

Quantum walks can find a marked element on any graph

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Outline

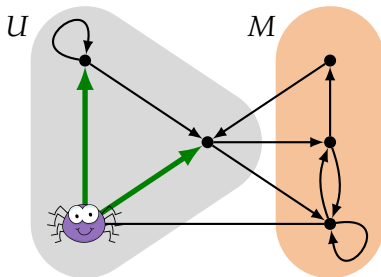
1. Problem and background
2. Main result
3. Classical intuition
4. Quantum algorithm
5. Hitting times

Problem and background

Problem: spatial search on a graph

Setup

- ▶ Directed graph on $X = U \cup M$
- ▶ Unknown **marked** vertices M
- ▶ **Edges** representing legal moves



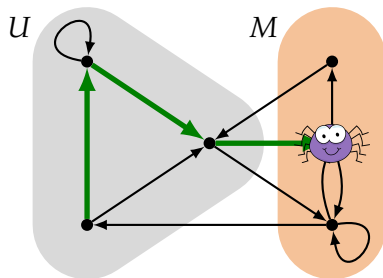
Problem: spatial search on a graph

Setup

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Goal

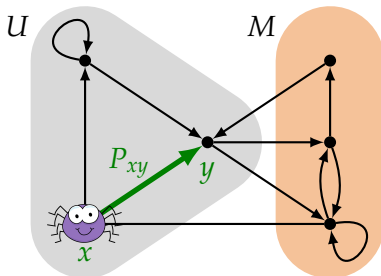
- ▶ Find any **marked** vertex
- ▶ Complexity = the number of steps



Approach: random walk

Setup

- ▶ Stochastic matrix $P = (P_{xy})$
- ▶ Restriction: $P_{xy} = 0$ if (x, y) is *not* an edge



Quantum walks

Useful early applications

- ▶ Element distinctness [[Amb04](#)]
- ▶ Triangle finding [[MSS05](#)]
- ▶ Verification of matrix products [[BŠ06](#)]
- ▶ Testing group commutativity [[MN07](#)]

Quantum walks

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Random walk \rightarrow quantum walk

- ▶ A general “quantization” technique [Sze04a]
- ▶ Walk on a complete graph \rightarrow Grover’s algorithm [Gro96]
- ▶ **Goal:** a quadratic quantum speedup for finding a marked vertex compared to any random walk

Finding with quadratic speedup

Previous results

- ▶ Quadratic speedup for **detecting** if marked vertices are present [Sze04a]
- ▶ Can find, but **no quadratic speedup** in general [MNRS07]
- ▶ Quadratic speedup for **state-transitive** Markov chains with a **unique** marked vertex [Tul08, MNRS12]

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Our contribution

- ▶ Quadratic speedup for any Markov chain with a **unique** marked vertex [KOR10, KMOR10]
- ▶ Note: Markov chain has to be **ergodic** and **reversible**

Main result

The main result

Theorem

Let P be a reversible, ergodic Markov chain on a set X , and $M \subseteq X$ be a set of marked elements. Then a quantum algorithm can find a marked element in $O(\sqrt{HT^+})$ steps where HT^+ is the “extended” hitting time of P

The main result

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Let P be a reversible, ergodic Markov chain on a set X , and $M \subseteq X$ be a set of marked elements. Then a quantum algorithm can find a marked element in $O(\sqrt{\text{HT}^+})$ steps where HT^+ is the “extended” hitting time of P

Note

- ▶ For any M , $\text{HT}^+ \geq \text{HT} =$ the hitting time of P
- ▶ If $|M| = 1$, $\text{HT}^+ = \text{HT}$

The main ~~result~~ question

Theorem

Let P be a reversible, ergodic Markov chain on a set X , and $M \subseteq X$ be a set of marked elements. Then a quantum algorithm can find a marked element in $O(\sqrt{\text{HT}^+})$ steps where HT^+ is the “extended” hitting time of P

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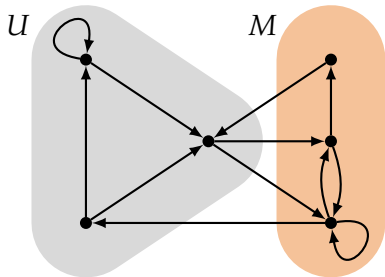
Question

Can we find in $O(\sqrt{\text{HT}})$ steps for *any* M ?

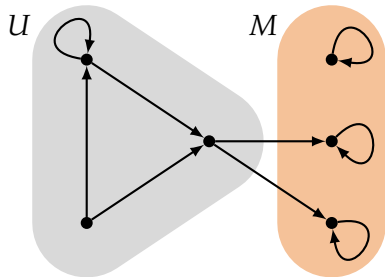
Classical intuition

Regular vs absorbing walk

Regular walk P

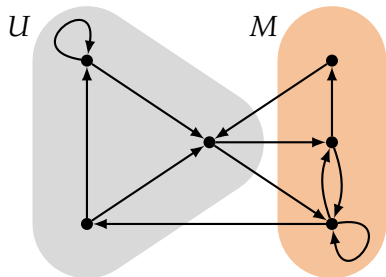


Absorbing walk P'



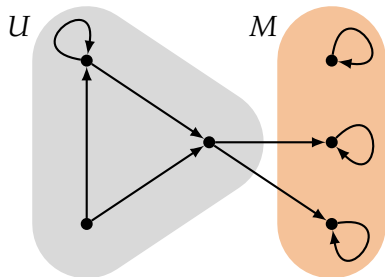
Regular vs absorbing walk

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$$P = \begin{pmatrix} P_{UU} & P_{UM} \\ P_{MU} & P_{MM} \end{pmatrix}$$

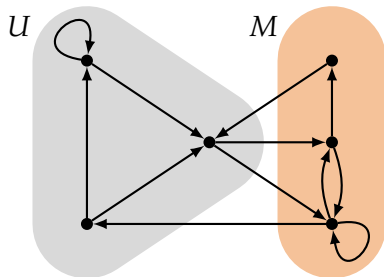
Absorbing walk P'



$$P' = \begin{pmatrix} P_{UU} & P_{UM} \\ 0 & I \end{pmatrix}$$

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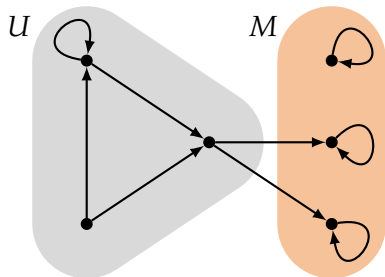
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$$\pi = (\pi_U, \pi_M)$$

Absorbing walk P'



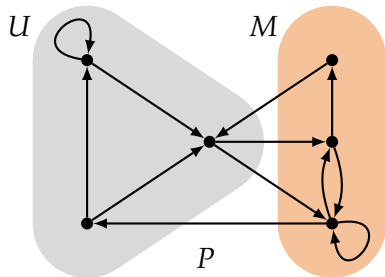
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$$\pi' \propto (0, \pi_M)$$

Classical search via random walk

First...

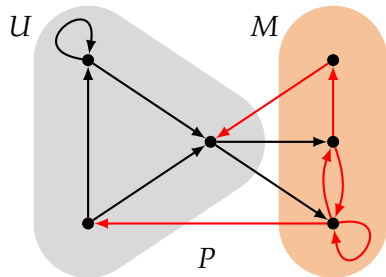
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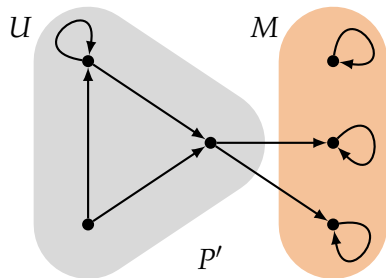
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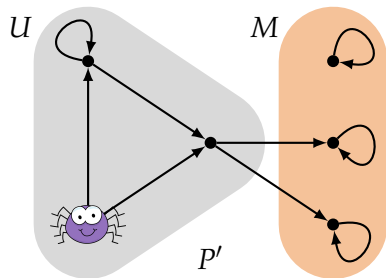
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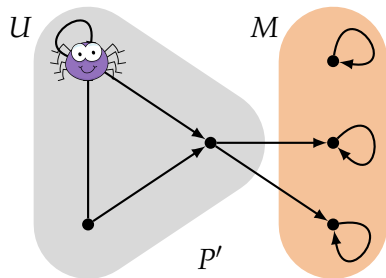
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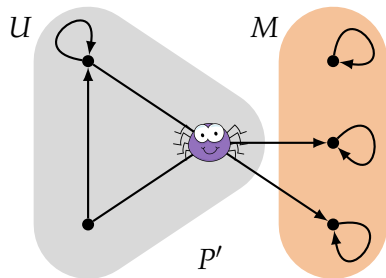
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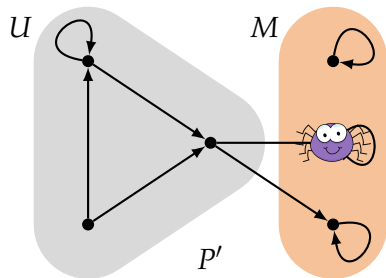
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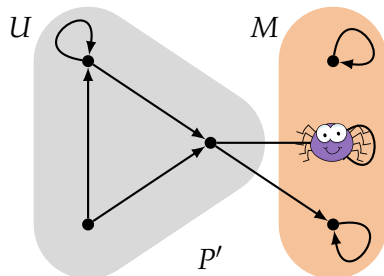
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Hitting time

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“Adiabatic” classical search

Semi-absorbing walk

- ▶ $P(s) := (1 - s)P + sP'$ for $s \in [0, 1]$
- ▶ Stationary distribution: $\pi(s) \propto ((1 - s)\pi_U, \pi_M)$

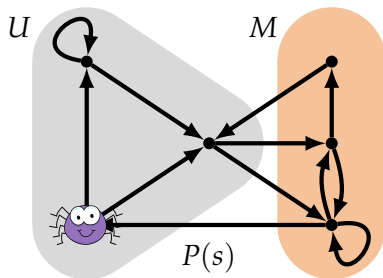
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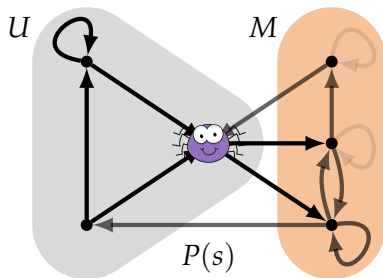
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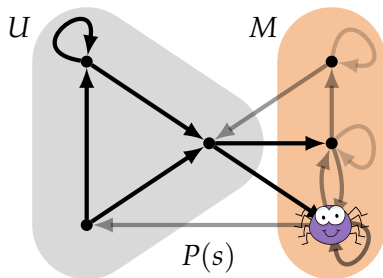
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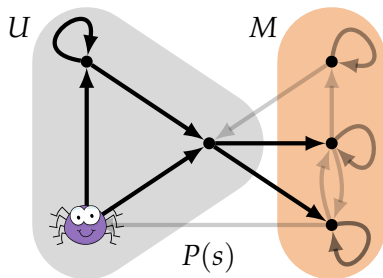
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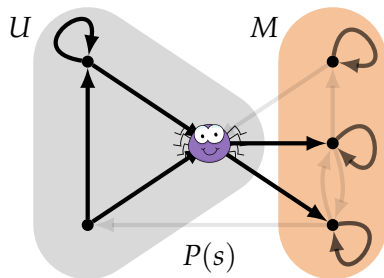
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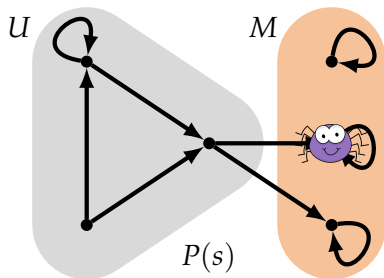
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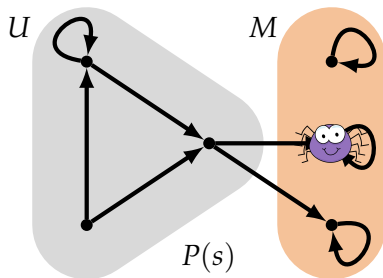
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Key observation

$\pi(s)$ changes continuously from π to π' as s ranges from 0 to 1

Quantum algorithm

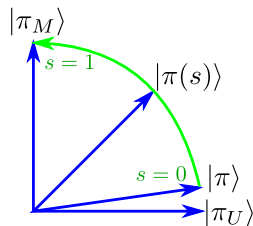
Adiabatic version [KOR10]

Construction

- ▶ Use the method of Somma and Ortiz [SO10] to convert $P(s)$ into a Hamiltonian $H(s)$

Algorithm

1. Prepare $|\pi\rangle$, the quantum state corresponding to π
2. Evolve by $H(s)$ while interpolating s from 0 to 1



Theorem

Let P be an ergodic and reversible Markov chain and assume the **adiabaticity requirement** holds $H(s)$. Then the adiabatic search algorithm finds a marked vertex with probability at least $1 - \varepsilon^2$ in time $T = \frac{\pi}{2\varepsilon} \sqrt{HT^+}$

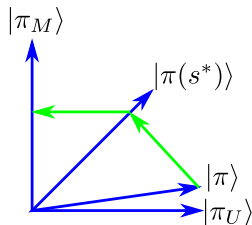
Circuit version [KMOR10]

Construction

- ▶ Use Szegedy's method [Sze04a] to define a unitary $W(P(s))$
- ▶ $W(P(s))$ has a unique 1-eigenvector $|\pi(s)\rangle$
- ▶ Use phase estimation to measure in the eigenbasis of $W(P(s))$

Algorithm

1. Prepare $|\pi\rangle$
2. Project onto $|\pi(s^*)\rangle = \frac{|\pi_U\rangle + |\pi_M\rangle}{\sqrt{2}}$
3. Measure current vertex



Theorem

If the values of p_M and HT^+ are known, then a quantum algorithm can find a marked vertex in $O(\sqrt{HT^+})$ steps

Spatial search on $G = (V, E)$

- ▶ State space: $\begin{array}{c} \text{vertex register} \\ V \end{array} \times \begin{array}{c} \text{workspace} \\ V \cup \{\bar{0}\} \end{array}$

Spatial search on $G = (V, E)$

- ▶ State space: $\begin{matrix} \text{vertex register} \\ V \end{matrix} \times \begin{matrix} \text{workspace} \\ V \cup \{\bar{0}\} \end{matrix}$
- ▶ Locality-respecting move:

$$\text{SHIFT } |x, y\rangle := \begin{cases} |y, x\rangle & \text{if } (x, y) \in E \\ |x, y\rangle & \text{otherwise} \end{cases}$$

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$$V(P)|x\rangle|\bar{0}\rangle := |x\rangle \sum_{y \in X} \sqrt{P_{xy}} |y\rangle$$

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- ▶ Szegedy's walk operator:

$$W(P) := \text{ref}_1 \cdot \text{ref}_2$$

$$\text{ref}_1 := V(P)^\dagger \text{SHIFT } V(P)$$

$$\text{ref}_2 := I \otimes (2|\bar{0}\rangle\langle\bar{0}| - I)$$

Hitting times

Operational definition

Algorithm (BASICWALK)

1. Pick a random $x \sim \pi$
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Ingredients

Umarked superposition

$$|U\rangle := \frac{1}{\sqrt{p_U}} \sum_{x \in U} \sqrt{\pi_x} |x\rangle$$

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Discriminant matrix

- ▶ $P(s)$ is not symmetric. Instead, consider

$$D(s) := \sqrt{P(s) \circ P(s)^\top}$$

- ▶ $P(s)$ and $D(s)$ are similar:

$$D(s) = \text{diag}(\sqrt{\pi(s)}) P(s) \text{diag}(\sqrt{\pi(s)})^{-1}$$

Eigenvalues and eigenvectors

- ▶ Spectral decomposition:

$$D(s) = \sum_{k=1}^n \lambda_k(s) |v_k(s)\rangle \langle v_k(s)|$$

$$0 \leq \lambda_1(s) \leq \lambda_2(s) \leq \cdots \leq \lambda_n(s) = 1$$

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$$1 \quad \text{when} \quad s \in [0, 1)$$

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- ▶ Overlap with $|U\rangle$:

$$\langle v_k(1)|U\rangle = 0 \quad \text{when } k > n - m$$

Operational definition (continued)

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Hitting times

- ▶ Hitting time:

$$\text{HT} := \sum_{k=1}^{n-m} \frac{|\langle v_k(1) | U \rangle|^2}{1 - \lambda_k(1)}$$

- ▶ Interpolated HT:

$$\text{HT}(s) := \sum_{k=1}^{n-1} \frac{|\langle v_k(s) | U \rangle|^2}{1 - \lambda_k(s)}$$

- ▶ Extended HT:

$$\text{HT}^+ := \lim_{s \rightarrow 1} \text{HT}(s)$$

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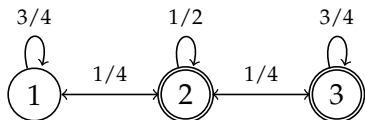
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Question

What is $\lim_{s \rightarrow 1} \frac{|\langle v_k(s) | U \rangle|^2}{1 - \lambda_k(s)}$ for $k > n - m$?

Example



$$P = \frac{1}{4} \begin{pmatrix} 3 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 3 \end{pmatrix} \quad M = \{2, 3\}$$

$$\text{HT} = 4 \quad \text{HT}(s) = \frac{20}{(3-s)^2} \quad \text{HT}^+ = 5$$

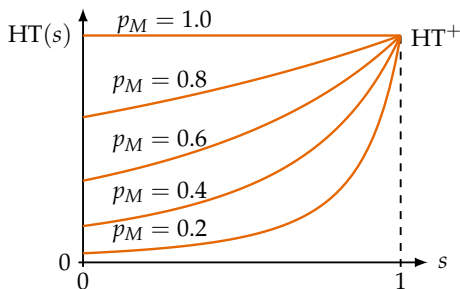
Main technical result

- ▶ Differential equation for $HT(s)$:

$$\frac{d}{ds} HT(s) = \frac{2p_U}{1 - sp_U} HT(s)$$

- ▶ Solution:

$$HT(s) = \left(\frac{1 - p_U}{1 - sp_U} \right)^2 HT^+$$



Explicit formulas

$$\begin{aligned}\text{HT} &= \langle \tilde{U} | (I - D_{UU})^{-1} | \tilde{U} \rangle \\ \text{HT}^+ &= \langle \tilde{U} | (I - D_{UU} - S)^{-1} | \tilde{U} \rangle\end{aligned}$$

where

$$S := D_{UM} \left[(I - D_{MM})^{-1} - \frac{(I - D_{MM})^{-1} |\tilde{M}\rangle \langle \tilde{M}| (I - D_{MM})^{-1}}{\langle \tilde{M} | (I - D_{MM})^{-1} | \tilde{M} \rangle} \right] D_{MU}$$

$$D := \begin{pmatrix} D_{UU} & D_{UM} \\ D_{MU} & D_{MM} \end{pmatrix} \quad |\tilde{U}\rangle := \sqrt{\frac{\pi_U}{p_U}} \quad |\tilde{M}\rangle := \sqrt{\frac{\pi_M}{p_M}}$$

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Important points

- ▶ HT depends only on transitions between *unmarked* states whereas HT^+ does not!

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Important points

- ▶ HT depends only on transitions between *unmarked* states whereas HT^+ does not!
- ▶ We end up sampling a specific distribution over marked states—this might be harder than merely finding one!

Conclusions

Results

- ▶ Quadratic quantum speed-up of HT for reversible, ergodic Markov chains with 1 marked state
- ▶ For multiple marked states, quadratic speedup over HT^+

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- ▶ What is the meaning of $HT(s)$ and HT^+ ?
- ▶ Can we get \sqrt{HT} for multiple marked elements?

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Thank you!