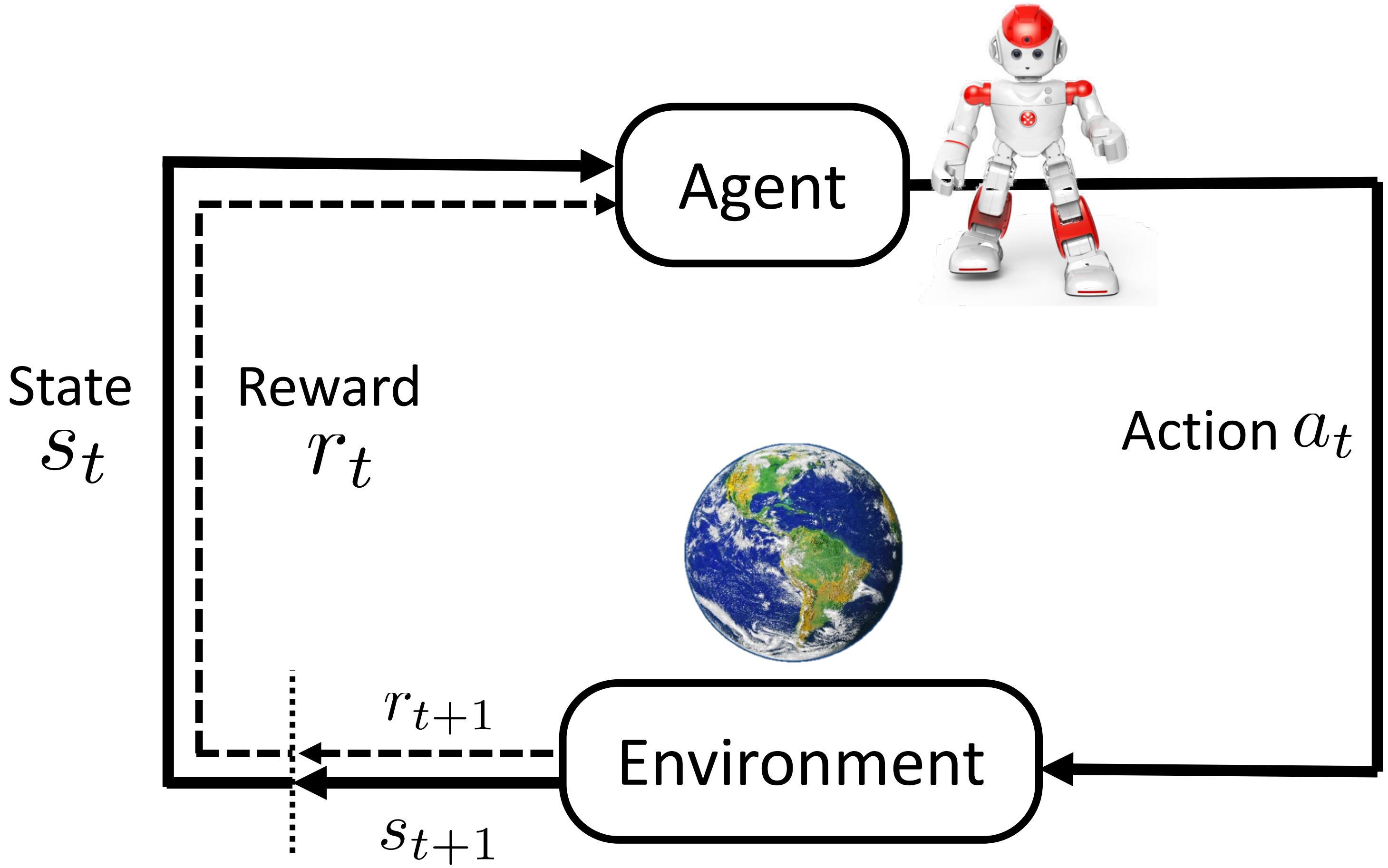
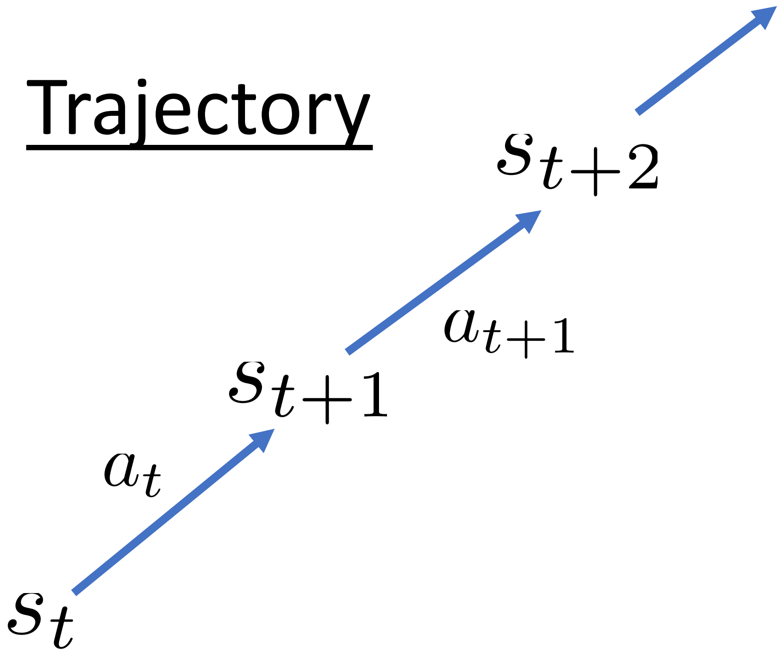
Building Scalable Framework and Environment of Reinforcement Learning

Yuandong Tian

Facebook AI Research

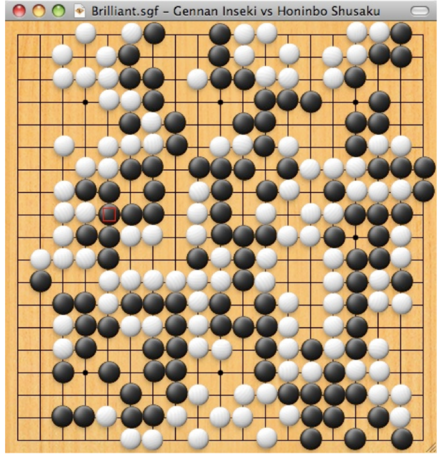
Reinforcement Learning





[R. S. Sutton and A. G. Barto, Reinforcement Learning: An Introduction]

Game as a testbed of Reinforcement Learning

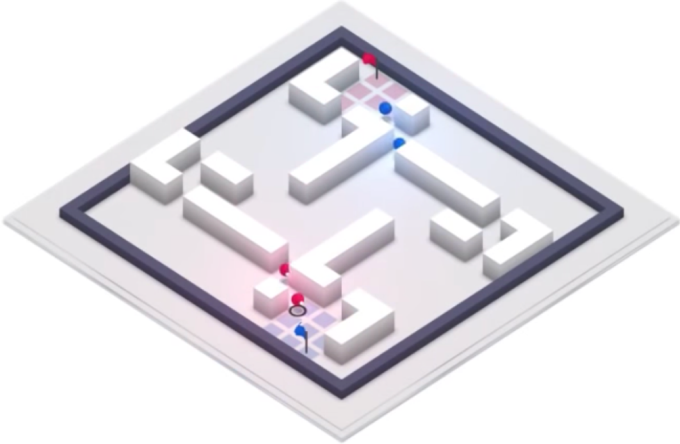


Go

Shogi

StarCraft II

Chess



Quake 3

Dota 2

Game as a testbed of Reinforcement Learning

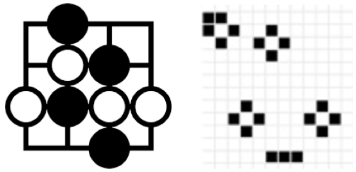
Infinite supply of *fully* labeled data

Controllable and replicable

Low cost per sample

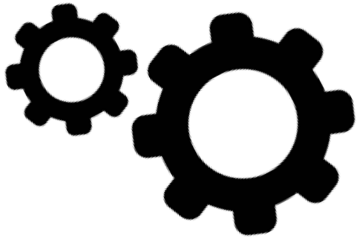
Faster than real-time

Less safety and ethical concerns



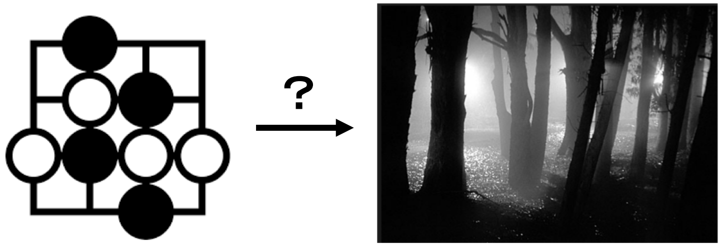
Complicated dynamics with simple rules.

Game as a testbed of Reinforcement Learning



Need good simulator

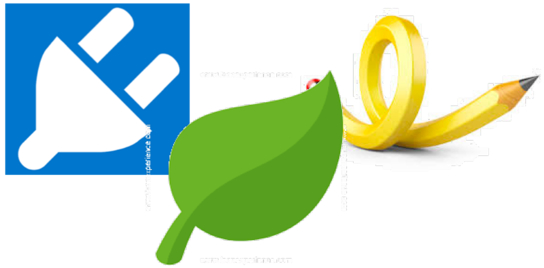
Require a lot of data/resources.



Sim2real issue

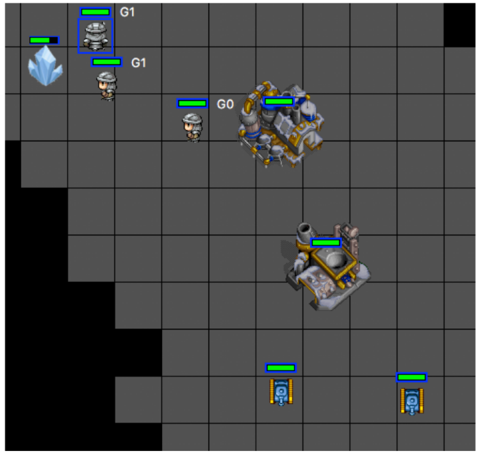
Applications?

Our work

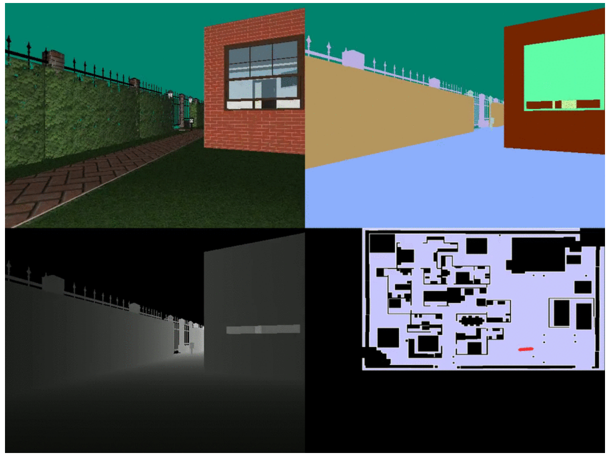


ELF Framework

ELF OpenGo



MiniRTS

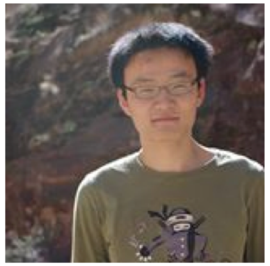


House3D

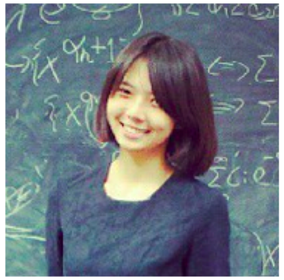
ELF: Extensive, Lightweight and Flexible Framework for Game Research

Yuandong Tian, Qucheng Gong, Wendy Shang, Yuxin Wu, Larry Zitnick (NIPS 2017 Oral)

- Extensive
    - Any games with C++ interfaces can be incorporated.
- Lightweight
    - Fast. Mini-RTS (40K FPS per core)
    - Minimal resource usage (1GPU+several CPUs)
    - Fast training (a couple of hours for a RTS game)
- Flexible
    - Environment-Actor topology
    - Parametrized game environments.
    - Choice of different RL methods.



Qucheng Gong



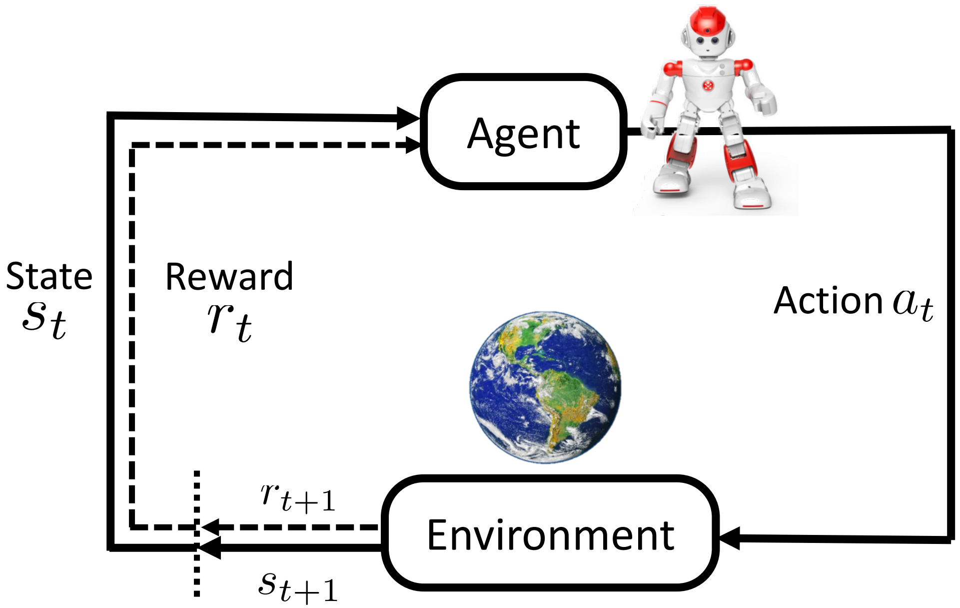
Wendy Shang

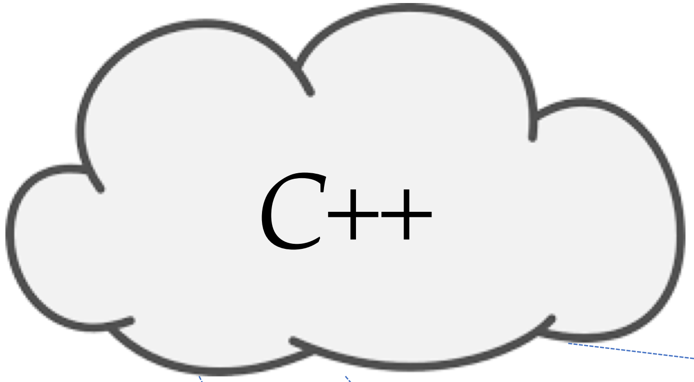
Yuxin Wu

Larry Zitnick

Arxiv: https://arxiv.org/abs/1707.01067

ELF: A simple for-loop

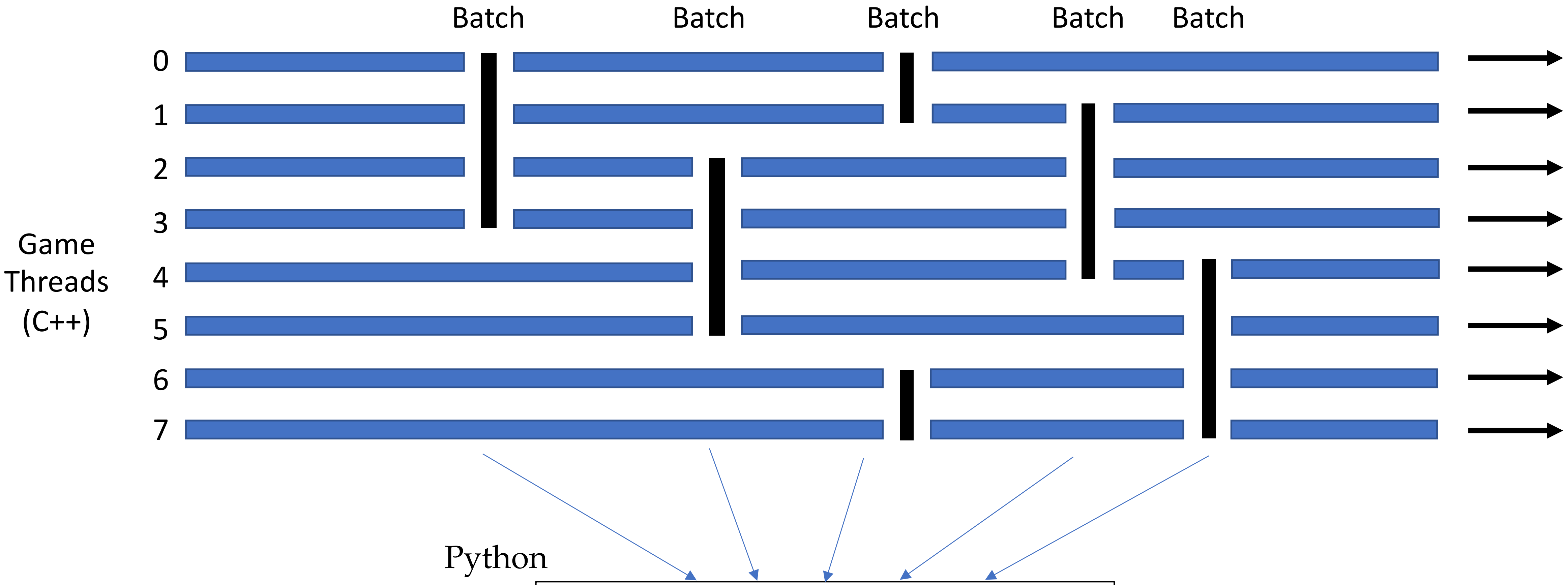




Python

```
while True:
    batched_states = GameContext.Wait()
    replies = model(batched_states)
    GameContext.Steps(replies)
```

How ELF works




```
while True:
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```

ELF Characteristics

Extensive

Any games with C++ interfaces
can be incorporated.

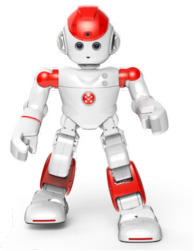
Flexible

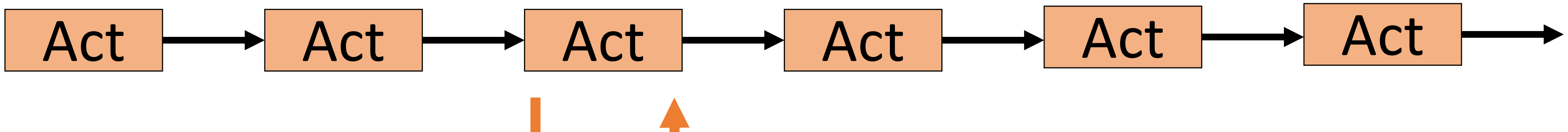
Environment-Actor topology
Parametrized game environments.
Choice of different RL methods.

Lightweight

Fast. Mini-RTS (40K FPS per core)
Minimal resource usage (1GPU+several CPUs)
Fast training (half a day for a RTS game)

Flexibility

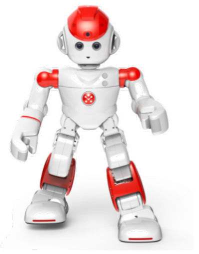


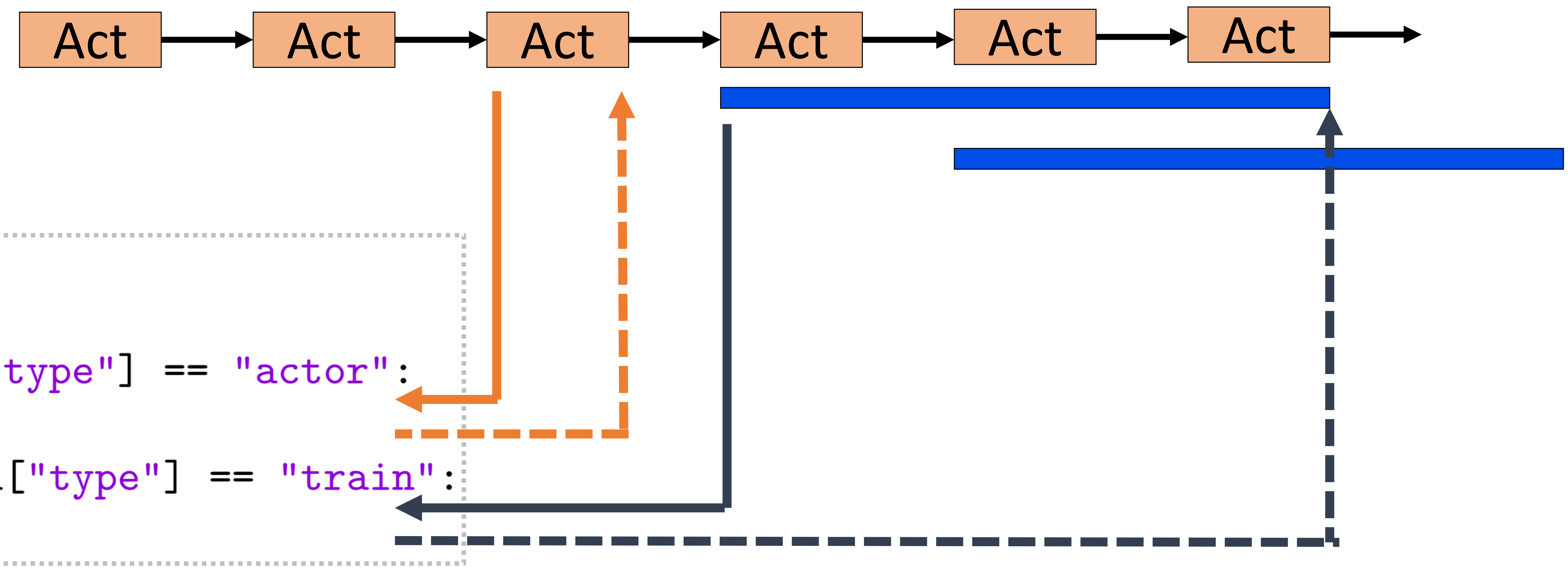



```python
while True:
    batched = GameContext.Wait()
    replies = model(batched)
    GameContext.Steps(replies)
```

Evaluation

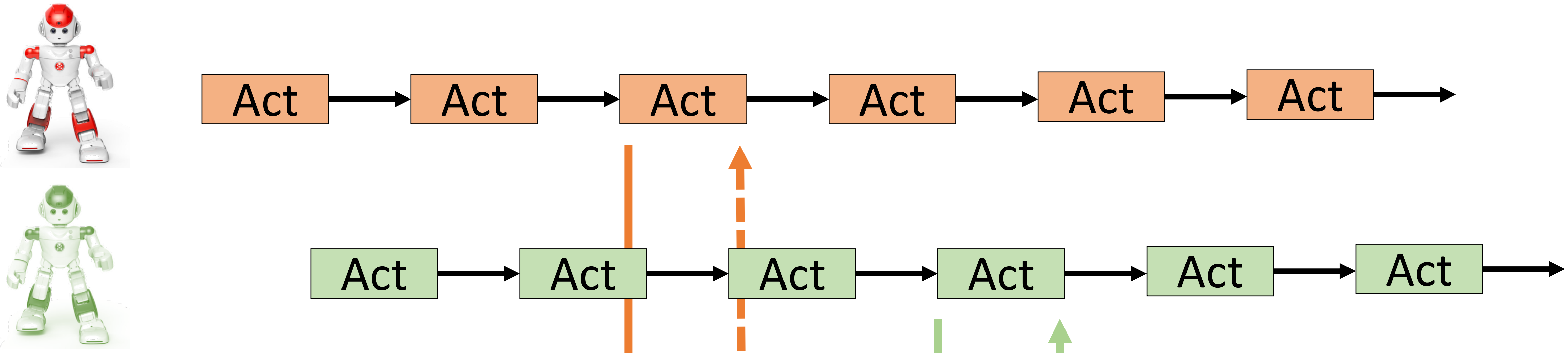
Flexibility





Training

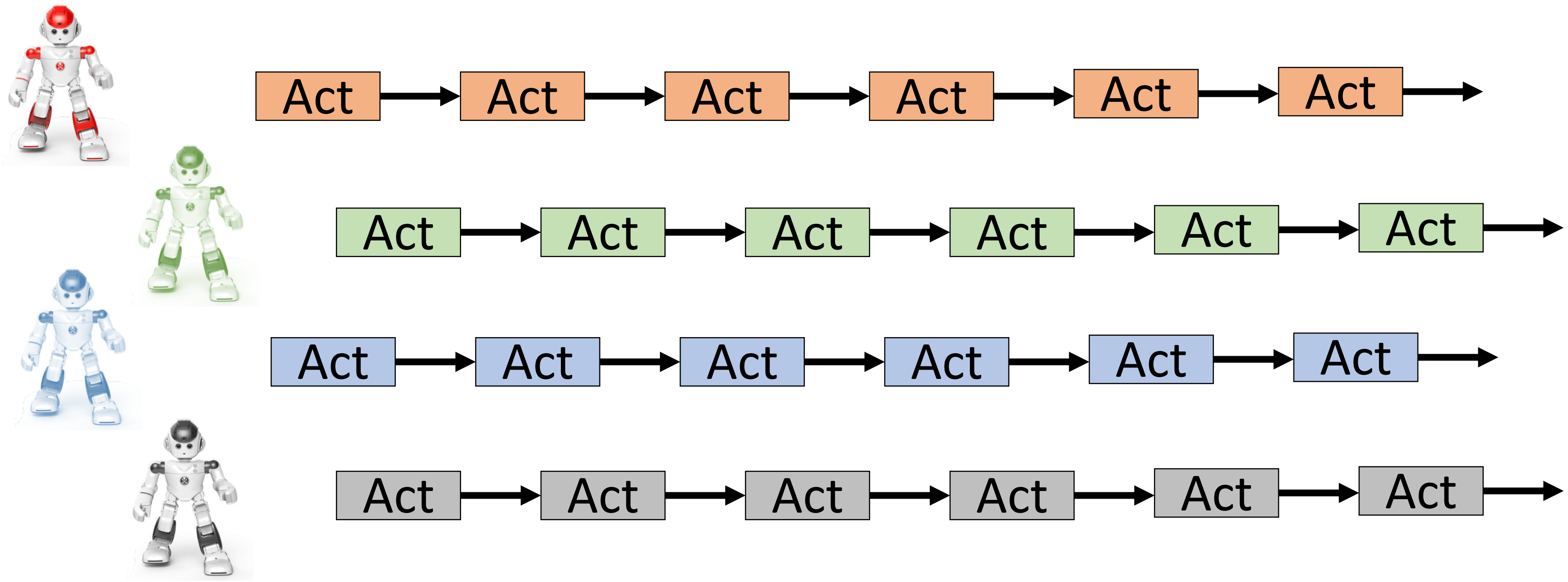
Flexibility




```python
while True:
    ...
    if batch["type"] == "actor0":
        ...
    elif batch["type"] == "actor1":
        ...
```

Self-play

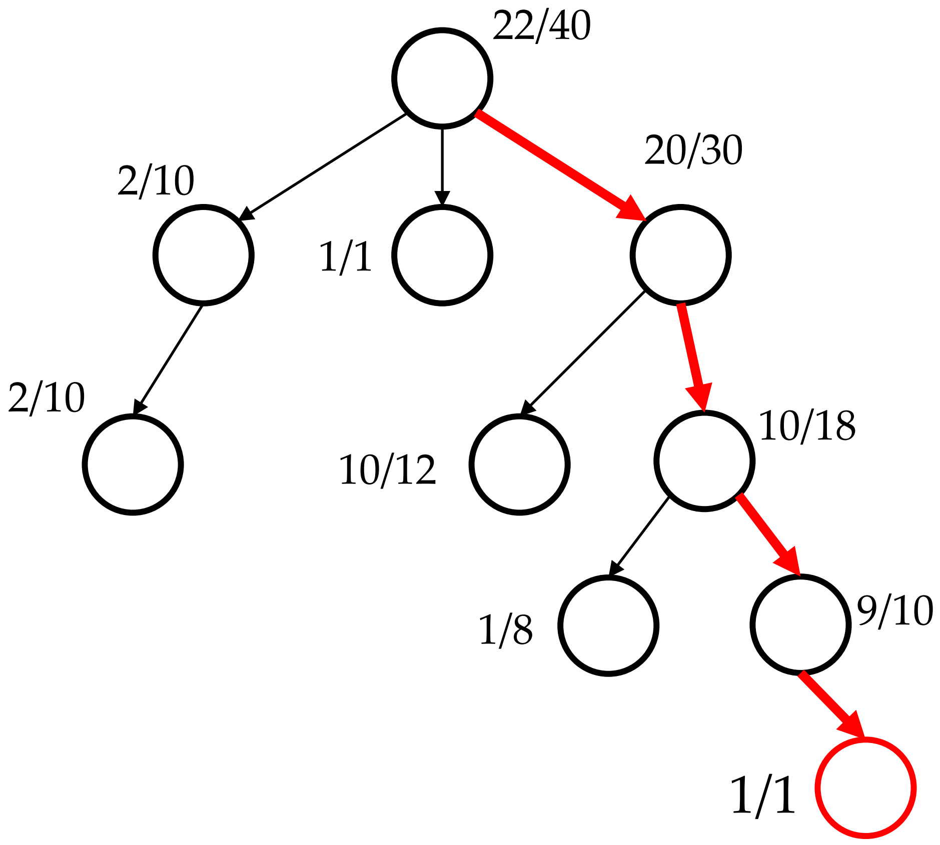
Flexibility




```
while True:
    ...
    for i in range(n):
        if batch["type"] == "actor%d" % i:
            ...
```

Multi-agent

Flexibility

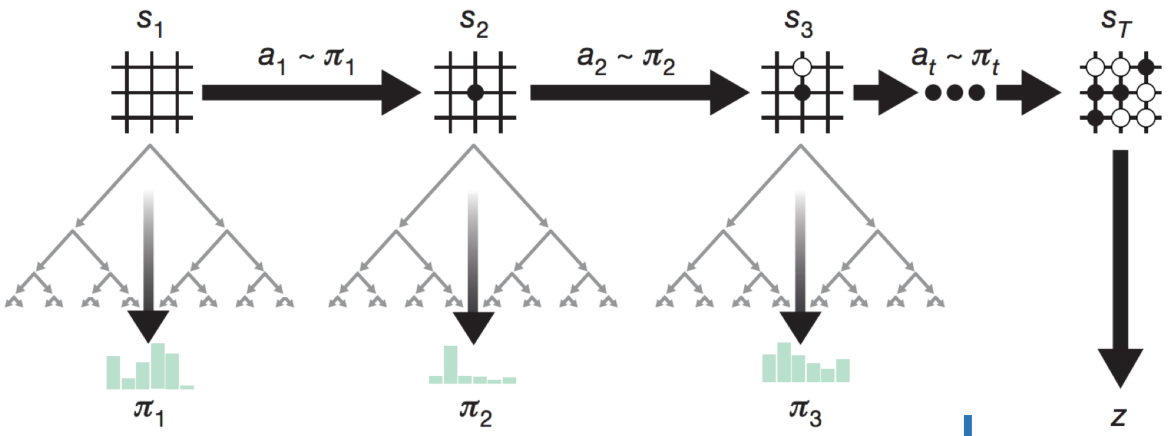



```python
while True:
    batched = GameContext.Wait()
    replies = model(batched)
    GameContext.Steps(replies)
```

Monte-Carlo Tree Search

Reimplementation of AlphaGo Zero

Generate Training data



Zero-human knowledge

θ_i

Update Models

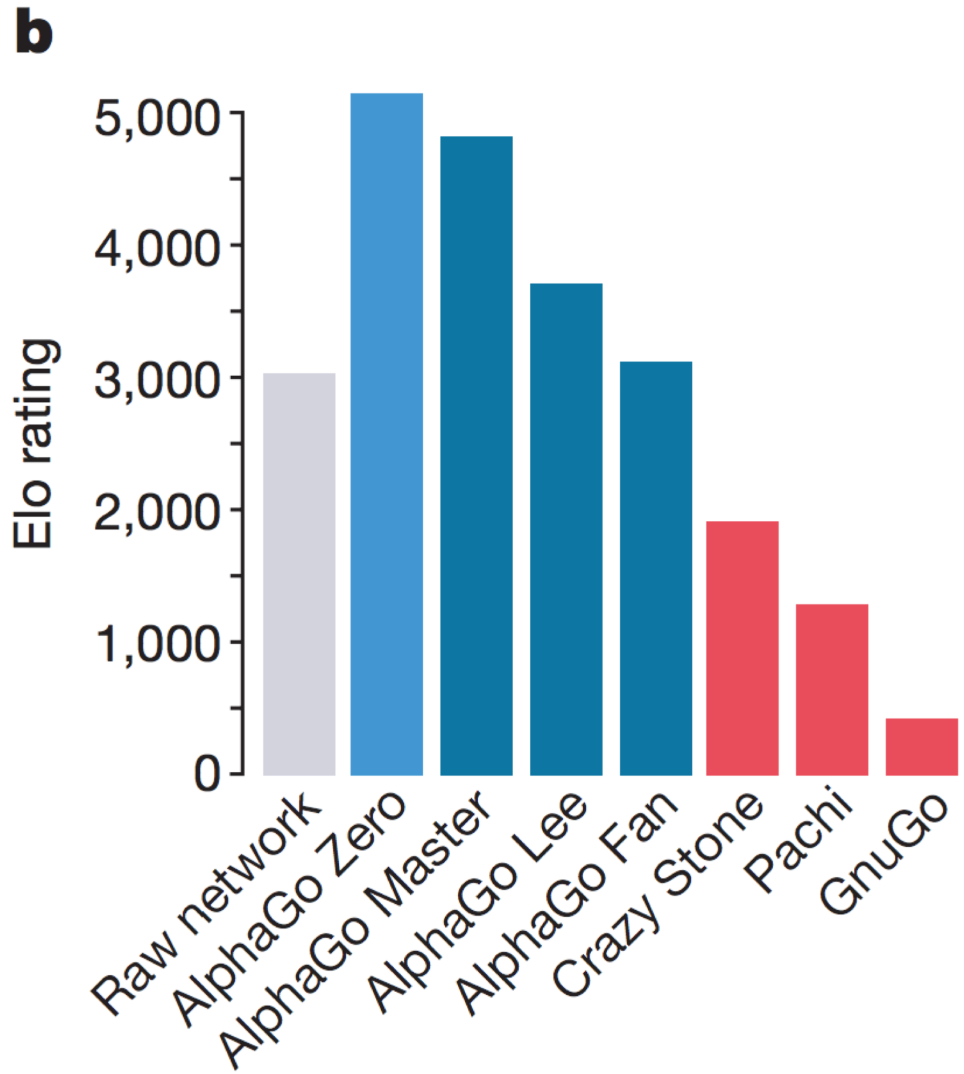
Self-Replays

[Silver et al, Mastering the game of Go without human knowledge, Nature 2017]

AlphaGo Zero Strength

- 3 days version
  - 4.9M Games, 1600 rollouts/move
  - 20 block ResNet
  - Defeat AlphaGo Lee.

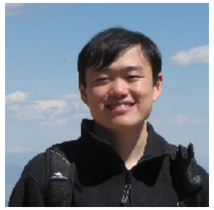
- 40 days version
  - 29M Games, 1600 rollouts/move
  - 40 blocks ResNet.
  - Defeat AlphaGo Master by 89:11



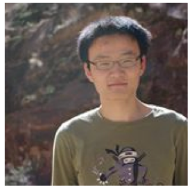
Demystifying AlphaGoZero/AlphaZero

- Amazing performance but no code available.
  - Huge computational cost (15.5 years to generate 4.9M selfplays with 1 GPU)
  - Sophisticated (distributed) systems.
- Lack of ablation analysis
  - What factor is critical for the performance?
  - Is the algorithm robust to random initialization and changes of hyper parameters?
  - How the ladder issue is solved?
- Lots of mysteries
  - Is the proposed algorithm really universal?
  - Is the bot almighty? Is there any weakness in the trained bot?

ELF OpenGo

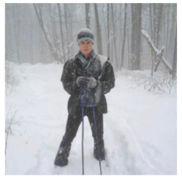

Yuandong Tian


Jerry Ma


Qucheng Gong


Shubho Sengupta


Zhuoyuan Chen


James Pinkerton


Larry Zitnick

- System can be trained with 2000 GPUs in 2 weeks (20 block version)
- Superhuman performance against professional players and strong bots.
- Abundant ablation analysis
- Decoupled design, code reusable for other games.

pytorch / ELF

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ELF: a platform for game research with AlphaGoZero/AlphaZero reimplementation

Edit

reinforcement-learning | alphago-zero | rl | rl-environment | alpha-zero | Manage topics

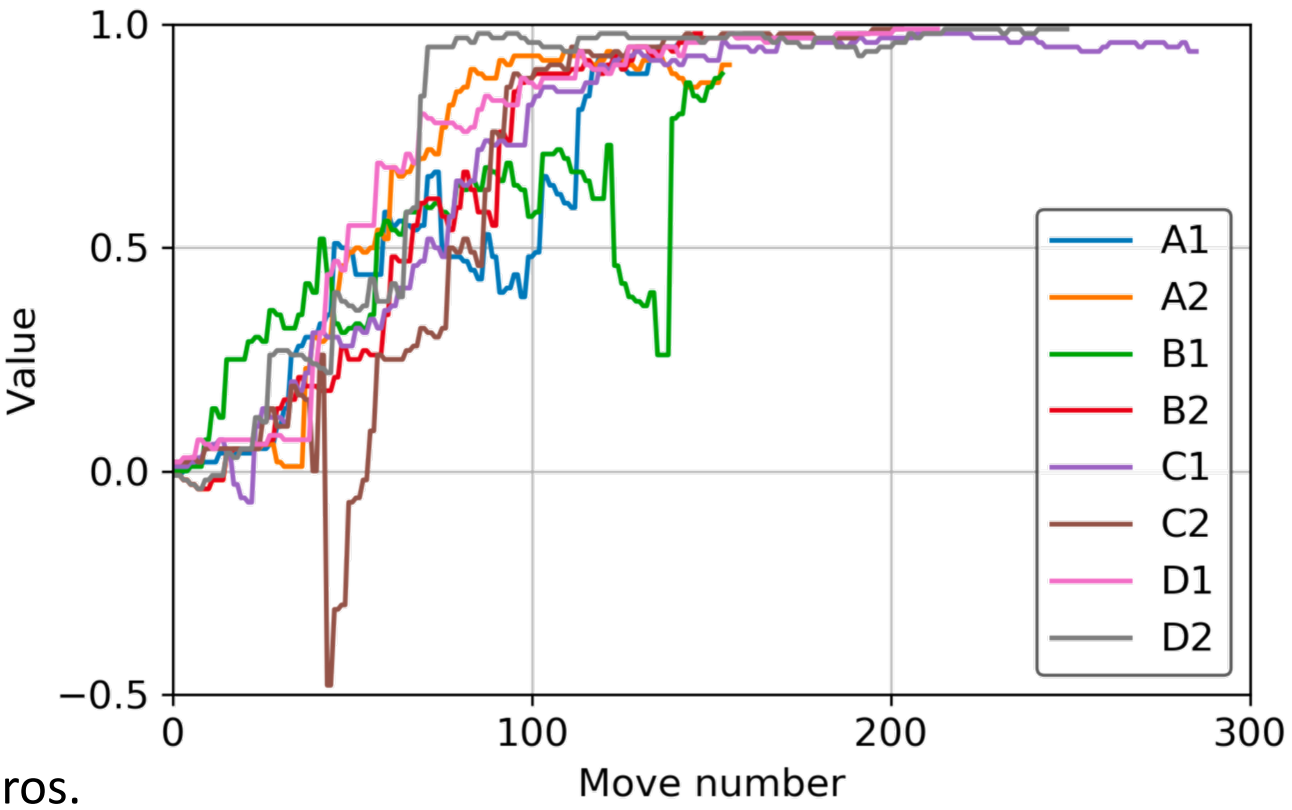
We open source the code and the pre-trained model for the Go and ML community

ELF OpenGo Performance

Vs top professional players

Name (rank)	ELO (world rank)	Result
Kim Ji-seok	3590 (#3)	5-0
Shin Jin-seo	3570 (#5)	5-0
Park Yeonghun	3481 (#23)	5-0
Choi Cheolhan	3466 (#30)	5-0

Single GPU, 80k rollouts, 50 seconds
Offer unlimited thinking time for the players



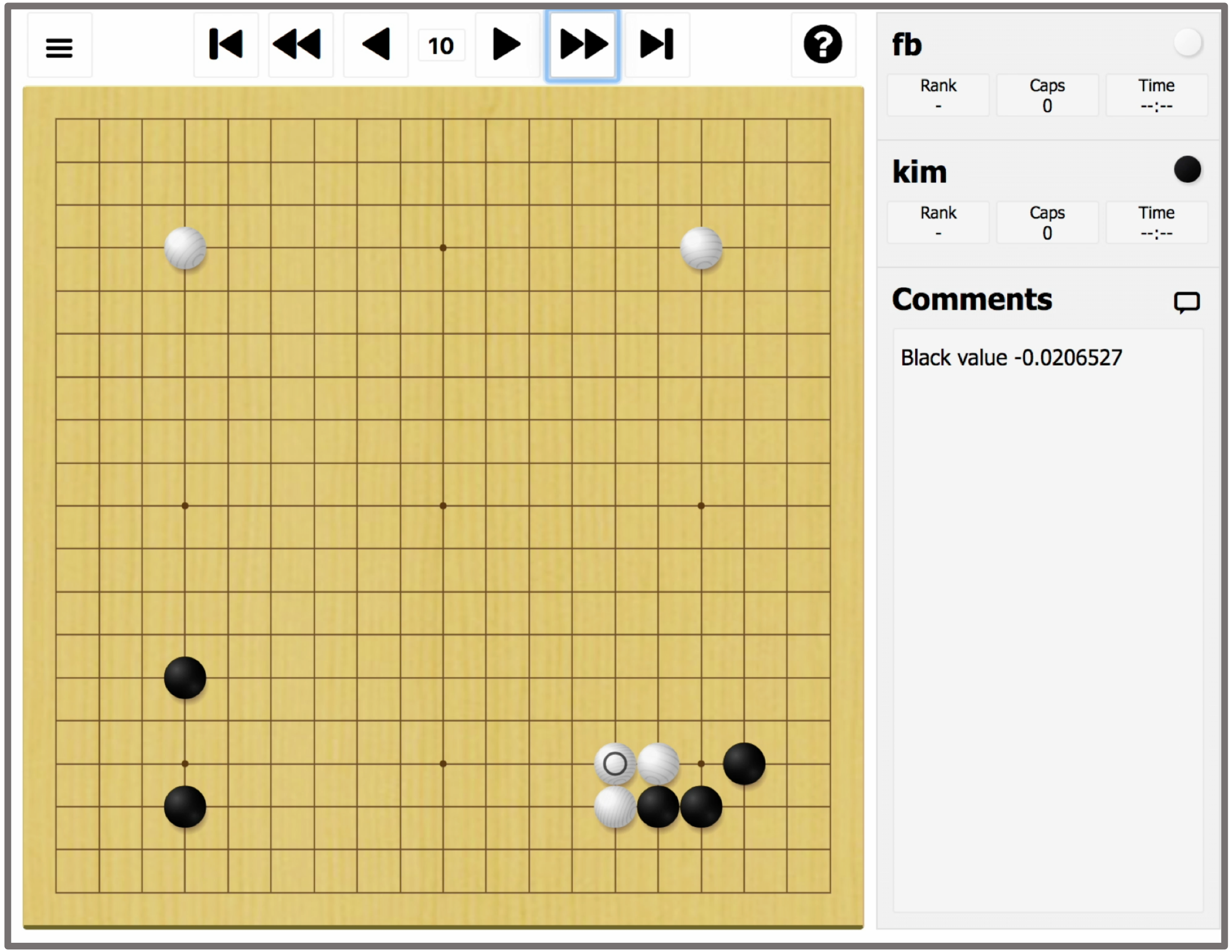
Vs professional players

Single GPU, 2k rollouts, 27-0 against Taiwanese pros.

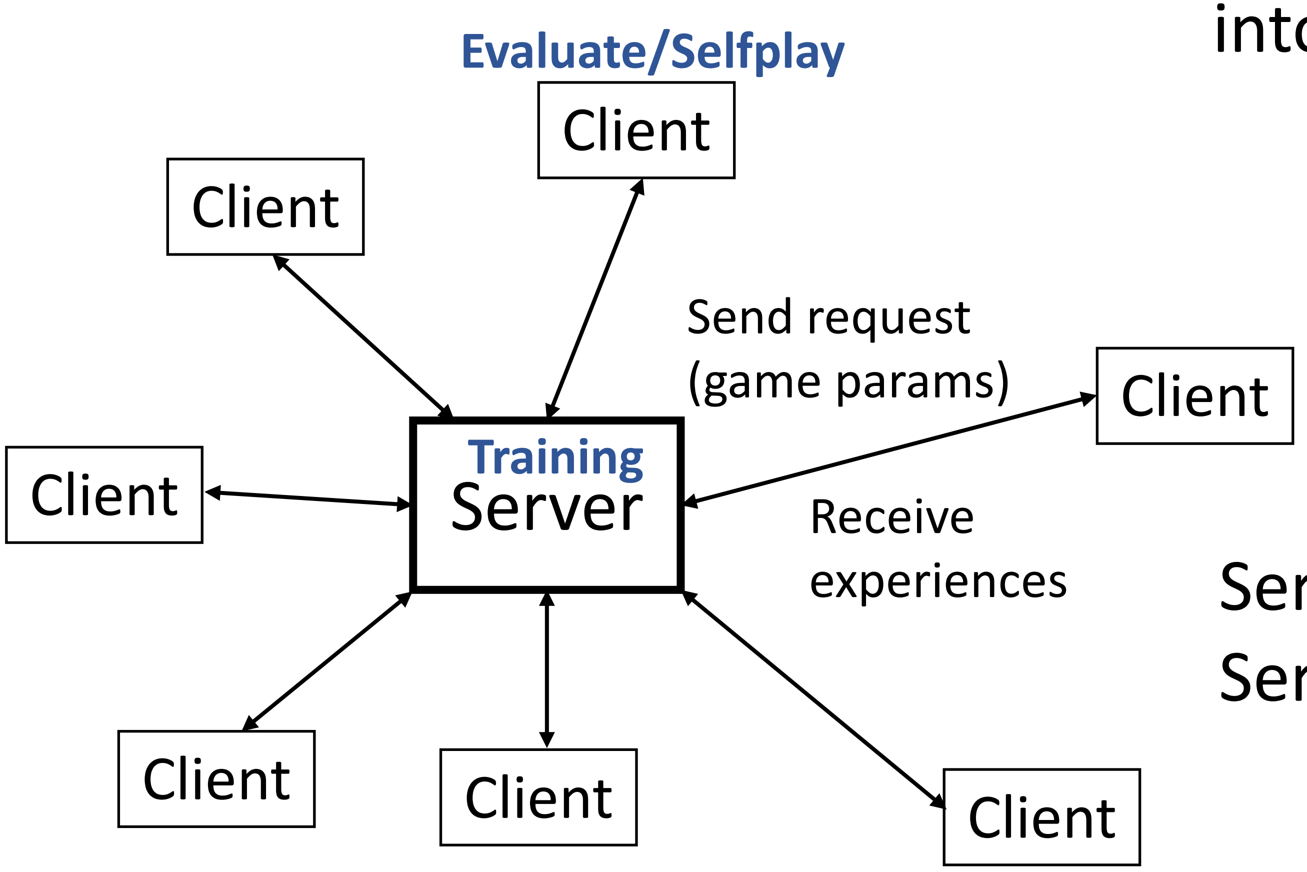
Vs strong bot (LeelaZero)

[158603eb, 192x15, Apr. 25, 2018]: 980 wins, 18 losses (98.2%)

ELF OpenGo Sample Game



Distributed ELF

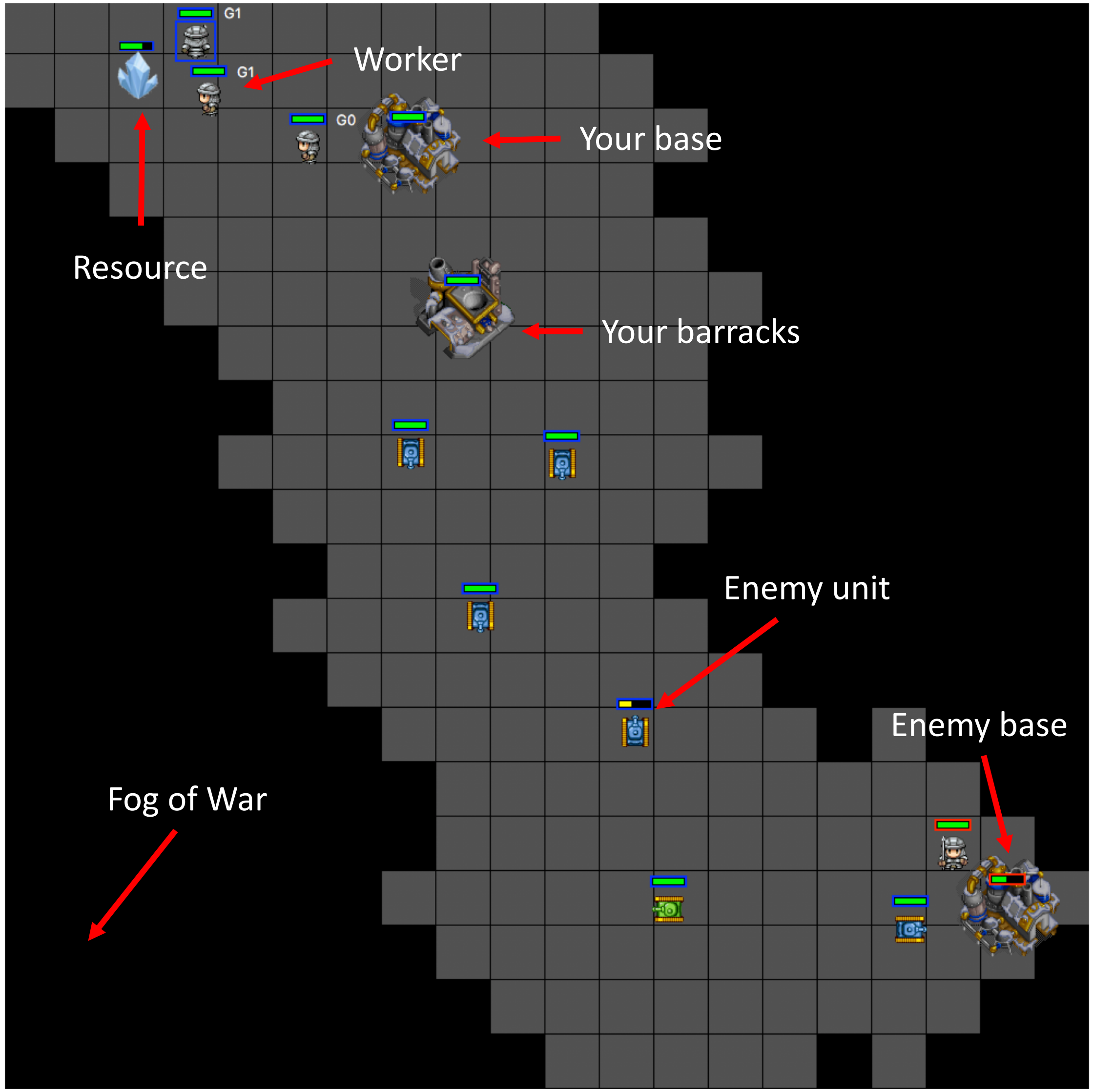


Putting AlphaGoZero and AlphaZero into the same framework

AlphaGoZero (more synchronization)
AlphaZero (less synchronization)

Server controls synchronization
Server also does training.

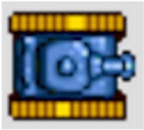
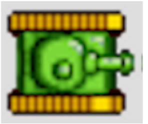
MiniRTS: A miniature RTS engine



Platform	Frame per second
ALE	6,000
Open AI Universe	60
Malmo	120
DeepMind Lab	287*/866**
VizDoom	7,000
TorchCraft	2,000
MiniRTS	40,000

* Using CPU only ** Using CPUs and GPU

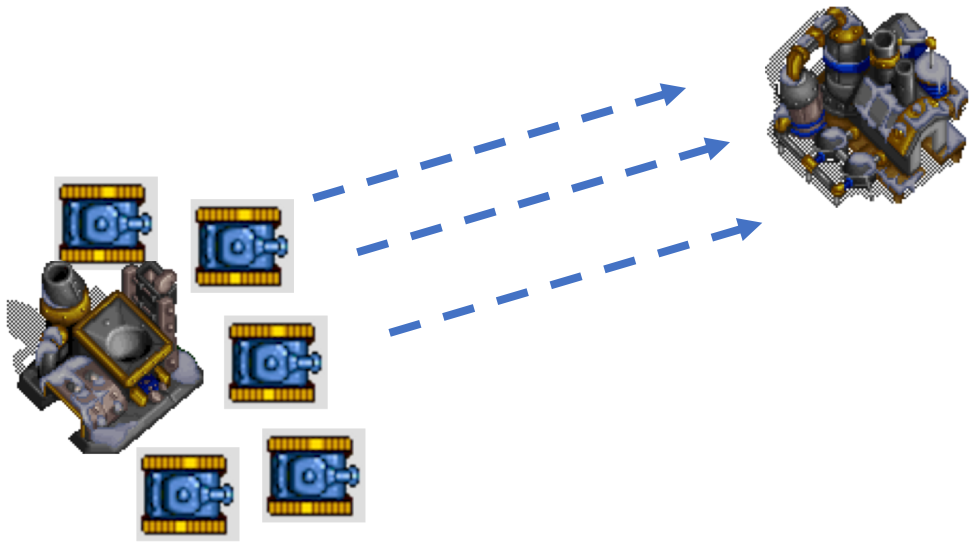
MiniRTS

Base		Build workers and collect resources.
Resource		Contains 1000 minerals.
Barracks		Build melee attacker and range attacker.
Worker		Build barracks and gather resource. Low speed in movement and low attack damage.
Melee Tank		High HP, medium movement speed, short attack range, high attack damage.
Range Tank		Low HP, high movement speed, long attack range and medium attack damage.

9 Discrete Strategic Actions

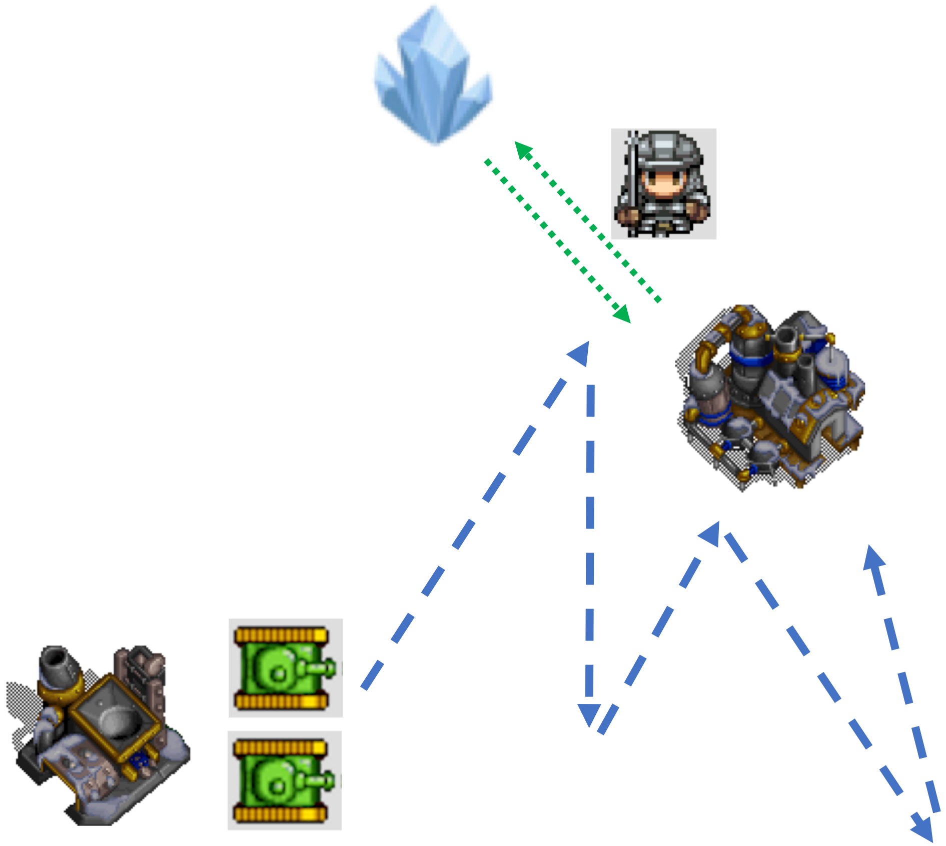
No.	Action name	Descriptions
1	IDLE	Do nothing
2	BUILD WORKER	If the base is idle, build a worker
3	BUILD BARRACK	Move a worker (gathering or idle) to an empty place and build a barrack.
4	BUILD MELEE ATTACKER	If we have an idle barrack, build an melee attacker.
5	BUILD RANGE ATTACKER	If we have an idle barrack, build a range attacker.
6	HIT AND RUN	If we have range attackers, move towards opponent base and attack. Take advantage of their long attack range and high movement speed to hit and run if enemy counter-attack.
7	ATTACK	All melee and range attackers attack the opponent's base.
8	ATTACK IN RANGE	All melee and range attackers attack enemies in sight.
9	ALL DEFEND	All troops attack enemy troops near the base and resource.

Rule-based AIs



`AI_SIMPLE`

Build 5 tanks and attack

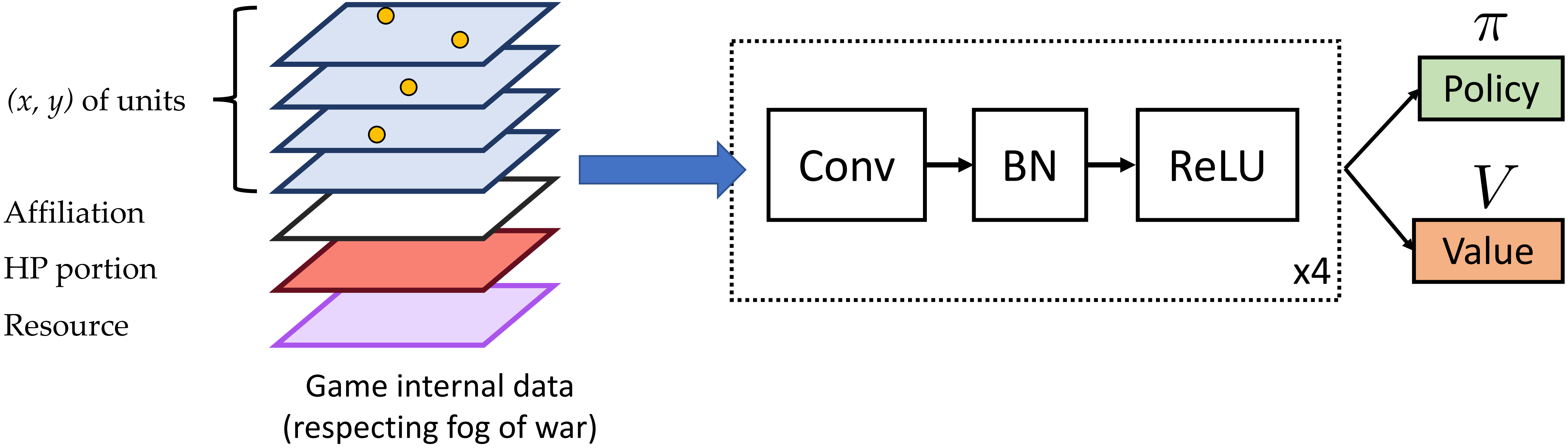


`AI_HIT_AND_RUN`

Build 2 tanks and harass

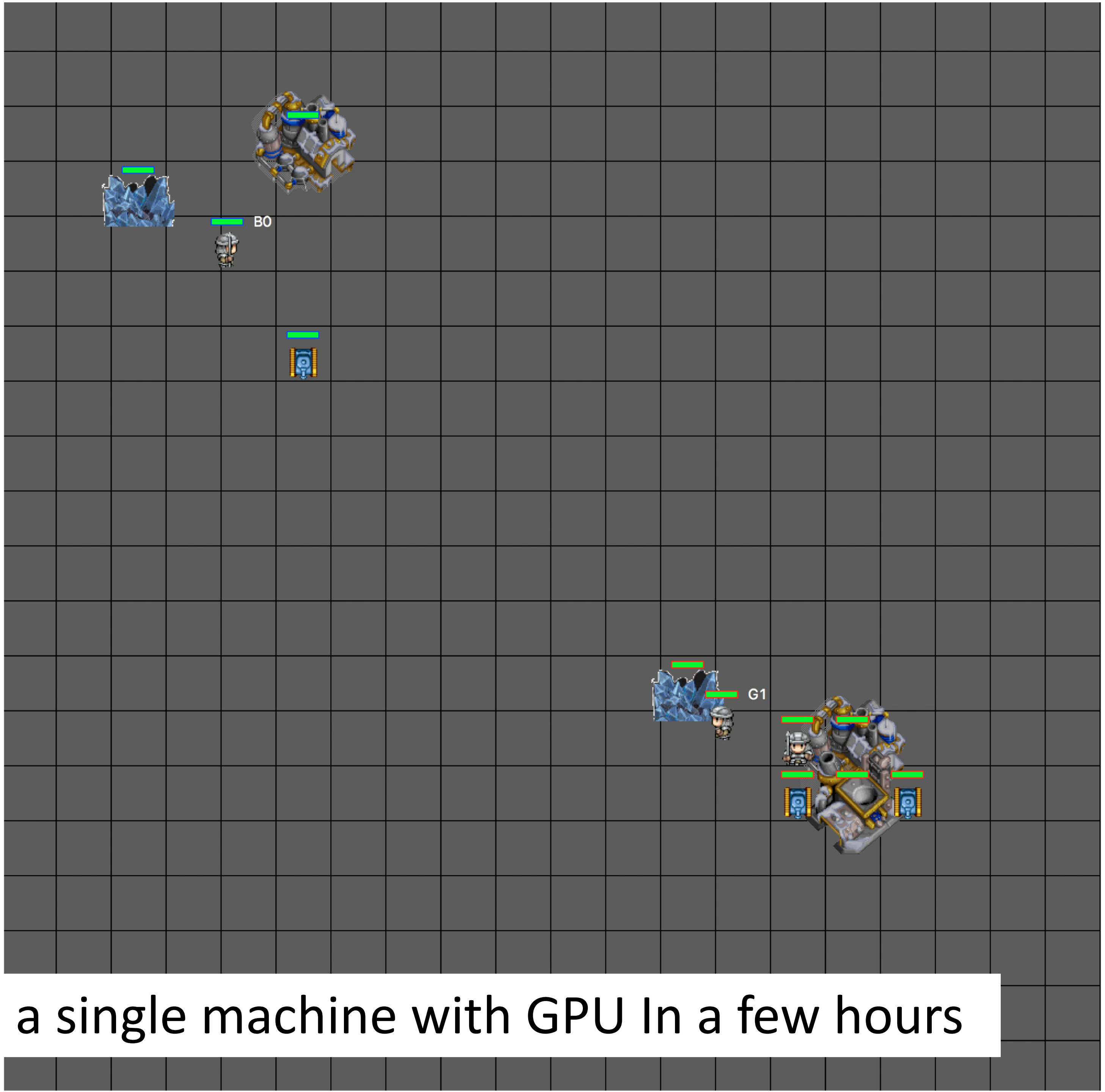
<u>MiniRTS trains with a single GPU and 6 CPUs in half a day.</u>

Training AI



Using Internal Game data and Off-policy Actor-Critic Methods.
Reward is only available once the game is over.

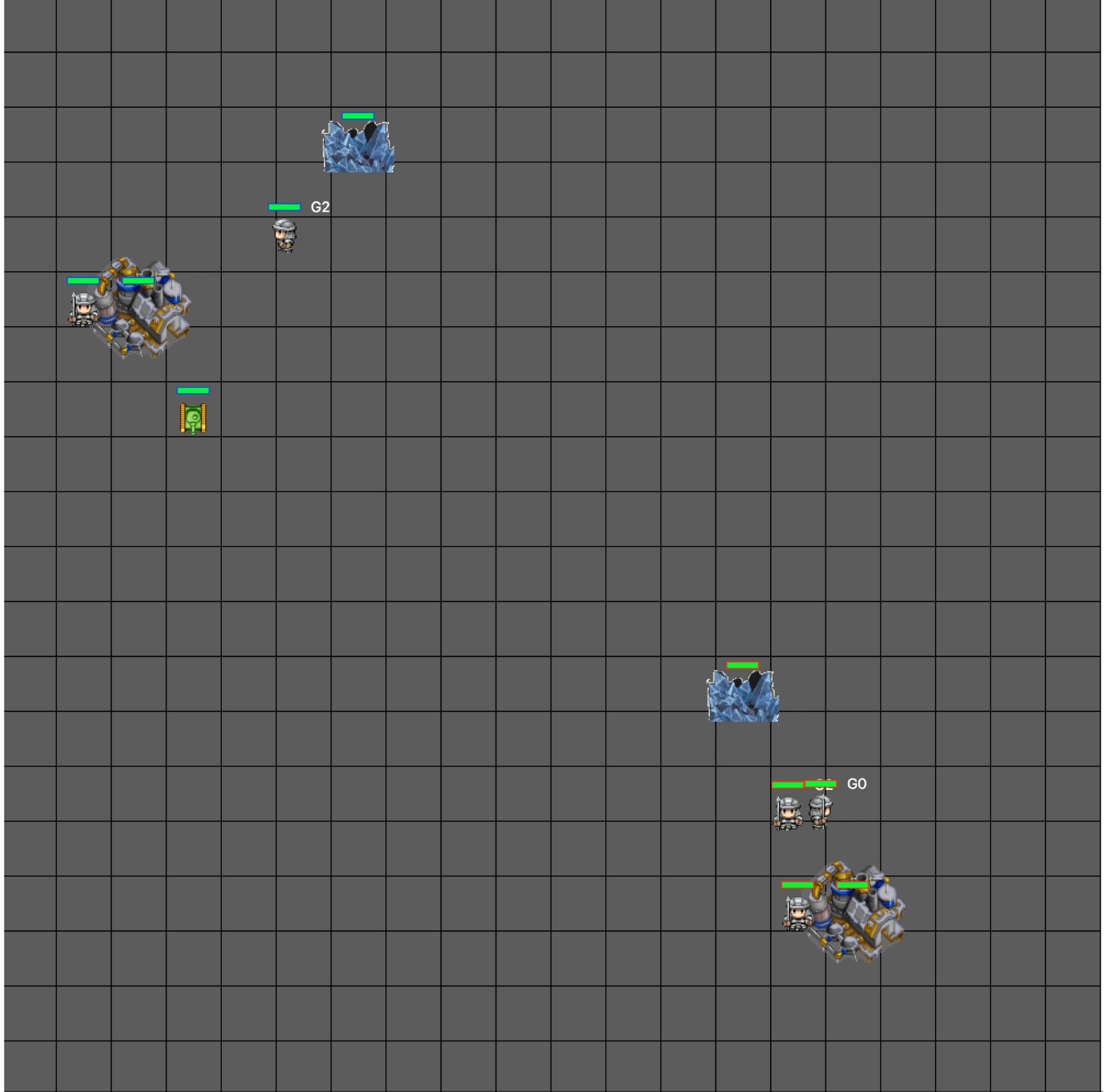
Trained AI



AI_SIMPLE

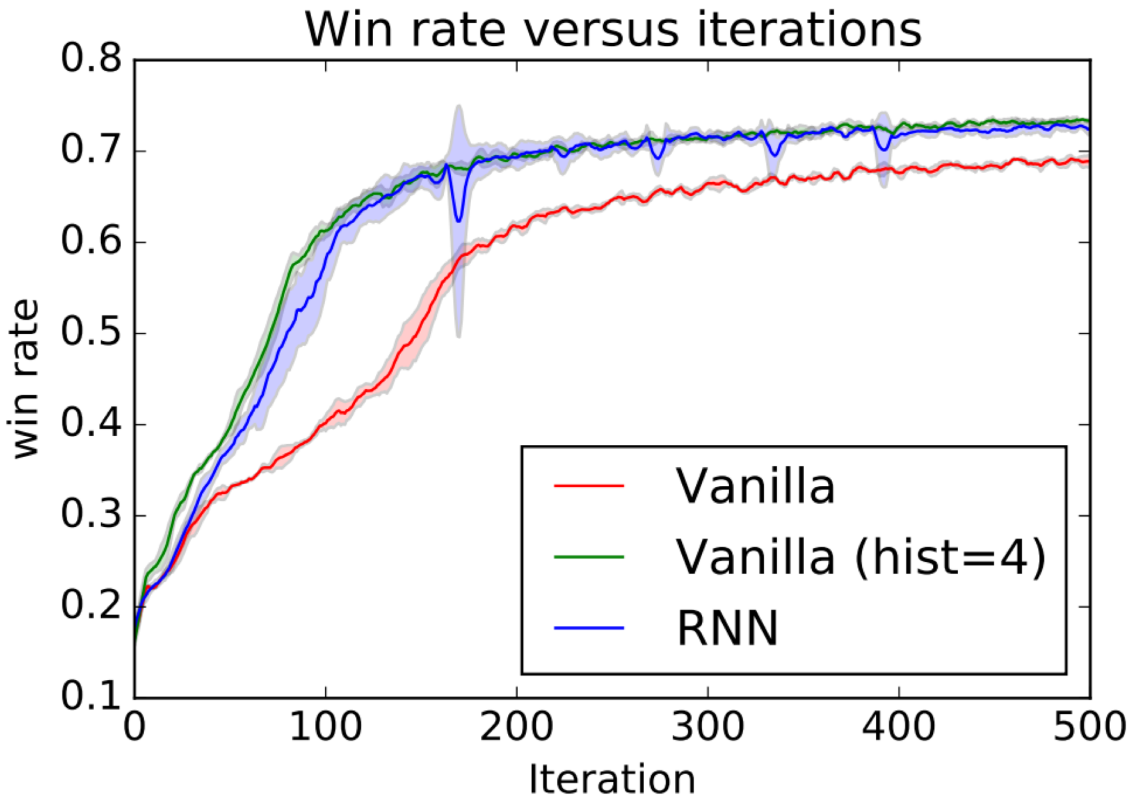
Trained with a single machine with GPU In a few hours

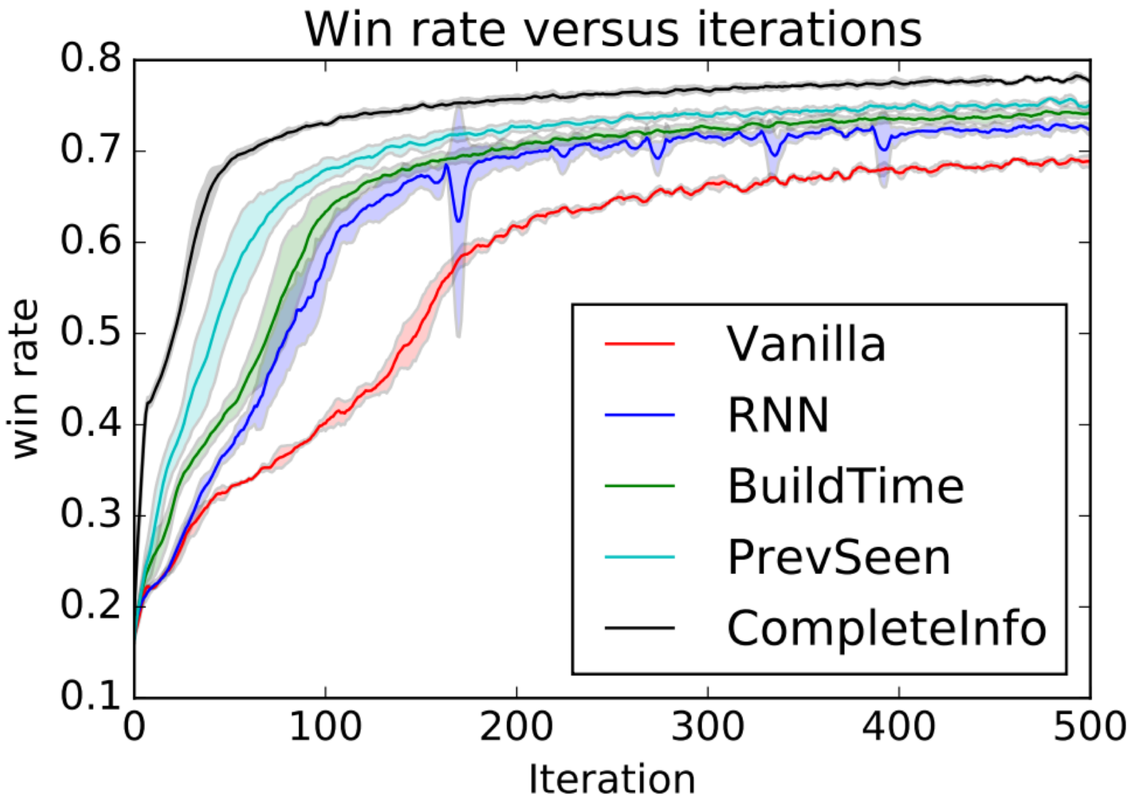
Trained AI



AI_SIMPLE

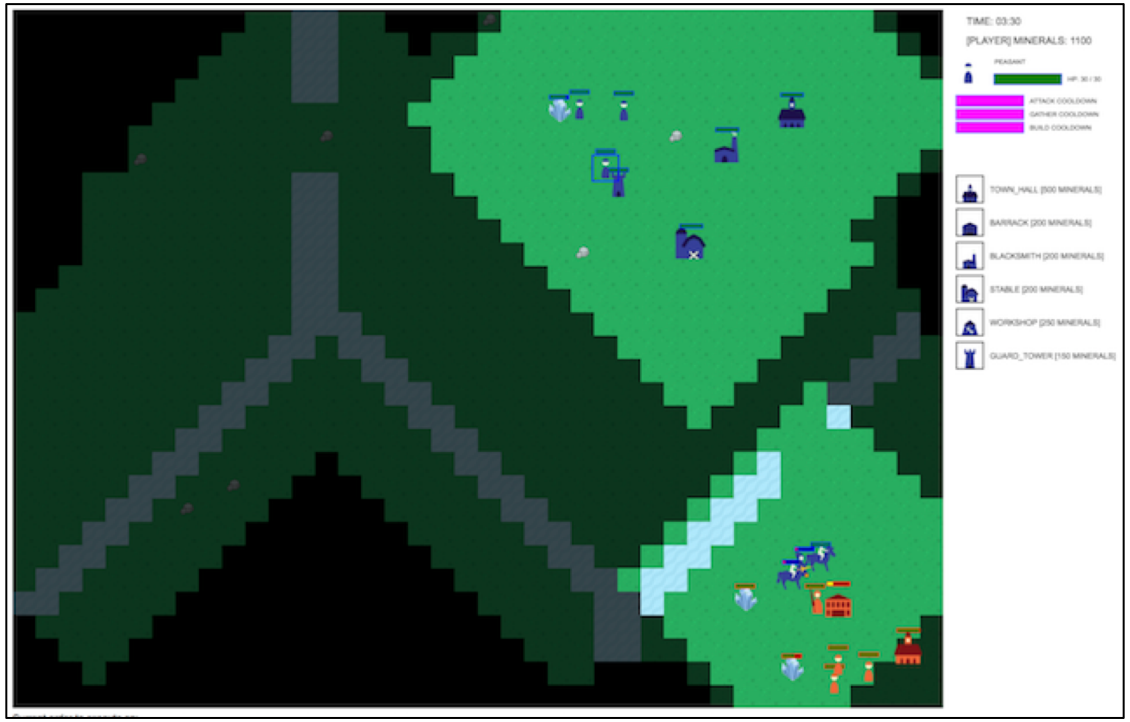
Comparison between different models

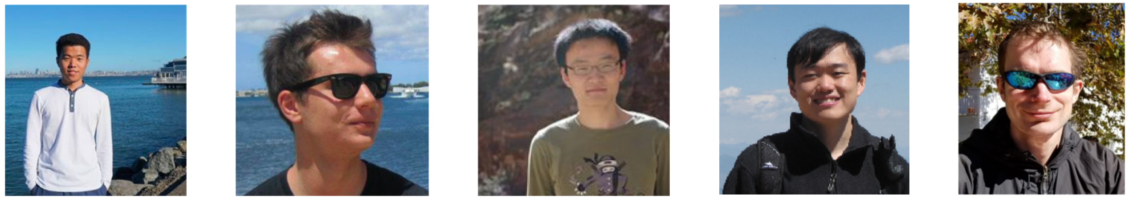




Method	*Vanilla*	*Vanilla*(hist=4)	RNN	*BuildHistory*	*PrevSeen*	Complete Info
Win rate	72.9±1.8	79.8±0.7	79.7±1.3	80.8±1.7	81.4±0.8	81.7±0.7

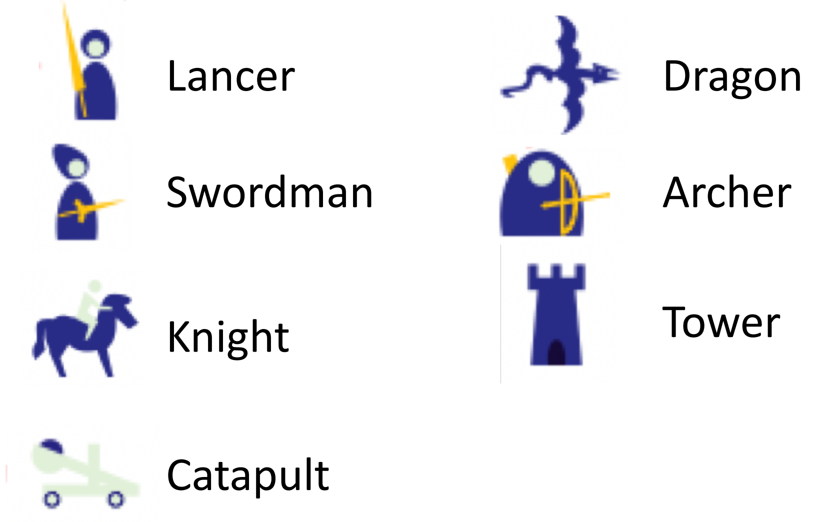
MiniRTS v2



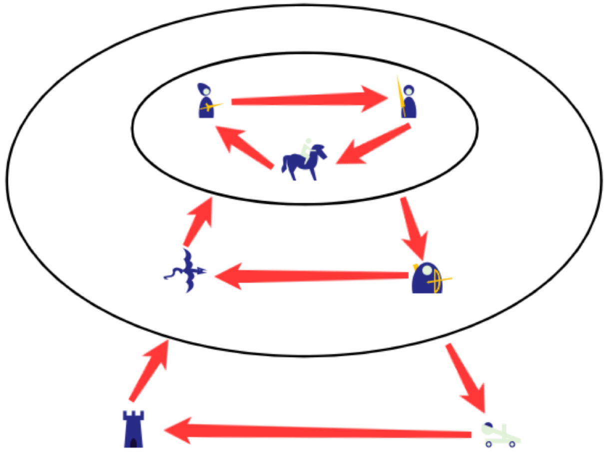


Hengyuan Hu* Denis Yarats* Qucheng Gong Yuandong Tian Michael Lewis

More units

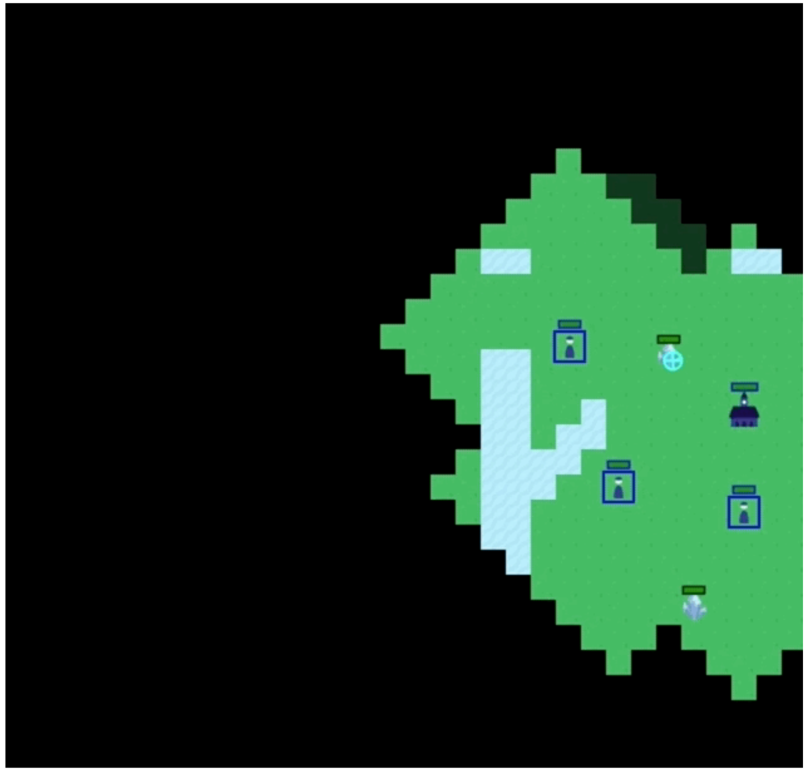


Rock-Paper-Scissor dynamics



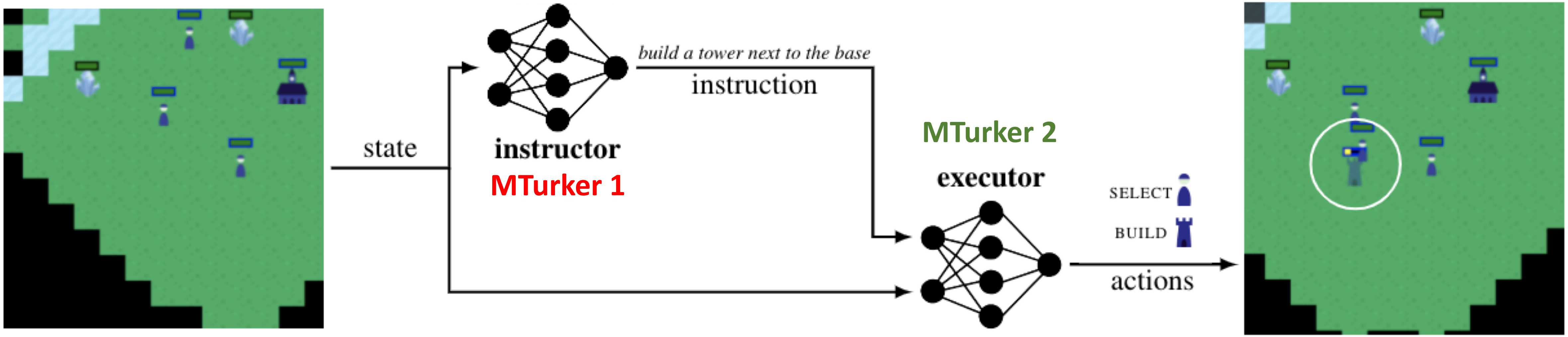
Language-driven Actions

$\pi_\theta(a|s, \text{"gather enough resources and build a barrack"})$



$\pi_\theta(a|s, \text{"take the catapult and destroy towers from the distance"})$

Training Paradigm



Instructor: Only gives language descriptions

Executor: Turn language description into unit-level actions

Data Collection

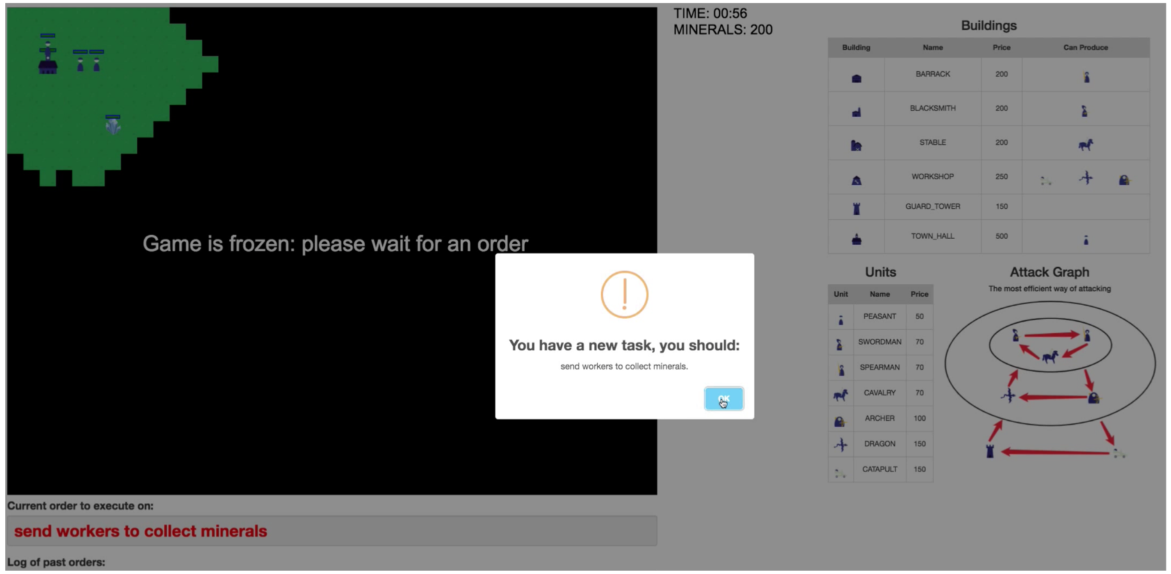
Ask Turkers to play the game in pairs.

One Turker plays as a **coach:**

- High-level strategy
- Communicate via language

The other Turker plays as a **player:**

- Clicks through high-level commands
- Only makes local decisions



ParlAI

https://github.com/facebookresearch/ParlAI

The Dataset

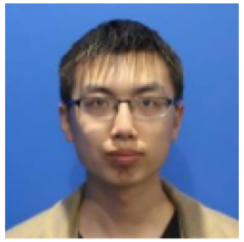
Statistics	Value
#Games	5392
Human win rate	58.67%
#instructions	76045
#Unique instructions	39598
#words	307162
#Vocabulary	2851
#words / instruction	7.76
#instruction / game	13.09
#actions / instruction	7.18

Linguistic Phenomena	Example
Counting	*Build 3 dragons.*
Spatial Reference	*Send him to the choke point behind the tower.*
Composed Actions	*Attack archers, then peasants.*
Cross-instruction anaphora	*Use it as a lure to kill them.*

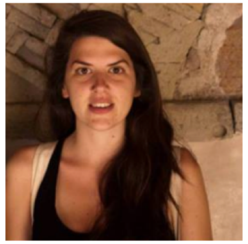
Each game has a complete sequence of user actions.

House3D

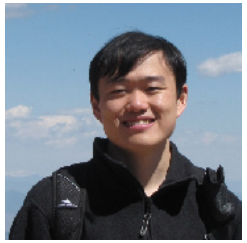
Yi Wu



Yuxin Wu



Georgia Gkioxari

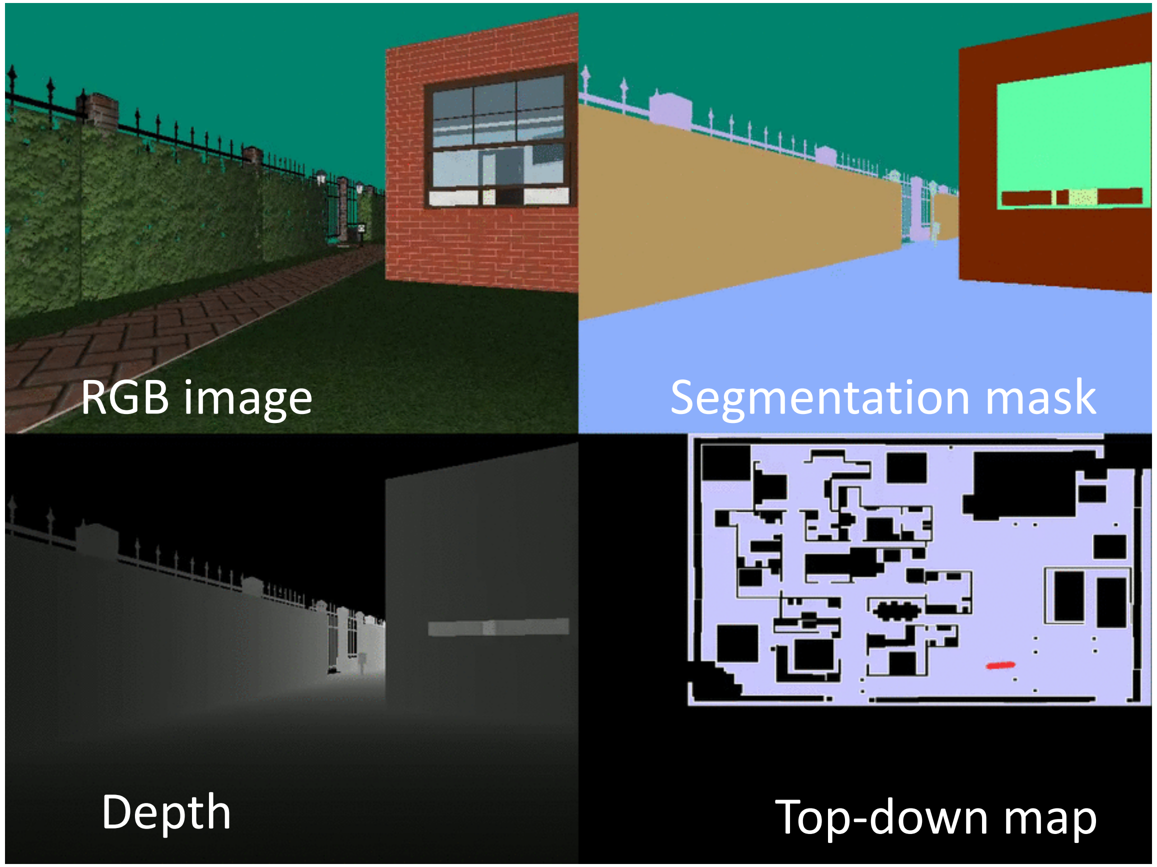


Yuandong Tian

How to plan the trajectory
in **unknown** environments?

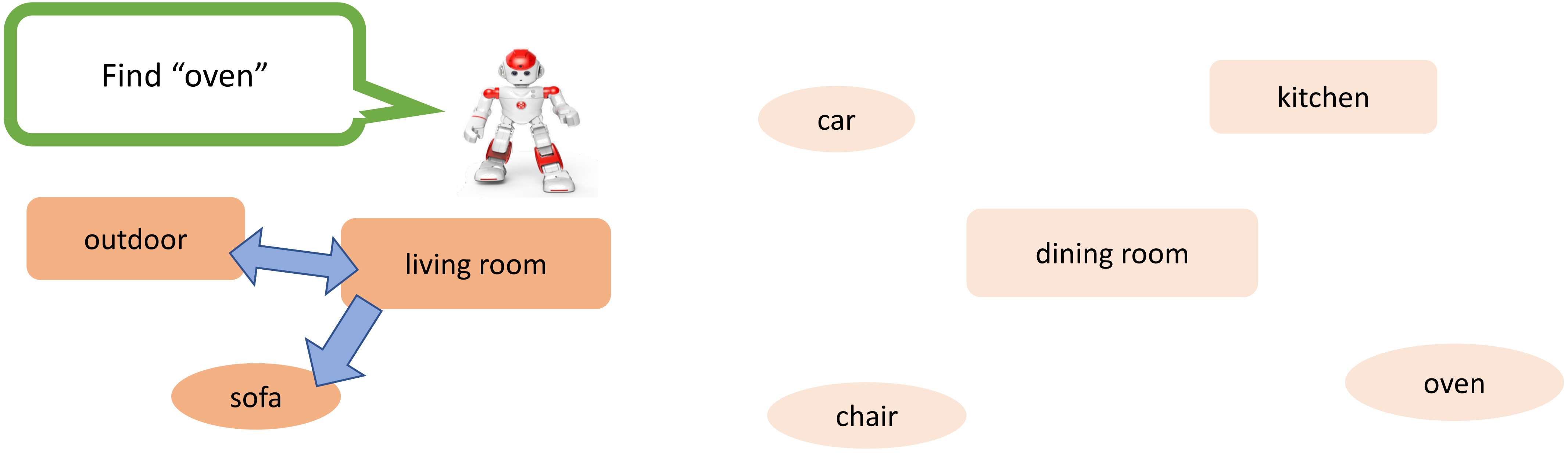
House3D

SUNCG dataset, 45K scenes, all objects are fully labeled.



https://github.com/facebookresearch/House3D

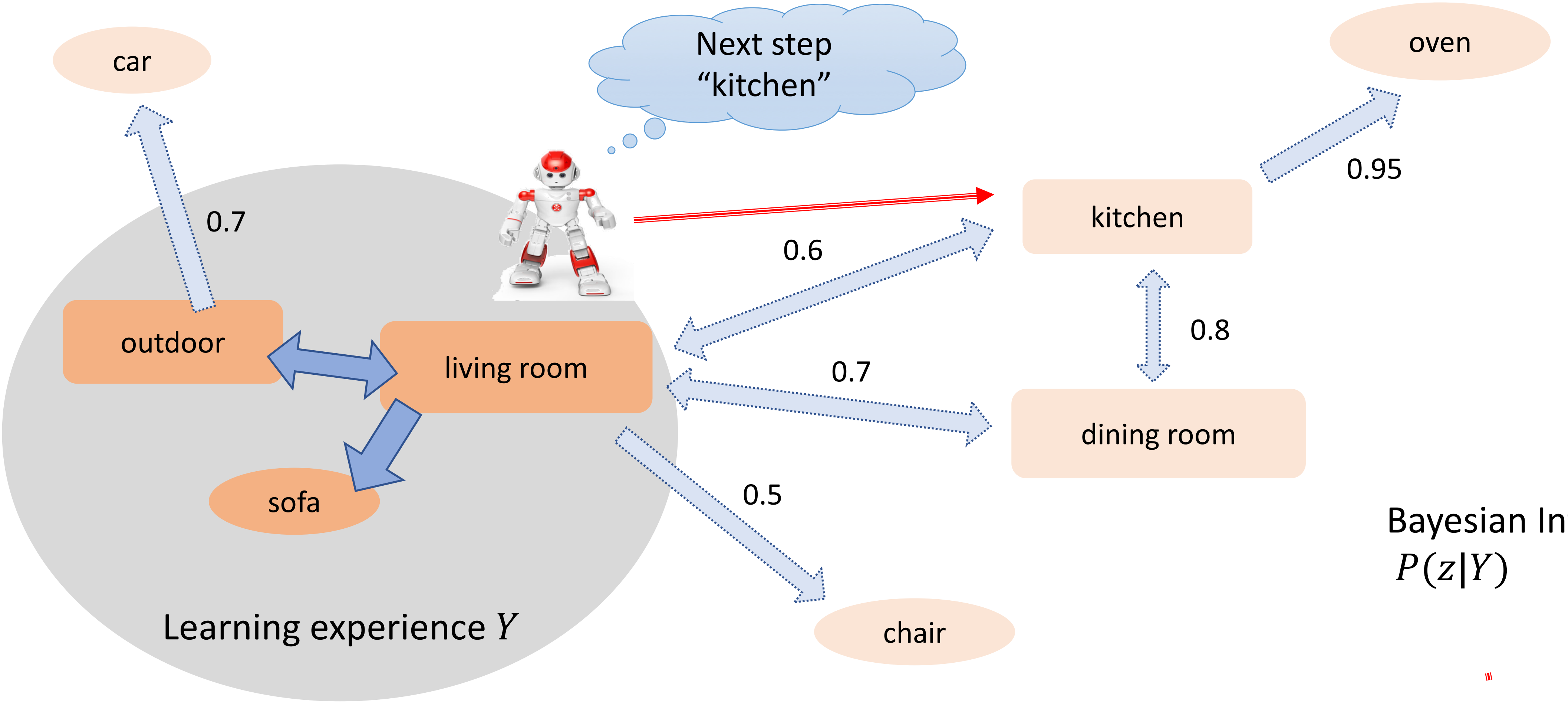
Build a semantic model



Incomplete model of the environment

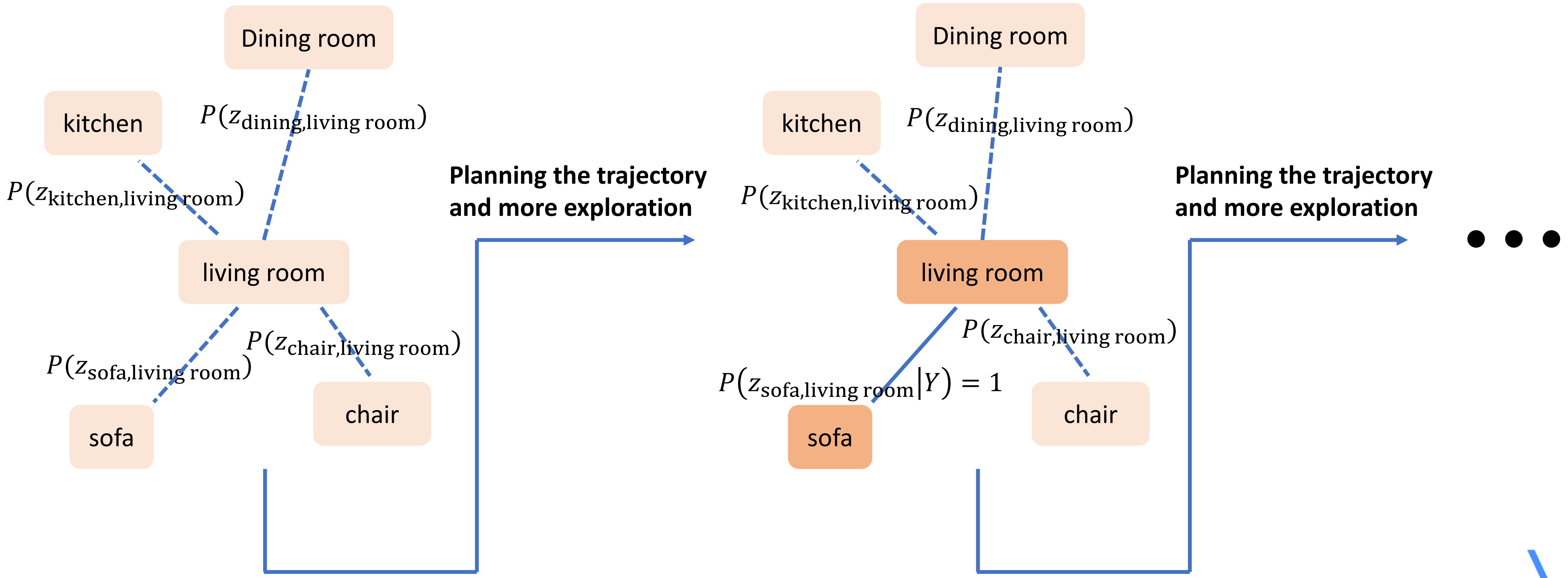
[Y. Wu et al, Learning and Planning with a Semantic Model, submitted to ICLR 2019]

Build a semantic model

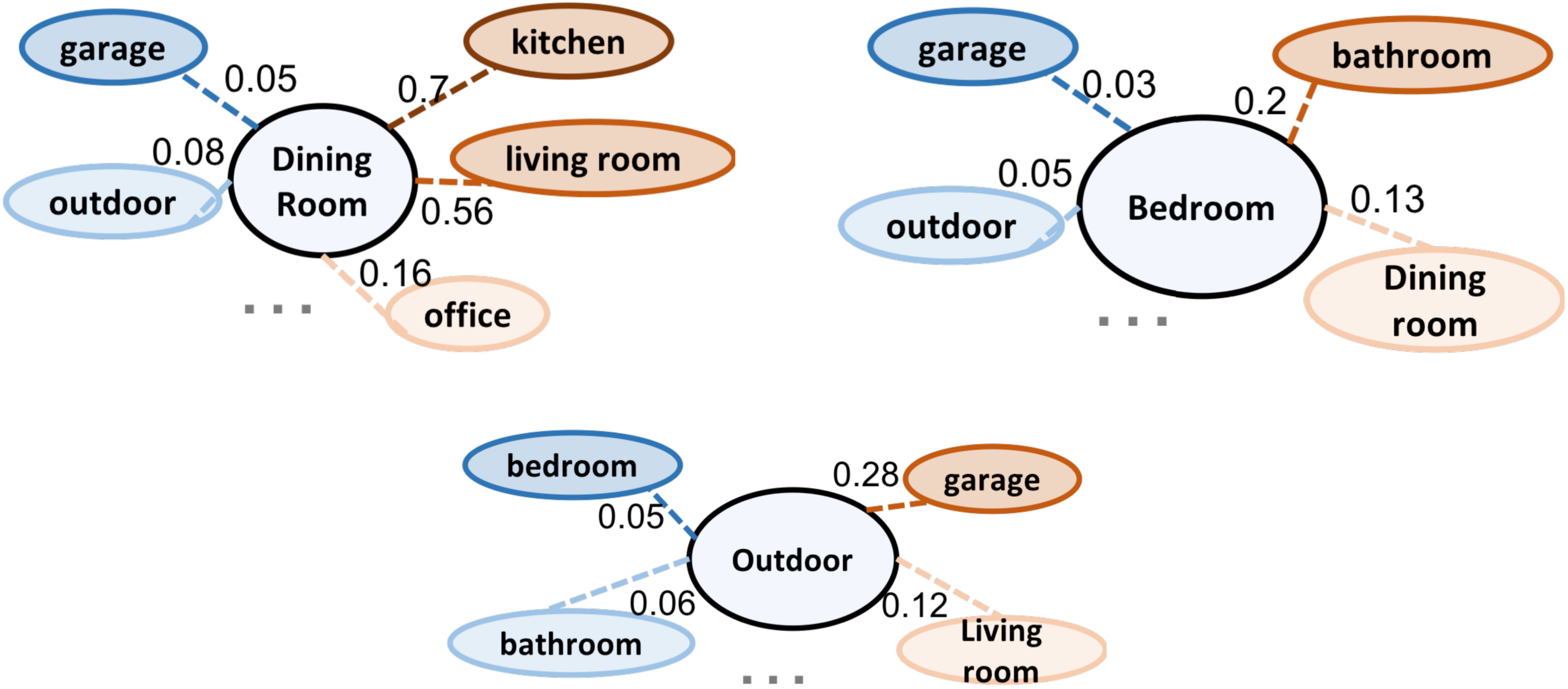


Bayesian Inference
$P(z|Y)$

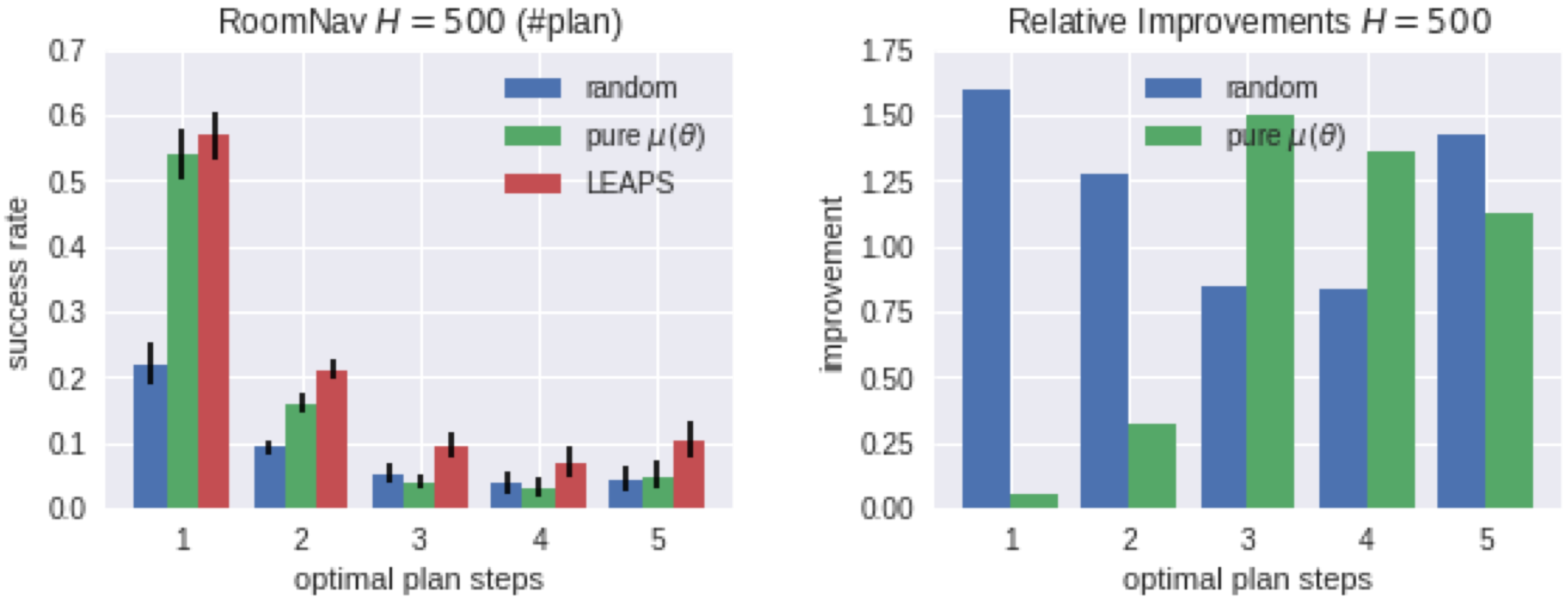
LEAPS
LEArning and Planning with a Semantic model



Learning the Prior between Different Rooms

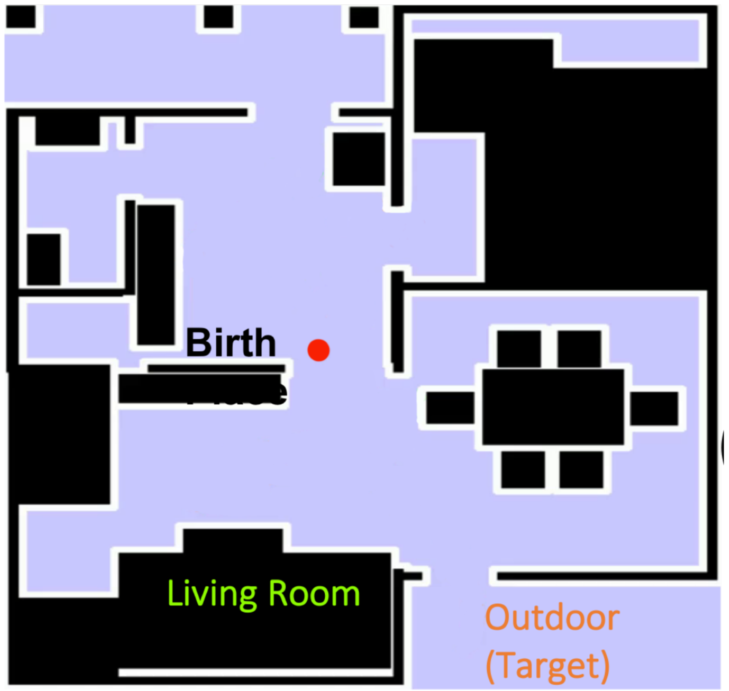


Test Performance on ConceptNav

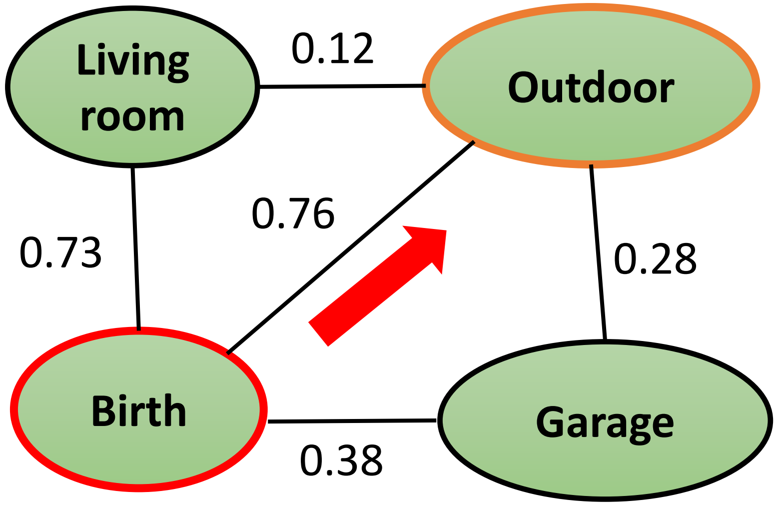


Case Study

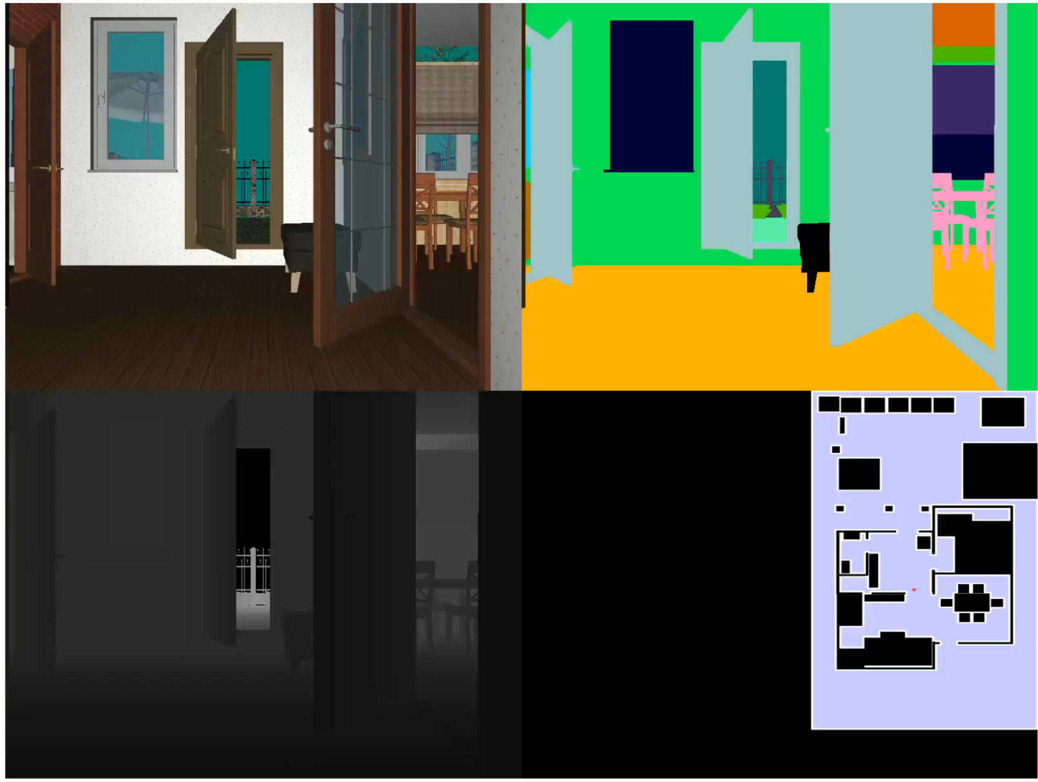
- A case study
  - **Go to “outdoor”**



Prior: $P(z)$



Sub-Goal: Outdoor



Case Study

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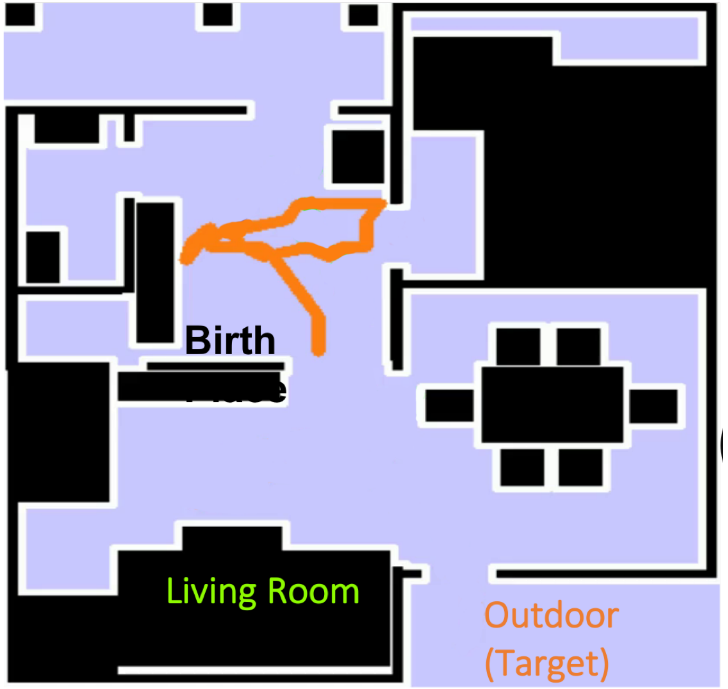
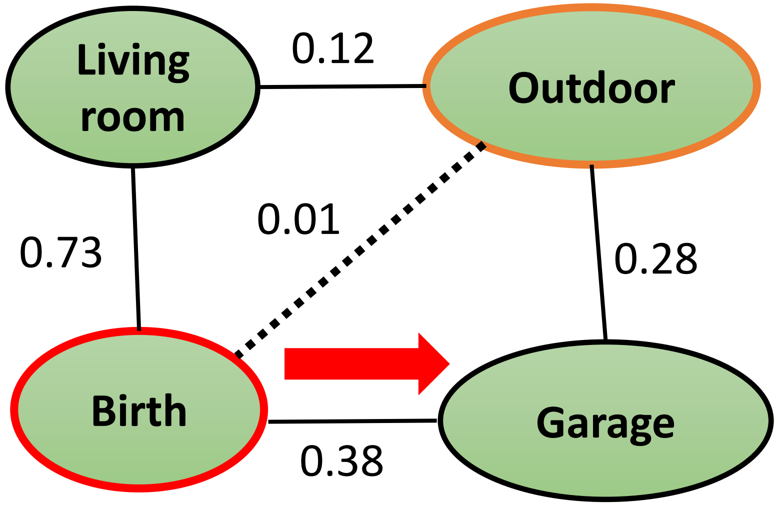


Posterior: $P(z|E)$



Sub-Goal: Outdoor

Case Study

- A case study
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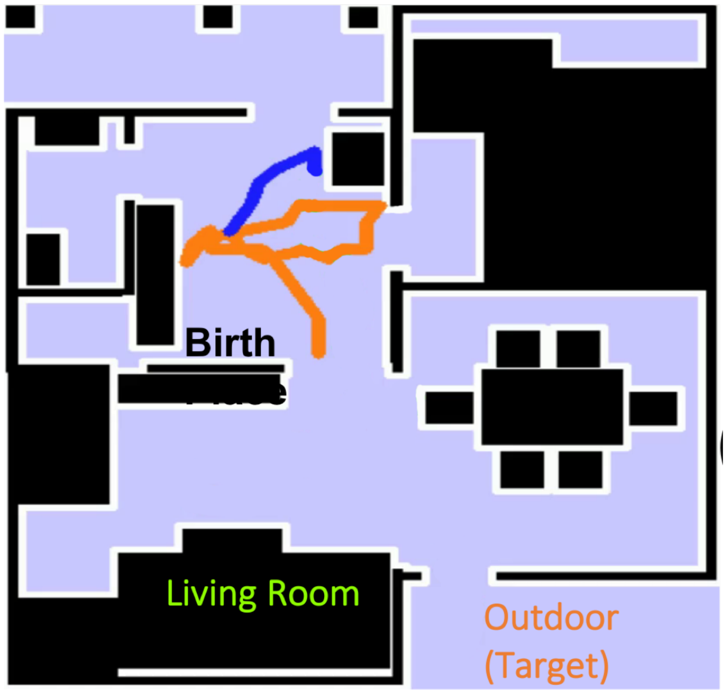
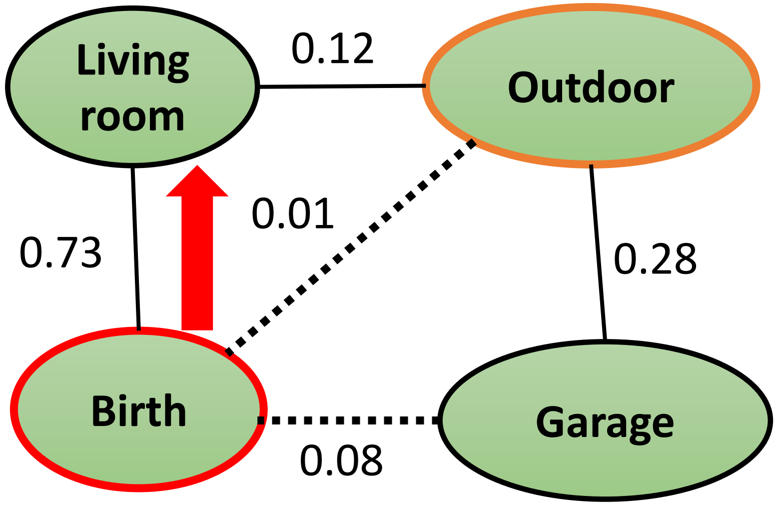
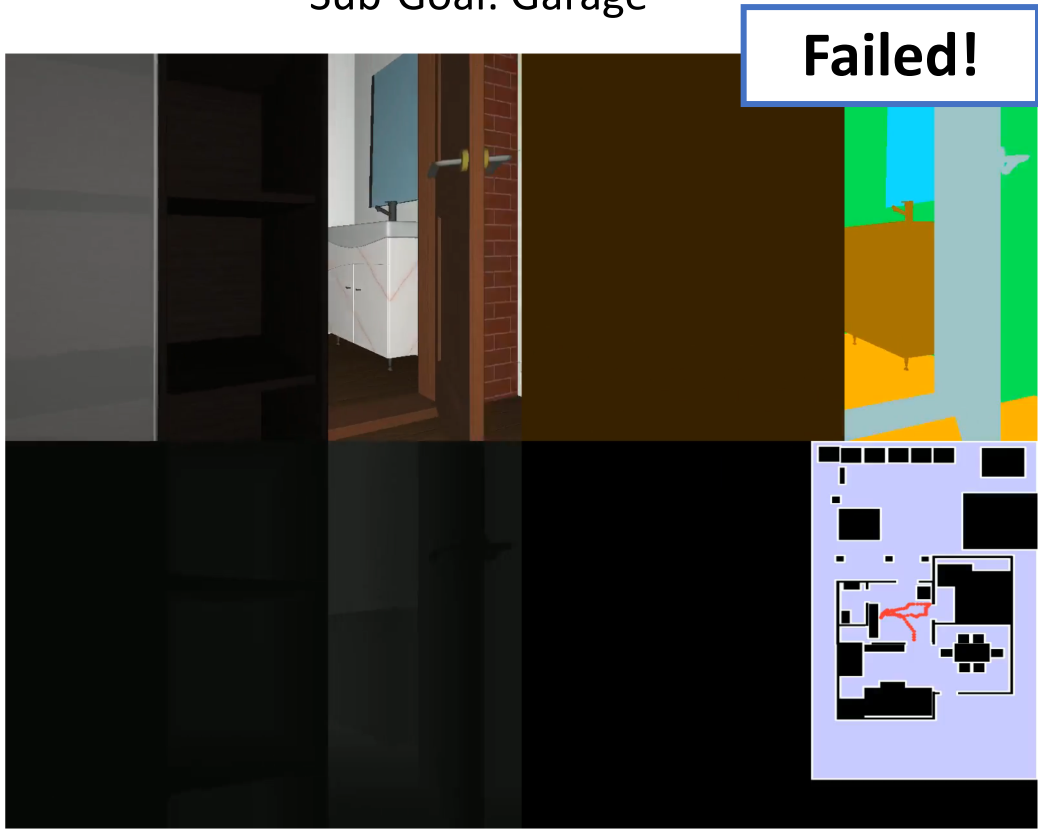


Posterior: $P(z|E)$

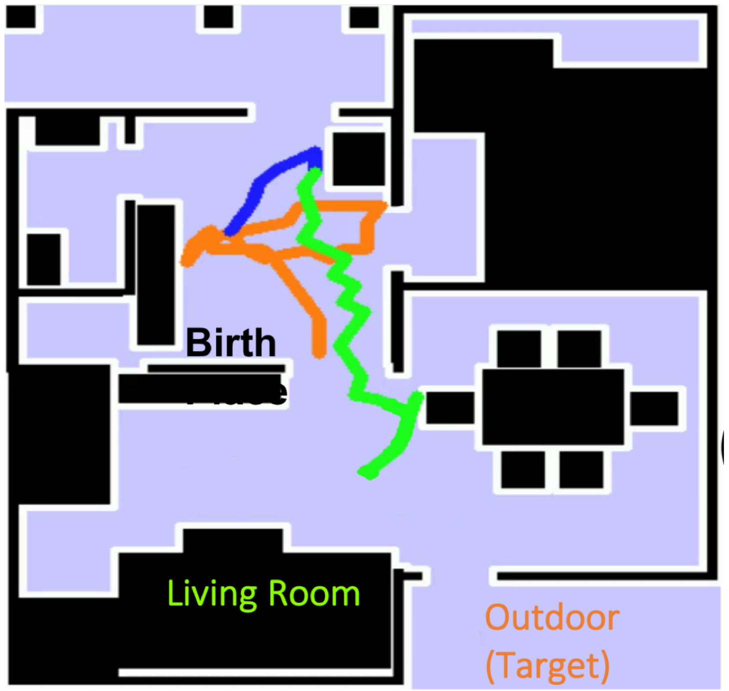


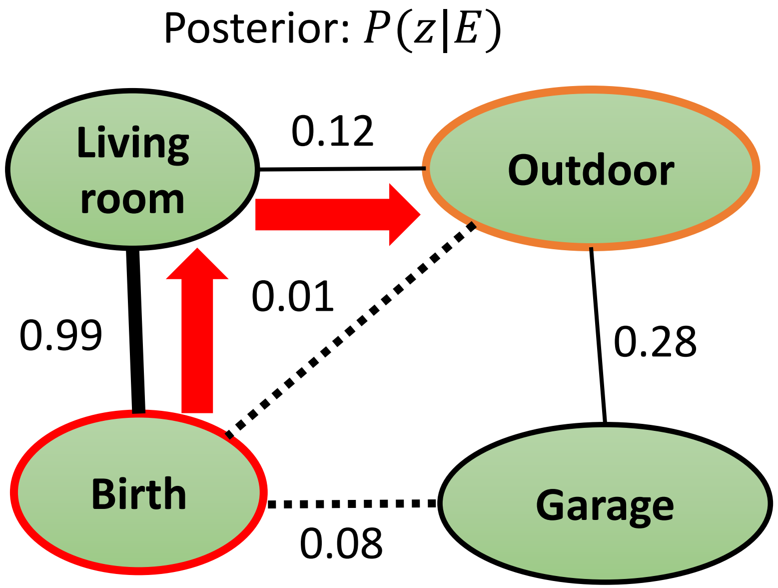
Sub-Goal: Garage

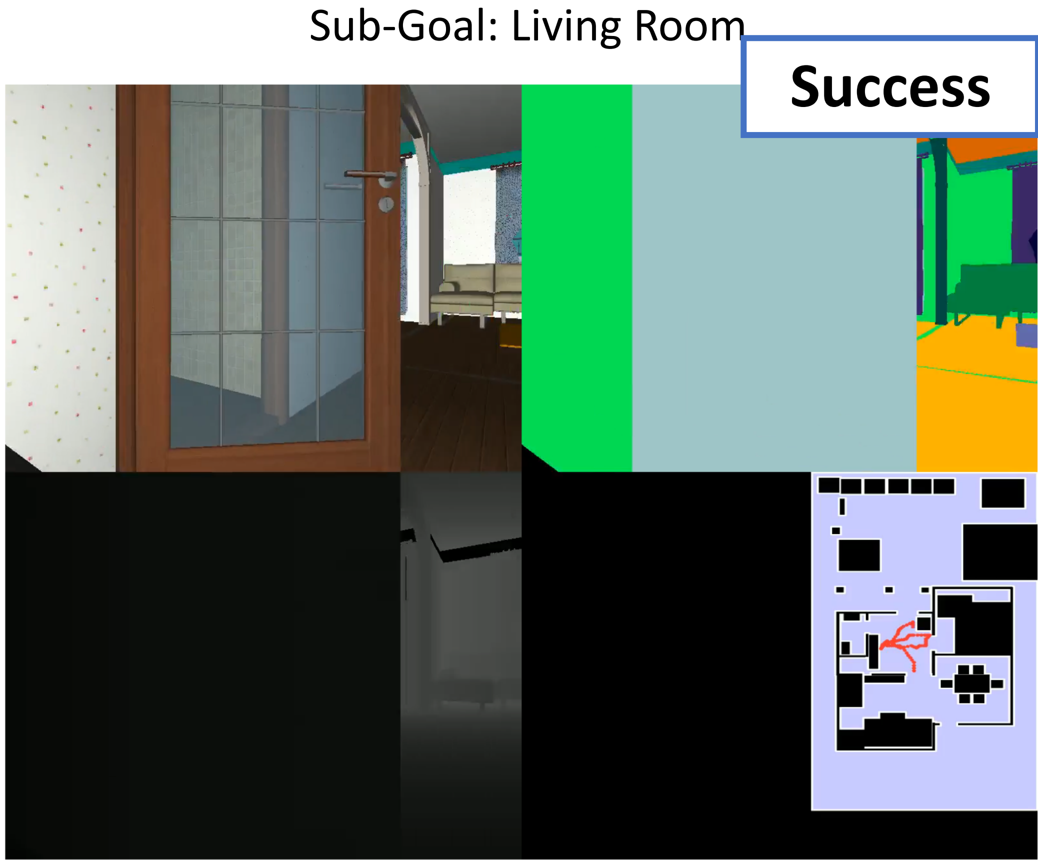


Case Study

- A case study
  - Go to "outdoor"

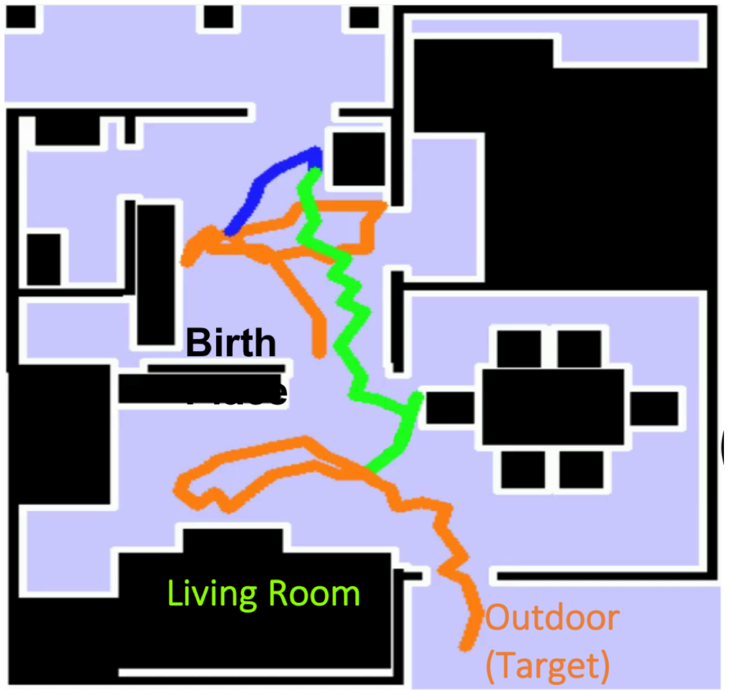




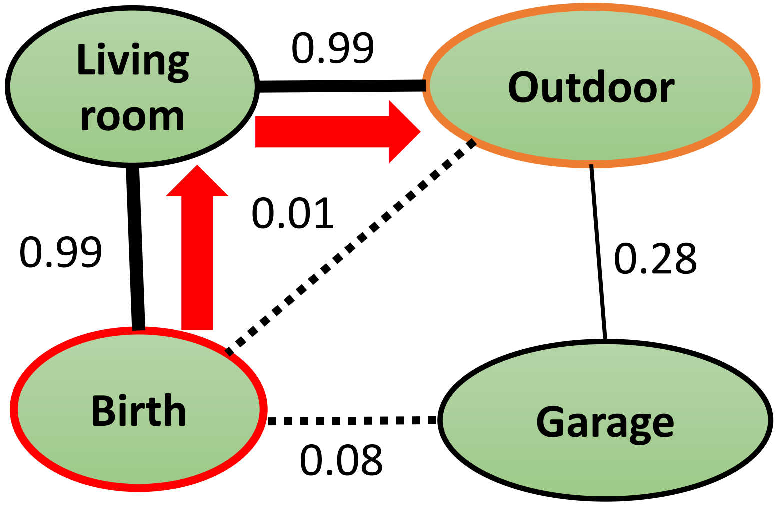


Case Study

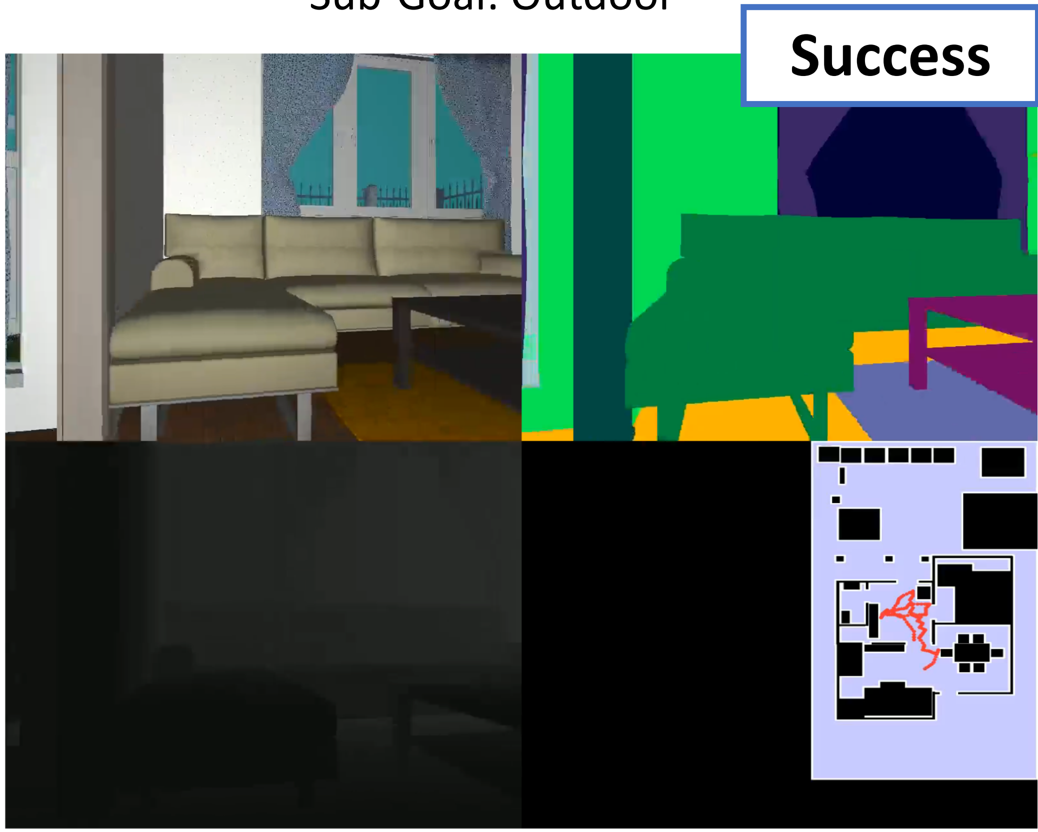
- A case study
  - Go to “outdoor”



Posterior: $P(z|E)$



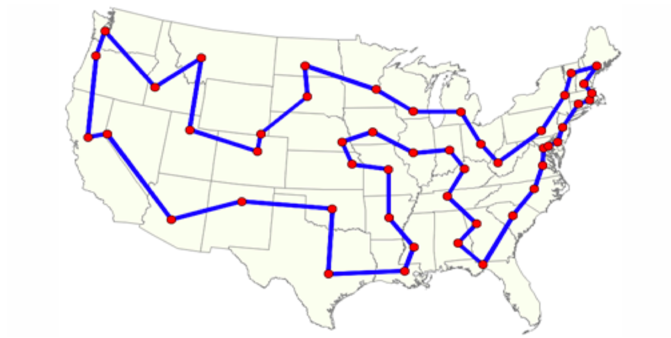
Sub-Goal: Outdoor



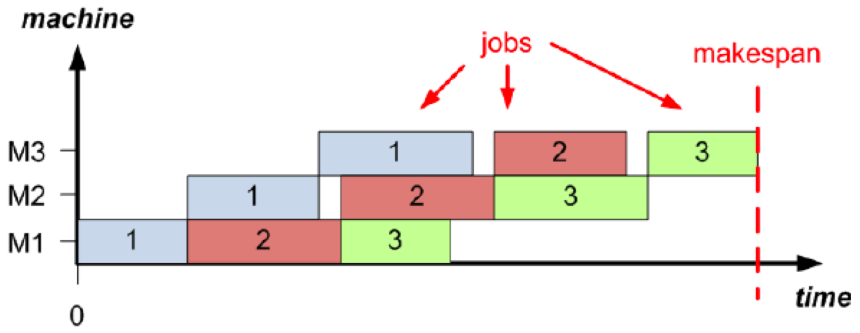
opt. plan-steps	1	2	3	4	5	overall
Horizon $H = 300$						
random	20.5 / 15.9	6.9 / 16.7	3.8 / 10.7	1.6 / 4.2	3.0 / 8.8	7.2 / 13.6
pure $\mu(\theta)$	49.4 / 47.6	11.8 / 27.6	2.0 / 4.8	2.6 / **10.8**	4.2 / 13.2	13.1 / 22.9
aug.$\mu_S(\theta_s)$	47.8 / 45.3	11.4 / 23.1	3.0 / 7.8	3.4 / 8.1	4.4 / 11.2	13.0 / 20.5
RNN control.	52.7 / 45.2	13.6 / 23.6	3.4 / 9.6	3.4 / 10.2	6.0 / 17.6	14.9 / 21.9
LEAPS	**53.4 / 58.4**	**15.6 / 31.5**	**4.5 / 12.5**	**3.6** / 6.6	**7.0 / 18.0**	**16.4 / 27.9**
Horizon $H = 500$						
random	21.9 / 16.9	9.3 / 18.3	5.2 / 12.1	3.6 / 6.1	4.2 / 9.9	9.1 / 15.1
pure $\mu(\theta)$	54.0 / 57.5	15.9 / 25.6	3.8 / 7.7	2.8 / 6.4	4.8 / 8.6	16.2 / 22.9
aug.$\mu_S(\theta_s)$	54.1 / 51.8	15.5 / 26.5	4.6 / 8.2	3.0 / **11.8**	4.6 / 12.5	16.1 / 23.5
RNN control.	**57.4** / 43.8	20.2 / 28.0	7.2 / 14.6	4.2 / 8.0	9.0 / 16.0	19.9 / 24.6
LEAPS	57.2 / **61.9**	**21.5 / 34.4**	**10.0 / 14.8**	**6.4** / 11.6	**12.0 / 23.5**	**21.6 / 31.1**
Horizon $H = 1000$						
random	24.3 / 17.6	13.5 / 20.3	9.1 / 14.3	8.0 / 9.3	7.0 / 11.5	13.0 / 17.0
pure $\mu(\theta)$	60.8 / **58.4**	23.3 / 29.5	7.6 / 8.8	8.2 / 12.9	11.0 / 17.2	22.5 / 26.5
aug.$\mu_S(\theta_s)$	61.3 / 50.1	23.0 / 26.2	9.4 / 12.0	5.8 / 9.6	9.0 / 13.6	22.4 / 23.8
RNN control.	**66.7** / 49.0	30.1 / 31.5	13.8 / 15.4	9.0 / 10.0	14.0 / 20.8	28.2 / 27.7
LEAPS	66.4 / **58.4**	**31.9 / 40.5**	**15.0 / 18.3**	**11.4 / 17.0**	**15.4 / 27.1**	**29.7 / 35.2**

What’s Beyond Game for RL?

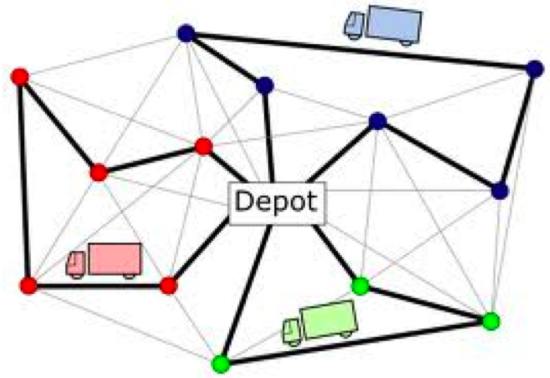
RL for optimization



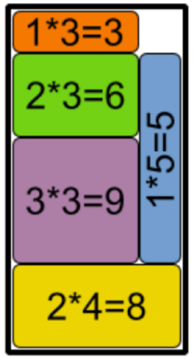
Travel Salesman Problem



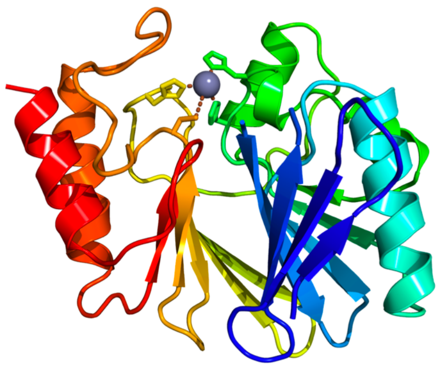
Job Scheduling



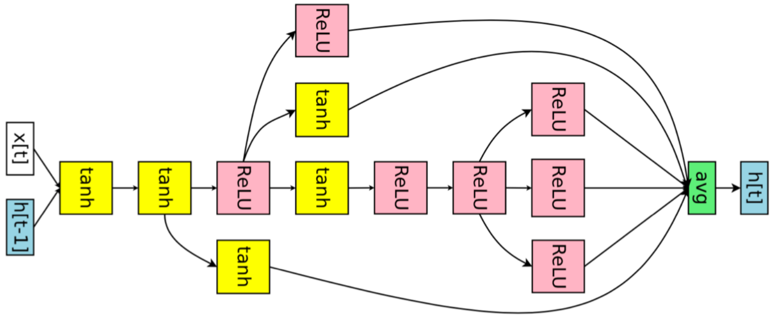
Vehicle Routing



Bin Packing



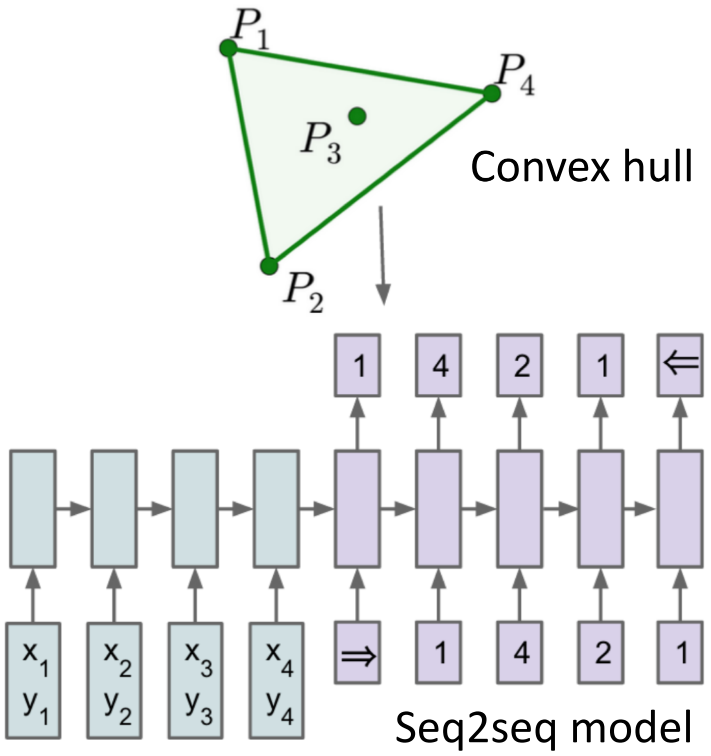
Protein Folding



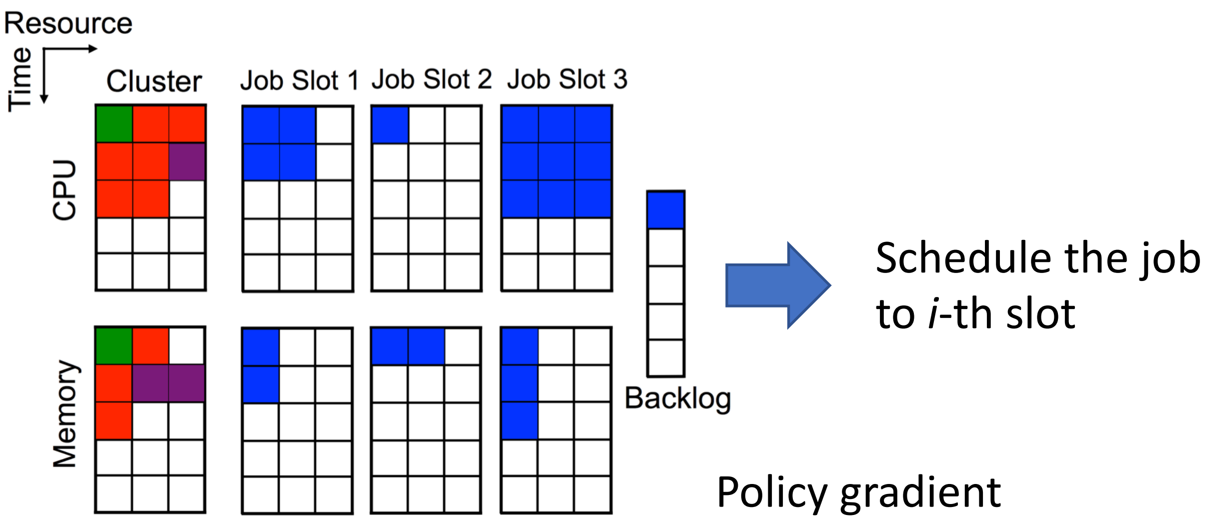
Model-Search

Non-differentiability

- Direct predicting combinatorial solutions.

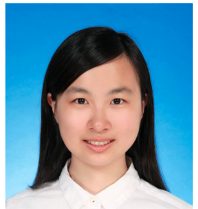


[O. Vinyals. et al, *Pointer Networks, NIPS 2015*]

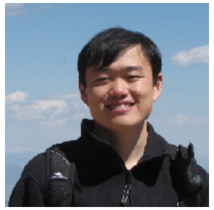


[H. Mao et al, Resource Management with Deep Reinforcement Learning, ACM Workshop on Hot Topics in Networks, 2016]

Local Rewriting Framework



Xinyun Chen

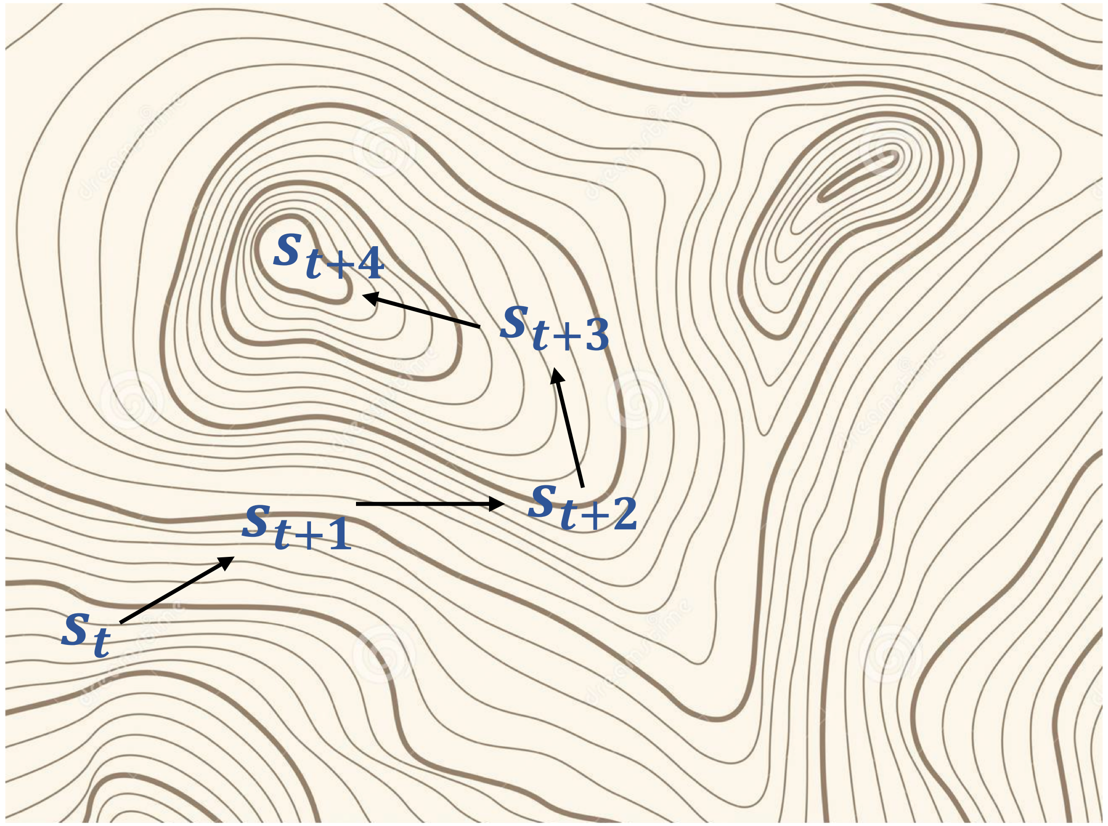


Yuandong Tian

A learned "gradient descent" that

starts from a feasible solution
iteratively converges to a good solution

How to learn it?



Local Rewriting Framework

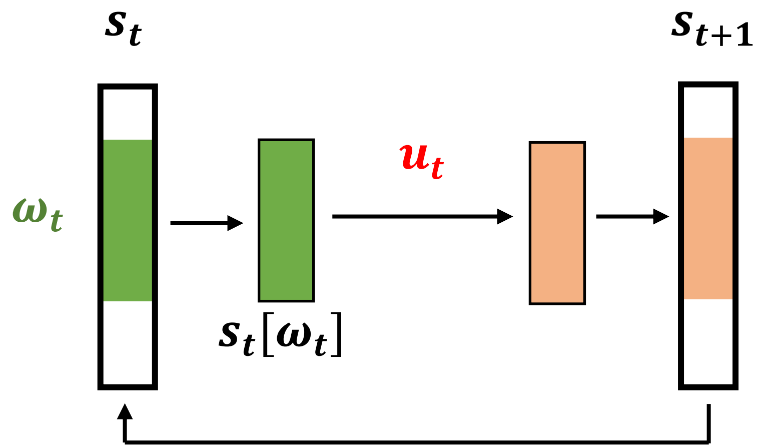
Current State
(i.e. Solution)

Region-Picker

Rule-Picker

$s_t \longrightarrow \omega_t \sim \pi_\omega(\cdot\,|s_t) \longrightarrow u_t \sim \pi_u(\cdot\,|s_t\,[\omega_t])$

$s_{t+1} = f(s_t, \omega_t, u_t)$



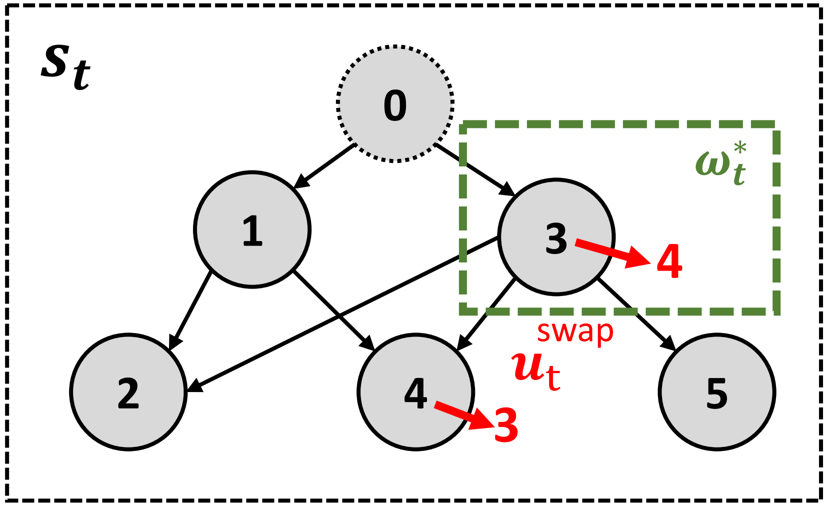
Q-Actor-Critic Training of two policies $\pi_\omega(\cdot\,|s_t)$ and $\pi_u(\cdot\,|s_t\,[\omega_t])$

$\pi_\omega(\cdot\,|s_t)$: Q-learning with soft policy $\pi_\omega(\omega_t|s_t;\theta) = \frac{\exp(Q(s_t,\omega_t;\theta))}{\sum_{\omega_t}\exp(Q(s_t,\omega_t;\theta))}$

$\pi_u(\cdot\,|s_t\,[\omega_t])$: Actor-Critic with learned Q $L_u(\phi) = -\sum_{t=0}^{T-1}\Delta(s_t,(\omega_t,u_t))\log\pi_u(u_t|s_t[\omega_t];\phi)$

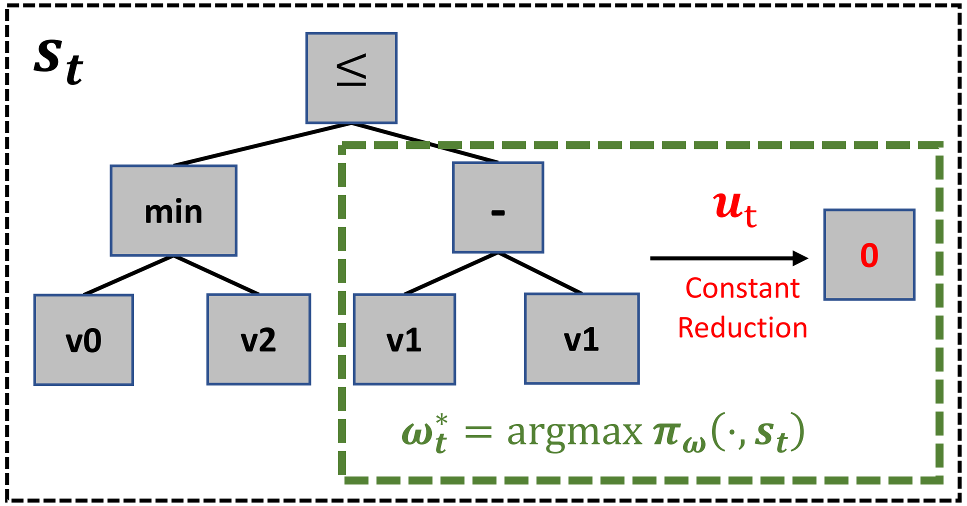
Applications

(a)



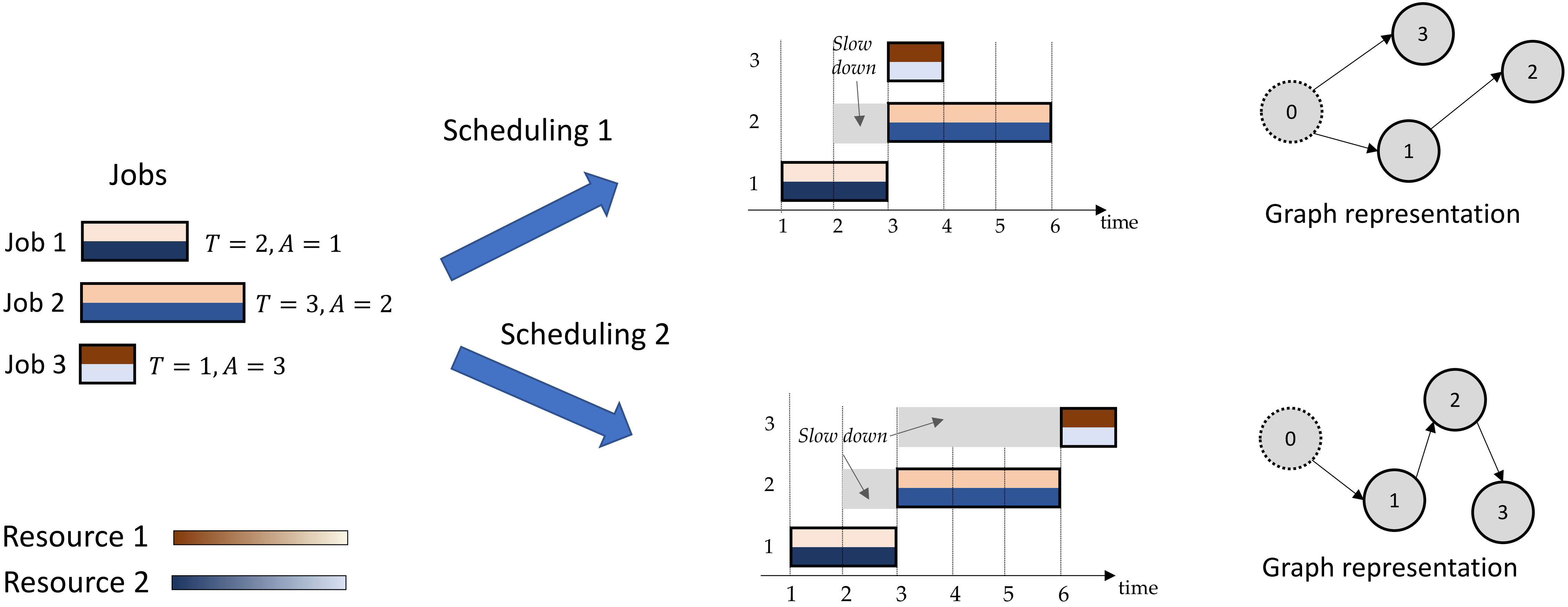
Online Job Scheduling

(b)

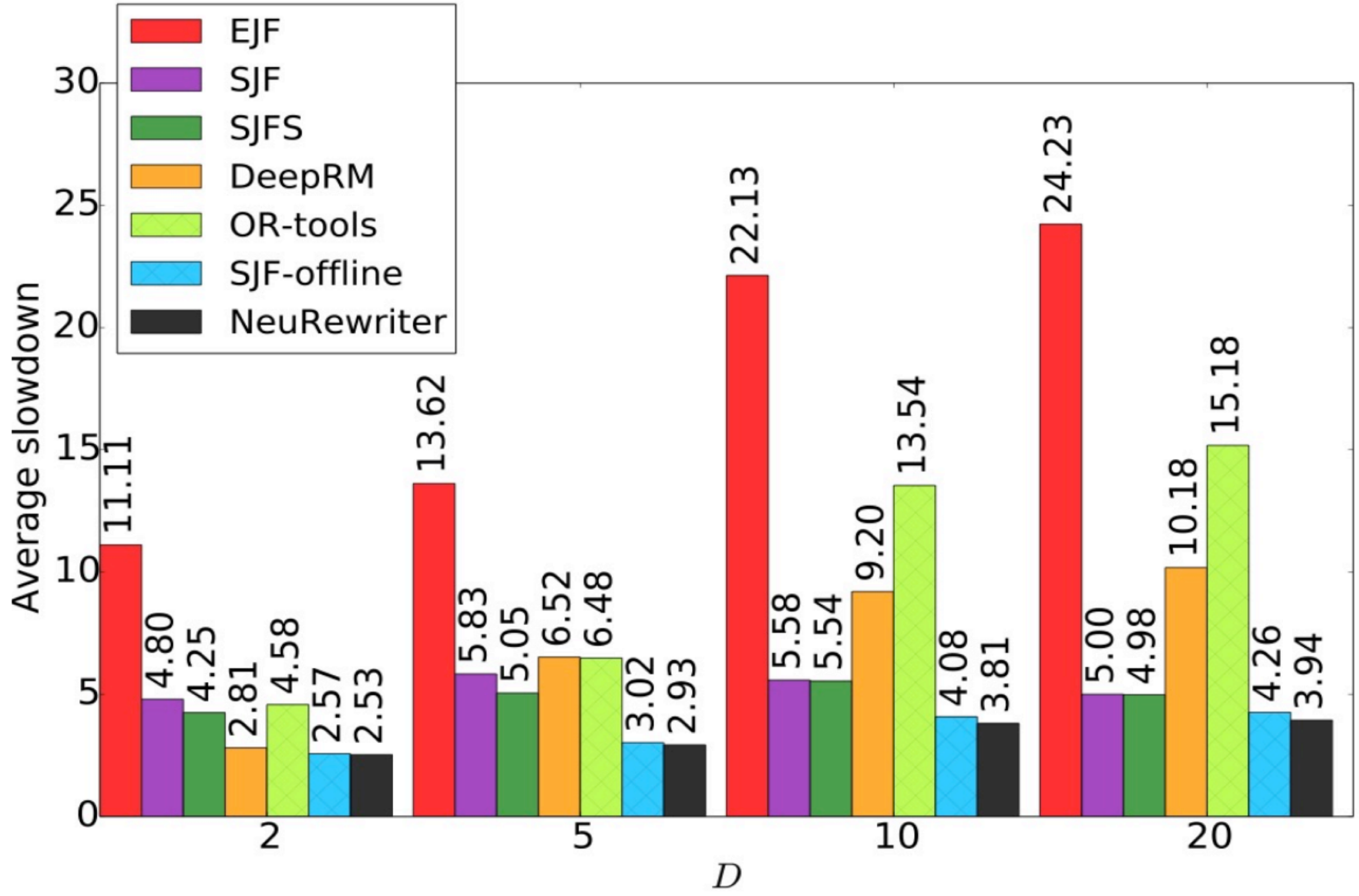


Expression Simplification

Online Job Scheduling



Online Job Scheduling



D: Number of resources

Baselines:

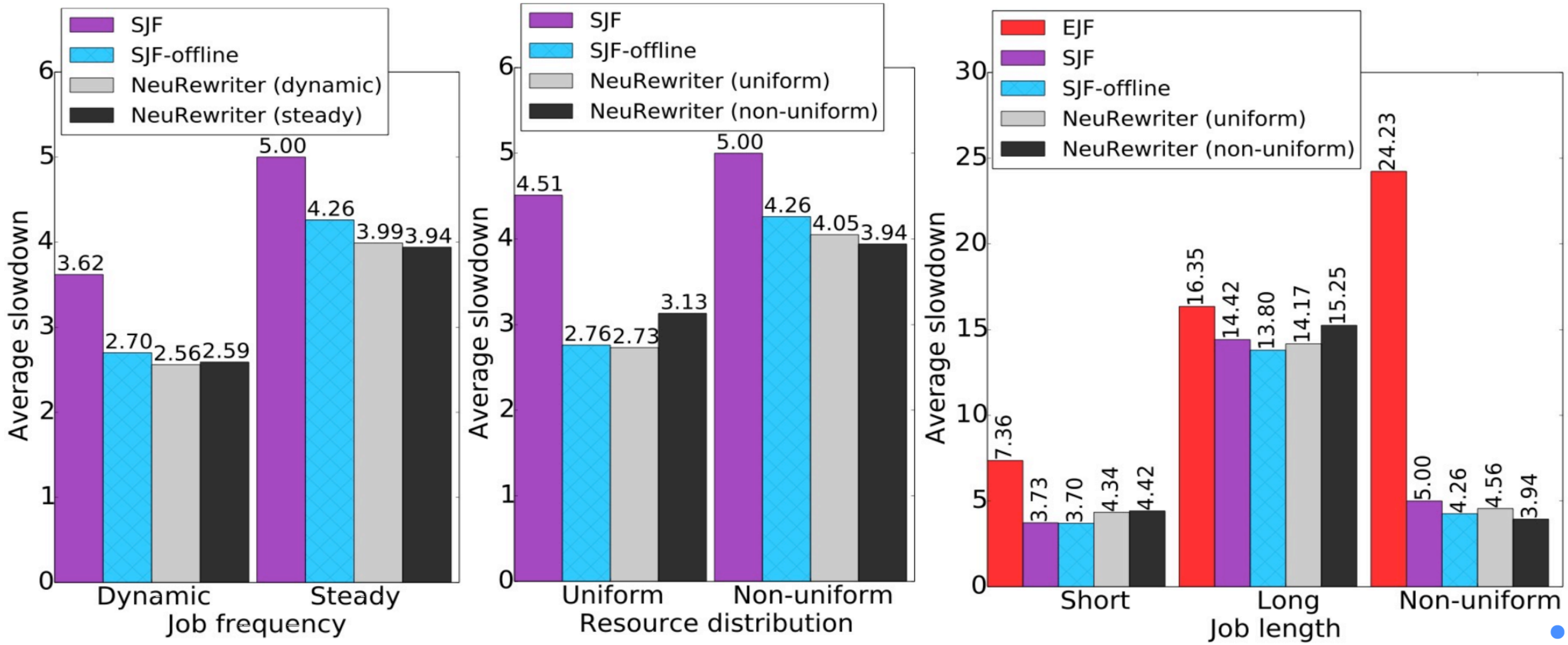
- Earliest Job First (EJF)
- Shortest Job First (SJF)
- Shortest First Search (SJFS)
- DeepRM

Offline baselines:

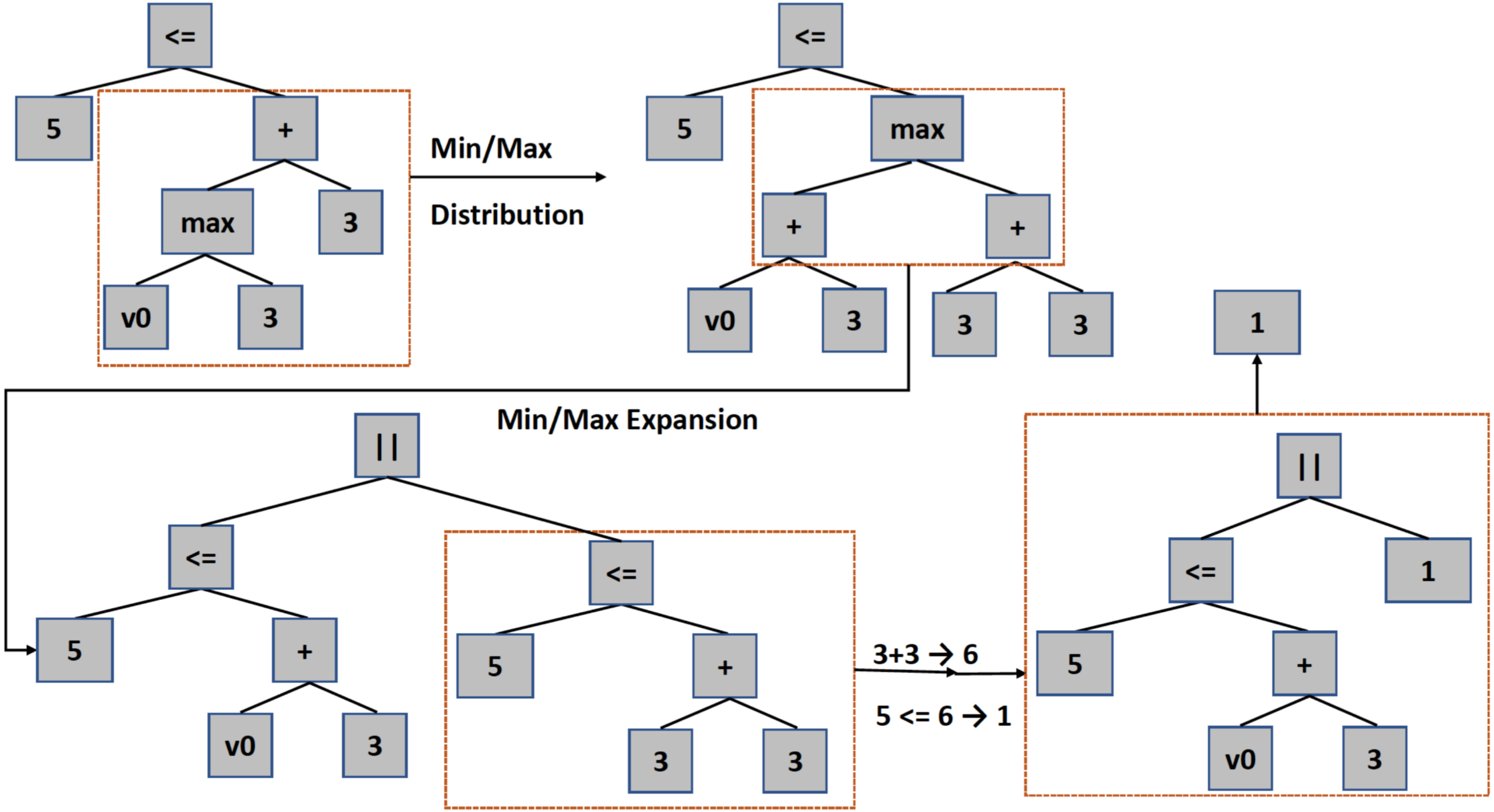
- Google OR-tools (OR-tools)
- SJF-offline

Online Job Scheduling: Ablation Study

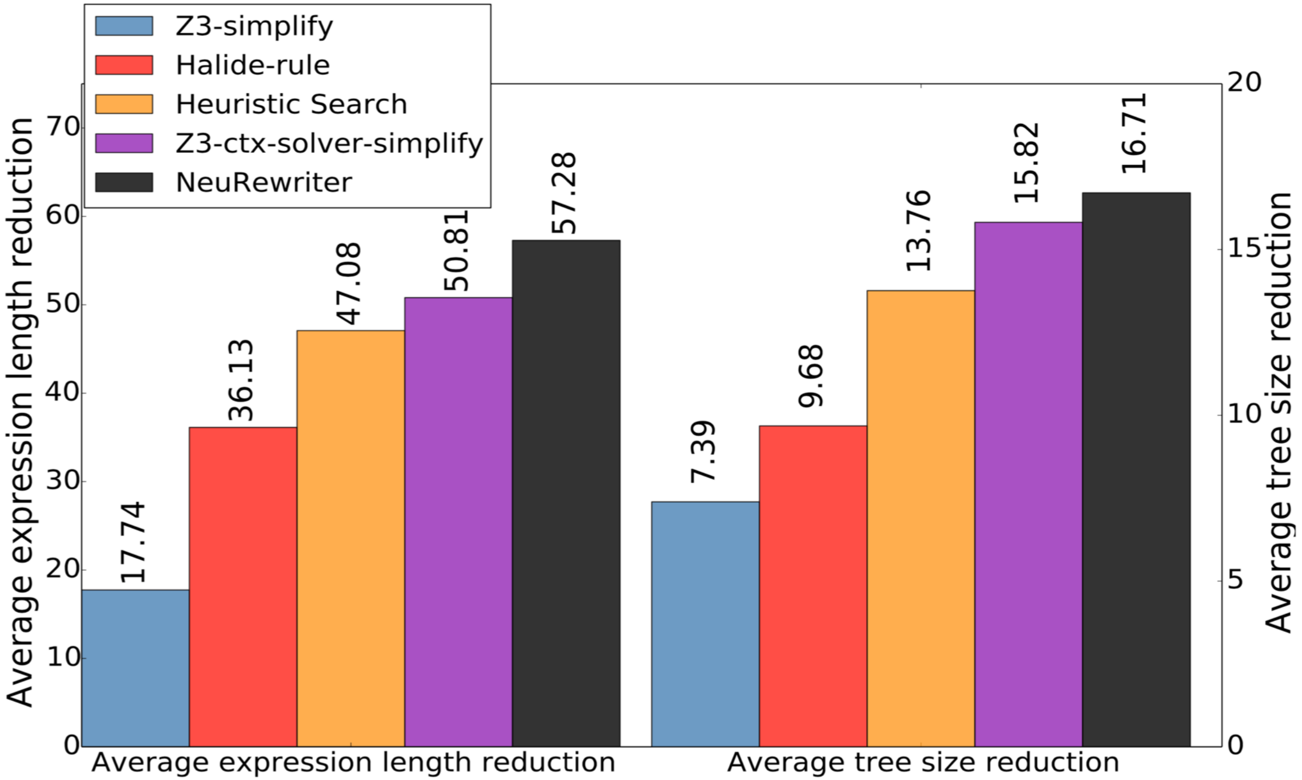
The learned model can generalize to different job distributions.



Expression Simplification



Expression Simplification



Baselines:

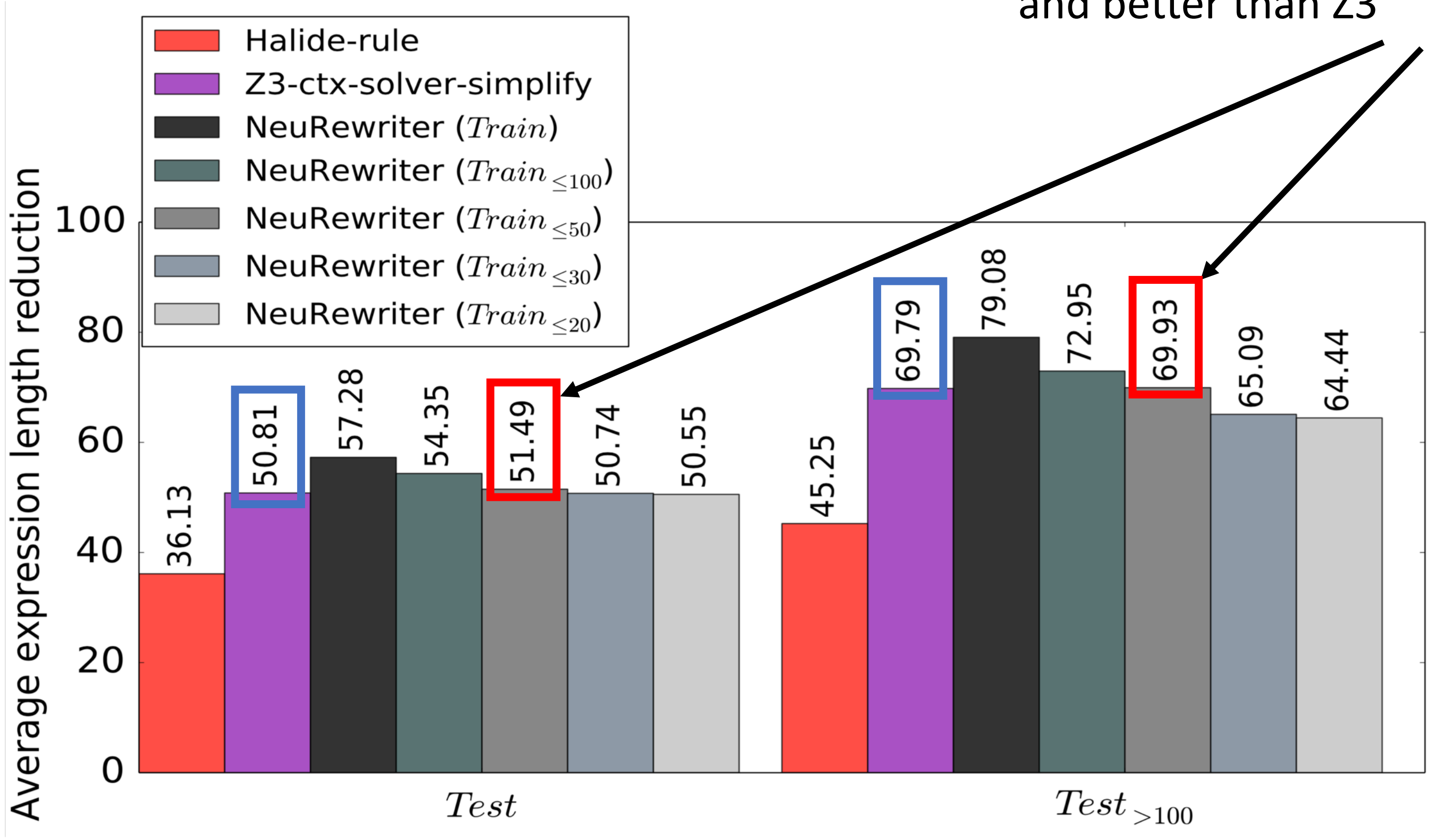
Z3-simplify
Z3-ctx-solver-simplify
Heuristic Search
Halide rules

Z3 is a state-of-the-art theorem prover.

Expression Simplification

Transfer learning still works well.

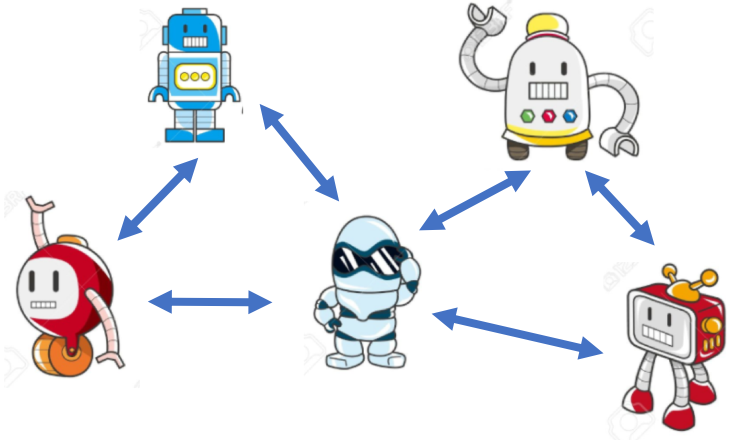
A model trained with expression length ≤ 50 has good performance on test set with expression length ≥ 100, and better than Z3



Future Directions

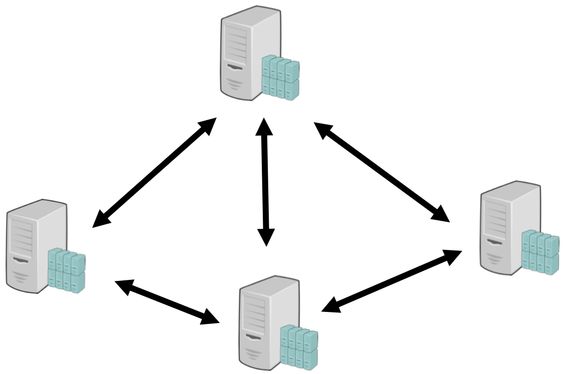
Admiral (General) Captain Lieutenant

Hierarchical RL

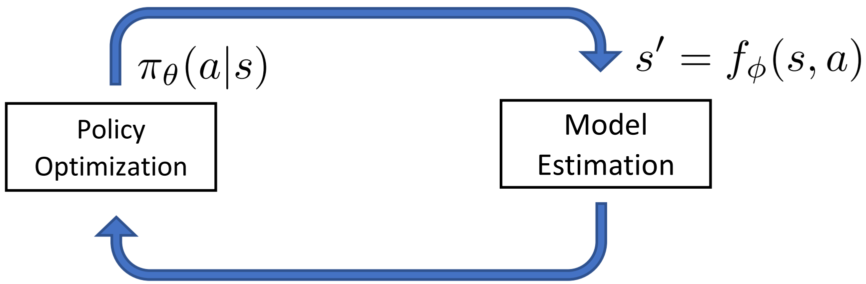


Multi-Agent

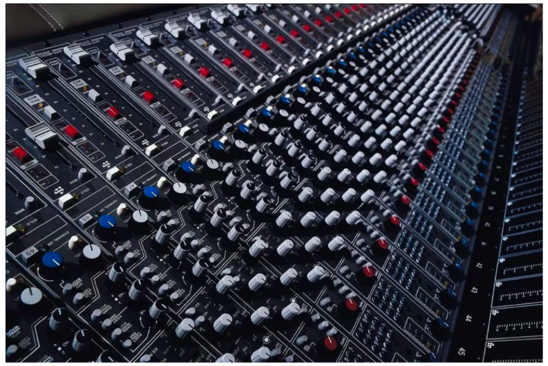
RL applications



RL Systems



Model-based RL



RL for Optimization

Thanks!