LBfT: Learning Bayesian Network Structures from Text in Autonomous Typhoon Response Systems

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ABSTRACT

Discovering variables and understanding their relations, which impacts emergency response, provide important knowledge to the development of decision models, e.g. Bayesian networks, in autonomous typhoon response systems (ATRS). Given the text inputs (containing natural language), learning the network structures still remains a challenge although learning Bayesian networks from data has been extensively investigated in various fields. In this demo, we develop a deep learning based framework for identifying typhoon relevant variables and build their causal relations from text. We use the *CausalBank* dataset and typhoon specific relation rules to refine the learned relations and allow users to further improve the models through their domain knowledge. We integrate the new learning tool into the existing ATRS and demonstrate the empirical results through real-world typhoon reports.

KEYWORDS

Autonomous Typhoon Response Systems, Decision Models, Learning Bayesian Networks

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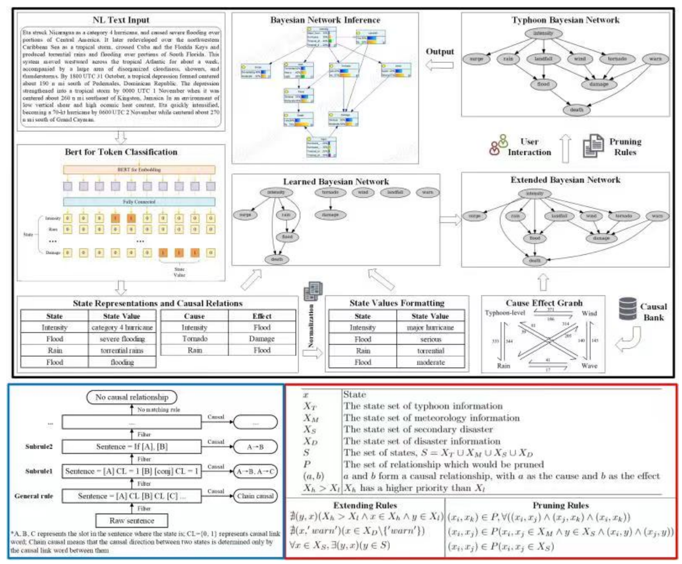

Figure 1: LBfT: The deep learning framework constructs Bayesian networks from text and it interacts with domain experts who could refine the model.

1 INTRODUCTION

Agent-based decision models play an important role in emergency response management for dealing with events of natural disasters, e.g. typhoon or hurricane, where information, including data and text, needs to be collected and analysed in an autonomous way. In particular, such a emergency response system often interacts with general users of non-technical knowledge background who expect to visualise and operate the decision process in a transparent way. Hence, probabilistic graphical models (PGMs), e.g. Bayesian networks (BNs), have become a desirable option in developing decision models in the emergency response system [5, 6]. On the other hand, inputs to the system are not limited to data, but involve an increasing volume of natural language based texts or documents from official guidelines to disaster response published by public sectors, various situation reports, a collection of messages in social media platforms and so on. This requires a new tool of learning Bayesian networks from text, which has been seldom explored in the PGM learning research since most the existing techniques focus on the model learning from data [1, 4]. The challenge lies in two aspects: (*a*) Identifying variables of interest (corresponding to nodes in Bayesian networks); and (*b*) Mining relations of the variables, particularly causal relations in Bayesian networks, from available text. In this demo, we develop a deep learning based engine, which is enhanced by the *CausalBank* dataset [3], to automate construction of Bayesian networks from the text. We implement the learning engine in the existing web-based autonomous typhoon response system (ATRS) in which a learning engine for building the AI planning model - Planning Domain Definition Language (PDDL) - has been developed [7]. The system is under the field evaluation including typhoon management personnel and general audience.

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2 LEARNING BAYESIAN STRUCTURES

In Fig. 1, we show the learning framework (the black-frame box) that identifies variables and their relations from the text input.

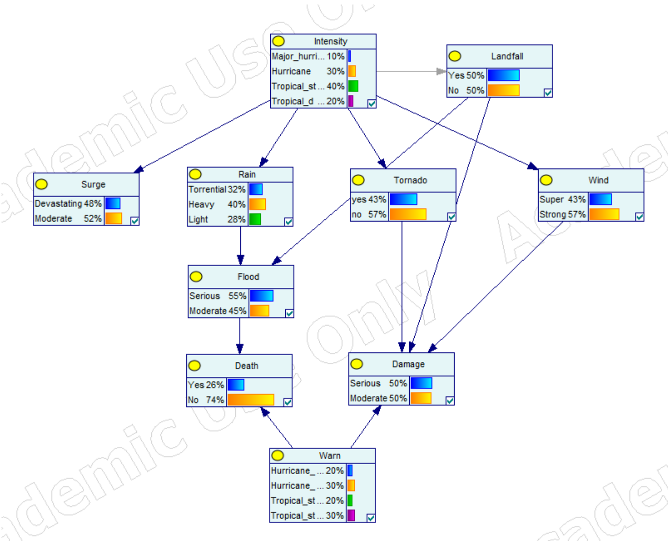

Figure 2: One example of Bayesian networks in a practical typhoon application where nodes and their causal relations are learned from the text input.

The resulting Bayesian networks can be compiled by a general PGM tool, e.g. the GeNIe [1] or HUGIN application [2]. We use the deep learning techniques, e.g. bidirectional encoder representations from transformers (BERT) [2], and retrieve a set of variables and their relevant values from the input. Particularly in the typhoon application, we adopt domain knowledge to set the states for the variables involving numerical values. For example, the ground speed is classified as $fast$ if its value is larger than $20km/h$, *slow* if it is smaller than $15km/h$, and *medium* if it is between the two values.

Once we get the variables, we first use a set of rules (as shown the blue-frame box), which are defined through a number of *Causal Links* words, e.g. therefore, because, etc., *Causative Verbs* words, e.g. cause, produce, etc., and *Resultative Constructions*, to decide their relations. The different types of words indicate the directions of arcs that link one variable to another. However, the commonly used casual words [3] may lose potential relations that are specific for typhoon relevant statements in the learning.

We make a further step to discover cause-effect statements through the *Causalbank* dataset where more specific causal words on the typhoon context are retrieved. Subsequently, we use a set of rules (based on typhoon-specific casual relations) to extend the relations (the red-frame box). Meanwhile, we proceed to prune some complex relations among the variables therefore simplifying the learned Bayesian networks. The operation is mainly designed to preserve V-structures in Bayesian networks and remove either redundant arcs or weak relations according to a series of principles in defining situations and risks of natural disasters [8]. Once we get the learned model, we can ask users to further refine the networks given their domain knowledge. We train the learning engine through the documents ranged of 2011-2021 in the National Hurricane Center's Tropical Cyclone Reports [4]. The documents contain 170 hurricane reports and have 8393 sentences among which the casual relations can be found within 2167 sentences. Fig. 2 shows one example of Bayesian networks in our demo. The learned network was verified by a domain expert who also provided conditional probability tables to every variables in the typhoon applications.

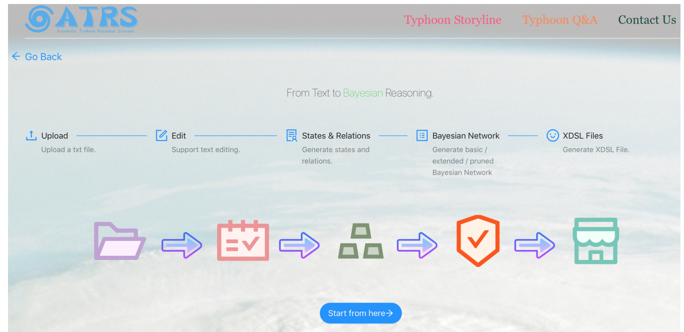

Figure 3: The learning engine is embedded into the existing ATRS where we also host the learning engine for building PDDL from text.

3 WEB-BASED ATRS WITH DOUBLE LEARNING ENGINES

We add the BN structure learning engine in the existing ATRS and complement its capability in learning decision models (besides PDDL) from text. Fig. 3 shows the web-based interaction system where users can upload a text file and conduct a series of operations in the learning engine. Since we haven't found any work on learning BN from text, we resort to domain experts to verify the outputs of Bayesian networks in typhoon applications. As mentioned above, we allow users to modify the networks and can accommodate any change in the models. Recently, we are investigating the transformation between learned BNs and PDDL models in ATRS. The demo can be viewed through the link [5].

4 CONCLUSION

We present the new learning engine to build Bayesian network structures from text and implement it in the autonomous typhoon response system. This research complements Bayesian networks learning research and significantly extends its applications. We are continuing to train the learning engine when more and more typhoon-relevant documents are collected in the system. In addition, we will improve the existing agent-based decision models by learning individual preferences in emergency response to imminent disasters.

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[1] https://www.bayesfusion.com
[2] https://www.hugin.com
[3] https://www.grammar-quizzes.com/19-2.html
[4] https://www.nhc.noaa.gov/data/tcr/
[5] https://github.com/lamingic/LBfT

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