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IEEE Student Branch
KU Leuven Brugge & Gent

A Tutorial on Epistemic Uncertainty and its Application

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Uncertainty in AI - Optimisation - Decision

Mecha(tro)nic System Dynamics (LMSD), Bruges Campus, KU Leuven

17^{th} *Oct. 2024 – Let's Meet Event - IEEE Student Branch KU Leuven Brugge & Gent*

Still Mathematician

[1995-1999] BSc **Applied Mathematics** - Computer Simulation [Sharif University]

[1999-2001] MSc **Applied Mathematics** - Control Theory [Sharif University]

[2001-2007] Lecturer & member of faculty of Mathematics [Qazvin University]

[2001-2005] PhD **Pure Mathematics** - Control Theory, Stability [Sharif University]

[2007-2012] Research Assistant Fuzzy Finite Element [Ghent University]

[2012-2017] Research Engineer, R&D Project Manager, Automotive [Dana Belgium]

[2017-2021] PhD **Mathematical** Engineering, Optimisation under Uncertainty [KU Leuven]

[2021 - Now] Senior Research Fellow, **Epistemic AI, FET-Open Project** [KU Leuven]

Epistemic AI
A new learning paradigm

Uncertainty in Everyday Life

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Motivation: Importance of handling uncertainty in scientific modeling and decision-making.

Aleatory vs. Epistemic Uncertainty

Aleatory: Natural variability (randomness).

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These uncertainties are handled differently in models (e.g., deterministic vs. non-deterministic approaches).

Focus on Epistemic Uncertainty

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- Engineering predictions
- Forecasting in uncertain environments

Importance of Epistemic Uncertainty

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- Engineering and predictive maintenance
- Healthcare diagnosis
- Artificial intelligence systems

Example: Predicting Events with Limited Data

Scenario: Predicting rainfall with limited data.

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How adding data reduces epistemic uncertainty but leaves aleatory uncertainty intact.

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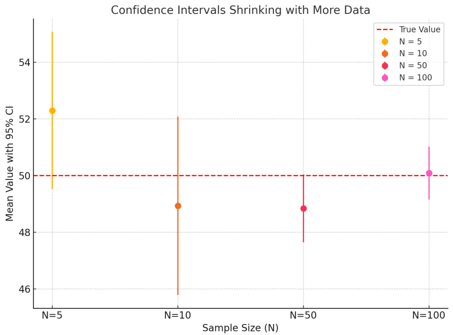
Visual example showing confidence intervals shrinking with more data.



Approaches to Handle Epistemic Uncertainty

Collecting more data to reduce uncertainty.

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Using prior knowledge (Bayesian models) in the absence of sufficient data.

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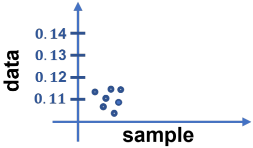
Alternative methods: Ensemble modelling, expert judgment, and non-Bayesian models e.g., Evidence Theory.

Let's collect some data!

Dealing with Epistemic Uncertainty



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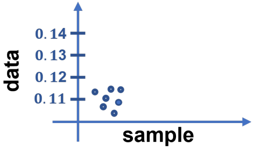

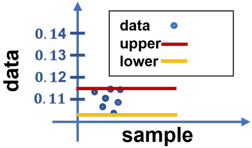

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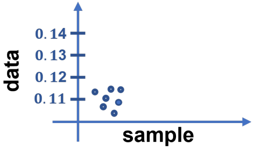

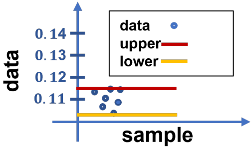

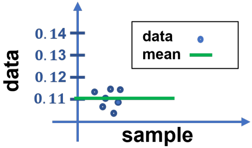

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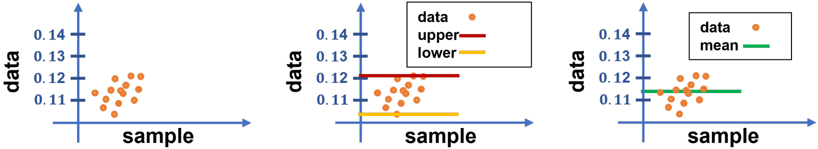

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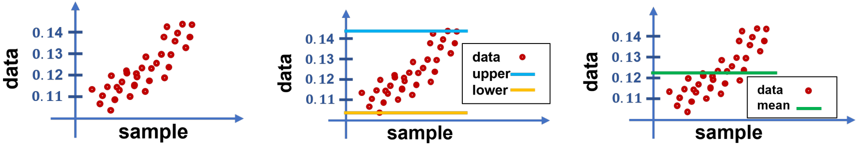
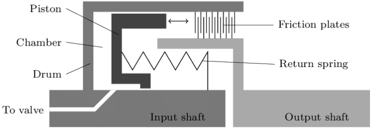


Clutch control design

Clutch control design

Wet-Plate Clutch



Aim	Model
Maximum output torque?	$\max_{\mu} \tau_f$
such that	st. $\tau_f = \mu.RNA.p_k.\Delta\omega$
the clutch is closing	$f_{spring} > p_k.A$: open
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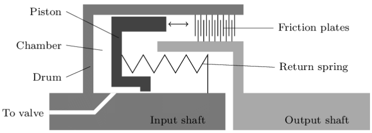
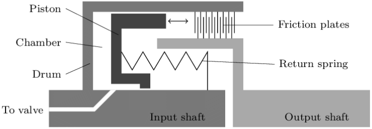
Clutch control design

Wet-Plate Clutch	Aim
	**Maximum output torque?** such that the clutch is **closing** the clutch is **opening**

Clutch control design

Wet-Plate Clutch	Aim	Model
	**Maximum output torque?**	$\max_\mu \tau_f$
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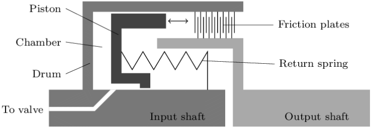

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μ is function of *speed*, *pressure*, *load*, *oil*, and *temperature*.

Clutch control design

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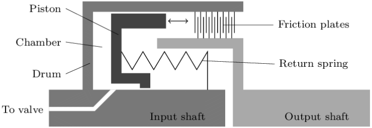

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COF is varying i.e., $\mu \in [\underline{\mu}, \overline{\mu}]$

How to efficiently control the torque under fixed uncertain μ?

Measuring Epistemic Uncertainty

Techniques to measure epistemic uncertainty:

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Measuring Epistemic Uncertainty

- Techniques to measure epistemic uncertainty:
  - (Probability) Intervals
  - Bounds and Fuzzy Sets
- Example of modelling uncertainty with limited data points.

1. Overview
2. Introduction to Uncertainty
   - Types of Uncertainty
   - Simple Example of Epi Uncertainty
   - Dealing with Epistemic Uncertainty
3. **Real-World Applications**
   - **From Epistemic to Decisions**
4. Summary
5. Conclusion
6. Q&A

Example: Predictive Maintenance

Predictive maintenance involves anticipating equipment failure based on sparse data.

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Reducing epistemic uncertainty allows industries to better understand the behaviour of their processes, leading to improved predictions (cost), optimised decision-making (best), increased safety (EMC), and enhanced reliability (design).

Leads to better performance, lower costs, competitive advantage in complex industrial environments (Smart Factory).

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Epistemic (Un)Supervise Learning involves anticipating Epistemic Uncertainty using Interval NN.

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Epistemic Reinforcement Learning deals with e.g., Epistemic Reward Function. Bellman Equation:

$$V_\pi(S_t) := \max_\pi [R_{t+1} + \gamma . V_\pi(S_{t+1})]$$

where the total return at time t: $R_t := r_{t+1} + \gamma . R_{t+1}$
e.g., local reward at t: r_t is unknown: $r_t \in [a, b]$!

Decision-Making Under Epistemic Uncertainty

Strategies for decision-making when model uncertainty is high:

DECISION-MAKING UNDER EPISTEMIC UNCERTAINTY

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- Optimistic decision-making with risk assessments (less conservative scenario).

Generic Method for Problem Solving

Step-by-step problem-solving framework under uncertainty:

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Provide two hypothetical solution sets to reason.

Applications in AI and Engineering

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- Machine learning (e.g., uncertainty in model predictions).
- Autonomous systems (e.g., self-driving cars operating under uncertainty).

*K. Wang, F. Cozzulin, K. Shariatmadar, D. Moens, H. Hallez, Credal Deep Ensembles for Uncertainty Quantification, The Thirty-eighth Annual Conference on Neural Information Processing Systems **NeurIPS** 2024.*

NEURAL INFORMATION PROCESSING SYSTEMS

Epistemic AI—Paradigm Shift in AI:

Aim is to create a new paradigm for a **next-generation AI** providing worst-case guarantees on its predictions thanks to proper modelling of real-world uncertainties.

5-year EU EIC FET-Open/Pathfinder-Open project, started on 1 March 2021, with a budget of **3.2 M€** with Oxford Brookes University, KU Leuven and TU Delft. **3-6 % success rate**.

Oxford Brookes University KU Leuven TU Delft

Epistemic AI A new learning paradigm

Applications in AI and Engineering

Engineering designs (e.g., construction/optimisation with incomplete information).

Linear programming under uncertainty (LPUU)

$$\max_{\text{decisions}} \quad \textbf{Goal}$$
$$\text{such that} \quad \textbf{Conditions}$$

Optimal **decision** which is satisfying in the constraints?

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$$\underset{\textit{decisions}}{\text{maximise}} \quad \textbf{Goal} \qquad\qquad \underset{\textbf{decisions}}{\text{maximise}} \quad \textbf{Uncertain goal}$$

$$\text{such that} \quad \textbf{Conditions} \quad \rightarrow \quad \text{such that} \quad \textbf{Uncertain conditions}$$

Optimal **decision** which is satisfying in the constraints under **uncertainty**?

LINEAR PROGRAMMING UNDER UNCERTAINTY (LPUU)

$$\max_{\textit{decisions}} \quad \textbf{Goal} \qquad \text{such that} \quad \textbf{Conditions} \quad \rightarrow \quad \max_{\textbf{decisions}} \quad \textbf{Uncertain goal} \qquad \text{such that} \quad \textbf{Uncertain conditions}$$

$$\text{maximise} \quad U^T x$$
$$\text{such that} \quad Yx \leq Z$$

x is the optimisation variable taking values in a bounded set $M \subseteq \mathbb{R}^n_{\geq 0}$,
Y, Z, U are random variables taking values y, z, u in $\mathbb{R}^{m \times n}, \mathbb{R}^m, \mathbb{R}^n$. The elements of Y, Z and U are *independent* and modelled as *imprecise uncertainty*.

Linear programming under uncertainty (LPUU)

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Simplest case

What is the **largest** value x which is (strictly) smaller than $y \in \mathbb{R}$ and we don't know y ?

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$$\begin{array}{ll} \text{maximise} & x \\ \text{such that} & x < {\color{red}Y} \end{array}$$

Y is a random variable taking values y in $\mathbb{R}$. x is in a bounded subset in $\mathbb{R}_{\geq 0}$.

Key Takeaways

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- Uncertainty is unavoidable, but it can be quantified and managed.
- Epistemic uncertainty arises due to a lack of knowledge or data/second-level uncertainty.
- Proper handling of epistemic uncertainty leads to more robust models and decisions.

Final Remarks and Conclusion

Practical relevance of epistemic uncertainty in real-world applications:
Human – Weather – Ttraffic – **Unknown unknowns**

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Why we first start with Probabilities!?

Be Uncertain about the **Uncertainty**...

Be Uncertain about the **Uncertainty**...

Further reading and exploration of advanced methods to handle uncertainty:

Focus: Advanced Uncertainty

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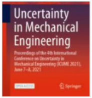
What are the problems?

What are the problems?

Identification: How to know there is advanced uncertainty?



Identification of Imprecision in Data Using ϵ-Contamination Advanced Uncertainty Model

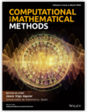
Authors | Authors and affiliations

Keivan Shariatmadar, Hans Hallez, David Moens

https://doi.org/10.1007/978-3-030-77256-7_14

What are the problems?

Classification: How to choose the best model to quantify the advanced uncertainty?



RESEARCH ARTICLE

WILEY

CMMSE: Linear programming under ϵ-contamination uncertainty

Keivan Shariatmadar | Matthias De Ryck | Kristof Driesen | Frederik Debrouwere | Mark Versteyhe

https://doi.org/10.1002/cmm4.1077

IEEE Xplore®

Linear programming under p-box uncertainty model

Publisher: IEEE

Keivan Shariatmadar ; Mark Versteyhe

https://doi.org/10.1109/ICCMA46720.2019.8988632

What are the problems?

Reasoning: How to reason? An approach to solve the problems dealing with advanced uncertainty.

International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems | Vol. 28, No. 03, pp. 469-495 (2020)

Numerical Linear Programming under Non-Probabilistic Uncertainty Models — Interval and Fuzzy Sets

Keivan Shariatmadar and Mark Versteyhe

https://doi.org/10.1142/S0218488520500191

https://doi.org/10.1142/S0218488520500191

What are the problems?

Complexity: How to deal with the complexity in the proposed approach (*advanced decision theory*)?

energies MDPI

Article

Day-Ahead Energy and Reserve Dispatch Problem under Non-Probabilistic Uncertainty

Keivan Shariatmadar [1,*], Adriano Arrigo [2], François Vallée [2], Hans Hallez [3], Lieven Vandevelde [4,5] and David Moens [6]

https://doi.org/10.3390/en14041016

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contact

Questions?

Be Uncertain about the **Uncertainty**...

"**How NASA in Silicon Valley Will Use Webb to Study Distant Worlds.** *NASA's James Webb Space Telescope gives scientists new tools to search for the building blocks of life on distant planets.*
NASA's James Webb Space Telescope is getting ready to give us the best view of worlds beyond our solar system, commonly known as exoplanets. Scientists at NASA's Ames Research Center in California's Silicon Valley will be among the first to observe the cosmos with Webb, and they're looking for clues about how exoplanets form, what they're made of, and whether any could be potentially habitable. On Jan. 24, 2022, the telescope reached its destination, an orbit about one million miles from Earth around a location called Sun-Earth Lagrange point 2, also known as L2. Now, Webb is one step closer to launching its scientific mission to transform our understanding of the universe."