# The Billion Dollar Eigenvector

The mathematics behind Google's pagerank algorithm

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#### The Web

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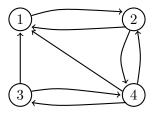
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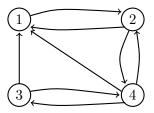
To make things concrete let's consider a simplified web with only four pages that are linked as follows:



## PageRank

The idea behind PageRank is that we should give each page a score which is based on the number of links to that page.

So, in our example network



page 1 should rank highly because it has a lot of incoming links. So the scores might be:

$$x_1 = 3, \quad x_2 = 2, \quad x_3 = 1, \quad x_4 = 2$$
?

#### Some votes matter more

There are two extra tricks that make this work well.

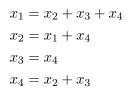
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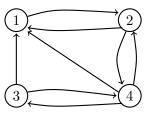
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This would suggest formulas such as

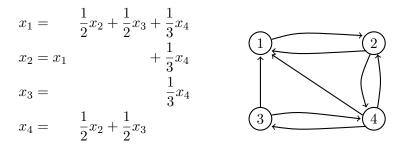




But, there are various problems with this. For example, there is **no non-zero solution** to this system!

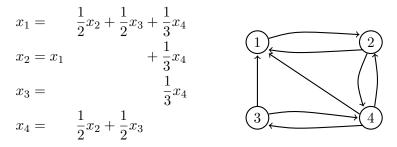
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This approach works well! For our web, it gives:

$$x_1 = 4, \quad x_2 = 5, \quad x_3 = 1, \quad x_4 = 3,$$

with page 2 ranked the highest.

## Matrix form

The equations we got

$$x_{1} = \frac{1}{2}x_{2} + \frac{1}{2}x_{3} + \frac{1}{3}x_{4}$$

$$x_{2} = x_{1} + \frac{1}{3}x_{4}$$

$$x_{3} = \frac{1}{3}x_{4}$$

$$x_{4} = \frac{1}{2}x_{2} + \frac{1}{2}x_{3}$$

can be written in matrix form:

$$\vec{x} = A\vec{x}$$

where

$$\vec{x} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{pmatrix} \quad \text{and} \quad A = \begin{pmatrix} 0 & \frac{1}{2} & \frac{1}{2} & \frac{1}{3} \\ 1 & 0 & 0 & \frac{1}{3} \\ 0 & 0 & 0 & \frac{1}{3} \\ 0 & \frac{1}{2} & \frac{1}{2} & 0 \end{pmatrix}$$

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is called finding an eigenvector of A with eigenvalue 1. Since A is a stochastic matrix, such an  $\vec{x}$  always exists.

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What's more surprising is that there is an efficient way to compute it, even when A is huge. (It might be 10 billion by 10 billion!) You simply start with a random  $\vec{x}$  and then compute  $A^k \vec{x}$  for large k to find an approximate steady-state vector.

For more details, see the excellent article by Kurt Bryan and Tanya Leise at

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# PS: When you are rich, don't forget who taught you Linear Algebra!