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A Framework for Managing Indeterministic Aspects in Enterprise AI Implementations

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Abstract: ***As organizations become more aware of how artificial intelligence (AI) can accelerate digital transformation, it will become crucial for them to manage the unpredictable aspects of AI-related projects to ensure sustained positive outcomes. This paper presents a structured approach to assist organizations that are tasked with dealing with the inherent indeterministic nature of AI-type projects. The structured approach includes uncovering the feasibility of AI in definite organizational contexts, initial project scoping and experiment planning, designing a human-in-the-loop (HITL) and feedback framework, and developing a sustainable governance and accountability model. By utilizing a structured process, organizations can align their AI deployments with business outcomes while mitigating corporate risks associated with the probabilistic nature of AI outputs.***

Keywords: Artificial Intelligence, Enterprise Strategy, Human-in-the-Loop, AI Governance, Experimentation, Feedback Loops

1. Introduction

Artificial Intelligence (AI) has become a common feature of many industries for organizations in their digital transformation strategies today, including telecommunications, financial services, healthcare, and manufacturing. Organizations will strive to implement AI and other technologies as technology-assisted technologies that provide the opportunity to access data, produce insights, automate decisions, and achieve productivity gains. From a deterministic perspective, AI exhibits a distinctly different performance output compared to earlier software systems. Importantly, only certain aspects of ML models and generative models are deterministic (e.g., performance in a song); essentially, you might get similar outputs, when inputs given were identical, yet the unique outputs will differ slightly even down to the 'random' nature of probabilistic models and the dataset or components being 'evolving'. While variability is often a positive attribute for innovation, this characteristic can pose significant risks to businesses that rely on consistency, predictability, and accountability in their operations. [1].

2. Understanding Indeterminism in AI

Unlike deterministic software systems, AI systems tend to produce outputs that differ, albeit marginally, every time they are executed, even in the presence of identical inputs. This variability is referred to as indeterminism and is attributed to probabilistic algorithms, stochastic optimization methods, datasets that contain noise or missing values, and the complexity associated with specific models or processes related to AI, such as deep neural networks. While this indeterminism leads to flexibility, creativity, and adaptability, it also introduces unpredictability, which can be hazardous in mission-critical enterprise environments [2].

2.1 Is AI the Right Solution?

Before any organization makes a commitment to AI as an answer to a business problem, the organization should conduct a methodical investigation of whether AI is necessary to solve the problem. Not every business problem is an appropriate candidate for the use of AI. As importantly, not every problem that AI can solve requires AI components [3]. In many situations, a deterministic rule-based system or traditional statistical methods can be more efficient, cost-effective, and produce more predictable results. The first step in the formative process is focused on framing the problem.

2.2 Experimentation and Success Metrics

Once an organization determines that AI is suitable for addressing a particular challenge, the next critical step is to establish a rigorous experimentation and validation process [4]. AI systems cannot simply be thrown into production or deployed without undergoing significant real-world testing. With AI systems, we seldom have a deterministic and repeatable model; therefore, these models are subject to multiple iterations of experimentation, including changes in algorithms, feature engineering, hyperparameter tuning, and data curation.

2.3 Human-in-the-Loop (HITL) and Feedback Loops

Although AI has made significant advancements towards fully automated decision-making processes, at least for now, AI systems still require the human factor to be present throughout the implementation of AI systems, and primarily to support critical decision-making. HITL refers to designing an AI system that incorporates a structured process for a human to intervene for decision quality assurance at any moment. Thus, when the AI system is faced with ambiguous, sensitive, and/or foreign aspects of the task being managed, an appropriately qualified human operator is left to make the final decision on whether to agree and/or override the decision made by the AI system.

2.4 Continuous Governance and Accountability

The fourth part of the proposed framework focuses on establishing and maintaining continuous governance throughout the lifecycle of AI systems, encompassing ethical, operational, and legal considerations. As previously stated, governance also extends beyond the day-to-day operation of the AI system, encompassing continuous monitoring, regular audits, and delineated accountabilities across role boundaries [5] [6].

3. Conclusion

As businesses increasingly turn to AI technologies, the challenges of managing the indeterministic aspects of experience will need to be more clearly defined as we move forward. This paper presents a holistic approach to managing typical AI-first problems for enterprises, which includes problem assessment as a starting point, thorough experimentation, integrated human oversight, and governance.

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