

# Updating the Stationary Distribution Vector for an Irreducible Markov Chain

*Prakash Chanchana*

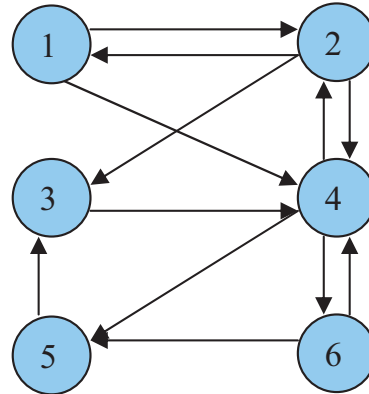
*Carl D. Meyer*

*Amy N. Langville*

## Outline

- PageRank Problem
- Updating Problem
- Exact Aggregation
- Approximate Updating Algorithm
- Updating Algorithm with the Iterative Aggregation
- Determining the Partition
- Future Work

### PageRank Problem

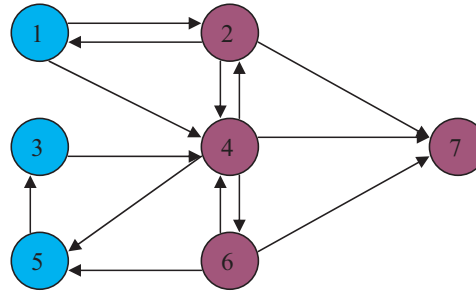


$$Q = \begin{pmatrix} 0 & 1/2 & 0 & 1/2 & 0 & 0 \\ 1/3 & 0 & 1/3 & 1/3 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1/2 & 0 & 0 & 0 & 1/2 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1/2 & 1/2 & 0 \end{pmatrix}_{6 \times 6}$$

Solving for the dominant eigenvector of a matrix  $Q$  by using the **Power Method**.

$$\phi^T Q = \phi^T$$

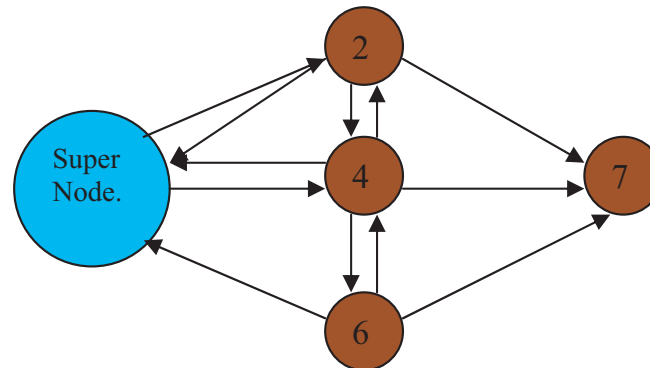
## Updating PageRank Problem



$$P = \begin{pmatrix} 0 & 1/2 & 0 & 1/2 & 0 & 0 & 0 \\ 1/3 & 0 & 0 & 1/3 & 0 & 0 & 1/3 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1/4 & 0 & 0 & 1/4 & 1/4 & 1/4 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1/3 & 1/3 & 0 & 1/3 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}_{7 \times 7}$$

- Given  $\phi^T$  and  $Q$  for the original system, find  $\pi^T$  of  $P$  for updated system.
- One way to solve this problem is to apply the Power Method (not good for a Huge matrix)

### Motivation



- Working with smaller system
- Paying more attention to the updated states

### Exact Aggregation

1. Partition states into  $k$  disjoint groups as  $S = G_1 \cup G_2 \cup \dots \cup G_k$  where each  $P_{ii}$  is a square block.

$$P_{n \times n} = \begin{pmatrix} P_{11} & P_{12} & \dots & P_{1k} \\ P_{21} & P_{22} & \dots & P_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ P_{k1} & P_{k2} & \dots & P_{kk} \end{pmatrix}$$

2. Find the stochastic complement  $S_i$  for each block  $P_{ii}$  where

$$S_i = P_{ii} + P_{i*} (I - P_i^*)^{-1} P_{*i}$$

$-P_{i*}$  and  $P_{*i}$  are, respectively, the  $i^{th}$ -row and the  $i^{th}$ -column of block with  $P_{ii}$  removed.

$-P_i^*$  is principle submatrix of  $P$  obtained by deleting the  $i^{th}$ -row and the  $i^{th}$ -column of blocks.

### Exact Aggregation

**Example:**

$$P = \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix}, \text{ then}$$

$$S_1 = P_{11} + P_{12}(I - P_{22})^{-1}P_{21}$$

$$S_2 = P_{22} + P_{21}(I - P_{11})^{-1}P_{12}$$

**3.** Form the smaller  $k \times k$  matrix called the *Aggregated Transition Matrix*.

$$A_{k \times k} = \begin{pmatrix} s_1^T P_{11} e & \dots & s_1^T P_{1k} e \\ \vdots & \ddots & \vdots \\ s_k^T P_{k1} e & \dots & s_k^T P_{kk} e \end{pmatrix}$$

where  $s_i^T$  is the stationary probability vector of  $S_i$ .

**Exact Aggregation**

4. Find the stationary distribution of A:  $\alpha^T = (\alpha_1, \alpha_2, \dots, \alpha_k)$
5. By the Exact Aggregation Theorem:  $\pi^T = (\alpha_1 s_1^T, \alpha_2 s_2^T, \dots, \alpha_k s_k^T)$

**Advantage** : Get the exact value of  $\pi^T$

**Disadvantage** : Very expensive for computing inverse  $S_i = P_{ii} + P_{i*}(I - P_i^*)^{-1}P_{*i}$



### Special Partition

$$P = \begin{matrix} & G & \bar{G} \\ \begin{matrix} G \\ \bar{G} \end{matrix} & \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix} \end{matrix}$$

Partition  $P$  into  $g + 1$  levels where first  $g$  diagonal blocks are  $1 \times 1$

$$P = \begin{pmatrix} p_{11} & \cdots & p_{1g} & P_{1*} \\ \vdots & \ddots & \vdots & \vdots \\ p_{g1} & \cdots & p_{gg} & P_{g*} \\ P_{*1} & \cdots & P_{*g} & P_{22} \end{pmatrix}$$

Advantage of this partition:

- Since  $p_{11} \dots p_{gg}$  are  $1 \times 1$  block  $\Rightarrow$  Stochastic complement = 1 and  $s_i = 1$

### Special Partition

- There is only one stochastic complement

$$S = P_{22} + P_{21}(I - P_{11})^{-1}P_{12}$$

- By Exact Aggregation Theorem

$$\tilde{s}^T = (\phi_{g+1}, \dots, \phi_n) / \sum_{i=g+1}^n \phi_i$$

So, the Exact Aggregated Transition Matrix associated with the new partition is

$$\tilde{A} = \left( \begin{array}{ccc|c} p_{11} & \dots & p_{1g} & P_{1*}e \\ \vdots & \ddots & \vdots & \vdots \\ p_{g1} & \dots & p_{gg} & P_{g*}e \\ \hline \tilde{s}^T P_{*1} & \dots & \tilde{s}^T P_{*g} & \tilde{s}^T P_{22}e \end{array} \right)_{(g+1) \times (g+1)}$$

### Special Partition

Since we use the old stationary vector  $\phi^T$  to find the updated stationary vector  $\pi^T$

$$\Rightarrow \pi^T \approx \phi^T$$

$$A \approx \tilde{A} = \begin{pmatrix} P_{11} & P_{12}e \\ \tilde{s}^T P_{21} & \tilde{s}^T P_{22}e \end{pmatrix}$$

$$\alpha^T \approx \tilde{\alpha}^T = (\tilde{\alpha}_1, \tilde{\alpha}_2, \dots, \tilde{\alpha}_g, \tilde{\alpha}_{g+1})$$

$$\pi^T \approx \tilde{\pi}^T = (\tilde{\alpha}_1, \tilde{\alpha}_2, \dots, \tilde{\alpha}_g, \tilde{\alpha}_{g+1} \tilde{s}^T)$$

(not bad approximation)

### Approximate Aggregation Algorithm

1. Partition states of updated as  $S = G \cup \bar{G}$  and reorder  $P = \begin{matrix} & G & \bar{G} \\ G & \begin{pmatrix} P_{11} & P_{12} \end{pmatrix} \\ \bar{G} & \begin{pmatrix} P_{21} & P_{22} \end{pmatrix} \end{matrix}$
2. Set  $\bar{\phi}^T = (\phi_{g+1}, \phi_{g+2}, \dots, \phi_n)$
3. Set  $\tilde{s}^T = \bar{\phi}^T / \bar{\phi}^T e$  where  $e$  is a column of ones
4. Set  $\tilde{A} = \begin{pmatrix} P_{11} & P_{12}e \\ \tilde{s}^T P_{21} & 1 - \tilde{s}^T P_{21} \end{pmatrix}_{(g+1) \times (g+1)}$
5. Find  $\tilde{\alpha}^T = (\tilde{\alpha}_1, \tilde{\alpha}_2, \dots, \tilde{\alpha}_g, \tilde{\alpha}_{g+1})$
6. Set  $\tilde{\pi}^T = (\tilde{\alpha}_1, \tilde{\alpha}_2, \dots, \tilde{\alpha}_g | \bar{\phi}^T)$

## Iterative Aggregation Algorithm

### Initialization

- Partition the states of the updated chain as  $S = G \cup \bar{G}$
- $\bar{\phi}^T \leftarrow$  the component from  $\phi^T$  corresponding to the states in  $\bar{G}$
- $s^T \leftarrow \bar{\phi}^T / (\bar{\phi}^T e)$

### Iterate until convergence

1.  $\tilde{A} \leftarrow \begin{pmatrix} P_{11} & P_{12}e \\ \tilde{s}^T P_{21} & 1 - \tilde{s}^T P_{21} \end{pmatrix}$
2.  $\alpha^T \leftarrow (\alpha_1, \alpha_2, \dots, \alpha_g, \alpha_{g+1})$
3.  $\chi^T \leftarrow (\alpha_1, \alpha_2, \dots, \alpha_g | \alpha_{g+1} s^T)$
4.  $\psi^T \leftarrow \chi^T \mathbf{P}$  (Move the iterates off the fixed point  $\longrightarrow$  the convergence.)
5. If  $\|\psi^T - \chi^T\| < \tau$  for a given tolerance  $\tau$ , then quit  
 else  $s^T \leftarrow \psi^T / \psi^T e$  go back to step 1.

## How to determine the partition for the updating problem ?

### Rules of the partition

- Put the updated states into  $G$ .
- Put the nearest states to the update into  $G$ .
- Put the states which have a large stationary probability into  $G$ .(slow converging states shown by Kamvar et al.)

**Experiments**

Topic	Number of Nodes	Number of Links	Total number of nodes	Total number of links
Genetics	2,952	6,485	3,200	6,900
California	9,664	16,150	10,300	17,000

- Adding and deleting some nodes
- Adding and deleting some links
- Stopping criterion  $\|\psi^T - \chi^T\|_1 < 10^{-10}$

**Genetics**

$g =  G $	<i>Iterations</i>	<i>Time (sec)</i>
10	163	2.16
50	19	.483
100	19	.456
250	17	.276
500	9	.313
1000	8	.319
<i>Power Method</i>	165	1.45

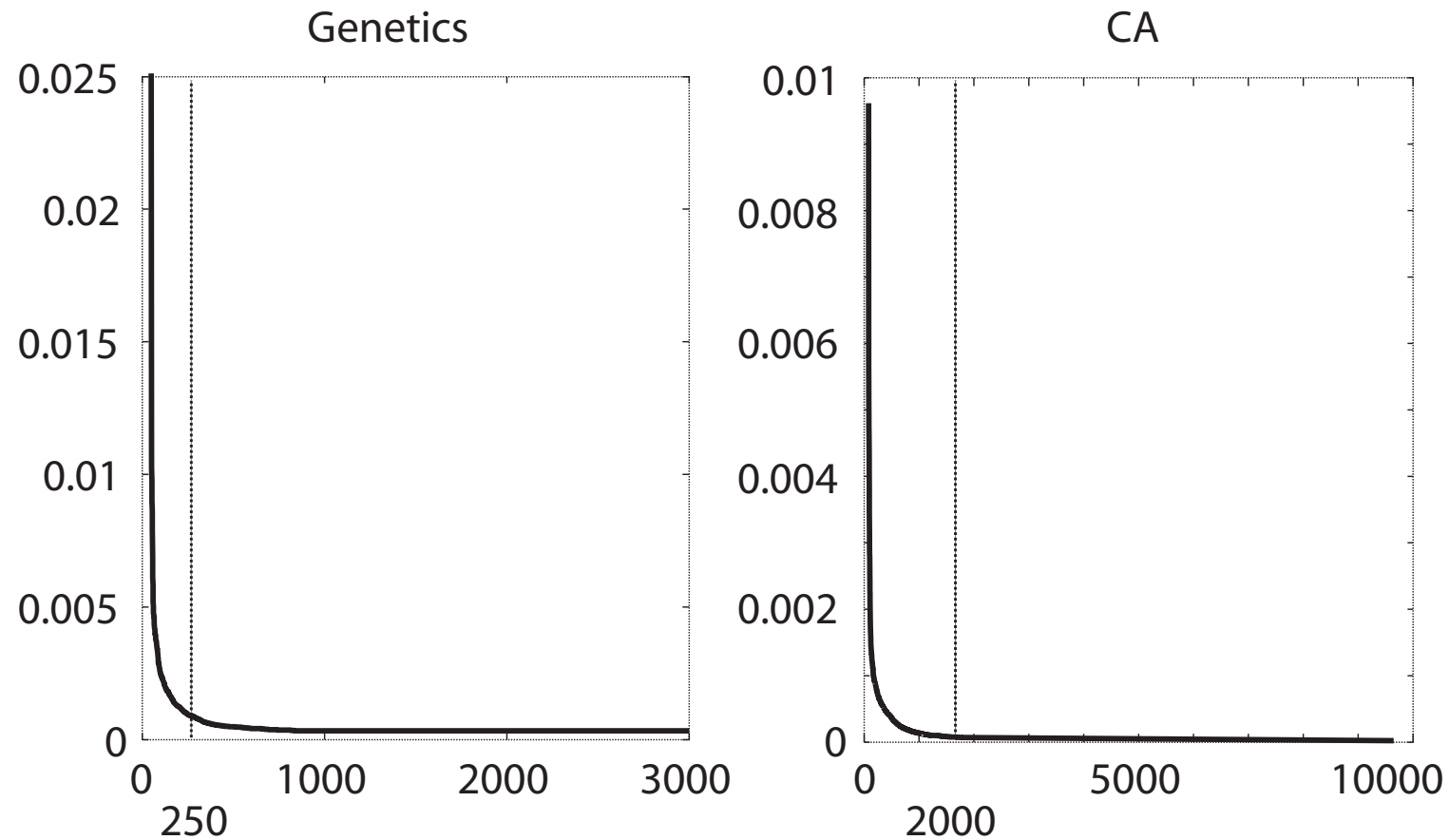
Iterative aggregation algorithm is about 5 times faster than Power method



## California

$g =  G $	<i>Iterations</i>	<i>Time (sec)</i>
10	170	7.75
50	75	3.56
100	57	3.75
250	51	2.59
500	34	2.01
1000	19	1.03
2000	10	.997
3000	7	1.17
4000	7	1.22
5000	7	1.56
<i>Power Method</i>	176	5.87

Iterative aggregation algorithm is about 6 times faster than Power method

**Location of G-Opt**

- Size of G near optimal stay around the right of the bend.

## Conclusion And Future Work

### Conclusion

Appropriate partitions can greatly speed up Stationary vector computation.

### Future work

- Combine the Iterative Aggregation with other methods to increase the speed of entire process.
- Find a concrete way to partition  $S = G \cup \bar{G}$ .
- Investigate the relationship between  $|\lambda_2|$  of the  $\mathbf{S}$  and  $|G|$ .
- Work with real life data.