

Simulation Runtime Optimization of Constrained Random Verification using Machine Learning Algorithms

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The Meeting

- University of Minnesota has a graduate level digital verification course
- Eldon did a guest lecture speaker one day in late 2017





Review 2017 Paper

Improving Constrained Random Testing by Achieving Simulation Design Goals through Target Functions, Rewinding and Dynamic Seed Manipulation









Simulation Time Intervals



Thoughts on Stimulus





2017 Paper Deficiencies

- A stimulus path is taken based of an entirely random approach to find solutions for the DUT that are proven to improve coverage (completeness)
- The problem is the "entirely random approach"
- A way to improve the odds of finding stimulus solutions for the DUT?





Quake III Arena Capture the Flag



• 2 versus 2 capture the flag





acce

SYSTEMS INITIATIVE

Capture the Flag 2018

- Google Deepmind project
- An approach for sequences
- Rather than training a single agent, we train a population of agents, which learn by playing with each other, providing a diversity of teammates and opponents.
- Each agent in the population learns its own internal reward signal, which allows agents to generate their own internal goals, such as capturing a flag. A two-tier optimisation process optimises agents' internal rewards directly for winning, and uses reinforcement learning on the internal rewards to learn the agents' policies.
- Agents operate at two timescales, fast and slow, which improves their ability to use memory and generate consistent action sequences.

"Agents operate at two timescales, fast and slow, which improves their ability to use memory and generate consistent action sequences."



https://deepmind.com/blog/capture-the-flag/ 8

FTW Agent Architecture



Useful Stimulus Odds Improvement

If a deficiency of the 2017 paper was too large of a state-space and its pure random approach, is there a way to improve the odds of navigating that state-space?





Ambalakkat Master **Thesis Paper**









accelle

SYSTEMS INITIATIVE

Take the ML model of stimulus and plug it into the simulation to dynamically update the constraints





Example DUT (comparator)





2017 Summary for DUT Width of 5



50% success of finding a combination of stimulus after 4000 iterations





Optimization of the Test Environment using Machine Learning Algorithms

 Generating the Training Sets
 Training the Machine Learning Model
 Updating the Constraints







OPTIMIZATION OF THE TEST ENVIRONMENT

function void generate_TS_and_track_hit_bins(

- bit [width-1:0] a,
- bit [width-1:0] b,
- bit [width-1:0] match);

1. Generating Training Sets (TS)

- Structures used to define the training sets
- Less Error Prone
- Addressing training sets easier
- Function used for generating necessary number of valid training sets and track output bins hit
- no_of_TS_required made configurable

```
// Load TS with "no of TS required" number of training sets
   // [Input=0 and Match = 0] cannot be used for training
  if(i<no of TS required && (match!=0))</pre>
      begin
        // Generating Training Sets
        TS[i].a
                        = a;
        TS[i].b
                        = b;
        TS[i].match
                        = match;
         TS[i]. TS ready = 1;
         // Tracking Output Bins hit
         OUT HIT[match] = 1;
         i = i+1;
                                    typedef struct {
      end
                                       bit [width-1:0] a;
   else
                                       bit [width-1:0] b;
                                       bit [width-1:0] match;
   begin
      OUT HIT[match] = 1;
                                       bit TS ready;
                                      training set;
   end
endfunction
```





tcl-fann

NAME SYNOPSIS INTRODUCTION DESCRIPTION TRAINING ALGORITHMS ACTIVATION FUNCTIONS ERROR FUNCTIONS ERROR STOP FUNCTIONS EXAMPLE OUTPUT AUTHOR COPYRIGHT

NAME

tcl-fann - A Tcl extension for Artificial Neural Networks

SYNOPSIS

package require fann

gaul create name ?-sparse connection_rate | -shortcut? layers layer1 layer2 ...

gaul load name filepath

name init ?min_weight max_weight?



http://tcl-fann.sourceforge.net 17



OPTIMIZATION OF THE TEST ENVIRONMENT USING ANN

*activation function

output laye

2. Training the Machine Learning Model (ANN): Using TCL extension, fann for implementing the ANN.

TCL Commands used to define the number of layers, number of neurons per layer, activation functions, connectivity, etc. of the neural network. For example:

```
fann create ANN 2 1 1

ANN function hidden linear

ANN function output linear

ANN trainondata 500000 0 {TS_inputs} {TS_outputs}
```

OPTIMIZATION OF THE TEST ENVIRONMENT

- 3. Updating the Constraints: Function to update the constraints, update_constraint called every iteration once beta_ready is asserted.
 - Efficient runtime update of constraints: Recompilation of environment not required after update
 - Ideally, coverage should improve every iteration, converging to 100% coverage goal much faster.

<pre>function void update_constraint(integer bet</pre>	a_value);
<pre>num_inside_queue = {};</pre>	
i = 0;	
<pre>repeat(2**width)</pre>	
<pre>if(!(OUT_HIT.exists(i))) begin</pre>	
num_inside_queue.push_back(i++/b	<pre>peta_value);</pre>
break;	<pre>function void rprint();</pre>
end	<pre>this.randomize() with {(num inside num_inside_queue);};</pre>
else i++;	<pre>`uvm info("CR", \$sformatf("num is: %d", num), UVM LOW)</pre>
endfunction	endfunction



OPTIMIZATION OF THE TEST ENVIRONMENT USING ANN

Training Machine Learning Model

Update Constraints

Updating Constraints (using ANN) ***** START run ANN INFO STATUS : TCL : RUNNING ANN at time: 60 ns INFO STATUS : TCL : Output Bin NOT Hit: 1; Predicted Input to Update Constraint Oueue: 1 ****** END run ANN UVM INFO sv/env pkg.sv(305) @ 61: uvm test top [ENV PKG] AFTER UPDATE num inside queue contain: '{'h1} UVM INFO sv/dut.sv(37)@ 61: reporter [dut if] AFTER drive regs A: 1 B: 1 UVM INFO sv/env pkg.sv(29) @ 66: reporter [ENV PKG] Generate training sets; Track output bins hit ----- START eval loop DEBUG current simulation time is ctime : 67 ns INFO STATUS : TCL : LOCAL ACCEPTED seed: 319 at time: 47 ns INFO STATUS : TCL : 67 ns : GOOD : 50.000000 > 37.500000 ----- END eval loop





2017 Experimental Data

2019 Experimental Data Linear Regression Model

Width of Comparator	No of Iterations
1	3
2	60
3	261
4 or more	Segmentation Fault

Width of Comparator	No of Iterations
1	5
2	14
3	24
4	26
5	78
6	96
7	144

2019 Experimental Data ANN Model

Width of Comparator	No of Iterations
1	3
2	16
3	24
4	29
5	96





2017 Experimental Data

Width of Comparator	No of Iterations
1	3
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2019 Experimental Data Linear Regression Model

Width of Comparator	No of Iterations
1	5
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Why does the 2019 approach improve the odds so much?

never mind this is not a statistical sample, but a discrete data set

SYSTEMS INITIATIVE

2019 Experimental Data ANN Model

Width of Comparator	No of Iterations
1	3
2	16
3	24
4	29
5	96



Future Work

- Deeper looks at Machine Learning models that can predict stimulus with state
- Is there a role of Formal to help generate deeper stimulus with this approach?
- Configuration space problem





Conclusion

- Improving the search for interesting stimulus using machine learning techniques
- Promising results for example test case by informing the randomization based off of previous automated learning
- Automated in terms of approach as it is based off of coverage





Questions

Please Vote at http://vote.dvcon.org





Backup Slides





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OPTIMIZATION OF THE TEST ENVIRONMENT USING A LINEAR REGRESSION MODEL

• Simulation Results using Linear Regression Model:

1. Generating Training Sets

UVM_INFO sv/dut.sv(26)@ 20: reporter [dut_if] AFTER drive regs A: 4 B: 4 UVM_INFO sv/env_pkg.sv(28) @ 26: reporter [ENV_PKG] A and B matching;

Generate training sets; Track output bins hit

rseed_interface.sv, 111 : begin ------ START eval_loop DEBUG current simulation time is ctime : 27 ns INFO STATUS : TCL : LOCAL ACCEPTED seed: 2 at time: 17 ns INFO STATUS : TCL : 27 ns : GOOD : 12.500000 > 0.000000 DEBUG stable_count == 0

----- END eval_loop

3. Update Constraints

UVM_INFO sv/env_pkg.sv(171) @ 90: reporter@@uvm_sequence_item [ENV_PKG]

Updating Constraints

UVM_INFO sv/env_pkg.sv(196) @ 90: reporter@@uvm_sequence_item [ENV_PKG]
AFTER UPDATE num_inside_queue contain: '{'h3}

UVM_INFO sv/dut.sv(26)@ 90: reporter [dut_if] AFTER drive regs a: 3 b: 3 UVM_INFO sv/env_pkg.sv(28) @ 96: reporter [ENV_PKG] A and B matching; Generate training sets; Track output bins hit

----- START eval_loop

DEBUG current simulation time is ctime : 97 ns

INFO STATUS : TCL : LOCAL ACCEPTED seed: 619 at time: 87 ns

INFO STATUS : TCL : 97 ns : GOOD : 87.500000 > 75.000000



----- END eval_loop

2. Training Machine Learning Model

4. Converges to 100% coverage goal in 24 iterations as opposed to 261 iterations in prior

W(INFO STATUS : TCL : WIDTH OF COMPARATOR = 3

INFO STATUS : TCL : ITERATIONS TOTAL = 24

INFO STATUS : TCL : final_report END

UVM_INFO sv/rseed_interface.sv(143) @ 117: reporter [RS]

COVERAGE GOAL MET coverage: 100 max_objective: 100



OPTIMIZATION OF THE TEST ENVIRONMENT USING A LINEAR REGRESSION MODEL

- 2. Training the Machine Learning Model (Linear Regression Model): TCL library, math::linearalgebra, used to solve the linear regression problem
 - Efficient techniques used to 'get' training set values from SV environment.
 - Compute the parameters, beta_a and beta_b using the training sets.
 - Computed parameters along with a flag beta_ready indicating that the ML model has been trained, forced on variables in SV environment.

```
proc ::rclass::eval_coeff {} {
    # Get the Training Sets
    set a0 [get top.dif.TS_a_0 -radix decimal]
    set b0 [get top.dif.TS_b_0 -radix decimal]
    set match0 [get top.dif.TS_match_0 -radix decimal]
    # Solve Linear Equation
    set beta_a [math::linearalgebra::solveGauss $a0 $match0]
    set beta_b [math::linearalgebra::solveGauss $b0 $match0]
    # Force Beta Values to SV Environment
    force top.rseed_interface.beta_a $beta_a;
    force top.rseed_interface.beta_b $beta_b;
    force top.rseed_interface.beta_ready 1; }
```





Updating Constraints

```
function void update constraint(integer beta value);
  num inside queue = {};
  i = 0;
  repeat(2**width)
    if(!(OUT HIT.exists(i))) begin
      num inside queue.push back(i++/beta value);
      break;
    end
    else i++;
endfunction
```



UVM_INFO sv/env_pkg.sv(171) @ 80: reporter@@uvm_sequence_item [ENV_PKG] Updating Constraints UVM INFO sv/env pkg.sv(196) @ 80: reporter@@uvm sequence item [ENV PKG] AFTER UPDATE num inside queue contain: '{'h2} UVM INFO sv/dut.sv(26)@ 80: reporter [dut if] AFTER drive regs a: 2 b: 2 UVM_INFO sv/env_pkg.sv(28) @ 86: reporter [ENV PKG] A and B matching; Generate training sets; Track output bins hit ----- START eval loop DEBUG current simulation time is ctime : 87 ns INFO STATUS : TCL : LOCAL ACCEPTED seed: 619 at time: 77 ns INFO STATUS : TCL : 87 ns : GOOD : 75.000000 > 62.500000 ----- END eval loop UVM INFO sv/env pkg.sv(171) @ 90: reporter@@uvm sequence item [ENV PKG] Updating Constraints UVM INFO sv/env pkg.sv(196) @ 90: reporter@@uvm sequence item [ENV PKG] AFTER UPDATE num inside queue contain: '{'h3} UVM INFO sv/dut.sv(26)@ 90: reporter [dut if] AFTER drive regs a: 3 b: 3 UVM INFO sv/env pkg.sv(28) @ 96: reporter [ENV PKG] A and B matching; Generate training sets; Track output bins hit ----- START eval loop DEBUG current simulation time is ctime : 97 ns INFO STATUS : TCL : LOCAL ACCEPTED seed: 619 at time: 87 ns INFO STATUS : TCL : 97 ns : GOOD : 87.500000 > 75.000000 ----- END eval loop