CAUSAL ALIGNMENT BASED FAULT ROOT CAUSES LOCALIZATION FOR WIRELESS NETWORK

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ABSTRACT

Localizing fault root causes is challenging but critical for wireless network operation and maintenance. Though supervised methods have shown promising results in training samples, most of the existing approaches assume that the training and the testing samples are independent and identical distributed. Such an i.i.d assumption usually does not hold due to network faults that may occur in different devices across different domains (well known as the distribution shift). Thus, it is necessary to align distributions between the training and test data set. Motivated by the stability of the causal mechanism across the domains, a Causal Alignment based Root Cause Localization (CARCL) framework, including the causal alignment and the multi-stage classifier, is proposed. CARCL first offers to align the distributions locally for each causal module but not globally on the complete variable set. We further develop a multi-stage classifier to determine the root causes with the help of predicted pseudo labels. The experiments demonstrate a superior performance of our method.

***Index Terms*—** Root Causes Localization, Multi-stage Classifier, Causal Alignment

1. INTRODUCTION

Localizing fault root causes of wireless network is challenging due to the complicated interaction among wireless networks such that a minor fault may cause abrupt and vast alarms [1]. Moreover, different types of faults occur in other devices, causing the distribution shift in collected data to bring much more difficulty in localizing the root causes. As a result, the wireless network operation requires a massive cost in human resources [2], especially when localizing the root causes. Thus it is crucial to develop a way for better localizing to reduce the maintenance cost and improve the user experience.

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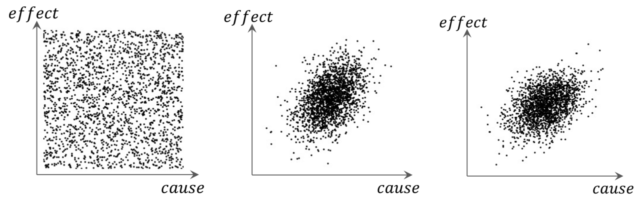
Recent research on root causes localization can be mainly categorized into generative and discriminative models. The generative model's classic root causes localization method is Bayesian network-based methods [3]. Such models give predicted root causes localization results by inferring the posterior distribution with or without root causes. At the same time, the classic model of the discriminative model is the classifier-based model [4]. They use the ensemble voting classifier to enhance the base classifier for fault root causes classification. Recently, pattern mining techniques that compress alarm data can assist in localizing and diagnosing faults [5]. Yuan et al. [6] proposed a framework that combined the path conditional time series algorithm to capture the causal relationship.

In many scenarios, however, different types of faults may occur in other devices across various domains, bringing the distribution shift into the collected data so that the training and test data could have different distributions. In this case, the works mentioned above would fail to identify the root causes due to inconsistent distribution between the training and test data set. Therefore, it is necessary to align training and test data set to obtain a releasable and generalizable prediction of the root causes. Inspired by the stability of the causal mechanism in the current literature [7, 8, 9], given a complete causal structure, one may align the different distributions by aligning each causal module in the causal structure instead.

Consider a *cause* feature and a *effect* feature, the joint distribution $P(\text{cause}, \text{effect})$ can be decomposed into the following form according to causal mechanism: $P(\text{cause}, \text{effect}) = P(\text{cause})P(\text{effect}|\text{cause})$. We can align distributions by aligning the above two decomposed causal modules. Take Fig. 1 as example. The causal module $P(\text{effect}|\text{cause})$ in the training data set is different from the test data set, making it very difficult to localize root causes using only the training data set. Thus, as shown in Fig. 1(c), our goal is to develop a way to align the data distributions between the training data set and the test data set, solving the problem of root causes localization under different data distribution.

In this work, we propose a Causal Alignment based Root Causes Localization (CARCL) framework. It first conducts a causal alignment to align the distribution among the training and test data set. Moreover, motivated by the pseudo la-



(a) Training distribution (b) Test distribution (c) Aligned training distribution

Fig. 1. Illustrative example of the causal alignment.

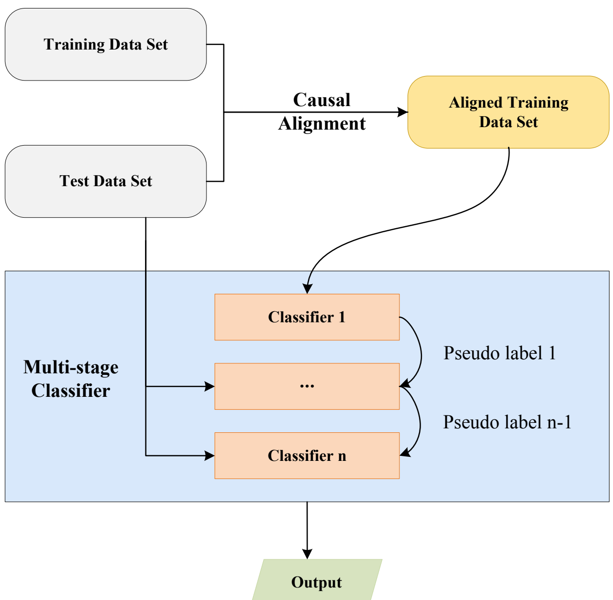


Fig. 2. A diagram of CARCL framework.

bel methods [10], as shown in Fig. 2, we further develop a multi-stage classifier to align the distribution and improve the adaptability of the proposed model. Experiments demonstrate the correctness and superior performance of our method.

The main contributions of this paper are summarized as follows:

- We propose a causal alignment based root causes localization framework.
- We develop a multi-stage classifier architecture based on the pseudo label to improve the tolerance of the model to inconsistent data distributions in the training and test domain.
- Experiments verify the effectiveness of our proposed framework.

2. CAUSAL ALIGNMENT BASED ROOT CAUSES LOCALIZATION FRAMEWORK

In this section, we first formally introduce the notation and the problem definition in our work. Then, we present the two main components of CARCL, respectively. Let $D_S = \{X_i^S, y_i^S\}_{i=1}^{n_S}$, $X_i^S \in R^{L_i \times d}$ denotes the collected training data set (*Source*), where X_i^S is the time slice in i-th sample containing L_i length of time series and d dimension features, and y_i denotes the label of each sample. Similarly, let $D_T = \{X_i^T\}_{i=1}^{n_T}$ denotes the collected test data set (*Target*). Our goal is to infer the test domain's root causes type label y_i^T based on the training set's root causes type label y_i^S. To achieve this goal, we propose a CARCL framework by aligning the distribution between the training and test data set to localize root causes correctly on the test domain. CARCL contains two stages of alignment, which are introduced in Section 2.1 and 2.2 respectively.

2.1. Causal Alignment Method

As shown in Fig. 2, we first conduct a causal alignment to produce an aligned training data set. In detail, the goal of the alignment is to align the distribution of root cause, e.g., align the distribution between $P_S(\text{Root cause}|\text{Feature})$ and $P_T(\text{Root cause}|\text{Feature})$ in the training set and testing set respectively. To do so, we first use the Bayesian network based method to classify the test data set into fault and fault-free parts. Then, by analyzing the causal mechanism behind the $P_S(\text{Root cause}|\text{Feature})$ and $P_T(\text{Root cause}|\text{Feature})$, i.e., taking the Root cause as the cause while Feature as the effect in the causal mechanism, we search for appropriate rules to filter the training data set to align the test data set, such that the Kullback–Leibler divergence [11] is minimized as follows:

$$\min_F KL\left(\frac{P_S(\text{effect}|\text{cause}, F)}{P_S(\text{effect}, F)/P_S(\text{cause}, F)} \| \frac{P_T(\text{effect}|\text{cause})}{P_T(\text{effect})/P_T(\text{cause})}\right), \tag{1}$$

where F is the filter. In practice, one may use the Maximum Mean Discrepancy-based methods or total variation based methods to approximate the divergence. By doing this, we can obtain the result in Fig. 1(c). Apparently, in the absence of domain alignment, the causal mechanisms of the training and test domain are inconsistent. After filtering the training data, we align the distribution of the data, which ensures that the model obtained in the training data set can locate the root causes in the test data set.

2.2. Multi-stage Classifier

As shown in Fig. 2, the second stage of CARCL is the multi-stage classifier. The reason is that, in the real-world scenario, it is hard to perfectly align the data distribution of the training set and test set in the above alignment method. Therefore, we propose the multi-stage classifier model to supplement the above alignment method. By doing this, we find that it can produce a better result for root causes localization.

Specifically, in the first stage, we train a classifier 1 using the aligned training data set by the light gradient boosting machine (LightGBM) [12]. Then, inspired by the pseudo label in the unsupervised domain adaption [13], we take the output of classifier 1 as the pseudo label in the second stage and train classifier 2 using the test data and the pseudo label. The input data is the test data set, and the input label is the pseudo label of the previous stage's output. Finally, we can repeat n_{stage} and obtain the final result of CARCL. The algorithm of our framework is present in Algorithm 1.

Algorithm 1 CARCL

Input: training data set $D_S = \{X_i^S, y_i^S\}_{i=1}^{n_S}$, test data set $D_T = \{X_i^T\}_{i=1}^{n_T}$, number of multi-stage classifier n_{stage}.
Output: Test data set root classification results y^T

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According to the causal mechanism reflected by D_T, the distribution of D_S is aligned to obtain the filtered training domain data D_{S*}.
model ← LightGBM(X^{S*}, y^{S*})
y^T ← model.predict(X^T)
for l = 2 : n_stage do
    model ← LightGBM(X^T, y^T)
    y^T ← model.predict(X^T)
end for
return y^T
```

3. EXPERIMENTS

3.1. Dataset Description

We implement our method on the real-world data 5G wireless network data set published by ICASSP-SPGC-2022 [14]. It contains a causal graph among features and the root cause (see Fig. 3). It contains 2984 training samples and 600 test sample respectively. While each sample is a time segment from different 5G road test scenarios, which contains the information of 23 observable characteristic features.

3.2. Data Pre-processng

We first calculate the maximums, minimums, and means value on each column at each time segment to characterize the distribution. Then we compare the performance of the algorithms under the following three strategies: 1) predict each root cause using the set of all features, 2) predict each root cause R_i by its children, and 3) predict each root cause by the children of set R.

3.3. Baselines and Ablation Study

We compare with the following existing baselines :

1. **k-NN:** The k-nearest neighbors (k-NN) algorithm is a non-parametric classification method [15, 16]. Its input consists of the k closest training examples in a data set. The output depends on whether k-NN is used for classification.

Algorithms	ALL	Ch(R_i)	Ch(R)
k-NN	0.566111	0.472222	0.566111
CatBoost	0.644722	0.642500	0.625277
Naive-Bayes	0.445000	0.457500	0.445000
CARCL-NCA	0.662499	0.675555	0.651944
CARCL-NM	0.901388	0.835278	0.910555
CARCL-L	0.627222	0.643055	0.607222
CARCL	**0.922778**	**0.869167**	**0.931945**

Table 1. The score of the baseline and CARCL with variants

2. **Naive-Bayes:** Naive-Bayes is a probabilistic based model assuming that each feature is conditional independent of each other. We use Naive-Bayes [17] to classify the root cause on each sample.
3. **CatBoost:** CatBoost [18] is a high-performance algorithm for gradient boosting on decision trees, whose source code is available from a open-source library.

Moreover, we conduct the ablation study on CARCL and develop three variants of CARCL, namely CARCL-NCA, CARCL-NM, and CARCL-L. In detail, CARCL-NCA remove the causal alignment part of CARCL, CARCL-NM replace the multi-stage classifier with a single LightGBM [12], and CARCL-L removes the causal alignment and multi-stage classifier–equivalent to the original LightGBM.

3.4. Evaluation Metric

Following the metric using in the competition, the metric is calculated as follow:

1. Give a normalized score s_i for the i-th sample (a time slice).
   (a) Initialize $s_i = 0$,
   (b) For all six root causes, $j \in \{1, 2, 3, 4, 5, 6\}$
      i. If $p_{ij} = 1$ and $l_{ij} = 1$, get 1 mark, $s_i = s_i + 1$.
      ii. If $p_{ij} = 1$ and $l_{ij} = 0$, deduct 1 mark, $s_i = s_i - 1$.
   (c) Normalize the score by the number of true causes $\parallel L_i \parallel_1$, $s_i = \frac{s_i}{\parallel L_i \parallel_1}$.
2. Calculate the final score: $S = \frac{\sum_{i=1}^{N_{te}} s_i}{N_{te}}$

3.5. Result Analysis

In this experiment, we filtered out the data that is not marked as abnormal in the training set and only used the abnormal data as the new training set. In the second stage of the multi-stage classifier, we used the three-stage LightGBM classifier. The results are given in Table 1.

As shown in Table 1, CARCL achieved the best results compared with all baseline methods. The Naive-Bayes is not practical because it assumes that the feature of data is mutual

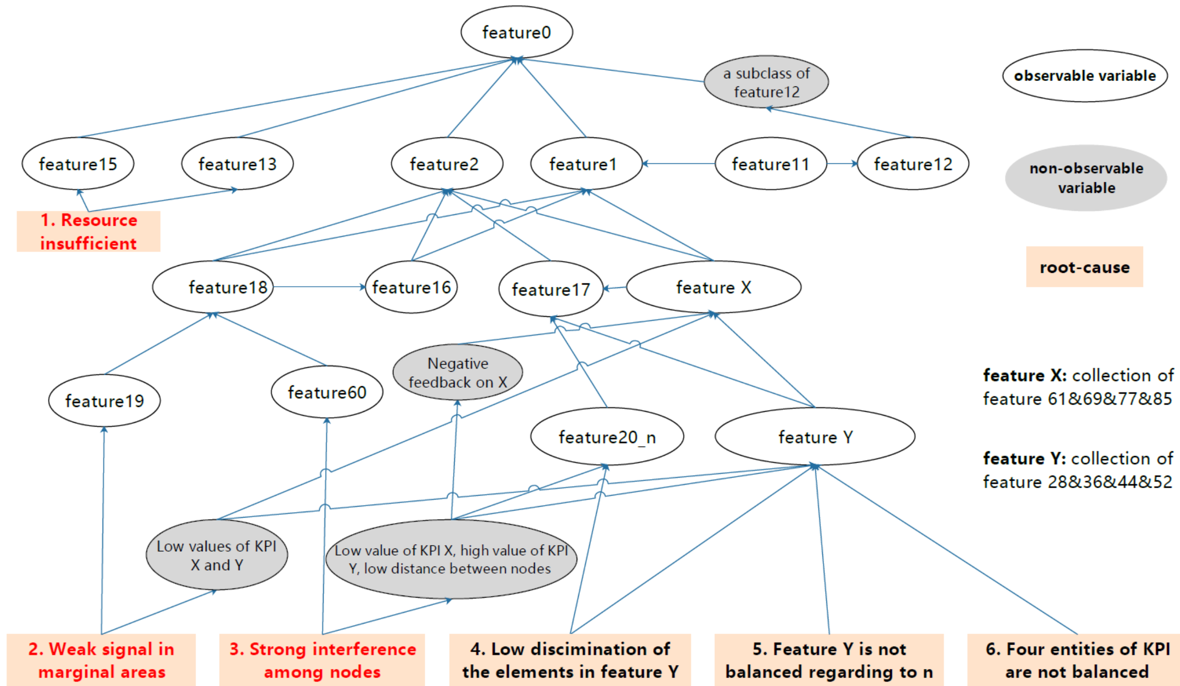
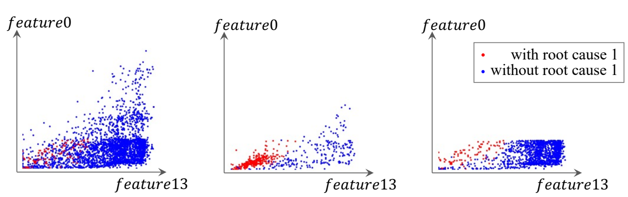


Fig. 3. The causal graph of the real-world data set



(a) Training distribution (b) Test distribution (c) Aligned training distribution

Fig. 4. Case study on root cause 1, in which the label in test distribution are obtained by the prediction of CARCL.

independent, which is clearly not hold according to Fig. 3. CatBoost and k-NN work relatively well, even in the absence of feature selection.

Overall, CARCL is more effective than CARCL-NCA, CARCL-NM, and CARCL-L, proving the necessity of utilizing the causal information and multi-stage classifier. Though CARCL-NCA does not use the causal alignment, it is still better than other baselines, which shows the effectiveness of CARCL.

3.6. Case Study

To show the effectiveness of our approach, we provide a case study with the root cause 1. In detail, we use feature 13 and feature 0 which are the descendent of the root cause 1 to show the effectiveness of our method. As shown in Fig. 4, the blue dot represents the sample without root cause 1, and the red dot represents the sample with root cause 1. There is a significant difference between the distribution of the training data set and the test data set without the distribution alignment. After distribution alignment, the distribution of the new training data set and the test data set is similar. This also proves the necessity of distribution alignment in root causes location and the correctness of our method.

4. CONCLUSION

We propose a root causes location framework based on causal alignment. Differ from previous methods, we consider the different distribution of data in training data set and test data set, and conduct the causal alignment processing according to the causal mechanism. In addition, we use the multi-stage classifier architecture based on the pseudo label in our method, which improves the tolerance of the model to the inconsistent data distribution in the training data set and the test data set. The excellent performance of the proposed method provides an effective solution for fault root causes localization.

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