

Complexity of the quantum adiabatic algorithm

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WHERE DISCOVERIES BEGIN
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Collaborators: S. Knysh and V. N. Smelyanskii

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Introduction



- Motivation for studying the complexity of the Quantum Adiabatic Algorithm for (much) larger sizes than has been studied before.
- The Monte Carlo method that will be used to do this.
- Results for the Exact Cover problem.
- Conclusions.

Problem Studied



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Here consider an important class of “optimization problems” called

NP-Hard.

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Could a quantum computer solve **typical** instances of NP-Hard problems with just **polynomial complexity**, i.e.

complexity $\propto N^\sigma$,

for some value of σ ?

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Add a “driver Hamiltonian”, which is simple and does not commute with \mathcal{H}_P . The simplest is a “transverse field” $\mathcal{H}_D = -h \sum_i \sigma_i^x$.

The total Hamiltonian is

$$\mathcal{H} = [1 - \lambda(t)] \mathcal{H}_D + \lambda(t) \mathcal{H}_P,$$

where the “**control parameter**” $\lambda(t)$ varies from **0** at $t = 0$ to **1** at $t = \mathcal{T}$, the **running time**, or **complexity**.

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At $t = \mathcal{T}$, just have \mathcal{H}_P . If the evolution is adiabatic, the system is in the ground state of \mathcal{H}_P and **the problem is solved**.

Complexity of the QAA



How does \mathcal{T} vary with N

in order to maintain adiabatic evolution with high probability?

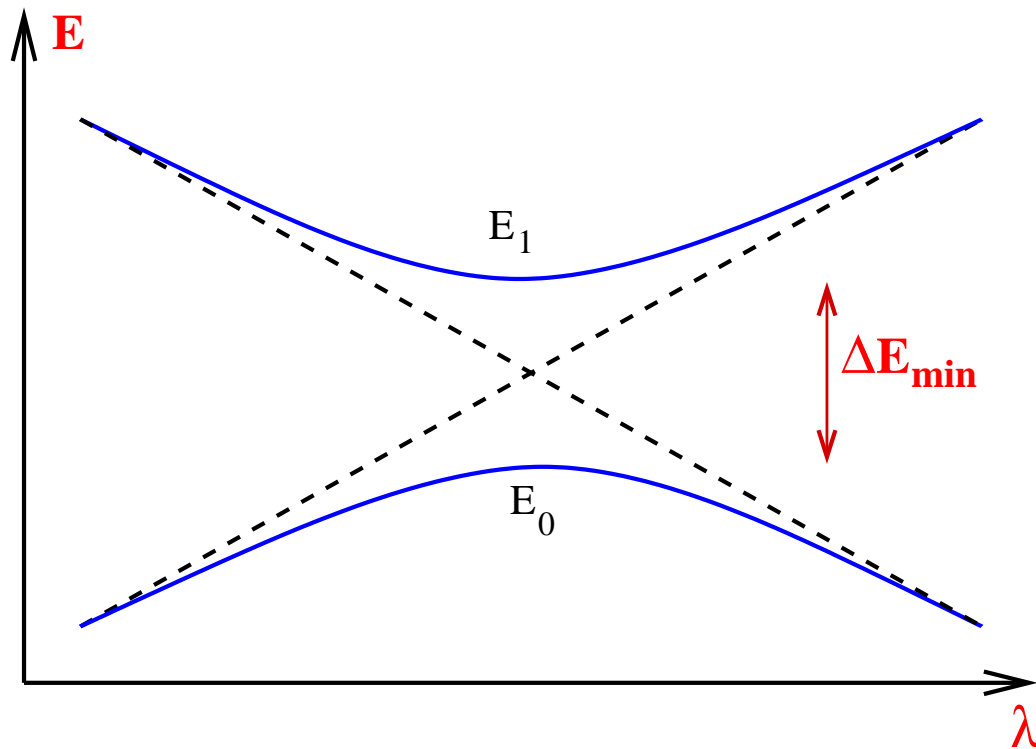
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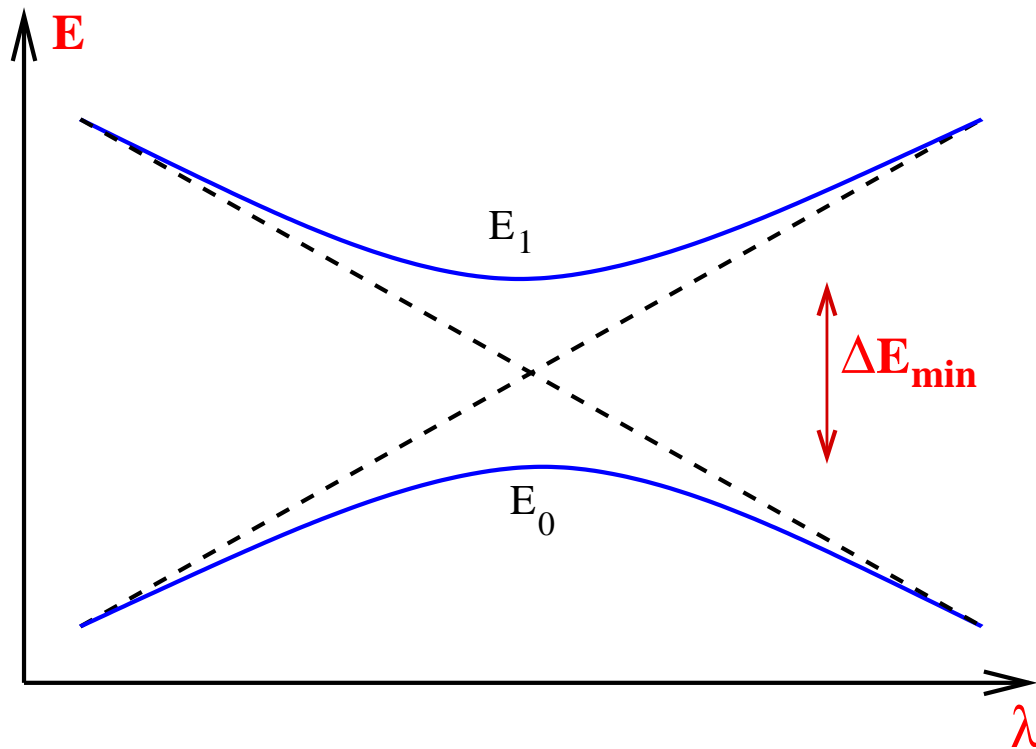
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Landau-Zener theory. To stay in ground state, $\text{time} \propto (\Delta E_{\min})^{-2}$.

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⇒ **“Monte Carlo” methods**

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One can then determine $\langle A \rangle$ as a **time average** from states generated after equilibration is reached, i.e.

$$\langle A \rangle \simeq \frac{1}{N_{\text{meas}}} \sum_{\alpha=1}^{N_{\text{meas}}} A_{\alpha} .$$

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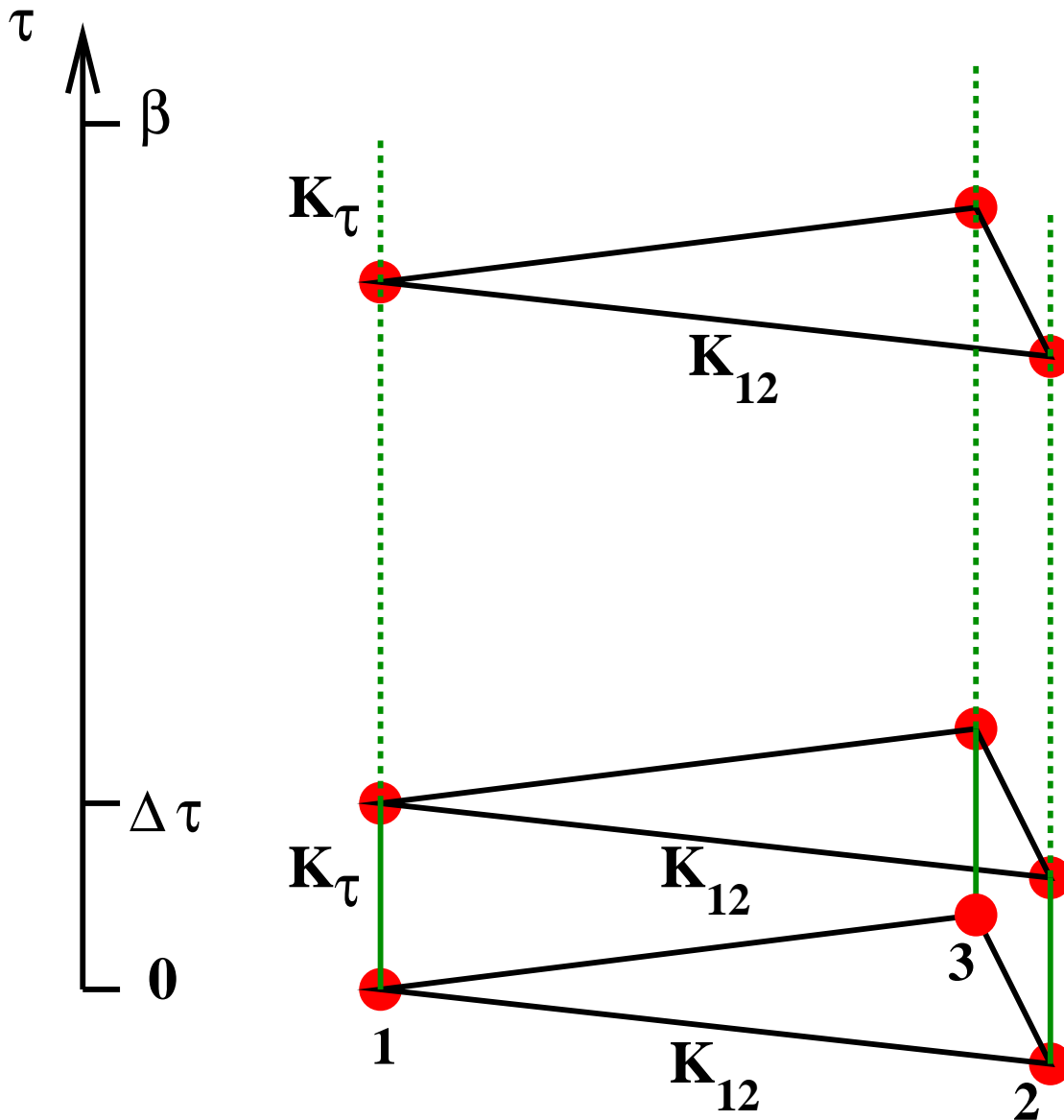
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The exact quantum mechanical Hamiltonian is reproduced in the limit $\Delta\tau \rightarrow 0$. However, we shall argue that this limit is not necessary for our purposes.

Quantum Monte Carlo: II



Trotter decomposition in QMC.

At each time slice 3 sites are shown. An independent spin $\sigma_i^z(\tau)$ lives at each site and each of the L_τ time slices. If spins i and j have an interaction in \mathcal{H}_P , then, each time slice, these spins interact with a coupling K_{ij} , the same for each slice. Spins on the same site but at neighboring time slices are coupled by an interaction K_τ , again the same for all slices. (Details on next slide.)

The slice at time $\tau = \beta$ is identified with the slice at $\tau = 0$ (i.e. we have periodic boundary conditions in the imaginary time direction).

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2. couplings between different spins at the same site but neighboring time slices arising from the driver Hamiltonian

$$\mathcal{H}_D = - \sum_i \sigma_i^x \implies - \sum_{m=0}^{L_\tau-1} K_\tau \sigma_i^z(\tau_m) \sigma_i^z(\tau_{m+1})$$

where $e^{-2K_\tau} = \tanh(\Delta\tau h)$.

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$$C(t) \equiv \frac{1}{N} \sum_{i=1}^N \langle \sigma_i^z(t_0) \sigma_i^z(t_0 + t) \rangle = \frac{1}{N} \sum_{i=1}^N \left[\sum_n |\langle 0 | \sigma_i^z | n \rangle|^2 \right] e^{i(E_n - E_0)t} .$$

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In imaginary time, the complex exponentials are replaced by real, decaying exponentials:

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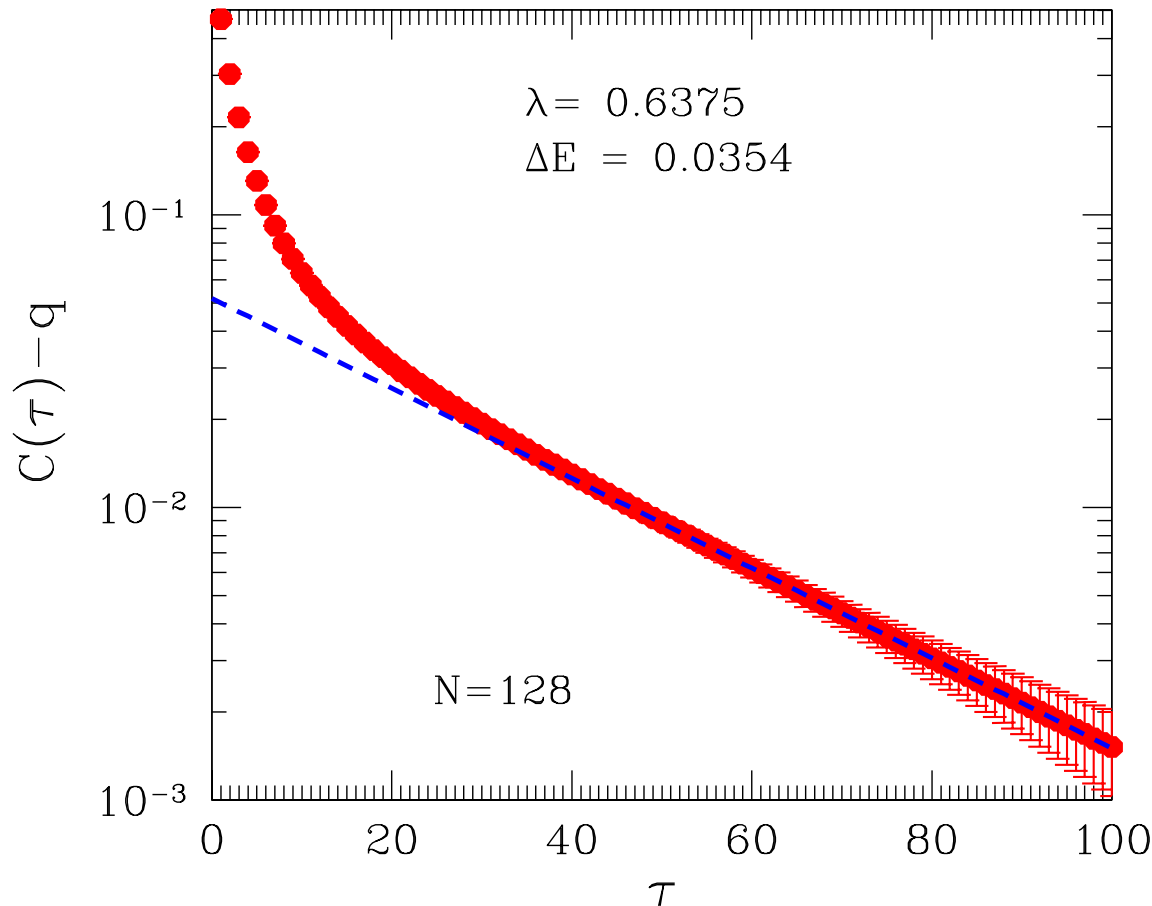
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Hence, at large τ , we have

$$C(\tau) = q + \frac{1}{N} \sum_{i=1}^N |\langle 0 | \sigma_i^z | 1 \rangle|^2 e^{-(E_1 - E_0)\tau},$$

where $q = N^{-1} \sum_i \langle \sigma_i^z \rangle^2$. (See next slide for some results.)

Sample results for $C(\tau)$



Results for the time dependent correlation function against τ for one instance of the Exact Cover problem with $N = 128$ near the location of the minimum gap. Note that the vertical axis is logarithmic. Fitting to the straight line region gives a slope (equal to the gap ΔE) equal to **0.0354**.

We took $L_\tau = 300$, $\Delta\tau = 1$, so $T^{-1} \equiv \beta = 300$. Hence the condition $T \ll \Delta E$ is well satisfied.

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$$\begin{aligned} \mathcal{H}_P = & \frac{1}{8} \sum_{\alpha=1}^M \left(5 - \sigma_{\alpha_1}^z - \sigma_{\alpha_2}^z - \sigma_{\alpha_3}^z + \sigma_{\alpha_1}^z \sigma_{\alpha_2}^z \right. \\ & \left. + \sigma_{\alpha_2}^z \sigma_{\alpha_3}^z + \sigma_{\alpha_3}^z \sigma_{\alpha_1}^z + 3 \sigma_{\alpha_1}^z \sigma_{\alpha_2}^z \sigma_{\alpha_3}^z \right), \end{aligned} \quad (1)$$

where α_1, α_2 and α_3 are the three spins in clause α .

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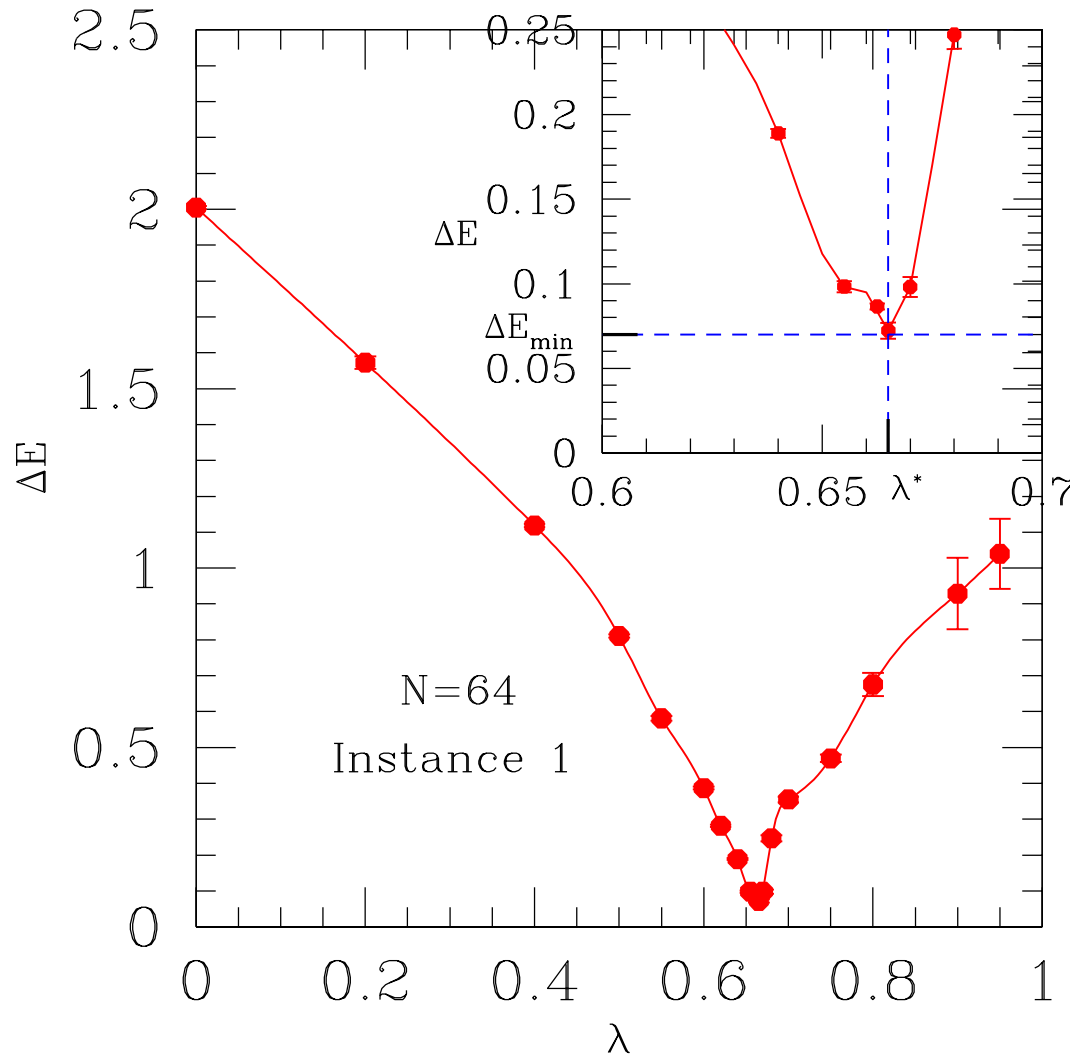
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Following Farhi et al. we take instances with a “**Unique Satisfying Assignment**” (USA). To find these with reasonable probability, we adjust the ratio M/N for each size N .

Dependence of gap on λ



Results for the gap to the first excited state ΔE as a function of the control parameter λ for one instance with $N = 64$. The gap has is finite for $\lambda = 0$ (this is due to the driver Hamiltonian, $\sum_i \sigma_i^x$). It is also finite for $\lambda = 1$ because we chose instances with this property (Unique Satisfying Assignment). There is a minimum of the gap at an intermediate value of λ , presumably close to a quantum phase transition. We compute ΔE_{\min} for many (50) instances for several different sizes, $N = 16, 32, 64, 128$.

Size dependence

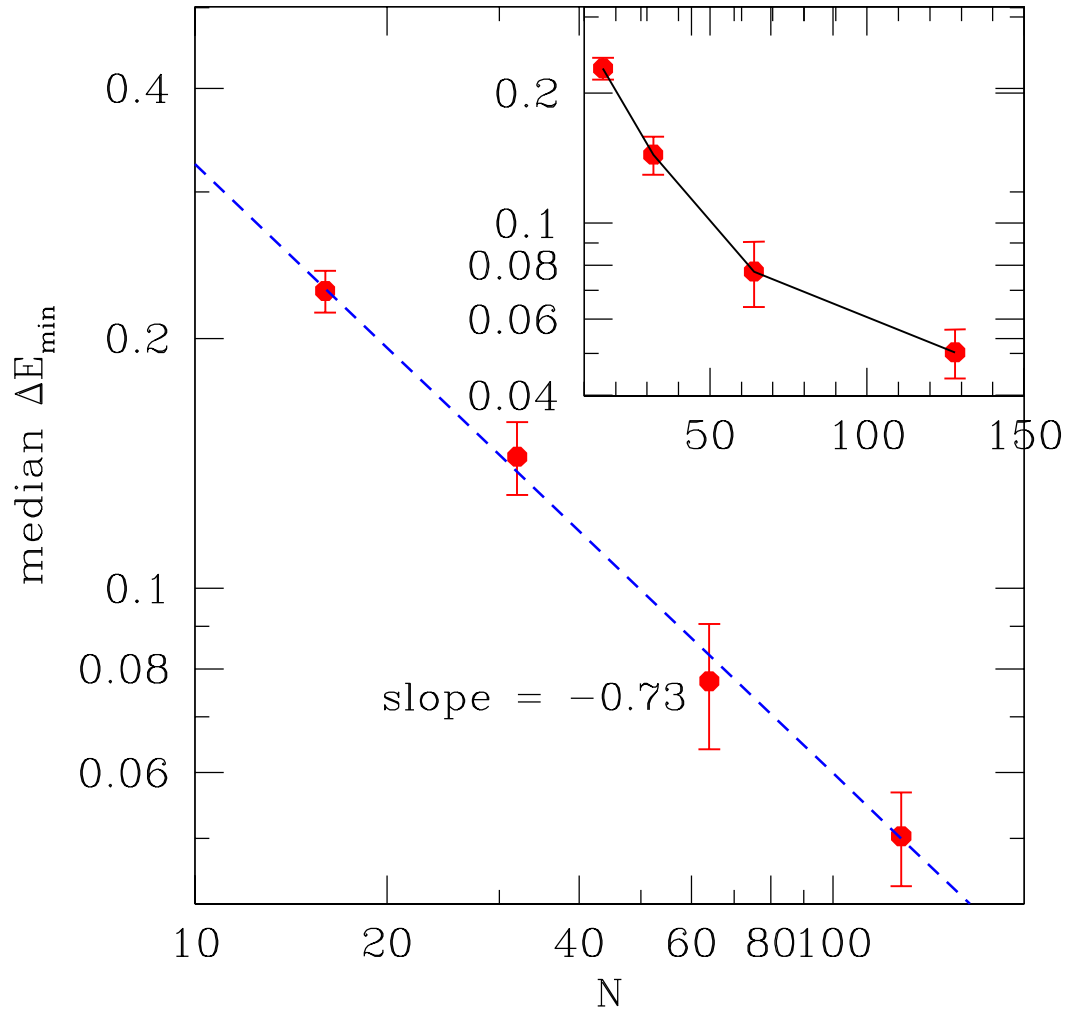


We take the **median** value of the minimum gap among different instances for a given size N to be a measure of the “**typical**” minimum gap.

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50 instances for each size.

A log-log plot of the **median** of the minimum gap as a function of the number of bits N up to $N = 128$. From the satisfactory straight line fit, it is seen that the median ΔE_{\min} *decreases as a power law*,

$$\text{median } \Delta E_{\min} \propto N^{-\mu},$$

for these sizes, with

$$\mu = 0.73 \pm 0.06.$$

The inset shows a log-linear plot. The pronounced curvature shows that the behavior is *not exponential* for this range of sizes.

Expect $\text{complexity} \propto N^{2\mu}$ (if matrix element effects are small).

Imaginary time discretization



Note: The discretization of imaginary time does not affect the way the complexity varies with N , though it does affect the precise value of the energy gap for given N and λ . Once the relaxation time $(\Delta E)^{-1}$ is much larger than the “lattice spacing” $\Delta\tau$ the lattice discretization is unimportant. Hence, whether the minimum gap varies exponentially with N or as a power law **will not depend on the value of $\Delta\tau$.**

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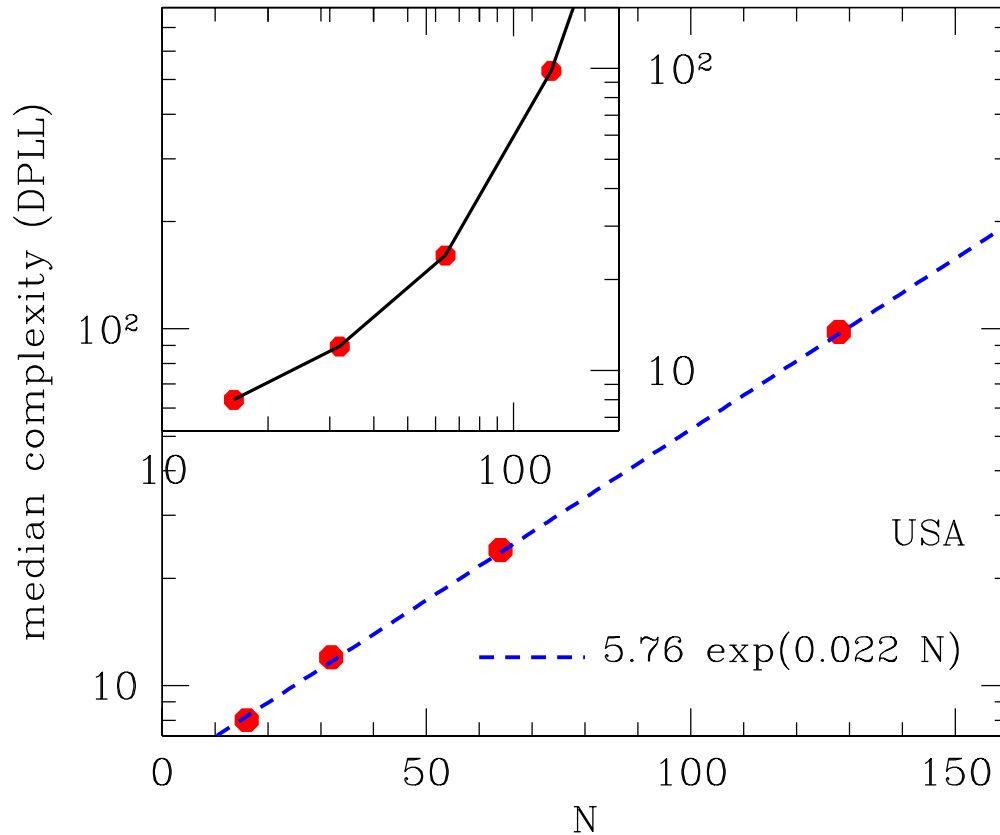
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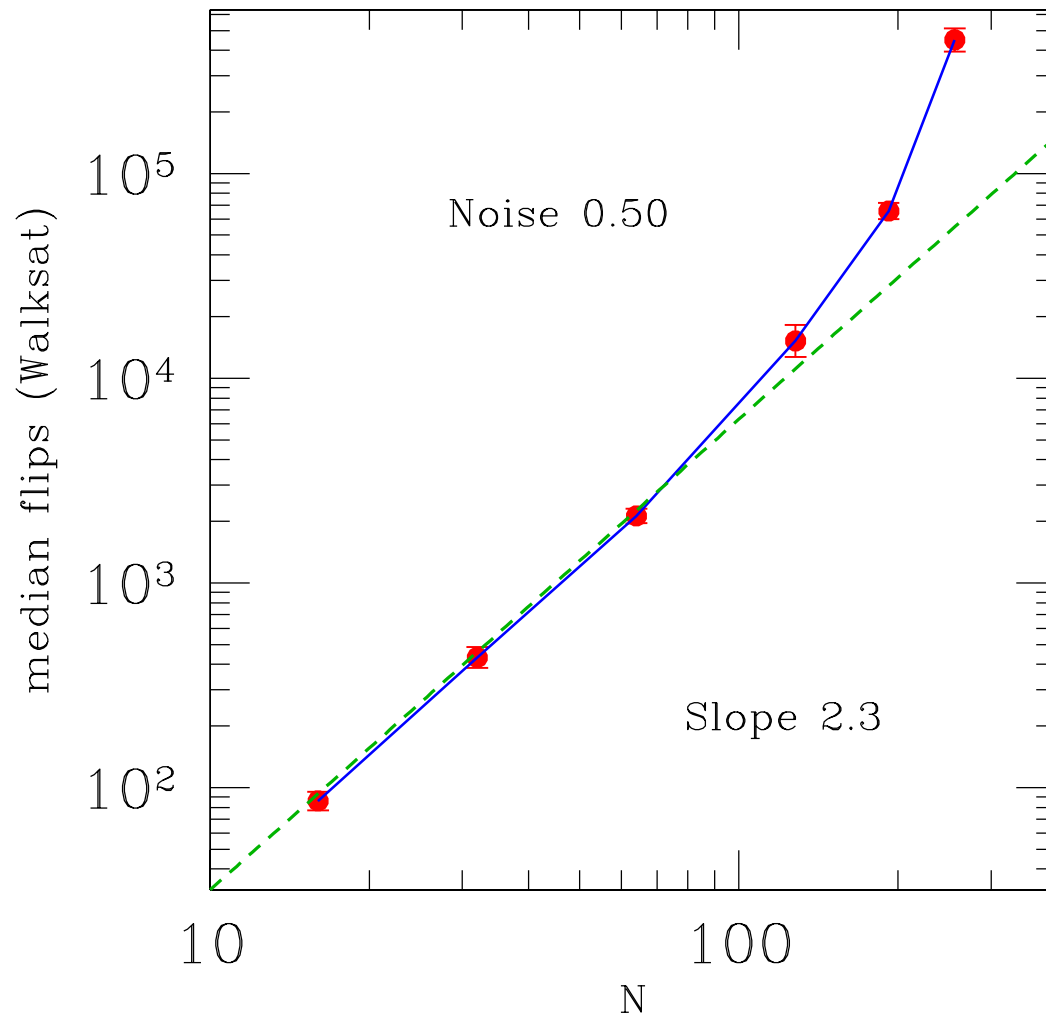
Note: One can simulate the $\Delta\tau \rightarrow 0$ limit, but this is more complicated.

Classical Algorithms: I



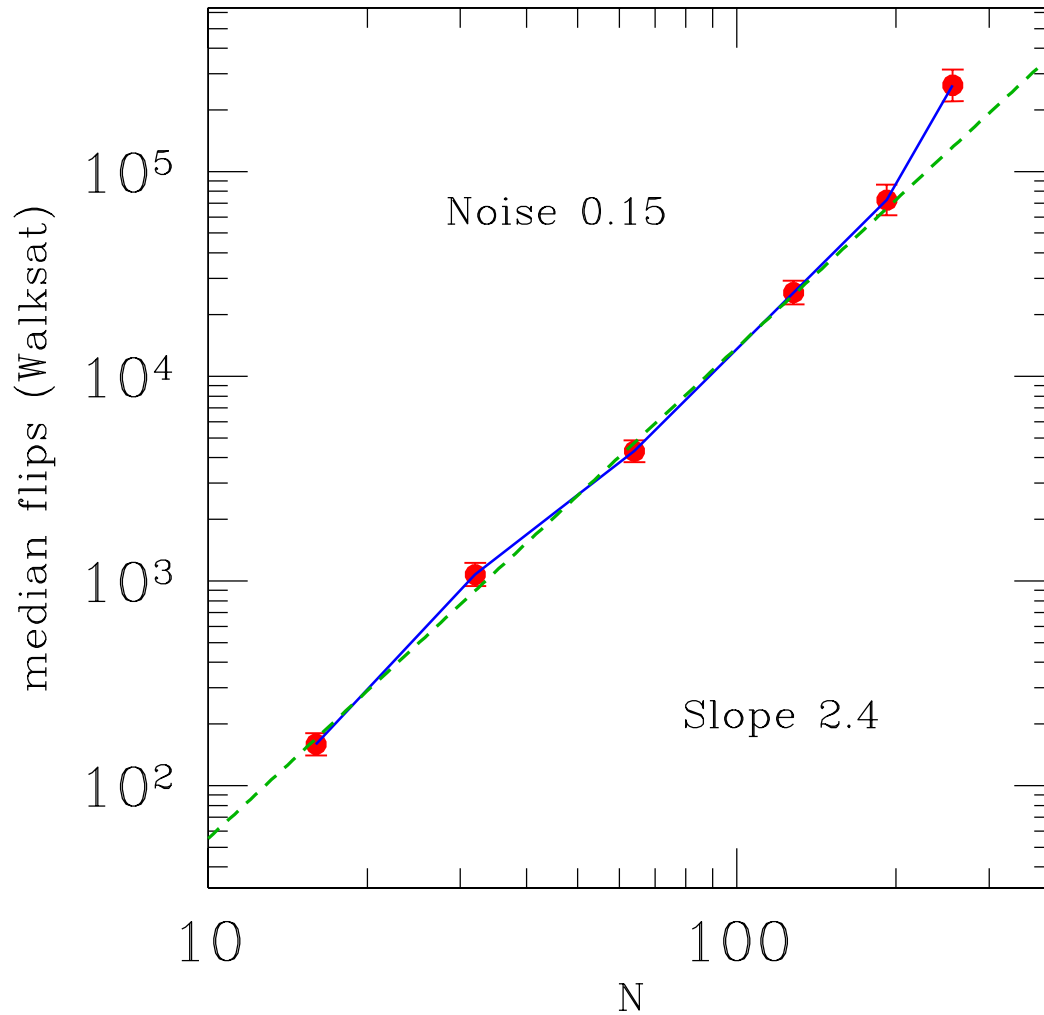
A commonly used algorithm for classical algorithms is the Davis Putnum algorithm. This is **guaranteed** to correctly say whether or not there is a satisfying assignment. The figure shows the complexity for the instances used in the QMC simulations. It is clearly **exponential** for the range of sizes studied.

Classical Algorithms: II



A classical algorithm which is more analogous to QAA is WALKSAT. Like simulated annealing, this is a local search algorithm which includes “up-hill” moves in a stochastic way. Using the default value of the “noise parameter” the complexity for the QAA instances with USA crosses over from power-law to (presumably) exponential for $N \gtrsim 100$. (But note the QMC is so far only for $N \leq 128$).

Classical Algorithms: IIb



Adjusting the noise parameter, the crossover to exponential behavior is pushed to larger sizes $N \gtrsim 200$. (Remember: the QMC is so far only for $N \leq 128$).

Conclusions



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Thank you