

Information Geometry in Epidemiology and Population Dynamics

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Based on: 2402.16390
with **B. Filoche** and **F. Sannino**

Information Geometry

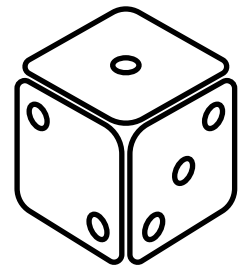
Probability distribution on a discrete set \mathbb{V}

$$p : \mathbb{V} \longrightarrow [0, 1]$$

such that

$$\sum_{X \in \mathbb{V}} p(X) = 1$$

Example: (faire) dice



$$\mathbb{V} = \left\{ \begin{array}{|c|} \hline \circ \\ \hline \end{array}, \begin{array}{|c|} \hline \circ \\ \circ \\ \hline \end{array}, \begin{array}{|c|} \hline \circ \\ \circ \circ \\ \hline \end{array}, \begin{array}{|c|} \hline \circ \circ \\ \hline \end{array}, \begin{array}{|c|} \hline \circ \circ \\ \circ \circ \\ \hline \end{array}, \begin{array}{|c|} \hline \circ \circ \\ \circ \circ \\ \hline \end{array} \right\} \cong \{1, 2, 3, 4, 5, 6\}$$

with the map

$$p\left(\begin{array}{|c|} \hline \circ \\ \hline \end{array}\right) = \frac{1}{6},$$

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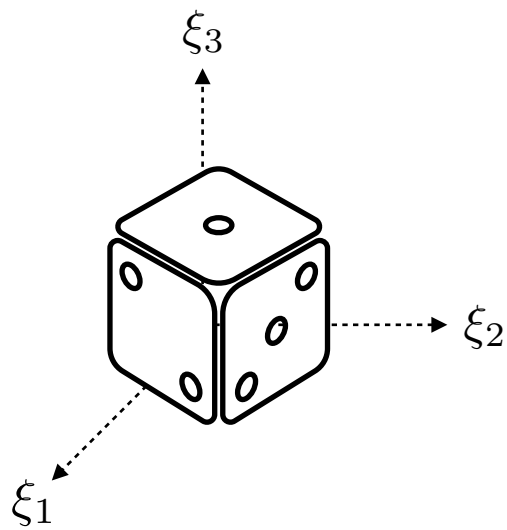
Allow probabilities to depend on (cont.) parameters $(\xi^1, \dots, \xi^d) \in \Xi \subset \mathbb{R}^d$

$$p : \mathbb{V} \times \Xi \longrightarrow [0, 1]$$

such that

$$\sum_{X \in \mathbb{V}} p(X, \xi) = 1 \quad \forall \xi \in \Xi$$

Example: loaded dice



shift center of mass of the dice by a vector

$$\xi = (\xi_1, \xi_2, \xi_3) \in \mathbb{R}^3$$

Changes probabilities in a non-trivial fashion:

$$p(\ominus, \xi) = p_1(\xi), \quad p(\ominus\circ, \xi) = p_2(\xi), \quad p(\ominus\circ\circ, \xi) = p_3(\xi),$$

$$p(\circ\circ, \xi) = p_4(\xi), \quad p(\circ\circ\circ, \xi) = p_5(\xi), \quad p(\circ\circ\circ\circ, \xi) = p_6(\xi)$$

which still satisfy $p_1(\xi) + p_2(\xi) + p_3(\xi) + p_4(\xi) + p_5(\xi) + p_6(\xi) = 1$

Fisher information metric

[Fisher 1922]
[Rao 1945]
[Jeffreys 1946]

$$g_{ij}(\xi) := \sum_{X \in \mathbb{V}} \left(\frac{\partial}{\partial \xi^i} \log p(X, \xi) \right) \left(\frac{\partial}{\partial \xi^j} \log p(X, \xi) \right) p(X, \xi) \quad \forall i, j \in \{1, \dots, d\}$$

defines the metric of a **Riemannian manifold**

[Amari, Nagaoka 2020]

Fisher-Rao distance: $d(\xi_1, \xi_2) = \int_0^1 d\tau \sqrt{\dot{\xi}_c^i \dot{\xi}_c^j g_{ij}(\xi_c)}$

geodesic $\xi_c : [0, 1] \rightarrow \Xi$

with $\xi_c(0) = \xi_1$ and $\xi_c(1) = \xi_2$

special case: 1 dimension and $\Xi = \mathbb{R}$

$$g_{tt}(t) = \sum_{X \in \mathbb{V}} \left(\frac{\partial \log p(X, t)}{\partial t} \right)^2 p(X, t) \quad \text{and} \quad d(t_1, t_2) = \left| \int_{t_1}^{t_2} \sqrt{g_{tt}(t')} dt' \right|$$

Towards Dynamics

$$g_{tt}(t) = \sum_{X \in \mathbb{V}} \left(\frac{\partial \log p(X, t)}{\partial t} \right)^2 p(X, t)$$

interpret $t \in \mathbb{R}$ as **time** variable

Resolve normalisation condition (denote cardinality of \mathbb{V} by $N + 1$)

$$p_i(t) = x_i(t) \quad \forall i \in \{1, \dots, N\}$$

$$p_{N+1}(t) = 1 - \sum_{i=1}^N x_i(t)$$

Fisher metric depends on time derivatives $\dot{x}_i(t)$

$$g_{tt} = \sum_{i=1}^N \frac{\left(1 - \sum_{j \neq i}^N x_j\right) \dot{x}_i^2}{x_i \left(1 - \sum_{j=1}^N x_j\right)} + 2 \sum_{1 \leq i < j \leq N} \frac{\dot{x}_i \dot{x}_j}{1 - \sum_{k=1}^N x_k}$$

$$g_{tt} = \sum_{i=1}^N \frac{\left(1 - \sum_{j \neq i}^N x_j\right) \dot{x}_i^2}{x_i \left(1 - \sum_{j=1}^N x_j\right)} + 2 \sum_{1 \leq i < j \leq N} \frac{\dot{x}_i \dot{x}_j}{1 - \sum_{k=1}^N x_k}$$

Can be simplified in certain cases, e.g.:

$$|\dot{x}_1| \gg |\dot{x}_i| \sim 0 \quad \forall i \in \{2, \dots, N\}$$

‘one probability is strongly growing at the expense of another’

define: $\sum_{i=2}^N x_i(t) \sim 1 - \alpha = \text{const.}$

In this case the expression for the metric simplifies

$$g_{tt} \sim \frac{\left(1 - \sum_{j=2}^N x_j\right)}{x_1 \left(1 - \sum_{j=1}^N x_j\right)} \dot{x}_1^2 + \mathcal{O}(\dot{x}_1) = \frac{\alpha \dot{x}_1^2}{x_1 (\alpha - x_1)} + \mathcal{O}(\dot{x}_1)$$

$$g_{tt} = \frac{\alpha \dot{x}_1^2}{x_1(\alpha - x_1)} + \mathcal{O}(\dot{x}_1)$$

Can be resolved to give a flow equation for $\dot{x}_1(t)$

$$\frac{dx_1}{dt} \sim \pm \sqrt{g_{tt} x_1 \left(1 - \frac{x_1}{\alpha}\right)} \quad \text{for} \quad x_1 \in [0, \alpha]$$

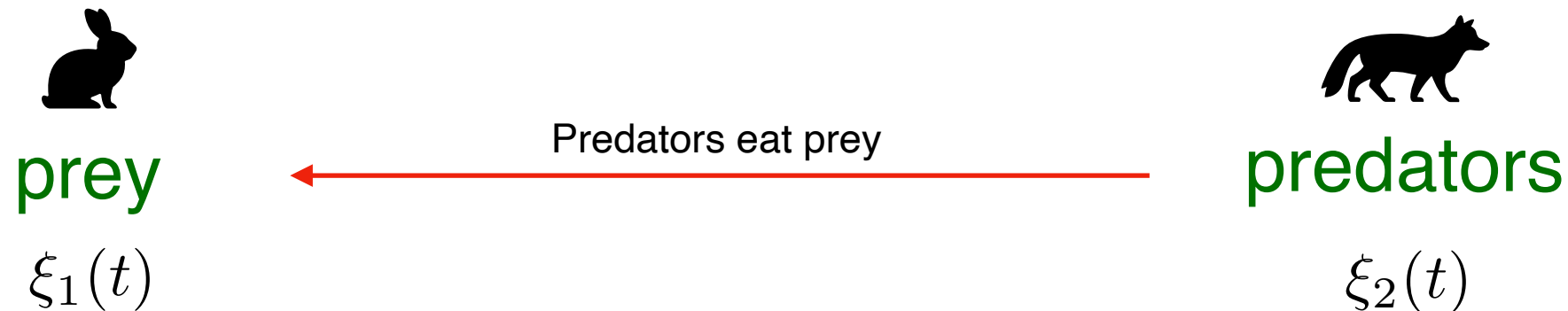
A priori only a re-writing of the definition of g_{tt}

Time dependence of metric in principle encodes dynamics of x_1

Is it possible to re-write g_{tt} as a function of x_1 ?

First Example: Lotka-Volterra Equation

Describes the time-evolution of a population of predators and prey



- have unlimited resources
- limited only through the pressure by the predators
(exponential growth in absence of predators)

- require prey for survival
(exponential decline in absence of prey)

Coupled differential equations:

[Lotka, 1909]
[Volterra 1926]

$$\frac{d\xi_1}{dt} = a_1 \xi_1 - b_1 \xi_1 \xi_2 ,$$

with

$$\frac{d\xi_2}{dt} = -a_2 \xi_2 + b_2 \xi_1 \xi_2 ,$$

$$a_{1,2} , b_{1,2} \in \mathbb{R}_+$$

(and initial conditions $\xi_{1,2}(t = 0)$)

Total population in general not conserved: $\frac{d}{dt}(\xi_1 + \xi_2) \neq 0$

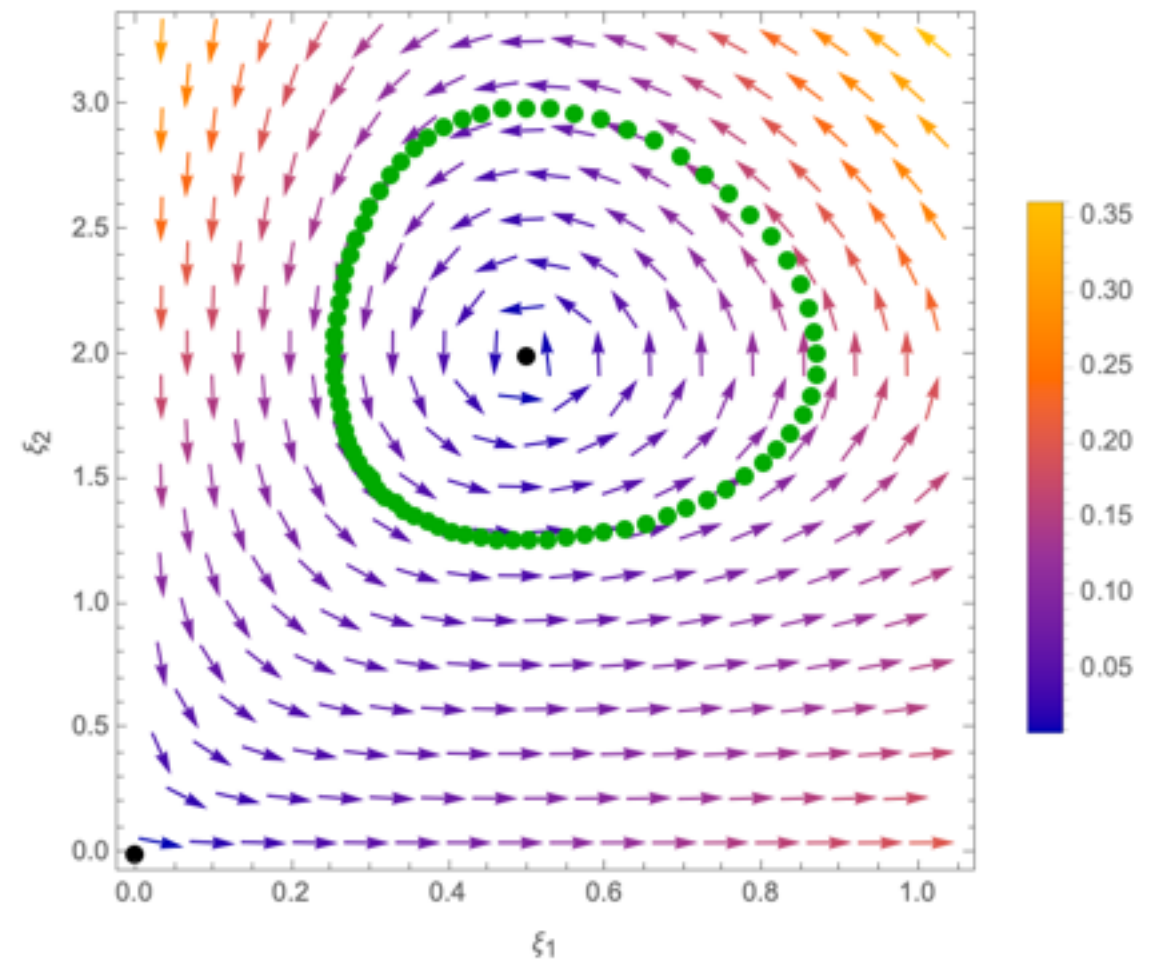
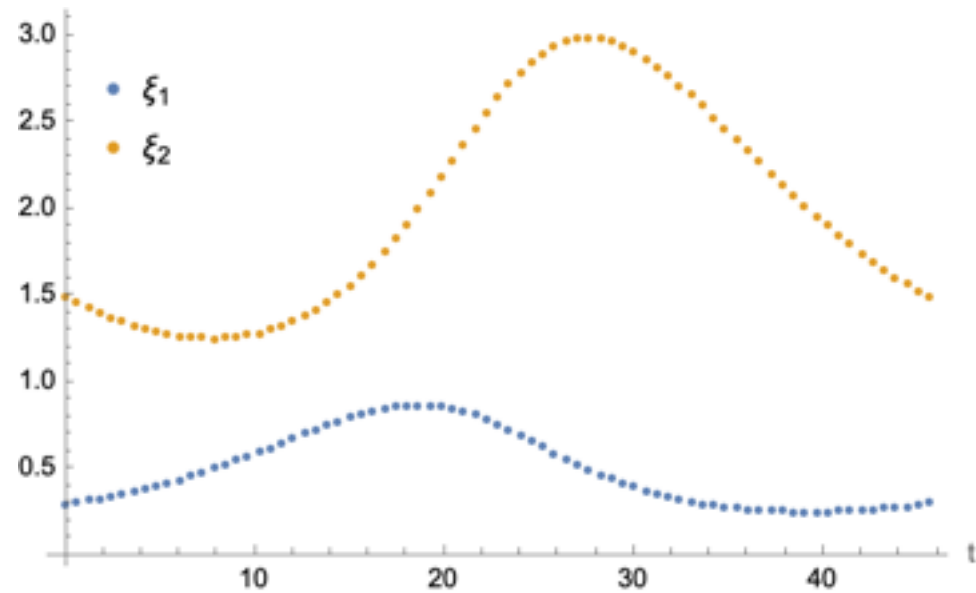
Two fixed points such that $\frac{d\xi_{1,2}}{dt} = 0$

$$(\xi_1, \xi_2) = (0, 0)$$

and

$$(\xi_1, \xi_2) = \left(\frac{a_2}{b_2}, \frac{a_1}{b_1} \right)$$

Away from these fixed points: periodic solutions



Introduce probability distribution

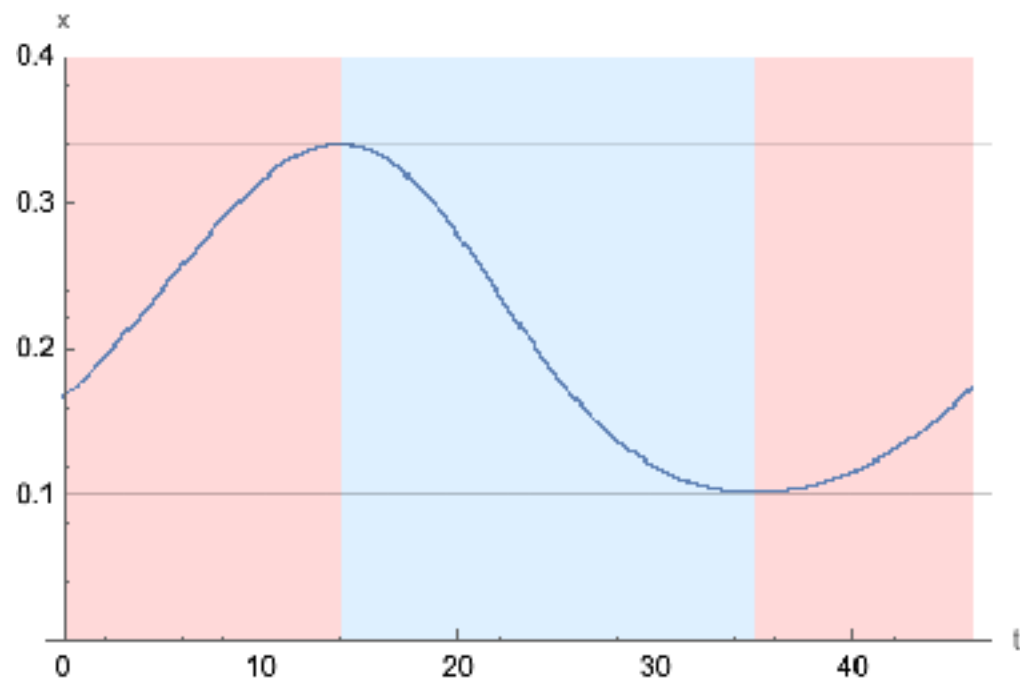
$$p_1 = \frac{\xi_1}{\xi_1 + \xi_2} =: x$$

$$x : \mathbb{R} \longrightarrow [0, 1]$$

with

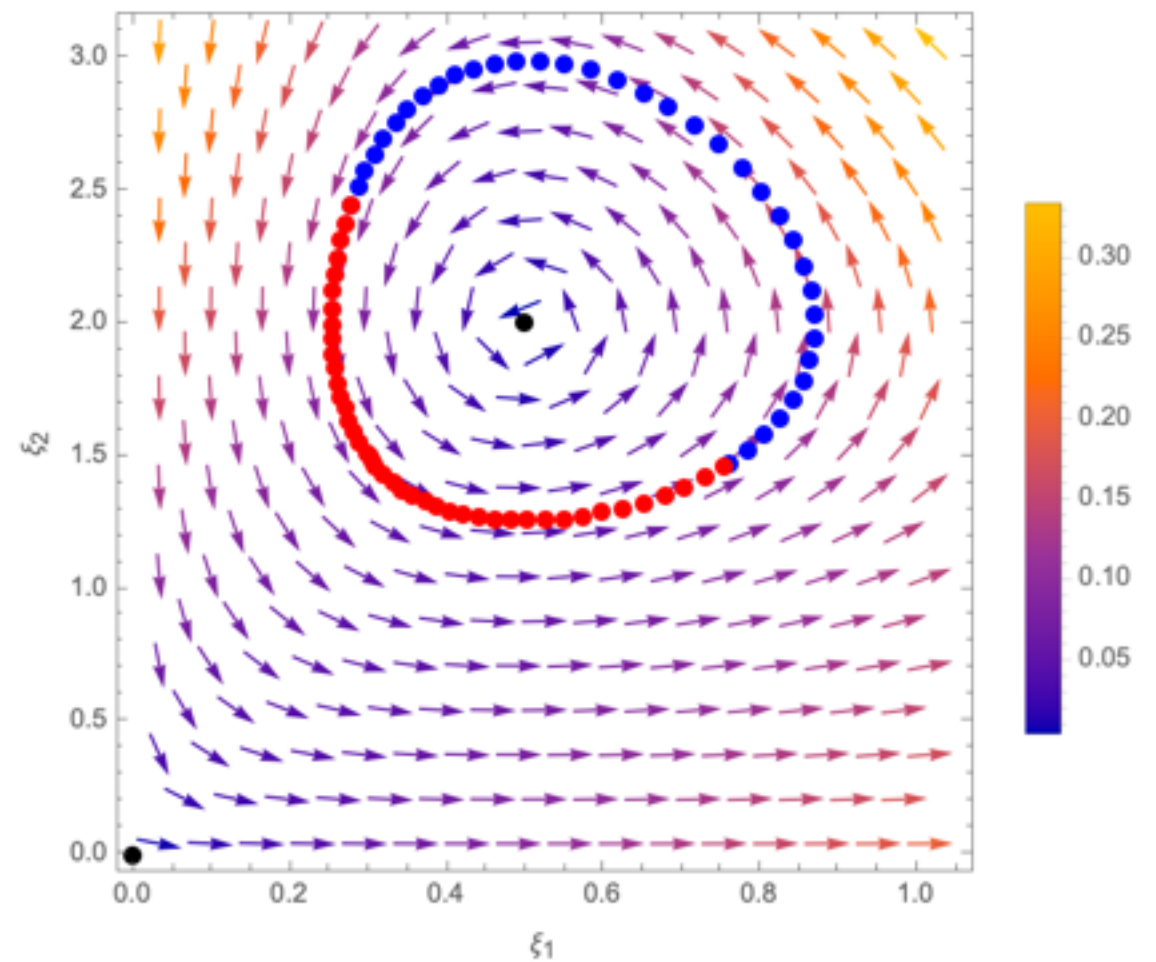
single degree of freedom

$$p_2 = \frac{\xi_2}{\xi_1 + \xi_2} = 1 - x$$

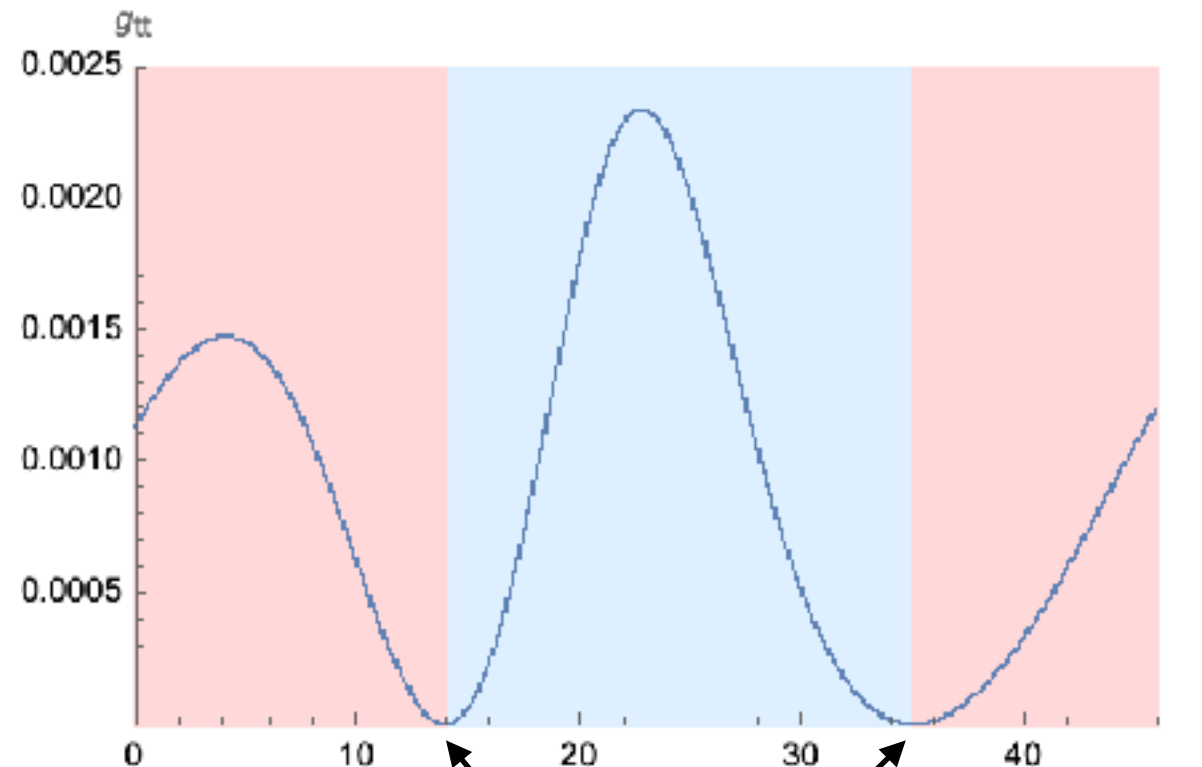


fraction of prey increasing

fraction of prey decreasing



$$g_{tt} = (\partial_t \log(p_1))^2 p_1 + (\partial_t \log(p_2))^2 p_2 = \frac{\xi_1 \xi_2 (a_1 + a_2 - b_2 \xi_1 - b_1 \xi_2)^2}{(\xi_1 + \xi_2)^2}$$

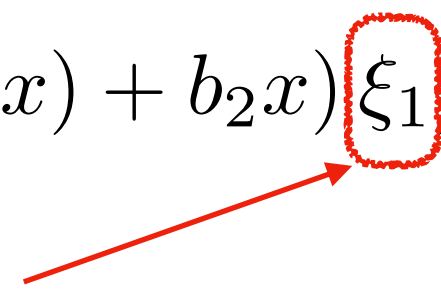


Zeroes of the metric correspond to extrema of x

Metric is a function of time: re-write it in terms of x :

$$g_{tt} = \frac{1-x}{x} (a_1 x + a_2 x - (b_1(1-x) + b_2 x) \xi_1)^2$$

requires solving the dynamics of the system



$$\frac{d\xi_1}{dt} = a_1 \xi_1 - b_1 \xi_1 \xi_2,$$

$$\frac{d\xi_2}{dt} = -a_2 \xi_2 + b_2 \xi_1 \xi_2,$$

Integrating the equations gives an algebraic equation:

$$\left(b_2 + b_1 \frac{1-x}{x} \right) \xi_1 - (a_1 + a_2) \log \xi_1 - a_1 \log \left(\frac{1-x}{x} \right) = L$$

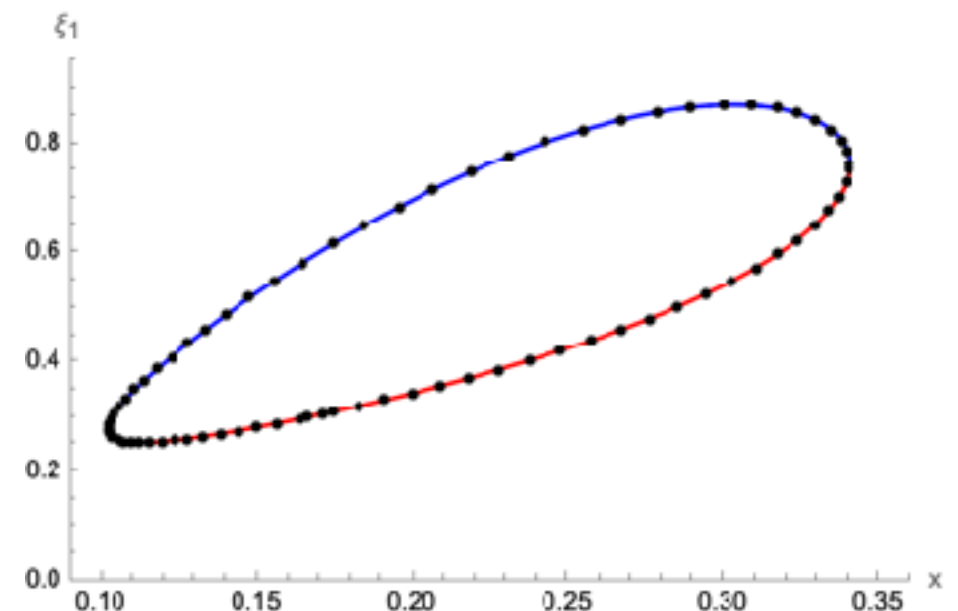
fixed by initial conditions:

$$L = b_2 \xi_1(0) - a_2 \log \xi_1(0) + b_1 \xi_2(0) - a_1 \log \xi_2(0)$$

leads to

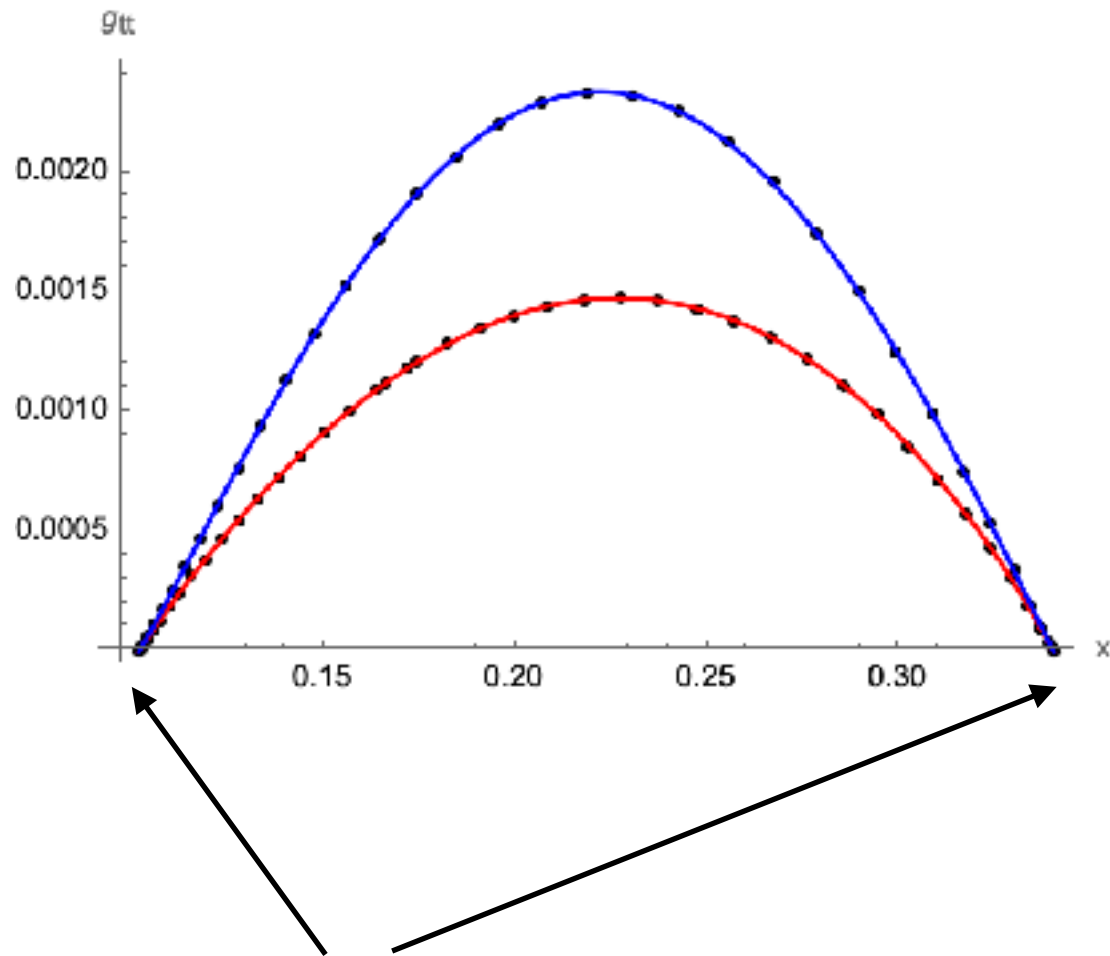
$$\xi_1 = -\frac{(a_1 + a_2)x}{b_1(1-x) + b_2x} W \left(-\frac{e^{-\frac{L}{a_1+a_2}} \left(\frac{1-x}{x}\right)^{-\frac{a_1}{a_1+a_2}} (b_1(1-x) + b_2x)}{x(a_1 + a_2)} \right)$$

Lambert function with 2 real branches



Fisher information metric as function of x

$$g_{tt} = (a_1 + a_2)^2 x (1 - x) \left[1 + W \left(-\frac{e^{-\frac{L}{a_1+a_2}} \left(\frac{1-x}{x}\right)^{-\frac{a_1}{a_1+a_2}} (b_1(1-x) + b_2x)}{x(a_1 + a_2)} \right) \right]^2$$



Two branches:

- x growing: $\frac{dx}{dt} > 0$
- x declining: $\frac{dx}{dt} < 0$

both branches meet at the same zeroes $x_{1,2}$
which are solutions of

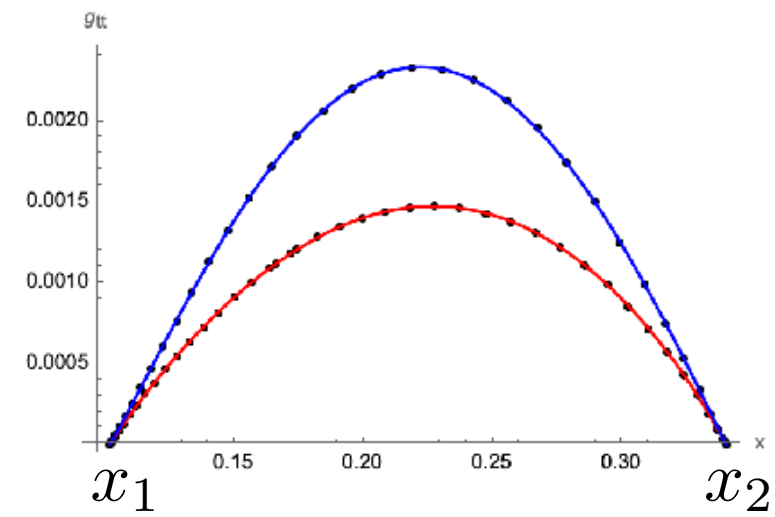
$$b_1 \left(\frac{1-x}{x} \right)^{\frac{a_2}{a_1+a_2}} + b_2 \left(\frac{1-x}{x} \right)^{-\frac{a_1}{a_1+a_2}} = (a_1 + a_2) e^{\frac{L}{a_1+a_2} - 1}$$

periodicity

Metric can be very well approximated by

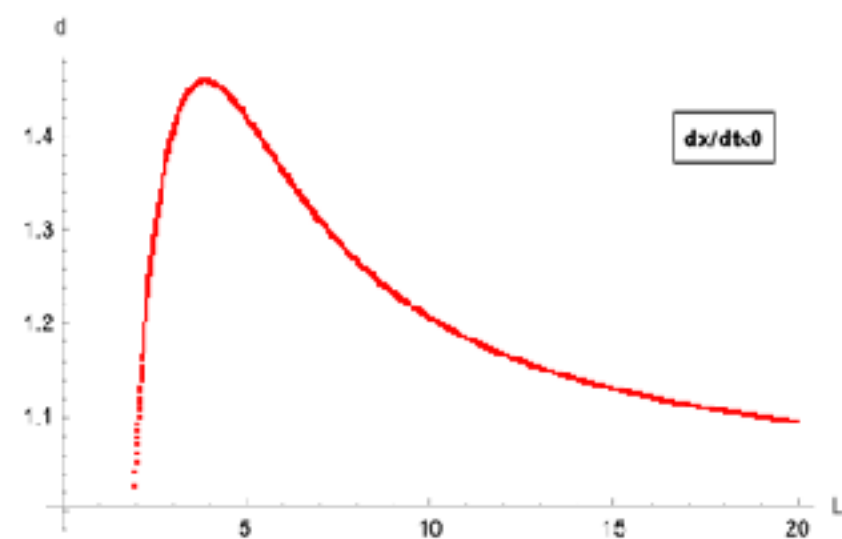
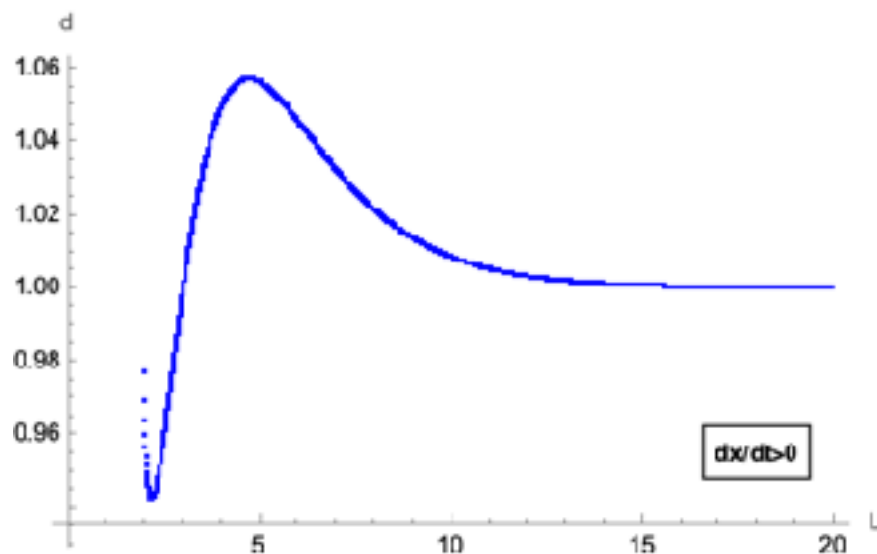
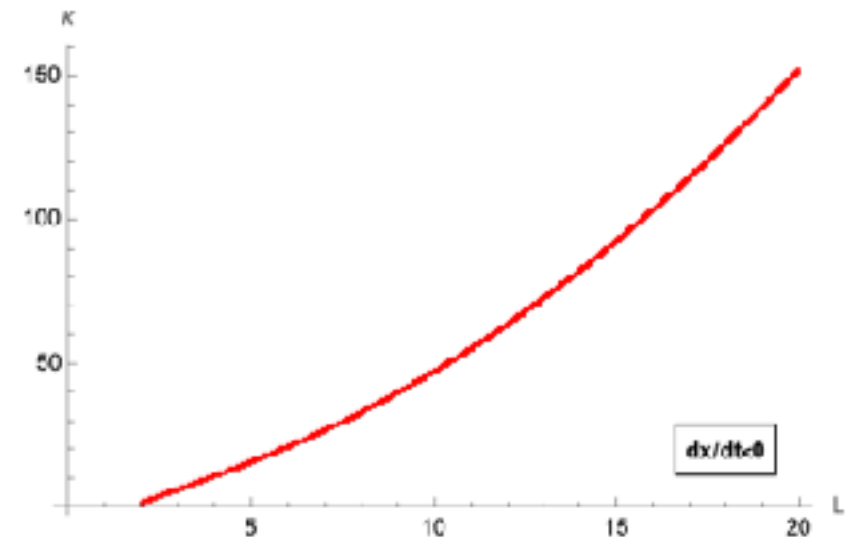
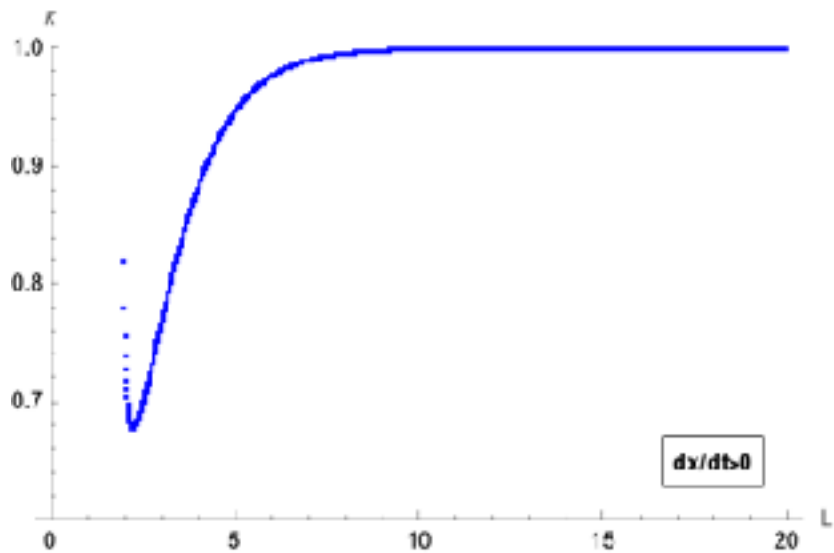
$$g_{tt}(x) = a (x - x_1)^b (x_2 - x)^c \quad \forall x \in [x_1, x_2]$$

suitable fitting parameters



Simple example: $a_1 = a_2 = b_1 = b_2 = 1$

$$g_{tt} \sim 4\kappa (x - x_1)^d (x_2 - x)^d \quad x_{1,2} = \frac{1}{2} \left(1 \mp \sqrt{1 - e^{2-L}} \right) \quad \forall L > 2$$



Second Example: SIR(S) Model

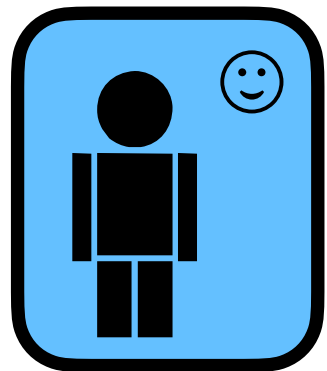
Oldest mathematical models in epidemiology

[Ross, 1916]

[Ross, Hudson 1917]

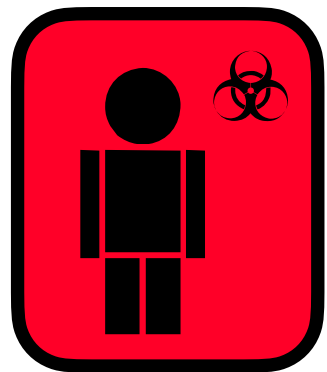
[Kermack, McKendrick 1927]

Idea: group members of the population into compartments



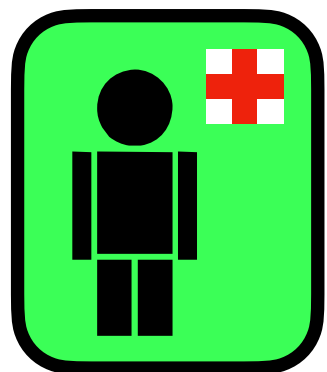
Susceptible: not infectious; can become infectious if in contact with the pathogen

$S(t)$



Infectious: infected with the pathogen; can actively transmit the pathogen to a susceptible individual

$I(t)$



Removed: can neither be infected themselves, nor infect other individuals

$R(t)$

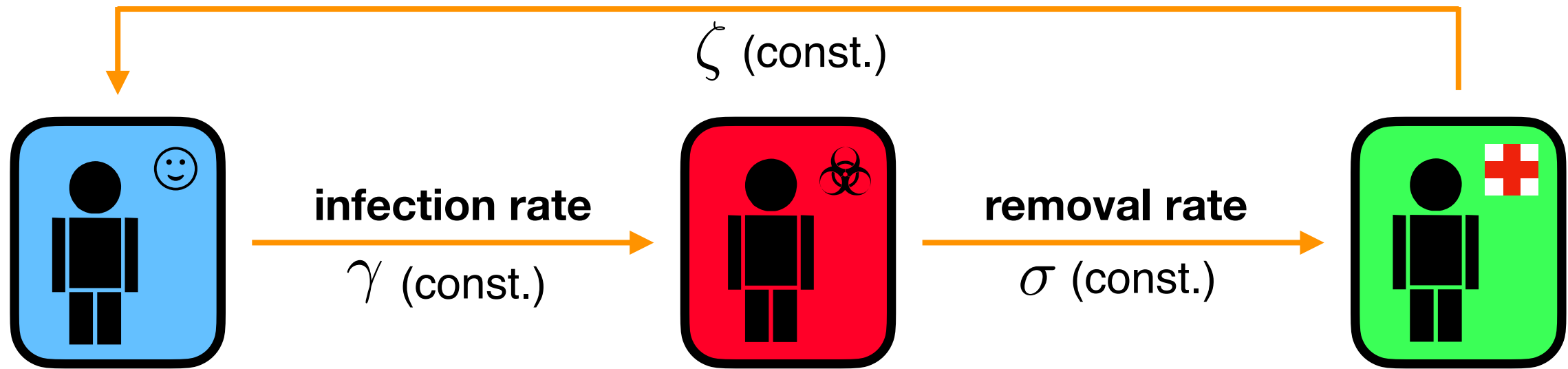
Population conserved:

$$(S + I + R)(t) = 1$$

$$\forall t \in \mathbb{R}$$

Equations for the time evolution of the number of individuals:

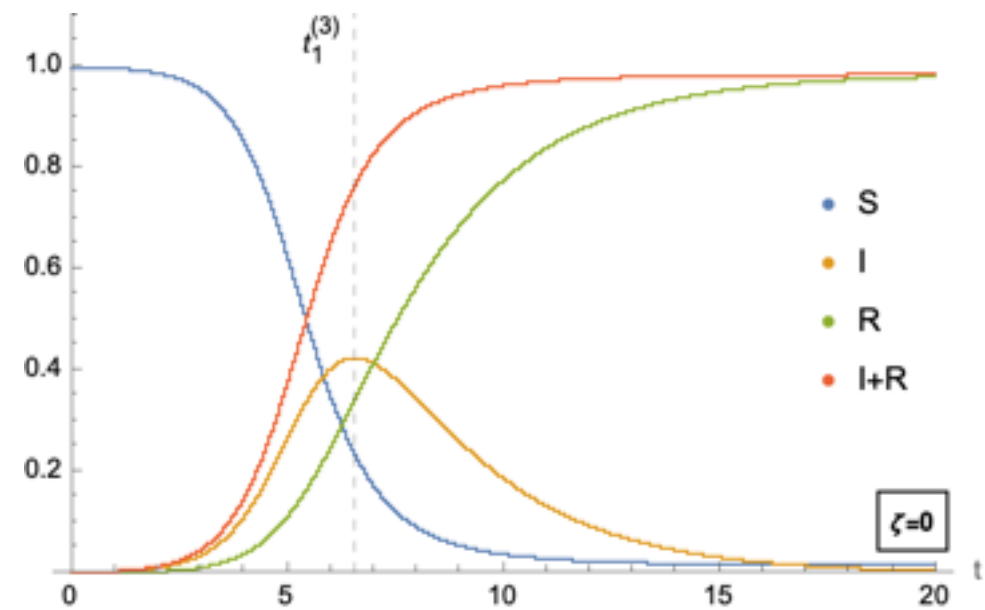
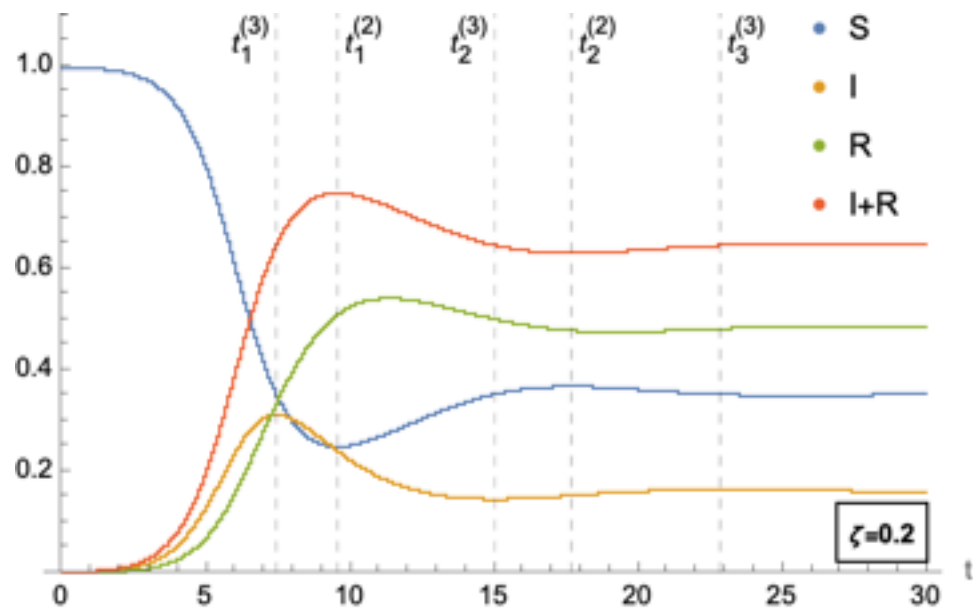
rate at which individuals become susceptible again



$$\frac{dS}{dt} = -\gamma S I + \zeta R$$

$$\frac{dI}{dt} = \gamma S I - \sigma I$$

$$\frac{dR}{dt} = \sigma I - \zeta R$$



Different ways to define probability distributions:

$$p^{(1)} : \{1, 2, 3\} \times \mathbb{R} \rightarrow [0, 1] \quad \text{with}$$

$$p_1^{(1)}(t) = S(t)$$

$$p_2^{(1)}(t) = I(t)$$

$$p_3^{(1)}(t) = R(t)$$



$$p^{(2)} : \{1, 2\} \times \mathbb{R} \rightarrow [0, 1] \quad \text{with}$$

$$p_1^{(2)}(t) = S(t)$$

$$p_2^{(2)}(t) = (I + R)(t)$$



+



$$p^{(3)} : \{1, 2\} \times \mathbb{R} \rightarrow [0, 1] \quad \text{with}$$

$$p_1^{(3)}(t) = (S + R)(t)$$

$$p_2^{(3)}(t) = I(t)$$



+



Probability distributions with only one degree of freedom

$$p^{(2)} = \left(\text{[Blue Person]}, \text{[Red Person]} + \text{[Green Person]} \right)$$

$$p^{(3)} = \left(\text{[Blue Person]} + \text{[Green Person]}, \text{[Red Person]} \right)$$

Fisher information metric:

$$g_{tt}^{(2)}(t) = \frac{\gamma^2 I^2 S}{(I + R)}$$

$$g_{tt}^{(3)}(t) = \frac{I(\gamma S - \sigma)^2}{R + S}$$

Single degree of freedom:

$$x(t) = (I + R)(t) = \text{[Red Person]} + \text{[Green Person]}$$

$$x(t) = (S + R)(t) = \text{[Blue Person]} + \text{[Green Person]}$$

Resolve dynamics:

$$I = x + \frac{\sigma}{\gamma} \log \left(\frac{1-x}{1-x_0} \right)$$

initial conditions
 $x_0 = x(t=0)$

$$S = -\frac{\sigma}{\gamma} W \left(-\frac{x_0 \gamma}{\sigma} e^{-\frac{x \gamma}{\sigma}} \right)$$

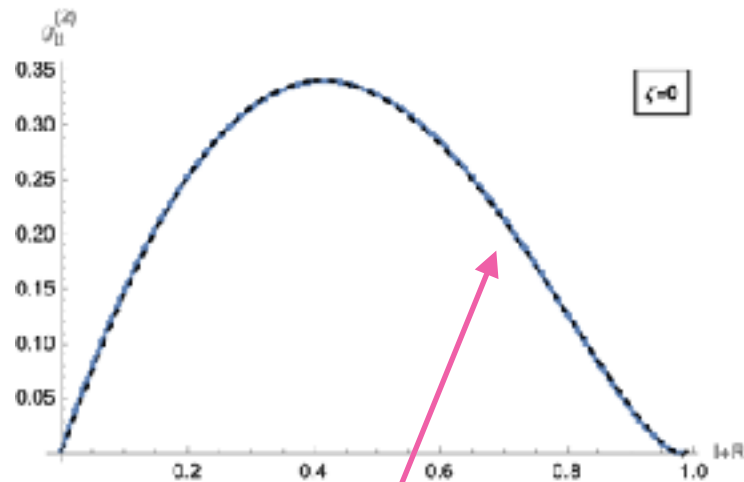
two real branches (two solutions)

Metric as a function of x

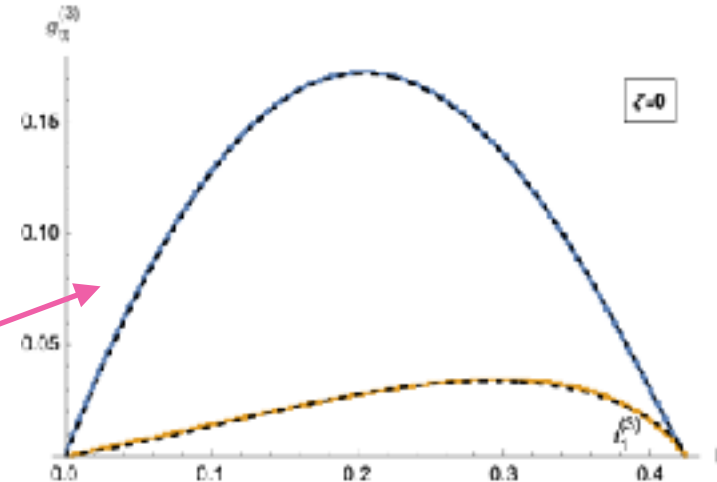
$$g_{tt}^{(2)} = \frac{1-x}{x} \left(x\gamma + \sigma \log \left(\frac{1-x}{1-x_0} \right) \right)^2$$

$$g_{tt}^{(3)}(x) = \frac{1-x}{x} \sigma^2 \left(1 + W \left(-\frac{x_0 \gamma}{\sigma} e^{-\frac{x \gamma}{\sigma}} \right) \right)^2$$

$$g_{tt}^{(2)} = \frac{1-x}{x} \left(x\gamma + \sigma \log \left(\frac{1-x}{1-x_0} \right) \right)^2$$



$$g_{tt}^{(3)}(x) = \frac{1-x}{x} \sigma^2 \left(1 + W \left(-\frac{x_0\gamma}{\sigma} e^{-\frac{x\gamma}{\sigma}} \right) \right)^2$$



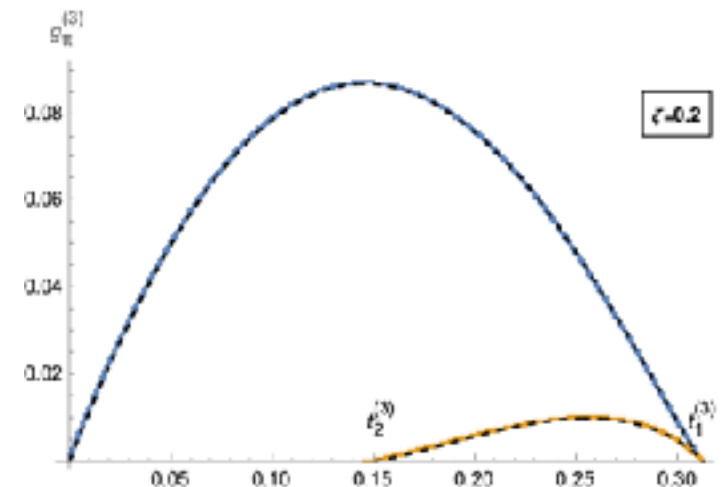
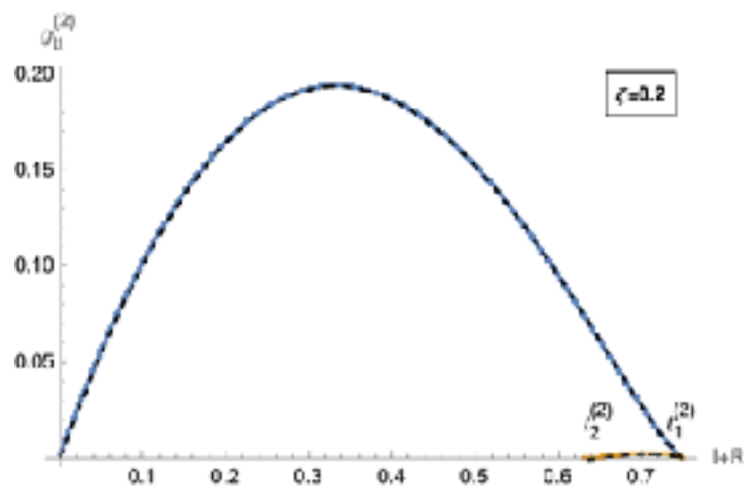
two real branches corresponding to

$$\frac{dx}{dt} > 0 \quad \text{and} \quad \frac{dx}{dt} < 0$$

dashed lines correspond to approximations

$$g_{tt}(x) = a (x - x_1)^b (x_2 - x)^c$$

Generalisation to $\zeta > 0$



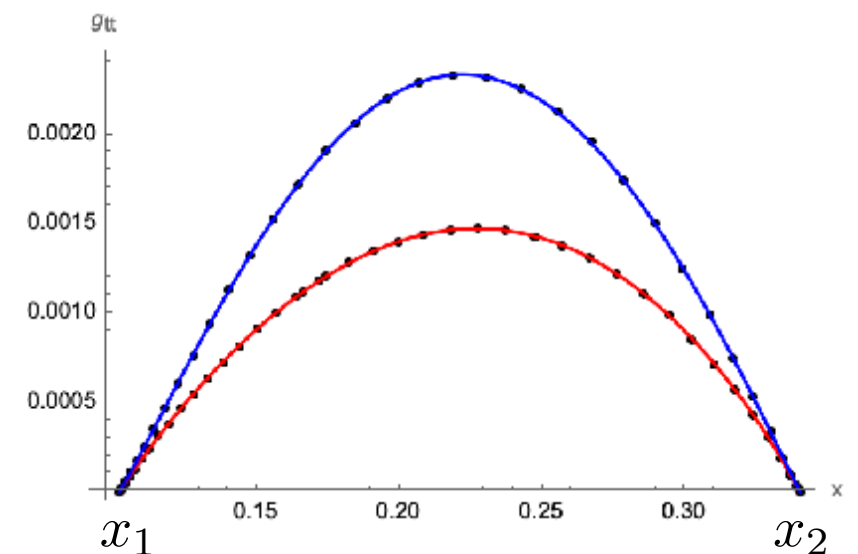
Common Features of all Examples

For systems with single degree of freedom $x(t)$

- real zeroes of the metric correspond to extrema of $x(t)$
- g_{tt} described piecewise between two consecutive extrema of $x(t)$

$$g_{tt} = a(x - x_1)^b (x_2 - x)^c$$

$$\text{for } 0 \leq x_1 < x < x_2 \leq 1$$



(imaginary zeroes possible in more complicated systems,
e.g. SIR(S) model with multiple pathogens)

- branches of the metric can be glued together along the zeroes

Inverse Problem

Assume that the Fisher metric for a 1-dimensional system is

$$g_{tt}(x) = a(x - x_1)(x_2 - x) \quad \text{for} \quad \begin{array}{l} a \in \mathbb{R}_+ \\ 0 \leq x_1 \leq x \leq x_2 \leq 1 \end{array}$$

and solve the **flow equation** $\frac{dx}{dt} = \kappa \sqrt{g_{tt} x (1 - x)}$

↑ sign ±1

For $0 < x_1 < x_2 < 1$ direct integration (initial condition: $x(t_0) = x_0$)

$$t - t_0 = \frac{2i\kappa (F(u(x), m) - F(u(x_0), m))}{\sqrt{a(1 - x_1)x_2}}$$

inverted for $x(t)$

$$x(t) = \frac{x_1 \operatorname{sn} \left(\frac{i\kappa(t-t_0)}{2} \sqrt{a(1 - x_1)x_2} - F(u(x_0), m), m \right)}{1 - x_1 + x_1 \operatorname{sn} \left(\frac{i\kappa(t-t_0)}{2} \sqrt{a(1 - x_1)x_2} - F(u(x_0), m), m \right)}$$

Definition:

Jacobi elliptic function

first kind

$$\operatorname{sn}(u, k^2) = \frac{\theta_3(0, \tau) \theta_1(u/\theta_3^2(0, \tau), \tau)}{\theta_2(0, \tau) \theta_4(u/\theta_3^2(0, \tau), \tau)} \operatorname{in}^2 z$$

with argument $k = \frac{\theta_2^2(0, \tau)}{\theta_3^2(0, \tau)}$

$m = \frac{x_2(1 - x_1)}{x_1(1 - x_2)}$ and

$$u(x) = \operatorname{arcsin} \left(\sqrt{\frac{x(1 - x_1)}{x_1(1 - x_2)}} \right)$$

use the solution to describe piecewise time evolution:

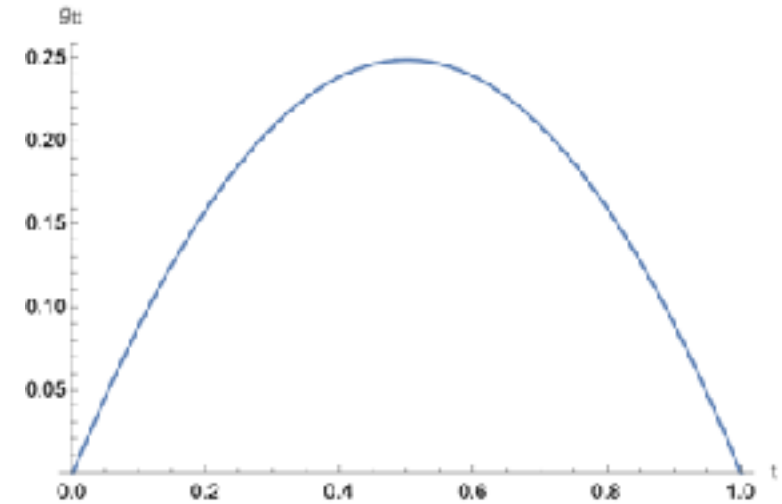
$$x(t) = \frac{x_1 \operatorname{sn} \left(\frac{i\kappa(t-t_0)}{2} \sqrt{a(1-x_1)x_2} - F(u(x_0), m), m \right)^2}{1 - x_1 + x_1 \operatorname{sn} \left(\frac{i\kappa(t-t_0)}{2} \sqrt{a(1-x_1)x_2} - F(u(x_0), m), m \right)^2}$$

(i) monotonic time evolution:

take $x_1 = 0$ and $x_2 = 1$

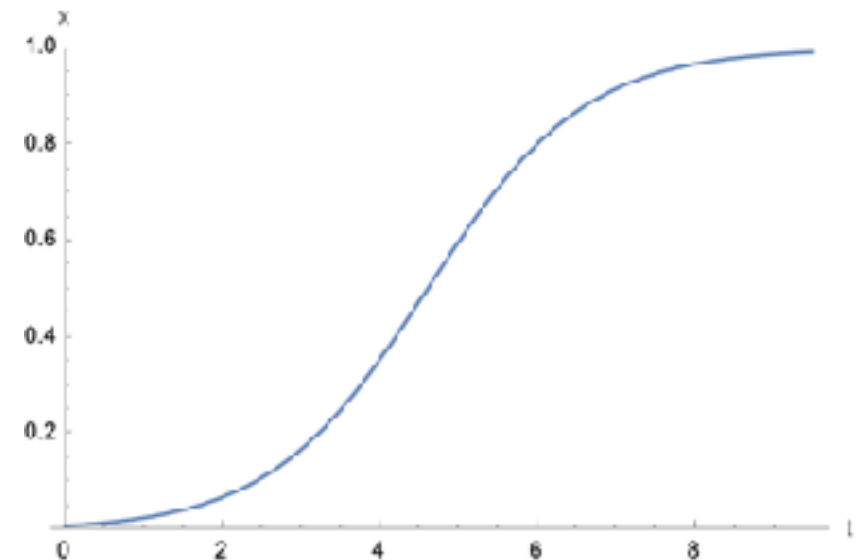
$$t - t_0 = \frac{\kappa}{\sqrt{a}} \log \left(\frac{x(1-x_0)}{x_0(1-x)} \right)$$

takes $t \rightarrow \infty$ for $x \rightarrow 0$ or $x \rightarrow 1$



logistic function

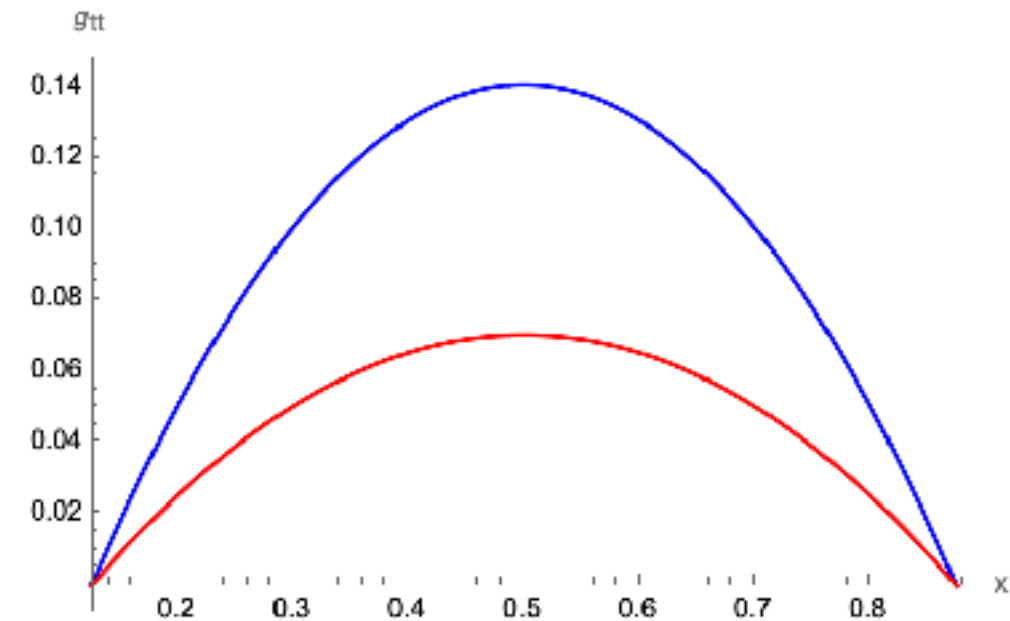
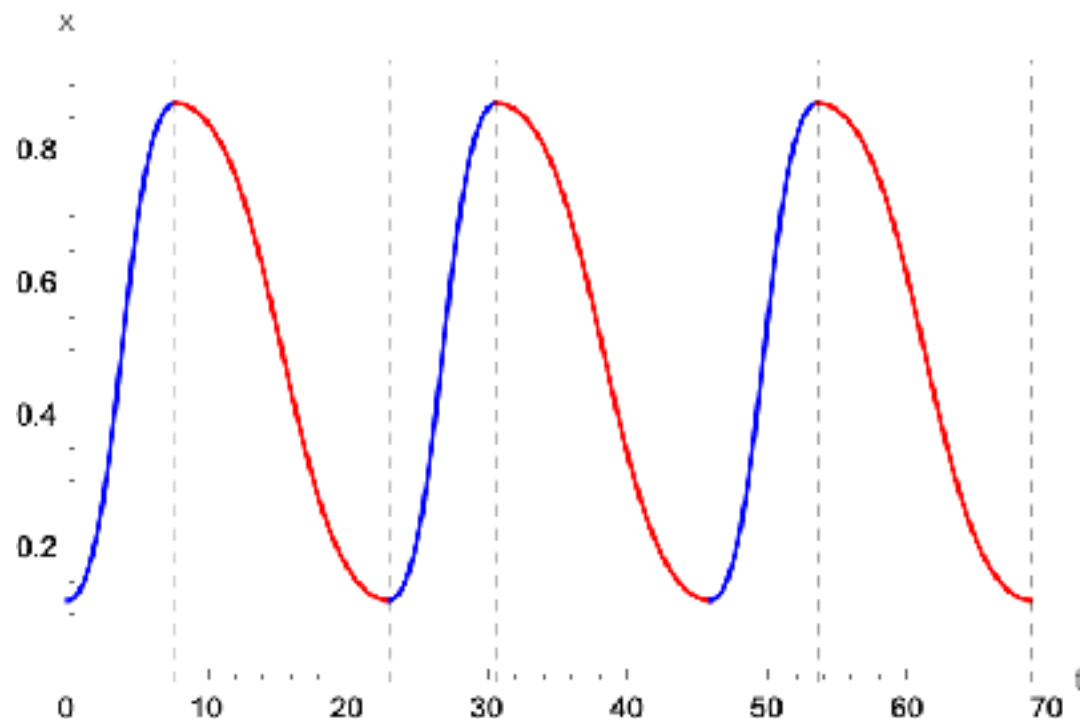
$$x(t) = \frac{x_0 e^{\sqrt{a} \kappa (t-t_0)}}{1 - x_0 + x_0 e^{\sqrt{a} \kappa (t-t_0)}}$$



(ii) periodic time evolution

$$g_{tt} = \begin{cases} a_1 (x - x_1)(x_2 - x) & \text{for } \frac{dx}{dt} > 0, \\ a_2 (x - x_1)(x_2 - x) & \text{for } \frac{dx}{dt} < 0 \end{cases} \quad \text{with} \quad \begin{aligned} & a_1, a_2 \in \mathbb{R}_+ \\ & 0 < x_1 \leq x \leq x_2 < 1 \end{aligned}$$

periodic solution for $x(t)$



periodicity:
$$T = \frac{2(\sqrt{a_1} + \sqrt{a_2}) K\left(\frac{x_2 - x_1}{(1 - x_1)x_2}\right)}{\sqrt{a_1 a_2 (1 - x_1)x_2}}$$

Definition:

complete elliptic integral of first kind

$$K(m) = \frac{\pi}{2} \sum_{n=0}^{\infty} \left(\frac{(2n-1)!!}{(2n)!!} \right)^2 m^n$$

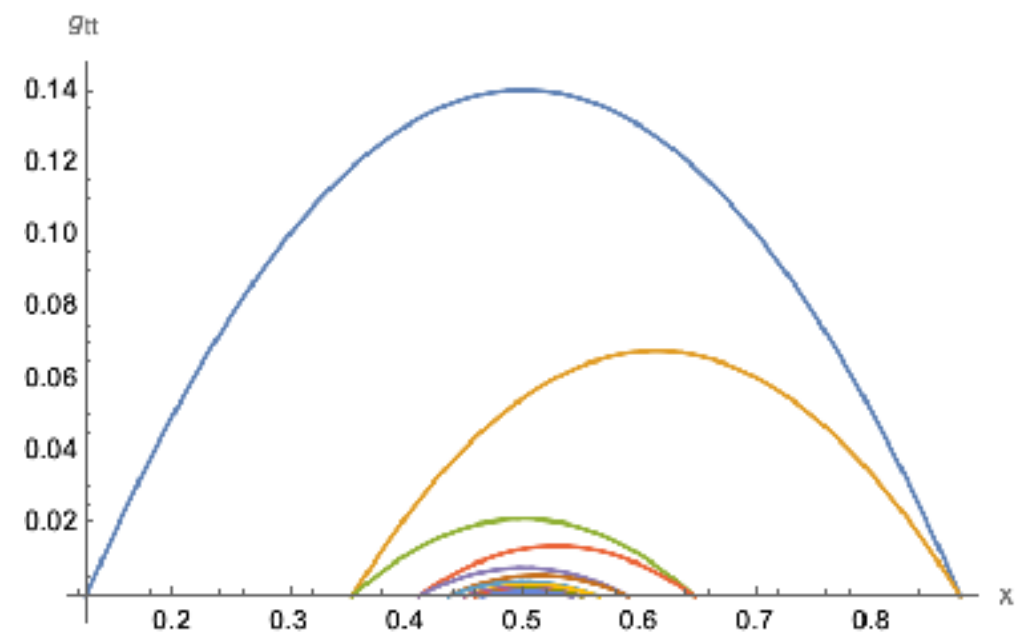
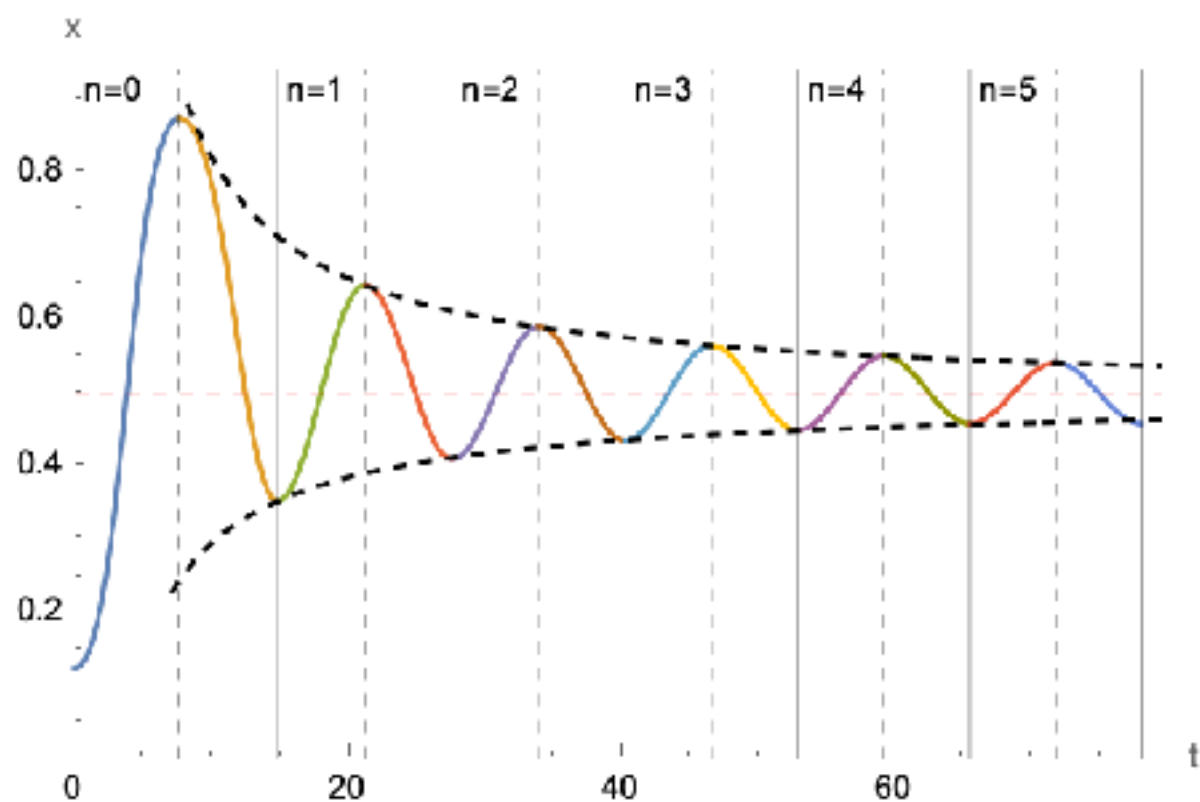
(iii) oscillating time evolution

$\{x_1(n)\}_{n \in \mathbb{N}^*}$ and $\{x_2(n)\}_{n \in \mathbb{N}^*}$ convergent series with

$0 < x_1(n) < x_1(n+1) \leq x_2(n+1) < x_2(n) < 1$ then

$$g_{tt}(n) = \begin{cases} a_1 (x - x_1(n))(x_2(n) - x) & \text{for } \frac{dx}{dt} > 0, \\ a_2 (x - x_1(n))(x_2(n) - x) & \text{for } \frac{dx}{dt} < 0 \end{cases} \quad \text{with} \quad \begin{aligned} & a_1, a_2 \in \mathbb{R}_+ \\ & 0 < x_1 \leq x \leq x_2 < 1 \end{aligned}$$

oscillating solution of the form



Conclusions

- simple models in epidemiology/population dynamics in terms of probability distributions
- in certain scenarios dynamics re-formulated in terms of the Fisher information metric
- universal features across different models (Lotka-Volterra, compartmental models)
- re-organisation around zeroes of the metric

Outlook

- more general models with more degrees of freedom
- include further elements of information theory/geometry