Bivariate Causal Discovery via Conditional Divergence

Data set	Baselines				CDCI				
	ANM	CDS	IGCI	RECI	CCS	CHD	CKL	CKM	CTV
Synthetic data									
CE-Net	0.865	*0.884*	0.574	0.660	**0.897**	**0.905**	**0.893**	**0.943**	**0.919**
CE-Multi	0.263	0.413	0.778	*0.948*	**0.960**	**0.976**	**0.955**	0.906	**0.958**
CE-Gauss	0.884	*0.905*	0.160	0.710	0.905	**0.914**	**0.910**	**0.916**	**0.918**
CE-Cha	*0.705*	0.695	0.556	0.590	0.693	**0.720**	0.698	0.697	**0.722**
CE-All	0.653	0.713	0.512	*0.742*	**0.866**	**0.884**	**0.867**	**0.865**	**0.881**
Real data									
D4-S1	*0.604*	0.582	0.380	0.550	**0.646**	**0.651**	**0.635**	**0.632**	**0.646**
D4-S2A	*0.616*	0.580	0.447	0.592	**0.649**	**0.630**	**0.652**	**0.667**	**0.673**
D4-S2B	0.521	*0.529*	0.450	0.491	**0.594**	**0.600**	**0.602**	**0.614**	**0.609**
D4-S2C	0.556	*0.564*	0.441	0.521	**0.565**	**0.565**	**0.573**	**0.584**	**0.590**
D4-All	*0.561*	0.556	0.445	0.532	**0.602**	**0.599**	**0.608**	**0.620**	**0.622**

Table 1: Causal Direction Prediction Performance on Synthetic and Real Datasets. The performance metric is AUC (higher is better). We compare five variants of our proposed **CDCI** (Conditional Divergence based Causal Inference) approach namely CCS, CHD, CKL, CKM, and CTV with four popular baselines: ANM (Mooij et al., 2016), CDS (Fonollosa, 2019), IGCI (Daniušis et al., 2010), and RECI (Blöbaum et al., 2019). *Italics*: best performance of baselines, **bold**: better than the best baseline, **red**: best performance among all.

References

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