

# Explainable AI via Argumentation: Theory & Practice

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<https://www.argument-theory.com/>

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# Lecture 5

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- **Summary of Course**
  
- **Hands-on Projects**
  - **Student Presentation of Projects.**
  - **Future development of Projects?**
  
- **Advanced Topics**
  - **Direct Authoring in Natural Language:**
    - **COGNICA with LLM**
  - **Explainable ML:**
    - **ArgEML: Learning Arg. Theories & Arg-Based Explainable Models Reading**

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# SUMMARY

# Argumentation-based Decision Making

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- **Decision of option O:**
  - **Argument case supporting O – O is plausible**
  - **No argument case for any other O'**
    - This is an **IDEAL** situation of **optimal** decision
- **In PRACTICE, Good/Satisficing decisions.**
- **On-line on demand computation!**
- **Could be in Dilemma**
  - **A Difficult problem case ⇒ Need more information.**

# Computational Argumentation: a “Roadmap”

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From **<Args, ATT>** ... to **<Args, Att, Def>** ... to

... to **<As, C, ρ>** ...

... to **GORGIAS <As U Prs, C >** ...

From **Theory** to **Practice**

... to **SoDA Methodology for Knowledge Acquisition**

... to **rAISON**

... to **Applications**

# *Software Development* via *Argumentation* *SoDA Methodology*

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## **Identify** the **Language** of **Options** & **Factors** for **Preference**

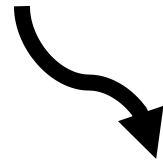
- **Consider application scenarios** and **state** the preferred/desired option(s) in each scenario.
  - **Identify** different **initial scenarios**.
- Successively **refine** the **scenarios**, **restating** at each **refinement** the new **preferred option(s)**.
- Considering **combinations** of **conflicting** of **scenarios**

## **Hierarchies of Scenario-based Preferences (SBPs)**

# rAIsOn

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**Authoring - No coding  
Knowledge Representation**

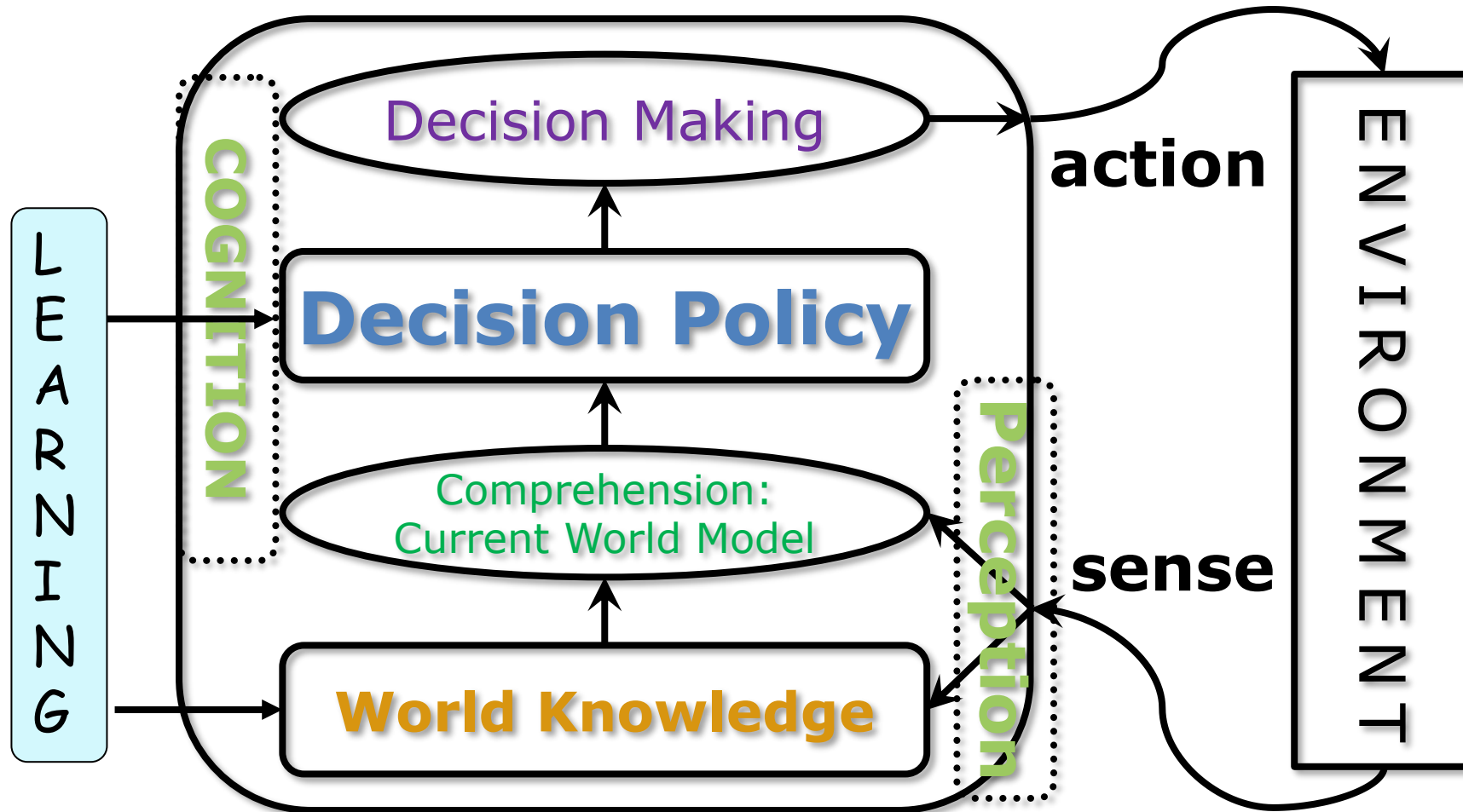


**Hierarchies of Scenario-based  
Preferences (SBPs)**



**Executable  
GORGIAS Argumentation Framework**

# Building Argumentation-based Decision Machines





# Building Decision Machines

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## Two major Challenges

- 1. Acquisition** of problem Knowledge - **Decision Policy**
  - **At a Language Level of the Application – Natural Language?**
  - **Extracting Hidden Preferences from Natural Language Specs**

**Addressed by SoDA and rAIson**

# Building Decision Machines

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## Second major Challenge

- 2. Middleware** from Sensory Information to Policy Concepts
- **Comprehension** of current **Context** of the application environment from its low-level sensory information
  - In other words, **“Establishing the (high-level) facts.”**

Intelligence is in the Abstraction of the Decision Policy  
Large number of cases grouped into high-level concepts

Addressed by **API** of **rAIson**

# Hands-on Projects

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- **Presentations/Discussion of Projects**
- **Future Development**
  - Redo a **more realistic** problem.
  - **Finalize** your project.
    - Send us a report document
  - **Keep** rAIson Accounts Open?
    - rAIson also suitable for **Freelancers**

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# ADVANCED TOPICS

# COGNICA: Cognitive Argumentation

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- **Cognitive Argumentation is a Synthesis of:**
  - **Argumentation theory in AI**
    - GORGIAS Argumentation framework
  - **Empirical and theoretical studies of the Psychology of Reasoning from Cognitive psychology and Philosophy**
    - P. N. Johnson-Laird and R. M. Byrne, "**Conditionals: a theory of meaning, pragmatics, and inference.**" Psychol. Rev., vol. 109, (4), pp. 646, 2002.
- **Cognitive Machine Argumentation (2022) on ResearchGate**

# COGNICA<sub>c</sub>

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## Decision Policy in **Natural language**

Policy complementary options

GPT 4 TURBO translates policy to Cognica Middle language (Cognica D.P. CNL )

Parse Cognica Middle language (Cognica D.P. CNL ) to Cognica CNL.

Parse Cognica to **GORGIAS** Argumentation

Query Cognica on policy.

Get **Explanation** in **Natural Language**

# COGNICAc Middle language

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- **NORMALLY** {Conclusion}
- **IF** {Condition} **THEN** {Conclusion}
- **IF** {Condition} **THEN ALWAYS** {Conclusion}
- **IF** {Condition} **THEN MAYBE** {Conclusion}
- **IF** {Condition} **THEN** {Conclusion} **UNLESS** {Condition2} **IN SUCH CASES** {Conclusion2}
- **ONLY IF** {Condition} **THEN MAYBE** {Conclusion}
- **WHENEVER NOT** {Condition1} **THEN NOT** {Conclusion1} **BUT IF** {Condition2} **THEN MAYBE** {Conclusion1}

# COGNICAc: Demo

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## **Demo of Call Assistant**

<http://cognica.cs.ucy.ac.cy/COGNICAc/login.php>



# Building XAI Systems from Natural Specifications

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## Call Assistant (Personal Policy)

“Normally, allow a call. When at work deny a call from an unknown number. When busy at work deny a call unless it is an emergency family call. Always allow a call from my manager.”

**Options: allow a call, deny a call.**

**Busy at work**

**Busy at work, Emergency Family Call (not Unknown)**

**Busy at work, Manager call**

# Calendar Assistant in COGNICAc

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“Business meetings should be scheduled in the afternoon unless it is with a very important customer. Also, when presenting final solutions to customers prefer a morning meeting.

Meetings with the CEO can be scheduled morning or afternoon. I prefer to have meetings related to ongoing internal projects in the morning.

Meetings with new customers must be scheduled in the morning.”

**Options:** morning meeting, afternoon meeting.

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# ADVANCED TOPIC

## **Explainable Machine Learning via Argumentation**

*N. Prentzas, C. S. Pattichis, A. C. Kakas: **Explainable Machine Learning via Argumentation**. xAI (3) 2023: pp. 371-398.*

*A. K. & L. Michael, **Abduction and Argumentation for Explainable Machine Learning: A Position Survey**, <https://arxiv.org/abs/2010.12896>*

# Argumentation-based Machine Learning (ArgML)

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**Rules**  $\rightarrow$  **Arguments**

***ML Prediction/Reasoning via  
Dialectic Argumentation***

***In ArgML Prediction can be:  
Definite or Dilemma***

# Argumentation-based Explainable Machine Learning (*ArgEML*)

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**ArgML  $\equiv$  ArgEML**

**Explanation Model  $\equiv$  Argumentation Theory**

# Argumentation-based Explainable Machine Learning (*ArgEML*)

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## Output of *ArgEML*:

### A. Explanatory Predictions

*Attributive and Contrastive Explanations*

*B. Explanatory Problem Partition (XPP)*

# *ArgEML* Metrics

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- **Definite Accuracy**
- **Amount of Ambiguity**
- **Quality of Explanations**
- **Compactness of Explanatory Problem Partition (XPP)**



# Medical Peer Companion Applications

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**Integrated XML with Symbolic Reasoning**  
**Hybrid approach**

- **CARDIOLOGICA: U-prevent Calculators to Reasoners**
- *M. Sclerosis, Alzheimer, Aneurysm: XAI analysis*
- *Emergency Hospitalization (ICU): Chart problem space*

# Endometrial cancer Explanation Spaces

$$\text{Compactness (Theory-b1)} = 0.1/0.9 * 10 = 1.1$$

preferred

Theory-b1					
Group	Explanation Pattern	prediction	type	coverage	accuracy
Group 1	r1	benign	definite	30%	79%
Group 2	r2	malignant	definite	27%	87%
Group 3	r3	benign	definite	11%	60%
Group 4	r4	malignant	definite	9%	67%
Group 5	p3;r1 p4;r9	dilemma	dilemma	3%	n/a
Group 6	p14;p1;r3 p2;r8	dilemma	dilemma	3%	n/a
Group 7	p14;r3 p15;r9	dilemma	dilemma	3%	n/a
Group 8	r3 r8	dilemma	dilemma	3%	n/a
Group 9	p5;r1 p6;r8	dilemma	dilemma	2%	n/a
Other				10%	

$$\text{Compactness (Theory-b2)} = 0.1/0.9 * 11 = 1.22$$

Theory-b2					
Group	Explanation Pattern	prediction	type	coverage	accuracy
Group 1	r1	benign	definite	31%	80%
Group 2	r2	malignant	definite	27%	87%
Group 3	r3	benign	definite	11%	60%
Group 4	r4	malignant	definite	9%	67%
Group 5	p35;p14;p23;r3 p15;p36;p2;p34;r8	dilemma	dilemma	3%	n/a
Group 6	r3;p29;r1 p30;r8	dilemma	dilemma	3%	n/a
Group 7	p14;p35;r3 p2;p24;r9	dilemma	dilemma	2%	n/a
Group 8	p3;p25;r1	benign	definite	2%	71%
Group 9	p5;p27;r1 p2;p6;p28;r8	dilemma	dilemma	2%	n/a
Group 10	r3 p4;p26;r9	dilemma	dilemma	2%	n/a
Other				11%	

# Aneurysm

## Example Explanation

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«This case is **Predicted to "Unrupture"**:

This is **supported** by the fact "the aspect ratio is medium". This reason is **strengthened** against the reason "the mean curvature is medium" supporting **rupture** by the fact that the "mean radius is high" and the fact that the "location is not aca".

Also, the prediction for **urupture** in this case is **positively affected** by the facts: "size ratio is vlow" and "maneyrsm is 0". »

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**THANK YOU**