Research and Teaching with University of Aberdeen

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Graduate Initiative EIF

Structure of the presentation

1. Introduction of the project
   - Presentation of the project
2. Investigating collaborations
   - Why the University of Aberdeen?
   - The department of Computing Science
   - Synergy with the master DISS
3. Research project
   - The context
   - The problem
   - Some results
4. Conclusion

Research and Teaching with University of Aberdeen

There are two objectives to this project:

1. Investigate interest for lecturers from the University of Aberdeen (UoA) to teach in the M2 DISS (Data and Intelligence for Smart Systems) at UCBL.

2. Collaborate with *Prof. Nir Oren* on computation argumentation research topics.

Duration: 1 week (5 working days)

The University of Aberdeen

- Founded in 1495 - in the 4 oldest universities in Scotland.
- 16,565 students in 2021/2022
- 2nd for student satisfaction in Scotland (2023)
- In the top 20 UK university (2024)
- Composed of 12 Schools

The department of Computing Science

- Within the School of Natural & Computing Sciences.
- Composed of 43 permanent staffs teaching:
  - Locally at the UoA
  - at the South China Normal University (Foshan)
- Undergraduate (4 years) + Master (1 year)
- 5 research themes:
  - Autonomous Agents
  - Natural Language Generation and Computational Linguistics
  - General Machine Learning
  - Cybersecurity and Privacy
  - Human-Centred Computing

 

Possible teaching collaborations for M2 DISS

I have identified possible suitable collaborators:

Dr. Dewei Yi

Dr. Raja Akram

Dr. Wanpeng Li

Prof. Felipe Meneguzzi

Dr. Rafael Cardoso

Dr. Aiden Durrant

Discussions are ongoing for future steps.

Structure of the presentation

What is argumentation theory?

"Argumentation theory is the interdisciplinary study of how conclusions can be supported or undermined by premises through logical reasoning."

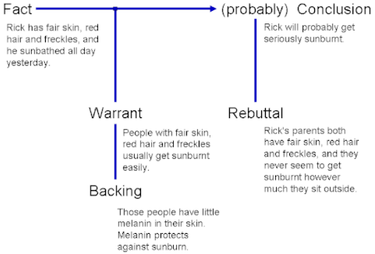

Figure: The Toulmin model of argument (1958)

Weighted abstract argumentation frameworks (WAFs)

Definition

A WAF is $\boldsymbol{A} = \langle \mathcal{A}, \mathcal{D}, w \rangle$, where $\mathcal{A}$ is a finite set of arguments, $\mathcal{D} \subseteq \mathcal{A} \times \mathcal{A}$, and $w : \mathcal{A} \to [0, 1]$ assigns an initial weight to each argument.

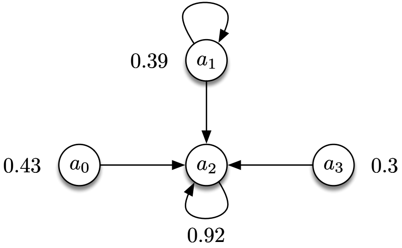

Figure: Example of the graphical representation of a WAF.

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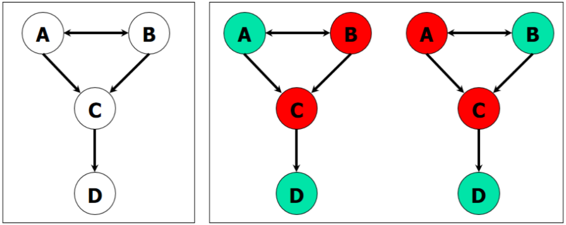
- Weights = *the* ***likelihood*** *of its premises, the degree of* ***trust*** *in its source, or an aggregation of* ***votes*** *provided by users*.
- Empirical evaluations have motivated the use of probabilistic approaches (Polberg and Hunter, 2018)

Reasoning with abstract argumentation framework

- Semantics can be used to:
  - Extract justifiable arguments **(Extension-based semantics)**



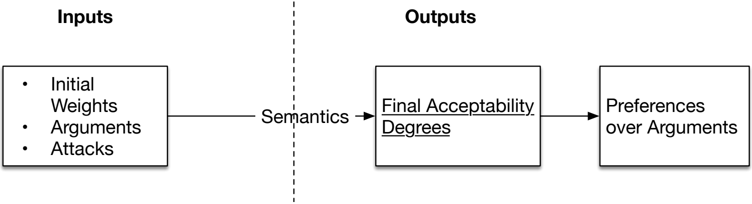
  - Rank arguments **(Ranking-based semantics)**

$$D > A, B > C$$

Can we study inverse problems for ranking-based semantics in WAFs?

What are inverse problems for gradual semantics?

Inverse problems start from the “output” and try to determine one or more elements from the “input”.



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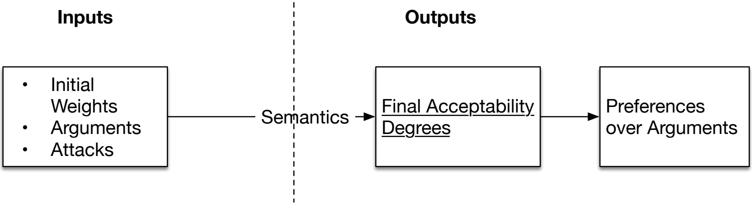
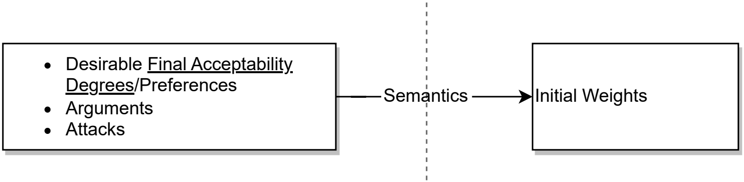


Inverse problem - Inferring initial weights:



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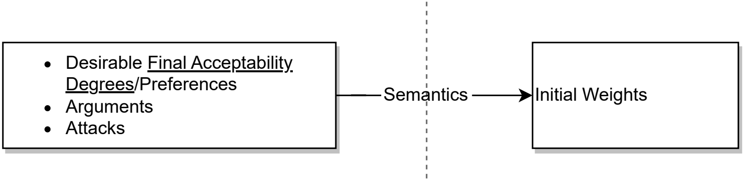
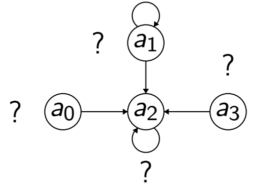
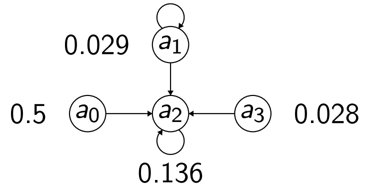


Input	Output
	
$a_1 \simeq a_3 \prec a_2 \prec a_0$	

Computational approach: a 2-steps approach

We split the problem into two steps:

1. We find *valid* acceptability degrees that can be achieved.
2. We use the bisection method to find initial weights that satisfy those degrees. This involves:
   - Randomly initialising weights
   - Picking arguments *(using a strategy)* and modifying their weights
   - Repeating the previous step until convergence

We evaluated on 3 semantics: weighted card-based, max-based, and h-categoriser.

Evaluation

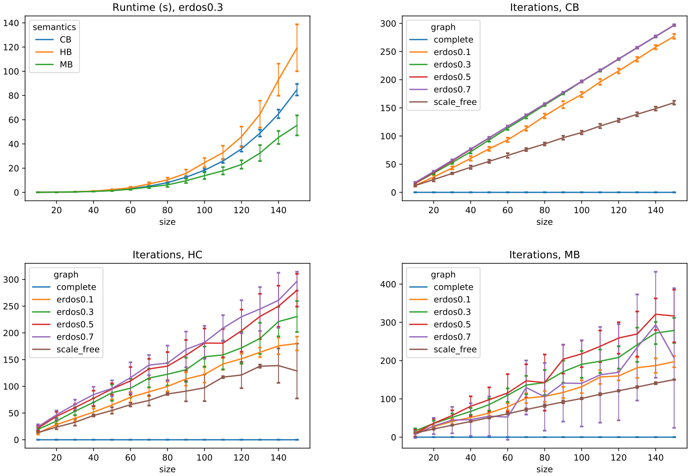


Figure: Runtime (top-left) and number of iterations for the different semantics and graph types

What is next?

- We have a way to find valid acceptability degrees
- We have a heuristic that can find the weights in a reasonable time.

Can we be more efficient?

Re-writing using matrix multiplication: Weighted h-categoriser

The semantics can be defined as:

$$\overrightarrow{HC}_\infty = \frac{\overrightarrow{w}}{\overrightarrow{1} + \mathbb{A}\overrightarrow{HC}_\infty}$$

Which we can re-write as:

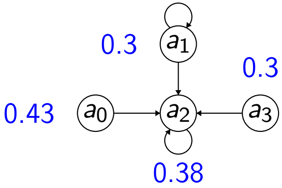
$$\overrightarrow{HC}_\infty + \mathbb{M}\mathbb{A}\overrightarrow{HC}_\infty = \overrightarrow{w}$$

where $\mathbb{A}$ is the inverse adjacency matrix, $\overrightarrow{HC}_\infty$ is the vector of degrees, and $\mathbb{M}$ is a diagonal matrix with acceptability degrees on the diagonal.

Re-writing using matrix multiplication: Weighted h-categoriser

$$\overrightarrow{HC}_\infty + \mathbb{MA}\overrightarrow{HC}_\infty = \vec{w}$$

For example:



$$\begin{bmatrix} 0.43 \\ 0.3 \\ 0.38 \\ 0.3 \end{bmatrix} + \begin{bmatrix} 0.43 & 0 & 0 & 0 \\ 0 & 0.3 & 0 & 0 \\ 0 & 0 & 0.38 & 0 \\ 0 & 0 & 0 & 0.3 \end{bmatrix} \times \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} 0.43 \\ 0.3 \\ 0.38 \\ 0.3 \end{bmatrix}$$

Re-writing using matrix multiplication: Weighted h-categoriser

$$\overrightarrow{HC}_\infty + \mathbb{MA}\overrightarrow{HC}_\infty = \overrightarrow{w}$$

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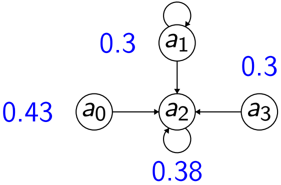

$$\begin{bmatrix} 0.43 \\ 0.3 \\ 0.38 \\ 0.3 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0.3 & 0 & 0 \\ 0.38 & 0.38 & 0.38 & 0.38 \\ 0 & 0 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} 0.43 \\ 0.3 \\ 0.38 \\ 0.3 \end{bmatrix}$$

Re-writing using matrix multiplication: Weighted h-categoriser

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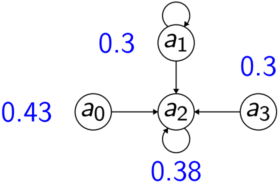

$$\begin{bmatrix} 0.43 \\ 0.3 \\ 0.38 \\ 0.3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0.09 \\ 0.54 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.43 \\ 0.39 \\ 0.92 \\ 0.3 \end{bmatrix}$$

Re-writing for weighted max-based/card-based semantics

- We provide similar re-writing:
  - **Weighted max-based semantics.**

$$\overrightarrow{MB}_{\infty} + \mathbb{M} \max\{\mathbb{A}\mathbb{O}\} = \overrightarrow{w}$$

  - **Weighted card-based semantics.**

$$\overrightarrow{CB}_{\infty} + \mathbb{D}\overrightarrow{CB}_{\infty} + \mathbb{D}^{-1}\mathbb{M}\mathbb{A}\overrightarrow{CB}_{\infty} = \overrightarrow{w}$$

- We provide similar re-writing:
  - **Weighted max-based semantics.**

$$\overrightarrow{MB}_{\infty} + \mathbb{M} \max\{\mathbb{A}\mathbb{O}\} = \overrightarrow{w}$$

  - **Weighted card-based semantics.**

$$\overrightarrow{CB}_{\infty} + \mathbb{D}\overrightarrow{CB}_{\infty} + \mathbb{D}^{-1}\mathbb{M}\mathbb{A}\overrightarrow{CB}_{\infty} = \overrightarrow{w}$$

The inverse problem is easy for those semantics!

Conclusion

To summarise:

- I explored teaching collaborations with the University of Aberdeen.
- We studied research questions around inverse problems for WAFs and ranking-based semantics.
- Future works:
  - Explore weight intervals in abstract argumentation frameworks.
  - Expand the results to classes of ranking-based semantics.

Thank You