

# Optimal Control of the Intestinal Microbiome using Lotka-Volterra Model

(BB-JR)

Stein et al.  
Jones et al.

## 1. Mathematical Model

$$\dot{x}_i = \underbrace{(d_i - g_i x_i)}_{\text{Lotka-Volterra}} (\beta x_i + r) + \underbrace{(d_i - g_i x_i) \sum u_i(t)}_{\text{Probiotic, Antibiotic}} \epsilon_i + \underbrace{\sum \lambda_i S(t - t_i) v_i}_{\text{Transplantation, bactericide}}$$

- $x = (x_1, x_2, \dots, x_N) \quad N = 11$

- $x_1 = C\text{-difficile} \text{ (infected population)}$

Complexity  $X(x) = (d_i - g_i x_i)(\beta x_i + r)$   
up to  $2^{11} = 2048$  equilibria

Aim: Reduce  $x_1$ -population

- Two types of controls

- Probiotics, antibiotics : permanent care but can be set in the sample-data control frame
- Transplantation, bactericides : invasive treatments : sampled-data control frame.

Volterra 1931

### Origin of the Model : Lotka-Volterra

Historical d'Ancona : study the effect of the reduction of the fishing during the First World War on a prey-predator model :

$$\begin{aligned}\dot{N}_1 &= N_1 [r_1 - \alpha \lambda(t) - \alpha_{12} N_2] \\ \dot{N}_2 &= N_2 [-r_2 - \beta \lambda(t) + \alpha_{21} N_1]\end{aligned}$$

- $\lambda(t) = 0$  : no fishing
- Every trajectory is periodic
- $S^2 = (K_1, K_2)$  : interior equilibria

Theorem  $\underbrace{\langle N_i \rangle}_{\text{Averaged population}} = \frac{1}{T} \int_0^T N_i(t) dt = K_i$

- $\lambda(t) = ct$  : intensity of the fishing activity

Effect Shift the interior equilibria  
and the averaged population

### Objective of the talk

[Present the techniques from optimal control to analyze the problem]

- Step 1 { One antibiotic or probiotic only :  $\dot{x} = X(x) + u \gamma(x)$   
 $u \in [0,1]$
- Step 2 2d-case
  - $x_1$  : C-difficile population
  - $x_2$  : reduced model : aggregation of  $(x_2, \dots, x_N)$

Formulation optimal problem terminal manifold  $N$

- $\text{Min } x_1(E_F)$   $\Longleftarrow$  dual Reach :  $x_1(b_F) = 0$   
in minimum time
- Indirect Method : Maximum Principle  
(permanent case and sampled-data case)
- Direct Methods : MPC scheme

## Sketch of the analysis

### Maximum Principle

Open loop analysis :

$(x(\cdot), u(\cdot))$  optimal on  $[0, t_f]$  s.t.

of :

$$H = p \cdot \dot{x} + u r$$

$$\left\{ \begin{array}{l} \dot{\bar{x}} = \frac{\partial H}{\partial p}, \quad \dot{\bar{p}} = -\frac{\partial H}{\partial x} \\ H(x, p, u) = \max_{N \leq i} H(x, p, v) \end{array} \right.$$

## Classification

• Regular controls:  $u(t) = 1$  if

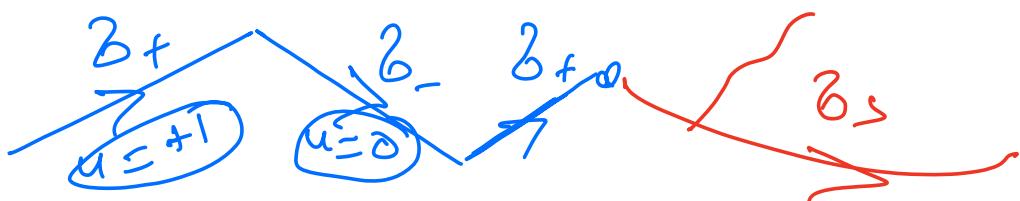
$p(t) \cdot r(gc(t)) > 0$  and  $u(t) = 0$  if

$p(t) \cdot r(gc(t)) < 0$

• Singular case  $p(t) \cdot r(gc(t)) \approx 0$

identically.

singular arc



## Computations singub- a/cs

Derive 1 t :  $P(E) \cdot Y(\eta c(t)) = 0$

$$-P \cdot \frac{\partial X}{\partial x} + u \frac{\partial Y}{\partial x} + P \cdot \frac{\partial Y}{\partial x} (x + uY) = 0$$

Hence  $P(E)[Y, X](\eta c(t)) = 0$  Lie bracket

Derive 1 E

$$P(E) \cdot [Y, X](\eta c(t)) + u_s [Y, X](\eta c(t)) = 0$$

Theorem Singub- a/cs are located on the determinantal set  $\mathcal{S}$ :  $\det(Y, [Y, X]) = 0$  and the singular control is given by :

$$u_s(k) = u_s(\eta c) = -\frac{\det(Y, [Y, X])}{\det(Y, [[Y, X], X])}$$

Computation  $\{X, Y\}$   $\begin{cases} X : (\text{diag } \eta c)(Ax + r) \\ Y : (\text{diag } \eta c) \in \end{cases}$

Singular locus In the permanent domain:  $x > 0, y > 0$  :  $\mathcal{S}$  = line passing through the origin

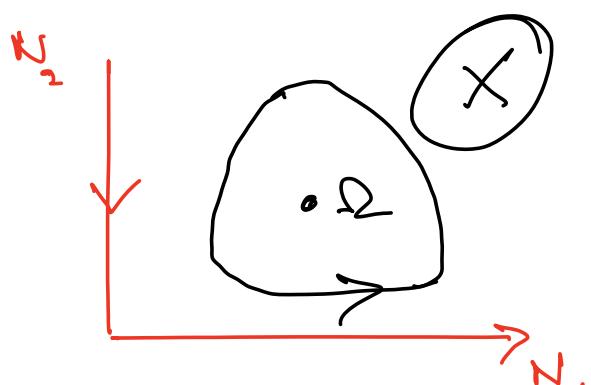
Collinear locus  $\mathcal{C}$  :  $\det(X, Y) = 0$

## Back to Lotka-Volterra model

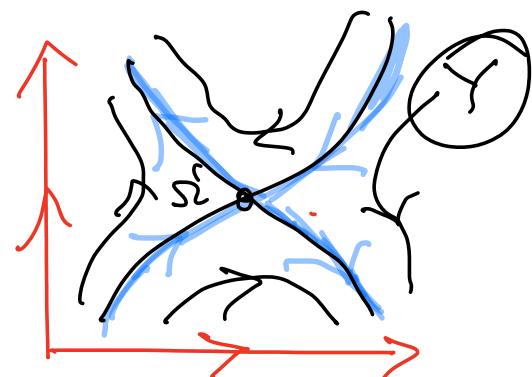
$$\dot{N}_1 = N_1(r_1 - a_{12}N_2)$$

$$\dot{N}_2 = N_2(r_2 - a_{21}N_1)$$

Two different cases



Prey-predator :  $\rightarrow$   
Equilateral Ellipse



Equilateral Hyperbola

Control system  $\dot{x} = uX + (1-u)Y$   
 $u \in [0,1]$

$u = \lambda$  Bifurcation parameter

$$X \rightarrow Y$$

Interpretation

$$\begin{cases} u=0 & : \text{no treatment} \\ u=1 & : \text{maximal dosing} \end{cases}$$

For every intermediate value  $u = \lambda$  there exist a constant control  $u_c$  such that  $(X + Y)(u_c)$  admits a persistent equilibria

$$x_e = \Omega(\lambda)$$

Hence One has a general picture in the 2d-case to analyze the problem geometrically using:

$\mathcal{S}$ : singular locs

$\mathcal{G}$ : collinearity locs



key point Understanding the time minimal synthesis (closed loop optimal control) at the point O.

Construction of a semi-normed form

$$\begin{cases} \dot{x} = -\alpha x + w y + \alpha^2 y^2 \\ \dot{y} = (u - u_e) \end{cases}$$

$$X \left| \begin{array}{l} -x + w y + \alpha^2 y^2 \\ -u_e \end{array} \right. \quad Y \left| \begin{array}{l} 0 \\ 1 \end{array} \right.$$

Singular line  $\approx y=0$

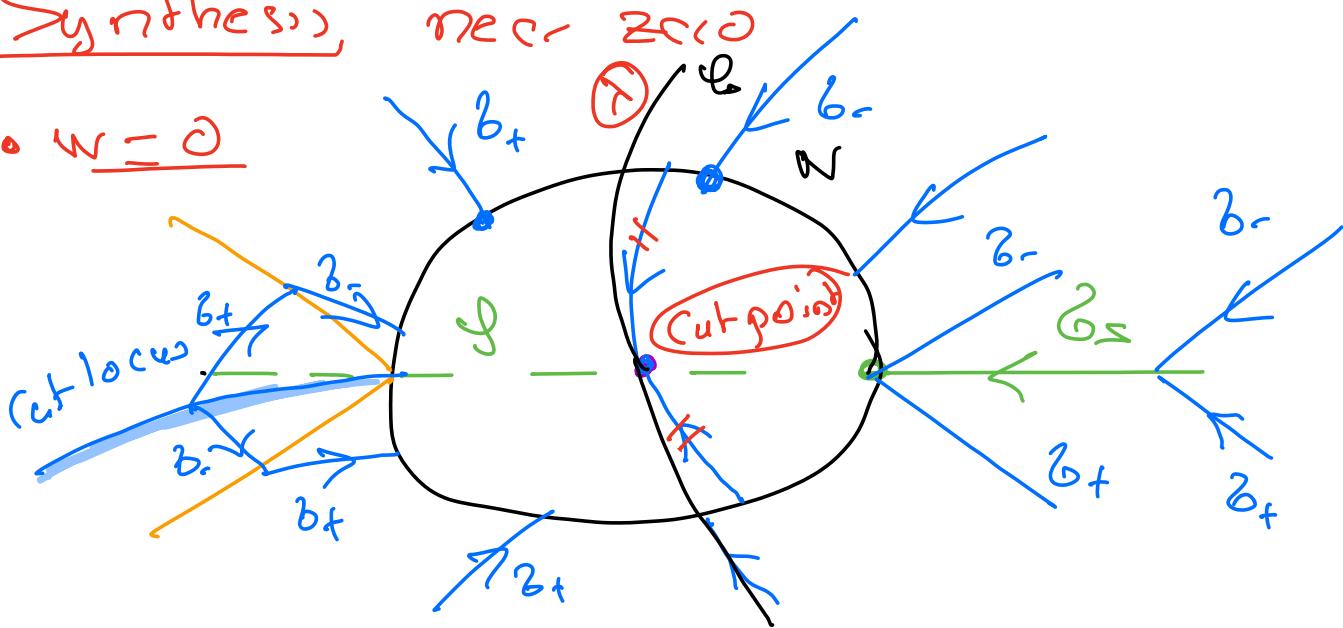
Singular dynamics  $\dot{x} = -\alpha x$

$$\bullet \{X, Y\} = \begin{bmatrix} w + 2\alpha y & [X, Y], Y \\ 0 & 0 \end{bmatrix} \Bigg| \begin{array}{l} 2\alpha \\ 0 \end{array}$$

Target  $N$ : circle of radius  $0$   
centered at  $0$

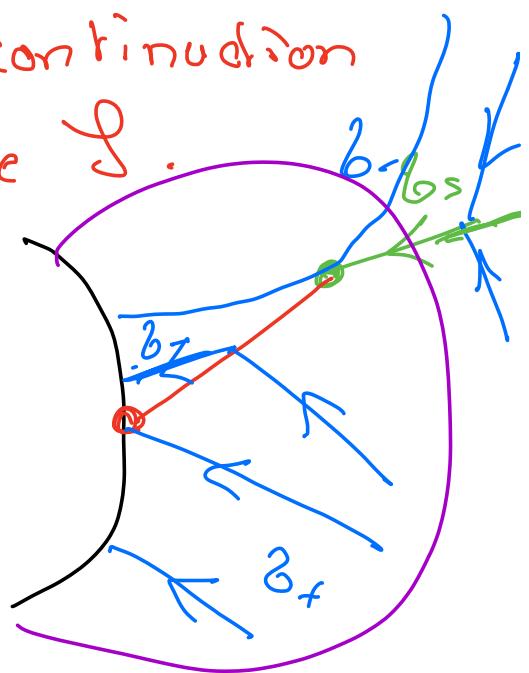
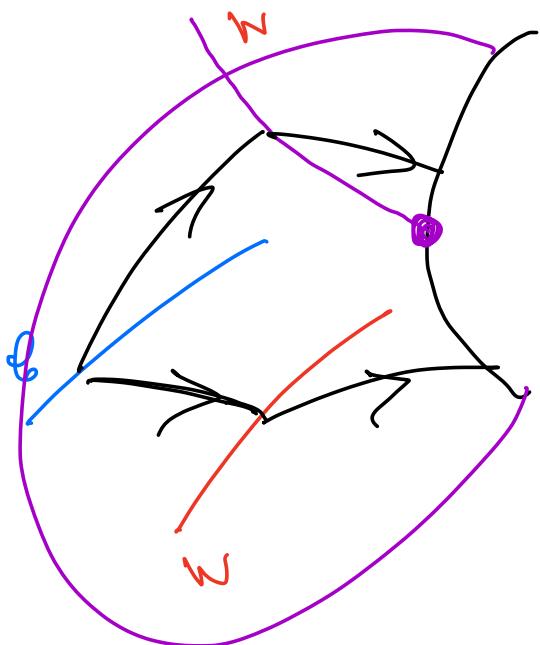
Synthesis, nec  $2\alpha < 0$

$$\bullet w = 0$$



- $w \neq 0$  paramètre de continuation

déploiement le long de  $\mathcal{S}$ .



- detachment of one branch of switching locus
- detachment of the cut locus

- birth of a switching locus

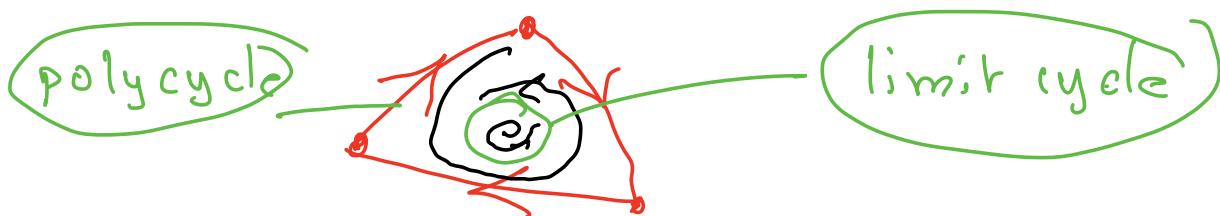
- detachment of the singular locus

## Conclusion

- Geometric study  $\rightarrow$  automatic computation of the time minimal synthesis / Continuation method

- Singularity analysis: intersection of the collinearity locus and of the singular locus  
 generalization N-dimensional case

- More complicated 2d-models in relation with 16<sup>th</sup> Hilbert problem

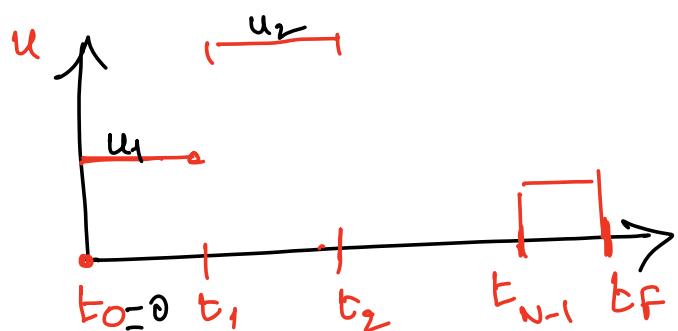


Sampled-data control - Finite dimensional optimization - MPC

$$\dot{x} = x(c) + u \gamma(c)$$

$$u \in [0, 1]$$

Digital constraints



- $t_f$ : duration of the medical treatment
- $N$ : fixed number of medical interventions

Inter-pulse:  $T_k = t_k - t_{k-1} \geq \varepsilon > 0$   
•  $t_1, \dots, t_{N-1}$  are free  $0 < t_1 < t_2 < \dots < t_{N-1} < t_f$

The LV-dynamics defines a finite-dimensional input-output mapping:

$$(t_1, u_1, \dots, t_{N-1}, u_{N-1}) \xrightarrow{\quad} x(t, \lambda)$$

and a Mayer problem:  $\min_{\lambda} P(t_f)$

Indirect scheme: Maximum Principle  
sampled-data frame

Origin: Back to the standard  
calculus of variations

List of admissible perturbations

•  $L^\infty$ -type:  $u_i$  on  $[t_i, t_{i+1}]$   
 Replace:  $u_i \rightarrow u_i + \varepsilon s_{ui}$   
 on  $[t_i, t_{i+1}]$

Maximum Principle: sampled case:

$$\sum_{t_i}^{t_{i+1}} P(s) \gamma(x_s(t, u_i)) s_{ui} \leq 0 \quad (*)$$

"Averaged" Condition

- L<sup>t</sup>-type  $u: u_i \text{ on } [t_i, t_{i+1}]$   
 $\hookrightarrow u^*: u_i \text{ on } [t_i + \varepsilon S t_i, t_{i+1}]$

As before : Evaluate :

$$\lim_{\varepsilon \rightarrow 0} \left[ \frac{\varphi(x(t_F, u^*)) - \varphi(x(t_F, u))}{\varepsilon} \right]$$

One can apply the different variations to get a set of necessary optimality conditions.

Difficult to implement numerically :

"Variational Inequalities"

see condition (\*)

A more suitable optimization scheme has to be applied

$$\min_{\lambda} \varphi(x(t_F, \lambda))$$

Practical application : MPC-scheme

Optimize over a finite horizon  
of length  $k$  of sampling time:

- Step 1  $t_0 : \min_{\substack{u \\ u \in \Delta \leq k}} P(t_0, \lambda)$   
 $x(0) = x_0$
- Step 2 Apply  $u_{\min}$  on  $[t_0, t_0 + 1]$   
 $x(0) \rightarrow x(t_0 + 1)$
- Iterate the construction up to  $t_F$ .

### Short bibliography

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Nice, 14 October 22  
Gdr. MOA

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