



1. Consider the “triangle graph” shown above. Solve the linearized naive network SI model for this graph with  $\beta = 1$  and  $\langle x_1(t=0) \rangle = 1$  and  $\langle x_2(t=0) \rangle = \langle x_3(t=0) \rangle = 0$

**Solution:** Since the adjacency matrix is symmetric, the procedure is essentially the same as for question 4 on problem sheet 6. The eigenvalues of  $\mathbf{A}$  are  $\lambda_1, \lambda_2, \lambda_3 = 2, -1, -1$ , with the same orthonormal eigenvectors that we have for the Laplacian, and then,  $\mathbf{A} = \mathbf{V}\mathbf{\Lambda}\mathbf{V}^T$  with  $\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3]$ . Let  $\mathbf{g}_0 = \mathbf{V}^T \langle \mathbf{x}(t=0) \rangle$ . Then  $g_i = g_{0,i}e^{it}$  and  $\langle \mathbf{x} \rangle = \mathbf{V}\mathbf{g}$ . Symmetry dictates that nodes 2 and 3 will have the same solutions and at long times  $\langle x_i \rangle$  will grow exponentially for all nodes.

2. Consider the naive network-SI model on an  $N$ -node complete graph. Derive an approximate nonlinear ODE for  $\bar{x} = \frac{1}{N} \sum_{i=1}^N \langle x_i \rangle$  when  $N$  is large (the accuracy of the approximation should increase as  $N$  increases)

**Solution:** The naive network-SI model on a complete graph is,

$$d \langle x_i \rangle / dt = \beta (1 - \langle x_i \rangle) \left[ \sum_{j=1}^N \langle x_j \rangle - \langle x_i \rangle \right].$$

Then take the sum of both sides over all nodes and divide by  $N$ :

$$\frac{d\bar{x}}{dt} = \beta \sum_{i=1}^N (1 - \langle x_i \rangle) \left[ \bar{x} - \frac{\langle x_i \rangle}{N} \right]$$

For sufficiently large  $N$ , we can use the approximation,  $\bar{x} - \frac{\langle x_i \rangle}{N} \approx \bar{x}$ . The ODE then can be simplified to,

$$\frac{d\bar{x}}{dt} \approx \beta N (1 - \bar{x}) \bar{x}$$

which is usually simply referred to as *the* SI model.

3. Consider a “cloud” of particles undergoing random walks on a simple  $N$ -node graph. Let  $n_i(t)$  and  $n_j(t)$  be the number of particles on nodes  $i$  and  $j$  at time  $t$ . Given  $n_i(t)$  and  $n_j(t)$ , what is the expected net flux of particles from node  $j$  to  $i$  between  $t$  and  $t + \Delta t$ . In other words, how many more particles are expected to move from node  $j$  to node  $i$  than from  $i$  to  $j$  during a time step? Give your answer in terms of  $n_i(t)$ ,  $n_j(t)$ ,  $k_i$ , and  $k_j$ . How does your result compare to the net flux of particles associated with diffusion on a graph?

(It may be helpful to work with an indicator random variable,  $X_{ija}$ , which is 1 if particle  $a$  on node  $j$  moves to  $i$  and is zero otherwise.)

**Solution:** Let  $X_{ija}$  be an indicator variable which is 1 if particle  $a$  on node  $j$  moves to  $i$  and is 0 otherwise. The net flux is then

$$j_{ij,net} = \sum_{a=1}^{n_j} X_{ija} - \sum_{a=1}^{n_i} X_{jia}.$$

Using linearity of expectation,

$$\langle j_{ij,net} \rangle = \sum_{a=1}^{n_j(t)} \langle X_{ija} \rangle - \sum_{a=1}^{n_i(t)} \langle X_{jia} \rangle,$$

and  $\langle X_{ija} \rangle = P(X_{ija} = 1) = 1/k_j$  with an analogous result for  $\langle X_{jia} \rangle$ . So the net flux is,  $\langle j_{ij,net} \rangle = n_j(t)/k_j - n_i(t)/k_i$ . The net flux in graph-diffusion does not depend on the node degrees.

4. Consider the following definition of a step of a random walk on a connected directed  $N$ -node graph with adjacency matrix  $\mathbf{A}$ . Each step begins with a Bernoulli trial with probability of success,  $\pi$ . If successful, the walker chooses an outward link uniformly at random and follows it to a neighboring node. If unsuccessful, the walker finds itself picked up and “dropped” back onto the graph which we model as selecting a node uniformly at random.

- (a) What is the master equation for this process? Let  $p_i^{(l+1)}$  be the probability a walker is at node  $i$  after  $l + 1$  steps. You should derive an equation relating  $p_i^{(l+1)}$  to the elements in the probability vector at iteration  $l$ , as well as  $N$ ,  $\mathbf{A}$ ,  $\pi$  and the node degrees (e.g.  $k_i^{out}$ ).

**Solution:** Consider the probability that walker is at node  $j$  at iteration  $l + 1$ . It can reach this node via a step from a neighboring node or by being dropped onto the node. The probability that a walker is at node  $i$  at iteration  $l$  and then takes a step to  $j$  is  $A_{ji}/k_i^{out} p_i^{(l)}$ . The probability of  $j$  being the node a walker is dropped on is,  $1/N$ . Combining these probabilities, we find,  $p_j^{(l+1)} = \sum_{i=1}^N \left[ \pi p_i^{(l)} A_{ji}/k_i^{out} \right] + (1 - \pi)/N$ , and since the sum of the probability vector is 1, this can be rearranged as,  $p_j^{(l+1)} = \sum_{i=1}^N \left[ \pi A_{ji}/k_i^{out} + (1 - \pi)/N \right] p_i^{(l)}$

- (b) Interpret the equation for the stationary state as a node centrality. What is the role of the probability,  $\pi$ ?

**Solution:** The equation for the stationary state is identical to the equation for PageRank centrality with  $\pi$  replacing  $(1 - m)$ . This interpretation of PageRank as a random walk with “teleportation” was provided by Brin & Page in their initial paper on PageRank and Google.

5. Consider the following modification to the network-SI model: the probability that an infectious node becomes susceptible in time  $\Delta t$  is  $\gamma \Delta t$ . Taking this modification into account, and applying the limit  $\Delta t \rightarrow 0$ , derive the resulting system of ODEs known as the *network-SIS model*

**Solution:** The master equation for the network-SI model is,

$$P(x_i(t + \Delta t) = 1) = P(x_i(t) = 1) + \beta \Delta t \sum_{j=1}^N A_{ij} P(x_i(t) = 0, x_j(t) = 1) + O(\Delta t^2).$$

The first term on the RHS is the probability that the node is infected at time  $t$ . We have to modify this to account for the possibility that the node recovers between  $t$  and  $t + \Delta t$ . Specifically, we replace  $P(x_i(t) = 1)$  with  $P(x_i(t) = 1, x_i \not\rightarrow 0)$  where  $x_i \not\rightarrow 0$  indicates that an infectious node does not recover between  $t$  and  $t + \Delta t$ . Then,

$$P(x_i(t) = 1, x_i \not\rightarrow 0) = P(x_i \not\rightarrow 0 | x_i(t) = 1)P(x_i(t) = 1) = (1 - \gamma\Delta t)P(x_i(t) = 1).$$

Replacing  $P(x_i(t) = 1)$  with this expression in the master equation, rewriting probabilities as expectations, and letting  $\Delta t \rightarrow 0$  gives us the network-SIS model:

$$d\langle x_i \rangle / dt = \beta \sum_{l=1}^N A_{il} \langle s_i x_l \rangle - \gamma \langle x_i \rangle,$$

$$s_i = 1 - x_i.$$

Note that I have not considered the probability that a node both recovers and is then reinfected during time  $\Delta t$ . This effect will be  $O(\Delta t^2)$  and will vanish when  $\Delta t \rightarrow 0$ .