

# **A flat histogram stochastic growth algorithm (with application to polymers and proteins)**

Thomas Prellberg

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TU Clausthal

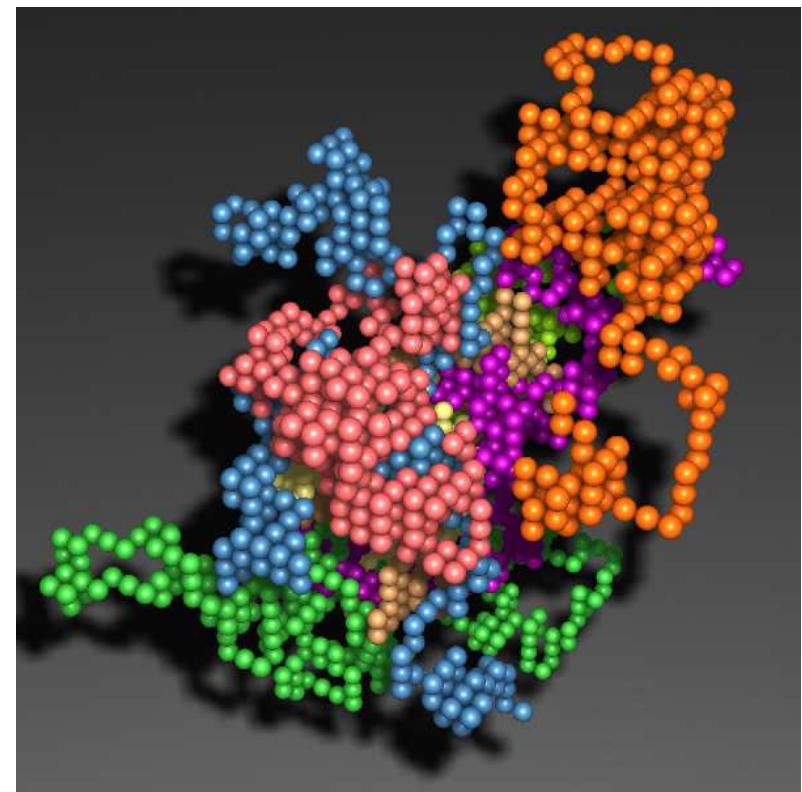
Joint work with Jaroslaw Krawczyk, TU Clausthal



# *Introduction*

# *Modelling of Polymers in Solution*

- Polymers:  
long chains of monomers
- “Coarse-Graining”:  
beads on a chain
- “Excluded Volume”:  
minimal distance
- Contact with solvent:  
effective short-range interaction
- Good/bad solvent:  
repelling/attracting interaction
- Consequence:  
chains clump together



Eight polymers in a bad solvent  
(Grassberger, FZ Jülich)

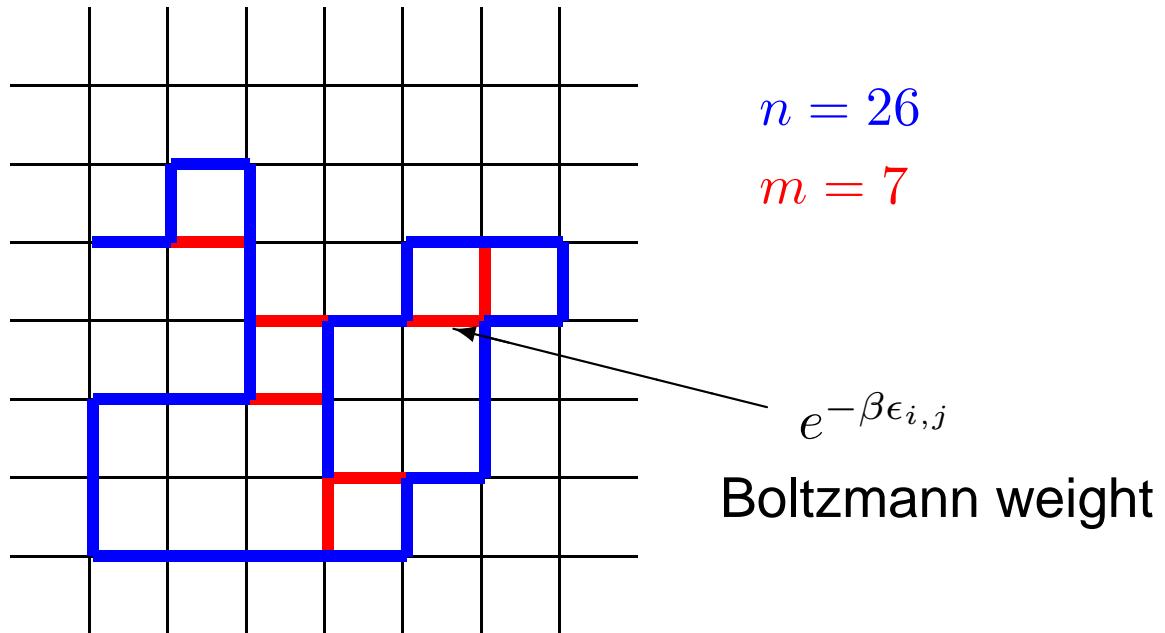
## Self-Avoiding Walks with Interactions

- Physical space → lattice  $\mathbb{Z}^3$  (or  $\mathbb{Z}^d$ )
- Polymer in solution → random walk with self-avoidance
- Quality of solvent → short-range interaction  $\epsilon$
- Properties of monomers  $i, j$  → interaction  $\epsilon = \epsilon_{i,j}$

## Self-Avoiding Walks with Interactions

- Physical space → lattice  $\mathbb{Z}^3$  (or  $\mathbb{Z}^d$ )
- Polymer in solution → random walk with self-avoidance
- Quality of solvent → short-range interaction  $\epsilon$
- Properties of monomers  $i, j \rightarrow$  interaction  $\epsilon = \epsilon_{i,j}$
- Two examples:
  - ISAW model: interaction  $\epsilon_{i,j} = -1$   
of interest: thermodynamic limit ( $V = \infty$  and  $n \rightarrow \infty$ )
  - HP model: two types of monomers H and P  
 $\epsilon_{HH} = -1, \epsilon_{HP} = \epsilon_{PH} = \epsilon_{PP} = 0$   
of interest: fixed finite sequence, density of states

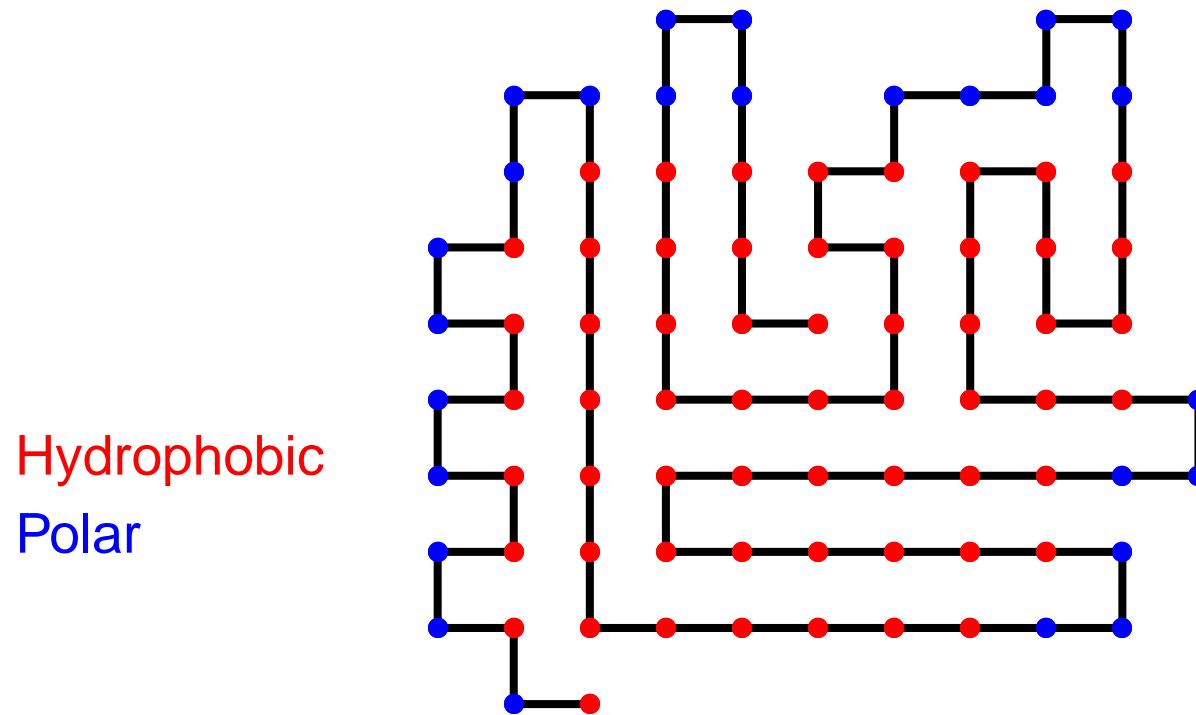
# Lattice Model: ISAW



- ISAW model: interaction  $\epsilon_{i,j} = -1$ ,  $\omega = e^\beta$
- Partition function:  $Z_n(\omega) = \sum_m C_{n,m} \omega^m$
- $C_{n,m}$  number of SAW with length  $n$  and  $m$  interactions

# Lattice Model: HP model

- HP model: interaction  $\epsilon_{HH} = -1$ ,  $\epsilon_{HP} = \epsilon_{PH} = \epsilon_{PP} = 0$



Hydrophobic  
Polar

- Groundstate of sequence with 85 monomers ( $d = 2$ )

# *Why Simulations?*

---

- ISAW model:
  - Tricritical phase transition,  $d_u = 3$
  - In principle understood, however surprising details  
e.g. “pseudo-first-order transition” for  $d > 3$
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  - Design of sequences with specific ground state structure
  - Density of states – folding dynamics

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  - No good understanding of collapsed regime
- HP model:
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  - Design of sequences with specific ground state structure
  - Density of states – folding dynamics
- Most interesting open questions in collapsed regime

Collapsed regime is notoriously difficult to simulate

# ***Stochastic Growth Algorithms***

# ***PERM: “Go With The Winners”***

**PERM = Pruned and Enriched Rosenbluth Method**

Grassberger, Phys Rev E 56 (1997) 3682

- **Rosenbluth Method: kinetic growth**



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- **Pruning:** weight too small → remove configuration occasionally

# ***PERM: “Go With The Winners”***

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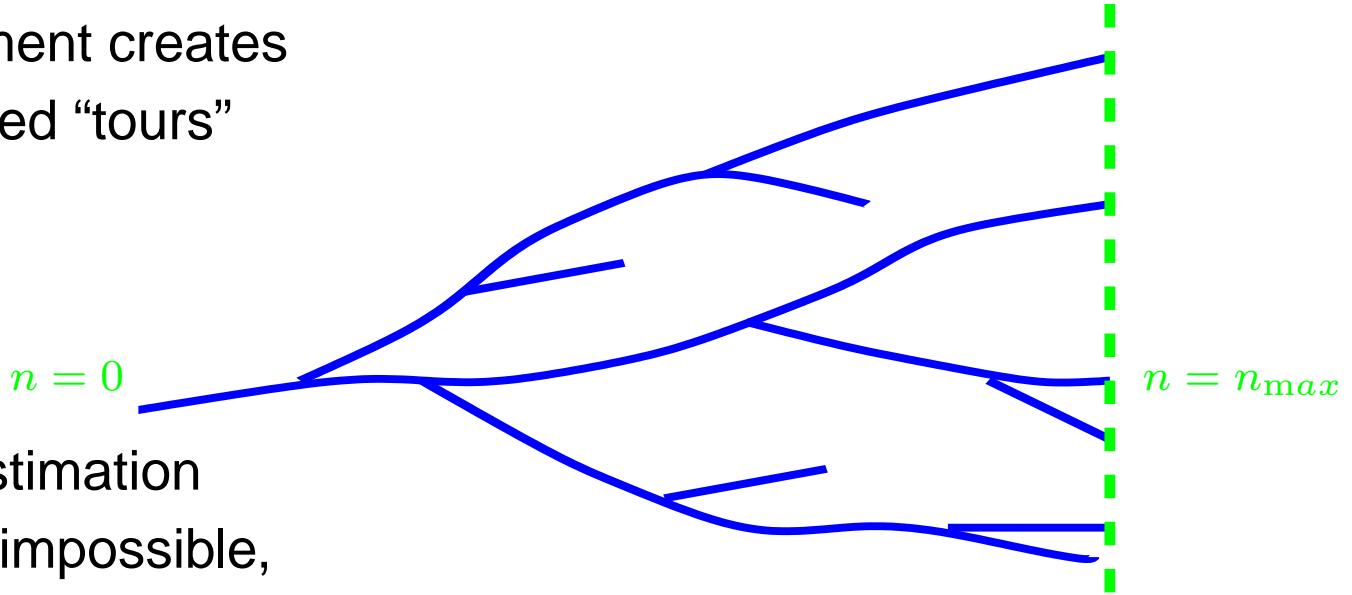
Grassberger, Phys Rev E 56 (1997) 3682

- **Rosenbluth Method:** kinetic growth



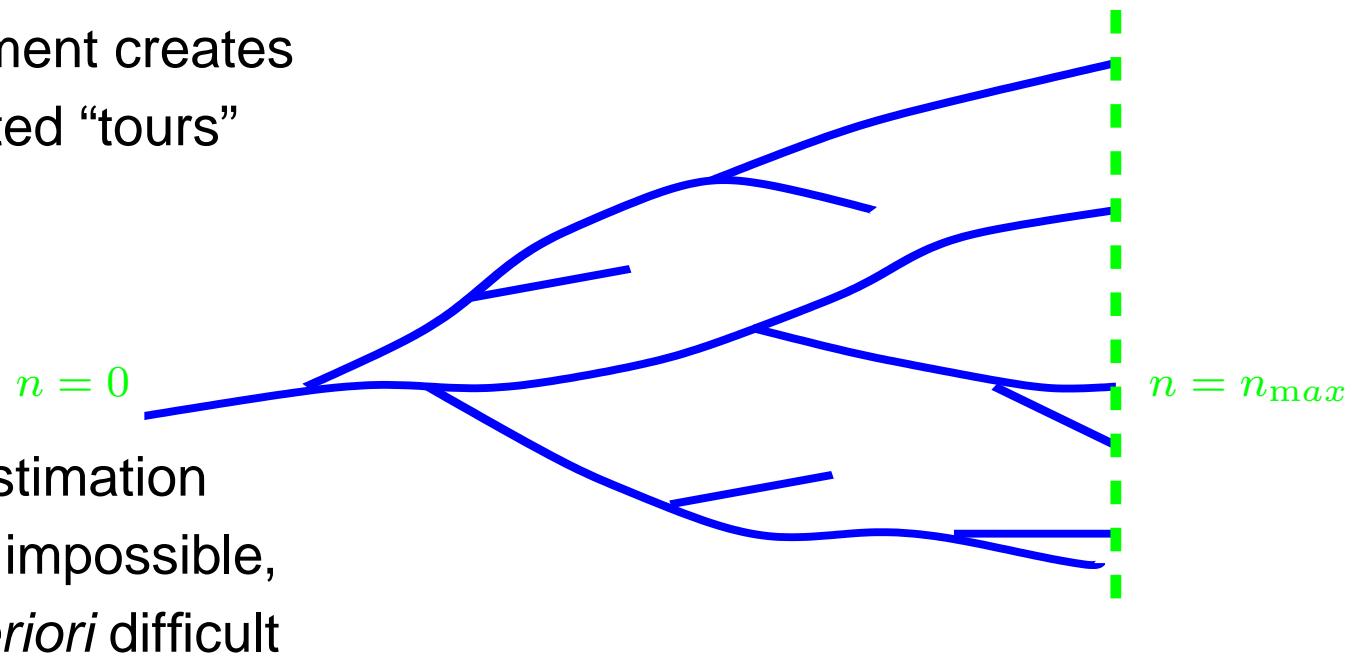
- **Enrichment:** weight too large → make copies of configuration
- **Pruning:** weight too small → remove configuration occasionally

Observation: kinetic growth weights and interactions balance each other at suitable temperatures (in the collapse region)

- PERM well suited for simulation of collapsing polymers
- Enrichment creates correlated “tours”
- Error estimation  
*a priori* impossible,  
*a posteriori* difficult

# PERM – continued

- PERM well suited for simulation of collapsing polymers
- Enrichment creates correlated “tours”



- Error estimation  
*a priori* impossible,  
*a posteriori* difficult

PERM is “blind” - it benefits from “visual aids”, such as

- Markovian anticipation (learning from experience)

# *PERM – further developments*

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- A significant improvement: nPERM = “new” PERM

Hsu et al, J Chem Phys 118 (2003) 444

- Enforce distinct enrichment steps
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- Current work: flatPERM = “flat histogram” PERM

TP and JK, cond-mat/0312253, PRL (2004)

- flatPERM samples a generalised multicanonical ensemble
- Covers the whole temperature range in one simulation!

Related: multicanonical chain growth algorithm

Bachmann and Janke, PRL 91 208105 (2003)

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Applications:

- linear and branched polymers, proteins, percolation, . . .



# *Algorithm details - kinetic growth*

---

View kinetic growth as approximate enumeration



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- Exact enumeration: choose *all*  $a$  continuations with equal weight
- Kinetic growth: chose *one* continuation with  $a$ -fold weight ( $a$  may be zero).



# ***Algorithm details - kinetic growth***

View kinetic growth as approximate enumeration

- Exact enumeration: choose *all*  $a$  continuations with equal weight
- Kinetic growth: chose *one* continuation with  $a$ -fold weight ( $a$  may be zero).
- An  $n$  step configuration gets assigned a weight

$$W = \prod_{k=0}^{n-1} a_k$$

- $S$  growth chains with weights  $W_n^{(i)}$  give estimate

$$C_n^{\text{est}} = \langle W \rangle_n = \frac{1}{S} \sum_i W_n^{(i)}$$

# ***Algorithm details - pruning/enrichment***

---

- $W_n^{(i)}$  is estimate of  $C_n$
- Consider ratio  $r = W_n^{(i)} / C_n^{est}$ 
  - $r > 1 \rightarrow$  enrichment step:  
make  $c = \min(\lfloor r \rfloor, a_n)$  distinct copies with weight  $\frac{1}{c} W_n^{(i)}$
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continue growing with probability  $r$  and weight  $C_n^{est}$
- Consequences
  - Number of samples generated for each  $n$  is roughly constant
  - Ideally, unbiased random walk in configuration size
  - We have a flat histogram algorithm

# *From PERM to flatPERM*

---

- PERM: estimate number of configurations  $C_n$ 
  - $C_n^{est} = \langle W \rangle_n$
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Consider energy  $E_m = \epsilon m$ , temperature  $\beta = 1/k_B T$

- thermal PERM: estimate partition function  $Z_n(\beta)$ 
  - $Z_n^{est}(\beta) = \langle W \exp(-\beta E) \rangle_n$
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- flatPERM: estimate density of states  $C_{n,m}$

- $C_{n,m}^{est} = \langle W \rangle_{n,m}$
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- Generalization to more microcanonical parameters possible

- Implementation details
  - Parameter free implementation
  - Equilibrate by slowly increasing maximal size of configurations
  - Reduce correlations by considering “effective” sample size

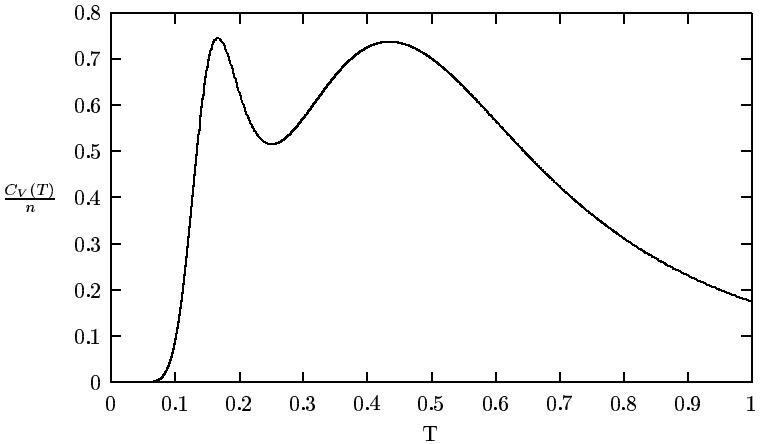
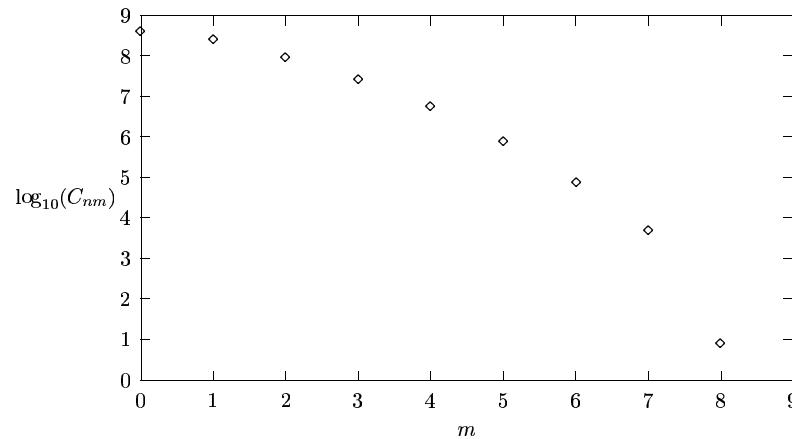
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- What if we don’t need the whole histogram?
  - Restriction of histogram possible
  - e.g. impose internal energy restriction  $m/n < u_{cutoff}$
- What if we don’t want a “flat” histogram?
  - Sample profile can be tuned
  - Selectively perform pruning/enrichment with respect to profile shape  $f_{n,m}$

# ***Simulation Results***

# Simulation results: HP model

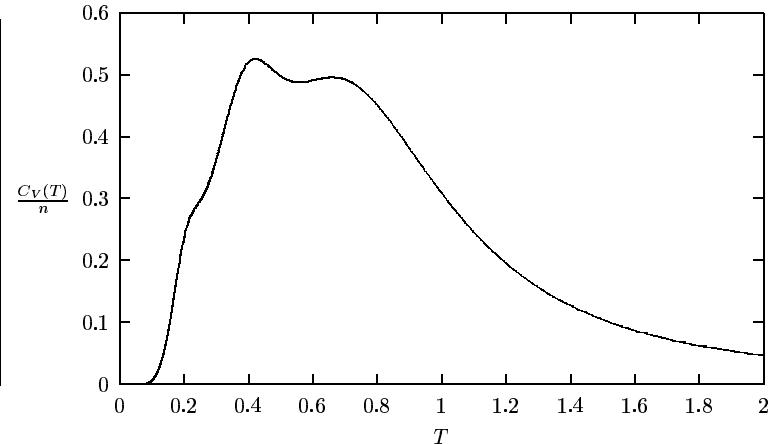
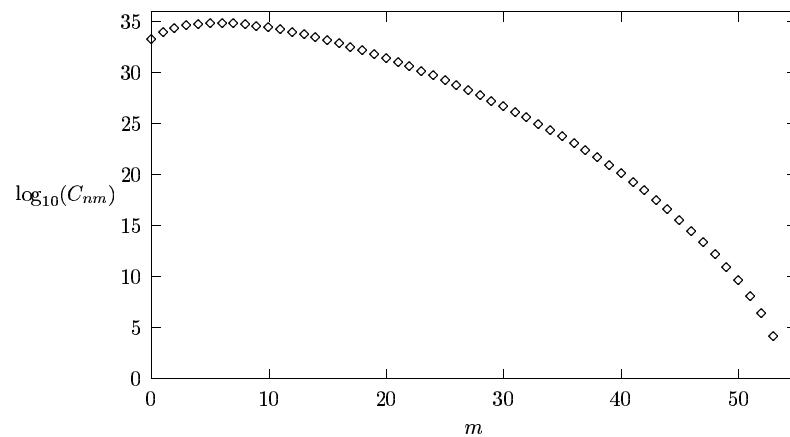
- Sequence I (14 Monomers, HPHPHHPPHPPH,  $d = 3$ ):



- Pedagogical example, engineered for native ground state
- Perfect agreement with exact enumeration

# Simulation results: HP model

- Sequence II (85 Monomers,  $d = 2$ ):



- Investigated several other sequences in  $d = 2$  and  $d = 3$
- Collapsed regime accessible
- Reproduced known ground state energies
- Obtained  $C_{n,m}$  over large range

# *Simulation: Equilibration for 2d ISAW*

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2d ISAW simulation up to  $n = 1024$

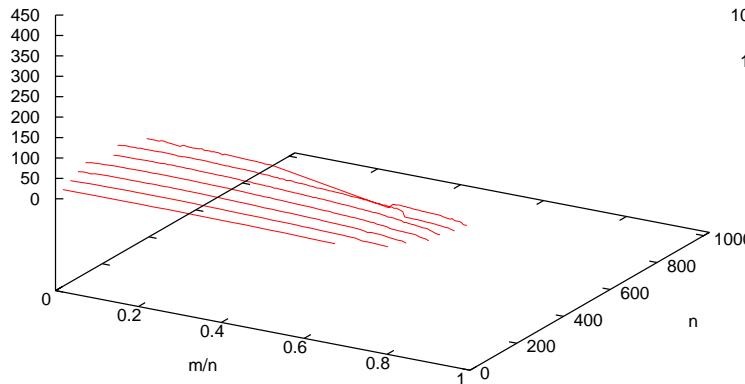
- Equilibration with delay 0.1:  
after  $t$  tours growth up to length  $10t$

# *Simulation: Equilibration for 2d ISAW*

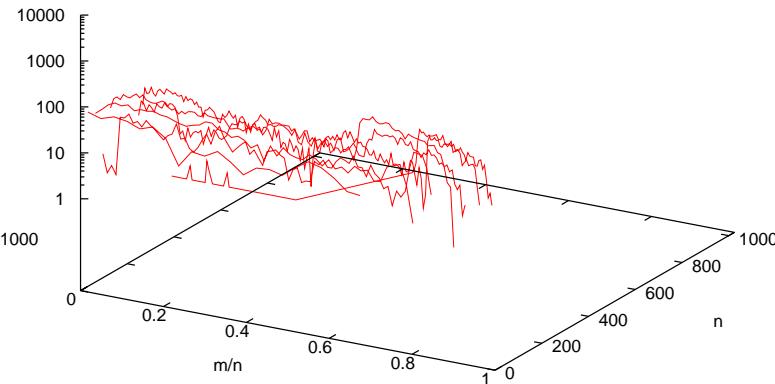
2d ISAW simulation up to  $n = 1024$

- Total sample size: 1,000,000

$\log_{10}(C_{nm})$



$S_{nm}$

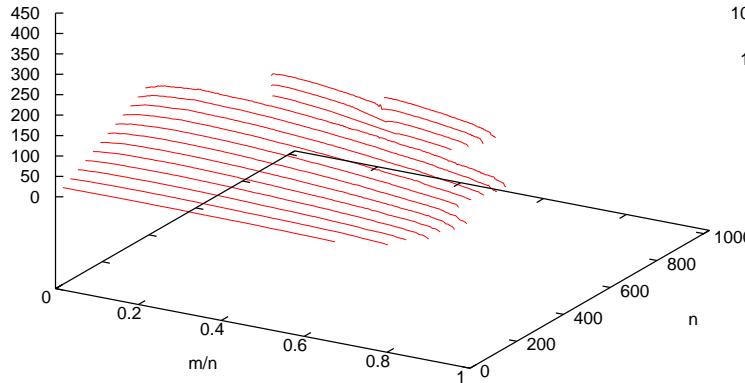


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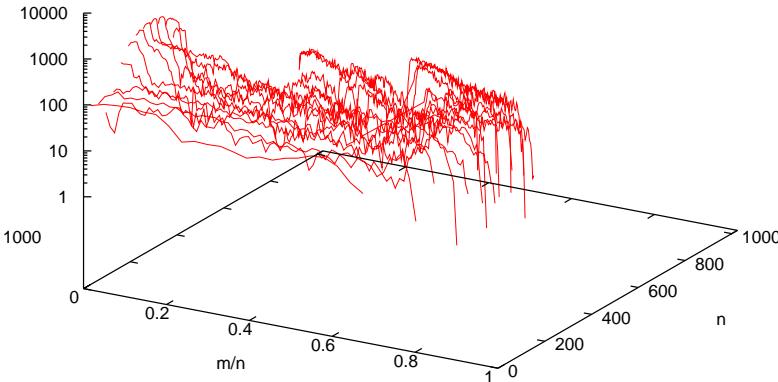
2d ISAW simulation up to  $n = 1024$

- Total sample size: 10,000,000

$\log_{10}(C_{nm})$



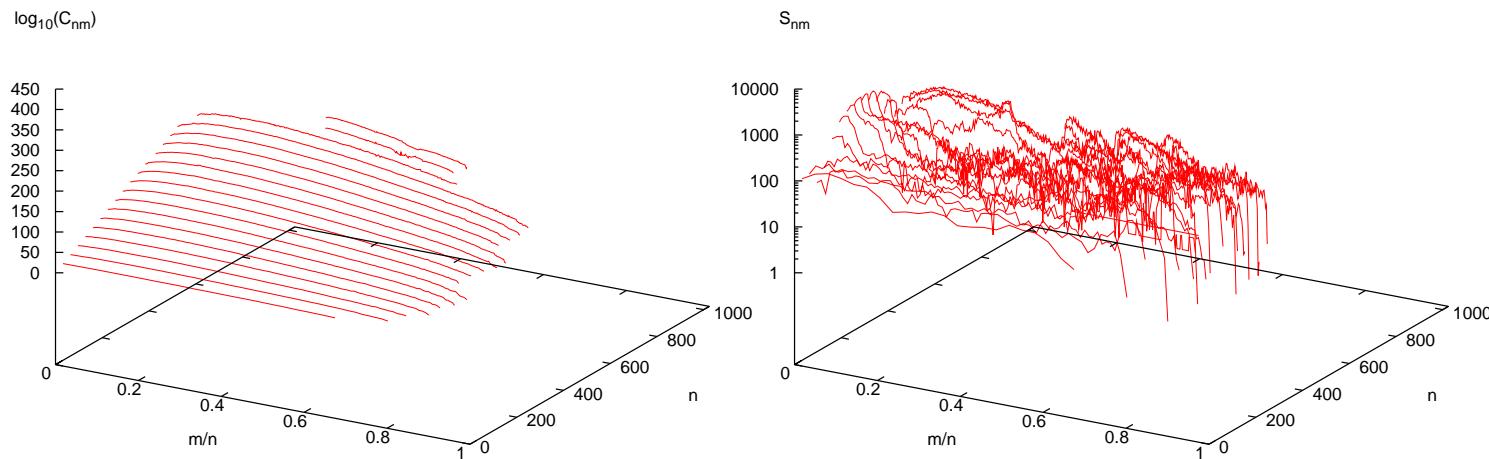
$S_{nm}$



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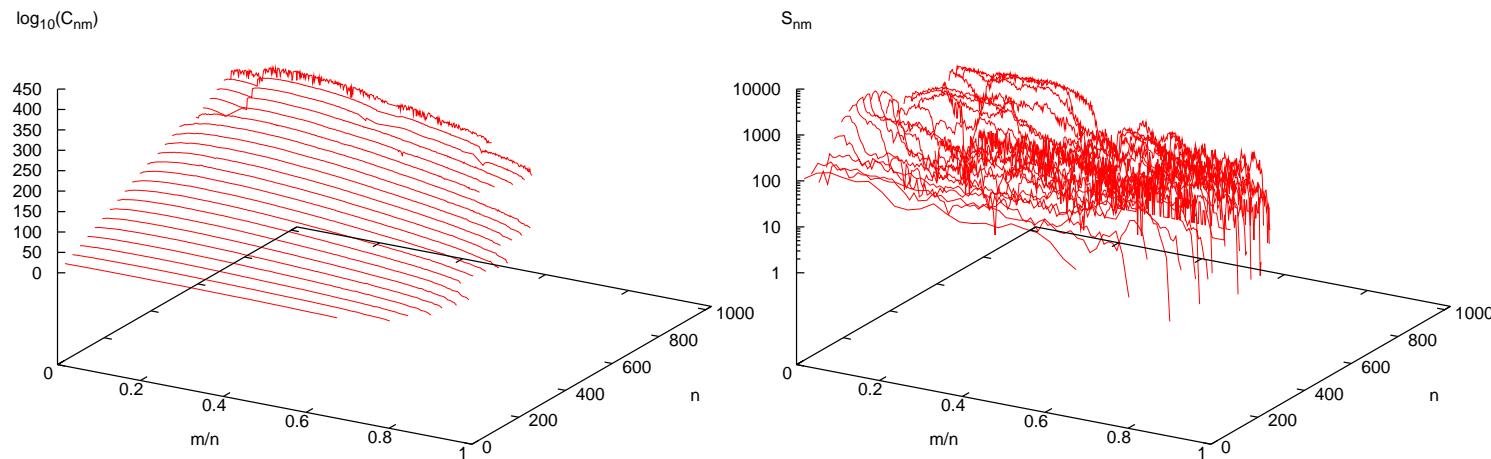
- Total sample size: 20,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

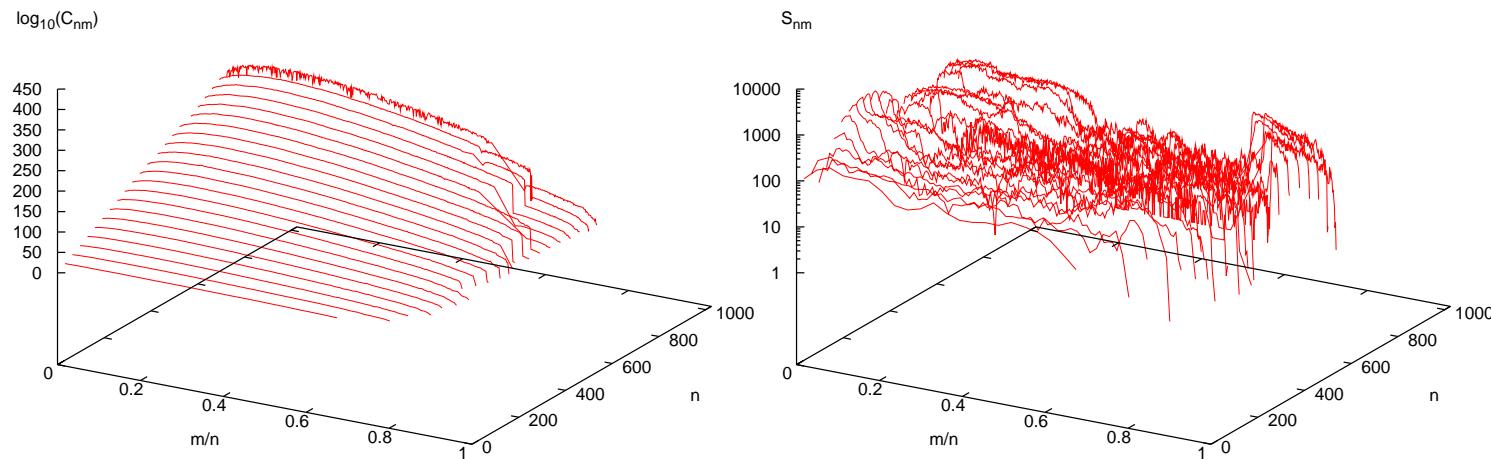
- Total sample size: 30,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

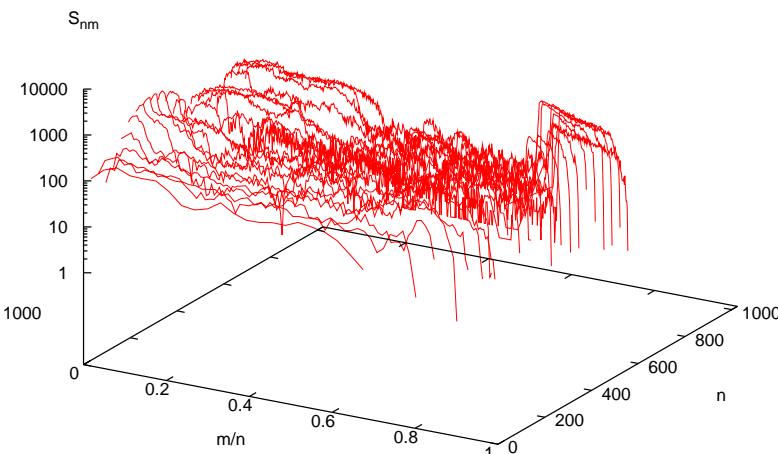
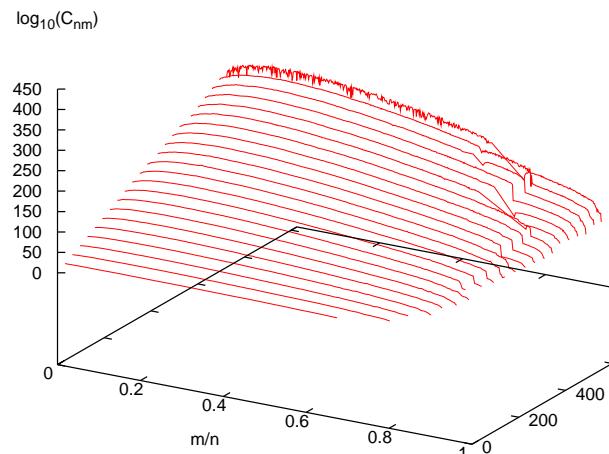
- Total sample size: 40,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

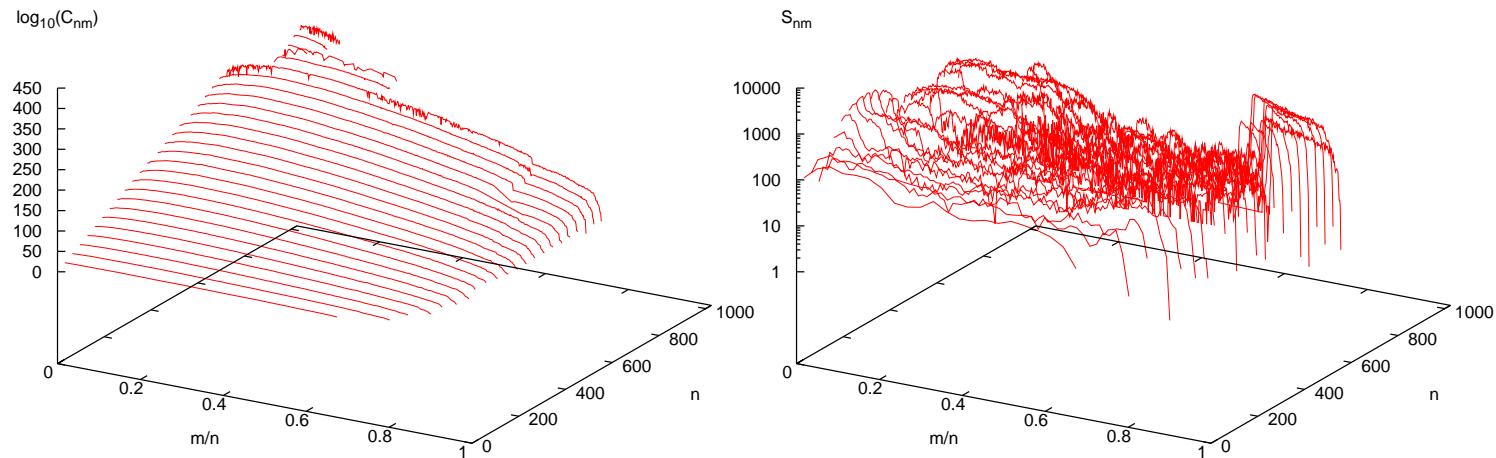
- Total sample size: 50,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

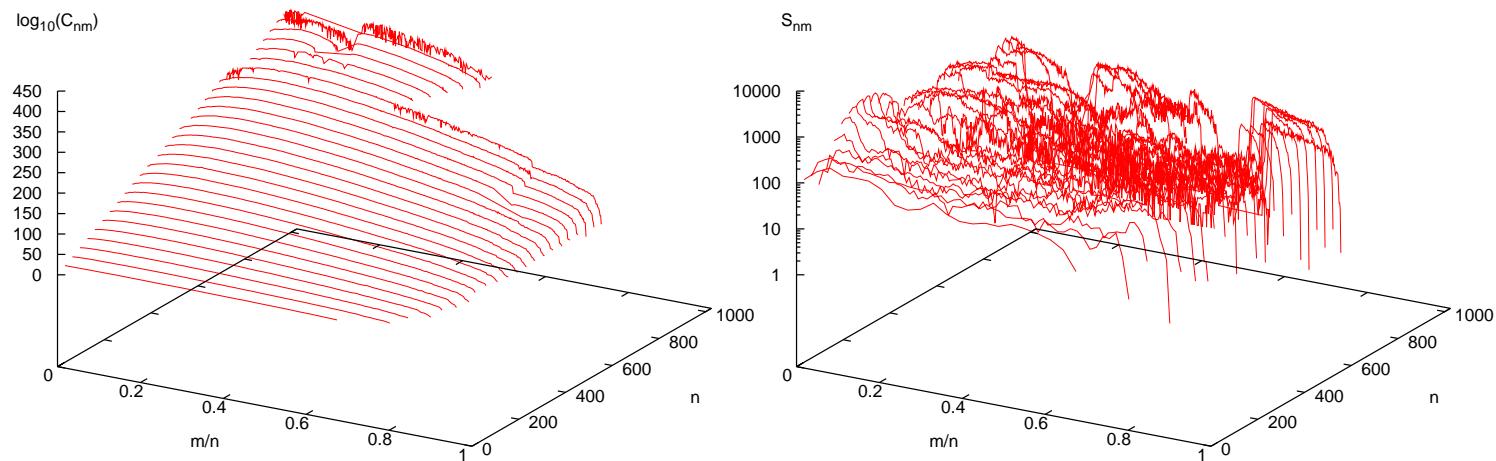
- Total sample size: 60,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

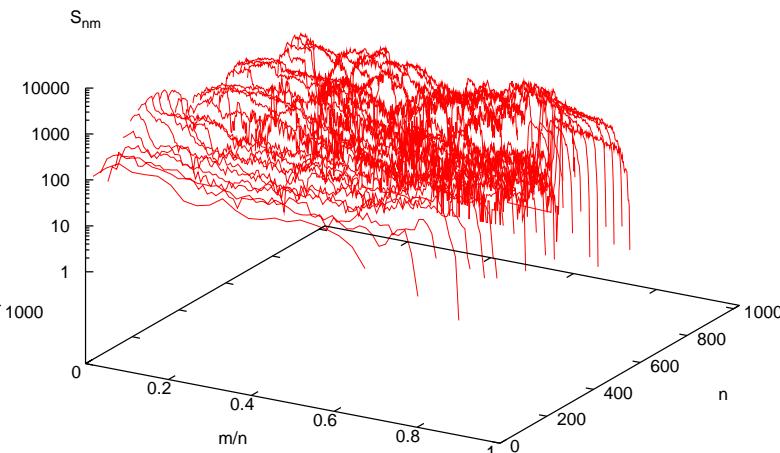
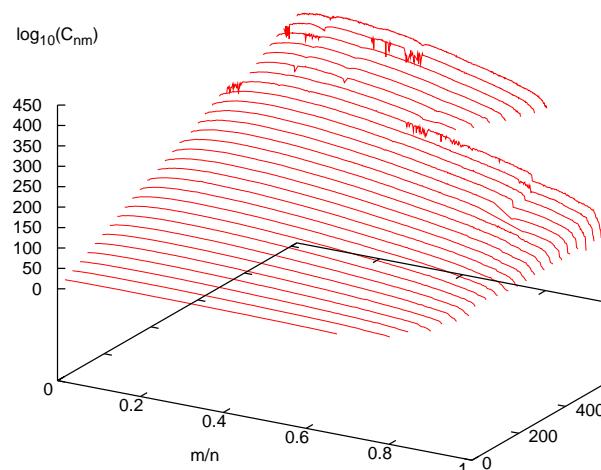
- Total sample size: 70,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

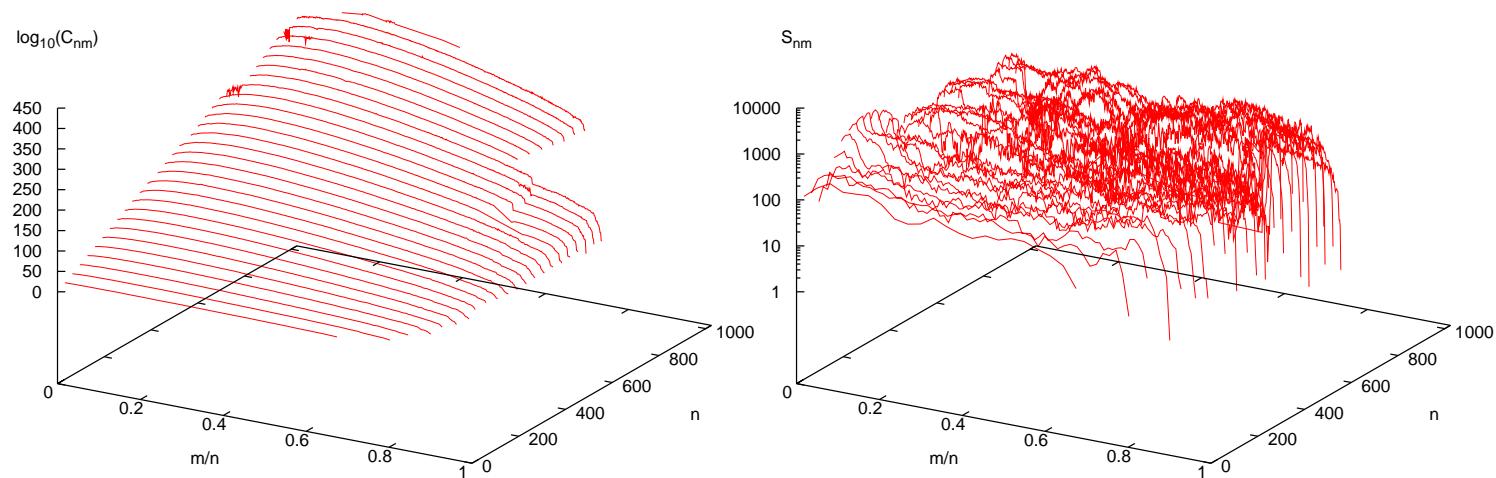
- Total sample size: 80,000,000



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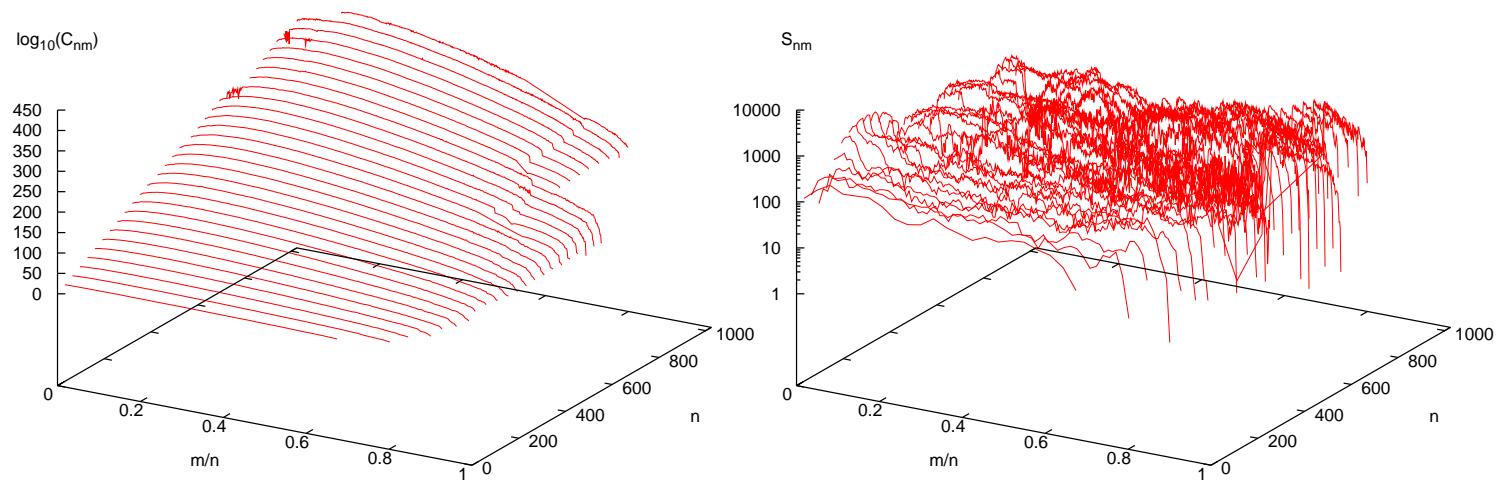
- Total sample size: 90,000,000



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2d ISAW simulation up to  $n = 1024$

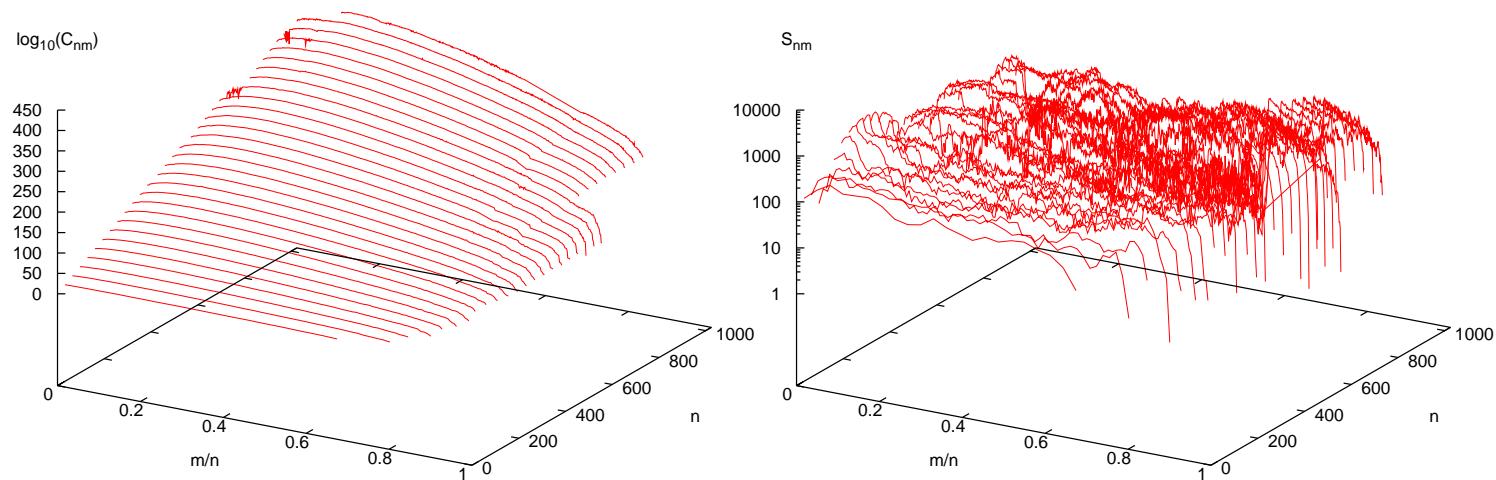
- Total sample size: 100,000,000



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2d ISAW simulation up to  $n = 1024$

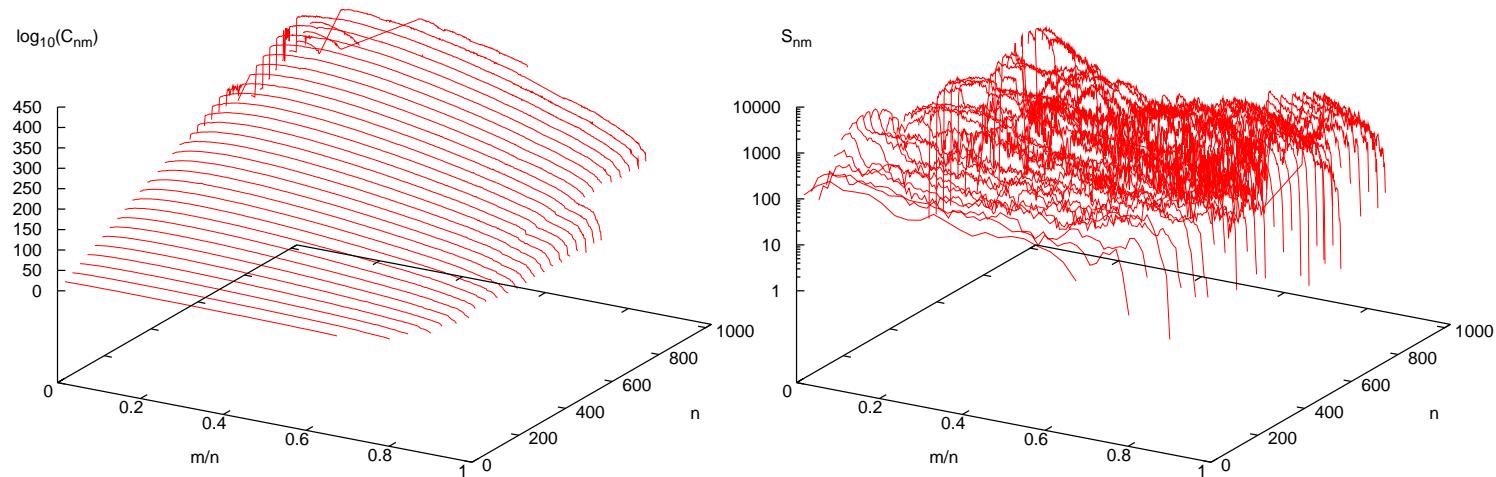
- Total sample size: 110,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

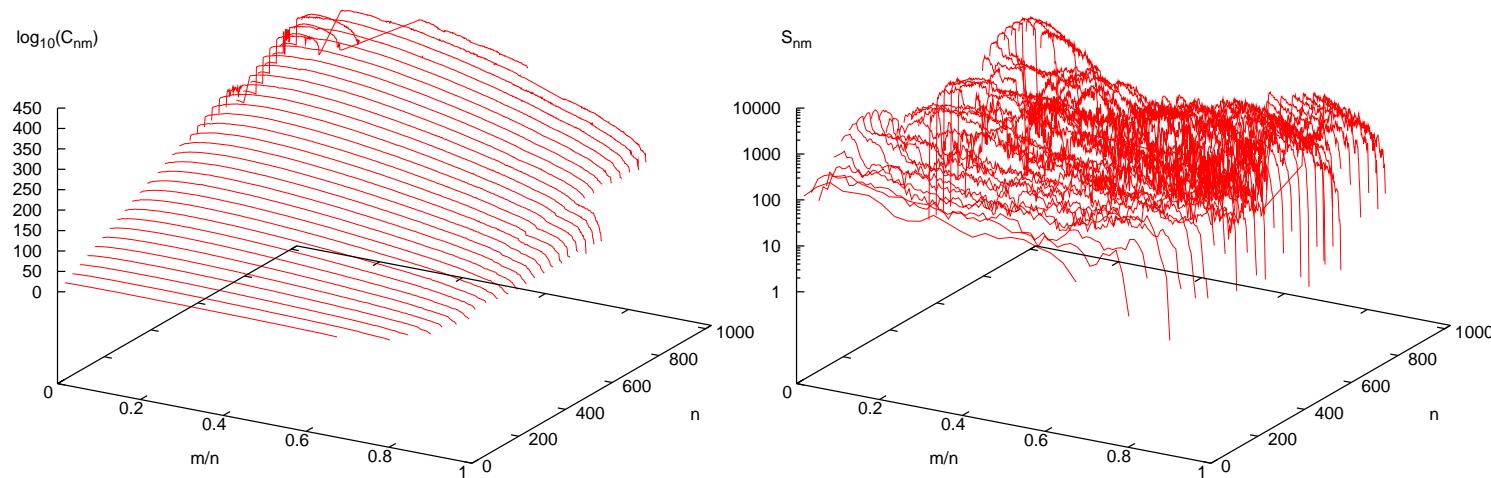
- Total sample size: 120,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

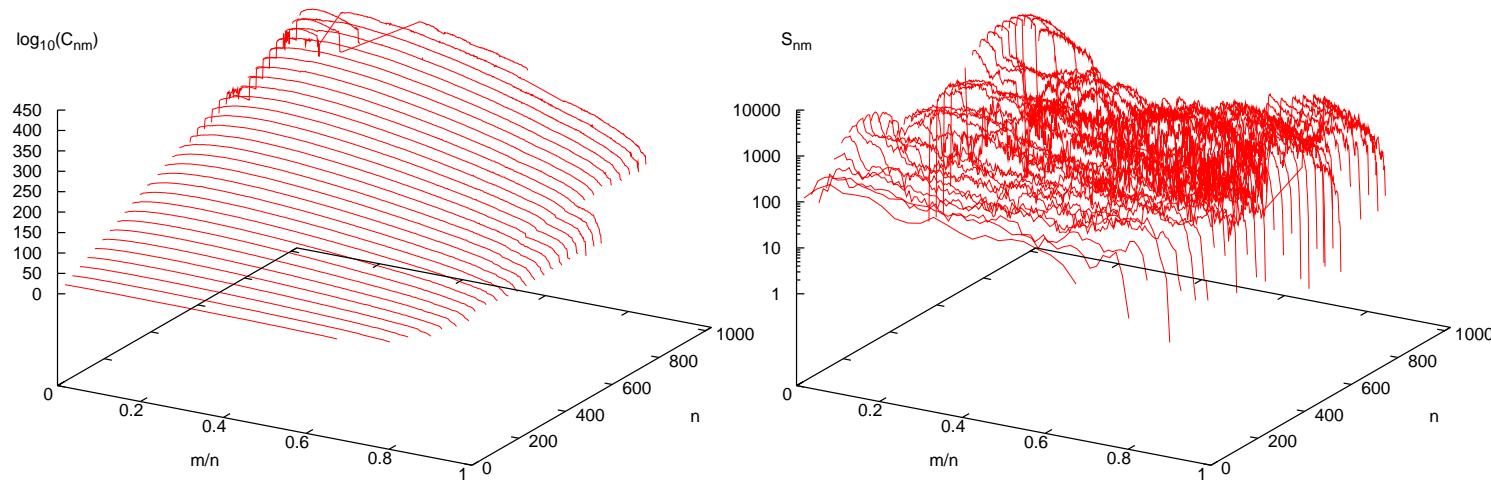
- Total sample size: 130,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

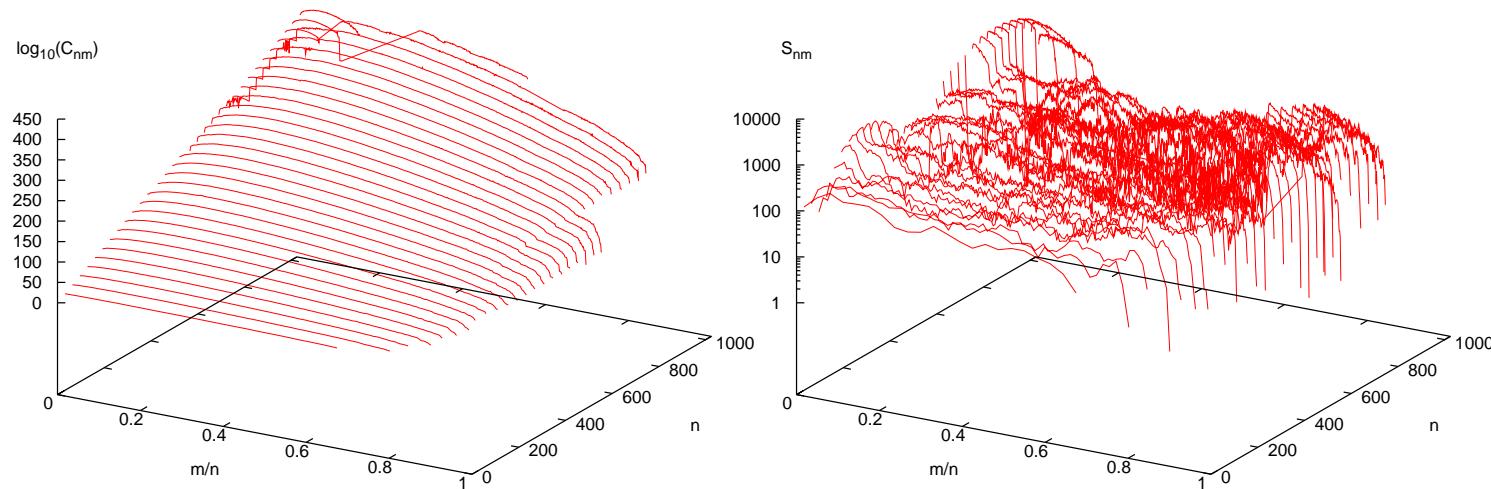
- Total sample size: 140,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

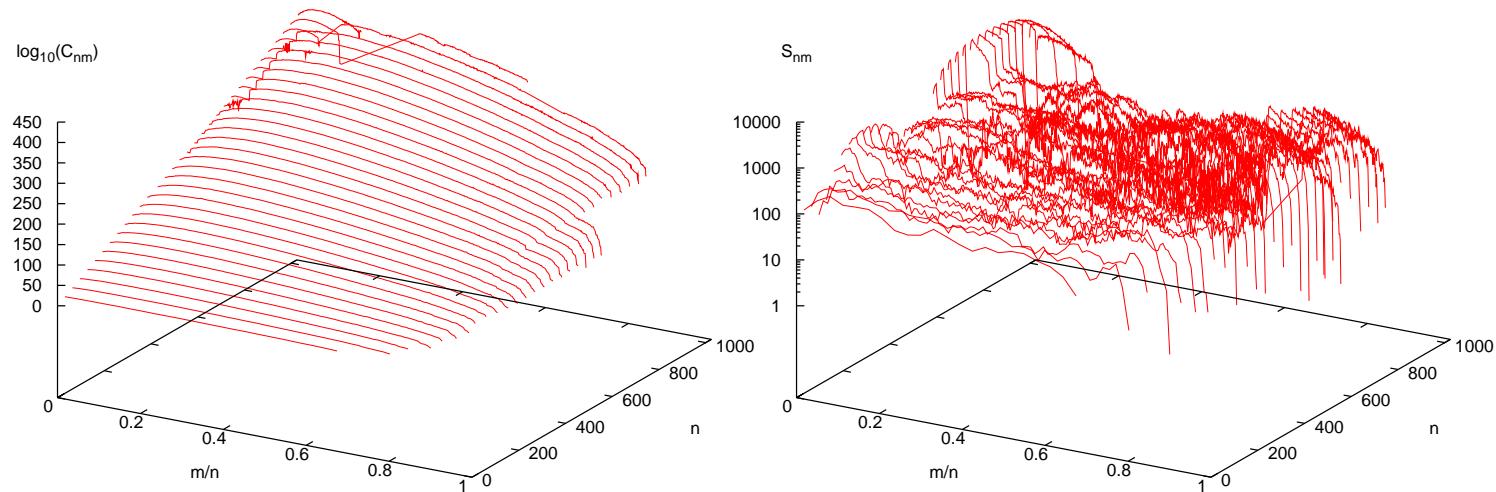
- Total sample size: 150,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

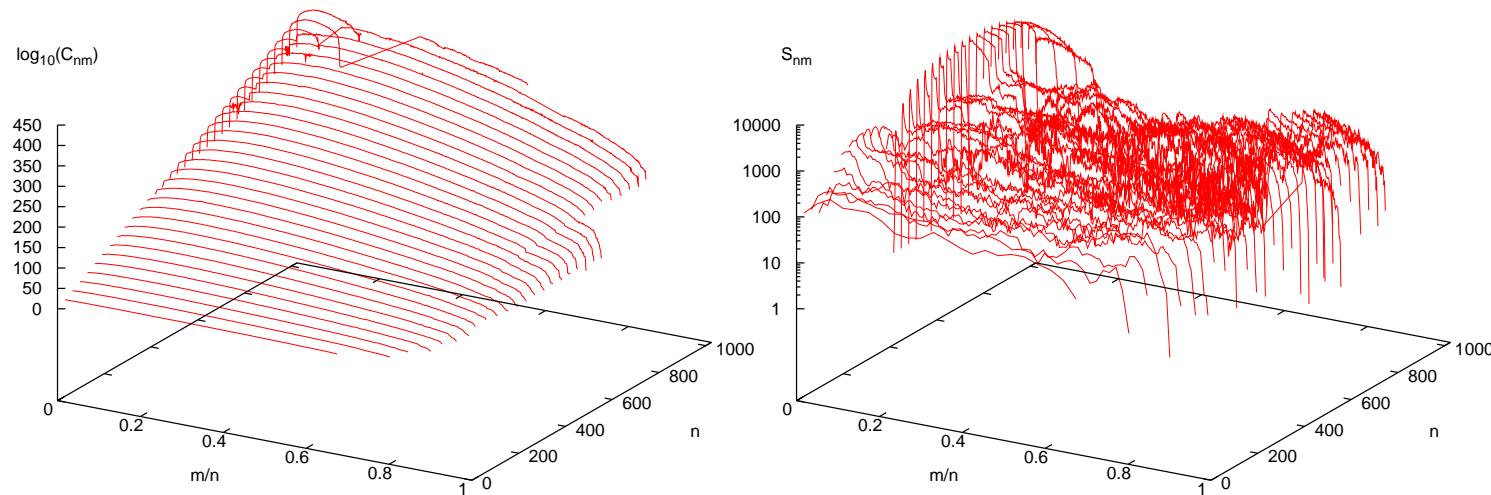
- Total sample size: 160,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

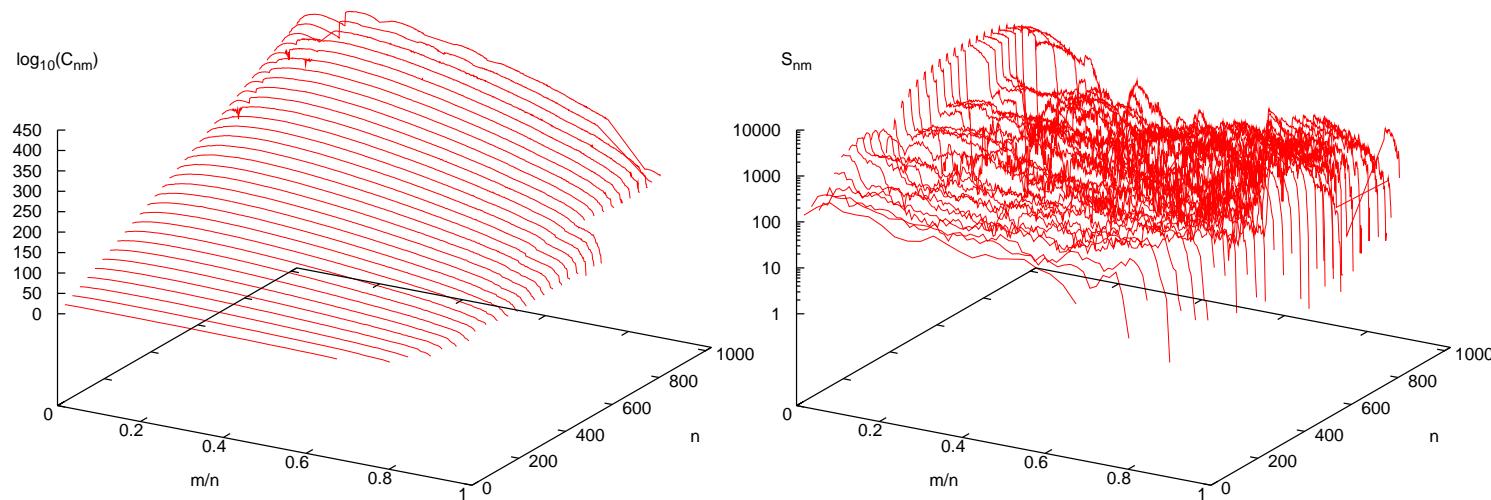
- Total sample size: 170,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

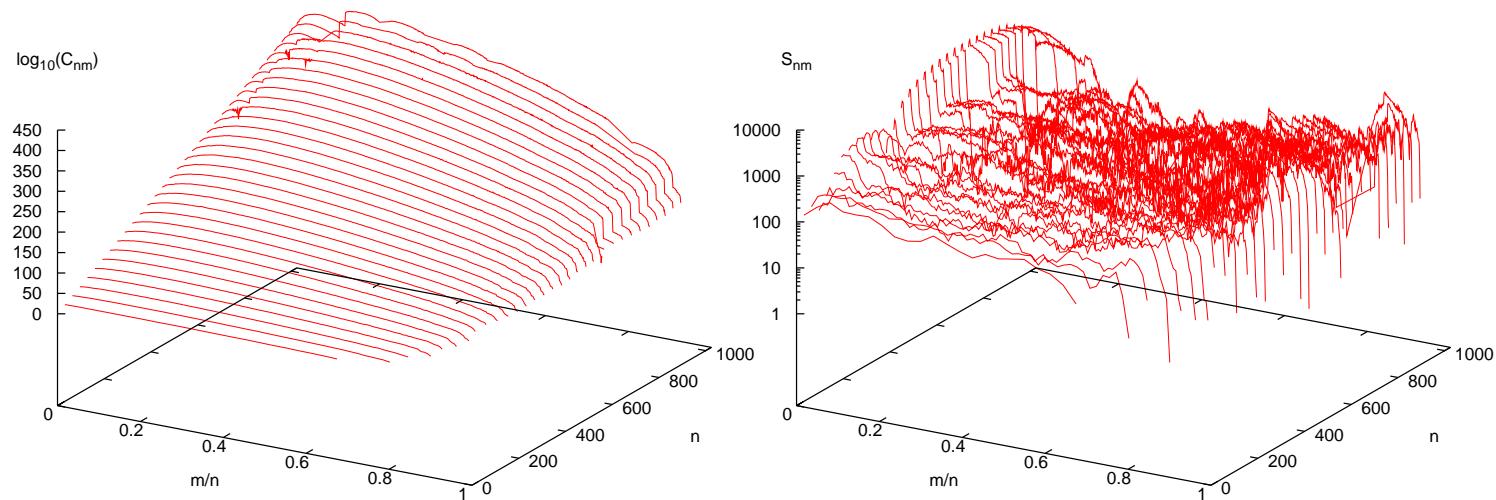
- Total sample size: 180,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

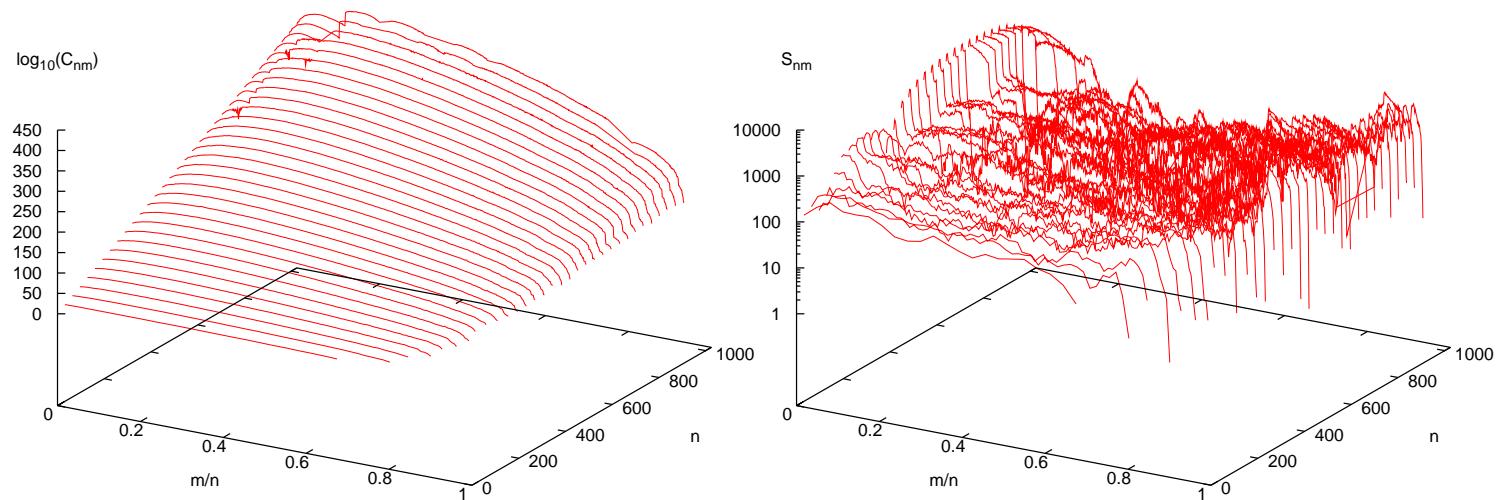
- Total sample size: 190,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

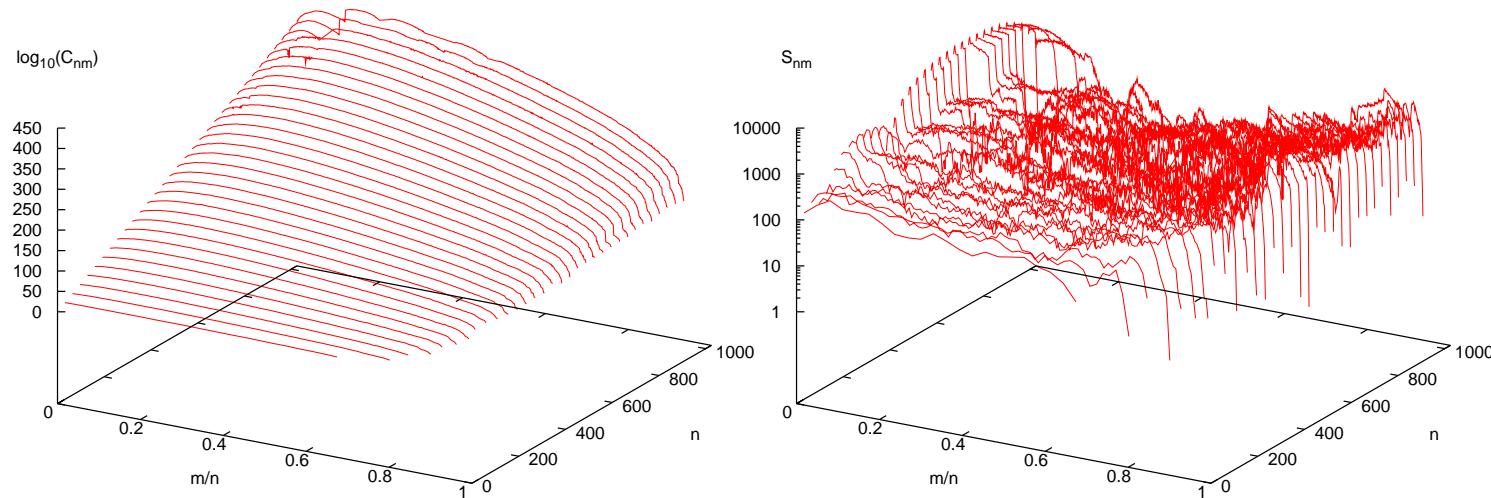
- Total sample size: 200,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

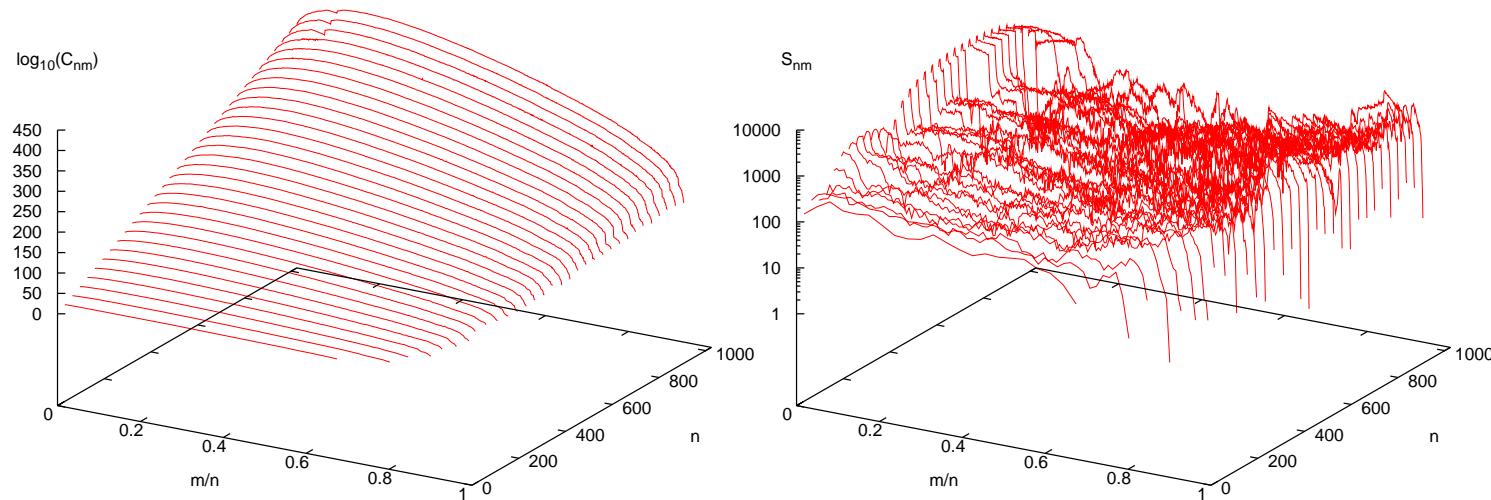
- Total sample size: 210,000,000



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2d ISAW simulation up to  $n = 1024$

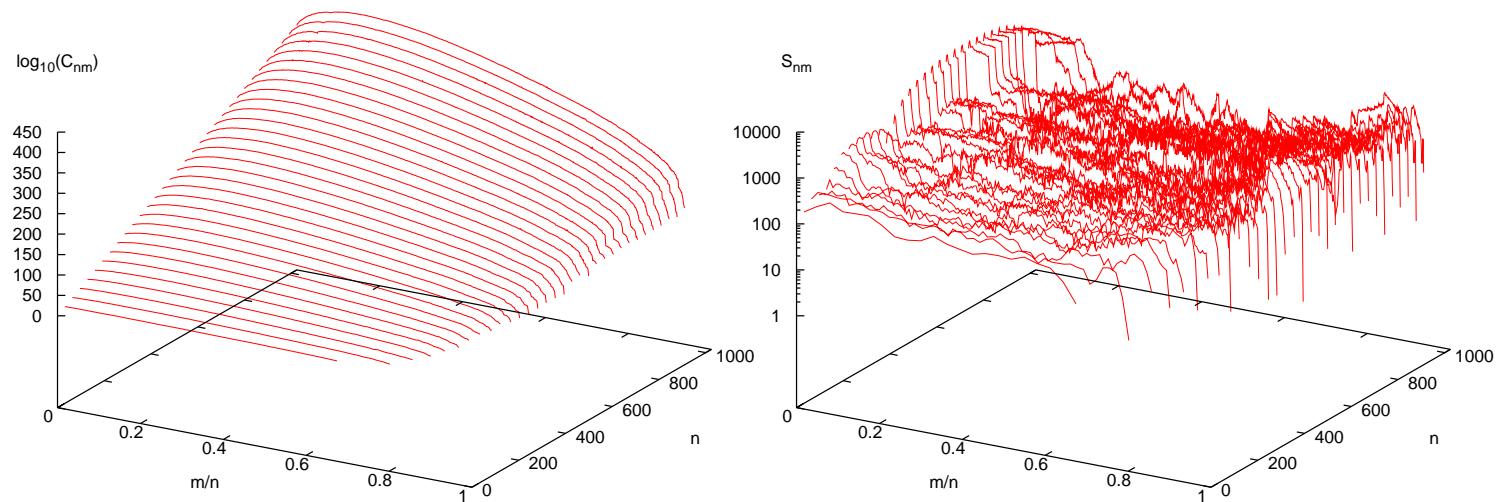
- Total sample size: 220,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

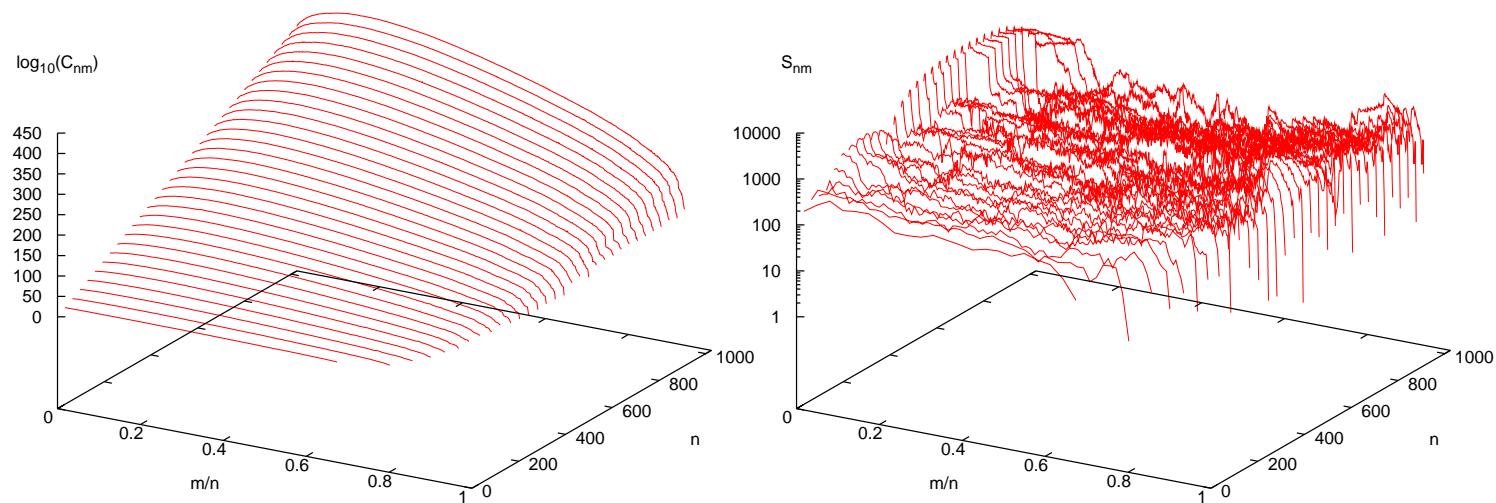
- Total sample size: 230,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

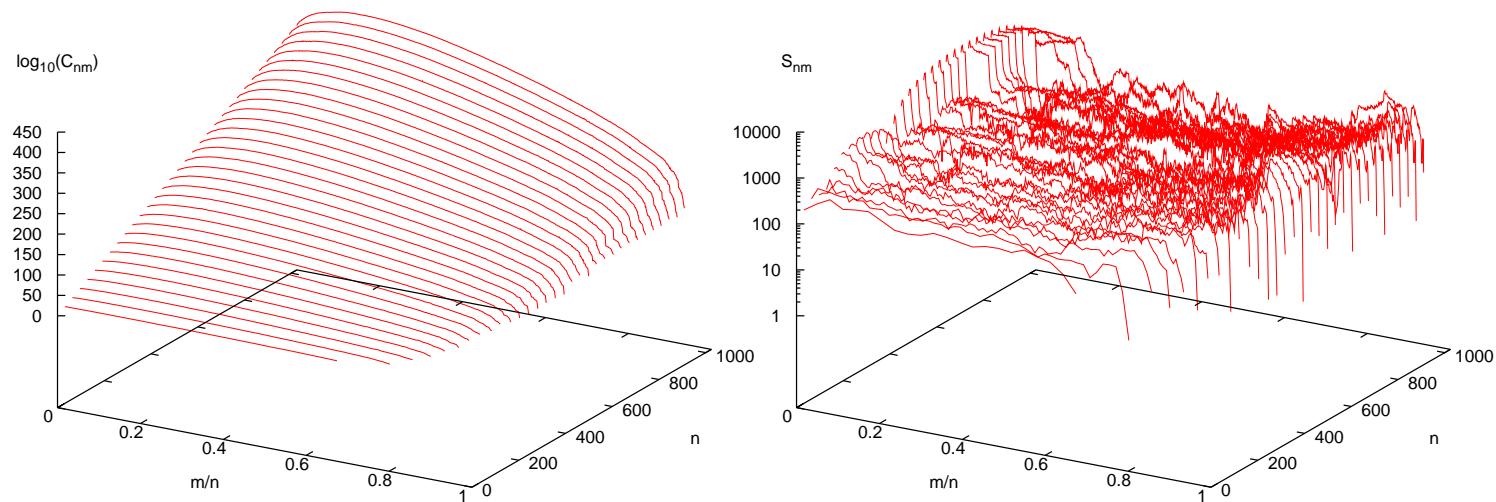
- Total sample size: 240,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

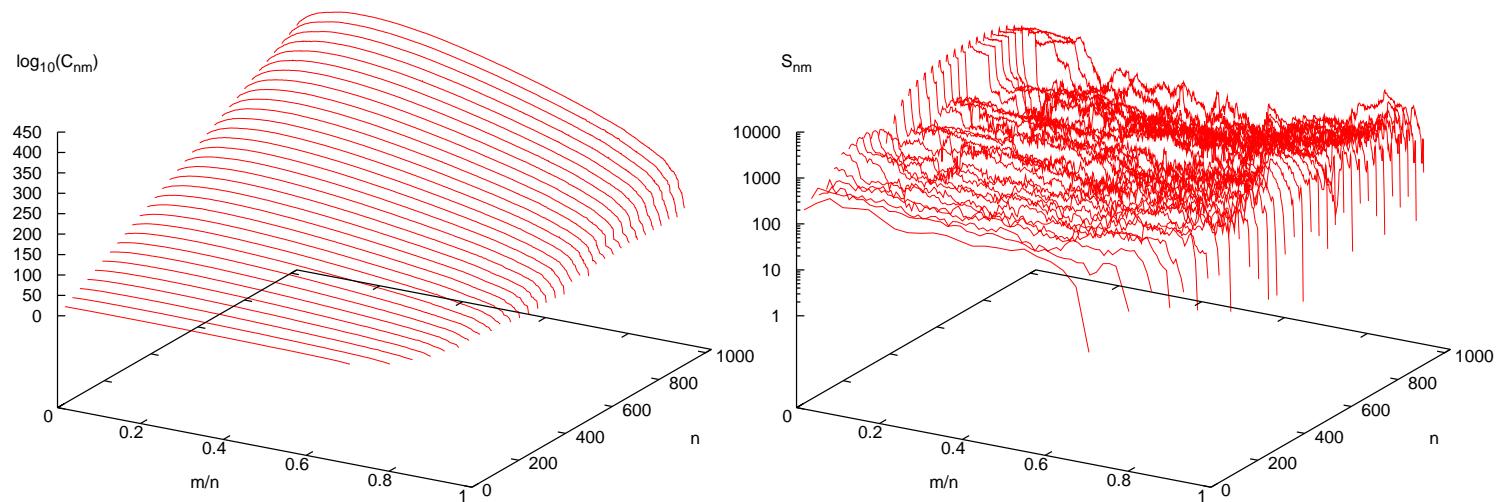
- Total sample size: 250,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

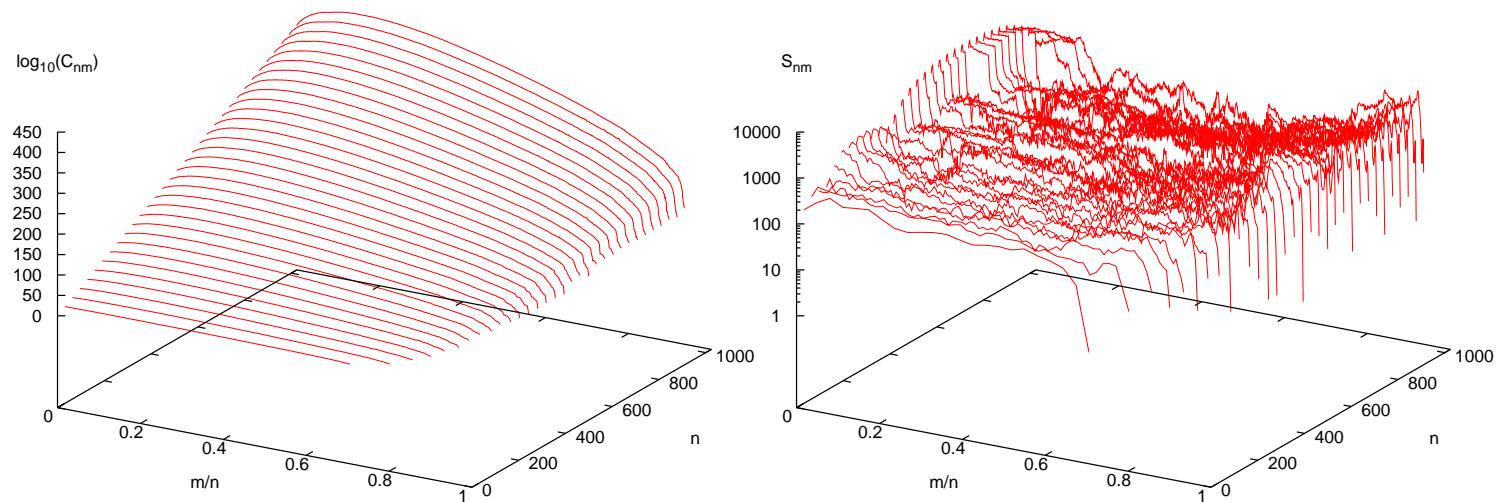
- Total sample size: 260,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

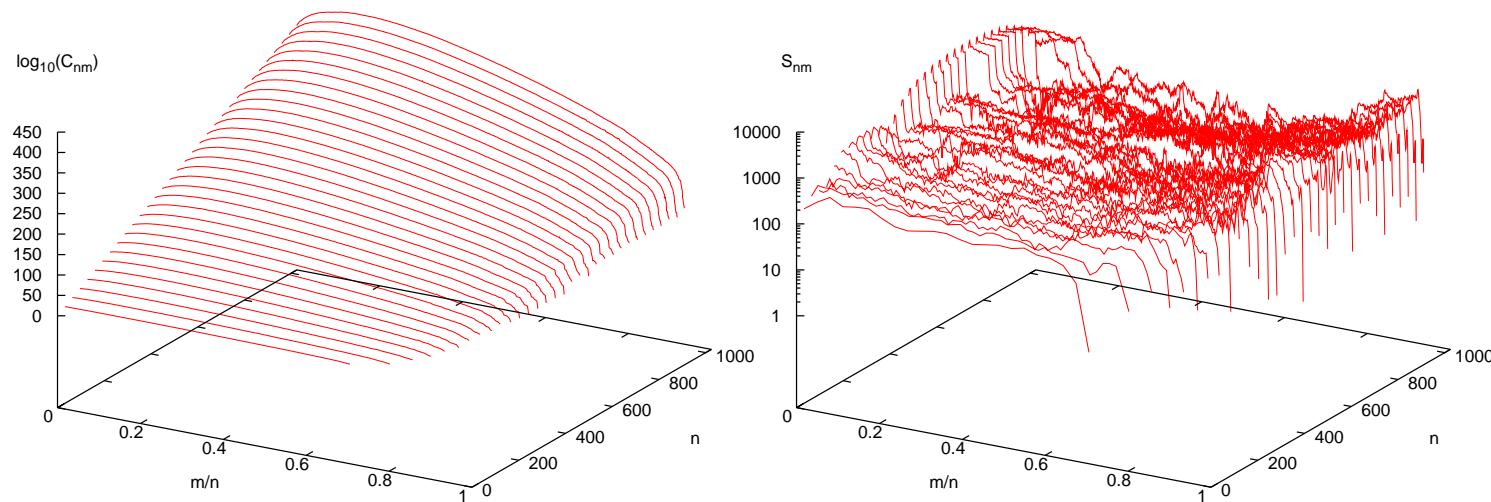
- Total sample size: 270,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

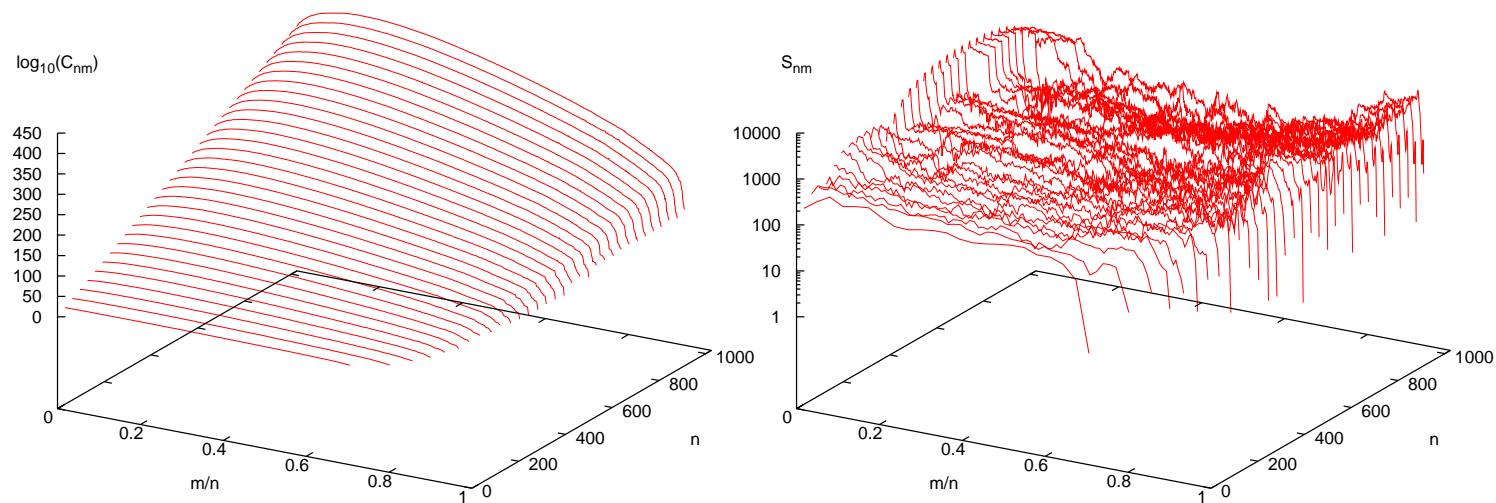
- Total sample size: 280,000,000



# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

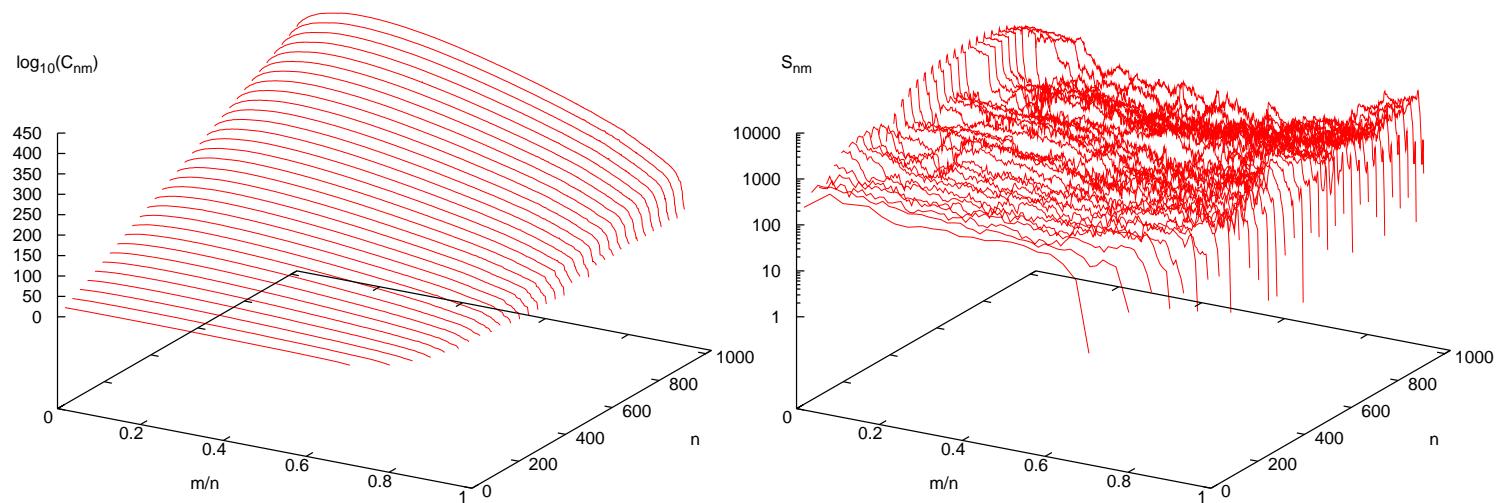
- Total sample size: 290,000,000



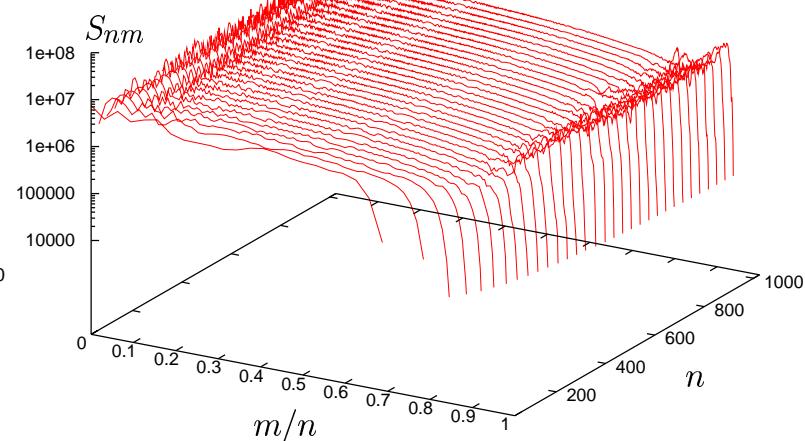
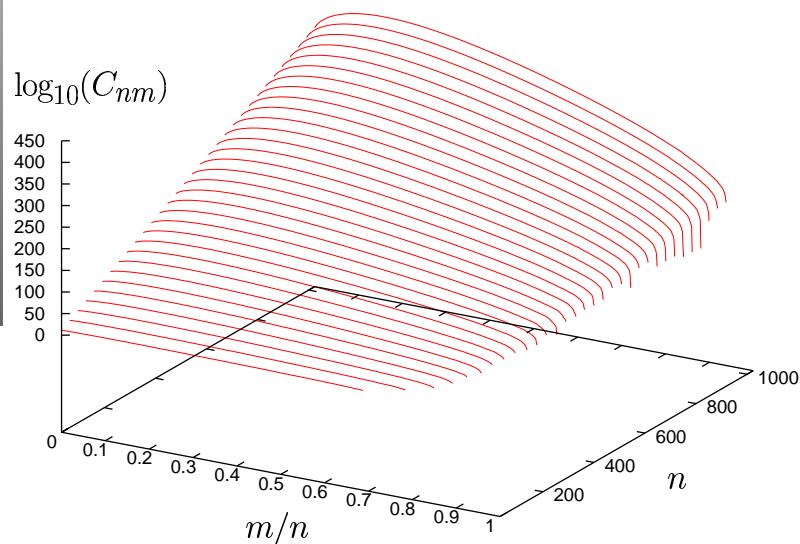
# *Simulation: Equilibration for 2d ISAW*

2d ISAW simulation up to  $n = 1024$

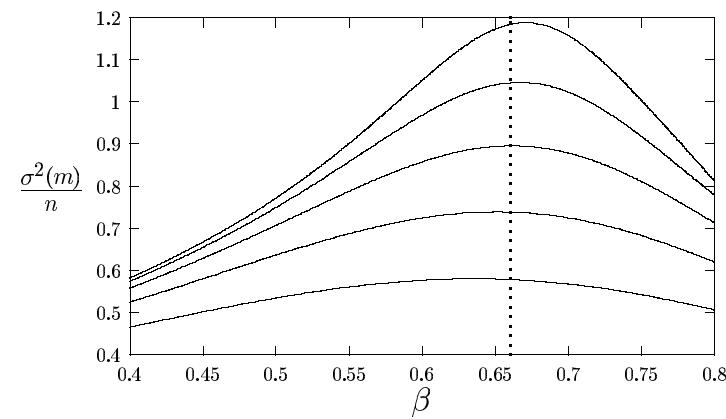
- Total sample size: 300,000,000



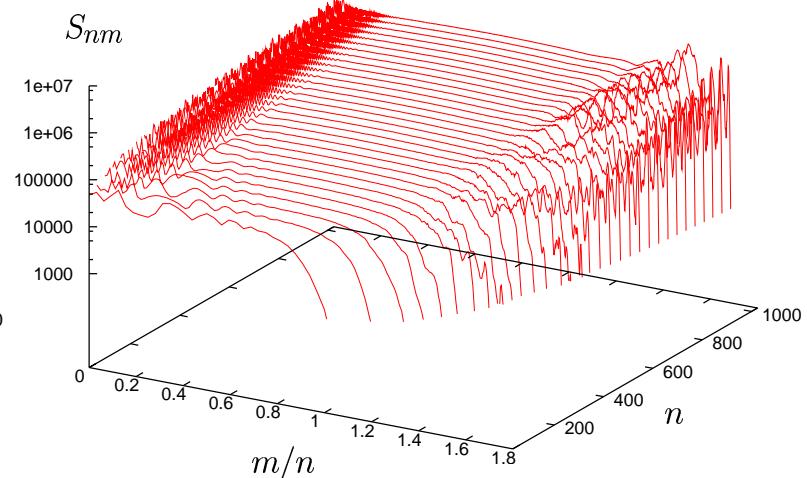
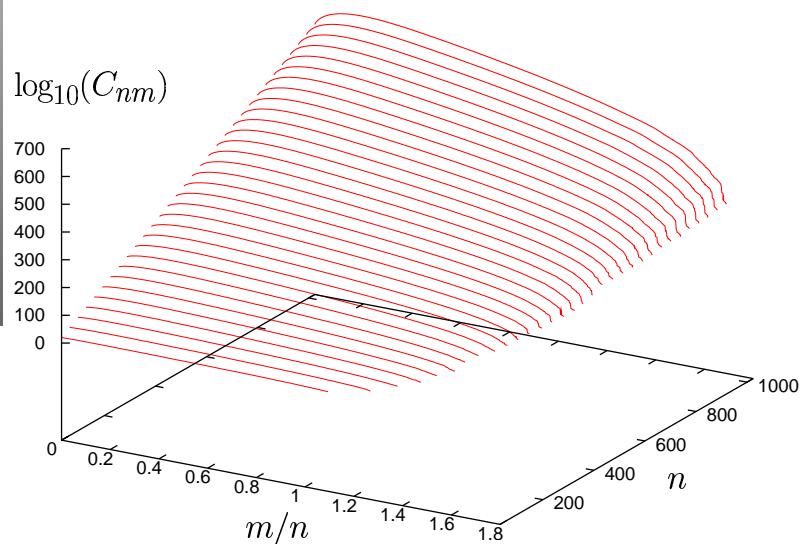
# Simulation results: 2d ISAW



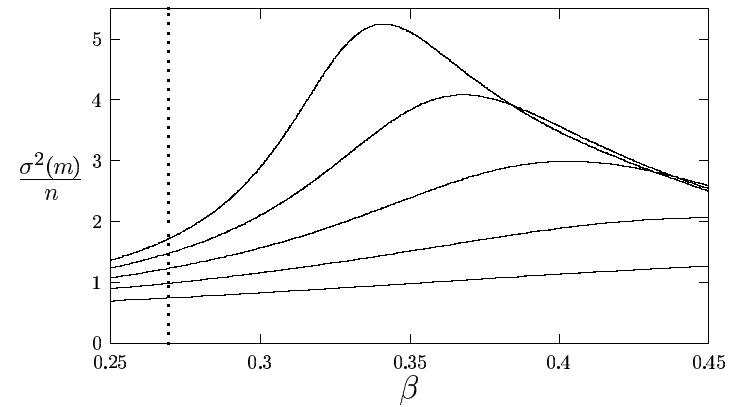
- 2d ISAW up to  $n = 1024$
- One simulation suffices
- 300 orders of magnitude



# Simulation results: 3d ISAW



- 3d ISAW up to  $n = 1024$
- One simulation suffices
- 400 orders of magnitude



# *Summary*

# ***Conclusion: A Promising New Algorithm***

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- Reviewed Stochastic Growth Algorithms for Polymers
- Presented “flat histogram” version of PERM
  - One simulation for complete density of states!  
(the range can also be selectively restricted)
- Applications: HP model, ISAW



# ***Conclusion: A Promising New Algorithm***

---

- Reviewed Stochastic Growth Algorithms for Polymers
- Presented “flat histogram” version of PERM
  - One simulation for complete density of states!  
(the range can also be selectively restricted)
- Applications: HP model, ISAW

Outlook: applications to further models, e.g.

- Square lattice trees / branched polymers: with A. Rechnitzer
  - Connective constant estimate  $5.1435(5)$   
(compare to  $5.1434(7)$  with Pivot algorithm)
- Two-dimensional density of states with *one* simulation
  - Absorbing collapsing polymers: with A. Owczarek
  - Extended Domb-Joyce model: with J. Krawczyk

***The End***

