### Task Scheduling and Execution for Long-Term Autonomy

Nick Hawes Dave Parker

University of Birmingham



### Part 2: Formal Guarantees for Robotic Navigation Planning

ICAPS Summer School, June 2016

### Overview

- Formal verification
  - probabilistic model checking
- Markov decision processes (MDPs)
  - verification vs. strategy synthesis
- Linear temporal logic (LTL)
  - probabilistic model checking + MDPs + LTL
- Multi-objective probabilistic model checking
  - partially satisfiable task specifications

# Formal verification

- Formal verification
  - the application of rigorous, mathematics-based techniques to check the correctness of computerised systems
- Verifying probabilistic systems...
  - unreliable or unpredictable behaviour
    - e.g. failures, message loss, delays, unreliable sensors/actuators
  - randomisation in algorithms/protocols
    - · e.g. random back-off in communication protocols
- We need to verify quantitative system properties
  - "the probability of the airbag failing to deploy within 0.02 seconds of being triggered is at most 0.001"
  - not just correctness: reliability, timeliness, performance, ...
  - not just verification: correctness by construction

# Probabilistic model checking

- Construction and analysis of probabilistic models
  - state-transition systems labelled with probabilities (e.g. Markov chains, Markov decision processes)
  - from a description in a high-level modelling language
- Properties expressed in temporal logic, e.g. PCTL:
  - trigger  $\rightarrow$  P<sub> $\geq 0.999$ </sub> [F<sup> $\leq 20$ </sup> deploy ]
  - "the probability of the airbag deploying within 20ms of being triggered is at at least 0.999"
  - properties checked against models using exhaustive search and numerical computation





0.5 20.4

# Probabilistic model checking

#### • Key benefits

- exact results: guarantees, optimality, ...
- fully automated, tools available (e.g. PRISM)
- wide range of models, properties expressible

#### Key challenges

- scalability! state space explosion problem
- results are only as good as the model

#### Application domains

 network/communication protocols, security, biology, power management, robotics & planning, ...

# Markov decision processes (MDPs)

- Markov decision processes (MDPs)
  - model nondeterministic as well as probabilistic behaviour



- Nondeterminism for:
  - control: decisions made by a controller or scheduler
  - adversarial behaviour of the environment
  - concurrency/scheduling: interleavings of parallel components
  - abstraction, or under-specification, of unknown behaviour

# Strategies

- A strategy (or "policy", "adversary", "scheduler")
  - is a resolution of nondeterminism, based on history
  - i.e. a mapping from finite paths to (distributions over) actions
  - induces (infinite-state) Markov chain (and probability space)



- Classes of strategies:
  - memory: memoryless, finite–memory, or infinite–memory
  - randomisation: deterministic or randomised

# Verification vs. Controller synthesis

#### • 1. Verification

- quantify over all possible strategies (i.e. best/worst-case)
- $P_{\leq 0.1}$  [ F *err* ] : "the probability of an error occurring is  $\leq 0.1$  for all strategies"



 applications: randomised communication protocols, randomised distributed algorithms, security, ...

#### • 2. Controller synthesis

- generation of "correct-by-construction" controllers
- $P_{\leq 0.1}$  [F *err*]: "does there exist a strategy for which the probability of an error occurring is  $\leq 0.1$ ?"
- applications: robotics, power management, security, ...
- Two dual problems; same underlying computation:
  - compute optimal (minimum or maximum) values

### Running example

#### • Example MDP

- robot moving through terrain divided in to 3 x 2 grid



### Larger example







## Example – Reachability



Verify:  $P_{\leq 0.6}$  [ F goal<sub>1</sub> ]

or Synthesise for:  $P_{\geq 0.4}$  [ F goal<sub>1</sub> ]  $\downarrow$ 

Compute: P<sub>max=?</sub> [ F goal<sub>1</sub> ]

Optimal strategies: memoryless and deterministic

Computation:

graph analysis + numerical soln. (linear programming, value iteration, policy iteration)

## Example – Reachability



Verify:  $P_{\leq 0.6}$  [ F goal<sub>1</sub> ]

```
or
Synthesise for: P_{\geq 0.4} [F goal<sub>1</sub>]
```

Compute:  $P_{max=?}$  [ F goal<sub>1</sub> ] = 0.5

Optimal strategies: memoryless and deterministic

Computation:

graph analysis + numerical soln. (linear programming, value iteration, policy iteration)

# Linear temporal logic (LTL)

- Logic for describing properties of executions [Pnueli]
- LTL syntax:

 $- \psi ::= true \mid a \mid \psi \land \psi \mid \neg \psi \mid X \psi \mid \psi \cup \psi \mid F \psi \mid G \psi$ 

- Propositional logic + temporal operators:
  - a is an atomic proposition (labelling a state)
  - $X \, \psi$  means " $\psi$  is true in the next state"
  - $F \psi$  means " $\psi$  is eventually true"
  - $G~\psi$  means " $\psi$  remains true forever"
  - $-\psi_1 \cup \psi_2$  means " $\psi_2$  is true eventually and  $\psi_1$  is true until then"

#### Simple examples

- $G\neg$ (critical<sub>1</sub>  $\land$  critical<sub>2</sub>) "the two processes never enter the critical section simultaneously"
- ¬error U end "the program terminates without any errors"

## Linear temporal logic (LTL)

- LTL syntax:
  - $-\psi ::= true \mid a \mid \psi \land \psi \mid \neg \psi \mid X \psi \mid \psi \cup \psi \mid F \psi \mid G \psi$
- Commonly used LTL formulae:
  - G (a  $\rightarrow$  F b) "b always eventually follows a"
  - G (a  $\rightarrow$  X b) "b always immediately follows a"
  - GFa "a is true infinitely often"
  - FGa "a becomes true and remains true forever"
- Robot task specifications in LTL
  - (G¬hazard)  $\land$  (G F goal<sub>1</sub>) "avoid hazard and visit goal<sub>1</sub> infinitely often"
  - $-\neg zone_3$  U (zone<sub>1</sub>  $\land$  (F zone<sub>4</sub>) "patrol zone 1 then 4, without passing through 3".

# LTL for robot navigation

#### Probabilistic LTL on MDPs

- e.g.  $P_{>0.7}$  [ (G¬hazard)  $\land$  (GF goal<sub>1</sub>) ] "is the probability of avoiding hazard and visiting goal<sub>1</sub> infinitely often > 0.7?"
- e.g.  $P_{max=?}$  [  $\neg zone_3$  U ( $zone_1 \land (F zone_4)$  ] "max. probability of patrolling zones 1 then 4, without passing through 3?"
- LTL + expected costs/times on MDPs
  - minimise expected time to satisfy (co-safe) LTL formulas
- Benefits of the approach
  - LTL: flexible, unambiguous property specification
  - guarantees on performance ("correct by construction")
  - meaningful properties: probabilities, time, energy,...
    - · c.f. ad-hoc reward structures, e.g. with discounting
  - efficient, fully-automated techniques
    - · LTL-to-automaton conversion, MDP solution

## Probabilistic model checking LTL

- Probabilistic model checking of LTL on MDPs
  - convert LTL formula  $\psi$  to deterministic automaton  $A_{\psi}$  (Buchi, Rabin, finite, ...)
  - build/solve product MDP  $M \otimes A_{\psi}$ (i.e. reduce to simpler problem)
  - optimal strategies are deterministic, finite-memory



### Example: Product MDP construction



### Example: Product MDP construction



## Co-safe LTL (and expected cost)

- Often focus on tasks completed in finite time
  - can restrict to co-safe fragment(s) of LTL
  - (any satisfying execution has a "good prefix")
  - e.g.  $P_{max=?}$  [  $\neg zone_3$  U ( $zone_1 \land (F zone_4)$  ]
  - for simplicity, can restrict to syntactically co-safe LTL
- Expected cost/reward to satisfy (co-safe) LTL formula
  - e.g.  $R_{min=?}$  [ $\neg zone_3$  U ( $zone_1 \land (F zone_4)$ ] "minimise exp. time to patrol zones 1 then 4, without passing through 3".
- Solution:
  - product of MDP and DFA
  - expected cost to reach accepting states in product



# Probabilistic model checking

- Further use of probabilistic model checking...
  - (various probabilistic models, query languages)
- Nested queries
  - e.g.  $R_{min=?}$  [ safe U (zone<sub>1</sub>  $\land$  (F zone<sub>4</sub>) ] "minimise exp. time to patrol zones 1 then 4, passing only through safe".
  - where safe denotes states satisfying ((ctrl)) R<sub><2</sub> [F base] "there is a strategy to return to base with expected time < 2"</li>
- Analysis of generated controllers
  - expected power consumption to complete tasks?
  - conditional expectation, e.g. expected time to complete task, assuming it is completed successfully?
  - more detailed timing information (not just mean time)

## Multi-objective model checking

- Multi-objective probabilistic model checking
  - investigate trade-offs between conflicting objectives
  - in PRISM, objectives are probabilistic LTL or expected costs
- Achievability queries: multi(P<sub>>0.95</sub> [ F send ], R<sup>time</sup><sub>>10</sub> [ C ])
  - e.g. "is there a strategy such that the probability of message transmission is > 0.95 and expected battery life > 10 hrs?"
- Numerical queries: multi(P<sub>max=?</sub> [ F send ], R<sup>time</sup><sub>>10</sub> [ C ])
  - e.g. "maximum probability of message transmission, assuming expected battery life-time is > 10 hrs?"

#### Pareto queries:

- multi(P<sub>max=?</sub>[F send], R<sup>time</sup>max=?[C])
- e.g. "Pareto curve for maximising probability of transmission and expected battery life-time"



# Multi-objective model checking

- Multi-objective probabilistic model checking
  - investigate trade-offs between conflicting objectives
  - in PRISM, Abjectives are probabilistic LTL or expected rewards
- Achievability queries: multi(P<sub>>0.95</sub> [ F send ], R<sup>time</sup><sub>>10</sub> [ C ])
  - e.g. "is there a strategy such that the probability of message transmission is > 0.95 and expected battery life > 10 hrs?"
- Numerical queries: Phulti(Penax=? [ F sind ], R<sup>time</sup>>10 [ C ])
  - e.g. "maximum probability of mess e transmission, assuming expected battery life-times > 10 hrs?"
- Pareto queries:
  - multi(P<sub>max=?</sub>[F **9**<del>end</del>], R<sup>time</sup>max=?[C])
  - e.g. "Pareto curve for maximising probability of transmission and expected battery life-time"

obj₁

# Multi-objective model checking

- Optimal strategies:
  - usually finite-memory (e.g. when using LTL formulae)
  - may also need to be randomised

#### Computation:

- construct a product MDP (with several automata), then reduces to linear programming [TACAS'07,TACAS'11]
- can be approximated using iterative numerical methods, via approximation of the Pareto curve [ATVA'12]

#### • Extensions [ATVA'12]

- arbitrary Boolean combinations of objectives
  - · e.g.  $\psi_1 \Rightarrow \psi_2$  (all strategies satisfying  $\psi_1$  also satisfy  $\psi_2$ )
  - · (e.g. for assume-guarantee reasoning)
- time-bounded (finite-horizon) properties

### Example - Multi-objective



- Achievability query
  - $P_{\geq 0.7}$  [ G ¬hazard ]  $\land$   $P_{\geq 0.2}$  [ GF goal<sub>1</sub> ] ? True (achievable)
- Numerical query
  - $P_{max=?}$  [ GF goal<sub>1</sub> ] such that  $P_{\geq 0.7}$  [ G  $\neg$  hazard ]? ~0.2278
- Pareto query
  - for  $P_{max=?}$  [ G ¬hazard ]  $\land$   $P_{max=?}$  [ GF goal<sub>1</sub> ] ?

### Example – Multi-objective

 $\Psi_1$ 



0.6

0.8

0.2 **-**0.1 **-**

0

0

0.2

0.4

### Example – Multi–objective

 $\Psi_1$ 



0.6

0.8

0.3 -0.2 -0.1 -

0

0

0.2

0.4

(deterministic) s<sub>0</sub> : south s<sub>1</sub>: south  $s_2$ : -**S**<sub>3</sub> : s<sub>4</sub> : east s<sub>5</sub> : west

26

### Example – Multi-objective



Optimal strategy: (randomised)  $s_0$  : 0.3226 : east 0.6774 : south  $s_1$  : 1.0 : south  $s_2$  :  $s_3$  :  $s_4$  : 1.0 : east  $s_5$  : 1.0 : west

27

# Application: Partially satisfiable tasks

- Partially satisfiable task specifications
  - via multi-objective probabilistic model checking [IJCAI'15]
  - e.g.  $P_{max=?}$  [  $\neg zone_3$  U (room<sub>1</sub>  $\land$  (F room<sub>4</sub>  $\land$  F room<sub>5</sub>) ] < 1
- Synthesise strategies that, in decreasing order of priority:
  - maximise the probability of finishing the task;
  - maximise progress towards completion, if this is not possible;
  - minimise the expected time (or cost) required
- Progress metric constructed from DFA
  - (distance to accepting states, reward for decreasing distance)
- Encode prioritisation using multi-objective queries:
  - $p = P_{max=?} [task]$
  - $\mathbf{r} = \text{multi}(R_{\text{max}=?}^{\text{prog}} [C], P_{>=p} [task])$
  - multi( $R_{min=?}^{time}$  [ task ],  $P_{>=p}$  [ task ]  $\land R_{>=r}^{prog}$  [ C ])

# Conclusion

- Rigorous probabilistic guarantees for robot navigation
  - formal verification + probabilistic model checking
  - Markov decision processes (MDPs)
  - linear temporal logic (LTL)
  - multi-objective model checking

#### • More details

- Lacerda/Parker/Hawes. Optimal & Dynamic Planning for Markov Decision Processes with Co-Safe LTL Specifications, IROS'14
- Lacerda/Parker/Hawes. Optimal Policy Generation for Partially Satisfiable Co-Safe LTL Specifications, IJCAI'15
- PRISM: <u>www.prismmodelchecker.org</u>