Introduction

Introduction

• **Discrete models** for total population at discrete times t_n :

$$P_{n+1} = f(t_n, P_n).$$

• Continuous models for total populations, using **ODEs**:

$$\frac{dP}{dt} = f(t, P).$$

• Leslie model divided population into discrete age classes:

$$P_{n+1} = LP_n$$
.

- Continuous PDE model, p(t, a):
 - Allow the population to vary in both time t and age a.
 - Model described by a **PDE**.
 - Dynamics better describe population, but harder to follow from complexities of analysis.

Age-Structured Model: Modeling with a hyperbolic PDE.

- Mathematical modeling of *populations* often needs information about the ages of the individuals in the population.
- This modeling approach was developed primarily by McKendrick (1926) and Von Foerster (1959).
- Key Elements in Model
 - Let n(t, a) denote the **population** at time t and age a.
 - The **birth rate** of individuals b(a) depends on the age of the adult population.
 - Similarly, the **death** rate of individuals $\mu(a)$ depends on the age of the individuals.
 - Must specify the *initial age distribution* of the population, f(a).

Age-Structured Population

Age-Structured Population: Consider a population, n(t, a), dependent on time, t, and structured by age of individuals, a.

The dynamics in time must satisfy:

$$\frac{d}{dt}n(t,a) = \frac{\partial n}{\partial t} + \frac{da}{dt}\frac{\partial n}{\partial a},$$

by the *chain rule*.

Most commonly, the age clocks along with time, so $\frac{da}{dt} = 1$, so it follows that

$$\frac{d}{dt}n(t,a) = \frac{\partial n}{\partial t} + \frac{\partial n}{\partial a}.$$

The *births* all occur at a=0 (the boundary), so the dynamics of the population above is only deaths or

$$\frac{\partial n}{\partial t} + \frac{\partial n}{\partial a} = -g(t, a, n).$$

Age-Structured Model: The McKendrick-Von Foerster equation is:

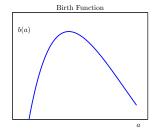
$$\frac{\partial n}{\partial t} + \frac{\partial n}{\partial a} + \mu(a)n(t, a) = 0,$$

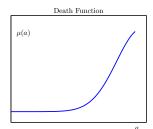
with the birth boundary condition (Malthusian):

$$n(t,0) = \int_0^\infty b(a)n(t,a) da,$$

and the *initial condition*:

$$n(0,a) = f(a).$$





Discussion for the Age-Structured Model

$$\frac{\partial n}{\partial t} + \frac{\partial n}{\partial a} = -\mu(a)n(t, a).$$

- The **PDE** shows that age advances with time.
- The right side shows that there is only a loss of population through death with death increasingly likely with age.
- The birth function:
 - Young individuals are incapable of giving birth
 - The birth function increases to peak fertility.
 - Births are Malthusian proportional to the population.
 - After peak fertility, reproductive ability decreases, and it could again decrease to zero.
- The initial population distribution could be anything
- However, in general the population distribution should decrease with increasing time.

Age-Structured Model - Method of Characteristics

The Age-Structured Model:

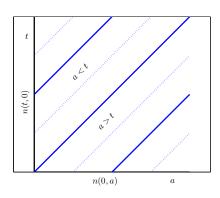
$$\frac{\partial n}{\partial t} + \frac{\partial n}{\partial a} = -\mu(a)n(t, a).$$

can be written as an ODE:

$$\frac{d}{dt}n(t,a) = -\mu(a)n(t,a),$$

along the *characteristic*,

$$a(t) = t + c.$$



This has the solution:

$$N(t) = N_0 e^{-\int_0^t \mu(s) \, ds},$$

which follows the population of a particular age cohort.

Age-Structured Model - Survival

We can define a *survival function*

$$L(a) = e^{-\int_0^a \mu(s) \, ds}$$

which gives the fraction of individuals surviving from birth to age a.

The survival from a to b is given by

$$L(a,b) = e^{-\int_a^b \mu(s) \, ds}.$$

From the diagram above, we follow the characteristics to obtain the solution of the **age-structured model**:

$$a < t$$
: $n(t,a) = n(t-a,0)L(0,a),$
 $a > t$: $n(t,a) = n(0,a-t)L(a-t,a).$

The *age-structured model* gives the dynamics of a particular age cohort following a characteristic.

The **long term behavior** depends significantly on the *birth process* on the boundary.

Since this is a type of $Malthusian\ growth$ (with no limiting nonlinearities), we expect a type of $exponential\ growth$ (or decline) with some rate r and having the form:

$$n(t,a) = Cn^*(a)e^{rt},$$

where $n^*(a)$ is the **stable age distribution** and C depends on the initial conditions.

For convenience, assume $n^*(0) = 1$, so that $n^*(a)$ is the fraction of age a individuals surviving to age a relative to age a.

Age-Structure Model - Birth Function

The boundary condition of births is

$$n(t,0) = \int_0^\infty b(a)n(t-a,0)L(a) da.$$

Inserting the assumed **stable form**, $n(t, a) = Cn^*(a)e^{rt}$, gives

$$Ce^{rt} = \int_0^\infty b(a)Ce^{r(t-a)}L(a) da,$$

$$1 = \int_0^\infty e^{-ra}L(a)b(a) da.$$

Whether r is positive or negative determines if the overall population grows or decays.

If r > 0, then the total population grows like Ce^{rt}

Age-Structure Model - R_0

Ecologists and epidemiologists define an important constant R_0 , which is used to determine if a population (or disease) expands or contracts.

For this population, define

$$R_0 = \int_0^\infty L(a)b(a) \, da,$$

where R_0 represents the average number of (female) offspring from an individual (female) over her lifetime (integral of births times lifespan).

Note that if $R_0 < 1$, then r < 0 and if $R_0 > 1$, then r > 0. The latter condition indicates that each female during her lifetime must produce more than one female offspring for the population to grow.

Since n(t, a) = n(t - a, 0)L(a), the **stable age distribution** satisfies

$$Ce^{rt}n^*(a) = Ce^{r(t-a)}n^*(0)L(a) = Ce^{r(t-a)}L(a),$$

 $n^*(a) = e^{-ra}L(a).$

Age-Structured Model - Example

We can define the *average generation time*, T, to satisfy:

$$e^{rT} = R_0,$$

so on average a mother replaces herself with R_0 offspring.

The value

$$T = \frac{1}{R_0} \int_0^\infty aL(a)b(a) \, da,$$

gives the average age of reproduction.

Example: Let us examine the age-structured model

$$\frac{\partial n}{\partial t} + \frac{\partial n}{\partial a} + \mu(a)n(t, a) = 0,$$

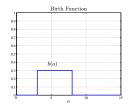
with the birth boundary condition:

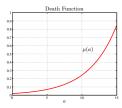
$$n(t,0) = \int_0^\infty b(a)n(t,a) \, da.$$

In order to perform calculations (with the help of Maple), we take *birth and death functions*

$$b(a) = \begin{cases} 0.3, & 3 < a < 8, \\ 0, & \text{otherwise,} \end{cases}$$
 and $\mu(a) = 0.02 e^{0.25a}$.

The *birth function* assumes a constant fecundity of 0.3 between the ages of 3 and 8, while the *death function* assumes an ever increasing function with age.



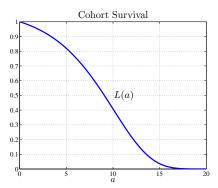


Note: These functions are very crude approximations to the forms displayed earlier.

The age-structured model had a survival function

$$L(a) = e^{-\int_0^a \mu(s) \, ds} = e^{-0.08(e^{0.25a} - 1)},$$

which gives the fraction of individuals surviving from birth to age a.



The **basic reproduction number**, R_0 , was given by

$$R_0 = \int_0^\infty L(a)b(a) \, da = \int_3^8 0.3e^{-0.08(e^{0.25a} - 1)} da = 1.1678,$$

which is the average number of (female) offspring from an individual (female) over her lifetime.

With the help of Maple, we can determine the average overall $growth\ rate,\ r,$ for this example.

Maple solves the equation for r:

$$1 = \int_0^\infty e^{-ra} L(a)b(a) da = \int_3^8 0.3 e^{-ra} e^{-0.08(e^{0.25a} - 1)} da,$$

and obtains

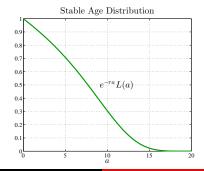
$$r = 0.02925985$$
.

This shows the overall population is growing about 3% per unit time.

The *Malthusian growth* would not be sustainable over long periods of time, so nonlinear terms for crowding and other factors would need to be included in the model, *e.g.*, *logistic growth*.

With the overall population growth rate, we can obtain the *steady-state age distribution* of this population:

$$n^*(a) = e^{-ra}L(a) = e^{-0.02926a}e^{-0.08(e^{0.25a}-1)}.$$



The average generation time, T, satisfies:

$$e^{rT} = R_0$$
 or $e^{0.02926T} = 1.1678$.

so on average a mother replaces herself with R_0 offspring in T = 5.3024 time units.

The value,

$$T = \frac{1}{R_0} \int_0^\infty aL(a)b(a) da = \frac{1}{1.1678} \int_3^8 0.3a \, e^{-0.08(e^{0.25a} - 1)} da = 5.33205,$$

gives the average age of reproduction.

In summary, the *method of characteristics* allows solutions for the *age-structured model*, which can provide interesting information about the behavior of a population.

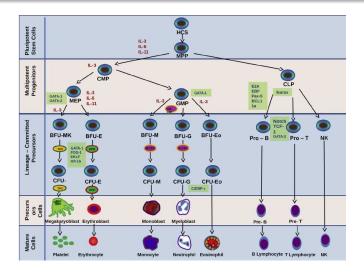
Needless to say, these models must be significantly expanded to manage more realistic populations, which in turn significantly complicates the mathematical analysis.

Introduction - Hematopoiesis

Hematopoiesis for Erythrocytes and Platelets

- All cells in bloodline begin as undifferentiated stem cells (Multipotential Hematopoietic Stem Cells)
- Different hormonal signals cause differentiation (Common Myeloid Progenitor (CMP))
- Further signals for differentiation
 - Erythropoiesis Proerythroblast
 - Thrombopoiesis Megakaryoblast
- Proliferation via cell doubling
- Specialization
 - Erythropoiesis Reticulocytes with hemoglobin
 - Thrombopoiesis Endomitosis forming Megakaryocytes
- Maturation producing Erythrocytes and Platelets
- Cell number and volume monitored by body with negative feedback Erythropoietin and Thrombopoietin

Diagram for Hematopoiesis



Erythropoiesis





Erythropoiesis is the process for producing *Erythrocytes* or *Red Blood Cells (RBCs)*.

- RBCs are the most numerous cells that we produce in our bodies, accounting for almost 85% by numbers.
- Critical for carrying O₂ to our other cells, using the protein hemoglobin (Hb).
- By volume, **RBCs** are about 40% of blood ($\sim 3\%$ body wt).

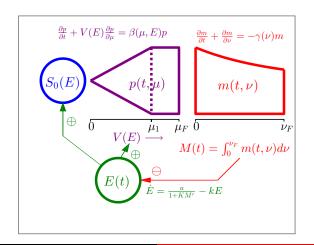
Erythropoiesis

Erythrocytes or Red Blood Cells

- RBCs begin from undifferentiated stem cells (multipotent progenitors), then based on *erythropoietin (EPO)* levels multiply and specialize.
- The body senses O_2 levels in the body and releases *erythropoietin* (*EPO*) inversely to the O_2 in the blood (negative feedback).
- Progenitor cells specialize though a series of cell divisions and intracellular changes (taking about 6 days), building hemoglobin (Hb) levels and becoming RBCs.
- RBCs circulate in the bloodstream for about 120 days, then are actively degraded.

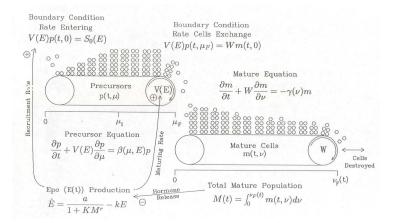
Model for Erythropoiesis

Age-Structured Model for Erythropoiesis



Model for Erythropoiesis

Age-Structured Model viewed as a conveyor system



Active Degradation of RBCs

Active Degradation of RBCs

- RBCs are lost from normal leakage (breaking capillaries), which is simply proportional to the circulating numbers
- RBCs age Cell membrane breaks down (no nucleus to repair) from squeezing through capillaries
- Aged membrane is marked with antibodies
- Macrophages destroy least pliable cells based on the antibody markers
- Model assumes constant supply macrophages
 - Saturated consumption of **Erythrocytes**
 - Satiated predator eating a constant amount per unit time
 - Constant flux of **RBCs** being destroyed

Constant Flux Boundary Condition

Constant Flux Boundary Condition

- Let Q be rate of removal of erythrocytes
- Erythrocytes lost are $Q\Delta t$
- Mean Value Theorem average number RBCs

$$m(\xi, \nu_F(\xi))$$
 for $\xi \in (t, t + \Delta t)$

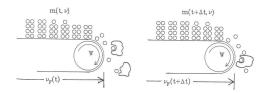
Balance law

$$Q\Delta t = W\Delta t \ m(\xi, \nu_F(\xi))$$
$$-[\nu_F(t + \Delta t) - \nu_F(t)]m(\xi, \nu_F(\xi))$$

• As $\Delta t \to 0$.

$$Q = [W - \dot{\nu}_F(t)]m(t, \nu_F(t))$$

Constant Flux Boundary Condition



• If macrophages consume a constant amount of RBCs at the end of their, we obtain the *natural BC*

$$Q = [W - \dot{\nu}_F(t)]m(t, \nu_F(t))$$

- This results in the lifespan of the **RBCs** either lengthening or shortening from the normal 120 days
- This implies that the lifespan of the **RBCs** depends on the *state* of the *system*

Model Reduction

Model Reduction: Several simplifying assumptions are made:

 \bullet Assume that both velocities of aging go with time, t,

$$V(E) = W = 1.$$

• Assume the birth rate β satisfies:

$$\beta(\mu, E) = \begin{cases} \beta, & \mu < \mu_1, \\ 0, & \mu \ge \mu_1, \end{cases}$$

• Assume that γ is constant.

The model satisfies the *age-structured partial differential equations*:

$$\begin{split} \frac{\partial p}{\partial t} + \frac{\partial p}{\partial \mu} &= \beta(\mu)p, \\ \frac{\partial m}{\partial t} + \frac{\partial m}{\partial \nu} &= -\gamma m. \end{split}$$

Model for Erythropoiesis

The boundary conditions for the age-structured PDEs are:

 Recruitment of the *precursors* based on EPO concentration circulating in the blood:

$$p(t,0) = S_0(E).$$

 Continuity of precursors maturing and entering the bloodstream as mature RBCs:

$$p(t, \mu_F) = m(t, 0).$$

• Active destruction of mature RBCs:

$$(1 - \dot{\nu}_F(t))m(t, \nu_F(t)) = Q.$$

The negative feedback by **EPO** satisfies the **ODE**:

$$\dot{E} = \frac{a}{1 + KM^r} - kE,$$

where the total mature erythrocyte population is

$$M(t) = \int_0^{\nu_F(t)} m(t, \nu) d\nu.$$

Method of Characteristics

The precursor equation generally has maturing depending on **EPO**, E(t), but we assume that V(E) = 1, so time and age are in lockstep.

If we define $P(s) = p(t(s), \mu(s))$, then

$$\frac{dP}{ds} = \frac{\partial p}{\partial t}\frac{dt}{ds} + \frac{\partial p}{\partial \mu}\frac{d\mu}{ds} = \beta(\mu(s))P(s).$$

The *method of characteristics* suggests we want

$$\frac{dt}{ds} = 1$$

or

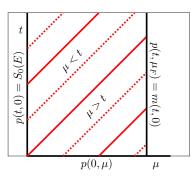
$$t(s) = s + t_0,$$

and

$$\frac{d\mu}{da} = 1$$

or

$$\mu(s) = s + \mu_0.$$



Method of Characteristics

With the method of characteristics, the precursor equation,

$$\frac{dP}{ds} = \beta(\mu(s))P(s),$$

is a birth only population model.

The model assumes that the body uses *apoptosis* at the early recruitment stage (CFU-E) to decide how many *precursor cells* are allowed to mature.

The solution to the **ODE** above is

$$P(s) = p(t, \mu) = P(0)e^{\int_0^s \beta(\mu(r))dr},$$

which is valid for $0 < \mu < \mu_F$, focusing on the larger time solution.

Method of Characteristics

This aging process of the *precursor cells* is primarily a time of *amplification* in numbers before the final stages of simply add *hemoglobin*.

The model shows how recruited cells amplify, then enter the *mature* compartment (bloodstream) to circulate and carry O_2 :

$$p(t, \mu_F) = p(t_0, 0)e^{\int_0^s \beta(\mu(r))dr}$$
$$= p(t - \mu_F, 0)e^{\beta\mu_1} = e^{\beta\mu_1}S_0(E(t - \mu_F)).$$

From the *method of characteristics* on the *mature RBCs*, a similar result gives:

$$m(t,\nu) = m(t-\nu,0)e^{-\gamma\nu}.$$

The continuity between the *precursors* and the *mature RBCs* gives:

$$m(t - \nu, 0) = p(t - \nu, \mu_F) = e^{\beta \mu_1} S_0(E(t - \mu_F - \nu)).$$

Total RBCs

The O_2 carrying capacity of the body depends on the total number of **RBCs**, which is the integral over all $m(t, \nu)$ in ν :

$$\begin{split} M(t) &= \int_0^{\nu_F(t)} m(t-\nu,0)e^{-\gamma\nu} d\nu \\ &= \int_0^{\nu_F(t)} e^{\beta\mu_1} S_0(E(t-\mu_F-\nu))e^{-\gamma\nu} d\nu, \\ &= e^{-\gamma(t-\mu_F)} e^{\beta\mu_1} \int_{t-\mu_F-\nu_F(t)}^{t-\mu_F} S_0(E(w))e^{\gamma w} dw. \end{split}$$

We apply Leibnitz's rule for differentiating an integral:

$$\begin{split} \dot{M}(t) &= -\gamma e^{-\gamma(t-\mu_F)} e^{\beta\mu_1} \int_{t-\mu_F-\nu_F(t)}^{t-\mu_F} S_0(E(w)) e^{\gamma w} dw, \\ &+ e^{\beta\mu_1} \left[S_0(E(t-\mu_F)) - S_0(E(t-\mu_F-\nu_F(t))) e^{-\gamma\nu_F(t)} (1-\dot{\nu}_F(t)) \right] \\ &= -\gamma M(t) + e^{\beta\mu_1} S_0(E(t-\mu_F)) - Q, \end{split}$$

Model for Erythropoiesis with Delays

After reduction of PDEs, the state variables become **total mature erythrocytes**, M, **EPO**, E, and age of RBCs, ν_F .

$$\frac{dM(t)}{dt} = e^{\beta\mu_1} S_0(E(t - \mu_F)) - \gamma M(t) - Q$$

$$\frac{dE(t)}{dt} = f(M(t)) - kE(t)$$

$$\frac{d\nu_F(t)}{dt} = 1 - \frac{Qe^{-\beta\mu_1}e^{\gamma\nu_F(t)}}{S_0(E(t - \mu_F - \nu_F(t)))}$$

This is a state-dependent delay differential equation.

Model for Erythropoiesis with Delays

Properties of the Model: Integrating along the *characteristics* shows that the maturation process acts like a delay, changing the *age-structured model* into a *delay differential equation*.

- The *state-dependent delay model* has a unique positive equilibrium.
- The delay μ_F accounts for maturing time.
- The *state-dependent delay* in equation for $\nu_F(t)$ comes from the varying age of mature cells.
- The $\nu_F(t)$ differential equation is uncoupled from the differential equations for M and E.
- Stability is determined by equations for M and E

DDE with One Delay

Consider the delay differential equation (DDE) with one delay:

$$\dot{y}(t) = ay(t) + by(t - r)$$

If one tries the solution, $y(t) = ce^{\lambda t}$, then

$$c\lambda e^{\lambda t} = ace^{\lambda t} + bce^{\lambda(t-r)},$$

which gives the characteristic equation

$$\lambda - a = be^{-\lambda r}$$

The boundary of stability is a subset of solutions to the characteristic equation with $\lambda = i\omega$ or

$$i\omega - a = be^{-i\omega r} = b\left(\cos(\omega r) - i\sin(\omega r)\right),$$

or for $\lambda = 0$, the **real root crossing** satisfies:

$$a = -b$$

DDE with One Delay

From the *characteristic equation* with $\lambda = i\omega$, the real and imaginary parts give the parametric equations:

$$a(\omega) = -b(\omega)\cos(\omega r),$$

 $\omega = -b(\omega)\sin(\omega r).$

Solving these equations for $a(\omega)$ and $b(\omega)$ gives

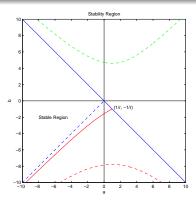
$$a(\omega) = \omega \cot(\omega r),$$

 $b(\omega) = -\frac{\omega}{\sin(\omega r),}$

which are clearly singular at any $\frac{n\pi}{r}$, n = 0, 1, ...

This creates distinct curves $\omega \in \left(\frac{(n-1)\pi}{r}, \frac{n\pi}{r}\right)$ for $n=1,2,\dots$

Stability Region - DDE with One Delay



- Real root crossing solid blue line $(\lambda = 0 \text{ with } a = -b)$.
- "Hopf bifurcation" crossing solid red line.
- Curves above create a D-partitioning of the complex plane into distinct regions with distinct integer number of eigenvalues with real positive parts.

Comments DDE with One Delay

The characteristic equation of a delay differential equation (DDE) is an exponential polynomial, which can rarely be solved exactly.

Stability of the \mathbf{DDE} is demonstrated by showing all roots (infinite) have negative real parts.

The analysis above finds the **stability region** for the **DDE**

$$\dot{y}(t) = ay(t) + by(t - r)$$

- Region with a < 0 and |b| < |a| is stable independent of the delay
- As $r \to 0$, the DDE approaches the ODE with stability region a + b < 0
- Stability region comes to a point at $(\frac{1}{r}, -\frac{1}{r})$
- Imaginary root crossings are distinct, non-intersecting curves, leaving this **stability boundary** generated by the parametric equations with $\omega \in (0, \frac{\pi}{r})$.

Argument Principle

The **Argument Principle** from complex variables is one technique for locating the eigenvalues.

Theorem (Argument Principle)

If f(z) is a **meromorphic** function inside and on some closed contour C, with f having no zeros or poles on C, then the following formula holds:

$$\oint_C \frac{f'(z)}{f(z)} dz = 2\pi i (N - P),$$

where N and P denote respectively the number of zeros and poles of f(z) inside the contour C, with each zero and pole counted as many times as its multiplicity and order, respectively. This assumes that the contour C is simple and is oriented counter-clockwise.

Argument Principle: Stability Analysis

- Since the characteristic equation, $f(\lambda)$, is an analytic function, then the Argument Principle finds the zeroes of $f(\lambda)$.
- A geometric method of employing the Argument Principle is to consider a contour, C, (counterclockwise), then create a map f(C) with the analytic function, $f(\lambda)$.
- The map f(C) creates a curve in the complex plan, and the **Argument Principle** states that this map will encircle the origin N times (counterclockwise), where N is the number of **zeroes** inside C.
- Stability analysis for differential equations with the Argument Principle
 (sometimes called Nyquist criterion) uses an appropriate contour in the
 right half of complex plane.
 - For **ODEs**, create semi-circle radius R with diameter on imaginary axis, then let $R \to \infty$.
 - For **DDEs**, often sufficient to take rectangle from $\left[-\frac{\pi}{r}, \frac{\pi}{r}\right]$ on imaginary axis and real part arbitrarily large.

MatLab Application for ODEs

We want to show stability of examples from ODEs

$$0 \ddot{y} + \dot{y} - 6y = 0$$

- Characteristic equation: $\lambda^2 + \lambda 6 = 0$
- Shows 1 encirclements (Unstable)

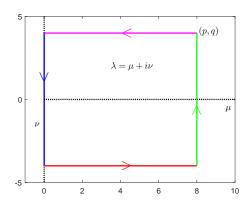
- Characteristic equation: $\lambda^2 2\lambda + 2 = 0$
- Shows 2 encirclements (Unstable)

3
$$\ddot{y} + 2\dot{y} + 2y = 0$$

- Characteristic equation: $\lambda^2 + 2\lambda + 2 = 0$
- Shows no encirclements (Stable)

Contour

The graph below is the contour to which we apply our *characteristic equations*.



Argument Principle for Polynomial

Consider the *polynomial equation*

$$p(\lambda) = \lambda^2 + a\lambda + b.$$

```
function poly(a,b,p,q)
   % Polynomial x^2 + ax + b
   % p = x_max, q = y_max
4
  h=p/100;
  k=q/50;
7 \times (1) = 0;
  y(1) = q;
  u1(1) = x(1)^2-y(1)^2+a*x(1)+b;
   w1(1) = 2*x(1)*y(1)+a*y(1);
   for i=2:101
11
    x(i) = 0;
12
       v(i) = v(i-1)-k;
13
       u1(i) = x(i)^2-y(i)^2+a*x(i)+b;
14
```

Argument Principle for Polynomial

```
15
       w1(i) = 2*x(i)*v(i)+a*v(i);
16
   end
   for i = 102:201
17
       x(i) = x(i-1)+h;
18
       y(i) = -q;
19
       u2(i-101) = x(i)^2-y(i)^2+a*x(i)+b;
20
       w2(i-101) = 2*x(i)*y(i)+a*y(i);
21
   end
22
   for i=202:301
23
       x(i) = p;
24
       y(i) = y(i-1)+k;
25
       u3(i-201) = x(i)^2-y(i)^2+a*x(i)+b;
26
       w3(i-201) = 2*x(i)*y(i)+a*y(i);
27
28
   end
```

Argument Principle for Polynomial

```
29  for i=302:401
30      x(i) = x(i-1)-h;
31      y(i) = q;
32      u4(i-301) = x(i)^2-y(i)^2+a*x(i)+b;
33      w4(i-301) = 2*x(i)*y(i)+a*y(i);
34  end
35  plot(u1,w1,'b-',u2,w2,'r-',u3,w3,'g-',u4,w4,'m-');grid
```

MatLab Application for DDEs

Eigenvalues for *Examples from DDEs*

$$\dot{y}(t) = -y(t) - 3y(t-1)$$

- Characteristic equation: $\lambda + 1 = -3e^{-\lambda}$
- Shows 2 encirclements (Unstable)

$$\dot{y}(t) = -y(t) - 3y(t - 0.5)$$

- Characteristic equation: $\lambda + 1 = -3e^{-0.5\lambda}$
- Shows no encirclements (Stable)

$$\dot{y}(t) = -y(t) + 6y(t-1)$$

- Characteristic equation: $\lambda + 1 = 6e^{-\lambda}$
- Shows 3 encirclements (Unstable)

Argument Principle for DDE

Consider the *characteristic equation*

$$f(\lambda) = \lambda - a - b e^{-r\lambda}.$$

```
function delay_labr(a,b,r,p,q)
2
   % One-delay z - a - b*e^(-r*z)
   % p = x_max, q = y_max
5
   h=p/100;
   k=q/50;
  x(1) = 0;
  y(1) = q;
   u1(1) = x(1)-a-b*exp(-r*x(1))*cos(r*y(1));
10
   w1(1) = y(1) + b \cdot exp(-r \cdot x(1)) \cdot sin(r \cdot y(1));
11
   for i=2:101
12
        x(i) = 0;
13
        y(i) = y(i-1)-k;
14
```

Argument Principle for DDE

```
u1(i) = x(i)-a-b*exp(-r*x(i))*cos(r*y(i));
15
        w1(i) = y(i) + b \cdot exp(-r \cdot x(i)) \cdot sin(r \cdot y(i));
16
   end
17
   for i=102:201
18
       x(i) = x(i-1)+h;
19
       v(i) = -\alpha;
20
        u2(i-101) = x(i)-a-b*exp(-r*x(i))*cos(r*y(i));
21
        w2(i-101) = y(i)+b*exp(-r*x(i))*sin(r*y(i));
22
   end
23
   for i=202:301
24
25
        x(i) = p;
26
       v(i) = v(i-1)+k;
        u3(i-201) = x(i)-a-b*exp(-r*x(i))*cos(r*y(i));
27
        w3(i-201) = y(i)+b*exp(-r*x(i))*sin(r*y(i));
28
   end
29
```

Argument Principle for DDE

Linear Analysis of the Model

Due to the *negative control* by **EPO**, it can be shown that this model has a *unique equilibrium*:

$$(\bar{M}, \bar{E}, \bar{\nu}_F).$$

With the change of variables, $x_1(t) = M(t) - \bar{M}$, $x_2(t) = E(t) - \bar{E}$, and $x_3(t) = \nu_F(t) - \bar{\nu}_F$ and keeping only the *linear terms*, we obtain the *linear system*:

$$\dot{x}_1(t) = e^{\beta \mu_1} S_0'(\bar{E}) x_2(t - \mu_F) - \gamma x_1(t),
\dot{x}_2(t) = f'(\bar{M}) x_1(t) - k x_2(t),
\dot{x}_3(t) = \frac{1}{\bar{E}} x_2(t - \mu_F - \bar{\nu}_F) - \gamma x_3(t).$$

Linear Analysis of the Model

Let $X(t) = [x_1(t), x_2(t), x_3(t)]^T$, then the linear system can be written:

$$\dot{X}(t) = A_1 X(t) + A_2 X(t - \mu_F) + A_3 X(t - \mu_F - \bar{\nu}_F),$$

where

$$A_1 = \left(\begin{array}{ccc} -\gamma & 0 & 0 \\ f'(\bar{M}) & -k & 0 \\ 0 & 0 & -\gamma \end{array} \right), \quad A_2 = \left(\begin{array}{ccc} 0 & e^{\beta\mu_1} S_0'(\bar{E}) & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{array} \right),$$

and

$$A_3 = \left(\begin{array}{ccc} 0 & 0 & 0\\ 0 & 0 & 0\\ 0 & \frac{1}{E} & 0 \end{array}\right).$$

We try solutions of the form $X(t) = \xi e^{\lambda t}$ giving:

$$\lambda I \xi e^{\lambda t} = \left[A_1 + A_2 e^{-\lambda \mu_F} + A_3 e^{-\lambda (\mu_F + \bar{\nu}_F)} \right] \xi e^{\lambda t}.$$

Characteristic Equation

Dividing by $e^{\lambda t}$ results in the *eigenvalue equation*:

$$\left(A_1 + A_2 e^{-\lambda \mu_F} + A_3 e^{-\lambda(\mu_F + \bar{\nu}_F)} - \lambda I\right) \xi = 0.$$

So we must solve

$$\det \left| \begin{array}{ccc} -\gamma - \lambda & e^{\beta \mu_1} S_0'(\bar{E}) e^{-\lambda \mu_F} & 0 \\ f'(\bar{M}) & -k - \lambda & 0 \\ 0 & \frac{1}{\bar{E}} e^{-\lambda (\mu_F + \bar{\nu}_F)} & -\gamma - \lambda \end{array} \right| = 0,$$

which gives the *characteristic equation*

$$(\lambda + \gamma) \left[(\lambda + \gamma)(\lambda + k) + \bar{A}e^{-\lambda \mu_F} \right] = 0,$$

where
$$\bar{A} \equiv -e^{\beta\mu_1} S_0'(\bar{E}) f'(\bar{M}) > 0$$
.

Stability Analysis of Delay Model

Stability Analysis of the Delay Model

The *characteristic equation* is an *exponential polynomial* given by

$$(\lambda + \gamma) \left((\lambda + \gamma)(\lambda + k) + \bar{A}e^{-\lambda\mu_F} \right) = 0,$$

which has one solution $\lambda = -\gamma$.

This shows the stability of the ν_F equation, which was the **state-dependent** portion of the **delay model**.

Remains to analyze

$$(\lambda + \gamma)(\lambda + k) = -\bar{A}e^{-\lambda\mu_F}.$$

The boundary of the stability region occurs at a **Hopf bifurcation**, where the *eigenvalues* are $\lambda = i\omega$, purely imaginary.

Stability Analysis of Delay Model

Properties of the Exponential Polynomial (Characteristic Equation)

$$(\lambda + \gamma)(\lambda + k) + \bar{A}e^{-\lambda\mu_F} = 0.$$

- The solution of the *characteristic equation* has infinitely many roots.
- Discrete delay model is infinite dimensional as the initial data must be a function of the history over the longest delay.
- The *exponential polynomial* has a leading pair of *eigenvalues* and many of trailing having negative real part (*Stable Manifold Theorem*).
- Analysis of the delay model is easier than the generalized age-structured model.
- The models are equivalent under the assumption that V(E) = W = 1.
- Stability changes to oscillatory when the leading pair of eigenvalues cross the imaginary axis, a *Hopf bifurcation*.

Stability Analysis of Delay Model

Hopf Bifurcation Analysis

A Hopf bifurcation occurs when $\lambda = i\omega$ solves the characteristic equation,

$$(i\omega + \gamma)(i\omega + k) = -\bar{A}e^{-i\omega\mu_F}.$$

From complex variables, we match the *magnitudes*:

$$|(i\omega + \gamma)(i\omega + k)| = \bar{A},$$

where the left side is monotonically increasing in ω , and the **arguments**

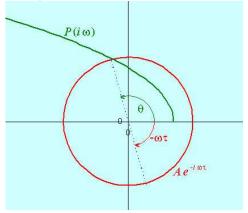
$$\Theta(\omega) \equiv \arctan\left(\frac{\omega}{\gamma}\right) + \arctan\left(\frac{\omega}{k}\right) = \pi - \omega \mu_F,$$

which has infinitely many solutions.

Solve for ω by varying parameters such as γ or μ_F .

Argument Principle

Hopf Bifurcation: One significant method for finding the roots of the *characteristic equation* at a Hopf bifurcation is the **Argument Principle** from complex variables.



Experiments and Model

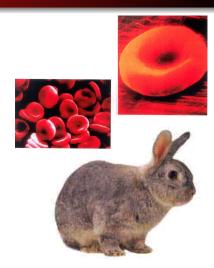
Experiment:

Give rabbits regular antibodies to **RBCs**.

This increases destruction rate γ .

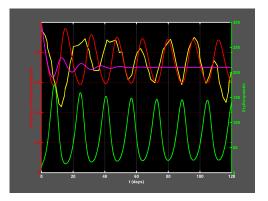
Observe *oscillations* in **RBCs**.

Model undergoes Hopf bifurcation with increasing γ .



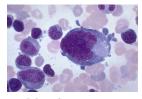
Model for Erythropoiesis

Model can reasonably match the rabbit data by fitting parameters that are reasonable.



The **model** stabilizes with *variable velocity*, V(E), but a more complicated model.

Thrombopoiesis







Platelets

Thrombopoiesis is the process for producing *Thrombocytes* or *Platelets*.

- Platelets are about 20% the size of RBCs and there are only about 10-20% by numbers compared to RBCs.
- They are critical for repairing damage to blood vessels by clumping together and creating clots.
- The half-life for platelets is significantly lower and results in a very high turnover.

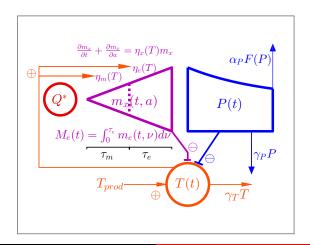
Thrombopoiesis

Thrombocytes or Platelets

- Platelets begin from undifferentiated stem cells (multipotent progenitors), and based on thrombopoietin (TPO) levels multiply then stop dividing and undergo endomitosis, forming megakaryocytes (2-256 nuclei).
- Thrombopoietin (TPO) is produced constantly then absorbed by megakaryocytes and platelets (negative feedback).
- Maturation takes 10-14 days, then *megakaryocytes* protrude **filopodia** into blood vessels and platelets are released.
- Platelets circulate in the bloodstream for about 10 days, then are actively degraded.
- TPO circulates at significantly lower concentrations compared to EPO.

Age-Structured Model for Thrombopoiesis

Age-Structured Model for Thrombopoiesis



Model for Thrombopoiesis Model for Thrombopoiesis

$$\frac{dP}{dt} = \frac{D_0}{\beta_P} m_e (t, \tau_e) - \gamma_P P - \alpha_P \frac{P^{n_P}}{b_P^{n_P} + P^{n_P}},$$

$$\frac{dT}{dt} = T_{prod} - \gamma_T T - \alpha_T \left(M_e (t) + k_S \beta_P P \right) \frac{T^{n_T}}{k_T^{n_T} + T^{n_T}},$$

where

$$m_{e}\left(t,a\right) = V_{m}\kappa_{P}Q^{*}\exp\left[\int_{t-a-\tau_{m}}^{t-a}\eta_{m}\left(T\left(s\right)\right)ds\right]\exp\left[\int_{t-a}^{t}\eta_{e}\left(T\left(s\right)\right)ds\right],$$

$$M_{e}\left(t\right) = \int_{0}^{\tau_{e}}m_{e}\left(t,a\right)da.$$

$$\eta_{m}\left(T\left(t\right)\right) = \eta_{m}^{min} + \left(\eta_{m}^{max} - \eta_{m}^{min}\right)\frac{T^{n_{m}}}{b_{m}^{n_{m}} + T^{n_{m}}},$$

Notes on Model for Thrombopoiesis

Notes on Model for Thrombopoiesis

- The *thrombopoiesis model* is more complex with many more parameters than the *erythropoiesis model*.
- The *Functional differential equation* form is substantially more complex, especially the **2 delays** of maturation (η_m and η_e).
- Age-structure reductions are very similar.
- The negative feedbacks differ significantly.
- Simulations show clear *Hopf bifurcations*.
- *Linear analysis* is significantly more difficult.

Parameters for Model for Thrombopoiesis

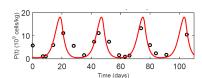
Parameters for Model for Thrombopoiesis

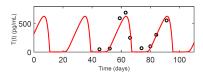
- Over 20 parameters in model.
- Extensive literature search
 - Identify some directly.
 - Fit many with existing experimental data.
 - Insufficient sensitivity analysis at this time.
- Found asymptotically stable equilibrium for normal subject.
- Could vary several parameters (4) to match diseased patients.

Cyclical Thrombocytopenia

Cyclical Thrombocytopenia

- Rare, but dangerous pathological state, with very high and low platelet counts oscillating with about a month period.
- Source of the disease is unknown, but suspect defective peripheral control No good treatment to date.





Unique Equilibrium

From before, we have the **Thrombopoiesis Model**:

$$\begin{split} \frac{dP}{dt} &= \frac{D_0}{\beta_P} m_e \left(t, \tau_e \right) - \gamma_P P - \alpha_P \frac{P^{n_P}}{b_P^{n_P} + P^{n_P}}, \\ \frac{dT}{dt} &= T_{prod} - \gamma_T T - \alpha_T \left(M_e \left(t \right) + k_S \beta_P P \right) \frac{T^{n_T}}{k_T^{n_T} + T^{n_T}}, \end{split}$$

where the functions $m_e(t, \tau_e)$ and $M_e(t)$ are defined as before.

Theorem (Unique Equilibrium)

The **Thrombopoiesis Model** has a unique positive equilibrium, (P^*, T^*) .

Proof: The proof of this result uses the monotonicity of the functions composing the right hand sides of this system of DEs. It is a highly nonlinear system, but the positive and negative feedbacks combine to give a unique equilibrium.

Linearization

Let $x(t) = P(t) - P^*$ and $y(t) = T(t) - T^*$ and ignore higher order terms, then the *linearized system* becomes:

$$\begin{split} \frac{dx}{dt} &= A_2 \left[\partial_T \eta_m(T^*) \int_{t-\tau_e-\tau_m}^{t-\tau_e} y(s) \, ds + \partial_T \eta_e(T^*) \int_{t-\tau_e}^t y(s) \, ds \right] \\ &- \left(\gamma_P + \partial_P F(P^*) \right) x, \\ \frac{dy}{dt} &= -\alpha_T k_S \beta_P G(T^*) x - \left(\gamma_T + \alpha_T (A_1 E_1 + k_S \beta_P P^*) \partial_T G(T^*) \right) y \\ &- \alpha_T A_1 G(T^*) \left(\partial_T \eta_m(T^*) \int_0^{\tau_e} e^{\eta_e(T^*) a} \left(\int_{t-a-\tau_m}^{t-a} y(s) \, ds \right) \, da \\ &+ \partial_T \eta_e(T^*) \int_0^{\tau_e} e^{\eta_e(T^*) a} \left(\int_{t-a}^t y(s) \, ds \right) \, da \right), \end{split}$$

where

$$A_2 = \frac{D_0 V_m \kappa_P Q^*}{\beta_P} e^{\eta_M (T^*) \tau_M + \eta_E (T^*) \tau_E}, \quad A_1 = V_m \kappa_P Q^* e^{\eta_M (T^*) \tau_M}, \quad E_1 = \frac{e^{\eta_E (T^*) \tau_E} - 1}{\eta_E (T^*)}.$$

Characteristic Equation

With solutions of the form $[x(t), y(t)]^T = [c_1, c_2]^T e^{\lambda t}$, the *linear functional equation* becomes:

$$\lambda \mathbf{I} \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} = \begin{pmatrix} -L_1 & L_2(\lambda) \\ -L_3 & -L_4(\lambda) \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \end{pmatrix}.$$

The coefficients L_1 , L_2 , L_3 , and L_4 are given by

$$L_1 = \gamma_P + \partial_P F(P^*),$$

$$L_2(\lambda) = \frac{A_2}{\lambda} \left[\partial_T \eta_m(T^*) e^{-\lambda \tau_e} \left(1 - e^{-\lambda \tau_m} \right) + \partial_T \eta_e(T^*) \left(1 - e^{-\lambda \tau_e} \right) \right],$$

$$L_3 = \alpha_T k_S \beta_P G(T^*),$$

$$\begin{split} L_3 &= \alpha_T \kappa_S \rho_P G(T), \\ L_4(\lambda) &= C_1 + \frac{C_2}{\lambda} \left[\partial_T \eta_m(T^*) \left(1 - e^{-\lambda \tau_m} \right) \frac{\left(1 - e^{-(\lambda - \eta_e(T^*))\tau_e} \right)}{(\lambda - \eta_e(T^*))} \right. \\ &+ \partial_T \eta_e(T^*) \left(\frac{e^{\eta_e(T^*)\tau_e} - 1}{\eta_e(T^*)} + \frac{e^{-(\lambda - \eta_e(T^*))\tau_e} - 1}{\lambda - \eta_e(T^*)} \right) \right], \end{split}$$

Characteristic Equation

From the definitions above the *Characteristic Equation* becomes:

$$\det \begin{vmatrix} -L_1 - \lambda & L_2(\lambda) \\ L_3 & -L_4(\lambda) - \lambda \end{vmatrix} = (\lambda + L_1)(\lambda + L_4(\lambda)) - L_2(\lambda)L_3 = 0.$$

Eliminating the λ terms in the denominator leaves a complicated **exponential polynomial** of the form:

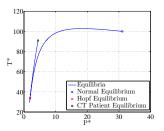
$$P_4(\lambda) + (\alpha_1 \lambda + \alpha_0)e^{-\lambda \tau_m} + (\beta_1 \lambda + \beta_0)e^{-\lambda \tau_e} + (\gamma_1 \lambda + \gamma_0)e^{-\lambda(\tau_e + \tau_m)} = 0.$$

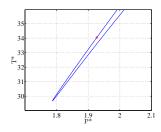
We have **failed** to obtain any analytic intuition on this *exponential polynomial*, but it is readily solved numerically in **Maple** and **MatLab**.

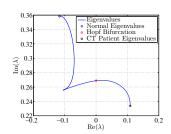
Numerical Hopf Bifurcation

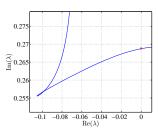
- As noted earlier, parameters were fit for a *normal subject*.
 - Leading *eigenvalues* were $\lambda_1 \approx -0.059 \pm 0.053i$, which has the wrong frequency for observed diseased individuals.
 - The second set of *eigenvalues* were $\lambda_2 \approx -0.114 \pm 0.359i$.
 - λ_2 has appropriate frequency and connects numerically to all diseased patients studied.
- Created hyperline in parameter space connecting the 4
 parameters varied between normal subject and each diseased
 patient.
- Following graphs show variations in the values of the *equilibria* and the *eigenvalues* as the 4 parameters vary continuously.

Numerical Hopf Bifurcation



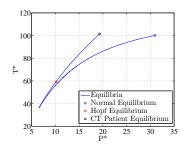


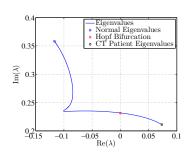




Numerical Hopf Bifurcation

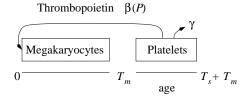
- As the 4 parameters vary linearly, the *equilibria* and the *eigenvalues* vary continuously.
- However, we observe a cusp-like change in a very small region of the hyperline (rapid transition).
- This needs more detailed exploration.





Bélair and Mackey Platelet Model

Two-delay Model for Platelets (Bélair and Mackey, 1987)



$$\frac{dP}{dt} = -\gamma P(t) - \gamma P(t) + \beta (P(t - T_m)) \beta (P(t - T_m)) \beta (P(t - T_m)) - \beta (P(t - T_m)) \beta (P(t - T_m)) \beta (P(t - T_m)) - \beta (P(t - T_m)) \beta (P(t - T_m))$$

Linear loss of platelets, (γP)

Discounted destruction of platelets $(\beta(P)e^{-\gamma T_s})$

Time delays for maturation (T_m) and life expectancy (T_s)

• Examine a modified form:

$$\frac{dP}{dt} = -\gamma P(t) + \frac{\beta_0 \theta^n P(t-R)}{\theta^n + P^n(t-R)} - f \cdot \frac{\beta_0 \theta^n P(t-1)}{\theta^n + P^n(t-1)}$$

- Scaled time to **normalize** the larger delay
- Chose parameters similar to Bélair and Mackey after scaling
- Introduced parameter f, which is different
- Wanted a scaling factor, instead of time delay varying discount.

$$\frac{dP}{dt} = -\gamma P(t) + \frac{\beta_0 \theta P(t-R)}{\theta^n + P^n(t-R)} - f \cdot \frac{\beta_0 \theta P(t-1)}{\theta^n + P^n(t-1)}$$

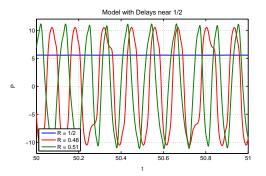


Figure shows stability at $R = \frac{1}{2}$, but irregular oscillations for delays nearby

$$\frac{dP}{dt} = -\gamma P(t) + \frac{\beta_0 \theta P(t-R)}{\theta^n + P^n(t-R)} - f \cdot \frac{\beta_0 \theta P(t-1)}{\theta^n + P^n(t-1)}$$

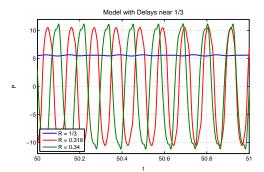


Figure shows stability at $R = \frac{1}{3}$, but irregular oscillations for delays nearby (Same parameters as $R = \frac{1}{2}$)

Two-Delay Differential Equation

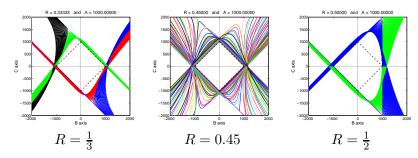
Two-Delay Differential Equation

$$\dot{y}(t) + Ay(t) + By(t-1) + Cy(t-R) = 0$$

- Delay equations are important in modeling
- Two-delay problem
 - E. F. Infante noted an odd stability property observed in a two delay economic model, rational delays created a larger region of stability
 - Multiple delays are important for biological models
 - Developed special geometric techniques for analysis of delay equations
 - JM and T. C. Busken, Regions of stability for a linear differential equation with two rationally dependent delays, DCDS A, 35, 4955-4986 (2015)

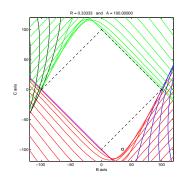
Stability Regions for Different Delays

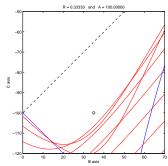
- Technique creates parametric families of curves from the image of the imaginary axis
- Similarity of limited family types prevent approach of Minimum Region of Stability (Black dashed lines)
- Below shows first 100 parametric curves for A = 1000



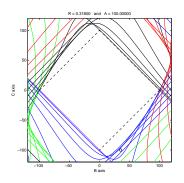
Returning to the modified platelet model

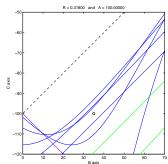
- The coefficients of the linearized model are approximately (A, B, C) = (100, 35, -100) (black circle)
- Our D-partitioning curves for $R = \frac{1}{3}$ are below





- The coefficients of the linearized model are approximately (A, B, C) = (100, 35, -100) (black circle)
- Our D-partitioning curves for R = 0.318 are below





Discussion/Conclusions

- Created age-structured models for hematopoiesis
- Can fit parameters to experimental data
- Reasonably fit normal and diseased patients
 - Provides some insight to *cyclical thrombocytopenia*
- Remains some sensitivity issues with parameters start examining a simpler model
- Ultimately want model to give insights into treatments