



# Adaptive Test Generation for Fast Functional Coverage Closure

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# Outline

- Main Goal in Google
  - Improve chip design flow
- Challenges in standard Constraint Random Verification flow
- Introduce Smart Constraint Solver
  - Propose CDG4CDG
  - Scalability
- Experimental Results
  - Achieved up to 21.7× speedup in a fully automated flow.
- Conclusion

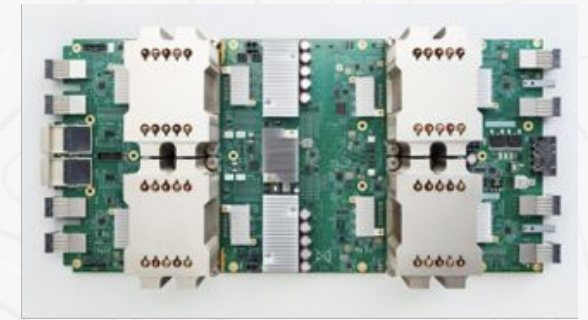
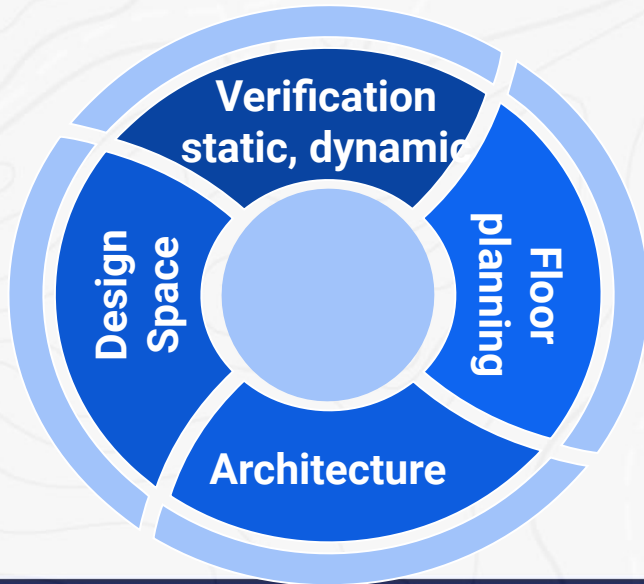
# Using AI/ML to Accelerate Design Flows

## Goal

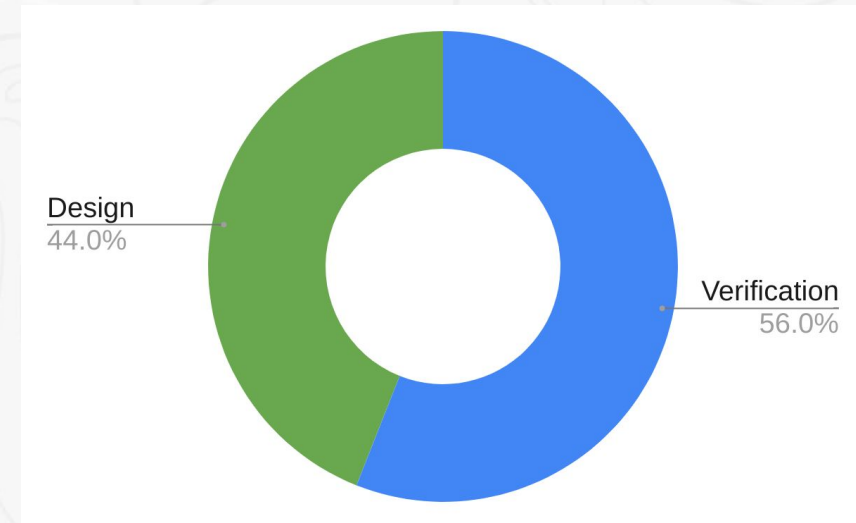
Develop scalable, and generalizable machine learning framework with rapid evaluation and turn-around time to shorten the chip design process.

## Research Direction

- Apply ML into four different stages of chip design



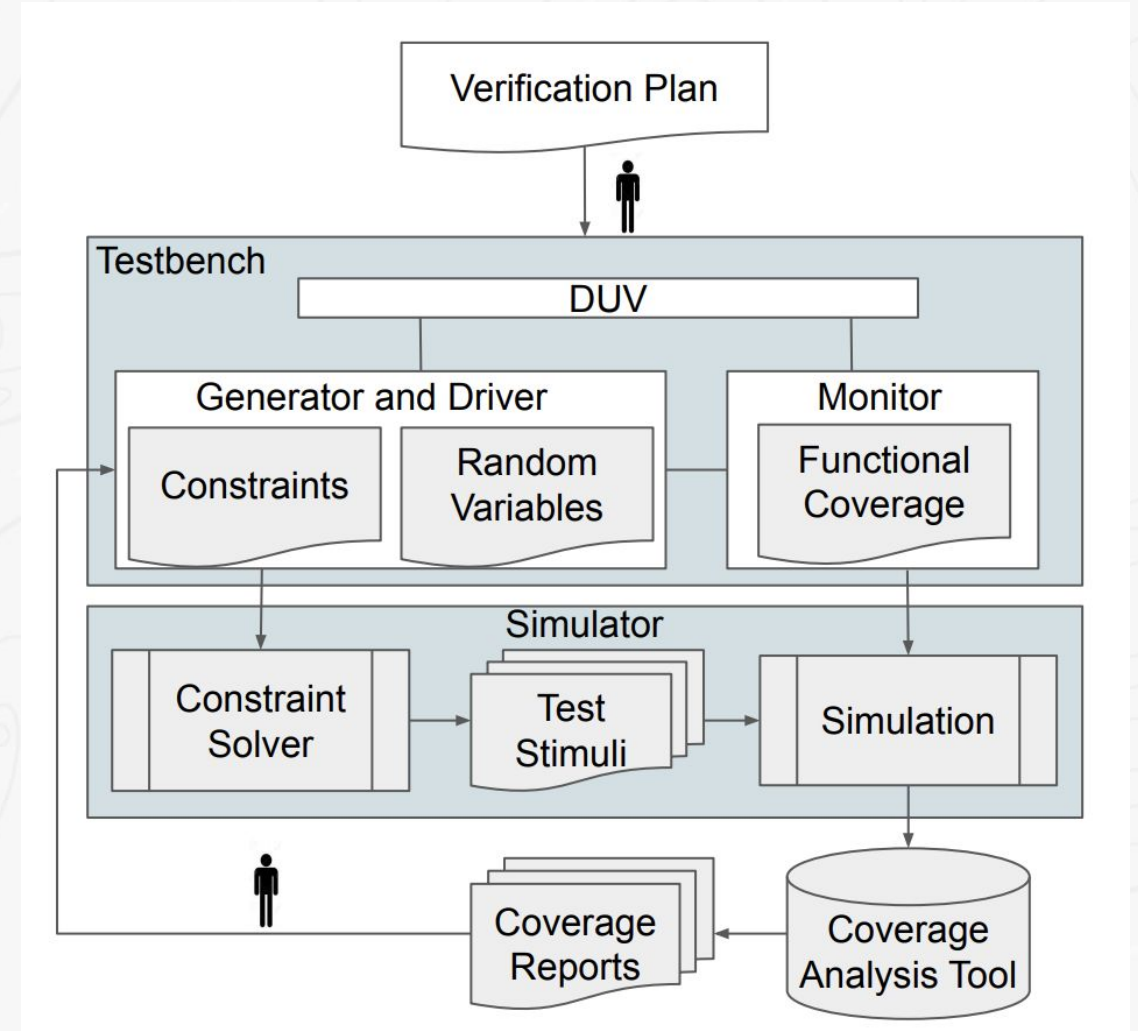
Design More Efficient Accelerator



Source: Wilson Research Group/Mentor

# Standard Constraint Random Verification Flow

- Verification of complex designs starts with the definition of a verification plan
- Verification engineers create a testbench to simulate the designs at the code level
  - Checker verifies the design output against the modeled output
- Test Stimuli is generated from the feasible solutions of the constraint solver





# Constraints and Coverage

- Distribution Constraint

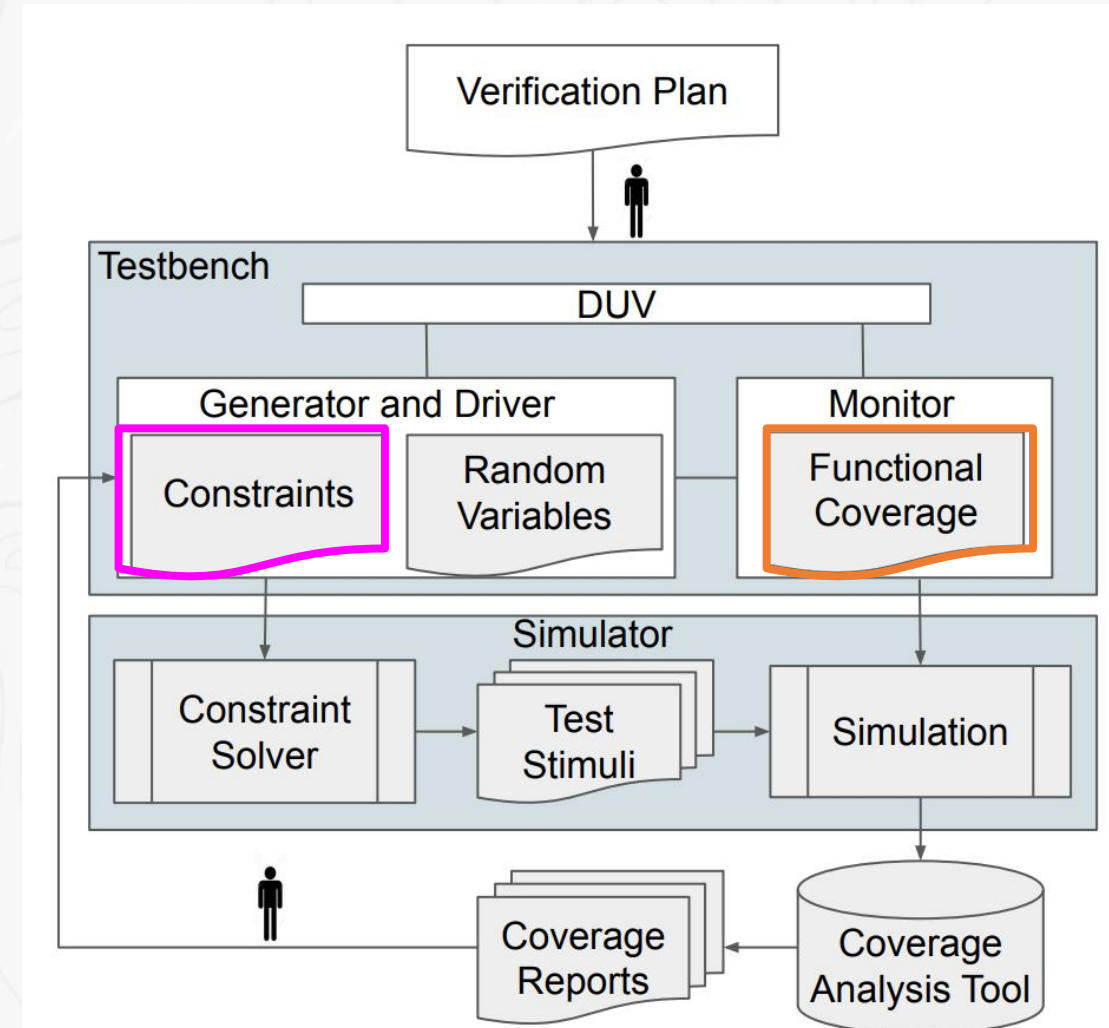
```
rand bit [1:0] State;  
constraint con_State {  
    State dist {  
        idle := 10,  
        start := 10,  
        read := 10,  
        write := 10  
    };  
};
```

- Legalization Constraint

```
constraint c {  
    // inclusive  
    src_port inside { [8'h0:8'hA],8'h14,8'h18 };  
    // exclusive  
    ! (des_port inside { [8'h4:8'hFF] });  
}
```

- Ordering Constraint

```
constraint frame_sizes {  
    solve zero before data.size;  
    zero -> data.size == 0;  
    data.size inside {[0:10]};  
}
```

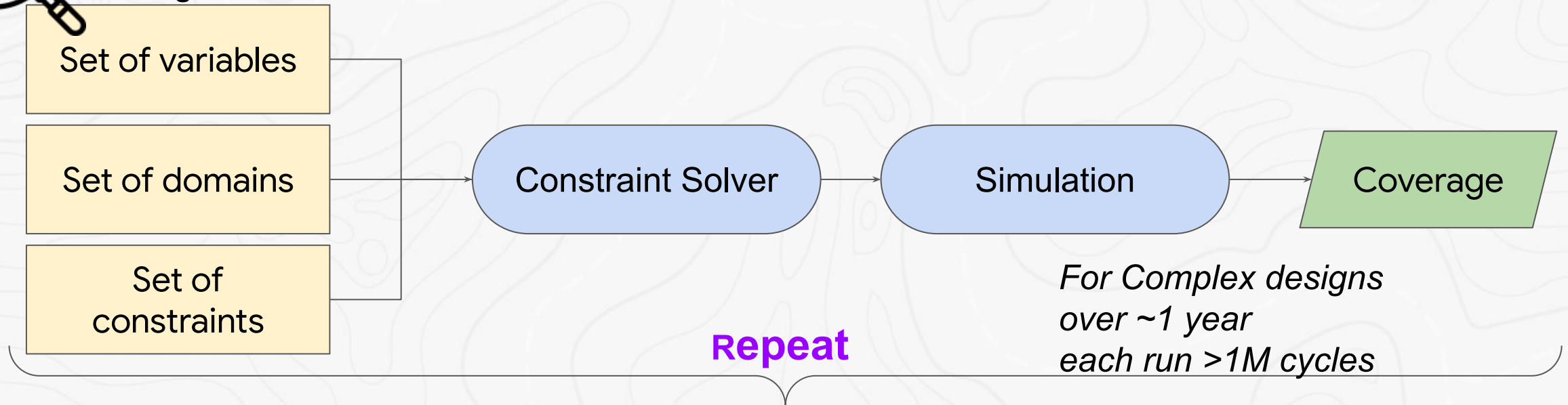


# Design Sign-off: Coverage Closure

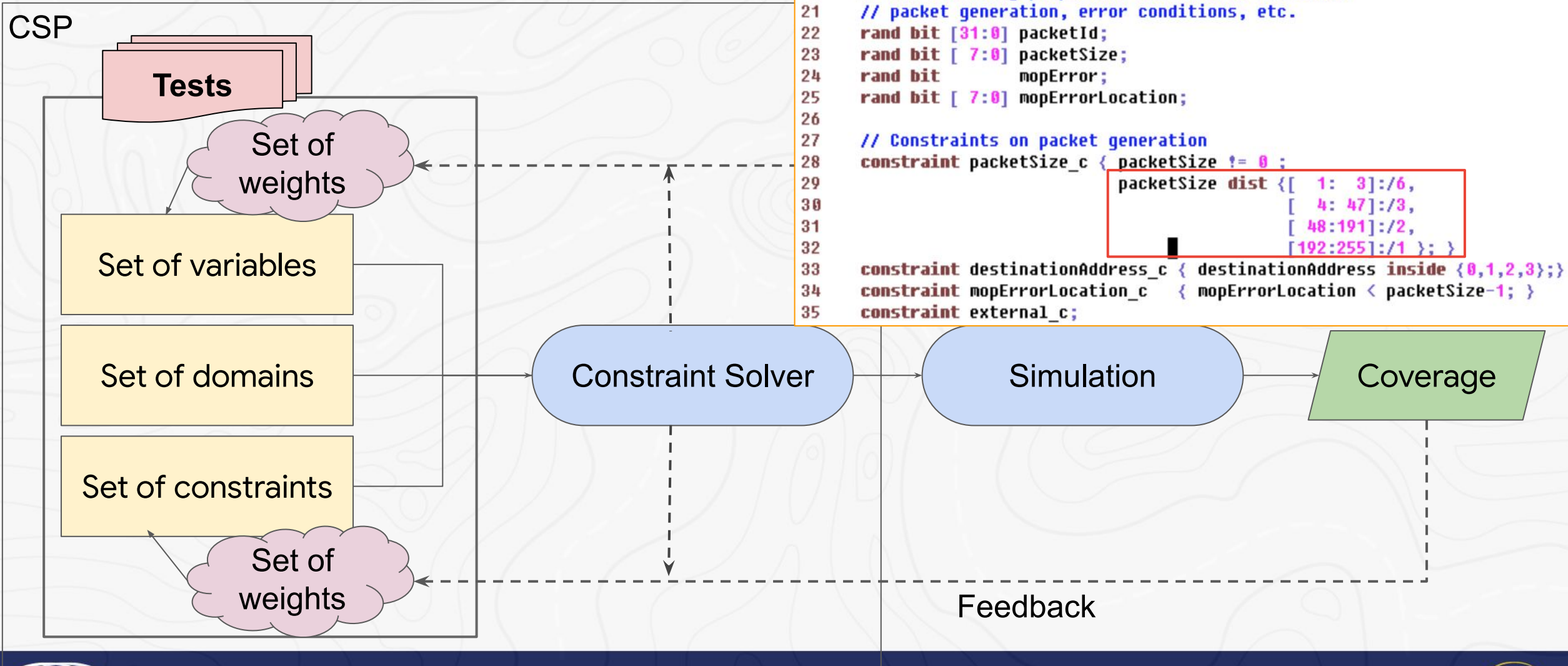
- CRV mostly relies on randomness
  - At every simulation cycle the seed is changed
- Constraints are defined by DV engineer once and updating them for better coverage is nontrivial



DV Engineer



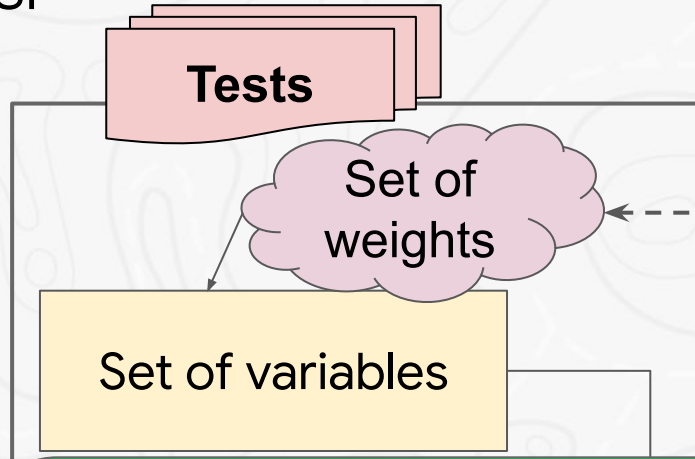
# Smart Constraint Solver





# Smart Constraint Solver

CSP



```
13 class packet;
14
15 // The following properties are visible to the DUT
16 rand bit [7:0] destinationAddress;
17 rand bit [7:0] sourceAddress;
18     bit [7:0] packetData[$];
19
20 // The following properties are used to influence
21 // packet generation, error conditions, etc.
22 rand bit [31:0] packetId;
23 rand bit [ 7:0] packetSize;
24 rand bit      mopError;
25 rand bit [ 7:0] mopErrorLocation;
26
27 // Constraints on packet generation
28 constraint packetSize_c { packetSize != 0 ;
29                             packetSize dist {[ 1: 3]:/6,
30                                                  [ 4: 47]:/3,
31                                                  [ 48:191]:/2,
32                                                  [192:255]:/1 ]; }
33
34 constraint destinationAddress_c { destinationAddress inside {0,1,2,3}; }
35 constraint mopErrorLocation_c { mopErrorLocation < packetSize-1; }
36 constraint external_c;
```

Complexity:

PacketSize: [1,255], Weight: [1, 10],

The search space for possible **distribution constraints**:  $10^{252}$

Feedback



# Related Work: Coverage-directed Test Generation

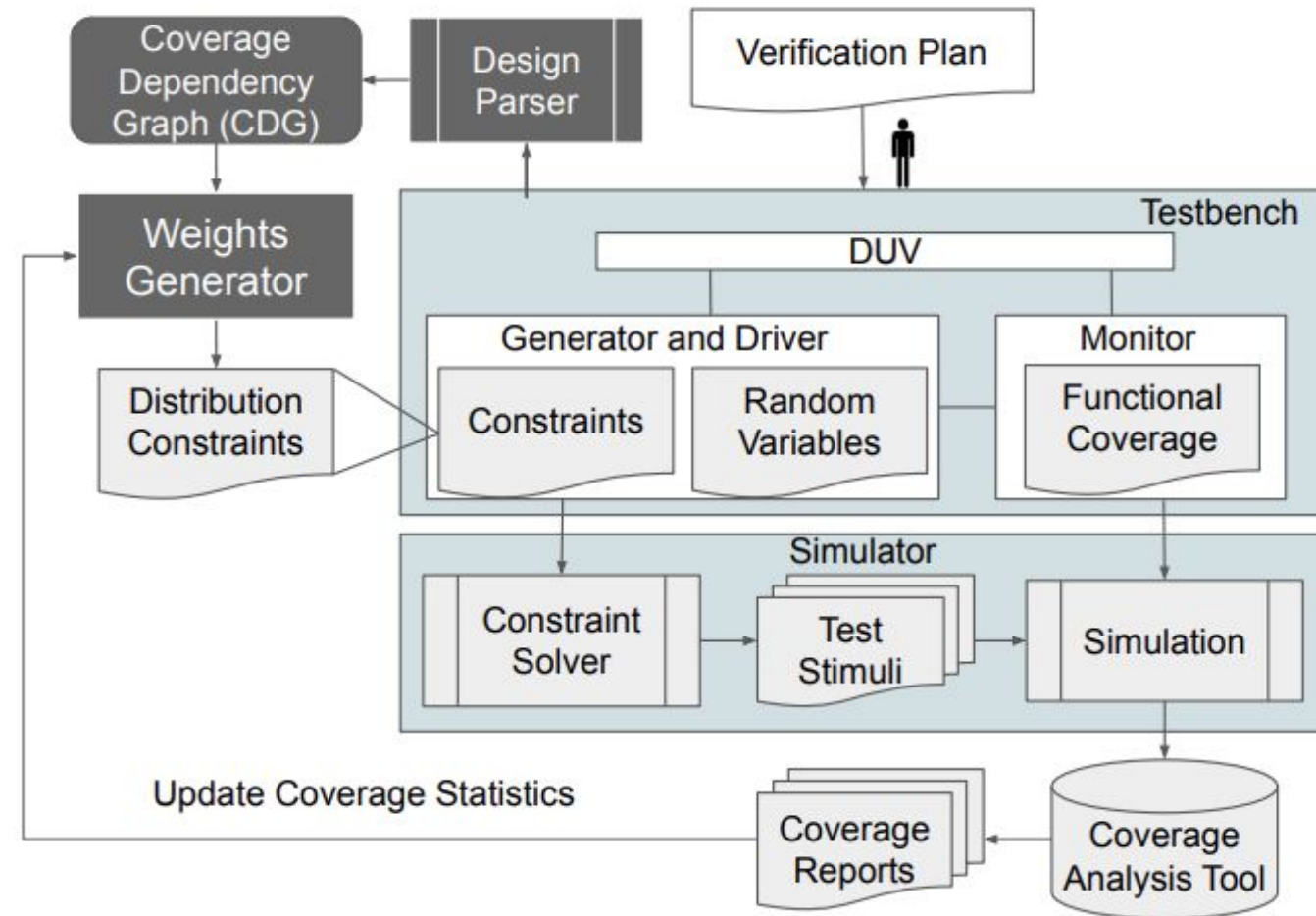
- Model-driven
  - Converting the design into an abstract finite-state machine
  - Mainly suffers from the need to create and maintain an accurate model
- Data-driven
  - Models the relationships between coverage and stimuli directives from the simulation feedback
    - Use observations to build and train a model that captures the casualty between input variables and coverage

## Limitations:

- Rely on a significant amount of domain knowledge
- Require a considerable number of simulations to obtain enough training data
- Very challenging for modern large-scale designs as data collection and model training may take several months.

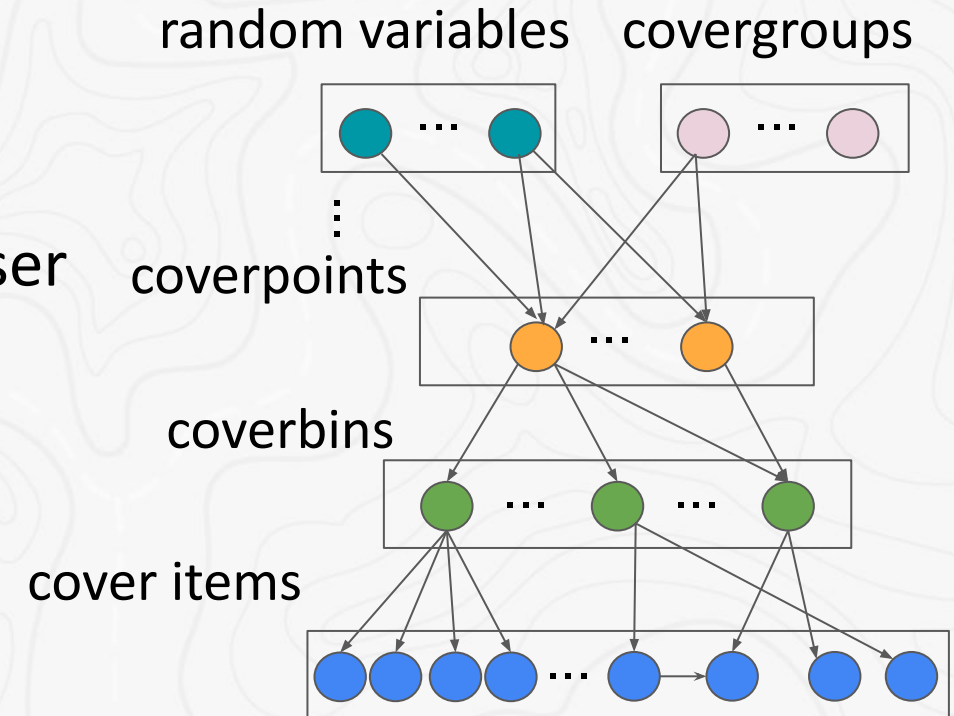
# CDG4CDG: Coverage Dependency Graph for Coverage Driven Test Generation

- Coverage Dependency Graph (CDG) Extraction
  - Build Bayesian Network automatically
- Find conditional probabilities
- Generate/update constraints by statistical inference on CDG



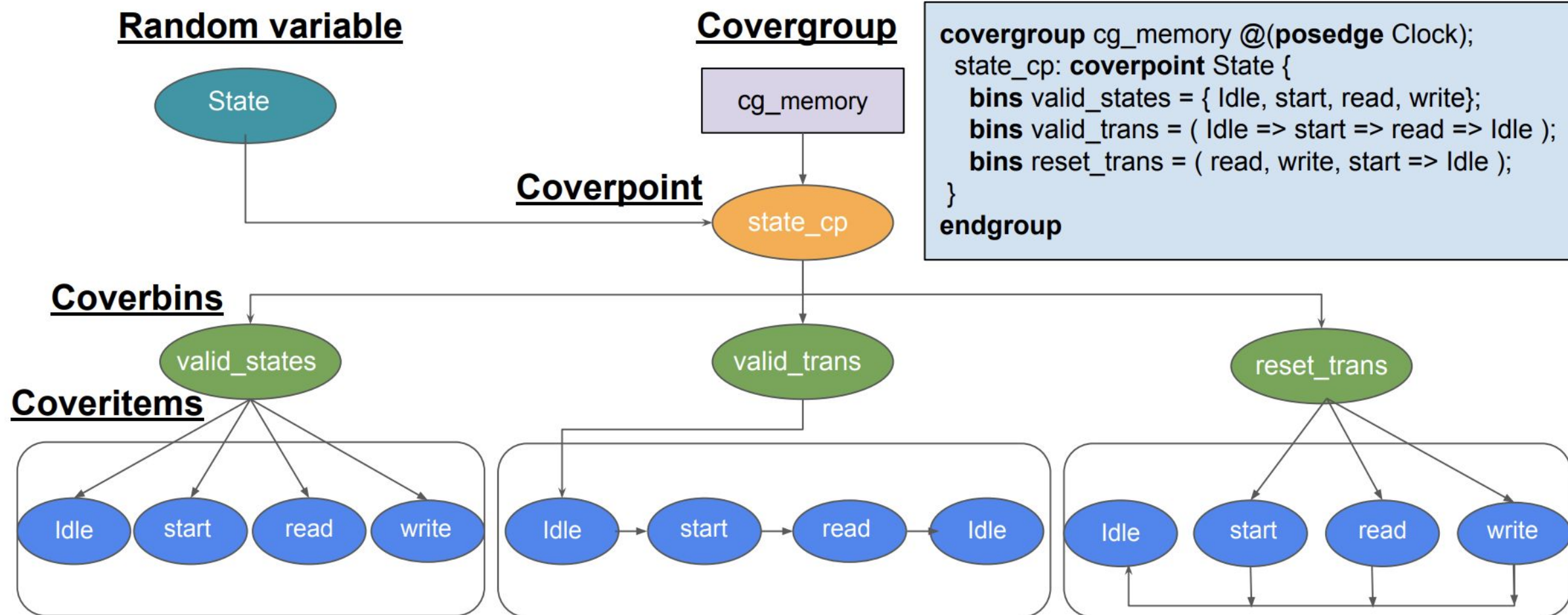
# CDG: Model Functional Coverage as a Bayesian Network

- We use design parser to find the correlation of the cover items and the random variables
  - For each coverpoint we query the parser until we reach a random variable
  - For each coverbin, the coveritems are the values of the random variables required to be sampled in a test





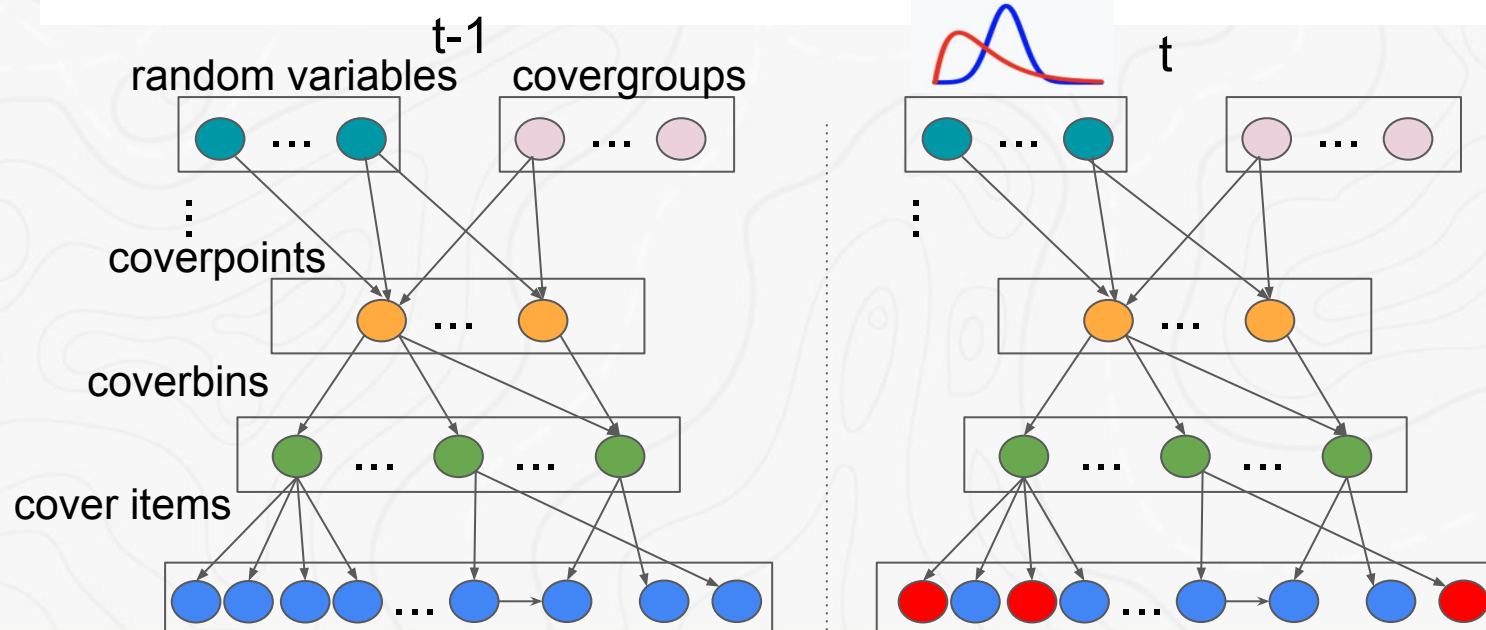
# CDG Example





# end-to-end algorithm

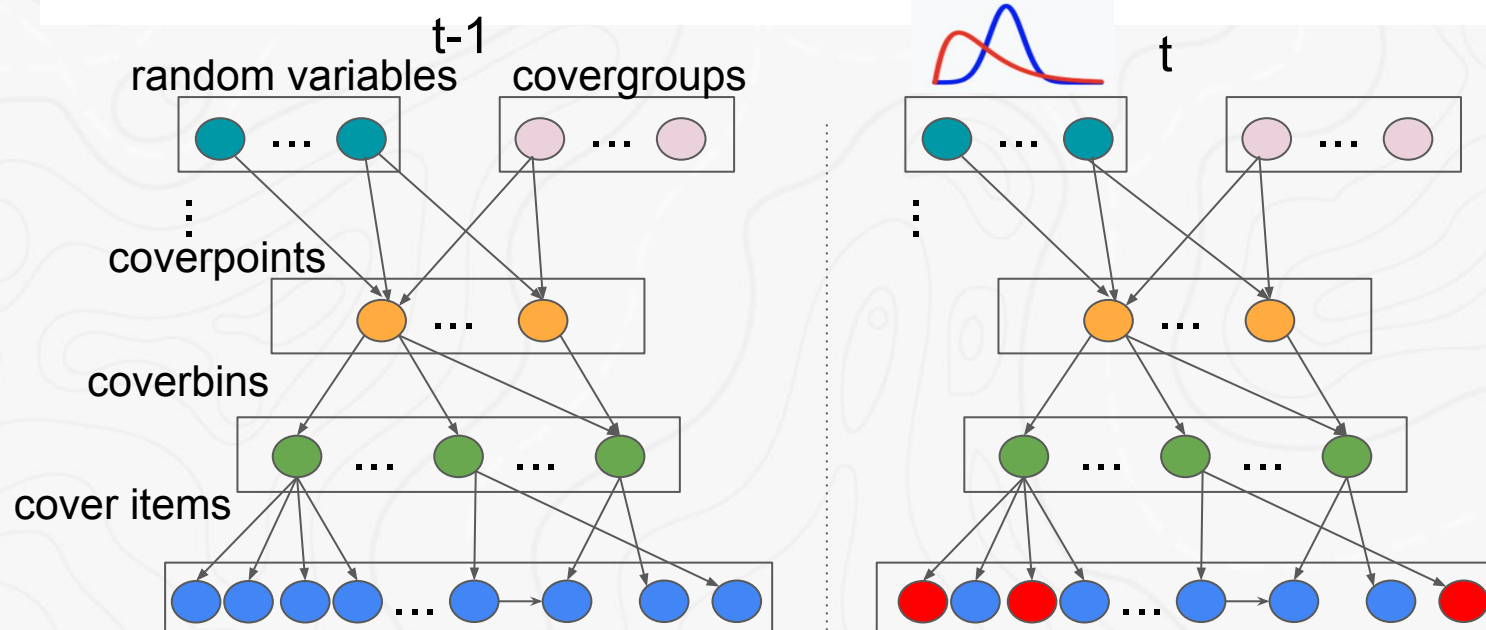
- 1: Query testbench modules and automatically extract the CDG graph
- 2: **while** ! Coverage Closure **do**
- 3:   Run simulation and get the coverage feedback
- 4:   Estimate conditional probabilities for nodes in CDG graph
- 5:   Update CDG graph by pruning cover items that are covered
- 6:   for coverage holes  $x$  update distribution constraints by solving  $\theta_{MLE} = \operatorname{argmax}_{\theta} P(x; \theta)$
- 7: **end while**



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Scalability?

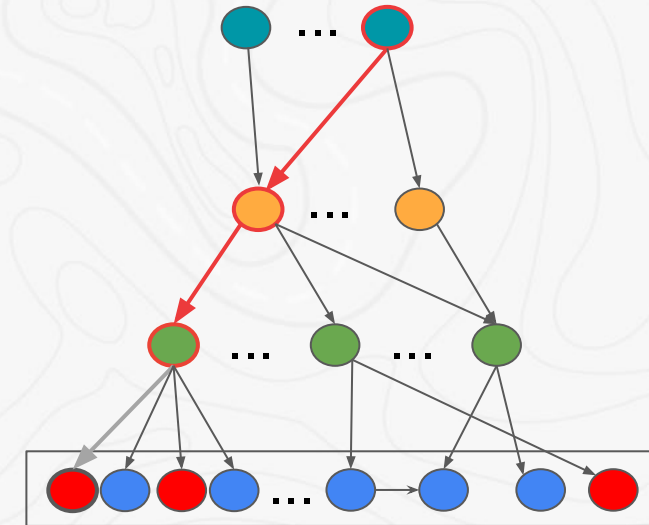


# Our Approach to Handle Scalability Challenges

Challenge 1: Exact inference in Bayes nets is NP-hard [1]

- Our CDG structure is polytree, thus belief propagation performs inference efficiently linear in number of nodes [2]
  - We use simulation feedback to calculate probability of hit/no hit for each coverpoint
  - We leverage the polytree property since there is only one path from a coverpoint to the variables
  - We iteratively update distribution constraints by aggregation of no hit counts

random variables



[1] Cooper, G. F., 1990. The computational complexity of probabilistic inference using Bayesian belief networks.

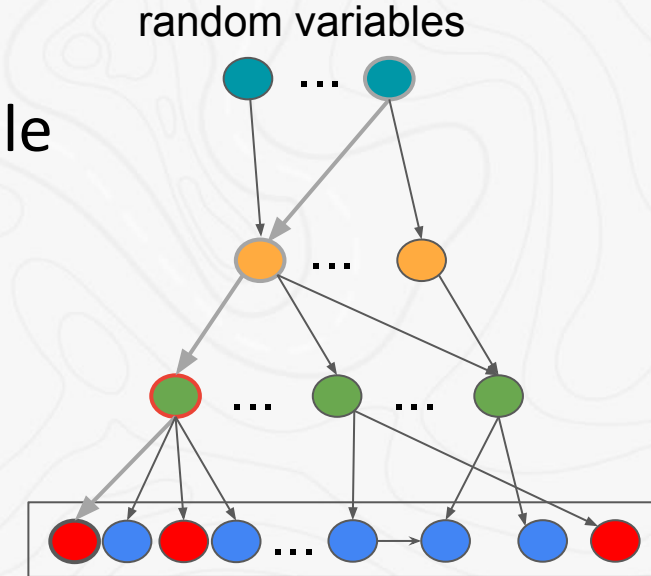
[2] Bayesian Artificial Intelligence (2004), Kevin B. Korb and Ann E. Nicholson, Chapman and Hall, CRC Press

# Our Approach to Handle Scalability Challenges

Challenge 2: Modern large-scale designs may have over thousands of variables and adding constraints over each variable significantly hampers practicality of the constraint solver

## Solution

- We pick top-k variables from CDG graph
  - Rank variables by the number of coverpoints related to them from its induced subgraph
  - Define distribution over range of values





# Evaluation Setup

## Baselines

- default\_dist
  - Existing distribution (if any)
- random\_dist
  - Change the distribution constraints randomly

## Designs

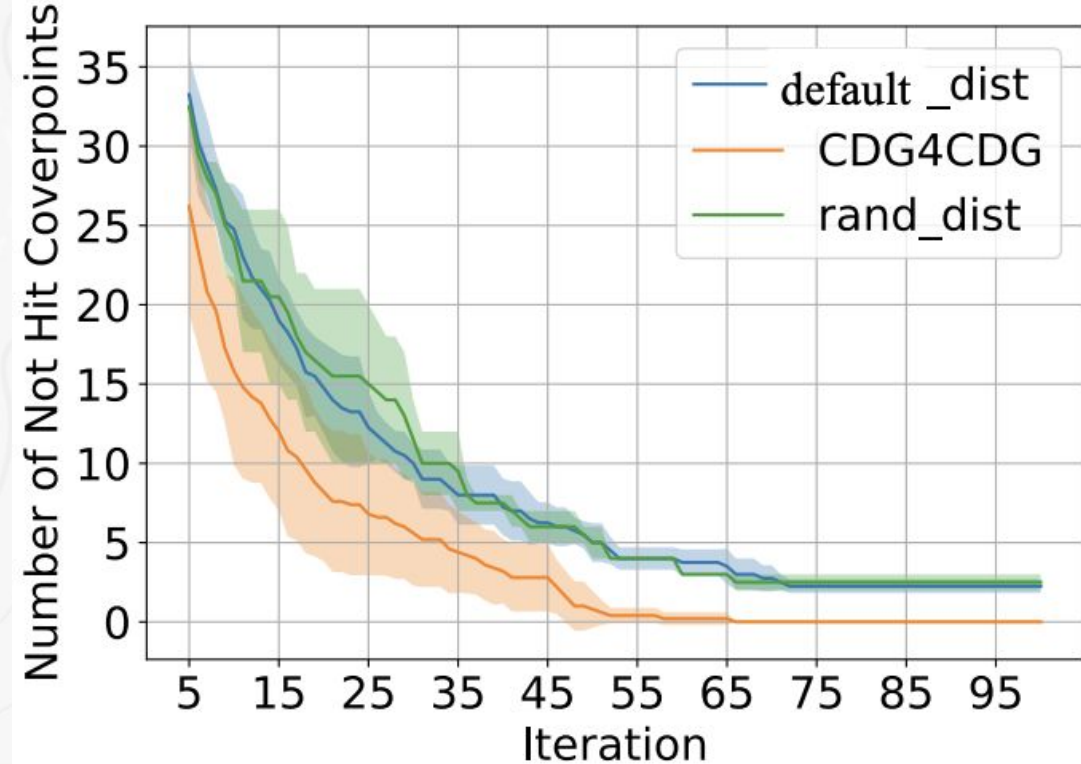
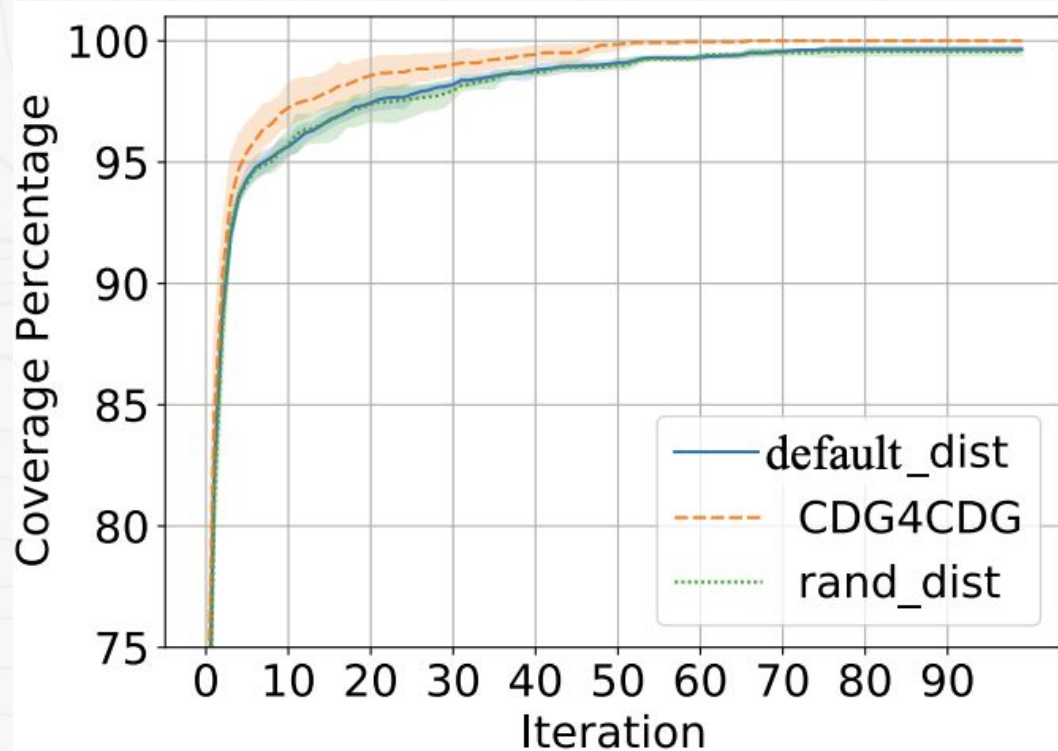
- Industrial Accelerator SML: TPU block
  - TPU block consists of multiple large and complex designs
  - Considered three designs in this TPU block (SML1-3)
- RISC-V Ibex

## Experimental Results:

- Evaluate CDG4CDG
- Theoretical bound on baseline + Empirical result
- Impact on code coverage

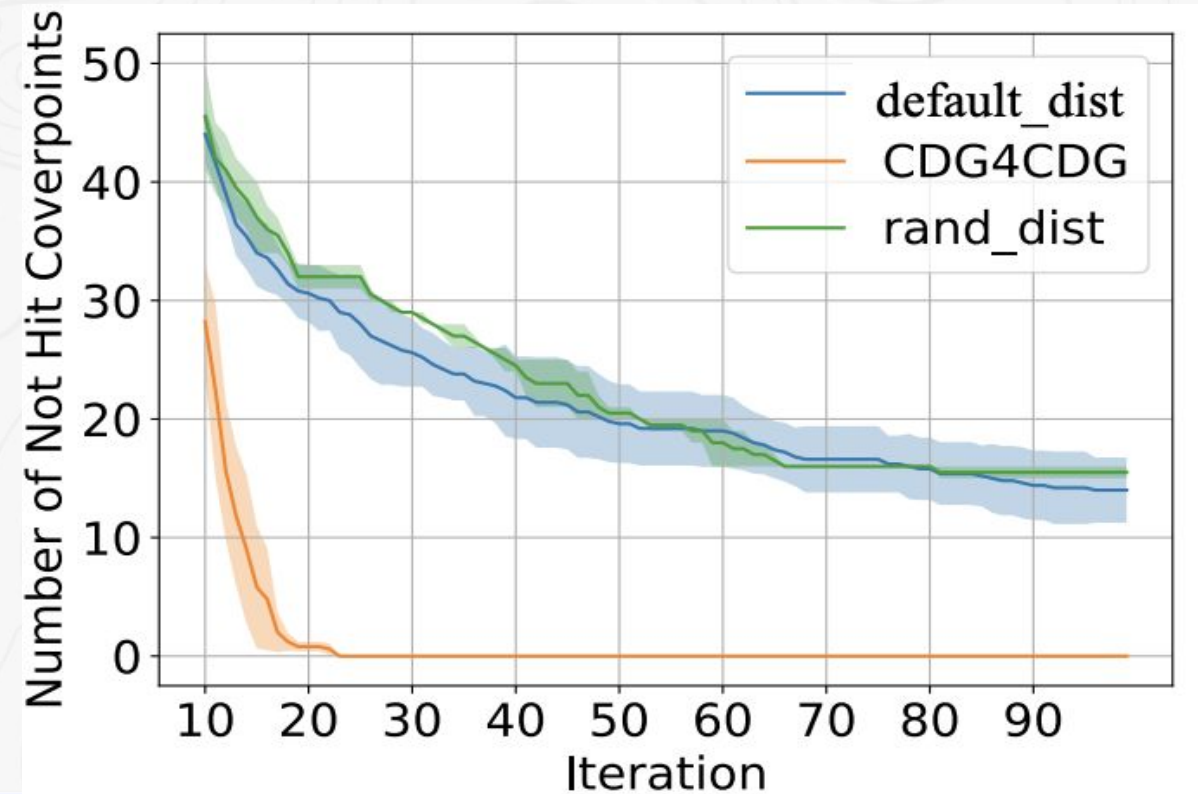
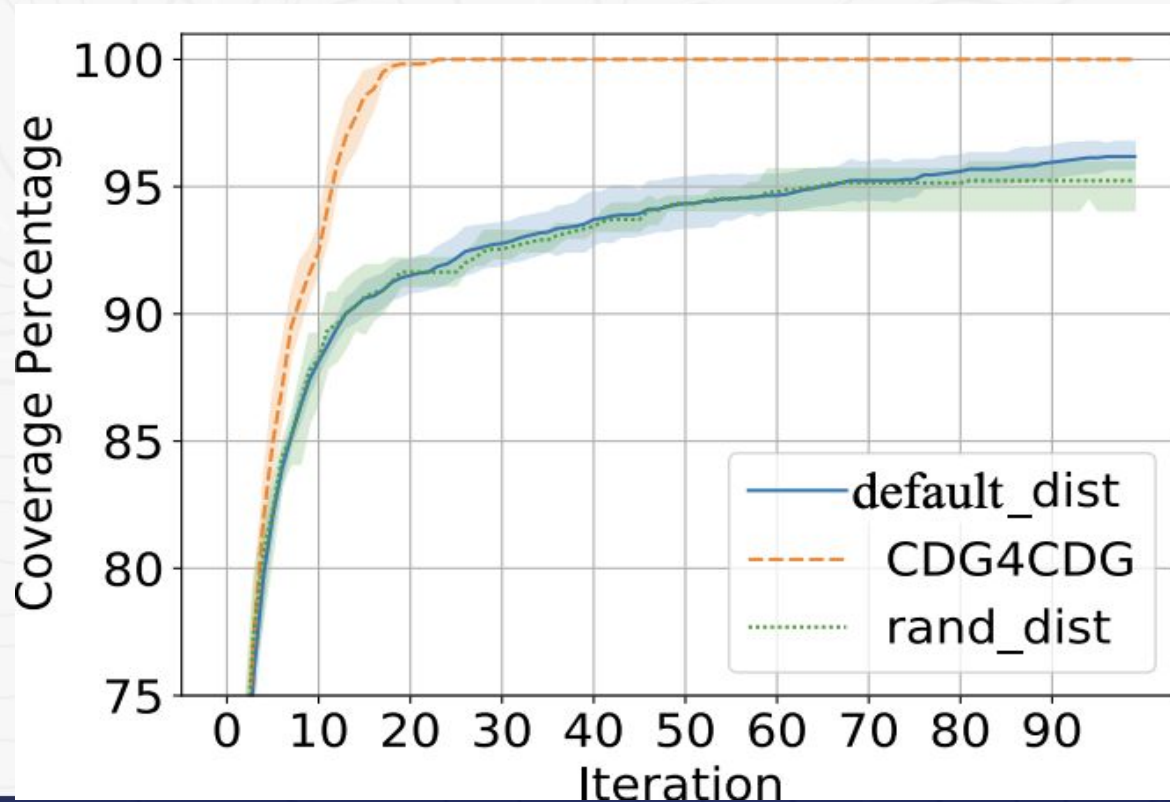
# TPU: SML 1

	#coverpoints	#random variables	Coverage closure	#bundles	Speed up
SML1	371	$5 \sim 10^{(2^{22})}$	66 vs 340	528 vs ~3k	=5.15x



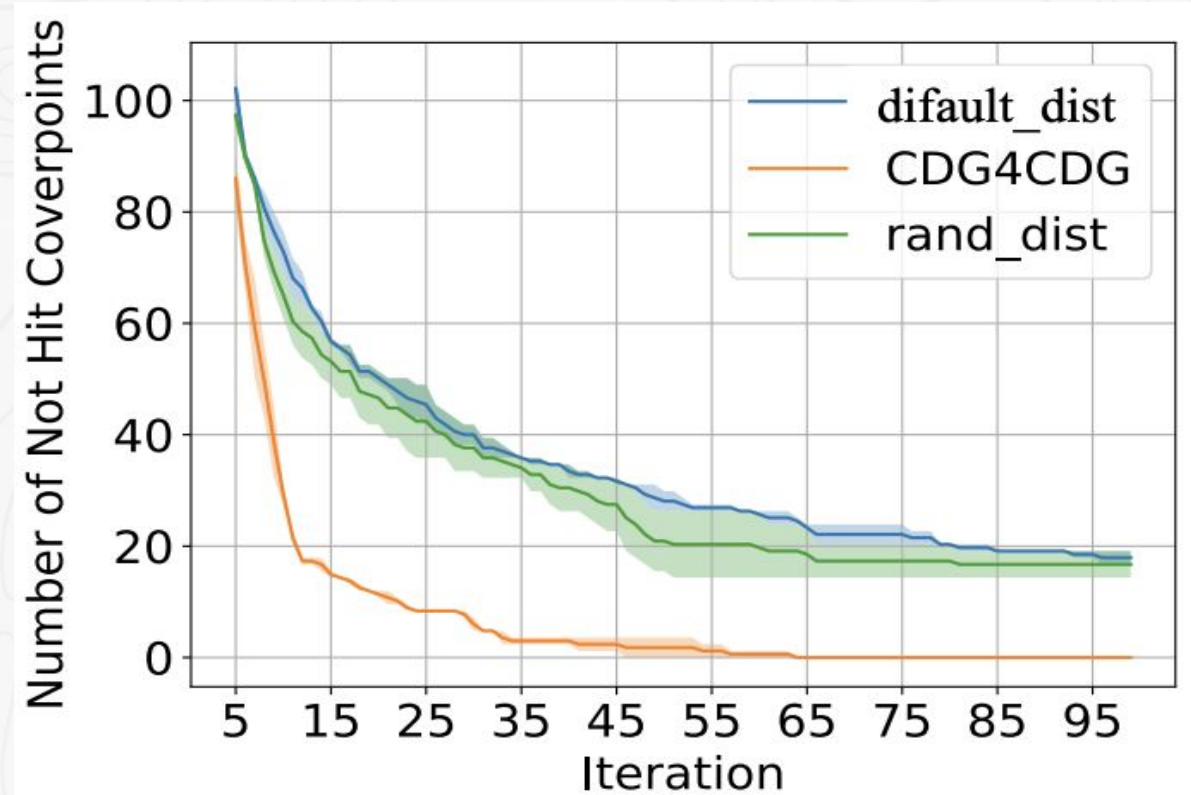
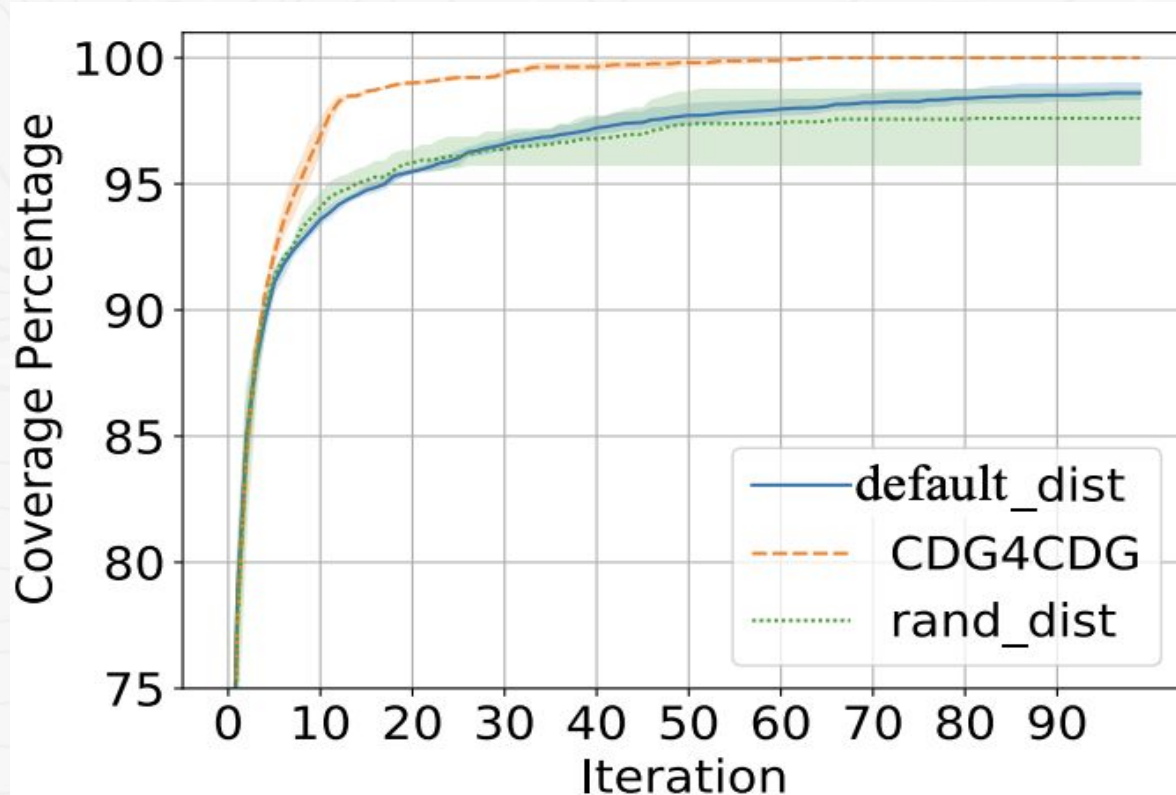
# TPU: SML 2

	#coverpoints	#random variables	Coverage closure	#bundles	Speed up
SML 2	574	7, $\sim 10^{(2^{43})}$	23 vs 500+	184 vs 4k	>21.7x



# TPU: SML 3

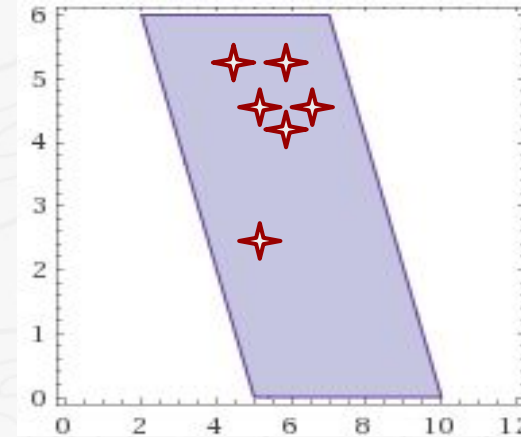
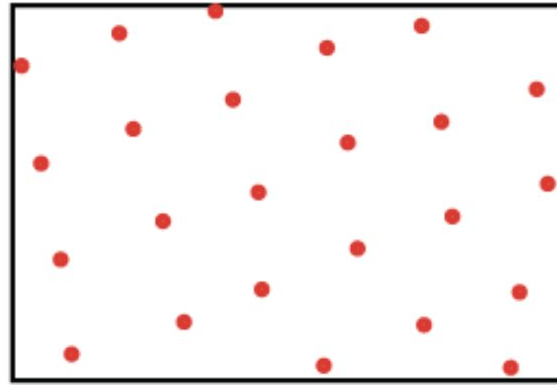
	#coverpoints	#random variables	Coverage closure	#bundles	Speed up
SML 3	1129	12, $\sim 10^{(2^{65})}$	66 vs 500+	504 vs 4k	>7.9x





# Bound on default\_dist Baseline

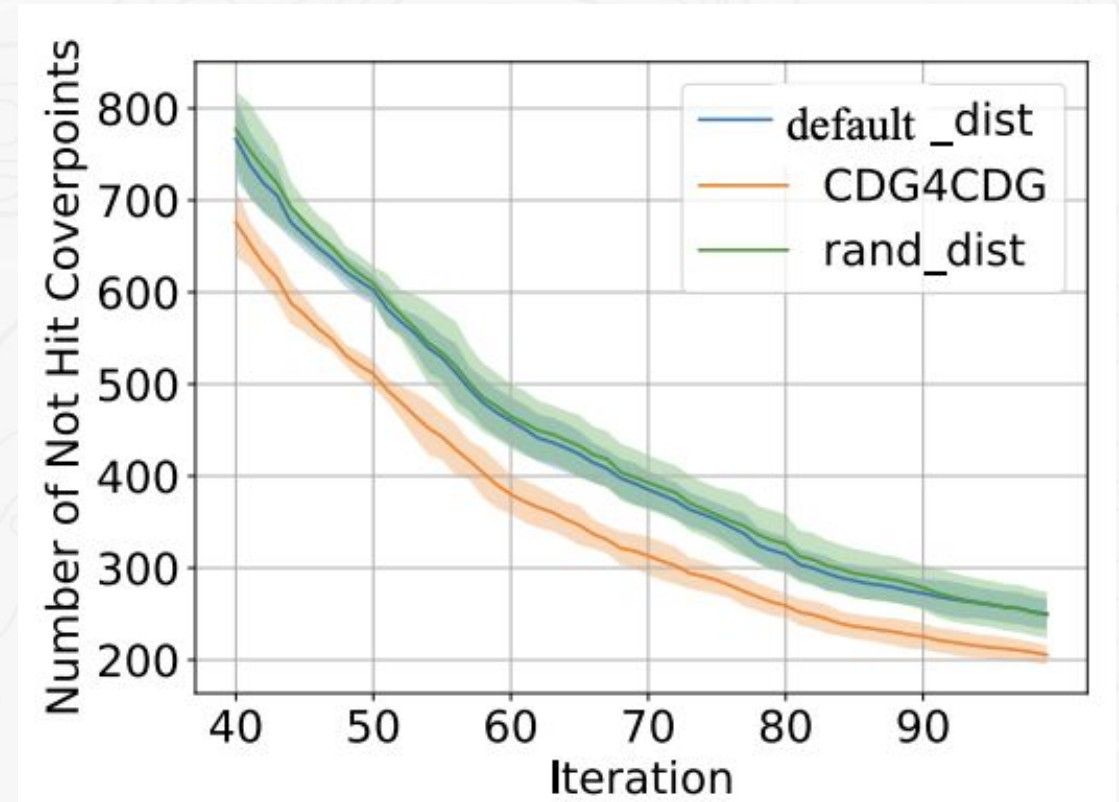
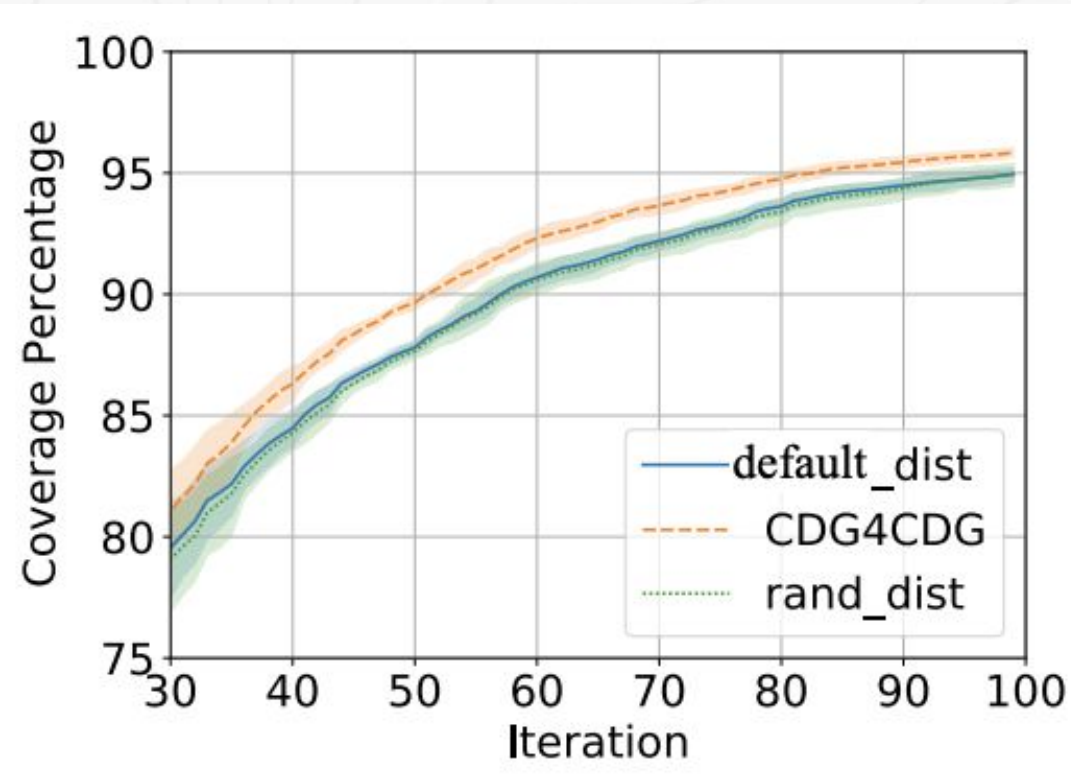
For the baseline, the lower bound of the expected number of simulation runs to cover all  $m$  coveritems is  $O(m \log m)$ , while the upper bound is infinite



- The best scenario is when the distribution constraint is uniform and coveritems are equally likely to be covered. In this case, the problem is reduced to an instance of well known Coupon collector's problem

# Empirical results

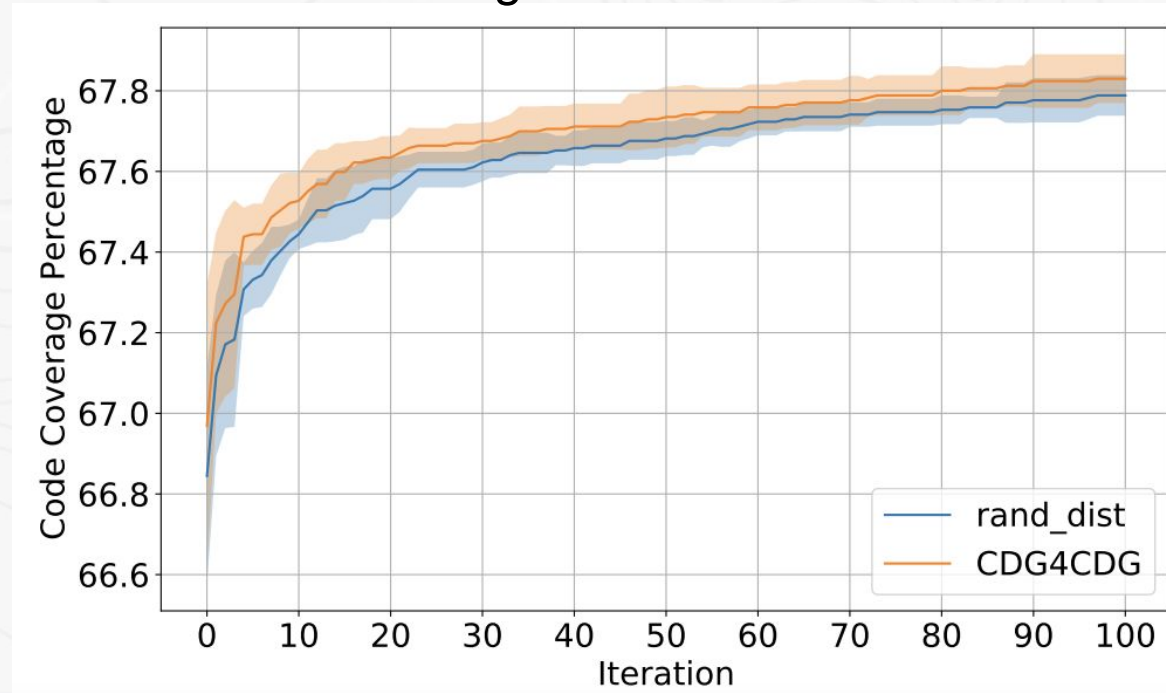
Most of the coveritems in RISC-V-Ibex are uniformly specified among all random variable values



# Impact of Functional Coverage on Code Coverage

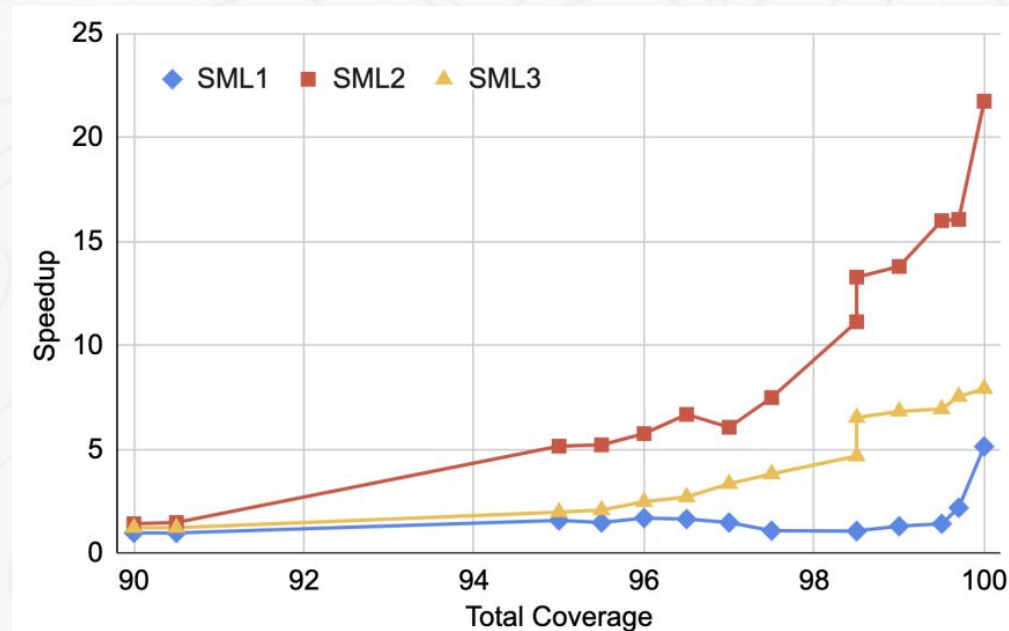
Though CDG4CDG is designed to improve the functional coverage, it alters the variable values and the execution paths of the simulation, and subsequently may affect code coverage as well.

Code coverage on the RISCV-Ibex



# Conclusion

- We introduced an automated test generation framework, CDG4CDG, to accelerate the functional coverage convergence
- CDG4CDG achieves consistent coverage improvement
- Reaches the coverage closure significantly faster with up to 21.7× speedup in a fully automated flow





# Questions

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