

# Lec 1 Reaction Modeling KINETICS

## Mass Action Kinetics

the rate of reaction is equal to probability of collision  $\propto$  con. of the particles.

### Drawbacks:

A large set of ODE to be solved

## Basic Reaction

0th order

$$\frac{dx}{dt} = k \quad \text{constant synthesis}$$

1st order

$$\frac{dx}{dt} = -kx \quad \text{linear degradation}$$

$$x(t) = x_0 e^{-kt}$$

2nd order

$$\frac{d[XY]}{dt} = k[X][Y] \quad \text{heterodimer}$$

$$= k(T_x - [XY])(T_y - [XY])$$

Rule-based modeling. Based on relational network shown in Fig 1.2A

Drawbacks: sets of ODE to describe the model

## Hill Kinetics

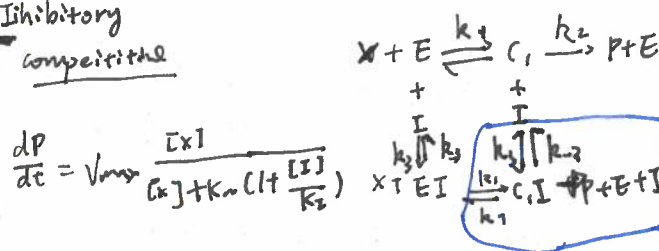
$$\frac{d[P]}{dt} = v_{max} \frac{[X]^n}{K^n + [X]^n}$$

subsequent reaction when the next is triggered by one before.

第一个 low binding 其半饱和  $\pi$  increase

$$K = (\pi k_2)^{1/n}$$

## Inhibitory competitive

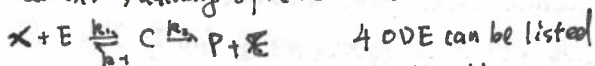


## Allosteric

$$\frac{dP}{dt} = V = \frac{v_{max}}{1 + \frac{I}{K_i}} \frac{[X]}{K_m + [X]}$$

## Simplification Approximation

Quasi-stationary of a reaction



4 ODE can be listed

To avoid non linearization { Grouping Variables, Normalization,

### Michaelis-Menten kinetics

$$\frac{d[EP]}{dt} = k_2[C] = k_2 E_T \frac{k_1 [X]}{k_1 [X] + k_{-1} + k_2} = v_{max} \frac{[X]}{[X] + K_m}$$

$k_2 E_T$  is the maximal rate

$$K_m = \frac{k_{-1} + k_2}{k_1} \quad \text{specificity}$$

$$\frac{d[C]}{dt} = -(k_1 + k_2)[C] + k_{-1} X_T (E_T - [C])$$

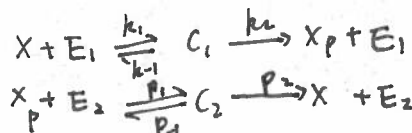
$$\frac{d[C]}{dt} = -[C] + E_T \frac{X_T}{X_T + K_m}$$

This can be solved is needed exponentially fast.

### Requirement/Assumption

Quasi-steady state.

## Goldbeter - Koshland kinetics



Phosphorylation of protein.

$$\frac{d[X_P]}{dt} = -\frac{d[X]}{dt} = k_{phos} \left( \frac{X_T - [X_P]}{K_{m1} + X_T - [X_P]} \right) - k_{de} \left( \frac{[X_P]}{K_{m2} + [X_P]} \right)$$

# Linear stability Analysis for travelling wave systems In 2-component system

The idea is to introduce small perturbation to a system at the **steady state** to study whether the perturbation grows

1. System has to be linearized around ss.
2. Based on the Jacobian matrix the stability is known.

Example  $\begin{cases} \dot{u} = f(u,v) \\ \dot{v} = g(u,v) \end{cases}$   $\vec{x}_s = (u_s, v_s)^T$  is a state

$$\frac{d\vec{x}_s}{dt} = \begin{pmatrix} \dot{u} \\ \dot{v} \end{pmatrix} = 0$$

Let  $w = x - x_s = \begin{pmatrix} u - u_s \\ v - v_s \end{pmatrix}$  be the small perturbation

Stable if  $\vec{w} \rightarrow 0$  as  $t \rightarrow \infty$

Linearized around  $\vec{x}_s$  by Taylor Expansion

$$f(u,v) \approx f(u_s, v_s) + \frac{\partial f}{\partial u} (u - u_s) + \frac{\partial f}{\partial v} (v - v_s)$$

$$g(u,v) \approx g(u_s, v_s) + \frac{\partial g}{\partial u} (u - u_s) + \frac{\partial g}{\partial v} (v - v_s)$$

$$\frac{d\vec{w}}{dt} = \begin{pmatrix} f(u,v) - f(u_s, v_s) \\ g(u,v) - g(u_s, v_s) \end{pmatrix} = \begin{pmatrix} \frac{\partial f}{\partial u} & \frac{\partial f}{\partial v} \\ \frac{\partial g}{\partial u} & \frac{\partial g}{\partial v} \end{pmatrix}_{ss} \begin{pmatrix} u - u_s \\ v - v_s \end{pmatrix}$$

$J$

$J\vec{w} = \frac{d\vec{w}}{dt}$  find eigenvalues "因为要 decouple ODE"

For  $u, v$

$$\lambda_{1,2} = \frac{-tr(J) \pm \sqrt{tr(J)^2 - 4det(J)}}{2}$$

$$\vec{w} = \sum_i w_i \vec{v}_i \Rightarrow \frac{d\vec{w}}{dt} = J\vec{w}$$

$$\sum_i \frac{dw_i}{dt} \vec{v}_i = \sum_i J w_i \vec{v}_i$$

$$\sum_i \frac{dw_i}{dt} \vec{v}_i = \sum_i w_i(t) \lambda_i \vec{v}_i$$

$$\sum_i \left[ \frac{dw_i(t)}{dt} - w_i(t) \lambda_i \right] \vec{v}_i = 0$$

uncoupled since it's eigen-basis

$$\frac{dw_i(t)}{dt} = w_i(t) \lambda_i \Rightarrow w_i = w_i(0) e^{\lambda_i t}$$

$$\Rightarrow \vec{w}(t) = \sum_i w_i \vec{v}_i \exp(\lambda_i t) \quad \lambda_i = Re(\lambda_i) + i Im(\lambda_i)$$

$$= \sum_i \exp[Re(\lambda_i) t] \exp[i Im(\lambda_i) t]$$

$$= \sum_i \exp[Re(\lambda_i) t] [\cos(Im(\lambda_i) t) + i \sin(Im(\lambda_i) t)]$$

$\vec{w}(t)$  depends on  $e^{Re(\lambda_i t)}$

$$\Rightarrow \begin{cases} Re(\lambda_i) \forall i \leq 0, \text{ decays to zero} \Rightarrow \text{STABLE} \end{cases}$$

$$tr(J) < 0 \quad det(J) > 0$$

如  $\lambda_i$  有一个 non-zero imaginary part

$$\vec{w} = \sum_i w_i \vec{v}_i \exp[Re_i t] \{ \cos(Im_i t) + i \sin(Im_i t) \}$$

$$\sum_i w_i \vec{v}_i \exp(Re_i t) (\cos(Im_i t) + i \sin(Im_i t))$$

Oscillations are determined by the imaginary part

## Phase Plane Analysis

Nullclines: where the component derivatives are set to zero eg.  $RCT = 0$  by  $\frac{dR}{dt} = 0$

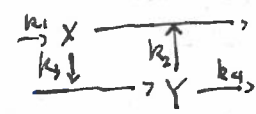
Sets of pts. in the phase plane where the state **DON'T** change wrt time.

Steady State: Pts where All state remains stable wrt time **Intersection of nullcline**

Phase vectors: vectors with length — speed of change direction — where they are going.

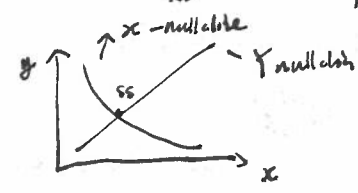
总而言之, 这就是 Graphic methods to find how the dynamic system evolves from a initial point.

那你看那个图的方向的图就是“方向”



$$\frac{dx}{dt} = k_1 - k_2 xy \quad \frac{dy}{dt} = k_3 x - k_4 y$$

$$\begin{aligned} f(u,v) &= 0 & g(u,v) &= 0 \\ y &= \frac{k_1}{k_2 x} & y &= \frac{k_3 x}{k_4} \end{aligned}$$



## Lec 2 Diffusion-based patterning

$c(x, t)$  describes the concentration given location "x" and time "t".

In 1D case:  $\frac{\partial D}{\partial t} = D \frac{\partial^2 c}{\partial x^2}$   $x \in [0, L]$  where it is a bounded domain

How to derive:

Fick's First Law:  $J = -D \frac{\partial c}{\partial x}$  where  $D = \frac{(\Delta x)^2}{2\Delta t}$  The Diffusion coefficient.

Based on the fact Random Walk in a small interval. / h

$$-\frac{1}{2} [N(x+\Delta x, t) - N(x, t)] \rightarrow \leftarrow \begin{matrix} N(x) \\ \text{一半向左一半向右} \end{matrix}$$

$$J = -\frac{1}{2} [N(x+\Delta x, t) - N(x, t)] / \Delta t$$

$$= -\frac{1}{2} \frac{\Delta x^2}{\Delta t} \left[ \frac{N(x+\Delta x, t) - N(x, t)}{\Delta x^2} \right]$$

$$= -\frac{1}{2} D \frac{c(x+\Delta x, t) - c(x, t)}{\Delta x} = -D \frac{\partial c}{\partial x}$$

Flux: the amount of particles moved in a given area  $[a]$

Fick's Second Law:

Based on the conservation of mass.

$$\frac{\Delta c}{\Delta t} = - \frac{J(x+\Delta x, t) - J(x, t)}{\Delta x}$$

$$\frac{\partial c}{\partial t} = - \frac{\partial J}{\partial x} = \frac{\partial}{\partial x} D \frac{\partial c}{\partial x} = D \frac{\partial^2 c}{\partial x^2}$$

In 3D case: It's similar but  $D = \frac{(\Delta L)^2}{6\Delta t}$

First Law:

$$J = -D \nabla c$$

Second Law

$$\frac{\partial c}{\partial t} = -\nabla \cdot J = (\nabla^2 c) \text{ if } D \text{ is constant}$$

$$= -\nabla \cdot (-D \nabla c)$$

## Solving PDE

$$\begin{cases} \frac{\partial c}{\partial t} = D \frac{\partial^2 c}{\partial x^2} & \text{这不是标准模型} \\ c(t, 0) = c(t, L) = 0 & \text{而是一个made up} \\ c(0, x) = \sin x & \end{cases}$$

### 1 separation of variables

$c = T(t) X(x)$  Proposed 假设, 可以这样写

$$\frac{\partial T(t) X(x)}{\partial t} = D \frac{\partial^2 T(t) X(x)}{\partial x^2} \quad D \text{ 可以约去}$$

$$\frac{T'}{T} = \frac{X''}{X} = \lambda$$

For Temporal part  $T'(t) = T(t) \cdot \lambda$

$$\Rightarrow T(t) = T(0) e^{\lambda t}$$

For Spatial part  $X''(x) = \lambda X(x)$

$$\Rightarrow X(x) = c_1 e^{\sqrt{\lambda} x} + c_2 e^{-\sqrt{\lambda} x}$$

### 2

Boundary Condition

$$c(t, 0) = c(t, L) = 0$$

$$\lambda < 0 \Rightarrow \sqrt{\lambda} = i\omega$$

$$X(x) = c_1 [\cos(\omega x) + i \sin(\omega x)] + c_2 [\cos(-\omega x) + i \sin(-\omega x)]$$

$$= \cos(\omega x) [c_1 + c_2] + i \sin(\omega x) [c_1 - c_2]$$

$$c_1 + c_2 = 0 \quad \sin c(t, x) = 0$$

$$\Rightarrow X(x) = 2i c_1 \sin(\omega x) \Rightarrow u = u$$

$$\Rightarrow \lambda = -\omega^2 \quad \omega = 1, 2, \dots$$

By principle of superposition

$$c(t, x) = \sum_{n=1}^{\infty} A_n e^{-\omega_n^2 t} \sin(n\omega x), \quad A_n = 2i c_1 T_0$$

### 3

Initial Condition

$$c(0, x) = \sin x \Rightarrow A_n = \begin{cases} 1, & n=1 \\ 0, & \text{else} \end{cases}$$

$$\text{Final } c(t, x) = e^{-t^2} \sin(x)$$

这个是在 Domain 边界上始终为 0 的情况

Example: IC  $c(x, 0) = 0 \quad x > 0$  i.e. 最初浓度为 0  
BC  $c(0) = c_0 \quad c(L) = 0$  0, 有一端初始为一种浓度.

morphogen

Only Diffusion

$$\frac{\partial c}{\partial t} = D \frac{\partial^2 c}{\partial x^2} \quad x \in [0, L]$$

$$c(x) = c_0 \cdot \frac{1-x}{L} \quad \text{Steady State Solution}$$

Fick-Flag Model 提出的就是这种近似.

If IC:  $c(0, 0) = c_0, \quad c(0, x) = 0 \quad \forall x > 0$

This does not easily agree w/ the general solution

$$c(x, t) = T(0) e^{-\lambda t} [c_1 e^{-\sqrt{\lambda} x} + c_2 e^{\sqrt{\lambda} x}]$$

这样 BC 不满足 因为

$$u(0, t) = T(0) e^{-\lambda t} (c_1 + c_2) \neq c_0$$

## Solution

$$u(x, t) = c(x, t) - c_0(x) \quad \text{where}$$

$$c_0(x) = c_0 \frac{1-x}{L} \quad [x > 0]$$

这样的话

$$\text{BC } u(t, 0) = c(t, 0) - c_0(0) = 0$$

$$u(t, L) = 0$$

$$\text{IC } u(0, 0) = 0$$

$$u(0, x) = -c_0 \frac{1-x}{L} = f(x) \quad \forall x \in [0, L]$$

这满足了 homogeneous Boundary Condition, 这个就能解出来了

Following the steps on the left

$$X(x) = 2i c_1 \sin\left(\frac{n\pi x}{L}\right)$$

$$u(x, t) = \sum_{n=1}^{\infty} A_n e^{-\frac{n^2 \pi^2}{L^2} t} \sin\left(\frac{n\pi x}{L}\right) \quad A_n = 2i c_1 T_0$$

IF

$$u(0, x) = -c_0 \frac{1-x}{L} = f(x) = \sum_{n=1}^{\infty} A_n e^{-\frac{n^2 \pi^2}{L^2} t} \sin\left(\frac{n\pi x}{L}\right)$$

积分乘以  $\sin\left(\frac{m\pi x}{L}\right)$  Integrate from  $[0, L]$

$$\int_0^L f(x) \sin\left(\frac{m\pi x}{L}\right) dx = \int_0^L \sum_{n=1}^{\infty} A_n \sin\left(\frac{n\pi x}{L}\right) \sin\left(\frac{m\pi x}{L}\right) dx$$

$$\int_0^L \sin\left(\frac{n\pi x}{L}\right) \sin\left(\frac{m\pi x}{L}\right) dx = 0 \quad \forall m \neq n$$

=>

$$\int_0^L f(x) \sin\left(\frac{n\pi x}{L}\right) dx = \frac{1}{2} A_n$$

$$\Rightarrow A_n = \int_0^L f(x) \sin\left(\frac{n\pi x}{L}\right) dx \cdot \frac{2}{L}$$

$$= -\frac{2c_0}{n\pi}$$

Thus the final solution is  $c(t, x) = c_s(t, x) + u(t, x)$

$$= c_0 \frac{L-x}{L} + \sum_{n=1}^{\infty} \frac{2c_0}{n\pi} e^{-D \frac{n^2 \pi^2}{L^2} t} \sin\left(\frac{n\pi x}{L}\right)$$

Time to steady state

$$t = \frac{1}{k} = \frac{L^2}{D n^2 \pi^2}$$

since it reaches s.s. exponentially faster with rate  $k$

Constant Morphogen inflow

Example

IC:  $c(x, 0) = 0$

BC:  $\frac{\partial c}{\partial x}|_0 = -j$   $\frac{\partial c}{\partial x}|_L = 0$

$c_s(x) = ax + b$   $\Rightarrow$  no s.s.

If BC:  $\frac{\partial c}{\partial x}|_0 = -j$   $c(L, t) = 0$

$a = -j$   $b = Lj$   $c_s(x) = -jx + Lj$

With degradation

$$\frac{\partial c}{\partial t} = D \Delta c - kc \quad x \in [0, 1]$$

IC:  $c(x, 0) = 0$

BC:  $\frac{\partial c}{\partial x}|_0 = -j$   $\frac{\partial c}{\partial x}|_1 = 0$

$c(x) = a e^{\mu x} + b e^{-\mu x}$   $\mu = \sqrt{\frac{k}{D}}$  is the general solution

Importance of degradation

也是分离: Separation of variables

$\frac{1}{T} + k = 0 \Rightarrow \frac{k}{X}$

同样也是 Inhomogeneous 同样也是 减法 ( $c_s(x)$ )

Without degradation

$$\frac{\partial c}{\partial t} = D \Delta c$$

BC:  $\frac{\partial c}{\partial x}|_0 = -j$   $c(L, t) = 0$

$\Rightarrow c_s(x) = ax + b$

Standard Model: Boundary at infinity.

$$\frac{\partial c}{\partial t} = D \Delta c - kc \quad ; \quad 0 \leq x \leq \infty$$

IC:  $c(x, 0) = 0$

BC:  $c(0, t) = c_0$ ,  $c(x \rightarrow \infty) = 0$

Steady state solution

$$c(x) = c_0 \exp\left(-\frac{x}{\lambda}\right) \quad \lambda = \sqrt{\frac{D}{k}}$$

Lec 3 Morphogen gradient

How does the system maintain robustness with morphogen gradient?  
How will the readout at steady state be affected by change in changing term?

SEC self-enhanced decay.

$\frac{\partial c}{\partial t} = D \Delta c - f(c)$   
BC:  $\left\{ \begin{array}{l} \textcircled{1} \text{ Fixed con. at both ends} \\ c(0,t) = c_0 \text{ \& } c(L,t) = 0 \\ \textcircled{2} \text{ Fix. at source} \\ c(0,t) = c_0 \\ c(x \rightarrow \infty) = 0 \\ \textcircled{3} \frac{\partial c}{\partial x} \Big|_0 = -j; \quad \frac{\partial c}{\partial x} \Big|_L = 0 \end{array} \right.$   
IC:  $c(x \rightarrow 0, 0) = 0$   
 $f(c)$ :  
none  $\rightarrow$  linear gradient  
linear  $\rightarrow$  exponential gradient  
non-linear  $\rightarrow$  power-law gradient

For linear degradation  $c(x) = c_0 \exp\{-\frac{x}{\lambda}\}$   $\lambda = \sqrt{\frac{D}{k}}$   
standard model with  $c(x \rightarrow \infty) = 0$

In the setting of the standard model:

$\Delta x = x_0^* - x_0$   
 $c_0 = c_0^* \exp\{-\frac{x_0}{\lambda}\}$   $c_0^* = c_0^* \exp\{-\frac{x_0^*}{\lambda}\}$   
 $\frac{c_0^*}{c_0} = \exp\{-\frac{x_0}{\lambda} + \frac{x_0^*}{\lambda}\}$   $\Delta x = x_0^* - x_0 = \lambda \ln(\frac{c_0^*}{c_0})$

Readout shift

$\Delta x = \lambda \ln \frac{c_0^*}{c_0}$

Power-law (Non-linear decay)

PDE:  $\frac{\partial c}{\partial t} = D \Delta c - k c^n$

$c(x) = \frac{1}{A(x+\epsilon)^m}$  ;  $m = \frac{2}{n-1}$

$\ln(x_0^* + \epsilon) - \ln(x_0 + \epsilon) = \frac{1}{m} \ln(\frac{A^*}{A})$  shift

shift

shift



# D\wangyong (82.130.107.167)

ec4. Morphogen Gradients on growing domain.

How do we get the Reaction-Diffusion Equations

Reasoning: Total temporal change in  $\Omega$  = change due to  $j$  (fluxes) and Reaction  $R(c)$

$$\frac{d}{dt} \int_{\Omega} c_i(x,t) dx = \int_{\partial\Omega} j_n dS + \int_{\Omega} R(c) dx.$$

$$\int_{\Omega} \frac{dc_i}{dt} dV = - \int_{\Omega} \nabla \cdot j dx \quad (\text{Divergence Thm})$$

$\nabla \cdot j = -D \Delta c$

$$\int_{\Omega} \frac{dc_i}{dt} dV = \int_{\Omega} (D_i \Delta c_i + R(c)) dV$$

$$\int_{\Omega} \left[ \frac{dc_i}{dt} - D_i \Delta c_i - R(c) \right] dV = 0$$

$$\Rightarrow \frac{dc_i}{dt} = D_i \Delta c_i + R(c)$$

On a growing domain

Mapping  $\Omega_0 \rightarrow \Omega_t$

$$\begin{aligned} \frac{d}{dt} \int_{\Omega_t} c_i(x,t) dx &= \frac{d}{dt} \int_{\Omega_0} c_i(x(s,t),t) \det J ds \\ &= \int_{\Omega_0} \left[ \frac{dc_i}{dt} \det J + c_i \frac{d(\det J)}{dt} \right] ds \\ &= \int_{\Omega_0} \left[ \frac{dc_i}{dt} + u \nabla c_i + c_i \nabla u \right] \det J ds \\ &= \int_{\Omega_t} \left[ \frac{dc_i}{dt} + \nabla c_i u \right] dx \end{aligned}$$

$$\Rightarrow \frac{dc_i}{dt} + \nabla c_i u = D_i \Delta c_i + R(c) \quad \frac{dx}{dt} \text{ velocity}$$

⌊ Lagrangian Framework

粒子追踪法

Mapping b/w  $\psi$  is able to map from Euler to Lagrangian

$(x,t) \rightarrow (X,t)$

Euler.

Material Derivative

$$\frac{dF}{dt} = \frac{dF(x(X,t),t)}{dt} = \frac{dF(X,t)}{dt}$$

$F = F(x,t)$ : the value of  $F$  experienced at time  $t$  by the particle initially at  $x$

$$\frac{dF(X,t)}{dt} = \frac{\partial F}{\partial t} \Big|_x + \frac{\partial F}{\partial x_k} \frac{\partial x_k(X,t)}{\partial t} = \frac{\partial F}{\partial t} \Big|_x + u \nabla F$$

Lag

Euler.

In the case of uniform growth, stays the same in Lag.

⌊ ALE

advection dilution

$$\frac{dc_i}{dt} \Big|_x + u \nabla c_i + c_i \nabla u = D_i \Delta c_i + R(c_i)$$

$u = u - v$  [the velocity b/w materials and ALE]

material velocity

Example Uniform Growth

$x \sim$  stationary dom

$x(t) = L(t)x \sim$  Euler

把 Euler 坐标  $\rightarrow$  Lag 坐标

$$\frac{\partial x}{\partial t} = \frac{1}{L(t)} \quad u = \frac{dx}{dt} = \dot{L}(t)x \quad \frac{\partial u}{\partial x} = \dot{L}(t)$$

$$\frac{\partial c}{\partial t} + \nabla(cu) = D \frac{\partial^2 c}{\partial x^2} + R(c)$$

$$\frac{dc}{dt} + c \frac{\partial u}{\partial x} = D \frac{\partial^2 c}{\partial x^2} + R(c)$$

$$\frac{dc}{dt} + c \cdot \frac{\partial u}{\partial x} \cdot \frac{\partial x}{\partial x} = D \frac{\partial^2 c}{\partial x^2} \left( \frac{\partial x}{\partial x} \right)^2 + R(c)$$

$$\frac{dc}{dt} + c \cdot \dot{L}(t) \cdot \frac{1}{L(t)} = D \frac{\partial^2 c}{\partial x^2} \left( \frac{1}{L(t)} \right)^2 + R(c)$$

# lec 5 Turing Pattern

Patterns: SS (in-time) solution of sets of equations

$$\dot{u} = f(u, v) + D_1 \Delta u \quad \text{Diffusion term}$$

$$\dot{v} = g(u, v) + D_2 \Delta v$$

$$I: \quad u(x, 0) = u_0(x) \\ v(x, 0) = v_0(x)$$

$$\vec{w} = \begin{pmatrix} u - u^* \\ v - v^* \end{pmatrix} \quad \dot{\vec{w}} = J \vec{w}$$

$$w(x, t) = \sum_{i=1} a_i \vec{v}_i \exp(\lambda_i t)$$

$$\lambda_i = \frac{\text{tr}(J) \pm \sqrt{\text{tr}(J)^2 - 4 \det J}}{2}$$

$\lim_{t \rightarrow \infty} w(x, t) \rightarrow 0$  we have a stable system

$$\Rightarrow \lambda_i < 0 \quad \forall i=1, 2$$

$$\Rightarrow \text{tr}(J) < 0 \quad \det(J) > 0$$

## With Diffusion

$$\dot{\vec{w}} = J \vec{w} + D \Delta \vec{w} \quad D = \begin{bmatrix} D_1 & 0 \\ 0 & D_2 \end{bmatrix} \quad \begin{matrix} D_1 > 0 \\ D_2 > 0 \end{matrix} \quad \text{"Biological"}$$

1. By separation of variables

$$\vec{w} = \phi(t) w(x) \quad \begin{cases} \dot{\phi} = J \phi \\ \phi(t) = \sum_i a_i \vec{v}_i \exp(\lambda_i t) \\ w(x) = \sum_i a_i \vec{v}_i \exp(i k x) \end{cases} \quad \begin{cases} \dot{\phi} = J \phi \\ J w = -D \Delta w \end{cases}$$

$$w = \sum_i a_i \vec{v}_i \exp(\lambda_i t + i k x)$$

$$\begin{cases} \dot{\vec{w}} = \lambda \vec{w} \\ J \vec{w} + D \Delta \vec{w} = J \vec{w} - k^2 D \vec{w} \end{cases} \quad \text{因为可以代表或解出}$$

$$\Rightarrow \lambda \vec{w} = J \vec{w} - k^2 D \vec{w}$$

$$(H - \lambda I) \vec{w} = 0 \quad H = J - k^2 D$$

2. 非平凡 Non-trivial solution 存在

$$\det(H - \lambda I) = 0$$

$$\det(H) + \lambda^2 - \lambda \text{tr}(H) = 0$$

$$\Rightarrow \text{tr}(H) = \text{tr}(J) - k^2(D_1 + D_2)$$

$$\det(H) = D_1 D_2 k^4 - (D_2 f_u + D_1 g_v) k^2 + \det(J)$$

instability requires  $\det(H) < 0$

$$\Rightarrow D_2 f_u + D_1 g_v > D_1 D_2 k^2 + \frac{\det(J)}{k^2} > 0$$

$$\det(H) = h(k^2) \quad \text{二次方程}$$

$$k_{\min}^2 = \frac{D_2 f_u + D_1 g_v}{2 D_1 D_2}$$

$$\Rightarrow \det(H) = h_{\min} = -\frac{(D_2 f_u + D_1 g_v)^2}{4 D_1 D_2} + \det(J) < 0$$

$$-(D_2 f_u + D_1 g_v)^2 + 4 D_1 D_2 \det(J) < 0$$

要证  $D_2 f_u + D_1 g_v > 0$  且  $g_v + f_u = \text{tr}(J) < 0$

$\Rightarrow D_1, D_2$  不同且  $g_v + f_u$  不同方向

If  $\Omega = [0, L]$  zero flux

$$\sum a_n \vec{v}_n \exp(\lambda_i k^2 t) \cos\left(\frac{n\pi x}{L}\right)$$

Zero-flux  $(\vec{n} \cdot \nabla) \vec{w} = 0$  on  $\partial\Omega$

$$w(x) = \sum_n a_n \cos\left(\frac{n\pi x}{L}\right) \quad k^2 = \frac{n^2 \pi^2}{L^2}$$

$$\text{边界} \sin(kL) = 0 \Rightarrow kL = n\pi$$

$$v(x) = \sum_n a_n \exp(i k x) = \sum_n a_n \exp(i k x)$$

$$= \sum_n a_n (\cos(kx) + i \sin(kx)) \quad \sin kL = 0$$

$$= \sum_n a_n \cos\left(\frac{n\pi x}{L}\right)$$

Summary. 2-component system

$$\frac{\partial u}{\partial t} = D_1 \nabla^2 u + f(u, v)$$

$$\frac{\partial v}{\partial t} = D_2 \nabla^2 v + g(u, v)$$

Turing Instability iff

$$\begin{cases} f_u + g_v < 0 \Leftrightarrow \text{tr}(J) < 0 \\ \det(J) > 0 \\ D_1 g_v + D_2 f_u > 2 \sqrt{D_1 D_2 \det(J)} \end{cases}$$

STABLE solution w/o Diffusion

This is unstable w/o diffusion

Lec 9 Travelling wave.

$u(x,t)$  represents a travelling wave it will travel without change of shape. } speed of propagation is a const.  $c$

$Ca^{2+}$  wave in Amphibian eggs

$$u(x,t) = u(x-ct) = u(z) \quad z = x - ct$$

$z$  is the wave variables,

Example Logistics growth

general solution:

$$u(x,t) = \frac{c \exp(t)}{1 + c \exp(t)}$$

If IC:  $u(x,0) = \frac{1}{1 + \exp(x)}$

$\Rightarrow u(x,t) = \frac{\exp(t-x)}{1 + \exp(t-x)} \quad z = x - t$

Since  $z$  is const. then the shape does NOT change  
i.e.  $\frac{dx}{dt} = 1$

Wave pinning

If a travelling wave eventually halts. the phenomenon is referred as wave pinning.

PDE  $\Rightarrow$  sets of ODEs

$$u(x,t) = u(x-ct) = u(z)$$

$$\begin{cases} \frac{\partial u}{\partial t} = -c \frac{du}{dz} \\ \frac{\partial u}{\partial x} = \frac{du}{dz} \end{cases}$$

Diffusion

$$\frac{\partial u}{\partial t} = D \frac{\partial^2 u}{\partial x^2} \Rightarrow u_t = D u_{xx}$$

$\Rightarrow D u'' + c u' = 0$  since we have  $u_t = -c \frac{du}{dz}$

$\Rightarrow u(z) = A + B \exp(-cz/D)$  has to be bounded and non-negative.

$\Rightarrow B=0$  There's no physically realistic travelling solution for linear parabolic PDEs.

An additional term  $f(u)$

$$u_t = f(u) + D u_{xx}$$

$$D u'' + c u' + f(u) = 0$$

① Fisher equation  $f(u) = ku(1-u)$

undimensional  $u_t = ku(1-u) + D u_{xx}$

$$\begin{cases} u_t = u(1-u) + u_{xx} \\ u'' + c u' + u(1-u) = 0 \end{cases} \Rightarrow \begin{cases} u' = v \\ v' = -c v - u(1-u) \end{cases}$$

Determine the linear stability of the system

$$\vec{w} = (u - u_s, v - v_s)^T$$

$$\frac{d\vec{w}}{dt} = \begin{pmatrix} 0 & 1 \\ -c & -1 \end{pmatrix} \vec{w} = J \vec{w} \quad \lambda_{1,2} = \frac{-(1) \pm \sqrt{1 + 4c}}{2}$$

然  $f(u)$  可以  $u$  的 Nullline ..

$$\begin{aligned} u' &= v \\ v' &= -c v - u(1-u) \end{aligned} \quad \begin{matrix} (1,0) \text{ saddle node} \\ (0,0) \text{ stable pt.} \end{matrix}$$

For Travelling waves to exist we require one stable node and one saddle node.

$Ca^{2+}$  stimulated calcium release mechanism

$$\dot{u} = f(u) + D u_{xx} \Rightarrow D u'' + c u' + f(u) = 0$$

-kinetics for  $Ca^{2+}$ :  $\dot{u} = A(u) - r(u) + L = f(u)$

$$= \frac{k_1 u^2}{k_2 + u^2} - k_3 u + L$$

$$= A(u - u_1)(u - u_2)(u - u_3)$$

By looking at the graph of  $f(u)$

$\Rightarrow u' = \frac{du}{dz} = \alpha(u - u_1)(u - u_3)$

$$u' = \frac{du}{dz} = \alpha(u - u_1)(u - u_3) \quad \text{因 } u' = 0 \text{ at } u_1, u_3$$

$$\Rightarrow u'' = \alpha(2u - u_1 - u_3) u'$$

$$\Rightarrow \text{the } D \alpha(2u - u_1 - u_3) u' + \alpha(u - u_1)(u - u_3) + f(u - u_1) \dots = 0$$

$$(u - u_1)(u - u_3) [D \alpha(2u - u_1 - u_3) + \alpha(u - u_2)] = 0$$

To be zero for all  $u$



# lec 10 chemotaxis

the presence of a gradient in a chemoattractant give rise to movement up the con. gradient

## Continuum Model

(cell density  $n(x,t)$   
chemo  $c(x,t)$ )

1. Random Walk Diffusion

2. Chemical Flux

$$J_c = -\chi n \frac{\partial c}{\partial x} \quad \begin{matrix} \chi: \text{repell} \\ a: \text{attract} \end{matrix}$$

$$J_c = \chi n \frac{\partial c}{\partial x}$$

Keller-Segel Model

$$\begin{matrix} J_c = \chi n \nabla c & \text{chem} \\ J_D = -D \nabla n & \text{diffu} \end{matrix} \quad J = J_c + J_D$$

## General Model

$$\begin{matrix} \text{cells:} & \frac{\partial u}{\partial t} = D_u \nabla^2 u - \alpha \nabla \cdot (u \nabla v) + f(u,v) \\ \text{attractant:} & \frac{\partial v}{\partial t} = D_v \nabla^2 v + g(u,v) \end{matrix}$$

Parameter:  $\alpha, \chi, D_u, D_v$

To have patterns: Unstable steady state  $\Rightarrow$  Linear stability analysis.

$\vec{w} = \epsilon (u_i)$  around the steady state

$$\frac{\partial \vec{w}}{\partial t} = D \Delta \vec{w} + J \vec{w} \quad D = \begin{pmatrix} D_u & -\alpha u^* \chi v^* \\ 0 & D_v \end{pmatrix}$$

also using separation of variable.

$$J = \begin{pmatrix} f_u^* & f_v^* \\ g_u^* & g_v^* \end{pmatrix}$$

$$\Rightarrow w_i = \phi_i(x) w_i(x) = \exp(\lambda_i t) \cdot \exp(ik \cdot x)$$

与 Turing Pattern 那章相似

$$\frac{\partial w}{\partial t} = \lambda w = J \vec{w} + D \Delta \vec{w} = J \vec{w} - k^2 D \vec{w}$$

特征方程

$$\Rightarrow H \vec{w} = \lambda \vec{w} \quad H = J - k^2 D$$

$$H = \begin{pmatrix} f_u^* - D_u k^2 & f_v^* + \alpha \chi u^* k^2 \\ g_u^* & g_v^* - D_v k^2 \end{pmatrix}$$

稳定性分析

$$\text{Real part of } \lambda(i) < 0 \Rightarrow \text{tr}(J) = (f_u^* + g_v^*) < 0$$

what is a big mean or small mean?

the energy functions of this system  $\vec{s} = \{s_1, \dots, s_N\}$

$$H(\vec{s}) = - \sum_{i,j} J_{ij} s_i s_j - \sum_i h_i s_i$$

interaction      external affect

$\vec{s} \sim$  Boltzmann dist.

MWC - subclusters divided but little sure configure

Special case of the cluster.

$$\begin{cases} J = \infty & \text{同构} \\ J = 0 & \text{不同} \end{cases}$$

控制模拟 protein subunit interaction.

E. coli chemotaxis signal

加多 signal / ligand 的形状 运动 保持大致不变



Negative Feedback with a buffer node

Continuous Tissue Models

为啥不太会去写 cell-based 模型

cell-based modelling

why? since various cellular activities can be easily represented via this method

1. Cellular Potts Model. (on lattice)

aka Ising Model 自旋模型

- spin  $\phi(x) \in \mathbb{Z}^{+,0}$
- value: cell identity

Hamiltonian: Energy function describes how it evolves over time

$H = H_v + H_a$   
volume constraint      adhesion

Using Metropolis algo. to calculate the spin value and how it progress over time.

- Initialization: Random
- Real data.

2. Spheroid Model

- Represent cells as particles spherical
- Determined all the same of the form  $\rightarrow$  Movement

(eq)

3. Subcellular Model.

Using potery function (Morse potential)  
 $\Rightarrow$  Force acting on each subcellular components  
 $\Rightarrow$  Movement.

4. Vertex Model.

- Polygonal / sharing edges
- Forces derived from potentials. at each vertex

$$\mathcal{E}(C_i) = \sum_{\alpha} \frac{K_{\alpha}}{2} (A_{\alpha} - A_{\alpha}^0)^2 + \sum_{\langle ij \rangle} A_{ij} I_{ij} + \sum_{\alpha} \frac{\Gamma_{\alpha}}{2} L_{\alpha}^2$$
  
Elastic compared to resting area      Tension      Contractility

5. Immersed Boundary Cell Model

- Vertex 自旋模型
- cell-cell junction also approximated.

	Pros	Cons
Cellar Point	Simple, high abson	Expensive as you have to calculate at each time step.
Spherical	No cell Cheap.	No cellular details only spherical. No signaling / restricted
Subcellular	Shape details.	expensive
Vertex	details $\uparrow$ efficient	Shared edges.
LI 13	No junction 自旋	2D, expensive.

- Epithelial cells are well connected via a ring of Intercellular junctions.
- Usually the boundary are well-defined as a 'poly gonad' shape why on average we only have 6 neighbours.

1. Abov-van Leeuwen

$$M_n = 5 + \frac{8}{n}$$
 its average no. of neighbors

2. Lewis's Law

cell Area related to Polygon class

$$A_n = \frac{A_0}{N} \left( \frac{n-2}{4} \right)^2$$
 edge.

Total num of cells

3. Euler's Theorem - Averaging Neighbour Number.

$$F - E + V = \chi$$
  
Faces      Edge      vertices      geometrical character of the manifold

$$\sum n F_n = 2E$$

每个 edge 连接两个 vertex

$$\sum n F_n = F \sum \langle n \rangle = F \langle n^2 \rangle$$
 average number

$$F + \frac{2-\alpha}{\alpha} E = \chi \Rightarrow F + \frac{2-\alpha}{\alpha} \sum n F_n = \chi$$

$$\Rightarrow \langle n \rangle = \frac{2\alpha}{\alpha-2} + \frac{2\alpha\chi}{(\alpha-2)F}$$

limit of  $\langle n \rangle$  goes to  $\frac{2\alpha}{\alpha-2}$ . 在 2D  $\alpha=3 \Rightarrow$

1. Impact of cell size distrib. MC Theory I guess

2. Tissue Mechanics Modelled by vertex models.

$$F - E + V = \chi$$

$$V = \frac{2E}{\alpha}$$

$$E = \sum \frac{1}{2} n F_n$$