11th International Conference on Through-life Engineering Services – TESConf2022
8-9 November 2022, Cranfield UK

A Framework for Constructing a Common Knowledge Base for Human-Machine System to Perform Maintenance Tasks

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Abstract

A reliable and comprehensive maintenance is important to promise the system running in a normal state, but it is skill-intensive and heavily dependent on human labor. With the development of predictive maintenance in industry, an optimized solution can be posed for maintaining assets with less downtime and cost. However, most of current research on this topic is limited on a top-level algorithm design for prediction, but few consider how to perform the maintenance tasks according to the prediction results at a particular occasion and condition. Besides, the complexity of system is exploded, and it may take people much effort to cover every detail to achieve a credible maintenance result. Thus, machine is introduced to collaborate with human by undertaking some work and suggesting actions to take in order to reduce human physical and mental workload. This paper aims to present a framework to integrate human knowledge and machine learning into a common knowledge base to enable human and machine can contribute to shift the final maintenance decision from planning to performing. The proposed framework is based on a knowledge graph generated by ontology and machine learning, which can be conveniently retrieved by human via questions answering system or visualization platform and efficiently computed by machine via graph representation learning. Consequently, domain knowledge can be formally represented, systematically managed and easily reused by human-machine teaming to attack domain-specific problems. In a long term, the evolving knowledge based, with an accumulation on samples and information, can guide the team to draw a reasonable and delicate strategy for overhaul and recondition, moreover, ensure the next generation of maintenance: prescriptive maintenance.

Keywords: Human-machine collaboration; Knowledge graph; Prescriptive maintenance

1. Introduction

Human-machine collaboration (HMC) is a key technology for coordinating human and machine as a team to perform tasks together with greater flexibility, efficiency and productivity. By integrating human operators and automatic systems, massive products can be created and fabricated with flexible customization to satisfy a wide range of demands in the market [1], [2]. Fruitful results of human-machine collaboration and co-working in the industrial environment have been obtained by academia over the last decade [3], [4]. In addition, various types of collaborative robots, or say cobots, for different manufacturing purposes have also been developed and put into commercial usage by robot enterprises and organizations [5].

The coordination between human and machine is also introduced into the maintenance area with the advent of advanced data processing and machine learning algorithms [6]. Compared to conventional reactive or preventive maintenance relying on expert scheduling, predictive analysis based on a huge number of historical records of the system can foretell potential failure events, leading to an optimized and efficient outline for the maintenance. So far, by machine learning with various data collected from the system, human and surroundings, the role of the machine is altering from a tool to a communicator that can generate meaningful information [7]. With predictions from the machine, people can now decide the proper occasion to adopt actions before system degradation. It is positive to prolong the system life cycle and cut down the cost on periodic overhauls [8].

On top of prediction, people currently expect that the machine can be more collaborative to recommend how to handle or delay fault states occurring, and to indicate what possible influence may have on the system after taking a particular action. This concept is referred as prescriptive maintenance, and it is still a gap in the area of maintenance [9]. In fact, knowing how to deal with the problem is more practical than just being aware of what will happen. Commonly, in the case that the system is complicated with numerous degrees of freedom, predictions are probably treated as an alert and are easily skipped or even ignored by human operators [8]. Hence, machine is expected to be a more proactive advisor to provide optional actions and analysis to suggest to human [10].

In this way, the process of human decision making can be simplified. More importantly, machine is able to debias human judgments, which is meaningful from a safety perspective. In fact, it is potentially dangerous that people always keep being the main contributor to the system maintenance, since people's minds and conclusions are easily affected by lopsided observation, illusions and emotional factors and may cause serious errors and accidents in risk situations [11].

However, merely depending on current data-driven approaches is not enough to enable this kind of suggestive supporting. The main reason is that collected data may be imprecise, incomplete and inconsistent to reveal entire system states. Also, a lack of domain information in a specific context can cause difficulty in proper machine learning inference [12]. In other words, raw data has to be linked and enhanced by sematic and relational information to abstract rules and models of the system for machine learning, by which people's knowledge can come in and give a flavor. Besides, knowledge including mankind's skills and experience can also be introduced into machine learning to enable automatic systems can have a more flexible and general ability for execution without too much human intervention [13]. Therefore, complementary assistance between human and machine is established for a reduction in human workload and improvement in machine automation level.

Here comes a critical problem to tackle, how to integrate human knowledge and machine learning into a common ground to enable knowledge formal representation, management and usage by the human-machine team [14]. Furthermore, how all information in the shared information base including personal experience, expert skills and machine learning results can be structured into a knowledge base for human convenient retrieving and machine iterative learning. In this paper, such a framework for human-machine knowledge sharing will be constructed using knowledge graph (KG) and relevant methods for building and maintaining the KG will also be introduced to illustrate how human and machine can cooperate based on this framework.

The rest of this paper will be organized as followed. A detailed problem formalization will be further described in section 2 to set requirements for designing the framework. Then, the methodology for building the framework will be illustrated with explanations in section 3. In section 4, all mentioned methods will be put in together to form the conceptual framework satisfying proposed needs and the information flow for human-machine collaboration will be demonstrated. Finally, a brief conclusion will end the whole paper.

2. Problem formalization and analysis

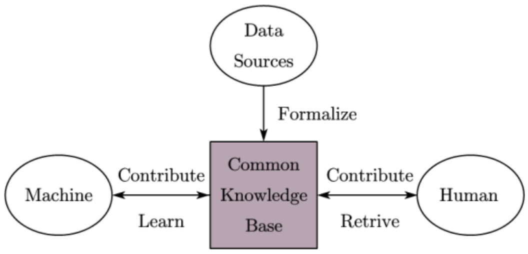


Fig. 1. The basic diagram for constructing the common knowledge base

Fig.1 shows desired features of the framework for allowing human and machine to contribute and use the knowledge base. Basically, it involves three components namely data sources, machine and human, with a connection through a shared information base which is the essential part of the system. Critical requirements of the shared information based are summarized as follows:

- Raw data can be structured and formalized for storage and management in the base.
- Both human and machine can contribute to and maintain the knowledge base
- Machine can recognize and understand the information in the base and learn on the base.
- Human can search information of interesting from the shared information based

The first purpose of the shown diagram is to allow the human-machine collaborative work for massive and various data formalization and management in an industrial environment. Besides, the organized dataset will be further elaborated and stored in a knowledge base, as an intermedium, to bridge human and machine. After that, both of them are able to read and use information in the base with retrieving on the human side and learning on the machine side for maintenance tasks performance. In another word, it is a cooperation between human and machine from a knowledge perspective using human knowledge and machine learning, which is less considered in the industry.

A notification is that the base should be built on a human and machine-readable format, neither in a natural linguistic expression nor a computer binary code. The difference in information representation existed in human-machine teams is the essential problem for constructing this common ground. Therefore, a translation between human and machine language is critical to align the meaning and understanding of shared ideas.

The knowledge base can also be used to let machine learn from linked data in order to improve their reasoning for not only reliable predicting but also offering feasible options to suggest human in maintenance scenarios, or even learn how to execute and action.

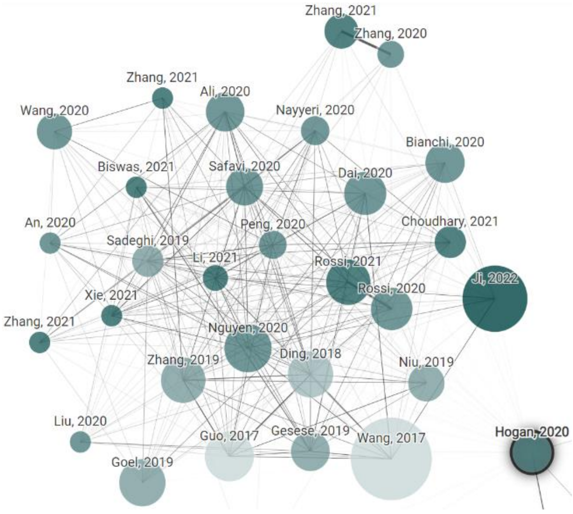


Fig. 2. An example of knowledge graph to show related paper to a target document

In the following sections, knowledge graph will be introduced to build up the framework. Also, methods for generating, expanding and operating the graph will be illustrated.

3. Methodology

3.1. Knowledge graph

Knowledge graph (KG), in short, is a graph for information acquisition, integration and derivation using semantic representation approaches and an inference engine [15]. Actually, KG is not a fancy concept, which was initially proposed in the 1970s and became well-known after Google announced the knowledge graph project to enhance their search engine [16]. Compared to traditionally document-centric systems, KG can present objects and relations as nodes and edges in the graph, thus raw data and discrete entries with abundant semantic information can be interlinked into a structured dataset [17].

Fig. 2 is a knowledge graph generated by Connected Paper [18] for correlating documents to an article "*Knowledge Graphs*" written by Hogan et al. [19]. The searching target is the node on the right bottom corner with a dark circle boundary, and other nodes in this graph stand for relevant materials. In this graph, the closer distance between two nodes, the stronger similarity between contents of these two documents. Besides, more conclusions can be drawn from this graph by reviewing colors and size of nodes, which stands for publishing years and citation numbers, respectively.

In this way, ordered and related objects can be created, edited, retrieved and deleted in a network without overlapping and conflict, enabling people to have a comprehensive view of their knowledge acquisition and to avoid tendentious opinions. These days, KG has been used in enterprises with specific domain knowledge and formal knowledge representation techniques such as logical operation, product rule system and ontology, thus it poses a feasible solution to construct an intuitive knowledge base for convenient managing and querying in manufacturing [20].

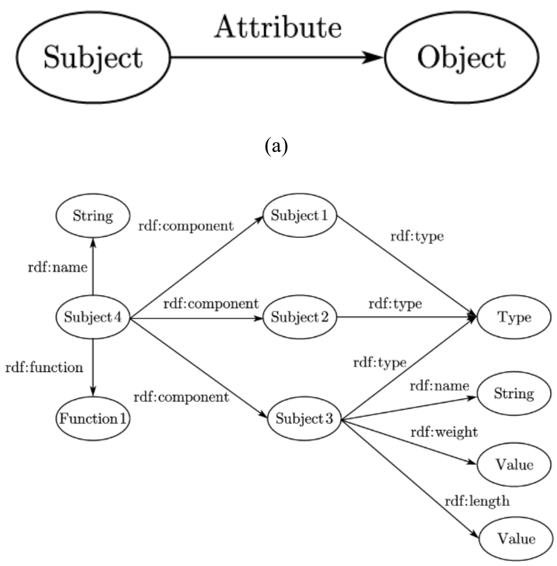
For machine, graph-structured data is a conventional data structure in computer science, and it can be recognized by devices. By a further transformation, vertexes in the graph can be vectorized while preserving proximity to make the machine take up less computational complexity and memory in machine learning.

In summary, KG is a promising medium to be the key component in human-machine knowledge sharing, because it can be simultaneously realized and operated by human and machine with scalability.

3.2. Knowledge graph construction

An effective initialization of KG is a challenge since only after raw data is structured into a graph at the first stage can it ensures later modification and expansion on the graph. Actually, only inputs from sensors cannot make much sense because they are just numerical values or text segments that can only express trivial statements unless logic and attributions are assigned to organize them into a nontrivial message to reflect a fact of the world.

Thus, an effective way to build the initial KG is knowledge representation, in more detail, to link data into useful information and then elevate them into knowledge in a formal symbolic and semantic way [21]. The straightest approach is to start by representing human knowledge to build the initial



(a)

(b)

Fig. 3. (a). A subject-attribute-object triple represented by a node-edge-node graph. (b). An example of knowledge graph to show related papers to a target document

KG, but the main problem is that carriers of human knowledge are commonly compiled texts and oral presentations, which are generally ambiguous, blurred and occasionally causal. It will therefore cause inconsistency and less standardization on knowledge formalization.

To vanish misleading and imprecise expression, ontology is then proposed to define objects and reveal certain relations between entries by a proper combination of a set of terms from an abstracted aspect [22]. In practical, ontology is commonly described by Web Ontology Language (OWL) based on RDF (Resources Description Framework) asserting a proposition by a <*subject-attribute-object*> triple, shown in Fig.3 (a). Multiple such triples can then be organized into a graph hierarchically as displayed in Fig.3 (b), forming the initial structure of a knowledge graph.

3.3. Graph representation learning and reasoning

Although graph-structured data can be stored and recognized by machines, it is still not straightforward to let them learn and operate on this kind of data, since algorithms and models are hard to implement, as relationships between entries are sometimes difficult to be measured, quantified and computed by machine. In addition, a more severe phenomenon, called the curse of dimension, referring to an explosion of computational states, will become a bottleneck for computation when machines work on large and complicated graph data [23].

To attack this problem, graph representation learning (GRL) is therefore proposed. The basic idea of GRL is to map all nodes in the graph into a low-dimensional Euclidean space, meanwhile preserving as much proximity information as possible, so the GRL is also referred as graph embedding [24]. Fig. 4. (a) demonstrates the GRL process: with the transformation $f(u)$, a node u can be embedded into the image space $\mathbb{R}^d$ as a vector (d is the dimension of the space). Fig. 4. (b) is an example to demonstrate a graph embedding into a 2-dimensional Euclidean space. In this case, a node can be represented by a vector $z_u(x_u, y_u)$ in the plane for downstream tasks.

By GRL, nodes are measured as a vector and relationships are operated by vector arithmetic such as addition and cosine similarity resulting in efficiency and simplicity for various following learning tasks such as predictions, summarization, or classification on entries, links and graph information.

4. A detailed framework to construct the common knowledge base for human-machine team usage

4.1. Human and machine contribution to the knowledge base

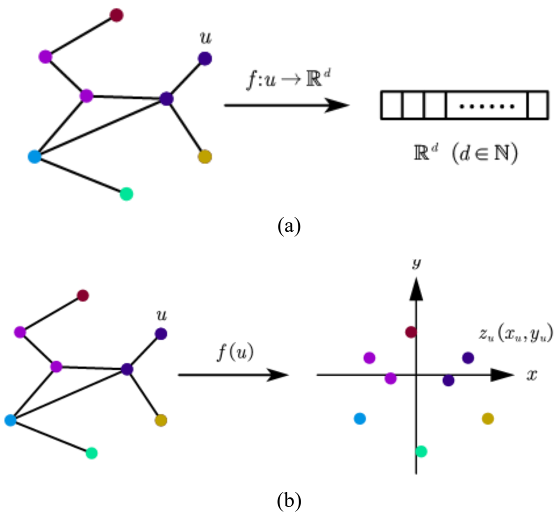


Fig. 4. (a). A process of graph embedding. (b). An example of embedding a graph into 2-dimensional Euclidean space.

Fig. 5 fulfills details in the basic diagrams shown in the Fig. 1 to complete the explanation of how human and machine can contribute to the common knowledge base. Basically, the contribution outcome is the RDF triple reflecting relations between entries of the system. For example, the hierarchical structure of the equipment configuration or a workflow map.

There are two ways to get triples, including direct structuring using ontology and indirect extraction by machine learning, in particular, by natural language processing (NLP). For the first method, human can define an evident proposition in an RDF triple that can further be represented by a linked-node pair shown in Fig.5, as a foundation of the knowledge graph. However, ontology can only work for declarations with clear and distinct which is difficult for fuzzy, subjective and implicit knowledge definition [25].

For the second one, documented texts such as handbook, manual and introductions will be initially gathered in a database, then fed to the NLP model to extract RDF triples automatically. By NLP, words and sentences can be encoded and computed statistically, and linguistic rules can be captured after training on a large text corpus. In particular, the advent of deep learning engaged the neural-network-based NLP in effectively simplifying the process of semantic information extraction and summarization from a complex context [26]. After that, what the NLP obtained has to be validated before getting into the knowledge graph to promise a reliable learning result.

Besides, sensor signals and data from surroundings will also be considered to find implicit regulations and factors affecting system running. In this way, machine learning will be applied for building up the map between the environmental variation and system states. After human experiments for testing these hypotheses, it can be a

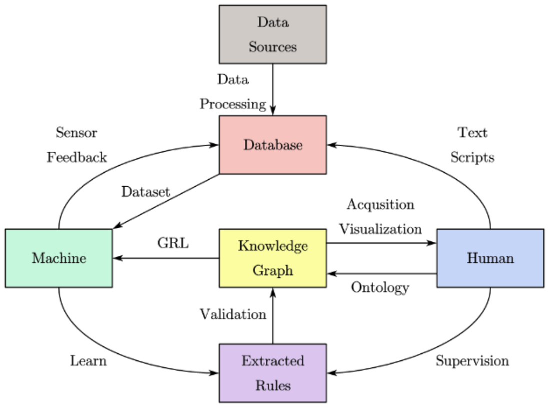


Fig. 5. A detailed illustration of the process for human-machine team to construct the common knowledge base

fact represented in an RDF triple. Therefore, KG can gather data from various sources with a composition of meaningful fragment as a data pre-processing for downstream machine learning tasks.

Actually, this step is the knowledge representation accomplished by machine pattern recognition and human knowledge engineering to process and elaborate raw data into relational information. The consequence is the conversion from massive, abstract, fragmented data into precise, pellucid and systematic expressions. Then, human and machine are able to work together to acquire knowledge of the system and environment to achieve the same background understanding of the task.

4.2. Human and machine use the knowledge base

A more important meaning of the common knowledge base is for both human and machine usage. For machine, using the GRL technique, the machine is able to transfer the graph-structured data into an efficient format for computation. Common GRL approaches include dimension reduction, random walk optimization, matrix factorization, neural network and hypergraph embedding [24].

Among mentioned methods, the architecture based on deep neural network, for instance, graph neural network (GNN), graph convolution network (GCN) and graph partition neural network (GPNN), is the most used method to maintain relationships among millions of nodes, whose power have been proven by state-of-the-art results [27]. This process can be further accelerated by compatible hardware such as graphic processing unit (GPU) or tensor processing unit (TPU), so the machine can handle a greater amount of data with better real-time properties. However, the obfuscation of the model may cause human suspecting how the result is derived from machine and whether it is reliable. This concern sometimes is unavoidable, especially in the circumstance of decision making involving legal, ethics and security issues [28].

Other approaches such as random-walk-based and factorization-based, outperform neural-network-based methods in terms of math intractability and simple implementation but are restricted in the scalability for embedding enormous nodes.

In actual application, many systems such as communication base network, data service center power grid and multi-sensor network deployed on equipment can be modeled as a graph with several nodes and edges. In these cases, machine can monitor entry in each node in real-time and log data for assessing the whole system running states with respect to time. Also, by applying attributes between nodes in the system (edge information), the machine can be aware of how each component contributes to the variation of other parts and the system. Therefore, it is possible to enable machine to predict how an adjustment may affect the system after considering the background knowledge from the common base, system information and machine learning results. This information and predictions allow human to make a schedule that can maximize the machine's service life, meanwhile minimizing cost and time on downtime for maintenance.

In addition, expert skills and professional knowledge are included in the knowledge base after a formal representation. Thus, machine can also learn how to plan and solve a problem as human with this information. Currently, transfer learning is a thrust in robotics community to allow robot to get the control policy by themselves without hard-core programming. The knowledge graph is now applied to enhance graph-based deep learning and reinforcement learning for state space representation and accelerate the policy learning speed using a pre-trained network through a question-answering process [29].

When it comes to human, the primary need for the KG is to memorize and manage vast discrete and diverse experience and routes for actual tasks so that people can reuse this knowledge for efficient planning and simplified implementation for a new task. From this perspective, retrieving is the top demand for using the KG. Currently, there are lots of applications and platforms developed for this purpose such as visualization interface, question answering system and recommendation system [23], [30].

4.3. A discussion on the proposed framework

In summary, the proposed framework in Fig.5, can satisfy all requirements set in section 2 with the following features:

- Diverse data can be processed and formalized as knowledge as well as stored in the knowledge graph

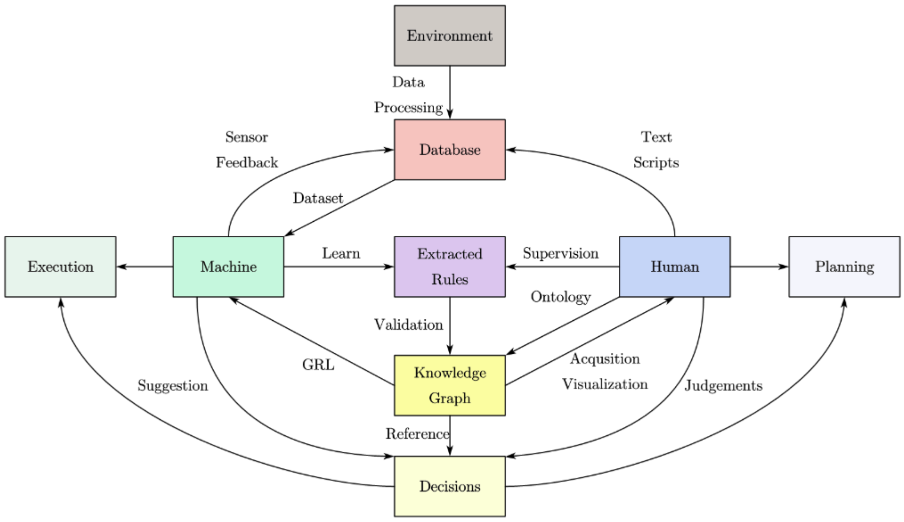


Fig. 6. An improved human-machine collaboration in term of comprehensive decision and adaptive execution

- The knowledge base can be built by direct human ontology and cooperation between machine learning and human supervision.
- Machine can learn from the knowledge base for control policy acquisition and actions suggestions
- Human can retrieve information of interest to perform new tasks using various means

Also, the knowledge graph can be recognized by human and machine so it can be a common ground for the human-machine team to work on together. The cooperation established based on this base is proactive assistance in a bidirectional way. Machine learning from massive data of the system and environmental data is a supplement to human limited perception. In the opposite direction, human abundant expert skills and professional experience can be a reference for machine execution. The bidirectional supporting can result in a reduction in human workload and an improvement in machine automation level, then agents in the team can take what they are expertise in to achieve the same targets with assistance from their partners.

Fig. 6 shows how human and machine can perform tasks under this cooperation pattern. Human can take machine suggestions and historical references into account to make a final determination for the planning. Machine is able to take the decisions to act with the adaptive control policy after being trained on linked data. In this way, the team can better deal with challenges in modern maintenance tasks.

5. Conclusion

Human and machine can cooperate on knowledge generation, management and application for maintenance tasks. The common ground for the human-machine team to work on is the essential foundation to enable this collaboration. In this paper, a framework is developed for solving the issues related to the integration of human knowledge and machine learning to build and use the shared knowledge base.

The limitation of the current work is twofold. Firstly, the consideration of uncertainty from data sources is missing in the knowledge graph construction process and may introduce unexpected errors in the learning and inference process. Thus, extra uncertainty modeling and elimination are required for a sound and reliable knowledge base. The second point is about the explainability of the knowledge generated from the machine. The trade-off between model comprehensibility and complexity has to be considered for creating a powerful and truthful human-machine partnership.

Future work for implementation of the framework includes:

- Develop algorithms for the machine (specific to robot) to learn from linked data, while taking noise and uncertainty into account.
- Develop methods to merge machine learning results into a knowledge graph and attempt to explain them by semantic information
- Investigate approaches to manage a dynamic knowledge graph in terms of correction and modification and reconfiguration.

Acknowledgements

This research was supported by the Centre for Digital Engineering and Manufacturing at Cranfield University (UK)

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