DeepGo: Predictive Directed Greybox Fuzzing

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- PART 1 Background and Motivation
- PART 2 Design
- PART 3 Evaluations
- PART 4 Conclusion

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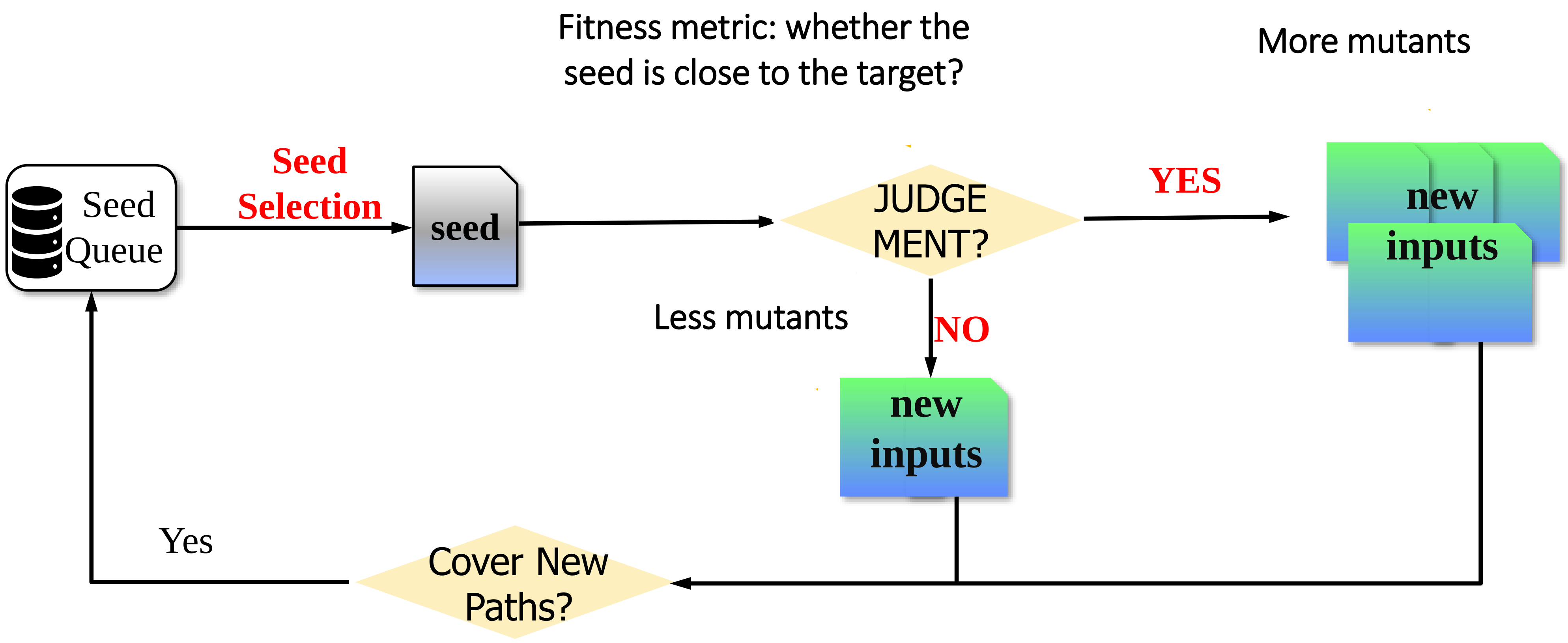
1. Background and Motivation

- **Fuzzing**
  - Effective approach to discovering vulnerabilities
  - e.g., AFL, Google’s OSS Fuzz
- **Directed Greybox Fuzzing (DGF)**
  - Designed technique for testing the given target code locations
  - Patch testing, bug reproduction, potential buggy code verification

1. Background and Motivation

- **Directed Greybox Fuzzing (DGF)**



1. Background and Motivation

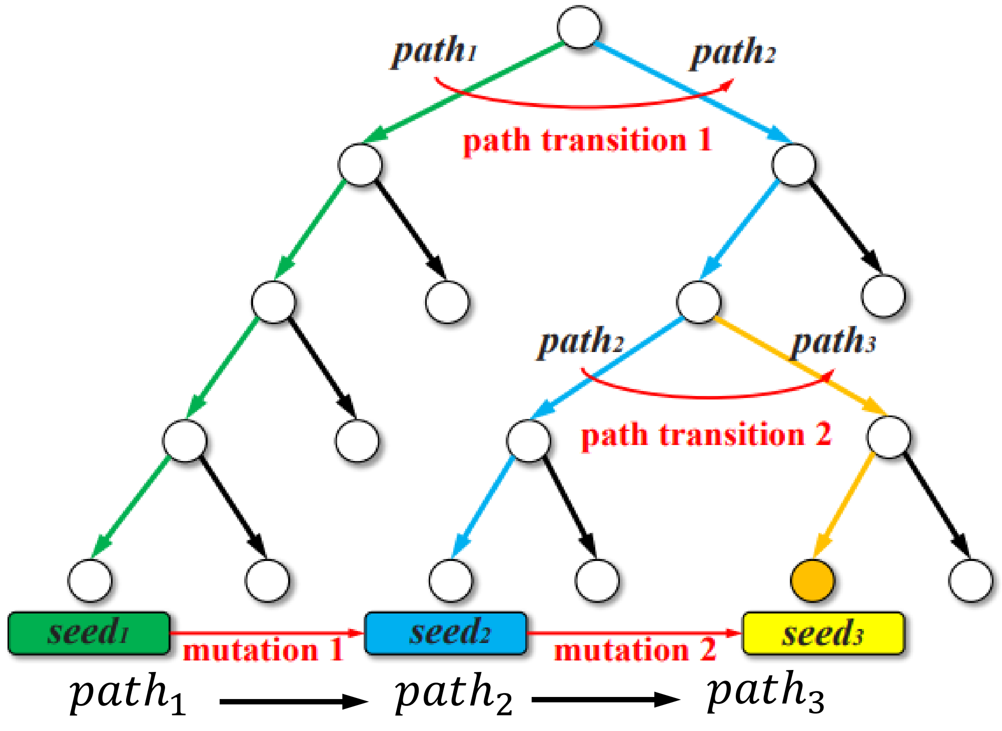
- **State-of-the-art DGF techniques**
  - The state-of-the-art DGF works leverage heuristic methods to optimize fitness metrics or exclude the irrelevant code locations.
    - e.g., BEACON (path pruning), CAFL and WindRanger (data condition)

- **However**
  - Heuristic methods **lack foresight** on paths that have not been exercised yet
  - Hard-to-execute paths with complex constraints would hinder DGF

- **For example**
  - Using BB distance, seeds with shorter distances are prioritized
  - Complex constraints along seeds' paths will hinder fuzzer from reaching targets

1. Background and Motivation

- **Our goal**
  - **Path Transition Model**.
    - Model DGF as a process of reaching the target site through specific path transition sequences.
  - Design a predictive directed greybox fuzzer to **predict the path transitions**.
  - Intelligently generate the optimal and viable path to the target site.



1. Background and Motivation

- **Challenges**
  - ***Challenge 1:*** How to predict path transitions that have not been taken?
  - ***Challenge 2:*** How to determine the optimal path among large numbers of path transitions?
  - ***Challenge 3:*** How to exercise the optimal path transition sequences by optimizing the fuzzing strategies?

1. Background and Motivation

- **Solutions**
  - ***For Challenge 1***
    - Design the **Virtual Ensemble Environment** to imitate the path transition model and predict the path transitions.
  - ***For Challenge 2***
    - Develop the **Reinforcement Learning for Fuzzing model** to learn the policy that can maximize sequence rewards.
  - ***For Challenge 3***
    - Propose the concept of the **action group** and the **MPSO** algorithm to guide the fuzzer to exercise the optimal path transition sequences

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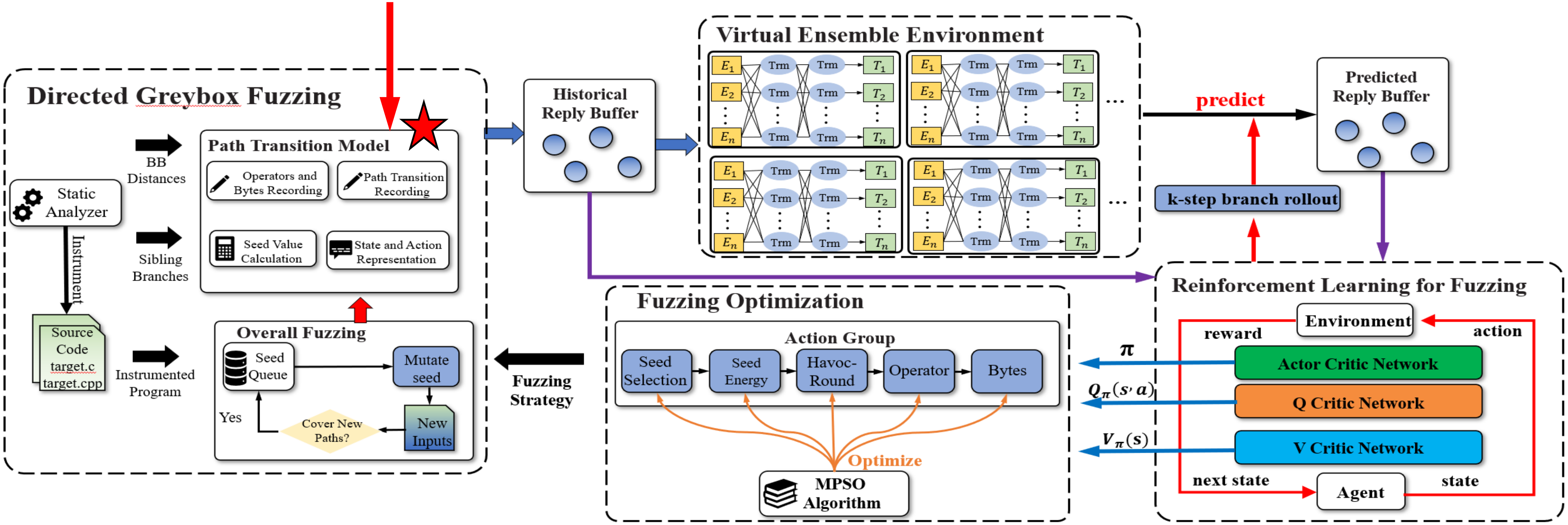
2. Design

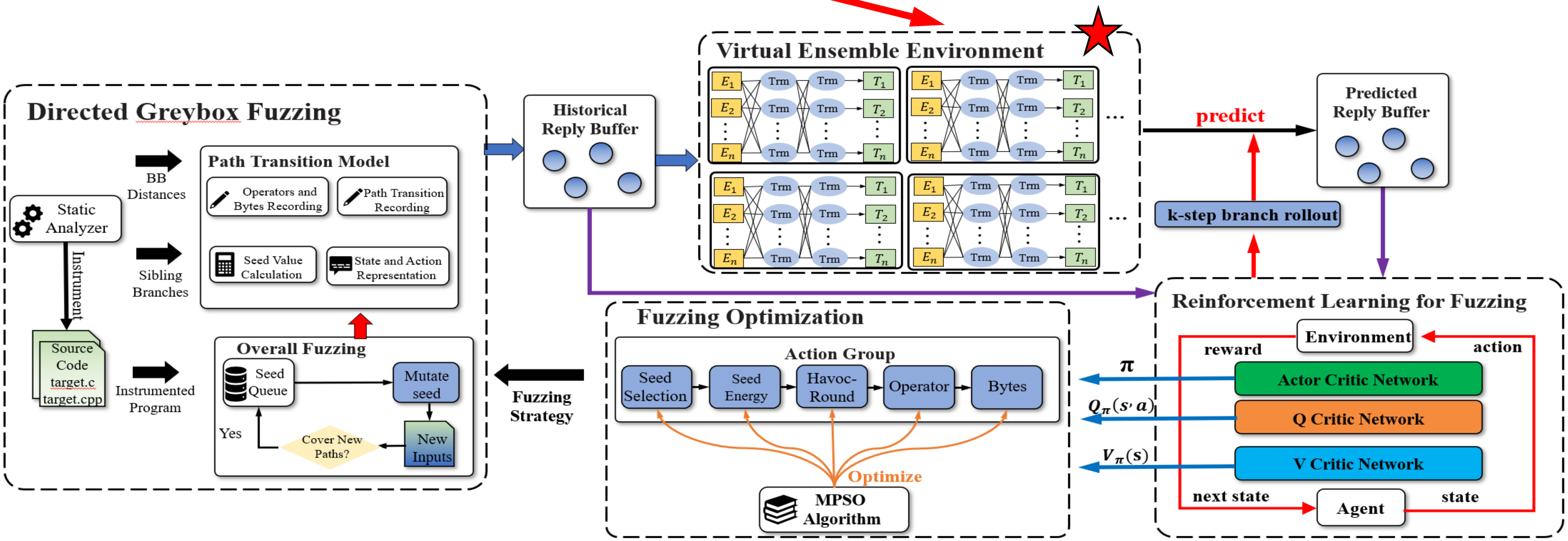
2.1 Overview of DeepGo



2. Design

2.1 Overview of DeepGo

Virtual Ensemble Environment



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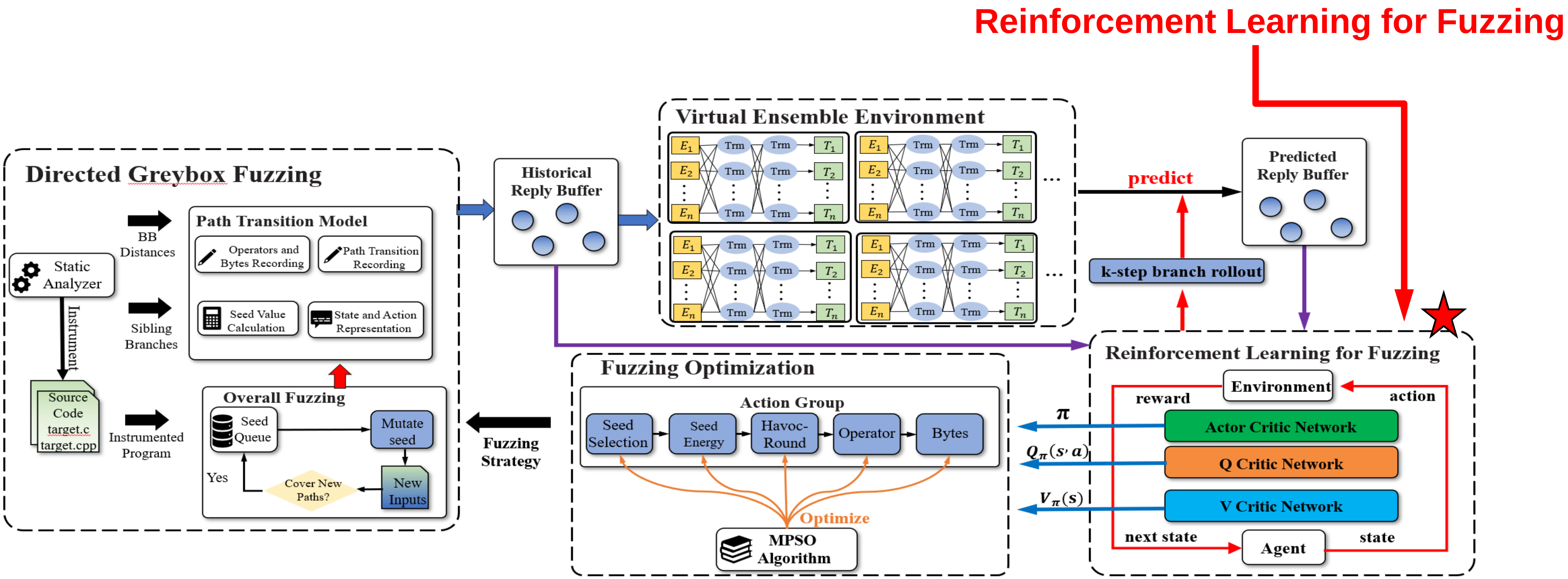

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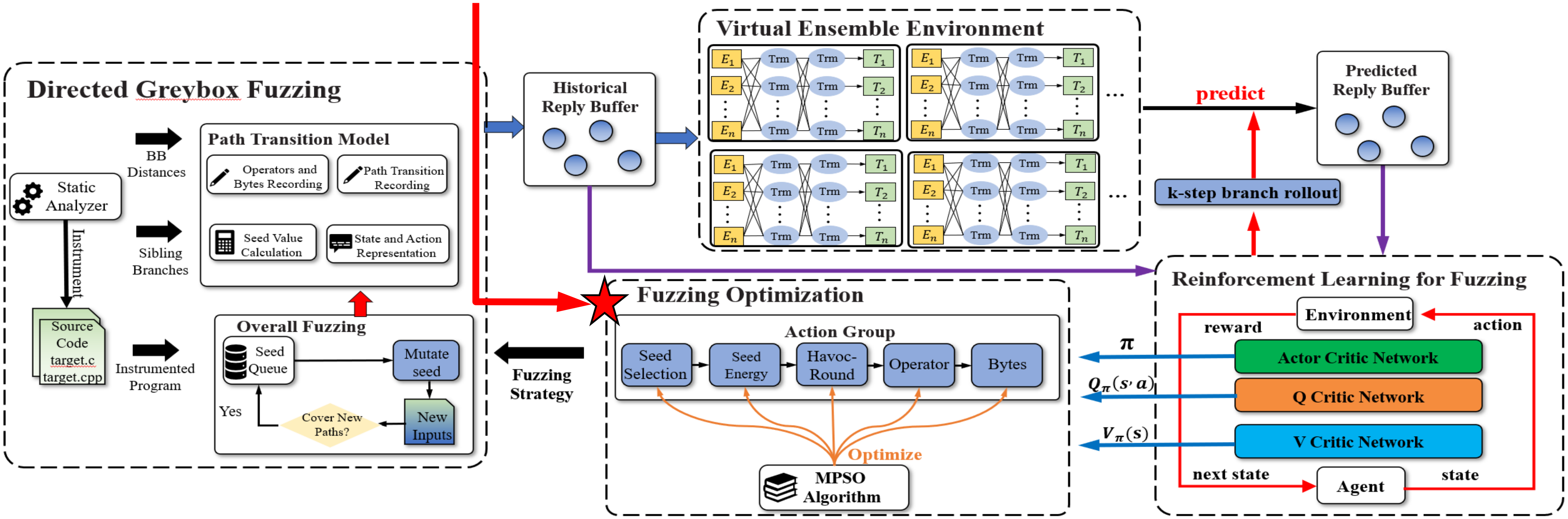
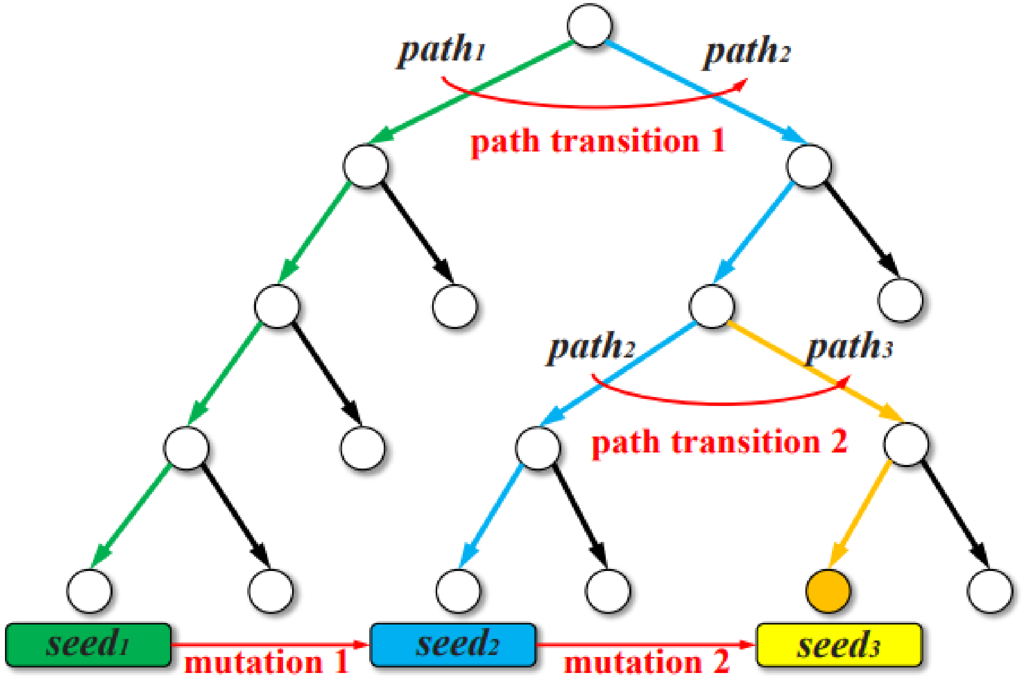


2. Design

2.2 Design of Path transition model



Reward: effectiveness of path transitions

Expected sequence reward: effectiveness of actions

***Seed value (Path value)*：**

(1) seed distance to targets

(2) the difficulty of satisfying the branch inversion

(3) execution speed

(4) “favored”?

$$V^s(p_t) = W_1 \cdot d_s + W_2 \cdot ED_s + W_3 \cdot Ex_s + W_4 \cdot Fv_s$$

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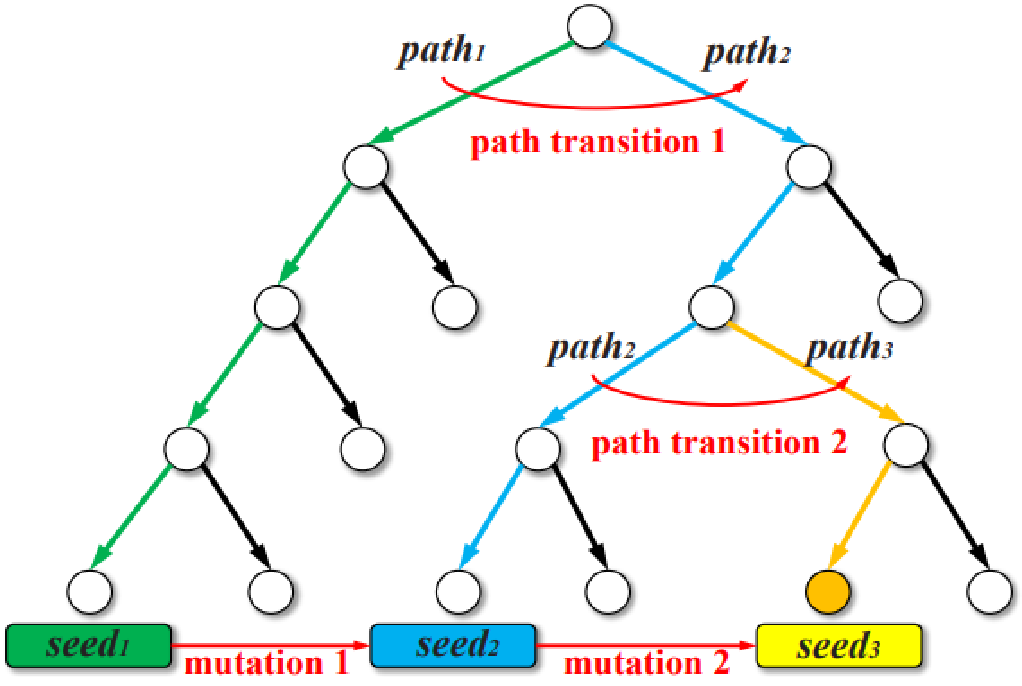


Reward:

$$r(p_t, a_t, p_{t+1}) = V^s(p_{t+1}) - V^s(p_t)$$

Path transition:

$$(p_t, a_t, p_{t+1}, r_t)$$

Expected sequence reward:

$$Q_\pi(p, a) = \underset{p' \sim P}{E}[r(p, a, p') + \gamma V_\pi^t(p')]$$

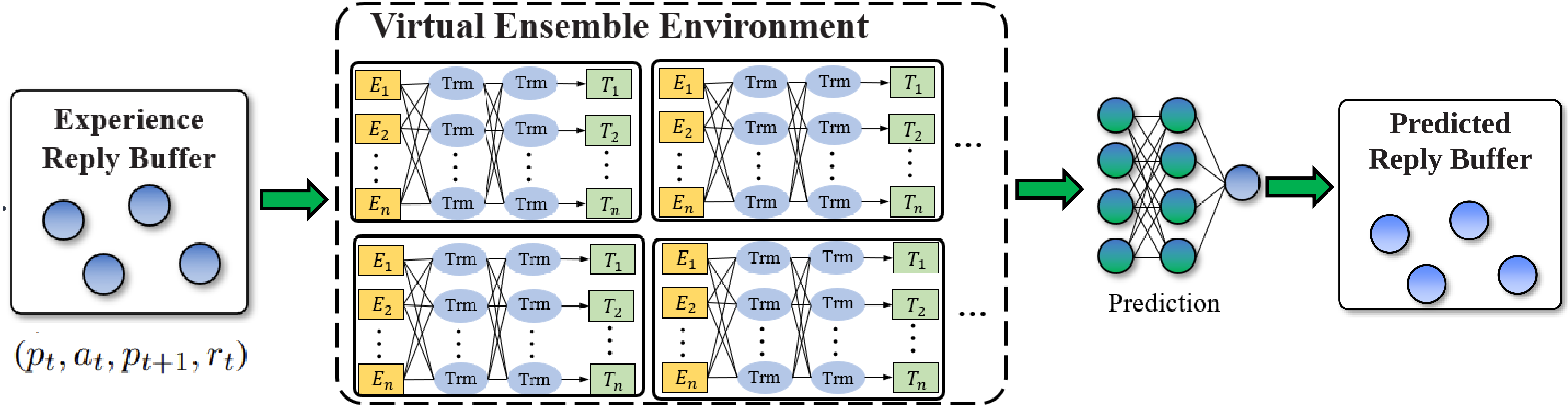
Transition value:

$$V_\pi^t(p') = \begin{cases} 0, & if \;\; p = p_{ter} \\ \sum_a \pi(a|p) \cdot Q_\pi(p', a), & others \end{cases}$$

2. Design

2.3 Design of Virtual Ensemble Environment

- Purpose: predict the potential path transitions and the corresponding rewards.
- Deep neural networks
- Experience reply buffer and predicted replay buffer



2.3 Design of Virtual Ensemble Environment

– Purpose: predict the potential path transitions and the corresponding rewards.

– Deep neural networks

- training: $f{:}(path,\ action) \rightarrow (next\_path,\ reward)$ $\mathbf{X} \longrightarrow \mathbf{Y}$
- Gaussian probability distribution of the next paths and rewards

$$P(p_{t+1}, r_t | p_t, a_t, \theta) = N(\mu_\theta(p_t, a_t), \Sigma_\theta(p_t, a_t))$$

- Average of the probabilities and rewards of DNNs

$$P(p_{t+1}, r_t | p_t, a_t, \theta) = \frac{1}{n} \sum_{i=1}^{n} P(p_{t+1}, r_t | p_t, a_t, \theta_i)$$

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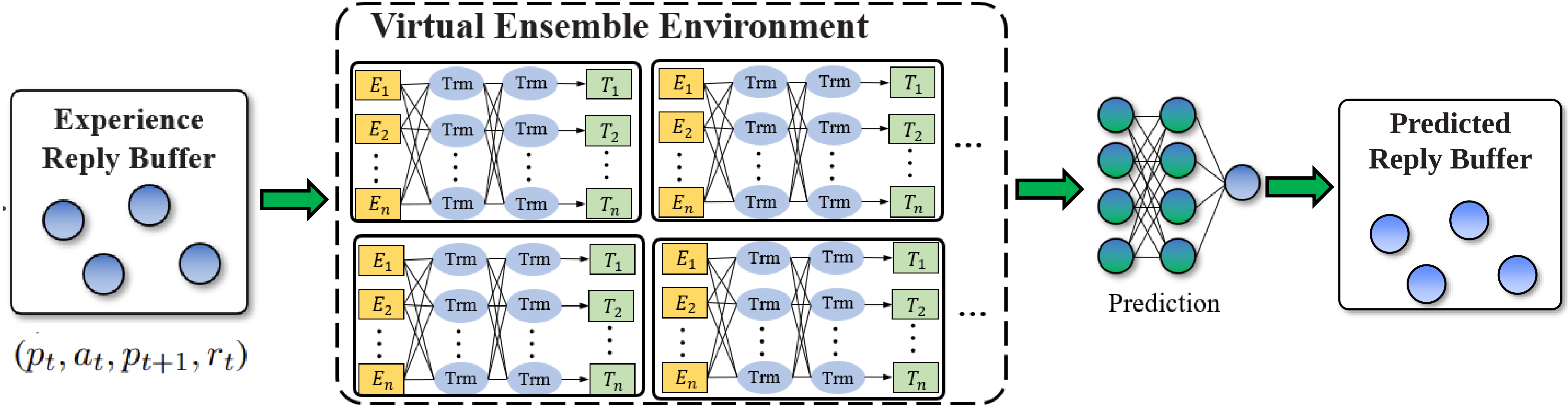

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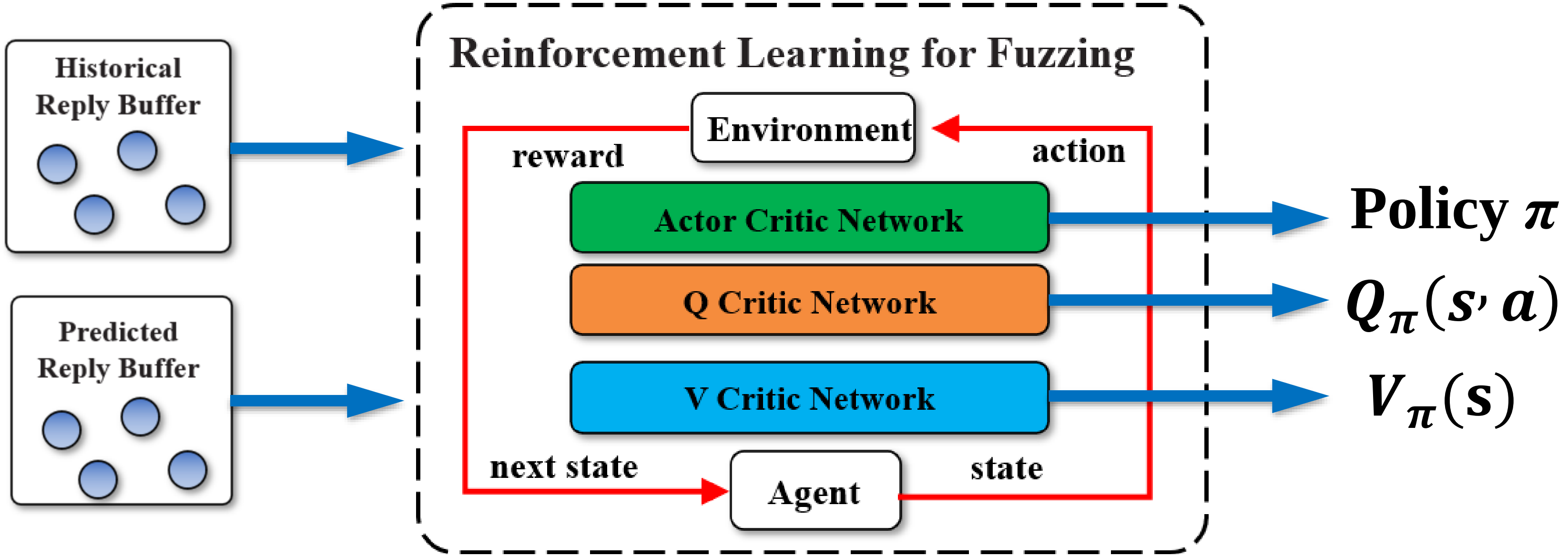
2.4 Reinforcement Learning for Fuzzing Model

– Purpose: learn the policy that can steer the fuzzer toward the high-reward path transition sequences

– Actor network, Q-Critic network, V-Critic network



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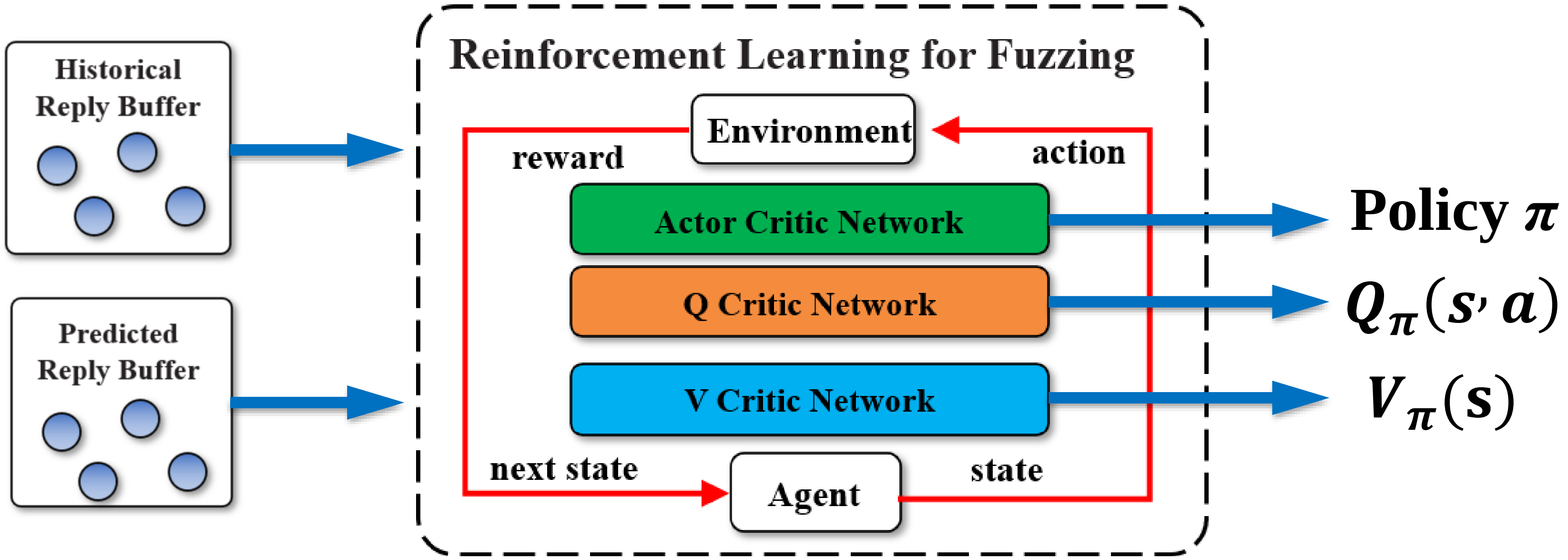


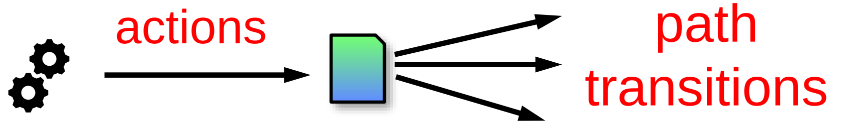
2. Design

2.4 Reinforcement Learning for Fuzzing Model

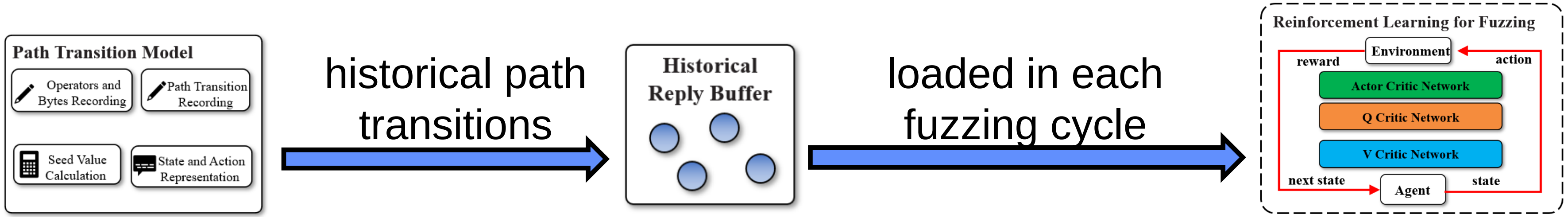
– To give the RLF model foresight, we combine historical path transitions and predicted path transitions to train RLF.

- Historical path transitions:

  - Fuzzer stay on a path and take actions to cause path transitions



  - Historical path transitions are stored in the historical reply buffer and loaded by the RLF model in each fuzzing cycle



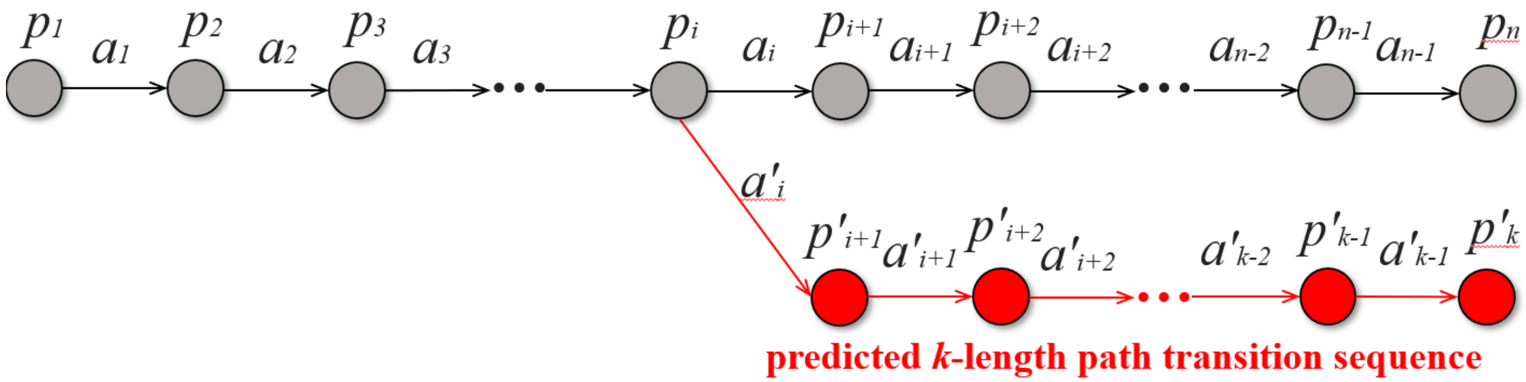
2.4 Reinforcement Learning for Fuzzing Model

– To give the RLF model foresight, we combine historical path transitions and predicted path transitions to train RLF.

- Predicted path transitions:

  - Well-trained VEE imitate path transition model

  - *K*-step branch rollout strategy to obtain predicted path transitions .

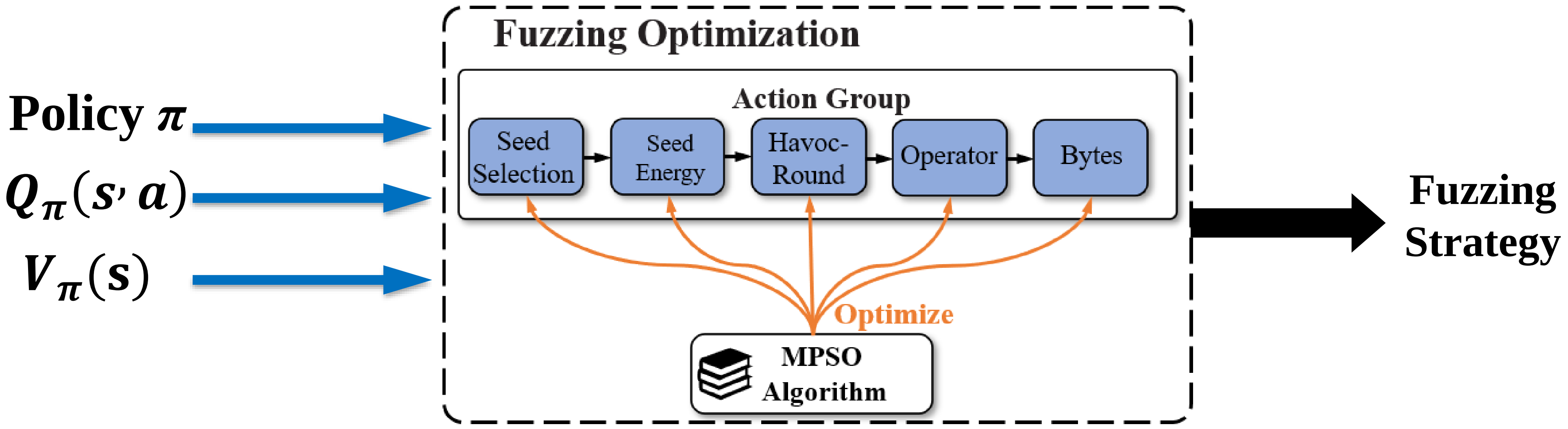


2.5 Fuzzing Optimization

– Purpose: guide the fuzzer to exercise the optimal path transition sequences.

– Action group

– Multi-elements Particle Swarm Optimization (MPSO) algorithm



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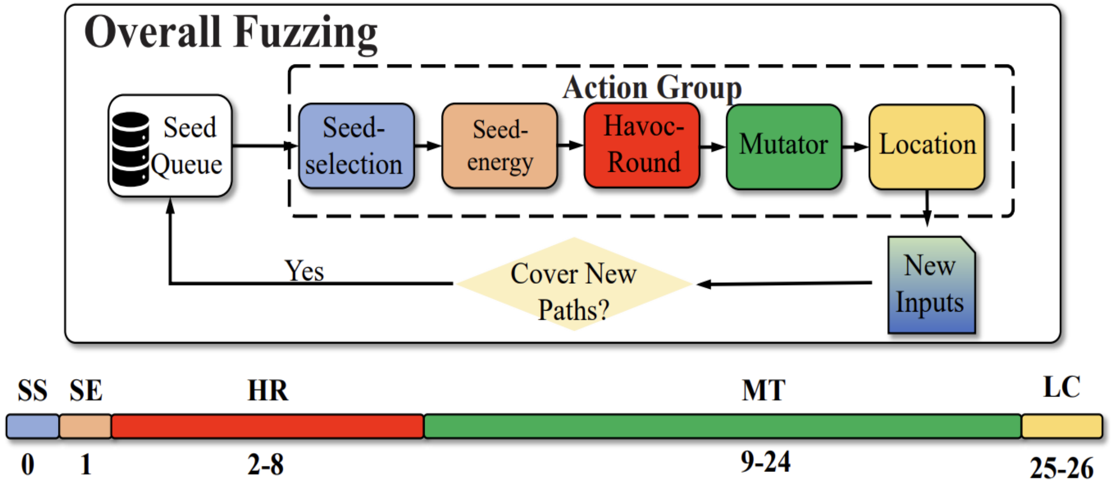


Seed-selection (SS):

- Representing the probability of a seed being selected to fuzz.

Seed-energy (SE) :

- Representing the energy assigned to the seed

Havoc-round (HR) :

- Representing the number of looping rounds used to select different mutators and bytes during the havoc stage.

Mutator (MT) :

- Representing the mutator selected to mutate the seed.

Location (LC) :

- Representing the mutation location of the seed that is selected to mutate

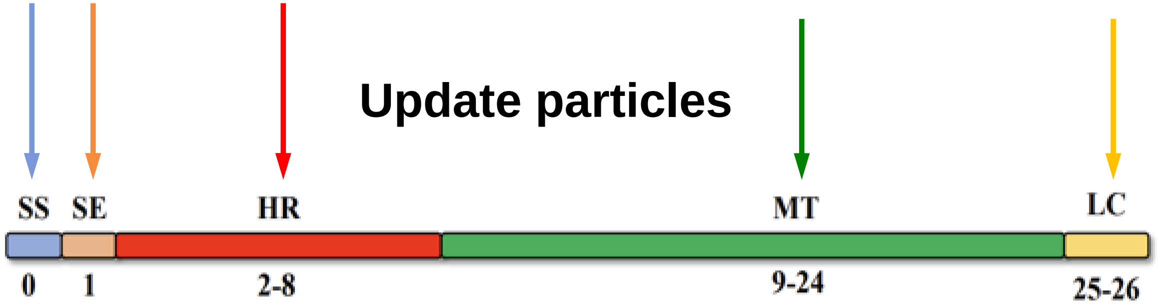
2. Design

2.5 Fuzzing Optimization

– Purpose

– Action group

– Multi-elements Particle Swarm Optimization.



– Update the location to find the local_best and global_best locations for each elements

– Optimize fuzzing strategies to **realize optimal path transition sequences**.

Algorithm 1 MPSO Algorithm

Input: $\Omega_{(s,p)}$
Output: U_s, $\Omega_{(s,p')}$

Initial($\Omega_{(s,p)}$)
while *fuzzing* **do**
  for (s_i, p_i) in $\Omega_{(s,p)}$ **do**
    if $Prob\_Sel_s(p_i(\mathbf{SS}))$ == **True then**
      $mn_i \leftarrow$Cal_MN($p_i(\mathbf{SE})$)
      for j in mn_i **do**
        $hr_j \leftarrow \$Prob\_Sel_h(p_i(\mathbf{HR})$, $hm_j \leftarrow$<>
        for k in hr_j **do**
          $lc_k \leftarrow Prob\_Sel_l(p_i(\mathbf{LC}))$,
          $mt_k \leftarrow Prob\_Sel_m(p_i(\mathbf{MT}))$,
          $hm_j \leftarrow hm_j \cup (lc_k, mt_k)$
        end for
        new_input = Mutate(hm_j, s_i)
        $eff_{local}, eff_{global}$ = Cal_eff(s_i, new_input)
        Update(lbest, gbest, p_i)
      end for
    end if
  end for
end while

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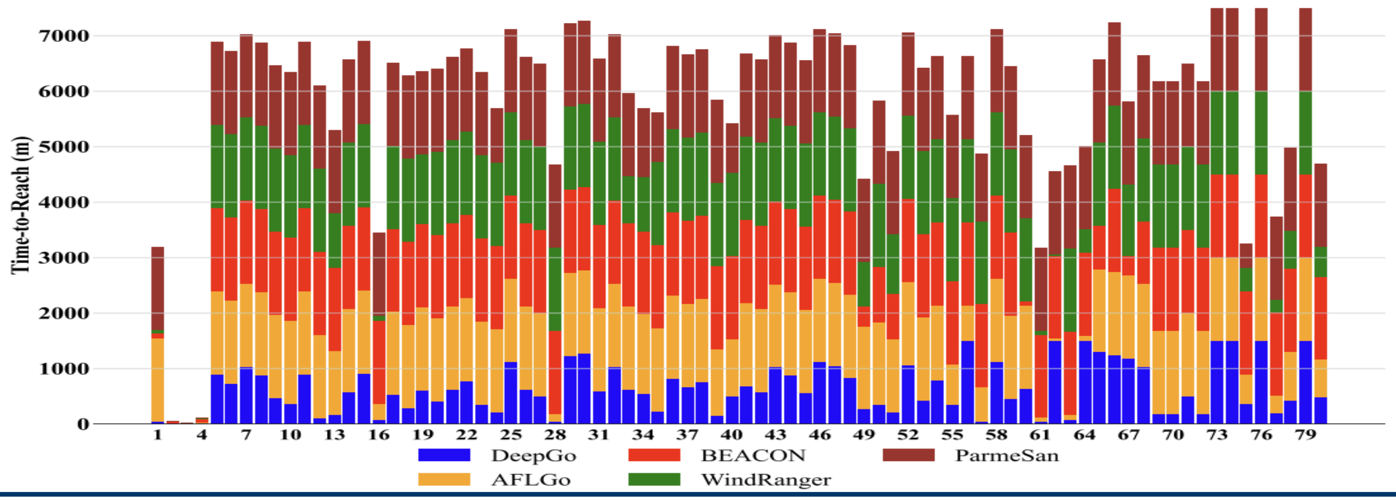
3. Evaluations

- **Benchmarks**
  - UniBench and CVE-Benchmark
  - **25** programs with a total **100** targets
- **Baselines**
  - WindRanger, BEACON, ParmeSan, and AFLGo
- **Evaluation setup**
  - Repeat **5** times
  - Run for **24** hours

3. Evaluations

- **Time-to-Reach (TTR):**
  - DeepGo can reach the most (**73/80**) target sites compared to AFLGo (**22/80**), BEACON (**11/80**), WindRanger (**19/80**), and ParmeSan (**9/80**) within the time budget.
  - DeepGo demonstrates 3.23×, 1.72×, 1.81×, and 4.83× speedup compared to AFLGo, BEACON, WindRanger, and ParmeSan, respectively



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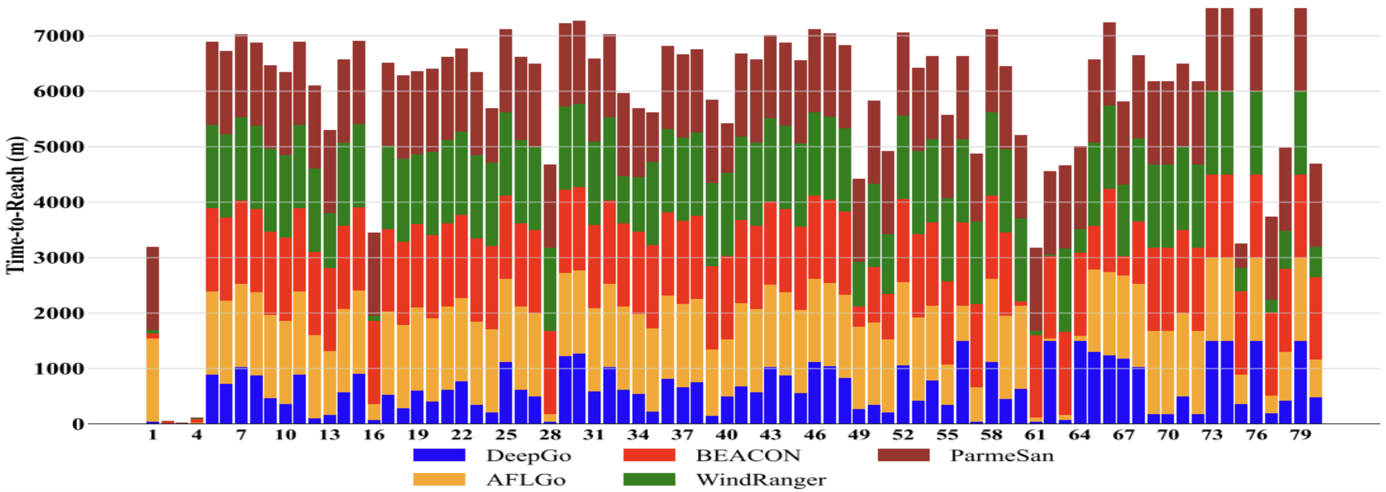

3. Evaluations

- **Time-to-Exposure(TTE):**
  - DeepGo (**19**) exposed the most compared to AFLGo (**14**), BEACON (**13**), WindRanger (**16**), and ParmeSan (**14**).
  - DeepGo demonstrated 2.61×, 3.32×, 2.43× and 2.53× speedup compared to AFLGo, BEACON, WindRanger, and ParmeSan, respectively.

Prog.	**CVE-ID**	AFLGo	BEACON	WindRa	ParmeS	DeepGo
$\text{binutils}_{2.26}$	2016-4487	2.33m	0.63m	1.21m	0.95m	1.34m
	2016-4488	4.23m	32.1m	3.32m	2.62m	2.69m
	2016-4489	3.36m	2.98m	5.88m	2.31m	1.23m
	2016-4490	1.15m	2.35m	2.63m	0.82m	1.97m
	2016-4491	448m	258m	298m	212m	129m
	2016-4492	10.8m	43.6m	7.47m	4.33m	6.94m
	2016-6131	348m	292m	318m	244m	68.1m
$\text{libming}_{4.48}$	2018-8807	331m	267m	171m	301m	101m
	2018-8962	234m	163m	121m	198m	54.8m
	2018-11095	T.O.	914m	1311m	T.O.	812m
	2018-11225	T.O.	438m	996m	T.O.	128m
$\text{LibPNG}_{1.5.1}$	2011-2501	10.2m	N/A	7.81m	4.53m	3.46m
	2011-3328	69.1m	N/A	49.3m	193m	17.5m
	2015-8540	0.88m	N/A	0.96m	3.41m	5.65m
$\text{xmllint}_{2.9.4}$	2017-9047	T.O.	T.O.	T.O.	T.O.	783m
	2017-9048	T.O.	T.O.	T.O.	T.O.	1389m
	2017-9049	T.O.	T.O.	T.O.	T.O.	T.O.
	2017-9050	T.O.	T.O.	T.O.	T.O.	911m
$\text{Lrzip}_{0.631}$	2017-8846	348m	156m	223m	466m	131m
	2018-11496	201m	98.1m	169m	126m	78.9m
speedup		**2.61×**	**3.32×**	**2.43×**	**2.53×**	-
mean $\hat{A}_{12}$		**0.79**	**0.72**	**0.75**	**0.81**	-
mean p-values		0.018	0.032	0.026	0.011	-

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3. Evaluations

- **Ablation study:**
  - Run DeepGo, DeepGo-v and DeepGo-r on UniBench for the TTR experiment
    - DeepGo-v: remove VEE from DeepGo
    - DeepGo-r: remove RLF and FO from DeepGo
  - DeepGo (73/80) can reach much more target sites than DeepGo-v (32/80) and DeepGo-r (18/80), respectively
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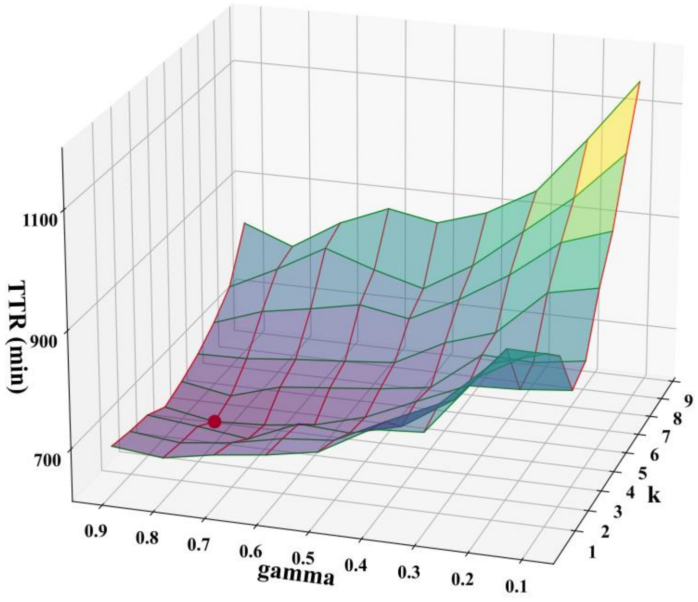
3. Evaluations

- **Setting of hyperparameters:**
  - Utilize DeepGo with different hyperparameter configurations to test 20 programs from UniBench and recorded the mean TTR for each test case
  - **γ = 0.8** and **k = 4** can achieve minimum TTR
  - The setting of γ and k has a relatively small impact on TTR if the value of **γ is between [0.5, 0.9]**, and the value of **k is between [3, 5]**



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Thank you !

If you have some questions about our work,
welcome to contact us!

Email: phlin22@nudt.edu.cn

Artifact of DeepGo: https://gitee.com/paynelin/DeepGo

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