Time to Learn – Learning Timed Automata from Tests

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August 28^{th}, 2019

Learning a Car Alarm System

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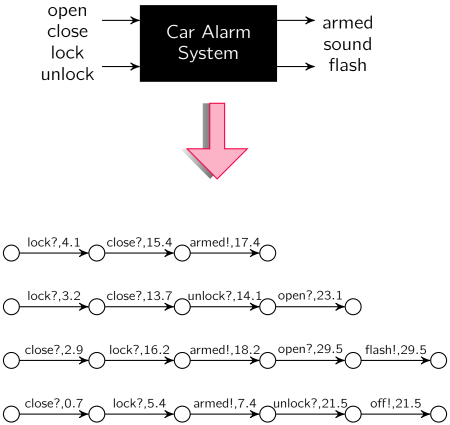

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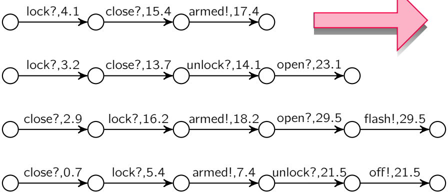

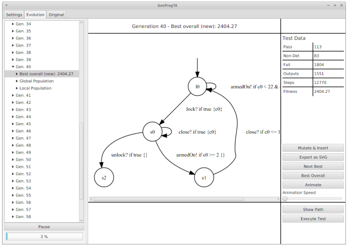

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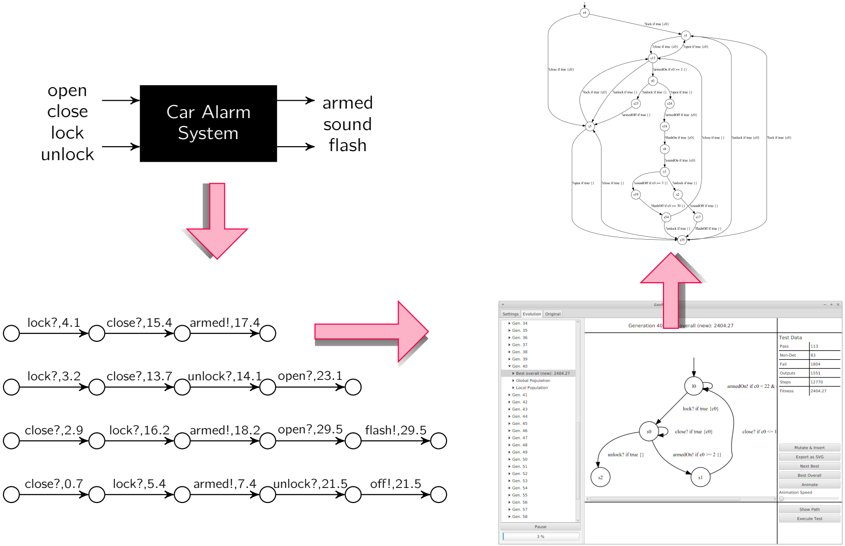


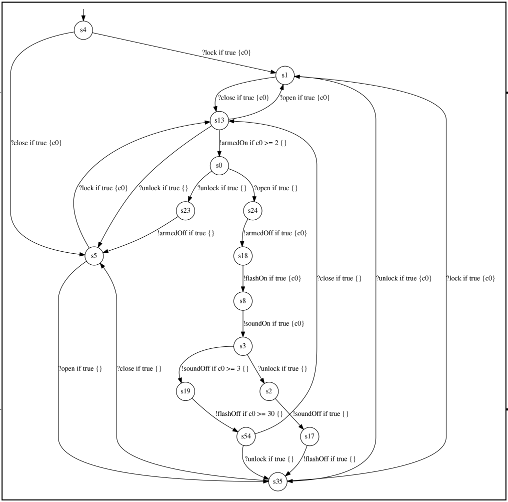
Learning a Car Alarm System

open

close

lock

unlock

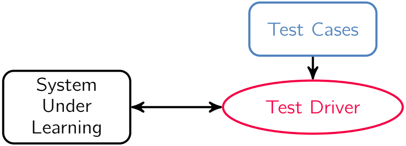


armed

sound

flash

Motivation – Learning-Based Verification



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$$out_{\mathrm{SUT}}(Con \cdot Ping) =$$

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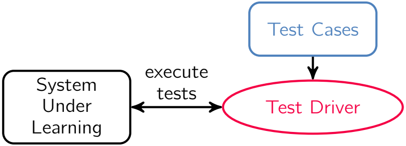

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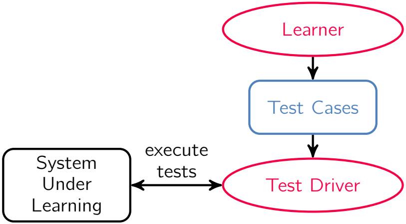

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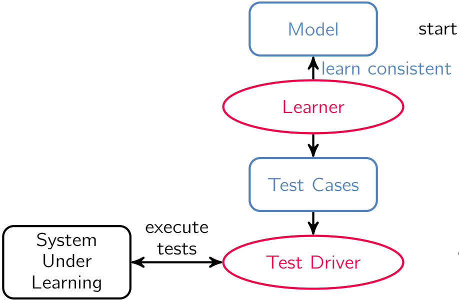

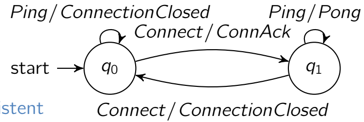

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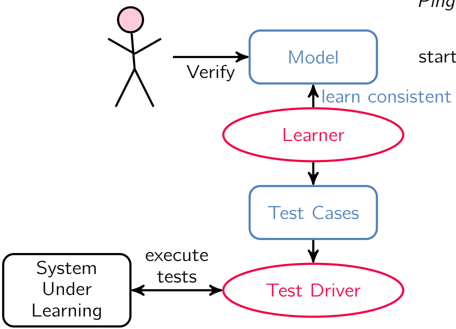

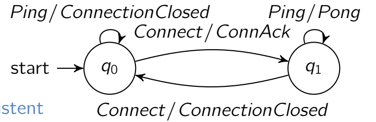

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Verification

- Model checking [Fiterau-Brostean et al., 2016], comparison of models [Aarts et al., 2012, Tappler et al., 2017]
- Issue: "we had to eliminate timing based behavior as well as re-transmissions" [Fiterau-Brostean et al., 2016]

Timed Automata

- Finite automata ...
- with inputs and outputs
- extended with real-valued clocks
  - used in guards
  - reset upon transitions
- constraints limiting sojourn time
- Assumptions for testing [Hessel et al., 2003]:
  - output urgent: outputs fire as soon as possible
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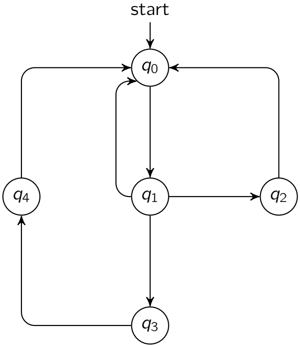

A Lamp Touch Sensor

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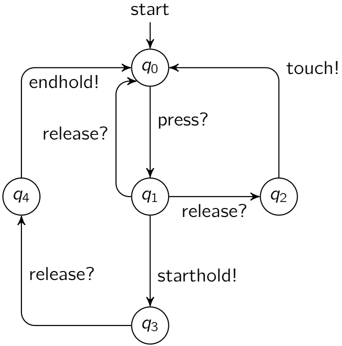

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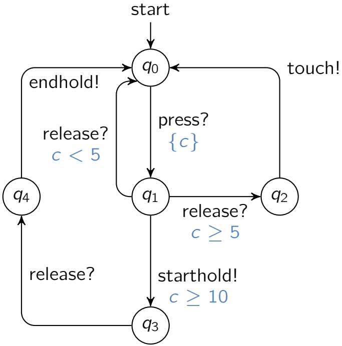

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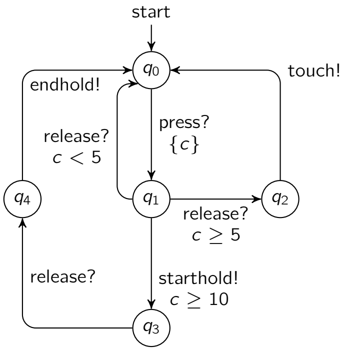

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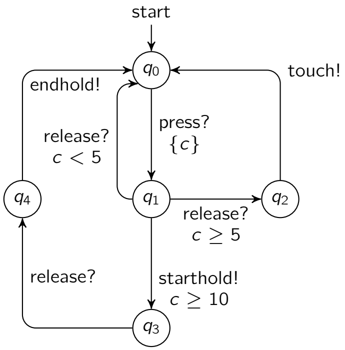

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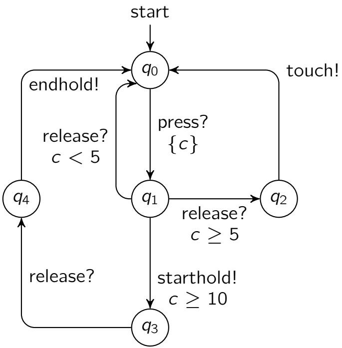

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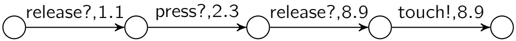

Automata Learning for Timed Systems

- Motivation: Model-based analysis for black-box timed systems
- Existing approaches:
  - Passive learning of real-time automata [Verwer et al., 2010, Verwer et al., 2012]
  - Active learning of event-recording automata [Grinchtein et al., 2010, Grinchtein et al., 2006]
  - Both: restrictions on clock resets
- Promising results of genetic programming in program synthesis (e.g. mutual exclusion algorithms) [Katz and Peled, 2017]
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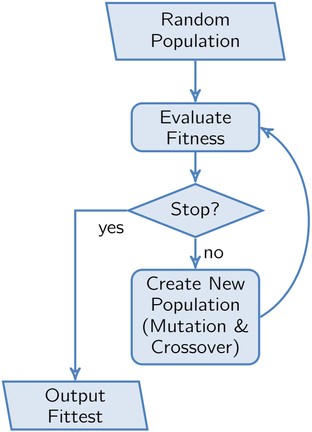
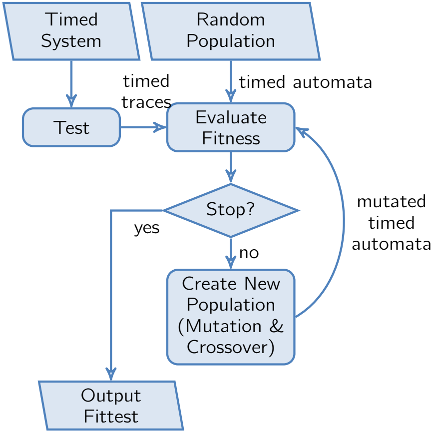
Genetic Programming



1. Create small random timed automata
2. Test system to get timed traces
3. Fitness: simulate automata
   - # accepted traces
   - # outputs of accepted traces
   - determinism
   - penalty for model size
4. New population: mutate & crossover
5. Stop if all traces accepted or max. # rounds

Genetic Programming of TA – Basic



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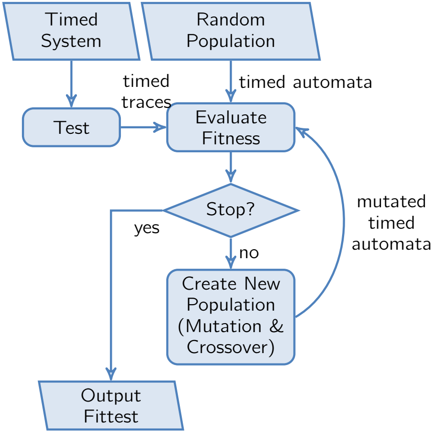

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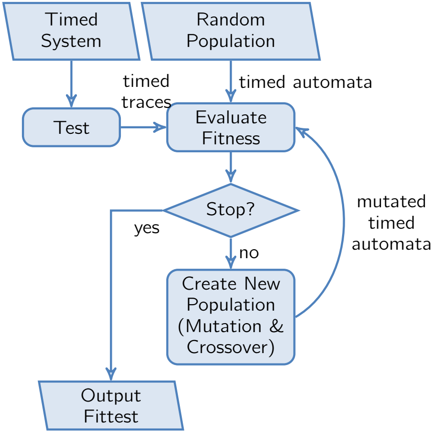

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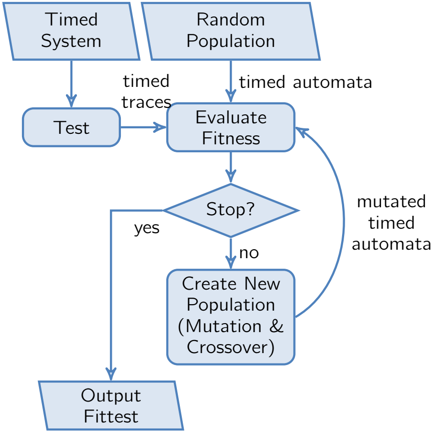

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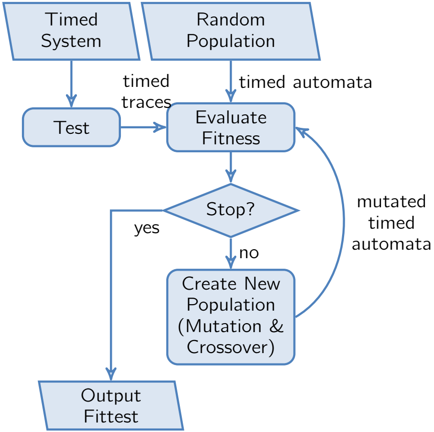

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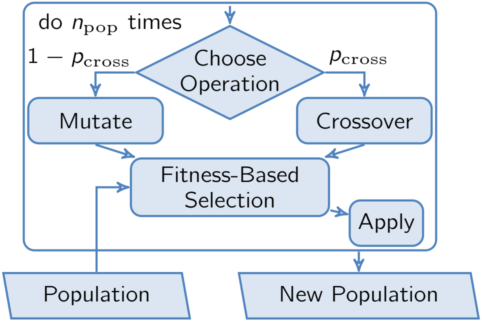
- Probabilistic choice between mutation and crossover
- Fitness-based selection of parents from population
- Repeat n_{pop} times



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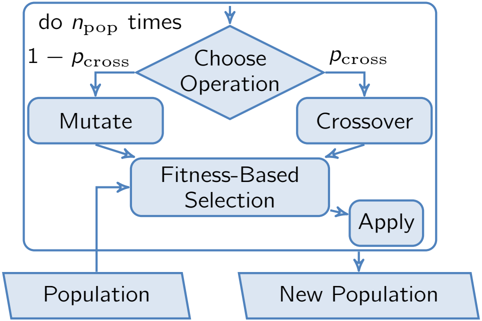
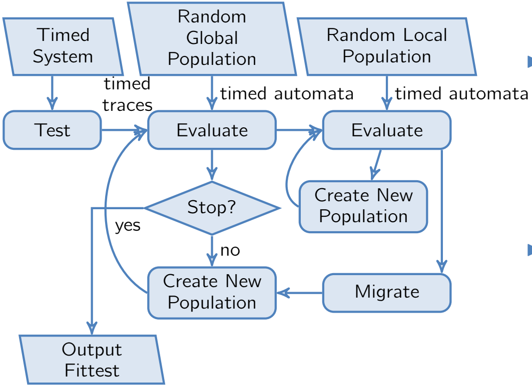


Genetic Programming of TA – Optimized



- Two populations:
  1. Global search: all timed traces
  2. Local search: timed traces not accepted by global population
- From local search to global search:
  - Migration
  - Crossover

Mutation & Crossover (1)

- Mutation operators for changing all aspects of timed automata
- Chosen at random
- An operator inspired by passive automata learning: merge location

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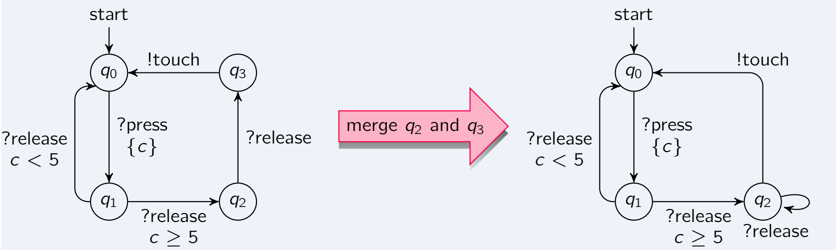
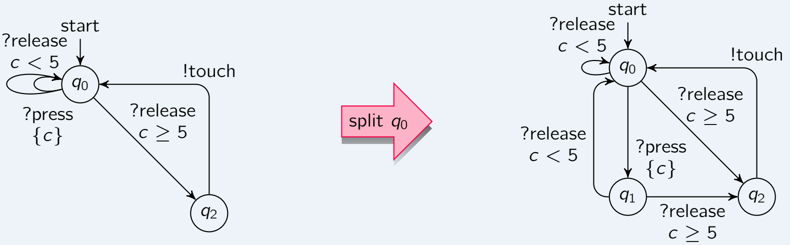
Merge Location Example



Mutation & Crossover (2)

- An operator inspired by active automata learning: split location

Split Location Example



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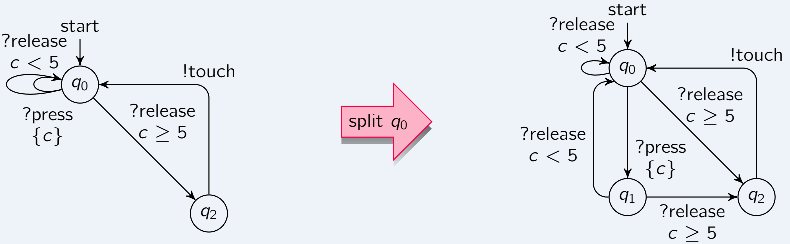

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Challenge: Parameter Configuration

- Lots of Parameters
  - # clocks, clock-bound range
  - weights for fitness computation
  - # tests, population size, # generations, test length
  - crossover probability

→ We have guidelines

- Some are fixed

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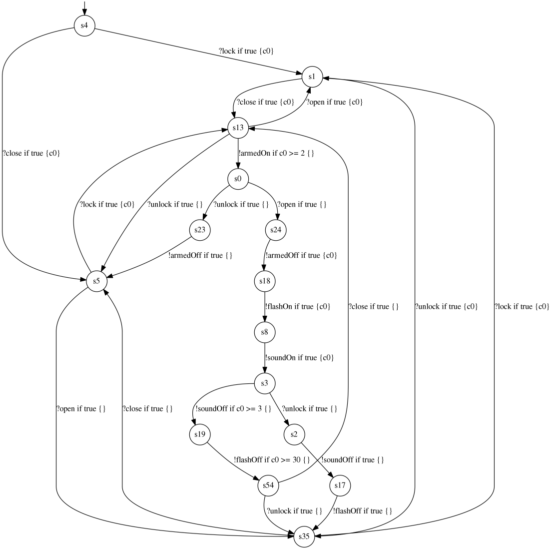

- Automatic generation of human-readable models
- Experiments with:
  - 40 random TA
  - 4 TA from the literature
  - up to 26 locations and 1 clock
  - up to 10 locations and 2 clocks
- Evaluation
  1. learn from training data
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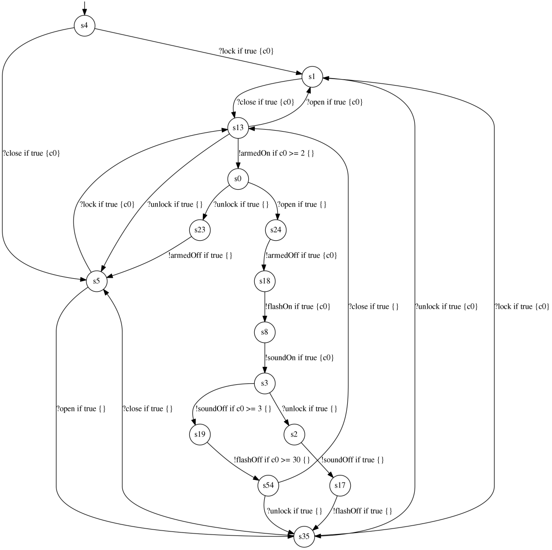

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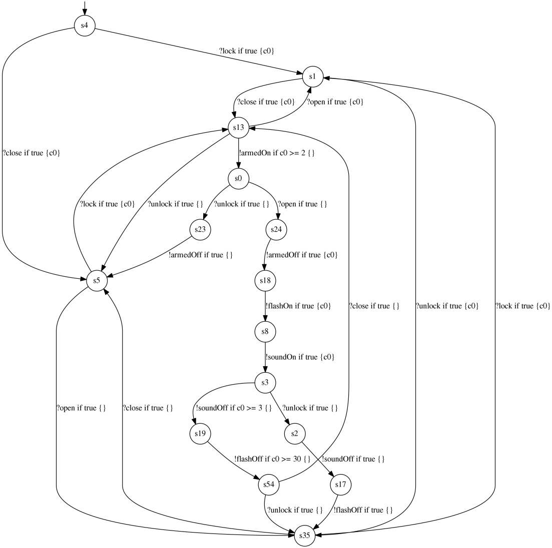

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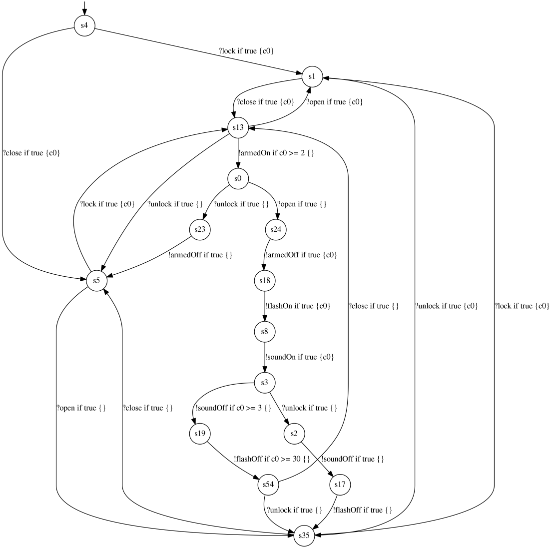

- Results:
  - successfully learned all 44 models
  - consistent with given training data
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- Runtime:
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- GUI demo: link in paper

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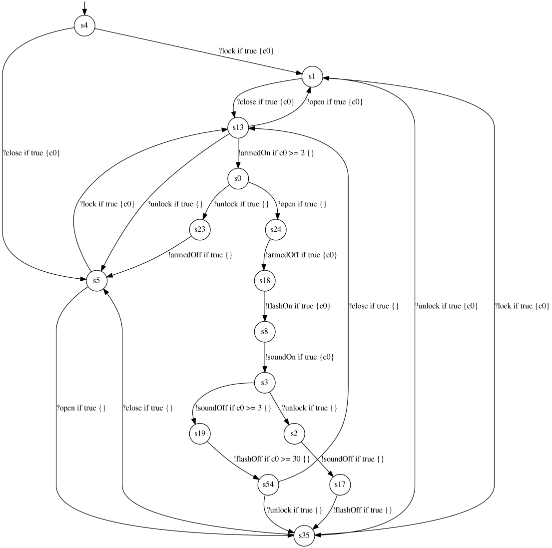

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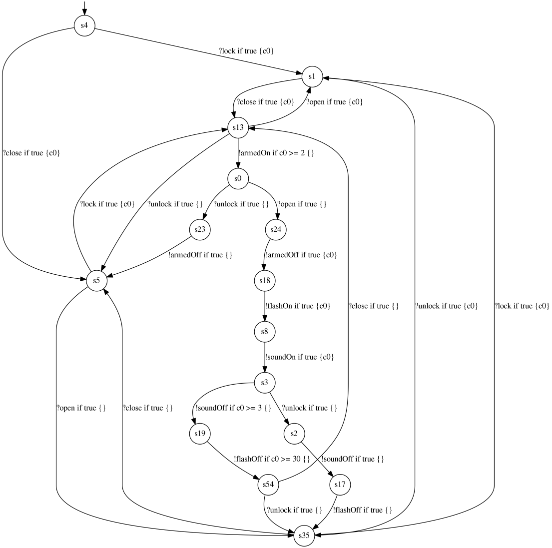

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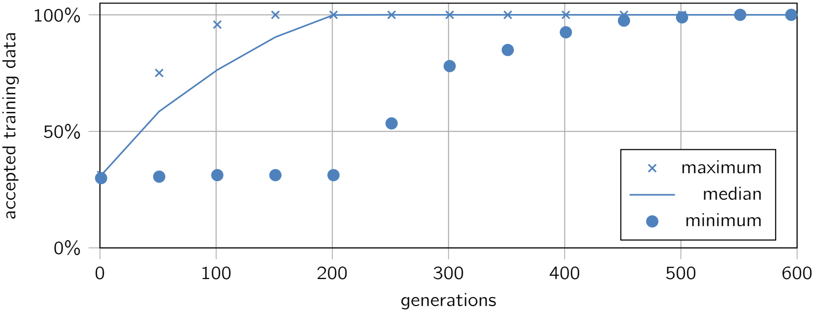
Fitness of Car Alarm System Models



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- Further behaviour continuously added

→ Random generation infeasible

- Final generations decrease model size

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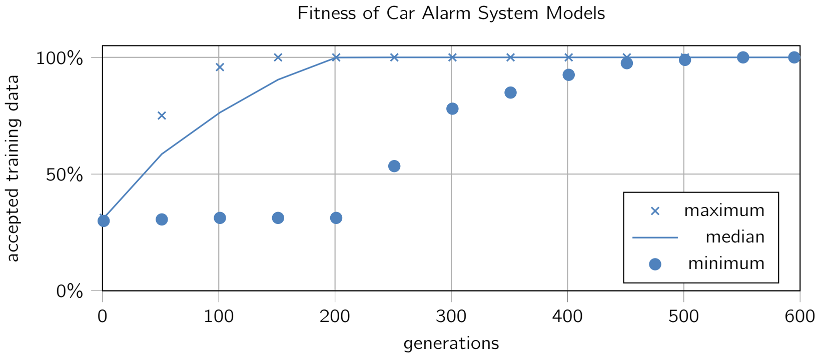

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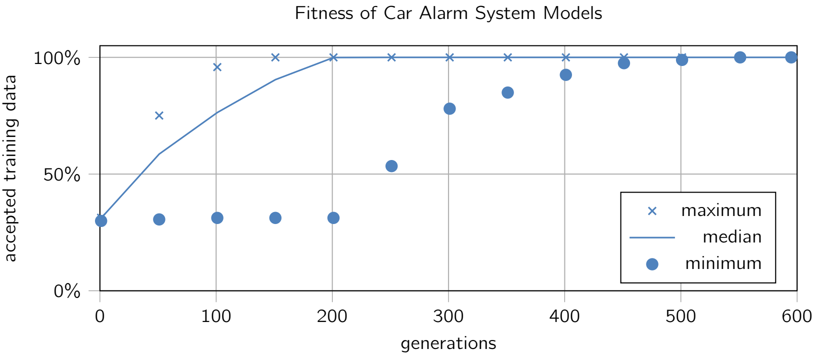
Experiments – Evolution of Fitness



- Early generations accept only initial inputs
- Further behaviour continuously added

→ Random generation infeasible

- Final generations decrease model size

Concluding Remarks

Summary

- Genetic Programming for timed automata including mutation, crossover, subpopulations, and fine-grained fitness computation
- Evaluated on 44 timed automata used as black boxes
  - up to 26 locations
  - up to two clocks with arbitrary resets
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  - relaxing assumptions
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Thank you!

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