

1a) First-step analysis equations: $d_x = P(\text{ever reach state 1} \mid \text{start in state } x)$,
 $x=2,3,4$.

$$\Rightarrow d_2 = \frac{3}{5} + \frac{2}{5}d_3 \quad (1)$$

$$d_3 = \frac{3}{5}d_2 \quad (2)$$

Substitute (2) in (1): $d_2 = \frac{3}{5} + \frac{2}{5} \cdot \frac{3}{5}d_2$

$$\Rightarrow 19d_2 = 15$$

$$\Rightarrow d_2 = \frac{15}{19} \quad \text{as stated.}$$

b) Let $h_x = P(\text{ever reach state 4} \mid \text{start at state } x)$, $x=0, \dots, 4$.

$$\text{Then: } \underline{h_0 = 0}, \quad \underline{h_4 = 1}$$

$$\text{and: } h_1 = \frac{2}{5}h_2$$

$$h_2 = \frac{3}{5}h_1 + \frac{2}{5}h_3$$

$$\underline{h_3 = \frac{3}{5}h_2 + \frac{2}{5}}$$

c) Consider $P(D|S_2nW) = P_2(D|W)$ where $P_2(\cdot) = P(\cdot|S_2)$
 for shorthand.

$$= \frac{P_2(W|D)P_2(D)}{P_2(W)} \quad (*) \text{ Bayes Thm.}$$

Now $P_2(D) = P(D|S_2) = d_2 = \frac{15}{19}$ from definitions and (a).

Also $P_2(W) = P(W|S_2) = h_2 = \frac{20}{65}$ (given).

Finally, $P_2(W|D) = P(W|S_1)$ because trajectory starts in state 2, and later reaches state 1 (event D), so only the most recent state (state 1) is relevant.

1c cont.) So $P_2(W|D) = P(W|S_1) = h_1 = \frac{8}{65}$ (given).

Substituting all in (*):

$$P(D|S_2nW) = \frac{\frac{8}{65} * \frac{15}{19}}{\frac{20}{65}} \quad \text{i.e.} \quad \frac{h_1 * d_2}{h_2}$$

$$\underline{P(D|S_2nW) = \frac{6}{19}} \quad (0.316).$$

So $P(D|S_2) = d_2 = \frac{15}{19}$ is larger than $P(D|S_2nW) = \frac{6}{19}$.

This is expected because $P(D|S_2)$ includes trajectories where the game is lost, all of which must go through state 1; whereas

$P(D|S_2nW)$ includes only trajectories where the game is won, many of which will avoid state 1 altogether (e.g. trajectory 2→3→4).
 *See also comment below

1d) Communicating classes: $\{0\}$ closed,

$\{1, 2, 3\}$ not closed,

$\{4\}$ closed.

1e) The Markov chain does not converge to equilibrium independent of start state. For example, if the start state is state 0, then $X_t = 0$ for all t with probability 1; whereas if the start state is 4, then $X_t = 4$ for all t w.p. 1.

*Further comment on Q1c: it is NOT correct to say that $P(D|S_2)$ is larger because S_2nW is a smaller set than S_2 , or because there are fewer paths from state 2 → state 1 → win than from state 2 → 1. We condition on S_2nW so its size or probability relative to that of S_2 is irrelevant. The question is whether we are more likely to visit state 1 if we do or don't condition on W as well as on S_2 . Note $P_2(D) = P_2(D|W)P_2(W) + P_2(D|\bar{W})P_2(\bar{W}) > P_2(W)P_2(W) + P_2(\bar{W})P_2(\bar{W}) = P_2(W)$

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2a) $G(s) = (1 + \mu - \mu s)^{-1}$
 $\Rightarrow G'(s) = -(1 + \mu - \mu s)^{-2} * (-\mu)$
 $\Rightarrow G'(1) = \frac{\mu}{(1 + \mu - \mu)^2} = \mu$

So $\mathbb{E}(Y) = G'(1) = \mu$ as stated.

b) γ is the smallest non-negative solution of $G(s) = s$:

$G(s) = s \Rightarrow \frac{1}{1 + \mu - \mu s} = s$
 $1 = s + \mu s - \mu s^2$
 $\Rightarrow \mu s^2 - (\mu + 1)s + 1 = 0$

Factorising: we know $(s-1)$ must be a factor.

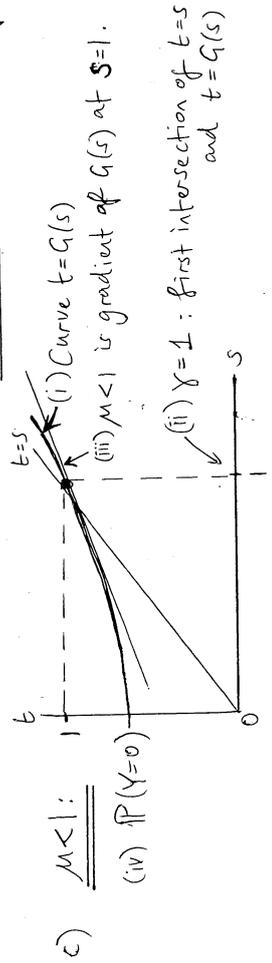
$\Rightarrow (s-1)(\mu s - 1) = 0$

Solutions: $s=1, s = \frac{1}{\mu}$. The smaller of these is γ .

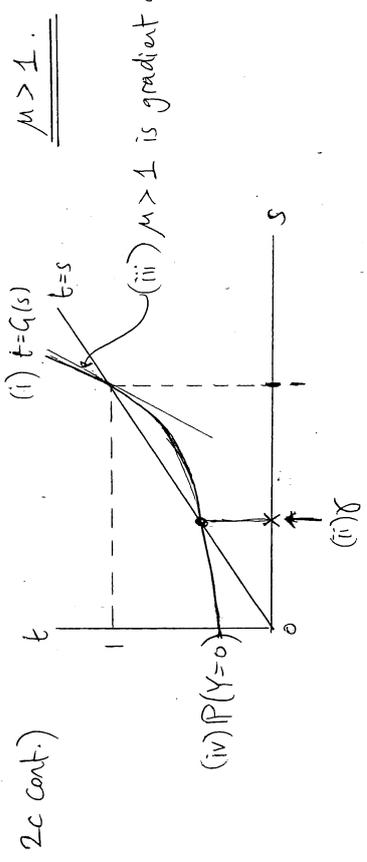
Case (i): $\mu < 1 \Rightarrow \frac{1}{\mu} > 1 \Rightarrow \gamma = 1$ (definite extinction).

Case (ii): $\mu = 1 \Rightarrow \frac{1}{\mu} = 1 \Rightarrow \gamma = 1$ (definite extinction).

Case (iii): $\mu > 1 \Rightarrow \frac{1}{\mu} < 1 \Rightarrow \gamma = \frac{1}{\mu}$ (extinction possible but not definite).



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2c cont.)

$\mu > 1$

2d) $\mu = 1 \Rightarrow G(s) = \frac{1}{1 + \mu - \mu s} = \frac{1}{2 - s}$

Then $P(Z_1=0) = G(0) = \frac{1}{2}$

and $P(Z_2=0) = G(G(0)) = \frac{1}{2 - 1/2} = \frac{2}{3}$

2e) RTP: $G_n(0) = \frac{n}{n+1}$ for $n=1, 2, 3, \dots$

Base case: $n=1$.

LHS $\textcircled{*} = G_1(0) = G(0) = \frac{1}{2}$ from part (d).

RHS $\textcircled{*} = \frac{1}{1+1} = \frac{1}{2} = \text{LHS} \textcircled{*}$.

So $\textcircled{*}$ is proved for base case $n=1$.

General case: Suppose $\textcircled{*}$ is true for $n=1, 2, \dots, x$.

So we may assume $G_x(0) = \frac{x}{x+1}$.

RTP $\textcircled{*}$ holds for $n=x+1 \Rightarrow \text{RTP } G_{x+1}(0) = \frac{x+1}{x+2}$

2e cont.) LHS^(*) = $G_{n+1}(0)$

= $G(G_n(0))$ by hint in Question

= $G\left(\frac{x}{x+1}\right)$ using allowed (a)

= $\frac{1}{2 - \frac{x}{x+1}}$ using $G(s)$ from part (d)

= $\frac{x+1}{2(x+1) - x}$

= $\frac{x+1}{x+2}$

= RHS^(*)

So if $(*)$ holds for $n=x$, we have proved $(*)$ holds for $n=x+1$.

We proved $(*)$ holds for $n=1$, thus $(*)$ is proved for all $n=1, 2, 3, \dots$ \square

2f) $P(\text{first goes extinct at generation } 10) = P(Z_{10}=0 \cap Z_9 > 0)$

= $P(Z_{10}=0) - P(Z_9=0)$

= $G_{10}(0) - G_9(0)$

= $\frac{10}{11} - \frac{9}{10}$ using $G_n(0) = \frac{n}{n+1}$ from part (c)

= 0.0091

Comment about Qbd: NOT required for marks.

In the random walk (RW), a path ABAAB... is actually two possible paths, RLRL... or RLRL... So the probability of either of 2 paths of length $2t$, each of which has probability $(\frac{1}{2})^{2t}$, is $2 * (\frac{1}{2})^{2t} = (\frac{1}{2})^{2t-1}$.

In the branching process (BP), with $Y \sim \text{Geo}(\frac{1}{2})$, a Geometric "success" is required for the conclusion of every family (prob = $\frac{1}{2}$); and every individual except the first arises from a Geometric "failure" (prob = $\frac{1}{2}$). If $T=t$, there are t families, so we need t successes and $t-1$ failures. So each graph with $T=t$ has prob $(\frac{1}{2})^{2t-1}$.

3a) $P = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{4} & \frac{3}{4} \end{pmatrix}$

b) $P(C_2 \cap S_3 | C_1) = \frac{3}{4} * \frac{1}{4} = \frac{3}{16} \quad (0.188)$

c) Require $\tilde{\pi}^T P = \tilde{\pi}^T$ and $\pi_1 + \pi_2 = 1$ (2)

Sufficient to substitute the $\tilde{\pi}$ given:

LHS (1) = $\begin{pmatrix} \frac{1}{3} & \frac{2}{3} \end{pmatrix} \begin{pmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{4} & \frac{3}{4} \end{pmatrix} = \begin{pmatrix} \frac{1}{6} + \frac{2}{12} & \frac{1}{6} + \frac{6}{12} \end{pmatrix} = \begin{pmatrix} \frac{1}{3} & \frac{2}{3} \end{pmatrix} = \text{RHS (1)}$

So $\tilde{\pi}^T = (\frac{1}{3} \frac{2}{3})$ satisfies (1), and satisfies (2) clearly,

so $\tilde{\pi}^T = (\frac{1}{3} \frac{2}{3})$ is an equilibrium distribution for $\{Y_t\}$.

d) The chain is irreducible and aperiodic, and an equilibrium distn exists, so the chain does converge to this distn $\tilde{\pi}$ as $t \rightarrow \infty$.

e) $X_t = \sum_{i=1}^n Y_{it}$ so $E(X_t) = \sum_{i=1}^n E(Y_{it}) = n * E(Y_{it})$

So $\lim_{t \rightarrow \infty} \frac{E(X_t)}{t} = \frac{2}{3} n$

because as $t \rightarrow \infty$, each $Y_{it} = \begin{cases} 1 & \text{with probability } \pi_1 = \frac{2}{3} \\ 0 & \text{" " " " " " } \pi_0 = \frac{1}{3} \end{cases}$

and we established in part (d) that this is true because each chain $\{Y_{it}\}_{t \in \mathbb{N}}$ converges to equilibrium $\tilde{\pi}$.

f) X_t is the sum of n Bernoulli random variables Y_{1t}, \dots, Y_{nt} . As $t \rightarrow \infty$, each Y_{it} converges to equilibrium with $P(Y_{it}=1) = \frac{2}{3}$.

3f cont.) So X_t must converge to the equilibrium distribution constituting the sum of these independent Bernoulli r.v.s.
 So the equilibrium distn for $\{X_t\}$ is Binomial($n, \frac{2}{3}$)
 and it does converge to this distribution as $t \rightarrow \infty$.

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5a) $G_Y(t) = \mathbb{E}(t^Y) = \sum_{y=0}^{\infty} t^y \mathbb{P}(Y=y)$
 $= \sum_{y=0}^{\infty} t^y p(1-p)^y$
 $= p \sum_{y=0}^{\infty} \{t(1-p)\}^y$
 $= \frac{p}{1-(1-p)t}$ for $|t(1-p)| < 1$: sum of geometric series
 So $G_Y(t) = \frac{p}{1-(1-p)t}$ for $-\frac{1}{1-p} < t < \frac{1}{1-p}$.

b) $N = Y_1 + \dots + Y_k$
 so $G_N(s) = \mathbb{E}(s^N) = \mathbb{E}(s^{Y_1+Y_2+\dots+Y_k})$
 $= \mathbb{E}(s^{Y_1}) \mathbb{E}(s^{Y_2}) \dots \mathbb{E}(s^{Y_k})$ by independence
 $= G_Y(s) G_Y(s) \dots G_Y(s)$ by definition
 $= \{G_Y(s)\}^k$
 \Rightarrow $G_N(s) = \left\{ \frac{p}{1-(1-p)s} \right\}^k$ for $-\frac{1}{1-p} < s < \frac{1}{1-p}$.

c) $G_X(s) = \mathbb{E}(s^X)$
 $= \mathbb{E}_Y \{ \mathbb{E}(s^X | Y) \}$ Law of Total Expectation
 $= \mathbb{E}_Y \left\{ \left(\frac{2/3}{1-s/3} \right)^{Y+1} \right\}$ because $X|Y \sim \text{NegBin}(Y+1, \frac{2}{3})$
 $= \frac{2}{3-s} \cdot \mathbb{E}_Y \left\{ \left(\frac{2}{3-s} \right)^Y \right\}$ so $\mathbb{E}(s^X | Y) = \left(\frac{2/3}{1-s/3} \right)^{Y+1}$
 $= \frac{2}{3-s} \cdot G_Y(t)$ where $t = \frac{2}{3-s}$.

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3g) W_{t+1} is the number of the $n-X_t$ whales that were at sea on day t , that return to the coast on day $t+1$.
 Clearly, $W_{t+1} | X_t \sim \text{Binomial}(X_t, \frac{3}{4})$
 and $W_{t+1} | X_t \sim \text{Binomial}(n-X_t, \frac{1}{2})$.

3h) Option B is correct.
 We need $Q_{rs} = \mathbb{P}(X_{t+1}=s | X_t=r)$.
 Option A just specifies the equilibrium distribution for X_{t+1} , which is not the same as the one-step conditional distn of $X_{t+1} | X_t$.
 Option B partitions correctly over the values of U_{t+1} , $u=1, \dots, r$:
 $q_{rs} = \mathbb{P}(X_{t+1}=s | X_t=r) = \sum_{u=0}^r \mathbb{P}(U_{t+1}=u | X_t=r) \mathbb{P}(W_{t+1}=s-u | X_t=r)$.

4) A: Voter Process. Q1: yes, gives \mathbb{P} (consensus for one opinion).
 Q2: yes, e.g. in gene spread, \mathbb{E} (time to fixation).
 Q3: no: the presence of two absorbing states implies no convergence to equilibrium. Any distn. of the form $(\pi_0, 0, 0, \dots, 0, 1-\pi_0)$ is an equilibrium distn so we learn nothing about long-term behaviour by solving equilibrium eqns.
 B: Two-Armed Bandit. Q1: no, hitting probability is \perp for both states.
 Q2: no, there is no absorbing state.
 Q3: yes, interest in long-run prob of success.
 C: Random Walk. Q1: yes, interested in whether we will definitely reach particular states, studied via defective r.v.s and PGFs.
 Q2: no, there is no absorbing state.
 Q3: no, equilibrium distns won't exist.

5c cont.) So $G_X(s) = \frac{2}{3-s} \cdot \frac{2/5}{1-3t/5}$

for $Y \sim \text{Geometric}(\frac{2}{5})$:
 $G_Y(t) = \frac{2/5}{1-3t/5}$ by (a)

replacing $t = \frac{2-s}{3-s}$ from above

$$= \frac{2}{3-s} \cdot \frac{2}{5-3t}$$

$$= \frac{2}{3-s} \cdot \frac{2}{5-\frac{3(2-s)}{3-s}}$$

$$= \frac{4}{5(3-s)-6}$$

$\Rightarrow G_X(s) = \frac{4}{9-5s}$ as stated.

Thus $G_X(s) = \frac{4/9}{1-5s/9} = \frac{p}{1-(1-p)s}$ where $p = \frac{4}{9} = \text{PGF of Geo}(\frac{4}{9})$.

$\Rightarrow X \sim \text{Geometric}(\frac{4}{9})$.

5d) Consider $E(s^Z) = E(s^{X+Y}) = E_Y \{ E(s^{X+Y} | Y) \}$

$\Rightarrow E(s^Z) = E_Y \{ s^Y E(s^X | Y) \}$

$= E_Y \{ s^Y \cdot (\frac{2}{3-s})^{Y+1} \}$ using $E(s^X | Y)$ from above

$= \frac{2}{3-s} E_Y \{ (\frac{2s}{3-s})^Y \}$

$= \frac{2}{3-s} \cdot G_Y(t)$ where $t = \frac{2s}{3-s}$

$= \frac{2}{3-s} \cdot \frac{2}{5-\frac{3 \cdot 2s}{3-s}}$ using $G_Y(t) = \frac{2}{5-3t}$ and $t = \frac{2s}{3-s}$

$= \frac{4}{15-5s-6s}$

$\Rightarrow E(s^Z) = \frac{4/15}{1-(11/15)s}$ So $Z \sim \text{Geometric}(\frac{4}{15})$ as stated.

6a) $T^{(n)} = 1 + T_1^{(n-1)} + \dots + T_Y^{(n-1)}$

$\Rightarrow H_n(s) = E(s^{T^{(n)}})$

$= E(s^{1+T_1^{(n-1)}+\dots+T_Y^{(n-1)}})$

$= s E(s^{T_1^{(n-1)}+\dots+T_Y^{(n-1)}})$

$= s E_Y \{ E(s^{T_1^{(n-1)}+\dots+T_Y^{(n-1)}} | Y) \}$ LoTE

$= s E_Y \{ E(s^{T_1^{(n-1)}} \dots s^{T_Y^{(n-1)}}) \}$ where Y is considered constant inside $\{ \}$

Valid because $T_1^{(n-1)}, T_2^{(n-1)}, \dots$ are independent of Y .

$= s E_Y \{ E(s^{T_1^{(n-1)}}) \dots E(s^{T_Y^{(n-1)}}) \}$ because $T_1^{(n-1)}, T_2^{(n-1)}, \dots$ are indep. of each other

$= s E_Y \{ H_{n-1}(s)^Y \}$ by defn of $E(s^{T_i^{(n-1)}}) = H_{n-1}(s)$

$= s G_Y(H_{n-1}(s))$

$\Rightarrow H_n(s) = \frac{s}{2-H_{n-1}(s)}$ using $G_Y(t) = \frac{1}{2-t}$ given.

as stated.

6b) Take limit of both sides of $(*)$ as $n \rightarrow \infty$: $\lim_{n \rightarrow \infty} H_n(s) = \lim_{n \rightarrow \infty} H_{n-1}(s) = H(s)$ given

$\Rightarrow H(s) = \frac{s}{2-H(s)}$

$\Rightarrow 2H(s) - \{H(s)\}^2 = s$

$\Rightarrow \{H(s)\}^2 - 2H(s) + s = 0$

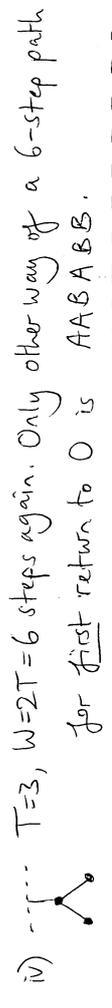
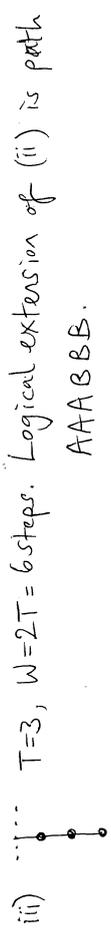
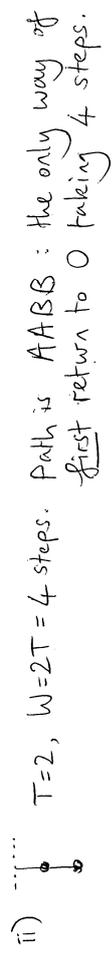
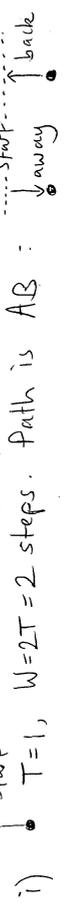
6c cont.) So $J(s) = E(s^W) = s E(s^V) = s K(s)$
 $\Rightarrow \underline{J(s) = 1 - \sqrt{1-s^2}}$ as stated.

6d) We have: $H(s) = E(s^T) = 1 - \sqrt{1-s}$ for $T = \text{total progeny}$
 $J(s) = E(s^W) = 1 - \sqrt{1-s^2}$ for $W = \text{return time}$

So $J(s) = H(s^2)$
 ie. $\underline{E(s^W) = E((s^2)^T) = E(s^{2T})}$

Thus W and $2T$ have the same PGF, so $\underline{W \sim 2T}$.
 (relationship between W and T).

This suggests that, for every completed graph of a branching process, containing T individuals, we should be able to construct a unique path from 0 to 0 in the random walk consisting of $2T$ steps, and that (assuming this correspondence does hold) the path should have the same probability as the graph does in the branching process.



Note: (i)-(iv) describe an algorithm for matching graphs of size T to paths of length $2T$. Not required, but for proof of same probability, see Box on Page 5.

6b cont.) Solving quadratic: $H(s) = \frac{2 \pm \sqrt{4-4s}}{2} = 1 \pm \sqrt{1-s}$

$\Rightarrow \underline{H(s) = 1 \pm \sqrt{1-s}}$

Now $H(0) = P(T=0) = 0$ is known, because $T=1+Z_1+\dots \geq 1$
 Check (+) root: $1 + \sqrt{1-0} = 2 \neq 0$, so (+) root is wrong.

Check (-) root: $1 - \sqrt{1-0} = 0$; correct.

So $\underline{H(s) = 1 - \sqrt{1-s}}$ as stated.

6c) Let $V = \# \text{steps to move one place to the right}$.

Note: V has the same distn as $\# \text{steps to move one place to the left}$, by symmetry.

Let $K(s) = E(s^V)$:

now $V = \begin{cases} 1 & \text{w.p. } 1/2 \\ 1+V' + V'' & \text{w.p. } 1/2 \end{cases}$ where $V' \sim V'' \sim V$
 V', V'' are indept.

So $E(s^V) = K(s) = \frac{1}{2}s + \frac{1}{2}s K(s)^2$ by indep of V', V''
 and because $V' \sim V'' \sim V$.

So $s K(s)^2 - 2K(s) + s = 0$

$\Rightarrow \underline{K(s) = \frac{2 \pm \sqrt{4-4s^2}}{2s} = \frac{1}{s} \{ 1 \pm \sqrt{1-s^2} \}}$.

Now $P(V=0) = 0 \Rightarrow K(0) = 0$, only possible with (-) root.

So $\underline{K(s) = E(s^V) = \frac{1}{s} \{ 1 - \sqrt{1-s^2} \}}$.

We require $W = \begin{cases} 1 + V^* & \text{w.p. } 1/2 \\ 1 + V^{**} & \text{w.p. } 1/2 \end{cases}$ where $V^* \sim V^{**} \sim V$