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| Title | 貨物輸送への応用を伴う行動と根本原因分析のためのハイブリッドモデルに関する研究 |
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# Abstract

Currently, data from multiple sensors and the Internet of Things (IoT) provide essential mobility information for both governments and industries. They use this information to support smart city planning, medical care, and transportation domains. Recently, the transportation domain has played an essential role in the era of digital eCommerce, especially in transport logistics. The rapid growth of logistics demand also reflects the cost and profit of the logistics industry.

Historical statistics show that in 2019, the logistics industry had only 56% fleet utilization in the United States and 54% in Europe. The lack of efficiency in vehicle route optimization caused difficulties in transportation planning and management and created a direct impact on operational costs. To solve this issue, logistics agencies use the data obtained from the IoT to support their operations, for instance, transportation scheduling, planning, and resource allocation. Their goal is to obtain a suitable policy that can minimize agency operational costs and reveal the potential of route optimization.

The policy described in this study is used for managing the vehicle route optimization process. Therefore, numerous methodologies have been introduced to extract rich information from these data. Furthermore, anomaly detection and root-cause analysis are performed to understand the transport operation characteristics. However, these data come from multiple sources. Therefore, conventional methods cannot handle these data directly because of different data formats, and the data are also dependent on spatial-temporal contexts and behavior attributes.

To address these problems, this study provides a novel methodology for performing anomaly detection (e.g., temporal and static anomalies) and root-cause analysis for transportation logistics (e.g., explanation of anomaly in transportation logistics). Later on, the anomaly detection models contributed to analyzing both transportation environment and reinforcement learning (RL) agent's behavior in optimizing daily vehicle routing for the logistics agency. This phenomenon is presented in the case studies. The author assumes that the RL agent has the same role as humans. Suppose that the optimal vehicle route is obtained by the RL agent, it denotes that when a human follows this recommended route pattern provided the optimal decision.

The methodology consists of five models. They are used in two different stages: (1) the detection stage and (2) root-cause analysis stage. In the first stage, anomaly detection using Long Short-Term Memory (LSTM)-based and unsupervised hybrid anomaly detection models is proposed. These two models are designed to detect point, contextual, and collective anomalies. In the second stage, forward and inverse problem analysis models are proposed. They are also compared with the machine learning-based model to derive the root cause of the detected anomaly. These outcomes will increase the reliability and interpretability of the anomaly detection result. The obtained outcomes also increase anomaly detection rates and significantly reduce the bias of labeling the data.

The data from multiple sensors are preprocessed and transformed into structured data, and the features are extracted using feature engineering to perform this experiment. A different set of anomaly detection methods is then used to distinguish between regular operation patterns and disturbances. Its outcome is further used as an input to analyze the root cause of disturbances. Finally, root-cause analysis is performed. Thus, these steps are employed to analyze environmental changes. The analyzed information is then used to adjust the RL agent's behavior when it optimized vehicle routes. The vehicle route optimization solution is therefore adapted to environmental changes by doing so.

To demonstrate the practicality of the proposed methodology, the experimental results are validated with real data and compared against state-of-the-art models. Once the model for detecting anomalies in transportation is developed, the model was also applied to the other application domains to demonstrate the model's generality. The results show an accuracy of up to 0.83 (0.88 of the area under the RoC curve) with less processing time than that required by other existing methods. The model is also general and can be employed in other application domains with minor modifications. Finally, real case studies are presented to demonstrate the practical significance of anomaly detection and root-cause analysis in assisting vehicle route optimization tasks.

The real case studies' results implied that the interconnection between RL, behavior analysis, and reward processing of the proposed model increased the ability of the agent to perform vehicle route optimizations in a similar way as humans for routine daily scheduling. Furthermore, when uncertain changes (e.g., the sudden change of customer demand, road-network traffic condition, and fleet resources) occurred in the environment, the agent also outperformed the humans when making rescheduling decisions. Thus, this proposed methodology improved the vehicle route optimization solution up to 57.91% of profit improvement when compared against the optimal baselines.

**Keywords**: Anomaly detection, Deep learning, Logistics, Root-cause analysis, Transportation.