

Quantum rejection sampling

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Motivation

We started with. . . [recall Martin's talk yesterday]

An algorithm for the Boolean hidden shift problem:

- ▶ Might be useful for breaking cryptosystems (LFSRs)
- ▶ Potential insights into the dihedral hidden subgroup problem

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...but ended up with

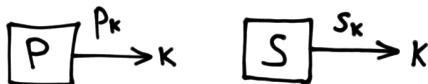
A useful primitive for constructing quantum algorithms:

- ▶ Quantum algorithm for linear systems of equations [HHL09]
- ▶ Quantum Metropolis algorithm [TOVPV11]
- ▶ Preparing PEPS [STV11]
- ▶ more...

Resampling

Classical $p \rightarrow s$ resampling problem

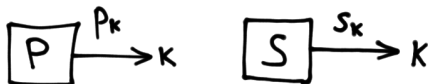
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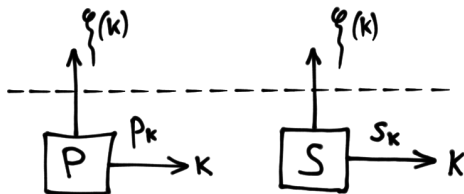
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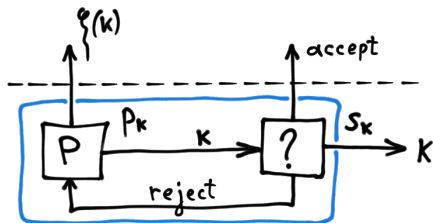
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- ▶ **Note:** Samples are pairs $(k, \xi(k))$ where $\xi(k)$ is not accessible



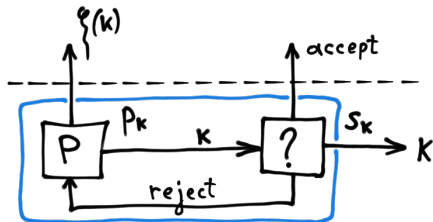
Classical rejection sampling

Algorithm



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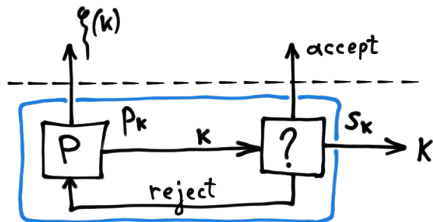
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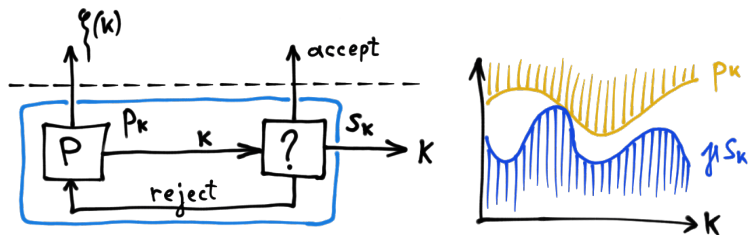
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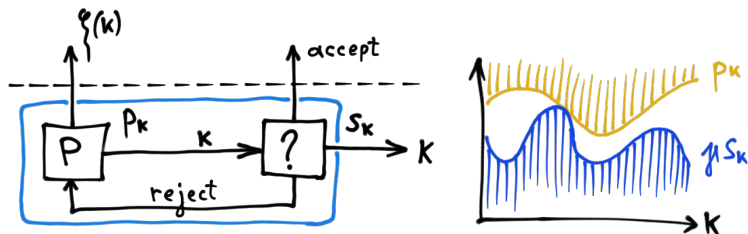
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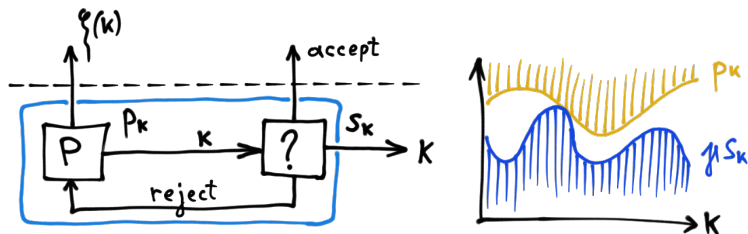
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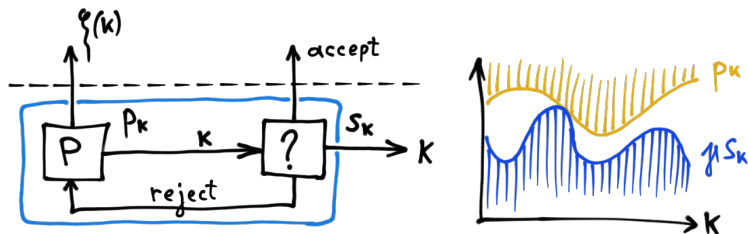
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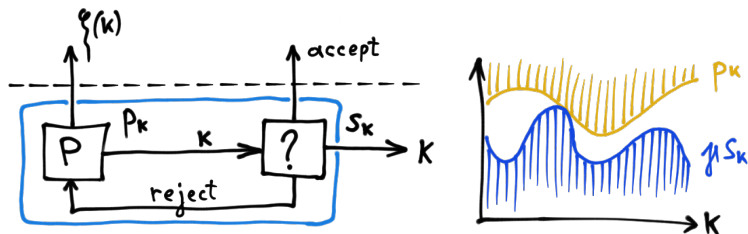
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- ▶ Query complexity: $\Theta(1/\gamma)$
- ▶ Introduced by von Neumann in 1951
- ▶ Has numerous applications:
 - ▶ Metropolis algorithm [MRRTT53]
 - ▶ Monte-Carlo simulations
 - ▶ optimization (simulated annealing), etc.

Quantum resampling

Quantum $\pi \rightarrow \sigma$ resampling problem

- ▶ **Given:** $\pi, \sigma \in \mathbb{R}_+^n$ with $\|\pi\|_2 = \|\sigma\|_2 = 1$
Oracle for preparing $|\pi\rangle = \sum_{k=1}^n \pi_k |k\rangle |\xi(k)\rangle$

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The quantum query complexity of the exact $\pi \rightarrow \sigma$ quantum resampling problem is $\Theta(1/\gamma)$ where $\gamma = \min_k |\pi_k/\sigma_k|$

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 \iff Prepare $|\delta\rangle$ with $\sigma \cdot \delta \geq \sqrt{1-\varepsilon}$

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1. Use the oracle to prepare

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- ▶ w.p. $\|\delta\|_2^2$ the state collapses to

$$\sum_{k=1}^n \hat{\delta}_k |k\rangle |\xi(k)\rangle$$

where $\hat{\delta}_k = \delta_k / \|\delta\|_2$

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Subroutine

$$\text{one copy of } |\pi\rangle \quad \mapsto \quad \sum_{k=1}^n \hat{\delta}_k |k\rangle |\xi(k)\rangle \quad \text{w.p.} \quad \|\boldsymbol{\delta}\|_2^2$$

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Goal: preparing $|\sigma\rangle$

- ▶ What δ should we choose?
- ▶ We are done if $\sigma \cdot \hat{\delta} \geq \sqrt{1 - \varepsilon}$ where $\hat{\delta} = \delta/\|\delta\|_2$

Optimization

Problem

► $\min_{\delta} 1/\|\delta\|_2$ s.t. $\sigma \cdot \hat{\delta} \geq \sqrt{1 - \varepsilon}$

Optimization

$$\sum_{k=1}^n (\sqrt{|\pi_k|^2 - |\delta_k|^2} |0\rangle + \delta_k |1\rangle) |k\rangle |\xi(k)\rangle$$

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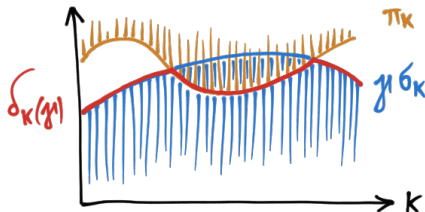
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Optimal solution

- ▶ Let $\delta_k(\gamma) = \min\{\pi_k, \gamma\sigma_k\}$



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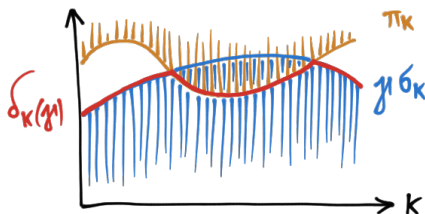
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- ▶ Let $\delta_k(\gamma) = \min\{\pi_k, \gamma\sigma_k\}$
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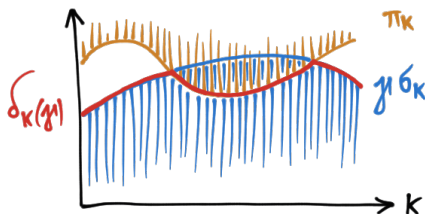
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Main theorem

The quantum query complexity of the ε -approximate $\pi \rightarrow \sigma$ quantum resampling problem is $\Theta(1/\|\delta(\bar{\gamma})\|_2)$

Weak vs. strong quantum rejection sampling

Weak quantum resampling problem

- ▶ **Given:** Description of $\boldsymbol{\pi}, \boldsymbol{\sigma} \in \mathbb{R}_+^n$
Oracle $O : |0\rangle \mapsto |\pi\rangle = \sum_{k=1}^n \pi_k |k\rangle |\xi(k)\rangle$
- ▶ **Task:** Prepare $|\sigma\rangle = \sum_{k=1}^n \sigma_k |k\rangle |\xi(k)\rangle$

Strong quantum resampling problem

- ▶ **Given:** Description of entry-wise ratios $\boldsymbol{\sigma}/\boldsymbol{\pi}$
Reflection $\text{ref}_{|\pi\rangle} = I - 2|\pi\rangle\langle\pi|$
One copy of $|\pi\rangle = \sum_{k=1}^n \pi_k |k\rangle |\xi(k)\rangle$
- ▶ **Task:** Prepare $|\sigma\rangle = \sum_{k=1}^n \sigma_k |k\rangle |\xi(k)\rangle$

Strong quantum rejection sampling algorithm

The τ -rotation

Let $\tau = \sin \theta \cdot \sigma / \pi$ for θ such that $\max_k \tau_k \leq 1$. Define

$$R_{\tau} = \sum_{k=1}^n \begin{pmatrix} \sqrt{1-\tau_k^2} & -\tau_k \\ \tau_k & \sqrt{1-\tau_k^2} \end{pmatrix} \otimes |k\rangle\langle k| \otimes I$$

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$$R_\tau \cdot |0\rangle |\pi\rangle = \sum_{k=1}^n (\sqrt{1-\tau_k^2} \pi_k |0\rangle + \tau_k \pi_k |1\rangle) |k\rangle |\xi(k)\rangle$$

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$$\begin{aligned} R_\tau \cdot |0\rangle |\pi\rangle &= \sum_{k=1}^n (\sqrt{1-\tau_k^2} \pi_k |0\rangle + \tau_k \pi_k |1\rangle) |k\rangle |\xi(k)\rangle \\ &= \cos \theta |0\rangle |\text{🐵}\rangle + \sin \theta |1\rangle |\sigma\rangle \end{aligned}$$

Note that $\tau_k \pi_k = \sin \theta \cdot \sigma_k$.

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Amplitude amplification

Let $|\Psi\rangle = R_{\tau} \cdot |0\rangle|\pi\rangle = \cos\theta|0\rangle|\text{🐒}\rangle + \sin\theta|1\rangle|\sigma\rangle$. One step of amplitude amplification is given by

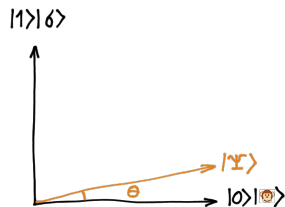
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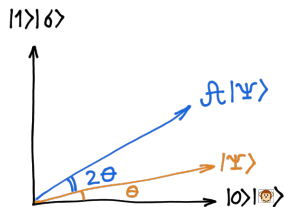
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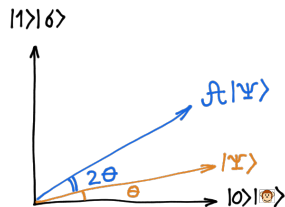
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Algorithm

1. Start with $|0\rangle|\pi\rangle$ and $l = 0$



Strong quantum rejection sampling algorithm

Amplitude amplification

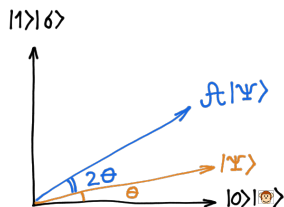
Let $|\Psi\rangle = R_\tau \cdot |0\rangle|\pi\rangle = \cos\theta|0\rangle|\text{🐒}\rangle + \sin\theta|1\rangle|\sigma\rangle$. One step of amplitude amplification is given by

$$\mathcal{A} = \text{ref}_{|\Psi\rangle} \cdot \text{ref}_{|1\rangle \otimes I} = (R_\tau \cdot \text{ref}_{|0\rangle|\pi\rangle} \cdot R_\tau^\dagger) \cdot (Z \otimes I)$$

This is a rotation by 2θ in the 2-dim subspace $\{|0\rangle|\text{🐒}\rangle, |1\rangle|\sigma\rangle\}$.

Algorithm

1. Start with $|0\rangle|\pi\rangle$ and $l = 0$
2. Apply R_τ and get $|\Psi\rangle$



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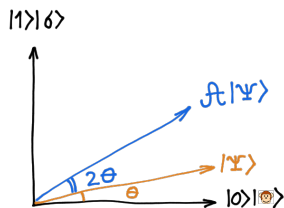
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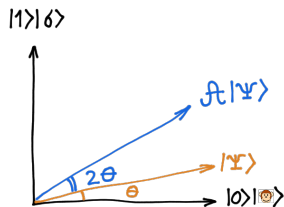
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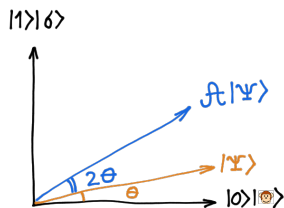
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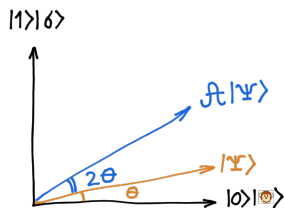
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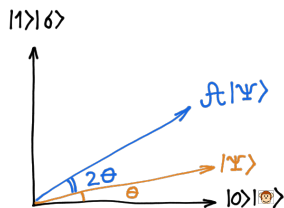
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5. Apply \mathcal{A}^t and go to step 3



Applications

Implicit use

- ▶ Synthesis of quantum states [Grover, 2000]
- ▶ Linear systems of equations [Harrow, Hassidim and Lloyd 2009]
- ▶ Fast amplification of QMA [Nagaj, Wocjan, Zhang, 2009]

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- ▶ Preparing PEPS [Schwarz, Temme, Verstraete, 2011]
- ▶ More...

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Linear systems of equations [HHL09]

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- ▶ **Given:** Invertible matrix $A \in \mathbb{C}^{d \times d}$, one copy of $|b\rangle \in \mathbb{C}^d$
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Main idea

- ▶ W.l.o.g. A is Hermitian: $A = \sum_{j=1}^d \lambda_j |\psi_j\rangle \langle \psi_j|$

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1. Apply phase estimation of e^{iAt} on $|b\rangle$ and get $\sum_{j=1}^d b_j |\psi_j\rangle |\lambda_j\rangle$
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3. Undo phase estimation and get $c \cdot \sum_{j=1}^d b_j / \lambda_j |\psi_j\rangle = |x\rangle$

Classical Metropolis sampling [MRRTT53]

Problem

- ▶ **Given:** A set of configurations S where $j \in S$ has energy E_j
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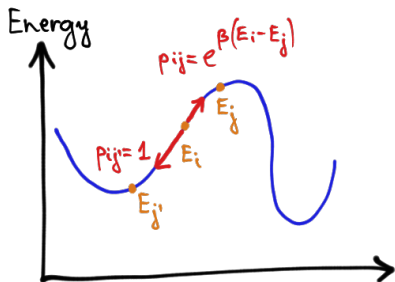
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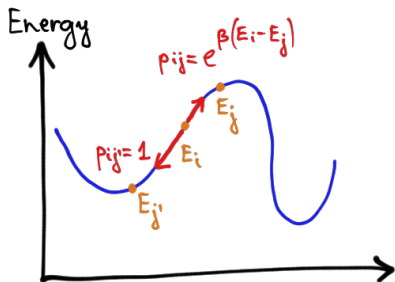
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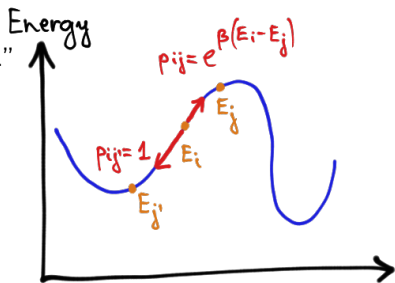
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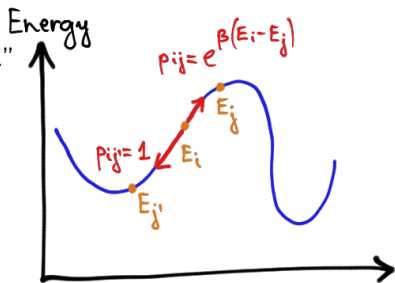
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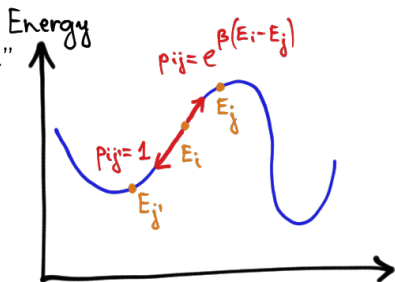
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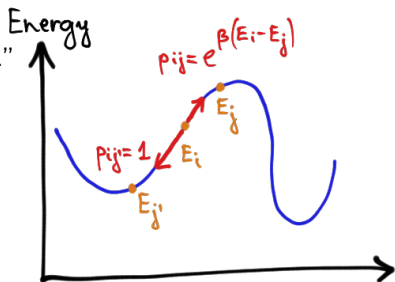
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3. Output the final configuration i



Quantum Metropolis sampling [TOVPV11] + QR sampling

Problem

- ▶ **Given:** Ability to implement Hamiltonian H
- ▶ **Task:** Prepare the thermal state

$$\rho = \exp(-\beta H) / Z(\beta)$$

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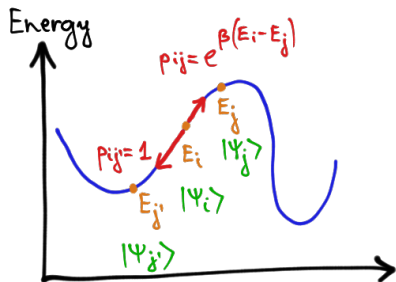
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Main idea

Set up the same *classical* random walk, but use a *quantum* subroutine to implement each steps and also keep track of the current eigenvector $|\psi_i\rangle$



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Recall, $H = \sum_j E_j |\psi_j\rangle\langle\psi_j|$. Let \mathcal{U} be a universal set of quantum gates and let $U_k \in \mathcal{U}$ act as $U_k |\psi_i\rangle = \sum_j u_{ij}^{(k)} |\psi_j\rangle$.

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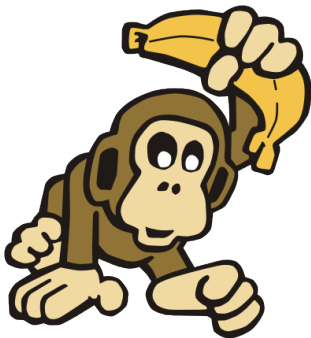
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3. $\frac{1}{\sqrt{|\mathcal{U}|}} \sum_j \left[\sum_k u_{ij}^{(k)} |k\rangle \right] |\psi_j\rangle|E_i\rangle \leftarrow$ apply U_k controlled on k
4. $\frac{1}{\sqrt{|\mathcal{U}|}} \sum_j \left[\sum_k u_{ij}^{(k)} |k\rangle \right] |\psi_j\rangle|E_i\rangle|E_j\rangle \leftarrow$ attach $|E_j\rangle$ using QPE
5. $\frac{1}{\sqrt{|\mathcal{U}|}} \sum_j \sqrt{p_{ij}} \left[\sum_k u_{ij}^{(k)} |k\rangle \right] |\psi_j\rangle|E_i\rangle|E_j\rangle \leftarrow$ using QRS
6. $|\psi_j\rangle|E_j\rangle \leftarrow$ after discarding $|k\rangle$ and $|E_i\rangle$

Conclusion

- ▶ Classical rejection sampling has many applications
- ▶ Quantum rejection sampling could be as useful
- ▶ Tight characterization of query complexity
- ▶ Three diverse applications:
 - ▶ Boolean hidden shift problem
 - ▶ Quantum Metropolis algorithm [TOVPV11]
 - ▶ Quantum algorithm for linear systems of equations [HHL09]



Thank you!

Funding:



Boolean hidden shift problem (BHSP)

Problem

- ▶ **Given:** Complete knowledge of $f : \mathbb{Z}_2^n \rightarrow \mathbb{Z}_2$ and access to a black-box oracle for $f_s(x) := f(x + s)$

$$x \Rightarrow \boxed{} \Rightarrow f_s(x)$$

- ▶ **Determine:** The hidden shift s

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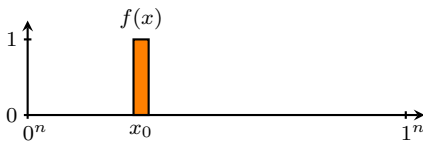
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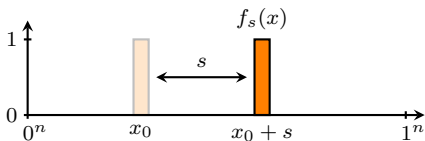
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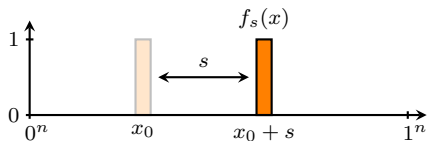
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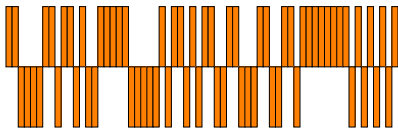
- ▶ $f(x) := \delta_{x, x_0}$
- ▶ Equivalent to Grover's search: $\Theta(\sqrt{2^n})$



Fourier transform of Boolean functions

The ± 1 -function (normalized)

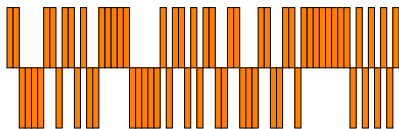
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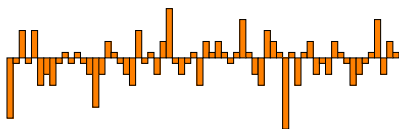
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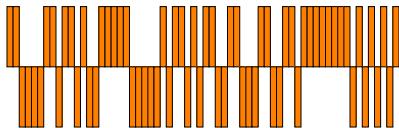
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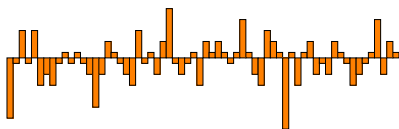
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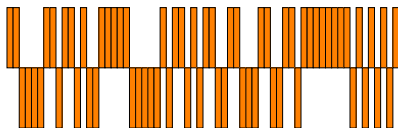
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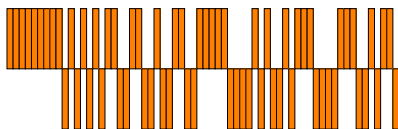
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Function f is **bent** if $\forall w : |\hat{F}(w)| = \frac{1}{\sqrt{2^n}}$

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Preparing the “phase state”

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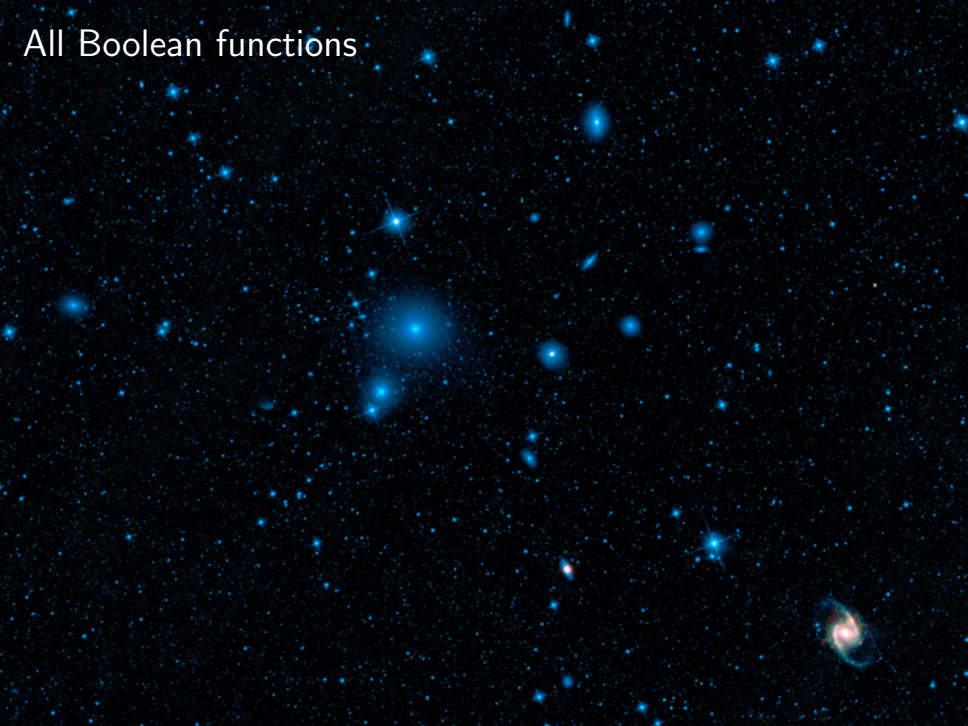
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All Boolean functions



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What about the rest?

Hard (*delta function*) ▶

Algorithm for any Boolean function

Resampling approach

$$\sum_{w \in \mathbb{Z}_2^n} (-1)^{s \cdot w} \hat{F}(w) |w\rangle \mapsto \sum_{w \in \mathbb{Z}_2^n} (-1)^{s \cdot w} \frac{1}{\sqrt{2^n}} |w\rangle$$

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Quantum query complexity

Recall that this can be solved using quantum rejection sampling in $O(1/\gamma)$ queries where $\gamma = \min_w \pi_w / \sigma_w$. In our case this is:

$$O\left(\frac{1}{\sqrt{2^n} \hat{F}_{\min}}\right)$$

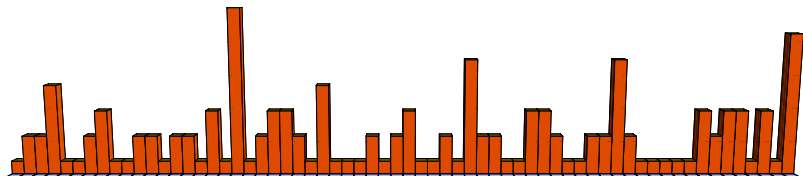
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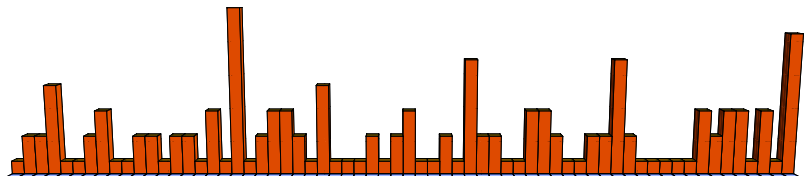
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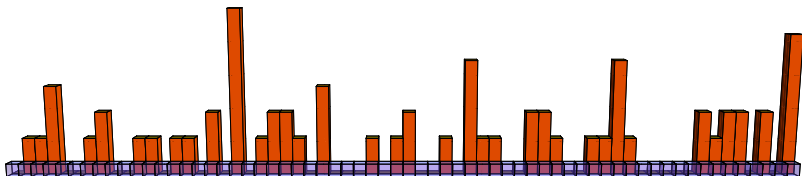
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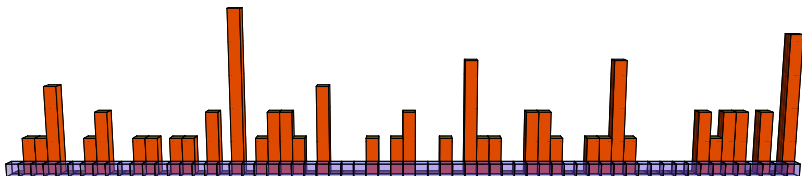
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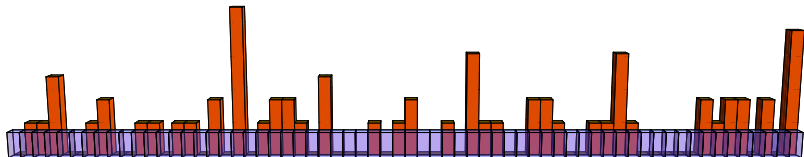
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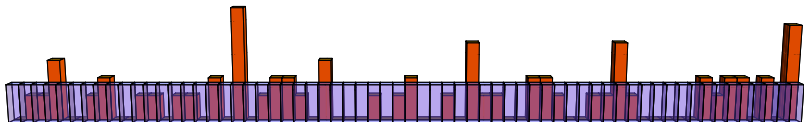
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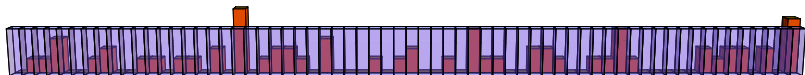
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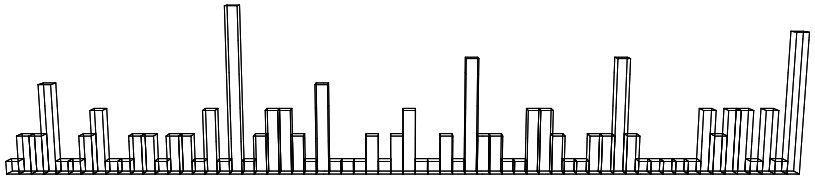
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4. Measure the resulting state in Fourier basis

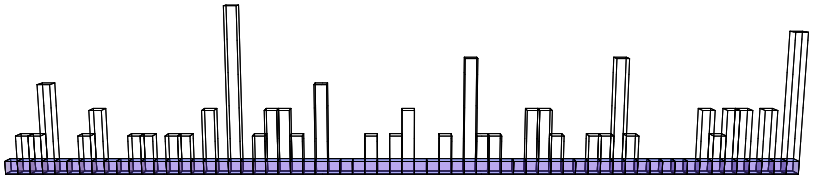


“Demo” (approximate version)



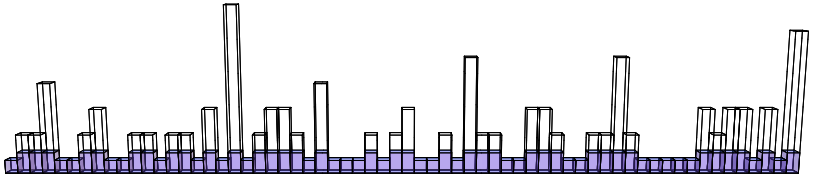
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- ▶ Instead of the “flat” state



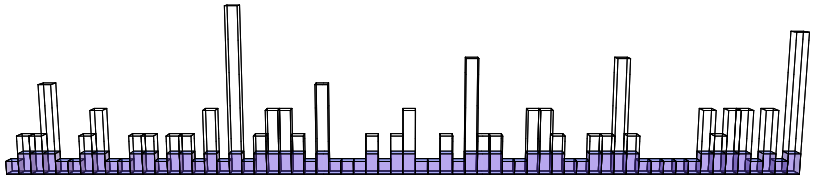
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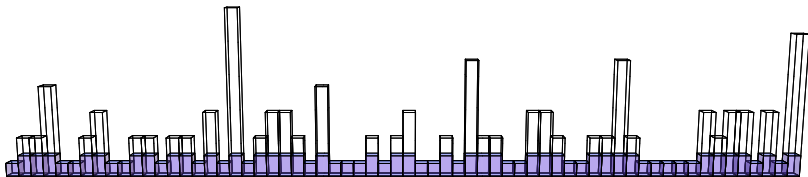
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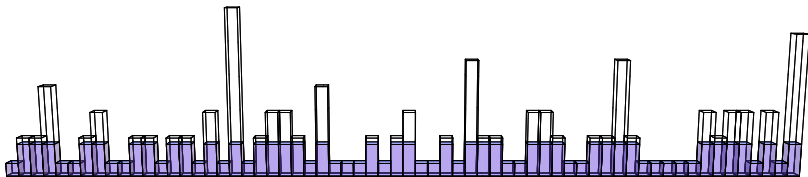
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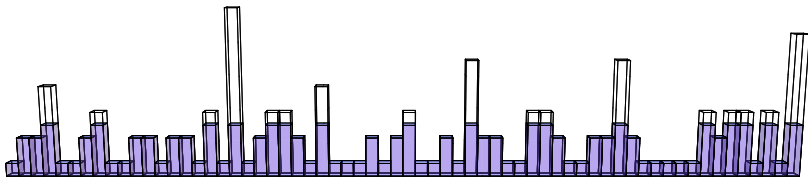
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- ▶ Query complexity: $O(1/\|\delta_p\|_2)$

