Learning Identifiable Structures Helps Avoid Bias in DNN-based Supervised Causal Learning

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GitHub Repository: microsoft/reliableAI



Microsoft Sony Research



Dataset D

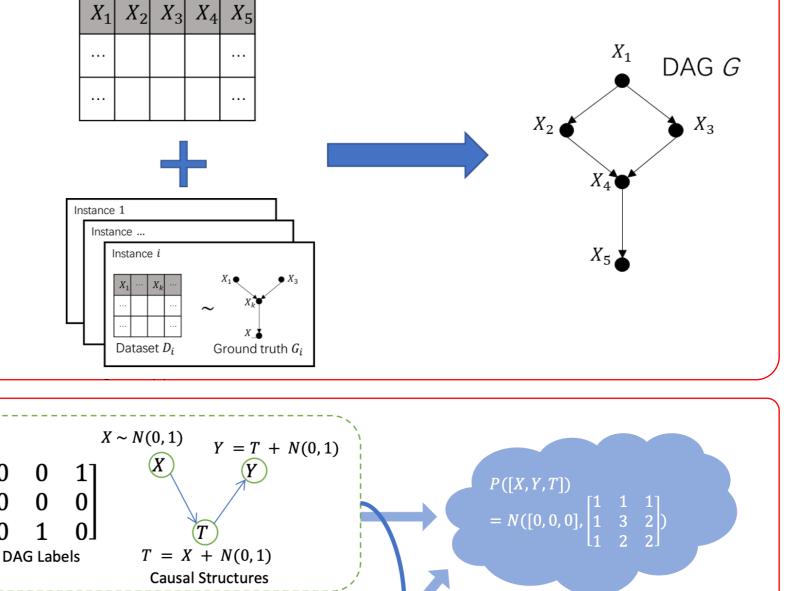
X = 0.5T + N(0, 0.5)

Background

- Supervised Causal Learning (SCL): learning causal relations from observational data by accessing previously seen datasets associated with ground truth causal relations.
- Existing Node-Edge model: node-wise feature
 + independent Bernoulli edge distribution

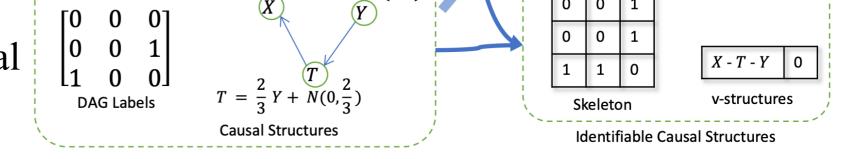


- It has an unavoidable error rate under a presented three-variable demo.
- It has a higher error rate of ~ 0.2642 under



Observational Data

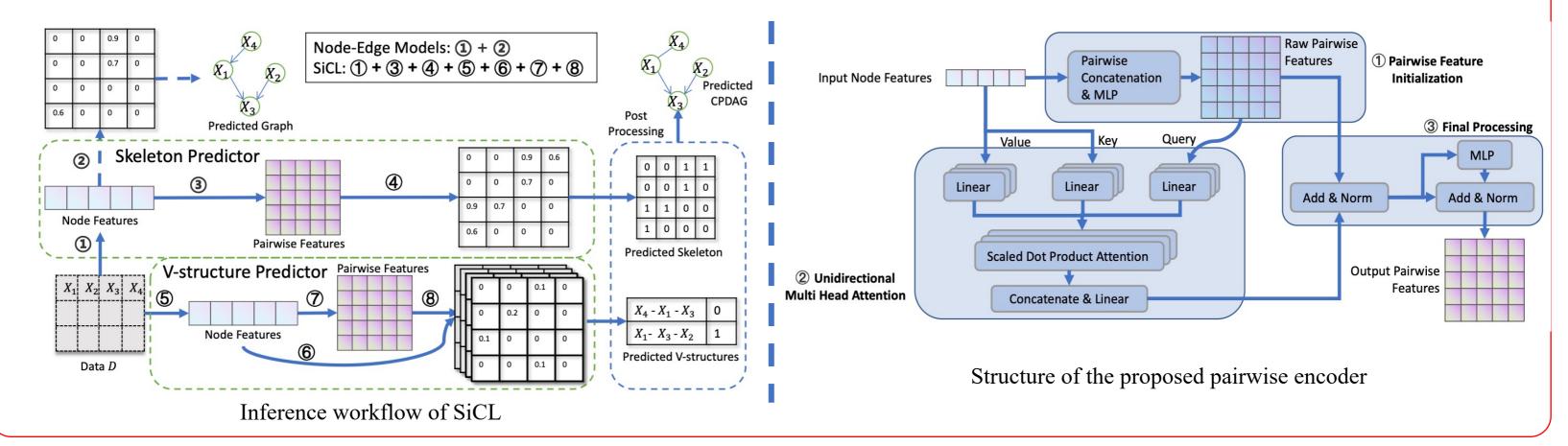
- a more general scenario.
- It does not explicitly represent the essential features about node pairs.



Y = N(0,3)

Our SiCL Approach

- Learning *identifiable* causal structure: skeleton + v-structures with two separate DNNs.
- Utilizing a pairwise encoder to encode pairwise features explicitly.
- Theoretical guarantee: DNNs with our learning targets have a theoretical guarantee for correctness in asymptotic sense.

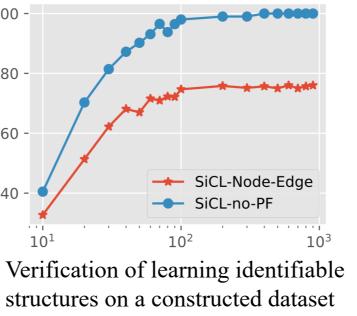


Experimental Results

- SiCL outperforms various baselines on both synthetic datasets and real-world Sachs dataset.
- Ablation study confirms the effectiveness

Comparison on synthetic datasets										
Method	WS-L-G		SBM-L-G		WS-RFF-G		SBM-RFF-G		ER-CPT-MC	
	$s-F1\uparrow$	o-F1 ↑	s-F1↑	o-F1↑	s-F1 \uparrow	o-F1↑	$s-F1\uparrow$	o-F1↑	s-F1 \uparrow	o-F1↑
PC	30.4	16.0	58.8	35.9	36.1	16.1	57.5	34.2	82.2	40.6
GES	*	*	70.8	55.0	41.7	23.6	56.5	38.0	82.1	42.4
NOTEARS	33.3	31.5	80.1	77.8	37.7	33.4	55.6	48.5	16.7	0.6
DAG-GNN	35.5	32.7	66.2	62.5	33.2	28.9	47.1	40.6	24.8	3.7
GRAN-DAG	16.6	11.7	22.6	14.4	4.7	1.1	17.4	3.8	40.8	7.3
GOLEM	30.0	19.3	68.5	65.2	27.6	17.7	41.1	24.8	37.6	9.3
AVICI	39.9	35.8	84.3	81.6	47.7	45.2	76.6	72.7	76.9	57.6
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of learning identifiable structures and using pairwise representation. A part of ablation study results $\frac{Method}{S-F1\uparrow} = \frac{WS-L-G}{S-F1\uparrow} = \frac{SBM-L-G}{S-F1\uparrow} = $	AUIauIUII					
A part of ablation study resultsMethodWS-L-GSBM-L-G $Method$ $s-F1\uparrow$ $o-F1\uparrow$ $s-F1\uparrow$ $o-F1\uparrow$ $s-F1\uparrow$ SiCL-Node-Edge39.935.884.381.6SiCL-no-PF42.437.985.582.2SiCL44.738.585.882.7	of learnin	res and				
A part of ablation study resultsMethodWS-L-GSBM-L-G $Method$ $s-F1\uparrow$ $o-F1\uparrow$ $s-F1\uparrow$ $o-F1\uparrow$ $s-F1\uparrow$ SiCL-Node-Edge39.935.884.381.6SiCL-no-PF42.437.985.582.2SiCL44.738.585.882.7	using pair	100 -				
A part of ablation study resultsMethodWS-L-GSBM-L-G $s-F1\uparrow$ $o-F1\uparrow$ $s-F1\uparrow$ SiCL-Node-Edge39.935.884.381.6SiCL-no-PF42.437.985.582.2SiCL44.738.585.882.7			•			00
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$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		WS	-L-G	SBM-L-G		60 -
SICL-Node-Edge 39.9 35.8 84.3 81.6 SiCL-no-PF 42.4 37.9 85.5 82.2 SiCL 44.7 38.5 85.8 82.7	Method	$s-F1\uparrow$	o-F1 ↑	$s-F1\uparrow$	o-F1 ↑	· / *
SiCI. $1/7$ 38 5 85 8 82 7	SiCL-Node-Edge	39.9	35.8	84.3	81.6	40 -
SiCL 44.7 38.5 85.8 82.7 Verification	SiCL-no-PF	42.4	37.9	85.5	82.2	10 ¹
	SiCL	44.7	38.5	85.8	82.7	Verificatio



SiCL 44.7 38.5 85.8 82.7 51.8 46.3 82.1 78.0 84.2 59.9

Comparison on Sachs dataset

Method	Skeleto s-F1↑	n Prediction s-Acc.↑	CPDAG Prediction SHD \downarrow #v-struc. \downarrow		
PC	68.6	80.0	19	12	
GES	70.6	81.8	19	8	
DAG-GNN	21.1	72.7	15	0	
NOTEARS	11.1	70.9	16	0	
GRAN-DAG	45.5	78.2	12	0	
GOLEM	36.4	74.5	14	0	
AVICI	66.7	83.5	18	14	
SiCL	71.4	86.8	6	0	