

Recap: Stationary Distribution of markov chain

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- ▶ If $\pi_n = \pi, \forall n$ then π is a stationary distribution
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- ▶ A stationary distribution always exists for a finite chain

Recap

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- ▶ A recurrent state y is called **null recurrent** if $m_y = \infty$.
- ▶ y is called **positive recurrent** if $m_y < \infty$
- ▶ The limiting fraction of time spent by the chain in transient and null recurrent states is zero.
- ▶ **Theorem:** Let x be positive recurrent and let x lead to y . Then y is positive recurrent.

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- ▶ Hence, in the partition: $S_R = C_1 + C_2 + \dots$, each C_i is either wholly positive recurrent or wholly null recurrent.
- ▶ We next show that a finite chain cannot have any null recurrent states.

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where we could take the limit inside the sum because C is finite.

- ▶ If C is a finite closed set of recurrent states then all states in it cannot be null recurrent.

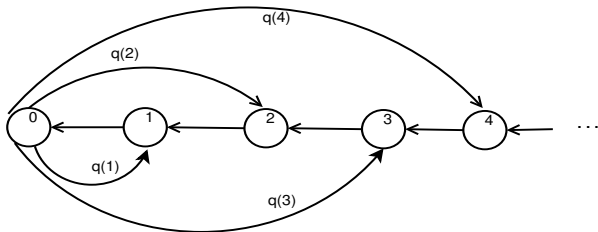
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- ▶ Actually what we showed is that any closed finite set must have at least one positive recurrent state.
- ▶ Hence, in a finite chain, every closed irreducible set of recurrent states contains only positive recurrent states.
- ▶ Hence, a finite chain cannot have a null recurrent state.

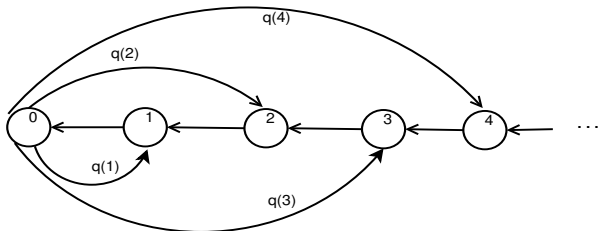
Example of null recurrent chain

- Consider the chain with state space $\{0, 1, \dots\}$ given by



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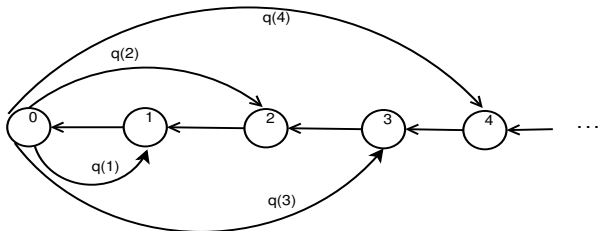
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- Here, $q(k) \geq 0, \forall k$ and $\sum_{k=1}^{\infty} q(k) = 1$.

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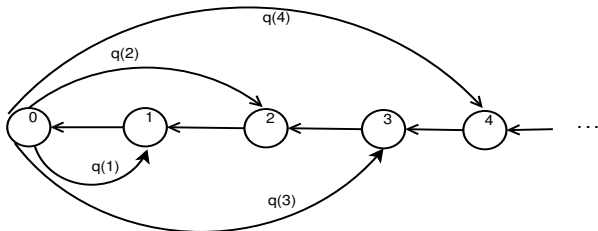
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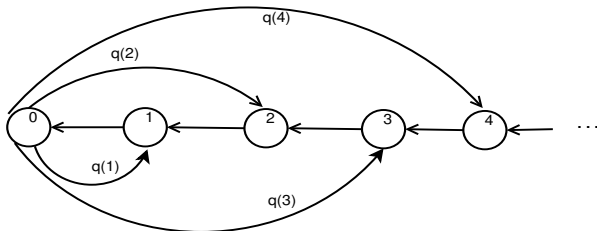
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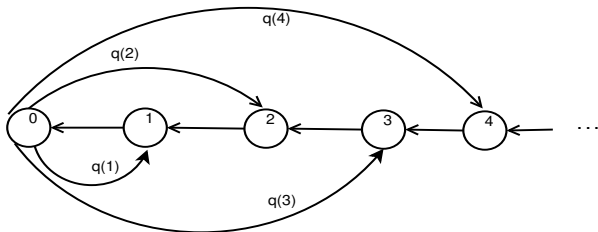
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- ▶ We can calculate ρ_{00} to test this.

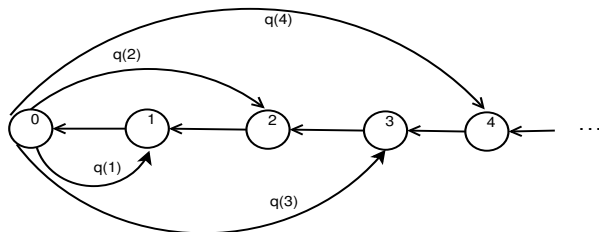
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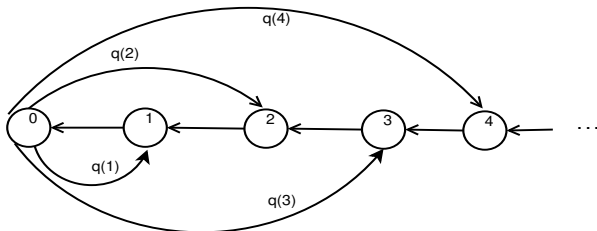
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$$P_0[T_0 = j + 1] = q(j), \quad j = 1, 2, \dots$$

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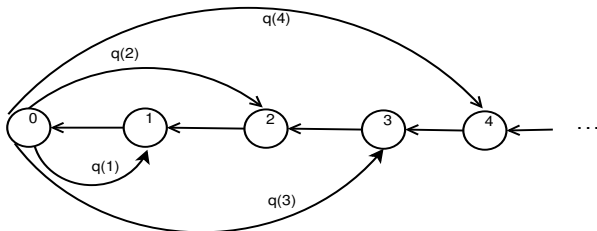
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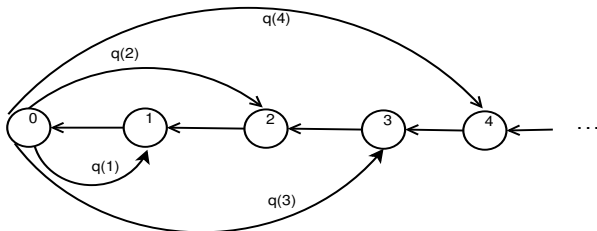
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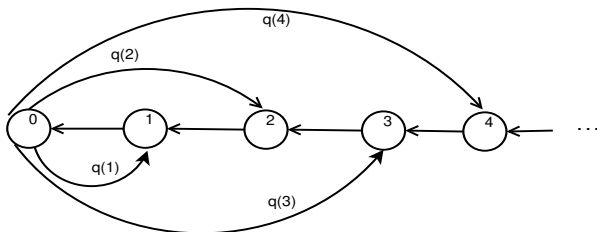
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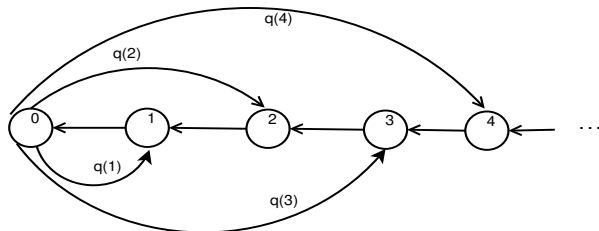
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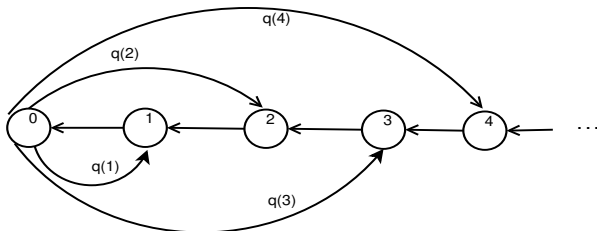
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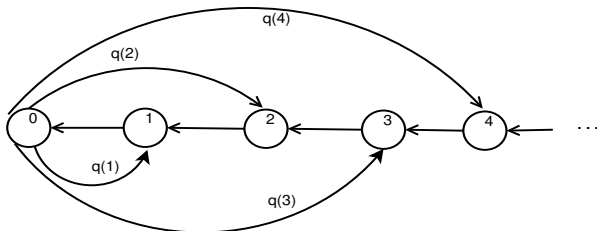


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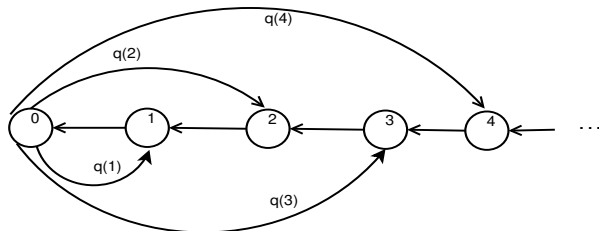
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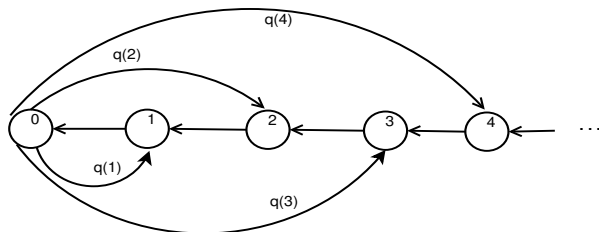
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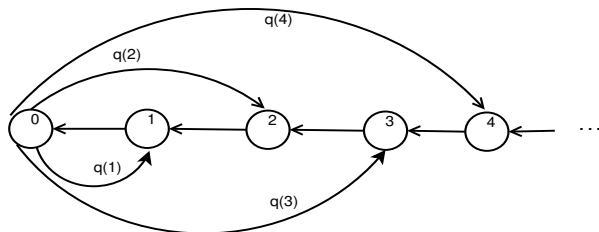
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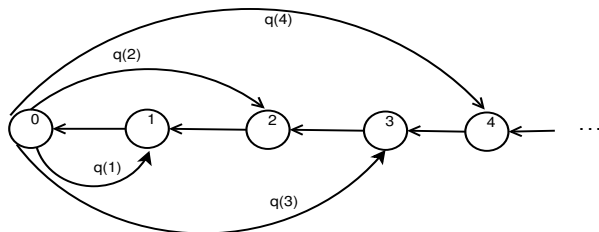
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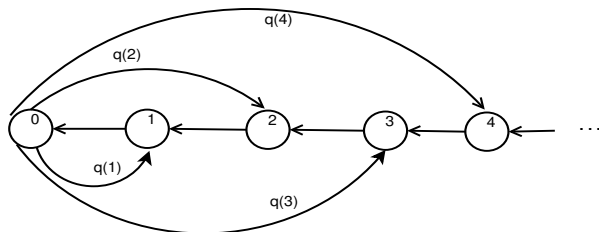
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- ▶ Then state 0 is null recurrent. Implies chain is null recurrent

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$$\Rightarrow \pi(y) = \frac{1}{n} \sum_{m=1}^n \sum_x \pi(x) P^m(x, y)$$

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$$\Rightarrow \pi(y) = \lim_{n \rightarrow \infty} \sum_x \pi(x) \frac{1}{n} \sum_{m=1}^n P^m(x, y)$$

- ▶ The proof is complete if we can take the limit inside the sum

Bounded Convergence Theorem

► **Bounded Convergence Theorem:**

1. Suppose $a(x) \geq 0$, $\forall x \in S$ and $\sum_x a(x) < \infty$.
2. Let $b_n(x)$, $x \in S$ be such that $|b_n(x)| \leq K$, $\forall x, n$ and

$$\lim_{n \rightarrow \infty} b_n(x) = b(x), \forall x \in S.$$

Then

$$\lim_{n \rightarrow \infty} \sum_{x \in S} a(x) b_n(x) = \sum_{x \in S} a(x) \lim_{n \rightarrow \infty} b_n(x) = \sum_{x \in S} a(x) b(x)$$

► **Bounded Convergence Theorem:** Suppose $a(x) \geq 0$, $\forall x \in S$ and $\sum_x a(x) < \infty$. Let $b_n(x)$, $x \in S$ be such that $|b_n(x)| \leq K$, $\forall x, n$ and suppose $\lim_{n \rightarrow \infty} b_n(x) = b(x)$, $\forall x \in S$. Then

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- Hence, if y is transient or null recurrent, then

$$\pi(y) = \sum_x \pi(x) \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{m=1}^n P^m(x, y) = 0$$

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- ▶ The null recurrent chain we considered earlier is an example of a Markov chain that does not have a stationary distribution.

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- ▶ Corollary: An irreducible chain has a stationary distribution if and only if it is positive recurrent

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Then there is a unique stationary distribution π that satisfies $\pi(y) = 0, \forall y \notin C$.
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- ▶ This answers all questions about existence and uniqueness of stationary distributions

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For example, $a_n = (-1)^n$

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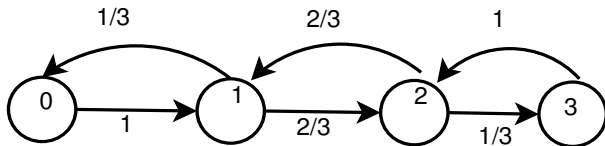
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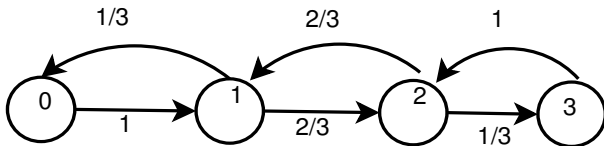
- One can show $\pi^T = [\frac{1}{8} \ \frac{3}{8} \ \frac{3}{8} \ \frac{1}{8}]$
- However, P^n goes to different limits based on whether n is even or odd

► The chain is the following



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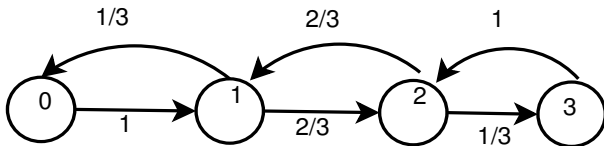
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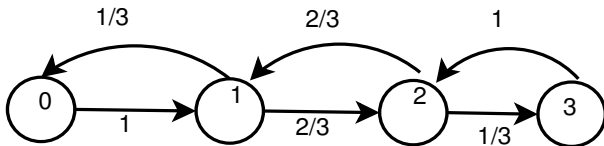
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- ▶ We can return to a state only after even number of time steps
- ▶ That is why P^n does not go to a limit
- ▶ Such a chain is called a periodic chain

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- ▶ An aperiodic, irreducible, positive recurrent chain is called an ergodic chain

Example

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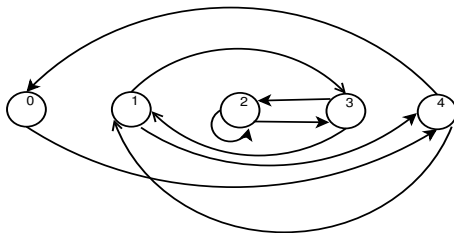
- Consider the umbrella problem

$$P = \left[\begin{array}{c|ccccc} & 0 & 1 & 2 & 3 & 4 \\ \hline 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1-p & p \\ 2 & 0 & 0 & 1-p & p & 0 \\ 3 & 0 & 1-p & p & 0 & 0 \\ 4 & 1-p & p & 0 & 0 & 0 \end{array} \right]$$

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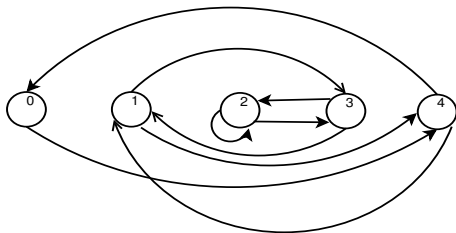
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- This is an irreducible, aperiodic positive recurrent chain

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- ▶ We are using the fact that this chain converges to the stationary distribution starting with any initial probabilities.

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The stationary distribution satisfies $\pi^T P = \pi^T$

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The stationary distribution satisfies $\pi^T P = \pi^T$

$$\pi(0) = (1-p)\pi(4)$$

$$\pi(1) = (1-p)\pi(3) + p\pi(4)$$

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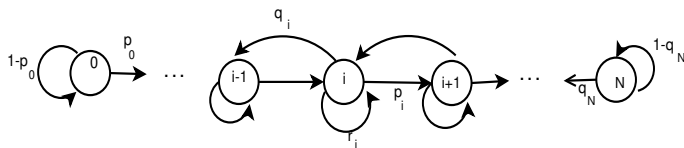
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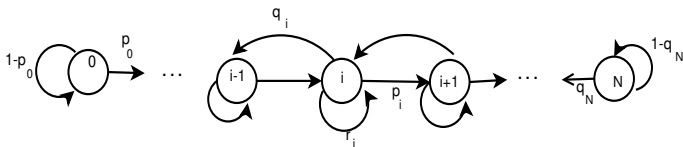
Birth-Death chains

- ▶ The following is a finite birth-death chain



Birth-Death chains

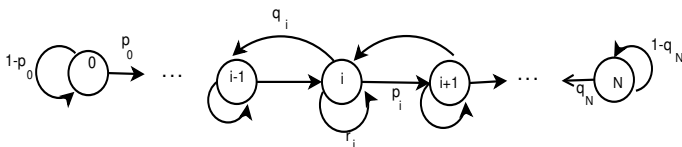
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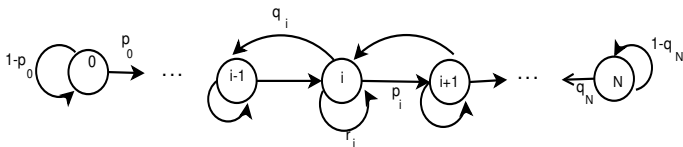
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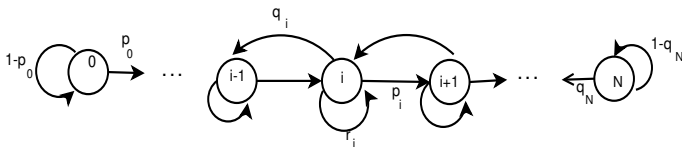
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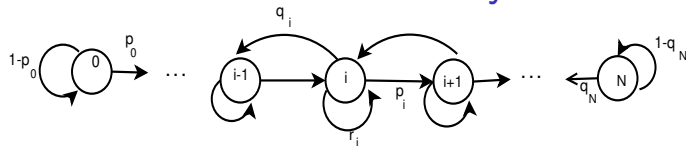
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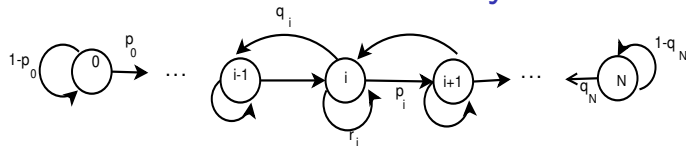


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- ▶ Then the chain is irreducible, positive recurrent
- ▶ It is also aperiodic
- ▶ We can derive a general form for its stationary probabilities

birth-death chains – stationary distribution

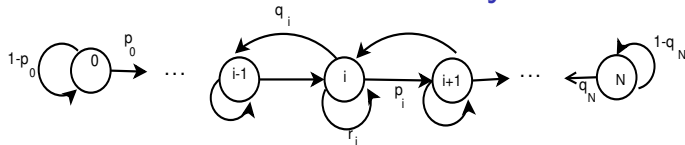


birth-death chains – stationary distribution



$$\pi(y) = \sum_x \pi(x) P(x, y)$$

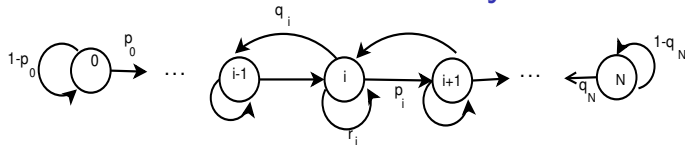
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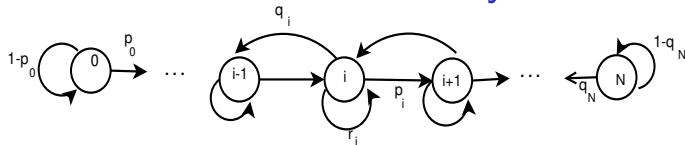
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birth-death chains – stationary distribution



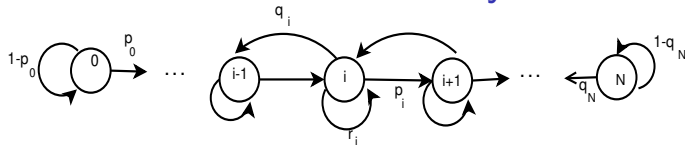
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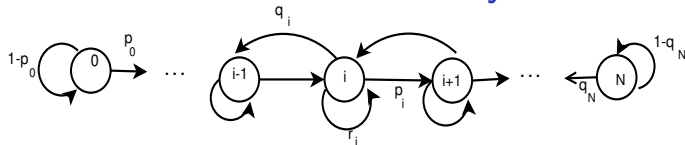
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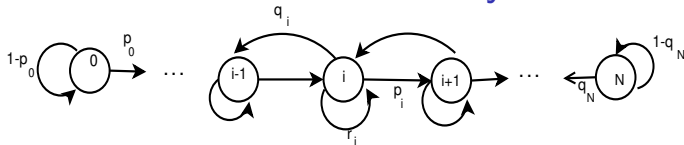
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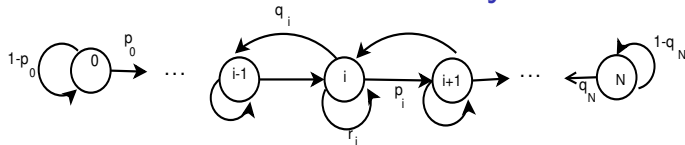
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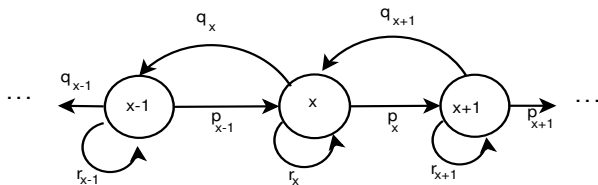
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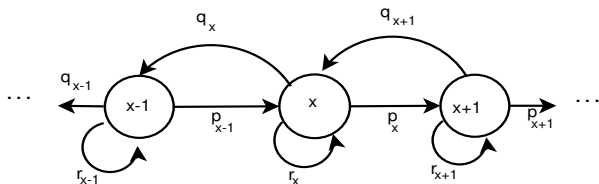
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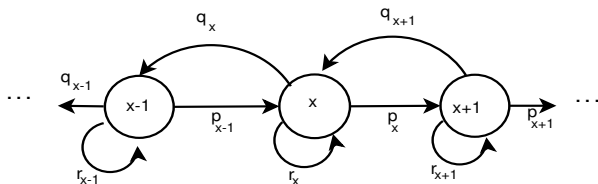
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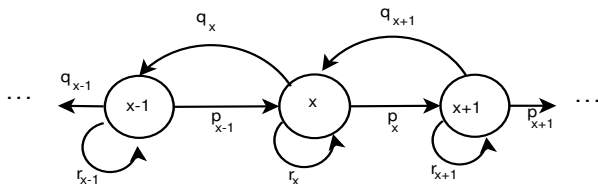
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► Iterating like this, we get

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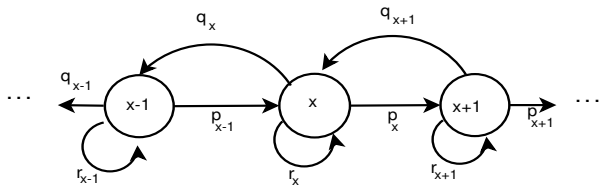
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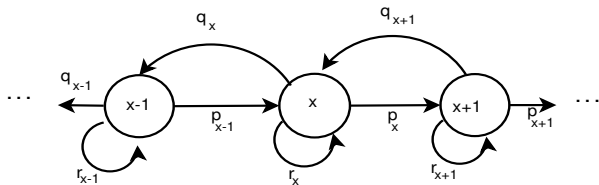
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- ▶ Note that this process is applicable even for infinite chains with state space $\{0, 1, 2, \dots\}$ (but there may not be a solution)

► Consider a birth-death chain

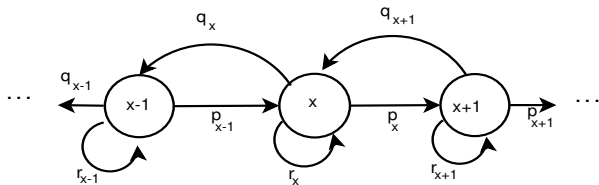


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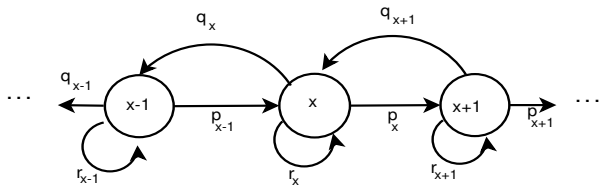
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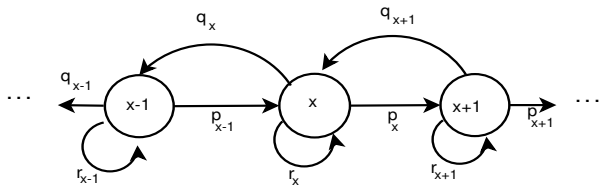
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$$U(x) = P_x[T_a < T_b], \quad a < x < b, \quad U(a) = 1, \quad U(b) = 0$$

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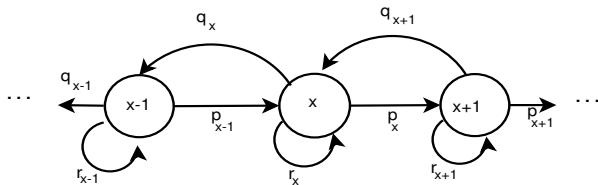


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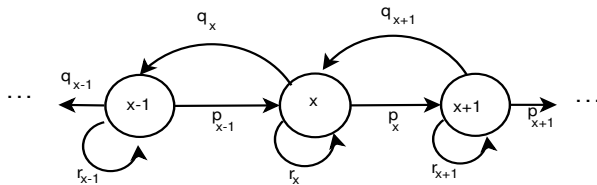
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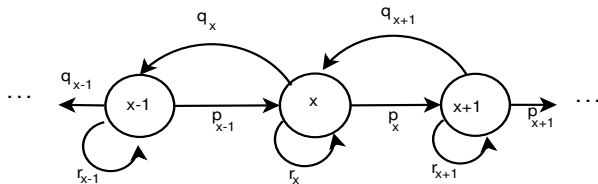


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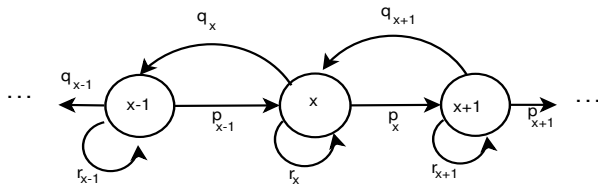
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- This can be useful, e.g., in the gambler's ruin chain

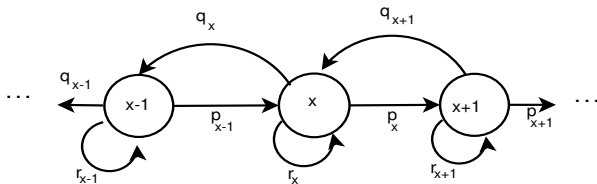




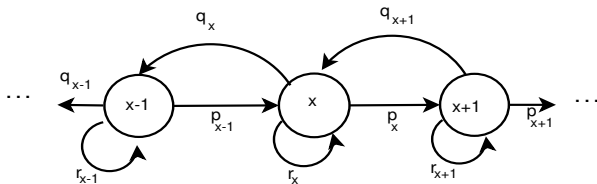
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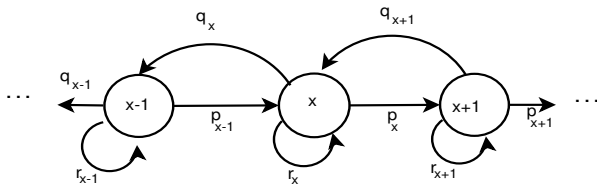
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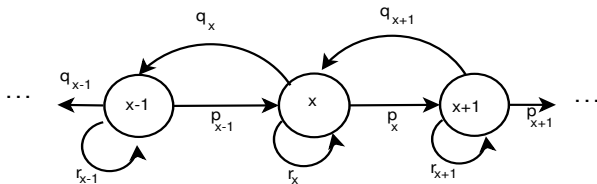
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$$\Rightarrow q_x[U(x) - U(x-1)] = p_x[U(x+1) - U(x)]$$

$$\Rightarrow U(x+1) - U(x) = \frac{q_x}{p_x} [U(x) - U(x-1)]$$

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Let $\gamma_y = \frac{q_y q_{y-1} \cdots q_{a+1}}{p_y p_{y-1} \cdots p_{a+1}}, \quad a < y < b, \quad \gamma_a = 1$

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Now we get

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► By taking $x = b-1, b-2, \dots, a+1, a,$

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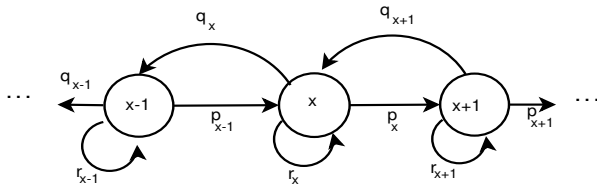
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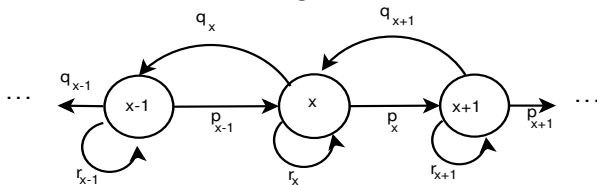
- Adding these we get

$$U(y) - U(b) = U(y) = \frac{\sum_{x=y}^{b-1} \gamma_x}{\sum_{x=a}^{b-1} \gamma_x}, \quad a < y < b$$

- We are considering birth-death chains



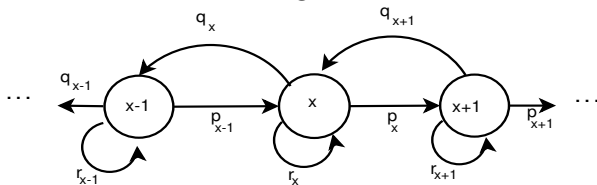
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- We have derived, for $a < y < b$,

$$U(y) = P_y[T_a < T_b] = \frac{\sum_{x=y}^{b-1} \gamma_x}{\sum_{x=a}^{b-1} \gamma_x}, \quad \gamma_x = \frac{q_x q_{x-1} \cdots q_{a+1}}{p_x p_{x-1} \cdots p_{a+1}}$$

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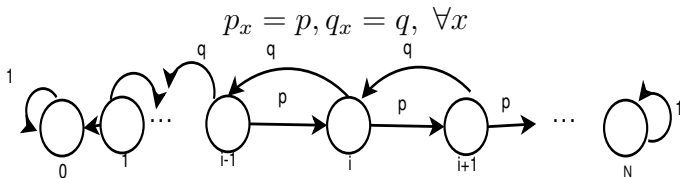
- Hence we also get

$$P_y[T_b < T_a] = \frac{\sum_{x=a}^{y-1} \gamma_x}{\sum_{x=a}^{b-1} \gamma_x}$$

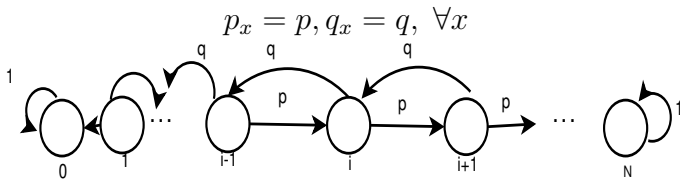
- ▶ Suppose this is a Gambler's ruin chain:

$$p_x = p, q_x = q, \forall x$$

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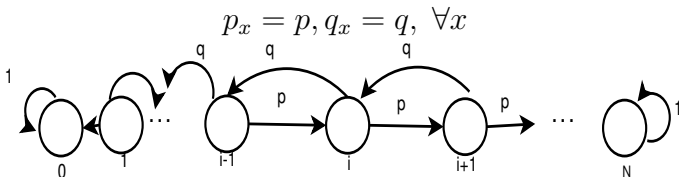


- Suppose this is a Gambler's ruin chain:



- Then, $\gamma_x = \left(\frac{q}{p}\right)^x$

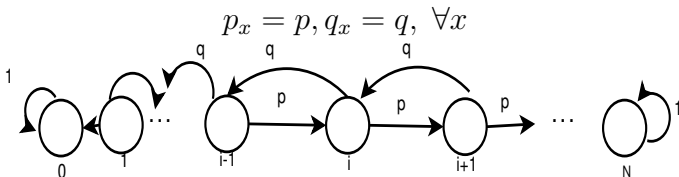
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$$P_i[T_N < T_0] = \frac{\sum_{x=0}^{i-1} \gamma_x}{\sum_{x=0}^{N-1} \gamma_x} = \frac{\left(\frac{q}{p}\right)^i - 1}{\left(\frac{q}{p}\right)^N - 1}$$

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- This is the probability of gambler being successful