Center for
Experimental Software Engineering

Requirements Extraction from Models of Automotive Software

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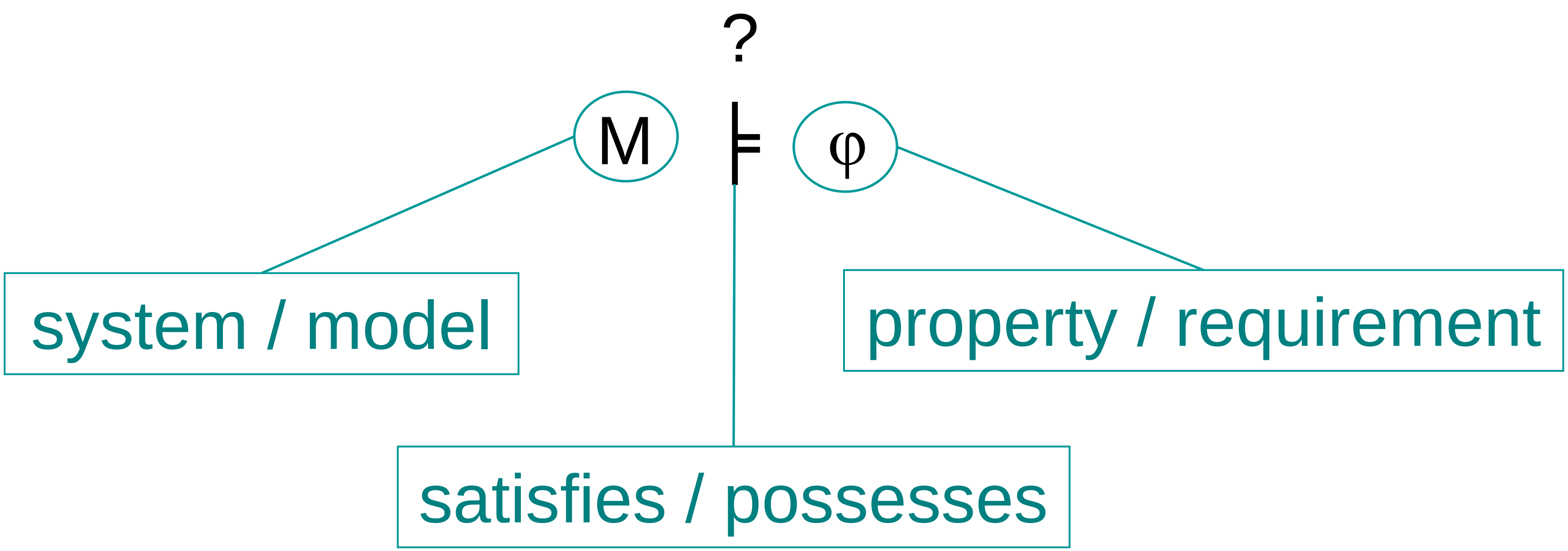
Joint work with Sam Huang, Chris Ackermann (UMD); Arnab Ray (Fraunhofer CESE); Charles Shelton, Beth Latronico (Robert Bosch)

The Model Checking Problem



The Synthesis Problem

$$? \models \varphi$$

The Requirements-Extraction Problem

$$M \models ?$$

Motivation for Requirements Extraction

- System comprehension
- Specification reconstruction
  - Missing / incomplete / out-of-date documentation
  - “Implicit requirements” (introduced by developers)

Requirements Extraction for Automotive Software

- Joint project: UMD, Fraunhofer, Bosch
- Outline
  - – Automotive software development
  - – Reqts-extraction via machine learning
  - – Pilot study
  - – Conclusion

Automotive Software

- Driver of innovation

  90% of new feature content based on sw [GM]
  50M+ lines of code [GM]

- Rising cost

  20% of 2006 vehicle cost due to software [Conti]

- Warranty, liability, quality

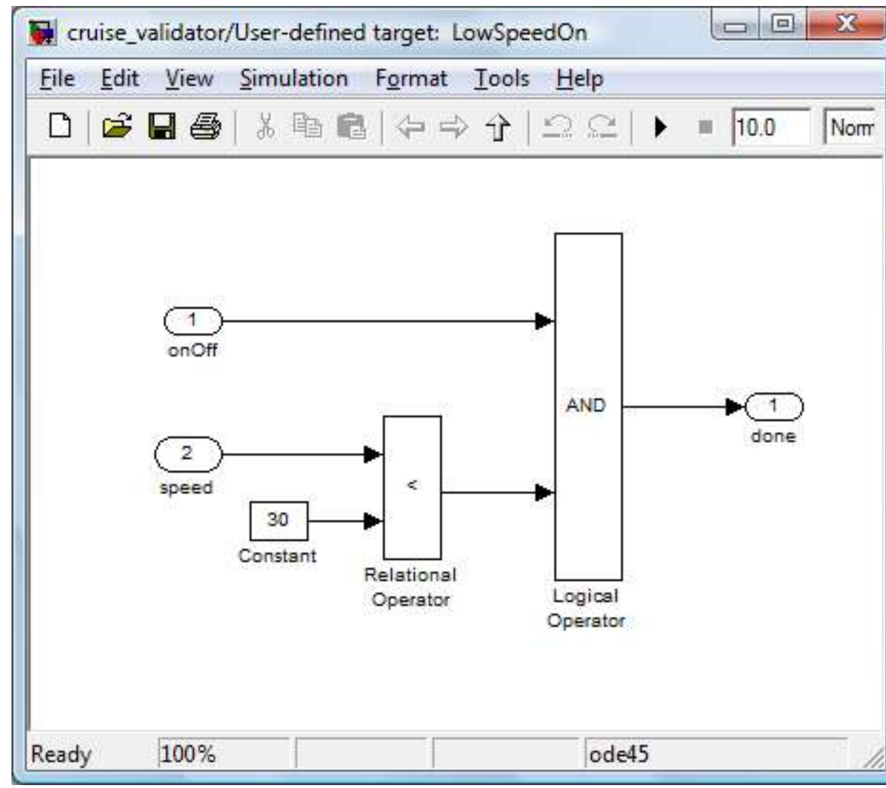
  High-profile recalls in Germany, Japan, US

Automotive Software Development

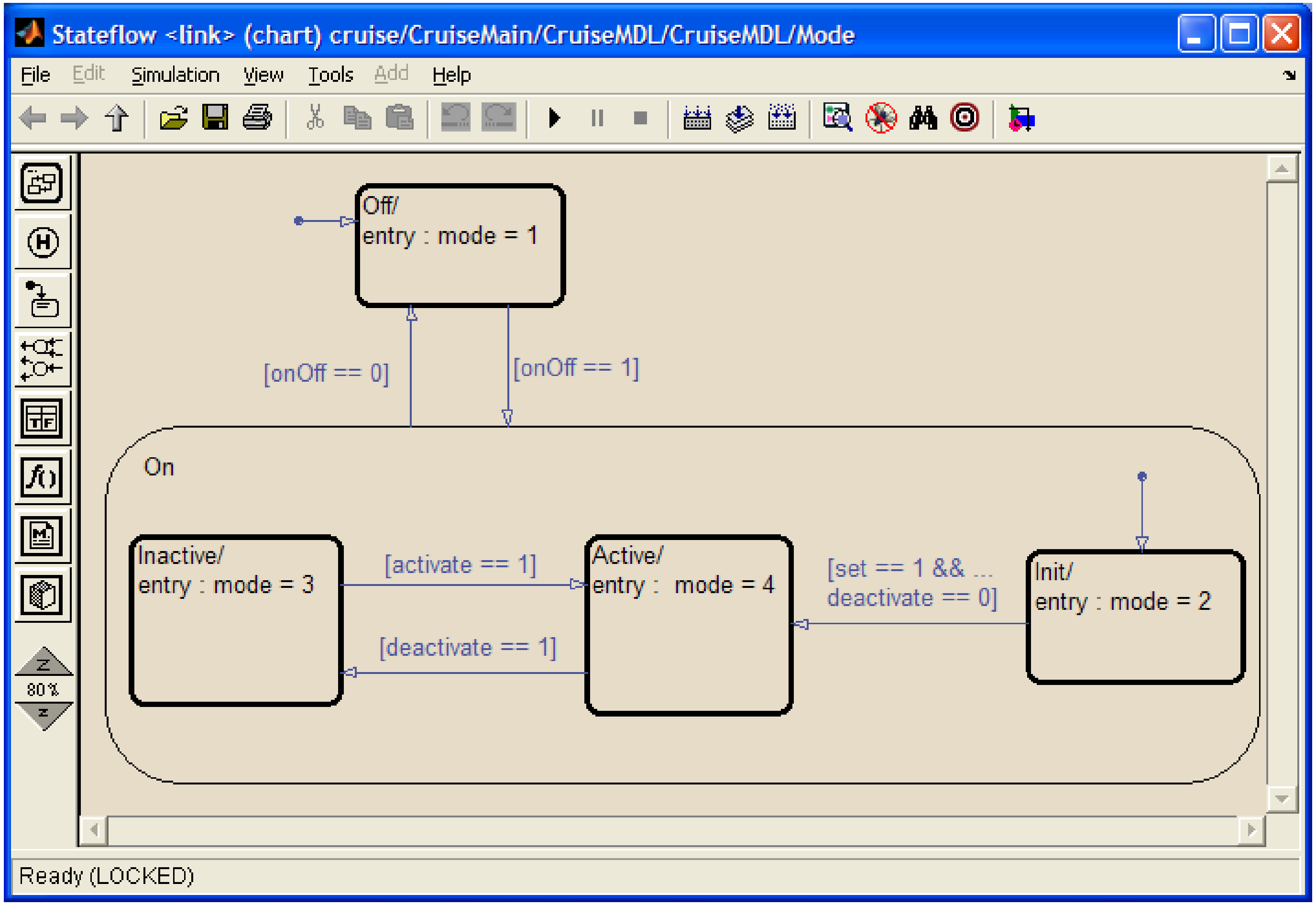
- Ensure high quality of automotive software
  - ... while preserving time to market
  - … at reasonable cost
- How?
  - Model-based development (MBD)
    Efficiencies in production
  - Automated testing
    Efficiencies in verification and validation (V&V)

Models: Simulink®

- Block-diagram modeling language of The MathWorks, Inc.
- Hierarchical modeling
- Simulation
- Continuous, discrete semantics



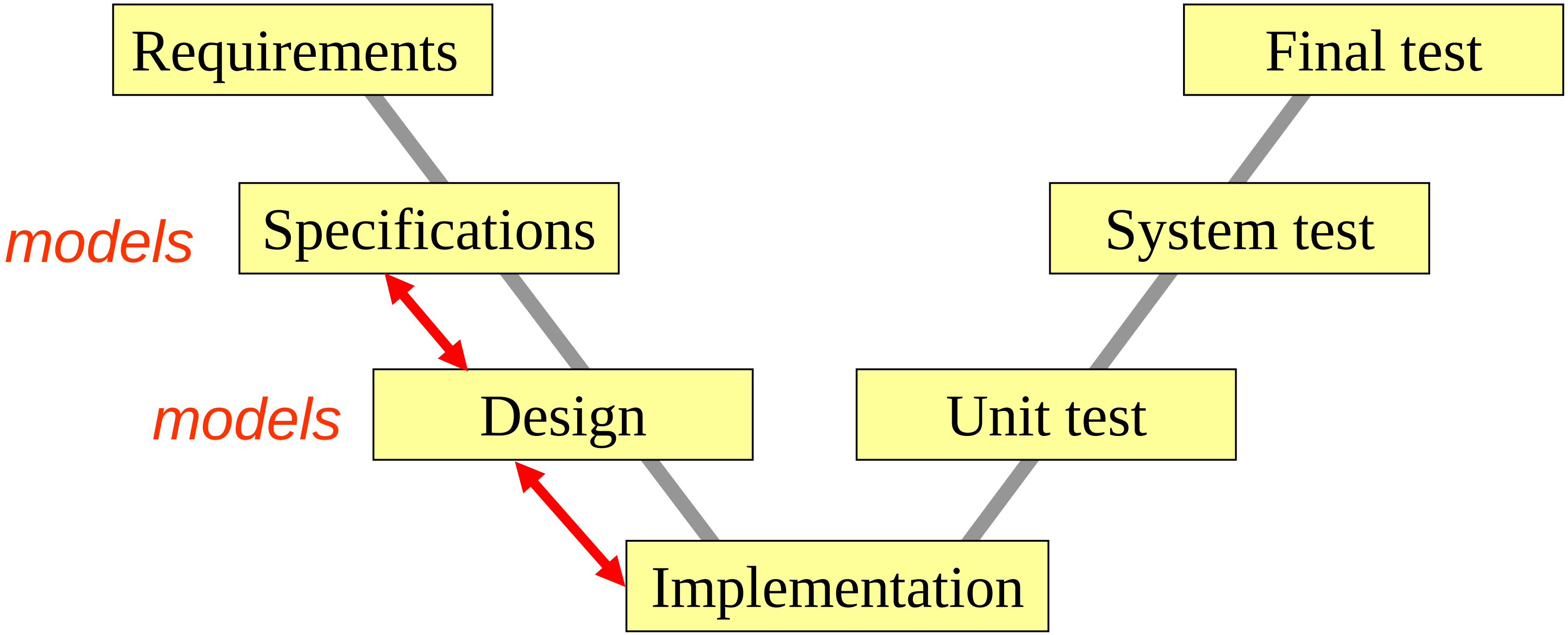
Models: Stateflow®



Semantics

- Simulink has different “solvers” (= semantics)
  - Continuous: inputs / outputs are signals
  - Discrete: inputs / outputs are data values
- Analog modeling: continuous solvers
- Digital-controller modeling: discrete solvers
  - Synchronous
  - Run-to-completion
  - Time-driven

(Model-Based) Development



- Models formalize specifications, design
- Models support V&V, testing, code generation
- Models facilitate communication among teams

Requirements Extraction

- The extraction problem
  - Given: system (M)
  - Produce: requirements (φ)
- Approach
  - Generate test data satisfying *coverage criteria*
  - Use *machine learning* to propose invariants
  - Check invariants using *instrumentation-based verification*

Coverage Testing via Guided Simulation

- Test = simulation run = *sequence* of I/O vectors
- Goal: maximize *model coverage*
  e.g. branch, state, transition, MC/DC, etc.
- Method: *guided simulation*
  - Simulate model, BUT
  - Choose input data to guide simulation to uncovered parts
  - Turn simulation runs into test data
- Input selection by Monte Carlo, constraint solving
- Implemented in Reactis® model-based testing and verification environment

Machine Learning

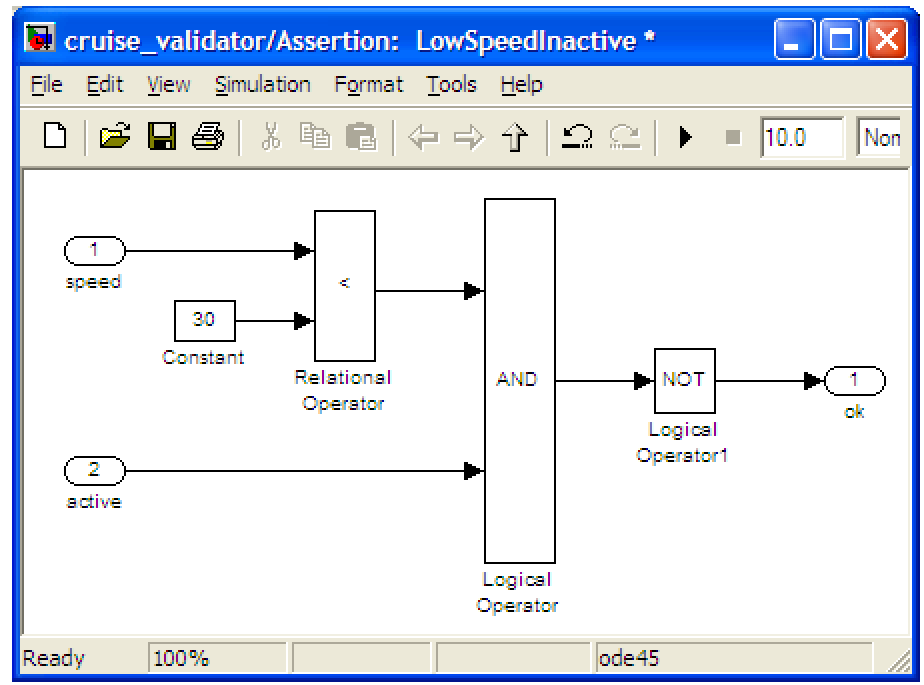
- Tools for inferring relationships among variables based on time-series data
  - Input: table

Time	*x*	*y*
0	1	0
1	-1	-1
2	2	1
…	…	…

  - Output: relationships ("association rules")
    e.g. $0 \leq x \leq 3 \;\; -> \;\; y \geq 0$

Instrumentation-Based Verification

- Formulate requirements as *monitor models*
  - Inputs: signals in model
  - Outputs: boolean flags
    - Flag = true: no violation so far
    - Flag = false: violation detected
- Instrument main model with monitors
- Test instrumented model to search for violations



“If speed is < 30, cruise control must remain inactive”

Machine Learning and Requirements Extraction

- General dea
  - Treat tests (I/O sequences) as experimental data
  - Use to infer relationships between inputs, outputs
- Our insight
  - Ensure test cases satisfy coverage criteria (e.g. branch coverage) to ensure "thoroughness"
  - Use IBV to double-check proposed relationships

Pilot Study: Production Body-Electronic Application

- Artifacts
  - Simulink model (ca. 75 blocks)
  - Requirements formulated as state machine
  - Requirements correspond to 42 invariants defining transition relation
- Goal: our approach, random testing [Raz]
  - Completeness (% of 42 detected?)
  - Accuracy (% false positives?)

Pilot Study: Tool Chain

- Automated test-generation tool: Reactis
- Machine-learning tool: Magnum Opus
- Additional tooling
  - Test-format conversions
  - Automated generation of monitor models, instrumentation

Experimental Design

- Repeat five times
  1. Generate coverage tests (Reactis)
  2. Create invariants (Magnum Opus)
  3. Use IBV to double-check invariants (Reactis)
  4. Combine original, IBV tests, rerun 2, 3
- Repeat five times
  1. Generate random tests (Reactis)
  2. Create invariants (Magnum Opus)
  3. Use IBV to double-check invariants (Reactis)
  4. Create second set of random tests, combine with first
  5. Repeat 3

Experimental Results

- Hypothesis: coverage-testing yields better invariants than random testing
- Coverage results:

  95% of inferred invariants true
  97% of requirements inferred
  Two missing requirements detected

- Random results:

  55% of inferred invariants true
  40% of requirements inferred

- Hypothesis confirmed

Conclusions and Directions for Future Research

- Coverage-testing yields better requirements
- IBV double-checks generated invariants effectively
- Future directions
  - Extraction of temporally complex requirements
  - Visualization of generated requirements
  - Requirements extraction as tool for model understanding, exploration, validation

Thank You!

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