

Probabilistic model checking for strategic equilibria-based decision making

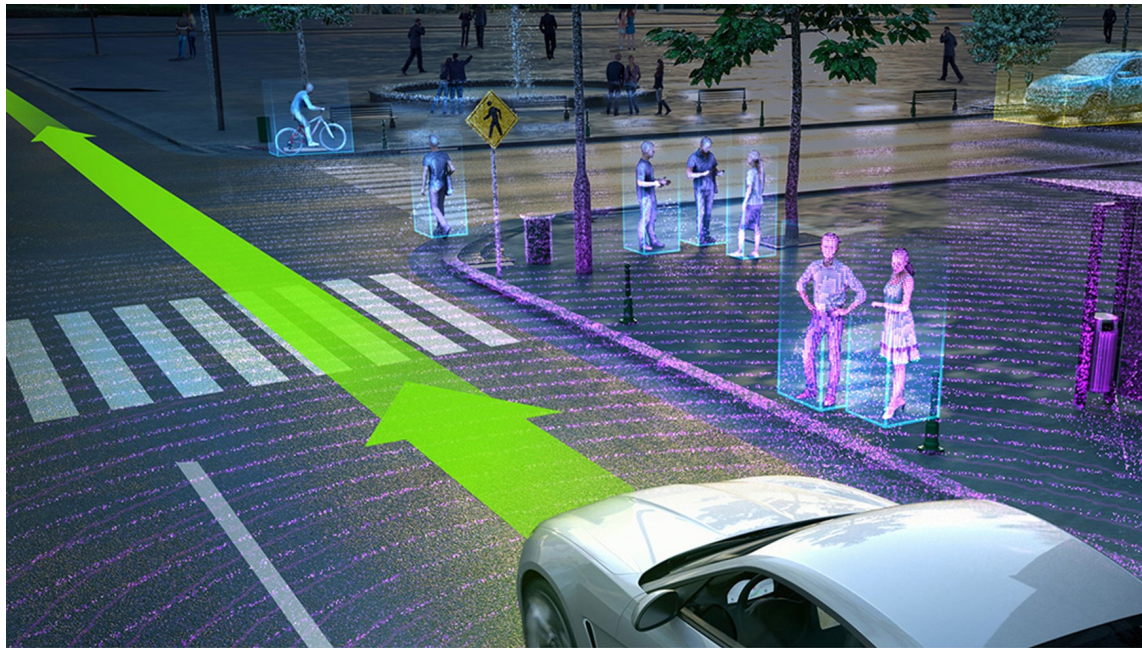


Prof. Marta Kwiatkowska

Department of Computer Science
University of Oxford

Software everywhere

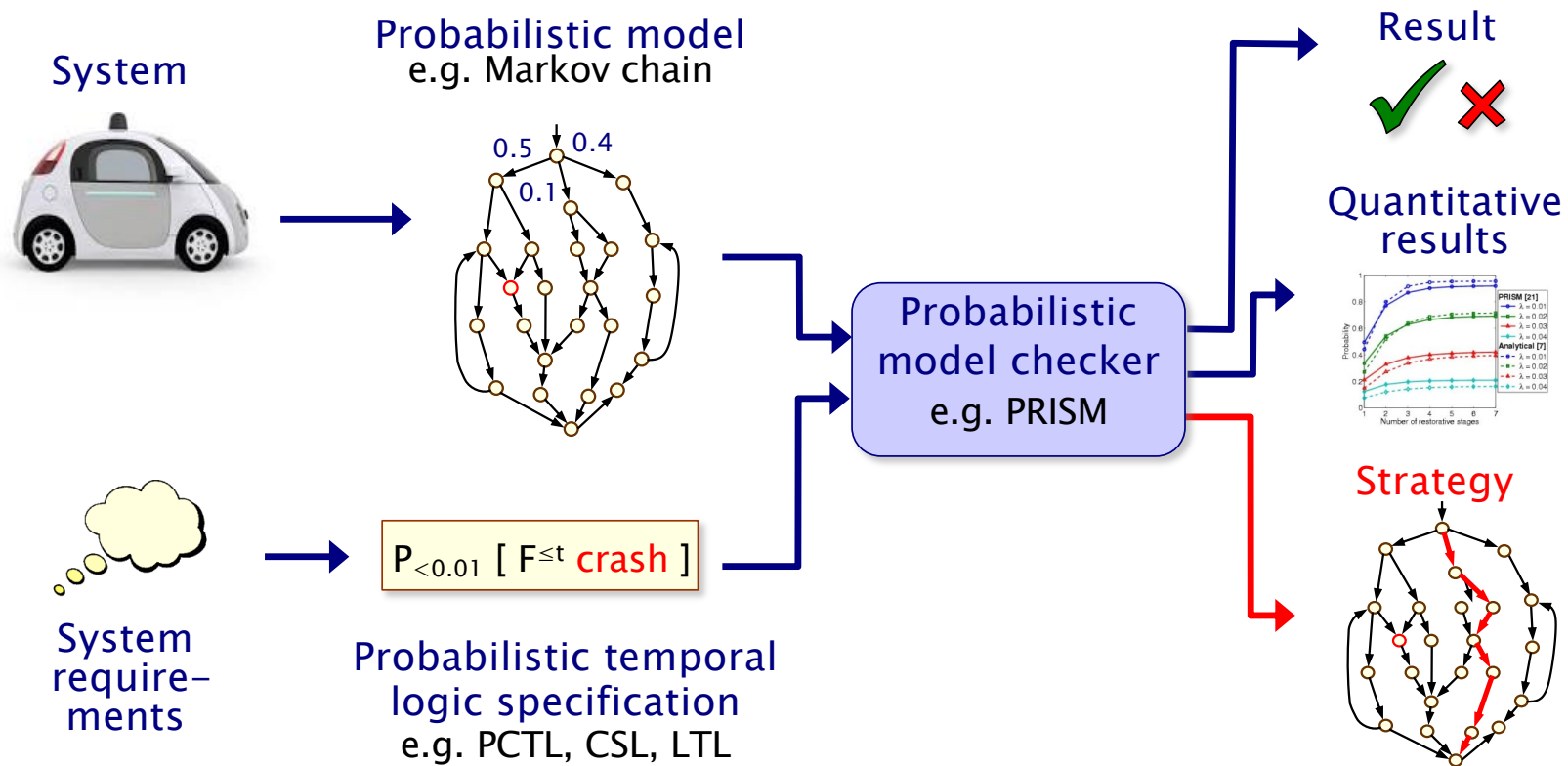
- Users expect: **predictability & high integrity** in presence of
 - component failure, environmental uncertainty, communication delays, ...



- Safety, security, reliability, robustness, ... can be expressed **probabilistically**
 - “the probability of an airbag failing to deploy within 0.02s is less than 0.001”

Probabilistic model checking

Automatic verification and strategy synthesis from temporal logic properties for probabilistic models



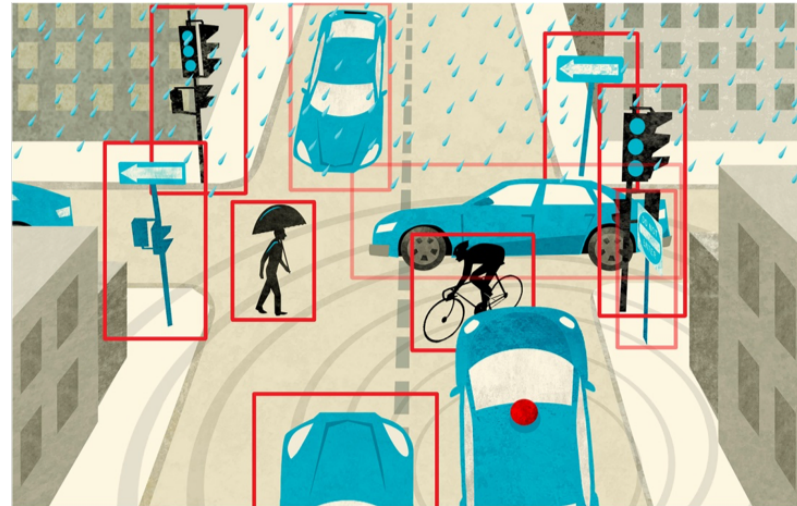
Tool support: PRISM

- First algorithms proposed in 1980s
 - algorithms [Vardi, Courcoubetis, Yannakakis, ...]
 - [Hansson, Jonsson, de Alfaro] & first implementations
- 2001: general purpose tools released
 - PRISM: efficient extensions of symbolic model checking [Kwiatkowska, Norman, Parker, and many more, ...]
- Now mature area, of industrial relevance, new model checkers, tool competition
 - PRISM successfully used by non-experts in many domains
 - distributed algorithms, communication protocols, security protocols, biological systems, quantum cryptography, planning, robotics, ...
 - genuine **flaws** found and corrected in real-world systems
 - www.prismmodelchecker.org



But which modelling abstraction?

- **Complex decisions!**
 - human and artificial agents
 - distinct goals
 - autonomy
 - competitive/collaborative behaviour
 - context
- **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, security, energy management, ...



Why games?



- Games serve as abstractions for **negotiation**, **strategic** game playing and **incentives** to achieve more effective behaviour
 - virtual vs human agents, turn-based vs concurrent, zerosum vs non-zerosum, rational vs non-rational behaviours, individual vs social gain, ...
- Relevant for a multitude of autonomous and AI scenarios
 - e.g. automated decisions, resource sharing, distributed coordination protocols, virtual assistants, etc
 - even autonomous driving...

Driving as a game-theoretic problem

2019 International Conference on Robotics and Automation (ICRA)
Palais des congrès de Montreal, Montreal, Canada, May 20-24, 2019

- Merging into traffic difficult for autonomous cars
- Human drivers are not behaving rationally!
- Here dynamic games, and interplay between long-horizon strategic game playing with short-horizon tactical moves, plus incentives

Hierarchical Game-Theoretic Planning for Autonomous Vehicles

Jaime F. Fisac^{*1} Eli Bronstein^{*1} Elis Stefansson² Dorsa Sadigh³ S. Shankar Sastry¹ Anca D. Dragan¹

Abstract—The actions of an autonomous vehicle on the road affect and are affected by those of other drivers, whether overtaking, negotiating a merge, or avoiding an accident. This mutual dependence, best captured by dynamic game theory, creates a strong coupling between the vehicle's planning and its predictions of other drivers' behavior, and constitutes an open problem with direct implications on the safety and viability of autonomous driving technology. Unfortunately, dynamic games are too computationally demanding to meet the real-time constraints of autonomous driving in its continuous state and action space. In this paper, we introduce a novel game-theoretic trajectory planning algorithm for autonomous driving, that enables real-time performance by hierarchically decomposing the underlying dynamic game into a long-horizon “strategic” game with simplified dynamics and full information structure, and a short-horizon “tactical” game with full dynamics and a simplified information structure. The value of the strategic game is used to guide the tactical planning, implicitly extending the planning horizon, pushing the local trajectory optimization closer to global solutions, and, most importantly, quantitatively accounting for the autonomous vehicle and the human driver's ability and incentives to influence each other. In addition, our approach admits non-deterministic models of human decision-making, rather than relying on perfectly rational predictions. Our results showcase richer, safer, and more effective autonomous behavior in comparison to existing techniques.

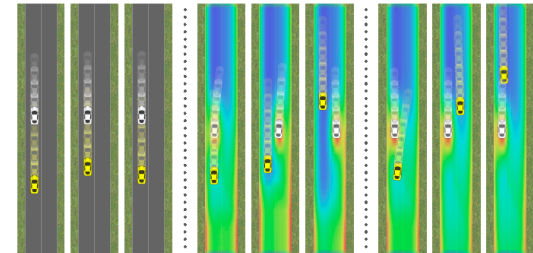


Fig. 1: Demonstration of our hierarchical game-theoretic planning framework on a simulated overtaking scenario. The heatmap displays the hierarchical planner's strategic value, ranging from red (low value) to blue (high value), which accounts for the outcome of possible interactions between the two vehicles. *Left*: Using a short-horizon trajectory planner, the autonomous vehicle slows down and is unable to overtake the human. *Center*: Using the hierarchical game-theoretic planner, the autonomous vehicle approaches the human from behind, incentivizing her to change lanes and let it pass (note the growth of a high-value region directly behind the human in the left lane). *Right*: If the human does not maneuver, the autonomous vehicle executes a lane change and overtakes, following the higher values in the right lane.

autonomous driving. Most approaches in the literature follow a “nine-line” approach that generates predictions of the traiec-

This lecture...

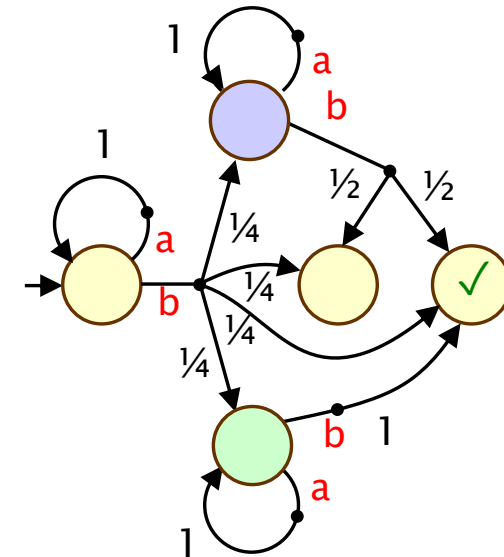
- Introduce **stochastic multi-player games**
 - modelling abstraction for competitive/cooperative behaviour, in adversarial environments
 - stochasticity to model e.g. failure, sensor uncertainty
 - turn-based and **concurrent** games
- Property specification: rPATL (based on PCTL and ATL)
 - zerosum and **equilibria**
 - model checking and strategy synthesis
 - case studies
- Tool support: PRISM-games 3.0
- Challenges and future directions

Stochastic multi-player games (SMGs)

- A stochastic game involves
 - **multiple** players (competitive or collaborative behaviour)
 - **nondeterminism** (decisions, control, environment)
 - **probability** (failures, noisy sensors, randomisation)
- Game variants
 - turn-based vs concurrent, zero sum vs distinct goals
 - here, **complete information** games
- Widely studied, esp. algorithmic complexity, 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
 - $\Delta : S \times A \rightarrow \text{Dist}(S)$ is a (partial) transition probability function
 - $L : S \rightarrow 2^{AP}$ is a labelling with atomic propositions from AP
- NB concurrent games coming later



Strategies, probabilities & rewards

- **Strategy** for player i : resolves choices in S_i states
 - based on execution history, i.e. $\sigma_i : (SA)^*S_i \rightarrow \text{Dist}(A)$
 - can be: deterministic (pure), randomised, memoryless, finite-memory, ...
 - Σ_i denotes the set of all strategies for player i
- **Strategy profile**: strategies for all players: $\sigma = (\sigma_1, \dots, \sigma_n)$
 - probability measure Pr_s^σ over (infinite) paths from state s
 - expectation $E_s^\sigma(X)$ of random variable X over Pr_s^σ
- **Rewards (or costs)**
 - non-negative integers on states/transitions
 - e.g. elapsed time, energy consumption, number of packets lost, net profit, ...

Property specification: rPATL

- **rPATL** (reward probabilistic alternating temporal logic)
 - branching-time temporal logic for SMGs
- **CTL, extended with:**
 - coalition operator $\langle\langle C \rangle\rangle$ of ATL
 - probabilistic operator **P** of PCTL
 - generalised (expected) reward operator **R** from PRISM
- **In short:**
 - **zero-sum**, probabilistic reachability + expected total reward
- **Example:**
 - $\langle\langle\{1,3\}\rangle\rangle P_{<0.01} [F^{\leq 10} \text{error}]$
 - “players 1 and 3 have a strategy to ensure that the probability of an error occurring within 10 steps is less than 0.01, regardless of the strategies of other players”

rPATL syntax/semantics

- Syntax:

$$\phi ::= \text{true} \mid a \mid \neg\phi \mid \phi \wedge \phi \mid \langle\langle C \rangle\rangle P_{\bowtie q}[\psi] \mid \langle\langle C \rangle\rangle R^r_{\bowtie x}[\rho]$$
$$\psi ::= X\phi \mid \phi U^{\leq k}\phi \mid \phi U\phi$$
$$\rho ::= I^k \mid C^{\leq k} \mid F\phi$$

- where:

- $a \in AP$ is an atomic proposition, $C \subseteq N$ is a coalition of players,

- $\bowtie \in \{\leq, <, >, \geq\}$, $q \in [0, 1] \cap \mathbb{Q}$, $x \in \mathbb{Q}_{\geq 0}$, $k \in \mathbb{N}$,

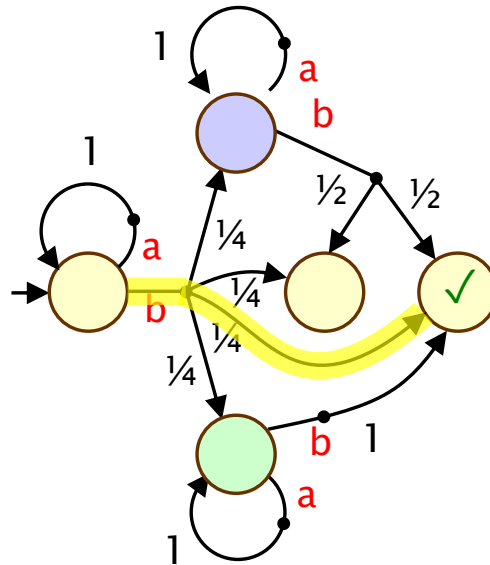
- r is a reward structure

- Semantics:

- e.g. P operator: $s \models \langle\langle C \rangle\rangle P_{\bowtie q}[\psi]$ iff:

- “there exist strategies for players in coalition C such that,
for all strategies of the other players, the **probability** of path formula ψ being true
from state s satisfies $\bowtie q$ ”

Examples



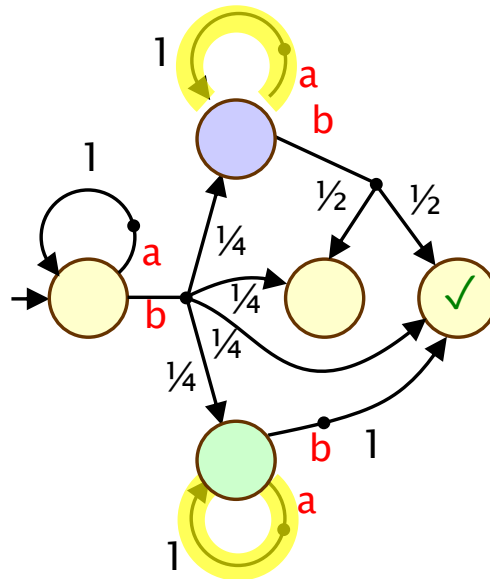
$\langle\langle \bigcirc \rangle\rangle P_{\geq \frac{1}{4}} [F \checkmark]$

true in initial state

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

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

Examples

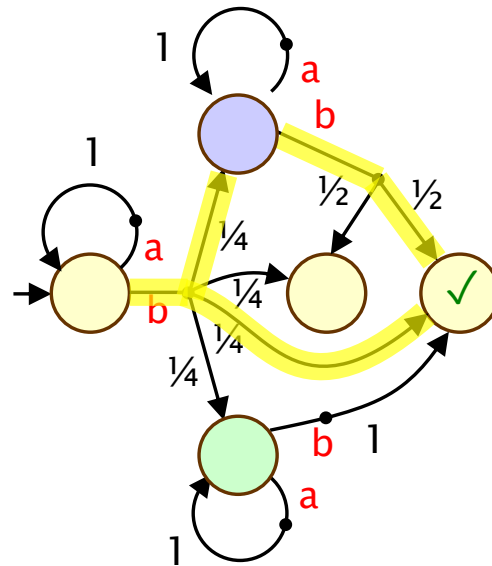


$\langle\langle \bigcirc \rangle\rangle P_{\geq 1/4} [F \checkmark]$
 true in initial state

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

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

Examples



$\langle\langle \text{yellow} \rangle\rangle P_{\geq 1/4} [F \checkmark]$
 true in initial state

$\langle\langle \text{yellow} \rangle\rangle P_{\geq 1/3} [F \checkmark]$
 false in initial state

$\langle\langle \text{yellow}, \text{purple} \rangle\rangle P_{\geq 1/3} [F \checkmark]$
 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 a game 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
 - 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), cf P for MDPs

Example: Probabilistic reachability

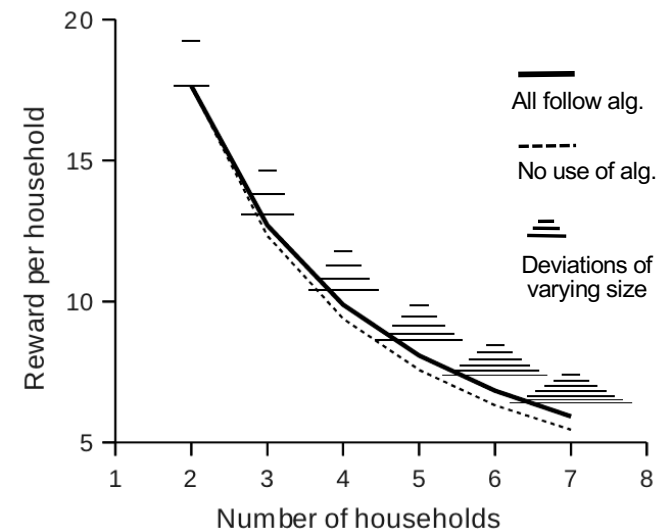
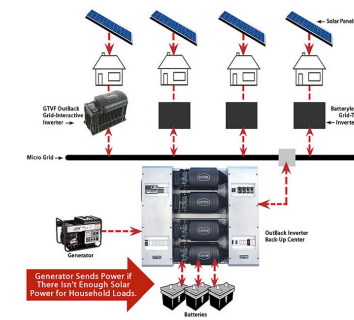
- E.g. $\langle\langle C \rangle\rangle P_{\geq q} [F \phi]$: max/min reachability probabilities
 - compute $\sup_{\sigma_1 \in \Sigma_1} \inf_{\sigma_2 \in \Sigma_2} \Pr_s^{\sigma_1, \sigma_2} (F \phi)$ for all states s
 - deterministic memoryless strategies suffice
- Value $p(s)$ for state s is least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

$$p(s) = \begin{cases} 1 & \text{if } s \in \text{Sat}(\phi) \\ \max_{a \in A(s)} \sum_{s' \in S} \delta(s, a)(s') \cdot p(s') & \text{if } s \in S_1 \setminus \text{Sat}(\phi) \\ \min_{a \in A(s)} \sum_{s' \in S} \delta(s, a)(s') \cdot p(s') & \text{if } s \in S_2 \setminus \text{Sat}(\phi) \end{cases}$$

- Computation (value iteration):
 - start from zero, propagate probabilities backwards
 - guaranteed convergence; apply “usual” termination criteria

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

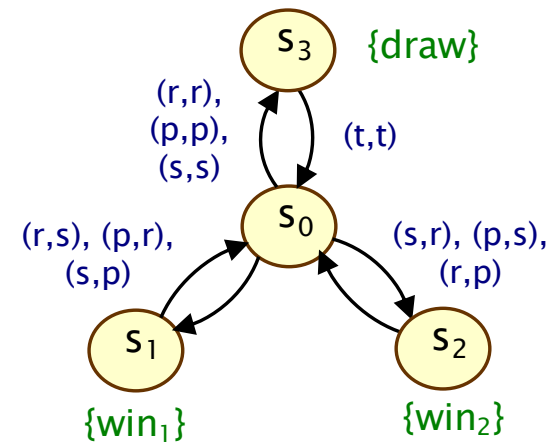


Concurrent stochastic games

- **Concurrent** stochastic games (CSGs)
 - players choose actions concurrently
 - jointly determines (probabilistic) successor state
 - generalises turn-based stochastic games
- **Key motivation:**
 - more realistic model of components operating concurrently, making action choices without knowledge of others
- **Formally**
 - set of n players N , state space S , actions A_i for player i
 - transition probability function $\delta : S \times A \rightarrow \text{Dist}(S)$
 - where $A = (A_1 \cup \{\perp\}) \times \dots \times (A_n \cup \{\perp\})$
 - strategies $\sigma_i : (S \times A)^* S_i \rightarrow \text{Dist}(A_i)$, strategy profiles $\sigma = (\sigma_1, \dots, \sigma_n)$
 - probability measure Pr_s^σ , expectations $E_s^\sigma(X)$

Example CSG: rock-paper-scissors

- Rock-paper-scissors game
 - 2 players repeatedly draw rock (**r**), paper (**p**), scissors (**s**), then restart the game (**t**)
 - rock > scissors, paper > rock, scissors > paper,
 - otherwise draw
- Example CSG
 - 2 players: $N=\{1,2\}$
 - $A_1 = A_2 = \{r,p,s,t\}$
 - NB: no probabilities here



Matrix games

- Matrix games solved in each state
 - finite, one-shot, 2-player, zero-sum games
 - utility function $u_i: A_1 \times A_2 \rightarrow \mathbb{R}$ for each player i
 - represented by matrix Z where $z_{ij} = u_1(a_i, b_j) = -u_2(a_i, b_j)$

- Example:

- one round of rock-paper-scissors

$$Z = \begin{matrix} & \begin{matrix} r & p & s \end{matrix} \\ \begin{matrix} r \\ p \\ s \end{matrix} & \begin{pmatrix} 0 & -1 & 1 \\ 1 & 0 & -1 \\ -1 & 1 & 0 \end{pmatrix} \end{matrix}$$

- Optimal (player 1) strategy via LP solution (minimax):

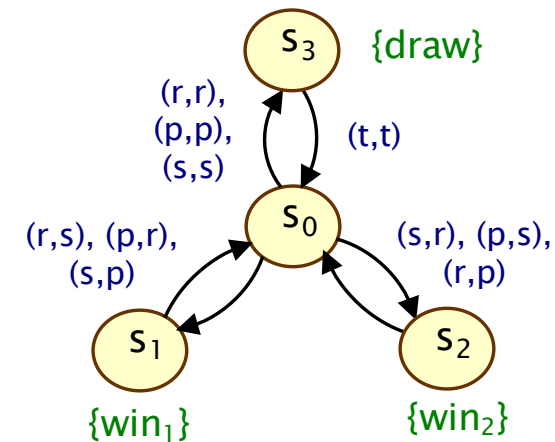
- compute value $\text{val}(Z)$: maximise value v subject to:
 - $v \leq x_p - x_s$
 - $v \leq x_s - x_r$,
 - $v \leq x_s - x_p$
 - $x_r + x_p + x_s = 1$
 - $x_r \geq 0, x_p \geq 0, x_s \geq 0$

Optimal strategy (randomised):

$$(x_r, x_p, x_s) = (1/3, 1/3, 1/3)$$

rPATL for CSGs

- We use the same logic rPATL as for SMGs
- Examples for rock–paper–scissors game:
 - $\langle\langle 1 \rangle\rangle P_{\geq 1} [F \text{ win}_1]$ – player 1 can ensure it eventually wins a round of the game with probability 1
 - $\langle\langle 2 \rangle\rangle P_{\max=?} [\neg \text{win}_1 U \text{ win}_2]$ – the maximum probability with which player 2 can ensure it wins before player 1
 - $\langle\langle 1 \rangle\rangle R_{\max=?}^{\text{utility}_1} [C^{\leq 2K}]$ – the maximum expected utility player 1 can ensure over K rounds (utility = 1/0/−1 for win/draw/lose)

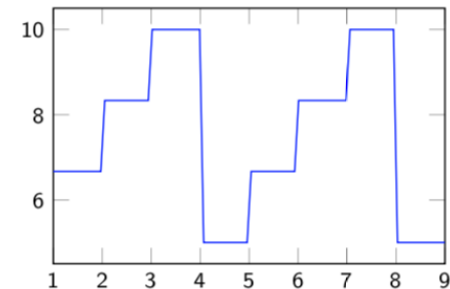
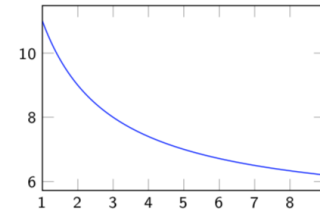


rPATL model checking for CSGs

- Extends model checking algorithm for SMGs [QEST'18]
 - key ingredients are solution of (zero-sum) 2-player CSGs
- E.g. $\langle\langle C \rangle\rangle P_{\geq q} [F \phi]$: max/min reachability probabilities
 - compute $\sup_{\sigma_1 \in \Sigma_1} \inf_{\sigma_2 \in \Sigma_2} \Pr_s^{\sigma_1, \sigma_2} (F \phi)$ for all states s
 - note that optimal strategies are now randomised
 - solution of the 2-player CSG is in PSPACE
 - we use a value iteration approach
- Value $p(s)$ for state s is least fixed point of:
 - $p(s) = 1$ if $s \in \text{Sat}(\phi)$ and otherwise $p(s) = \text{val}(Z)$ where:
 - Z is the matrix game with $z_{ij} = \sum_{s' \in S} \delta(s, (a_i, b_j))(s') \cdot p(s')$
 - so each iteration requires solution of a matrix game for each state (LP problem of size $|A|$, where A = action set)

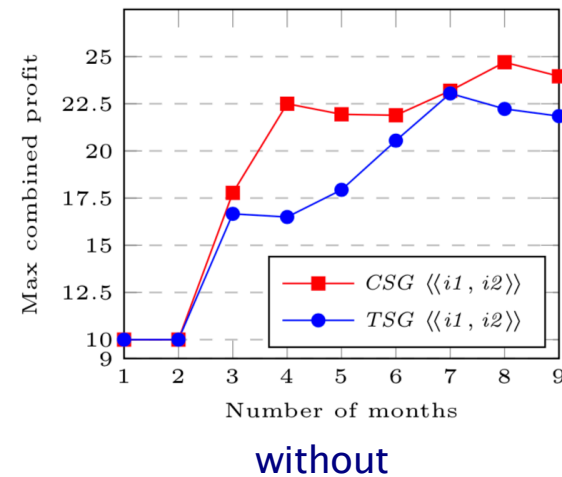
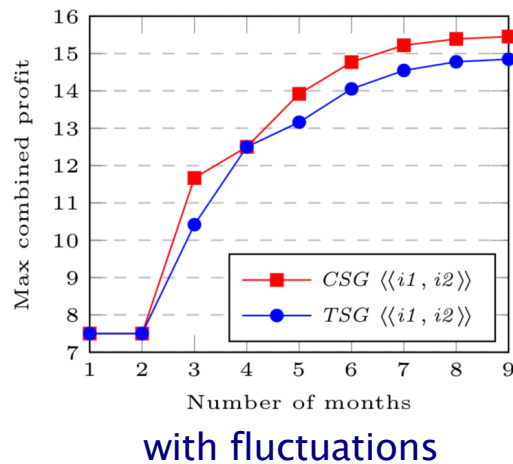
Case study: Future markets investor

- **Model of interactions between:**
 - stock market, evolves stochastically
 - two investors i_1, i_2 decide when to invest
 - market decides whether to bar investors
- **Modelled as a 3-player CSG**
 - extends simpler model originally from [McIver/Morgan'07]
 - investing/barring decisions are simultaneous
 - profit reduced for simultaneous investments
 - market **cannot** observe investors' decisions
- **Analysed with rPATL model checking & strategy synthesis**
 - distinct profit models considered: 'normal market', 'later cash-ins' and 'later cash-ins with fluctuation'
 - comparison between turn-based and concurrent game models



Case study: Future markets investor

- Example rPATL queries:
 - $\langle\langle \text{investor}_1 \rangle\rangle R_{\max=?}^{\text{profit}_1} [F \text{ finished}_1]$
 - $\langle\langle \text{investor}_1, \text{investor}_2 \rangle\rangle R_{\max=?}^{\text{profit}_{1,2}} [F \text{ finished}_{1,2}]$
 - i.e. maximising individual/joint profit
- Results (joint profit) – cooperation pays off in a concurrent game model
 - optimal (randomised) investment strategies synthesised



Multiple objectives: Nash equilibria

- Now consider **distinct** objectives X_i for each player i
 - i.e., no longer restricted to zero-sum goals
- We use **Nash equilibria (NE)**
 - no incentive for any player to unilaterally change strategy
 - more precisely **subgame-perfect ϵ -Nash equilibrium**
 - a strategy profile $\sigma = (\sigma_1, \dots, \sigma_n)$ for a CSG is a subgame-perfect ϵ -Nash equilibrium for objectives X_1, \dots, X_n iff:
$$E_s^\sigma(X_i) \geq \sup \{ E_s^{\sigma'}(X_i) \mid \sigma' = \sigma_{-i}[\sigma'_i] \text{ and } \sigma'_i \in \Sigma_i \} - \epsilon \text{ for all } i, s$$
 - ϵ -NE (but not 0-NE) guaranteed to exist for CSGs
- In particular: **social welfare/cost Nash equilibria (SWNE/SCNE)**
 - NE which maximise/minimise sum $E_s^\sigma(X_1) + \dots E_s^\sigma(X_n)$

rPATL + Nash operator

- Extension of rPATL for Nash equilibria

$$\phi ::= \text{true} \mid a \mid \neg\phi \mid \phi \wedge \phi \mid \langle\langle C \rangle\rangle P_{\bowtie q}[\psi] \mid \langle\langle C \rangle\rangle R^r_{\bowtie x}[\rho] \mid \langle\langle C, C' \rangle\rangle_{\max \bowtie x} [\theta]$$

$$\theta ::= P[\psi] + P[\psi] \mid R^r[\rho] + R^r[\rho]$$

$$\psi ::= X\phi \mid \phi U^{\leq k} \phi \mid \phi U \phi$$

$$\rho ::= I^{\leq k} \mid C^{\leq k} \mid F\phi$$

- where:

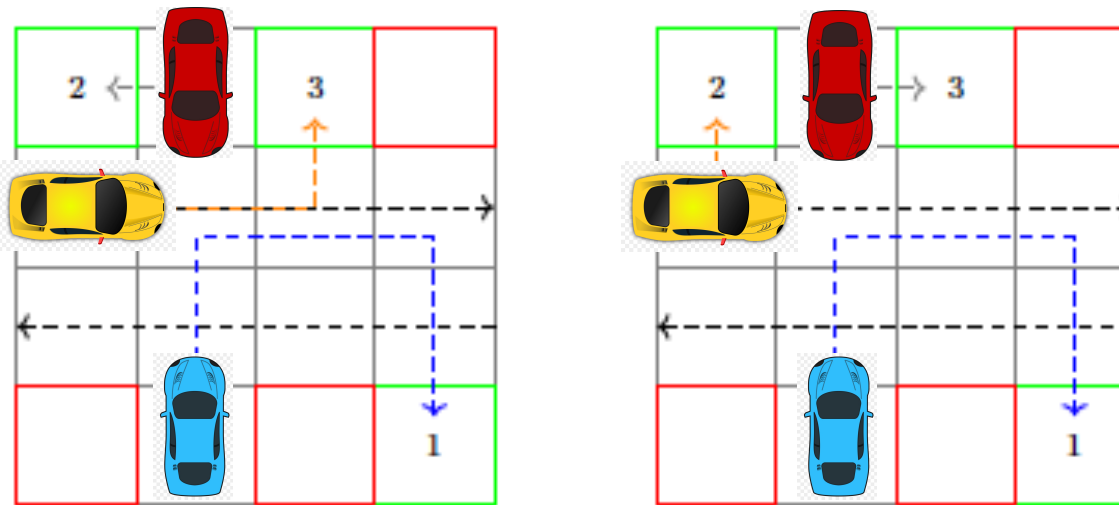
- $a \in AP$ is an atomic proposition, $C \subseteq N$ is a coalition of players and $C' = N \setminus C$
- $\bowtie \in \{\leq, <, >, \geq\}$, $q \in [0, 1] \cap \mathbb{Q}$, $x \in \mathbb{Q}_{\geq 0}$, $k \in \mathbb{N}$
- r is a reward structure

- Semantics: $\langle\langle C, C' \rangle\rangle_{\max \bowtie x} [\theta]$

- is satisfied if there exist strategies for all players that form a SWNE between coalitions C and $C' (= N \setminus C)$, and under which the sum of the two objectives in θ is $\bowtie x$
- now also extended to **m-coalitional** properties

Example – Automated parking

- **Safe parking**
 $\langle \langle v_1, v_2, v_3 \rangle \rangle_{\max \geq 3} (P[\neg \text{coll}_1 \cup \text{park}_1] + P[\neg \text{coll}_2 \cup \text{park}_2] + P[\neg \text{coll}_3 \cup \text{park}_3])$
- **Minimise collective travelled distance**
 $\langle \langle v_1, v_2, v_3 \rangle \rangle_{\min=?} (R[F \text{ park}_1] + R[F \text{ park}_2] + R[F \text{ park}_3])$

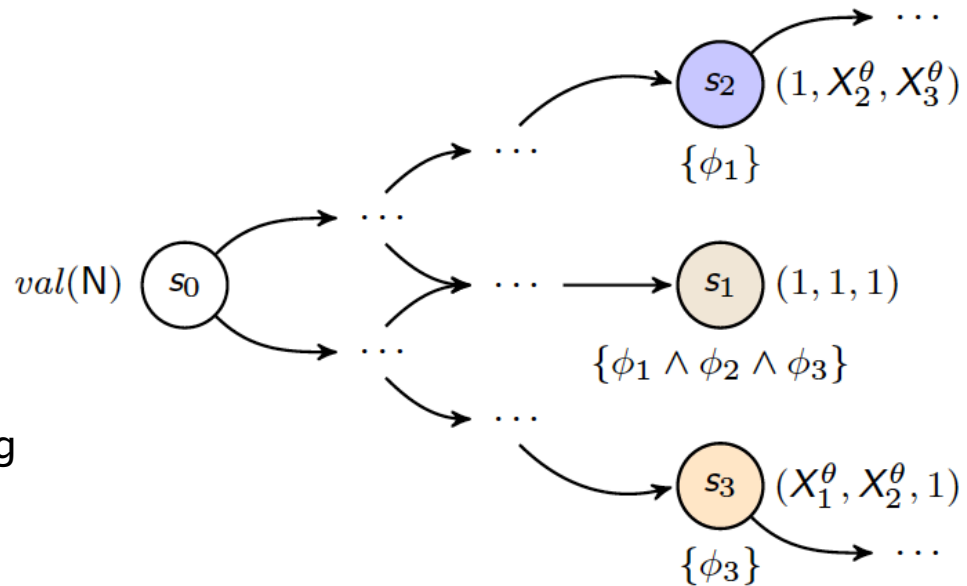


Two equilibria: distance **10**

distance **8 (SCNE)**

Model checking for equilibria properties

- Need to compute **NE in each state**, under certain restrictions on games (PSPACE)
 - bimatrix games (labelled polytopes), support enumeration
- For finite-horizon
 - property values computed via **backward induction**
- For infinite-horizon
 - use **value iteration** to approximate values as the limit
- For two-coalitional equilibria
 - employ MDP model model checking
- Implementation makes use of SMT solvers and non-linear optimization
- Also **strategy synthesis**

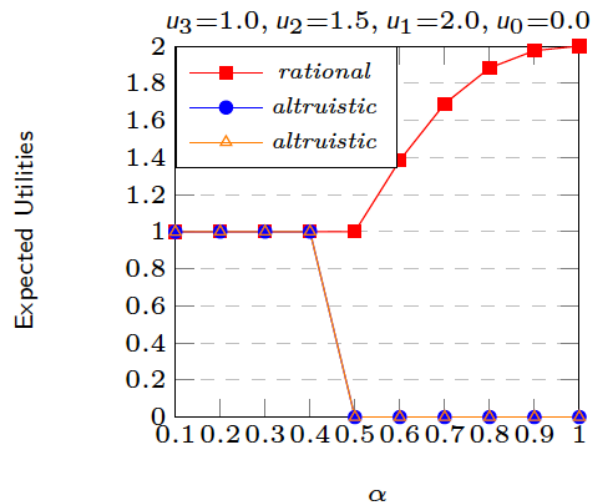


Case study: Secret sharing

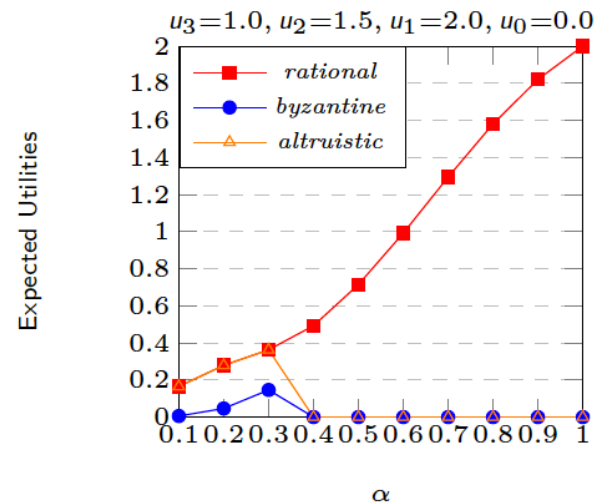
- Protocol proposed by Halpern and Teague, theoretical analysis only
- Each agent has an unfair coin with the same bias (α)
- Step 1: agents flip their coins. If the coin lands on heads, the agent is supposed to send its share of the secret to others
- Step 2: everyone reveals the value of their coin to the other agents
- The protocol ends if:
 - All agents obtain all shares and therefore can all reconstruct the secret
 - An agent cheats, i.e. fails to send their share to another agent when supposed to

Case study: Secret sharing

- **Cannot** be modelled using two-coalitional variant of rPATL
- Property $\langle\langle \text{usr}_1, \text{usr}_2, \text{usr}_3 \rangle\rangle_{\max=?} (R[F \text{ done}] + R[F \text{ done}] + R[F \text{ done}])$ for $p_{\text{fail}} = 0.2$



((a)) 2 altruistic and 1 rational

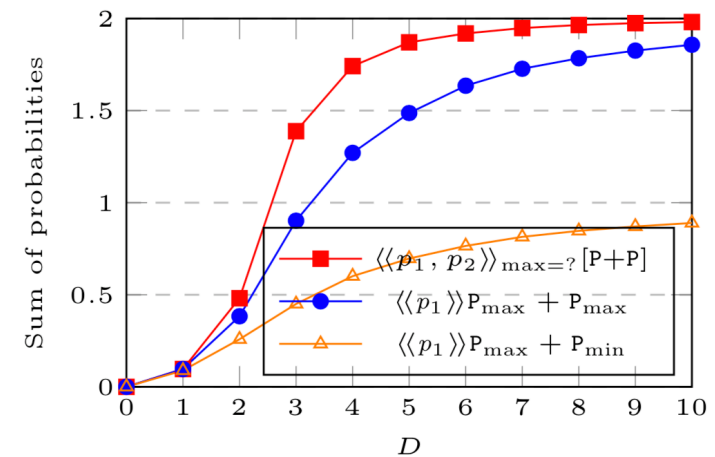


((b)) 1 altruistic, 1 byzantine and 1 rational

- **Confirms** theoretical analysis: a rational player would cheat given a high enough probability other players would share

PRISM-games 3.0

- **Implementation in PRISM-games**
 - needed further extensions to modelling language
 - implements CSG rPATL model checking
 - SMT plus backward induction and value iteration
 - scales up to CSGs with ~2 million states
- **Extensions (not discussed)**
 - multiobjective properties, Pareto sets, probabilistic real-time games
- **Applications**
 - robot navigation in a grid, medium access control, Aloha communication protocol, power control
 - SWNE strategies outperform those found with rPATL
 - ϵ -Nash equilibria found typically have $\epsilon=0$



Case studies (selected)

- Turn-based games
 - futures market investor model [McIver & Morgan]
 - energy management in microgrids [TACAS'12]
 - DNS bandwidth amplification attack [Deshpande et al]
 - self-adaptive software architectures [Camara, Garlan et al]
 - attack-defence scenarios in RFID goods management [Aslanyan et al]
- Multi-objective turn-based games
 - UAV path planning with operator (multi-objective) [ICCPS'15]
 - aircraft electric power control (compositional) [TACAS'15]
- Concurrent games
 - public good game [CAV 2020]
 - intrusion detection policies [QEST 2018]
 - Aloha protocol [QEST 2020]

Where next for probabilistic model checking?

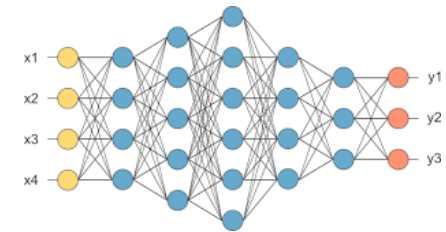
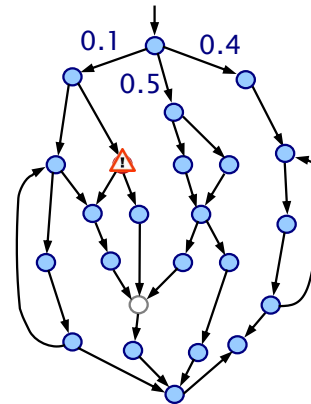
- Data rich, data-enabled models

- achieved through **learning**
- parameter **estimation**
- continuous **adaptation**

- Bayesian neural networks have **prior** on weights

- account for noise, uncertainty in measurements, etc
- return an uncertainty measure along with the output



- Define safety with prob $1 - \varepsilon$: $Prob(\exists \mathbf{y} \in \eta \text{ s.t. } f(\mathbf{x}) \neq f(\mathbf{y}) \mid D) \leq \varepsilon$
- i.e. **conditioned** on training data D
- Extending probabilistic verification to such settings



Conclusions

- Probabilistic model checking: PRISM & PRISM-games
 - theory and tool implementation
 - rPATL model checking for
 - stochastic multi-player games (SMGs)
 - concurrent stochastic games (CSGs)
 - CSGs + (social welfare) Nash equilibria
 - wide variety of case studies studied
- Challenges & directions
 - scalability, e.g. symbolic methods, abstraction
 - partial information/observability & greater efficiency
 - further applications and case studies
 - neural networks as games
 - probabilistic verification for Bayesian neural networks

Acknowledgements

- My group and collaborators in this work
- Project funding
 - ERC Advanced Grant  VERIWARE
 - EPSRC Mobile Autonomy Programme Grant
- See also
 - PRISM www.prismmodelchecker.org
- New ERC Advanced Grant  fun2model
 - “From FUNction-based TO MOdel-based automated probabilistic reasoning for DEep Learning”
 - Postdoc positions