Prototype Pseudo-Metacognition Module for

AI Reasoning

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Bottom Line Up Front

The Challenge of Robust Dialogue Management (RDM), which is a core capability needed for: Conversational AI Agents (CAA)

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1 Introduction

CAA Inductive Reasoning (IndR) Approaches have been largely unexplored…

1 Introduction cont’d

Aristotle/Ptolemy/Galileo & Kepler

1 Introduction cont’d

Aristotle & Apollo 15 Hammer-Feather Drop

Source: National Aeronautics and Space Administration (NASA)

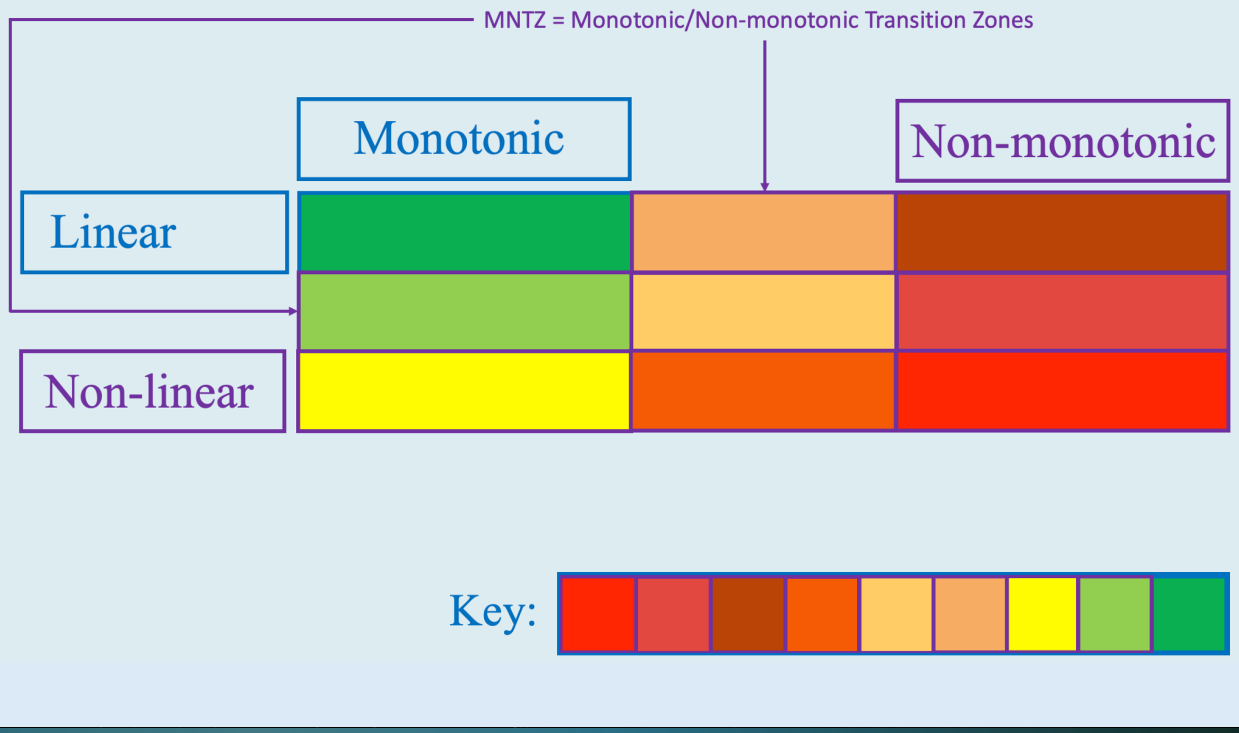
1 Introduction cont'd

At the event horizon, even light cannot escape…

Source: U.S. Department of Energy and Sophia Dagnello, National Radio Astronomy Observatory (NRAO)/Associated Universities (AUI)/National Science Foundation (NSF)

1 Introduction cont'd

Monotonic versus Non-monotonic



2 Background

A Pragmatic Reasoning Method & Reasoning Behavior for CAA: Case-Based Reasoning (CBR)->Graph-Based Reasoning (GBR)

2 Background cont'd

Reasoning Methods with their Validities & Temporal Spans

RM	*Validity*	*Temporal Span*	
DedR	*Guaranteed to be true*, if the premises and argument are valid.	Typically back-loaded, as it unfolds ineratively in a "bottom-up" fashion.	UDC
IndR (can include AnaR, CBR, and GBR)	*Likely to be true*, but it could be false despite the observations being accurate.	Typically front-loaded, but it can also unfold in a "bottom-up" fashion.	CDC
AbdR	*Can be true* (but might not be), as it involves a plausible best guess approximation or a posit as to the optimal explanation.	Typically front-loaded, but as it has various sensitivities (e.g., uncertainty/information gaps/ambiguity/ multiplicity, etc.) it can also unfold in a "bottom-up" fashion.	

Source: U.S. Department of Energy and Sophia Dagnello, National Radio Astronomy Observatory (NRAO)/Associated Universities (AUI)/National Science Foundation (NSF)

2 Background cont'd

Low Ambiguity Higher Uncertainty (LAHU)/HALU Module (LHM)

Ambiguity/ Uncertainty	*Descriptor*
Higher Ambiguity, Lower Uncertainty (HALU)	Under a paradigm of UDC, and for the situation wherein prior cases do *not* exist (i.e., a paradigm of higher ambiguity), there needs to be a proactive seeking of more data (since time is readily available under UDC) so as "to lower uncertainty" and move towards a more acceptable state (i.e., a paradigm of lower uncertainty)
Lower Ambiguity, Higher Uncertainty (LAHU)	Under a paradigm of CDC, and for the situation wherein prior cases do indeed exist (i.e., a paradigm of lower ambiguity), there is more tolerance for sparse data/no data (a paradigm of "higher uncertainty"), particularly if time is of the essence)

2 Background cont'd

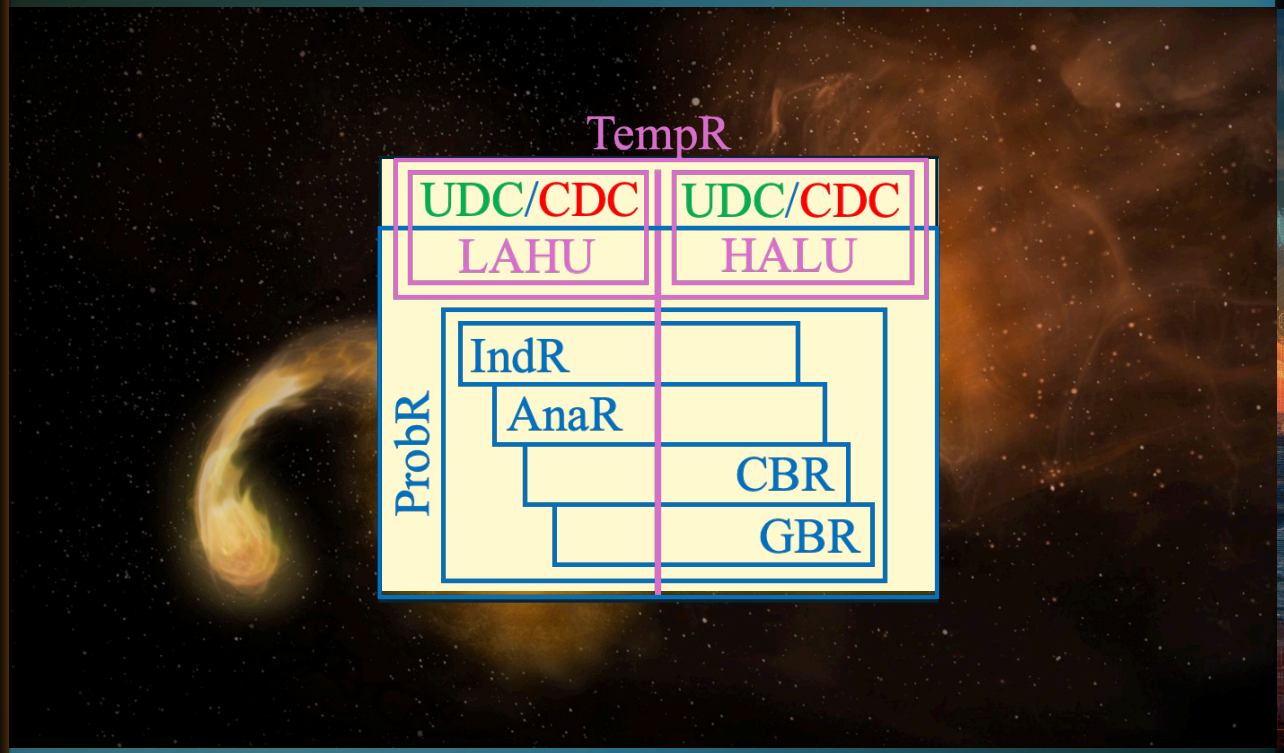
RMs and RPs under UDC and CDC (with zero-shot circumstances)

Validity	*HALU-centric*		*Validity*	*LAHU-centric*		
	UDC			*CDC*		
Guaranteed	DedR	*MR*	Probable	IndR	*WMR*	*NMR*
				AnaR	*NMR*	
				CBR	*CMR*	*NMR*
				GBR	*MR*	*NMR*
			Possible	AbdR	*NMR*	

Source: U.S. Department of Energy and Sophia Dagnello, National Radio Astronomy Observatory (NRAO)/Associated Universities (AUI)/National Science Foundation (NSF)

2 Background cont'd

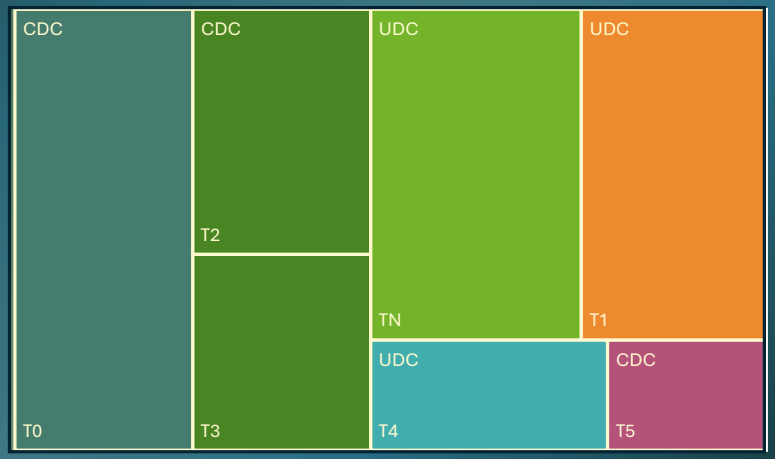
Temporal Span & Temporal Reasoning



Source: U.S. Department of Energy and Sophia Dagnello, National Radio Astronomy Observatory (NRAO)/Associated Universities (AUI)/National Science Foundation (NSF)

2 Background cont'd

TempR embodiment over an Elongated Temporal Span via LAHU:HALU amidst UDC/CDC circumstances

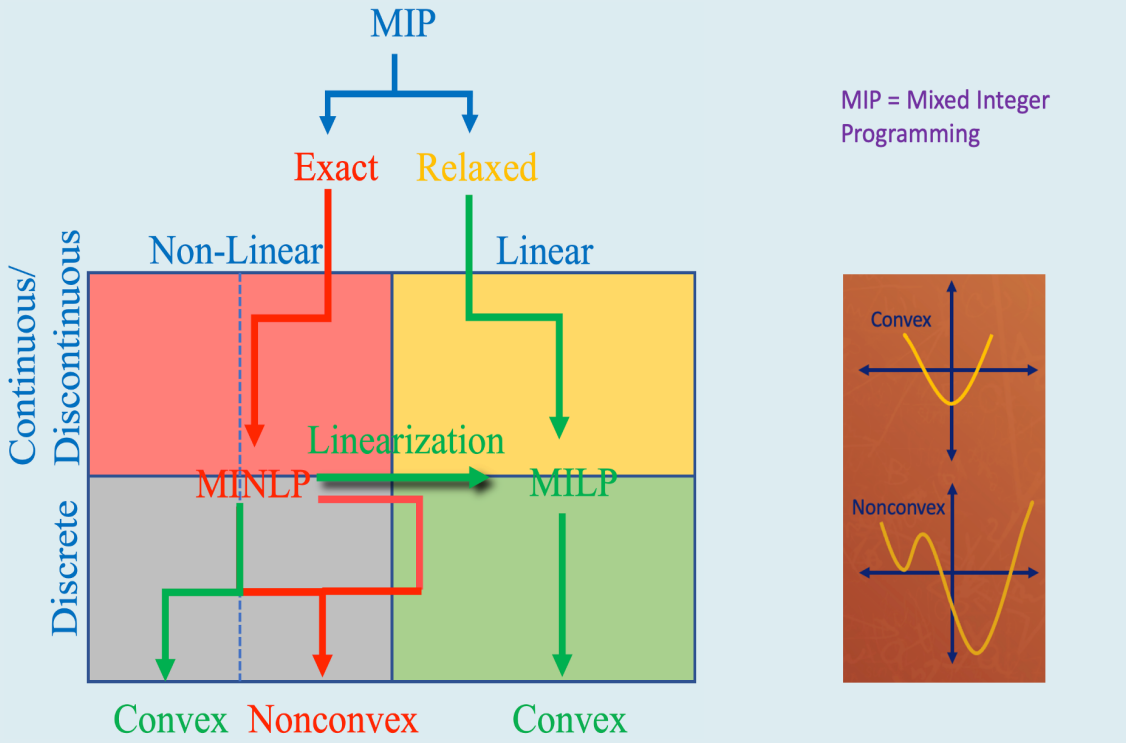


3 The Paradox

(Deductive) Top-Down versus (Inductive) Bottom-Up

3 The Paradox cont'd

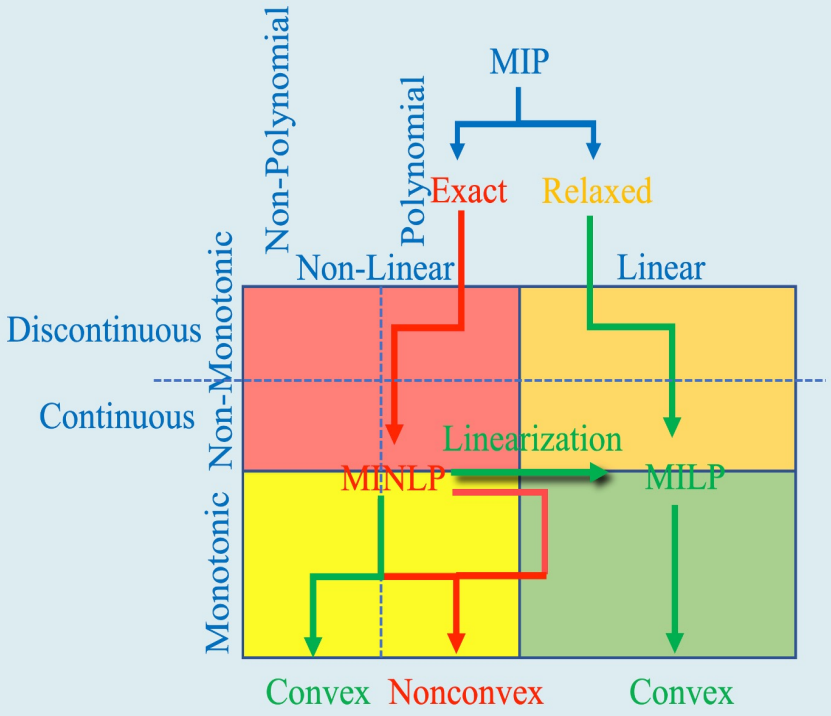
Monotonic versus Non-monotonic



MIP = Mixed Integer Programming

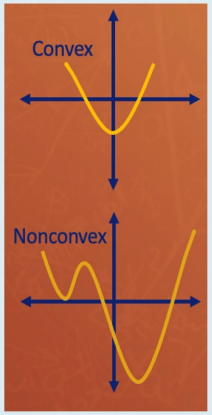
3 The Paradox cont'd

Monotonic versus Non-monotonic



MINLP = Mixed Integer Non-linear Programming

MILP = Mixed Integer Linear Programming

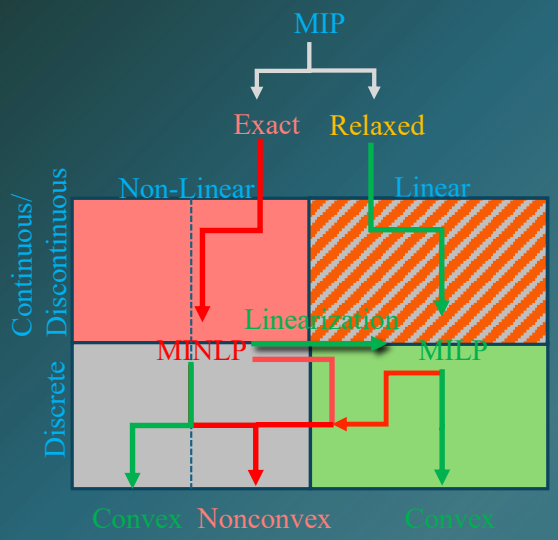


3 The Paradox cont'd

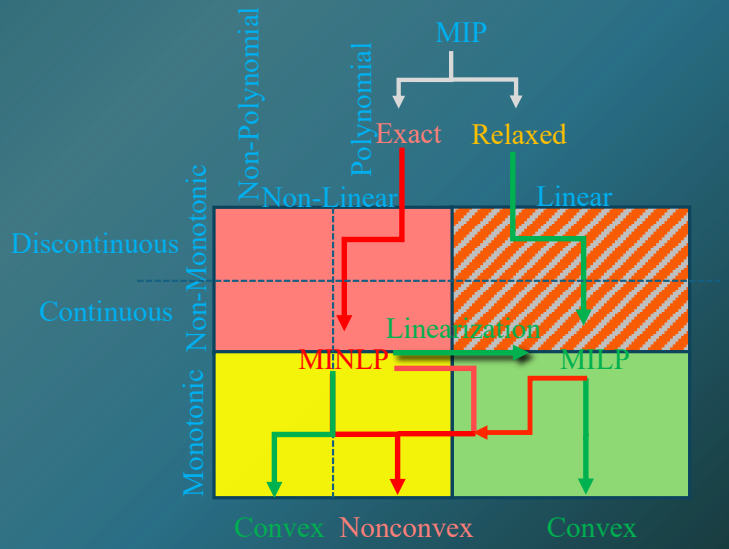
NP-Hard Spawning

- Mixed Integer Programming (MIP)
- Mixed Integer Linear Programming (MILP)
- Mixed Integer Non-Linear Programming (MINLP)

Non-convex to convex Transformation Pathways (e.g., non-convex discontinuous non-linear MINLPs to convex form)



Non-convex to convex Transformation Pathways (e.g., non-convex[non-monotonic, discontinuous] non-polynomial MINLPs to convex form)



3 The Paradox cont'd

Data-based Decision Support/Decision-Making and Kahneman, Klein, and the isomorphic-centric LAHU/HALU

- **Kahneman System 1 -> potential biases**
- **Klein Recognition-Primed Decision-Making (RPD)**
  - Highly-trained Tasks
- **Low Ambiguity High Uncertainty (LAHU)**
  - Reduces the need for more Big Data
- **High Ambiguity Low Uncertainty (HALU)**
  - Necessitates more Big Data (and elongates Gestaltian Closure)
- **Kahneman System 2 -> potential overthinking/overtraining**

3 The Paradox cont'd

Algorithm vs. Heuristic vs. Hyper-Heuristic

- **Algorithm**
  - According to computer scientist Harold Stone, an algorithm involves "a set of rules that precisely define a sequence of operations" (i.e., "it endeavors to determine an optimal solution that usually involves more computational time").
- **Heuristic**
  - According to Gigerenzer & Gaissmaier, a heuristic is "a problem-solving method that does 'not guarantee an optimal solution,' and is 'a strategy that ignores part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods'" (i.e., "it endeavors to determine a good solution with less computational time"). STEA/I&E can help detect for potential errors, biases, and brittleness as well as areas for optimization and enhancement.
- **Hyper-Heuristic:**
  - According to Drake and Carvalho, a hyper-heuristic is a "problem-solving method that 'intelligently select[s] or generat[es] a suitable heuristic for a given situation;' it can start simply as a 'heuristic to choose heuristics;' however, when an appropriate heuristic or amalgam of heuristics is not available or sub-optimal, a new heuristic(s) may need to be generated. Zhao and others (e.g., Bouazza) refer to this as an algorithm 'that adaptively selects the optimizer to address complex problems.'"

4 Experimentation

Explorations into a Prospective Metacognition Module (MM)

4 Experimentation cont'd

Monotonic versus Non-monotonic

	Monotonic	Non-monotonic
Linear	D rho tau PPMCC PBCC dCor	N/A
Non-linear	PPMCC rho tau PBCC dCor D	MC dCor D PPMCC rho
Curvilinear	Rho PBCC dCor PPMCC tau	dCor D PPMCC rho

PCC = Pearson Correlation Coefficient — Linear, Monotonic

dCor = Distance Correlation Coefficient — Any Dependence

D = Hoeffding's D Correlation — Nonlinear, Non-monotonic

ICC = Information Coefficient of Correlation — Can't tell direction…

MI = Mutual Information

MC = Maximal Correlation

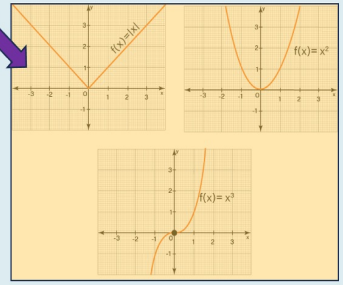
MIC = Maximum Information Coefficient

PPMCC = Pearson's [Product]-Moment Correlation Coefficient (PPMCC)

PBCC = Percentage Bend Correlation Coefficient (PBCC)

rho = Spearman's Rho Correlation Coefficient — No Non-monotonic

Tau = Kendall's Tau Correlation Coefficient — No Non-monotonic



Distinction Between Curvilinear and Non-linear

Source: https://www.cuemath.com/calculus/nonlinear-functions/

4 Experimentation cont'd

Monotonic versus Non-monotonic

Close to 0	Close to 1	Close to -1	Relationship Posits
dCor D tau PPMCC PBCC rho	N/A	N/A	None
rho tau PPMCC PBCC	N/A	N/A	Random
N/A	rho PPMCC	N/A	Strong Positive Monotonic
N/A	N/A	rho PPMCC	Strong Negative Monotonic
rho tau PPMCC PBCC	dCor	N/A	Non-monotonic

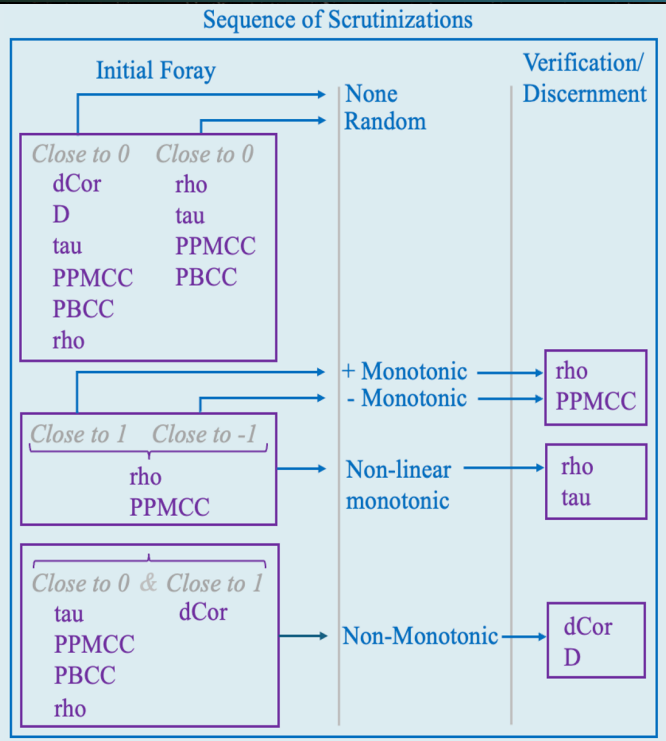
4 Experimentation cont'd

Monotonic versus Non-monotonic

	Mirtagioglu *(M)*	Ranio (*R*)	Heuvel (*H*)
Linear Monotonic	rho PBCC PPMCC dCor tau	PPMCC rho tau	PPMCC MIC
Non-linear Monotonic	rho PBCC dCor tau D	rho tau PPMCC	PPMCC MIC
Curvilinear	dCor D	N/A	PPMCC rho MIC

4 Experimentation cont'd

Monotonic versus Non-monotonic



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Tau = Kendall's Tau Correlation Coefficient

4 Experimentation cont'd

Epistemological constructs

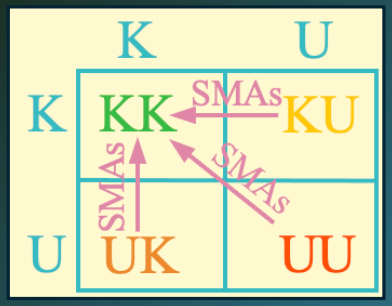
Known Knowns (KK) "Things we are aware of and understand"	***Known Unknowns (KU)*** "Things we are aware of and do not understand"
Unknown Knowns (UK) "Things we are not aware of, but understand"	***Unknown Unknowns (UU)*** "Things we are not aware of and do not understand"

Gekhman's Sampling-based Categorization of Knowledge (Slick) Model

Type	*Category*	*Validity*
Known	"Highly Known" (HK)	"Always"
	"Maybe Known" (MK)	"Sometimes"
	"Weakly Known" (WK)	Almost Never, but Sometimes
Unknown	"Unknown"	"Never"

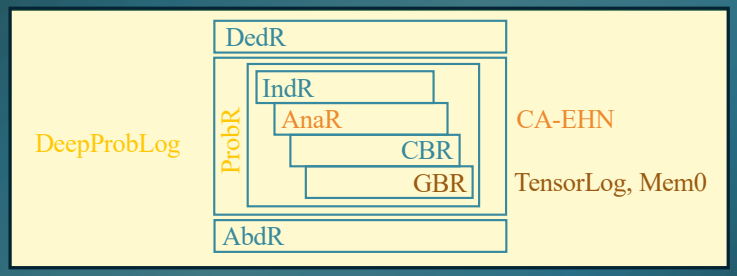
4 Experimentation cont'd

Kanthan's Posit regarding bridging the Known to Unknown



Kanthan's thoughts that the constituent elements of figurative language, such as Similes, Metaphors, and Analogies (SMAs) can "bridge the Known to the Unknown"

Notional Quasi-Mixture of Experts (MOE) Embodiment of Gekhman and Kanthan



Li's Commonsense Analogy from E-HowNet (CA-EHN) and AnaR

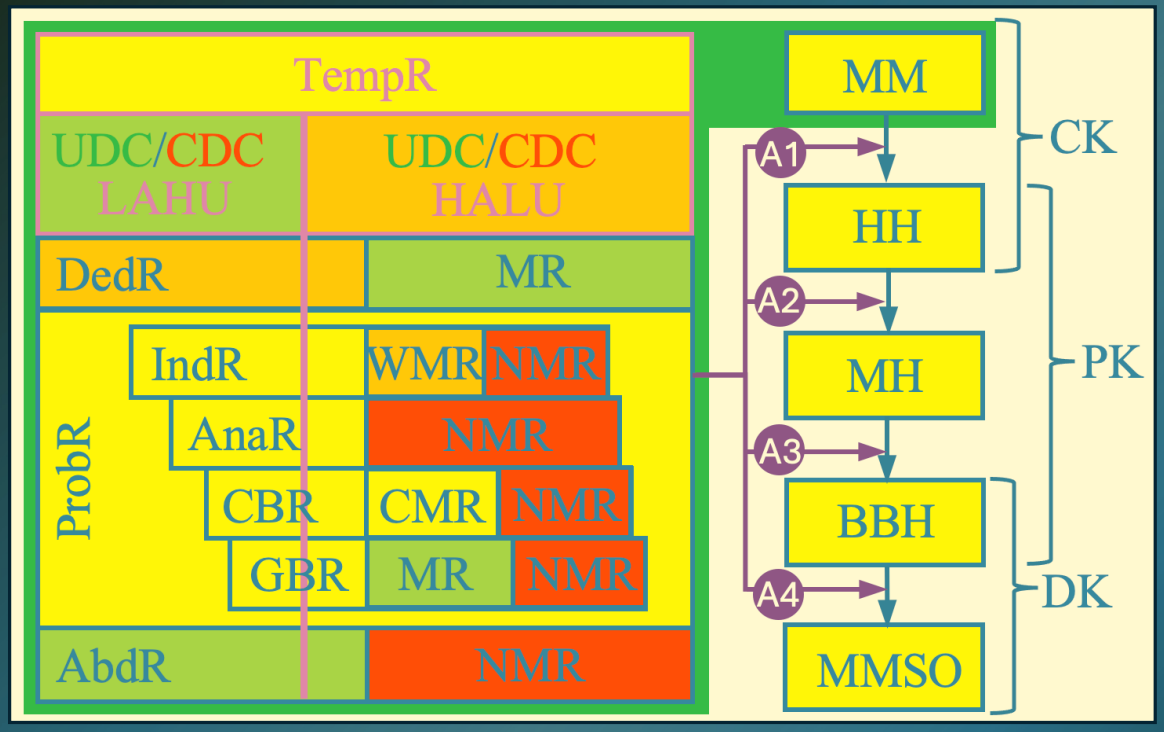
Chhikara's Mem0 and GBR

Cohen's TensorLog and GBR

Manhaeve's DeepProbLog and ProbR

4 Experimentation cont'd

Prototype MM Embodiment Architecture



Multi-Attribute Decision-Making (MADM) and/or Multi-Objective Decision-Making (MODM) Subjective/Objective (MMSO)

Declarative Knowledge (DK): (e.g., recitals of fact, concepts)

Procedural Knowledge (DK): (e.g., step-by-step skills, knowing how)

Conditional Knowledge (CK): (e.g., knowing when and why)

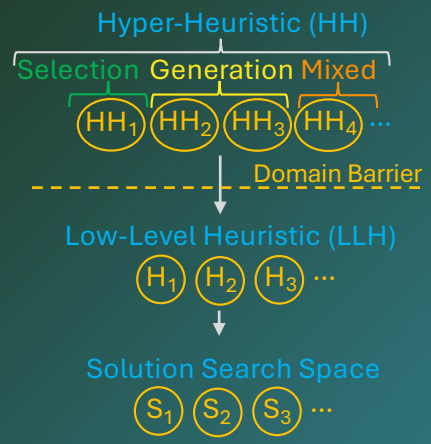
Dong:
2 error types: (1) factual, such as mistakes in specific solution steps, and (2) thinking errors, which are flaws in the reasoning.

5 Conclusion

IndR Possibilities and the Prospects for Enhanced Coherence

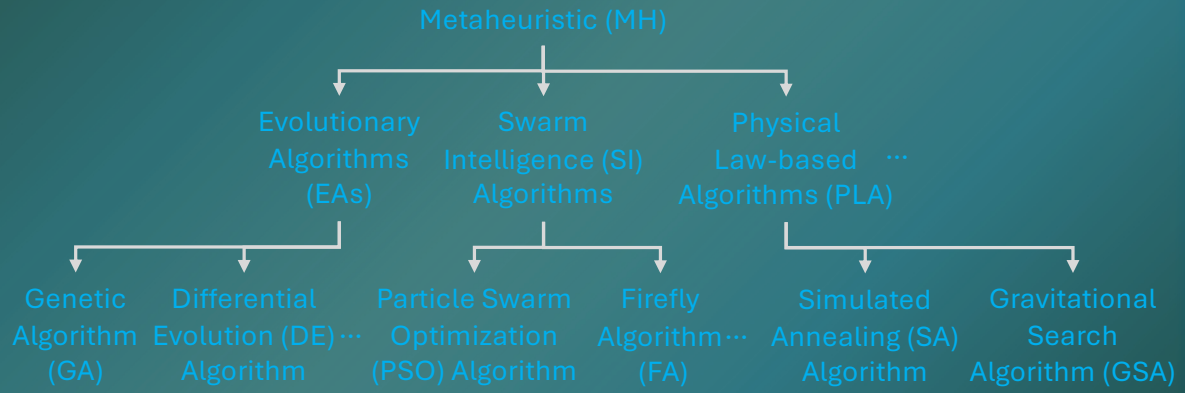
5 Conclusion cont'd

Exemplar HH Construct

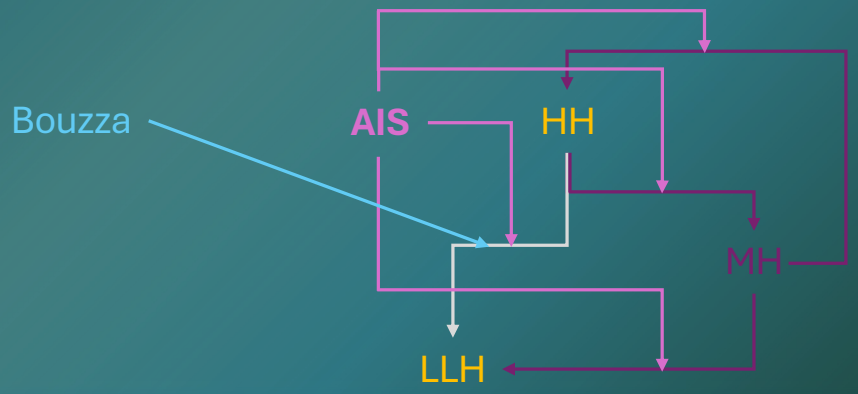


Based upon Bouazza's work in: W. Bouazza, "Machine Learning-Based Hyper-Heuristics: A Clear Insight," Proc. of the 2024 7th Int. Conf. on Comput. Intell. And Intell. Syst. (CIIC), Feb. 2025, pp. 29-37.

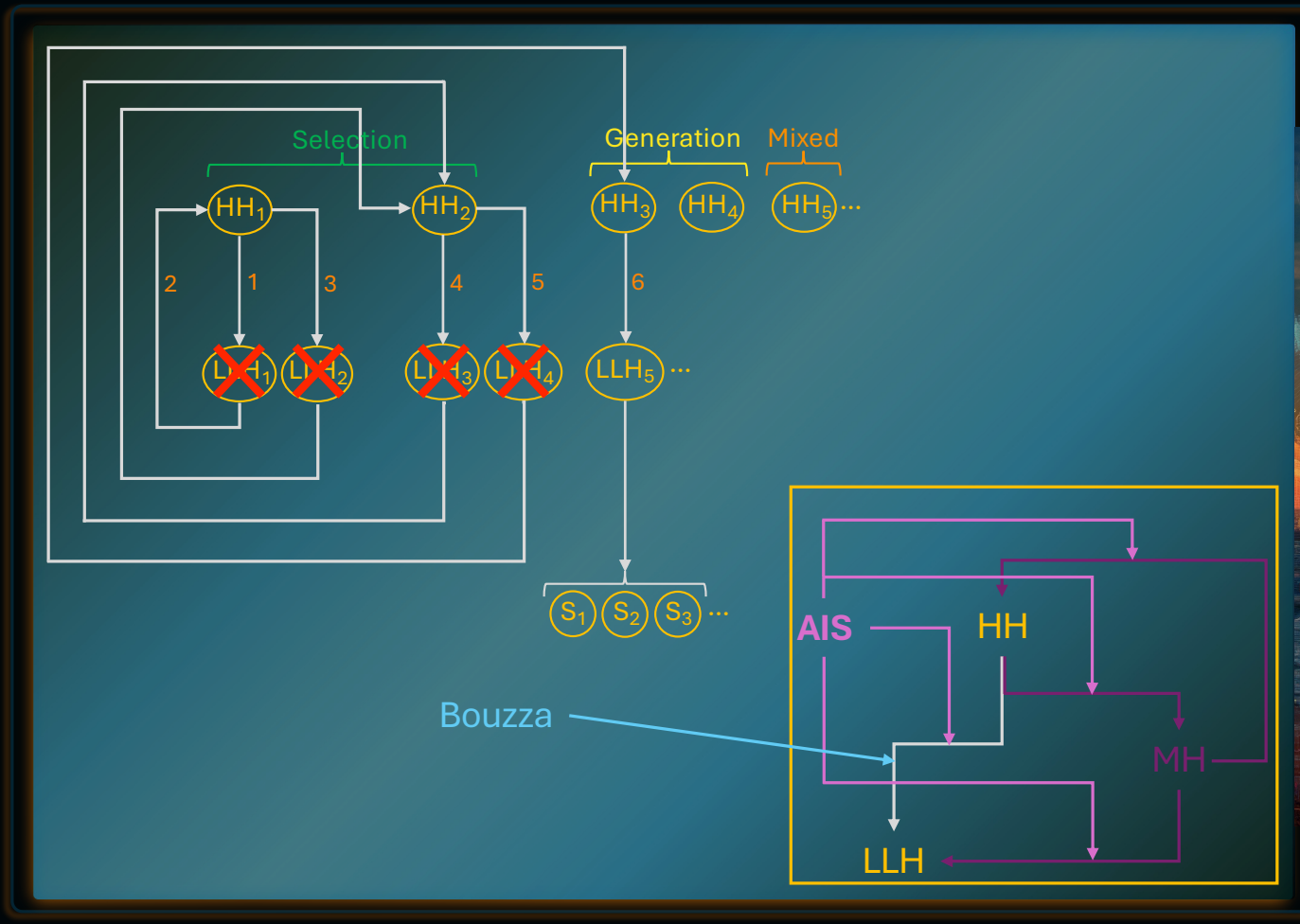
Exemplar Metaheuristic Schema



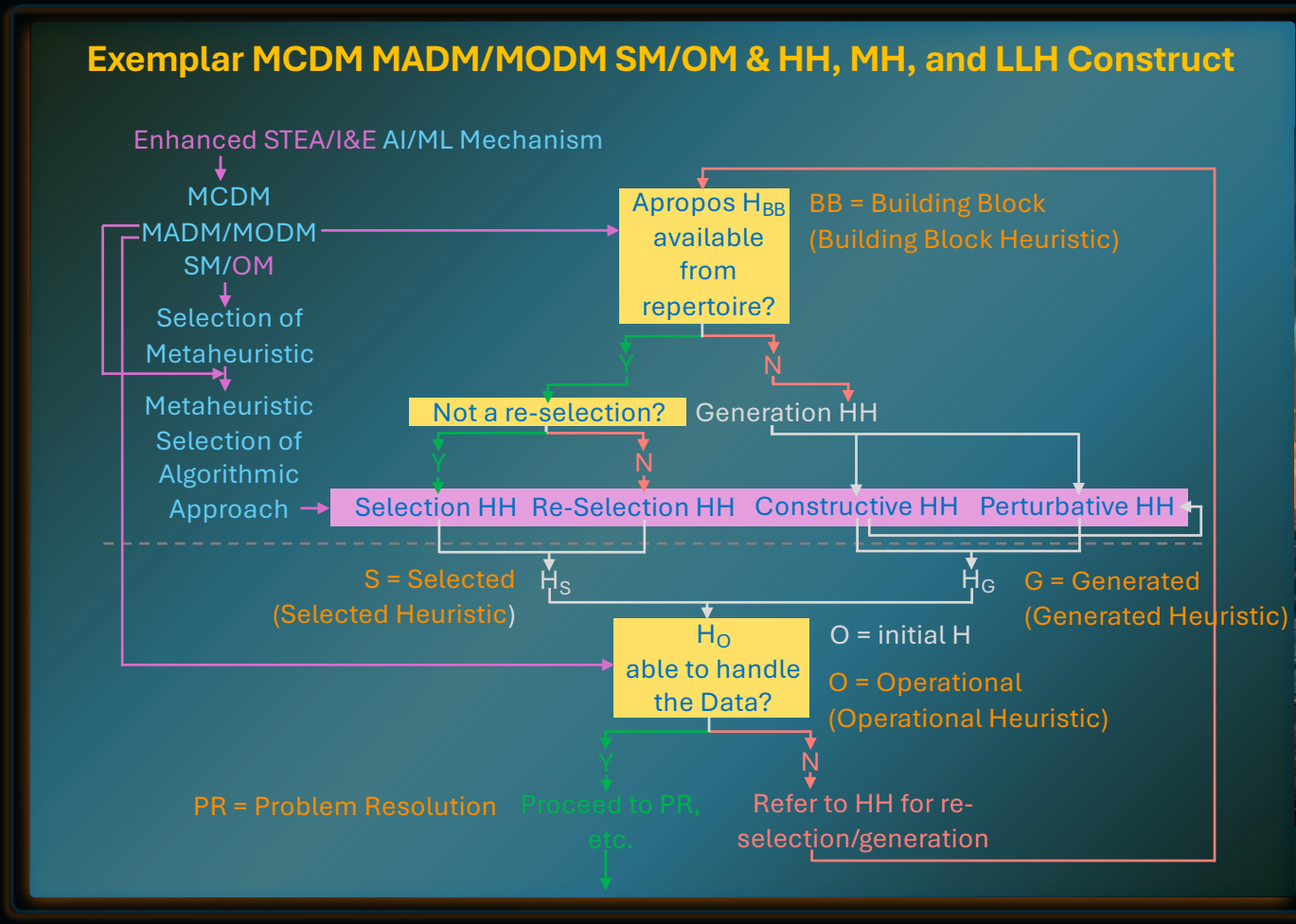
Exemplar HH, MH, and LLH Schema



5 Conclusion cont'd



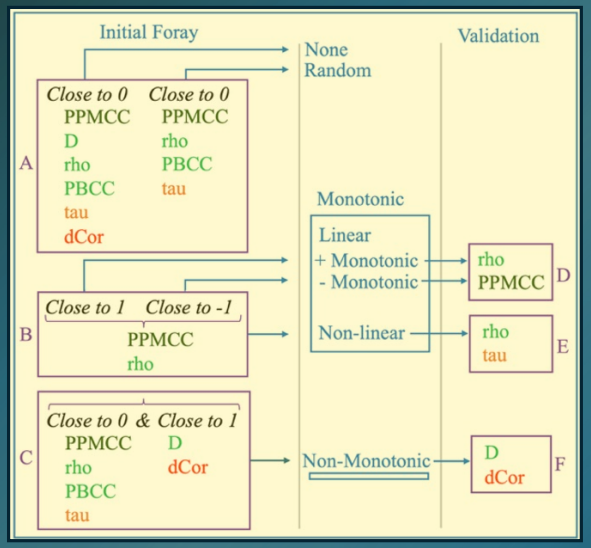
5 Conclusion cont'd



5 Conclusion cont'd

- **Advancing the state of CAA Coherency:**
  - IndR, AnaR, CBR
  - Graph-Based Reasoning (GBR) to support CBR
  - Pre-Isomorphic Paradigms (IsoP), Relaxed IsoP, IsoP, and Post-IsoP

- **MNTZ inclinations for various measures, RMs, and RPs:**



UDC		*CDC*		
DedR	*MR*	IndR	*W MR*	*NMR*
		AnaR	*NMR*	
		CBR	*C MR*	*NMR*
		GBR	*MR*	*NMR*
		AbdR	*NMR*	

5 Conclusion cont'd

Paradigm of "Construct Validity Amidst Uncertainty:"

- *CnVx = Content Validity*
  - Topic
- *CsVx = Construct Validity*
  - Concept

Depth (& Accuracy); Breadth → Depth vs. Breadth

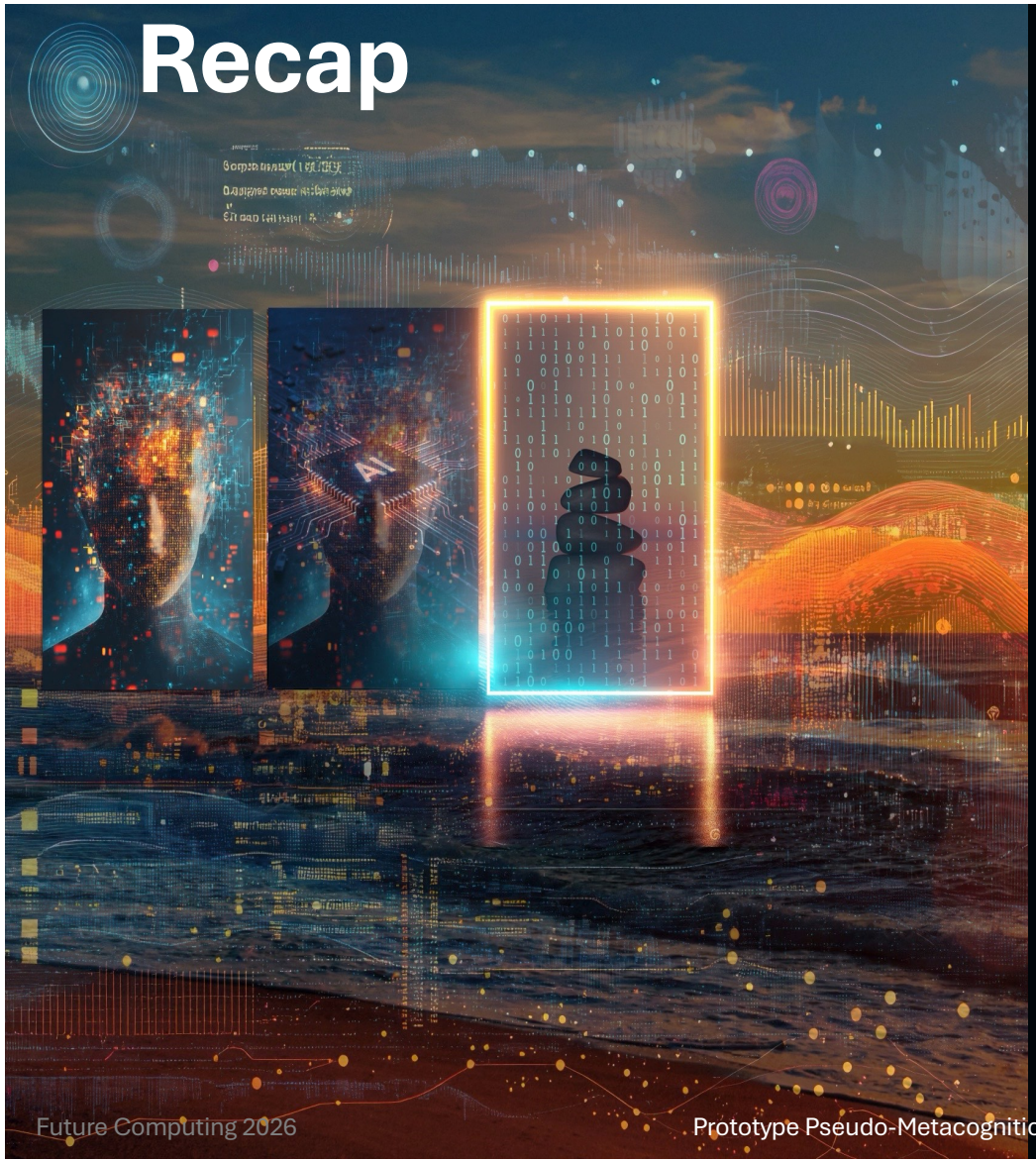
- *CcVx = Concurrent Validity*
  - Correlation of new test with previously validated tests
- *CtVx = Criterion-related Validity*
  - Extent of Agreement with "Platinum Standard"

Temporal considerations; Conventional metrics → Temporal vs. Non-temporal

- *PdVx = Predictive Validity*
  - Robustness of Posit with regards to future behavior

Non-Temporal "Platinum Standard" Consideration

Recap



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(Deductive) Top-Down versus (Inductive) Bottom-Up

4 Experimentation
Explorations into a Prospective Metacognition Module (MM)

5 Conclusion
IndR Possibilities and the Prospects for Enhanced Coherence

Thank you very much for your time and attention!

Questions?