Quantum PageRank for Complex Networks

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A collaboration of

Quantum



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Complex



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Outline

- Google's PageRank
- Quantum PageRank, a route for Quantum Networks
- Results on tree networks and more general ones
- Quantum PageRank for large scale Complex Networks
- Features on scale-free, hierarchical and Erdös-Renyi
- General properties of the algorithm (localization, scaling behavior, stability)

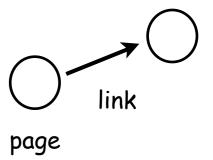
Classical ranking problem

The internet in 1998: the -mostly static- WWW: how to search?





"Searching" in the WWW: database search vs objective ranking



database search

link analysis

Problems: Scalability and Objectivity of the search results

Marchiori's idea (among others): the relevance of a page is given by the relation to the web!

Look at the hyperlink structure!

Brin and Page (Google's founders) base PageRank on this idea

In doing this a webpage is reduced to a number: a ranking!

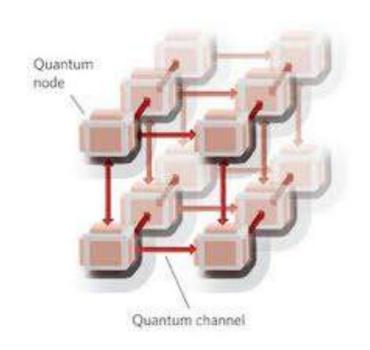
An audacious idea!

The scenario

New Quantum technologies:

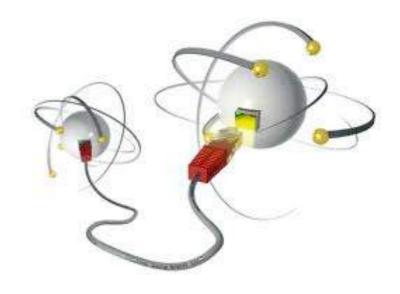


Quantum Networks: storing information on quantum degrees of freedom.



Allows for provably secure quantum communication.



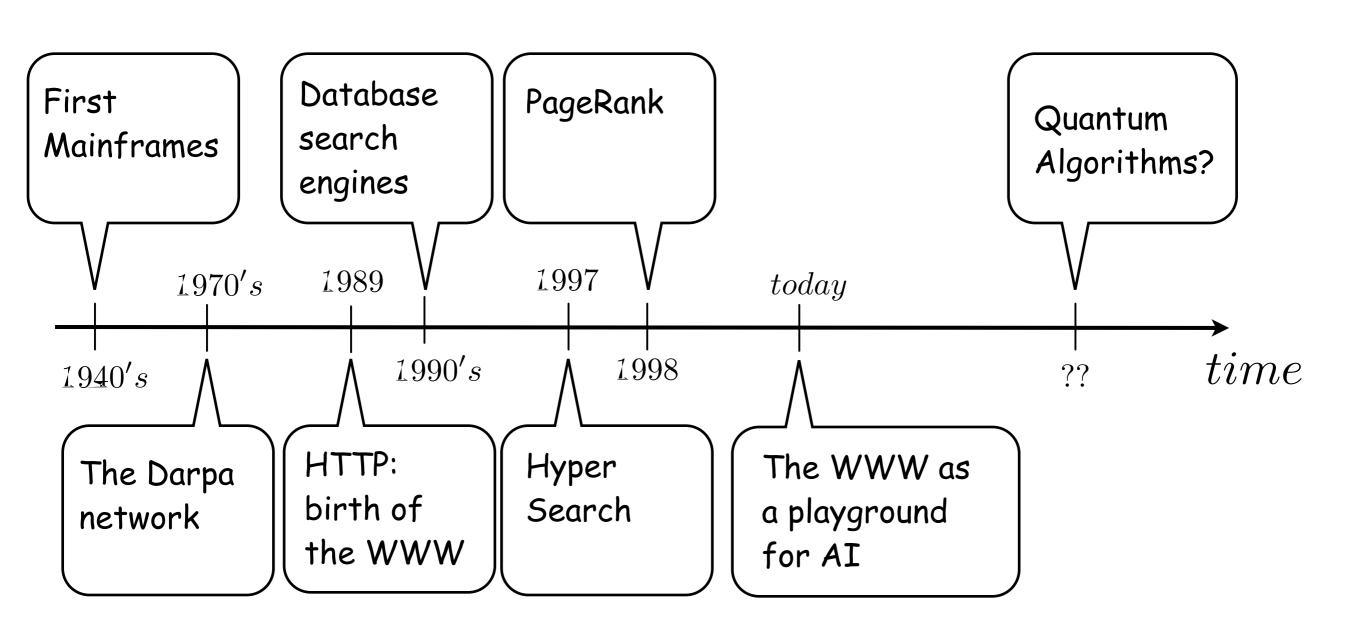


Nowadays: Small (~10 nodes) Quantum Networks have been built.

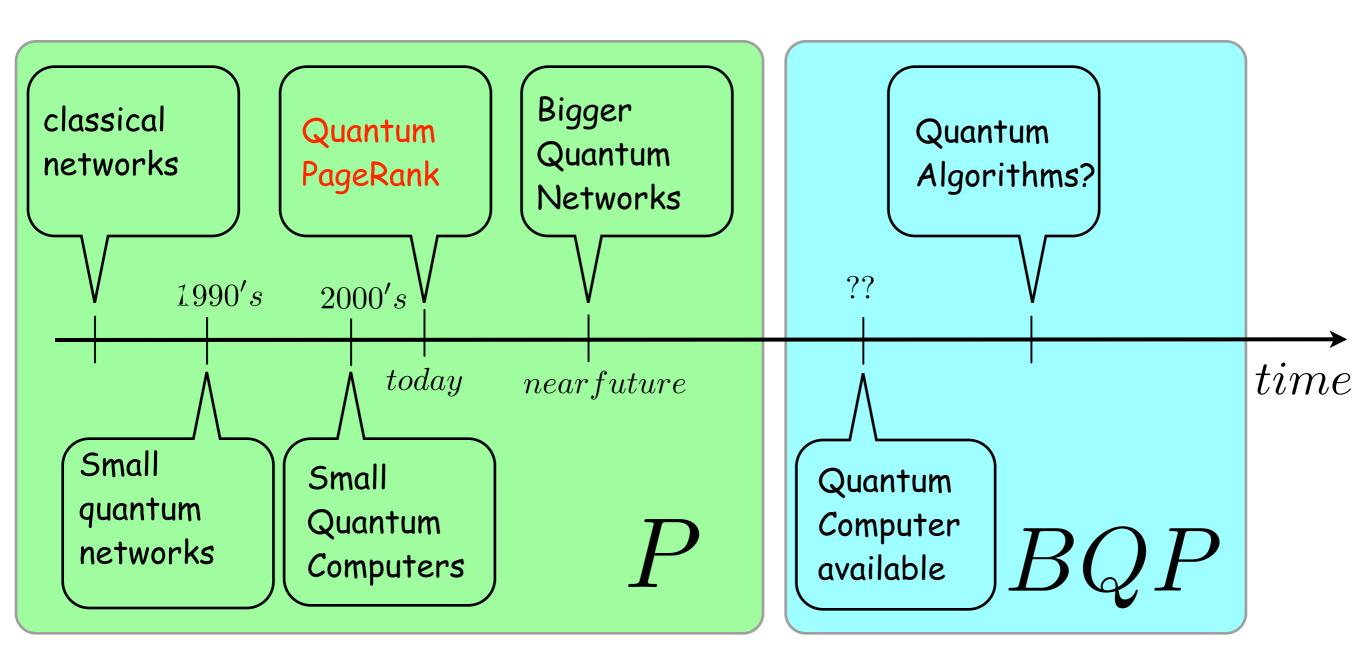
•Quantum Internet: a large scale quantum network: the quantum follow up of the WWW.



The Timeline



The Timeline



Searching in a Classical Web

Task: search for "a word" on the internet

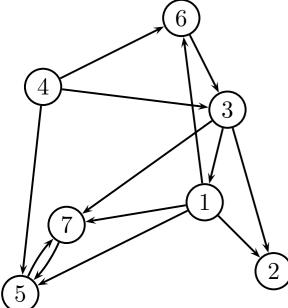


what is behind a search engine?

Two step process:

- 1. Output all pages containing "a word".
- 2. Rank the most important/relevant first.

Google's PageRank /1



5. Brin and L. Page's idea: Look into the hyperlink structure!

PageRank's Key Idea:

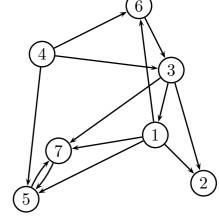
A node's importance is given by the pages that link to it. The more important these pages are the better. The fewer the outgoing links they have the better.

$$I(P_i) := \sum_{j \in B_i} \frac{I(P_j)}{\text{outdeg}(P_j)}$$

Google's PageRank 12

$$I(P_i) := \sum_{j \in B_i} \frac{I(P_j)}{\text{outdeg}(P_j)}$$

$$R_{ij} := \begin{cases} 1/\text{outdeg}(P_j) & \text{if } P_j \in B_i \\ 0 & \text{otherwise} \end{cases}$$



Hyperlink matrix

Computing PageRank is equivalent to:

$$I = RI$$

Solving it iteratively: the "Power Method": $I^{k+1} = I I^k$

But... not that easy... some tinkering is needed...

Problem and Patch/1

$$(P_1)$$
 Hyperlink matrix: $R = \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix}$

Easy guess: 2 is more important than 1

feed
$$I_0 = (1,0)^t \longrightarrow I^{k+1} = RI^k \longrightarrow I = (0,0)^t$$
 ?!?!

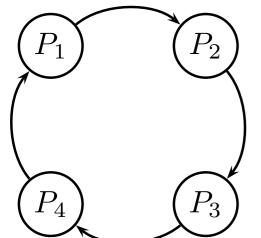
Patch: add artificial links to "dangling nodes"

$$(P_1)$$
 with matrix: $E=\left(egin{array}{cc} 0 & 1/2 \ 1 & 1/2 \end{array}
ight)$

Now: $I = (1/3, 2/3)^t$ Sound!

We have a stochastic matrix! (columns sum to 1)

Problem and Patch/2



Hyperlink matrix:
$$E = \begin{pmatrix} 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

feed
$$I_0 = (1, 0, 0, 0)^t \longrightarrow I^k = EI^{k-1} \longrightarrow \text{no convergence ?!?!}$$

Hint from theory: convergence ensured by second eigenvalue smaller than 1

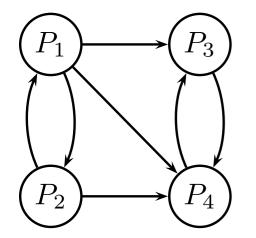
An m exists s.t. E^m with positive entries \longleftrightarrow (Primitivity)

Insight: Importance = probability to find the walker

Interpretation: after m steps any node is reachable, wherever the walker starts

Patch: require primitivity

Problem and Patch/3



Hyperlink matrix:
$$E = \begin{pmatrix} 0 & 1/2 & 0 & 0 \\ 1/3 & 0 & 0 & 0 \\ 1/3 & 1/2 & 0 & 1 \\ 1/3 & 0 & 1 & 0 \end{pmatrix}$$

$$I_0 = (1, 0, 0, 0)^t \longrightarrow I^k = EI^{k-1} \longrightarrow$$

 $I_0 = (1,0,0,0)^t \longrightarrow I^k = EI^{k-1} \rightarrow \text{page 1 and 2 with}$ ZERO importance ?!?!

No links from subgraph (3,4) to subgraph (1,2)

"Drain" of importance from subgraph (1,2)

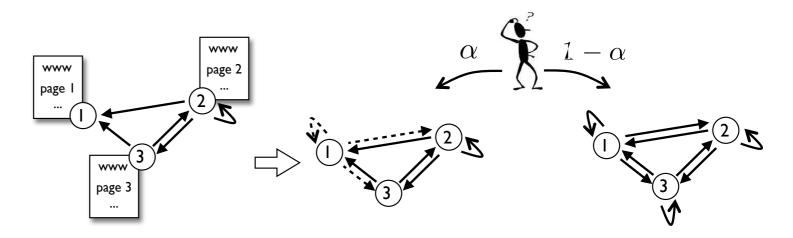
Reason: E is reducible \longleftrightarrow Graph not "strongly connected"

Patch: require Irreducibility

Google's PageRank

Solution: follow the web for a fraction lpha of time and jump anywhere else for

a fraction $1-\alpha$ of time!



i.e.
$$G := \alpha E + \frac{(1-\alpha)}{N} 1$$

Now: "Power method":

- Stochastic
- Primitive
- Irreducible

- Converges
- to the unique stationary vector
- Not dependent on initial condition

Tune the parameter $\alpha \longrightarrow \alpha = 0.85$

Random walks

PageRank has a random walk at its heart

from
$$I^k = GI^{k-1}$$
 with $G := \alpha E + \frac{(1-\alpha)}{N} 1$

 \mathcal{I}^k is a vector of probabilities of finding the walker Google's matrix G is a transition matrix:

$$P_{1} \cdots P_{j} \cdots P_{N}$$

$$P_{i} \sim P_{i} \sim P_{i$$

Markov Chain or Random Walk! How about quantizing?

Quantum walks

$$\cdots \boxed{-2} - \boxed{0} - \boxed{1} - \boxed{2} \cdot$$

with prob. p go right, with 1-p go left

Naive quantization: (1-2)

$$\cdots$$
 $(|-2 \rangle)$ $(|-1 \rangle)$ $(|0 \rangle)$ $(|2 \rangle)$ \cdots

evolution:
$$\nabla = \sqrt{p} |i + 1\rangle \langle i| + \sqrt{1-p} |i - 1\rangle \langle i|$$

But... start from $|0\rangle$ or $|2\rangle$ after a time step BOTH nonzero amplitude on $|1\rangle$

So
$$\langle 0|2\rangle=0$$
 but $\langle 0|\mathcal{V}^{\dagger}\mathcal{V}|2\rangle\neq 0$ No unitarity!?

Solutions:

→ enlarge Hilbert space (coin space)

Scattering Quantum Walk

* Szegedy's Quantum Walk

Szegedy's Quantum Walks/I

states are links:

$$P_1$$
 $|12\rangle$ P_2

States containing info on outgoing links of j:

$$|\psi_j
angle:=|j
angle_1\otimes\sum_{k=1}\sqrt{G_{kj}}\,|k
angle_2$$
 G: Markov Chain
$$|j
angle\otimes\sqrt{G_{kj}}\,|k
angle$$

M. Szegedy: Proceedings of the 45th Annual IEEE Symposium on Foundations of Computer Science (2004), pp. 32-41.

Szegedy's Quantum Walks/II

evolution is a reflection around these states and a swap!

$$2\mathbf{I} - \mathbf{1} = \sum_{j=1}^{N} \left(2 |\psi_{j}\rangle \langle \psi_{j}| - \frac{1}{N} \mathbf{1} \right) \qquad S = \sum_{j,k=1}^{N} |j,k\rangle \langle k,j|$$

$$\Rightarrow |\psi\rangle$$

$$\Rightarrow |\psi\rangle$$

$$\Rightarrow |\Sigma \text{pan}\{|\psi_{j}\rangle\}$$

$$\Rightarrow (2\mathbf{I} - \mathbf{I})|\psi\rangle$$

$$\mathcal{U} = S(2\mathbb{Z} - 1)$$
 Unitary and directedness preserving

We'll consider two-step evolution operators:

Quantum PageRank/1

Key idea: use quantization of Markov Chain to obtain a Quantum PageRank algorithm

Use Google Matrix: $G := \alpha E + \frac{(1-\alpha)}{N} \mathbf{1}$

$$|\psi_j
angle:=|j
angle_1\otimes\sum_{k=1}^{N}\sqrt{G_{kj}}|k
angle_2$$

Idea: the (instantaneous) Quantum PageRank of a node is the probability to find a quantum Walker that has evolved under a Quantized Markov Chain.

$$I_{\mathcal{Q}}(P_i, m) = \langle \psi(0) | \mathcal{D}^{\dagger 2m} | i \rangle_2 \langle i | \mathcal{D}^{2m} | \psi(0) \rangle.$$

Unitarity suggests it will vary in time < _ _ Average

Error (variance)

Quantum PageRank/2

Algorithm to calculate the Quantum PageRank:

1. Write down the Google Matrix:

2. Start from the state:

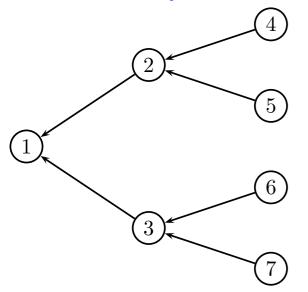
$$|\psi_0\rangle = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} |\psi_j\rangle$$

3. Let it evolve according to a Szegedy Walk: $|{m v}^2|\psi_0
angle$

$$I_{\sigma}(P_i, m) = \langle \psi(0) | \mathcal{T}^{\dagger 2m} | i \rangle_2 \langle i | \mathcal{T}^{2m} | \psi(0) \rangle.$$

5. Calculate the time averaged Quantum PageRank and its variance

Quantum PageRank/Tree

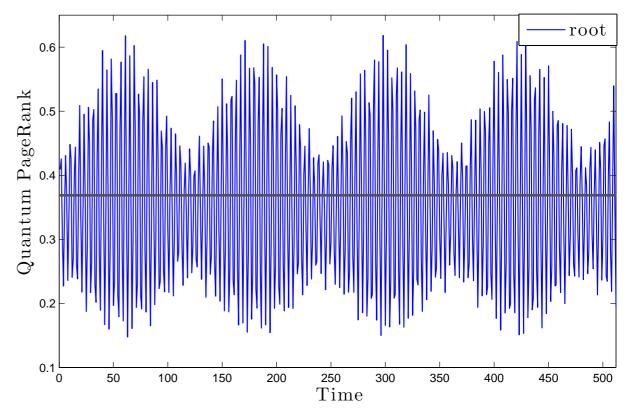


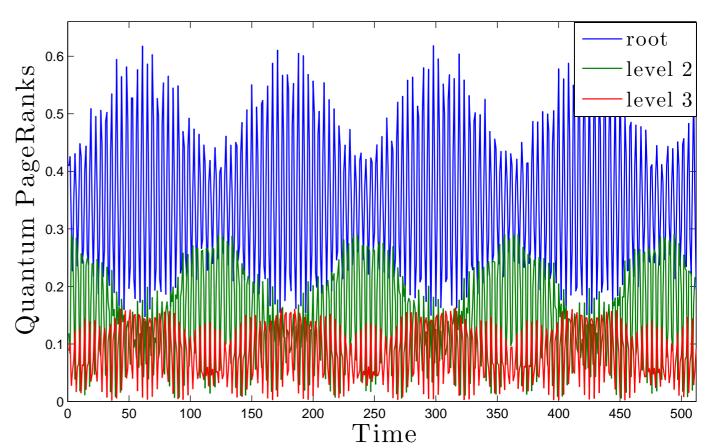
Root:

1. The root's Q-PageRank is higher:

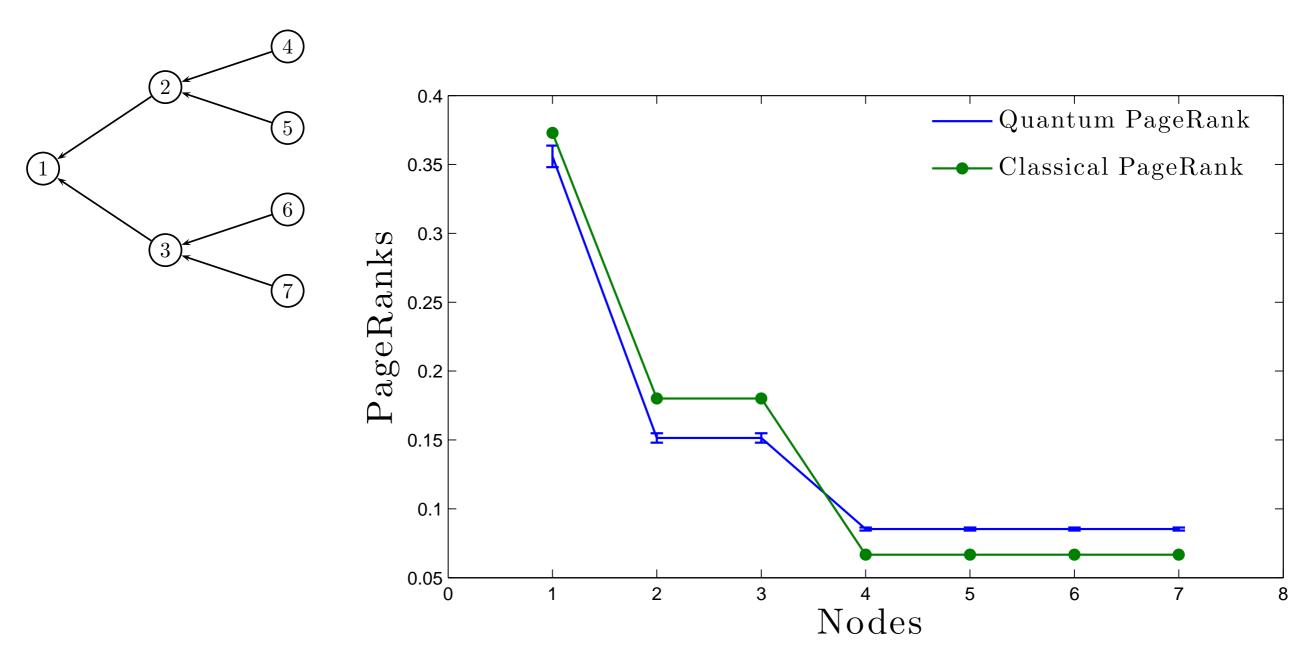
(Instantaneous)
Outperformance!

2. Hierarchy is not preserved at any given time!



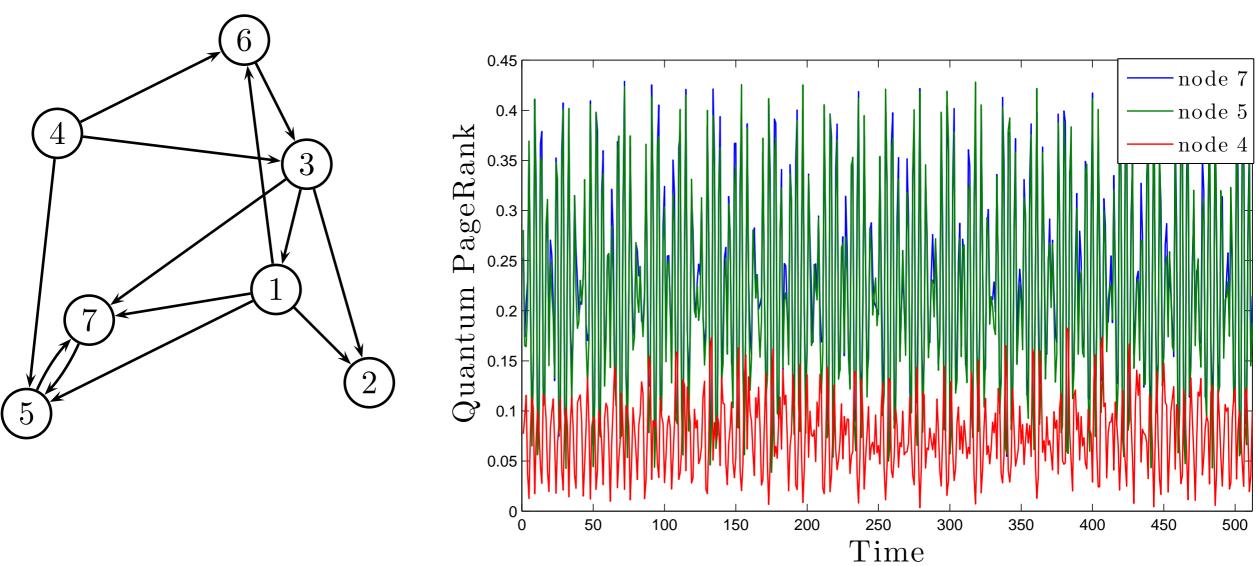


Quantum PageRank/Tree 2



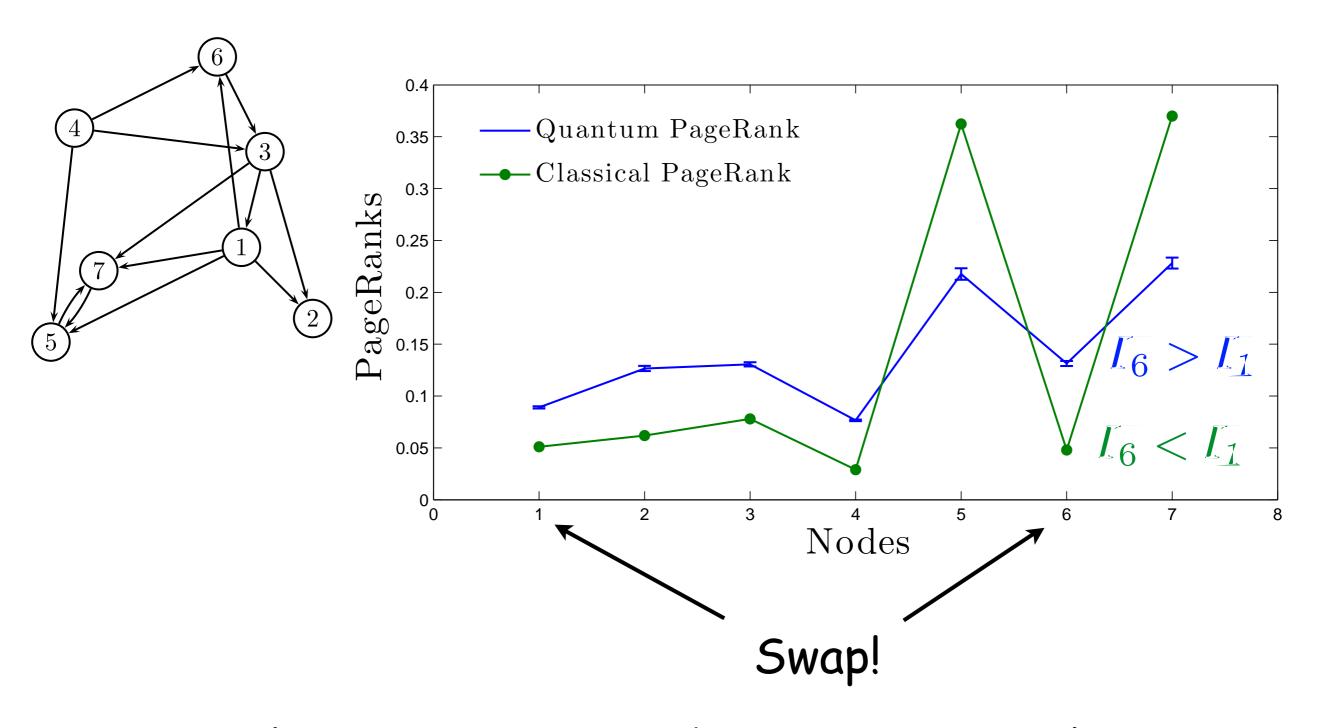
Strong Hierarchical preserving on average!

Quantum PageRank/a Graph



Hierarchy is not preserved at any given time!

Quantum PageRank/a Graph

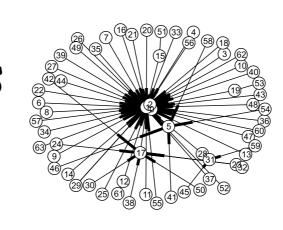


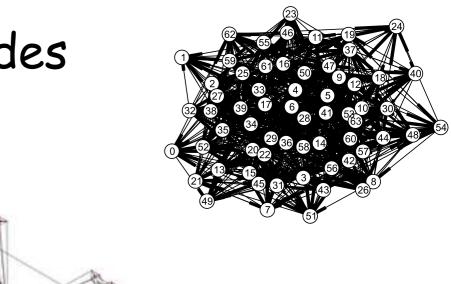
Hierarchy is not preserved even on average! More homogenous importance distribution

Q.PageRank: Bigger Networks

Do these effects persist on bigger networks? ... studies for up to 512 nodes

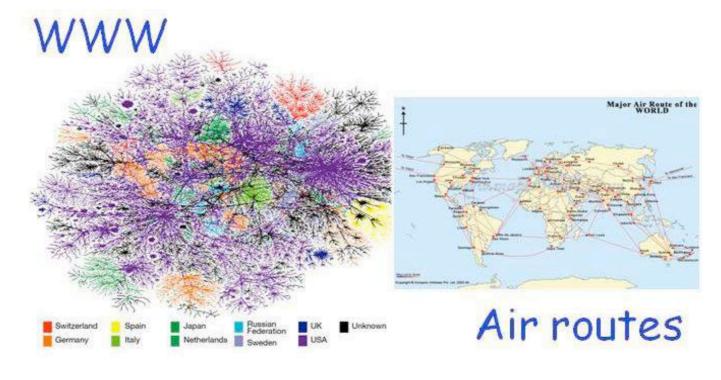
- 1. Erdös Rényi graphs
- 2. Hierarchical graphs
- 3. Scale free graphs





Scale-Free Networks

Model of the WWW



Model of the Air routes network

scale-free degree distribution:

$$P(k) \approx k^{-\gamma}$$

$$2 \le \gamma \le 3$$

How to grow a scale-free: Barabási-Albert model with preferential attachment

Quantum networks will likely grow with this topology and will reuse the existing communication networks with the underlying classical communication channels



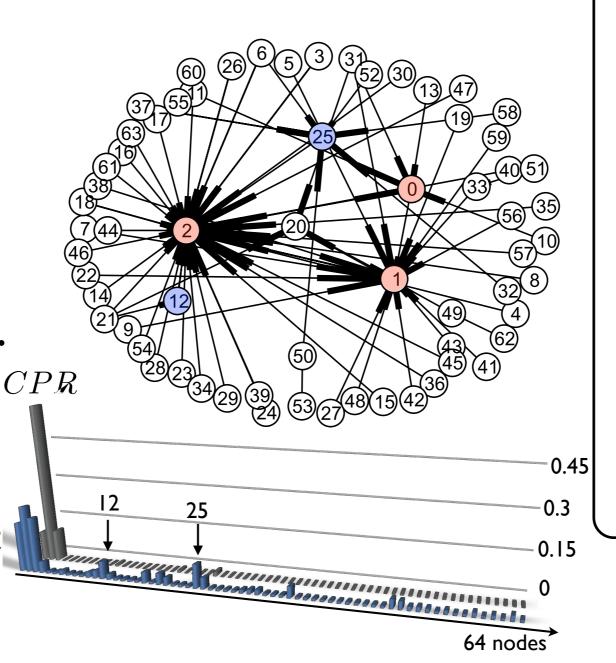
A.-L. Barabási, R. Albert, and H. Jeong, Physica A: Statistical Mechanics and its Applications 281, 69 (2000); A. Barrat, M. Barthelemy, R. Pastor-Satorras, and A. Vespignani, PNAS 101, 3747 (2004); A.-L. Barabási and R. Albert, Science 286, 509 (1999).

Scale-Free Networks

Results of the Quantum PageRank

Highlights the main hubs.

Increased visibility of the secondary hubs.



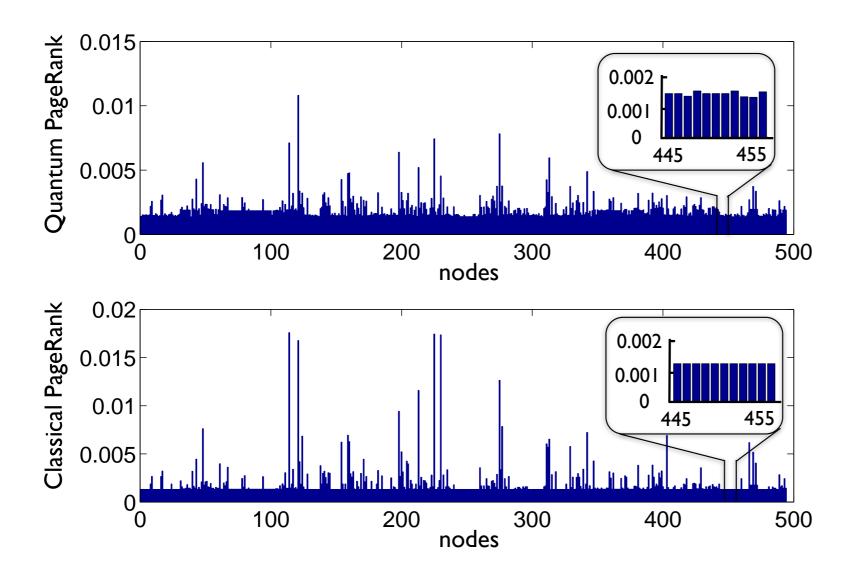
Observations

•Increased resolution

Scale-Free Networks/2

Results of the Quantum PageRank

Lifts the degeneracy of nodes



Observations

- Increased resolution
- Degeneracy partially lifted

Scale-Free Networks only?

What about the other known topologies?

Like Hierarchical graphs?

Observations

- Increased resolution
- Degeneracy partially lifted

Questions

Dependence on the topology

Observations

- Increased resolution
- Degeneracy partially lifted

Questions

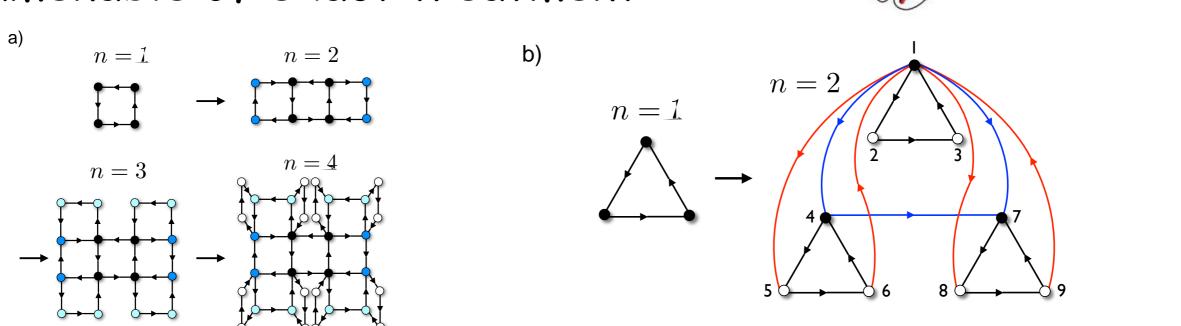
- Dependence on the topology
- Smoothness of ranking
- •Stability with respect to the damping parameter
- Localization properties

Hierarchical Networks

Networks composed of self repeating moduli

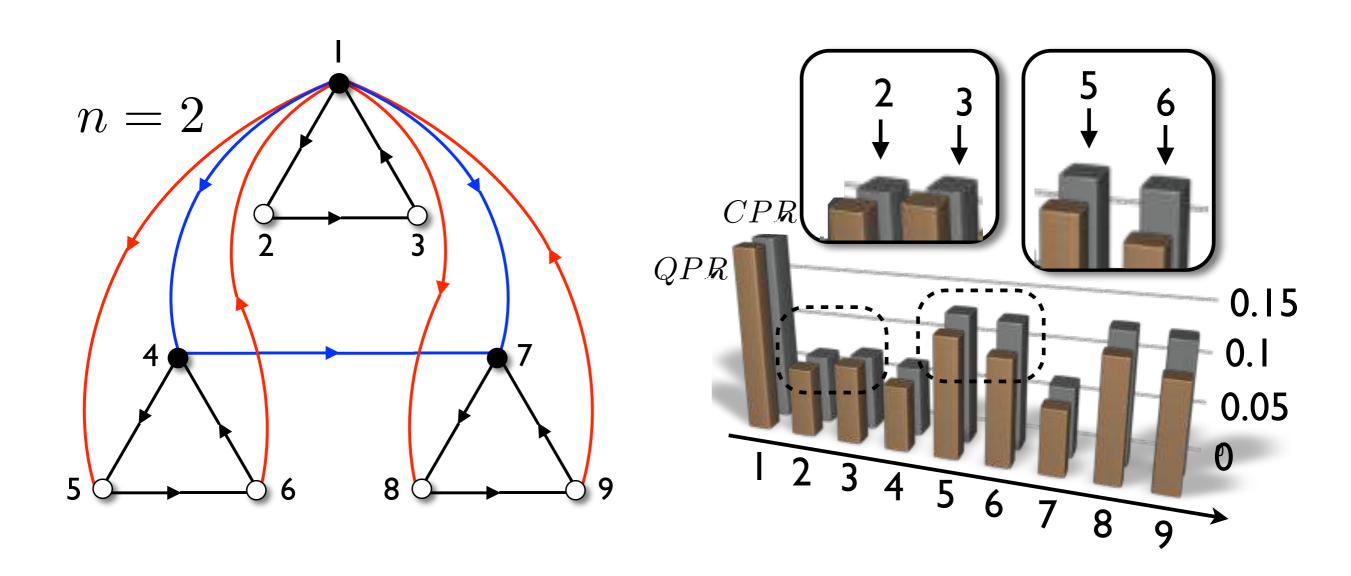
WWW is self-similar

Hierarchical networks are often amenable of exact treatment



C. Song, S. Havlin, and H. A. Makse, Nature 433, 392 (2005); F. Comellas and A. Miralles, Physica A: Statistical Mechanics and its Applications 388, 2227 (2009); F. Comellas and A. Miralles, Journal of Physics A: Mathematical and Theoretical 42, 425001 (2009).

Hierarchical networks



Global hierarchy is preserved but local connectivity structure is more visible.

Scaling Behavior

Scaling behavior of the PageRanks:

$$I_j \sim j^{-\beta}$$

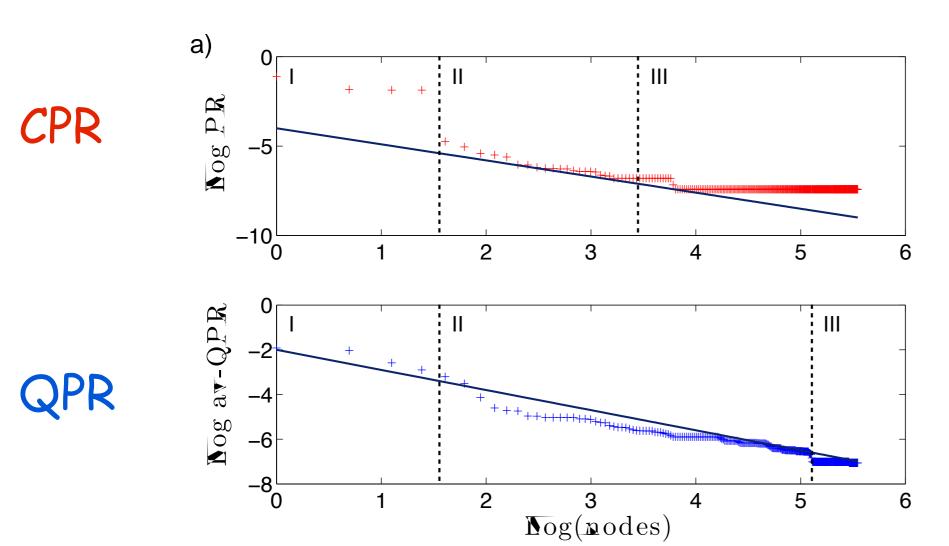
 $\beta_{cl} \approx 0.9$

How do Quantum PageRanks scale?

$$\langle I_q(P_j)\rangle \sim j^{-\beta_q}$$

Power law! With a smoother scaling $~eta_{\it q}=0.85$

$$\beta_q = 0.85$$



3 Zones:

I) Hubs

II) Well fitted

III) Degenerate

Scaling Behavior

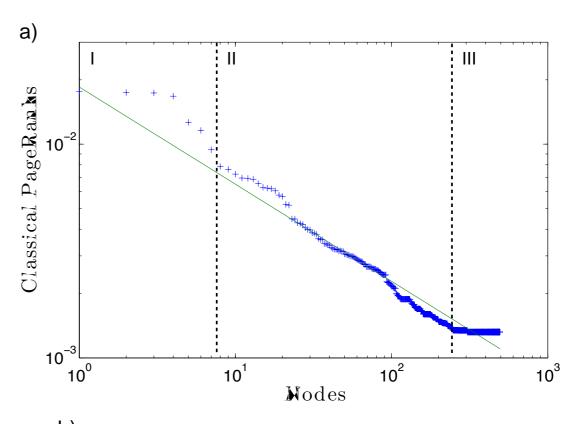
A real network from EPA

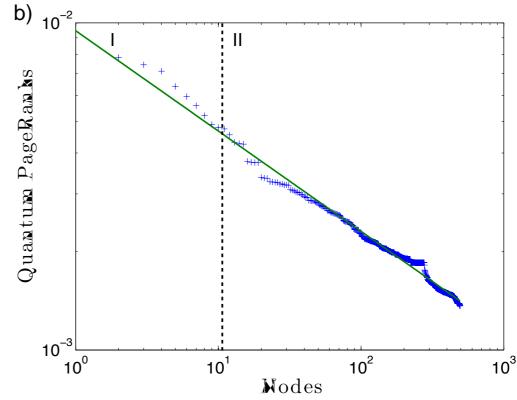


Smoother behavior means better ranking

$$\beta_c = 0.30 \ vs \ \beta_{cl} = 0.45$$

Smoother scaling
Well fitted in the whole range
Degeneracy resolved





The Problem of Stability

Damping parameter α in the Google matrix is arbitrary



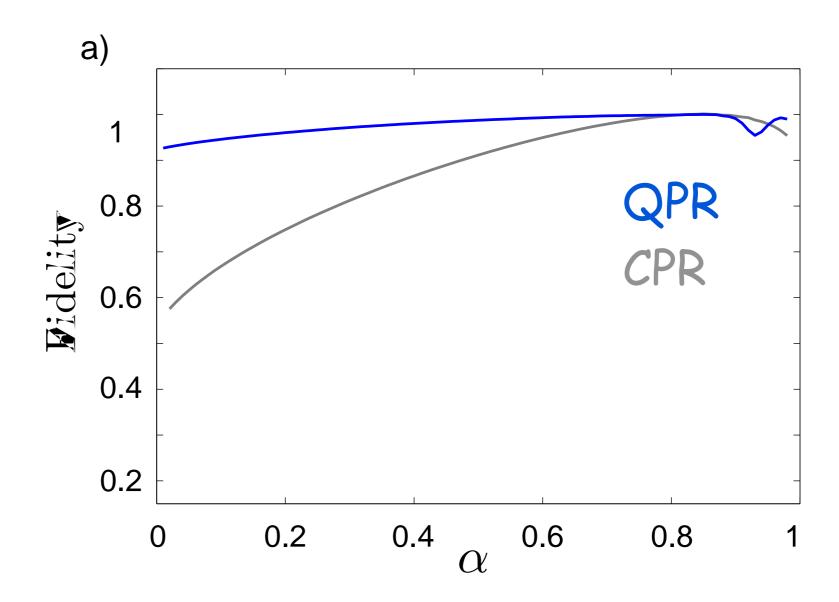
We need a way to measure the "fidelity"

$$f(\alpha, \alpha') = \sum_{j} \sqrt{I(P_j, \alpha)I(P_j, \alpha')}$$

Classically the fidelity can reach zero for values of the damping parameter that are sufficiently far.

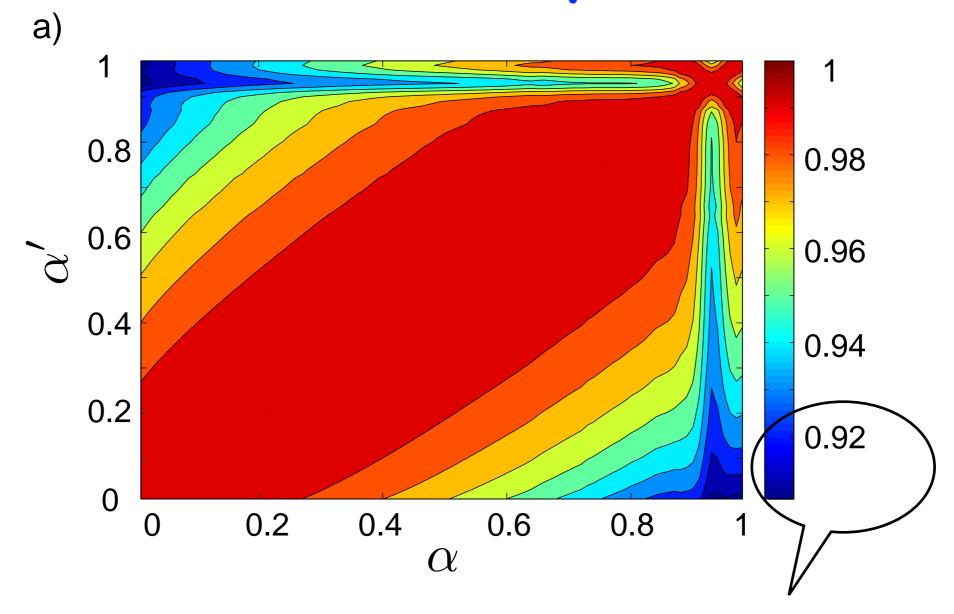
Stability

More robust with respect to the variation of the damping parameter.



$$f(\alpha, 0.85) = \sum_{j} \sqrt{I(P_j, \alpha)I(P_j, 0.85)}$$

Stability



Minimum Fidelity ≥ 0.90

More robust with respect to the variation of the damping parameter.

Conclusions

- Found a valid quantization of Google's PageRank
- Quantum PageRanks show nontrivial features when ranking
- It's able to rank better e.g. in scale-free networks
- When applied on bigger SF Complex Networks the algorithm displays: localization, a more favorable scaling behavior and it is more stable
- All these elements make it a valuable tool to analyze classical networks

Collaborators



GICC (Grupo de Información y Computación Cuántica)



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Universidad Complutense de Madrid (UCM)



Thank You for your attention!

Sci. Rep. 2, 444 (2012) (ArXiv: 1112.2079) and Sci. Rep. 3, 2773 (2013) (Arxiv 1303.3891) Eur. Phys. J. Plus 129: 150 (2014) (Arxiv 1409.3793)

PICC: The Physics of Ion Coulomb Crystals



















Additional Slides

Localization of Walker

Why is studying the localization important?

Localization implies good ranking: scale-free display a little fraction of "hubs"

The method: The Inverse Participation Ratio (IPR)

$$\xi_{cl} := \sum_{i=1}^{N} \left[\Pr(N = i) \right]^{2r} vs \quad \xi_{\overline{q}} := \sum_{i=1}^{N} \langle I_q(P_i) \rangle^{2r} \qquad \xi := \begin{cases} 1 & \text{if the walker is localized} \\ N^{1-2r} & \text{if the walker is delocalized.} \end{cases}$$

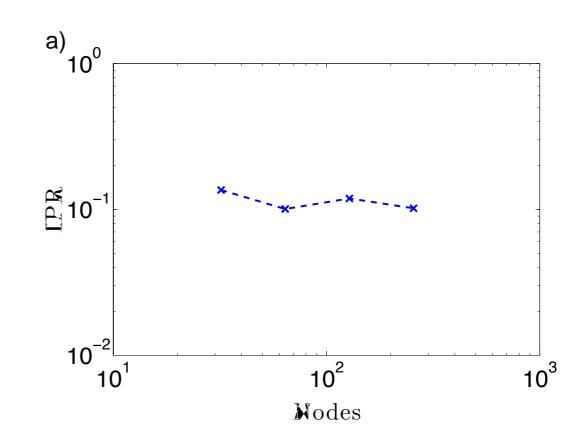
Good witness of localization: we will look at the slope of:

$$\log \xi vs \log X$$

Localization: Results on SF

Localization found in SF networks classically

and Quantumly! (slope close to zero)



$$\log \xi vs \log X$$

A small fraction of nodes will concentrate all the importance: This algorithm can rank well.

Other Approaches / Outlook

- Use Adiabatic Q. Computation to calculate the classical Google PageRank (Silvano Garnerone, P. Zanardi & D. Lidar)
- Use dissipative protocols (Gómez-Gardeñes & Zueco, Silvano Garnerone)
- Multiparticle quantum walks to rank nodes in quantum networks?