# Research topics: control questions in Lotka-Volterra and cross-diffusion models

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- (with S.Dipierro, L.Rossi, E.Valdinoci) a model of competitive and asymmetric aggressive interaction between two species; we consider a system of ODEs and a controllability problem.
- (with S.Dipierro and E.Valdinoci) a class of evolution equations with both classic and fractional time derivatives; we study the asymptotic decay of solutions.



#### 1 An aggressive competition Lotka-Volterra system





Defining the model Results

# Section 1

# An aggressive competition Lotka-Volterra system

Defining the model Results

Two populations Lotka-Volterra competitive system

Two populations:

- u size of the first population,  $u \ge 0$
- **v** size of the second population,  $\mathbf{v} \ge \mathbf{0}$

Defining the model Results

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**Reproduction** (Verhulst): depends on the size of the population and the quantity of available resources  $\dot{u} = u(1 - u)$ 

**Interaction**: if the populations live in the same environment, there is **competition for resources**:

$$\begin{cases} \dot{u} = u(1-u-v), \quad t > 0, \\ \dot{v} = v(1-u-v), \quad t > 0. \end{cases}$$

Defining the model Results

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Complicated dynamics:

- If  $k_u \alpha_u < 1$  and  $k_v \alpha_v < 1$ , coexistence equilibrium
- If  $k_u \alpha_u < 1 < k_v \alpha_v$ : *u* prevails
- If  $k_{\mu}\alpha_{\mu}, k_{\nu}\alpha_{\nu} > 1$ : phase plane splits into two basins

Defining the model Results

## A model for civil war

We derive the model from basic principles.

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The first population attacks the second one.

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The war stops at the extinction of one of the populations.

Space is not taken into account (yet).

Defining the model Results

## Modelling civil war

Parameters and how to use them:

<sup>&</sup>lt;sup>1</sup>Vandenbroucke: "During World War I (1914-1918) the birth rate in France fell by 50%", (*Fertility and Wars*, American Economic Journal: Macroeconomics, 2014).

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Defining the model Results

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Rescaling, we get:

$$\begin{cases} \dot{u} = u(1 - u - v) - acu, \quad t > 0, \\ \dot{v} = \rho v(1 - v - u) - au, \quad t > 0. \end{cases}$$
(1)

a aggressiveness,  $\rho$  fitness of the second population wrt the first, c losses of war for the first population wrt the second

Defining the model Results

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We can define the stopping time

$$\mathcal{T}_{s}(u(0), v(0)) = \begin{cases} T & \text{if } v(T) = 0, \ u(T) > 0, \\ +\infty & \text{otherwise}, \end{cases}$$

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$$\mathcal{B} := \left\{ (u(0), v(0)) \mid \mathcal{T}_{s}(u(0), v(0)) = +\infty, (u(t), v(t)) \stackrel{t \to \infty}{\longrightarrow} (0, 1) \right\}_{10/26}$$

Civil wars

Defining the model Results

Cross-diffusion models Reinforcement learning

Dynamics 1: ac < 1

Defining the model Results

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### Equilibria:

(0,0) unstable, (0,1) stable,  $\left(\frac{1-ac}{1+\rho c}\rho c, \frac{1-ac}{1+\rho c}\right)$  saddle,  $\Gamma$  its stable manifold



Figure: a = 0.8, c = 0.5,  $\rho = 2$ 

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Defining the model Results

# Strategy

We sympathize with one of the two populations.

Defining the model Results

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### We sympathize with the **first** population.



Defining the model Results

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### Main questions

- Characterising  $\mathcal{V}$ ;
- Are constant strategies successful?
- O How to construct a winning strategy?
- What strategy minimises duration of the war?

**Difficulty**: the problem is not controllable; we use geometrical methods.

Defining the model Results

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Case "
$$a = +\infty$$
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Defining the model Results

# Dependence on *a* (aggressiveness)

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$$\mathcal{E} \stackrel{a\to\infty}{\longrightarrow} \{(u,v) \mid v < \frac{u}{c}\},\$$

Case "*a* = 0"

$$\mathcal{E} \stackrel{a \to 0}{\longrightarrow} \{ (u, v) \mid v < ku^{\rho} \},$$
  
where  $k = \frac{(1+\rho c)^{\rho-1}}{(\rho c)^{\rho}}$ 





Defining the model Results

## Theorem: Characterisation of $\mathcal{V}$

[A., Dipierro, Rossi, Valdinoci, 2020]

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If the population are **indistinguishable** up to the aggressiveness, the initial condition determines the outcome.



Defining the model Results

For  $\rho < 1$ , we have that

 $\mathcal{V} = \left\{ (u, v) \mid v < \gamma_0(u) \text{ if } u \le u_s^0, v < \frac{1}{c}u + \frac{1-\rho}{1+\rho c} \text{ if } u \ge u_s^0 \right\},$ 

where  $\gamma_0(u) := \frac{v_s^0}{(u_s^0)^{\rho}} u^{\rho}$ ,  $u_s^0 = \frac{\rho c}{1+\rho c}$ .



Figure:  $\rho = 0.5$ , c = 0.5,  $a_1 = 0.01$ ,  $a_2 = 100$ 

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Defining the model Results

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where  $u_{\infty} = \frac{c}{c+1}$ ,  $\zeta(u) := \frac{(1+c)}{c^{\rho}}$ 



Figure:  $\rho = 2$ , c = 0.5,  $a_1 = 0.01$ ,  $a_2 = 100$ 

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# Section 2

# Cross-diffusion models

## Cross-diffusion systems

 $y_1$  size of the first population  $y_2$  size of the second population

Lotka-Volterra with diffusion (due to natural displacement):

$$\begin{cases} \partial_t y_1 - d_1 \Delta y_1 &= y_1 (1 - y_1 - y_2), \\ \partial_t y_2 - d_2 \Delta y_2 &= y_2 (1 - y_1 - y_2). \end{cases}$$

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**Cross-diffusion**: impact of the presence of the first species on the movement of the individuals of the second one through a **repulsive effect**; new diffusion rate:

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$$\begin{cases} \partial_t y_1 - d_1 \Delta y_1 &= y_1 (1 - y_1 - y_2), \\ \partial_t y_2 - \Delta [y_2 d_2 (1 + y_1)] &= y_2 (1 - y_1 - y_2), \end{cases}$$

with homogeneous Neumann boundary conditions.

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with homogeneous Neumann boundary conditions.

Presents strong **nonlinear coupling**, resulting in Turing instability and causing the pattern formation typical of **segregation of populations** 

## My problem in cross-diffusion models

Problem: adding some control terms on the boundary

$$\begin{cases} \partial_t y_1 - d_1 \Delta y_1 = y_1 \left( 1 - y_1 - y_2 \right), & \text{in } \Omega, \\ \partial_t y_2 - \Delta [v \, d_2 (1 + y_1)] = y_2 \left( 1 - y_1 - y_2 \right), & \text{in } \Omega, \\ (y_1, y_2) = \left( u_1, u_2 \right) & \text{on } \Gamma \subset \partial \Omega \\ y_1 \cdot \nu = y_2 \cdot \nu = 0 & \text{on } \partial \Omega \setminus \Gamma. \end{cases}$$

# My problem in cross-diffusion models

Problem: adding some control terms on the boundary

$$\begin{cases} \partial_t y_1 - d_1 \Delta y_1 = y_1 \left( 1 - y_1 - y_2 \right), & \text{in } \Omega, \\ \partial_t y_2 - \Delta [v \ d_2(1 + y_1)] = y_2 \left( 1 - y_1 - y_2 \right), & \text{in } \Omega, \\ (y_1, y_2) = \left( u_1, u_2 \right) & \text{on } \Gamma \subset \partial \Omega \\ y_1 \cdot \nu = y_2 \cdot \nu = 0 & \text{on } \partial \Omega \setminus \Gamma. \end{cases}$$

**Question**: Can we find a control  $(u_1, u_2)$  that drives an initial condition  $(y_1^0, y_2^0)$  in a target state  $(\tilde{y_1}, \tilde{y_2})$ 

- In finite time?
- 2 approximately?
#### Solution strategy:

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**Microscopic model**: The cross-diffusion effect is approximated by the existence of two states for the repulsed population; the stressed state  $y_{2B}$  has higher diffusivity. Then, one writes again the model for  $y_1$  and  $y_{2A}$ ,  $y_{2B}$  such that  $y_2 = y_{2A} + y_{2B}$ 

## Section 3

#### Reinforcement learning

#### What is reinforcement learning?

Reinforcement learning is an area of machine learning concerned with how intelligent agents ought to take actions in an environment in order to maximize a cumulative reward, but without knowing the exact dynamics without knowing the exact dynamics of the environment.



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Solve an error-friendly optimization problem:

owing the estimate, minimize the cost for the worst case among all the (A, B) within the confidence intervals by using Robust Synthesis

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# Thank you for your attention!

# Section 4

#### Other results on civil wars

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Are constant strategies good enough?

K ⊊

constants

piecewise continuous

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For  $\rho \neq 1$ , there exists a point in V for which strategy works.



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If  $(u_0, v_0) \in \mathcal{V}$ , then either there exists a constant winning strategy or u wins for a strategy

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for suitable  $a_1$ ,  $a_2$ , T. We can win the war with bang-bang strategies.