A Prospective Monotonic/Non-Monotonic Transition Zone Impediment for Concept Model-Centric Artificial Intelligence Systems

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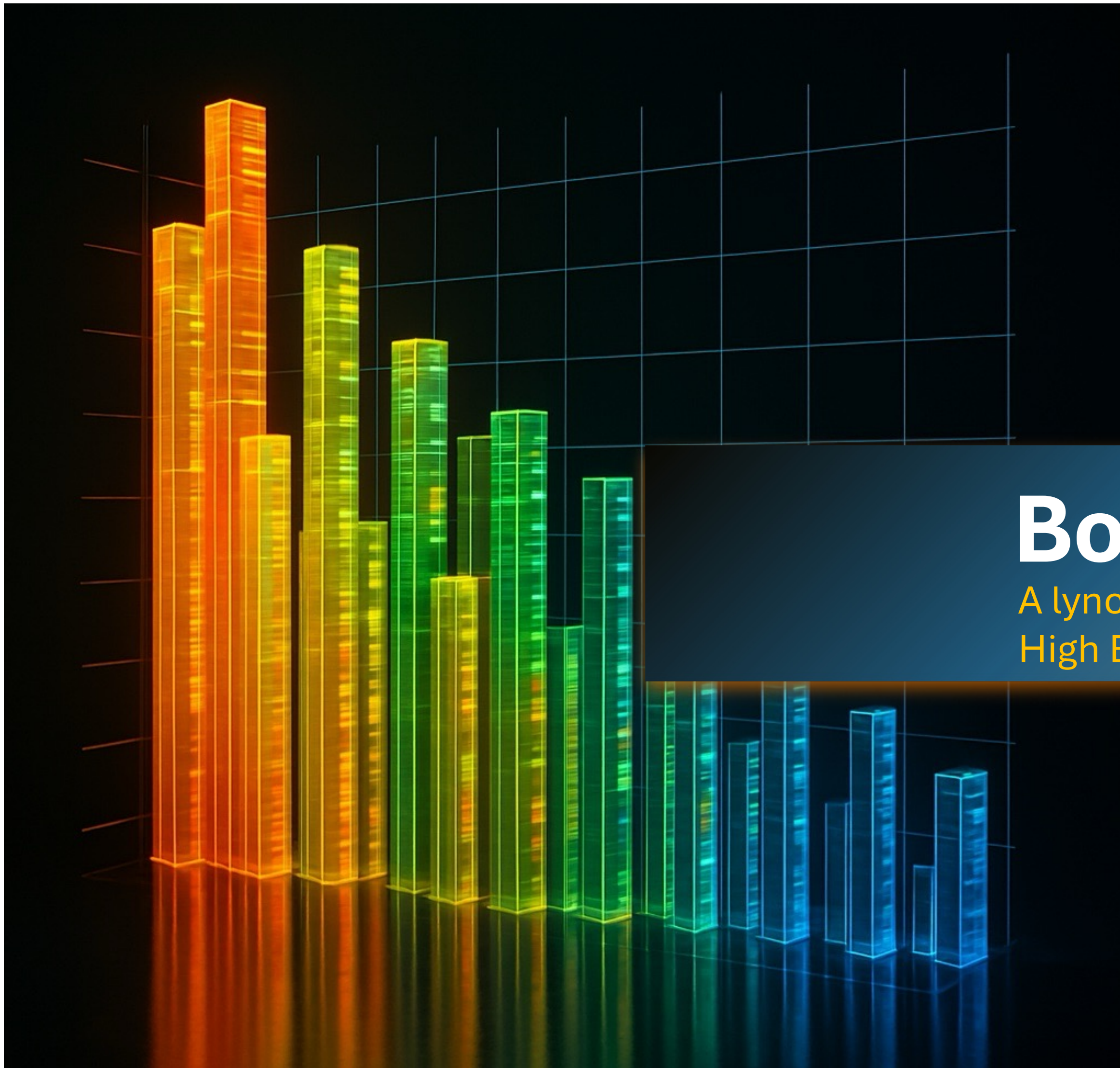

Bottom Line Up Front

A lynchpin for Machine Learning (ML) on ML:
High Efficacy Knowledge Transfer (KT)

BLUF cont'd

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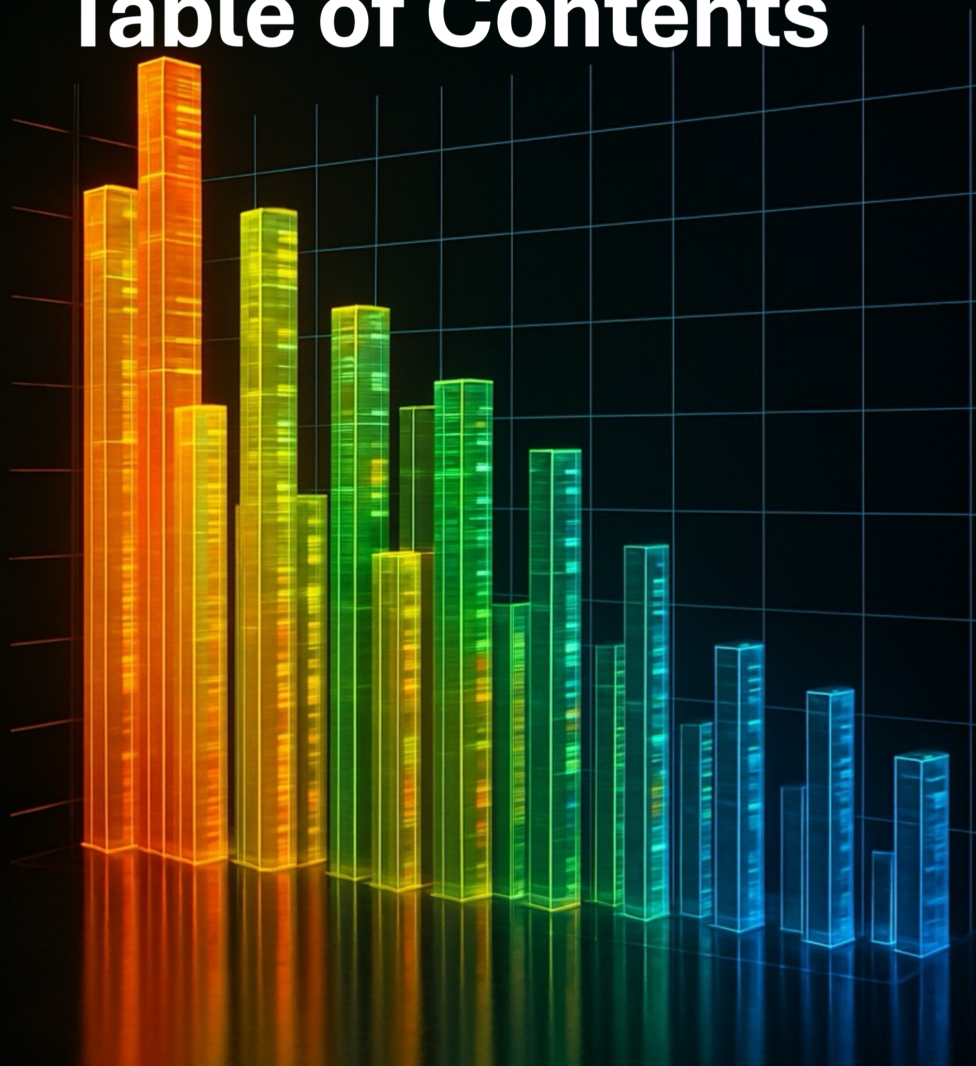
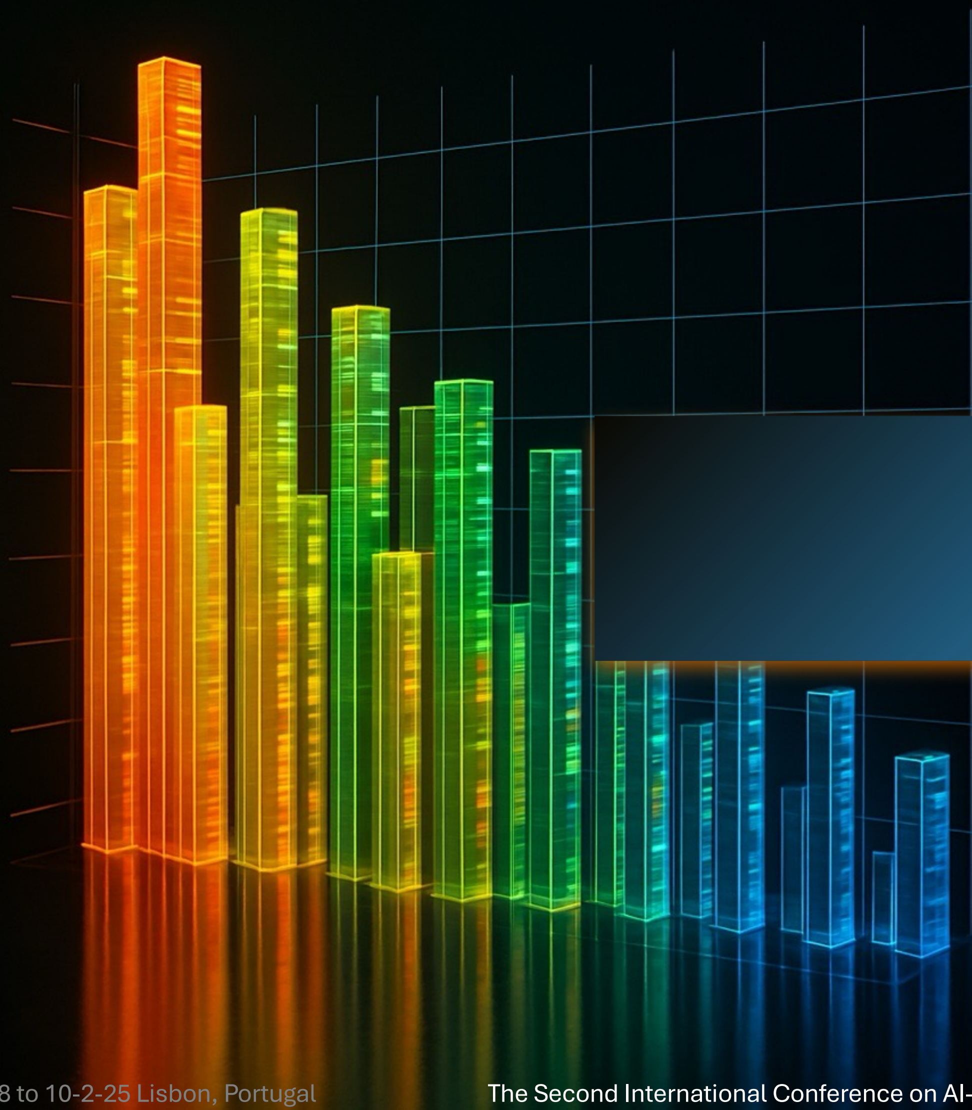
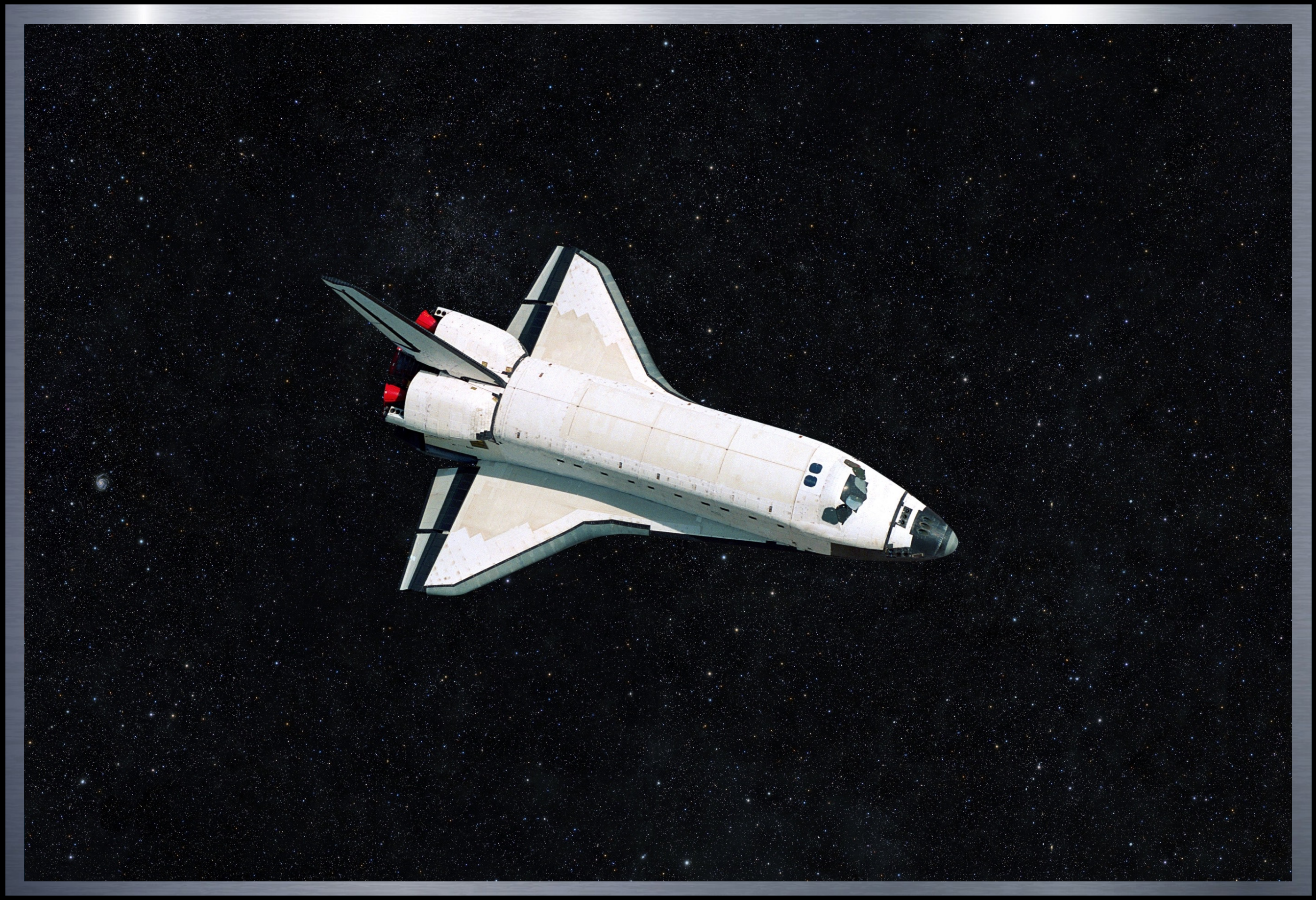




1 Introduction

Historical case study and contemporary case of a prospective AI System (AIS) Achilles heel

Introduction cont'd

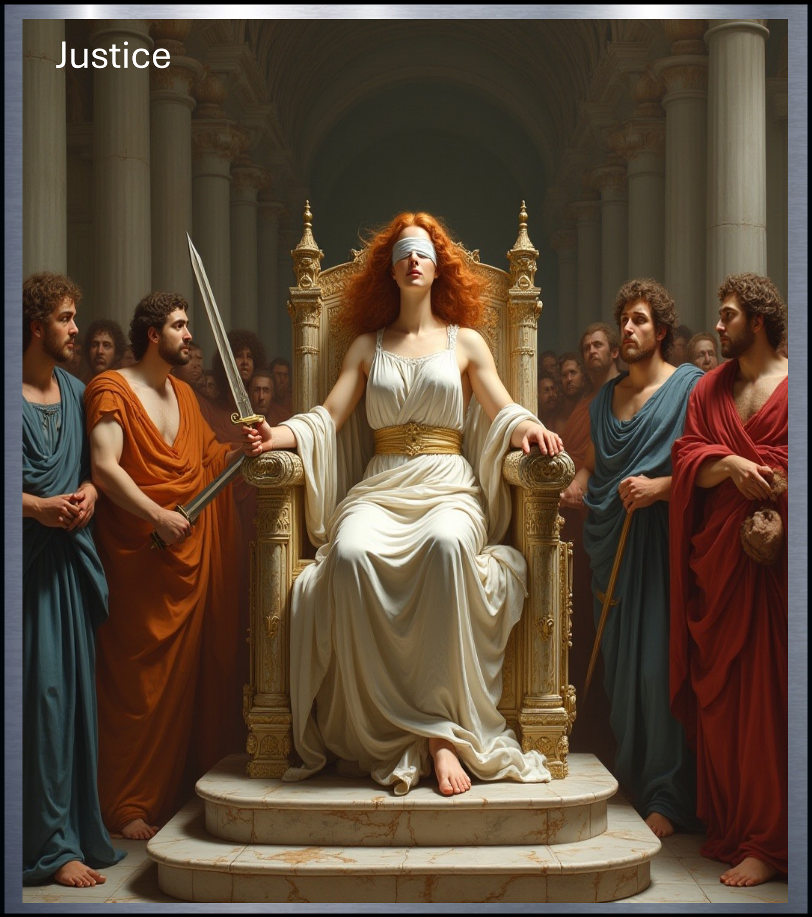


Introduction cont'd

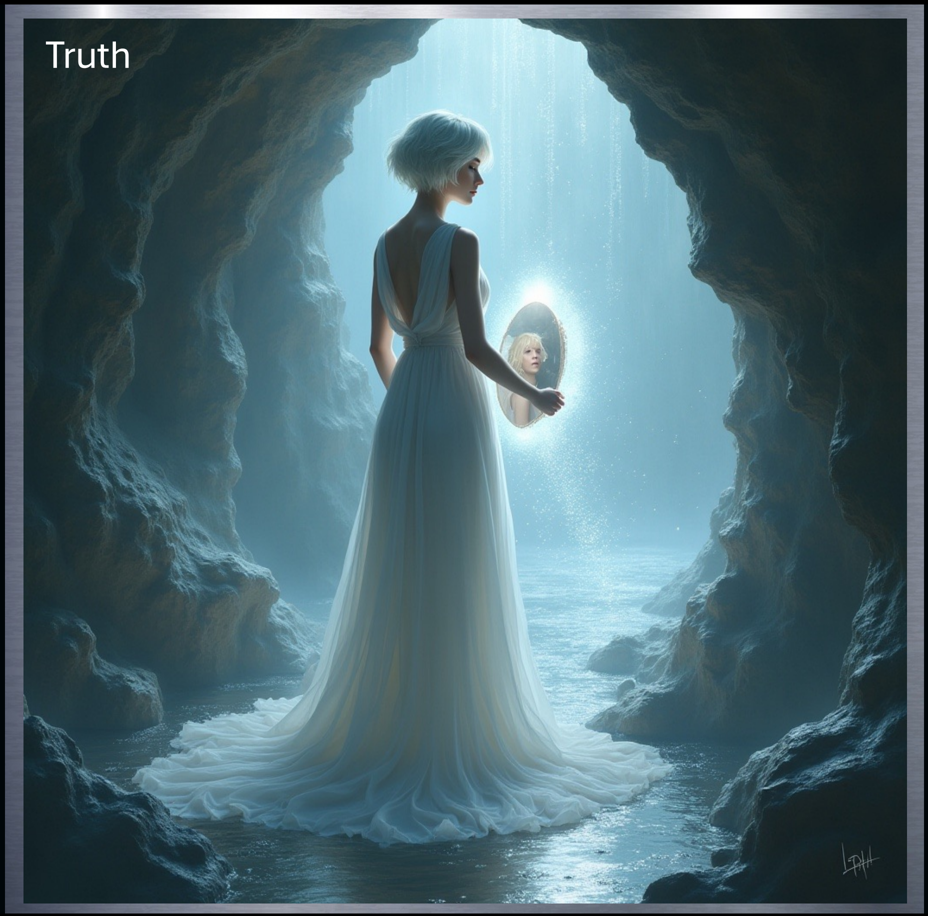
- **Historical Case Study: Foam Shedding**
  - Space Shuttle Columbia disintegration on 1 Feb 2003.
  - NASA Commission: certain phenomena had become accepted over time; thermal insulating foam (which prevented ice from forming when the external fuel tank was full of liquid hydrogen and oxygen) had been observed falling off on several prior NASA mission – Challenger, Atlantis, and Challenger.
  - Cause of disintegration: a piece of insulating foam breaking off, striking the left wing, and cause a hole that allowed "super-hot atmospheric gases" to enter the wing when the Space Shuttle Columbia later re-entered the atmosphere.
  - NASA Commission: "the Shuttle is now an aging system but still developmental in character."
  - NASA Commission: "reliance on past success as a substitute for sound engineering practices."
  - "Foam Shedding."

Introduction cont'd: Parables/Allegories

Introduction cont'd: Allegories



Introduction cont'd: Allegories



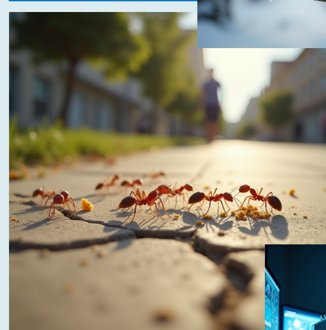
Introduction cont'd

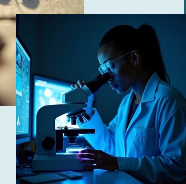
- **Contemporary Case: Inferred Latent Variables (ILVs)**
  - Machine Learning (ML) on ML
  - Knowledge Transfer (KT)
  - Domain Communication Channel (DKC)
  - *Varied Connotational Meaning versus Denotational Meaning*
  - *Attributes -> ILVs -> Estimated Parameter Class (i.e., abstract concept)*
  - *Issues when the ratio of Attributes : ILVs is 1-to-Many or Many-to-1*
  - **The above 3 items are among contemporary "foam shedding" items**

Introduction cont'd

Prototypical Categories

Estimated Parameter Class	Interim Notions	Attributes
Abstract Concept Notion Predicted Class Unknown Parameter Estimated Parameter Class	Unobserved Variables Interim Notions Hidden Underlying Factors Latent Traits Inferred Latent Variables	Observed Observation Variables Measured Variables Indicators Items Measures Attributes





Introduction cont'd

- **Contemporary Case: Inferred Latent Variables (ILVs)** cont'd
  - Interpretability & Explainability (I&E)
  - Human-Informed Repertoire of Experience (HIRE) versus Machine-Processed Repertoire of Experience (MPRE)
  - Likert vs Non-Likert-based information approaches
  - *Information loss and bias in Likert approaches*
  - **The above item are among contemporary "foam shedding" items**
  - Likert-based HIRE may potentially constitute "foam shedding" for current decision-making/decision-support architectures

Introduction cont’d

- **Contemporary Case: Inferred Latent Variables (ILVs)** cont’d
  - Likert vs Non-Likert-based information approaches

Likert

Pros	Cons
Data-Driven Decisions Converts feedback into measurable data	**Neutral Bias** Middle option may mask true opinions
User-Friendly Easy and quick to complete	**Lacks Detail** Doesn’t reveal reasons behind responses
Rich Feedback Suitable across industries	**Safe Responses** Neutral or “safe” choices may distort results
Quick Analysis Easy to spot trends	**Oversimplified** Scale points can be misunderstood
Versatile Goes beyond yes/no answers	**Interpretation Issues** May miss subtle differences

https://www.zonkafeedback.com/blog/likert-scale

Introduction cont'd

- **Contemporary Case: Inferred Latent Variables (ILVs)** cont'd
  - Likert vs Non-Likert-based information approaches

Non-Likert

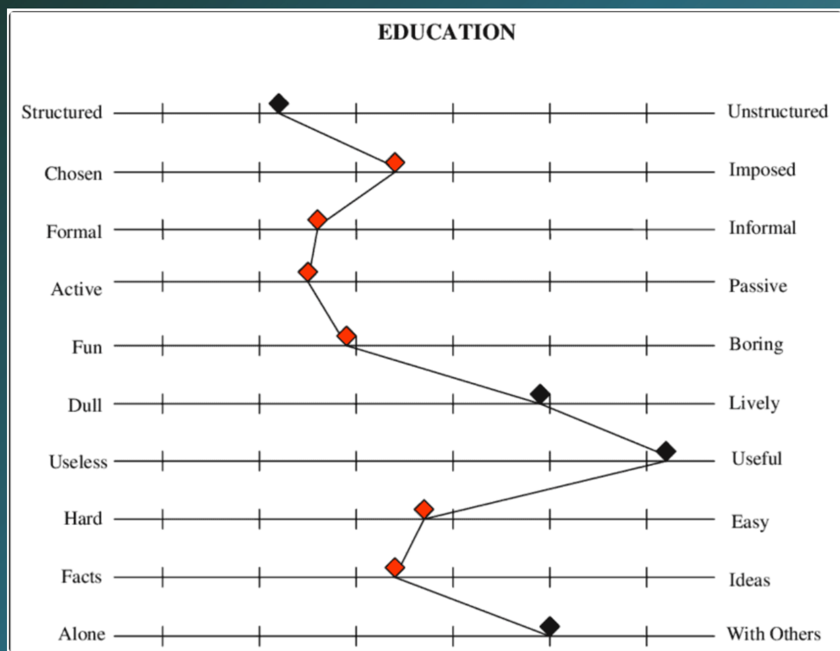
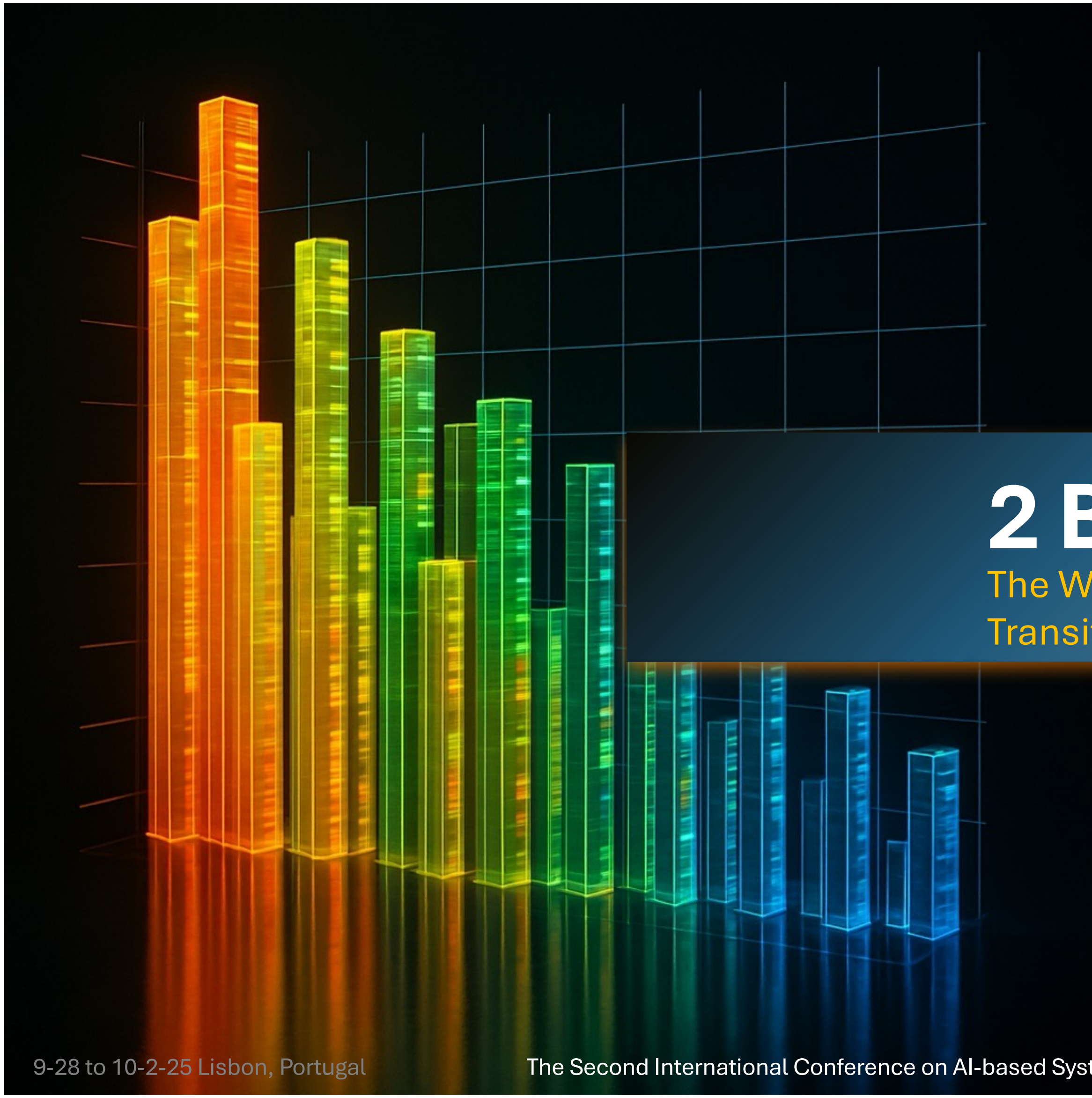


Image: ResearchGate

https://ahaslides.com/blog/semantic-differential-scale/

Introduction cont’d

- **Contemporary Case: Inferred Latent Variables (ILVs)** cont’d
  - Non-Likert-based approaches (e.g., Semantic Differential, which uses polar opposites, such as “strong weak”) necessitate a higher level of abstraction-level (i.e., concept-centric) thinking
  - Inductive Reasoning (IndR) -> Analogical Reasoning (AnaR) -> Case-Based Reasoning (CBR), ideally, leverage Lower Ambiguity Higher Uncertainty (LAHU) & Higher Ambiguity Lower Uncertainty (HALU)
  - The leveraging of LAHU/HALU moves the paradigm closer to Real-World Scenarios (RWS), which also involve temporal considerations, such as System 1/System 2 (which constrains the computational approaches utilized).
  - The Unknowns of the involved computational approaches segues into the notion of Monotonic/Non-Monotonic Transition Zones (MNTZ).



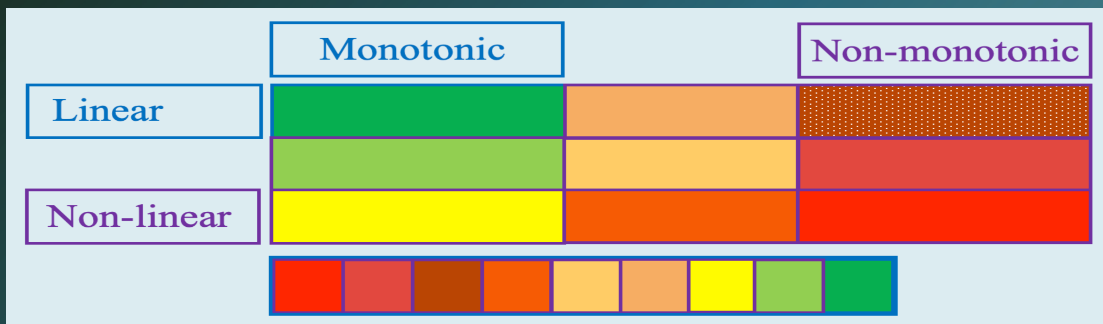
2 Background

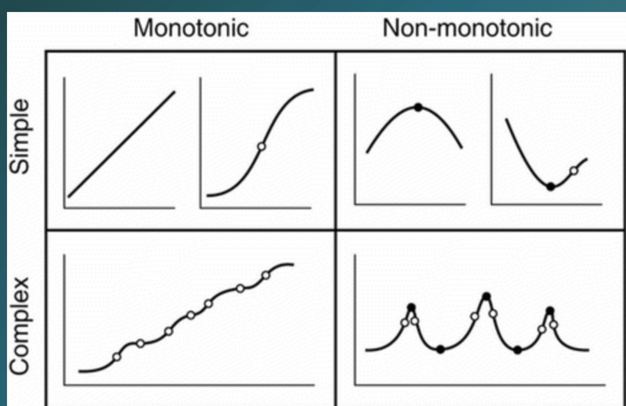
The Wild Wild West of Monotonic Non-Monotonic Transition Zones (MNTZs)

Background cont'd

Background cont’d

- **Brittleness and Volatility in the Monotonic Non-Monotonic Transition Zones (MNTZs):**





Source: https://www.sciencedirect.com/science/article/abs/pii/S0167865524000898

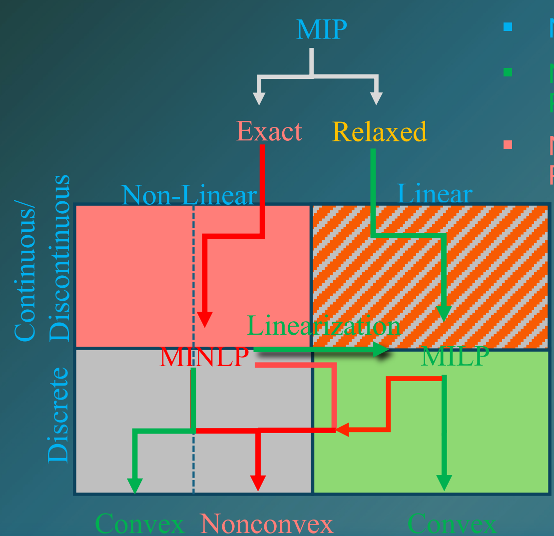
Background cont'd

- **Spawning of Non-deterministic Polynomial Time (NP)-Hard Non-Monotonic, Non-Polynomial, and Non-Continuous Functions within and abutting the MNTZ**

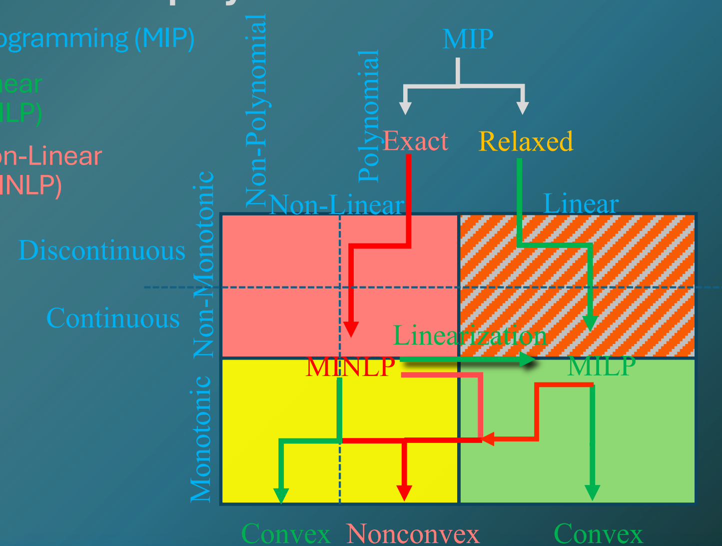
NP-Hard Spawning

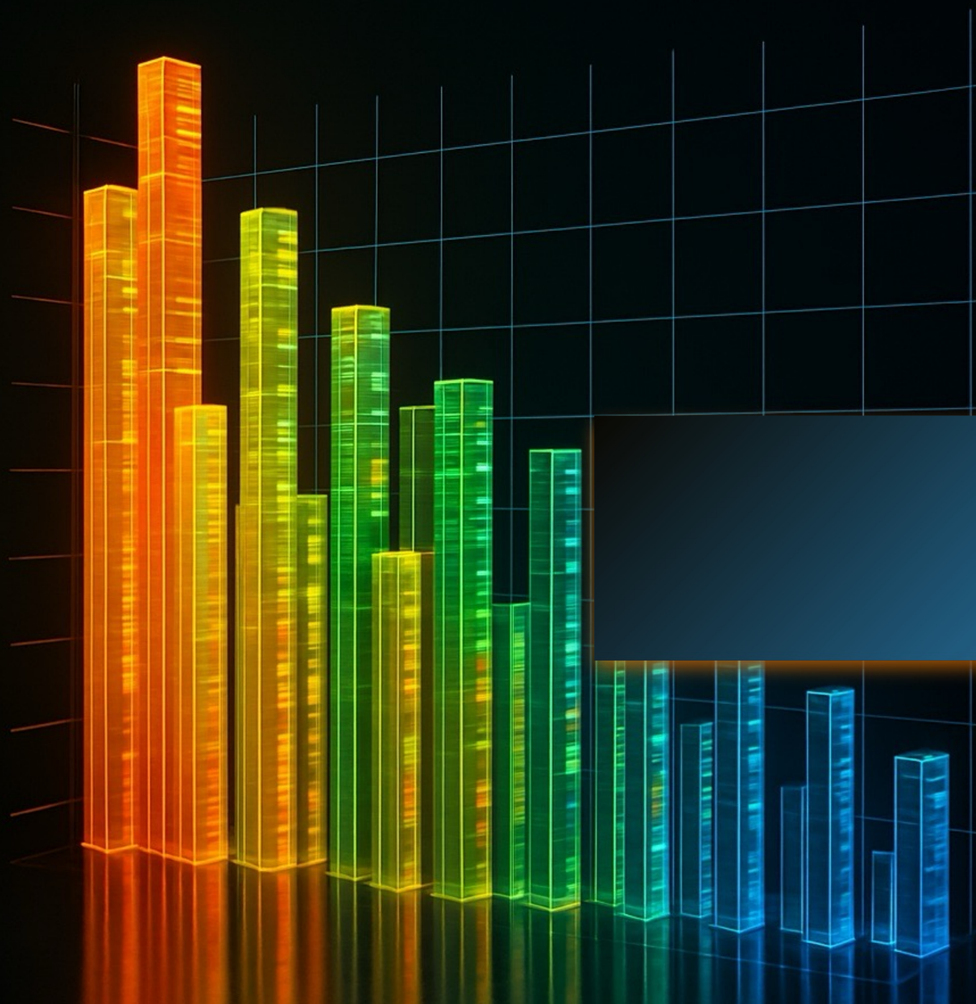
Non-convex to convex Transformation Pathways (e.g., non-convex discontinuous non-linear MINLPs to convex form)

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



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





3 Experimentation

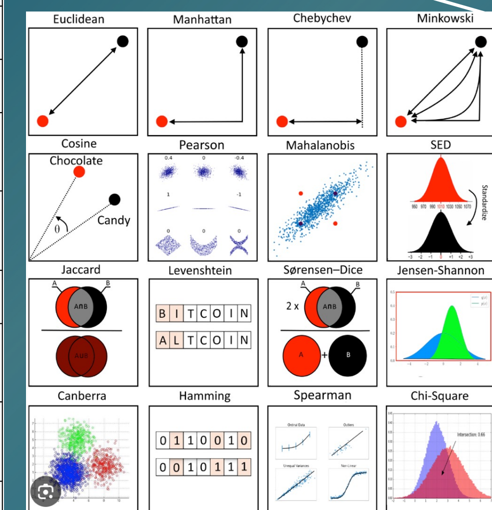
Sorting/Ranking (SR) is critical for gauging various Verification/Discernment (VD) measures

3a Experimentation cont’d

3a Similarity Measures

- **Various Similarity**/[Dissimilarity] **Measures**

Measure	*Descriptor*
Distance Correlation Coefficient (dCor) [23]	dCor is “better at revealing complex… relationships… compared with other correlation metrics” by “integrating both linear and non-linear dependence” [27].
Hoeffding’s D Correlation Coefficient (D) [23][24]	D can reflect a certain degree of concordance and discordance.
Information Coefficient of Correlation (ICC) [25]	ICC can provide a gauge of alignment between the posited and actual value.
Kendall’s Tau Correlation Coefficient (tau) [23][26]	Tau can illuminate correlations of import when the distributions of the sample set and population are not necessarily known.
Maximal Correlation (MC) [25]	MC pertains to transformations of the data, which are considered to maximize the correlation.
Maximum Information Coefficient (MIC) [25]	MIC encompasses both linear and nonlinear correlations between the “variable pairs.”
Mutual Information (MI) [25]	MI is a paradigm, wherein one of the variables conveys a quantifiable amount of information about the other.
Pearson’s [Product]-Moment Correlation Coefficient (PPMCC) [23]	PPMCC measures the relationship strength and direction between the “variable pairs.”
Percentage Bend Correlation Coefficient (PBCC) [23]	PBCC refers to a paradigm, wherein a specified percentage of marginal observations deviating from the median are weighted downward [28].
Spearman’s Rho Correlation Coefficient (rho) [23][26]	Rho scrutinizes the dependence between two random variables [29].



https://towardsdatascience.com/17-types-of-similarity-and-dissimilarity-measures-used-in-data-science-3eb914d2681/

3a Similarity Measures

3a Experimentation cont'd

- **Various Similarity Measures cont'd**

	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

3b Experimentation cont'd

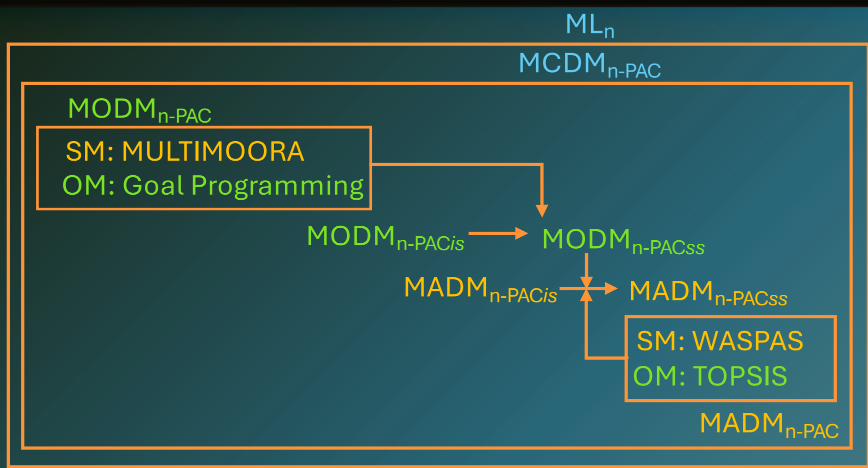
3b Sort & Rank

MADM vs. MODM vs. MCDM

- **Multi-Attribute Decision-Making (MADM):**
  - "According to Qin, MADM 'refers to making preference decisions via assessing a finite number of pre-specified alternatives under multiple and usually conflicting attributes'" for a single objective.
- **Multi-Objective Decision-Making (MODM):**
  - "According to Roostaee, 'the main characteristics of MODM problems are that decision makers need to achieve multiple objectives while these multiple objectives are noncommensurable and conflict with each other.' Roostaee further notes that MODM 'involves the design of alternatives that optimizes or most satisfies the objectives of decision makers.'" However, there are an infinite number alternatives.
- **Multi-Criteria Decision-Making (MCDM):**
  - "According to Sorooshian, MCDM — also known as Multi-Criteria Decision Analysis (MCDA) — is a structured approach that endeavors to consider multiple criteria/objectives (often conflicting) and is comprised of the sub-categories of MADM and MODM."

3b Experimentation cont'd

3b Sort & Rank



MULTIMOORA = Multi-Objective Optimization by a Ratio Analysis plus the Full Multiplicative Form
GP = Goal Programming
WASPAS = Weighted Aggregated Sum Product Assessment
COPRAS = Complex Proportional Assessment
CRITIC = Criteria Importance through Intercriteria Correlation
DEA = Data Envelopment Analysis
ELECTRE = Elimination Et Choix Traduisant la Realite
F-VIKOR = Fuzzy VIseKriterijumska Optimizacija I Kompromisno Resenje
PROMETHEE = Preference Ranking Organization Method for Enrichment Evaluation
TOPSIS = Technique of Order Preference by Similarity to an Ideal Solution

MCDM = Multi-Criteria Decision-Making
MODM = Multi-Objective Decision-Making
MADM = Multi-Attribute Decision-Making
MMSO = MADM/MODM SM/OM, where SM=Subjective Method and OM=Objective Method

3b Experimentation cont'd

3b Sort & Rank

ML_n

$MCDM_{n\text{-}CAC}$

$MODM_{n\text{-}CAC}$

SM: MULTIMOORA
OM: Goal Programming

$MODM_{n\text{-}CACis} \rightarrow MODM_{n\text{-}CACss}$

$MADM_{n\text{-}CACis} \rightarrow MADM_{n\text{-}CACss}$

SM: WASPAS
OM: 1-7

$MADM_{n\text{-}CAC}$

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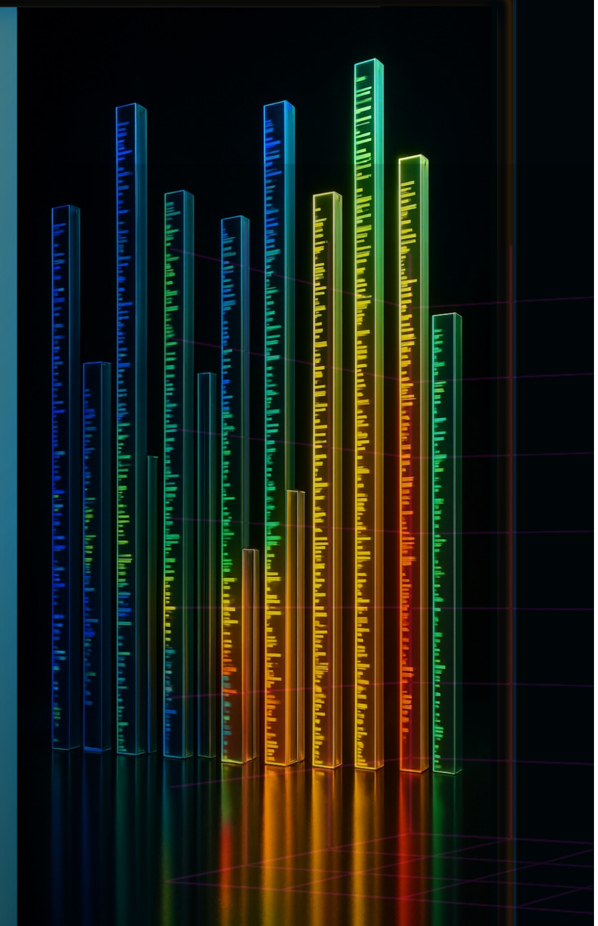
3b Experimentation cont'd

3b Sort & Rank

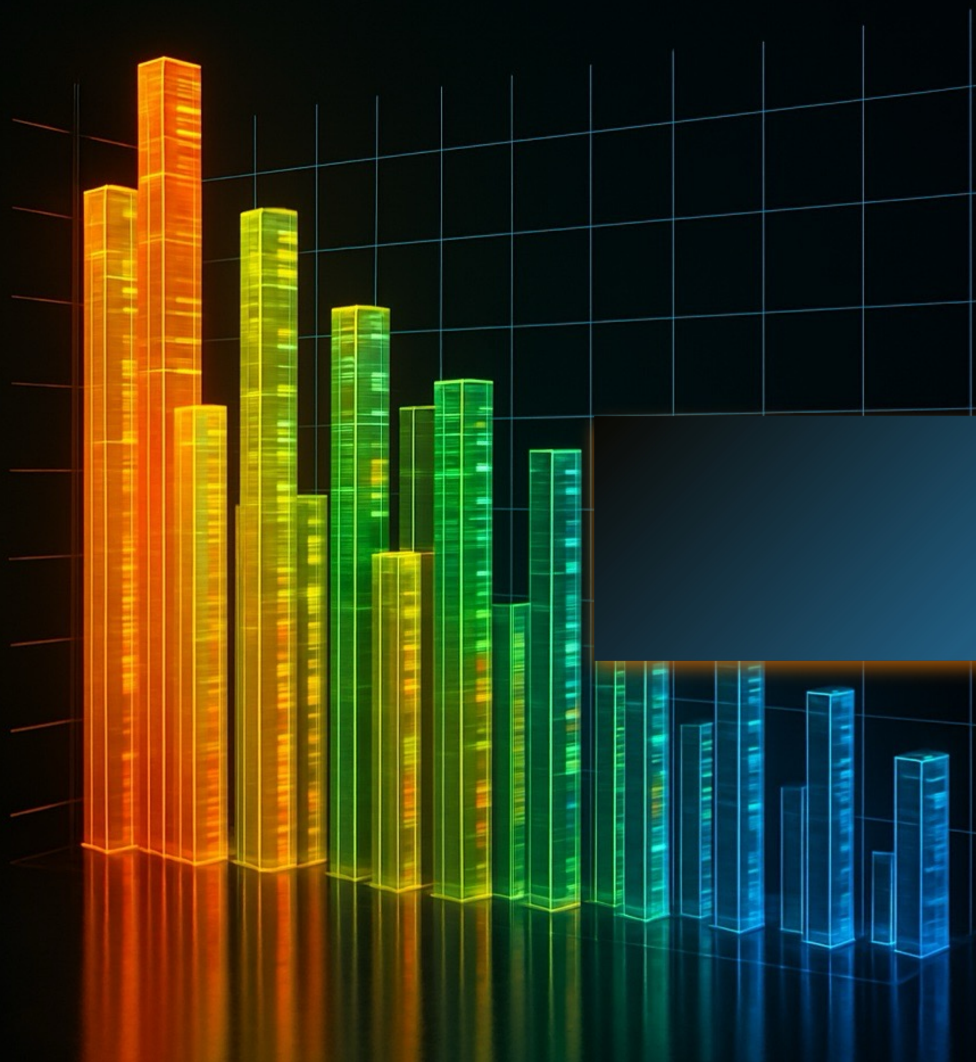
P	COPRAS/TOPSIS	Varatharajulu
	COPRAS, TOPSIS, and VIKOR	Hezer
C	TOPSIS & PROMETHEE > VIKOR	Salabun
	ELECTRE > TOPSIS	Ezhilarasan
F	ELECTRE & TOPSIS extensions	Akram
S	TOPSIS	Kokaraki
U	ELECTRE	Jordehi and Lofti
	PROMETHEE	Ziemba
	PROMETHEE & ELECTRE	Taherdoost, Oubahman, and Moreira
V	PROMETHEE > ELECTRE	Ozman
I	ELECTRE & PROMETHEE	Leyva-Lopez and Yedjour



3c Experimentation cont'd

3c Sample Size

- **Previous Exemplar Sample Size Recommendations:**
  - 200-300 | Guadagnoli & Velicer
  - >=200 | Hair et al.
  - >=200-1000 | Nevitt & Hancock
  - 300 | Comrey & Lee; Clark & Watson; VanVoorhis & Moorgan; White
  - >=300 is deemed "good enough" (e.g., sample sizes < 300 "tend to diverge")
  - >=400 | Aleamoni
  - 500 is "very good" | Comrey & Lee
  - >=1,000 is "excellent" | Gunawan; Comrey & Lee
- **Gelman opines that "you need 16 times the sample size to estimate an interaction than to estimate a main effect:"**
  - Need to detect association between the variables.
  - Validity/Discernment (VD) measures become important.
  - In addition to Gelman, Rainio opines on power (e.g., the efficacy to ascertain whether there is "some association between the variables or not") and generality (e.g., capability, at the involved sample quantity, to "detect linear, monotonic, or functional dependence" and "recognize more complicated relationships between the variables")

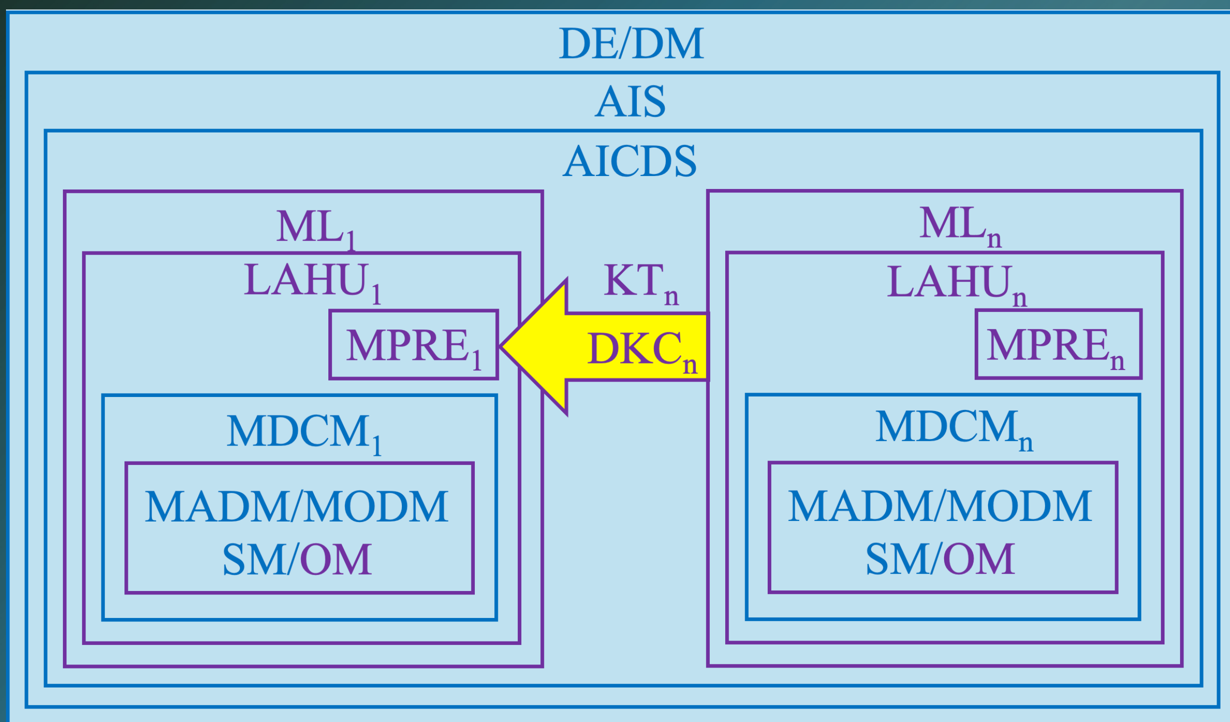


4 Discussion

RLBI can likely be a prospective impediment (e.g., at the MNTZ) for concept model-centric AIS

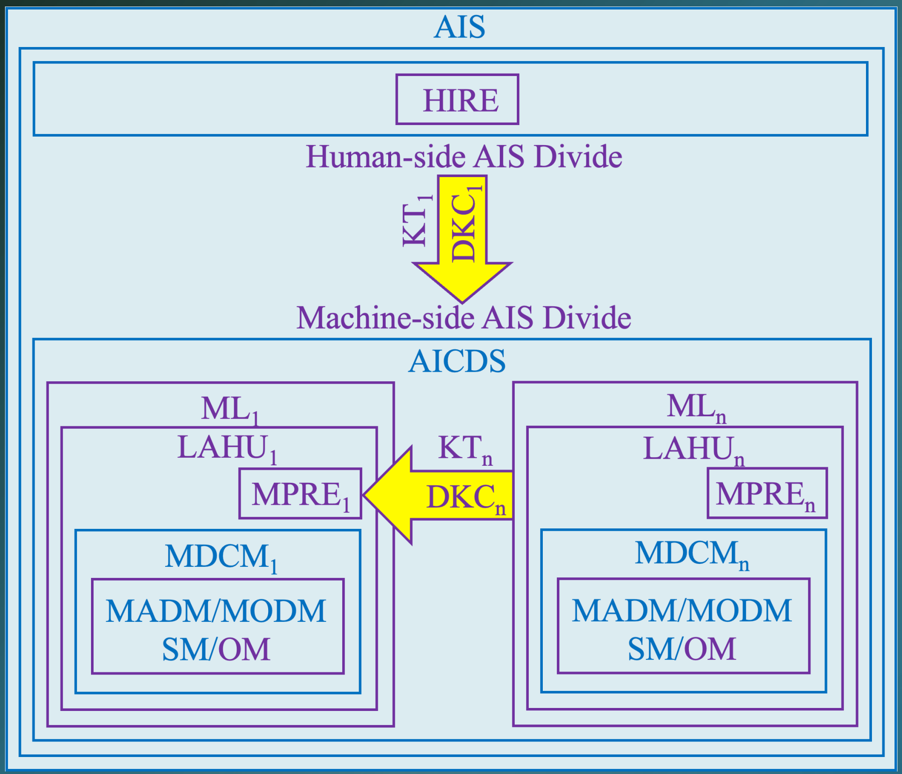
Discussion

- **AIS/AICDS ML on ML KT (via DKC) with the LAHU/HALU MCDM (e.g., a MADM/MODM SM/OM counterpoising) supporting a Machine-Processed Repertoire of Experience (MPRE).**



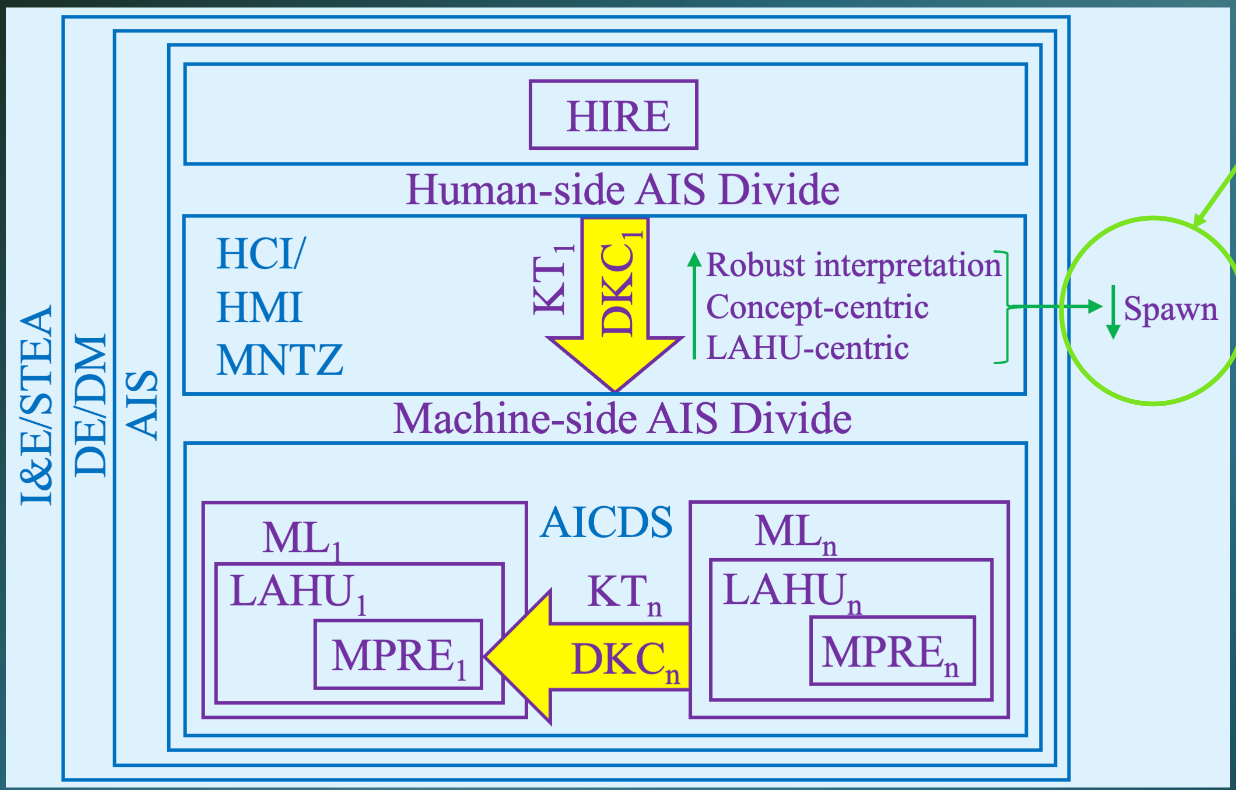
Discussion

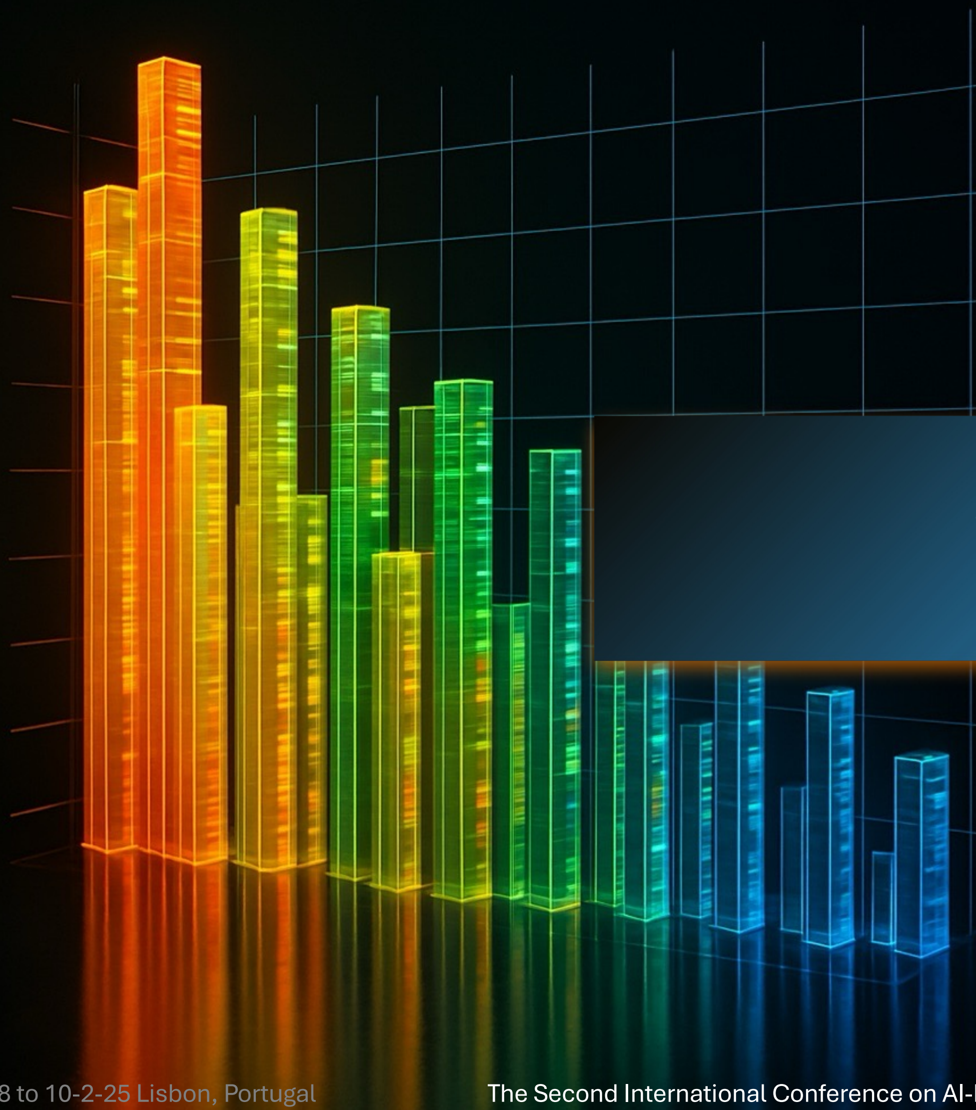
- **Human-side Human-Informed Repertoire of Experience (HIRE) and Machine-side MPRE of the AIS Divide with KT/DKCs :**



Discussion

- **Overall MNTZ and Spawn Reduction Posits:**





5 Concluding Remarks

RNLBI are potentially more amenable to higher nuance/insight for concept model-centric AIS

Concluding Remarks

- **Enhancing ML on ML:**
  - RLBI can likely be a prospective impediment, particularly within or around the MNTZ for concept model-centric AIS.
  - The spawn rate (e.g., the spawning of NP-hard "non-monotonic, non-polynomial, and even non-continuous functions") for RLBI may be higher than that for RNLBI.
  - For mission-critical RWS AIS/AICDS, an effective ML on ML paradigm necessitates robust STEA/I&E, which can facilitate the assurance of the intended interpretation, such as via the DKC channel, for KT.
  - The myriad of varied connotational interpretations (i.e., alternative explanations), enhanced interpretation, via the DKC interpretand, is particularly vital within/around the MNTZ.
  - The DKC, in the case of this paper, is akin to the LCM in that it is more akin to being concept-based. Accordingly, for meaningful KT to occur, the I&E for the utilized hierarchical/non-hierarchical LVM needs to be of sufficient robustness.
  - HIRE, which is often replete with RLBI, can skew matters for the AIS/AICDS, as it is not intrinsically concept-based.

Concluding Remarks

- **Enhancing ML on ML:**
  - RNLBI, such as SD, can intrinsically be more concept-based (e.g., via its bipolar dichotomy and the in-between continuum).
  - With regards to the DKC recognition element, such as via the quasi-isomorphic engine, the various morphisms as well as the various subgraph isomorphism relaxations need to be well treated.
  - The utilized quasi-isomorphic engine approach (e.g., robust convex relaxations) can also further spawn further non-convex MINLP problems, so a reduction in spawning is key.
  - RNLBI seems to lend towards a reduction of this spawning, and given this prospective mitigation approach, the described machinations at/or abutting the DKC, such as within the MNTZ, can serve to enhance the robustness of the inferences/predictions/posits/insights of the involved AIS with relatively reasonable computational efficacy.

Concluding Remarks

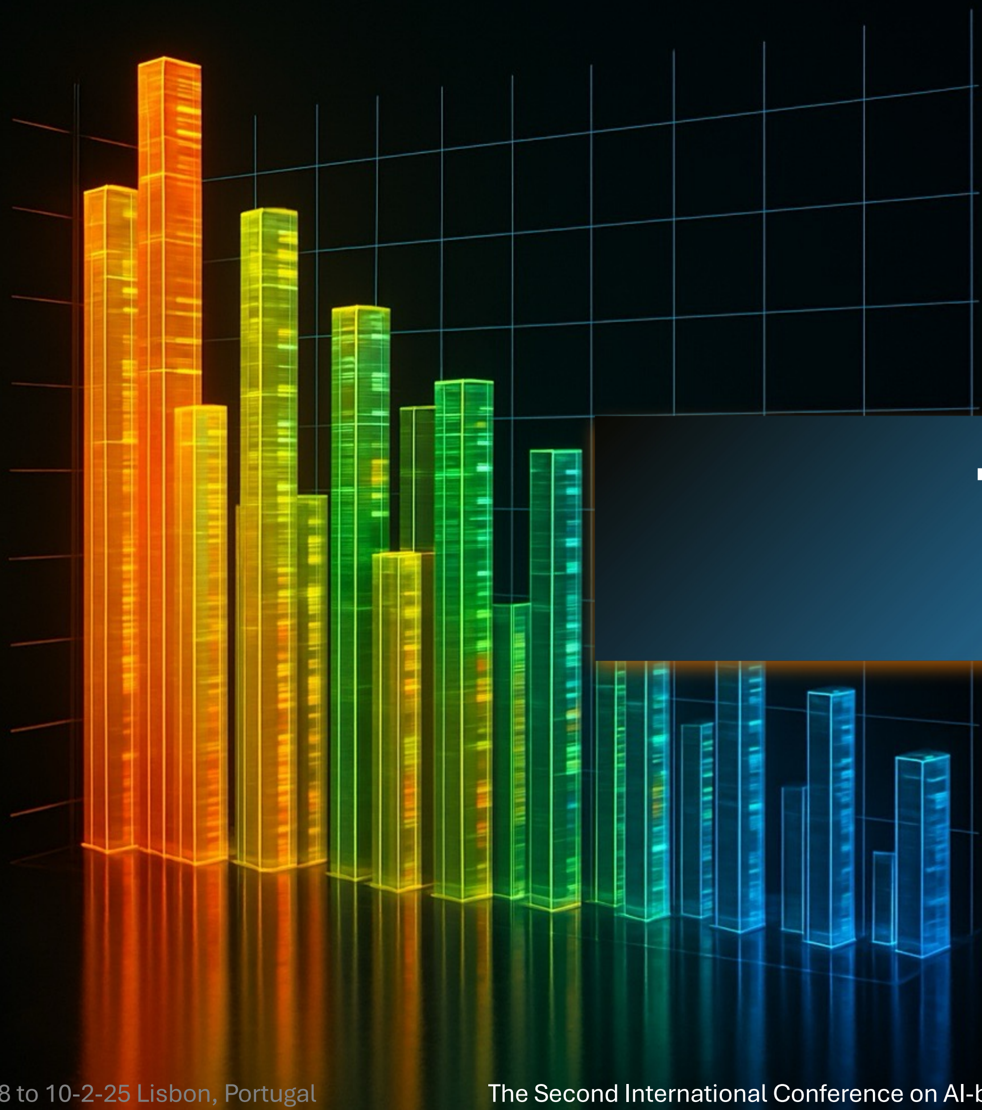
- **Enhancing ML on ML:**
  - Of note, the intrinsic wherewithal to accommodate both discrete and continuous paradigms is critical. Along this vein, the LAHU/HALU MCDM, which is at the heart of DE/DM, encompasses MODM for “undetermined continuous alternatives” as well as MADM for “discrete alternatives.” Axiomatically, these require continuous as well as discrete evaluations, respectively.
  - It then follows that since RLBI do not contain “0,” discrete testing is not possible; restated, only continuous distribution testing is possible. On the contrary, RNLBI (e.g., SD) do indeed contain “0” and are able to accommodate both discrete and continuous distribution testing. The preliminary experimental findings seem to affirm that RNLBI lend toward a higher P, C, F, U, V, I and a lower S than RLBI, particularly in and/or around the MNTZ (with less spawn observed).
  - RNLBI are potentially more amenable to higher nuance/insight and seem to warrant further investigation.
  - Of significance, Gelman and Rainio’s thoughts are central to the findings that allude to a paradigm of decreased spawning with RNLBI over RLBI (i.e., power and generality).

Concluding Remarks

- **Enhancing ML on ML (in summary):**
  - Foam Shedding: RLBI versus RNLBI
  - Spawning: inadvertent increase in NP-Hard non-convex[non-monotonic, discontinuous] non-polynomials
  - Power & Generality: Interaction(s) over Main Effect
  - Paradigm of prospective decreased spawning with RNLBI over RLBI
  - RNLBI tend to be more concept-centric
  - Decreased spawning is concomitant with LCM-centric models (e.g., https://github.com/dame-cell/BaseLCM, https://github.com/styalai/LCM-torch, etc.)
  - Prospective High Efficacy KT for Enhanced ML on ML (the BLUF) with the use of RNLBI and LCM-centric models

Thank you very much for your time and attention!

Questions?



Thank you

& please have a wonderful conference at AISyS 2025!