Applied Causality: Syllabus

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Spring 2022

Updated May 9, 2022

By each date, please read about the topic at hand.

Date	Topic
2022-01-24	Foundations
2022-01-31	
2022-02-07	
2022-02-14	
2022-02-24	Synthetic Controls
2022-02-28	
2022-03-07	Causal Representation Learning
2022-03-21	
2022-03-28	
2022-04-11	Invariance and Causality
2022-04-18	
2022-04-20	Multiple Causal Inference (Statistics PhD seminar)
2022-05-02	Causality and Algorithmic Fairness
2022-05-09	David Freedman on Causality

It is your choice what to read. Suggested readings are below.

Foundations

- Hernan and Robins (2020), Ch. 1, 2
- Imbens and Rubin (2015)
- Morgan and Winship (2015)
- Pearl et al. (2016)
- Shalizi (2021), Ch 21

Synthetic Controls

- Abadie et al. (2010)
- Abadie (2021)
- Agarwal et al. (2021)
- Athey et al. (2021)

- Shi et al. (2022)

Causal Representation Learning

- Ahuja et al. (2021)
- von Kugelgen et al. (2021)
- Lu et al. (2021)
- Schölkopf et al. (2021)
- Suter et al. (2019)
- Trauble et al. (2021)
- Veitch et al. (2021)
- Wang and Jordan (2021)

Other papers, cited in Schölkopf et al. (2021):

- Bengio et al. (2019)
- Besserve et al. (2021)
- Goyal et al. (2020)
- Huang et al. (2020)
- Ke et al. (2020)
- Leeb et al. (2020)
- Locatello et al. (2019)
- Locatello et al. (2020)
- Parascandolo et al. (2018)
- Pfister et al. (2019)
- Shu et al. (2020)

Invariance and Causality

- Arjovsky et al. (2019)
- Lu et al. (2021) (also above)
- Peters et al. (2016)

Multiple Causal Inference

- D'Amour (2019)
- Grimmer et al. (2020)
- Ogburn et al. (2020)
- Song et al. (2015)
- Wang and Blei (2019)
- Wang and Blei (2020)
- Zheng et al. (2021)

Causality and Algorithmic Fairness

- Coston et al. (2020)
- Hu and Kohler-Hausmann (2020)
- Imai and Jiang (2020)
- Kusner et al. (2017)
- Russell et al. (2017)
- Zhang and Bareinboim (2018)

David Freedman on Causality

- Freedman (2009)

References

Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature*, 59(2):391–425.

Abadie, A., Diamond, A., and Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association*, 105(490):493–505.

Agarwal, A., Shah, D., and Shen, D. (2021). Synthetic interventions. *arXiv:2006.0769*.

Ahuja, K., Hartford, J., and Bengio, Y. (2021). Properties from mechanisms: An equivariance perspective on identifiable representation learning. *arXiv:2110.1579*.

Arjovsky, M., Bottou, L., Gulrajani, I., and Lopez-Paz, D. (2019). Invariant risk minimization. *arXiv:1907.02893*.

Athey, S., Bayati, M., Doudchenko, N., Imbens, G., and Khosravi, K. (2021). Matrix completion methods for causal panel data models. *arXiv:1710.10251*.

Bengio, Y., Deleu, T., Rahaman, N., Ke, R., Lachapelle, S., Bilaniuk, O., Goyal, A., and Pal, C. (2019). A meta-transfer objective for learning to disentangle causal mechanisms. *arXiv:1901.10912*.

Besserve, M., Sun, R., Janzing, D., and Schölkopf, B. (2021). A theory of independent mechanisms for extrapolation in generative models. In *American Association for Artificial Intelligence*.

Coston, A., Mishler, A., Kennedy, E., and Chouldechova, A. (2020). Counterfactual risk assessments, evaluation, and fairness. In *FAT**.

D'Amour, A. (2019). On multi-cause causal inference with unobserved confounding: Counterexamples, impossibility, and alternatives. In *Artificial Intelligence and Statistics*.

Freedman, D. (2009). *Statistical Models and Causal Inference: A Dialogue with the Social Sciences*. Cambridge University Press.

Goyal, A., Lamb, A., Hoffmann, J., Sodhani, S., Levine, S., Bengio, Y., and Schölkopf, B. (2020). Recurrent independent mechanisms. *arXiv:1909.10893*.

Grimmer, J., Knox, D., and Stewart, B. (2020). Naïve regression requires weaker assumptions than factor models to adjust for multiple cause confounding. *arXiv 2007.12702*.

Hernan, M. and Robins, J. (2020). *Causal Inference: What If?* Chapman & Hall/CRC.

Hu, L. and Kohler-Hausmann, I. (2020). What's sex got to do with fair machine learning. *arXiv 2006.01770*.

Huang, B., Zhang, K., Zhang, J., Ramsey, J., Sanchez-Romero, R., Glymour, C., and Schoelkopf, B. (2020). Causal discovery from heterogenous/nonstationary data. *Journal of Machine Learning Research*.

Imai, K. and Jiang, Z. (2020). Principal fairness for human and algorithmic decision-making. *arXiv:2005.10400*.

Imbens, G. and Rubin, D. (2015). *Causal Inference in Statistics, Social and Biomedical Sciences: An Introduction*. Cambridge University Press.

Ke, N., Bilaniuk, O., Goyal, A., Bauer, S., Larochelle, H., Schoelkopf, B., Mozer, M., Pal, C., and Bengio, Y. (2020). Learning neural causal models from unknown interventions. *arXiv:1910.01075*.

Kusner, M., Loftus, J., Russell, C., and Silva, R. (2017). Counterfactual fairness. *Neural Information Processing Systems*.

Leeb, F., Annadani, Y., Bauer, S., and Schölkopf, B. (2020). Structural autoencoders improve representations for generation and transfer. *arXiv:2006.07796*.

Locatello, F., Bauer, S., Lucic, M., Rätsch, G., Gelly, S., Schölkopf, B., and Bachem, O. (2019). Challenging common assumptions in the unsupervised learning of disentangled representations. *International Conference on Machine Learning*.

Locatello, F., Poole, B., Ratsch, G., Schölkopf, B., Bachem, O., and Tschannen, M. (2020). Weakly-supervised disentanglement without compromises. In *International Conference on Machine Learning*.

Lu, C., Wu, Y., Hernandez-Lobato, J., and Schoelkopf, B. (2021). Nonlinear invariant risk minimization: A causal approach. *arxiv:2102.12353*.

Morgan, S. and Winship, C. (2015). *Counterfactuals and Causal Inference*. Cambridge University Press, 2nd edition.

Ogburn, E., Shpitser, I., and Tchetgen, E. T. (2020). Counterexamples to "the blessings of multiple causes" by wang and blei. *arXiv:2020.001*.

Parascandolo, G., Kilbertus, N., Rojas-Carulla, M., and Schölkopf, B. (2018). Learning independent causal mechanisms. In *International Conference on Machine Learning*.

Pearl, J., Glymour, M., and Jewell, N. (2016). *Causal Inference in Statistics: A Primer*. John Wiley & Sons.

Peters, J., Bühlmann, P., and Meinshausen, N. (2016). Causal inference by using invariant prediction: Identification and confidence intervals. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 78(5):947–1012.

Pfister, N., Bauer, S., and Peters, J. (2019). Learning stable and predictive structures in kinetic systems. *Proceedings of the National Academy of Sciences*, 116(51):25405–25411.

Russell, C., Kusner, M., Loftus, J., and Silva, R. (2017). When worlds collide: Integrating different counterfactual assumptions in fairness. In *Neural Information Processing Systems*.

Schölkopf, B., Locatello, F., Bauer, S., Ke, N., Kalchbrenner, N., Goyal, A., and Bengio, Y. (2021). Towards causal representation learning. *arXiv:2102.11107*.

Shalizi, C. (2021). *Advanced Data Analysis from an Elementary Point of View*. in preparation.

Shi, C., Sridhar, D., Misra, V., and Blei, D. (2022). On the assumptions of synthetic control methods. In *Artificial Intelligence and Statistics*.

Shu, R., Chen, Y., Kumar, A., Ermon, S., and Poole, B. (2020). Weakly supervised disentanglement with guarantees. In *International Conference on Learning Representations*.

Song, M., Hao, W., and Storey, J. (2015). Testing for genetic association in arbitrarily structured populations. *Nature Genetics*.

Suter, R., Miladinovic, D., Schoelkopf, B., and Bauer, S. (2019). Robustly disentangled causal mechanisms: Validating deep representations for interventional robustness. *International Conference on Machine Learning*.

Trauble, F., Creaker, E., Kilbertus, N., Locatello, F., Dittadi, A., Goyal, A., Schoelkopf, B., and Bauer, S. (2021). On disentangled representations learned from correlated data. *International Conference on Machine Learning*.

Veitch, V., D'Amour, A., Yadlowsky, S., and Eisenstein, J. (2021). Counterfactual invariance to spurious correlations: Why and how to pass stress tests. *arXiv:2106.00545*.

von Kugelgen, J., Sharma, Y., Gresele, L., Brendel, W., Schoelkopf, B., Besserve, M., and Locatello, F. (2021). Self-supervised learning with data augmentations provably isolates content from style. *Neural Information Processing Systems*.

Wang, Y. and Blei, D. (2019). The blessings of multiple causes. *Journal of the American Statistical Association*, 114(528):1574–1596.

Wang, Y. and Blei, D. (2020). Towards clarifying the theory of the deconfounder. *arXiv 2003.04948*.

Wang, Y. and Jordan, M. (2021). Desiderata for representation learning: A causal perspective. *arXiv:2109.03795*.

Zhang, J. and Bareinboim, E. (2018). Fairness in decision-making–the causal explanation formula. In *32nd AAAI Conference on Artificial Intelligence*.

Zheng, J., d'Amour, A., and Franks, A. (2021). Bayesian inference and partial identification in multi-treatment causal inference with unobserved confounding. *arXiv:2111.07973*.