## Math 361 Winter 2001/2002 Assignment 3 - Solutions

1. 

$$
L=\left(\begin{array}{ccc}
1 / 3 & 4 & 2 \\
2 / 3 & 0 & 0 \\
0 & 1 / 2 & 0
\end{array}\right)
$$

To determine the long term growth rate and stable age distribution, one would have to find the dominant eigenvalue of $L$ and the corresponding eigenvector.
2. a.

$$
x_{n+2}+x_{n}=0
$$

Let $y_{n+1}=x_{n}$. The system reduces to:

$$
\binom{x_{n+1}}{y_{n+1}}=\left(\begin{array}{cc}
0 & -1 \\
1 & 0
\end{array}\right)\binom{x_{n}}{y_{n}}
$$

Eigenvalues:

$$
\begin{aligned}
(-\lambda)(-\lambda)+1 & =0 \\
\Longrightarrow \lambda_{1 / 2} & = \pm i=\cos (\pi / 2) \pm i \sin (\pi / 2)
\end{aligned}
$$

This system exhibits sustained oscillations with constant amplitude $=1$ and frequency $(\pi / 2) /(2 \pi)=1 / 4$.
b.

$$
x_{n+2}-x_{n+1}+x_{n}=0
$$

Let $y_{n+1}=x_{n}$. The system reduces to:

$$
\binom{x_{n+1}}{y_{n+1}}=\left(\begin{array}{cc}
1 & -1 \\
1 & 0
\end{array}\right)\binom{x_{n}}{y_{n}}
$$

Eigenvalues:

$$
\begin{aligned}
(1-\lambda)(-\lambda)+1 & =0 \\
\Longrightarrow \lambda_{1 / 2} & =\frac{1}{2} \pm i \frac{\sqrt{3}}{2}=\cos (\pi / 3) \pm i \sin (\pi / 3)
\end{aligned}
$$

The has oscillatory solutions with constant amplitude $=1$ and frequency 1/6.
c.

$$
x_{n+2}-2 x_{n+1}+2 x_{n}=0
$$

Let $y_{n+1}=x_{n}$. The system reduces to:

$$
\binom{x_{n+1}}{y_{n+1}}=\left(\begin{array}{cc}
2 & -2 \\
1 & 0
\end{array}\right)\binom{x_{n}}{y_{n}}
$$

Eigenvalues:

$$
\begin{aligned}
(2-\lambda)(-\lambda)+2 & =0 \\
\Longrightarrow \lambda_{1 / 2} & =1 \pm i=\sqrt{2}(\cos (\pi / 4) \pm i \sin (\pi / 4))
\end{aligned}
$$

This has oscillatory solutions whose amplitude increases with time as $\left|\lambda_{1}\right|^{t}=$ $\left|\lambda_{2}\right|^{t}=\sqrt{2}^{t}$ and with frequency $1 / 8$.
d.

$$
x_{n+2}+2 x_{n+1}+3 x_{n}=0
$$

Let $y_{n+1}=x_{n}$. The system reduces to:

$$
\binom{x_{n+1}}{y_{n+1}}=\left(\begin{array}{cc}
-2 & -3 \\
1 & 0
\end{array}\right)\binom{x_{n}}{y_{n}}
$$

Eigenvalues:

$$
\begin{aligned}
(-2-\lambda)(-\lambda)+3 & =0 \\
\Longrightarrow \lambda & =-1 \pm i \sqrt{2}=\sqrt{3}\left(\operatorname { c o s } \left(\pi-\tan ^{-1}(\sqrt{2)}) \pm i \sin \left(\pi-\tan ^{-1}(\sqrt{2)})\right)\right.\right.
\end{aligned}
$$

This has oscillatory solutions whose amplitude increases with time as $\left|\lambda_{1}\right|^{t}=$ $\left|\lambda_{2}\right|^{t}=\sqrt{3}^{t}$ and with frequency $\left(\pi-\tan ^{-1}(\sqrt{2)}) /(2 \pi)\right.$.
3. To calculate the eigenvalues we solve the equation

$$
\mu^{2}-\operatorname{tr}(A) \mu+\operatorname{det}(A)=\mu^{2}-2 \lambda \mu+\lambda^{2}=(\mu-\lambda)^{2}=0
$$

for $\mu$, which yields

$$
\mu_{1 / 2}=\lambda
$$

i.e., both eigenvalues are equal to $\lambda$. To find the eigenvectors, we solve

$$
\left(\begin{array}{ll}
\lambda & 1 \\
0 & \lambda
\end{array}\right)\binom{x}{y}=\lambda\binom{x}{y}
$$

hence

$$
\begin{aligned}
\lambda x+y & =\lambda x \\
\lambda y & =\lambda y
\end{aligned}
$$

Clearly, $y=0$ because of the first of these equation, and we conclude that the only eigenvectors are multiples of

$$
\binom{1}{0}
$$

Thus, there is only one eigenvector.
(Note: this is not a direct consequence of the fact that both eigenvalues are equal, for if you consider the matrix $A=\left(\begin{array}{cc}\lambda & 0 \\ 0 & \lambda\end{array}\right)$, then both eigenvalues of $A$ are equal to $\lambda$, but clearly $A$ has two different eigenvectors $\binom{1}{0}$ and $\binom{0}{1}$.)
4. a .

$$
x_{n}=(1-\alpha) x_{n-1}+\beta x_{n}
$$

This equation is linear:

$$
x_{n}=\left(\frac{1-\alpha}{1-\beta}\right) x_{n-1}
$$

Solution:

$$
x_{n}=\left(\frac{1-\alpha}{1-\beta}\right)^{n} x_{0}
$$

b.

$$
x_{n+1}=\frac{x_{n}}{1+x_{n}}
$$

This equation is non-linear.
Steady state:

$$
\begin{aligned}
x^{*} & =\frac{x^{*}}{1+x^{*}} \\
x^{* 2} & =0
\end{aligned}
$$

Therefore $x^{*}=0$ is the only steady state.
c.

$$
x_{n+1}=x_{n} e^{-a x_{n}}
$$

This equation is non-linear.

Steady states:

$$
\begin{aligned}
& x^{*}=x^{*} e^{-a x^{*}} \\
& x^{*}=0
\end{aligned}
$$

d.

$$
\left(x_{n+1}-\alpha\right)^{2}=\alpha^{2}\left(x_{n}^{2}-2 x_{n}+1\right)
$$

This equation is non-linear.
Steady states:

$$
\begin{aligned}
x^{*}\left(x^{*}\left(1-\alpha^{2}\right)+2 \alpha(\alpha-1)\right) & =0 \\
x^{*} & =0, \frac{2 \alpha(1-\alpha)}{\left(1-\alpha^{2}\right)}
\end{aligned}
$$

e.

$$
x_{n+1}=\frac{K}{k_{1}+k_{2} / x_{n}}
$$

This equation is non-linear.
Steady states:

$$
\begin{aligned}
k_{1} x^{*}+k_{2} & =K \\
x^{*} & =\frac{K-k_{2}}{k_{1}}
\end{aligned}
$$

5. a.

$$
A \cdot w_{i}=\lambda_{i} \cdot w_{i}, i=1,2
$$

Therefore:

$$
\begin{aligned}
A(u+i v) & =c(\cos \theta+i \sin \theta)(u+i v) \\
A(u-i v) & =c(\cos \theta-i \sin \theta)(u-i v) \\
A \cdot u+i A \cdot v & =c(\cos \theta \cdot u-\sin \theta \cdot v+i(\cos \theta \cdot v+\sin \theta \cdot u)) \\
A \cdot u-i A \cdot v & =c(\cos \theta \cdot u-\sin \theta \cdot v-i(\cos \theta \cdot v+\sin \theta \cdot u))
\end{aligned}
$$

and so

$$
\begin{aligned}
& 2 A \cdot u=c(2 \cos \theta \cdot u-2 \sin \theta \cdot v) \\
& 2 A \cdot v=c(2 \cos \theta \cdot v+2 \sin \theta \cdot u)
\end{aligned}
$$

b.

$$
\begin{aligned}
A \cdot\left(A \cdot w_{i}\right) & =A \cdot\left(\lambda_{i} w_{i}\right) \\
& =\lambda_{i}\left(A \cdot w_{i}\right) \\
& =\lambda_{i}\left(\lambda_{i} w_{i}\right) \\
& =\lambda_{i}^{2} w_{i}
\end{aligned}
$$

This can be continued to show that

$$
A^{t} \cdot w_{i}=\lambda_{i}^{t} w_{i}
$$

So

$$
\begin{aligned}
& A^{t} \cdot w_{1}=c^{t}(\cos \theta+i \sin \theta)^{t} \cdot w_{1} \\
& A^{t} \cdot w_{2}=c^{t}(\cos \theta-i \sin \theta)^{t} \cdot w_{2}
\end{aligned}
$$

Using trigonometric identities one can show that

$$
c^{t}(\cos \theta \pm i \sin \theta)^{t}=c^{t}(\cos (t \theta) \pm i \sin (t \theta))
$$

(De Moivre's theorem). Thus:

$$
\begin{aligned}
A^{t} \cdot w_{1} & =c^{t}(\cos (t \theta)+i \sin (t \theta)) \cdot w_{1} \\
A^{t} \cdot w_{2} & =c^{t}(\cos (t \theta)-i \sin (t \theta)) \cdot w_{2}
\end{aligned}
$$

The result follows from these identities as in part (a).
6. a. The function $f(x)$ is a monotone decreasing function of $x$, which attains its maximal value at $0: f(0)=\lambda$. In general, the function $f(x)$ takes on larger values for larger $\lambda$ and $K$.
b. $K$ determines how fast the per capita number of descendants decreases with population size, e.g. due to competition. $\lambda$ determines the maximal number of per capita descendants, realized when the population size is 0 , i.e. when there is no competition. (The maximal number of per capita descendants is $\lambda \cdot e$.)
c.

$$
x(t+1)=f(x(t)) \cdot x(t)=F(x(t))
$$

The function $F(x)$ has the following general properties:
$F(0)=0 ;$
$F(x) \rightarrow 0$ for $x \rightarrow \infty$;
$F(x)$ has a single maximum, which lies to the left of the single equilibrium $x^{*}>0$ for which $F\left(x^{*}\right)=x^{*}$. (Such an equilibrium exists is $\lambda \cdot e>1$.)
$F(x)$ has a single inflection point, which lies to the right of the equilibrium $x^{*}$ for which $F\left(x^{*}\right)=x^{*}$.
d. Clearly, $x^{*}=0$ i a steady state of the dynamical system, because $F(0)=$ 0 , and to find its stability we have to calculate

$$
\frac{d F}{d x}(0)=\lambda \cdot e .
$$

Thus, the steady state $x^{*}=0$ is locally stable if and only if $\lambda \cdot e<1$.
If $\lambda \cdot e>1$, i.e. if $x^{*}=0$ is unstable, then there is an additional steady state $x^{*}>0$, which we can find by solving the equation $F\left(x^{*}\right)=x^{*}$, or, equivalently, the equation

$$
f\left(x^{*}\right)=\lambda \exp \left(1-x^{*} / K\right)=1
$$

which yields

$$
x^{*}=K(1+\ln (\lambda))
$$

To determine the stability of $x^{*}$, we have to calculate

$$
\frac{d F}{d x}\left(x^{*}\right)=-\ln (\lambda)
$$

Thus, the second steady state is locally stable if and only if $\ln (\lambda)<1$, i.e., if and only if $\lambda<e$.
7.a.

$$
\begin{aligned}
x_{n+1} & =r x_{n}\left(1-x_{n}\right) \\
f(x) & =r x(1-x) \\
\frac{d f}{d x} & =r-2 r x \\
\left.\frac{d f}{d x}\right|_{x^{*}=0} & =r
\end{aligned}
$$

Stable when $r<1$.
b.

$$
\begin{aligned}
x_{n+1} & =-x_{n}^{2}\left(1-x_{n}\right) \\
f(x) & =-x^{2}(1-x) \\
\frac{d f}{d x} & =-2 x+3 x^{2} \\
\left.\frac{d f}{d x}\right|_{x^{*}=\frac{1+\sqrt{5}}{2}} & =\frac{7+\sqrt{5}}{2}>1 .
\end{aligned}
$$

This equilibrium is unstable.
c.

$$
\begin{aligned}
x_{n+1} & =\frac{1}{2+x_{n}} \\
f(x) & =\frac{1}{2+x} \\
\frac{d f}{d x} & =-\frac{1}{(2+x)^{2}} \\
\left.\frac{d f}{d x}\right|_{x^{*}=\sqrt{2}-1} & =3+2 \sqrt{2}>1
\end{aligned}
$$



Figure 1: Cobwebbing in a single species model with predation

This equilibrium is unstable.
d.

$$
\begin{aligned}
x_{n+1} & =x_{n} \ln x_{n}^{2} \\
f(x) & =x \ln x^{2} \\
\frac{d f}{d x} & =2+\ln x^{2} \\
\left.\frac{d f}{d x}\right|_{x=e^{1 / 2}} & =3>1
\end{aligned}
$$

This equilibrium is unstable.
8. a. The function $F(x)$ has the following properties:
$F(0)=0$;
$F(x) \rightarrow \lambda$ for $x \rightarrow \infty$;
$F^{\prime}(x)>0$ for all $x$, i.e. $F(x)$ is monotonically increasing.
b. If $\lambda<1$, then 0 is the only equilibrium of the dynamical system defined by $F(x)$.

If $\lambda>1$, there is an additional steady state $x^{*}>0$ for which $F\left(x^{*}\right)=x^{*}$.
The steady state $x^{*}=0$ is locally stable if and only if $\lambda<1$. The steady state $x^{*}>0$ is always locally stable.
9.
a. Figure 1 shows typical cobwebbing behavior for this model, and we see some interesting behaviour, in that there are 2 non-zero equilibrium points, i.e.
two intersection points between the graph of $F(x)$ and the diagonal (assuming that $\lambda>1$, and that $h$ is not too large). In this example, if the population starts at a density greater than 1 , the population will converge to the upper equilibrium. On the other hand, if the population starts at a density less than one it will go to negative values, i.e. it will go extinct due to predation. In particular, the lower equilibrium is unstable.
b. For $\lambda<1$, the curve of $x(t+1)$ vs. $x(t)$ is always lower than the $y=x$ line regardless of the value of $h$, which tells us that the population will eventually go extinct (if we assume negative population sizes is extinction). For $\lambda>1$, changing $h$ will cause the curve $x(t+1)$ vs. $x(t)$ to move up or down. As $h$ approaches 0 , the dynamics are the same as in problem 8. As the predation pressure $h$ increases from 0 , the range of initial population sizes increases for which the population will go to negative values. For sufficiently large $h$, the curve $x(t+1)$ vs. $x(t)$ will again always be lower than the $y=x$ which means that, as with the case when $\lambda<1$, the population will always go to negative values (extinction).
c. The reason why this model is problematic is because it allows for negative population sizes!
d. A better way to model predation is to multiply the per capita growth rate in the prey, $f(x(t))$, by some factor $h$ with $0<h<1$, resulting in a model of the form

$$
x(t+1)=h \cdot f(x(t)) \cdot x(t)=h \cdot F(x(t)) .
$$

10. We are given that

$$
\left|\left(\left.\frac{d f}{d x}\right|_{x_{1}^{* *}}\right)\left(\left.\frac{d f}{d x}\right|_{x_{2}^{* *}}\right)\right|<1
$$

where $x_{i}^{* *}, i=1,2$ are steady states of $f(f(x))=g(x)$ (i.e. $g\left(x_{i}^{* *}\right)=x_{i}^{* *}$ for $i=1,2$; note that $x_{1}^{* *}=f\left(x_{2}^{* *}\right)$ and $x_{2}^{* *}=f\left(x_{1}^{* *}\right)$.)

Taking the derivative of $g(x)=f(f(x))$ at either of the stable states gives:

$$
\left.\frac{d}{d x} g(x)\right|_{x_{i}^{* *}}=\left.\frac{d}{d x} f(f(x))\right|_{x_{i}^{* *}}=\left.\left.\frac{d f}{d x}\right|_{x_{i}^{* *}} \frac{d f}{d x}\right|_{x_{j}^{* *}}
$$

Thus, $\left.\left|\frac{d}{d x} g(x)\right|_{x_{i}^{* *}} \right\rvert\,<1$ by assumption, hence both steady states of $g$ are stable, and hence these two steady states give rise to a stable 2-point cycle of the dynamical system defined by the function $f$.

