Inferring Temporal System Properties

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Model Checking Problem

$$\text{Ask:} \quad M \models \phi \quad ?$$

- M is a model
- ϕ is a property/requirement
- $\models$ is a satisfaction relation

Related Problems

Synthesis Problem

Find a suitable M: $\quad \Box \models \phi$

Property extraction problem

Find all suitable ϕ: $\quad M \models \{\Box\}$

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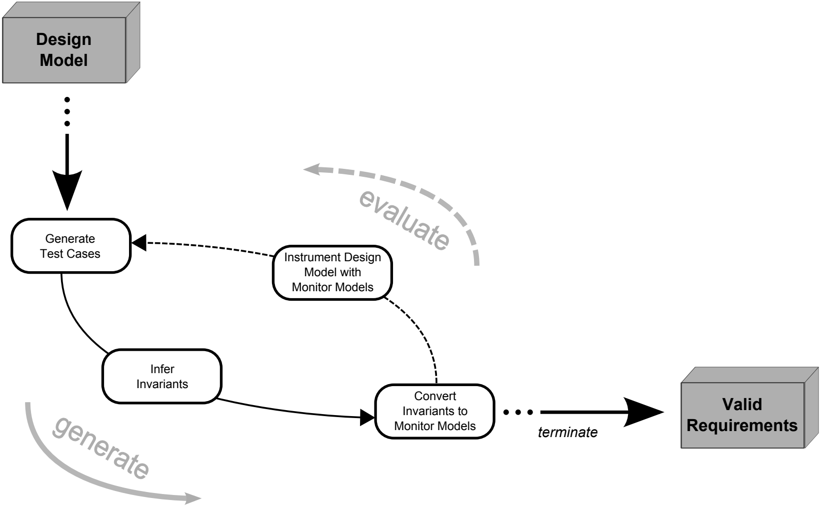
Motivation for Requirements Extraction

- System comprehension
- System reconstruction
  - Incomplete/missing/out-dated documentation
  - "Implicit" (and sometimes unintended) requirements (during construction of system)
- Requirements extraction can serve as a way to estimate high level behavior of a system in terms of the properties that it exhibits.

Automatic Requirement Extraction from Test Cases [ACH+10]

(joint work with Fraunhofer and Robert Bosch)



Observations

- By varying the method by which test cases are generated, we extracted different degrees of requirements
  - Randomized - yielded sparse and lower total number of requirements
  - Structurally guided (MCDC coverage) - more complete overall requirement set
- Iterating requirement extraction process helped lead to refinement of final results

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A Caveat, and Moving On

- In this work we assumed the model was known to us, and a test suite was generated to satisfy some coverage criterion on the model. What can be done without knowledge of the model?
- Given a set of a system's executions E, what properties can be discovered of the system that hold "true?"
- Here a "true" property means one with some measure of accuracy over the execution set E, such as satisfying some *support*. [AIS93]
- The properties discovered should be in some understandable and usable format, such as a temporal logic.

Learning from executions

- Treat set E as a sequence database, and incorporate sequential pattern mining. [AS95, YHA03, Moe07]
- Can mine patterns of the form

$$A \rightarrow B \rightarrow C \rightarrow \ldots$$

- Which can be rewritten as

$$\mathrm{F}\,(A \rightarrow \mathrm{XF}\,(B \rightarrow \mathrm{XF}\,(\ldots)))$$

Support Metric

- Sequential pattern mining algorithms do not only return patterns that are correct 100% of the time. Typically they require a support parameter, which specifies how often rules must be correct to be considered significant.
- The previous rule is more properly written as

$$P_{=s}\left[\mathrm{F}\left(A \rightarrow \mathrm{XF}\left(B \rightarrow \mathrm{XF}\left(\ldots\right)\right)\right)\right]$$

  Here, the rule has been written in probabilistic temporal logic expressing uncertainty in its occurrence.

Related work

- Recent work [LKL07, LKL08] discovers rules of a software code base (JBoss Application Server) in an effort to uncover underlying program design and identify bugs. Characterization of temporal logic fragments that are covered is unclear.
- BIOCHAM [CFS06] - ad hoc machine learning inference of temporal logic formulae for bio-molecular interaction networks.

Next Steps

- Expand supported fragement of temporal logic as much as possible. How far can we go?
- Different fragments are useful for different application domains
  - Software engineering/program analysis:

$$event \longrightarrow F\neg(\mathrm{power\_stays\_on})$$

  - Metabolic pathways:

$$protA \longrightarrow protB \longrightarrow \neg protC \longrightarrow protD$$

$$protA \longrightarrow protB \dashv protC \longrightarrow protD$$

Thanks!

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