# Multiagent Dynamics of Gradual Argumentation Semantics

Louise Dupuis de Tarlé[1], Elise Bonzon[2] and Nicolas Maudet[3]

1 - LAMSADE - Université Paris Dauphine - louise.dupuis@dauphine.eu
2 - LIPADE - Université Paris Cité - elise.bonzon@u-paris.fr
3 - LIP6 - Sorbonne Université, CNRS - nicolas.maudet@lip6.fr

# Motivation

- **Abstract argumentation** is a way of representing abstract arguments as networks
- Several functions have been developed to compute the strength of such arguments $\rightarrow$ **Gradual Semantics**

If agents indeed reason and interact using some gradual semantics, together with some protocol, how will debates and agents opinion evolve?

$\Rightarrow$ Normative point of view, but inspired by online debates.

Amgoud, L., Ben-Naim, J., Doder, D., & Vesic, S. *Acceptability semantics for weighted argumentation framework*. IJCAI 2017.

# Related Works

### Agent polarization through exchange of arguments

Banisch, S., Olbrich, E. *An Argument Communication Model of Polarization and Ideological Alignment.* . JASSS 2021.

### Abstract Argumentation in Opinion Diffusion

Butler, G., Pigozzi, G., Rouchier, J. *An opinion diffusion model with deliberation.*. 20th International Workshop on Multi-Agent-Based Simulation 2019.

Taillandier, P., Salliou, N., Thomopoulos, R. *Introducing the Argumentation Framework Within Agent-Based Models to Better Simulate Agents' Cognition in Opinion Dynamics: Application to Vegetarian Diet Diffusion.*. JASSS 2021.

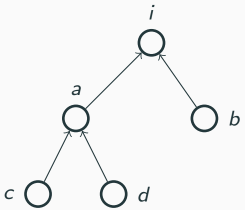
# Outline

1. Abstract argumentation theory
2. The protocol
3. Simulation Results
4. Conclusion

# Abstract argumentation theory

# Abstract Argumentation Theory

- Arguments are abstract: no content is analyzed
- $AF = \langle \mathcal{A}, \mathcal{R} \rangle$, where
  - $\mathcal{A}$ is a finite and non-empty set of arguments
  - $\mathcal{R} \subseteq \mathcal{A} \times \mathcal{A}$ is an attack relation

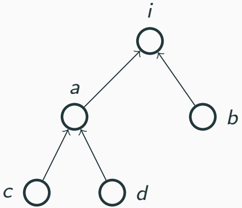



Dung, P. M.. *On the acceptability of arguments and its fundamental role in non-monotonic reasoning, logic programming and n-person games*. Artificial intelligence 1995.

# Gradual Semantics

- Formal methods to assess the acceptability of arguments
- Gradual semantics: quantitative way to assess arguments
- A **gradual semantics** associates a scoring to each argument $S : \mathcal{A} \rightarrow \mathbb{R}$

For example, with the h-categorizer semantics:




- $Hbs(b) = Hbs(c) = Hbs(d) = 1$
- $Hbs(a) = 0.333$
- $Hbs(i) = 0.4286$

Amgoud, L., Ben-Naim, J., Doder, D., & Vesic, S. *Acceptability semantics for weighted argumentation framework*. IJCAI 2017.

# The protocol

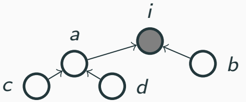
# Profile of a Game

## Issue Oriented Argumentation Graph (IOAG)

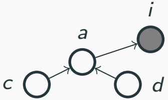
Each argument is part of a path towards the **issue** of the graph. The issue is the main question of the debate.
The **value** of the graph is the value of the issue.

The **Universe graph** contains every relevant argument of the debate:

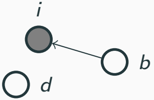
Agents are each equipped with an **agent's graph**, subset of the universe graph




Universe graph, $V_{UG} = 0.4286$




Agent 1, $V_1 = 0.75$

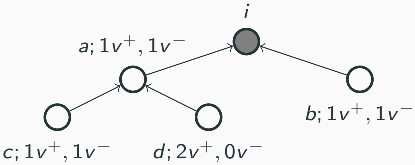



Agent 2, $V_2 = 0.5$

# Merged graph

## Merged graph

The **merged graph** is a weighted argumentation framework constructed from agent' graphs, where each agent holding an argument in her AF "virtually" vote for it, while the others vote against

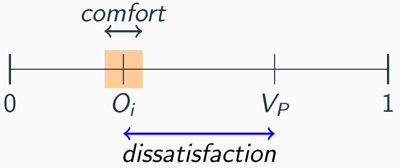



Merged graph, $V_{MG} = 0.6277$

$\longrightarrow$ this graph is a tool for analysing the debate

# Evaluation and Strategies

**Agent's goal:** They want the public debate to reflect their opinion.




- **If not comfortable :** agents can play any argument which brings the $V_P$ closer to their opinion.
- **If comfortable :** agents can play any argument which leaves the $V_P$ in their comfort interval.

**Dissatisfaction**

The **dissatisfaction** of an agent is the distance between the agent's opinion and the value of the public graph.

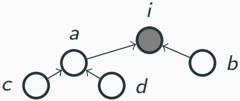
# Learning Arguments

- After every step, agents can "learn" arguments : add the new arguments to their opinion graphs.
- Learning is based on **confirmation bias** : agents are more likely to learn arguments which favor their opinion.

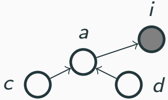
$\longrightarrow$ Agent's opinion changes throughout the game.

# An example course of the protocol

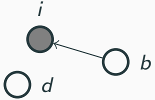
Universe Graph




**Agent 1**



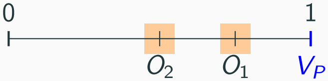

**Agent 2**




**Public Graph**


$O_1 = 0.75$

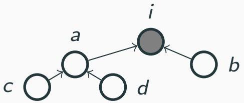
$O_2 = 0.5$



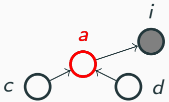

$V_P = 1$

# An example course of the protocol

Universe Graph

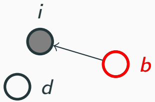



**Agent 1**




$O_1 = 0.75$

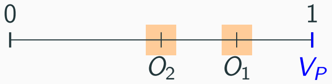
**Agent 2**




$O_2 = 0.5$

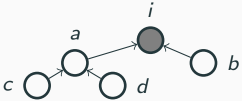
**Public Graph**


$V_P = 1$

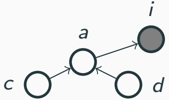


# An example course of the protocol

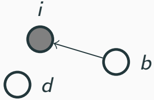
Universe Graph



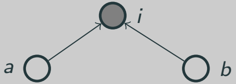

**Agent 1**




**Agent 2**



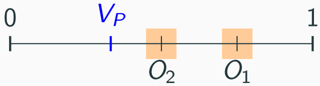

**Public Graph**




$V_P = 0.33$

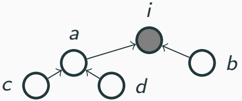
$O_1 = 0.75$

$O_2 = 0.5$

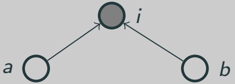


# An example course of the protocol

Universe Graph

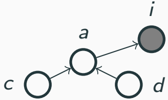



**Public Graph**



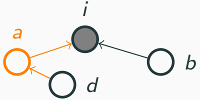

$V_P = 0.33$

**Agent 1**

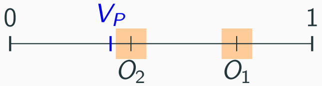



$O_1 = 0.75$

**Agent 2**

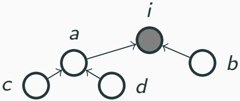



$O_2 = 0.4$

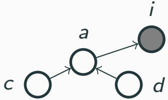


# An example course of the protocol

Universe Graph

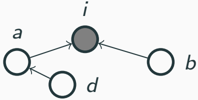



**Agent 1**



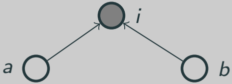

$O_1 = 0.75$

**Agent 2**

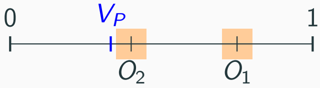



$O_2 = 0.4$

**Public Graph**




$V_P = 0.33$



# Simulation Results

# Hypotheses

**H1 : "Outcome"** For a given debate, if the learning probabilities increase, the outcome gets closer to the merged value.

**H2 : "Flexibility"** Increasing the size of the comfort zone increases the agent's satisfaction.

**H3 : "Open Mind"** If the learning probability of an agent increases, she will be more satisfied at the end of the debate.

**H4 : "Strength of the Group"** When many agents share the same initial information, they have a greater chance to be satisfied by the final result.

**H5 : "Power of Knowledge"** Agents that know more arguments at the beginning of the game are more satisfied at the end.

**H6 : "Convergence of Views"** The highest the learning probabilities, the lower the distance between the agent's final values.

# Results

| | Variable 1 | Variable 2 | $R$ | $p$ value |
|---|---|---|---|---|
| H1 | $P_L$ | $\lvert V_F - V_M \rvert$ | -0,55029 | 2,44E-80 |
| H2 | $c_l$ | $N_C$ | 0,680451 | 4,1E-137 |
| H3 | $P_L$ | $AD$ | -0,70346 | 2,1E-150 |
| H4 | Nb of Clones | $AD_{clones}$ | -0,28678 | 2,19E-20 |
| H5 | $\lvert Arg(DG_k) \rvert$ | $d_k$ | -0,40972 | 9,3E-38 |
| H6 | $P_L$ | $STD$ | -0,6683870 | 1,2764E-130 |

**Table 1:** Testing the hypotheses. Correlation level: Dark green = high, light green = moderate, yellow = low.

# An improved protocol with votes

| | Variable 1 | Variable 2 | $R$ | $p$ value |
|---|---|---|---|---|
| H1 | $P_L$ | $\|V_F - V_M\|$ | -0,0645 | 0,04 |
| H2 | $c_l$ | $N_C$ | 0,604745 | 6,6E-101 |
| H3 | $P_L$ | $AD$ | -0,53363 | 1,39E-171 |
| H4 | Nb of Clones | $AD_{clones}$ | -0,23606 | 3,94E-14 |
| H5 | $\|Arg(DG_k)\|$ | $d_k$ | -0,40972 | 9,3E-38 |
| H6 | $P_L$ | $STD$ | -0.62242 | 1.8E-108 |

**Table 2:** Testing the hypotheses. Correlation level: Dark green = high, light green = moderate, yellow = low, red = no.

# Conclusion

# Conclusion

- We showed that a number of desirable hypotheses were verified.
- Our work shows that dynamics game of argumentation can be used to model the convergence of the opinion of agents.
- On the downside, one hypothesis was not verified any longer when we augment the protocol with votes, which reminds us of the importance of such seemingly minor design choices.