



WHITEPAPER

THE SIMULATION FRAMEWORK
FOR YOUR BUSINESS

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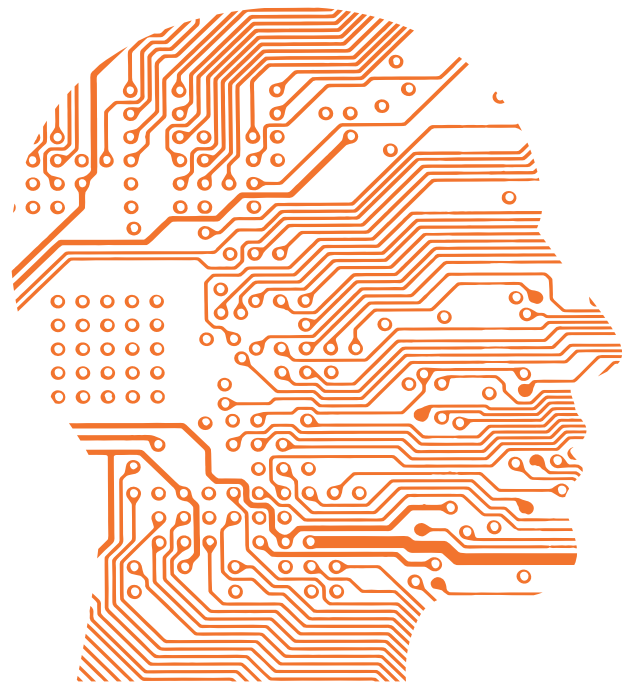
Executive Summary



STRG.Reason is an innovative software solution for industrial enterprises based on the principles of Causal-AI. It is engineered to elevate business decisions through explainable planning and forecasting. It achieves this by integrating cutting-edge Causal Artificial Intelligence (Causal AI) methods with the structural processing power of Graph Neural Networks (GNNs).

➔ **Traditional AI** often relies on statistical correlation, leading to "Black-Box" predictions that lack transparency. STRG.Reason pioneers the "White-Box" paradigm by moving beyond correlation to understand and model true cause-and-effect relationships. This enables users to answer crucial "Why" and "What-if" questions essential for informed decision-making.

➔ **Causal AI** applies cause-and-effect reasoning to decisions, so you can run trustworthy "what-if" interventions, quantify impact, and choose actions—not just generate plausible text—making it fundamentally more valuable for business outcomes than any LLM alone.



STRG.Reason's core capability is its integrated end-to-end workflow, which includes three main components: Causal Discovery, Causal Inference and Causal Modeling. This entire system is complemented by a novel Risk Minimisation Process and an Explainability Module powered by Large Language Models (LLMs) to translate complex causal insights into clear, actionable language for both technical and non-technical users. STRG.Reason is specifically designed to strengthen user trust in AI for industrial applications, leading to enhanced efficiency, reduced warehousing costs and increased operational resilience.

Causal AI learns the cause-and-effect structure embedded in your historical data, so we can simulate realistic "what-if" interventions—changing pricing, staffing, supply, or policies—and forecast the downstream business impact as if you had actually made those changes.



Product capabilities and value proposition

STRG.Reason is designed to overcome the limitations of traditional AI models, which have seen slow adoption in industrial environments due to their inability to recognize or consider causal relationships. The software delivers explainable, transparent and robust results, particularly for complex industrial scenarios.

Explainable Decisions:

The inherent explainability, based on the mathematical formulation of causal analysis, allows users to query why a specific output was achieved. For instance: “What impact will an investment in new machinery have on production output?”

"What-if" Analysis:

By structuring models based on causal relationships, STRG.Reason bridges the gap between complex industrial data and human understanding, fostering trust and accelerating the integration of AI across the industry.

Trust and Transparency:

Utilising Causal Inference, STRG.Reason enables rigorous simulation of interventions and counterfactual scenarios (e.g., “What impact would a price change have had on customer demand?”).

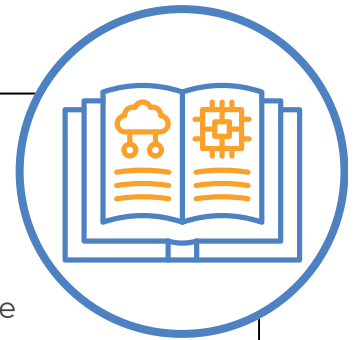
Core Components and Functionality



STRG.Reason's architecture is built on three interconnected causal components:

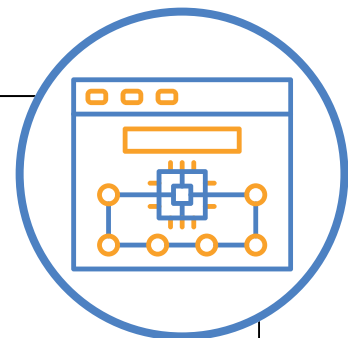
Causal Discovery:

This component identifies the underlying causal structure of a system to learn genuine cause-and-effect relationships. It employs various causal detection methods (Constraint-based, Score-based, or hybrid approaches) to create causal representations in the form of diagrams. The primary challenge addressed is the identification and mitigation of confounder variables that create spurious correlations.



Causal Inference:

This function predicts the effects of interventions and answers counterfactual questions. Key tools, including the Do-calculus and Causal Reasoning (counterfactual inference), are implemented. A novel approach is the simulation of interventions directly within the causal diagram by strategically masking or manipulating nodes or edges, allowing users to explore alternative realities and understand causal consequences.



Core Components and Functionality



Causal Modeling



This component integrates causal inference to enhance and confirm the results of predictive AI models. It uses Causal Bayesian Networks and the inclusion of causal constraints in Deep Learning architectures to improve predictive power and robustness. The central application area is decision-making and risk minimisation by applying the software's intervention representation capabilities to industrial data.

Ladder of Causation

From Correlation to Causal Intelligence



Technical Architecture and Methodology



GNN Causal Pipeline

STRG.Reason employs a multi-stage pipeline that fundamentally transcends correlation-based AI by facilitating the learning of causal representations, or Causal Embeddings, which inherently capture the causal roles of entities within a dataset.



Data Transformation: Raw data is transformed into two relevant graph structures: a Causal Graph (directed edges indicating the flow of causality, derived from Causal Discovery) and a Data Graph (showing non-causal patterns).



GNN Processing: The Causal Graph is processed by a specially designed GNN architecture to learn causal embeddings. Simultaneously, the Data Graph is processed by a separate GNN to generate non-causal (associative) embeddings.



Feature Vector Creation: The causal and non-causal embeddings are concatenated to form a comprehensive feature vector.

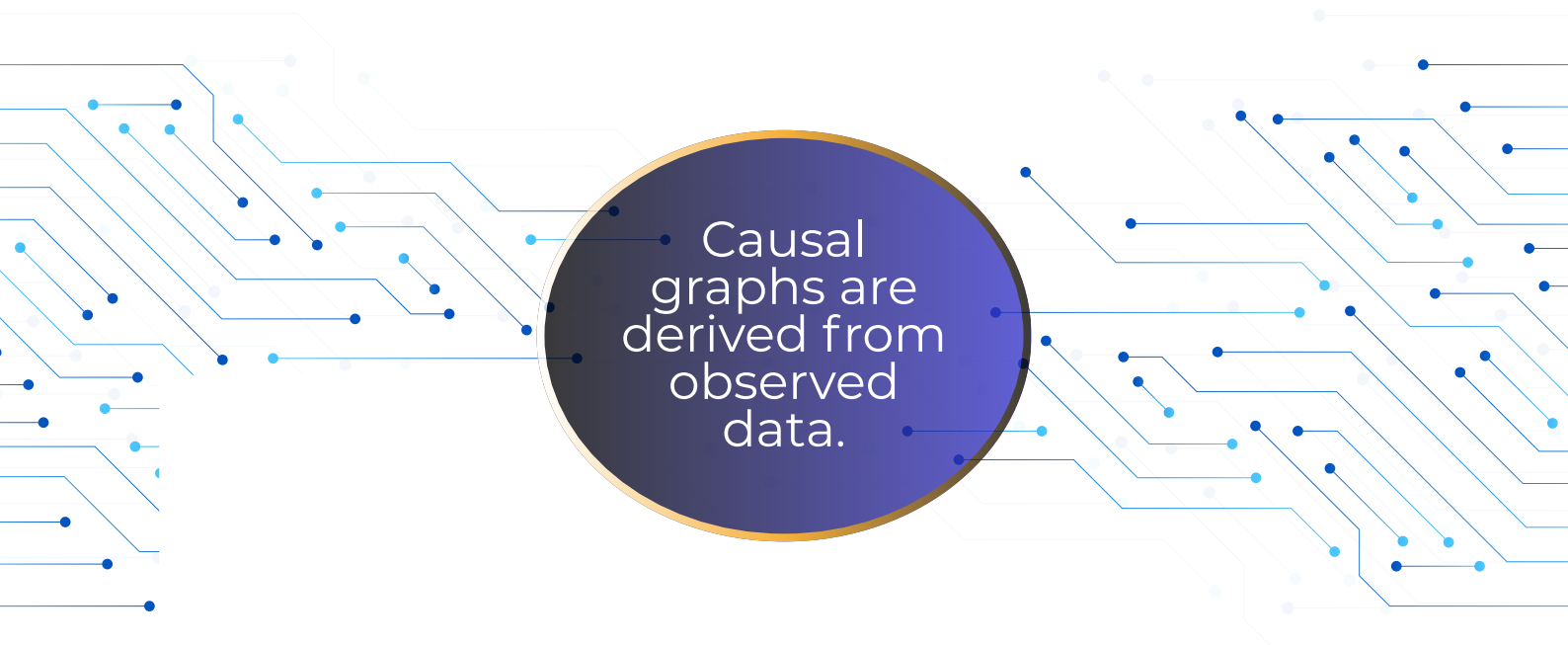


Downstream Tasks: This integrated representation is fed into a Neural Network to perform various downstream tasks, such as prediction, classification, or regression. This utilisation of causal information improves accuracy, robustness, and the basis for explainability in applications like supply-demand forecasting and root cause analysis.



Intervention Learning Methodology

A key innovation is the scheme for learning intervention representations:



Causal graphs are derived from observed data.

Intervention Graph Generation:

The causal graph serves as the basis for simulating interventions on nodes. An Intervention Graph is generated by applying transformations (masking or manipulating nodes/edges) directly to the causal structure. This explicit use of the causal diagram is critical to correctly model causality and propagate effects, especially with confounding factors.

Intervention Embeddings:

Both the original Causal Graph and the transformed Intervention Graph are processed by separate GNN architectures, yielding causal and Intervention Embeddings.

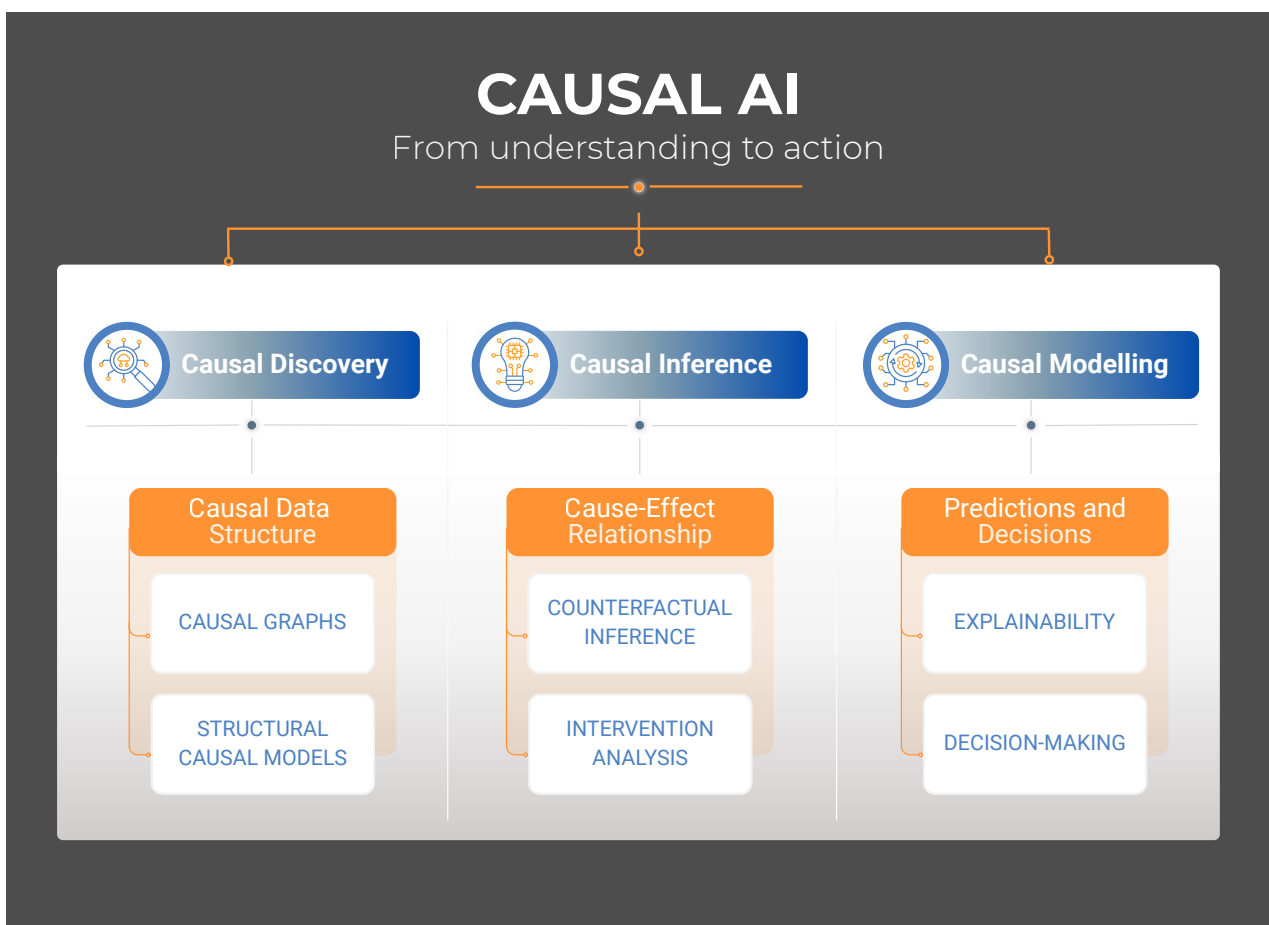


Intervention Learning Methodology

A key innovation is the scheme for learning intervention representations:

Optimized Decision Support:

The concatenation of both embeddings creates a robust representation of the system's causal state and the effect of simulated interventions, which is then used by a Neural Network to predict outcomes under specific intervention scenarios and support counterfactual analyses.



Explainability and Risk Minimisation



STRG.Reason integrates advanced features for usability and risk governance:

- **Explainability Module (LLM-Powered):** The system deploys Large Language Models (LLMs) to translate complex causal relationships, root cause analyses, and results into clear, simple human language, ensuring that the generated causal insights are easily understandable for technically non-savvy users.
- **Risk Minimisation Process:** This integrated process utilizes the software's explainability to quantify the associated risks of an AI prediction, not just identify them. By understanding the causal origins of a prediction, users can better assess the likelihood and extent of potential negative outcomes, enabling informed, risk-minimized decision-making.

The Shift to Causal AI

Causal AI represents a necessary evolution in machine learning, offering the fundamental ability to answer the “Why” behind phenomena, a critical function in industrial applications.

Theoretical Basis: The formal mathematical frameworks developed by pioneers like Judea Pearl, Peter Spirtes, and Clark Glymour—particularly Causal Diagrams and the Do-calculus—provide the theoretical foundation for representing and inferring causal effects from data. While open-source libraries like DoWhy and CausalML exist, STRG.Reason offers a user-friendly, end-to-end industrial workflow that eliminates the need for considerable expertise.

Graph Neural Networks (GNNs): Causal relationships are naturally represented by graphs. GNNs, which learn representations of nodes and edges that embed the structural information of a graph, are employed as the powerful architectural tool for leveraging these causal dependencies. The software tests and adapts various GNN architectures (e.g., GCN, GAT, GraphSAGE) using the causal graphs generated through Causal Discovery.



GNNs in Causal Tasks

Current research, such as Causal Attention Learning (CAL) and the CIGNN-Framework (Causal Intervention Graph Neural Network), highlights the use of GNNs in Causal AI to identify causal patterns, mitigate confounding factors, and reliably identify root causes of failures. STRG.Reason leverages and extends this work, focusing on adapting GNN architectures to process the unique structure of causal diagrams generated from real-world industrial data.⁵ Benefits and Sustainable Impact

Business and Technical Advantages

Integrated Solution: Unites Causal Discovery, Causal Inference, and Causal Modeling, offering an advantage over using multiple different tools by reducing complexity and inconsistencies.

STRG.Reason offers significant advantages over conventional AI/ML platforms and basic Causal Inference libraries by providing an integrated, end-to-end solution tailored for industrial decision-making.

Targeted Interventions: The method for learning the representation of interventions via masking and manipulation of nodes and edges enables sophisticated "what-if" analysis and the ability to predict the cascading effects of actions across the entire system.

Insights and Optimisation: Enables users to overcome misleading correlations, perform root cause analysis, and gain insights into non-obvious relationships between entities (components, processes, products), facilitating the optimisation of business strategies.



Product Robustness and Implementation Strategy

STRG.Reason and its underlying models are maintained as Closed Source. Generalisable partial successes are intended for publication in scientific papers. The development was meticulously managed to ensure robustness and efficacy, with solutions designed to address inherent challenges in Causal AI implementation:

- ➔ **Dataset Suitability:** The software is validated using industrial datasets from cooperation partners (for real-world ground truth) and publicly available academic datasets. Robust processes and systematic criteria are used to assess the causal suitability of datasets.
- ➔ **GNN Training Complexity:** An incremental strategy is applied to manage the computational complexity of training GNNs with causal graphs. Initially, performance is verified on reliable ground-truth datasets before moving to more complex industrial data.
- ➔ **Causal Discovery Robustness:** To counter the risk of non-convergence or implausible results from causal detection algorithms, STRG.Reason tests and integrates various established methods (Constraint-based, Score-based, Hybrid). Causal diagrams are designed to be validated by industry experts.
- ➔ **Intervention Representation:** The novel GNN-based approach for learning intervention representations is rigorously tested using historical data with well-described interventions and counterfactuals to ensure robust and accurate effect estimates.

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Thanks

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