

## 8 Space



Mathematics  
and Statistics

$$\int_M d\omega = \int_{\partial M} \omega$$

# Mathematics 4MB3/6MB3 Mathematical Biology

Instructor: David Earn

Lecture 8

Space

Tuesday 29 October 2024

# Announcements

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## ■ Midterm test:

- *Date:* Tuesday 12 November 2024
- *Time:* 2:30pm–4:30pm
- *Location:* in class, HH-102
- Test structure will be discussed in class next week.

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- **Assignment 4** is due the day before the midterm.

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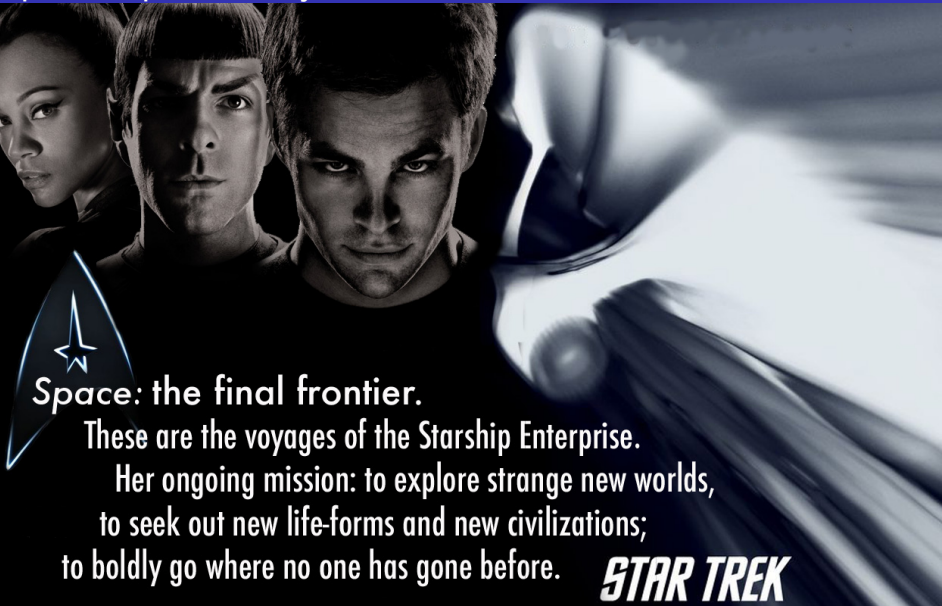
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- Make sure you personally can do the question on calculating  $\mathcal{R}_0$  on this assignment before the midterm test.

# Spatial Epidemic Dynamics

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**Space: the final frontier.**

**These are the voyages of the Starship Enterprise.**

**Her ongoing mission: to explore strange new worlds,  
to seek out new life-forms and new civilizations;  
to boldly go where no one has gone before.**

***STAR TREK***



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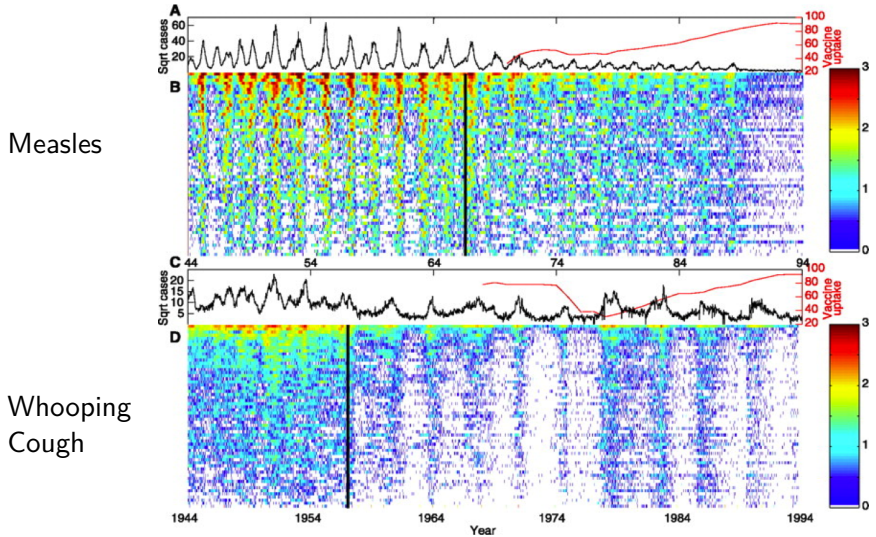
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- Can we reduce the eradication threshold below  $p_{\text{crit}} = 1 - \frac{1}{\mathcal{R}_0}$ ?

# Measles and Whooping Cough in 60 UK cities



Rohani, Earn & Grenfell (1999) *Science* 286, 968–971

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- Can we eradicate measles?

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- But analytical theory of synchrony in a periodically forced system of differential equations is mathematically demanding. . .
- So let's consider a much simpler biological model. . .

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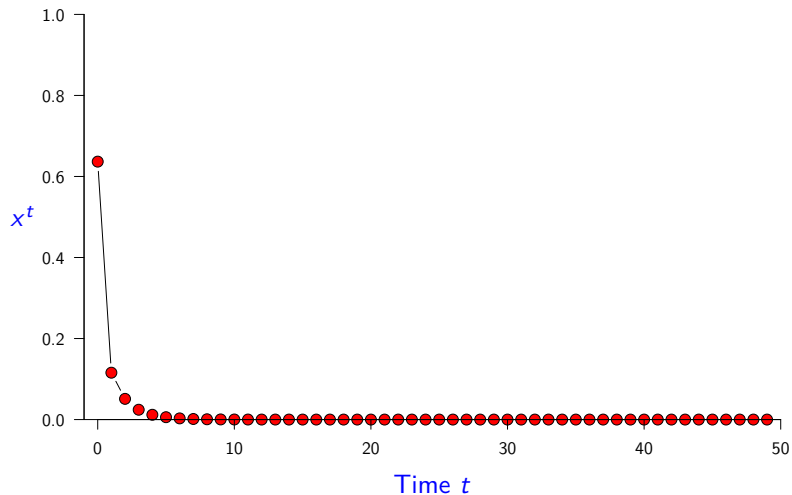
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- What kinds of dynamics are possible for the Logistic Map?

# Logistic Map Time Series, $r = 0.5$

Logistic Map Time Series,  $r = 0.5$ 

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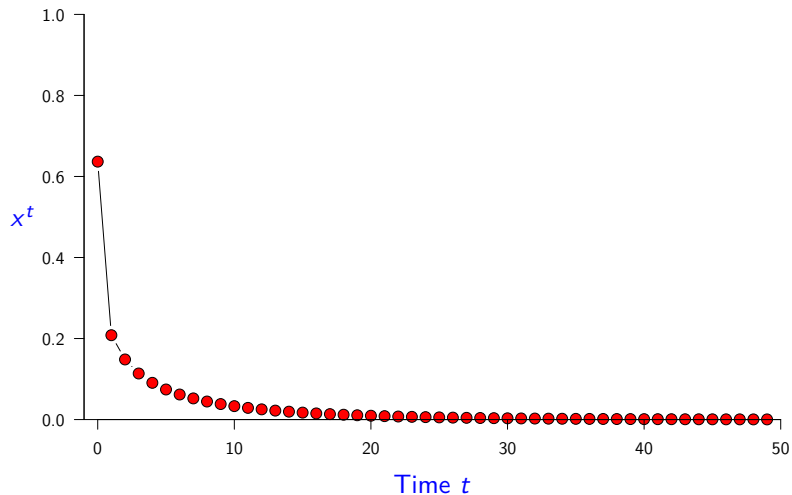


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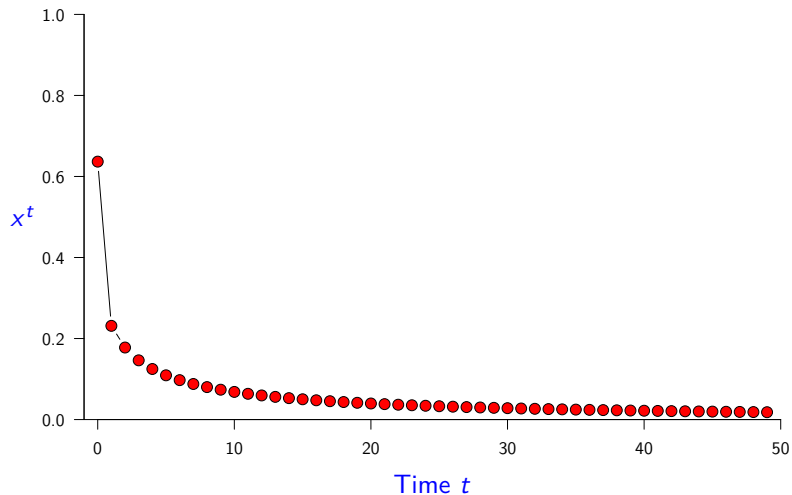
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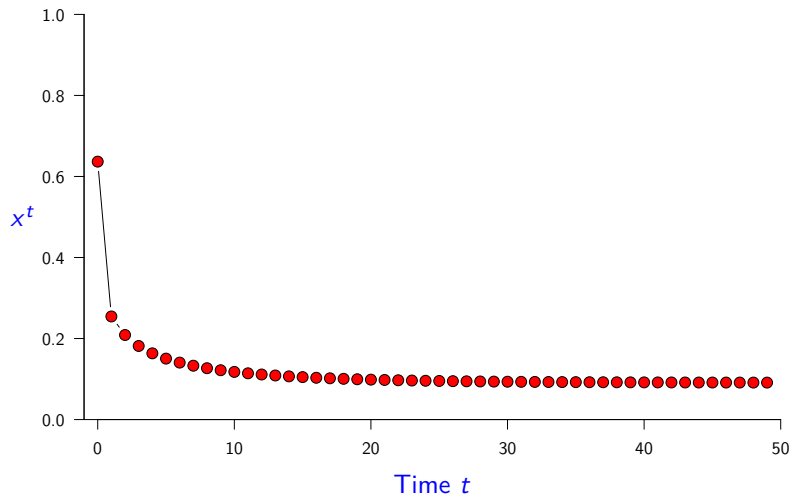
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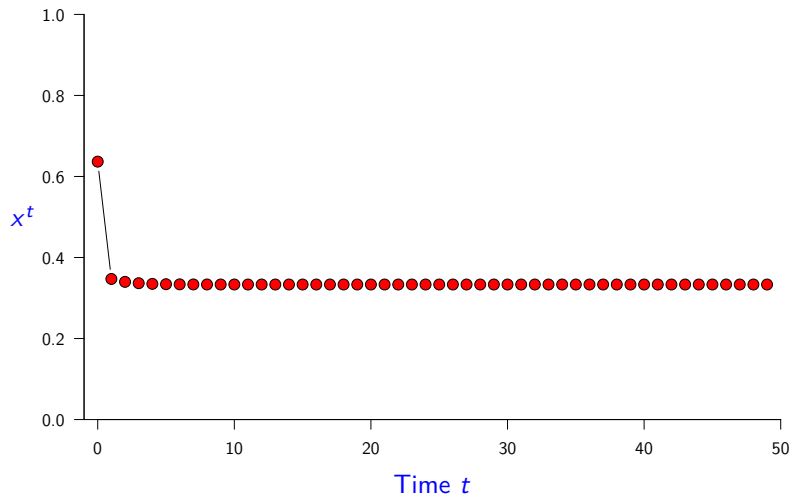
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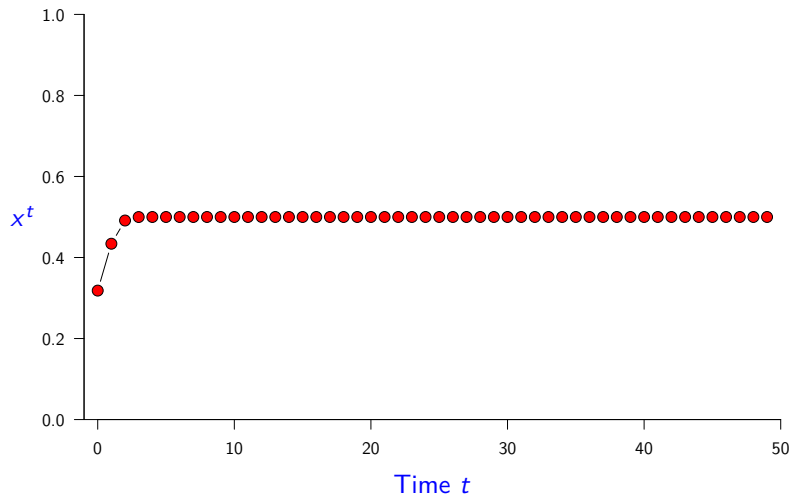


# Logistic Map Time Series, $r = 2$



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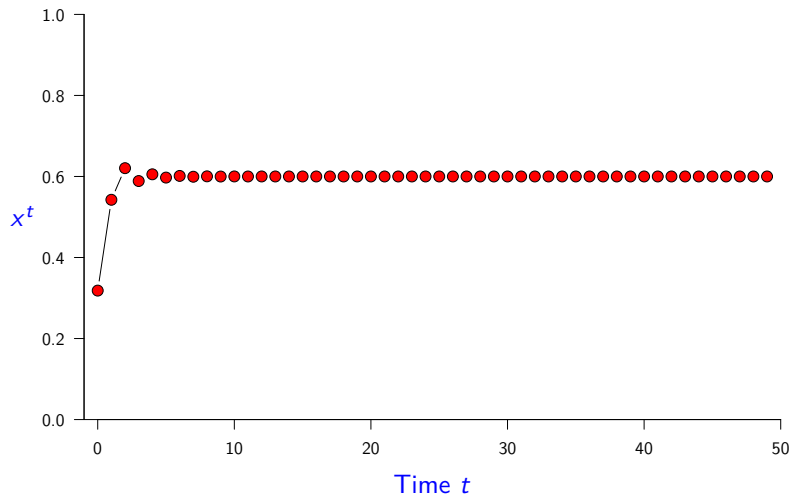
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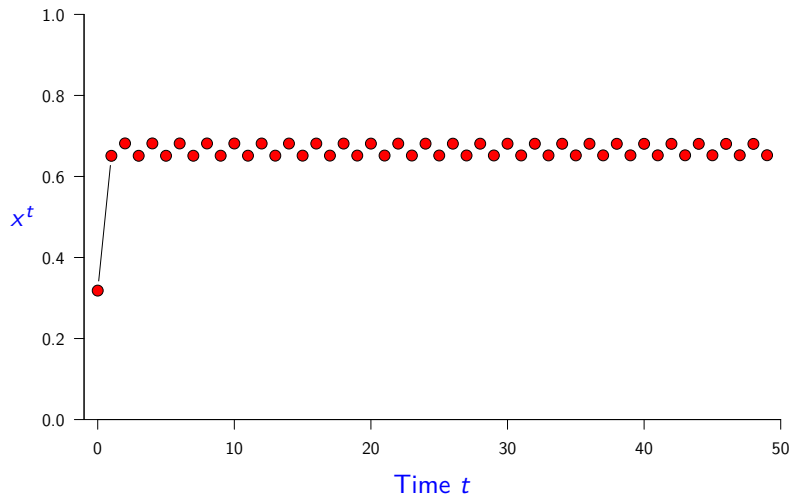
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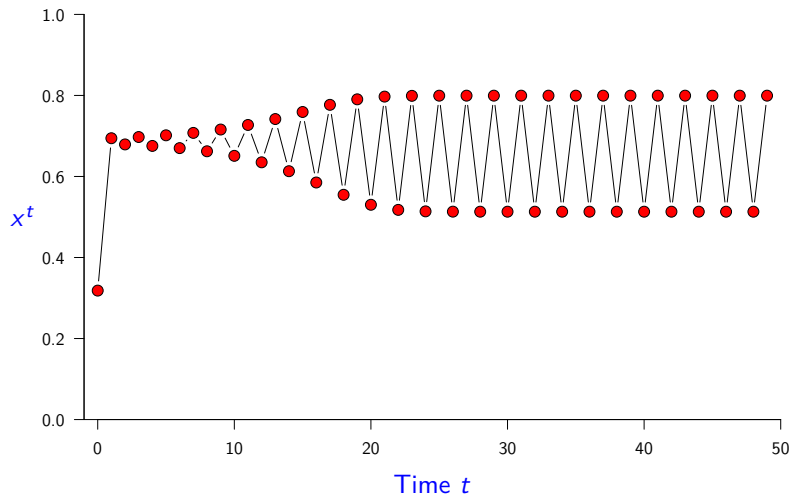
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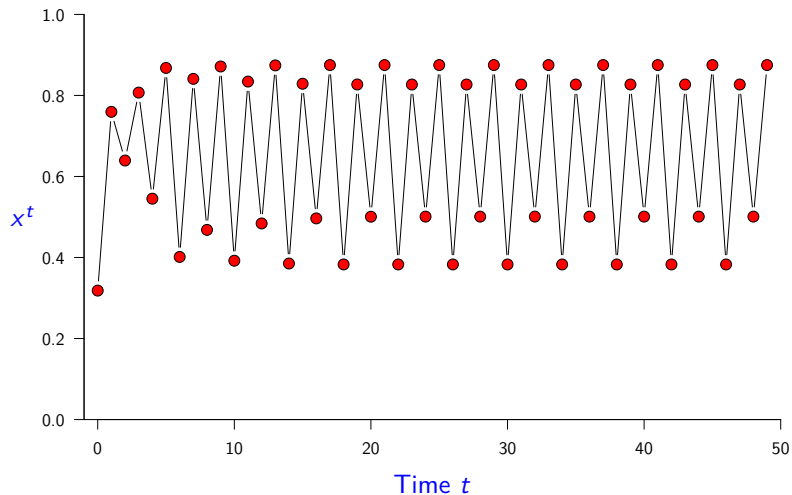


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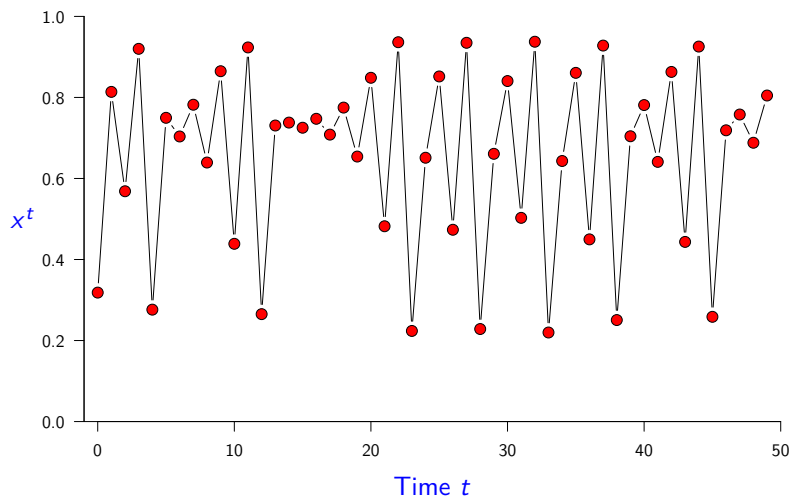
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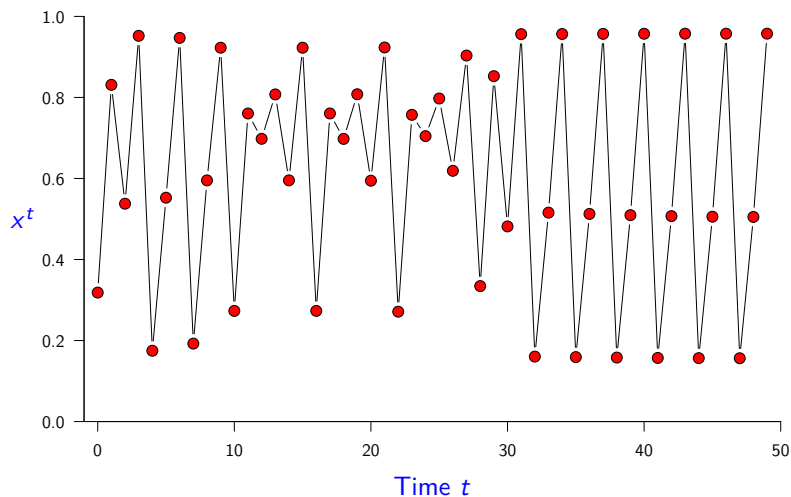
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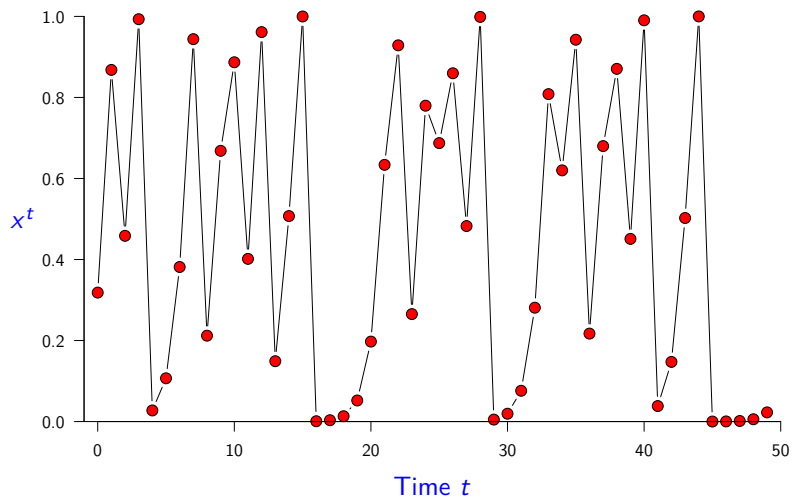
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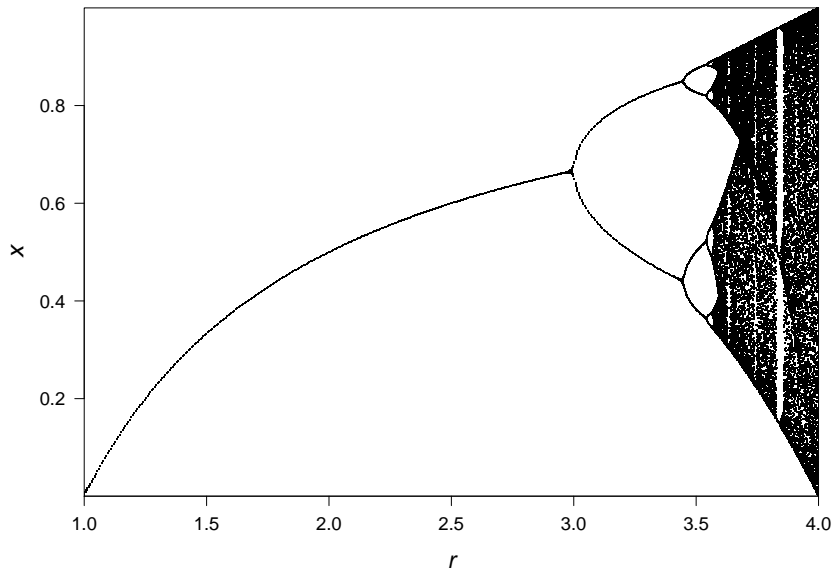
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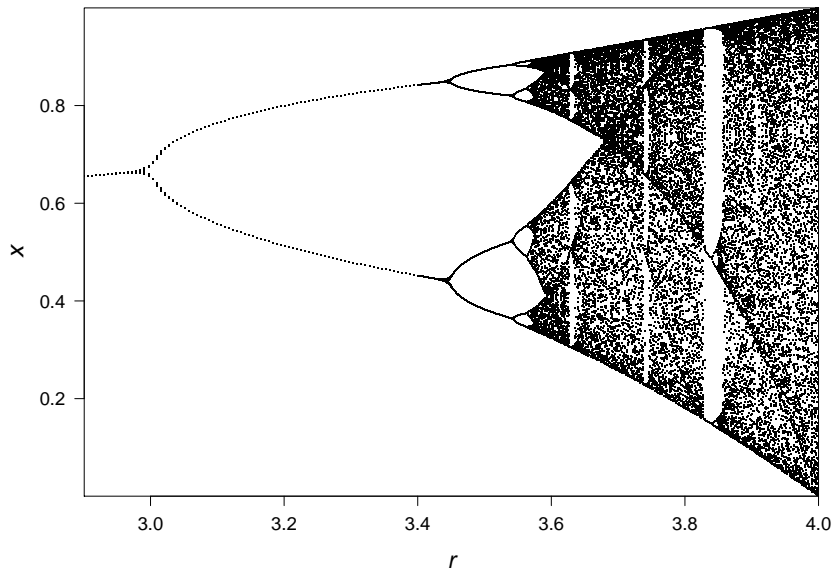
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  - Ignore transient behaviour: just show attractor.

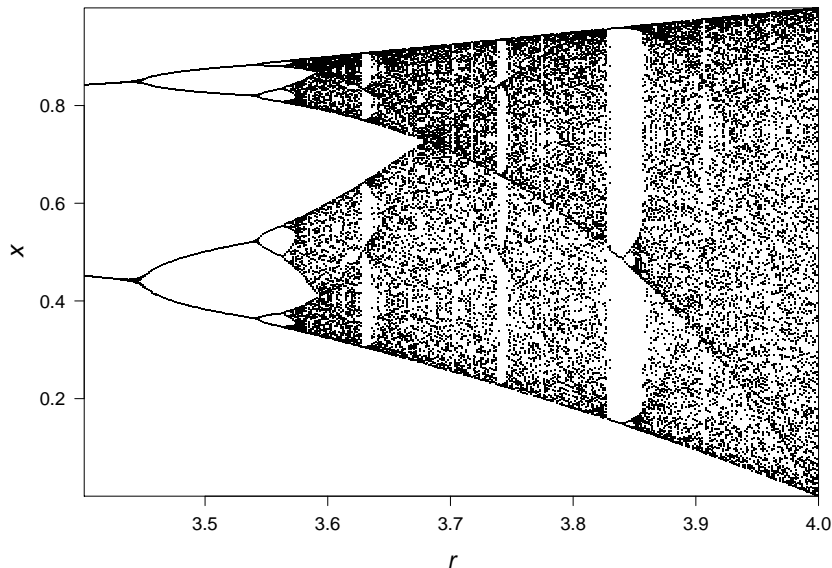
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- Connectivity of patches specified by a *dispersal matrix*  
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- System is *coherent* (perfectly synchronous) if the state is the same in all patches  
i.e.,  $\mathbf{x}_1 = \mathbf{x}_2 = \dots = \mathbf{x}_n$

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- *Colour coding of matrix indices:*
  - row indices are red
  - column indices are cyan

# Basic properties of dispersal matrices $M = (m_{ij})$

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An  $n \times n$  matrix  $M = (m_{ij})$  is said to be a ***no loss dispersal matrix*** if all its entries are non-negative ( $m_{ij} \geq 0$  for all  $i$  and  $j$ ) and its column sums are all 1, *i.e.*,

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*so any coherent state can be written  $x\mathbf{e}$ , for some  $x \in \mathbb{R}$ .*

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# Back to Space and Synchrony

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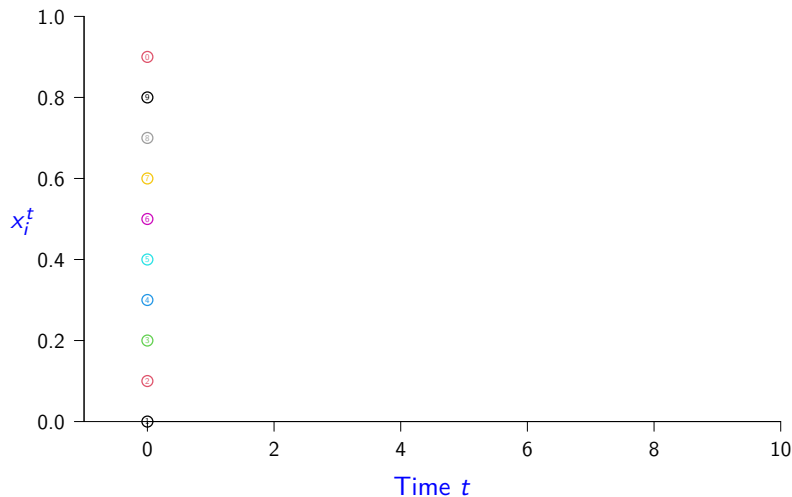
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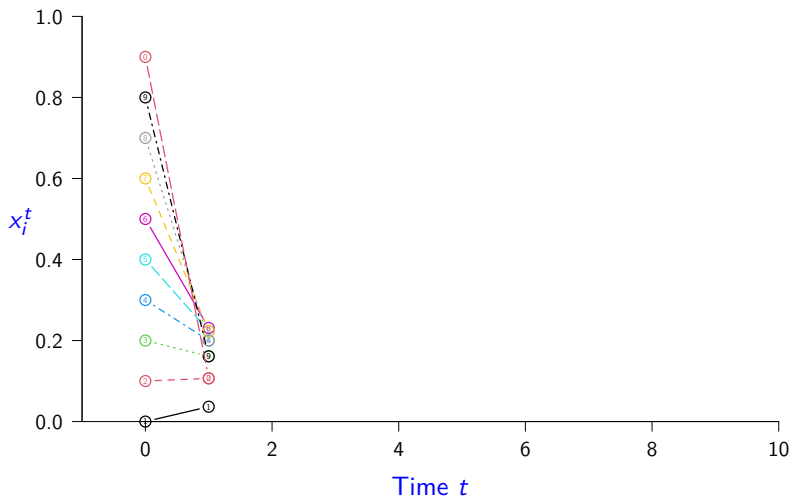
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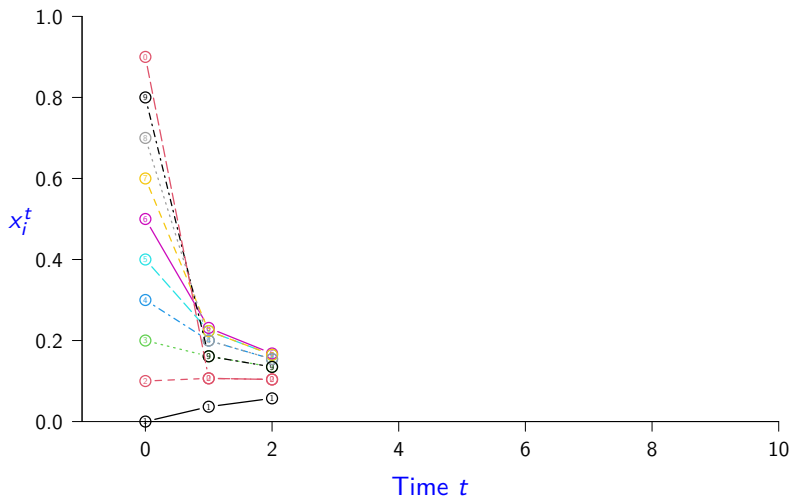
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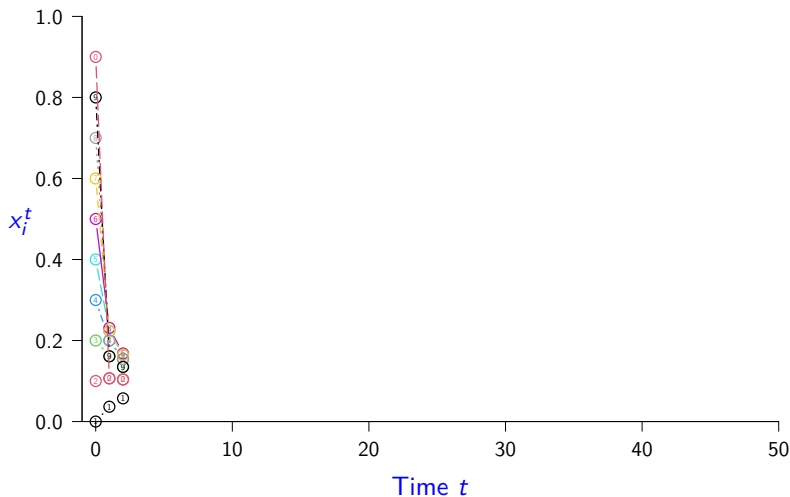
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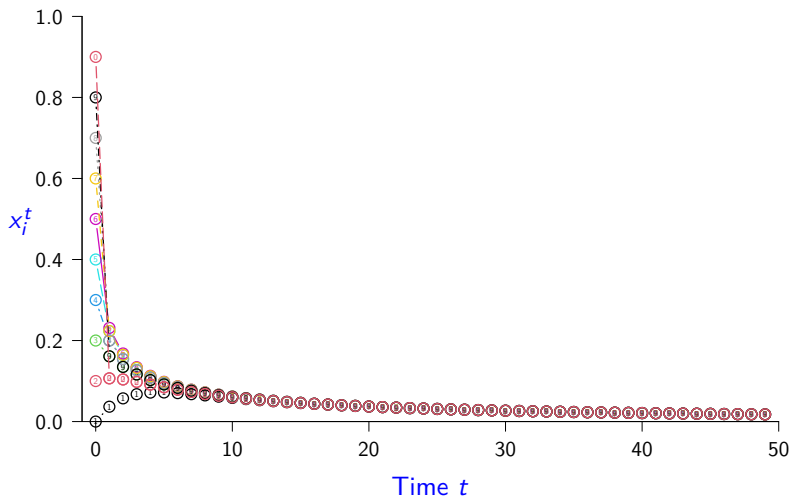
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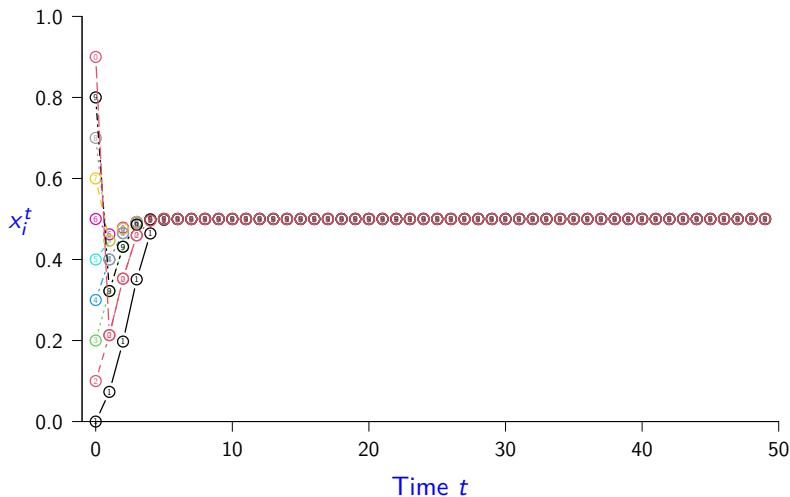




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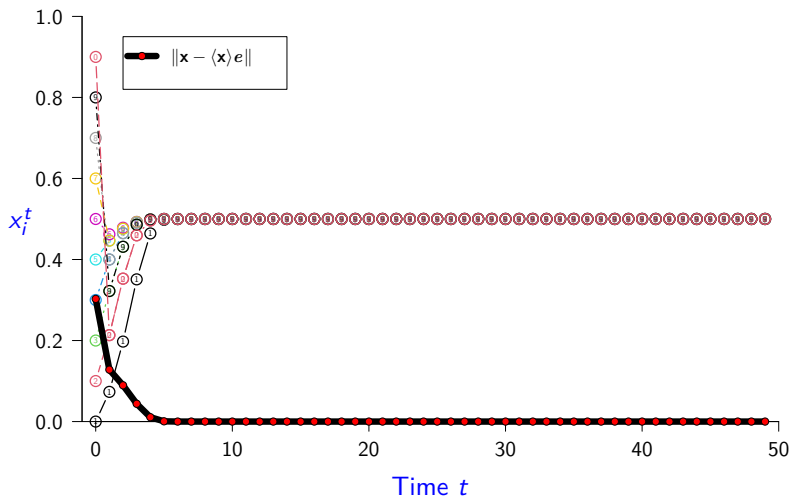
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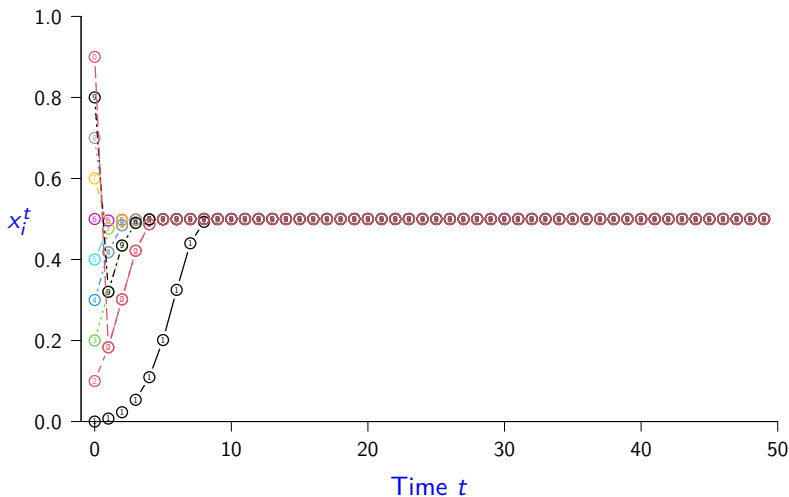
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# Logistic Metapopulation Simulation ( $r = 2$ , $m = 0.02$ )

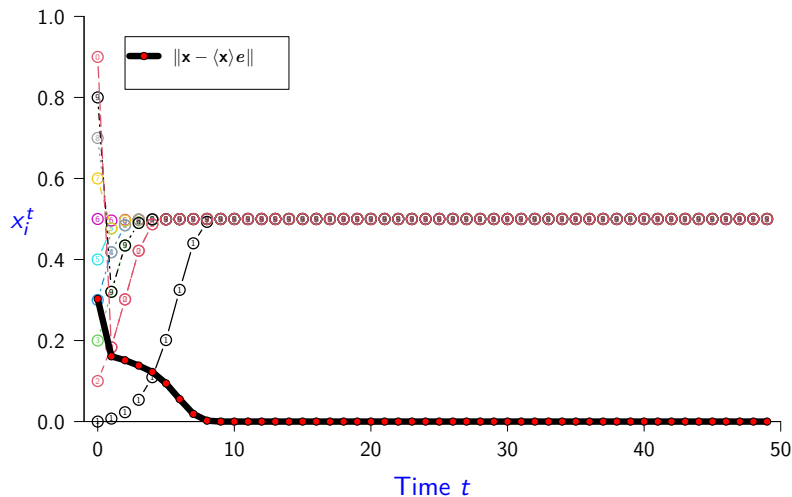
Logistic Metapopulation Simulation ( $r = 2$ ,  $m = 0.02$ )

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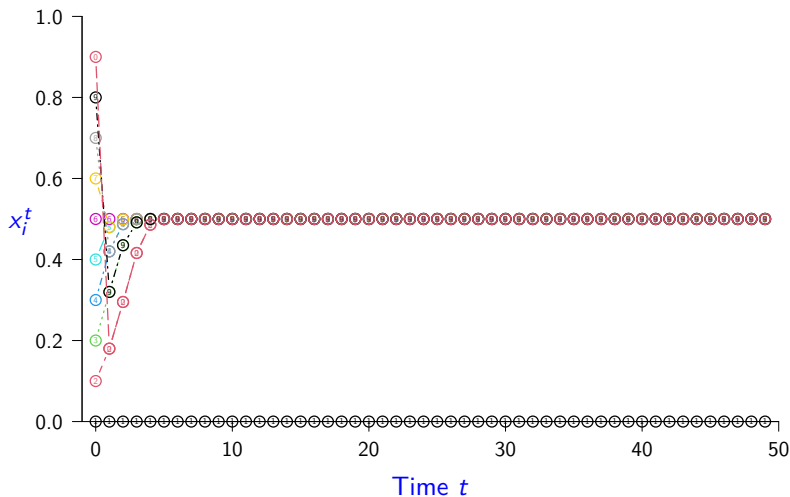
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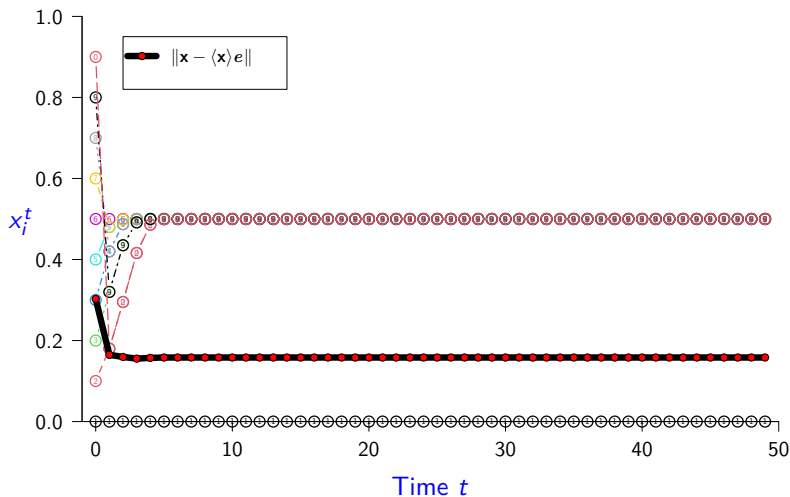
$$n = 10, \quad r = 2, \quad m = 0, \quad \lambda = 1$$



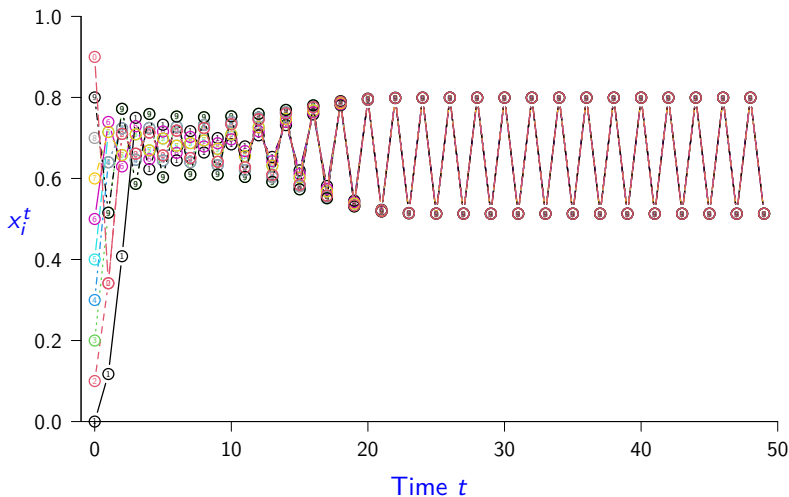


# Logistic Metapopulation Simulation ( $r = 2, m = 0$ )

$$n = 10, \quad r = 2, \quad m = 0, \quad \lambda = 1$$

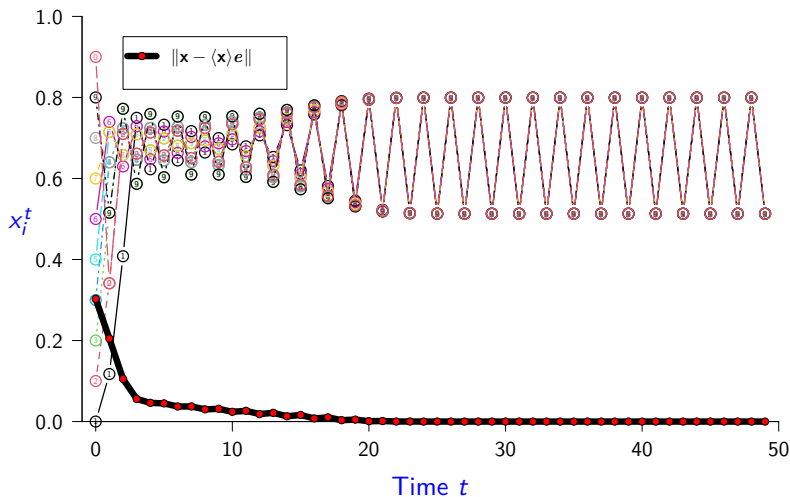


# Logistic Metapopulation Simulation ( $r = 3.2, m = 0.2$ )

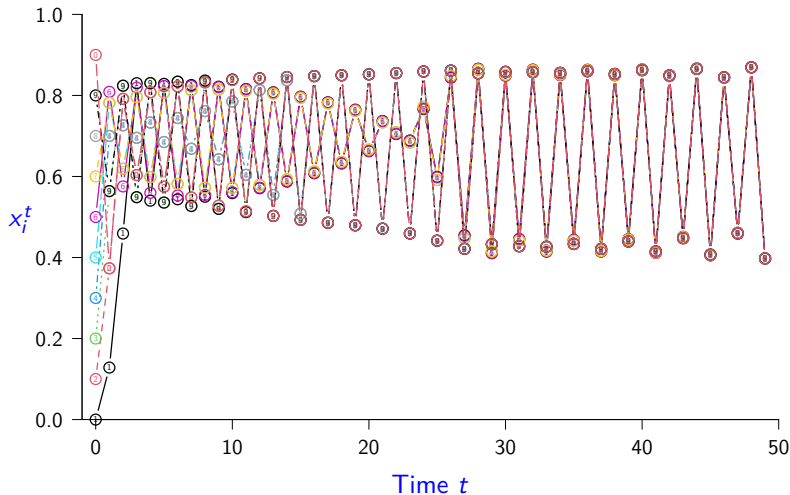
Logistic Metapopulation Simulation ( $r = 3.2, m = 0.2$ ) $n = 10, r = 3.2, m = 0.2, \lambda = 0.778$ 

# Logistic Metapopulation Simulation ( $r = 3.2, m = 0.2$ )

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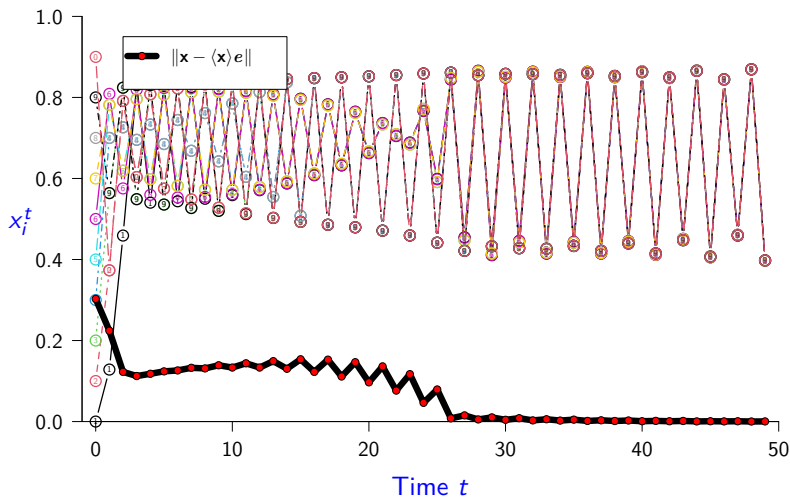


# Logistic Metapopulation Simulation ( $r = 3.5, m = 0.2$ )

Logistic Metapopulation Simulation ( $r = 3.5$ ,  $m = 0.2$ ) $n = 10$ ,  $r = 3.5$ ,  $m = 0.2$ ,  $\lambda = 0.778$ 

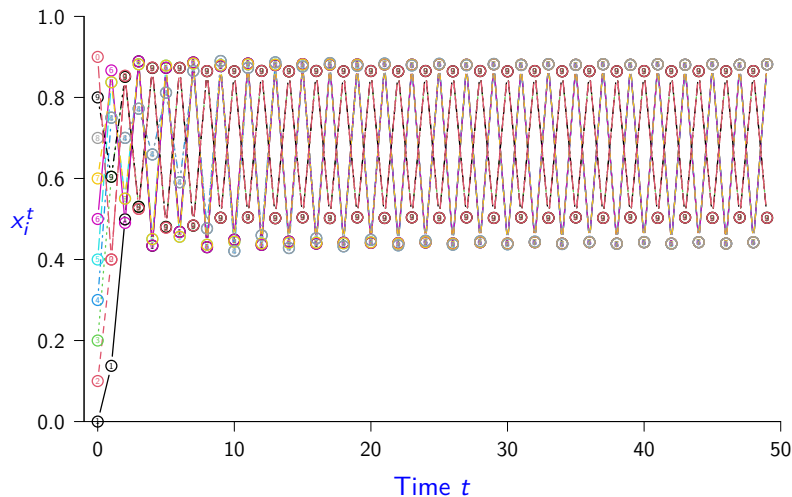
# Logistic Metapopulation Simulation ( $r = 3.5, m = 0.2$ )

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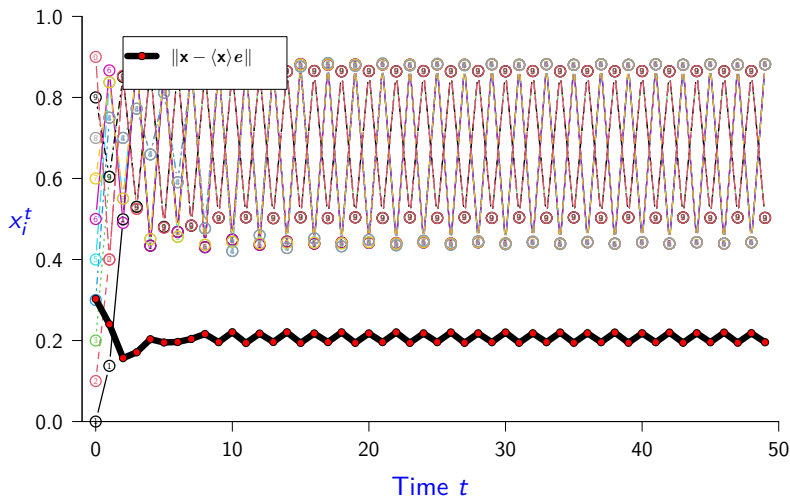
# Logistic Metapopulation Simulation ( $r = 3.75$ , $m = 0.2$ )



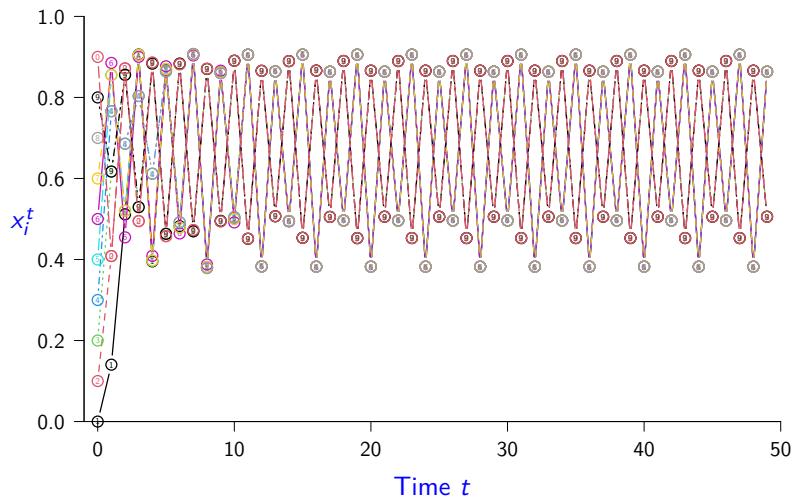
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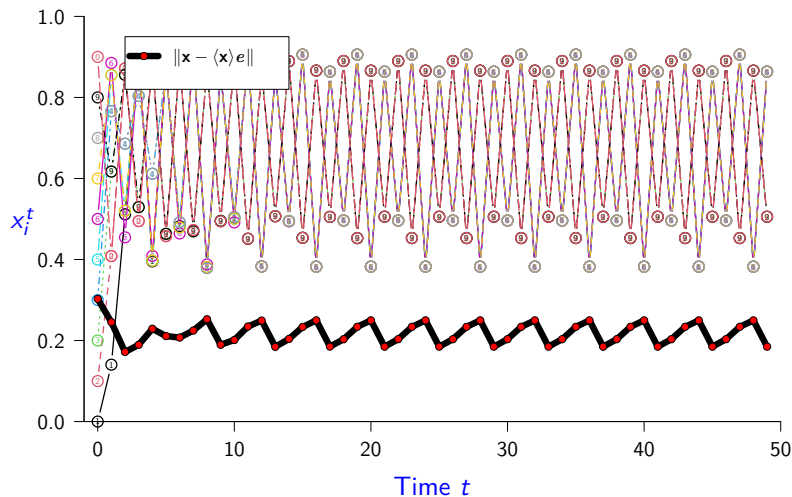
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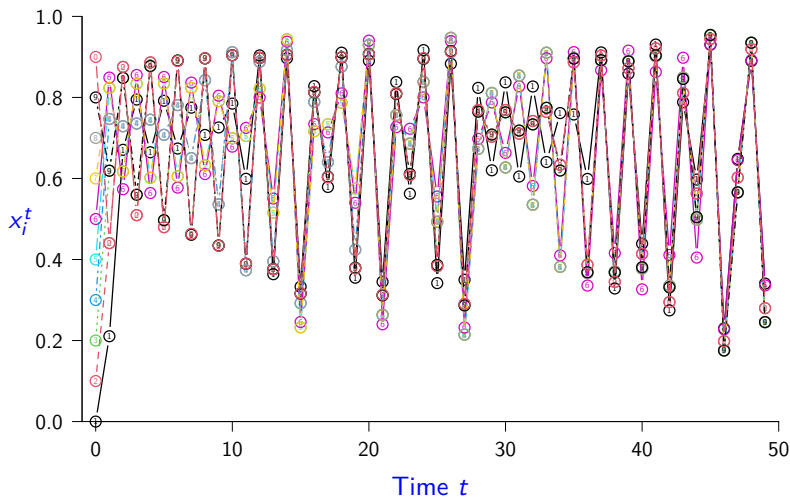


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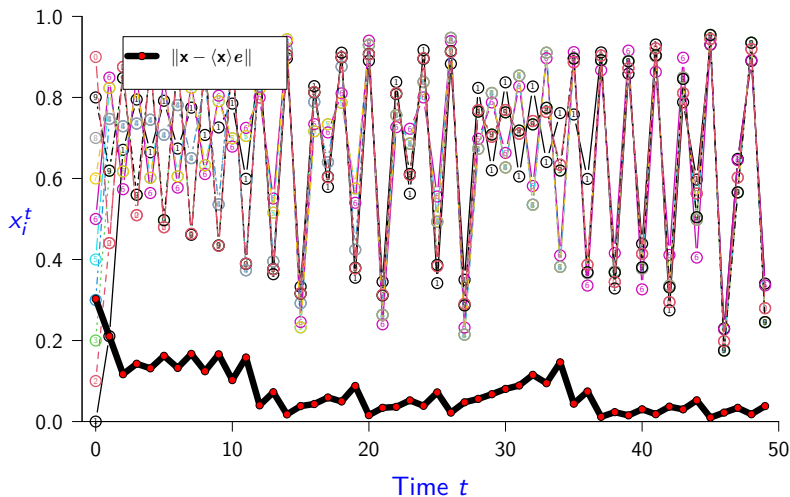
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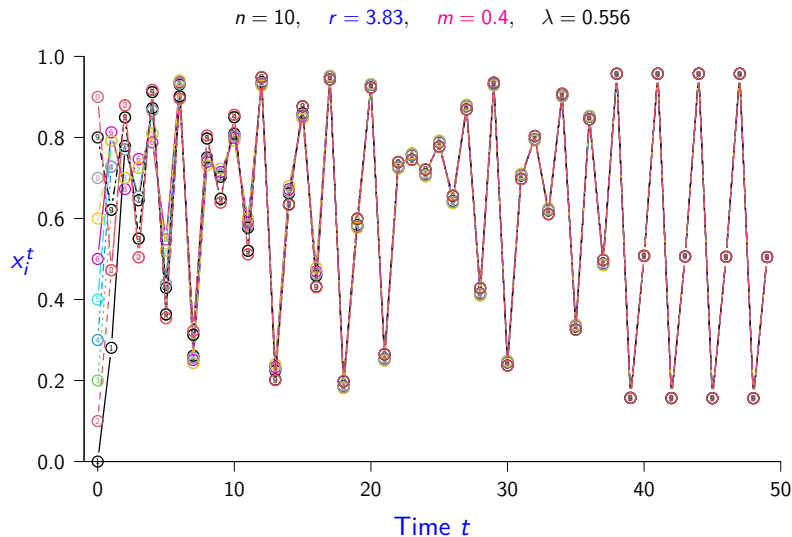
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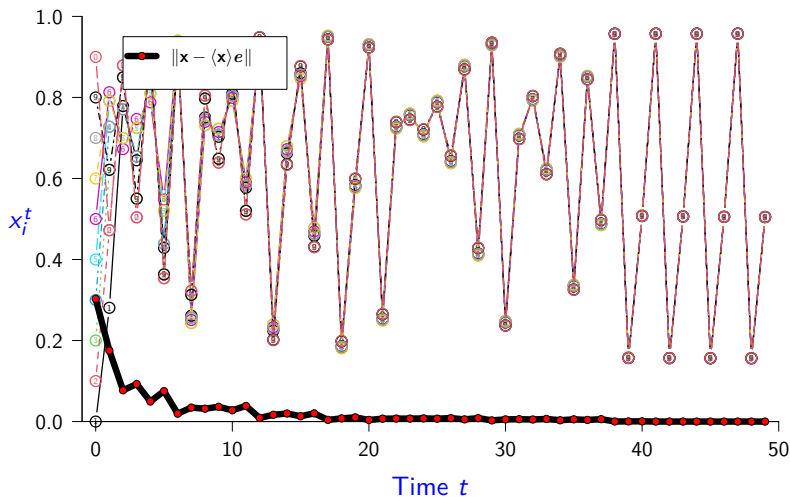


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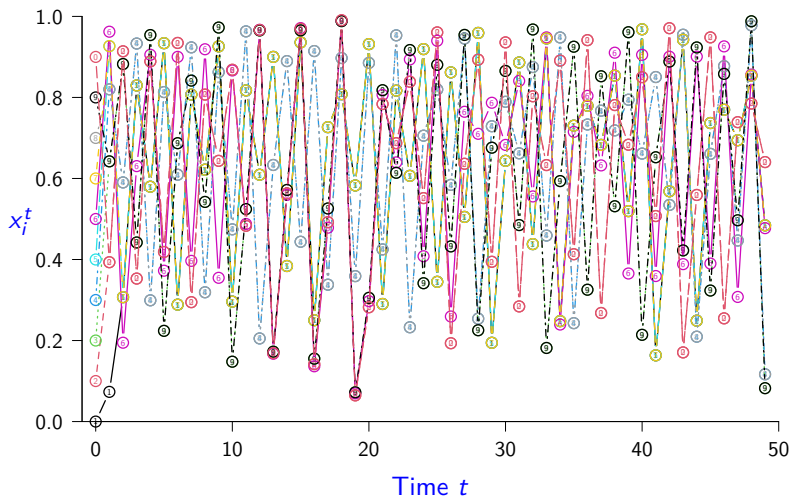
$n = 10$ ,  $r = 3.83$ ,  $m = 0.4$ ,  $\lambda = 0.556$



# Logistic Metapopulation Simulation ( $r = 4$ , $m = 0.1$ )

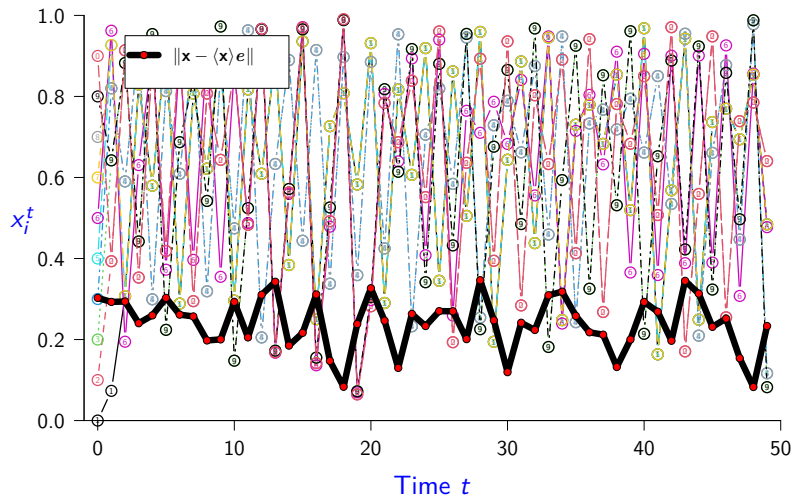
# Logistic Metapopulation Simulation ( $r = 4, m = 0.1$ )

$n = 10, r = 4, m = 0.1, \lambda = 0.889$



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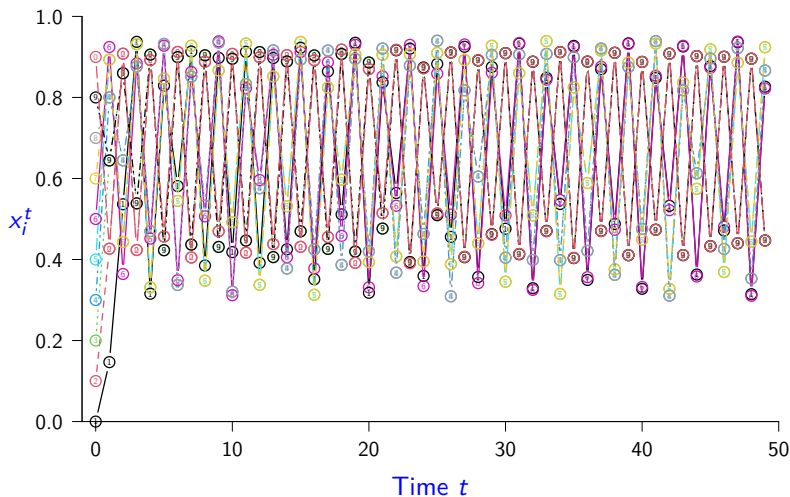
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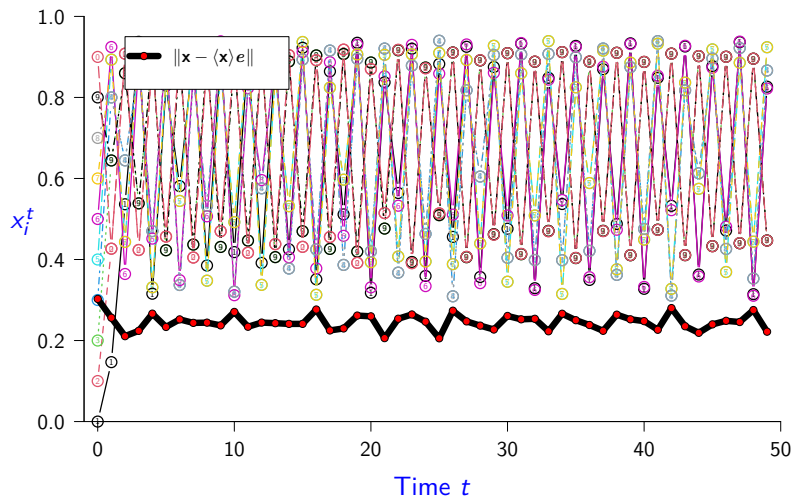
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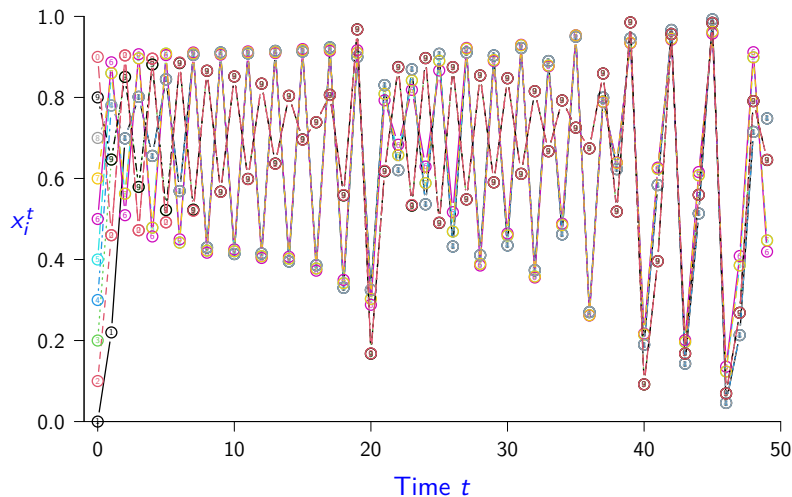


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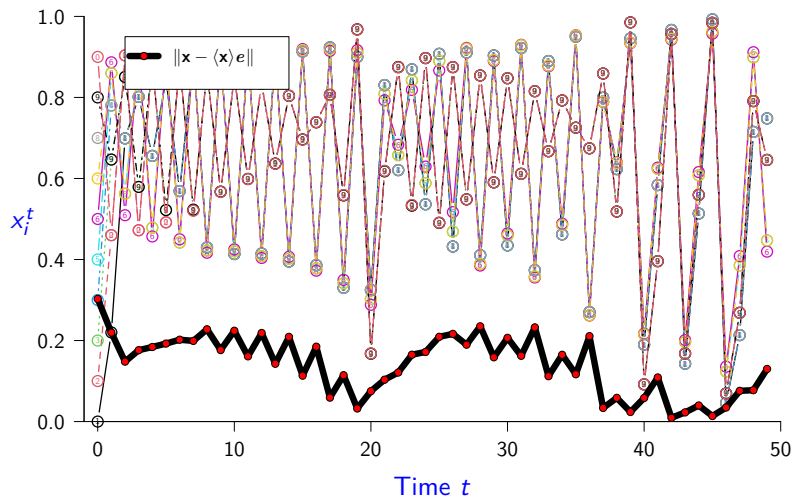


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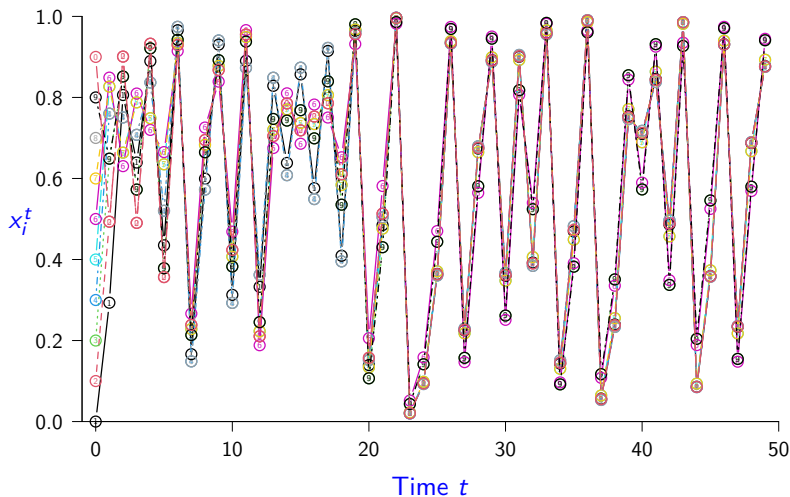
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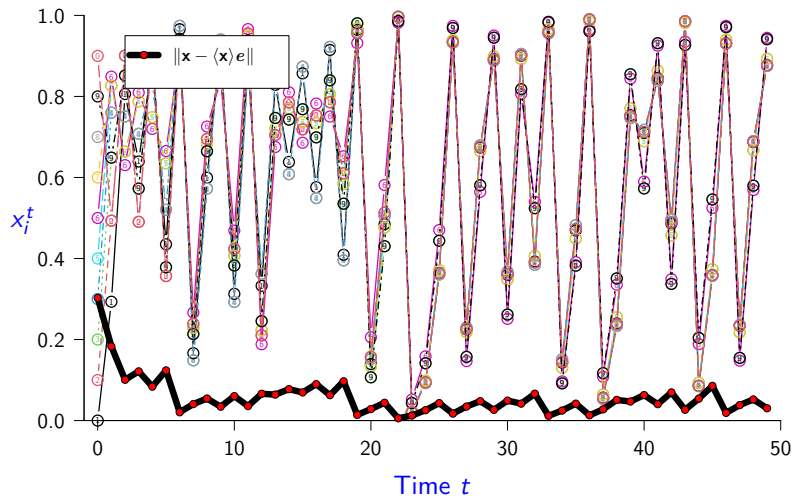
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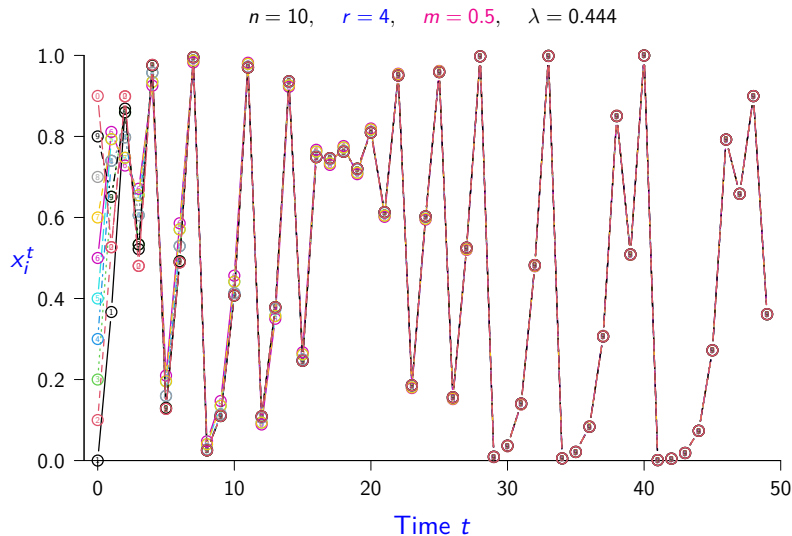
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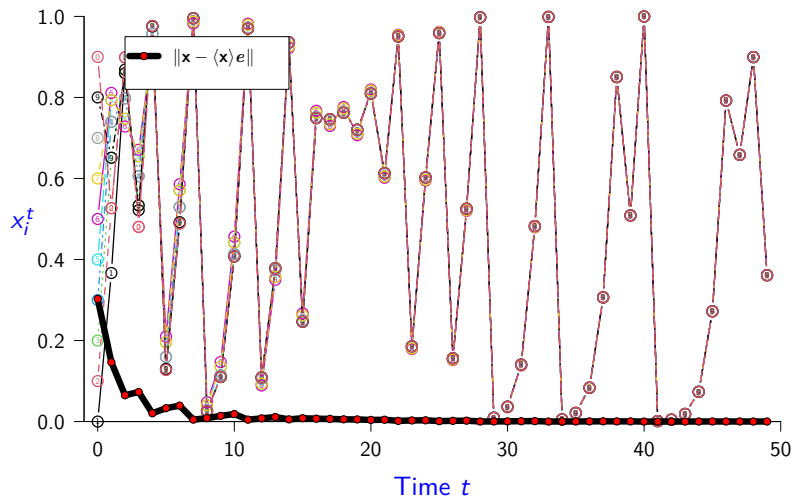
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- Logistic Metapopulation Simulations (10 patches)

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See Horn & Johnson (2013) *Matrix Analysis*, Corollary 8.1.30, p. 522.  $\square$

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$$x_i^{t+1} = \sum_{j=1}^n m_{ij} F(x_j^t), \quad i = 1, \dots, n. \quad (\heartsuit)$$

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But  $e$  is a positive vector, hence by the lemma on the previous slide, 1 is a dominant eigenvalue of  $M$ . □

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- Geometric mean turns out to be more important:

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This is called the maximum (Lyapunov) *characteristic exponent* of the single patch map.

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