

# Extreme Fluctuations and Finite-Size Corrections in Spin Glasses and other Combinatorial Problems

Stefan  
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Funding:

▶ NSF-DMR, Los Alamos-LDRD, Emory-URC

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Tuesday, June 1, 2010





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- ◉ How can we use it to optimize?
  - Extremal Driving:
    - ★ Select and eliminate the “bad”,
    - ★ Replace it *at random*,
    - ★ Eventually, only the “good” is left!



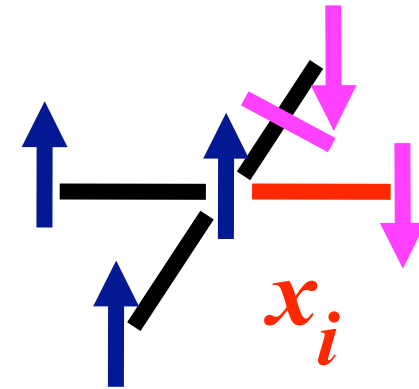
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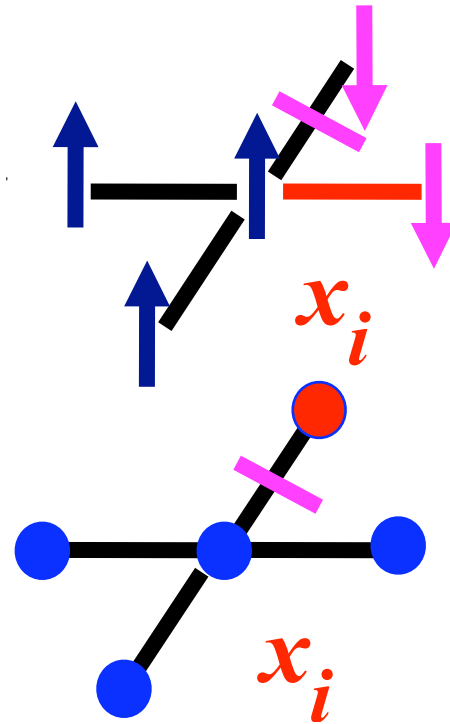
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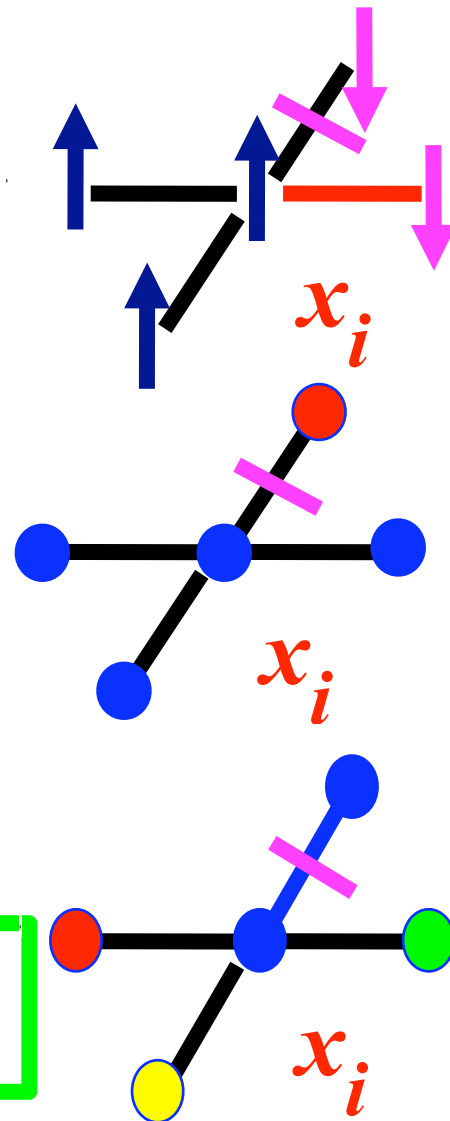
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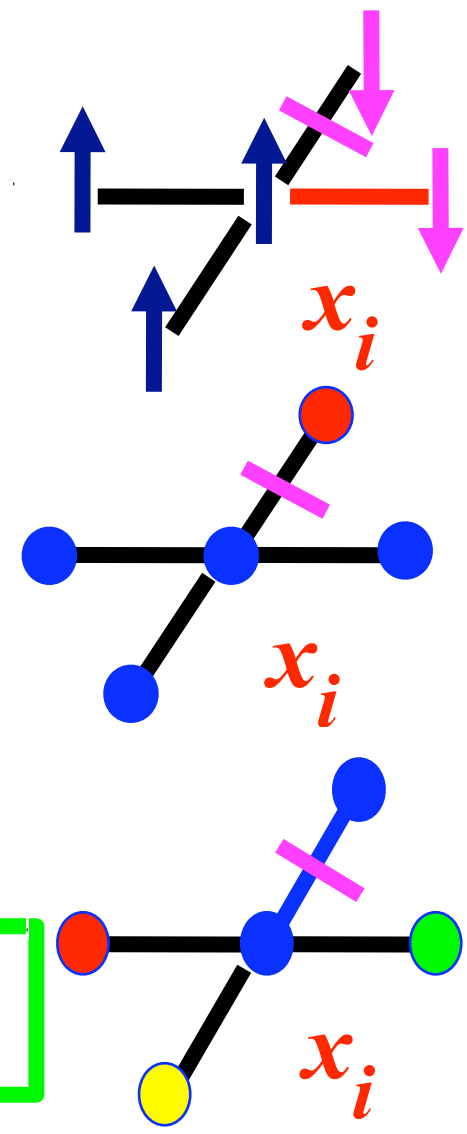
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$$Cost \propto H = - \sum_i \lambda_i$$



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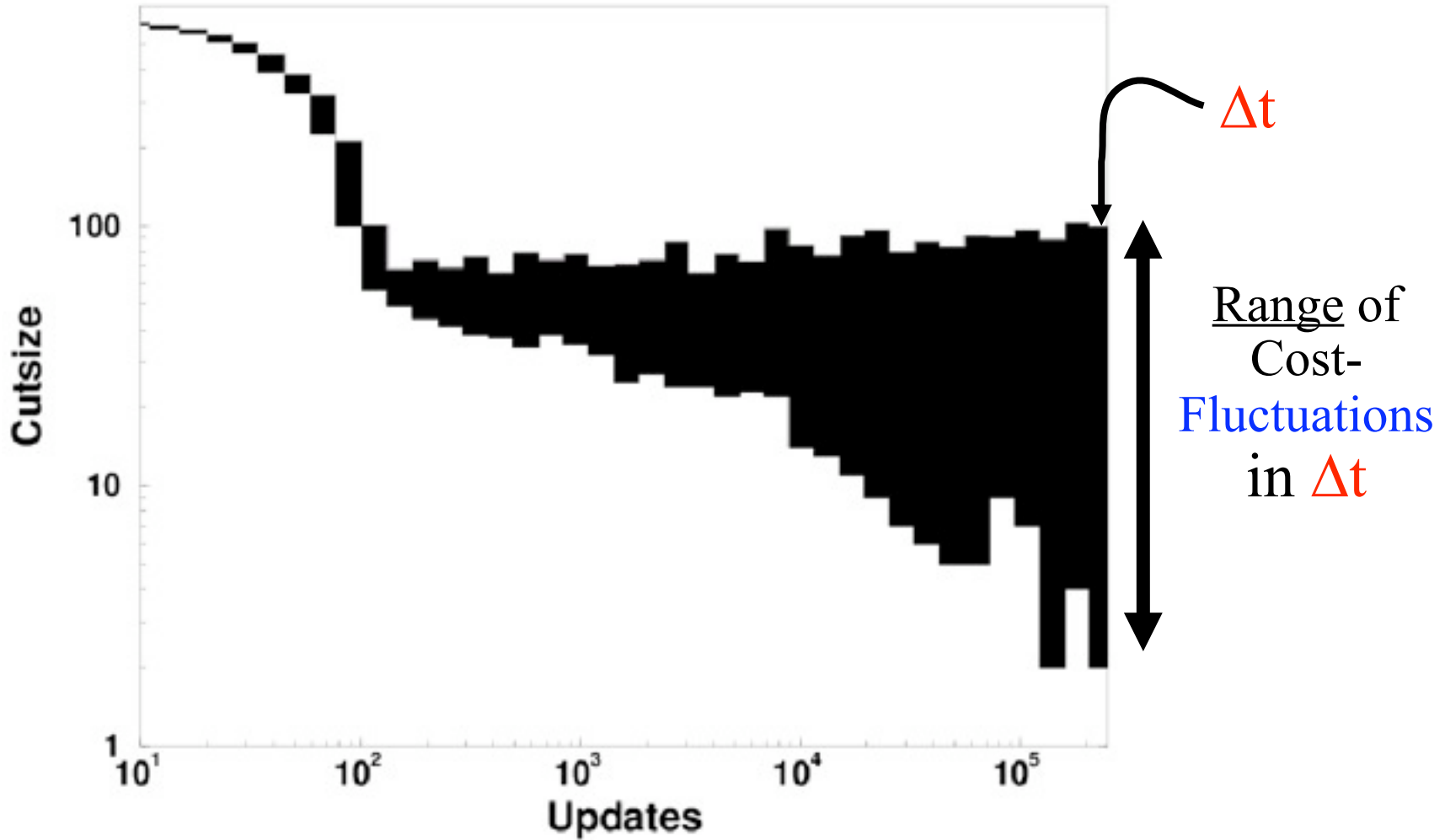
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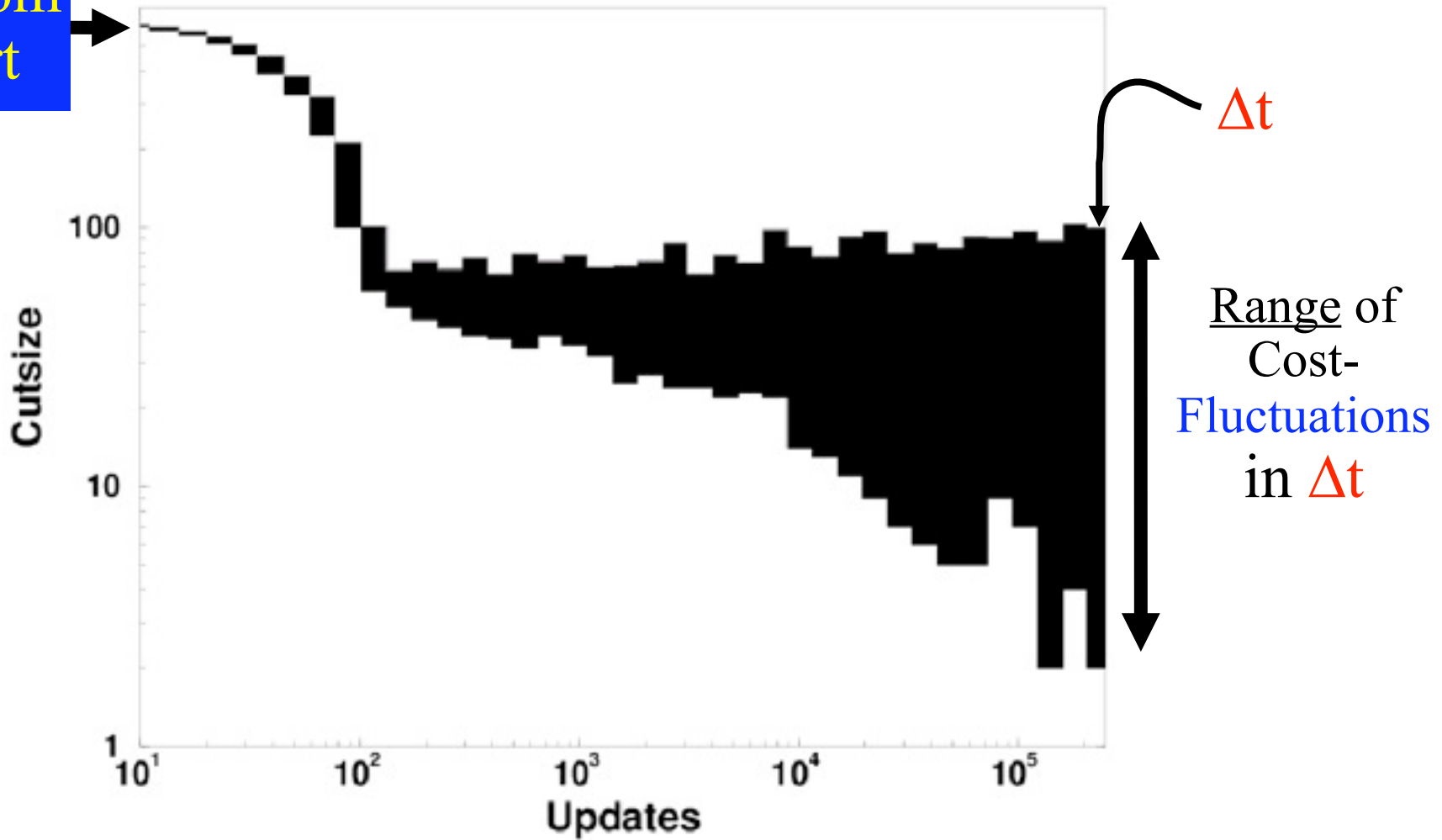
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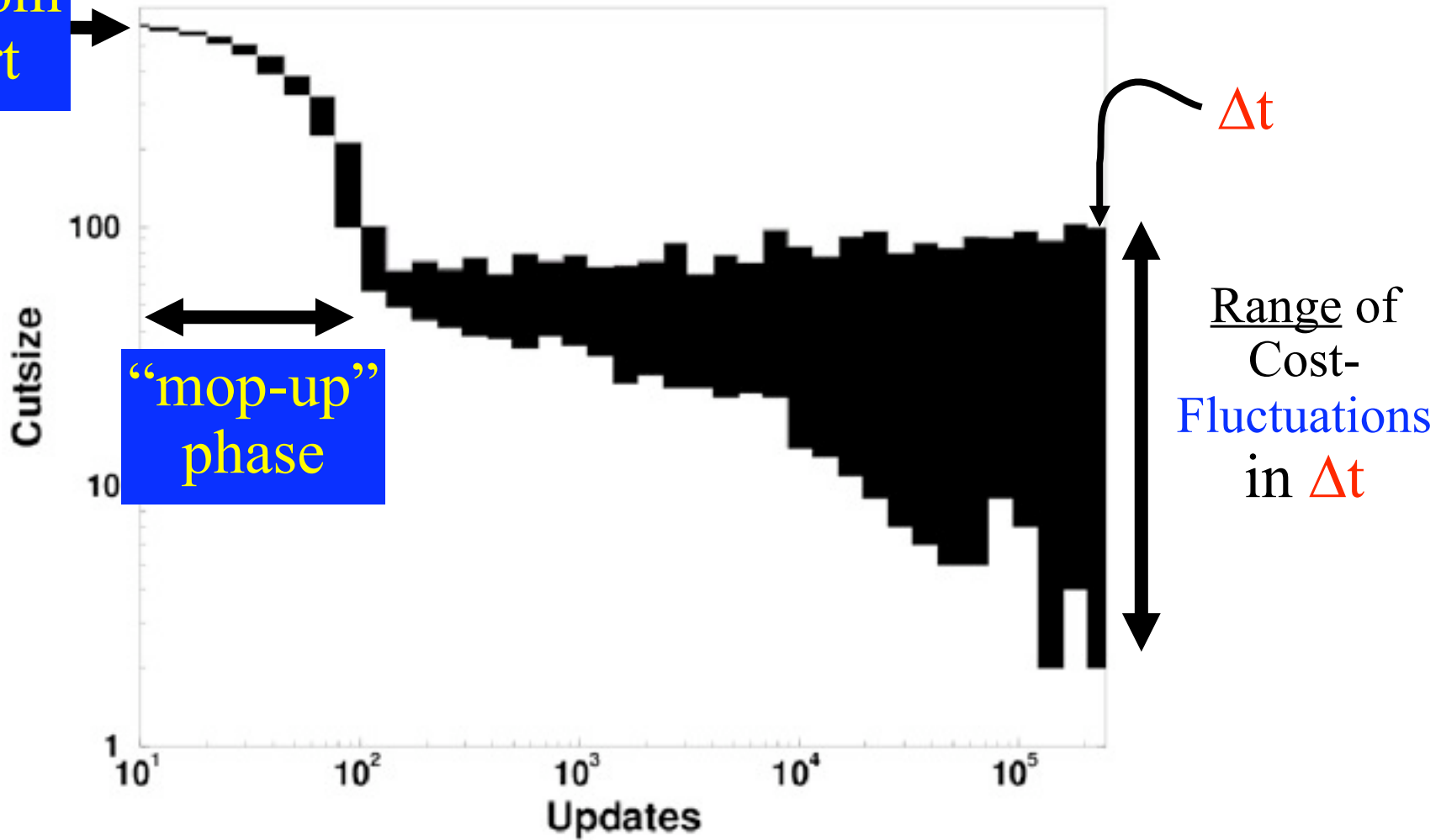
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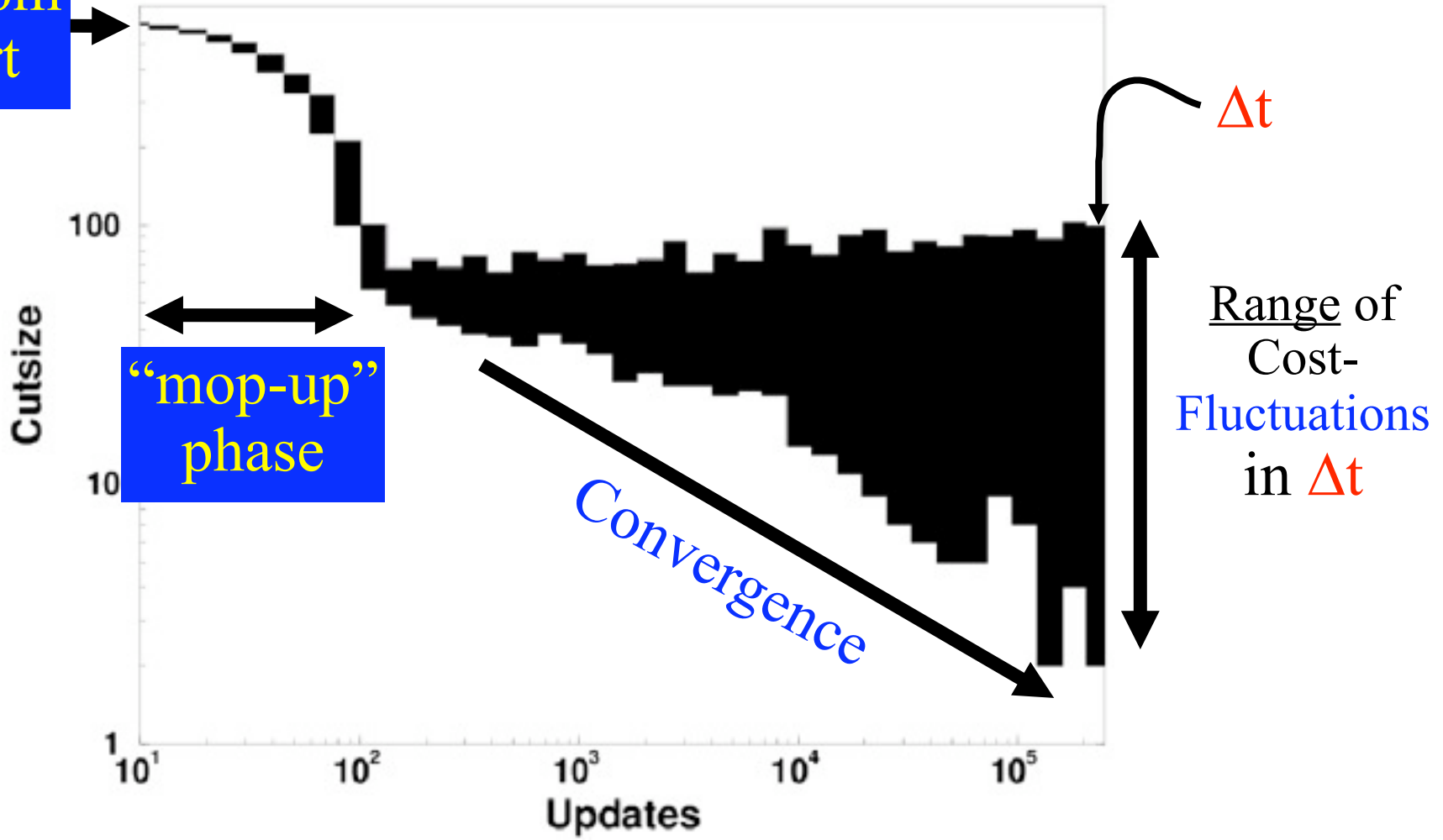
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For Ranks  $\lambda_{\Pi(1)} \leq \dots \leq \lambda_{\Pi(n)}$ , update  $i = \Pi(k)$  with  
scale-free, power-law distribution

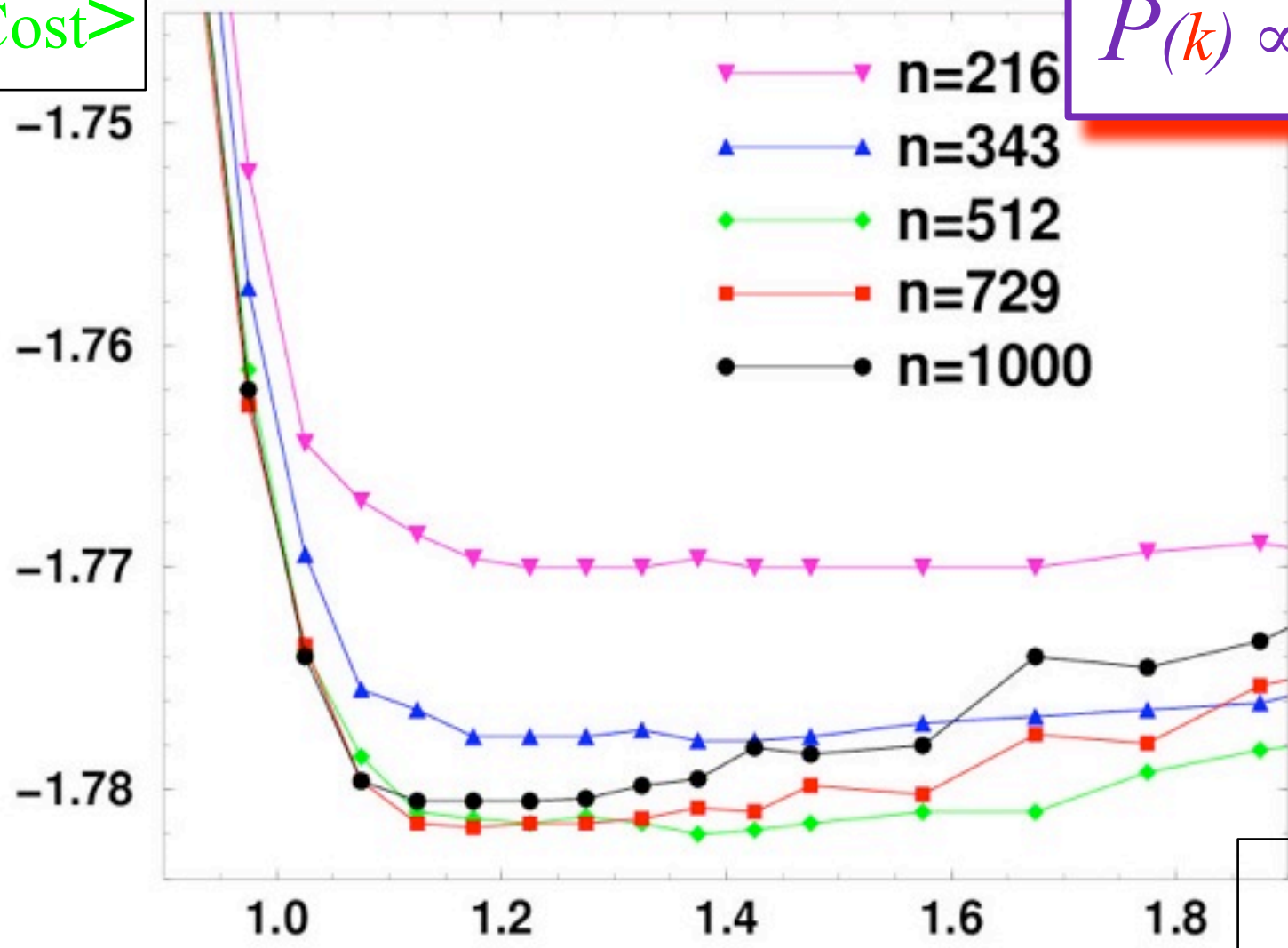
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$\langle \text{Cost} \rangle$



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-1.76

- $\nabla$  n=216
- $\blacktriangle$  n=343
- $\blacklozenge$  n=512
- $\blacksquare$  n=729
- $\bullet$  n=1000

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$0 \leftarrow \tau$   
random walk,  
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$\mathcal{T} \rightarrow \infty$   
greedy + frozen,  
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$$\tau - 1 \sim \frac{1}{\ln(n)}$$

“ergodic edge”

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1.2

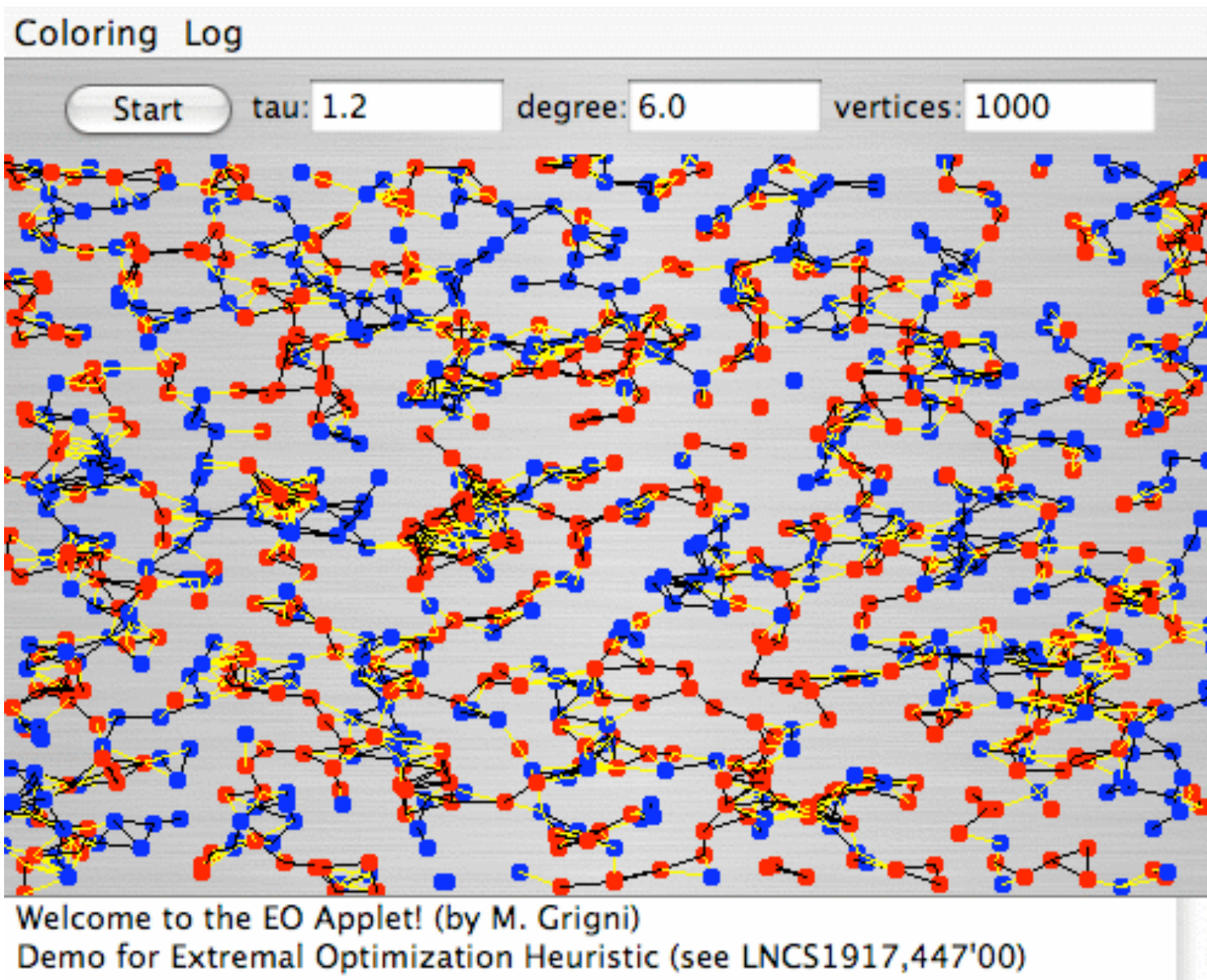
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$\tau$

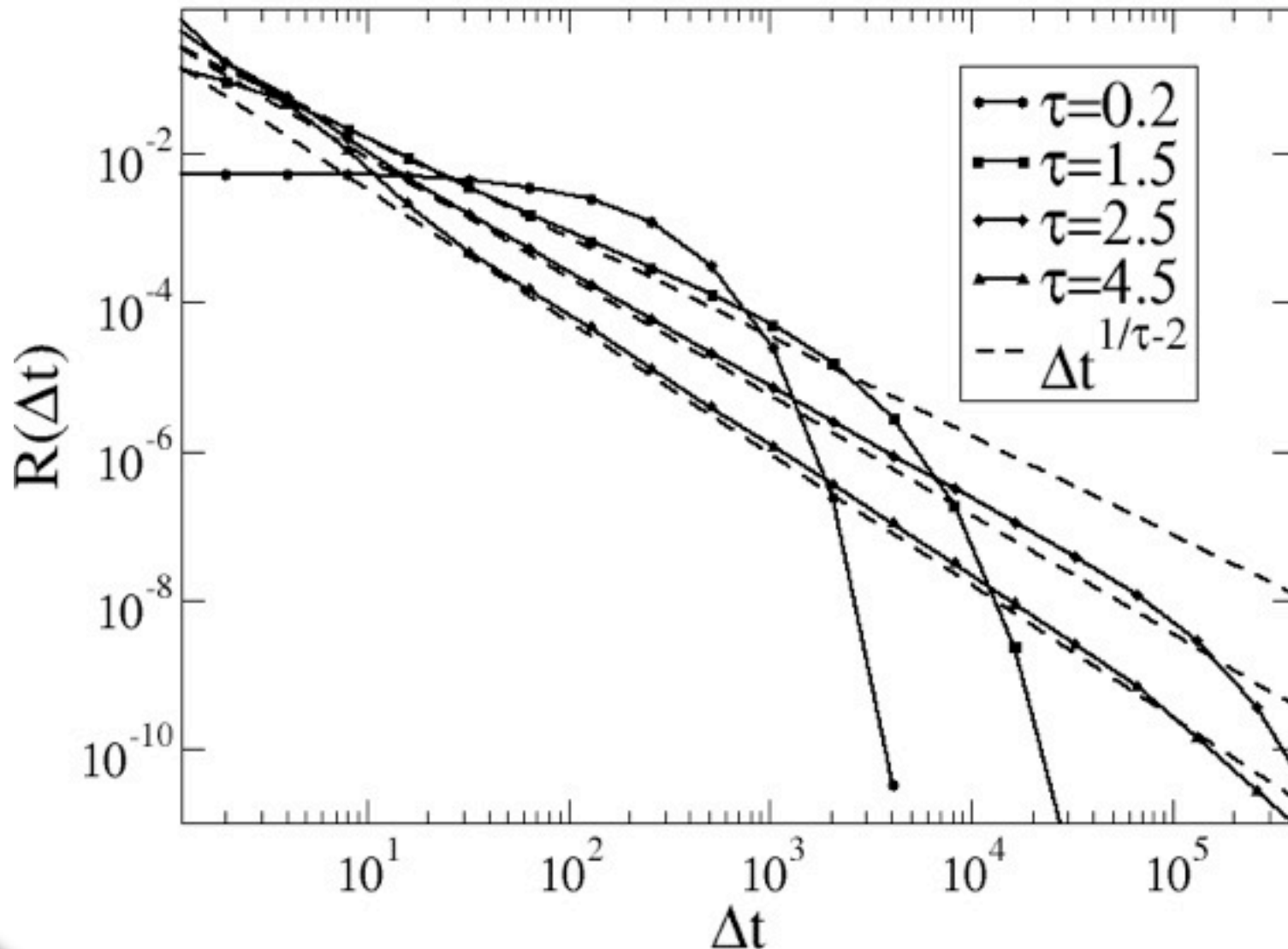
# Animation of $\tau$ -EO for Graph-Partitioning





# Dynamics of $\tau$ -EO: (for $\pm J$ -Spin Glass on 3-reg. Graph, $N=256$ )

First-return time distribution  $R(\Delta t)$ :





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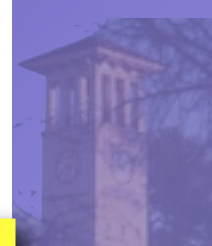
Stretched-exponential Autocorrelations:





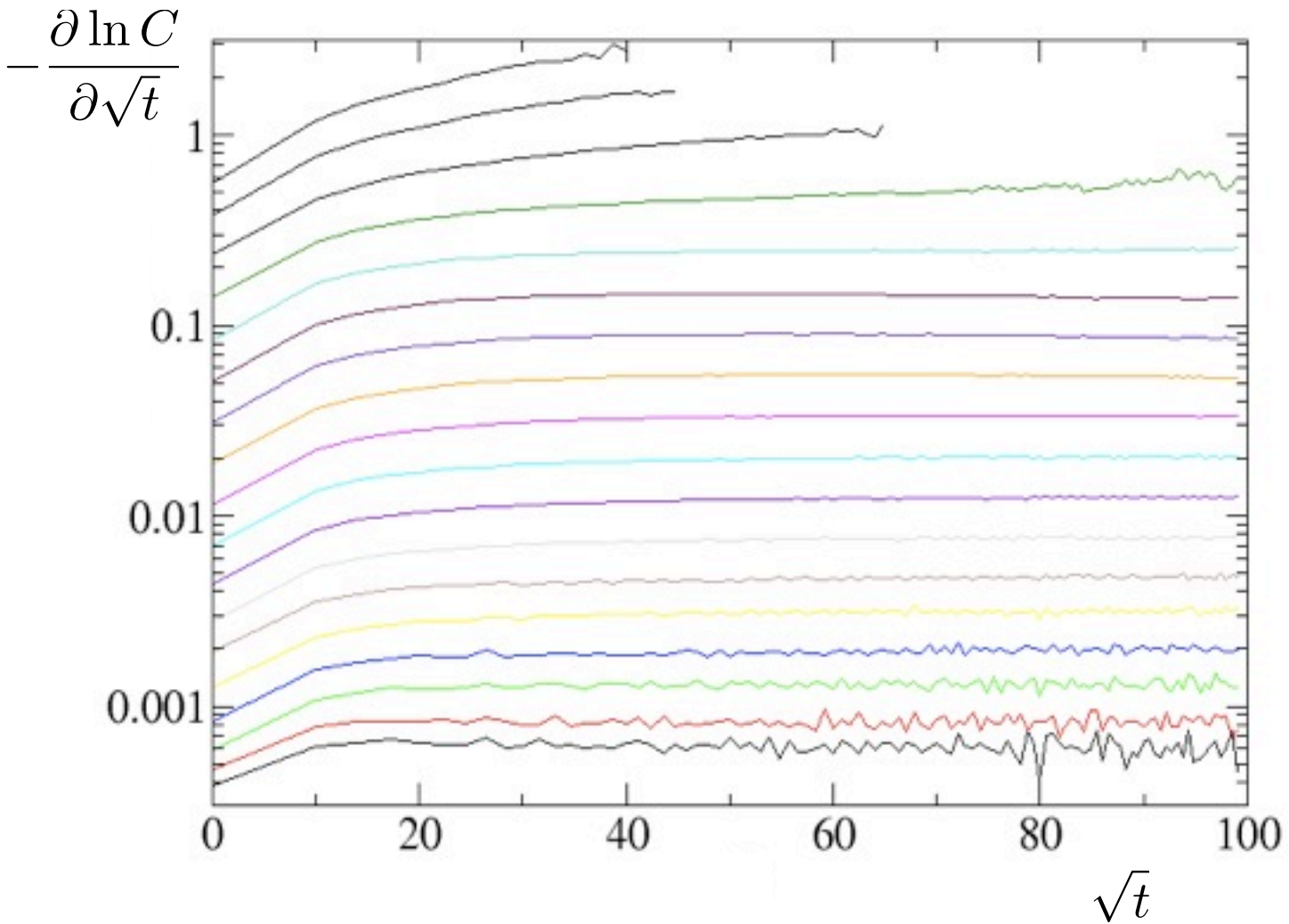
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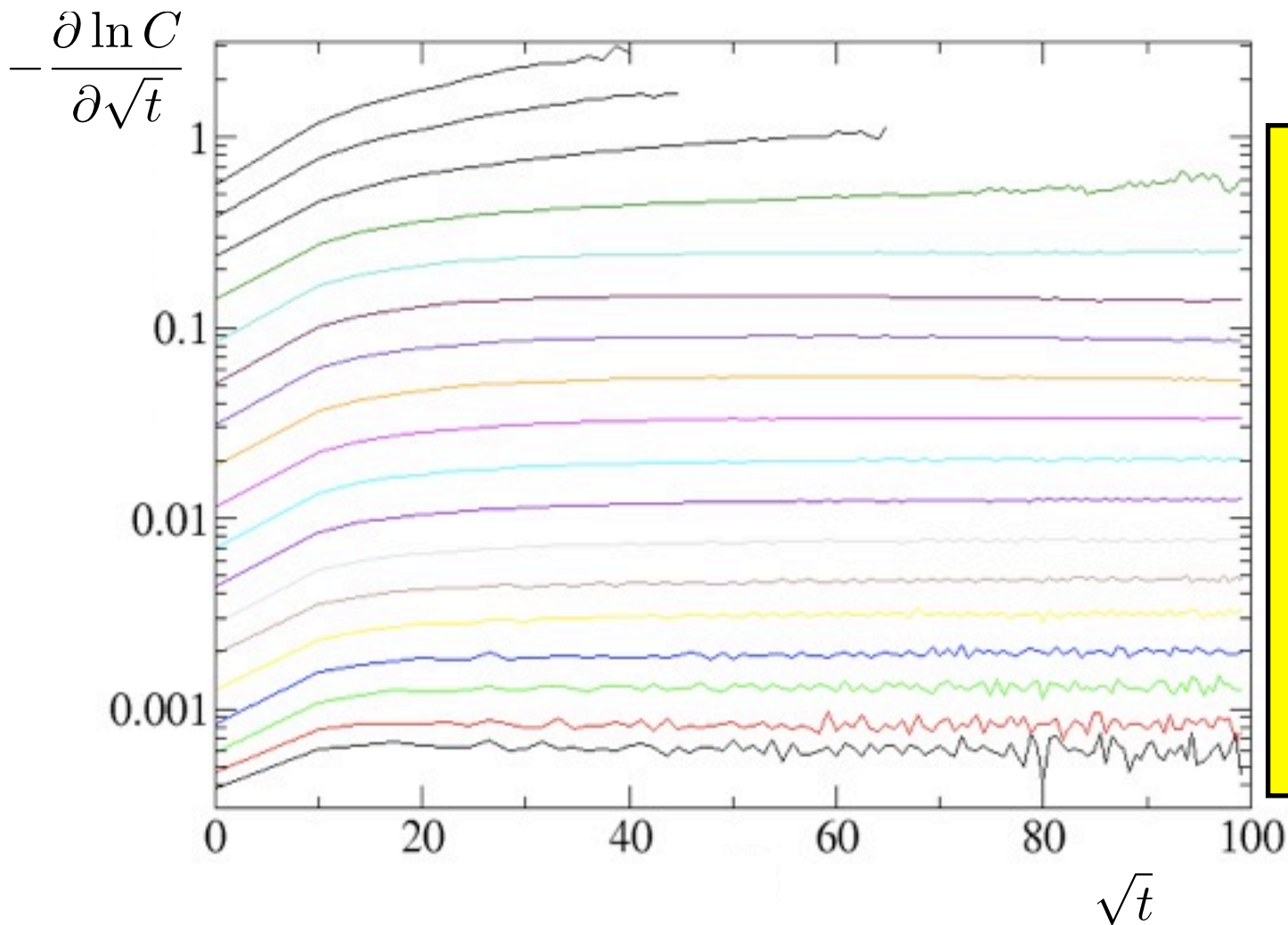
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$$\tau = 1.1$$

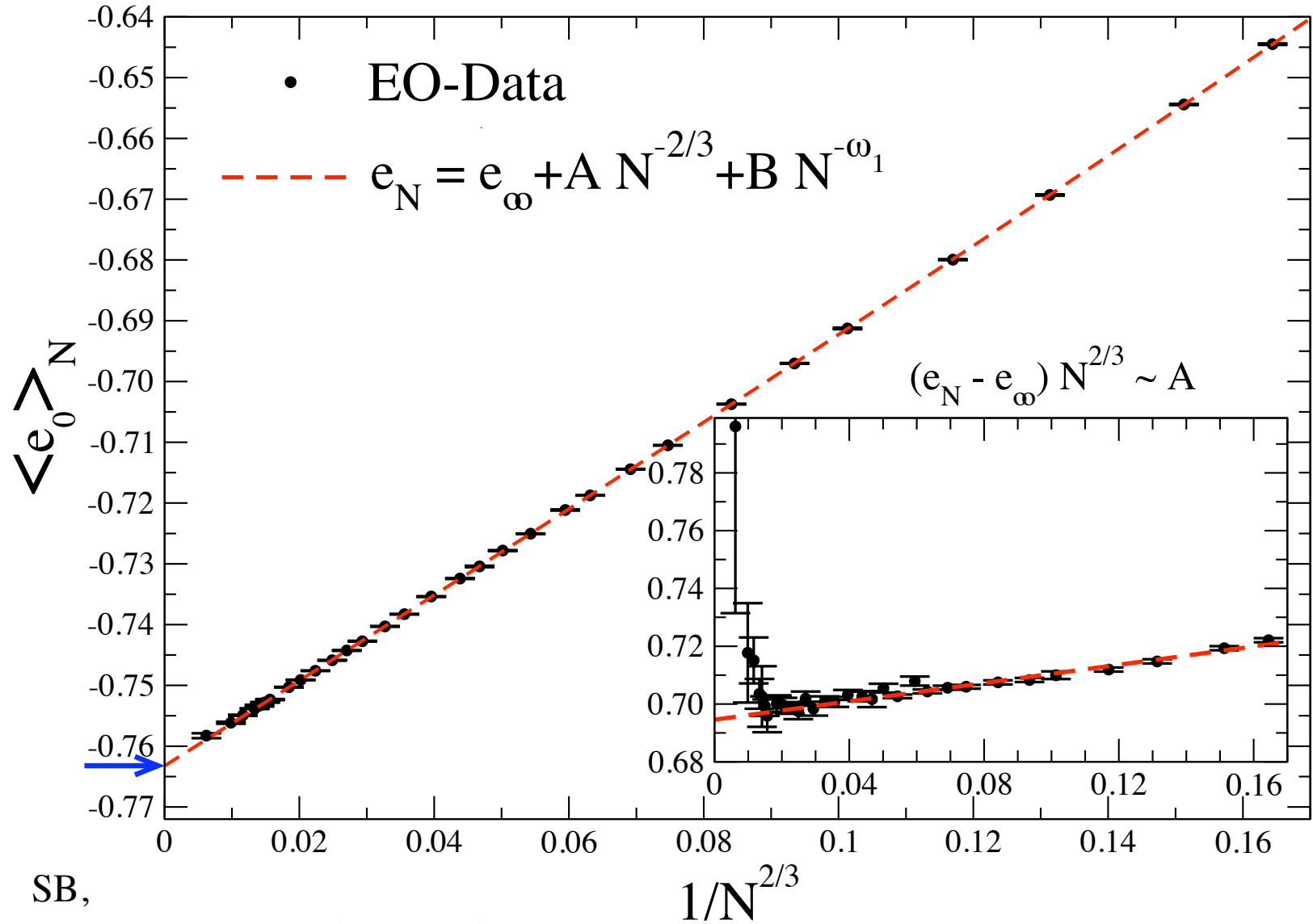
$$B_\tau \sim -\frac{\partial \ln C(t)}{\partial \sqrt{t}}$$

$$\sim 1.6 e^{-2.4\tau}$$

$$\tau = 3.9$$

# $\tau$ -EO for Sherrington-Kirkpatrick

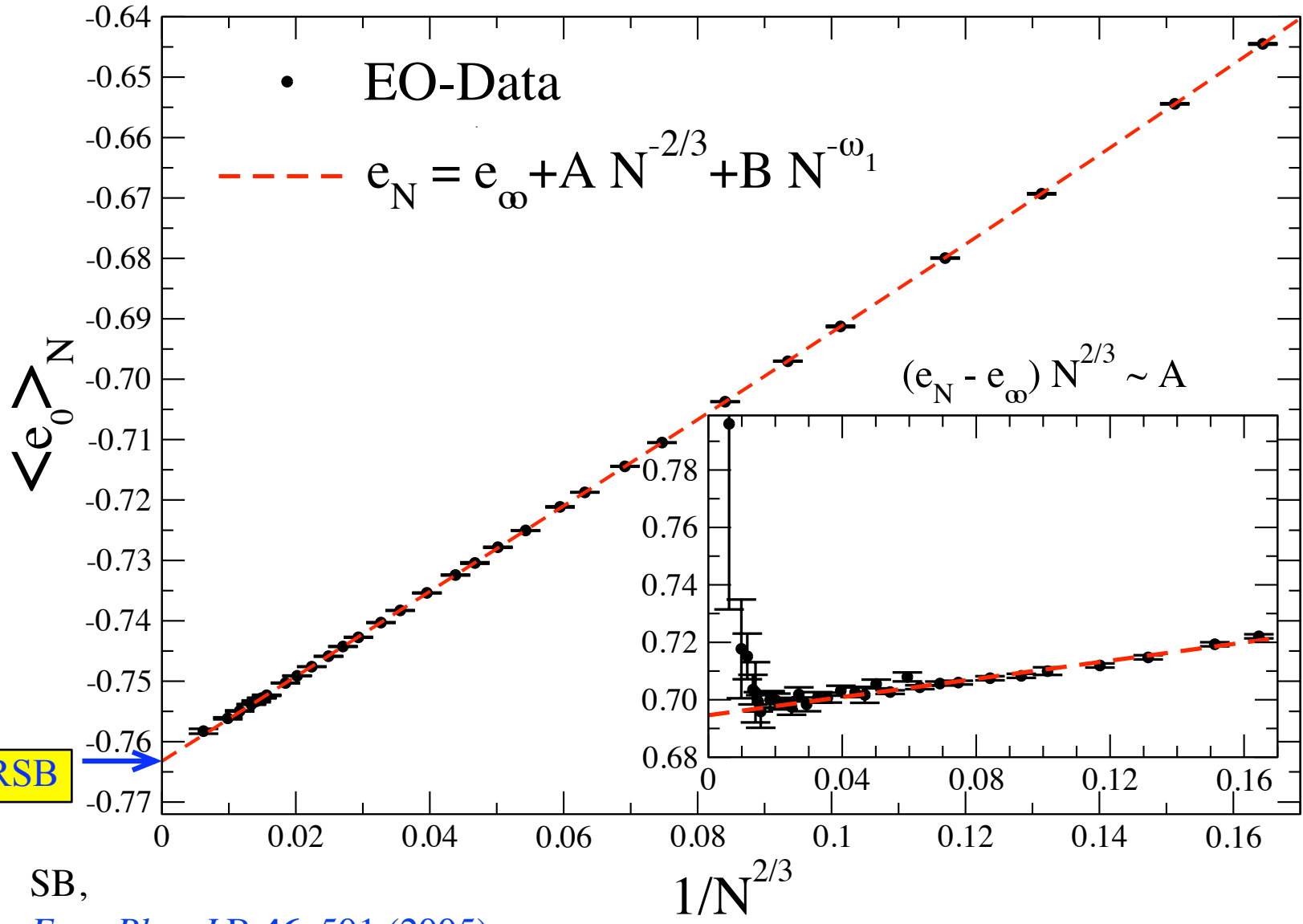
- Mean-Field ( $d \rightarrow \infty$ ) Spin Glasses:



[Euro Phys J B 46, 501 \(2005\)](http://www.physik.uni-wuerzburg.de/~sb/)

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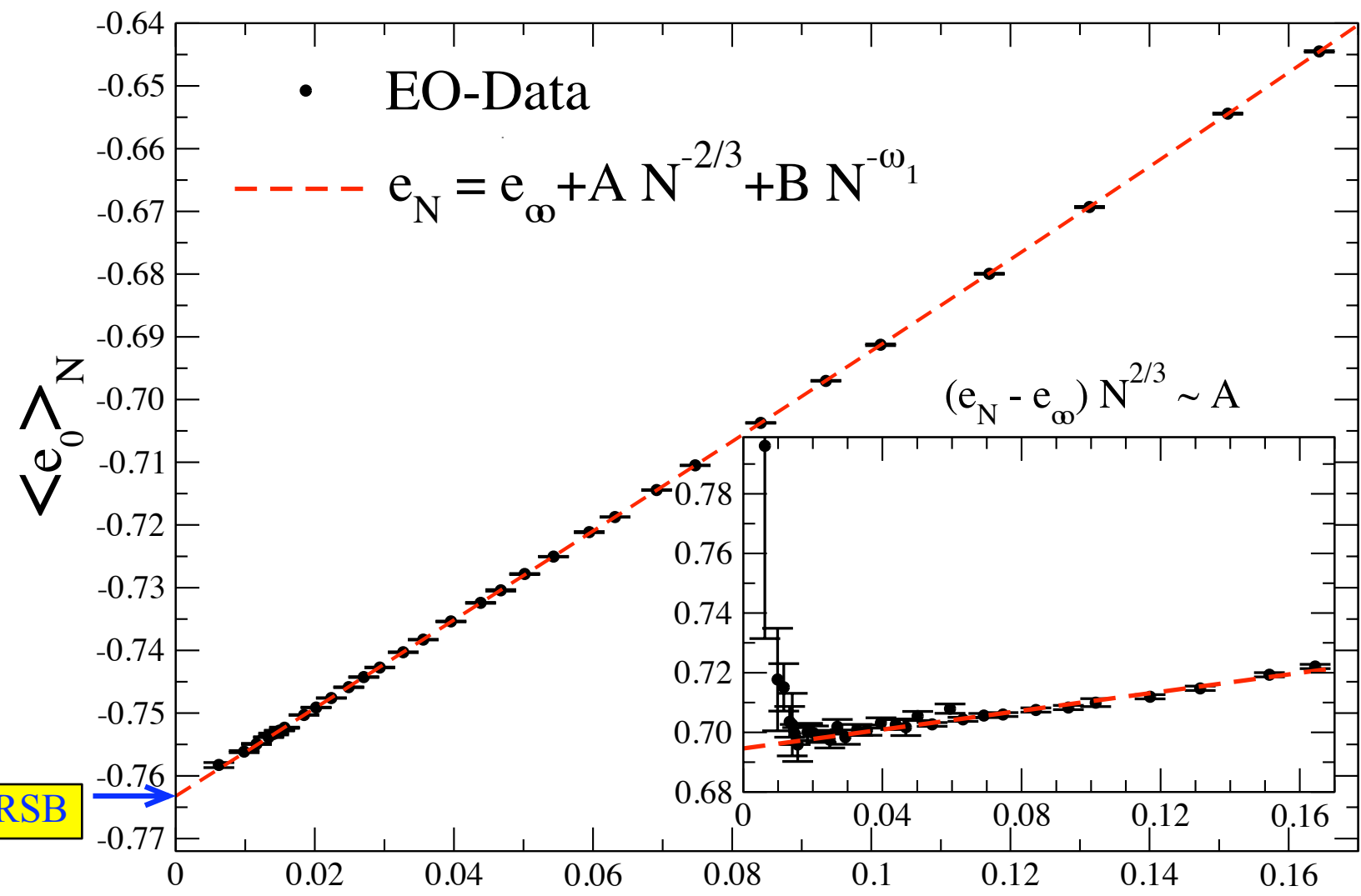


SB,  
[Euro Phys J B 46, 501 \(2005\)](http://www.physica.uni-siegen.de/physik/boettcher/)



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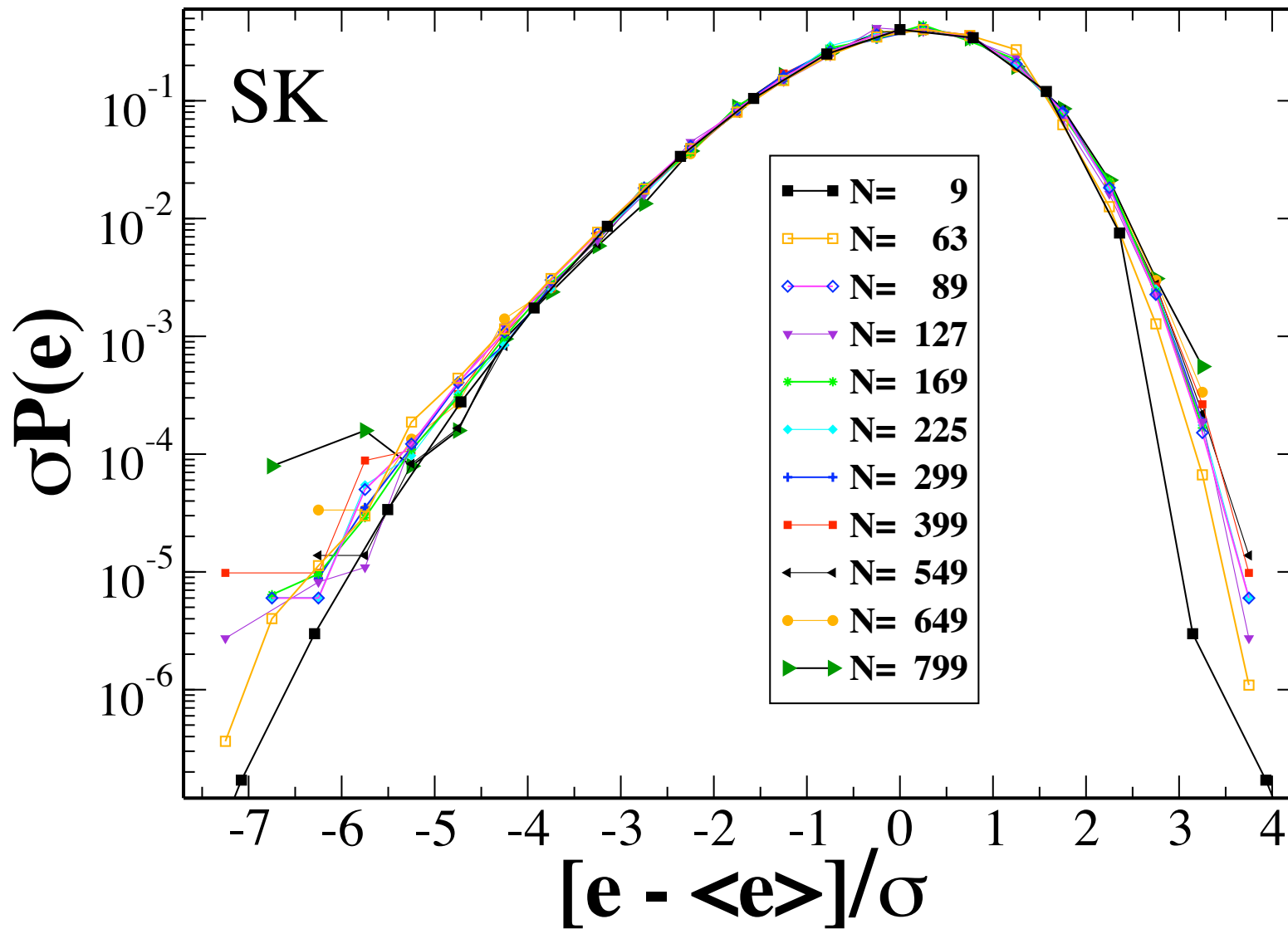
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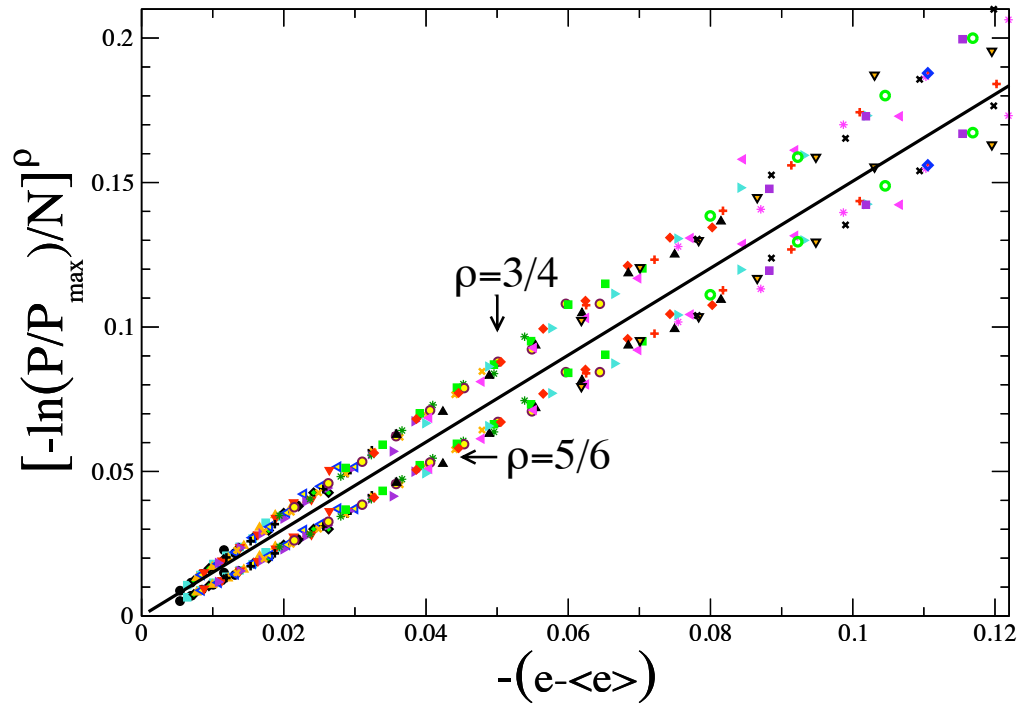
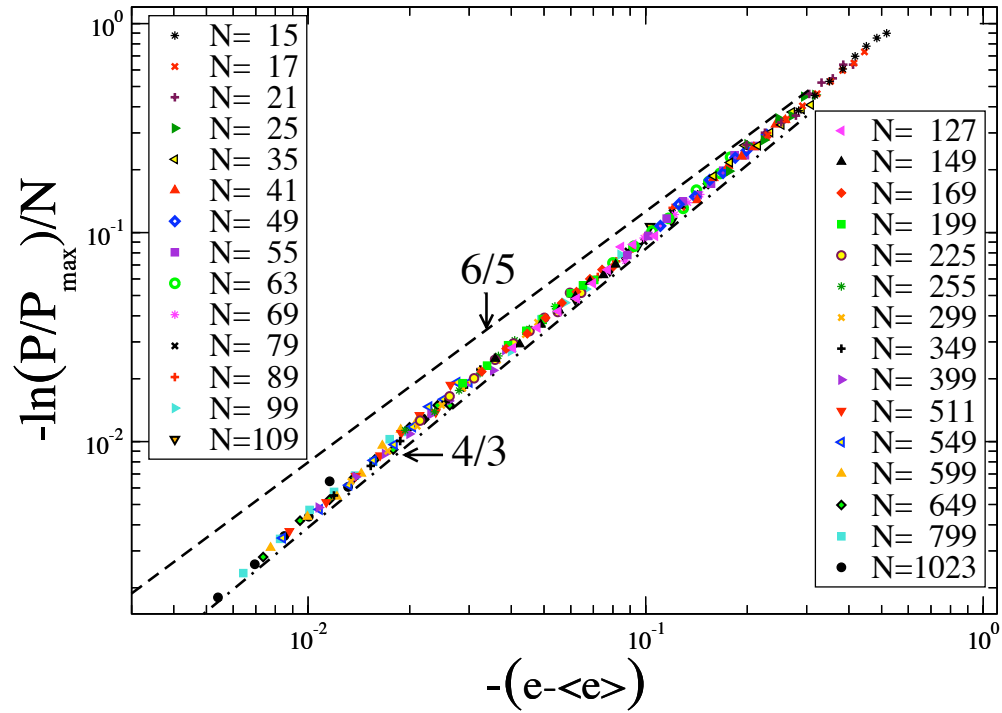


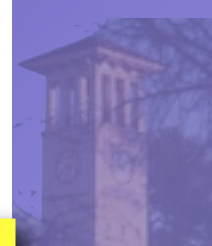
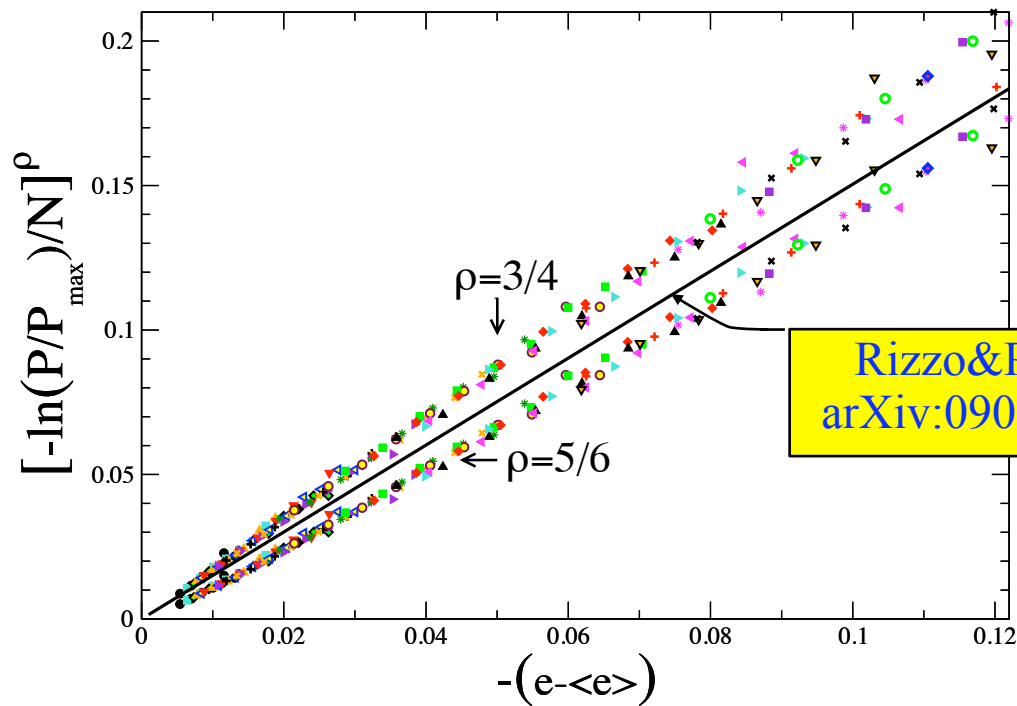
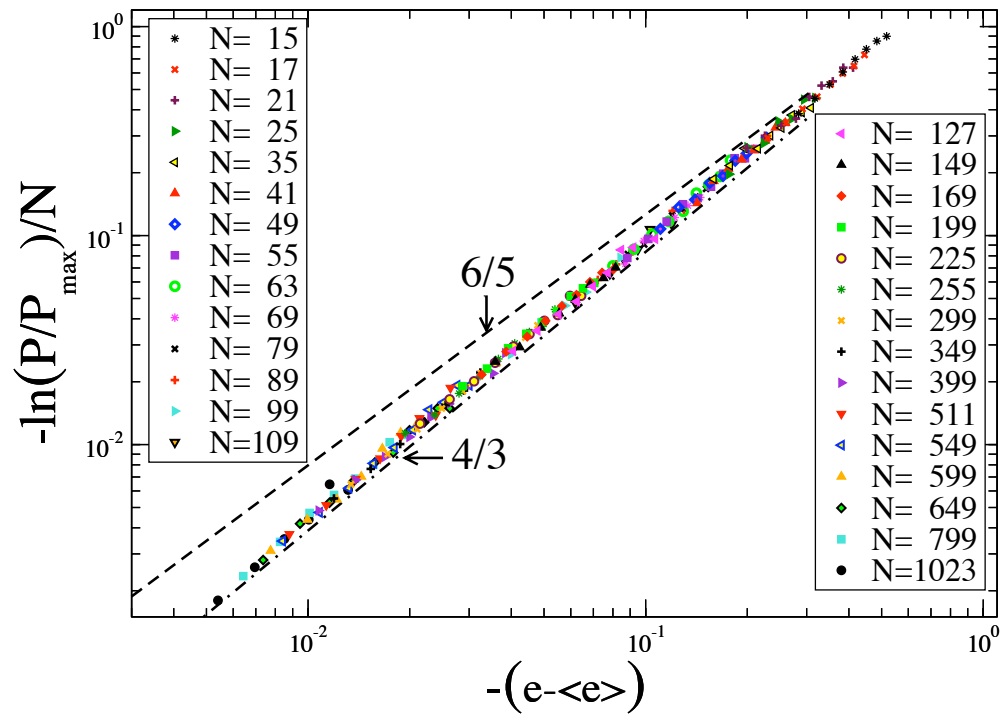


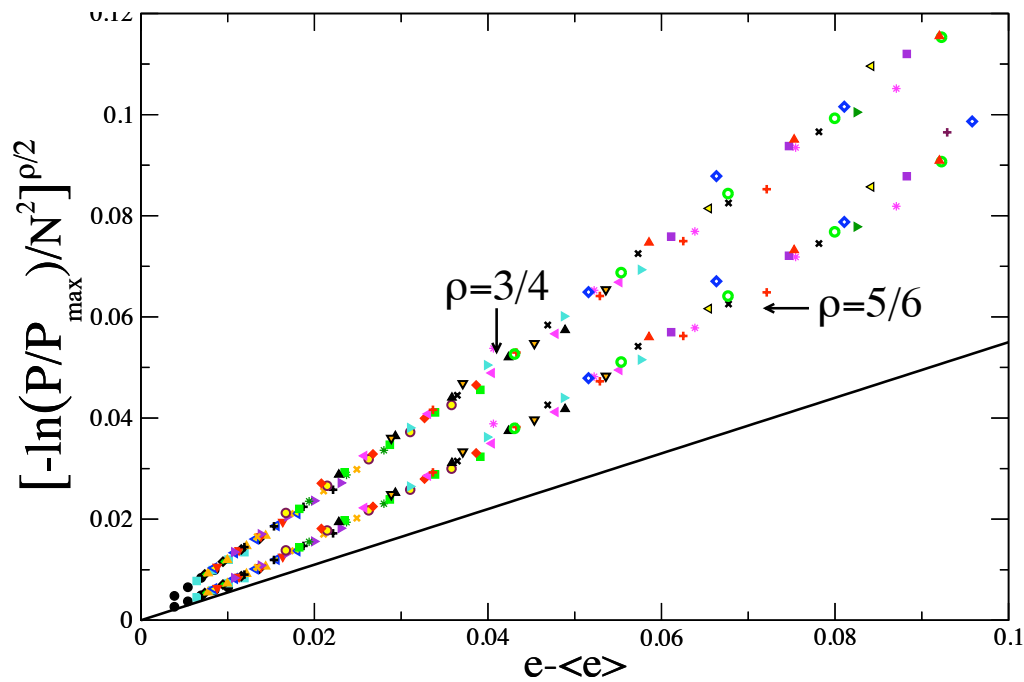
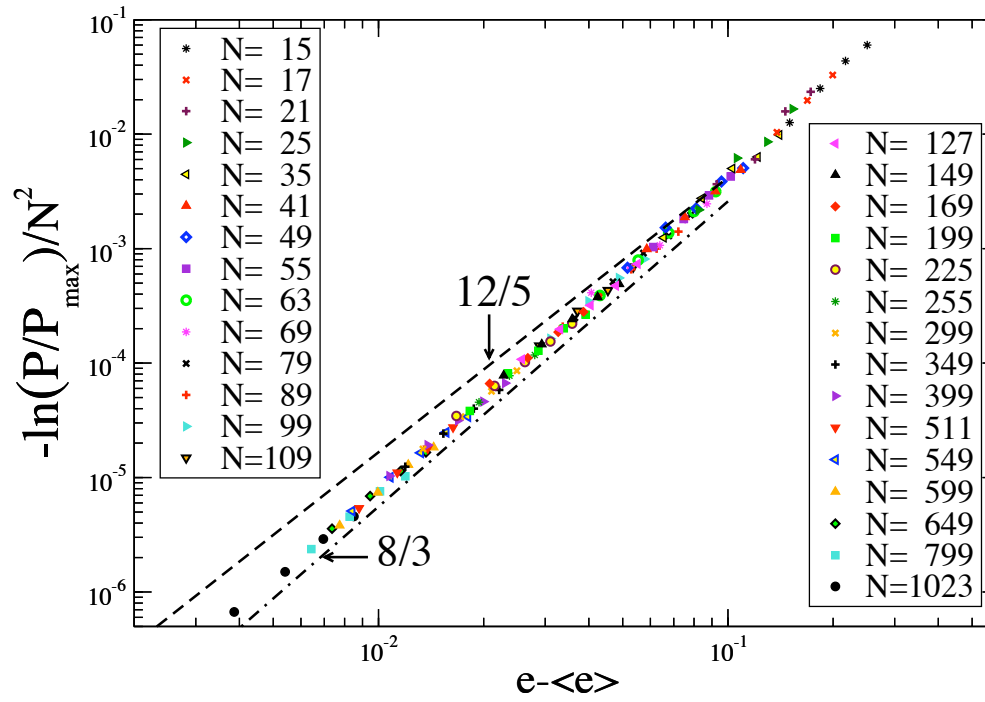
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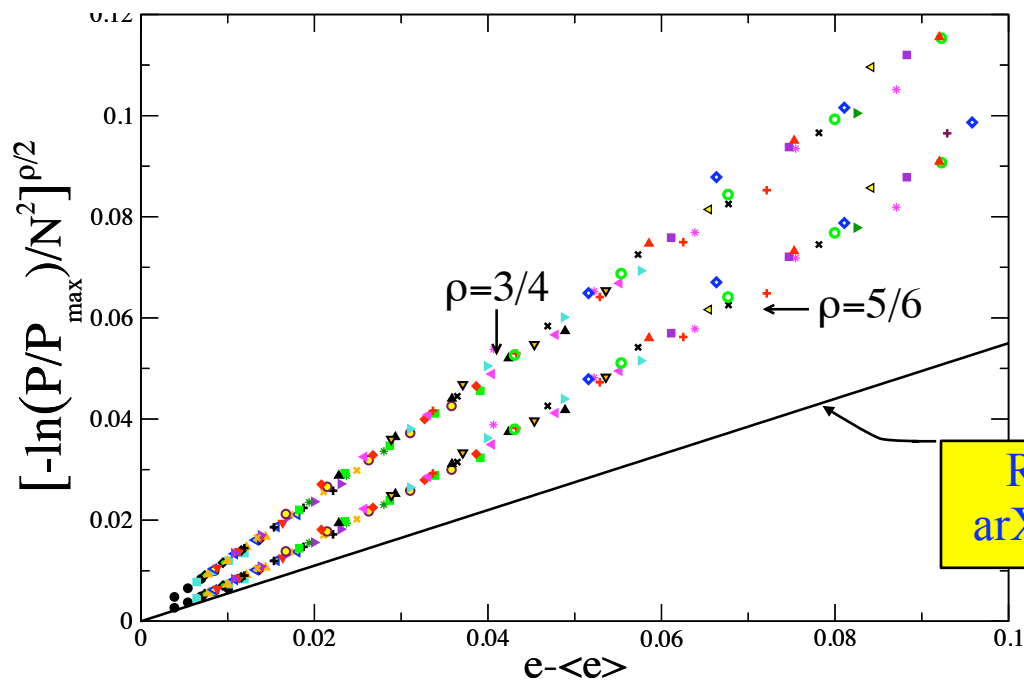
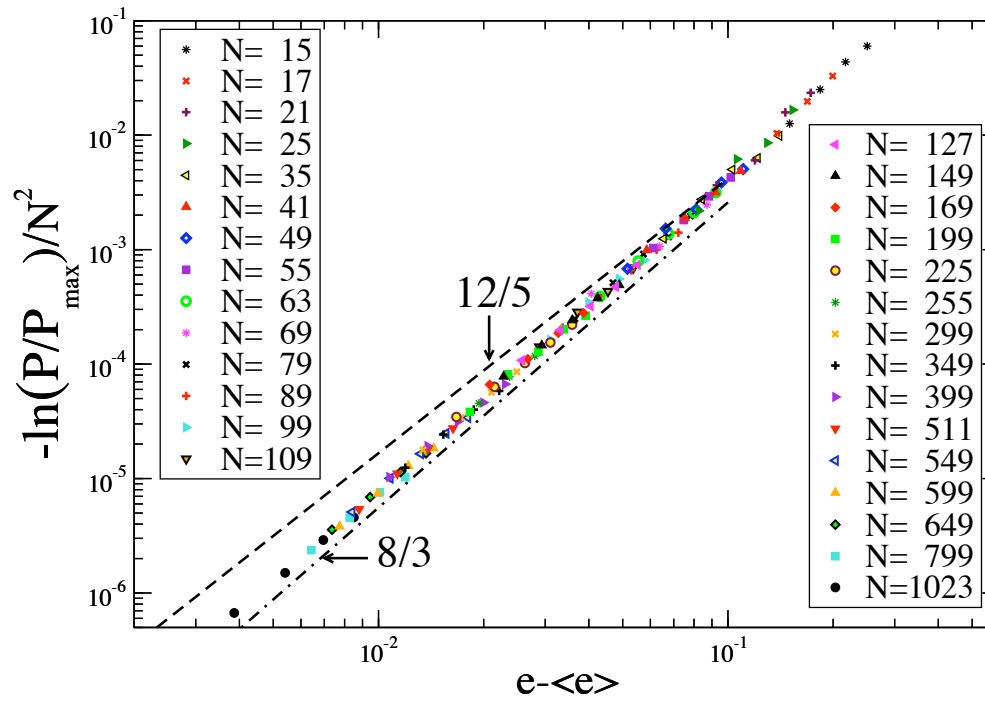
- Mean-Field ( $d \rightarrow \infty$ ) Spin Glasses:











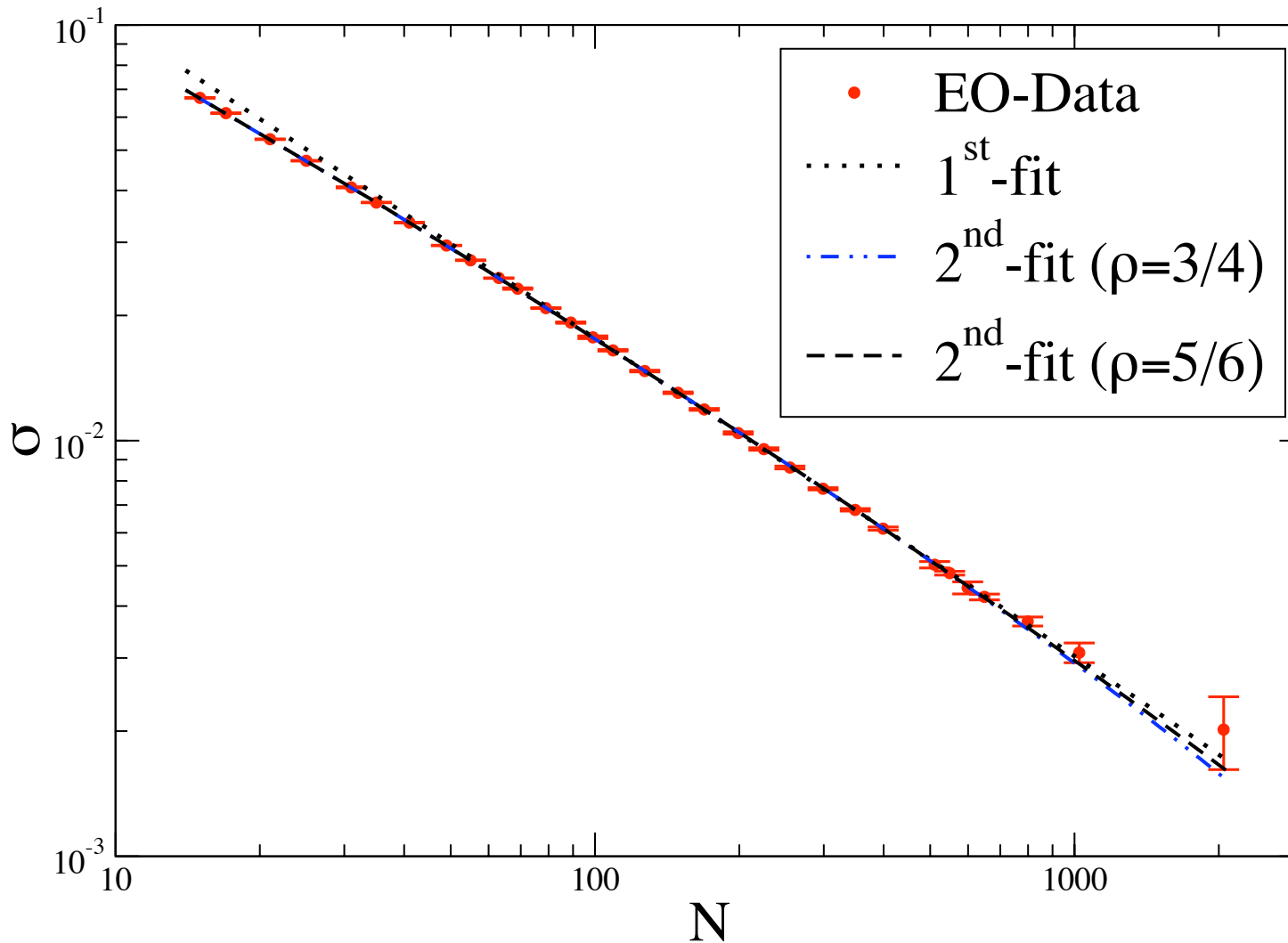
Rizzo&Parisi  
arXiv:0901.1100



# $\tau$ -EO for Sherrington-Kirkpatrick

- Mean-Field ( $d \rightarrow \infty$ ) Spin Glasses:

Fluctuation Exponent  $\rho$



## $\tau$ -EO for Sherrington-Kirkpatrick

- “Width”  $\sigma$  of the GS-Energy:

$$\begin{aligned}\sigma &= \sqrt{\langle e_0^2 \rangle - \langle e_0 \rangle^2}, \\ &\sim A \frac{1}{N^\rho} + B \frac{1}{N^\alpha}, \quad (\alpha > \rho),\end{aligned}$$

$$\ln \sigma \sim -\rho \ln(N) + \ln(A) + \ln \left( 1 + \frac{B}{A} N^{\rho-\alpha} \right),$$

$$\begin{aligned}-\frac{\ln \sigma}{\ln N} &\sim \rho + a x + b x \exp \left[ \frac{\rho - \alpha}{x} \right], \\ &\left( x = \frac{1}{\ln N} \rightarrow 0 \right).\end{aligned}$$

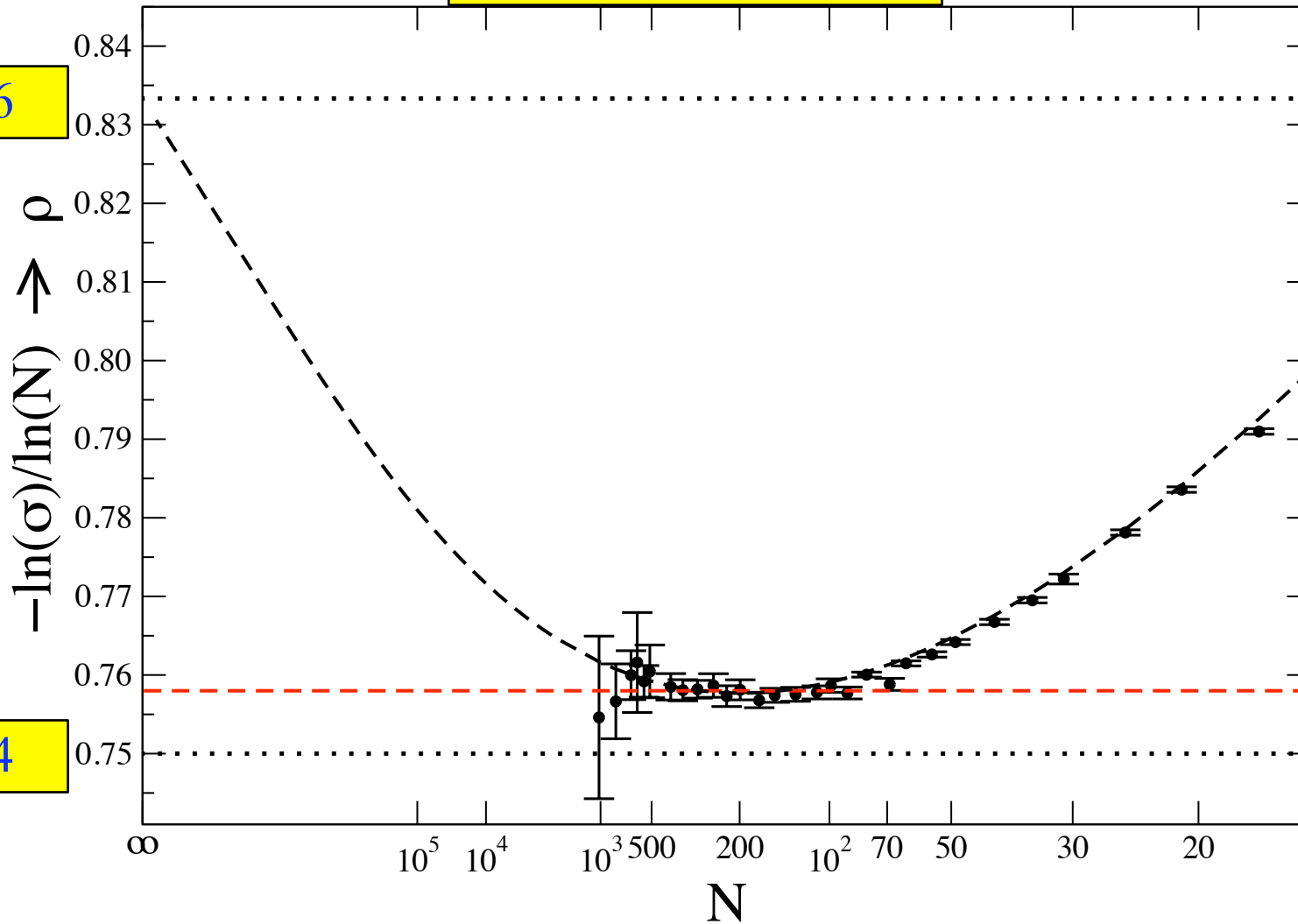
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Fluctuation Exponent  $\rho$

$\rho = 5/6$

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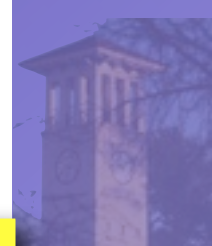
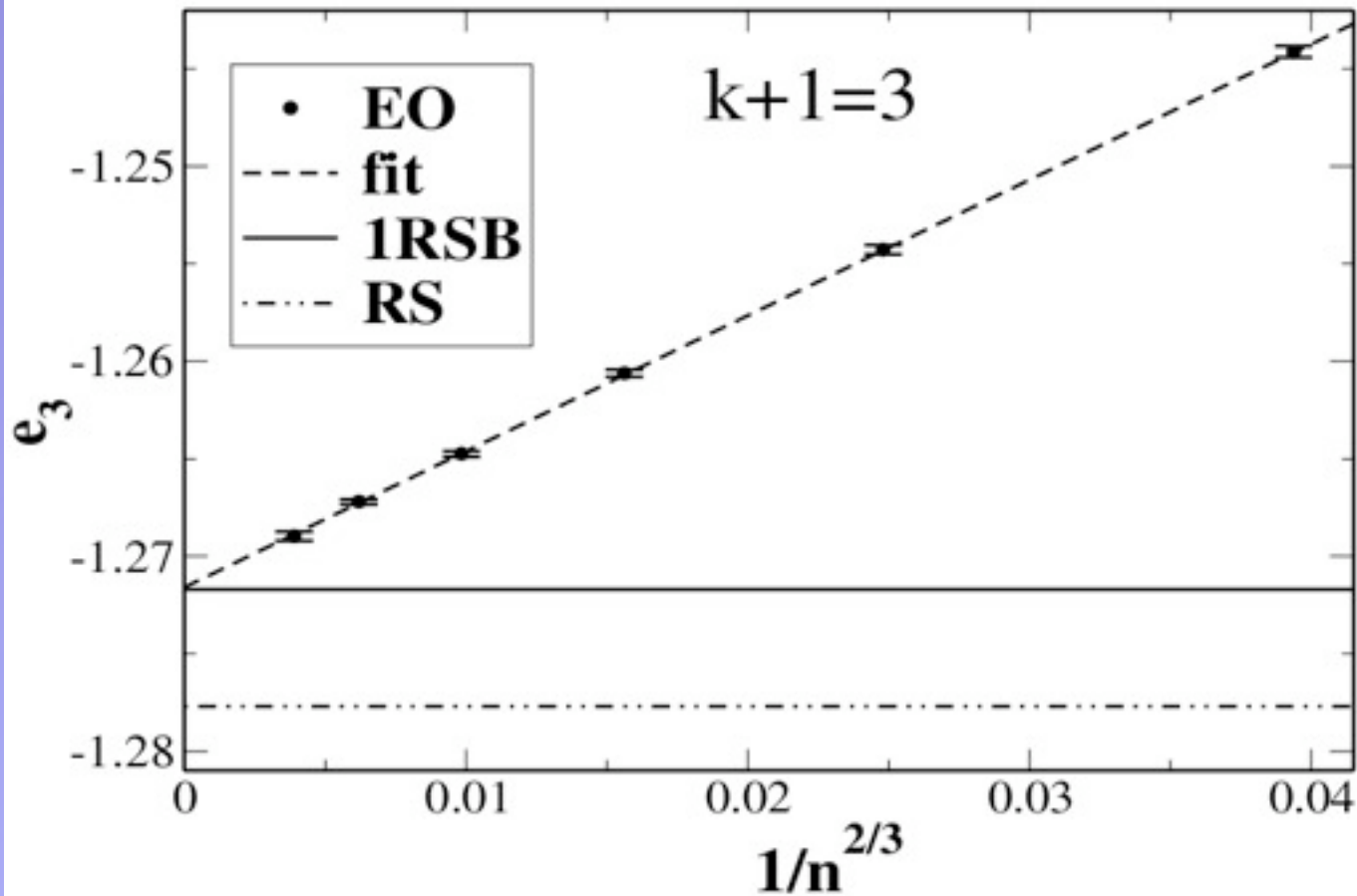






# $\tau$ -EO for Bethe Lattices:

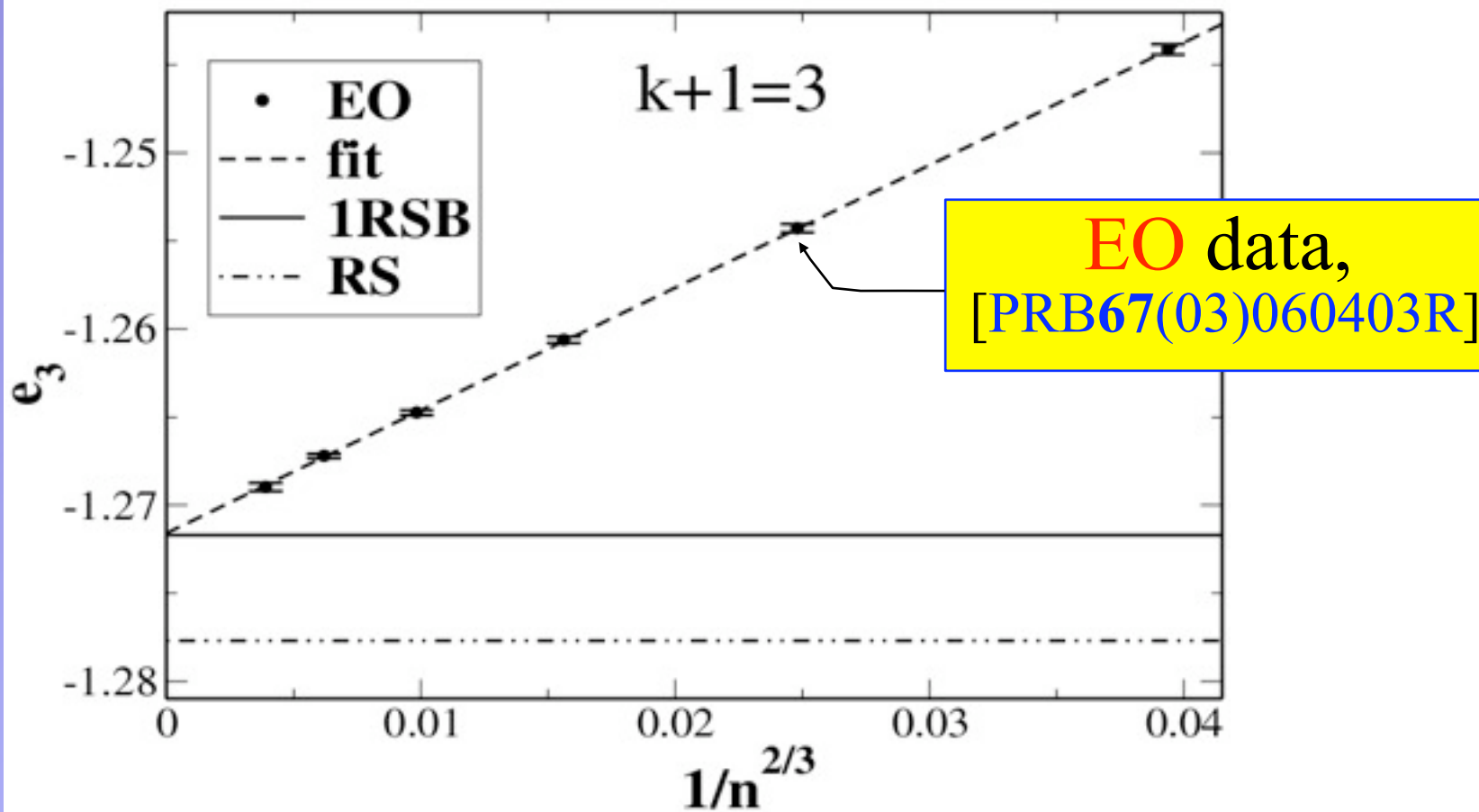
EO for 3-connected Bethe Lattice Glass w/ Replica Sym. Breaking:





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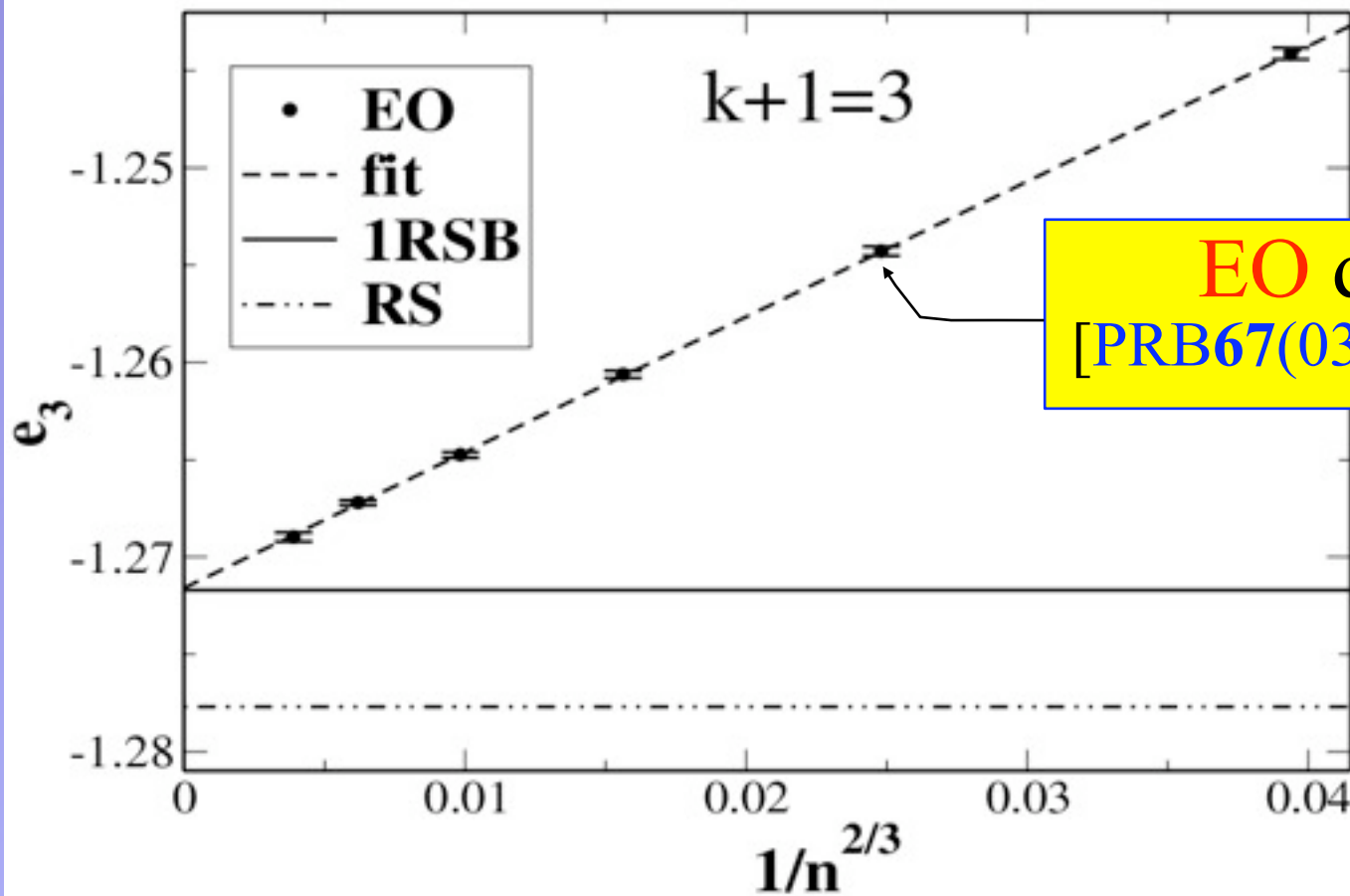
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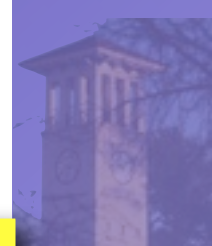
EO data,  
[PRB67(03)060403R]

Replica Theory:

$\Leftarrow$  1RSB,

$\Leftarrow$  no RSB,

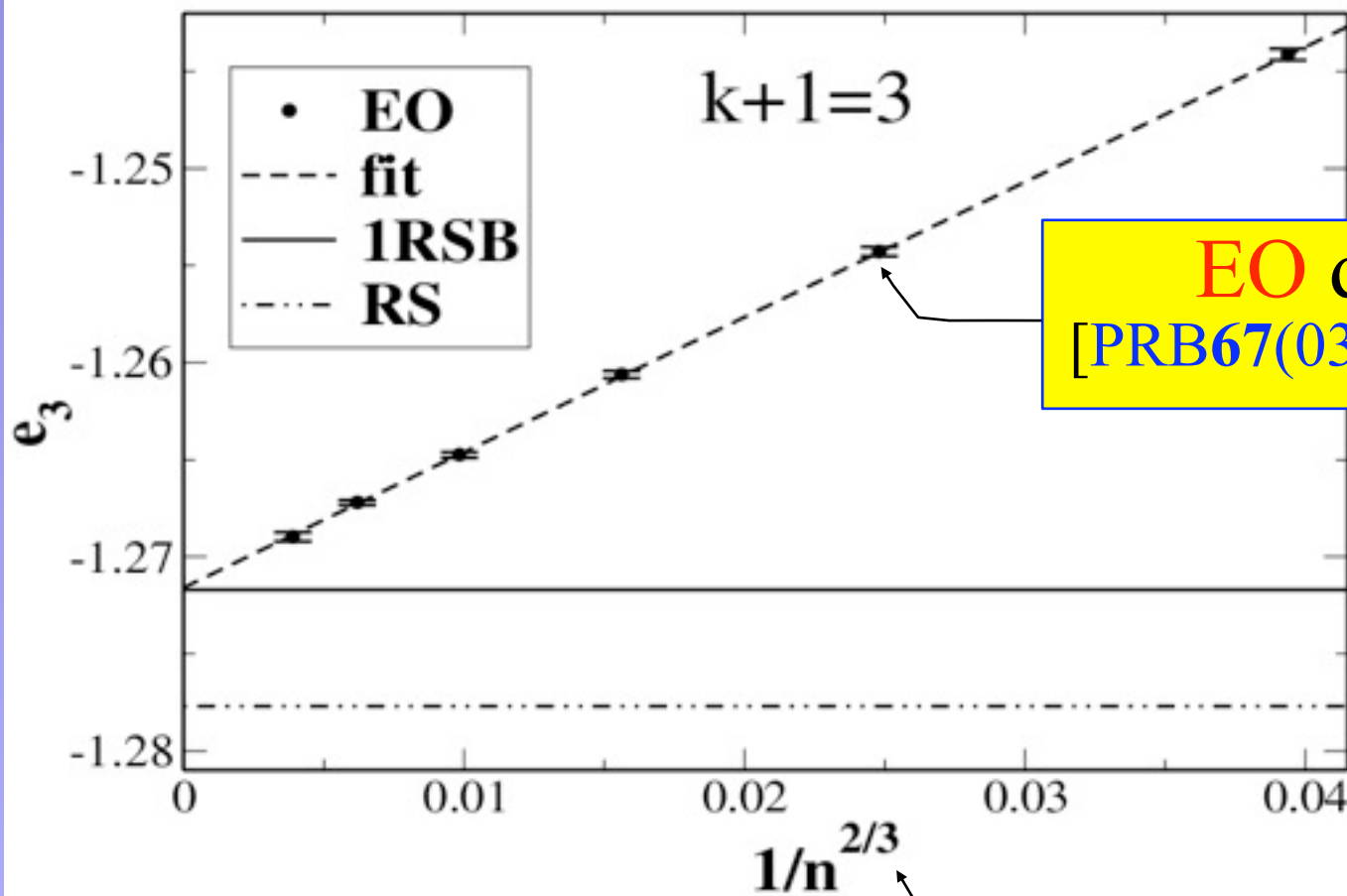
[J.Stat.Phys.111(03)1]





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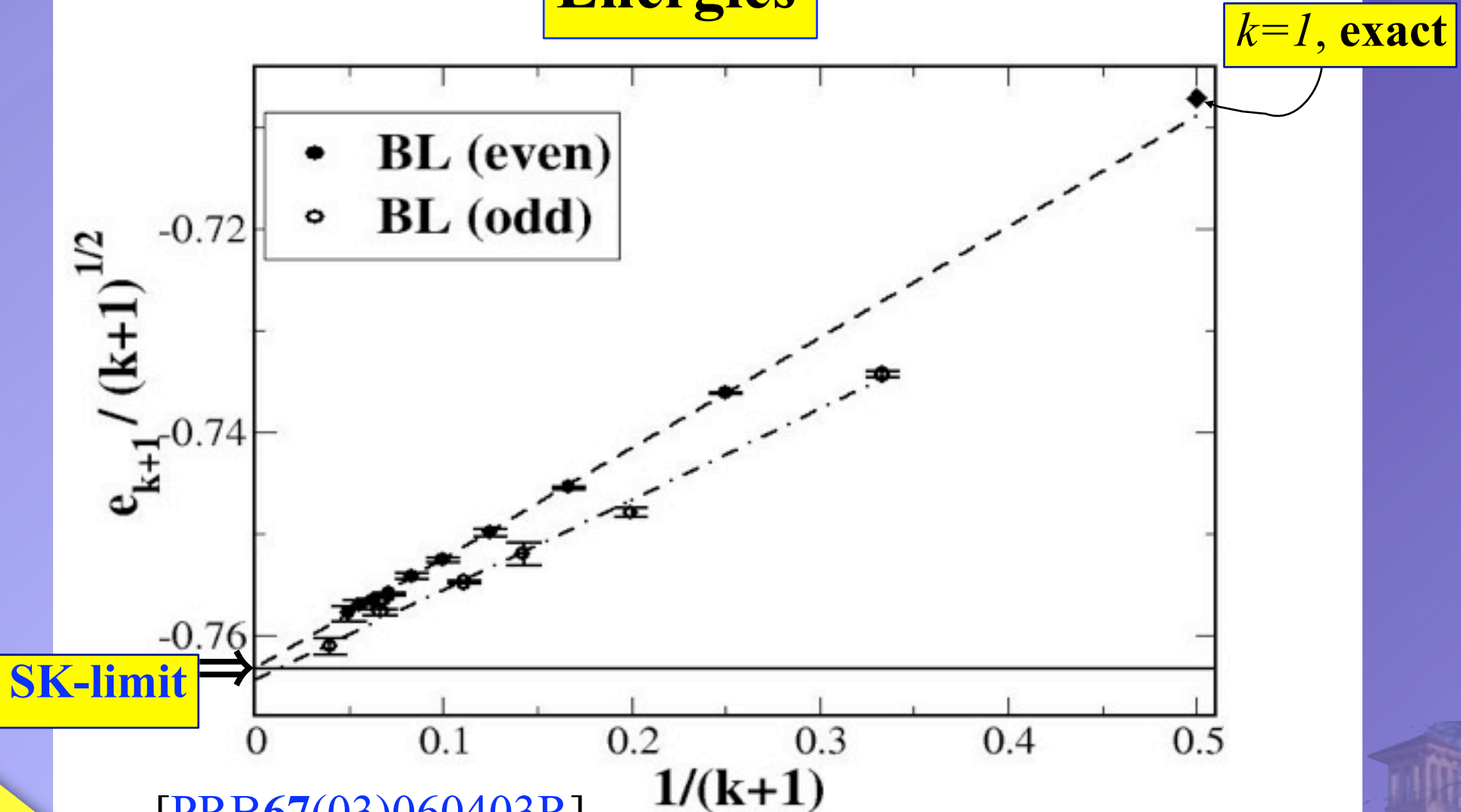
Scaling corrections  $\omega \approx 2/3$



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EO for  $(k+1)$ -connected Bethe Lattice Glasses for  $(k+1) \rightarrow \infty$ :

## Energies



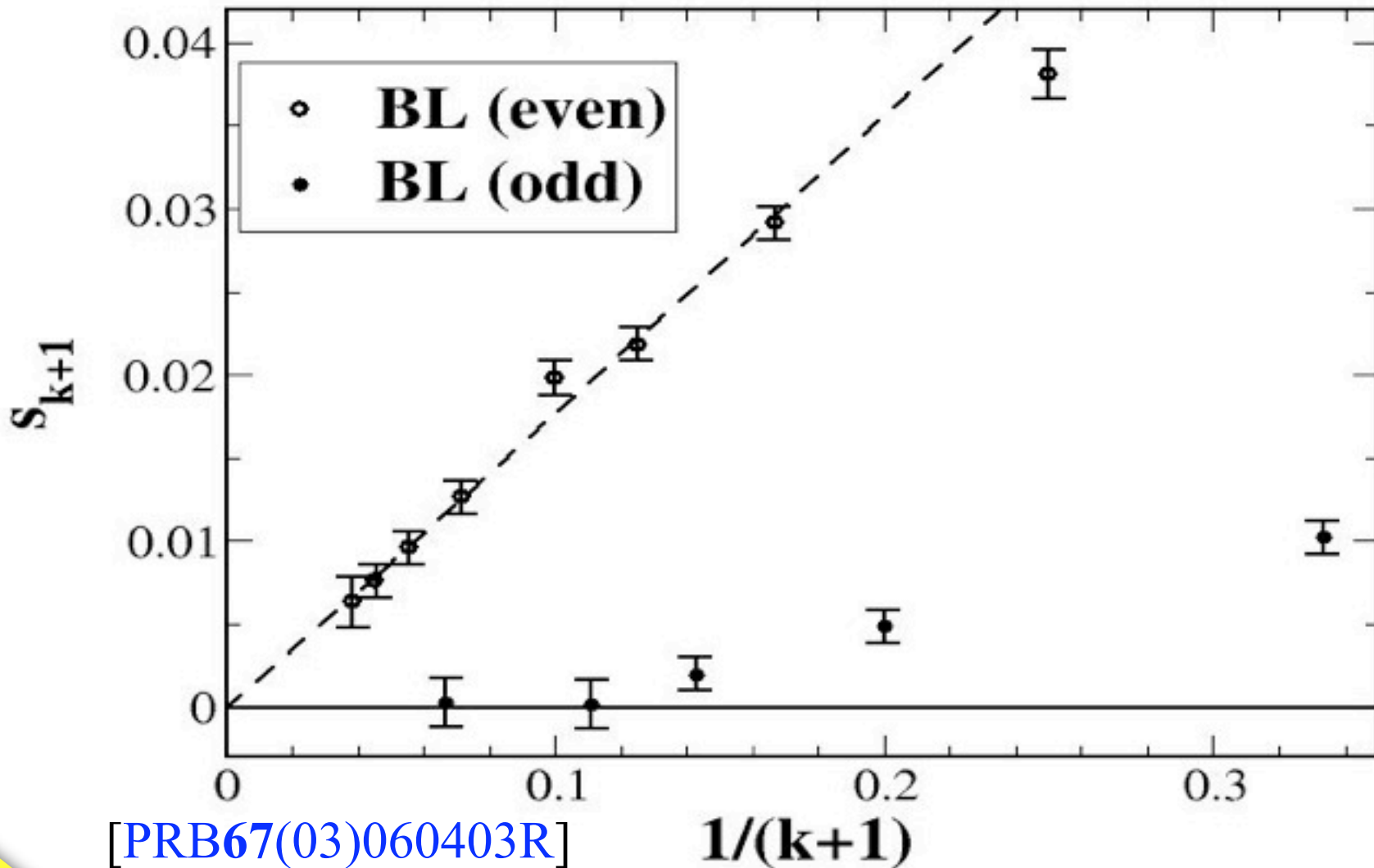
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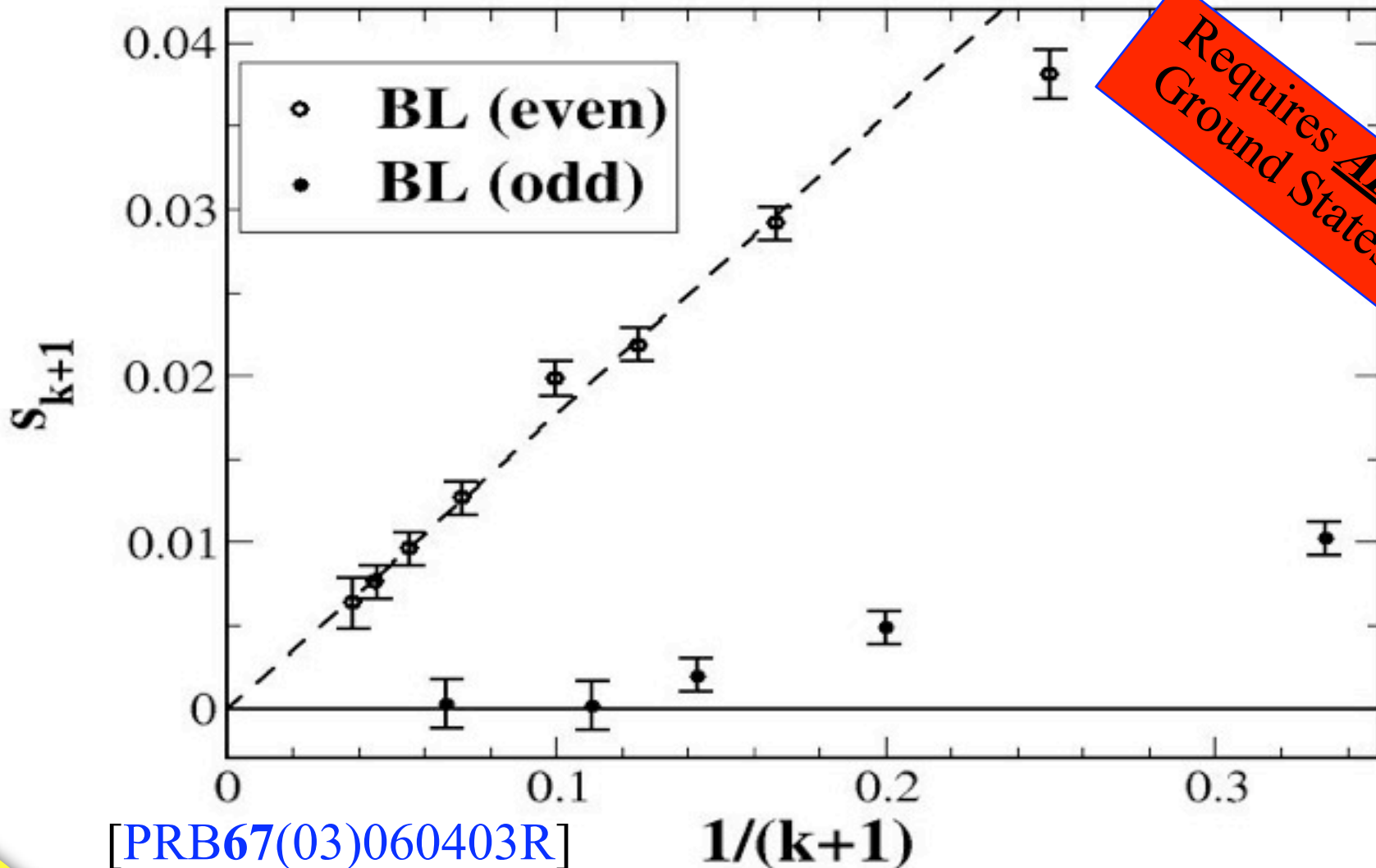




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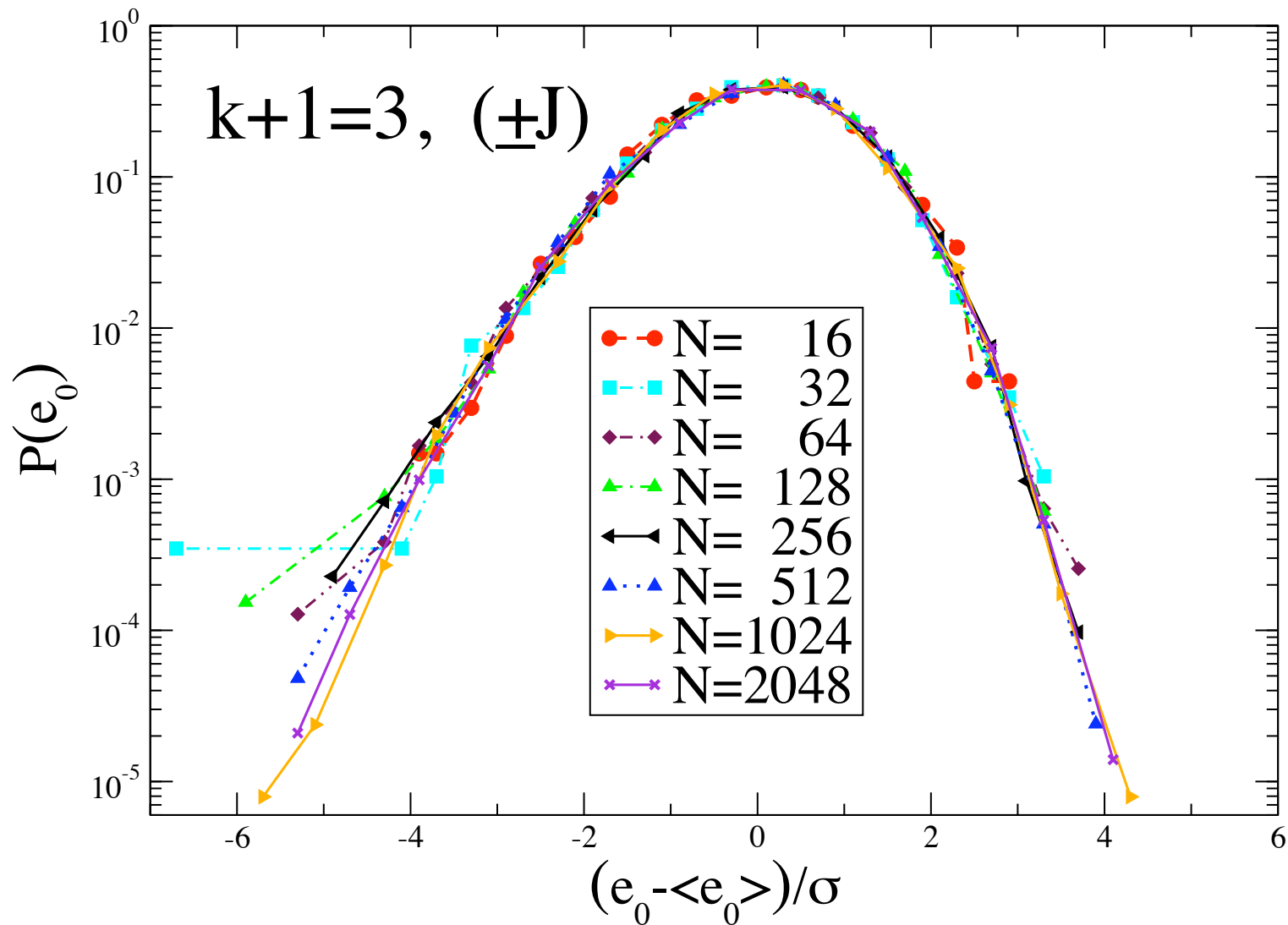
## Entropies



Requires ALL  
Ground States!

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EO for 3-connected Bethe Lattice Glass:





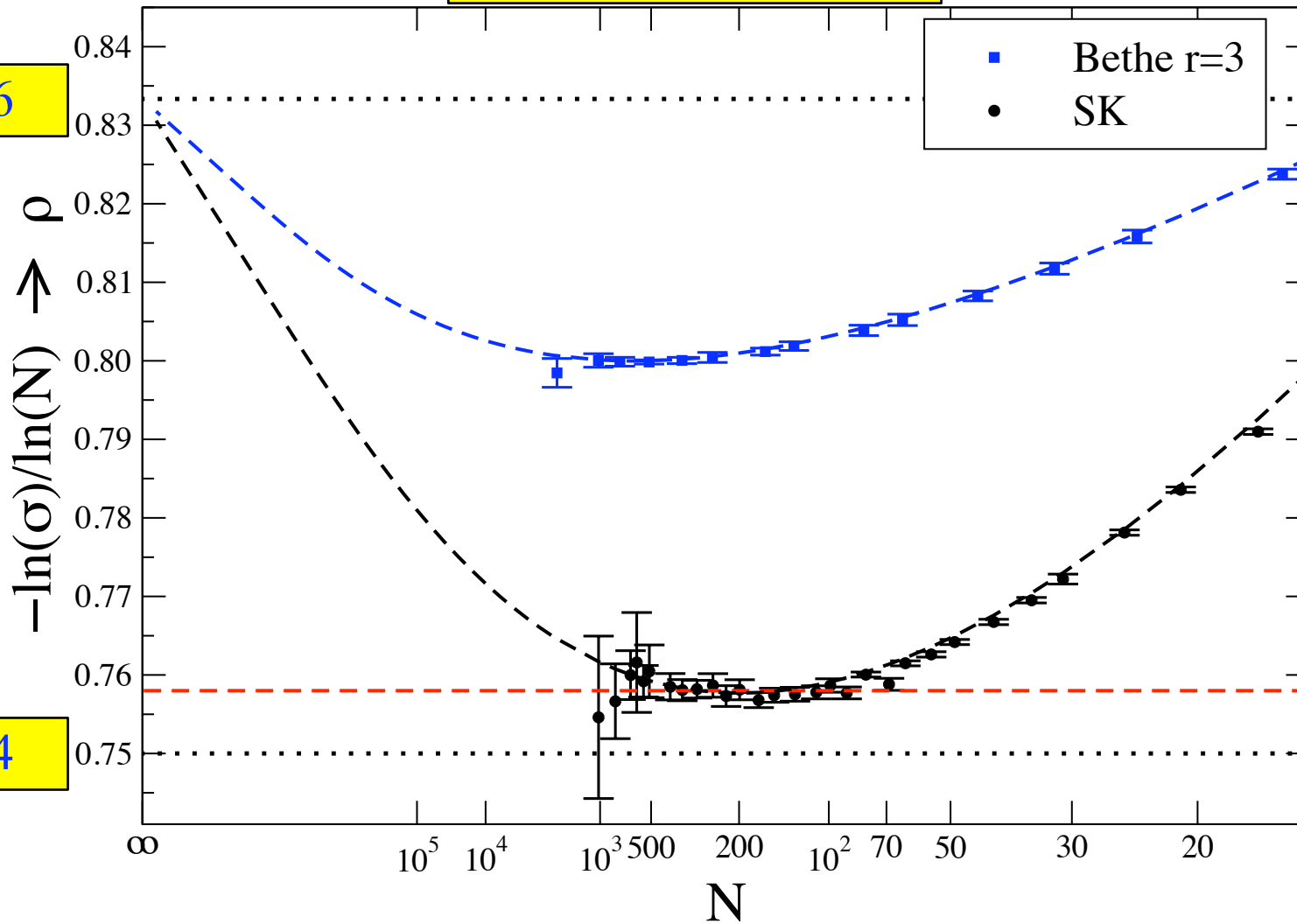
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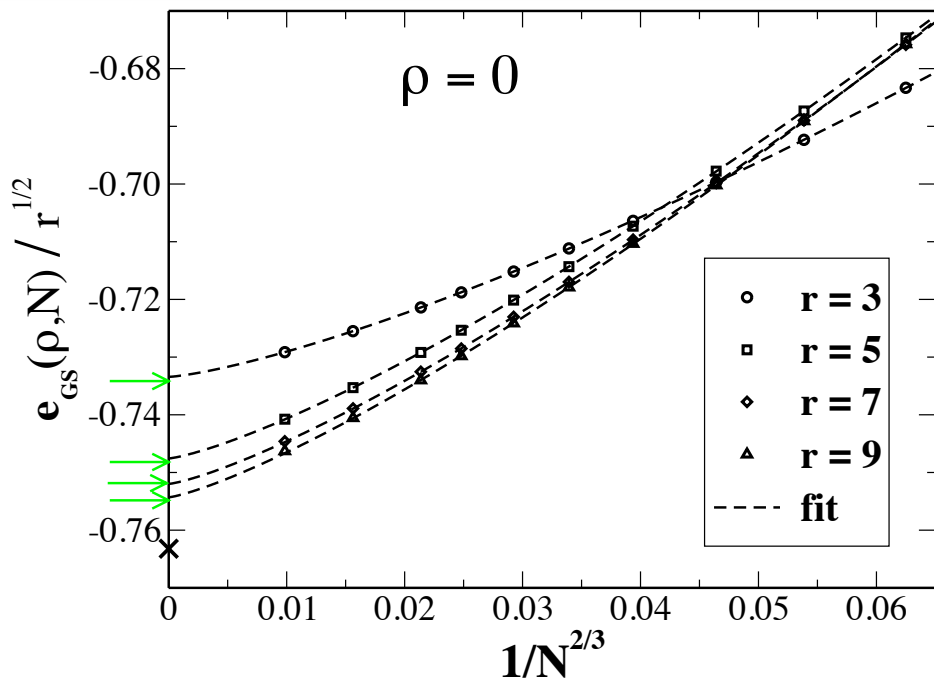
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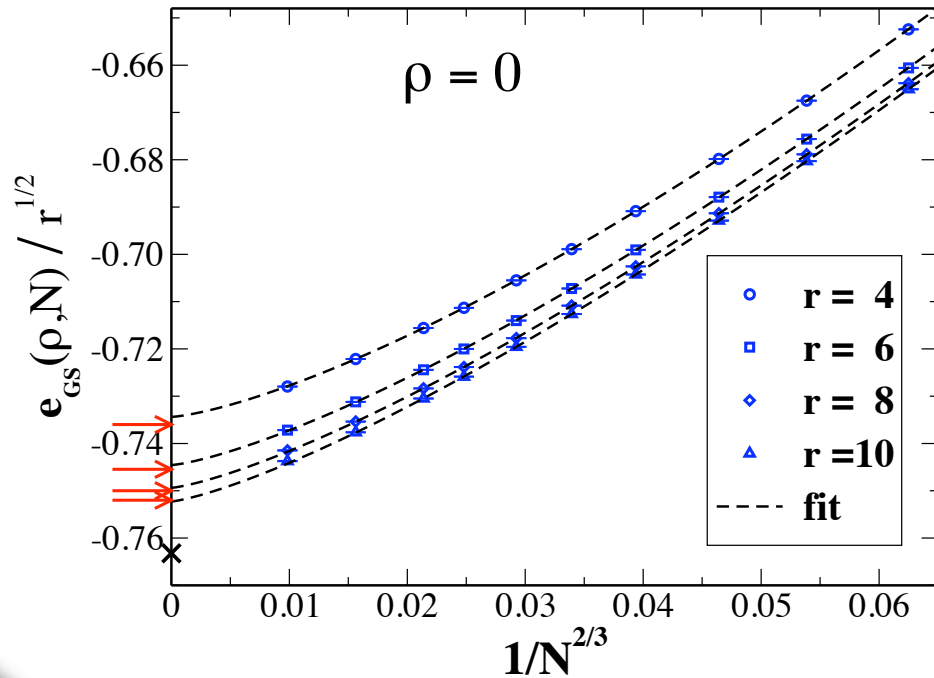
$\rho = 5/6$

$\rho = 3/4$

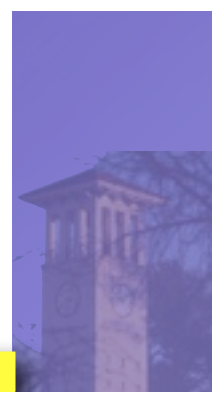
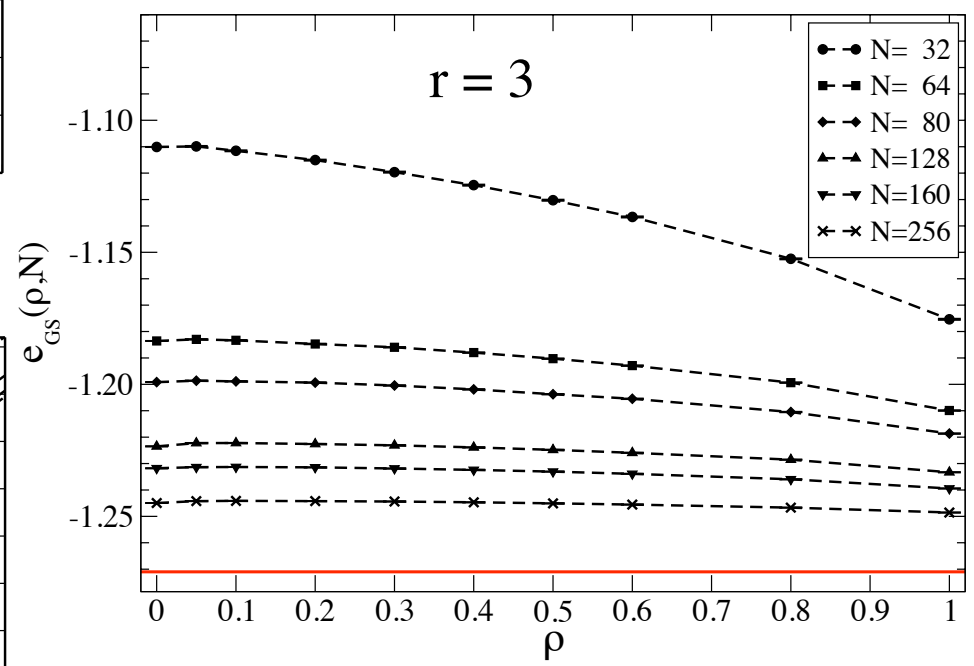
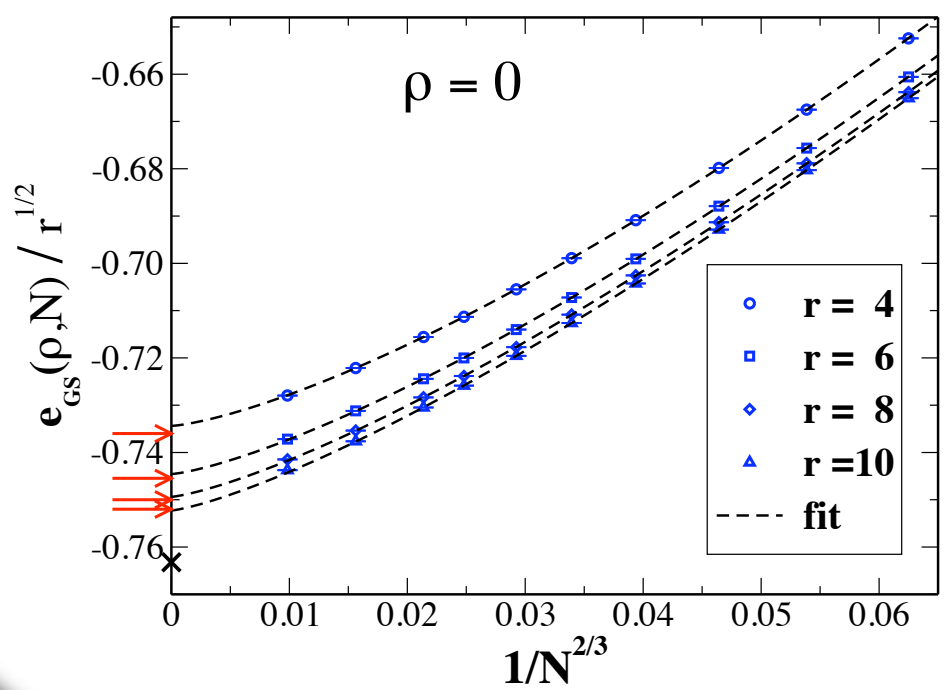
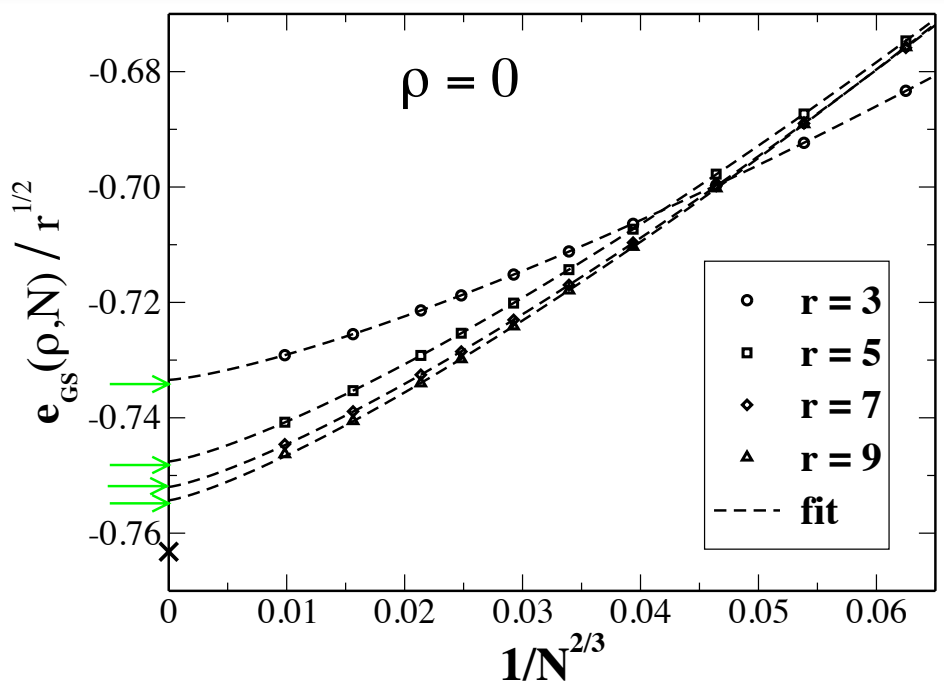




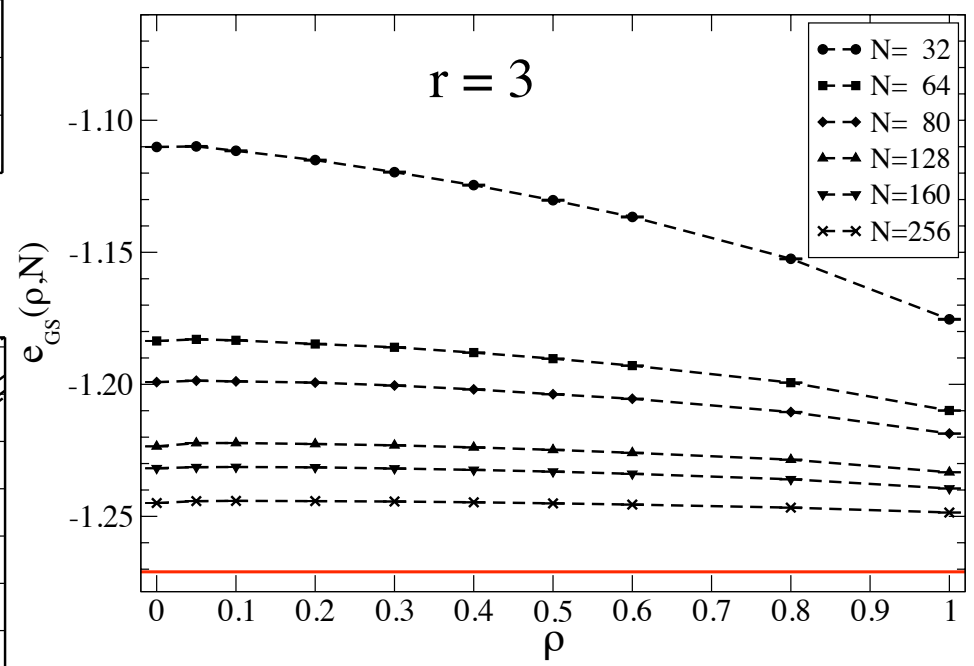
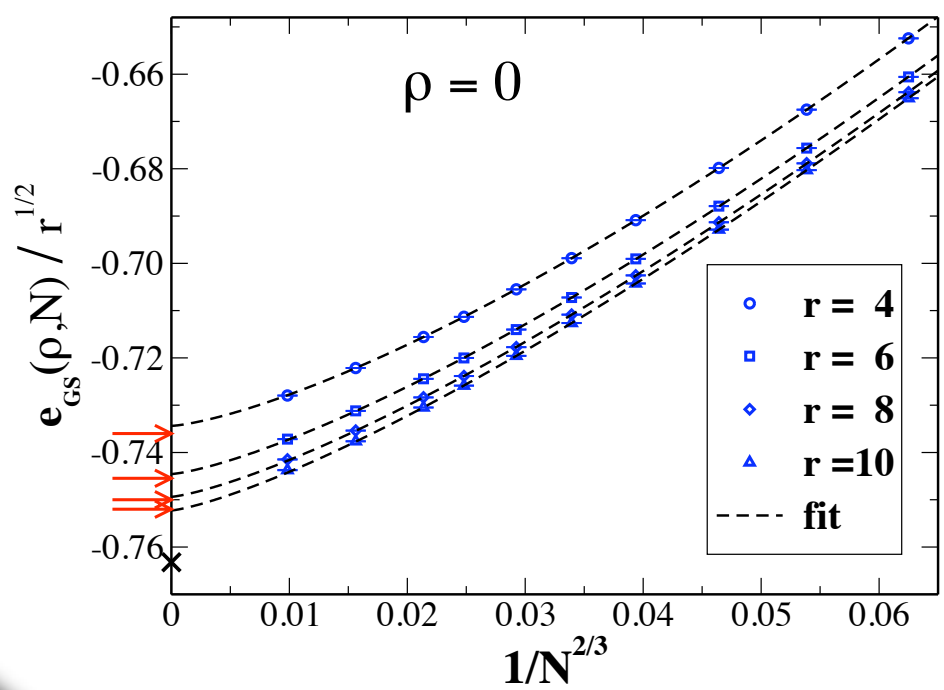
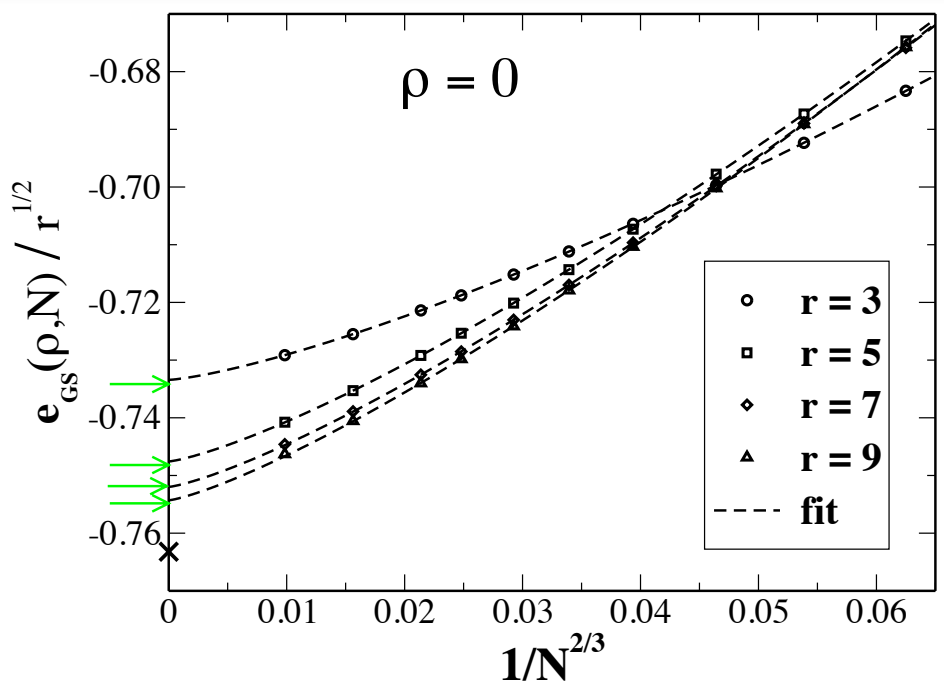
L. Zdeborova & SB,  
J Stat Mech, P02020 (2010).



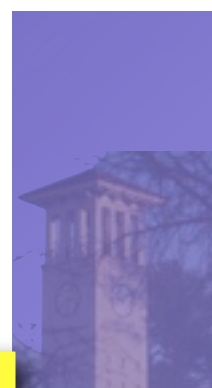
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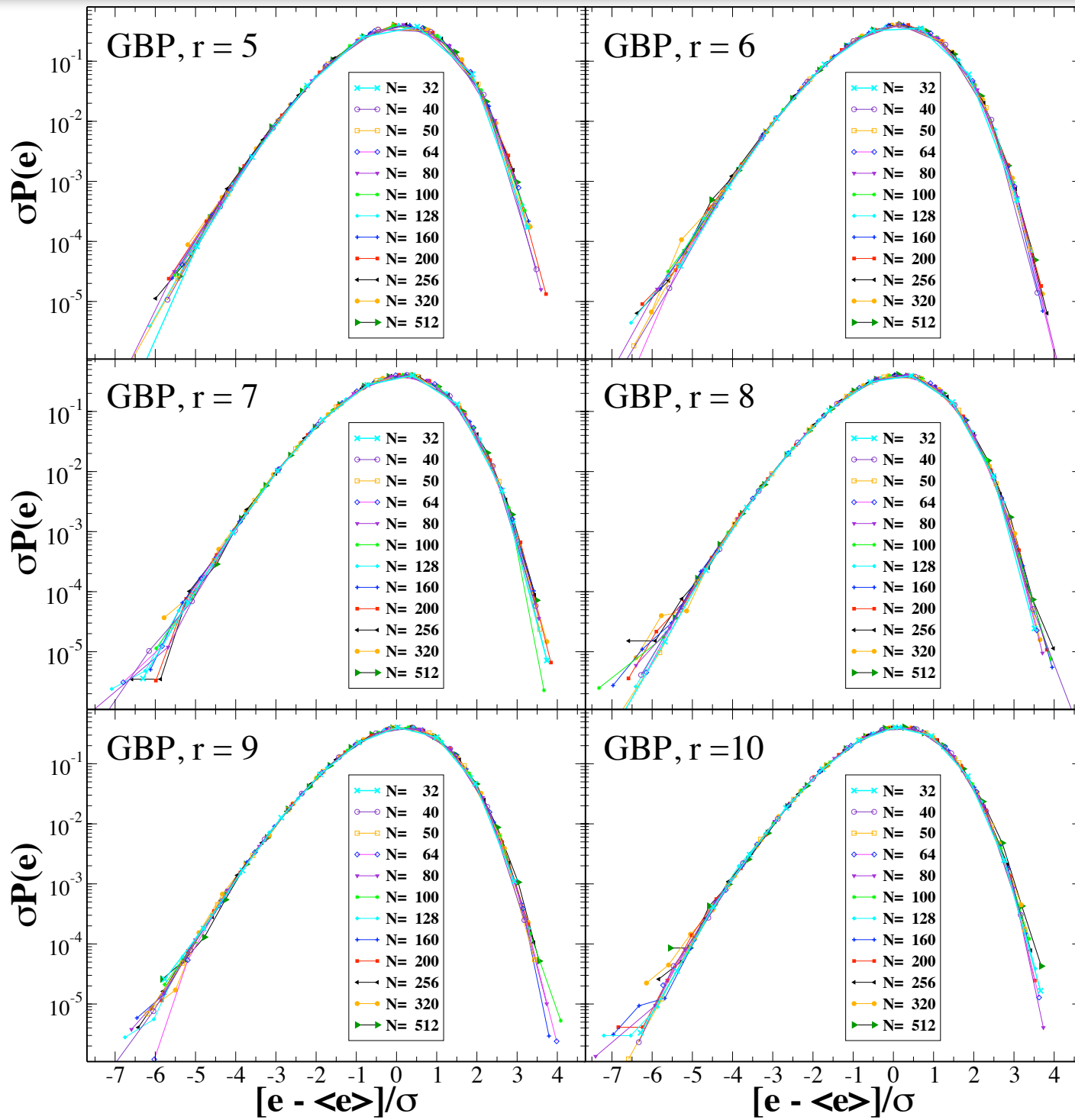


L. Zdeborova & SB,  
J Stat Mech, P02020 (2010).



maximum cut  $\Leftrightarrow$  bisection!

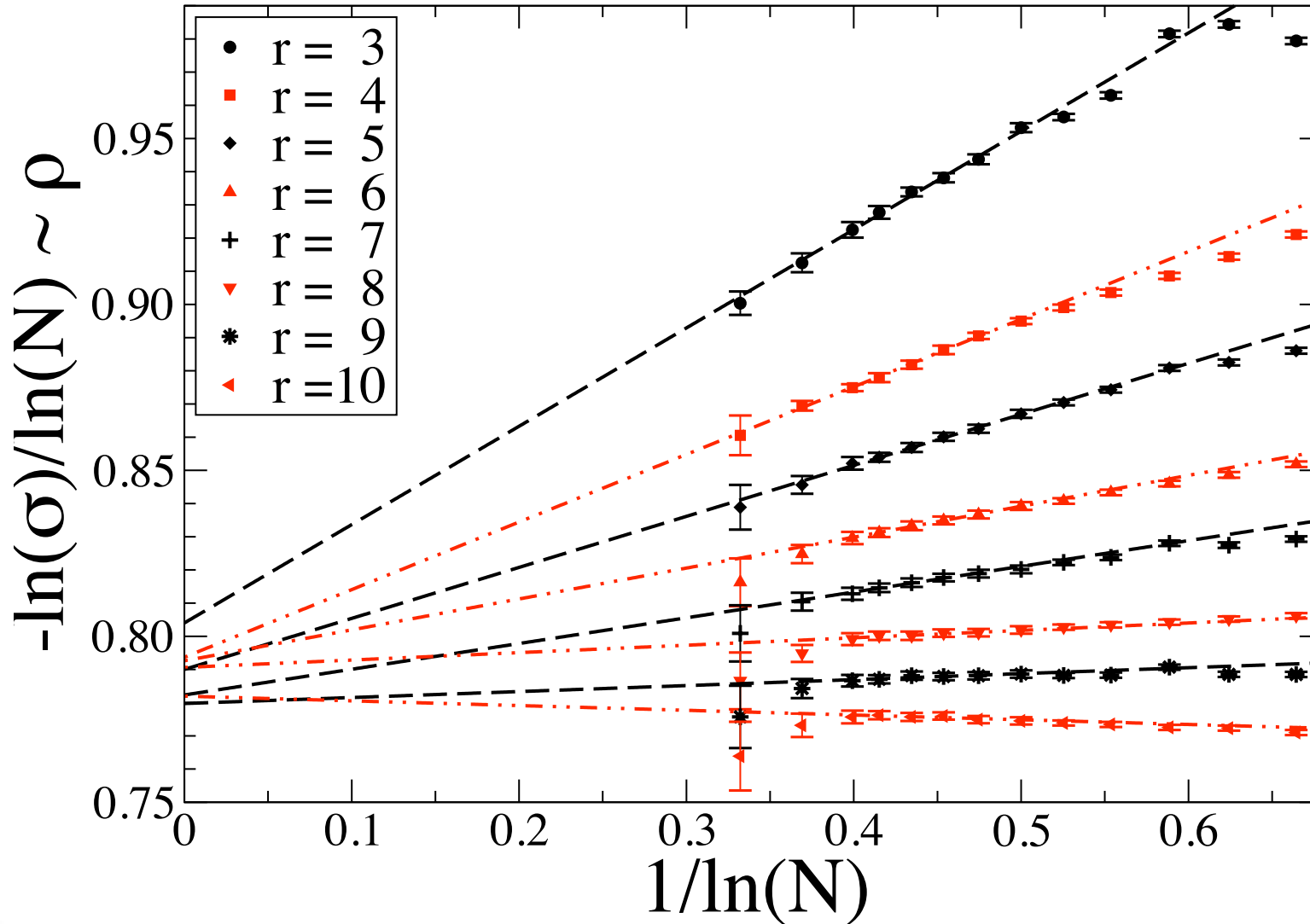




# $\tau$ -EO for Bethe Lattice Spin Glasses:

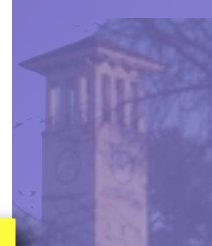
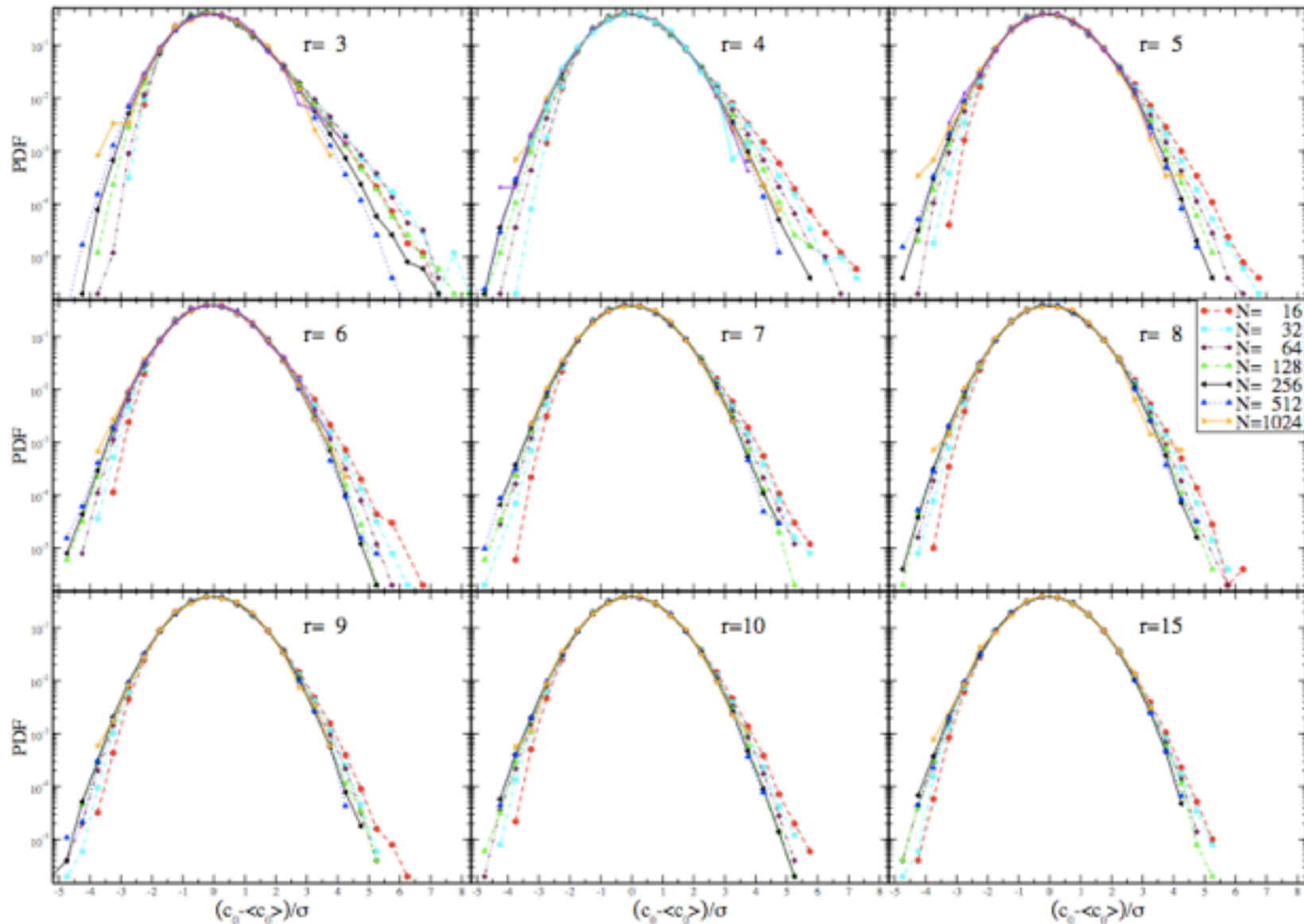
- $\pm J$  Bonds:

Fluctuation Exponent  $\rho$



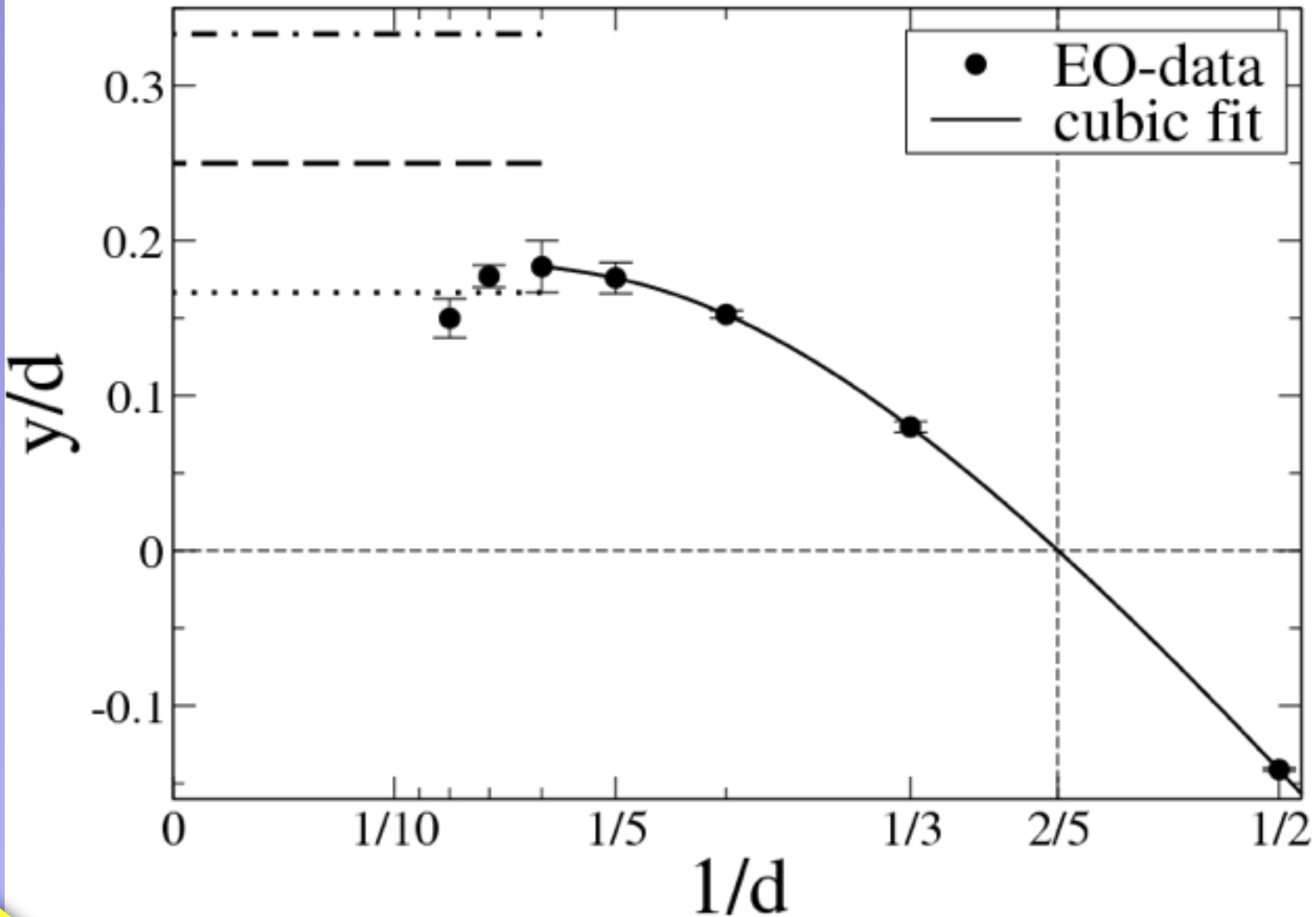
# $\tau$ -EO for Bethe Lattice Spin Glasses:

- Gaussian Bonds:



# Spin Glass on Dilute Hyper-Cubes (EA):

“Stiffness”:  $\sigma(\Delta E) \sim L^\gamma$

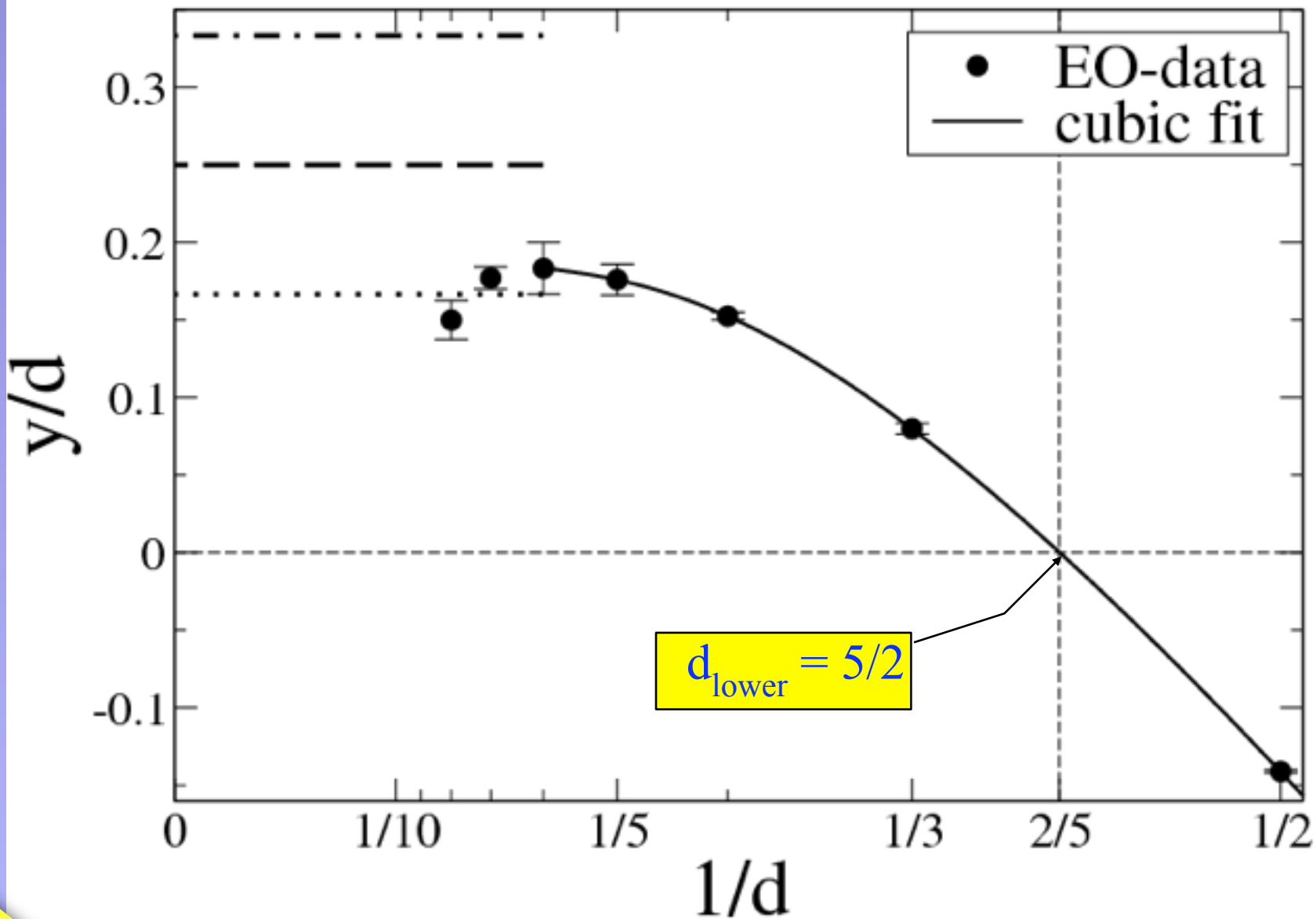






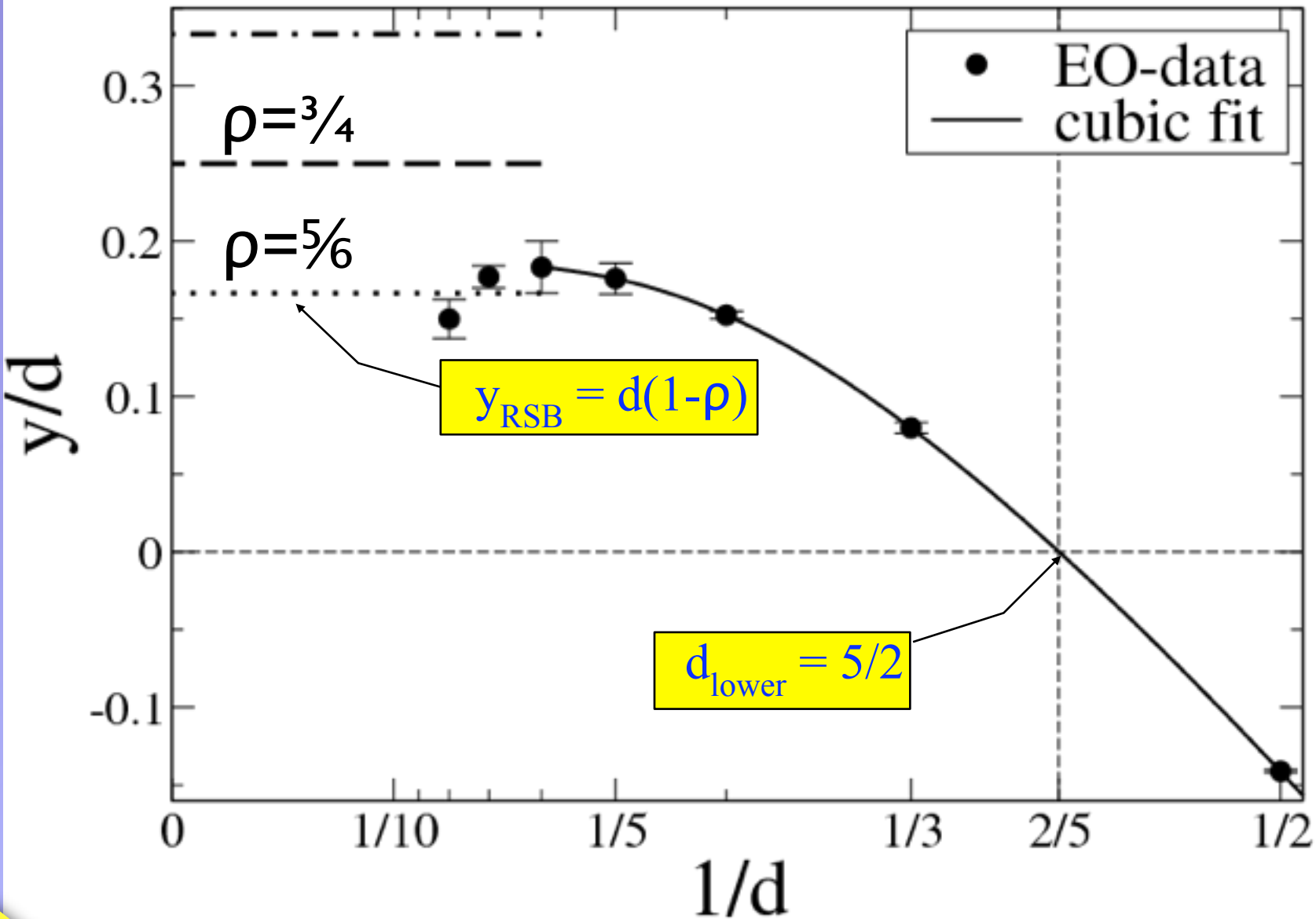
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## Finite-Size Corrections in EA:

Ground State Energy:  $E(L) \sim e_0 L^d + AL^y \quad (L \rightarrow \infty)$

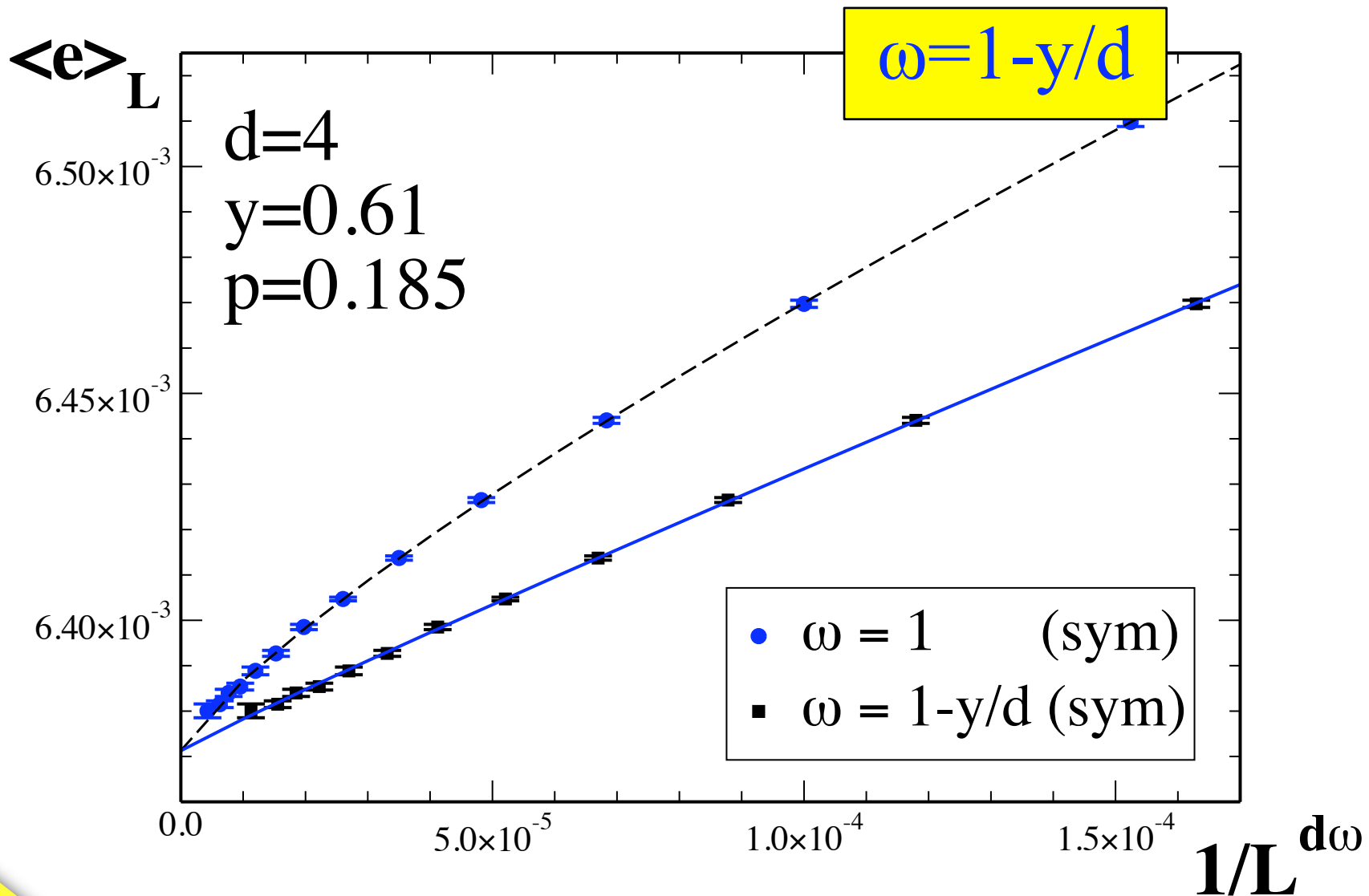
## Finite-Size Corrections in EA:

Ground State Energy:  $E(L)/L^d \sim e_0 + A/L^{d-y} \quad (L \rightarrow \infty)$

$$\omega = 1 - y/d$$

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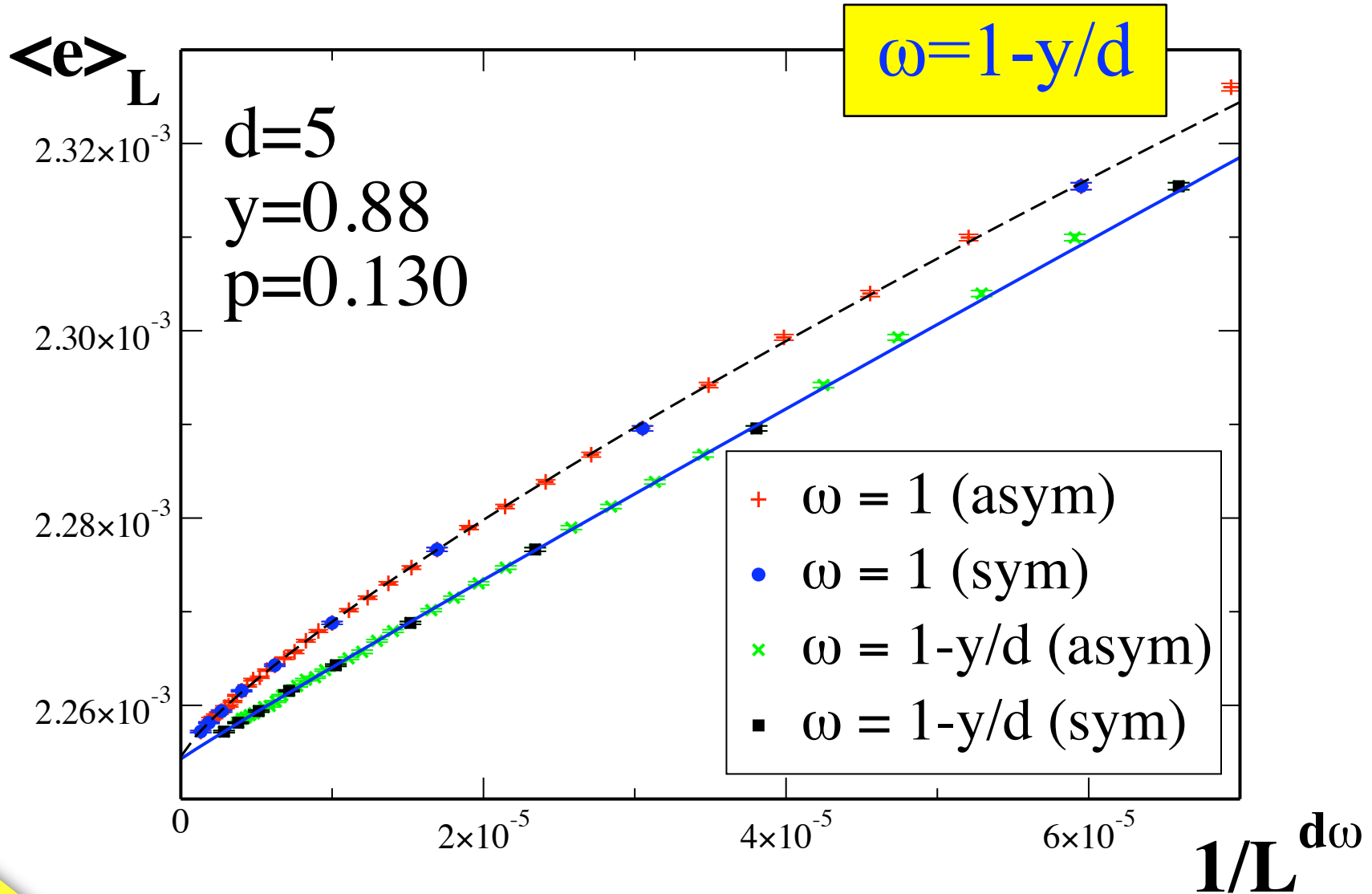
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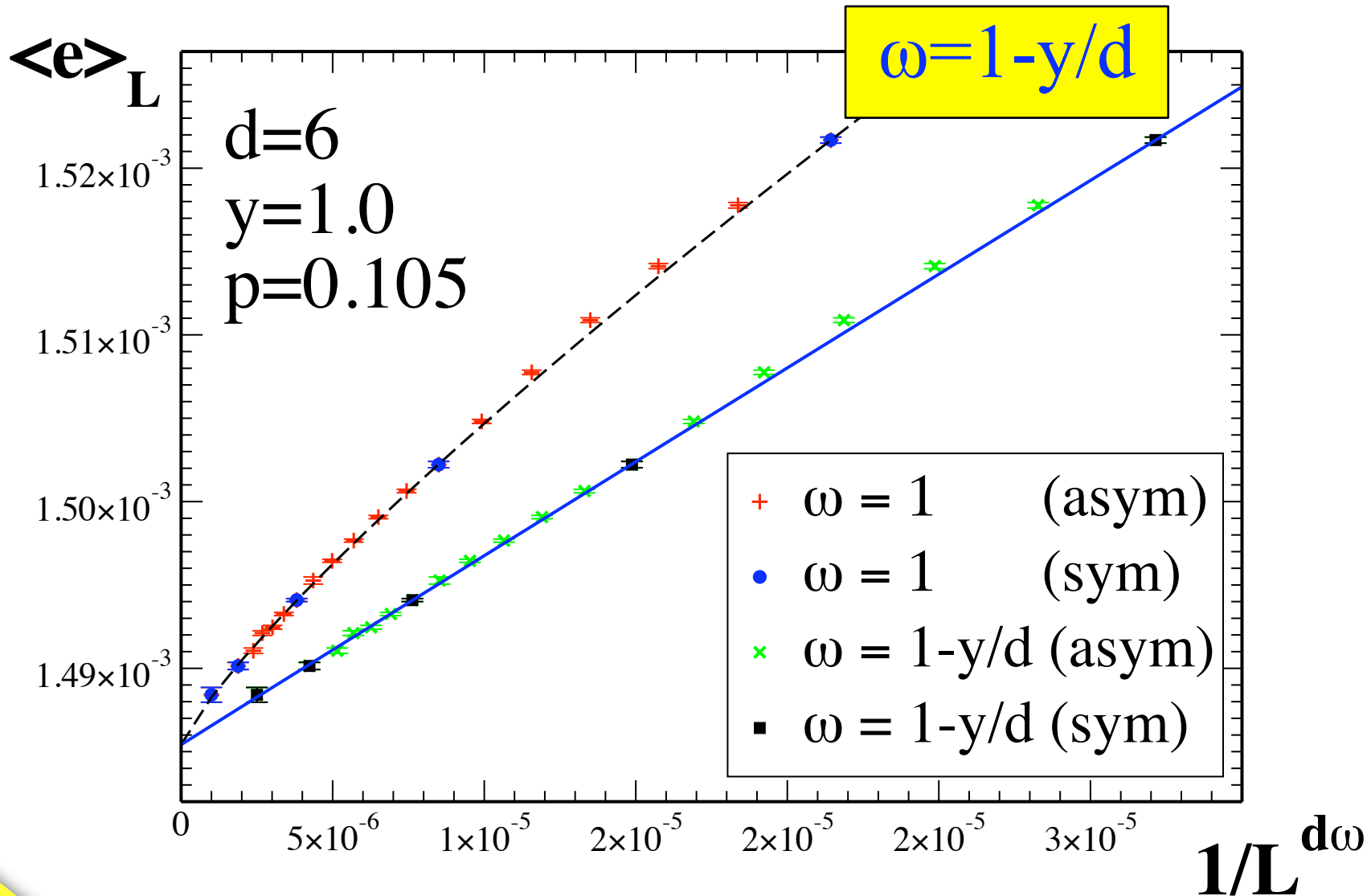
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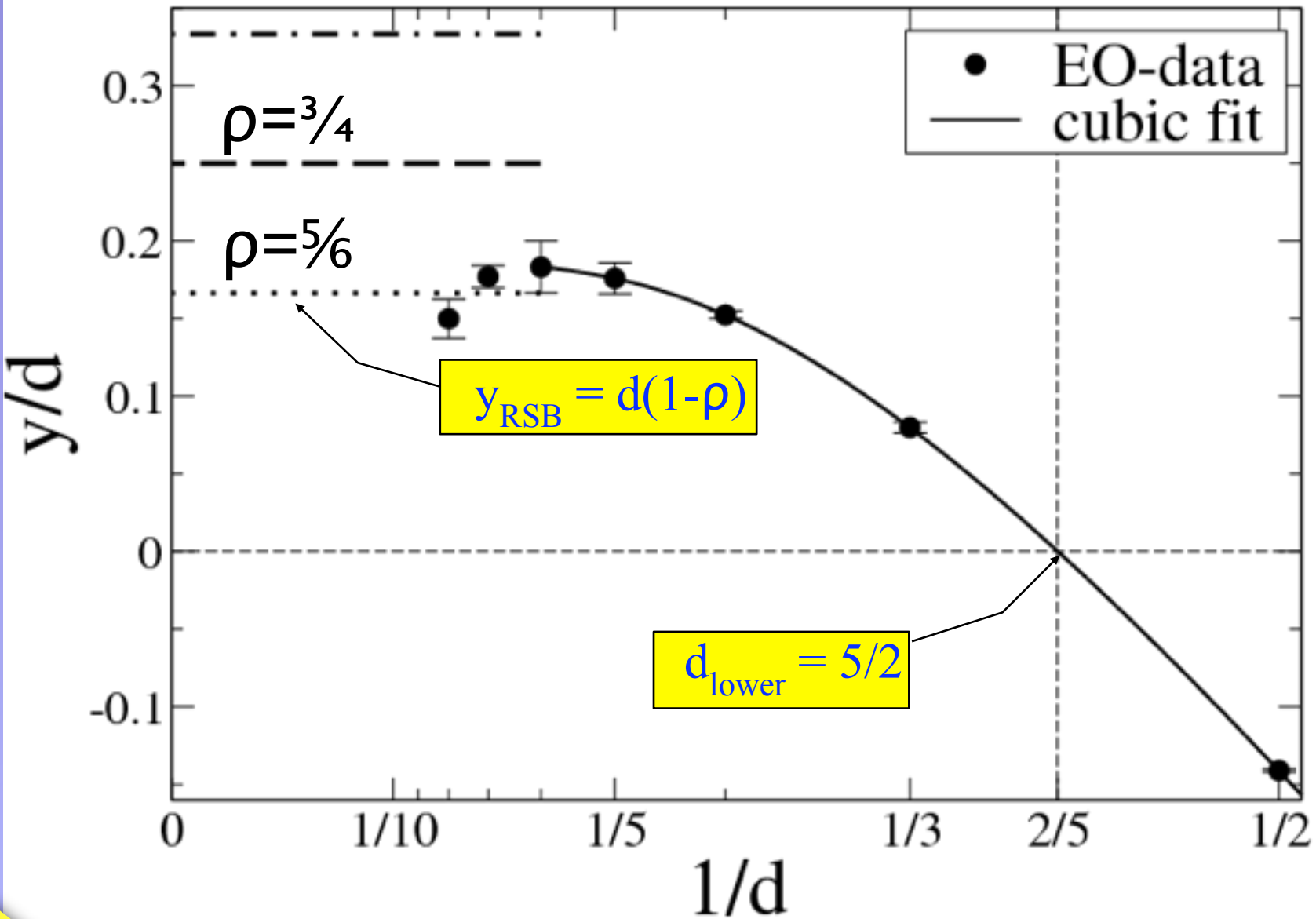
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