DMIRLAB

# Quickly Locate Faults Method

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# Contents

Part I

# Background

# Introduction to the Topic

The scale of the network is huge, and the structure is interconnected

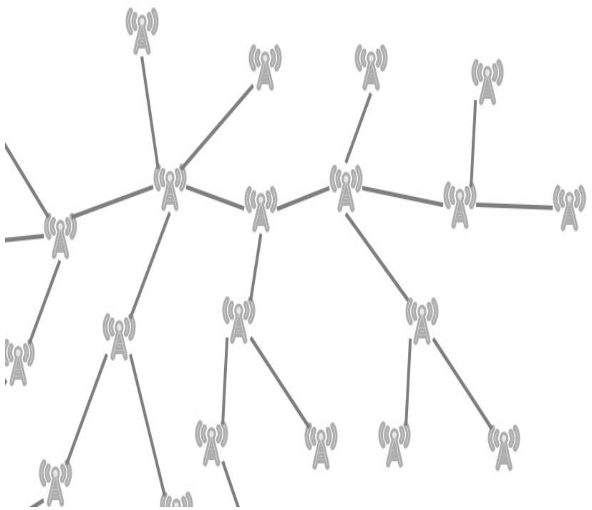
A single fault may trigger multiple types of alarms

Design a causal discovery model

Learn causality from alarm data

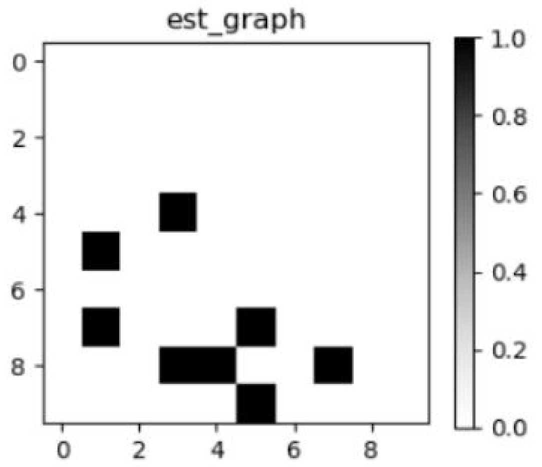
Suitable for non-topological and topological structures

Intelligent operation and maintenance



Topology and alarms data

Offline Casual Discovery Model




Alarm causal diagram

## Part II

# PTHP Method

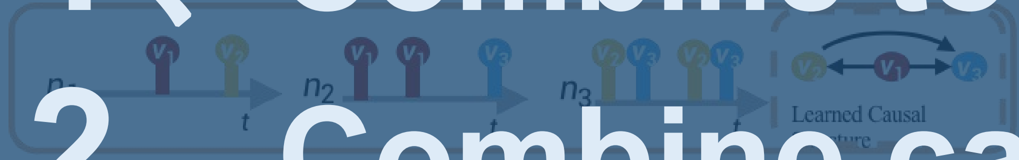
# Why PTHP Is Needed

- **Difficulties in the current competition data set:**
  - **Different devices is not independent**. The alarm of a device will not only cause other alarms of its own device, but also affect the alarms of its topological neighbors.
  - Simply merge all node alarms ... causality ... causality relationship.

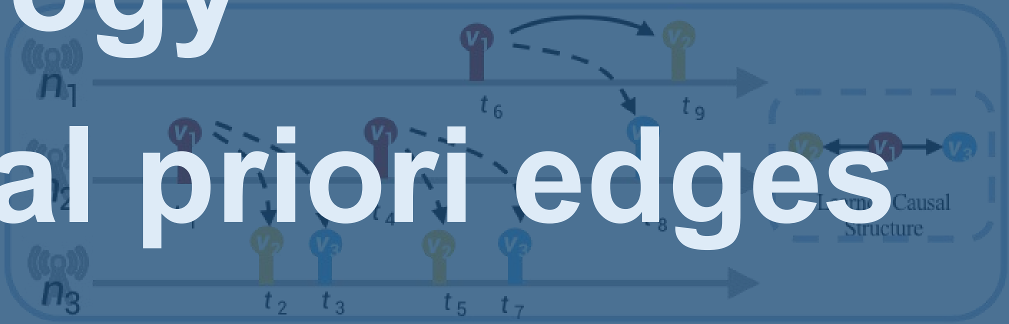
# Solution goals：

## 1、Combine topology

## 2、Combine causal priori edges




(b) False Detection with i.i.d Assumption



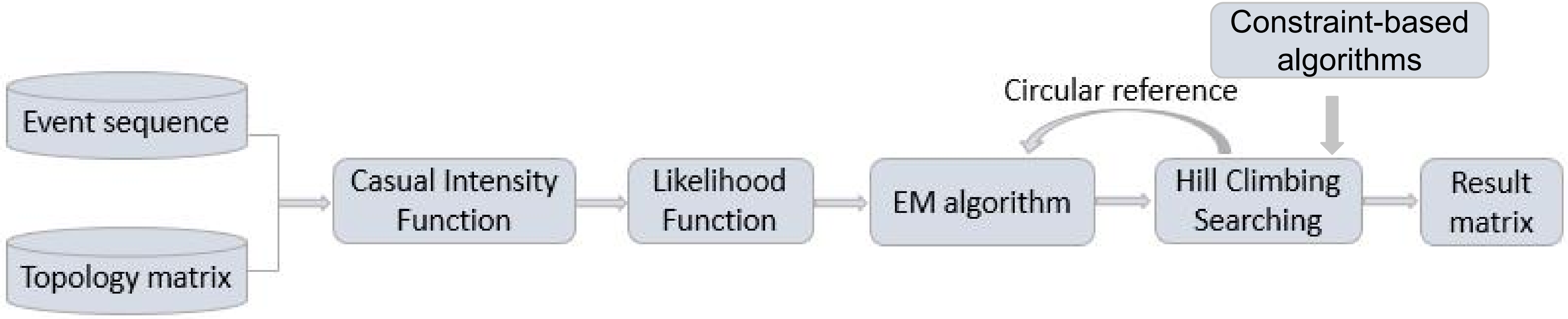

(c) Correct Detection with topology Information

FALSE

True

# Introduction of PTHP

## A Priori-based Topological Hawkes Process (PTHP):




### Topology

The event is generated in the topological network

### Time and space

Considering both time and space domain information

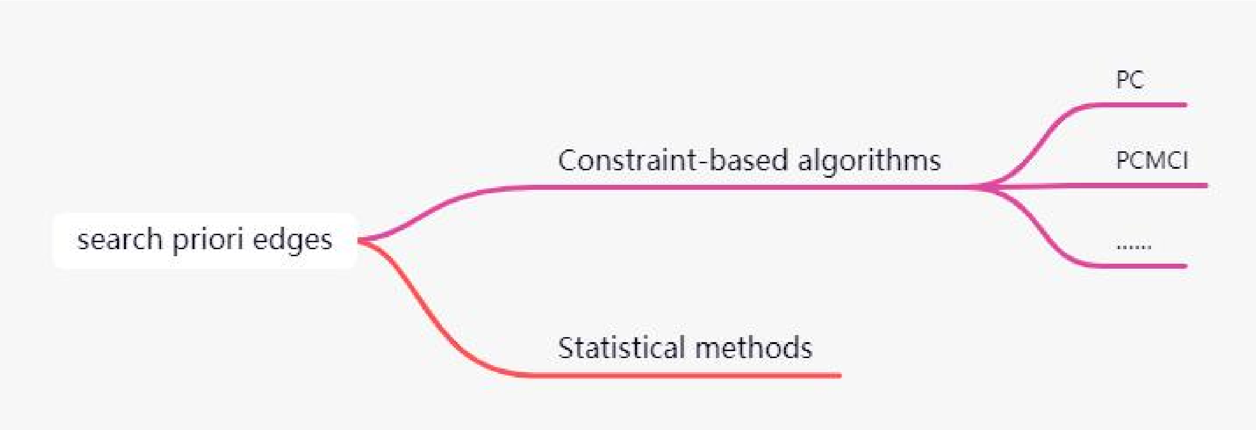
### Sparse rule

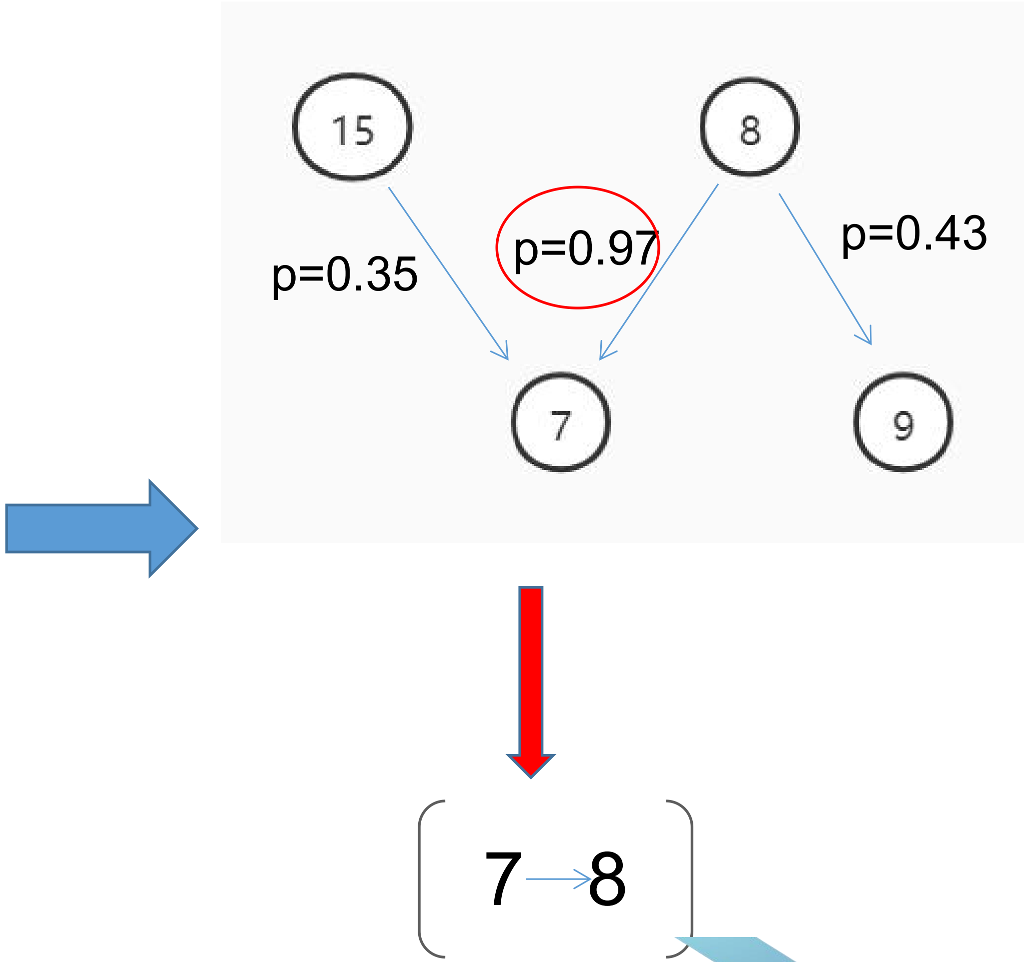
Designed an efficient sparse optimization rule

### Practical

The actual results of the algorithm are excellent

# Introduction of PTHP



# Solution Introduction - PTHP

- **The causal graph search based on climbing method with a priori:**

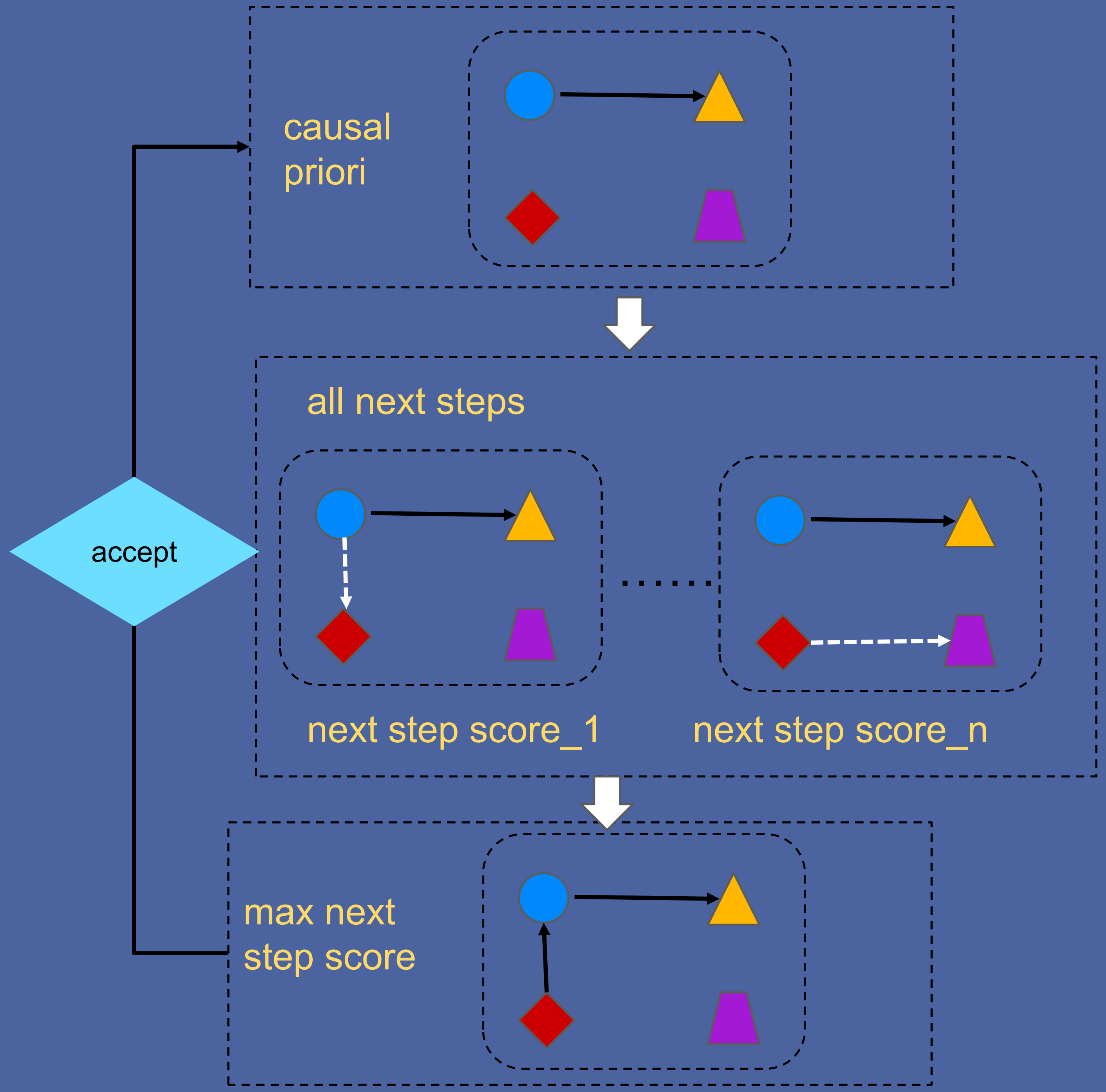
Optimize the target (BIC) :

$$\max_{\mathcal{G}_V}[\max_{\Theta} L_B(\mathcal{G}_V, \Theta; \mathcal{E}, \mathcal{G}_N)]$$

Where: $$L_B(\mathcal{G}_V, \Theta; \mathcal{E}, \mathcal{G}_N) = \underbrace{L(\mathcal{G}_V, \Theta; \mathcal{E}, \mathcal{G}_N)}_{\text{似然度}} + \underbrace{\frac{p\log(m)}{2}}_{\text{BIC罚项}}$$

$$\begin{aligned} & L(G_V, \Theta; \mathcal{E}, G_N) \\ &= \sum_{n \in \mathrm{N}} \sum_{v \in \mathrm{V}} \int_{t \in \mathrm{T}} \log\left[e^{-\lambda_v(n,t)\Delta t} (\lambda_v(n,t)dt)^{dC(n,v)}\right] \\ &= \sum_{v \in \mathrm{V}} \sum_{n \in \mathrm{N}} \int_{t \in \mathrm{T}} [-\lambda_v(n,t)dt + \log(\lambda_v(n,t))dC(n,v)] + const \end{aligned}$$

- **EM step:**
  **Calculate the likelihood score of the causal structure $\mathcal{G}_V$**
- **Hill-Climbing step:**
  **Search for the highest-score causal structure: $\mathcal{G}_V$**



Part III

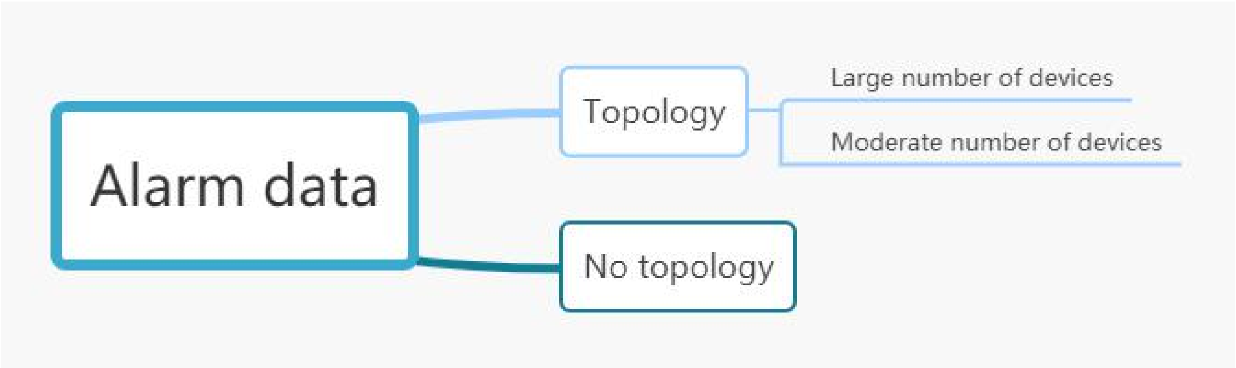
# Case Study

# Data Classification

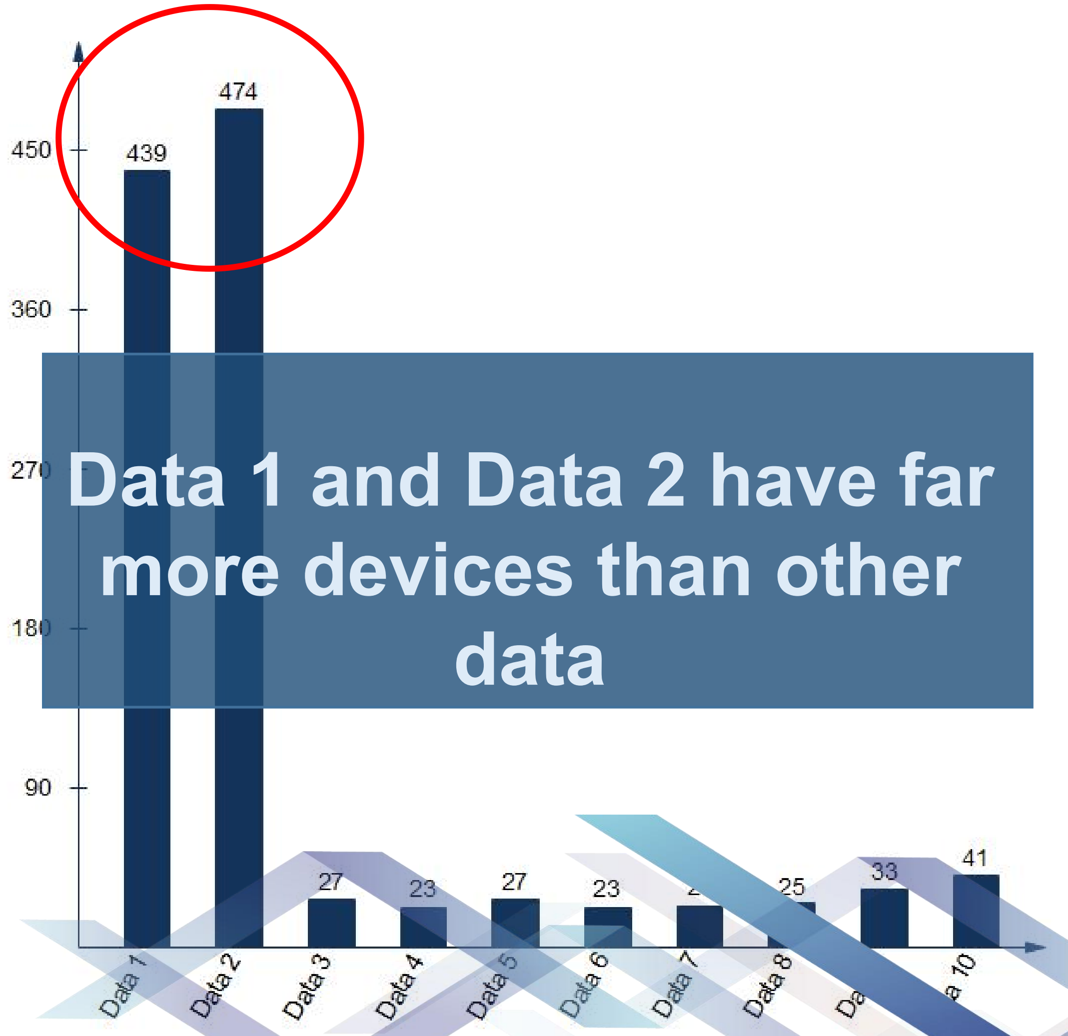
- The alarm data including the alarm id, the id of the device where the alarm occurred, and the start and end time.

| alarm_id | device_id | start_timestamp | end_timestamp |
|---|---|---|---|
| 11 | 55 | 0 | 0 |
| 12 | 260 | 23 | 23 |
| 5 | 107 | 32 | 32 |
| 3 | 107 | 32 | 32 |

- We classify data based on **whether there is a topological structure provided between devices as the primary condition**, and **the number of devices as a secondary condition**.




## The number of devices included in each data of the finals data




**Data 1 and Data 2 have far more devices than other data**

# Choice of Parameters

- According to the above-mentioned data classification principle, we use the PTHP model in the preliminary stage, take **data 1-4 (real causal diagrams have been given)** as the experimental subjects, set up multiple experimental groups, and obtain the best parameters through **the control variables**.

| dataset2 | | | | | |
|---|---|---|---|---|---|
| delta | max_hop | penalty | max_iter | data_num | |
| | | | 100 | | |
| 0.05 | 1 | AIC | 150 | 2500 | |
| 0.1 | 2 | BIC | 200 | 5000 | |
| 0.2 | 3 | | 250 | 7500 | |
| | | | | 10000 | |
| | fdr | tpr | fpr | shd | gscore |
| delta | | | | | |
| 0.01 | 0.12 | 0.9167 | 0.037 | 5 | 0.7917 |
| 0.1 | 0.2414 | 0.9167 | 0.0864 | 9 | 0.625 |
| 0.2 | 0.3548 | 0.8333 | 0.1358 | 15 | 0.375 |
| | | | | | |
| max_hop | | | | | |
| 1 | 0.303 | 0.9583 | 0.1235 | 11 | 0.5417 |
| 2 | 0.2414 | 0.9167 | 0.0864 | 9 | 0.625 |
| 3 | 0.2143 | 0.9167 | 0.0741 | 8 | 0.6667 |
| | | | | | |
| penalty | | | | | |
| AIC | 0.3684 | 1 | 0.1728 | 14 | 0.4167 |
| BIC | 0.2414 | 0.9167 | 0.0864 | 9 | 0.625 |

**Through full experimentation and verification on the rest of the test data, we get the following applicable standard parameters.**

| Data With Topology | |
|---|---|
| epsilon | 1 |
| delta | 0.01 |
| max hop | 2 |
| penalty | BIC |
| sample size | 5000 |

| Data Without Topology | |
|---|---|
| epsilon | 1 |
| delta | 0.01 |
| max hop | 0 |
| penalty | BIC |
| sample size | 5000 |

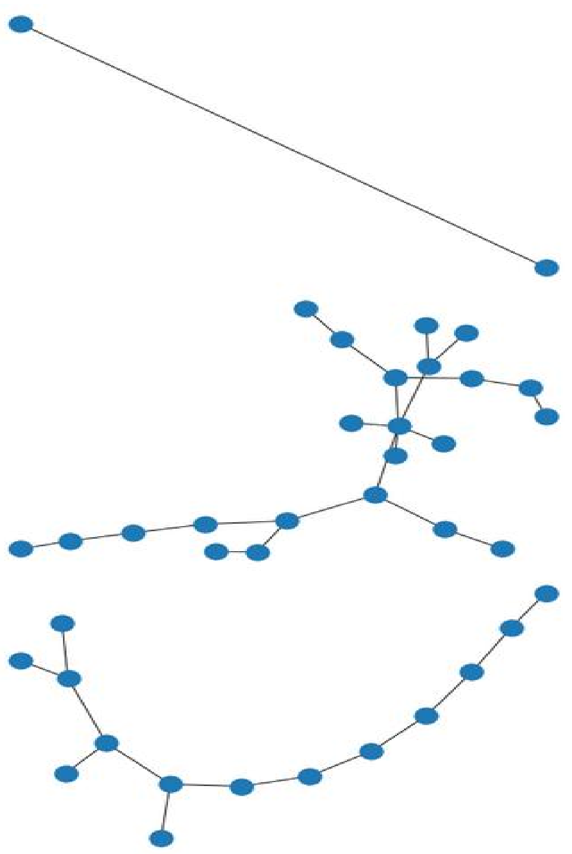
# Problems with Data 1 And Data 2

Through the standard parameters, we got a great performance of data 3~10, but the effect of data 1 and data 2 is not good.

- **After the data analysis stage, we found that data 1 and data 2 have the following characteristics:**
  - The direct debugging parameter score is low, and the guess is caused by the hidden variable.
  - There are as many as hundreds of devices, which results in a large amount of data used for training and has a certain impact on the results of training.
  - After studying the topological graph, it can be found that the topological graphs of data 1 and 2 are composed of multiple connected subgraphs.

| Data | Number of connected graphs |
|---|---|
| 1 | 53 |
| 2 | 48 |
| 3-10 | 1 |

**Partial topological graph of data 1**



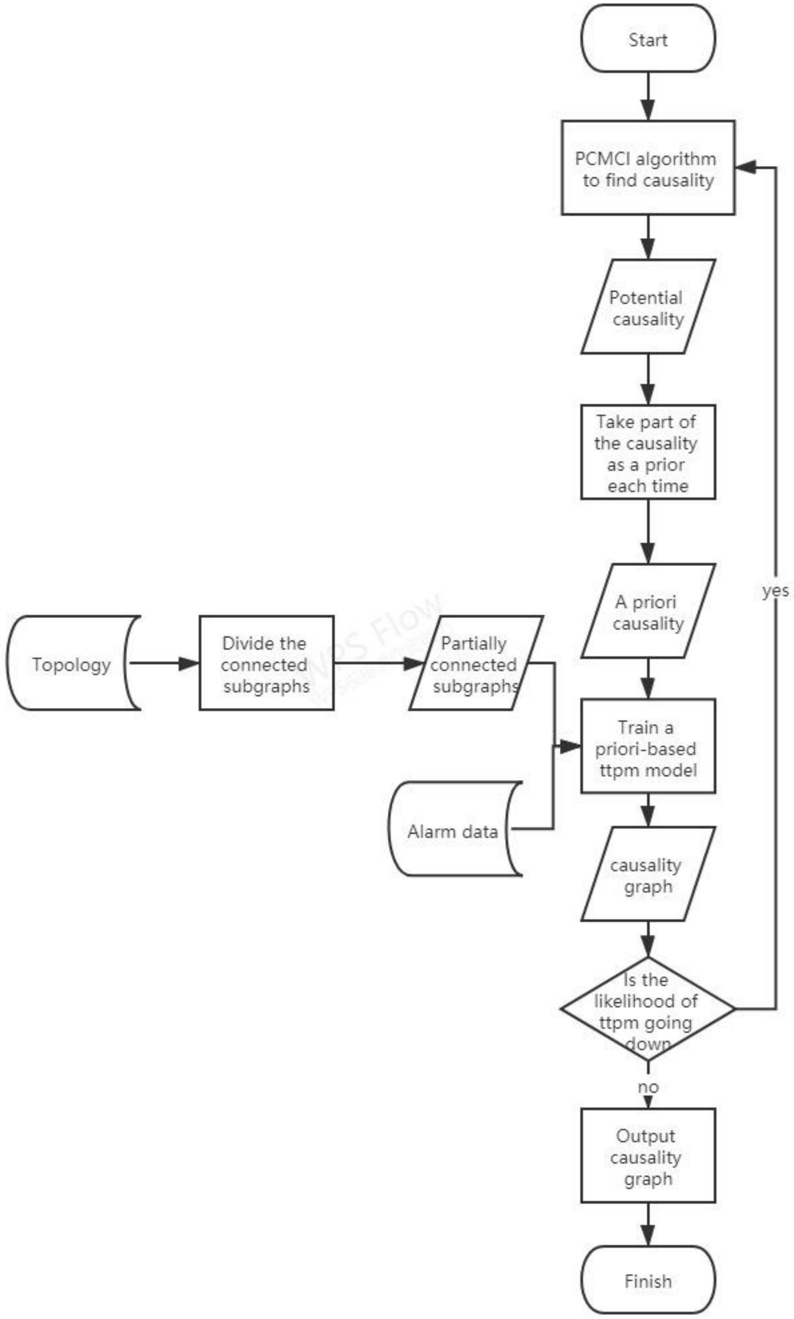
# Processing of Data 1 And Data 2

Aiming at the data characteristics of data 1 and data 2 , we adopted a priori-based processing method:

A. we divide the topological graph into different connected subgraphs and use only partial connected subgraphs to reduce the training data.

B. Through the PCMCI algorithm and other methods, the possible causal relationship is found as a priori.

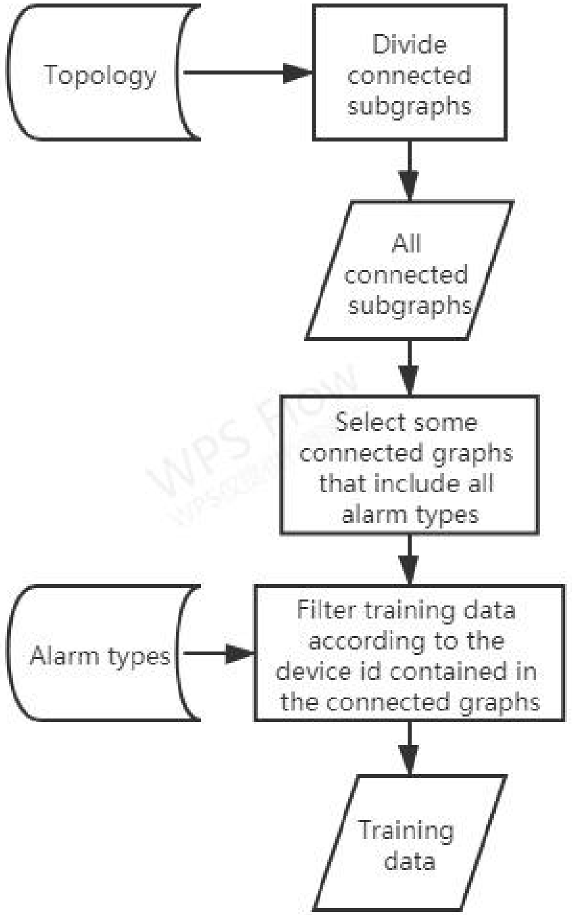
C. Use part of the priori causality for iteratively training the PTHP model to gradually adjust the causal diagram to improve the model effect.



## Get Training Data

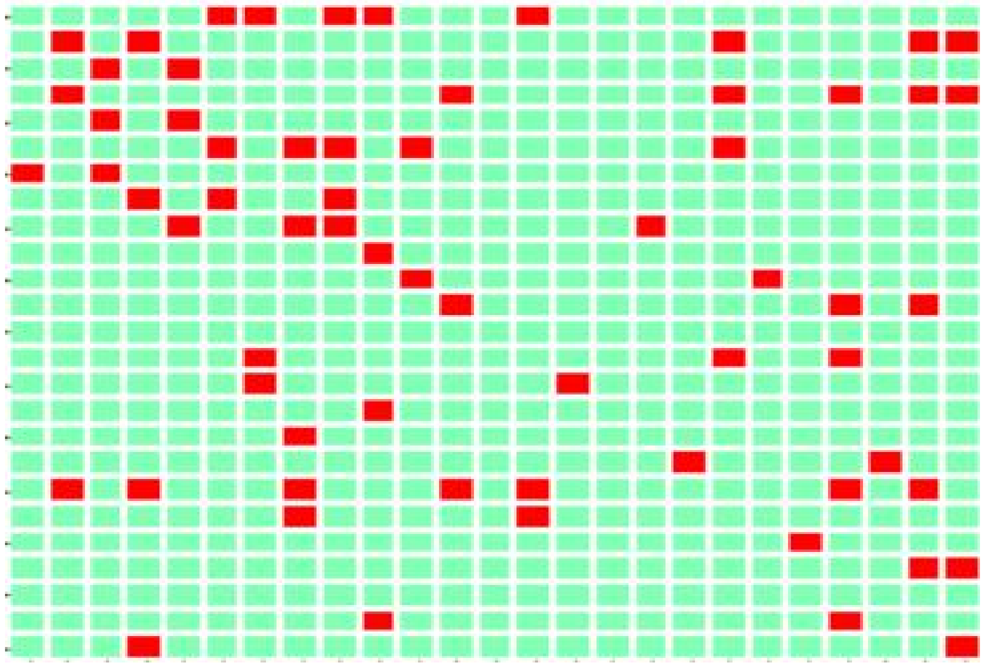
- In order to extract the training data, We choose the connected subgraphs that includes all alarm ids:
  - The set of device ids is composed of multiple selected connection subgraphs. In other words, there is no edge connection between the selected device ids and the unselected device ids in the topology graph, and they do not affect each other.
  - The data required to include contains all types of alarms.

**Obtain training data according to the connected subgraphs**



# Get Priori Edges

➢ **Find the priori through the pcmci algorithm**



**the results of PCMCI**

➢ Obtain a priori by counting the number of alarms

```
0: [2, 6, 4, 5, 1, 3, 9, 7, 8, 10]
1: [3, 0, 2, 5, 6, 4, 11, 7, 8, 9]
2: [0, 6, 4, 5, 1, 3, 7, 9, 8, 10]
3: [1, 0, 2, 6, 5, 4, 11, 7, 8, 9]
4: [2, 6, 0, 10, 5, 7, 8, 11, 3, 1]
5: [8, 7, 9, 2, 10, 0, 4, 6, 16, 14]
6: [0, 2, 4, 5, 7, 8, 10, 3, 1, 9]
7: [8, 5, 10, 9, 2, 6, 0, 4, 16, 1]
8: [5, 7, 10, 9, 2, 4, 6, 0, 16, 14]
9: [5, 8, 2, 0, 7, 6, 10, 4, 15, 11]
```

**Potential parent node obtained by statistics**

➢ Get priori edges from the data

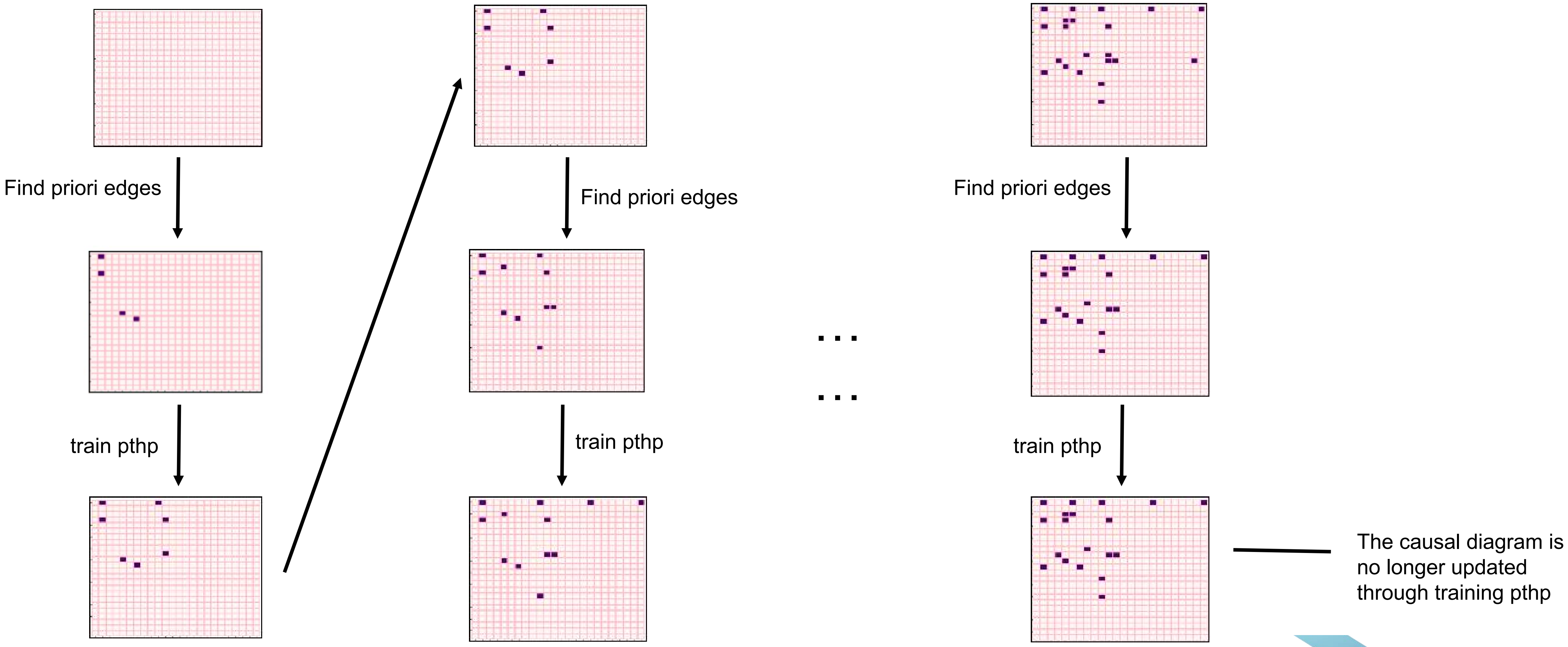
| | | | | |
|---|---|---|---|---|
| 11447 | 1 | 172 | 107523 | 107523 |
| 11526 | 3 | 1 | 107706 | 107706 |

| | | | | |
|---|---|---|---|---|
| 11071 | 1 | 1 | 107204 | 107204 |
| 11081 | 3 | 1 | 107204 | 107204 |

| | | | | |
|---|---|---|---|---|
| 7192 | 1 | 172 | 83082 | 83082 |
| 7241 | 3 | 1 | 83091 | 83091 |

1→3

# Based on Priori Training PTHP Model



Part IV

# Summary

## Model effect is remarkable

1. First place in the preliminary and finals
2. The relevant code is open source

Phase1 Phase2

排名刷新时间：2021-08-11 09:29:45

我的排名

| 排名 | 团队名 | 得分 |
|---|---|---|
| 1 | DMIRLAB | 0.9151 |

| 排名 | 团队名 | 得分 |
|---|---|---|
| 1 | DMIRLAB | 0.9151 |
| 2 | SMS | 0.9075 |
| 3 | 无盐 | 0.9049 |

Preliminary

Phase1 Phase2

排名刷新时间：2021-08-26 09:02:45

我的排名

| 排名 | 团队名 | 得分 |
|---|---|---|
| 1 | DMIRLAB | 0.8097 |

| 排名 | 团队名 | 得分 |
|---|---|---|
| 1 | DMIRLAB | 0.8097 |
| 2 | JayceHaHa | 0.8056 |
| 3 | cug_402 | 0.7984 |

Semi-finals

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# Thanks for listening

Team members: Liu Yuequn, Huang Zhengting, Huang Xiaokai