

# Finite-Size Scaling for Dense Associative Memory

## Phase Boundaries on the $N$ -Sphere:

### Metastability and the Limits of Linear Extrapolation

## 1 Introduction

We study the retrieval phase boundaries of Dense Associative Memory (DAM) models on the  $N$ -sphere  $S^{N-1}(\sqrt{N})$  using GPU-accelerated Metropolis–Hastings Monte Carlo simulations. Two energy kernels are considered:

- **LSE** (Gaussian / log-sum-exp):  $E(\mathbf{x}) = -\frac{1}{\beta_{\text{net}}} \log \sum_{\mu=1}^P e^{-\beta_{\text{net}}(N - \boldsymbol{\xi}^\mu \cdot \mathbf{x})}$ ,
- **LSR** (Epanechnikov / log-sum-ReLU,  $b = 2 + \sqrt{2}$ ):  $E(\mathbf{x}) = -\frac{N}{b} \log \sum_{\mu=1}^P \max(0, 1 - b + \frac{b}{N} \boldsymbol{\xi}^\mu \cdot \mathbf{x})$ .

Here  $\boldsymbol{\xi}^1, \dots, \boldsymbol{\xi}^P$  are random i.i.d. patterns on  $S^{N-1}(\sqrt{N})$ , and the number of patterns scales exponentially:  $P = e^{\alpha N}$ , where  $\alpha = \ln P/N$  is the load parameter.

The goal is to map the order parameter  $\varphi(\alpha, T)$  — the overlap with the target pattern — across the  $(\alpha, T)$  plane, and compare the observed phase boundary with the theoretical prediction derived in the  $N \rightarrow \infty$  limit.

## 2 Monte Carlo Setup

### 2.1 Adaptive- $N$ approach

For each value of  $\alpha$ , the number of neurons is determined by

$$N(\alpha) = \left\lfloor \frac{\ln P(\alpha)}{\alpha} \right\rfloor, \quad (1)$$

where  $P(\alpha)$  is interpolated linearly between  $P_{\min}$  and  $P_{\max}$  across the  $\alpha$  grid ( $\alpha \in [0.01, 0.55]$ , step 0.01;  $T \in [0.05, 2.50]$ , step 0.05).

### 2.2 Simulation parameters

Each simulation uses:

- $N_{\text{eq}} = 5,000$  equilibration steps (no measurements),
- $N_{\text{samp}} = 5,000$  sampling steps with overlap accumulation,
- Adaptive step size  $\sigma = \max(0.1, 2.4/\sqrt{N})$ ,
- Initialization near the target pattern:  $\mathbf{x}_0 = \boldsymbol{\xi}^1 + 0.05 \boldsymbol{\eta}$ , projected onto  $S^{N-1}(\sqrt{N})$ .

The overlap is averaged over multiple independent trials (each with freshly generated random patterns).

### 3 Finite-Size Scaling: Approach and Motivation

#### 3.1 The problem at finite $N$

The theoretical phase boundaries are derived in the thermodynamic limit  $N \rightarrow \infty$ . At any finite  $N$ , the phase transition is broadened:

- The overlap  $\varphi$  does not jump discontinuously at the critical point but changes gradually over a region of width  $\sim 1/\sqrt{N}$ .
- The apparent critical temperature  $T_c^{\text{eff}}(N)$  differs from the theoretical  $T_c(\infty)$ .

Since  $N = \ln P/\alpha$ , at a given  $\alpha$  one can increase  $N$  only by increasing  $P$ . Even increasing  $P$  by orders of magnitude yields only modest gains in  $N$ : for instance, at  $\alpha = 0.10$ , going from  $P = 1,000$  to  $P = 300,000$  changes  $N$  from 69 to 110 (a factor of  $1.6\times$ ).

#### 3.2 Three P-scales

We ran Monte Carlo sweeps at three progressively larger P-scales:

	$P$ range	Trials	$N$ at $\alpha = 0.01$	$N$ at $\alpha = 0.55$
Scale 1	200 – 5,000	256	530	15
Scale 2	2,000 – 50,000	256	760	20
Scale 3	10,000 – 300,000	64	921	23

Table 1: Parameters for the three P-scales used in finite-size scaling.

#### 3.3 Linear extrapolation to $N \rightarrow \infty$

For each grid point  $(\alpha, T)$ , we have three values of  $\varphi$  at three different  $N$  values. The finite-size scaling ansatz assumes

$$\varphi(N) = \varphi_\infty + \frac{c}{N} + O(1/N^2), \quad (2)$$

where  $\varphi_\infty$  is the thermodynamic-limit value. We perform a least-squares linear fit of  $\varphi$  vs.  $1/N$  and extrapolate to  $1/N = 0$ .

## 4 Results Across Scales

### 4.1 Scale 1: $P = 200\text{--}5,000$ (maps1.png)

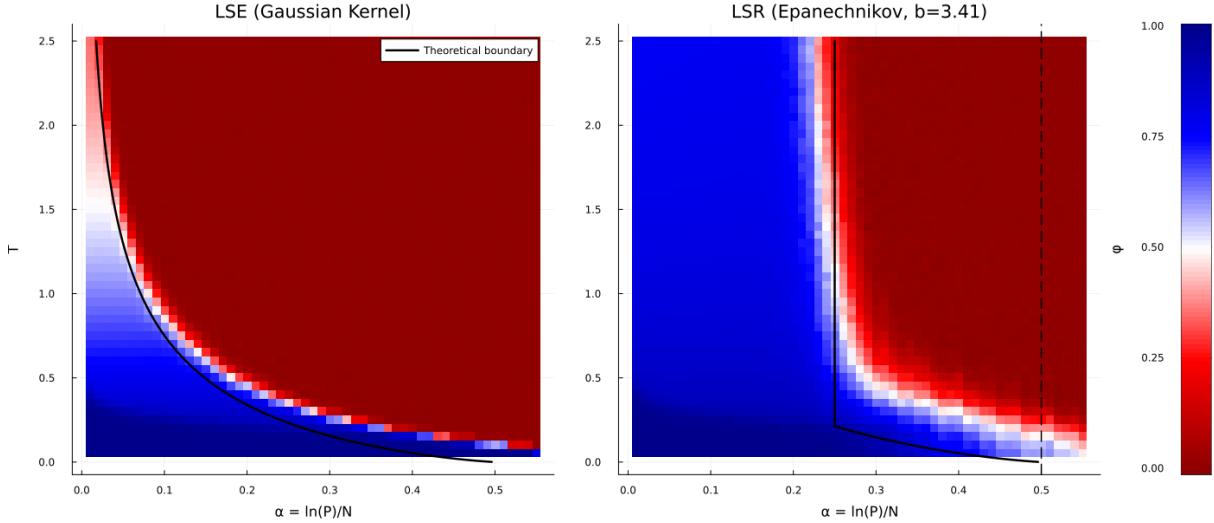


Figure 1: Scale 1 heatmaps. Left: LSE kernel. Right: LSR kernel ( $b = 2 + \sqrt{2}$ ). Black curves show the theoretical phase boundaries. The transition is broad, especially at large  $\alpha$  where  $N$  is small ( $N \leq 31$ ). Despite the broadening, the apparent boundary roughly follows the theoretical curve.

At Scale 1,  $N$  ranges from 530 (at  $\alpha = 0.01$ ) to 15 (at  $\alpha = 0.55$ ). The transition is visibly broadened but the phase boundary location is reasonable. At  $\alpha = 0.10$ ,  $N = 69$ , and the transition occurs at  $T \approx 0.5\text{--}0.8$ , close to the theoretical  $T_c \approx 0.75$ .

### 4.2 Scale 2: $P = 2,000\text{--}50,000$ (maps2.png)

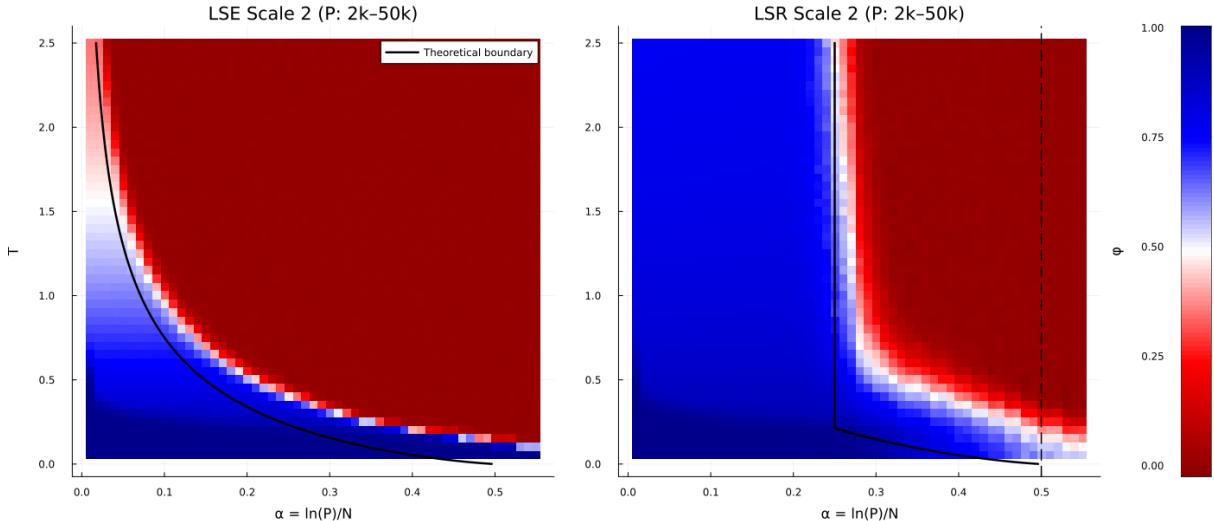


Figure 2: Scale 2 heatmaps. The transition has sharpened somewhat compared to Scale 1, but the apparent boundary has *shifted upward* in  $T$ . The retrieval region (red/warm colors) extends to higher temperatures than predicted by theory.

At Scale 2,  $N$  increases to 760 at  $\alpha = 0.01$  and 40 at  $\alpha = 0.25$ . The transition is sharper, but the apparent critical temperature  $T_c^{\text{eff}}$  is *higher* than at Scale 1. For example, at  $\alpha = 0.10$ :

$\varphi(T = 1.0) = 0.33$  (Scale 2) vs. 0.065 (Scale 1), even though  $T = 1.0$  is above the theoretical  $T_c = 0.75$ .

### 4.3 Scale 3: $P = 10,000\text{--}300,000$ (maps3.png)

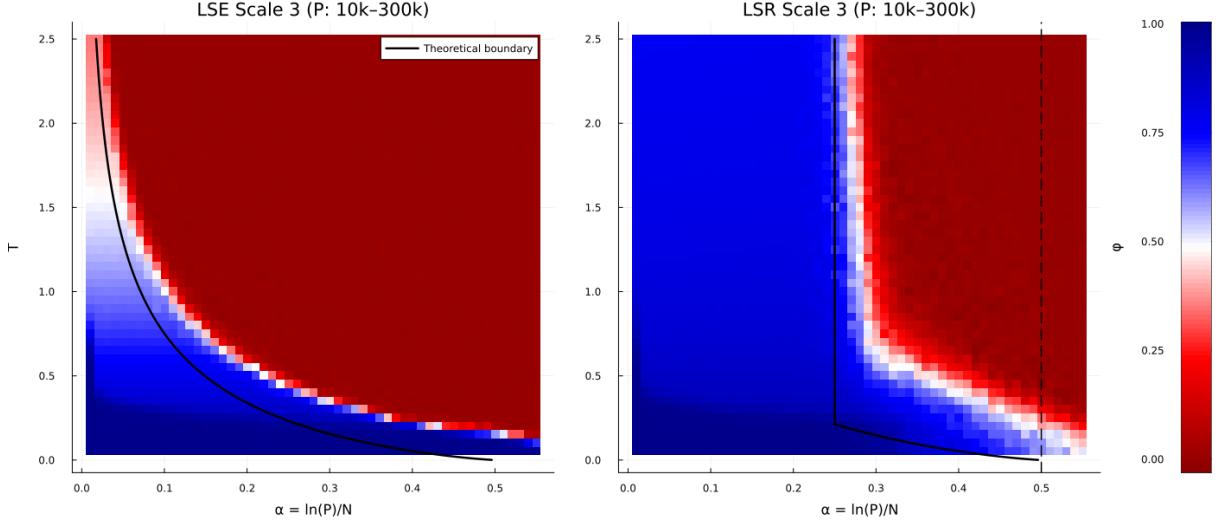


Figure 3: Scale 3 heatmaps. The boundary has shifted even further from the theoretical curve. The retrieval region extends well above  $T_c$ .

Scale 3 has the largest  $N$  values (921 at  $\alpha = 0.01$ , 47 at  $\alpha = 0.25$ ), yet the match with theory is *worse*, not better. At  $\alpha = 0.10$ ,  $T = 1.0$ :  $\varphi = 0.49$  (Scale 3), indicating the system appears to be in the retrieval phase at a temperature well above  $T_c = 0.75$ .

### 4.4 Extrapolated map (maps.png)

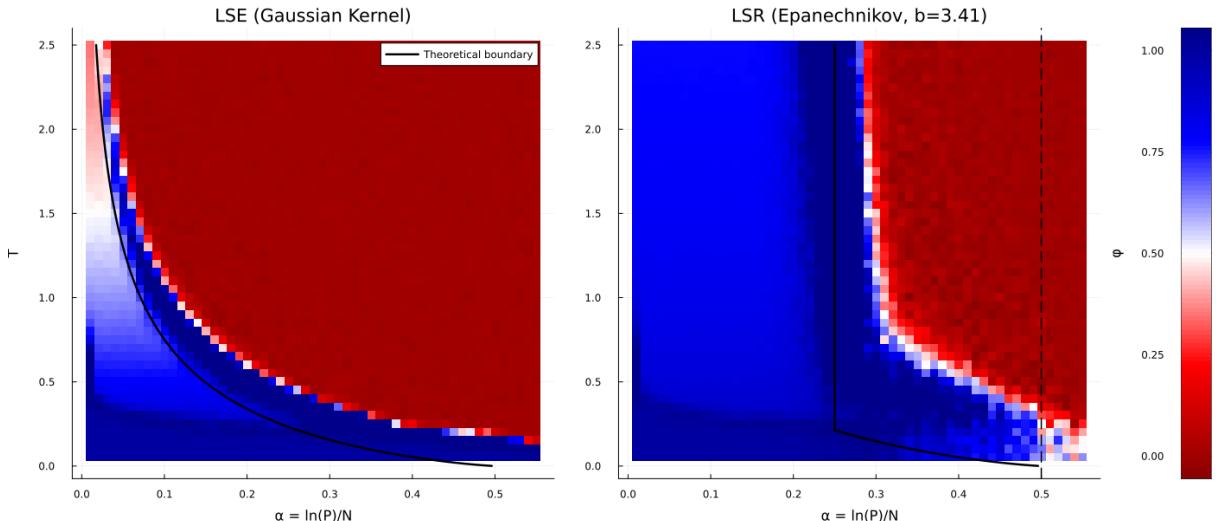


Figure 4: Extrapolated heatmaps ( $N \rightarrow \infty$  via linear fit). The extrapolation amplifies the metastability artifact, producing unphysical  $\varphi > 1$  values (clamped to 1.05) in the critical region. 234 LSE points and 473 LSR points exceed  $\varphi = 1.0$ .

The linear extrapolation produces 234 unphysical points ( $\varphi > 1$ ) for LSE and 473 for LSR, concentrated in the critical region just above the theoretical boundary.

## 5 Diagnosis: Metastability and Critical Slowing Down

### 5.1 The first-order nature of the transition

The retrieval-disordered phase transition in DAM models on the  $N$ -sphere is *first order*: the order parameter  $\varphi$  jumps discontinuously at the critical point in the thermodynamic limit. This means the free energy landscape has two distinct minima (retrieval state with  $\varphi > 0$  and disordered state with  $\varphi \approx 0$ ) separated by a *free energy barrier*  $\Delta F$ .

For a first-order transition, this barrier grows with system size:

$$\Delta F \sim N^\gamma, \quad \gamma > 0. \quad (3)$$

The Kramers escape time from the metastable state scales as

$$\tau_{\text{escape}} \sim e^{\Delta F/T} \sim e^{N^\gamma/T}, \quad (4)$$

which grows *exponentially* with  $N$ .

### 5.2 Initialization bias

Our Monte Carlo chains are initialized near the target pattern:  $\mathbf{x}_0 \approx \boldsymbol{\xi}^1$ . This places the chain squarely in the retrieval state. If the equilibrium state is actually the disordered phase (above  $T_c$ ), the chain must cross the free energy barrier to reach it.

- At **small**  $N$  (Scale 1): The barrier is low. With  $N_{\text{eq}} = 5,000$  steps, the chain can cross the barrier and equilibrate to the disordered state. Result:  $\varphi \approx 0$  above  $T_c$  (correct).
- At **larger**  $N$  (Scales 2, 3): The barrier is higher. With the same  $N_{\text{eq}} = 5,000$  steps, the chain *cannot* escape the metastable retrieval state. Result:  $\varphi$  remains elevated above  $T_c$  (incorrect — metastability artifact).

### 5.3 Quantitative evidence

Table 2 shows  $\varphi$  across scales at points that theory predicts to be in the disordered phase ( $T > T_c$ ).

$\alpha$	$T$	$T_c$ (theory)	Scale 1	Scale 2	Scale 3	Extrap.
0.05	1.50	1.30	0.228	0.423	0.489	<b>0.908</b>
0.10	0.80	0.75	0.601	0.672	0.678	<b>0.824</b>
0.10	1.00	0.75	0.065	0.328	0.491	<b>&gt;1.05</b>
<i>Correctly equilibrated points (far above <math>T_c</math>):</i>						
0.10	1.50	0.75	-0.003	0.002	0.001	0.011
0.10	2.50	0.75	0.000	-0.001	-0.001	-0.002

Table 2: Overlap  $\varphi$  at points above the theoretical  $T_c$ . In the critical region (top rows),  $\varphi$  *increases* with  $N$ , opposite to the expected finite-size scaling. Far above  $T_c$  (bottom rows), the chain equilibrates correctly.

The pattern is clear:  $\varphi$  monotonically *increases* with  $N$  in the critical region just above  $T_c$ , because the larger system is more deeply trapped in the metastable retrieval state. The linear extrapolation (2) then projects this increasing trend to  $1/N = 0$ , producing the unphysical  $\varphi > 1$ .

## 5.4 Why the boundary shifts upward

The visual effect on the heatmap is that the apparent phase boundary shifts to higher  $T$  with increasing  $N$ . This is the opposite of what standard finite-size scaling predicts (boundary converging toward theory). The mechanism is:

1. In the **retrieval phase** (below  $T_c$ ):  $\varphi$  is high and nearly  $N$ -independent. Correct.
2. In the **critical region** ( $T \lesssim T_c + \Delta T$ ): the MC chain remains trapped in the retrieval state at larger  $N$ . The apparent  $\varphi$  stays high  $\Rightarrow$  boundary appears at higher  $T$ .
3. **Deep in the disordered phase** ( $T \gg T_c$ ): thermal fluctuations are strong enough to kick the chain out of the metastable state even at large  $N$ .  $\varphi \approx 0$  for all scales. Correct.

The width of the “metastability band” above  $T_c$  where the MC fails to equilibrate *grows* with  $N$ , explaining the worsening match with theory.

## 6 Why Linear Extrapolation Fails

The finite-size scaling ansatz  $\varphi(N) = \varphi_\infty + c/N$  assumes that the MC correctly samples the equilibrium Gibbs distribution at each  $N$ . When metastability violates this assumption, the measured  $\varphi(N)$  is *not the equilibrium value* but a metastable artifact:

$$\varphi_{\text{measured}}(N) = \varphi_{\text{eq}}(N) + \Delta\varphi_{\text{meta}}(N), \quad (5)$$

where  $\Delta\varphi_{\text{meta}}(N)$  increases with  $N$  in the critical region. The linear fit then extrapolates the sum, and since  $\Delta\varphi_{\text{meta}}$  grows with  $N$  (decreases with  $1/N$ ), the extrapolated  $\varphi_\infty$  overshoots.

The severity depends on the region:

- **Deep retrieval:**  $\Delta\varphi_{\text{meta}} \approx 0$  (system is in correct state). Extrapolation valid.
- **Critical region:**  $\Delta\varphi_{\text{meta}}$  dominates. Extrapolation fails catastrophically ( $\varphi > 1$ ).
- **Deep disordered:**  $\Delta\varphi_{\text{meta}} \approx 0$  (thermal fluctuations overcome barrier). Extrapolation valid.

## 7 Possible Remedies

### 7.1 Parallel tempering (replica exchange)

Run multiple replicas at different temperatures simultaneously. Allow replicas to exchange configurations, enabling the system to escape metastable states by “borrowing” thermal energy from higher-temperature replicas. This is the most robust approach for first-order transitions.

### 7.2 Dual-initialization protocol

For each  $(\alpha, T)$  point, run the MC from two starting conditions: (a) near the target pattern (testing retrieval stability) and (b) from a random point on  $S^{N-1}$  (testing whether the system spontaneously finds the retrieval state). If the two give different  $\varphi$ , the system is in the metastable/hysteresis region and  $N_{\text{eq}}$  is insufficient.

### 7.3 Binder cumulant analysis

Instead of extrapolating  $\varphi$  directly, compute the Binder cumulant  $U_4 = 1 - \langle \varphi^4 \rangle / (3 \langle \varphi^2 \rangle^2)$  at each scale. The crossing point of  $U_4(T)$  curves for different  $N$  gives  $T_c$  without requiring equilibration in the correct phase.

## 7.4 Adaptive equilibration

Scale  $N_{\text{eq}}$  with  $N$ , e.g.,  $N_{\text{eq}} \propto N^2$  or even exponentially. This is computationally expensive but addresses the root cause.

## 7.5 Simulated annealing initialization

Instead of starting near the target, start from a random configuration and slowly cool the system (decrease  $T$ ) in a pre-equilibration phase. This avoids the initialization bias entirely, but may fail to find the retrieval state at low  $T$  if the basin of attraction is narrow.

# 8 Conclusions

The finite-size scaling approach—running MC simulations at three P-scales and linearly extrapolating  $\varphi$  vs.  $1/N$ —was designed to remove finite- $N$  artifacts and converge to the theoretical  $N \rightarrow \infty$  phase boundary. However, the approach fails in the critical region due to **metastability**:

1. The retrieval-disordered transition is first order, with a free energy barrier that grows with  $N$ .
2. MC chains initialized near the target pattern become exponentially harder to equilibrate at larger  $N$  when  $T > T_c$ .
3. The measured  $\varphi$  in the critical region increases with  $N$  (opposite to equilibrium finite-size scaling), and the linear extrapolation amplifies this artifact.

The result is that larger P-scales produce *worse* agreement with theory near the phase boundary, and the extrapolated map contains unphysical values ( $\varphi > 1$ ). Addressing this requires fundamentally different MC strategies (parallel tempering, dual initialization) rather than simply increasing system size.