

imp and dynamical processes on complex networks are highly dependent on the network structure. The largest eigenvalue of the network adjacency matrix (which we denote by λ_1) is the key quantity determining a variety of different dynamical processes on networks. For example, (i) for a heterogeneous collection of chaotic and/or periodic dynamical systems coupled by a network of connections, the critical coupling strength [2] for the emergence of coherence is proportional to $1/\lambda_1$; (ii) in a class of percolation problems on directed networks [closely related to the problem of epidemic spreading [3]], the condition for the emergence of a giant component also involves λ_1 [4]. For other examples where λ_1 plays a similar role, see Refs. [5–7].

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In recent years, there has been much interest in the study of the structure of networks arising from real world systems, of dynamical processes taking place on networks, and of how network structure impacts such dynamics [1]. The largest eigenvalue of the network adjacency matrix (which we denote by λ_1) is the key quantity determining a variety of different dynamical processes on networks. For example, (i) for a heterogeneous collection of chaotic and/or periodic dynamical systems coupled by a network of connections, the critical coupling strength [2] for the emergence of coherence is proportional to $1/\lambda_1$; (ii) in a class of percolation problems on directed networks [closely related to the problem of epidemic spreading [3]], the condition for the emergence of a giant component also involves λ_1 [4]. For other examples where λ_1 plays a similar role, see Refs. [5–7].

In many situations it might be desirable to control dynamical processes that take place on networks. For example, nodes, and we associate to it an adjacency matrix whose elements

are positive if there is a link going from node i to node j with $A_{ij} \neq 0$ and zero otherwise ($A_{ij} = 0$). We denote the largest eigenvalue of A by λ_1 , where $\lambda_1 = \max_i \sum_j A_{ij}$ and $\lambda_1 = \max_j \sum_i A_{ij}$ with \mathbf{r} and \mathbf{l} denoting the right and left eigenvectors of A . According to Perron's theorem [7], of all the eigenvalues of A , the one with largest magnitude

$$(1 + \epsilon)(1 + \delta) = (1 + \delta)(1 + \epsilon) \quad (3)$$

by neglecting second order terms and ϵ , we obtain $\delta = -\epsilon$. Upon removal of edge (i, j) , the perturbation matrix is $(\delta_{ij}) = -\epsilon$, and therefore

$$\delta_{ij} = -\epsilon \quad (4)$$

We now examine the effect of removing node i . Upon its removal, the perturbation matrix is given by $(\delta_{ij}) = -\epsilon$ ($i < j$). However, in this case we cannot assume ϵ is small as we did before, since $\delta_{ij} = -\epsilon$ (the left and right eigenvectors have zero i th entry after the removal of node i). Therefore, we set $\delta_{ij} = -\epsilon \hat{e}_i$, where \hat{e}_i is the unit vector for the i component, and we assume ϵ is small.

Our next example is motivated by the fact that it is sometimes observed that real networks can be subdivided

where n is the number of removed nodes and λ_1 is the largest eigenvalue of the resulting network. We see that using the dynamical importance (solid lines) greatly improves the results over using the degree (short dashed