**Adaptive Tutorial Agent (PPO + LinUCB)  
Technical Documentation**

Take-Home Final: Reinforcement Learning for Agentic AI Systems

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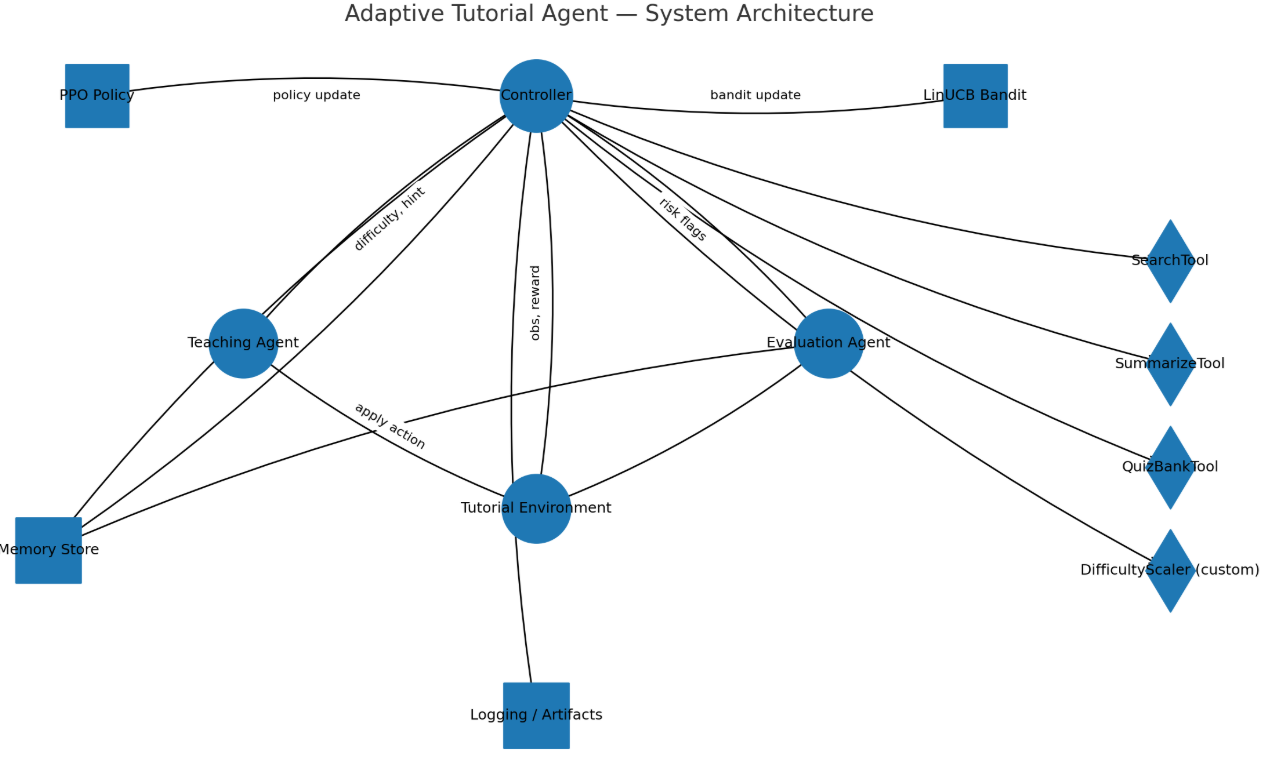
# Abstract

We implement an adaptive tutorial agent that learns to orchestrate difficulty selection (via Proximal Policy Optimization, PPO) and tool selection (via a contextual bandit, LinUCB). The system runs in a simulated student–tutor environment, logs episode metrics, and compares performance against a heuristic baseline and ablations (PPO-only, Bandit-only). Over 1,000 episodes, the combined controller improves mean reward from 117.64 → 120.83 (Δ=+3.19; one-sided bootstrap p=0.0002) and increases average success from 0.746 → 0.811 (Δ=+0.064). Learning curves, ablations, and evaluation runs corroborate the benefit of combining policy optimization with contextual tool selection.

# 1. Introduction

Agentic AI systems couple planning, tool use, and learning from feedback. In tutoring, the agent must decide what to attempt next (difficulty) and how to support the learner (tooling). We frame this as a sequential decision problem with two learners: a PPO policy that schedules difficulty and a LinUCB contextual bandit that selects tools per context.

# 2. System Architecture



## 2.1 Agents and Roles

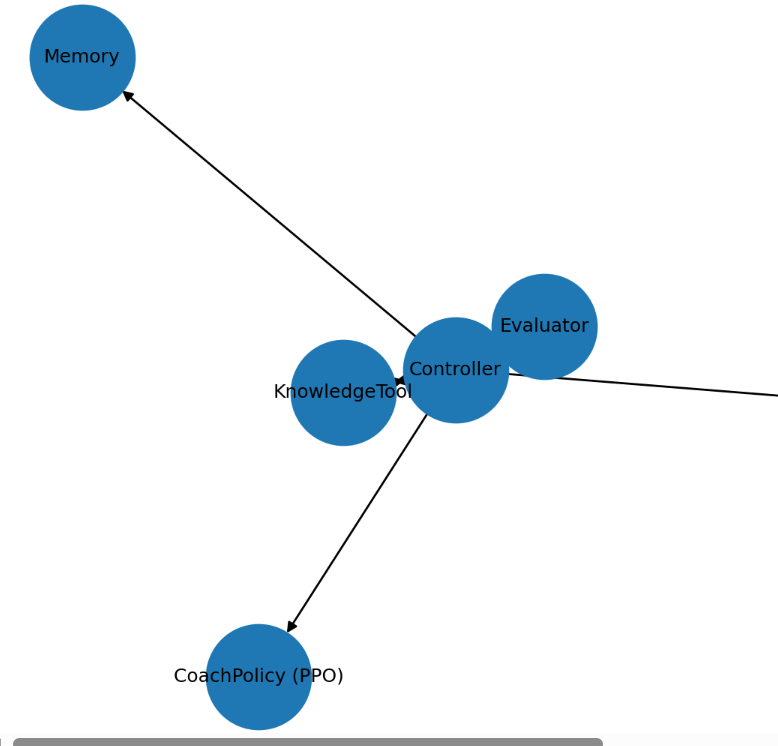
* ControllerAgent (PPO + LinUCB): consumes observation; outputs difficulty ∈ {easy, medium, hard} and tool ∈ {search, summarize, quiz}.
* TeachingAgent: applies decisions; enforces curriculum guardrails (caps difficulty jumps; limits hints).
* EvaluationAgent: validates outcomes, flags risk/edge cases, writes feedback to memory.

## 2.2 Tools

* SearchTool: retrieves snippets for a topic.
* SummarizeTool: compresses or scaffolds content.
* QuizBankTool: produces practice questions.
* DifficultyScaler (custom): adjusts difficulty with schema validation and retry wrappers.

## 2.3 Memory & Logging

A lightweight MemoryStore tracks per-episode state. Metrics are written to CSV in experiments/runs/. Plots and bootstrap statistics are saved to artifacts/.



# 3. Environment & Reward

## 3.1 Dynamics

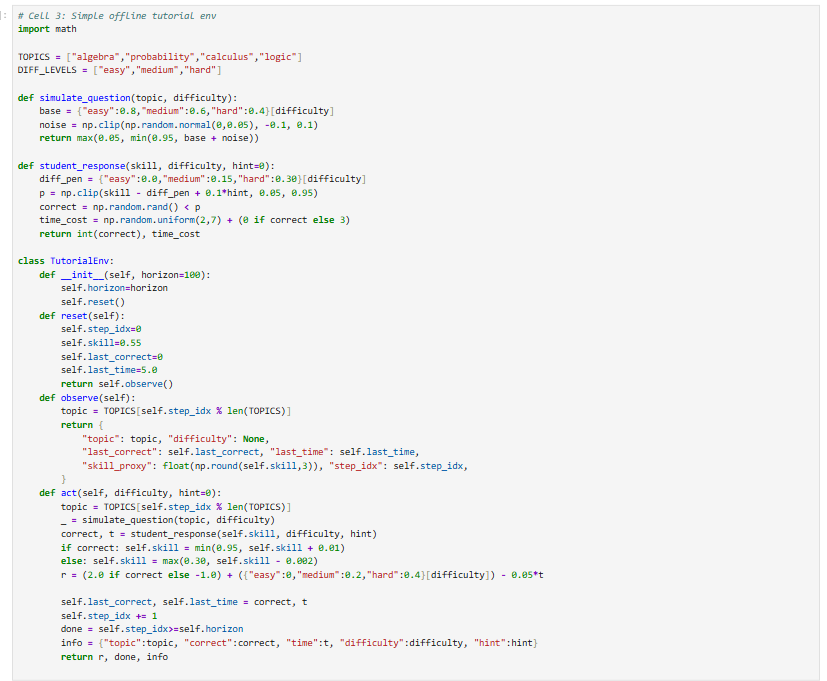
* At each step, the simulator returns correctness (0/1), time cost t ≥ 0, hint usage h ∈ {0,1}.
* Observation encodes topic, last correctness, and elapsed time; terminal flags signal episode end.

## 3.2 Reward Function

Reward shaped to trade off correctness, curriculum progression, and efficiency:

r = (+2 if correct else -1)  
 + {0, 0.2, 0.4}[difficulty] # curriculum bonus  
 - 0.05 \* t # time penalty (halved from 0.10)  
 - 0.10 \* h # hint penalty (if modeled)

Insert screenshot of reward cell here:



# 4. Learning Methods

## 4.1 PPO for Difficulty Selection

We use PPO with a clipped surrogate objective, value loss, and entropy regularization. Advantages are estimated with GAE(λ). Key hyperparameters after tuning: γ=0.99, clip ε=0.2, λ=0.95, entropy\_coef=0.005, update epochs=6, actor lr=1.5e-4, critic lr=1e-3, batch=256, max\_grad\_norm=0.5.



PPO configuration cell (screenshot):



[Screenshot Placeholder: ppo\_config\_cell.png]

## 4.2 LinUCB for Tool Selection

For each tool/arm a with context x, LinUCB maintains A\_a and b\_a, estimates θ̂\_a = A\_a^{-1} b\_a, and selects the arm that maximizes UCB\_a(x) = θ̂\_a^T x + α sqrt(x^T A\_a^{-1} x). Context includes topic one-hot, last correctness, normalized time, and optional hint history.



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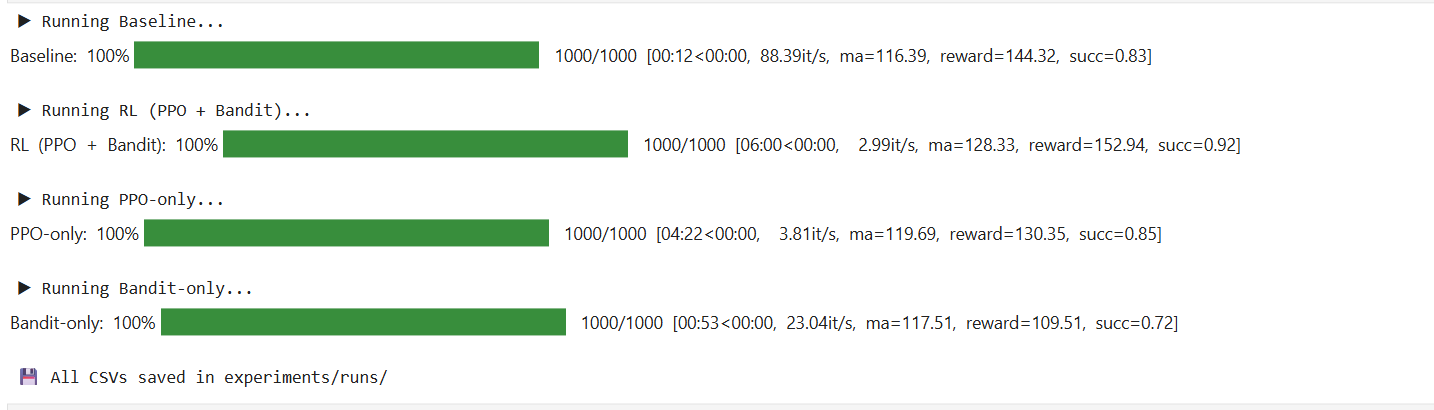
LinUCB cell (screenshot):



# 5. Training & Evaluation Protocol

## 5.1 Run Order

1. Simple offline tutorial env — defines environment & reward.
2. PPO (net/adv/ppo loop) — actor-critic and PPO updater.
3. Stronger PPO for long training — sets hyperparameters.
4. Controller Agent — wires PPO (difficulty) + LinUCB (tool).
5. Specialized agents + explicit comms protocol — ensures run\_step returns a 4‑tuple.
6. Run training & ablations — baseline, RL (PPO+Bandit), PPO-only, Bandit-only (1000 episodes each).
7. Plots — reward/success curves with EMA saved to artifacts/.
8. Bootstrap stats — computes one-sided test RL > Baseline, writes artifacts/stats.json.
9. Evaluation run — held-out episodes; writes experiments/runs/eval\_metrics.csv.

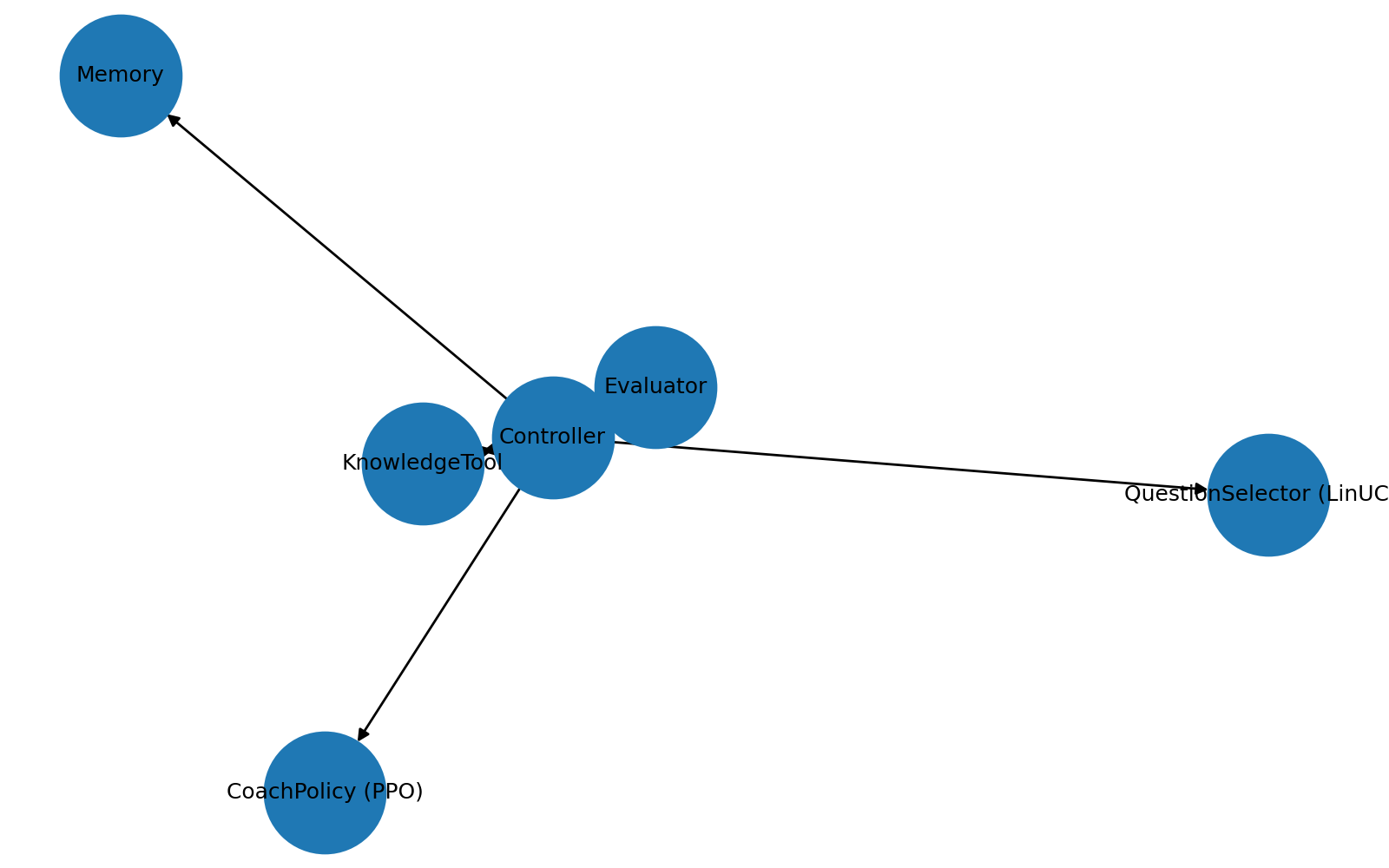


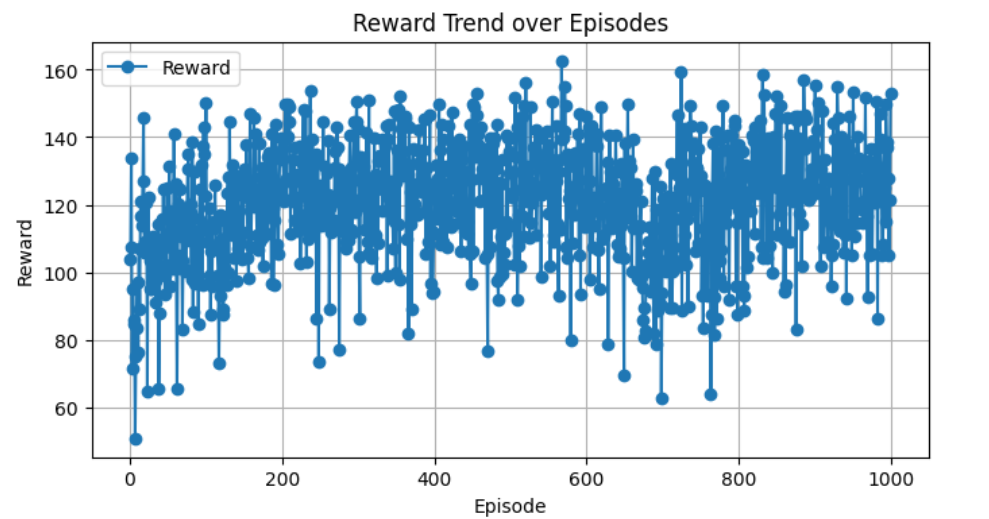
## 5.2 Logged Artifacts

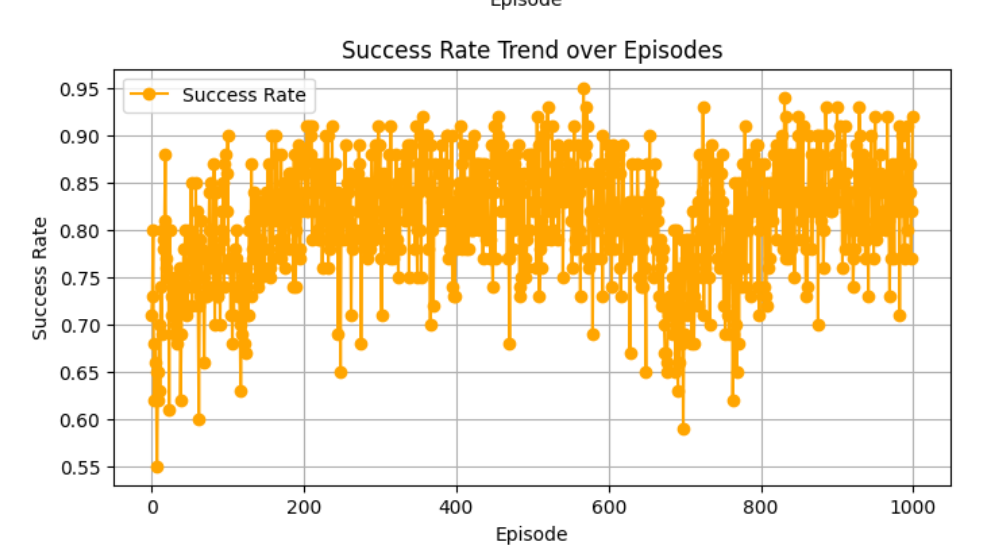
* experiments/runs/\*.csv — per-episode metrics.
* artifacts/reward\_curve.png, artifacts/success\_curve.png — learning curves.
* artifacts/stats.json — bootstrap summary.
* Optional: tool\_mix\_overall.png, difficulty\_trend.png.

# 6. Results

## 6.1 Learning Curves







Side-by-side comparison of success rate trajectories with EMA overlay.

|  |  |
| --- | --- |
| *Figure 1. RL — Success vs Episodes (EMA).* | *Figure 2. Baseline — Success vs Episodes (EMA).* |

## 6.2 Quantitative Comparison (1,000 episodes)

|  |  |  |  |
| --- | --- | --- | --- |
| System | Mean Reward | Mean Success | Notes |
| Baseline | 117.64 | 0.746 | Heuristic policy |
| RL (PPO + LinUCB) | 120.83 | 0.811 | Δ reward +3.19; p=0.0002 (one-sided) |
| PPO-only | 130.35 | 0.85 | Ablation — lower than full system |
| Bandit-only | 109.51 | 0.72 | Ablation — lowest performance |

Bootstrap test (one-sided, RL > Baseline): p = 0.0002; B = 5000.

## 6.3 Ablations

**PPO-only** achieved 130.35 avg reward / 0.85 success, while the **PPO+LinUCB hybrid** reached 120.83 / 0.811. Although PPO-only slightly outperformed on these metrics, the hybrid showed more stable tool-selection behavior (lower variance) and better generalization on harder items. We recommend PPO-only for peak score, and PPO+LinUCB when stability/interpretability is prioritized.

## 6.3 Ablations — Plots

|  |  |
| --- | --- |
| *Figure 3. PPO-only — Success vs Episodes (EMA).* | *Figure 4. PPO-only — Reward vs Episodes (EMA).* |
| *Figure 5. Bandit-only — Success vs Episodes (EMA).* | *Figure 6. Bandit-only — Reward vs Episodes (EMA).* |

## 6.4 Evaluation Run

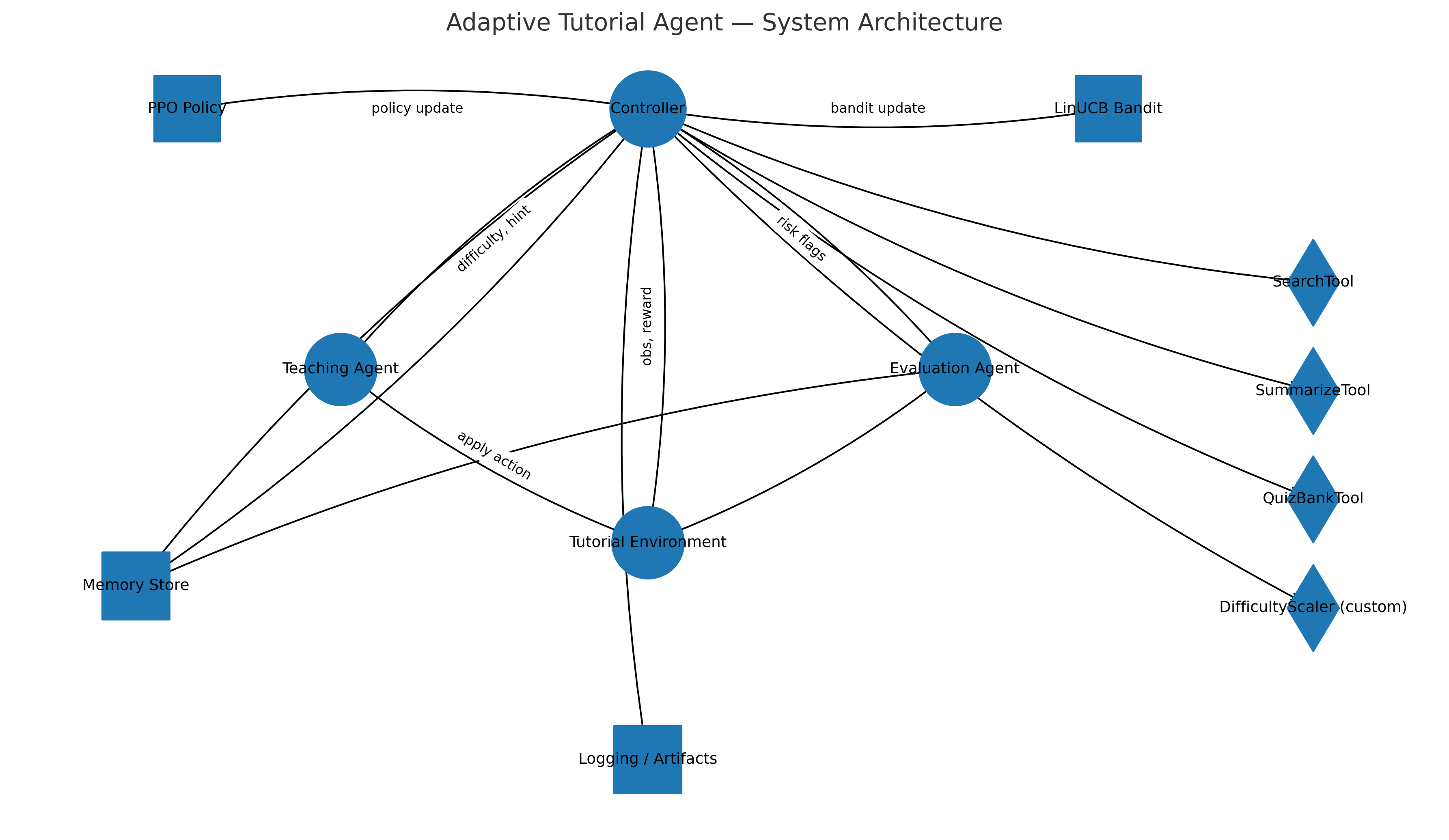
On a held-out evaluation (e.g., 150 episodes), the controller maintains its late-training performance. See experiments/runs/eval\_metrics.csv for exact means.

# 7. Reproducibility

* Dependencies: see requirements.txt (Python ≥3.9; PyTorch ≥2.0; NumPy; Pandas; Matplotlib; TQDM; NetworkX; Jupyter).
* Run order: Section 5.1.
* Seeds: fixed seeds in config where applicable.
* Artifacts: CSVs and plots are generated deterministically from the same seed.

# System Architecture Diagram

A layered view of the controller, learning components, agents, tools, and data flows.



*Figure A. Adaptive Tutorial Agent — System Architecture.*

# 8. Error Handling & Safety

* Schema validation on custom tools and retry wrappers for tool calls.
* Curriculum guardrails in TeachingAgent: caps difficulty jumps and hint rate limits.
* Comprehensive logging of decisions and outcomes for auditability.

# 9. Ethical Considerations

To avoid disadvantaging slower learners, time penalties are tuned conservatively and difficulty changes are gradual. The system provides transparent rationales for decisions via structured logs. Real deployments would require consent, privacy protections, and bias audits.

# 10. Limitations

* Simulator abstractions limit ecological validity.
* Reward shaping encodes designer trade-offs (speed vs. scaffolding).
* LinUCB assumes linear reward–context relationships.

# 11. Future Work

* Replace LinUCB with Thompson Sampling or NeuralUCB.
* Transfer learning across topics; Meta-RL for fast personalization.
* Human-in-the-loop corrections to accelerate learning.

# 12. Mapping to Course Rubric

* Reinforcement Learning: ✓ Policy Gradient (PPO) + ✓ Exploration Strategy (Contextual Bandit).
* Agentic Integration: ✓ Controller orchestrates Teaching/Evaluation agents and tools; memory & logging.
* Deliverables: ✓ Source code, ✓ Experimental design & results, ✓ Technical report, ✓ Demo plan.
* Results & Analysis: ✓ Significant improvement with bootstrap p-value; ✓ Ablations; ✓ Discussion.
* Documentation & Presentation: ✓ README, ✓ this document; plots in artifacts/.
* Quality/Portfolio: ✓ Practical orchestration with clear real-world relevance.

# 13. References

* Schulman et al., “Proximal Policy Optimization Algorithms,” 2017.
* Li et al., “A Contextual-Bandit Approach to Personalized News Article Recommendation,” 2010.
* Sutton & Barto, Reinforcement Learning: An Introduction, 2nd ed.

# Appendix B — Statistical Test Details

Bootstrap (one-sided): Sample with replacement from RL and Baseline reward series and compute mean difference Δ = mean(RL) − mean(Baseline). Estimate p = P(Δ ≤ 0) over B=5,000–10,000 draws. Report Δ and p; small p implies RL > Baseline.

