KTH VETENSKAP OCH KONST

KTH Computer Science and Communication

HSST 2015

Learning-Based Testing for Procedural and Reactive Systems

Karl Meinke,

karlm@kth.se

School of Computer Science and Communication

KTH Royal Institute of Technology Stockholm

0. Overview of the Course

Part 1: Introduction to Learning-based Testing

1. Requirements Based Black-box Testing
2. Learning Based Testing Paradigm (LBT)
3. Two Frameworks for Study

based on: K. Meinke, F. Niu and M. Sindhu: *Learning-Based Software Testing: a Tutorial,* in: Proc. ISoLA 2011

Overview

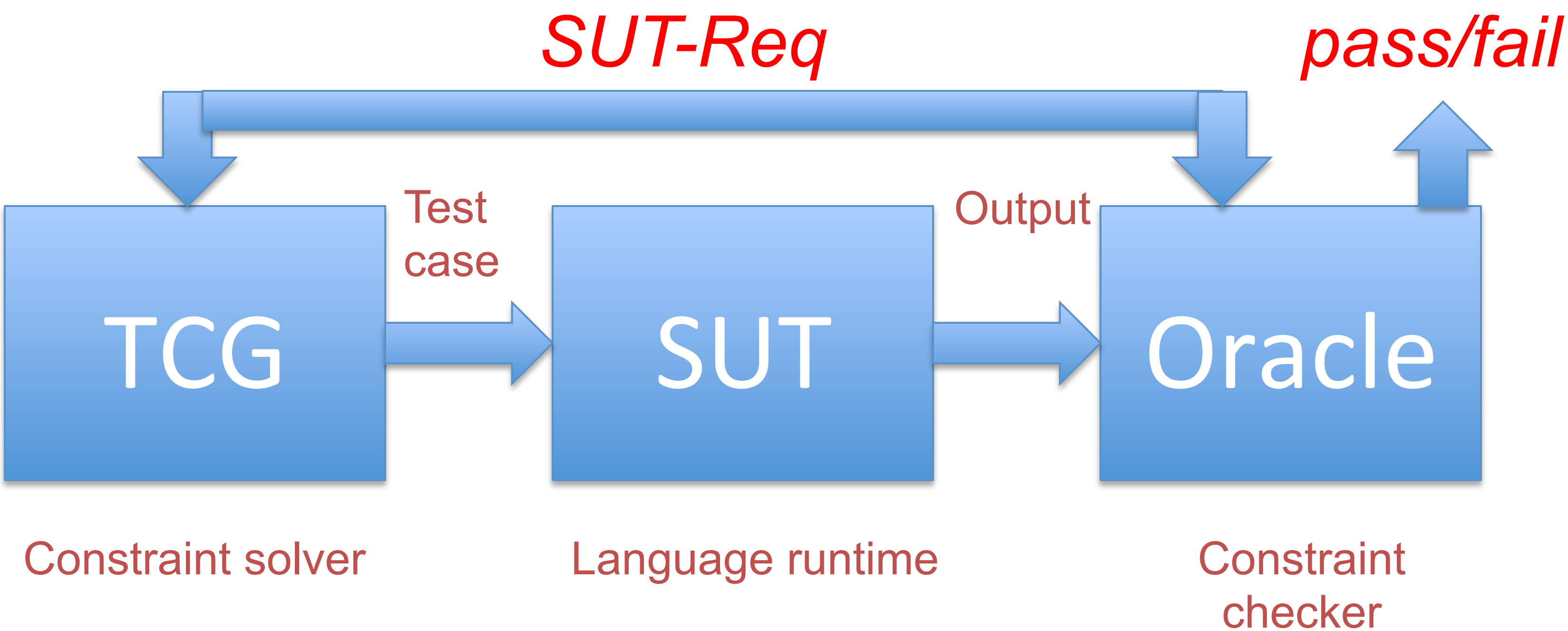
Part 2: LBT for reactive systems: theory

Part 3: LBT for reactive systems: praxis

Part 4: LBT for procedural systems

1. Requirements Based Black-Box Testing

1. User requirement *SUT-Req*
2. System under Test *SUT*
3. Test verdict pass/fail *Oracle*



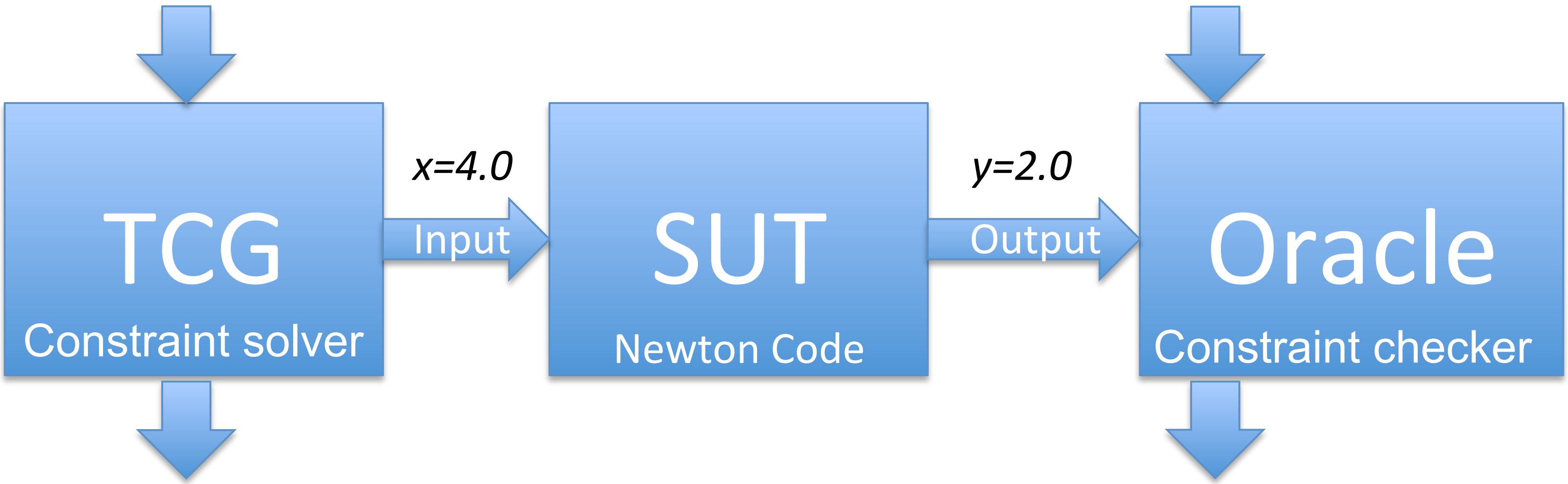
1.1. Procedural Code Example:

Newton's Square Root Algorithm

Postcondition

$| y*y - x | \leq \varepsilon$

Precondition $x \geq 0.0$



$x=4.0$ satisfies $x \geq 0.0$

Verdict

$x=4.0, y=2.0$ satisfies $| y*y - x | \leq \varepsilon$

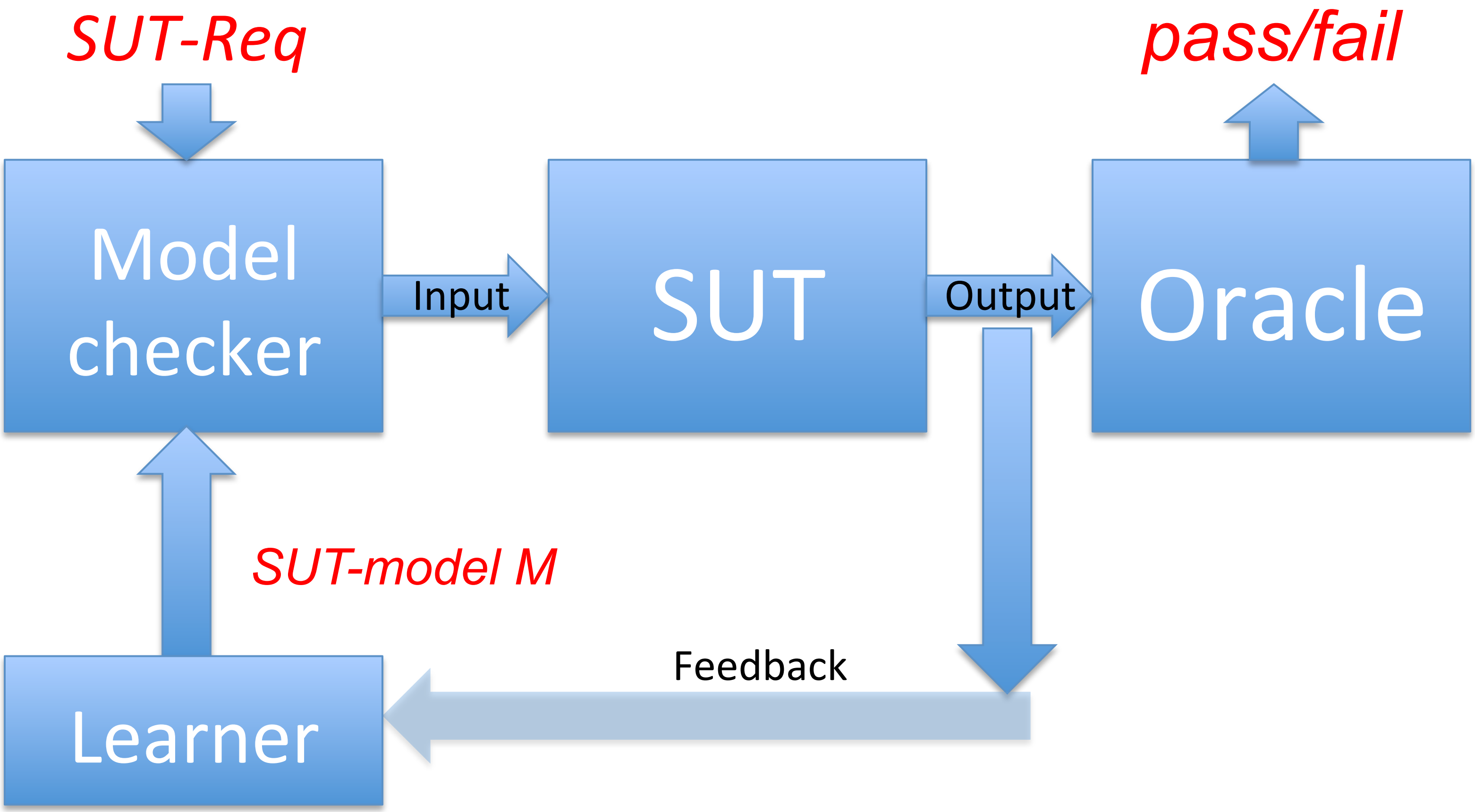
1.2. Key Problem: Feedback

<u>Problem</u>: How to modify this architecture to..

1. Improve next test case using previous test outcomes
2. Execute a large number of good quality tests?
3. Obtain good coverage?
4. Find bugs quickly?

2. Learning-Based Testing (LBT)

Meinke 2004, Proc. ISSTA-04



"*aka*. Model based testing without a model"

2.1. Basic Idea …

LBT is a search heuristic that:

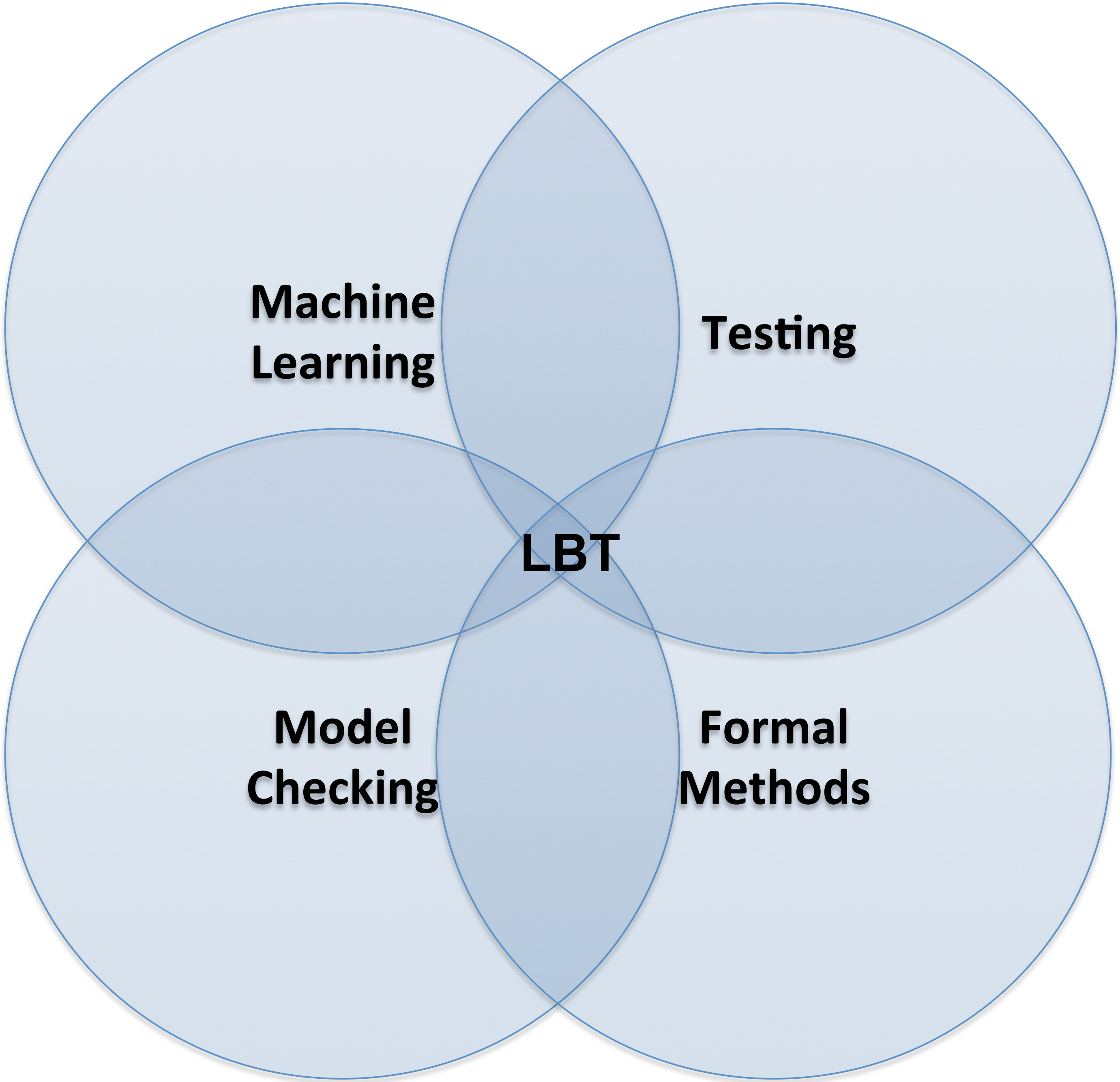
1. Partially and incrementally learns an SUT model
2. Uses generalisation (*inductive inference*) to predict unseen bugs!
3. Uses best prediction as next test case
4. Iteratively refines model according to each test outcome

2.2. Abstract LBT Algorithm

1. Start from *null hypothesis* M_0
2. For each $k >= 0$ do
    1. Model check M_k against *SUT-Req*
    2. Choose "best counterexample" i_{k+1} from step 2.1
    3. Execute i_{k+1} on SUT to produce o_{k+1}
    4. if (i_{k+1}, o_{k+1}) satisfies !*SUT-Req* label i_{k+1} as a bug
    5. Use (i_{k+1}, o_{k+1}) to refine M_k to M_{k+1}
    6. If *finished* break.

When Step 2.2 fails we fall back on:

- Active learning queries
- Equivalence checking queries


Machine Learning
Testing
LBT
Model Checking
Formal Methods

2.3. Technical Difficulties

General problem is to find combinations of

models, requirements languages and solvers (*M*, *L*, *S*)

so that …

1. models *M* are:
   - expressive,
   - compact,
   - partial and/or local (an abstraction method)
   - easy to construct and learn
   - behaviour is captured by *L*
2. *M* and *L* are feasible to model check with *S*
3. Supervised learning of *M* admits a notion of convergence

2.4. Convergence and Test Case Choice

- How reliable are counterexamples $c_1, \ldots, c_n$?
- Question of false negatives
- Some (parts of) SUTs more easily learned than others
- Measure local convergence around model points
- Convergence is a proxy for model reliability …
  "*Counterexamples from locally well-converged regions are more reliable*"

2.5. Convergence and Coverage

- Convergence is also proxy for coverage
- If no counterexamples ($n = 0$)
  - choose point from least converged region (breadth first search)

- Question: *Do formal models of approximation and convergence always exist*?
- Answer: sometimes, but important exceptions also exist.

3. Two Frameworks for Study: Procedural Numerical Code

Generally data-oriented testing

1. Requirements Language – pre and postconditions
   – first-order logic of real-closed fields
2. Models
   – non-gridded *n*-dimensional piecewise polynomials
3. Model checker
   – Hoon-Collins CAD algorithm, (Mathematica)
4. Learning algorithm
   – *n*-dimensional polynomial interpolation

Framework 2: Reactive Systems

Generally *control-oriented* testing

1. Requirements language = propositional linear temporal logic (PLTL)
2. Model = FSM, Moore machine
3. Model checker = BDD/SAT-based checkers
4. Learning = regular inference algorithms

Why not Neural Networks?

Neural and deep neural networks have notable recent success … but several problems here …

1. NN are implicit continuous models unsuited to symbolic model checking
2. NN learning paradigm based on iterative training (*weight optimisation*) on big data

   Testing does not fit this paradigm

   Single test case can take 1-10 minutes!
3. NN models are statistical in character

5. Conclusions

- A promising approach …
- Flexible general heuristic,
  - many models and requirement languages seem possible
- Many SUT types might be testable
  - procedural, reactive, real-time, hybrid etc.

Open Questions

- Benchmarking?
- Scalability? abstraction, dimension reduction?
- Bottlenecks? model checking, learning, SUT?