

OVERCOMING ERGODICITY PROBLEMS OF THE HMC USING RADIAL UPDATES

JULY 30TH 2024 | FINN TEMMEN | FORSCHUNGSZENTRUM JÜLICH

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IN COLLABORATION WITH

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XINHAO YU	(UNIVERSITY OF EDINBURGH)
EVAN BERKOWITZ	(FORSCHUNGSZENTRUM JÜLICH)
THOMAS LUU	(FORSCHUNGSZENTRUM JÜLICH)



MOTIVATION

Ergodicity and convergence of HMC

Ergodicity violations due to potential barriers

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Ergodicity violations due to potential barriers

- In-principle: infinite potential, e.g. vanishing fermion determinant
- In-practice: regions separated by exponentially large potential

[Wynen et al., arXiv:1812.09268]

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Convergence of HMC

- Proof for geometrical convergence of HMC on non-compact manifolds

[Kennedy, Yu, to be published]

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**Radial updates:
Augment HMC with Metropolis-Hastings update in radial direction**

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MOTIVATION

Ergodicity and convergence of HMC

Talk by Dominic Schuh at 4:15 PM
"Simulating the Hubbard Model
with Normalizing Flows"

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**Radial updates:
Augment HMC with Metropolis-Hastings update in radial direction**

HUBBARD MODEL

Setting the stage

- Hubbard Hamiltonian in particle/hole basis

$$H = -\kappa \sum_{\langle x,y \rangle} (a_x^\dagger a_y - b_x^\dagger b_y) + \frac{U}{2} \sum_x (a_x^\dagger a_x - b_x^\dagger b_x)^2$$

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- Exponential discretization
- Hubbard-Stratonovich introduces non-compact auxiliary fields ϕ_{xt}
- Integrate out fermionic DoF

$$S[\phi] = \frac{N_t}{2U\beta} \sum_{x,t} \phi_{xt}^2 - \log \det M[i\phi] - \log \det M[-i\phi]$$

HUBBARD MODEL

Setting the stage

$$S[\phi] = \frac{N_t}{2U\beta} \sum_{x,t} \phi_{xt}^2 \underbrace{-\log \det M[i\phi] - \log \det M[-i\phi]}_{\text{Fermionic contribution}}$$

- Fermion matrix: Ulybyshev et al., arXiv:1712.02188
 - Manifolds of vanishing $\det M[i\phi]$ with codimension 1
 - Separated regions constitute problem for perfect Molecular Dynamics

HUBBARD MODEL

Setting the stage

$$S[\phi] = \frac{N_t}{2U\beta} \underbrace{\sum_{x,t} \phi_{xt}^2}_{:= R^2} - \log \det M[i\phi] - \log \det M[-i\phi]$$

- Fermion matrix:

Ulybyshev et al., arXiv:1712.02188

- Manifolds of vanishing $\det M[i\phi]$ with codimension 1
- Separated regions constitute problem for perfect Molecular Dynamics

- Define radius $R = \sqrt{\sum_{x,t} \phi_{xt}^2}$

RADIAL UPDATES

Initial configuration $\phi = (\phi_1, \phi_2, \dots, \phi_d)$



- e.g. output of HMC

RADIAL UPDATES

Initial configuration $\phi = (\phi_1, \phi_2, \dots, \phi_d)$

Sample update $\gamma \sim \mathcal{N}(0, \sigma^2)$

- e.g. output of HMC
- Tunable standard deviation σ

RADIAL UPDATES

Initial configuration $\phi = (\phi_1, \phi_2, \dots, \phi_d)$

Sample update $\gamma \sim \mathcal{N}(0, \sigma^2)$

Propose new configuration

$$\tilde{\phi} = e^\gamma \phi$$

- e.g. output of HMC
- Tunable standard deviation σ
- Scales radius $\tilde{R} = e^\gamma R$
- e^γ has median of 1

RADIAL UPDATES

Initial configuration $\phi = (\phi_1, \phi_2, \dots, \phi_d)$

Sample update $\gamma \sim \mathcal{N}(0, \sigma^2)$

Propose new configuration
 $\tilde{\phi} = e^\gamma \phi$

Accept/reject with acceptance probability
 $\alpha(\phi, \tilde{\phi}) = \min(1, \exp\{-\Delta S + d\gamma\})$

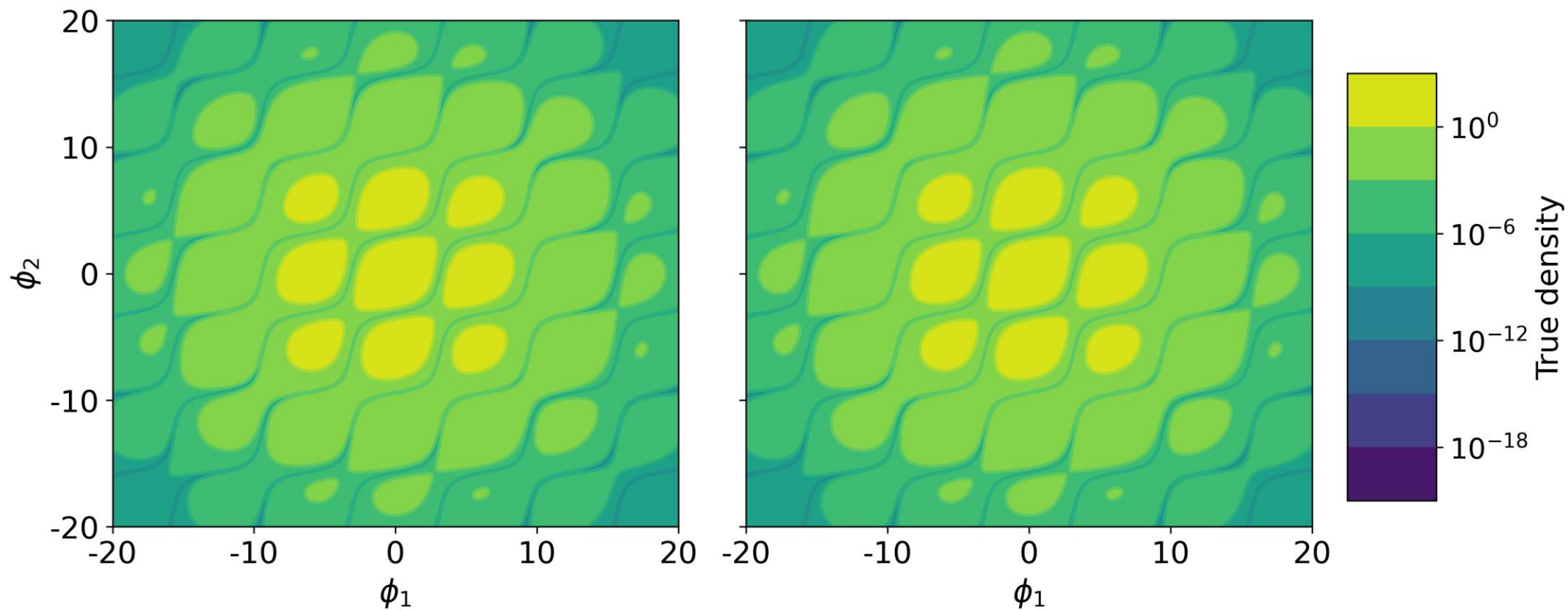
- e.g. output of HMC
- Tunable standard deviation σ
- Scales radius $\tilde{R} = e^\gamma R$
- e^γ has median of 1
- Independent of proposal distribution
- Low computational cost
- Special case of RDMH or TMCMC
- Satisfies detailed balance

Dutta, arXiv:1008.5227v2 & Dutta et al., arXiv:1106.5850v3

RESULTS

Resolving ergodicity violations

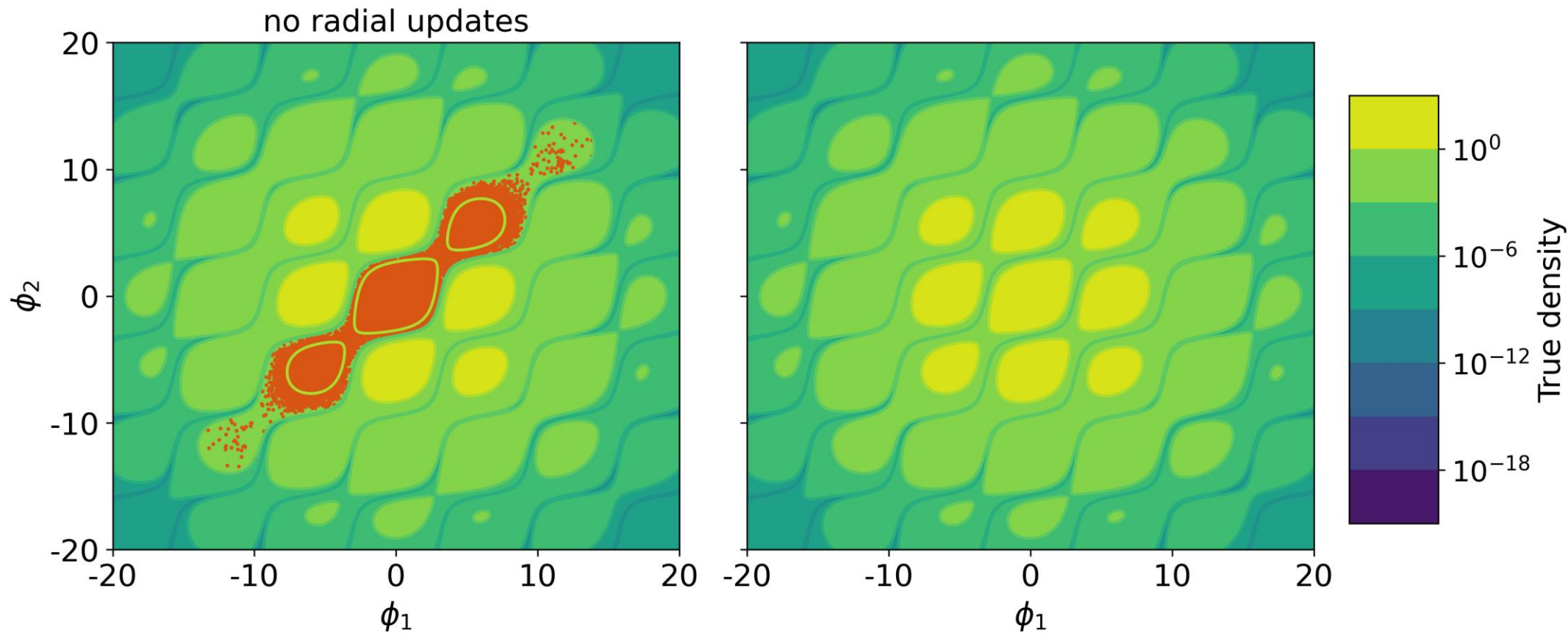
$$N_x = 2, N_t = 1, U = 18, \beta = \kappa = 1$$



RESULTS

Resolving ergodicity violations

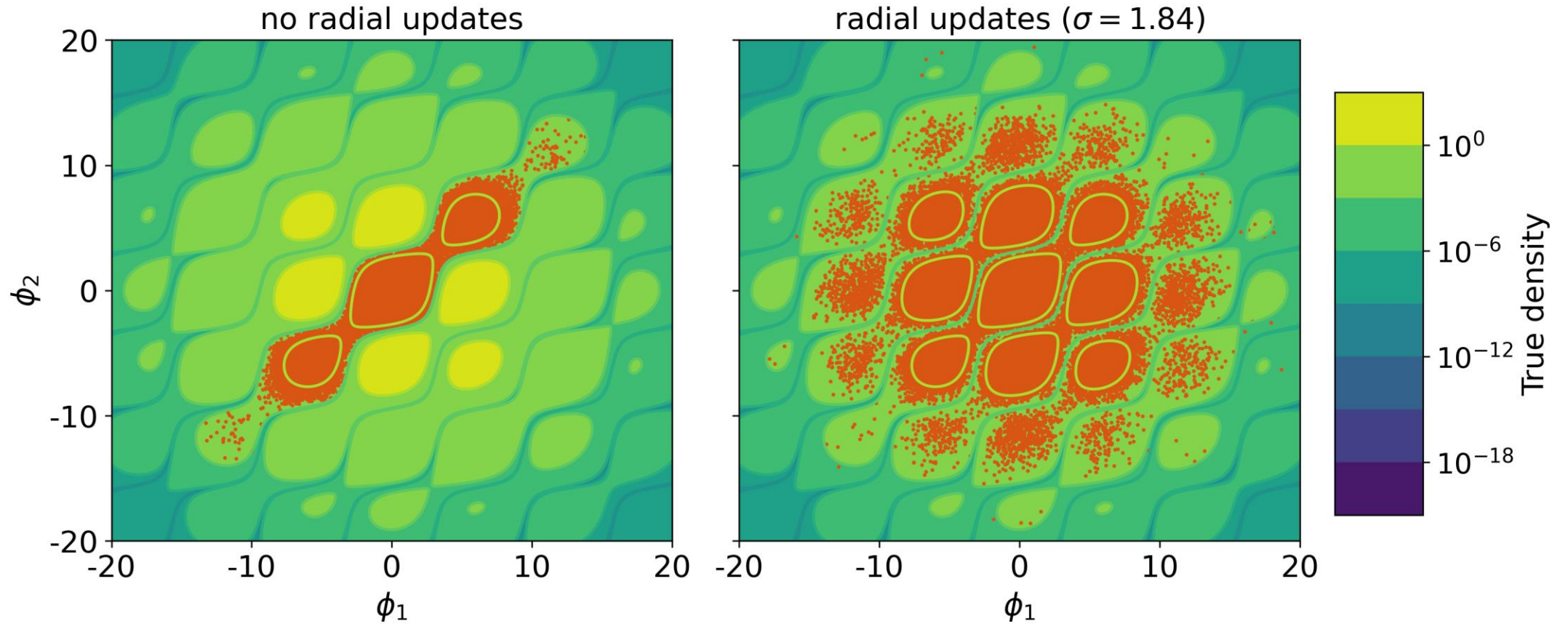
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RESULTS

Resolving ergodicity violations

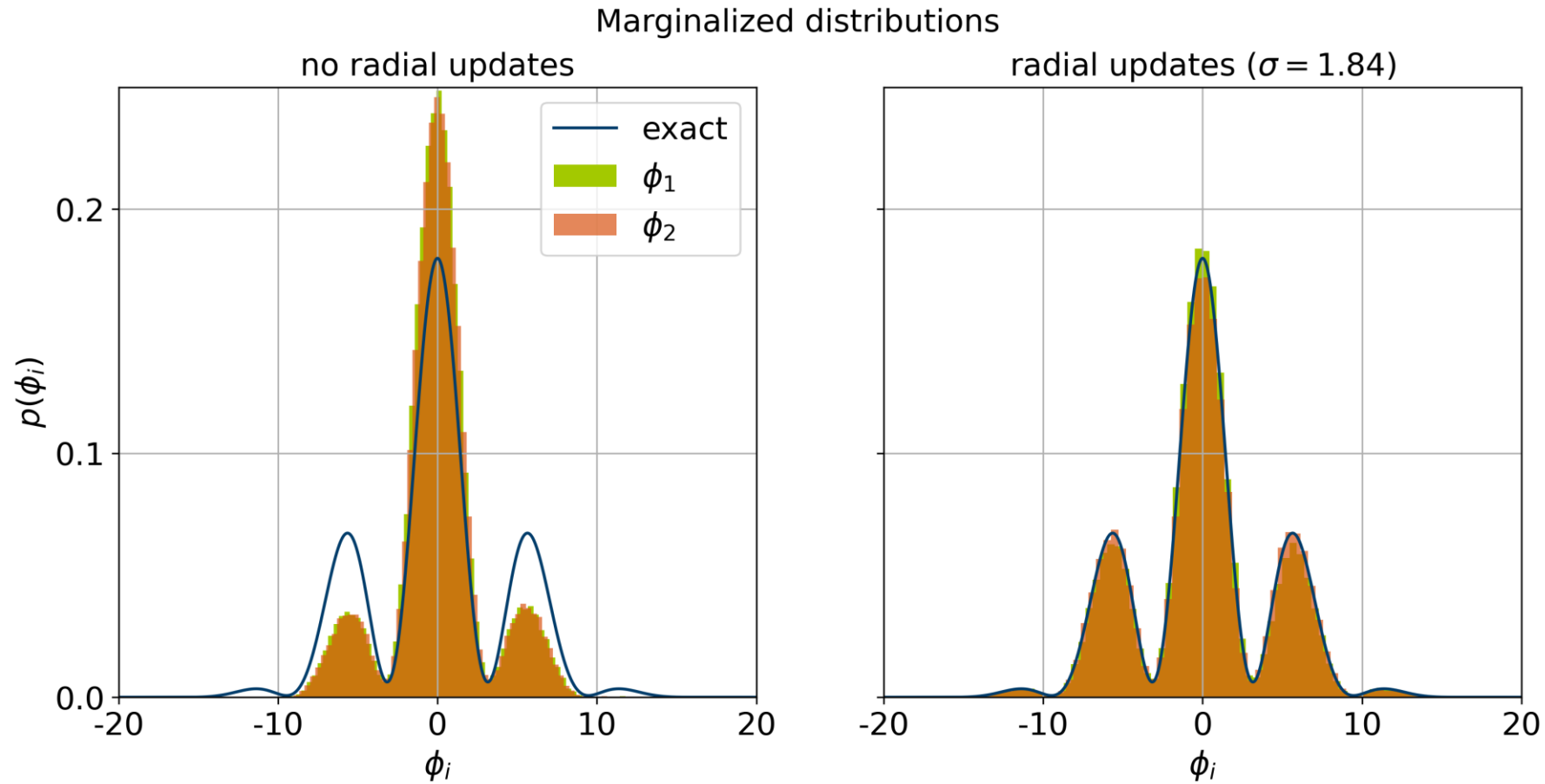
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RESULTS

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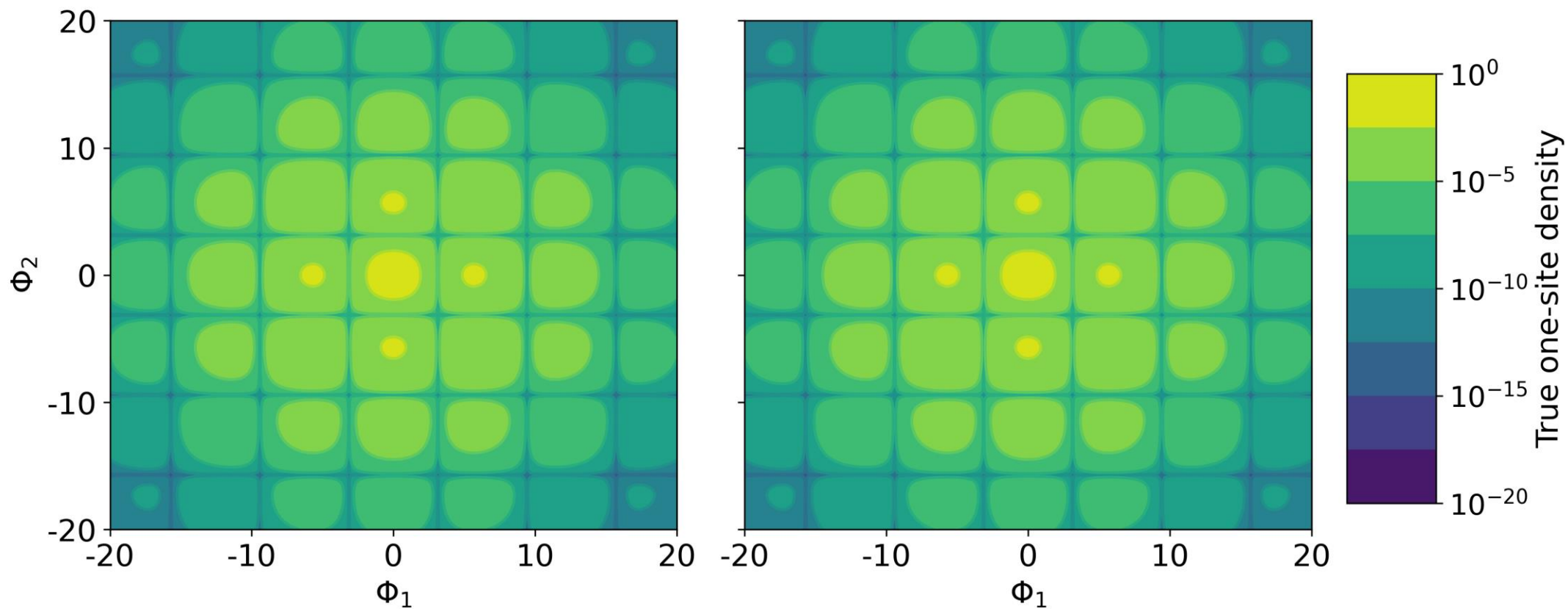


RESULTS

Resolving ergodicity violations

$$\Phi_x = \sum_t \phi_{xt}$$

$$N_x = 2, N_t = 8, U = 18, \beta = \kappa = 1$$

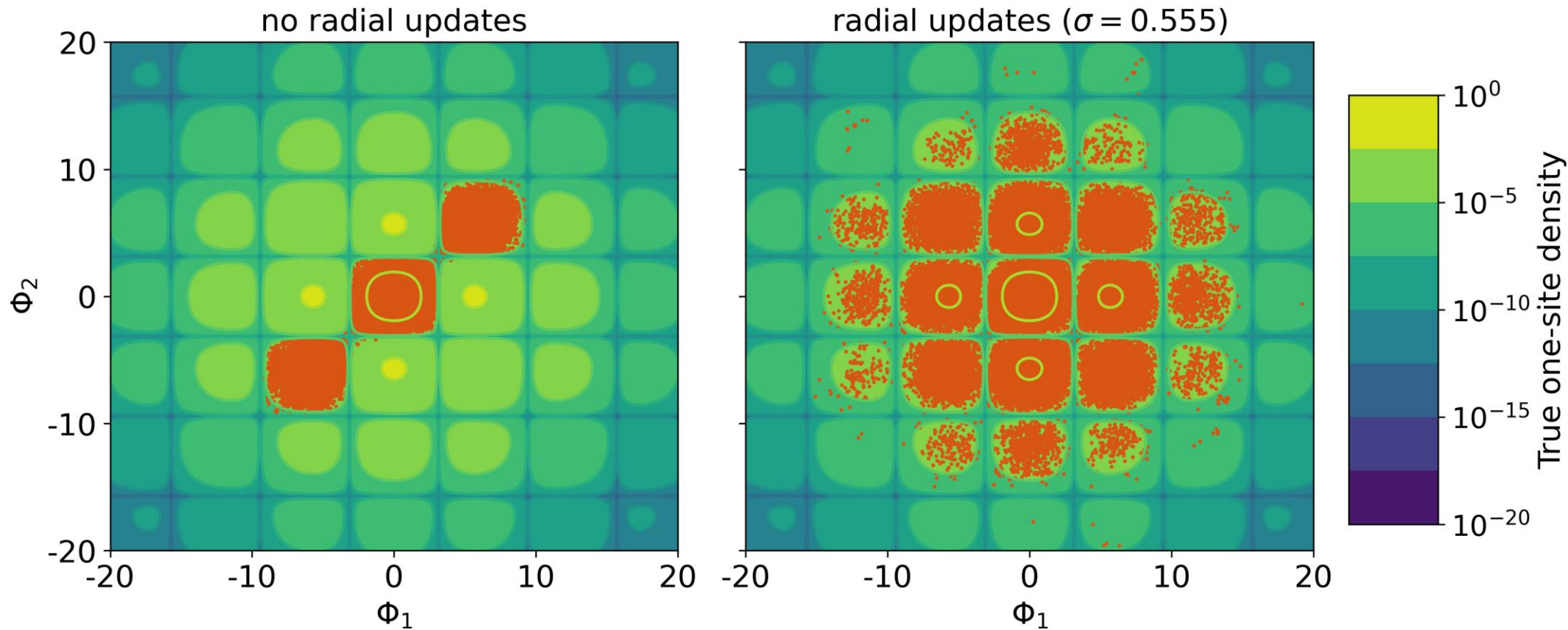


RESULTS

Resolving ergodicity violations

$$\Phi_x = \sum_t \phi_{xt}$$

$$N_x = 2, N_t = 8, U = 18, \beta = \kappa = 1$$



RESULTS

Autocorrelations, Scaling and Parameter Tuning

- Compute $\tau_{\theta, \text{int}}$ as a function of σ for increasing N_t

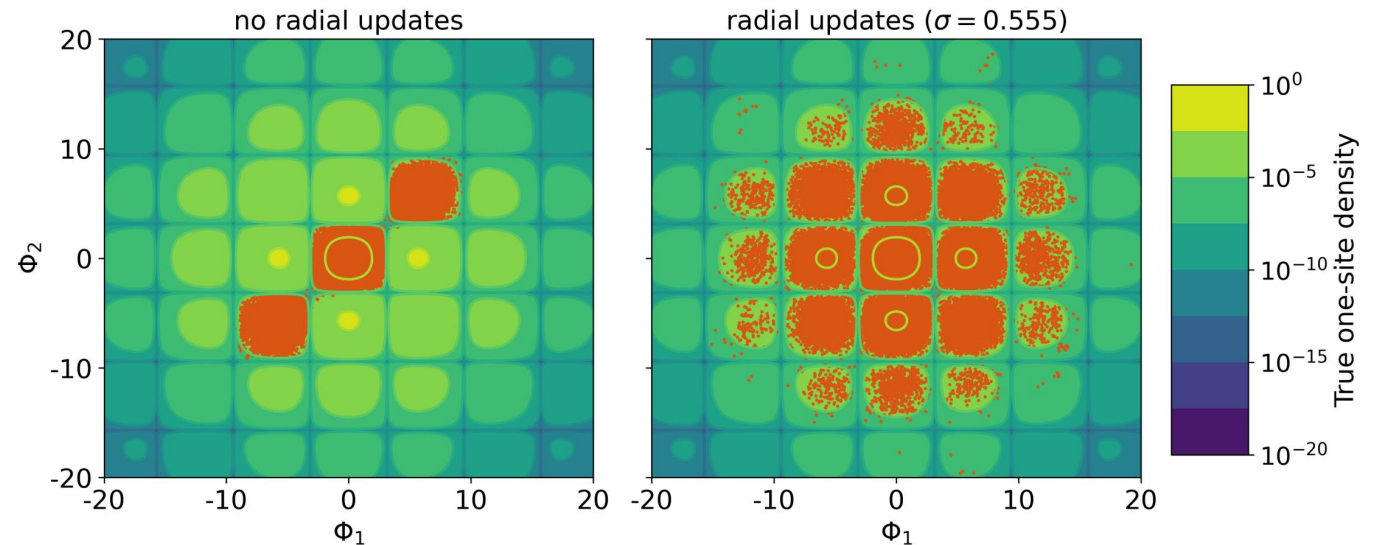
RESULTS

Autocorrelations, Scaling and Parameter Tuning

- Compute $\tau_{\mathcal{O},\text{int}}$ as a function of σ for increasing N_t
- Consider two observables:

- $\mathcal{O}_0 = \sqrt{\sum_x \Phi_x^2}$

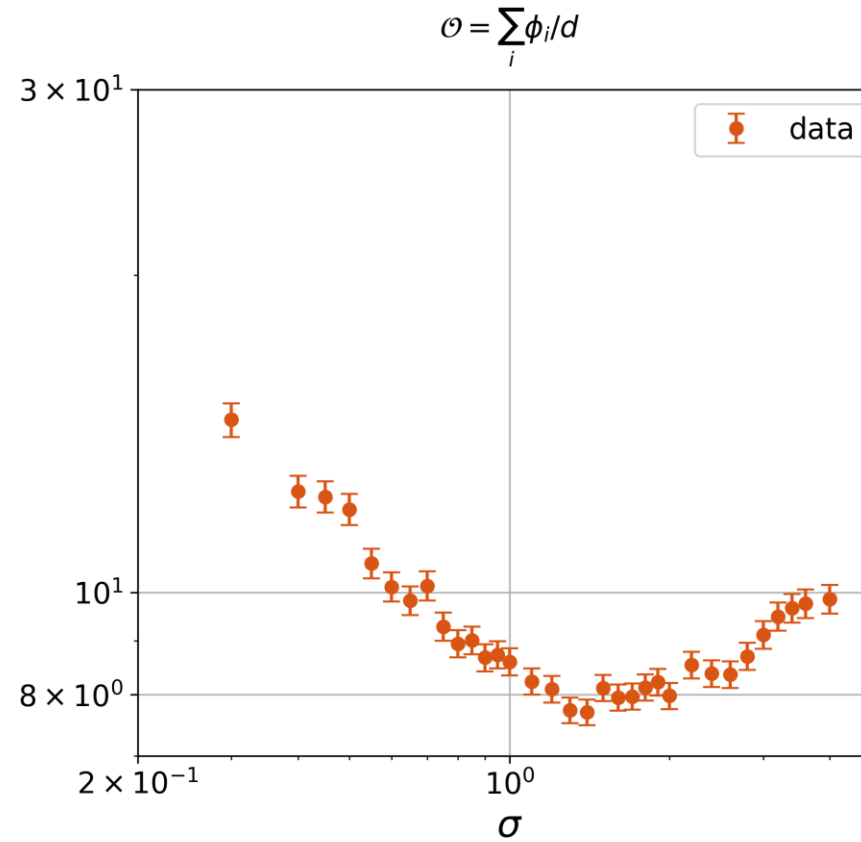
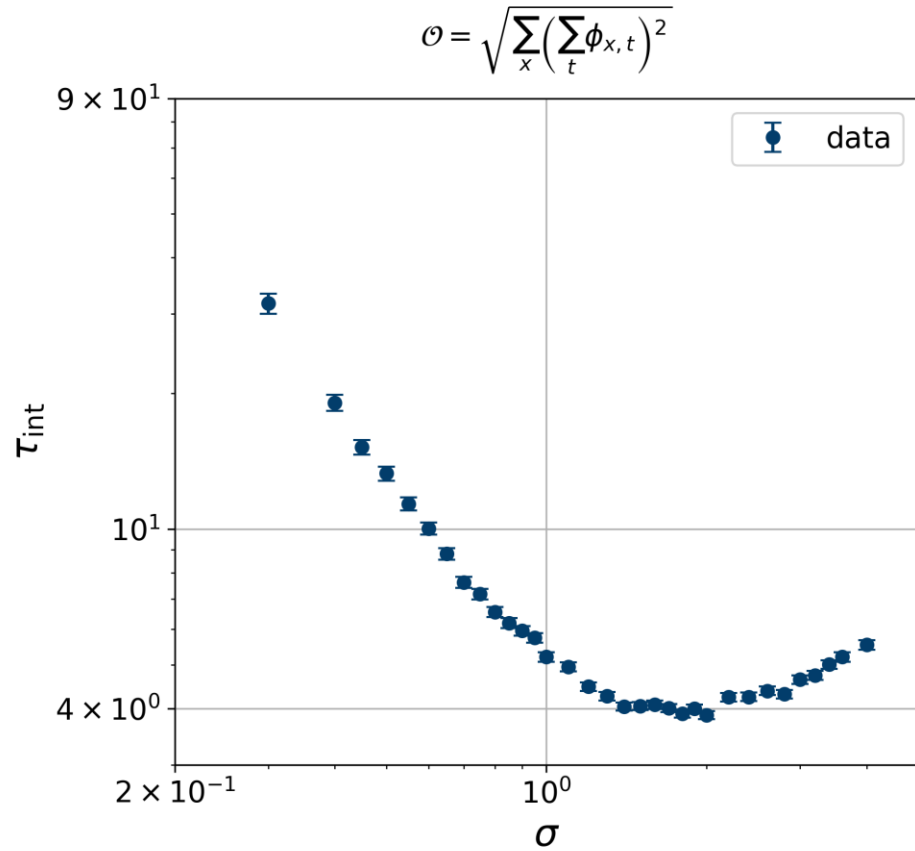
- $\mathcal{O}_1 = \sum_{xt} \phi_{xt}$ (charge)



RESULTS

Autocorrelations, Scaling and Parameter Tuning

$N_x = 2; N_t = 1$

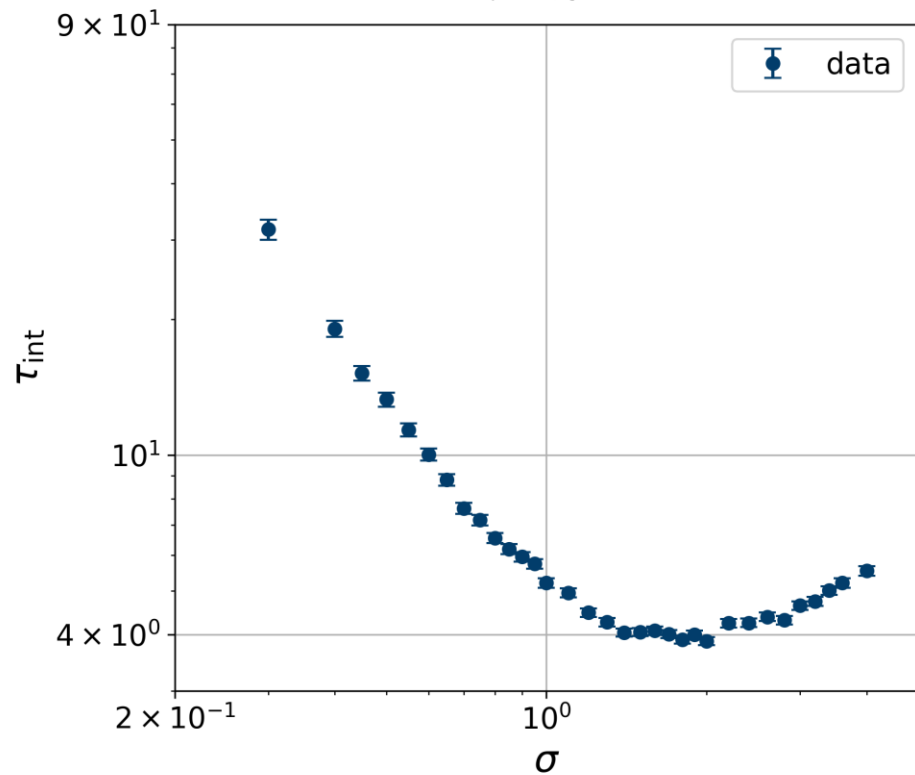


RESULTS

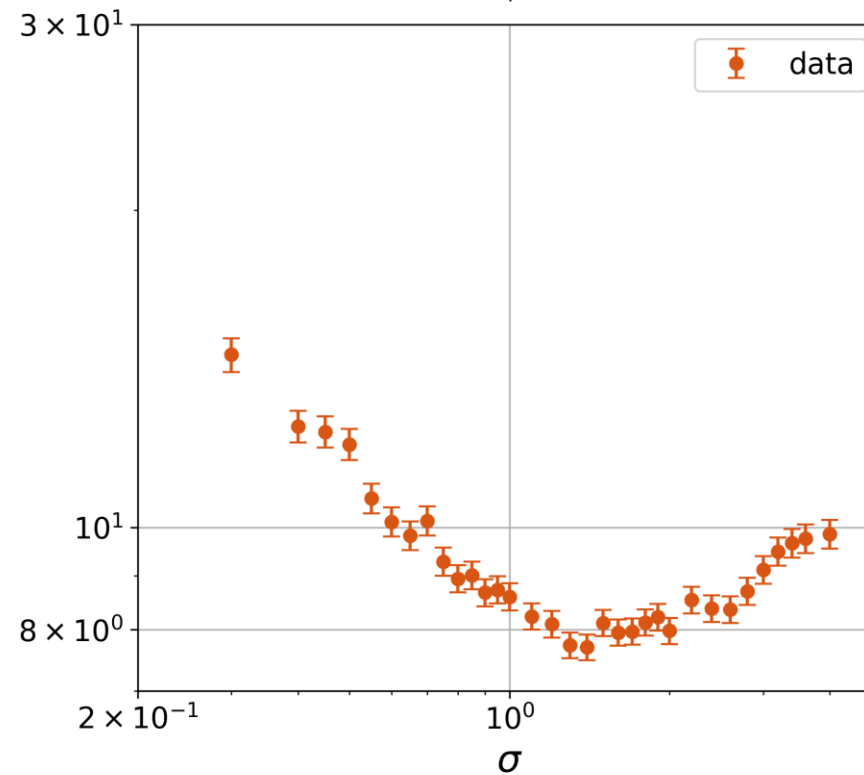
Autocorrelations, Scaling and Parameter Tuning

$$N_x = 2; N_t = 1$$

$$\vartheta = \sqrt{\sum_x \left(\sum_t \phi_{x,t} \right)^2}$$



$$\vartheta = \sum_i \phi_i / d$$

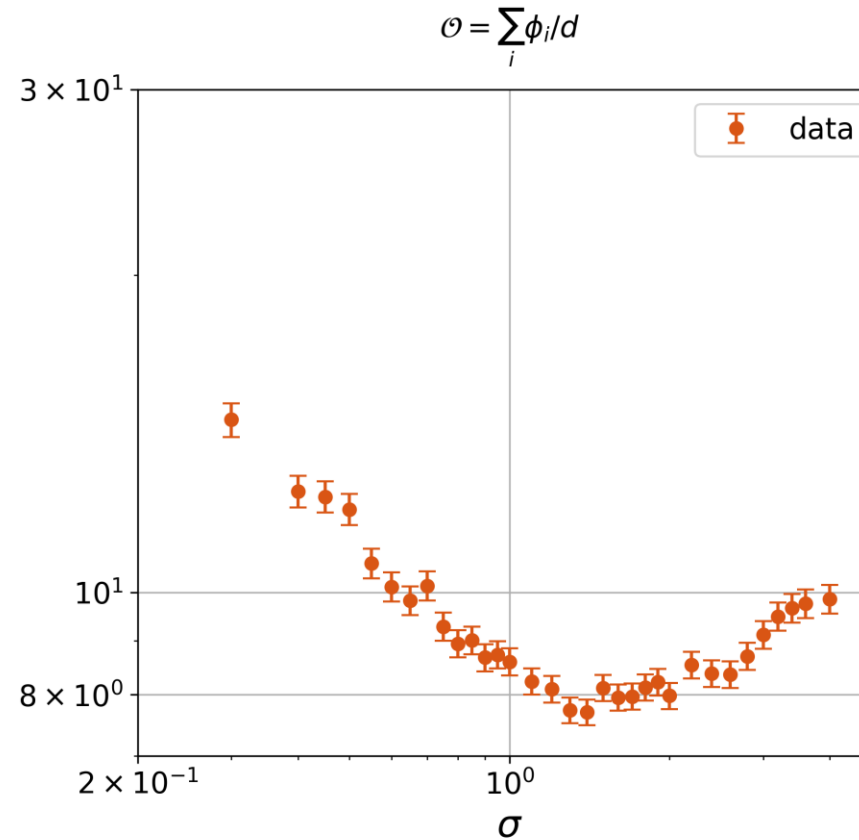
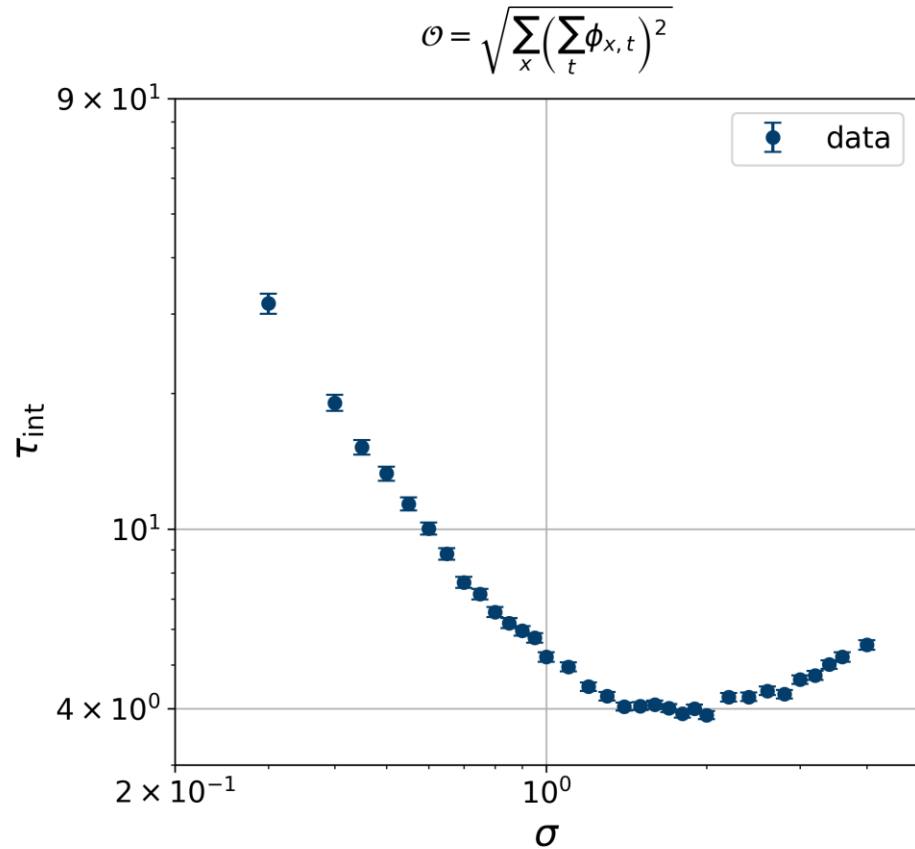


- Random walk and diffusive regime for small σ , i.e. $\tau_{\text{int}} \propto \sigma^{-2}$

RESULTS

Autocorrelations, Scaling and Parameter Tuning

$$N_x = 2; N_t = 1$$



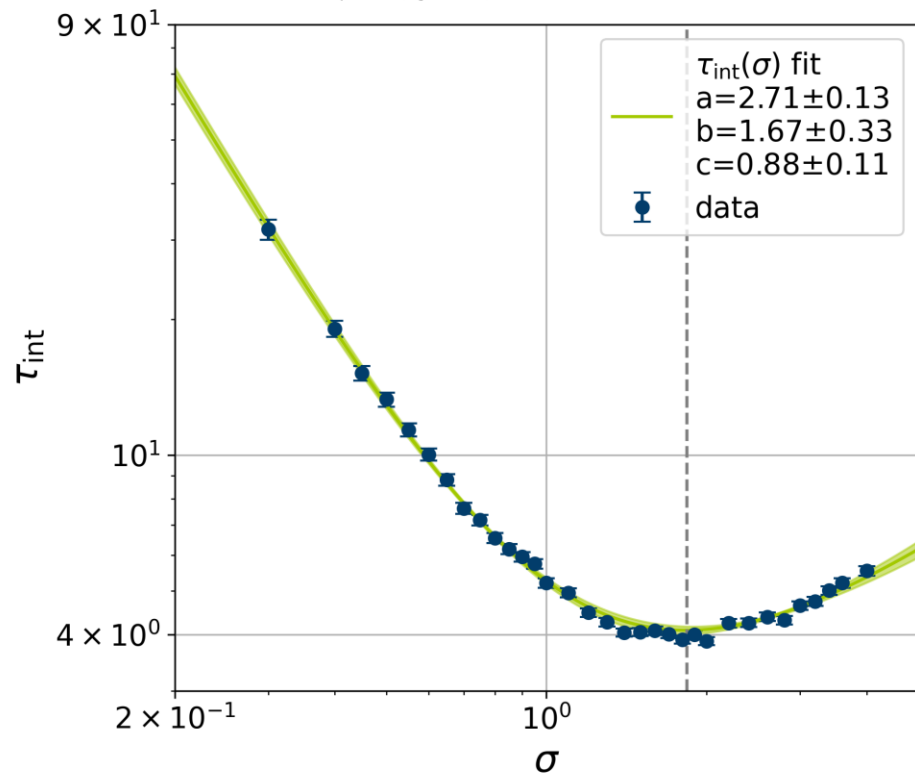
- Random walk and diffusive regime for small σ , i.e. $\tau_{\text{int}} \propto \sigma^{-2}$
- Linear regime for large σ , i.e. $\tau_{\text{int}} \propto \sigma$
- Fit function
$$\tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

RESULTS

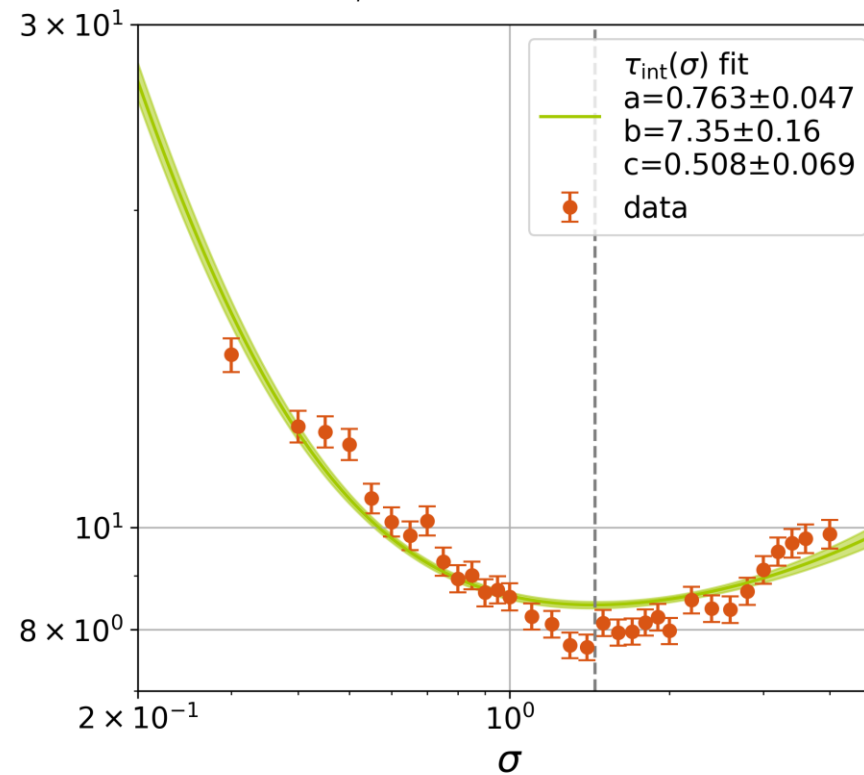
Autocorrelations, Scaling and Parameter Tuning

$$N_x = 2; N_t = 1; \text{Fit } \tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

$$\vartheta = \sqrt{\sum_x \left(\sum_t \phi_{x,t} \right)^2}; \sigma_{\text{min}} = 1.837 \pm 0.055$$



$$\vartheta = \sum_i \phi_i / d; \sigma_{\text{min}} = 1.447 \pm 0.054$$

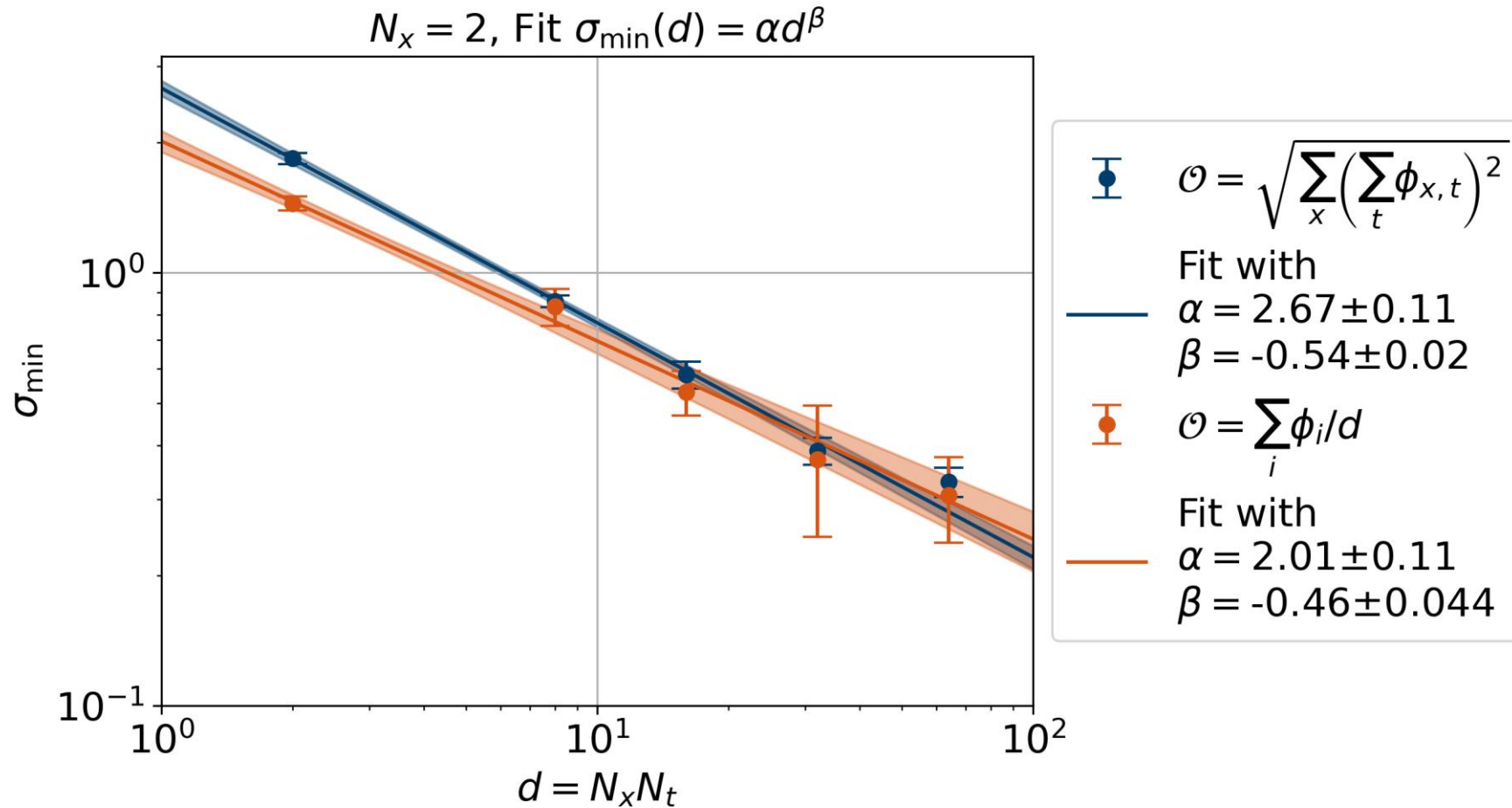


- Fit function

$$\tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

RESULTS

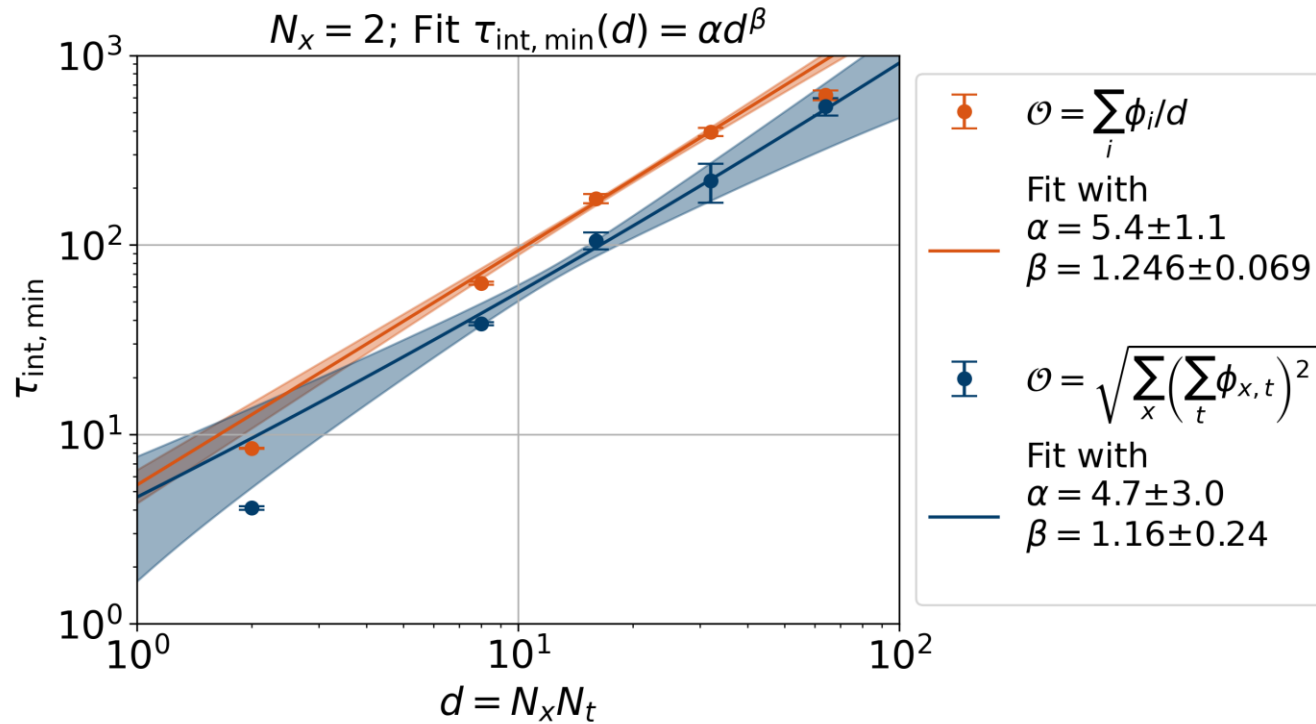
Autocorrelations, Scaling and Parameter Tuning



- From theoretical considerations
 $\sigma_{\min}(d) \propto d^{-0.5} + \mathcal{O}(d^{-1})$
- Fit function
 $\sigma_{\min}(d) = \alpha d^\beta$

RESULTS

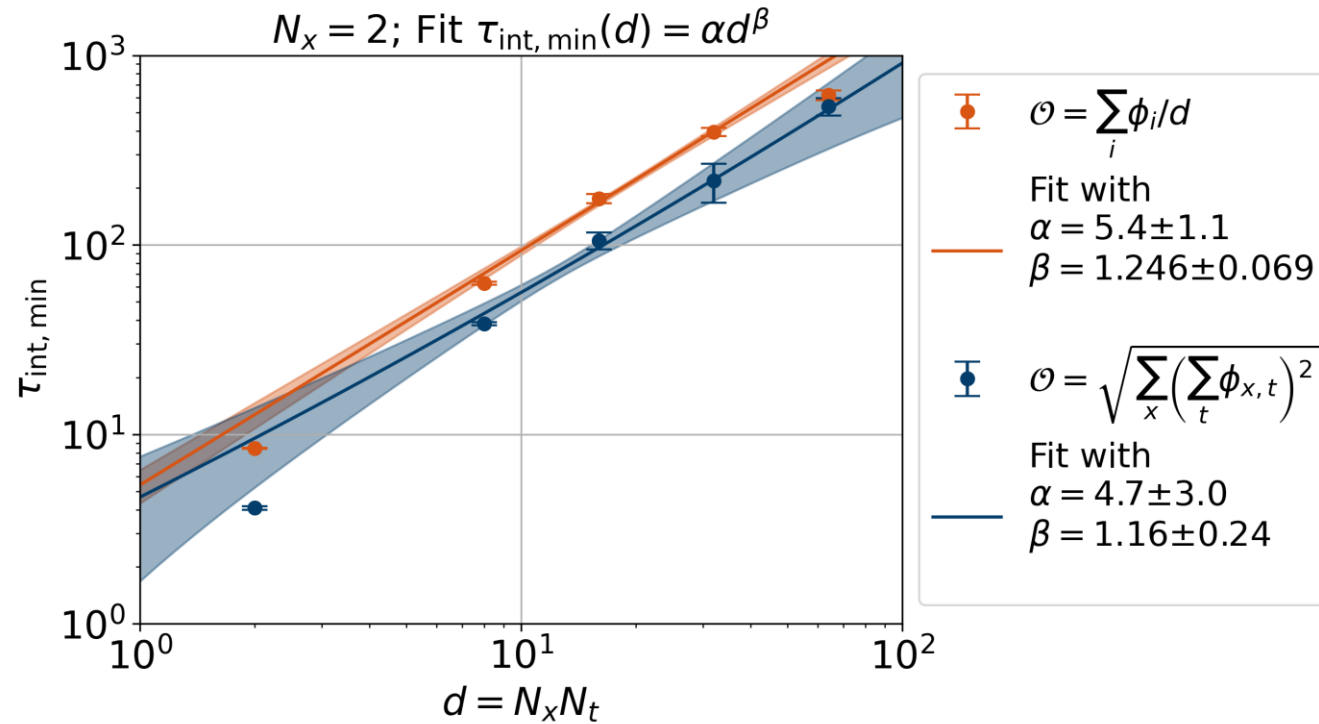
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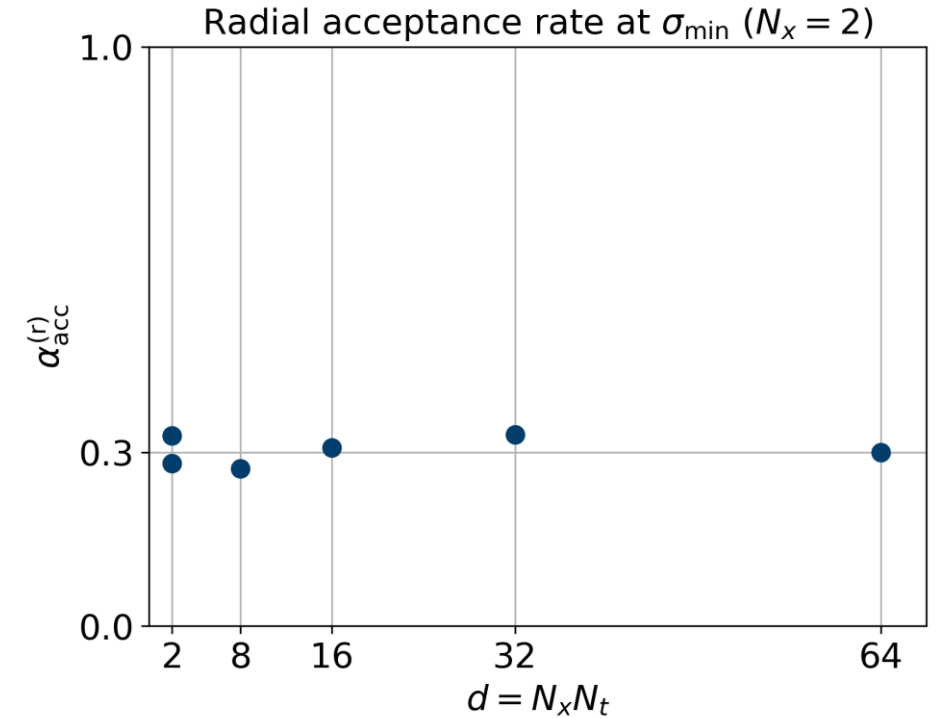
- $\tau_{\text{int}}(\sigma_{\text{min}})$ scales almost linearly with d

RESULTS

Autocorrelations, Scaling and Parameter Tuning



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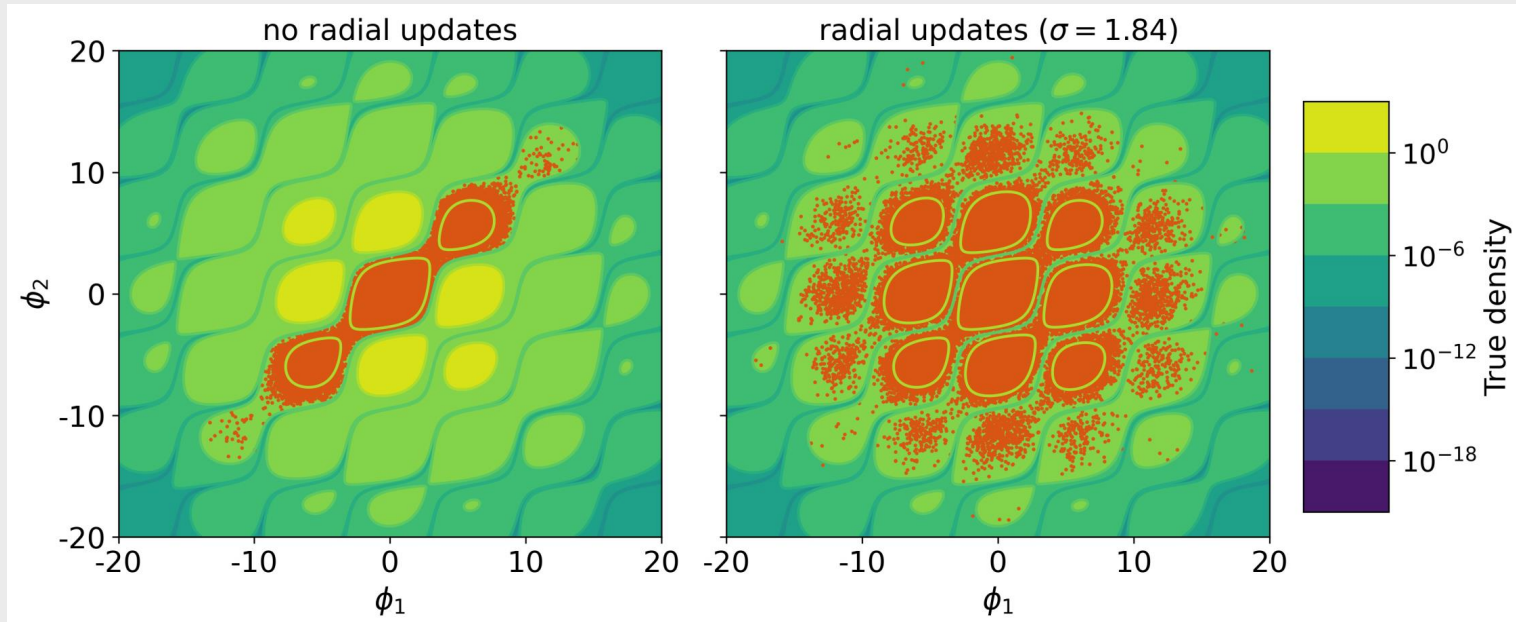
- At σ_{min} radial acceptance rate $\sim 30\%$

SUMMARY AND OUTLOOK

Take home message and future avenues

▼ Radial updates successfully restore ergodicity in the Hubbard model

- Capability to jump over large or even infinite potential barriers



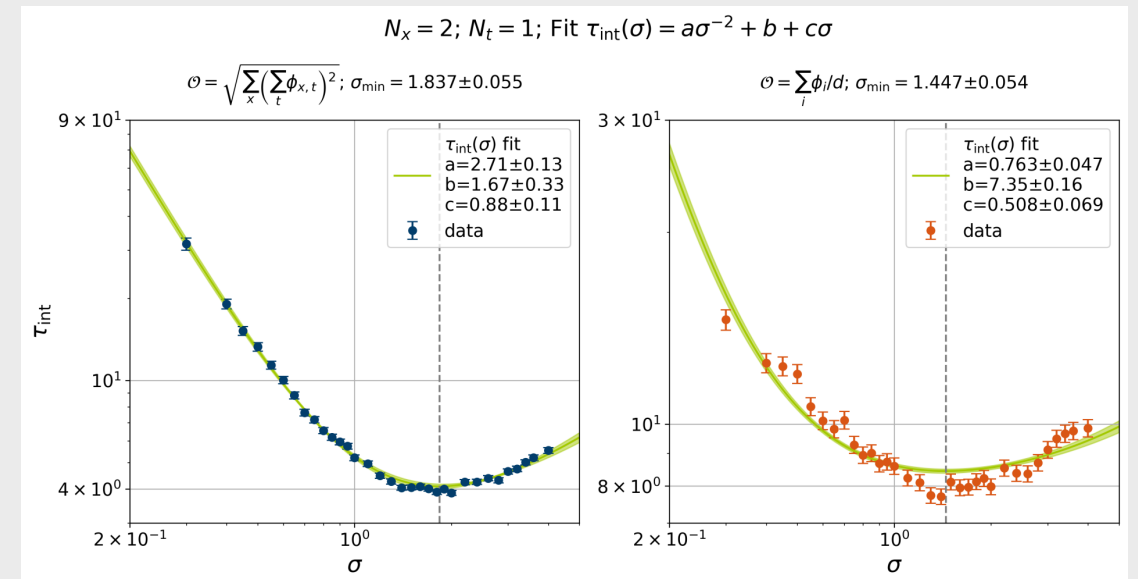
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▶ Radial updates successfully restore ergodicity in the Hubbard model

▼ Radial updates reduce autocorrelations at low computational cost

- Can be used to tune additional parameter σ



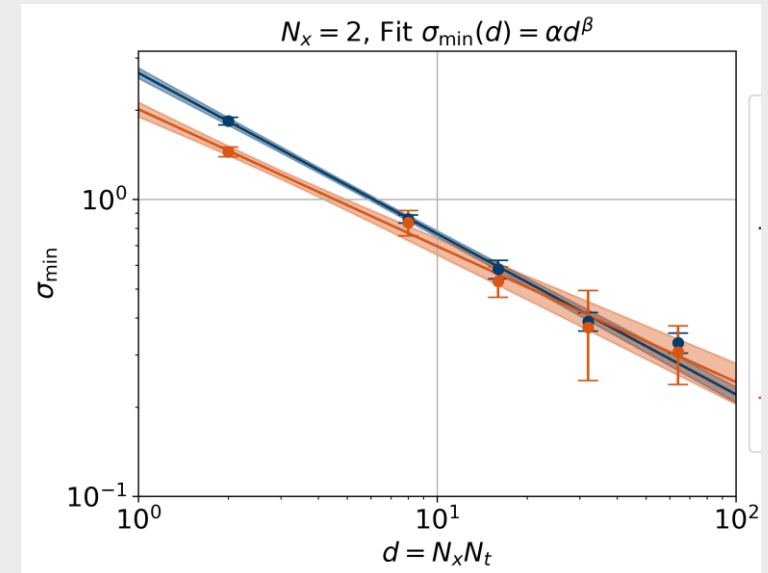
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- Can be used to tune additional parameter σ
- $\sigma_{\min} \propto d^{-0.5}$ at leading order



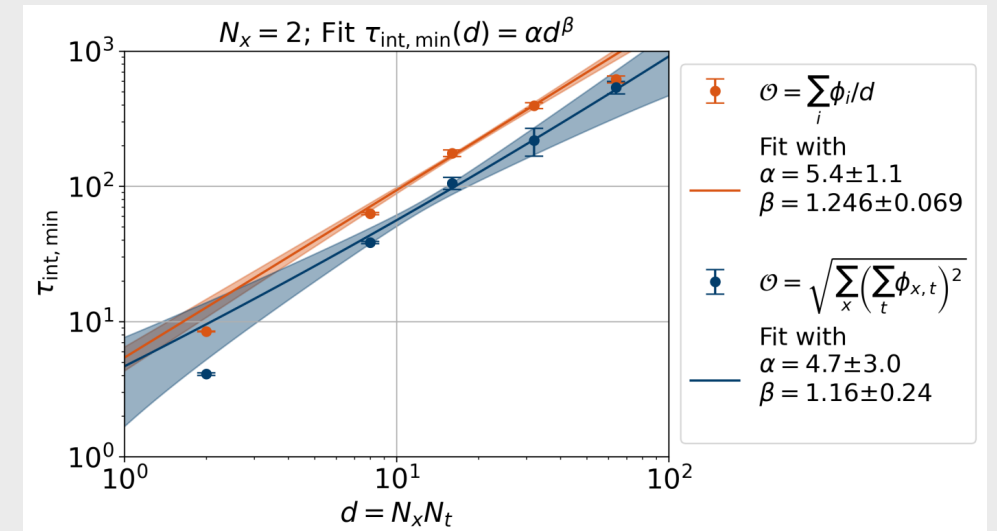
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- Can be used to tune additional parameter σ
- $\sigma_{\min} \propto d^{-0.5}$ at leading order
- τ_{int} scales almost linearly when employing radial updates



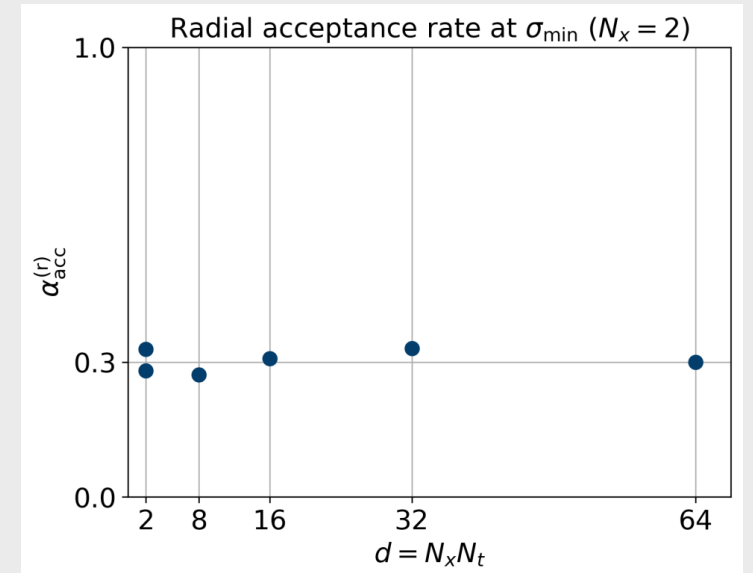
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- Can be used to tune additional parameter σ
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- τ_{int} scales almost linearly when employing radial updates
- Optimal radial acceptance rate $\sim 30\%$



SUMMARY AND OUTLOOK

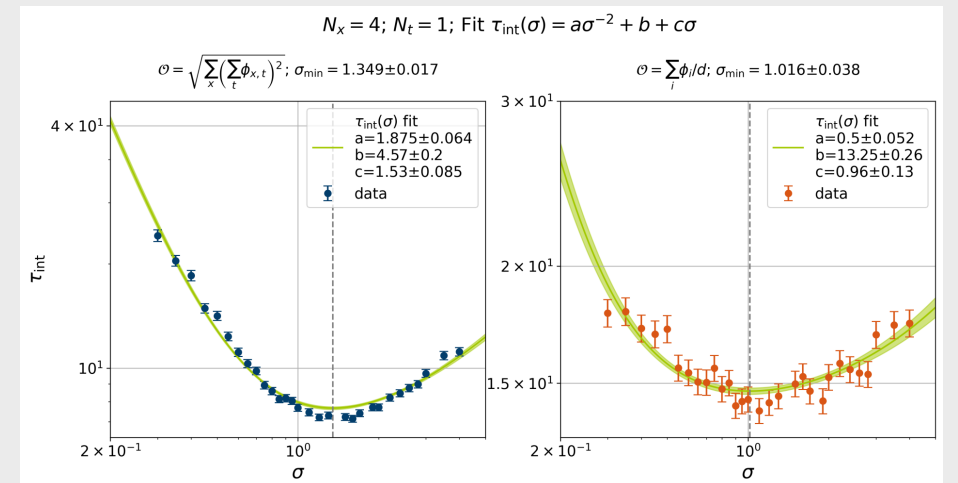
Take home message and future avenues

▶ Radial updates successfully restore ergodicity in the Hubbard model

▶ Radial updates reduce autocorrelations at low computational cost

▼ Outlook: Scaling to larger systems and realistic simulation

- Increase N_x and add more spatial dimensions



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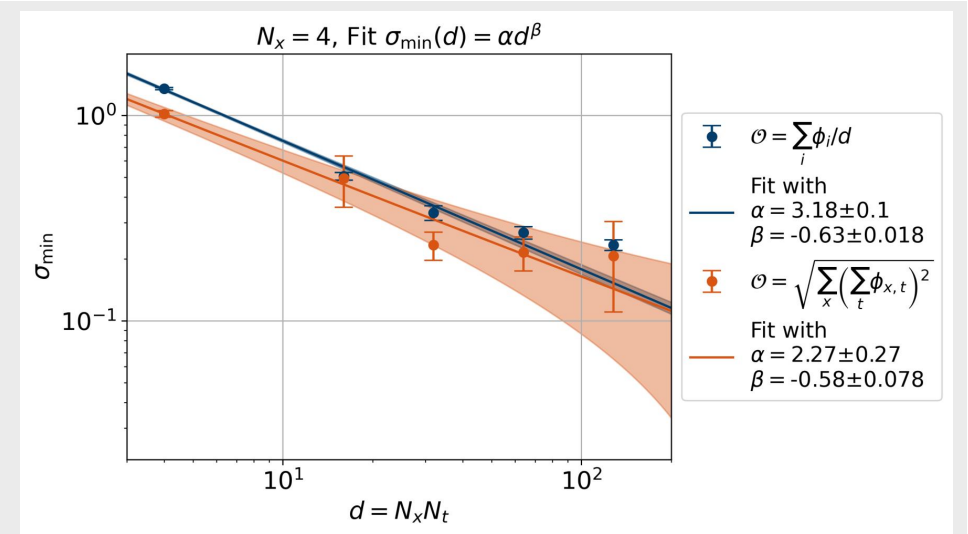
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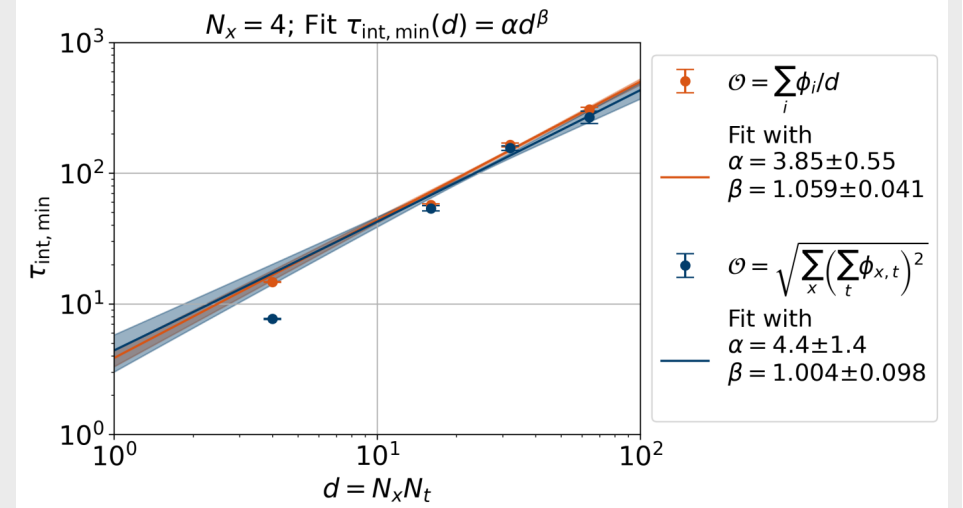
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Rodekamp et al., arXiv:2406.06711v1

- Perform realistic simulation with tuned acceptance rate, e.g. Perylene

SUMMARY AND OUTLOOK

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▶ Radial updates reduce autocorrelations at low computational cost

▶ Outlook: Scaling to larger systems and realistic simulation

▼ Bonus: Geometric convergence of HMC

- Talk by Xinhao Yu on Friday, August 2nd 2:55 PM

”On the geometric convergence of HMC on Riemannian manifolds.”

THANK YOU!

Member of the Helmholtz Association



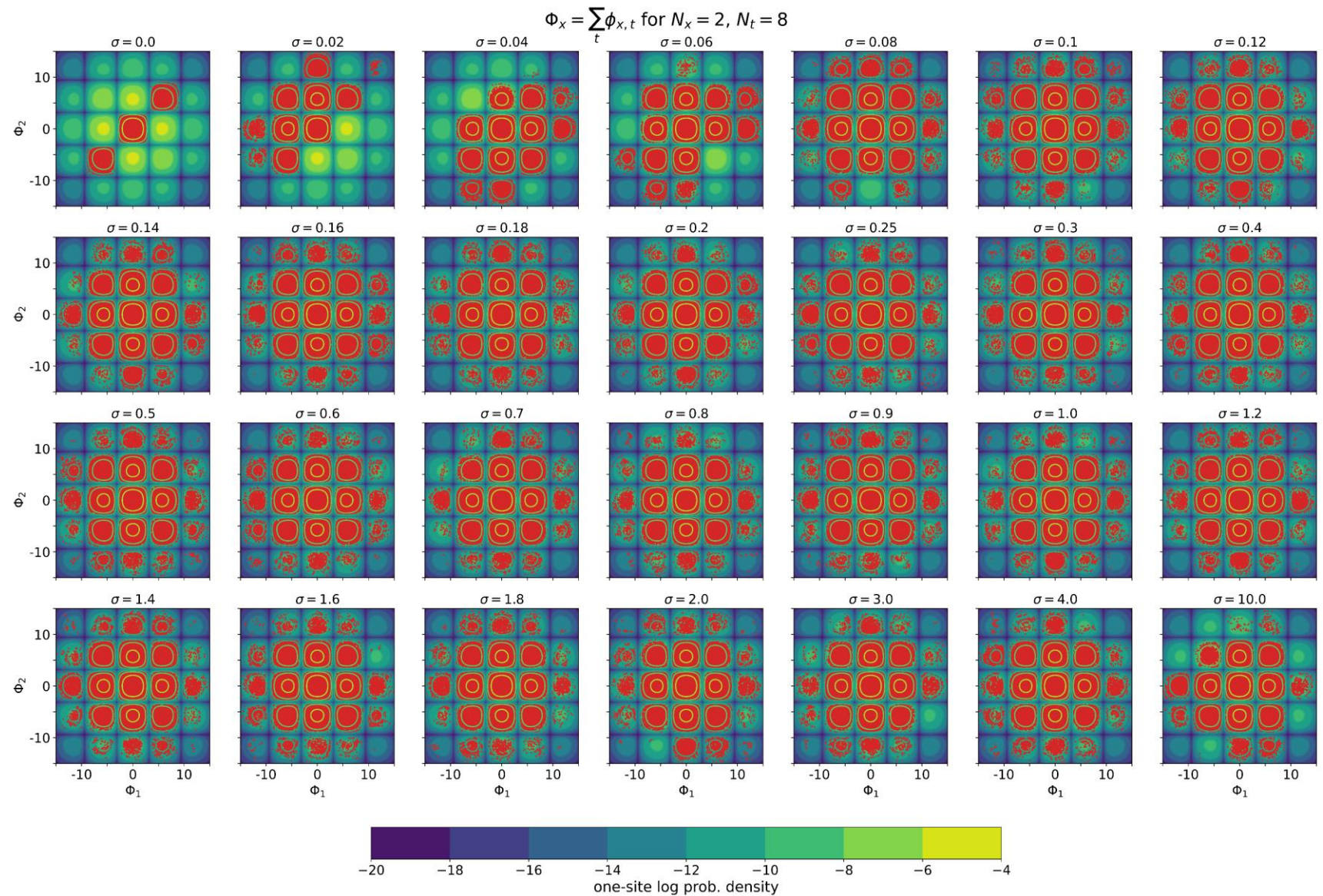
BACKUP SLIDES



RESULTS

Ergodicity for very small σ

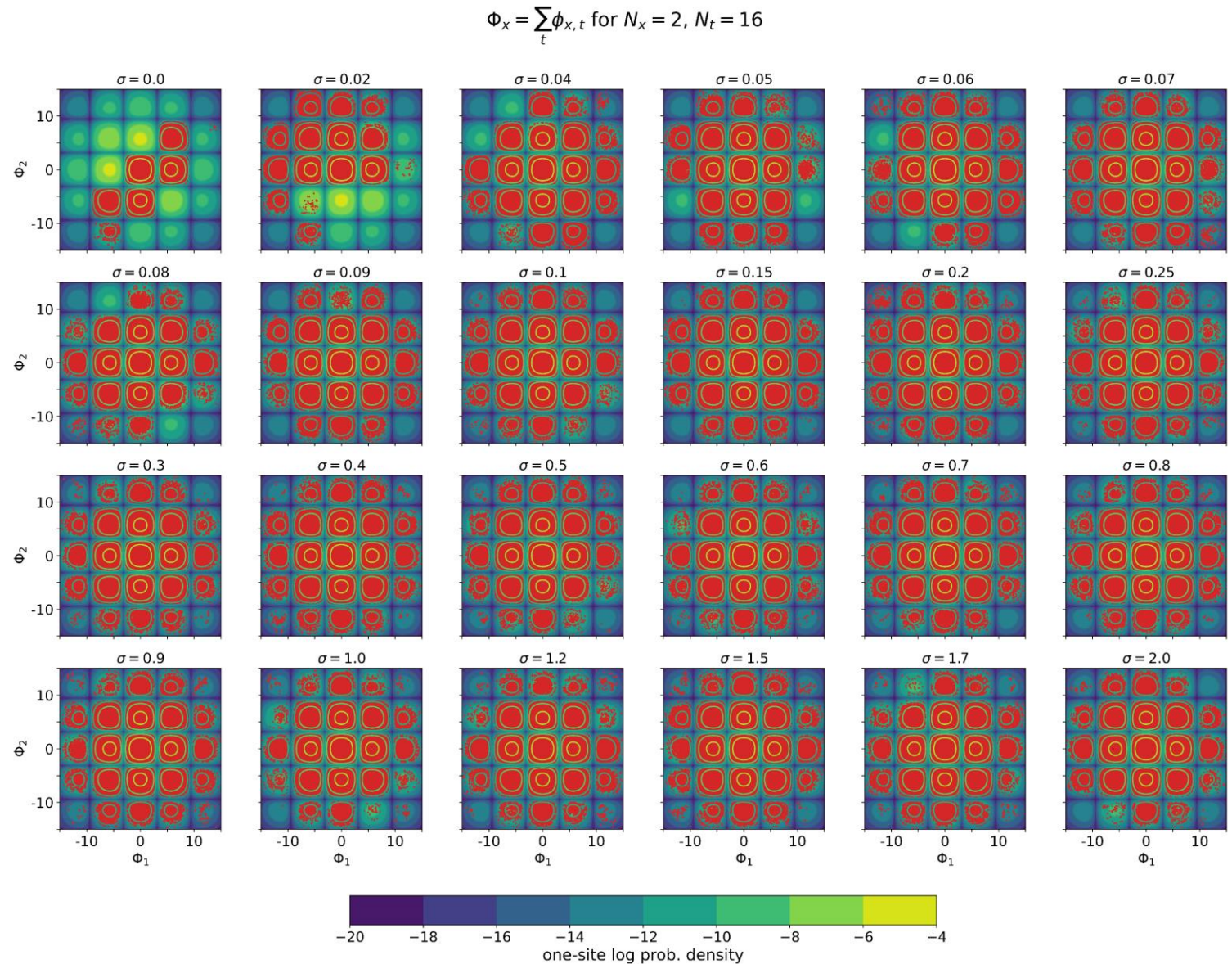
- Strong ergodicity problem for $\sigma = 0$
- Reduced ergodicity problem for $\sigma \approx 0$ but slow exploration



RESULTS

Tunneling of HMC

- In practice: energy violations due to imperfect MD
- HMC can tunnel through potential barriers
- Also happens at $\sim 99\%$ acceptance rate for long trajectories



RADIAL UPDATES

The Algorithm - Pseudocode

```
function RADIAL_UPDATE( $\phi, \sigma$ )  
     $\gamma = \text{SAMPLE\_NORMAL}(\text{mean} = 0, \text{standard\_deviation} = \sigma^2)$   
     $\tilde{\phi} = e^\gamma \phi$   
     $\alpha = \exp\{-(S(\tilde{\phi}) - S(\phi)) + d\gamma\}$   
     $u = \text{SAMPLE\_UNIFORM}(\text{low} = 0, \text{high} = 1)$   
    if  $u \leq \alpha$  then  
        return  $\tilde{\phi}$   
    else  
        return  $\phi$ 
```

RADIAL UPDATES

The Algorithm - Pseudocode

```
for  $i = 0$  to  $N_{\text{cfgs}}$  do  
     $\phi = \text{HMC}(\phi)$   
    if  $i \% \text{radial\_frequency} == 0$  then  
        for  $j = 0$  to  $N_{\text{Radial}}$  do  
             $\phi = \text{RADIAL\_UPDATE}(\phi, \sigma)$ 
```

RESULTS

2-SITE MODEL

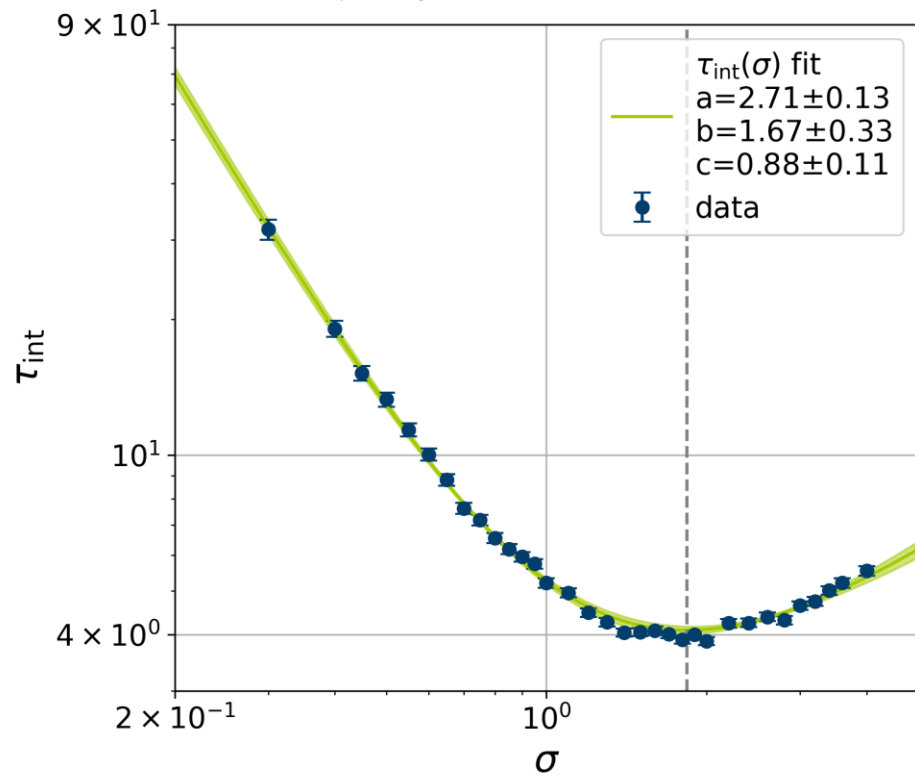


RESULTS

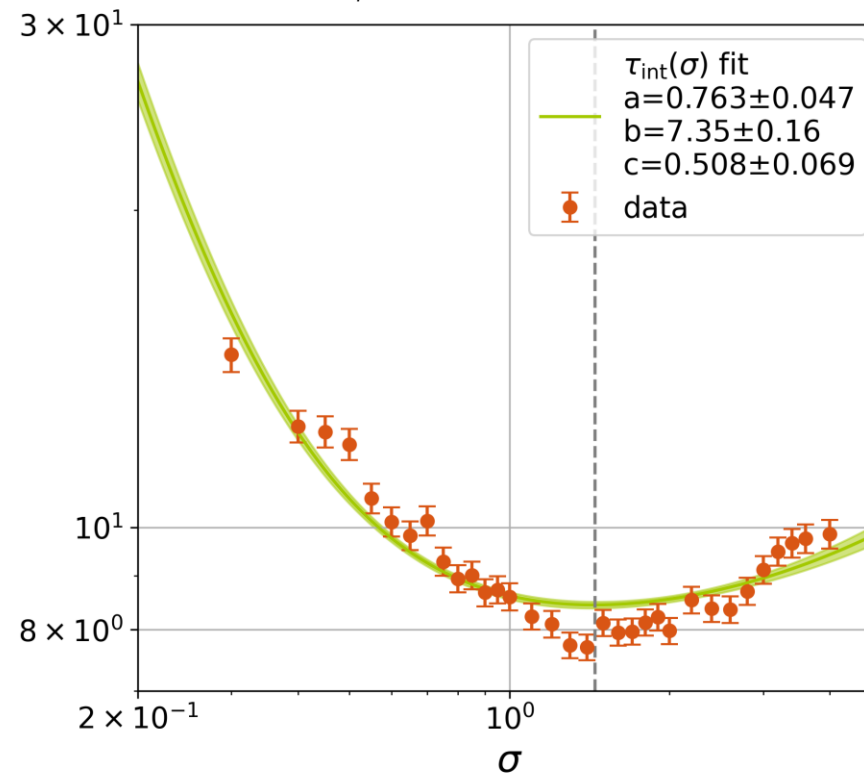
Autocorrelations, Scaling and Parameter Tuning

$$N_x = 2; N_t = 1; \text{Fit } \tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

$$\vartheta = \sqrt{\sum_x \left(\sum_t \phi_{x,t} \right)^2}; \sigma_{\text{min}} = 1.837 \pm 0.055$$



$$\vartheta = \sum_i \phi_i / d; \sigma_{\text{min}} = 1.447 \pm 0.054$$



- Fit function

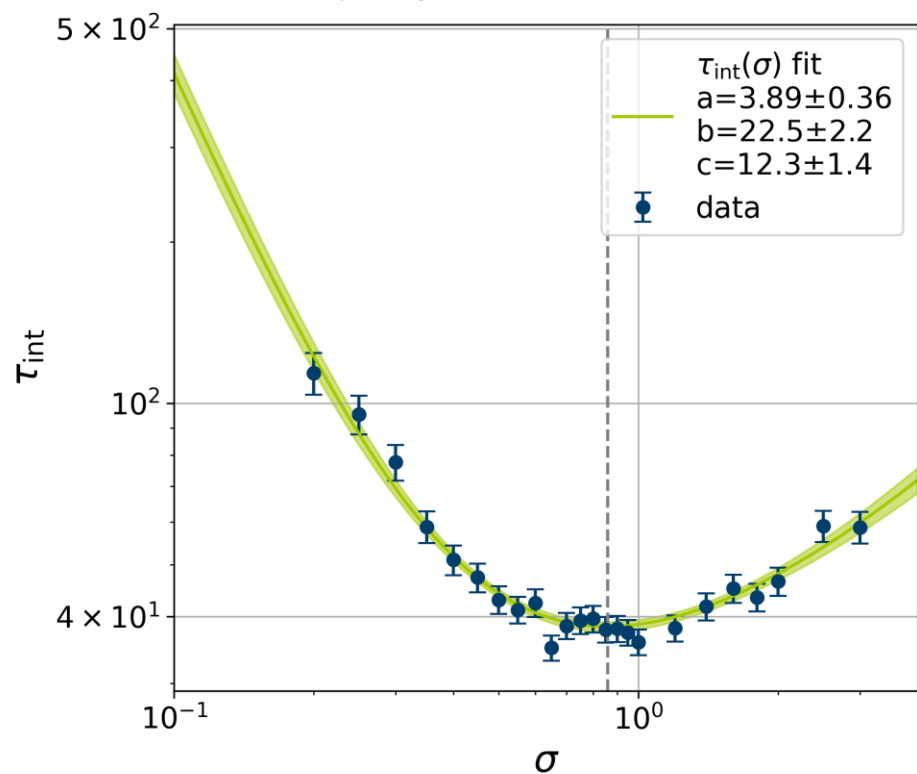
$$\tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

RESULTS

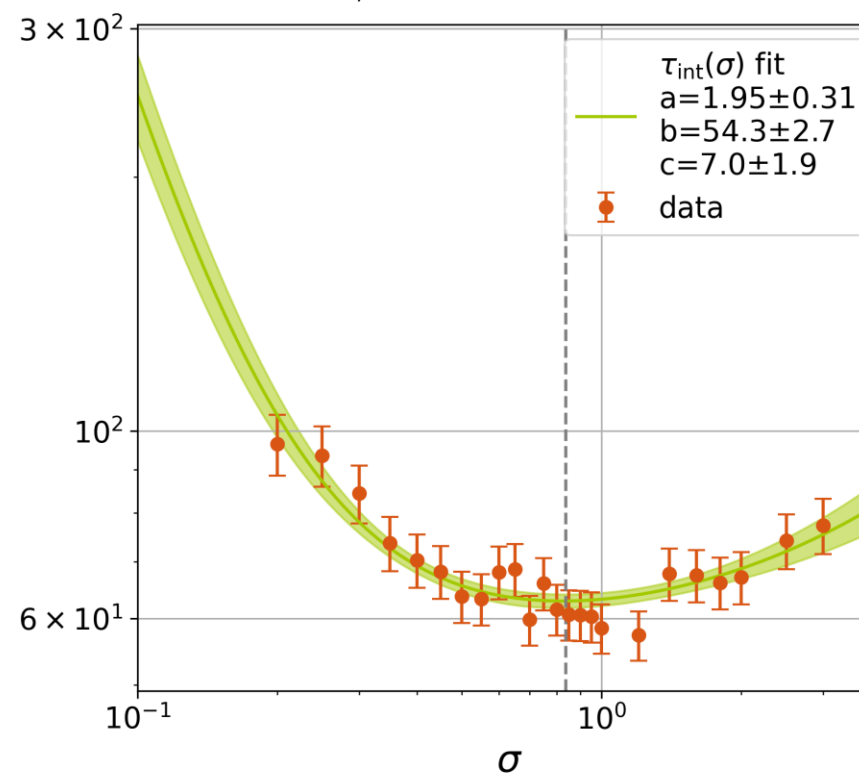
Autocorrelations, Scaling and Parameter Tuning

$$N_x = 2; N_t = 4; \text{Fit } \tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

$$\vartheta = \sqrt{\sum_x \left(\sum_t \phi_{x,t} \right)^2}; \sigma_{\text{min}} = 0.859 \pm 0.026$$



$$\vartheta = \sum_i \phi_i / d; \sigma_{\text{min}} = 0.836 \pm 0.083$$



- Fit function

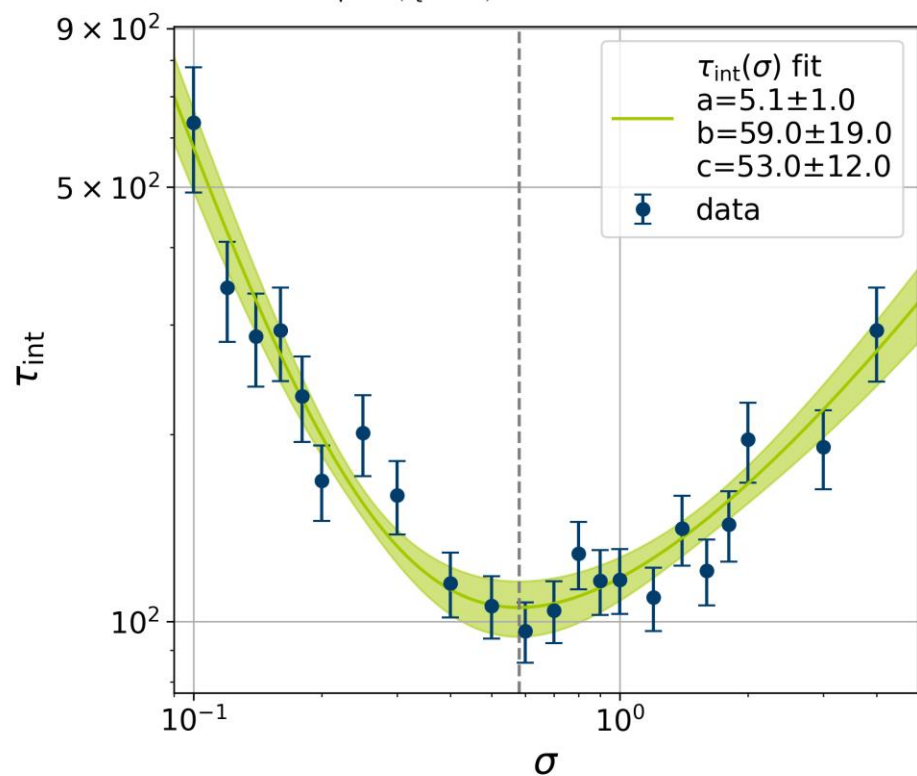
$$\tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

RESULTS

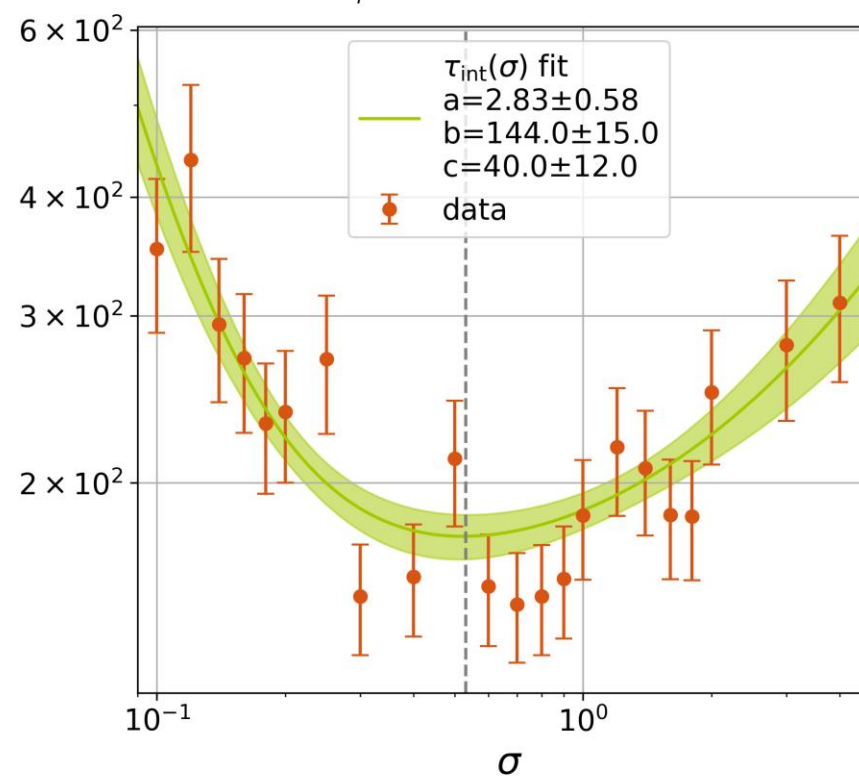
Autocorrelations, Scaling and Parameter Tuning

$$N_x = 2; N_t = 8; \text{Fit } \tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

$$\vartheta = \sqrt{\sum_x \left(\sum_t \phi_{x,t} \right)^2}; \sigma_{\text{min}} = 0.582 \pm 0.042$$



$$\vartheta = \sum_i \phi_i / d; \sigma_{\text{min}} = 0.531 \pm 0.062$$



- Fit function

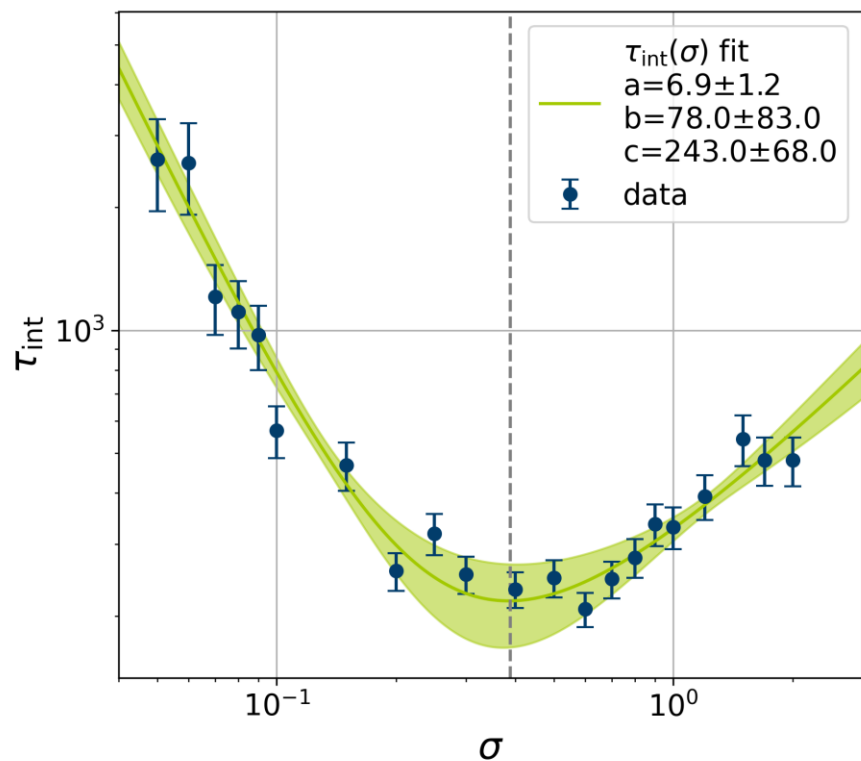
$$\tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

RESULTS

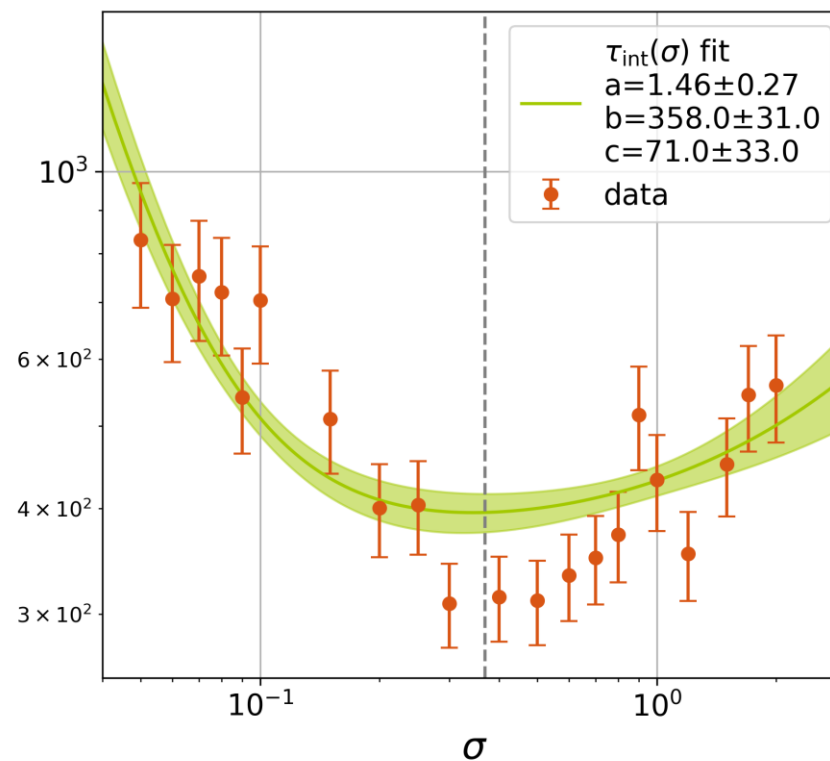
Autocorrelations, Scaling and Parameter Tuning

$$N_x = 2; N_t = 16; \text{Fit } \tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

$$\vartheta = \sqrt{\sum_x \left(\sum_t \phi_{x,t} \right)^2}; \sigma_{\text{min}} = 0.389 \pm 0.027$$



$$\vartheta = \sum_i \phi_i / d; \sigma_{\text{min}} = 0.37 \pm 0.1$$



- Fit function

$$\tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

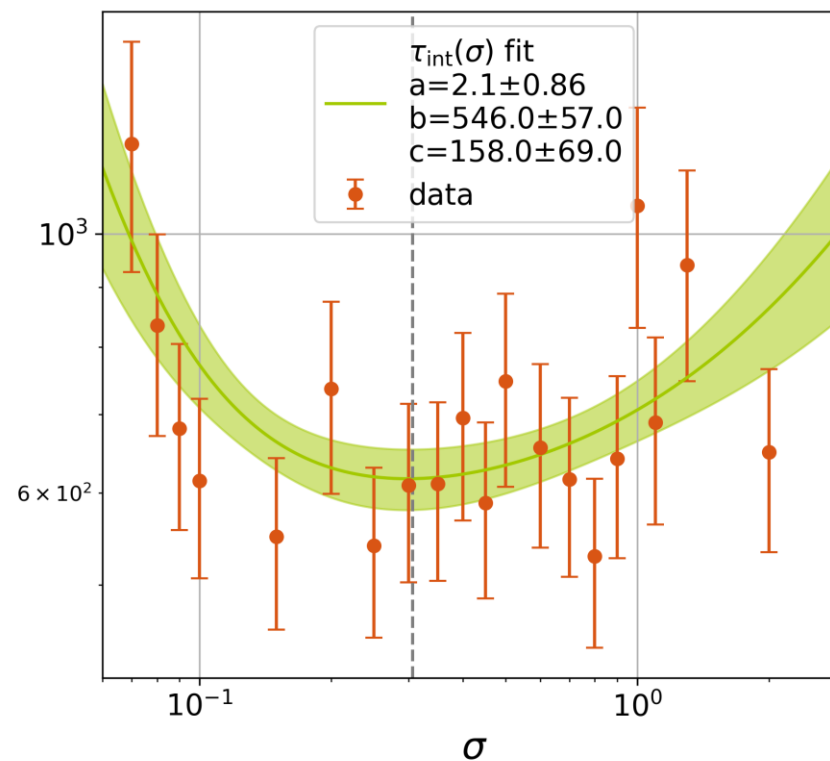
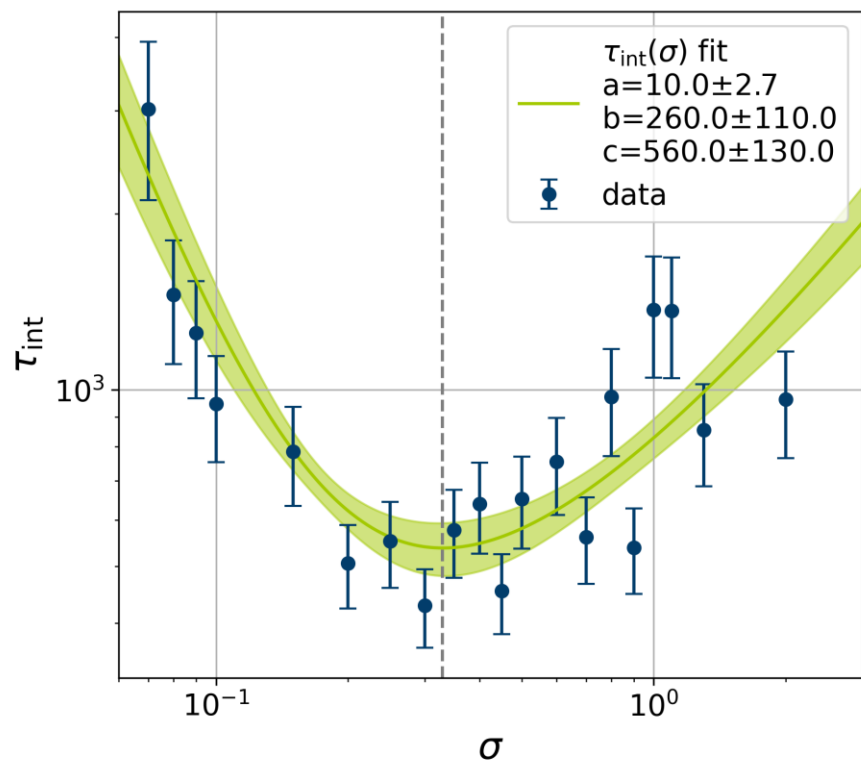
RESULTS

Autocorrelations, Scaling and Parameter Tuning

$$N_x = 2; N_t = 32; \text{Fit } \tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

$$\vartheta = \sqrt{\sum_x \left(\sum_t \phi_{x,t} \right)^2}; \sigma_{\text{min}} = 0.329 \pm 0.026$$

$$\vartheta = \sum_i \phi_i / d; \sigma_{\text{min}} = 0.307 \pm 0.069$$



- Fit function

$$\tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

PRELIMINARY RESULTS

4-SITE MODEL

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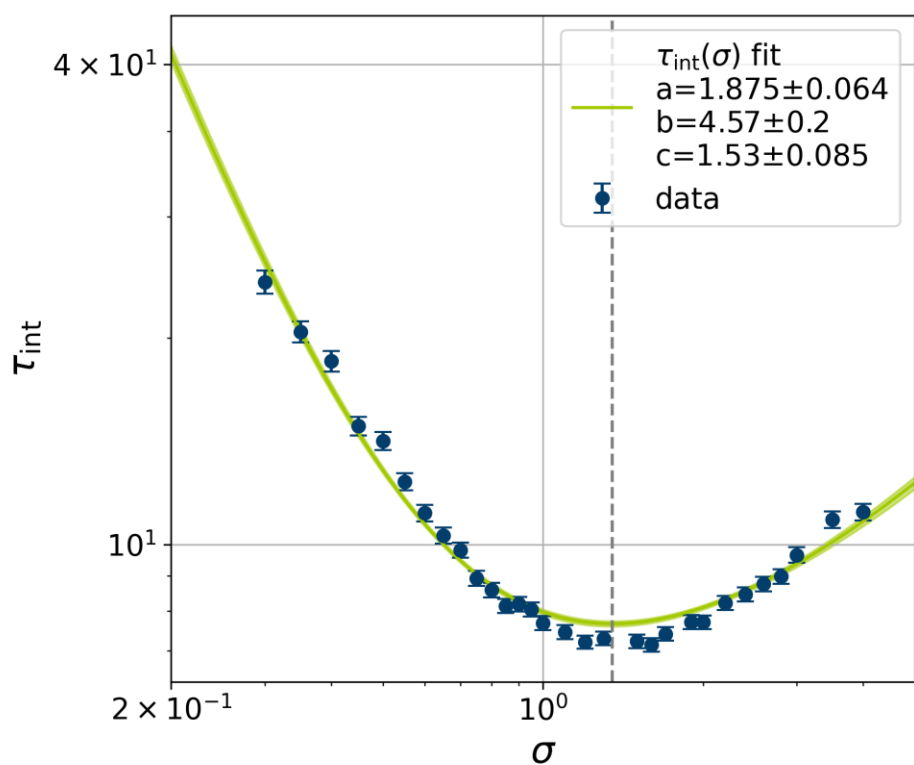


RESULTS – 4-SITE MODEL

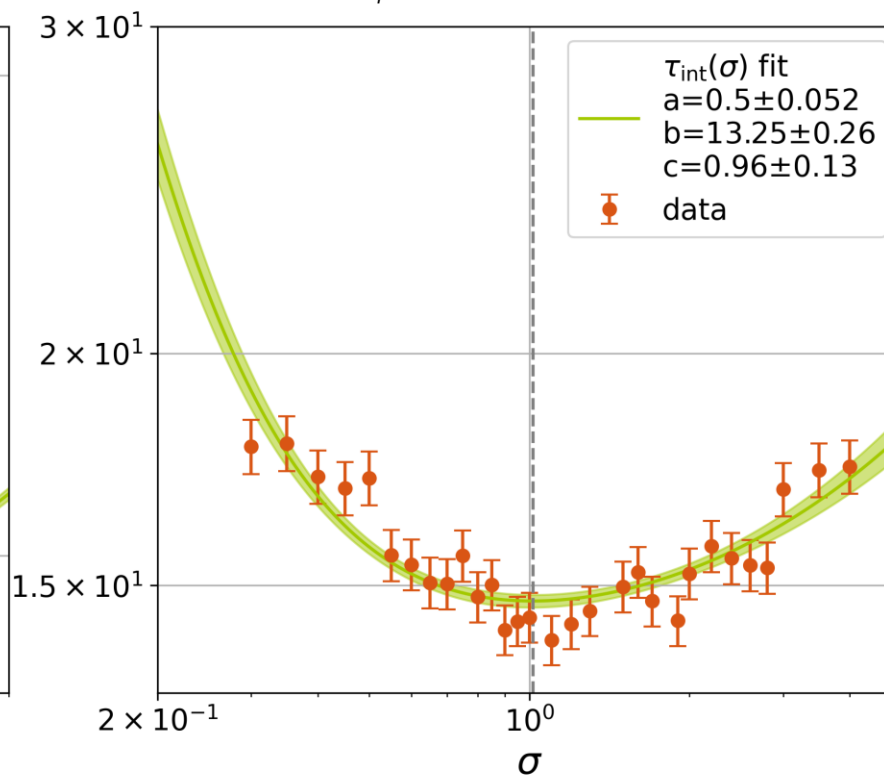
Autocorrelations, Scaling and Parameter Tuning

$$N_x = 4; N_t = 1; \text{Fit } \tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

$$\vartheta = \sqrt{\sum_x \left(\sum_t \phi_{x,t} \right)^2}; \sigma_{\text{min}} = 1.349 \pm 0.017$$



$$\vartheta = \sum_i \phi_i / d; \sigma_{\text{min}} = 1.016 \pm 0.038$$



- Fit function

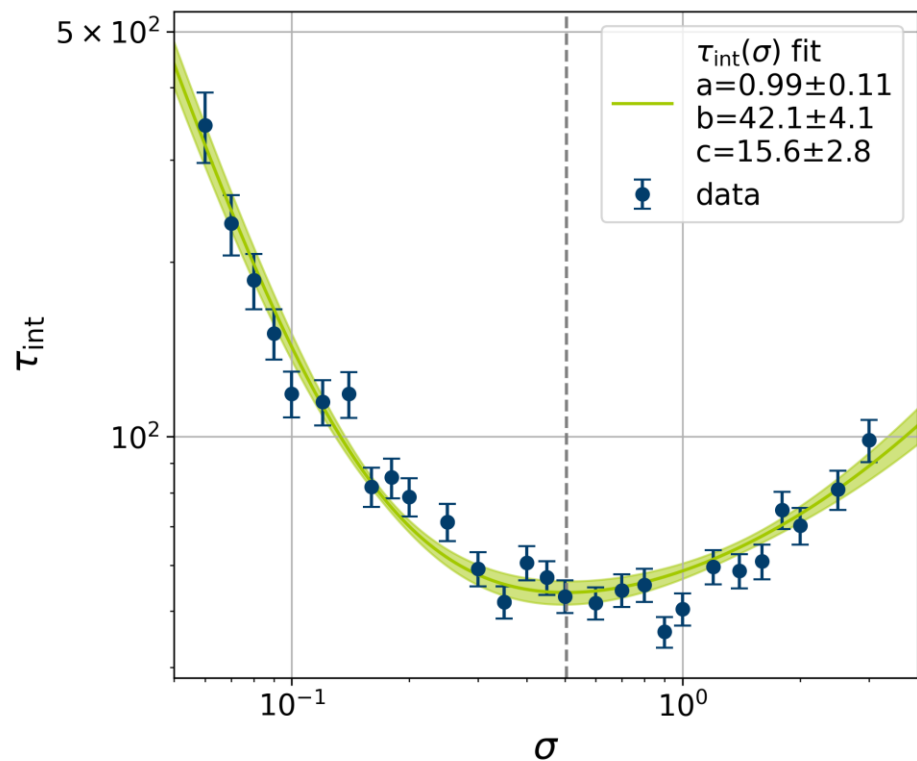
$$\tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

RESULTS – 4-SITE MODEL

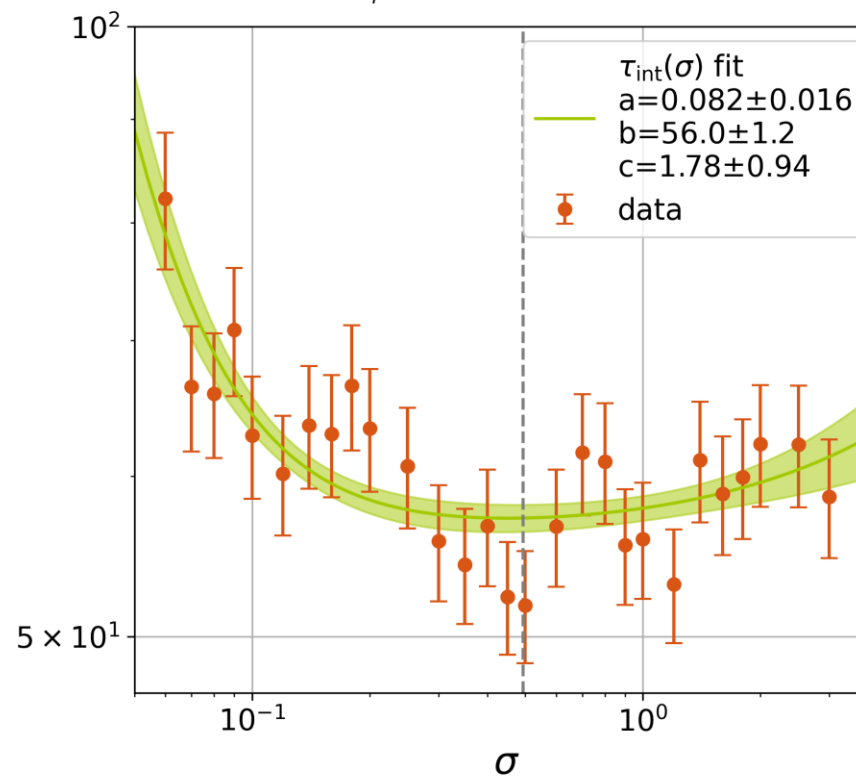
Autocorrelations, Scaling and Parameter Tuning

$$N_x = 4; N_t = 4; \text{Fit } \tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

$$\vartheta = \sqrt{\sum_x \left(\sum_t \phi_{x,t} \right)^2}; \sigma_{\text{min}} = 0.505 \pm 0.021$$



$$\vartheta = \sum_i \phi_i / d; \sigma_{\text{min}} = 0.49 \pm 0.14$$



- Fit function

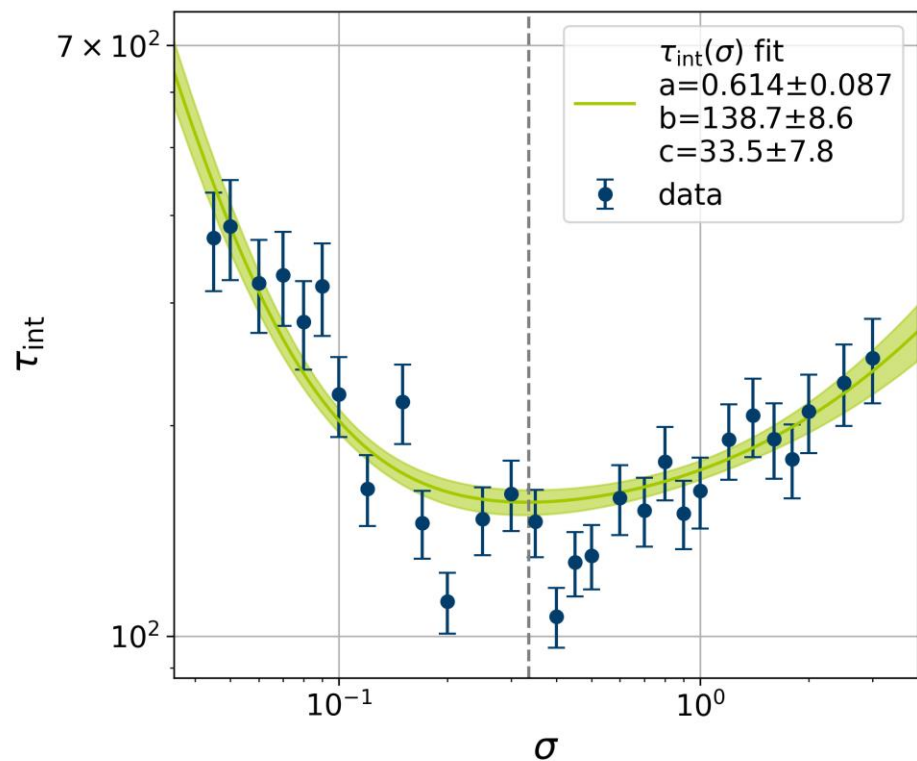
$$\tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

RESULTS – 4-SITE MODEL

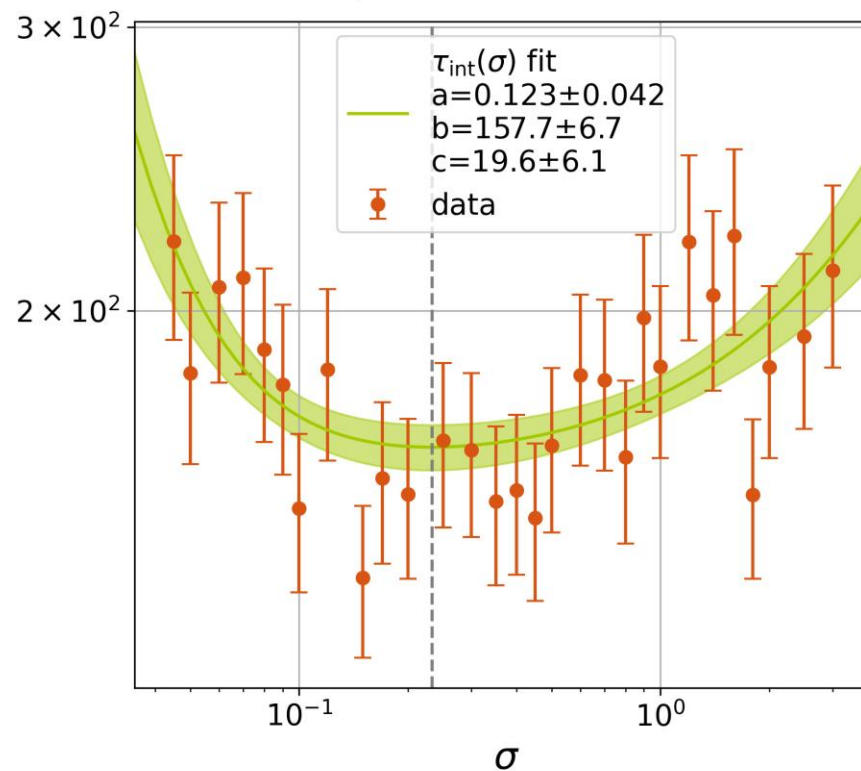
Autocorrelations, Scaling and Parameter Tuning

$$N_x = 4; N_t = 8; \text{Fit } \tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

$$\vartheta = \sqrt{\sum_x \left(\sum_t \phi_{x,t} \right)^2}; \sigma_{\text{min}} = 0.335 \pm 0.027$$



$$\vartheta = \sum_i \phi_i / d; \sigma_{\text{min}} = 0.233 \pm 0.037$$



- Fit function

$$\tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

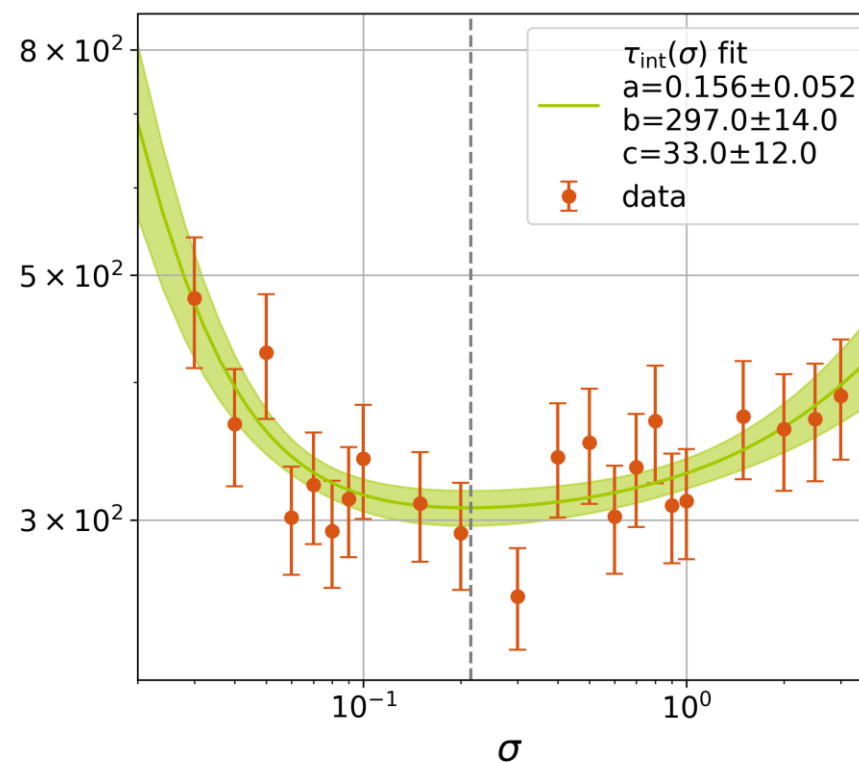
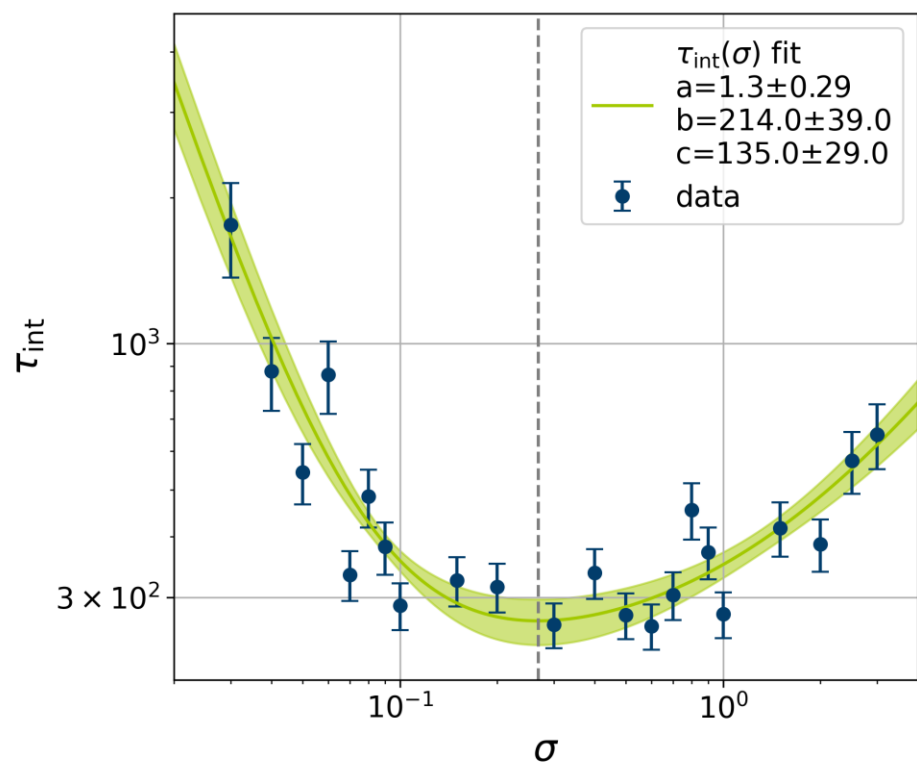
RESULTS – 4-SITE MODEL

Autocorrelations, Scaling and Parameter Tuning

$$N_x = 4; N_t = 16; \text{Fit } \tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

$$\vartheta = \sqrt{\sum_x \left(\sum_t \phi_{x,t} \right)^2}; \sigma_{\text{min}} = 0.268 \pm 0.019$$

$$\vartheta = \sum_i \phi_i / d; \sigma_{\text{min}} = 0.215 \pm 0.041$$



- Fit function

$$\tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

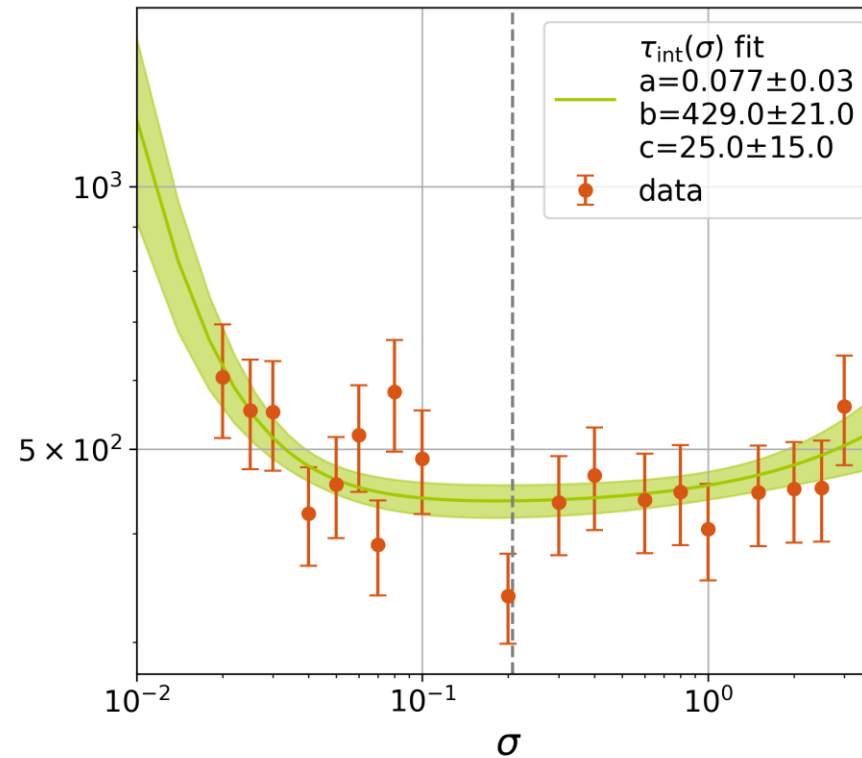
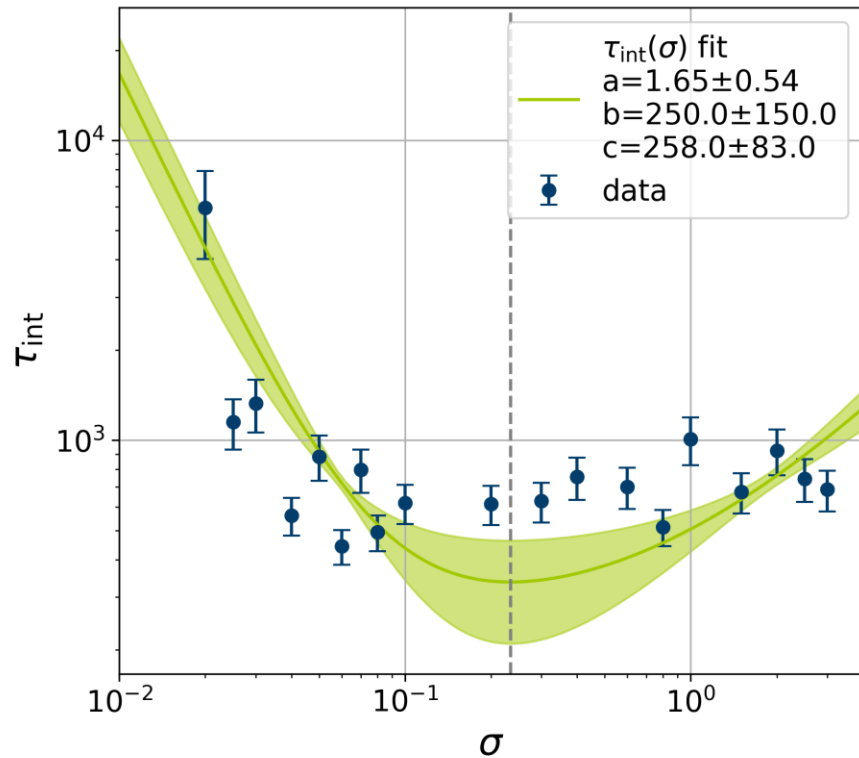
RESULTS – 4-SITE MODEL

Autocorrelations, Scaling and Parameter Tuning

$$N_x = 4; N_t = 32; \text{Fit } \tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

$$\vartheta = \sqrt{\sum_x \left(\sum_t \phi_{x,t} \right)^2}; \sigma_{\text{min}} = 0.234 \pm 0.014$$

$$\vartheta = \sum_i \phi_i / d; \sigma_{\text{min}} = 0.207 \pm 0.097$$

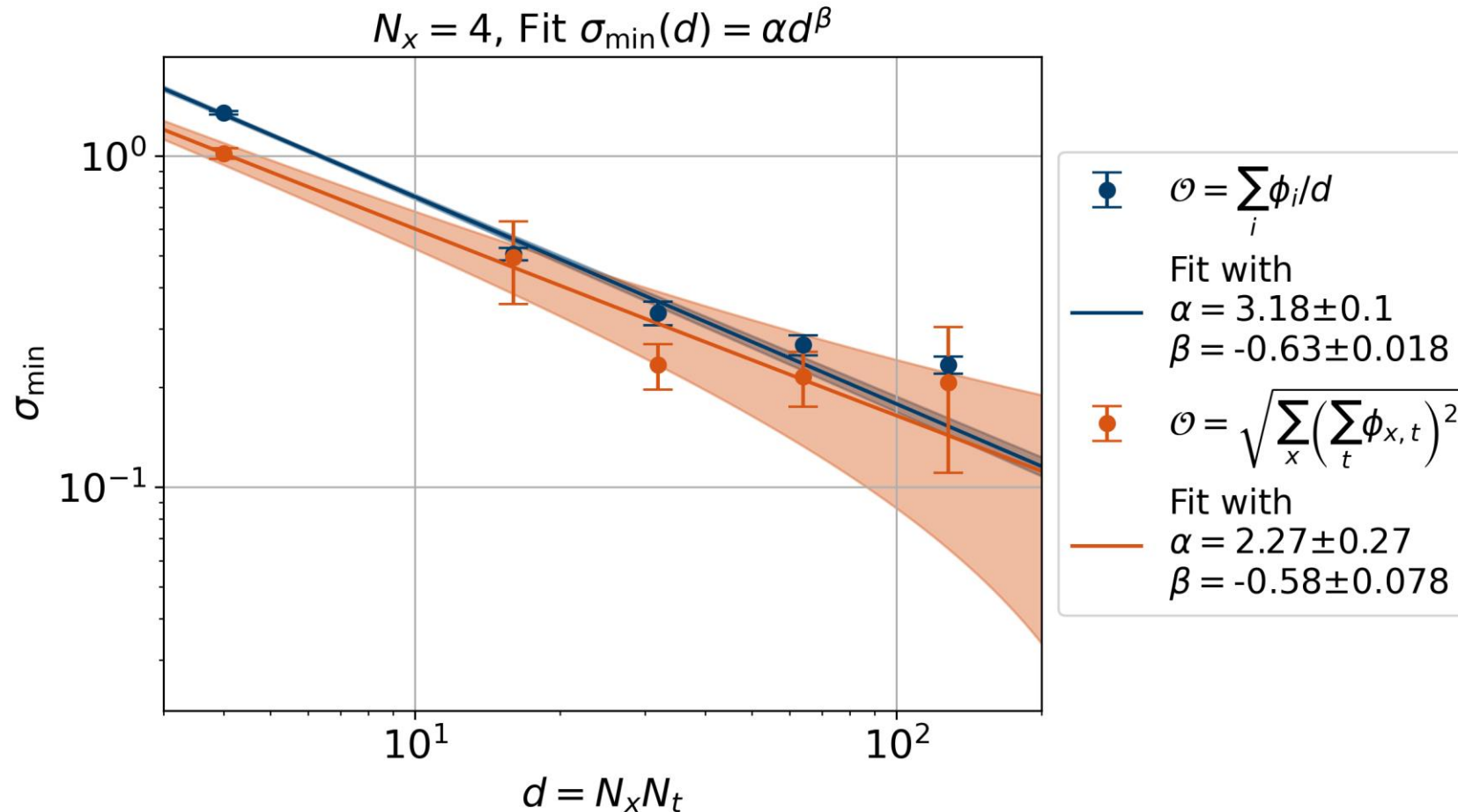


- Fit function

$$\tau_{\text{int}}(\sigma) = a\sigma^{-2} + b + c\sigma$$

RESULTS – 4-SITE MODEL

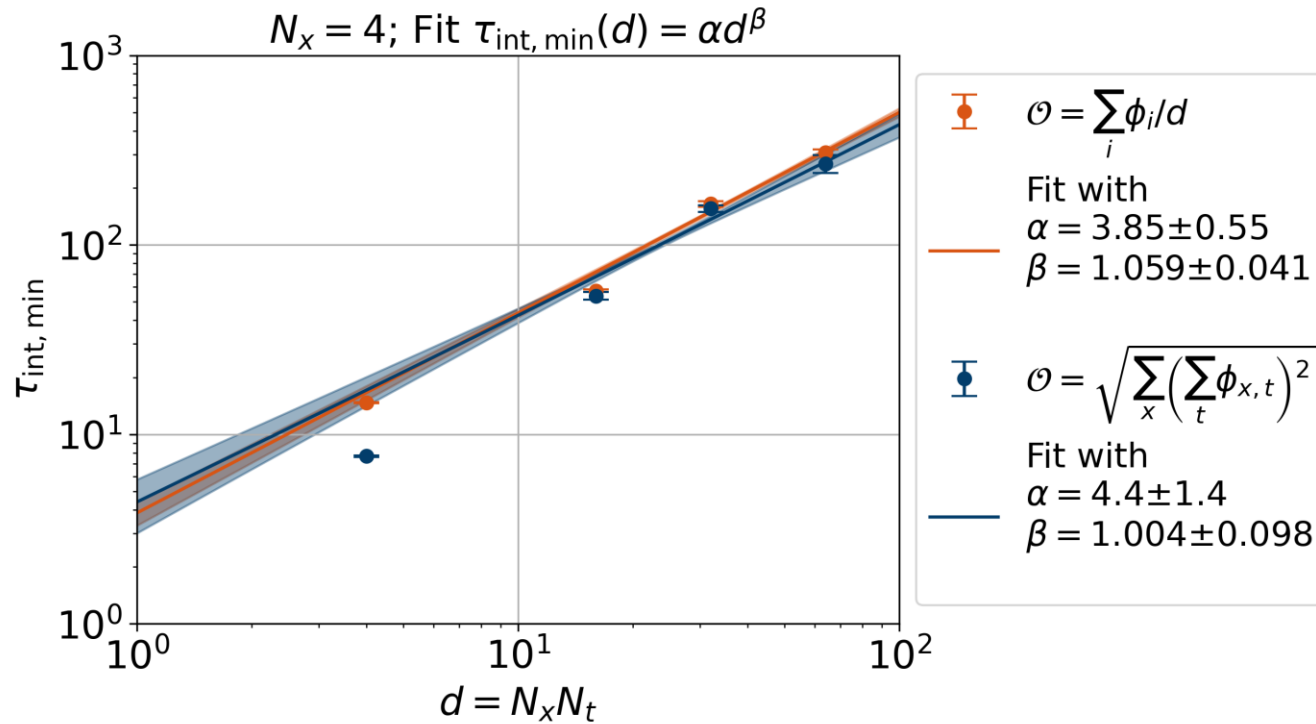
Autocorrelations, Scaling and Parameter Tuning



- From theoretical considerations
 $\sigma_{\min}(d) \propto d^{-0.5} + \mathcal{O}(d^{-1})$
- Fit function
 $\sigma_{\min}(d) = \alpha d^\beta$

RESULTS – 4-SITE MODEL

Autocorrelations, Scaling and Parameter Tuning



- $\tau_{\text{int}}(\sigma_{\text{min}})$ scales almost linearly with d