

Reputation-based Distributed Coordination for Heterogeneous Autonomous Agents

Towards Effective Coordination, Cooperation & Coalition Formation for Autonomous Software Agents Belonging to Different End-Users

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Abstract—Decentralized, partially or fully distributed multi-agent coordination, cooperation and coalition formation have been studied extensively over the past 20 years. Ensembles of autonomous software, robotic or other autonomous agents may need to coordinate and form coalitions in order to share resources, divide-and-conquer tasks, or enable themselves to complete tasks too complex for any individual agent alone. Much of prior research on multi-agent coordination and coalition formation focuses on the *distributed problem* solving context, in which all agents belong to the same end-user and share the overarching system-level objectives. As the Internet is evolving towards “Web 3.0” and “the Internet of Things”, modeling systems and designing protocols for scenarios in which autonomous agents that belong to *different* end-users, and hence in general do not share common goals, yet may still need to coordinate and cooperate with each other, is becoming a research challenge of paramount importance. In this paper, we outline a general vision and some key properties of an “Internet of (Software) Agents”, and propose a reputation-based model for effective multi-agent coordination among autonomous agents that need to coordinate with (yet don’t *a priori* know to what extent they can trust) each other.

Keywords— *Software agents; Internet of Agents; Distributed AI; distributed coordination; distributed coalition formation; models of cooperation; self-interested agents*

I. INTRODUCTION: MULTI-AGENT SYSTEMS AND IOA

In recent years, there has been a great progress in the areas of personal digital assistants capable of increasingly sophisticated *natural language processing* (NLP), speech understanding & generation, reasoning with respect to “plain language” goal or task specifications, and other “AI functions”. Researchers at leading academic institutions, as well as companies such as Google or Microsoft, have made great strides not only on individual AI technologies (such as NLP or speech understanding or task planning), but also on integrating various such components into unified systems with which, at least in some knowledge/application domains, it’s increasingly possible to interact the way we interact with other humans. However, the promise of *Internet of Things* (IoT) and, in particular, *Internet of Agents* (IoA), lies in enabling different technologies (and different artificial intelligent agents) to effectively interact with each other, including communication, coordination, and various forms of cooperation. Since different agents in this “soup” of IoA will in general represent different human users or organizations, they will have different

(possibly conflicting) goals with respect to each other. Just like in human societies, certain groups of agents will have better aligned interests and goals with each other than with agents outside of their “circle”. Similarly, again just like with human societies, certain agents will be more reputable or trustworthy than others when it comes to delivering on promises or commitments made as a part of a multi-agent cooperation, or the quality of expertise they provide about a particular domain. These simple observations suggest some important elements, indeed a roadmap, for the next-generation AI/MAS research and design of effective autonomous software agents for this up-and-coming Internet of Agents. In this paper, we focus on the *desiderata* pertaining to such an intelligent software agent’s abilities to coordinate and cooperate with other agents and create coalitions, taking into account other agents’ reputations.

Distributed coordination among robotic, software or other types of *autonomous agents* has been one of the most fundamental challenges in Distributed AI. There are a number of interesting multi-agent coordination problems; among those, we have primarily investigated decentralized *coalition formation*. Distributed coalition formation is a common challenge in many *multi-agent system* (MAS) applications. Software, robotic, unmanned vehicle or other agents may need to coordinate and, in particular, self-organize into coalitions in order to divide-and-conquer tasks, share resources, and/or reach consensus on various matters of common interest [1-8]. Some examples of *collaborative* cyber-physical MAS applications in which coalition formation has a prominent role include autonomous micro unmanned (aerial, ground or underwater) vehicles, teams of robots, and smart wireless sensors [1, 2, 3]. Likewise, distributed coordination and coalition formation have been studied in the context of purely software agents. Distributed coordination and, in particular, task and/or resource allocation via coalition formation, have been extensively researched for both robotic/cyber-physical and software agents since the 1990’s (see, e.g., [4-7]).

While from the MAS design and analysis standpoints there are many important differences between physical autonomous agents such as robots or unmanned vehicles on one hand, and “virtual”, that is, purely software agents on the other, all strictly collaborative MAS domains share some important properties. The main one is that all individual agents in the

system are assumed to belong to the same organization or “end-user”, and hence to share the over-arching objectives. This assumption has considerable implications, such as that each autonomous agent would be designed so that it puts “common good” ahead of its individual utility or goals; or, that any coalition structure that achieves high (ideally, maximum) team payoff is acceptable, without having to worry about how is that overall payoff going to be distributed among the individual agents [6]. These properties hold even when the individual agents may “see the world differently” (for instance, in the team robotics or unmanned vehicle domains, due to different physical locations and constraints on local sensing and communication) – as those agents are still striving to achieve shared objectives (see, e.g., [2, 3, 5, 7]). This general problem setting has been appropriately dubbed (collaborative) multi-agent *distributed problem solving* (DPS) [6, 7, 8].

Let’s consider concrete examples; say, Google vs. Bing: the two compete for advertisers’ dollars, and hence have very tangible economic incentives to be the best search engines they can be – and in particular, to be better than the other. While at times these and other search providers may share information and knowledge with each other, they ultimately remain fierce competitors. Similar reasoning applies to various general-purpose as well as specialized recommender systems (such as, for example, Web-based online travel agents or restaurant recommender systems; see [9]). An individual Web user would hope to benefit from this competition, as the search engines and recommender systems need to keep improving themselves in order to get or stay ahead in what is a very competitive economic environment. Further, an individual user’s objectives differ from those of search engine or recommendation providers such as Google or Bing: when we search the Web for particular information, we want a quick and easy access to the most relevant and accurate sources, regardless of which search engine(s) provide those links. In contrast, each search provider claims that it wants to “maximize the user satisfaction”, but the ultimate over-arching objective clearly is to maximize profits, which is typically strongly correlated to maximizing revenue coming from the advertisers – and this objective sometimes may, but in general, *need not always be* well-aligned with an individual search user’s informational needs or preferences.

II. ON COORDINATION, COOPERATION AND LEARNING AMONG SELF-INTERESTED AGENTS: PRIOR ARTS

Autonomous software, robotic, unmanned vehicle or other types of agents often need to coordinate and cooperate with each other, even when they belong to different “owners” and do not share common objectives. Designing agents that are going to be effective in such scenarios, in general, is more challenging than designing purely collaborative, DPS agents. The modeling and analysis methodology for such more complex multi-agent encounters that has been applied the most is that of game theory and mechanism design, as a suitable formal framework for a broad variety of strategic encounters in which, in general, each participant (or “player”) is striving to maximize its own, individual utility or objective function – and different players’ objectives may be in conflict with each other; that is, the scenarios in which agents are in general *competitive* with each other (e.g., [8, 10]). There is a broad consensus among the Distributed AI research community that the DPS

multi-agent systems are easier to analyze, understand and predict behavior of, than the multi-agent scenarios where different agents belong to different organizations, have different goals, and, in general, are self-interested entities with differing, possibly conflicting, individual objectives. However, differing objectives and consequently a combination of collaboration and competition among agents are a commonplace, from the biological world, to almost all social, economic and political systems to, most importantly for our purposes, the Internet. The World Wide Web can be viewed as a marketplace with a broad variety of players that in general have broadly varying objectives; consequently, realistic models of coordination, resource and/or knowledge sharing and other distributed intelligence activities on the Web should take into account the diversity of various end-users and their in general broadly differing goals and interests [9].

As our simple example of Google vs. Bing vs. an individual Web user searching for some information suggests, the Internet of Agents is a domain in which interactions among different participants will be complex, and certainly not purely collaborative (since different agents will have different “owners” and hence different objectives). Within the game-theoretic framework for more complex, non-DPS multi-agent interactions, researchers have addressed problems such as, for example, how are a group of self-interested agents forming a coalition to distribute the “spoils” or utility from the tasks they complete together; in DPS context this “wealth distribution” isn’t a concern, but for self-interested agents belonging to different owners, it is absolutely crucial. Similar considerations apply to other forms of coordination and cooperation among self-interested agents beside coalition formation.

It is desirable, that individual agents in a MAS (whether it’s IoA or one of the more traditional varieties, such as teams of robots, ensembles of autonomous unmanned vehicles, etc.) be capable of *learning over time* [11]. In many applications, an autonomous agent will engage in the same or similar type of interactions with other agents repeatedly; so, capability to log summaries of past interactions and then learn from them is very important for an agent to become successful in the long-run (whatever the measure of success may be in a particular situation). The dominant paradigm in both DPS (i.e., strictly collaborative) MAS and more general, competitive MAS has been that of *reinforcement learning* (RL); see, e.g., [8, 11]. This is not surprising: in most MAS applications involving repeated interactions, an agent gets the feedback in the form of how much utility (or what fraction of its goals) were earned in the past – but usually there is no “teacher” instructing the agent, what would have been the optimal past course of action. That is, the feedback signal is usually of the reinforcement, as opposed to supervised learning, nature. However, researchers have started expanding their focus; in particular, the promise of *meta-learning* in the MAS context has been explored [12]. The need for *multi-tiered learning*, spanning scales from individual agents to small groups of agents to large-scale agent ensembles, has been identified and, in particular, applied to distributed coalition formation [13, 14]. Some applications that meta-learning and multi-tiered learning have been applied to include autonomous unmanned vehicles [15]; however, these learning-for-MAS paradigms and proposed models are quite

general, and can be readily adapted to purely software MAS domains, including but not limited to IoA.

In our view, the main intersection and cross-fertilization between design of autonomous agents and devices for IoA on one hand, and MAS coordination, cooperation and coalition formation models, paradigms and protocols on the other, will take place along the lines of *ad hoc coordination* [16]. Some notable recent efforts have addressed game-theoretic modeling and best-response *ad hoc* learning [16], policy communication to enable coordination with *a priori* unknown partners [17], and impact of various types of *benevolence* on synergistic effects in large networks of agents [18].

III. LEARNING AND PROSPERING IN AN INTERNET OF AGENTS USING AGENTS' REPUTATIONS

We outline our vision of the *Internet of Agents* (IoA) of the fairly near future, and in particular the role of reputation-based coordination and cooperation among autonomous agents belonging to different "owners" (and hence that are not sharing the common objectives), via a simple real-world example. A PhD student needs to travel from the US to a conference in Europe. She designs and deploys an intelligent software agent to do the heavy lifting for her, in terms of finding flight options and airfares, booking the hotel, exploring on-site ground transportation alternatives, etc. This intelligent agent is provided an overall, high-level specification of the end-user's goals ("Book travel from Seattle, WA, USA to Amsterdam, NL for June 1-4, 2020") and a set of hard and soft constraints. Examples of hard constraints include the total allowable budget (e.g., "total cost needs to stay within \$3,000), the latest allowable time to arrive to the destination, etc. Additionally, the user can specify a number of soft-constraints or preferences (e.g., the star-ranking and Yelp reviews of candidate hotels; hotel's proximity to the conference venue; public transit from the airport to the hotel preferred over taxi cab, etc.). Based on the goal and stated constraints and preferences, the software agent takes the following actions:

- Crawls websites searching for appropriate flights; this includes both individual airlines' websites and travel meta-search engines such as Expedia, Orbitz or Travel Papa;
- Searches for hotels using both general-purpose search engines (e.g., Google) and specialized ones (Hotels.com);
- Searches for ground transportation to the airport in Seattle (incl. the option of driving one's own car, that takes into account estimated parking costs at the airport), from the airport to the hotel in Amsterdam, and looks into various options on commuting from candidate hotels to the conference venue, etc.
- For each main aspects of the travel (flight, hotel, etc.), the agent does relevance/preference ranking and makes recommendations to the user. In addition to ensuring that each recommendation meets the overall objective and satisfies all hard constraints, the travel assistant agent's ranking of recommendations takes into account the soft constraints and preferences.
- In addition to taking appropriately into account the hard and the soft constraints as specified by the user, the travel

assistant agent bases its preference rankings and final list of recommendations based on two additional factors: one, the meta-knowledge about the user, her general travel preferences, her habits, what she was happy vs. not so happy about on her previous travels, and similar; and, two, the meta-knowledge about various sources of information on the web: e.g., whether Booking-Buddy or Orbitz has better reputation when it comes to booking flights from the US to Amsterdam; or, whether hotels.com or Expedia is more trustworthy when it comes to hotels in Europe in general and Amsterdam in particular, etc.

In an IoA, many intelligent agents like the (digital) travel assistant that performs tasks outlined above will be co-existing and interacting with each other. A travel assistant agent above has been deployed by a single human user in this case, and its goals are to maximize satisfaction or happiness of that human user. Maximizing happiness involves finding relatively inexpensive flights with good connection times, and comfortable but affordable lodging in a particular city for particular dates, and many other things; however, it is not exactly synonymous, or equivalent, with any of those individual sub-goals or "aspects of happiness". Furthermore, the goal(s) of the travel assistant agent are clearly rather different from those of hotels, airlines, travel search engines, online travel recommenders, and other entities.

When I am booking a flight, the total cost (of course!) matters, but so do the total number of flight segments each way, the layover times, the reputation (or at least, my view of the reputation) of the airline(s) with which I'd be flying, and other factors. I have certain preferences, and may be willing to make certain tradeoffs to maximize my "flying happiness", differently from someone who has either much more or much less money to spend on air travel than I do; or, someone who doesn't suffer from travel anxiety as much I do; or, someone who is more concerned about the back pain and blood circulation problems on long flights than I am, and so on. Moreover, the same person (me in this case) may have very different preferences over what an ideal flight itinerary or choice of a hotel would be, depending on the specific context of a particular travel: is it for business or pleasure? Am I travelling by myself or with my family? Am I travelling to a very familiar city/country, or a part of the world I know very little about? In spite of considering myself a very savvy user of various search engines, travel recommender systems, online (as well as offline) travel agents and other resources, due to complex, mutually conflicting goals and constraints, I often end up spending excruciating amounts of time booking that "ideal" flight, hotel etc. for my trip. It would be great, if I could just specify, in a high-level language close to "everyday English", my travel objectives, hard and soft constraints, and most relevant aspects of the particular travel's "context", and let an intelligent Web-crawling agent do the rest.

Such a "digital travel assistant" of the near future should have at least three capabilities that the current special-purpose search engines, recommendation systems and Web-crawling agents do not have. One, it needs to maintain a personalized, highly contextual model of me as a user (and in particular, in our example, as a traveler); that model needs to be much more detailed, accurate and context-sensitive than, for example, how

Amazon.com recommends which books to consider buying, based on what I purchased or reviewed online in the past. Second, it needs to maintain, update as needed and intelligently use models of other agents. Crucially, in addition to tracking other agents' resources, capabilities, expertise etc. as declared by those agents' (or their designers) themselves, our agent needs to somehow capture, and make decisions accordingly, the *trustworthiness* of each other agent it considers cooperating with, "renting" resources or knowledge from, or forming a MAS coalition with [19]. As an early step in quantifying that trustworthiness of other agents, a simple model of reputation-based decision making has been recently proposed, incl. which among many candidate agents a given agent should choose for cooperation, coalition formation, resource sharing and other "group activities" [20]. Third, our travel assistant agent needs to be able to dynamically update both its model of its end-user, and model(s) of other agents; those updates need to be based on what has been learnt from the previous interactions and their outcomes (cf. in terms of the feedback from the end-user about her overall satisfaction with the choices and decisions the travel assistant agent has made on her behalf I the past).

IV. SUMMARY AND FUTURE DIRECTIONS

We have outlined a desiderata for the design and functional capabilities of autonomous software agents required of such agents to become effective "citizens of the Internet of Agents" and as such, useful to their end-users (individual humans or organizations). The autonomous agents for the future IoA will need to be able to effectively communicate coordinate and cooperate with each other. Therefore, their design will be driven by the multi-agent system considerations, techniques and methodologies, as opposed to those for "stand-alone" digital assistants or other AI or expert systems. Among many MAS-for-IoA challenges, we focus on those pertaining to coordination, coalition formation and reinforcement learning, and argue that to be useful to its end user, a participant agent in the IoA needs to be able to model other agents, and in particular to evaluate their levels of trustworthiness and reputation. An IoA with many thousands or even millions of such autonomous software and device agents working with each other on a broad variety of tasks, in our view, will become a reality within the next 15-20 years.

In the future work, we will expand on the ideas outlined here, and design some concrete distributed coordination and coalition formation protocols for the IoA. (Those protocols will necessarily fundamentally differ from our prior work, as they will apply to ensembles of interacting agents that do not share common objectives, unlike the framework in [1, 2, 14, 20, 21].) We also plan to (i) investigate concrete reputation models – that is, how can an agent initialize, maintain and use in its decision making, quantitative metrics of other agents' reputations; and (ii) evaluate effectiveness of an agent in IoA making coordination and coalition formation decisions based in part on simple quantitative models of other agents' reputations.

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