A CBR-Based Emergency Plan Generation Method Under the Federated Learning Framework

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Abstract. In order to use the emergency case data of multiple industrial enterprises to support the decision-making of target cases on the premise of protecting data privacy, this paper proposes a CBR-based emergency plan generation method under the framework of federated learning. First of all, each enterprise carries out feature extraction and case representation of local historical emergency cases. Then, based on the federated learning framework, under the premise of fully guaranteeing data privacy, each enterprise uses local data to collaboratively train a federated k-means model (FL-K-means) for the extraction of similar historical emergency cases. On this basis, we use the trained federal clustering model to extract similar cases across enterprises, reuse and adjust the information and experience of similar historical emergency cases, and then generate the emergency plan of the target case. On the premise of protecting enterprise data privacy, the method proposed in this paper can fully mine and utilize the emergency case data of different enterprises, effectively solve the data island problem between enterprises, support the decision-making of target emergency cases and generate the decision-making scheme of target emergency cases through the adjustment of similar historical emergency cases.

Keywords: Emergency decision-making · Federated learning · CBR · K-means

1 Introduction

In recent years, with the continuous expansion of the production scale of industrial enterprises, major production accidents and disasters have also occurred frequently, which not only seriously affected people's life safety and social stability, but also brought huge economic losses to the country [1]. As the occurrence of emergencies seriously threatens people's lives and property safety, how to quickly and effectively formulate emergency measures and emergency plans is the primary task of all emergency management departments. However, due to emergency decision makers have different cognitions of specific things and different processing capabilities of information, it is relatively difficult to use inherent and traditional decision theory methods or traditional decision analysis paradigms to solve emergency decision-making problems.

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In view of the current emergency decision-making theories and methods cannot solve the emergency decision-making problems with complex characteristics, we can learn from the previous historical emergency cases to assist decision-making, that is, Case-based Reasoning (CBR). CBR technology uses the "analogy" idea to solve the problem. By judging the similarity between the current target case problem to be solved and the historical case, the emergency plan of the current target emergency case is formulated according to the emergency plan adopted in the historical emergency case, that is, the use of case-based reasoning to solve the current emergency decision-making problem.

In recent years, some studies have shown that Federated Learning (FL) can break the data island and achieve local training and global updating of models on the premise of ensuring the privacy of user data. Unlike in the past, all data were centralized to a central server for modeling, FL technology can jointly model multiple data owners on the premise of protecting user data privacy and security. In the framework of FL, the edge nodes do not need to upload the original data, but only upload the parameters of the local model, and the central service aggregates the model, so as to realize the local training and global optimization of the model. It can be seen that federal learning technology can effectively solve the problem of data island formed by data privacy protection among different enterprises, and realize the effective mining and full utilization of historical emergency case data of different enterprises.

The purpose of this paper is to propose a CBR based emergency plan generation method under the framework of federal learning. Firs, each enterprise carries out feature extraction and case representation for local historical emergency cases. Then, based on the federal learning framework, under the premise of fully ensuring data privacy, each enterprise uses local data to jointly train the federated K-means model (FL-K-means) for the extraction of similar historical emergency cases. On this basis, we use the trained federal clustering model to extract similar cases across enterprises, reuse and adjust the information and experience of similar historical emergency cases, so as to support the decision-making of target emergency cases and generate the emergency plan of target cases.

The rest of the paper is structured as follows: Sect. 2 reviews the relevant literature. Section 3 presents a CBR based emergency plan generation method under the federal learning framework. Section 4 summarizes the main conclusions and future research prospects.

2 Literature Review

The research in this paper is closely related to two aspects: (1) the application of federal learning; (2) the application of CBR in the field of emergency management. Next, we review the literature on these two aspects respectively.

In recent years, with the rise and maturity of federal learning, it has attracted the attention of many scholars. For example, McMahan et al. [6] first proposed the theory of FL. As an emerging paradigm of machine learning, federated learning provides a novel solution for user data sharing, enabling users to obtain a more optimized model without the need for local data, so as to achieve "data immobility model". Li et al.

[4] introduced the application of Federated learning model in mobile devices, medical treatment, industry, etc. Kulkarni et al. [3] introduced the research progress of heterogeneous technologies in federated learning from the aspects of multi task learning and meta learning. In order to solve the problem of cross client variation in medical image data, Yan et al. [9] proposed a variation aware federated learning (VAFL) framework for the first time, evaluated it with multi-source dispersed apparent diffusion coefficient (ADC) image data, and achieved good stability. Khan et al. [2] proposed a Stackelberg game method, which can enable participating users to strategically set the number of local iterations to maximize its utility. The results show that this method is effective in modeling the interaction between the simulation center server and the edge device. Mothukuri et al. [7] comprehensively introduced the current security threats faced by federal learning and countermeasures.

CBR also has many related studies in the field of emergency management. For example, Feng et al. [1] combined with the poor self-learning ability of emergency intelligence intelligent decision support system (IDSS), proposed an emergency intelligence intelligent decision support system based on case-based reasoning. The use of the system model greatly improved the retrieval and matching speed and accuracy of large case base. Zhang et al. [10] aiming at the problem of improper emergency decision-making caused by untimely and incomplete information transmission on the scene of dangerous goods air transportation accidents, a case-based reasoning model for emergency decision-making of dangerous goods air transportation accidents was established, which can provide emergency decision-making guidance for dangerous goods air transportation accidents. Shi et al. [8] proposed a demand acquisition scheme for medical materials in major public health emergencies, taking acute respiratory infectious diseases in previous major public health emergencies as cases, extracting the categories of emergency medical supplies as characteristic attributes and constructing Case library, based on case-based reasoning technology to obtain the plan of the demand for medical materials for New Coronavirus pneumonia. Liao et al. [5] proposed the Internet of vehicles network security emergency response method based on the set of experience knowledge structure (SOEKS) and case-based reasoning (CBR) to realize the automatic and rapid processing of specific security events, design the knowledge representation method of Internet of vehicles data sources and cases, and design the double similarity matching algorithm based on the nearest neighbor algorithm to quickly match security events, so as to get a fast and accurate response.

From the above research, we can see that at present, the research in the field of emergency decision-making combined with FL and CBR technology is rarely carried out. Based on the obvious advantages of federal learning in data sharing and privacy protection, we carry out the research on the generation method of cross enterprise emergency plan based on the federal learning framework and the basic idea of CBR.

3 A CBR-Based Emergency Plan Generation Method Under the FL Frame Work

In this section, we first propose the research framework of this paper, and then introduce the corresponding methods.

3.1 Research Framework

In order to solve the problems mentioned above, this paper proposes a CBR-based emergency plan generation method under the federated learning framework. The research framework is mainly divided into the following three parts.

1) Representation of emergency cases. The features of emergency cases include not only numerical features that can be calculated directly and quantitatively, but also category and text features that can not be understood by computers directly. In order to meet the needs of subsequent parties to jointly train the global model, firstly, the central server needs to abstract the required case features into several data types, and standardize various types of data in the complex semantic space in combination with the actual meaning. Then, the central server sends the unified data standardization processing method to the clients of each enterprise in the federation. Finally, the client performs distributed local data preprocessing according to unified rules and methods, including feature extraction and case representation.
2) K-means model training under the federal learning framework. Under the federal learning framework, each enterprise collaboratively trains the K-means model adapted to the data of all parties, and obtains an improved global model, FL-K-means, which is used to extract similar emergency cases. The central server sends the initialized K-means model to the client. The client uses the local historical emergency case data to train the local model, and trains the clustering model based on the feature extraction in the previous step. There is no need to exchange original data between the client and the central server, only the communication of model parameters is carried out. The central server aggregates the models of all parties and iterates continuously until the local model of the client converges or reaches the maximum number of iterations. Finally, the optimal global model is obtained for subsequent extraction of historical emergency cases similar to the target case.
3) Generation of emergency plans for target cases. Based on the work of the first two stages, CBR method is used to extract similar emergency cases across institutions. This method is mainly divided into the following steps: first, the central server vectorially represents the target case and sends it to the clients of each enterprise. Then, each client uses the global FL-K-means model to retrieve emergency cases similar to the target case from the local historical cases. Finally, the similar historical case set of each enterprise is obtained by setting the similarity threshold. Each enterprise desensitizes the final similar historical emergency cases and returns them to the central server.

3.2 Representation of Emergency Cases

The representation of emergency cases refers to the formalized representation of emergency cases according to certain rules, which is the basis and premise for emergency decision-makers to carry out emergency decision-making under emergencies. In order to meet the needs of subsequent parties to jointly train the global machine learning model, all parties must represent the original case according to a unified specification. How to choose an appropriate case representation method is not only related to the effect of similar case retrieval, but also related to whether it can provide help for emergency decision-makers. At present, many scholars have studied the case representation method in CBR technology, and proposed the representation method of probability, the representation method of concept lattice, the representation method of Petric net concept, the representation method of frame and so on. Among them, the more representative is the case representation method proposed by Li Yonghai, Fan Zhiping and others. They represent the historical case and target case as a triplet.

According to the core idea of CBR, the representation and paradigm of emergency cases are described as follows. In the scenario studied in this paper, it is assumed that there are n participant (enterprise), $F = \{F^1, F^2, \cdots, F^n\}$, F^i represents the i-th enterprise. The historical emergency case set of each enterprise is $Z = \{Z^1, Z^2, \cdots, Z^n\}$, Z^i represents the historical case set of the i-th enterprise. The number of historical cases of each enterprise are $S = \{S^1, S^2, \cdots, S^n\}$, S^i represents the number of historical emergency cases owned by the i-th enterprise. P_a^i represents the i-th historical case in the historical case set of the i-th enterprise, where $i \epsilon \{1, 2, \cdots, n\}$, $a \epsilon \left\{1, 2, \cdots, S^i\right\}$. Z^* is the target case. Usually, each case involves multiple features. Let the feature set of the case be $C = \{C_1, C_2, \cdots, C_k\}$, where C_k represents the k-th feature of the case, $k \epsilon \{1, 2, \cdots, K\}$. Let $\overset{\sim i}{p_a} = (p_{a1}^i, p_{a2}^i, \cdots, p_{aK}^i)$ and $\overset{\sim *}{p} = (p_1, p_2, \cdots, p_k)$ represent the case feature value vectors of historical cases and target cases respectively.

3.3 Model Training

After each enterprise completes the feature extraction and representation of local historical cases, the global FL-K-means model is jointly trained based on the local emergency case data of each enterprise under the federated learning framework to extract similar historical emergency cases.

K-means belongs to unsupervised learning algorithm. The connotation of unsupervised algorithm is to observe the unlabeled data set, automatically discover the hidden structure and hierarchy, and find the hidden law in the unlabeled data. The goal of K-means clustering is to divide n observation data points into k clusters according to certain standards, and the data points are divided according to similarity. Each cluster has a centroid, which is the point obtained by averaging the positions of all points in the cluster. Each observation point belongs to the cluster represented by the nearest centroid.

The basic steps of FL-K-means algorithm are as follows:

- Select the initialized K samples as the initial clustering center, i.e. $\alpha = \alpha_1, \alpha_2, \cdots, \alpha_k$;
- For each sample x_j, in the data set, the distance from it to k cluster centers is calculated and divided into the class corresponding to the cluster center with the smallest distance;
- For each category α_k, recalculate its cluster center$\alpha_k = \frac{1}{|c_i|} \sum_{x \in c_i} x$;
- Repeat steps (b) and (c) until a certain stop condition is reached (e.g. number of iterations, minimum error change, etc.).

After the client completes the training of the local model locally, it returns the parameters of the local model to the central server, which aggregates the model using the federal average algorithm, and then sends the parameters of the aggregated global

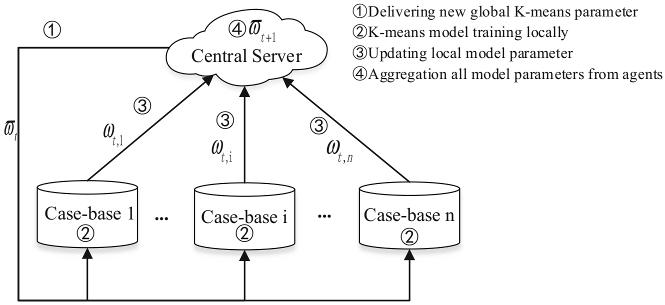

Fig. 1. The FL-K-means model training flowchart under the FL framework

Table 1. The FL-K-means model training steps under the FL framework

The FL-K-means model training steps under the FL framework
Step 1: The FL center server delivers an initial global K-means model parameter w_t to agents, as the baseline setting at time t.
Step 2: By using the initial model parameter, the local K-means model is trained by using local data in i-th agent.
Step 3: The i-th agent send the local parameter update on the K-means model $w_{t,i}$ to the FL center server.
Step 4: The FL center server aggregates all model parameters from agents. The weight average of the model parameters is computed as $w_{t+1} \leftarrow \frac{1}{\sum_{i=1}^{I} s^i} \sum_{i=1}^{I} s^i \bullet w_{t,i}$.
Step 5: An improved global FL-K-means model with the parameter w_{t+1} is built accordingly. The above steps are repeated until the local model converges or reaches the maximum number of iterations.

FL-K-means model to each client again, iterating continuously until the model converges or reaches the maximum number of iterations. Table 1 shows the steps of collaborative training of global FL-K-means model by all participants under the federal learning framework, and the corresponding flow chart is shown in Fig. 1.

Based on the federal learning model training process given in Table 1, all enterprises cooperate to train under the federal learning framework to obtain a global FL-K-means model suitable for all data sets, which is used to retrieve similar historical emergency cases.

3.4 Generation of the Emergency Plans for Target Cases

Next, extract similar historical emergency cases based on the basic processes and steps of CBR. The specific process is as follows:

1) Determine the target case, formally describe and represent the target case for the emergency decision-making problem under the current emergency, and the feature value vector of the target case Z^* is expressed as $\tilde{p}^* = (p_1, p_2, \cdots, p_k)$.
2) Distributed retrieval of similar historical cases, using the global FL-K-means model obtained by joint training based on the local historical case data of each enterprise under the federal learning framework, we can obtain historical cases similar to the target cases from the historical emergency cases of each enterprise.
3) According to the similar historical cases retrieved in the previous step, the emergency plan corresponding to the historical case is extracted, and the extracted emergency plan is modified and adjusted in combination with the actual situation of emergency decision-making under the current emergency.
4) Generate an alternative emergency plan for the target case and evaluate the alternative emergency plan.
5) According to the evaluation results, the alternative emergency decision-making scheme is selected, so as to determine the emergency decision-making scheme suitable for the target case.

4 Conclusions

In order to use the emergency case data of multiple industrial enterprises to support the decision-making of target cases on the premise of protecting data privacy, this paper proposes a CBR-based emergency plan generation method under the framework of federated learning.

The main contributions of this paper are as follows: first, a clustering model FL-K-means under the federal learning framework is proposed. Multiple enterprises use their local data to jointly train the global model to extract similar cases and further generate the decision-making scheme of target cases. Secondly, a CBR based emergency plan generation method under the federal learning framework is proposed, which can fully mine and utilize the emergency case data of different enterprises on the premise of protecting the data privacy of enterprises, effectively solve the problem of data island among enterprises, and support the decision-making of target emergency cases through the adjustment of similar historical emergency cases.

The future research work can also be extended to the design of the federated learning incentive mechanism, that is, how to motivate multiple enterprises to participate in the federation. Enterprises participating in the training of federated models will consume computing and communication resources, resulting in certain costs. Therefore, how to design an effective incentive mechanism to enable more enterprises to participate in the federation is an important research direction in the future.

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