SGEN2: Evolution of a Sequence-Based Stimulus Engine for Micro-Processor Verification

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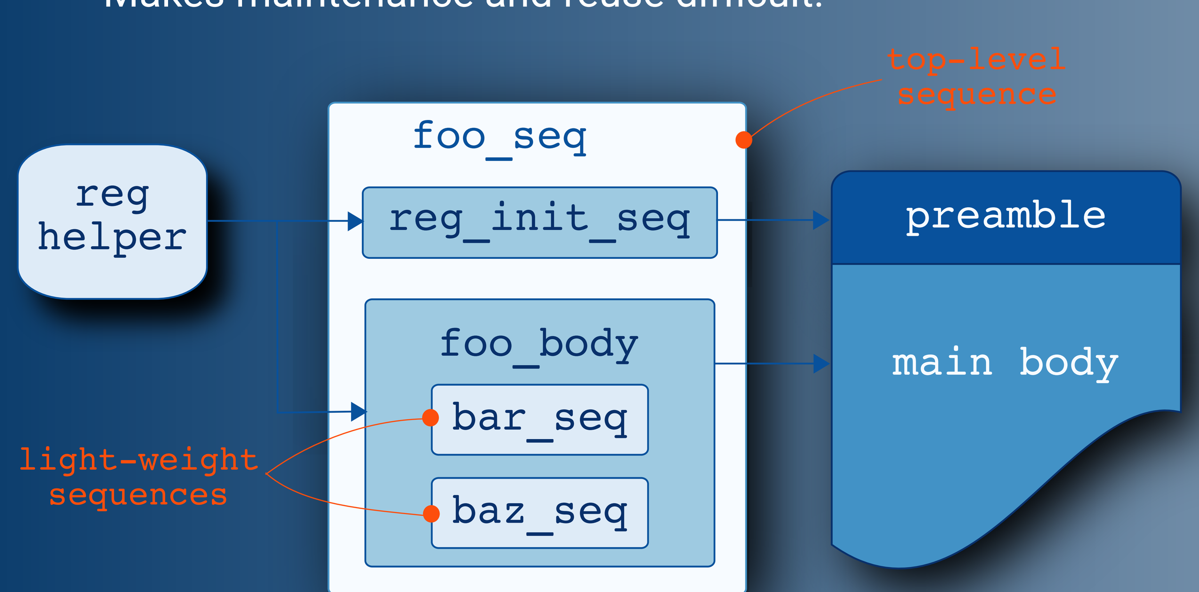
1) Introduction

- SGEN is a sequence-based stimulus engine written in C++11 that generates assembly programs used to verify the Cavium ThunderX® ARM micro-processor.
- SGEN1 was originally presented at DVCON'2017:
  - Limitations with the original methodology became apparent over time and a refactoring effort was undertaken to address them.
- SGEN2 is the *new and improved* version:
  - OOP techniques and C++11 features were used to add layers of abstraction and to simplify creation of new sequences:
    - Automates resource management and initialization.
    - Reduces the amount of code required for new sequences.
    - Facilitates code/sequence reuse.
    - 2x performance improvement.
  - Support for machine learning was added to automate exerciser tuning:
    - A genetic algorithm was used to improve the failure rate of a selected exerciser.

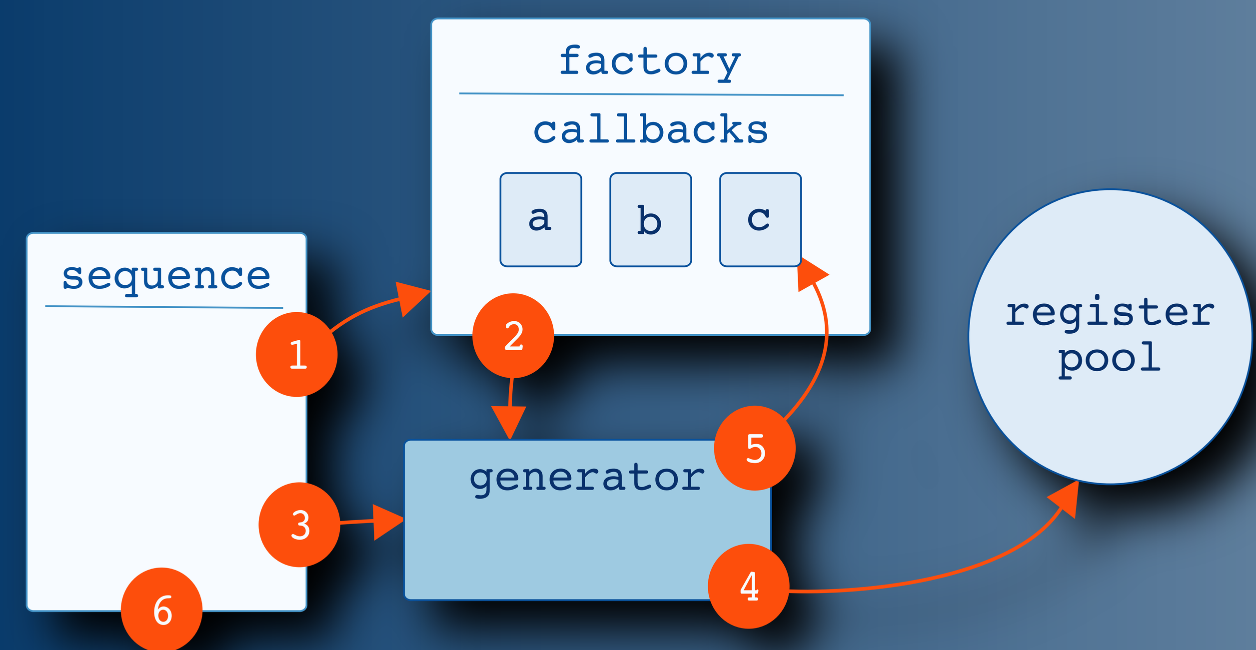
2) SGEN1

- SGEN evolved from a need to better control stimulus:
  - Bridge the gap between directed and knob-based generation.
  - C++11 was chosen for it's rich set of data structures, 3rd party libraries, fast compile and run times and ease of debugging.
  - *No constraints!* — randomization provided by C++11 lambda functions.
  - Successfully used to create directed random sequences in production.
- First version required helper sequences and manual tracking of base registers to generate valid programs.
  - This made sequences difficult to reuse and necessitates a lot of *boilerplate*.
    - Makes maintenance and reuse difficult.



3) SGEN2

- SGEN2 provides layers of abstraction that automates repetitive tasks such as object configuration and resource reservation and release through the use of OOP techniques.
- The most important new classes are:
  - The *register pool* centralizes and simplifies register management by using *RAII*.
  - The *instruction generator* class provides a simple way for a user to create and randomize instruction objects.
    - Uses *lazy initialization* as well as callback hooks to enable customization.
  - The *instruction generator factory* class returns pre-configured generator objects using the most commonly used defaults.
    - The user can override the defaults by attaching *C++11 lamda* functions.



- The figure above shows the new structure of a sequence:
  1. The sequence uses the generator factory to create a generator object.
  2. The factory configures the generator object by attaching callbacks.
  3. The sequence gets an instruction from the generator.
  4. The generator reserves registers from the register pool.
  5. The generator executes callbacks.
  6. Sequence terminates and goes out of program scope, causing the generator object to destruct which automatically returns registers to the pool.
- The listing below shows SGEN2 code that generates random SIMD instructions.
  - The code is much more compact than the equivalent SGEN1 code.
  - *Only 7 total lines of code required!*

```
auto num randutils::random_number<int>::select(500, 1500);
auto inst_gen = InstructionGeneratorFactory<inst::simd>::create(this,  num);
for(auto i  :  inst_gen);
{
    i->randomize();
    driver_p->do_item(*i);
};
```

4) Automation Through Machine Learning

- Hand-tuning exercisers is often necessary towards the end of a project when failure rates fall below 1%.
  - Hand tuning is ad-hoc and time consuming.
  - We attempted to automate tuning by using a *genetic algorithm*.
    - Our goal was to generate initial exerciser states that had a higher chance of failure.
- The final population of tuned exercisers were generated as follows:
  1. The initial population consisted of 1000 shortened exerciser runs.
  2. The pass/fail status of each test as well as configuration weights were saved.
  3. The next generation consisted of:
     - The weights of all failed tests from the prior generation.
     - Mutated weights from failing and passing tests.
     - Newly generated weights.
  4. Steps (2) and (3) were repeated a maximum of 10 times or until 100 failing tests were found.
- The algorithm generated 100 failing states after 6 generations.
  - We ran 2000 exercisers initialized with the failing states and the failure rate *increased from 1% to 2.5%*.

5) Conclusions and Future Work

- The limitations of SGEN1 were addressed through a large refactoring effort to create SGEN2.
  - OOP techniques such as *factories*, *generators*, *lazy initialization* and *RAII* were used to provide layers of abstraction that greatly reduce the overhead associated with creating new stimulus.
  - Code reduction was *significant* — often by as much as *70–90%!*
  - Resulting code was *less buggy* and *easier to maintain and reuse*.
  - Please see full paper for examples of more complex sequence code.
- A *genetic algorithm* was used to automate exerciser tuning.
  - Initial results have been promising — failure rates for a selected exerciser were increased from ~1% to ~2.5%.
- Future work includes:
  - Continuing to improve SGEN by adding features suchs as multi-threading and stateful sequences.
  - Explore other machine learning techniques such as clustering, partitioning and logarithmic regression to improve exerciser efficiency.