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Lecture 2 - Google's PageRank: Why math helps

OBJECTIVE: Motivate linear algebra and probability as important and necessary tools for understanding large datasets. We also describe the algorithm at the core of the Google search engine.

\diamond PAGERANK

Consider the following mini-web of 3 pages (the data):

The nodes are the webpages and the arrows are links. The numbers are the normalised number of links. We can re-write this directed graph as a **transition matrix**:

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T is a **stochastic matrix**: its columns add up to 1, so that

 $T_{i,j} = P(x_j | x_i)$ $\sum_j T_{i,j} = 1$

In information retrieval, we want to know the "relevance" of each webpage. That is, we want to compute the probability of each webpage: $p(x_i)$ for i = 1, 2, 3.

Let's start with a random guess $\pi = (0.5, 0.2, 0.3)$ and "crawl the web" (multiply by *T* several times). After, say N = 100, iterations we get:

$$\pi^T T^N = (0.2, 0.4, 0.4)$$

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We soon notice that no matter what initial π we choose, we always converge to p = (0.2, 0.4, 0.4). So

 $p^T T =$

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The distribution p is a measure of the relevance of each page. Google uses this. But will this work always? When does it fail?



The **Perron-Frobenius Theorem** tell us that for any starting point, the chain will converge to the invariant distribution p, as long as T is a stochastic transition matrix that obeys the following properties:

1. **Irreducibility**: For any state of the Markov chain, there is a positive probability of visiting all other states. That is, the matrix T cannot be reduced to separate

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smaller matrices, which is also the same as stating that the transition graph is connected.

2. **Aperiodicity**: The chain should not get trapped in cycles.

Google's strategy is to add am matrix of uniform noise E to T:

$L = T + \epsilon E$

where ϵ is a small number. *L* is then normalised. This ensures irreducibility.

How quickly does this algorithm converge? What determines the rate of convergence? Again matrix algebra and spectral theory provide the answers: CPSC-340: Machine Learning and Data Mining



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