Random walks and diffusion on networks Complex Networks, Course 303A, Spring, 2009

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# Random walks on networks-basics:

- Imagine a single random walker moving around on a network.
- At t = 0, start walker at node j and take time to be discrete.
- Q: What's the long term probability distribution for where the walker will be?
- Define p<sub>i</sub>(t) as the probability that at time step t, our walker is at node i.
- We want to characterize the evolution of  $\vec{p}(t)$ .
- First task: connect  $\vec{p}(t+1)$  to  $\vec{p}(t)$ .
- Let's call our walker Barry.
- Unfortunately for Barry, he lives on a high dimensional graph and is far from home.
- Worse still: Barry is hopelessly drunk.

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## Random walks on networks

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# Where is Barry?

- Consider simple undirected networks with an edges either present of absent.
- Represent network by a symmetric adjacency matrix A where

 $a_{ij} = 1$  if *i* and *j* are connected,  $a_{ij} = 0$  otherwise.

- Barry is at node *i* at time *t* with probability  $p_i(t)$ .
- In the next time step he randomly lurches toward one of *i*'s neighbors.
- Equation-wise:

$$p_j(t+1) = \sum_{i=1}^n \frac{1}{k_i} a_{ji} p_i(t).$$

where  $k_i$  is *i*'s degree. Note:  $k_i = \sum_{i=1}^n a_{ii}$ .

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# Where is Barry?

• Linear algebra-based excitement:  $p(t+1) = \sum_{i=1}^{n} 1 = p(t)$  is more use

 $p_j(t+1) = \sum_{i=1}^n \frac{1}{k_i} a_{ji} p_i(t)$  is more usefully viewed as

 $\vec{p}(t+1) = AK^{-1}\vec{p}(t)$ 

where  $[K_{ij}] = [\delta_{ij}k_i]$  has node degrees on the main diagonal and zeros everywhere else.

- So... we need to find the dominant eigenvalue of AK<sup>-1</sup>.
- Expect this eigenvalue will be 1 (doesn't make sense for total probability to change).
- The corresponding eigenvector will be the limiting probability distribution (or invariant measure).
- Extra concerns: multiplicity of eigenvalue = 1, and network connectedness.

# Other pieces:

- Good news: AK<sup>-1</sup> is similar to a real symmetric matrix.
- Consider the transformation  $M = K^{-1/2}$ :

$$K^{-1/2}AK^{-1}K^{1/2} = K^{-1/2}AK^{-1/2}$$

• Since  $A^{\mathrm{T}} = A$ , we have

$$(K^{-1/2}AK^{-1/2})^{\mathrm{T}} = K^{-1/2}AK^{-1/2}$$

- Upshot: AK<sup>-1</sup> has real eigenvalues and a complete set of orthogonal eigenvectors.
- Can also show that maximum eigenvalue magnitude is indeed 1.
- Other goodies: next time round.

Where is Barry?

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By inspection, we see that

$$\vec{p}(\infty) = \frac{1}{\sum_{i=1}^{n} k_i} \vec{k}$$

satisfies  $\vec{p}(\infty) = AK^{-1}\vec{p}(\infty)$  with eigenvalue 1.

- We will find Barry at node *i* with probability proportional to its degree k<sub>i</sub>.
- Nice implication: probability of finding Barry travelling along any edge is uniform.
- Diffusion in real space smooths things out.
- > On networks, uniformity occurs on edges.
- So in fact, diffusion in real space is about the edges too but we just don't see that.

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