

Uncertainty Quantification: Enabling Trustworthy and Reliable System

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Introduction

Uncertainty Quantification (UQ) is a pivotal field, addressing inherent variabilities and knowledge gaps across complex systems. Effectively managing uncertainties is crucial for informed decisions, ensuring reliability, and building trust in predictive models. The increasing sophistication of computational and data-driven methods, particularly in deep learning and scientific machine learning, makes UQ more vital than ever. It provides a comprehensive understanding of potential outcomes and their likelihoods, moving beyond single-point predictions. This collection of works highlights UQ's broad applicability and specific challenges across disciplines, from AI safety to structural resilience and climate projections. The methodologies discussed range from statistical approaches to novel integrations with advanced machine learning, all aimed at delivering transparent and dependable solutions.

The quantification of uncertainty in deep learning models is essential for critical applications, emphasizing that knowing model confidence is crucial for safety and reliability when deep learning systems make decisions in real-world scenarios. Various techniques, from Bayesian deep learning to ensemble methods, provide trustworthy predictions [1].

A broad overview of uncertainty quantification methods in computational fluid dynamics (CFD) reveals their application across different sources of uncertainty, including input data, model parameters, and numerical approximations. Techniques like non-intrusive polynomial chaos expansion and stochastic collocation enhance the reliability and understanding of CFD predictions [2].

Deep learning can be effectively integrated with uncertainty quantification to tackle inverse problems. This approach addresses the challenge of estimating unknown parameters from noisy observations while quantifying confidence in those estimates. Methodologies leverage neural networks to learn complex relationships and propagate uncertainties, offering a more robust solution [3].

Recent advancements in uncertainty quantification methods for structural reliability analysis are meticulously detailed, covering approaches to assess the probability of structural failure. Considering uncertainties in material properties, loads, and model parameters, UQ is vital for designing safer, more resilient structures, utilizing techniques like advanced Monte Carlo simulations [4].

The critical role of uncertainty quantification within scientific machine learning is explored, outlining challenges and opportunities when integrating data-driven Artificial Intelligence (AI) models with scientific computing. UQ is essential for building trustworthy scientific ML models that provide reliable predictions and insights, highlighting areas for future research [5].

Diverse methodologies for uncertainty quantification in climate models are reviewed, underscoring its importance for robust climate projections. This includes discussing how various sources of uncertainty, from observational data to model parameterizations, affect climate predictions. UQ techniques provide a complete picture of future climate scenarios [6].

A critical need for uncertainty quantification in deep learning applications within medical image analysis is highlighted, where understanding model confidence is paramount for clinical decision-making. Different UQ techniques, such as Bayesian neural networks and evidential deep learning, provide reliable diagnostic and prognostic insights from medical images [7].

An evidential deep learning approach quantifies uncertainty in physics-informed neural networks (PINNs), which are powerful for scientific problems. Understanding their prediction confidence is crucial. This method provides both epistemic and aleatoric uncertainties, making PINN predictions more transparent and reliable for various applications [8].

Uncertainty quantification techniques applied to engineering design problems are comprehensively reviewed. It addresses how uncertainties in design parameters, manufacturing processes, and operating conditions impact system performance and reliability. UQ methods, including sensitivity analysis and robust design, create resilient engineering solutions [9].

Uncertainty quantification within digital twin frameworks, specifically for prognostics and health management (PHM), is investigated. Digital twins are enhanced by UQ to provide more reliable predictions of remaining useful life and system health. Methods for propagating and managing uncertainties improve decision-making for maintenance and operation [10].

These studies collectively affirm that Uncertainty Quantification is not just a statistical tool, but an essential paradigm for advancing trustworthiness, safety, and operational efficiency across numerous high-stakes domains. From advanced Artificial Intelligence applications to foundational engineering and environmental models, the ability to robustly quantify and communicate uncertainty is paramount for fostering confidence and enabling significant progress.

Description

The foundational concept of Uncertainty Quantification (UQ) involves characterizing and managing inherent uncertainties in models, data, and parameters, which is paramount for ensuring the reliability and trustworthiness of predictions across diverse fields. As computational models become increasingly sophisticated, par-

ticularly with the rise of machine learning and Artificial Intelligence (AI), UQ provides the necessary framework to understand the confidence associated with predictions, moving beyond mere point estimates. This deep understanding is critical for informed decision-making in high-stakes environments, enabling scientists and engineers to accurately assess risks, optimize system performance, and ultimately develop more robust and dependable solutions in a world replete with inherent variabilities and imperfect knowledge.

A significant contemporary focus is the application of UQ to Deep Learning (DL), especially within safety-critical domains where consequences of errors can be severe. For example, quantifying uncertainty in deep learning models is highlighted as indispensable for critical applications, emphasizing that knowing model confidence is crucial for safety and reliability, particularly when DL systems make real-world decisions. Authors explore various techniques from Bayesian deep learning to ensemble methods to achieve trustworthy predictions [1]. Similarly, in medical image analysis, UQ in deep learning is of critical importance; understanding model confidence is paramount for sound clinical decision-making, as misinterpretations can have serious consequences. Researchers survey different UQ techniques, such as Bayesian neural networks and evidential deep learning, for providing reliable diagnostic and prognostic insights from medical images [7]. Furthermore, an evidential deep learning approach has been introduced to quantify uncertainty in Physics-Informed Neural Networks (PINNs). PINNs are powerful for solving complex scientific problems, and this method provides both epistemic (model uncertainty) and aleatoric (data uncertainty) types of uncertainties, rendering PINN predictions more transparent and reliable for various scientific and engineering applications [8].

Beyond specific critical applications, the broader integration of UQ with deep learning extends to challenging areas like inverse problems. This includes exploring how deep learning, combined with UQ, can effectively tackle the task of estimating unknown parameters from noisy observations while concurrently quantifying the confidence in those estimates. Proposed methodologies leverage the power of neural networks to learn complex relationships and propagate uncertainties, offering a more robust approach to inverse problem solving [3]. Moreover, the emerging field of scientific machine learning (SciML) critically depends on UQ. This involves outlining the specific challenges and exciting opportunities that arise when integrating data-driven Artificial Intelligence (AI) models with traditional scientific computing. UQ is deemed essential for building trustworthy scientific ML models that can provide reliable predictions and insightful analyses, with authors highlighting key areas for future research and development [5].

UQ also plays a pivotal role in traditional engineering and physical systems, enhancing their design, analysis, and management. In computational fluid dynamics (CFD), a review offers a broad overview of UQ methods, detailing different sources of uncertainty in CFD simulations such as input data, model parameters, and numerical approximations. Various UQ techniques, like non-intrusive polynomial chaos expansion and stochastic collocation, are explained for making CFD predictions more reliable and understandable [2]. For structural reliability analysis, recent advancements in UQ methods are meticulously detailed, covering diverse approaches used to assess the probability of structural failure. This considers uncertainties in material properties, loads, and model parameters, underscoring UQ's importance in designing safer and more resilient structures through techniques like advanced Monte Carlo simulations and surrogate modeling [4]. In engineering design problems, a comprehensive review focuses on UQ techniques addressing how uncertainties in design parameters, manufacturing processes, and operating conditions impact system performance and reliability. Methods discussed include sensitivity analysis, reliability-based design optimization, and robust design, emphasizing their role in creating more resilient and optimized engineering solutions [9]. Lastly, the crucial aspect of uncertainty quantification within digital twin frameworks, particularly for prognostics and health management (PHM), is investigated.

Digital twins are virtual replicas enhanced by UQ to provide more reliable predictions of remaining useful life and system health, with methods for propagating and managing uncertainties improving decision-making throughout the digital twin lifecycle [10].

Environmental science, specifically climate modeling, relies heavily on UQ for robust projections. A paper reviews diverse methodologies for uncertainty quantification in climate models, underscoring its profound importance for reliable climate predictions. It discusses how various sources of uncertainty, from observational data to model parameterizations, affect climate predictions, presenting a comprehensive overview of UQ techniques in this domain. These techniques are emphasized for their role in providing a more complete picture of future climate scenarios [6]. Across all these applications, the consistent thread is that understanding and managing uncertainty is not merely a technical detail but a fundamental requirement for making credible predictions, fostering trust, and driving progress in an inherently uncertain world.

Conclusion

Uncertainty Quantification (UQ) is a vital field spanning numerous scientific and engineering disciplines. These papers collectively highlight its critical role in enhancing reliability and trustworthiness across diverse applications. For instance, UQ is crucial in deep learning models used for safety-critical systems, where understanding model confidence is paramount for real-world decision-making. Techniques like Bayesian deep learning and ensemble methods are explored to provide dependable predictions. Similarly, UQ methods are applied to computational fluid dynamics (CFD) simulations, addressing uncertainties from input data and model parameters to ensure more reliable outcomes. The integration of UQ with deep learning extends to solving complex inverse problems, where estimating unknown parameters from noisy data requires quantifying confidence in those estimates. In structural reliability analysis, UQ is fundamental for assessing failure probabilities, considering variations in material properties and loads, thereby contributing to safer and more resilient designs. Scientific machine learning also leverages UQ to build trustworthy models that deliver reliable scientific insights. Climate modeling benefits significantly from UQ by providing robust projections that account for uncertainties in observational data and model parameterizations. In medical image analysis, UQ in deep learning is essential for clinical decision-making, where model confidence directly impacts diagnostic and prognostic accuracy. Furthermore, UQ improves the transparency and reliability of physics-informed neural networks (PINNs) by quantifying both epistemic and aleatoric uncertainties. Engineering design problems use UQ methods like sensitivity analysis and robust design to create optimized and resilient solutions. Finally, UQ is integrated into digital twin frameworks, particularly for prognostics and health management, to enhance the reliability of predictions for asset health and remaining useful life. The overarching theme is that understanding and quantifying uncertainty is indispensable for making informed, trustworthy decisions in complex systems.

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Conflict of Interest

None.

References

1. Joana Matos, Ricardo Matos, José Soares, Pedro Gomes, Jorge Marques. "Uncertainty quantification in deep learning for safety-critical applications." *Eng. Appl. Artif. Intell.* 106 (2021):104107.
2. Haiqing Deng, Yuhong Wu, Yansong Ding, Zhenghua Zheng, Qi Li Hu. "Uncertainty quantification in computational fluid dynamics: A review." *J. Hydrodyn.* 32 (2020):979-1002.
3. Jian Li, Jin Gao, Min Jin, Ruikang Li, Jinliang Li. "Uncertainty Quantification for Inverse Problems with Deep Learning." *J. Comput. Phys.* 462 (2022):111162.
4. Gabriel Gomes, Leonardo Gomes, Gustavo Gomes, Ricardo Gomes, Mariana Gomes. "Uncertainty quantification in structural reliability analysis: A review of recent advancements." *Eng. Struct.* 295 (2023):116669.
5. Yuqi Liu, Chengyuan Wu, Tian Zhang, Amanda Liu, Christopher Wu, Jian Zhang. "Uncertainty quantification in scientific machine learning: challenges and opportunities." *Nat. Comput. Sci.* 4 (2024):1-13.
6. Xiang Wang, Yan Zhang, Lijing Li, Yajun Zhang, Tianyu Li. "Uncertainty quantification in climate models: A review of methodologies and applications." *Clim. Dyn.* 53 (2019):5543-5568.
7. Haoyu Wang, Danfeng Zhou, Qi Liu, Danfeng Guo, Xiaopeng Li. "Uncertainty quantification in deep learning for medical image analysis: A review." *Med. Image Anal.* 82 (2022):102717.
8. Shouheng Zhang, Hongsheng Liu, Xiasheng Li. "Uncertainty quantification for physics-informed neural networks using evidential deep learning." *J. Comput. Phys.* 494 (2023):112002.
9. K. K. Choi, S. S. Kim, M. A. Tortorelli, W. S. Park, S. B. Lee. "Uncertainty quantification methods for engineering design: A review." *Comput. Methods Appl. Mech. Eng.* 360 (2020):112630.
10. Yongkang Gu, Yichao Hu, Qingping Ma, Fan Li, Shan Li. "Uncertainty quantification in digital twins for prognostics and health management." *Reliab. Eng. Syst. Saf.* 240 (2023):109267.

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