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# OPTIMAL VACCINATION: VARIOUS (COUNTER) INTUITIVE EXAMPLES

JEAN-FRANÇOIS DELMAS, DYLAN DRONNIER, AND PIERRE-ANDRÉ ZITT

ABSTRACT. In previous articles, we formalized the problem of optimal allocation strategies for a (perfect) vaccine in an infinite-dimensional metapopulation model. The aim of the current paper is to illustrate this theoretical framework with multiple examples where one can derive the analytic expression of the optimal strategies. We discuss in particular the following points: whether or not it is possible to vaccinate optimally when the vaccine doses are given one at a time (greedy vaccination strategies); the effect of assortativity (that is, the tendency to have more contacts with similar individuals) on the shape of optimal vaccination strategies; the particular case where everybody has the same number of neighbors.

## 1. INTRODUCTION

1.1. **Motivation.** The basic reproduction number, denoted by  $R_0$ , plays a fundamental role in epidemiology as it determines the long-term behavior of an epidemic. For a homogeneous model, it is defined as the number of secondary cases generated by an infected individual in an otherwise susceptible population. When this number is below 1, an infected individual causes less than one infection before its recovery in average; the disease therefore declines over time until it eventually dies out. On the contrary, when the reproduction number is greater than 1, the disease invades the population. It follows from this property that a proportion equal to  $1 - 1/R_0$  of the population should be immunized in order to stop the outbreak. We refer the reader to the monograph of Keeling and Rohani [34] for a reminder of these basic properties on the reproduction number.

In heterogeneous generalizations of classical compartmental models, also called metapopulation models, see [5, 10, 37], the population is stratified into homogeneous groups sharing the same characteristics (time to recover from the disease, interaction with the other groups, ...). For these models, it is still possible to define a meaningful reproduction number  $R_0$ , as the number of secondary cases generated by a typical infectious individual when all other individuals are uninfected; see [15]. The reproduction number can then be identified as the spectral radius of the so-called next generation matrix, see [48]. With this definition, it is still true that the outbreak dies out if  $R_0$  is smaller than 1 and invades the population otherwise; see [10, 28, 46, 47, 48] for instance.

Suppose now that we have at our disposal a vaccine with *perfect efficacy*, that is, vaccinated individuals are completely immunized to the disease. After a vaccination campaign, let  $\eta$  denote the proportion of **non-vaccinated** individuals in the population: in inhomogeneous models,  $\eta$  depends *a priori* on the group as different groups may be vaccinated differently. We will call  $\eta$  a *vaccination strategy*. For any strategy  $\eta$ , let us denote by  $R_e(\eta)$  the corresponding

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reproduction number of the non-vaccinated population, also called the *effective reproduction number*. In the metapopulation model, it can also be expressed as the spectral radius of the effective next generation matrix, see Equation (5) below. The choice of  $\eta$  naturally raises a question that may be expressed as the following informal constrained optimization problem:

$$(1) \quad \begin{cases} \text{Minimize:} & \text{the quantity of vaccine to administrate} \\ \text{subject to:} & \text{herd immunity is reached, that is, } R_e \leq 1. \end{cases}$$

For practical reasons, we will instead look at the problem the other way around. If the vaccine is only available in limited quantities, the decision makers could try to allocate the doses so as to maximize efficiency; a natural indicator of this efficiency is the effective reproduction number. This reasoning leads to the following constrained problem:

$$(2) \quad \begin{cases} \text{Minimize:} & \text{the effective reproduction number } R_e \\ \text{subject to:} & \text{a given quantity of available vaccine.} \end{cases}$$

In accordance with [13], we will denote by  $R_{e^*}$  the value of this problem: it is a function of the quantity of available vaccine. The graph of this function is called the *Pareto frontier*. In order to measure how bad a vaccination strategy can be, we will also be interested in maximizing the effective reproduction number given a certain quantity of vaccine:

$$(3) \quad \begin{cases} \text{Maximise:} & \text{the effective reproduction number } R_e \\ \text{subject to:} & \text{a given quantity of available vaccine.} \end{cases}$$

The value function corresponding to this problem is denoted by  $R_e^*$  and its graph is called the *anti-Pareto frontier*. We will quantify the “quantity of available vaccine” for the vaccination strategy  $\eta$  by a cost  $C(\eta)$ . Roughly speaking the “best” (resp. “worst”) vaccination strategies are solutions to Problem (2) (resp. Problem (3)). Still following [13], they will be called *Pareto optimal* (resp. *anti-Pareto optimal*) strategies.

The problem of optimal vaccine allocation has been studied mainly in the metapopulation setting where the population is divided into a finite number of subgroups with the same characteristics. Longini, Ackerman and Elverback were the first interested in the question of optimal vaccine distribution given a limited quantity of vaccine supply [38]. Using the concept of next-generation matrix introduced by Diekmann, Heesterbeek and Metz [15], Hill and Longini reformulated this problem thanks to the reproduction number [30]. Several theoretical and numerical studies followed focusing on Problem (1) and/or Problem (2) in the metapopulation setting [16, 23, 26, 44]. We also refer the reader to the introduction of [13] for a detailed review of the bibliography.

In two previous works [11, 13], we provided an infinite-dimensional framework generalizing the metapopulation model where Problems (2) and (3) are well-posed, justified that the optimizers are indeed Pareto optimal and studied in detail the Pareto and anti-Pareto frontiers. Since there is no closed form for the effective reproduction number, Problems (2) and (3) are hard to solve in full generality: our goal here is to exhibit examples where one can derive analytic expressions for the optimal vaccination strategies. The simple models we study give a gallery of examples and counter-examples to natural questions or conjectures, and may help understanding common rules of thumb for choosing vaccination policies. We will in particular be interested in the following three notions.

- (i) **Greedy parametrization of the frontiers.** For the decision maker it is important to know if global optimization and sequential optimization are the same as one cannot unvaccinated people and redistribute the vaccine once more doses become available.

More precisely, there is a natural order on the vaccination strategies: let us write  $\eta' \leq \eta$  if all the people that are vaccinated when following the strategy  $\eta$  are also vaccinated when following the strategy  $\eta'$ . Let  $\eta$  be an optimal solution of (2) for cost  $c = C(\eta)$ , that is,  $R_e(\eta) = R_{e^*}(c)$ . If, for  $c' > c$ , we can find a strategy  $\eta' \leq \eta$  such that  $R_e(\eta') = R_{e^*}(c')$ , then the optimization may be, at least in principle, found in a greedy way: giving sequentially each new dose of vaccine so as to minimize  $R_e$  gives, in the end, an optimal strategy for any quantity of vaccine. By analogy with the corresponding notion for algorithms we will say in this case that there exists a *greedy parametrization* of the Pareto frontier. The existence of such a greedy parametrization was already discussed by Cairns in [8] and is examined for each model throughout this paper.

- (ii) **Assortative/Disassortative network.** The second notion is a property of the network called *assortativity*: a network is called assortative when the nodes tend to attach to others that are similar in some way and *disassortative* otherwise. The assortativity or disassortativity of a network is an important property that helps to understand its topology. It has been observed that social networks are usually assortative while biological and technological networks are disassortative, see for example [41]. The optimal vaccination strategies can differ dramatically in the case of assortative versus disassortative mixing, see Galeotti and Rogers [21] for a study in a population composed of two groups. This question is in particular addressed in Section 4 for an elementary model with an arbitrary number of groups.
- (iii) **How to handle individuals with the same level of connection.** Targeting individuals that are the most connected is a common approach used to prevent an epidemic in a complex network [43]. In [14], we show that these strategies are optimal for the so-called monotonic kernel models, in which the individuals may be naturally ordered by a score related to their connectivity. When many individuals or groups are tied for the best score, either from the beginning or after some vaccine has been distributed, the optimal way of vaccinating them may be surprisingly varied according to the situation. This variety of answers appears already in the treatment of such individuals in the assortative/disassortative toy model developed in Section 4. To go further in this direction, a large part of the current paper, see Sections 5-7, is devoted to regular or “constant degree” models where all individuals share the same degree. We shall in particular ask whether uniform vaccination strategies are either the “best” or the “worst” or even neither the “best” nor the “worst” possible strategies.

**1.2. Main results.** Section 2 is dedicated to classical finite-dimensional metapopulation models. We present two simple models that, despite being seemingly very similar, display totally different behaviors: the asymmetric and symmetric circle graphs. For the first one, where individuals of the group  $i$  can only be infected by individuals of the group  $i - 1$  and which corresponds to a next generation matrix given by:

$$K_{ij} = \mathbb{1}_{\{i=j+1 \pmod N\}},$$

with  $N$  the number of groups or nodes in the circle, we derive a greedy parametrization of the Pareto frontier. On the second one, where individuals of the group  $i$  can only be infected by individuals of the group  $i - 1$  or  $i + 1$  and which corresponds to a next generation matrix given by:

$$K_{ij} = \mathbb{1}_{\{i=j\pm 1 \pmod N\}},$$

we observe numerically that the Pareto frontier is much more complicated, and in particular cannot be parametrized greedily. Those two models are in fact constant degree models; the

uniform vaccination strategies are the “worst” for the first model, and neither the “best” nor the “worst” strategies for the second.

After Section 3, where we recall the kernel setting used in [13] for infinite dimensional models, we focus in Section 4 on the effect of assortativity on optimal vaccination strategies. We define a simple kernel model that may be assortative or disassortative depending on the sign of a parameter. In the discrete metapopulation model, the next generation matrix can be written (up to a multiplicative constant) as:

$$K_{ij} = (1 + \varepsilon \mathbb{1}_{\{i \neq j\}}) \mu_j,$$

where  $\mu_j \geq 0$  represents the proportional size of group  $j$ . The model is assortative if  $\varepsilon < 0$  (and  $\varepsilon \geq -1$  so that the matrix  $K$  is non-negative) and disassortative if  $\varepsilon > 0$ . We describe completely the optimal vaccination strategies, see Theorem 4.2, and show that the best strategies for the assortative case are the worst ones if the mixing pattern is disassortative, and vice-versa. We also prove that all the Pareto and anti-Pareto frontiers admit greedy parametrizations, and that Pareto optimal strategies prioritize individuals that in some sense have the highest degree, that is, are the most connected.

In Section 5, we consider constant degree models, which are the analogue of regular graphs in the infinite-dimensional setting. In the discrete metapopulation model, the sums over each row and the sums over each column of the next generation matrix are constant. We prove, see Proposition 5.4, that if the effective reproduction function  $R_e$  is convex then the uniform strategies are the “best” and they give a greedy parametrization of the Pareto frontier; and that if  $R_e$  is concave, the uniform strategies are the “worst”. Section 6 is then devoted to a particular model of rank two, which corresponds in the discrete metapopulation model to a next generation matrix of the form:

$$K_{ij} = (1 + \varepsilon \alpha_i \alpha_j) \mu_j \quad \text{with} \quad \sum_j \alpha_j \mu_j = 0,$$

where  $\varepsilon$  may be  $+1$  or  $-1$ , and  $\sup_i \alpha_i^2 \leq 1$ , so that the matrix  $K$  is non-negative. The condition  $\sum_j \alpha_j \mu_j = 0$  ensures that the model has a constant degree. In those cases, we give a complete description of the “best” and the “worst” vaccination strategies, the uniform one being “best” for  $\varepsilon = +1$  and “worst” otherwise, see Proposition 6.2. In Section 6.4, we also provide an example of kernel (in infinite dimension) for which the set of optimal strategies has an infinite number of connected components. In this particular case, there is no greedy parametrization of the Pareto frontier.

As another application of the results of Section 5, we investigate in Section 7 geometric constant degree kernels defined on the unit sphere  $\mathbb{S}^{d-1} \subset \mathbb{R}^d$ . Intuitively an individual at point  $x$  on the sphere is infected by an individual at point  $y$  with an intensity  $k(x, y)$  depending on the distance between  $x$  and  $y$ . Those kernels appear in the graphon theory as limit of large dense random geometric graphs. We give a particular attention to the affine model in Section 7.3, where:

$$k(x, y) = 1 + \varepsilon \langle x, y \rangle, \quad \varepsilon \geq -1,$$

where  $\langle x, y \rangle$  is the usual scalar product in the ambient space  $\mathbb{R}^d$ . Intuitively, for  $\varepsilon > 0$ , the infection propagates through the nearest neighbors: this may be seen as a kind of spatial assortativity. By contrast, for  $\varepsilon < 0$  the infection propagates through the furthest individuals neighbors, in a spatially disassortative way. For this affine model, we completely describe the “best” and the “worst” vaccination strategies, see Proposition 7.8.

## 2. FIRST EXAMPLES IN THE DISCRETE SETTING

In this section, we use the framework developed by Hill and Longini in [30] for metapopulation models and provide optimal vaccination strategies for two very simple examples. Despite their simplicity, these examples showcase a number of interesting behaviors, that will occur in a much more general setting, as we will see in the rest of the paper.

**2.1. The reproduction number in metapopulation models.** In metapopulation models, the population is divided into  $N \geq 2$  different subpopulations and we suppose that individuals within a same subpopulation share the same characteristics. The different groups are labeled  $1, 2, \dots, N$ . We denote by  $\mu_1, \mu_2, \dots, \mu_N$  their respective size (in proportion with respect to the total size) and we suppose that those do not change over time. By the linearization of the dynamic of the epidemic at the disease-free equilibrium, we obtain the so-called *next-generation matrix*  $K$ , see [48], which is a  $N \times N$  matrix with non-negative coefficients. For a detailed discussion on the biological interpretation of the coefficients of the next-generation matrix, we refer the reader to [11, Section 2]. We also refer to [12] for an extensive treatment of the two-dimensional case.

The basic reproduction number is equal to the spectral radius of the next-generation matrix:

$$(4) \quad R_0 = \rho(K),$$

where  $\rho$  denotes the spectral radius. Since the matrix  $K$  has non-negative entries, the Perron-Frobenius theory implies that  $R_0$  is also an eigenvalue of  $K$ . If  $R_0 > 1$ , the epidemic process grows away from the disease-free equilibrium while if  $R_0 < 1$ , the disease cannot invade the population; see [48, Theorem 2].

We now introduce the effect of vaccination. Suppose that we have at our disposal a vaccine with perfect efficacy, *i.e.*, vaccinated individuals are completely immunized to the infection. We denote by  $\eta = (\eta_1, \dots, \eta_N)$  the vector of the proportions of **non-vaccinated** individuals in the different groups. We shall call  $\eta$  a vaccination strategy and denote by  $\Delta = [0, 1]^N$  the set of all possible vaccination strategies. According to [11, 13], the next-generation matrix corresponding to the dynamic with vaccination is equal to the matrix  $K$  multiplied by the matrix  $\text{Diag}(\eta)$  on the right, where  $\text{Diag}(\eta)$  is the  $N \times N$  diagonal matrix with coefficients  $\eta \in \Delta$ . We call the spectral radius of this matrix the *effective reproduction number*:

$$(5) \quad R_e(\eta) = \rho(K \cdot \text{Diag}(\eta)).$$

The effective reproduction number accounts for the vaccinated (and immunized) people in the population, as opposed to the basic reproduction number, which corresponds to a fully susceptible population. When nobody is vaccinated, that is  $\eta = \mathbf{1} = (1, \dots, 1)$ ,  $\text{Diag}(\eta)$  is equal to the identity matrix, the next-generation matrix is unchanged and  $R_e(\eta) = R_e(\mathbf{1}) = R_0$ .

We suppose that the *cost* of a vaccination strategy is, up to an irrelevant multiplicative constant, equal to the total proportion of vaccinated people and is therefore given by:

$$(6) \quad C(\eta) = \sum_{i=1}^N (1 - \eta_i) \mu_i = 1 - \sum_{i=1}^N \eta_i \mu_i,$$

where  $\eta = (\eta_1, \dots, \eta_N) \in \Delta$ . We refer to [13, Section 5.1, Remark 5.2] for considerations on more general cost functions.

*Example 2.1* (Uniform vaccination). The uniform strategy of cost  $c$  consists in vaccinating the same proportion of people in each group:  $\eta = (1 - c)\mathbf{1}$ . By homogeneity of the spectral radius, the reproduction number  $R_e(\eta)$  is then equal to  $(1 - c)R_0$ .

**2.2. Optimal allocation of vaccine doses.** As mentioned in the introduction and recalled in Section 2.1, reducing the reproduction number is fundamental in order to control and possibly eradicate the epidemic. However, the vaccine may only be available in a limited quantity, and/or the decision maker may wish to limit the cost of the vaccination policy. This motivates our interest in the following related problem:

$$(7) \quad \begin{cases} \min & R_e(\eta), \\ \text{such that} & C(\eta) = c. \end{cases}$$

According to [13], one can replace the constraint  $\{C(\eta) = c\}$  by  $\{C(\eta) \leq c\}$  without modifying the solutions. The opposite problem consists in finding out the *worst possible way* of allocating vaccine. While this does not seem at first sight to be as important, a good understanding of bad vaccination strategies may also provide rules of thumb in terms of anti-patterns. In order to estimate how bad a vaccination strategy can be, we therefore also consider the following problem:

$$(8) \quad \begin{cases} \max & R_e(\eta), \\ \text{such that} & C(\eta) = c. \end{cases}$$

According to [13], one can replace the constraint  $\{C(\eta) = c\}$  by  $\{C(\eta) \geq c\}$  without modifying the solutions.

Since the coefficients of the matrix  $K \cdot \text{Diag}(\eta)$  depend continuously on  $\eta$ , it is classical that its eigenvalues also depend continuously on  $\eta$  (see for example [32, Appendix D]) and in particular the function  $R_e$  is continuous on  $\Delta = [0, 1]^N$ . Since the function  $C$  is also continuous on  $\Delta$ , the compactness of  $\Delta$  ensures the existence of solutions for Problems (7) and (8). For  $c \in [0, 1]$ ,  $R_{e\star}(c)$  (resp.  $R_e^\star(c)$ ) stands for the minimal (resp. maximal) value taken by  $R_e$  on the set of all vaccination strategies  $\eta$  such that  $C(\eta) = c$ :

$$(9) \quad R_{e\star}(c) = \min\{R_e(\eta) : \eta \in \Delta \text{ and } C(\eta) = c\},$$

$$(10) \quad R_e^\star(c) = \max\{R_e(\eta) : \eta \in \Delta \text{ and } C(\eta) = c\}.$$

It is easy to check that the functions  $R_{e\star}$  and  $R_e^\star$  are non increasing. Indeed, if  $\eta^1$  and  $\eta^2$  are two vaccination strategies such that  $\eta^1 \leq \eta^2$  (where  $\leq$  stands for the pointwise order), then  $R_e(\eta^1) \leq R_e(\eta^2)$  according to the Perron-Frobenius theory. This easily implies that  $R_{e\star}$  and  $R_e^\star$  are non-increasing. We refer to [11, 13] for more properties on those functions; in particular they are also continuous. For the vaccination strategy  $\eta = \mathbb{0} = (0, \dots, 0)$  (everybody is vaccinated) with cost  $C(\mathbb{0}) = 1$ , the transmission of the disease in the population is completely stopped, *i.e.*, the reproduction number is equal to 0. In the examples below, we will see that for some next-generation matrices  $K$ , this may be achieved with a strategy  $\eta$  with cost  $C(\eta) < 1$ . Hence, let us denote by  $c_\star$  the minimal cost required to completely stop the transmission of the disease:

$$(11) \quad c_\star = \inf\{c \in [0, 1] : R_{e\star}(c) = 0\}.$$

In a similar fashion, we define by symmetry the maximal cost of totally inefficient vaccination strategies:

$$(12) \quad c^\star = \sup\{c \in [0, 1] : R_e^\star(c) = R_0\}.$$

According to [13, Lemma 5.13], we have  $c^\star = 0$  if the matrix  $K$  is irreducible, *i.e.*, not similar via a permutation to a block upper triangular matrix. The two matrices considered below in this section are irreducible.

Following [13], the *Pareto frontier* associated to the “best” vaccination strategies, solution to Problem (7), is defined by:

$$(13) \quad \mathcal{F} = \{(c, R_{e^*}(c)) : c \in [0, c_*]\}.$$

The set of “best” vaccination strategies, called *Pareto optimal* strategies, is defined by:

$$(14) \quad \mathcal{P} = \{\eta \in \Delta : (C(\eta), R_e(\eta)) \in \mathcal{F}\}.$$

When  $c^* = 0$  (which will be the case for all the examples considered in this paper), the *anti-Pareto frontier* associated to the “worst” vaccination strategies, solution to Problem (8), is defined by:

$$(15) \quad \mathcal{F}^{\text{Anti}} = \{(c, R_e^*(c)) : c \in [0, 1]\}.$$

The set of “worst” vaccination strategies, called *anti-Pareto optimal* strategies, is defined by:

$$(16) \quad \mathcal{P}^{\text{Anti}} = \{\eta \in \Delta : (C(\eta), R_e(\eta)) \in \mathcal{F}^{\text{Anti}}\}.$$

The set of uniform strategies will play a role in the sequel:

$$(17) \quad \mathcal{S}^{\text{uni}} = \{t\mathbf{1} : t \in [0, 1]\}.$$

We denote by  $\mathbf{F} = \{(C(\eta), R_e(\eta)) : \eta \in \Delta\}$  the set of all possible outcomes. According to [13, Section 6.1], the set  $\mathbf{F}$  is a subset of  $[0, 1] \times [0, R_0]$  delimited below by the graph of  $R_{e^*}$  and above by the graph of  $R_e^*$ ; it is compact, path connected and its complement is connected in  $\mathbb{R}^2$ .

A *path* of vaccination strategies is a measurable function  $\gamma : [a, b] \rightarrow \Delta$  where  $a < b$ . It is *monotone* if for all  $a \leq s \leq t \leq b$  we have  $\gamma(s) \geq \gamma(t)$ , where  $\leq$  denotes the pointwise order. A *greedy parametrization* of the Pareto (resp. anti-Pareto) frontier is a monotone continuous path  $\gamma$  such that the image of  $(C \circ \gamma, R_e \circ \gamma)$  is equal to  $\mathcal{F}$  (resp.  $\mathcal{F}^{\text{Anti}}$ ). If such a path exists, then its image can be browsed by a greedy algorithm which performs infinitesimal locally optimal steps.

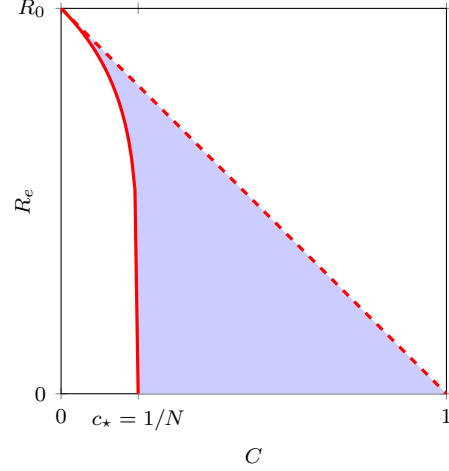
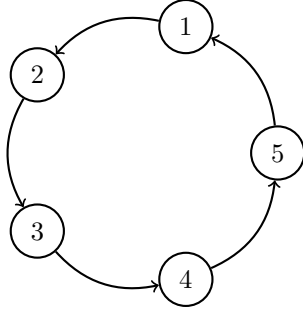
*Remark 2.2.* Let  $K$  be the next-generation matrix and let  $\lambda \in \mathbb{R}_+ \setminus \{0\}$ . By homogeneity of the spectral radius, we have  $\rho(\lambda K \cdot \text{Diag}(\eta)) = \lambda \rho(K \cdot \text{Diag}(\eta))$ . Thus, the solutions of Problems (7) and (8) and the value of  $c_*$  are invariant by scaling of the matrix  $K$ . As for the functions  $R_{e^*}$  and  $R_e^*$ , they are scaled by the same quantity. Hence, in our study, the value of  $R_0$  will not matter. Our main concern will be to find the best and the worst vaccination strategies for a given cost and compare them to the uniform strategy.

**2.3. The fully asymmetric circle model.** We consider a model of  $N \geq 2$  equal subpopulations (*i.e.*  $\mu_1 = \dots = \mu_N = 1/N$ ) where each subpopulation only contaminates the next one. The next-generation matrix, which is equal to the cyclic permutation matrix, and the effective next generation matrix are given by:

$$(18) \quad K = \begin{pmatrix} 0 & 1 & & & \\ & 0 & 1 & & \\ & & \ddots & \ddots & \\ 0 & & & 0 & 1 \\ 1 & 0 & & & 0 \end{pmatrix} \quad \text{and} \quad K \cdot \text{Diag}(\eta) = \begin{pmatrix} 0 & \eta_2 & & & \\ & 0 & \eta_3 & & \\ & & \ddots & \ddots & \\ 0 & & & 0 & \eta_N \\ \eta_1 & 0 & & & 0 \end{pmatrix},$$

where  $\eta = (\eta_1, \dots, \eta_N) \in \Delta = [0, 1]^N$ . The next-generation matrix can be interpreted as the adjacency matrix of the fully asymmetric cyclic graph; see Figure 1(A).





(A) Graphical representation of the transmission of the disease. (B) Solid line: the Pareto frontier  $\mathcal{F}$ ; dashed line: the anti-Pareto frontier  $\mathcal{F}^{\text{Anti}}$  (which corresponds to the uniform strategies); blue region: all possible outcomes  $\mathbf{F}$ .

FIGURE 1. Example of optimization for the fully asymmetric circle model with  $N = 5$  subpopulations.

By an elementary computation, the characteristic polynomial of the matrix  $K \cdot \text{Diag}(\eta)$  is equal to  $X^N - \prod_{1 \leq i \leq N} \eta_i$ . Hence, the effective reproduction number can be computed via an explicit formula; it corresponds to the geometric mean:

$$(19) \quad R_e(\eta) = \left( \prod_{i=1}^N \eta_i \right)^{1/N}.$$

The Pareto and anti-Pareto frontier are totally explicit for this elementary example, and given by the following proposition. For additional comments on this example see also Example 5.9 below.

**Proposition 2.3** (Asymmetric circle). *For the fully asymmetric circle model, we have:*

- (i) *The least quantity of vaccine necessary to completely stop the propagation of the disease is  $c_* = 1/N$ . Pareto optimal strategies have a cost smaller than  $c_*$ , and correspond to giving all the available vaccine to one subpopulation:*

$$\mathcal{P} = \{ \eta = (\eta_1, \dots, \eta_N) \in [0, 1]^N : \eta_i = 1 \text{ for all } i \text{ but at most one} \}.$$

*The Pareto frontier is given by the graph of the function  $R_{e_*}$  on  $[0, c_*]$ , where  $R_{e_*}$  is given by:*

$$R_{e_*}(c) = (1 - Nc)_+^{1/N} \quad \text{for } c \in [0, 1].$$

- (ii) *The maximal cost of totally inefficient vaccination strategies is  $c^* = 0$ . The anti-Pareto optimal strategies consist in vaccinating uniformly the population, i.e.:*

$$\mathcal{P}^{\text{Anti}} = \mathcal{S}^{\text{uni}}.$$

*The anti-Pareto frontier is given by the graph of the function  $R_e^* : c \mapsto 1 - c$  on  $[0, 1]$ .*

In Figure 1(B), we have plotted the Pareto and the anti-Pareto frontiers corresponding to asymmetric circle model with  $N = 5$  subpopulations.

*Remark 2.4* (Greedy parametrization). From Proposition 2.3, we see that there exists a greedy parametrization of the Pareto frontier, which consists in giving all the available vaccine to one subpopulation until its complete immunization. Similarly, the anti-Pareto frontier is greedily parametrized by the uniform strategies.

*Proof.* We first prove (i). Suppose that  $c \geq 1/N$ . There is enough vaccine to protect entirely one of the groups and obtain  $R_e(\eta) = 0$  thanks to Equation (19). This gives  $c_\star \leq 1/N$  and  $R_{e_\star}(c) = 0$  for  $c \geq 1/N$ .

Let  $0 \leq c < 1/N$ . According to [7, Section 3.1.5], the map  $\eta \mapsto R_e(\eta)$  is concave. According to Bauer's maximum principle [42, Corollary A.3.3],  $R_e$  attains its minimum on  $\{\eta \in [0, 1]^N : C(\eta) = c\}$  at some extreme point of this set. These extreme points are strategies  $\eta \in [0, 1]^N$  such that  $\eta_i = 1 - Nc$  for some  $i$  and  $\eta_j = 1$  for all  $j \neq i$ . Since  $R_e$  is a symmetric function of its  $N$  variables, it takes the same value  $(1 - Nc)^{1/N}$  on all these strategies, so they are all minimizing, which proves Point (i).

We give another elementary proof of (i) when  $c < 1/N$ . Let  $\eta$  be a solution of Problem (7). Assume without loss of generality that  $\eta_1 \leq \dots \leq \eta_N$ . Suppose for a moment that  $\eta_2 < 1$ , and let  $\varepsilon > 0$  be small enough to ensure  $\eta_1 > \varepsilon$  and  $\eta_2 < 1 - \varepsilon$ . Then the vaccination strategy  $\tilde{\eta} = (\eta_1 - \varepsilon, \eta_2 + \varepsilon, \eta_3, \dots, \eta_N)$  is admissible, and:

$$R_e(\tilde{\eta})^N = R_e(\eta)^N - (\varepsilon(\eta_2 - \eta_1) + \varepsilon^2) \prod_{i=3}^N \eta_i < R_e(\eta)^N,$$

contradicting the optimality of  $\eta$ . Therefore the Pareto-optimal strategies have only one term different from 1, and must be equal to  $((1 - Nc), 1, \dots, 1)$ , up to a permutation of the indices.

Now, let us prove (ii). Let  $\eta$  such that  $C(\eta) = c$ . According to the inequality of arithmetic and geometric means:

$$R_e(\eta) \leq \frac{\eta_1 + \dots + \eta_N}{N} = 1 - c.$$

By Example 2.1, the right hand side is equal to the effective reproduction number of the uniform vaccination at cost  $c$ . This ends the proof of the proposition.  $\square$

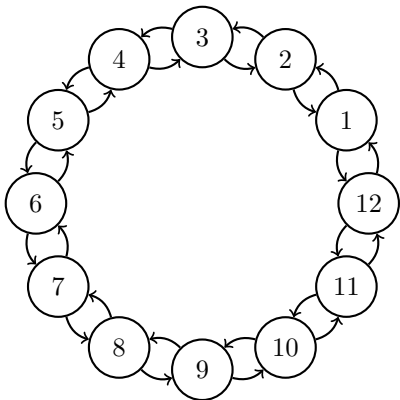
**2.4. Fully symmetric circle model.** We now consider the case where each of the  $N$  subpopulation may infect both of their neighbours. The next-generation matrix and the effective next-generation matrix are given by:

$$(20) \quad K = \begin{pmatrix} 0 & 1 & & 0 & 1 \\ 1 & 0 & 1 & & 0 \\ & 1 & \ddots & \ddots & \\ 0 & & \ddots & 0 & 1 \\ 1 & 0 & & 1 & 0 \end{pmatrix} \quad \text{and} \quad K \cdot \text{Diag}(\eta) = \begin{pmatrix} 0 & \eta_2 & & 0 & \eta_N \\ \eta_1 & 0 & \eta_3 & & 0 \\ & \eta_2 & \ddots & \ddots & \\ 0 & & \ddots & 0 & \eta_N \\ \eta_1 & 0 & & \eta_{N-1} & 0 \end{pmatrix}.$$

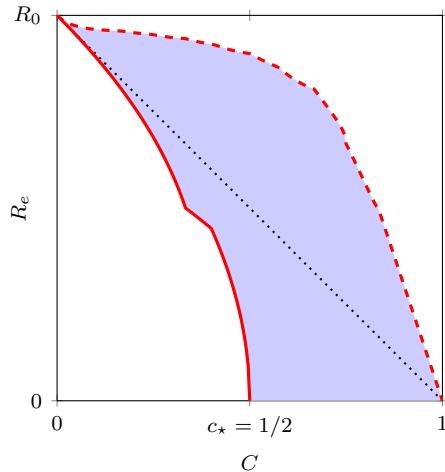
Again, we can represent this model as a graph; see Figure 2(A).

There is no closed-form formula to express  $R_e$  for  $N \geq 5$  and the optimization is way harder than the asymmetric case. Since  $K$  is irreducible, we have  $c_\star = 0$ . Our only analytical result for this model is the computation of  $c_\star$ .

**Proposition 2.5** (Optimal strategy for stopping the transmission). *For the fully symmetric circle model, the strategy  $\eta' = \mathbb{1}_{i \text{ even}}$  is Pareto optimal for the fully symmetric circle and  $R_e(\eta') = 0$ . In particular,  $c_\star$  is equal to  $C(\eta') = \lceil N/2 \rceil / N$ .*



(A) Graphical representation of the transmission of the disease.

(B) Solid line: the Pareto frontier  $\mathcal{F}$ ; dashed line: the anti-Pareto frontier  $\mathcal{F}^{\text{Anti}}$ ; dotted line: outcomes of the uniform strategies; blue region: all possible outcomes  $\mathbf{F}$ .FIGURE 2. Example of optimization for the fully symmetric circle model with  $N = 12$  subpopulations.

*Proof.* The term  $X^{N-2}$  of the characteristic polynomial of  $K \cdot \text{Diag}(\eta)$  has a coefficient equal to the sum of all principal minors of size 2:

$$(21) \quad -(\eta_1\eta_2 + \eta_2\eta_3 + \dots + \eta_{N-1}\eta_N + \eta_N\eta_1).$$

If  $\eta$  is such that  $NC(\eta) < \lceil N/2 \rceil$ , then at least one of the term above is not equal to 0, proving that the sum is negative. Hence, there is at least one eigenvalue of  $K \cdot \text{Diag}(\eta)$  different from 0, and  $R_e(\eta) > 0$ . We deduce that  $c_* \geq \lceil N/2 \rceil / N$ .

Now, let  $\eta'$  such that  $\eta'_i = 0$  for all odd  $i$  and  $\eta'_i = 1$  for all even  $i$ , so that  $C(\eta') = \lceil N/2 \rceil / N$ . The matrix  $K \cdot \text{Diag}(\eta')$  is nilpotent as its square is 0. Since the spectral radius of a nilpotent matrix is equal 0, we get  $R_e(\eta') = 0$ . This ends the proof of the proposition.

We can give another proof of the proposition: it is enough to notice that the nodes labelled with an odd number form a maximal independent set of the cyclic graph. Taking  $\eta'$  equal to the indicator function of this set, we deduce from [11, Section 6.4] that  $\eta'$  is Pareto optimal,  $R_e(\eta') = 0$  and  $c_* = C(\eta')$ .  $\square$

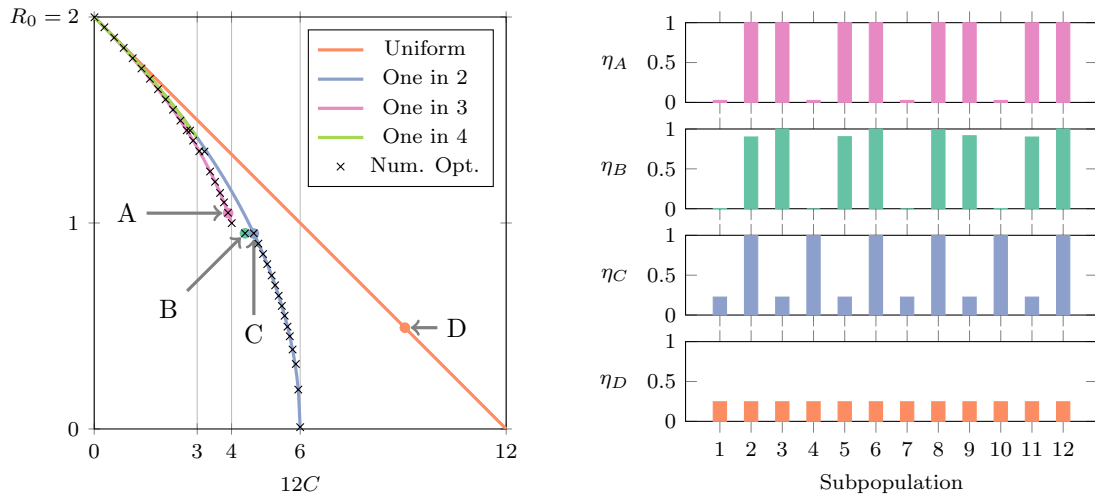
We pursue the analysis of this model with numerical computations. We choose  $N = 12$  subpopulations, and compute an approximate Pareto frontier, using the Borg multiobjective evolutionary algorithm<sup>1</sup>. The results are plotted in Figure 3. We represent additionally the curves  $(c, R(\eta(c)))$  where the vaccination strategy  $\eta(c)$  for a given cost  $c$  are given by deterministic path of “meta-strategies”:

- **Uniform strategy:** distribute the vaccine uniformly to all  $N$  subpopulations;
- **“One in  $j$ ” strategy:** vaccinate one in  $j$  subpopulation, for  $j = 2, 3, 4$ .

Let us follow the scatter plot of  $R_{e_*}$  in Figure 3(A), starting from the upper left.

- (1) In the beginning nobody is vaccinated, and  $R_0$  is equal to 2.

<sup>1</sup>The algorithm is described in [25]; we use the version coded in the `BlackBoxOptim` package for the Julia programming language.



(A) Effective reproduction number  $R_e$  against vaccination cost  $c$  for various meta-strategies. (B) Vaccination strategies corresponding to the four labelled points.

FIGURE 3. Pareto frontier and computation of the outcomes for the paths of the four meta-strategies. Some meta-strategies  $\{\eta_A, \eta_B, \eta_C, \eta_D\}$  are represented on the right with their corresponding outcome points  $\{A, B, C, D\}$  on the left.

- (2) For small costs all strategies have similar efficiency. Zooming in shows that the (numerically) optimal strategies split the available vaccine equally between four subpopulations that are separated from each other by two subpopulations. This corresponds to the “one in 3” meta-strategies path. As represented in Figure 3(B),  $\eta_A$  with outcome point  $A = (C(\eta_A), R_e(\eta_A))$  belongs to this path. In particular, note that disconnecting the graph is not Pareto optimal for  $12c = 3$  as the disconnecting “one in 4” strategy gives values  $R_e = \sqrt{2} \simeq 1.41$  opposed to the value  $R_e \simeq 1.37$  for the “one in 3” strategy with same cost. However, note that, in agreement with [11, Proposition 6.5], this disconnecting “one in 4” strategy is also not anti-Pareto optimal, since it performs better than the uniform strategy with the same cost.
- (3) When  $12c = 4$  the circle has been split in four “islands” of two interacting subpopulations. There is a small interval of values of  $c$  for which it is (numerically) optimal to split the additional vaccine uniformly between the four “islands”, and give it entirely to one subpopulation in each island: see point B and the associated strategy  $\eta_B$ .
- (4) Afterwards (see point C), it is in fact better to try and vaccinate all the (say) even numbered subpopulations. Therefore, the optimal vaccinations *do not vary monotonously* with respect to the amount of available vaccine; in other words, distributing vaccine in a greedy way is not optimal. This also suggests that, even though the frontier is continuous (in the objective space  $(c, r)$ ), the set of optimal *strategies* may not be connected: the “one in two” vaccination strategy of point C cannot be linked to “no vaccination” strategy by a continuous path of optimal strategies. In particular, the Pareto frontier cannot be greedily parametrized. The disconnectedness of the set of optimal strategies will be established rigorously in Section 6 for another model.
- (5) For  $12c = 6$ , that is  $c = c_*$  as stated in Proposition 2.5, it is possible to vaccinate completely all the (say) odd numbered subpopulations, thereby disconnecting the graph completely. The infection cannot spread at all.

- (6) Even though the problem is symmetric and all subpopulations play the same role, the proportional allocation of vaccine is far from optimal; on the contrary, the optimal allocations focus on some subpopulations.

Using the same numerical algorithm, we have also computed the anti-Pareto frontier for this model; see the dashed line in Figure 2(B). Although we do not give a formal proof, the anti-Pareto frontier seems to be perfectly given by the following greedy parametrization:

- (1) Distribute all the available vaccine supply to one group until it is completely immunized.
- (2) Once this group is fully vaccinated, distribute the vaccine doses to one of its neighbour.
- (3) Continue this procedure by vaccinating the neighbour of the last group that has been immunized.
- (4) When there are only two groups left, split the vaccine equally between these two.

### 3. THE KERNEL MODEL

In order to get a finer description of the heterogeneity, we could divide the population into a growing number of subgroups  $N \rightarrow \infty$ . The recent advances in graph limits theory [4, 39] justify describing the transmission of the disease by a kernel defined on a probability space. We already used this type of model in [10, 11, 13], in particular for an SIS dynamics, see also [11, Section 2] for other epidemic models.

Let  $(\Omega, \mathcal{F}, \mu)$  be a probability space that represents the population: the individuals have features labeled by  $\Omega$  and the infinitesimal size of the population with feature  $x$  is given by  $\mu(dx)$ . Let  $L^2(\mu)$  ( $L^2$  for short) be the space of real-valued measurable functions  $f$  defined on  $\Omega$  such that  $\|f\|_2 = (\int_{\Omega} f^2 d\mu)^{1/2}$  is finite, where functions which agree  $\mu$ -a.s. are identified. Let  $L^2_+ = \{f \in L^2 : f \geq 0\}$  be the subset of non-negative functions of  $L^2$ . We define a *kernel* on  $\Omega$  as a  $\mathbb{R}_+$ -valued measurable function defined on  $(\Omega^2, \mathcal{F}^{\otimes 2})$ . We will only consider kernels with finite double-norm on  $L^2$ :

$$(22) \quad \|k\|_{2,2} = \left( \int_{\Omega \times \Omega} k(x,y)^2 \mu(dx)\mu(dy) \right)^{1/2} < +\infty.$$

To a kernel  $k$  with finite double norm on  $L^2$ , we associate the integral operator  $T_k$  on  $L^2$  defined by:

$$(23) \quad T_k(g)(x) = \int_{\Omega} k(x,y)g(y) \mu(dy) \quad \text{for } g \in L^2 \text{ and } x \in \Omega.$$

The operator  $T_k$  is bounded, and its operator norm  $\|T_k\|_{L^2}$  satisfies:

$$(24) \quad \|T_k\|_{L^2} \leq \|k\|_{2,2}.$$

According to [24, p. 293],  $T_k$  is actually compact (and even Hilbert-Schmidt). A kernel is said to be symmetric if  $k(x,y) = k(y,x)$ ,  $\mu(dx)\mu(dy)$ -almost surely. It is said to be *irreducible* if for all  $A \in \mathcal{F}$ , we have:

$$(25) \quad \int_{A \times A^c} k(x,y) \mu(dx)\mu(dy) = 0 \implies \mu(A) \in \{0, 1\}.$$

If  $k$  is not irreducible, it is called *reducible*.

By analogy with the discrete setting and also based on [10, 11], we define the basic reproduction number in this context thanks to the following formula:

$$(26) \quad R_0 = \rho(T_k),$$

where  $\rho$  stands for the spectral radius of an operator. According to the Krein-Rutman theorem,  $R_0$  is an eigenvalue of  $T_k$ . Besides, there exists left and right eigenvectors associated to this eigenvalue in  $L^2_+$ ; such functions are called Perron eigenfunctions.

For  $f, g$  two non-negative bounded measurable functions defined on  $\Omega$  and  $k$  a kernel on  $\Omega$  with finite double norm on  $L^2$ , we denote by  $fk g$  the kernel on  $\Omega$  defined by:

$$(27) \quad (fk g)(x, y) = f(x) k(x, y) g(y).$$

Since  $f$  and  $g$  are bounded, the kernel  $fk g$  has also a finite double norm on  $L^2$ .

Denote by  $\Delta$  the set of measurable functions defined on  $\Omega$  taking values in  $[0, 1]$ . A function  $\eta$  in  $\Delta$  represents a vaccination strategy:  $\eta(x)$  represents the proportion of **non-vaccinated** individuals with feature  $x$ . In particular  $\eta = \mathbb{1}$  (the constant function equal to 1) corresponds to the absence of vaccination and  $\eta = \mathbb{0}$  (the constant function equal to 0) corresponds to the whole population being vaccinated. The uniform strategies are given by:

$$\eta^{\text{uni}} = t\mathbb{1}$$

for some  $t \in [0, 1]$ , and we denote by  $\mathcal{S}^{\text{uni}} = \{t\mathbb{1} : t \in [0, 1]\}$  the set of uniform strategies.

The (uniform) cost of the vaccination strategy  $\eta \in \Delta$  is given by the total proportion of vaccinated people, that is:

$$(28) \quad C(\eta) = \int_{\Omega} (1 - \eta) d\mu = 1 - \int_{\Omega} \eta d\mu.$$

The measure  $\eta d\mu$  corresponds to the *effective population*, that is the individuals who effectively play a role in the dynamic of the epidemic. The effective reproduction number is defined by:

$$(29) \quad R_e(\eta) = \rho(T_{k\eta}),$$

We consider the weak topology on  $\Delta$ , so that with a slight abuse of notation we identify  $\Delta$  with  $\{\eta \in L^2 : 0 \leq \eta \leq 1\}$ . According to [13, Theorem 4.2], the function  $R_e : \eta \mapsto R_e(\eta)$  is continuous on  $\Delta$  equipped with the weak topology. The compactness of  $\Delta$  for this topology implies the existence of solutions for Problems (7) and (8). We will conserve the same notation and definitions as in the discrete setting for: the value functions  $R_{e^*}$  and  $R_e^*$ , the minimal/maximal costs  $c_*$  and  $c^*$ , the various sets of strategies  $\mathcal{P}$  and  $\mathcal{P}^{\text{Anti}}$ , and the various frontiers  $\mathcal{F}$  and  $\mathcal{F}^{\text{Anti}}$ , see Equations (9)-(17) in Section 2.2.

We shall also use the following result from [11, Corollary 6.1] (recall that a vaccination strategy is defined up the a.s. equality).

**Lemma 3.1.** *Let  $k$  be a kernel on  $\Omega$  with finite double norm on  $L^2$  such that a.s.  $k > 0$ . Then, we have  $c^* = 0$ ,  $c_* = 1$  and the strategy  $\mathbb{1}$  (resp.  $\mathbb{0}$ ) is the only Pareto optimal as well as the only anti-Pareto optimal strategy with cost  $c = 0$  (resp.  $c = 1$ ).*

*Example 3.2* (Discrete and continuous representations of a metapopulation model). We recall the natural correspondence between metapopulation models (discrete models) and kernel models (continuous models) from [13, Section 7.4.1]. Consider a metapopulation model with  $N$  groups given by a finite set  $\Omega_d = \{1, 2, \dots, N\}$  equipped with a probability measure  $\mu_d$  giving the relative size of each group and a next generation matrix  $K = (K_{ij}, i, j \in \Omega_d)$ . The corresponding discrete kernel  $k_d$  on  $\Omega_d$  is defined by:

$$(30) \quad K_{ij} = k_d(i, j) \mu_j \quad \text{where} \quad \mu_i = \mu_d(\{i\}).$$

Then, the matrix  $K \cdot \text{Diag}(\eta)$  is the matrix representation of the endomorphism  $T_{k_d \eta}$  in the canonical basis of  $\mathbb{R}^N$ .

Following [13], we can also consider a continuous representation on the state space  $\Omega_c = [0, 1)$  equipped with the Lebesgue measure  $\mu_c$ . Let  $I_1 = [0, \mu_1)$ ,  $I_2 = [\mu_1, \mu_1 + \mu_2)$ ,  $\dots$ ,

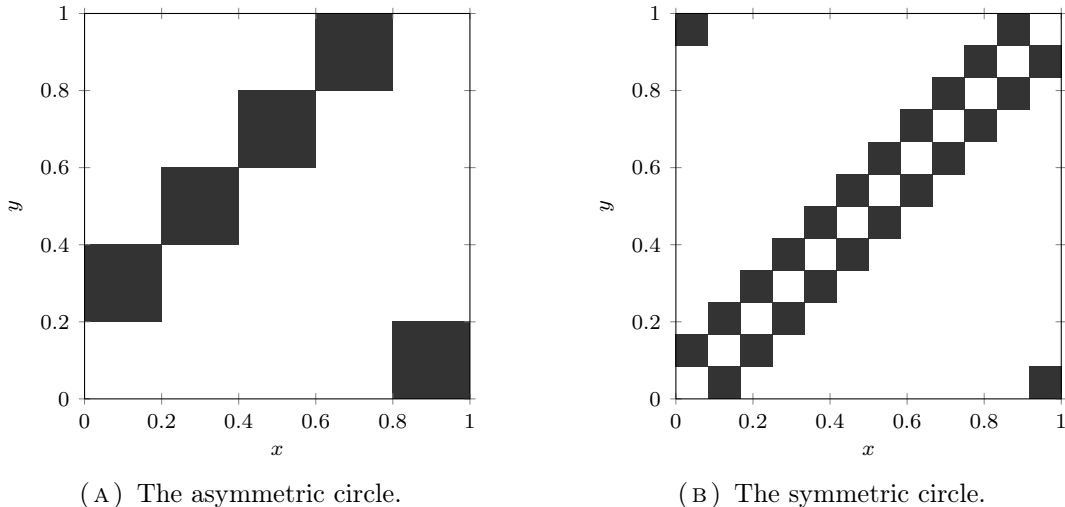


FIGURE 4. Kernels  $k_c$  (equal to 0 in the white zone and to 1 in the black zone) on  $\Omega_c = [0, 1)$  and  $\mu_c$  the Lebesgue measure of the continuous model associated to discrete metapopulation models.

$I_N = [1 - \mu_N, 1)$ , so that the intervals  $(I_n, 1 \leq n \leq N)$  form a partition of  $\Omega$ . Now define the kernel:

$$(31) \quad k_c(x, y) = \sum_{1 \leq i, j \leq N} k_d(i, j) \mathbb{1}_{I_i \times I_j}(x, y).$$

Denote by  $R_e^d$  and  $R_e^c$  the effective reproduction number in the discrete and continuous representation models. In the same manner, the uniform cost in each model is denoted by  $C^d$  and  $C^c$ . According to [13], these functions are linked through the following relation:

$$R_e^d(\eta^d) = R_e^c(\eta^c), \quad \text{and} \quad C^d(\eta^d) = C^c(\eta^c),$$

for all  $\eta^d : \Omega_d \rightarrow [0, 1]$  and  $\eta^c : \Omega_c \rightarrow [0, 1]$  such that:

$$\eta^d(i) = \frac{1}{\mu_i} \int_{I_i} \eta^c d\mu_c \quad \text{for all } i \in \Omega_d.$$

Let us recall that the Pareto and anti-Pareto frontiers for the two models are the same.

In Figure 4, we have plotted the kernels of the continuous models associated to the asymmetric and symmetric circles models from Sections 2.3 and 2.4.

#### 4. ASSORTATIVE VERSUS DISASSORTATIVE MIXING

**4.1. Motivation.** We consider a population divided into an at most countable number of groups. Individuals within the same group interact with intensity  $a$  and individuals in different groups interact with intensity  $b$ . Hence, the model is entirely determined by the coefficients  $a$  and  $b$  and the size of the different groups. This simple model allows to study the effect of assortativity, that is, the tendency for individuals to connect with individuals belonging to their own subgroup. The mixing pattern is called *assortative* (higher interaction in the same subgroup) if  $a > b$ , and *disassortative* (lower interaction in the same subgroup) when  $b > a$ . Our results illustrate how different the optimal vaccination strategies can be between assortative

and disassortative models, an effect that was previously studied by Galeotti and Rogers [21] in a population composed of two groups.

When the population is equally split in a finite number of subgroups, and  $a$  is equal to 0, the next-generation matrix of this model corresponds, up to a multiplicative constant, to the adjacency matrix of a complete multipartite graph. Recall that an  $m$ -partite graph is a graph that can be colored with  $m$  different colors, so that all edges have their two endpoints colored differently. When  $m = 2$  these are the so-called bipartite graphs. A complete multipartite graph is a  $m$ -partite graph (for some  $m \in \mathbb{N}^*$ ) in which there is an edge between every pair of vertices from different colors.

The complete multipartite graphs have interesting spectral properties. Indeed, Smith [45] showed that a graph with at least one edge has its spectral radius as its only positive eigenvalue if and only if its non-isolated vertices induce a complete multipartite graph. In [18], Esser and Harary proved that two complete  $m$ -partite graphs with the same number of nodes are isomorphic if and only if they have the same spectral radius. More precisely, they obtained a comparison of the spectral radii of two complete  $m$ -partite graphs by comparing the sizes of the sets in their partitions through majorization; see [18, Lemma 3].

The goal of this section is to generalize and complete these results and give a full picture of the Pareto and anti-Pareto frontiers for the assortative and the disassortative models.

**4.2. Spectrum and convexity.** We will use an integer intervals notation to represent the considered kernels. For  $i, j \in \mathbb{N} \cup \{+\infty\}$ , we set  $\llbracket i, j \rrbracket$  (resp.  $\llbracket i, j \llbracket$ ) for  $[i, j] \cap (\mathbb{N} \cup \{+\infty\})$  (resp.  $[i, j) \cap \mathbb{N}$ ). Let  $N \in \llbracket 2, +\infty \rrbracket$  and  $\Omega = \llbracket 1, N \rrbracket$  if  $N$  is finite and  $\Omega = \llbracket 1, +\infty \llbracket$  otherwise. The set  $\Omega$  is endowed with the discrete  $\sigma$ -algebra  $\mathcal{F} = \mathcal{P}(\Omega)$  and a probability measure  $\mu$ . To simplify the notations, we write  $\mu_i$  for  $\mu(\{i\})$  and  $f_i = f(i)$  for a function  $f$  defined on  $\Omega$ . Without loss of generality, we can suppose that  $\mu_i \geq \mu_j > 0$  for all  $i \leq j$  elements of  $\Omega$ . We consider the kernel  $k$  defined for  $i, j \in \Omega$  by:

$$(32) \quad k(i, j) = \begin{cases} a & \text{if } i = j, \\ b & \text{otherwise,} \end{cases}$$

where  $a$  and  $b$  are two non-negative real numbers.

If  $b = 0$ , then the kernel is reducible, see [11, Section 7], and the effective reproduction number is given by the following formula:  $R_e(\eta) = a \max_{i \in \Omega} \eta_i \mu_i$ , for all  $\eta = (\eta_i, i \in \Omega) \in \Delta$ . This is sufficient to treat this case and we have  $c^* = 1 - \mu_1$ .

From now on, we assume that  $b > 0$ . The next two results describe the spectrum of  $T_k$  in both the assortative and disassortative case. Notice the spectrum of  $T_k$  is real as  $k$  is symmetric. Recall that  $R_0 = \rho(T_k)$ .

**Proposition 4.1** (Convexity/concavity of  $R_e$ ). *Let  $k$  be given by (32), with  $b > 0$  and  $a \geq 0$ .*

- (i) **Assortative model.** *If  $a \geq b > 0$ , then the operator  $T_k$  is positive semi-definite and the function  $R_e$  is convex.*
- (ii) **Disassortative model.** *If  $b \geq a \geq 0$  and  $b > 0$ , then  $R_0$  is the only positive eigenvalue of  $T_k$ , and it has multiplicity one. Furthermore, the function  $R_e$  is concave.*

In the following proof, we shall consider the symmetric matrix  $M_n$  of size  $n \times n$ , with  $n \in \mathbb{N}^*$ , given by:

$$M_n(i, j) = \begin{cases} a & \text{if } i = j, \\ b & \text{otherwise.} \end{cases}$$



The matrix  $M_n$  is the sum of  $b$  times the all-ones matrix and  $a - b$  times the identity matrix. Thus,  $M_n$  has two distinct eigenvalues:  $nb + a$  with multiplicity 1 and  $a - b$  with multiplicity  $n - 1$ .

*Proof.* We first prove (i). For any  $g \in L^2$ , we have:

$$\int_{\Omega \times \Omega} g(x)k(x, y)g(y) \mu(dx)\mu(dy) = a \sum_{i \in \Omega} g_i^2 \mu_i^2 + b \sum_{i \neq j} g_i g_j \mu_i \mu_j \geq b \|g\|_2^2.$$

This implies that  $T_k$  is positive semi-definite. Thus, as  $k$  is symmetric, the function  $R_e$  is convex, thanks to [11, Theorem 5.5].

We now prove (ii). We give a direct proof when  $N$  is finite, and use an approximation procedure for  $N = \infty$ . We first assume that  $N$  is finite. For  $n \leq N$ , let  $v_n = \mathbb{1}_{[1, n]}$  and set  $T_n = T_{v_n k v_n}$ . The non-null eigenvalues of  $T_n$  (with their multiplicity) are the eigenvalues of the matrix  $M_n \cdot \text{Diag}_n(\mu)$ , where  $\text{Diag}_n(\mu)$  is the diagonal  $n \times n$ -matrix with  $(\mu_1, \dots, \mu_n)$  on the diagonal. Thanks to [32, Theorem 1.3.22], these are also the eigenvalues of the matrix  $Q_n = \text{Diag}_n(\mu)^{1/2} \cdot M_n \cdot \text{Diag}_n(\mu)^{1/2}$ . By Sylvester's law of inertia [32, Theorem 4.5.8], the matrix  $Q_n$  has the same signature as the symmetric matrix  $M_n$ . In particular, since we have supposed  $a - b \leq 0$ ,  $M_n$  has only one positive eigenvalue. Thus  $Q_n$  has only one positive eigenvalue: thanks to the Perron-Frobenius theory, it is its spectral radius. This concludes the proof when  $N$  is finite by choosing  $n = N$ .

If  $N = \infty$ , we consider the limit  $n \rightarrow N$ . Since:

$$\lim_{n \rightarrow \infty} \|k - v_n k v_n\|_{2,2} = 0,$$

the spectrum of  $T_n$  converges to the spectrum of  $T_k$ , with respect to the Hausdorff distance, and the multiplicity on the non-zero eigenvalues also converge, see [11, Corollary 3.2]. This shows that  $\rho(T_k)$  is the only positive eigenvalue of  $T_k$ , and it has multiplicity one. Since  $k$  is symmetric, we deduce the concavity of the function  $R_e$  from [11, Theorem 5.5].  $\square$

**4.3. Explicit description of the Pareto and anti-Pareto frontiers.** For  $c \in [0, 1]$ , we define an “horizontal vaccination”  $\eta^h(c) \in \Delta$  with cost  $c$  in the following manner. Rather than defining directly the proportion of non-vaccinated people in each class, it will be convenient to define first the resulting effective population size, which will be denoted by  $\xi$ . For all  $\alpha \in [0, \mu_1]$ , let  $\xi^h(\alpha) \in \Delta$  be defined by:

$$(33) \quad \xi_i^h(\alpha) = \min(\alpha, \mu_i), \quad i \in \Omega.$$

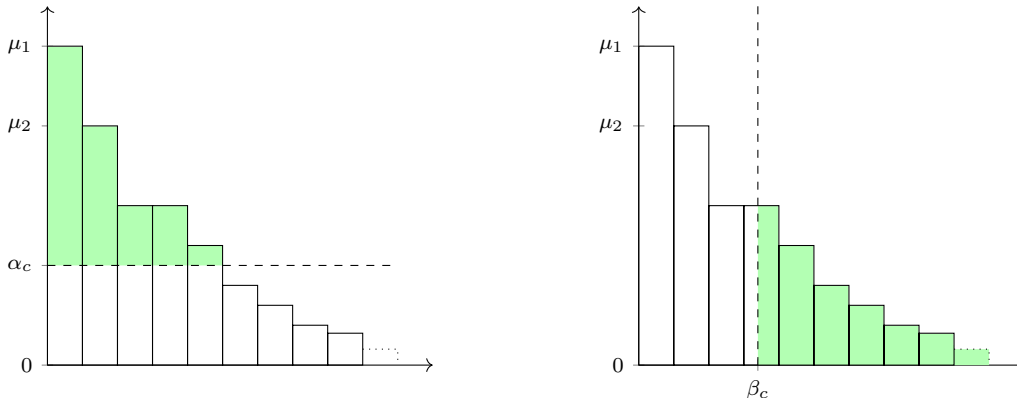
For all  $i \in \Omega$ ,  $\xi_i^h(\alpha)$  is a non-decreasing and continuous function of  $\alpha$ . The map  $\alpha \mapsto \sum_i \xi_i^h(\alpha)$  is continuous and increasing from  $[0, \mu_1]$  to  $[0, 1]$ , so for any  $c \in [0, 1]$ , there exists a unique  $\alpha_c$  such that  $\sum_i \xi_i^h(\alpha_c) = 1 - c$ . We then define the horizontal vaccination profile  $\eta^h(c) \in \Delta$  by:

$$(34) \quad \eta_i^h(c) = \xi_i^h(\alpha_c) / \mu_i, \quad i \in \Omega.$$

In words, it consists in vaccinating in such a way that the quantity of the non-vaccinated individuals  $\xi_i^h = \eta_i \mu_i$  in each subpopulation is always less than the “horizontal” threshold  $\alpha$ : see Figure 5(A). The cost of the vaccination strategy  $\eta^h(c)$  is indeed  $c$ . Note that  $\eta^h(0) = \mathbb{1}$  (no vaccination), whereas  $\eta^h(1) = 0$  (full vaccination), and that the path  $c \mapsto \eta^h(c)$  is greedy. We denote its range by  $\mathcal{P}_h$ .

For  $c \in [0, 1]$ , we define similarly a “vertical vaccination”  $\eta^v(c) \in \Delta$  with cost  $c$ . First let us define for  $\beta \in [0, N]$ :

$$(35) \quad \xi_i^v(\beta) = \mu_i \cdot \min(1, (\beta + 1 - i)_+), \quad i \in \Omega.$$



(A) Representation of the greedy path  $\mathcal{P}_h$ . (B) Representation of the greedy path  $\mathcal{P}_v$ .

FIGURE 5. Greedy parametrization of the (anti-)Pareto front. The bar plot represents the measure  $\mu$ . The proportion of green in each bar correspond to the proportion of vaccinated individuals in each subpopulation.

The map  $\beta \mapsto \sum_i \xi_i^v(\beta)$  is increasing and continuous from  $[0, N]$  to  $[0, 1]$ , so for any  $c \in [0, 1]$  there exists a unique  $\beta_c$  such that  $\sum_i \xi_i^v(\beta_c) = 1 - c$ . We then define the vertical vaccine profile  $\eta^v(c)$  by:

$$(36) \quad \eta_i^v(c) = \xi_i^v(\beta_c) / \mu_i, \quad i \in \Omega.$$

In words, if  $\lceil \beta \rceil = \ell$ , this consists in vaccinating all subpopulations  $j$  for  $j > \ell$ , and a fraction  $\lceil \beta \rceil - \beta$  of the subpopulation  $\ell$ , see Figure 5(B) for a graphical representation. The cost of the vaccination strategy  $\eta^v(c)$  is by construction equal to  $c$ .

For all  $i \in \Omega$ ,  $\eta_i^v(c)$  is a non-increasing and continuous function of  $c$ . Just as in the horizontal case, we have  $\eta^v(0) = \mathbb{1}$  (no vaccination),  $\eta^v(1) = 0$  (full vaccination), and the path  $c \mapsto \eta^v(\beta(c))$  is also greedy. We denote its range by  $\mathcal{P}_v$ .

These two paths give a greedy parametrization of the Pareto and anti-Pareto frontiers for the assortative and disassortative models: more explicitly, we have the following result, whose proof can be found in Section 4.4.

**Theorem 4.2** (Assortative vs disassortative). *Let  $k$  be given by (32), with  $b > 0$  and  $a \geq 0$ .*

- (i) **Assortative model.** *If  $a \geq b > 0$ , then  $\mathcal{P}_v$  and  $\mathcal{P}_h$  are greedy parametrizations of the anti-Pareto and Pareto frontiers respectively.*
- (ii) **Disassortative model.** *If  $b \geq a > 0$ , then  $\mathcal{P}_v$  and  $\mathcal{P}_h$  are greedy parametrizations of the Pareto and anti-Pareto frontiers respectively.*
- (iii) **Complete multipartite model.** *If  $a = 0$  and  $b > 0$ , then  $\mathcal{P}_h$  is a greedy parametrization of the anti-Pareto frontier and the subset of strategies  $\eta \in \mathcal{P}_v$  such that  $C(\eta) \leq 1 - \mu_0$  is a greedy parametrization of the Pareto frontier. In particular, we have  $c_\star = 1 - \mu_1$  and  $c^\star = 0$ .*

Notice that  $c^\star = 0$  and  $c_\star = 1$  in cases (i) and (ii) as  $k$  is positive thanks to Lemma 3.1.

*Remark 4.3* (Highest Degree vaccination). The effective degree function of a symmetric kernel  $k$  at  $\eta \in \Delta$  is the function  $\text{deg}_\eta$  defined on  $\Omega$  by:

$$(37) \quad \text{deg}_\eta(x) = \int_{\Omega} k(x, y) \eta(y) \mu(dy).$$

When  $\eta = \mathbb{1}$ , it is simply called the degree of  $k$  and is denoted by  $\text{deg}$ . In our model, the effective degree of the subgroup  $i$  is given by

$$(38) \quad \text{deg}_\eta(i) = a\eta_i\mu_i + b \sum_{\ell \neq i} \eta_\ell \mu_\ell,$$

and thus the degree of the subgroup  $i$  is given by  $\text{deg}(i) = (a - b)\mu_i + b$ . As  $\mu_i \geq \mu_j$  for  $i < j$  elements of  $\Omega$ , we deduce that the degree function is monotone: non-increasing in the assortative model and non-decreasing in the disassortative model. The group with the highest degree therefore corresponds to the largest group in the assortative model and the smallest group (if it exists) in the disassortative model.

Consider the assortative model where all the groups have different size, *i.e.*,  $\mu_1 > \mu_2 > \dots$ . Following the parametrization  $c \mapsto \eta^h(c)$ , starting from  $c = 0$ , will first decrease the effective size of the group 1 (the group with the highest degree) until it reaches the effective degree of group 2 (with the second highest degree). Once these two groups share the same effective degree which corresponds to reaching  $\mu_1 \eta_1^h = \mu_2$ , they are vaccinated uniformly (that is, ensuring that they keep the same effective degree: using (38) this corresponds to  $\mu_1 \eta_1^h = \mu_2 \eta_2^h$ ) until their effective degree is equal to the third highest degree, and so on and so forth.

In the disassortative model, the function  $\text{deg}_\eta$  remains (strictly) increasing when the vaccination strategies in  $\mathcal{P}_v$  are applied. In particular, if  $\mu_1 > \mu_2 > \dots$ , then the optimal strategies prioritize the groups with the higher effective degree until they are completely immunized. If multiple groups share the same degree, it is optimal to give all available doses to one group.

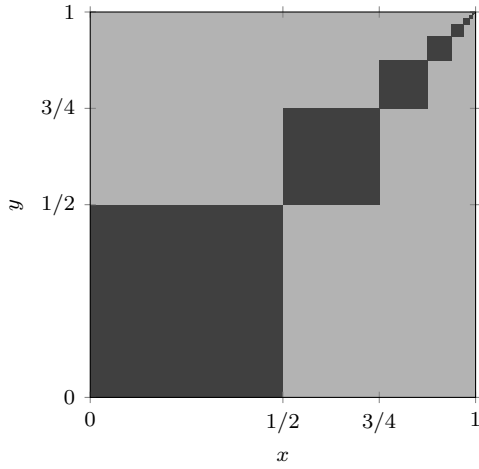
In conclusion, in both models, the optimal vaccination consists in vaccinating the groups with the highest effective degree in priority if this group is unique. But if multiple groups share the same degree (*i.e.*, have the same size), the optimal strategies differ between the assortative and the disassortative case. In the assortative case, groups with the same size must be vaccinated uniformly while in the disassortative case, all the vaccine doses shall be given to one group until it is completely vaccinated.

*Example 4.4* (Group sizes following a dyadic distribution). Let  $N = \infty$ ,  $\Omega = \mathbb{N}^*$  and  $\mu_i = 2^{-i}$  for all  $i \in \Omega$ . Following [13, Section 7.4.1], we will couple this discrete model with a continuum model for a better visualization on the figures. Let  $\Omega_c = [0, 1)$  be equipped with the Borel  $\sigma$ -field  $\mathcal{F}_c$  and the Lebesgue measure  $\mu_c$ . The set  $\Omega_c$  is partitionned into a countable number of intervals  $I_i = [1 - 2^{-i+1}, 1 - 2^{-i})$ , for  $i \in \mathbb{N}^*$ , so that  $\mu_c(I_i) = \mu_i$ . The kernel of the continuous model corresponding to  $k$  in (32) is given by:

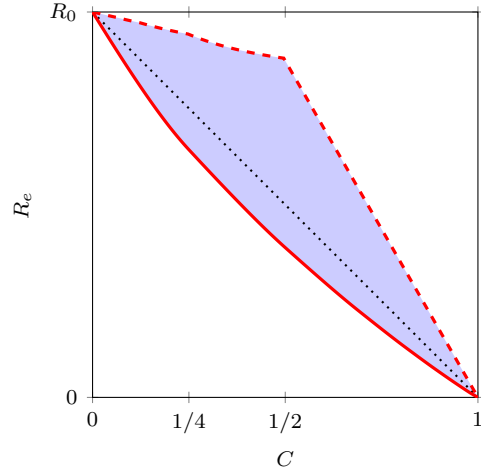
$$(39) \quad k_c = (a - b) \sum_{i \in \mathbb{N}^*} \mathbb{1}_{I_i \times I_i} + b\mathbb{1}.$$

The kernel  $k_c$  is plotted in Figures 6(A), 7(A) and 8(A) for different values of  $a$  and  $b$  corresponding respectively to the assortative, the disassortative and the complete multipartite case corresponding to points (i), (ii) and (iii) of Theorem 4.2 respectively. Their respective Pareto and anti-Pareto frontiers are plotted in Figures 6(B), 7(B) and 8(B), using a finite-dimensional approximation of the kernel  $k$  and the power iteration method. In Figure 8(B), the value of  $c_\star$  is equal to  $1 - \mu_1 = 1/2$ . With this continuous representation of the population, the set  $\mathcal{P}_v$  corresponds to the strategies of the form  $\mathbb{1}_{[0,t]}$  for  $t \in [0, 1]$ .

Notice that the Pareto frontier in the assortative case is convex. This is consistent with [13, Proposition 6.6] since the cost function is affine and  $R_e$  is convex when  $a \geq b$ ; see Proposition 4.1 (i). In the same manner, the anti-Pareto frontier in the disassortative and the multipartite cases is concave. Once again, this is consistent with [13, Proposition 6.6] since the cost function is affine and  $R_e$  is concave when  $b \geq a$ ; see Proposition 4.1 (ii).

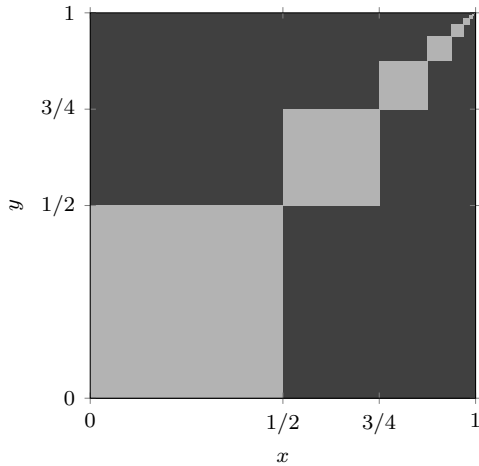


(A) Grayplot of the kernel  $k_c$  from (39) on  $\Omega_c = [0, 1)$  with  $k_c = a = 5$  on the dark gray zone, and  $k_c = b = 2$  on the light gray zone.

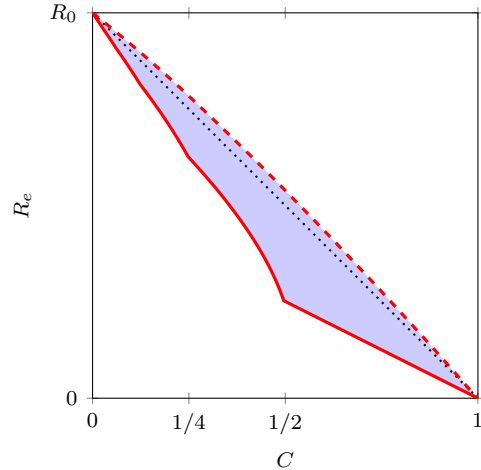


(B) Solid line: the Pareto frontier  $\mathcal{F}$ ; dashed line: the anti-Pareto frontier  $\mathcal{F}^{\text{Anti}}$ ; dotted line: path of the uniform strategies; blue region: all possible outcomes  $\mathbf{F}$ .

FIGURE 6. An assortative model.



(A) Grayplot of the kernel  $k_c$  from (39) on  $\Omega_c = [0, 1)$  with  $k_c = a = 2$  on the light gray zone, and  $k_c = b = 5$  on the dark gray zone.



(B) Solid line: the Pareto frontier  $\mathcal{F}$ ; dashed line: the anti-Pareto frontier  $\mathcal{F}^{\text{Anti}}$ ; dotted line: path of the uniform strategies; blue region: all possible outcomes  $\mathbf{F}$ .

FIGURE 7. A disassortative model.

**4.4. Proof of Theorem 4.2.** After recalling known facts of majorization theory, we first consider the finite dimension models, and then the general case by an approximation argument.

**4.4.1. Majorization.** In this section, we recall briefly some definitions and results from majorization theory, and refer to [2, 40] for an extensive treatment of this topic.

Let  $n \geq 1$  and  $\xi, \chi \in \mathbb{R}_+^n$ . We denote by  $\xi^\downarrow$  and  $\chi^\downarrow$  their respective order statistics, that is the vectors in  $\mathbb{R}_+^n$  with the same components, but sorted in descending order. We say that  $\xi$  is

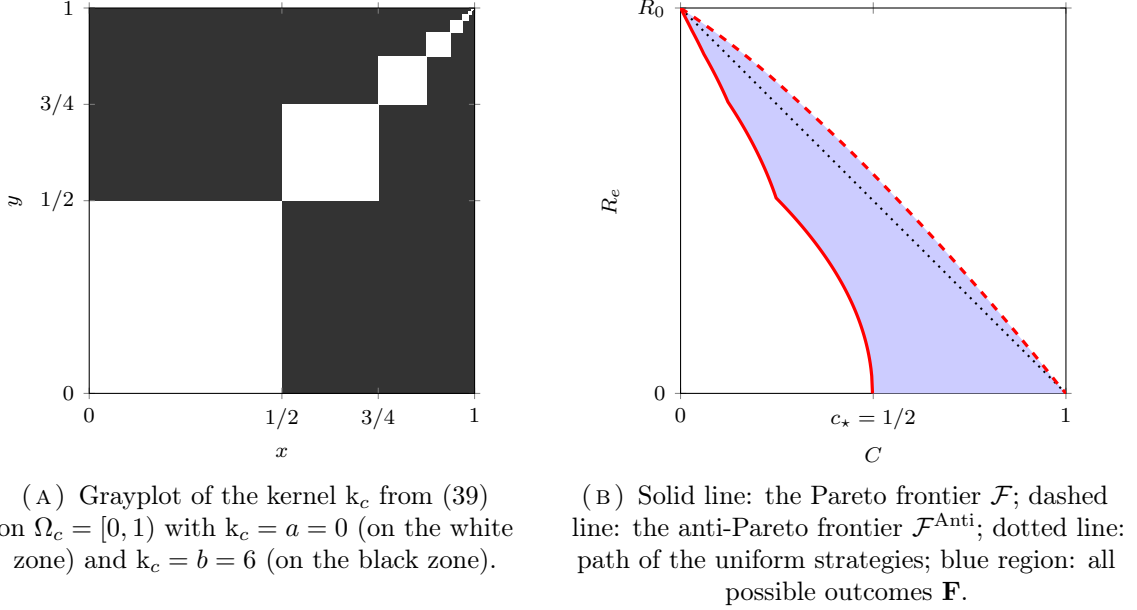


FIGURE 8. An example of the complete multipartite model.

majorized by  $\chi$ , and write  $\xi \prec \chi$ , if:

$$(40) \quad \sum_{j=1}^i \xi_j^\downarrow \leq \sum_{j=1}^i \chi_j^\downarrow \quad \text{for all } i \in \{1, \dots, n\}, \quad \text{and} \quad \sum_{j=1}^n \xi_j = \sum_{j=1}^n \chi_j.$$

Among the various characterizations of majorization, we will use the following by Hardy, Littlewood and Pólya; see [40, Proposition I.4.B.3]:

$$(41) \quad \xi \prec \chi \iff \sum_i (\xi_i - t)_+ \leq \sum_i (\chi_i - t)_+ \quad \text{for all } t \in \mathbb{R}_+,$$

where  $u_+ = \max(u, 0)$ , for all  $u \in \mathbb{R}$ . A real-valued function  $\Theta$  defined on  $\mathbb{R}_+^n$  is called *Schur-convex* if it is non-decreasing with respect to  $\prec$ , that is,  $\xi \prec \chi$  implies  $\Theta(\xi) \leq \Theta(\chi)$ . A function  $\Theta$  is called *Schur-concave* if  $(-\Theta)$  is Schur-convex.

4.4.2. *Schur convexity and concavity of the spectral radius in finite dimension.* We define the function  $\Theta_n$  on  $\mathbb{R}_+^n$  by:

$$\Theta_n(\xi) = \rho(M_n \cdot \text{Diag}(\xi)),$$

where  $\text{Diag}(\xi)$  is the diagonal  $n \times n$ -matrix with  $\xi$  on the diagonal. By construction, for  $\eta = (\eta_1, \dots, \eta_n, 0, \dots)$ , we have:

$$(42) \quad R_e(\eta) = \Theta_n(\eta_1 \mu_1, \dots, \eta_n \mu_n).$$

The key property below will allow us to identify the optimizers.

**Lemma 4.5** (Schur-concavity and Schur-convexity). *Let  $b > 0$  and  $a \geq 0$ . The function  $\Theta_n$  is Schur-convex if  $a \geq b$ , and Schur-concave if  $a \leq b$ .*

*Proof.* Let us consider the disassortative case where  $a \leq b$ . By a classical result of majorization theory [40, Proposition I.3.C.2.], it is enough to show that  $\Theta_n$  is symmetric and concave.

To prove that  $\Theta_n$  is symmetric, consider  $\sigma$  be a permutation of  $\{1, 2, \dots, n\}$  and  $P_\sigma$  the associated permutation matrix of size  $n \times n$ . Since  $P_\sigma M_n P_\sigma^{-1} = M_n$ , we deduce that  $\Theta_n(\xi_\sigma) = \Theta_n(\xi)$ , where  $\xi_\sigma$  is the  $\sigma$ -permutation of  $\xi \in \mathbb{R}_+^n$ . Thus  $\Theta_n$  is symmetric.

We now prove that  $\Theta_n$  is concave on  $\mathbb{R}_+^n$ . Since  $R_e$  is concave thanks to Proposition 4.1 (ii), we deduce from (42), that the function  $\Theta_n$  is concave on  $[0, \mu_1] \times \dots \times [0, \mu_n]$ . Since  $\Theta_n$  is homogeneous, it is actually concave on the whole domain  $\mathbb{R}_+^n$ . This concludes the proof when  $a \leq b$ .

The proof is the same for the assortative case  $a \geq b$ , replacing the reference to Proposition 4.1 (ii) by (i).  $\square$

**4.4.3. Extreme vaccinations for fixed cost.** Let us show that the horizontal and vertical vaccinations give extreme points for the preorder  $\prec$  on finite sets, when the quantity of vaccine is fixed. Recall that  $\xi^h$  and  $\xi^v$  are defined in (33) and (35) respectively.

**Proposition 4.6** (Extreme vaccinations). *Let  $n \in \Omega$ ,  $\beta \in [0, n)$  and  $\alpha \in [0, \mu_1]$ . Let  $\xi^{v,n} = (\xi_1^v(\beta), \dots, \xi_n^v(\beta))$ , and  $\xi^{h,n} = (\xi_1^h(\alpha), \dots, \xi_n^h(\alpha))$ . For any  $\xi = (\xi_1, \dots, \xi_n) \in [0, \mu_1] \times \dots \times [0, \mu_n]$ , we have:*

$$\left( \sum_{i=1}^n \xi_i = \sum_{i=1}^n \xi_i^{v,n} \right) \implies \xi \prec \xi^{v,n}, \quad \text{and} \quad \left( \sum_{i=1}^n \xi_i = \sum_{i=1}^n \xi_i^{h,n} \right) \implies \xi^{h,n} \prec \xi.$$

*Proof.* Let  $\xi \in [0, \mu_1] \times \dots \times [0, \mu_n]$  be such that  $\sum_{i=1}^n \xi_i = \sum_{i=1}^n \xi_i^{v,n}$ . The reordered vector  $\xi^\downarrow$  clearly satisfies the same conditions, so without loss of generality we may assume that  $\xi$  is sorted in descending order. Using Equation (35), we get:

$$\sum_{i=1}^{\ell} \xi_i \leq \sum_{i=1}^{\ell} \mu_i = \sum_{i=1}^{\ell} \xi_i^{v,n}, \quad \text{for } 1 \leq \ell \leq \lfloor \beta \rfloor.$$

We also have:

$$\sum_{i=1}^{\ell} \xi_i \leq \sum_{i=1}^n \xi_i = \sum_{i=1}^n \xi_i^{v,n} = \sum_{i=1}^{\ell} \xi_i^{v,n}, \quad \text{for } \ell > \lfloor \beta \rfloor.$$

Therefore, we get  $\xi \prec \xi^{v,n}$ , by the definition of  $\prec$ .

Similarly, let  $\xi \in [0, \mu_1] \times \dots \times [0, \mu_n]$  be such that  $\sum_{i=1}^n \xi_i = \sum_{i=1}^n \xi_i^{h,n}$ . If  $t \geq \alpha$  then:

$$\sum_i (\xi_i^{h,n} - t)_+ = 0 \leq \sum_i (\xi_i - t)_+,$$

while if  $t \in [0, \alpha)$ , using the fact that  $\sum_{i=1}^n \xi_i = \sum_{i=1}^n \xi_i^{h,n}$ , the expression  $\xi_i^{h,n} = \min(\alpha, \mu_i)$ , and the inequalities  $\xi_i \leq \mu_i$ , we get:

$$\begin{aligned} \sum_{i=1}^n (\xi_i^{h,n} - t)_+ &= \sum_{i=1}^n (\xi_i^{h,n} - t) + \sum_{i=1}^n (t - \xi_i^{h,n})_+ \\ &= \sum_{i=1}^n (\xi_i - t) + \sum_{i=1}^n (t - \mu_i)_+ \\ &\leq \sum_{i=1}^n (\xi_i - t) + \sum_{i=1}^n (t - \xi_i)_+ \\ &= \sum_{i=1}^n (\xi_i - t)_+. \end{aligned}$$

This gives  $\xi^{h,n} \prec \xi$ , by the characterization (41).  $\square$

4.4.4. “Vertical” Pareto optima in the disassortative case. We consider here the disassortative model  $b \geq a \geq 0$  and  $b > 0$ . Let  $c \in (0, 1)$  and  $D(c) = \{\eta \in \Delta : C(\eta) = c\}$  be the set of vaccination strategies with cost  $c$ . We will solve the constrained optimization Problem (7) that corresponds to:

$$(43) \quad \begin{cases} \min & R_e(\eta), \\ \text{such that} & \eta \in D(c). \end{cases}$$

Recall the definitions of  $\beta_c$  and  $\eta^v(c)$  given page 17. Let  $\eta \in D(c)$ . Let  $n$  be large enough so that  $\sum_{j>n} \mu_j < 1 - c$  so that  $\sum_{j \leq n} \eta_j \mu_j > 0$ , and assume that  $n > \beta$ . Let  $\eta^{(n)} \in \Delta$  be defined by:

$$\eta_i^{(n)} = \frac{\sum_{j \leq n} \eta_j^v(c) \mu_j}{\sum_{j \leq n} \eta_j \mu_j} \mathbb{1}_{\{i \leq n\}} \eta_i.$$

Note that since  $C(\eta^v(c)) = c = C(\eta)$ , we have  $\lim_{n \rightarrow \infty} \eta^{(n)} = \eta$  (pointwise and in  $L^2$ ). Let  $\xi^n = (\eta_1^{(n)} \mu_1, \dots, \eta_n^{(n)} \mu_n)$  and  $\xi^{v,n}$  be defined as in Proposition 4.6 with  $\beta = \beta_c$ . By construction, we have  $\sum_{i=1}^n \xi_i^n = \sum_{i=1}^n \xi_i^{v,n}$ , so by Proposition 4.6, we get  $\xi^n \prec \xi^{v,n}$ . This implies that:

$$R_e(\eta^{(n)}) = \Theta_n(\xi^n) \geq \Theta_n(\xi^{v,n}) = R_e(\eta^v(c)),$$

where the inequality follows from the Schur concavity of  $\Theta_n$  in the disassortative case (see Lemma 4.5) and where the last equality holds as  $n \geq \lceil \beta_c \rceil$ . Since  $R_e$  is continuous and  $\eta^{(n)}$  converges pointwise and in  $L^2$  to  $\eta$ , we get  $R_e(\eta) \geq R_e(\eta^v)$ . This implies that  $\eta^v$  is a solution of Problem (43).

If  $a > 0$ , then  $k$  is positive everywhere, and we deduce from Lemma 3.1 that  $c_* = 1$ . If  $a = 0$ , it is easy to prove that  $\{0\}$  is a maximal independent set of  $k$ ; this gives that  $c_* = 1 - \mu_1$ , thanks to [11, Section 6.4]. Since for all  $c \in [0, c_*)$  there exists  $\eta \in \mathcal{P}_v$  such that  $C(\eta) = c$ , we also get that  $\mathcal{P}_v \cap \{\eta \in \Delta : C(\eta) \leq c_*\}$  is a parametrization of the Pareto frontier. This gives the parametrization of the Pareto frontier using  $\mathcal{P}_v$  from Theorem 4.2 (ii) and (iii).

4.4.5. “Horizontal” anti-Pareto optima in the disassortative case. We still consider  $b \geq a \geq 0$  and  $b > 0$ . Let  $c \in (0, 1)$ . We now turn to the anti-Pareto frontier by studying the constrained maximization Problem (8) that corresponds to:

$$(44) \quad \begin{cases} \max & R_e(\eta), \\ \text{such that} & \eta \in D(c). \end{cases}$$

Recall the definitions of  $\alpha_c$  and  $\eta^h(c)$  given page 16. Let  $\eta \in D(c)$ . Let  $n$  be large enough so that  $\sum_{j>n} \mu_j < 1 - c$  and thus  $\sum_{j \leq n} \eta_j \mu_j > 0$ . Define  $\eta^{(n)} \in \Delta$  by:

$$\eta_i^{(n)} = \frac{\sum_{j \leq n} \eta_j^h(c) \mu_j}{\sum_{j \leq n} \eta_j \mu_j} \mathbb{1}_{\{i \leq n\}} \eta_i.$$

Let  $\xi^n = (\eta_1^{(n)} \mu_1, \dots, \eta_n^{(n)} \mu_n)$  and let  $\xi^{h,n}$  be defined as in Proposition 4.6 with  $\alpha = \alpha_c$ . By construction, we have  $\sum_{i=1}^n \xi_i^n = \sum_{i=1}^n \xi_i^{h,n}$ , so by Proposition 4.6, we obtain  $\xi^{h,n} \prec \xi^n$ . This implies that:

$$R_e(\eta^{(n)}) = \Theta_n(\xi^n) \leq \Theta_n(\xi^{h,n}) = R_e(\eta^h(c) \mathbb{1}_{[1,n]}),$$

where the inequality follows from the Schur concavity of  $\Theta_n$ .

Now, as  $n$  goes to infinity  $\eta^{(n)}$  converges pointwise and in  $L^2$  to  $\eta$ , and  $\eta^h(c) \mathbb{1}_{[1,n]}$  converges pointwise and in  $L^2$  to  $\eta^h(c)$ , so by continuity of  $R_e$  we get  $R_e(\eta) \leq R_e(\eta^h(c))$ , and  $\eta^h(c)$

is solution of the Problem (44) and is thus anti-Pareto optimal for  $c \in (0, 1)$  as  $c^* = 0$ . Since  $c^* = 0$ , we also deduce from [13, Propostion 5.8 (iii)] that  $\mathbb{0}$  and  $\mathbb{1}$  are anti-Pareto optimal. Since for all  $c \in [0, 1]$  there exists  $\eta \in \mathcal{P}_h$  such that  $C(\eta) = c$ , we deduce that  $\mathcal{P}_h$  is a parametrization of the anti-Pareto frontier.

4.4.6. *The assortative case.* The case  $a \geq b > 0$ , corresponding to point (i) in Proposition 4.2, is handled similarly, replacing concavity by convexity, minima by maxima and vice versa.

## 5. CONSTANT DEGREE KERNELS AND UNIFORM VACCINATIONS

5.1. **Motivation.** We have seen in the previous section an example of model where vaccinating individuals with the highest degree is the best strategy. A similar phenomenon is studied in [14], where under monotonicity arguments on the kernel, vaccinating individuals with the highest (resp. lowest) degree is Pareto (resp. anti-Pareto) optimal. However, in case multiple individuals share the same maximal degree, the optimal strategies differ completely between the assortative and the disassortative models: the Pareto optimal strategies for one model correspond to the anti-Pareto optimal strategies for the other and vice versa.

Motivated by this curious symmetry, we investigate in this section constant degree kernels, that is, the situation where all the individuals have the same number of connections. In Section 5.2, we define these kernels formally and give the main result on the optimality of the uniform strategies when  $R_e$  is either convex or concave, see Proposition 5.4. Section 5.3 is devoted to the proof of this main result. We study in more detail the optimal strategies in an example of constant degree symmetric kernels of rank two in Section 6. Eventually, we study in Section 7 geometric kernels on the sphere, which are constant degree kernels.

5.2. **On the uniform strategies for constant degree kernels.** In graph theory, a regular graph is a graph where all vertices have the same number of in-neighbors, and the same number of out-neighbors. In other words all vertices have the same in-degree and the same out-degree. Limits of undirected regular graphs have been studied in details by Backhausz and Szegedy [4] and Kunszenti-Kovács, Lovász and Szegedy [36]. When the graphs are dense, their limit can be represented as a regular graphon, that is a symmetric kernel with a constant degree function.

Since we do not wish to assume symmetry, we give the following general definition. For a kernel  $k$  on  $\Omega$ , we set, for all  $z \in \Omega$  and  $A \in \mathcal{F}$ :

$$k(z, A) = \int_A k(z, y) \mu(dy) \quad \text{and} \quad k(A, z) = \int_A k(x, z) \mu(dx).$$

For  $z \in \Omega$ , its in-degree is  $k(z, \Omega)$  and its out-degree is  $k(\Omega, z)$ .

**Definition 5.1** (Constant degree kernel). *A kernel  $k$  with a finite  $L^2$  double-norm and a positive spectral radius  $R_0 > 0$  is called constant degree if all the in-degrees and all the out-degrees have the same value, that is, the maps  $x \mapsto k(x, \Omega)$  and  $y \mapsto k(\Omega, y)$  defined on  $\Omega$  are constant, and thus equal.*

*Remark 5.2.* Let  $k$  be a constant degree kernel with spectral radius  $R_0 > 0$ . Notice the condition “all the in-degrees and out-degrees have the same value” is also equivalent to  $\mathbb{1}$  being a left and right eigenfunction of  $T_k$ . We now check that the corresponding eigenvalue is  $R_0$ .

Let  $h \in L^2_+(\Omega) \setminus \{0\}$  be a left Perron-eigenfunction. Denote by  $\lambda$  the eigenvalue associated to  $\mathbb{1}$ . Then, we have:

$$\lambda \int_{\Omega} h(x) \mu(dx) = \int_{\Omega} h(x) k(x, y) \mu(dx) \mu(dy) = R_0 \int_{\Omega} h(y) \mu(dy),$$



where the first equality follows from the regularity of  $k$  and from the fact that  $h$  is a left Perron-eigenfunction of  $T_k$ . Since  $h$  is non-negative and not equal to 0 almost everywhere, we get that  $\lambda = R_0$  and  $\mathbb{1}$  is a right Perron-eigenvector of  $T_k$ . With a similar proof, we show that  $\mathbb{1}$  is a left Perron-eigenvector of  $T_k$ . In particular, if  $k$  is constant degree, then the reproduction number is given by:

$$(45) \quad R_0 = \int_{\Omega \times \Omega} k(x, y) \mu(dx) \mu(dy).$$

*Example 5.3.* We now give examples of constant degree kernels.

- (i) Let  $G = (V, E)$  be a finite non-oriented simple graph, and  $\mu$  the uniform probability measure on the vertices  $V$ . The degree of a vertex  $x \in V$  is given by

$$\deg(x) = \#\{y \in V : (x, y) \in E\}.$$

The graph  $G$  is constant degree if all its vertices have the same degree, say  $d \geq 1$ . Then the kernel defined on the finite space  $\Omega = V$  by the adjacency matrix is constant degree with  $R_0 = d$ . Notice it is also symmetric.

- (ii) Let  $G = (V, E)$  be a finite directed graph, and  $\mu$  be the uniform probability measure on the vertices  $V$ . The in-degree of a vertex  $x \in V$  is given by

$$\deg_{\text{in}}(x) = \#\{y \in V : (y, x) \in E\},$$

and the out-degree is given by

$$\deg_{\text{out}}(x) = \#\{y \in V : (x, y) \in E\}.$$

The graph  $G$  is regular if all its vertices have the same in-degree and out-degree, say  $d \geq 1$ . Then the kernel defined on the finite space  $\Omega = V$  by the adjacency matrix is regular with  $R_0 = d$ . Notice it might not be symmetric.

- (iii) Let  $\Omega = (\mathbb{R}/(2\pi\mathbb{Z}))^m$  be the  $m$ -dimensional torus endowed with its Borel  $\sigma$ -field  $\mathcal{F}$  and the normalized Lebesgue measure  $\mu$ . Let  $f$  be a measurable square-integrable non-negative function defined on  $\Omega$ . We consider the geometric kernel on  $\Omega$  defined by:

$$k_f(x, y) = f(x - y).$$

The kernel  $k_f$  has a finite double norm as  $f \in L^2$ . The operator  $T_{k_f}$  corresponds to the convolution by  $f$ , and its spectral radius is given by  $R_0 = \int_{\Omega} f d\mu$ . Then the kernel  $k_f$  is constant degree as soon as  $f$  is not equal to 0 almost surely. This example is developed in Section 7 in the case  $m = 1$  (corresponding to  $d = 2$  therein), see in particular Examples 7.2 and 7.3.

- (iv) More generally, let  $(\Omega, \cdot)$  be a compact topological group and let  $\mu$  be its left Haar probability measure. Let  $f$  be non-negative square-integrable function on  $\Omega$ . Then the kernel  $k_f(x, y) = f(y^{-1} \cdot x)$  is constant degree.

We summarize our main result in the next proposition, whose proof is given in Section 5.3. We recall that a strategy is called uniform if it is constant over  $\Omega$ .

**Proposition 5.4** (Uniform strategies for constant degree kernels). *Let  $k$  be a constant degree kernel on  $\Omega$ .*

- (i) *If the map  $R_e$  defined on  $\Delta$  is convex, then all uniform strategies are Pareto optimal (i.e.  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}$ ). Consequently,  $c_{\star} = 1$ , the Pareto frontier is the segment joining  $(0, R_0)$  to  $(1, 0)$ , and for all  $c \in [0, 1]$ :*

$$R_{e_{\star}}(c) = (1 - c)R_0.$$

- (ii) If the map  $R_e$  defined on  $\Delta$  is concave, then the kernel  $k$  is irreducible and all uniform strategies are anti-Pareto optimal (i.e.  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}^{\text{Anti}}$ ). Consequently,  $c^* = 0$ , the anti-Pareto frontier is the segment joining  $(0, R_0)$  to  $(1, 0)$ , and for all  $c \in [0, 1]$ :

$$R_e^*(c) = (1 - c)R_0.$$

In [11, Section 5.2], we give sufficient condition on the spectrum of  $T_k$  to be either concave or convex. Combining this result with Proposition 5.4, we get the following corollary.

**Corollary 5.5.** *Let  $k$  be a constant degree symmetric kernel.*

- (i) *If the eigenvalues of  $T_k$  are non-negative, then the uniform vaccination strategies are Pareto optimal and  $c_* = 1$  (i.e.  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}$ ).*  
(ii) *If  $R_0$  is a simple eigenvalue of  $T_k$  and the others eigenvalues are non-positive, then the kernel  $k$  is irreducible, the uniform vaccination strategies are anti-Pareto optimal and  $c^* = 0$  (i.e.  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}^{\text{Anti}}$ ).*

*Remark 5.6* (Equivalent conditions). Let  $k$  be a constant degree symmetric kernel. The eigenvalues of the operator  $T_k$  are non-negative if and only if  $T_k$  is semi-definite positive, that is:

$$(46) \quad \int_{\Omega \times \Omega} k(x, y)g(x)g(y)\mu(dx)\mu(dy) \geq 0 \quad \text{for all } g \in L^2.$$

Similarly, the condition given in Corollary 5.5 (ii) that implies the concavity of  $R_e$  is equivalent to the semi-definite negativity of  $T_k$  on the orthogonal of  $\mathbb{1}$ :

$$(47) \quad \int_{\Omega \times \Omega} k(x, y)g(x)g(y)\mu(dx)\mu(dy) \leq 0 \quad \text{for all } g \in L^2 \quad \text{such that} \quad \int_{\Omega} g d\mu = 0.$$

*Remark 5.7* (Comparison with a result from [44]). Poghotanyan, Feng, Glasser and Hill [44, Theorem 4.7] obtained a similar result in finite dimension using a result from Friedland [20]: if the next-generation non-negative matrix  $K$  of size  $N \times N$  satisfies the following conditions

- (i)  $\sum_{j=1}^N K_{ij}$  does not depend on  $i \in \llbracket 1, N \rrbracket$  (which corresponds the parameters  $a_i$  in [44, Equation (2.4)] being all equal),  
(ii)  $\mu_i K_{ij} = \mu_j K_{ji}$  for all  $i, j \in \llbracket 1, N \rrbracket$  where  $\mu_i$  denote the relative size of population  $i$  (which corresponds to [44, Equation (2.4)]),  
(iii)  $K$  is not singular and its inverse is an M-matrix (i.e., its non-diagonal coefficients are non-positive),

then the uniform strategies are Pareto optimal (i.e., they minimize the reproduction number among all strategies with same cost). Actually, this can be seen as a direct consequence of Corollary 5.5 (i). Indeed, the corresponding kernel  $k_d$  defined by (30) in the discrete probability space  $\Omega = \llbracket 1, N \rrbracket$  endowed with the discrete probability measure  $\mu_d$  also defined by (30) has constant degree thanks to Point (i) and is symmetric thanks to Point (ii). Since  $K^{-1}$  is an M-matrix, its real eigenvalues are positive according to [6, Chapter 6 Theorem 2.3]. The eigenvalues of  $T_{k_d}$  and  $K$  are actually the same as  $K$  is the representation matrix of  $T_{k_d}$  in the canonic basis of  $\mathbb{R}^N$ . We conclude that the operator  $T_{k_d}$  is positive definite. Hence Corollary 5.5 (i) can be applied to recover that the uniform strategies are Pareto optimal.

However, the converse is not true. As a counter-example, consider a population divided in  $N = 3$  groups of same size (i.e.  $\mu_1 = \mu_2 = \mu_3 = 1/3$ ) and the following next-generation matrix:

$$K = \begin{pmatrix} 3 & 2 & 0 \\ 2 & 2 & 1 \\ 0 & 1 & 4 \end{pmatrix} \quad \text{with inverse} \quad K^{-1} = \begin{pmatrix} 1.4 & -1.6 & 0.4 \\ -1.6 & 2.4 & -0.6 \\ 0.4 & -0.6 & 0.4 \end{pmatrix}.$$

Clearly Points (i) and (ii) hold and Point (iii) fails as  $K^{-1}$  is not an M-matrix. Nevertheless, the matrix  $K$  is definite positive as its eigenvalues  $\sigma(K) = \{5, 2 + \sqrt{3}, 2 - \sqrt{3}\}$  are positive. And thus, thanks to Corollary 5.5 (i), we get that the uniform strategies are Pareto optimal. Hence, Corollary 5.5 (i) is a strict generalization of [44, Theorem 4.7] even for finite metapopulation models.

*Remark 5.8.* We also refer the reader to the paper of Friedland and Karlin [19]: from the Inequality (7.10) therein, we can obtain Corollary 5.5 (i) when  $\Omega$  is a compact set of  $\mathbb{R}^n$ ,  $\mu$  is a finite measure,  $k$  is a continuous symmetrizable kernel such that  $k(x, x) > 0$  for all  $x \in \Omega$ .

Further comments on related results may be found in the discussion of [11, Theorem 5.1].

Below, we give examples of metapopulation models from the previous sections where Proposition 5.4 applies. For continuous models, we refer the reader to Sections 6 and 7.

*Example 5.9* (Fully asymmetric cycle model). We consider the fully asymmetric circle model with  $N \geq 3$  vertices developed in Section 2.3. Since the in and out degree of each vertex is exactly one, the adjacency matrix is constant degree according to Example 5.3 (ii).

The spectrum of the adjacency matrix is given by the  $N$ th roots of unity, so for  $N \geq 3$  it does not lie in  $\mathbb{R}_- \cup \{R_0\}$ , so Corollary 5.5 does not apply. However, in this case the effective spectral radius  $R_e$  is given by formula (19), which corresponds to the geometric mean. According to [7, Section 3.1.5], the map  $\eta \mapsto R_e(\eta)$  is concave, so Proposition 5.4 (ii) applies. This proves that the spectral condition given in Corollary 5.5 and [11, Section 5.2] to get the concavity of  $R_e$  is only sufficient.

*Example 5.10* (Finite assortative and disassortative model). Let  $\Omega = \{1, 2, \dots, N\}$  and  $\mu$  be the uniform probability on  $\Omega$ . Let  $a, b \in \mathbb{R}_+$ . We consider the kernel from the models developed in Section 4:

$$k(i, j) = a\mathbb{1}_{i=j} + b\mathbb{1}_{i \neq j}.$$

Since  $\mu$  is uniform, the kernel  $k$  is constant degree; provided its spectral radius is positive, *i.e.*,  $a$  or  $b$  is positive.

In the assortative model  $0 < b \leq a$ , according to Proposition 4.1 (i), the eigenvalues of the symmetric operator  $T_k$  are non-negative. Hence, Corollary 5.5 (i) applies: the uniform strategies are Pareto optimal. This is consistent with Theorem 4.2 (i).

In the disassortative model, we have  $0 \leq a \leq b$  and  $b > 0$ . According to Proposition 4.1 (ii), the eigenvalues of  $T_k$  different from its spectral radius are non-positive. Hence, Corollary 5.5 (ii) applies: the uniform strategies are anti-Pareto. This is consistent with Theorem 4.2 (ii) and (iii).

**5.3. Proof of Proposition 5.4.** By analogy with [17], we consider the following definition.

**Definition 5.11** (Completely reducible kernels). *A kernel  $k$  is said to be completely reducible if there exist an at most countable index set  $I$ , and measurable sets  $\Omega_0$  and  $(\Omega_i, i \in I)$ , such that  $\Omega$  is the disjoint union  $\Omega = \Omega_0 \sqcup (\bigsqcup_{i \in I} \Omega_i)$ , the kernel  $k$  decomposes as  $k = \sum_{i \in I} \mathbb{1}_{\Omega_i} k \mathbb{1}_{\Omega_i}$  a.e., and, for all  $i \in I$ , the kernel  $k$  restricted to  $\Omega_i$  is irreducible.*

As in the discrete case for so-called line sum symmetric matrices, see [17, Lemma 1], kernels for which for any  $x$  the out-degree is equal to the in-degree are necessarily completely reducible; the fact that these degrees do not depend on  $x$  impose further constraints.

**Lemma 5.12** (Complete reduction). *If  $k$  is a constant degree kernel on  $\Omega$ , then  $k$  is completely reducible. Furthermore, the set  $\Omega_0$  from Definition 5.11 is empty, the cardinal of the partition  $(\Omega_i, i \in I)$  is equal to the multiplicity of  $R_0$  and thus is finite; and, for all  $i \in I$ , the kernel  $k$  restricted to  $\Omega_i$  is a constant degree irreducible kernel with spectral radius equal to  $R_0$ .*

*Proof.* We recall that a set  $A \in \mathcal{F}$  is invariant if  $k(A^c, A) = 0$ , where for  $A, B \in \mathcal{F}$ :

$$k(B, A) = \int_{B \times A} k(x, y) \mu(dx) \mu(dy).$$

Since for each  $x$ , the in-degree  $k(x, \Omega)$  is equal to the out-degree  $k(\Omega, x)$ , we get by integration  $k(A, \Omega) = k(\Omega, A)$ , so

$$k(A^c, A) = k(A^c, \Omega) - k(A^c, A^c) = k(\Omega, A^c) - k(A^c, A^c) = k(A, A^c).$$

Therefore if  $A$  is invariant, then so is its complement  $A^c$ . According to [11, Section 7] and more precisely Remark 7.1(iv), there exists then an at most countable partition of  $\Omega$  made of  $\Omega_0$  and  $(\Omega_i, i \in I)$  such that  $k = \sum_{i \in I} k_i$ , with  $k_i = \mathbb{1}_{\Omega_i} k \mathbb{1}_{\Omega_i}$ ,  $\mu(\Omega_i) > 0$  and  $k_i$  restricted to  $\Omega_i$  is irreducible. Since  $\mathbb{1}$  is an eigenvector of  $T_k$  associated to the eigenvalue  $R_0$  and the sets  $\Omega_0$  and  $(\Omega_i, i \in I)$  are pairwise disjoint, we deduce that  $\Omega_0$  is of zero measure and  $\mathbb{1}_{\Omega_i}$  is an eigenvector of  $T_{k_i}$  with eigenvalue  $R_0 > 0$ , for all  $i \in I$ . Hence, all the kernels  $k_i$  restricted to  $\Omega_i$  are irreducible constant degree kernels with spectral radius equal to  $R_0$ . Thus, the cardinal of  $I$  is equal to the multiplicity of  $R_0$  (for  $T_k$ ). Since  $k$  has finite  $L^2$  double-norm, the operator  $T_k$  is compact, and the multiplicity of  $R_0 > 0$ , and thus the cardinal of  $I$ , is finite.  $\square$

**Lemma 5.13.** *Let  $k$  be a constant degree irreducible kernel on  $\Omega$ . Then the uniform strategy is a critical point for  $R_e$  among all the strategies with the same cost in  $(0, 1)$ , and more precisely: for all  $\eta$  with the same cost in  $(0, 1)$  as  $\eta^{\text{uni}} \in \mathcal{S}^{\text{uni}}$  and  $\varepsilon > 0$  small enough, we have:*

$$R_e((1 - \varepsilon)\eta^{\text{uni}} + \varepsilon\eta) = R_e(\eta^{\text{uni}}) + O(\varepsilon^2).$$

*Proof.* Let  $\eta^{\text{uni}}$  be the uniform strategy with cost  $c \in (0, 1)$ . Since  $k$  is irreducible, we get that  $(1 - c)R_0$  is a simple isolated eigenvalue of  $k\eta^{\text{uni}}$ , whose corresponding left and right eigenvector are  $\mathbb{1}$  as  $k\eta^{\text{uni}}$  is also constant degree. For  $\eta \in \Delta$ , we get that  $T_{k((1-\varepsilon)\eta^{\text{uni}}+\varepsilon\eta)}$  converges to  $T_{k\eta^{\text{uni}}}$  (in operator norm, thanks to (24)) as  $\varepsilon$  goes down to 0. Notice that:

$$\left\| T_{k(\eta^{\text{uni}}+\varepsilon(\eta-\eta^{\text{uni}}))} - T_{k\eta^{\text{uni}}} \right\|_{L^2}^2 = O(\varepsilon^2).$$

According to [35, Theorem 2.6], we get that for any  $\eta \in \Delta$  and  $\varepsilon > 0$  small enough:

$$\begin{aligned} R_e((1 - \varepsilon)\eta^{\text{uni}} + \varepsilon\eta) - R_e(\eta^{\text{uni}}) &= \varepsilon \int_{\Omega} k(x, y)(\eta(y) - \eta^{\text{uni}}(y)) \mu(dx) \mu(dy) + O(\varepsilon^2) \\ &= \varepsilon R_0 \int_{\Omega} (\eta(y) - \eta^{\text{uni}}(y)) \mu(dy) + O(\varepsilon^2), \end{aligned}$$

where for the last equality we used that  $k$  is constant degree. In particular, if  $\eta$  and  $\eta^{\text{uni}}$  have the same cost  $c \in (0, 1)$ , then  $R_e((1 - \varepsilon)\eta^{\text{uni}} + \varepsilon\eta) - R_e(\eta^{\text{uni}}) = O(\varepsilon^2)$ , which means that the uniform strategy is a critical point for  $R_e$  among all the strategies with cost  $c \in (0, 1)$ .  $\square$

*Proof of Proposition 5.4.* We prove (i), and thus consider  $k$  constant degree and  $R_e$  convex. We first consider the case where  $k$  is irreducible. For any  $\eta$ , Lemma 5.13 and the convexity of  $R_e$  imply that

$$R_e(\eta^{\text{uni}}) + O(\varepsilon^2) = R_e((1 - \varepsilon)\eta^{\text{uni}} + \varepsilon\eta) \leq (1 - \varepsilon)R_e(\eta^{\text{uni}}) + \varepsilon R_e(\eta),$$

where  $\eta^{\text{uni}}$  the uniform strategy with the same cost as  $\eta$ . Letting  $\varepsilon$  go to 0, we get  $R_e(\eta) \geq R_e(\eta^{\text{uni}})$ , so  $R_e$  is minimal at  $\eta^{\text{uni}}$ .

Since  $C(\eta^{\text{uni}}) = c$  and  $R_e(\eta^{\text{uni}}) = (1 - c)R_0$ , we deduce that  $R_{e^*}(c) = (1 - c)R_0$  and thus, the Pareto frontier is a segment given by  $\mathcal{F} = \{(c, (1 - c)R_0) : c \in [0, 1]\}$ .

In what follows, we write  $R_e[k]$  to stress that the reproduction function on  $\Delta$  defined by (29) depends on the kernel  $k$ :  $R_e[k](\eta) = \rho(T_{k\eta})$  for  $\eta \in \Delta$ . If  $k$  is not irreducible, then use the

representation from Lemma 5.12, to get that  $R_e[k] = \max_{i \in I} R_e[k_i]$ . Since the cost is affine, we deduce that a strategy  $\eta$  with  $R_e[k](\eta) = \ell \in [0, R_0]$  is Pareto optimal if and only if, for all  $i \in I$ , the strategies  $\eta_i = \eta \mathbb{1}_{\Omega_i}$  are Pareto optimal for the kernel  $k$  restricted to  $\Omega_i$  and  $R_e[k_i](\eta_i) = \ell$ ; see also [11, Corollary 7.4]. Then the first step of the proof yields that  $\eta_i = \ell \mathbb{1}_{\Omega_i}$  and thus the uniform strategy  $\eta^{\text{uni}} = \ell \mathbb{1}_{\Omega}$  is Pareto optimal. This ends the proof of (i).

We now prove (ii). We first check that the kernel  $k$  is irreducible. Thanks to Lemma 5.12, the kernel  $k$  is completely reducible with a zero measure  $\Omega_0$ . However, [11, Lemma 7.3] also implies that it is *monatomic*, a notion introduced in [11, Section 3.4] which intuitively states that  $k$  has only one irreducible component. Together with complete reducibility, this implies that  $k$  is irreducible. The rest of the proof is then similar to the proof of (i) under the irreducibility assumption.  $\square$

## 6. CONSTANT DEGREE SYMMETRIC KERNELS OF RANK TWO

**6.1. Pareto and anti-Pareto frontiers.** Any constant degree symmetric kernel may be decomposed spectrally in  $L^2(\Omega^2, \mu^{\otimes 2})$  as  $k(x, y) = R_0 + \sum_{n \in \mathbb{N}^*} \varepsilon_n \alpha_n(x) \alpha_n(y)$ , with  $\varepsilon_n \in \{-, +\}$ ,  $(\alpha_n, n \in \mathbb{N}^*)$  an orthogonal family of  $L^2$  also orthogonal to  $\mathbb{1}$ . As an application of the results from the previous section, we will treat the case of symmetric constant degree kernel whose associated operator is of rank 2, where one can explicitly minimize and maximize  $R_e$  among all strategies of a given cost.

We suppose that  $\Omega = [0, 1]$  is equipped with the Borel  $\sigma$ -field  $\mathcal{F}$  and a probability measure  $\mu$  whose cumulative distribution function  $\varphi$ , defined by  $\varphi(x) = \mu([0, x])$  for  $x \in \Omega$ , is continuous and increasing. We consider the following two kernels on  $\Omega$ :

$$(48) \quad k^\varepsilon(x, y) = R_0 + \varepsilon \alpha(x) \alpha(y), \quad \text{with } \varepsilon \in \{-, +\},$$

where  $R_0 > 0$  and  $\alpha \in L^2$  is strictly increasing and satisfies:

$$(49) \quad \sup_{\Omega} \alpha^2 \leq R_0 \quad \text{and} \quad \int_{\Omega} \alpha \, d\mu = 0.$$

*Remark 6.1 (Generality).* We note that this particular choice of  $\Omega$  may be made without loss of generality, and that the strict monotonicity assumption on  $\alpha$  is almost general: we refer the interested reader to Section 6.2 for further discussion of this point.

For  $\varepsilon \in \{-, +\}$ , the kernel  $k^\varepsilon$  is symmetric and constant degree. Furthermore, we have that  $R_0$  and  $\varepsilon \int_{\Omega} \alpha^2 \, d\mu$  are the only non-zero eigenvalues (and their multiplicity is one) of  $T_{k^\varepsilon}$  with corresponding eigenvector  $\mathbb{1}$  and  $\alpha$ . Since  $\alpha^2 \leq R_0$ , we also get that  $R_0$  is indeed the spectral radius of  $T_{k^\varepsilon}$ .

The Pareto (resp. anti-Pareto) frontier is already greedily parametrized by the uniform strategies for the kernel  $k^+$  (resp.  $k^-$ ), see Corollary 5.5. The following result restricts the choice of anti-Pareto (resp. Pareto) optimal strategies to two extreme strategies. Hence, in order to find the optima, it is enough to compute and compare the two values of  $R_e$  for each cost.

We recall the set of uniform strategies  $\mathcal{S}^{\text{uni}} = \{t\mathbb{1} : t \in [0, 1]\}$  and consider the following set of extremal strategies:

$$\mathcal{S}_0 = \{\mathbb{1}_{[0,t]} : t \in [0, 1]\} \quad \text{and} \quad \mathcal{S}_1 = \{\mathbb{1}_{[t,1]} : t \in [0, 1]\}$$

as well as the following set of strategies which contains  $\mathcal{S}^{\text{uni}}$  thanks to (49):

$$\mathcal{S}^{\perp \alpha} = \left\{ \eta \in \Delta : \int_{\Omega} \alpha \eta \, d\mu = 0 \right\}.$$

Recall that strategies are defined up to the a.s. equality. The proof of the next proposition is given in Section 6.3

**Proposition 6.2** (Optima are uniform or on the sides). *Let  $[0, 1]$  be endowed with a probability measure whose cumulative distribution function is increasing and continuous. Let  $k^\varepsilon$  be given by (48) with  $R_0 > 0$  and  $\alpha$  a strictly increasing function on  $[0, 1]$  such that (49) holds.*

(i) **The kernel  $k^+$ .** *A strategy is Pareto optimal if and only if it belongs to  $\mathcal{S}^{\perp\alpha}$ . In particular, for any  $c \in [0, 1]$ , the strategy  $(1 - c)\mathbb{1}$  costs  $c$  and is Pareto optimal. The only possible anti-Pareto strategies of cost  $c$  are  $\mathbb{1}_{[0, 1-c]}$  and  $\mathbb{1}_{[c, 1]}$ . In other words,*

$$\mathcal{P} = \mathcal{S}^{\perp\alpha} \quad \text{and} \quad \mathcal{P}^{\text{Anti}} \subset \mathcal{S}_0 \cup \mathcal{S}_1.$$

(ii) **The kernel  $k^-$ .** *A strategy is anti-Pareto optimal if and only if it belongs to  $\mathcal{S}^{\perp\alpha}$ . In particular, for any  $c \in [0, 1]$ , the strategy  $(1 - c)\mathbb{1}$  costs  $c$  and is anti-Pareto optimal. The only possible Pareto strategies of cost  $c$  are  $\mathbb{1}_{[0, 1-c]}$  and  $\mathbb{1}_{[c, 1]}$ . In other words,*

$$\mathcal{P} \subset \mathcal{S}_0 \cup \mathcal{S}_1 \quad \text{and} \quad \mathcal{P}^{\text{Anti}} = \mathcal{S}^{\perp\alpha}.$$

In both cases, we have  $c^* = 0$  and  $c_* = 1$ .

*Remark 6.3.* Intuitively, the populations  $\{\alpha < 0\}$  and  $\{\alpha > 0\}$  behave in an assortative way for  $k^+$  and in a disassortative way for  $k^-$ . As in Section 4, the uniform strategies are Pareto optimal in the ‘‘assortative’’  $k^+$  case and anti-Pareto optimal in the ‘‘disassortative’’  $k^-$  case.

*Remark 6.4.* Under the assumptions of Proposition 6.2, if furthermore  $\alpha$  is anti-symmetric with respect to  $1/2$ , that is  $\alpha(x) = -\alpha(1 - x)$  for  $x \in (0, 1)$ , and  $\mu$  is symmetric with respect to  $1/2$ , that is  $\mu([0, x]) = \mu([1 - x, 1])$ , then it is easy to check from the proof of Proposition 6.2 that the strategies from  $\mathcal{S}_0$  and  $\mathcal{S}_1$  are both optimal:  $\mathcal{P}^{\text{Anti}} = \mathcal{S}_0 \cup \mathcal{S}_1$  for  $k^+$  and  $\mathcal{P} = \mathcal{S}_0 \cup \mathcal{S}_1$  for  $k^-$ . We plotted such an instance of  $k^+$  and the corresponding Pareto and anti-Pareto frontiers in Figure 9. We refer to Section 6.4 for an instance where  $\alpha$  is not symmetric and  $\mathcal{P} \neq \mathcal{S}_0 \cup \mathcal{S}_1$  for  $k^-$ .

**6.2. On the choice of  $\Omega = [0, 1]$  and on the monotonicity assumption.** Using a reduction model technique from [13, Section 7], let us first see that there is no loss of generality by considering the kernel  $k^\varepsilon = R_0 + \varepsilon\alpha \otimes \alpha$  on  $\Omega = [0, 1]$  endowed with the Lebesgue measure  $\mu$  and with  $\alpha$  non-decreasing.

Suppose that the function  $\alpha$  in (48) is replaced by an  $\mathbb{R}$ -valued measurable function  $\alpha_0$  defined on a general probability space  $(\Omega_0, \mathcal{F}_0, \mu_0)$  such that (49) holds. Thus, with obvious notations, for  $\varepsilon \in \{-, +\}$ , the kernel  $R_0 + \varepsilon\alpha_0 \otimes \alpha_0$  is a kernel on  $\Omega_0$ . Denote by  $F$  the repartition function of  $\alpha_0$  (that is,  $F(r) = \mu_0(\alpha_0 \leq r)$  for  $r \in \mathbb{R}$ ) and take  $\alpha$  as the quantile function of  $\alpha_0$ , that is, the right continuous inverse of  $F$ . Notice the function  $\alpha$  is defined on the probability space  $(\Omega, \mathcal{F}, \mu)$  is non-decreasing and satisfies (49). Consider the probability kernel  $\kappa : \Omega_0 \times \mathcal{F} \rightarrow [0, 1]$  defined by  $\kappa(x, \cdot) = \delta_{F(\alpha_0(x))}(\cdot)$ , with  $\delta$  the Dirac mass, if  $\alpha$  is continuous at  $\alpha_0(x)$  (that is,  $F(\alpha_0(x)-) = F(\alpha_0(x))$ ) and the uniform probability measure on  $[F(\alpha_0(x)-), F(\alpha_0(x))]$  otherwise. On the measurable space  $(\Omega_0 \times \Omega, \mathcal{F}_0 \otimes \mathcal{F})$ , we consider the probability measure  $\nu(dx_1, dx_2) = \mu_0(dx_1)\kappa(x_1, dx_2)$ , whose marginals are exactly  $\mu_0$  and  $\mu$ . Then, for  $\varepsilon \in \{-, +\}$ , we have that  $\nu(dx_1, dx_2) \otimes \nu(dy_1, dy_2)$ -a.s.:

$$R_0 + \varepsilon\alpha_0(x_1)\alpha_0(y_1) = R_0 + \varepsilon\alpha(x_2)\alpha(y_2).$$

According to [13, Section 7.3], see in particular Proposition 7.3 therein, the kernels  $R_0 + \varepsilon\alpha_0 \otimes \alpha_0$  and  $R_0 + \varepsilon\alpha \otimes \alpha$  are coupled and there is a correspondence between the corresponding (anti-)Pareto optimal strategies and their (anti-)Pareto frontiers are the same.

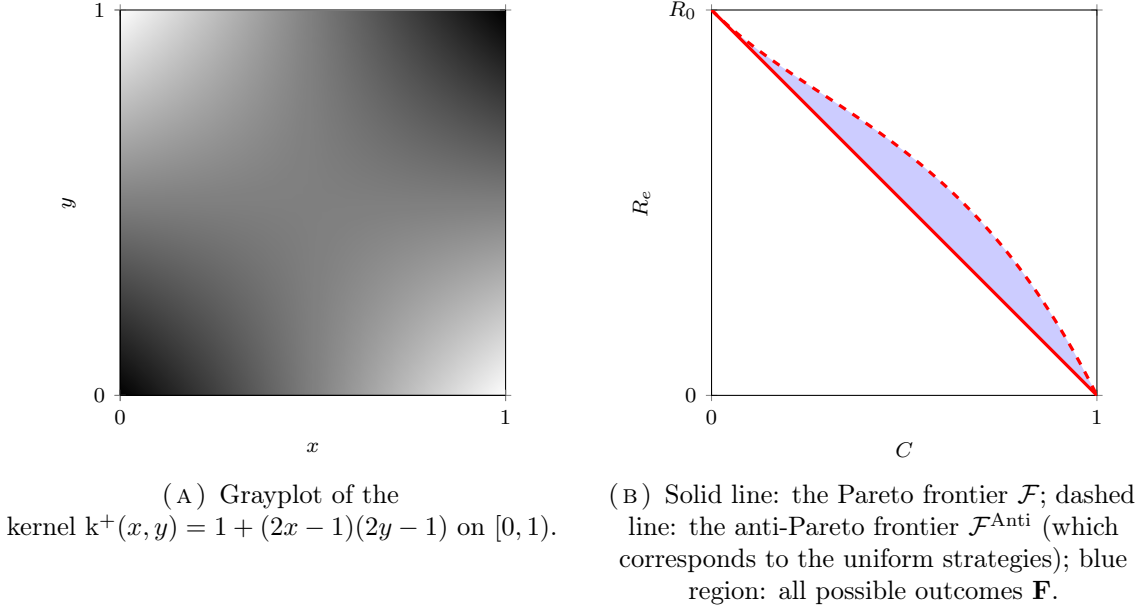


FIGURE 9. An example of a constant degree kernel operator of rank 2.

Hence, there is no loss in generality in assuming that the function  $\alpha$  in (48) is indeed defined on  $[0, 1)$  and is non-decreasing.

On the contrary, one cannot assume in full generality that  $\alpha$  is *strictly* increasing, as when it is only non-decreasing, the situation is more complicated. Indeed, let us take the parameters  $R_0 = 1$  and  $\alpha = \mathbb{1}_{[0,0.5)} - \mathbb{1}_{[0.5,1)}$ . Then, the kernel  $k^-$  is complete bi-partite:  $k^- = \mathbb{1}_{[0,0.5) \times [0.5,1)} + \mathbb{1}_{[0.5,1) \times [0,0.5)}$ . Hence, according to Theorem 4.2 (iii), we have  $c_* = 0.5$  for the kernel  $k^-$ . In a similar fashion, one can see that  $k^+ = \mathbb{1}_{[0,0.5) \times [0,0.5)} + \mathbb{1}_{[0.5,1) \times [0.5,1)}$  is assortative and reducible; it is then easy to check that  $c^* = 0.5$  for the kernel  $k^+$ . However, it is still true that, for all costs  $c$ :

- $\mathbb{1}_{[0,1-c)}$  or  $\mathbb{1}_{[c,1)}$  is solution of Problem (8) when the kernel  $k^+$  is considered,
- $\mathbb{1}_{[0,1-c)}$  or  $\mathbb{1}_{[c,1)}$  is solution of Problem (7) when the kernel  $k^-$  is considered.

From the proof of Proposition 6.2, we can not expect to have strict inequalities in (59) if  $\alpha$  is only non-decreasing, and thus one can not expect  $\mathcal{S}_0 \cup \mathcal{S}_1$  to contain  $\mathcal{P}^{\text{Anti}}$  for the kernel  $k^+$  or  $\mathcal{P}$  for the kernel  $k^-$ .

**6.3. Proof of Proposition 6.2.** We assume that  $R_0 > 0$  and  $\alpha$  is a strictly increasing function defined on  $\Omega = [0, 1)$  such that (49) holds. Without loss of generality, we shall assume that  $R_0 = 1$  unless otherwise specified. We write  $R_e^\varepsilon$  for the effective reproduction function associated to the kernel  $k^\varepsilon$ . We shall also write  $\varepsilon a$  for  $a$  if  $\varepsilon = +$  and  $-a$  if  $\varepsilon = -$ . We first rewrite  $R_e^\varepsilon$  in two different ways in Section 6.3.1. Then, we consider the kernel  $k^-$  in Section 6.3.2 and the kernel  $k^+$  in Section 6.3.3.

**6.3.1. Two expressions of the effective reproduction function.** We provide an explicit formula for the function  $R_e^\varepsilon$ , and an alternative variational formulation, both of which will be needed below.

**Lemma 6.5.** *Assume  $R_0 = 1$  and  $\alpha$  is a strictly increasing function defined on  $\Omega = [0, 1)$  such that (49) holds. We have for  $\varepsilon \in \{+, -\}$  and  $\eta \in \Delta$ :*

$$(50) \quad 2R_e^\varepsilon(\eta) = \int \eta \, d\mu + \varepsilon \int \alpha^2 \eta \, d\mu + \sqrt{\left(\int \eta \, d\mu - \varepsilon \int \alpha^2 \eta \, d\mu\right)^2 + 4\varepsilon \left(\int \alpha \eta \, d\mu\right)^2}.$$

Alternatively,  $R_e^\varepsilon(\eta)$  is the solution of the variational problem:

$$(51) \quad R_e^\varepsilon(\eta) = \sup_{h \in B_+^\eta} \left( \int_0^1 h \eta \, d\mu \right)^2 + \varepsilon \left( \int_0^1 h \alpha \eta \, d\mu \right)^2,$$

where

$$B_+^\eta = \left\{ h \in L_+^2 : \int_0^1 h^2 \eta \, d\mu = 1 \right\}.$$

The supremum in (51) is reached for the right Perron eigenfunction of  $T_{k\eta}$  chosen in  $B_+^\eta$ .

*Proof.* We first prove (50). For all  $\eta \in \Delta$ , the rank of the kernel operator  $T_{k^\varepsilon\eta}$  is smaller or equal to 2 and  $\text{Im}(T_{k^\varepsilon\eta}) \subset \text{Vect}(\mathbf{1}, \alpha)$ . The matrix of  $T_{k^\varepsilon\eta}$  in the basis  $(\mathbf{1}, \alpha)$  of the range of  $T_{k^\varepsilon\eta}$  is given by:

$$(52) \quad \begin{pmatrix} \int \eta \, d\mu & \int \alpha \eta \, d\mu \\ \varepsilon \int \alpha \eta \, d\mu & \varepsilon \int \alpha^2 \eta \, d\mu \end{pmatrix}.$$

An explicit computation of the spectrum of this matrix yields Equation (50) for its largest eigenvalue.

The variational formula (51) is a direct consequence of general Lemma 6.6 below.  $\square$

**Lemma 6.6** (Variational formula for  $R_e$  when  $k$  is symmetric). *Suppose that  $k$  is a symmetric kernel on  $\Omega$  with a finite double norm in  $L^2$ . Then, we have that for all  $\eta \in \Delta$ :*

$$(53) \quad R_e(\eta) = \sup_{h \in B_+^\eta} \int_{\Omega \times \Omega} h(x)\eta(x) k(x, y) h(y)\eta(y) \mu(dx)\mu(dy),$$

where

$$B_+^\eta = \left\{ h \in L_+^2 : \int_{\Omega} h^2 \eta \, d\mu = 1 \right\}.$$

The supremum in (53) is reached for the right Perron eigenfunction of  $T_{k\eta}$  chosen in  $B_+^\eta$ .

*Proof.* For a finite measure  $\nu$  on  $(\Omega, \mathcal{F})$ , as usual, we denote by  $L^2(\nu)$  the set of measurable real-valued functions  $f$  such that  $\int_{\Omega} f^2 d\nu < +\infty$  endowed with the usual scalar product, so that  $L^2(\nu)$  is an Hilbert space. Let  $\eta \in \Delta$ . We denote by  $\mathcal{T}_{k\eta}$  the integral operator associated to the kernel  $k\eta$  seen as an operator on the Hilbert space  $L^2(\eta d\mu)$ : for  $g \in L^2(\eta d\mu)$  and  $x \in \Omega$  we have  $\mathcal{T}_{k\eta}(g)(x) = \int_{\Omega} k(x, y) \eta(y) g(y) \mu(dy)$ . The operator  $\mathcal{T}_{k\eta}$  is self-adjoint and compact since the double-norm of  $k$  in  $L^2(\eta d\mu)$  is finite. It follows from the Krein-Rutman theorem and the Courant–Fischer–Weyl min-max principle that its spectral radius is given by the variational formula:

$$\rho(\mathcal{T}_{k\eta}) = \sup_{h \in B_+^\eta} \int_{\Omega \times \Omega} h(x) k(x, y) h(y) \eta(x) \mu(dx) \eta(y) \mu(dy).$$

Besides, the set  $L^2(\mu)$  is densely and continuously embedded in  $L^2(\eta d\mu)$  and the restriction of  $\mathcal{T}_{k\eta}$  to  $L^2(\mu)$  is equal to  $T_{k\eta}$ . Thanks to [13, Lemma 3.2 (iii)], we deduce that  $\rho(T_{k\eta})$  is equal to  $\rho(\mathcal{T}_{k\eta})$ , which gives (53).



Let  $h_0$  be the right Perron eigenfunction of  $T_{k\eta}$  chosen such that  $h_0 \in B_+^\eta$ . We get:

$$\int_{\Omega \times \Omega} \eta(x)h_0(x)k(x,y)\eta(y)h_0(y)\mu(dx)\mu(dy) = R_e(\eta) \int_{\Omega} \eta(x)h_0(x)^2\mu(dx) = R_e(\eta).$$

Thus, the supremum in (53) is reached for  $h = h_0$ .  $\square$

6.3.2. *The kernel  $k^-$ .* Since  $\alpha$  is increasing, we have  $\mu(\alpha^2 = R_0) = 0$  and thus the symmetric kernel  $k^-$  is  $\mu^{\otimes 2}$ -a.s. positive. It follows from Remark 3.1 that  $c^* = 0$  and  $c_* = 1$ , and the strategy  $\mathbb{1}$  (resp.  $\mathbb{0}$ ) is the only Pareto optimal as well as the only anti-Pareto optimal strategy with cost  $c = 0$  (resp.  $c = 1$ ). Since the kernel  $k^-$  is constant degree and symmetric, and the non-zero eigenvalues of  $T_{k^-}$  are given by  $R_0 = 1$  and  $-\int \alpha^2 d\mu$ , the latter being negative, we deduce from Corollary 5.5 (ii) that  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}^{\text{Anti}}$ . On the one hand, if  $\eta$  is anti-Pareto optimal with the same cost as  $\eta^{\text{uni}} \in \mathcal{S}^{\text{uni}}$ , one can use that  $R_e^-(\eta) = \int \eta d\mu$  (as  $R_e^-(\eta^{\text{uni}}) = \int \eta^{\text{uni}} d\mu$ ) and (50) to deduce that  $\eta \in \mathcal{S}^{\perp\alpha}$ . On the other hand, if  $\eta$  belongs to  $\mathcal{S}^{\perp\alpha}$ , we deduce from (50) that  $R_e(\eta) = \int \eta d\mu$ , and thus  $\eta$  is anti-Pareto optimal. In conclusion, we get  $\mathcal{P}^{\text{Anti}} = \mathcal{S}^{\perp\alpha}$ .

We now study the Pareto optimal strategies. We first introduce a notation inspired by the stochastic order of real valued random variables: we say that  $\eta_1, \eta_2 \in \Delta$  with the same cost are in *stochastic order*, and we write  $\eta_1 \leq_{\text{st}} \eta_2$  if:

$$(54) \quad \int_0^t \eta_1 d\mu \geq \int_0^t \eta_2 d\mu \quad \text{for all } t \in [0, 1].$$

We also write  $\eta_1 <_{\text{st}} \eta_2$  if the inequality in (54) is strict for at least one  $t \in (0, 1)$ . If  $\eta_1 <_{\text{st}} \eta_2$  and  $h$  is an increasing bounded function defined on  $[0, 1]$ , then we have:

$$(55) \quad \int_{\Omega} h \eta_1 d\mu < \int_{\Omega} h \eta_2 d\mu.$$

Let  $c \in (0, 1)$  be fixed. Define the vaccination strategies with cost  $c$ :

$$(56) \quad \eta_0 = \mathbb{1}_{[0, 1-c]} \quad \text{and} \quad \eta_1 = \mathbb{1}_{[c, 1]}.$$

In particular we have  $\eta_0 <_{\text{st}} \eta_1$  as  $\mu$  has no atom and  $\Omega$  as full support. Let  $\eta \notin \{\eta_0, \eta_1\}$  be a vaccination strategy with cost  $c$ ; necessarily

$$\eta_0 <_{\text{st}} \eta <_{\text{st}} \eta_1.$$

We now rewrite the function  $R_e^-$  in order to use the stochastic order on the vaccination strategies. We deduce from (50) that:

$$(57) \quad 4R_e^-(\eta) = 4 \int \eta d\mu - H(\eta)^2 \quad \text{with} \quad H(\eta) = \sqrt{\int (1+\alpha)^2 \eta d\mu} - \sqrt{\int (1-\alpha)^2 \eta d\mu}.$$

Then, using that  $\alpha$  is increasing and  $[-1, 1]$ -valued, we deduce from (55) (with  $h = (1+\alpha)^2$  and  $h = -(1-\alpha)^2$ ) and the definition of  $H$  in (57) that:

$$H(\eta_0) < H(\eta) < H(\eta_1).$$

This readily implies that  $R_e^-(\eta) > \min(R_e^-(\eta_0), R_e^-(\eta_1))$ . Thus, among strategies of cost  $c$ , the only possible Pareto optimal ones are  $\eta_0$  and  $\eta_1$ . We deduce that  $\mathcal{P} \subset \mathcal{S}_0 \cup \mathcal{S}_1$ .

6.3.3. *The kernel  $k^+$ .* Arguing as for  $k^-$ , we get that  $c^* = 0$  and  $c_* = 1$ , and the strategy  $\mathbb{1}$  (resp.  $\mathbb{0}$ ) is the only Pareto optimal as well as the only anti-Pareto optimal strategy with cost  $c = 0$  (resp.  $c = 1$ ). Since the kernel  $k^+$  is constant degree and symmetric, and the non-zero eigenvalues of  $T_{k^+}$  given by  $R_0$  and  $\int_{\Omega} \alpha^2 d\mu$  are positive, we deduce from Corollary 5.5 (i) that  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}$ .

Arguing as in Section 6.3.2 for the identification of the anti-Pareto optima based on (50) (with  $\varepsilon = +$  instead of  $\varepsilon = -$ ) and using that  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}$  (instead of  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}^{\text{Anti}}$ ), we deduce that  $\mathcal{P} = \mathcal{S}^{\perp\alpha}$ .

We now consider the anti-Pareto optima. Let  $c \in (0, 1)$ . We first start with some comparison of integrals with respect to the vaccination strategies, with cost  $c$ ,  $\eta_0$  and  $\eta_1$  defined by (56). Let  $\eta$  be a strategy of cost  $c$  not equal to  $\eta_0$  or  $\eta_1$  (recall that a strategy is defined up to the a.s. equality). Consider the monotone continuous non-negative functions defined on  $[0, 1]$ :

$$\phi_0 : x \mapsto \varphi^{-1} \left( \int_{[0,x]} \eta d\mu \right), \quad \text{and} \quad \phi_1 : x \mapsto \varphi^{-1} \left( 1 - \int_{[x,1]} \eta d\mu \right).$$

Let  $i \in \{0, 1\}$ . Let  $\phi_i^{-1}$  denote the generalized left-continuous inverse of  $\phi_i$ . Notice that  $\eta(x) \mu(dx)$ -a.s.  $\phi_i^{-1} \circ \phi_i(x) = x$ . The measure  $\eta_i d\mu$  is the push-forward of  $\eta d\mu$  through  $\phi_i$ , so that for  $h$  bounded measurable:

$$(58) \quad \int h \eta d\mu = \int h_i \eta_i d\mu \quad \text{with} \quad h_i = h \circ \phi_i^{-1}.$$

Since  $\eta$  is not equal to  $\eta_0$  a.s., there exists  $x_0 < 1 - c$  such that  $\phi_0(x) = x$  for  $x \in [0, x_0]$  and  $\phi_0(x) < x$  for  $x \in (x_0, 1]$ . Thus, we deduce that  $\phi_0^{-1}(y) = y$  for all  $y \in [0, x_0]$  and  $\phi_0^{-1}(y) > y$  for all  $y \in (x_0, 1 - c]$ . Similarly, since  $\eta$  is not equal to  $\eta_1$  almost surely, there exists  $x_1 > c$  such that  $\phi_1^{-1}(y) = y$  for all  $y \in (x_1, 1]$  and  $\phi_1^{-1}(y) < y$  for all  $y \in [c, x_1]$ . Since  $\alpha$  is increasing and  $\mu$  has no atom and full support in  $\Omega$ , we deduce from (58), applied to  $h\alpha$ , that if  $h$  is positive a.s., then:

$$(59) \quad \int h_0 \alpha \eta_0 d\mu < \int h \alpha \eta d\mu < \int h_1 \alpha \eta_1 d\mu.$$

Let  $h$  be the right Perron eigenfunction of  $T_{k^+ \eta}$  chosen such that  $h \in B_+^{\eta}$ . Since  $k^+$  is positive a.s. and thus, irreducible, we have that  $h$  is positive a.s. Thanks to Lemma 6.5, we have:

$$(60) \quad R_e^+(\eta) = \left( \int h \eta d\mu \right)^2 + \left( \int h \alpha \eta d\mu \right)^2 \quad \text{and} \quad \int h^2 \eta d\mu = 1.$$

We deduce from (58) that for  $i \in \{0, 1\}$ :

$$\int h \eta d\mu = \int h_i \eta_i d\mu \quad \text{and} \quad 1 = \int h^2 \eta d\mu = \int h_i^2 \eta_i d\mu.$$

In particular  $h_i$  belongs to  $B_+^{\eta_i}$ . Using that a.s.  $h > 0$ , we then deduce from (60) and (59) that:

$$R_e^+(\eta) < \max_{i \in \{0, 1\}} \left( \int h_i \eta_i d\mu \right)^2 + \left( \int h_i \alpha \eta_i d\mu \right)^2 \leq \max_{i \in \{0, 1\}} R_e(\eta_i).$$

We conclude that only  $\eta_0$  or  $\eta_1$  can maximize  $R_e^+$  among the strategies of cost  $c \in (0, 1)$ . We deduce that  $\mathcal{P}^{\text{Anti}} \subset \mathcal{S}_0 \cup \mathcal{S}_1$ .

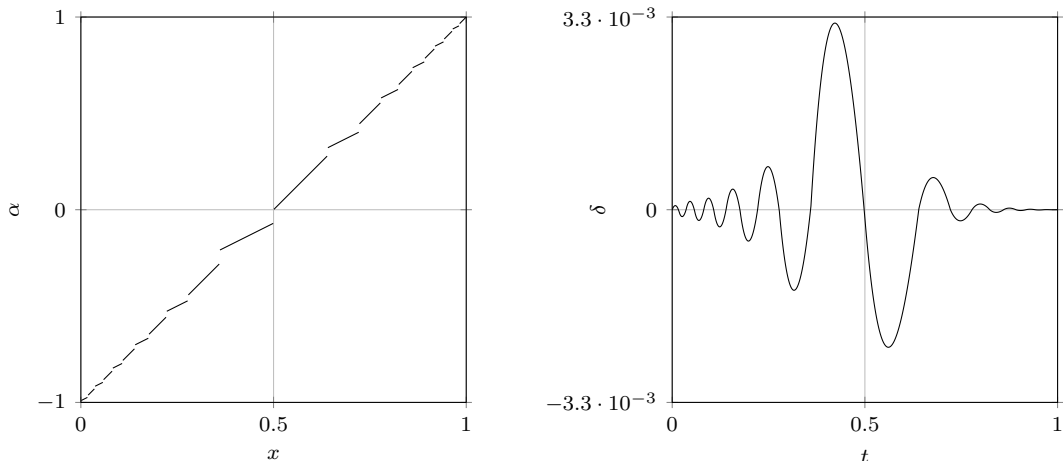
(A) Graph of the function  $\alpha$  defined by Equation (61) and Example 6.9.(B) Graph of the corresponding function  $\delta$  defined in Equation (64).

FIGURE 10. Plots of the functions of interest in Section 6.4.

**6.4. An example where all parametrizations of the Pareto frontier have an infinite number of discontinuities.** The purpose of this section is to give a particular example of kernel on a continuous model where we rigorously prove that the Pareto frontier cannot be greedily parametrized, that is, parametrized by a continuous path in  $\Delta$  (as in the fully symmetric circle), and that all the parametrizations have an arbitrary large number of discontinuities (possibly countably infinite).

We keep the setting from Section 6.1. Without loss of generality, we assume that  $R_0 = 1$ , and we consider the kernel  $k^- = 1 - \alpha \otimes \alpha$  on  $\Omega = [0, 1)$  endowed with its Lebesgue measure. We know from the previous section that, for any cost, either  $\eta_0$  or  $\eta_1$  are Pareto optimal, and that all other strategies are non-optimal. The idea is then to build an instance of the function  $\alpha$  in such a way that for some costs, one must vaccinate “on the left” and for other costs “on the right”.

Let  $N \in \llbracket 2, +\infty \rrbracket$ . Consider an increasing sequence  $(x_n, n \in \llbracket 0, N \rrbracket)$  such that  $x_0 = 1/2$ ,  $x_N = 1$  and  $\lim_{n \rightarrow \infty} x_n = 1$  if  $N = \infty$ . For  $0 \leq n < N$ , let  $p_n = x_{n+1} - x_n$  and assume that  $p_{n+1} < p_n$  for  $n \in \llbracket 0, N \rrbracket$ . For  $n \geq 1$ , let  $x_{-n}$  be the symmetric of  $x_n$  with respect to  $1/2$ , i.e.,  $x_{-n} = 1 - x_n$ . The function  $\alpha$  is increasing piecewise linear defined on  $(0, 1)$  by:

$$(61) \quad \alpha(x) = \begin{cases} 2x - 1, & \text{for } x \in [x_{2m}, x_{2m+1}), \\ x - 1 + \frac{x_{2m-1} + x_{2m}}{2} & \text{for } x \in [x_{2m-1}, x_{2m}). \end{cases}$$

See Figure 10(A) for an instance of the graph of  $\alpha$  given in Example 6.9. Note that for all  $n \in \llbracket 0, N \rrbracket$ , we have:

$$(62) \quad \int_{x_n}^{x_{n+1}} \alpha \, d\mu = - \int_{x_{-n-1}}^{x_{-n}} \alpha \, d\mu.$$

This proves that the integral of  $\alpha$  over  $[0, 1)$  is equal to 0. Of course,  $\sup_{[0,1)} \alpha^2 = 1 = R_0$ . Hence,  $\alpha$  satisfies Condition (49).

We recall that a function  $\gamma : [0, c_\star] \mapsto \Delta$  is a parametrization of the Pareto frontier if for all  $c \in [0, c_\star]$  the strategy  $\gamma(c)$  is Pareto optimal with cost  $C(\gamma(c)) = c$ . Now we can prove there exists no greedy parametrization of the Pareto frontier of the kernel  $k^-$  and even impose an arbitrary large lower bound for the number of discontinuities.

**Proposition 6.7.** *Let  $N \in \llbracket 2, +\infty \rrbracket$ . Consider the kernel  $k^- = 1 - \alpha \otimes \alpha$  from (48) on  $\Omega = [0, 1)$  endowed with its Lebesgue measure, with  $\alpha$  given by (61). Then, any parametrization of the Pareto frontier has at least  $2N - 2$  and at most  $20N - 2$  discontinuities.*

The proof is given at the end of this section, and relies on the following technical lemma based on the comparison of the following monotone paths  $\gamma_0$  and  $\gamma_1$  from  $[0, 1]$  to  $\Delta$ :

$$(63) \quad \gamma_0(t) = \mathbb{1}_{[0,t]}, \quad \text{and} \quad \gamma_1(t) = \mathbb{1}_{[1-t,1]}, \quad t \in [0, 1]$$

which parameterizes  $\mathcal{S}_0$  and  $\mathcal{S}_1$  as  $\gamma_0([0, 1]) = \mathcal{S}_0$  and  $\gamma_1([0, 1]) = \mathcal{S}_1$ . Notice that strategies  $\gamma_0(t)$  and  $\gamma_1(t)$  have the same cost  $1 - t$ .

Consider the function  $\delta : [0, 1] \rightarrow \mathbb{R}$  which, according to Proposition 6.2, measures the difference between the effective reproduction numbers at the extreme strategies:

$$(64) \quad \delta(t) = R_e(\gamma_0(t)) - R_e(\gamma_1(t)).$$

The function  $\delta$  is continuous and  $\delta(0) = \delta(1) = 0$ ; see for example Figure 10(B) for its graph when  $\alpha$  is taken from Example 6.9. We say that  $t \in (0, 1)$  is a zero crossing of  $\delta$  if  $\delta(t) = 0$  and there exists  $\varepsilon > 0$  such that  $\delta(t+r)\delta(t-r) < 0$  for all  $r \in (0, \varepsilon)$ . The following result gives some information on the zeros of the function  $\delta$ .

**Lemma 6.8.** *Under the assumptions of Proposition 6.7, the function  $\delta$  defined in (64) has at least  $2N - 2$  zero-crossings in  $(0, 1)$  and at most  $20N$  zeros in  $[0, 1]$ . Besides, if  $N = \infty$ , 0 and 1 are the only accumulation points of the set of zeros of  $\delta$ .*

*Proof.* Using the explicit representation of  $R_e^-$  from Lemma 6.5, see (50) with  $\varepsilon = -$ , we get the function  $\delta$  can be expressed as:

$$(65) \quad 2\delta(t) = V_1(t) - V_0(t) + \sqrt{V_0(t)^2 - M_0(t)^2} - \sqrt{V_1(t)^2 - M_1(t)^2},$$

where, as  $\int \alpha d\mu = 0$ :

$$M_0(t) = 2 \int_0^t \alpha d\mu, \quad V_0(t) = t + \int_0^t \alpha^2 d\mu, \quad M_1(t) = M_0(1-t) \quad \text{and} \quad V_1(t) = t + \int_{1-t}^1 \alpha^2 d\mu.$$

Elementary computations give that for all  $n \in \llbracket 0, N \rrbracket$ :

$$(66) \quad \int_{x_n}^{x_{n+1}} \alpha(x)^2 dx - \int_{x_{-n-1}}^{x_{-n}} \alpha(x)^2 dx = \frac{(-1)^n p_n^3}{4},$$

where we recall that  $p_n = x_{n+1} - x_n$ . Hence, we obtain that for all  $n \in \llbracket -N, N \rrbracket$ :

$$(67) \quad V_1(x_n) - V_0(x_n) = \frac{1}{4} \sum_{i=|n|}^{\infty} (-1)^i p_i^3.$$

Since the sequence  $(p_n, n \in \llbracket 0, N \rrbracket)$  is decreasing, we deduce that the sign of  $V_1(x_n) - V_0(x_n)$  alternates depending on the parity of  $n \in \llbracket -N, N \rrbracket$ : it is positive for odd  $n$  and negative for even  $n$ . The same result holds for the numbers  $\delta(x_n)$  since  $M_0(x_n) = M_1(1 - x_n)$  for all  $n \in \llbracket -N, N \rrbracket$  according to (62) (use that, with  $b > 0$ , the function  $x \mapsto x - \sqrt{x^2 - b^2}$  is decreasing for  $x \geq \sqrt{b}$  as its derivative is negative). This implies that  $\delta$  has at least  $2N - 2$  zero-crossings in  $(0, 1)$ .

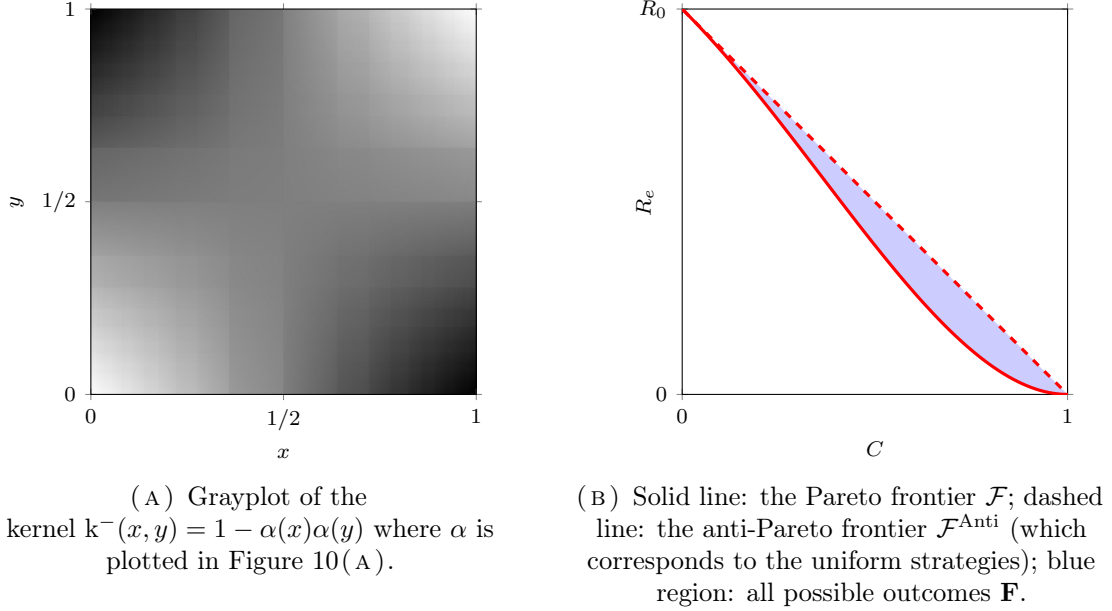


FIGURE 11. An example of a constant degree kernel operator of rank 2.

We now prove that  $\delta$  has at most  $20N$  zeros in  $[0, 1]$  and that 0 and 1 are the only possible accumulation points of the set of zeros of  $\delta$ . It is enough to prove that  $\delta$  has at most 10 zeros on  $[x_n, x_{n+1}]$  for all finite  $n \in \llbracket -N, N \llbracket$ . On such an interval  $[x_n, x_{n+1}]$ , the function  $\alpha$  is a polynomial of degree one. Consider first  $n$  odd and non-negative, so that for  $t \in [x_n, x_{n+1}]$ , we get that with  $a = 1 - (x_n + x_{n+1})/2$ :

$$\begin{aligned} M_0(t) &= 2t^2 - 2t + b_1, & V_0(t) &= \frac{4}{3}t^3 - 2t^2 + 2t + b_2, \\ M_1(t) &= t^2 - 2at + b_3, & V_1(t) &= -\frac{1}{3}t^3 + at^2 + (1 - a^2)t + b_4, \end{aligned}$$

where  $b_i$  are constants. If  $t$  is a zero of  $\delta$ , then it is also a zero of the polynomial  $P$  given by:

$$P = 4(V_1 - V_0)(V_0M_1^2 - V_1M_0^2) - (M_0^2 - M_1^2)^2.$$

Since the degree of  $P$  is exactly 10, it has at most 10 zeros. Thus  $\delta$  has at most 10 zeros on  $[x_n, x_{n+1}]$ . This ends the proof.  $\square$

*Proof of Proposition 6.7.* According to Proposition 6.2, the only possible Pareto strategies of cost  $c = 1 - t \in [0, 1]$  are  $\gamma_0(t)$  and  $\gamma_1(t)$ , and only one of them is optimal when  $\delta \neq 0$ . A zero crossing of the function  $\delta$  on  $(0, 1)$  therefore corresponds to a discontinuity of any parametrization of the Pareto frontier. We deduce from Lemma 6.8 that in  $(0, 1)$  there are at least  $2N - 2$  and at most  $20N - 2$  zeros crossing and thus discontinuities of any parametrization of the Pareto frontier.  $\square$

*Example 6.9.* In Figure 10(A), we have represented the function  $\alpha$  defined by (61) where:

$$x_n = \frac{1}{2} \log_{12}(12(n+1)), \quad 0 \leq n \leq N = 11.$$

Hence, the mesh  $(x_n, -N \leq n \leq N)$  is composed by  $2N + 1 = 23$  points. The graph of the corresponding function  $\delta$  defined in (64) is drawn in Figure 10(B). The grayplot of the

kernel  $k^- = 1 - \alpha \otimes \alpha$  is given in Figure 11(A) and the associated Pareto and anti-Pareto frontiers are plotted in Figure 11(B).

## 7. GEOMETRIC KERNELS ON THE SPHERE

A geometric random graph is an undirected graph constructed by assigning a random point in a latent metric space to each node and by connecting two nodes according to a certain probability that depends on the distance between their latent point. Because of its geometric structure, this model is appealing for a wide-range of applications such as wireless networks modelling [27], social networks [31] and biological networks [29]. A geometric random graph model can be represented as a symmetric kernel defined on the latent space (also called *graphon*) according to [39].

In this section, we focus our study on the latent space given by the unit sphere. In Section 7.1 we present the mathematical model, and give in Section 7.2 sufficient conditions on the kernel for uniform strategies to be Pareto or anti-Pareto optimal. Section 7.3 is devoted to the explicit descriptions of the Pareto and anti-Pareto optimal vaccination strategies in the affine case.

**7.1. The model.** Let  $d \geq 2$ . Let  $\Omega = \mathbb{S}^{d-1}$  be the unit sphere of the Euclidean  $d$ -dimensional space  $\mathbb{R}^d$  endowed with the usual Borel  $\sigma$ -field and the uniform probability measure  $\mu$ . Let  $\langle \cdot, \cdot \rangle$  denote the usual scalar product on  $\mathbb{R}^d$  and let

$$\delta(x, y) = \arccos(\langle x, y \rangle)$$

denote the geodesic distance between  $x, y \in \mathbb{S}^{d-1}$ . By symmetry, the distribution on  $[-1, 1]$  of the scalar product of two independent uniformly distributed random variables in  $\mathbb{S}^{d-1}$  is equal to the distribution of the first coordinate of a uniformly distributed unit vector: it is the probability measure on  $[-1, 1]$  with density with respect to the Lebesgue measure proportional to the function  $w_d$  defined on  $[-1, 1]$  by:

$$w_d(t) = (1 - t^2)^{(d-3)/2} \mathbb{1}_{(-1,1)}(t).$$

In particular, we deduce from the Funk-Heck formula (take  $n = 0$  in [9, Theorem 1.2.9]) that for any non-negative measurable function  $h$  defined on  $[-1, 1]$  and  $x \in \mathbb{S}^{d-1}$ , we have:

$$(68) \quad \int_{\mathbb{S}^{d-1}} h(\langle x, y \rangle) \mu(dy) = c_d \int_{-1}^1 h(t) w_d(t) dt \quad \text{with} \quad c_d = \frac{\Gamma(\frac{d}{2})}{\Gamma(\frac{d-1}{2})\sqrt{\pi}}.$$

We consider a symmetric kernel  $k$  on  $\mathbb{S}^{d-1}$  corresponding to a geometric random graph model on  $\mathbb{S}^{d-1}$ , given by:

$$(69) \quad k(x, y) = p(\langle x, y \rangle) = f \circ \delta(x, y), \quad x, y \in \mathbb{S}^{d-1},$$

where  $p : [-1, 1] \rightarrow \mathbb{R}_+$  is a measurable function and  $f = p \circ \cos : [0, \pi] \rightarrow \mathbb{R}_+$ . We assume that  $k$  has finite double norm on  $L^2$ ; thanks to (68), this is equivalent to:

$$(70) \quad \int_{-1}^1 p(t)^2 w_d(t) dt = \int_0^\pi f(\theta)^2 \sin(\theta)^{d-2} d\theta < \infty.$$

By symmetry, using that the scalar product and the measure  $\mu$  are invariant by rotations, we deduce that the kernel  $k$  is a constant degree kernel. According to (45) and using (68), we get that the basic reproduction number is given by:

$$(71) \quad R_0 = c_d \int_{-1}^1 p(t) w_d(t) dt = c_d \int_0^\pi f(\theta) \sin(\theta)^{d-2} d\theta.$$

By [9, Theorem 1.2.9], the eigenvectors of the symmetric operator  $T_k$  on  $L^2(\mathbb{S}^{d-1})$  are the spherical harmonics, and in particular, they don't depend on the function  $p$ . We recall the linear subspace of spherical harmonics of degree  $n$  for  $n \in \mathbb{N}$  has dimension  $d_n$  given by  $d_0 = 1$  and for  $n \in \mathbb{N}^*$ :

$$d_n = \frac{2n + d - 2}{n + d - 2} \binom{n + d - 2}{n}.$$

The corresponding eigenvalues  $(\lambda_n, n \in \mathbb{N})$  are real and given by:

$$(72) \quad \lambda_n = c_d \int_{-1}^1 p(t) \frac{G_n(t)}{G_n(1)} w_d(t) dt = c_d \int_0^\pi f(\theta) \frac{G_n(\cos(\theta))}{G_n(1)} \sin(\theta)^{d-2} d\theta,$$

where  $G_n$  is the Gegenbauer polynomial of degree  $n$  and parameter  $(d-2)/2$  (see [9, Section B.2] with  $G_n = C_n^{(d-1)/2}$ ). We simply recall that  $G_0 = 1$  and that for  $d = 2$ , the Gegenbauer polynomials are, up to a multiplicative constant, the Chebyshev polynomials of the first kind:

$$G_n(\cos(\theta)) = \frac{2}{n} \cos(n\theta) \quad \text{for } \theta \in [0, \pi] \text{ and } n \in \mathbb{N}^*;$$

and that for  $d \geq 3$ ,  $r \in (-1, 1)$  and  $\theta \in [0, \pi]$ :

$$\sum_{n=0}^{\infty} r^n G_n(\cos(\theta)) = (1 + r^2 - 2r \cos(\theta))^{-(d-2)/2} \quad \text{and} \quad G_n(1) = \binom{n + d - 3}{n} \quad \text{for } n \in \mathbb{N}^*.$$

Thus, if  $\lambda \neq 0$  is an eigenvalue of  $T_k$ , then its multiplicity is the sum of all the dimensions  $d_n$  such that  $\lambda_n = \lambda$ . The eigenvalue  $R_0$  (associated to the eigenvector  $\mathbf{1}$  which is the spherical harmonic of degree 0) is in fact simple according to the next Lemma.

**Lemma 7.1.** *Let  $k$  be a kernel on  $\mathbb{S}^{d-1}$  given by (69), with finite double norm and such that  $R_0 > 0$ . Then the kernel  $k$  is constant degree and irreducible, and its eigenvalue  $R_0$  is simple.*

*Proof.* The kernel  $k$  is trivially a constant degree kernel. Since  $d_0 = 1$ , we only need to prove that  $\lambda_n < \lambda_0 = R_0$  for all  $n \in \mathbb{N}^*$  to get that  $R_0$  is simple, and then use Lemma 5.12 to get that  $k$  is irreducible.

According to [1, Equation 22.14.2] or [3, Section 3.7.1], we get that  $|G_n(t)| \leq G_n(1)$  for  $t \in [-1, 1]$ . Since  $G_n$  is a polynomial, the inequality is strict for a.e.  $t \in [-1, 1]$ . Using (72), we obtain that  $\lambda_n < \lambda_0$  for all  $n \in \mathbb{N}^*$ .  $\square$

*Example 7.2* (The circle:  $d = 2$ ). In case  $d = 2$ , we identify the circle  $\mathbb{S}^1$  with  $\Omega = \mathbb{R}/2\pi\mathbb{Z}$  and the scalar product  $\langle \theta, \theta' \rangle = \cos(\theta - \theta')$ . The kernel  $k$  from (69) is the convolution kernel given by  $k(\theta, \theta') = p(\cos(\theta - \theta')) = f(\theta - \theta')$ , where  $f$  is symmetric non-negative and  $2\pi$  periodic and its restriction to  $[0, \pi]$  is square integrable. Then, we can consider the development in  $L^2([0, \pi])$  of  $f$  as a Fourier series:

$$(73) \quad f(\theta) = \sum_{n=0}^{\infty} a_n(f) \cos(n\theta), \quad \theta \in [0, \pi],$$

where:

$$(74) \quad a_0(f) = \frac{1}{\pi} \int_0^\pi f(\theta) d\theta \quad \text{and} \quad a_n(f) = \frac{2}{\pi} \int_0^\pi \cos(n\theta) f(\theta) d\theta \quad \text{for } n \geq 1.$$

It follows from Equation (73) that the kernel has the following decomposition in  $L^2([0, 2\pi]^2)$ :

$$(75) \quad k(\theta, \theta') = a_0(f) + \sum_{n=1}^{\infty} a_n(f) (\cos(n\theta) \cos(n\theta') + \sin(n\theta) \sin(n\theta')), \quad \theta, \theta' \in [0, 2\pi].$$

Assume that  $a_0(f) > 0$ , that is,  $f$  is non-zero. Then, the spectral radius  $R_0 = a_0(f)$  is an eigenvalue with multiplicity one associated to the eigenfunction  $\mathbb{1}$  (and thus  $k$  is a constant degree kernel). The other eigenvalues are given by  $\lambda_n = a_n(f)/2$  for all  $n \geq 1$  and, when non zero and distinct, have multiplicity 2.

**7.2. Sufficient condition for convexity or concavity.** We would like to provide conditions on the function  $f$  or  $p$  that ensure that the eigenvalues  $(\lambda_n, n \geq 1)$  given by (72) of the operator  $T_k$  with the kernel  $k$  defined by (69) are all non-negative or all non-positive so that  $R_e$  is convex or concave according to Corollary 5.5. Schoenberg's theorem, see [9, Theorem 14.3.3] or [22, Theorem 1], characterizes the continuous function  $f$  such that the kernel  $k$  is positive semi-definite (and thus the eigenvalues  $(\lambda_n, n \geq 1)$  are all non-negative) as those with non-negative Gegenbauer coefficients:  $f = \sum_{n=0}^{\infty} a_n G_n$ , where the convergence is uniform on  $[-1, 1]$ , with  $a_n \geq 0$  for all  $n \in \mathbb{N}$  and  $\sum_{n=0}^{\infty} a_n G_n(1)$  finite. When  $d = 2$ , this corresponds to the Böchner theorem. We refer to [22] and references therein for some characterization of functions  $f$  such that the kernel  $k$  from (69) is definite positive. We end this section with some examples.

*Example 7.3.* We give an elementary example in the setting of Example 7.2 when  $d = 2$ . Set

$$f_+(\theta) = (\pi - \theta)^2 \quad \text{and} \quad f_-(\theta) = \pi^2 - (\pi - \theta)^2 \quad \text{for } \theta \in [0, \pi].$$

We can compute the Fourier coefficients of  $f_+$  and  $f_-$  as:

$$(\pi - \theta)^2 = \frac{\pi^2}{3} + \sum_{n=1}^{\infty} \frac{4}{n^2} \cos(n\theta), \quad \theta \in [0, \pi].$$

Using Corollary 5.5 and [11, Theorem 5.5], we deduce that the function  $R_e$  associated to the convolution kernel  $k = f_+ \circ \delta$  is convex and  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}$ ; whereas the function  $R_e$  associated to the convolution kernel  $k = f_- \circ \delta$  is concave and  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}^{\text{Anti}}$ .

*Example 7.4 (Kernel from a completely monotone function).* Let  $\varphi$  be a continuous non-negative function defined on  $\mathbb{R}_+$ , such that  $\varphi$  is completely monotone, that is,  $\varphi$  is infinitely differentiable on  $(0, +\infty)$  and  $(-1)^n \varphi^{(n)} \geq 0$  on  $(0, +\infty)$  for all  $n \geq 1$ . Using [22, Theorem 7], we get that the geometric kernel  $k = f \circ \delta$  on  $\mathbb{S}^{d-1}$ , with  $d = 2$ , where  $f = \varphi_{[0, \pi]}$  is positive definite (thus all the eigenvalues of  $T_k$  are non-negative). Thanks to Corollary 5.5 and [11, Theorem 5.5], we deduce that  $R_e$  is convex and the uniform strategies are Pareto optimal:  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}$ .

*Example 7.5 (Kernel from a Bernstein function).* Let  $\varphi$  be a Bernstein function, that is a non-negative  $C^1$  function defined on  $\mathbb{R}_+$  such that  $\varphi^{(1)}$  is completely monotone. Assume furthermore that  $\sup_{\mathbb{R}_+} \varphi < \infty$ . This gives that the function  $t \mapsto (\sup_{\mathbb{R}_+} \varphi) - \varphi(t)$  defined on  $\mathbb{R}_+$  is continuous non-negative and completely monotone. Consider the geometric kernel  $k = f \circ \delta$  on  $\mathbb{S}^{d-1}$ , with  $d = 2$ , where  $f = \varphi_{[0, \pi]}$ . We deduce from [22, Theorem 7], see also the previous example, that all the eigenvalues of the integral operator  $T_k$ , but for  $R_0$ , are non-positive. Then, using Corollary 5.5 and [11, Theorem 5.5], we get that  $R_e$  is concave and the uniform strategies are anti-Pareto optimal:  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}^{\text{Anti}}$ .

*Example 7.6 (Kernel from a power function).* Let  $m \geq 1$  be an integer and  $\theta_0 \geq \pi$  a real number. Using [22, Lemma 4], we get that for  $f(\theta) = (\theta_0 - \theta)^m$ ,  $R_e$  is convex and the uniform vaccination strategies are Pareto optimal; and that for  $f(\theta) = \theta_0^m - (\theta_0 - \theta)^m$ ,  $R_e$  is concave and the uniform strategies are anti-Pareto optimal.

*Example 7.7 (The function  $p$  is a series).* According to [22, Theorem 1], if the function  $p$  can be written as  $p(t) = \sum_{n \in \mathbb{N}} b_n t^n$  with  $b_n$  non-negative and  $\sum_{n \in \mathbb{N}} b_n$  finite, then, for all  $d \geq 2$ , the kernel  $k$  defined by (69) on  $\mathbb{S}^{d-1}$  is semi definite positive (and definite positive if the coefficients



$b_n$  are positive for infinitely many even and infinitely many odd integers  $n$ ), and thus the function  $R_e$  is convex and the uniform vaccination strategies are Pareto optimal thanks to Corollary 5.5 and [11, Theorem 5.5].

Consider the kernel  $k(x, y) = |x - y|^\nu$ , that is,  $p(t) = 2^{\nu/2}|1 - t|^{\nu/2}$ , with  $\nu > (1 - d)/2$ , so that condition (70) holds. According to [3, Section 3.7.1] and Equation (3.74) therein, for  $n \geq 1$ , the eigenvalues  $\lambda_n$  have the same sign as  $\prod_{k=0}^{n-1} (-\nu + 2k)$ . So, we deduce that for  $\nu \in ((1 - d)/2, 0)$  all the eigenvalues are positive and thus  $R_e$  is convex and the uniform vaccination strategies are Pareto optimal; and for  $\nu \in (0, 2)$  all the eigenvalues (but  $\lambda_0 = R_0 > 0$ ) are negative and thus  $R_e$  is concave and the uniform strategies are anti-Pareto optimal. The latter case is also a consequence of [22, Theorem 1], whereas the former case is not a direct consequence of [22, Theorem 1] as  $\sum_{n \in \mathbb{N}} b_n$  is not finite when  $\nu$  is negative.

**7.3. The affine model.** Recall  $\Omega = \mathbb{S}^{d-1} \subset \mathbb{R}^d$ , with  $d \geq 2$ , is endowed with the uniform probability measure  $\mu$ . In this section, we suppose that the model is affine, that is, the kernel  $k$  given by (69), *i.e.*  $k(x, y) = p(\langle x, y \rangle)$ , has a linear envelope:

$$p(t) = a + bt \quad \text{for } t \in [-1, 1].$$

The kernel  $k$  being non-negative non-constant with  $R_0 > 0$  is equivalent to the condition  $a \geq |b| > 0$  on the parameter  $(a, b)$ . This model corresponds to  $f(\theta) = a + b \cos(\theta)$  for  $\theta \in [0, \pi]$ . Since the Gegenbauer polynomials  $(G_n, n \in \mathbb{N})$  are orthogonal with respect to the measure  $w_d(t) dt$ , we easily deduce from (72) that the non-zero eigenvalues of the integral operator  $T_k$  are  $R_0 = a$  (with multiplicity  $d_0 = 1$ ) and  $\lambda_1 = b/d$  (with multiplicity  $d_1 = d$ ).

For  $x \in \mathbb{S}^{d-1}$  and  $t \in [-1, 1]$ , we consider the following balls centered at  $x$ :

$$B(x, t) = \{y \in \mathbb{S}^{d-1} : \langle x, y \rangle \geq t\}.$$

Recall that strategies are defined up to equality almost surely. We consider the following sets of extremal strategies, for  $x \in \mathbb{S}^{d-1}$ :

$$\mathcal{S}^{\text{balls}} = \left\{ \mathbb{1}_{B(x, t)} : x \in \mathbb{S}^{d-1}, t \in [-1, 1] \right\},$$

as well as the following set of strategies which contains the set of uniform strategies  $\mathcal{S}^{\text{uni}} = \{t\mathbb{1} : t \in [0, 1]\}$ :

$$\mathcal{S}^{\perp \text{id}} = \left\{ \eta \in \Delta : \int_{\mathbb{S}^{d-1}} x \eta(x) \mu(dx) = 0 \right\}.$$

**Proposition 7.8.** *Let  $a \geq |b| > 0$  and the kernel  $k$  on  $\mathbb{S}^{d-1}$ , with  $d \geq 2$ , be given by:*

$$k(x, y) = a + b\langle x, y \rangle.$$

(i) **The case  $b > 0$ .** *A strategy is Pareto optimal if and only if it belongs to  $\mathcal{S}^{\perp \text{id}}$ . In particular, for any  $c \in [0, 1]$ , the strategy  $(1 - c)\mathbb{1}$  costs  $c$  and is Pareto optimal. The anti-Pareto optimal strategies are  $\mathbb{1}_{B(x, t)}$  for  $x \in \mathbb{S}^{d-1}$  and  $t \in [-1, 1]$ . In other words:*

$$\mathcal{P} = \mathcal{S}^{\perp \text{id}} \quad \text{and} \quad \mathcal{P}^{\text{Anti}} = \mathcal{S}^{\text{balls}}.$$

(ii) **The case  $b < 0$ .** *A strategy is anti-Pareto optimal if and only if it belongs to  $\mathcal{S}^{\perp \text{id}}$ . In particular, for any  $c \in [0, 1]$ , the strategy  $(1 - c)\mathbb{1}$  costs  $c$  and is anti-Pareto optimal. The Pareto optimal strategies are  $\mathbb{1}_{B(x, t)}$  for  $x \in \mathbb{S}^{d-1}$  and  $t \in [-1, 1]$ . In other words:*

$$\mathcal{P}^{\text{Anti}} = \mathcal{S}^{\text{balls}} \quad \text{and} \quad \mathcal{S}^{\text{uni}} = \mathcal{S}^{\perp \text{id}}.$$

In both cases, we have  $c_\star = 1$  and  $c^\star = 0$ .

*Example 7.9.* We consider the kernel  $k = 1 + b\langle \cdot, \cdot \rangle$  on the sphere  $\mathbb{S}^{d-1}$ , with  $d = 2$ . This model has the same Pareto and anti-Pareto frontiers as the equivalent model given by  $\Omega = [0, 1)$  endowed with the Lebesgue measure and the kernel  $(x, y) \mapsto 1 + b \cos(\pi(x - y))$ , where the equivalence holds in the sense of [13, Section 7], with an obvious deterministic coupling  $\theta \mapsto \exp(2i\pi\theta)$ . We provide the Pareto and anti-Pareto frontiers in Figure 12 with  $b = 1$  (top) and with  $b = -1$  (bottom).

*Proof.* The proof of Proposition 7.8 is decomposed in four steps.

*Step 1:*  $R_e(\eta)$  is the eigenvalue of a  $2 \times 2$  matrix  $M(\eta)$ . Without loss of generality, we shall assume that  $R_0 = a = 1$ . Since  $k$  is positive a.s., we deduce that  $c_\star = 1$  and  $c^\star = 0$  thanks to Lemma 3.1; and the strategy  $\mathbb{1}$  (resp.  $0$ ) is the only Pareto optimal as well as the only anti-Pareto optimal strategy with cost  $0$  (resp.  $1$ ). So we shall only consider strategies  $\eta \in \Delta$  such that  $C(\eta) \in (0, 1)$ .

Let  $z_0 \in \mathbb{S}^{d-1}$ . Write  $b = \varepsilon\lambda^2$  with  $\varepsilon \in \{-1, +1\}$  and  $\lambda \in (0, 1]$ , and define the function  $\alpha$  on  $\mathbb{S}^{d-1}$  by:

$$\alpha = \lambda \langle \cdot, z_0 \rangle.$$

Let  $\eta \in \Delta$  with cost  $c \in (0, 1)$ . As  $c_\star = 1 > C(\eta)$ , we get that  $R_e(\eta) > 0$ . We deduce from the special form of the kernel  $k$  that the eigenfunctions of  $T_{k\eta}$  are of the form  $\zeta + \beta\lambda\langle \cdot, y \rangle$  with  $\zeta, \beta \in \mathbb{R}$  and  $y \in \mathbb{S}^{d-1}$ . Since  $R_e(\eta) > 0$ , the right Perron eigenfunction, say  $h_\eta$ , being non-negative, can be chosen such that  $h_\eta = 1 + \beta_\eta\lambda\langle \cdot, y_\eta \rangle$  with  $\beta_\eta \geq 0$  and  $\beta_\eta\lambda \leq 1$ . Up to a rotation on the vaccination strategy, we shall take  $y_\eta = z_0$ , that is:

$$h_\eta = 1 + \beta_\eta \alpha.$$

From the equality  $R_e(\eta)h_\eta = T_{k\eta}h_\eta$ , we deduce that:

$$(76) \quad R_e(\eta) = \int_{\mathbb{S}^{d-1}} \eta(y) \mu(dy) + \beta_\eta \lambda \int_{\mathbb{S}^{d-1}} \eta(y) \langle y, z_0 \rangle \mu(dy),$$

$$(77) \quad \beta_\eta R_e(\eta) \langle \cdot, z_0 \rangle = \varepsilon \lambda \int_{\mathbb{S}^{d-1}} \eta(y) \langle \cdot, y \rangle \mu(dy) + \beta_\eta \varepsilon \lambda^2 \int_{\mathbb{S}^{d-1}} \eta(y) \langle \cdot, y \rangle \langle y, z_0 \rangle \mu(dy).$$

Evaluating the latter equality at  $x = z_0$ , we deduce that  $R_e(\eta)$  is a positive eigenvalue of the matrix  $M(\eta)$  associated to the eigenvector  $(1, \beta_\eta)$ , where:

$$(78) \quad M(\eta) = \begin{pmatrix} \int \eta d\mu & \int \alpha \eta d\mu \\ \varepsilon \int \alpha \eta d\mu & \varepsilon \int \alpha^2 \eta d\mu \end{pmatrix}.$$

We end this step by proving the following equivalence:

$$(79) \quad \beta_\eta = 0 \iff \int \alpha \eta d\mu = 0.$$

Indeed, if  $\beta_\eta = 0$ , then the vector  $(1, 0)$  is an eigenvector of  $M(\eta)$  associated to the eigenvalue  $R_e(\eta)$ . We deduce from (78) that  $\int \alpha \eta d\mu = 0$ . Conversely, if  $\int \alpha \eta d\mu = 0$ , then the matrix  $M(\eta)$  is diagonal with eigenvalues  $\int \eta d\mu$  and  $\int \alpha^2 \eta d\mu$ . As  $\alpha^2 \leq 1$  with strict inequality on a set of positive  $\mu$ -measure, we deduce that:

$$(80) \quad \int \eta d\mu > \int \alpha^2 \eta d\mu.$$

Since  $(1, \beta_\eta)$  is an eigenvector of  $M(\eta)$ , this implies that  $\beta_\eta = 0$ . This proves (79).

*Step 2:*  $R_e(\eta)$  is the spectral radius of the matrix  $M(\eta)$ , that is,  $R_e(\eta) = \rho(M(\eta))$ . We first consider the case  $\varepsilon = -1$ . Since  $\alpha$  is non constant as  $\lambda > 0$ , we deduce from the Cauchy-Schwarz inequality, that the determinant of  $M(\eta)$  is negative. As a.s.  $c_\star = 1$ , we deduce that  $R_e(\eta) > 0$ ,

and thus the other eigenvalue is negative. Since  $\alpha^2 \leq 1$ , the trace of  $M(\eta)$  is non-negative, thus  $R_e(\eta)$  is the spectral radius of the matrix  $M(\eta)$ .

We now consider the case  $\varepsilon = +1$ . Let  $\eta^{\text{uni}}$  be the uniform strategy with the same cost as  $\eta$ . Thanks to (76), we get  $R_e(\eta^{\text{uni}}) = \int \eta^{\text{uni}} d\mu = \int \eta d\mu$ . Since the non-zero eigenvalues of  $T_k$ , that is, 1 and  $\lambda^2/d$ , are positive, we deduce from Corollary 5.5 (i), that the uniform strategies are Pareto optimal ( $\mathcal{S}^{\text{uni}} \subset \mathcal{P}$ ), so we have:

$$R_e(\eta) \geq R_e(\eta^{\text{uni}}) = \int \eta d\mu.$$

We deduce from (76) that  $\beta_\eta \int \alpha \eta d\mu \geq 0$ .

On the one hand, if  $\beta_\eta \int \alpha \eta d\mu = 0$ , then, by (79), the matrix  $M(\eta)$  is diagonal. Using (80), we obtain that  $R_e(\eta) = \rho(M(\eta))$ . On the other hand, if  $\beta_\eta \int \alpha \eta d\mu > 0$ , then the matrix  $M(\eta)$  has positive entries. Since the eigenvector  $(1, \beta_n)$  also has positive entries, it is the right Perron eigenvector and the corresponding eigenvalue is the spectral radius of  $M(\eta)$ , that is,  $R_e(\eta) = \rho(M(\eta))$ . To conclude, the equality  $R_e(\eta) = \rho(M(\eta))$  holds in all cases.

*Step 3:*  $R_e(\eta) = \int \eta d\mu \iff \eta \in \mathcal{S}^{\perp \text{id}}$ . Let  $\eta \in \Delta$  such that  $R_e(\eta) = \int \eta d\mu$ . We deduce from (76) that  $\beta_\eta \int \alpha \eta d\mu = 0$ . Thanks to (79), this implies that  $\beta_\eta = 0$ . Using (77), we obtain that  $\int y \eta(y) \mu(dy) = 0$  and thus  $\eta \in \mathcal{S}^{\perp \text{id}}$ . Clearly if  $\eta \in \mathcal{S}^{\perp \text{id}}$ , we deduce from (76) that  $R_e(\eta) = \int \eta d\mu$ .

As a consequence and since  $\mathcal{S}^{\text{uni}} \subset \mathcal{S}^{\perp \text{id}}$ , we deduce from Corollary 5.5 that if  $\varepsilon = +1$ , then  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}$  and thus  $\mathcal{P} = \mathcal{S}^{\perp \text{id}}$ ; and that if  $\varepsilon = -1$ , then  $\mathcal{S}^{\text{uni}} \subset \mathcal{P}^{\text{Anti}}$  and thus  $\mathcal{P}^{\text{Anti}} = \mathcal{S}^{\perp \text{id}}$ .

*Step 4:* A relation with the constant degree symmetric kernels of rank two from Section 6. This step is in the spirit of [13, Section 7] on coupled models. Let  $X$  be a uniform random variable on  $\mathbb{S}^{d-1}$ . Let  $\Omega_0 = [-1, 1]$  endowed with the probability measure  $\mu_0(dt) = c_d w_d(t) dt$ , and set  $\Delta_0$  the set of  $[0, 1]$ -valued measurable functions defined on  $\Omega_0$ . According to [33, Theorem 8.9], there exists  $\eta_0 \in \Delta_0$  such that a.s.:

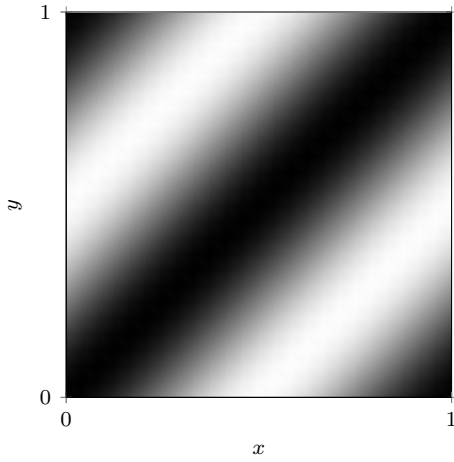
$$(81) \quad \eta_0(\langle X, z_0 \rangle) = \mathbb{E}[\eta(X) | \langle X, z_0 \rangle].$$

Set  $\alpha_0 = \lambda t$ , and define the matrix:

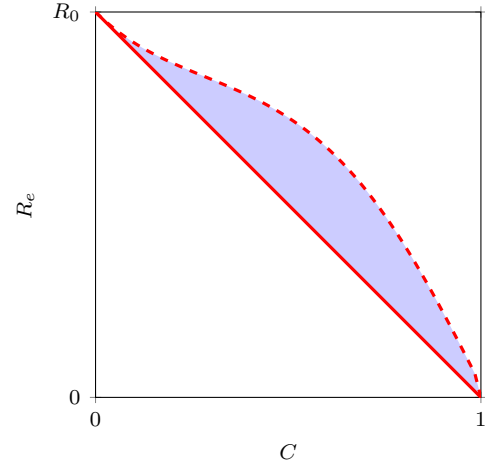
$$M_0(\eta_0) = \begin{pmatrix} \int_{\Omega_0} \eta_0 d\mu_0 & \int_{\Omega_0} \alpha_0 \eta_0 d\mu_0 \\ \varepsilon \int_{\Omega_0} \alpha_0 \eta_0 d\mu_0 & \varepsilon \int_{\Omega_0} \alpha_0^2 \eta_0 d\mu_0 \end{pmatrix}.$$

By construction of  $\eta_0$ , we have  $M_0(\eta_0) = M(\eta)$ . Thanks to Section 6, see Lemma 6.5 (but for the fact that  $\Omega$  therein is replaced by  $[-1, 1]$ ), we get that  $M_0(\eta_0)$  is exactly the matrix in (52), and thus the spectral radius of  $M_0(\eta_0)$  is the effective reproduction number of the model associated to the constant degree symmetric kernel of rank two  $k_0^\varepsilon = 1 + \varepsilon \alpha_0 \otimes \alpha_0$  given in (48) (with  $\Omega, \mu, \alpha$  replaced by  $\Omega_0, \mu_0$  and  $\alpha_0$ ). We deduce that: if  $\eta$  is Pareto or anti-Pareto optimal for the model  $(\mathbb{S}^{d-1}, \mu, k)$  then so is  $\eta_0$  for the model  $(\Omega_0, \mu_0, k_0^\varepsilon)$ ; and if  $\eta_0$  is Pareto or anti-Pareto optimal for the model  $(\Omega_0, \mu_0, k_0^\varepsilon)$ , so is any strategy  $\eta$  such that (81) holds.

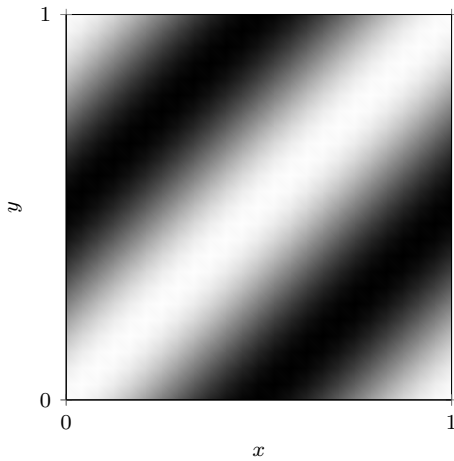
We first consider the case  $\varepsilon = +1$ . According to Proposition 6.2, we get that the anti-Pareto optimal strategies are  $\eta_0 = \mathbb{1}_{[-1, t]}$  or  $\eta_0 = \mathbb{1}_{[-t, 1]}$  for a given cost  $c$  (with  $t$  uniquely characterized by  $c$ ). Using that  $0 \leq \eta \leq 1$ , we deduce that the only possible choice for  $\eta$  such that (81) holds is to take  $\eta = \mathbb{1}_{B(-z_0, t)}$  or  $\eta = \mathbb{1}_{B(z_0, t)}$ . Since  $z_0$  was arbitrary, we get that the only possible anti-Pareto optimal strategies belong to  $\mathcal{S}^{\text{balls}}$ . Notice that anti-Pareto optimal strategies exist for all cost  $c \in [0, 1]$  as  $k > 0$  a.s., see Lemma 3.1 and [13, Section 5.4] for



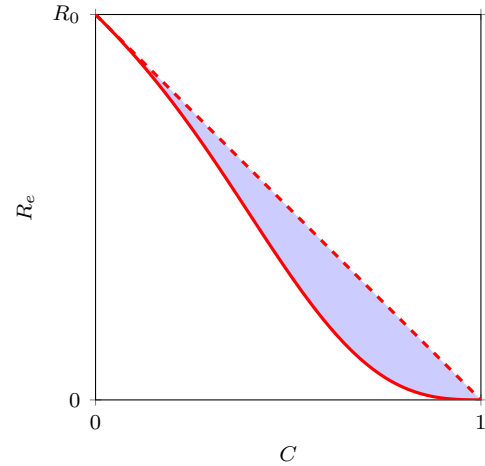
(A) Grayplot of the kernel  $k = 1 + \cos(\pi(x - y))$  on  $[0, 1)$ .



(B) Solid line: the Pareto frontier  $\mathcal{F}$  (which corresponds to the uniform strategies); dashed line: the anti-Pareto frontier  $\mathcal{F}^{\text{Anti}}$ ; blue region: all possible outcomes  $\mathbf{F}$ .



(C) Grayplot of the kernel  $k = 1 - \cos(\pi(x - y))$  on  $[0, 1)$ .



(D) Solid line: the Pareto frontier  $\mathcal{F}$ ; dashed line: the anti-Pareto frontier  $\mathcal{F}^{\text{Anti}}$  (which corresponds to the uniform strategies); blue region: all possible outcomes  $\mathbf{F}$ .

FIGURE 12. Two examples of a geometric kernel on the circle  $\mathbb{R} \setminus \mathbb{Z}$ .

irreducible kernels, loss function  $R_e$  and uniform cost function  $C$  given by (28). Since the set of anti-Pareto optimal strategies is also invariant by rotation, we deduce that  $\mathcal{P}^{\text{Anti}} = \mathcal{S}^{\text{balls}}$ .

The case  $\varepsilon = -1$  is similar and thus  $\mathcal{P} = \mathcal{S}^{\text{balls}}$  in this case. (Notice the irreducibility of the kernel  $k$  is only used in [13, Lemma 5.13] for the study of anti-Pareto frontier.)  $\square$

## REFERENCES

- [1] M. Abramowitz and I. A. Stegun. *Handbook of mathematical functions with formulas, graphs, and mathematical tables*. Vol. 55. US Government printing office, 1972.

- [2] B. C. Arnold. *Majorization and the Lorenz Order: A Brief Introduction*. Vol. 43. Lecture Notes in Statistics. Springer-Verlag, 1987.
- [3] K. Atkinson and W. Han. *Spherical harmonics and approximations on the unit sphere: an introduction*. Vol. 2044. Lecture Notes in Mathematics. Springer, Heidelberg, 2012.
- [4] Á. Backhausz and B. Szegedy. “Action convergence of operators and graphs”. *Canadian Journal of Mathematics* (2020), pp. 1–50.
- [5] E. Beretta and V. Capasso. “Global Stability Results for a Multigroup SIR Epidemic Model”. *Mathematical Ecology*. Proceedings of the Autumn Course Research Seminars (Trieste, Italy, Nov. 24–Dec. 12, 1986). World Scientific, 1986, pp. 317–342.
- [6] A. Berman and R. J. Plemmons. *Nonnegative Matrices in the Mathematical Sciences*. Classics in Applied Mathematics. Society for Industrial and Applied Mathematics, 1994.
- [7] S. Boyd and L. Vandenberghe. *Convex optimization*. Cambridge University Press, 2004.
- [8] A. J. G. Cairns. “Epidemics in Heterogeneous Populations: Aspects of Optimal Vaccination Policies”. *Mathematical Medicine and Biology* 6.3 (1989), pp. 137–159.
- [9] F. Dai and Y. Xu. *Approximation Theory and Harmonic Analysis on Spheres and Balls*. Springer Monographs in Mathematics. Springer-Verlag, 2013.
- [10] J.-F. Delmas, D. Dronnier, and P.-A. Zitt. *An Infinite-Dimensional SIS Model*. Version 1. 2020. arXiv: 2006.08241 [math.DS].
- [11] J.-F. Delmas, D. Dronnier, and P.-A. Zitt. *Effective reproduction number: convexity, invariance and cordons sanitaires*. Version 1. 2021. arXiv: 2110.12693 [math.OC].
- [12] J.-F. Delmas, D. Dronnier, and P.-A. Zitt. “Optimal vaccination for a 2 sub-populations SIS model”. Forthcoming.
- [13] J.-F. Delmas, D. Dronnier, and P.-A. Zitt. *Targeted Vaccination Strategies for an Infinite-dimensional SIS model*. Version 2. 2021. arXiv: 2103.10330v2 [math.PR].
- [14] J.-F. Delmas, D. Dronnier, and P.-A. Zitt. “Vaccinating highly connected people is (sometimes) optimal”. Forthcoming.
- [15] O. Diekmann, J. A. P. Heesterbeek, and J. A. J. Metz. “On the definition and the computation of the basic reproduction ratio  $R_0$  in models for infectious diseases in heterogeneous populations”. *Journal of Mathematical Biology* 28.4 (1990), pp. 365–382.
- [16] L. E. Duijzer, W. L. van Jaarsveld, J. Wallinga, and R. Dekker. “Dose-optimal vaccine allocation over multiple populations”. *Production and Operations Management* 27.1 (2018), pp. 143–159.
- [17] B. C. Eaves, A. J. Hoffman, U. G. Rothblum, and H. Schneider. “Line-sum-symmetric scalings of square nonnegative matrices”. Springer Berlin Heidelberg, 1985, pp. 124–141.
- [18] F. Esser and F. Harary. “On the spectrum of a complete multipartite graph”. *European Journal of Combinatorics* 1.3 (1980), pp. 211–218.
- [19] S. Friedland and S. Karlin. “Some inequalities for the spectral radius of non-negative matrices and applications”. *Duke Mathematical Journal* 42.3 (1975), pp. 459–490.
- [20] S. Friedland. “Convex spectral functions”. *Linear and Multilinear Algebra* 9.4 (1981), pp. 299–316.
- [21] A. Galeotti and B. W. Rogers. “Strategic Immunization and Group Structure”. *American Economic Journal: Microeconomics* 5.2 (2013), pp. 1–32.
- [22] T. Gneiting. “Strictly and non-strictly positive definite functions on spheres”. *Bernoulli* 19.4 (2013), pp. 1327–1349.
- [23] E. Goldstein, A. Apolloni, B. Lewis, J. C. Miller, M. Macauley, S. Eubank, M. Lipsitch, and J. Wallinga. “Distribution of vaccine/antivirals and the ‘least spread line’ in a stratified population”. *Journal of The Royal Society Interface* 7.46 (2010), pp. 755–764.

- [24] J. J. Grobler. “Compactness conditions for integral operators in Banach function spaces”. *Indagationes Mathematicae (Proceedings)* 32 (1970), pp. 287–294.
- [25] D. Hadka and P. Reed. “Borg: An Auto-Adaptive Many-Objective Evolutionary Computing Framework”. *Evolutionary Computation* 21.2 (2013), pp. 231–259.
- [26] L. Hao, J. W. Glasser, Q. Su, C. Ma, Z. Feng, Z. Yin, J. L. Goodson, N. Wen, C. Fan, H. Yang, L. E. Rodewald, Z. Feng, and H. Wang. “Evaluating vaccination policies to accelerate measles elimination in China: a meta-population modelling study”. *International Journal of Epidemiology* 48.4 (2019), pp. 1240–1251.
- [27] R. Hekmat and P. Van Mieghem. “Degree distribution and hopcount in wireless ad-hoc networks”. *ICON2003. The 11th IEEE International Conference on Networks* (Sydney, Australia, Sept. 28–Oct. 1, 2003). IEEE, pp. 603–610.
- [28] H. W. Hethcote and H. R. Thieme. “Stability of the endemic equilibrium in epidemic models with subpopulations”. *Mathematical Biosciences* 75.2 (1985), pp. 205–227.
- [29] D. J. Higham, M. Rašajski, and N. Pržulj. “Fitting a geometric graph to a protein/protein interaction network”. *Bioinformatics* 24 (8 2008), pp. 1093–1099.
- [30] A. N. Hill and I. M. Longini Jr. “The critical vaccination fraction for heterogeneous epidemic models”. *Mathematical Biosciences* 181.1 (2003), pp. 85–106.
- [31] P. D. Hoff, A. E. Raftery, and M. S. Handcock. “Latent Space Approaches to Social Network Analysis”. *Journal of the American Statistical Association* 97 (460 2002), pp. 1090–1098.
- [32] R. A. Horn and C. R. Johnson. *Matrix analysis*. 2nd ed. Cambridge University Press, 2013.
- [33] O. Kallenberg. *Foundations of modern probability*. 3rd ed. Vol. 99. Probability Theory and Stochastic Modelling. Springer-Verlag, 2021.
- [34] M. J. Keeling and P. Rohani. *Modeling infectious diseases in humans and animals*. Princeton University Press, 2008.
- [35] B. R. Kloeckner. “Effective perturbation theory for simple isolated eigenvalues of linear operators”. *Journal of Operator Theory* 81.1 (2019), pp. 175–194.
- [36] D. Kunszenti-Kovács, L. Lovász, and B. Szegedy. *Random homomorphisms into the orthogonality graph*. Version 1. 2021. arXiv: 2105.03657 [math.CO].
- [37] A. Lajmanovich and J. A. Yorke. “A deterministic model for gonorrhea in a nonhomogeneous population”. *Mathematical Biosciences* 28.3 (1976), pp. 221–236.
- [38] I. M. Longini, E. Ackerman, and L. R. Elveback. “An optimization model for influenza A epidemics”. *Mathematical Biosciences* 38.1-2 (1978), pp. 141–157.
- [39] L. Lovász. *Large networks and graph limits*. American Mathematical Society colloquium publications 60. American Mathematical Society, 2012.
- [40] A. W. Marshall, I. Olkin, and B. C. Arnold. *Inequalities: Theory of Majorization and Its Applications*. 2nd ed. Springer Series in Statistics. Springer-Verlag, 2011.
- [41] M. E. J. Newman. “Assortative Mixing in Networks”. *Physical Review Letters* 89.20 (2002).
- [42] C. P. Niculescu and L.-E. Persson. *Convex Functions and Their Applications*. CMS Books in Mathematics. Springer-Verlag, 2006.
- [43] R. Pastor-Satorras and A. Vespignani. “Immunization of complex networks”. *Physical Review E* 65.3 (2002).
- [44] G. Poghotanyan, Z. Feng, J. W. Glasser, and A. N. Hill. “Constrained minimization problems for the reproduction number in meta-population models”. *Journal of Mathematical Biology* 77.6 (2018), pp. 1795–1831.
- [45] J. H. Smith. “Some properties of the spectrum of a graph”. *Combinatorial Structures and their Applications*. Proceedings of the Calgary International Conference on Combinatorial

- Structures and their Applications (Calgary, Canada, June 1969). Gordon and Breach, 1970, pp. 403–406.
- [46] H. R. Thieme. “Global stability of the endemic equilibrium in infinite dimension: Lyapunov functions and positive operators”. *Journal of Differential Equations* 250.9 (2011), pp. 3772–3801.
- [47] H. R. Thieme. “Local Stability in Epidemic Models for Heterogeneous Populations”. *Mathematics in Biology and Medicine*. Proceedings of an International Conference (Bari, Italy, July 18–22, 1983). Vol. 57. Lecture Notes in Biomathematics. Springer-Verlag, 1985, pp. 185–189.
- [48] P. Van Den Driessche and J. Watmough. “Reproduction numbers and sub-threshold endemic equilibria for compartmental models of disease transmission”. *Mathematical Biosciences* 180.1 (2002), pp. 29–48.

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