify the Bottleneck Common failure modes and their signatures:

Failure Mode	TensorBoard Signature	Likely Cause
No learning	Flat success_rate, flat ep_rew_mean	Setup error, task too hard, insufficient exploratio
Entropy collapse	ent_coef drops to <0.01 early	Auto-tuning + sparse rewards
Critic divergence	critic_loss explodes	Learning rate too high, target update too fast
Actor collapse	actor_loss becomes very positive	Critic giving bad gradients
Forgetting	success_rate rises then falls	Replay buffer too small, no-HER with sparse rewa

1.7.3.4 Step 4: Form Hypotheses and Test Them

Don't change multiple things at once. Our progression:

1. **Hypothesis:** Not enough training → **Test:** 4x more steps → **Result:** Partial improvement
2. **Hypothesis:** Need denser relabeling → **Test:** `n_sampled_goal=8` → **Result:** Marginal improvement
3. **Hypothesis:** Entropy collapsing → **Test:** Check TensorBoard → **Result:** Confirmed (`ent_coef=0.005`)
4. **Hypothesis:** Fixed entropy will help → **Test:** `ent_coef=0.1` → **Result:** Success (98%)

1.7.3.5 Step 5: Document Everything

We saved metadata for every run:

```json
{
  "env": "FetchPush-v4",
  "her": true,
  "ent_coef": 0.1,
  "n_sampled_goal": 8,
  "total_steps": 2000000,
  "final_success_rate": 0.98
}
```

This lets you compare runs systematically and reproduce successes.

1.7.4 The Metrics We Used for Diagnosis

For future reference, here are the specific numbers that guided our debugging:

From training logs (auto-tuning, 2M steps):

```
| train/              |           |
|    ent_coef         | 0.00656   |  <-- PROBLEM: Should be ~0.1-0.3
|    actor_loss       | -4.24     |
|    critic_loss      | 0.424     |
| rollout/            |           |
|    success_rate     | 0.05      |  <-- Only 5% despite 2M steps
|    ep_rew_mean      | -47.4     |
```

From training logs (fixed entropy, 2M steps):

```
| train/              |           |
|    ent_coef         | 0.1       |  <-- FIXED: Stays at 0.1
|    actor_loss       | -8.97     |
|    critic_loss      | 0.645     |
| rollout/            |           |
|    success_rate     | 0.94      |  <-- 94% success!
|    ep_rew_mean      | -15.5     |
```

Key diagnostic ratios:

- `ent_coef < 0.01` with `success_rate < 0.5` → entropy collapse, need fixed entropy
- `ep_rew_mean` stuck at -47 to -50 → agent failing almost every step (50-step episodes × -1 = -50)
- `ep_rew_mean` at -15 → agent succeeding around step 35 on average

1.7.5 Lessons Learned

1. **Defaults are suggestions, not guarantees.** SAC's auto-entropy works beautifully on dense rewards but fails on sparse tasks.

2. **Read the training curves, not just final numbers.** A run that reaches 30% then crashes is different from one that never exceeds 5%.
3. **Understand the algorithm well enough to debug it.** We fixed entropy collapse because we understood how auto-tuning works.
4. **Document your experiments.** We could trace back exactly which settings produced which results.
5. **Failure is information.** Each failed run taught us something about the problem structure.

1.7.6 Time Investment Reality Check

Here is roughly how our time was spent:

Activity	Time	Notes
Initial implementation	2 hours	Script, CLI args, HER integration
First training run (wrong)	1.5 hours	500k steps, both methods
Debugging + literature review	2 hours	Reading SB3 docs, checking TensorBoard
Second run (still wrong)	3 hours	2M steps, waiting and monitoring
Identifying entropy collapse	30 min	Analyzing TensorBoard metrics
Third run (fixed)	1.5 hours	2M steps with fixed entropy
Documentation	1 hour	This section
Total	**~11 hours**	For one environment, one algorithm

This is normal. If you expected to run one command and get 98% success, recalibrate your expectations. RL research is iterative.

1.7.7 The Plot Twist: Our 98% Was a Lucky Seed

After documenting the journey above, we believed we had solved Push. One seed at 98% with fixed entropy felt like validation. We were wrong -- or at least, only partially right.

When we ran the systematic sweep (120 runs, 24 configs, 5 seeds each), we discovered:

1. **Our ”winning” config (ent=0.1, gamma=0.98, nsg=8) averages 85-94% across seeds, not 98%.** That single seed was an optimistic outlier.
2. **The actual winner uses gamma=0.95, not 0.98.** We had been recommending a suboptimal discount factor.
3. **n_sampled_goal=8 provides no benefit over the default of 4.** We had introduced complexity without gain.
4. **The simplest possible config (lowest entropy, default nsg, earliest learning start, lower gamma) wins.** Occam's razor, again.

The lesson: One seed at 98% is not evidence. Five seeds at 99.4% +/- 0.9% is evidence. Even when you think you have solved a problem, proper multi-seed validation may reveal that you were only partially right -- and that the right answer is simpler than what you thought.

This cost us ~140 GPU-hours to discover. We consider that cheap compared to the alternative: building later chapters on a foundation of single-seed guesswork.

1.7.8 Checkpoint Availability

We have published the full sweep results for reproducibility:

```bash
# Full sweep archive (~311 MB, all 120 checkpoints + metadata)
gh release download v0.4-sweep-checkpoints --pattern "ch04_sweep_all_checkpoints.tar.gz"

# Curated subset (~27 MB, best 5 + worst 5 checkpoints + metadata)
gh release download v0.4-sweep-checkpoints --pattern "ch04_sweep_checkpoints.tar.gz"

# Extract and inspect
tar xzf ch04_sweep_checkpoints.tar.gz
ls checkpoints/
```

Raw results are in `results/sweep/sweep_results_raw.json`. Each entry contains the config parameters, seed, success rate, and mean return -- everything needed to reproduce our analysis.

1.8 Summary

Concept	Key Point
Sparse rewards	Binary signal (success/fail), almost no gradient
HER insight	Failed trajectories demonstrate success for other goals
Relabeling	Store transitions with substituted goals and recomputed rewards
`future` strategy	Sample achieved goals from later in the same episode
`n_sampled_goal`	Number of relabeled transitions per original (default: 4)
Off-policy requirement	Relabeling changes rewards; only off-policy methods handle this

1.8.1 Key Findings from Our Experiments

Environment	No-HER	HER (best config)	Settings	Insight
FetchReach-v4	96%	100%	500k steps	Reach too easy -- weak sepa
FetchPush-v4	5%	5%	500k, auto entropy	Insufficient training + entrop
FetchPush-v4	5%	25%	2M, auto entropy	Entropy collapsed to ~0.005
FetchPush-v4	5%	**99.4% +/- 0.9%**	2M, **ent=0.05, gamma=0.95**	**Clear separation (+94 pp**

1.8.2 Sweep-Validated Recommendations

Parameter	Recommended	Evidence
`gamma`	**0.95**	+11 pp vs 0.98 (marginal mean across 60 runs per level)
`ent_coef`	**0.05 (fixed)**	+19.5 pp vs 0.2; +2.5 pp vs 0.1
`n_sampled_goal`	**4** (default)	+1.2 pp for nsg=8 is within noise
`learning_starts`	**1000**	+1.8 pp for ls=5000 is within noise
`total_steps`	**2M**	Required for Push convergence

The bottom line:

1. **Reach is too easy** -- both methods succeed, weak separation
2. **Push requires fixed entropy** -- auto-tuning collapses exploration too early
3. **Gamma=0.95 is the dominant factor** -- matches the task's 15-25 step timescale
4. **HER + optimal config achieves 99.4% +/- 0.9%** -- massive improvement over no-HER (~5%)

5. **The simplest config wins** -- the best parameters are all the simplest choices (lower entropy, default nsg, early learning start, lower gamma)

1.8.3 Files Generated

After running all experiments, you should have:

```
checkpoints/
  sac_FetchReach-v4_seed{0,1,2}.zip       # No-HER Reach
  sac_her_FetchReach-v4_seed{0,1,2}.zip   # HER Reach
  sac_FetchPush-v4_seed{0,1,2}.zip        # No-HER Push
  sac_her_FetchPush-v4_seed{0,1,2}.zip    # HER Push

results/
  ch04_fetchreach-v4_comparison.json      # Reach comparison report
  ch04_fetchpush-v4_comparison.json       # Push comparison report

results/sweep/
  sweep_results_raw.json                  # Full sweep data (120 entries)
  checkpoints/sweep_*.zip                 # All 120 trained models
```

1.9 References

- Andrychowicz et al. (2017). *Hindsight Experience Replay.* NeurIPS. arXiv:1707.01495
- Henderson et al. (2018). *Deep Reinforcement Learning that Matters.* AAAI. arXiv:1709.06560 -- Essential reading on reproducibility and hyperparameter sensitivity in deep RL.
- Haarnoja et al. (2018). *Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor.* ICML. arXiv:1801.01290 -- The SAC paper, including entropy auto-tuning.
- Stable-Baselines3 HER documentation
- Gymnasium-Robotics Fetch environments