

Graphs in Machine Learning Google PageRank: Computation

Power Method and Large-Scale Implementation

Michal Valko

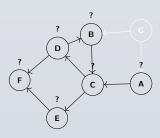
Inria & ENS Paris-Saclay, MVA

Partially based on material by: Andreas Krause, Branislav Kveton, Michael Kearns

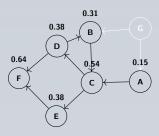
Google matrix: $\mathbf{G} = (1 - p)\mathbf{M} + p \cdot \frac{1}{N}\mathbb{1}_{N \times N}$, where p = 0.15

Google matrix: $\mathbf{G} = (1-p)\mathbf{M} + p \cdot \frac{1}{N}\mathbb{1}_{N \times N}$, where p = 0.15 **G** is **stochastic** why? What is Ga for any a? We look for $\mathbf{G}\mathbf{v} = 1 \times \mathbf{v}$, steady-state vector, a right eigenvector with eigenvalue 1. why?

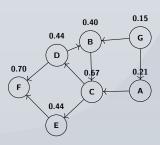
Google matrix: $\mathbf{G} = (1-p)\mathbf{M} + p \cdot \frac{1}{N}\mathbb{1}_{N \times N}$, where p = 0.15 \mathbf{G} is stochastic why? what is Ga for any a? We look for $\mathbf{G}\mathbf{v} = 1 \times \mathbf{v}$, steady-state vector, a right eigenvector with eigenvalue 1. why? Perron's theorem: Such v exists and it is unique if the entries of \mathbf{G} are positive.



Google matrix: $\mathbf{G} = (1-p)\mathbf{M} + p \cdot \frac{1}{N}\mathbb{1}_{N \times N}$, where p = 0.15 \mathbf{G} is stochastic why? what is Ga for any a? We look for $\mathbf{G}\mathbf{v} = 1 \times \mathbf{v}$, steady-state vector, a right eigenvector with eigenvalue 1. why? Perron's theorem: Such v exists and it is unique if the entries of \mathbf{G} are positive.



Google matrix: $\mathbf{G} = (1-p)\mathbf{M} + p \cdot \frac{1}{N}\mathbb{1}_{N \times N}$, where p = 0.15 \mathbf{G} is **stochastic** why? What is Ga for any a? We look for $\mathbf{G}\mathbf{v} = 1 \times \mathbf{v}$, steady-state vector, a right eigenvector with eigenvalue 1. why? **Perron's theorem:** Such v exists and it is **unique** if the entries of \mathbf{G} are positive.



History: [Desikan, 2006]

 The anatomy of a large-scale hypertextual web search engine [Brin & Page 1998]

- The anatomy of a large-scale hypertextual web search engine [Brin & Page 1998]
- US patent for PageRank granted in 2001

- The anatomy of a large-scale hypertextual web search engine [Brin & Page 1998]
- US patent for PageRank granted in 2001
- Google indexes 10's of billions of web pages (1 billion = 10^9)

- The anatomy of a large-scale hypertextual web search engine [Brin & Page 1998]
- US patent for PageRank granted in 2001
- Google indexes 10's of billions of web pages (1 billion = 10^9)
- Google serves ≥ 200 million queries per day

- The anatomy of a large-scale hypertextual web search engine [Brin & Page 1998]
- US patent for PageRank granted in 2001
- Google indexes 10's of billions of web pages (1 billion = 10^9)
- Google serves ≥ 200 million queries per day
- Each query processed by ≥ 1000 machines

- The anatomy of a large-scale hypertextual web search engine [Brin & Page 1998]
- US patent for PageRank granted in 2001
- Google indexes 10's of billions of web pages (1 billion = 10^9)
- Google serves ≥ 200 million queries per day
- Each query processed by ≥ 1000 machines
- All search engines combined process more than 500 million queries per day

$$n = 10^9 !!!$$

- $n = 10^9 !!!$
- luckily: sparse

- $n = 10^9 !!!$
- luckily: sparse (average outdegree: 7)

- $n = 10^9 !!!$
- luckily: sparse (average outdegree: 7)
- power method

- $n = 10^9 111$
- luckily: sparse (average outdegree: 7)
- power method

$$\mathbf{v}_0 = (1_A \quad 0_B \quad 0_C \quad 0_D \quad 0_E \quad 0_F)^\mathsf{T}$$

- $n = 10^9 !!!$
- luckily: sparse (average outdegree: 7)
- power method

$$\mathbf{v}_0 = (1_A \quad 0_B \quad 0_C \quad 0_D \quad 0_E \quad 0_F)^\mathsf{T}$$
$$\mathbf{v}_1 = \mathbf{G}\mathbf{v}_0$$

- $n = 10^9 !!!$
- luckily: sparse (average outdegree: 7)
- power method

$$\mathbf{v}_0 = (1_A \quad 0_B \quad 0_C \quad 0_D \quad 0_E \quad 0_F)^\mathsf{T}$$

$$\mathbf{v}_1 = \mathbf{G}\mathbf{v}_0$$

$$\mathbf{v}_{t+1} = \mathbf{G}\mathbf{v}_t$$

- $n = 10^9 !!!$
- luckily: sparse (average outdegree: 7)
- power method

$$\mathbf{v}_0 = (1_A \quad 0_B \quad 0_C \quad 0_D \quad 0_E \quad 0_F)^\mathsf{T}$$

$$\mathbf{v}_1 = \mathbf{G}\mathbf{v}_0$$

$$\mathbf{v}_{t+1} = \mathbf{G}\mathbf{v}_t$$

$$\mathbf{v}_{t+1} = \mathbf{v}_t \implies \mathbf{G}\mathbf{v}_t = \mathbf{v}_t$$

- $n = 10^9 !!!$
- luckily: sparse (average outdegree: 7)
- power method

$$\mathbf{v}_0 = (1_A \quad 0_B \quad 0_C \quad 0_D \quad 0_E \quad 0_F)^\mathsf{T}$$

$$\mathbf{v}_1 = \mathbf{G}\mathbf{v}_0$$

$$\mathbf{v}_{t+1} = \mathbf{G}\mathbf{v}_t$$

$$\mathbf{v}_{t+1} = \mathbf{v}_t \implies \mathbf{G} \mathbf{v}_t = \mathbf{v}_t$$
 and we found the steady vector

Problem: Find an eigenvector of a stochastic matrix.

- $n = 10^9 !!!$
- luckily: sparse (average outdegree: 7)
- power method

$$\mathbf{v}_0 = (1_A \quad 0_B \quad 0_C \quad 0_D \quad 0_E \quad 0_F)^\mathsf{T}$$

$$\mathbf{v}_1 = \mathbf{G}\mathbf{v}_0$$

$$\mathbf{v}_{t+1} = \mathbf{G}\mathbf{v}_t$$

$$\mathbf{v}_{t+1} = \mathbf{v}_t \implies \mathbf{G} \mathbf{v}_t = \mathbf{v}_t$$
 and we found the steady vector

But wait, M is sparse, but G is dense! What to do?

Problem: Find an eigenvector of a stochastic matrix.

- $n = 10^9 111$
- luckily: sparse (average outdegree: 7)
- power method

$$\mathbf{v}_0 = (1_A \quad 0_B \quad 0_C \quad 0_D \quad 0_E \quad 0_F)^\mathsf{T}$$

$$\mathbf{v}_1 = \mathbf{G}\mathbf{v}_0$$

$$\mathbf{v}_{t+1} = \mathbf{G}\mathbf{v}_t$$

$$\mathbf{v}_{t+1} = \mathbf{v}_t \implies \mathbf{G} \mathbf{v}_t = \mathbf{v}_t$$
 and we found the steady vector

But wait, M is sparse, but G is dense! What to do?

we store only M but do computations as with G



Michal Valko

michal.valko@inria.fr Inria & ENS Paris-Saclay, MVA

https://misovalko.github.io/mva-ml-graphs.html