Formal Verification Meets Machine Learning

Introduction

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https://moves.rwth-aachen.de/teaching/ss-18/fvmml/

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Outline

Overview

Aims of this Seminar

Important Dates

Verification of Properties

Learning of Invariants

Model Learning

Synthesis of Programs and Algorithms

Final Hints

Formal Verification Meets Machine Learning

Formal verification

- Computer-supported mathematical analysis methods for ensuring correctness of systems
  - model checking, theorem proving, ...
- Often applied to safety-critical systems
- Complementary to testing methods

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Research issues

- Safety-related issues for machine learning
- Explainability in AI and in model checking
- Scalability and applicability of formal verification

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Goals

Aims of this seminar

- **Independent understanding** of a scientific topic
- Acquiring, reading and understanding **scientific literature**
- Writing of your **own report** on this topic
- **Oral presentation** of your results

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Requirements on Report

Your report

- Independent writing of a report of **10–15 pages**
- **Complete** set of references to all consulted literature
- **Correct citation** of important literature
- **Plagiarism**: taking text blocks (from literature or web) without source indication causes immediate **exclusion from this seminar**
- Font size **12pt** with “standard” page layout
- **Language**: German or English
- We expect the **correct usage** of spelling and grammar
  - $\geq$ 10 errors per page $\Longrightarrow$ abortion of correction
- **LaTeX template** will be made available on seminar web page

Aims of this Seminar

Requirements on Talk

Your talk

- Talk of **30 minutes**
- Available: projector, presenter, [laptop]
- Focus your talk on the **audience**
- **Descriptive** slides:
  - $\leq$ 15 lines of text
  - use (base) colors in a useful manner
  - number your slides
- **Language:** German or English
- No spelling mistakes please!
- Finish **in time**. Overtime is bad
- Ask for **questions**
- Have **backup slides** ready for expected questions
- **LaTeX template** will be made available on seminar web page

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Deadlines

- 14 May: Detailed outline of report due
- 11 June: Report due
- 2 July: Presentation slides due
- 19 July (?): Seminar

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Missing a deadline causes **immediate exclusion** from the seminar

Selecting Your Topic

Procedure

- You obtain(ed) a list of topics of this seminar.
- Indicate the preference of your topics (first, second, third).
- Return sheet **by Monday (16 April)** via e-mail (`noll@cs.rwth-aachen.de`) or to secretary.
- We do our best to find an adequate topic-student assignment.
  - disclaimer: no guarantee for an optimal solution
- Assignment will be published on web site next week.
- Then also your **supervisor** will be indicated.

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Withdrawal

- You have up to **three weeks** to refrain from participating in this seminar.
- Later cancellation (by you or by us) causes a **not passed** for this seminar and reduces your (three) possibilities by one.

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1: Safety Verification of Deep Neural Networks

Context

- Deep neural networks are impressive for image classification
- Minimal changes to the input image may yield a misclassification
- What does that mean in a safety-critical context?
- How to guarantee that deep neural networks are safe?

Topic

One of the first works on verifying neural networks:

- Verifying multi-layer neural networks based on Satisfiability Modulo Theory (SMT)
- Safety = invariance of a classification within a small neighbourhood of true image
- Verification works directly with the network code and can guarantee that adversarial examples, if they exist, are found

2: Verification of Markov Decision Processes Using Learning Algorithms

Context

- MDPs are transition systems with non-determinism and probabilities
- Their verification amounts to solve linear programs
- The size of these linear programs is the main bottleneck for MDP analysis

Topic

- Avoiding an exhaustive exploration of the state space by machine learning
- Alg 1: A heuristic-driven partial MDP exploration for reachability
- Alg 2: A sampling-based approach for reachability

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3: Smoothed Model Checking

Context

- CTMCs are transition systems with stochastic state delays
- These models are used in biology, performance analysis, etc.
- Verification assumes all transition rates to be known a priori

Topic

- For which parametric rate values does a CTMC satisfy a property?
- Predict the value of the satisfaction probability at all values of the uncertain parameters from individual model simulations at a finite (and generally rather small) number of distinct parameter values
- Exploits that satisfaction probabilities are smooth functions
- Approximates the satisfaction function by a sample from a Gaussian Process

4: Formal Verification of Neural Networks

Context

- Neural networks are layered systems mapping inputs to outputs
- The outcomes of neural networks come with weak guarantees
- Can formal verification be applied to prove hard guarantees?

Topic

- Verifying feed-forward neural networks where all nodes are piece-wise linear functions
- Adds a global linear approximation of the overall network behavior
- Exploits this using SAT-inspired algorithms such as unit propagation
- Infers additional conflict clauses from the analysis results during the search

5: Verification and Control of Partially Observable Probabilistic Systems

Context

- Partially observable systems are (probabilistic) transition systems in which only observations are identifiable; states are not
- How to steer a robot when it does not recognize its environment completely?

Topic

- Automated verification techniques for partially observable, probabilistic systems
- Considers extension of MDPs and of timed automata
- Synthesize a controller for POMDPs which makes a given property true
- Exploits a grid-based abstraction of the uncountable belief space induced by partial observability
- Applications: task and network scheduling, computer security and planning

6: Counterexample Explanation for Probabilistic Systems

Context

- Model checking yields counterexamples if model refutes property
- For transition systems, counterexamples are finite paths
- For probabilistic systems, they are (possibly infinite) sets of finite paths
- How to obtain such counterexamples, and how to represent them succinctly?

Topic

- Use decision trees to compactly represent counterexamples

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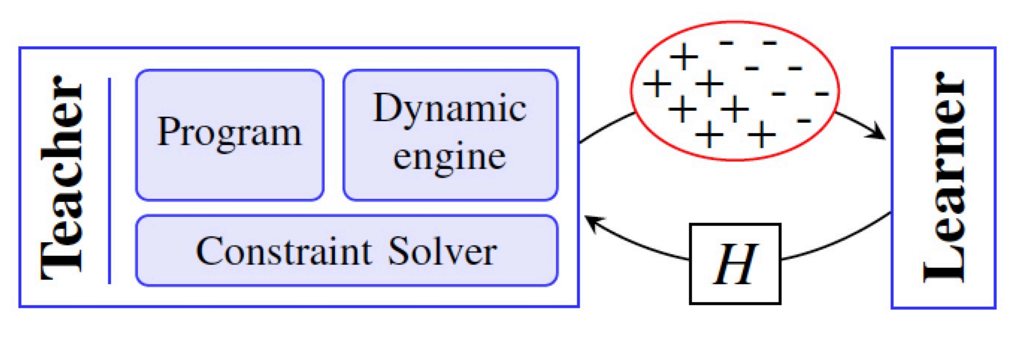
7: Learning Loop Invariants

Main principle

2 parts: a Learner and a Teacher. In each iteration of the algorithm,
a learner generates a candidate invariant, and the teacher validates the conjecture and,
if necessary, generates feedback in a form of a positive or negative example.
The learner uses the example to improve its conjecture.
Termination once the teacher determines that an inductive invariant is found.



7: Learning Loop Invariants

Context

- Finding loop invariants is the main obstacle in program verification
- It is this task that makes program verification undecidable
- Can learning be used to automatically synthesize loop invariants?
- Use that invariants represent over-approximations of the set of reachable program loop states

Topic

- Represents loop invariants by a kind of finite-state automata
- Synthesizes invariants by learning using examples, counter-examples, and implications
- Type 1: Learns Boolean combinations of numerical invariants for scalar variables
- Type 2: Learns quantified invariants for arrays and dynamic lists

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8: Learning Data Structure Invariants

Context

- Can learning be used to obtain loop invariants over linear data structures?

Topic

- Represents (quantified) invariants over linear data structures by quantified data automata over words
- Poly-time active learning algorithms for such automata
- Every QDA has a unique minimally-over-approximating “elastic” QDA
- Elastic QDAs can be represented by decidable logics
- Learning such automata from samples obtained by running programs

9: Syntax-Guided Invariant Synthesis

Context

- SyGiS problem = find invariant generated by a given grammar that meets a specification
- Idea: use correctness specification + a syntactic template for the desired invariant
- Approach:
  1. Construct a formal grammar based on the symbolic program encoding
  2. Use probabilistic search through the candidate formulas in that grammar

Topic

Accelerating SyGiS by:

- enumerative learning with inductive- subset extraction
- leverages counterexamples-to-induction and
- Craig interpolation-based bounded proofs.

Experiments show that this leads to significant improvements

10: Synthesizing Inductive Invariants

Context

- IC3 is a popular SAT-MC technique in hardware and software verification for safety properties

  iteratively conjecture safe candidate invariants until either a candidate is proven inductive or a counterexample is found
- ICE is a rather new ML technique for learning loop invariants (see topic 7)

Topic

- Goal: study the similarities and differences between the two frameworks
- RICE = ICE + relative induction
- Show how IC3 can be implemented as an instance of RICE.

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11: Generating Models of Communication Protocols

Context

- Automata learning learns an automaton by examples (finite words)
- Recent progress learns register automata = automata + data
- Using abstraction techniques, these algorithms can be applied to complex systems
- Model learning emerges as an effective bug-finding technique
- Applications include banking cards, network protocols, and legacy software

Topic

- A framework which adapts regular inference to include data parameters in messages and states for generating components with large or infinite message alphabets
- Examples: regular inference of session initiation protocol (SIP) and TCP

12: Learning Finite Automata

Context

- Automata learning focuses on learning deterministic finite-state automata
- For DFA, minimal automata are canonical
- But NFAs can be exponentially more succinct; can we learn NFA?

Topic

- How can automata learning be adapted to obtain small NFA?
- What is a canonical representation of “minimal” NFA?

13: Learning and Planning with Timing Information in MDPs

Context:

- MDPs are probabilistic automata used for decision making and planning
- Main aim: determine an optimal policy for the decisions given a certain objective
- Typical assumption: actions are instantaneous

Topic

- Learn the duration of courses of action that an agent might take
- A spectral algorithm for learning option duration models
- Application: navigation of robots

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14: Policy Learning in Continuous-Time Markov Decision Processes

Context:

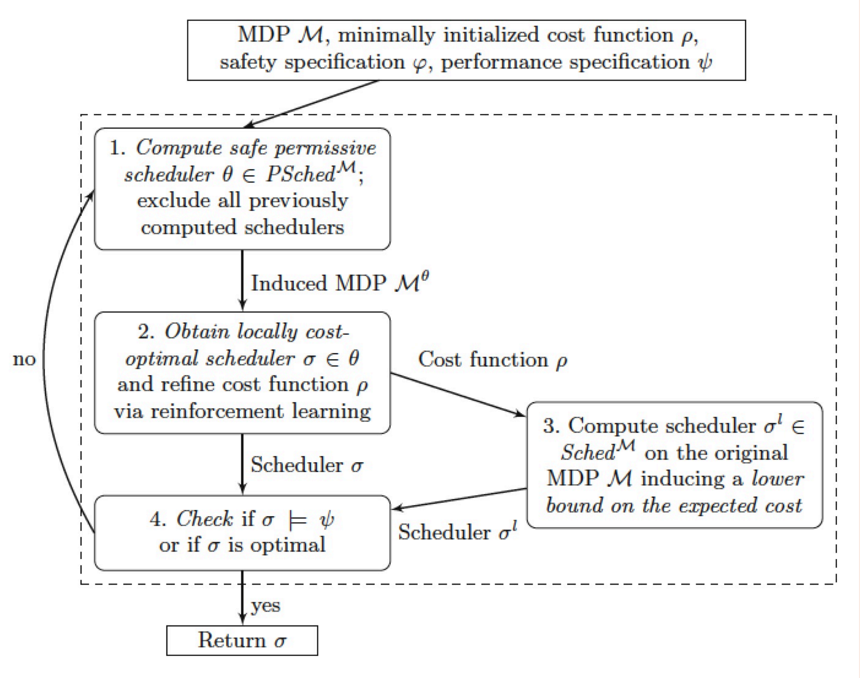
- Continuous-time MDPs extend MDPs with random state delays
- Applications: financial mathematics, control of populations, scheduling, . . .
- Aim: compute an optimal policy to control the CTMDP to maximise the probability of satisfying an objective
- Statistical model checking (SMC) = discrete-event simulation to check temporal logic objectives

Topic

- New method to obtain optimal policies for CTMDPs
- Key: use a stochastic moment-based gradient ascent algorithm to guide the search for optimal policies
- Gaining performance on an epidemiology model and a queuing system

15: Safety-Constrained Reinforcement Learning for Markov Decision Processes

Topic



16: Learning Static Analyzers

Context

- Static program analysis is the analysis of computer software that is performed without actually executing programs
- The Clang Static Analyzer is a source code analysis tool that finds bugs in C
- Popular approach: use inference rules to steer the static analysis
- How to obtain the right inference rules?

Topic

- A new, automated approach for creating static analyzers
- Key idea: learn inference rules from a dataset of programs
- Two ingredients:
  1. a synthesis algorithm for learning a candidate analyzer from a given dataset
  2. a counter-example guided learning procedure to generate programs outside the dataset
- Case study: learn JavaScript static analysis rules for points-to analysis

17: Learning Disjunctions of Predicates

Topic

- Let F be a set of predicates (i.e., boolean functions)
- Goal: learn the class $F_\vee$ of any disjunction of predicates in F.
- Learning algorithm SPEX, which learns any function in $F_\vee$ with polynomially many queries.
- Imposing some computational complexity conditions on the set of predicates, SPEX runs in polynomial time.
- Two (practical) cases: polytopes, and conjunctions of form $x_i > x_j$
- Integration of this technique in programming by example (PBE)

18: Learning Explanatory Rules from Noisy Data

Context

- ILP (Inductive Logic Programming):
  - Given a set of positive examples, and a set of negative examples, ILP constructs a logic program that entails all positive examples but does not entail any negative example
- Major shortcoming: inability to handle noisy, erroneous, or ambiguous data

Topic

- Extend ILP with the possibility to use neural networks for learning programs
- The δILP achieves reasonable performance with up to 20% of mislabelled training data
- It is able to solve moderately complex tasks requiring recursion and predicate invention
- Examples: length of a list, (grand)parent in a tree, cyclicity of graphs

19: Discovery of Divide-&-Conquer Algorithms

Context

- The divide-and-conquer (D-and-C) paradigm is popular in algorithm design
- Examples include many sorting algorithms, dynamic programming (DP)
- Key for DP problems is to find a recurrence relation
- Is it possible to automate the generation of a (parallel) program from such recurrences? In a memory-efficient manner?

Topic

- An algorithm that for DP problems automatically discovers (parallel) recursive D-and-C algorithms from iterative descriptions of DP recurrences
- Several synthesized algorithms significantly outperform existing parallel algorithms

20: Multi-Objective Policy Generation for Mobile Robots

Context

- Multi-objective model checking for Markov decision processes
- Probabilistic time-bounded guarantees on successful task completion, whilst also trying to satisfy soft goals

Topic

- Setting: a stochastic model of the robots environment and action execution times, a set of soft goals, and a formal task specification in co-safe LTL
- Contribution: new technique to do multi-objective model checking on MDPs
- Case: generate policies on a delivery task in a care home scenario, where the robot also tries to engage in entertainment activities with the patients

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Hints

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- Be **proactive**! Look for **additional** literature and information.
- Discuss the content of your report with other students.
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- Prepare the meeting(s) with your supervisor.
- Forget the idea that you can prepare a talk in a day or two.

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We wish you success and look forward to an enjoyable and high-quality seminar!