Local Causal Discovery for Structural Evidence of Direct Discrimination

Jacqueline Maasch

maasch@cs.cornell.edu | arXiv:2405.14848

Joint work by: J Maasch,[1] K Gan,[1] V Chen,[2] A Orfanoudaki,[3] N Akpinar,[4] F Wang,[5]

[1]Cornell Tech, [2]Stevens Institute of Technology, [3]University of Oxford, [4]Amazon AWS, [5]Weill Cornell

2024 INFORMS Annual Meeting | Seattle, WA | 21 October 2024

Presentation overview

1. What is causal fairness analysis?
2. How can we detect direct discrimination?
3. A new causal discovery method for practical use.
4. Real-world fairness analysis on clinical data.

Fairness with respect to protected attributes

- Fairness is essential in policy design and algorithmic decision-making.

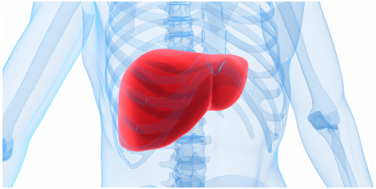
- Under the law, **mechanism matters**:
  1. Direct discrimination.
  2. Indirect unfairness.
  3. Spurious unfairness (common cause).

- **Problem**: Statistical associations cannot disentangle mechanisms.
- **Solution**: Causal inference can (*with prior knowledge*).

Case study: Is liver transplant allocation fair?

1 Background

Liver transplantation is a critical therapeutic for acute liver failure.



Sex-based disparities have been observed.[1,2]

Case study: Is liver transplant allocation fair?

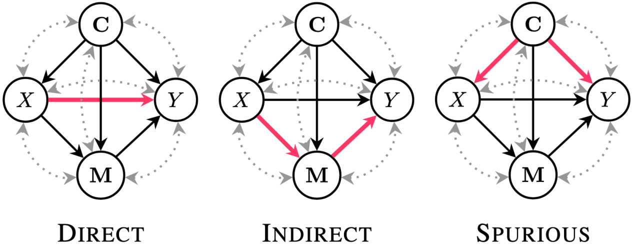
1 Background

Fairness query: Are sex-based disparities in liver allocation due to direct discrimination?

Graphical query: Is patient sex (S) a causal parent of liver allocation (L)?

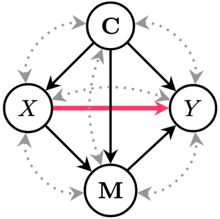
Sex is a **parent** (direct cause)	$S \rightarrow L$
Sex is an **ancestor** (indirect cause)	$S \rightarrow \cdot \rightarrow L$
Common cause (spurious)	$S \leftarrow \cdot \rightarrow L$

A theoretical framework for disentanglement in the language of **structural causal models** (SCMs) and **graphical modeling**.



Graphical signatures of direct discrimination

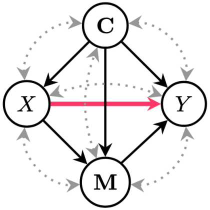
1. **Structural direct criterion** (SDC).[3]
2. **Direct effect estimation**.
   - Controlled direct effect.[4]
   - Natural direct effect.[4]
   - Counterfactual direct effect.[5]



DIRECT

Structural direct criterion (SDC)

Detecting direct discrimination == causal parent discovery. [3]



DIRECT

$$SDC = \begin{cases} 1 & \text{if } X \text{ is a parent of } Y, \\ 0 & \text{if } X \text{ is not a parent of } Y. \end{cases}$$

Weighted Controlled Direct Effect (WCDE)

- **WCDE**: Expected change in outcome as the exposure changes, adjusting for mediators $\mathbf{M}$ (blocking indirect effects).
- For potential cause X, outcome Y, mediators $\mathbf{M}$, and covariates $\mathbf{S}$,

$$WCDE = \sum_{\mathbf{m}} \sum_{\mathbf{s}} \big[\mathbb{E}[Y|x, \mathbf{s}, \mathbf{m}] - \mathbb{E}[Y|x^*, \mathbf{s}, \mathbf{m}]\big] P(\mathbf{m}) P(\mathbf{s}). \tag{1}$$

WCDE is nonzero if and only if X is a parent of Y.

What if the graph is unknown?

We can learn it from observational data via causal discovery.

- Prior methods pose limitations:
  - Disagreement with expert knowledge.[6,7]
  - High sample and time complexity.
  - Conflicting fairness conclusions.[8]
- **What if we tailor discovery to CFA for direct discrimination?**

LD3: Contributions

2 Local Discovery for Direct Discrimination (LD3)

- **Parent discovery.**
  — Linear no. of conditional independence tests w.r.t. total input variables.
- **Addresses both indicators of direct discrimination.**
  1. SDC.[3]
  2. WCDE.[4]
- **Real-world fairness analysis.**
  — LD3 recovered known relations more effectively than baselines.

Learn labels, not the global graph

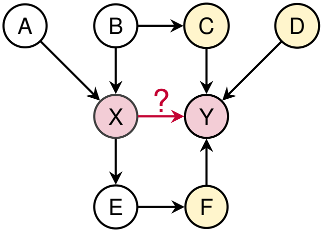
- **Goal**: Learn the relationship of each variable to the protected attribute and outcome to identify parents of outcome.

- **Any variable can take on exactly one of eight causal roles** (labels) w.r.t. a cause-effect pair of interest, as shown in Maasch et al. (UAI'24).[9]

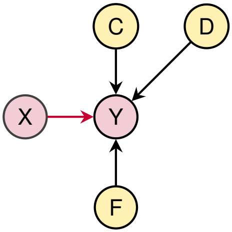
- **Local discovery**: We learn these labels, and abstract away the rest.

Learn labels, not the global graph

Does the red edge exist? Finding other parents of Y can tell us.

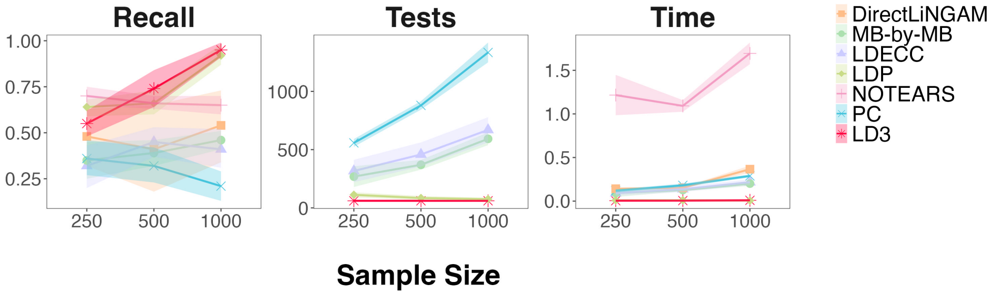


(A) Unknown graph of input data.



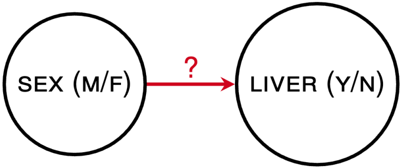
(B) WCDE adjustment set returned by LD3.

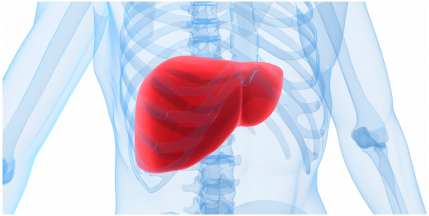
LD3: faster, fewer tests, better parent recall



Benchmark: Linear-Gaussian model of grape production[10] from bnlearn.[11]
Baselines: On all datasets, 11–$1021\times$ more tests and 46–$5870\times$ more time.

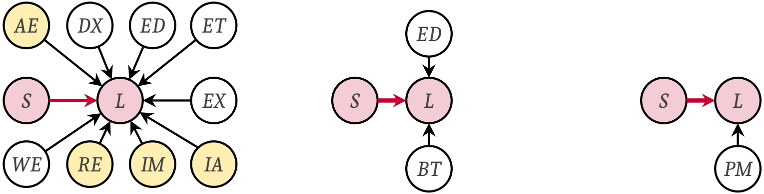
Is liver allocation fair?





- **Fairness query:** Are sex-based disparities due to direct discrimination?
- **Graphical query:** Is patient sex a causal parent of liver allocation?
- **Data:** Ntl. Standard Transplant Analysis and Research (STAR), 2017-2019.[12]
- **Sample size:** $n = 21,101$ (36% female).

LD3 detects known relations



LD3
(local discovery)

PC
(global discovery)

LDECC
(local discovery)

SDC = 1, WCDE $\neq$ 0: All methods detect sex (S) as a parent of liver allocation (L).[1]
Known parents: MELD score (IM), age (IA), region (RE), active exception case (AE).

[1] Same independence test, same significance level.

Thank you! Any questions?

maasch@cs.cornell.edu

arXiv:2405.14848

jmaasch.github.io

References

[1] O. O. Oloruntoba et al. “Gender-based disparities in access to and outcomes of liver transplantation”. In: *World journal of hepatology* 7.3 (2015), p. 460.

[2] A. M. Allen et al. “Reduced access to liver transplantation in women: role of height, MELD exception scores, and renal function underestimation”. In: *Transplantation* 102.10 (2018), pp. 1710–1716.

[3] D. Plečko et al. “Causal Fairness Analysis: A Causal Toolkit for Fair Machine Learning”. In: *Foundations and Trends® in Machine Learning* 17.3 (2024), pp. 304–589.

[4] J. Pearl. “Direct and Indirect Effects”. In: *Proceedings of the Seventeenth Conference on Uncertainty in Artificial Intelligence*. 2001.

[5] J. Zhang et al. “Fairness in Decision-Making —The Causal Explanation Formula”. In: *Proceedings of the AAAI Conference on Artificial Intelligence* 32.1 (2018). DOI: 10.1609/aaai.v32i1.11564.

[6] X. Shen et al. “Challenges and Opportunities with Causal Discovery Algorithms: Application to Alzheimer’s Pathophysiology”. In: *Scientific Reports* 10.2975 (2020).

[7] A. H. Petersen et al. “Constructing Causal Life-Course Models: Comparative Study of Data-Driven and Theory-Driven Approaches”. In: *American Journal of Epidemiology* 192.11 (2023), pp. 1917–1927.

[8] R. Binkytė et al. “Causal discovery for fairness”. In: *Workshop on Algorithmic Fairness through the Lens of Causality and Privacy*. PMLR. 2023, pp. 7–22.

References

[9] J. Maasch et al. "Local Discovery by Partitioning: Polynomial-Time Causal Discovery Around Exposure-Outcome Pairs". In: *Proceedings of the 40th Conference on Uncertainty in Artificial Intelligence*. 2024. DOI: https://doi.org/10.48550/arXiv.2310.17816.

[10] A. Magrini et al. "A conditional linear Gaussian network to assess the impact of several agronomic settings on the quality of Tuscan Sangiovese grapes". In: *Biometrical Letters* 54.1 (2017), pp. 25–42.

[11] M. Scutari. *Learning Bayesian Networks with the bnlearn R Package*. en. arXiv:0908.3817 [stat]. 2010.

[12] OPTN. *Data Request Instructions*. Accessed: 2024-05-20. 2024.

Causal partitions

EXHAUSTIVE, DISJOINT CAUSAL PARTITIONS W.R.T. $\{X, Y\}$	
$\mathbf{Z}_1$	Confounders and their proxies.
$\mathbf{Z}_2$	Colliders and their proxies.
$\mathbf{Z}_3$	Mediators and their proxies.
$\mathbf{Z}_4$	Non-descendants of Y where $\mathbf{Z}_4 \perp\!\!\!\perp X$ and $\mathbf{Z}_4 \not\perp\!\!\!\perp X \mid Y$.
$\mathbf{Z}_5$	Instruments and their proxies.
$\mathbf{Z}_6$	Descendants of Y. All active paths with X are mediated by Y.
$\mathbf{Z}_7$	Descendants of X. All active paths with Y are mediated by X.
$\mathbf{Z}_8$	Nodes that share no active paths with X nor Y.

Assumptions

1. **Y has no descendants in the observed variable set.** This is satisfied when Y is a terminal variable in the temporal ordering (e.g., outcome is death, or a policy or algorithmic decision made at a known time point).

2. **All parents of Y are observed.** Latent variables that are not parents of Y are permissible. Thus, this is a milder condition than assuming causal sufficiency.

Pseudocode

Algorithm 1: *LD3: Learning structural evidence of direct discrimination from observational data.*

Input: Exposure X, outcome Y, variable set $\mathbf{Z}$, independence test, significance level α.
Output: Adjustment set $\mathbf{A}_{\mathrm{DE}}$, SDC results.
Assumptions: Sufficient conditions A1 and A2.

$\mathbf{Z}' \leftarrow \mathbf{Z}$
for $\forall\, Z \in \mathbf{Z}'$ **do**
  if $Z \perp\!\!\!\perp X \wedge Z \perp\!\!\!\perp Y$ **then** $Z \in \widehat{\mathbf{Z}}_8$
  if $Z \not\perp\!\!\!\perp Y \wedge Z \perp\!\!\!\perp Y | X$ **then** $Z \in \widehat{\mathbf{Z}}_{5,7}$
  if $Z \perp\!\!\!\perp X \wedge Z \not\perp\!\!\!\perp X | Y$ **then** $Z \in \widehat{\mathbf{Z}}_4$
$\mathbf{Z}' \leftarrow \mathbf{Z}' \setminus \widehat{\mathbf{Z}}_8 \cup \widehat{\mathbf{Z}}_{5,7} \cup \widehat{\mathbf{Z}}_4$
for $\forall\, Z \in \mathbf{Z}'$ **do**
  if $Z \not\perp\!\!\!\perp Y | X \cup \widehat{\mathbf{Z}}_4 \cup \{\mathbf{Z}' \setminus Z\}$ **then** $Z \in \widehat{\mathbf{Z}}_{1 \in pa(Y)} \cup \widehat{\mathbf{Z}}_{3 \in pa(Y)}$
for $\forall\, \widehat{Z}_4 \in \widehat{\mathbf{Z}}_4$ **do**
  if $\widehat{Z}_4 \not\perp\!\!\!\perp Y | X \cup \widehat{\mathbf{Z}}_{1 \in pa(Y)} \cup \widehat{\mathbf{Z}}_{3 \in pa(Y)} \cup \{\widehat{\mathbf{Z}}_4 \setminus \widehat{Z}_4\}$ **then** $\widehat{Z}_4 \in \widehat{\mathbf{Z}}_{4 \in pa(Y)}$
$\mathbf{A}_{\mathrm{DE}} \leftarrow \widehat{\mathbf{Z}}_{1 \in pa(Y)} \cup \widehat{\mathbf{Z}}_{3 \in pa(Y)} \cup \widehat{\mathbf{Z}}_{4 \in pa(Y)}$
if $X \perp\!\!\!\perp Y | \widehat{\mathbf{Z}}_{1 \in pa(Y)} \cup \widehat{\mathbf{Z}}_{3 \in pa(Y)}$ **then** $SDC \leftarrow 0$
else $SDC \leftarrow 1$
return $\mathbf{A}_{\mathrm{DE}}, SDC$

STAR liver data

1. **Sex (exposure, protected attribute):** Recipient sex.
2. **Liver allocation (outcome):** Did the candidate receive a liver transplant?
3. **Recipient blood type:** Recipient blood group at registration.
4. **Initial age:** Age in years at time of listing.
5. **Ethnicity:** Recipient ethnicity category.
6. **Hispanic/Latino:** Is the recipient Hispanic/Latino?
7. **Education:** Recipient highest educational level at registration.
8. **Initial MELD:** Initial waiting list MELD/PELD lab score.
9. **Active exception case:** Was this an active exception case?
10. **Exception type:** Type of exception relative to hepatocellular carcinoma (HCC).
11. **Diagnosis:** Primary diagnosis at time of listing.
12. **Initial status:** Initial waiting list status code.
13. **Number of previous transplants:** Number of prior transplants that the recipient received.
14. **Weight:** Recipient weight (kg) at registration.
15. **Height:** Recipient height at registration.
16. **BMI:** Recipient body mass index (BMI) at listing.
17. **Payment method:** Recipient primary projected payment type at registration.
18. **Region:** Waitlist UNOS/OPTN region where recipient was listed or transplanted.

STAR liver data

	UNOS POLICY (2017-2019)			
	Female ($n = 7679$)	*Male* ($n = 13422$)	*p-value*	*Test*
Active exception case	0.36 (0.73)	0.48 (0.83)	7.241e-28	t-test
Diagnosis 1 (PSC: Primary Sclerosing Cholangitis)	0.03 (0.18)	0.04 (0.2)	0.037	χ^2
Diagnosis 6 (AHF: acute hepatic failure)	0.06 (0.23)	0.02 (0.15)	0.004	χ^2
Diagnosis 7 (Cancer)	0.09 (0.28)	0.16 (0.37)	0.010	χ^2
Height	161.9 (7.46)	175.91 (8.51)	0.000	t-test
Initial MELD	20.5 (10.21)	18.83 (9.87)	1.588e-31	t-test
Payment method	0.53 (0.5)	0.54 (0.5)	0.012	χ^2
Recipient age	54.46 (12.42)	56.03 (10.74)	4.091e-22	t-test
Weight	75.97 (18.53)	90.63 (19.59)	0.000	t-test
	UNOS POLICY (2020-2022)			
	Female ($n = 8574$)	*Male* ($n = 14233$)	*p-value*	Test
Active exception case	0.39 (0.58)	0.43 (0.63)	3.629e-07	t-test
Ethnicity 9 (Multiracial, non-hispanic)	0.01 (0.08)	0.0 (0.07)	0.022	Fisher's exact
Exception type 1 (Unknown)	0.29 (0.45)	0.28 (0.45)	0.022	χ^2
Height	161.96 (7.8)	176.36 (8.25)	0.000	t-test
Initial MELD	22.13 (10.52)	20.99 (10.48)	1.862e-15	t-test
Initial status	0.04 (0.2)	0.02 (0.12)	2.858e-31	t-test
Recipient age	53.83 (12.75)	54.74 (11.64)	3.059e-08	t-test
Weight	75.76 (18.71)	91.1 (20.32)	0.000	t-test

Table D.6: Mean values (standard deviations) for features with statistically significant differences between males and females ($\alpha = 0.05$). Summary statistics for all features are available on GitHub (`https://anonymous.4open.science/r/LD3-4440`).

Reduces unnecessary adjustment

	All $\mathbf{Z}$		True $\mathbf{A}_{\text{DE}}$		Pred $\mathbf{A}_{\text{DE}}$		
n	*Mean*	*Variance*	*Mean*	*Variance*	*Mean*	*Variance*	$\mathbf{A}_{\text{DE}}$ *F1*
500	0.239	0.052	0.347	**0.004**	0.344	**0.004**	0.99 [0.98,1.0]
1000	-0.011	0.038	0.35	**0.003**	0.349	**0.003**	0.99 [0.98,1.0]
10000	0.151	0.013	0.345	**0.000**	0.344	**0.000**	0.99 [0.98,1.0]

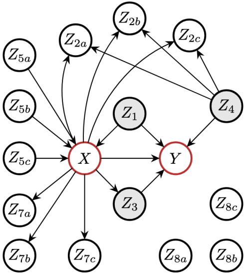


Figure C.5: The true $\mathbf{A}_{\text{DE}}$ for X and Y is in gray.

COMPAS results

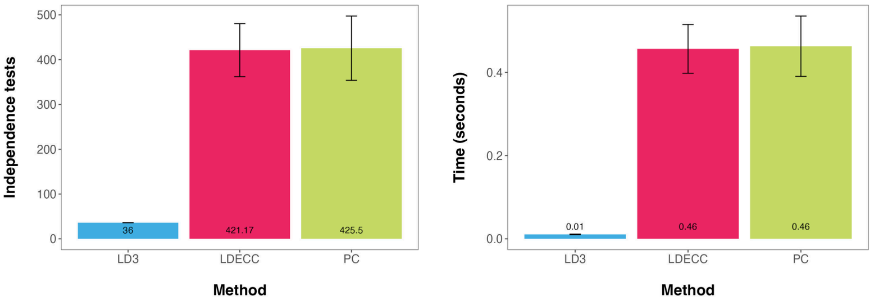


Figure D.2: Average number of independence tests performed and average time (seconds) per method on COMPAS experiments.