Compiler Test-Program Generation via Memoized Configuration Search

Junjie Chan, Chenyao Suo, Jiajun Jiang, Peiqi Chen, Xingjian Li

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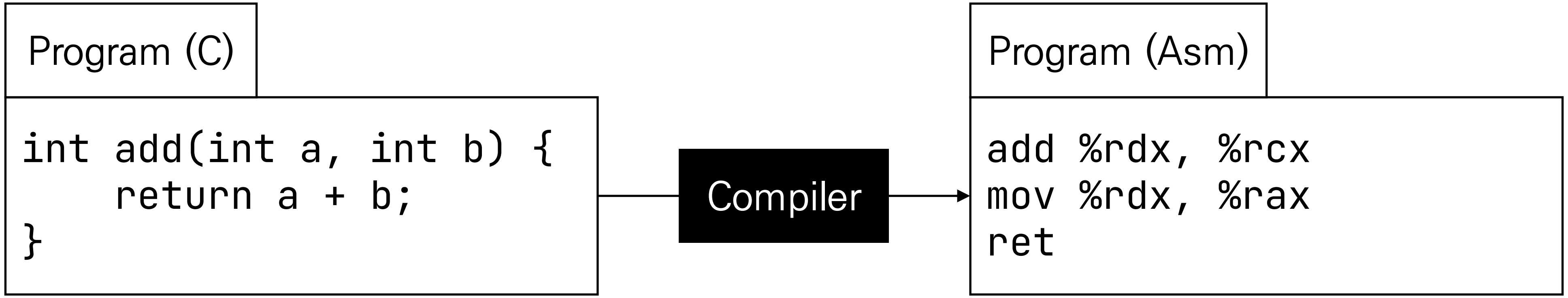

Bugs in Compiler

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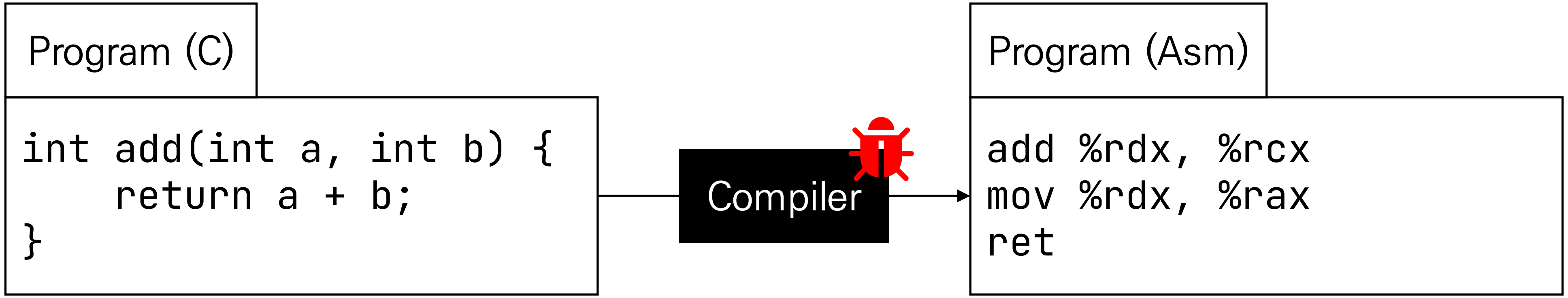

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- Unexpected Behavior
- Aggravate debugging difficulty

Solution: Test Configuration Exploration

- MCS: memorized configuration search
- Attached to test program generators

- Found 16 new bugs on GCC and LLVM
- Outperformed preexisting approaches
  - Detected ~2× more bugs
- Has been deployed in *Huawei* for testing their in-house compiler

Ensuring Quality of Compilers

- Compiler testing
  - Test-program generators (e.g., Csmith [1])

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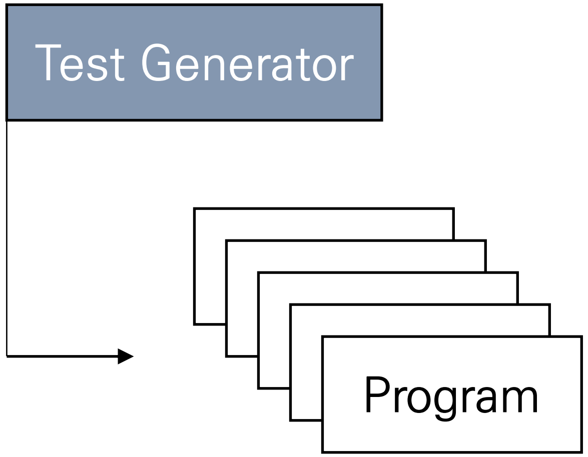

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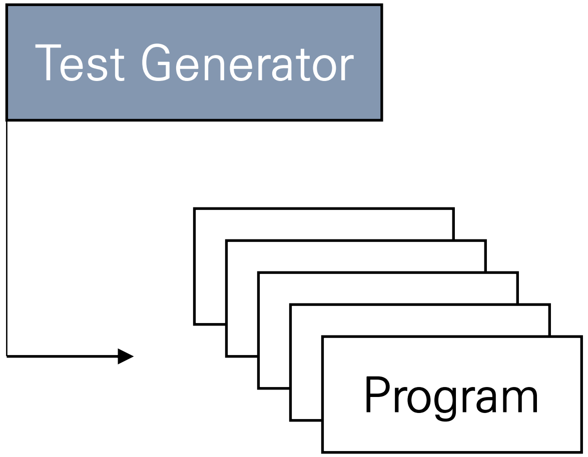


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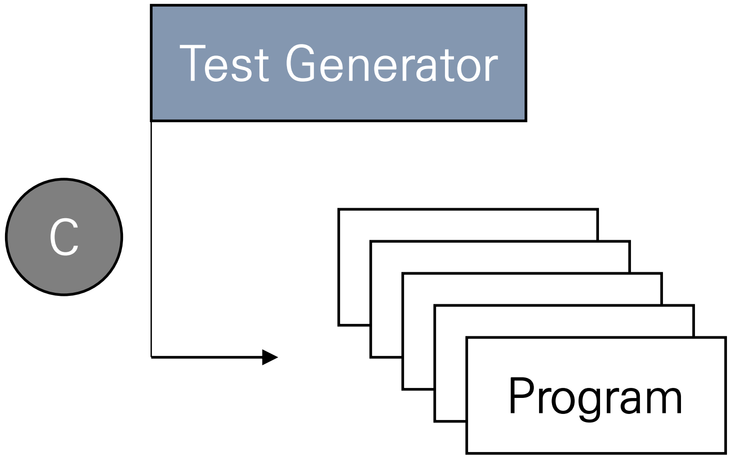


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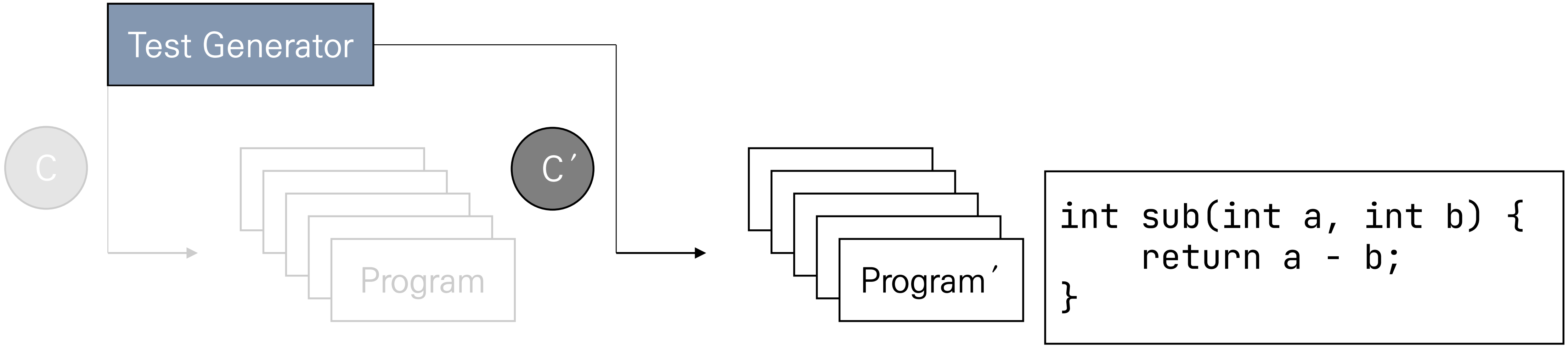

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- Relying on only one (default) test configuration is not enough
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Key observation

- **Options in configuration require elaborate coordination.**

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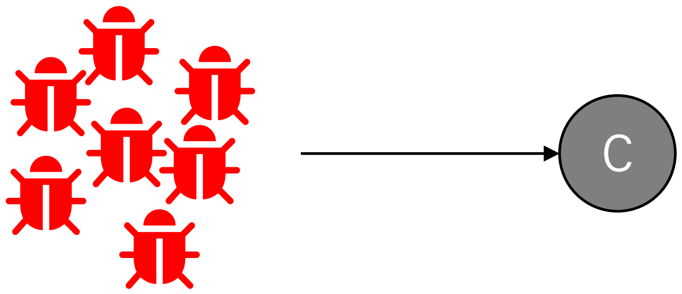

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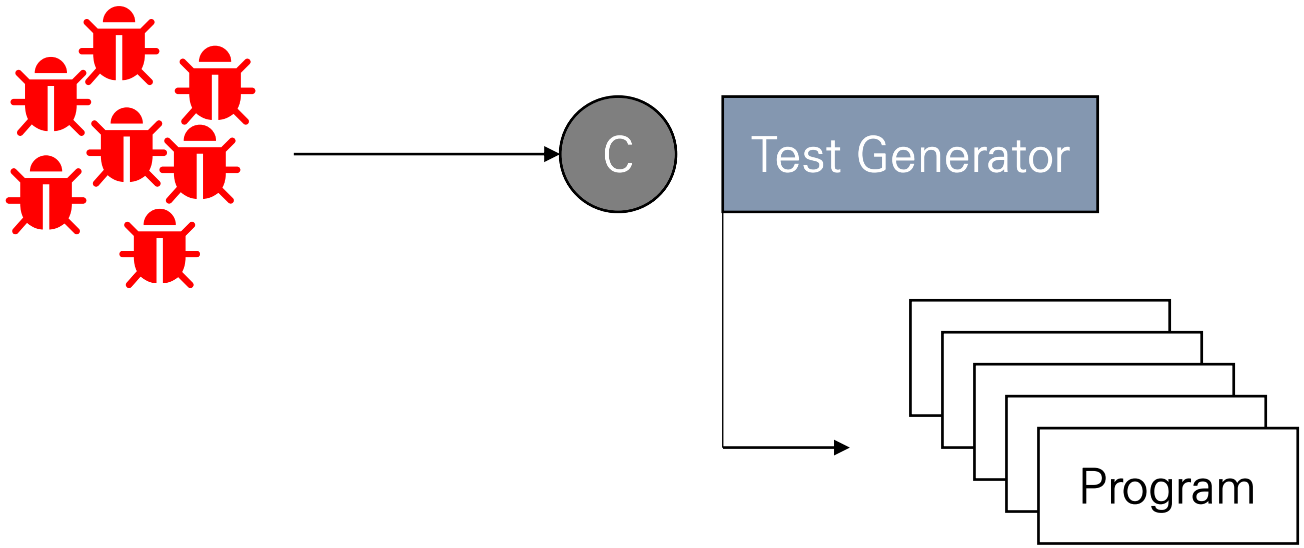

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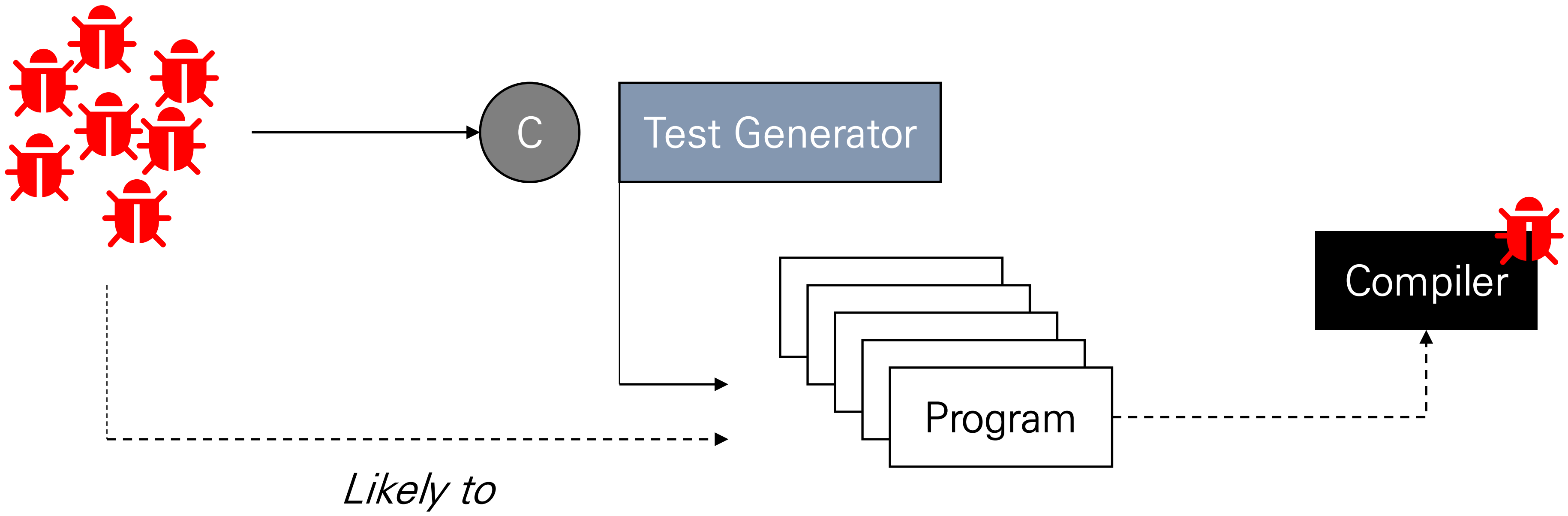

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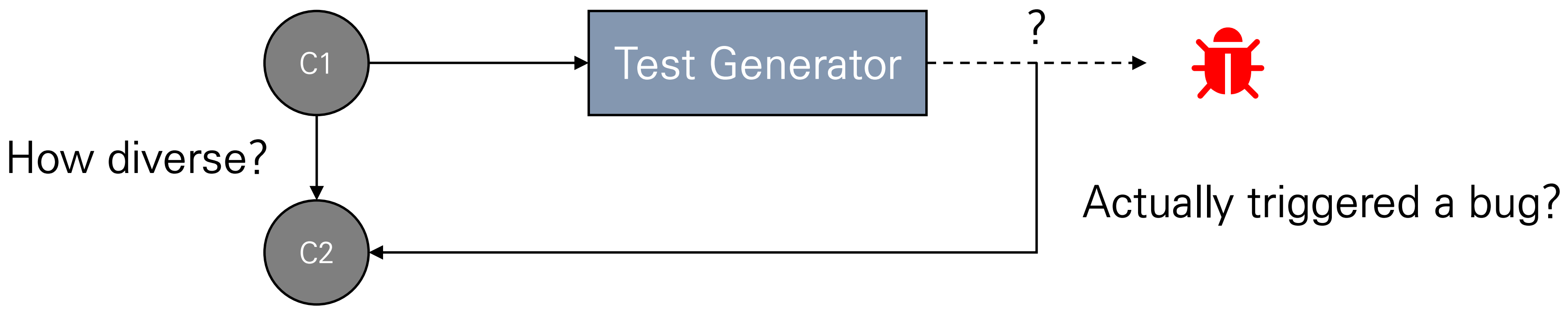

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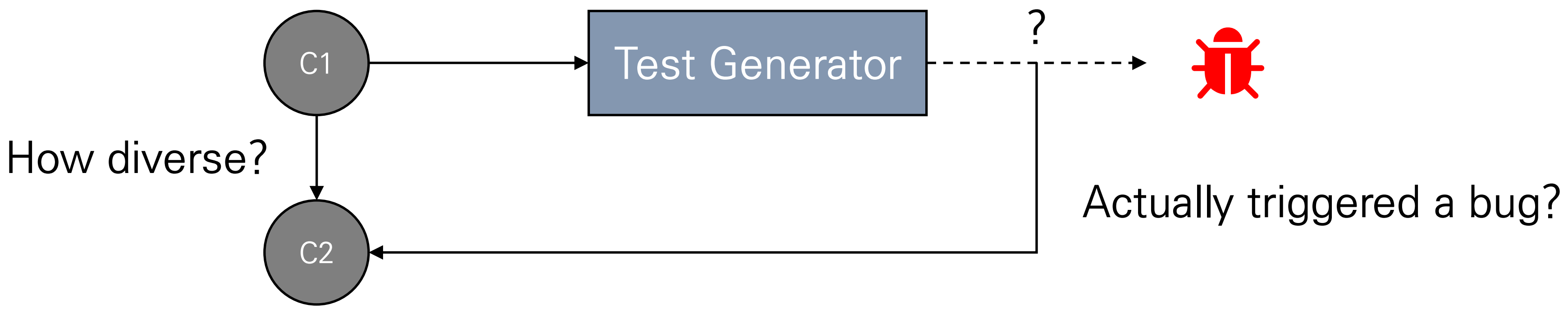

Multi-agent Reinforcement Learning

- "…. MCS innovatively adopt the *multi-agent RL* method to achieve our search goal. …"
- Wait, what is that?

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- Agents learn an optimal control policy that interact with unknown environment
  - Choosing sequence that maximizes cumulative reward in a long run

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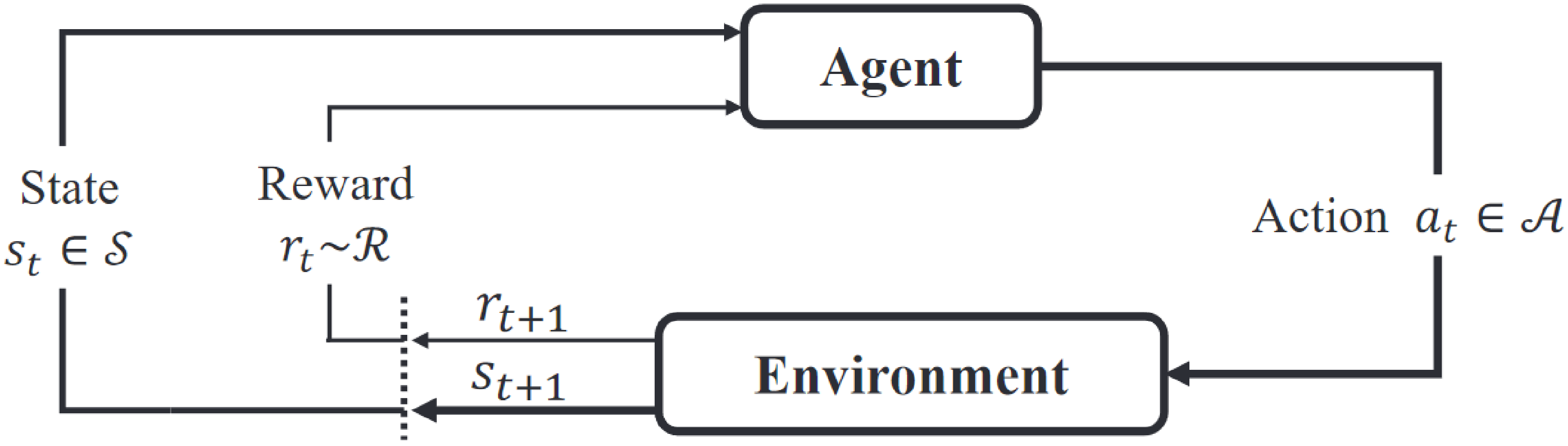

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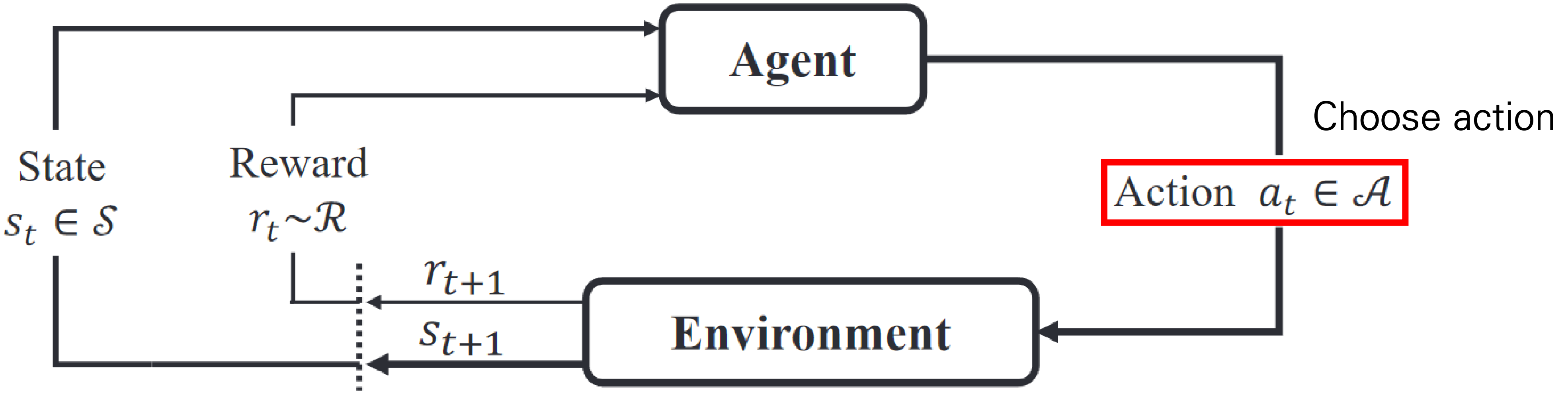

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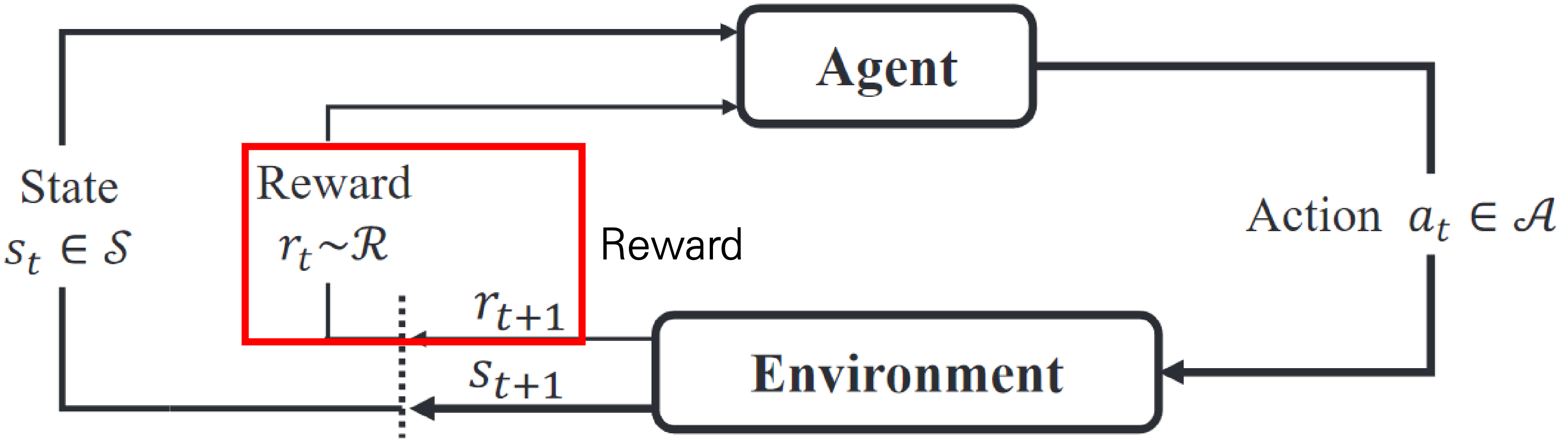

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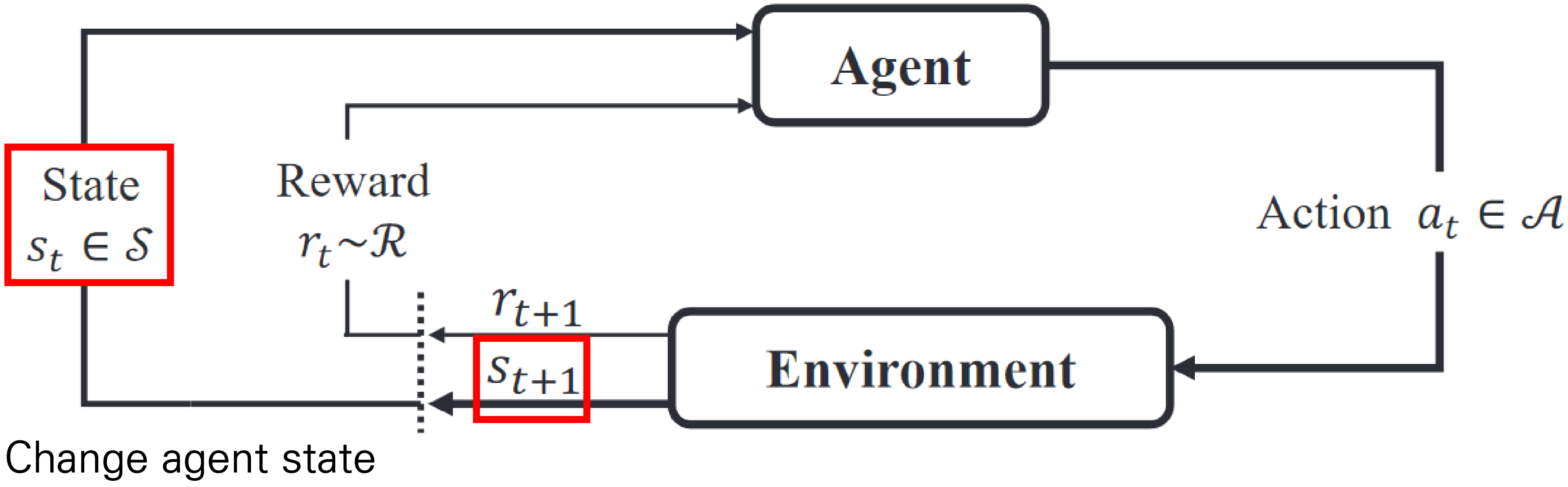

Reinforcement Learning

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- Questions:
  - Why choose RL?
  - What is multi-agent RL and why choose multi-agent RL?

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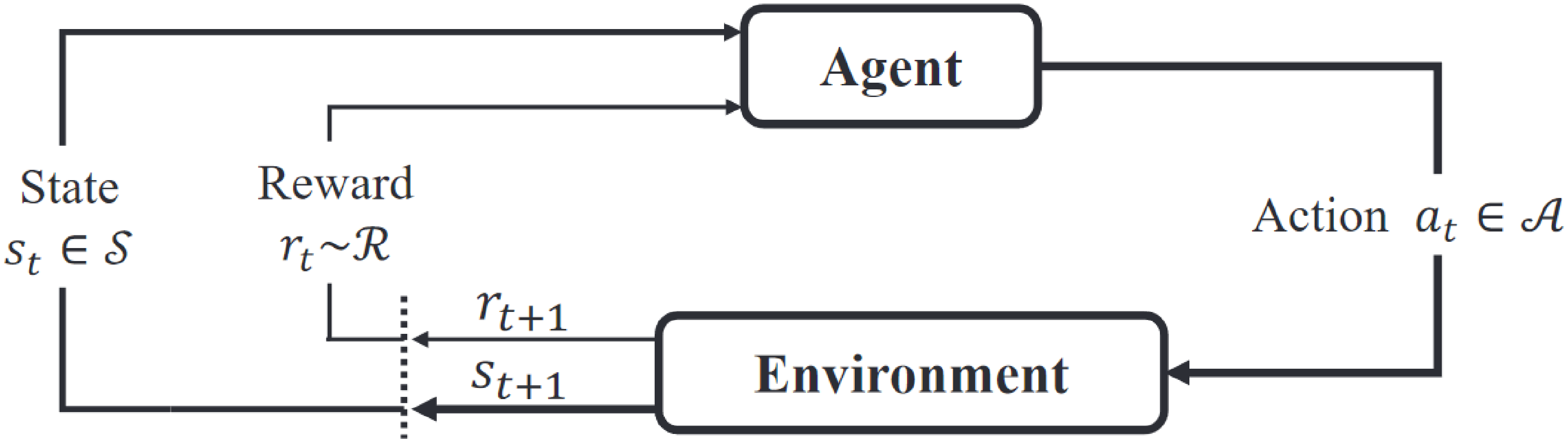

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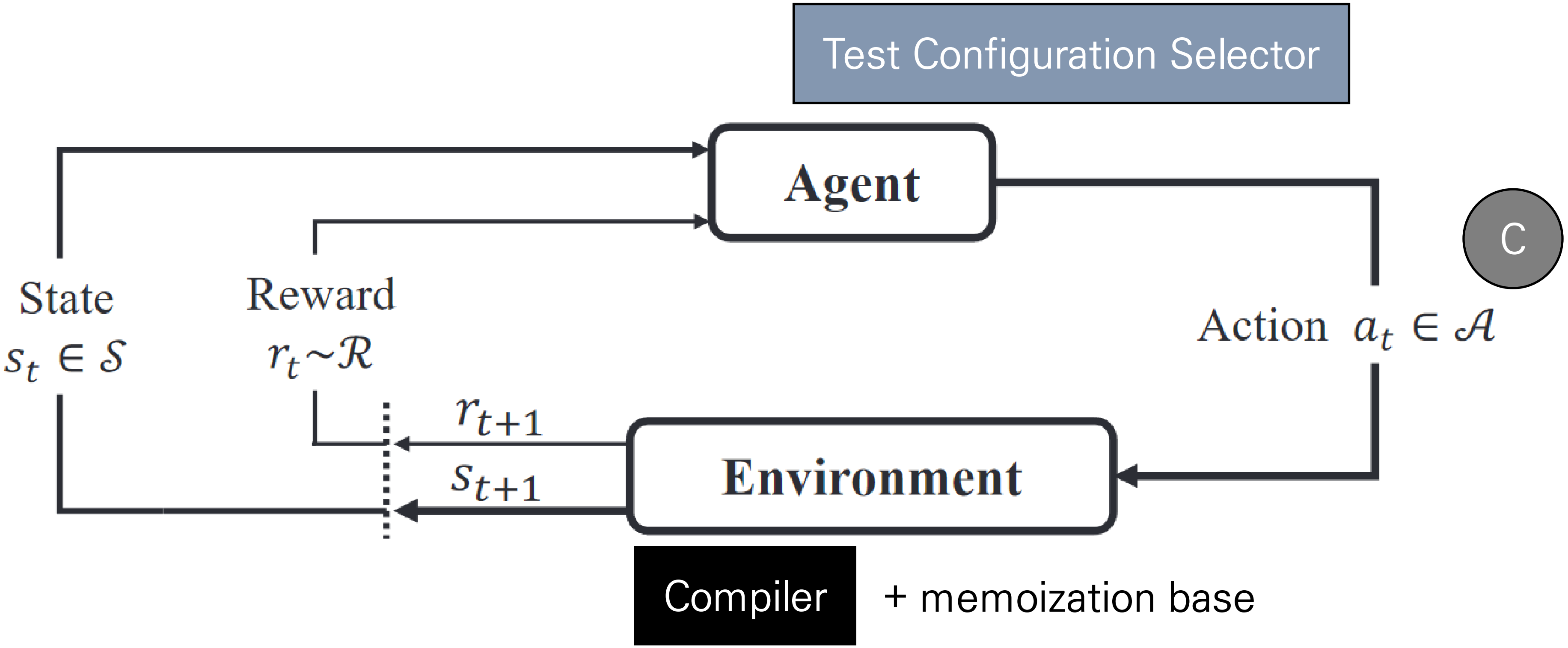

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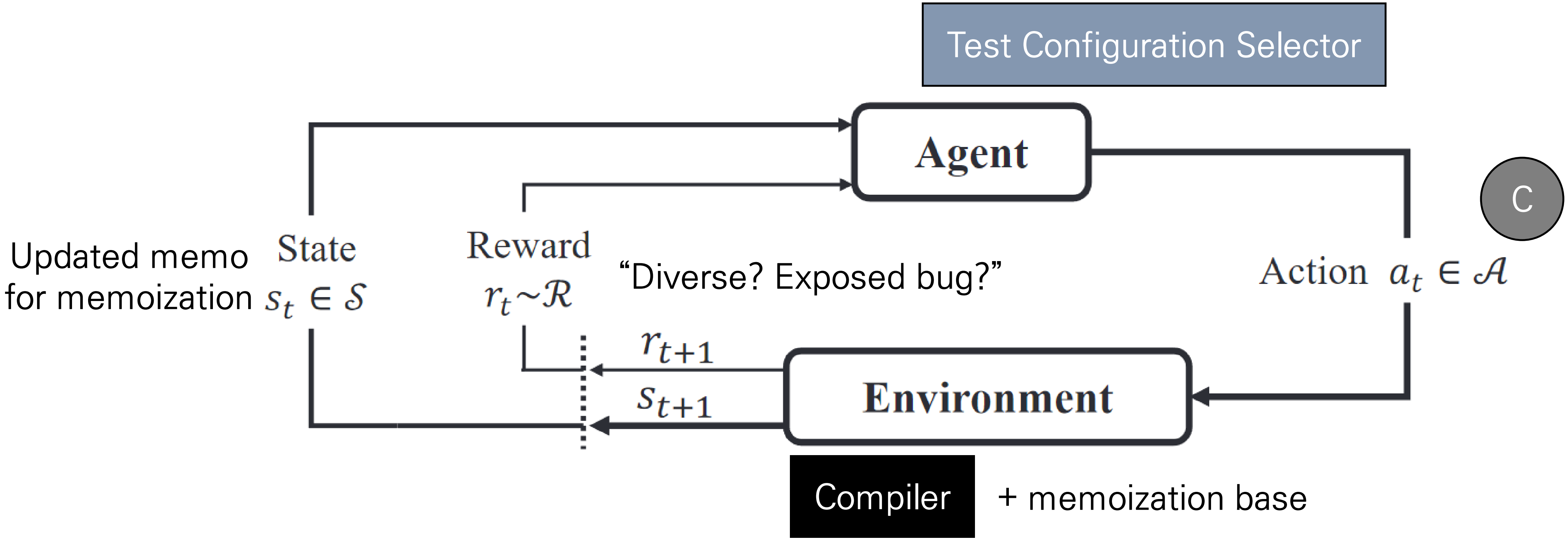

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- Adopts A2C algorithm [5] for learning strategy
  - Skipped
  - Generate → *learn* → take action (update configuration) → loop

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- Triggering bug tends to involve the specific **combination** of several program features
- MARL (**M**ulti-**A**gent **RL**)
  - Treat each configuration option as individual agent
  - Shares same environment

Multi-agent RL

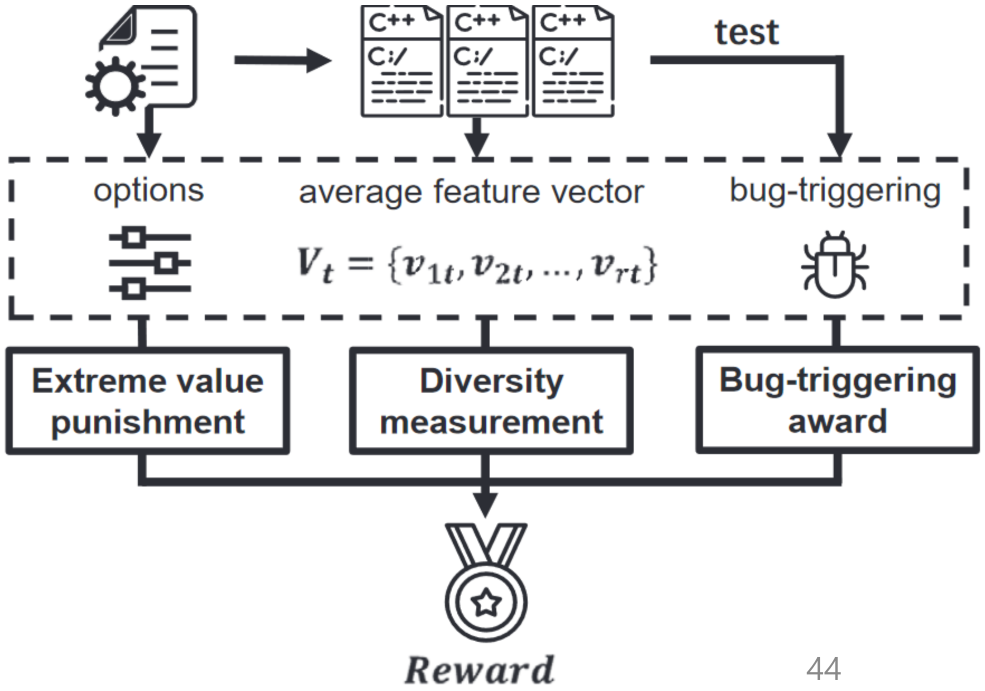
- Test configuration $c = \{o_1, \cdots, o_r\}$ (o_i: configuration option)
- Agent for option o_i: $\mathbf{agent}_i$
  - State of agent_i: $s_{it} = c_t = \{o_{1t}, \cdots, o_{rt}\}$
  - Action of agent_i: $a_{it} \in A_i$
- Learning task: for each agent_i, predict a action sequence $\langle a_{i1}, \cdots, a_{iT} \rangle$, which can produce the large cumulative rewards

Multi-agent RL

- MARL and the compiler configuration, in shorts:
  - Agents: each configuration option
  - Action: tuning (e.g., on/off)
  - Environment: compiler test campaign
  - Reward: “How diverse?” & “Exposed a bug?”
  - State: configuration set (option vector)

Approach

- Reward function: $R_t = R_t^{\text{div}} + R_t^{\text{trg}} + R_t^{\text{neg}}$
  - R_t^{div}: Diversity among configurations
  - R_t^{trg}: Testing results under the configuration
  - R_t^{neg}: Negative-effectiveness
    - Skipped
    - Avoid configuration of test time > 10 min.



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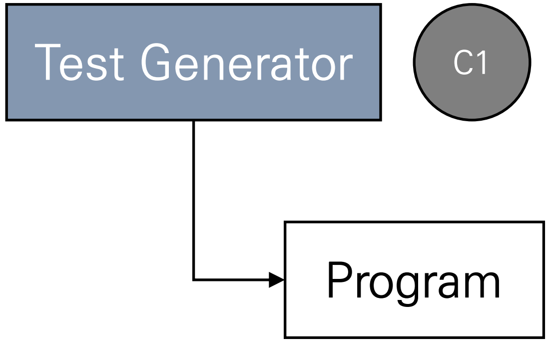

$$\begin{pmatrix} \text{\# goto statements} \\ \vdots \\ \text{\# loops} \end{pmatrix}$$

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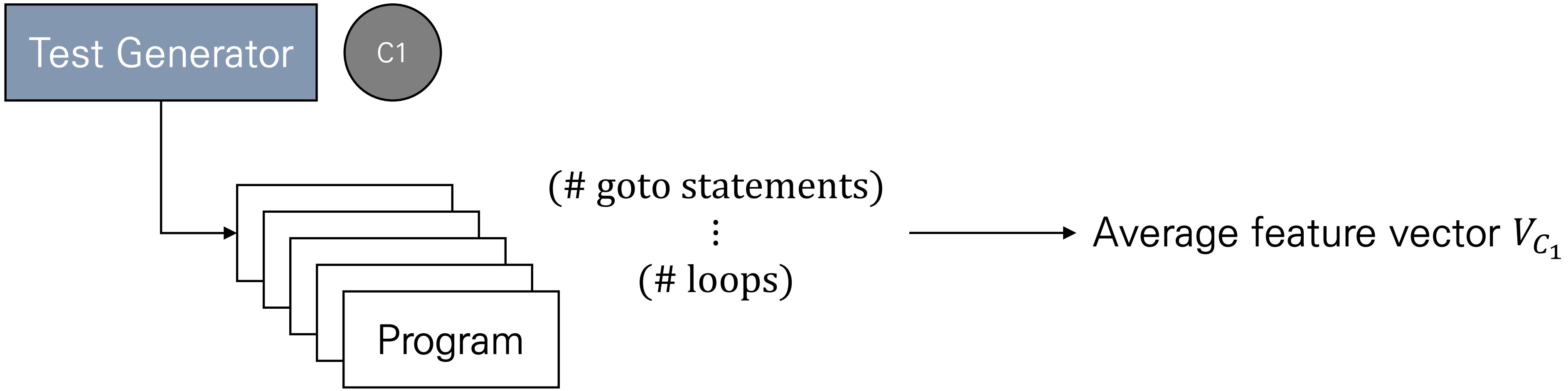

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Cosine similarity

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- Diversity
  - C_h: set of explored test configurations that are closest to c_t
    (i.e., $\forall c_i \in C_h, c_j \in C_t, \mathrm{Dist}(c_i, c_t) \le \mathrm{Dist}\left(c_j, c_t\right)$)

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$$\text{div}_t = \frac{1}{|C_h|} \sum_{c_i \in C_h} \text{Dist}(c_i, c_t) \qquad R_t^{\text{div}} = \frac{1}{m} \sum_{i=1}^{m} (\text{div}_t - \text{div}_{t-i})$$

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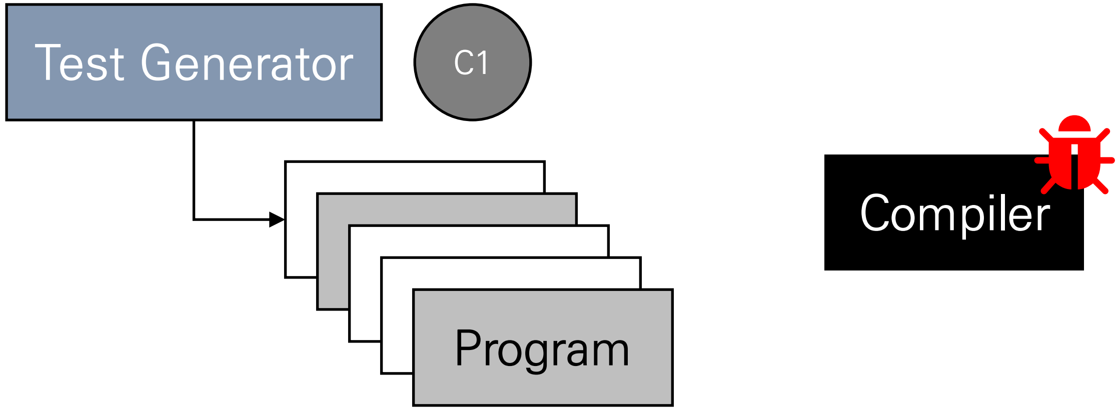

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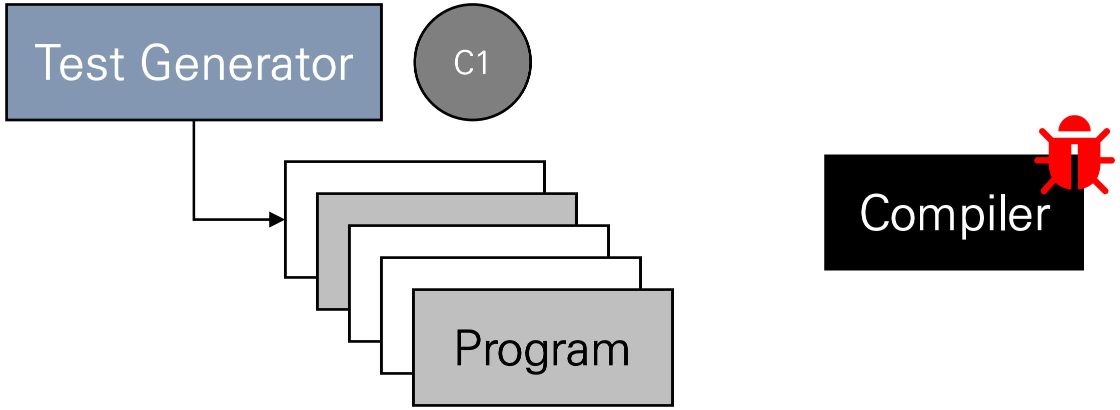

$R_1^{\text{trg}} = 2$

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Configurations of MCS itself

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〉8 months experiment

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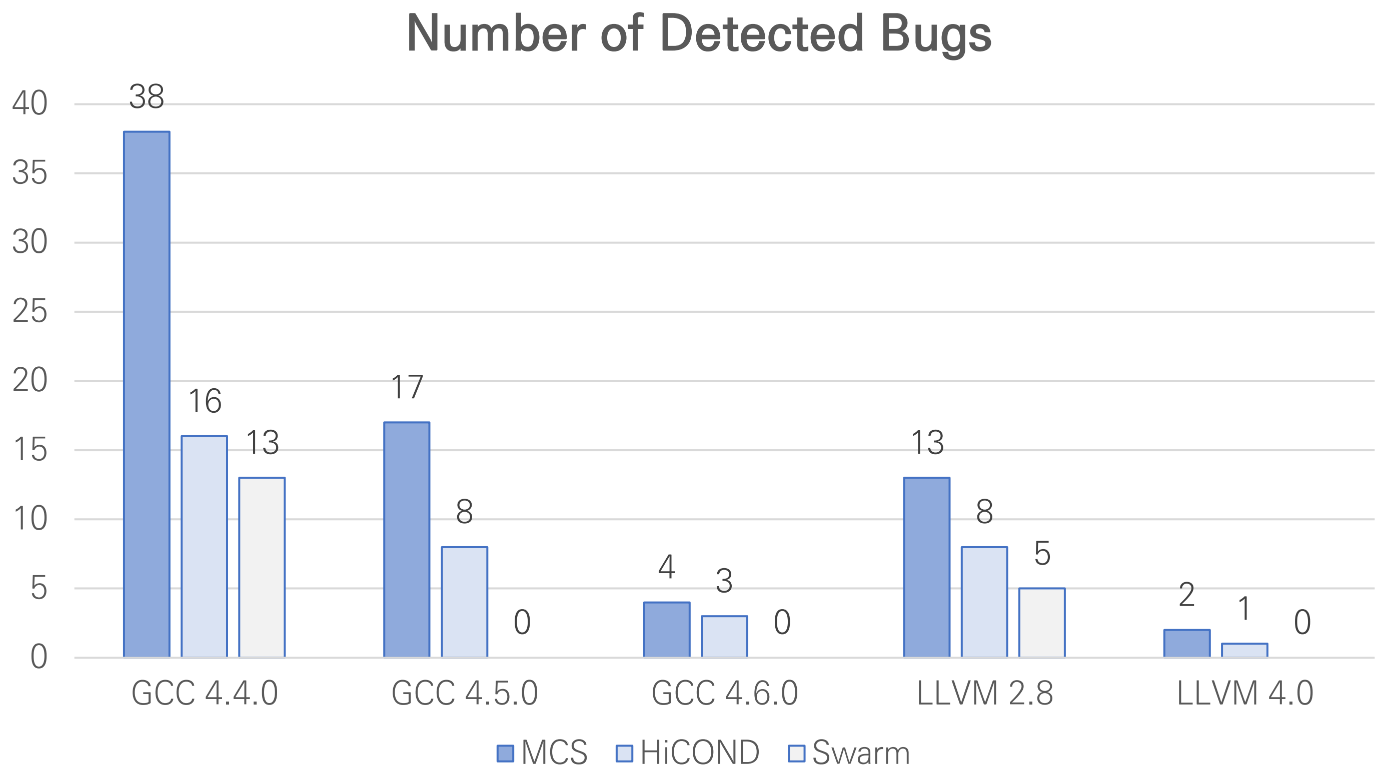
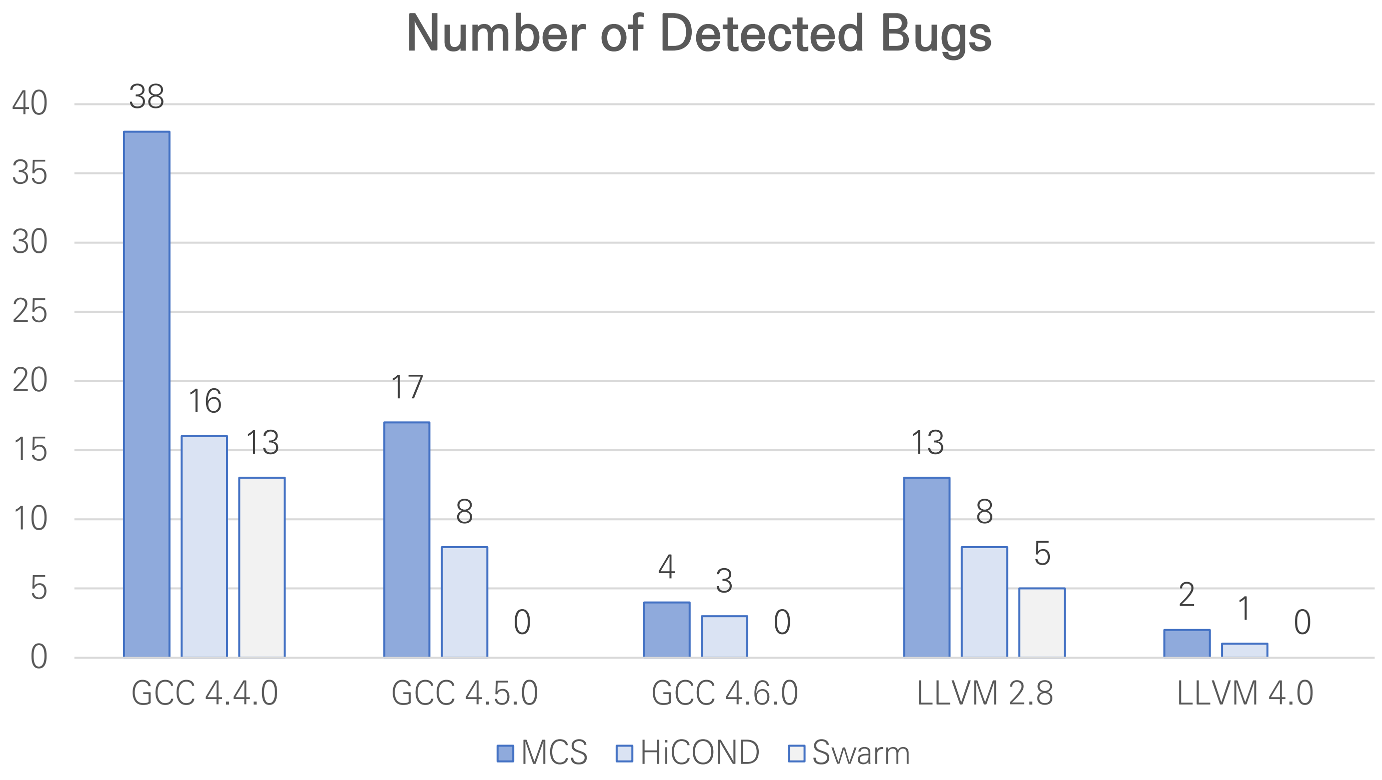


* HiCOND: mines historical bugs to set configuration
* Swarm: randomly update test configuration

Experiment

- RQ1: how does MCS perform in detecting compiler bugs compared with SOTA approaches?



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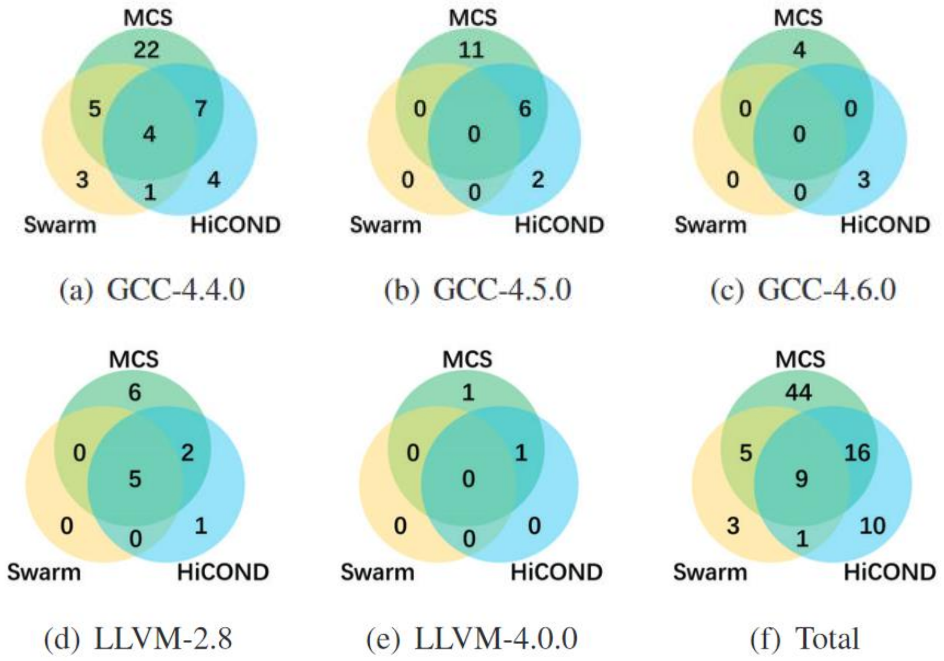
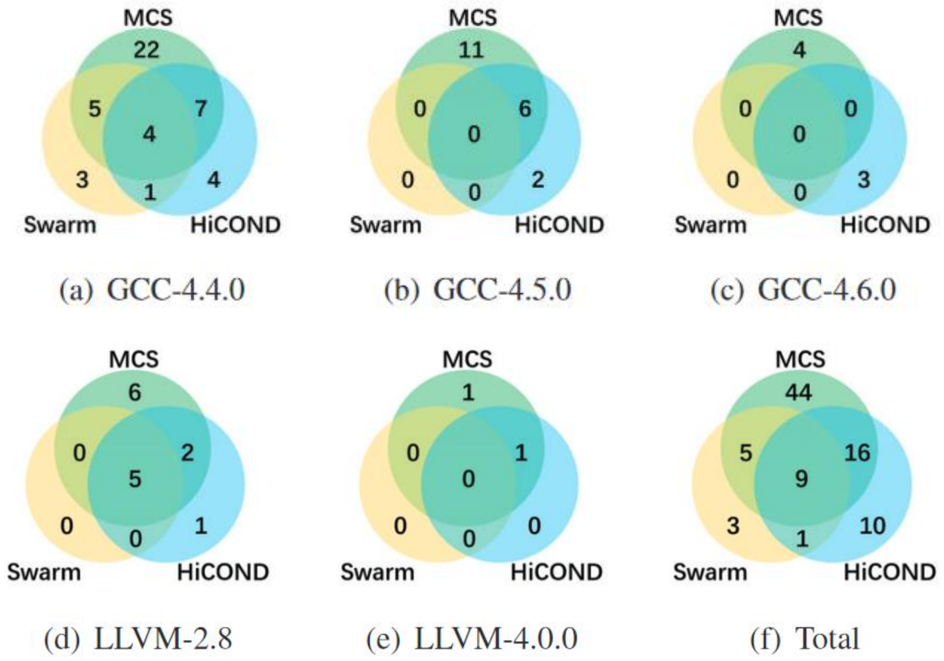


* HiCOND: mines historical bugs to set configuration
* Swarm: randomly update test configuration

Experiment

- RQ1: how does MCS perform in detecting compiler bugs compared with SOTA approaches?
  - HiCOND:
    focus on a certain portion of input space
  - Swarm:
    no guidance,
    can explore input space missed by other approaches

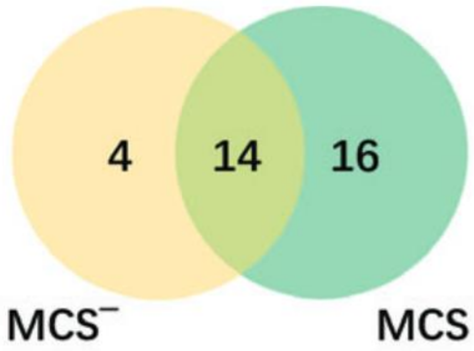


Experiment

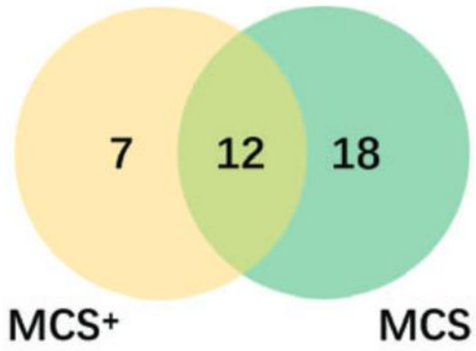
- RQ2: How does MCS perform under different configurations?
  - Removing $R_t^{\mathbf{trg}}$, $R_t^{\mathbf{Neg}}$ terms in reward function

Experiment

- RQ2: How does MCS perform under different configurations?
  - Removing R_t^{trg}, R_t^{Neg} terms in reward function



(a) w/o extreme value punishment.



(b) w/o bug-triggering award.

Experiment

- RQ2: How does MCS perform under different configurations?
  - Removing $R_t^{\mathbf{trg}}$, $R_t^{\mathbf{Neg}}$ terms in reward function
  - Modifying $|C_h| \in \{5, 10, 15, 20\}$, $m = \{5, 10, 15, 20\}$

Experiment

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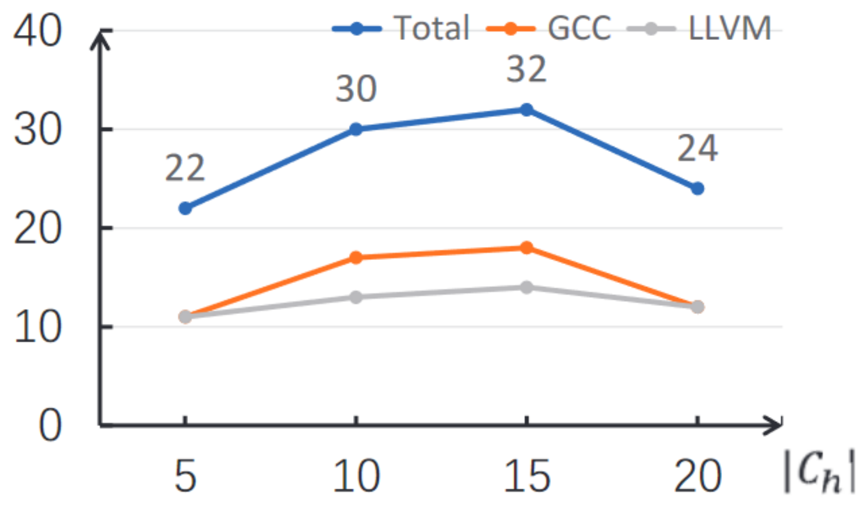
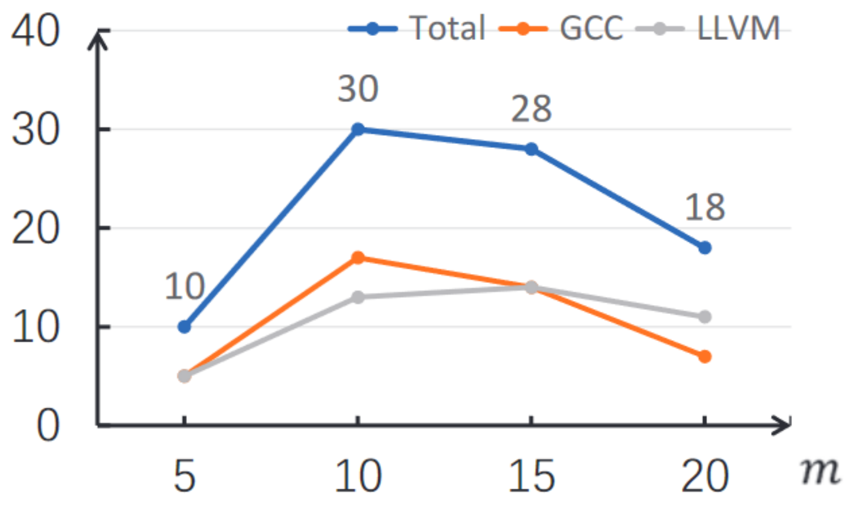


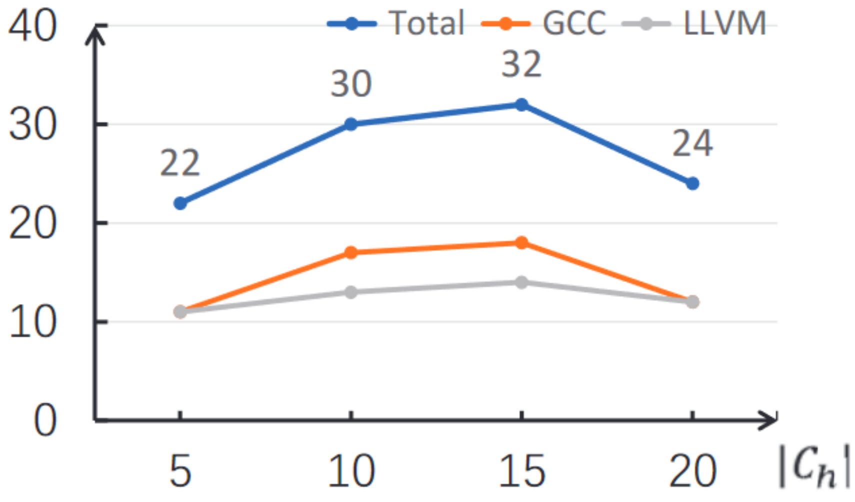
($m = 10$)



($|C_h| = 10$)

Experiment

- RQ2: How does MCS perform under different configurations?
  - Removing R_t^{trg}, R_t^{Neg} terms in reward function
  - Modifying $|C_h| \in \{5, 10, 15, 20\}$, $m = \{5, 10, 15, 20\}$
    - Too small/large parameters lowers performance (efficiency, search space)



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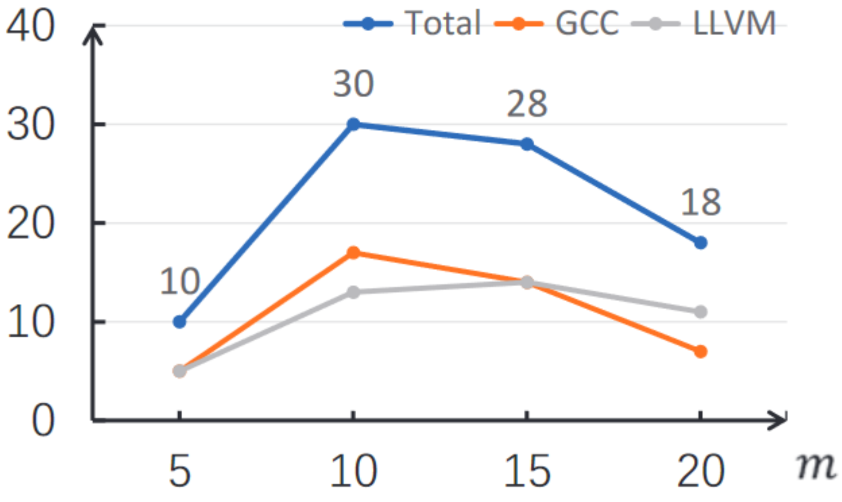

$(|C_h| = 10)$

My Review

- Key observation is effectively connected to interesting idea
  - **Coordination of option → MLIR**
  - Sufficiently supported by references

- Policy is gradually learned
  - Ineffectiveness of config generation in initial stage of RL
  - How about trashing some initially-generated configurations after some steps?

- Can there be other terms for reward function?

Summary

- MCS: Memoized Configuration Search
  - Via MARL
  - Reward function: triggering bugs, diversity, extreme value penalty

- MCS largely outperforms the SOTA approaches

- Fresh contributions
  - Found new 16 GCC and LLVM bugs
  - Has been deployed in *Huawei* for testing their in-house compiler

Aux: RL and our purpose

- Please note that there is a **slight difference between the original purpose of RL and our purpose for using RL**. The former is to learn the control policy, while the latter is to construct as effective a test configuration as possible at each time step by using the gradually-learned policy.

Aux: dead code

- There may be a portion of dead code in the program, but MCS does not distinguish them as dead code has been demonstrated to be also useful for compiler testing. Then, MCS calculates diversity based on the feature vectors.

Aux: negative effectiveness

- Although larger diversity helps explore diverse test configurations and leads to more bug- triggering test programs, it may increase the risk of producing unexpected ones, which could generate negative-effect test programs (i.e., those running for an extremely long time) for compiler testing. As explained in Section III-B, the number of options set to extreme values has correlations to the generation of negative-effect test programs. To avoid the generation of such test programs, we should give a punishment for the test configurations, in which many options are set to extreme values. Specifically, when there are more than q% options that are set to their extreme values in a test configuration, MCS gives a punishment λ to it, i.e., R^neg_t = λ, otherwise 0.

Aux: using C_h

- As the explored configuration space could be larger and larger, there may be outliers that can dominate the average distance, and thus MCS calculates the average distance between ct and a set of closest explored ones (rather than all the explored ones) as the approximation.

Aux: using m

- To avoid the exploration of test configurations falling into local optimum, we expect the configurations explored within a relatively short time interval are also diverse and the search process always proceeds towards a good direction.