Learning Ising Models from Evolutions (Extended Abstract)

Jason Gaitonde JASON.GAITONDE@DUKE.EDU
Duke University

Ankur Moitra MOITRA@MIT.EDU
Elchanan Mossel ELMOS@MIT.EDU
Massachusetts Institute of Technology

Editors: Steve Hanneke and Tor Lattimore

Abstract

In this work, we revisit the problem of learning the structure and parameters of an Ising model from dynamics. While the problem of learning from i.i.d. samples has been intensively studied in several communities (Chow and Liu, 1968; Ravikumar et al., 2010; Bresler, 2015; Klivans and Meka, 2017; Vuffray et al., 2016), recent work has considered learning from temporally correlated samples arising from some stochastic process. However, all prior work (Bresler et al., 2018; Dutt et al., 2021; Gaitonde and Mossel, 2024; Gaitonde et al., 2025) studied this problem in the *synthetic* observation model that assumes knowledge of internal steps of the standard algorithm for generating samples, which goes far beyond what we should expect to naturally observe from the system evolution in important physics and network applications. Extending these algorithmic guarantees to more realistic observation models has been an important direction highlighted in recent work (Bresler et al., 2018; Gaitonde et al., 2025).

We give the first efficient algorithm for learning from the natural continuous-time observation model where we only observe the actual evolution of the state of the system, as opposed to usually unobservable details like failed update attempts of sites. For Ising models with maximum degree d, our algorithm first recovers the graph structure in $\mathsf{poly}(d) \cdot n^2 \log n$ time, which qualitatively matches the state-of-the-art even in the cleaner i.i.d. setting, and then estimates the parameters in additional $\widetilde{O}(2^d \cdot n)$ time. Our analysis is based on a new family of cycle statistics, which crucially remains measurable for *any* stochastic process, and in fact succeeds more generally for a broad family of reversible, single-site Markov chains that includes both the Glauber dynamics and the Metropolis chain.[1]

Keywords: learning from dynamics, Ising models, Glauber dynamics

Acknowledgments

JG was supported by EM's Vannevar Bush Faculty Fellowship ONR-N00014-20-1-2826 and Simons Investigator Award 622132. AM is supported in part by a Microsoft Trustworthy AI Grant, NSF-CCF 2430381, ONR N00014-22-1-2339, and a David and Lucile Packard Fellowship. EM is supported in part by Vannevar Bush Faculty Fellowship ONR-N00014-20-1-2826, Simons Investigator Award 622132, ONR MURI N-00014-24-1-2742, and NSF DMS-2031883.

1. "Extended abstract. Full version appears as arXiv:2507.15173.

© 2026 J. Gaitonde, A. Moitra & E. Mossel.

References

Guy Bresler. Efficiently Learning Ising Models on Arbitrary Graphs. In *Proceedings of the Forty-Seventh Annual ACM on Symposium on Theory of Computing, STOC 2015*, pages 771–782. ACM, 2015. doi: 10.1145/2746539.2746631. URL https://doi.org/10.1145/2746539.2746631.

Guy Bresler, David Gamarnik, and Devavrat Shah. Learning Graphical Models from the Glauber Dynamics. *IEEE Trans. Inf. Theory*, 64(6):4072–4080, 2018. doi: 10.1109/TIT.2017.2713828. URL https://doi.org/10.1109/TIT.2017.2713828.

Chao-Kong Chow and Chao-Ning Liu. Approximating discrete probability distributions with dependence trees. *IEEE Transactions on Information Theory*, 14(3):462–467, 1968. doi: 10.1109/TIT.1968.1054142.

Arkopal Dutt, Andrey Y. Lokhov, Marc Vuffray, and Sidhant Misra. Exponential Reduction in Sample Complexity with Learning of Ising Model Dynamics. In *Proceedings of the 38th International Conference on Machine Learning, ICML 2021*, volume 139 of *Proceedings of Machine Learning Research*, pages 2914–2925. PMLR, 2021.

Jason Gaitonde and Elchanan Mossel. A Unified Approach to Learning Ising Models: Beyond Independence and Bounded Width. In *Proceedings of the 56th Annual ACM Symposium on Theory of Computing, STOC 2024*, pages 503–514. ACM, 2024. doi: 10.1145/3618260.3649674. URL https://doi.org/10.1145/3618260.3649674.

Jason Gaitonde, Ankur Moitra, and Elchanan Mossel. Bypassing the Noisy Parity Barrier: Learning Higher-Order Markov Random Fields from Dynamics. In *Proceedings of the 57th Annual ACM Symposium on Theory of Computing, STOC 2025*, pages 348–359. ACM, 2025. doi: 10.1145/3717823.3718231. URL https://doi.org/10.1145/3717823.3718231.

Adam R. Klivans and Raghu Meka. Learning Graphical Models Using Multiplicative Weights. In *58th IEEE Annual Symposium on Foundations of Computer Science, FOCS 2017*, pages 343–354. IEEE Computer Society, 2017. doi: 10.1109/FOCS.2017.39. URL https://doi.org/10.1109/FOCS.2017.39.

Pradeep Ravikumar, Martin J Wainwright, and John D Lafferty. High-Dimensional Ising Model Selection Using ℓ_1-Regularized Logistic Regression. *The Annals of Statistics*, pages 1287–1319, 2010. doi: 10.1214/09-AOS691.

Marc Vuffray, Sidhant Misra, Andrey Y. Lokhov, and Michael Chertkov. Interaction Screening: Efficient and Sample-Optimal Learning of Ising Models. In *Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016*, pages 2595–2603, 2016.