Model Assisted Process Fault Diagnosis

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Outline

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- Fault Diagnosis Problem
- Transfer Learning Idea
- Deep Transfer Learning for Fault Diagnosis
  - Two Test Benchmark
  - Results
- Transfer Learning with Non-identical Fault Label Sets
- Knowledge Model Based Alarm Management

Fault Diagnosis Problem

Failures of chemical plant

Loss of life and money

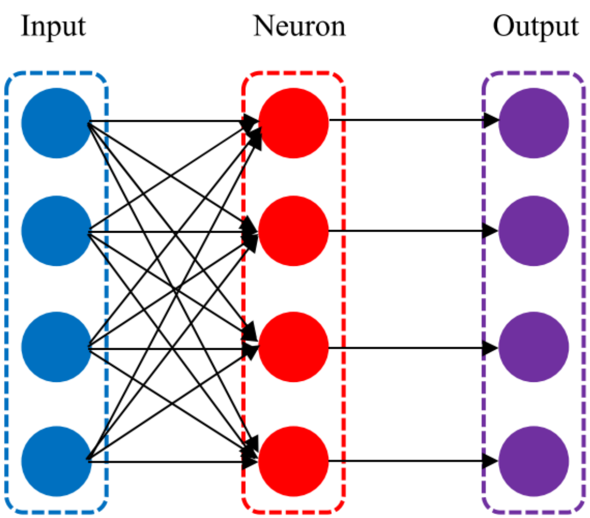
Highly coupled chemical plant

Fault propagation

Fault Diagnosis Problem

Fault diagnosis can be formulated as a classification problem

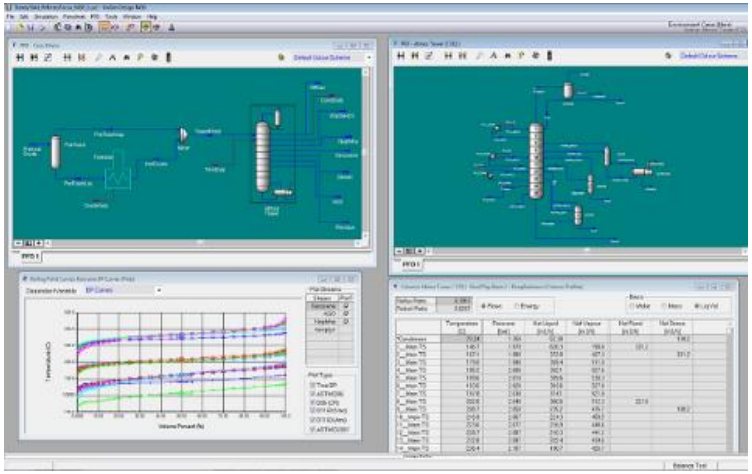
Deep learning



operational data

fault types

Feed deep learning with simulated data

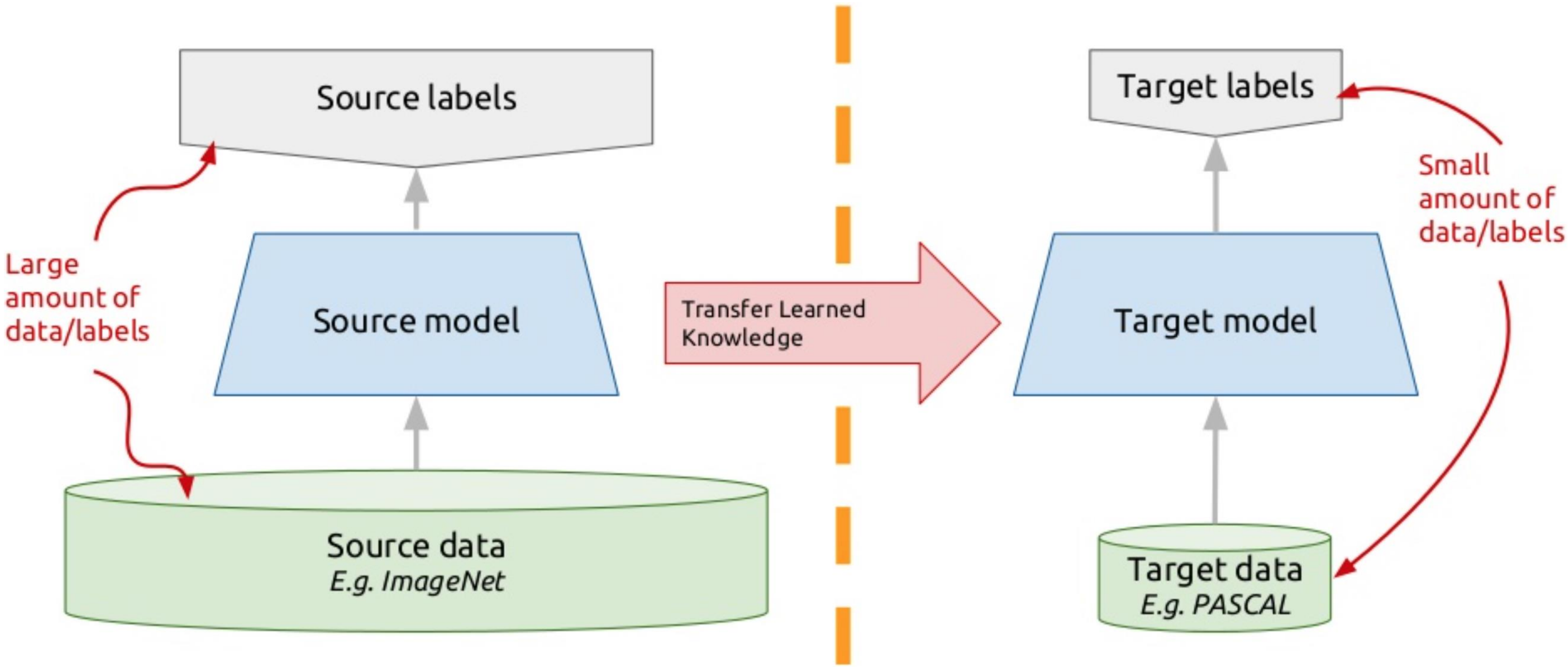


Lack of labelled fault data

Inevitable model-process mismatches

The diagnostic model trained on simulation can be result in significant misdiagnosis

Transfer learning idea



Similar to our diagnosis problem

Deep Transfer Learning for Fault Diagnosis

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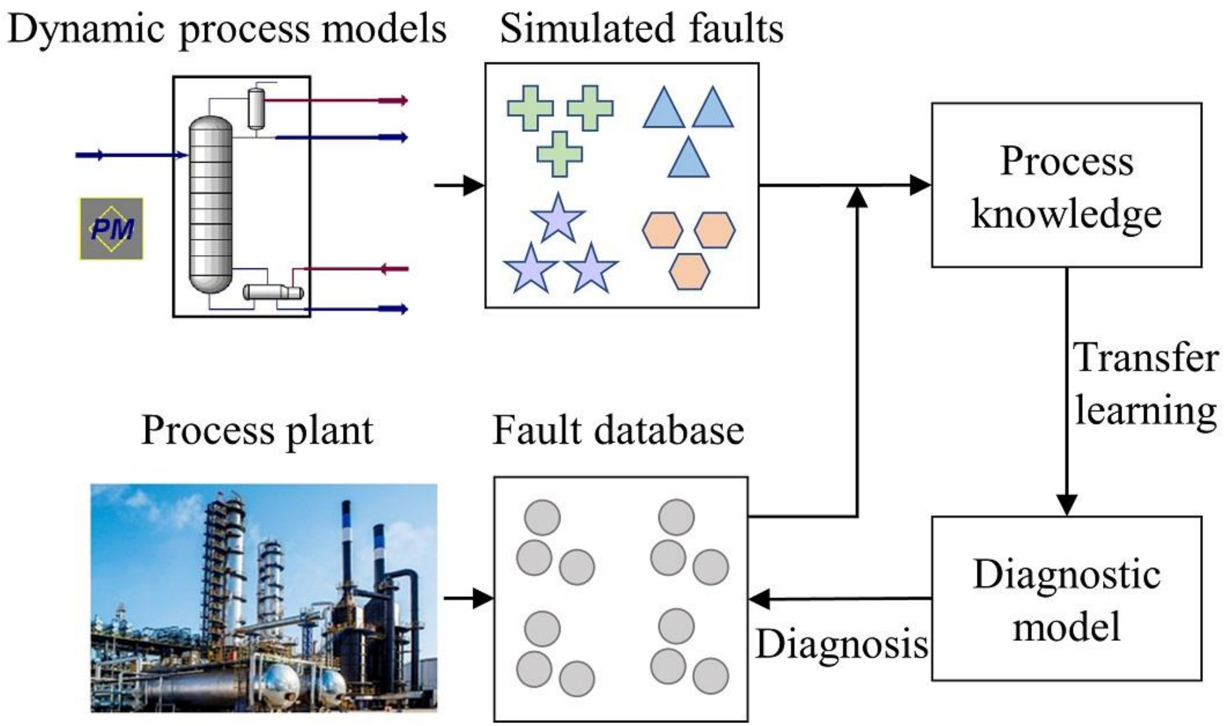
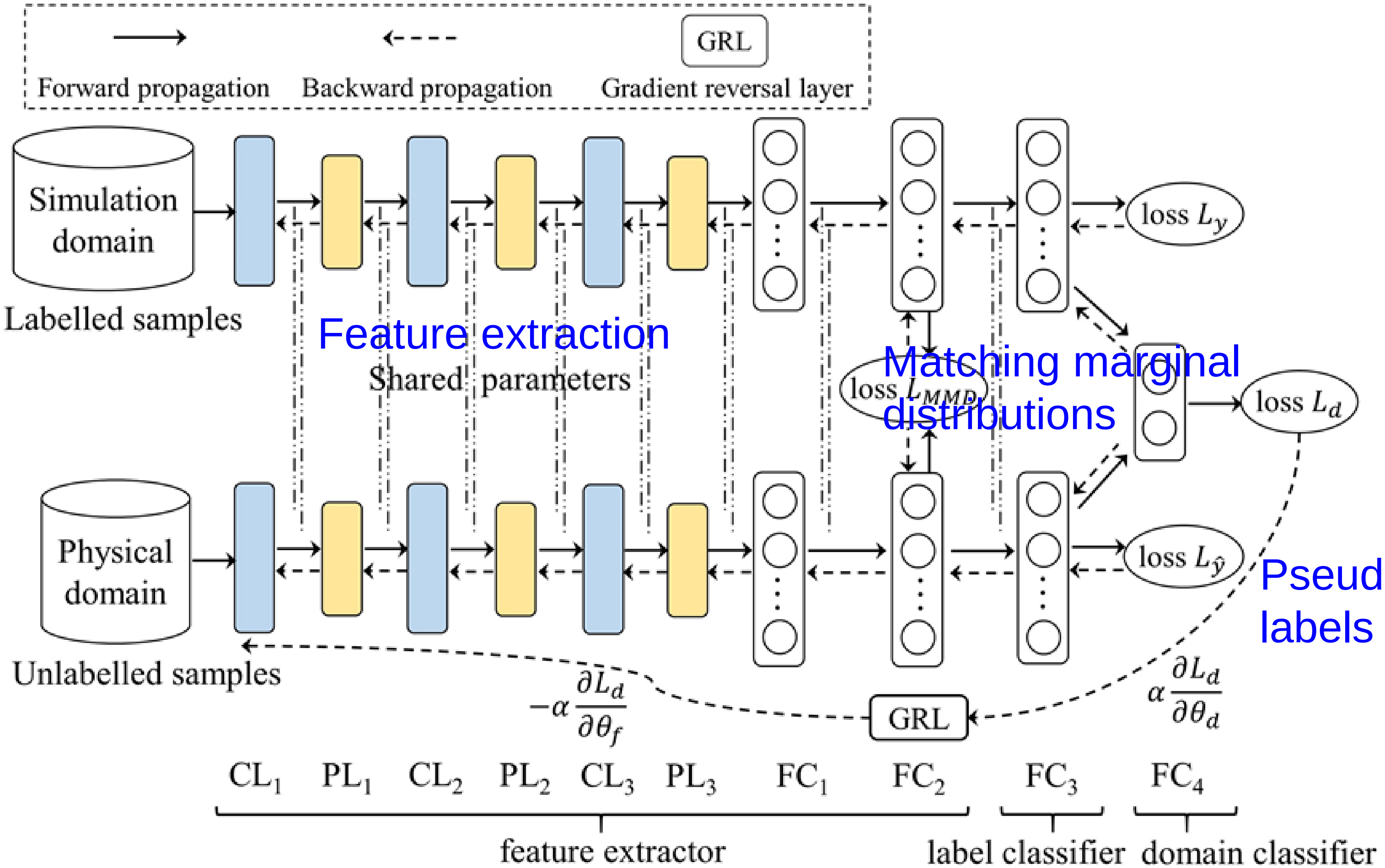
Sufficient labelled data



Classifier

Limited unlabeled data

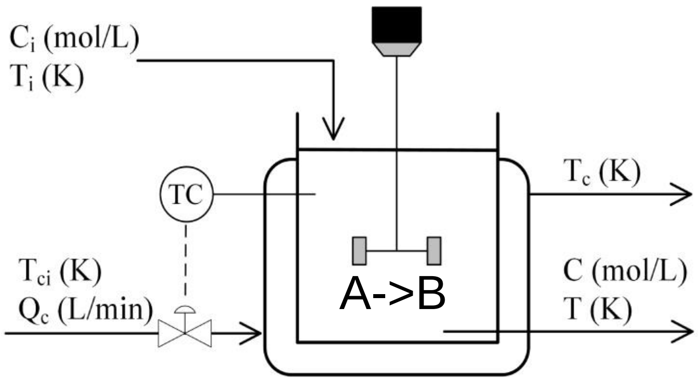
Transfer learning to address model-plant mismatches and utilize simulated data and historical data



Architecture of the proposed deep transfer network

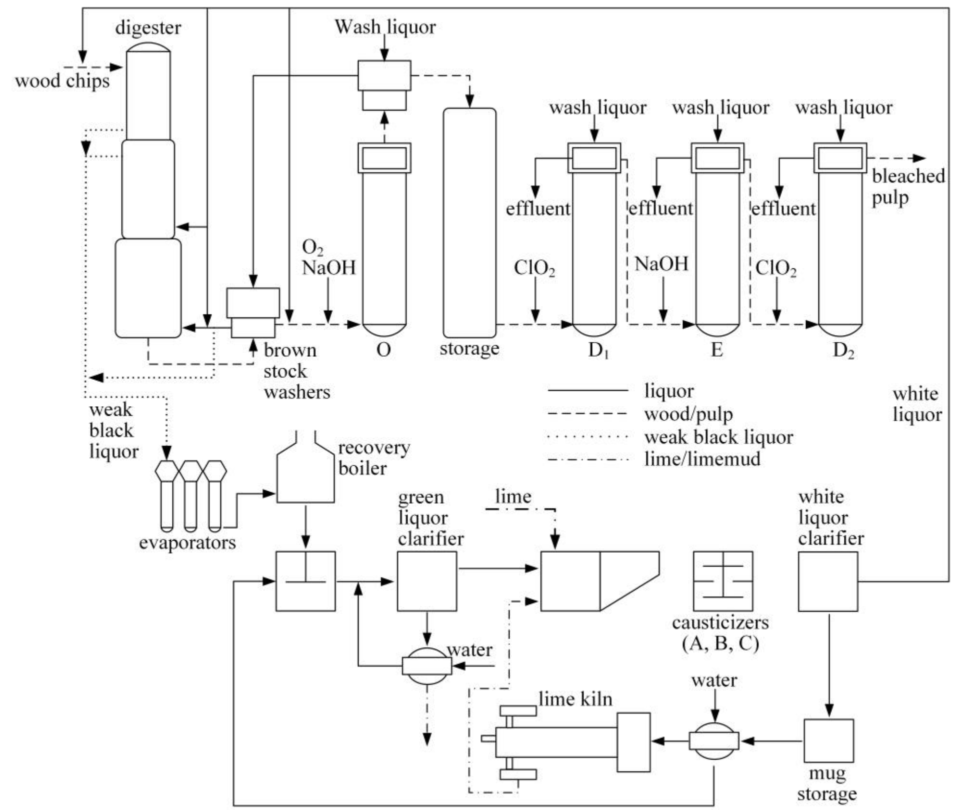
Two Test Benchmarks

CSTR benchmark



12 fault types for each benchmark

Pulp mill plant benchmark: 8200 states, 82 manipulated variables, 114 outputs



To emulate the mismatch:
CSTR and pulp mill processes have 6 and 258 erroneous parameters.
We further consider erroneous reaction order in the CSTR benchmark

Results

Process	Parameter errors	Reaction order*	CNN	DANN	DaNN	DTN
CSTR	[-10%, 10%]	N=1**	58.2(1.0)	74.3(1.7)	78.7(0.6)	87.3(1.0)
	[-15%, 15%]	N=1**	54.7(1.1)	70.0(1.3)	73.0(0.9)	82.0(1.6)
	[-20%, 20%]	N=1**	45.5(0.8)	55.3(1.4)	70.7(1.1)	73.4(2.0)
	[-15%, 15%]	N=0.5	41.4(1.1)	58.7(1.2)	69.8(0.9)	74.4(1.9)
	[-15%, 15%]	N=1.5	35.5(0.6)	63.3(2.6)	72.2(0.6)	77.0(2.0)
	[-15%, 15%]	N=2	30.8(1.5)	66.2(2.8)	66.9(0.5)	74.3(1.7)
Pulp mill	[-10%, 10%]	-	44.2(12.5)	74.2(6.5)	74.2(2.1)	89.6(3.6)
	[-15%, 15%]	-	19.1(4.0)	57.2(10.3)	47.6(4.3)	80.9(6.4)
	[-20%, 20%]	-	18.6(3.1)	52.7(5.4)	43.8(3.1)	61.6(4.0)

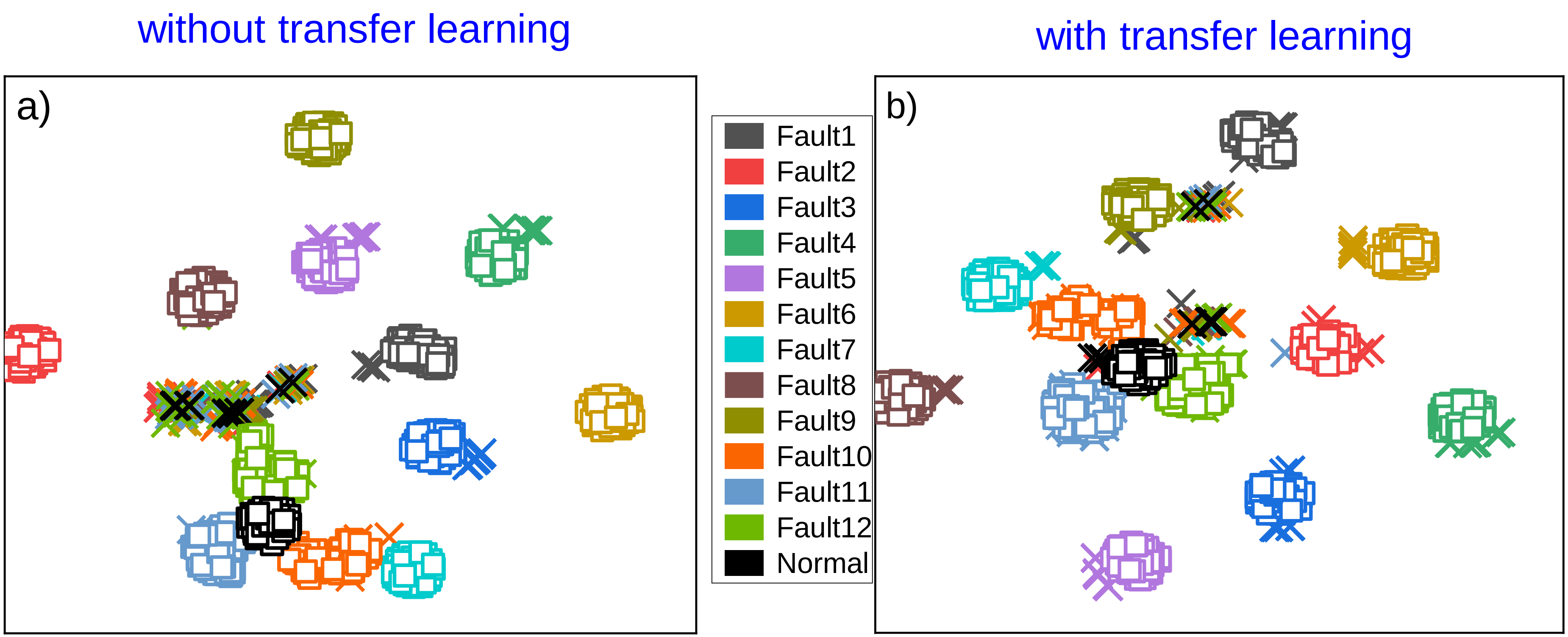
**no mismatch in the reaction order in these cases as N=1 is used in the simulation domain.

CNN: convolutional neural network, without transfer learning
DANN: domain adversarial neural network
DaNN: deep adaptation neural network

They are three comparative methods to demonstrate the effectiveness of our method

Visualisation of Transfer Learning Effect

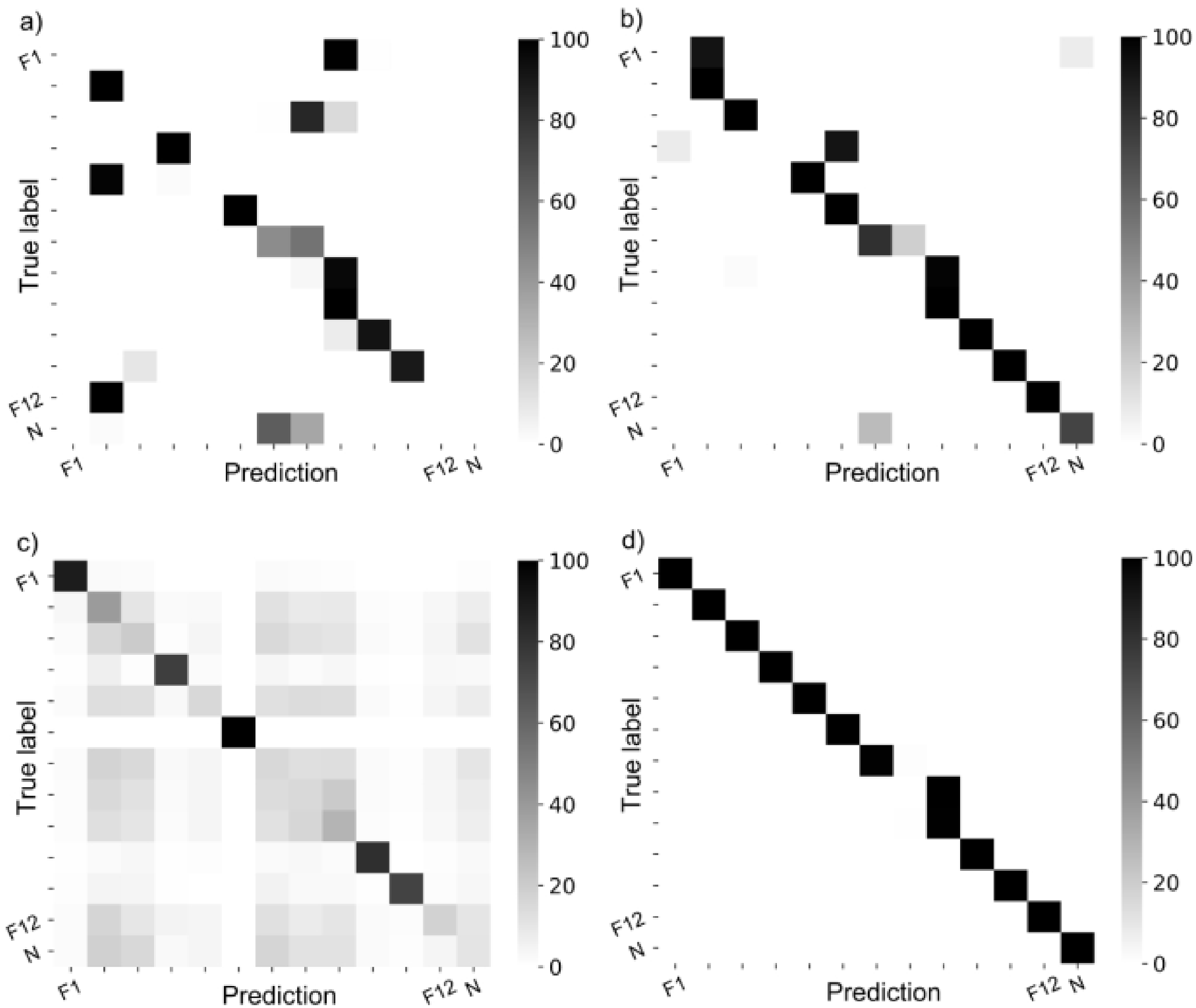
Results on the CSTR benchmark



Visualisation of cross-domain distribution using t-SNE:
"Square" and "Cross" refer to the simulation domain and the physical domain

Confusion Matrix

Results on the pulp mill benchmark



Diagnostic accuracy(%):
a) CNN, b) DANN,
c) DaNN, d) DTN

Transfer Learning with Non-identical Fault Label Sets

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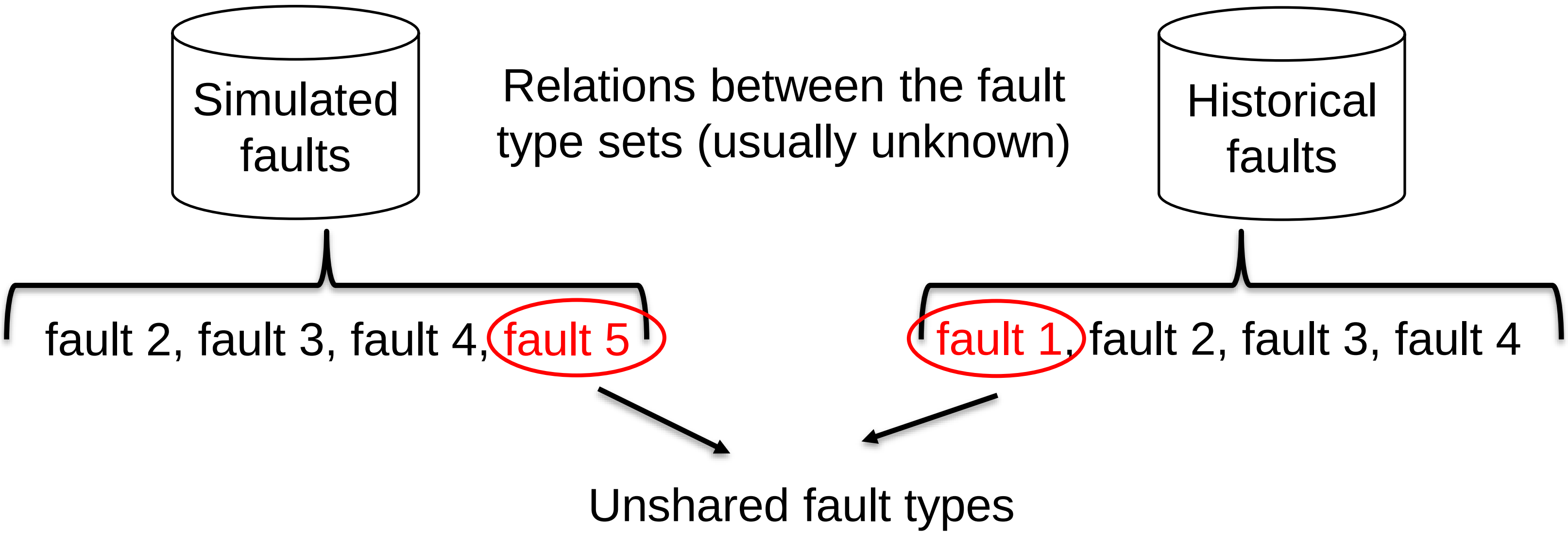
Simulation domain fault label set

Physical domain fault label set



These unshared fault types can deteriorate the model performance

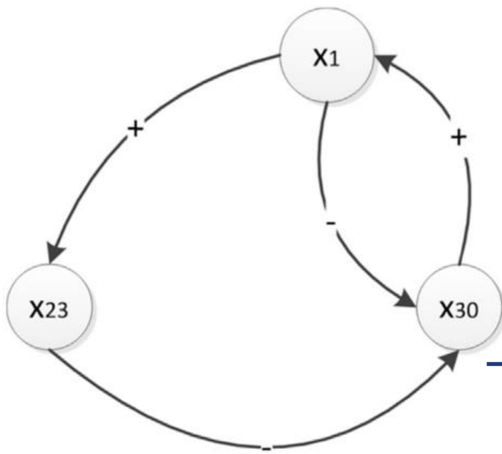
- This issue has been addressed by a method named universal domain adaptation (UDA), presented in CVPR, 2019.
- Based on UDA, we proposed a new method which pushes the unshared fault data away from the shared fault data during training and result in improved accuracy.

Knowledge Model Based Alarm Management

Industry alarm systems suffer from alarm flooding.
Consequential alarm caused by abnormality propagation has major contribution to this.

Signed directed graph to model causal relations

Alarm sequences



1) identify correlated alarms
2) reduce alarms

+

Temporal information

Deliverables

FW Yang, **WJ Li**, et. al., “A Multi-Platform Virtual Practice for Education in Chemical Engineering”, Conference Paper accepted by Industry 4.0 Academia, April, 2019

WJ Li, H Li, S Gu, T, Chen, “Process fault diagnosis with model- and knowledge-based approaches: advances and opportunities”, Journal paper under review

WJ Li, XP Zhang, S Gu, T, Chen, “A pattern matching and active simulation method for process fault diagnosis”, Journal Paper accepted

WJ Li, XP Zhang, S Gu, T, Chen, “Transfer Learning for Process Fault Diagnosis: Knowledge Transfer from Simulation to Physical Processes”, Journal paper accepted

Thank you