

Mathematics for Informatics 4a

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Lecture 18
23 March 2012

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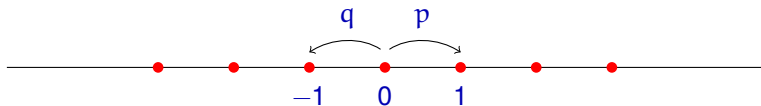
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- In today's lecture we will look at random walks on simpler graphs and will focus on a different sort of questions

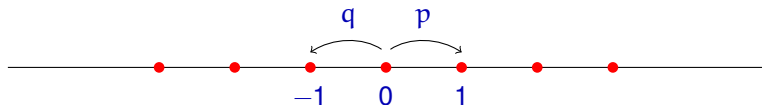
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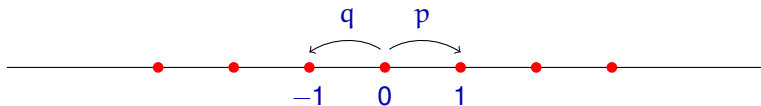


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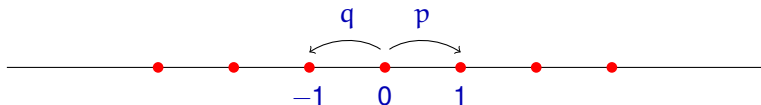
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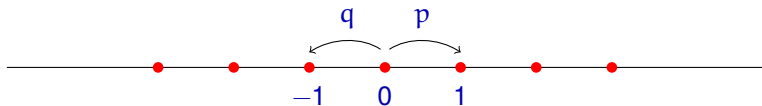
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$$T_r = \begin{cases} \text{number of steps until we visit } r \text{ for the first time,} & r \neq 0 \\ \text{number of steps until we revisit } 0, & r = 0. \end{cases}$$

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Question: How the T_r are distributed? i.e., $\mathbb{P}(T_r = n) = ?$

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- $T_r = T_{0,1} + T_{1,2} + \cdots + T_{r-1,r}$ and by independence

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$$\mathbb{E}(s^{T_r}) = \mathbb{E}(s^{T_1})^r$$

- Conditioning on the first jump,

$$\begin{aligned}\mathbb{E}(s^{T_1}) &= \mathbb{E}(s^{T_1} \mid J_1 = 1)\mathbb{P}(J_1 = 1) + \mathbb{E}(s^{T_1} \mid J_1 = -1)\mathbb{P}(J_1 = -1) \\ &= sp + s\mathbb{E}(s^{T_{-1,0} + T_{0,1}})q \\ &= sp + sq\mathbb{E}(s^{T_1})^2\end{aligned}$$

which we solve for $\mathbb{E}(s^{T_1})$

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$$\mathbb{E}(s^{T_1}) = \frac{1 - \sqrt{1 - 4pqs^2}}{2sq}$$

- Hence for $r > 0$,

$$\mathbb{E}(s^{T_r}) = \left(\frac{1 - \sqrt{1 - 4pqs^2}}{2sq} \right)^r$$

and for $r < 0$ we simply replace $p \leftrightarrow q$

Hitting times for random walks III

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- We condition on the first jump:

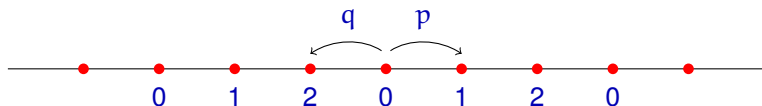
$$\begin{aligned}\mathbb{E}(s^{T_0}) &= \mathbb{E}(s^{T_0} \mid J_1 = 1)\mathbb{P}(J_1 = 1) + \mathbb{E}(s^{T_0} \mid J_1 = -1)\mathbb{P}(J_1 = -1) \\ &= s\mathbb{E}(s^{T_{1,0}})p + s\mathbb{E}(s^{T_{-1,0}})q \\ &= sp\mathbb{E}(s^{T_{-1}}) + sq\mathbb{E}(s^{T_1})\end{aligned}$$

$$\begin{aligned}&= sp \left(\frac{1 - \sqrt{1 - 4pqs^2}}{2sp} \right) + sq \left(\frac{1 - \sqrt{1 - 4pqs^2}}{2sq} \right) \\ &= 1 - \sqrt{1 - 4pqs^2}\end{aligned}$$

$$\therefore \mathbb{E}(T_0) = \frac{4pq}{\sqrt{1 - 4pq}} \rightarrow \infty \quad \text{if } p = q$$

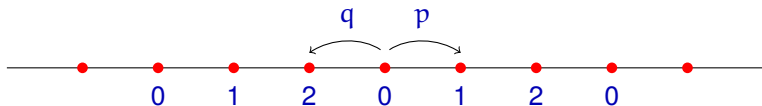
Random walk on a triangle

Let us consider again the random walk on the integers, but this time we only keep track of the position *modulo* 3:

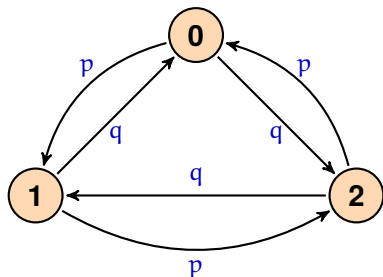


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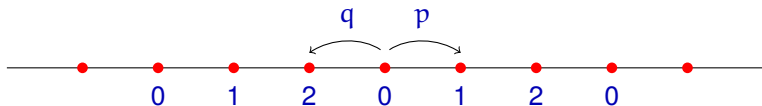


This is equivalent to the following 3-state Markov chain describing a random walk on a triangle:

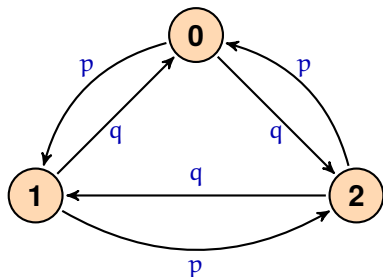


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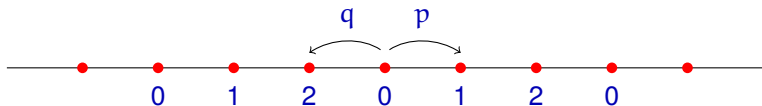
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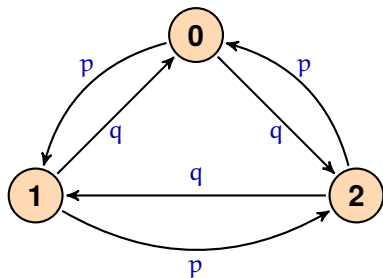
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$$\pi = \left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3} \right)$$

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(We will not prove it; although it is not hard.)

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In terms of $\gamma_i = \mathbb{E}(s^{T_i})$, we have

$$\gamma_0 = s(p\gamma_1 + q\gamma_2) \quad \gamma_1 = s(q + p\gamma_2) \quad \gamma_2 = s(p + q\gamma_1)$$

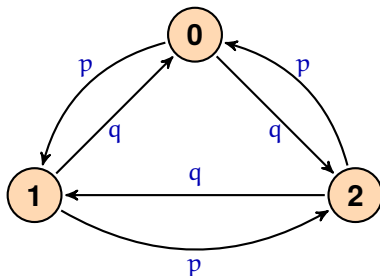
Hitting times distribution II

The unique solution is

$$\mathbb{E}(s^{T_0}) = \frac{s^2(2pq + p^3s + q^3s)}{1 - pq s^2} = 2pqs^2 + (p^3 + q^3)s^3 + 2p^2q^2s^4 + \dots$$

$$\mathbb{E}(s^{T_1}) = \frac{s(q + p^2s)}{1 - pq s^2} = qs + p^2s^2 + pq^2s^3 + \dots$$

$$\mathbb{E}(s^{T_2}) = \frac{s(p + q^2s)}{1 - pq s^2} = ps + q^2s^2 + p^2qs^3 + \dots$$



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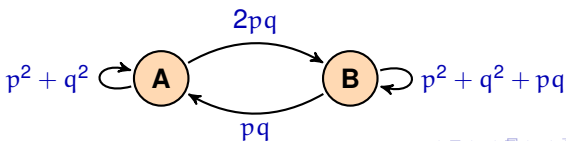
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In terms of $\theta = pq$, the transition matrix is

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$$\implies \mathbb{E}(U) = \frac{1}{pq} \implies \mathbb{E}(T) = 3$$

Three independent random walks I

Now consider *three* particles moving in a triangle, but let us assume for simplicity that the random walk is symmetric, so that

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Three independent random walks I

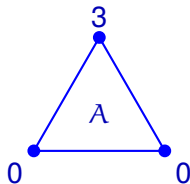
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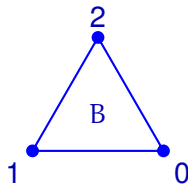
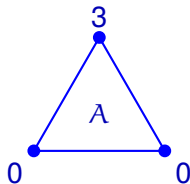


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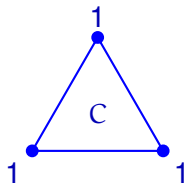
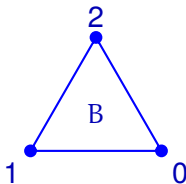
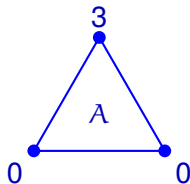


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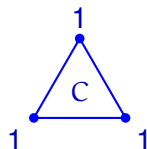
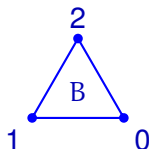
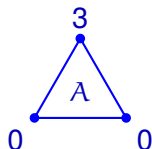
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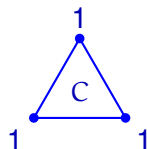
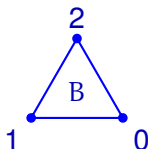
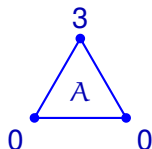
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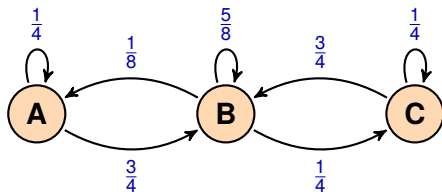
Three independent random walks II



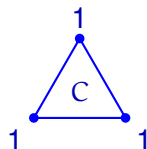
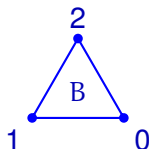
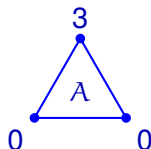
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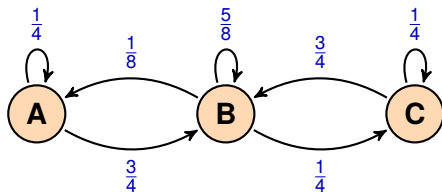
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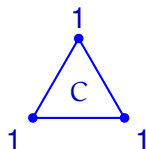
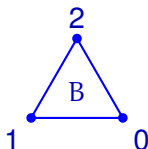
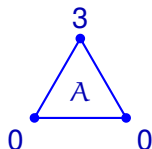


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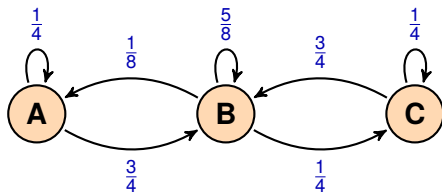


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Three independent random walks II



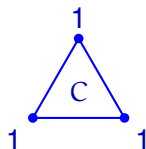
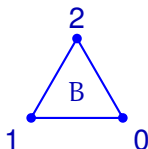
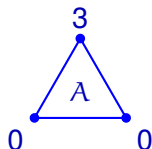
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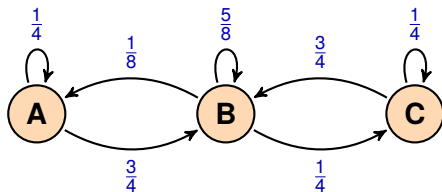
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Therefore $\mathbb{E}(T) = 9$.

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$$\begin{aligned}\mathbb{E}(T) &= 9 \\ \implies \mathbb{E}(U) &= \frac{32}{3} \\ \mathbb{E}(V) &= 12\end{aligned}$$

Three independent random walks III

Let Z be the number of steps until the particles meet again at the *starting* vertex. What is $\mathbb{E}(Z)$?

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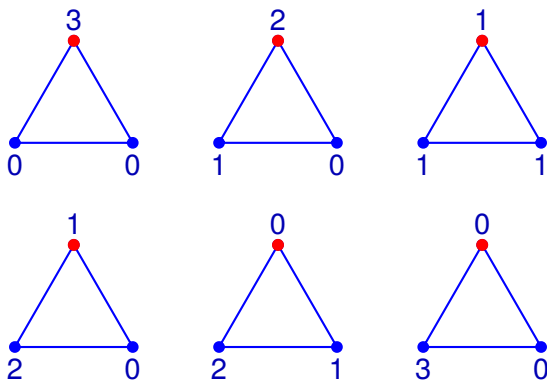
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We now have four types of configurations, labelled by how many of the particles are at the starting vertex: 0, 1, 2 or 3.

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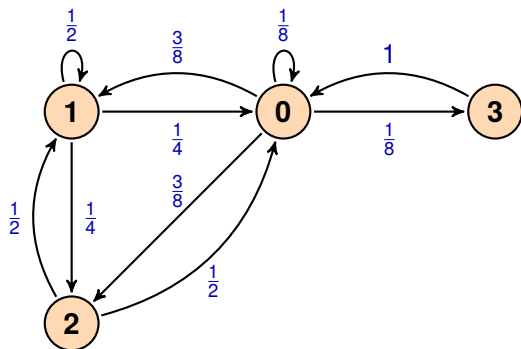
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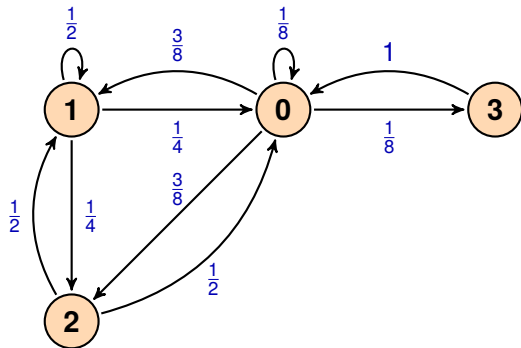
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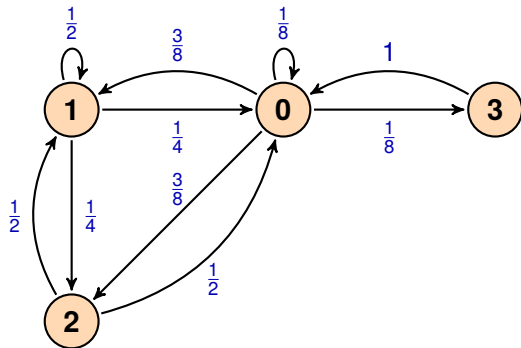
The corresponding 4-state Markov chain is:



$$P = \begin{pmatrix} \frac{1}{8} & \frac{3}{8} & \frac{3}{8} & \frac{1}{8} \\ \frac{1}{4} & \frac{1}{2} & \frac{1}{4} & 0 \\ \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}$$

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$$\pi = \left(\frac{8}{27}, \frac{4}{9}, \frac{2}{9}, \frac{1}{27} \right)$$
$$\implies \mathbb{E}(Z) = 27$$

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- Pick your favourite graphs and work out a couple of examples: the last assignment in this course will ask you to do this for K_4