Building Scalable Systems for Reinforcement Learning and Using Reinforcement Learning for Better Systems

Presented by Yuandong Tian

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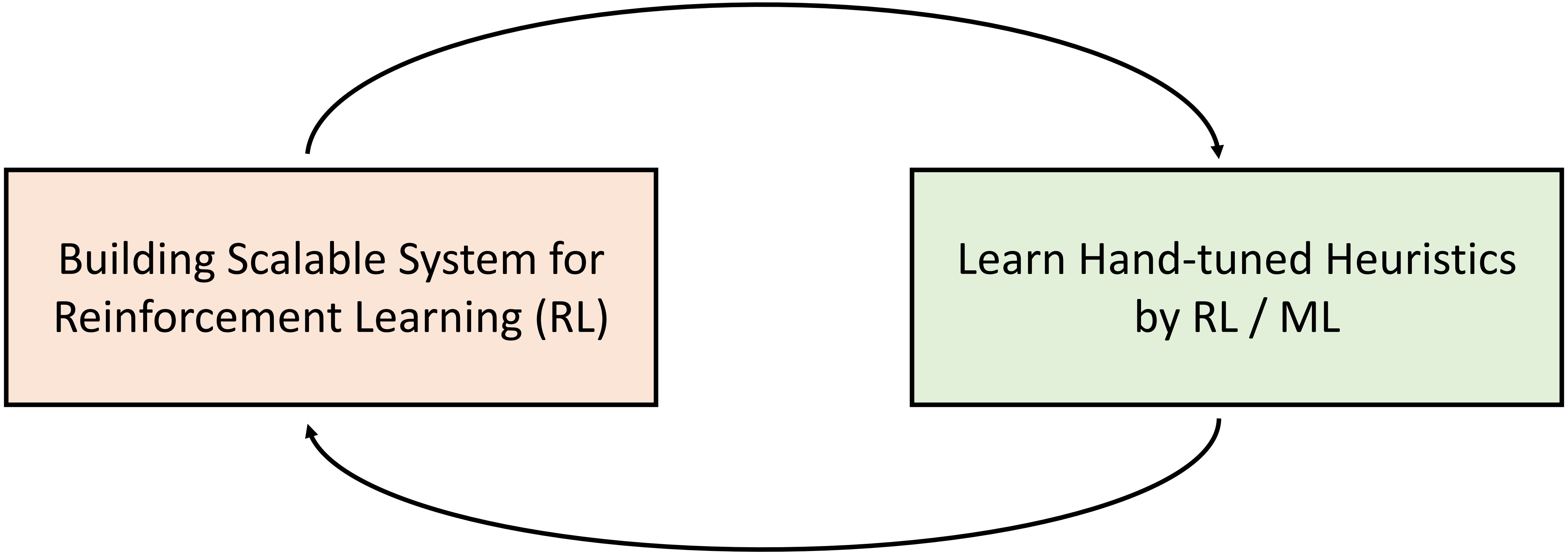
Facebook AI Research

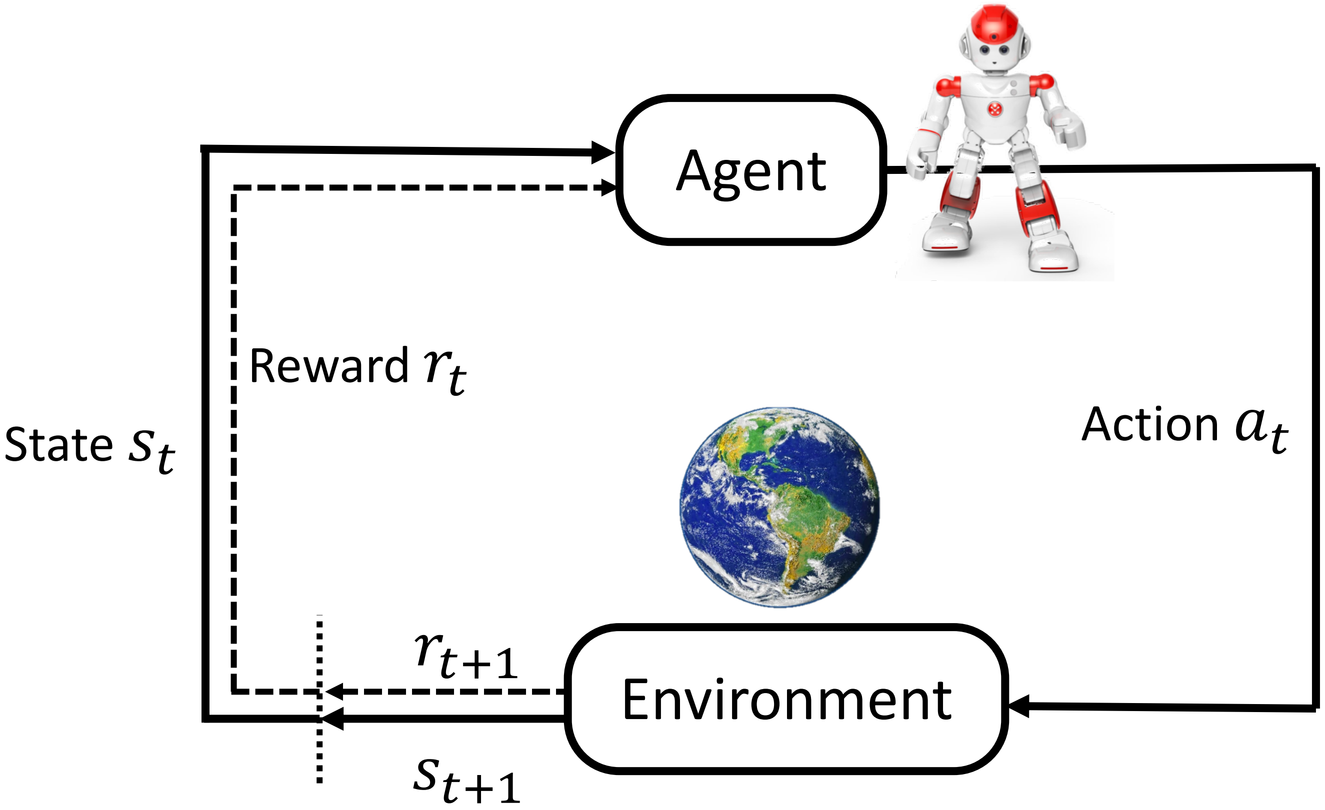
facebook Artificial Intelligence

Overview


Building Scalable System for Reinforcement Learning (RL)
Learn Hand-tuned Heuristics by RL / ML

Building Scalable System for RL

Crash Course of Reinforcement Learning



Reinforcement Learning works, but expensive



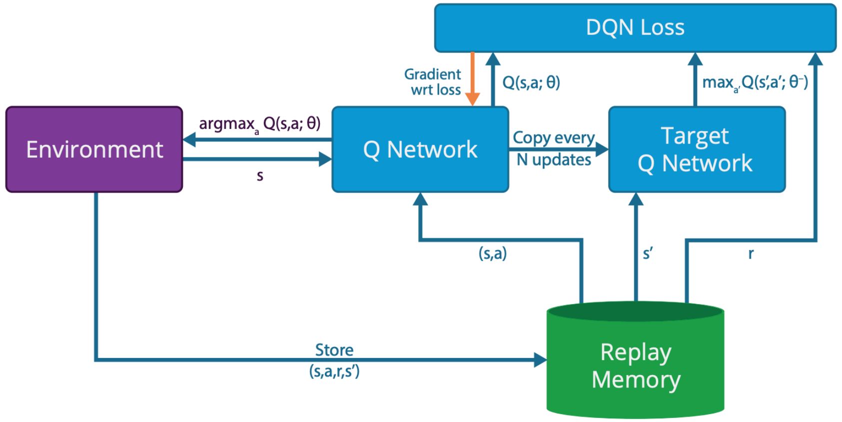


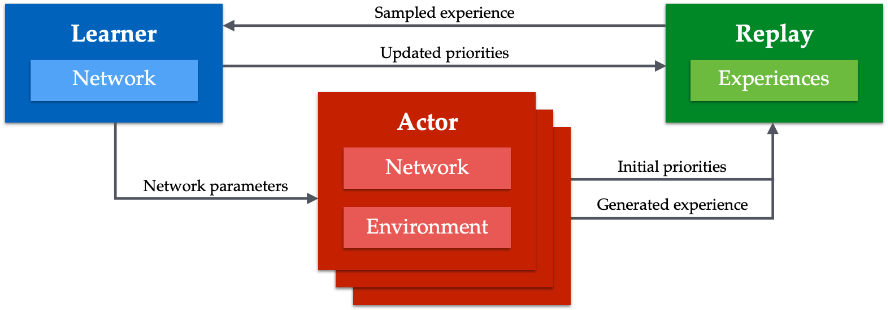
Year	Projects	Human Data	Training Resource	Training time
2016	DeepMind's AlphaGo	Yes	~50 GPUs + ? CPUs	~1 week
2017	DeepMind's AlphaGo Zero (20 blocks)	No	~2000 TPUs	3 days
2017	DeepMind's AlphaZero (20 blocks)	No	~5000 TPUs	8 hours
2018	OpenAI Five	No	128,000 CPUs + 256 GPUs	Several months
2019	DeepMind's AlphaStar	Yes	16,000 CPUs + 3072 TPUv3 cores	44 days

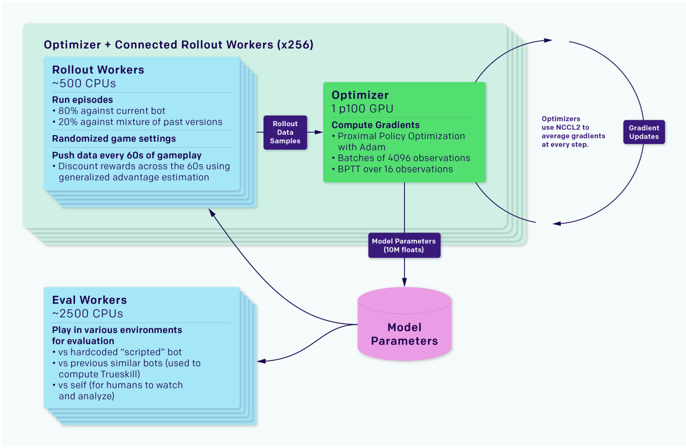
Challenges in large-scale RL Training System

- Trade-offs in a *heterogenous* system
  - **Different kind of objects**: Actor / Environment / Trainer / Replay buffer
  - CPUs / GPUs Allocations
  - Multi-threading versus Multiple Processes, Batching issues
  - Local versus Distributed
  - Synchronization / Asynchronization.
    - On-policy versus off-policy methods
    - Perfect synchronization might NOT give you the best performance
- Mingled Algorithm Design and System Design
  - New System design ←→ New RL algorithm

Distributed System for training RL agent







GORILLA

[Massively Parallel Methods for Deep Reinforcement Learning, AAAI 2015]

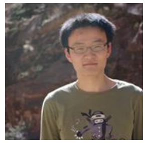
Ape-X / R2D2

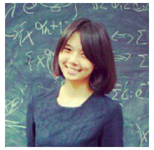
[Distributed Prioritized Experience Replay, Horgan et al, ICLR 2018]
[Recurrent Experience Replay in Distributed Reinforcement Learning Kapturowski et al, ICLR 2019]

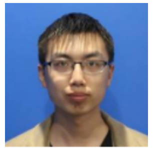
OpenAI Rapid

ELF: RL Framework for Game Research

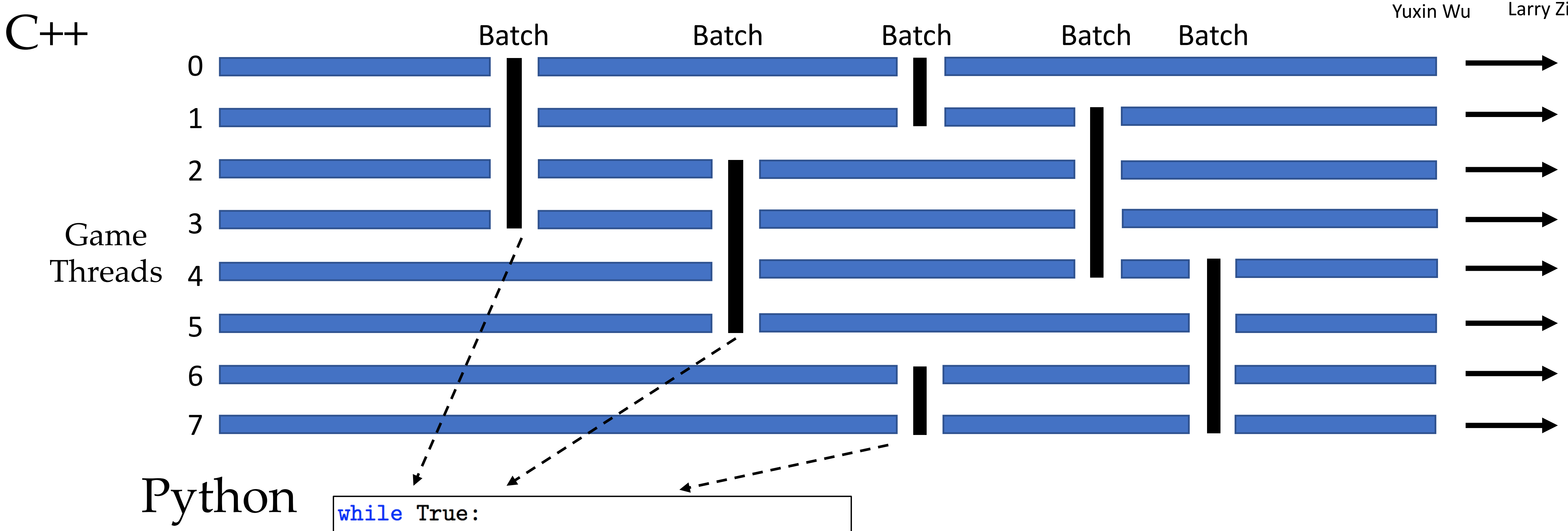

Yuandong Tian


Qucheng Gong


Wendy Shang


Yuxin Wu


Larry Zitnick




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

[ELF: Extensive, Lightweight and Flexible Framework for Game Research, Tian et al, NeurIPS 2019]

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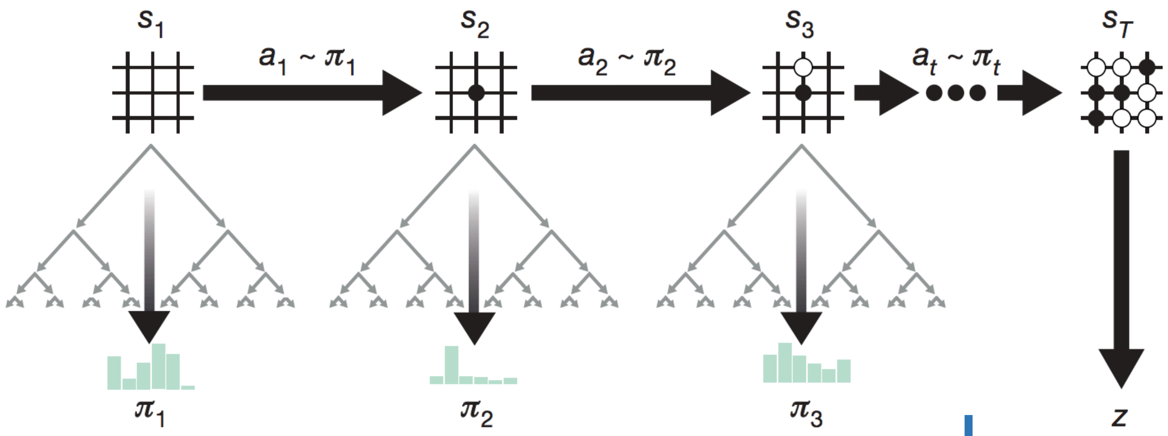
AlphaGoZero / AlphaZero



Generate Training data

<u>Without human knowledge</u>

θ_i ← Update Models ← Self-Replays

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

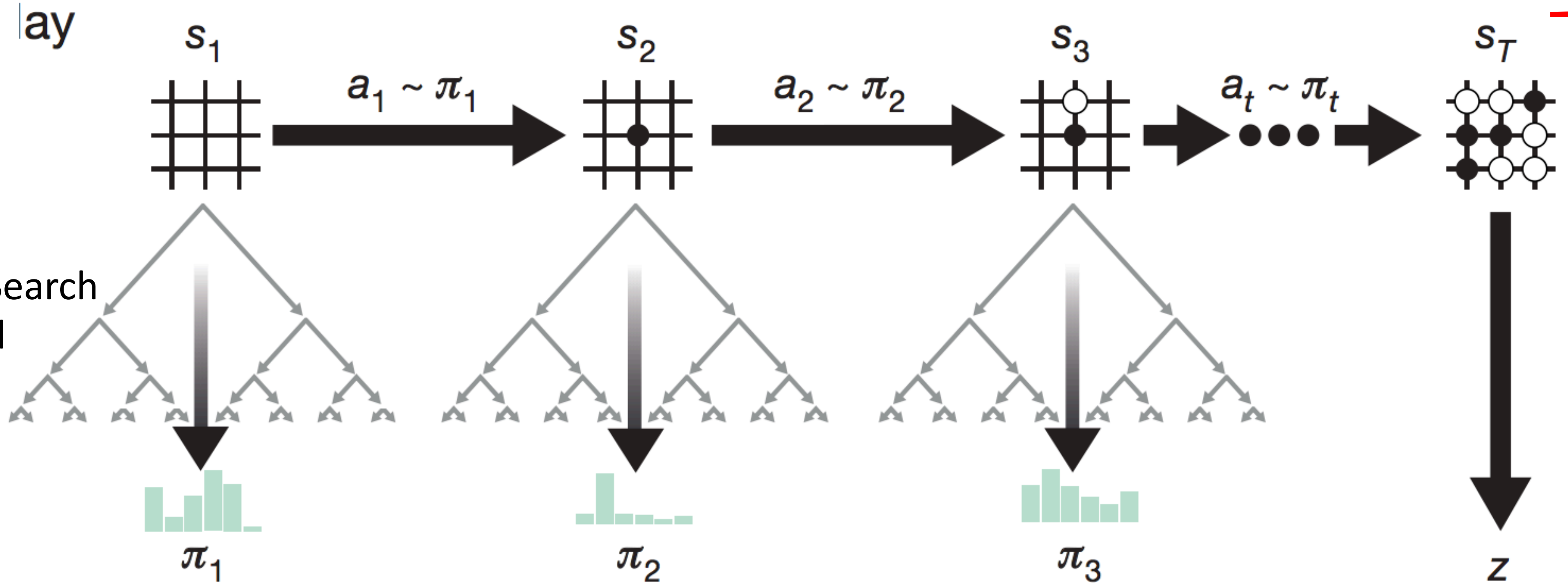
Generate Self-play Games

$\left(s_1, \pi_1, z\right)$

$\left(s_2, \pi_2, z\right)$

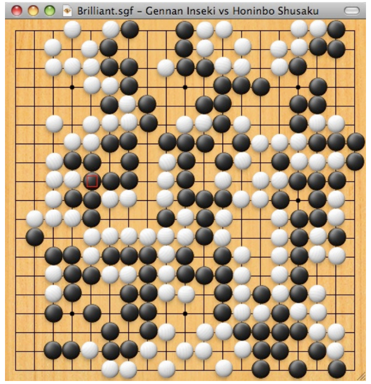
$\left(s_3, \pi_3, z\right)$

Training samples for θ_{i+1}

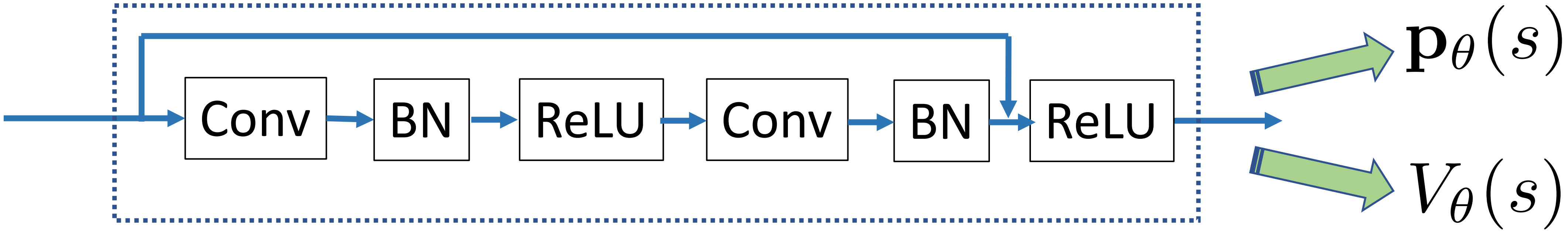


Monte Carlo Tree Search with current model θ_i

Update Models



$\boldsymbol{s}$



Player situation at time 0

Opponent situation at time 0

Player situation at t=-7

Color to play

Input features (19x19x17): $(X, Y, X_{-1}, Y_{-1}, \ldots, X_{-7}, Y_{-7}, C)$

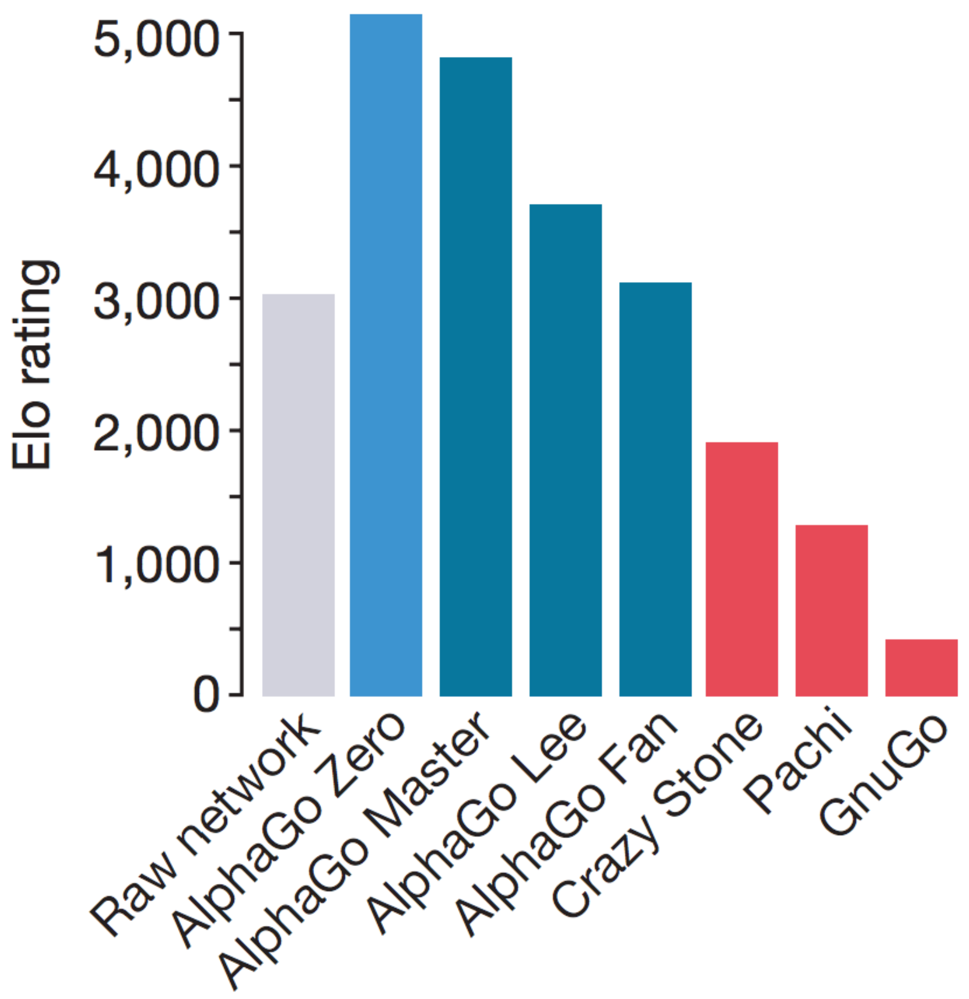
Objective: $(s, \boldsymbol{\pi}, z)$

$$J(\theta) = (z - V_\theta)^2 - \boldsymbol{\pi}^T \log \mathbf{p}_\theta + c\|\theta\|^2$$

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



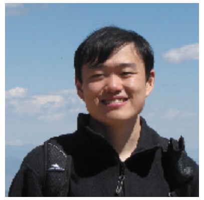
The Mystery of AlphaZero

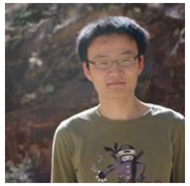
- Mystery
  - Is the proposed algorithm really universal?
  - Is the bot almighty? Is there any weakness in the trained bot?

- Lack of Ablation Studies
  - What factor is critical for the performance?
  - Is the algorithm robust to random initialization and changes of hyper parameters?
  - Any adversarial samples?

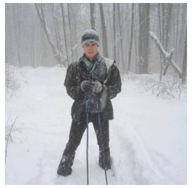
Impressive Results, No code, No model

ELF OpenGo


Yuandong Tian

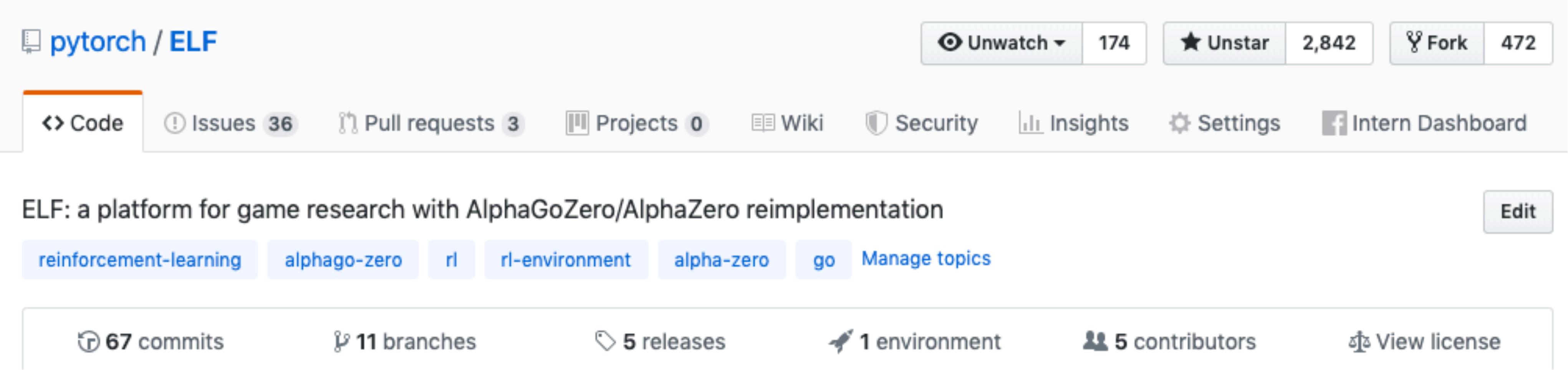
Jerry Ma*

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.



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

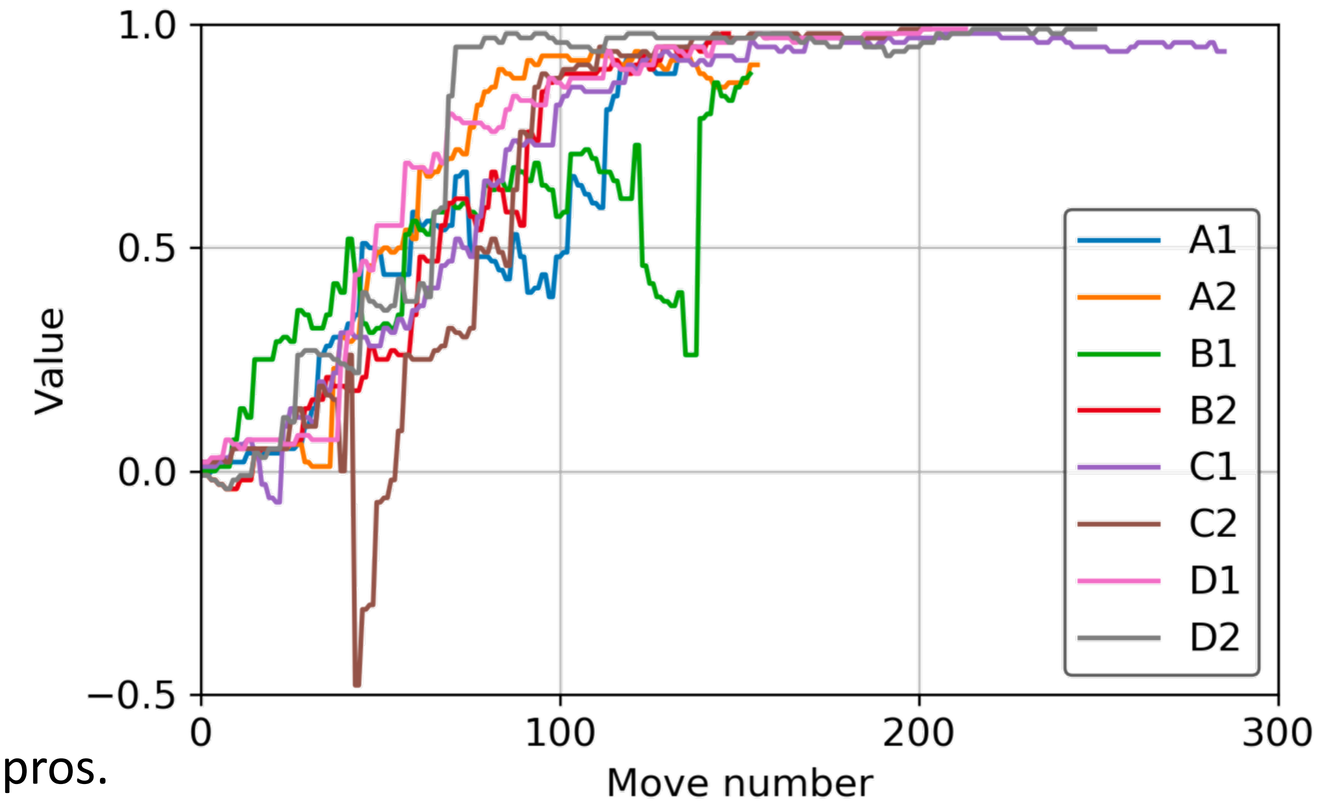
[ELF OpenGo: An Analysis and Open Reimplementation of AlphaZero, Y. Tian et al, ICML 2019]

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



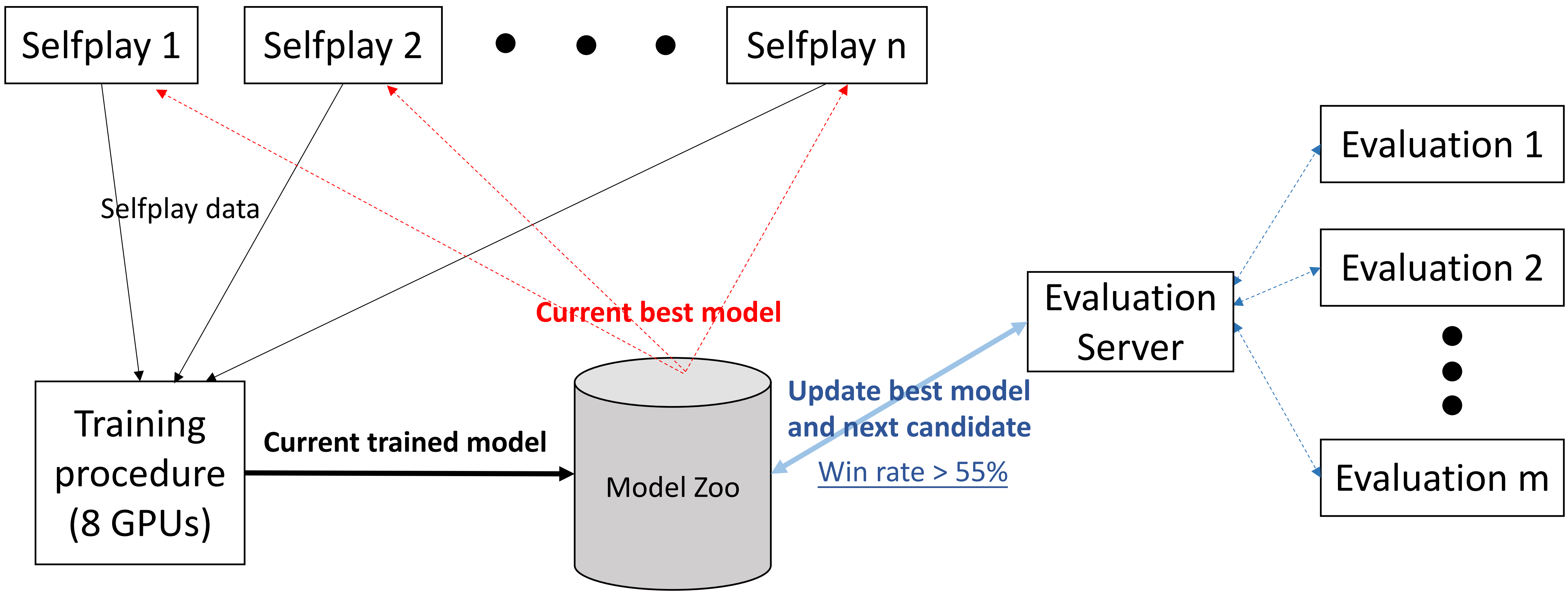
Vs professional players

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

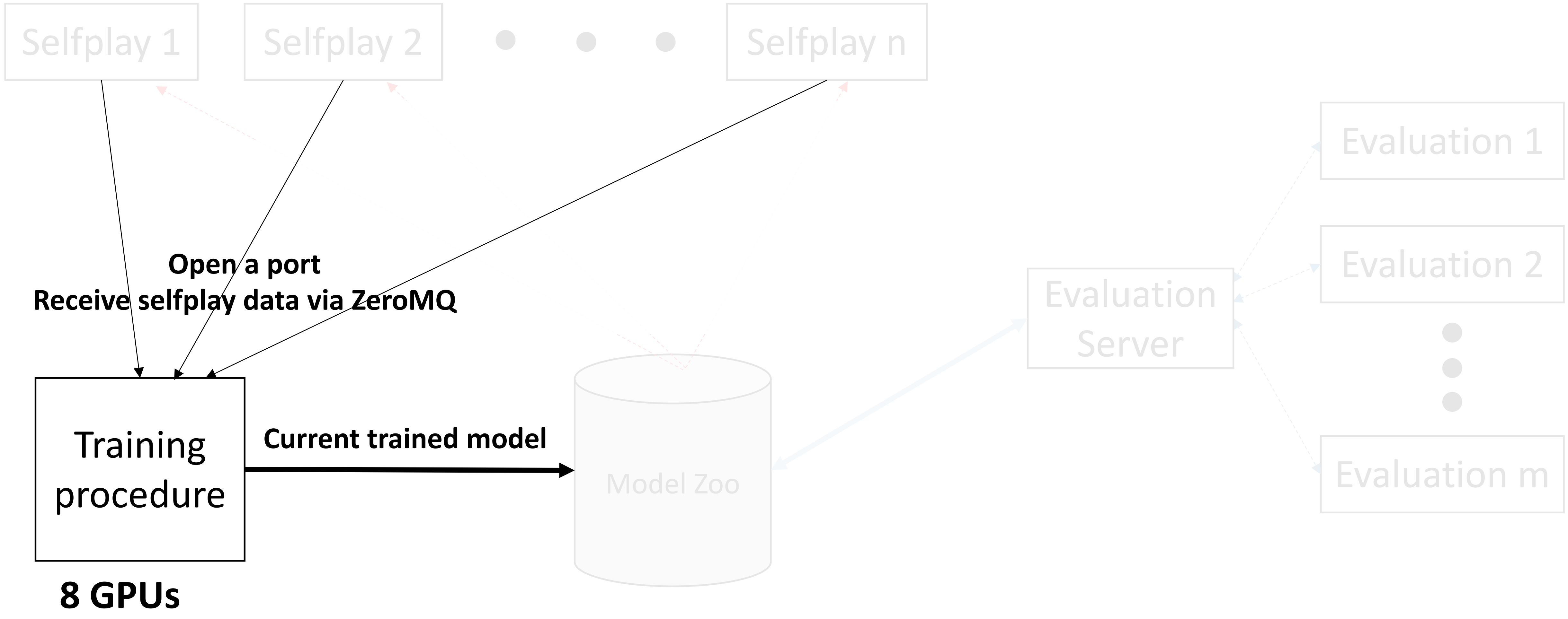
Vs strong bot (LeelaZero)

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

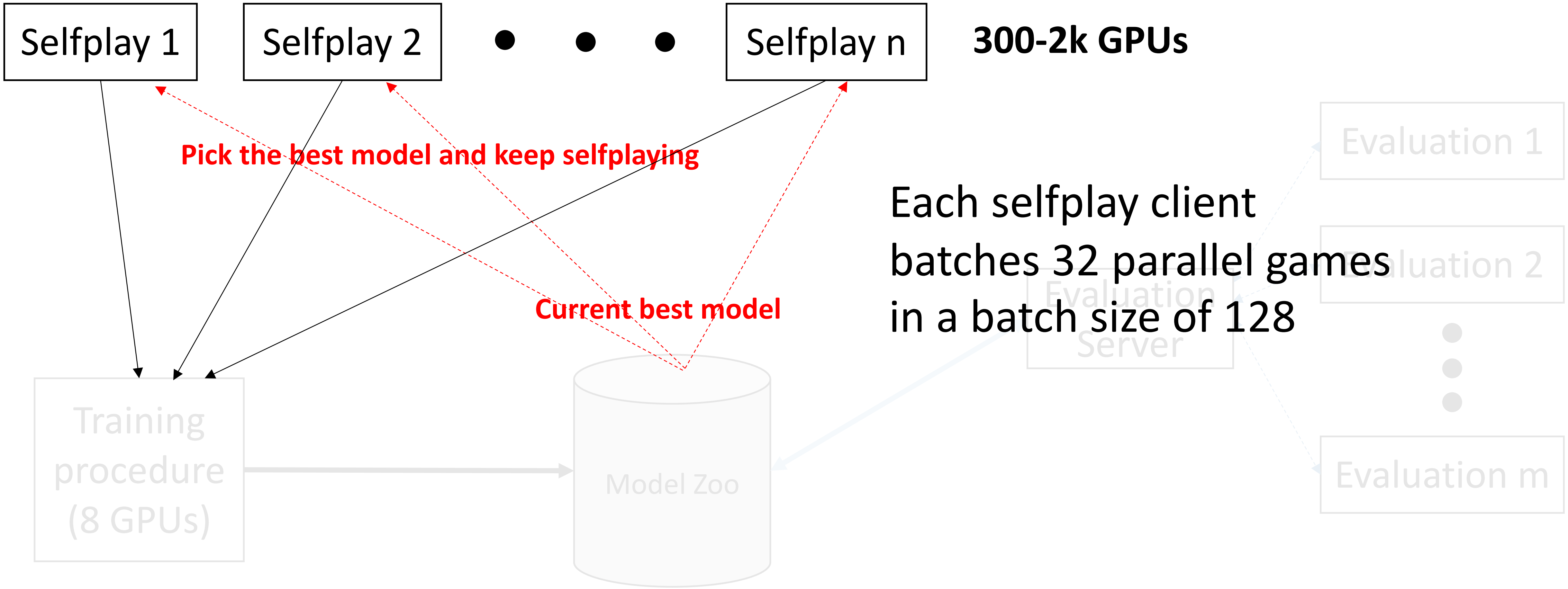
Distributed ELF (version 1, AlphaGoZero)



Distributed ELF (version 1)

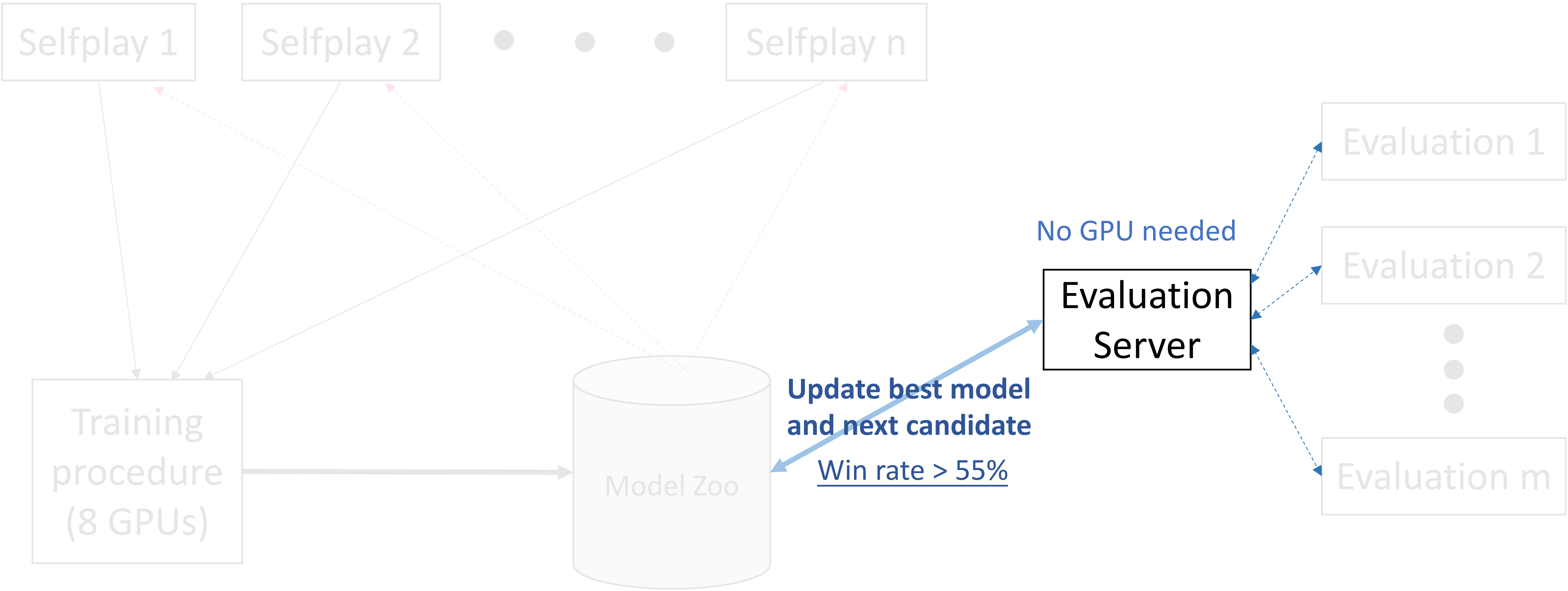


Distributed ELF (version 1)

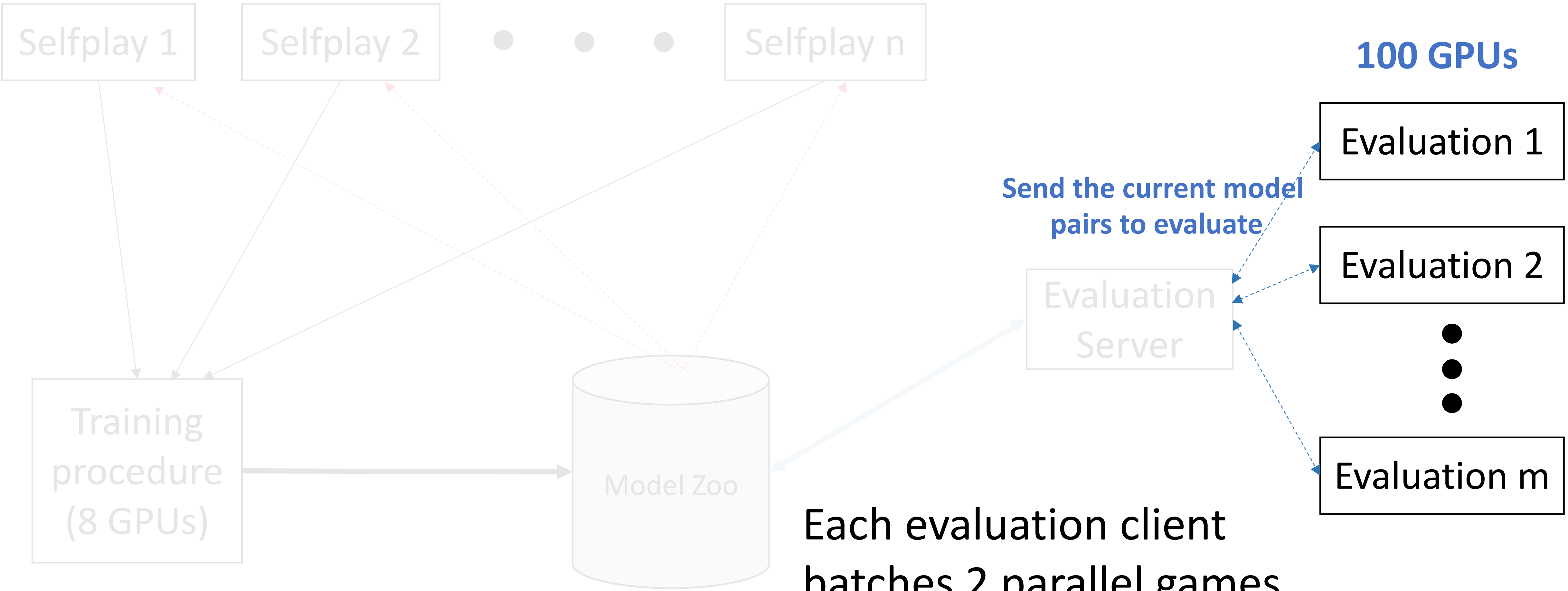


Each selfplay client batches 32 parallel games in a batch size of 128

Distributed ELF (version 1)

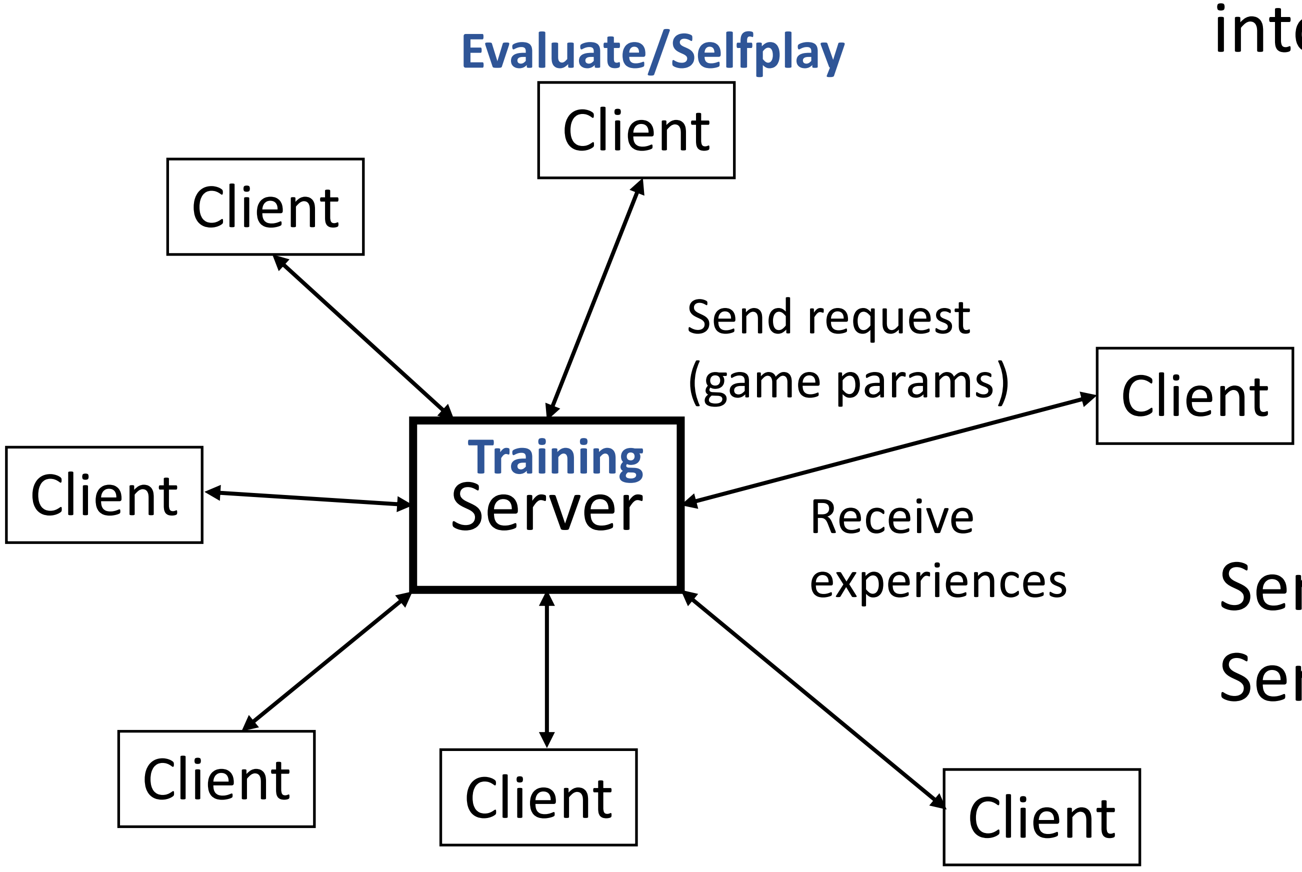


Distributed ELF (version 1)



Each evaluation client batches 2 parallel games

Distributed ELF (v2)



Putting AlphaGoZero and AlphaZero into the same framework

AlphaGoZero (more synchronization)
AlphaZero (less synchronization)

Server controls synchronization
Server also does training.

Next Step: **RL Assembly**

- Backbone infrastructure for ongoing projects (Hanabi, Bridge, etc)
- Reimplementation of SoTA off-policy RL methods like Ape-X and R2D2
- Incorporate OpenGo and SoTA implementation of MCTS.
- Efficient on single machine (SoTA training FPS so far)

Open source soon

Frame Per Second (FPS) on Atari Games

ReLA: 12.5 KFPS

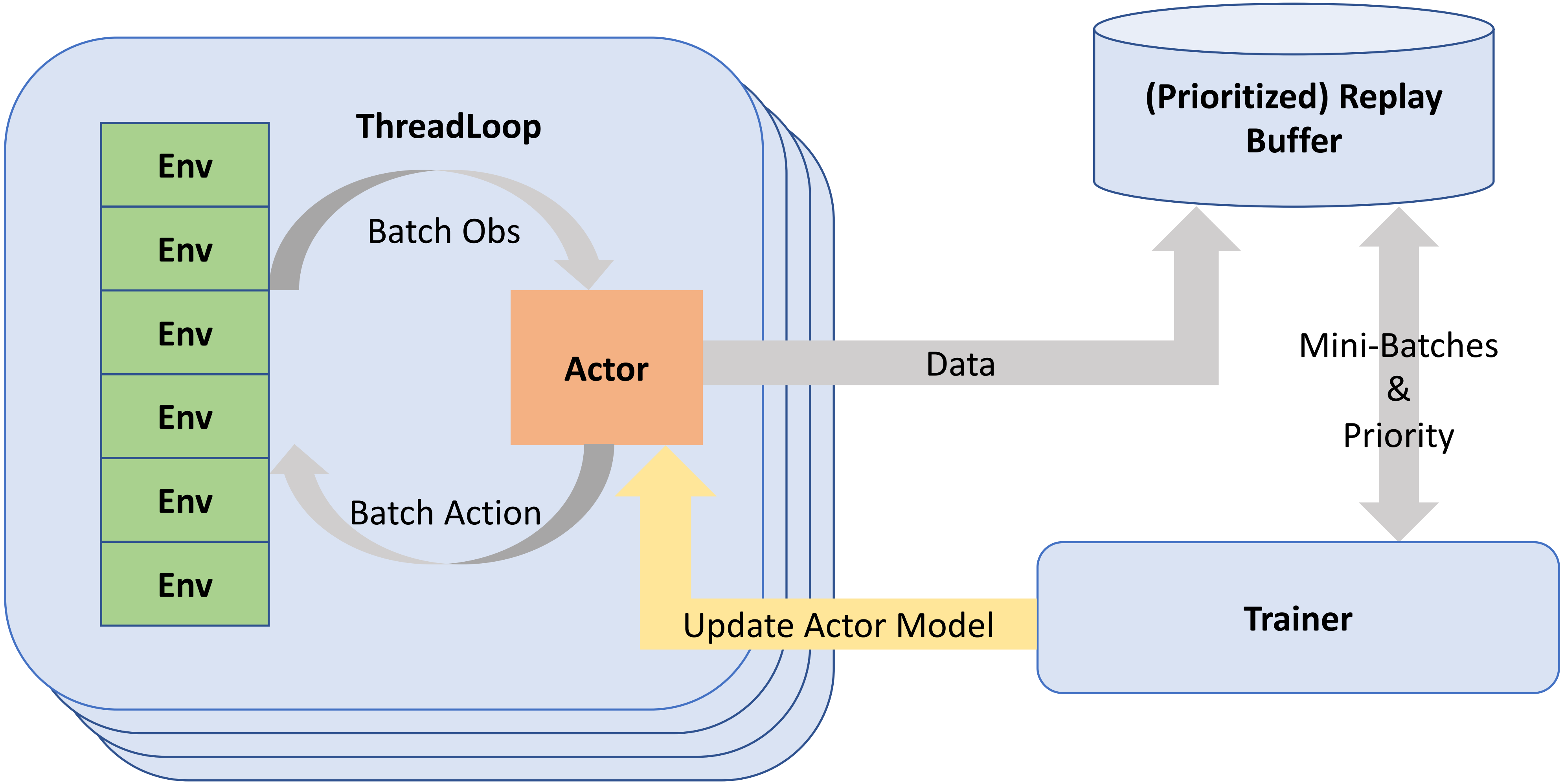
using 40 CPU cores + 2 GPU (P100) on a single machine

Ape-X: 12.5 KFPS

using 360 CPU cores + 1 GPU (distributed system)

- ReLA is GPU bound. Performance is better with more GPUs
- A few more improvements to achieve better performance when releasing.

Architecture



User Interface (API)

```python
env = rela.VectorEnv()
for _ in range(num_env_per_thread):
    game = create_atari(...)
    env.append(game)
actor = rela.DQNActor(...)
thread = rela.ThreadLoop(actor, env)
```

All objects (env, agent, replay buffer, etc) are created & configured in Python

User Interface (API)

```python
class ApexAgent(torch.jit.ScriptModule):
    @torch.jit.script_method
    def td_err(self, obs: Dict[str, torch.Tensor], ...) -> torch.Tensor:
        online_q = self.online_net(obs)
        online_qa = online_q.gather(1, action.unsqueeze(1)).squeeze(1)

        next_a = self.greedy_act(next_obs)
        bootstrap_q = self.target_net(next_obs)
        bootstrap_qa = bootstrap_q.gather(1, next_a.unsqueeze(1)).squeeze(1)
        target = reward + bootstrap * (self.gamma ** self.multi_step) * bootstrap_qa
        return target.detach() - online_qa
```

Model is written in **Python** with **PyTorch's TorchScript**,
and executed in **C++** with multi-threading for maximum throughput.

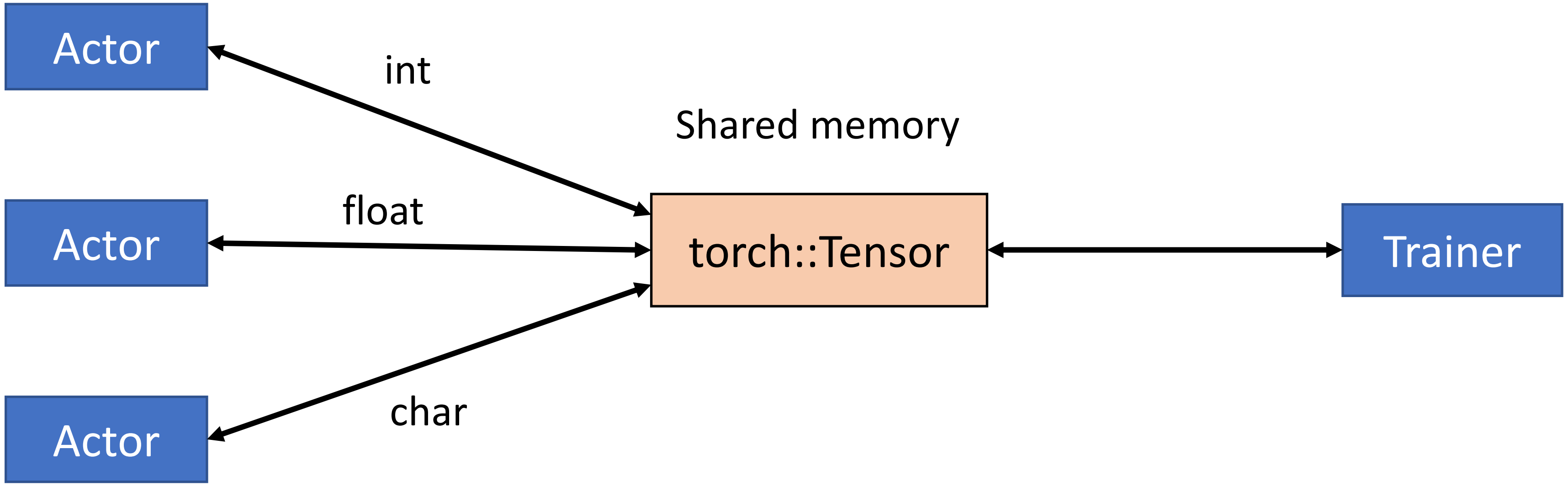
Native integration with PyTorch C++ API

- Simple/Intuitive manipulations of PyTorch tensors in C++
  - Same as/Similar to Python Interface
  - No extra library needed for operations like downsample/upsampling.

```cpp
torch::Tensor s = getObservation();
s = s.view({1, 3, height, width});
// rescale the image
s = torch::upsample_bilinear2d(s, {sHeight, sWidth}, true);
s = s.view({3, sHeight, sWidth});
// convert to grey scale
s = 0.21 * s[0] + 0.72 * s[1] + 0.07 * s[2];
```

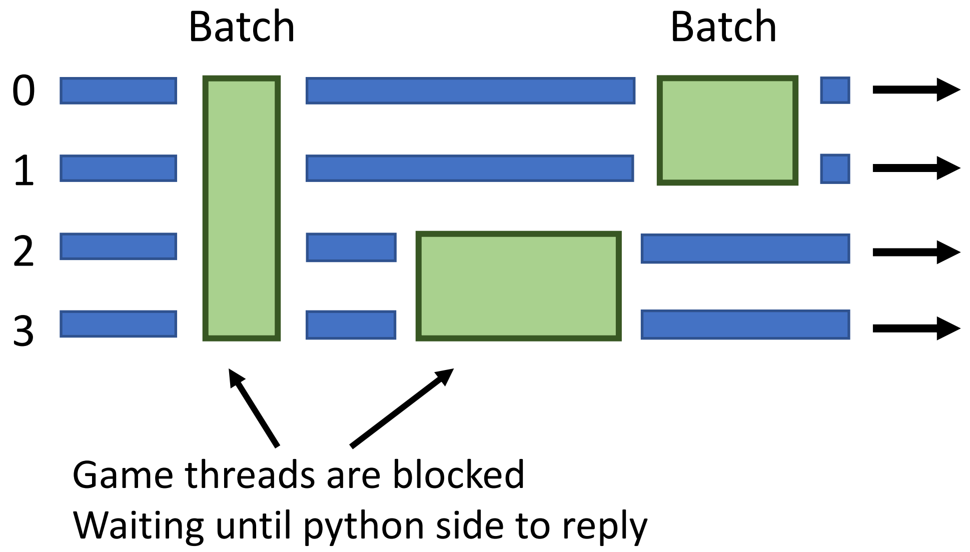
Native integration with PyTorch C++ API

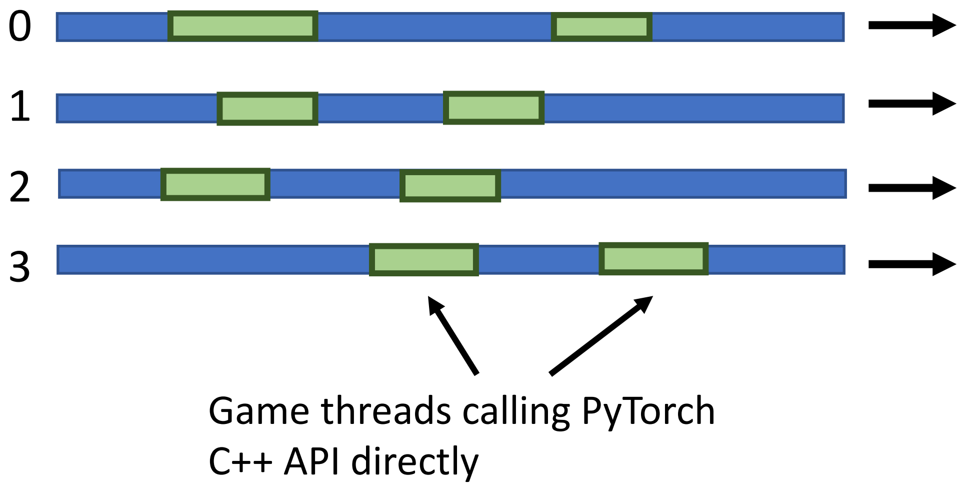
- Easier communication between threads/processes via Tensor.
  - No extra copy when sending data from/to environments.



Native integration with PyTorch C++ API

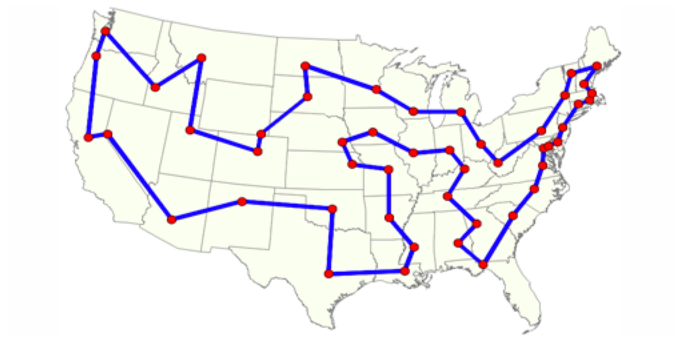
- Simultaneous network forwarding at different threads
  - Python GIL becomes irrelevant.
  - No need to block the environment
    - good for simple environments like Go, Bridge, Hanabi and others.



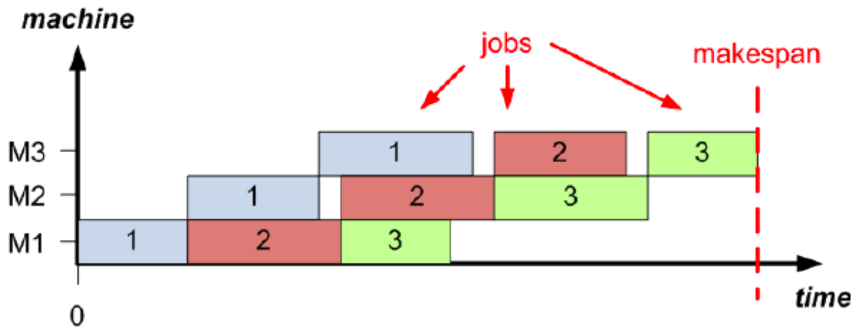


Learning Hand-tuned Heuristics with RL/ML

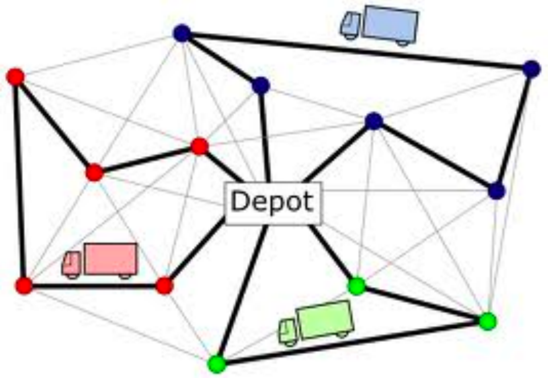
Combinatorial optimization



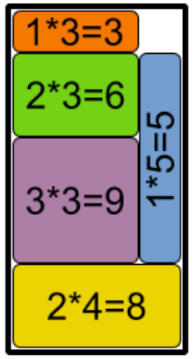
Travel Salesman Problem



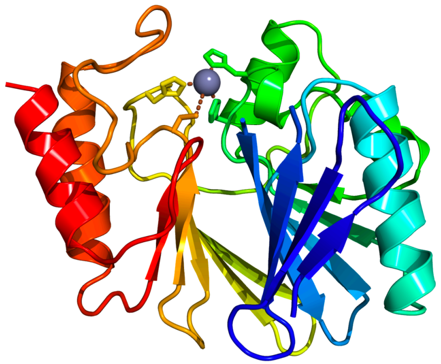
Job Scheduling



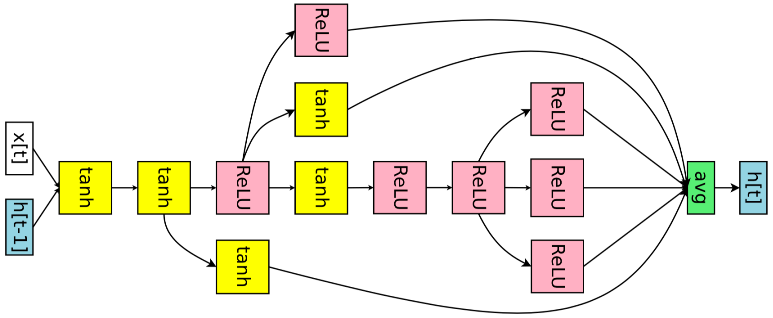
Vehicle Routing



Bin Packing



Protein Folding



Model-Search

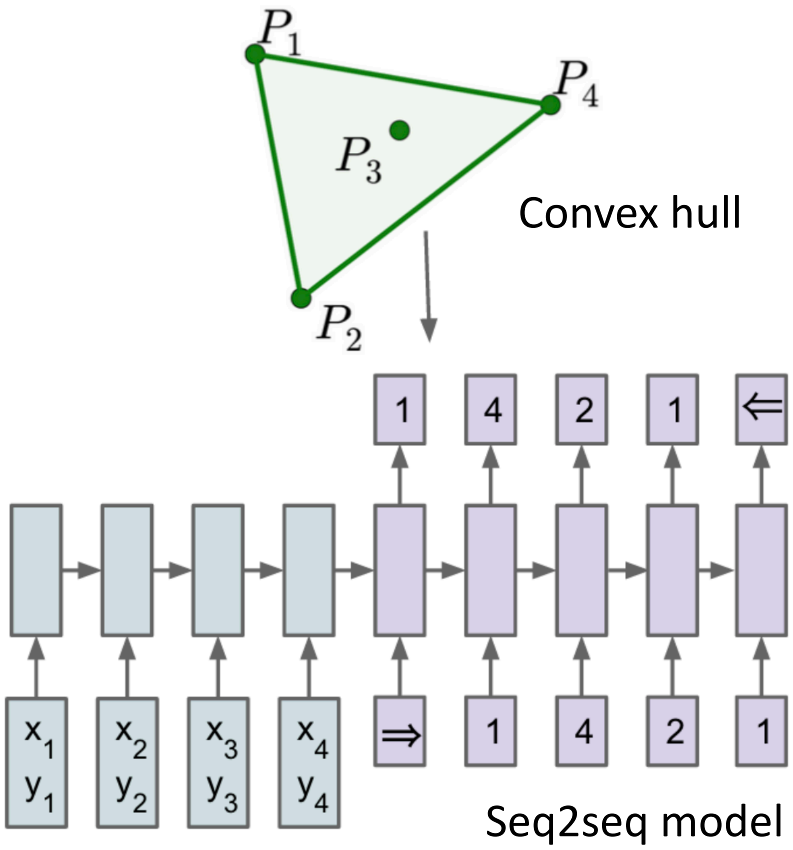
Wait...What?

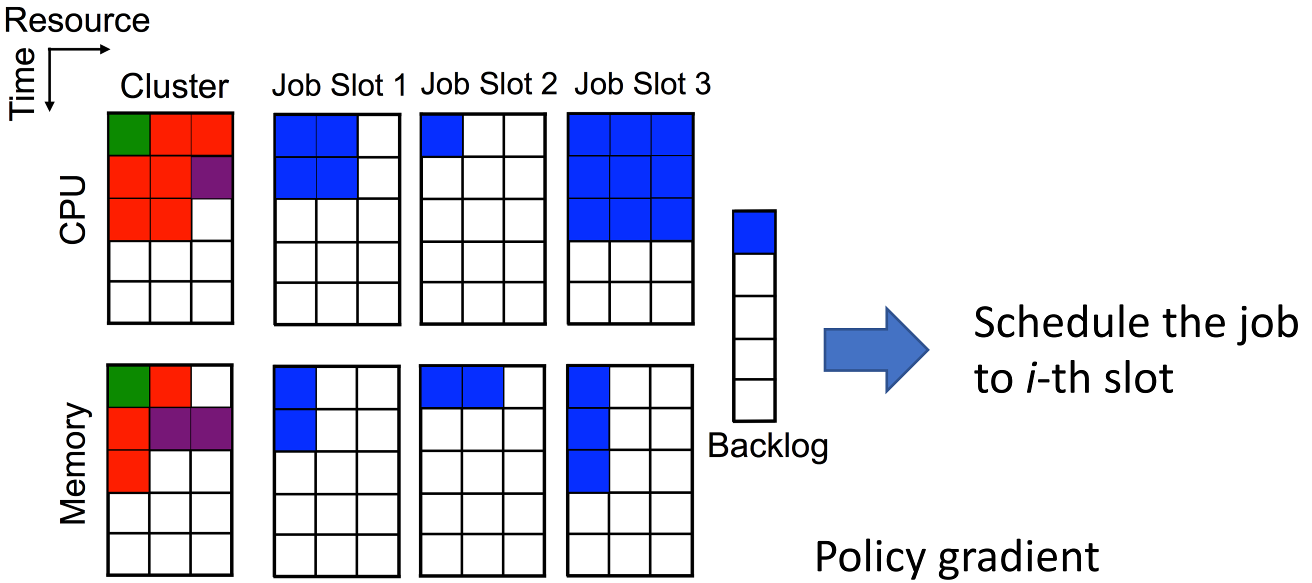
- These are NP-hard problems.
  - No good algorithm unless $P = NP$

- These guarantees are worst-case ones.
  - To prove a lower-bound, construct an adversarial example to fail the algorithm

- For specific distribution, there might be better heuristics.
  - Human heuristics are good but may not be suitable for everything

Direct predicting combinatorial solutions



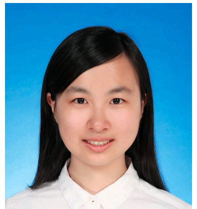


[H. Mao et al, Resource Management with Deep Reinforcement Learning, ACM Workshop on Hot Topics in Networks, 2016]

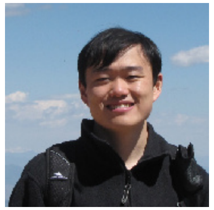
[O. Vinyals. et al, Pointer Networks, NIPS 2015]

Local Rewriting Framework

Code: https://github.com/facebookresearch/neural-rewriter



Xinyun Chen

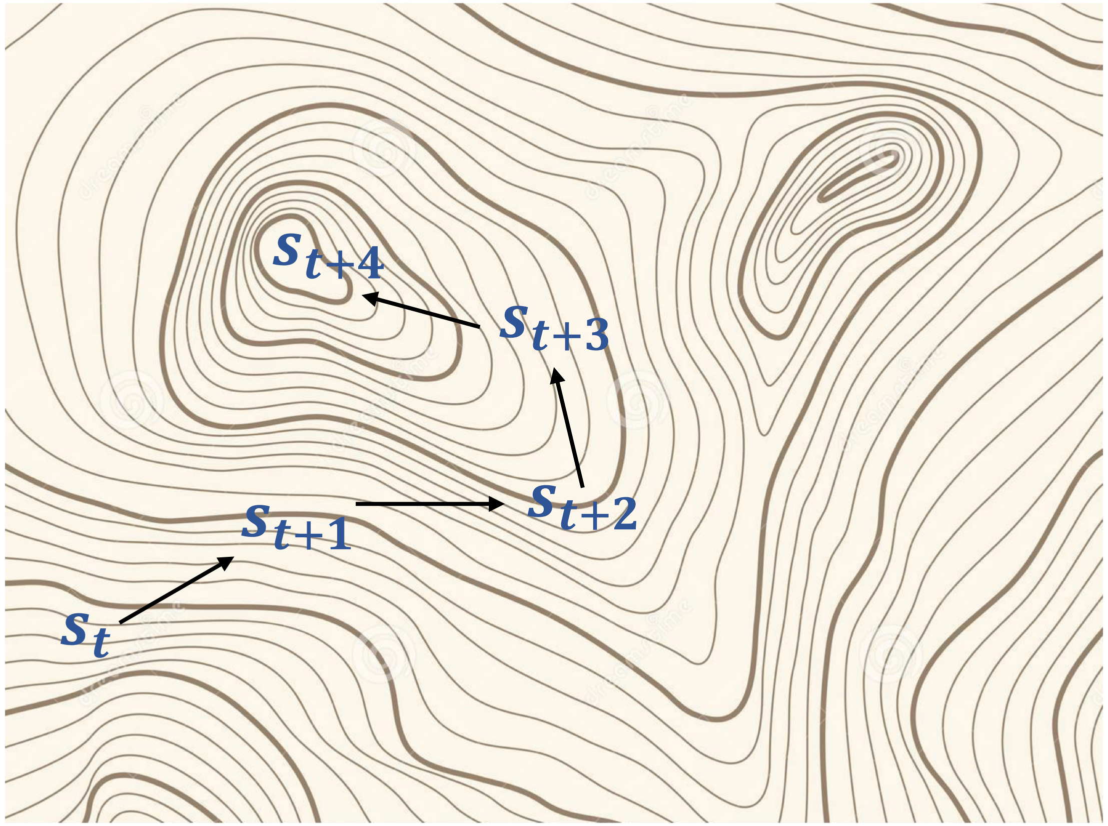


Yuandong Tian

A learned "gradient descent" that

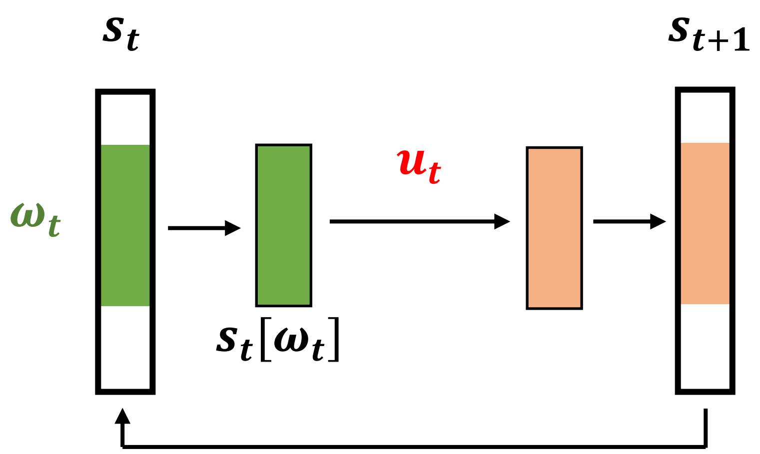
starts from a feasible solution
iteratively converges to a good solution

How to learn it?



 [Learning to Perform Local Rewriting for Combinatorial Optimization, X. Chen and Y. Tian, NeurIPS 2019]

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

How to train two policies $\boldsymbol{\pi_\omega}(\cdot\,|\boldsymbol{s_t})$ and $\boldsymbol{\pi_u}(\cdot\,|\boldsymbol{s_t}\ [\boldsymbol{\omega_t}])$?

Learn Q to fit cumulative rewards:

$$L_\omega(\theta) = \frac{1}{T}\sum_{t=0}^{T-1}\Big(\sum_{t'=t}^{T-1}\gamma^{t'-t} r(s'_t, (\omega'_t, u'_t)) - Q(s_t, \omega_t; \theta)\Big)^2$$

$\boldsymbol{\pi_\omega}(\cdot\,|\boldsymbol{s_t})$: Q-learning with soft policy:

$$\pi_\omega(\omega_t|s_t;\theta) = \frac{\exp(Q(s_t, \omega_t; \theta))}{\sum_{\omega_t}\exp(Q(s_t, \omega_t; \theta))}$$

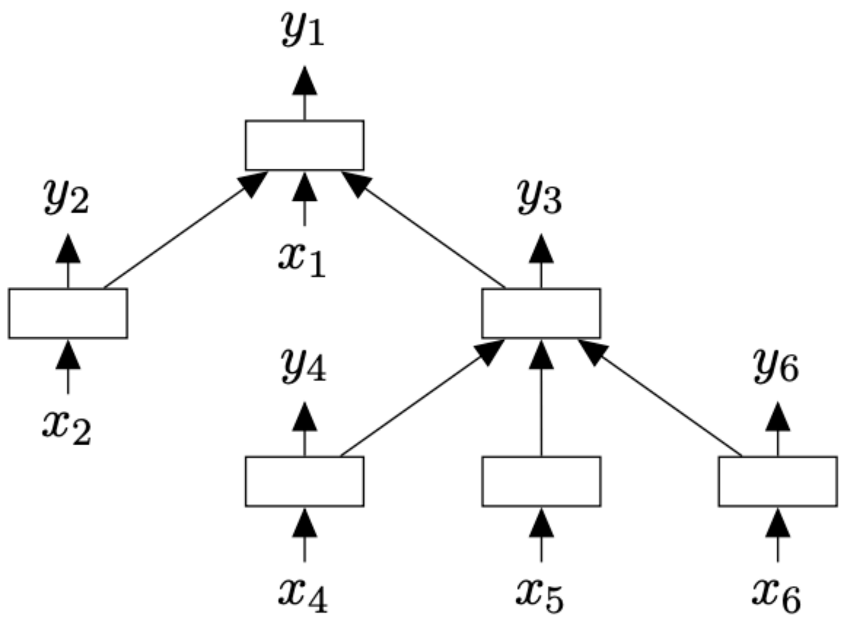
$\boldsymbol{\pi_u}(\cdot\,|\boldsymbol{s_t}\ [\boldsymbol{\omega_t}])$: Actor-Critic with learned Q:

$$L_u(\phi) = -\sum_{t=0}^{T-1}\Delta(s_t, (\omega_t, u_t))\log \pi_u(u_t|s_t[\omega_t];\phi)$$

Advantage:

$$\Delta(s_t, (\omega_t, u_t)) \equiv \sum_{t=t'}^{T-1}\gamma^{t'-t} r(s'_t, (\omega'_t, u'_t)) - Q(s_t, \omega_t; \theta)$$

How to encode Structure Data



Child-Sum LSTM

$$y_1 = f(y_2, y_3, x_1)$$

f can be very complicated:

$$\tilde{h}_j = \sum_{k \in C(j)} h_k,$$

$$i_j = \sigma\left(W^{(i)} x_j + U^{(i)} \tilde{h}_j + b^{(i)}\right),$$

$$f_{jk} = \sigma\left(W^{(f)} x_j + U^{(f)} h_k + b^{(f)}\right),$$

$$o_j = \sigma\left(W^{(o)} x_j + U^{(o)} \tilde{h}_j + b^{(o)}\right),$$

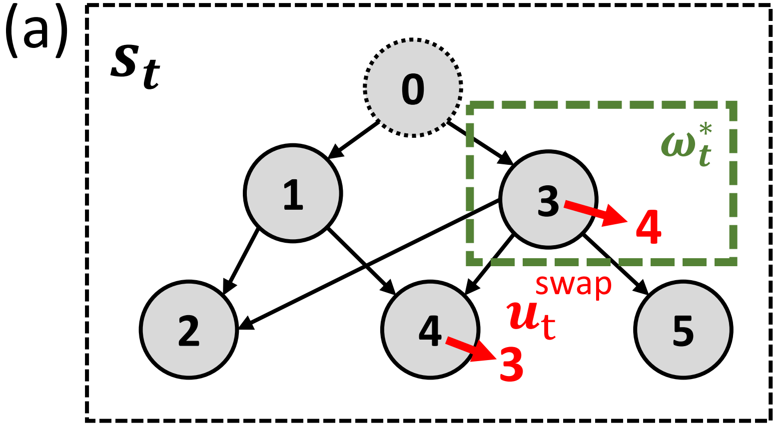
$$u_j = \tanh\left(W^{(u)} x_j + U^{(u)} \tilde{h}_j + b^{(u)}\right),$$

$$c_j = i_j \odot u_j + \sum_{k \in C(j)} f_{jk} \odot c_k,$$

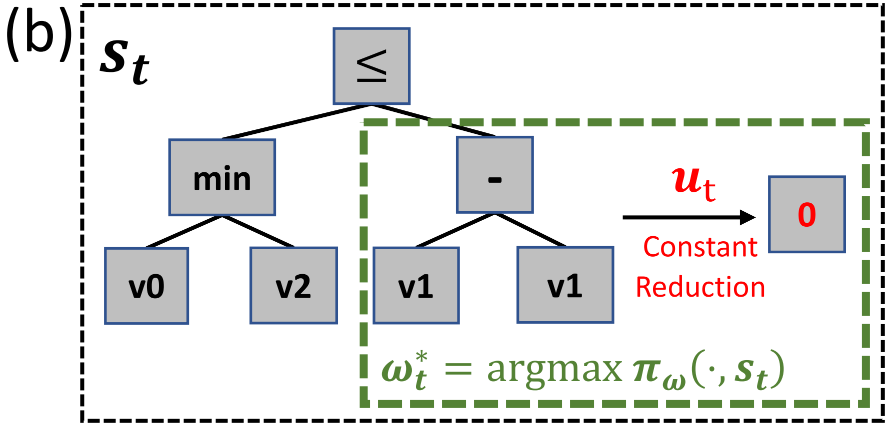
$$h_j = o_j \odot \tanh(c_j),$$

[Improved Semantic Representation From Tree-Structured Long Short-Term Memory Networks. K. Tai et al]

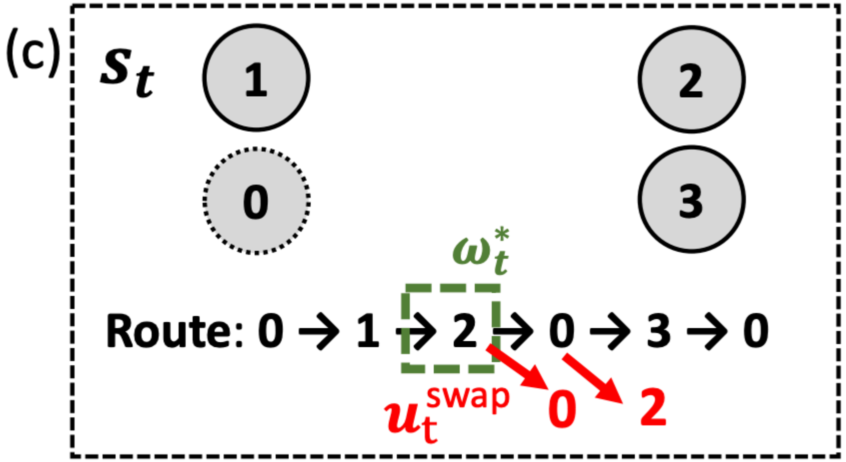
Applications



Online Job Scheduling

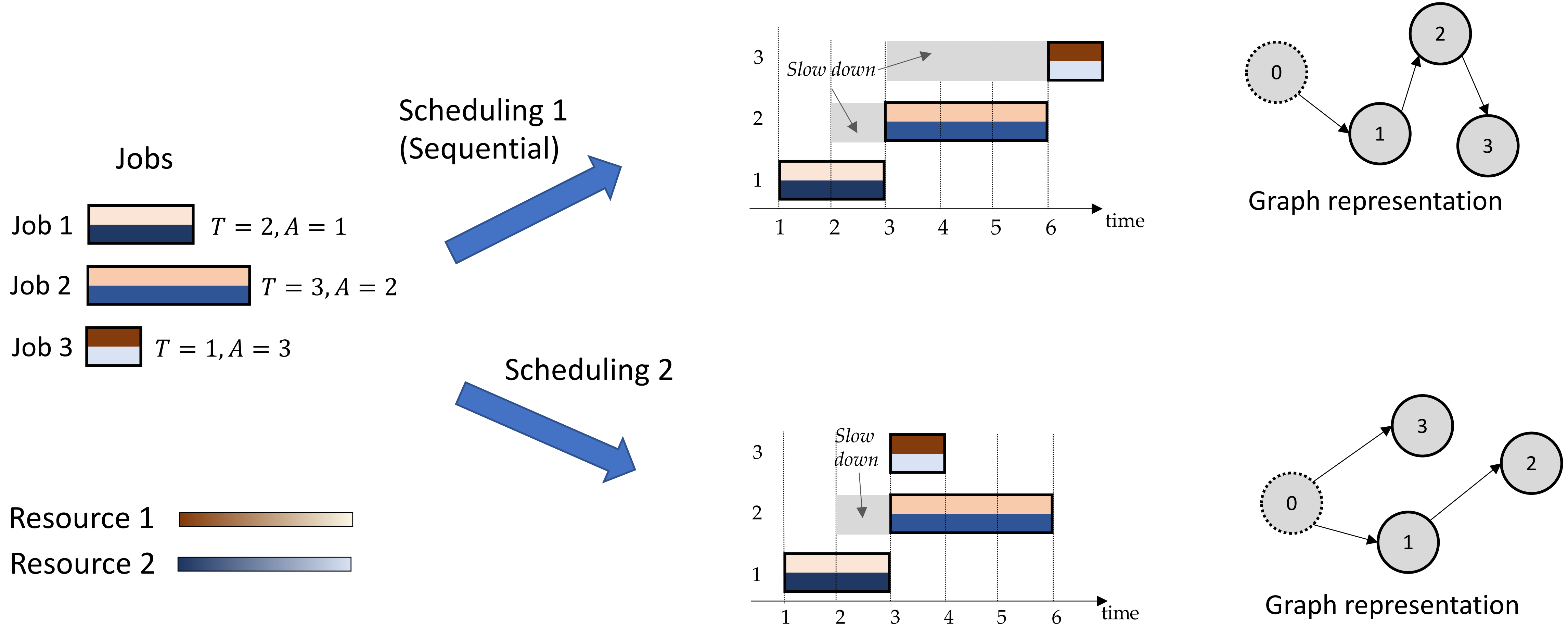


Expression Simplification

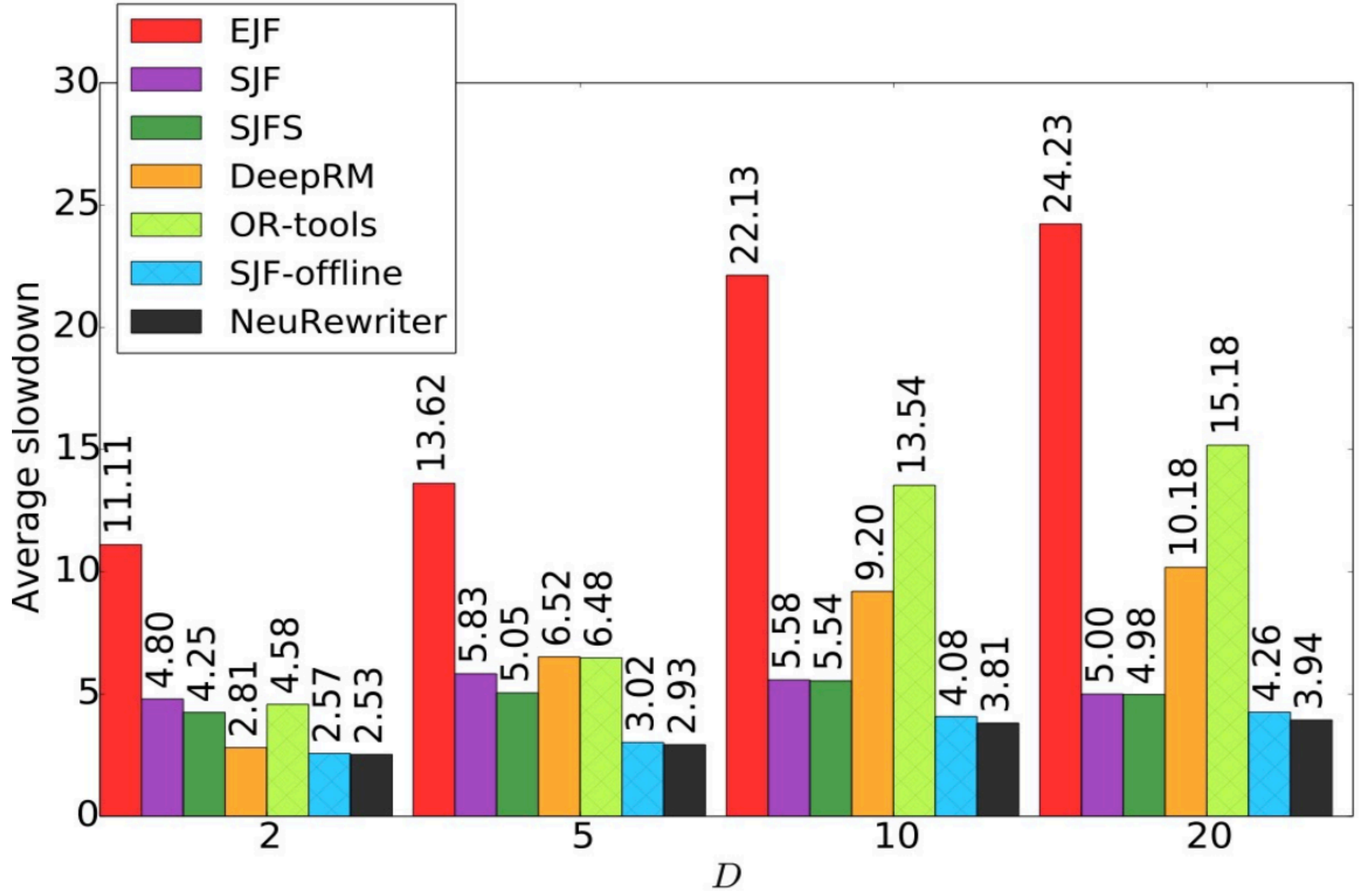


Vehicle Routing

Online Job Scheduling



Online Job Scheduling



D: Number of resources

Baselines:

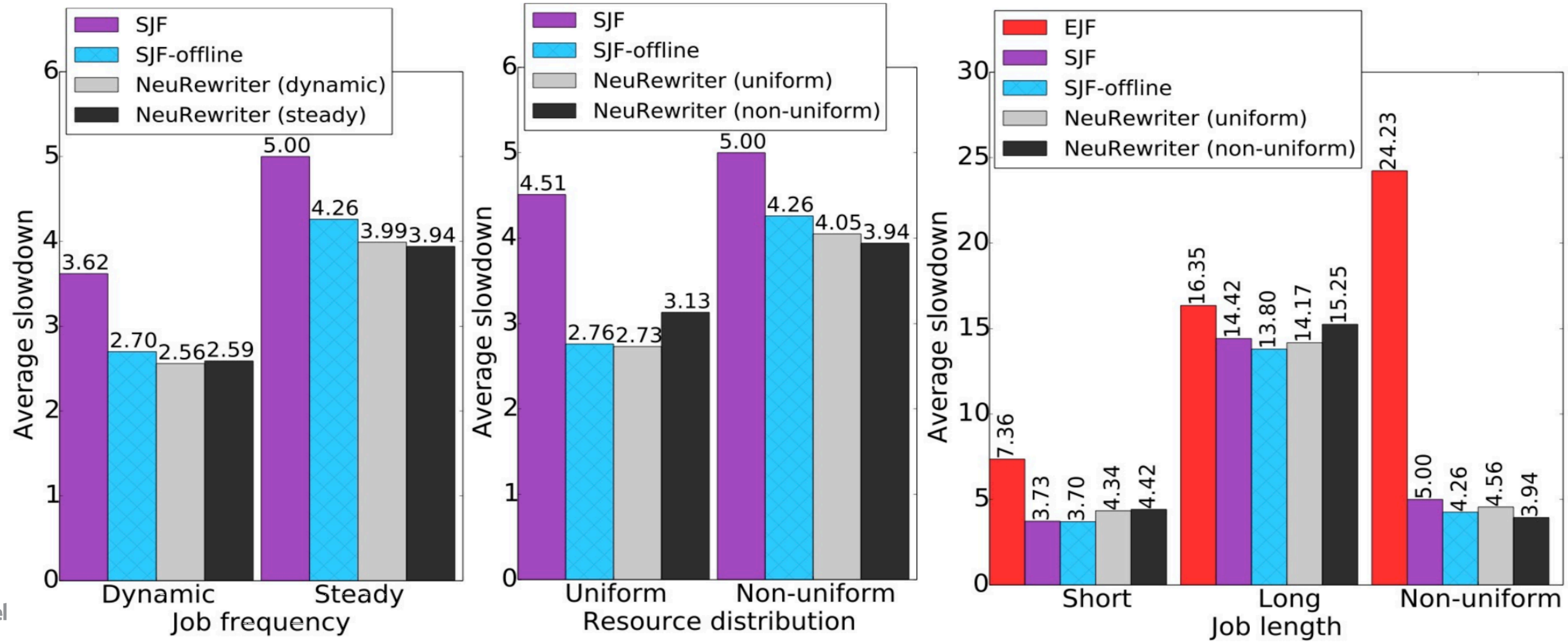
- Earliest Job First (EJF)
- Shortest Job First (SJF)
- Shortest First Search (SJFS)
- DeepRM

Offline baselines:

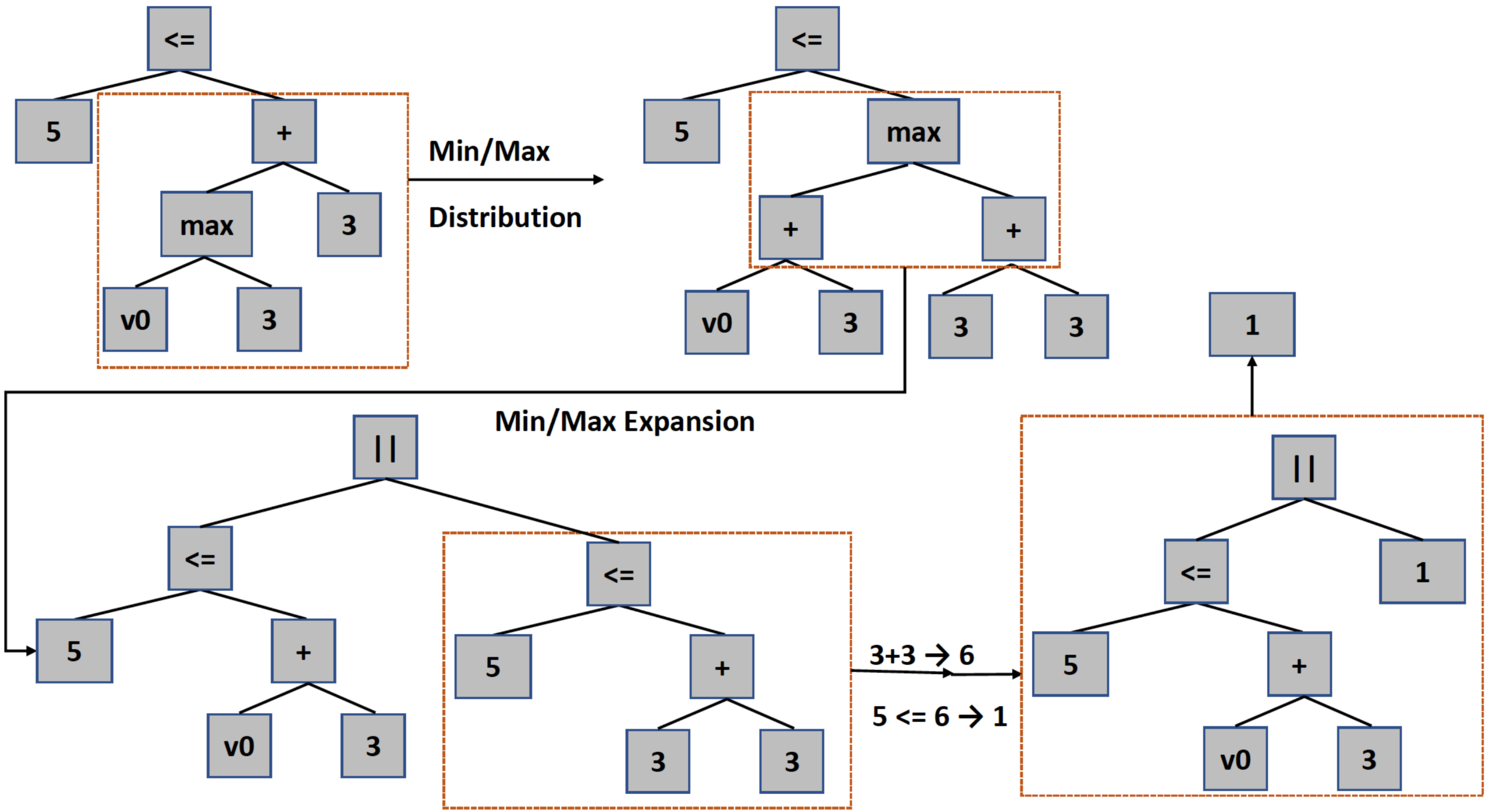
- Google OR-tools (OR-tools)
- SJF-offline

Online Job Scheduling: Ablation Study

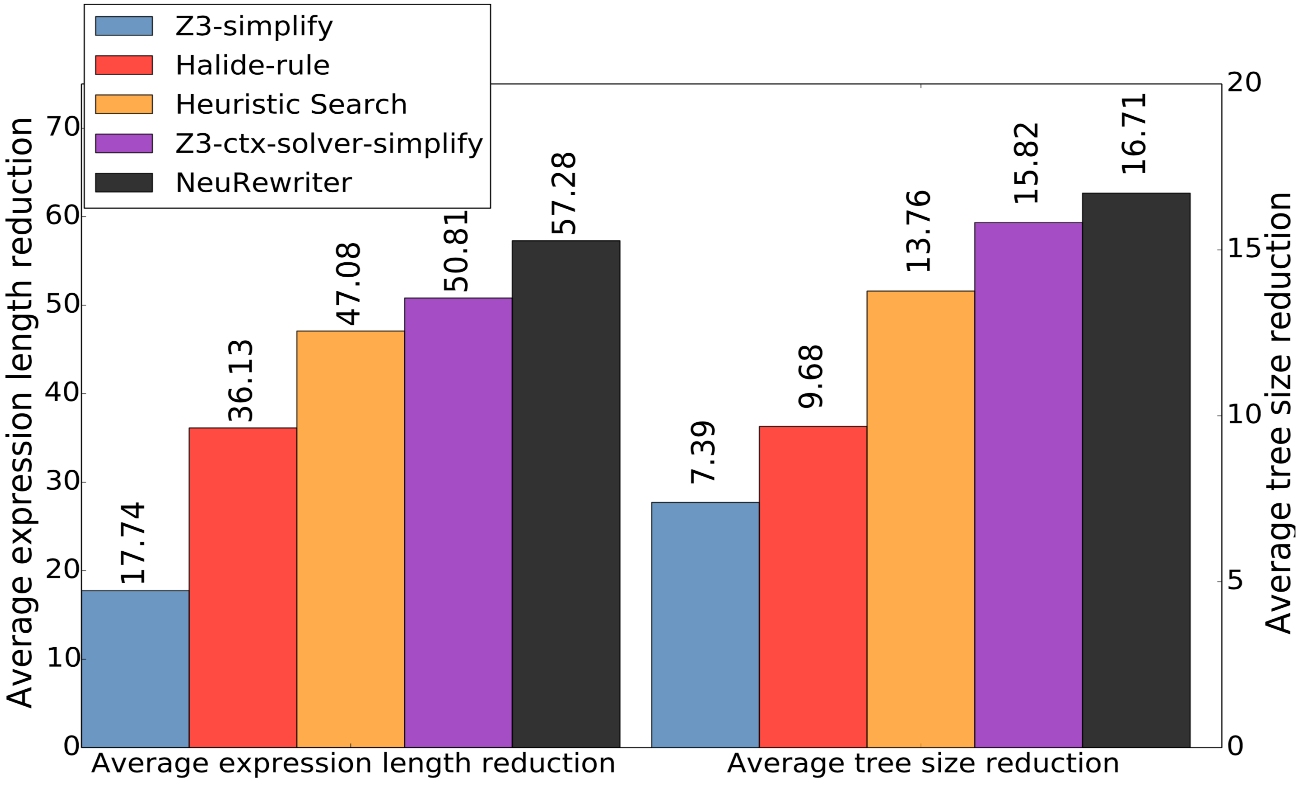
The learned model can generalize to different job distributions.



Expression Simplification



Expression Simplification



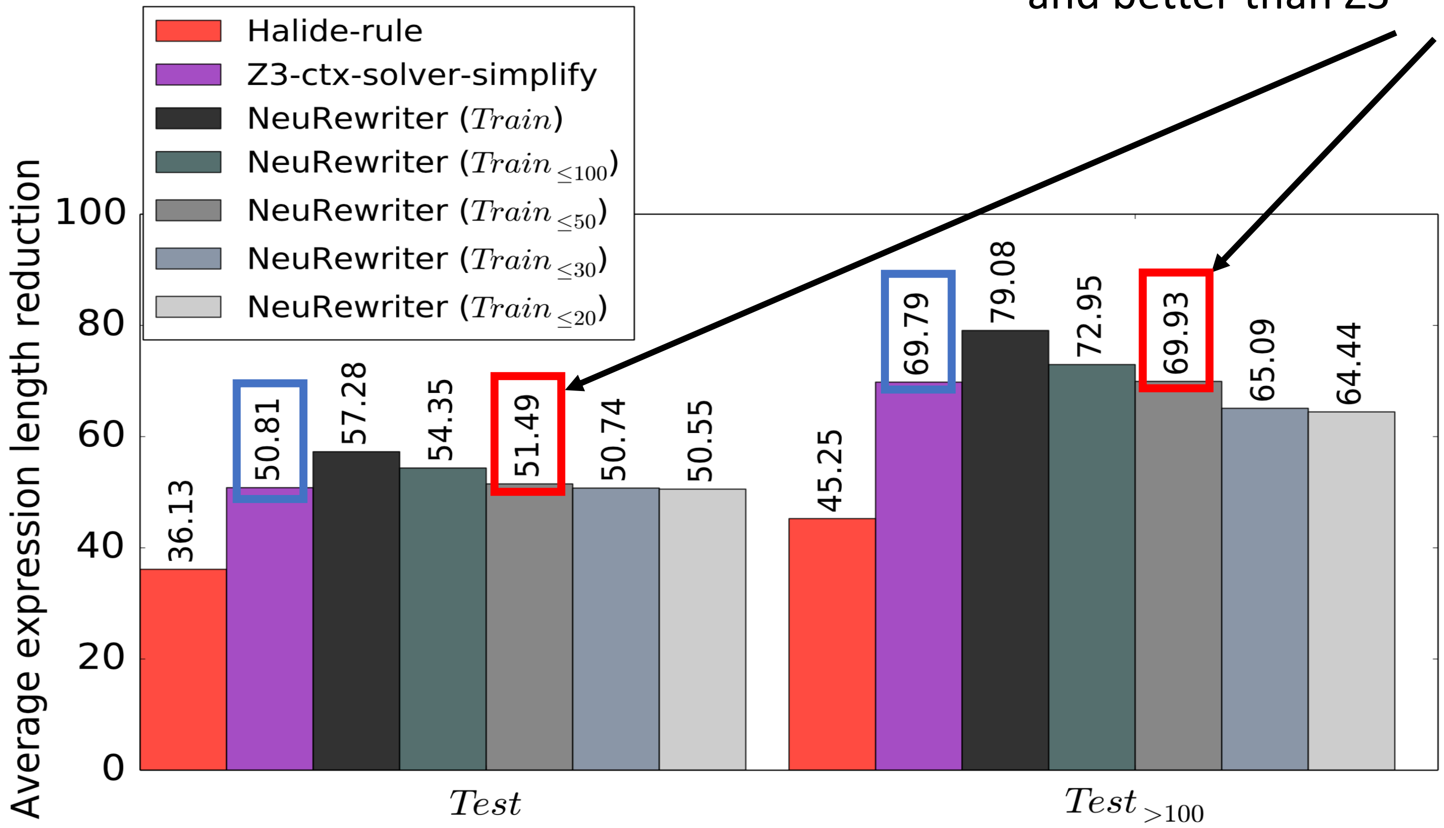
Baselines:

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

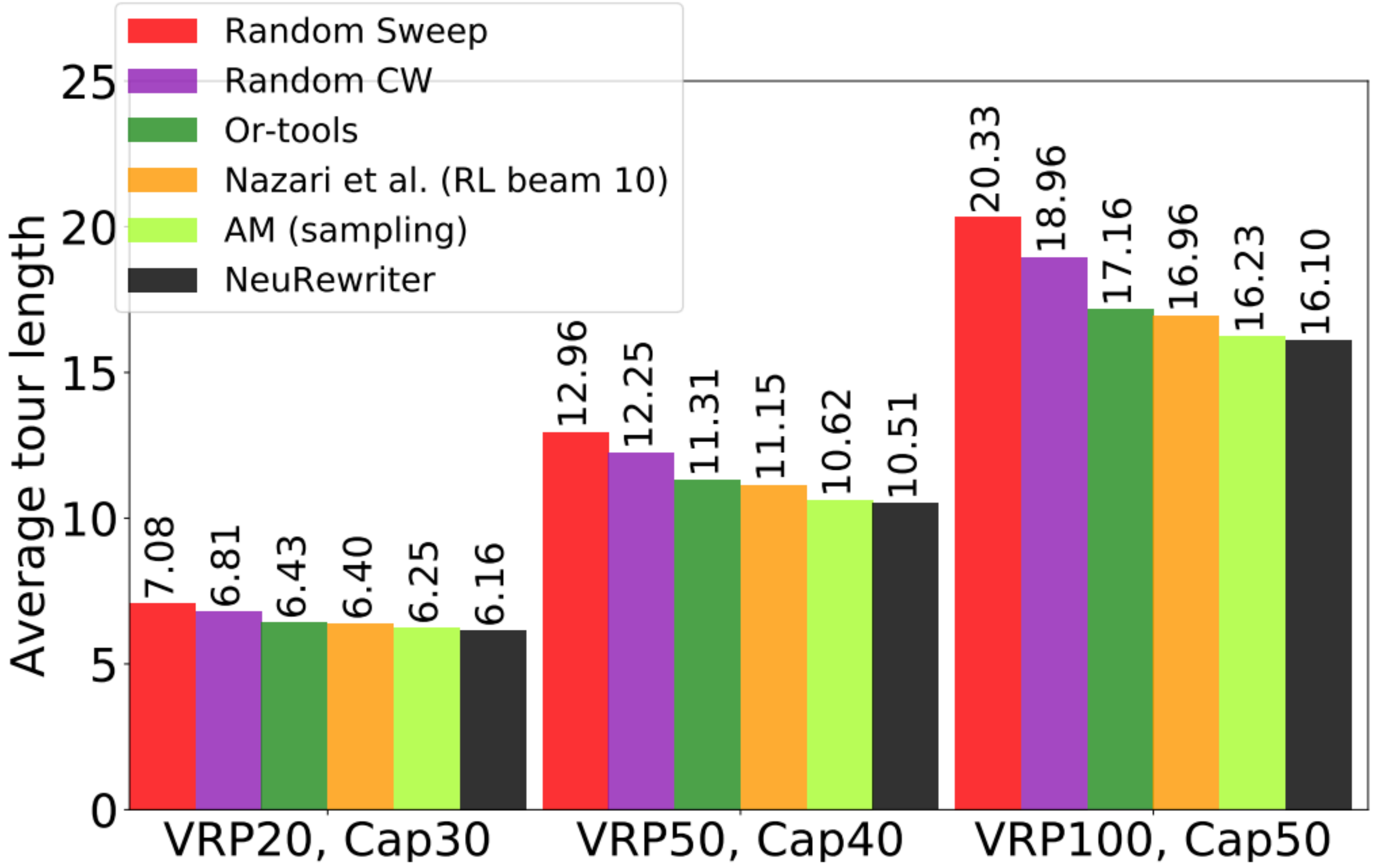
Expression Simplification

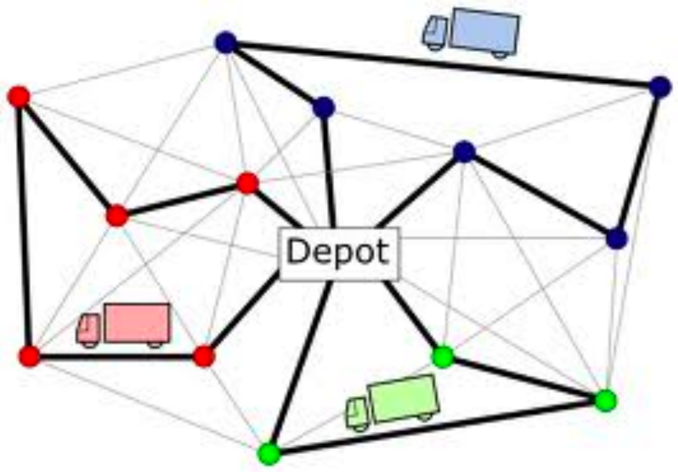
Transfer learning still works well.

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



Capacitated Vehicle Routing





fa

Coda: An End-to-End Neural Program Decomplier

Cheng Fu[1], Huili Chen[1], Haolan Liu[1], Xinyun Chen[3], Yuandong Tian[2], Farinaz Koushanfar[1], Jishen Zhao[1]

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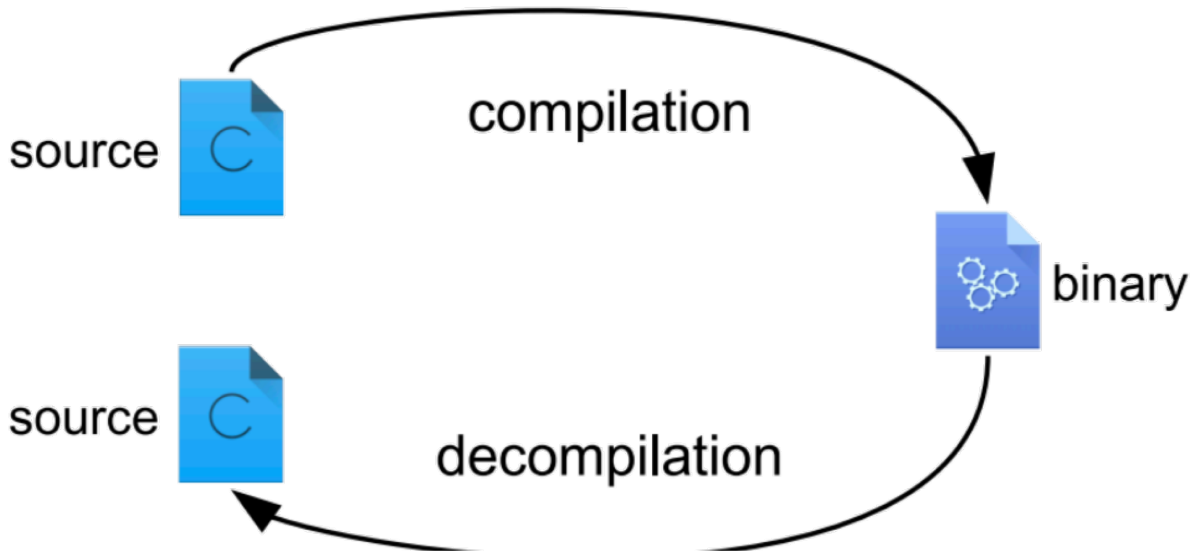
NeurIPS 2019

Background: Decompilation

- Goal of Decompilation
  - From Binary Execution to High-level program language



Challenges

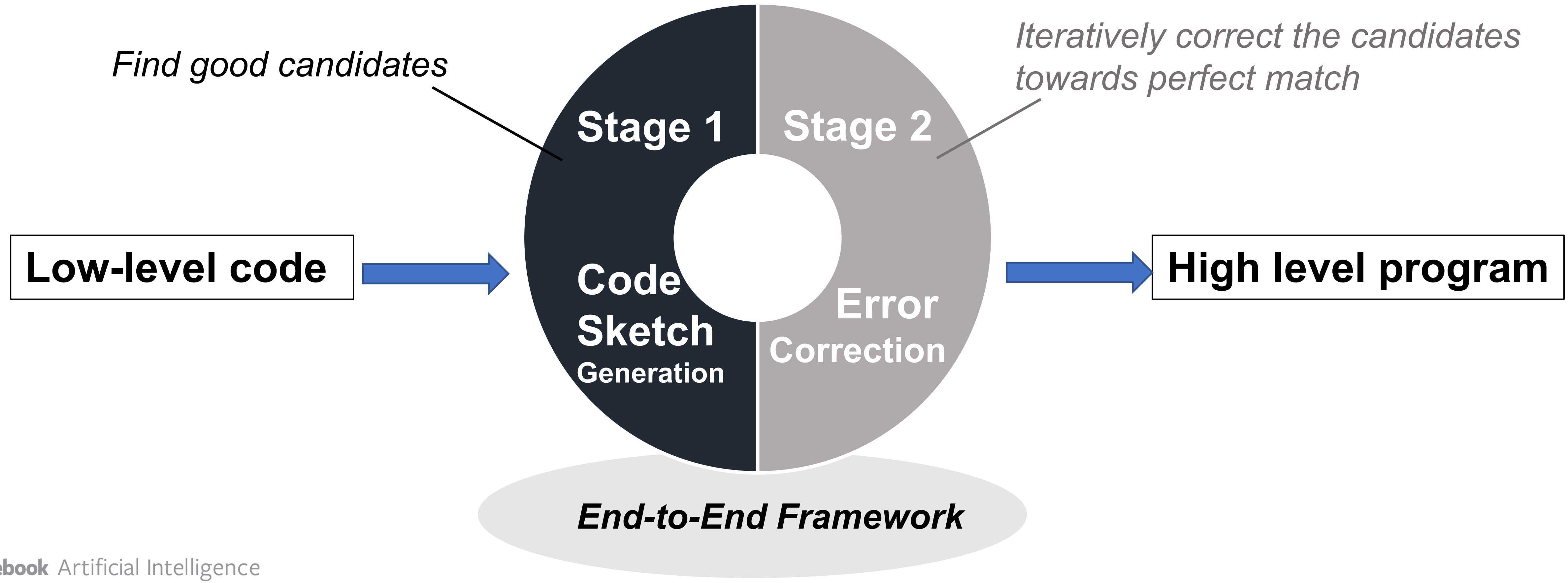
- Many hardware architectures (ISA): x86, MIPS, ARM

- Many Programming Languages (PL)
  - Extra Human effort to extend to the new version of the hardware architectures or programming languages

- Our goals:
  - Maintain both the functionality and semantics of the binary executables
  - Make the design process end-to-end (generalizable to various ISAs and PLs)

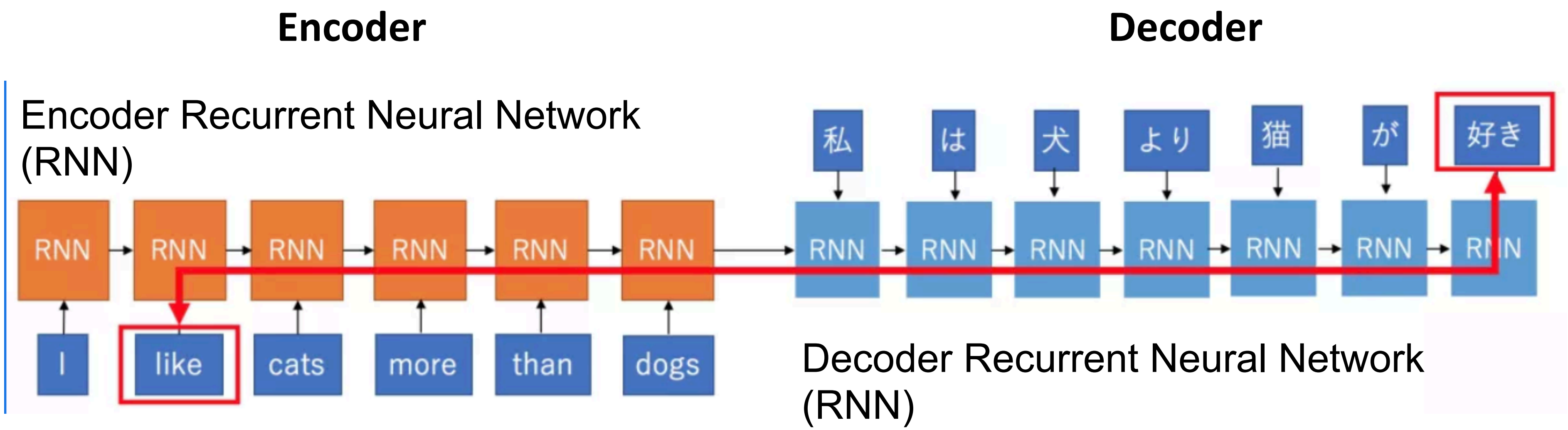
Coda Design

Leverage both syntax and dynamic information



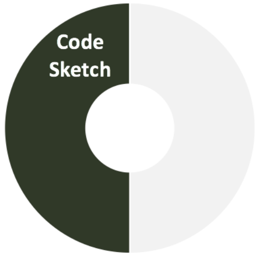
Stage 1: Coda Sketch Generation

- Is Decompilation simply a translation problem?



More than a translation problem!

Stage 1: Coda Sketch Generation

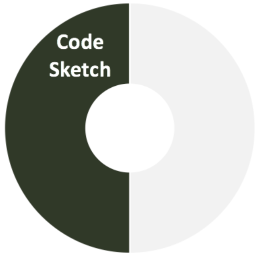


- **Encoder**
  - N-ary Tree Encoder to capture **inter** and **intra** dependencies of the low-level code.
  - Opcode and its operands are encoded together
  - Different encoder is used for different instruction types
    - memory (mem)
    - branch (br)
    - arithmetic (art).

```
# source C program
 a = b * c ;
 if( a > c ){
   c = a * c - b;
 }
```

```
lw     $1, 24($fp)      mem h0
lw     $2, 20($fp)      mem h1
mul    $1, $1, $2       art h2
sw     $1, 28($fp)      mem h3
lw     $1, 28($fp)      mem h4
lw     $2, 20($fp)      mem h5
slt    $1, $2, $1       art h6
beqz   $1, $BB0_3        br h7
j  $B2                   br h8
$B2:                     br h9
lw     $1, 28($fp)      mem h10
lw     $2, 20($fp)      mem h11
mul    $1, $1, $2       art h12
lw     $2, 24($fp)      mem h13
subu   $1, $1, $2       art h14
j      $B3               br h15
sw     $1, 20($fp)      mem h16
```

Stage 1: Coda Sketch Generation



- **Decoder**
  - Generate Abstract Syntax Tree (AST)
  - AST can be equivalently translated into its corresponding high level Program
  - Advantages:
    - Prevent error propagation/ Preserve node dependency / capture PL grammar
    - Boundaries are more explicit (terminal nodes)
  - Using Attention Mechanism

Stage 2: Iterative Error Correction

- The sketch generated in Stage 1 may contain errors:
  - mispredicted tokens, missing lines, redundant lines

Golden program

```
If( a > c ) {
    a = b + c * a;
    b = a – c;
}
```

Wrongly predicted

```
If( a > b ) {
    a = b + c * a;
    b = a - b;
}
```

Missing lines

```
If( a > c ) {
    a = b + c * a;
}
```

Redundant lines

```
If( a > c ) {
    a = b + c * a;
    b = a;
    b = a;
}
```

Stage 2: Iterative Error Correction

- Correct the error by iterative Error Predictor (EP)
  - Iterative rewriting!
  - Spot errors in the generated assembly codes
  - Fix errors and recompile
  - Repeat 10 times

Experimental Setup

- Compiler configuration: Clang **–O0** (no code optimization)
- Benchmarks:
  - Synthetic programs:
    - **Karel library (Karel)** – only function calls
    - **Math library (Math)** – function calls with arguments
    - **Normal expressions (NE)** – (^,&,*,-,<<,>>,|,% ....)
    - **Math library + Normal expressions (Math+NE)** – replaces the variables in NE with a return value of math function.
- Metrics:
  - Token Accuracy
  - Program Accuracy

Result – Stage 1 Performance

- Token accuracy (%) across benchmarks

Benchmarks	Seq2Seq	Seq2Seq+Attn	Seq2AST+Attn	Inst2seq+Attn	Inst2AST+Attn
Karel_S	51.61	97.13	99.81	98.83	**99.89**
Math_S	23.12	94.85	99.12	96.20	**99.72**
NE_S	18.72	87.36	90.45	88.48	**94.66**
$(\text{Math+NE})_S$	14.14	87.86	91.98	89.67	**97.90**
Karel_L	33.54	94.42	98.02	98.12	**98.56**
Math_L	11.32	91.94	96.63	93.16	**98.63**
NE_L	11.02	81.80	85.92	85.97	**91.92**
$(\text{Math+NE})_L$	6.09	81.56	85.32	86.16	**93.20**

- Highest token accuracy across all benchmarks (96.8% on average) compared to baselines.
- 10.1% and 80.9% margin over a naive Seq2Seq model with and without attention.
- More tolerant to the growth of program length.

Result – Stage 2 Performance

- Program accuracy (%)

BenchMarks	(i) Error Detection		(ii) Befor EC		After EC	
	$s2s$,10	$i2a$,10	$s2s$	$i2a$	$s2s$	$i2a$
Math_S	91.4	94.2	40.1	64.8	91.2	**100.0**
NE_S	83.5	88.7	6.6	12.2	53.0	**78.6**
$(\mathrm{Math+NE})_S$	83.6	90.1	3.5	43.2	63.6	**89.2**
Math_L	87.5	91.3	21.7	51.8	83.9	**99.5**
NE_L	78.1	84.5	0.2	2.6	33.1	**56.4**
$(\mathrm{Math+NE})_L$	80.2	85.3	0.1	4.9	38.3	**67.2**

Baseline

Ours

s2s = sequence-to-sequence with attention

I2a = instruction encoder to AST decoder with attention

Summarization and Future Works

- Summary
  - Gives examples of scalable RL system
  - RL/ML can be used to learn heuristics for system

- Large Open Space Ahead
  - ML captures statistics regularity and leads to better solutions
  - Application to large-scale systems?
  - Theoretical Guarantees?

Thanks!