

parQ - A Transition Matrix Method to Calculate the Density of States

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Outline

1. Methods
2. Models
3. Results
4. Conclusion

par Q Method

- par Q is a transition matrix approach utilising an infinite temperature transition matrix
- it is independent of Monte Carlo scheme
 - e. g. can use standard Metropolis, Wang-Landau or even Threshold Accepting, as well as other methods
- uses all available data

- Master equation of a random walker being in state E_j :

$$p(E_j, t + 1) = \sum_{i=1}^N \Gamma_{ji}(T) \cdot p(E_i, t)$$

- Γ temperature dependent TM $\sum_k \Gamma_{ki}(T) = 1 \quad \forall i$

- right eigenvector to eigenvalue 1 of the stationary solution $p^*(E_j)$ has to be the Boltzmann distribution

$$p^*(E_j) = \frac{1}{Z(T)} \Omega(E_j) e^{-\beta E_j}$$

- for $t \rightarrow \infty$ we get:

$$\Omega(E_j) e^{-\beta E_j} = \sum_{i=1}^N \Gamma_{ji}(T) \Omega(E_i) e^{-\beta E_i}$$

- taking the limit $T \rightarrow \infty$

$$\Omega(E_j) = \sum_i Q_{ji} \Omega(E_i)$$

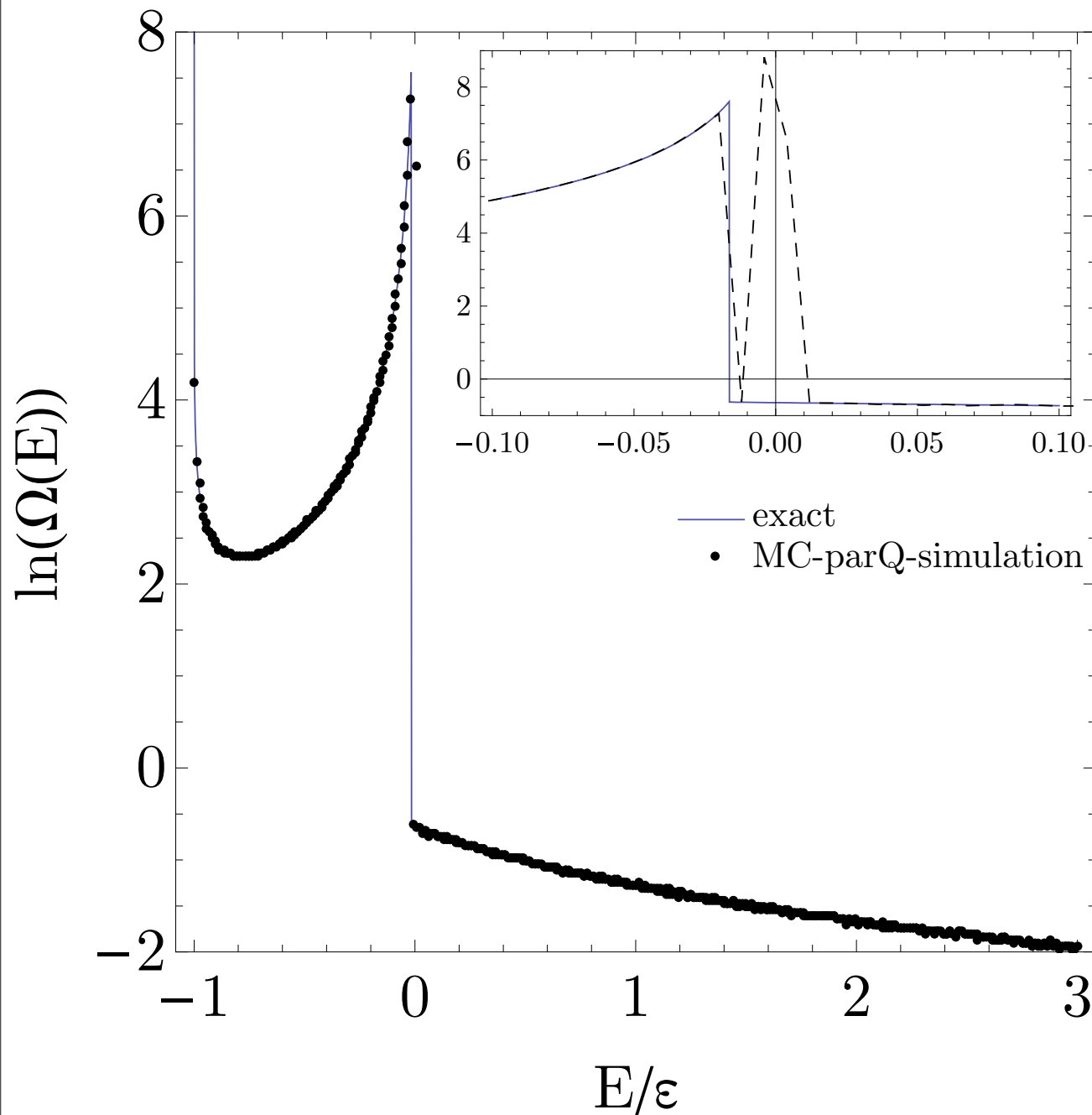
where Q is the infinite temperature transition matrix

- algorithm:
 1. execute Monte Carlo step
 2. count *proposed* transitions from E_{old} to E_{proposed} in a matrix

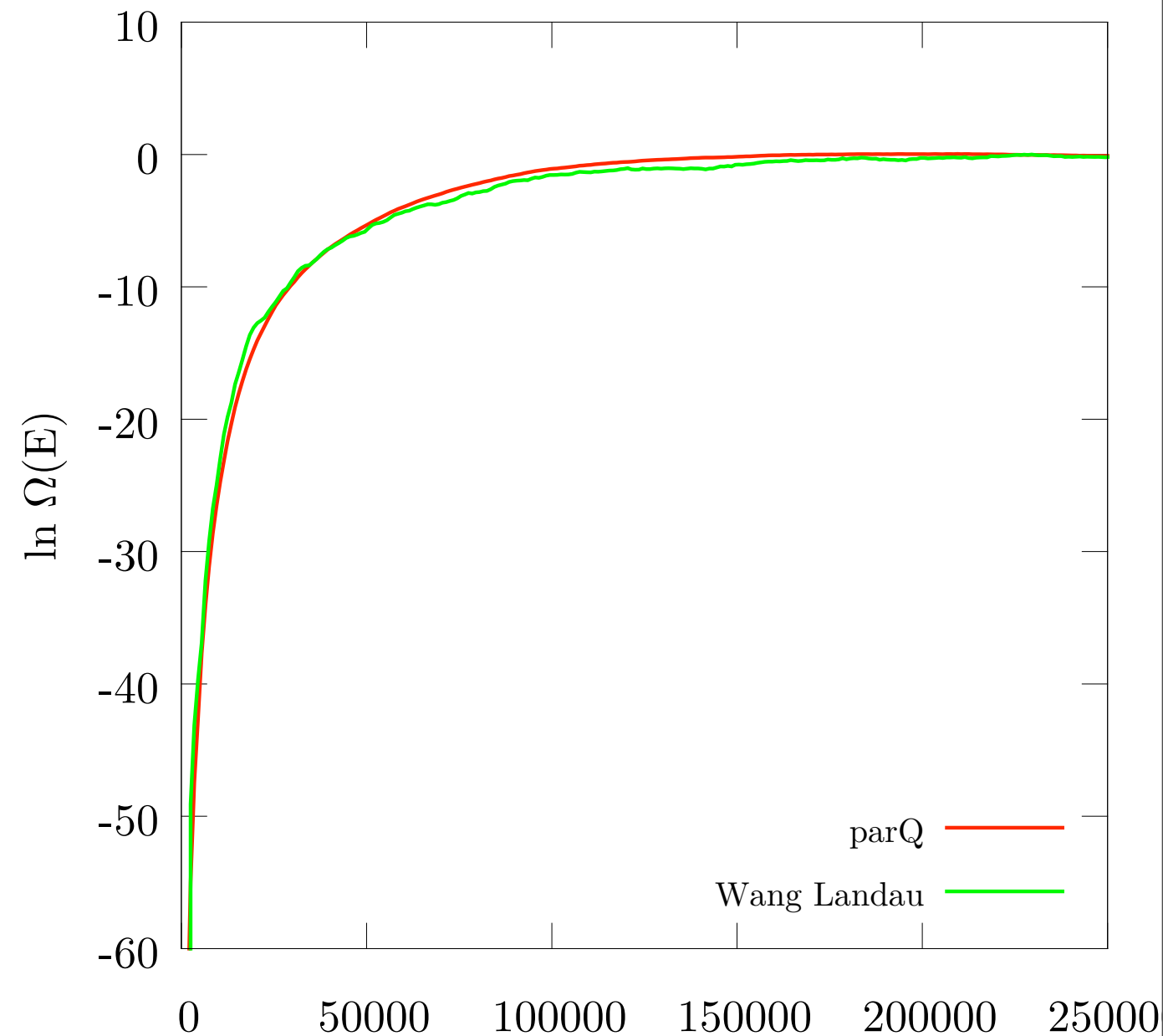
$$\tilde{Q}_{ji} = \tilde{Q}_{ji} + 1$$
 - accept according to underlying Monte Carlo scheme
 3. go to 1. until abort condition
 4. normalize the matrix

$$Q_{ji} = \frac{\tilde{Q}_{ji}}{\sum_k \tilde{Q}_{ki}}$$
 5. calculate eigenvector belonging to eigenvalue 1

Density of states of a simple systems



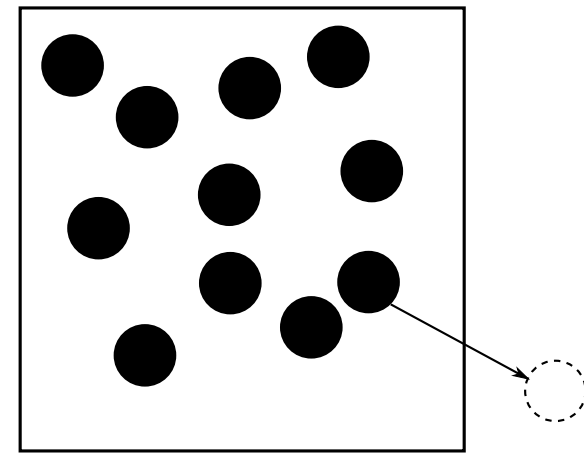
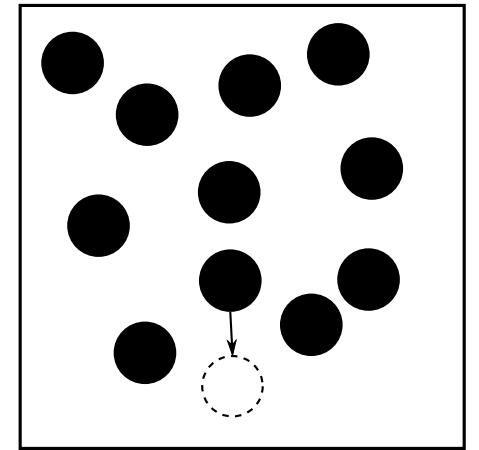
Comparison exact / parQ data
of two particle LJ system



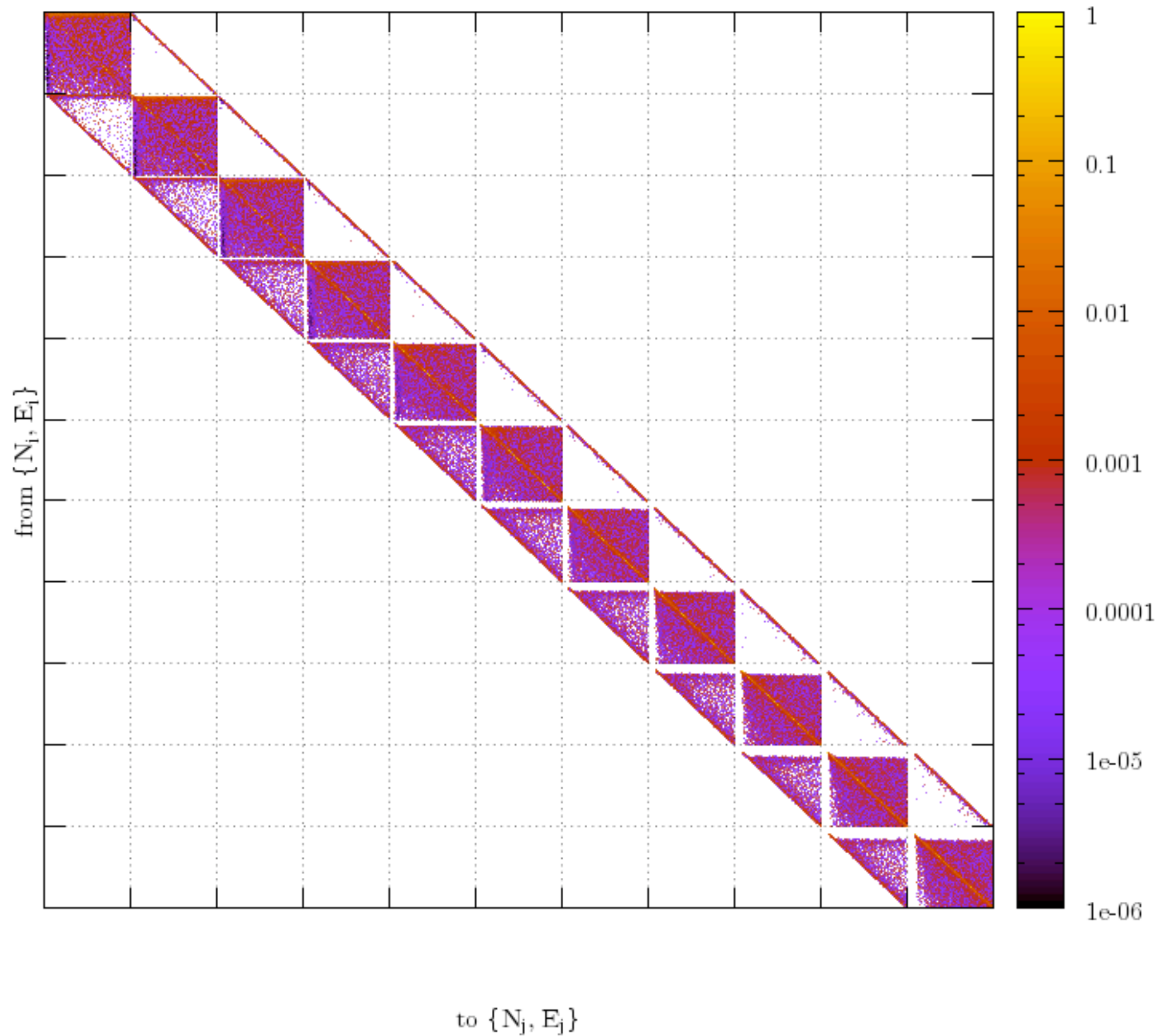
Comparison parQ / Wang-Landau
data from simulation of a single
hexadecan molecule

par Q in the Grand Canonical Ensemble

- two types of transitions:
 - changes in energy
(e. g. molecule move or rotation)
 - changes in particle number
(e. g. particle insertion or removal,
changes energy as well)
- structure: three band block matrix



Q matrix of hexadecan



Wang-Landau algorithm

- generalized ensemble Monte Carlo algorithm
- estimates the density of states without having an initial guess
- DoS is constantly modified during simulation while being used as control measure
- detailed balance is not satisfied, especially at beginning of simulation

F.Wang and D. P. Landau. Physical Review E, 64(5):056101, 2001.

F.Wang and D. P. Landau. Physical Review Letters, 86(10):2050-2053, 2001.

- algorithm:

1. initialize $H(E) = 0, \Omega(E) = 1 \ \forall E, f = e^1$

2. execute Monte Carlo step

3. accept according to $p_{\text{acc}} = \min \left[1, \frac{\Omega(E_{\text{old}})}{\Omega(E_{\text{new}})} \right]$

4. if accepted: $\Omega(E_{\text{new}}) = \Omega(E_{\text{new}}) \cdot f$

else: $\Omega(E_{\text{old}}) = \Omega(E_{\text{old}}) \cdot f$

5. check flatness of histogram $H(E)$

- if histogram is flat reset H and $f := \sqrt{f}$

6. proceed with 2 until f is small enough

- grand canonical enhancements:
- Ω is a function of energy E and particle number N
- two possible acceptance criteria for particle insertion / deletion moves:

$$p_{\text{acc}}(E_{\text{old}}, N \rightarrow E_{\text{new}}, N + 1) = \min \left[1, \frac{V}{(N + 1)\Lambda^3} \frac{\Omega(E_{\text{old}}, N)}{\Omega(E_{\text{new}}, N + 1)} \right]$$

$$p_{\text{acc}}(E_{\text{old}}, N \rightarrow E_{\text{new}}, N - 1) = \min \left[1, \frac{N\Lambda^3}{V} \frac{\Omega(E_{\text{old}}, N)}{\Omega(E_{\text{new}}, N - 1)} \right]$$

$$p_{\text{acc}}(E_{\text{old}}, N \rightarrow E_{\text{new}}, N \pm 1) = \min \left[1, \frac{\Omega(E_{\text{old}}, N)}{\Omega(E_{\text{new}}, N \pm 1)} \right]$$

M. S. Shell et al. Physical Review E, 66(5):056703, 2002.

Q. Yan et al. Physical Review Letters, 90(3):035701, 2003.

- different acceptance schemes correspond to difference between excess contribution and configurational density of states:

$$\Omega_{\text{ex}}(N, V, E) \propto \frac{N!}{V^N} \Omega_{\text{config}}(N, V, E)$$

Eigenvector calculation

- Power iteration:

$$b_{k+1} = \frac{Qb_k}{\|Qb_k\|}$$

- pros:

- easy to implement
- stable
- easy to parallelize, even on GPU

- cons:

- slow if largest eigenvalues λ_1 and λ_2 are of same magnitude

- other methods possible?:
 - GTH method (M. Fenwick, J. Chem. Phys 125, 2006)
pro: solves directly in one step
cons: does not work with sparse matrices,
not always stable
 - partial LU decomposition + invers iteration
con: gives very inaccurate results
 - Arnoldi, Lanczos or Krylov-Schur methods:
tried methods available in SLEPc package

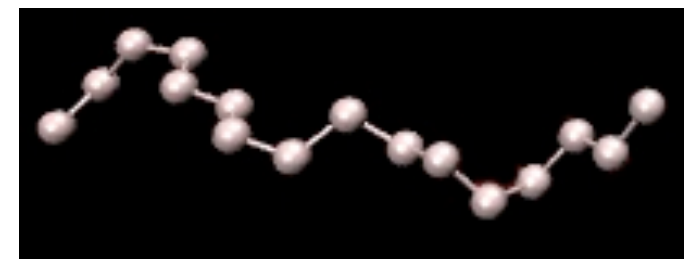
Models

- Lennard-Jones system:

$$V(r) = 4\epsilon \left\{ \left(\frac{\sigma}{r} \right)^{12} - \left(\frac{\sigma}{r} \right)^6 \right\}$$

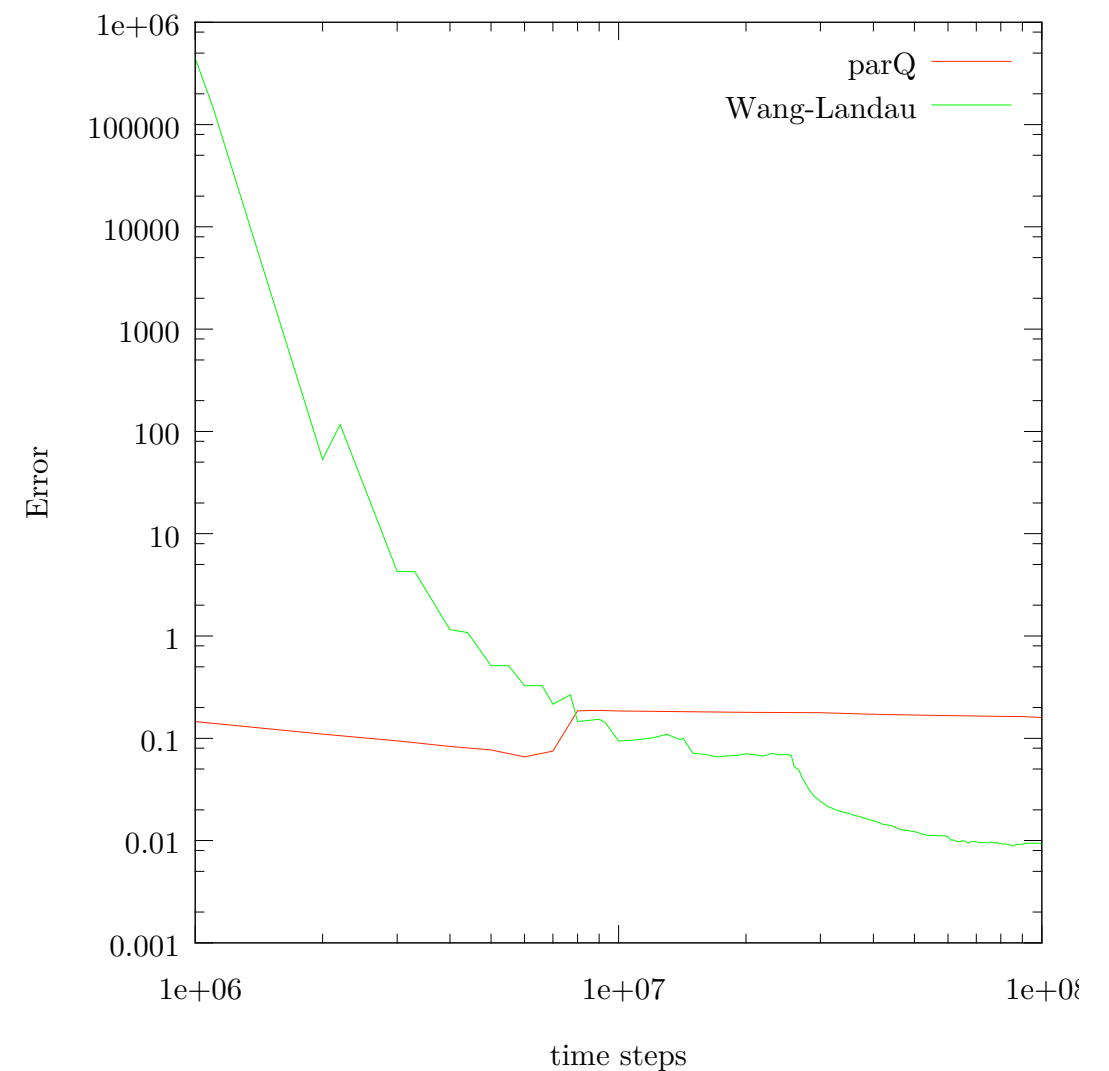
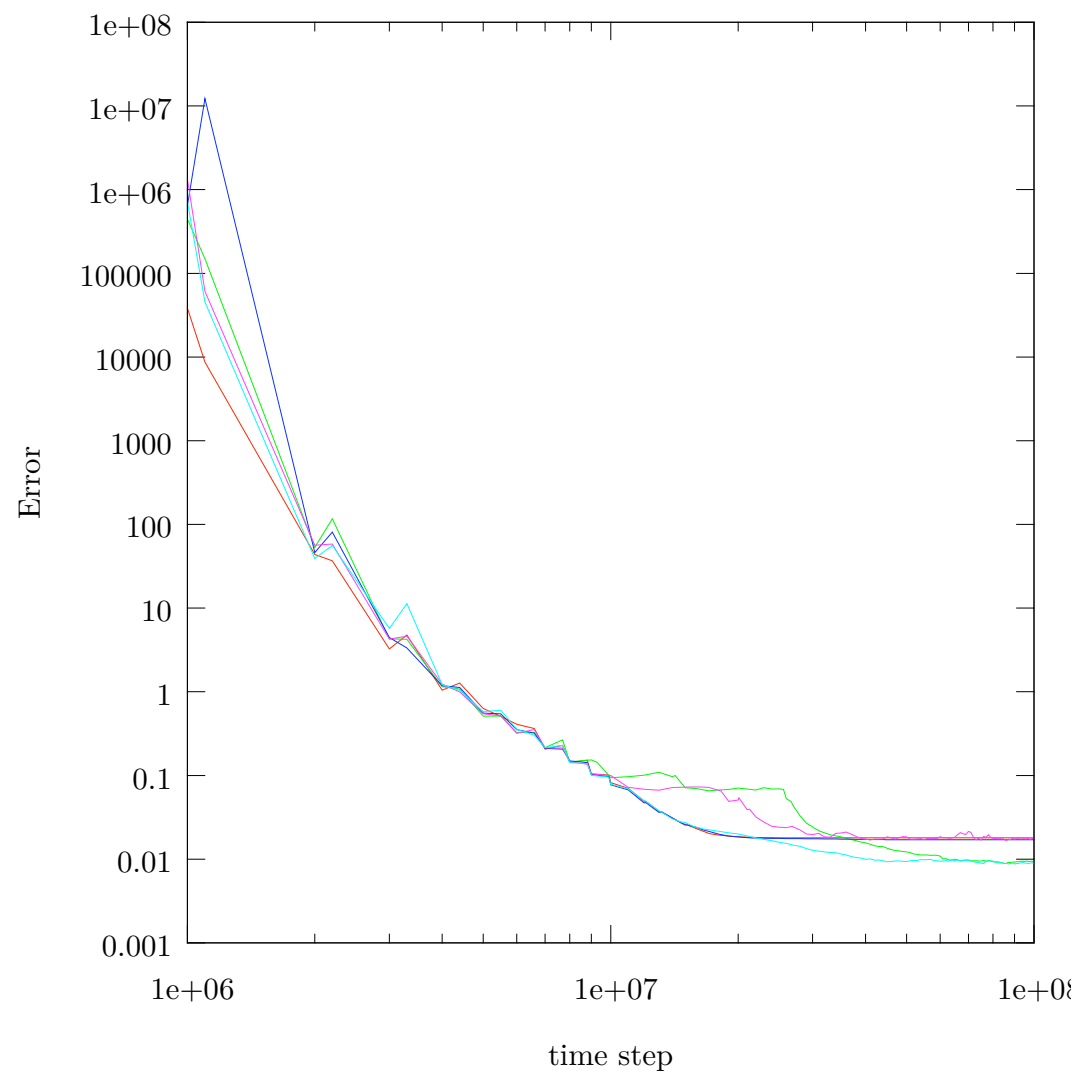
with cut-off at 2.5σ

- Hexadecan $C_{16}H_{34}$ system of 16 beads:
- TraPPE-UA (united atom) forcefield
(hydrogens are lumped into neighbouring carbon atoms)

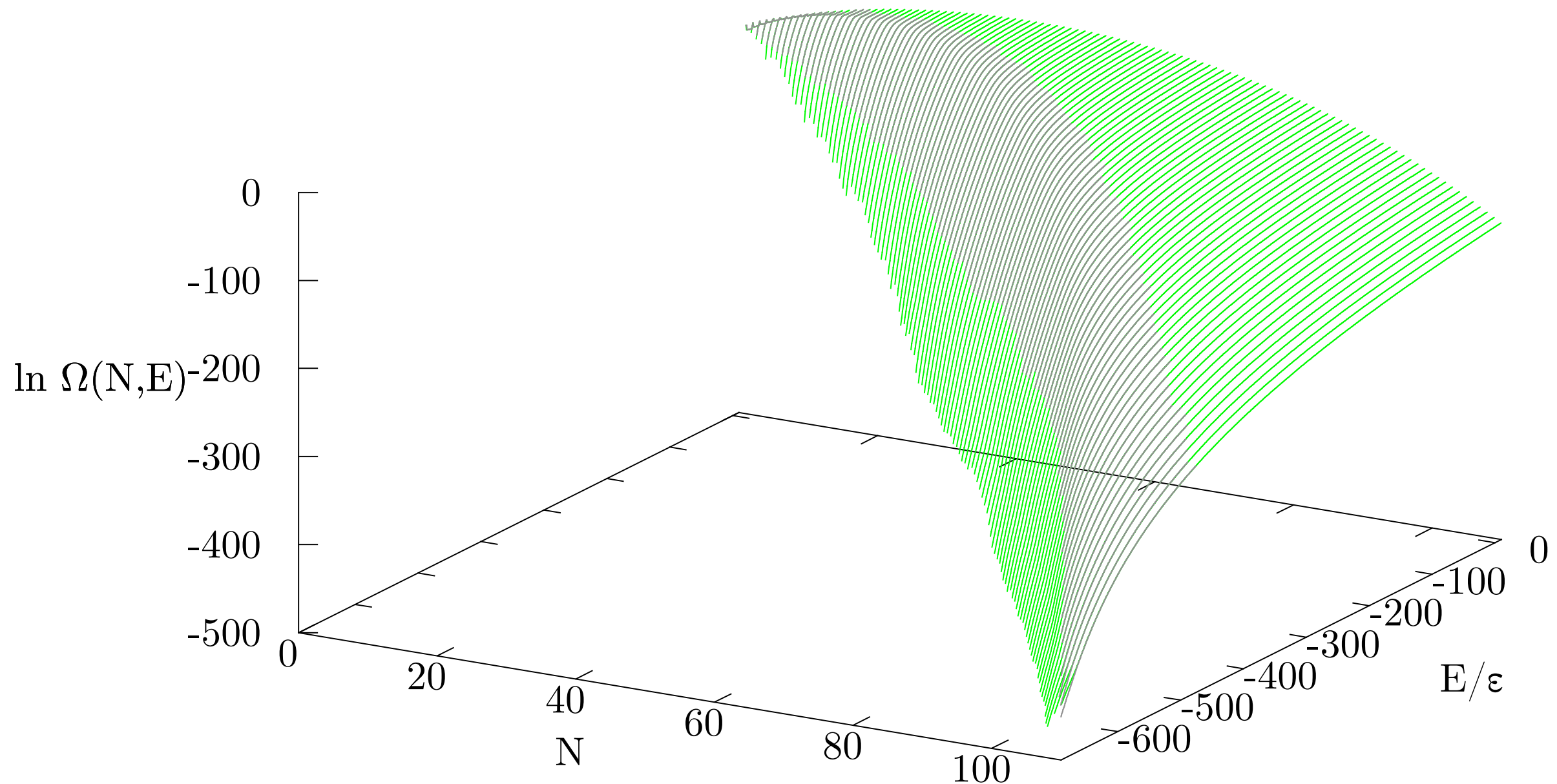


Results

- Wang-Landau simulations typically exhibit saturation of error
- parQ can achieve better results, especially in the beginning:



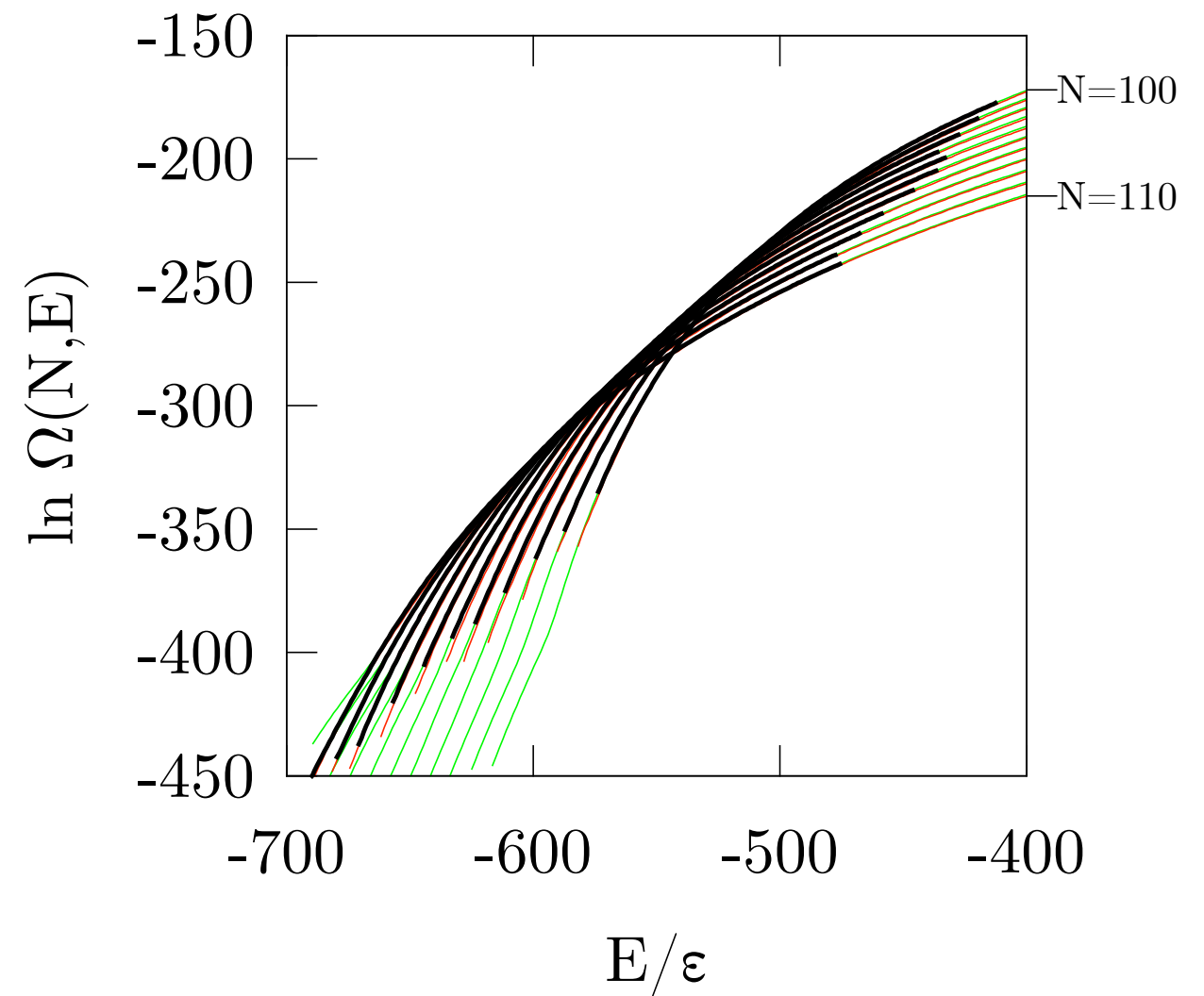
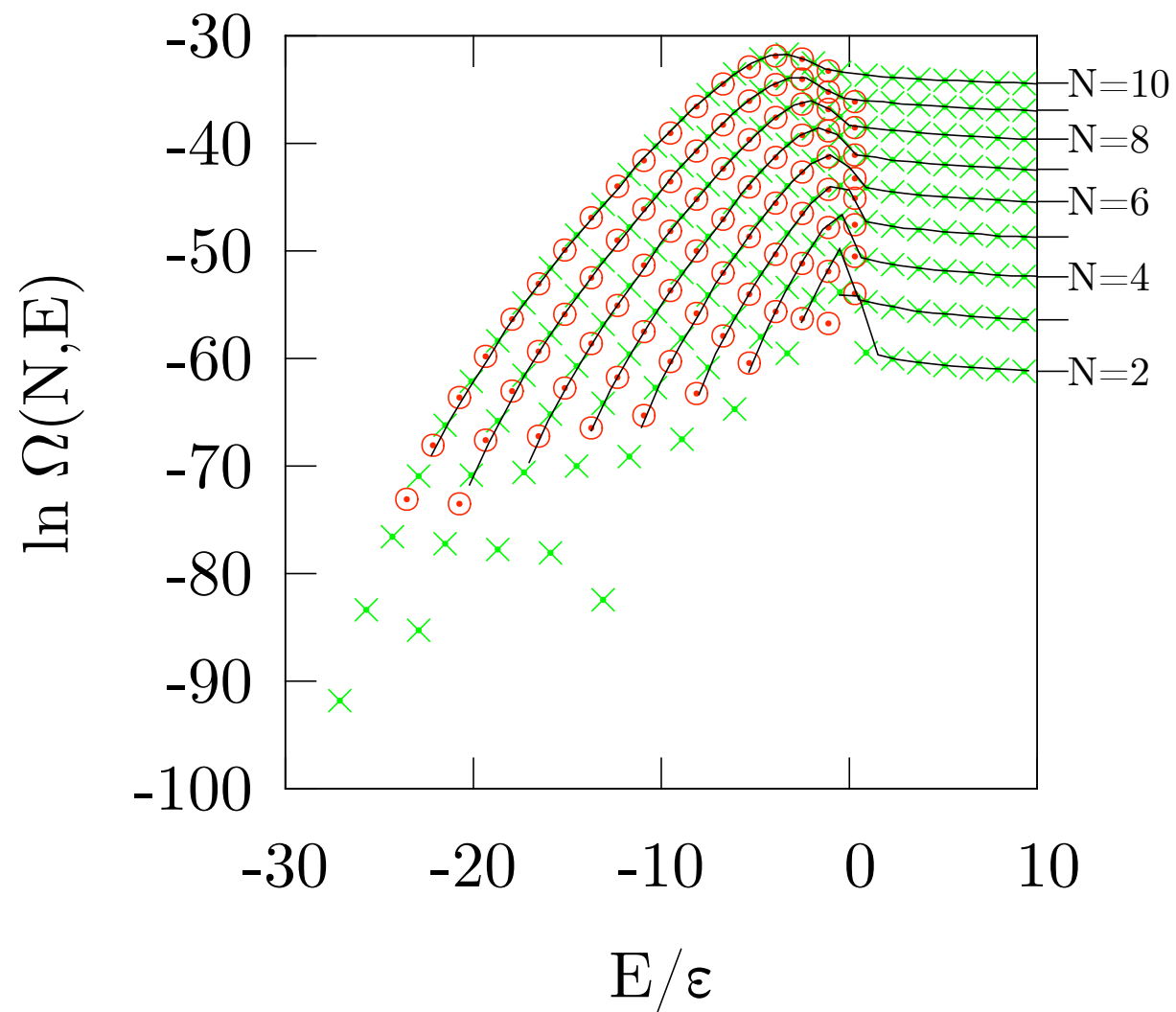
Wang-Landau Results for LJ System



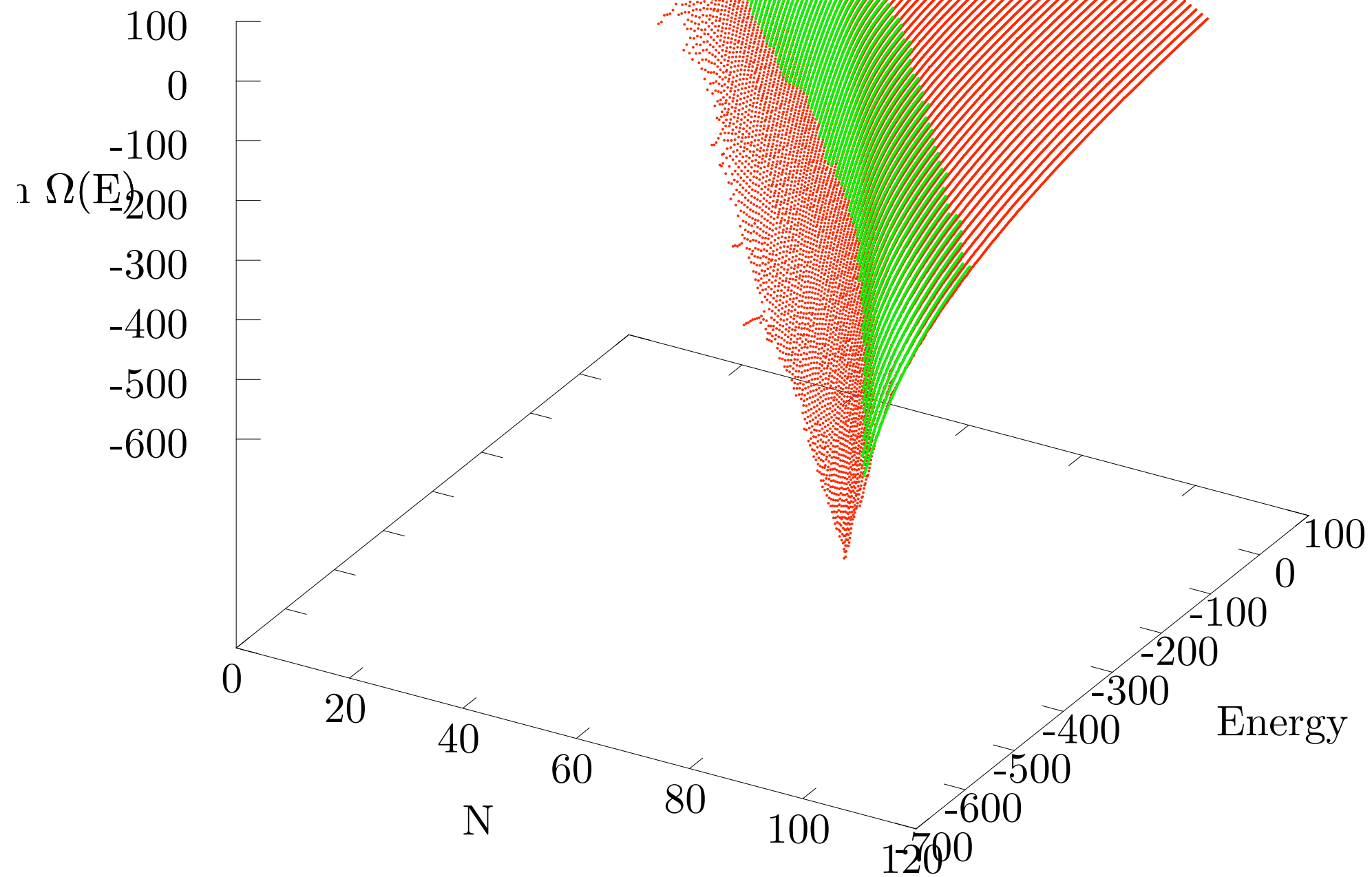
green - WL simulation

black - literature data

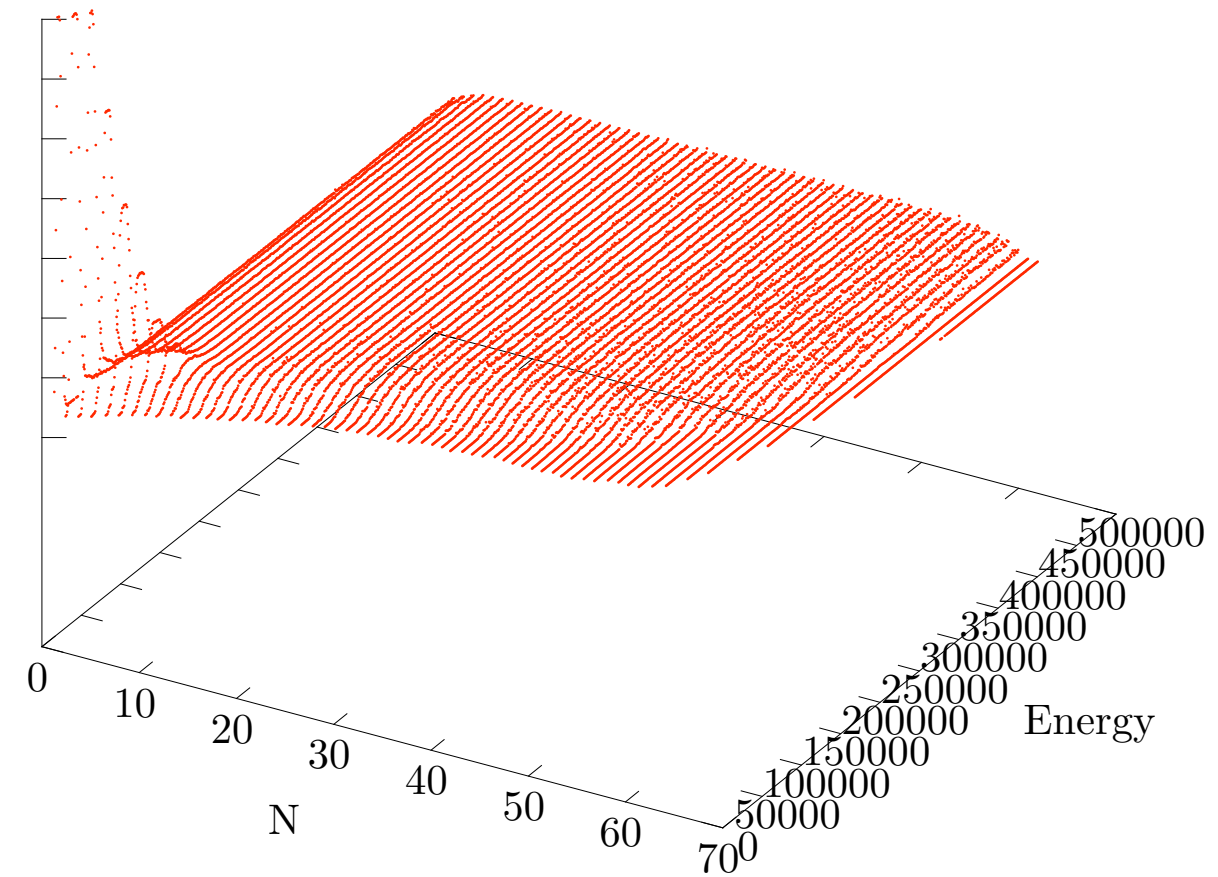
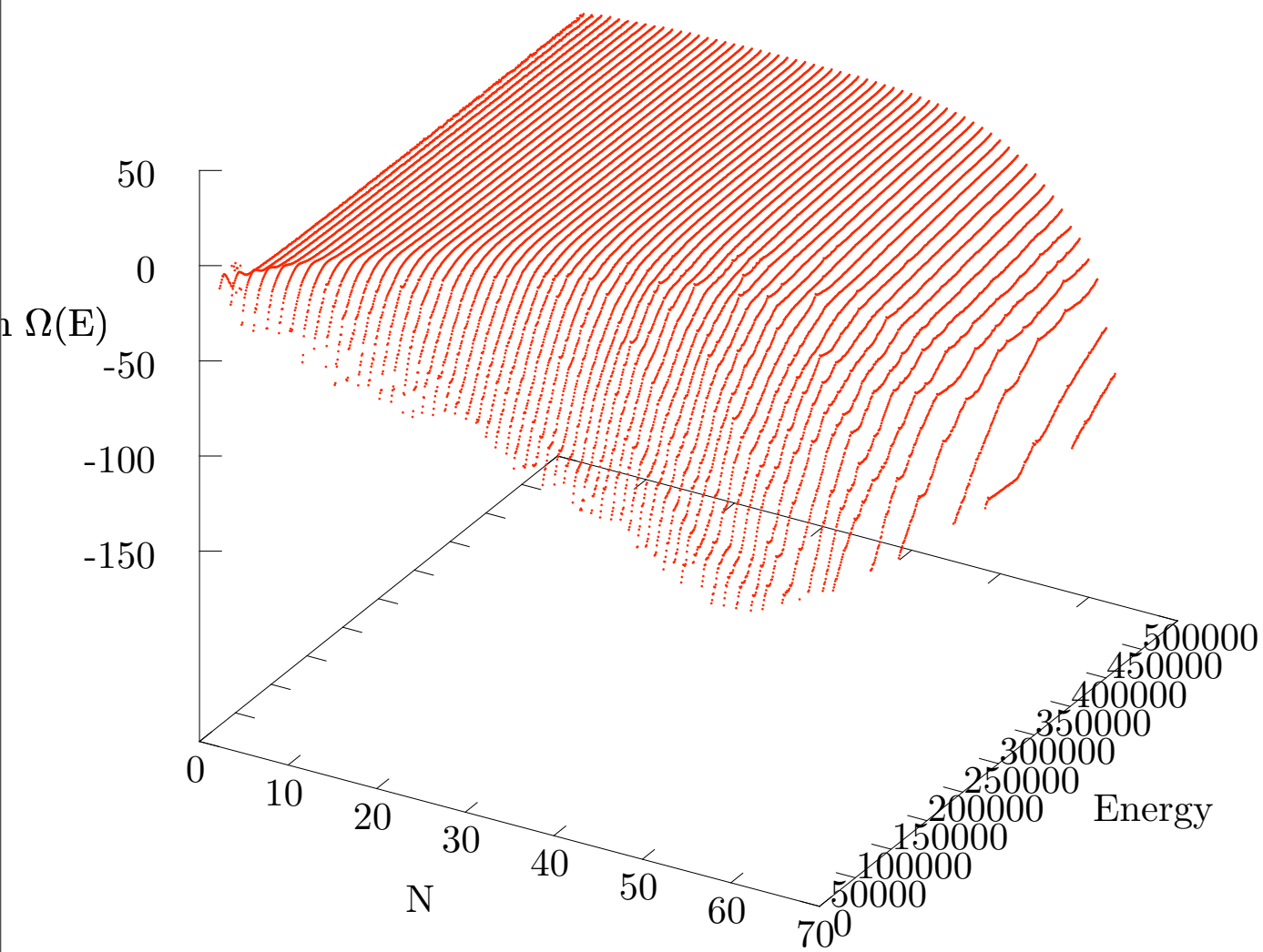
(cf. Q. Yan et al. Physical Review Letters, 90(3):035701, 2003)



- red - WL simulation with per-particle-number constrained energy range
- green & black as before



- red - parQ
- green - reference



- Hexadecan
left parQ, right Wang-Landau

Further development

- find optimal sampling scheme for par Q
- quality criterion for transition matrix
- faster eigenvector calculation
- direct exchange of data between WL algorithm and par Q data during simulation

Conclusion

- parQ can be used to calculate the density of states
- delivers results equal to or even better than established Wang-Landau method
- easy to parallelize
- easy to adopt to other sampling schemes