Strategic behavior in argumentative debates

Journée Mondiale de la Logique

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Research questions

- **Optimizing the strategy of a debating agent**
  - A strategic agent optimizing her sequence of moves to be put forward in a dialogue
  - Need to anticipate how the other debating agents (opponents) will react
- **Mediation of debates**
  - A mediator acting as a referee among debating parties (single agents or teams).
  - Allocate turn-taking, decide on issues being discussed, set the agenda of the discussion.

Thimm. *Strategic argumentation in multi-agent systems*. KI-2014.

Hadoux, Beynier, Maudet, Weng and Hunter. *Optimization of probabilistic argumentation with Markov Decision Models*. IJCAI 2015.

Hadoux, Beynier, Maudet and Weng. *Mediation of Debates with Dynamic Argumentative Behaviors*. COMMA 2018.

Formalizing debate problems

- agents have **private** beliefs and argumentation systems
- agents have different **argumentative goals**
- argumentative moves are governed by **protocols**.

Quoting Brewka: "Formal models of argumentation must be highly flexible and adjustable, otherwise they simply will be unable to capture important aspects of realistic argumentation processes": declarative representation of the argumentation protocol, protocol violations, dynamic changes of the protocol.

Brewka. *Dynamic Argumentation Systems: A formal model of argumentation processes based on situation calculus*. Journal of Logic and Computation, 2000.

Executable Logic

- **Executable logic** "declarative past and imperative present and future"
- Developed in the 90's and popular in the agent community and distributed AI for agent-oriented programming (e.g. METATEM and its concurrent variant)
- Useful to encode reactive systems thanks to rule-based specifications

Gabbay. *The declarative past and imperative future: Executable temporal logic for interactive systems*. Temp. Logic in Spec. 1987.

Barringer et al.. *Metatem: an introduction*. Formal Aspects of Computing, 1995.

Executable Logic for Dialogical Argumentation

Black and Hunter proposed to apply executable logic to model dialogical argumentation

- state at time $n = \langle s_1(n), p(n), s_2(n), act_x(n), act_y(n) \rangle$ where $s_x(n)$ is the private state of agent x, $act_x(n)$ his action state, and $p(n)$ the public state
- the **reasoning state** of agent x in state n is $s_x(n) \cup p(n)$
- actions to be taken in the next **private** state ($\boxplus$: add, $\boxminus$: delete) or next **public** state ($\oplus$: add, $\ominus$: delete)

$$bel(\phi) \wedge t(X) \Rightarrow \boxplus claim(X, \phi) \wedge \boxminus t(X) \wedge \boxplus t(Y)$$

$$claim(X, \phi) \Rightarrow \boxplus why(Y, \phi) \vee \boxplus agree(Y, \phi)$$

Black and Hunter. *Executable Logic for Dialogical Argumentation*. ECAI-2014.

Argumentation problem with Probabilistic Strategies (APS)

Later, Hunter augmented this model to account for **probabilistic strategies**

- action rules have consequents in DNF, disjuncts summing up to 1

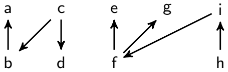
$$bel(Y, \neg\phi) \wedge claim(X, \phi) \Rightarrow 0.9 : \boxplus why(Y, \phi) \vee 0.1 : \boxplus agree(Y, \phi)$$

- agents have **argumentative goals**

Hunter. *Probabilistic Strategies in Dialogical Argumentation*. SUM-2014.

Abstract argumentation

- an **abstract argumentation framework** $\mathcal{AF} = (\mathcal{A}, \mathcal{E})$ with:
  - $\mathcal{A}$, a finite set of arguments,
  - $\mathcal{E}$, a binary relation between the arguments called **attack relation**, such that $(a, b) \in \mathcal{E}$ if $a \in \mathcal{A}$, $b \in \mathcal{A}$ and a attacks b.



- different ways to attach **argumentative status** to arguments, eg. **extensions**
- **grounded extension**: argument is in if not attacked or all attackers are out, argument is out if attacked by at least one argument in
- for instance, an agent could have the **argumentative goal** to make some arguments acceptable (under the grounded extension) in the public state, at the end of the debate)

$$g_2 = \{in(d), in(h)\}$$

Example: is E-sport a sport?

A famous debate in the gamer community is either e-sport is a sport or not.

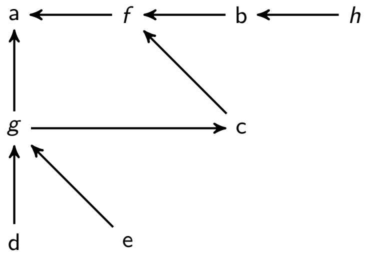
- a E-sport is a sport
- b E-sport requires focusing, precision and generates tiredness
- c Not all sports are physical
- d Sports not referenced by IOC exist
- e Chess is a sport
- f E-sport is not a physical activity
- g E-sport is not referenced by IOC
- h Working requires focusing and generates tiredness but is not a sport

We assume agents only use **claims**, and use predicates $h(\mathbf{x})$ for arguments endorsed in the private state, $a(\mathbf{x})$ and $e(\mathbf{x},\mathbf{y})$ for arguments and attacks stated in the public state.
We specify the corresponding APS as:

$$\langle \mathcal{N}, \mathcal{A}, \mathcal{E}, (\mathcal{S}_i)_{i\in\mathcal{D}}, \mathcal{P}, (g_i)_{i\in\mathcal{D}}, (\mathcal{R}_i)_{i\in\mathcal{D}}, \rangle$$

Example: Formalization

- $\mathcal{A} = \{\mathbf{a}, \mathbf{b}, \mathbf{c}, \mathbf{d}, \mathbf{e}, \mathbf{f}, \mathbf{g}, \mathbf{h}\}$
- $\mathcal{E} = \{e(\mathbf{f}, \mathbf{a}), e(\mathbf{g}, \mathbf{a}), e(\mathbf{b}, \mathbf{f}), e(\mathbf{c}, \mathbf{f}), e(\mathbf{h}, \mathbf{b}), e(\mathbf{g}, \mathbf{c}), e(\mathbf{d}, \mathbf{g}), e(\mathbf{e}, \mathbf{g})\}$



Attacks graph of Example

Example Formalization

- Initial state: $\langle\{a, b, c, d, e\}, \{\}, \{f, g, h\}\rangle$ and goal $g_1 = in(\mathbf{a})$
- $\mathcal{R}_1 = \{h(\mathbf{a}) \Rightarrow \boxplus a(\mathbf{a}),$

$$h(\mathbf{b}) \wedge a(\mathbf{f}) \wedge h(\mathbf{c}) \wedge e(\mathbf{b}, \mathbf{f}) \wedge e(\mathbf{c}, \mathbf{f}) \Rightarrow$$
$$0.5 : \boxplus a(\mathbf{b}) \wedge \boxplus e(\mathbf{b}, \mathbf{f}) \vee 0.5 : \boxplus a(\mathbf{c}) \wedge \boxplus e(\mathbf{c}, \mathbf{f}),$$

$$h(\mathbf{d}) \wedge a(\mathbf{g}) \wedge h(\mathbf{e}) \wedge e(\mathbf{d}, \mathbf{g}) \wedge e(\mathbf{e}, \mathbf{g}) \Rightarrow$$
$$0.8 : \boxplus a(\mathbf{e}) \wedge \boxplus e(\mathbf{e}, \mathbf{g}) \vee 0.2 : \boxplus a(\mathbf{d}) \wedge \boxplus e(\mathbf{d}, \mathbf{g})\}$$

- $\mathcal{R}_2 = \{h(\mathbf{h}) \wedge a(\mathbf{b}) \wedge e(\mathbf{h}, \mathbf{b}) \Rightarrow \boxplus a(\mathbf{h}) \wedge \boxplus e(\mathbf{h}, \mathbf{b}),$

$$h(\mathbf{g}) \wedge a(\mathbf{c}) \wedge e(\mathbf{g}, \mathbf{c}) \Rightarrow \boxplus a(\mathbf{g}) \wedge \boxplus e(\mathbf{g}, \mathbf{c}),$$

$$a(\mathbf{a}) \wedge h(\mathbf{f}) \wedge h(\mathbf{g}) \wedge e(\mathbf{f}, \mathbf{a}) \Rightarrow$$
$$0.8 : \boxplus a(\mathbf{f}) \wedge \boxplus e(\mathbf{f}, \mathbf{a}) \vee 0.2 : \boxplus a(\mathbf{g}) \wedge \boxplus e(\mathbf{g}, \mathbf{a})\}$$

Note that private states are never modified here, we only represent public state next.

Probabilistic Finite State Machine: States

$\sigma_1 = \{\}$,

$\sigma_2 = \{a(a)\}$, ✔

$\sigma_3 = \{a(a), a(f), e(f, a)\}$,

$\sigma_4 = \{a(a), a(g), e(g, a)\}$,

$\sigma_5 = \{a(a), a(f), e(f, a), a(b), e(b, f)\}$, ✔

$\sigma_6 = \{a(a), a(f), e(f, a), a(c), e(c, f)\}$, ✔

$\sigma_7 = \{a(a), a(f), e(f, a), a(c), e(c, f), a(g), e(g, c)\}$,

$\underline{\sigma_8} = \{a(a), a(f), e(f, a), a(b), e(b, f), a(h), e(h, b)\}$,

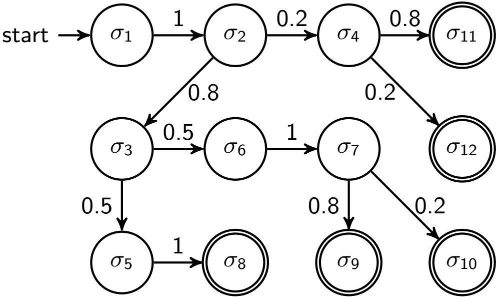
$\underline{\sigma_9} = \{a(a), a(f), e(f, a), a(c), e(c, f), a(g), e(g, c), a(e), e(e, g)\}$, ✔

$\underline{\sigma_{10}} = \{a(a), a(f), e(f, a), a(c), e(c, f), a(g), e(g, c), a(d), e(d, g)\}$, ✔

$\underline{\sigma_{11}} = \{a(a), a(g), e(g, a), a(e), e(e, g)\}$, ✔

$\underline{\sigma_{12}} = \{a(a), a(g), e(g, a), a(d), e(d, g)\}$ ✔

Probabilistic Finite State Machine: Graph



PFSM of Example

Exploiting the Probabilistic Finite State Machine

- a **mediator** can use the PFSM to analyze how the debate is likely to evolve
- an **agent** could also exploit the PFSM so as to select his best actions given the probabilistic behaviour of the other agent

However note that

1. it is dependent of the starting state
2. it requires knowledge of the private state of the opponent

We assume probabilistic knowledge on the starting state and non-observable private state of opponent.

When planning meets abstract argumentation

Strategic argumentation

- Exchanging arguments to share some knowledge, deliberate, or persuade.
- Strategically decide for the arguments to put forward in the debate
  → **plan the sequence of arguments**

Planning under uncertainty in argumentation

An agent may be uncertain about

- the beliefs and the states of the other debating agents,
- the argumentative strategies of the other debating agents.
  → plan the sequence of arguments **under uncertainty**

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Markov Decision Processes under Partial Observability

- Formalize and solve **sequential decision making problems under uncertainty** (represented by probability distributions).
- A **POMDP** [Bellman, 1957] is defined by a tuple $\langle S, A, T, R, O, \Omega \rangle$
  - S is the finite set of states s.
  - A is the finite set of actions a the agent can take.
  - T formalizes the uncertainty on action outcomes. $T(s'|s, a)$ is the probability that the system moves from state s to state s' when the agent takes action a.
  - R formalized the agent's objectives. $R(s, a)$ is the reward obtained by the agent when she executes action a from state s.
  - O is the finite state of observations o of the agent.
  - Ω is the observation function. $\Omega(O|s', a)$ is the probability of the observation o when the agent executes action a and the system moves to s'.
- A **solution**: a mapping $\pi : \bar{O} \rightarrow A$ called a policy.
- An **optimal solution**: a policy maximizing the expected reward of the agent.

Mixed-Observability Markov Decision Process

A *Mixed-Observability Markov Decision Process* (*MOMDP*) [Ong et al., 2010] is characterized by $\langle S_v, S_h, A, T, R, O_v, O_h, \Omega \rangle$:

- A, R, as previously
- $S_v \times S_h = S$, the visible and hidden parts of the state
- $T : S_v \times A \times S_h \to \Pr(S_v \times S_h)$, the transition function
- $O_v = S_v$, the observation set on the visible part of the state
- O_h, the observation set on the hidden part of the state
- $\Omega : S_v \times A \times S_h \to \Pr(O_v \times O_h)$, the observation function

From APS to MOMDP

- We take the point of view of **one** agent.
- In order to **optimize the argumentation strategy of an agent**, we transform the APS into a MOMDP defined as follows:
  - $S_v = \mathcal{S}_1 \times \mathcal{P}$
  - $S_h = \mathcal{S}_2$
  - $A = \{p \Rightarrow c_i \text{ s.t. } r : p \Rightarrow \bigvee_i \tau_i : c_i, \forall r \in \mathcal{R}_1\}$, deterministic actions for agent 1 (e.g., $\boxplus a(\mathbf{b}) \wedge \boxplus e(\mathbf{b}, \mathbf{f}) \vee \boxplus a(\mathbf{c}) \wedge \boxplus e(\mathbf{c}, \mathbf{f})$)
  - $O_v = S_v$ and $O_h = \emptyset$
  - $\Omega(\langle s_v, s_h \rangle, a, \langle s_v \rangle) = 1$, otherwise 0
  - T, see after

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From APS to MOMDP: Transition function

Compatibility

A rule r: prem $\Rightarrow$ claims is compatible with a set of predicates ω iff $\nexists p \in \omega$ s.t. $\neg p \in$ prem. We denote $C_\omega(\mathcal{R}_i)$ the set of all rules of $\mathcal{R}_i$ compatible with ω.

Application set

The application set $F(c, \omega)$ is the set of predicates resulting from the application of the claims c of a rule r on ω. If r is not compatible with ω, $F(c, \omega) = \omega$.

From APS to MOMDP: Transition function

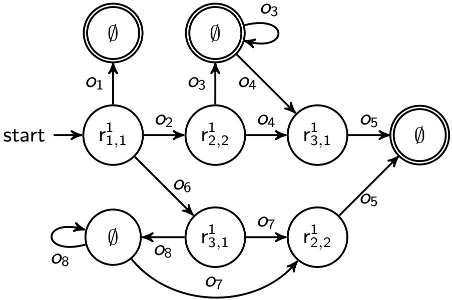
- s, a state
- $a : \rho \Rightarrow c$, an action (a deterministic rule) of agent 1
- $s' = F(c, s)$
- $a' \in C_{s'}(\mathcal{R}_2)$ s.t. $a' : \rho' \Rightarrow \bigvee_i \tau_i : c_i$
- $s''_i = F(c_i, s')$

Function T such that $T(s, a, s''_i) = \tau_i$

From APS to MOMDP

- On the previous example:
  - APS: 8 arguments, 8 attacks, 6 rules
  - POMDP: $|S| = |S_v| \times |S_h| = 4\,294\,967\,296$
  - MOMDP: $|S_v| = 256 * 65536 = 16\,777\,216 = |O_v|$, $|S_h| = 256$, $|A| = 5$
- This POMDP is then solved using one of the three algorithms :
  - *MO-IP* [Araya L. et al., 2010], IP of POMDP on MOMDP (exact method)
  - *MO-SARSOP* [Ong et al., 2010], SARSOP of POMDP on MOMDP (approximate method albeit very efficient)
  - *POMCP for HS3MDP* [Hadoux et al., 2014], optimization of POMCP [Silver and Veness, 2010] on a subclass of MOMDP (approximate method)
- We proposed optimization techniques to reduce the size of the model.

Experiments: Policy graph



The observations of agent 1 are :
$o_1 = \{a(\mathbf{a})\}$, $o_2 = \{a(\mathbf{a}), a(\mathbf{f})\}$,
$o_3 = \{a(\mathbf{a}), a(\mathbf{c}), a(\mathbf{f})\}$
$o_4 = \{a(\mathbf{a}), a(\mathbf{c}), a(\mathbf{f}), a(\mathbf{g})\}$
$o_5 = \{a(\mathbf{a}), a(\mathbf{c}), a(\mathbf{e}), a(\mathbf{f}), a(\mathbf{g})\}$,
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$$\mathcal{R}_1 = \{h(\mathbf{a}) \Rightarrow \boxplus a(\mathbf{a}),$$
$$h(\mathbf{b}) \wedge a(\mathbf{f}) \wedge h(\mathbf{c}) \wedge e(\mathbf{b},\mathbf{f}) \wedge e(\mathbf{c},\mathbf{f}) \Rightarrow \boxplus a(\mathbf{b}) \wedge \boxplus e(\mathbf{b},\mathbf{f}) \vee \boxplus a(\mathbf{c}) \wedge \boxplus e(\mathbf{c},\mathbf{f}),$$
$$h(\mathbf{d}) \wedge a(\mathbf{g}) \wedge h(\mathbf{e}) \wedge e(\mathbf{d},\mathbf{g}) \wedge e(\mathbf{e},\mathbf{g}) \Rightarrow \boxplus a(\mathbf{e}) \wedge \boxplus e(\mathbf{e},\mathbf{g}) \vee \boxplus a(\mathbf{d}) \wedge \boxplus e(\mathbf{d},\mathbf{g})\}$$

Outline

Mediation of debates

- Mediation of debates is a longstanding issue in democracies.
- **Teams of debating agents** exchanging arguments to persuade each other.
- The mediator **chooses the agent of the team to speak next**.
- The mediator is **uncertain** about the argumentation strategy of each agent.
- Debating agents are assumed to play **probabilistic strategies** as in APS.
- **Non-stationary debating strategies**: as the debate progresses, each agent may change her current topic or her argumentative behavior.

Non-stationary debating strategies

We exploit the topology of **constructive vs. destructive** behavior [Moore, 1993]:

- **Constructive** mode: the agent tries to build her goal.
- **Destructive** mode: the agent tries to defeat the goal of the other.

$$\mathrm{a} \longrightarrow \mathrm{b} \longrightarrow \mathrm{c} \longleftarrow \mathrm{d}$$

$$\begin{array}{ll} \text{constructive:} & a(\mathbf{a}) \Rightarrow [0.7/a(\mathbf{d}) \vee 0.3/a(\mathbf{b})] \\ \text{destructive:} & a(\mathbf{a}) \Rightarrow [0.2/a(\mathbf{d}) \vee 0.8/a(\mathbf{b})] \end{array}$$

Dynamic Mediation Problem (DMP)

Non-formally, a DMP is composed by:

- a set of teams and their agents,
- a set of arguments and attacks,
- a set of rules for each agent (the probabilistic strategies),
- the behaviour evolution function for each agent,
- the goals for each team and the mediator.

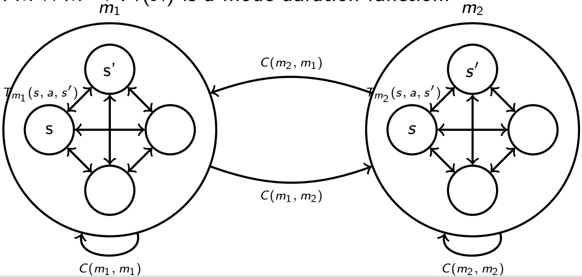
Mediator's objectives

Inspired by Robert's Rules of Order [Robert, 1876], we identified **different objectives for the mediator**:

- **Debate efficiency**
  - Impact on the audience (each step/end step)
  - Progress of the debate (avoid useless moves from the agents)
  - Length of the debate (short debates are preferred)
- **Debate fairness**
  - Alternation between teams
  - Fair opportunity to respond (notion of relevance)
  - Full participation (agents should be allowed to play if they can)

From Dynamic Mediation to HS3MDP

- The **decision problem of the mediator** can be viewed as a **sequential decision problem under uncertainty** in **non-stationary** environments.
- Existing Markov Decision Processes assume stationary environments.
- Non-Stationary environments can be seen as **a set of stationary modes** between which the environment can switch.
- An Hidden Semi-Markov-Mode MDP (HS3MDP) is defined as:
  - $M = \{m_1, \ldots, m_p\}$, a finite set of modes where $m_i = \langle S, \mathcal{A}, T_i, R_i \rangle$,
  - $C : M \to \Pr(M)$, a transition function over mode,.
  - $H : M \times M \to \Pr(\mathbb{N})$ is a *mode duration function*.



Hadoux, Beynier and Weng. *Solving Hidden-Semi-Markov-Mode Markov Decision Problems.* SUM 2014.

From Dynamic Mediation to HS3MDP

We formalized the mediation problem as an **HS3MDP** from the point of view of the mediator:

- actions $\Rightarrow$ the agents,
- states $\Rightarrow$ the public states of the debate,
- transition function over the modes and the duration function $\Rightarrow$ induced by the evolution of the behaviors,
- transition function inside the modes $\Rightarrow$ induced by the rules,
- reward function $\Rightarrow$ formalizes the objectives of the mediator and has to be defined in compliance with the semantics of the problem.

  For instance: progress of the debate is captured by assigning negative rewards to vacuous acts, i.e. acts that do not change the state of the debate.

Experiments on mediation

- **Illustration of the mediator's strategy**:
  - Two Teams: $\mathcal{T}_1 = (1, 2, 3)$ and $\mathcal{T}_2 = (4, 5, 6, 7, 8)$.
  - Turn-taking strategy of the mediator:
    (6, 3, 5, 1, 4, 1, 7, 2, 6, 1, 5, 3, 7).

- **Performances over a mean model using POMCP**:

Teams	# Sim.	Step-wise	Final
3-4	8	-93.66 / **-86.28**	-116.97 / **-108.90**
	16	-52.26 / **-39.40**	-79.27 / **-64.99**
	32	-10.29 / **-4.99**	-35.49 / **-30.40**
	64	3.12 / **4.46**	-21.27 / **-19.73**
	128	4.57 / **5.73**	-19.89 / **-18.82**
	256	4.36 / **5.97**	-19.90 / **-18.51**
12-12	64	-8.70 / **-5.82**	-36.20 / **-32.87**
	128	16.15 / **16.75**	-9.81 / **-9.46**
	256	20.58 / **20.87**	**-4.94** / -4.97
25-25	128	-5.08 / **-3.56**	-31.93 / **-30.68**
	256	-15.59 / **16.74**	-10.56 / **-10.28**
50-50	256	-1.50 / **-0.31**	-27.84 / **-27.32**

Table: Perf. for Teams 3-4, 12-12, 25-25 and 50-50

- Relative improvements are up to 79%.
- Improvement statistically significant under Student t-test.

Conclusion and Perspectives

Strategic argumentation and planning under uncertainty

- **New abstract formalization** of decision problems in argumentation.
- Definition of **strategic argumentation problems using Markovian decision models**.
- **Optimization of models and algorithms** to improve scalability and efficiency.
- **Experiments** on the performances of the computed strategies.

Perspectives

- Other models of the opponent behaviors
- On-line learning and refinement of the opponent model
- Debates with strategic agents

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Thank you for your attention

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