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Math 430 Mathematical Biology – Homework 1

Due: Thursday, February 10, 2022.

NAME: EDDIE BAKKO

(1) [15pts] Recall the simple growth with harvesting model

$$x_{n+1} = \lambda x_n - h$$

where x_n is the chicken population after n years, x_0 is the initial population, λ is the growth rate and h is the harvesting rate (chickens per year).

- Find a formula for the harvesting rate h^* at which the population remains constant.
- Find a formula for the number of years $\bar{n}$ it takes for the population to die out when it is over harvested, i.e. $h > h^*$.
- Let $\lambda = 1.05$, $x_0 = 100$, $h = 7$. Use Matlab to simulate the run using n between 0 and 30 with x and y plotting ranges in $[0, 30]$, $[0, 300]$, respectively. Use your formula in b) to verify the $\bar{n}$ at which the population dies out. Label your calculated value $\bar{n}$ as a point on the n versus x_n plot. Include a hardcopy of the plot and one of the Matlab code.

(2) [15pts] Find the (real) general solution of each of the following difference equations.

$$2x_{n+2} - 7x_{n+1} + 3x_n = 0$$

$$x_{n+2} - 4x_{n+1} + 4x_n = 0$$

$$x_{n+2} - \sqrt{3}x_{n+1} + x_n = 0$$

One characteristic polynomial has two real distinct roots, another one real repeated root and the other has a complex roots with a simple polar representation $\lambda = re^{i\theta}$.

(3) [10pts] Read the textbook description of the Red Blood Cell (RBC) population model in Section 1.9, Problem 2:

$$R_{n+1} = (1-f)R_n + M_n \quad (1)$$

$$M_{n+1} = \gamma f R_n \quad (2)$$

- Convert the system above model to a single equation involving only R_{n+1} , R_n , R_{n-1} .
- Show that the eigenvalues of the difference equation in a) are

$$\lambda_{\pm} = \frac{(1-f) \pm \sqrt{(1-f)^2 + 4\gamma f}}{2}$$

- Homeostasis is when the number of red blood cells R_n is roughly constant. This can be achieved when $\lambda_+ = 1$. Show that for this to happen, γ must equal 1.
- With $\lambda_+ = 1$ in c), show $\lambda_- = -f$ and then write down the general solution for R_n . What does R_n approach as $n \rightarrow \infty$.

HOMEWORK 01

EDDIE BAKKO
Math Bio

#1 Simple Growth with HARVESTING MODEL

$$x_{n+1} = \lambda x_n - h \quad \text{where,}$$

$x_n \equiv$ chicken pop. after n years

$x_0 \equiv$ initial population

$\lambda \equiv$ growth rate

$h \equiv$ harvesting rate (chickens/yr)

(a) We seek a formula for an h^* which keeps the population constant

$$\text{i.e. } x_{n+1} = x_n$$

$$\lambda x_n - h^* = x_n$$

$$h^* = \lambda x_n - x_n$$

$$\boxed{h^* = x_n(\lambda - 1)}$$

Indeed, for $h = h^*$

$$\text{Note } \left\{ \begin{aligned} x_n &= \lambda^n x_0 + \frac{(1-\lambda^n)}{(\lambda-1)} h = \lambda^n x_0 + \frac{(1-\lambda^n)}{(\lambda-1)} x_n(\lambda-1) \\ &= \lambda^n x_0 + x_n - \lambda^n x_n \\ &\Rightarrow x_0 = x_n \end{aligned} \right.$$

$$\text{(pop. constant)} \Rightarrow x_0 = x_n$$

$$= x_n$$

(b) Find formula for number of years $\bar{n}$ it takes for the population to die out with overharvested ($h > h^*$). i.e. what n is $x_n = 0$?

We know

$$x_n = \lambda^n x_0 + \frac{(1-\lambda^n)}{(\lambda-1)} h = 0 \Rightarrow -\lambda^n x_0 = \frac{(\lambda^n-1)}{(\lambda-1)} h$$

$$\Rightarrow \frac{x_0(1-\lambda) + h}{h} = \frac{1}{\lambda^n} \checkmark$$

$$\Rightarrow \ln(h) - \ln(x_0(1-\lambda) + h) = n \ln \lambda$$

$$\Rightarrow \boxed{\bar{n} = \frac{\ln(h) - \ln(x_0(1-\lambda) + h)}{\ln \lambda}} \checkmark$$

$$\text{c) } \lambda = 1.05$$

$$x_0 = 100$$

$$h = 7$$

With these values, we see that

$$h^* = 100(1.05-1)$$

$$= 100(.05)$$

$$= 5$$

$$\text{So } h = 7 > 5 = h^*$$

$$\bar{n} = \frac{\ln(7) - \ln(100(1-1.05) + 7)}{\ln(1.05)} \approx 25.677 \text{ years} \checkmark$$

As is shown in the Matlab code.

15

#2] Find the (real) gen. soln to each of the following:

(a) $2x_{n+2} - 7x_{n+1} + 3x_n = 0$

yields char. poly $P(\lambda) = 2\lambda^2 - 7\lambda + 3 = 0$
 $(2\lambda - 1)(\lambda - 3) = 0$

$\Rightarrow \lambda = 1/2, 3 = \lambda_1, \lambda_2$ (two distinct real λ)

$\lambda_1 \neq \lambda_2$ real: $x_n = C_1 (1/2)^n + C_2 (3)^n$

(b) $x_{n+2} - 4x_{n+1} + 4x_n = 0$

yields char. poly $P(\lambda) = \lambda^2 - 4\lambda + 4 = 0$
 $(\lambda - 2)^2 = 0$

$\lambda = 2$ (repeated real λ)

$\lambda_1 = \lambda_2$ real: $x_n = (C_1 + C_2 n) 2^n$

(c) $x_{n+2} - \sqrt{3}x_{n+1} + x_n = 0$

yields char. poly $P(\lambda) = \lambda^2 - \sqrt{3}\lambda + 1 = 0$

By quadratic eqn, $\lambda = \frac{\sqrt{3} \pm \sqrt{(\sqrt{3})^2 - 4(1)(1)}}{2}$

$\lambda = \frac{\sqrt{3}}{2} \pm \frac{1}{2}\sqrt{-1}$
 $= \frac{\sqrt{3}}{2} \pm \frac{1}{2}i$ ✓

$\lambda = \frac{\sqrt{3}}{2} \pm \frac{1}{2}i \Rightarrow r = \sqrt{(\frac{\sqrt{3}}{2})^2 + (\frac{1}{2})^2} = \sqrt{3/4 + 1/4} = 1$ ✓

By inspection, $\theta = \pi/6$

Hence, $\lambda = e^{i\pi/6}$

So, $x_n = C_1 \cos(\frac{n\pi}{6}) + C_2 \sin(\frac{n\pi}{6})$ ✓

15

#3] Red Blood Cell (RBC) population model:

(1) $R_{n+1} = (1-f)R_n + M_n$

(2) $M_{n+1} = \gamma f R_n$

$R_n \equiv \#$ of RBCs in circulation on day n

$M_n \equiv \#$ of RBCs produced by marrow on day n

$f \equiv$ fraction of RBCs removed by spleen

$\gamma \equiv$ production constant ($\#$ produces per $\#$ lost)

(a) convert to single eqn:

$M_{n+1} = \gamma f R_n \Rightarrow M_n = \gamma f R_{n-1}$

So, (1) becomes $R_{n+1} = (1-f)R_n + \gamma f R_{n-1}$ (3) ✓

(b) We might rewrite (3) as $R_{n+1} + (f+1)R_n - \gamma f R_{n-1} = 0$ which has char poly

$P(\lambda) = \lambda^2 + (f+1)\lambda - \gamma f = 0$

By quadratic eqn, $\lambda = \frac{-(f+1) \pm \sqrt{(f+1)^2 + 4\gamma f}}{2}$ as was to be shown.
 $\uparrow$ eigenvalues

(c) Homeostasis $\equiv R_n$ constant-ish. $\lambda = 1 \Rightarrow$ Homeostasis. Seek to show necessary for $\gamma = 1$.

$\lambda = 1 = \frac{-(f+1) \pm \sqrt{(f+1)^2 + 4\gamma f}}{2} \Rightarrow 2 = -(f+1) + \sqrt{f^2 + (4\gamma - 2)f + 1}$

$\Rightarrow (f+1)^2 = f^2 + (4\gamma - 2)f + 1$

$\Rightarrow f^2 + 2f + 1 = f^2 + (4\gamma - 2)f + 1$

ie polynomial, this is only true if

$2 = 4\gamma - 2$ or $\gamma = 1$ ✓, as was to be shown.

(d) From this, $\lambda = \frac{-(f+1) - \sqrt{(f+1)^2 + 4\gamma f}}{2} = \frac{-(f+1) - \sqrt{f^2 + (4\gamma - 2)f + 1}}{2} = \frac{-(f+1) - \sqrt{f^2 + (4 - 2)f + 1}}{2} = \frac{-(f+1) - (f+1)}{2} = -f$

So, $\lambda = 1 \neq -f = \lambda_1$ (real) yields gen. soln of

$R_n = C_1 + C_2 (-f)^n$

Clearly, it must be the case that $f < 1$ (otherwise $\#RBC = 0 \Rightarrow$ death).

Hence, as $n \rightarrow \infty$, $R_n \rightarrow C_1$ (stays constant)

i.e. Homeostasis

Math 430 Mathematical Biology – Homework 2

Due: Thursday, February 24, 2022.

NAME: _____

1 [10pts] For the following difference equation:

$$x_{n+1} = f(x_n) = \frac{x_n}{x_n - 3}$$

i) Compute the first 3 terms of the orbit using $x_0 = 1$

$$\gamma(x_0) = \{x_0, x_1, x_2, \dots\}$$

Write out x_0, x_1, x_2 as approximate decimals.

ii) Find all fixed points $\bar{x}$ of the map.

iii) Determine the stability of each fixed point.

2 [10pts] For the following difference equation:

$$x_{n+1} = f(x_n) = -x_n^2(1 - x_n)$$

i) Compute the first 3 terms of the orbit using $x_0 = 1$

$$\gamma(x_0) = \{x_0, x_1, x_2, \dots\}$$

Write out x_0, x_1, x_2 as approximate decimals.

ii) Find all fixed points $\bar{x}$ of the map.

iii) Determine the stability of each fixed point.

3 [20pts] A frequently encountered model of fish population is given by Ricker's equation (see Greenwell 1984):

$$x_{n+1} = \alpha x_n e^{-\beta x_n}$$

Here x_n is the population in thousands at year n , $\alpha > 0, \beta > 0$.

a) Find the sole positive fixed point $\bar{x} > 0$. For what α is this fixed point positive?

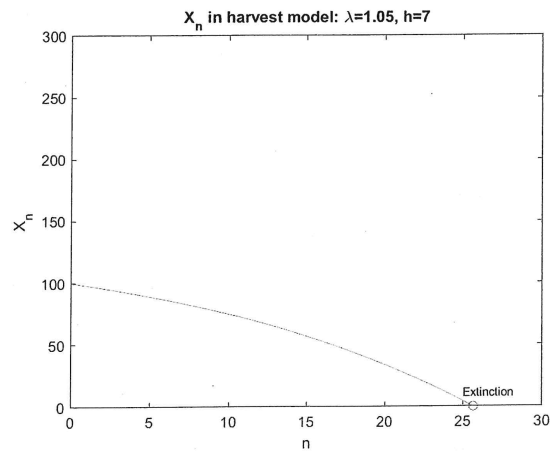
b) Show that $\bar{x}$ is stable only if the growth rate α satisfies:

$$|1 - \ln \alpha| < 1$$

This is equivalent to $\alpha \in (\alpha_1, \alpha_2)$. What are α_k ?

c) Modify the posted code cobweb.m to create 3 cobweb figures of the model showing an attraction to a fixed point, an attraction to a period 2 orbit, and an attraction to a period 4 orbit.

d) What is the maximum possible value of x_n ? I want the formula involving α and β .
Hint: What's the maximum value of $f(x)$ for $x > 0$?



HOMEWORK 2

EDDIE BAKKO
Math Bio

$$x_{n+1} = f(x_n) = \frac{x_n}{x_n - 3}$$

(i) What first 3 terms of orbit using $x_0 = 1$.

$$x_0 = 1$$

$$x_1 = f(1) = \frac{1}{1-3} = -1/2$$

$$x_2 = f(-1/2) = \frac{-1/2}{-1/2-3} = 1/7$$

$$x_3 = f(1/7) = \frac{1/7}{1/7-3} = -1/20$$

$$\gamma(x_0=1) = \{1, -1/2, 1/7, -1/20, \dots\}$$

$$\gamma(1) = \{1, -0.5, 0.14, -0.05, \dots\}$$

(ii) Find all fixed pts of the map.

$$\text{Want } f(\bar{x}) = \bar{x} \rightarrow \frac{\bar{x}}{\bar{x}-3} = \bar{x}$$

$$\bar{x} = \bar{x}^2 - 3\bar{x}$$

$$0 = \bar{x}^2 - 4\bar{x}$$

$$0 = \bar{x}(\bar{x}-4) \Rightarrow \boxed{\bar{x}_1 = 0 \text{ \& } \bar{x}_2 = 4}$$

(iii) What stability of fixed pts

$$\text{Note, } f'(x) = \frac{-3}{(x-3)^2} \text{ and } |f'(x)| = \frac{3}{(x-3)^2} \checkmark$$

$$\text{Then } |f'(\bar{x}_1)| = |f'(0)| = \frac{3}{(0-3)^2} = 3/9 = 1/2 < 1 \Rightarrow \boxed{\bar{x}_1 = 0 \text{ stable}}$$

$$|f'(\bar{x}_2)| = |f'(4)| = \frac{3}{(4-3)^2} = 3/1 = 3 > 1 \Rightarrow \boxed{\bar{x}_2 = 4 \text{ unstable}}$$

#2

$$x_{n+1} = f(x_n) = -x_n^2(1-x_n)$$

(i) What first 3 terms of orbit using $x_0 = 1$

$$x_0 = 1$$

$$x_1 = f(1) = -(1)^2(1-1) = 0$$

$$x_2 = f(0) = -(0)^2(1-0) = 0$$

$$x_3 = f(0) = x_2 = 0$$

$$\gamma(1) = \{1, 0, 0, 0, \dots\}$$

(ii) What fixed pts of $f(x_n)$.

$$\text{Seek } \bar{x} = f(\bar{x}) \rightarrow \bar{x} = -(\bar{x})^2(1-\bar{x})$$

$$\bar{x} = -\bar{x}^2 + \bar{x}^3$$

$$0 = \bar{x}^3 - \bar{x}^2 + \bar{x}$$

$$0 = \bar{x}(\bar{x}^2 - \bar{x} + 1)$$

From this, we get that $\bar{x}_1 = 0$ is a fixed pt

and, by quadratic eqn on (4),

$$\boxed{\bar{x}_2 = 1/2 + \sqrt{5}/2}$$

$$\boxed{\bar{x}_3 = 1/2 - \sqrt{5}/2}$$

fixed pts

#2 Continued

(iii) Want to know stability of $\bar{x}_1 = 0$, $\bar{x}_2 = 1/2 + \sqrt{5}/2$, $\bar{x}_3 = 1/2 - \sqrt{5}/2$

$$\text{Note, } f'(x) = x(3x-2) \checkmark$$

$$\text{Then, } |f'(\bar{x}_1)| = |f'(0)| = |0(0-2)| = 0 < 1 \Rightarrow \boxed{\bar{x}_1 = 0 \text{ stable}}$$

$$|f'(\bar{x}_2)| = |f'(\frac{1+\sqrt{5}}{2})| = |(\frac{1+\sqrt{5}}{2})(3(\frac{1+\sqrt{5}}{2})-2)| \approx 4.62 > 1 \Rightarrow \boxed{\bar{x}_2 \text{ unstable}}$$

$$|f'(\bar{x}_3)| = |f'(\frac{1-\sqrt{5}}{2})| = |(\frac{1-\sqrt{5}}{2})(3(\frac{1-\sqrt{5}}{2})-2)| \approx 2.38 > 1 \Rightarrow \boxed{\bar{x}_3 \text{ unstable}}$$

#3

$$\text{Ricker's Eqn: } x_{n+1} = \alpha x_n e^{-\beta x_n} = f(x_n)$$

$$\text{with } x_n = \text{pop-o-fish } n \text{ years } \alpha > 0 \quad \beta > 0$$

a) Seek sole fixed pt.

$$\bar{x} = f(\bar{x}) \rightarrow \bar{x} = \alpha \bar{x} e^{-\beta \bar{x}}$$

$$1 = \alpha e^{-\beta \bar{x}}$$

$$\ln \alpha = -\beta \bar{x}$$

$$-\ln(\alpha) = \ln(1) - \ln(\alpha) = \ln(1/\alpha) = -\beta \bar{x}$$

$$\Rightarrow \boxed{\bar{x} = \frac{\ln(\alpha)}{\beta}}$$

with $\bar{x} \geq 0$ for $\alpha \geq 1$ b/c, for $\alpha > 0$ (by assumption), $\ln(\alpha) \geq 0$ iff $\alpha \geq 1$ ✓

b) Seek to show $\bar{x}$ stable only if growth rate, α , satisfies $|1 - \ln \alpha| < 1$

We know $\bar{x}$ stable iff $|f'(\bar{x})| < 1$.

$$\text{Here, } f'(x) = \alpha e^{-\beta x} - \alpha x \beta e^{-\beta x} = \alpha e^{-\beta x}(1 - \beta x)$$

$$\rightarrow |f'(\frac{\ln(\alpha)}{\beta})| = \left| \alpha e^{-\beta(\frac{\ln(\alpha)}{\beta})} (1 - \beta(\frac{\ln(\alpha)}{\beta})) \right|$$

$$= \left| \alpha e^{-\ln(\alpha)} (1 - \ln(\alpha)) \right|$$

$$= \left| \frac{\alpha}{e^{\ln(\alpha)}} (1 - \ln(\alpha)) \right|$$

$$= \left| \frac{\alpha}{\alpha} (1 - \ln(\alpha)) \right|$$

$$= |1 - \ln(\alpha)|$$

Hence, $\bar{x}$ stable only if $|1 - \ln(\alpha)| < 1$, as was to be shown. ✓

$$\text{This is equivalent to } 0 < \ln(\alpha) < 2 \text{ or } 1 < \alpha < e^2 \Rightarrow \boxed{\alpha \in (1, e^2)}$$

QUESTION 3

$$f(x) = \alpha x e^{-\beta x}$$

$$\bar{x} = \frac{\ln(\alpha)}{\beta} > 0 \quad \text{only if } \alpha > 1$$

$$f'(x) = \alpha e^{-\beta x} (1 - \beta x)$$

$$f'(\bar{x}) = 1 - \ln \alpha$$

Stable if

$$-1 < 1 - \ln \alpha < 1$$

$$-2 < -\ln \alpha < 0$$

$$2 > \ln \alpha > 0$$

$$e^2 > \alpha > 1 \quad (1, e^2)$$

$$\text{Maximum } f'(x) = 0 \text{ at } \tilde{x} = \frac{1}{\beta}$$

$$f(\tilde{x}) = \frac{\alpha}{\beta} e^{-\beta \cdot \frac{1}{\beta}} = \frac{\alpha}{\beta} e^{-1}$$

$$f(\tilde{x}) = \frac{\alpha}{\beta} e^{-1}$$

(c) $T=1, 2, 4$ orbits.

Math 430 Mathematical Biology – Homework 3

Due: Thursday, March 10, 2022.

NAME: _____

1) [20] For each of the four linear systems

- find the general solution,
- classify the type of equilibria the origin is (saddle, center, etc)
- use pplane8.m to create a phase portrait for $-2 < x < 2, -2 < y < 2$

$$\frac{d\vec{x}}{dt} = A\vec{x} = \begin{bmatrix} 3 & 2 \\ 4 & 1 \end{bmatrix} \vec{x} \quad (1)$$

$$\frac{d\vec{x}}{dt} = A\vec{x} = \begin{bmatrix} 0 & 1 \\ -2 & -3 \end{bmatrix} \vec{x} \quad (2)$$

$$\frac{d\vec{x}}{dt} = A\vec{x} = \begin{bmatrix} -4 & -17 \\ 2 & 2 \end{bmatrix} \vec{x} \quad (3)$$

$$\frac{d\vec{x}}{dt} = A\vec{x} = \begin{bmatrix} 1 & 1 \\ -17 & -1 \end{bmatrix} \vec{x} \quad (4)$$

2) [10] For the following two nonlinear systems

- sketch all the x-nullclines (solid lines)
- y-nullclines (dashed lines)
- label all fixed point locations.
- Then use Figure 5.14 (pg190 text) to categorize the equilibria types.

$$\begin{aligned} \frac{dx}{dt} &= x^2 - y & \frac{dx}{dt} &= x(1-x) \\ \frac{dy}{dt} &= x - 1 & \frac{dy}{dt} &= y(1-\frac{y}{x}) \end{aligned}$$

3) [10] The dimensionless chemostat model is:

$$\frac{dn}{dt} = \alpha_1 \frac{nc}{1+c} - n \quad (5)$$

$$\frac{dc}{dt} = -\frac{nc}{1+c} - c + \alpha_2 \quad (6)$$

- The coexistence equilibria is physical only if (α_1, α_2) satisfy two inequalities (see posted notes or text for these). These in turn define a region in the (α_1, α_2) -plane. Accurately draw (sketch or shade) this region (along with its bounding curves) only for positive (physical) α_k .
- Determine the equality (or equalities) which (α_1, α_2) must satisfy for the extinction state (of bacteria) to be stable. As in i), draw/sketch the region in the (α_1, α_2) -plane where the extinction state is stable.

3ii) When is $P_0 = (0, \alpha_2)$ stable extinction.

Following notes, only if

$$(1) \text{Tr } D\vec{F} = \alpha_1 B - 2 < 0$$

$$(2) \det D\vec{F} = 1 - \alpha_1 B > 0$$

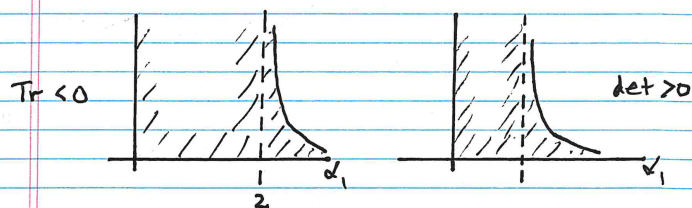
where $B = \alpha_2 / (1 + \alpha_2)$.

$$\text{Tr } D\vec{F} < 0 \quad \alpha_2 < \frac{2}{\alpha_1 - 2} \quad \text{if } \alpha_1 - 2 > 0$$

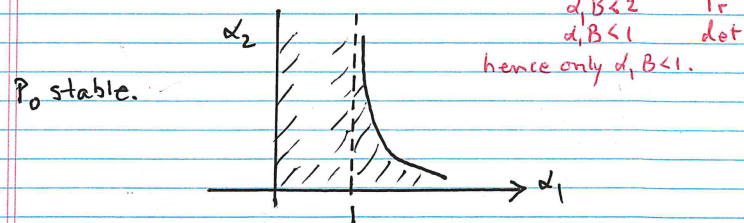
$$\alpha_2 > \frac{2}{\alpha_1 - 2} \quad \text{if } \alpha_1 - 2 < 0$$

$$\det D\vec{F} > 0 \quad \alpha_2 < \frac{1}{\alpha_1 - 1} \quad \text{if } \alpha_1 > 1$$

$$\alpha_2 > \frac{1}{\alpha_1 - 1} \quad \text{if } \alpha_1 < 1$$



Intersection of these



Simpler need

$\alpha_1 B < 2$ Tr
 $\alpha_1 B < 1$ det
 hence only $\alpha_1 B < 1$.

Math 430 Mathematical Biology – Homework 3

Due: Thursday, March 10, 2022.

NAME: _____

1) [20] For each of the four linear systems

i) find the general solution,

ii) classify the type of equilibria the origin is (saddle, center, etc)

iii) use pplane8.m to create a phase portrait for $-2 < x < 2$, $-2 < y < 2$

$$\frac{d\vec{x}}{dt} = A\vec{x} = \begin{bmatrix} 3 & 2 \\ 4 & 1 \end{bmatrix} \vec{x} \quad (1)$$

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$$\frac{d\vec{x}}{dt} = A\vec{x} = \begin{bmatrix} -4 & -17 \\ 2 & 2 \end{bmatrix} \vec{x} \quad (3)$$

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i) The coexistence equilibria is physical only if (α_1, α_2) satisfy two inequalities (see posted notes or text for these). These in turn define a region in the (α_1, α_2) -plane. Accurately draw (sketch or shade) this region (along with its bounding curves) only for positive (physical) α_k .

ii) Determine the equality (or equalities) which (α_1, α_2) must satisfy for the extinction state (of bacteria) to be stable. As in i), draw/sketch the region in the (α_1, α_2) -plane where the extinction state is stable.

Question 1

System 1: $\frac{d\vec{x}}{dt} = \begin{bmatrix} 3 & 2 \\ 4 & 1 \end{bmatrix} \vec{x}$

(i) Finding general solution.
First, compute

$$\det(A - \lambda I) = \begin{vmatrix} 3-\lambda & 2 \\ 4 & 1-\lambda \end{vmatrix} = (3-\lambda)(1-\lambda) - 8$$

$$= \lambda^2 - 4\lambda - 5$$

$$= (\lambda - 5)(\lambda + 1)$$

Which yields

$$\lambda_1 = 5 \text{ and } \lambda_2 = -1 \quad \checkmark$$

Then, for λ_1 , we find eigenvector $\vec{e}_1$

$$\begin{pmatrix} -2 & 2 \\ 4 & -4 \end{pmatrix} \vec{e}_1 = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$\rightarrow -2e_{1x} + 2e_{1y} = 0 \Rightarrow e_{1x} = e_{1y} \Rightarrow \vec{e}_1 = \langle 1, 1 \rangle$$

Then, for λ_2 we find eigenvector $\vec{e}_2$

$$\begin{pmatrix} 4 & 2 \\ 4 & 2 \end{pmatrix} \vec{e}_2 = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$$\rightarrow 4e_{2x} + 2e_{2y} = 0 \Rightarrow e_{2x} = -\frac{1}{2}e_{2y} \Rightarrow \vec{e}_2 = \langle 1, -2 \rangle$$

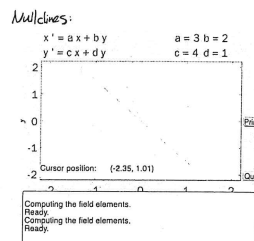
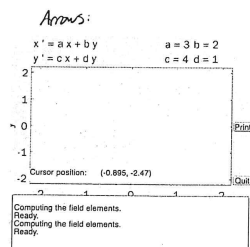
So, we conclude with the general solution

$$\vec{x}(t) = c_1 e^{5t} \begin{pmatrix} 1 \\ 1 \end{pmatrix} + c_2 e^{-t} \begin{pmatrix} 1 \\ -2 \end{pmatrix} \quad \checkmark$$

(ii) Classifying equilibria

As $\lambda_2 < 0 < \lambda_1$ (i.e. the eigenvalues have opposite signs), we determine (by page 185 of the text) that the origin has equilibria classification of a saddle. $\checkmark$

(iii) Phase Portrait



System 2: $\frac{d\vec{x}}{dt} = \begin{bmatrix} 0 & 1 \\ -2 & -3 \end{bmatrix} \vec{x}$

(i) Finding general solution.

First, compute

$$\det(A - \lambda I) = \begin{vmatrix} -\lambda & 1 \\ -2 & -3-\lambda \end{vmatrix} = (-\lambda)(-3-\lambda) - 2 = (\lambda + 2)(\lambda + 1)$$

Which yields

$$\lambda_1 = -2 \quad \lambda_2 = -1 \quad \checkmark$$

Then, for $\lambda_1 = -2$ we solve for eigenvector $\vec{e}_1$

$$\begin{pmatrix} 2 & 1 \\ -2 & -1 \end{pmatrix} \vec{e}_1 = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \Rightarrow 2e_{1x} + e_{1y} = 0 \Rightarrow \vec{e}_1 = \langle 1, -2 \rangle$$

Then, for $\lambda_2 = -1$ we solve for eigenvector $\vec{e}_2$

$$\begin{pmatrix} 1 & 1 \\ -2 & -2 \end{pmatrix} \vec{e}_2 = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \Rightarrow e_{2x} + e_{2y} = 0 \Rightarrow \vec{e}_2 = \langle 1, -1 \rangle$$

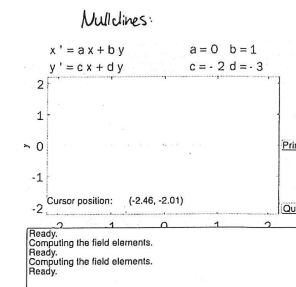
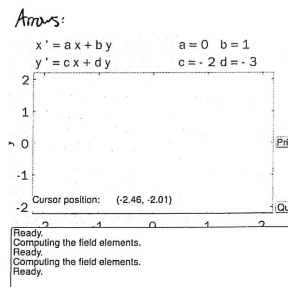
So, we conclude the general solution is

$$\vec{x}(t) = c_1 e^{-2t} \begin{pmatrix} 1 \\ -2 \end{pmatrix} + c_2 e^{-t} \begin{pmatrix} 1 \\ -1 \end{pmatrix} \quad \checkmark$$

(ii) Classifying Equilibria

As $\lambda_1 < \lambda_2 < 0$ (i.e. both eigenvalues have negative signs), by page 185 of the book we determine that the origin for this system is a stable node. $\checkmark$

(iii) Phase Portrait:



System 3: $\frac{dx}{dt} = \begin{bmatrix} -4 & -17 \\ 2 & 2 \end{bmatrix} \vec{x}$

(i) Finding general solution.

First, compute

$$\det(A - \lambda I) = \begin{vmatrix} -4-\lambda & -17 \\ 2 & 2-\lambda \end{vmatrix} = (\lambda^2 + 2\lambda - 8) + 34 = \lambda^2 + 2\lambda + 26$$

Which yields

$$\lambda_{\pm} = \frac{-2 \pm \sqrt{4 - 104}}{2} = -1 \pm 5i \quad \checkmark$$

And therefore

$$\lambda_1 = -1 + 5i \quad \lambda_2 = -1 - 5i$$

Then, for $\lambda_1 = -1 + 5i$, we can compute (using MATLAB's eig() function)

$$\vec{v} = \langle 17, -3 - 5i \rangle$$

Therefore,

$$\begin{aligned} \vec{x}(t) &= e^{-t} (\cos(5t) + i \sin(5t)) \left(\begin{pmatrix} 17 \\ -3 \end{pmatrix} + i \begin{pmatrix} 0 \\ -5 \end{pmatrix} \right) \\ &= e^{-t} \begin{pmatrix} 17 \cos 5t + 17i \sin 5t \\ -3 \cos 5t - 5i \cos 5t - 5 \sin 5t \end{pmatrix} \\ &= e^{-t} \begin{pmatrix} 17 \cos 5t \\ -3 \cos 5t - 5 \sin 5t \end{pmatrix} + e^{-t} \begin{pmatrix} 17 \sin 5t \\ -5 \cos 5t \end{pmatrix} \end{aligned}$$

So, we conclude the general solution is

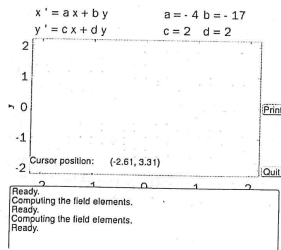
$$\vec{x}(t) = e^{-t} \left(C_1 \begin{pmatrix} 17 \cos 5t \\ -3 \cos 5t - 5 \sin 5t \end{pmatrix} + C_2 \begin{pmatrix} 17 \sin 5t \\ -5 \cos 5t \end{pmatrix} \right) \quad \checkmark$$

(ii) Classifying equilibria.

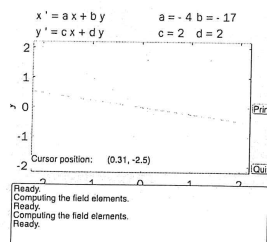
As the eigenvalues are complex (in the form $\lambda_{1,2} = a \pm ib = -1 \pm 5i$), and they have a negative real part ($a = -1 < 0$), we determine from page 185 of the book that the origin for this system is a stable spiral. $\checkmark$

(iii) Phase Portrait:

Arrows:



Mullclines:



System 4: $\frac{dx}{dt} = \begin{bmatrix} 1 & 17 \\ -17 & -1 \end{bmatrix} \vec{x}$

(i) Finding general solution.

First, compute

$$\det(A - \lambda I) = \begin{vmatrix} 1-\lambda & 17 \\ -17 & -1-\lambda \end{vmatrix} = (\lambda^2 - 1) + 17 = \lambda^2 + 16$$

Which yields

$$\lambda_{\pm} = \frac{\pm \sqrt{-4(4)}}{2} = \pm 4i \quad \checkmark$$

And therefore

$$\lambda_1 = 4i \quad \text{and} \quad \lambda_2 = -4i$$

Then, for $\lambda_1 = 4i$ we can compute (using MATLAB's eig() function)

$$\vec{v} = \langle -1 - 4i, 17 \rangle$$

Therefore,

$$\begin{aligned} \vec{x}(t) &= (\cos(4t) + i \sin(4t)) \left(\begin{pmatrix} -1 \\ 17 \end{pmatrix} + i \begin{pmatrix} -4 \\ 0 \end{pmatrix} \right) \\ &= \begin{pmatrix} -\cos 4t - 4i \cos 4t - i \sin 4t - 4 \sin 4t \\ 17 \cos 4t + 17i \sin 4t \end{pmatrix} \\ &= \begin{pmatrix} -\cos 4t - 4 \sin 4t \\ 17 \cos 4t \end{pmatrix} + i \begin{pmatrix} -4 \cos 4t - \sin 4t \\ 17 \sin 4t \end{pmatrix} \end{aligned}$$

And we conclude the general solution is

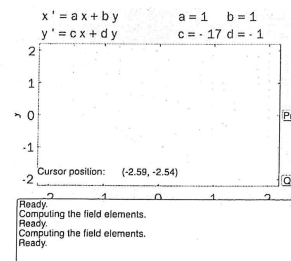
$$\vec{x}(t) = C_1 \begin{pmatrix} -\cos 4t - 4 \sin 4t \\ 17 \cos 4t \end{pmatrix} + C_2 \begin{pmatrix} -4 \cos 4t - \sin 4t \\ 17 \sin 4t \end{pmatrix} \quad \checkmark$$

(ii) Classifying Equilibria

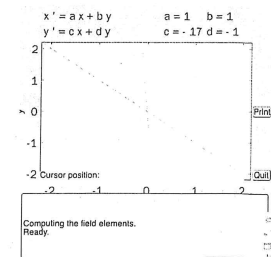
As λ_1 and λ_2 are complex (i.e. in the form $\lambda_{1,2} = a \pm ib = 0 \pm 4i$), and $a = 0$ (the eigenvalues are pure imaginary), by page 185 of the textbook we determine that the origin for this linear system is a center. $\checkmark$

(iii) Phase portrait:

Arrows:



Mullclines:



Question 2)

System 1: $\frac{dx}{dt} = x^2 - y$ $\frac{dy}{dt} = x - 1$

(i) Find the x-nullclines

The x-nullcline occurs where

$$f(x, y) = x^2 - y = 0 \Rightarrow y = x^2$$

This nullcline is sketched as the solid line on the plot below.

(ii) Find y-nullclines

The y-nullcline occurs where

$$g(x, y) = x - 1 = 0 \Rightarrow x = 1$$

This nullcline is sketched as the dashed line on the plot below.

(iii) Find fixed point locations

Fixed points occur where the x and y nullclines intersect. I.e., where

$$x = 1$$

$$y = x^2 = (1)^2 = 1$$

So, we conclude the system has a fixed point

$$(\bar{x}, \bar{y}) = (1, 1)$$

This point is indicated on the plot below.

(iv) Classify equilibria

First, we calculate the Jacobian matrix about the fixed point

$$DF(\bar{x}, \bar{y}) = DF(1, 1) = \begin{bmatrix} 2x & -1 \\ 1 & 0 \end{bmatrix} \bigg|_{(1,1)}$$

$$= \begin{bmatrix} 2 & -1 \\ 1 & 0 \end{bmatrix} \checkmark$$

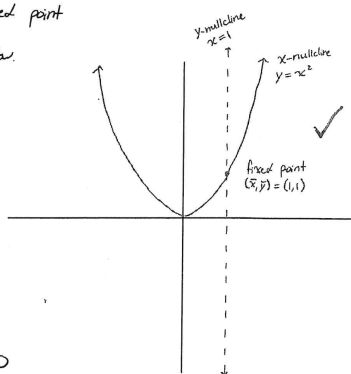
Then, we note

$$\det(DF(1, 1)) = 0 - (-1) = 1 > 0$$

$$\text{Tr}(DF(1, 1)) = 2 + 0 = 2 > 0$$

$$(\text{Tr}(DF(1, 1)))^2 - 4(\det(DF(1, 1))) = (2)^2 - 4(1) = 0$$

So, by Page 10 of the text, we determine that the fixed point is stable and directly between being a node or a spiral. $\checkmark$



5-

System 2: $\frac{dx}{dt} = x(1-x)$ $\frac{dy}{dt} = y(1-\frac{y}{x})$

(i) Find the x-nullclines

The x-nullclines occur where

$$f(x, y) = x(1-x) = 0 \Rightarrow x = 0 \text{ and } x = 1$$

however, as $x=0$ makes $\frac{dy}{dt}$ undefined, the x-nullcline occurs only at $x=1$ also at $x=0$

(ii) Find the y-nullclines

The y-nullclines occur where

$$g(x, y) = y(1-\frac{y}{x}) = 0 \Rightarrow y = 0 \text{ and } y = x$$

These nullclines are sketched as dashed lines on the plot below.

(iii) Find fixed points

Fixed points occur where the x and y nullclines intersect, i.e. where

$$\begin{matrix} x=1 \\ y=0 \end{matrix} \Rightarrow P_1 = (\bar{x}_1, \bar{y}_1) = (1, 0)$$

$$\begin{matrix} x=1 \\ y=x=1 \end{matrix} \Rightarrow P_2 = (\bar{x}_2, \bar{y}_2) = (1, 1)$$

So we conclude the system has two fixed points

$$P_1 = (1, 0) \checkmark$$

here is where

$$P_2 = (1, 1) \checkmark$$

$x=0$ excluded.

(iv) Categorize the equilibria

First, we calculate the Jacobian matrix

$$DF(x, y) = \begin{bmatrix} 1-2x & 0 \\ \frac{y}{x^2} & 1-\frac{y}{x} \end{bmatrix}$$

Then, we see for the two fixed points

$$P_1 = (1, 0): \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \checkmark$$

which yields

$$\text{Tr}(DF(P_1)) = 0$$

$$\det(DF(P_1)) = -1$$

So, by Figure 5.14 we conclude P_1 is a saddle point.

$$P_2 = (1, 1): \begin{bmatrix} -1 & 0 \\ 1 & -1 \end{bmatrix} \checkmark$$

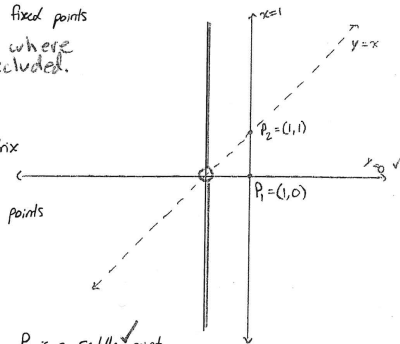
which yields

$$\text{Tr}(DF(P_2)) = -2$$

$$\det(DF(P_2)) = 1$$

$$(\text{Tr}(DF(P_2)))^2 - 4(\det(DF(P_2))) = 0$$

So, by Figure 5.14 we conclude that at P_2 the system is stable, and directly between a node and a spiral. $\checkmark$



Question 3

$$\frac{dn}{dc} = \alpha_1 \frac{nc}{1+c} - n \quad \frac{dc}{dt} = \frac{-nc}{1+c} - c + \alpha_2$$

(i) First, we find the equilibria of the system.

$$(1) \quad n(\alpha_1 \frac{c}{1+c} - 1) = 0$$

$$(2) \quad \frac{-nc}{1+c} - c + \alpha_2 = 0$$

We note the first equilibria is the extinction state, $n=0$.
Then plugging this into (2) we find that $c = \alpha_2$.
Hence, our first equilibria is

$$P_0(\bar{n}_0, \bar{c}_0) = (0, \alpha_2)$$

Note that this equilibria is always physical.

Then, we seek to find the equilibria of the coexistence state, i.e. where $n \neq 0$.
So, we know

$$\alpha_1 \frac{c}{1+c} - 1 = 0$$

Which by $\star_1$, we find

$$\bar{c}_1 = \frac{1}{\alpha_1 - 1}$$

Then, we use the above in (2), and by $\star_2$ find

$$\bar{n}_1 = \alpha_1 (\alpha_2 - \frac{1}{\alpha_1 - 1})$$

Therefore, we determine the second point of equilibria

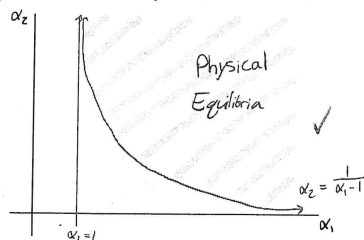
$$P_1(\bar{n}_1, \bar{c}_1) = (\alpha_1 (\alpha_2 - \frac{1}{\alpha_1 - 1}), \frac{1}{\alpha_1 - 1})$$

Now, we determine that $P_1(\bar{n}_1, \bar{c}_1)$ is physical if

$$1) \quad \frac{1}{\alpha_1 - 1} > 0 \Rightarrow \alpha_1 > 1 \quad \checkmark$$

$$2) \quad \alpha_2 > \frac{1}{\alpha_1 - 1} \quad \checkmark$$

This region of physical equilibria can be depicted as:



$$\begin{aligned} \star_1 & \quad \alpha_1 \frac{c}{1+c} - 1 = 0 \\ & \equiv \alpha_1 \frac{\bar{c}_1}{1+\bar{c}_1} = 1 \\ & \equiv \frac{1+\bar{c}_1}{\bar{c}_1} = \alpha_1 \\ & \equiv \frac{1}{\bar{c}_1} + 1 = \alpha_1 \\ & \equiv \frac{1}{\bar{c}_1} = \alpha_1 - 1 \\ & \equiv \bar{c}_1 = \frac{1}{\alpha_1 - 1} \\ \star_2 & \quad \frac{-1}{\alpha_1} \bar{n}_1 - \frac{1}{\alpha_1 - 1} + \alpha_2 = 0 \\ & \equiv \frac{-1}{\alpha_1} \bar{n}_1 = -\alpha_2 + \frac{1}{\alpha_1 - 1} \\ & \equiv \bar{n}_1 = \alpha_1 (\alpha_2 - \frac{1}{\alpha_1 - 1}) \end{aligned}$$

5

(ii) We first compute the partial derivatives to find the Jacobian matrix.

$$\frac{df}{dn} = \frac{\partial}{\partial n} \left[n(\alpha_1 \frac{c}{1+c} - 1) \right] = \alpha_1 \frac{c}{1+c} - 1$$

$$\frac{df}{dc} = \frac{\partial}{\partial c} \left[n(\alpha_1 \frac{c}{1+c} - 1) \right] = n \frac{\partial}{\partial c} \left[\alpha_1 \frac{c}{1+c} \right] = \frac{\alpha_1 n}{(1+c)^2}$$

$$\frac{dg}{dn} = \frac{\partial}{\partial n} \left[\frac{-nc}{1+c} - c + \alpha_2 \right] = \frac{-c}{1+c}$$

$$\frac{dg}{dc} = \frac{\partial}{\partial c} \left[\frac{-nc}{1+c} - c + \alpha_2 \right] = \frac{\partial}{\partial c} \left[\frac{-nc}{1+c} - c \right] = \frac{-n(1+c) - (-nc)}{(1+c)^2} - 1 = \frac{-n}{(1+c)^2} - 1$$

Then, the Jacobian Matrix is

$$DF = \begin{bmatrix} \alpha_1 \frac{c}{1+c} - 1 & \frac{\alpha_1 n}{(1+c)^2} \\ \frac{-c}{1+c} & \frac{-n}{(1+c)^2} - 1 \end{bmatrix}$$

So, for the extinction state $P_0 = (0, \alpha_2)$ ✓

$$DF(P_0) = \begin{bmatrix} \alpha_1 \frac{\alpha_2}{1+\alpha_2} - 1 & 0 \\ \frac{-\alpha_2}{1+\alpha_2} & -1 \end{bmatrix}$$

For simplicity, define

$$A = \frac{\alpha_2}{1+\alpha_2} \quad \checkmark$$

Then,

$$DF(P_0) = \begin{bmatrix} \alpha_1 A - 1 & 0 \\ -A & -1 \end{bmatrix} \quad \checkmark$$

In order for the system to be stable at the extinction state P_0 , we need

$$\text{Tr } DF(P_0) < 0$$

$$\det DF(P_0) > 0$$

Or,

$$\text{Tr } DF(P_0) = \alpha_1 A - 1 \stackrel{X}{<} 0$$

$$\det DF(P_0) = 1 - \alpha_1 A > 0 \quad \checkmark$$

Then,

$$\alpha_1 A - 1 < 0$$

$$\equiv \alpha_1 A < 1$$

$$\equiv \alpha_1 \frac{\alpha_2}{1+\alpha_2} < 1$$

$$\equiv \alpha_1 \alpha_2 < 1 + \alpha_2$$

$$\equiv \alpha_2 (\alpha_1 - 1) < 1$$

$$\equiv \alpha_2 < \frac{1}{\alpha_1 - 1} \quad \checkmark$$

$$1 - \alpha_1 A > 0$$

$$\equiv 1 - \alpha_1 \frac{\alpha_2}{1+\alpha_2} > 0$$

$$\equiv \alpha_1 \frac{\alpha_2}{1+\alpha_2} < 1$$

$$\equiv \alpha_1 \alpha_2 < 1 + \alpha_2$$

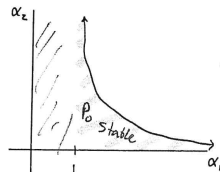
$$\equiv \alpha_2 (\alpha_1 - 1) < 1$$

$$\equiv \alpha_2 < \frac{1}{\alpha_1 - 1} \quad \checkmark$$

So, the region for which the extinction state of the bacteria is stable is

$$\alpha_2 < \frac{1}{\alpha_1 - 1}$$

which can be reflected as



Between this plot and the plot from (i), we see that the regions where the equilibria are physical and the extinction state is stable do not overlap, so a stable extinction state is not possible.

Eli Quist - M430 HW3 Phase Portraits (Question 1 Part 3)

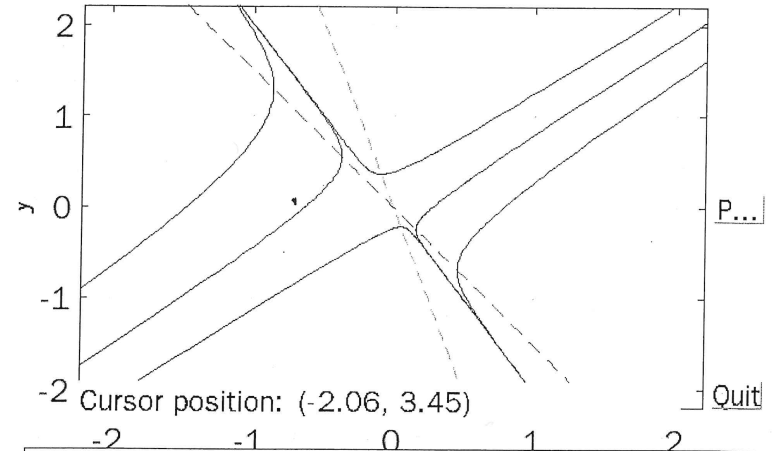
System 1

$$x' = ax + by$$

$$a = 3 \quad b = 2$$

$$y' = cx + dy$$

$$c = 4 \quad d = 1$$



The backward orbit from (0.89, 0.14) left the computation window.

Ready.

The forward orbit from (0.53, 0.3) left the computation window.

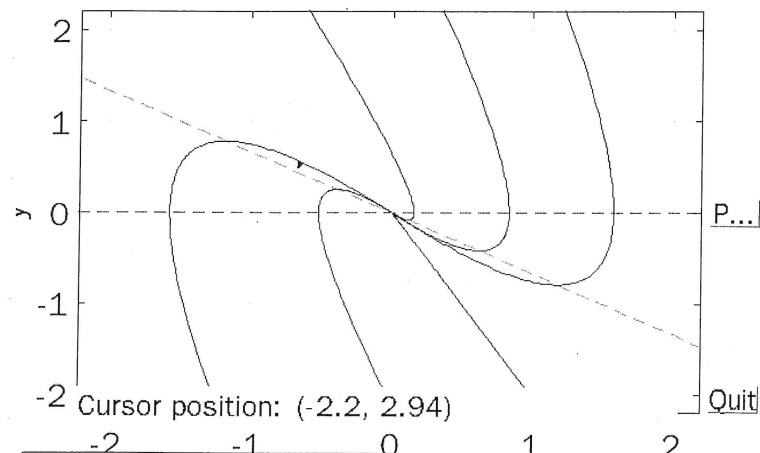
System 2

$$x' = ax + by$$

$$a = 0 \quad b = 1$$

$$y' = cx + dy$$

$$c = -2 \quad d = -3$$



The backward orbit from (1.5, 0.53) left the computation window.

Ready.

The forward orbit from (-1.5, 0.42) --> a possible eq.

pt. near (7e 17, 2.2e 17)

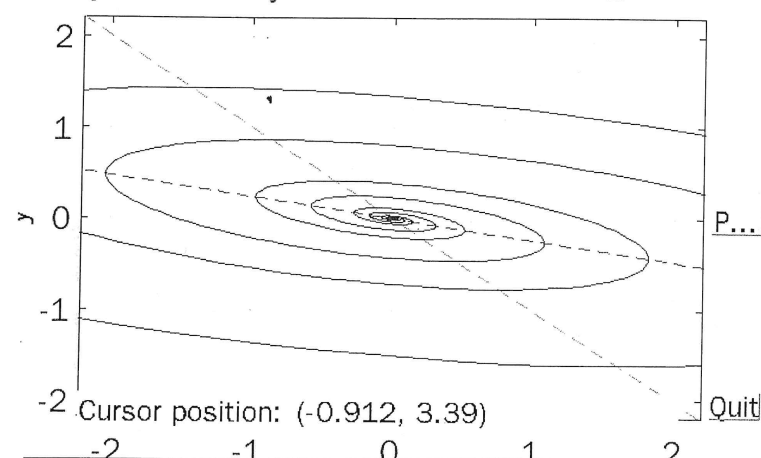
System 3

$$x' = ax + by$$

$$a = -4 \quad b = -17$$

$$y' = cx + dy$$

$$c = 2 \quad d = 2$$



The backward orbit from (0.072, 0.8) left the computation window.

Ready.

The forward orbit from (-0.34, 1.4) --> a possible eq.

pt. near (1.2e 14, 1.9e 16)

Math 430 Mathematical Biology – Homework 3

Due: Thursday, March 10, 2022.

NAME: _____

1) [20] For each of the four linear systems

i) find the general solution,

ii) classify the type of equilibria the origin is (saddle, center, etc)

iii) use pplane8.m to create a phase portrait for $-2 < x < 2$, $-2 < y < 2$

$$\frac{d\vec{x}}{dt} = A\vec{x} = \begin{bmatrix} 3 & 2 \\ 4 & 1 \end{bmatrix} \vec{x} \quad (1)$$

$$\frac{d\vec{x}}{dt} = A\vec{x} = \begin{bmatrix} 0 & 1 \\ -2 & -3 \end{bmatrix} \vec{x} \quad (2)$$

$$\frac{d\vec{x}}{dt} = A\vec{x} = \begin{bmatrix} -4 & -17 \\ 2 & 2 \end{bmatrix} \vec{x} \quad (3)$$

$$\frac{d\vec{x}}{dt} = A\vec{x} = \begin{bmatrix} 1 & 1 \\ -17 & -1 \end{bmatrix} \vec{x} \quad (4)$$

2) [10] For the following two nonlinear systems

i) sketch all the x-nullclines (solid lines)

ii) y-nullclines (dashed lines)

iii) label all fixed point locations.

iv) Then use Figure 5.14 (pg190 text) to categorize the equilibria types.

$$\begin{aligned} \frac{dx}{dt} &= x^2 - y & \frac{dx}{dt} &= x(1-x) \\ \frac{dy}{dt} &= x - 1 & \frac{dy}{dt} &= y(1-\frac{y}{x}) \end{aligned}$$

3) [10] The dimensionless chemostat model is:

$$\frac{dn}{dt} = \alpha_1 \frac{nc}{1+c} - n \quad (5)$$

$$\frac{dc}{dt} = -\frac{nc}{1+c} - c + \alpha_2 \quad (6)$$

i) The coexistence equilibria is physical only if (α_1, α_2) satisfy two inequalities (see posted notes or text for these). These in turn define a region in the (α_1, α_2) -plane. Accurately draw (sketch or shade) this region (along with its bounding curves) only for positive (physical) α_k .

ii) Determine the equality (or equalities) which (α_1, α_2) must satisfy for the extinction state (of bacteria) to be stable. As in i), draw/sketch the region in the (α_1, α_2) -plane where the extinction state is stable.

Math 430 Mathematical Biology

Midterm - Takehome (max=50)

Due Thursday March 24, 2022.

Name: _____

Instructions : The following guidelines must be observed:

- You may use the textbook, notes on the course website, or your own classroom notes
- You must work alone and may not talk to fellow classmates. You may ask me clarifying questions.
- Merely stating an answer is insufficient. You must show your work.
- This test (with your name on it) must be stapled to your work.
- You may use matlab and/or a calculator.
- Make sure your work is legible and in the proper order.

1. [10pts] Recall the simple *growth with harvesting model*

$$x_{n+1} = \lambda x_n - h$$

where x_n is the chicken population after n years, x_0 is the initial population, λ is the growth rate and h is the harvesting rate (chickens per year). The units are in hundreds of chickens so that $x_n=5$ means 500 chickens. The solution derived in class was:

$$x_n = \lambda^n x_0 - \left(\frac{\lambda^n - 1}{\lambda - 1} \right) h \quad 0 = \lambda^{10} x_0 - \left(\frac{\lambda^{10} - 1}{\lambda - 1} \right) h$$

Suppose $x_0 = 10$, $\lambda = 5$ and the population becomes extinct after $n = 10$ years. At what rate h were the chickens harvested? $h = 40$

2. [10pts] Find the general solution of the following difference equation:

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

What does x_n approach as $n \rightarrow \infty$

3. [10pts] Define a map by:

$$x_{n+1} = f(x_n) = -\alpha x_n \ln x_n \quad (1)$$

For $\alpha > 0$, $f(x) > 0$ on $x \in (0, 1)$.

- Draw an accurate sketch of $y = x$ and $y = f(x)$ for $0 < x \leq 1$ labelling the positive fixed point $\bar{x}$. You may use the fact that $\lim_{x \rightarrow 0^+} f(x) = 0$.
- Find a formula for the positive fixed point $\bar{x}$ of (1) in terms of α .
- Compute and then simplify $f'(\bar{x})$ (it really simplifies!).
- Given your result in c), for what α is the fixed point stable, i.e. $|f'(\bar{x})| < 1$.

Math 430 Mathematical Biology – Homework 4

Due: Thursday, April 7, 2022. NAME: _____

1) [10] Capasso and Serio (1978) considered the following *SIR* epidemic model with emigration of the susceptible *S*:

$$\frac{dS}{dt} = -g(I)S - \lambda S \quad (1)$$

$$\frac{dI}{dt} = g(I)S - \beta I \quad (2)$$

$$\frac{dR}{dt} = \lambda S + \beta I \quad (3)$$

where $g(I) = \alpha I e^{-I}$. The parameters α, β, λ are all **positive**. The function $g(I)$ is meant to take into account "psychological" effects. In particular, when the number of infectives *I* is large the number of interactions $g(I)S$ is smaller since the susceptibles *S* notice the infected people and actively try to stay away from them.

- Is the total population $N = S + I + R$ conserved?
- Show the (S, I) system has no positive (physical $S > 0, I > 0$) equilibria.
- Show the $(S, I) = (0, 0)$ extinction state is stable.
- Create a phase plane diagram showing that *S, I* both die out and hence all people recover. Include the nullclines and at least one trajectory illustrating the aforementioned dynamic. You may use $\alpha = \beta = \lambda = 1$ as parameter values.

2) [5] Nondimensionalize the SIR model

$$\frac{dS}{dt} = -\alpha SI \quad (4)$$

$$\frac{dI}{dt} = \alpha SI - \beta I \quad (5)$$

$$\frac{dR}{dt} = \beta I \quad (6)$$

In particular, scale the dependent and independent variables :

$$S = sS^*, \quad I = iI^*, \quad R = rR^*, \quad t = \tau t^*,$$

and show that for a certain choice of the constants S^*, I^*, R^* and t^* the resulting system for lower case s, i, r, τ contains no parameters.

The new dimensionless system should look like:

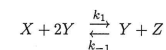
$$\frac{ds}{d\tau} = -si \quad (7)$$

$$\frac{di}{d\tau} = si - i \quad (8)$$

$$\frac{dr}{d\tau} = i \quad (9)$$

State the constants S^*, I^*, R^* and t^* formulae in terms of α and β .

3) [5] Use Law of Mass Action to write out the (molar) concentration differential equations for the following reactions.



1) [10] Capasso and Serio (1978) considered the following SIR epidemic model with emigration of the susceptible S :

$$\frac{dS}{dt} = -g(I)S - \lambda S \quad (1)$$

$$\frac{dI}{dt} = g(I)S - \beta I \quad (2)$$

$$\frac{dR}{dt} = \lambda S + \beta I \quad (3)$$

where $g(I) = \alpha I e^{-I}$. The parameters α, β, λ are all positive. The function $g(I)$ is meant to take into account "psychological" effects. In particular, when the number of infectives I is large the number of interactions $g(I)S$ is smaller since the susceptibles S notice the infected people and actively try to stay away from them.

a) Is the total population $N = S + I + R$ conserved?

First, we note that $N = S + I + R$. Then, consider the rate of change of the population,

$$\begin{aligned} \frac{dN}{dt} &= \frac{d}{dt}(S + I + R) \\ &= \frac{dS}{dt} + \frac{dI}{dt} + \frac{dR}{dt} \\ &= -g(I)S - \lambda S + g(I)S - \beta I + \lambda S + \beta I \\ &= -g(I)S - \lambda S + g(I)S - \beta I + \lambda S + \beta I \\ &= 0. \end{aligned}$$

As the rate of change of the total population, $\frac{dN}{dt}$, is zero, we know the total population does not change over time. Therefore, we conclude that the total population is conserved.

b) Show the (S, I) system has no positive (physical $S > 0, I > 0$) equilibria.

Recall, an equilibria occurs when $\frac{dS}{dt}$ or $\frac{dI}{dt}$ equal zero. First, consider $\frac{dS}{dt} = S(-g(I) - \lambda)$

This equals zero when,

Case 1: $S = 0$.

By definition, physical equilibria occur when $S > 0$, so this case is not valid.

Case 2: $-g(I) - \lambda = 0$.

As $I > 0$ (due to hypothesis of physicality), $g(I) = \alpha I e^{-I} > 0$, and then it follows that $-g(I) < 0$. By hypothesis, $\lambda > 0$, and therefore $-\lambda < 0$. So, it becomes clear that $-g(I) - \lambda < 0$, and therefore $-g(I) - \lambda \neq 0$.

As neither case holds, we see that

$$\frac{dS}{dt} \neq 0$$

for $S, I > 0$, and therefore the (S, I) system has no physical equilibria.

c) Show the $(S, I) = (0, 0)$ extinction state is stable.

$$\frac{dS}{dt} = f(S, I) = -g(I)S - \lambda S$$

$$\frac{dI}{dt} = g(S, I) = g(I)S - \beta I$$

$$g(I) = \alpha I e^{-I}$$

First, we calculate the Jacobian,

$$DF = \begin{bmatrix} f_S & f_I \\ g_S & g_I \end{bmatrix}$$

$$\frac{\partial f}{\partial S} = -g(I) - \lambda = -\alpha I e^{-I} - \lambda$$

$$\frac{\partial f}{\partial I} = -S \frac{\partial g(I)}{\partial I} = S \alpha e^{-I} (I - 1)$$

$$\frac{\partial g}{\partial S} = g(I) = \alpha I e^{-I}$$

$$\frac{\partial g}{\partial I} = S \alpha e^{-I} (I - 1) - \beta$$

And therefore,

$$DF = \begin{bmatrix} -\alpha I e^{-I} - \lambda & S \alpha e^{-I} (I - 1) \\ \alpha I e^{-I} & S \alpha e^{-I} (I - 1) - \beta \end{bmatrix}$$

Then, consider the extinction state

$$DF(0,0) = \begin{bmatrix} -\lambda & 0 \\ 0 & -\beta \end{bmatrix}$$

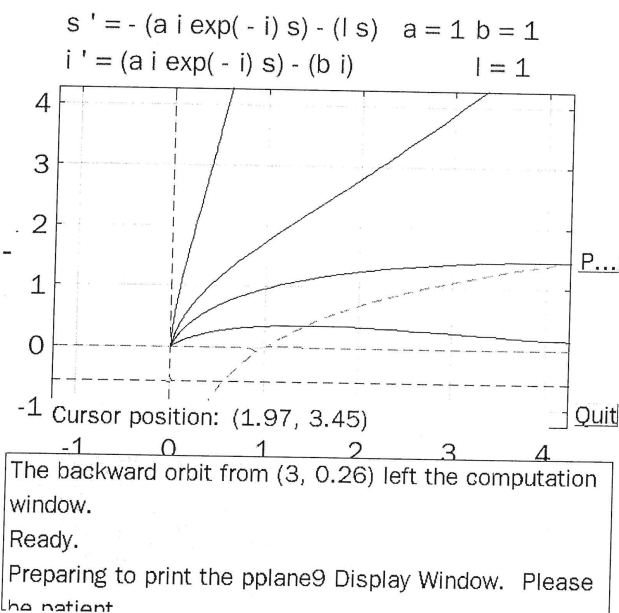
So, it follows that

$$\det DF(0,0) = \beta \lambda > 0$$

$$\text{Tr } DF(0,0) = -\lambda - \beta < 0$$

As $\det DF(0,0) > 0$ and $\text{Tr } DF(0,0) < 0$, by Page 110 of the textbook we conclude that $(S, I) = (0, 0)$ is stable.

- d) Create a pplane9 (phase plane) diagram showing that S, I both die out and hence all people recover. Include the nullclines and at least one trajectory illustrating the aforementioned dynamic. You may use $\alpha = \beta = \lambda = 1$ as parameter values.



As all trajectories travel to (0,0), we know eventually $S=I=0$. Then, as $N=S+I+R$,

$$N = (0) + (0) + R \Rightarrow R = N.$$

So, we conclude that the entire population, N , will eventually end up in the "Recovered" group.

2) [5] Nondimensionalize the SIR model

$$\frac{dS}{dt} = -\alpha SI \quad (4)$$

$$\frac{dI}{dt} = \alpha SI - \beta I \quad (5)$$

$$\frac{dR}{dt} = \beta I \quad (6)$$

In particular, scale the dependent and independent variables:

$$S = sS^*, \quad I = iI^*, \quad R = rR^*, \quad t = \tau t^*,$$

and show that for a certain choice of the constants S^*, I^*, R^* and t^* the resulting system for lower case s, i, r, τ contains no parameters.

First, we scale the system, and simplify each

$$(4a) \quad \frac{dS^*}{dt^*} = -\alpha S^* I^*$$

$$(4b) \quad \frac{dS}{dt} = -\alpha S^* I^* \alpha$$

$$(5a) \quad \frac{dI^*}{dt^*} = \alpha S^* I^* - \beta I^*$$

$$(5b) \quad \frac{dI}{dt} = \alpha S^* I^* - \beta I^*$$

$$(6a) \quad \frac{dR^*}{dt^*} = \beta I^*$$

$$(6b) \quad \frac{dR}{dt} = \beta I^* \frac{\beta I^* t^*}{R^*}$$

Then, from (4b), (5b), and (6b), to make the system dimensionless we generate a system of equations setting the parameters and scaling constants equal to 1.

$$(4c) \quad t^* I^* \alpha = 1$$

$$(5c.1) \quad \alpha S^* t^* = 1$$

$$(5c.2) \quad \beta t^* = 1$$

$$(6c) \quad \frac{\beta I^* t^*}{R^*} = 1$$

Starting with (5c.2), we let $t^* = 1/\beta$. Then, using (5c.1) we see $\alpha S^* t^* = \alpha S^* (1/\beta) = 1 \Rightarrow S^* = \frac{\beta}{\alpha}$

Similarly, using (4c), it can be shown $I^* = \frac{\beta}{\alpha}$, and then using (6c) that $R^* = \beta/\alpha$ also.

So, in summary, we have chosen the constants

$$t^* = 1/\beta \quad I^* = \beta/\alpha$$

$$S^* = \beta/\alpha \quad R^* = \beta/\alpha$$

Then, we want to show that this choice of constants makes the system for s, i, r, τ contain no parameters.

First, consider (4b)

$$\frac{ds}{dt} = -s i t^* I^* \alpha = -s i \left(\frac{1}{\beta}\right) \left(\frac{\beta}{\alpha}\right) \alpha = -s i$$

Then, consider (5b)

$$\frac{di}{dt} = s i \alpha S^* t^* - i \beta t^* = s i \cdot \alpha \left(\frac{\beta}{\alpha}\right) \left(\frac{1}{\beta}\right) - i \cdot \beta \left(\frac{1}{\beta}\right) = s i - i = i(s-1)$$

Finally, consider (6a)

$$\frac{dr}{dt} = i \frac{\beta I^* t^*}{R^*} = i \frac{\beta \left(\frac{\beta}{\alpha}\right) \left(\frac{1}{\beta}\right)}{\left(\frac{\beta}{\alpha}\right)} = i$$

In summary, for $t^* = 1/\beta$, $S^* = \alpha/\beta$, $I^* = \alpha/\beta$, $R^* = \alpha/\beta$, we see

$$\frac{ds}{dt} = -s i$$

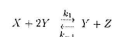
$$\frac{di}{dt} = i(s-1)$$

$$\frac{dr}{dt} = i$$

And therefore, for constants chosen as above, the system for s, i, r contains no parameters.

you flipped them here. See (*)

3) [9] Use Law of Mass Action to write out the (molar) concentration differential equations for the following reactions.



Using the general formula (as discussed in class), we compute the molar concentration differential equations as

$$\frac{dX}{dt} = -k_1 X Y^2 + k_{-1} Y Z$$

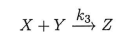
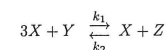
$$\frac{dY}{dt} = -k_1 X Y^2 + k_{-1} Y Z$$

$$\frac{dZ}{dt} = k_1 X Y^2 - k_{-1} Y Z$$

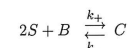
Math 430 Mathematical Biology – Homework 5

Due: Tuesday, April 26, 2022. NAME: _____

1) [5] Use Law of Mass Action to write out the (molar) concentration differential equations for the following reactions.



2) [10] Let S =substrate, B =buffer and C =complex. A slightly different form of buffering is given by the reaction equations:



Using the Law of Mass Action the differential equations governing the molar concentrations is given by:

$$\frac{dS}{dt} = -2k_{+}BS^2 + 2k_{-}C, \quad S(0) = S_0 \quad (1)$$

$$\frac{dB}{dt} = -k_{+}BS^2 + k_{-}C, \quad B(0) = B_0 \quad (2)$$

$$\frac{dC}{dt} = k_{+}BS^2 - k_{-}C, \quad C(0) = C_0 \quad (3)$$

a) Find the function $f(S, B)$ such that the above system can be reduced to

$$\begin{aligned} S' &= 2f(B, S) \\ B' &= f(B, S) \end{aligned}$$

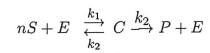
b) Find the function $g(S)$ such that $f = 0$ only if

$$B = g(S) = \frac{\bar{V}}{K_E + S^2}$$

for certain parameters $\bar{V}$ and K_E (write these out in terms of the original model parameters : k_{-}, k_{+}, S_0, B_0)

- c) Use Matlab or any other plotting program to make a phase plane portrait like that done in my lecture notes for the regular buffering problem. It should be in the (S,B)-plane, be first quadrant only, have an accurate plot of $f = 0$ and several trajectories. Use the parameter values $k_+ = k_- = S_0 = B_0 = 1$ and S values in $[0, 2]$

3) [10] A variation of Michaelis-Menten kinetics is n -site cooperativity where n substrate molecules S must bind in order for the product P to be made. The reaction equations are:



The subsequent dimensional differential equations for the reaction are

$$\begin{aligned} \frac{dS}{dt} &= f_1 = -nk_1S^nE + nk_{-1}C, & S(0) &= S_0 \\ \frac{dE}{dt} &= f_2 = -k_1S^nE + (k_{-1} + k_2)C, & E(0) &= E_0 \\ \frac{dC}{dt} &= -f_2 = k_1S^nE - (k_{-1} + k_2)C, & C(0) &= 0 \\ \frac{dP}{dt} &= k_2C \end{aligned}$$

- a) Without nondimensionalizing the equations, use conservation of receptors to find the quasi-steady state approximation of the production rate

$$\frac{dP}{dt} = V(S)$$

that only depends on S (and not E, C). This is the ubiquitous "Hille" function.

- b) According to the fast-subsystem analysis (in class and notes), the complex concentration very quickly rises from 0 to a maximum value C_{max} . Find a formula for C_{max}

First order linear difference eqn population model

a_n = # females in n^{th} generation

p_n = # progeny in n^{th} generation

f = # progeny per female

m = fractional mortality of progeny

r = fraction of females in total population

Given these definitions

$$(1) \quad p_{n+1} = f a_n$$

and

$$(2) \quad a_{n+1} = r \underbrace{(1-m) p_{n+1}}_{\text{progeny that survived generation.}}$$

Combining (1)-(2)

$$\boxed{\begin{aligned} a_{n+1} &= \lambda a_n \\ \lambda &\equiv fr(1-m) \end{aligned}}$$

Linear first order solution

$$x_{n+1} = \lambda x_n \quad n=0,1,2,\dots$$

Here x_0 is the initial condition

$$x_1 = \lambda x_0$$

$$x_2 = \lambda x_1 = \lambda^2 x_0$$

$$x_3 = \lambda x_2 = \lambda^3 x_0$$

By induction

$$\boxed{x_n = \lambda^n x_0}$$

Solution also works if $\lambda \in \mathbb{C}$ is complex.

$$|\lambda| < 1 \quad \Rightarrow \quad x_n \rightarrow 0$$

$$|\lambda| > 1 \quad \Rightarrow \quad x_n \rightarrow \infty$$

When $|\lambda| = 1$, x_n is constant or period 2.

Ex Let x_n = number of bacteria after n days

$$x_{n+1} = \lambda x_n$$

what is the doubling time?

$$x_n = \lambda^n x_0$$

In how many days n does $x_n = 2x_0$

$$2 = \lambda^n$$

$$n = \frac{\ln 2}{\ln \lambda}$$

Ex Conversion of time units

x_n = # bact after n days

X_N = # bact after N weeks

If we model x_n as before $x_{n+1} = \lambda x_n$

$$X_1 = x_7$$

$$X_2 = x_{14}$$

$$X_3 = x_{21}$$

Clearly

$$X_{N+1} = \lambda^7 X_N$$

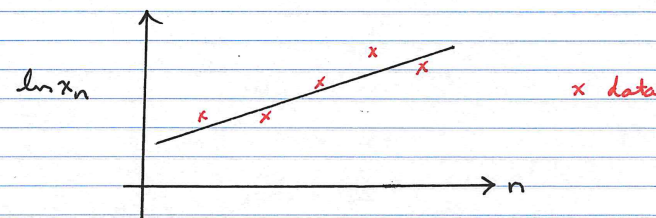
Ex Experimental Data

$$x_{n+1} = \lambda x_n$$

$$x_n = \lambda^n x_0$$

From which we derive

$$(1) \quad \underset{\substack{\uparrow \\ \text{plot}}}{\ln x_n} = n \underset{\substack{\uparrow \\ \text{don't know}}}{\ln \lambda} + \underset{\substack{\uparrow \\ \text{know}}}{\ln x_0}$$



Choose slope $\ln \lambda$ to best match data.

Generally done with linear regression.

Harvesting Model

$$(1) \quad \boxed{x_{n+1} = \lambda x_n - h} \quad \lambda > 1, h \geq 0$$

where

x_n = number of chicken at year n

h = number of chickens harvested per year

To solve (1) we translate x_n into a form we know how to solve

$$(2) \quad x_n = y_n + \bar{x}$$

Substitute (2) into (1)

$$y_{n+1} + \bar{x} = \lambda(y_n + \bar{x}) - h$$

Rearrange terms

$$y_{n+1} = \lambda y_n + \underbrace{(\lambda - 1)\bar{x} - h}_{\text{choose } \bar{x} \text{ so this vanishes}}$$

Thus, for

$$(3) \quad \bar{x} = \frac{h}{\lambda - 1}$$

we have

$$(4) \quad y_{n+1} = \lambda y_n$$

This we know how to solve: $y_n = \lambda^n y_0$.

Hence

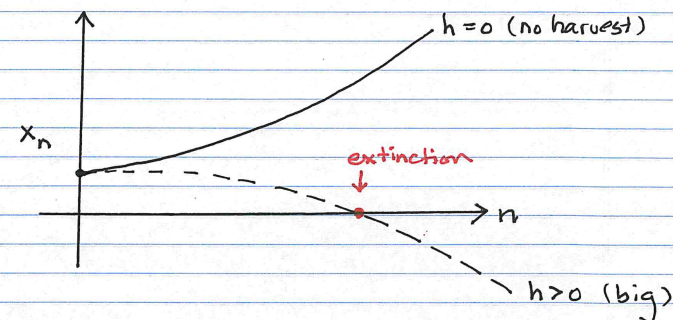
$$x_n = \lambda^n y_0 + \bar{x}$$

$$x_n = \lambda^n (x_0 - \bar{x}) + \bar{x}$$

Collecting terms and using (3)

$$\boxed{x_n = \lambda^n x_0 - \left(\frac{\lambda^n - 1}{\lambda - 1} \right) h}$$

↑ ↑
regular loss to
growth harvesting



QUESTION ONE : For what h does population remain constant?

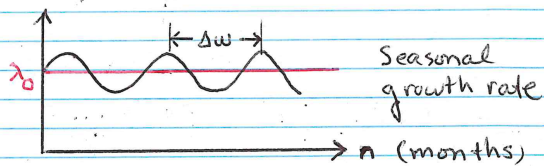
QUESTION TWO : At what year does population become extinct?

Seasonal Growth Rates and Harvesting

$$x_{n+1} = \lambda_n x_n - h$$

↑
growth rate varies with time n .
As an example

$$\lambda_n = \lambda_0 + \alpha \sin(\omega n)$$



Here

$$\omega = \frac{2\pi}{12}$$

gives an annual oscillation frequency $\Delta\omega = 12$

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Harvesting model
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% X(n+1) = lambda X(n) - h
%
% with initial condition X(0)=X0
% has exact solution:
%
% X(n) = lambda^n X0 - (lambda^n - 1) / (lambda - 1) * h
%
% First calculate X(n) without the formula above.
%
clear X;
lambda = 1.1;
X(1) = 2;
h = 0.20;
h = 0.30;
N = 10;
for n = 1:N
    X(n+1) = lambda * X(n) - h;
end;
figure(4)
plot(0:N, X)
%
% Now compute Y=X using formula above
%
m = 0:N;
Y = lambda.^m * X(1) - (lambda.^m - 1) ./ (lambda - 1) * h;
hold on
plot(m, Y, 'r*')
title(['X_n in harvest model: ', num2str(lambda), ', h = ', num2str(h)])
xlabel('n')
ylabel('X_n')
hold off

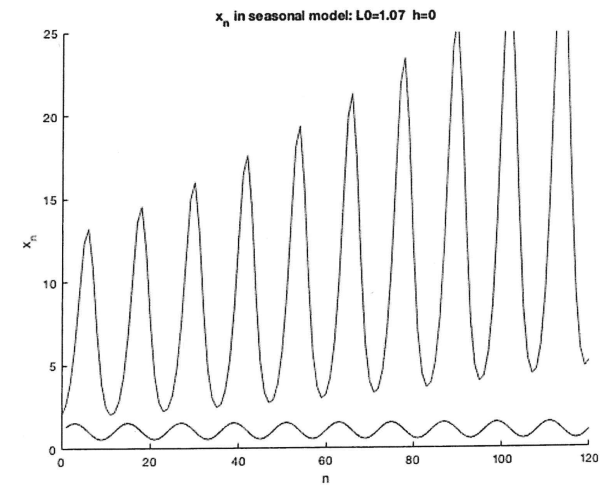
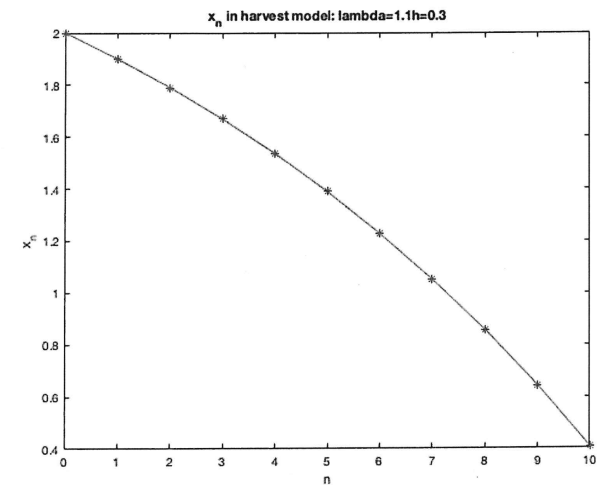
%
%
%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Harvesting model with Seasonal Variation
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%
% Seasonal variation of growth rate. Suppose
% n = time (in months) since start growth rate at
% time n is L(n):
%
% L = L0 + alpha * sin(omega * n)
%
% X(n+1) = L(n) X(n) - h
%

```

```

% with initial condition X(1)=X0.
%
%
clear X;
N=120;
L0=1.07;
alpha=0.5;
omega=2*pi./12;
L=L0+alpha*sin(omega*(1:N));
%
%
X(1)=2;
h=0.000;
%h=0.035;
for n=1:N
    X(n+1)=L(n)*X(n)-h;
end;
%
figure(5)
clf
hold on
plot(0:N,X,'r-')
plot(1:N,L,'b-')
title(['x_n in seasonal model: L0=',num2str(L0),' h=',num2str(h)])
xlabel('n')
ylabel('x_n')
axis([0,N,0,25])
hold off

```

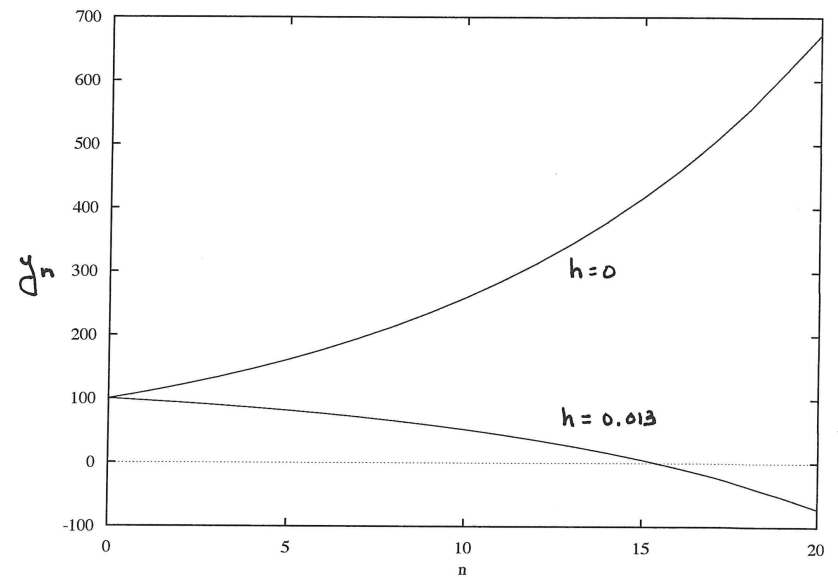


xppaut code for difference (discrete) eqns

$$x_{n+1} = c_1 x_n$$
$$y_{n+1} = c_2 y_n - h$$

```
#  
#  
#  
par c1=1.1,c2=1.1,h=13  
init x=100,y=100  
#  
#  
x(t+1)=c1*x  
y(t+1)=c2*y-h  
#  
#  
@ total=20,method=discrete,nout=1  
done
```

xppaut output "Graph.Stuff.... postscript"



Maple Code for x_n (notes)

```
> restart;
```

```
> x0:=100;lambda:=1.1;h:=13;
```

```
x0:=100
```

```
λ:=1.1
```

```
h:=13
```

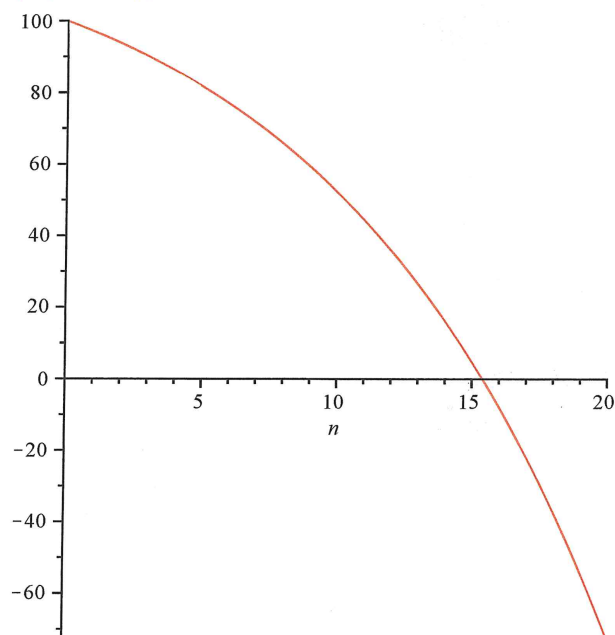
(1)

```
> xn:=lambda^n*x0-h*(lambda^n-1)/(lambda-1);
```

```
xn := -30.00000000 1.1^n + 130.00000000
```

(2)

```
> plot(xn,n=0..20);
```



Nonlinear Density Dependent Models

$$(1) \quad x_{n+1} = x_n g(x_n) = f(x_n)$$

where here

$$g(x) = \text{growth rate at density } x$$

Remarks

a) If $g(x) = r$, $r > 0$ constant then the model in (1) is the linear model

$$x_{n+1} = r x_n$$

b) If at some time n we have $g(x_n) = 1$ then

$$x_{n+1} = x_n$$

$$x_{n+2} = x_{n+1} g(x_{n+1}) = x_n$$

$$x_{n+3} = x_{n+2} g(x_{n+2}) = x_n$$

In other words, if $g(x_n) = 1$ then

$$x_N = x_n \quad \forall N \geq n$$

Note " $\forall$ " means for all.

An orbit of $x_{n+1} = f(x_n)$

$$\gamma(x_0) = \{x_0, x_1, x_2, x_3, \dots\}$$

$$\gamma(x_0) = \{x_0, f(x_0), f^2(x_0), f^3(x_0), \dots\}$$

gives discrete time series for population given an initial density x_0 .

EXAMPLE $f(x) = x(1-x)$ $x_0 = \frac{1}{2}$

$$x_1 = f(x_0) = \frac{1}{2} \left(1 - \frac{1}{2}\right) = \frac{1}{4}$$

$$x_2 = f(x_1) = \frac{1}{4} \left(1 - \frac{1}{4}\right) = \frac{3}{16}$$

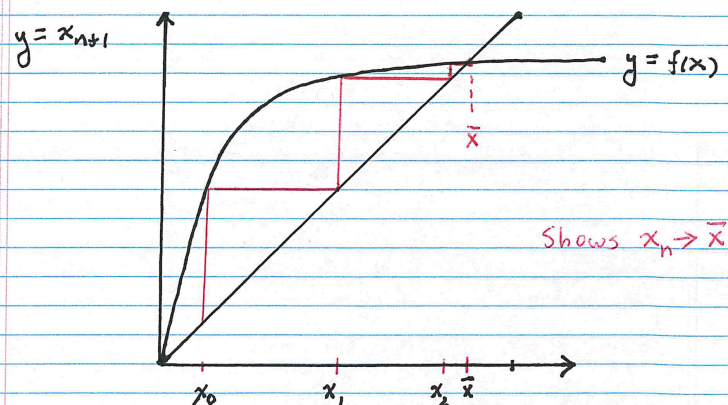
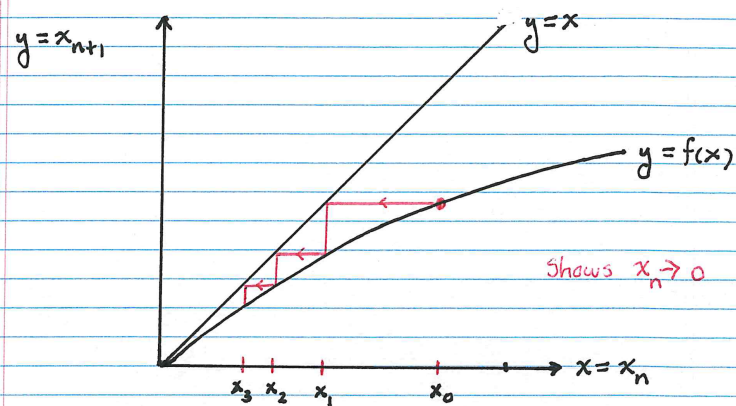
$$x_3 = f(x_2) = \frac{3}{16} \left(1 - \frac{3}{16}\right) = \frac{39}{256}$$

Hence

$$\gamma(x_0) = \left\{ \frac{1}{2}, \frac{1}{4}, \frac{3}{16}, \frac{39}{256}, \dots \right\}$$

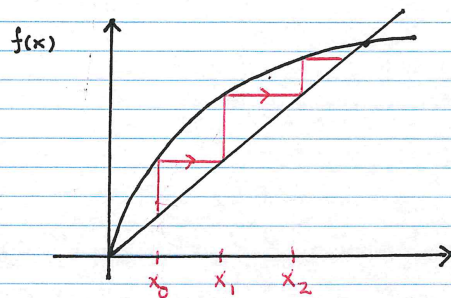
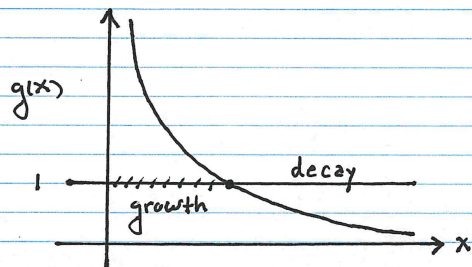
Cobwebs $x_{n+1} = f(x_n)$

Is a graphical method for finding orbits.



EXAMPLE Varley, Gradwell, Hassel (1975)

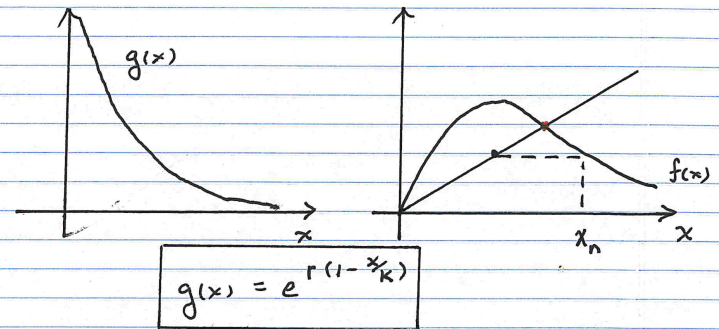
$$g(x) = \lambda x^{-b} \quad 0 < b < 1$$



$$f(x) = x g(x)$$

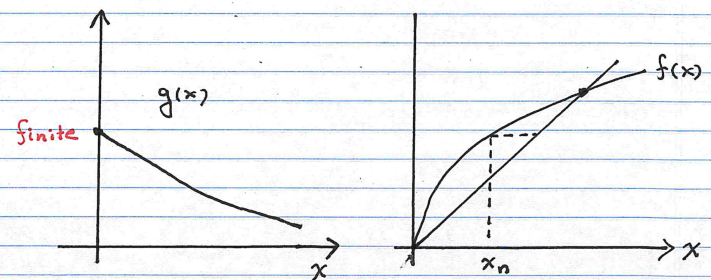
$$f(x) = \lambda x^{1-b}$$

EX May 1975



$$g(x) = e^{r(1-\frac{x}{k})}$$

EX Hassel 1973



$$g(x) = \lambda (1+ax)^{-b}$$

Fixed points and Linear stability

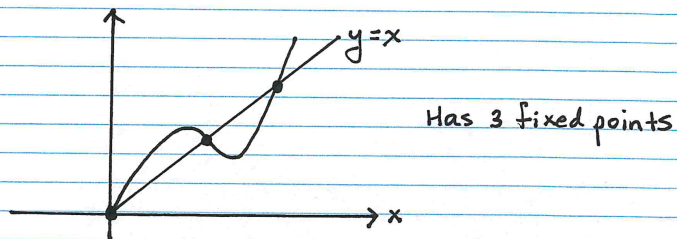
$$(1) \quad x_{n+1} = f(x_n)$$

A fixed point of (1) is a value $\bar{x}$ such that

$$(2) \quad \bar{x} = f(\bar{x})$$

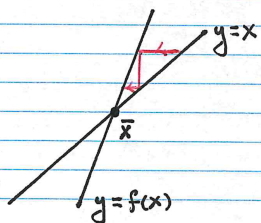
For these values $x_n = \bar{x}$ for all n if $x_0 = \bar{x}$

EX

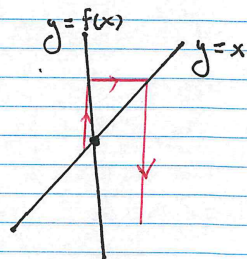


Linear stability

A fixed point $\bar{x}$ is linearly stable if $x_n \rightarrow \bar{x}$ for all x_0 sufficiently close to $\bar{x}$



$\bar{x}$ lin. stable



$\bar{x}$ unstable

Linear Stability

Let $\bar{x}$ be a fixed point of

$$(1) \quad x_{n+1} = f(x_n)$$

Then

$$|f'(\bar{x})| < 1 \Rightarrow \bar{x} \text{ stable}$$

$$|f'(\bar{x})| > 1 \Rightarrow \bar{x} \text{ unstable}$$

Proof Sketch using Taylor series. Define

$$(2) \quad x_n = \bar{x} + \Delta x_n \quad \leftarrow |\Delta x_n| = \text{distance from } \bar{x}$$

Substitute (2) into (1)

$$x_{n+1} = f(x_n)$$

$$\bar{x} + \Delta x_{n+1} = f(\bar{x} + \Delta x_n)$$

$$f(\bar{x}) = \bar{x} \quad \bar{x} + \Delta x_{n+1} = \bar{x} + f'(\bar{x})\Delta x_n + \frac{1}{2}f''(\bar{x})\Delta x_n^2 + \dots \quad (\text{smaller})$$

$$\Delta x_{n+1} \approx f'(\bar{x})\Delta x_n$$

Looks like $\Delta x_{n+1} = \lambda \Delta x_n$ which decays only if $|\lambda| < 1$

$$|f'(\bar{x})| < 1 \Rightarrow \Delta x_n \rightarrow 0$$

$$|f'(\bar{x})| > 1 \Rightarrow \Delta x_n \rightarrow \infty$$

EXAMPLE

Find any positive fixed point(s) and stability of the difference equation (map)

$$x_{n+1} = x_n \ln x_n^2$$

$$x_{n+1} = f(x_n)$$

Here $f(x) = x \ln x^2$ and $\bar{x}$ is a fixed point if

$$\bar{x} = \bar{x} \ln \bar{x}^2$$

$$1 = \ln \bar{x}^2$$

$$e = \bar{x}^2$$

$$\boxed{e^{1/2} = \bar{x}}$$

To find the stability we need to compute $f'(\bar{x})$

$$f'(x) = \ln x^2 + x \cdot \left(\frac{1}{x^2} \cdot 2x\right)$$

$$f'(x) = \ln x^2 + 2$$

Hence

$$f'(\bar{x}) = \ln \bar{x}^2 + 2 = \ln e + 2 = 3$$

Since $|f'(\bar{x})| = 3 > 1$ we conclude $\bar{x} = e^{1/2}$ unstable

Logistic Model Analysis

$$(1) \quad x_{n+1} = f(x_n) = r x_n (1 - x_n)$$

Solution behavior

$$0 < r < 1$$

extinction

$$1 < r < 3$$

stable fixed point

$$3 < r < 1 + \sqrt{6}$$

period 2 solutions

To prove requires considerable work

Fixed Point existence and stability

$$(2) \quad \bar{x} = f(\bar{x})$$

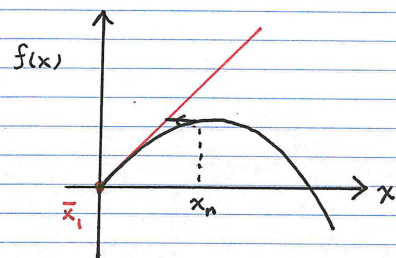
$$\bar{x} = r \bar{x} (1 - \bar{x})$$

Solving (2) yields two fixed points

$$\bar{x}_1 = 0$$

$$\bar{x}_2 = 1 - \frac{1}{r} > 0 \quad (\text{only if } r > 1)$$

For $\bar{x}_1$ we use a cobweb argument.



"Global Stability"

Graph of $f = rx(1-x)$
for $r \in (0,1)$

Cobweb implies

$$x_n \rightarrow 0$$

Can also check linear stability of $\bar{x}_1 = 0$

$$|f'(\bar{x}_1)| < 1$$

Explicitly this condition can be shown to be

$$|r| < 1$$



extinction
stable

other stuff

like wise we can consider other fixed point

$$\bar{x}_2 = 1 - \frac{1}{r} > 0 \quad (r > 1)$$

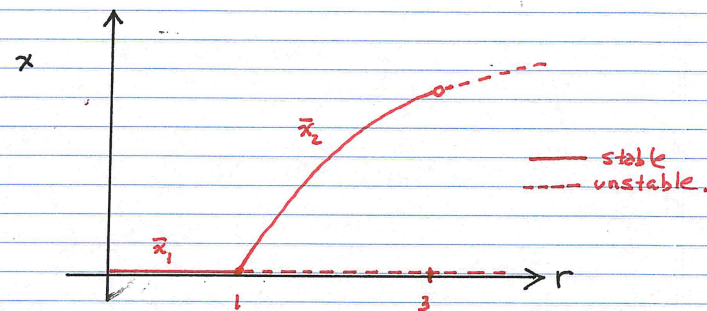
For this fixed point we have stability if

$$|f'(\bar{x}_2)| < 1$$

$$|2 - r| < 1$$

$$r \in (1, 3)$$

Bifurcation diagram $\bar{x}_1 = 0, \bar{x}_2 = 1 - \frac{1}{r}$



Note that fixed point $\bar{x}_2$ unstable for all $r > 3$

Period Doubling

(1) $x_{n+1} = f(x_n)$

Consider fixed points of the second iterate map. That is, consider roots x of

(2) $x = f(f(x))$

The orbit associated with x is

(3) $\{x, f(x), x, f(x), x, f(x), \dots\}$ period 2

This will be period 2 so long as $x \neq f(x)$

The latter corresponds to x not being a fixed point. Recall $\bar{x} = f(\bar{x})$ for a fixed point in which case

$$\bar{x} = f(f(\bar{x})) = f(\bar{x}) \quad \checkmark$$

whence (3) would be

$$\{\bar{x}, \bar{x}, \bar{x}, \bar{x}, \bar{x}, \bar{x}, \dots\} \quad \text{period 1}$$

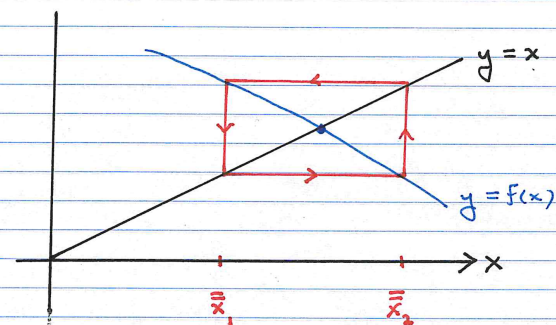
As in the text we shall use double overbar to denote true period two x values:

$$\bar{\bar{x}}_{1,2} = f(f(\bar{\bar{x}}_{1,2}))$$

so the orbit in (3) is

$$\{\bar{\bar{x}}_1, \bar{\bar{x}}_2, \bar{\bar{x}}_1, \bar{\bar{x}}_2, \bar{\bar{x}}_1, \bar{\bar{x}}_2, \dots\}$$

A typical period two cobweb looks like



Stability $g(x) \equiv f(f(x))$

A period two cycle is stable only if the fixed point of $g(x)$ is:

(5) $|g'(\bar{\bar{x}})| < 1$ stable

Since

$$g'(x) = f'(f(x))f'(x)$$

and $\bar{\bar{x}}_2 = f(\bar{\bar{x}}_1)$ the stability condition (5) is:

$|f'(\bar{\bar{x}}_1) f'(\bar{\bar{x}}_2)| < 1$

stable
period 2

Logistic Difference Eqn (Period 2)

$$x_{n+1} = f(x_n) \quad f(x) = rx(1-x)$$

We already know two fixed points

$$(1) \quad \bar{x}_1 = 0 \quad \bar{x}_2 = 1 - \frac{1}{r}$$

To find period two orbits we need to find all the real roots of

$$x = f(f(x))$$

$$x = rf(x)(1-f(x))$$

$$x = r^2x(1-x)(1-rx(1-x))$$

In summary we need the roots of the quartic

$$(2) \quad P(x) = r^2x(1-x)(1-rx(1-x)) - x$$

All is not lost. Two roots of (2) must be the fixed points $\bar{x}_k$. Long division yields (not shown)

$$P(x) = x(x - \bar{x}_2) \overset{\text{quadratic}}{Q(x)}$$

Roots of the quadratic $Q(x)$ can be found

$$(3) \quad \bar{x}_{\pm} = \frac{r+1 \pm \sqrt{r^2-2r-3}}{2r}$$

The condition that $\bar{x}$ is stable is

$$(4) \quad |f'(\bar{x}_+)f'(\bar{x}_-)| < 1$$

After a huge amount of calculations eqn (4) simplifies to:

$$(5) \quad |4+2r-r^2| < 1$$

We find a range of r for stability by setting the quadratic in (5) equal to ± 1

$$4+2r-r^2 = +1 \quad \Rightarrow \quad r=3$$

$$4+2r-r^2 = -1 \quad \Rightarrow \quad r=1+\sqrt{6}$$

Conclude period 2 orbit stable only if

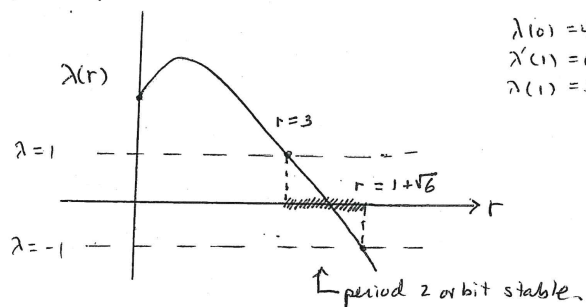
$$3 < r < 1+\sqrt{6} \approx 3.45$$

Calculations reveal

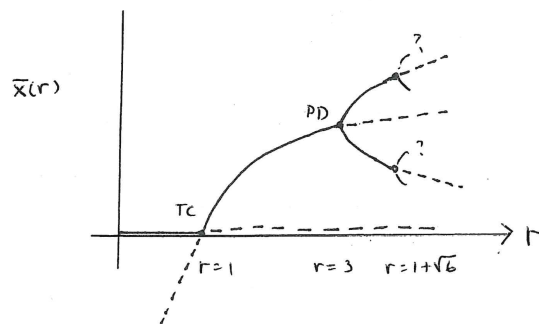
$$\lambda = r^2(1-2a)(1-2b) = f'(a)f'(b)$$

$$\lambda = 4 + 2r - r^2$$

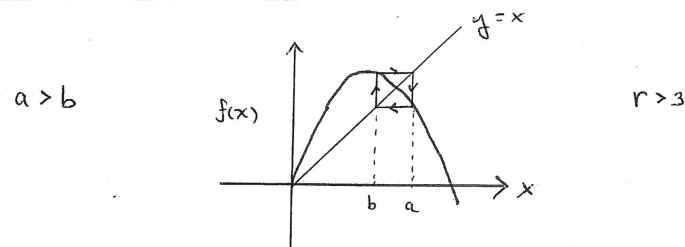
The requirement that $|\lambda| < 1$ can be found graphically:



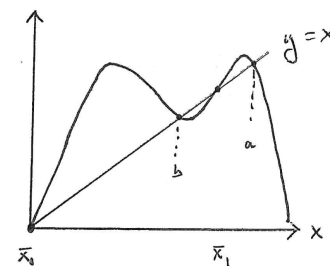
Bifurcation diagram



Period 2 orbit Cobweb



Second-iterate map



Stability of (sole) periodic orbit

Sufficient to show that $\bar{x} = a, b$ are stable fixed points of $f^2(x)$

$$\frac{d}{dx} f(f(x)) = f'(f(x)) f'(x)$$

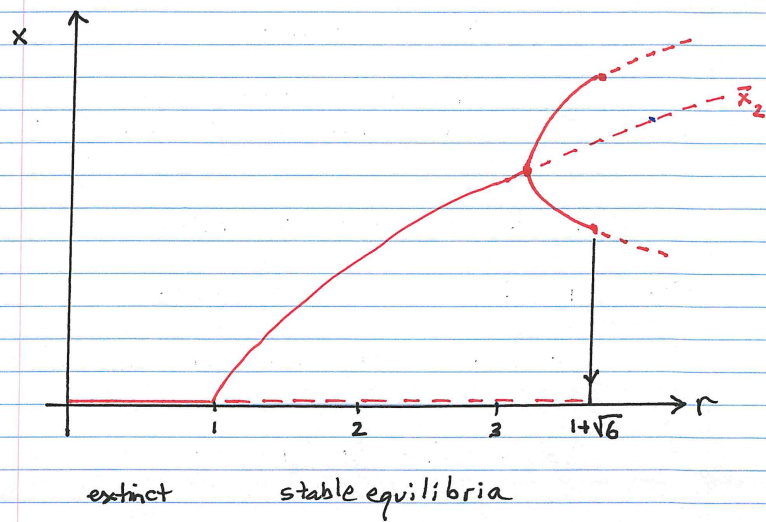
Multiplier

$$\lambda = \left. \frac{d}{dx} f(f(x)) \right|_{x=a} = f'(f(a)) f'(a) = f'(a) f'(b)$$

Logistic model Bifurcation diagram

Plot fixed points $\bar{x}_1, \bar{x}_2$ and period 2 $\bar{\bar{x}}_1$.

By convention solid line means stable,
dashed line means unstable



Plant Propagation

Consider plants that produce seeds each August. Seeds can germinate only one or two years later.

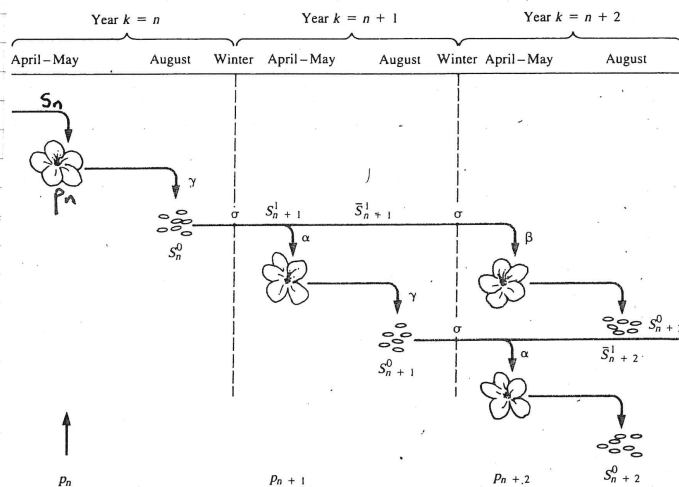


Figure 1.2 Annual plants produce γ seeds per plant each summer. The seeds can remain in the ground for up to two years before they germinate in the springtime. Fractions α of the one-year-old and β of the two-year-old seeds give rise to a new plant generation. Over the winter seeds age, and a certain proportion of them die. The model for this system is discussed in Section 1.2.

γ = # seeds per plant in August

α = fraction of 1-yr old seeds germinate

β = fraction of 2-yr old seeds germinate

σ = fraction of seeds survive winter.

Variable Defns (year n)

p_n = number of plants (May)

s_n^1 = number of 1yr old seeds before April germ.

$\bar{s}_n^1$ = number of 1yr old seeds left in May after germ.

s_n^2 = number of 2yr old seeds before April germ.

$\bar{s}_n^2$ = number of 2yr old seeds left in May after germ

s_n^0 = number new seeds produced in August

Parameter Defns

γ = # seeds per plant in August

α = fraction of 1yr old seeds that germinate

β = fraction of 2yr old seeds that germinate

σ = fraction of seeds that survive winter.

Relation between variables (at year n)

$$(1) \quad p_n = \alpha S_n^1 + \beta S_n^2$$

These plants will produce seeds in August.

$$(2) \quad \bar{S}_n^1 = (1-\alpha) S_n^1$$

$$(3) \quad \bar{S}_n^2 = (1-\beta) S_n^2$$

Seeds produced by plants in August

$$(4) \quad S_n^0 = \gamma p_n$$

Winter mortality

$$(5) \quad S_{n+1}^1 = \nabla S_n^0$$

$$(6) \quad S_{n+1}^2 = \nabla \bar{S}_n^1$$

Simplify system

$$p_{n+1} = \alpha \bar{S}_{n+1}^1 + \beta S_{n+1}^2$$

use (4)-(5)

$$p_{n+1} = \alpha \gamma \nabla p_n + \beta S_{n+1}^2$$

use (2), (6)

$$(7) \quad p_{n+1} = \alpha \gamma \nabla p_n + \beta \nabla (1-\alpha) S_n^1$$

Eqs (7) and (5) can then be written as a system of two first order difference equations

$$p_{n+1} = \alpha \gamma \nabla p_n + \beta \nabla (1-\alpha) S_n^1$$

$$S_{n+1}^1 = \gamma \nabla p_n$$

system of
1st order
diff. eqns

Given we know initial values p_0, S_0^1
then (p_n, S_n^1) can be found

To determine fate of population is easier to eliminate S_n^1 noting

$$(4), (5) \quad S_n^1 = \gamma \nabla p_{n-1}$$

hence

$$p_{n+1} = \alpha \gamma \nabla p_n + \beta \nabla^2 (1-\alpha) \gamma p_{n-1}$$

second
order
difference
eqn.

Need to know math for solving this.

Plant model as a system

$$\begin{cases} p_{n+1} = \alpha \gamma \sigma p_n + \beta \sigma (1-d) s_n^i \\ s_{n+1}^i = \gamma \sigma p_n \end{cases}$$

is equivalent to the system

$$(1) \quad \mathbf{x}_{n+1} = A \mathbf{x}_n \quad \mathbf{x}_n \in \mathbb{R}^2, A \in \mathbb{R}^{2 \times 2}$$

$$\mathbf{x}_n = \begin{pmatrix} p_n \\ s_n^i \end{pmatrix} \quad A = \begin{bmatrix} \alpha \gamma \sigma & \beta \sigma (1-d) \\ \gamma \sigma & 0 \end{bmatrix}$$

Plant model as 2nd order difference equation

$$p_{n+1} - \alpha \gamma \sigma p_n - \beta \sigma^2 (1-d) \gamma p_{n-1} = 0$$

is equivalent to

$$(2) \quad a x_{n+1} + b x_n + c x_{n-1} = 0$$

$$a = 1$$

$$b = -\alpha \gamma \sigma$$

$$c = \beta \sigma^2 (1-d) \gamma$$

$$x_n = p_n$$

Mathematics of second
order difference
equations

Second Order Difference Equations

(1)

$$ax_{n+1} + bx_n + cx_{n-1} = 0$$

Seek solutions of the form

(2) $x_n = \lambda^n$ $\lambda \in \mathbb{C}$ (complex)

Substitute (2) into (1) and simplify

$$a\lambda^{n+1} + b\lambda^n + c\lambda^{n-1} = 0$$

$$\lambda^{n-1} (a\lambda^2 + b\lambda + c) = 0$$

must vanish

Hence $x_n = \lambda^n$ is a solution only if λ is a root of the characteristic polynomial

$$P(\lambda) = a\lambda^2 + b\lambda + c$$

Solutions depend on whether roots of $P(\lambda)$ are real, equal, complex.

General Solutions (without proof)

Categorized by roots λ_k of $P(\lambda)$

$\lambda_1 \neq \lambda_2$ real $x_n = c_1 \lambda_1^n + c_2 \lambda_2^n$

$\lambda_1 = \lambda_2$ real $x_n = (c_1 + c_2 n) \lambda_1^n$

$\lambda = re^{i\theta}$ complex $x_n = c_1 r^n \cos(n\theta) + c_2 r^n \sin(n\theta)$

Conversion in complex case

Complex roots of $P(\lambda)$ can be written

(1) $\lambda = \alpha + i\beta$ $\alpha, \beta \in \mathbb{R}$

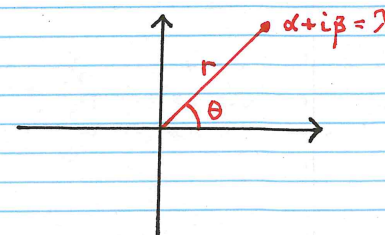
To convert λ to polar note

(2) $\lambda = re^{i\theta} = r\cos\theta + ir\sin\theta$

Compare (1) and (2)

$$\begin{aligned} r\cos\theta &= \alpha \\ r\sin\theta &= \beta \end{aligned}$$

solve for (r, θ)



More on complex solutions

$$L(z_n) = a z_{n+2} + b z_{n+1} + c z_n = 0$$

Solutions may be complex even if a, b, c real

$$z_n = x_n + i y_n$$

where x_n, y_n are both real. From (1) it is easy to see

$$L(z_n) = L(x_n) + i L(y_n) = 0$$

which is true only if both $L(x_n) = 0$ and $L(y_n) = 0$.

Thus, real and complex parts of z_n are each solutions of the difference eqn.

$$z_n = (\sqrt{r} + i\beta)^n$$

$$z_n = (r e^{i\theta})^n$$

$$z_n = r^n e^{i n \theta}$$

$$z_n = r^n (\cos(n\theta) + i \sin(n\theta))$$

$\uparrow$
 x_n

$\uparrow$
 y_n

Hence general solution is

$$x_n = c_1 r^n \cos(n\theta) + c_2 r^n \sin(n\theta)$$

EXAMPLE

$$x_{n+2} - 5x_{n+1} + 6x_n = 0$$

Let $x_n = \lambda^n$ ultimately yields characteristic eqn

$$\lambda^2 - 5\lambda + 6 = 0$$

which has two real roots:

$$\lambda_1 = 2 \quad \lambda_2 = 3$$

General solution of difference eqn is:

$$(1) \quad x_n = c_1 2^n + c_2 3^n$$

where c_k are arbitrary constants.

If one also stipulates initial conditions these constants can be found. For instance

$$(2) \quad x_{n+1} - 5x_n + 6x_{n-1} = 0 \quad x_0 = 1 \quad x_1 = 2$$

Use gen. soln (1) to find c_k

$$n=0 \quad x_0 = c_1 2^0 + c_2 3^0 = 1$$

$$n=1 \quad x_1 = c_1 2^1 + c_2 3^1 = 2$$

Solving these $\Rightarrow c_1 = 1, c_2 = 0$.

$$x_n = 2^n$$

EXAMPLE $x_{n+2} - 6x_{n+1} + 9x_n = 0$ (repeated)

$$\lambda^2 - 6\lambda + 9 = 0$$

Hence $\lambda = 3$ repeated yields a gen. soln.

$$x_n = (c_1 + c_2 n) 3^n$$

EXAMPLE $x_{n+2} - x_{n+1} + x_n = 0$ (complex)

$$\lambda^2 - \lambda + 1 = 0$$

has complex roots $\lambda = \frac{1}{2} \pm \frac{\sqrt{3}}{2} i$

$$\lambda = r e^{i\theta} = r \cos \theta + i r \sin \theta = \frac{1}{2} + \frac{\sqrt{3}}{2} i$$

hence

$$\begin{aligned} r \cos \theta &= \frac{1}{2} \\ r \sin \theta &= \frac{\sqrt{3}}{2} \end{aligned}$$

whose soln: $r = 1, \theta = \pi/3$

$$= c_1 \left(1\right)^n \cos\left(\frac{n\pi}{3}\right) + c_2 \left(1\right)^n \sin\left(\frac{n\pi}{3}\right)$$

Asymptotic Behavior

$$a x_{n+1} + b x_n + c x_{n-1} = 0$$

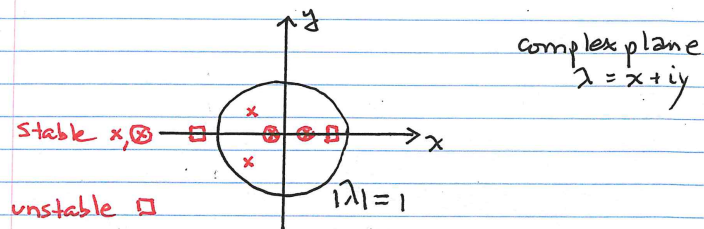
The general solution is $(\lambda_1 \neq \lambda_2)$

$$x_n = c_1 \lambda_1^n + c_2 \lambda_2^n$$

Even when λ_k are complex, very simple conditions determine the large n asymptotic behavior of x_n .

stable $|\lambda_1| < 1$ and $|\lambda_2| < 1 \Rightarrow |x_n| \rightarrow 0$

unstable $|\lambda_k| > 1$ for some $k \Rightarrow |x_n| \rightarrow \infty$



Systems of Difference Equations

$$(1) \quad x_{n+1} = a_{11}x_n + a_{12}y_n$$

$$(2) \quad y_{n+1} = a_{21}x_n + a_{22}y_n$$

Can be re-expressed in vector form

$$(3) \quad \mathbf{x}_{n+1} = A \mathbf{x}_n$$

where

$$\mathbf{x}_n = \begin{pmatrix} x_n \\ y_n \end{pmatrix} \quad A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \in \mathbb{R}^{2 \times 2}$$

An example of the solution of (3)

Suppose $\lambda_i, \vec{z}_i$ are eigenvalue/vector pairs of A

$$A \vec{z}_i = \lambda_i \vec{z}_i \quad i=1,2$$

General solution of (3) is

$$\mathbf{x}_n = c_1 \lambda_1^n \vec{z}_1 + c_2 \lambda_2^n \vec{z}_2 \quad \lambda_1 \neq \lambda_2$$

Proof:

$$\begin{aligned} A \mathbf{x}_n &= c_1 \lambda_1^n \widehat{A \vec{z}_1} + c_2 \lambda_2^n \widehat{A \vec{z}_2} \\ &= c_1 \lambda_1^n \cdot \lambda_1 \vec{z}_1 + c_2 \lambda_2^n \cdot \lambda_2 \vec{z}_2 \\ &= c_1 \lambda_1^{n+1} \vec{z}_1 + c_2 \lambda_2^{n+1} \vec{z}_2 = \mathbf{x}_{n+1} \quad \square \end{aligned}$$

EXAMPLE $\mathbf{x}_{n+1} = A \mathbf{x}_n \quad A = \begin{bmatrix} -10 & -4 \\ 24 & 10 \end{bmatrix}$

First find eigenvalues of A . Characteristic Polynomial

$$P(\lambda) = \det(A - \lambda I) = \lambda^2 - 4$$

Roots of $P(\lambda)$ are eigenvalues of A

$$\lambda_1 = 2 \quad \lambda_2 = -2$$

Now find eigenvectors for λ_1 and λ_2

$$A - \lambda_1 I = \begin{bmatrix} -12 & -4 \\ 24 & 8 \end{bmatrix} \sim \begin{bmatrix} 3 & 1 \\ 0 & 0 \end{bmatrix} \quad \vec{z}_1 = \begin{pmatrix} 1 \\ -3 \end{pmatrix}$$

$$A - \lambda_2 I = \begin{bmatrix} -8 & -4 \\ 24 & 12 \end{bmatrix} \sim \begin{bmatrix} 2 & 1 \\ 0 & 0 \end{bmatrix} \quad \vec{z}_2 = \begin{pmatrix} 1 \\ -2 \end{pmatrix}$$

Given we now know $\lambda_i, \vec{z}_i$ we have

$$\mathbf{x}_n = c_1 2^n \begin{pmatrix} 1 \\ -3 \end{pmatrix} + c_2 (-2)^n \begin{pmatrix} 1 \\ -2 \end{pmatrix} \quad \square$$

Remarks

General solutions when λ_i are repeated or complex are not shown here.

Analysis of Plant Model

Plant model revisited

Recall the plant population p_n at year n satisfies the second order difference equation

$$(1) \quad \begin{aligned} p_{n+1} - \alpha \gamma p_n - \beta \gamma^2 (1-\alpha) \gamma p_{n-1} &= 0 \\ p_{n+1} - a p_n - b p_{n-1} &= 0 \end{aligned}$$

where

α = fraction of 1-yr old seeds that germinate

β = fraction of 2-yr old seeds that germinate

γ = fraction of seeds that survive winter

γ = number of seeds per plant in August

Wish to answer the simple question:

do the plants thrive (survive)?

To answer we note the solution to (1) is

$$(2) \quad \begin{aligned} p_n &= c_1 \lambda_-^n + c_2 \lambda_+^n \\ \lambda_{\pm} &= \frac{1}{2} (a \pm \sqrt{a^2 + 4b}) \end{aligned}$$

Note: Both eigenvalues $\lambda_{\pm}$ are real.
Does not preclude oscillations
if $\lambda_- < 0$ though.

We make a few observations

$$\sqrt{a^2 + 4b} > a > 0$$

Consequently

$$\lambda_+ = \frac{1}{2}(a + \sqrt{a^2 + 4b}) > a > 0$$

$$\lambda_- = \frac{1}{2}(a - \sqrt{a^2 + 4b}) < 0$$

Summarize

$$\lambda_- < 0 < \lambda_+$$

$$|\lambda_+| > |\lambda_-|$$

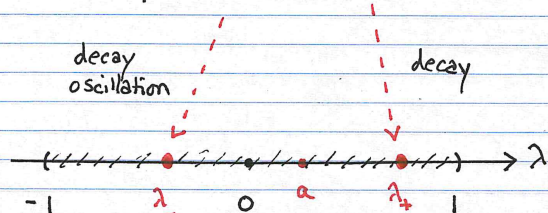
Thus the term λ_-^n in (2) does oscillate.

A necessary condition for the plant population to survive is

$$\lambda_+ > 1$$

Were this not true $p_n \rightarrow 0$ as $n \rightarrow \infty$

$$p_n = c_1 \lambda_-^n + c_2 \lambda_+^n$$



Necessary Condition $\lambda_+ > 1$

We will first determine when $\lambda_+ < 1 \Rightarrow p_n \rightarrow 0$.
Same as

$$a + \sqrt{a^2 + 4b} < 2$$

$$\sqrt{a^2 + 4b} < 2 - a$$

$$a^2 + 4b < (2 - a)^2$$

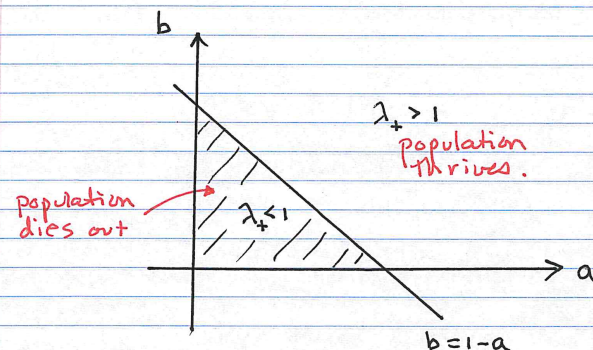
$$a^2 + 4b < 4 - 4a + a^2$$

$$4b < 4 - 4a$$

Conclude $\lambda_+ < 1$ only if

$$b < 1 - a$$

* For all other (a, b) positive $\lambda_+ > 1$



Survival $\lambda_+ > 1$

Given the definitions for (a, b)

$$a = \alpha \gamma \tau$$

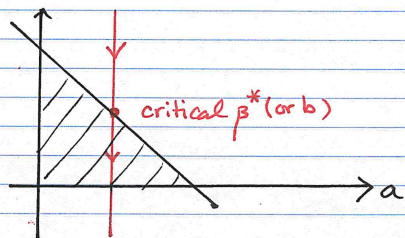
$$b = \beta \tau^2 (1 - \alpha) \gamma$$

the condition $b > 1 - a$ is equivalent to

$$(3) \quad \gamma > \frac{1}{\alpha \tau + \beta \tau^2 (1 - \alpha)}$$

Decreasing β (2nd yr seeds)

Note only b of (a, b) contains " β ".
Decreasing β in (a, b) -plane with other parameters fixed



The change in behavior at β^* is called a bifurcation

Approximations

Condition (3) is hard to understand.
But, when

$$(4) \quad \epsilon \equiv \frac{\beta}{\alpha} \ll 1$$

is small, an approximation can be derived.
Using (4) in (3)

$$\gamma > \frac{1}{\alpha \tau (1 + \epsilon \tau (1 - \alpha))}$$

$$\gamma > \frac{1}{\alpha \tau} f(\epsilon)$$

which has a Taylor Series approximation

$$\gamma > \frac{1}{\alpha \tau} \left(\underbrace{f(0)}_1 + \underbrace{\epsilon f'(0)}_{\text{small}} + \underbrace{O(\epsilon^2)}_{\text{smaller}} \right)$$

The first term yields

$$\gamma > \frac{1}{\alpha \tau} \quad \text{if } \beta \ll \alpha$$

Problem 2: A Schematic Model of Red Blood Cell Production

The following problem³ deals with the number of red blood cells (RBCs) circulating in the blood. Here we will present it as a discrete problem to be modeled by difference equations, though a different approach is clearly possible.

In the circulatory system, the red blood cells (RBCs) are constantly being destroyed and replaced. Since these cells carry oxygen throughout the body, their number must be maintained at some fixed level. Assume that the spleen filters out and destroys a certain fraction of the cells daily and that the bone marrow produces a number proportional to the number lost on the previous day. What would be the cell count on the n th day?

To approach this problem, consider defining the following quantities:

R_n = number of RBCs in circulation on day n ,

M_n = number of RBCs produced by marrow on day n ,

f = fraction RBCs removed by spleen,

γ = production constant (number produced per number lost).

It follows that equations for R_n and M_n are

$$\begin{aligned} R_{n+1} &= (1 - f)R_n + M_n, \\ M_{n+1} &= \gamma f R_n. \end{aligned} \quad (47)$$

Problem 16 discusses this model. By solving the equations it can be shown that the only way to maintain a nearly constant cell count is to assume that $\gamma = 1$. Moreover, it transpires that the delayed response of the marrow leads to some fluctuations in the red cell population.

As in problem 2, we apply a discrete approach to a physiological situation in which a somewhat more accurate description might be that of an underlying continuous process with a time delay. (Aside from practice at formulating the equations of a discrete model, this will provide a further example of difference equations analysis.)

Growth of Microorganisms

$N(t)$ = bacteria density at time t

K = reproduction rate per unit time

The meaning of K is the number of new bacteria that spawn from one bacteria in one unit of time

$$(1) \quad N(t+\Delta t) - N(t) = K N(t) \Delta t$$

hence

$$(2) \quad \frac{N(t+\Delta t) - N(t)}{\Delta t} = K N(t)$$

Let $\Delta t \rightarrow 0$ in (2) to arrive at

$$(1) \quad \boxed{\frac{dN}{dt} = K N} \quad \text{Malthusian Growth.}$$

When K is constant and the initial condition is $N(0) = N_0$ the solution of (1) is

$$(2) \quad N(t) = N_0 e^{Kt}$$

Many alternate assumptions can be made about the reproduction rate.

Notes on units

Throughout we will use the square bracket notation $[X]$ to denote the units of X

Additionally we shall let

L = unit of length

M = unit of mass

T = unit of time

Examples

v = velocity $[v] = L T^{-1}$

g = gravity constant $[g] = L T^{-2}$

F = force $[F] = M L T^{-2}$

E = energy $[E] = M L^2 T^{-2}$

EXAMPLE Microorganism where N is bacteria density

$$\frac{dN}{dt} = K N \quad [N] = \frac{\#}{L^3} \quad [K] = T^{-1}$$

where $\#$ is "number of bacteria". Now suppose the bacteria are confined to a vat of volume V and let $n = NV$. Then

$$\frac{dn}{dt} = K n \quad [n] = \#$$

n = total number of bacteria.

Doubling time and experimental correspondence

$$\frac{dn}{dt} = K n \quad n(0) = n_0$$

has the solution

$$(1) \quad n(t) = n_0 e^{Kt}$$

The time T it takes for population doubling:

$$2n_0 = n_0 e^{KT}$$

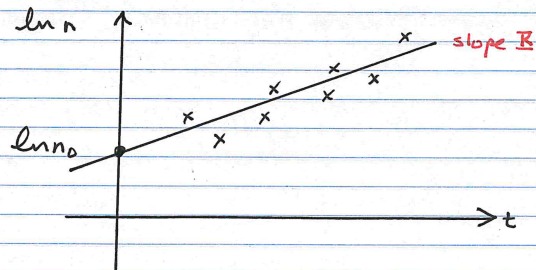
solving for T

$$(2) \quad T = \frac{\ln 2}{K}$$

To find K from raw data first note taking log of (1) yields

$$(3) \quad \ln n = \ln n_0 + Kt$$

Measure many (t, n) pairs and find slope that best fits



Nutrient Dependent Growth

Reasonable to assume bacteria growth rate depends on the nutrient concentration C

C = nutrient concentration

$$[C] = M L^{-3}$$

Simplest assumption:

$$(1) \quad K(C) = \mu C$$

Next we introduce yield $Y = \alpha^{-1}$ where

α = mass of nutrient consumed in producing one new bacteria

$$[\alpha] = M/\#$$

So defined such that

$$(2) \quad \frac{dG}{dt} = -\alpha \frac{dN}{dt}$$

In (2) the units of both sides must match:

$$\frac{M}{T L^3} = [\alpha] \frac{\#}{T L^3}$$

hence

$$[\alpha] = \frac{M}{\#} \quad \text{mass bacteria}$$

Given assumptions (1) - (2) we have

$$(3) \quad \frac{dN}{dt} = B(C)N = \gamma CN$$

$$(4) \quad \frac{dC}{dt} = -\alpha \frac{dN}{dt} = -\alpha \gamma CN$$

are two coupled ODE's for C and N .

We reduce the order of the system by first integrating (4)

$$\frac{dC}{dt} = -\alpha \frac{dN}{dt}$$

(5)

$$C(t) = C_0 - \alpha N(t)$$

$$C(0) = C_0$$

Consequently (3) becomes

(6)

$$\frac{dN}{dt} = \gamma (C_0 - \alpha N) N$$

same as density dependent growth.

The separable 1st order ODE (6) can be solved via partial fractions, i.e. integ. in N :

$$\frac{dN}{N(C_0 - \alpha N)} = \left(\frac{A}{N} + \frac{B}{C_0 - \alpha N} \right) dN$$

Solution of:

$$\frac{dN}{dt} = \gamma (C_0 - \alpha N) N \quad N(0) = N_0$$

$$(1) \quad \frac{dN}{N(C_0 - \alpha N)} = \left(\frac{1}{C_0} \frac{1}{N} + \frac{\alpha}{C_0} \frac{1}{C_0 - \alpha N} \right) dN = \gamma dt$$

Integrate over $[N_0, N]$

$$(2) \quad \ln N - \ln(C_0 - \alpha N) \Big|_{N_0}^N = \underbrace{\gamma C_0}_{r} t$$

$$(3) \quad \ln \left(\frac{N_0 (N - C_0)}{N (N_0 - C_0)} \right) = -rt$$

where $r = \gamma C_0$. Solve (3) for $N(t)$

$$(4) \quad N(t) = \frac{N_0 B}{N_0 + (B - N_0) e^{-rt}}$$

where

$$r = \gamma C_0 \quad \text{growth parameter}$$

$$B = C_0 / \alpha \quad \text{carrying capacity} \quad N' = 0$$

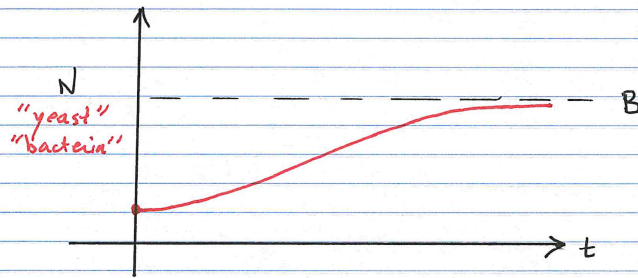
Population Density

$$N(t) = \frac{N_0 B}{N_0 + (B - N_0) e^{-rt}}$$

where $N_0 = N(0)$ and

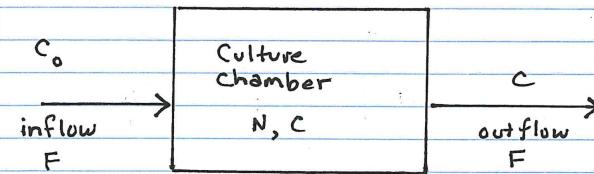
$r = k C_0 =$ growth parameter

$B = C_0 / \alpha =$ carrying capacity



* More realistic since population remains bounded

Chemostat Model



Bacteria of density N are in a culture chamber having nutrient concentration C . Nutrient of fixed concentration C_0 flows into the chamber at a constant flow rate F . The bacteria nutrient mix is pumped out at the same rate. Thus the volume V in the chamber is fixed.

$N(t)$ = bacteria concentration $\# L^{-3}$

$C(t)$ = nutrient concentration ML^{-3}

C_0 = reservoir concentration ML^{-3}

F = flow rate $L^3 T^{-1}$

V = volume L^3

$\gamma = \frac{1}{\alpha}$ yield constant $\# M^{-1}$

Conservation of Bacteria

$$\frac{dN}{dt} = \text{reproduction} - \text{outflow}$$

Given K is the reproduction rate

$$(1) \quad \frac{dN}{dt} = K N - \frac{F N}{V}$$

Division by V is required for units to match:

$$\left[\frac{F N}{V} \right] = \frac{L^3}{T} \cdot \frac{1}{L^3} \cdot \frac{\#}{L^3} = \frac{\#}{T \cdot L^3}$$

which matches the other terms in (1)

Conservation of Nutrient

$$\frac{dC}{dt} = \text{bacteria consumption} - \text{outflow} + \text{inflow}$$

Given the same unit considerations

$$(2) \quad \frac{dC}{dt} = -\alpha K N - \frac{F C}{V} + \frac{F C_0}{V}$$

Again note the units

$$\left[\frac{F C}{V} \right] = \frac{L^3}{T} \cdot \frac{1}{L^3} \cdot \frac{M}{L^3} = \frac{M}{L^3 T}$$

Summary

One generally assumes the bacteria growth rate depends on the nutrient concentration

$$K = K(C)$$

for some function K .

$$\begin{aligned} \frac{dN}{dt} &= K(C) N - \frac{F N}{V} \\ \frac{dC}{dt} &= -\alpha K(C) N - \frac{F C}{V} + \frac{F C_0}{V} \end{aligned}$$

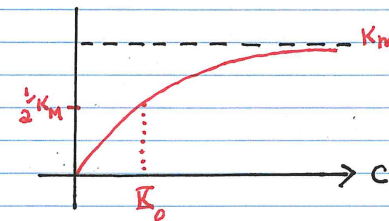
Two coupled nonlinear differential equations.

Michaelis Menten Kinetics

$$K(C) = \frac{K_M C}{K_0 + C}$$

Common assumed form. Derivation later

This reproduct rate has a saturation:



Graph of $K(C)$. Saturates at maximal rate of K_M .

Dimensional Analysis

Is a process by which dependent and independent variables are scaled by constants of like units in a manner which simplifies the model equations. Here

$$(1) \quad n = \frac{N}{N^*} \quad c = \frac{C}{C^*} \quad \tau = \frac{t}{t^*}$$

Here N^* , C^* and t^* are constants having units of $[N]$, $[C]$, $[t]$. We get to choose these constants. And note that (n, c, τ) are now dimensionless!

Substitute (1) into the model equations:

$$\frac{d(nN^*)}{d(\tau t^*)} = \left(\frac{K_M C^* c}{K_0 + C^* c} \right) (nN^*) - \frac{F}{V} (nN^*)$$

$$\frac{dn}{d\tau} \cdot \frac{N^*}{t^*} = \frac{K_M \cdot \overset{\uparrow}{N^*} \cdot \overset{\downarrow}{c}}{K_0/C^* + c} \cdot \overset{\downarrow}{n} - \left(\frac{F N^*}{V} \right) \overset{\downarrow}{n}$$

isolate

Ultimately for N -equation we get the dimensionless form

$$\frac{dn}{d\tau} = (K_M t^*) \frac{\overset{\uparrow}{c} \overset{\downarrow}{n}}{K_0/C^* + c} - \left(\frac{F t^*}{V} \right) \overset{\downarrow}{n}$$

Non-arrowed terms are constants.

Pre-dimensionless scaled equations:

$$(2) \quad \frac{dn}{d\tau} = (K_M t^*) \left(\frac{c}{K_0/C^* + c} \right) n - \left(\frac{F t^*}{V} \right) n$$

$$(3) \quad \frac{dc}{d\tau} = \left(\frac{K_M t^* N^*}{C^*} \right) \left(\frac{c}{K_0/C^* + c} \right) - \left(\frac{F t^*}{V} \right) c + \left(\frac{t^* F C_0}{V C^*} \right)$$

Pick t^* so term ① equals one

$$(4) \quad t^* = \frac{V}{F}$$

Pick C^* so term ② equals one

$$(5) \quad C^* = K_0$$

Pick N^* so term ③ equals one

$$(6) \quad N^* = \frac{K_0}{K_M t^*}$$

With these choices (2)-(3) greatly simplify!

$$\begin{aligned}\frac{dn}{d\tau} &= \alpha_1 \frac{nc}{1+c} - n \\ \frac{dc}{d\tau} &= -\frac{nc}{1+c} - c + \alpha_2\end{aligned}$$

Dimensionless
Model

Has only two parameters

$$\alpha_1 = \frac{VK_M}{F}$$

$$\alpha_2 = \frac{C_0}{K_0}$$

Much better than original dimensional
model

$$F, V, \alpha, C_0, K_M, K_0$$

six parameters!!

Planar Differential Systems

(1)

$$\begin{aligned}x' &= f(x, y) \\ y' &= g(x, y)\end{aligned}$$

Some systems like (1) can be solved explicitly.
For instance the linear system

$$(2) \quad x' = -y$$

$$(3) \quad y' = x$$

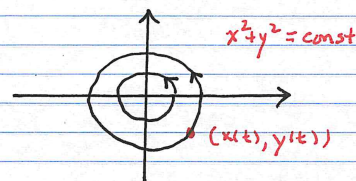
can be shown to have the general soln (Math 274)

$$(4) \quad \vec{x}(t) = c_1 \begin{pmatrix} \sin t \\ -\cos t \end{pmatrix} + c_2 \begin{pmatrix} \cos t \\ \sin t \end{pmatrix}$$

Such explicit formulae are not always informative
but do illustrate solutions (or trajectories)
are curves in the (x, y) -plane. We often
resort to "qualitate" techniques to get a
better idea of what these trajectories look
like. For (2)-(3) note:

$$\frac{d}{dt}(x^2 + y^2) = 2xx' + 2yy' = -2xy + 2xy = 0$$

says its trajectories are circles

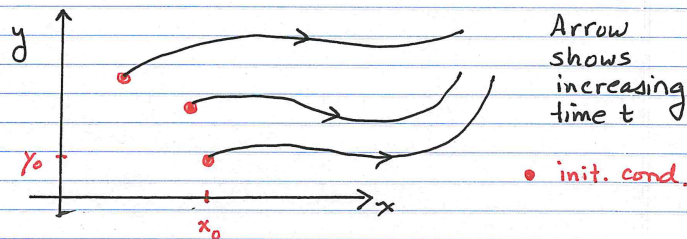


concentric
circles for
diff init cond.

Again let's recall our general planar problem

$$(1) \quad \begin{cases} x' = f(x, y) \\ y' = g(x, y) \end{cases}$$

Each initial condition pair generates its own unique trajectory (or solution). Potentially it might look like



If we pose (1) as a vector equation we can say more

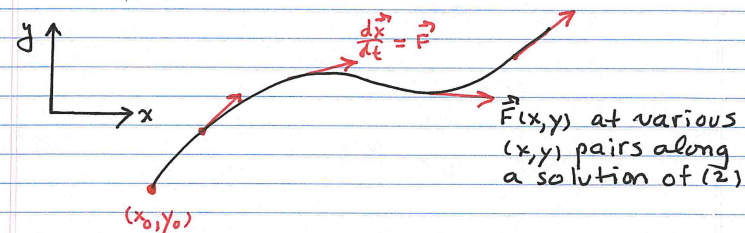
$$(2) \quad \frac{d\vec{x}}{dt} = \vec{F}(x, y)$$

is equivalent to

$$\frac{d}{dt} \begin{pmatrix} x(t) \\ y(t) \end{pmatrix} = \begin{pmatrix} f(x, y) \\ g(x, y) \end{pmatrix} = \vec{F}(x, y)$$

In (2), $\vec{F}(x, y)$ is a known vector field which can be drawn independent of knowing the solution $\vec{x}(t)$.

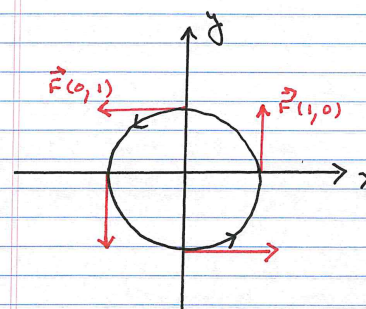
More importantly (2) states that solutions $\vec{x}(t)$ are everywhere tangent to the vector field $\vec{F}(x, y)$



EXAMPLE

$$\begin{cases} x' = -y \\ y' = +x \end{cases}$$

$$\vec{F}(x, y) = \begin{pmatrix} -y \\ x \end{pmatrix}$$



(x, y)	$\vec{F}(x, y)$
$(1, 0)$	$(0, 1) \uparrow$
$(0, 1)$	$(-1, 0) \leftarrow$
$(-1, 0)$	$(0, -1) \downarrow$
$(0, -1)$	$(1, 0) \rightarrow$

$\vec{F}(x, y)$ is the direction field for the system

Equilibria and Nullclines

Recall the system

$$(1) \quad x' = f(x, y)$$

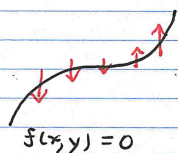
$$(2) \quad y' = g(x, y)$$

Drawing $\vec{F}(x, y)$ can result in a cluttered mess in the (x, y) phase plane. Typically, one uses only a limited selection of $\vec{F}(x, y)$ to infer the direction (or flow) of the solution.

For example, where is the flow horizontal? where is it vertical?

Consider $f(x, y) = 0$. This is a curve(s) called the x-nullcline. For (x, y) on this curve

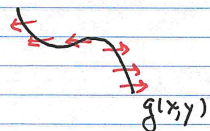
$$\vec{F} = \begin{pmatrix} 0 \\ g(x, y) \end{pmatrix}$$



and $\vec{F}$ is vertical.

Consider $g(x, y) = 0$. This is a curve(s) called the y-nullcline. For (x, y) on this curve

$$\vec{F} = \begin{pmatrix} f(x, y) \\ 0 \end{pmatrix}$$



and $\vec{F}$ is horizontal

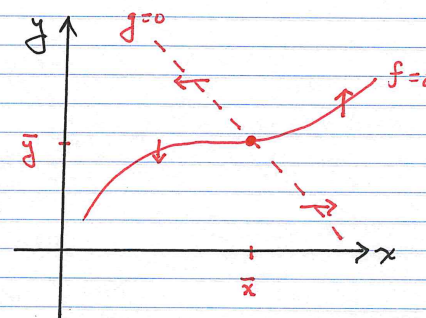
Lastly consider equilibria. At equilibria both f and g vanish.

We shall use overbar notation to denote these special points

(1)

$$\begin{aligned} f(\bar{x}, \bar{y}) &= 0 \\ g(\bar{x}, \bar{y}) &= 0 \end{aligned}$$

Equilibria occur at the intersection of the x and y nullclines



To find equilibria you must find all solutions to the algebraic problem (1) above. Generally these are two nonlinear equations and may have no soln, one solution or many solutions.

Equilibria summary

Found by solving the coupled algebraic sys:

$$f(\bar{x}, \bar{y}) = 0$$

$$g(\bar{x}, \bar{y}) = 0$$

They occur where nullclines intersect and if the initial condition is $(\bar{x}, \bar{y})$ the solution is $x(t) = \bar{x}$, $y(t) = \bar{y}$ for all time t .

$$\begin{cases} x' = f(x, y), & x(0) = \bar{x} \\ y' = g(x, y), & y(0) = \bar{y} \end{cases} \Rightarrow \begin{cases} x(t) = \bar{x} \\ y(t) = \bar{y} \end{cases}$$

EXAMPLE

$$\begin{cases} x' = x - y \\ y' = 1 - xy \end{cases}$$

x-nullcline

$$f=0 \Rightarrow y=x$$

y-nullcline

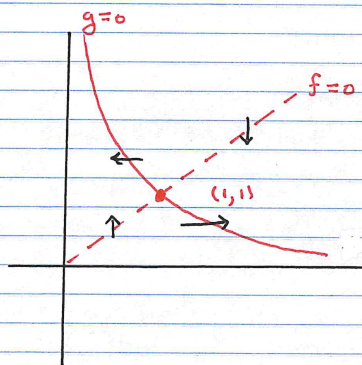
$$g=0 \Rightarrow y = \frac{1}{x}$$

Equilibria

$$\begin{cases} x - y = 0 \\ 1 - xy = 0 \end{cases}$$

yields $x^2 = 1$ or $x = \pm 1$
hence

$$(1, 1) \quad (-1, -1)$$



Linear System Review - Planar

$$(1) \quad \frac{d\vec{x}}{dt} = A\vec{x} \quad \vec{x} = \begin{pmatrix} x(t) \\ y(t) \end{pmatrix}$$

Eigenvalues and eigenvectors of the matrix A determine the general solution of (1)
Letting

$$(2) \quad \vec{x}(t) = e^{\lambda t} \vec{z} \quad \vec{z} \text{ const. vector}$$

we find (2) is a solution of (1) only if

$$(3) \quad A\vec{z} = \lambda\vec{z}$$

Moreover, for $\vec{z} \neq 0$ we need $(A - \lambda I)$ not invertible, or, its determinant must vanish

$$(4) \quad P(\lambda) = \det(A - \lambda I) \quad I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

For $A \in \mathbb{R}^{2 \times 2}$ this characteristic polynomial is a quadratic with two roots called eigenvalues. The vectors $\vec{z}$ in (3) are not unique and are called eigenvectors

Summary

$$\vec{x}(t) = e^{\lambda t} \vec{z}$$

$$\det(A - \lambda I) = 0$$

$$A\vec{z} = \lambda\vec{z}$$

Real Distinct eigenvalues $\lambda_1 \neq \lambda_2 \in \mathbb{R}$

The general solution of (1) is

$$\vec{x} = c_1 e^{\lambda_1 t} \vec{z}_1 + c_2 e^{\lambda_2 t} \vec{z}_2$$

↑
eigenvectors for λ_1, λ_2

EXAMPLE

$$\frac{d\vec{x}}{dt} = \begin{bmatrix} 6 & -3 \\ 2 & 1 \end{bmatrix} \vec{x} = A \vec{x}$$

$$P(\lambda) = \det(A - \lambda I) = (\lambda - 3)(\lambda - 4)$$

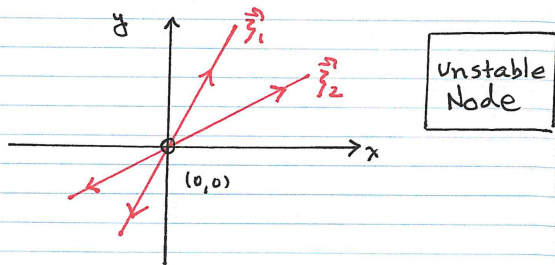
after some calculations.

$$\lambda_1 = 3 \quad (A - \lambda_1 I) \vec{z} = \begin{bmatrix} 3 & -3 \\ 2 & -2 \end{bmatrix} \vec{z} = \vec{0} \quad \vec{z}_1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

$$\lambda_2 = 4 \quad (A - \lambda_2 I) \vec{z} = \begin{bmatrix} 2 & -3 \\ * & * \end{bmatrix} \vec{z} = \vec{0} \quad \vec{z}_2 = \begin{pmatrix} 3 \\ 2 \end{pmatrix}$$

General solution

$$\vec{x}(t) = c_1 e^{3t} \begin{pmatrix} 1 \\ 1 \end{pmatrix} + c_2 e^{4t} \begin{pmatrix} 3 \\ 2 \end{pmatrix} \quad \text{grows.}$$



EXAMPLE (Saddle)

$$\lambda_2 < 0 < \lambda_1$$

$$\frac{d\vec{x}}{dt} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \vec{x} = A \vec{x}$$

Here the characteristic polynomial is

$$P(\lambda) = \lambda^2 - 1 \quad \lambda = \pm 1$$

It is easily verified we have eigenvectors:

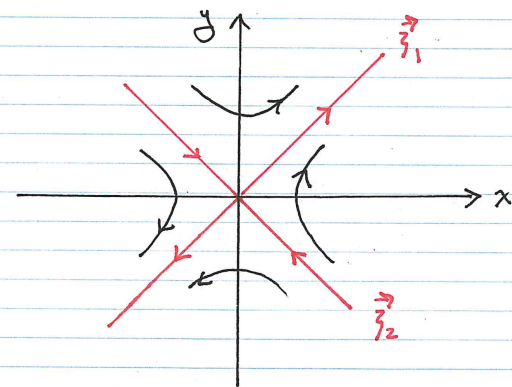
$$\lambda_1 = +1 \quad (A - \lambda_1 I) \vec{z} = \begin{bmatrix} -1 & 1 \\ * & * \end{bmatrix} \vec{z} \quad \vec{z}_1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

$$\lambda_2 = -1 \quad (A - \lambda_2 I) \vec{z} = \begin{bmatrix} 1 & 1 \\ * & * \end{bmatrix} \vec{z} \quad \vec{z}_2 = \begin{pmatrix} 1 \\ -1 \end{pmatrix}$$

General Solution

$$\vec{x}(t) = c_1 e^{\lambda_1 t} \vec{z}_1 + c_2 e^{\lambda_2 t} \vec{z}_2$$

grows decays



Complex eigenvalues $\lambda = \alpha + i\beta \in \mathbb{C}$

Eigenvalues and eigenvectors are both complex.
The complex solution is

$$\vec{x}(t) = e^{\lambda t} \vec{z} = \vec{x}_r(t) + i \vec{x}_i(t)$$

Each of the real and imaginary parts of $\vec{x}$ are independent solutions to

$$\frac{d\vec{x}}{dt} = A \vec{x}$$

After computing $\vec{z} = \vec{a} + i\vec{b}$ and expanding
 $\vec{x} = e^{(\alpha + i\beta)t} (\vec{a} + i\vec{b})$

and using $e^{i\beta t} = \cos \beta t + i \sin \beta t$, two real independent solutions are

$$\vec{x}_1(t) = e^{\alpha t} (\cos \beta t \vec{a} - \sin \beta t \vec{b})$$

$$\vec{x}_2(t) = e^{\alpha t} (\sin \beta t \vec{a} + \cos \beta t \vec{b})$$

Note even though solns always oscillate

$$\alpha > 0 \quad \vec{x}_k \text{ grow}$$

$$\alpha < 0 \quad \vec{x}_k \rightarrow 0$$

$$\alpha = 0 \quad \vec{x}_k \text{ periodic}$$

Here β is the frequency.

EXAMPLE Simple Purely imaginary case $\lambda = i\beta$

$$\vec{x}' = A \vec{x} = \begin{bmatrix} 0 & -8 \\ 2 & 0 \end{bmatrix} \vec{x}$$

Characteristic Polynomial

$$P(\lambda) = \lambda^2 + 16$$

$$\lambda = 4i$$

Eigenvector

$$(A - \lambda I) = \begin{bmatrix} -4i & -8 \\ 2 & -4i \end{bmatrix} \quad \vec{z} = \begin{pmatrix} 2i \\ 1 \end{pmatrix}$$

General solution

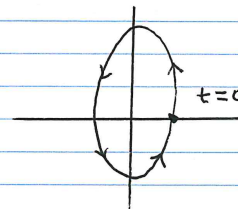
$$\vec{x}(t) = c_1 \begin{pmatrix} -2 \sin 4t \\ \cos 4t \end{pmatrix} + c_2 \begin{pmatrix} 2 \cos 4t \\ \sin 4t \end{pmatrix}$$

$\vec{x}_2(t)$

To see what these trajectories, look at $\vec{x}_2(t)$

$$\vec{x}_2 = \begin{pmatrix} x(t) \\ y(t) \end{pmatrix} = \begin{pmatrix} 2 \cos 4t \\ \sin 4t \end{pmatrix} \Rightarrow \left(\frac{x}{2}\right)^2 + y^2 = 1$$

is an ellipse



EXAMPLE Complex λ = Spiral

$$\frac{d\vec{x}}{dt} = \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \vec{x} = A\vec{x}$$

Characteristic Polynomial

$$P(\lambda) = \lambda^2 - 2\lambda + 2 = 0 \Rightarrow \lambda = 1 + i \quad (\alpha + i\beta)$$

with associated eigenvector

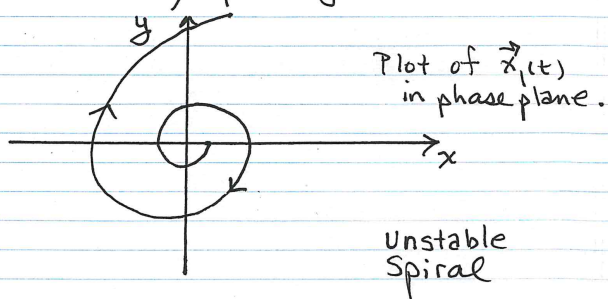
$$\vec{z} = \begin{pmatrix} 1 \\ i \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \end{pmatrix} + i \begin{pmatrix} 0 \\ 1 \end{pmatrix} = \vec{a} + i\vec{b}$$

Ultimately $\vec{x} = e^t (\cos t + i \sin t) (\vec{a} + i\vec{b})$ yields the general solution

$$\vec{x}(t) = c_1 \vec{x}_1(t) + c_2 \vec{x}_2(t) = c_1 \begin{pmatrix} e^t \cos t \\ -e^t \sin t \end{pmatrix} + c_2 \begin{pmatrix} e^t \sin t \\ e^t \cos t \end{pmatrix}$$

$\vec{x}_1(t) \quad \vec{x}_2(t)$

Notice $\|\vec{x}_1(t)\| = e^t$ so $\vec{x}_1(t) \rightarrow \infty$ as $t \rightarrow \infty$ but it does so by spiraling outward. Same with $\vec{x}_2$



EXAMPLE Purely Imaginary $\lambda = i\beta$

$$\vec{x}' = A\vec{x} \quad A = \begin{bmatrix} -2 & -4 \\ 10 & 2 \end{bmatrix}$$

Characteristic Polynomial (after calculations)

$$P(\lambda) = \lambda^2 + 36 = 0 \quad \lambda = 6i \quad (\alpha = 0)$$

Eigenvector

$$(A - \lambda I) = \begin{bmatrix} -2-6i & -4 \\ * & * \end{bmatrix} \quad \vec{z} = \begin{pmatrix} 2 \\ -1-3i \end{pmatrix}$$

General solution

$$\vec{x}(t) = c_1 \begin{pmatrix} 2 \cos 6t \\ -\cos 6t + 3 \sin 6t \end{pmatrix} + c_2 \begin{pmatrix} 2 \sin 6t \\ -\sin 6t - 3 \cos 6t \end{pmatrix}$$

$\vec{x}_1(t)$

Are ellipses with different axes. From $\vec{x}_1(t)$

$$\left(\frac{x}{2}\right)^2 + \left(\frac{x+y}{6+3}\right)^2 = 1$$

$\cos^2 + \sin^2 = 1$

Has axes:

$$x = 0 \quad x + 2y = 0$$

Linearization about equilibria

A useful tool in the study of ODE models is the process of linearization. Typically one wants to know if some given equilibria is stable or not.

Let $(\bar{x}, \bar{y})$ be an equilibria of

$$(1) \quad \dot{x} = f(x, y)$$

$$(2) \quad \dot{y} = g(x, y)$$

Then

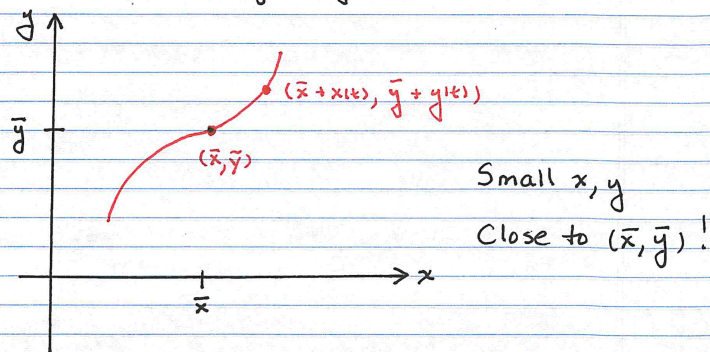
$$(3) \quad f(\bar{x}, \bar{y}) = 0$$

$$(4) \quad g(\bar{x}, \bar{y}) = 0$$

Let $(\bar{x}(t), \bar{y}(t))$ be solution trajectories near the equilibria

$$(5) \quad \bar{x}(t) = \bar{x} + x(t)$$

$$(6) \quad \bar{y}(t) = \bar{y} + y(t)$$



Start with

$$(1) \quad \bar{X}' = f(\bar{X}, \bar{Y})$$

$$(2) \quad \bar{Y}' = g(\bar{X}, \bar{Y})$$

where

$$\bar{X}(t) = \bar{x} + x(t)$$

$$\bar{Y}(t) = \bar{y} + y(t)$$

Then since $(\bar{x}, \bar{y})$ are constant

$$(3) \quad x' = f(\bar{x} + x, \bar{y} + y)$$

$$(4) \quad y' = g(\bar{x} + x, \bar{y} + y)$$

A Taylor series (linear approx) of (3)-(4) is:

$$x' = f(\bar{x}, \bar{y}) + f_x(\bar{x}, \bar{y})x + f_y(\bar{x}, \bar{y})y + \text{smaller}$$

$$y' = g(\bar{x}, \bar{y}) + g_x(\bar{x}, \bar{y})x + g_y(\bar{x}, \bar{y})y + \text{smaller}$$

Noting first terms vanish since $(\bar{x}, \bar{y})$ an equilibria and neglecting the smaller terms yields the linearized system:

$$\begin{pmatrix} x \\ y \end{pmatrix}' = \begin{bmatrix} f_x(\bar{x}, \bar{y}) & f_y(\bar{x}, \bar{y}) \\ g_x(\bar{x}, \bar{y}) & g_y(\bar{x}, \bar{y}) \end{bmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$

called the Jacobian matrix $DF(\bar{x}, \bar{y})$

Summary of Linearization

$$\begin{aligned}\vec{x}' &= f(\vec{x}, \vec{y}) \\ \vec{y}' &= g(\vec{x}, \vec{y})\end{aligned}\quad \text{original system}$$

Find equilibria

$$\begin{aligned}0 &= f(\bar{x}, \bar{y}) \\ 0 &= g(\bar{x}, \bar{y})\end{aligned}\quad \text{equilibria eqns}$$

There may be more than one equilibria satisfying the two eqns above.

$$\begin{aligned}\vec{x}(t) &= \bar{x} + x(t) \\ \vec{y}(t) &= \bar{y} + y(t)\end{aligned}$$

Linearized system in vector form $\vec{x}' = (x, y)$

$$(1) \quad \frac{d\vec{x}}{dt} = A \vec{x} \quad A = D\vec{F}(\bar{x}, \bar{y}) \text{ Jacobian}$$

where the Jacobian

$$A = D\vec{F}(\bar{x}, \bar{y}) = \begin{bmatrix} f_x(\bar{x}, \bar{y}) & f_y(\bar{x}, \bar{y}) \\ g_x(\bar{x}, \bar{y}) & g_y(\bar{x}, \bar{y}) \end{bmatrix}$$

Given how $\vec{x}(t)$ is defined, the system (1) describes the flow/solution only near the equilibria.

Application to linearized system (example)

$$\begin{aligned}x' &= f(x, y) = (x-1)y \\ y' &= g(x, y) = xy - x\end{aligned}$$

Can easily verify the system has two equilibria

$$P_0 = (0, 0) \quad P_1 = (1, 1)$$

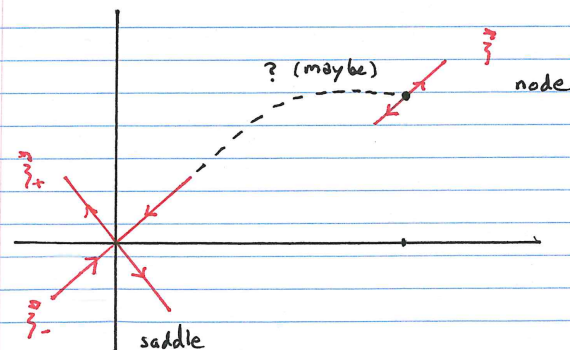
Jacobian at (x, y)

$$DF(x, y) = \begin{bmatrix} y & (x-1) \\ y-1 & x \end{bmatrix} = \begin{bmatrix} f_x & f_y \\ g_x & g_y \end{bmatrix}$$

Jacobian at P_0, P_1 and e-vals:

$$A_0 = DF(P_0) = \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix} \quad \lambda_{\pm} = \pm 1 \quad \text{saddle}$$

$$A_1 = DF(P_1) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad \lambda = 1 \text{ repeated} \quad \text{unstable node}$$



Classification of equilibria

$$(1) \quad \vec{x}' = A\vec{x} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \vec{x}$$

After some calculations the characteristic polynomial is found

$$P(\lambda) = \det(A - \lambda I)$$

$$P(\lambda) = \lambda^2 - (a+d)\lambda + (ad-bc)$$

or in terms of the trace $\text{Tr}A$ and determinant of the matrix

$$(2) \quad P(\lambda) = \lambda^2 - \text{Tr}A \lambda + \det A$$

where

$$\text{Tr}A = a+d$$

$$\det A = ad-bc$$

The stability of (1) will then be determined by the sign of the real part of the eigenvalues

$$(3) \quad \lambda_{\pm} = \frac{1}{2} (\text{Tr}A \pm \sqrt{\text{Tr}A^2 - 4\det A})$$

Again, whether $\lambda_{\pm}$ are real or complex the real part alone determines stability. To a large extent the sign of $\text{Tr}A^2 - 4\det A$ matters

Case: $\det A < 0$

$$\lambda_- < 0 < \lambda_+ \quad \text{unstable saddle}$$

Case: $\det A > 0$, $\text{Tr}A^2 - 4\det A > 0$

$$\text{Tr}A > 0 \quad \lambda_+ > \lambda_- > 0 \quad \text{unstable node}$$

$$\text{Tr}A < 0 \quad \lambda_- < \lambda_+ < 0 \quad \text{stable node}$$

Case: $\det A > 0$, $\text{Tr}A^2 - 4\det A < 0$

$$\lambda = \alpha \pm i\beta \quad \text{complex} \quad \beta = \frac{1}{2} \sqrt{4\det A - \text{Tr}A^2}$$

$$\text{Tr}A > 0 \quad \text{unstable spiral}$$

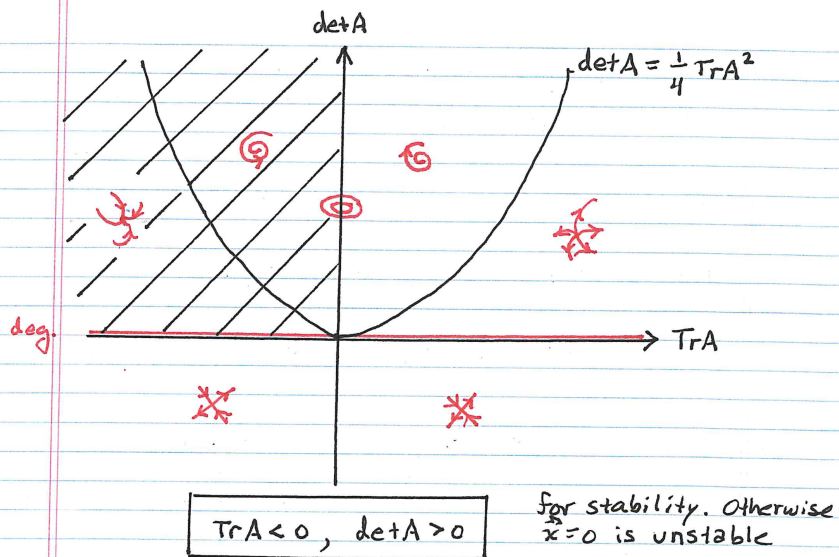
$$\text{Tr}A < 0 \quad \text{stable spiral}$$

Case: $\det A > 0$, $\text{Tr}A = 0$

$$\lambda = i\beta \quad \text{center}$$

Case: $\det A = 0$

degenerate line of equilibria



Applications to nonlinear systems $\vec{x}' = \vec{f}(\vec{x}, y)$

If we get a linearized system

$$\frac{d\vec{x}}{dt} = A\vec{x} \quad A = D\vec{F}(\vec{x}, \vec{y})$$

where one of the following is true

$$\text{Tr } A = 0 \quad \det A = 0$$

we can't conclude anything. Such points are "nonhyperbolic" and the linearized system doesn't necessarily well approximate the true system. We exclude all this theory.

Classification using $\text{Tr } A$, $\det A$

Ex $\vec{x}' = A\vec{x} \quad A = \begin{bmatrix} 1 & 1 \\ 3 & -1 \end{bmatrix}$

$$\det A = -4$$

$$\text{Tr } A = 0$$

$$\det A < 0 \Rightarrow \vec{x}=0 \text{ saddle}$$

Ex $\vec{x}' = A\vec{x} \quad A = \begin{bmatrix} 3 & -1 \\ -1 & 3 \end{bmatrix}$

$$\det A = 8 > 0$$

$$\text{Tr } A = 6$$

$$\det A - \frac{1}{4} \text{Tr } A^2 = -1 < 0 \Rightarrow \text{unstable node}$$

Ex $\vec{x}' = A\vec{x} \quad A = \begin{bmatrix} 4 & -4 \\ 20 & -4 \end{bmatrix}$

$$\det A = 64 > 0$$

$$\text{Tr } A = 0$$

Hence $\vec{x}=0$ a center.

EX $A = \begin{bmatrix} -13 & -27 \\ -9 & -31 \end{bmatrix}$

$$\det A = 160 > 0$$

$$\text{Tr} A = -44$$

$$\det A - \frac{1}{4} \text{Tr} A^2 = -324$$

$\vec{x} = 0$
stable
node

EX $A = \begin{bmatrix} 4 & -6 \\ 2 & -3 \end{bmatrix}$

$$\det A = 0$$

$$\text{Tr} A = 1$$

degenerate
line of fixed
points

EX $A = \begin{bmatrix} 1 & -2 \\ 3 & -2 \end{bmatrix}$

$$\det A = 4 > 0$$

$$\text{Tr} A = -1$$

$$\det A - \frac{1}{4} \text{Tr} A^2 > 0$$

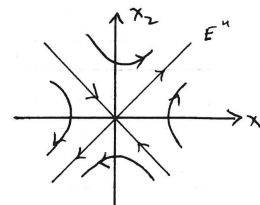
Stable
Spiral.

Classification Examples

EX SADDLE

$$A = \begin{bmatrix} 1 & 1 \\ 3 & -1 \end{bmatrix}$$

$$\lambda_{\pm} = \pm 2, \quad \vec{z}_+ = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \quad \vec{z}_- = \begin{pmatrix} 1 \\ -3 \end{pmatrix}$$

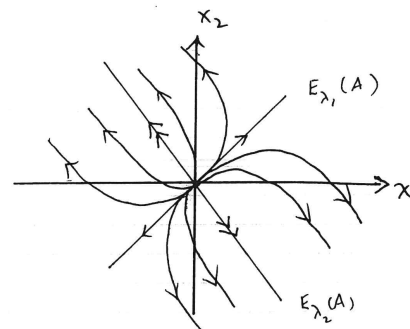


EX UNSTABLE NODE

$$A = \begin{bmatrix} 3 & -1 \\ -1 & 3 \end{bmatrix}$$

$$\lambda_1 = 2 \quad \lambda_2 = 4$$

$$\vec{z}_1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix} \quad \vec{z}_2 = \begin{pmatrix} 1 \\ -1 \end{pmatrix}$$



$$x(t) = c_1 e^{2t} \vec{z}_1 + c_2 e^{4t} \vec{z}_2$$

$$x(t) \sim c_2 e^{4t} \vec{z}_2 \quad \text{as } t \rightarrow \infty$$

EX Center

$$A = \begin{bmatrix} 4 & -4 \\ 20 & -4 \end{bmatrix}$$

$$\lambda = \pm 2i \quad ; \quad T = \frac{2\pi}{\omega} = \pi \text{ period}$$

$$z = \begin{pmatrix} 2 \\ 2-i \end{pmatrix} = \begin{pmatrix} 2 \\ 2 \end{pmatrix} + i \begin{pmatrix} 0 \\ -1 \end{pmatrix}$$

$$z = z_R + i z_I$$

$$x(t) = c_1 u(t) + c_2 v(t)$$

$$u(t) = \cos 2t z_R - \sin 2t z_I$$

$$v(t) = \sin 2t z_R + \cos 2t z_I$$

$$u(0) = z_R$$

$$v(0) = z_I$$

Suppose I.C. chosen so that $x(0) = c_1 u(0) = x_0$ with $c_1 = 1$

$$x(t) = u(t)$$

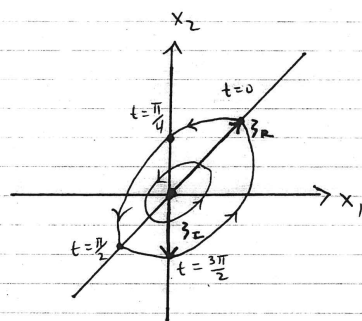
$$u(0) = z_R$$

$$u(\frac{\pi}{4}) = -z_I$$

$$u(\frac{\pi}{2}) = -z_R$$

$$u(\frac{3\pi}{4}) = +z_I$$

$$u(\pi) = z_R$$



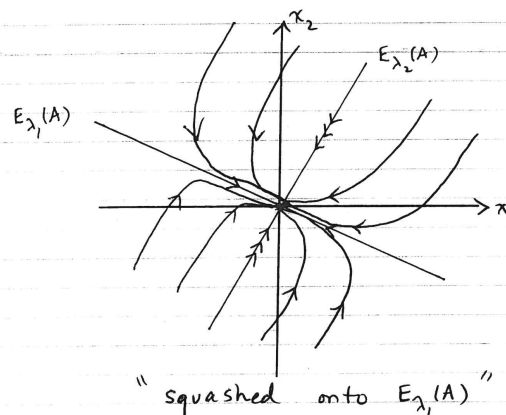
Neutral Stable

EX STABLE NODE

$$A = \begin{bmatrix} -13 & -27 \\ -9 & -31 \end{bmatrix}$$

$$\lambda_1 = -4 \quad z_1 = \begin{pmatrix} -3 \\ 1 \end{pmatrix}^T$$

$$\lambda_2 = -40 \quad z_2 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}^T$$



$$x(t) = c_1 e^{-4t} z_1 + c_2 e^{-40t} z_2$$

E

$$E^s(0) = \mathbb{R}^2$$

$$E^u(0) = \{0\}$$

"squashed onto $E_{\lambda_1}(A)$ "

EX DEGENERATE (LINE OF FIXED)

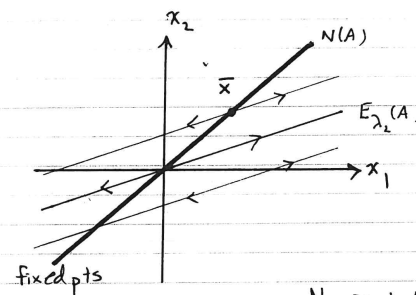
$$A = \begin{bmatrix} 4 & -6 \\ 2 & -3 \end{bmatrix}$$

$$\lambda_1 = 0$$

$$z_1 = \begin{pmatrix} 3 \\ 1 \end{pmatrix}$$

$$\lambda_2 = 1$$

$$z_2 = \begin{pmatrix} 2 \\ 1 \end{pmatrix}$$



$$x(t) = c_1 z_1 + c_2 e^t z_2$$

Non isolated, Neutral stability.

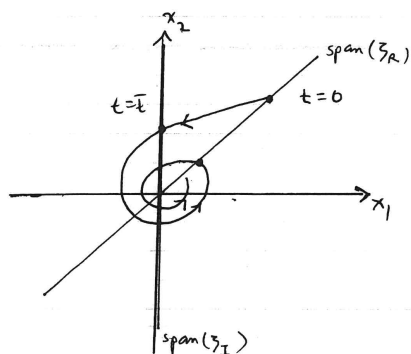
$$E^s(\bar{x}) = \{\bar{x}\}. \text{ However, for } \bar{x} = (\bar{x}_1, \bar{x}_2)$$

$$E^u(\bar{x}) = \{(x_1, x_2) : x_2 - \bar{x}_2 = \frac{1}{2}(x_1 - \bar{x}_1)\}$$

is a straight line. $E^s(\bar{x}) \cup E^u(\bar{x}) \neq \mathbb{R}^2$ in this case

EX STABLE SPIRAL

$$A = \begin{bmatrix} 1 & -2 \\ 3 & -2 \end{bmatrix}$$



$$\lambda_{\pm} = -\frac{1}{2} \pm \frac{\sqrt{15}}{2} i$$

$$z = \begin{pmatrix} 4 \\ 3 \end{pmatrix} + i \begin{pmatrix} 0 \\ -\sqrt{15} \end{pmatrix} = z_R + i z_I$$

$$\omega = \frac{\sqrt{15}}{2}; \text{ NOT PERIODIC.}$$

Choose I.C. so that

$$x(t) = u(t) = e^{-\frac{1}{2}t} \left(\cos \omega t \vec{z}_R + \sin \omega t \vec{z}_I \right)$$

$$\text{Then, when } t = \bar{t} = \frac{\pi}{2\omega}, \quad x(\bar{t}) = -e^{-\frac{1}{2}\bar{t}} \vec{z}_I$$

EXAMPLE

$$\begin{aligned} \dot{x} &= ax \\ \dot{y} &= -y \end{aligned}$$

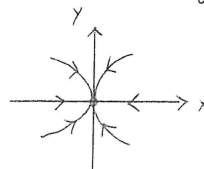
$(\bar{x}, \bar{y}) = (0, 0)$ sole f.p.t.
if $a \neq 0$.

Solution for $x(0) = x_0, y(0) = y_0$ is

$$x(t) = x_0 e^{at}$$

$$y(t) = y_0 e^{-t}$$

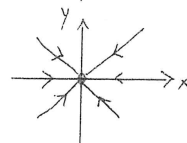
$$a < -1$$



isolated, a.s.

NODE

$$a = -1$$

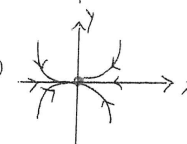


$\frac{y(t)}{x(t)} = K = \frac{y_0}{x_0}, \forall t \in \mathbb{R}$
so long as $x(t) \neq 0$.
isolated, a.s.

NODE

(Star)

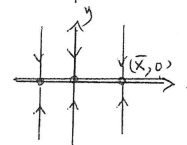
$$a \in (-1, 0)$$



isolated, a.s.

NODE

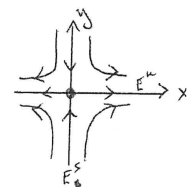
$$a = 0$$



non isolated. $y=0, x \in \mathbb{R}$ line of fixed pts.

NOT ATTRACTING, IS $\Rightarrow$ Neutral.
LIAPUNOV

$$a > 0$$



UNSTABLE.

SADDLE

(Stable and unstable manifolds)

Chemostat Model Analysis

$$\begin{aligned}\frac{dn}{dt} &= \alpha_1 \frac{nc}{1+c} - n = f(n, c) \\ \frac{dc}{dt} &= -\frac{nc}{1+c} - c + \alpha_2 = g(n, c)\end{aligned}$$

where

n = bacterial concentration

c = chemical/nutrient concentration

We aim to prove that when a positive (physical) equilibrium exists the extinction state with $n=0$ is unstable.

- find the equilibria
- determine for what (α_1, α_2) parameter pairs the equilibria are positive/physical.
- Compute the Jacobian
- Use the $\text{Tr}A/\det A$ classification to determine when each equilibria is stable.

Find the equilibria

$$(1) \quad f(n, c) = n \left(\alpha_1 \frac{c}{c+1} - 1 \right) = 0$$

$$(2) \quad g(n, c) = -\frac{nc}{c+1} - c + \alpha_2 = 0$$

Extinction state

If $n = 0$ in (1)-(2) then $c = \alpha_2$

$$P_0 = (\bar{n}_0, \bar{c}_0) = (0, \alpha_2)$$

is always physical if $\alpha_2 > 0$.

Coexistence state

Here we assume $n \neq 0$. Then (1) above $\Rightarrow$

$$(3) \quad \alpha_1 \frac{c}{c+1} - 1 = 0$$

Solve this for c

$$(4) \quad c = \frac{1}{\alpha_1 - 1}$$

Substitute (4) into (2) and solve for n . The algebra is simpler than one might think since (3) implies

$$\frac{c}{c+1} = \frac{1}{\alpha_1}$$

Then $g(n, c) = 0$ becomes

$$(5) \quad -n \left(\frac{1}{\alpha_1} \right) - \frac{1}{\alpha_1 - 1} + \alpha_2 = 0$$

Solve this to get

$$P_1 = (\bar{n}_1, \bar{c}_1) = \left(\alpha_1 \left(\alpha_2 - \frac{1}{\alpha_1 - 1} \right), \frac{1}{\alpha_1 - 1} \right)$$

For $\bar{n}_1$ and $\bar{c}_1$ to be positive need $\alpha_1 > 1$ and $\alpha_2 > (\alpha_1 - 1)^{-1}$.

Summary

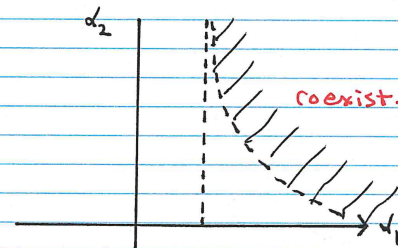
$$P_0 = (0, \alpha_2)$$

extinction state
always exists

$$P_1 = \left(\alpha_1 \left(\alpha_2 - \frac{1}{\alpha_1 - 1} \right), \frac{1}{\alpha_1 - 1} \right)$$

coexistence only if

$$\boxed{\begin{array}{l} \alpha_1 > 1 \\ \alpha_2 > \frac{1}{\alpha_1 - 1} \end{array}}$$



Jacobian (general)

$$\frac{dn}{dt} = f(n, c) = \alpha_1 \frac{nc}{1+c} - n$$

$$\frac{dc}{dt} = g(n, c) = -\frac{nc}{1+c} - c + \alpha_2$$

Recall Jacobian is

$$D\vec{F} = \begin{bmatrix} \frac{\partial f}{\partial n} & \frac{\partial f}{\partial c} \\ \frac{\partial g}{\partial n} & \frac{\partial g}{\partial c} \end{bmatrix}$$

Explicitly this is a bit of a mess

$$D\vec{F}(n, c) \equiv \begin{bmatrix} \alpha_1 c / (1+c) - 1 & \alpha_1 n / (1+c)^2 \\ -c / (1+c) & -n / (1+c)^2 - 1 \end{bmatrix}$$

Jacobian at P_1 coexistence

To simplify calculations define

$$A = \frac{\bar{n}_1}{(1+\bar{c}_1)^2}$$

After some calculations

$$D\vec{F}(P_1) = \begin{bmatrix} 0 & \alpha_1 A \\ -\frac{1}{\alpha_1} & -(A+1) \end{bmatrix}$$

Despite the complexity of P_1 , we get some simple results

$$\text{Tr } D\vec{F} = -(A+1) \quad < 0 \text{ for stability}$$

$$\det D\vec{F} = A \quad > 0 \text{ for stability}$$

Then we have

$$\bar{n}_1 > 0 \Leftrightarrow A > 0 \Rightarrow P_1 \text{ stable}$$

In plain language

$P_1 \text{ stable} \Leftrightarrow P_1 \text{ physical}$

Jacobian at P_0 extinction

To simplify calculations

$$B = \frac{\alpha_2}{1 + \alpha_2} > 0$$

After calculations

$$D\vec{F}(P_0) = \begin{bmatrix} \alpha_1 B - 1 & 0 \\ -B & -1 \end{bmatrix}$$

from which P_0 is stable only if

$$\text{Tr } D\vec{F} = \alpha_1 B - 2 < 0$$

$$\det D\vec{F} = -(\alpha_1 B - 1) > 0$$

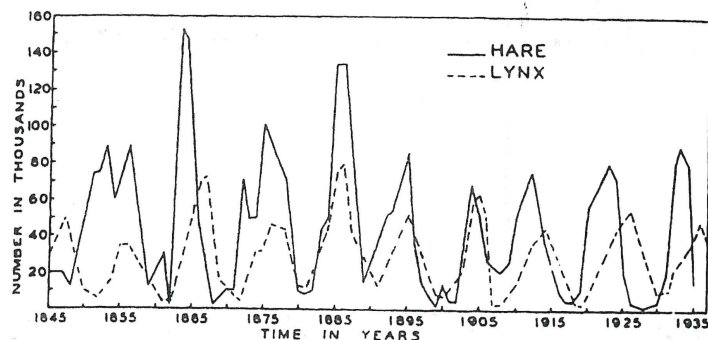
These two inequalities define a region in (α_1, α_2) -plane where P_0 stable. } part of HW

Can be used to show

P_0 stable only when P_1 not

or that no positive equilibria $\Rightarrow$ extinction.

Predator Prey (Lotka Volterra) model



Model Equations

$$(1) \quad x' = ax - bxy$$

$$(2) \quad y' = -cy + dxy$$

Here

$$x = \text{prey} \quad [x] = \#$$

$$y = \text{predators} \quad [y] = \#$$

and predation terms proportional to xy

xy = number of possible interactions

Considerations: $b=0, d=0$ in model. Predators die out!

Model analysis

System has two equilibria

$$P_1(0,0) \quad P_2\left(\frac{c}{d}, \frac{a}{b}\right)$$

Jacobian

$$D\vec{F}(P) = \begin{bmatrix} a-by & -bx \\ dy & dx-c \end{bmatrix}$$

Hence

$$D\vec{F}(P_1) = \begin{bmatrix} a & 0 \\ 0 & -c \end{bmatrix} \quad \det < 0 \quad \text{saddle}$$

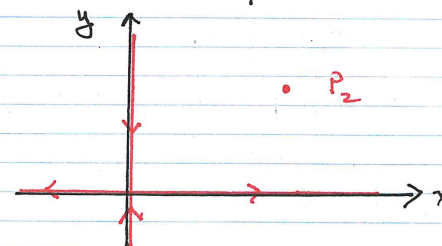
$$D\vec{F}(P_2) = \begin{bmatrix} 0 & -bc/d \\ ad/b & 0 \end{bmatrix} \quad \det > 0 \quad \text{center} \\ \text{Tr} = 0$$

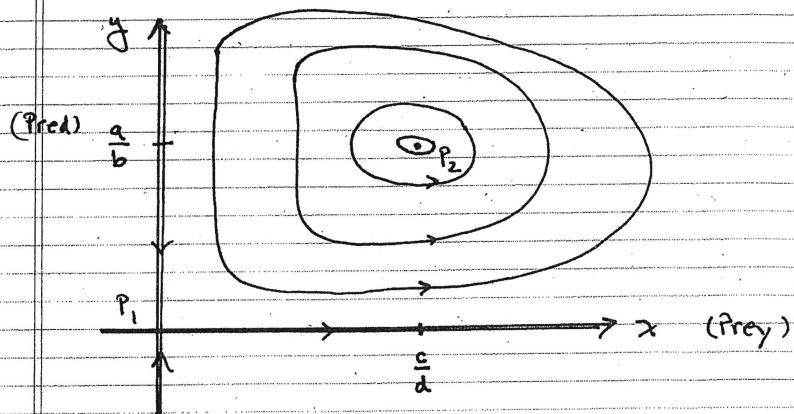
For the saddle

$$\lambda_1 = a > 0 \quad \vec{z}_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \quad \text{unstable}$$

$$\lambda_2 = -c < 0 \quad \vec{z}_2 = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \quad \text{stable}$$

In fact $x=0$ and $y=0$ are "invariant".





Neutrally stable concentric periodic orbits

Matlab code for contours of $\phi(x,y)$

```
%
% phase portrait of predator prey system
% as contourplots of phi(x,y)
%
x=linspace(0,3);
y=linspace(0,3);
[X,Y]=meshgrid(x,y);
%
a=1;
b=2;
c=1;
d=1;
phi=-c*log(X)-a*log(Y)+d*X+b*Y;
contour(X,Y,phi)
```

Since $\text{TrDF}(P_2) = 0$ it is not "hyperbolic" and linear theory may fail. Here linear theory predicts a center behavior near P_2 . The validity of this remains to be shown:

First Integral

A function $\phi(x,y)$ is said to be a first integral if it is constant on trajectories.

A very lucky guess:

$$(3) \quad \phi(x,y) \equiv -c \ln x - a \ln y + dx + by$$

For the model (1)-(2) and some calculations

$$\frac{d\phi}{dt} = -\frac{c}{x}x' - \frac{a}{y}y' + dx' + by'$$

$$\frac{d\phi}{dt} = -\frac{c}{x}(ax - bxy) - \frac{a}{y}(-cy + dxy) + d(ax - bxy) + b(-cy + dx)$$

$$\frac{d\phi}{dt} = 0$$

Thus, level sets of ϕ are trajectories of (1)-(2)

Need software to compute these level sets.

Predator Prey with density dependence

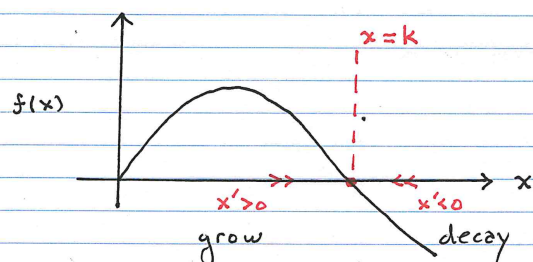
Prey are often more numerous than predators. Hence, they are more subject to density growth rate effects. Predators are not. We examine such effects through a minor change in the previous model.

Model Equations (Logistic Growth Rate)

$$\begin{array}{ll} (1) & x' = ax \left(1 - \frac{x}{K}\right) - bxy \quad \text{prey} \\ (2) & y' = -cy + dxy \quad \text{pred.} \end{array}$$

In the absence of predation ($y=0$)

$$x' = ax \left(1 - \frac{x}{K}\right) = f(x)$$



Then $x(t) \rightarrow K$ called carrying capacity

Equilibria

$$0 = ax \left(1 - \frac{x}{K}\right) - bxy$$

$$0 = -cy + dxy$$

has three solutions (after calculations)

$$P_1(0, 0) \quad \text{both extinct}$$

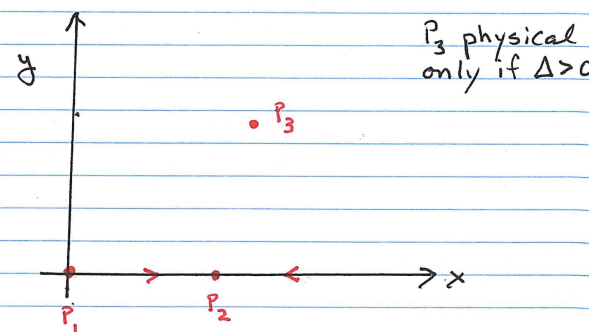
$$P_2(K, 0) \quad \text{only pred. extinct}$$

$$P_3\left(\frac{c}{d}, \frac{a\Delta}{bkd}\right) \quad \text{coexistence}$$

where

$$\Delta = kd - c$$

must be positive for a physical coexist P_3



Given P_3 the coexistence value of predators:

$$\text{pred. with density} = \left(\frac{\Delta}{kd}\right) \times \text{pred. no density.}$$

where $\frac{\Delta}{kd} = 1 - \frac{c}{kd} > 0$ smaller!!

```

> restart;
> with(linalg):
> f:=a*x*(1-x/k)-b*x*y;
> g:=-c*y+d*x*y;

> P:=solve({f=0,g=0},{x,y});
      P:= {x=0,y=0}, {x=k,y=0}, {x= c/d, y= -a(-kd+c)/bkd}

> DF:=map(simplify,jacobian([f,g],[x,y]));
      DF:= [ [ a*k-2*a*x-b*y*k, -b*x ],
             [ y*d, -c+d*x ] ]

> DF1:=subs(P[1],evalm(DF));det(DF1);
      DF1:= [ [ a, 0 ],
              [ 0, -c ] ]
      -a*c

> DF2:=subs(P[2],evalm(DF));det(DF2);
      DF2:= [ [ -a, -b*k ],
              [ 0, k*d-c ] ]
      -a*(k*d-c)

> DF3:=map(simplify,subs(P[3],evalm(DF)));det(DF3);trace(DF3);
      DF3:= [ [ -a*c/k*d, -b*c/d ],
              [ -a*(-k*d+c)/b*k, 0 ],
              [ -c*a*(-k*d+c)/d*k, -a*c/k*d ] ]

```

Jacobians at P_k (calculations omitted here)

$$DF_k = DF(P_k)$$

(1)

Both extinct

$$DF_1 = \begin{bmatrix} a & 0 \\ 0 & -c \end{bmatrix}$$

$$\det DF_1 = -ac < 0$$

Saddle always

(2)

Pred. extinct

$$DF_2 = \begin{bmatrix} -a & -bk \\ 0 & \Delta \end{bmatrix}$$

$$\det DF_2 = -a\Delta < 0$$

when P_3 physical ($\Delta > 0$)
Saddle.

(3)

Coexistence

$$DF_3 = \begin{bmatrix} -\frac{ac}{kd} & -\frac{bc}{d} \\ \frac{a\Delta}{bk} & 0 \end{bmatrix}$$

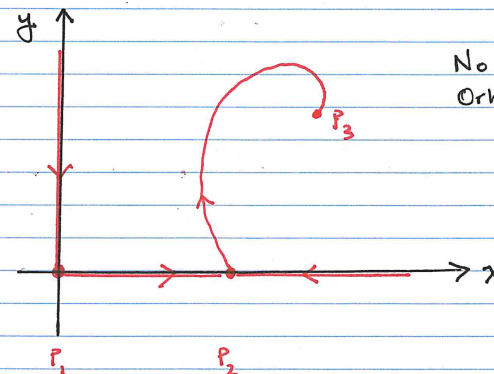
$$\det DF_3 = \frac{ac\Delta}{dk}$$

$$\text{Tr } DF_3 = -\frac{ac}{dk} < 0$$

(4)

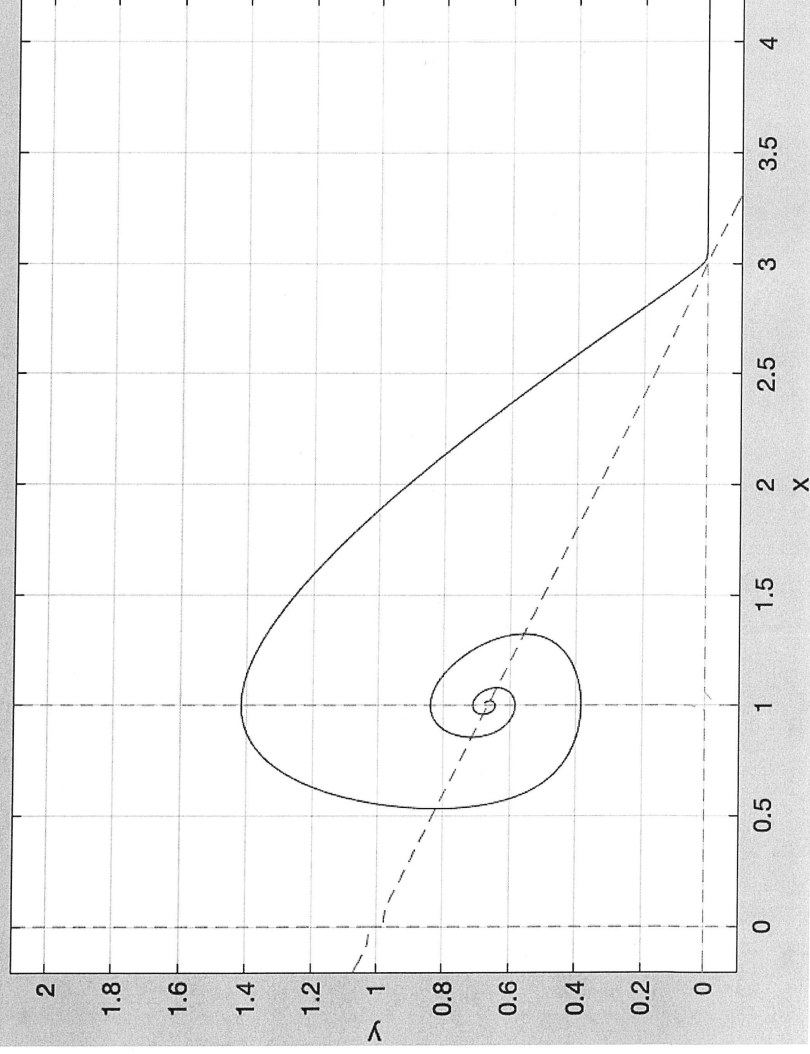
Hence P_3 is stable when physical.

(5)



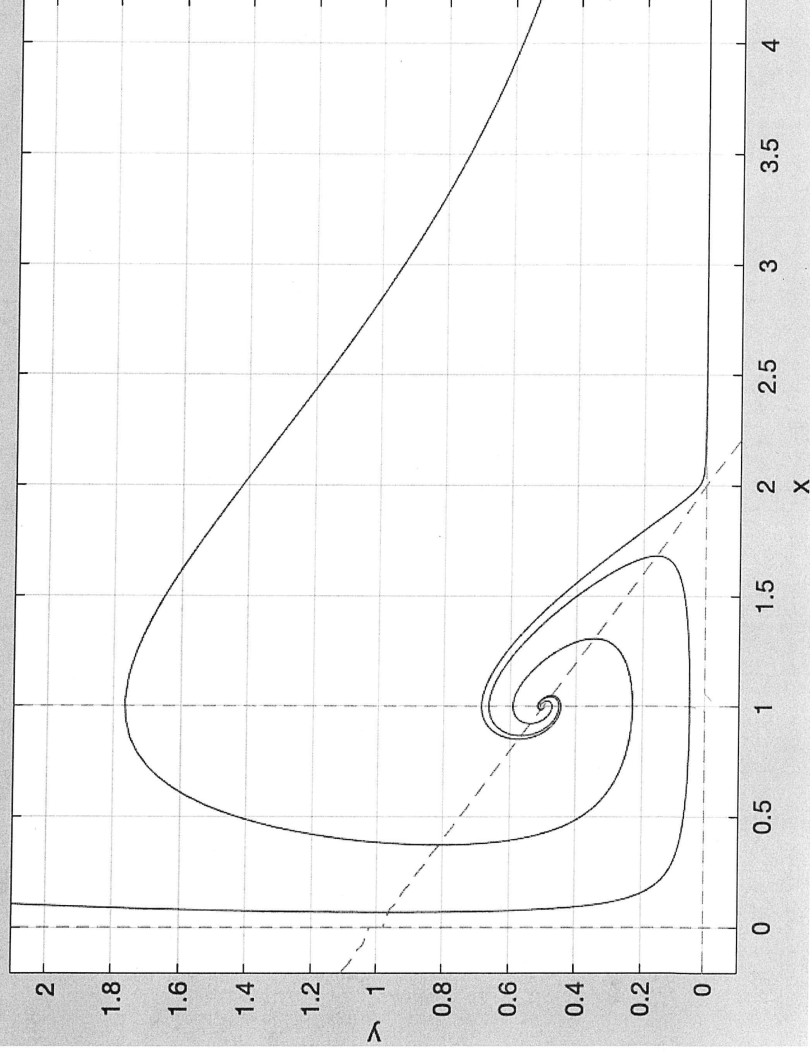
$$\begin{aligned}x' &= ax(1 - x/k) - bxy \\ y' &= -cy + dxy\end{aligned}$$

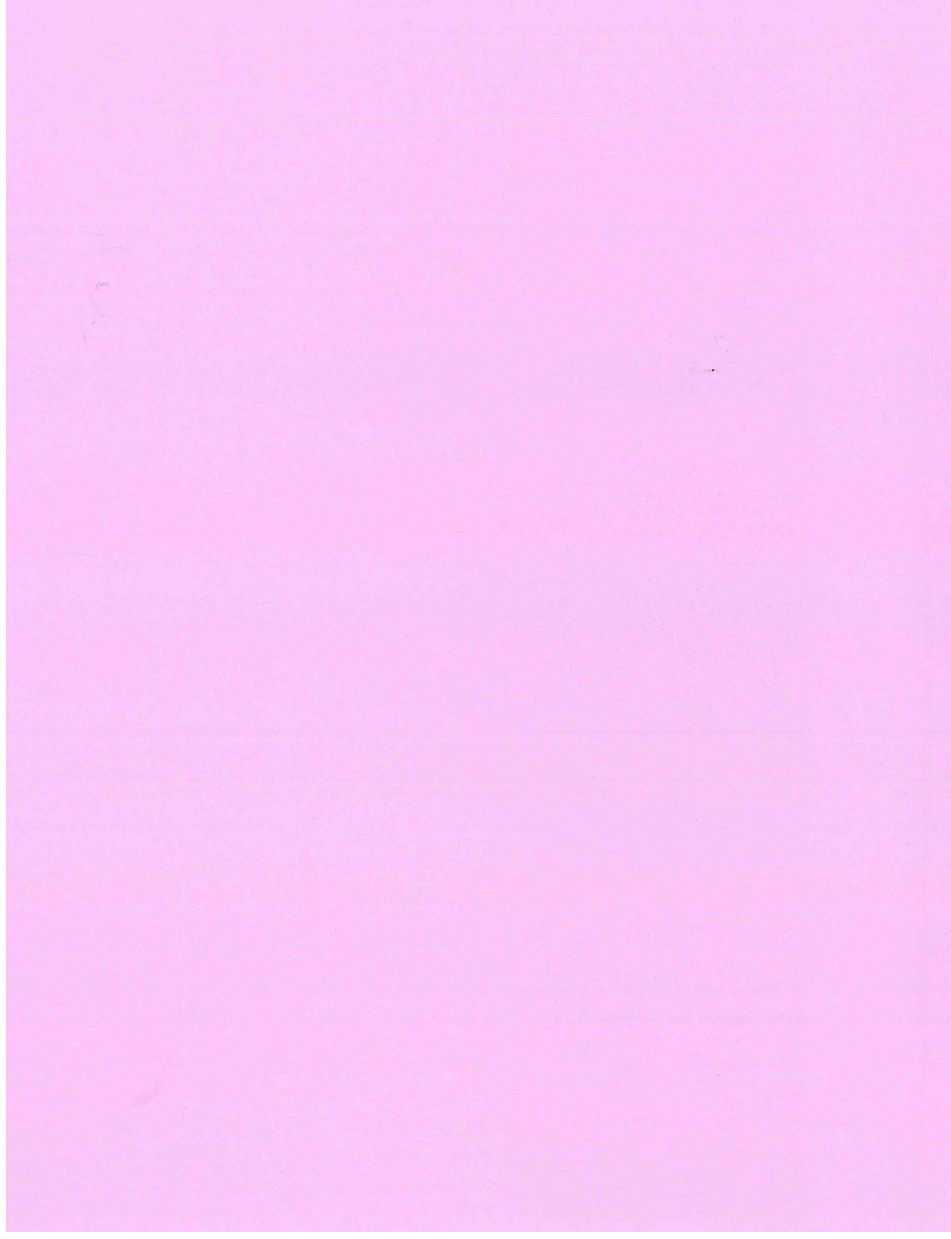
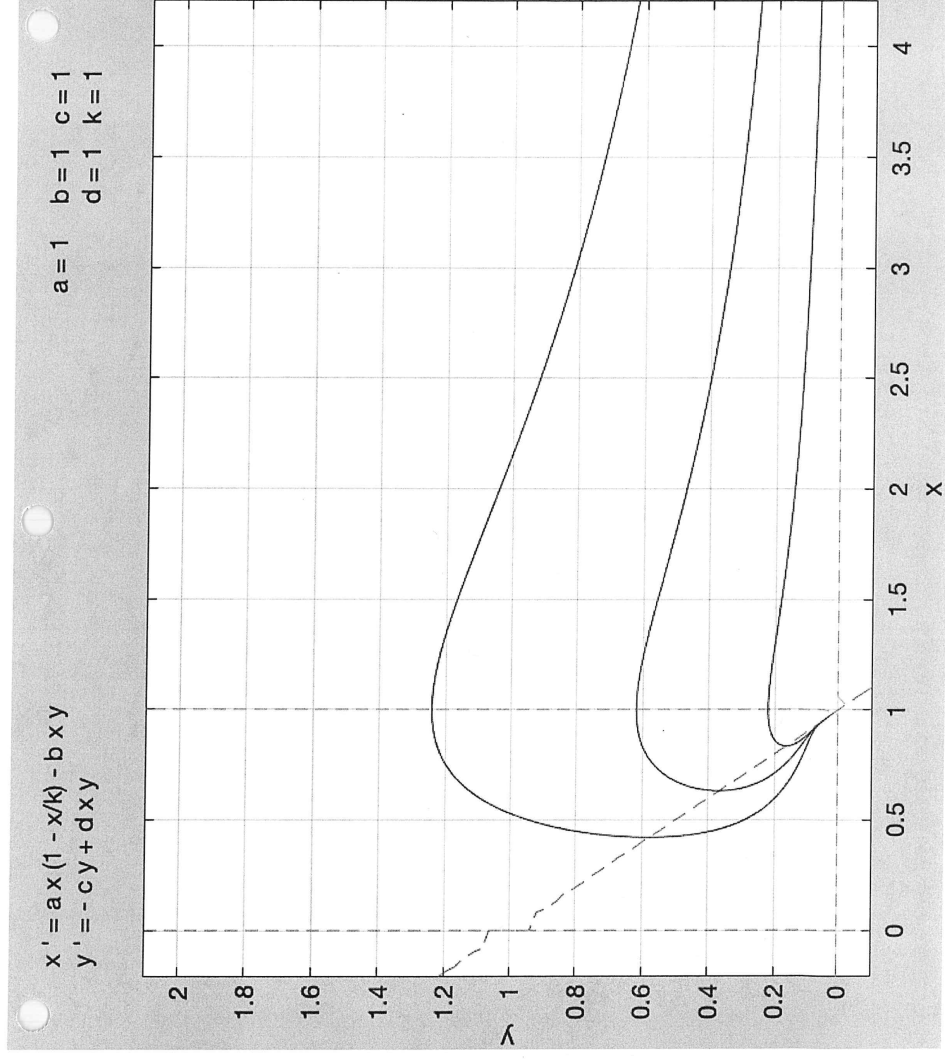
$$\begin{aligned}a &= 1 & b &= 1 & c &= 1 \\ d &= 1 & k &= 3\end{aligned}$$



$$\begin{aligned}x' &= ax(1 - x/k) - bxy \\ y' &= -cy + dxy\end{aligned}$$

$$\begin{aligned}a &= 1 & b &= 1 & c &= 1 \\ d &= 1 & k &= 2\end{aligned}$$





Competition Models

Two species (or more) competing for the same resources

Though they share the same habitat, their carrying capacities K_i differ.

$$\frac{dN_1}{dt} = r_1 N_1 (K_1 - a_{11} N_1 - a_{12} N_2)$$

$$\frac{dN_2}{dt} = r_2 N_2 (K_2 - a_{21} N_1 - a_{22} N_2)$$

Note the density dependence weighted average growth rate (underbrace above)

Rather than analyze model directly (8 parameters) we nondimensionalize.

$$x = \frac{N_1}{N_1^*} \quad y = \frac{N_2}{N_2^*} \quad \tau = \frac{t}{t^*}$$

Excluding lengthy calculations we use

$$N_1^* = \frac{K_1}{a_{11}} \quad N_2^* = \frac{K_2}{a_{22}} \quad t^* = \frac{1}{r_1 K_1}$$

Nondimensionalization of Competition Model

$$(1) \quad \frac{dN_1}{dt} = r_1 N_1 (K_1 - a_{11} N_1 - a_{12} N_2)$$

$$(2) \quad \frac{dN_2}{dt} = r_2 N_2 (K_2 - a_{21} N_1 - a_{22} N_2)$$

Has 8 parameters. Goal is to scale dependent and independent variables so new variables are dimension free and new system has fewer parameters.

$$x = \frac{N_1}{N_1^*} \quad y = \frac{N_2}{N_2^*} \quad \tau = \frac{t}{t^*}$$

At this point, N_1^* , N_2^* and t^* are unknown. We get to pick these.

$$(3) \quad N_1 = x N_1^* \quad N_2 = y N_2^* \quad t = \tau t^*$$

First we nondimensionalize (1) using (3)

$$\frac{N_1^*}{t^*} \frac{dx}{d\tau} = r_1 N_1^* x (K_1 - a_{11} N_1^* x - a_{12} N_2^* y)$$

$$\left\| \frac{dx}{d\tau} = (r_1 K_1 t^*) x \left(1 - \frac{a_{11} N_1^*}{K_1} x - \frac{a_{12} N_2^*}{K_1} y \right) \right\|$$

↑
choose t^*
so this
equals 1

↑
choose N_1^*
so this
equals 1

↑
define new
parameters

Hence

$$\frac{dx}{dt} = x(1-x-by)$$

where

$$(4) \quad t^* = \frac{1}{r_1 K_1} \quad N_1^* = \frac{K_1}{a_{11}}$$

and

$$(5) \quad b = \frac{a_{12} N_2^*}{K_1}$$

where N_2^* has yet to be determined.

Next we nondimensionalize (2) keeping in mind t^* and N_1^* are now known in (4). In a similar fashion we get

$$\left\| \frac{dy}{dt} = (r_2 K_2 t^*) y \left(1 - \frac{a_{21} N_1^*}{K_2} x - \frac{a_{22} N_2^*}{K_2} y \right) \right\|$$

↑
become
parameter
 η

↑
becomes
parameter
 c

↑
choose N_2^*
so this
equals 1

So in particular

$$(6) \quad N_2^* = \frac{K_2}{a_{22}}$$

Summary

If we choose

$$N_1^* = \frac{K_1}{a_{11}} \quad N_2^* = \frac{K_2}{a_{22}} \quad t^* = \frac{1}{r_1 K_1}$$

and define the parameters

$$b = \frac{a_{12} K_2}{a_{22} K_1} \quad c = \frac{a_{21} K_1}{a_{11} K_2} \quad \eta = \frac{r_2 K_2}{r_1 K_1}$$

we obtain the dimensionless system

$$\begin{aligned} \frac{dx}{dt} &= x(1-x-by) \\ \frac{dy}{dt} &= \eta y(1-cx-y) \end{aligned}$$

ONLY 3 PARAMETERS!

Dimensionless Model

$$\begin{aligned}\dot{x} &= f(x, y) = x(1 - x - by) \\ \dot{y} &= g(x, y) = \eta y(1 - cx - y)\end{aligned}$$

where

$$b = \frac{a_{12}K_2}{a_{22}K_1} \quad c = \frac{a_{21}K_1}{a_{11}K_2} \quad \eta = \frac{r_2K_2}{r_1K_1}$$

The dimensionless model has only 3 params!

Equilibria

Solving $f = g = 0$ we find four possible equilibria

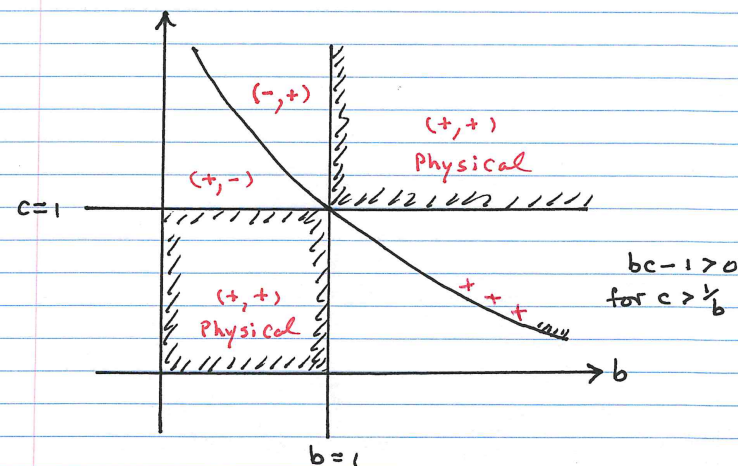
$P_0 = (0, 0)$	both die
$P_x = (1, 0)$	x survives
$P_y = (0, 1)$	y survives
$P_1 = \left(\frac{b-1}{bc-1}, \frac{c-1}{bc-1}\right)$	possible coexistence.

Existence of positive interior P_1

The coexistence state P_1 is positive (physical) if both coefficients of P_1 are positive:

$$P_1 = \left(\frac{b-1}{bc-1}, \frac{c-1}{bc-1}\right)$$

Plot $b=1$, $c=1$ and $c = \frac{1}{b}$



Shows sign of components of P_1 in (b, c) -plane.

P_1 physical only in shaded regions

Stability Conditions

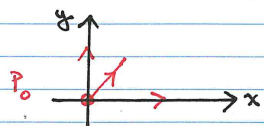
Must evaluate Jacobian at each equilibria.

$$DF(x,y) = \begin{bmatrix} 1-2x-by & -xb \\ -\eta y c & \eta - \eta cx - 2\eta y \end{bmatrix}$$

Total Extinction P_0

$$DF(P_0) = \begin{bmatrix} 1 & 0 \\ 0 & \eta \end{bmatrix}$$

$\lambda = 1, \eta$ unstable node
with axes as trajectories

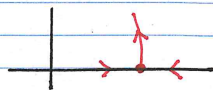


Species x survives P_x

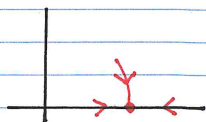
$$DF(P_x) = \begin{bmatrix} -1 & -b \\ 0 & \eta(1-c) \end{bmatrix}$$

$$\lambda = -1, \eta(1-c)$$

$c < 1$ P_x saddle



$c > 1$ P_x stable



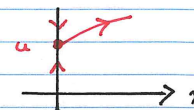
Species y survives P_y

$$DF(P_y) = \begin{bmatrix} 1-b & 0 \\ -\eta c & -\eta \end{bmatrix}$$

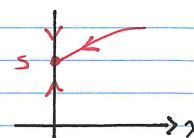
$$\lambda = 1-b, -\eta$$

From the eigenvalues we conclude

$b < 1$ P_y saddle



$b > 1$ P_y stable

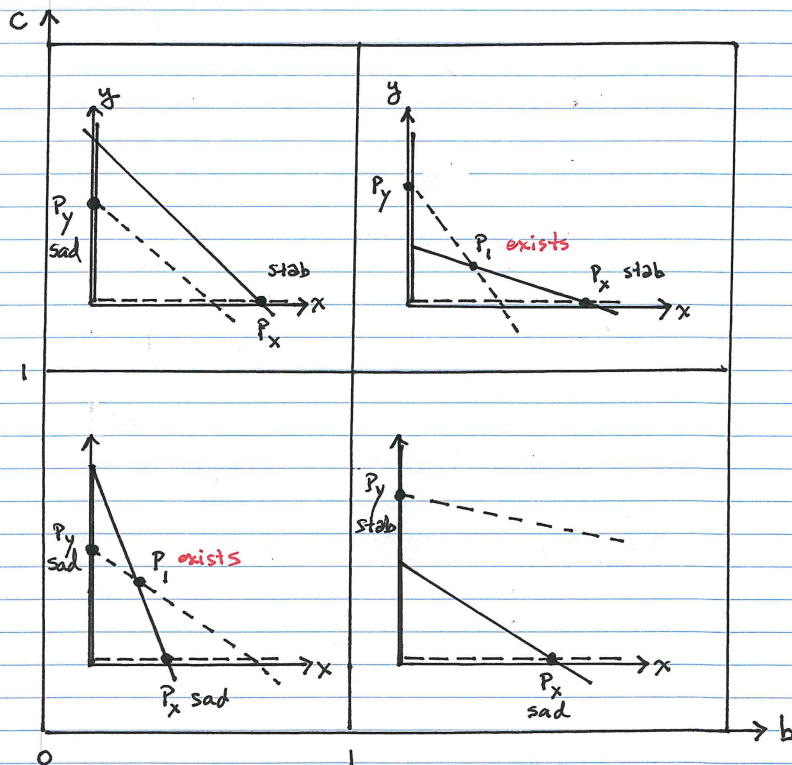


Nullclines and Equilibria Existence

$$\dot{x} = 0 \Leftrightarrow x=0, y = \frac{1}{b}(1-x) \quad \text{-----}$$

$$\dot{y} = 0 \Leftrightarrow y=0, y = 1-cx \quad \text{-----}$$

Below are nullclines of system for (b, c) -pairs



To completely understand what happens for all (b, c) need to examine stability of P_1 when it exists.

Coexistence Equilibria P_1

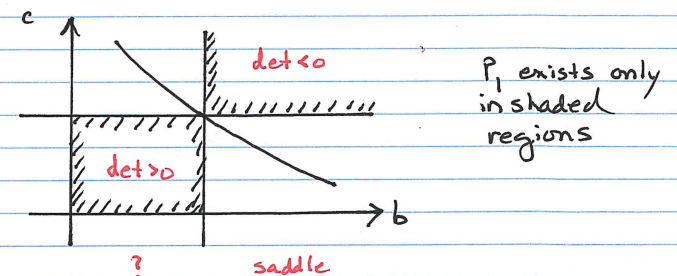
One can calculate the Jacobian at P_1 :

$$DF(P_1) = \frac{1}{(1-bc)} \begin{bmatrix} b-1 & b(b-1) \\ c(c-1) & c(c-1) \end{bmatrix}$$

After some calculations

$$\det DF(P_1) = \frac{c(b-1)(c-1)}{1-bc}$$

the sign of which can be deduced in the (b, c) -plane



So, for $b > 1, c > 1$ we know P_1 exists and is a saddle.

To ascertain the stability when $b < 1, c < 1$ we need to examine the Trace of $DF(P_1)$.

Stability of coexistence $(b, c) \in (0, 1)^2$

For

$$0 < b < 1 \quad 0 < c < 1$$

we found $\det DF > 0$ so that equilibria P_1 is not a saddle. Therefore, its stability depends entirely on

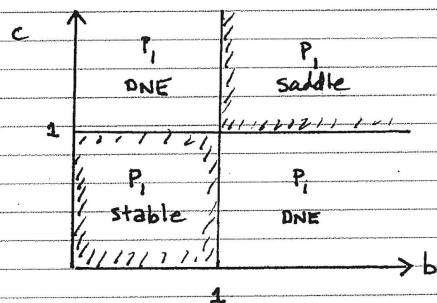
$$\text{Tr } DF(P_1) = \frac{(b-1) + \eta(c-1)}{1-bc}$$

For the parameter range being discussed the numerator is negative while the denominator is positive. Hence

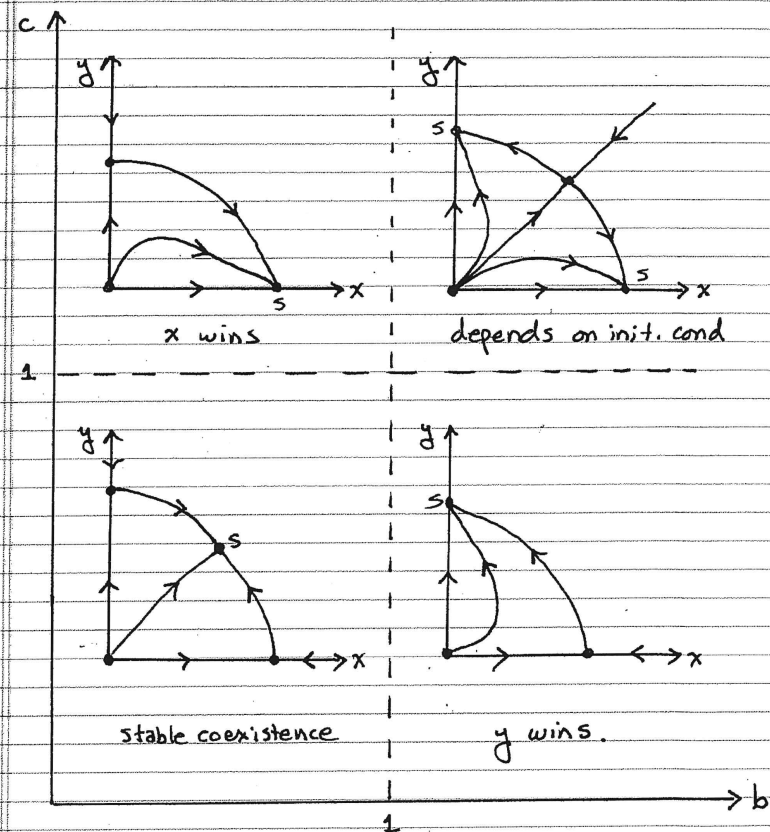
$$\text{Tr } DF(P_1) < 0$$

P_1 stable

Summary of P_1 existence and stability:



Conclusion of Phase Portraits

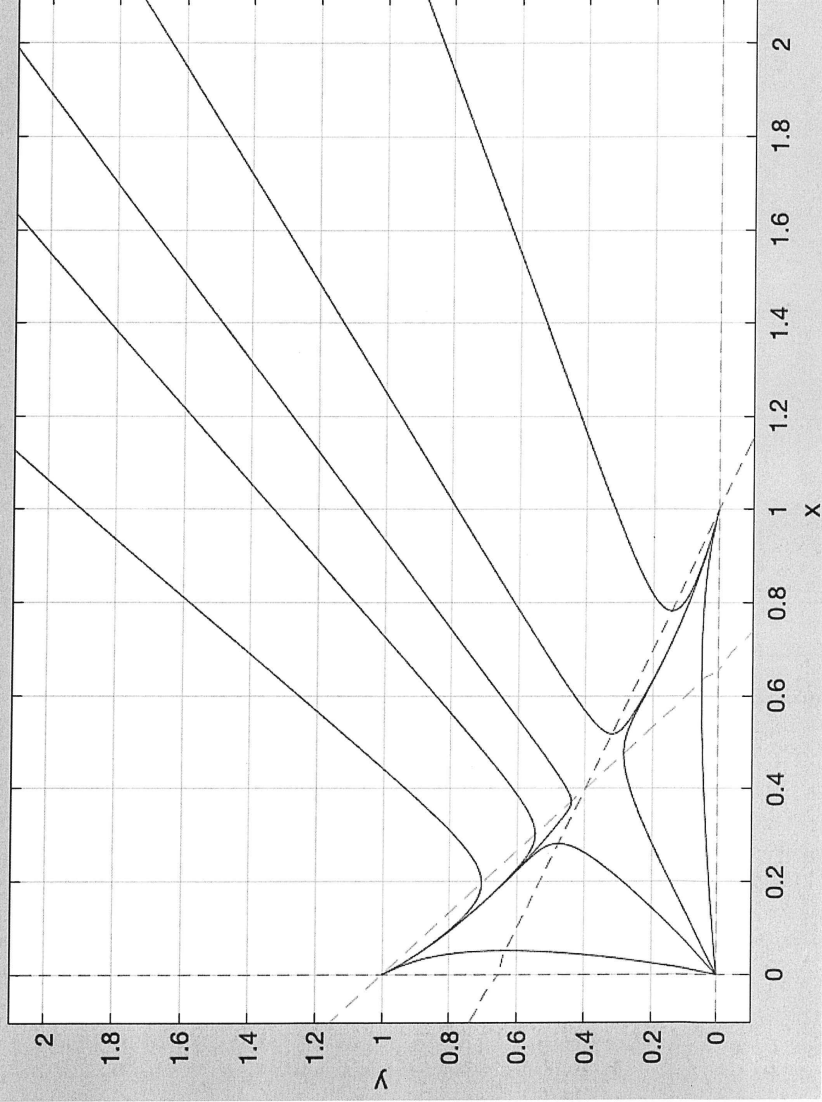


$$x' = x(1 - x - by)$$

$$y' = \text{eta } y(1 - cx - y)$$

$$b = 1.5 \quad c = 1.5$$

$$\text{eta} = 1$$

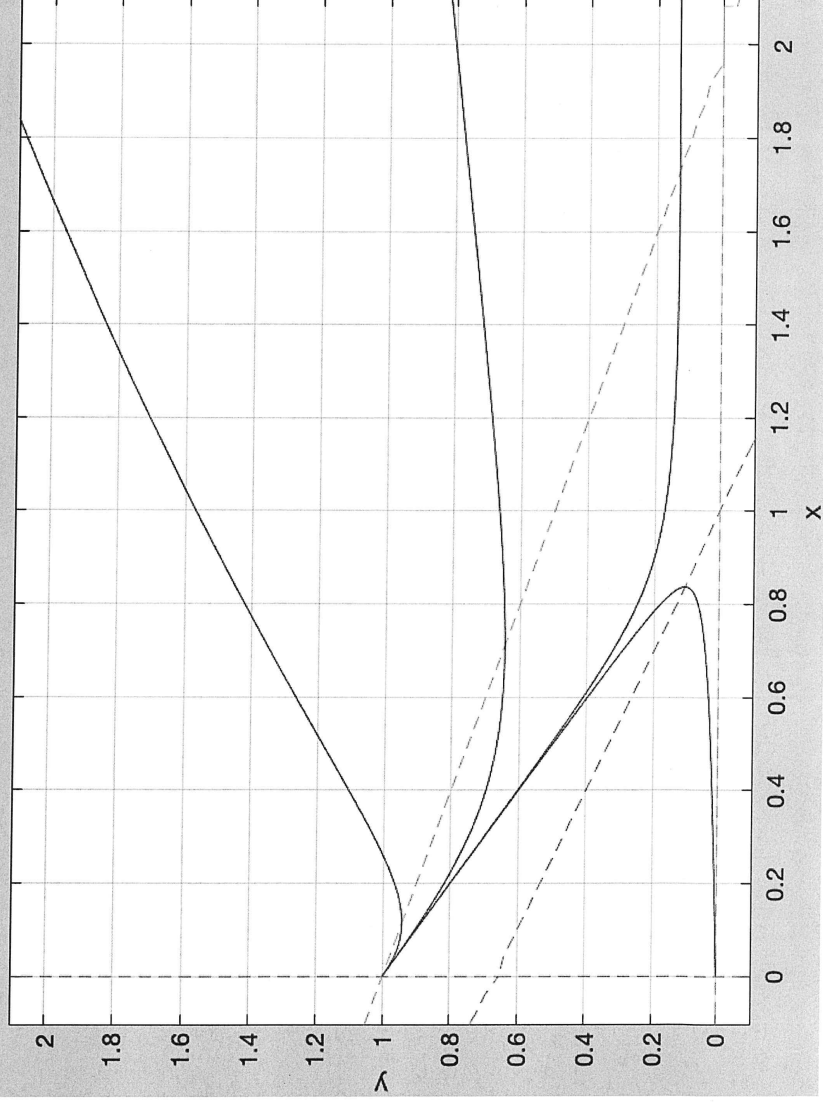


$$x' = x(1 - x - by)$$

$$y' = \text{eta } y(1 - cx - y)$$

$$b = 1.5 \quad c = 0.5$$

$$\text{eta} = 1$$



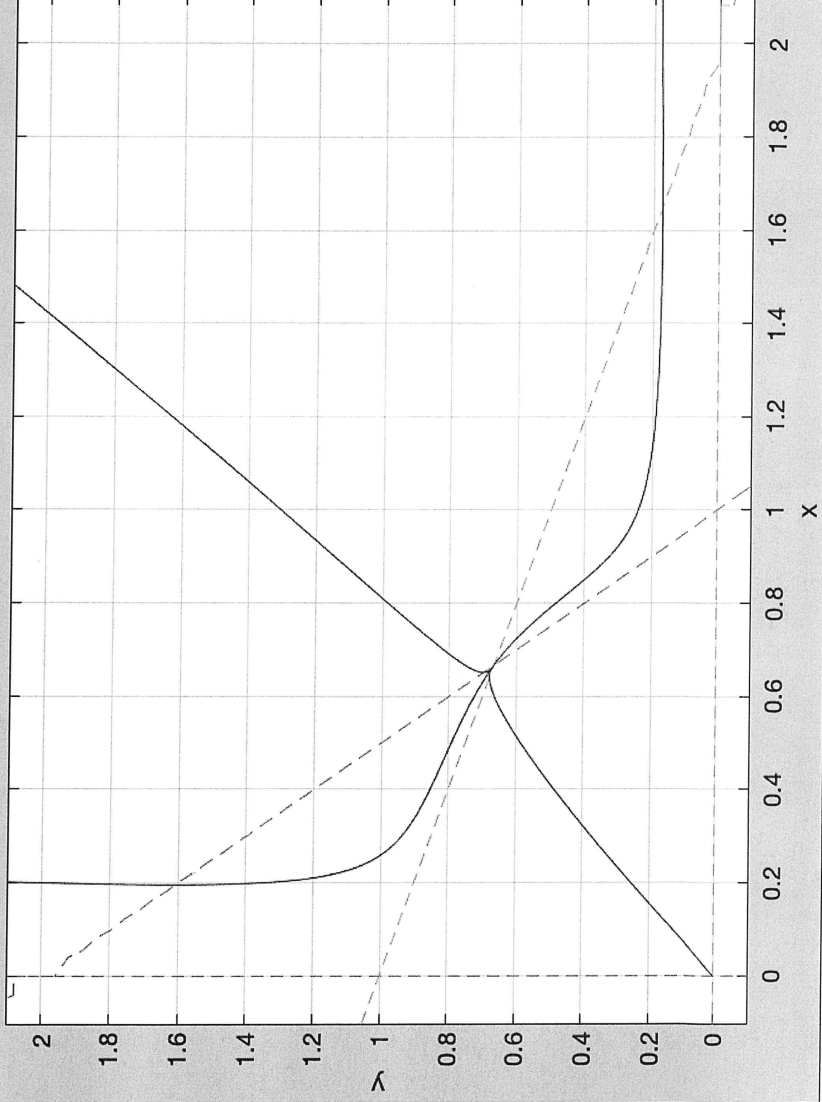
$$x' = x(1 - x - by)$$

$$y' = \text{eta } y(1 - cx - y)$$

$$b = 0.5$$

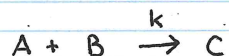
$$c = 0.5$$

$$\text{eta} = 1$$



Law of Mass Action - simple

Rate of change of concentration is proportional to the product of reactants



results in system

$$A' = -kAB$$

$$B' = -kAB$$

$$C' = +kAB$$

where k is the reaction rate.

Remarks

- (1) Concentration usually in molarity M

$$[A] = 1M \Leftrightarrow \begin{array}{l} \text{liter contains} \\ N_A = 6.02 \times 10^{23} \text{ molecules} \end{array}$$

Mass action law only works for molarity. Once differential eqns have been found they can be converted to gm/liter use the gram molecular weights.

- (2) AB proportional to total number of reactions (collisions) at any given instant

Arrhenius Theory

$$k = \alpha e^{-E_a/RT}$$

Reaction rate is proportional to the exponential term where

E_a = activation energy
for reaction

$$[E_a] = \text{J/mole}$$

T = temperature

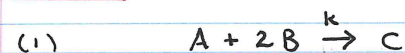
$$[T] = \text{Kelvin}$$

$$R = \text{Gas constant} = 8.314 \text{ J/mole/K}$$

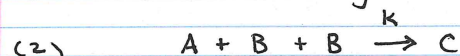
In some cases $\alpha = \alpha_0 T^n$ for $n \in (-1, 1)$.

Note that $T \uparrow$ implies rate $k \uparrow$

EXAMPE Stoichiometric coefficients



Number of possible collisions is $[A][B]^2$
so (1) should be thought of as

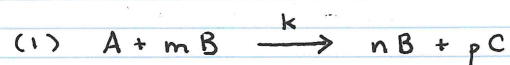


having "three" reactants. L.O.M.A. then $\Rightarrow$

$$\frac{dC}{dt} = +kAB^2$$

Here "2" in eqn (1) is a stoichiometric coeff.

Law of Mass Action - general



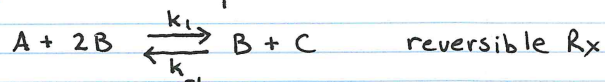
$$(2) \quad kAB^m = -\frac{dA}{dt} = \frac{1}{p} \frac{dc}{dt} = \frac{1}{(n-m)} \frac{dB}{dt}$$

The stoichiometric coefficients reflect the fact for every molecule of A

p molecules of C produced

(m-n) net loss of molecules of B

EXAMPLE Reaction equations for



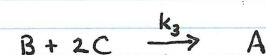
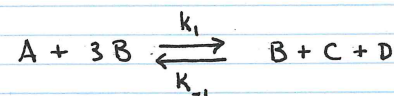
Is a set of three chem. Rx eqns

$$A' = -k_1 AB^2 + k_{-1} BC - k_2 AC$$

$$B' = -k_1 AB^2 - k_{-1} BC + k_2 AC$$

$$C' = k_1 AB^2 - k_{-1} BC - k_2 AC$$

EXAMPLE Autocatalytic / Stoichiometry



Reaction equations for A, B, C, D

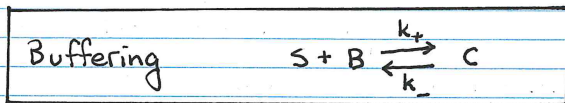
$$A' = -k_1 AB^3 + k_{-1} BCD - k_2 AD + k_3 BC^2$$

$$B' = -2k_1 AB^3 + 2k_{-1} BCD + k_2 AD - k_3 BC^2$$

$$C' = k_1 AB^3 - k_{-1} BCD - 2k_3 BC^2$$

$$D' = k_1 AB^3 - k_{-1} BCD - k_2 AD$$

Reaction equations autocatalytic since A is ultimately involved in its own creation.



S = Substrate (Ca^{2+})
 B = Buffer (Protein)
 C = complex (Protein- Ca^{2+} complex)

Law of Mass Action

$$\begin{aligned}
 (1) \quad S' &= -k_+SB + k_-C & S(0) &= S_0 \\
 (2) \quad B' &= -k_+SB + k_-C & B(0) &= B_0 \\
 (3) \quad C' &= k_+SB - k_-C & C(0) &= C_0
 \end{aligned}$$

Conservation of receptors

$$(B+C)' = 0$$

$$(4) \quad B + C = N = B_0 + C_0 \quad \# \text{ receptor sites}$$

Use (4) to simplify (1)-(3)

$$\begin{aligned}
 S' &= f(B, S) \\
 B' &= f(B, S)
 \end{aligned}$$

where

$$f(B, S) = -k_+SB + k_-(N-B)$$

The sign of f determines trajectory direction.

Sign of $f(S, B)$

$$f(S, B) < 0$$

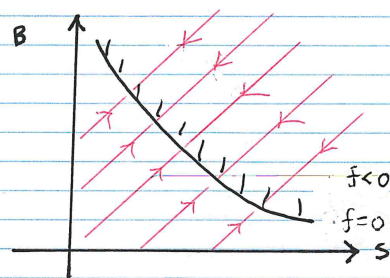
$$-k_+SB + k_-(N-B) < 0$$

$$-(k_+S + k_-)B + k_-N < 0$$

solving for B

$$f < 0 \Leftrightarrow B < g(S) = \frac{K_E N}{K_E + S}$$

where the equilibrium constant $K_E = \frac{k_-}{k_+}$



physical region
(shaded)
for $c(0) = 0$

Notes

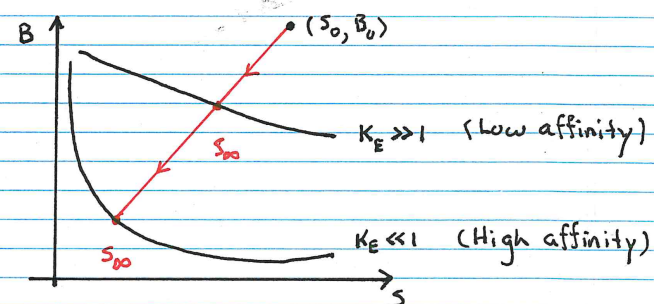
- $f=0$ is a line of fixed points
- $f < 0$ is physical region since $\frac{ds}{dt} < 0$ there.
- $f=0$ is a "stable invariant manifold"

Low and High affinity binding

Trajectories in the SB-plane have slope one and approach the curve

$$B = g(S) = \frac{K_E N}{K_E + S} \quad K_E = \frac{k_-}{k_+}$$

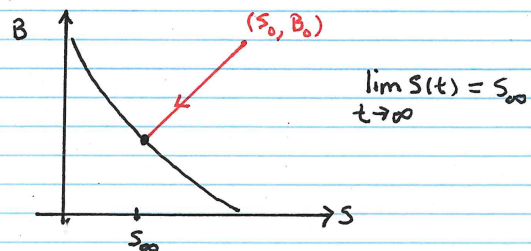
Consider the two cases $K_E \gg 1$ and $K_E \ll 1$



In the high affinity case the asymptotic value S_{∞} of S is smaller meaning more substrate molecules are bound.

$K_E \gg 1$	Low Affinity	larger S_{∞}
$K_E \ll 1$	High Affinity	smaller S_{∞}

Asymptotic behavior



S_∞ can be found as the intersection of the two curves

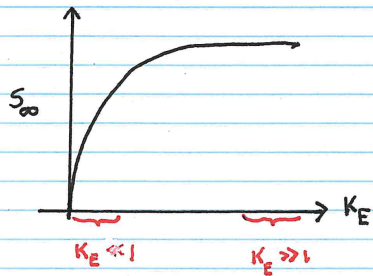
$$B = S + \Delta \quad \Delta = B_0 - S_0$$

$$B = g(S)$$

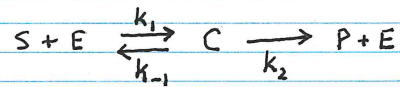
Results in a quadratic eqn for S

$$(1) \quad \boxed{S + \Delta = \frac{K_E N}{K_E + S}}$$

Solving and plotting S_∞ versus K_E one gets



Michaelis-Menten Kinetics

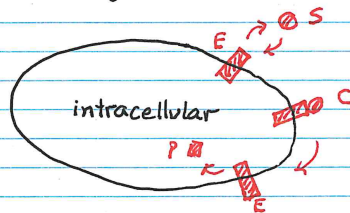


where

S = substrate (small)
E = enzyme (large)
C = complex
P = product

Can model cell nutrient uptake via membrane proteins E. Typically

$$E_0 \ll S_0$$



Law of Mass Action

$$\begin{aligned} (1) \quad \dot{S} &= k_{-1}C - k_1SE & S(0) &= S_0 \\ (2) \quad \dot{E} &= (k_{-1} + k_2)C - k_1SE & E(0) &= E_0 \\ (3) \quad \dot{C} &= -\dot{E} & C(0) &= 0 \\ (4) \quad \dot{P} &= k_2C & P(0) &= 0 \end{aligned}$$

Conservation of receptors: $E + C = E_0$

Nondimensionalization

$$s = S/S^* \quad e = E/E^* \quad c = C/C^* \quad p = P/P^* \quad \tau = t/t^*$$

For the following choices

$$S^* = S_0 \quad E^* = C^* = E_0 \quad P^* = \frac{k_2}{k_1} \quad t^* = \frac{1}{k_1 E_0}$$

one can derive the dimensionless eqns for the dimensionless variables (s, e, c, p, \tau)

$$\left\{ \begin{array}{ll} (1) & s' = \eta_1 c - se \quad s(0) = 1 \\ (2) & \epsilon e' = \eta_2 c - se \quad e(0) = 1 \\ (3) & \epsilon c' = -\eta_2 c + se \quad c(0) = 0 \\ (4) & p' = c \quad p(0) = 0 \end{array} \right.$$

where

$$\epsilon = \frac{E_0}{S_0} \ll 1$$

and

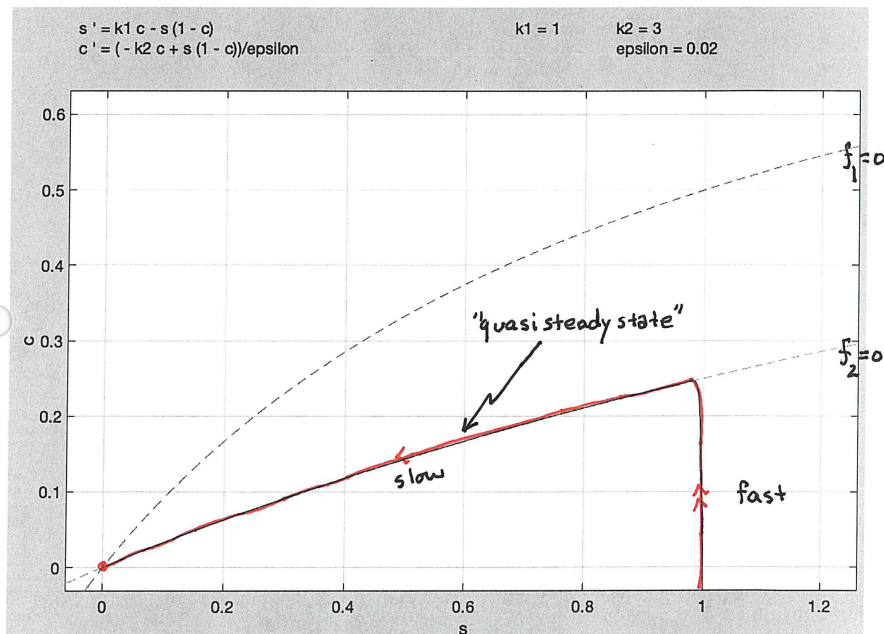
$$\eta_1 = \frac{k_{-1}}{k_1 S_0} \quad \eta_2 = \frac{k_{-1} + k_2}{k_1 S_0}$$

Notice that for positive k_1 , k_{-1} , and k_2

$$\eta_2 > \eta_1 \quad \text{physicality condition}$$

Typical Numerical solution

$$K_2 > K_1 \quad \epsilon \ll 1$$



s and c nullclines shown

FAST-SLOW TIME APPROXIMATIONS

Using conservation of receptors

$$e + c = 1$$

in (1)-(3) we get a planar system

$$(5) \quad \begin{aligned} \frac{ds}{dt} &= f_1(s, c) = k_1 c - s(1-c) \\ \epsilon \frac{dc}{dt} &= f_2(s, c) = -k_2 c + s(1-c) \end{aligned}$$

along with initial conditions:

$$s(0) = 1 \quad c(0) = 0$$

These equations are exact.

Nullclines/Equilibrium

Are easy to define

$$f_1 = 0 \quad \Leftrightarrow \quad c = H_1(s) = \frac{s}{k_1 + s}$$

$$f_2 = 0 \quad \Leftrightarrow \quad c = H_2(s) = \frac{s}{k_2 + s}$$

From these it is easy to show $(0,0)$ is the sole equilibrium.

To understand the solutions of system (5) we introduce fast and slow times

$$\tau \quad \text{slow time}$$

$$t = \frac{\tau}{\varepsilon} \quad \text{fast time}$$

Since $\varepsilon \ll 1$, only a small change in the slow time τ is needed to make the fast time change by order 1 or $O(1)$. For instance, $\varepsilon = 10^{-3}$ and $\tau = 2 \times 10^{-3}$ yields $t = 2$.

Lastly, system (5) can be expressed with either time using the chain rule.

$$\frac{ds}{d\tau} = \frac{ds}{dt} \frac{dt}{d\tau} = \frac{1}{\varepsilon} \frac{ds}{dt}$$

(SS)	$\frac{ds}{d\tau} = f_1(s, c)$ $\varepsilon \frac{dc}{d\tau} = f_2(s, c)$	$\frac{ds}{dt} = \varepsilon f_1(s, c)$ $\frac{dc}{dt} = f_2(s, c)$	(FS)
	SLOW SUBSYSTEM	FAST SUBSYSTEM	
	$\tau = \text{slow time}$	$t = \text{fast time}$	

Quasi Steady State (QSS)

Is a science term where one lets $\varepsilon \rightarrow 0$ as an approximation to (1)-(4). This yields from the $\varepsilon \varepsilon'$ eqn

$$(5) \quad k_2 c - s c = 0$$

Conservation of receptors (dimensionless) is:

$$(6) \quad e + c = 1$$

One may solve the system (5)-(6) for e in terms of s or c in terms of s

$$e = \frac{k_2}{k_2 + s} \quad c = \frac{s}{k_2 + s}$$

Next page shows a typical numerical solution of (1)-(4)

$$k_1 = 1 \quad k_2 = 3$$

Leading order Fast Subsystem (FS)

Let

$$S(t) = S_0(t) + \epsilon S_1(t) + \dots$$

smaller higher order terms

$$C(t) = C_0(t) + \epsilon C_1(t) + \dots$$

in the (FS) yields leading order behavior

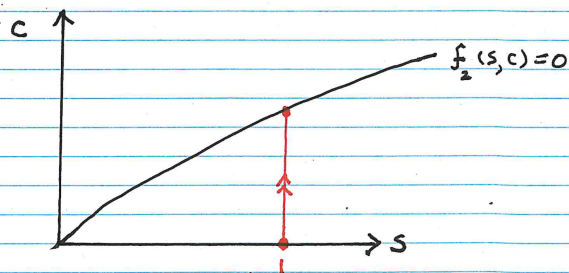
$$\left\| \begin{array}{ll} \frac{dS_0}{dt} = 0 & S_0(0) = 1 \\ \frac{dC_0}{dt} = f_2(S_0, C_0) & C_0(0) = 0 \end{array} \right\|$$

Solving with initial conditions

$$S_0(t) = 1$$

$$C_0(t) = \frac{1}{\mu} (1 - \exp(-\mu t)) \quad \mu \equiv \kappa_2 + 1$$

Note $C_0(t) \rightarrow \frac{1}{\kappa_2 + 1}$ or that $f_2(1, C_0) \rightarrow 0$



Leading order Slow Subsystem (SS)

Let

$$S(\tau) = S_0(\tau) + \epsilon S_1(\tau) + \dots$$

functions of slow time

$$C(\tau) = C_0(\tau) + \epsilon C_1(\tau) + \dots$$

in the (SS) yields leading order behavior

$$(6) \quad \left\| \begin{array}{l} \frac{dS_0}{d\tau} = f_1(S_0, C_0) \\ 0 = f_2(S_0, C_0) \end{array} \right\| \quad \begin{array}{l} \text{Differential} \\ \text{Algebraic} \\ \text{Equations} \end{array}$$

Recall that $f_2 = 0 \Leftrightarrow C_0 = H_2(S_0) = \frac{S_0}{\kappa_2 + S_0}$

$$(7) \quad \frac{dS_0}{d\tau} = F(S_0) = f_1(S_0, H_2(S_0))$$

Explicitly (7) is

$$\frac{dS_0}{d\tau} = (\kappa_1 - \kappa_2) \cdot H_2(S_0) < 0$$

This is separable and its implicit soln is

$$S_0 + \kappa_2 \ln(S_0) - 1 = -(\kappa_2 - \kappa_1) \tau$$

Equilibria Stability (FS)

$$\frac{ds}{dt} = \epsilon f_1(s, c)$$

$$\frac{dc}{dt} = f_2(s, c)$$

Sole equilibria is $P=(0,0)$. Nullclines are

$$f_1=0 \quad c = H_1(s) = \frac{s}{\eta_1 + s}$$

$$f_2=0 \quad c = H_2(s) = \frac{s}{\eta_2 + s}$$

Jacobian at $P=(0,0)$

$$D\vec{f}(0,0) = \begin{bmatrix} -\epsilon & \epsilon\eta_1 \\ 1 & -\eta_2 \end{bmatrix}$$

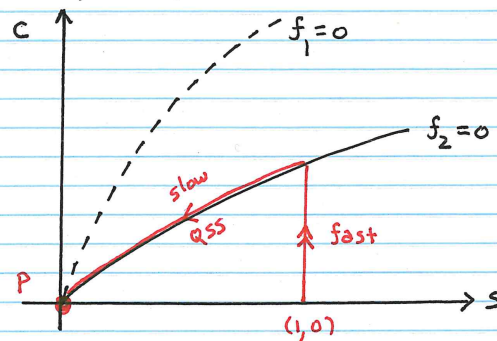
From this we see

$$\det D\vec{f} = \epsilon(\eta_2 - \eta_1) > 0$$

$$\text{Tr } D\vec{f} = -(\eta_2 + \epsilon) < 0$$

hence P is stable.

Summary of Dynamics



(1) Rapidly achieves QSS

(2) Measurable dynamic more likely to only be motion on slow subsystem manifold $f_2=0$ or

$$c = \frac{s}{\eta_2 + s}$$

(3) Continues until substrate depleted

(4) Since $e+c=1$, $e \rightarrow 1$ as $t \rightarrow \infty$.

(5) Production rate given by slow subsystem

$$\frac{dp}{dt} = c = \frac{s}{\eta_2 + s}$$

Production Rate

The dimensionless production rate v is

$$v \equiv \frac{dp}{dt} = \frac{s}{s + k_2}$$

This can be converted back to dimensional form

$$(1) \quad V = \frac{dP}{dt} = \frac{\bar{V}S'}{K_m + S'}$$

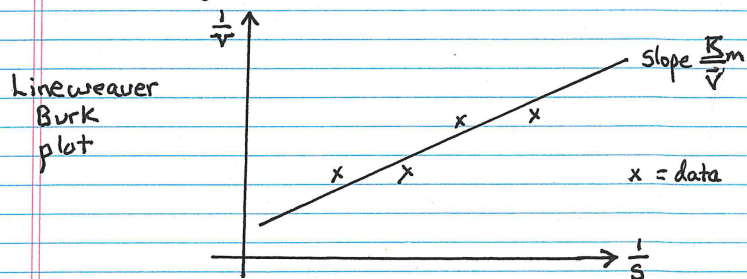
where

$$\bar{V} = k_2 E_0 \quad K_m = \frac{k_{-1} + k_2}{k_1}$$

Eqn (1) can be re-written

$$\boxed{\frac{1}{V} = \frac{1}{\bar{V}} + \frac{K_m}{\bar{V}} \frac{1}{S}}$$

Measure production rate and S . Use linear regression to find $\bar{V}$ and K_m



Quick Derivation (Michaelis-Menten)

Suppose you know apriori that E and C are fast variables then production rates can be computed directly from the dimensional equations

$$S' = k_1 C - k_1 S E$$

$$E' = (k_1 + k_2) C - k_1 S E$$

$$C' = -(k_1 + k_2) C + k_1 S E$$

$$P' = k_2 C$$

} Both zero when in QSS

Noting that the number of receptors is conserved

$$(k_1 + k_2) C - k_1 S E = 0$$

QSS

$$E + C = E_0$$

receptors.

These are two eqns for (E, C) . Solving these we get C and E as functions of S :

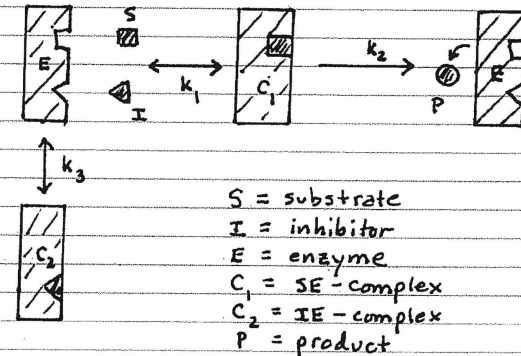
$$C = \frac{S E_0}{K_m + S}$$

so that

$$\frac{dP}{dt} = k_2 C = \frac{\bar{V} S}{S + K_m}$$

as before.

Competitive Inhibition

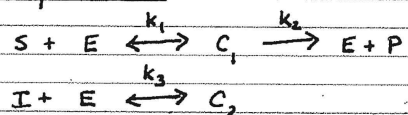


Enzyme has two binding sites but only SE complex can make product P so I acts to inhibit such production.

Law of mass action ($E = E_0/s_0 \ll 1$ assumed)

- | | |
|--|---------------------|
| (1) $S' = -k_1 SE + k_{-1} C_1$ | } slow |
| (2) $I' = -k_3 IE + k_{-3} C_2$ | |
| (3) $C_1' = k_1 SE - (k_{-1} + k_2) C_1$ | } fast |
| (4) $C_2' = k_3 IE - k_{-3} C_2$ | |
| (5) $E' = -C_1' - C_2'$ | conserved receptors |
| (6) $P' = k_2 C_1$ | production rate |

Reaction Equations



With nondimensionalizing we know (3)-(4) will be fast. If E, C_k are scaled by E_0 and S by S_0 the dimensionless forms will be

$$E, C_k = O(1) \quad E = \frac{E_0}{S_0} \ll 1$$

Quasi Steady State

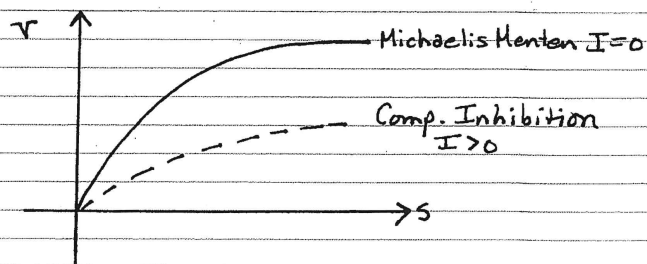
Set $\dot{C}_1 = \dot{C}_2 = 0$ and use conservation law (5) to solve for C_k in terms of slow variables S, I to ultimately get production rate

$$\frac{dP}{dt} = V = \frac{\bar{V} S}{S + K_m (1 + I/K_i)}$$

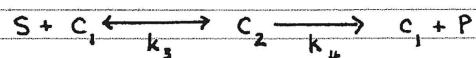
↑ inhibition

where $\bar{V} = k_2 E_0$ maximal rate and

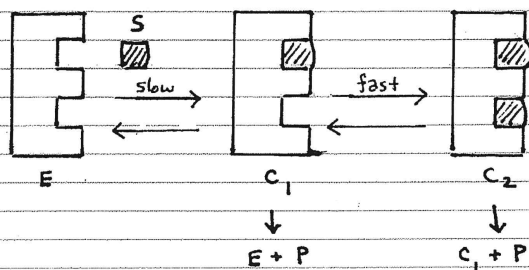
$$K_m = \frac{k_{-1} + k_2}{k_1} \quad K_i = \frac{k_{-3}}{k_3}$$



Cooperativity



Cartoon



Indicated rates k_1 and k_3 are, respectively, assumed to be small and large. System favors cooperative C_2 state.

QSS Approximation, conservation receptors, $\varepsilon = \frac{E_0}{S_0} \ll 1$

$$V = \frac{dP}{dt} = \frac{(k_2 K_2 + k_4 S) E_0 S}{K_1 K_2 + K_2 S + S^2}$$

where

$$K_1 = \frac{k_{-1} + k_2}{k_1} \quad K_2 = \frac{k_{-4} + k_{-3}}{k_3}$$

Large Positive Cooperativity

As indicated we assume (see cartoon) that k_1 is relatively small while k_3 is relatively large:

$$k_1 = \delta \ll 1 \quad k_3 = \frac{k}{\delta} \gg 1$$

for some constant k . Then V is a function of S

$$V = V(S) \quad \delta \ll 1$$

Since $V \sim V(0)$ we have an approximate production rate

$$(1) \quad V = \frac{\bar{V} S^2}{K + S^2} \quad K = K_1 K_2$$

where $\bar{V} = k_4 E_0$. $V(S)$ is a Hill function of Hill coefficient $n=2$.

n-site Positive Cooperativity

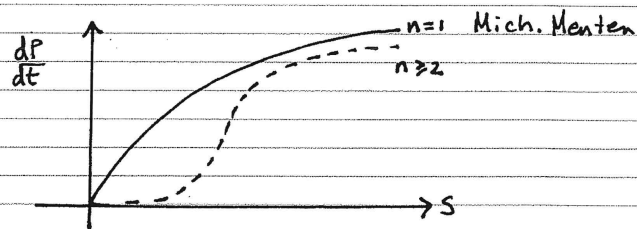
Assume formation of C_1 is slow ($k_1 \ll 1$)
but formation C_k , $k \geq 1$ fast.

Here E has n -sites and C_k = complex
of E with k -substrate molecules
attached.

Same analysis

$$\frac{dP}{dt} = v = \frac{\bar{V} S^n}{K + S^n} \quad \text{Hill eqn, coeff } n$$

where $K = \prod_{j=1}^n K_j$



Experimental Correlation

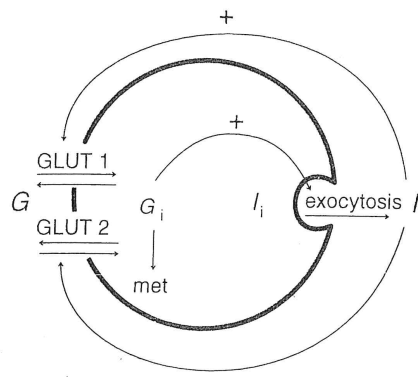
$$n \ln S = n \ln K + \ln \left(\frac{v}{v - \bar{V}} \right)$$

$$n \alpha_k = n \ln K + \beta_k$$

Data $\{(\alpha_k, \beta_k)\}$ and linear regression for n, K .

Glucose-dependent insulin secretion

Pancreatic β -cells secrete insulin I via exocytosis at a rate dependent on intra and extracellular glucose.



The following rates and assumptions apply

R_1 = rate of transport into cell through insulin activated GLUT1 transporters

R_2 = rate of transport into cell through insulin inactivated GLUT2 transporters

R_3 = insulin production rate

R_m = intracellular glucose metabolism rate

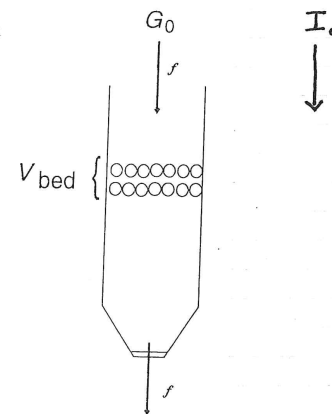
G = extracellular glucose

G_i = intracellular glucose

I = insulin

I = inhibition variable

Experimentally β -cells in a bed (V_{bed}) and glucose of concentration G_0 is continuously flushed through at flow rate f :



Controlled: inflow G_0, I_0

measured: outflow G, I

Nondimensionalized model (Fall et al, pg 87)

$$(1) \quad g' = -R_1 - R_2 - k_0(g - g_0)$$

$$(2) \quad g_i' = R_1 + R_2 - R_m$$

$$(3) \quad i' = R_s - k_0 i$$

$$(4) \quad j' = j_\infty(i) - j \quad (\text{phenomenological})$$

where

$$R_1 = \frac{K_1 V_1 (g - g_i)}{(K_1 + g)(K_1 + g_i)} \cdot \frac{i^n}{K_i^n + i^n}$$

$$R_2 = \frac{K_2 V_2 (g j_m - g_i)}{(K_2 + g)(K_2 + g_i)}$$

$$R_m = \frac{V_m g_i}{1 + g_i} \quad \text{Mich-Menten QSS}$$

$$R_s = \frac{V_s (R_m^4 + L^4)}{K_s^4 + R_m^4 + L^4} \quad (\text{phenomenological})$$

The latter assumes insulin secretion rate that grows with glucose metabolism rate. looks like 4-site cooperativity (were it not for L). Lastly

$$j_\infty(i) = \frac{1}{1 + i}$$

Model Parameters

Table 4.1 Standard Dimensional Parameters

Fixed by experiment	V_m	0.24 mM/min
	K_m	9.8 mM
	V_s	0.034 mM/min
	K_s	0.13 mM/min
	$V_{\max 2}$	32.0 mM/min
	K_2	17.0 mM
	$V_{\max 1}$	120.0 mM/min
	K_1	1.4 mM
Experimentally variable	L	0.01 mM/min
	k_0	400.0/min
	l_0	0.0 mM
Adjustable in the model	G_0	8-22 mM
	K_i	1×10^{-6} mM
	τ	4.0×10^{-5} min

Table 4.2 Standard Dimensionless Parameters

Dimensionless parameter	Dimensional definition	Standard value	
$\hat{V}_m$	$\tau V_m / K_m$	0.50	
$\hat{V}_s$	$\tau V_s / K_i$	6.8×10^5	large
$\hat{K}_s$	$\tau K_s / K_m$	0.27	
$\hat{V}_{\max 2}$	$\tau V_{\max 2} / K_m$	65.3	
$\hat{K}_2$	K_2 / K_m	1.7	
$\hat{V}_{\max 1}$	$\tau V_{\max 1} / K_m$	245.0	
$\hat{K}_1$	K_1 / K_m	0.14	
$\hat{L}$	$\tau L / K_m$	0.02	
$\hat{k}_0$	τk_0	8×10^3	large
$\hat{G}_0$	G_0 / K_m	0.8-2.2	
$\hat{K}_i$	K_i / K_i	40.0	

Fast-slow dynamics.

Since $k_0 \gg 1$ in

$$g' = -R_1 + R_2 - k_0(g - g_0)$$

$$i' = R_5 - k_0 i$$

yields (QSS) approximations:

$$0 = -R_1 + R_2 - k_0(g - g_0)$$

$$0 = R_5 - k_0 i$$

Using these one can eliminate (g, i)
to get a slow subsystem of the
form

$$g_i' = F_1(g_i, j)$$

$$j' = F_2(g_i, j)$$

This system has oscillations!

Passive Transport

Transport of S from high to low concentrations through a membrane transporter such as extracellular glucose into cells. No energy input is required.

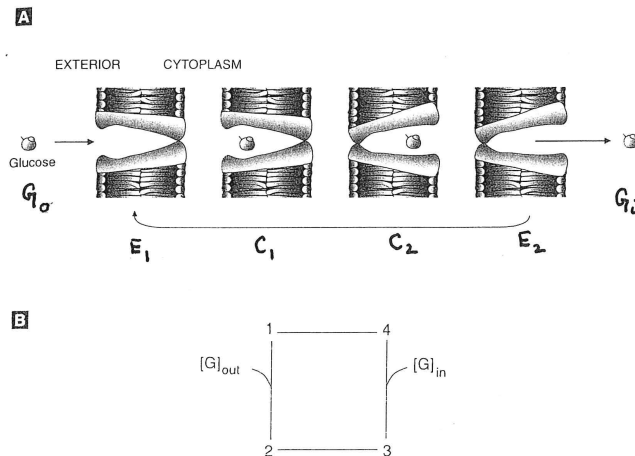


Figure 3.1 (A) Cartoon of four states of a GLUT transporter, showing the empty pore facing the exterior of the cell, glucose bound facing the exterior, glucose bound facing the interior, and the open pore facing the interior of the cell. Adapted from Leinhard et al. (1992). (B) Four-state kinetic diagram of a GLUT transporter based on the cartoon in (A).

E_1 = one unbound conformational state
 C_1 = one bound conformational state
 C_2 = another bound conformational state
 E_2 = another unbound conformational state

(QSS)
$$V = \frac{dG_i}{dt} = \frac{\alpha_0 + \alpha_1 G_0 + \alpha_2 G_i + \alpha_3 G_0 G_i}{\beta_0 + \beta_1 G_0 + \beta_2 G_i + \beta_3 G_0 G_i}$$

SERCA Pumps

$$[Ca^{2+}]_o > [Ca^{2+}]_i$$

pump Ca^{2+}
up gradient

Rate of Ca^{2+} accumulation inside cell measured by rate of radioactive $^{45}Ca^{2+}$ uptake at ER (endoplasmic reticulum). Conversion of ATP to ADP generates energy (loss of PO_4 phosphate group)

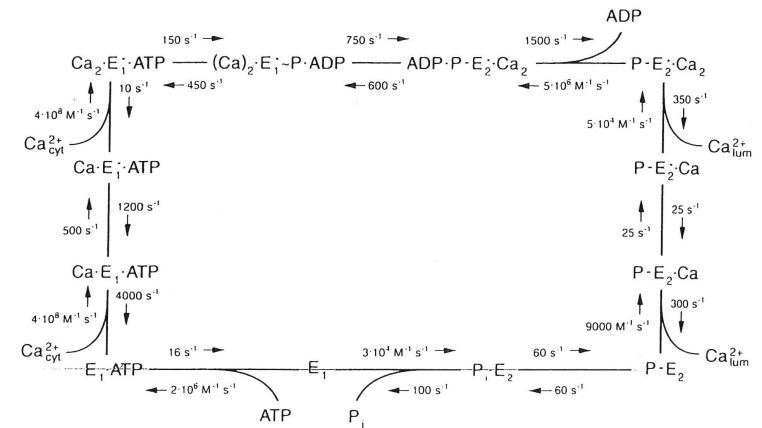


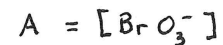
Figure 3.14 A twelve-state model of the SERCA pump. Note the two sequential Ca^{2+} binding steps on the left-hand side. Although the cycle is driven by the hydrolysis of ATP, all of the steps in the diagram contribute to the steady-state rate. Redrawn from Lauger (1991).

Twelve State model well approximated by 2-site cooperativity model hence intracellular production rate (QSS)

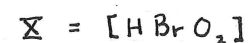
$$V = \frac{dCa_i}{dt} = \frac{\bar{V} [Ca_i]^2}{K^2 + [Ca_i]^2}$$

Chemical Oscillators - Brusselator (1968)

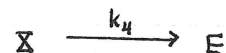
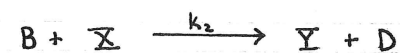
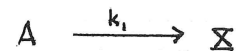
Mostly inorganic chemical species.



B = organic species



where the reactions are



Here D and E are other products.

It is assumed that the concentrations of A, B are artificially maintained at (nearly) constant levels. Resulting nondimensionalized eqns are called the Brusselator

Autocatalysis since X involved in its own production.

$$\begin{aligned} (1) \quad \dot{x} &= a - (b+1)x + x^2y \\ (2) \quad \dot{y} &= bx - x^2y \end{aligned}$$

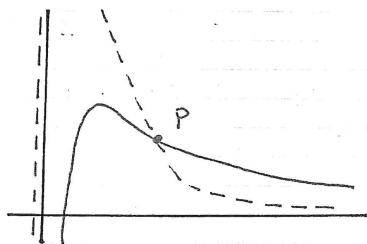
where (x, y) are dimensionless $(\mathbb{X}, \mathbb{Y})$.

Nullclines, equilibria

$$\begin{aligned} \dot{x} = 0 & \quad y = F(x) = \frac{(b+1)}{x} - \frac{a}{x^2} \\ \dot{y} = 0 & \quad x = 0, \quad y = \frac{b}{x} \end{aligned}$$

Sole equilibria

$$P = \left(a, \frac{b}{a}\right)$$



$$\begin{aligned} \text{---} & \quad \dot{y} = 0 \\ \text{---} & \quad \dot{x} = 0 \end{aligned}$$

Jacobian at P

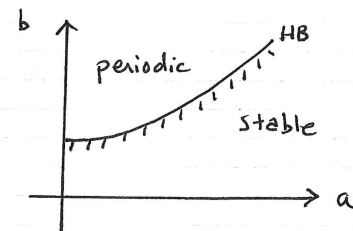
$$DF(P) = \begin{bmatrix} b-1 & a^2 \\ -b & -a^2 \end{bmatrix}$$

from which

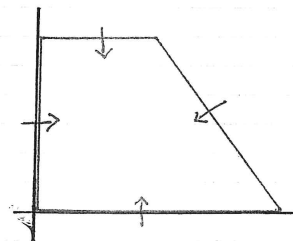
$$\det DF(P) = a^2 > 0$$

$$\text{Tr } DF(P) = b-1-a^2$$

Hopf bifurcations occur when $\text{Tr } DF(P)$



Hopf points alone only prove small amplitude periodic orbits



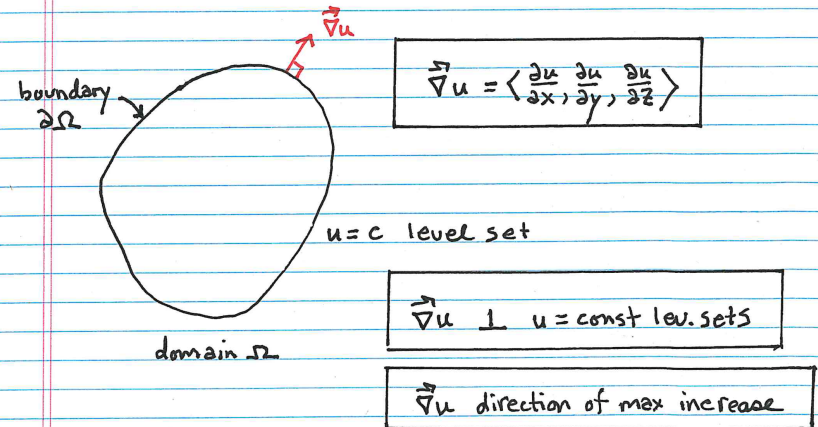
Trapping region
shape to prove
existence
given $\text{Tr } DF(P) > 0$

Spatial inhomogeneity

In nature, molecules, microorganisms and even larger species (such as plants) move within their environment. As a consequence their density depends on position $\mathbf{x}$ (as well as time). Typically such movement is

- a consequence of random motion
- a consequence of motion triggered by environmental factors such as food concentration, temperature and electric fields (for ions)

Gradients $u(\mathbf{x}, t) = \text{density at } (\mathbf{x}, t)$



EXAMPLE

The concentration of nutrient particles in a pond is

$$c(x, y, z) = C_0 \exp(-\alpha(x^2 + y^2 + z^2))$$

$$c(x, y, z) = C_0 \exp(-\alpha r^2)$$

where $r^2 = x^2 + y^2 + z^2$. An organism at $(1, -1, 1)$ moves in the direction in which c is increasing most rapidly. What direction is it?

$$\vec{\nabla} c(P) \quad P = \langle 1, -1, 1 \rangle$$

Generally

$$\frac{\partial c}{\partial x} = -2\alpha x c \quad \frac{\partial c}{\partial y} = -2\alpha y c \quad \frac{\partial c}{\partial z} = -2\alpha z c$$

Hence

$$\vec{\nabla} c(x, y, z) = c(x, y, z) \langle -2\alpha x, -2\alpha y, -2\alpha z \rangle$$

and at $P = \langle 1, -1, 1 \rangle$

$$\vec{\nabla} c(P) = c(P) \langle -2\alpha, 2\alpha, -2\alpha \rangle$$

$$\vec{\nabla} c(P) = +2\alpha c(P) \langle -1, 1, -1 \rangle$$

direction parallel

(non unique answer)

Conservation laws

Let $u(\vec{x}, t)$ be the concentration of something at position $\vec{x} \in \Omega$ and time t . For instance

u = mass density of a fluid (gas)

u = chemical concentration

u = population density of an organism

u = ionic concentration

Then at any given instant

$$M(t) = \int_{\Omega} u(\vec{x}, t) d\vec{x}$$

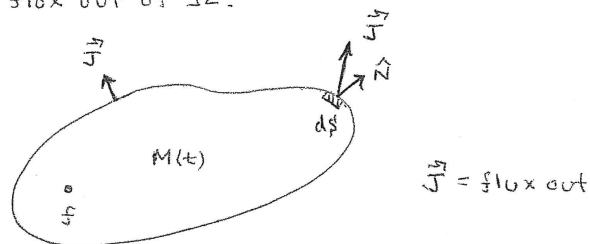
is the total amount at time t . Here M could be total mass, population or net charge

Let

$\vec{J}$ = flux of u at $\vec{x} \in \Omega$

f = internal sources or sinks of u at $\vec{x}$. For instance if u is a chemical concentration $f(\vec{x}, t, u)$ is the local production rate per unit volume

If u is conserved the rate of change of M must balance the rate of production and flux out of Ω .



For any domain Ω

$$\frac{d}{dt} \int_{\Omega} u(\vec{x}, t) d\vec{x} = - \int_{\partial\Omega} \vec{J} \cdot \hat{n} dS + \int_{\Omega} f(\vec{x}, t, u) d\vec{x}$$

where the minus sign indicates a flux out.

Assuming u is sufficiently smooth and applying the Divergence theorem

$$\int_{\Omega} \frac{\partial u}{\partial t} d\vec{x} = - \int_{\Omega} \vec{\nabla} \cdot \vec{J} d\vec{x} + \int_{\Omega} f(\vec{x}, t, u) d\vec{x}$$

If the integrands are continuous then since the domain is arbitrary the integrands on each side must match:

$$(i) \quad \frac{\partial u}{\partial t} = - \vec{\nabla} \cdot \vec{J} + f(\vec{x}, t, u)$$

Differential form of conservation law.

Functional forms for $\vec{J}$ and f are assumptions based off "constitutive laws".

A constitutive law is a measured or assumed mathematical relationship between physical quantities.

For instance, the ideal gas law

$$PV = nRT$$

may be viewed as a "constitutive law".

Generally, for models there may be many different kinds of fluxes and sources so that (i) becomes

$$u_t = - \sum_{i=1}^N \vec{\nabla} \cdot \vec{J}_i + \sum_{j=1}^M f_j(\vec{x}, t, u)$$

EXAMPLE Diffusion

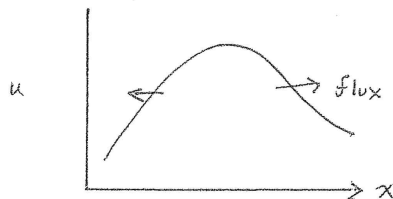
Let u = concentration of a substance

$$(1) \quad \vec{J} = -D \vec{\nabla} u \quad \text{Fick's Law}$$

is an assumed law for the flux. Here D is the diffusivity of the substance in the medium.

$\vec{\nabla} u$ = direction u $\uparrow$ most rapidly

Thus flux in (1) indicates substance moves in direction u decreasing most rapidly



In some media D depends on $\vec{x}$.

Large molecules typically have a small D .

Spatial dependence of D on $\vec{x}$ may be due to the medium is not homogeneous (perhaps stratified in some manner)

If one assumes $\vec{J} = -D(\vec{x}) \vec{\nabla} u$ in the conservation equation we arrive at

$$(2) \quad \frac{\partial u}{\partial t} = \vec{\nabla} \cdot (D(\vec{x}) \vec{\nabla} u)$$

and when $D > 0$ is constant, eqn (2) becomes the diffusion eqn

$$(3) \quad u_t = D \nabla^2 u \quad \vec{x} \in \mathbb{R}^n, t > 0$$

With sources present

$$(4) \quad u_t = D \nabla^2 u + f(\vec{x}, t, u)$$

is a reaction-diffusion equation

Remarks on units:

Let M, L, T be mass, time and length.

$$[u] = M L^{-3}$$

$$[u_{xx}] = M L^{-5}$$

Thus since $[u_t] = [D][\nabla^2 u]$ we have

$$[D] = L^2 T^{-1}$$

$$[\vec{J}] = M L^{-2} T^{-1}$$

EXAMPLE Heat Eqn (Thermal Transport)

$$\begin{aligned} T(\vec{x}, t) &= \text{temperature} & [T] &= ^\circ \\ u(\vec{x}, t) &= \text{energy density} & [u] &= \text{J/m}^3 \\ \rho &= \text{medium density} & [\rho] &= \text{kg/m}^3 \\ C &= \text{specific heat} & [C] &= \text{J/(m}^\circ\text{)} \\ K &= \text{thermal conductivity of medium} & [K] &= \text{J/(m sec}^\circ\text{)} \end{aligned}$$

Most generally K , C and ρ could depend on $\vec{x}$. For example the medium insular properties could vary.

Empirical (Constitutive) laws

$$\begin{aligned} u(\vec{x}, t) &\equiv C \rho T(\vec{x}, t) \\ \vec{J}(\vec{x}, t) &= -K \vec{\nabla} T \end{aligned}$$

in which case

$$C \rho T_t = \nabla \cdot (K \vec{\nabla} T) + f$$

If C, ρ, K are constant

$$\frac{\partial T}{\partial t} = D \nabla^2 T + F(\vec{x}, t, T), \quad \vec{x} \in \Omega$$

is a PDE whose solution yields the spatio-temporal variations of temperature

$$D = \frac{K}{C \rho} \quad F = \frac{f}{C \rho}$$

EXAMPLE Advection/Diffusion

$$\begin{aligned} \vec{J}_{\text{diff}} &= -D(\vec{x}) \vec{\nabla} u & \text{Diffusion} \\ \vec{J}_{\text{Adv}} &= +u \vec{V}(\vec{x}) & \text{Advection} \end{aligned}$$

where D = diffusivity and $\vec{V}(\vec{x})$ is the velocity of the fluid that u is in.

Conservation of u implies

$$u_t = \vec{\nabla} \cdot (D(\vec{x}) \vec{\nabla} u) - \vec{\nabla} \cdot (\vec{V} u) + f$$

Is a reaction-diffusion-advection eqn.

If $D, \vec{V}$ are constant

$$u_t = D \nabla^2 u - \vec{V} \cdot \vec{\nabla} u + f$$

which in one dimensional spatial domain becomes

$$u_t = D u_{xx} - v u_x + f$$

Remark For diffusion the "-" sign is needed for u to move toward lower concentrations

For advection the "+" sign implies u moves along with the fluid flow

Spatial Models

$$\frac{\partial u}{\partial t} = - \sum_i \vec{\nabla} \cdot \vec{J}_i + \sum_j f_j \quad \left. \vphantom{\frac{\partial u}{\partial t}} \right\} \text{conservation law}$$

↑ ↑

Sum of assumed Sum of sources
fluxes of u and sinks

Must be accompanied by Boundary Conditions

Dirichlet u known on boundary $\partial\Omega$

Neumann
(No Flux) $\frac{\partial u}{\partial n} = 0$ on $\partial\Omega$. Normal
derivative $\frac{\partial u}{\partial n} = \vec{\nabla} u \cdot \hat{N}$

Mixed $u + \alpha \frac{\partial u}{\partial n}$ known on $\partial\Omega$.

EXAMPLE Population Models

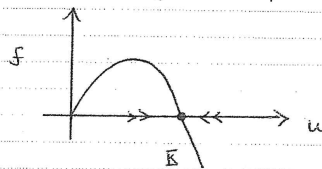
$u(\vec{x}, t)$ = population density at $\vec{x} \in \Omega$.

Notion of density works better for bacteria or cells. Could be trees, etc.

Logistic source term

$$f(u) = ru \left(1 - \frac{u}{K}\right)$$

where K = carrying capacity of environment.



Fact $f(u) < 0$ for $u > K$ meant to reflect death due to overcrowding (competition).

Other source terms

Suppose a substance $c(\vec{x}, t)$ is the primary food source.

$$f = f(u, c)$$

may have the generic property $f_c > 0$ to reflect (bacterial) birth rate is higher if c is larger. Perhaps

$$f(u, c) = \eta \frac{uc}{c + K} \quad \eta, K \in \mathbb{R}$$

Constitutive laws for organism movement

$$\vec{J} = -D \vec{\nabla} u \quad \text{Diffusive (random)}$$

$$\vec{J} = +u \vec{V} \quad \text{Advection}$$

$$\vec{J} = +\alpha u \vec{\nabla} c \quad \text{Chemotaxis}$$

$$\vec{J} = +\alpha u \vec{\nabla} T \quad \text{Thermotaxis}$$

where $\vec{V}$ = fluid velocity, c = food concentration, T = temperature

Some bacteria are chemotactic. They tend to move toward food.

Slime mold and nematodes are thermotactic.

MODEL ONE

$$\frac{\partial u}{\partial t} = D_1 \nabla^2 u + f_1(u, c)$$

$$\frac{\partial c}{\partial t} = D_2 \nabla^2 c + f_2(u, c)$$

Both organism and food diffuse through homogeneous medium.

$$f_1 > 0 \quad \frac{\partial f_1}{\partial c} > 0$$

and f_2 reflects a loss of c that u eats.

MODEL TWO (Logistic)

$$\vec{J} = -D \vec{\nabla} u \quad D \in \mathbb{R}^+ \text{ const.}$$

$$f = r u \left(1 - \frac{u}{K}\right)$$

yields in one spatial domain

$$u_t = D u_{xx} + r u \left(1 - \frac{u}{K}\right)$$

MODEL THREE (very slow fluid flow)

$$\vec{J}_1 = -D_1 \vec{\nabla} u \quad D_1 \in \mathbb{R}^+ \text{ const.}$$

$$\vec{J}_2 = +\alpha u \vec{\nabla} c \quad \alpha \in \mathbb{R}^+ \text{ const.}$$

and certain source terms f_k . Conservation law implies

$$(1) \quad \frac{\partial u}{\partial t} = -\vec{\nabla} \cdot \vec{J}_1 - \vec{\nabla} \cdot \vec{J}_2 + f_1$$

If c merely diffuses we obtain coupled equations for u, c

$$(2) \quad \frac{\partial u}{\partial t} = \underbrace{D_1 \nabla^2 u}_{\text{diff}} - \underbrace{\alpha \vec{\nabla} \cdot (u \vec{\nabla} c)}_{\text{chemotaxis}} + f_1$$

$$(3) \quad \frac{\partial c}{\partial t} = D_2 \nabla^2 c + f_2$$

For $\Omega \subset \mathbb{R}$ eqn (2) would be

$$u_t = D_1 u_{xx} - \alpha (u c_x)_x + f_1$$

EXAMPLE Electro Diffusion

Charged particles diffuse through a medium having electric field $\vec{E}(\vec{x})$.

$$u(\vec{x}, t) = \text{charge density}$$

Ohmic flux law

$$\vec{J} = z \nabla \phi \quad z = \text{valence}$$

and ∇ is conductivity (generally a matrix for anisotropic non homogeneous media)

If the electric field is given by

$$\vec{E} = -\vec{\nabla} \phi$$

where ϕ is the electric potential one obtains

$$\frac{\partial u}{\partial t} = \underbrace{D \nabla^2 u}_{\text{diff}} + \underbrace{z \nabla \cdot \nabla^2 \phi}_{\text{electric}}$$

The eqn for ϕ is obtained using Maxwell's eqn. Steady state version is

$$0 = D \nabla^2 u + z \nabla \cdot \nabla^2 \phi$$

$$-\beta u = \nabla^2 \phi \quad (\vec{\nabla} \cdot \vec{E} = 4\pi \rho)$$

for an appropriate constant β

Steady States of PDEs

More generally the steady states $\bar{u}(x)$ of some PDE (system) is a time t independent solution which satisfies all boundary conditions. Stability is a separate condition. By way of example:

$u_t = u_{xx}$	$x \in [0, 1]$
$u_x(0, t) = 0$	no flux BC
$u_x(1, t) = 0$	no flux BC
$u(x, 0) = f(x)$	initial cond I.C.

Associated problem for steady state $\bar{u}(x)$

$0 = \bar{u}_{xx}$	$x \in [0, 1]$
$\bar{u}_x(0) = 0$	no-flux
$\bar{u}_x(1) = 0$	no-flux

This is an ODE problem! The general solution of $\bar{u}_{xx} = 0$ is

$$\bar{u}(x) = Ax + B \quad A, B \text{ constants}$$

Find A using B.C.

$$\bar{u}'(x) = A$$

$$\bar{u}'(0) = A = 0$$

Hence

$$\bar{u}(x) = B$$

This also satisfies the other B.C. $\bar{u}'(1) = 0$. But, we don't know B yet.

Recall that

$$M(t) = \int_0^1 u(x, t) dx$$

is the total amount of $u(x, t)$ in the domain $[0, 1]$. Since the B.C. are no flux at both endpoints (boundary), $M(t)$ must remain constant. Hence

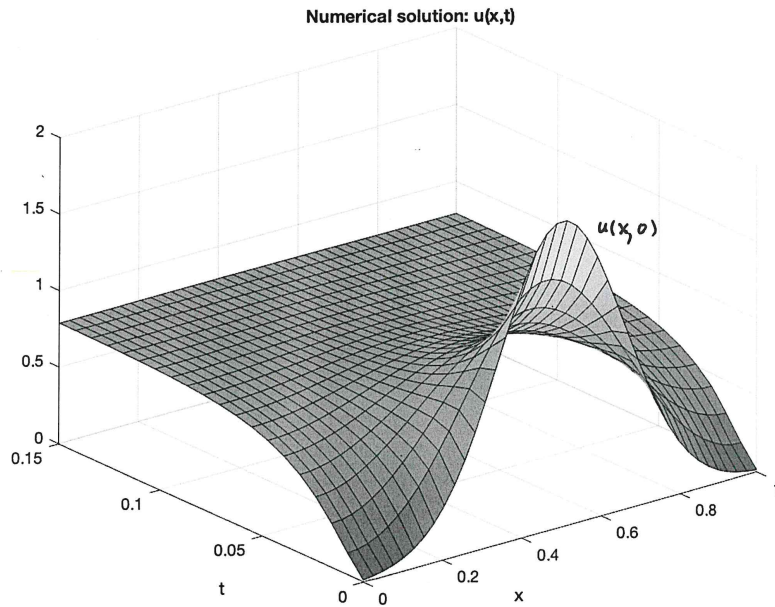
$$M(0) = \int_0^1 \bar{u}(x) dx = \int_0^1 u(x, 0) dx$$

For the initial condition

$$u(x, 0) = 2 \exp(-(x - \frac{1}{2})^2 / 0.05)$$

we find $\bar{u}(x) = B$ where

$$B = \int_0^1 u(x, 0) dx \approx 0.79$$



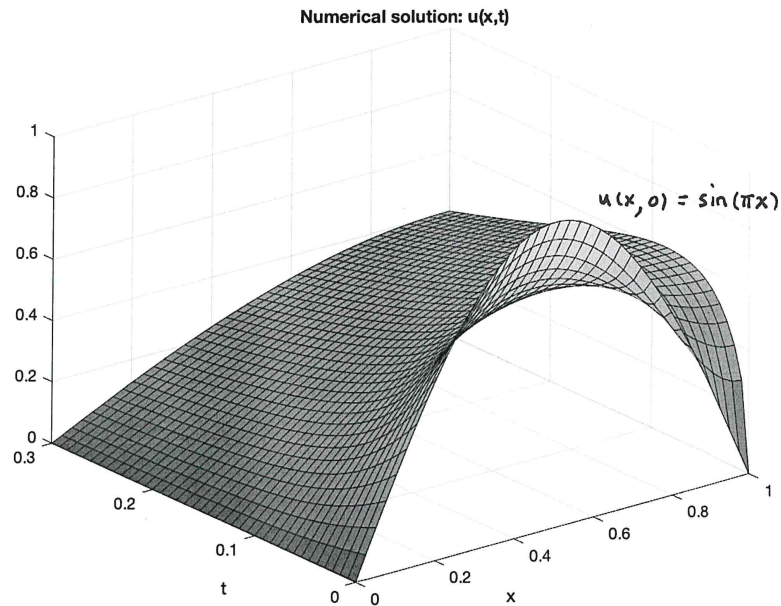
$$u_t = u_{xx}$$

$$u_x(0,t) = 0$$

$$u_x(1,t) = 0$$

} Both no-flux
Boundary Conditions

```
% Heat equation with Neumann BC on [0,1]
%
function pdex01
m = 0;
x = linspace(0,1,40);      x ∈ [0,1]
t = linspace(0,0.15,20);
sol = pdepe(m,@pdex1pde,@pdex1ic,@pdex1bc,x,t);
% Extract the first solution component as u.
u = sol(:,:,1);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Surface plot of u(x,t)
surf(x,t,u)
title('Numerical solution: u(x,t)')
xlabel('x')
ylabel('t')
% Solution profile u(x,*) at last time.
figure
plot(x,u(end,:))
title('u(x,t) at t = 0.15')
xlabel('x')
ylabel('u(x,0.15)')
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Defining the problem (m=0)
%
% c(x,t,u,u_x) u_t = (f(x,t,u,u_x))_x + s(x,t,u,u_x)
%
function [c,f,s] = pdex1pde(x,t,u,DuDx)
c = 1;
f = 1*DuDx;
s = 0;
% u(x,0)=u0(x)
%
function u0 = pdex1ic(x)
u0 = 2*exp(-(x-0.5)^2/(0.05));    u(x,0) = A exp(-(x-x_0)^2/σ^2)
%
% p + q*f = 0      x=xl,xr
%
% where f is the flux f declared in the PDE above
%
function [pl,ql,pr,qr] = pdex1bc(xl,ul,xr,ur,t)
pl = 0;
ql = 1;      u_x(0,t) = 0
pr = 0;
qr = 1;      u_x(1,t) = 0
```



$$\begin{aligned} u_t &= u_{xx} \\ u(0,t) &= 0 \\ u_x(1,t) &= 0 \end{aligned}$$

Dirichlet B.C.
no-flux B.C.

```
% Heat equation with Neumann BC on [0,1]
%
function pdex02
m = 0;
x = linspace(0,1,40); % x in [0,1]
t = linspace(0,0.30,40);
sol = pdepe(m,@pdex1pde,@pdex1ic,@pdex1bc,x,t);
% Extract the first solution component as u.
u = sol(:,:,1);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Surface plot of u(x,t)
surf(x,t,u)
title('Numerical solution: u(x,t)')
xlabel('x')
ylabel('t')
% Solution profile u(x,*) at last time.
figure
plot(x,u(end,:))
title('u(x,t) at t = 0.15')
xlabel('x')
ylabel('u(x,0.15)')
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Defining the problem (m=0)
%
% c(x,t,u,u_x) u_t = (f(x,t,u,u_x))_x + s(x,t,u,u_x)
%
function [c,f,s] = pdex1pde(x,t,u,DuDx)
c = 1;
f = 1*DuDx;
s = 0;
% u(x,0)=u0(x)
%
function u0 = pdex1ic(x)
u0=sin(pi*x); % u(x,0) = sin(pi*x)
%
% p + q*f = 0 % x=xl,xr
%
% where f is the flux f declared in the PDE above
%
function [pl,ql,pr,qr] = pdex1bc(xl,ul,xr,ur,t)
pl = ul; % u(0,t) = 0
ql = 0;
pr = 0; % u_x(1,t) = 0
qr = 1;
```


EXAMPLE Find the steady state of

$$u_t = u_{xx}$$

$$u(0,t) = 0 \quad \text{Dirichlet}$$

$$u_x(1,t) = 0 \quad \text{Neumann (no-flux)}$$

$$u(x,0) = \sin(\pi x)$$

Steady state problem

$$\bar{u}_{xx} = 0 \quad \bar{u}(0) = 0 \quad \bar{u}'(1) = 0$$

General Soln

$$\bar{u}(x) = Ax + B$$

Use B.C.

$$\bar{u}(0) = B = 0$$

$$\bar{u}'(1) = A = 0$$

Conclude

$$\bar{u}(x) = 0$$

More on Diffusion
and
Applications

Diffusion

Is a result of random particle motion, which tends to disperse particles throughout the medium. Continuum limits of random walk processes can be used to derive flux formulae. Most common is

$$\vec{J} = -D \vec{\nabla} u \quad D = \text{diffusivity}$$

Since $\vec{\nabla} u$ is the direction in which concentration u increases most rapidly, particles move down gradient.

$$\vec{J} = -D(x) \vec{\nabla} u \quad \begin{array}{l} \text{nonhomogeneous} \\ \text{isotropic diffusion} \end{array}$$

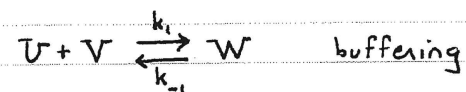
$$\vec{J} = -\underline{D} \vec{\nabla} u \quad \underline{D} \in \mathbb{R}^{3 \times 3} \text{ yields anisotropic diffusion.}$$

For particles of radius a , viscosity μ

$$D = \frac{kT}{6\pi\mu a} \quad \text{Einstein formula}$$

Here T = temperature, k = Boltzmann constant

EXAMPLE Reaction Diffusion Equation



Law of mass action for source terms. If buffering sites are immobile then $D_V = D_W = 0$.

Since U allowed to diffuse in cell we arrive at the Rx-Diff system

$$\begin{aligned} u_t &= D_u \nabla^2 u - k_1 uv + k_{-1} w, \quad x \in \Omega \\ v_t &= -k_1 uv + k_{-1} w \\ w_t &= k_1 uv - k_{-1} w \end{aligned}$$

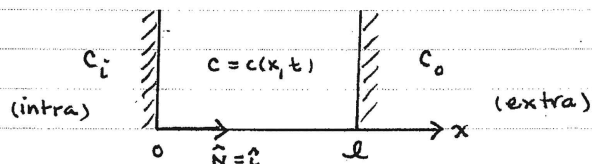
Boundary conditions needed to complete model

$$\vec{u}_t = D \nabla^2 \vec{u} + f(\vec{u}) \quad D = \text{diag}(D_u, 0, 0)$$

A common B.C. for diffusion is "no flux" as in $\vec{J} \cdot \hat{n}|_{\partial\Omega} = 0$ on $\partial\Omega$. For diffusion:

$$\vec{\nabla} u \cdot \hat{n} = \frac{\partial u}{\partial n} \Big|_{\partial\Omega} = 0$$

Diffusion thru a membrane (passive)



Diffusion equation for membrane

$$(1) \quad \frac{\partial c}{\partial t} = D \frac{\partial^2 c}{\partial x^2} \quad c(0,t) = c_i, \quad c(l,t) = c_o$$

At equilibrium, $c_t = 0$ implies

$$c(x) = c_i + (c_o - c_i) \left(\frac{x}{l} \right)$$

Using $\vec{J} = -D \vec{\nabla} c$, one can compute the steady state flux thru membrane.

$$J = \frac{D}{l} (c_i - c_o) \quad \vec{J} = J \hat{x}$$

If $c_i > c_o$ there is a steady flow out.

For cell membranes sometimes called "leaky" channels. Also, no energy is utilized hence passive transport

Facilitated Transport (of Oxygen in Muscle)



where

$S = [O_2]$	oxygen	(gmm) 32
$E = [Mb]$	myoglobin	17K
$C = [Mb O_2]$	oxymyoglobin	17K

Here E and C are large (intracellular) molecules

Dimensional Reaction Diffusion Equations

$$(1) \quad S_t = D_s S_{xx} + F \quad x \in (0, l)$$

$$(2) \quad E_t = D_e E_{xx} + F$$

$$(3) \quad C_t = D_c C_{xx} - F$$

where l is the membrane thickness.

$$F = k_+ S E - k_- C$$

and the boundary conditions are

$$S(0,t) = S_o \quad S(l,t) = \beta S_o$$

$$E_x(0,t) = 0 \quad E_x(l,t) = 0$$

$$C_x(0,t) = 0 \quad C_x(l,t) = 0$$

The latter for E, C are "no flux" or Neumann B.C.

Dimensional Analysis

$$S = s S_0 \quad E = E_0 e \quad C = E_0 c$$

$$x = y L \quad t = t_0 \tau$$

where $t_0 = (k_+ E_0)^{-1}$. Define dimensionless param:

$$\epsilon = \frac{E_0}{S_0} \quad \alpha = \frac{k_-}{k_+ S_0} \quad \epsilon_1 = \frac{D_s}{E_0 k_+ L^2} \quad \epsilon_2 = \frac{D_e}{E_0 k_+ L^2}$$

Since $D_e \approx D_c$ (large similar weight molecules)

$$(4) \quad S_\tau = \epsilon_1 S_{yy} + f \quad s(0, \tau) = 1, s(1, \tau) = \beta$$

$$(5) \quad e_\tau = \epsilon_2 e_{yy} + \frac{1}{\epsilon} f \quad \text{Neumann}$$

$$(6) \quad c_\tau = \epsilon_2 c_{yy} - \frac{1}{\epsilon} f \quad \text{Neumann}$$

and

$$(7) \quad f = -se + \alpha c$$

Parameter assumptions

$$(A1) \quad 0 < \epsilon \ll 1 \quad E_0 \text{ low relative to } S_0$$

$$(A2) \quad \epsilon_2 \ll \epsilon_1 \quad \text{since large } E \text{ molecules (move) diffuse more slowly than } D_2.$$

Initial Condition Assumptions

$$s(y, 0) = \text{any fn satisfying B.C. on } s$$

$$e(y, 0) = 1 \quad \text{throughout membrane}$$

$$c(y, 0) = 0 \quad \text{" "}$$

The latter mimics Michaelis-Menten I. Cond.

Conservation of Myoglobin

Total amount of Mb (bound or not) is

$$v = e + c$$

Given (5)-(6), boundary and initial conditions

$$(8) \quad v_\tau = \epsilon_2 v_{yy} \quad y \in (0, 1), \tau > 0$$

$$(9) \quad v_{y(0, \tau)} = v_{y(1, \tau)} = 0 \quad \forall \tau > 0$$

$$(10) \quad v(y, 0) = 1 \quad y \in (0, 1)$$

The unique solution of (8)-(10) is $v(y, \tau) \equiv 1$

$$e + c = 1 \quad \forall (y, \tau)$$

Quasi-Steady State

On account $\epsilon \ll 1$, $\epsilon_2 \ll 1$ eqn (5) $\Rightarrow f = 0$ at QSS

$$c = \frac{s}{s + \alpha}$$

is dimensionless form of QSS

Dimensional Flux at Equilibrium

$$S_t + C_t = 0$$

Adding (1)-(2) yields

$$D_s S_{xx} + D_e C_{xx} = 0 \quad x \in (0, l)$$

Integrate

$$(1) \quad -J = D_s S_x + D_e C_x$$

where J is the (constant) equilibrium flux.
Integrate (1) over $(0, l)$ using B.C.

$$(2) \quad -Jl = D_s(p-1)S_0 + D_e(C_0 - C_l)$$

Don't know C_0, C_l so use QSS approximation in dimensional form

$$(13) \quad C_l = \left(\frac{E_0}{K_l}\right) \frac{S_l}{K + S_l} \quad K \equiv \frac{k_-}{k_+}$$

Since $S_l = S(l), S_0 = S(0)$ in (13) to get C_0, C_l .

After much algebra (12)-(13) yield flux

$$J = \frac{D_s}{l} \overbrace{(1 + \mu p)}^{>1} (S_0 - S_l) \quad \text{Facilitated Diffusion}$$

where facilitation factor μp is

$$\mu p = \frac{D_e K}{D_s k_+} \frac{E_0}{(K + S_l)(K + S_0)}$$

Diffusion and Random walks

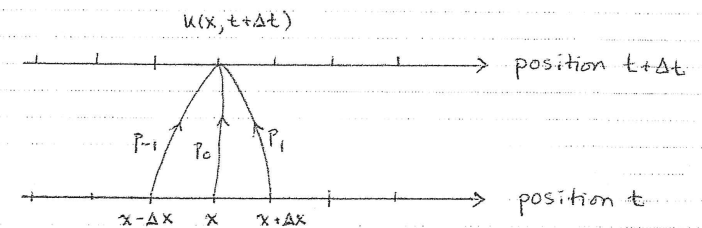
Diffusion can be viewed as the continuum limit of a discrete random walk process.

Let $X(t)$ be the random variable for the position of an organism and let $u(x, t)$ be probability density function.

$u(x, t) \Delta x$ = probability organism is located in the interval $(x, x + \Delta x)$ at time t

$$u(x, t) \Delta x = P(x < X(t) < x + \Delta x)$$

In a random walk one attributes probabilities to the organisms movement from time t to $t + \Delta t$.



Schematic illustrates a random walk where organism position at $x, t + \Delta t$ could have arisen from organism moving left or right Δx units with probabilities p_{-1}, p_1 or remaining stationary with prob p_0 .

For such a random walk (assuming independence)

$$u(x, t + \Delta t) = p_{-1} u(x - \Delta x, t) + p_0 u(x, t) + p_1 u(x + \Delta x, t)$$

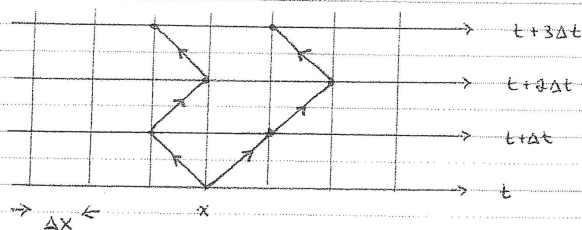
where

$$p_{-1} + p_0 + p_1 = 1$$

As a special case we consider $p = p_1 = \frac{1}{2}, p_0 = 0$

$$(1) \quad u(x, t + \Delta t) = \frac{1}{2} u(x - \Delta x, t) + \frac{1}{2} u(x + \Delta x, t)$$

Here the organism moves left/right Δx units with equal probability and with certainty moves (doesn't stay a posit. x)



Shows two potential realizations for the random walk.

Continuum limit ($\Delta x, \Delta t \rightarrow 0$)

$$(1) \quad u(x, t + \Delta t) = \frac{1}{2} u(x - \Delta x, t) + \frac{1}{2} u(x + \Delta x, t)$$

Seek a PDE that $u(x, t)$ satisfies. Expand each term in a Taylor series about (x, t) :

$$u(x, t + \Delta t) = u + u_t \Delta t + \frac{1}{2} u_{tt} \Delta t^2 + O(\Delta t^3)$$

$$u(x + \Delta x, t) = u + \Delta x u_x + \frac{1}{2} u_{xx} \Delta x^2 + O(\Delta x^3)$$

$$u(x - \Delta x, t) = u - \Delta x u_x + \frac{1}{2} u_{xx} \Delta x^2 + O(\Delta x^3)$$

After substituting these into the assumed rule (1) the u terms cancel:

$$(2) \quad u_t \Delta t + \frac{1}{2} u_{tt} \Delta t^2 = \frac{1}{2} \Delta x^2 u_{xx} + \text{h.o.t.}$$

where h.o.t. denotes higher order terms.

Dividing both sides by Δt and rearranging

$$(3) \quad u_t = \left(\frac{\Delta x^2}{2 \Delta t} \right) u_{xx} - \frac{1}{2} u_{tt} \Delta t + \text{h.o.t.}$$

$\uparrow$ fix constant $\uparrow$ as $\Delta t \rightarrow 0$

and we arrive at the diffusion eqn for $u(x, t)$

$$(4) \quad u_t = D u_{xx}$$

where

$$D = \frac{\Delta x^2}{2 \Delta t}$$

Earlier we showed that

$$(5) \quad u(x,t) = \frac{1}{\sqrt{4\pi Dt}} e^{-x^2/4Dt} \quad x \in \mathbb{R}, t > 0$$

was a solution to the diffusion eqn (4).
It is readily verified that

$$\int_{\mathbb{R}} u(x,t) dx = 1$$

so the fundamental solution in (5) is the probability density function for the random walk. Moreover,

$$P(a < X(t) < b) = \int_a^b u(x,t) dx$$

is the probability the organism is in (a,b) at time t .

Connection to concentration

If the "organism" in the preceding discussion is a molecule and Ω contains N such molecules which randomly move (independently) then

$$c(x,t) = N u(x,t) = \text{molecular (\#) concentrat.}$$

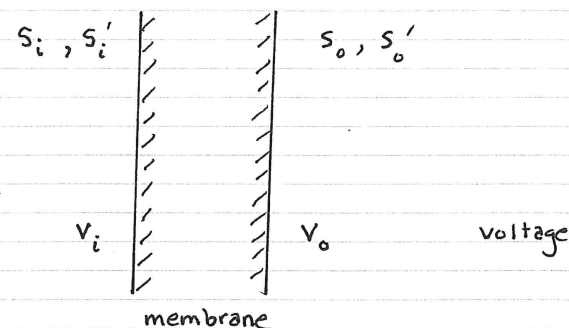
and $c(x,t)$ also satisfies a diffusion equation

$$c_t = D c_{xx}$$

Transmembrane ionic transport

Ionic concentrations inside and outside cells are typically different and as a consequence the electric potential across the membrane is not zero.

Cations (positive) are designated by S .
Anions (negative) are designated by S' .



Remarks

- (1) $S = Na^+, K^+, Ca^{2+}$ whereas $S' = Cl^-$
- (2) Typically membrane only permeable to S (not S')
- (3) If $[S_i] \neq [S_o]$ concentration then this gradient induces a flux of S until the induced potential

$$V = V_i - V_o$$

balances electrodiffusion.

Typical Values (mM)

		intra	extra	
<u>Skeletal Muscle</u>	K^+	150	4.5	$\rightarrow$
	Na^+	12	145	$\leftarrow$
	Cl^-	4.2	116	$\leftarrow$
<u>Squid Axon</u>	K^+	400	20	
	Na^+	50	440	
	Cl^-	40	560	
	Ca^{2+}	0.0003	10	
<u>Generic Mammal</u>	K^+	139	4.5	
	Na^+	15	145	
	Cl^-	20	116	
	Ca^{2+}	<0.0002	1.8	

Some cells that have electrical behavior:

- muscle
- heart
- neurons
- sensory cells
- endocrine (pancreas, hypothalamus, ...)

Electrodiffusion Summary

1) Planck's Equation for flux of charged particles

$$\vec{J}_\phi = -u \frac{z}{|z|} c \vec{\nabla} \phi$$

where

u = ion mobility

z = ion valence

c = ionic concentration

ϕ = electric potential

$\vec{E} = -\vec{\nabla} \phi$ electric field

2) Einstein Diffusivity

$$D = \frac{uRT}{|z|F}$$

$$\frac{RT}{F} = 25.8 \text{ mV @ } 27^\circ\text{C}$$

$$F = 96485 \text{ Coul/mole}, R = 8.31 \text{ J/mole/}^\circ\text{K (Gas Const)}$$

3) Nernst-Planck Electrodiffusion

$$\vec{J} = -D \left(\vec{\nabla} c + \frac{zF}{RT} c \vec{\nabla} \phi \right)$$

$\uparrow$
diffusive
flux

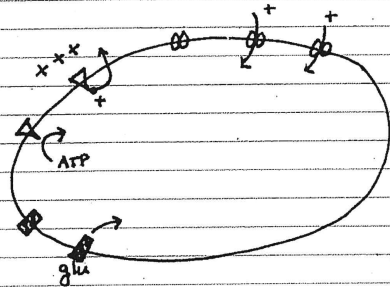
$\uparrow$
electro
flux

Remark: A low velocity $\vec{v}$ the drag force $\vec{f} = \frac{1}{u} \vec{v}$ where u is the mobility. For a sphere from Nav-Stokes $u = (6\pi\mu a)^{-1}$, μ = viscosity, a = radius. Then

$$D = \frac{kT}{6\pi\mu a} = ukT = \frac{uRT}{|z|F}$$

since $R = N_A k$, $N_A = 6.02 \times 10^{23}$ particles/mole.

Transmembrane transport



membrane is a phospholipid bilayer and is impermeable

- ion channels (down gradient)
- ▼ ion pumps (up gradient) - need energy
- receptors (non ionic transport)

Cell capacitance

Neutral membrane separates different ionic concentrations (intra, extra cellular). As such, the membrane has a capacitance C typically given in Farads/ m^2 of cell surface.

$$C = \frac{k\epsilon_0}{d}$$

is the capacitance of a plate

k = dielectric constant of media

ϵ_0 = permittivity of free space

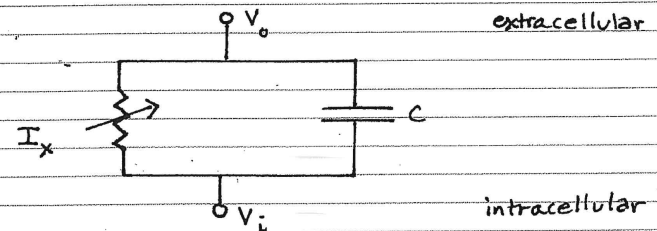
d = plate thickness

Membrane circuit model

For a (plate) capacitor $Q = CV$ where Q is total charge. Thus, capacitive current is

$$I = \frac{dQ}{dt} = C \frac{dV}{dt}$$

Regard whole cell as a circuit



Here I_x is an (sum of) ionic current(s).

Conservation of charge then implies

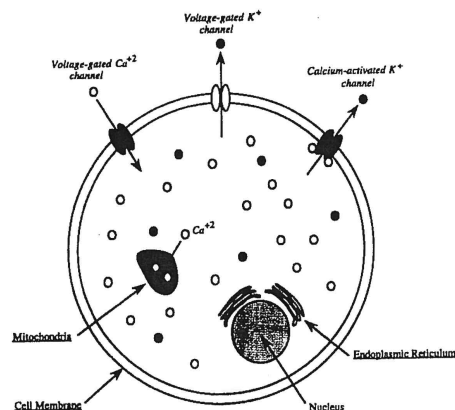
$$C \frac{dV}{dt} + I_x = 0$$

For a given ionic channel (or pump)

$$I_x = g_x (V - V_x)$$

where conductance g_x

Single Cell Models-generic



$$\frac{dv}{dt} = -\sum_X I_X(v, w, \vec{c}), \quad (4)$$

$$\frac{dw}{dt} = \frac{w_{\infty}(v, \vec{c}) - w}{\tau(v, \vec{c})}, \quad (5)$$

$$\frac{d\vec{c}}{dt} = \epsilon \vec{h}(v, w, \vec{c}), \quad \vec{c} \in \mathbb{R}^K, \quad (6)$$

- v = potential across cellular membrane
- I_X = membrane ionic current through channels of type X
- w = channel activation parameter
- $\vec{c}$ = concentrations of agents which regulate the electrical activity

General Single cell model

$$C_m \frac{dv}{dt} = \sum_X I_X(V, \phi, c) + I_a(t)$$

$$\frac{d\phi_i}{dt} = \frac{\phi_{\infty,i}(V) - \phi_i}{\tau_{\phi,i}(V)} \quad i = 1, 2, \dots, N_i$$

$$\frac{dc_j}{dt} = f_j(V, c)$$

where

V = membrane potential

ϕ_i = subunit gating variables

c_j = ionic or chemical concentrations

Broadly

I_X = current thru channel or pump of type X . Ion specific

I_a = experimentally applied current or currents from elsewhere, i.e. coupling, synaptic.

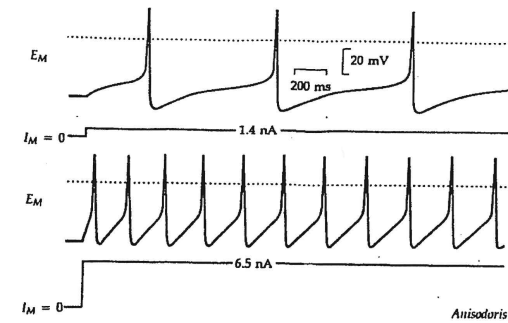
C_m = membrane capacitance

Examples of excitable cells

Cell	Type	Stimulus
Mechanoreceptor	neuron	mechanical
Photoreceptor	neuron	light
Chemoreceptors	neuron	smell
Thermoreceptors	neuron	heat
Muscle		electrical mechanical
Pancreas	endocrine	hormone
Hippocampal	endocrine	hormone
		electrical

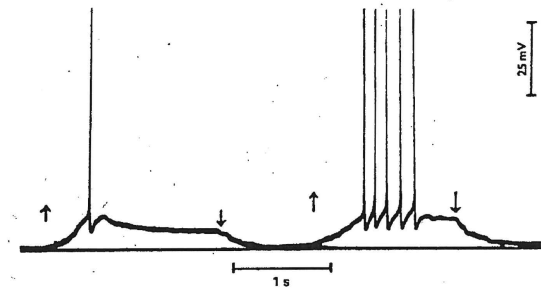
REPETITIVE FIRING OF AN ISOLATED NEURON

(Anisodoris neuron, soma electrical stimulus) (Seaslug)



REPETITIVE FIRING OF AN MECHANORECEPTOR NEURON

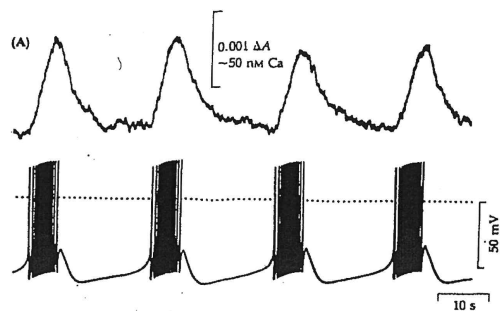
(Crayfish neuron, mechanical (stretching) stimulus)



PARABOLIC BURSTING IN A PACEMAKER NEURON

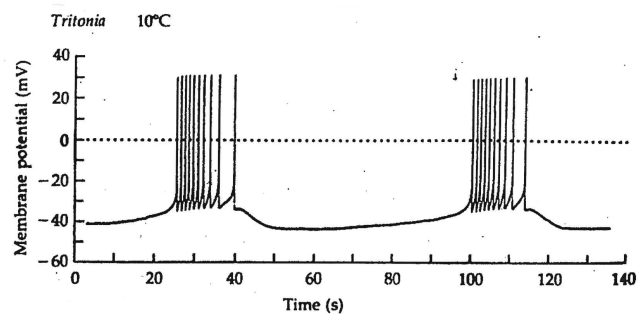
(Aplysia neuron, slow calcium oscillations)

(Sni)



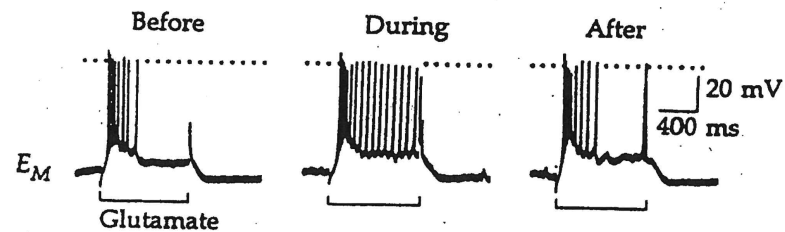
BURSTING IN A PACEMAKER NEURON

(Tritonia neuron)



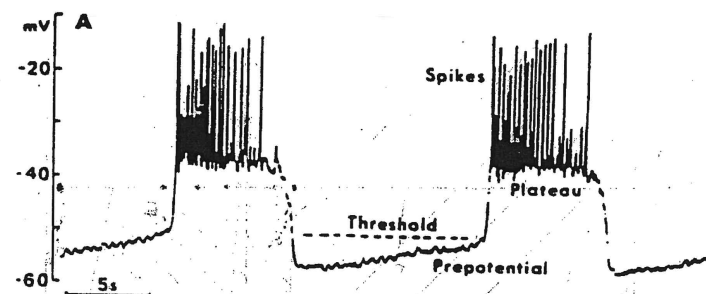
BURSTING INITIATED BY HORMONES

(pyramidal cells in hippocampus, Norepinephrine stimulus)



BURSTING IN PANCREATIC β -CELL

(mouse β -cell, glucose stimulus)



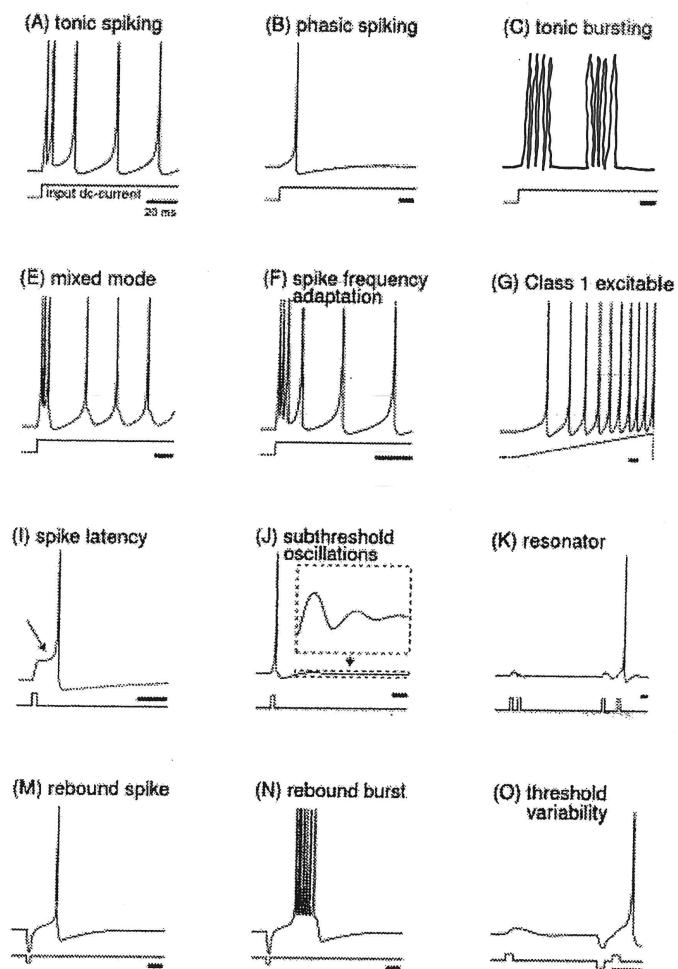


Figure 8.8: Summary of neurocomputational properties exhibited by see exercise 11. The figure is reproduced, with permission, from w (An electronic version of the figure, the MATLAB code that generates responses, and reproduction permissions are available at www.izhil)

Ion pumps versus Ion Channels.

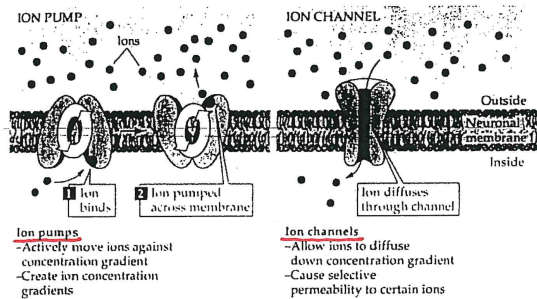
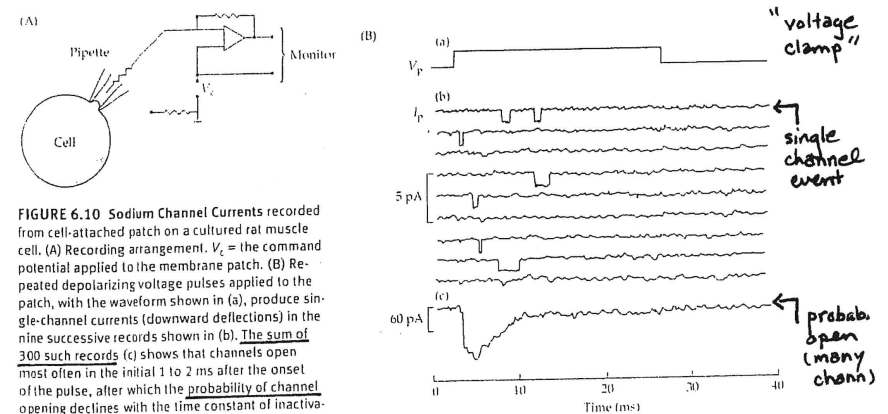
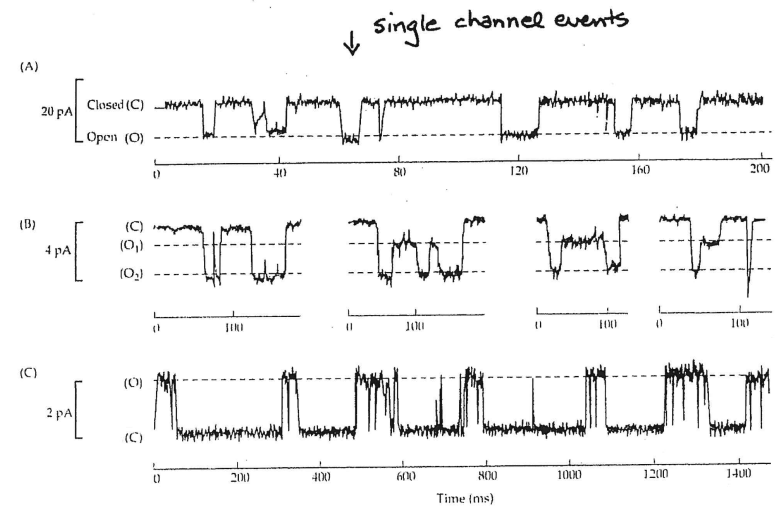
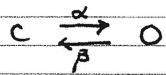


Figure 2.2 Ion pumps and ion channels are responsible for ionic movements across neuronal membranes. Pumps create ion concentration differences by actively transporting ions against their chemical gradients. Channels take advantage of these concentration gradients, allowing selected ions to move, via diffusion, down their chemical gradients.



Two state K^+ channel



where C, O are closed and open states. Let

n = fraction of open channels

$1-n$ = fraction of closed channels

Tacitly assumed number of channels constant.

Law of mass action yields

$$(1) \quad \frac{dn}{dt} = \alpha(V) \frac{(1-n)}{C} - \beta(V) n$$

We assume the rates depend on Voltage.
Can rewrite (1) as

$$(2) \quad \frac{dn}{dt} = \frac{n_{\infty}(V) - n}{\tau_n(V)}$$

for

$$n_{\infty}(V) = \frac{\alpha}{\alpha + \beta} \quad \tau_n(V) = \frac{1}{\alpha + \beta}$$

Thus a Nernst current with conductance g_K for ion K^+ might be

$$(3) \quad I_K = \bar{g}_K n (V - V_K)$$

where $\bar{g}_K$ is the maximal conductance.

Multiple subunit models

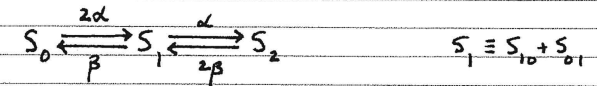
- each unit is closed or open
- all units must be open for ions to flow

Two unit model

S_{ij} = state of two units

Here $i, j \in \{0, 1\}$, where 0 denotes closed

Assume S_{01} and S_{10} states identical.
Hence reaction equations are:



let

x_i = fraction of channels in state S_i

Resulting differential equations

$$\dot{x}_0 = \beta x_1 - 2\alpha x_0$$

$$\dot{x}_1 = -\dot{x}_0 - \dot{x}_2$$

$$\dot{x}_2 = \alpha x_1 - 2\beta x_2$$

and channels are conserved

$$(1) \quad x_0 + x_1 + x_2 = 1$$

Using conservation of channels

$$(2) \quad \dot{x}_0 = f(x_0, x_2) = \beta(1 - x_0 - x_2) - 2\alpha x_0$$

$$(3) \quad \dot{x}_2 = g(x_0, x_2) = \alpha(1 - x_0 - x_2) - 2\beta x_2$$

Nonhomogeneous, linear, planar system.

If we define n to be solution of

$$\frac{dn}{dt} = \alpha(1-n) - \beta n$$

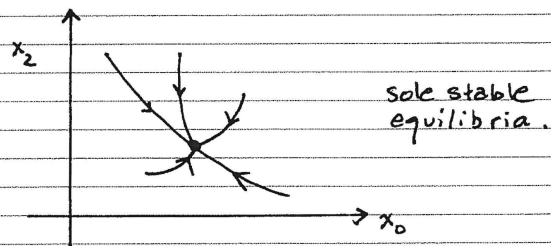
then

$$x_0 = (1-n)^2$$

$$x_1 = 2n(1-n)$$

$$x_2 = n^2$$

solves (1)-(3). Such a solution in (x_0, x_2) -plane



Linearization about this solution

$$x_0 = (1-n)^2 + y_0$$

$$x_2 = n^2 + y_2$$

yields

$$\dot{y}_0 = -2\alpha y_0 - \beta(y_0 + y_2)$$

$$\dot{y}_2 = -\alpha(y_0 + y_2) - 2\beta y_2$$

which is homogeneous linear system with eigenvalues

$$\lambda_1 = -(\alpha + \beta) \quad \lambda_2 = -2(\alpha + \beta)$$

Since $\lambda_k < 0$ we conclude

$x_0 = (1-n)^2$	Stable Invariant Manifold
$x_2 = n^2$	

Remarks

(1) n = "probability" that each unit open

(2) Current model for two subunits

$$I_k = \bar{g}_k n^2 (V - V_k)$$

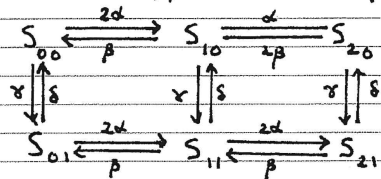
where $\bar{g}_k$ = maximal conductance.

(3) For k subunits get n^k term

Na⁺ multiunit channel model (sketch)

S_{ij} = i open m type subunits and
 j open h type subunits

Assume 2- m type and 1- h type subunits.



Only S_{21} state allows ions thru

$$\left. \begin{array}{l} (1) \quad \dot{x}_{21} = m^2 h \\ (2) \quad \dot{m} = \alpha(1-m) - \beta m \\ (3) \quad \dot{h} = \gamma(1-h) - \delta h \end{array} \right\} \begin{array}{l} \text{manifold} \\ \text{defined here} \\ \text{is stable} \end{array}$$

Other states

$$\begin{aligned} x_{00} &= (1-m)^2(1-h) \\ x_{01} &= (1-m)^2 h \\ x_{10} &= 2m(1-m)(1-h) \\ x_{20} &= m^2(1-h) \\ x_{11} &= 2m(1-m)h \end{aligned}$$

Resulting current I_{Na} given by

$$I_{Na} = \bar{g}_{Na} m^2 h (V - V_{Na})$$

where m, h satisfy (2)-(3).