

基本情况



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学校专业：电子科技大学
机械与电气工程学院，机械设计制造及其自动化

阶段：大三（2023级） 均分：91 专业排名：1/83

所获主要奖项/荣誉

- 国家奖学金×2
- 一作发表SCI论文两篇
- 一作在投SCI论文两篇
- 主持国家级大创一项

国家级奖项

中科院1, 2区

中科院1区

结题优秀

创社核心，副会长：UESTC IA 交叉学科协会
科研助理：UESTC系统可靠性与安全性研究中心
科研助理：SJTU人工智能学院

公众号报道

【机电idol】段之续：稳扎每一步，自有远方来

原创 机电idol 积淀态度 2025年11月26日 09:53 四川

1 INDUCTION
人物简介

积淀态度

赞 分享 推荐 写留言

基本情况



本科研究方向：
机械装备智能可靠性 **系统连贯**

Stage1
零故障样本下异常检测

Stage2
未知域泛化诊断

Explore
工业大模型

1. Pseudo-fault data enhanced relation network for fault detection and localization in train transmission systems

第一作者, 已发表 *Engineering Applications of Artificial Intelligence (EAAI, 中科院一区TOP, IF=7.7)*

2. Parallel Relation Network for Intelligent Fault Detection and Localization of Train Transmission Systems with Zero-fault Sample

第一作者, 已发表并英文报告 (科研入门作) *IEEE Reliability and PHM Conference (PHM-Beijing)*

3. Unified Health Domain Relation Learning for Train Transmission Systems Fault Detection under Complex Operating Conditions

共一第二 (导师第一), 已发表 *Structural Health Monitoring (SHM, 中科院二区TOP, IF=5.7)*

4. Decoupling Intrinsic Fault Features from Domain Variations via Domain-Attribute Fusion for Unseen-Domain Fault Diagnosis

第一作者, 小修 *Advanced Engineering Informatics (AEI, 中科院一区TOP, IF=9.9)*

5. Collaborative Teacher-Student Learning: Simulated Domain Attacks for Class-Intrinsic Feature Learning in Multi-Domain Generalized Fault Diagnosis

第一作者, Under Review *TII (IEEE Transactions on Industrial Informatics, 中科院一区TOP, IF=9.9)*

6. Open-Set Fault Diagnosis Using CLIP with Forward-Reverse Reasoning

第二作者 (导师一作), 小修 *COMPUT IND (Computers in Industry, 中科院一区, IF=9.1)*

7. Reinforcing Cross-Domain Few-Shot Fault Diagnosis of Train Transmission Systems via Reducing Intra-Class and Maximizing Inter-Class Variations

第二作者, Under Review *TII (IEEE Transactions on Industrial Informatics, 中科院一区TOP, IF=9.9)*

8. IndustryCode: A Benchmark for Industry Code Generation

第三作者, Under Review *ICML (CCF-A)*

Stage1: 零故障样本下异常检测

工业场景中对高端机械装备可靠性要求极高，往往不存在可供传统数据驱动方法应用的实际故障样本，如何仅依赖健康状态下运行数据及时对装备异常进行检测和定位？

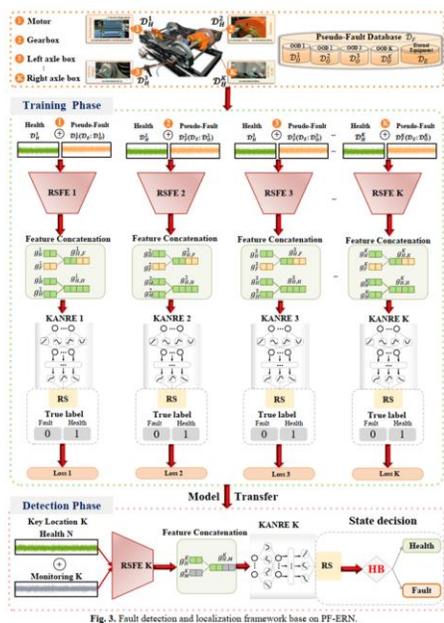


Fig. 3. Fault detection and localization framework based on PF-ERN.

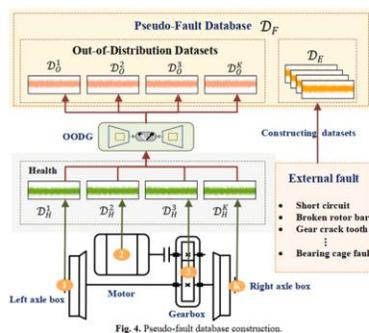


Fig. 4. Pseudo-fault database construction.

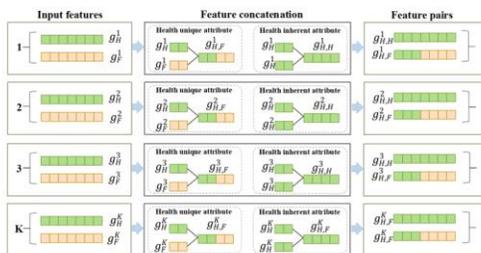


Fig. 6. Feature concatenation mechanism.

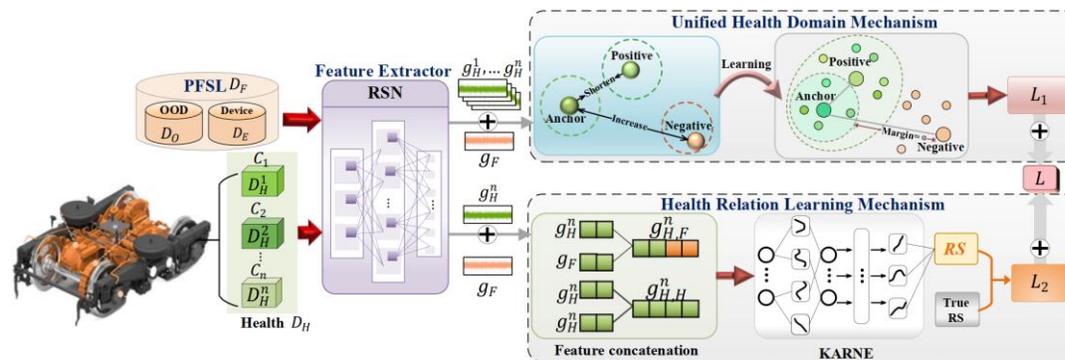
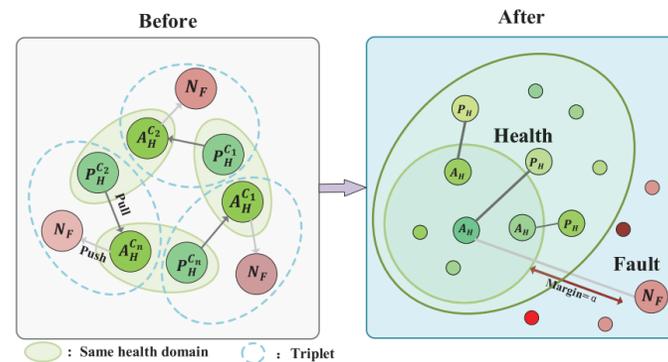


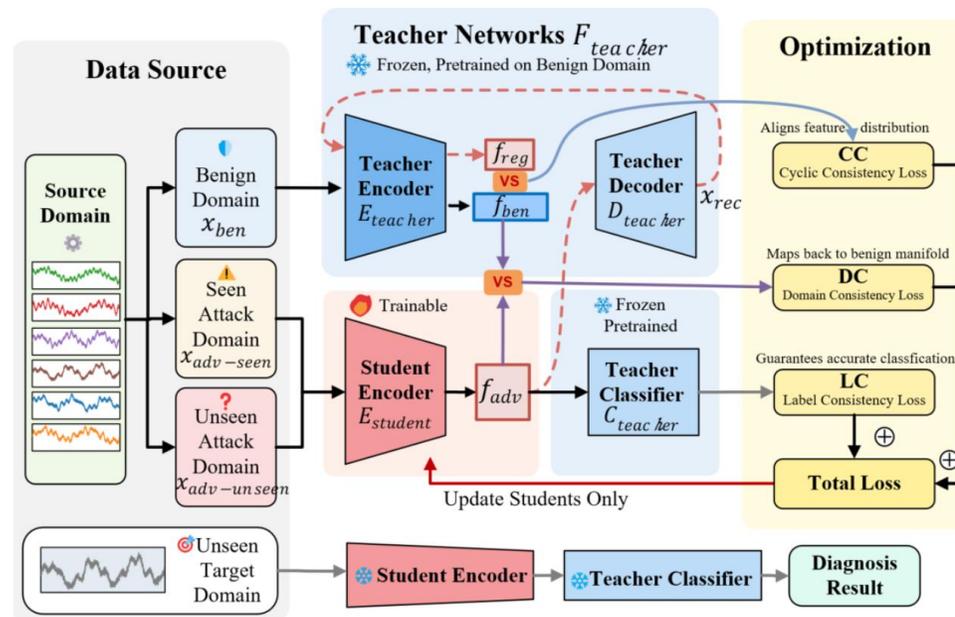
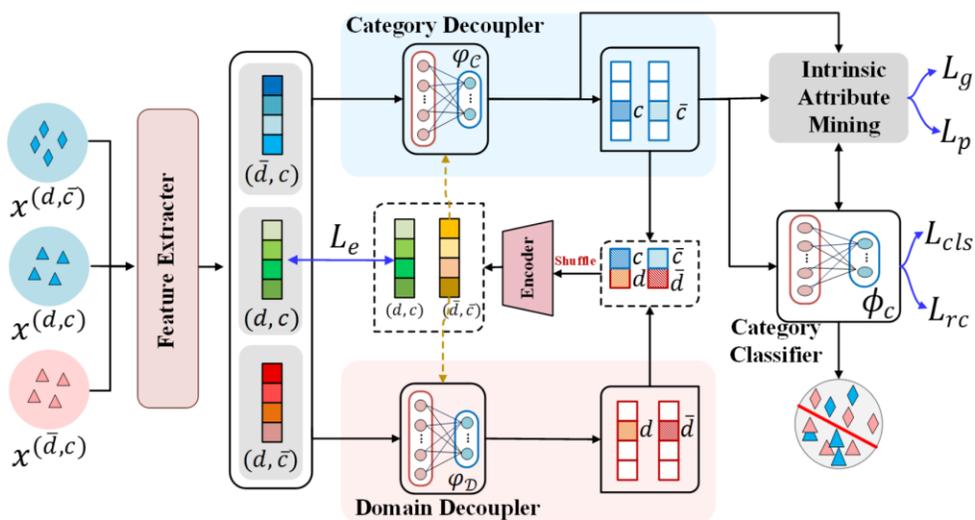
Fig. 1. UHDRL structure.



Legend: ● : Same health domain ○ : Triplet

Stage2: 未知域泛化诊断

机械装备在实际工业应用时，速度负载等等环境因素会使传感器采集数据产生严重的分布差异，现有数据驱动方法在应用时会出现很严重的性能下降。如何利用多源数据训练模型而能够在一个完全未知的目标域仍能保证性能？



Stage1 零故障样本下异常检测



Pseudo-fault data enhanced relation network for fault detection and localization in train transmission systems

第一作者已发表 Engineering Applications of Artificial Intelligence (EAAI, 中科院一区TOP, IF=7.7)以及一篇会议论文

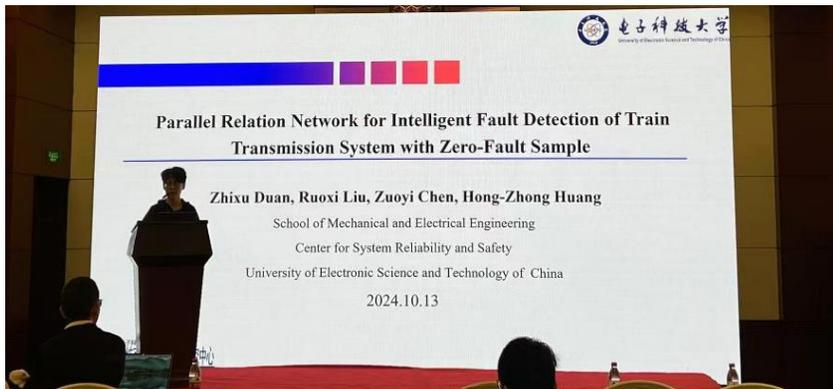
Engineering Applications of Artificial Intelligence 158 (2025) 111515



Pseudo-fault data enhanced relation network for fault detection and localization in train transmission systems

Zhixu Duan^a, Ruoxin Liu^a, Zuoyi Chen^{a,b,*}, Hong-Zhong Huang^{a,b}

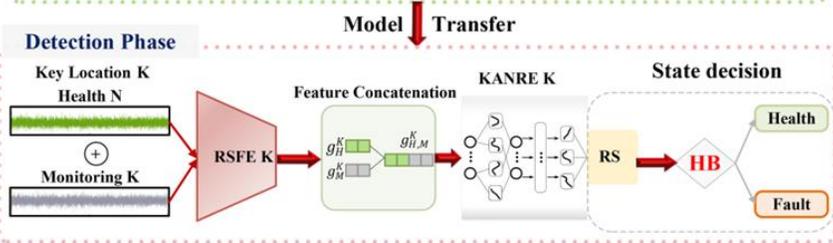
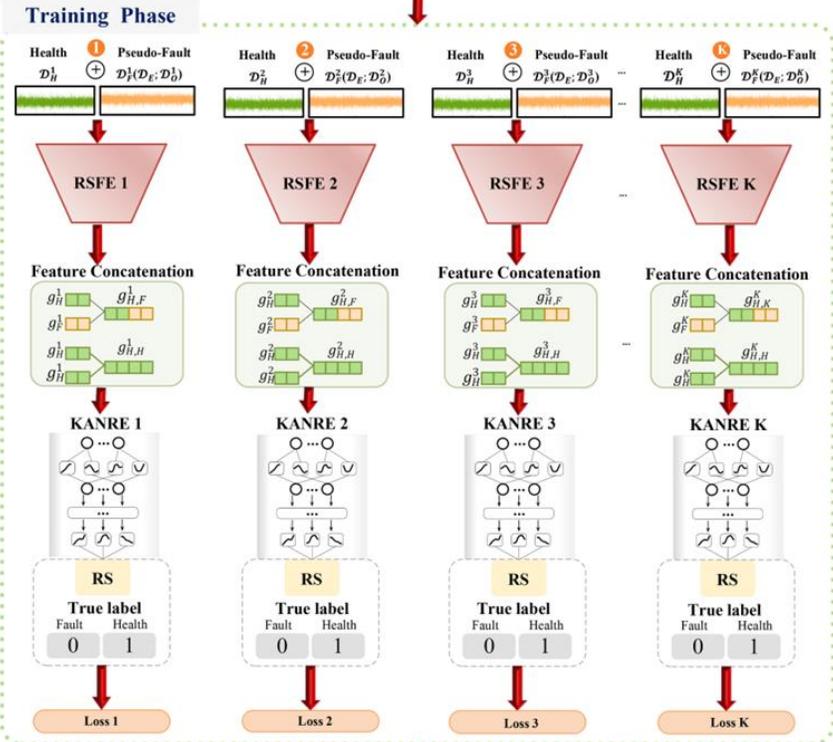
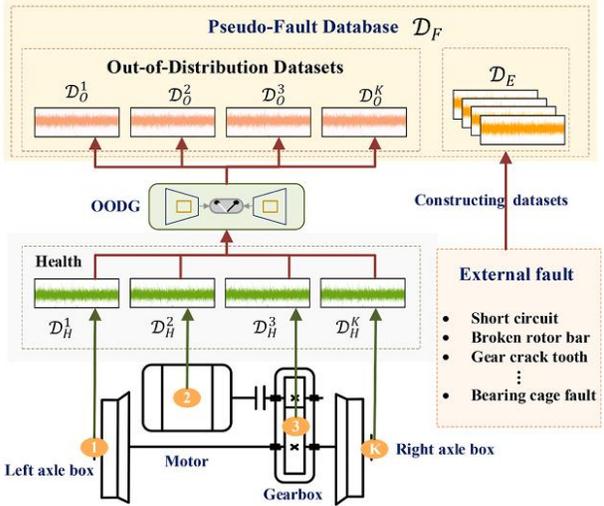
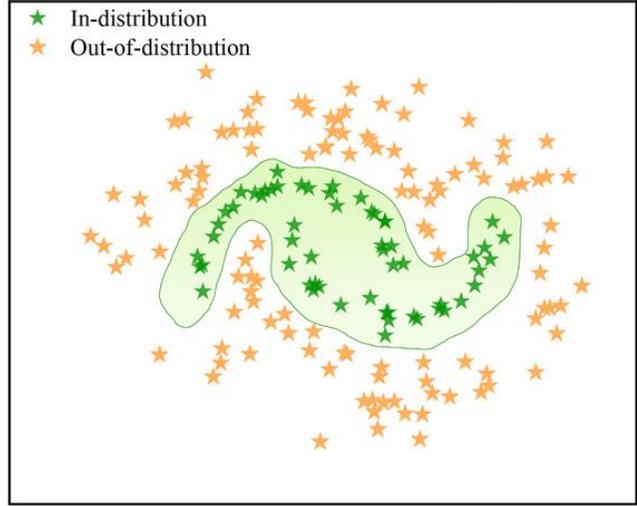
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^b Center for System Reliability and Safety, University of Electronic Science and Technology of China, Chengdu, 611731, China



高速列车往往运行在健康状态下，没有故障数据来赋能数据驱动方法。在这种情景下如何**仅依赖健康数据**对异常进行及时检测？

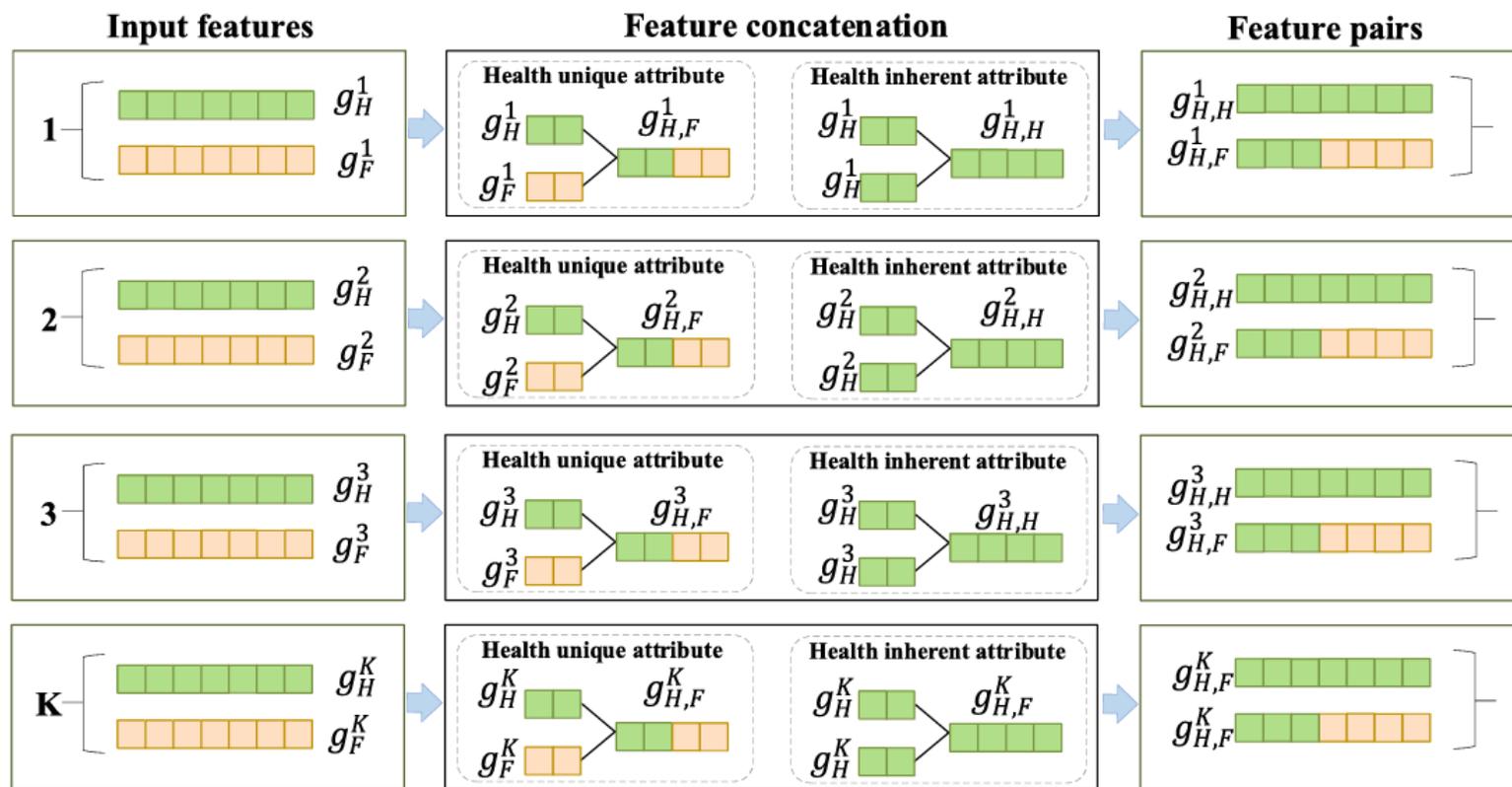
- 提出一种伪故障数据增强关系网络（PE-ERN）框架。打破对真实故障标签的依赖
- 构建伪故障数据库
- 结合特征拼接机制强化决策边界

Stage 1



ASL的构建

通过生成分布 (OOD) 外数据构建伪故障样本, 结合其他设备样本构建辅助样本库 (ASL), 模拟故障数据



设计特征拼接机制:

健康特征相互拼接，表征**共有属性**
 健康与故障特征相互拼接，表征**独有属性**

通过关系网络计算拼接后特征对的关系分数，量化二者的相似性

Unified Health Domain Relation Learning for Train Transmission Systems Fault Detection under Complex Operating Conditions

共一第二 (导师第一) 已发表 Structural Health Monitoring (SHM, 中科院二区TOP, IF=5.7), 已受理专利一项

高速列车常年运行在降水风沙等极端环境下, 运行工况多变复杂。如何在**复杂多变的工况下实现零故障样本的异常检测?**



Original Research Article

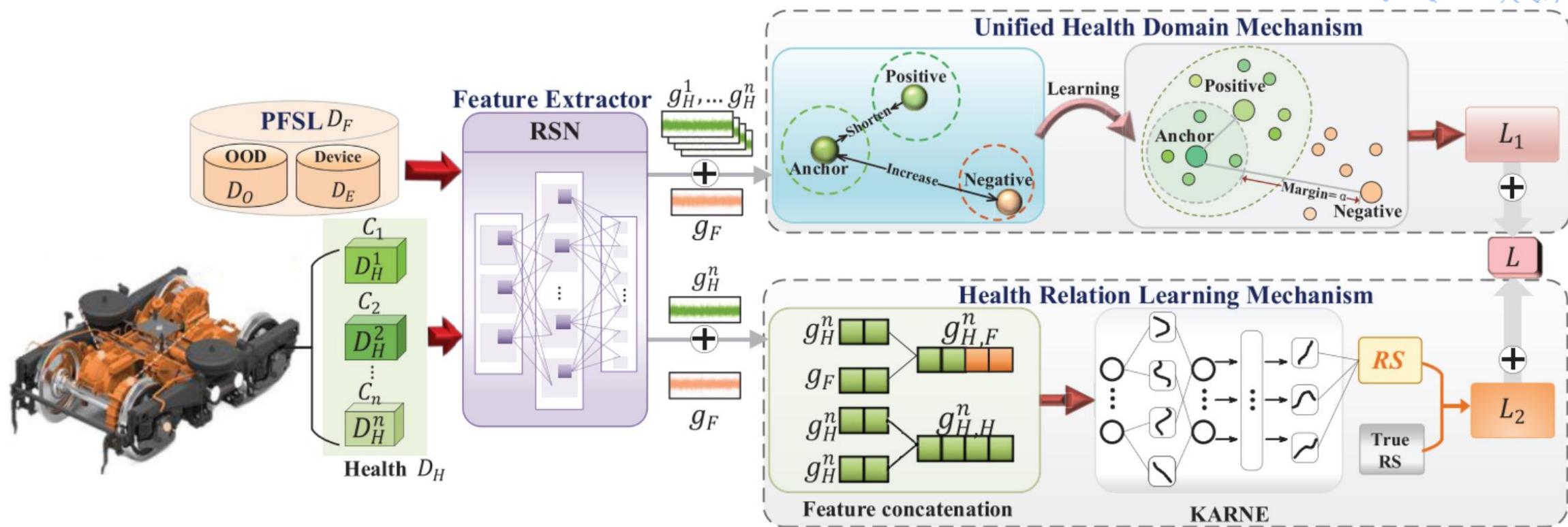
Unified health domain relation learning for train transmission systems fault detection under varying operating conditions

Structural Health Monitoring
1-25
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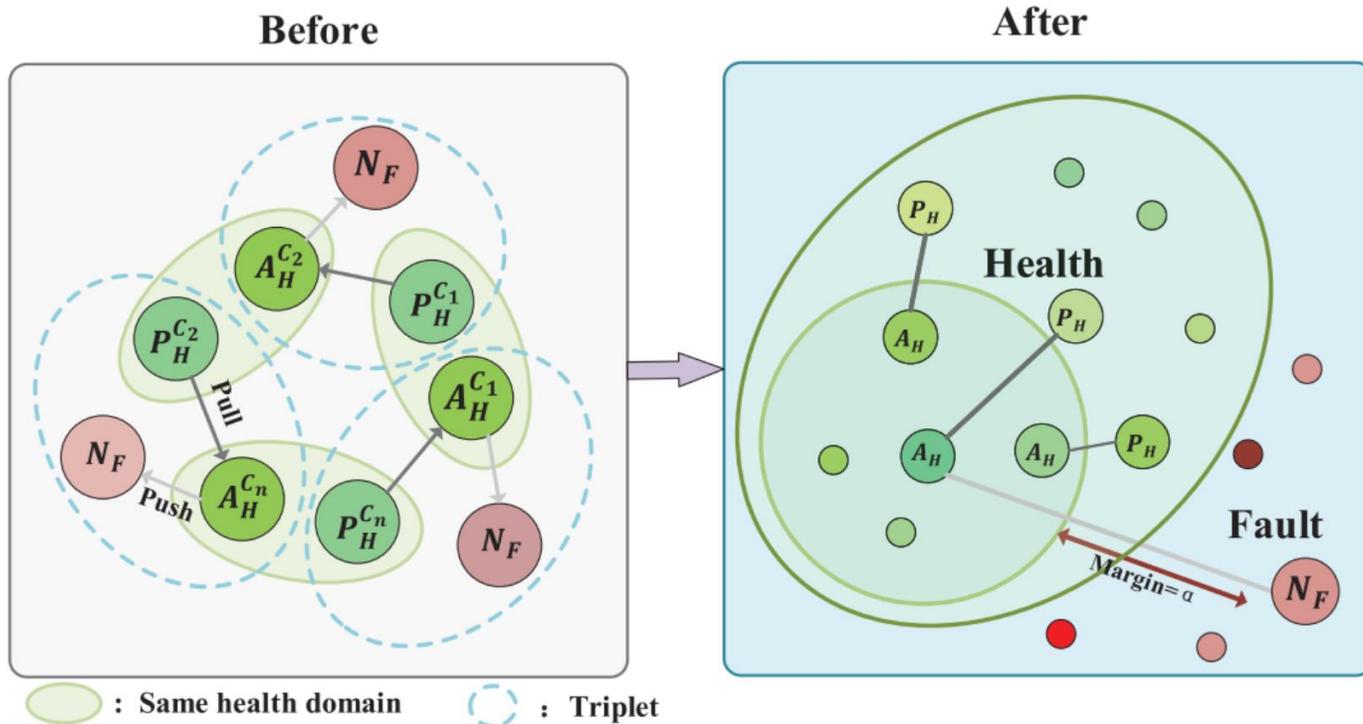

Zuoyi Chen^{1,2*}, **Zhixu Duan^{1*}**, Hua-Ming Qian^{1,2} and Hong-Zhong Huang^{1,2}

- 提出了统一健康域关系学习 (UHDRL) 的方法
- 设计统一健康域对齐机制, 实现多工况下健康样本间的表征统一





健康关系学习 + 健康领域统一



- 用不同工况下的健康样本形成锚点样本+正向样本
- 辅助样本库作为负向样本。

$$\mathcal{L}_1 = L(A, P, N) = \max(0, d(A_H^{C_i}, P_H^{C_j}) - d(A_H^{C_i}, N_F) + \alpha)$$

拉近锚点样本和正向样本的距离，最大化锚点和负向样本的距离形成**统一健康域**

Collaborative Teacher-Student Learning: Simulated Domain Attacks for Class-Intrinsic Feature Learning in Multi-Domain Generalized Fault Diagnosis

小修 第一作者 Advanced Engineering Informatics(AEI, 中科院一区TOP, IF=9.9), 已受理专利一项

Decoupling Intrinsic Category Features from Domain Variations via Domain-Attribute Fusion for Unknown Domain Fault Diagnosis

Zhixu Duan^a, Zuoyi Chen^{a,b,*}, Hong-Zhong Huang^{a,b}

School of Mechanical and Electrical Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China

^b Center for System Reliability and Safety, University of Electronic Science and Technology of China, Chengdu 611731, China

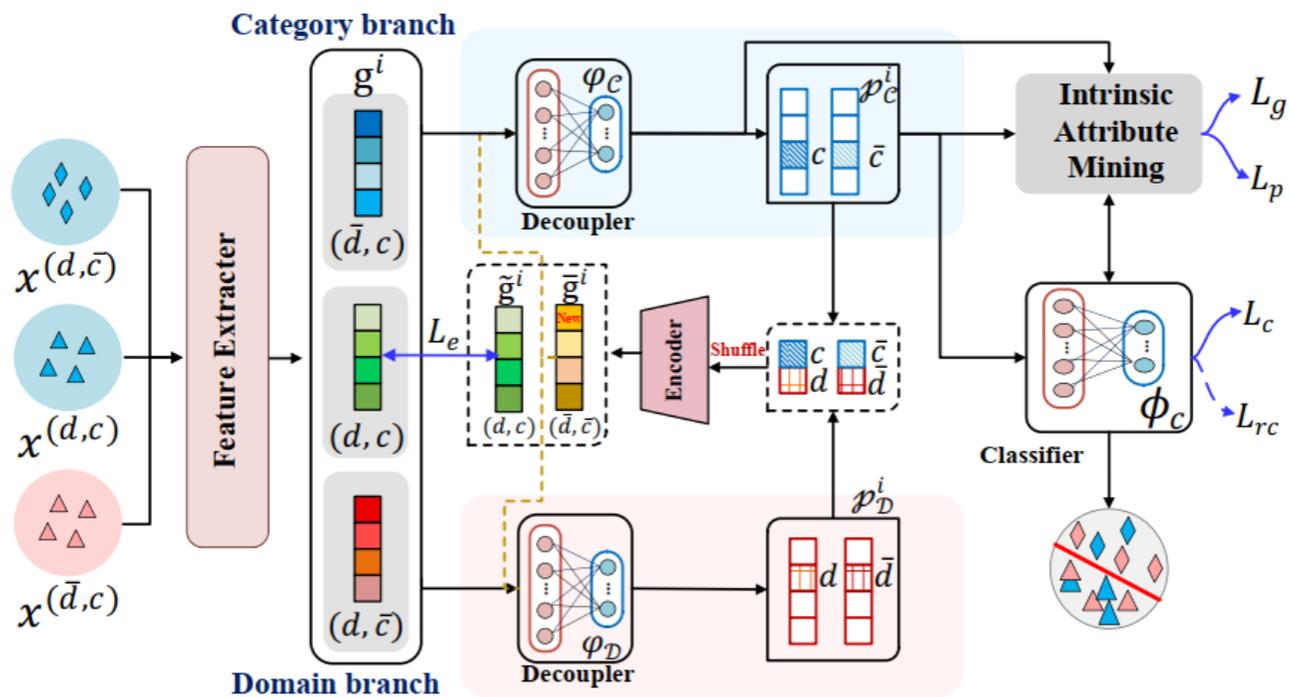
ARTICLE INFO ABSTRACT

Decoupling Intrinsic Category Features from Domain Variations via Domain-Attribute Fusion for Unknown Domain Fault Diagnosis
--Manuscript Draft--

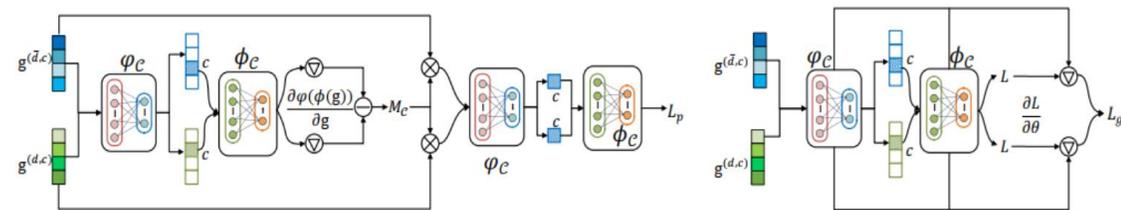
Manuscript Number:	INFFUS-D-25-05312
Article Type:	Research paper
Section/Category:	For all regular articles
Keywords:	Fault diagnosis Attribute decoupling Unknown domain Domain generalization
Corresponding Author:	Zuoyi Chen, Ph.D. University of Electronic Science and Technology of China Chengdu, China. Select One --- CHINA
First Author:	Zhixu Duan
Order of Authors:	Zhixu Duan Zuoyi Chen, Ph.D. Hong-Zhong Huang

机械装备在实际工业应用时数据会产生严重的分布差异，如何利用（多）源数据训练模型而适应于完全未知的目标域？

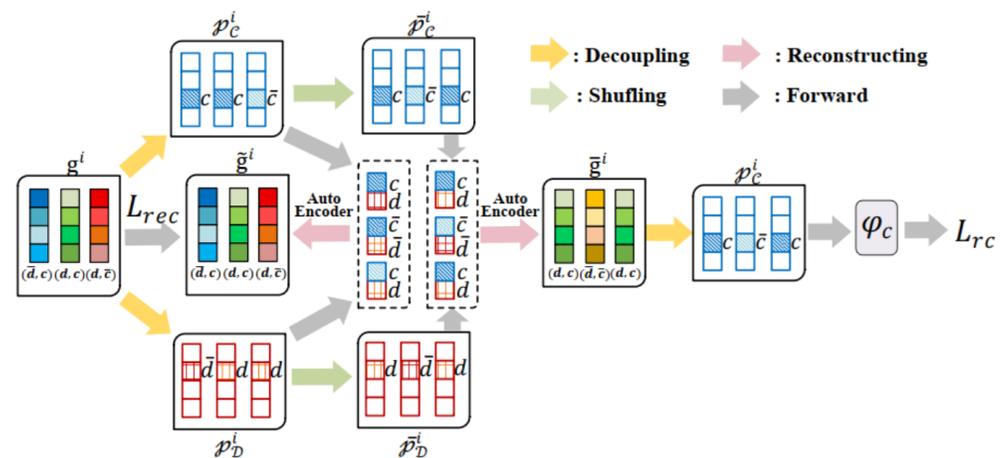
- 现有思路绝大部分是对齐不同域中数据特征的分布，本文则提出解耦故障和域特征
- 双分支属性解耦架构，将状态分解为故障和域
- 随机重构故障和域的组合，增强数据，强化解耦
- 本征属性挖掘：1.表征一致性mask对域变化敏感的特征通道，2.梯度一致性要求优化路径（梯度）保持一致



双分支解耦架构



本征属性挖掘：表征一致性，梯度一致性



随机重构

Decoupling Intrinsic Fault Features from Domain Variations via Domain-Attribute Fusion for Unseen-Domain Fault Diagnosis

送审 第一作者 IEEE Transactions on Industrial Informatics

(TII, 中科院一区TOP, IF=9.9)

IEEE Transactions on Industrial Informatics: Manuscript submitted - Manuscript No. TII-26-1348

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TII是盲审

Simulated Domain Attacks for Class-Intrinsic Feature Learning in Multi-Domain Generalization Fault Diagnosis

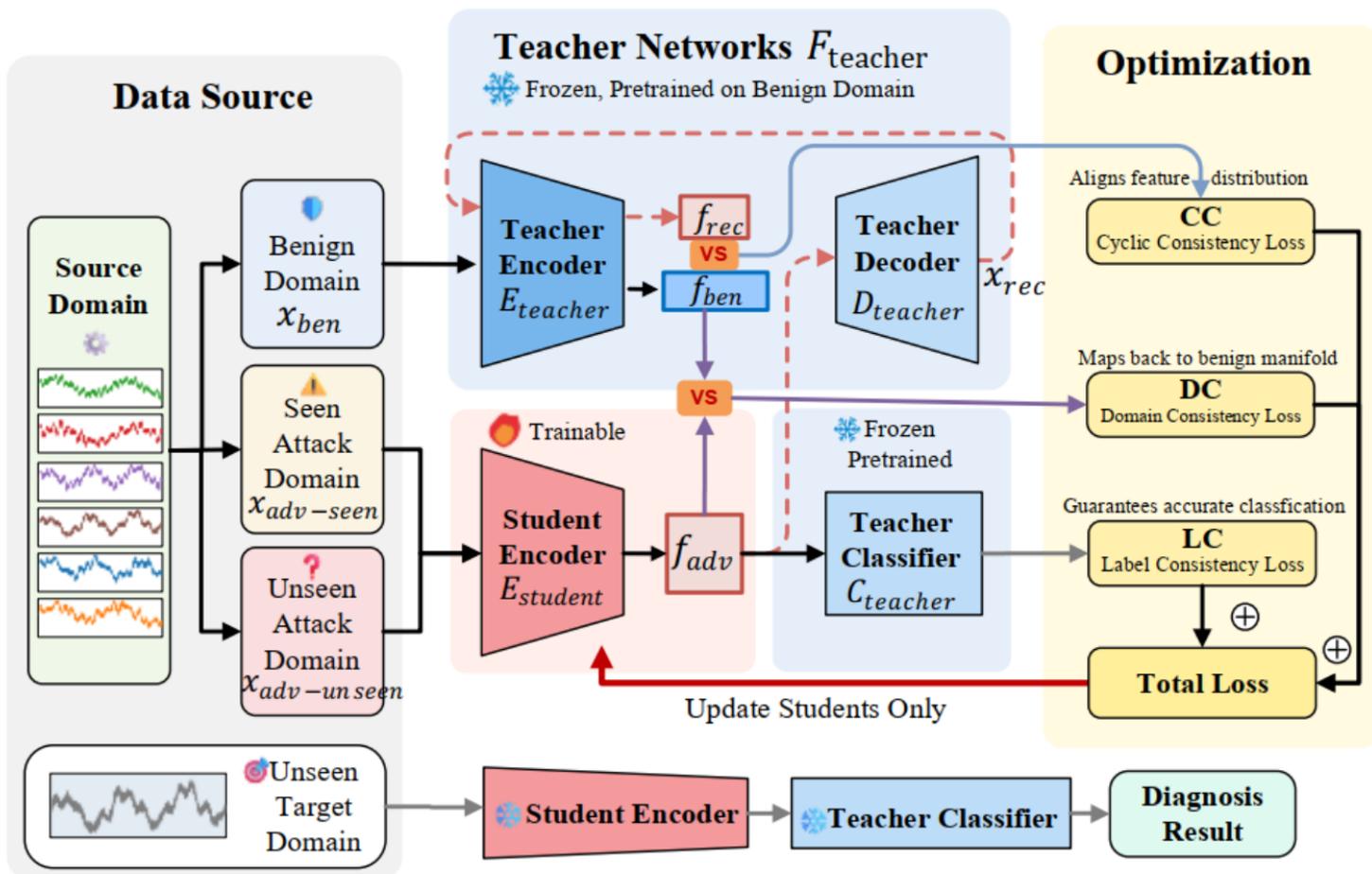
Abstract—Prevailing Domain Generalization (DG) methodologies predominantly rely on passive distribution alignment to minimize domain data distribution discrepancies. Inspired by cognitive invariance mechanisms, a new paradigm shift from passive alignment to active defense is proposed. Distinct from minimizing domain discrepancies, distribution shifts are conceptualized as adversarial simulated domain attacks. Specifically, a novel collaborative teacher student learning framework is constructed, in which a frozen teacher network guides a student encoder to actively defend against simulated domain attacks, thereby extracting class-intrinsic features. Furthermore, to ensure defense efficacy, a

specifically tailored for fault diagnosis under unknown rotating speeds. Li et al. [14] proposed an adversarial DG network based on class boundary feature detection. Furthermore, Ren et al. [15] developed a domain-invariant feature fusion network to explore the potential of semi-supervised DG models in intelligent fault diagnosis.

Despite the advancements in alignment-based DG approaches, they still encounter severe challenges in complex industrial scenarios. Primarily, given the substantial distributional shifts induced by drastic fluctuations in operating conditions, the coercive alignment of data with distinct physical characteristics risks distorting

机械装备在实际工业应用时数据会产生严重的分布差异，如何利用（多）源数据训练模型而适应于完全未知的目标域？

- 摒弃了传统DG中容易扭曲数据的强制对齐策略，采用一种更灵活的知识蒸馏范式
- 模拟未知域为域攻击
- 多一致性蒸馏协议（三个一致性）
- 双阶段模拟优化策略

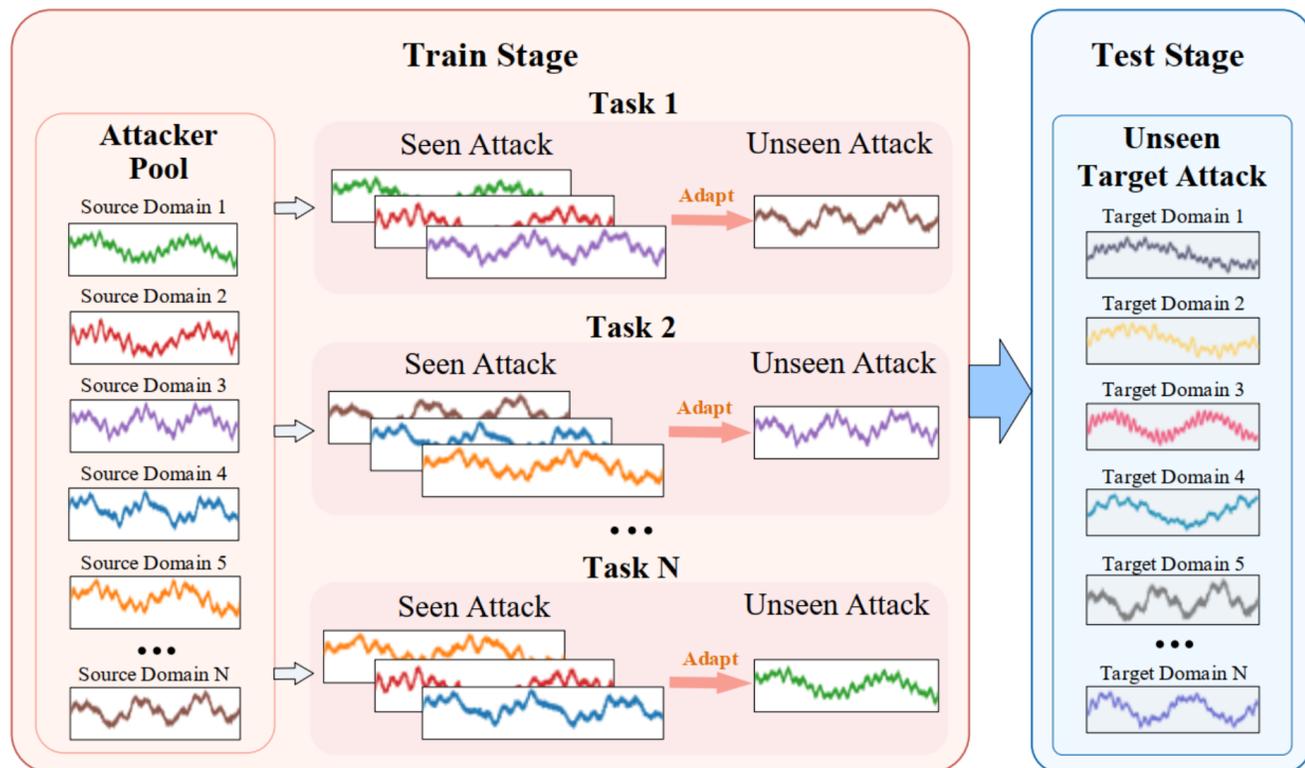


➤ 教师网络预先在一个干净的“**良性基准域**”上训练好，用于提供标准的诊断先验知识

➤ 学生编码器被放置在一个**动态变化的对抗环境中**，在教师网络的指导下主动学习如何抵御各种域攻击

多一致性蒸馏协议

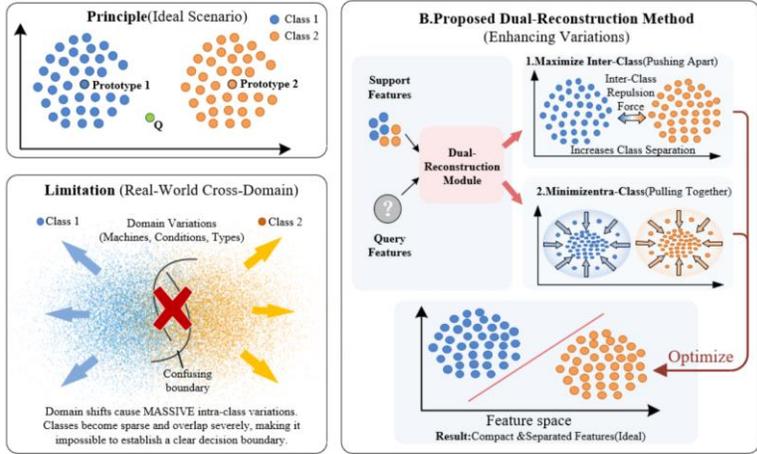
- 域一致性
- 循环一致性
- 标签一致性 Encoder学生for CLS教师



双阶段模拟优化策略

- 防御优化：抽取源域作为**可见攻击域**
- 刻意保留一部分源域不参与阶段一的训练，将其作为“**未知攻击域**”输入到当前模型中进行泛化模拟

有一些非我全权负责的合作成果

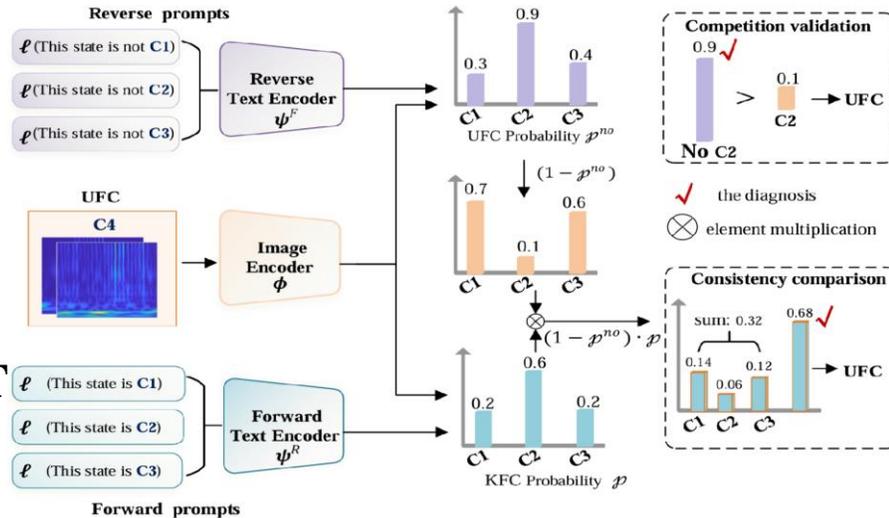


Reinforcing Cross-Domain Few-Shot Fault Diagnosis of Train Transmission Systems via Reducing Intra-Class and Maximizing Inter-Class Variations

二作, Submitted to AEI

Open-Set Fault Diagnosis Using CLIP with Forward-Reverse Reasoning

二作 (导师一作), Submitted to COMPUT IND



IndustryCode: A Benchmark for Industry Code Generation Submitted to ICML2026

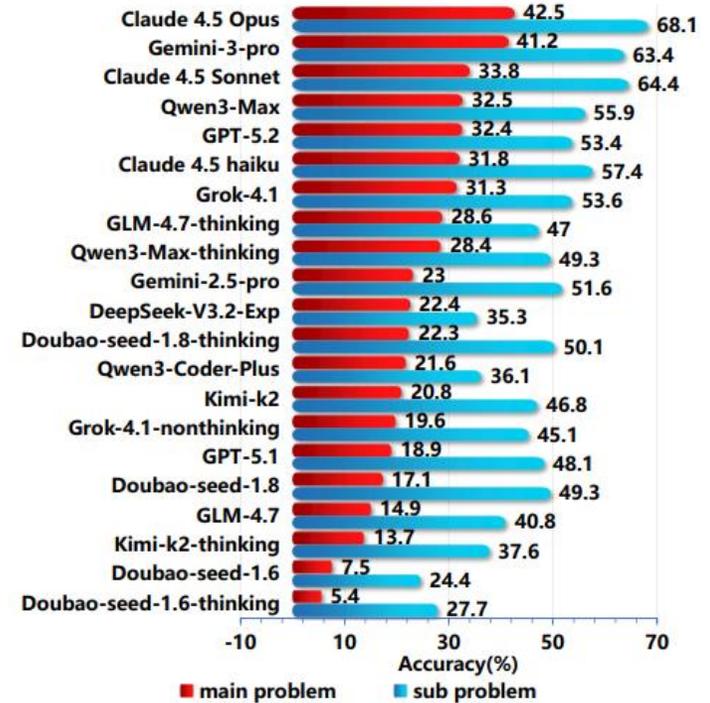
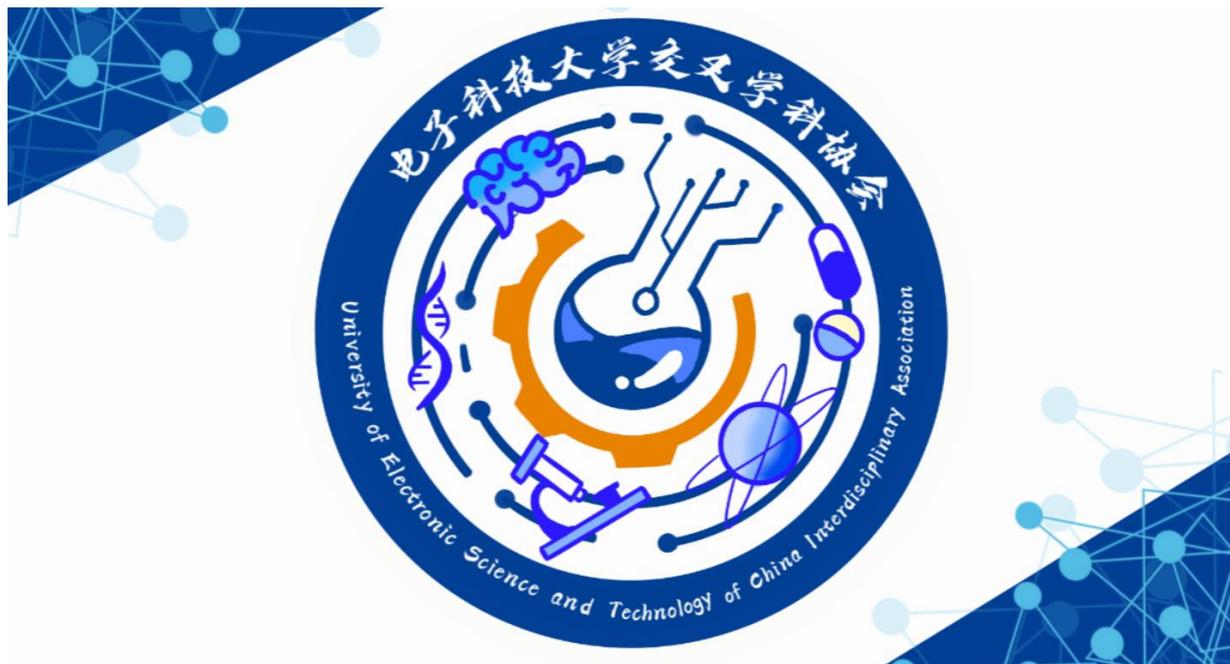


Figure 4. Performance comparison on main problems and sub-problems. The observed trends indicate that strong foundational capabilities in sub-problems generally translate to better performance in main problems.

副会长，创社核心成员：电子科技大学交叉学科协会

Motivation: 得益于自己科研经历中的AI赋能，创办协会推动AI+发展，旨在推动人工智能驱动的跨学科创新

邀请一些教授担任指导老师，与校内外多个企业(如深势科技，亚信科技，咪咕等)开展广泛合作领导带动



独立负责协会官网 uestc-ia.github.io 的构建与维护



带队参与Uni-Lab开发者线下Workshop

电子科技大学交叉学科协会赴宜宾参加Uni-Lab开发者线下Workshop

发布于: 2025年12月14日

撰稿人: Shine Yuan

2025年12月14日, 协会成员一同前往宜宾市大数据产业园, 参与了由深势科技公司主办的Uni-Lab开发者线下Workshop。活动聚焦“表征设备智能化改造”, 旨在通过系统的理论学习与实践训练, 探索AI for Science背景下实验室自动化的技术路径。



图片1: 协会成员合影



图片2: 活动现场



图片3: 授课过程记录

全流程深度参与

在上午的日程中, 协会成员完成了开发环境部署, 并在导师指导下深入理解了Uni-Lab OS的底层架构。下午的实践教学环节中, 成员们通过编写控制代码, 先后实现了对单台表征设备的精准控制, 以及对多台设备的协同调度, 直观体验了自动化工作在提升实验效率与数据标准化方面的核心价值。



图片4: 参观实验室



图片5: 设备实操教学

单一/复合故障类型诊断结果

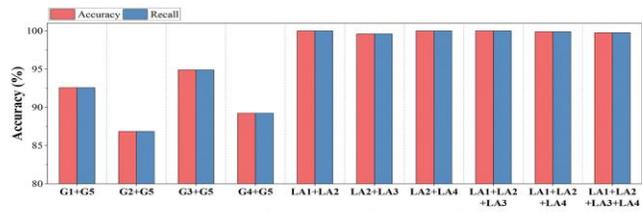
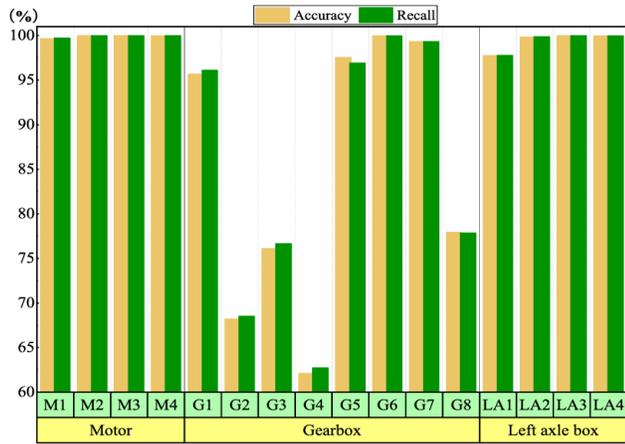
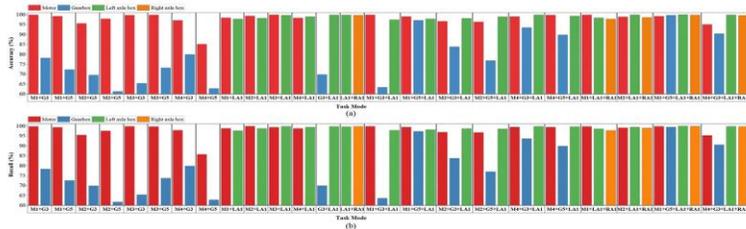
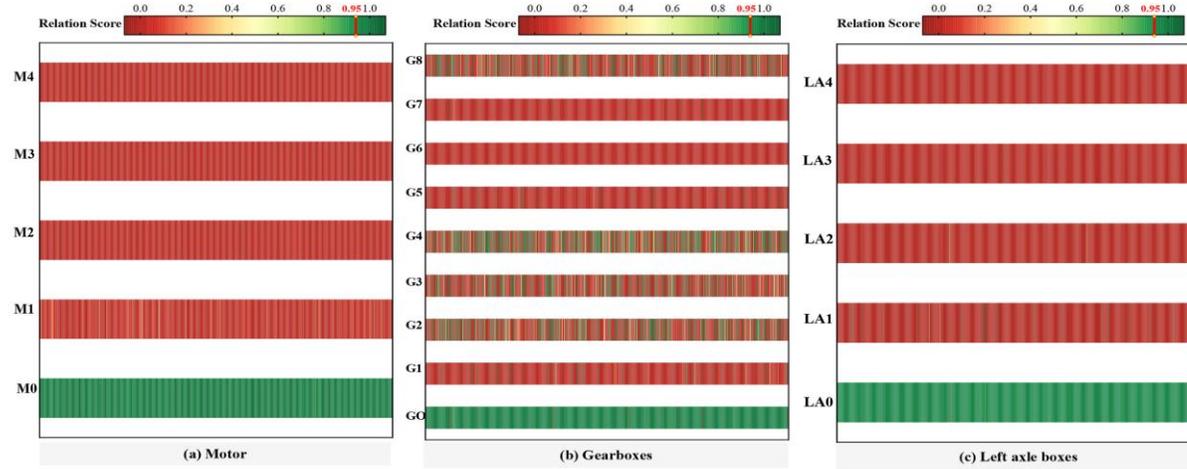


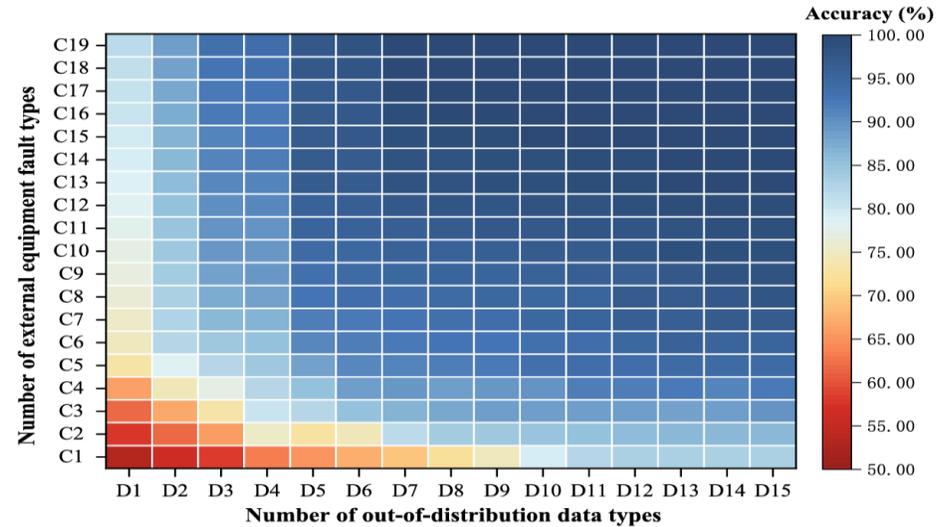
Fig. 16. Detection results of PF-ERN in component-level compound-fault scenario.



关系分数可视化

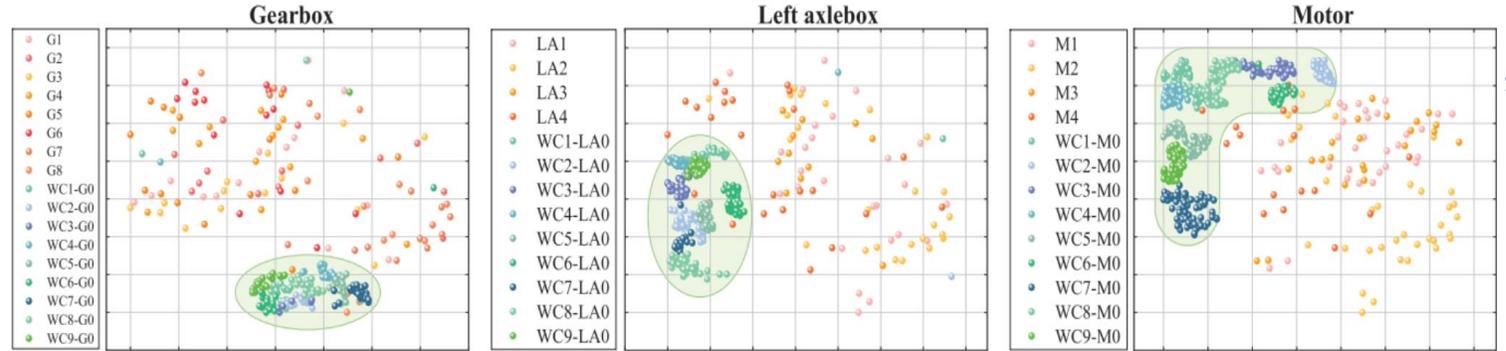
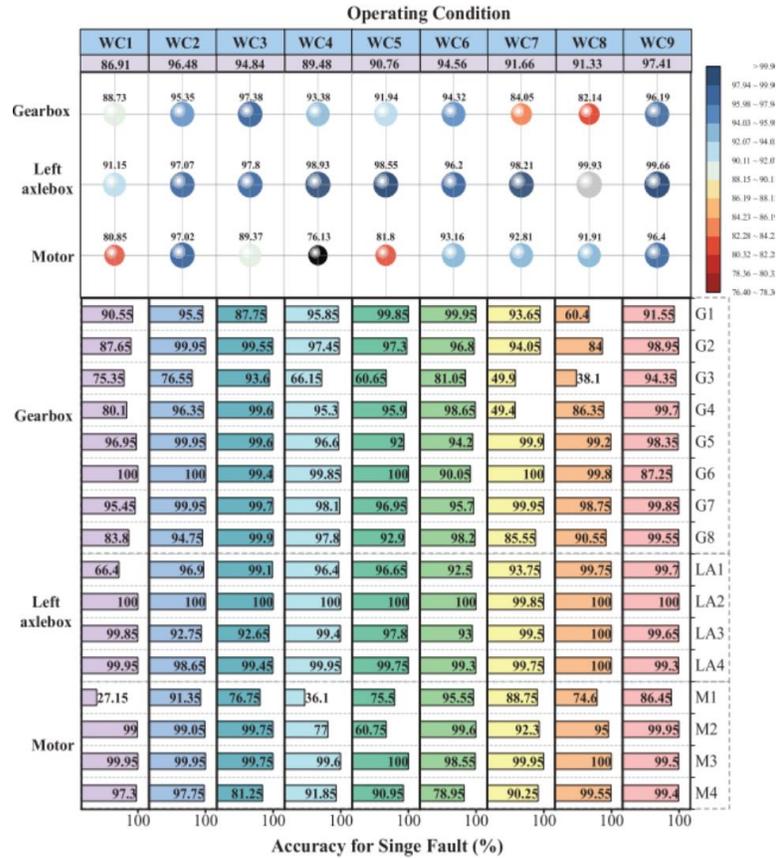


ASL的比例平衡

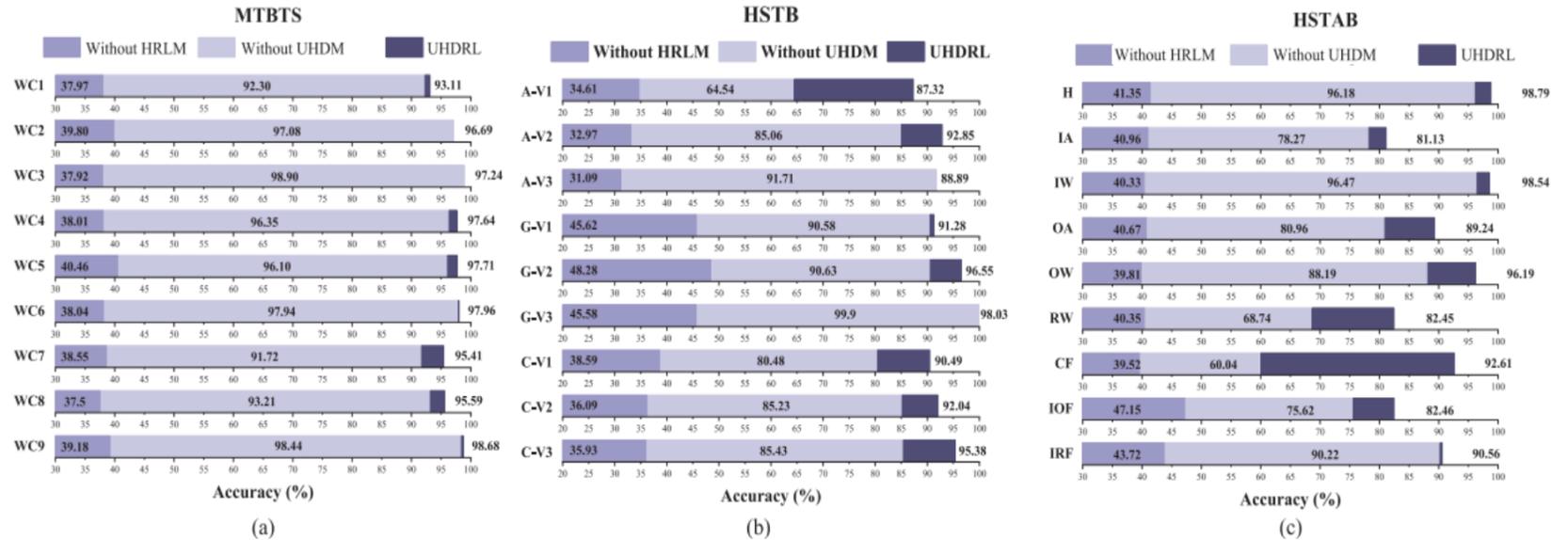


T-SNE健康分布可视化

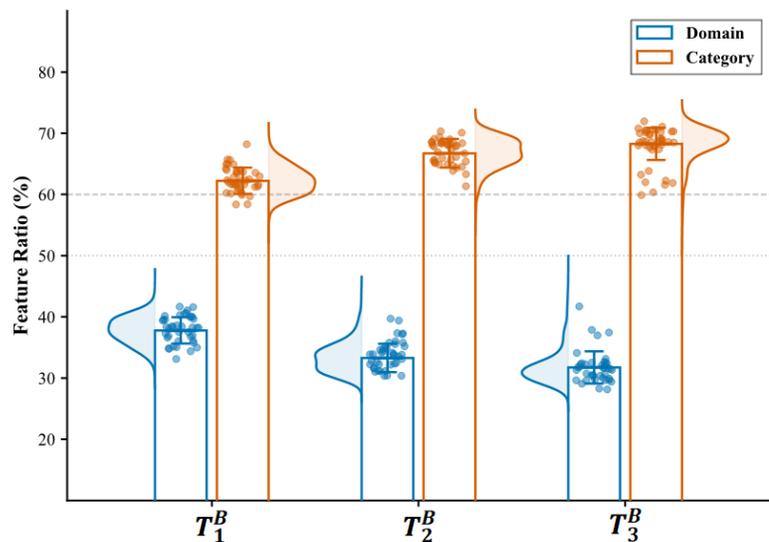
整体实验结果



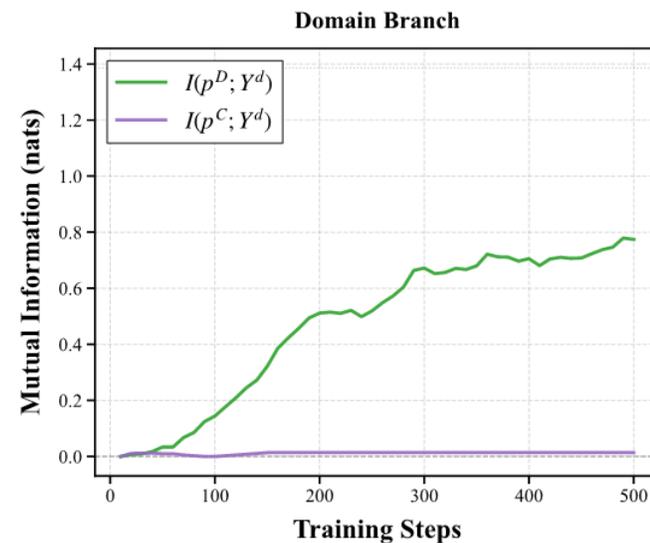
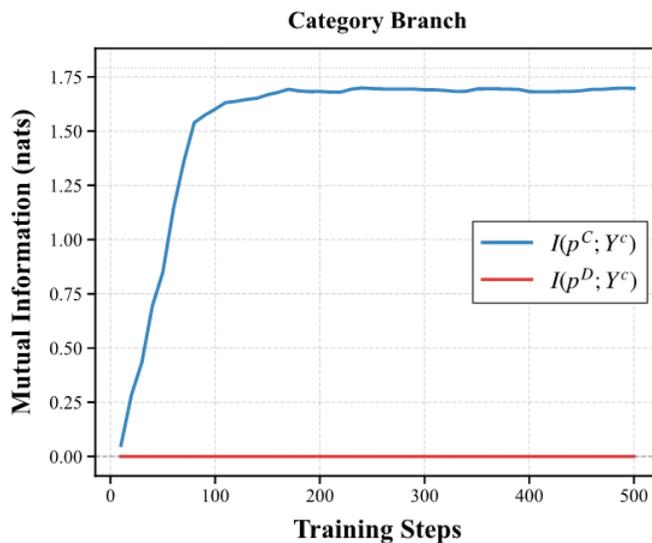
Ablation Study



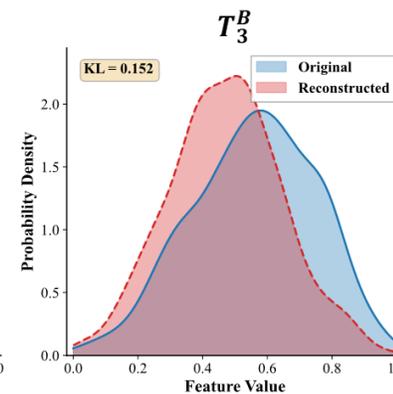
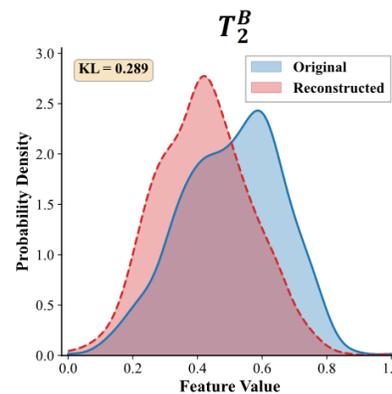
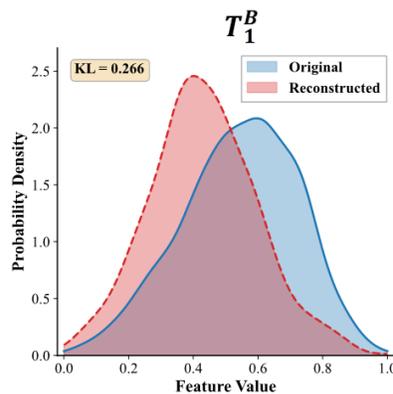
关于解耦和重构...



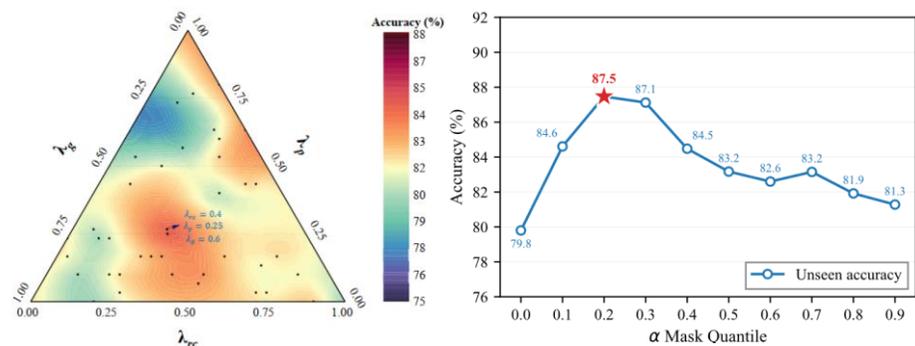
双分支特征占比



MI分析证明是解耦而非去噪



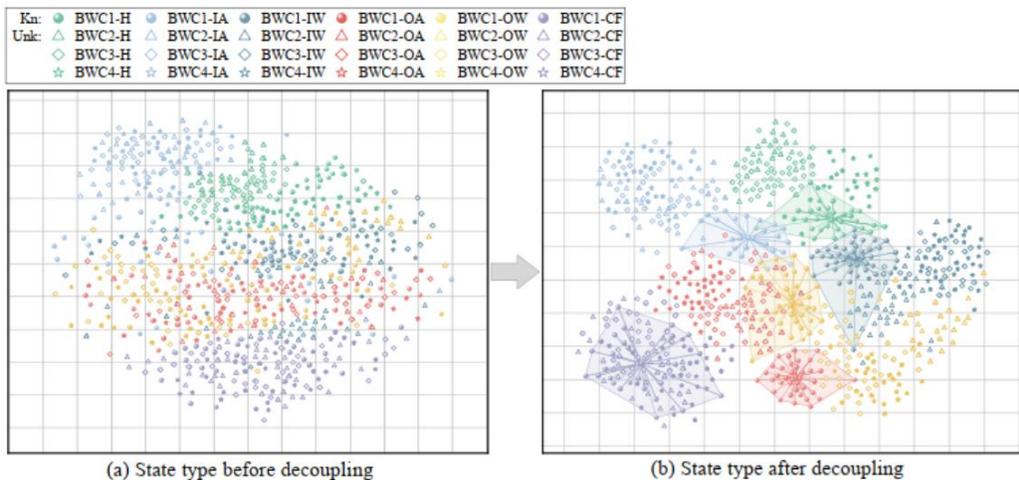
重构前后分布



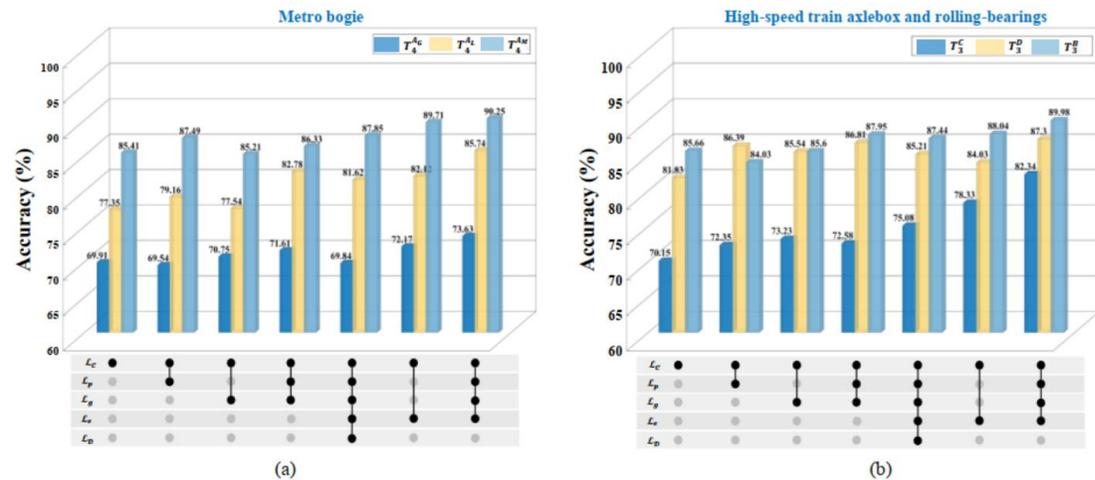
超参数间平衡



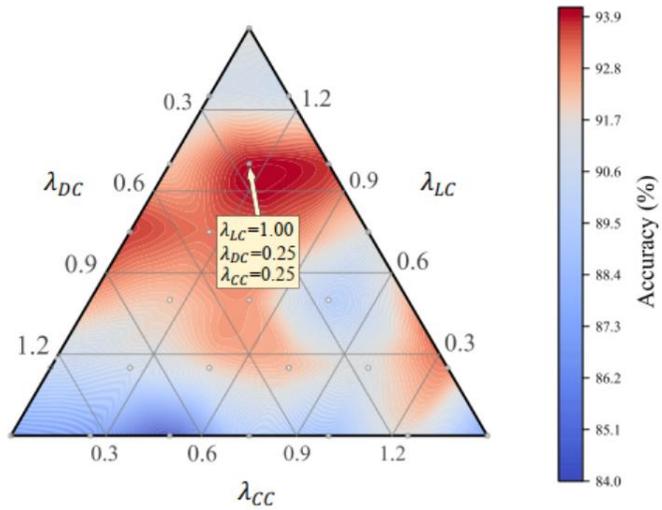
组合缺失模拟



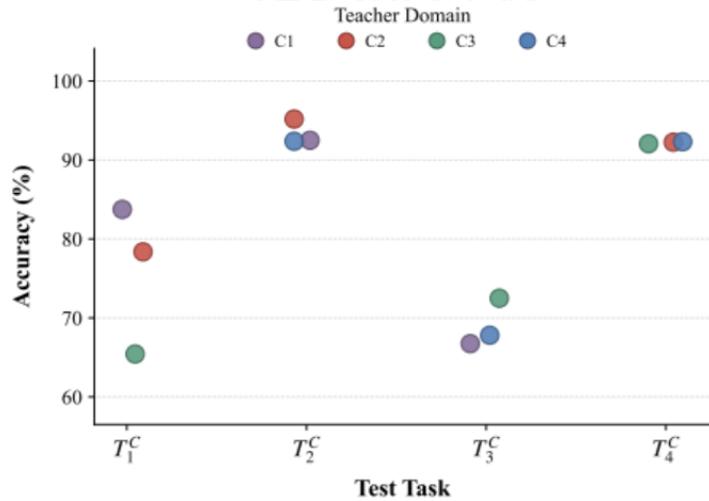
特征分布可视化



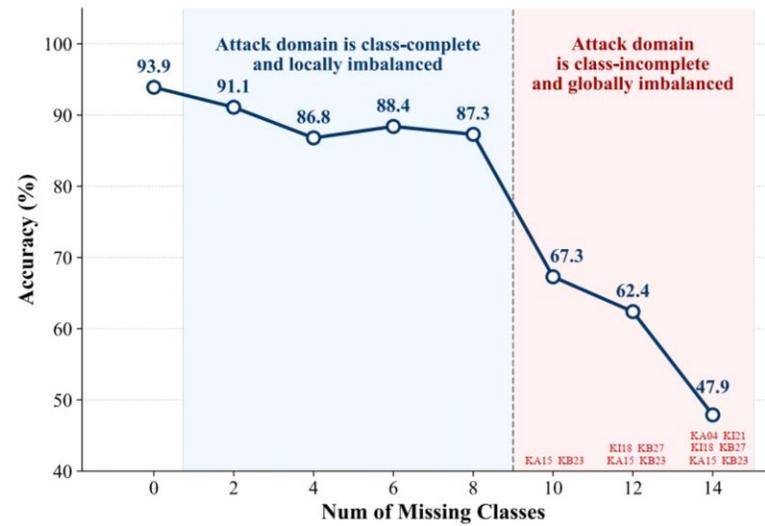
Ablation Study



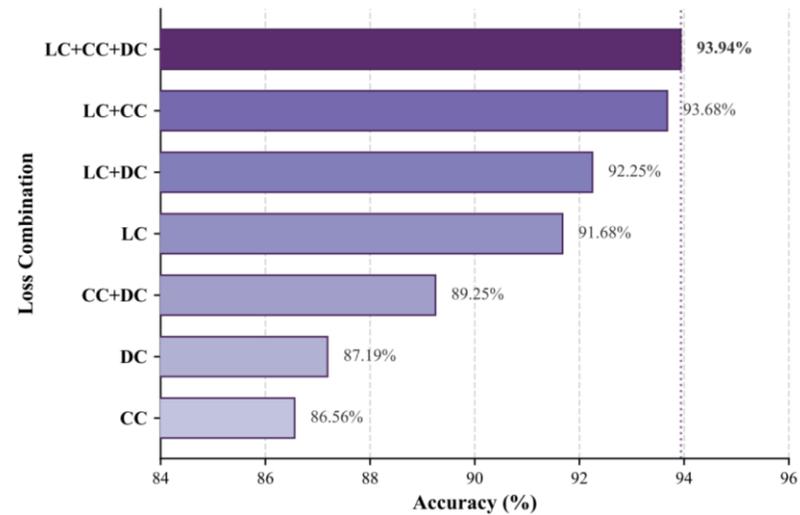
超参数间平衡



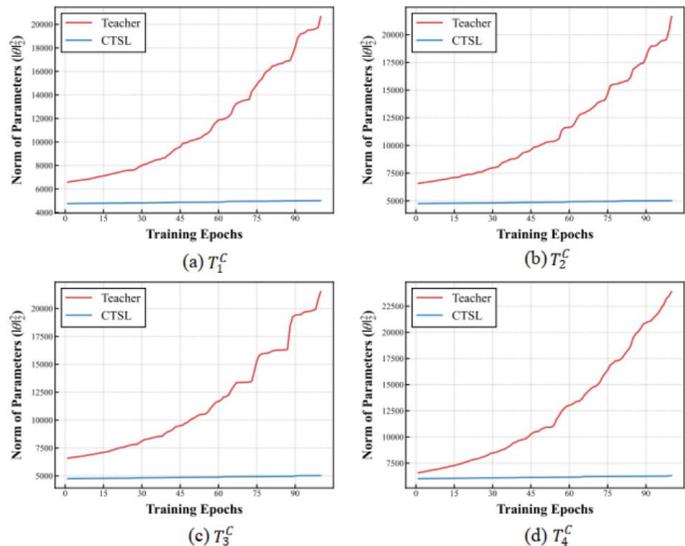
良性域的选择



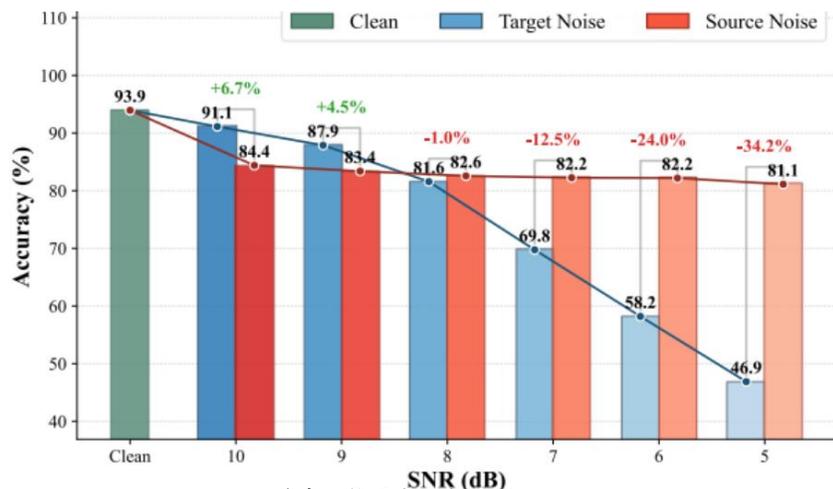
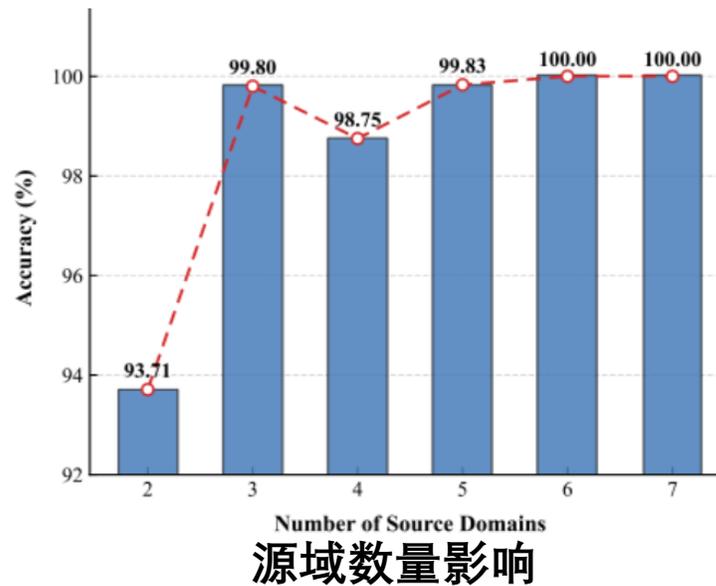
组合缺失模拟



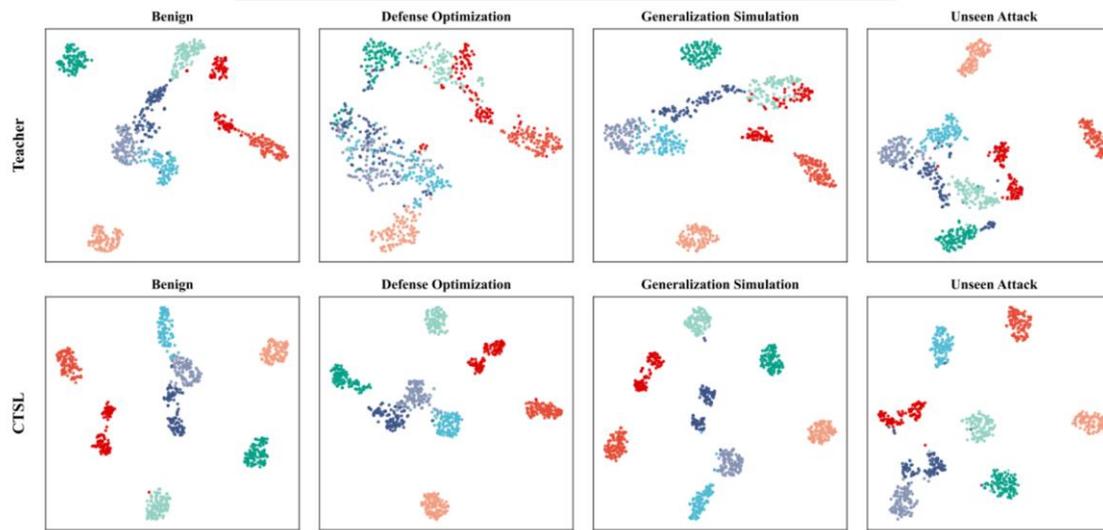
Ablation Study



训练稀疏性分析



● K001 ● KA15 ● KA04 ● K118 ● KI21 ● KB27 ● KB23 ● KB24



特征分布可视化