Counting without Sampling: Approximation Algorithms for Quantum Many-Body Systems at *Finite Temperatures*

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Interactions described by $H = \sum_i H_i$



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 H_i acting on a geometrically-local region





 H_i acting on a geometrically-local region

Energy



 H_i acting on a geometrically-local region

At zero temperature

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 H_i acting on a geometrically-local region

At zero temperature, in the ground state $|\psi_0
angle$

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At zero temperature, in the ground state $|\psi_0\rangle$ with energy E_0



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Dense Lattice











At non-zero temperature $T = 1/\beta$



$$\phi \propto \sum_{k} e^{-\beta E_{k}} |\psi_{k}\rangle \langle \psi_{k}|$$



At non-zero temperature $T = 1/\beta$, system in state Gibbs state $\rho \propto \sum_{k} e^{-\beta E_{k}} |\psi_{k}\rangle\langle\psi_{k}|$



At non-zero temperature $T = 1/\beta$, system in state Gibbs state $\rho = \frac{1}{Z} \sum_{k} e^{-\beta E_{k}} |\psi_{k}\rangle \langle \psi_{k}|$

$$Z(\beta) = \sum_{k} e^{-\beta E_{k}} = \operatorname{Tr}[e^{-\beta H}]$$



At non-zero temperature $T = 1/\beta$, system in state Gibbs state $\rho = \frac{1}{Z} \sum_{k} e^{-\beta E_{k}} |\psi_{k}\rangle \langle \psi_{k}|$ Partition function $Z(\beta) = \sum_{k} e^{-\beta E_{k}} = \text{Tr}[e^{-\beta H}]$



At non-zero temperature $T = 1/\beta$, system in state Gibbs state $\rho = \frac{1}{2} \sum_{k} e^{-\beta E_{k}} |\eta_{k}\rangle \langle \eta_{k}|$

$$\rho = \frac{1}{Z} \sum_{k} e^{-\beta E_{k}} |\psi_{k}\rangle \langle \psi_{k}|$$

Partition function $\beta \to \infty, \rho \to |\psi_0\rangle\langle\psi_0|$ $\beta \to 0, \rho \to I/d^n$

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Gibbs state

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Free energy

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Goal: design an algorithm that

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Output: estimate $\hat{Z}(\beta)$ such that

 $|\log Z(\beta) - \log \hat{Z}(\beta)| \le 1/\text{poly}(n)$
Finding $Z(\beta)$ exactly is **#P-hard** [Val'79]

Goal: design an algorithm that

Input: H, β, ε

Output: estimate $\hat{Z}(\beta)$ such that

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Hardness depends on temperature

$$\begin{array}{c} & & & \\ \beta = 0 & & & \\ T = \infty & & T = 0 \end{array} \end{array} \begin{array}{c} \beta = \infty \\ T = 0 \end{array}$$

Maximally mixed state Trivial $\beta = 0$ $\beta = \infty$ $T = \infty$ $\beta = 0$ T = 0







but we also know about



but we also know about Transition in the phase



but we also know about Transition in the phase

Physical properties abruptly change



Transition in the hardness but we also know about Transition in the phase Physical properties abruptly change



Transition in the hardness but we also know about Transition in the phase Physical properties abruptly change Hardness of approximating $Z(\beta)$ VS Physical phase transition?





• Above *T_c* there is a polynomial time algorithm



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- Below T_c no efficient algorithm unless NP = RP [Sly'10]



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Computational phase transition matches Physical phase transition



To design approximation algorithms good to understand why physical phase transition happens

Two ways to study phase transition

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Location of complex zeros of $Z(\beta)$

Two ways to study phase transition

Location of complex zeros of $Z(\beta)$



Location of complex zeros of $Z(\beta)$



Location of complex zeros of $Z(\beta)$

























$$Z(\beta) = \sum_k e^{-\beta E_k}$$



$$Z(\beta) = \sum_k e^{-\beta E_k}$$

Sum of strictly positive terms





x : zeros of
$$Z(\beta) = \sum_k e^{-\beta E_k}$$














• Studying zeros initiated by Lee and Yang [LY'52]

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Phase transition in **classical** Ising model by changing the external magnetic field

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Phase transition in **classical** Ising model by changing the external magnetic field

• Extended to thermal phase transition by Fisher [F'65]





We made two observations



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$$H, \beta, \varepsilon$$

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Result 1:

An approximation algorithm for $Z(\beta)$ with running time $n^{O(\log(n/\epsilon))}$ that works above the phase transition point

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Result 1:

An approximation algorithm for $Z(\beta)$ with running time $n^{O(\log n)}$ that works above the phase transition point



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Extrapolate the solution in the easy regime (high T)

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Keeping first few terms of expansion

Need to make sure Taylor expansion converges





X








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$$\left|\log Z(\beta) - \sum_{\ell=0}^{K} \frac{1}{\ell!} \frac{d^{\ell} \log Z(0)}{d^{\ell} \beta} \beta^{\ell} \right| \leq O(n) e^{-\alpha K}$$
where we start
$$\left| \sum_{\beta=0}^{K} 2ero \text{ free} \right|_{\beta} \int_{\beta_{c}}^{\beta_{c}} e^{-\beta_{c}} e^{-\beta_{c}}$$
we want to know $Z(\beta)$ here
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 $K = O(\log n)$ derivatives needed

Sufficient to find $O(\log n)$ derivative of $Z(\beta)$

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So takes time $n^{O(K)}$ to find $Tr[H^K]$

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So takes time $n^{O(\log n)}$ to find all the derivatives

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- Algorithms are deterministic on the other hand
 Compared to randomized ones based on sampling















There is a constant β_0 such that no zeros in disk $|\beta| \leq \beta_0$



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We lower bound $Z(\beta)$ recursively using "cluster expansions" [Hastings'05, KGK+'14]





new qudit to be added

First show

 $|Z_{\ell+1}(\beta)| \ge c^{-1} |Z_{\ell}(\beta)|$





new qudit to be added






Extrapolating $\log Z(\beta)$

• $\log Z(\beta)$ is analytic in zero free region

$$|\log Z(\beta)| \le O(n)$$

$$\left|\log Z(\beta) - \sum_{\ell=0}^{K} \frac{1}{i!} \frac{d^{\ell} \log Z(0)}{d^{\ell} \beta} \beta^{\ell} \right| \leq O(n) e^{-\alpha K}$$
where we start
$$\int_{\beta=0}^{\infty} \operatorname{zero free}_{\beta} \int_{\beta_{c}}^{\beta_{c}} \operatorname{Re}(\beta)$$

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$Z_{\ell+1}(\beta) = Z_{\ell}(\beta) +$ corrections

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Cluster expansion: for $|\beta| \leq \beta_0$, $e^{-\beta H} \approx \sum \text{product of } H_i \text{ 's}$

 $Z_{\ell+1}(\beta) = Z_{\ell}(\beta) +$ corrections

 $|\operatorname{corrections}/Z_i(\beta)| \le O(1)$











 $|\operatorname{Tr}[AB\rho] - \operatorname{Tr}[A\rho]\operatorname{Tr}[B\rho]| \le c \ e^{-\operatorname{dist}(A,B)/\xi}$

Decay of correlations is a signature of phase transition

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- Below *T_c* there is long range order
- Above *T_c* exponential decay of correlations

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Classical spin systems [Weitz'99,...]
 Mixing in time = Mixing in space

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Algorithmic implications?

• Classical spin systems [Weitz'99,...]



• Commuting Hamiltonians [BK'14]

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efficient sampling algorithm

exponential decay of correlations

Commuting Hamiltonians [BK'14]
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General Hamiltonians [BK'16]
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Mixing in time



efficient sampling algorithm

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General Hamiltonians [BK'16]

Mixing in time \leftarrow

Mixing in space + Decay of quantum CMI "Markov property"





What is the relation between zeros of $Z(\beta)$ and decay of correlations?

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For translationally-invariant *classical* system proved to be equivalent [DS'85]

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How about quantum systems?


We show absence of zeros near real axis

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We show absence of zeros near real axis implies exponential decay of correlations

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- *H* consists of commuting terms $H = \sum_i H_i$, $[H_i, H_j] = 0$
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When

- *H* consists of commuting terms $H = \sum_i H_i$, $[H_i, H_j] = 0$
- General *H* on a one-dimensional chain
- For any quantum system if $dist(A, B) = \Omega(\log n)$

• Define a function that measures correlations btw A, B

f(A,B)



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 $f_{\beta}(A,B)$



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Result 4:

Decay of correlations at real temperature β implies no zeros close to real axis at β

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Decay of correlations at real temperature β implies no zeros close to real axis at β

- Proved for translationally-invariant classical systems [DS'85]
- We can extend their proof for general classical systems

Similar to **Result 2**



new qudit added

Similar to **Result 2**



Similar to **Result 2**



Similar to **Result 2**



Similar to **Result 2**



Similar to **Result 2**



Similar to **Result 2**

Instead of cluster expansions use decay of correlations



Decouple contribution of this region from the rest



Extrapolation in other parameters

Extrapolating in external field

Extrapolating in external field








Easy regime



Hard regime

$$H = -\sum_{ij} K_{ij} Z_i Z_j - \sum_{ij} J_{ij} (X_i X_j + Y_i Y_j) - \sum_i J_i Z_i$$
$$K_{ij} \ge |J_{ij}|$$

$$H = -\sum_{ij} K_{ij} Z_i Z_j - \sum_{ij} J_{ij} (X_i X_j + Y_i Y_j) - \mu \sum_i J_i Z_i$$
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$$K_{ij} \ge |J_{ij}|$$

$$Im(\mu)$$

$$End here$$

$$K_{ij} = 0$$

$$K_{ij} \ge |J_{ij}|$$

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$$K_{ij} \ge |J_{ij}|$$
ee-Yang zeros on
imaginary μ
[SF'71]
$$End here$$

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Solved by reducing to counting perfect matchings

 Absence of zeros + decay of qCMI implies decay of correlation for general *H*?

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- Other algorithms for $Z(\beta)$ like convex relaxations?

Thanks!

