EECS 219C: Computer-Aided Verification

Compositional Reasoning and Learning for Model Generation

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Compositional Reasoning

Need for Compositional Reasoning

- Model checking "flat" designs/programs does not scale
  – Can be applied locally, to small modules
  – Globally to simplified models
- Model checking simplified, flat designs is mainly a "best-effort debugging" tool

How do we scale up the method so we can use it for "verification", not just "debugging"?

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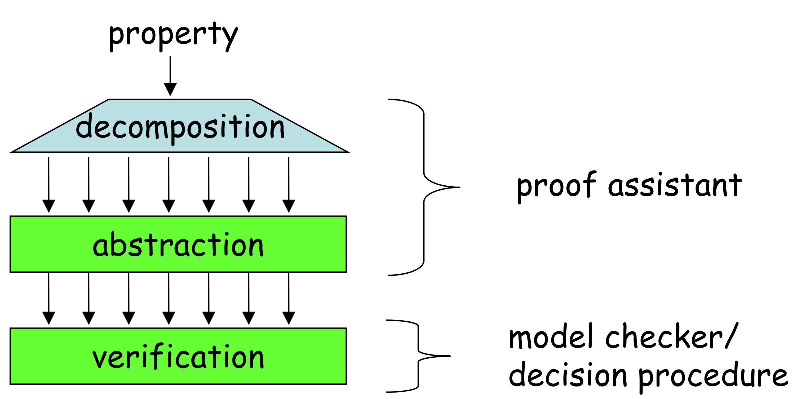
Compositional Reasoning: Divide-and-Conquer

- Idea: use proof techniques to reduce a property to easier, localized properties.



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Notation

Proof rule specified as:

$$\frac{A_1 \; A_2 \;\; A_3 \;\; \ldots \;\; A_n}{C}$$

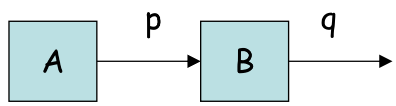
assumptions

conclusion

Assume/Guarantee Reasoning

- System and its Environment
- Each makes an assumption about the other's behavior
- In return, each guarantees something about its own behavior
- Come up with a proof rule
  - Assumptions are what we verify
  - Conclusion is the desired property

Simple assume/guarantee proof



$$\begin{array}{c} p \\ p \Rightarrow q \\ \hline q \end{array}$$

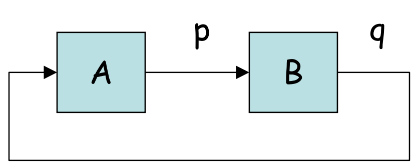
verify using A

verify using B

- Thus, we localize the verification process
- Note abstraction is needed to benefit from decomposition (why?)

Mutual property dependence

- What about the case of mutual dependence?



$$\begin{array}{c} q \Rightarrow p \\ p \Rightarrow q \\ \hline p \wedge q \end{array}$$

- Note, this doesn't work (why?)

"Circular" compositional proofs

- Let $p \rightarrow q$ stand for

  "if p up to time t-1, then q at t"
- Equivalent in LTL of

  $\neg(p \ U \ \neg q)$
- Now we can reason as follows:

$$\frac{\begin{array}{c} q \rightarrow p \\ p \rightarrow q \end{array}}{Gp \wedge Gq}$$

verify using A

verify using B

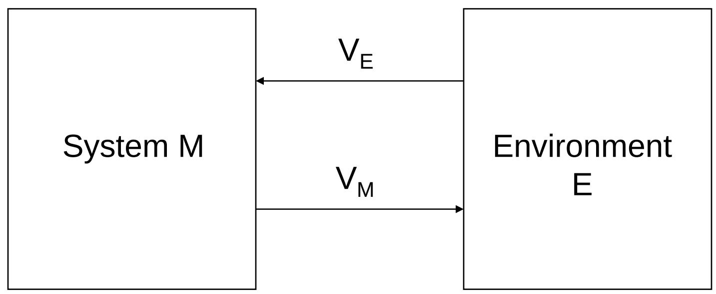
That is, A only has to "behave" as long as B does, and vice-versa.

Model Generation

- Generating models of finite-state systems by observing execution traces
  - Based on a machine learning algorithm first proposed by D. Angluin in '87 and improved upon by Rivest & Schapire in '93

Setting

State variables $V = V_E \cup V_M$, $V_E \cap V_M = \phi$



Want to observe E and generate a good model of it
Usually easy to get a model of M

Why Learn Models?

Generating Environment models

- As a middle ground between
  - Traditional, pessimistic (worst-case) verification
  - Optimistic verification ("does there exist an environment that makes my system work?")
- To generate *environment assumptions* for use in assume-guarantee reasoning

Another use: Generating Abstractions

A Quote

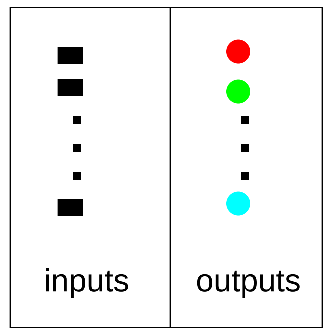
- “Assumptions are the things you don't know you're making”
  — Douglas Adams, Mark Cawardine,
  "Last Chance to See"

Learning Env. Model

- Model: (Deterministic) Finite Automaton
  - As a representation of the set of traces of env.
- What we can do:
  - Provide inputs to the environment
  - Observe (finite) prefixes of environment’s output trace
- Note:
  - Env. is a reactive system too, has infinitely long traces but we can only observe finite prefixes
  - So we are learning a finite automaton (not a Buchi automaton)

An Intuitive View

- Environment is a box, with input buttons and output lights
  - Outputs capture observable part of env state
- We can press some subset of input buttons at any time step
- Observe what lights turn on



Assumption for this lecture:
We can "reset" the environment at any time

Angluin's DFA Learning Algo.

(adapted to our setting)

- Input: A box as in the previous picture
  - inputs from an alphabet Σ
- Outputs: a DFA that accurately represents all (finite) output traces seen so far
- What it can do:
  - Generate environment traces by supplying inputs
  - Ask an oracle whether a candidate DFA is indeed correct (if not, get a counterexample)
  - Reset environment model to initial state

Angluin's DFA Learning Algo.

(adapted to our setting)

- Input: A box as in the previous picture
  - inputs from an alphabet Σ
- Outputs: a DFA that accurately represents all (finite) output traces seen so far
  - Given an oracle that precisely knows the environment, *it learns the DFA whose language is exactly the output traces of the env*.
- What it can do:
  - Generate environment traces by supplying inputs
  - Ask an oracle whether a candidate DFA is indeed correct (if not, get a counterexample)
  - Reset environment model to initial state

Formal Setup

- Want to learn (synthesize) a DFA (Q, Σ, δ, L)
  - Q : set of states
  - Σ : input alphabet
  - δ : transition function: $Q \times \Sigma \rightarrow Q$
  - L : labeling/output function
- What does it mean for two states of the DFA to be different?

  (In terms of the labels we observe)

Formal Setup

- Want to learn a DFA (Q, Σ, δ, L)
  - Q : set of states
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  - δ : transition function: Q x Σ → Q
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- What does it mean for two states of the DFA to be different?
  - q and q' are different if there is a input sequence s.t. the states reachable on that sequence from q and q' respectively have different labels

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What defines a state

- Its label (observable part)
- The input sequence that reaches that state
  - Could be many, pick a representative
- The output sequences we see from that state
  - Perform "experiments" from that state to see this
- Angluin's algorithm "names" a state by the latter two things
  - A prefix and a suffix

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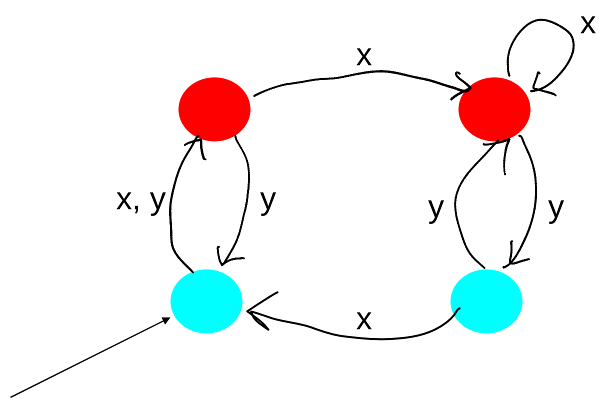
Algorithm Sketch

1. Start with only the DFA's initial state q_0
2. Generate a "new" state by supplying inputs
3. Check if its next states are observationally different from those of existing states
   - If yes, add it in
   - If not, ask the oracle if we have the correct DFA
     - If yes, we're done
     - If not, use the counterexample to figure out what new state(s) to add so that counterex goes away
   - Go back to step 2

An Example



This is the DFA we want to learn
(the correct environment model)

How the algorithm works on the previous example – worked out on board

Complexity

- Polynomial in size of environment model
- Good if environment model is small
  - This is why it is especially good for learning assumptions or concise env specifications

Some Early Refs.

- "Adaptive Model Checking" -- Groce, Peled, Yannakakis, TACAS'02
- "Learning Assumptions for Compositional Verification" -- Cobleigh et al., TACAS'03