Neuro-Symbolic AI at Bosch: Data Foundation, Insights, and Deployment

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Motivation. Neuro-symbolic AI [1] refers to the integration of connectionist AI (neural networks) and symbolic AI approaches (e.g. ontology and logics). Neuro-symbolic AI in the industry becomes possible thanks to the technological advances of Industry 4.0 [2], which bring a fast growth in volume and complexity of heterogeneous manufacturing (big) data [3]. Despite the popularity of this topic, how neuro-symbolic AI can be realised in the industry remains to be studied. In this paper, we exemplify neuro-symbolic AI with the activities of at Bosch (Fig. 1), where semantic technologies play an essential role, including 1) the data foundation, which relies on semantic data integration to unify heterogeneous data to uniform formats, 2) the insights, which exploit data-driven methods especially machine learning (ML) to extract knowledge from the data, and 3) the deployment, which gives industrial examples of value generation from the data.

Data Foundation: Semantic Data Integration. Bosch models industrial assets with their *semantic digital counterparts* as ontologies, such as resistance spot welding (welding that connects car bodies parts via welding nuggets). Bosch is also developing domain core ontology, based on manufacturing standards of ISO and harmonised with the top level ontology such as BFO to improve the Bosch applications interoperability. *Industrial KGs.* Bosch experts annotate heterogeneous manufacturing data with unified vocabularies from the ontologies, which are enhanced by the ontology reshaping method [4] that removes classes unmapped to data. Following the reshaped ontologies as KG schemata, knowledge graphs (KG) are semi-automatically generated as homogeneous data formats/databases, which allow uniform access and interoperability [4].

Insights: AI-Powered Analytics. We give examples of such analytics built on the unified KG data to extract insights, including numeric data such as sensor measurements as well as text data like machine status text. *Executable KG Analytics.* Executable KGs [5] represent executable data pipelines in a standardised and transparent way (namely *executable KGs*) for visual, statistical and ML analytics (such as quality prediction), and these KGs can be transformed into executable

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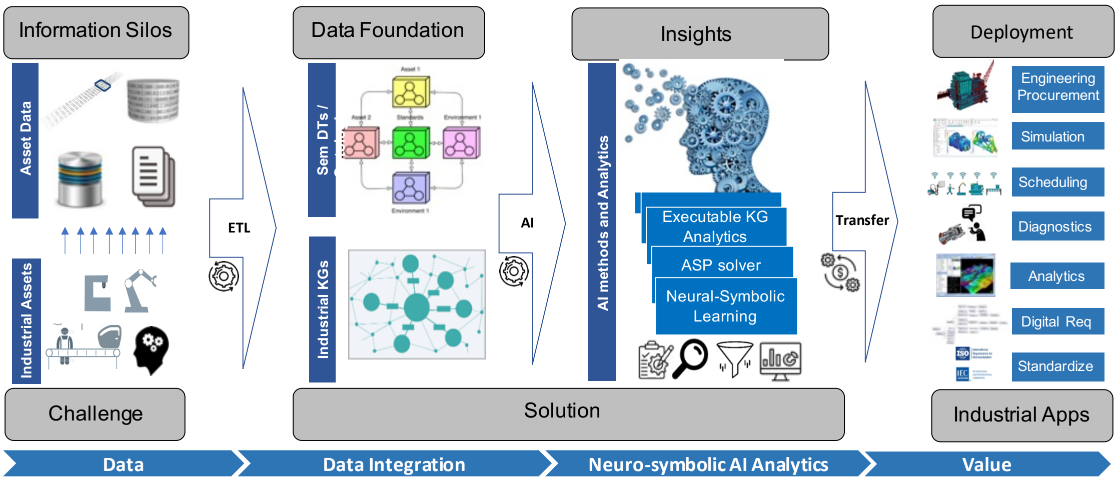

Figure 1: Overview: Semantic ETL creates the data foundation of AI-powered analytics, which extracts insights that can be transferred to value in industrial deployment.

scripts in a highly reusable and modularised fashion, improving transparency and adoption in the industry. *ASP Solver.* Bosch relies on Answer Set Programming (ASP) for solving difficult (primarily NP-hard) search problems, which is a form of declarative programming and based on the stable model (answer set) semantics of logic programming. ASP is beneficial for solving knowledge-intense combinatorial (optimisation) problems. *Neuro-Symbolic Learning.* Currently we focus on the state of the art KG embedding methods (e.g, TransE, RotatE) and GNN relevant methods. Examples: 1) We rely on *neuro-symbolic methods* with dynamic link prediction for complex query answering, which is more explainable compared to black-box neural models for classification/regression, since the neuro-symbolic approach accompanies answers with symbolic knowledge and confidence level. 2) Bosch studies different *KG uncertainties* caused by e.g., inconsistency and incompleteness to reduce the learning/inference uncertainty.

Deployment: Industrial Applications. We give three examples 1) *Process Diagnostics*: in manufacturing, some anomalous welding operations (that produce quality failures), machines (that produce more quality failures), etc. need to be identified and their root-causes need to be analysed via visual and statistical analytics; 2) *Quality Monitoring*: the numerical or categorical quality indicators (such as welding diameter)need to be estimated/predicted by ML analytics with classification/regression; 3) *Personnel Scheduling*: the automatic arrangement of personnel with different available or preferred time and tasks need to be solved by ASP solver.

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