Developing Neuro-Symbolic Conversational Systems for Reliable Multi-Perspective Production Process Intelligence

Angelo Casciani[1], Livia Lestingi[2], Andrea Marrella[1], and Andrea Matta[2]

[1] Sapienza Universitá di Roma, Rome, Italy
{casciani,marrella}@diag.uniroma1.it
[2] Politecnico di Milano, Milan, Italy
{livia.lestingi,andrea.matta}@polimi.it

Abstract. This tutorial presents the required steps to build trusted neuro-symbolic conversational systems that integrate Large Language Models (LLMs) with reasoning engines and process intelligence tools for faithful and accurate process analysis. By adopting an "LLM-as-formalizer" approach, where the LLM captures user intent, translates it into machine-readable instructions, and orchestrates external tools to generate actionable insights, we demonstrate how Information Systems practitioners can effectively design and implement such systems.

Keywords: Neuro-Symbolic AI, Process Intelligence, LLM

1 Motivation and goals of the tutorial

Large Language Models (LLMs) have shown impressive capabilities across various process analysis tasks, including process modeling, simulation, and mining [2, 1, 9, 4]. Nonetheless, the extent to which current LLMs can perform genuine logical reasoning remains a critical area of investigation. Indeed, the reasoning mechanism in LLMs is fundamentally based on probabilistic pattern recognition rather than formal logic. While they can approximate abstract reasoning patterns, they fall short of true logical inference [11]. Their outputs are highly sensitive to small input variations, and accuracy declines as the number of reasoning steps increases, limiting their reliability for complex tasks [10].

This limitation is especially relevant in production systems, where operating and interpreting multiple reasoning and process intelligence tools requires highly specialized expertise [6, 8, 5]. For example, revising a production plan to meet delivery deadlines while minimizing disruptions, optimizing resources and inventory, and ensuring system correctness demands complex multi-criteria analysis. Nowadays, this work is performed manually by expert users using many external tools, making the process time-consuming, skill intensive, and prone to suboptimal decisions due to the limited exploration of available data and alternatives [7]. As LLMs are increasingly used to support operators in these tasks, analytical methods must deliver accurate and reliable diagnostic and prognostic insights within strict time constraints, a guarantee that LLMs alone cannot provide [12].

Pre-print copy of the manuscript published by Springer
(available at: https://link.springer.com/book/10.1007/978-3-032-28117-3)
identified by doi: 10.1007/978-3-032-28117-3

To address this challenge, in this tutorial we discuss the *methodological and development steps to create a new breed of trusted neuro-symbolic conversational systems*. These systems integrate LLMs with reasoning engines and process intelligence tools to support accurate, multi-perspective analysis of production processes. Rather than adopting an "LLM-as-reasoner" approach, which may generate seemingly coherent yet potentially inaccurate and unverifiable explanations for human tasks [3], we advocate an "LLM-as-formalizer" paradigm [13], in which the LLM is trained to capture the user's intent, translate it into machine readable instructions, orchestrate external reasoning and process intelligence tools and generate actionable insights and predictions to analyze and optimize process performance. This hybrid approach ensures that the flexibility of natural language is backed by the sound guarantees of formal solvers. Through a real world production process, we demonstrate how Information Systems practitioners can design and implement such systems effectively.

Acknowledgments. This work was supported by the Sapienza project FOND-AIBPM, the PRIN 2022 project MOTOWN, and the Horizon EU Research and Innovation Programme (AutoTwin - Grant 101092021). A. Casciani conducted this research while enrolled in the Italian National PhD in AI (Sapienza Univ.).

References

1. Agostinelli, S., et al.: Automating Performance Insights: Suggesting and Computing Process Performance Indicators from Event Logs. In: CAiSE 2025 (2025)
2. Casciani, A., Bernardi, M.L., Cimitile, M., Marrella, A.: Conversational Systems for AI-Augmented Business Process Management. In: RCIS 2024 (2024)
3. Casciani, A., et al.: A Conversational Framework for Faithful Multi-Perspective Analysis of Production Systems. In: CAiSE 2025 (2025)
4. Casciani, A., et al.: Enhancing next activity prediction in process mining with Retrieval-Augmented Generation. Inf. Syst. **137** (2026)
5. De Luzi, F., Leotta, F., Marrella, A., Mecella, M.: On the Interplay Between Business Process Management and Internet-of-Things. Bus. Inf. Syst. Eng. **67**(2) (2025)
6. Frigerio, N., Tan, B., Matta, A.: Simultaneous control of multiple machines for energy efficiency: a simulation-based approach. Int. J. Prod. Res. **62**(3) (2024)
7. Keskin, Z., Joosten, D., Klasen, N., Huber, M., Liu, C., Drescher, B., Schmitt, R.H.: LLM-Enhanced Human–Machine Interaction for Adaptive Decision-Making in Dynamic Manufacturing Process Environments. IEEE Access **13** (2025)
8. Lestingi, L., et al.: Analyzing the impact of human errors on interactive service robotic scenarios via formal verification. Softw. Syst. Model. **23**(2) (2024)
9. Li, J., et al.: Fundamental Capabilities and Applications of Large Language Models: A Survey. ACM Comput. Surv. **58**(2) (2026)
10. Lunardi, R., Mea, V.D., Mizzaro, S., Roitero, K.: On Robustness and Reliability of Benchmark-Based Evaluation of LLMs. In: ECAI 2025 (2025)
11. Song, P., Han, P., Goodman, N.: Large Language Model Reasoning Failures. Trans. Mach. Learn. Res. **2026** (2026)
12. Stechly, K., Valmeekam, K., Kambhampati, S.: On the self-verification limitations of large language models on reasoning and planning tasks. In: ICLR 2025 (2025)
13. Tantakoun, M., et al.: LLMs as Planning Formalizers: A Survey for Leveraging Large Language Models to Construct Automated Planning Models. In: ACL (2025)