Causal Neuro-Symbolic AI for Root Cause Analysis in Smart Manufacturing

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Abstract

Root cause analysis is the process of investigating the cause of a failure and providing measures to prevent future failures. It is an active area of research due to the complexities in manufacturing production lines and the vast amount of data that requires manual inspection. We present a combined approach of causal neuro-symbolic AI for root cause analysis to identify failures in smart manufacturing production lines. We have used data from an industry-grade rocket assembly line and a simulation package to demonstrate the effectiveness and relevance of our approach.

Keywords

Causality, neuro-symbolic AI, root cause analysis, smart manufacturing

1. Root Cause Analysis in Smart Manufacturing

Smart Manufacturing, or Industry 4.0, represents a wave of innovations and new technologies that are shaping the future of manufacturing with the goal of achieving more efficient production lines. Advanced sensors and Internet of Things devices collect data about various aspects of the production process, marking the onset of data-driven manufacturing. The collected data is utilized for predictive maintenance, process optimization, and root cause analysis (RCA). Traditional RCA is a costly and time-consuming process that involves manual inspection by domain experts, potentially leading to production delays. The automation of RCA is an active research area in smart manufacturing, aimed at minimizing downtime and ensuring cost-effective production lines. Current work on RCA leverages ontologies, knowledge graphs (KG), and neuro-symbolic methods to store expert knowledge, model production line dependencies, and conduct reasoning to identify the time, location, and cause of failures [1]. In order to better understand and explain the root cause of failures and provide preventive measures, it is important to comprehend and model the causal associations in the data. However, parametric causal AI approaches for RCA do not consider prior knowledge about the relationships and parameters in the data [2]. Furthermore, traditional causal association approaches, which predict causal relations between variables, do not scale well for large volumes of data [3]. Effective

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RCA necessitates the integration of causal associations (via causal models) among the data and knowledge from diverse sources, offering enhanced explainability, scalability, and the ability to perform intervention and counterfactual analysis.

2. Causal Neuro-Symbolic AI for Root Cause Analysis

Causal Neuro-Symbolic AI (NSAI) is a hybrid framework that blends the strengths of causal and NSAI representations and techniques [4]. Our Causal NSAI-enhanced RCA approach supports RCA by expressing the causal association among the data into symbolic representation. A KG that encodes causal Bayesian network (CBN) based representation explicitly expresses the causal association. The framework utilizes NSAI methods such as KG link prediction, providing better scalability for inferring causal relations within large volumes of data. Causal NSAI provides the following benefits: 1) Explainability- it enhances explanations for failures by combining causality with symbolic (i.e., ontology and KG) reasoning and neural networks; 2) Robustness- it leverages causal associations to improve the robustness of AI models to changes in data distribution, and out-of-distribution data; 3) Generalization- it enhances generalizability by incorporating prior domain knowledge with causal associations; 4) Intervention- it leads to models which can predict the impact of interventions in the production line and make informed decisions to achieve desired outcomes. This integration of causal associations with NSAI enables dynamic adaptation to new manufacturing environments. The framework is applied to an industry-grade dataset for a rocket assembly line[1] and the causalAssembly[2] based simulated dataset [5]. The rocket assembly is a multi-modal data setup with four robots, rocket parts, conveyor belts, a material handling station, stoppers, image and video recording, and sensors such as temperature, potentiometer, load cells, robot angles, programmable logic controls, etc. A failure in the assembly is defined as the absence of a rocket part in the final product. The Causal NSAI framework is utilized to 1) provide explanations for the cause of the failure, 2) suggest measures that can be taken to obtain a final product despite the failure, and 3) identify interventions and counterfactuals using the causal associations to prevent future failures. **Acknowledgments:** NSF Awards #2335967 and #2119654.

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[1]Our public data is at https://www.kaggle.com/datasets/ramyharik/ff-2023-12-12-analog-dataset
[2]https://github.com/boschresearch/causalAssembly