1 Summary

Nature of the challenge. Systems built on the insights of Artificial Intelligence are increasingly deployed in the world as *agents*, e.g., software agents negotiating on our behalf on the internet, driverless cars, robots exploring new and dangerous environments, bots playing games with humans. There is an obvious need for humans to be able to *trust* the decisions made by artificial agents, the need for meaningful interactions between humans and agents, and the need for transparent agents [2, 43]. This grand challenge will require integrating research from a variety of fields besides computer science, including psychology and economics.

One contribution that computer scientists must make towards this challenge is to be able to model, control and predict the behaviour of agents. This is made all the more complicated since: 1) agents are often deployed with *other* agents leading to *multi-agent systems*, 2) agent behaviour extends into the future, leading to the need for reasoning about *time*, 3) agents are often "self-interested", leading to the need to reason about *strategies*, 4) agents may have uncertainty about the state, or even the structure, of other agents and the environment, leading to the need to reason about *knowledge*.

Broadly speaking, there are two existing approaches to building agents: model-based and function-based. In the model-based approach one *represents and reasons* about the domain of interest, e.g., state-based models of dynamical systems in automated planning (the main tools are logic and probability). In the function-based approach one *fits functions to data* (an important tool today is neural networks). The long-term goal for scientists is to reconcile these two approaches, i.e., a) to clearly understand the scope limitations of each approach, and b) to integrate the approaches [21].

Goals. My long-term goal is to contribute to bridging formal-methods and artificial intelligence.

In the next 5-15 years I aim to expand our understanding of the limitations and techniques of the model-based approach to building trustworthy agents. This will involve tackling foundational mathematical problems, integrating various approaches (i.e., logic, probability, connectionist), as well as tackling issues in Knowledge Representation (e.g., what language should be used to express domains and specifications).

In the next 5 years I have three specific goals: 1) discover new classes of systems, with applications in mind, for which synthesis and analysis is computationally tractable, 2) develop the theory of reasoning about optimal strategies and socially optimal equilibria, and 3) establish scalable algorithms and tools for solving these computational problems. This rests on the following:

> Hypothesis: The model-based approach is the best approach we have for understanding the behaviour of systems, and thus for building trustworthy systems.

Candidate. I have a background in formal methods and am open to ideas coming from other fields, including Artificial Intelligence. In particular, my background in mathematical logic and formal methods has enabled me to devise effective conceptual frameworks to address problems in Artificial Intelligence and Multi-agent systems [48, 8, 22, 6, 15, 30, 15, 10, 11, 13].

My standing is reflected in the fact that I serve as PC member of top conferences in Artificial Intelligence and Multi-agent systems (IJCAI 2017, AAAI 2017, AAAI 2018, AAMAS 2018); I have chaired one national conference on theoretical computer science (ICTCS 2017, Italy), one international workshop on strategic reasoning (SR 2017), and one international workshop on Formal Methods in Artificial Intelligence (FMAI 2017) that attracted leaders in Formal Methods and Artificial Intelligence including Giuseppe De Giacomo, Michael Wooldridge, Michael Fischer, and Hector Geffner; I have served as an external reviewer for the Icelandic Research Fund (IRF 2017).

2 Short-term

The short-term aims are to generate new mathematics, algorithms, and tools for describing, reasoning-about and building trustworthy agents.

I now describe three challenges that should be met in order to achieve these aims.

2.1 Challenges

1. We need to discover meaningful *new classes* of multi-agent systems for which synthesis and reasoning is decidable and tractable.

Not surprisingly, reasoning about the behaviour of multi-agent systems is computationally hard. In fact, it is *undecidable* when it involves agents with private knowledge, a fact known since the late 1970s and rediscovered in multiple contexts, i.e., decentralised POMDPs [12], multiplayer non-cooperative games of imperfect information [46], distributed synthesis [47]. The classic approach to ameliorate this is to restrict to classes of multi-agent systems in which agents' private knowledge is hierarchical (typically, one assumes some sort of hierarchy on agent observation or information [46, 47, 34, 14, 13]). Although mathematically elegant and well-explored, the *applicability of such assumptions is not very high* since in almost all meaningful scenarios, agents' private knowledge are not hierarchical. An orthogonal approach that does not suffer from this long-standing limitation is to limit the way agents communicate/interact. One such assumption is that *agent actions are fully observable*. In such a setting, multi-agent epistemic planning is tractable [32], synthesis of epistemic extensions of linear-temporal logic is decidable [54], and the model-checking problem against an epistemic extension of strategy logic is decidable *and no harder than the case of agents with no private knowledge* [10, 11]. Many scenarios already fall into this class, e.g., distributed computing and multi-party computation based on broadcast communication [39, 1], multi-player games with public play such as poker [17], and e-auctions with public bidding [27].

2. We need to define, analyse, and tackle the problem of reasoning about optimal strategies and *socially optimal equilibria*.

In order to have evidence that one agent's behaviour is better or worse than another, or whether a collection of agents are acting in the good of society, we need to be able to measure the quality of agent strategies against each other. This, in turn, would be facilitated by endowing agent objectives with a quantitative component. Although most work in verification deals with qualitative objectives, there has been a recent focus on verification of quantitative models of programs [31, 4]. However, this has yet to be systematically generalised to complex reasoning for multi-agent systems.

Building on more classic work [5, 42], I have recently introduced expressive logics that can be used to reason about socially optimal equilibria in cases agents have qualitative objectives [7, 10, 13]. For instance, in games that model security, robustness to deviations from the behaviour of attackers is a critical issue []. This, together with recent insights from quantitative verification [53, 31, 41, 4], lays the foundation for *designing useful logics and measures of strategy-quality* for reasoning about socially optimal equilibria.

3. We need to establish *scalable algorithms and tools* for reasoning about multi-agent systems.

To automatically reason about multi-agent systems, including reasoning about social equilibria, we need scalable algorithms and tools. Since the worst-case complexity of such reasoning is typically very high, we need tools that can deal with large but "easy" cases. This grand challenge is being met by a number of branches of computer science, notably the Automated Planning community in Artificial Intelligence.

Automated Planning is a *form of synthesis* that is central to the development of agents. It is a branch of Artificial Intelligence that addresses the problem of generating a course of actions to achieve a specified goal, given a description of the domain of interest and its initial state. The Automated Planning community has developed a "science of search", based on heuristic-search and symbolic methods, that efficiently plans for most problems of practical interest [29, 36]. The most successful of this technology is for "classical planning", i.e., single agent, deterministic environment, with perfect information, and simple reachability goals, and "fully observable non-deterministic planning" (which amounts to the case of one agent in an adversarial environment).

Previous work has reduced planning with temporal goals or epistemic goals to classical and fully-observable nondeterministic planning [9, 51, 32, 20]. This lays the foundation for refining and extending the translations to handle full Temporal-Strategic-Epistemic reasoning for multi-agent systems.

2.2 Work plan

The challenges will be met using methods and insights from Logic and Formal Methods (including program synthesis), and Game Theory (including its development in multi-agent systems).

1a. In order to discover richer decidable classes, I propose to *generalise* systems in which all actions are fully observable.

The class of systems in which all actions are fully observable holds promise since a) reasoning in it is no harder than the non-epistemic case, b) it can be used to formalise many scenarios. I now outline the first directions I will pursue in order to expand this theory to encompass even more scenarios:

1. Incorporate stochastic initial states, which is *widely applicable*. Indeed, not only do finite horizon stochastic systems fall into this setting [37], but so do probabilistic multi-agent systems, called decentralised partially observable Markov decision processes [45], which are a framework for modeling uncertainty with respect to outcomes, environmental information and communication. That is, this extension will addresses the problem of ensuring *agents behave well in unknown environments*.
2. Incorporate symmetric and asymmetric encryption, which is applicable to online *privacy and security*. Indeed, private-keys can be stored in an agent's private state, and thus private-key encryption can already be simulated by fully observable actions. Furthermore, public-key encryption consists of public keys that can be widely disseminated, and thus encrypting with a public key can be modeled as a public action.
3. Limiting the number of non-public actions, which is applicable to design and analysis of *collusion analysis* in e-auctions [27].
4. Tuning the amount of observability of actions. Indeed, although systems with hidden actions are undecidable and fully observable actions are decidable, there is likely a measure of "action observability" that can be tuned so that one can incorporate systems in which certain actions are partially observable (but not completely hidden). Whatever this measure will look like, the result will be a *deeper understanding* of the borders between decidability and undecidability for various systems.

Here are some scenarios that could be handled by such extensions:

– various models of collaborative robot exploration in controlled but dynamic environments [44, 33],
– various models of cloud manufacturing [28],
– various models of collusion in e-auctions and auction-based mechanisms [27],
– various models of social networks that use broadcast communication, and thus also formalisations of *twitter* [26, 40],
– various models of secure cloud-storage that use data-dispersal [35] and secret-sharing protocols [1],
– various models of multi-player games in which bidding and play is public, such as poker [17].

1b. In order to discover tractable classes of agents, I propose to *restrict* to sub-systems of those in 1a.

The complexity of reasoning in multi-agent systems identified in 1a is expected to be high. To achieve better computational complexity I propose to restrict them to sub-systems, while still maintaining the features in 1a that allow one to model systems from a wide variety of fields (e.g., that agent's observations need not be hierarchical). In particular, I will start by restricting to classes in which:

1. the set of initial states is homogenous [38]. This is applicable to situations in which agents are initially ignorant of each others local states;
2. the size of the epistemic states is bounded, which is applicable to situations in which each agent has full observation except of its *own* finite state;
3. the strategies considered do not depend on the full history, but on a bounded summary of the history. Besides lowering the complexity, this assumption reflects the assumption of *bounded rationality* [50].

2. In order to reason about socially optimal equilibria, I propose to enrich the models and specification languages with costs/rewards and analyse these with measures of *strategy quality*.

Agents are typically "self-interested", and thus they may not act in a way that is socially optimal. Moreover, it is often not possible to ascribe agent behaviour as simply being good or bad. Thus, I will explore measures of strategy quality and algorithms for synthesising socially optimal strategies. Although many game-theoretic solution concepts, such as Nash equilibria, can be expressed in recently introduced strategic logics [42], and their epistemic extensions [13, 11], these logics can only express qualitative agent objectives. Thus, I will define and explore logics that can reason about quality of agent behaviour. In particular I will extend and evaluate state-of-the-art proposals for measuring quality of strategies to reasoning about multi-agent systems, i.e.: the logic $\mathsf{LTL}[\mathcal{F}]$, and extension of LTL with a set of quality operators $\mathcal{F}$ [4], that was designed to reason about the quality of programs and can be used to reason about the *quality of agent behaviour*; the logic LTL_f with costs [18], that allows one to reason about non-Markovian objectives; logics that combine qualitative behaviour (expressed for instance in LTL or LTL_f) and quantitative, expressed for instance as long-term average of the cost of some resource [30] or as the total cost of some resource [19].

3. In order to establish scalable tools and algorithms, I propose to *translate* reasoning tasks to Automated Planning.

I will extend and refine the translations that handle temporal goals and epistemic goals [9, 51, 20] to full Temporal-Strategic-Epistemic reasoning for the multi-agent setting. I will do this by leveraging the automata-theoretic approach to model-checking of strategic epistemic logics [11, 13], as well as search through strategy-space [16]. One parallel direction to meet this objective is to explore generalisations of specification formalisms over finite traces [25, 23, 24], adopted in automated planning [9, 51, 3, 20]. Indeed, specifications on finite traces allow one to avoid notorious difficulties of infinite-traces [49], namely complementation of Büchi-automata [52]. In particular, I will define and study "epistemic strategy logic over finite traces", and extend the mentioned translations to this logic.

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