

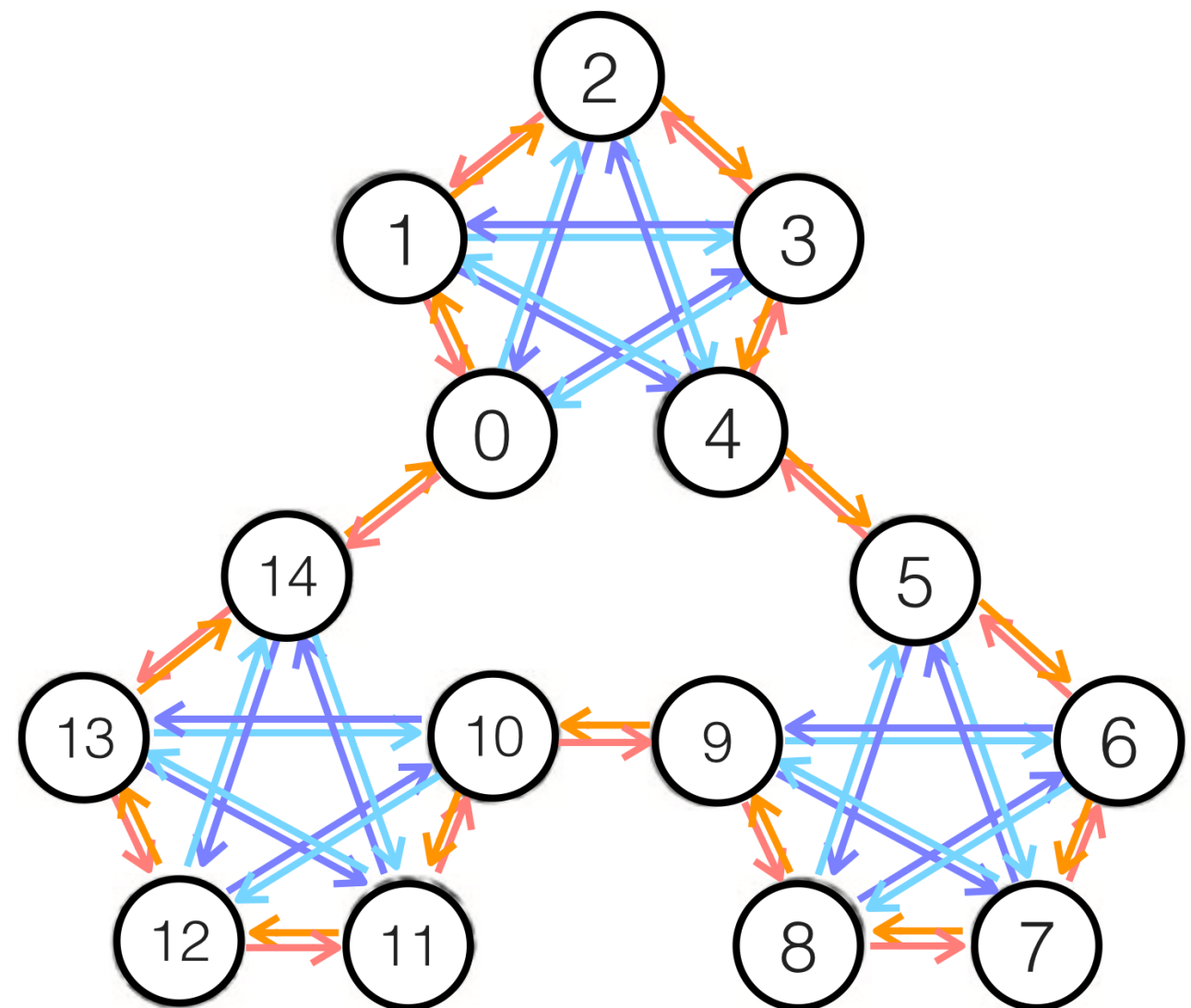
# Curious transition learning facilitates subsequent planning

Effie Li | EDUC234 pre-report

# World 1

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15 states, connected by 4 actions



# Question

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Does learning step-level transitions facilitate subsequent multi-step planning?

Transition learning:

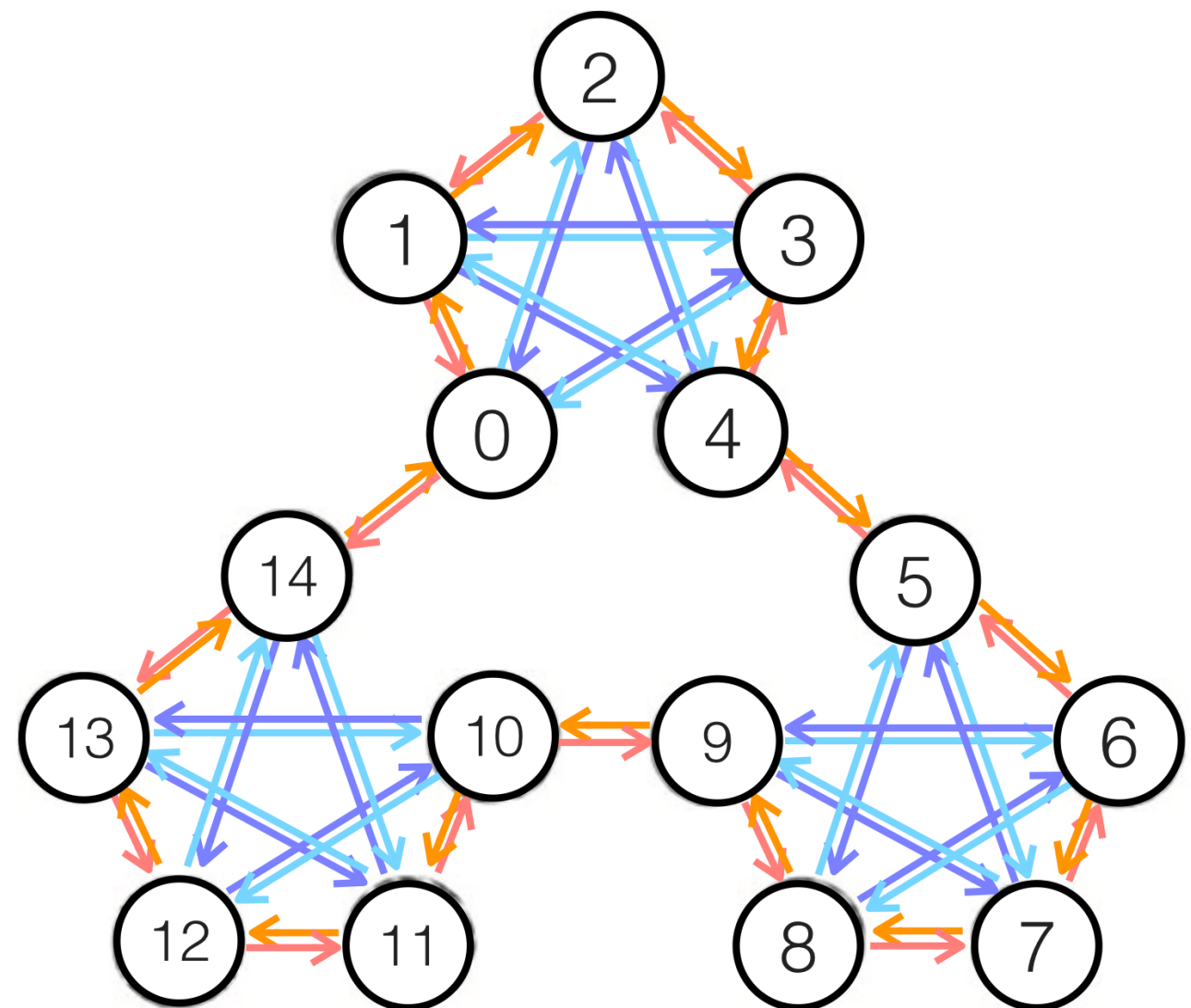
$(s1, s2) \longrightarrow a$

where  $s1, s2$  are adjacent

Multi-step planning:

$(s, g) \longrightarrow (a1, a2, \dots)$

where  $s, g$  are non-adjacent



# Model

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Transition learning:  
3-layer MLP

Multi-step planning:  
actor-critic agent + weights from the transition learning model

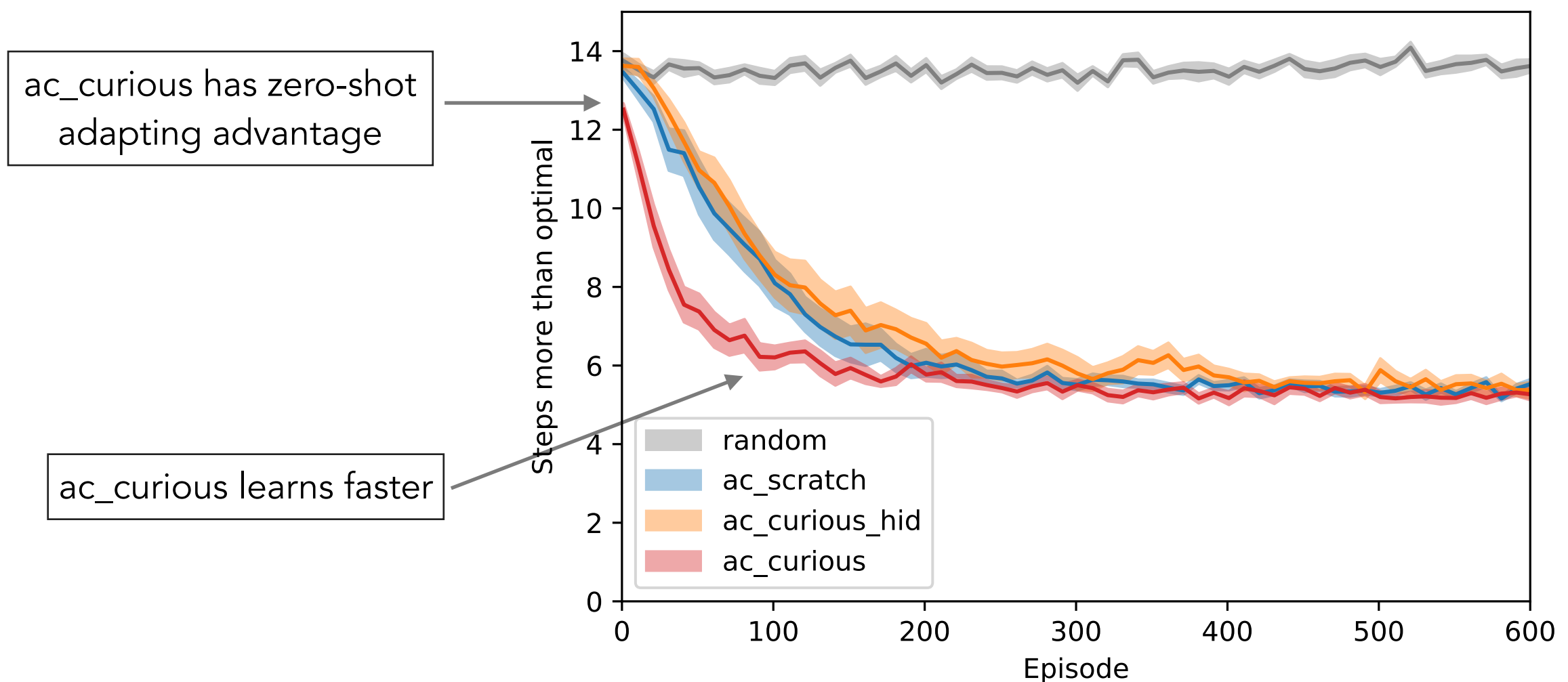
# Performance on multi-step planning

Baseline 1 (random): random walk agent

Baseline 2 (`ac_scratch`): actor-critic trained from scratch

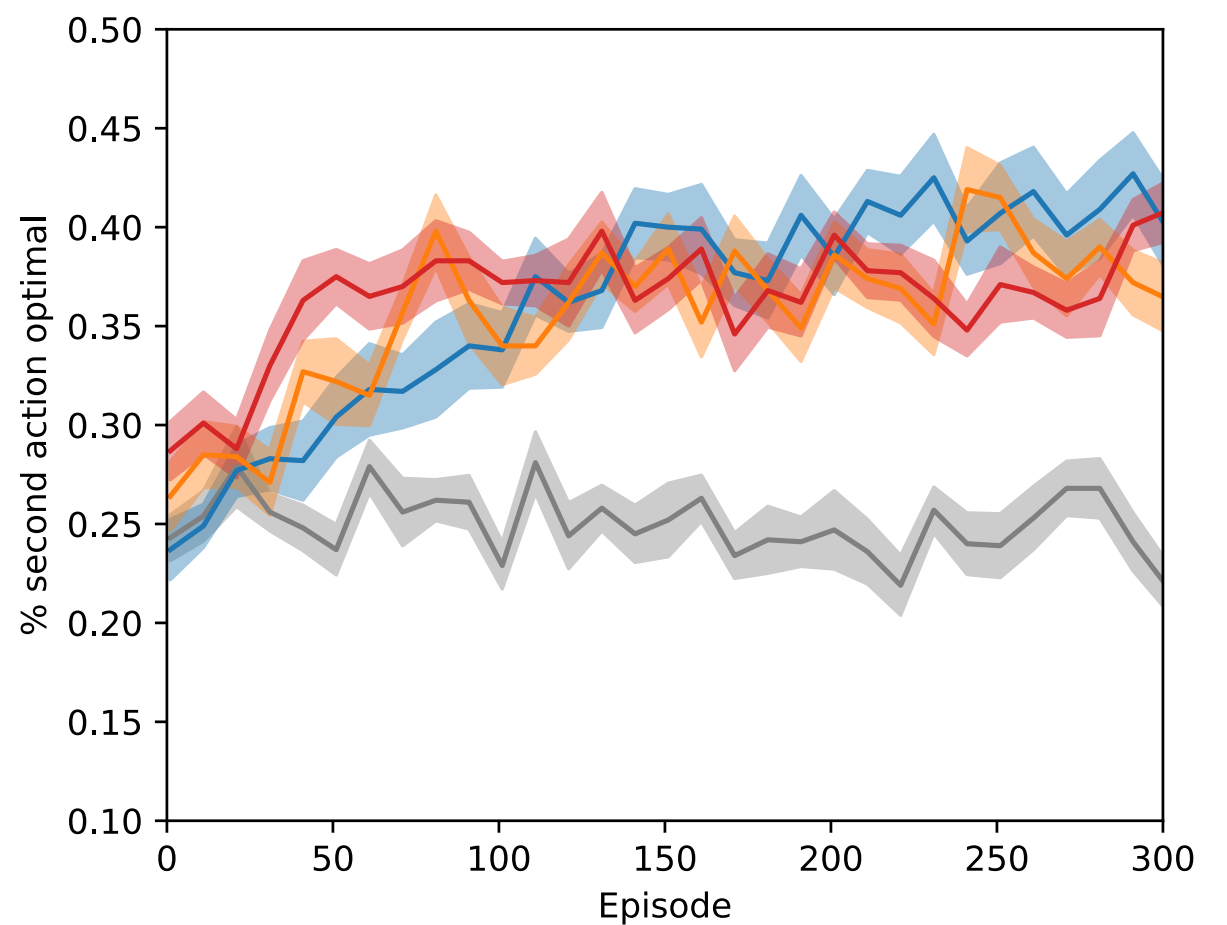
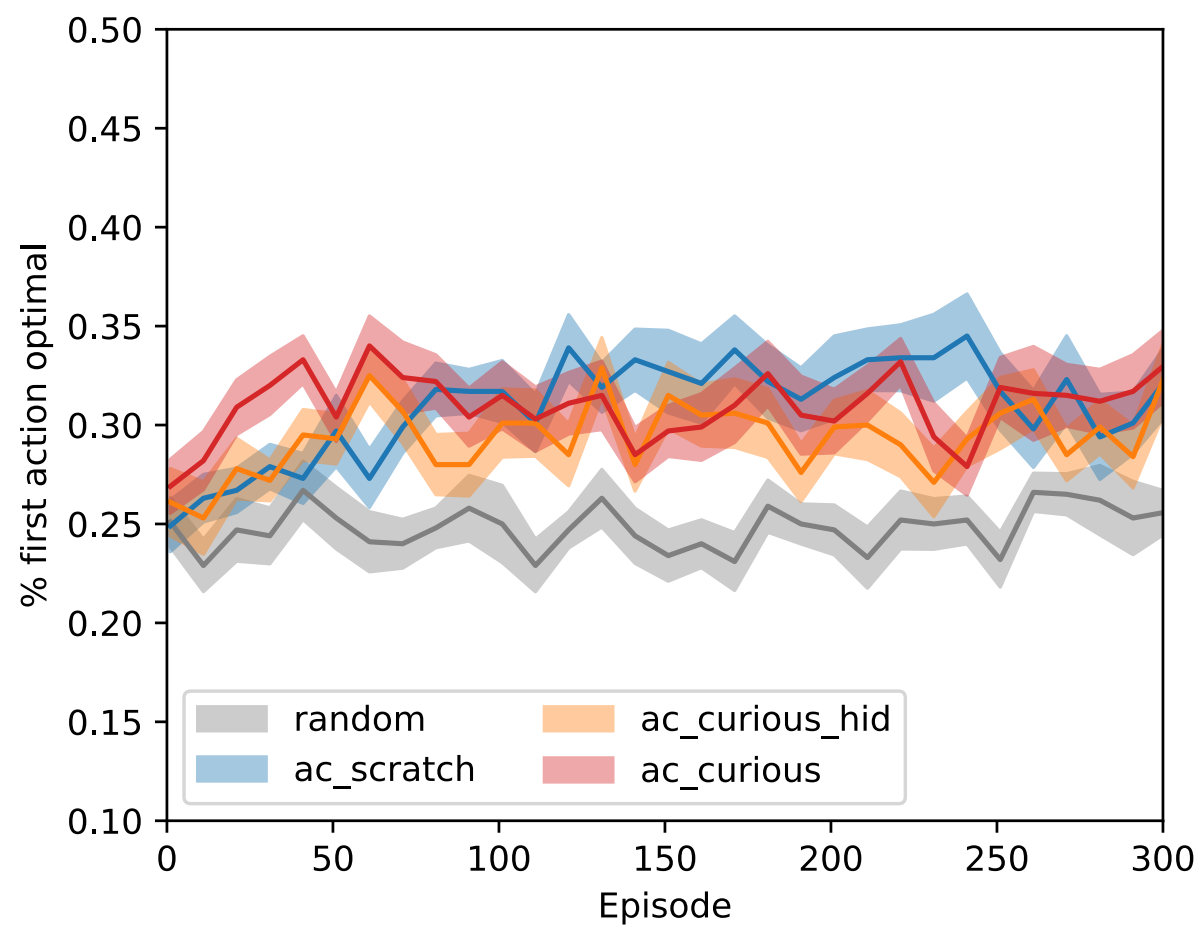
Baseline 3 (`ac_curious_hid`): actor\_critic + transition learning hidden layer

Model (`ac_curious`): actor\_critic + transition learning hidden layer & output layer



# Performance on multi-step planning

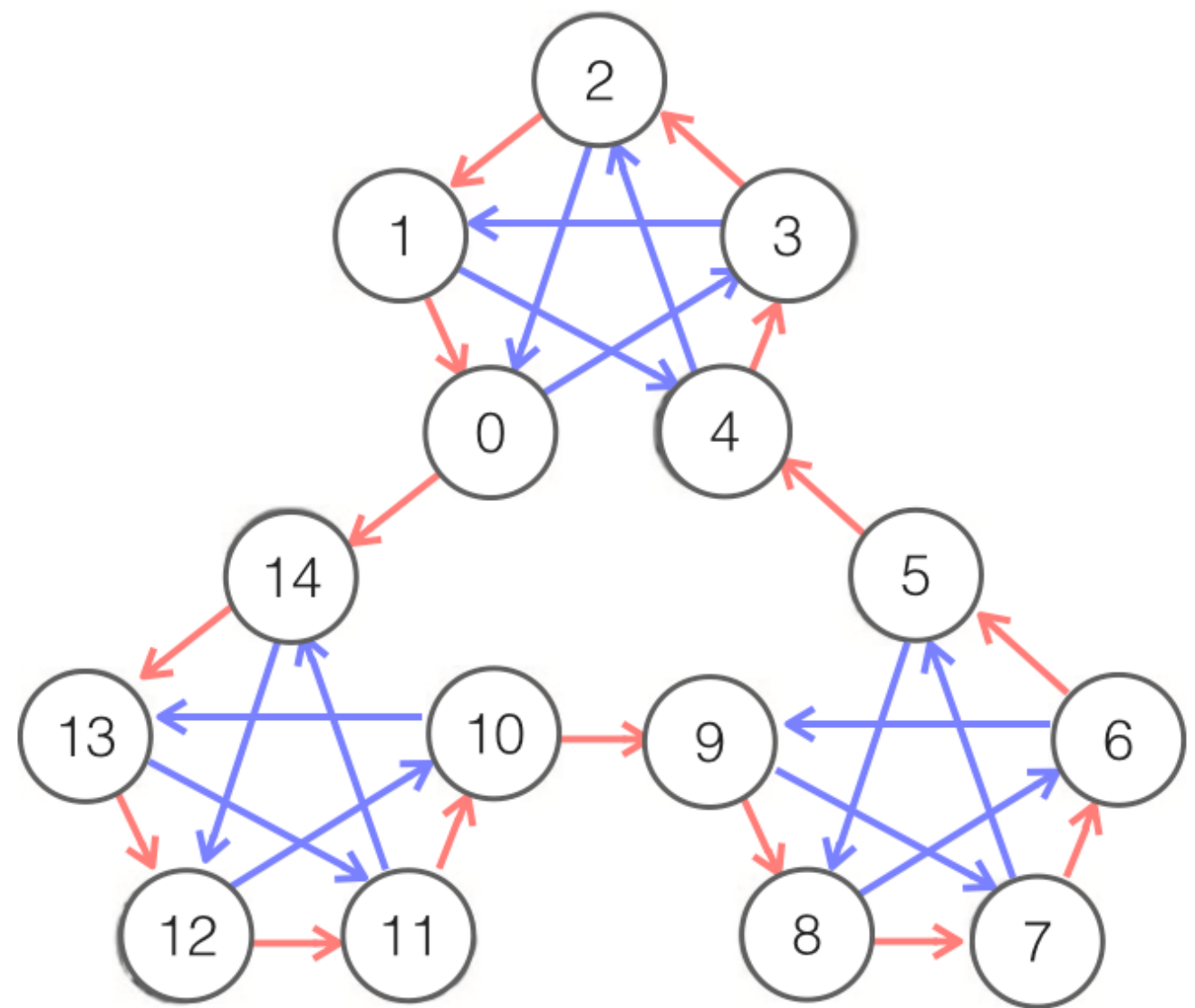
Action optimal rate in 2-step problems



# World 2

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15 states, connected by 2 actions



# Question

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Does learning step-level transitions facilitate subsequent multi-step planning?

Transition learning:

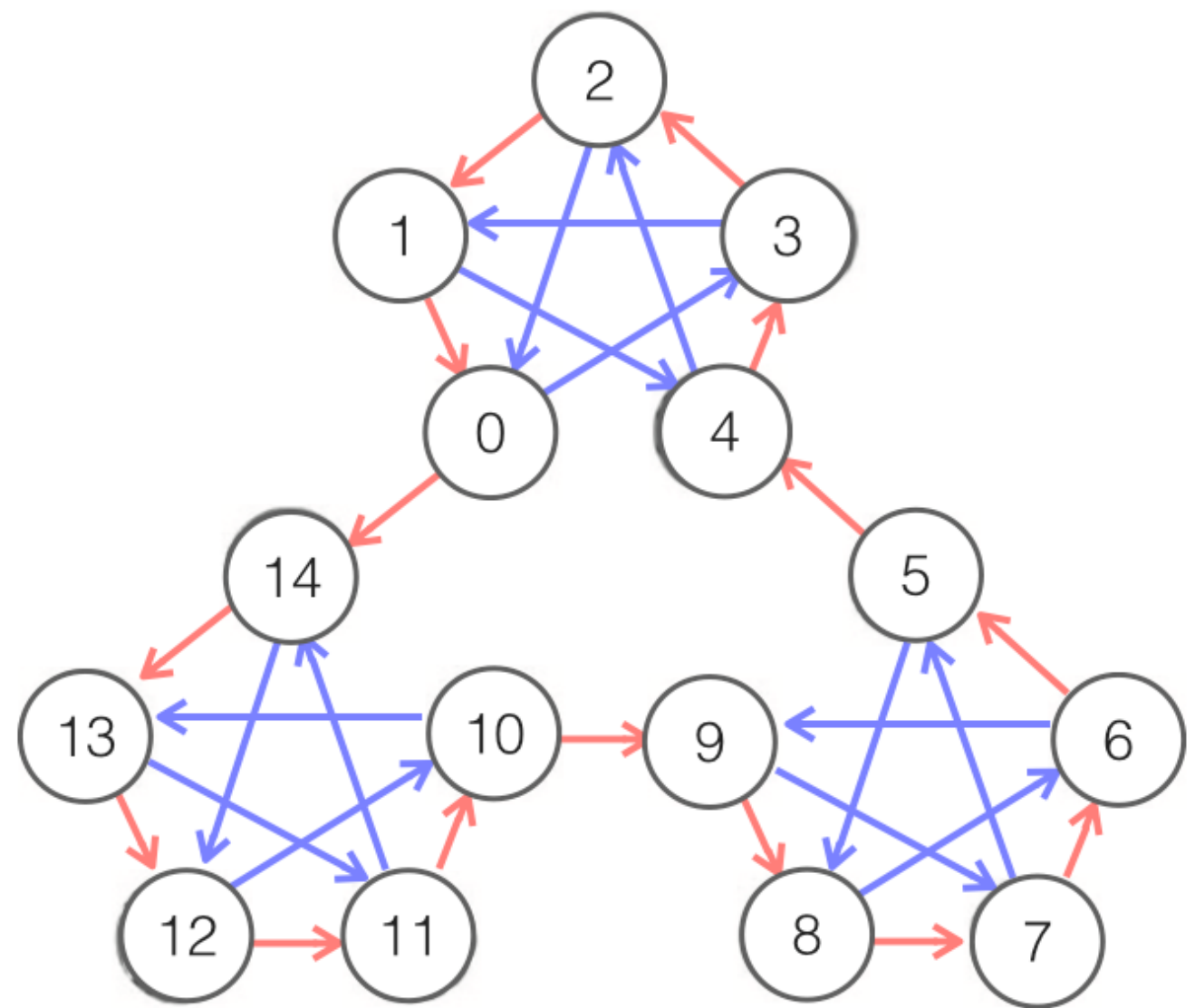
$(s1, s2) \longrightarrow a$

where  $s1, s2$  are adjacent

Multi-step planning:

$(s, g) \longrightarrow (a1, a2, \dots)$

where  $s, g$  are non-adjacent





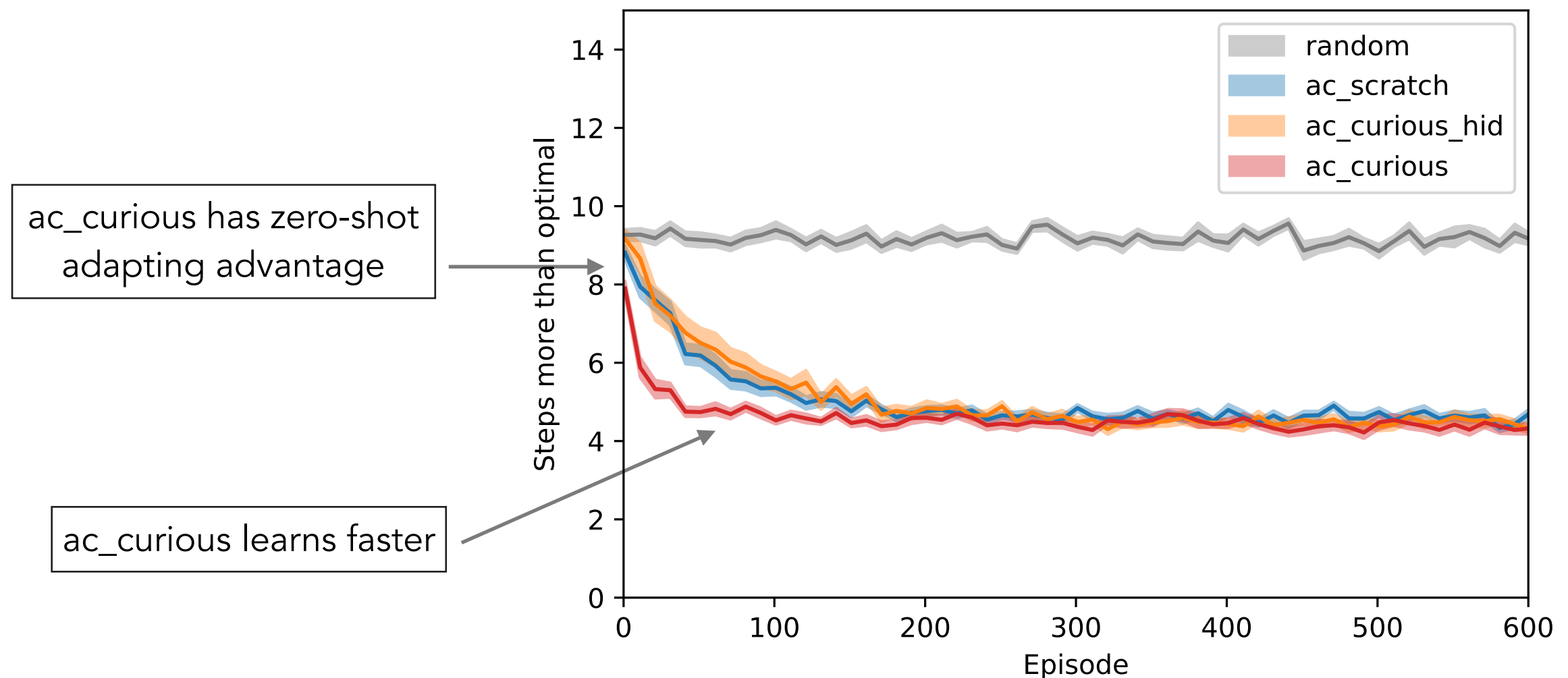
# Performance on multi-step planning

Baseline 1 (random): random walk agent

Baseline 2 (ac\_scratch): actor-critic trained from scratch

Baseline 3 (ac\_curious\_hid): actor\_critic + transition learning hidden layer

Model (ac\_curious): actor\_critic + transition learning hidden layer & output layer



# Next steps

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1. Adjust model for better performance.
2. Systematically vary the transitions exposed to the transition learning model.
3. Test robustness to randomized state labels.