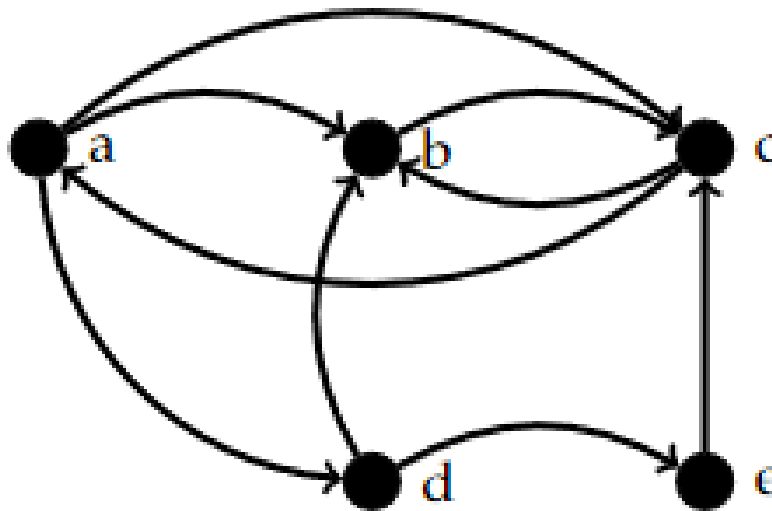


Exercise P22: Consider the graph of five web pages a, b, c, d, e, shown below, where each page links to some of the other pages as show. The goal of this problem, is to compute the Google PageRank of the pages., In factm, this proble, ios about the essential idea which created Google, only about 25 years ago.

Figure 1: P22 graph



- a. Start by asking Google to document itself. Go to Google Scholar and search for 'pagerank citation ranking'. The first link, the one with highest PageRank, will be a technical preprint by Page, Brin Motwani, and Winograd; it has more than 150,000 citations. Download the 17 page PDF and read it. It describes a simpler time. The main ideas are about a web as a directed graph, as in the example shown above, that the limiting probability that a certain random web surfer visits any particular page is its PageRank, and finally that a search engine should report results in the Page Rank order. We can regard PageRank as simply an eigenvector of a certain matrix A , a transition probability matrix for a Markov chain. To build A we will start with the adjacency matrix G of the web. Here is how to start with a web as directed graph and construct G, A and the eigen vector of PageRank values:
- Let W be a connected, directed graph of n webpages, Index the pages 1 through n . Let G , be the $n \times n$ connectivity matrix W that is,

The number of nonzeros in G is the total number of hyperlinks in W . Let c_j be the

columns sums of G ;

$$c_j = \sum_{i=1}^n g_{ij}$$

The value of c_j gives the outdegree of the j th page. Let p be the fraction of the time that the random walk follows some link, so $1 - p$ is the fraction of time that an arbitrary page is chosen. Define $\sigma = (1 - p)/n$. Now let A be the $n \times n$ matrix whose entries are,

$$a_{ij} = \frac{pg_{ij}}{c_j} + \sigma$$

The matrix A is the transition probability matrix of the random-surfer Markov chain. An old theorem says the largest eigenvalue of A is equal to one and the corresponding eigenvector, which satisfies

$$Ax = x$$

is unique up to a scaling factor, and has positive entries. Choose the scaling so that,

$$1 = \sum_{i=1}^n x_i$$

the entries of x are the Page Ranks of webpages in W .

For a realistic web, G is huge and sparse because most pairs of webpages are not connected by a single link. Google suggests $p = .85$. Matrix A is not sparse because most entries are equal to the small constant $\sigma > 0$. The 'old' Perron-Frobenius Theorem says that if all entries in a matrix are positive then all the entries of the eigenvector associated to the largest eigenvalue can be chosen to be positive.

1. b. Following my description of the process, compute G for the web shown above.

Solution:

From the passage above we know that G is the adjacency matrix for the figure 1. Building the adjacency matrix we get,

$$\begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

- c. Continuing from my description, build A from G using $p = .85$ as suggested. Finally, use Matlab's `eig` to compute the PageRanks. Which page gets the highest PageRank? explain in intuitive terms.

Solution:

The following Matlab script computes A from G , and uses the `eig()` function to compute the PageRanks