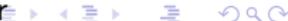


Law of large numbers for epidemic models with countably many types

Malwina J Luczak ¹

Department of Mathematics
London School of Economics
London WC2A 2AE
UK
e-mail: m.j.luczak@lse.ac.uk

October 2008

¹This presentation is based on joint work with Andrew Barbour 

Introduction

- ▶ We consider a class of stochastic models of epidemics.
- ▶ These models describe the spread of a certain parasitic disease.
- ▶ They are generalisations of stochastic models studied by Barbour & Kafetzaki (1993) and Luchsinger (1999,2001).
- ▶ They also include a stochastic version (and with truncated infection rates) of the model studied by Kretzschmar (1993).
- ▶ In this context, it is natural to distinguish hosts according to the number of parasites that they carry.
- ▶ This leads to models with **countably infinitely** many types, one for each possible number of parasites.

Introduction

- ▶ We consider a class of stochastic models of epidemics.
- ▶ These models describe the spread of a certain parasitic disease.
- ▶ They are generalisations of stochastic models studied by Barbour & Kafetzaki (1993) and Luchsinger (1999,2001).
- ▶ They also include a stochastic version (and with truncated infection rates) of the model studied by Kretzschmar (1993).
- ▶ In this context, it is natural to distinguish hosts according to the number of parasites that they carry.
- ▶ This leads to models with **countably infinitely** many types, one for each possible number of parasites.

Introduction

- ▶ We consider a class of stochastic models of epidemics.
- ▶ These models describe the spread of a certain parasitic disease.
- ▶ They are generalisations of stochastic models studied by **Barbour & Kafetzaki (1993)** and **Luchsinger (1999,2001)**.
- ▶ They also include a stochastic version (and with truncated infection rates) of the model studied by **Kretzschmar (1993)**.
- ▶ In this context, it is natural to distinguish hosts according to the number of parasites that they carry.
- ▶ This leads to models with **countably infinitely** many types, one for each possible number of parasites.

Introduction

- ▶ We consider a class of stochastic models of epidemics.
- ▶ These models describe the spread of a certain parasitic disease.
- ▶ They are generalisations of stochastic models studied by [Barbour & Kafetzaki \(1993\)](#) and [Luchsinger \(1999,2001\)](#).
- ▶ They also include a stochastic version (and with truncated infection rates) of the model studied by [Kretzschmar \(1993\)](#).
- ▶ In this context, it is natural to distinguish hosts according to the number of parasites that they carry.
- ▶ This leads to models with **countably infinitely** many types, one for each possible number of parasites.

Introduction

- ▶ We consider a class of stochastic models of epidemics.
- ▶ These models describe the spread of a certain parasitic disease.
- ▶ They are generalisations of stochastic models studied by [Barbour & Kafetzaki \(1993\)](#) and [Luchsinger \(1999,2001\)](#).
- ▶ They also include a stochastic version (and with truncated infection rates) of the model studied by [Kretzschmar \(1993\)](#).
- ▶ In this context, it is natural to distinguish hosts according to the number of parasites that they carry.
- ▶ This leads to models with **countably infinitely** many types, one for each possible number of parasites.

Introduction

- ▶ We consider a class of stochastic models of epidemics.
- ▶ These models describe the spread of a certain parasitic disease.
- ▶ They are generalisations of stochastic models studied by [Barbour & Kafetzaki \(1993\)](#) and [Luchsinger \(1999,2001\)](#).
- ▶ They also include a stochastic version (and with truncated infection rates) of the model studied by [Kretzschmar \(1993\)](#).
- ▶ In this context, it is natural to distinguish hosts according to the number of parasites that they carry.
- ▶ This leads to models with **countably infinitely** many types, one for each possible number of parasites.

Laws of large numbers

- ▶ We want to show that the proportion of hosts with k parasites is close to a certain deterministic function, for each k , **with explicit rates of convergence**.
- ▶ Infinitely many types cause difficulty: many arguments standard in **finite case** are not so in **infinite case**.
- ▶ Example: supercritical Galton-Watson process, finitely many types, irreducible & aperiodic matrix \Rightarrow proportions of individuals of different types obey LLN.
- ▶ This is only known to hold under **extra conditions** in the **infinite case**.

Laws of large numbers

- ▶ We want to show that the proportion of hosts with k parasites is close to a certain deterministic function, for each k , **with explicit rates of convergence**.
- ▶ Infinitely many types cause difficulty: many arguments standard in **finite case** are not so in **infinite case**.
- ▶ Example: supercritical Galton-Watson process, finitely many types, irreducible & aperiodic matrix \Rightarrow proportions of individuals of different types obey LLN.
- ▶ This is only known to hold under **extra conditions** in the **infinite case**.

Laws of large numbers

- ▶ We want to show that the proportion of hosts with k parasites is close to a certain deterministic function, for each k , **with explicit rates of convergence**.
- ▶ Infinitely many types cause difficulty: many arguments standard in **finite case** are not so in **infinite case**.
- ▶ Example: supercritical Galton-Watson process, finitely many types, irreducible & aperiodic matrix \Rightarrow proportions of individuals of different types obey LLN.
- ▶ This is only known to hold under **extra conditions** in the **infinite case**.

Laws of large numbers

- ▶ We want to show that the proportion of hosts with k parasites is close to a certain deterministic function, for each k , **with explicit rates of convergence**.
- ▶ Infinitely many types cause difficulty: many arguments standard in **finite case** are not so in **infinite case**.
- ▶ Example: supercritical Galton-Watson process, finitely many types, irreducible & aperiodic matrix \Rightarrow proportions of individuals of different types obey LLN.
- ▶ This is only known to hold under **extra conditions** in the **infinite case**.

Laws of large numbers

- ▶ We want to show that the proportion of hosts with k parasites is close to a certain deterministic function, for each k , **with explicit rates of convergence**.
- ▶ Infinitely many types cause difficulty: many arguments standard in **finite case** are not so in **infinite case**.
- ▶ Example: supercritical Galton-Watson process, finitely many types, irreducible & aperiodic matrix \Rightarrow proportions of individuals of different types obey LLN.
- ▶ This is only known to hold under **extra conditions** in the **infinite case**.

Laws of large numbers

For epidemics with **finitely many types** there are LLN approximations, in the limit of **large populations** (i.e. as population size goes to infinity). \Rightarrow FINITE DIMENSIONAL SYSTEMS OF DIFFERENTIAL EQUATIONS

INFINITE DIMENSIONAL SYSTEMS OF DIFFERENTIAL EQUATIONS:

Barbour & Kafetzaki (1993), Luchsinger (2001), Arrigoni (2003).

Still, the arguments there are quite involved, and make use of special assumptions about detailed form of transition rates.

Laws of large numbers

For epidemics with **finitely many types** there are LLN approximations, in the limit of **large populations** (i.e. as population size goes to infinity). \Rightarrow **FINITE DIMENSIONAL SYSTEMS OF DIFFERENTIAL EQUATIONS**

INFINITE DIMENSIONAL SYSTEMS OF DIFFERENTIAL EQUATIONS:

Barbour & Kafetzaki (1993), Luchsinger (2001), Arrigoni (2003).

Still, the arguments there are quite involved, and make use of special assumptions about detailed form of transition rates.

Laws of large numbers

For epidemics with **finitely many types** there are LLN approximations, in the limit of **large populations** (i.e. as population size goes to infinity). \Rightarrow **FINITE DIMENSIONAL SYSTEMS OF DIFFERENTIAL EQUATIONS**

INFINITE DIMENSIONAL SYSTEMS OF DIFFERENTIAL EQUATIONS:

Barbour & Kafetzaki (1993), Luchsinger (2001), Arrigoni (2003).

Still, the arguments there are quite involved, and make use of special assumptions about detailed form of transition rates.

Laws of large numbers

For epidemics with **finitely many types** there are LLN approximations, in the limit of **large populations** (i.e. as population size goes to infinity). \Rightarrow **FINITE DIMENSIONAL SYSTEMS OF DIFFERENTIAL EQUATIONS**

INFINITE DIMENSIONAL SYSTEMS OF DIFFERENTIAL EQUATIONS:

Barbour & Kafetzaki (1993), Luchsinger (2001), Arrigoni (2003).

Still, the arguments there are quite involved, and make use of special assumptions about detailed form of transition rates.

Laws of large numbers

For epidemics with **finitely many types** there are LLN approximations, in the limit of **large populations** (i.e. as population size goes to infinity). \Rightarrow **FINITE DIMENSIONAL SYSTEMS OF DIFFERENTIAL EQUATIONS**

INFINITE DIMENSIONAL SYSTEMS OF DIFFERENTIAL EQUATIONS:

Barbour & Kafetzaki (1993), Luchsinger (2001), Arrigoni (2003).

Still, the arguments there are quite involved, and make use of special assumptions about detailed form of transition rates.

Laws of large numbers

- ▶ Things are considerably more delicate in **infinite dimensions!**
An extra difficulty in our case is caused by the fact that the operator driving the limiting differential equation is non-Lipschitz.
- ▶ Our goal: **TO ESTABLISH LLN IN SUBSTANTIAL GENERALITY**, quantifying rate of convergence.
- ▶ Models constructed by superimposing **state-dependent transitions** upon a process with otherwise **independent** and well-behaved dynamics **within the individuals**.

Laws of large numbers

- ▶ Things are considerably more delicate in **infinite dimensions!**
An extra difficulty in our case is caused by the fact that the operator driving the limiting differential equation is non-Lipschitz.
- ▶ Our goal: **TO ESTABLISH LLN IN SUBSTANTIAL GENERALITY**, quantifying rate of convergence.
- ▶ Models constructed by superimposing **state-dependent transitions** upon a process with otherwise **independent** and well-behaved dynamics **within the individuals**.

Laws of large numbers

- ▶ Things are considerably more delicate in **infinite dimensions!**
An extra difficulty in our case is caused by the fact that the operator driving the limiting differential equation is non-Lipschitz.
- ▶ Our goal: **TO ESTABLISH LLN IN SUBSTANTIAL GENERALITY**, quantifying rate of convergence.
- ▶ Models constructed by superimposing **state-dependent transitions** upon a process with otherwise **independent** and well-behaved dynamics **within the individuals**.

Laws of large numbers

- ▶ Things are considerably more delicate in **infinite dimensions!**
An extra difficulty in our case is caused by the fact that the operator driving the limiting differential equation is non-Lipschitz.
- ▶ Our goal: **TO ESTABLISH LLN IN SUBSTANTIAL GENERALITY**, quantifying rate of convergence.
- ▶ Models constructed by superimposing **state-dependent transitions** upon a process with otherwise **independent** and well-behaved dynamics **within the individuals**.

Laws of large numbers

- ▶ Things are considerably more delicate in **infinite dimensions!**
An extra difficulty in our case is caused by the fact that the operator driving the limiting differential equation is non-Lipschitz.
- ▶ Our goal: **TO ESTABLISH LLN IN SUBSTANTIAL GENERALITY**, quantifying rate of convergence.
- ▶ Models constructed by superimposing **state-dependent transitions** upon a process with otherwise **independent** and well-behaved dynamics **within the individuals**.

Laws of large numbers

- ▶ State-dependent components have Lipschitz and growth conditions.
- ▶ This ensures the perturbation of the underlying semi-group governing independent dynamics not too severe.
- ▶ In the process, we also hope for new methods with applications in other contexts, e.g. models in genetics and cellular biology, random graph processes (e.g. web graphs), randomised algorithms.

Laws of large numbers

- ▶ State-dependent components have Lipschitz and growth conditions.
- ▶ This ensures the perturbation of the underlying semi-group governing independent dynamics not too severe.
- ▶ In the process, we also hope for new methods with applications in other contexts, e.g. models in genetics and cellular biology, random graph processes (e.g. web graphs), randomised algorithms.

Laws of large numbers

- ▶ State-dependent components have Lipschitz and growth conditions.
- ▶ This ensures the perturbation of the underlying semi-group governing independent dynamics not too severe.
- ▶ In the process, we also hope for new methods with applications in other contexts, e.g. [models in genetics and cellular biology](#), [random graph processes](#) (e.g. [web graphs](#)), [randomised algorithms](#).

- ▶ One of our methods is the two-stage approximation used in this work. We are now also working on another method, using exponential martingales, which covers certain models we have not been able to handle here.
- ▶ Later: hope to establish a central limit theorem.
- ▶ **ANOTHER IMPORTANT QUESTION:** what happens to the stochastic process and its deterministic approximation long-term?

- ▶ One of our methods is the two-stage approximation used in this work. We are now also working on another method, using exponential martingales, which covers certain models we have not been able to handle here.
- ▶ Later: hope to establish a central limit theorem.
- ▶ **ANOTHER IMPORTANT QUESTION:** what happens to the stochastic process and its deterministic approximation long-term?

- ▶ One of our methods is the two-stage approximation used in this work. We are now also working on another method, using exponential martingales, which covers certain models we have not been able to handle here.
- ▶ Later: hope to establish a central limit theorem.
- ▶ **ANOTHER IMPORTANT QUESTION:** what happens to the stochastic process and its deterministic approximation long-term?

Long-term behaviour

- ▶ This problem is almost completely wide-open, very little is known except in special cases...
- ▶ What about the convergence of the Markov chain to its stationary distribution? Under what conditions is it **rapidly mixing**, i.e. in time $O(\log N)$? (N is of the order of the population size.)
- ▶ Can we determine the stationary solutions of the limiting differential equation? In particular, when does it have a **unique, globally attractive fixed point**?
- ▶ Under what conditions does the stochastic process stay close to its deterministic limit long-term, perhaps even **uniformly** in time?

Long-term behaviour

- ▶ This problem is almost completely wide-open, very little is known except in special cases...
- ▶ What about the convergence of the Markov chain to its stationary distribution? Under what conditions is it **rapidly mixing**, i.e. in time $O(\log N)$? (N is of the order of the population size.)
- ▶ Can we determine the stationary solutions of the limiting differential equation? In particular, when does it have a **unique, globally attractive fixed point**?
- ▶ Under what conditions does the stochastic process stay close to its deterministic limit long-term, perhaps even **uniformly** in time?

Long-term behaviour

- ▶ This problem is almost completely wide-open, very little is known except in special cases...
- ▶ What about the convergence of the Markov chain to its stationary distribution? Under what conditions is it **rapidly mixing**, i.e. in time $O(\log N)$? (N is of the order of the population size.)
- ▶ Can we determine the stationary solutions of the limiting differential equation? In particular, when does it have a **unique, globally attractive fixed point**?
- ▶ Under what conditions does the stochastic process stay close to its deterministic limit long-term, perhaps even **uniformly** in time?

Long-term behaviour

- ▶ This problem is almost completely wide-open, very little is known except in special cases...
- ▶ What about the convergence of the Markov chain to its stationary distribution? Under what conditions is it **rapidly mixing**, i.e. in time $O(\log N)$? (N is of the order of the population size.)
- ▶ Can we determine the stationary solutions of the limiting differential equation? In particular, when does it have a **unique, globally attractive fixed point**?
- ▶ Under what conditions does the stochastic process stay close to its deterministic limit long-term, perhaps even **uniformly** in time?

Long-term behaviour

- ▶ This problem is almost completely wide-open, very little is known except in special cases...
- ▶ What about the convergence of the Markov chain to its stationary distribution? Under what conditions is it **rapidly mixing**, i.e. in time $O(\log N)$? (N is of the order of the population size.)
- ▶ Can we determine the stationary solutions of the limiting differential equation? In particular, when does it have a **unique, globally attractive fixed point**?
- ▶ Under what conditions does the stochastic process stay close to its deterministic limit long-term, perhaps even **uniformly** in time?

Our model

- ▶ Sequence of processes $X_N = (X_N^i(t) : i \in \mathbb{Z}_+)_{t \geq 0}$
- ▶ State space $\mathcal{X} := \{X \in \mathbb{Z}_+^\infty : \sum_{i \geq 0} X^i < \infty\}$
- ▶ $X_N^i(t) \in \mathbb{Z}_+$ is the i -th component, interpreted as number of individuals who carry i parasites at time t .
- ▶ We assume that $\sum_{j \geq 0} X_N^j(0) = N$.
- ▶ Transitions correspond to individuals changing type, new arrivals/births and departures/deaths.

Our model

- ▶ Sequence of processes $X_N = (X_N^i(t) : i \in \mathbb{Z}_+)_{t \geq 0}$
- ▶ State space $\mathcal{X} := \{X \in \mathbb{Z}_+^\infty : \sum_{i \geq 0} X^i < \infty\}$
- ▶ $X_N^i(t) \in \mathbb{Z}_+$ is the i -th component, interpreted as number of individuals who carry i parasites at time t .
- ▶ We assume that $\sum_{j \geq 0} X_N^j(0) = N$.
- ▶ Transitions correspond to individuals changing type, new arrivals/births and departures/deaths.

Our model

- ▶ Sequence of processes $X_N = (X_N^i(t) : i \in \mathbb{Z}_+)_{t \geq 0}$
- ▶ State space $\mathcal{X} := \{X \in \mathbb{Z}_+^\infty : \sum_{i \geq 0} X^i < \infty\}$
- ▶ $X_N^i(t) \in \mathbb{Z}_+$ is the i -th component, interpreted as number of individuals who carry i parasites at time t .
- ▶ We assume that $\sum_{j \geq 0} X_N^j(0) = N$.
- ▶ Transitions correspond to individuals changing type, new arrivals/births and departures/deaths.

Our model

- ▶ Sequence of processes $X_N = (X_N^i(t) : i \in \mathbb{Z}_+)_{t \geq 0}$
- ▶ State space $\mathcal{X} := \{X \in \mathbb{Z}_+^\infty : \sum_{i \geq 0} X^i < \infty\}$
- ▶ $X_N^i(t) \in \mathbb{Z}_+$ is the i -th component, interpreted as number of individuals who carry i parasites at time t .
- ▶ We assume that $\sum_{j \geq 0} X_N^j(0) = N$.
- ▶ Transitions correspond to individuals changing type, new arrivals/births and departures/deaths.

Our model

- ▶ Sequence of processes $X_N = (X_N^i(t) : i \in \mathbb{Z}_+)_{t \geq 0}$
- ▶ State space $\mathcal{X} := \{X \in \mathbb{Z}_+^\infty : \sum_{i \geq 0} X^i < \infty\}$
- ▶ $X_N^i(t) \in \mathbb{Z}_+$ is the i -th component, interpreted as number of individuals who carry i parasites at time t .
- ▶ We assume that $\sum_{j \geq 0} X_N^j(0) = N$.
- ▶ Transitions correspond to individuals changing type, new arrivals/births and departures/deaths.

Transitions

$$X \rightarrow X + (e(j) - e(i)) \text{ at rate } X^i \{\bar{\alpha}_{ij} + \alpha_{ij}(N^{-1}X)\}, \\ (i \geq 0, j \geq 0, j \neq i);$$

(Type changes.) This type of transition corresponds to an infection of one individual, or an individual's disease state evolving spontaneously or due to treatment.

$\alpha_{ij}(x)$ depends on the overall levels x of infection in community. Principally there to allow hosts to acquire further parasites through infection but can also model state-dependent loss of infection e.g. through treatment offered when higher levels of infection observed.

Transitions

$$X \rightarrow X + (e(j) - e(i)) \text{ at rate } X^i \{\bar{\alpha}_{ij} + \alpha_{ij}(N^{-1}X)\}, \\ (i \geq 0, j \geq 0, j \neq i);$$

(Type changes.) This type of transition corresponds to an infection of one individual, or an individual's disease state evolving spontaneously or due to treatment.

$\alpha_{ij}(x)$ depends on the overall levels x of infection in community. Principally there to allow hosts to acquire further parasites through infection but can also model state-dependent loss of infection e.g. through treatment offered when higher levels of infection observed.

Transitions

$$X \rightarrow X + (e(j) - e(i)) \text{ at rate } X^i \{\bar{\alpha}_{ij} + \alpha_{ij}(N^{-1}X)\}, \\ (i \geq 0, j \geq 0, j \neq i);$$

(Type changes.) This type of transition corresponds to an infection of one individual, or an individual's disease state evolving spontaneously or due to treatment.

$\alpha_{ij}(x)$ depends on the overall levels x of infection in community. Principally there to allow hosts to acquire further parasites through infection but can also model state-dependent loss of infection e.g. through treatment offered when higher levels of infection observed.

Transitions

$$X \rightarrow X + (e(j) - e(i)) \text{ at rate } X^i \{\bar{\alpha}_{ij} + \alpha_{ij}(N^{-1}X)\}, \\ (i \geq 0, j \geq 0, j \neq i);$$

(Type changes.) This type of transition corresponds to an infection of one individual, or an individual's disease state evolving spontaneously or due to treatment.

$\alpha_{ij}(x)$ depends on the overall levels x of infection in community. Principally there to allow hosts to acquire further parasites through infection but can also model state-dependent loss of infection e.g. through treatment offered when higher levels of infection observed.

Transitions

$$X \rightarrow X + e(i) \text{ at rate } N\beta_i(N^{-1}X), \quad i \geq 0;$$

(Births/arrivals)

Thus type of transition models births and immigration of individuals of different types. We allow dependence on community levels of infection.

Transitions

$$X \rightarrow X + e(i) \text{ at rate } N\beta_i(N^{-1}X), \quad i \geq 0;$$

(Births/arrivals)

Thus type of transition models births and immigration of individuals of different types. We allow dependence on community levels of infection.

Transitions

$$X \rightarrow X + e(i) \text{ at rate } N\beta_i(N^{-1}X), \quad i \geq 0;$$

(Births/arrivals)

Thus type of transition models births and immigration of individuals of different types. We allow dependence on community levels of infection.

Transitions

$$X \rightarrow X - e(i) \text{ at rate } X^i \{\bar{\delta}_i + \delta_i(N^{-1}X)\}, \quad i \geq 0.$$

(Deaths/departures)

This type of transition models deaths and emigration. Again, we allow dependence on community levels of infection.

Transitions

$$X \rightarrow X - e(i) \text{ at rate } X^i \{\bar{\delta}_i + \delta_i(N^{-1}X)\}, \quad i \geq 0.$$

(Deaths/departures)

This type of transition models deaths and emigration. Again, we allow dependence on community levels of infection.

Transitions

$$X \rightarrow X - e(i) \text{ at rate } X^i \{\bar{\delta}_i + \delta_i(N^{-1}X)\}, \quad i \geq 0.$$

(Deaths/departures)

This type of transition models deaths and emigration. Again, we allow dependence on community levels of infection.

Transitions summary and comments

- ▶ In the above the rates $\bar{\alpha}_{ij}, \alpha_{ij}, \beta_i, \bar{\delta}_i, \delta_i$ model different aspects of the underlying parasite life cycle.
- ▶ The rates $\bar{\alpha}_{ij}$ and $\bar{\delta}_i$ represent parasite communities developing independently within different hosts, according to a pure jump Markov process, with host death at rate $\bar{\delta}_i$ when parasite load is i .
- ▶ $\bar{\alpha}_0$ are all zero if only parasite mortality and reproduction are modelled by $\bar{\alpha}_{ij}$, but may include part of infection force, so not true in general.

Transitions summary and comments

- ▶ In the above the rates $\bar{\alpha}_{ij}, \alpha_{ij}, \beta_i, \bar{\delta}_i, \delta_i$ model different aspects of the underlying parasite life cycle.
- ▶ The rates $\bar{\alpha}_{ij}$ and $\bar{\delta}_i$ represent parasite communities developing independently within different hosts, according to a pure jump Markov process, with host death at rate $\bar{\delta}_i$ when parasite load is i .
- ▶ $\bar{\alpha}_0$ are all zero if only parasite mortality and reproduction are modelled by $\bar{\alpha}_{ij}$, but may include part of infection force, so not true in general.

Transitions summary and comments

- ▶ In the above the rates $\bar{\alpha}_{ij}, \alpha_{ij}, \beta_i, \bar{\delta}_i, \delta_i$ model different aspects of the underlying parasite life cycle.
- ▶ The rates $\bar{\alpha}_{ij}$ and $\bar{\delta}_i$ represent parasite communities developing independently within different hosts, according to a pure jump Markov process, with host death at rate $\bar{\delta}_i$ when parasite load is i .
- ▶ $\bar{\alpha}_0$ are all zero if only parasite mortality and reproduction are modelled by $\bar{\alpha}_{ij}$, but may include part of infection force, so not true in general.

Law of large numbers - candidate limit

Natural candidate approximation is by the solution to the 'average drift' infinite dimensional differential equation

$$\frac{dx^i(t)}{dt} = \sum_{l \geq 0} x^l(t) \bar{\alpha}_{li} + \sum_{l \neq i} x^l(t) \alpha_{li}(x(t)) - x^i(t) \sum_{l \neq i} \alpha_{il}(x(t)) + \beta_i(x(t)) - x^i(t) \delta_i(x(t)), \quad i \geq 0.$$

with initial condition $x(0) = N^{-1}X_N(0)$;

Law of large numbers - candidate limit

Natural candidate approximation is by the solution to the 'average drift' infinite dimensional differential equation

$$\begin{aligned} \frac{dx^i(t)}{dt} = & \sum_{l \geq 0} x^l(t) \bar{\alpha}_{li} + \sum_{l \neq i} x^l(t) \alpha_{li}(x(t)) - x^i(t) \sum_{l \neq i} \alpha_{il}(x(t)) \\ & + \beta_i(x(t)) - x^i(t) \delta_i(x(t)), \quad i \geq 0, \end{aligned}$$

with initial condition $x(0) = N^{-1}X_N(0)$;

Law of large numbers - candidate limit

Natural candidate approximation is by the solution to the 'average drift' infinite dimensional differential equation

$$\begin{aligned} \frac{dx^i(t)}{dt} = & \sum_{l \geq 0} x^l(t) \bar{\alpha}_{li} + \sum_{l \neq i} x^l(t) \alpha_{li}(x(t)) - x^i(t) \sum_{l \neq i} \alpha_{il}(x(t)) \\ & + \beta_i(x(t)) - x^i(t) \delta_i(x(t)), \quad i \geq 0, \end{aligned}$$

with initial condition $x(0) = N^{-1}X_N(0)$;

- ▶ This can be expressed as

$$\frac{dx}{dt} = Ax + F(x), \quad x(0) = N^{-1}X_N(0),$$

- ▶ where $(Ax)^i = \sum_{l \geq 0} x^l \bar{\alpha}_{li}$, $i \geq 0$, is a linear operator;
- ▶ and operator F is given by

$$(Fx)^i = \sum_{l \neq i} x^l \alpha_{li}(x) - x^i \sum_{l \neq i} \alpha_{il}(x) + \beta_i(x) - x^i \delta_i(x), \quad i \geq 0.$$

- ▶ This can be expressed as

$$\frac{dx}{dt} = Ax + F(x), \quad x(0) = N^{-1}X_N(0),$$

- ▶ where $(Ax)^i = \sum_{l \geq 0} x^l \bar{\alpha}_{li}$, $i \geq 0$, is a linear operator;
- ▶ and operator F is given by

$$(Fx)^i = \sum_{l \neq i} x^l \alpha_{li}(x) - x^i \sum_{l \neq i} \alpha_{il}(x) + \beta_i(x) - x^i \delta_i(x), \quad i \geq 0.$$

- ▶ This can be expressed as

$$\frac{dx}{dt} = Ax + F(x), \quad x(0) = N^{-1}X_N(0),$$

- ▶ where $(Ax)^i = \sum_{l \geq 0} x^l \bar{\alpha}_{li}$, $i \geq 0$, is a linear operator;
- ▶ and operator F is given by

$$(Fx)^i = \sum_{l \neq i} x^l \alpha_{li}(x) - x^i \sum_{l \neq i} \alpha_{il}(x) + \beta_i(x) - x^i \delta_i(x), \quad i \geq 0.$$

- ▶ This can be expressed as

$$\frac{dx}{dt} = Ax + F(x), \quad x(0) = N^{-1}X_N(0),$$

- ▶ where $(Ax)^i = \sum_{l \geq 0} x^l \bar{\alpha}_{li}$, $i \geq 0$, is a linear operator;
- ▶ and operator F is given by

$$(Fx)^i = \sum_{l \neq i} x^l \alpha_{li}(x) - x^i \sum_{l \neq i} \alpha_{il}(x) + \beta_i(x) - x^i \delta_i(x), \quad i \geq 0.$$

- ▶ This can be expressed as

$$\frac{dx}{dt} = Ax + F(x), \quad x(0) = N^{-1}X_N(0),$$

- ▶ where $(Ax)^i = \sum_{l \geq 0} x^l \bar{\alpha}_{li}$, $i \geq 0$, is a linear operator;
- ▶ and operator F is given by

$$(Fx)^i = \sum_{l \neq i} x^l \alpha_{li}(x) - x^i \sum_{l \neq i} \alpha_{il}(x) + \beta_i(x) - x^i \delta_i(x), \quad i \geq 0.$$

Our space

We shall be working in two spaces:

- ▶ The space

$$\ell_{11} = \{x \in \mathbb{R}^\infty : \sum_{i \geq 0} (i+1)|x^i| < \infty\},$$

with norm $\|x\|_{11} = \sum_{i \geq 0} (i+1)|x^i|$;

- ▶ And the usual ℓ_1 with norm $\|x\|_1 = \sum_{i \geq 0} |x^i|$.

Our space

We shall be working in two spaces:

- ▶ The space

$$l_{11} = \{x \in \mathbb{R}^\infty : \sum_{i \geq 0} (i+1)|x^i| < \infty\},$$

with norm $\|x\|_{11} = \sum_{i \geq 0} (i+1)|x^i|$;

- ▶ And the usual l_1 with norm $\|x\|_1 = \sum_{i \geq 0} |x^i|$.

Our space

We shall be working in two spaces:

- ▶ The space

$$l_{11} = \{x \in \mathbb{R}^\infty : \sum_{i \geq 0} (i+1)|x^i| < \infty\},$$

with norm $\|x\|_{11} = \sum_{i \geq 0} (i+1)|x^i|$;

- ▶ And the usual l_1 with norm $\|x\|_1 = \sum_{i \geq 0} |x^i|$.

Main theorem

Theorem

Suppose that certain technical conditions are satisfied, and that $x_N(0) := N^{-1}X_N(0)$ satisfies $\|x_N(0) - x(0)\|_{11} \rightarrow 0$ as $N \rightarrow \infty$, for some $x_0 \in \ell_{11}$. Let $[0, t_{\max})$ denote the interval where the above equation with x_0 as initial condition has a solution x in ℓ_{11} .

Then for any $T < t_{\max}$, there exists a constant $K(T)$ such that, as $N \rightarrow \infty$,

$$P\left[N^{-1} \sup_{0 \leq t \leq T} \|X_N(t) - Nx_N(t)\|_1 > K(T)N^{-1/2} \log^{3/2} N\right] = O(N^{-1/2}),$$

where x_N solves the differential equation with $x_N(0) = N^{-1}X_N(0)$.

Main theorem

Theorem

Suppose that certain technical conditions are satisfied, and that $x_N(0) := N^{-1}X_N(0)$ satisfies $\|x_N(0) - x(0)\|_{11} \rightarrow 0$ as $N \rightarrow \infty$, for some $x_0 \in \ell_{11}$. Let $[0, t_{\max})$ denote the interval where the above equation with x_0 as initial condition has a solution x in ℓ_{11} .

Then for any $T < t_{\max}$, there exists a constant $K(T)$ such that, as $N \rightarrow \infty$,

$$P\left[N^{-1} \sup_{0 \leq t \leq T} \|X_N(t) - Nx_N(t)\|_1 > K(T)N^{-1/2} \log^{3/2} N\right] = O(N^{-1/2}),$$

where x_N solves the differential equation with $x_N(0) = N^{-1}X_N(0)$.

Main theorem

Theorem

Suppose that certain technical conditions are satisfied, and that $x_N(0) := N^{-1}X_N(0)$ satisfies $\|x_N(0) - x(0)\|_{11} \rightarrow 0$ as $N \rightarrow \infty$, for some $x_0 \in \ell_{11}$. Let $[0, t_{\max})$ denote the interval where the above equation with x_0 as initial condition has a solution x in ℓ_{11} .

Then for any $T < t_{\max}$, there exists a constant $K(T)$ such that, as $N \rightarrow \infty$,

$$\mathbf{P}[N^{-1} \sup_{0 \leq t \leq T} \|X_N(t) - Nx_N(t)\|_1 > K(T)N^{-1/2} \log^{3/2} N] = O(N^{-1/2}),$$

where x_N solves the differential equation with $x_N(0) = N^{-1}X_N(0)$.

Other deviation sizes

Theorem

Suppose that certain technical conditions are satisfied, and that $x_N(0) := N^{-1}X_N(0)$ satisfies $\|x_N(0) - x(0)\|_{11} \rightarrow 0$ as $N \rightarrow \infty$, for some $x_0 \in \ell_{11}$. Let $[0, t_{\max})$ denote the interval where the above equation with x_0 as initial condition has a solution x in ℓ_{11} .

Then, for any $1/2 < \gamma \leq 1$, and for any $T < t_{\max}$, there exists a constant $K_\gamma(T)$ such that, as $N \rightarrow \infty$,

$$P\left[N^{-1} \sup_{0 \leq t \leq T} \|X_N(t) - Nx_N(t)\|_1 > K_\gamma(T) N^{\gamma-1} \log N\right] = O(N^{-\gamma}),$$

where x_N solves the differential equation with $x_N(0) = N^{-1}X_N(0)$.

Other deviation sizes

Theorem

Suppose that certain technical conditions are satisfied, and that $x_N(0) := N^{-1}X_N(0)$ satisfies $\|x_N(0) - x(0)\|_{11} \rightarrow 0$ as $N \rightarrow \infty$, for some $x_0 \in \ell_{11}$. Let $[0, t_{\max})$ denote the interval where the above equation with x_0 as initial condition has a solution x in ℓ_{11} . Then, for any $1/2 < \gamma \leq 1$, and for any $T < t_{\max}$, there exists a constant $K_\gamma(T)$ such that, as $N \rightarrow \infty$,

$$P[N^{-1} \sup_{0 \leq t \leq T} \|X_N(t) - Nx_N(t)\|_1 > K_\gamma(T) N^{\gamma-1} \log N] = O(N^{-\gamma}),$$

where x_N solves the differential equation with $x_N(0) = N^{-1}X_N(0)$.

Other deviation sizes

Theorem

Suppose that certain technical conditions are satisfied, and that $x_N(0) := N^{-1}X_N(0)$ satisfies $\|x_N(0) - x(0)\|_{11} \rightarrow 0$ as $N \rightarrow \infty$, for some $x_0 \in \ell_{11}$. Let $[0, t_{\max})$ denote the interval where the above equation with x_0 as initial condition has a solution x in ℓ_{11} .

Then, for any $1/2 < \gamma \leq 1$, and for any $T < t_{\max}$, there exists a constant $K_\gamma(T)$ such that, as $N \rightarrow \infty$,

$$\mathbf{P}\left[N^{-1} \sup_{0 \leq t \leq T} \|X_N(t) - Nx_N(t)\|_1 > K_\gamma(T) N^{\gamma-1} \log N\right] = O(N^{-\gamma}),$$

where x_N solves the differential equation with $x_N(0) = N^{-1}X_N(0)$.

What are the conditions required?

Without getting into technical details, we have conditions of the following types:

- ▶ Conditions ensuring the per capita infection, birth, immigration and death rates are finite, bounded by constant multiples of $\|x\|_1 + 1$.
- ▶ This excludes any model in which the per capita infection rate is a constant K times the parasite density $\|x\|_1$, e.g. Kretzschmar (1993).
- ▶ Conditions implying that cumulative differences between states x and y are limited by multiples of $\|x - y\|_1$, and these multiples are bounded if $\|x\|_1 \wedge \|y\|_1$ is.

What are the conditions required?

Without getting into technical details, we have conditions of the following types:

- ▶ Conditions ensuring the per capita infection, birth, immigration and death rates are finite, bounded by constant multiples of $\|x\|_1 + 1$.
- ▶ This excludes any model in which the per capita infection rate is a constant K times the parasite density $\|x\|_1$, e.g. Kretzschmar (1993).
- ▶ Conditions implying that cumulative differences between states x and y are limited by multiples of $\|x - y\|_1$, and these multiples are bounded if $\|x\|_1 \wedge \|y\|_1$ is.

What are the conditions required?

Without getting into technical details, we have conditions of the following types:

- ▶ Conditions ensuring the per capita infection, birth, immigration and death rates are finite, bounded by constant multiples of $\|x\|_1 + 1$.
- ▶ This excludes any model in which the per capita infection rate is a constant K times the parasite density $\|x\|_1$, e.g. Kretzschmar (1993).
- ▶ Conditions implying that cumulative differences between states x and y are limited by multiples of $\|x - y\|_1$, and these multiples are bounded if $\|x\|_1 \wedge \|y\|_1$ is.

What are the conditions required?

Without getting into technical details, we have conditions of the following types:

- ▶ Conditions ensuring the per capita infection, birth, immigration and death rates are finite, bounded by constant multiples of $\|x\|_1 + 1$.
- ▶ This excludes any model in which the per capita infection rate is a constant K times the parasite density $\|x\|_{11}$, e.g. [Kretzschmar \(1993\)](#).
- ▶ Conditions implying that cumulative differences between states x and y are limited by multiples of $\|x - y\|_1$, and these multiples are bounded if $\|x\|_{11} \wedge \|y\|_{11}$ is.

Conditions continued

- ▶ Conditions constraining overall rate of flow of parasites into the system through immigration to be finite, and bounded if parasite density is bounded.
- ▶ Conditions limiting the way this influx may depend on infection state
- ▶ Conditions restricting rates of influx of parasites into hosts through infection. (Limit imposed on the *multiplicative* rate of increase of parasites in host; useful if parasites can directly reproduce in their hosts, at rate influenced by immune response.)

Conditions continued

- ▶ Conditions constraining overall rate of flow of parasites into the system through immigration to be finite, and bounded if parasite density is bounded.
- ▶ Conditions limiting the way this influx may depend on infection state
- ▶ Conditions restricting rates of influx of parasites into hosts through infection. (Limit imposed on the *multiplicative* rate of increase of parasites in host; useful if parasites can directly reproduce in their hosts, at rate influenced by immune response.)

Conditions continued

- ▶ Conditions constraining overall rate of flow of parasites into the system through immigration to be finite, and bounded if parasite density is bounded.
- ▶ Conditions limiting the way this influx may depend on infection state
- ▶ Conditions restricting rates of influx of parasites into hosts through infection. (Limit imposed on the *multiplicative* rate of increase of parasites in host; useful if parasites can directly reproduce in their hosts, at rate influenced by immune response.)

Biological interpretation of our norms

- ▶ Norms $\|\cdot\|_1$ and $\|\cdot\|_{11}$ have natural interpretations.
- ▶ $\|X - Y\|_1$ is the 'natural' measure of difference as seen from the hosts' point of view
- ▶ $\|X - Y\|_{11}$ is the corresponding 'parasite norm', a measure of parasite density.

Biological interpretation of our norms

- ▶ Norms $\|\cdot\|_1$ and $\|\cdot\|_{11}$ have natural interpretations.
- ▶ $\|X - Y\|_1$ is the 'natural' measure of difference as seen from the hosts' point of view
- ▶ $\|X - Y\|_{11}$ is the corresponding 'parasite norm', a measure of parasite density.

Biological interpretation of our norms

- ▶ Norms $\|\cdot\|_1$ and $\|\cdot\|_{11}$ have natural interpretations.
- ▶ $\|X - Y\|_1$ is the ‘natural’ measure of difference as seen from the hosts’ point of view
- ▶ $\|X - Y\|_{11}$ is the corresponding ‘parasite norm’, a measure of parasite density.

Examples

- ▶ Our model includes the [stochastic non-linear model](#) from [Barbour & Kafetzaki \(1993\)](#) and [stochastic linear model](#) from [Barbour \(1994\)](#). Both generalised and studied in depth by [Luchsinger \(1999,2001\)](#).
- ▶ Also includes a stochastic version of [Kretzschmar \(1993\)](#) with truncated infection rates.

Examples

- ▶ Our model includes the [stochastic non-linear model](#) from [Barbour & Kafetzaki \(1993\)](#) and [stochastic linear model](#) from [Barbour \(1994\)](#). Both generalised and studied in depth by [Luchsinger \(1999,2001\)](#).
- ▶ Also includes a stochastic version of [Kretzschmar \(1993\)](#) with truncated infection rates.

Luchsinger's non-linear model

- ▶ Population size is always N ;
- ▶ $\beta_i(x) = \delta_i(x) = \bar{\delta}_i = 0, \quad \forall i \geq 0, x \in \ell_{11}$;
- ▶ $\bar{\alpha}$ is a superposition of generator of pure death process rate $\mu > 0$ (parasites die independently) and catastrophe process jumping to 0 at rate $\kappa \geq 0$ (hosts die independently);
- ▶ if a host dies, it is replaced by a healthy individual; hence

$$\bar{\alpha}_{i,i-1} = i\mu, \quad \bar{\alpha}_{i0} = \kappa, \quad i \geq 2; \quad \bar{\alpha}_{10} = \mu + \kappa;$$

also $\bar{\alpha}_{0j} = 0$;

- ▶ contacts at rate $\lambda > 0$, only infections of healthy hosts;

Luchsinger's non-linear model

- ▶ Population size is always N ;
- ▶ $\beta_i(x) = \delta_i(x) = \bar{\delta}_i = 0, \quad \forall i \geq 0, x \in \ell_{11}$;
- ▶ $\bar{\alpha}$ is a superposition of generator of pure death process rate $\mu > 0$ (parasites die independently) and catastrophe process jumping to 0 at rate $\kappa \geq 0$ (hosts die independently);
- ▶ if a host dies, it is replaced by a healthy individual; hence

$$\bar{\alpha}_{i,i-1} = i\mu, \quad \bar{\alpha}_{i0} = \kappa, \quad i \geq 2; \quad \bar{\alpha}_{10} = \mu + \kappa;$$

also $\bar{\alpha}_{0j} = 0$;

- ▶ contacts at rate $\lambda > 0$, only infections of healthy hosts;

Luchsinger's non-linear model

- ▶ Population size is always N ;
- ▶ $\beta_i(x) = \delta_i(x) = \bar{\delta}_i = 0, \quad \forall i \geq 0, x \in \ell_{11}$;
- ▶ $\bar{\alpha}$ is a superposition of generator of pure death process rate $\mu > 0$ (parasites die independently) and catastrophe process jumping to 0 at rate $\kappa \geq 0$ (hosts die independently);
- ▶ if a host dies, it is replaced by a healthy individual; hence

$$\bar{\alpha}_{i,i-1} = i\mu, \quad \bar{\alpha}_{i0} = \kappa, \quad i \geq 2; \quad \bar{\alpha}_{10} = \mu + \kappa;$$

also $\bar{\alpha}_{0j} = 0$;

- ▶ contacts at rate $\lambda > 0$, only infections of healthy hosts;

Luchsinger's non-linear model

- ▶ Population size is always N ;
- ▶ $\beta_i(x) = \delta_i(x) = \bar{\delta}_i = 0, \quad \forall i \geq 0, x \in \ell_{11}$;
- ▶ $\bar{\alpha}$ is a superposition of generator of pure death process rate $\mu > 0$ (parasites die independently) and catastrophe process jumping to 0 at rate $\kappa \geq 0$ (hosts die independently);
- ▶ if a host dies, it is replaced by a healthy individual; hence

$$\bar{\alpha}_{i,i-1} = i\mu, \quad \bar{\alpha}_{i0} = \kappa, \quad i \geq 2; \quad \bar{\alpha}_{10} = \mu + \kappa;$$

also $\bar{\alpha}_{0j} = 0$;

- ▶ contacts at rate $\lambda > 0$, only infections of healthy hosts;

Luchsinger's non-linear model

- ▶ Population size is always N ;
- ▶ $\beta_i(x) = \delta_i(x) = \bar{\delta}_i = 0, \quad \forall i \geq 0, x \in \ell_{11}$;
- ▶ $\bar{\alpha}$ is a superposition of generator of pure death process rate $\mu > 0$ (parasites die independently) and catastrophe process jumping to 0 at rate $\kappa \geq 0$ (hosts die independently);
- ▶ if a host dies, it is replaced by a healthy individual; hence

$$\bar{\alpha}_{i,i-1} = i\mu, \quad \bar{\alpha}_{i0} = \kappa, \quad i \geq 2; \quad \bar{\alpha}_{10} = \mu + \kappa;$$

also $\bar{\alpha}_{0j} = 0$;

- ▶ contacts at rate $\lambda > 0$, only infections of healthy hosts;

Luchsinger's non-linear model

- ▶ Population size is always N ;
- ▶ $\beta_i(x) = \delta_i(x) = \bar{\delta}_i = 0, \quad \forall i \geq 0, x \in \ell_{11}$;
- ▶ $\bar{\alpha}$ is a superposition of generator of pure death process rate $\mu > 0$ (parasites die independently) and catastrophe process jumping to 0 at rate $\kappa \geq 0$ (hosts die independently);
- ▶ if a host dies, it is replaced by a healthy individual; hence

$$\bar{\alpha}_{i,i-1} = i\mu, \quad \bar{\alpha}_{i0} = \kappa, \quad i \geq 2; \quad \bar{\alpha}_{10} = \mu + \kappa;$$

also $\bar{\alpha}_{0j} = 0$;

- ▶ contacts at rate $\lambda > 0$, only infections of healthy hosts;

Luchsinger's non-linear model

- ▶ If host with i parasites contacts a healthy one, probability p_{il} of infection with l parasites, $\sum_{l \geq 0} p_{il} = 1$, $\forall i$, $p_{00} = 1$;
- ▶ $F_i = (p_{il}, l \geq 0)$ is i -fold convolution of F_1 (parasites independent in transmitting offspring), has finite mean;
- ▶ Thus $\alpha_{ij}(x) = 0$, $i \neq 0$, and

$$\alpha_{0l}(x) = \lambda \sum_{i \geq 1} x^i p_{il}, \quad l \geq 1, x \in \ell_{11};$$

Luchsinger's non-linear model

- ▶ If host with i parasites contacts a healthy one, probability p_{il} of infection with l parasites, $\sum_{l \geq 0} p_{il} = 1$, $\forall i$, $p_{00} = 1$;
- ▶ $F_i = (p_{il}, l \geq 0)$ is i -fold convolution of F_1 (parasites independent in transmitting offspring), has finite mean;
- ▶ Thus $\alpha_{ij}(x) = 0$, $i \neq 0$, and

$$\alpha_{0l}(x) = \lambda \sum_{i \geq 1} x^i p_{il}, \quad l \geq 1, x \in \ell_{11};$$

Luchsinger's non-linear model

- ▶ If host with i parasites contacts a healthy one, probability p_{il} of infection with l parasites, $\sum_{l \geq 0} p_{il} = 1$, $\forall i$, $p_{00} = 1$;
- ▶ $F_i = (p_{il}, l \geq 0)$ is i -fold convolution of F_1 (parasites independent in transmitting offspring), has finite mean;
- ▶ Thus $\alpha_{il}(x) = 0$, $i \neq 0$, and

$$\alpha_{0l}(x) = \lambda \sum_{i \geq 1} x^i p_{il}, \quad l \geq 1, x \in \ell_{11};$$

Luchsinger's linear model

- ▶ Tacitly assume **infinite** pool of potential infectives, so no **0**-coordinate needed;
- ▶ Only infected hosts are of interest, their number may vary;
- ▶ $\bar{\alpha}$ is a generator of simple death process rate $\mu > 0$, but restricted to reduced state space, so $\bar{\alpha}_{i,i-1} = i\mu$, $i \geq 2$;
- ▶ incorporate hosts losing infection by taking $\bar{\delta}_i = \kappa$, $i \geq 2$ and $\bar{\delta}_1 = \kappa + \mu$;
- ▶ Only healthy individuals can be infected, and infections with i parasites occur at a rate $\lambda \sum_{l \geq 1} x^l p_{ll}$, so that $\beta_i(x) = \lambda \sum_{l \geq 1} x^l p_{ll}$, $i \geq 1$, and all $\alpha_{ij}(x) = \delta_i(x) = 0$;

Luchsinger's linear model

- ▶ Tacitly assume **infinite** pool of potential infectives, so no **0**-coordinate needed;
- ▶ Only infected hosts are of interest, their number may vary;
- ▶ $\bar{\alpha}$ is a generator of simple death process rate $\mu > 0$, but restricted to reduced state space, so $\bar{\alpha}_{i,i-1} = i\mu$, $i \geq 2$;
- ▶ incorporate hosts losing infection by taking $\bar{\delta}_i = \kappa$, $i \geq 2$ and $\bar{\delta}_1 = \kappa + \mu$;
- ▶ Only healthy individuals can be infected, and infections with i parasites occur at a rate $\lambda \sum_{l \geq 1} x^l p_{ll}$, so that $\beta_i(x) = \lambda \sum_{l \geq 1} x^l p_{ll}$, $i \geq 1$, and all $\alpha_{ij}(x) = \delta_i(x) = 0$;

Luchsinger's linear model

- ▶ Tacitly assume **infinite** pool of potential infectives, so no **0**-coordinate needed;
- ▶ Only infected hosts are of interest, their number may vary;
- ▶ $\bar{\alpha}$ is a generator of simple death process rate $\mu > 0$, but restricted to reduced state space, so $\bar{\alpha}_{i,j-1} = i\mu$, $i \geq 2$;
- ▶ incorporate hosts losing infection by taking $\bar{\delta}_i = \kappa$, $i \geq 2$ and $\bar{\delta}_1 = \kappa + \mu$;
- ▶ Only healthy individuals can be infected, and infections with i parasites occur at a rate $\lambda \sum_{j \geq 1} x^j p_{ij}$, so that $\beta_i(x) = \lambda \sum_{j \geq 1} x^j p_{ij}$, $i \geq 1$, and all $\alpha_{ij}(x) = \delta_i(x) = 0$;

Luchsinger's linear model

- ▶ Tacitly assume **infinite** pool of potential infectives, so no **0**-coordinate needed;
- ▶ Only infected hosts are of interest, their number may vary;
- ▶ $\bar{\alpha}$ is a generator of simple death process rate $\mu > 0$, but restricted to reduced state space, so $\bar{\alpha}_{i,j-1} = i\mu$, $i \geq 2$;
- ▶ incorporate hosts losing infection by taking $\bar{\delta}_i = \kappa$, $i \geq 2$ and $\bar{\delta}_1 = \kappa + \mu$;
- ▶ Only healthy individuals can be infected, and infections with i parasites occur at a rate $\lambda \sum_{l \geq 1} x^l p_{ll}$, so that $\beta_i(x) = \lambda \sum_{l \geq 1} x^l p_{ll}$, $i \geq 1$, and all $\alpha_{ij}(x) = \delta_{ij}(x) = 0$;

Luchsinger's linear model

- ▶ Tacitly assume **infinite** pool of potential infectives, so no **0**-coordinate needed;
- ▶ Only infected hosts are of interest, their number may vary;
- ▶ $\bar{\alpha}$ is a generator of simple death process rate $\mu > 0$, but restricted to reduced state space, so $\bar{\alpha}_{i,j-1} = i\mu$, $i \geq 2$;
- ▶ incorporate hosts losing infection by taking $\bar{\delta}_i = \kappa$, $i \geq 2$ and $\bar{\delta}_1 = \kappa + \mu$;
- ▶ Only healthy individuals can be infected, and infections with i parasites occur at a rate $\lambda \sum_{l \geq 1} x^l p_{li}$, so that $\beta_i(x) = \lambda \sum_{l \geq 1} x^l p_{li}$, $i \geq 1$, and all $\alpha_{ij}(x) = \delta_i(x) = 0$;

Luchsinger's linear model

- ▶ Tacitly assume **infinite** pool of potential infectives, so no **0**-coordinate needed;
- ▶ Only infected hosts are of interest, their number may vary;
- ▶ $\bar{\alpha}$ is a generator of simple death process rate $\mu > 0$, but restricted to reduced state space, so $\bar{\alpha}_{i,j-1} = i\mu$, $i \geq 2$;
- ▶ incorporate hosts losing infection by taking $\bar{\delta}_i = \kappa$, $i \geq 2$ and $\bar{\delta}_1 = \kappa + \mu$;
- ▶ Only healthy individuals can be infected, and infections with i parasites occur at a rate $\lambda \sum_{l \geq 1} x^l p_{li}$, so that $\beta_i(x) = \lambda \sum_{l \geq 1} x^l p_{li}$, $i \geq 1$, and all $\alpha_{ij}(x) = \delta_i(x) = 0$;

Luchsinger's linear model

- ▶ Tacitly assume **infinite** pool of potential infectives, so no **0**-coordinate needed;
- ▶ Only infected hosts are of interest, their number may vary;
- ▶ $\bar{\alpha}$ is a generator of simple death process rate $\mu > 0$, but restricted to reduced state space, so $\bar{\alpha}_{i,j-1} = i\mu$, $i \geq 2$;
- ▶ incorporate hosts losing infection by taking $\bar{\delta}_i = \kappa$, $i \geq 2$ and $\bar{\delta}_1 = \kappa + \mu$;
- ▶ Only healthy individuals can be infected, and infections with i parasites occur at a rate $\lambda \sum_{l \geq 1} x^l p_{li}$, so that $\beta_i(x) = \lambda \sum_{l \geq 1} x^l p_{li}$, $i \geq 1$, and all $\alpha_{il}(x) = \delta_i(x) = 0$;

Proof

- ▶ What kind of obstacles are we likely to encounter?
- ▶ The first one is to establish that the candidate limit differential equation has a (unique) solution.
- ▶ This is not straightforward, as we are working in infinite dimensions.
- ▶ The representation

$$\frac{dx}{dt} = Ax + F(x),$$

with A a linear operator and F a 'nice' operator is crucial to establishing existence and uniqueness of solution x .

Proof

- ▶ What kind of obstacles are we likely to encounter?
- ▶ The first one is to establish that the candidate limit differential equation has a (unique) solution.
- ▶ This is not straightforward, as we are working in infinite dimensions.
- ▶ The representation

$$\frac{dx}{dt} = Ax + F(x),$$

with A a linear operator and F a 'nice' operator is crucial to establishing existence and uniqueness of solution x .

Proof

- ▶ What kind of obstacles are we likely to encounter?
- ▶ The first one is to establish that the candidate limit differential equation has a (unique) solution.
- ▶ This is not straightforward, as we are working in infinite dimensions.
- ▶ The representation

$$\frac{dx}{dt} = Ax + F(x),$$

with A a linear operator and F a 'nice' operator is crucial to establishing existence and uniqueness of solution x .

Proof

- ▶ What kind of obstacles are we likely to encounter?
- ▶ The first one is to establish that the candidate limit differential equation has a (unique) solution.
- ▶ This is not straightforward, as we are working in infinite dimensions.
- ▶ The representation

$$\frac{dx}{dt} = Ax + F(x),$$

with A a linear operator and F a 'nice' operator is crucial to establishing existence and uniqueness of solution x .

Technical device: $\bar{\alpha}_{ij}$

- ▶ Let Δ denote an absorbing 'cemetery' state (host's death).
- ▶ Let

$$\bar{\alpha}_{i,\Delta} := \bar{\delta}_i, \quad \bar{\alpha}_{ij} := -\alpha^*(i) - \bar{\delta}_i, \quad i \geq 0,$$

where $\alpha^*(i) := \sum_{j \geq 0, j \neq i} \bar{\alpha}_{ij}$.

- ▶ Then $\bar{\alpha}$ is the infinitesimal matrix of a time homogeneous pure jump Markov process W on $\mathbb{Z}_+ \cup \Delta$.

Technical device: $\bar{\alpha}_{ij}$

- ▶ Let Δ denote an absorbing 'cemetery' state (host's death).
- ▶ Let

$$\bar{\alpha}_{i,\Delta} := \bar{\delta}_i, \quad \bar{\alpha}_{ij} := -\alpha^*(i) - \bar{\delta}_i, \quad i \geq 0,$$

where $\alpha^*(i) := \sum_{j \geq 0, j \neq i} \bar{\alpha}_{ij}$.

- ▶ Then $\bar{\alpha}$ is the infinitesimal matrix of a time homogeneous pure jump Markov process W on $\mathbb{Z}_+ \cup \Delta$.

Technical device: $\bar{\alpha}_{ij}$

- ▶ Let Δ denote an absorbing 'cemetery' state (host's death).
- ▶ Let

$$\bar{\alpha}_{i,\Delta} := \bar{\delta}_i, \quad \bar{\alpha}_{ij} := -\alpha^*(i) - \bar{\delta}_i, \quad i \geq 0,$$

where $\alpha^*(i) := \sum_{j \geq 0, j \neq i} \bar{\alpha}_{ij}$.

- ▶ Then $\bar{\alpha}$ is the infinitesimal matrix of a time homogeneous pure jump Markov process W on $\mathbb{Z}_+ \cup \Delta$.

Technical device: $\bar{\alpha}_{ij}$

- ▶ Let Δ denote an absorbing 'cemetery' state (host's death).
- ▶ Let

$$\bar{\alpha}_{i,\Delta} := \bar{\delta}_i, \quad \bar{\alpha}_{ij} := -\alpha^*(i) - \bar{\delta}_i, \quad i \geq 0,$$

where $\alpha^*(i) := \sum_{j \geq 0, j \neq i} \bar{\alpha}_{ij}$.

- ▶ Then $\bar{\alpha}$ is the infinitesimal matrix of a time homogeneous pure jump Markov process W on $\mathbb{Z}_+ \cup \Delta$.

Semigroups

- ▶ Then in our representation, the adjoint A^T of A is the Q -matrix of a time-homogeneous pure jump Markov process.
- ▶ By standard theory, the semigroup $T(t)$ it generates is strongly continuous on ℓ_1 .
- ▶ However, we need it to be strongly continuous on ℓ_{11} , and we prove this is the case under our assumptions.
- ▶ We further show that F is locally ℓ_{11} -Lipschitz continuous, and then the existence and uniqueness of a continuous (weak) solution in ℓ_{11} follows.

Semigroups

- ▶ Then in our representation, the adjoint A^T of A is the Q -matrix of a time-homogeneous pure jump Markov process.
- ▶ By standard theory, the semigroup $T(t)$ it generates is strongly continuous on ℓ_1 .
- ▶ However, we need it to be strongly continuous on ℓ_{11} , and we prove this is the case under our assumptions.
- ▶ We further show that F is locally ℓ_{11} -Lipschitz continuous, and then the existence and uniqueness of a continuous (weak) solution in ℓ_{11} follows.

Semigroups

- ▶ Then in our representation, the adjoint A^T of A is the Q -matrix of a time-homogeneous pure jump Markov process.
- ▶ By standard theory, the semigroup $T(t)$ it generates is strongly continuous on ℓ_1 .
- ▶ However, we need it to be strongly continuous on ℓ_{11} , and we prove this is the case under our assumptions.
- ▶ We further show that F is locally ℓ_{11} -Lipschitz continuous, and then the existence and uniqueness of a continuous (weak) solution in ℓ_{11} follows.

Semigroups

- ▶ Then in our representation, the adjoint A^T of A is the Q -matrix of a time-homogeneous pure jump Markov process.
- ▶ By standard theory, the semigroup $T(t)$ it generates is strongly continuous on ℓ_1 .
- ▶ However, we need it to be strongly continuous on ℓ_{11} , and we prove this is the case under our assumptions.
- ▶ We further show that F is locally ℓ_{11} -Lipschitz continuous, and then the existence and uniqueness of a continuous (weak) solution in ℓ_{11} follows.

Mild solution

Every solution x also satisfies

$$x(t) = T(t)x(0) + \int_0^t T(t-s)F(x(s)) ds,$$

where $T(t)$ is the C_0 semigroup generated by A .

Conversely, a continuous solution x of the integral equation is called a mild solution of the initial value problem.

Mild solution

Every solution x also satisfies

$$x(t) = T(t)x(0) + \int_0^t T(t-s)F(x(s)) ds,$$

where $T(t)$ is the C_0 semigroup generated by A .

Conversely, a continuous solution x of the integral equation is called a mild solution of the initial value problem.

Mild solution

Every solution x also satisfies

$$x(t) = T(t)x(0) + \int_0^t T(t-s)F(x(s)) ds,$$

where $T(t)$ is the C_0 semigroup generated by A .

Conversely, a continuous solution x of the integral equation is called a mild solution of the initial value problem.

Mild solution

Every solution x also satisfies

$$x(t) = T(t)x(0) + \int_0^t T(t-s)F(x(s)) ds,$$

where $T(t)$ is the C_0 semigroup generated by A .

Conversely, a continuous solution x of the integral equation is called a **mild** solution of the initial value problem.

Mild solution

The following result guarantees the existence and uniqueness of a mild solution if F is Lipschitz.

Theorem (Pazy 1983, Theorem 1.4, Chapter 6)

Let $F : S \rightarrow S$ be locally Lipschitz continuous. If A is the infinitesimal generator of a C_0 semigroup e^{tA} on S then for every $x_0 \in S$ there is a $t_{\max} \leq \infty$ such that the initial value problem

$$\frac{dx}{dt} = Ax + F(x), \quad x(0) \in S,$$

has a unique mild solution x on $[0, t_{\max})$. Moreover, if $t_{\max} < \infty$, then $\lim_{t \uparrow t_{\max}} \|x\| = \infty$.

Mild solution

The following result guarantees the existence and uniqueness of a mild solution if F is Lipschitz.

Theorem (Pazy 1983, Theorem 1.4, Chapter 6)

Let $F : S \rightarrow S$ be locally Lipschitz continuous. If A is the infinitesimal generator of a C_0 semigroup e^{tA} on S then for every $x_0 \in S$ there is a $t_{\max} \leq \infty$ such that the initial value problem

$$\frac{dx}{dt} = Ax + F(x), \quad x(0) \in S,$$

has a unique mild solution x on $[0, t_{\max})$. Moreover, if $t_{\max} < \infty$, then $\lim_{t \uparrow t_{\max}} \|x\| = \infty$.

Mild solution

The following result guarantees the existence and uniqueness of a mild solution if F is Lipschitz.

Theorem (Pazy 1983, Theorem 1.4, Chapter 6)

Let $F : S \rightarrow S$ be locally Lipschitz continuous. If A is the infinitesimal generator of a C_0 semigroup e^{tA} on S then for every $x_0 \in S$ there is a $t_{\max} \leq \infty$ such that the initial value problem

$$\frac{dx}{dt} = Ax + F(x), \quad x(0) \in S,$$

has a unique mild solution x on $[0, t_{\max})$. Moreover, if $t_{\max} < \infty$, then $\lim_{t \uparrow t_{\max}} \|x\| = \infty$.

Mild solution

The following result guarantees the existence and uniqueness of a mild solution if F is Lipschitz.

Theorem (Pazy 1983, Theorem 1.4, Chapter 6)

Let $F : S \rightarrow S$ be locally Lipschitz continuous. If A is the infinitesimal generator of a C_0 semigroup e^{tA} on S then for every $x_0 \in S$ there is a $t_{\max} \leq \infty$ such that the initial value problem

$$\frac{dx}{dt} = Ax + F(x), \quad x(0) \in S,$$

has a unique mild solution x on $[0, t_{\max})$. Moreover, if $t_{\max} < \infty$, then $\lim_{t \uparrow t_{\max}} \|x\| = \infty$.

In other words, our infinite-dimensional differential equation has a unique **weak** solution, so we at least have a function x_N to give substance to our limit result.

In fact, we also show that, under our conditions, x_N is a classical solution to the differential equation system.

- ▶ It would naturally be good to have $t_{max} = \infty$.
- ▶ However, our assumptions may not be enough to guarantee that this is true.
- ▶ On the other hand, $t_{max} = \infty$ if, for some $C < \infty$,

$$\|F(x)\|_{11} \leq C \|x\|_{11}.$$

- ▶ This is the case, for example, in Luchsinger's models.

- ▶ It would naturally be good to have $t_{max} = \infty$.
- ▶ However, our assumptions may not be enough to guarantee that this is true.
- ▶ On the other hand, $t_{max} = \infty$ if, for some $C < \infty$,

$$\|F(x)\|_{11} \leq C\|x\|_{11}.$$

- ▶ This is the case, for example, in Luchsinger's models.

- ▶ It would naturally be good to have $t_{max} = \infty$.
- ▶ However, our assumptions may not be enough to guarantee that this is true.
- ▶ On the other hand, $t_{max} = \infty$ if, for some $C < \infty$,

$$\|F(x)\|_{11} \leq C\|x\|_{11}.$$

- ▶ This is the case, for example, in Luchsinger's models.

- ▶ It would naturally be good to have $t_{max} = \infty$.
- ▶ However, our assumptions may not be enough to guarantee that this is true.
- ▶ On the other hand, $t_{max} = \infty$ if, for some $C < \infty$,

$$\|F(x)\|_{11} \leq C\|x\|_{11}.$$

- ▶ This is the case, for example, in Luchsinger's models.

- ▶ It would naturally be good to have $t_{max} = \infty$.
- ▶ However, our assumptions may not be enough to guarantee that this is true.
- ▶ On the other hand, $t_{max} = \infty$ if, for some $C < \infty$,

$$\|F(x)\|_{11} \leq C\|x\|_{11}.$$

- ▶ This is the case, for example, in Luchsinger's models.

Smooth dependence on initial conditions

- ▶ Our solution depends smoothly on initial conditions within the interval of existence.
- ▶ Useful for approximating sequence of processes, if initial condition not fixed for all N , but $N^{-1}X_N(0) \rightarrow x(0)$; gives the same order of approximation if we replace x_N by x .

Lemma

Fix a solution x to the integral equation, and suppose that $T < t_{max}$. Then there is an $\varepsilon > 0$ such that, if y is a solution with initial condition $y(0)$ satisfying $\|y - x\|_{11} \leq \varepsilon$, then

$$\sup_{0 \leq t \leq T} \|x(t) - y(t)\|_{11} \leq \|x(0) - y(0)\|_{11} C_T,$$

for a constant $C_T < \infty$.

Smooth dependence on initial conditions

- ▶ Our solution depends smoothly on initial conditions within the interval of existence.
- ▶ Useful for approximating sequence of processes, if initial condition not fixed for all N , but $N^{-1}X_N(0) \rightarrow x(0)$; gives the same order of approximation if we replace x_N by x .

Lemma

Fix a solution x to the integral equation, and suppose that $T < t_{max}$. Then there is an $\varepsilon > 0$ such that, if y is a solution with initial condition $y(0)$ satisfying $\|y - x\|_{11} \leq \varepsilon$, then

$$\sup_{0 \leq t \leq T} \|x(t) - y(t)\|_{11} \leq \|x(0) - y(0)\|_{11} C_T,$$

for a constant $C_T < \infty$.

Smooth dependence on initial conditions

- ▶ Our solution depends smoothly on initial conditions within the interval of existence.
- ▶ Useful for approximating sequence of processes, if initial condition not fixed for all N , but $N^{-1}X_N(0) \rightarrow x(0)$; gives the same order of approximation if we replace x_N by x .

Lemma

Fix a solution x to the integral equation, and suppose that $T < t_{max}$. Then there is an $\varepsilon > 0$ such that, if y is a solution with initial condition $y(0)$ satisfying $\|y - x\|_{11} \leq \varepsilon$, then

$$\sup_{0 \leq t \leq T} \|x(t) - y(t)\|_{11} \leq \|x(0) - y(0)\|_{11} C_T,$$

for a constant $C_T < \infty$.

Smooth dependence on initial conditions

- ▶ Our solution depends smoothly on initial conditions within the interval of existence.
- ▶ Useful for approximating sequence of processes, if initial condition not fixed for all N , but $N^{-1}X_N(0) \rightarrow x(0)$; gives the same order of approximation if we replace x_N by x .

Lemma

Fix a solution x to the integral equation, and suppose that $T < t_{max}$. Then there is an $\varepsilon > 0$ such that, if y is a solution with initial condition $y(0)$ satisfying $\|y - x\|_{11} \leq \varepsilon$, then

$$\sup_{0 \leq t \leq T} \|x(t) - y(t)\|_{11} \leq \|x(0) - y(0)\|_{11} C_T,$$

for a constant $C_T < \infty$.

Smooth dependence on initial conditions

- ▶ Our solution depends smoothly on initial conditions within the interval of existence.
- ▶ Useful for approximating sequence of processes, if initial condition not fixed for all N , but $N^{-1}X_N(0) \rightarrow x(0)$; gives the same order of approximation if we replace x_N by x .

Lemma

Fix a solution x to the integral equation, and suppose that $T < t_{max}$. Then there is an $\varepsilon > 0$ such that, if y is a solution with initial condition $y(0)$ satisfying $\|y - x\|_{11} \leq \varepsilon$, then

$$\sup_{0 \leq t \leq T} \|x(t) - y(t)\|_{11} \leq \|x(0) - y(0)\|_{11} C_T,$$

for a constant $C_T < \infty$.

Two-stage approximation

The rest of our proof goes in two stages:

- ▶ First we construct an approximating model $\tilde{X}_N(\cdot)$, starting with $\tilde{X}_N(0) = X_N(0)$, and consisting of independent individuals.
- ▶ The process \tilde{X}_N differs from X_N in having the non-linear elements of the transition rates made linear, by replacing the Lipschitz state-dependent elements $\alpha_{ij}(x), \beta_i(x), \delta_i(x)$ at any time t by their 'typical' values, derived from the differential equation.
- ▶ Standard Chernoff-type bounds show that $\tilde{X}_N(\cdot)$ stays close to $x_N(t)$ throughout $[0, T]$.
- ▶ Then we couple $\tilde{X}_N(\cdot)$ and $X_N(\cdot)$ so that the distance between them is small throughout $[0, T]$.

Two-stage approximation

The rest of our proof goes in two stages:

- ▶ First we construct an approximating model $\tilde{X}_N(\cdot)$, starting with $\tilde{X}_N(0) = X_N(0)$, and consisting of independent individuals.
- ▶ The process \tilde{X}_N differs from X_N in having the non-linear elements of the transition rates made linear, by replacing the Lipschitz state-dependent elements $\alpha_{ij}(x), \beta_i(x), \delta_i(x)$ at any time t by their 'typical' values, derived from the differential equation.
- ▶ Standard Chernoff-type bounds show that $\tilde{X}_N(\cdot)$ stays close to $x_N(t)$ throughout $[0, T]$.
- ▶ Then we couple $\tilde{X}_N(\cdot)$ and $X_N(\cdot)$ so that the distance between them is small throughout $[0, T]$.

Two-stage approximation

The rest of our proof goes in two stages:

- ▶ First we construct an approximating model $\tilde{X}_N(\cdot)$, starting with $\tilde{X}_N(0) = X_N(0)$, and consisting of independent individuals.
- ▶ The process \tilde{X}_N differs from X_N in having the non-linear elements of the transition rates made linear, by replacing the Lipschitz state-dependent elements $\alpha_{ij}(x), \beta_i(x), \delta_i(x)$ at any time t by their 'typical' values, derived from the differential equation.
- ▶ Standard Chernoff-type bounds show that $\tilde{X}_N(\cdot)$ stays close to $x_N(t)$ throughout $[0, T]$.
- ▶ Then we couple $\tilde{X}_N(\cdot)$ and $X_N(\cdot)$ so that the distance between them is small throughout $[0, T]$.

Two-stage approximation

The rest of our proof goes in two stages:

- ▶ First we construct an approximating model $\tilde{X}_N(\cdot)$, starting with $\tilde{X}_N(0) = X_N(0)$, and consisting of independent individuals.
- ▶ The process \tilde{X}_N differs from X_N in having the non-linear elements of the transition rates made linear, by replacing the Lipschitz state-dependent elements $\alpha_{ij}(x), \beta_i(x), \delta_i(x)$ at any time t by their 'typical' values, derived from the differential equation.
- ▶ Standard Chernoff-type bounds show that $\tilde{X}_N(\cdot)$ stays close to $x_N(t)$ throughout $[0, T]$.
- ▶ Then we couple $\tilde{X}_N(\cdot)$ and $X_N(\cdot)$ so that the distance between them is small throughout $[0, T]$.

Two-stage approximation

The rest of our proof goes in two stages:

- ▶ First we construct an approximating model $\tilde{X}_N(\cdot)$, starting with $\tilde{X}_N(0) = X_N(0)$, and consisting of independent individuals.
- ▶ The process \tilde{X}_N differs from X_N in having the non-linear elements of the transition rates made linear, by replacing the Lipschitz state-dependent elements $\alpha_{ij}(x), \beta_i(x), \delta_i(x)$ at any time t by their 'typical' values, derived from the differential equation.
- ▶ Standard Chernoff-type bounds show that $\tilde{X}_N(\cdot)$ stays close to $x_N(t)$ throughout $[0, T]$.
- ▶ Then we couple $\tilde{X}_N(\cdot)$ and $X_N(\cdot)$ so that the distance between them is small throughout $[0, T]$.

Independent process transition rates

Individual's parasite load evolves according to a time inhomogeneous Markov process \widetilde{W} on $\mathbb{Z}_+ \cup \Delta$ with infinitesimal matrix

$$\begin{aligned}q_{lj}(t) &= \bar{\alpha}_{lj} + \tilde{\alpha}_{lj}(t), & j \neq l, \Delta, l \geq 0, \\q_{l,\Delta}(t) &= \bar{\delta}_l + \tilde{\delta}_l(t), & l \geq 0, \\q_{ll}(t) &= -\sum_{j \neq l} q_{lj}(t) - \bar{\delta}_l - \tilde{\delta}_l(t), & l \geq 0,\end{aligned}\quad (4.1)$$

where

$$\tilde{\alpha}_{ll}(t) := \alpha_{ll}(x_N(t)); \quad \tilde{\delta}_l(t) := \delta_l(x_N(t)). \quad (4.2)$$

Individuals also immigrate with rates

$$N\tilde{\beta}_i(t) := N\beta_i(x_N(t)). \quad (4.3)$$

Independent process transition rates

Individual's parasite load evolves according to a time inhomogeneous Markov process \widetilde{W} on $\mathbb{Z}_+ \cup \Delta$ with infinitesimal matrix

$$\begin{aligned}q_{lj}(t) &= \bar{\alpha}_{lj} + \tilde{\alpha}_{lj}(t), & j \neq l, \Delta, l \geq 0, \\q_{l,\Delta}(t) &= \bar{\delta}_l + \tilde{\delta}_l(t), & l \geq 0, \\q_{ll}(t) &= -\sum_{j \neq l} q_{lj}(t) - \bar{\delta}_l - \tilde{\delta}_l(t), & l \geq 0,\end{aligned}\quad (4.1)$$

where

$$\tilde{\alpha}_{ll}(t) := \alpha_{ll}(x_N(t)); \quad \tilde{\delta}_l(t) := \delta_l(x_N(t)). \quad (4.2)$$

Individuals also immigrate with rates

$$N\tilde{\beta}_i(t) := N\beta_i(x_N(t)). \quad (4.3)$$

Independent process transition rates

Individual's parasite load evolves according to a time inhomogeneous Markov process \widetilde{W} on $\mathbb{Z}_+ \cup \Delta$ with infinitesimal matrix

$$\begin{aligned}q_{lj}(t) &= \bar{\alpha}_{lj} + \tilde{\alpha}_{lj}(t), & j \neq l, \Delta, l \geq 0, \\q_{l,\Delta}(t) &= \bar{\delta}_l + \tilde{\delta}_l(t), & l \geq 0, \\q_{ll}(t) &= -\sum_{j \neq l} q_{lj}(t) - \bar{\delta}_l - \tilde{\delta}_l(t), & l \geq 0,\end{aligned}\quad (4.1)$$

where

$$\tilde{\alpha}_{il}(t) := \alpha_{il}(x_N(t)); \quad \tilde{\delta}_i(t) := \delta_i(x_N(t)). \quad (4.2)$$

Individuals also immigrate with rates

$$N\tilde{\beta}_i(t) := N\beta_i(x_N(t)). \quad (4.3)$$

Independent process transition rates

Individual's parasite load evolves according to a time inhomogeneous Markov process \widetilde{W} on $\mathbb{Z}_+ \cup \Delta$ with infinitesimal matrix

$$\begin{aligned}q_{lj}(t) &= \bar{\alpha}_{lj} + \tilde{\alpha}_{lj}(t), & j \neq I, \Delta, \quad l \geq 0, \\q_{l,\Delta}(t) &= \bar{\delta}_l + \tilde{\delta}_l(t), & l \geq 0, \\q_{ll}(t) &= -\sum_{j \neq l} q_{lj}(t) - \bar{\delta}_l - \tilde{\delta}_l(t), & l \geq 0,\end{aligned}\quad (4.1)$$

where

$$\tilde{\alpha}_{ij}(t) := \alpha_{ij}(x_N(t)); \quad \tilde{\delta}_i(t) := \delta_i(x_N(t)). \quad (4.2)$$

Individuals also immigrate with rates

$$N\tilde{\beta}_i(t) := N\beta_i(x_N(t)). \quad (4.3)$$

Independent process transition rates

Individual's parasite load evolves according to a time inhomogeneous Markov process \widetilde{W} on $\mathbb{Z}_+ \cup \Delta$ with infinitesimal matrix

$$\begin{aligned}q_{lj}(t) &= \bar{\alpha}_{lj} + \tilde{\alpha}_{lj}(t), & j \neq l, \Delta, l \geq 0, \\q_{l,\Delta}(t) &= \bar{\delta}_l + \tilde{\delta}_l(t), & l \geq 0, \\q_{ll}(t) &= -\sum_{j \neq l} q_{lj}(t) - \bar{\delta}_l - \tilde{\delta}_l(t), & l \geq 0,\end{aligned}\quad (4.1)$$

where

$$\tilde{\alpha}_{ij}(t) := \alpha_{ij}(x_N(t)); \quad \tilde{\delta}_i(t) := \delta_i(x_N(t)). \quad (4.2)$$

Individuals also immigrate with rates

$$N\tilde{\beta}_i(t) := N\beta_i(x_N(t)). \quad (4.3)$$

Linearised process deviations

$N^{-1}\tilde{X}_N(t)$ and $x(t)$ stay 'close' together.

Lemma

Suppose that our assumptions hold, and that $X_N(0) \in \ell_{11}$. Then, for any $t \in [0, T]$ with $T < t_{max}^N$,

$$\mathbb{E} \|\tilde{X}_N(t) - Nx_N(t)\|_1 \leq 3(M_T^N + 1) \sqrt{N \log N},$$

where $M_T^N = \sup_{0 \leq t \leq T} \sum_{i \geq 1} (i+1) |x_N^i(t)|$. Furthermore, for any $r > 0$, there exist constants $K_r^{(1)} > 1, K_r^{(2)}$ such that

$$\mathbb{P}[\|\tilde{X}_N(t) - Nx_N(t)\|_1 > K_r^{(1)} (M_T^N + 1) N^{1/2} \log^{3/2} N] \leq K_r^{(2)} G_T^N(1) N^{-r},$$

where $G_T^N = \sup_{0 \leq t \leq T} \sum_{i \geq 0} |x_N^i(t)|$.

Linearised process deviations

$N^{-1}\tilde{X}_N(t)$ and $x(t)$ stay 'close' together.

Lemma

Suppose that our assumptions hold, and that $X_N(0) \in \ell_{11}$. Then, for any $t \in [0, T]$ with $T < t_{max}^N$,

$$\mathbb{E} \|\tilde{X}_N(t) - Nx_N(t)\|_1 \leq 3(M_T^N + 1) \sqrt{N \log N},$$

where $M_T^N = \sup_{0 \leq t \leq T} \sum_{i \geq 1} (i+1) |x_N^i(t)|$. Furthermore, for any $r > 0$, there exist constants $K_r^{(1)} > 1, K_r^{(2)}$ such that

$$\mathbb{P}[\|\tilde{X}_N(t) - Nx_N(t)\|_1 > K_r^{(1)} (M_T^N + 1) N^{1/2} \log^{3/2} N] \leq K_r^{(2)} G_T^N(1) N^{-r},$$

where $G_T^N = \sup_{0 \leq t \leq T} \sum_{i \geq 0} |x_N^i(t)|$.

Linearised process deviations

$N^{-1}\tilde{X}_N(t)$ and $x(t)$ stay 'close' together.

Lemma

Suppose that our assumptions hold, and that $X_N(0) \in \ell_{11}$. Then, for any $t \in [0, T]$ with $T < t_{max}^N$,

$$\mathbb{E} \|\tilde{X}_N(t) - Nx_N(t)\|_1 \leq 3(M_T^N + 1) \sqrt{N \log N},$$

where $M_T^N = \sup_{0 \leq t \leq T} \sum_{i \geq 1} (i+1) |x_N^i(t)|$. Furthermore, for any $r > 0$, there exist constants $K_r^{(1)} > 1, K_r^{(2)}$ such that

$$\mathbb{P}[\|\tilde{X}_N(t) - Nx_N(t)\|_1 > K_r^{(1)} (M_T^N + 1) N^{1/2} \log^{3/2} N] \leq K_r^{(2)} G_T^N(1) N^{-r},$$

where $G_T^N = \sup_{0 \leq t \leq T} \sum_{i \geq 0} |x_N^i(t)|$.

Linearised process deviations

$N^{-1}\tilde{X}_N(t)$ and $x(t)$ stay 'close' together.

Lemma

Suppose that our assumptions hold, and that $X_N(0) \in \ell_{11}$. Then, for any $t \in [0, T]$ with $T < t_{max}^N$,

$$\mathbf{E} \|\tilde{X}_N(t) - Nx_N(t)\|_1 \leq 3(M_T^N + 1)\sqrt{N \log N},$$

where $M_T^N = \sup_{0 \leq t \leq T} \sum_{i \geq 1} (i+1)|x_N^i(t)|$. Furthermore, for any $r > 0$, there exist constants $K_r^{(1)} > 1, K_r^{(2)}$ such that

$$\mathbf{P}[\|\tilde{X}_N(t) - Nx_N(t)\|_1 > K_r^{(1)}(M_T^N + 1)N^{1/2} \log^{3/2} N] \leq K_r^{(2)} G_T^N(1)N^{-r},$$

where $G_T^N = \sup_{0 \leq t \leq T} \sum_{i \geq 0} |x_N^i(t)|$.

Linearised process deviations

$N^{-1}\tilde{X}_N(t)$ and $x(t)$ stay 'close' together.

Lemma

Suppose that our assumptions hold, and that $X_N(0) \in \ell_{11}$. Then, for any $t \in [0, T]$ with $T < t_{max}^N$,

$$\mathbf{E}\|\tilde{X}_N(t) - Nx_N(t)\|_1 \leq 3(M_T^N + 1)\sqrt{N \log N},$$

where $M_T^N = \sup_{0 \leq t \leq T} \sum_{i \geq 1} (i+1)|x_N^i(t)|$. Furthermore, for any $r > 0$, there exist constants $K_r^{(1)} > 1, K_r^{(2)}$ such that

$$\mathbf{P}[\|\tilde{X}_N(t) - Nx_N(t)\|_1 > K_r^{(1)}(M_T^N + 1)N^{1/2} \log^{3/2} N] \leq K_r^{(2)} G_T^N(1)N^{-r},$$

where $G_T^N = \sup_{0 \leq t \leq T} \sum_{i \geq 0} |x_N^i(t)|$.

Linearised process deviations

$N^{-1}\tilde{X}_N(t)$ and $x(t)$ stay 'close' together.

Lemma

Suppose that our assumptions hold, and that $X_N(0) \in \ell_{11}$. Then, for any $t \in [0, T]$ with $T < t_{\max}^N$,

$$\mathbf{E}\|\tilde{X}_N(t) - Nx_N(t)\|_1 \leq 3(M_T^N + 1)\sqrt{N \log N},$$

where $M_T^N = \sup_{0 \leq t \leq T} \sum_{i \geq 1} (i+1)|x_N^i(t)|$. Furthermore, for any $r > 0$, there exist constants $K_r^{(1)} > 1, K_r^{(2)}$ such that

$$\mathbf{P}[\|\tilde{X}_N(t) - Nx_N(t)\|_1 > K_r^{(1)}(M_T^N + 1)N^{1/2} \log^{3/2} N] \leq K_r^{(2)} G_T^N(1)N^{-r},$$

where $G_T^N = \sup_{0 \leq t \leq T} \sum_{i \geq 0} |x_N^i(t)|$.

Coupling strategy

- ▶ To estimate deviations of \tilde{X}_N from X_N we couple them so “distance” between them is small over any finite interval.
- ▶ We pair each individual in state $i \geq 1$ in $X_N(0)$ with individual in state i in $\tilde{X}_N(0)$ so all their $\bar{\alpha}$ - and $\bar{\delta}$ -transitions are identical.
- ▶ Rates of remaining transitions not quite the same, and hence processes can gradually drift apart.
- ▶ Strategy: make transitions identical as far as we can; once a transition in one process is not matched in the other, the individuals are decoupled thereafter.
- ▶ We show that number of decoupled pairs is small.

Coupling strategy

- ▶ To estimate deviations of \tilde{X}_N from X_N we couple them so “distance” between them is small over any finite interval.
- ▶ We pair each individual in state $i \geq 1$ in $X_N(0)$ with individual in state i in $\tilde{X}_N(0)$ so all their $\bar{\alpha}$ - and $\bar{\delta}$ -transitions are identical.
- ▶ Rates of remaining transitions not quite the same, and hence processes can gradually drift apart.
- ▶ *Strategy*: make transitions identical as far as we can; once a transition in one process is not matched in the other, the individuals are decoupled thereafter.
- ▶ We show that number of decoupled pairs is small.

Coupling strategy

- ▶ To estimate deviations of \tilde{X}_N from X_N we couple them so “distance” between them is small over any finite interval.
- ▶ We pair each individual in state $i \geq 1$ in $X_N(0)$ with individual in state i in $\tilde{X}_N(0)$ so all their $\bar{\alpha}$ - and $\bar{\delta}$ -transitions are identical.
- ▶ Rates of remaining transitions not quite the same, and hence processes can gradually drift apart.
- ▶ *Strategy*: make transitions identical as far as we can; once a transition in one process is not matched in the other, the individuals are decoupled thereafter.
- ▶ We show that number of decoupled pairs is small.

Coupling strategy

- ▶ To estimate deviations of \tilde{X}_N from X_N we couple them so “distance” between them is small over any finite interval.
- ▶ We pair each individual in state $i \geq 1$ in $X_N(0)$ with individual in state i in $\tilde{X}_N(0)$ so all their $\bar{\alpha}$ - and $\bar{\delta}$ -transitions are identical.
- ▶ Rates of remaining transitions not quite the same, and hence processes can gradually drift apart.
- ▶ **Strategy:** make transitions identical as far as we can; once a transition in one process is not matched in the other, the individuals are decoupled thereafter.
- ▶ We show that number of decoupled pairs is small.

Coupling strategy

- ▶ To estimate deviations of \tilde{X}_N from X_N we couple them so “distance” between them is small over any finite interval.
- ▶ We pair each individual in state $i \geq 1$ in $X_N(0)$ with individual in state i in $\tilde{X}_N(0)$ so all their $\bar{\alpha}$ - and $\bar{\delta}$ -transitions are identical.
- ▶ Rates of remaining transitions not quite the same, and hence processes can gradually drift apart.
- ▶ **Strategy:** make transitions identical as far as we can; once a transition in one process is not matched in the other, the individuals are decoupled thereafter.
- ▶ We show that number of decoupled pairs is small.

Coupling details

- ▶ Coupling between X_N and \tilde{X}_N realised via a process $Z(\cdot)$ with

$$Z(t) = ((Z_l^i(t), i \geq 0, 1 \leq l \leq 3), Z_4(t)) \in \mathcal{X}^3 \times \mathbb{Z}_+.$$

- ▶ Here, $X_N(\cdot) = Z_1(\cdot) + Z_2(\cdot)$ and $\tilde{X}_N(\cdot) = Z_1(\cdot) + Z_3(\cdot)$.
- ▶ Also $Z_1(0) = X_N(0) = \tilde{X}_N(0)$, $Z_2(0) = Z_3(0) = 0 \in \mathcal{X}$, $Z_4(0) = 0$.
- ▶ Z_4 used only to keep count of certain uncoupled individuals, either unmatched Z_2 -immigrants, or Z_3 individuals that die; and of coupled individuals who become uncoupled when one but not the other dies.

Coupling details

- ▶ Coupling between X_N and \tilde{X}_N realised via a process $Z(\cdot)$ with

$$Z(t) = ((Z_l^i(t), i \geq 0, 1 \leq l \leq 3), Z_4(t)) \in \mathcal{X}^3 \times \mathbb{Z}_+.$$

- ▶ Here, $X_N(\cdot) = Z_1(\cdot) + Z_2(\cdot)$ and $\tilde{X}_N(\cdot) = Z_1(\cdot) + Z_3(\cdot)$.
- ▶ Also $Z_1(0) = X_N(0) = \tilde{X}_N(0)$, $Z_2(0) = Z_3(0) = 0 \in \mathcal{X}$,
 $Z_4(0) = 0$.
- ▶ Z_4 used only to keep count of certain uncoupled individuals, either unmatched Z_2 -immigrants, or Z_3 individuals that die; and of coupled individuals who become uncoupled when one but not the other dies.

Coupling details

- ▶ Coupling between X_N and \tilde{X}_N realised via a process $Z(\cdot)$ with

$$Z(t) = ((Z_l^i(t), i \geq 0, 1 \leq l \leq 3), Z_4(t)) \in \mathcal{X}^3 \times \mathbb{Z}_+.$$

- ▶ Here, $X_N(\cdot) = Z_1(\cdot) + Z_2(\cdot)$ and $\tilde{X}_N(\cdot) = Z_1(\cdot) + Z_3(\cdot)$.
- ▶ Also $Z_1(0) = X_N(0) = \tilde{X}_N(0)$, $Z_2(0) = Z_3(0) = 0 \in \mathcal{X}$, $Z_4(0) = 0$.
- ▶ Z_4 used only to keep count of certain uncoupled individuals, either unmatched Z_2 -immigrants, or Z_3 individuals that die; and of coupled individuals who become uncoupled when one but not the other dies.

Coupling details

- ▶ Coupling between X_N and \tilde{X}_N realised via a process $Z(\cdot)$ with

$$Z(t) = ((Z_l^i(t), i \geq 0, 1 \leq l \leq 3), Z_4(t)) \in \mathcal{X}^3 \times \mathbb{Z}_+.$$

- ▶ Here, $X_N(\cdot) = Z_1(\cdot) + Z_2(\cdot)$ and $\tilde{X}_N(\cdot) = Z_1(\cdot) + Z_3(\cdot)$.
- ▶ Also $Z_1(0) = X_N(0) = \tilde{X}_N(0)$, $Z_2(0) = Z_3(0) = 0 \in \mathcal{X}$, $Z_4(0) = 0$.
- ▶ Z_4 used only to keep count of certain uncoupled individuals, either unmatched Z_2 -immigrants, or Z_3 individuals that die; and of coupled individuals who become uncoupled when one but not the other dies.

Coupling transition rates

For $\bar{\alpha}$ - and α -transitions, for $i \neq l$ (writing $X = Z_1 + Z_2$ and e_j^i for coordinate vectors):

$$\begin{aligned} Z &\rightarrow Z + (e_1^l - e_1^i) && \text{at rate } Z_1^i \{ \bar{\alpha}_{il} + (\alpha_{il}(N^{-1}X) \wedge \alpha_{il}(x_N(t))) \}; \\ Z &\rightarrow Z + (e_2^l + e_3^i - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^+; \\ Z &\rightarrow Z + (e_2^l + e_3^i - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^-; \\ Z &\rightarrow Z + (e_2^l - e_2^i) && \text{at rate } Z_2^i \{ \bar{\alpha}_{il} + \alpha_{il}(N^{-1}X) \}; \\ Z &\rightarrow Z + (e_3^l - e_3^i) && \text{at rate } Z_3^i \{ \bar{\alpha}_{il} + \alpha_{il}(x_N(t)) \}, \end{aligned}$$

with possibilities for individuals in the two processes to become uncoupled, when $N^{-1}X \neq x(t)$.

Coupling transition rates

For $\bar{\alpha}$ - and α -transitions, for $i \neq l$ (writing $X = Z_1 + Z_2$ and e_j^i for coordinate vectors):

$$\begin{aligned}
 Z &\rightarrow Z + (e_1^l - e_1^i) && \text{at rate } Z_1^i \{ \bar{\alpha}_{il} + (\alpha_{il}(N^{-1}X) \wedge \alpha_{il}(x_N(t))) \}; \\
 Z &\rightarrow Z + (e_2^l + e_3^i - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^+; \\
 Z &\rightarrow Z + (e_2^l + e_3^i - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^-; \\
 Z &\rightarrow Z + (e_2^l - e_2^i) && \text{at rate } Z_2^i \{ \bar{\alpha}_{il} + \alpha_{il}(N^{-1}X) \}; \\
 Z &\rightarrow Z + (e_3^l - e_3^i) && \text{at rate } Z_3^i \{ \bar{\alpha}_{il} + \alpha_{il}(x_N(t)) \},
 \end{aligned}$$

with possibilities for individuals in the two processes to become uncoupled, when $N^{-1}X \neq x(t)$.

Coupling transition rates

For $\bar{\alpha}$ - and α -transitions, for $i \neq l$ (writing $X = Z_1 + Z_2$ and e_j^i for coordinate vectors):

$$\begin{aligned}
 Z &\rightarrow Z + (e_1^l - e_1^i) && \text{at rate } Z_1^i \{ \bar{\alpha}_{il} + (\alpha_{il}(N^{-1}X) \wedge \alpha_{il}(x_N(t))) \}; \\
 Z &\rightarrow Z + (e_2^l + e_3^i - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^+; \\
 Z &\rightarrow Z + (e_2^l + e_3^i - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^-; \\
 Z &\rightarrow Z + (e_2^l - e_2^i) && \text{at rate } Z_2^i \{ \bar{\alpha}_{il} + \alpha_{il}(N^{-1}X) \}; \\
 Z &\rightarrow Z + (e_3^l - e_3^i) && \text{at rate } Z_3^i \{ \bar{\alpha}_{il} + \alpha_{il}(x_N(t)) \},
 \end{aligned}$$

with possibilities for individuals in the two processes to become uncoupled, when $N^{-1}X \neq x(t)$.

Coupling transition rates

For $\bar{\alpha}$ - and α -transitions, for $i \neq l$ (writing $X = Z_1 + Z_2$ and e_j^i for coordinate vectors):

$$\begin{aligned}
 Z &\rightarrow Z + (e_1^l - e_1^i) && \text{at rate } Z_1^i \{ \bar{\alpha}_{il} + (\alpha_{il}(N^{-1}X) \wedge \alpha_{il}(x_N(t))) \}; \\
 Z &\rightarrow Z + (e_2^l + e_3^i - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^+; \\
 Z &\rightarrow Z + (e_2^i + e_3^l - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^-; \\
 Z &\rightarrow Z + (e_2^l - e_2^i) && \text{at rate } Z_2^i \{ \bar{\alpha}_{il} + \alpha_{il}(N^{-1}X) \}; \\
 Z &\rightarrow Z + (e_3^l - e_3^i) && \text{at rate } Z_3^i \{ \bar{\alpha}_{il} + \alpha_{il}(x_N(t)) \},
 \end{aligned}$$

with possibilities for individuals in the two processes to become uncoupled, when $N^{-1}X \neq x(t)$.

Coupling transition rates

For $\bar{\alpha}$ - and α -transitions, for $i \neq l$ (writing $X = Z_1 + Z_2$ and e_j^i for coordinate vectors):

$$\begin{aligned}
 Z &\rightarrow Z + (e_1^l - e_1^i) && \text{at rate } Z_1^i \{ \bar{\alpha}_{il} + (\alpha_{il}(N^{-1}X) \wedge \alpha_{il}(x_N(t))) \}; \\
 Z &\rightarrow Z + (e_2^l + e_3^i - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^+; \\
 Z &\rightarrow Z + (e_2^i + e_3^l - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^-; \\
 Z &\rightarrow Z + (e_2^l - e_2^i) && \text{at rate } Z_2^i \{ \bar{\alpha}_{il} + \alpha_{il}(N^{-1}X) \}; \\
 Z &\rightarrow Z + (e_3^l - e_3^i) && \text{at rate } Z_3^i \{ \bar{\alpha}_{il} + \alpha_{il}(x_N(t)) \},
 \end{aligned}$$

with possibilities for individuals in the two processes to become uncoupled, when $N^{-1}X \neq x(t)$.

Coupling transition rates

For $\bar{\alpha}$ - and α -transitions, for $i \neq l$ (writing $X = Z_1 + Z_2$ and e_j^i for coordinate vectors):

$$\begin{aligned} Z &\rightarrow Z + (e_1^l - e_1^i) && \text{at rate } Z_1^i \{ \bar{\alpha}_{il} + (\alpha_{il}(N^{-1}X) \wedge \alpha_{il}(x_N(t))) \}; \\ Z &\rightarrow Z + (e_2^l + e_3^i - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^+; \\ Z &\rightarrow Z + (e_2^i + e_3^l - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^-; \\ Z &\rightarrow Z + (e_2^l - e_2^i) && \text{at rate } Z_2^i \{ \bar{\alpha}_{il} + \alpha_{il}(N^{-1}X) \}; \\ Z &\rightarrow Z + (e_3^l - e_3^i) && \text{at rate } Z_3^i \{ \bar{\alpha}_{il} + \alpha_{il}(x_N(t)) \}, \end{aligned}$$

with possibilities for individuals in the two processes to become uncoupled, when $N^{-1}X \neq x(t)$.

Coupling transition rates

For $\bar{\alpha}$ - and α -transitions, for $i \neq l$ (writing $X = Z_1 + Z_2$ and e_i^j for coordinate vectors):

$$\begin{aligned} Z &\rightarrow Z + (e_1^l - e_1^i) && \text{at rate } Z_1^i \{ \bar{\alpha}_{il} + (\alpha_{il}(N^{-1}X) \wedge \alpha_{il}(x_N(t))) \}; \\ Z &\rightarrow Z + (e_2^l + e_3^i - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^+; \\ Z &\rightarrow Z + (e_2^i + e_3^l - e_1^i) && \text{at rate } Z_1^i \{ \alpha_{il}(N^{-1}X) - \alpha_{il}(x_N(t)) \}^-; \\ Z &\rightarrow Z + (e_2^l - e_2^i) && \text{at rate } Z_2^i \{ \bar{\alpha}_{il} + \alpha_{il}(N^{-1}X) \}; \\ Z &\rightarrow Z + (e_3^l - e_3^i) && \text{at rate } Z_3^i \{ \bar{\alpha}_{il} + \alpha_{il}(x_N(t)) \}, \end{aligned}$$

with possibilities for individuals in the two processes to become uncoupled, when $N^{-1}X \neq x(t)$.

Coupling transition rates

For birth/immigration transitions:

$$Z \rightarrow Z + e_1^i \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) \wedge \beta_i(x_N(t))\}, \quad i \geq 0;$$

$$Z \rightarrow Z + e_2^i + e_4 \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) - \beta_i(x_N(t))\}^+, \quad i \geq 0;$$

$$Z \rightarrow Z + e_3^i \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) - \beta_i(x_N(t))\}^-, \quad i \geq 0,$$

with some immigrations not being precisely matched.

Second transition includes an e_4 so that each Z_2 individual has a counterpart in either Z_3 or Z_4 .

Coupling transition rates

For birth/immigration transitions:

$$Z \rightarrow Z + e_1^i \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) \wedge \beta_i(x_N(t))\}, \quad i \geq 0;$$

$$Z \rightarrow Z + e_2^i + e_4 \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) - \beta_i(x_N(t))\}^+, \quad i \geq 0;$$

$$Z \rightarrow Z + e_3^i \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) - \beta_i(x_N(t))\}^-, \quad i \geq 0,$$

with some immigrations not being precisely matched.

Second transition includes an e_4 so that each Z_2 individual has a counterpart in either Z_3 or Z_4 .

Coupling transition rates

For birth/immigration transitions:

$$Z \rightarrow Z + e_1^i \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) \wedge \beta_i(x_N(t))\}, \quad i \geq 0;$$

$$Z \rightarrow Z + e_2^i + e_4 \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) - \beta_i(x_N(t))\}^+, \quad i \geq 0;$$

$$Z \rightarrow Z + e_3^i \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) - \beta_i(x_N(t))\}^-, \quad i \geq 0,$$

with some immigrations not being precisely matched.

Second transition includes an e_4 so that each Z_2 individual has a counterpart in either Z_3 or Z_4 .

Coupling transition rates

For birth/immigration transitions:

$$Z \rightarrow Z + e_1^i \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) \wedge \beta_i(x_N(t))\}, \quad i \geq 0;$$

$$Z \rightarrow Z + e_2^i + e_4 \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) - \beta_i(x_N(t))\}^+, \quad i \geq 0;$$

$$Z \rightarrow Z + e_3^i \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) - \beta_i(x_N(t))\}^-, \quad i \geq 0,$$

with some immigrations not being precisely matched.

Second transition includes an e_4 so that each Z_2 individual has a counterpart in either Z_3 or Z_4 .

Coupling transition rates

For birth/immigration transitions:

$$Z \rightarrow Z + e_1^i \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) \wedge \beta_i(x_N(t))\}, \quad i \geq 0;$$

$$Z \rightarrow Z + e_2^i + e_4 \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) - \beta_i(x_N(t))\}^+, \quad i \geq 0;$$

$$Z \rightarrow Z + e_3^i \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) - \beta_i(x_N(t))\}^-, \quad i \geq 0,$$

with some immigrations not being precisely matched.

Second transition includes an e_4 so that each Z_2 individual has a counterpart in either Z_3 or Z_4 .

Coupling transition rates

For birth/immigration transitions:

$$Z \rightarrow Z + e_1^i \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) \wedge \beta_i(x_N(t))\}, \quad i \geq 0;$$

$$Z \rightarrow Z + e_2^i + e_4 \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) - \beta_i(x_N(t))\}^+, \quad i \geq 0;$$

$$Z \rightarrow Z + e_3^i \quad \text{at rate} \quad N\{\beta_i(N^{-1}X) - \beta_i(x_N(t))\}^-, \quad i \geq 0,$$

with some immigrations not being precisely matched.

Second transition includes an e_4 so that each Z_2 individual has a counterpart in either Z_3 or Z_4 .

Coupling transition rates

For deaths/emigration:

$$Z \rightarrow Z - e_1^i \quad \text{at rate} \quad Z_1^i \{ \bar{\delta}_i + (\delta_i(N^{-1}X) \wedge \delta_i(x_N(t))) \}, \quad i \geq 0;$$

$$Z \rightarrow Z - e_1^i + e_3^i \quad \text{at rate} \quad Z_1^i \{ \delta_i(N^{-1}X) - \delta_i(x_N(t)) \}^+, \quad i \geq 0;$$

$$Z \rightarrow Z - e_1^i + e_2^i + e_4 \quad \text{at rate} \quad Z_1^i \{ \delta_i(N^{-1}X) - \delta_i(x_N(t)) \}^-, \quad i \geq 0;$$

$$Z \rightarrow Z - e_2^i \quad \text{at rate} \quad Z_2^i \{ \bar{\delta}_i + \delta_i(N^{-1}X) \}, \quad i \geq 0;$$

$$Z \rightarrow Z - e_3^i + e_4 \quad \text{at rate} \quad Z_3^i \{ \bar{\delta}_i + \delta_i(x_N(t)) \}, \quad i \geq 0.$$

Here $Z_4(\cdot)$ also counts deaths of uncoupled Z_3 -individuals, and uncoupled deaths in \bar{X}_N of coupled Z_1 individuals.

Coupling transition rates

For deaths/emigration:

$$Z \rightarrow Z - e_1^i \quad \text{at rate} \quad Z_1^i \{ \bar{\delta}_i + (\delta_i(N^{-1}X) \wedge \delta_i(x_N(t))) \}, \quad i \geq 0;$$

$$Z \rightarrow Z - e_1^i + e_3^i \quad \text{at rate} \quad Z_1^i \{ \delta_i(N^{-1}X) - \delta_i(x_N(t)) \}^+, \quad i \geq 0;$$

$$Z \rightarrow Z - e_1^i + e_2^i + e_4 \quad \text{at rate} \quad Z_1^i \{ \delta_i(N^{-1}X) - \delta_i(x_N(t)) \}^-, \quad i \geq 0;$$

$$Z \rightarrow Z - e_2^i \quad \text{at rate} \quad Z_2^i \{ \bar{\delta}_i + \delta_i(N^{-1}X) \}, \quad i \geq 0;$$

$$Z \rightarrow Z - e_3^i + e_4 \quad \text{at rate} \quad Z_3^i \{ \bar{\delta}_i + \delta_i(x_N(t)) \}, \quad i \geq 0.$$

Here $Z_4(\cdot)$ also counts deaths of uncoupled Z_3 -individuals, and uncoupled deaths in \bar{X}_N of coupled Z_1 individuals.

Coupling transition rates

For deaths/emigration:

$$Z \rightarrow Z - e_1^i \quad \text{at rate} \quad Z_1^i \{\bar{\delta}_i + (\delta_i(N^{-1}X) \wedge \delta_i(x_N(t)))\}, \quad i \geq 0;$$

$$Z \rightarrow Z - e_1^i + e_3^i \quad \text{at rate} \quad Z_1^i \{\delta_i(N^{-1}X) - \delta_i(x_N(t))\}^+, \quad i \geq 0;$$

$$Z \rightarrow Z - e_1^i + e_2^i + e_4 \quad \text{at rate} \quad Z_1^i \{\delta_i(N^{-1}X) - \delta_i(x_N(t))\}^-, \quad i \geq 0;$$

$$Z \rightarrow Z - e_2^i \quad \text{at rate} \quad Z_2^i \{\bar{\delta}_i + \delta_i(N^{-1}X)\}, \quad i \geq 0;$$

$$Z \rightarrow Z - e_3^i + e_4 \quad \text{at rate} \quad Z_3^i \{\bar{\delta}_i + \delta_i(x_N(t))\}, \quad i \geq 0.$$

Here $Z_4(\cdot)$ also counts deaths of uncoupled Z_3 -individuals, and uncoupled deaths in \bar{X}_N of coupled Z_1 individuals.

Coupling transition rates

For deaths/emigration:

$$Z \rightarrow Z - e_1^i \quad \text{at rate} \quad Z_1^i \{ \bar{\delta}_i + (\delta_i(N^{-1}X) \wedge \delta_i(x_N(t))) \}, \quad i \geq 0;$$

$$Z \rightarrow Z - e_1^i + e_3^i \quad \text{at rate} \quad Z_1^i \{ \delta_i(N^{-1}X) - \delta_i(x_N(t)) \}^+, \quad i \geq 0;$$

$$Z \rightarrow Z - e_1^i + e_2^i + e_4 \quad \text{at rate} \quad Z_1^i \{ \delta_i(N^{-1}X) - \delta_i(x_N(t)) \}^-, \quad i \geq 0;$$

$$Z \rightarrow Z - e_2^i \quad \text{at rate} \quad Z_2^i \{ \bar{\delta}_i + \delta_i(N^{-1}X) \}, \quad i \geq 0;$$

$$Z \rightarrow Z - e_3^i + e_4 \quad \text{at rate} \quad Z_3^i \{ \bar{\delta}_i + \delta_i(x_N(t)) \}, \quad i \geq 0.$$

Here $Z_4(\cdot)$ also counts deaths of uncoupled Z_3 -individuals, and uncoupled deaths in \bar{X}_N of coupled Z_1 individuals.

Coupling transition rates

For deaths/emigration:

$$Z \rightarrow Z - e_1^i \quad \text{at rate} \quad Z_1^i \{ \bar{\delta}_i + (\delta_i(N^{-1}X) \wedge \delta_i(x_N(t))) \}, \quad i \geq 0;$$

$$Z \rightarrow Z - e_1^i + e_3^i \quad \text{at rate} \quad Z_1^i \{ \delta_i(N^{-1}X) - \delta_i(x_N(t)) \}^+, \quad i \geq 0;$$

$$Z \rightarrow Z - e_1^i + e_2^i + e_4 \quad \text{at rate} \quad Z_1^i \{ \delta_i(N^{-1}X) - \delta_i(x_N(t)) \}^-, \quad i$$

$$Z \rightarrow Z - e_2^i \quad \text{at rate} \quad Z_2^i \{ \bar{\delta}_i + \delta_i(N^{-1}X) \}, \quad i \geq 0;$$

$$Z \rightarrow Z - e_3^i + e_4 \quad \text{at rate} \quad Z_3^i \{ \bar{\delta}_i + \delta_i(x_N(t)) \}, \quad i \geq 0.$$

Here $Z_4(\cdot)$ also counts deaths of uncoupled Z_3 -individuals, and uncoupled deaths in \tilde{X}_N of coupled Z_1 individuals.

Coupling transition rates

For deaths/emigration:

$$\begin{aligned} Z &\rightarrow Z - e_1^i && \text{at rate } Z_1^i \{\bar{\delta}_i + (\delta_i(N^{-1}X) \wedge \delta_i(x_N(t)))\}, && i \geq 0; \\ Z &\rightarrow Z - e_1^i + e_3^i && \text{at rate } Z_1^i \{\delta_i(N^{-1}X) - \delta_i(x_N(t))\}^+, && i \geq 0; \\ Z &\rightarrow Z - e_1^i + e_2^i + e_4 && \text{at rate } Z_1^i \{\delta_i(N^{-1}X) - \delta_i(x_N(t))\}^-, && i \\ Z &\rightarrow Z - e_2^i && \text{at rate } Z_2^i \{\bar{\delta}_i + \delta_i(N^{-1}X)\}, && i \geq 0; \\ Z &\rightarrow Z - e_3^i + e_4 && \text{at rate } Z_3^i \{\bar{\delta}_i + \delta_i(x_N(t))\}, && i \geq 0. \end{aligned}$$

Here $Z_4(\cdot)$ also counts deaths of uncoupled Z_3 -individuals, and uncoupled deaths in \tilde{X}_N of coupled Z_1 individuals.

Coupling transition rates

For deaths/emigration:

$$\begin{aligned} Z &\rightarrow Z - e_1^i && \text{at rate } Z_1^i \{\bar{\delta}_i + (\delta_i(N^{-1}X) \wedge \delta_i(x_N(t)))\}, && i \geq 0; \\ Z &\rightarrow Z - e_1^i + e_3^i && \text{at rate } Z_1^i \{\delta_i(N^{-1}X) - \delta_i(x_N(t))\}^+, && i \geq 0; \\ Z &\rightarrow Z - e_1^i + e_2^i + e_4 && \text{at rate } Z_1^i \{\delta_i(N^{-1}X) - \delta_i(x_N(t))\}^-, && i \geq 0; \\ Z &\rightarrow Z - e_2^i && \text{at rate } Z_2^i \{\bar{\delta}_i + \delta_i(N^{-1}X)\}, && i \geq 0; \\ Z &\rightarrow Z - e_3^i + e_4 && \text{at rate } Z_3^i \{\bar{\delta}_i + \delta_i(x_N(t))\}, && i \geq 0. \end{aligned}$$

Here $Z_4(\cdot)$ also counts deaths of uncoupled Z_3 -individuals, and uncoupled deaths in \tilde{X}_N of coupled Z_1 individuals.

Coupling - key bounds

With this construction, we have

$$\sum_{i \geq 0} Z_2^i(t) \leq Z_4(t) + \sum_{i \geq 0} Z_3^i(t) \quad (4.4)$$

for all t .

Also

$$V_N(t) := Z_4(t) + \sum_{i \geq 0} Z_3^i(t) \quad (4.5)$$

is a counting process. We thus have the bound

$$\begin{aligned} \|X_N(t) - \tilde{X}_N(t)\|_1 &= \|(Z_1(t) + Z_2(t)) - (Z_1(t) + Z_3(t))\|_1 \\ &\leq \sum_{i \geq 0} \{Z_2^i(t) + Z_3^i(t)\} \leq 2V_N(t). \end{aligned} \quad (4.6)$$

Coupling - key bounds

With this construction, we have

$$\sum_{i \geq 0} Z_2^i(t) \leq Z_4(t) + \sum_{i \geq 0} Z_3^i(t) \quad (4.4)$$

for all t .

Also

$$V_N(t) := Z_4(t) + \sum_{i \geq 0} Z_3^i(t) \quad (4.5)$$

is a counting process. We thus have the bound

$$\begin{aligned} \|X_N(t) - \tilde{X}_N(t)\|_1 &= \|(Z_1(t) + Z_2(t)) - (Z_1(t) + Z_3(t))\|_1 \\ &\leq \sum_{i \geq 0} \{Z_2^i(t) + Z_3^i(t)\} \leq 2V_N(t). \end{aligned} \quad (4.6)$$

Coupling - key bounds

With this construction, we have

$$\sum_{i \geq 0} Z_2^i(t) \leq Z_4(t) + \sum_{i \geq 0} Z_3^i(t) \quad (4.4)$$

for all t .

Also

$$V_N(t) := Z_4(t) + \sum_{i \geq 0} Z_3^i(t) \quad (4.5)$$

is a counting process. We thus have the bound

$$\begin{aligned} \|X_N(t) - \tilde{X}_N(t)\|_1 &= \|(Z_1(t) + Z_2(t)) - (Z_1(t) + Z_3(t))\|_1 \\ &\leq \sum_{i \geq 0} \{Z_2^i(t) + Z_3^i(t)\} \leq 2V_N(t). \end{aligned} \quad (4.6)$$