

# AMATH 536 Problem Set 2

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## 1 Problem 1

### 1.1 Part a

Let  $X$  be a r.v. that denotes the number of individuals in the normal population and let  $Y$  be a r.v. that denotes the number of individuals in the mutant population. Assume that  $X(0) = a, Y(0) = 0$ , both  $X$  and  $Y$  have growth rate  $\lambda$ , and division of normal bacteria produces a mutant with probability  $p$ . We compute

$$P\{X(t+\Delta t)-X(t) = 1, Y(t+\Delta t)-Y(t) = 0 | X(t), Y(t)\} = (1-p)\lambda\Delta t X(t) + o(\Delta t)$$

and

$$P\{X(t+\Delta t)-X(t) = 0, Y(t+\Delta t)-Y(t) = 1 | X(t), Y(t)\} = p\lambda\Delta t X(t) + \lambda\Delta t Y(t) + o(\Delta t).$$

Dividing through by  $\Delta t$ , we see by definition that

$$f_{10}(X, Y) = \lambda(1-p)X(t) + o(1)$$

and

$$f_{01}(X, Y) = \lambda(pX(t) + Y(t)) + o(1).$$

Now, note that the probability of more than one event occurring in a small time interval  $\Delta t$  is  $o(\Delta t)$ , meaning that  $f_{ij}(X, Y) = o(1)$  for  $i, j \geq 1$ . Sending  $\Delta t \rightarrow 0$  allows us to drop these asymptotic terms, so we can write

$$\begin{cases} f_{10}(X, Y) = \lambda(1-p)X(t) \\ f_{01}(X, Y) = \lambda(pX(t) + Y(t)) \\ f_{ij}(X, Y) = 0, \quad i, j \geq 1. \end{cases}$$

## 1.2 Part b

Now, we use this to write the PDE

$$\begin{aligned}\frac{\partial M(\theta, \phi, t)}{\partial t} &= \sum'_{j,k} (e^{j\theta+k\phi} - 1) f_{jk} \left( \frac{\partial}{\partial \theta}, \frac{\partial}{\partial \phi} \right) M(\theta, \phi, t) \\ &= (e^\theta - 1) f_{10} \left( \frac{\partial}{\partial \theta}, \frac{\partial}{\partial \phi} \right) M(\theta, \phi, t) + (e^\phi - 1) f_{01} \left( \frac{\partial}{\partial \theta}, \frac{\partial}{\partial \phi} \right) M(\theta, \phi, t) \\ &= (1-p)\lambda(e^\theta - 1) \frac{\partial M(\theta, \phi, t)}{\partial \theta} + \lambda(e^\phi - 1) \left( p \frac{\partial M(\theta, \phi, t)}{\partial \theta} + \frac{\partial M(\theta, \phi, t)}{\partial \phi} \right).\end{aligned}$$

Note that an initial condition is given by

$$M(\theta, \phi, 0) = P(e^\theta, e^\phi, 0) = \sum_{m,n} p_{mn}(0) e^{m\theta+n\phi} = e^{a\theta}.$$

## 1.3 Part c

To derive the PDE for the cumulant-generating function, we note that  $K = \log M$ , so

$$\frac{\partial K}{\partial t} = \frac{\partial K}{\partial M} \frac{\partial M}{\partial t} = \frac{1}{M} \frac{\partial M}{\partial t}.$$

Note that we get a similar result by replacing  $t$  with  $\theta$  or  $\phi$ . Then, we can rewrite our PDE as

$$M \frac{\partial K(\theta, \phi, t)}{\partial t} = M(1-p)\lambda(e^\theta - 1) \frac{\partial K(\theta, \phi, t)}{\partial \theta} + M\lambda(e^\phi - 1) \left( p \frac{\partial K(\theta, \phi, t)}{\partial \theta} + \frac{\partial K(\theta, \phi, t)}{\partial \phi} \right),$$

so

$$\frac{\partial K(\theta, \phi, t)}{\partial t} = (1-p)\lambda(e^\theta - 1) \frac{\partial K(\theta, \phi, t)}{\partial \theta} + \lambda(e^\phi - 1) \left( p \frac{\partial K(\theta, \phi, t)}{\partial \theta} + \frac{\partial K(\theta, \phi, t)}{\partial \phi} \right)$$

with initial condition

$$K(\theta, \phi, 0) = \log M(\theta, \phi, 0) = \log e^{a\theta} = a\theta.$$

## 1.4 Part d

Now, let

$$K(\theta, \phi, t) = \sum'_{j,k} \frac{k_{jk}(t) \theta^j \phi^k}{j!k!}.$$

Then, we compute

$$\begin{aligned}\frac{\partial K}{\partial t} &= \sum'_{j,k} \frac{k'_{jk}(t) \theta^j \phi^k}{j!k!}, \\ \frac{\partial K}{\partial \theta} &= \sum_{j=1}^{\infty} \sum_{k=0}^{\infty} \frac{k_{jk}(t) \theta^{j-1} \phi^k}{(j-1)!k!},\end{aligned}$$

$$\frac{\partial K}{\partial \phi} = \sum_{j=0}^{\infty} \sum_{k=1}^{\infty} \frac{k_{jk}(t) \theta^j \phi^{k-1}}{j!(k-1)!}.$$

Substituting this into part c,

$$\begin{aligned} \sum_{j,k}' \frac{k'_{jk}(t) \theta^j \phi^k}{j!k!} &= \lambda \left( (1-p) \sum_{\ell=1}^{\infty} \frac{\theta^{\ell}}{\ell!} + p \sum_{\ell=1}^{\infty} \frac{\phi^{\ell}}{\ell!} \right) \sum_{j=1}^{\infty} \sum_{k=0}^{\infty} \frac{k_{jk}(t) \theta^{j-1} \phi^k}{(j-1)!k!} \\ &\quad + \lambda \sum_{\ell=1}^{\infty} \frac{\phi^{\ell}}{\ell!} \sum_{j=0}^{\infty} \sum_{k=1}^{\infty} \frac{k_{jk}(t) \theta^j \phi^{k-1}}{j!(k-1)!}. \end{aligned}$$

## 1.5 Part e

Now, we use Mathematica<sup>1</sup> to equate coefficients of  $\theta$ ,  $\phi$ ,  $\theta^2$ ,  $\theta\phi$  and  $\phi^2$  on both sides of this expression. This yields the system of ODEs

$$\begin{aligned} k'_{10}(t) &= \lambda(1-p)k_{10}(t) \\ k'_{01}(t) &= \lambda(k_{01}(t) + pk_{10}(t)) \\ k'_{11}(t) &= \lambda((2-p)k_{11}(t) + pk_{20}(t)) \\ k'_{20}(t) &= \lambda(1-p)(k_{10}(t) + 2k_{20}(t)) \\ k'_{02}(t) &= \lambda(k_{01}(t) + 2k_{02}(t) + p(k_{10}(t) + 2k_{11}(t))). \end{aligned}$$

Since our initial condition only has one term, it is clear that  $k_{10}(0) = a$  and  $k_{ij}(0) = 0$  for all other  $i, j$ .

## 1.6 Part f

With Mathematica, we find that the solution to this system is given by

$$\begin{aligned} k_{10}(t) &= ae^{(1-p)\lambda t} \\ k_{01}(t) &= a(e^{\lambda t} - e^{(1-p)\lambda t}) \\ k_{11}(t) &= \frac{1}{2}a(1-p)p(e^{(1-p)\lambda t} - e^{(2-p)\lambda t} + e^{(1-p)\lambda t}\lambda t) \\ k_{20}(t) &= \frac{1}{2}ae^{(1-p)\lambda t}(1-p)\lambda t \\ k_{02}(t) &= -\frac{a}{2p}(e^{\lambda t}(1-p\lambda t) - e^{(1-p)\lambda t}(-1 + p^3 - p^2\lambda t + p^3\lambda t) - e^{(2-p)\lambda t}p^3). \end{aligned}$$

Of course, this means that

$$\begin{aligned} E[X(t)] &= ae^{(1-p)\lambda t} \\ E[Y(t)] &= a(e^{\lambda t} - e^{(1-p)\lambda t}) \\ \text{Var}[X(t)] &= \frac{1}{2}ae^{(1-p)\lambda t}(1-p)\lambda t \\ \text{Var}[Y(t)] &= -\frac{a}{2p}(e^{\lambda t}(1-p\lambda t) - e^{(1-p)\lambda t}(-1 + p^3 - p^2\lambda t + p^3\lambda t) - e^{(2-p)\lambda t}p^3). \end{aligned}$$

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<sup>1</sup>See Appendix A for code

## 2 Problem 2

### 2.1 Part a

Consider a biased random walk with probability  $p = b/(b + d)$  of moving  $+1$  and  $1 - p$  of moving  $-1$ . Assuming that we start at position  $x$ , let  $X_n$  denote the position of the walker at time  $n$ . Then,

$$\text{Prob}(X_{2n} = x) = \binom{2n}{n} p^n (1 - p)^n$$

for  $n \geq 1$  as we must make each move an equal amount of times and there are  $\binom{2n}{n}$  ways to do this. Now, let  $N_x$  denote the number of returns to  $x$ . Then, using Mathematica to compute the sum,

$$E[N_x] = \sum_{n=1}^{\infty} \text{Prob}(X_{2n} = x) = \frac{1}{\sqrt{(2p-1)^2}} - 1.$$

Of course, this implicitly assumes that  $p \neq \frac{1}{2}$ . In that case,

$$E[N_x] = \sum_{n=1}^{\infty} \binom{2n}{n} \frac{1}{2^{2n}} = \infty.$$

### 2.2 Part b

To compute the expected number of times a surviving birth-death process will visit a (large) positive integer  $x$ , we note that each  $x$  is visited at least once and use that first visit to initialize our random walk. This means that the expected total visits are given by

$$E[N_x] + 1 = \begin{cases} \frac{1}{\sqrt{(2p-1)^2}}, & p \neq \frac{1}{2} \\ \infty, & p = \frac{1}{2}. \end{cases}$$

### 2.3 Part c

If we assume that each birth of a birth-death process can result in one normal cell and one mutant with some small probability  $u$ , there are currently  $x$  normal cells, and at most one mutant can be produced before leaving state  $x$ , the probability that a mutant will be produced before the number of normal cells changes to  $x - 1$  or  $x + 1$  is simply the probability that the next event is a birth which results in a mutant. This is given by

$$pu = \frac{bp}{b + d}.$$

## 2.4 Part d

Now, the expected number of mutants produced when there are exactly  $x$  normal cells is simply given by the expected number of visits to  $x$  multiplied by the probability of producing a mutant at state  $x$ . Thus, it is given by

$$\begin{cases} \frac{bp}{(b+d)\sqrt{(2p-1)^2}}, & p \neq \frac{1}{2} \\ \infty, & p = \frac{1}{2}. \end{cases}$$

Of course, if our random walk is truly biased, we need not consider the  $p = \frac{1}{2}$  case for any part of these problems meaning that all values are finite.

## 3 Appendix A

The following Mathematica code was used to solve problem 1.

```
K = k10[t]*\[Theta] + k01[t] \[Phi] + k11[t]*\[Theta]*\[Phi] +
k20[t]*\[Theta]^2/2 + k02[t]*\[Phi]^2/2
spaceder[\[Theta]_, \[Phi]_] = \[Lambda]*((1 - p)*(E^\[Theta] - 1) +
p*(E^\[Phi] - 1))*D[K, \[Theta]] + \[Lambda]*(E^\[Phi] - 1)*
D[K, \[Phi]]
timeder[\[Theta]_, \[Phi]_] = D[K, t]
spacederseries =
Normal[Series[spaceder[\[Theta]*g, \[Phi]*g], {g, 0, 2}]] /. g -> 1
timederseries =
Normal[Series[timeder[\[Theta]*g, \[Phi]*g], {g, 0, 2}]] /. g -> 1
```

After noticing the coefficients on the LHS series, we can use

```
c10 = FullSimplify[
Coefficient[spacederseries, \[Theta]] /. \[Phi] -> 0]
c01 = FullSimplify[
Coefficient[spacederseries, \[Phi]] /. \[Theta] -> 0]
c11 = FullSimplify[Coefficient[spacederseries, \[Phi]*\[Theta]]]
c20 = 2*FullSimplify[Coefficient[spacederseries, \[Theta], 2]]
c02 = 2*FullSimplify[Coefficient[spacederseries, \[Phi], 2]]
diffeqn = { k10'[t] == d10,
            k01'[t] == d01,
            k11'[t] == d11,
            k20'[t] == d20,
            k02'[t] == d02,
            k10[0] == a,
            k01[0] == 0,
            k11[0] == 0,
            k20[0] == 0,
            k02[0] == 0
          }
ans = FullSimplify[DSolve[ODEsystem, {k10, k01, k11, k20, k02}, t]]
```

The following Mathematica code was used to compute infinite sums in problem 2.

```
FullSimplify[Sum[Binomial[2 n, n] p^n (1 - p)^n, {n, 1, Infinity }]]  
FullSimplify[Sum[Binomial[2 n, n] (1/2)^2 n, {n, 1, Infinity }]]
```