Using Knowledge Graph Embedding for Fault Detection: A Case Study in Electric Vehicle Parts Assembly

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Abstract

Automotive recalls due to manufacturing errors can be expensive, dangerous, and potentially fatal. The rollout of new electric vehicles (EVs) in a relatively short time adds complexity to the manufacturing process. Companies must use expensive fault detection systems to identify defects in the assembly process. Knowledge-based approaches for fault detection in manufacturing and assembly systems reflect modern practices in Industry 4.0. In this work, we use knowledge graphs (KG) for their effectiveness in detecting faults in a custom dataset. We implement a KG Completion (KGC) algorithm and compare different KG Embedding (KGE) models. We show results for the model achieving the best performance with the RotatE test on the Hits@100 metric.

Introduction

Automotive manufacturers are under stressful timelines as they shift their focus from internal combustion engines (ICE) to electric (EV) and hybrid-electric vehicles (HEV). The demand for this rapid change is crucial to meet a growing consumer market. New manufacturing challenges coupled with rapid change can lead to substantial safety risks for consumers as well as financial liability for automakers, especially when recalls happen. The resulting misplacement, misalignment, or defective assembly of any of the components or connectors can result in critical or even fatal outcomes for consumers.

Recent findings reported by CNBC revealed that the shift to electric vehicles had cost automakers billions of dollars (Kolodny 2022). The cost of recalling an EV far outweighs that of an ICE. For instance, the Ford Kuga plug-in HEV had recalls costs of about $19,000 per vehicle, in contrast to a typical ICE vehicle recall that averages around $500 per vehicle (Isidore and Vales-Dapena 2022). Furthermore, the EV recall rate has been higher. For instance, China's EV recall rate was approximately 6.9% of its total sales volume (Hao et al. 2021).

Automakers are highly motivated to prevent automotive recalls by implementing and employing several preventative measures. IoT sensor-based fault detection systems, as well as those with camera capabilities, have been used to detect defects during production and assembly processes. Industry 4.0 standards (Garofalo et al. 2022) have been adopted, particularly when companies employ an autonomous assembly process.

A critical issue in vision or sensor-based fault detection systems is their limitations, where they can only analyze and observe end components without analyzing the relationships and possible underlying connections with other components. For instance, these relationships can reveal whether a given component is missing or is connected correctly to another component. Simply relying on machine vision examining components in isolation, especially in uncontrolled manufacturing environments, becomes difficult and reliable, not to mention the extremely de-manding computational power needed for vision processing.

The motivation of this research work is to present an alternative perspective that employs a collective view of components, represented as a networked graph, particularly a knowledge graph (KG), that we hypothesize to be effective in analyzing data in the search for faults.

Methodology

KGs are a collection of real-world fact triplets of the structured form (head, relation, tail) (Hogan et al. 2022). Fundamentally, KGs can be expressed as a graph where nodes represent components or sub-components, and edges indicate a relationship between the two adjacent components. Hence, KG can be used to effectively represent and map interconnected components during and after manufacturing. Researchers have demonstrated the usefulness of Knowledge Graph Embedding (KGE) as a potential solution for automotive fault detection, and they have used it to advance their autonomous driving solutions (Bosch Global 2022).

This research aims at building KGs and testing their effectiveness in detecting faults in a custom dataset. We implement a KG Completion (KGC) algorithm and compare different KG Embedding (KGE) models. Furthermore, we measure and compare the Mean Reciprocal Rank (MRR) and Hits@K to evaluate the algorithm based on various KGE approaches and models. Our findings from our experiments pave a new pathway for vehicle manufacturers and car makers, allowing for a feasible and comprehensive fault detection system and framework. By combining state-of-the-art KGE models and a first-hand case study involving an electric vehicle knowledge graph dataset (EV-KG), this work solidifies future KG-related fault detection research in the field and opens numerous opportunities for further development and application in the real-world industry.

Link prediction in knowledge graphs has accelerated in recent years through various state-of-the-art research works and publications, especially KGE-based methods like RotatE (Bollacker et al. 2008), which allows for more accurate and efficient prediction of missing connections (or edges) between entities (or nodes) in a graph. Specifically, the integration of link prediction and KGs enables the ability for data to be analyzed not simply as individual components or entities but as an interconnected system made up of various components, such as those in an electric vehicle.

Experiment and Results

In our approach, we first embark on building the EV-KG dataset and develop the components of all physical connections and relations drawn from domain experts and manufacturer documentation. A dictionary file is built for each component and its defined relations with other components. Next, an RDF file format is generated for testing and validation. This is built using the (head, relation, tail) relationship such as (battery_positive_connection, terminal_of, battery_cell). We take the KG dataset and pre-process the data such that the data is randomized and split into three distinct sets: a training dataset, a validation dataset, and a testing dataset. Each dataset is analyzed individually by the KGE model for various phases, such as training (training dataset) and evaluation (validation and testing datasets). A score function is used to give a score for each of the candidate triples. The score represents the distance between the two nodes; thus, similar to a ranking metric, the lower the score, the better. The experiments were conducted on a high-performance cluster where we have compiled and built a KG specifically based on an electric vehicle's layout, factoring in various parts that can be faulty, and through that dataset, we will perform our experiment. The dataset we built contains 1378 nodes, 2200 edges, and 15 unique relations. The model was tested using RotatE, HRotatE, pRotatE, DistMult, ComplEx, and TransE modes (Sun et al, 2019), where we found RotatE achieved the best overall score of 0.922 Hits@100.

Conclusion

By studying the feasibility of implementing a KG-based fault detection system, this work heavily emphasizes the need for making a more efficient solution for detecting faults and defects in an automotive manufacturing environment. Just as important is the accuracy of this KG-based fault detection system since it will also affect potential losses if, for example, there are too many false negatives or false positives. One of the goals of this work is also to make sure automakers have a choice when it comes to fault detection systems that provide early detection of defects before it becomes in the hands of the consumer.

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