Analyzing Multi-agent Systems with Probabilistic Model Checking Approach

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Outline

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Probabilistic Model Checking!

Accurate result and automatic execution.

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1. PRISM has some work related to MAS; but it is not specific to MAS;
2. MCMAS supports several kinds of properties, however, it does not support probability;
3. MCK supports knowledge reasoning; but it just supports Discrete-time Markov Chain (DTMC) and lacks other properties.

Our Goal

We are aiming at designing a probabilistic model checker which focuses on MAS having stochastic and concurrent behaviors, and supports variety properties, such as reachability checking, LTL checking, reward checking and knowledge reasoning.

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Model checker PMA (Probabilistic Multi-Agent)

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Markov Decision Process

Given S, a distribution is defined as a function $\mu : S \to [0, 1]$ such that $\Sigma_{s \in S}\, \mu(s) = 1$. $Distr(S)$ is the set of all possible distributions over S.

Definition (MDP)

An MDP with action reward is a tuple $\mathcal{D} = (S, init, Act, T_r, rew)$ where

- S is a set of states;
- $init \in S$ is the initial state;
- Act is a set of actions;
- $T_r : S \times Act \times Distr(S)$ is a transition relation;
- rew is a function that assigns each action a reward value.

DTMC

- A DTMC can be defined as $\mathcal{D}^{\delta}$ given an MDP $\mathcal{D}$ and a scheduler δ;
- A rooted run in $\mathcal{D}^{\delta}$ is an alternating sequence of states and actions $\pi = \langle s_0, \alpha_0, s_1, \alpha_1 ... \rangle$ such that s_0 is the initial state;
- Suppose $(s_i, \alpha_i, \mu_i) \in T_r$, then the probability of exhibiting π in $\mathcal{D}^{\delta}$ is $\mu_0(s_1) * \mu_1(s_2) * \cdots$; and the *cumulative rewards* of this run is defined by $Rew(\pi) = rew(\alpha_0) + rew(\alpha_1) + \cdots$.

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Definition (Knowledge)

Agent i *knows* a fact φ in global state s, which is represented by $s \models K_i\varphi$, iff for each global state s', $s' \models \varphi$ as long as i has the same local state in s and s'.

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Modeling

- In our current progress, we assume each agent only communicate with the environment instead of communicating with each other directly;
- In agent level, each agent chooses its action according to the outcome of last round, and then updates its status;
- In system level, the global state we have $(s_e, s_1, \cdots, s_n) \xrightarrow{a} \mu$, where $a = (a_1, \cdots, a_n, a_e)$ is the joint action of each agent and the environment, meanwhile $\mu((s'_e, s'_1, \cdots, s'_n)) = \mu_1(s'_1) \times \cdots \times \mu_n(s'_n) \times \mu_e(s'_e)$.

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- Reward checking
- Knowledge reasoning: A simple combination of linear temporal operator and $K_i\varphi$ where i is the index of an agent and φ is a proposition. For example $P_r(system \models \Diamond K_i\varphi)$ represents the probability of reaching a state where agent *i knows* φ from the initial state of the system.

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Evaluation

- Dispersion game is the generalization of anti-coordination game to an arbitrary number of players and actions.
- We focus on one novel strategy designed for dispersion games: extended simple strategy (ESS) in this evaluation.
- In dispersion game, the desired outcome is called Maximal Dispersion Outcome (MDO).

Convergence to MDO

We first consider whether the agents adopting ESS are guaranteed to converge to an MDO. We express this property using $P_r(System \models \Diamond\Box MDO)$, which means finally the *system* will stay in an MDO forever.

Table: Probability of Convergence to an MDO of ESS

Sys	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10
k=2	0.0	1.0	0.0	1.0	0.0	1.0	0.0	1.0
k=3	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0
k=4	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0

Deviation from MDO

Because in some cases ESS cannot converge to an MDO, it is interesting to check the probability that the system deviates from MDO after reaching it. We use a reachability checking to analyze this property.

Table: Probability of Departure after reaching an MDO

Sys	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10
k=2	0.063	0.0	0.070	0.0	0.075	0.0	0.069	0.0
k=3	0.0	0.072	0.12	0.0	0.091	0.14	0.0	0.092
k=4	0.0	0.0	0.12	0.15	0.16	0.0	0.14	0.16

Average rounds to MDO

Another interesting property is that how many rounds does the ESS system take to reach an MDO, which could be verified using reward checking $R(system \models \Diamond Depart)$. Intuitively, if we set the action in the *Environment* of ESS having reward 1, then after each round, the *cumulative rewards* is increased by 1.

Table: Average rounds to MDO

Sys	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10
k=2	1.33	2.44	1.55	2.69	1.70	2.87	1.81	3.00
k=3	2.63	1.48	2.11	3.20	1.81	2.45	3.52	2.04
k=4	2.15	3.08	1.58	2.15	2.90	3.73	2.04	2.59

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The development of PMA reveals two research challenges.

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2. There are other kinds of knowledge such as $E_G\varphi$ (everyone in group G knows φ) and $C_G\varphi$ (φ is common knowledge in G). Besides, *subjective* probability in knowledge reasoning such as $K_i(P_r(\varphi) > b)$, where b is a probability threshold, also deserves our exploration.

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Conclusion

In this paper, we proposed a novel approach to analyze MAS.

- Our tool supports an expressive language, with which we could efficiently build accurate and compact models which have stochastic characteristics;
- Quantitative calculations for different kinds of properties guarantee that many aspects of the system could be accurately analyzed;
- Preliminary evaluation demonstrates the ability of PMA in modeling and verification.

Future Work

In the future, we will focus on two issues that we mentioned in our challenges:

1. Investigating multi-agent systems whose agents have dependency between each other, and
2. further exploring the combination of probability and logic of knowledge, which are useful in different multi-agent interaction scenarios.

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THANK YOU!