

28.07.2026 — College Park, Md

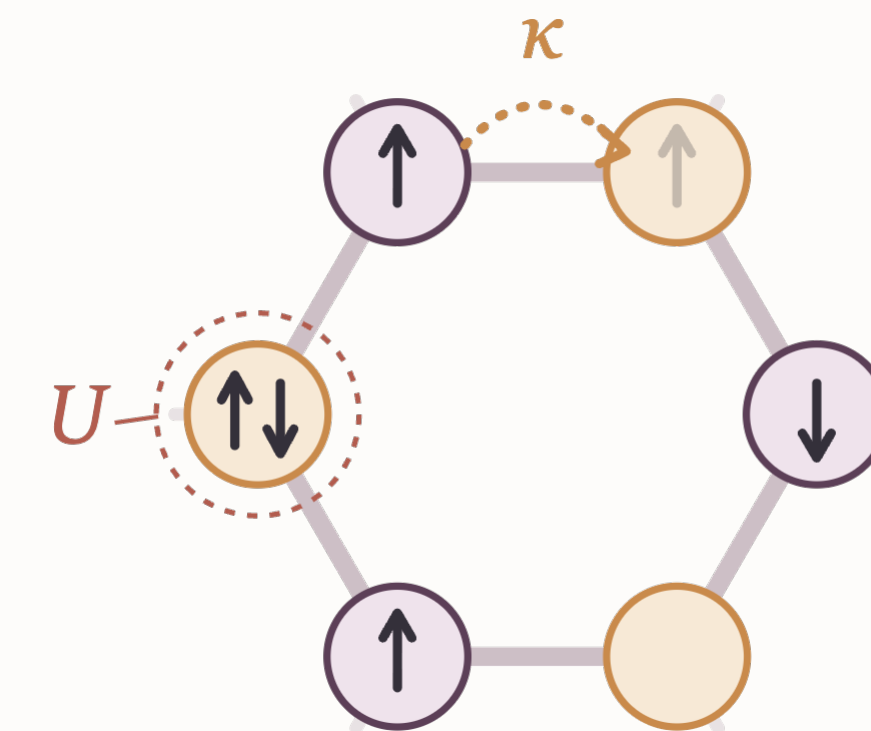
Tackling the Sign Problem in the Doped Hubbard Model with Normalizing Flows

Dominic Schuh

University of Bonn · TRA Matter · Helmholtz-Institute for Radiation and Nuclear Physics

The Hubbard Model

$$H = -\kappa \sum_{\langle x,y \rangle} \left(a_{x,\uparrow}^\dagger a_{y,\uparrow} + a_{x,\downarrow}^\dagger a_{y,\downarrow} \right) - \frac{U}{2} \sum_x (n_{x,\uparrow} - n_{x,\downarrow})^2 - \mu \sum_x q_x$$



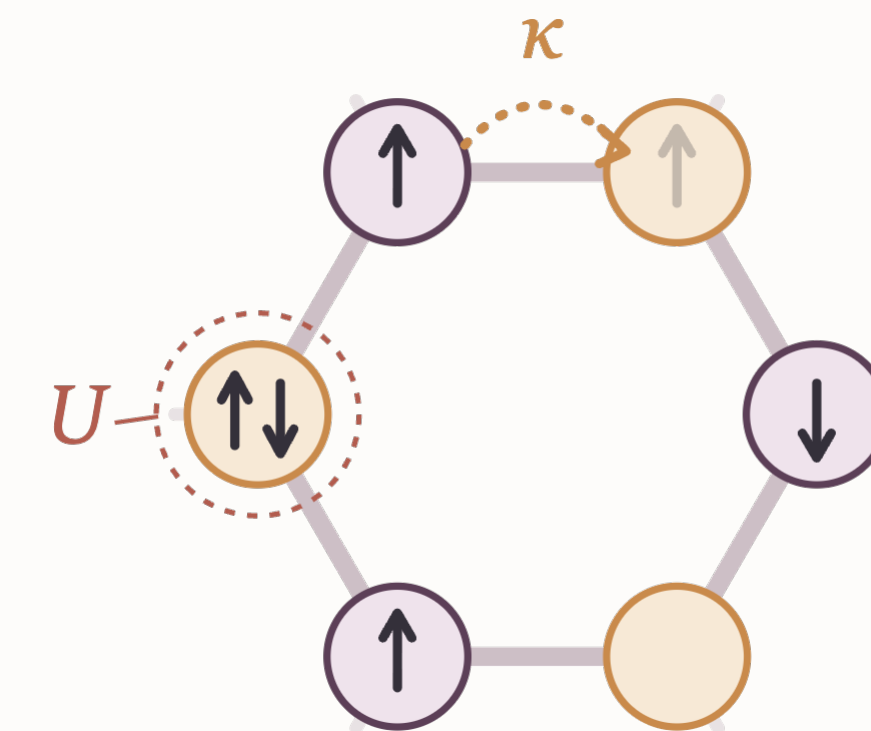
● A / B sublattice ↑↓ electron spin ⚡ hopping

U on-site interaction

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- Mott insulator
- Magnetism
- Superconductivity

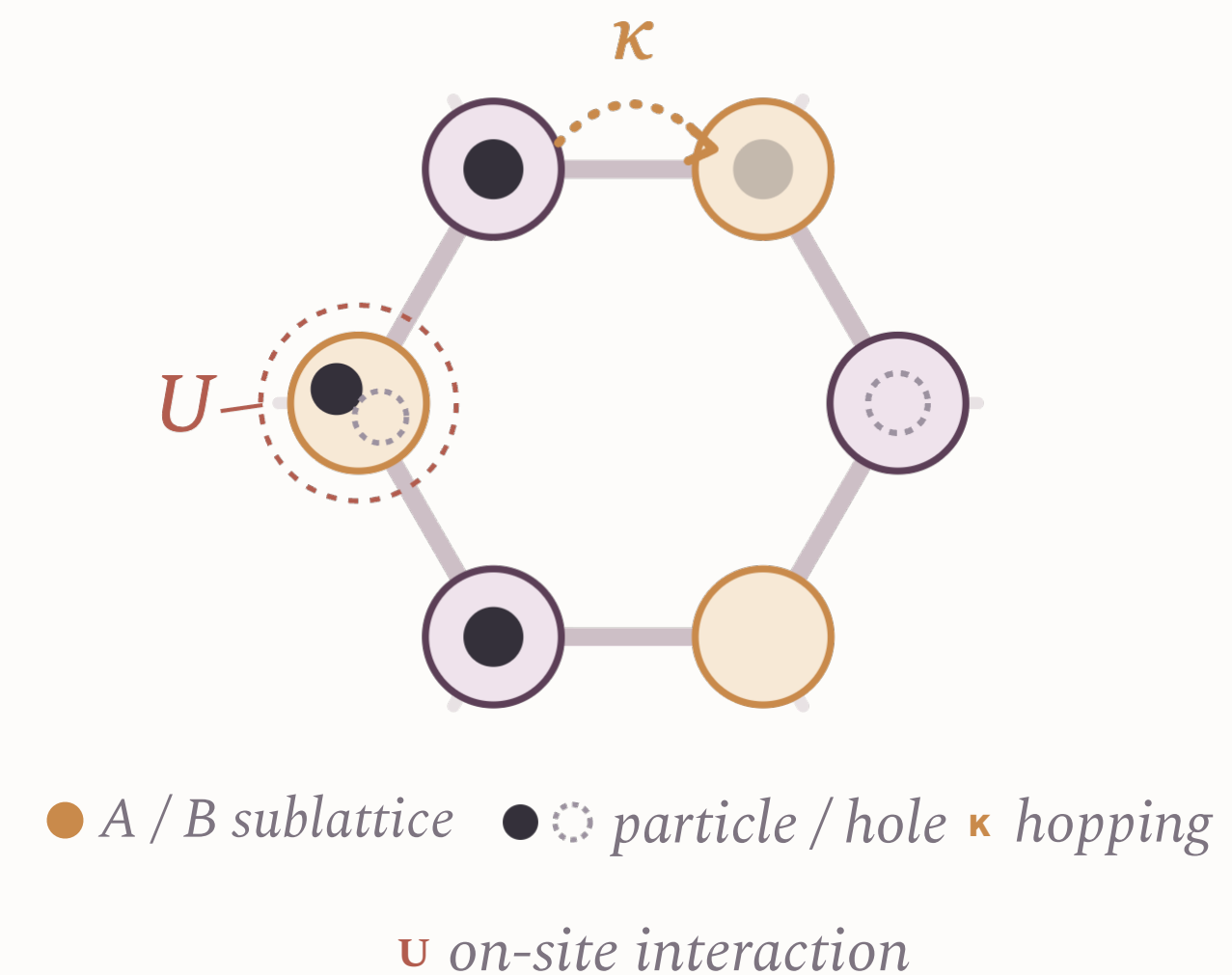


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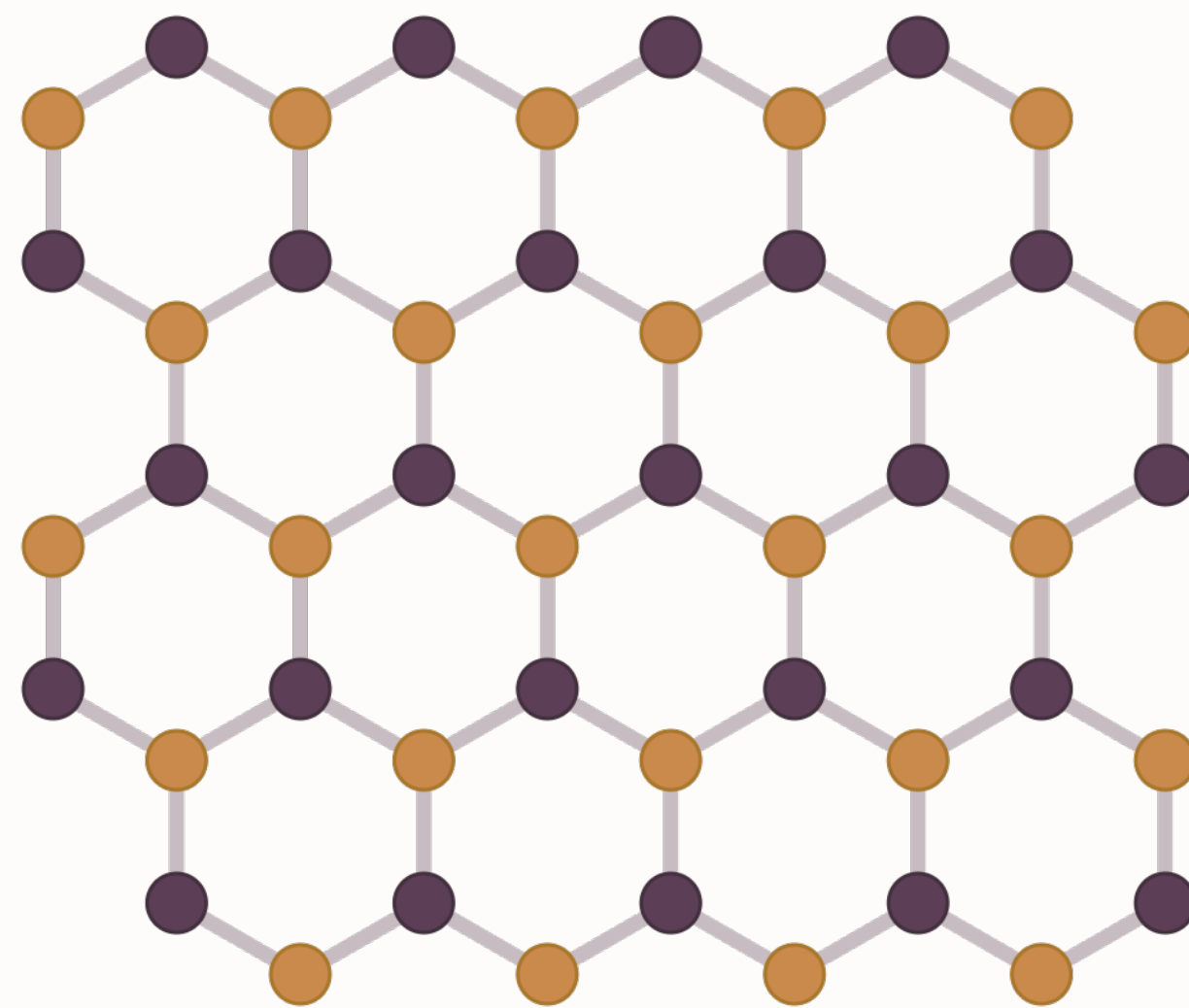
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Hubbard-Stratonovich
transformation



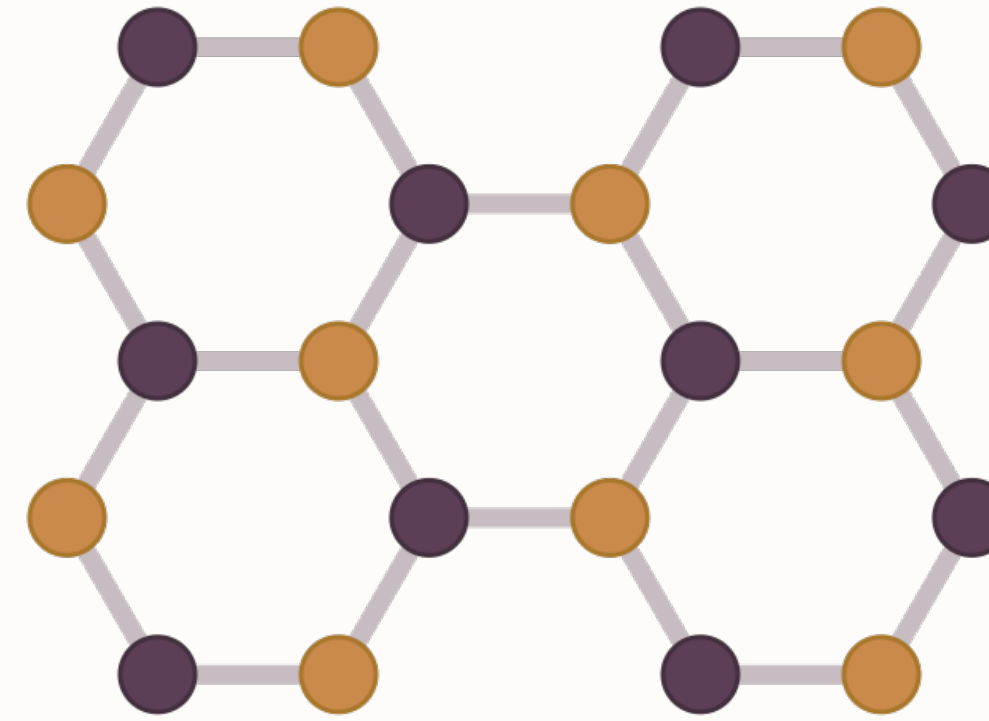
$$S[\phi] = \frac{1}{2\tilde{U}} \sum_{x,t} \phi_{x,t}^2 - \log \det M[\phi | \mu] - \log \det M[-\phi | \mu]$$

Carbon-based systems



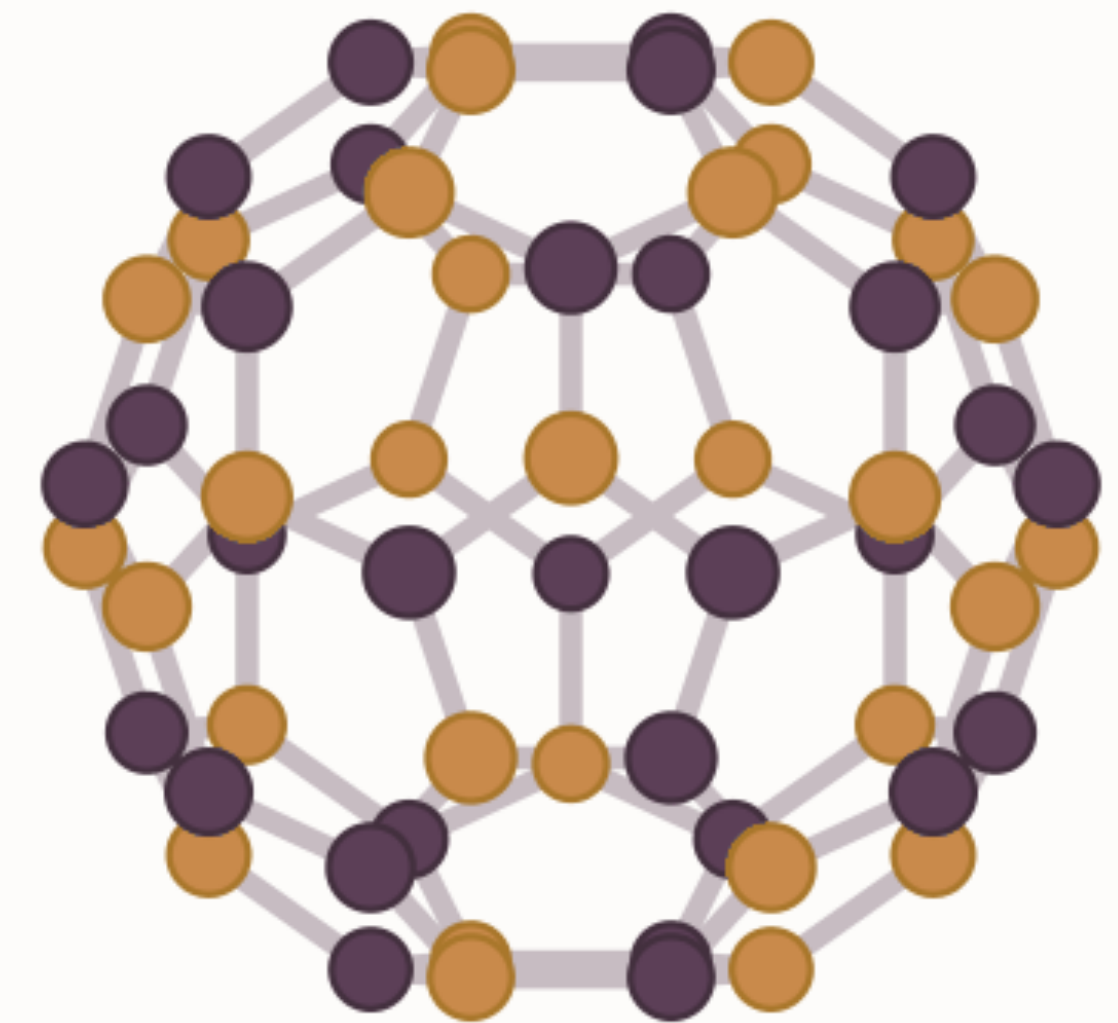
Graphene

Ostmeyer, et al. PRB 2021



$\text{C}_{20}\text{H}_{12}$

Rodekamp, et al. EPJB 2025

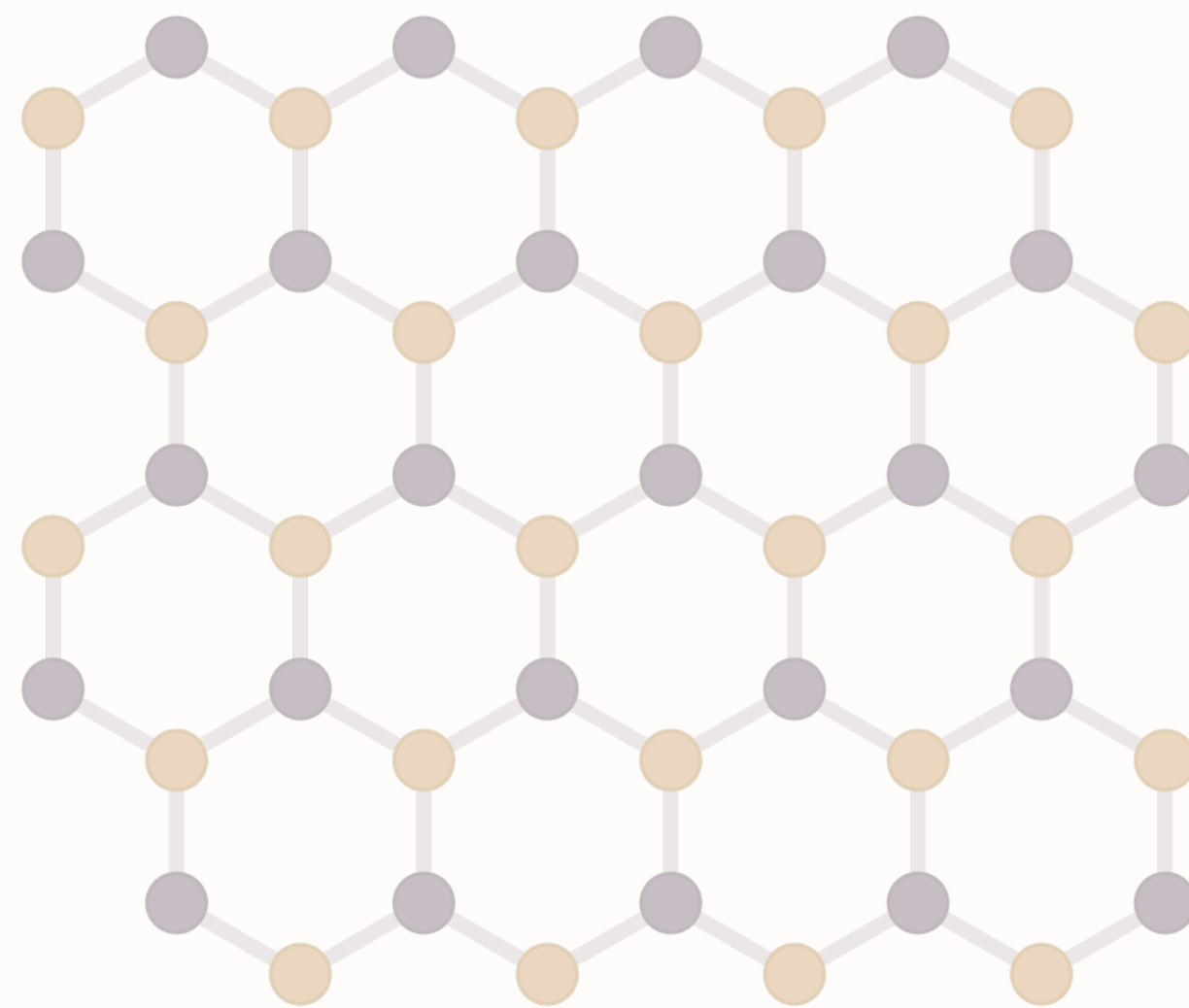


C_{60} Fullerene

Gäntgen, et al. PRB 2024

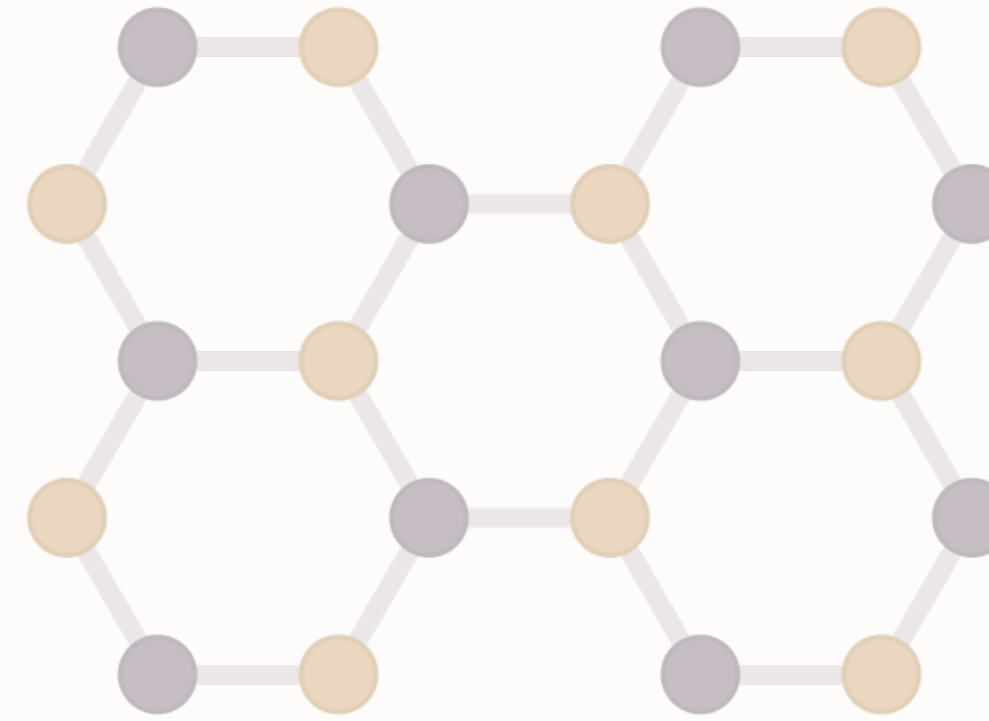
Carbon-based systems

Talk by
Janik Kreit!



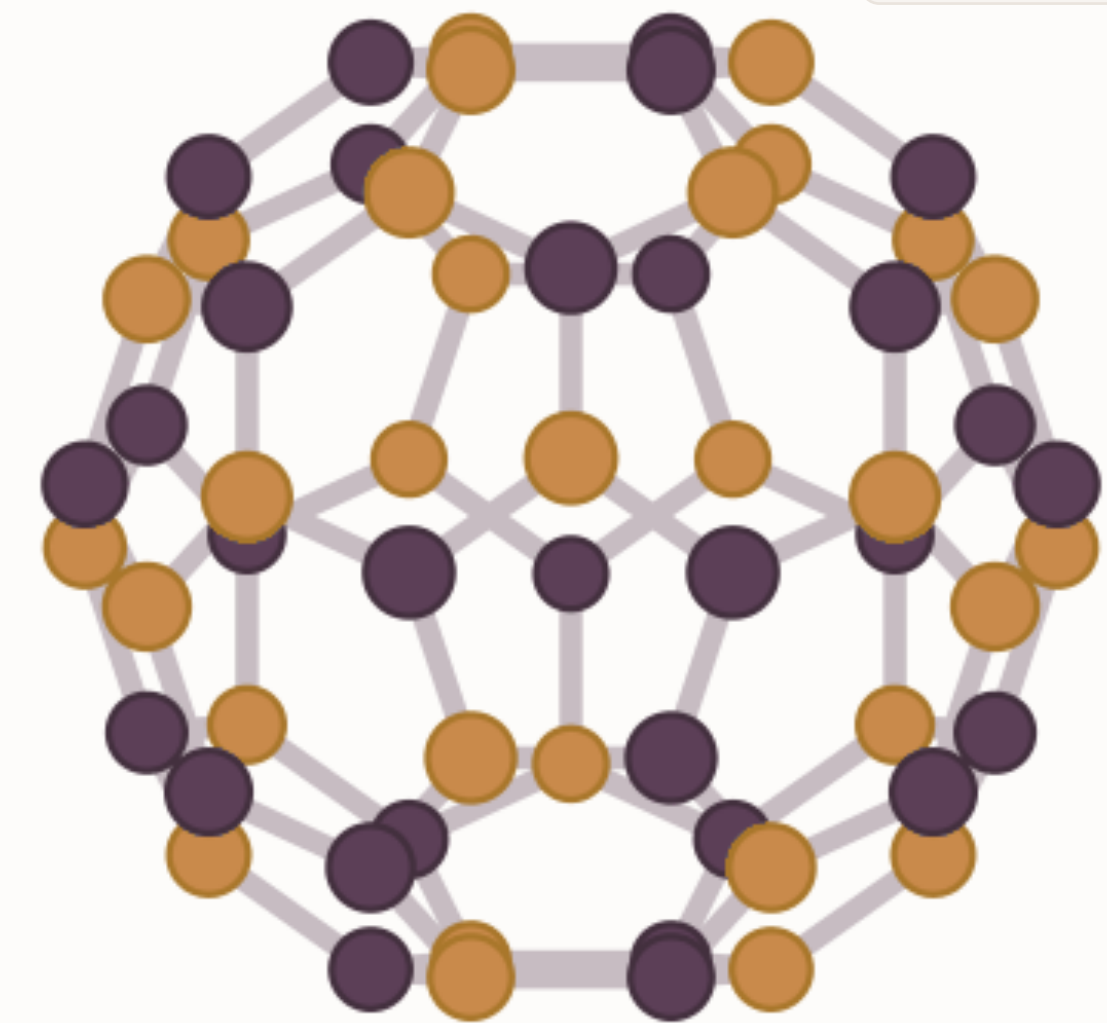
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C₂₀H₁₂

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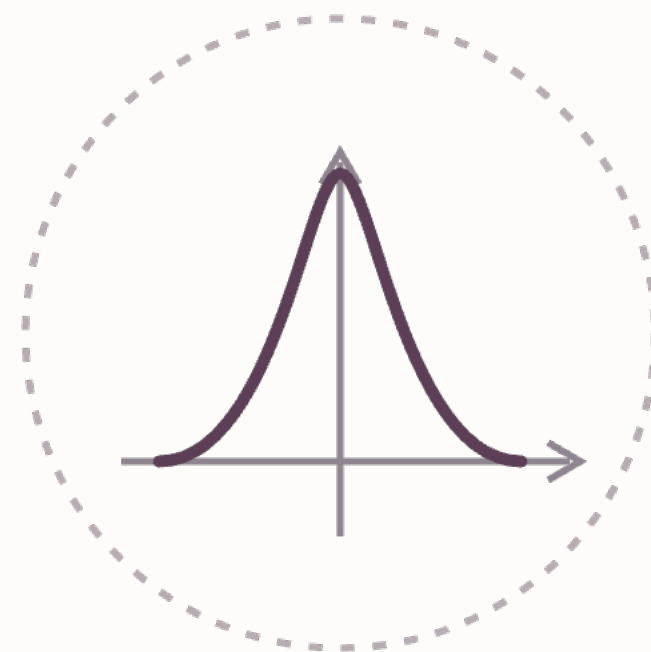
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Flow-based generative sampling

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Simple distribution

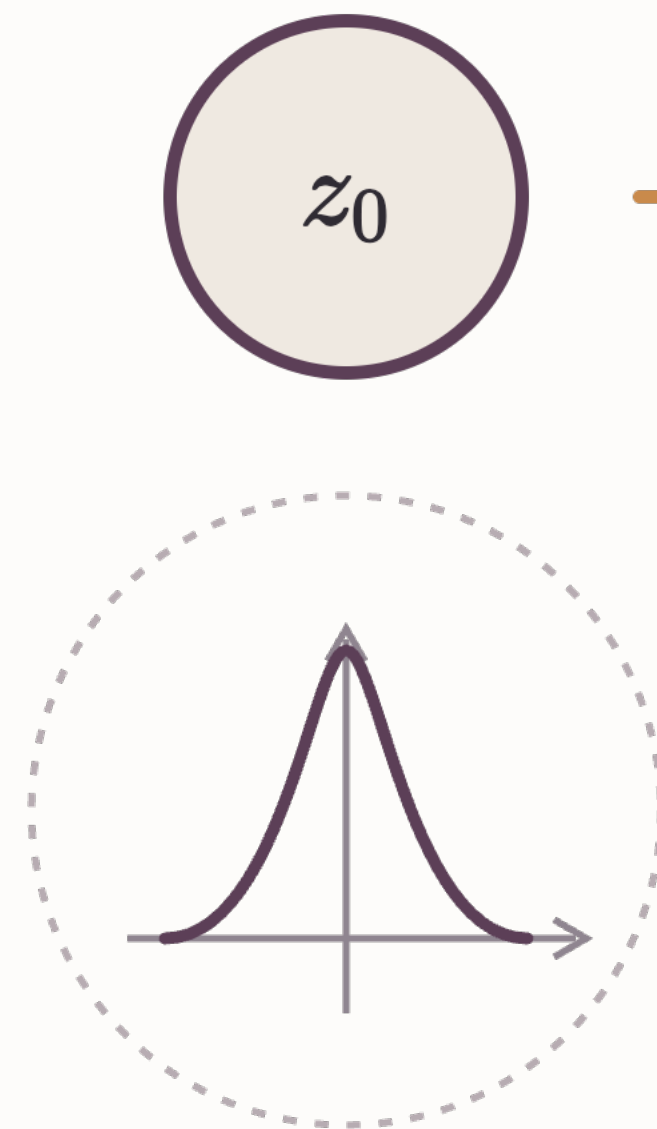


$$z_0 \sim q_Z(z)$$

D. Rezende & S. Mohamed, ICML 2016 · M. Albergo et al., PRD 2019

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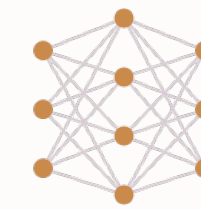
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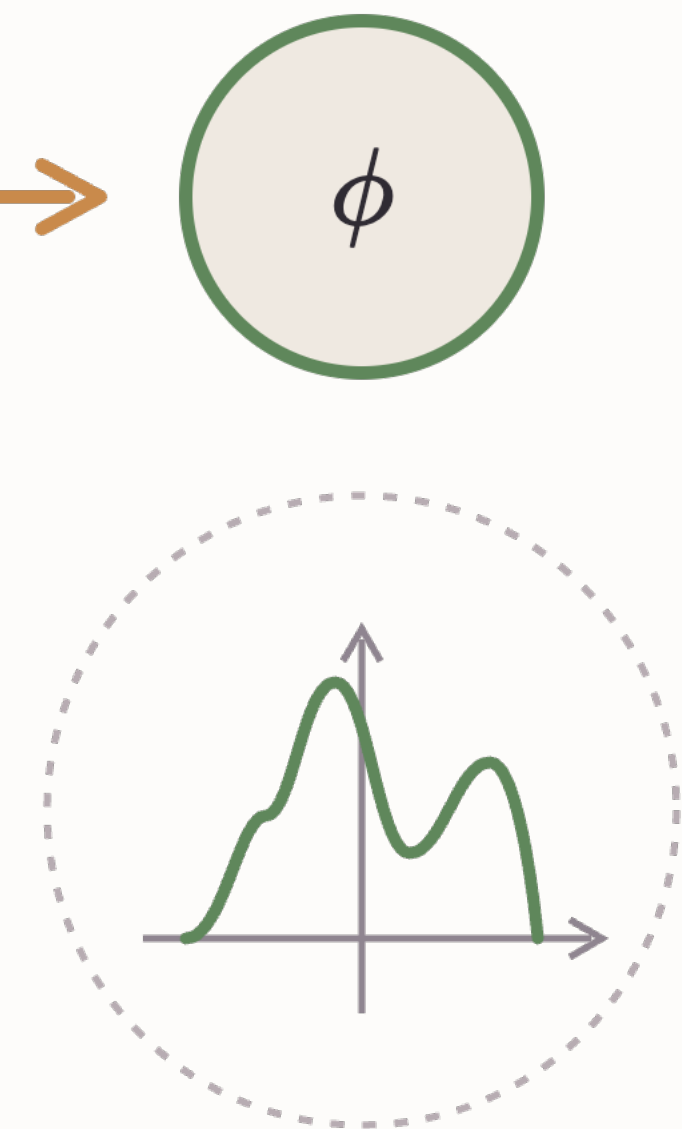
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Normalizing flow

$$\phi = f_\theta(z_0)$$



Path integral distribution

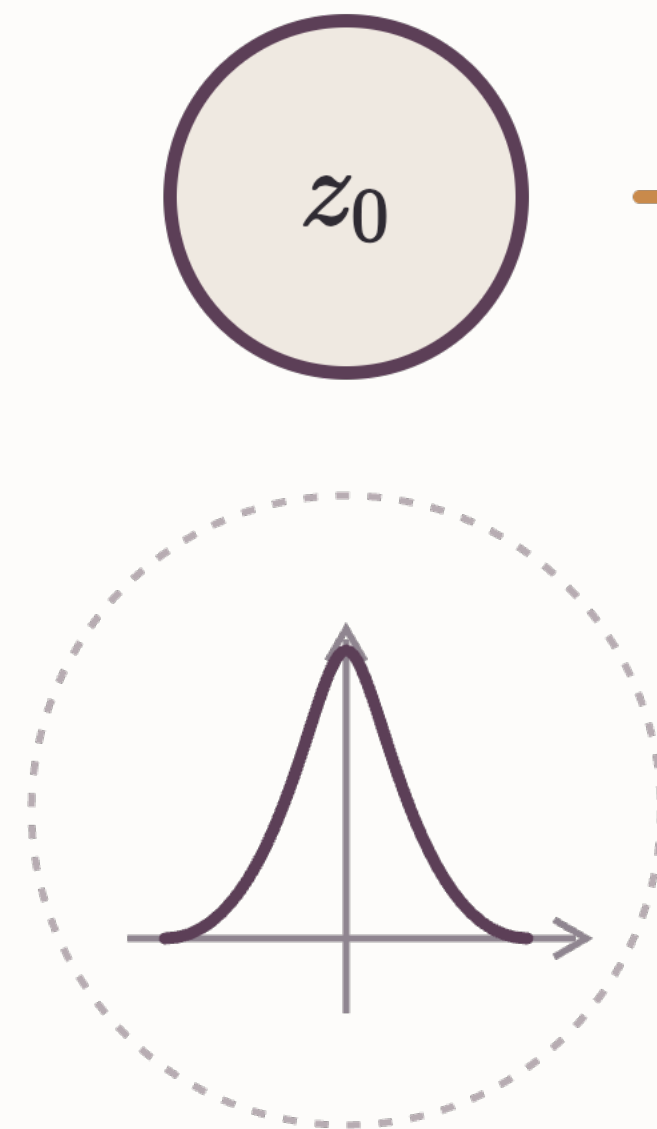


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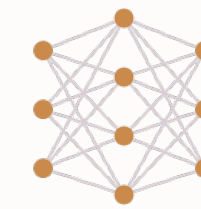
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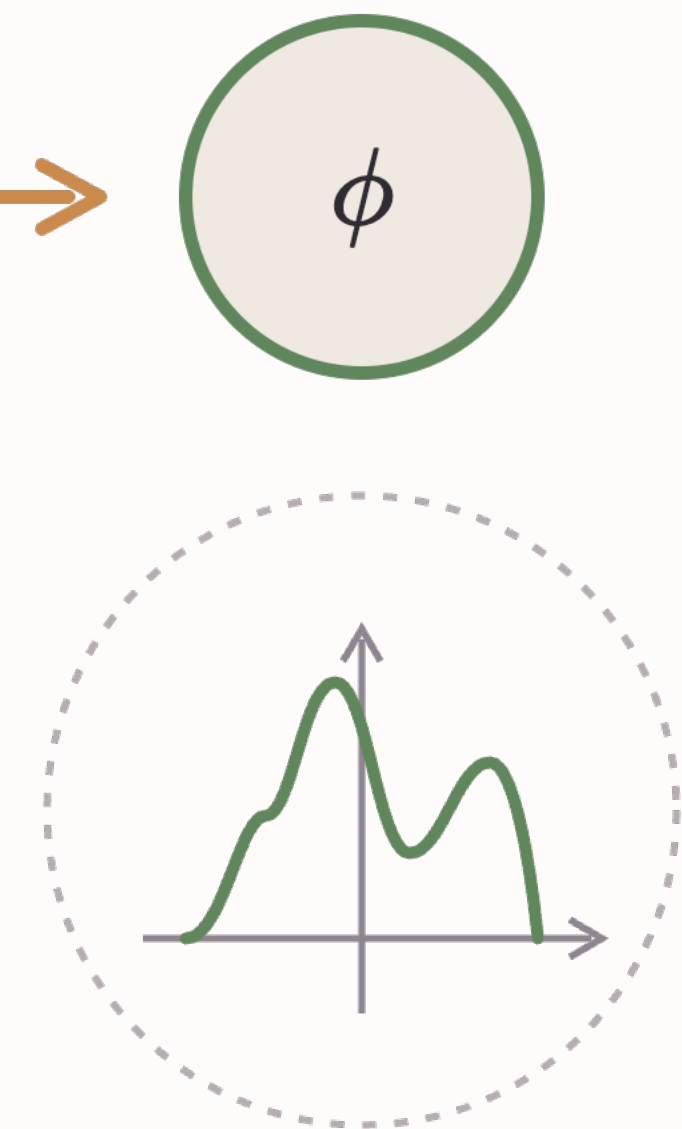
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(Approximate) Path integral distribution



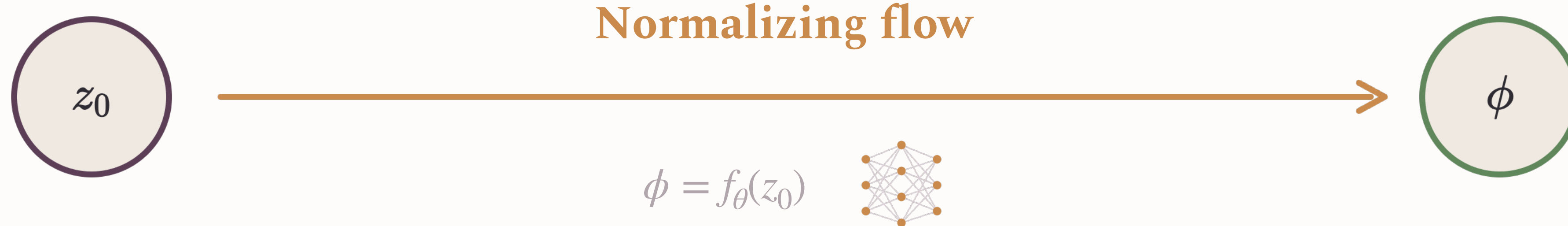
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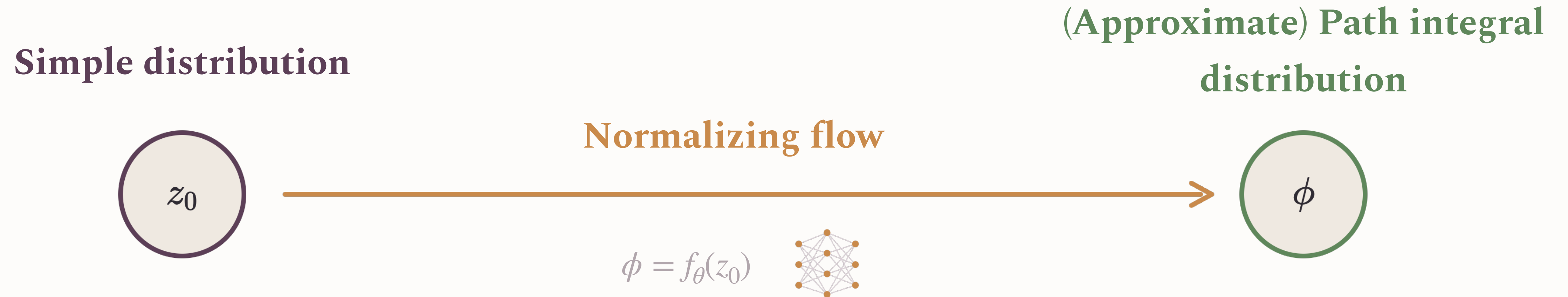
(Approximate) Path integral
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Invertibility allows for tractable and exact probability estimation, enabling reweighting and an *asymptotically unbiased* estimator.

D. Rezende & S. Mohamed, ICML 2016 · M. Albergo et al., PRD 2019 · K. Nicoli et al., PRE 2019

Flow-based generative sampling



Invertibility allows for tractable and exact probability estimation, enabling reweighting and an *asymptotically unbiased* estimator.

- Sampling is i.i.d. and highly parallelizable
- Data free training

D. Rezende & S. Mohamed, ICML 2016 · M. Albergo et al., PRD 2019 · K. Nicoli et al., PRE 2019

The sign problem in the Hubbard model

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Problem

Finite chemical potential μ breaks the charge symmetry that kept the probability weight positive and real.

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Solution

We sample the **sign-quenched** theory $|w|$, then restore the sign by reweighting.

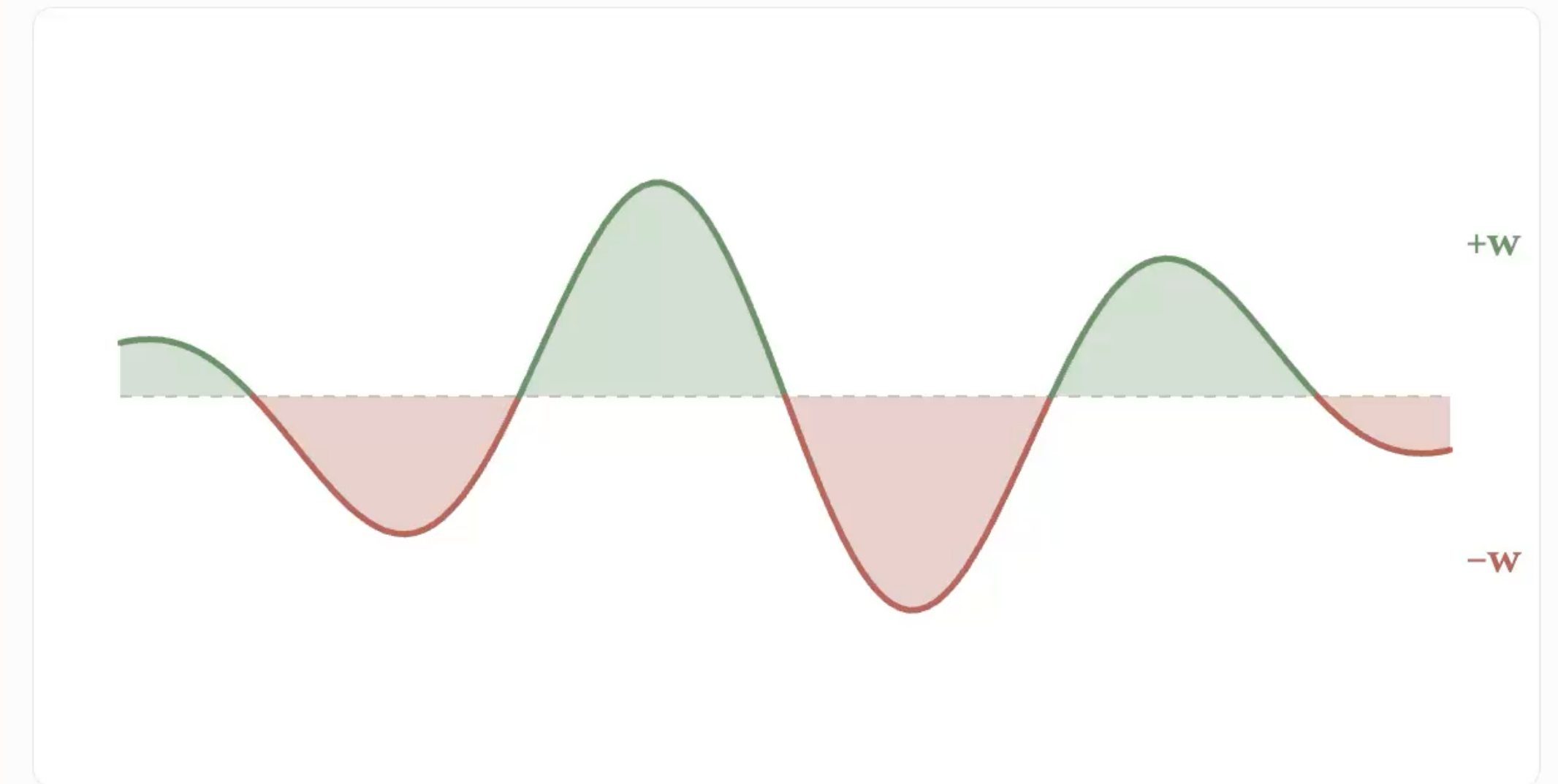
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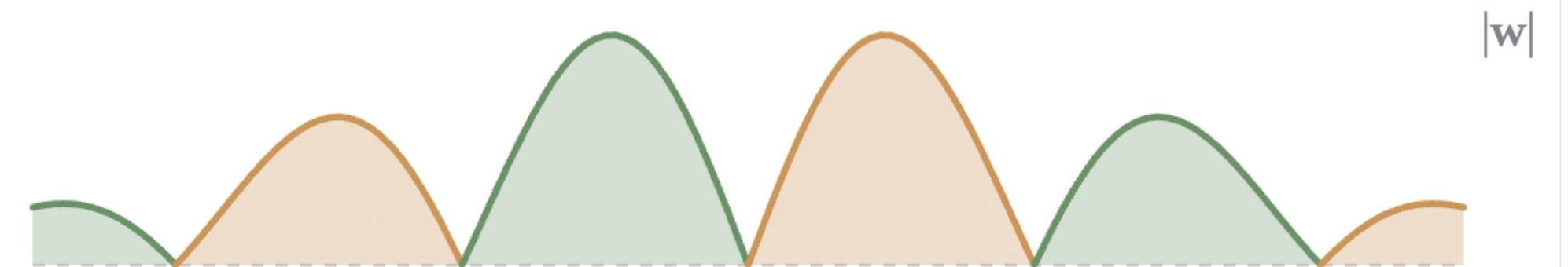
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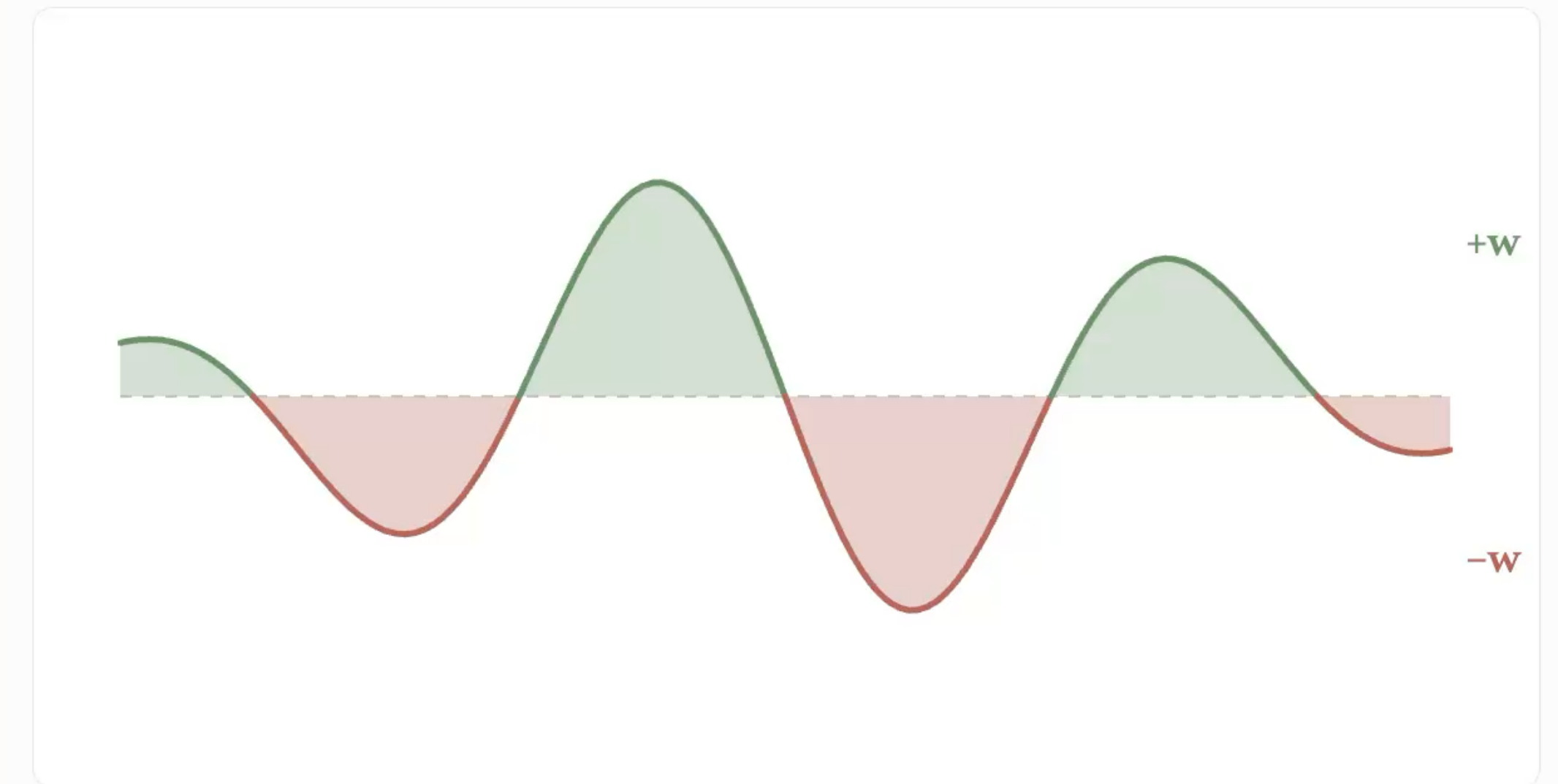
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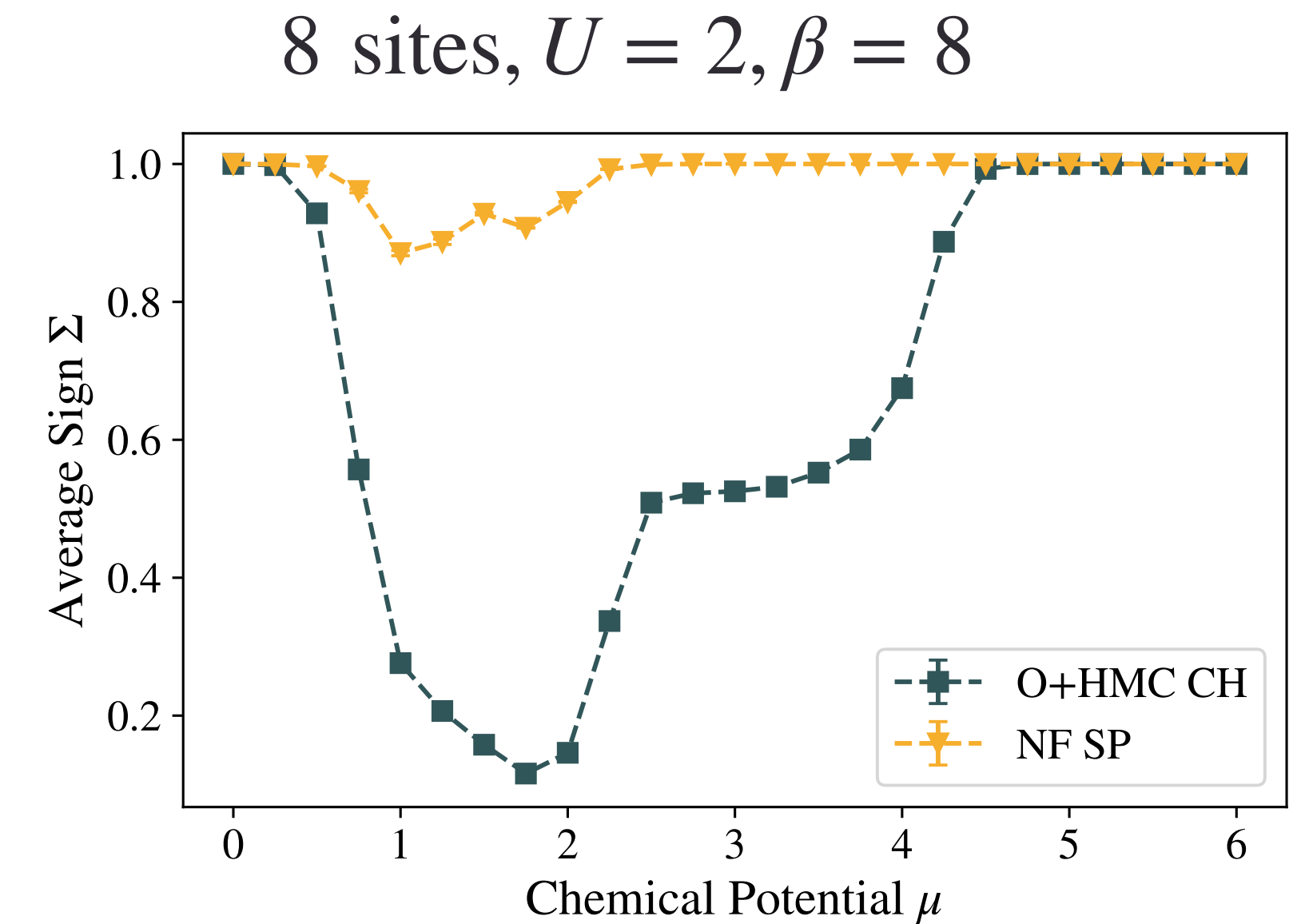
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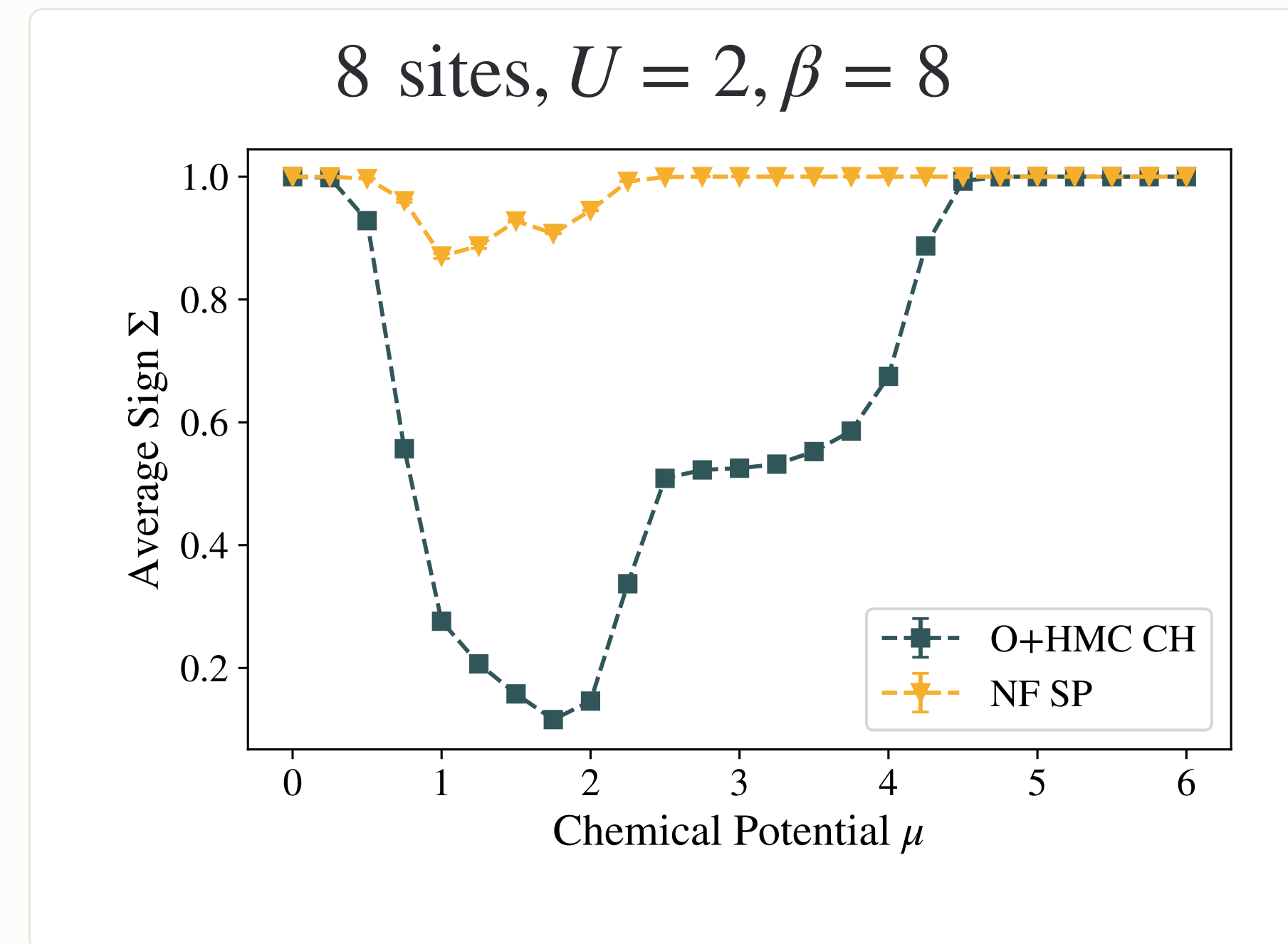
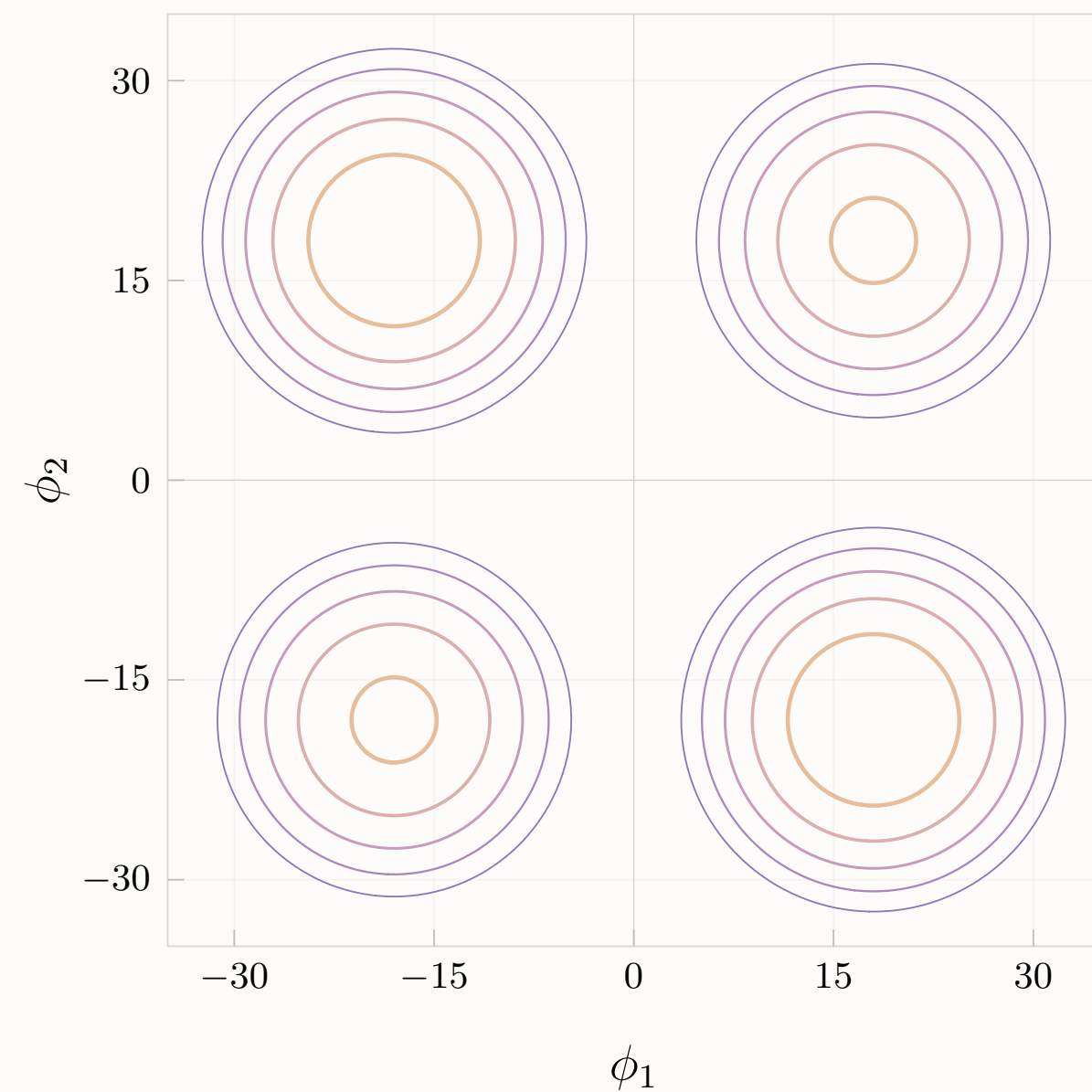
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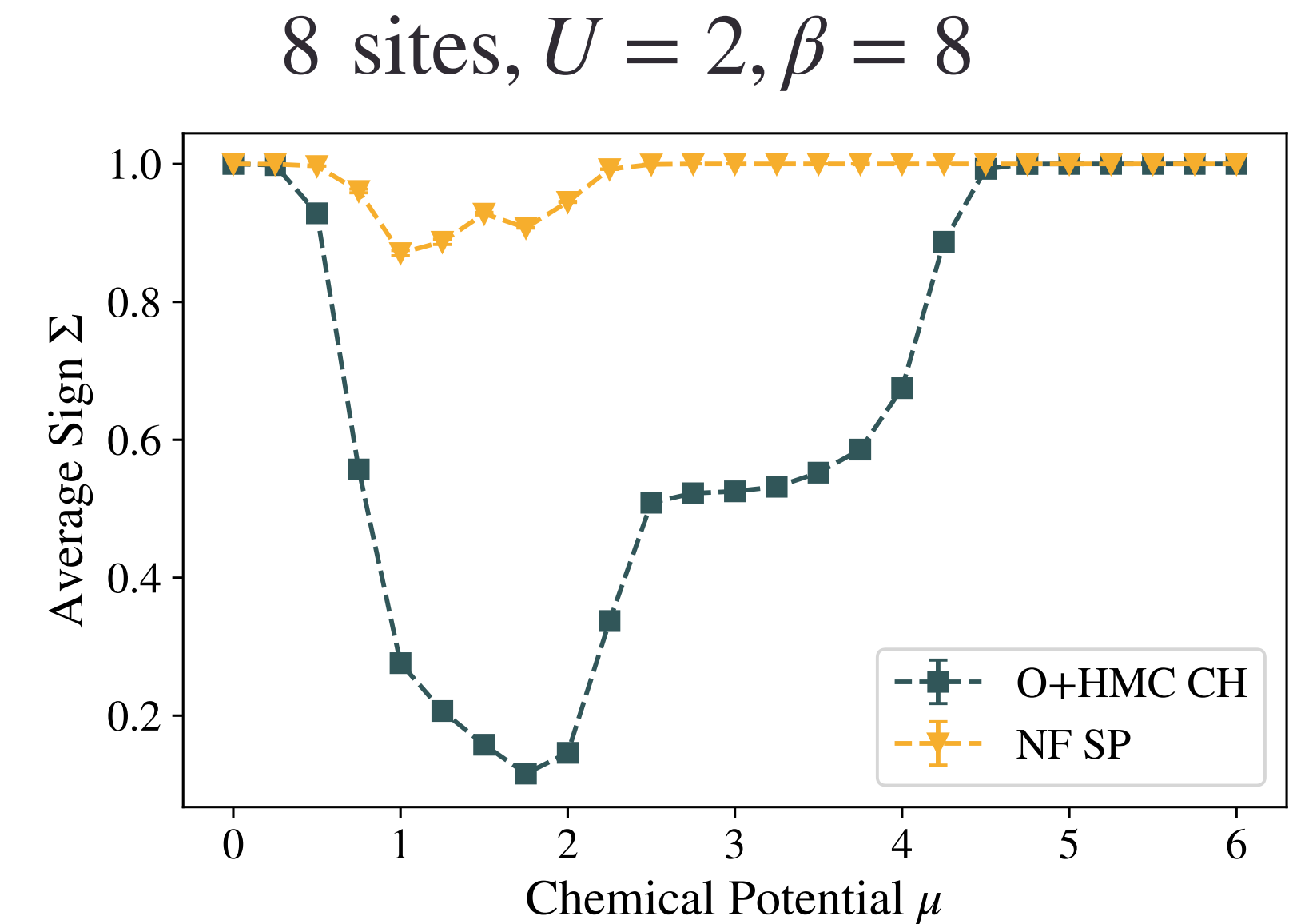
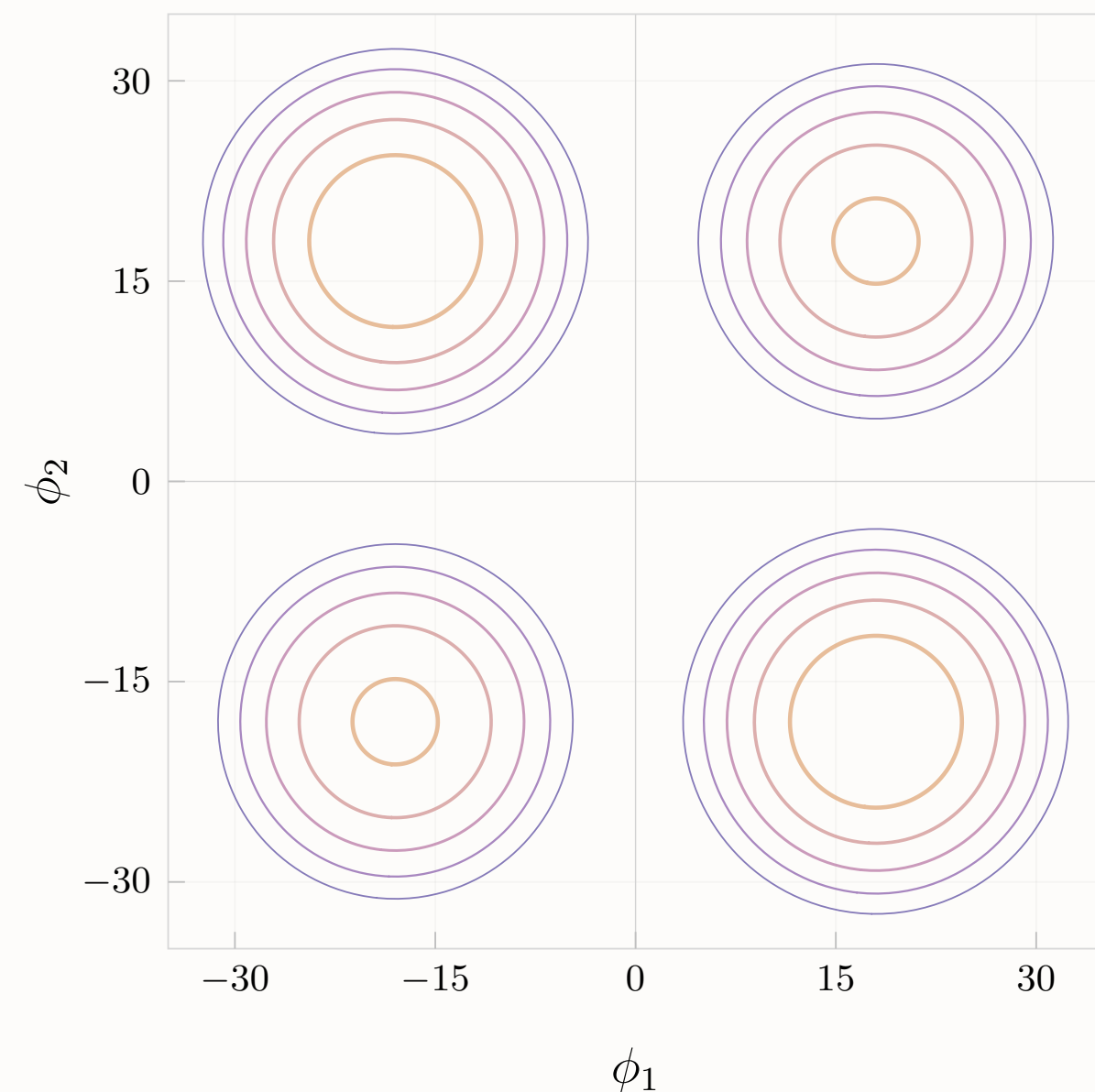
The sign problem in the Hubbard model



SPIN-BASIS TRADEOFF

Sign problem is structurally milder, but ergodicity concerns limit its applicability.

The sign problem in the Hubbard model



SPIN-BASIS TRADEOFF

Sign problem is structurally milder, but ergodicity concerns limit its applicability.

GOAL

Find a way to ergodically simulate the spin basis at intermediate couplings and finite density.

Annealing to the target distribution

Goal: get training signal from every mode, without deterministic symmetry transformations.

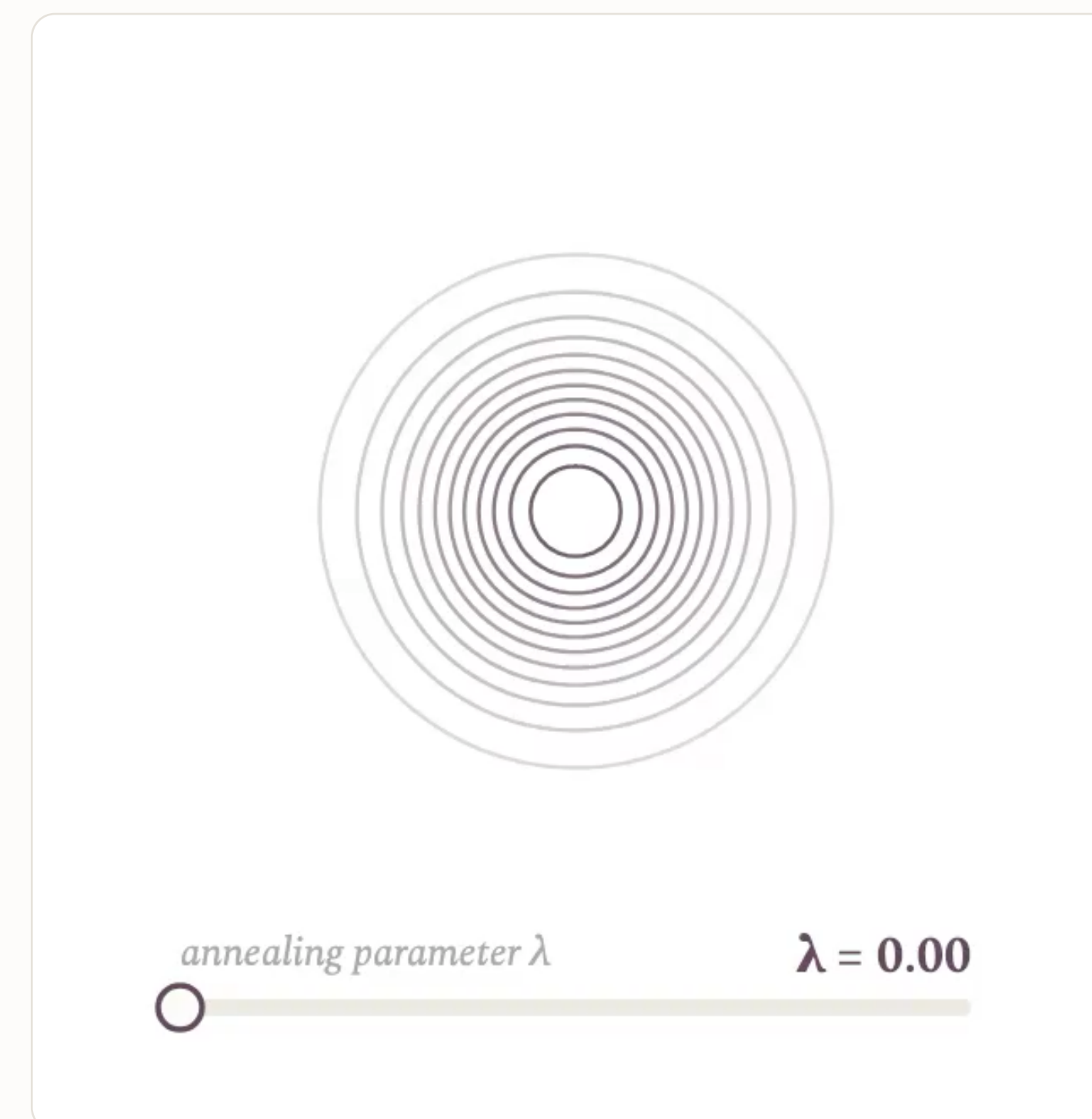
$$S_q[\phi] = \sum_{x,t \in \Lambda} \frac{\phi_{x,t}^2}{2\tilde{U}} - \log \left| \det (M[\phi]M[-\phi]) \right|$$

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$$S_{q,\lambda}[\phi] = \sum_{x,t \in \Lambda} \frac{\phi_{x,t}^2}{2\tilde{U}} - \lambda \cdot \log \left| \det (M[\phi]M[-\phi]) \right|$$

Smoothly introduce multimodality by slowly ramping fermionic contributions from $\lambda = 0$ to $\lambda = 1$ at the beginning of training.

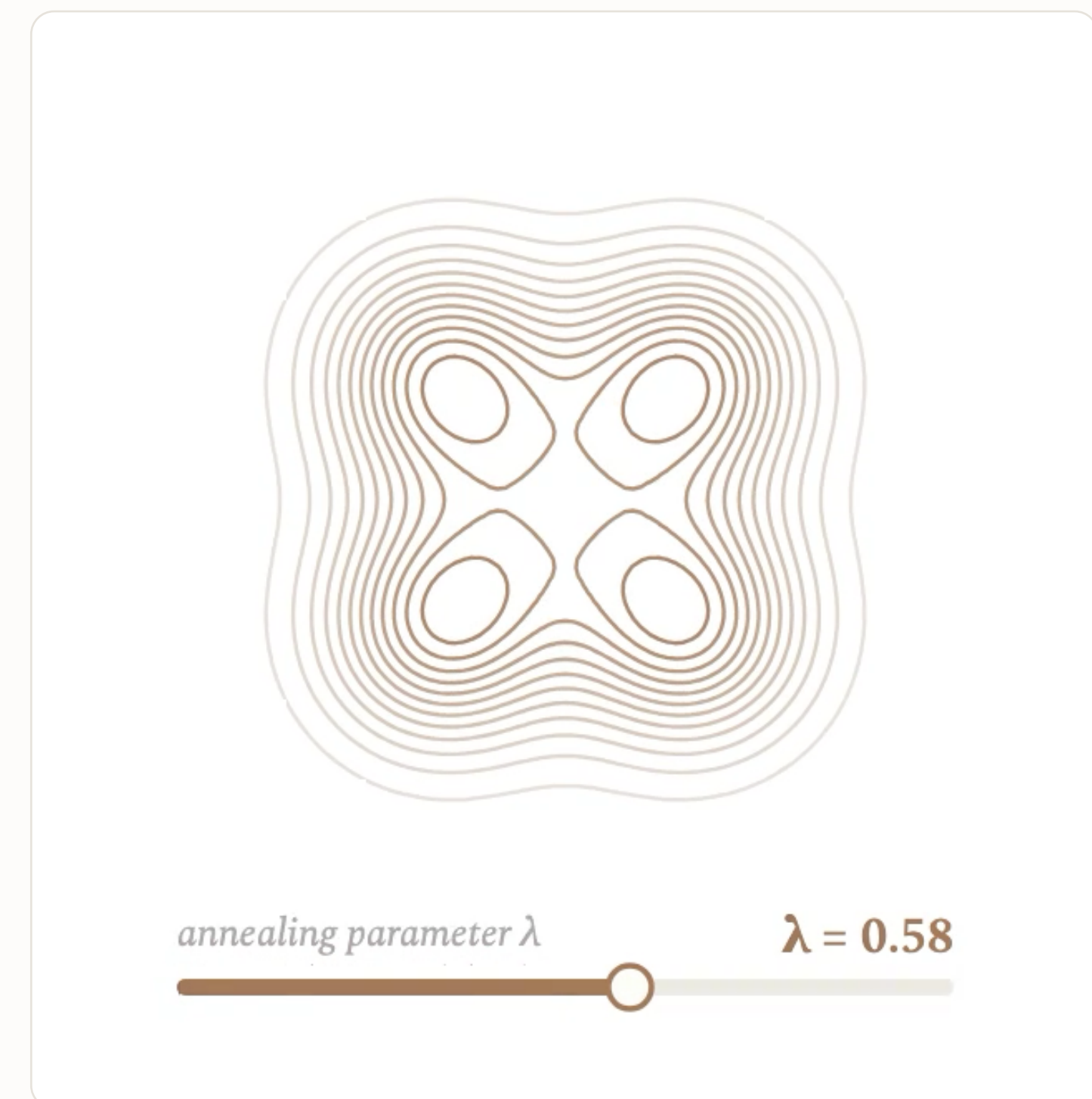


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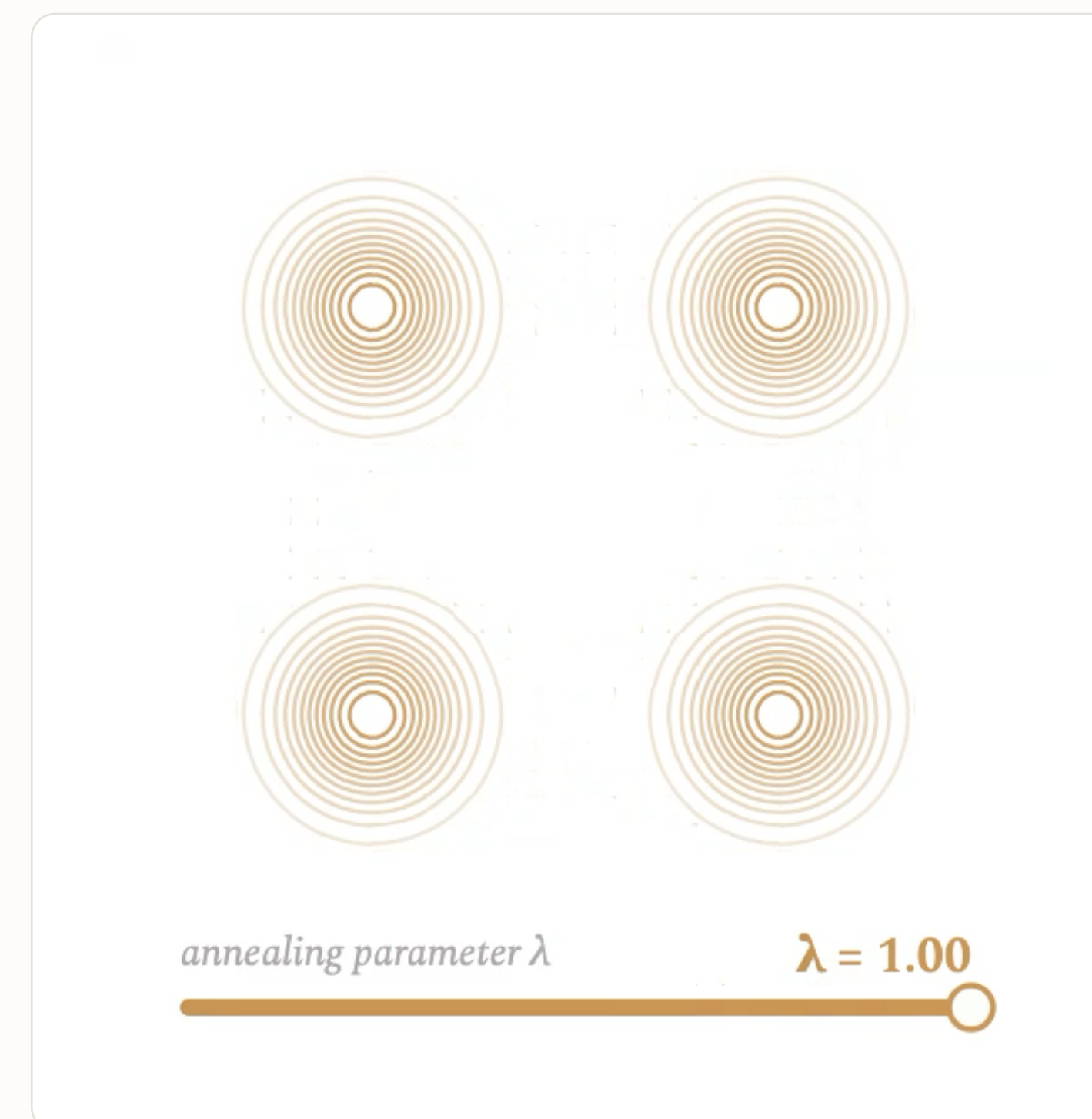


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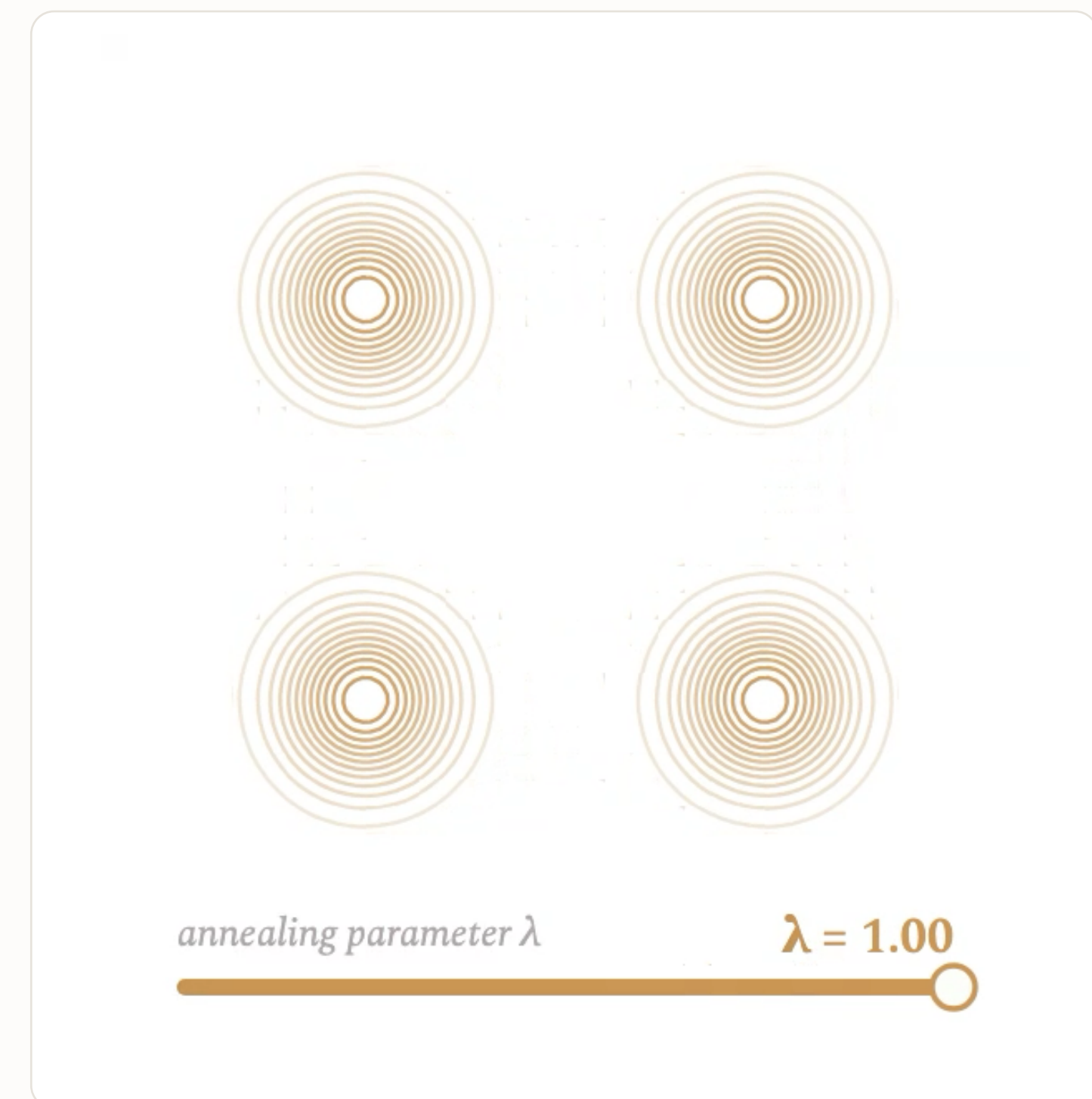
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Signal from *every mode* — independent of volume and parameter regime.



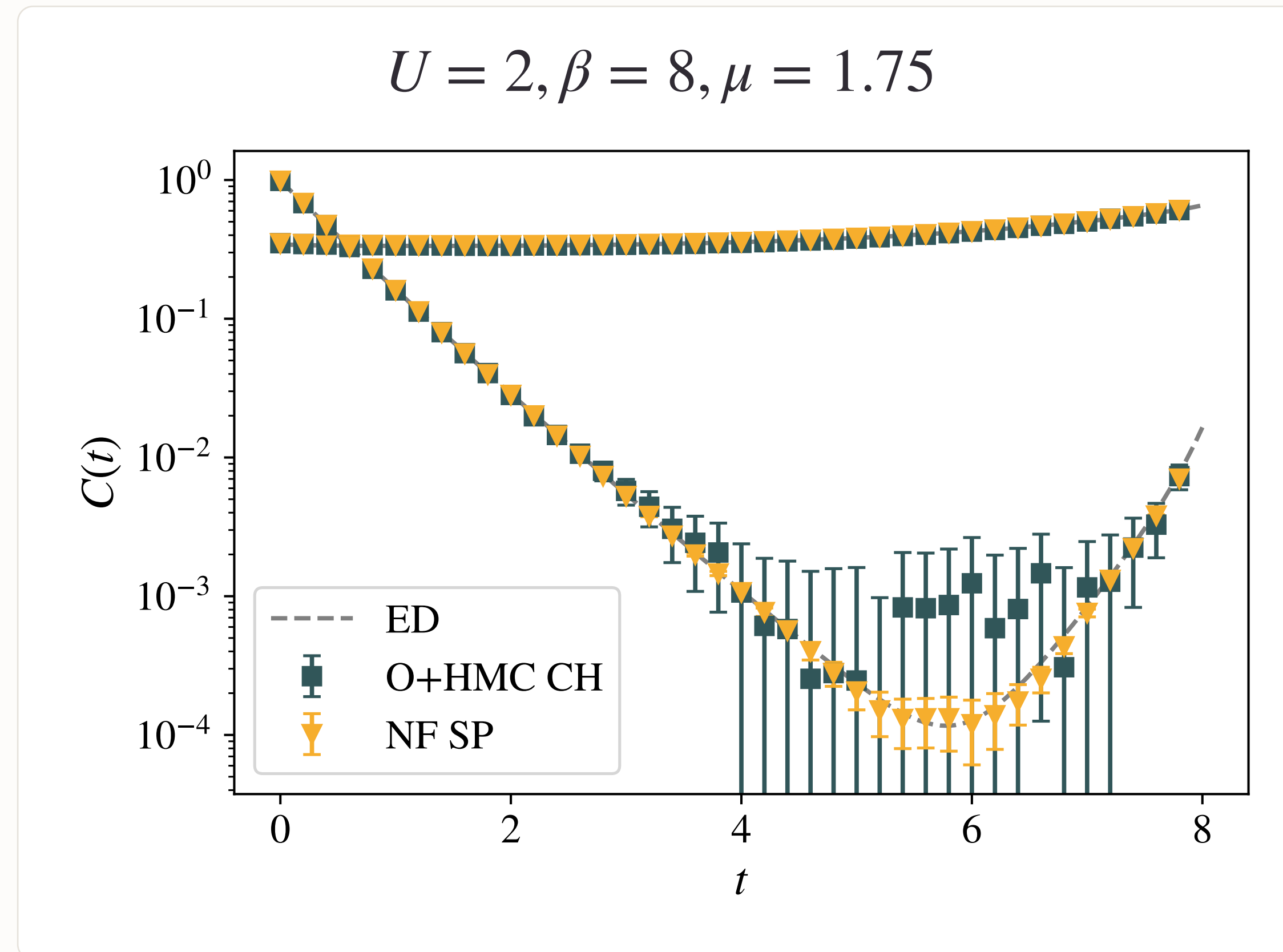
One-body correlation function

$$C_{xy}(t) = \left\langle a_x(t) a_y^\dagger(0) \right\rangle$$

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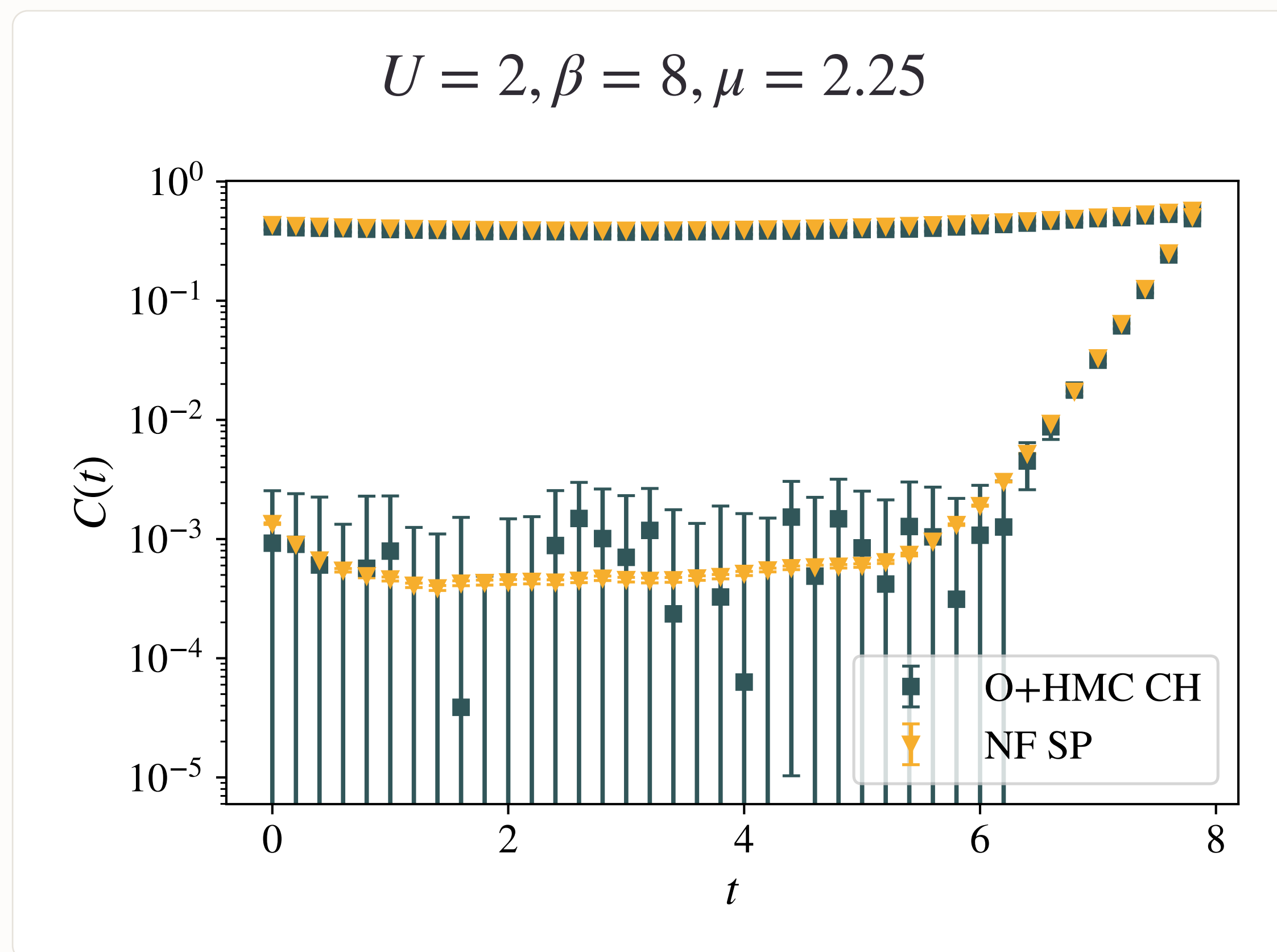
$$C_{xy}(t) = \left\langle a_x(t) a_y^\dagger(0) \right\rangle = \left\langle M_{(x,t);(y,0)}^{-1}[\phi] \right\rangle$$

8-sites correlator



$C(t)$ vs. Euclidean time — orange ∇ : NF (spin basis); dark $\blacksquare$: HMC with optimized shifts (particle/hole basis)

18-sites correlator



$C(t)$ vs. Euclidean time — orange ∇ : NF (spin basis); dark $\blacksquare$: HMC with optimized shifts (particle/hole basis)

Conclusion

Conclusion & outlook

Applied **flow-based sampling** with **annealing** to the Hubbard model at finite chemical potential.

Simulated **ergodically in the spin basis** with lower uncertainties.

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In collaboration with



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Lena Funcke



Thomas Luu

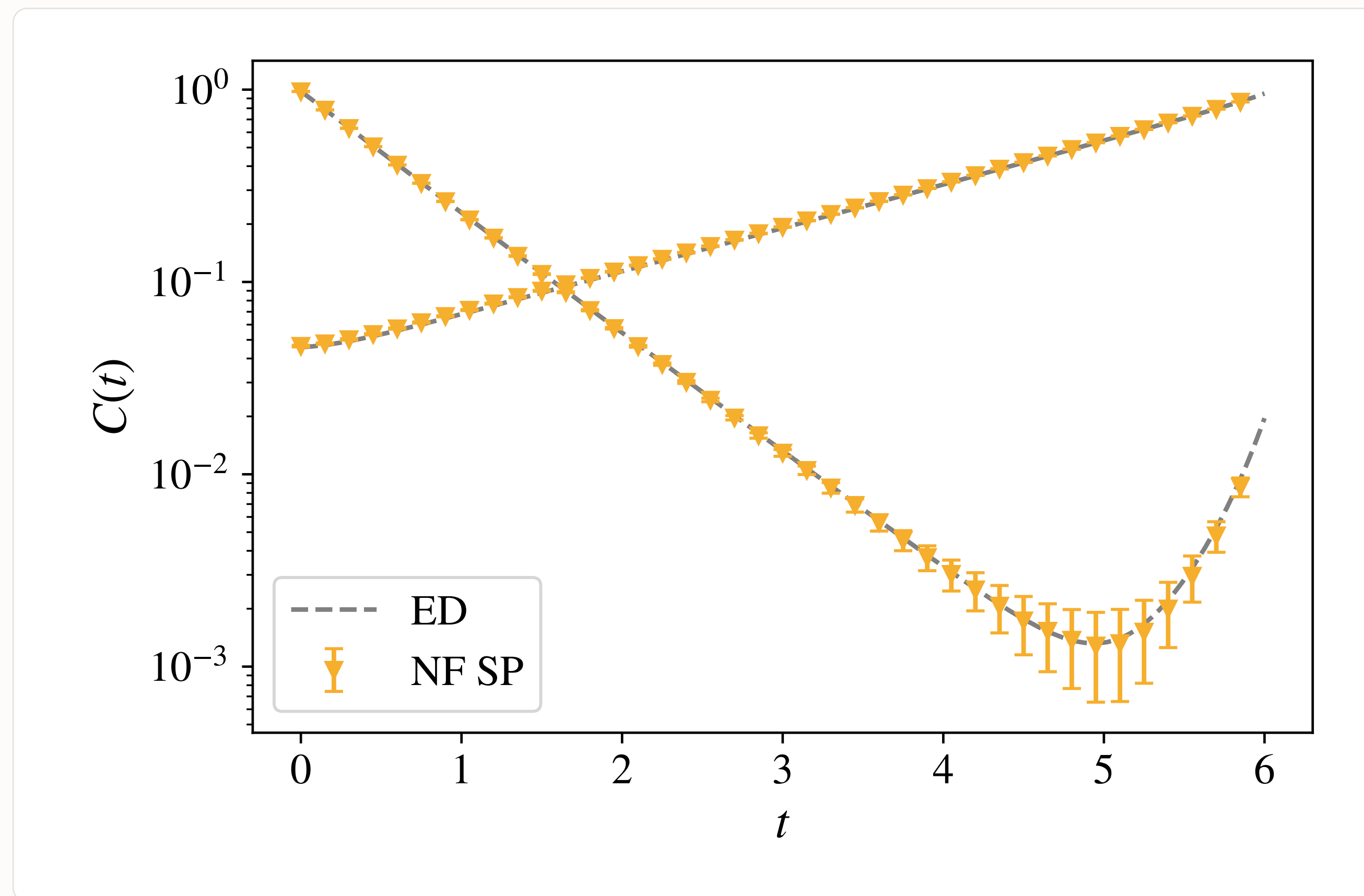


Simran Singh

Thank You!

Backup

Annealing 8-sites $U = 3$



Annealing HMC comparison 8-sites $U = 2$

