Suggested further readings

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First, there are a number of different perspectives on causality from multiple communities. Highly recommendable are:

Statistics:

Pearl, Judea, and Dana Mackenzie. The book of why: the new science of cause and effect . Basic Books, 2018 -> Super readable book on why causality matters so much. Not overly charitable about other communities.

Pearl, Judea. Causality . Cambridge university press, 2009 -> Foundational book for causal inference, DAG style and do- operators.

Hern n, Miguel A., and James M. Robins. " Causal inference: what if. " Boca Raton: Chapman & Hill/CRC 2020 (2020) -> Beautifully applied and with code samples.

Econometrics:

Angrist, Joshua D., and J rn-Steffen Pischke. Mastering metrics: The path from cause to effect . Princeton University Press, 2014 -> Very readable book for practical causal inference

Angrist, Joshua D., and J rn-Steffen Pischke. Mostly harmless econometrics: An empiricist's companion . Princeton university press, 2008. -> beautiful book highlighting the ways we can use real world data to get at causal estimates with strong computational treatments.

Imbens, Guido W., and Donald B. Rubin. Causal inference in statistics, social, and biomedical sciences . Cambridge University Press, 2015. -> another very broad book.

Epidemiology:

Aschengrau, Ann, and George R. Seage. Essentials of epidemiology in public health . Jones & Bartlett Publishers, 2013. -> This book shows how in epidemiology causality is often even harder than thought.

Machine learning:

Peters, Jonas, Dominik Janzing, and Bernhard Sch lkopf. Elements of causal inference . The MIT Press, 2017. -> This book combines Pearl type approaches with new ML inspired contributions.

A broad range of relevant papers:

Marinescu, Ioana E., Patrick N. Lawlor, and Konrad P. Kording. "Quasi-experimental causality in neuroscience and behavioural research." Nature human behaviour 2.12 (2018): 891-898. -> A broad overview of econ style/ quasiexperimental causality for neuroscience

Sch lkopf, Bernhard. "Causality for machine learning." arXiv preprint arXiv:1911.10500 (2019). -> discussing the role of causality for machine learning.

Kass, R.E., Amari, S.-I., Arai, K., Brown, E.N., Diekman, C.O., Diesmann, M., Doiron, B., Eden, U.T., Fairhall, A.L., Fiddyment, G.M., Fukai, T., Grün, S., Harrison, M.T., Helias, M., Nakahara, H., Teramae, J.-N., Thomas, P.J., Reimers, M., Rodu, J., Rotstein, H.G., Shea-Brown, E., Shimazaki, H., Shinomoto, S., Yu, B.M., and Kramer, M.A. (2018) Computational neuroscience: Mathematical and statistical perspectives , Annual Review of Statistics and its Application, 5: 183-214. -> Intro to computational neuroscience ideas.

Cooper, GF., and Herskovits, E. "A Bayesian method for the induction of probabilistic networks from data." Machine learning 9.4 (1992): 309-347.

Spirtes, P., Glymour, C. N., Scheines, R., & Heckerman, D. (2000). Causation, prediction, and search . MIT press.

Shimizu, S., Hoyer, P. O., Hyv rinen, A., & Kerminen, A. (2006). A linear non-Gaussian acyclic model for causal discovery. Journal of Machine Learning Research , 7 (Oct), 2003-2030.

Triantafillou, S., & Tsamardinos, I. (2015). Constraint-based causal discovery from multiple interventions over overlapping variable sets. The Journal of Machine Learning Research , 16 (1), 2147-2205.

Mooij, J. M., Peters, J., Janzing, D., Zscheischler, J., & Sch lkopf, B. (2016). Distinguishing cause from effect using observational data: methods and benchmarks. The Journal of Machine Learning Research , 17 (1), 1103-1204.

Peters, J., Bühlmann, P., & Meinshausen, N. (2016). Causal inference by using invariant prediction: identification and confidence intervals Series B Statistical methodology. Journal of the Royal Statistical Society, 78 , 947-1012. doi: 10.1111/rssb.12167

Kass, Robert E., Uri T. Eden, and Emery N. Brown. Analysis of neural data . Vol. 491. New York: Springer, 2014.-> Another Kass book that focuses on data analysis.
