Meïli Baragatti

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1er décembre 2025

Research interests

Current themes in methodological research:

- Approximate Bayesian Computation (ABC) or Likelihood-Free methods, in particular for the estimation of parameters of complex models.
- The linear functional model and its interpretability, in a Bayesian framework.
- Detection of spatial and spatio-temporal outliers.

Current themes in methodological research:

- Determination of factors influencing the monthly growth dynamics of mycelium in soil.
- Reconstruction of the epidemiology of Rift Valley Fever virus in Nouakchott, Mauritania, from 1950 to 2021.
- Online aromatic monitoring in wine fermentation and study of the aromatic production.
- Calibration of a complex hydro-ecological model using an ABC method.

Special interest in conformal prediction

Journal of Computational and Graphical Statistics
Taylor & Francis
ISSN: 1061-8600 (Print) 1537-2715 (Online) Journal homepage: www.tandfonline.com/journals/ucgs20

Approximate Bayesian Computation with Deep Learning and Conformal prediction

Meïli Baragatti, Céline Casenave, Bertrand Cloez, David Métivier & Isabelle Sanchez

New ABC implementation combining neural networks with Monte Carlo dropout and conformal procedure.

- **Neural Network (NN): deep learning**
- **Valid confidence sets: dropout + conformal**
  1. Dropout layers in NN: estimate θ with an associated uncertainty.
  2. Conformal procedure.

$$\hat{\theta}(x) + \text{heuristic uncertainty } \widehat{\mathbb{V}}[\theta \mid x] \xrightarrow[\text{procedure}]{\text{conformal}} \text{rigourous confidence set!}$$

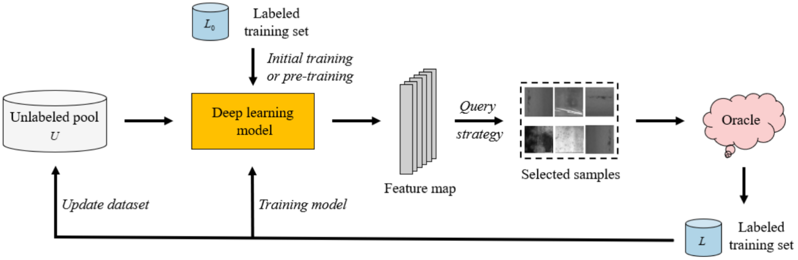
Active Learning and uncertainty quantification for machine vision

Second year of Phd in industry between LJK and Michelin

Julien Combes - Alexandre Derville - Jean-Francois Coeurjolly

Active Learning

Find which unlabeled images are the most informatives ?



(Ren et al. 2021)

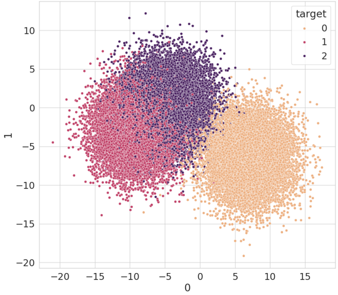
Based on uncertainty

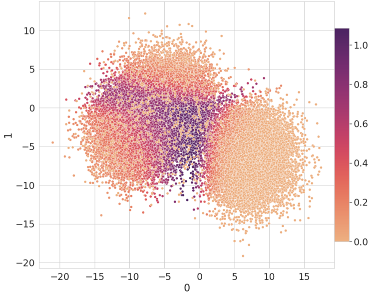
Two hypotheses :

- The most informative images are the ones difficult to solve for the model
- The algorithm we use is a good estimator of the uncertainty

Popular algorithms:

- Entropy ((Joshi, Porikli, and Papanikolopoulos 2009))
- BALD ((Gal, Islam, and Ghahramani 2017))

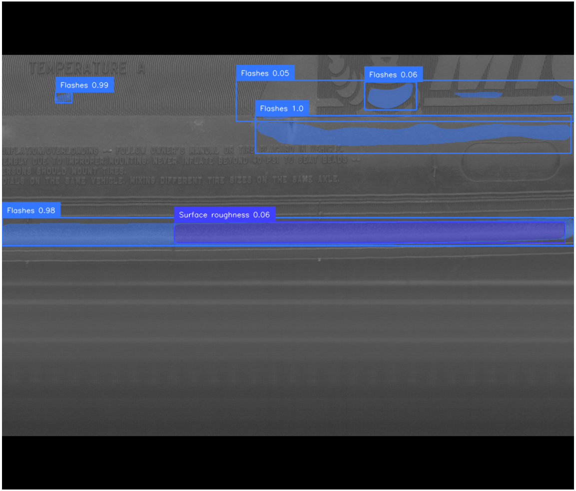




Problems with casual uncertainty

Warning

The second hypothese is wrong, indeed ML models are not calibrated



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Ren, Pengzhen, Yun Xiao, Xiaojun Chang, Po-Yao Huang, Zhihui Li, Brij B. Gupta, Xiaojiang Chen, and Xin Wang. 2021. "A Survey of Deep Active Learning." arXiv. https://doi.org/10.48550/arXiv.2009.00236.

Increasing The Prediction Horizon of the perceived scene to improve planning for vehicle ADAS (Level 2+ and 3) using AI-based method

Presented by: Abd Al-Rahman Hourani

Academic Supervisor: Sylvain Rousseau , Soundouss Messoudi.
Industrial Supervisor: Anna-Luara , Nicole El-zoughby

Decembre 2025

ECAS – SFDS 2025

Academic Background

2018

High School Diploma

- Speciality : **General Science**
- National Center for the Distinguished (NCD)

2023

Bachelor's degree (B.Sc.)

- Speciality : **Mechatronics Engineering**
- Higher Institute for Applied Sciences and Technology (HIAST)

2024

Master's Degree (M.Sc.)

- Speciality : **Mechatronics, Machine Vision and Artificial Intelligence**
- Paris Saclay University

2025 -2028

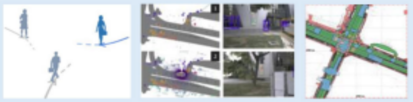
PhD in ADAS and Artificiel Intelligence

- Renault Group – Ampere
- UTC University – Heudiasyc Lab

Motion Forecasting

❖ **Problem statement:** Extend the prediction horizon (5–10s) of surrounding agents with reliable uncertainty modeling to improve ADAS planning decisions in complex environments.

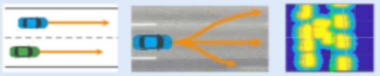
Input Modalities
- Past Trajectory
- Sensors Data
- HD Maps

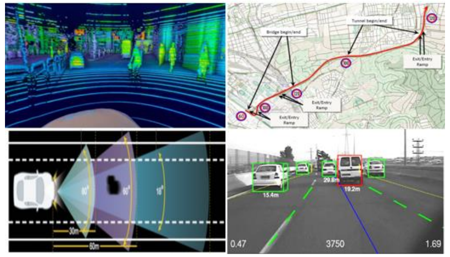


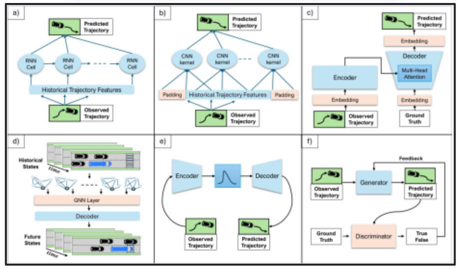
Modelling Features
- Target Agent Features
- Interaction Features
- Environment Features

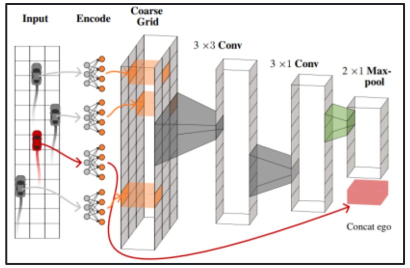
Modelling Approaches
- Conventional Prediction methods
- Deep Learning based methods
- Reinforcement Learning based methods

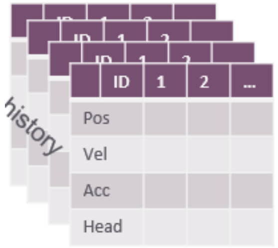
Output Modalities
- Unimodal
- Multimodal
- Intentions
- Occupancy Map

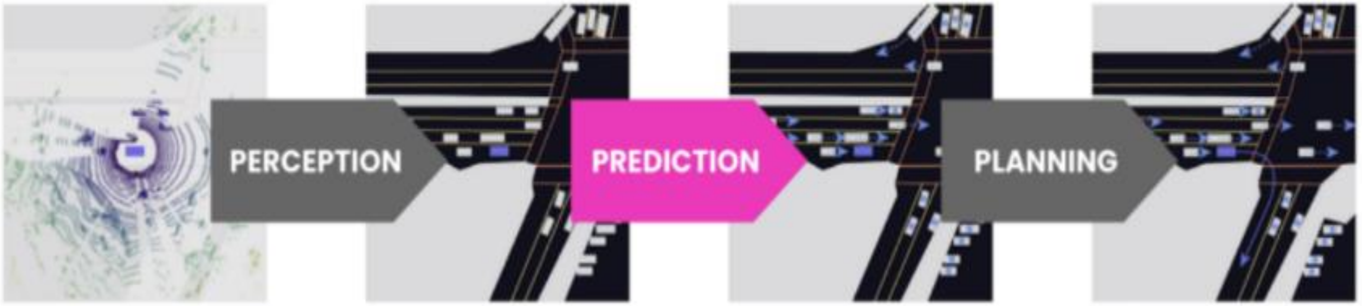


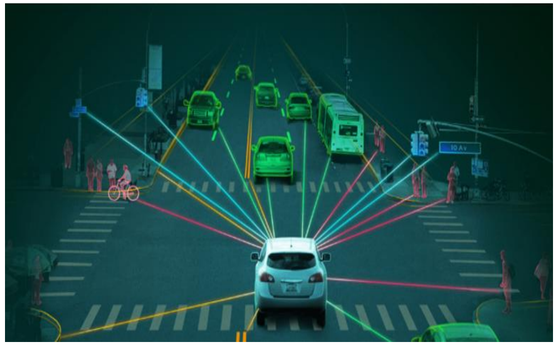












Conformal Prediction for time series

- **Categorizing Uncertainty by Source**
  - ***External Uncertainty*** (uncertain intentions, randomness of human behavior, violation of traffic rules)
  - ***Internal Uncertainty*** (uncertainty induce by prediction module, propagated uncertainty)
- **Categorizing Uncertainty by Nature**
  - ***Aleatoric uncertainty*** arises from the intrinsic randomness in data
  - ***Epistemic uncertainty*** arises from the lack of comprehensive training data

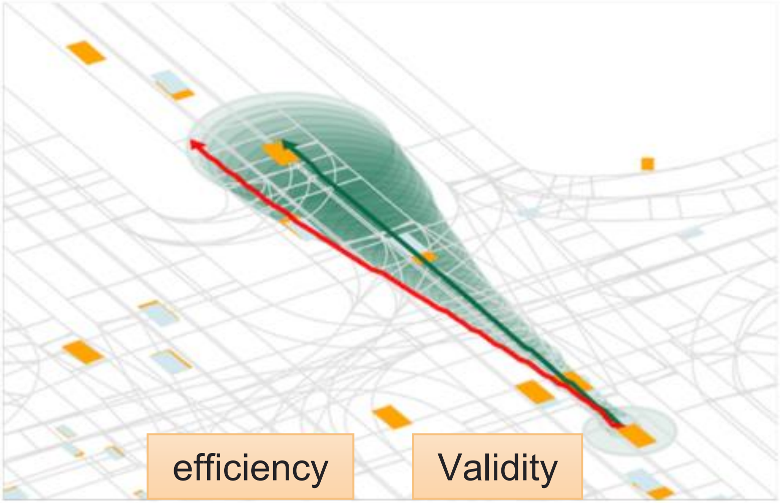
🚘 Why Uncertainty Matters in ADAS?

1. Sensor Noise & Occlusion
2. Multi-Agent Behavior
3. Long-Horizon Forecasting
4. Safety-Critical Decisions

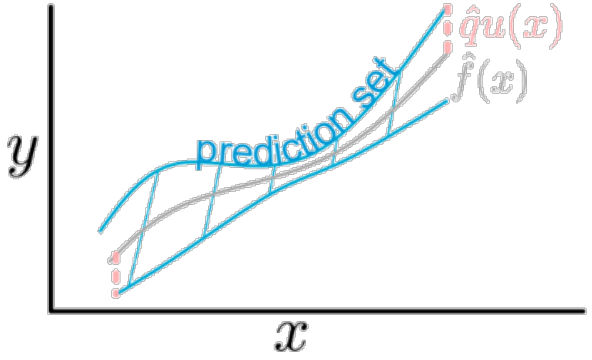
$$\boxed{P\Big(Y_{\text{test}} \in \mathcal{C}(X_{\text{test}})\Big) \geq 1 - \alpha.}$$

Conformal Prediction for Multi-Step Time Series Forecasting. (Exchangability!?)

No data Split , Handle Missing Data, guarantee validity and efficiency



$$\mathcal{C}(x) = \left[\hat{f}(x) - u(x)\hat{q}, \hat{f}(x) + u(x)\hat{q}\right].$$



Thanks for your Listening

Candidate:

Abd Al-Rahman Hourani

Decembre 2025

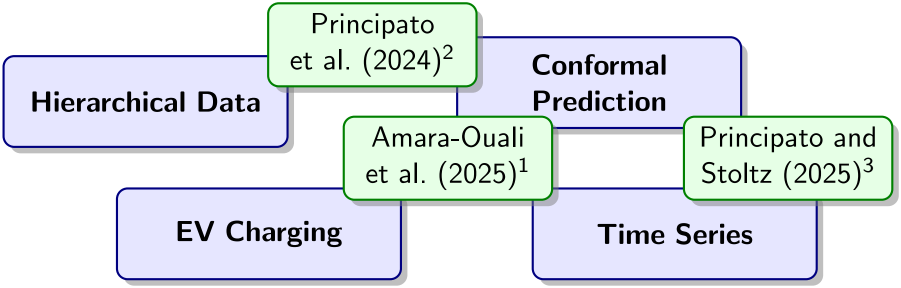
ECAS – SFDS 2025

Slides Présentation ECAS

Guillaume Principato

Doctorant CIFRE en début de 3ème année sous la direction de Gilles Stoltz et Jean-Michel Poggi du côté académique et Yvenn Amara-Ouali, Yannig Goude, Bachir Hamrouche du côté industrielle.

Les mots clés de ma thèse et articles les associés



[1] Quantifying the Uncertainty of Electric Vehicle Charging with Probabilistic Load
[2] Conformal Prediction for Hierarchical Data
[3] Blackwell's Approachability for Sequential Conformal Inference

Travaux en cours et références

Je travaille actuellement sur une application qui combine les 4 mots clés de ma thèse et qui porte sur les données ChargePlace Scotland.

Le challenge de cette étude réside dans les nombreuses non-stationnarités induites par l'adoption rapide des véhicules électriques et l'évolution temporelle de la hiérarchie.

Références:

Amara-Ouali, Y., Hamrouche, B., Principato, G., and Goude, Y. (2025). Quantifying the uncertainty of electric vehicle charging with probabilistic load forecasting. *World Electric Vehicle Journal*, 16(2):88.

Principato, G. and Stoltz, G. (2025). Blackwell's approachability for sequential conformal inference. Preprint arXiv:2510.15824.

Principato, G., Stoltz, G., Amara-Ouali, Y., Goude, Y., Hamrouche, B., and Poggi, J.-M. (2024). Conformal prediction for hierarchical data. Preprint arXiv:2411.13479.

About me

- **Thesis title**: Quantification of uncertainty and robustness via conformal strategies.
- **Funding** : CIFRE PhD Program with Safran Aircraft Engines in collaboration with the SAMM Lab at Paris 1 Panthéon-Sorbonne University.
- **Directors** : Jérôme Lacaille (Safran) et Alain Celisse (SAMM).
- **Me**: Davidson Lova RAZAFINDRAKOTO (Davidson).

- Some past works:
  - "Approximate Full Conformal Prediction via influence functions in regression" presented at JDS2024,
  - "Construction of tensile curves via Conformal Prediction" presented at CM2024 Bindt.
- Works discussed in the following:
  - "Approximate Full Conformal Prediction in RKHS" presented at JDS2025,
  - "Confidence bands for cumulative event number evolution curves" presented at CM2025 Bindt.

Approximate full conformal prediction in RKHS

The approximate Full Conformal Prediction (FCP) interval $\tilde{C}_\alpha^{\mathrm{up}}(X_{n+1})$ contains the actual FCP interval $\hat{C}_\alpha^{\mathrm{full}}(X_{n+1})$ and thus ensures coverage.

- **Objective function**:

$$\frac{1}{|D|}\sum_{(x,y)\in D} \ell(y, f(x)) + \lambda \|f\|_{\mathcal{H}}^2 .$$

- **Thickness**: $\mathrm{THK}_\alpha(X_{n+1})$ $:= \mathcal{L}\left(\tilde{C}_\alpha^{\mathrm{up}}(X_{n+1}) \setminus \hat{C}_\alpha^{\mathrm{full}}(X_{n+1})\right)$.
- **Implicit upper bound**: $\mathrm{THK}_\alpha(X_{n+1})$ $\leq \mathcal{L}\left(\tilde{C}_\alpha^{\mathrm{up}}(X_{n+1}) \setminus \tilde{C}_\alpha^{\mathrm{lo}}(X_{n+1})\right)$.
- **Explicit upper bound**:
  - With **algorithmic stability**: $\mathrm{THK}_\alpha(X_{n+1}) \leq O\left(\frac{1}{\lambda(n+1)}\right)$,
  - With **influence functions**: $\mathrm{THK}_\alpha(X_{n+1}) \leq O\left(\frac{1}{\lambda^3(n+1)^2}\right)$.

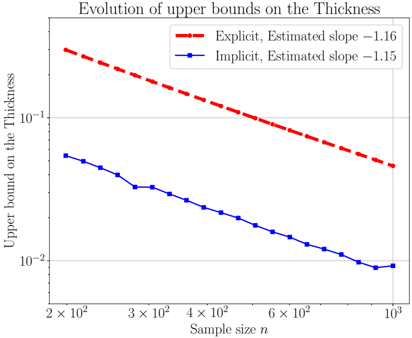


Figure: Rates of improvement of the **Thickness** for the approximation via **influence functions** on simulated data, for $\lambda \propto 1/n^{1/3}$.

- The approximation quality is quantified, and rates are known.
- Leveraging first order approximation via influence funtions improves the rates.
- Refs: Ndiaye (2022), Martinez et al. (2023), Lee and Zhang (2025), Tailor et al. (2025).

For some unwanted event (for instance In-Flight Shut Down), Cumulative event number evolution curves can be used to: guarantee the reliability of a fleet of engines, and set up the appropriate maintenance strategies.

- For the Empirical CDF non-conformity score, the FCP band $\left(\hat{B}_\tau\right)$ is computable and ensures coverage for every instant τ: $\mathbb{E}_{D_\tau}\left[\mathbb{P}\left[\xi_\tau \in \hat{B}_\tau(\alpha) \middle| D_\tau\right]\right] \geq 1-\alpha$.

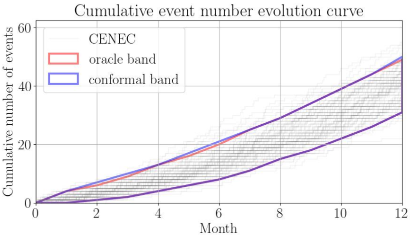


Figure: Examples of curves, and Oracle band (B_τ) and FCP band $\left(\hat{B}_\tau\right)$.

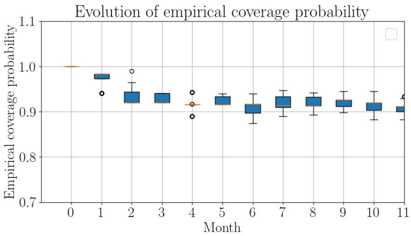


Figure: Empirical probability of coverage over 200 repetitions.

- The FCP band $\left(\hat{B}_\tau\right)$ approaches the Oracle band (B_τ) made of marginal inter-quantile ranges.
- Refs: Lei and Wasserman (2012).

Many thanks for your attention!

ECAS - SFdS 2025, Winter School

Towards Reliable Machine Learning:
Transfer & Physics Informed Learning, and Conformal Prediction

Louis Berthier[1,2], Ahmed Shokry[1], Maxime Moreaud[2], Guillaume Ramelet[2], Eric Moulines[1]

December 1-5, 2025

[1]Centre de Mathématiques Appliquées, Ecole Polytechnique

[2]Manufacture Française des Pneumatiques Michelin

1. Quick Overview

1.1 Batch Processes

Batch processes are widely used across various sectors of the chemical process industries, particularly for **high-value**, **low-volume**, **customer-specific** products [1]–[6].

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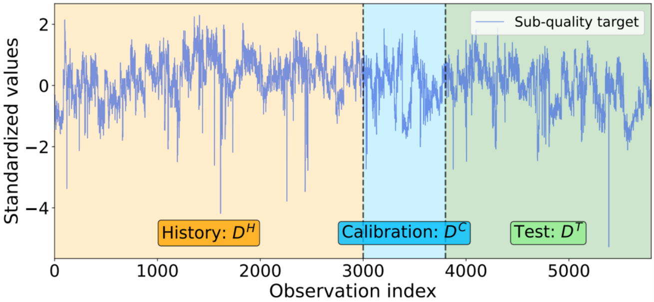

Figure 1: The mixing sub-quality of a Michelin mixing line [13].

1.2 Soft Sensors

To cope with such challenges, soft sensors have emerged as a promising alternative, especially considering Just-In-Time Learning (JITL) strategies which gained wide popularity [10], [14]–[18].

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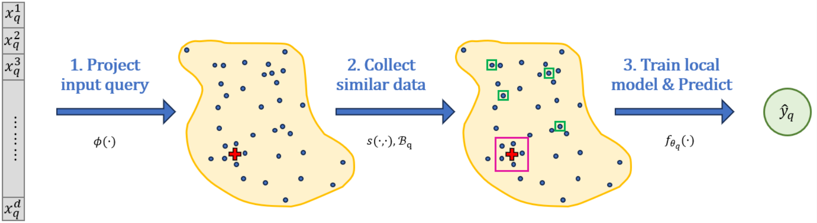

Figure 2: The proposed JITL strategy for soft sensing [13], [19].

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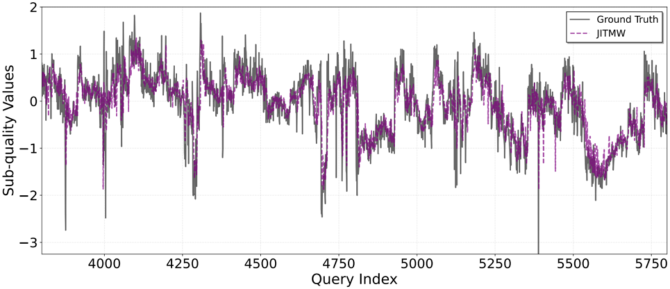

Figure 2: Results of the JITMW strategy on the Michelin mixing line.

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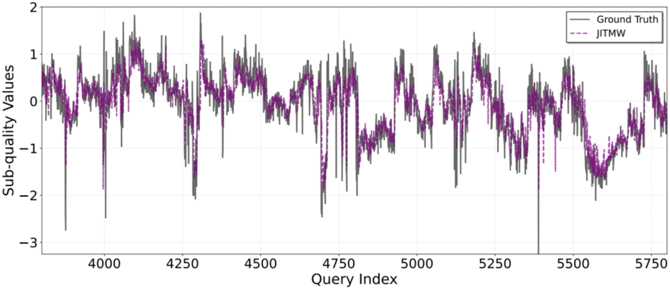

Figure 2: Results of the JITMW strategy on the Michelin mixing line.

Now, ensuring reliable predictions in the online context is **crucial**.

1.3 Online Uncertainty Quantification

To do so, we'll leverage uncertainty quantification methods such as conformal prediction (CP).

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$$((X_1, Y_1), \ldots, (X_n, Y_n)) \stackrel{d}{=} ((X_{\sigma(1)}, Y_{\sigma(1)}), \ldots, (X_{\sigma(n)}, Y_{\sigma(n)})) \tag{1}$$

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To address this issue, we'll refine existing online CP methods and try to propose theoretical guarantees when using latent spaces, particularly considering the case of JITL [24].

References i

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