Model checking and strategy synthesis for mobile autonomy: from theory to practice

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Mobile autonomy is here

Software everywhere

- Users expect: predictability & high integrity in presence of
  - component failure, environmental uncertainty, …
  - can be quantified probabilistically

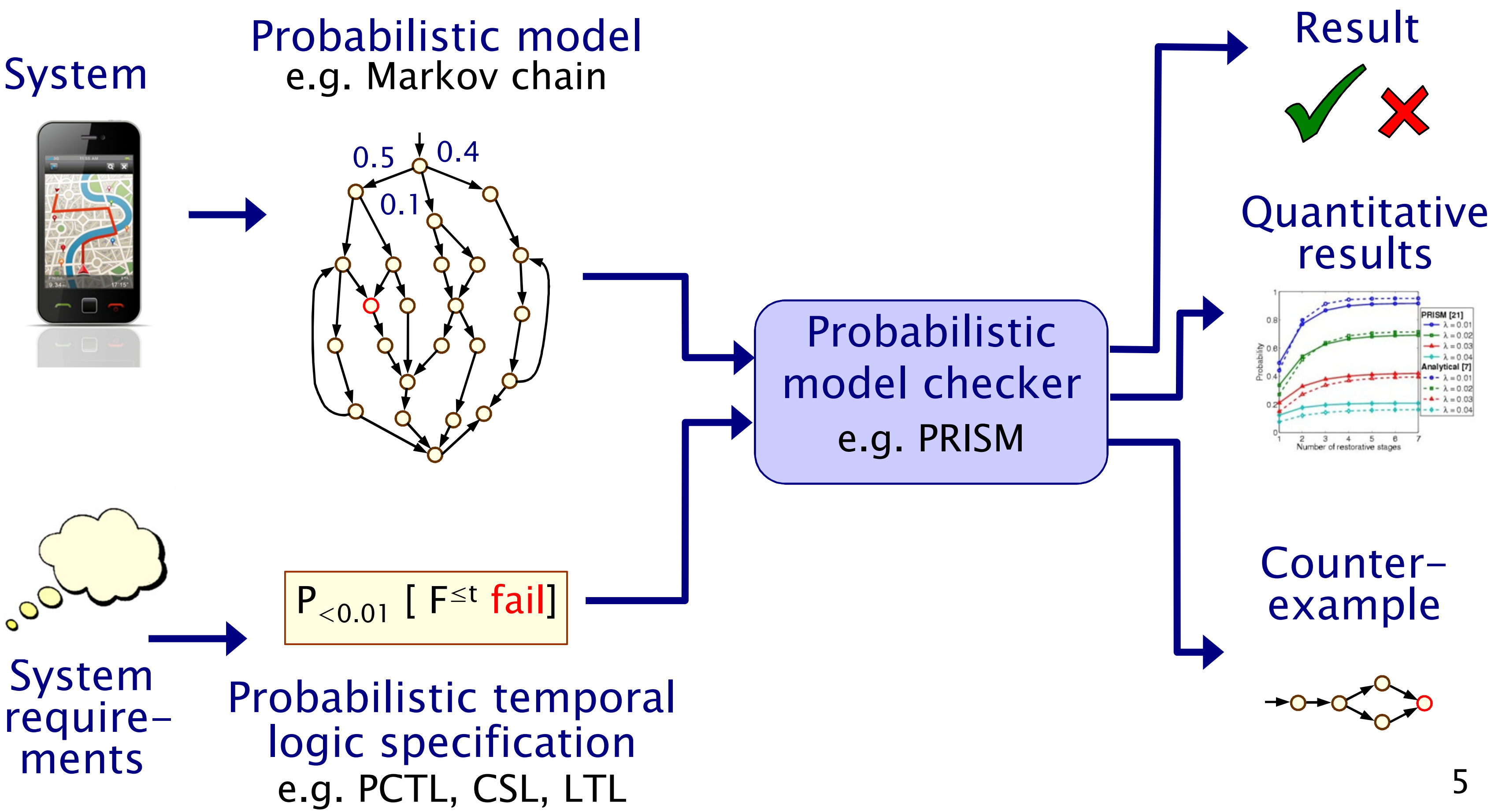
- Quantitative properties
  - safety, reliability, performance, …
  - “the probability of an airbag failing to deploy within 0.02s”
- Quantitative verification to the rescue
  - temporal logic specifications
  - quantitative verification

Quantitative verification

- Employ (quantitative) formal models
  - rigorous, unambiguous
  - can be derived or extracted from code
  - can also be used at runtime
- Specify goals/objectives/properties in temporal logic:
  - reliability, energy efficiency, performance, resource usage, …
  - (reliability) “alert signal will be delivered with high probability in 10ms”, for in-car communication
  - (energy) “maximum expected energy consumption in 1 hr is at most 10mA”, for an autonomous robot
- Focus on automated, tool-supported methodologies
  - model-based design
  - automated verification via model checking
  - controller synthesis from (temporal logic) specifications
  - NB employed in control, cf Murray’s work

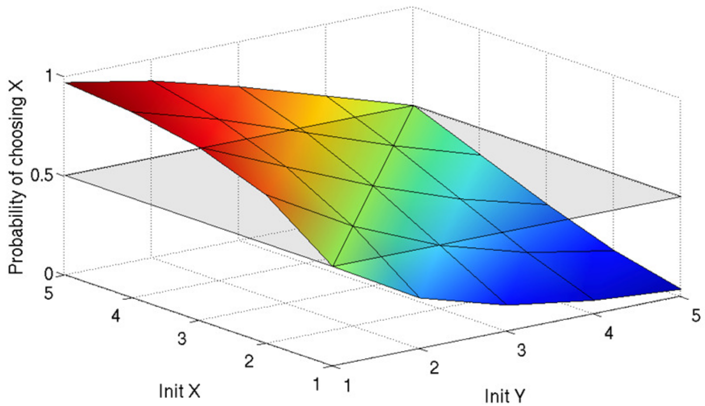
Quantitative/probabilistic verification

Automatic verification (aka model checking) of quantitative properties of probabilistic system models



Quantitative/probabilistic verification

- Property specifications based on temporal logic
  - PCTL, CSL, probabilistic LTL, PCTL*, …
- Simple examples:
  - $P_{\leq 0.01}$ [F "fail"] – "the probability of airbag failure is at most 0.01"
  - $S_{>0.999}$ ["up"] – "long-run probability of availability is >0.999"
- Usually focus on quantitative (numerical) properties:
  - $P_{=?}$ [F "crash"]
    "what is the probability of a crash occurring?"
  - then analyse trends in quantitative properties as system parameters vary



Historical perspective

- First algorithms proposed in 1980s
  - algorithms [Vardi, Courcoubetis, Yannakakis, …]
  - [Hansson, Jonsson, de Alfaro] & first implementations
- 2000: general purpose tools released
  - PRISM: efficient extensions of symbolic model checking [Kwiatkowska, Norman, Parker, …]
  - ETMCC: model checking for continuous-time Markov chains [Baier, Hermanns, Haverkort, Katoen, …]
- Now mature area, of industrial relevance
  - successfully used by non-experts for many application domains, but full automation and good tool support essential
    - distributed algorithms, communication protocols, security protocols, biological systems, quantum cryptography, planning, …
  - genuine flaws found and corrected in real-world systems
  - www.prismmodelchecker.org

But which modelling abstraction?

- Several probabilistic models supported…
- Markov chains (DTMCs and CTMCs)
  - discrete states + discrete or exponential probability
  - for: component failures, unreliable communication media, …
- Markov decision processes (MDPs)
  - probability + decisions (nondeterministic choices)
  - for: distributed coordination, motion planning in robotics…
- Probabilistic timed automata (PTAs)
  - probability + decisions+ real-time passage
  - for wireless comm. protocols, embedded control systems, …
- Towards stochastic hybrid systems
  - probability + decisions + continuous flows
  - for: control of physical processes, motion in space,…

The challenge of mobile autonomy

- Autonomous systems
  - are reactive, continuously interact with their environment
    - including other components or human users, adversarial
  - have goals/objectives
    - often quantitative, may conflict
  - take decisions based on current state and external events
- Natural to adopt a game-theoretic view
  - need to account for the uncontrollable behaviour of components, possibly with differing/opposing goals
  - in addition to controllable events
- Many occurrences in practice
  - e.g. decision making in economics, power distribution networks, motion planning, security, distributed consensus, energy management, sensor network co-ordination, semi-autonomous driving…

This lecture…

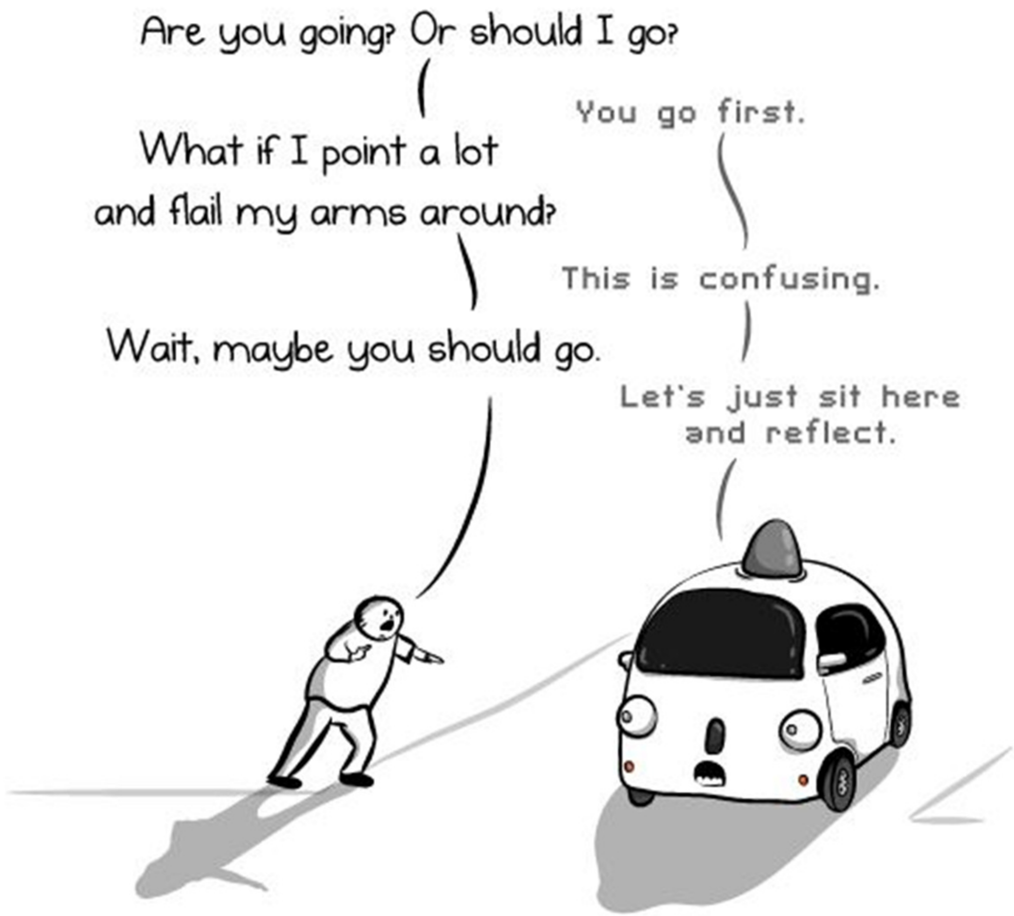
- Introduce stochastic multi-player games (SMGs)
  - argue that games are an appropriate modelling abstraction for competitive behaviour, in adversarial environments
  - stochasticity to model e.g. failure, sensor uncertainty
- Property specification: rPATL
  - single-objective properties
  - verification
  - strategy synthesis
- Extensions
  - multiobjective properties, Pareto sets
  - compositional strategy synthesis
- Tool support: PRISM-games 2.0
- Case studies

Quantitative Verification and Strategy Synthesis for Stochastic Games. M. Svorenova and M. Kwiatkowska, *European Journal of Control*, Elsevier. To appear, 2016.

What makes a game?

- Players with moves (turn-based or concurrent)
- Strategy for each player
  - plans for how to choose moves, based on information available
- Value (or payoff) for each player
- Winning
  - corresponds to optimising the value no matter how the others play the game
- Main question: is there a winning strategy?

Playing games with Google car…



– http://theoatmeal.com/blog/google_self_driving_car

Stochastic multi-player games (SMGs)

- A stochastic game involves
  - multiple players (competitive or collaborative behaviour)
  - nondeterminism (decisions, control, environment)
  - probability (failures, noisy sensors, randomisation)

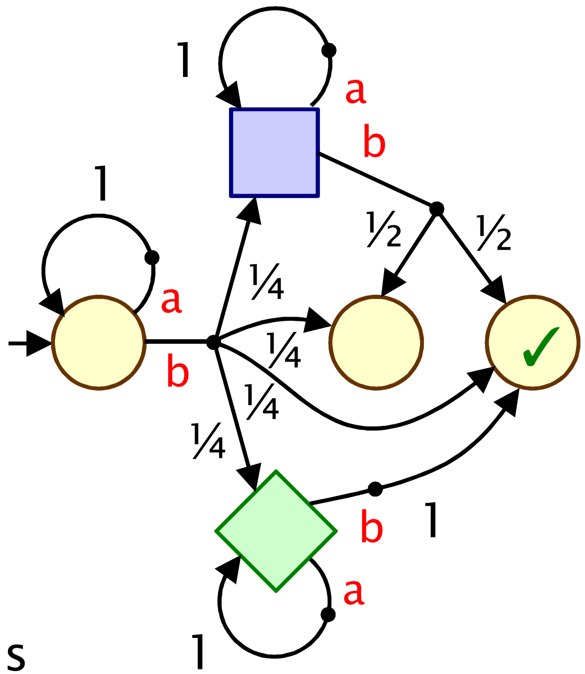
- Here consider only
  - turn-based, discrete time, zero sum, complete observation
  - timed/continuous extensions exist, but tool support lacking

- Many applications
  - autonomous traffic (risk averse vs risk taking)
  - distributed coordination (selfish agents vs unselfish)
  - controller synthesis (system vs. environment)
  - security (defender vs. attacker)

Stochastic multi-player games

- Stochastic multi-player game (SMGs)
  - multiple players + nondeterminism + probability
  - generalisation of MDPs: each state controlled by unique player

- A (turn-based) SMG is a tuple $(\Pi, S, \langle S_i \rangle_{i \in \Pi}, A, \Delta, L)$:
  - Π is a set of n players
  - S is a (finite) set of states
  - $\langle S_i \rangle_{i \in \Pi}$ is a partition of S
  - A is a set of action labels
  - $\Delta : S \times A \rightarrow Dist(S)$ is a (partial) transition probability function
  - $L : S \rightarrow 2^{AP}$ is a labelling with atomic propositions from AP



- Notation:
  - $A(s)$ denotes available actions in state s

Rewards

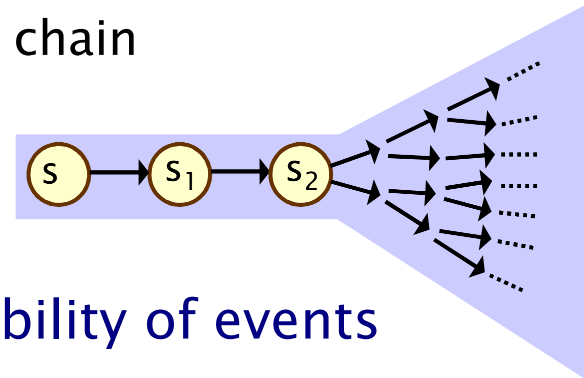
- Annotate SMGs with rewards (or costs)
  - real-valued quantities assigned to states (and/or transitions)
- Wide range of possible uses:
  - elapsed time, power consumption, number of messages successfully delivered, net profit, …
- We work with:
  - state rewards: $r : S \to \mathbb{R}_{\geq 0}$
- Form basis for a variety of quantitative objectives
  - expected cumulative (total) reward (denoted C)
  - mean-payoff (limit-average) reward (denoted S)
  - ratio reward
  - (can also consider discounted reward)

Paths, strategies + probabilities

- A path is an (infinite) sequence of connected states in SMG
  - i.e. $s_0 a_0 s_1 a_1 \ldots$ such that $a_i \in A(s_i)$ and $\Delta(s_i,a_i)(s_{i+1})>0$ for all i
  - represents a system execution (i.e. one possible behaviour)
  - to reason formally, need a probability space over paths
- A strategy for player $i \in \Pi$ resolves choices in S_i states
  - based on history of execution so far
  - i.e. a function $\sigma_i : (SA)^*S_i \rightarrow Dist(A)$
  - Σ_i denotes the set of all strategies for player i
  - deterministic if σ_i always gives a Dirac distribution
  - memoryless if $\sigma_i(s_0 a_0 \ldots s_k)$ depends only on s_k
  - also finite-memory, infinite memory, …
  - history based or explicit memory representation
- A strategy profile is tuple $\sigma=(\sigma_1,\ldots,\sigma_n)$
  - combining strategies for all n players

Paths, strategies + probabilities…

- For a strategy profile σ:
  - the game's behaviour is fully probabilistic
  - essentially an (infinite-state) Markov chain
  - yields a probability measure Pr_s^σ over set of all paths $Path_s$ from s



- Allows us to reason about the probability of events
  - under a specific strategy profile σ
  - e.g. any (ω-)regular property over states/actions

- Also allows us to define expectation of random variables
  - i.e. measurable functions $X : Path_s \rightarrow \mathbb{R}_{\geq 0}$
  - $E_s^\sigma[X] = \int_{Path_s} X \, dPr_s^\sigma$
  - used to define expected costs/rewards…

Property specification: rPATL

- Temporal logic rPATL:
  - reward probabilistic alternating temporal logic
- CTL, extended with:
  - coalition operator $\langle\langle C \rangle\rangle$ of ATL (Alternating Temporal Logic)
  - probabilistic operator P of PCTL, where $P_{\bowtie q}[\psi]$ means "the probability of ensuring ψ satisfies $\bowtie q$"
  - reward operator R of PRISM, where $R_{\bowtie q}[\rho]$ means "the expected value of ρ satisfies $\bowtie q$"
- Example:
  - $\langle\langle \{1,2\} \rangle\rangle \, P_{<0.01} [\, F^{\leq 10} \text{ error }]$
  - "players 1 and 2 have a strategy to ensure that the probability of an error occurring within 10 steps is less than 0.1, regardless of the strategies of other players"

rPATL properties

“ratio”

- Syntax:

$$\phi ::= \langle\langle C\rangle\rangle P_{\bowtie q}[\psi] \mid \langle\langle C\rangle\rangle R^{r}_{\bowtie q}[\rho] \mid \langle\langle C\rangle\rangle R^{r/c}_{\bowtie q}[\rho]$$

$$\psi ::= F\ a$$

“reachability”

$$\rho ::= C \mid S$$

“longrun average”

“cumulative”

- where:
  - $a \in AP$ is an atomic proposition, $C \subseteq \Pi$ is a coalition of players, $\bowtie \in \{\leq,<,>,\geq\}$, $q \in \mathbb{R}_{\geq 0}$, r and c are reward structures

- $\langle\langle C\rangle\rangle P_{\geq 1}$[F “end”]
  - “players in coalition C have a collective strategy to ensure that the game reaches an “end”-state almost surely, regardless of the strategies of other players”

rPATL reward properties

- Syntax:

  "ratio"

  $\phi ::= \langle\langle C\rangle\rangle P_{\bowtie q}[\psi] \mid \langle\langle C\rangle\rangle R^{r}_{\bowtie q}[\rho] \mid \langle\langle C\rangle\rangle R^{r/c}_{\bowtie q}[\rho]$

  $\psi ::= F\ a$

  "reachability"

  $\rho ::= C \mid S$

  "longrun average"

  "cumulative"

- $\langle\langle C\rangle\rangle R^{fuel}_{<q}\ [C]$
  - "players in coalition C have a strategy to ensure that the expected total fuel consumption is less than q, regardless of the strategies of other players"
- $\langle\langle C\rangle\rangle R^{fuel/time}_{\leq q}\ [S]$
  - "players in coalition C have a strategy to ensure that the expected longrun fuel consumption per time unit is at most q, regardless of the strategies of other players"

rPATL semantics

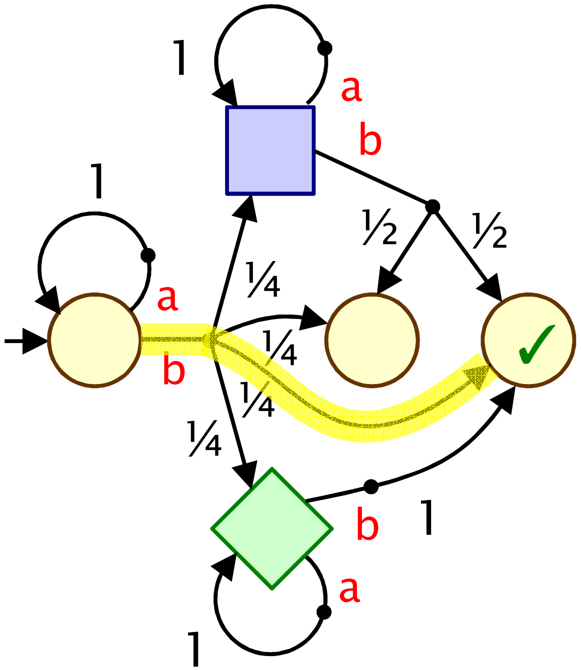
- Semantics for most operators is standard
- Just focus on P and R operators…
  - use reduction to a stochastic 2-player game

- Coalition game G_C for SMG G and coalition $C \subseteq \Pi$
  - 2-player SMG where C and $\Pi \backslash C$ collapse to players 1 and 2

- $\langle\langle C \rangle\rangle P_{\bowtie q}[\psi]$ is true in state s of G iff:
  - in coalition game G_C:
  - $\exists \sigma_1 \in \Sigma_1$ such that $\forall \sigma_2 \in \Sigma_2$. $Pr_s^{\sigma_1,\sigma_2}(\psi) \bowtie q$

- Semantics for R operator defined similarly…

Examples



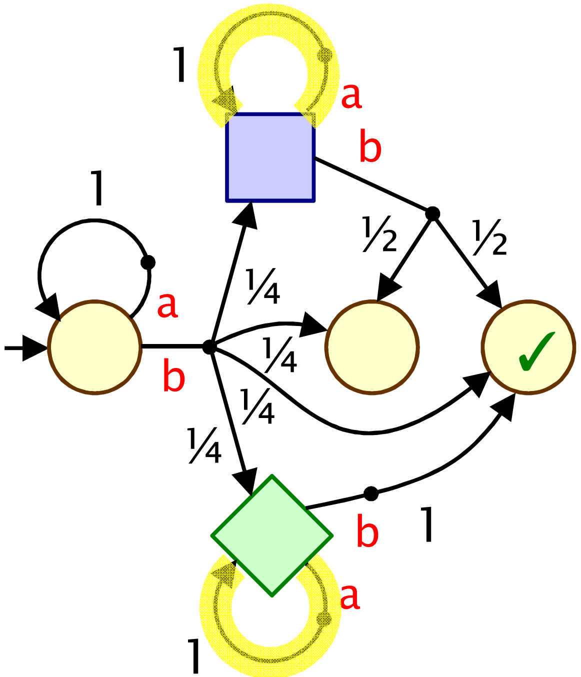
$\langle\langle \bigcirc \rangle\rangle P_{\geq 1/4}$[F ✓]

true in initial state

$\langle\langle \bigcirc \rangle\rangle P_{\geq 1/3}$ [F ✓]

$\langle\langle \bigcirc, \square \rangle\rangle P_{\geq 1/3}$ [F ✓]

Examples



$\langle\langle \bigcirc \rangle\rangle P_{\geq 1/4}[\ F\ ✓\ ]$

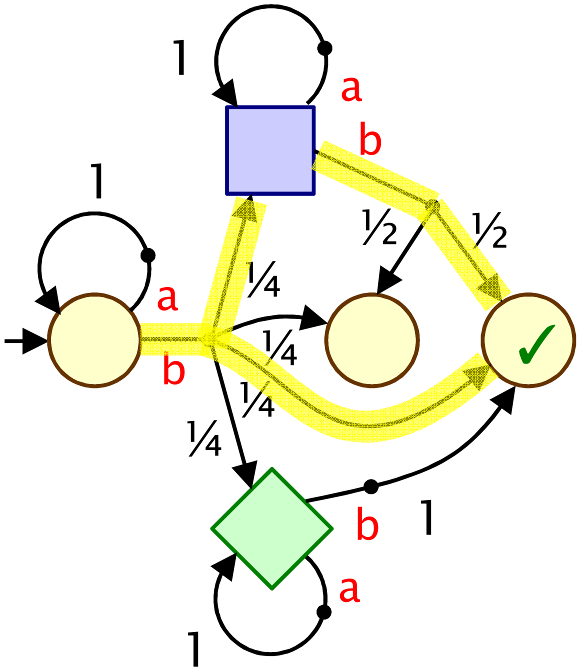
true in initial state

$\langle\langle \bigcirc \rangle\rangle P_{\geq 1/3}[\ F\ ✓\ ]$

false in initial state

$\langle\langle \bigcirc, \square \rangle\rangle P_{\geq 1/3}[\ F\ ✓\ ]$

Examples



$\langle\langle \bigcirc \rangle\rangle P_{\geq 1/4}[\ F\ \checkmark\ ]$

true in initial state

$\langle\langle \bigcirc \rangle\rangle P_{\geq 1/3}[\ F\ \checkmark\ ]$

false in initial state

$\langle\langle \bigcirc, \square \rangle\rangle P_{\geq 1/3}[\ F\ \checkmark\ ]$

true in initial state

Verification and strategy synthesis

- The verification problem is:
  - Given a game G and rPATL property ϕ, does G satisfy ϕ?
- e.g. $\langle\langle C\rangle\rangle P_{\bowtie q}[\psi]$ is true in state s of G iff:
  - in coalition game G_C:
  - $\exists\sigma_1\in\Sigma_1$ such that $\forall\sigma_2\in\Sigma_2$. $Pr_s^{\sigma_1,\sigma_2}(\psi) \bowtie q$
- The synthesis problem is:
  - Given an SMG G and a coalition property ϕ, find, if it exists, a coalition strategy σ that is a witness to G satisfying ϕ
- Reduce to computing optimal values and winning strategies in 2-player games
  - (epsilon-optimal) strategies can be typically extracted from optimal values in linear time (under restrictions)

Model checking for rPATL

- Basic algorithm: as for any branching-time temporal logic
- Main task: checking P and R operators
  - reduction to solution of stochastic 2-player game G_C
  - e.g. $\langle\langle C\rangle\rangle P_{\geq q}[\psi] \;\Leftrightarrow\; \sup_{\sigma_1\in\Sigma_1} \inf_{\sigma_2\in\Sigma_2} Pr_s^{\sigma_1,\sigma_2}(\psi) \geq q$
  - complexity: NP $\cap$ coNP (this fragment,)
  - no P algorithm known, compare to, e.g., P for Markov decision processes
- Quantitative (numerical) properties:
  - best/worst-case values
- e.g. $\langle\langle C\rangle\rangle P_{\max=?}[\psi] = \sup_{\sigma_1\in\Sigma_1} \inf_{\sigma_2\in\Sigma_2} Pr_s^{\sigma_1,\sigma_2}(\psi)$
- In practice:
  - employ value iteration
  - up to a desired level of convergence

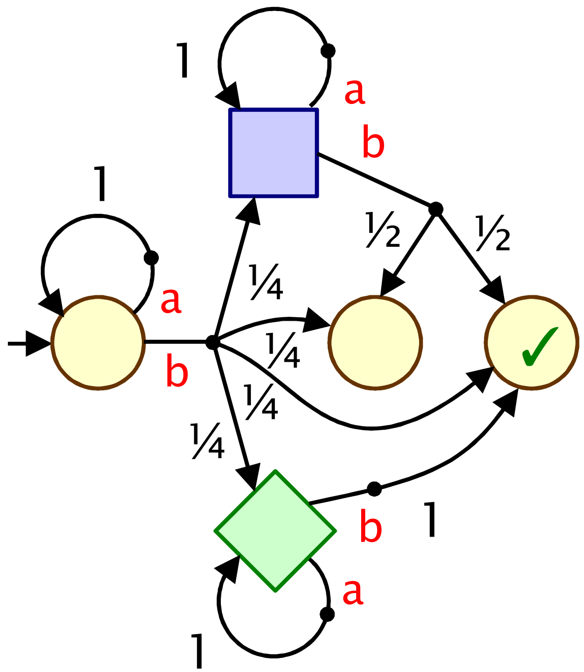
Probabilities for P operator

- E.g. $\langle\langle C\rangle\rangle P_{\geq q}[\ F\ a\ ]$: max/min reachability probabilities
  - compute $\sup_{\sigma_1 \in \Sigma_1} \inf_{\sigma_2 \in \Sigma_2} Pr_s^{\sigma_1,\sigma_2}(F\ a)$ for all states s
  - deterministic memoryless strategies suffice
- Value is:
  - 1 if $s \in Sat(a)$, and otherwise least fixed point of:

$$f(s) = \begin{cases} \max_{a \in A(s)} \left(\sum_{s' \in S} \Delta(s,a)(s') \cdot f(s') \right) & \text{if } s \in S_1 \\ \min_{a \in A(s)} \left(\sum_{s' \in S} \Delta(s,a)(s') \cdot f(s') \right) & \text{if } s \in S_2 \end{cases}$$

- Computation:
  - start from zero, propagate probabilities backwards
  - guaranteed to converge

Example



rPATL: $\langle\langle$○, □$\rangle\rangle P_{\geq 1/3}$ [F ✓]

Player 1: ○, □ Player 2: ◇

Compute: $\sup_{\sigma_1 \in \Sigma_1} \inf_{\sigma_2 \in \Sigma_2} Pr_s^{\sigma_1,\sigma_2}$ (F ✓)

Strategy synthesis for rPATL

- The verification problem is
  - Given a game G and rPATL property ϕ, does G satisfy ϕ?
- e.g. $\langle\langle C \rangle\rangle P_{\bowtie q}[\psi]$ is true in state s of G iff:
  - in coalition game G_C:
  - $\exists \sigma_1 \in \Sigma_1$ such that $\forall \sigma_2 \in \Sigma_2$. $Pr_s^{\sigma_1,\sigma_2}(\psi) \bowtie q$

- The synthesis problem is
  - Given a game G and rPATL property ϕ, find, if it exists, a coalition strategy σ_1 that is a witness to the satisfaction of ϕ

- In other words
  - find a controller working under all environment conditions, including adversarial
  - memoryless deterministic strategies suffice (this fragment)

Multi-objective properties

- Extension of rPATL: conjunctions of objectives (for stopping games), ie multidimensional
  - expected total rewards, mean-payoffs or ratios
  - almost sure mean-payoffs/ratios
- Explore trade-offs
  - e.g. between performance and resource usage
- Example
  - “coalition C can guarantee that the expected longrun average fuel consumption <u>and</u> profit are simultaneously at least v1 and v2, respectively, no matter what the other agents do”

  $\langle\langle C \rangle\rangle \; (R^{\mathrm{fuel}}_{\geq v1} \; [S] \; \& \; R^{\mathrm{profit}}_{\geq v2} \; [S] \;)$

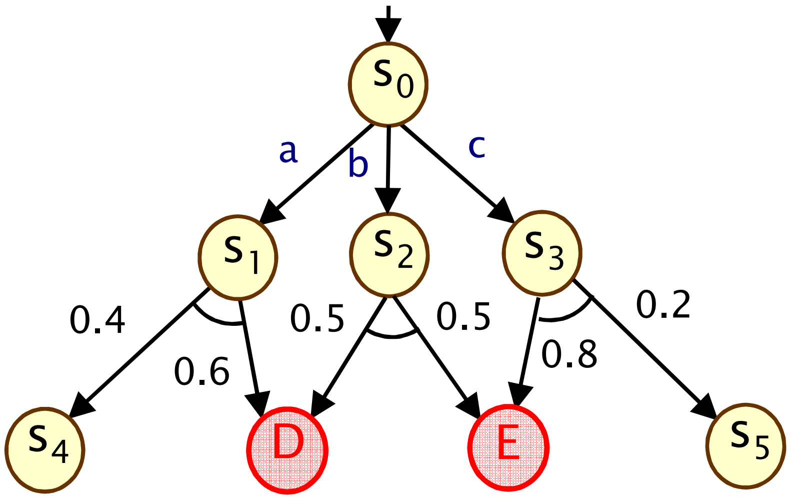
- NB Boolean combinations may be needed for implication

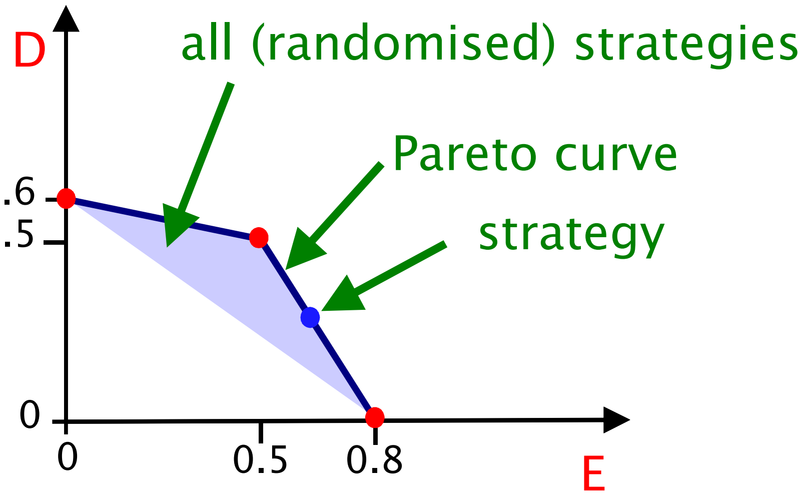
  $\langle\langle C \rangle\rangle \; (R^{\mathrm{fuel/time}}_{\geq v1} \; [S] \Rightarrow R^{\mathrm{profit}}_{\geq v2} \; [S] \;)$

Example

- Consider the simpler scenario of MDPs

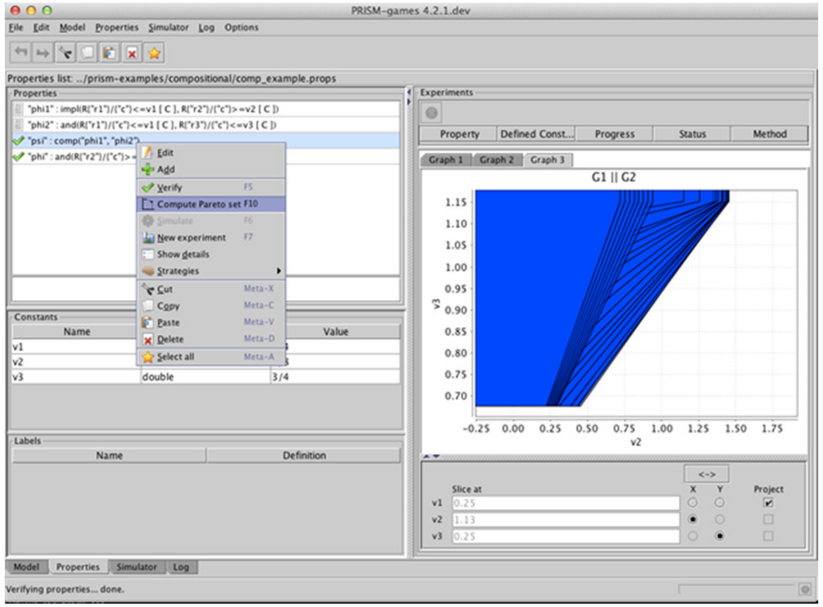
- Pareto optimum for multiple objectives
  - probability of reaching D is greater than 0.2 and
  - probability of reaching E is greater than 0.6



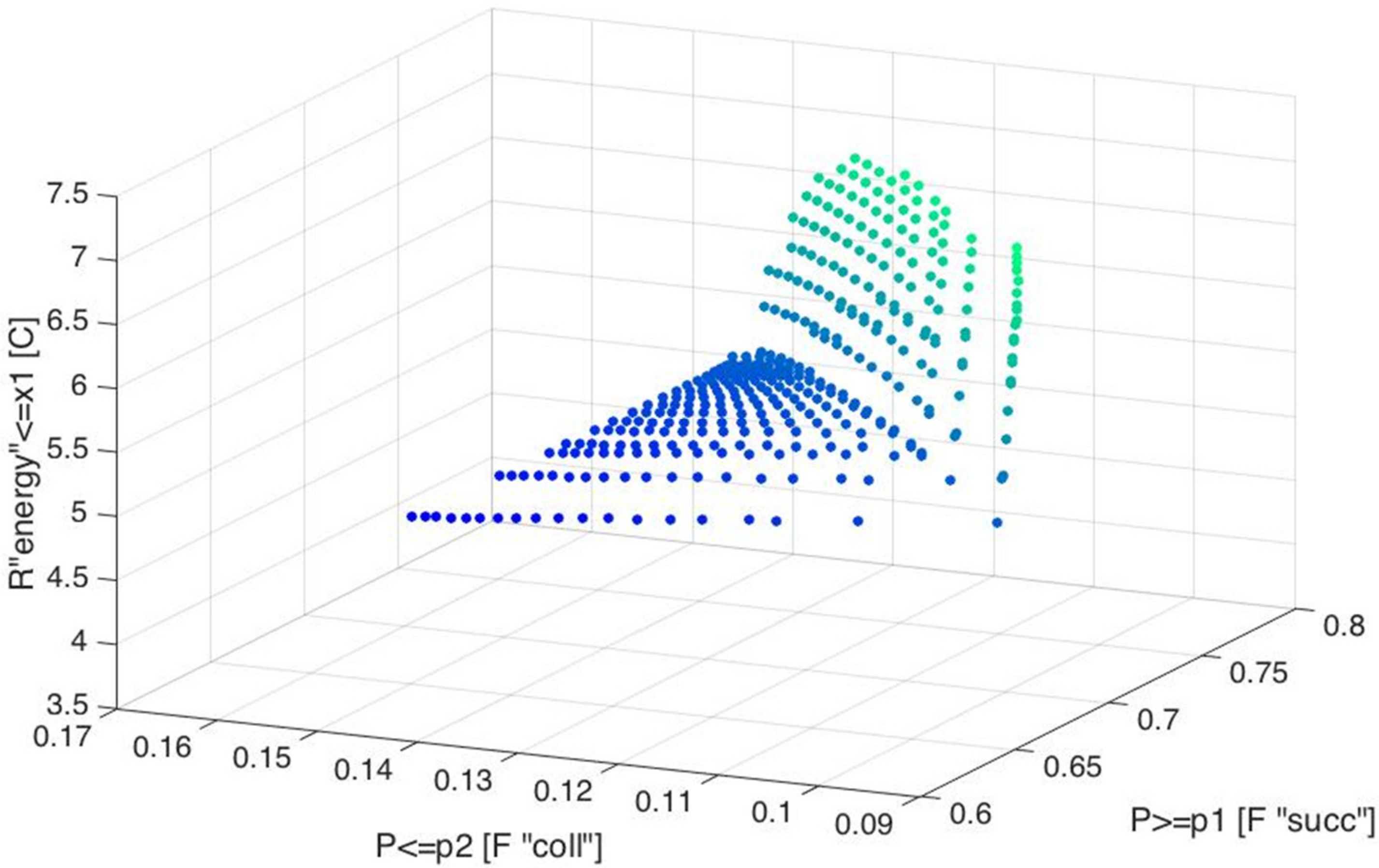


Computation of Pareto sets

- Multi-objective strategy synthesis
  - epsilon-optimal strategies, randomised
  - value iteration over polytopic sets
  - stochastic memory update representation
- Pareto sets
  - optimal achievable trade-offs between objectives
- Visualisation of high-dimensional Pareto sets
  - projection
  - slicing



Multidimentional Pareto set



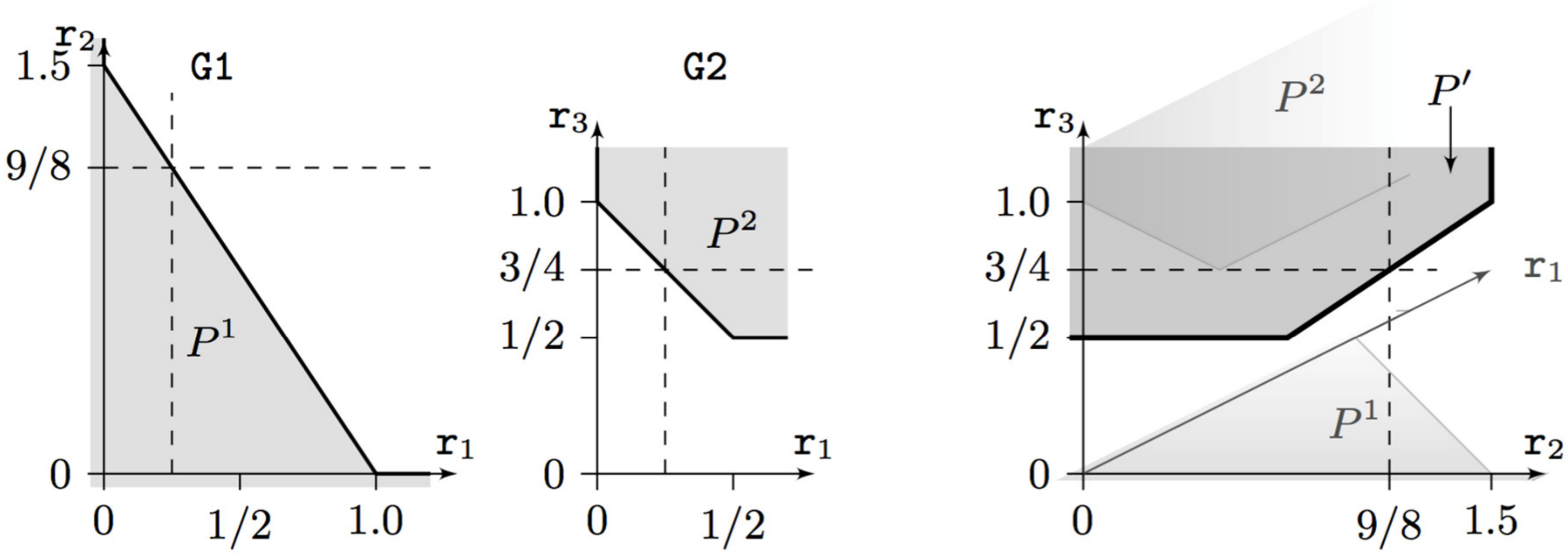
Pareto set approximation for a mixed multi-objective property

Compositional strategy synthesis

- Components
  - reduce design complexity, increase reliability via redundancy
  - improve scalability of analysis, avoid product state space
- Assume-guarantee synthesis:
  - need a strategy for the full system satisfying a global property
  - synthesise one strategy per component, for local properties
  - use assume-guarantee rules to compose local strategies
- Example: local strategies for $G_1 \models \phi^A$ and $G_2 \models \phi^A \Rightarrow \phi^B$ compose to a global strategy for $G_1 \| G_2 \models \phi^B$
- Need to extend synthesis methods:
  - multi-objective properties to use in local and global properties
  - admit also long-run properties (e.g. ratios of rewards)

Compositional strategy synthesis

- Based on assume-guarantee contracts over component interfaces
- Synthesise local strategies for components, then compose into a global strategy using assume-guarantee rules
- Under-approximation of Pareto sets



$\langle\langle 1\rangle\rangle(\mathtt{R}\{\text{“}\mathtt{r}_1\text{”}/\text{“}\mathtt{c}\text{”}\}_{\leq \mathtt{v}_1}[\mathtt{S}] \rightarrow \mathtt{R}\{\text{“}\mathtt{r}_2\text{”}/\text{“}\mathtt{c}\text{”}\}_{\geq \mathtt{v}_2}[\mathtt{S}])$

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Tool support: PRISM-games 2.0

- Model checker for stochastic games
  - integrated into PRISM model checker
  - using new explicit-state model checking engine
- SMGs added to PRISM modelling language
  - guarded command language, based on reactive modules
  - finite data types, parallel composition, proc. algebra op.s, …
- rPATL added to PRISM property specification language
  - implemented value iteration based model checking
- Supports strategy synthesis
  - single and multiple objectives, Pareto curve
  - total expected reward, longrun average, ratio rewards
  - compositional strategy synthesis
- Available now:
  - http://www.prismmodelchecker.org/games/

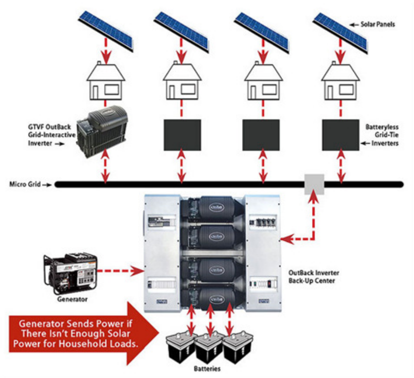
Case studies

- Evaluated on several case studies:
  - team formation protocol [CLIMA'11]
  - futures market investor model [McIver & Morgan]
  - collective decision making for sensor networks [TACAS'12]
  - energy management in microgrids [TACAS'12]
  - reputation protocol for user-centric networks [SR'13]
  - DNS bandwidth amplification attack [Deshpande et al]
  - self-adaptive software architectures [Camara, Garlan et al]
  - attack-defence scenarios in RFID goods man. [Aslanyan et al]
- Case studies using PRISM-games 2.0 functionality:
  - autonomous urban driving (multi-objective) [QEST'13]
  - UAV path planning with operator (multi-objective) [ICCPS'15]
  - aircraft electric power control (compositional) [TACAS'15]
  - temperature control (compositional) [Wiltsche PhD]

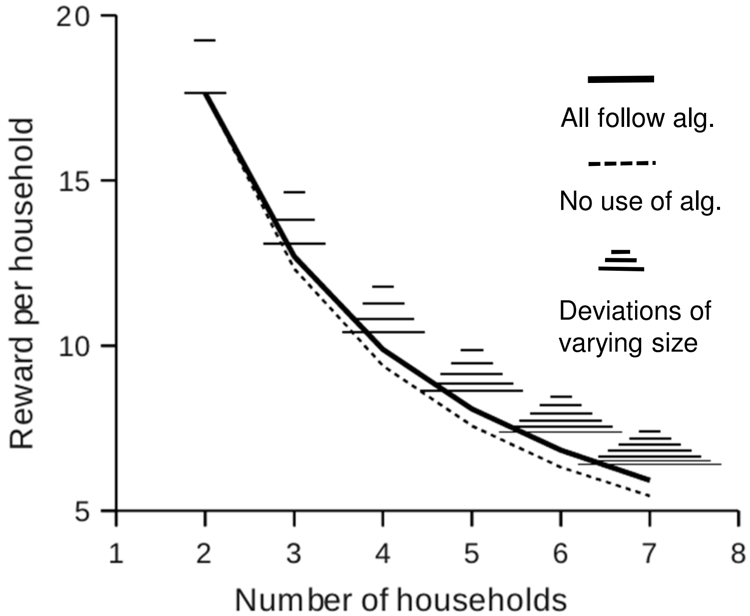
PRISM-games 2.0: A Tool for Multi-Objective Strategy Synthesis for Stochastic Games.
Kwiatkowska et al., In *Proc* TACAS 2016

Case study: Energy management

- Energy management protocol for Microgrid
  - Microgrid: local energy management
  - randomised demand management protocol [Hildmann/Saffre'11]
  - probability: randomisation, demand model, …



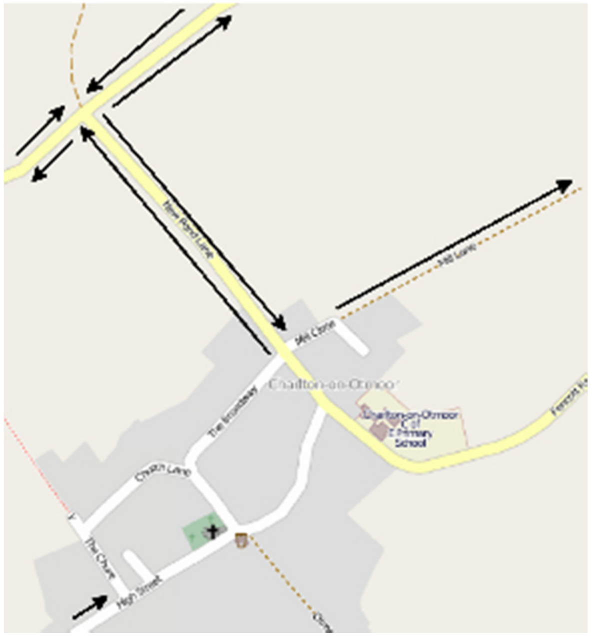
- Existing analysis
  - simulation-based
  - assumes all clients are unselfish
- Our analysis
  - stochastic multi-player game
  - clients can cheat (and cooperate)
  - exposes protocol weakness
  - propose/verify simple fix



[Automatic Verification of Competitive Stochastic Systems](), Chen et al., In *Proc* TACAS 2012

Case study: Autonomous urban driving

- Inspired by DARPA challenge
  - represent map data as a stochastic game, with environment active, able to select hazards
  - express goals as conjunctions of probabilistic and reward properties
  - e.g. “maximise probability of avoiding hazards and minimise time to reach destination”
- Solution (PRISM-games 2.0)
  - synthesise a probabilistic strategy to achieve the multi-objective goal

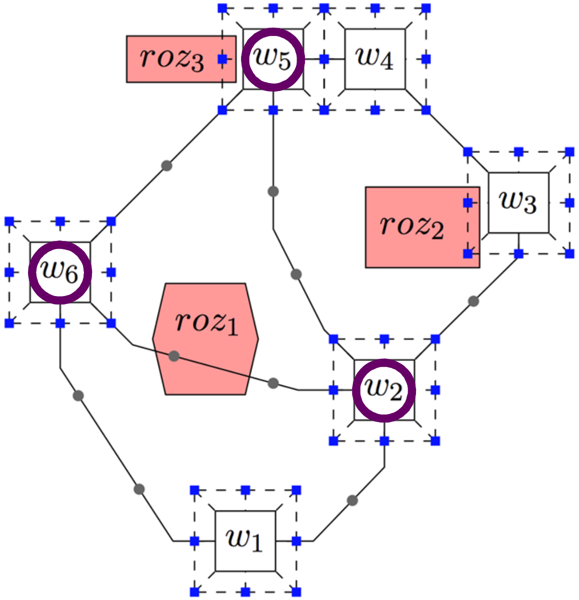


  - enable the exploration of trade-offs between subgoals
  - applied to synthesise driving strategies for English villages

Synthesis for Multi-Objective Stochastic Games: An Application to Autonomous Urban Driving, Chen et al., In *Proc* QEST 2013

Case study: UAV path planning

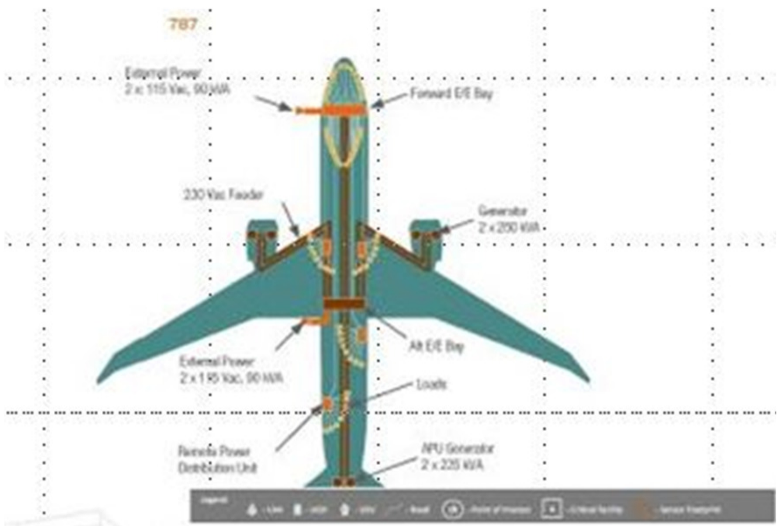
- Human operator
  - sensor tasks
  - high-level commands for piloting
- UAV autonomy
  - low-level piloting function
- Quantitative mission objectives
  - road network surveillance with the minimal time, fuel, or restricted operating zone visits
- Analysis of trade-offs
  - consider operator fatigue and workload
  - multi-objective, MDP and SMG models



Controller Synthesis for Autonomous Systems Interacting with Human Operators. L. Feng et al, In *Proc.* ICCPS 2015, ACM

Case study: Aircraft power distribution

- Consider Honeywell high-voltage AC (HVAC) subsystem
  - power routed from generators to buses through switches
  - represent as a stochastic game, modelling competition for buses, with stochasticity used to model failures
  - specify control objectives in LTL using longrun average
  - e.g. “maximise uptime of the buses and minimise failure rate”



- Solution (PRISM-games 2.0)
  - compositional strategy synthesis
  - enable the exploration of trade-offs between uptime of buses and failure rate

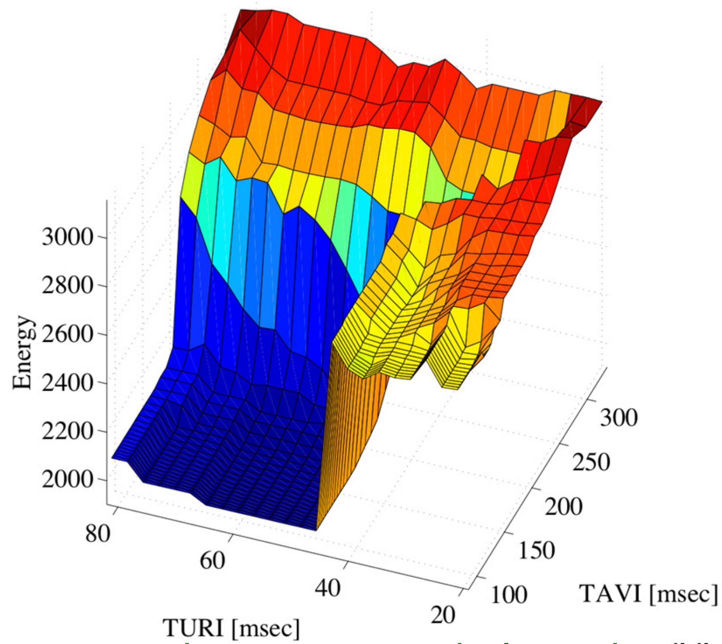
Compositional Controller Synthesis for Stochastic Games, Basset et al., In *Proc* CONCUR 2014

Conclusion

- Summary
  - games can model a wide range of competitive and cooperative goal-driven scenarios relevant for mobile autonomy
  - variety of quantitative objectives
  - multi-objective properties
  - compositional synthesis via assume-guarantee rules
  - implementation: explicit engine, Parma polyhedra library, value iteration
  - high complexity, performance sluggish
- Future work
  - mobility?
  - consider social aspects?
  - allow partial observability?
  - combine with Nash equilibria?
- Beyond games…

Personalised wearable/implantable devices

- Hybrid model-based framework
  - timed automata model for pacemaker software
  - hybrid heart models in Simulink, adopt synthetic ECG model (non-linear ODE)
- Properties
  - (basic safety) maintain 60-100 beats per minute
  - (advanced) detailed analysis energy usage, plotted against timing parameters of the pacemaker
  - parameter synthesis: find values for timing delays that optimise energy usage

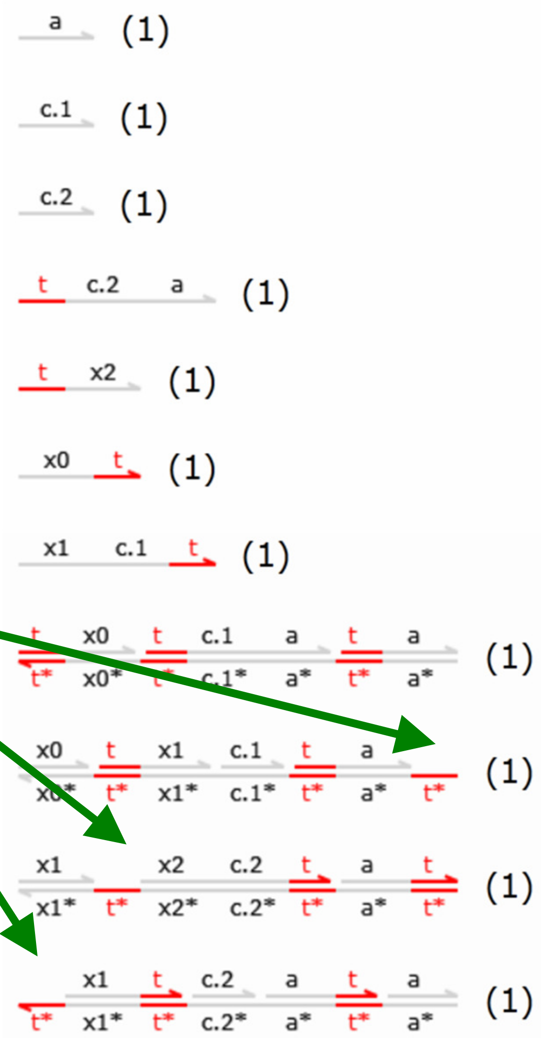


Synthesising robust and optimal parameters for cardiac pacemakers using symbolic and evolutionary computation techniques. Kwiatkowska, Mereacre, Paoletti and Patane, HSB'16

DNA computation

- Cardelli's DNA transducer gate
  - inputs/outputs single strands
  - two transducers connected
- PRISM identifies a bug: 5-step trace to a "bad" deadlock state
  - previously found manually [Cardelli'10]
  - detection now fully automated
- Bug is easily fixed
  - (and verified)

reactive gates

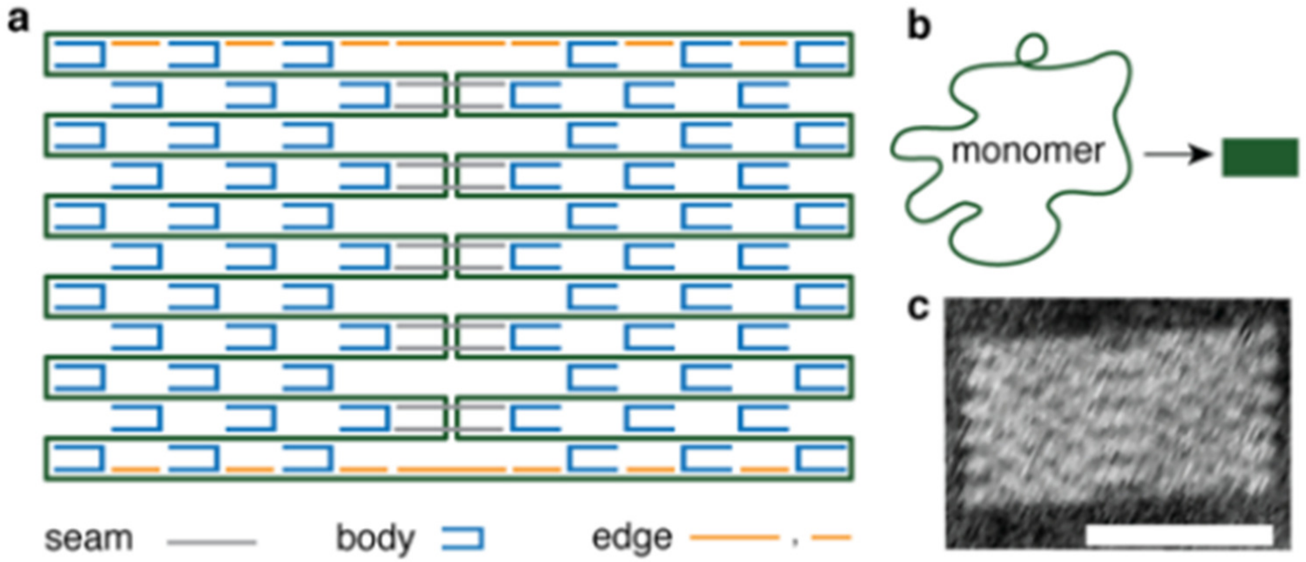


Counterexample:
(1,1,1,1,1,1,1,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0)
(0,1,1,0,1,1,1,1,1,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0)
(0,0,1,0,1,1,1,1,1,0,1,1,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0)
(0,0,1,0,1,1,1,1,0,0,1,1,1,0,0,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0)
(0,0,1,0,1,1,0,1,0,0,1,1,1,0,0,0,1,0,0,0,0,1,1,1,0,0,0,0,0,0,0,0)
(0,0,1,0,1,1,0,1,0,0,1,0,1,0,0,0,0,0,0,1,1,1,1,1,0,0,0,0,0,0,0,0)

Design and Analysis of DNA Strand Displacement Devices using Probabilistic Model Checking, Lakin *et al*, Journal of the Royal Society Interface, 9(72), 1470-1485, 2012

DNA origami tiles

- DNA origami tiles: molecular breadboard [Turberfield lab]



50nm

Aim to understand how to control the folding pathways

- formulate an abstract Markov chain model
- obtain model predictions using Gillespie simulation
- perform a range of experiments, consistent with preditions

Guiding the folding pathway of DNA origami. Dunne, Dannenberg, Ouldridge, Kwiatkowska, Turberfield & Bath, Nature 525, pages 82-86, 2015.

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- See also
  - VERIWARE www.veriware.org
  - PRISM www.prismmodelchecker.org