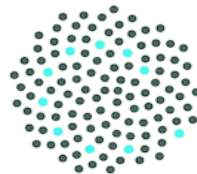


Ensemble behaviour in population processes

Phil Pollett

<http://www.maths.uq.edu.au/~pkp>



AUSTRALIAN RESEARCH COUNCIL
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and Statistics of Complex Systems



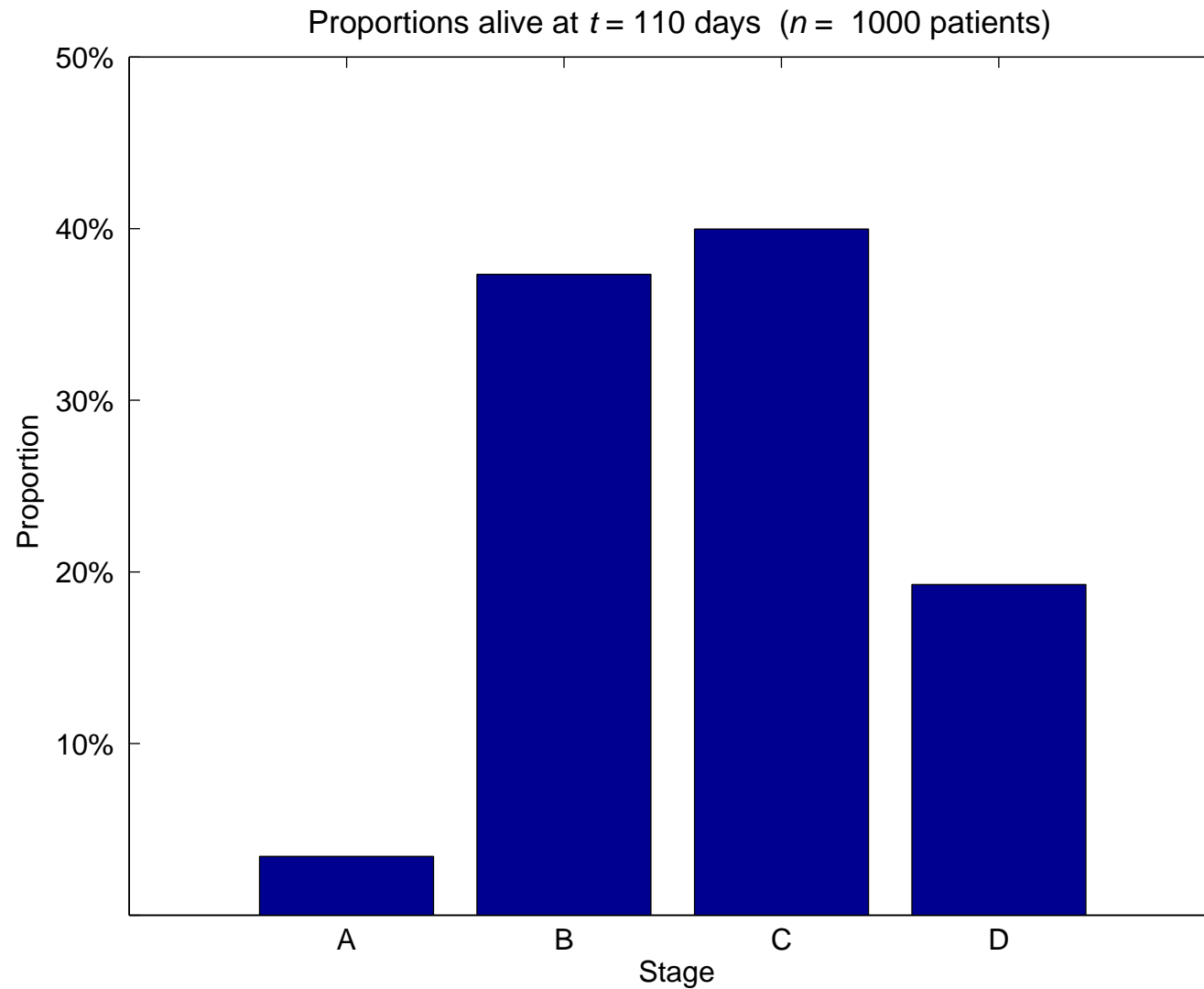
THE UNIVERSITY OF QUEENSLAND
AUSTRALIA

Motivating example

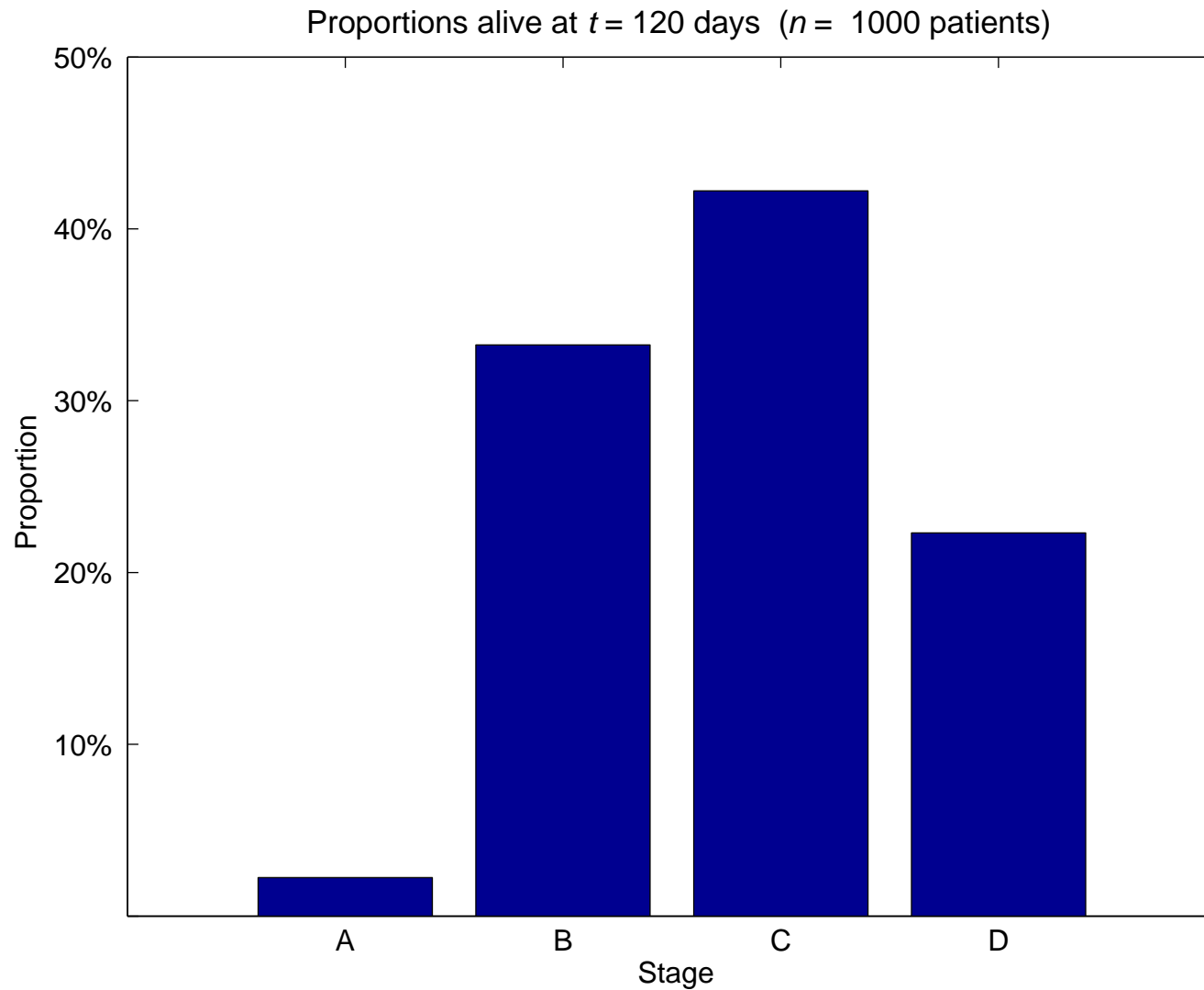
Patients in later stages of congestive heart failure.

Clinicians claimed that numbers appear to be “quasi-stationary”.

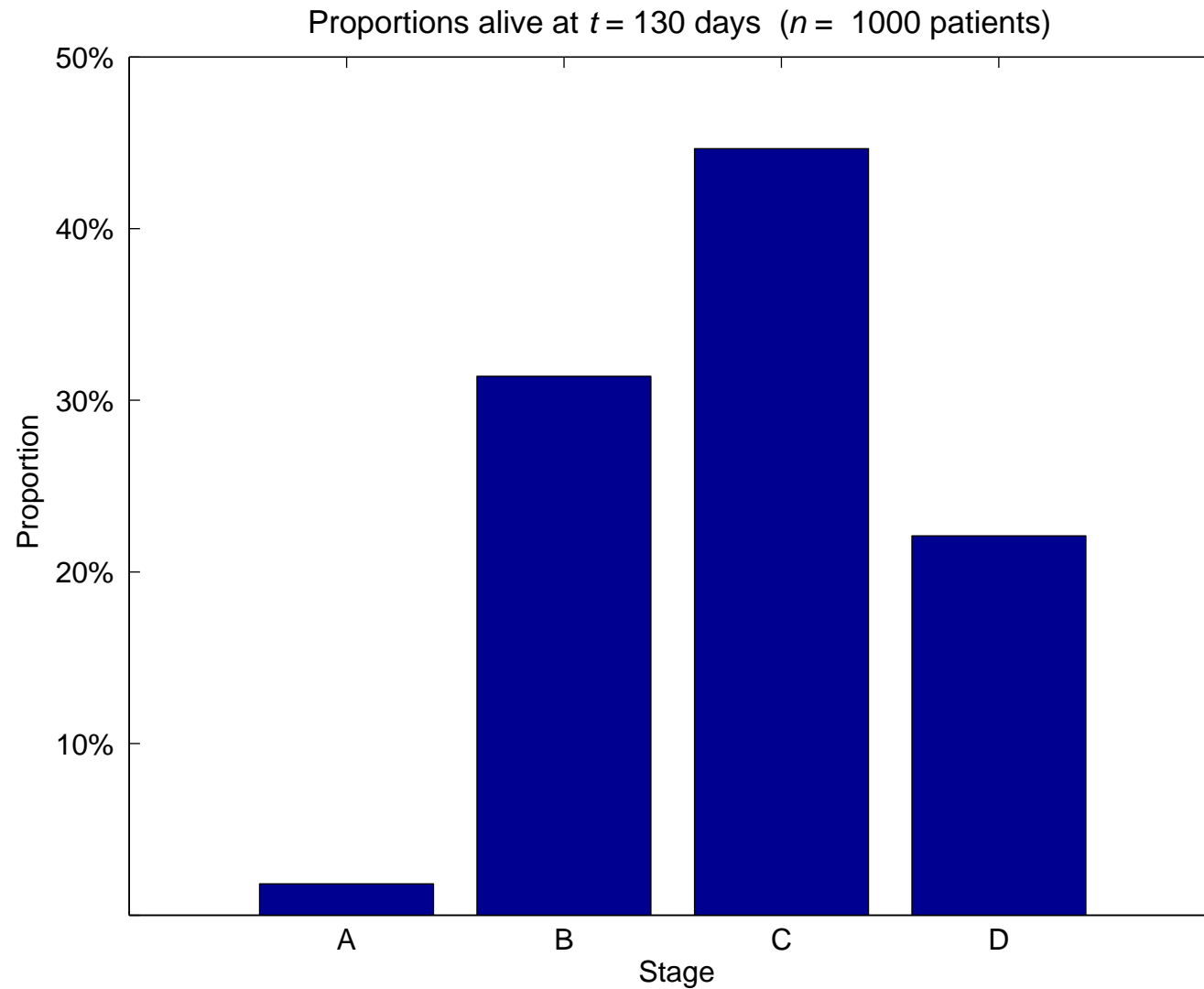
Proportions of patients



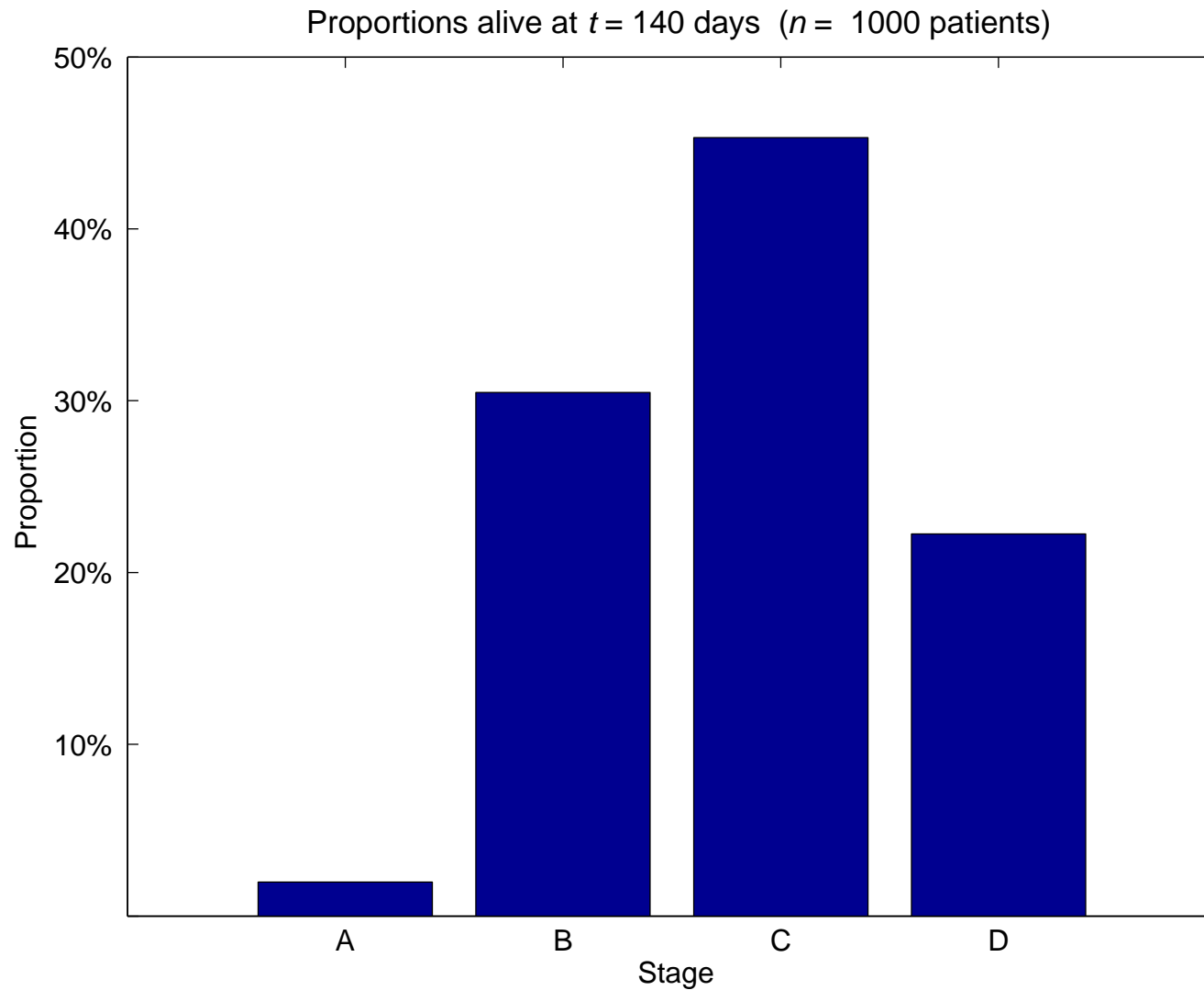
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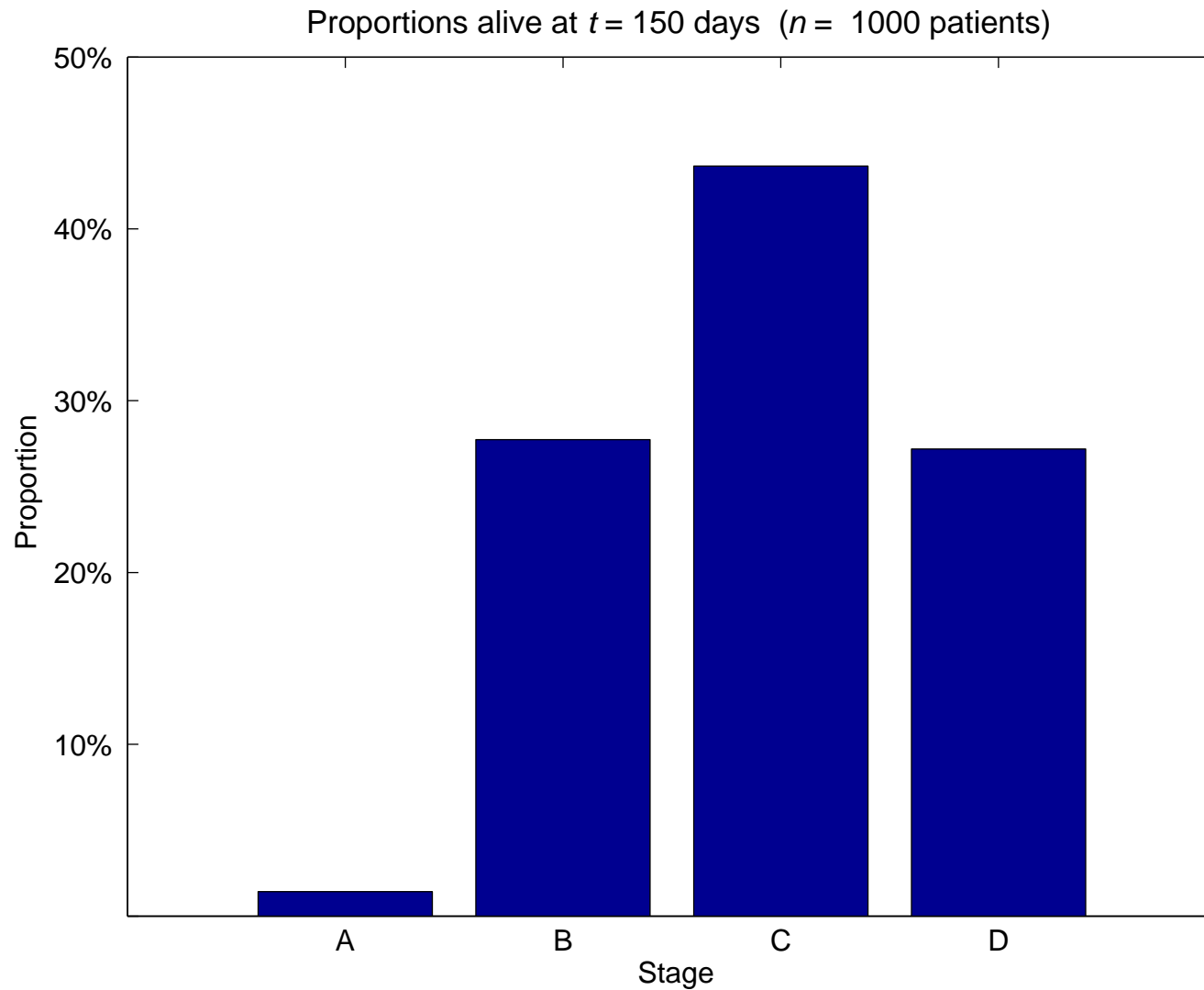
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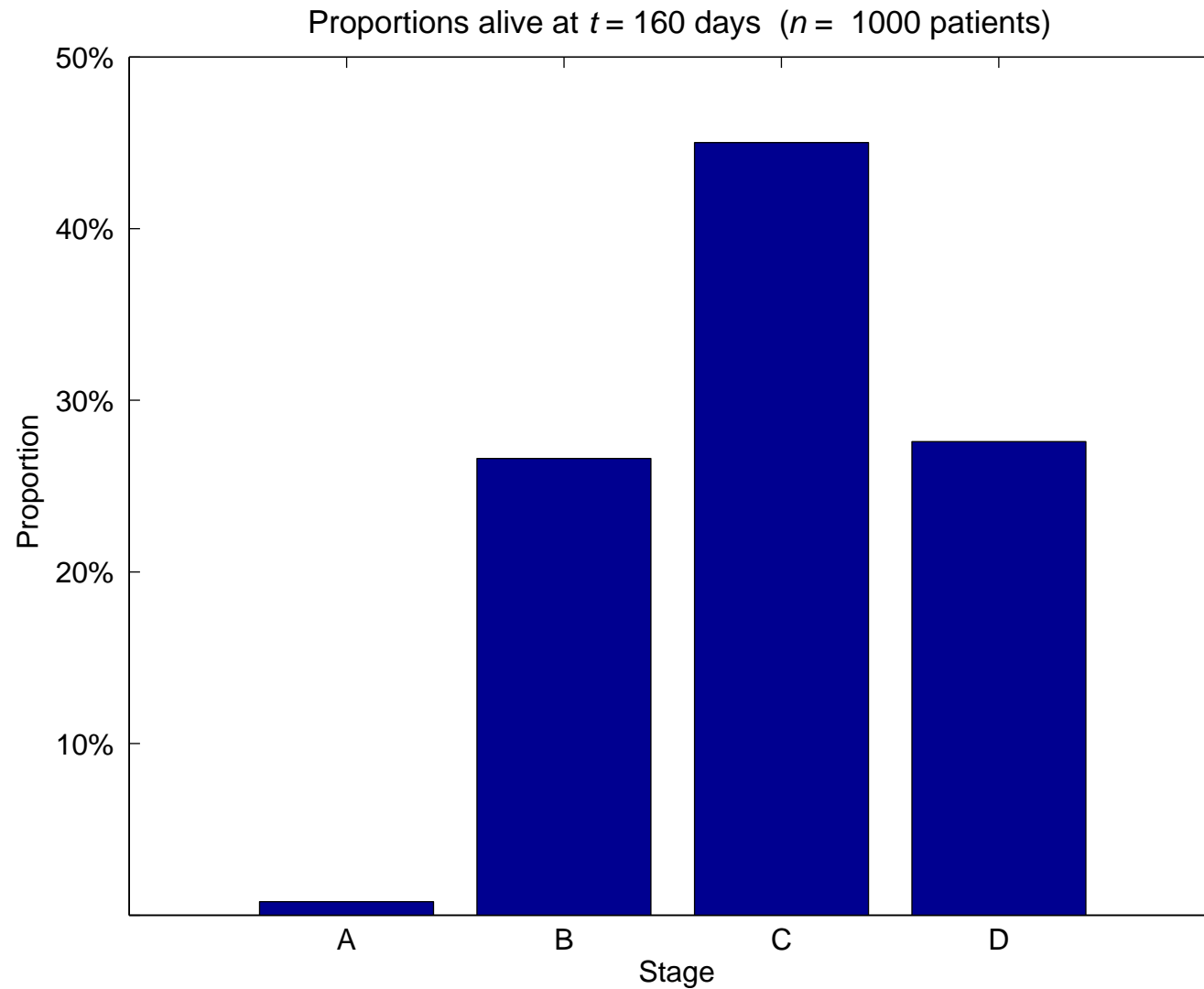
Proportions of patients



Proportions of patients



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Their model

A discrete-time Markov chain with state space $S = \{0, 1, 2, 3, 4\}$ and with 1-step transition matrix $P = (p_{ij})$ given by

$$p_{i,i-1} = 1 - p_{ii} = r_i \quad (i = 1, \dots, 4) \quad (r_1, \dots, r_4 \text{ given}).$$

$$p_{00} = 1.$$

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Correct!

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Further examples

Metapopulation

Example A *population network*, where a fixed number of individuals occupies geographically separated “patches”.

Patches may become empty, but can be recolonized through migration from other patches.

The individual spends a period of time in a given patch and might then emigrate to another patch, spend a period there, and so forth.

We could model the progress of the individual as a random walk on the patches, and thus evaluate quantities such as the probability $p_j(t)$ that the individual occupies patch j at time t . We expect that the *proportion* of individuals in patch j at time t should be approximately equal to $p_j(t)$.

Metapopulation

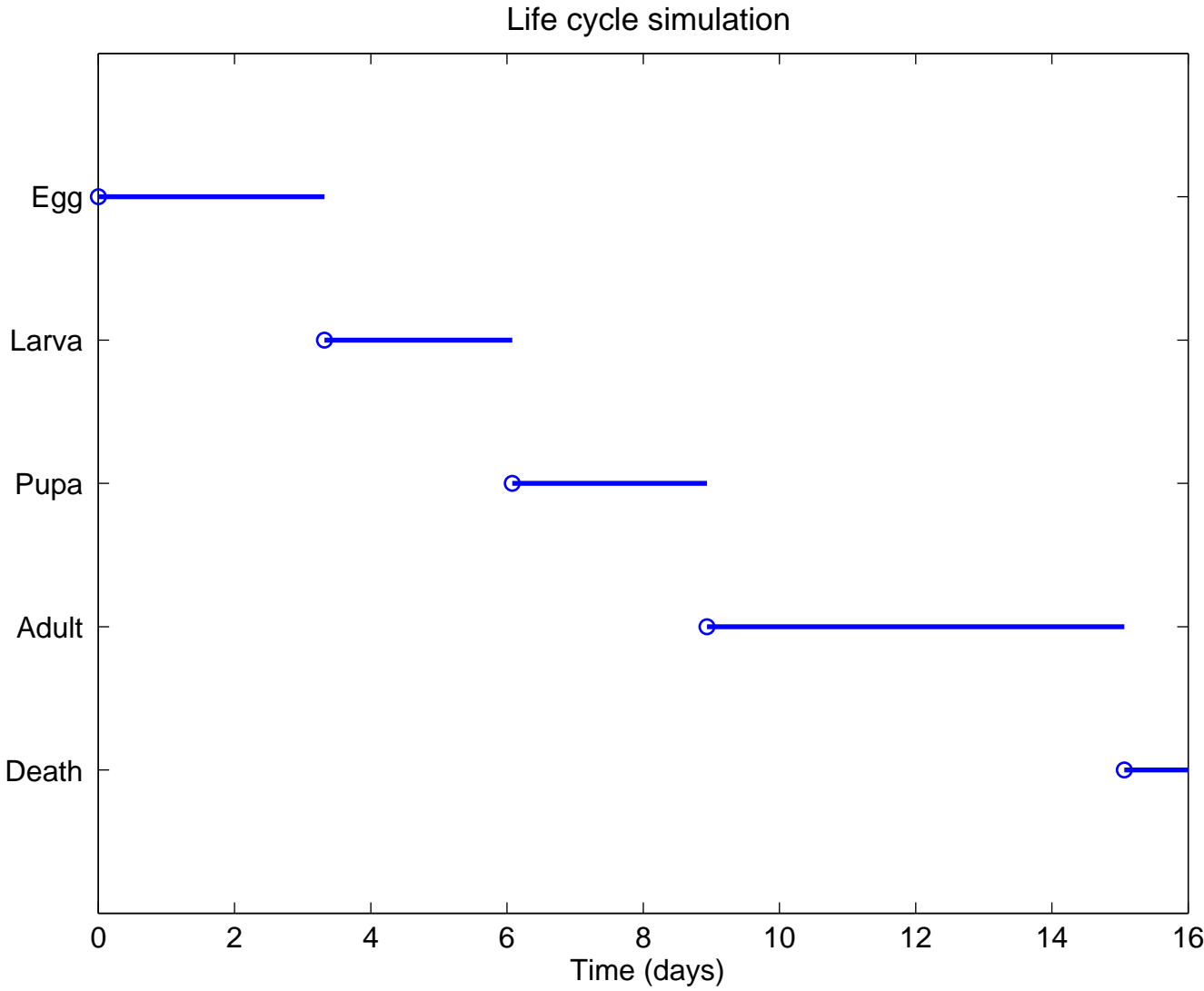
Example A variant where we allow death or external emigration from any patch.

There are two cases: (i) the *open* network, where there is external immigration to one or more patches, and (ii) the *closed* network, where all individuals eventually disappear from the network through death or external emigration.

Now individuals (perhaps arriving from outside the network) perform a random walk on the patches but then eventually leave.

The total number of individuals is now *random*, but we would expect to be able to draw similar conclusions concerning ensemble proportions.

Butterfly life cycle



Butterfly life cycle

Egg \simeq 4 days



Larva (caterpillar) \simeq 14 days



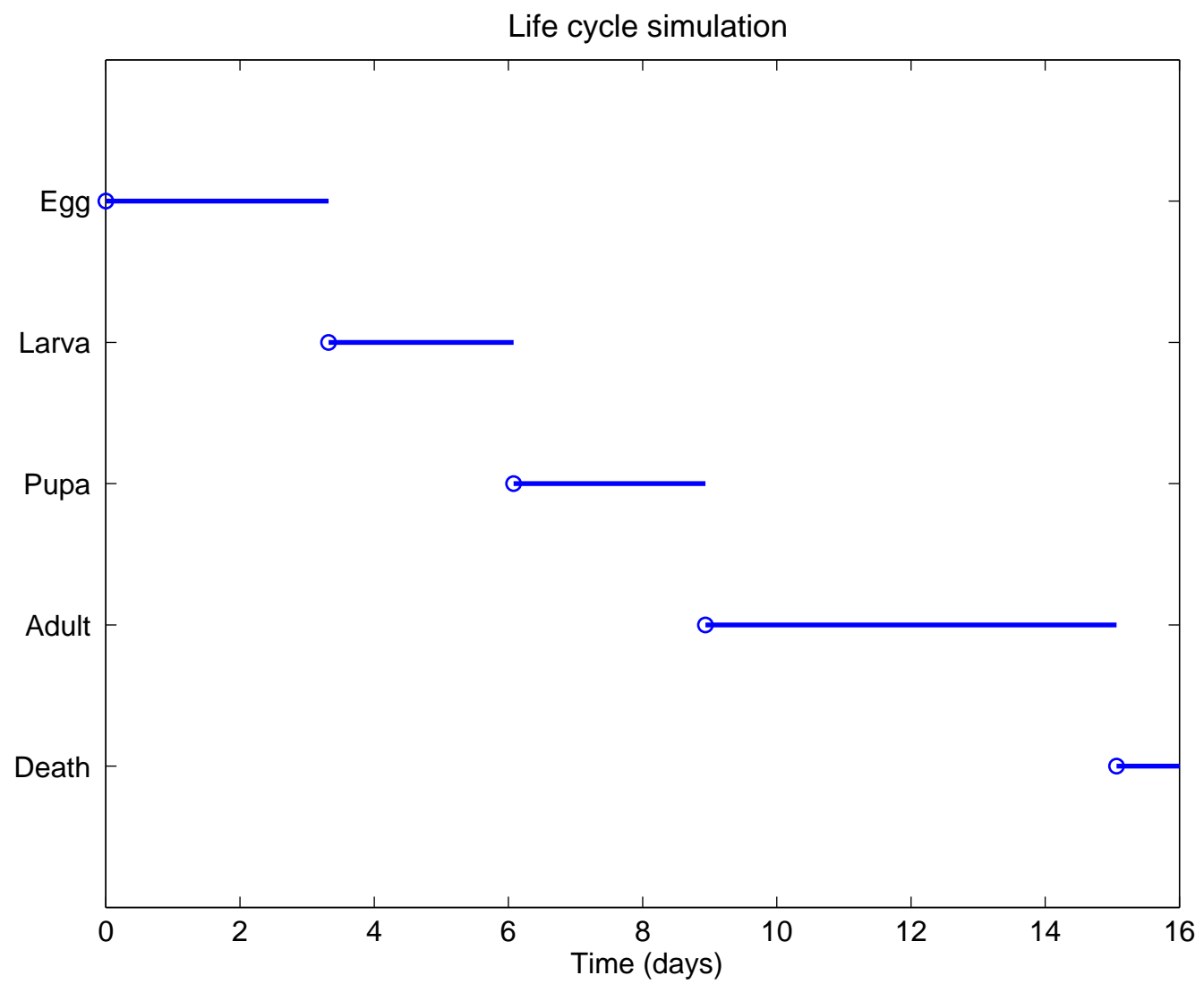
Pupa (chrysalis) \simeq 7 days



Adult (butterfly) \simeq 14 days

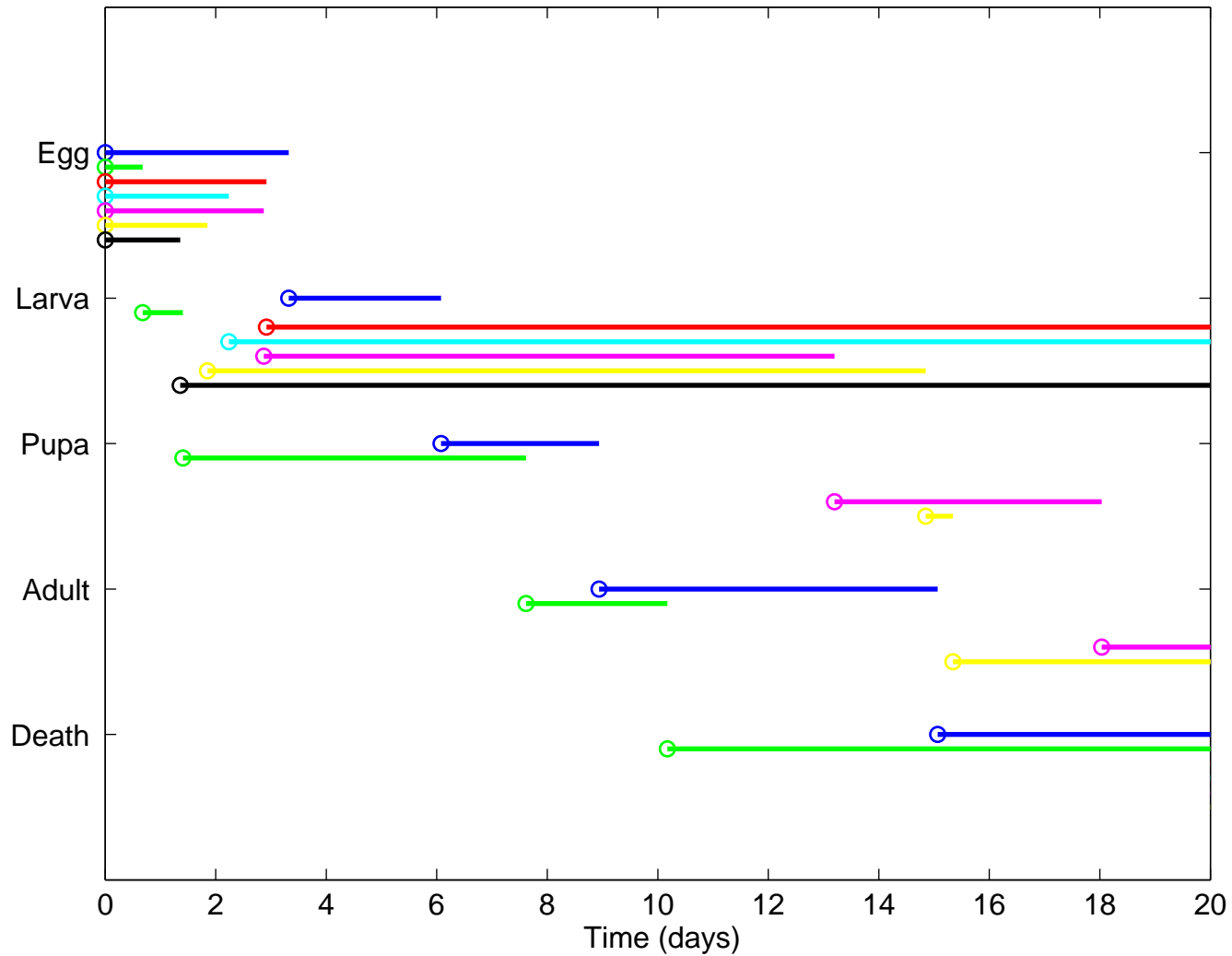


Butterfly life cycle



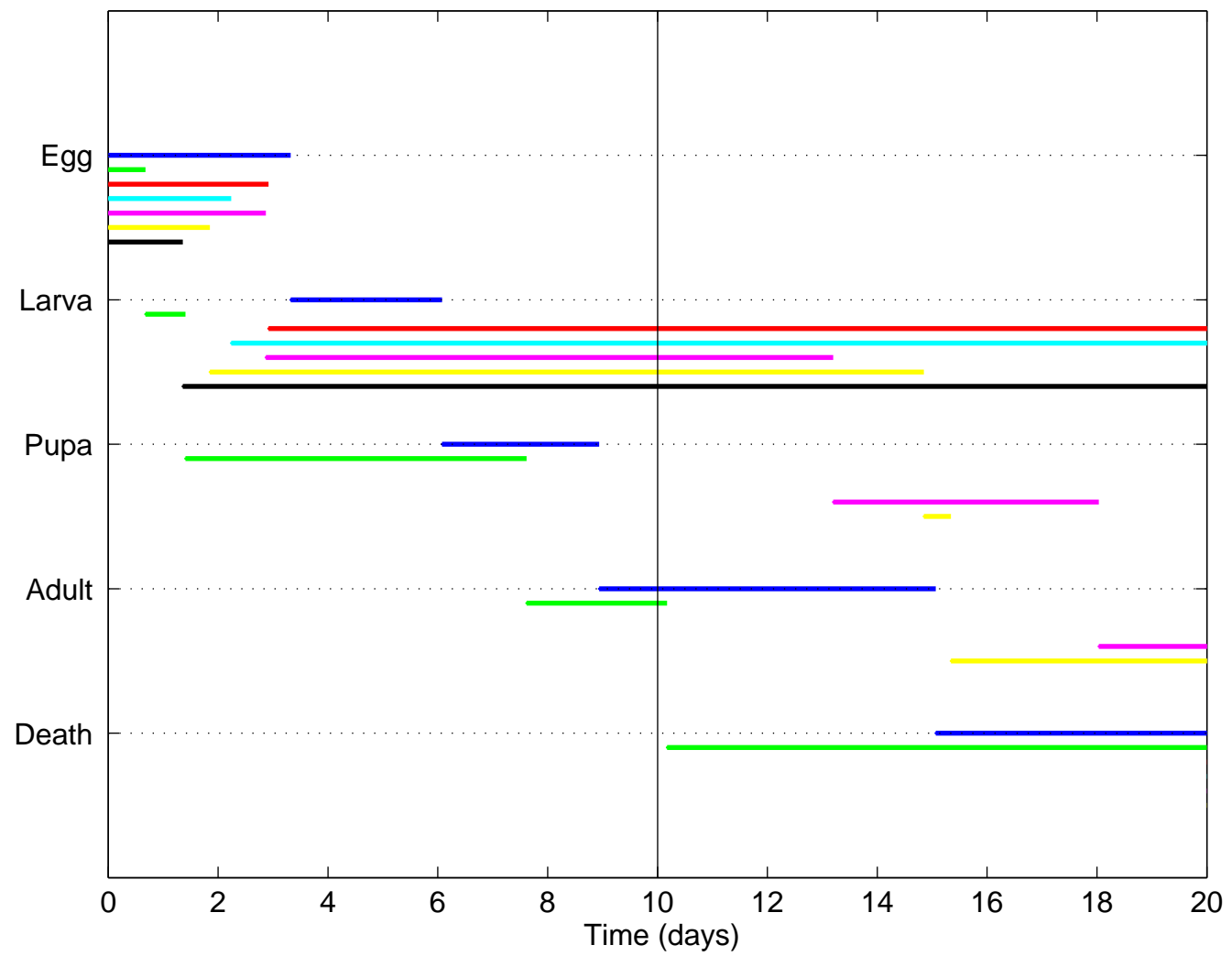
Ensemble of organisms

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For example, suppose we have n butterflies.

Our intuition tells us that, for the ensemble, the *proportion* of organisms in stage s at time t should be approximately equal to $p_s(t)$, the *probability* that the *individual* organism is in stage s at time t .

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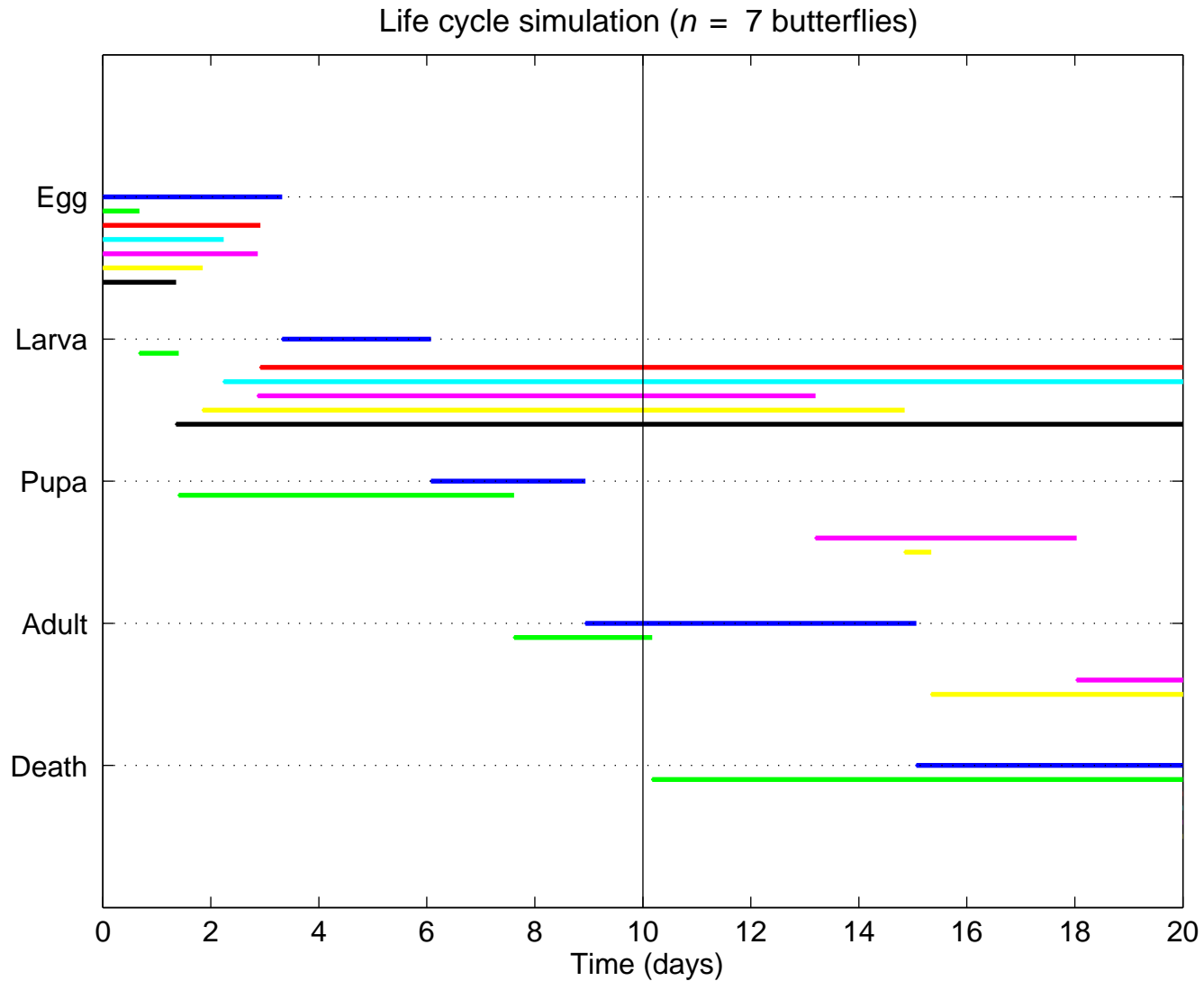
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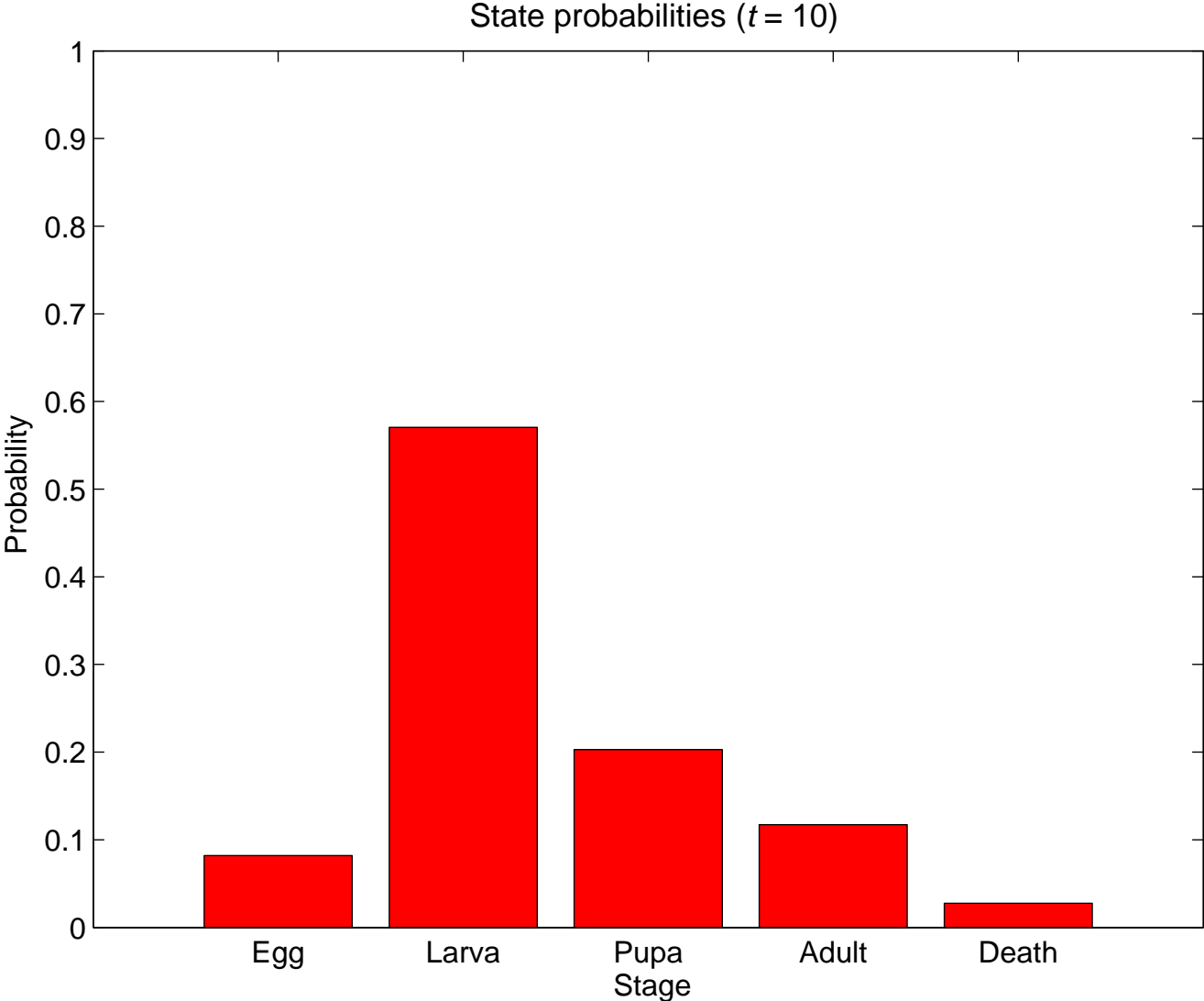
Our intuition tells us that, for the ensemble, the *proportion* of organisms in stage s at time t should be approximately equal to $p_s(t)$, the *probability* that the *individual* organism is in stage s at time t .

So strong is this intuition that scientists frequently model population proportions using individual-level models.

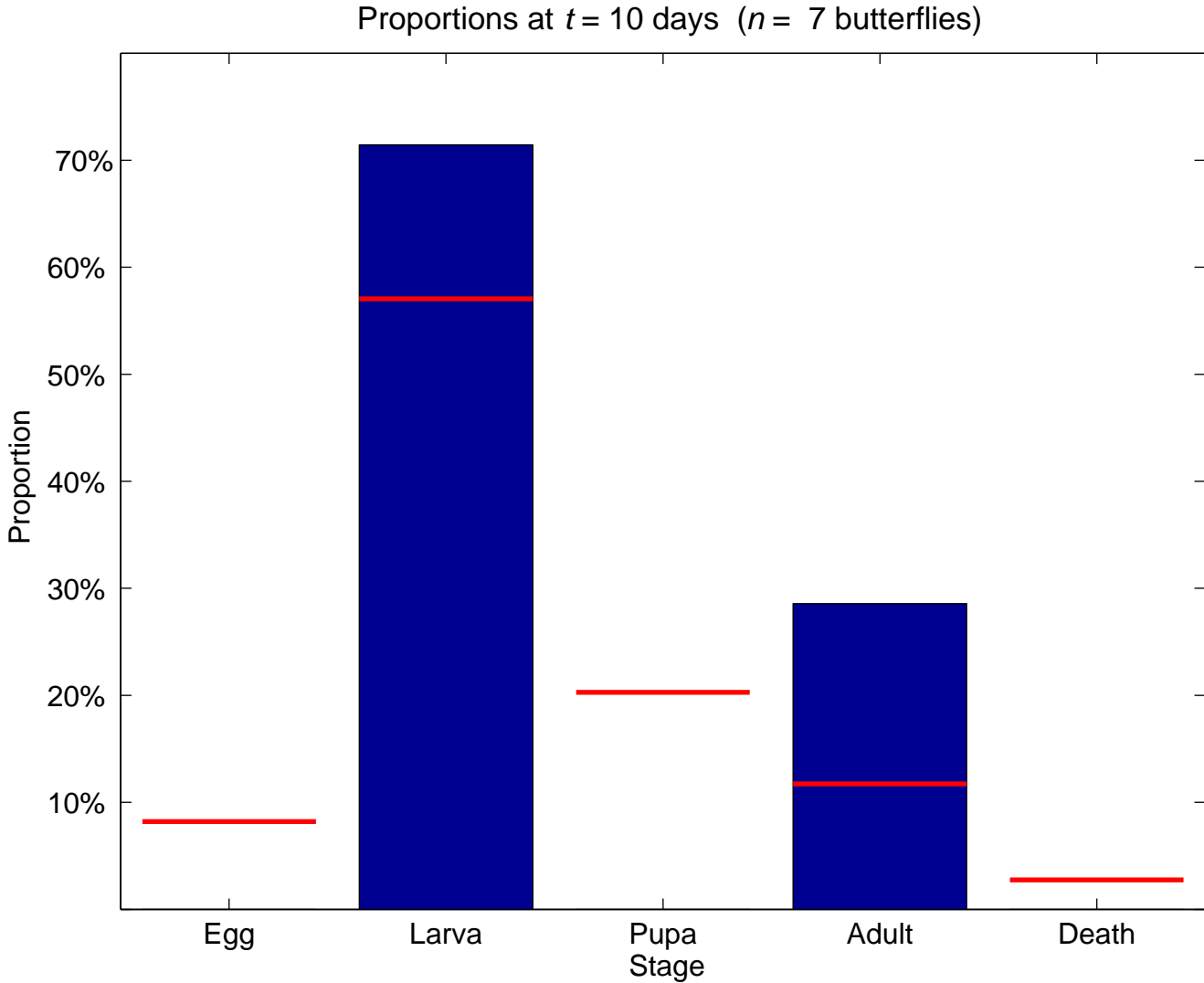
State probabilities (individual)



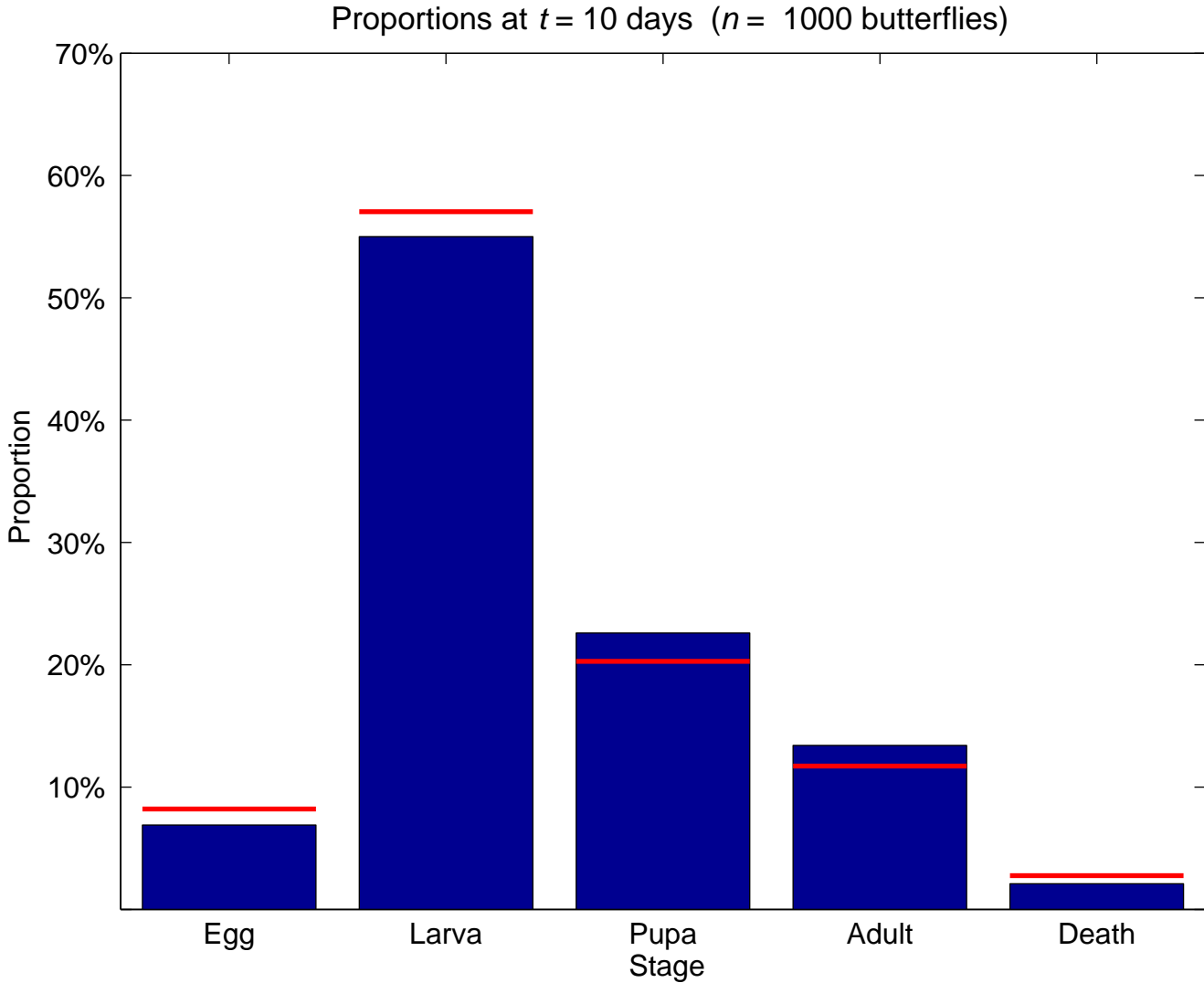
State probabilities (individual)



Simulated proportions (ensemble)



Simulated proportions (ensemble)



State proportions (ensemble)

Perhaps not surprising ...

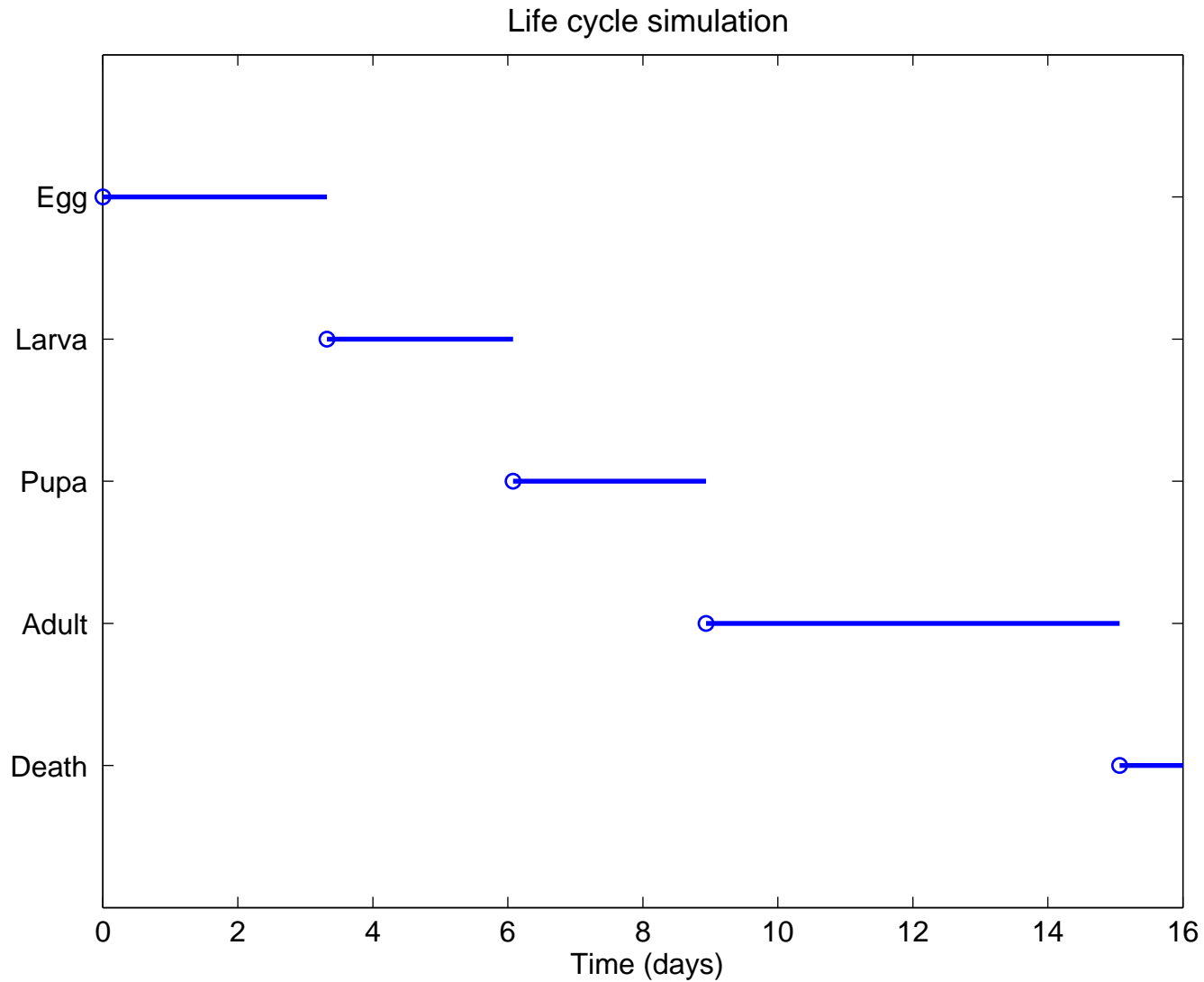
If the individual organisms behave independently, we can employ the Law of Large Numbers.

Look at the ensemble at a fixed time t . Fix a stage s and let

$$X_j = \begin{cases} 1 & \text{if organism } j \text{ is in stage } s \\ 0 & \text{if organism } j \text{ is in another stage.} \end{cases}$$

Clearly X_1, X_2, \dots are independent. So, $\frac{1}{n} \sum_{j=1}^n X_j$ (the proportion in stage s) converges *almost surely* to $\mathbb{E}(X_1)$, being the probability that any given organism is in stage s .

Individual organism



Evaluating state probabilities

What is the probability that the organism is in stage s of its life cycle at time t ?

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Using a simple Markov chain model, we can evaluate this for each stage s and for all times t .

Evaluating state probabilities

$X(t)$ - the state of an individual at time t (≥ 0), for example, the current stage in the individual's life cycle.

Suppose $(X(t), t \geq 0)$ is a continuous-time Markov chain taking values in a discrete set S with transition rates (q_{ij}) :

q_{ij} is the rate of transition from state $i \rightarrow j$ ($j \neq i$).

$q_i (= -q_{ii}) = \sum_{j \neq i} q_{ij}$ is the total rate out of state i .

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Example (Butterfly life cycle) $\{4\} \rightarrow \{3\} \rightarrow \{2\} \rightarrow \{1\} \rightarrow \{0\}$

$q_4 = q_{43} = 1/4$ \downarrow Egg ($\simeq 4$ days)

$q_3 = q_{32} = 1/14$ \downarrow Caterpillar ($\simeq 14$ days)

$q_2 = q_{21} = 1/7$ \downarrow Chrysalis ($\simeq 7$ days)

$q_1 = q_{10} = 1/14$ \downarrow Adult ($\simeq 14$ days)

Evaluating state probabilities

In matrix form

$$Q = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 1/14 & -1/14 & 0 & 0 & 0 \\ 0 & 1/7 & -1/7 & 0 & 0 \\ 0 & 0 & 1/14 & -1/14 & 0 \\ 0 & 0 & 0 & 1/4 & -1/4 \end{pmatrix}$$

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Why put minus the total rate on the diagonal?

For mathematical convenience ... the equations we must solve are then easier to write down.

Evaluating state probabilities

The state probabilities $\mathbf{p}(t) = (p_j(t), j \in S)$, where

$$p_j(t) = \Pr(X(t) = j),$$

can be obtained as the (unique) solution to

$$\mathbf{p}'(t) = \mathbf{p}(t) Q \quad \text{satisfying} \quad \mathbf{p}(0) = \mathbf{a},$$

where $\mathbf{a} = (a_j, j \in S)$ is a given initial distribution.

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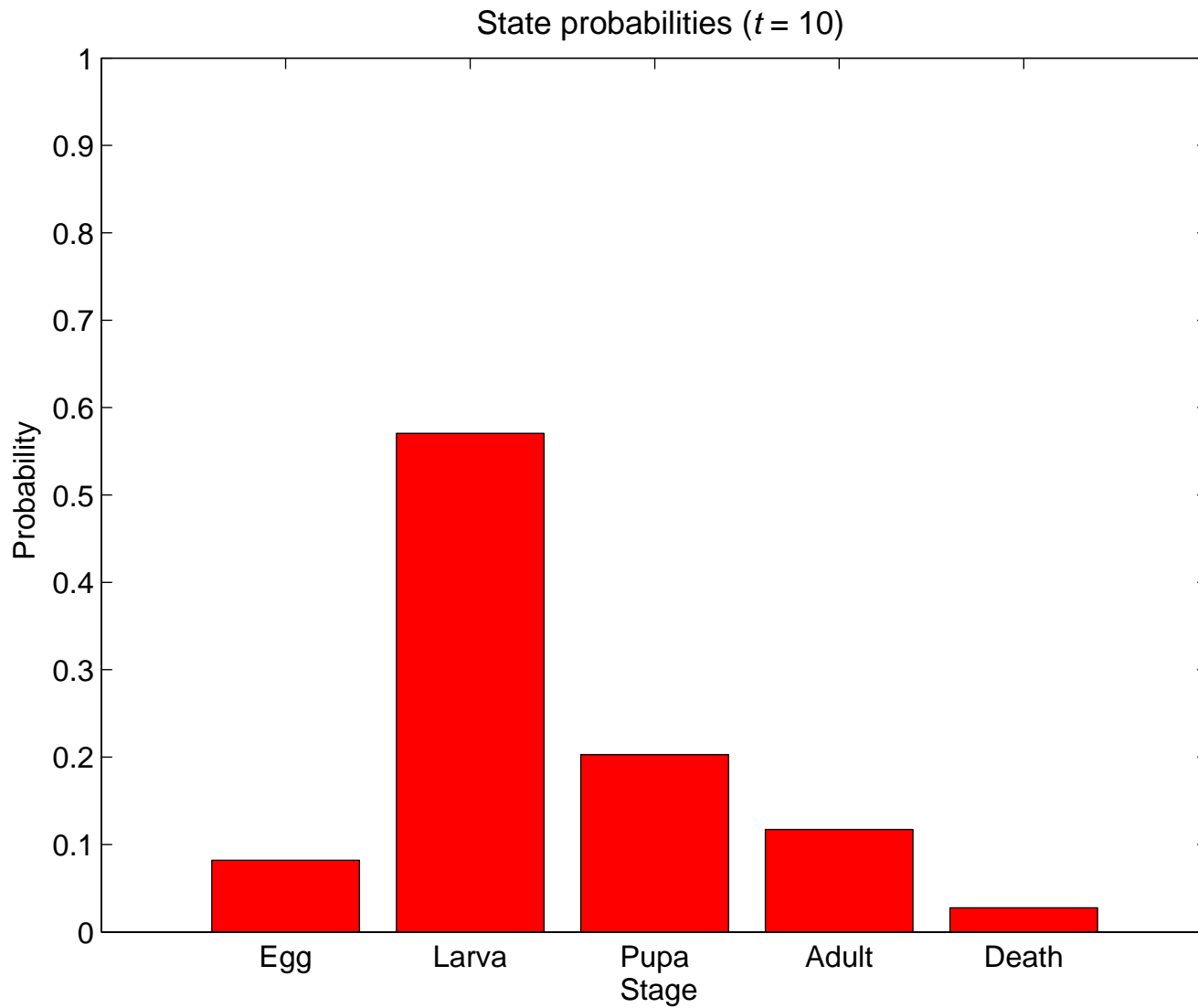
Customary disclaimer: It will be convenient to restrict our attention to the case where S is a *finite* set, but I note that many of the arguments presented hold more generally.

Using Matlab

```
% State probabilities (butterfly life cycle)

q(1)=1/14; q(2)=1/7; q(3)=1/14; q(4)=1/4;
Q=zeros(5,5);
for i=2:5
    state=i-1; % Matlab doesn't like a 0 index
    Q(i,i-1)=q(state); Q(i,i)=-q(state);
end
i=5; t=10;
P=expm(Q*t); % The solution to p'(t)=p(t)Q
p=P(i,1:5); % with p_4(0)=1
bar(0:4,p);
```

Individual organism



Analytically

The state probabilities can almost never be evaluated analytically.

Analytically

The state probabilities can almost never be evaluated analytically. There are exceptions ...

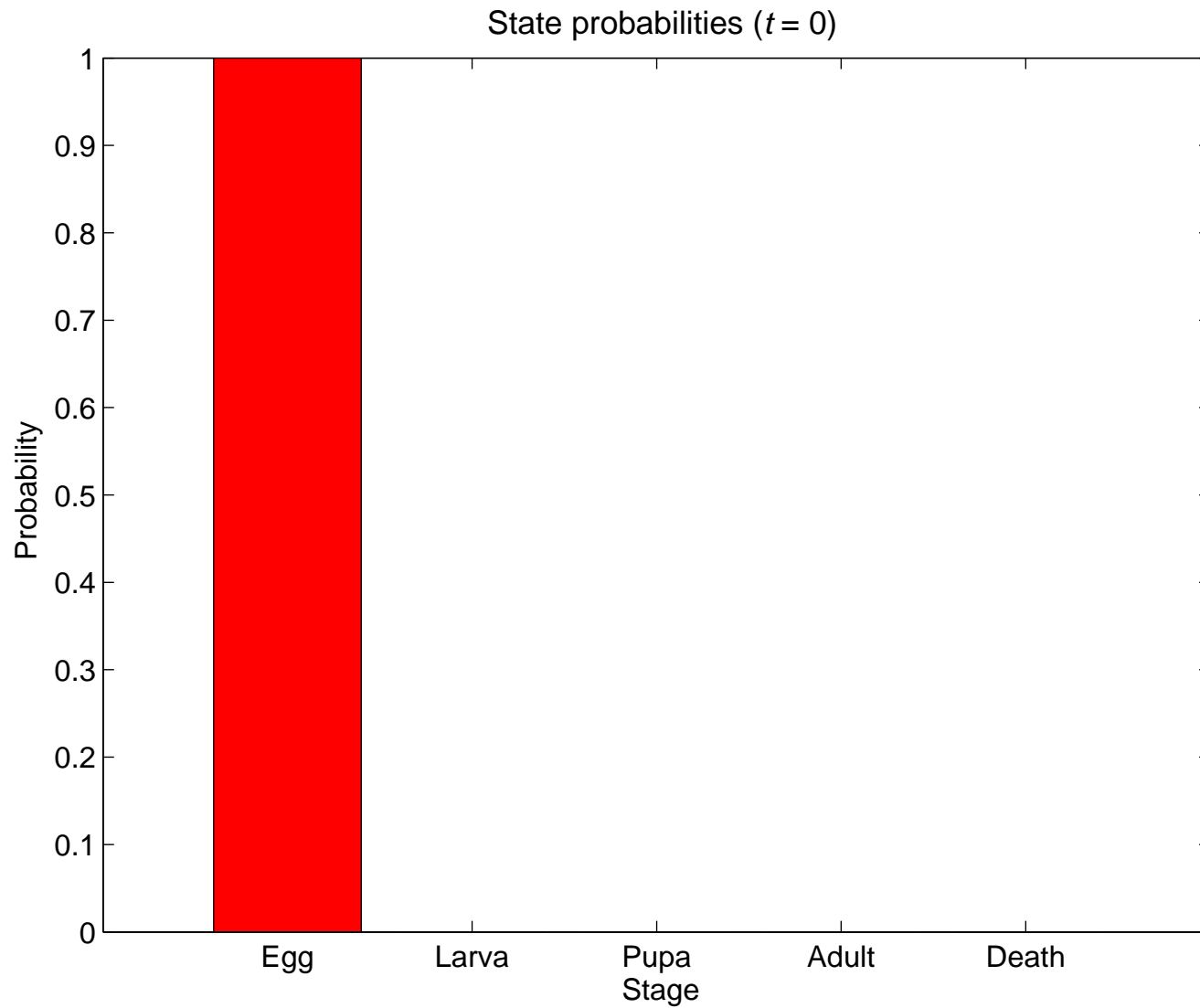
Suppose that an organism has M stages of life ($M = 4$ for the butterfly), and that the expected time spent in stage j is $1/q_j$ (q_j is the rate of departure from stage j).

Exercise (Grimmett and Stirzaker, Exercise 6.8.31): Show that if q_1, q_2, \dots, q_M are distinct, then

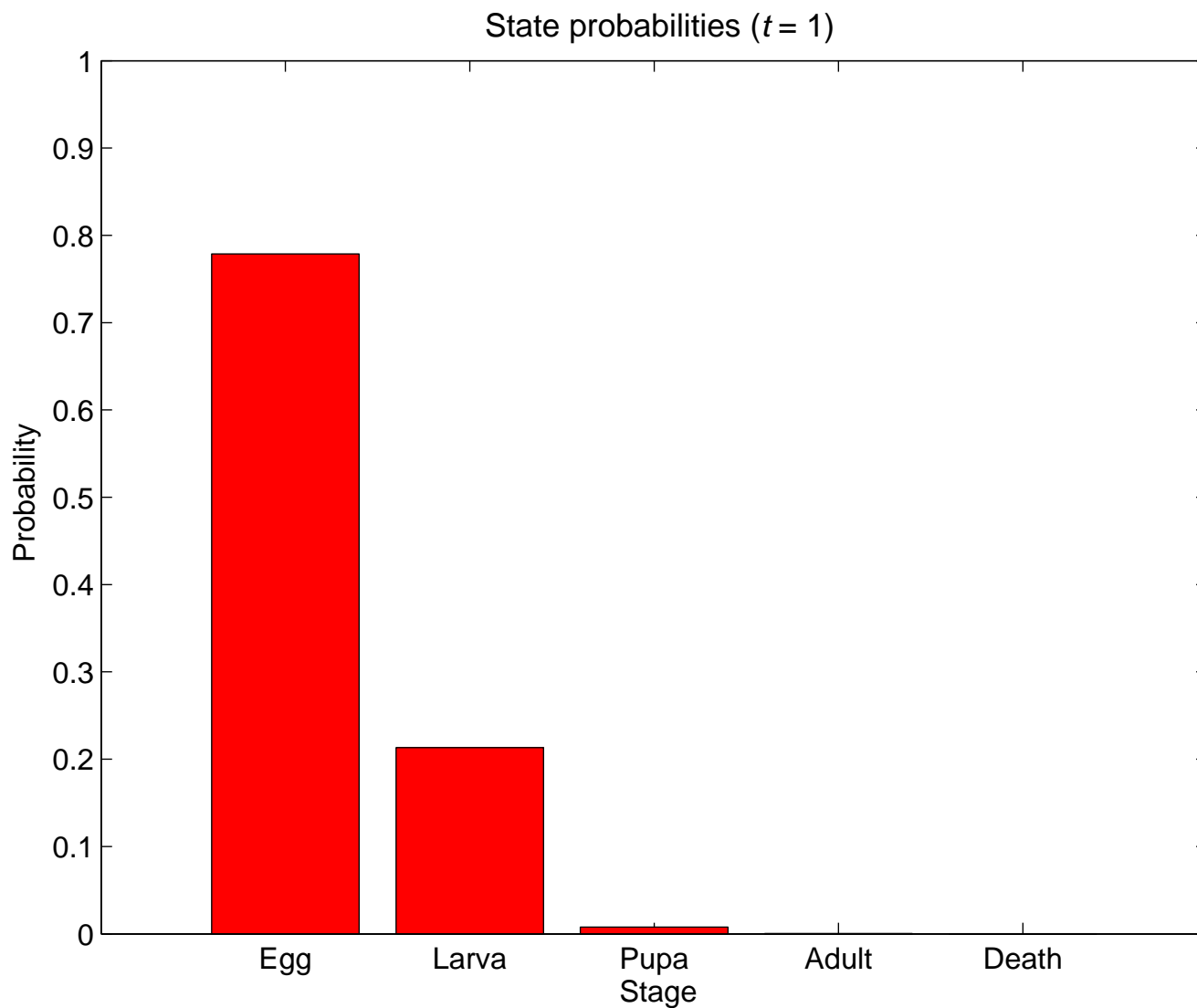
$$p_j(t) = \frac{1}{q_j} \sum_{k=j}^M q_k e^{-q_k t} \prod_{l=j, l \neq k}^M \frac{q_l}{q_l - q_k},$$

for $j = 1, \dots, M$, and $p_0(t) = 1 - \sum_{j=1}^M p_j(t)$.

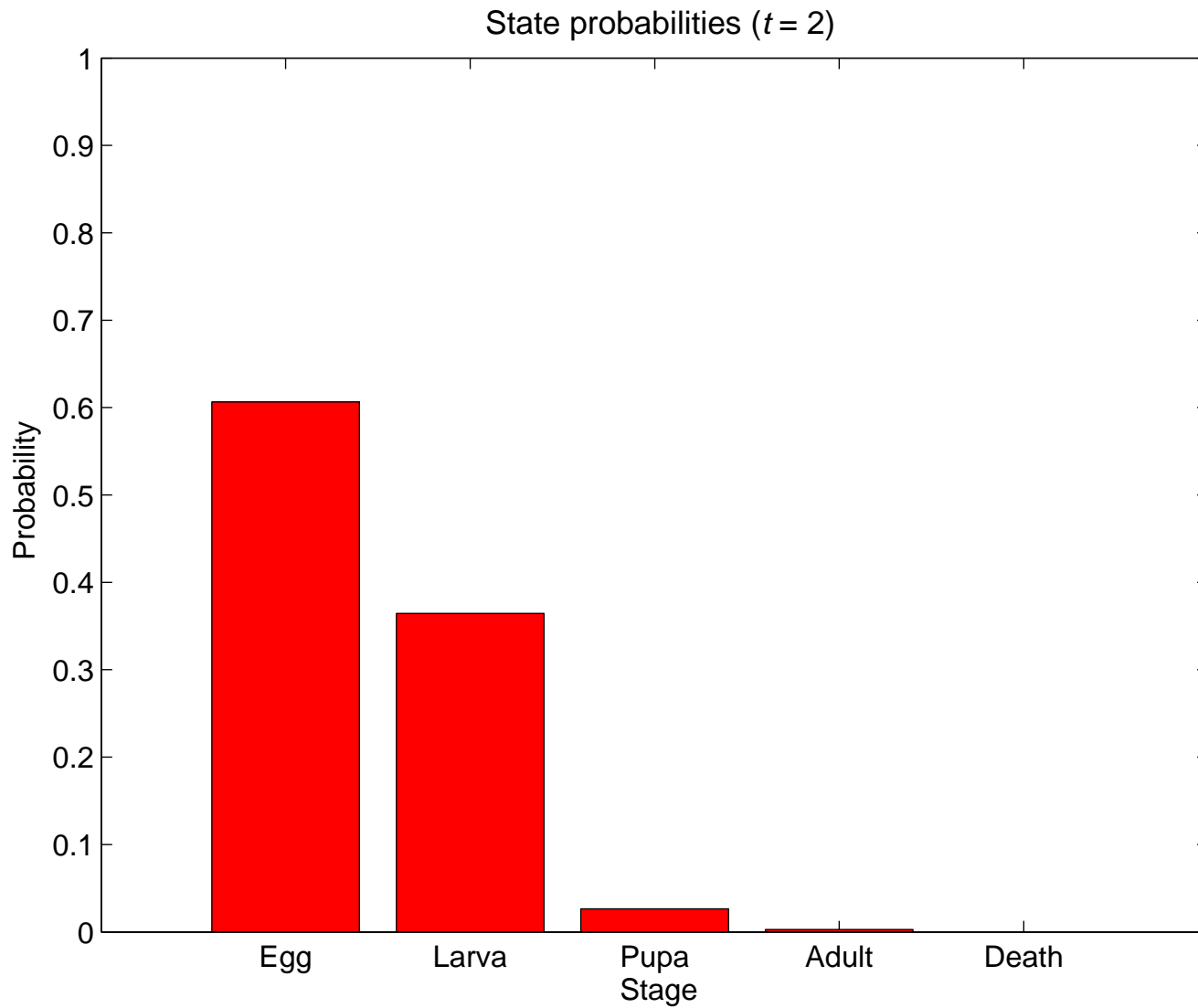
Individual organism



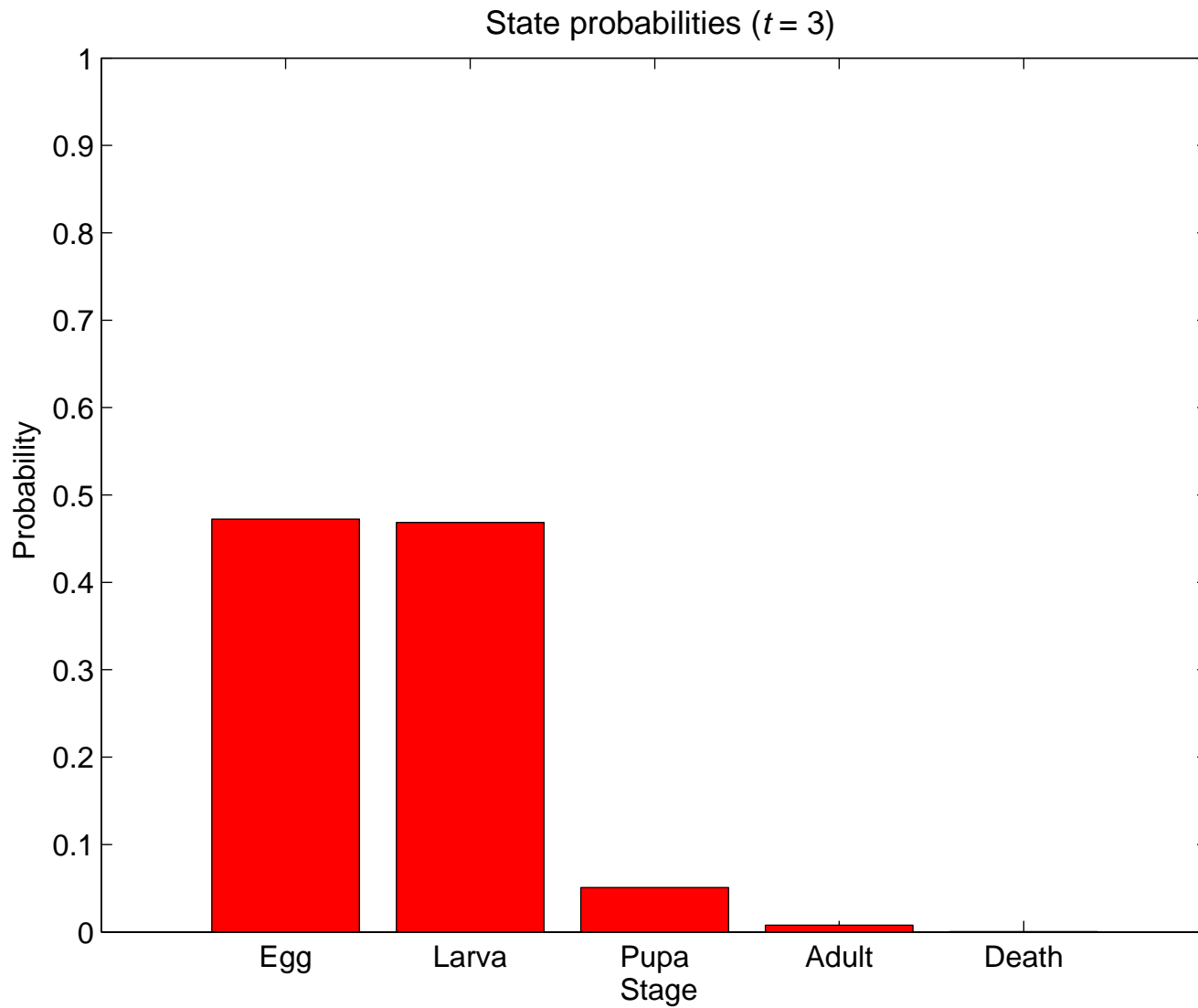
Individual organism



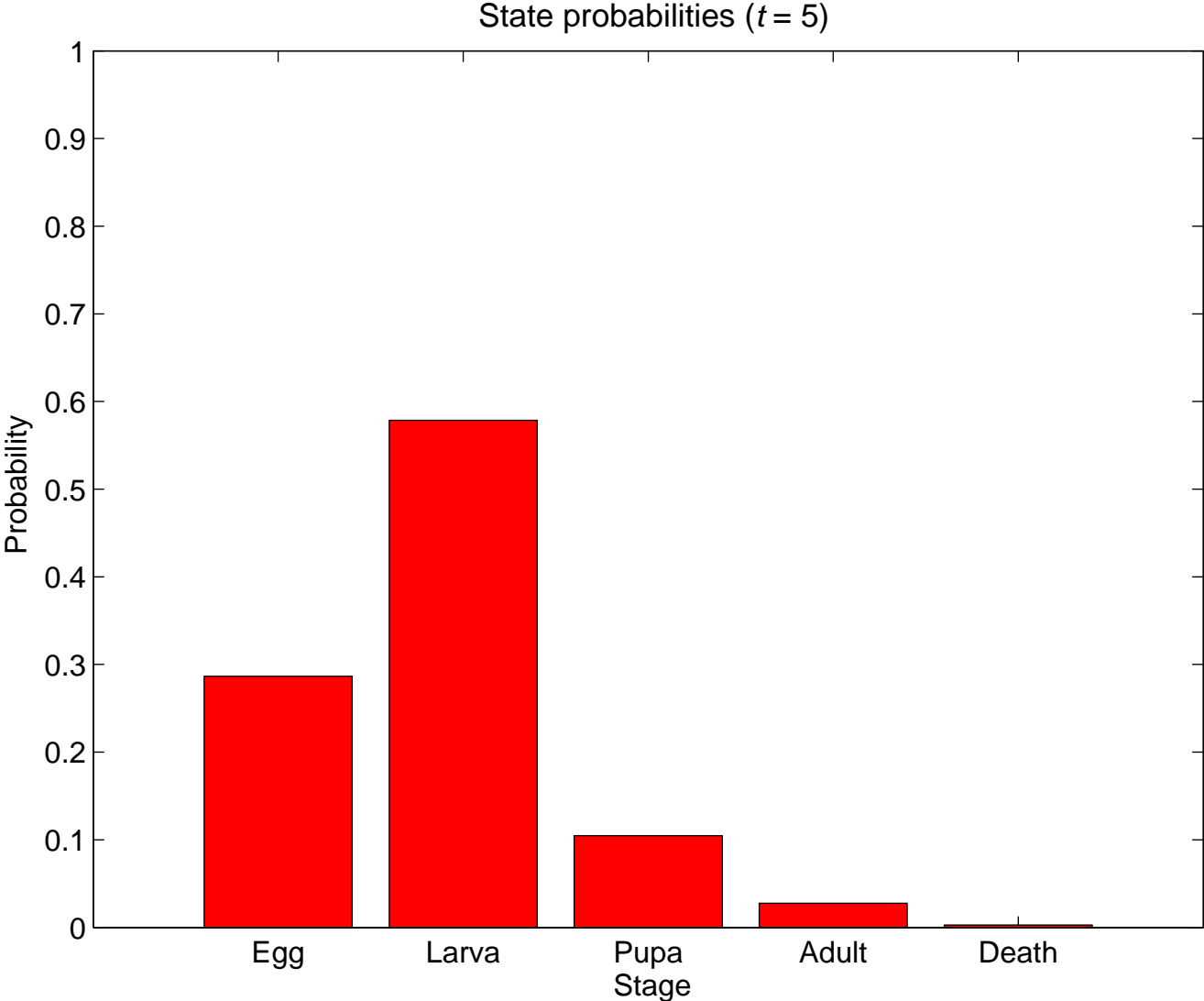
Individual organism



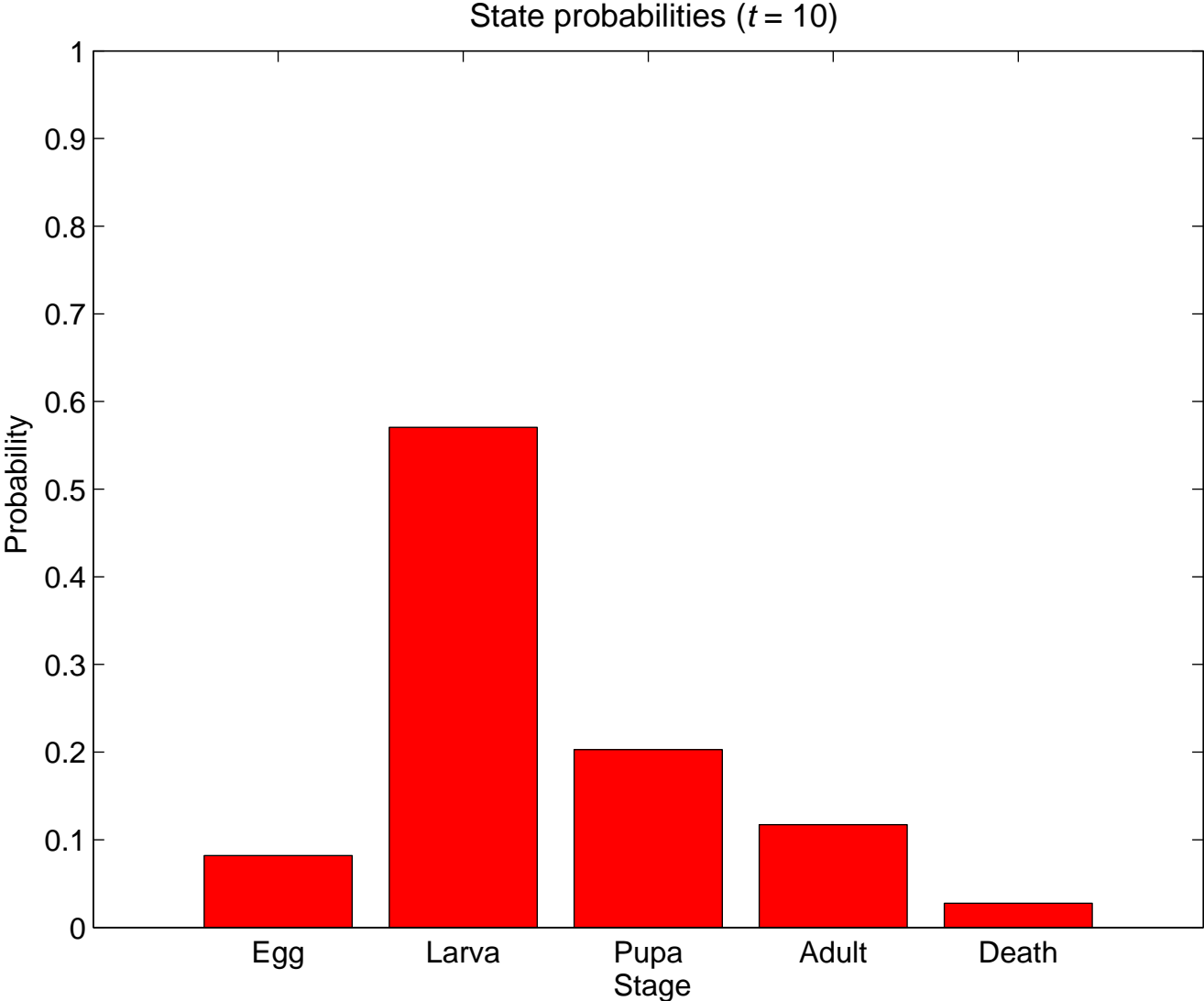
Individual organism



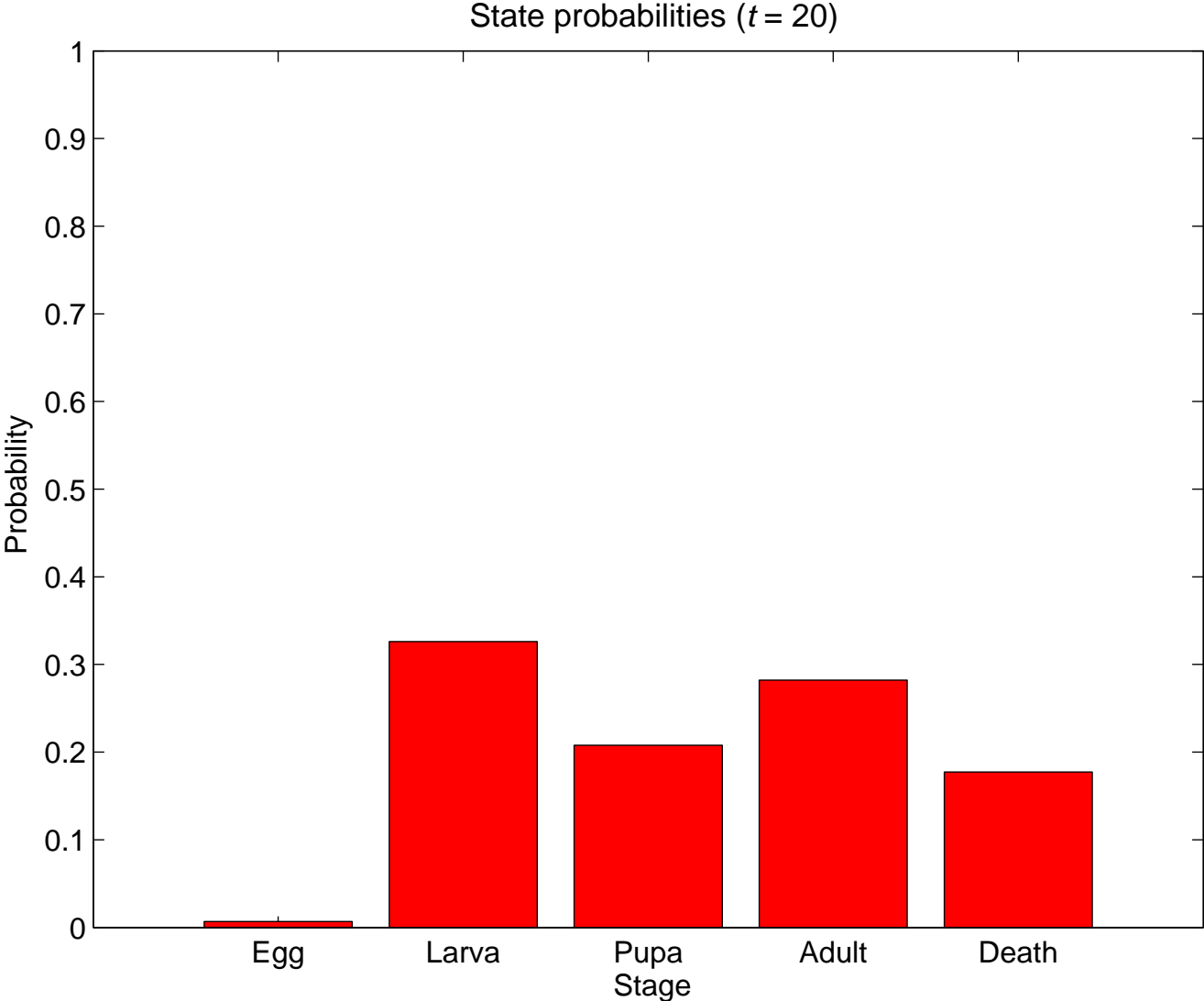
Individual organism



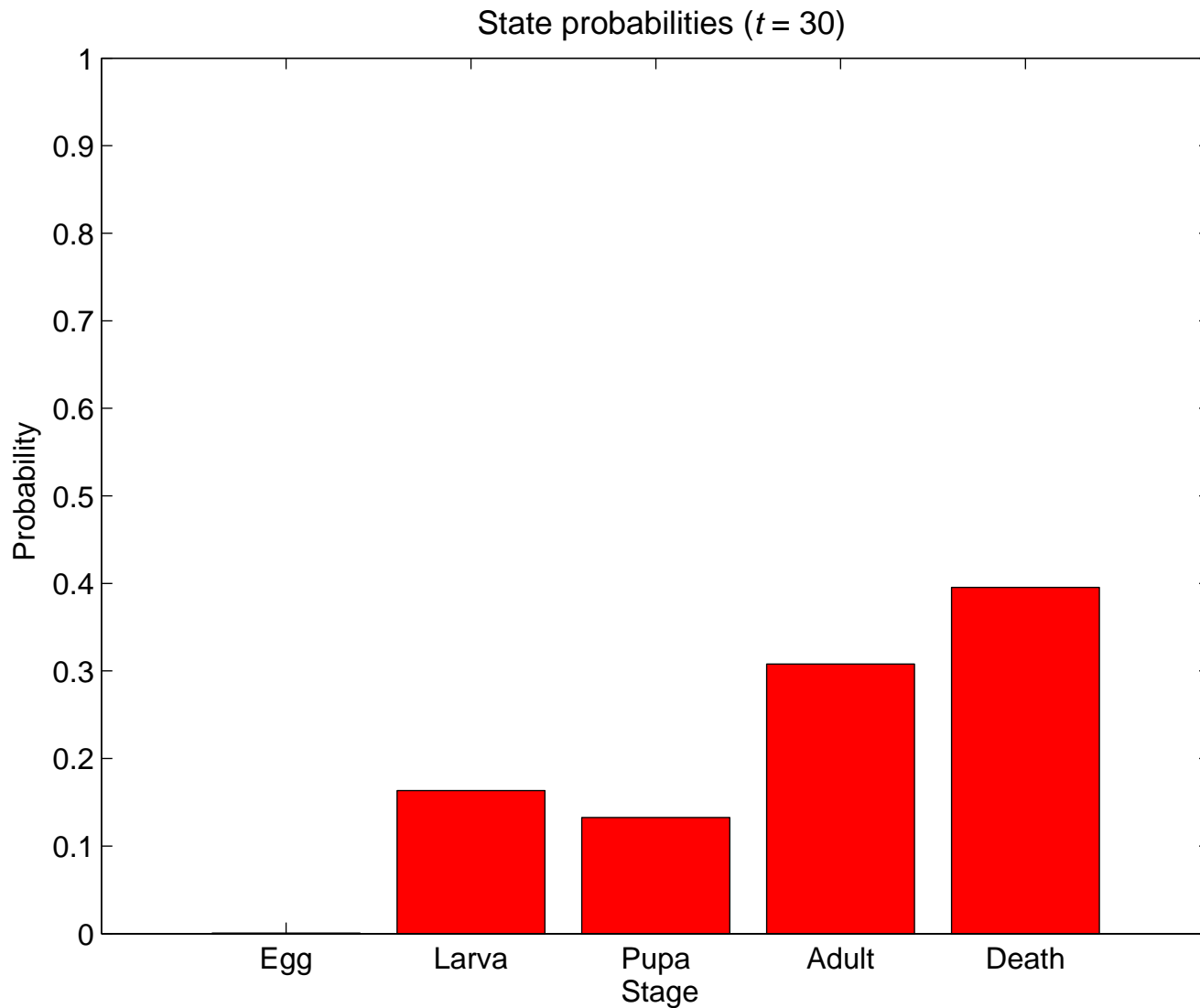
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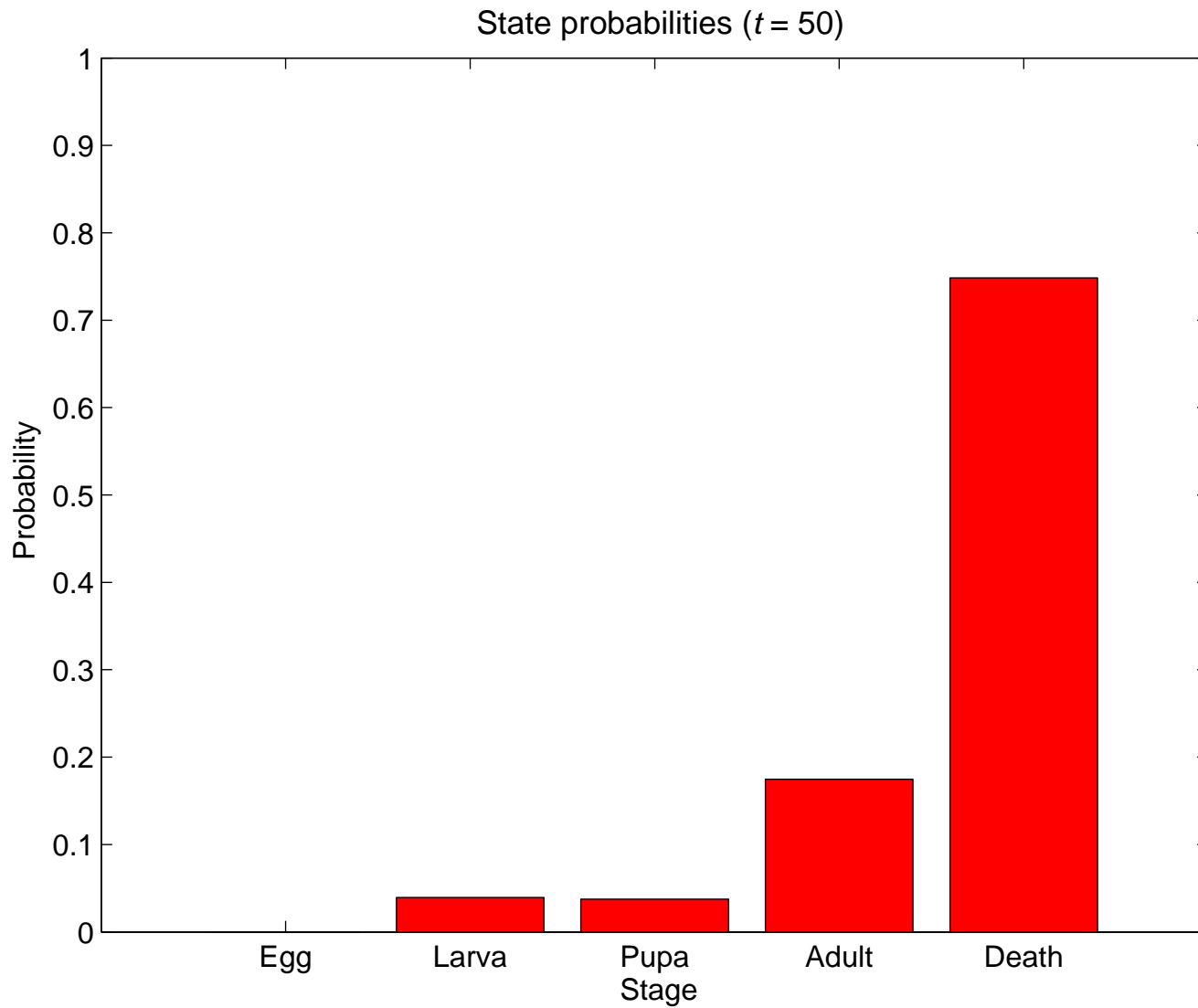
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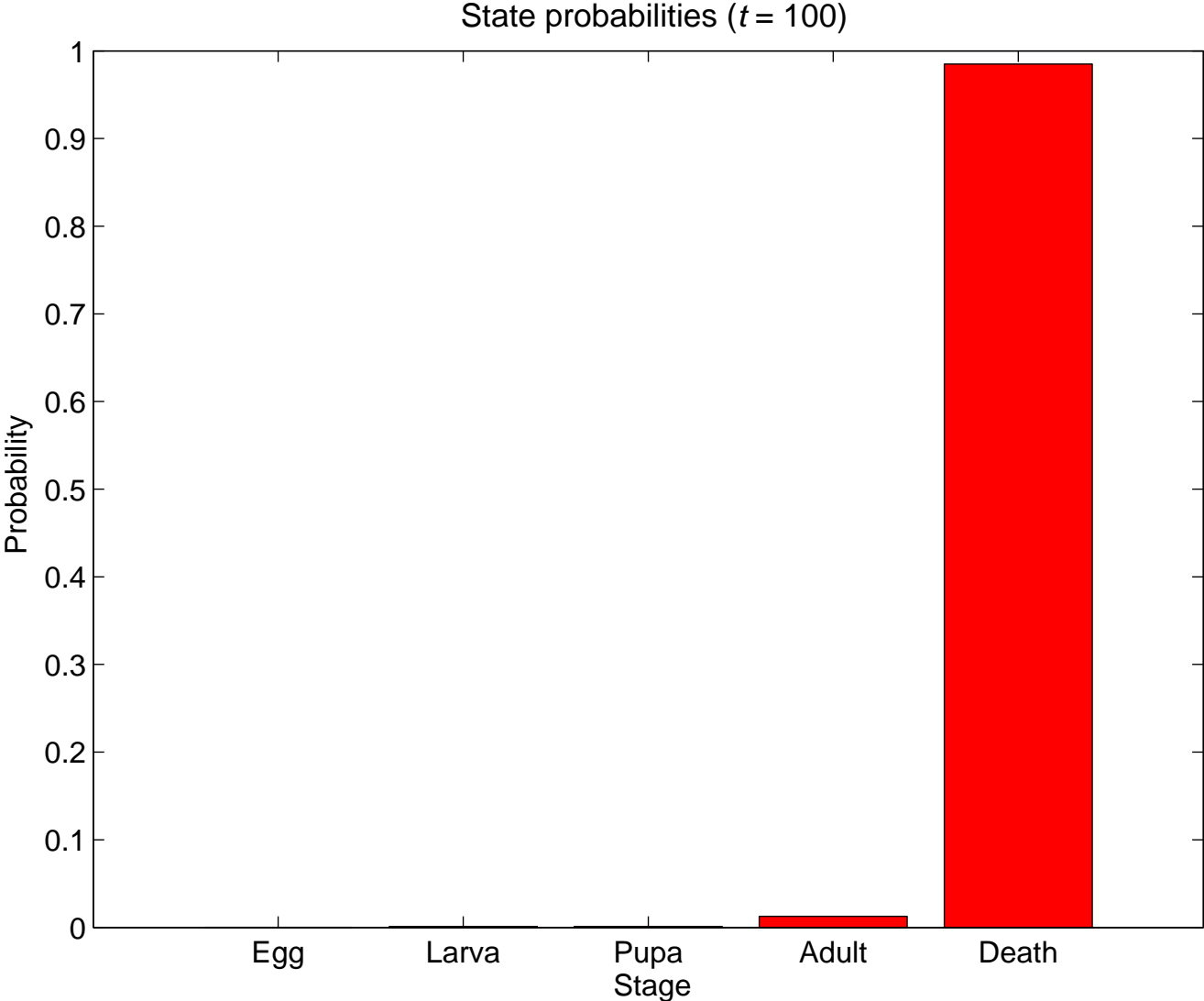
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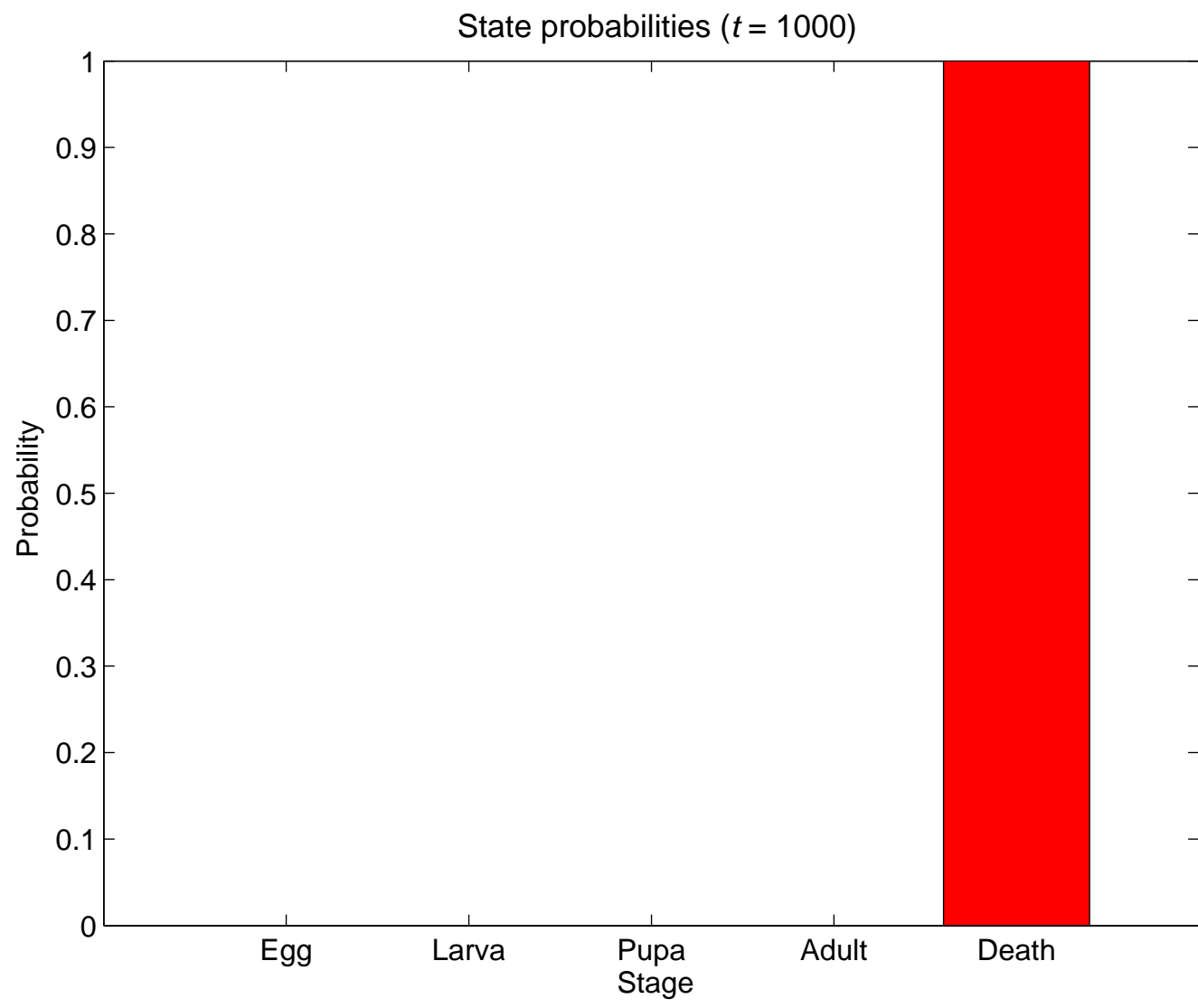
Individual organism



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Ensemble of organisms



The ensemble model

Suppose that at time $t = 0$ the individuals are assigned to the states according to some rule and then each moves independently in S as a Markov chain governed by Q .

The key assumption here is *independence*: individuals do not affect one another.

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We record only the *number* of individuals in the various states, rather than their positions.

Let $N_j(t)$ be the number of individuals in state j at time t , and let $\mathbf{N} = (N_j, j \in S)$. The process $(\mathbf{N}(t), t \geq 0)$ is also a continuous-time Markov chain.

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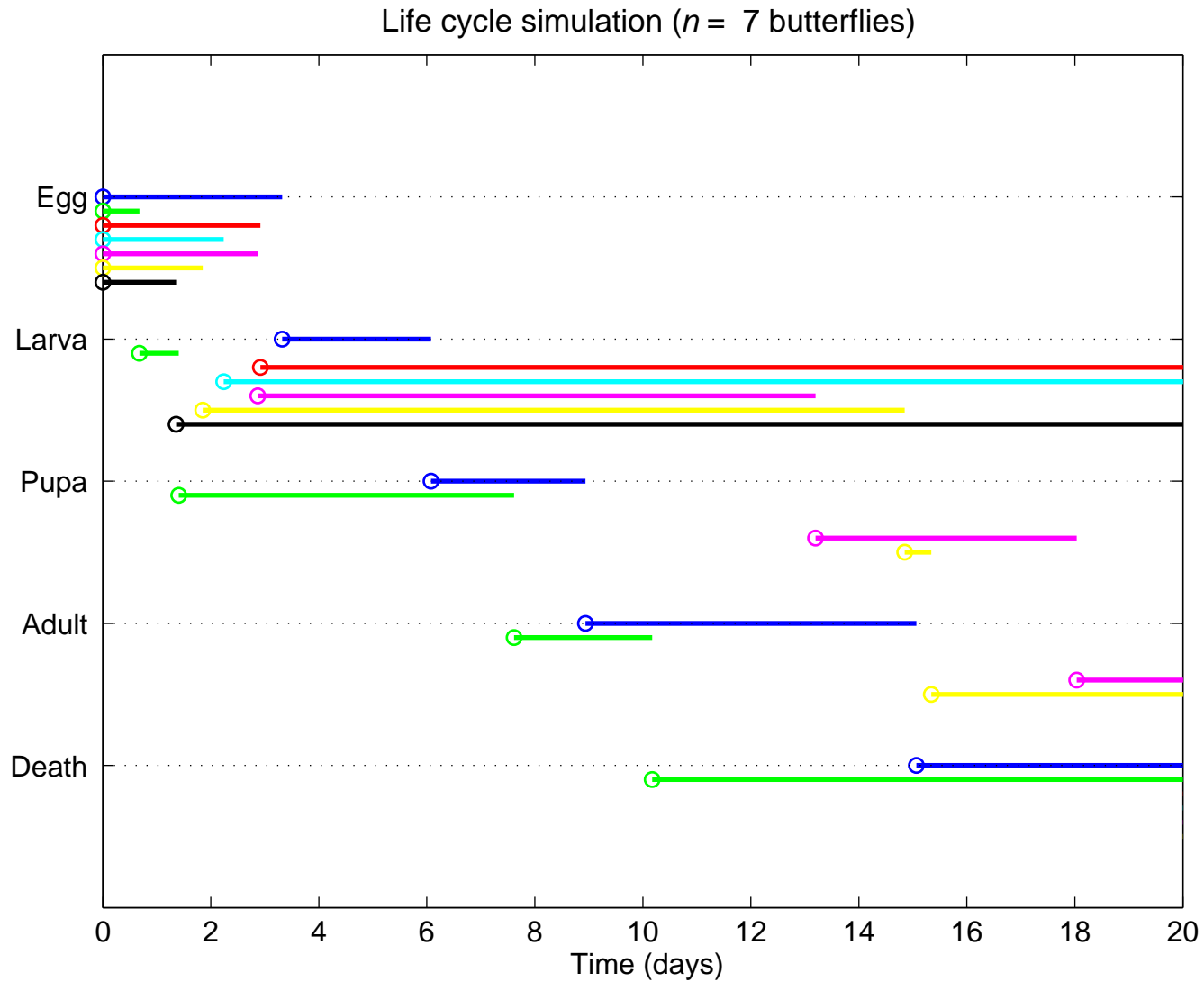
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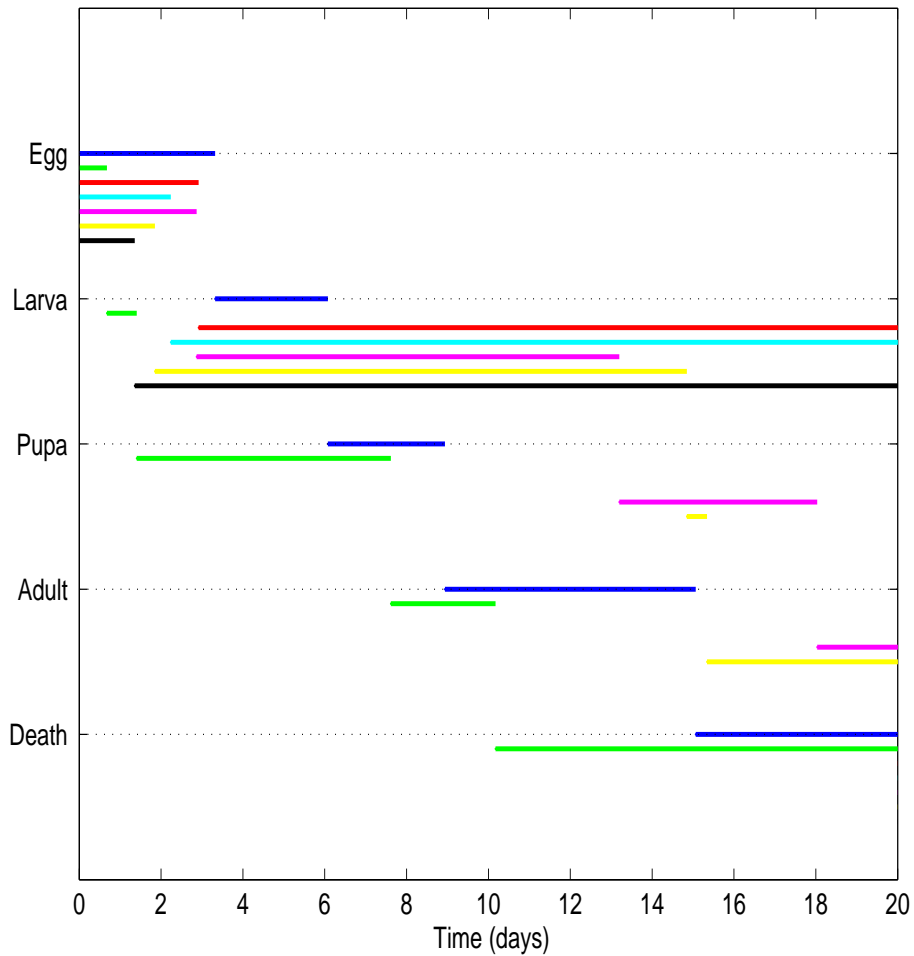
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Ensemble of organisms

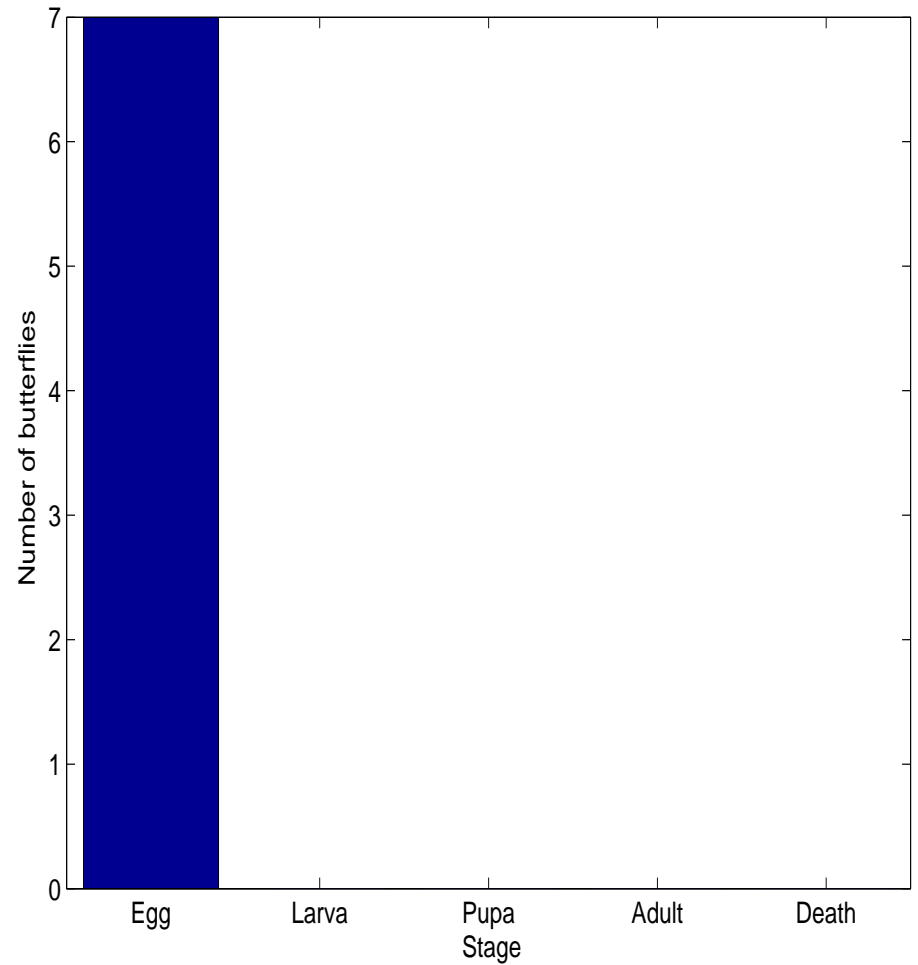


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

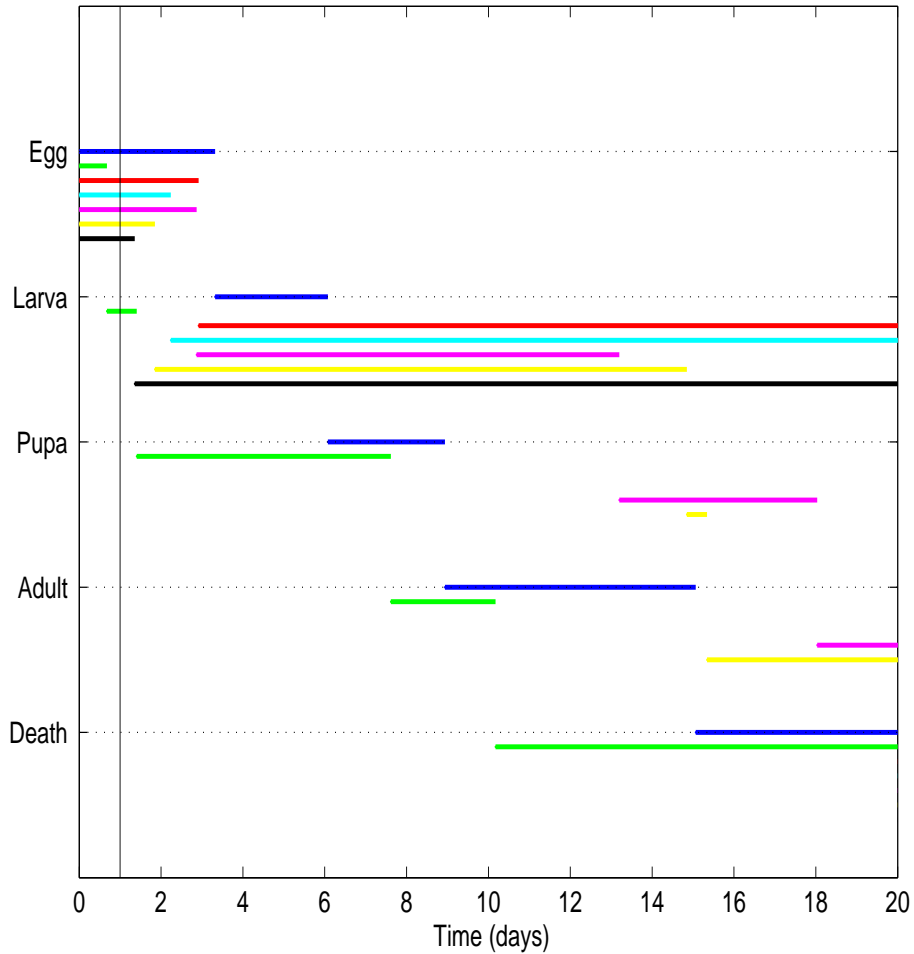


Numbers at $t = 0$ days ($n = 7$ butterflies)

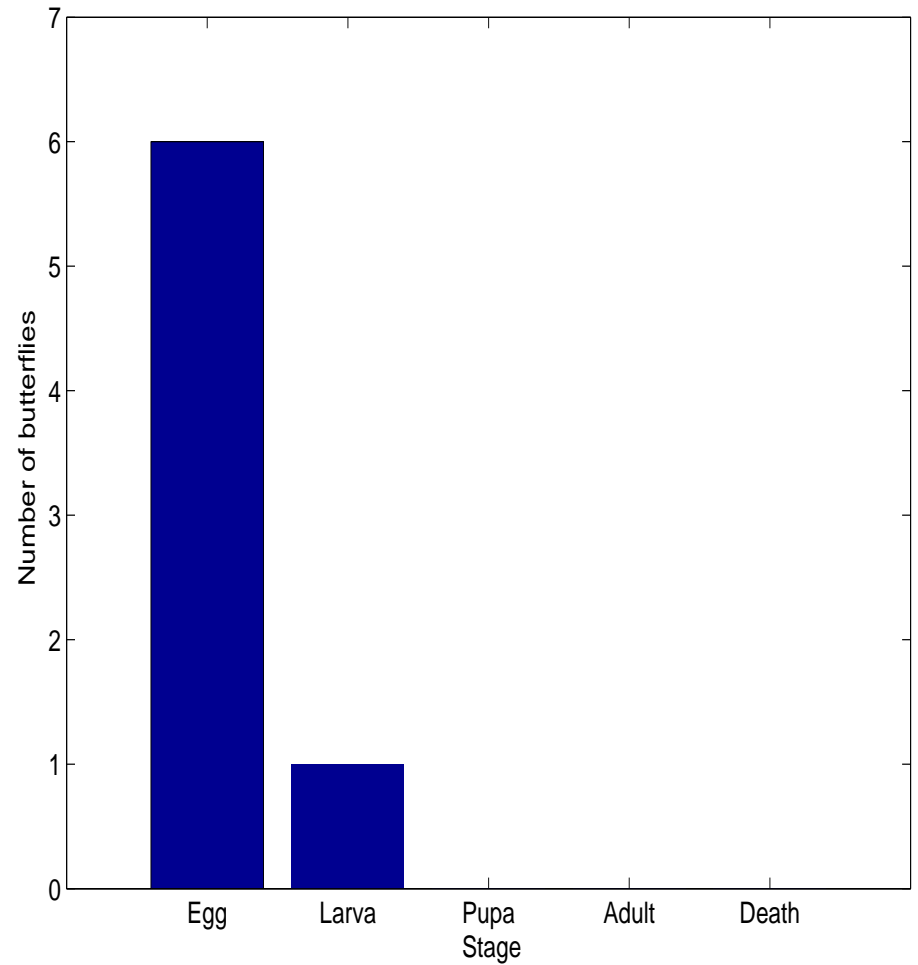


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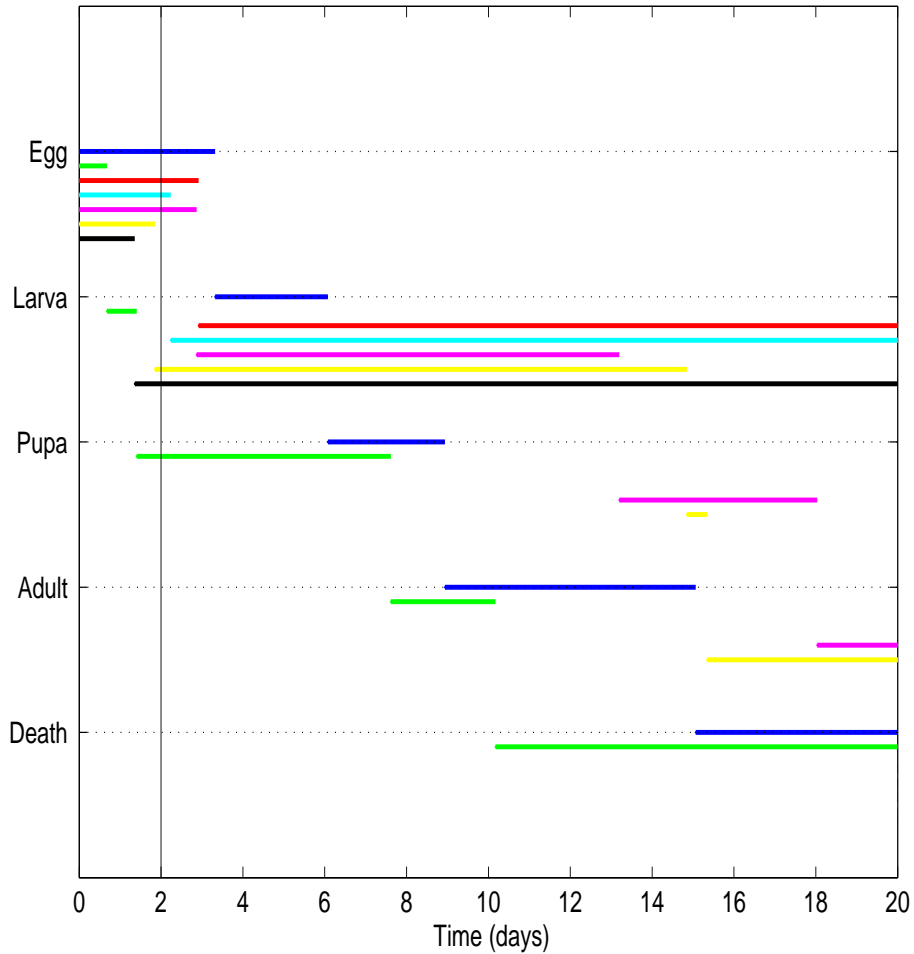


Numbers at $t = 1$ days ($n = 7$ butterflies)

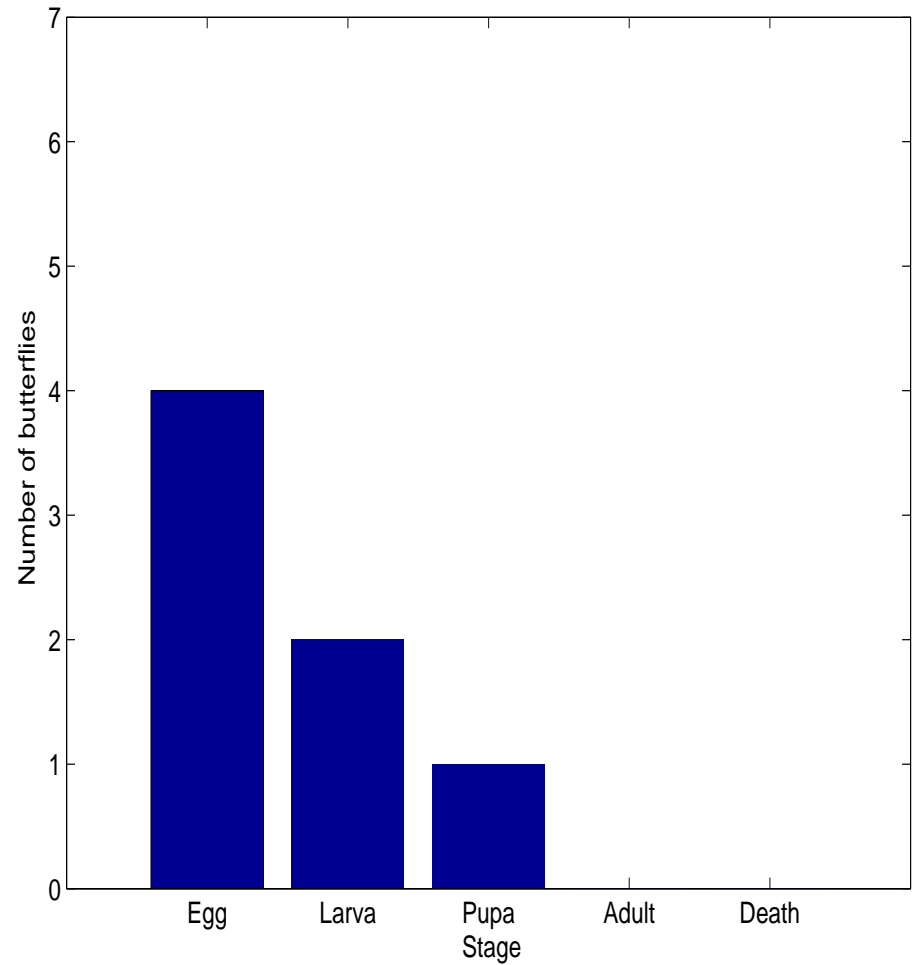


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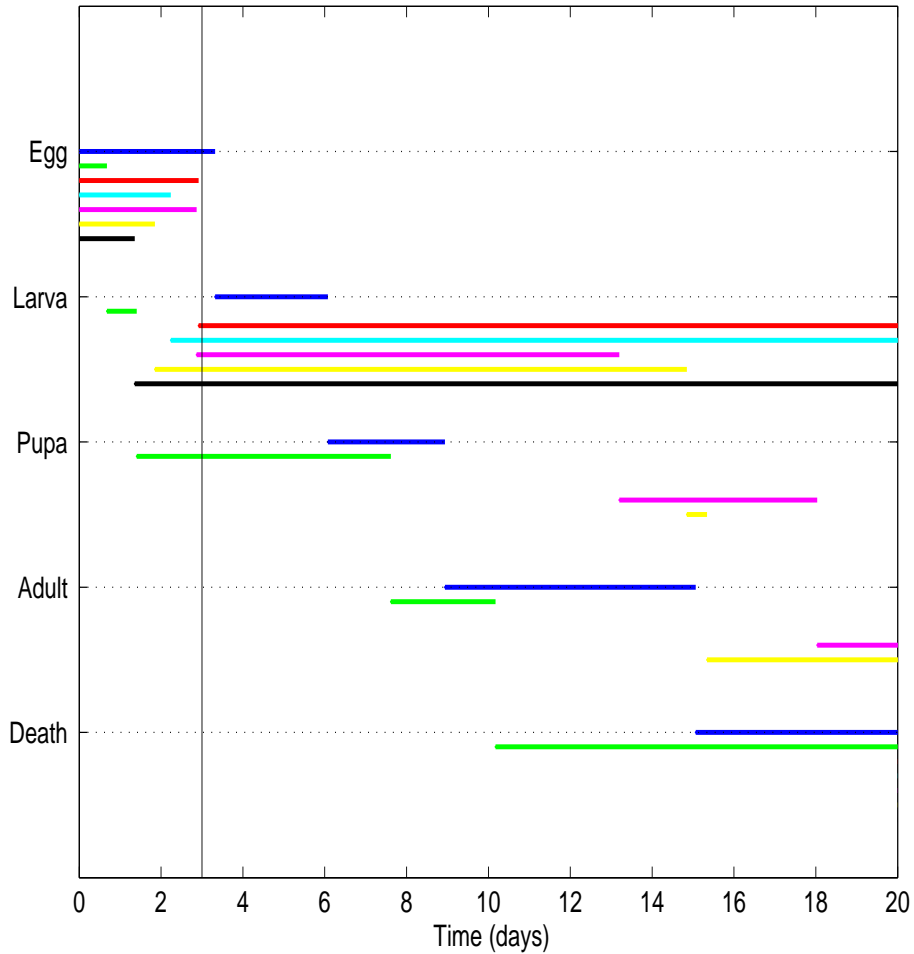


Numbers at $t = 2$ days ($n = 7$ butterflies)

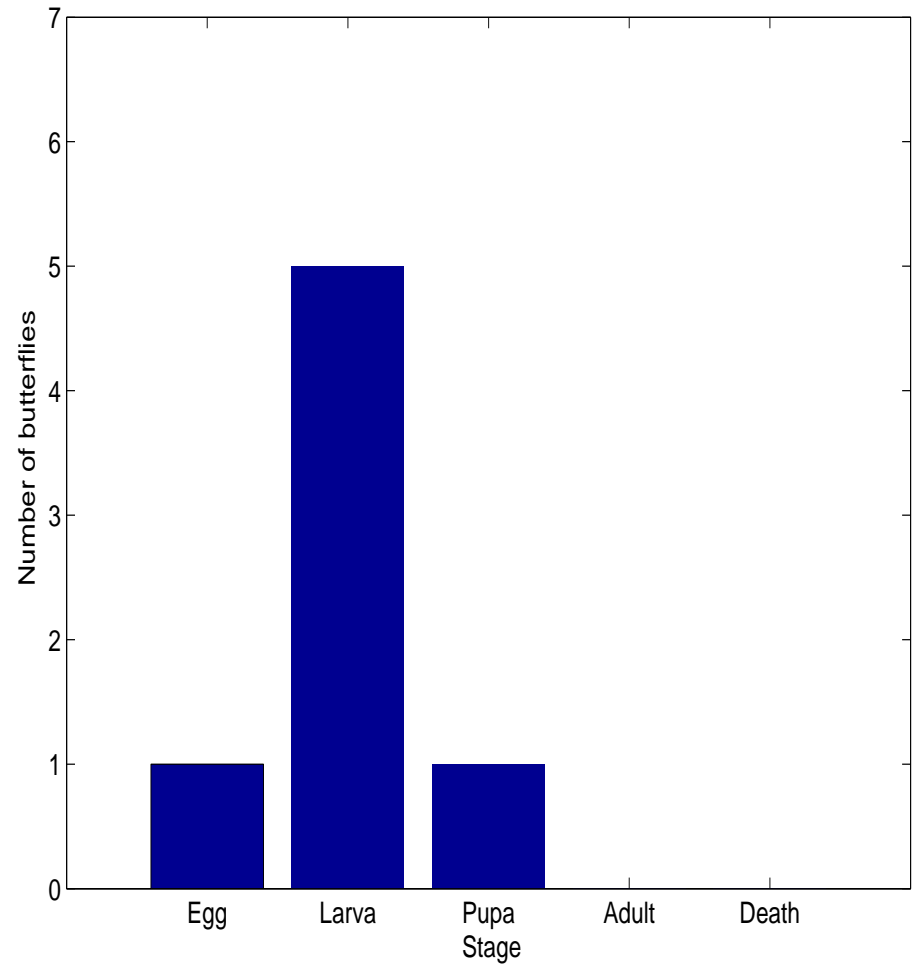


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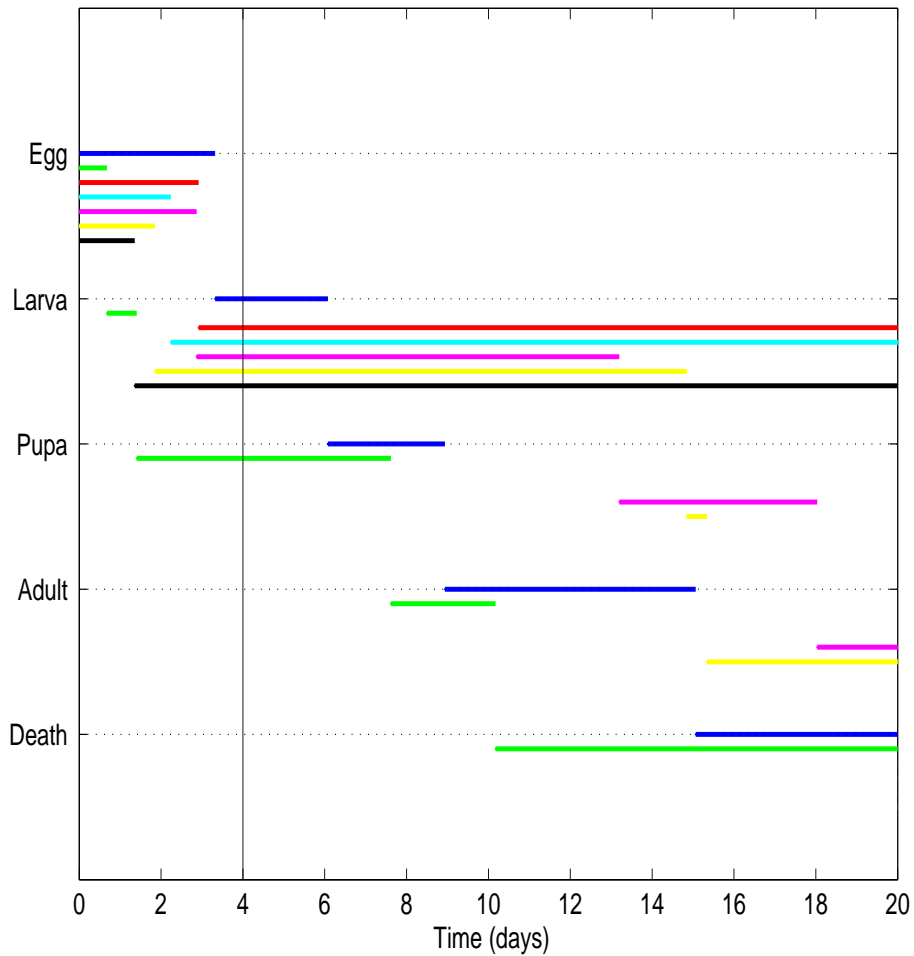


Numbers at $t = 3$ days ($n = 7$ butterflies)

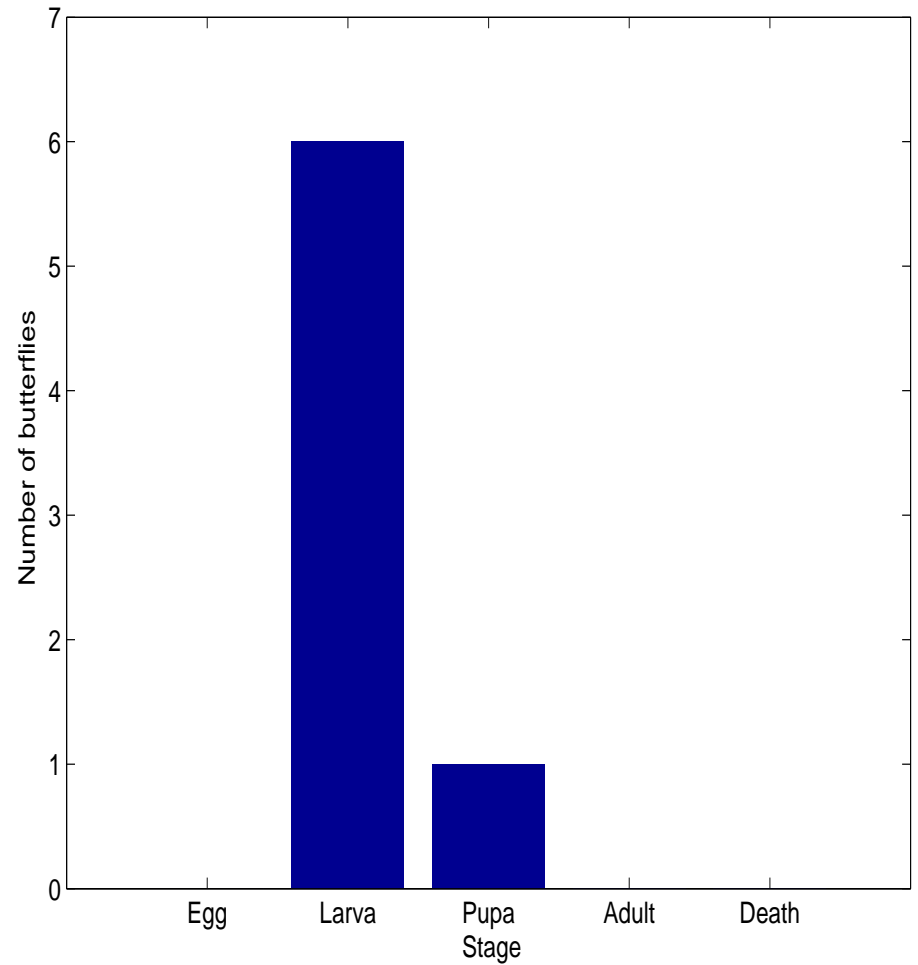


Ensemble state description

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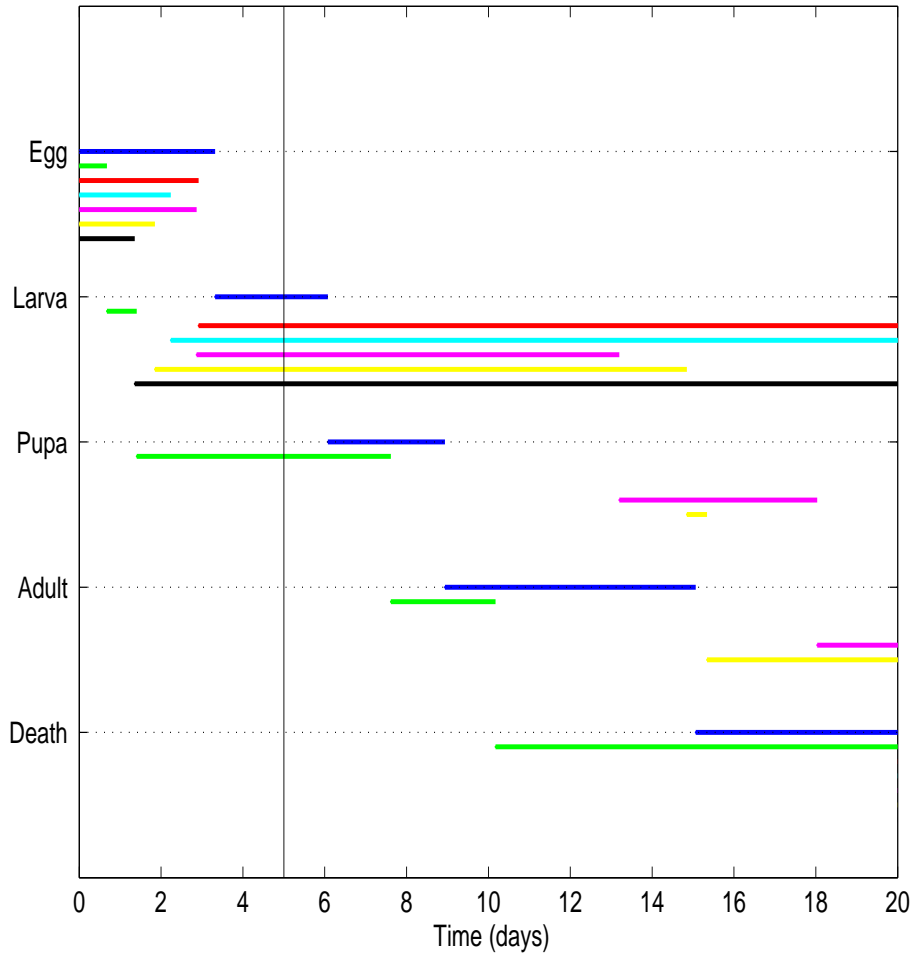


Numbers at $t = 4$ days ($n = 7$ butterflies)

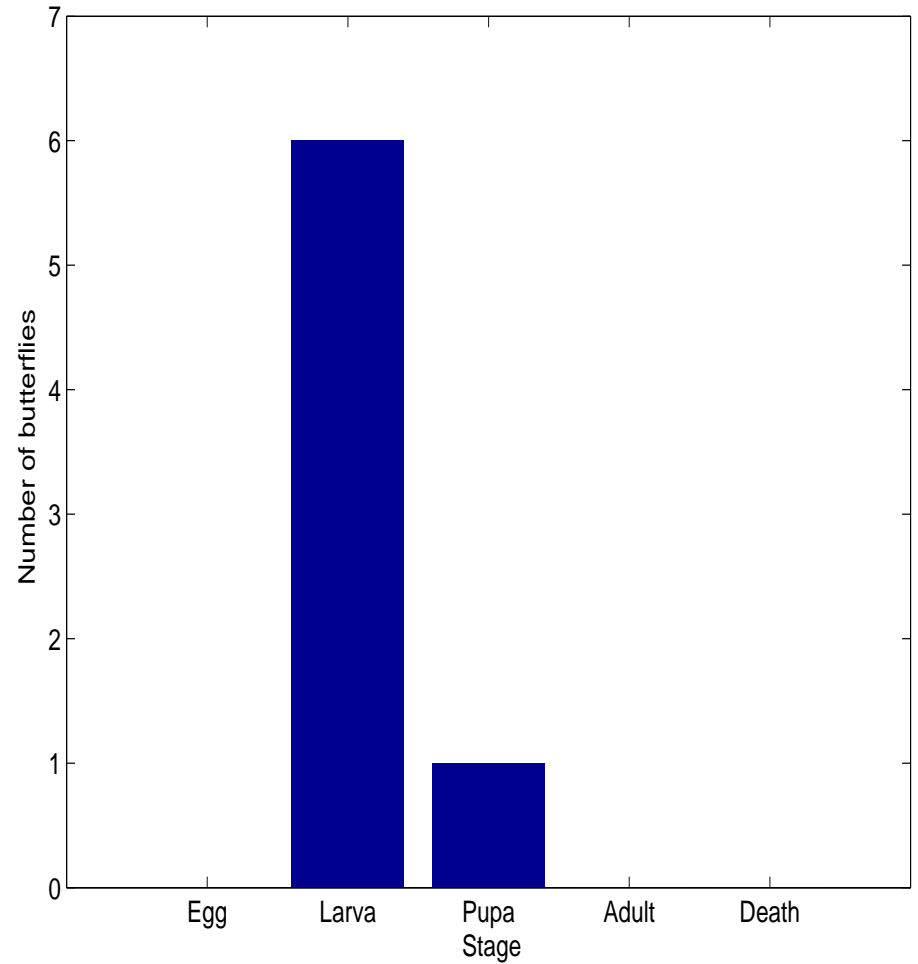


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

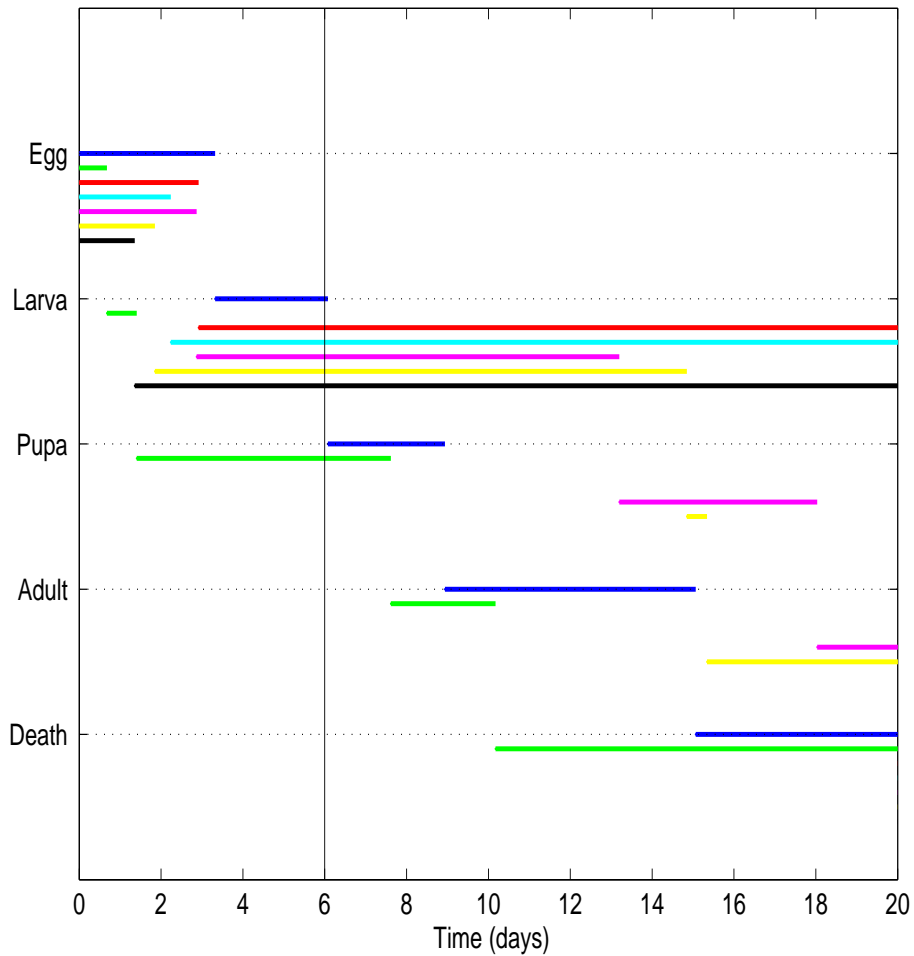


Numbers at $t = 5$ days ($n = 7$ butterflies)

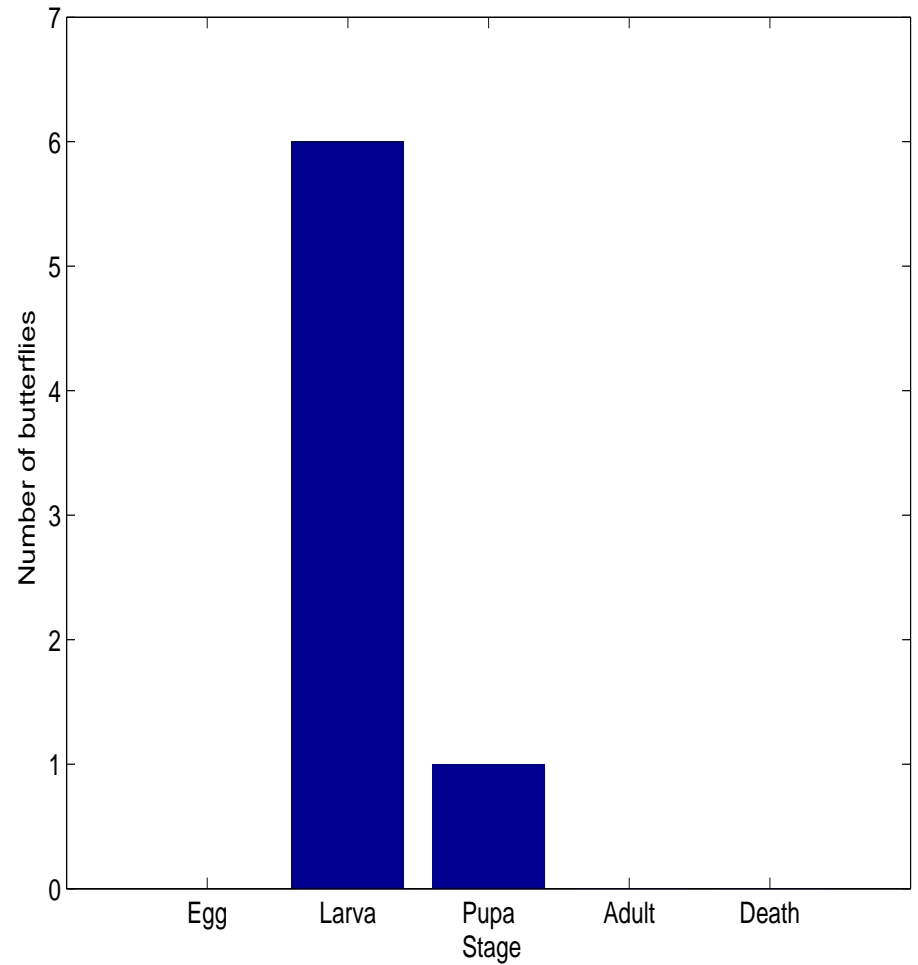


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

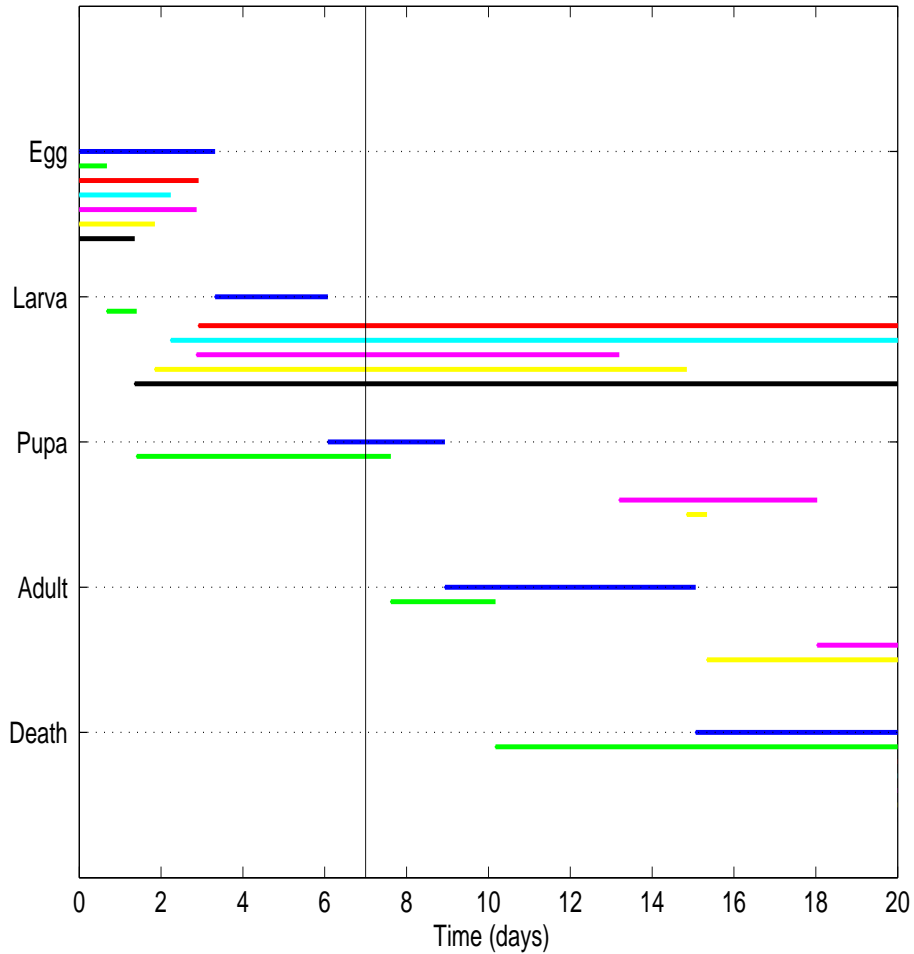


Numbers at $t = 6$ days ($n = 7$ butterflies)

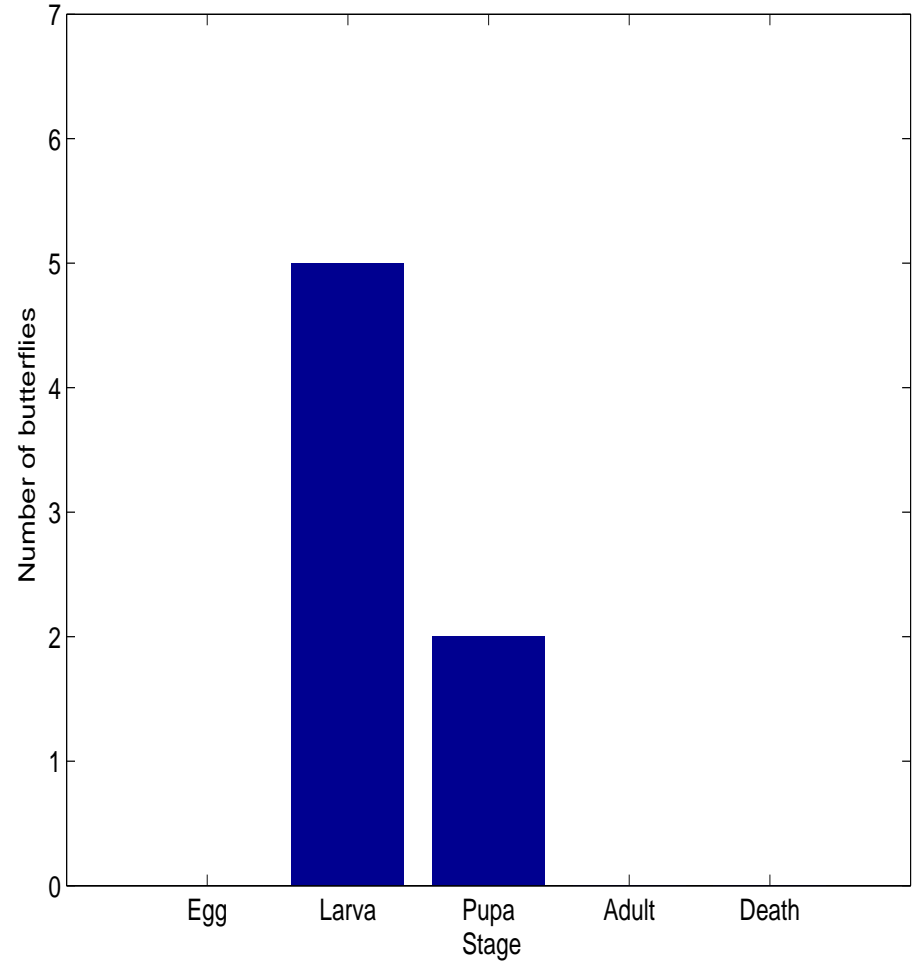


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

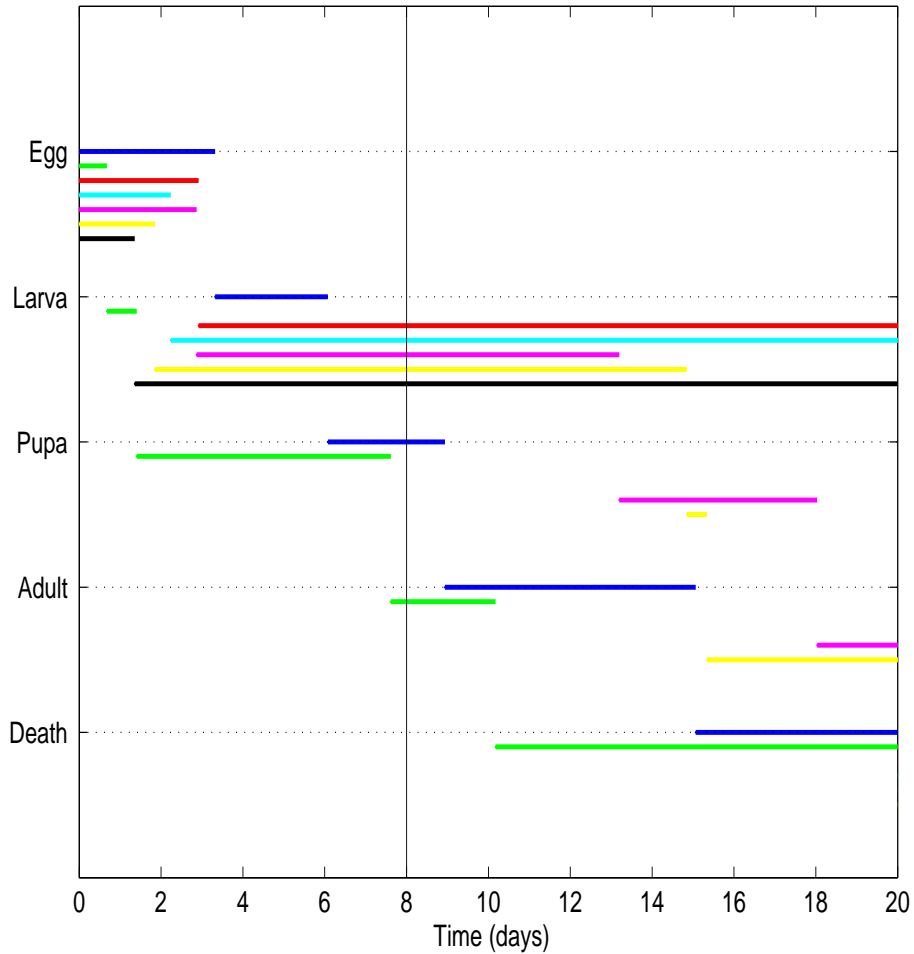


Numbers at $t = 7$ days ($n = 7$ butterflies)

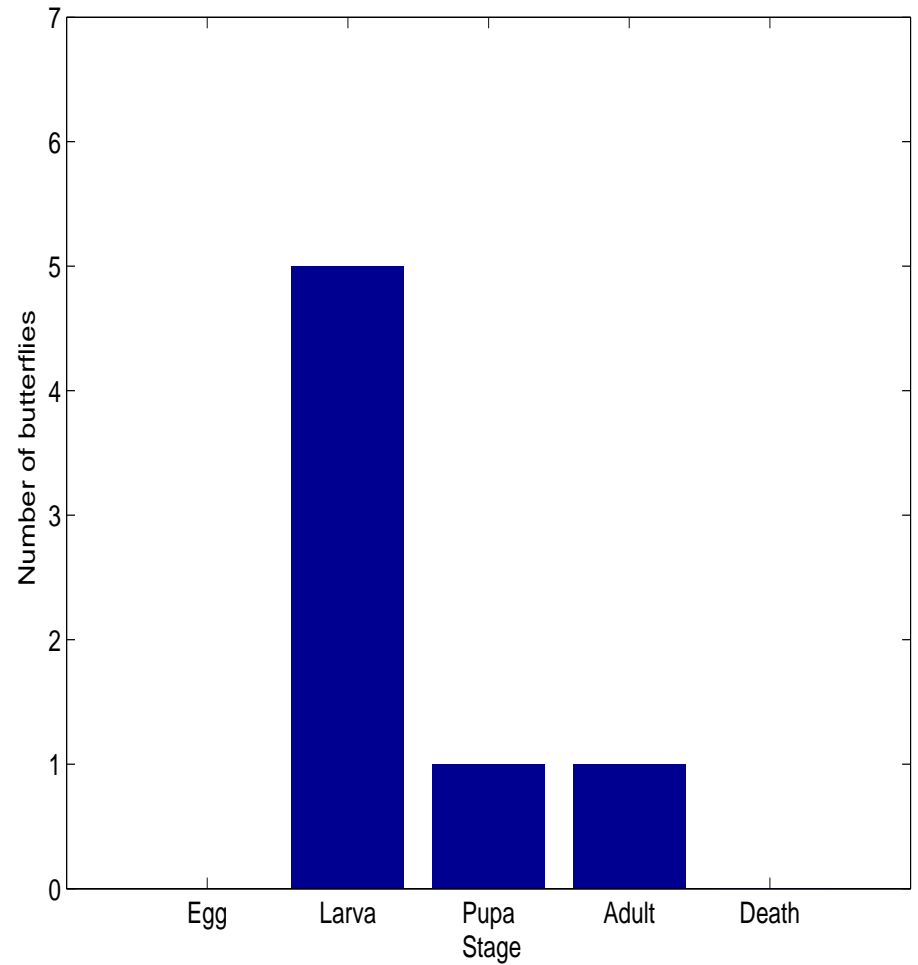


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

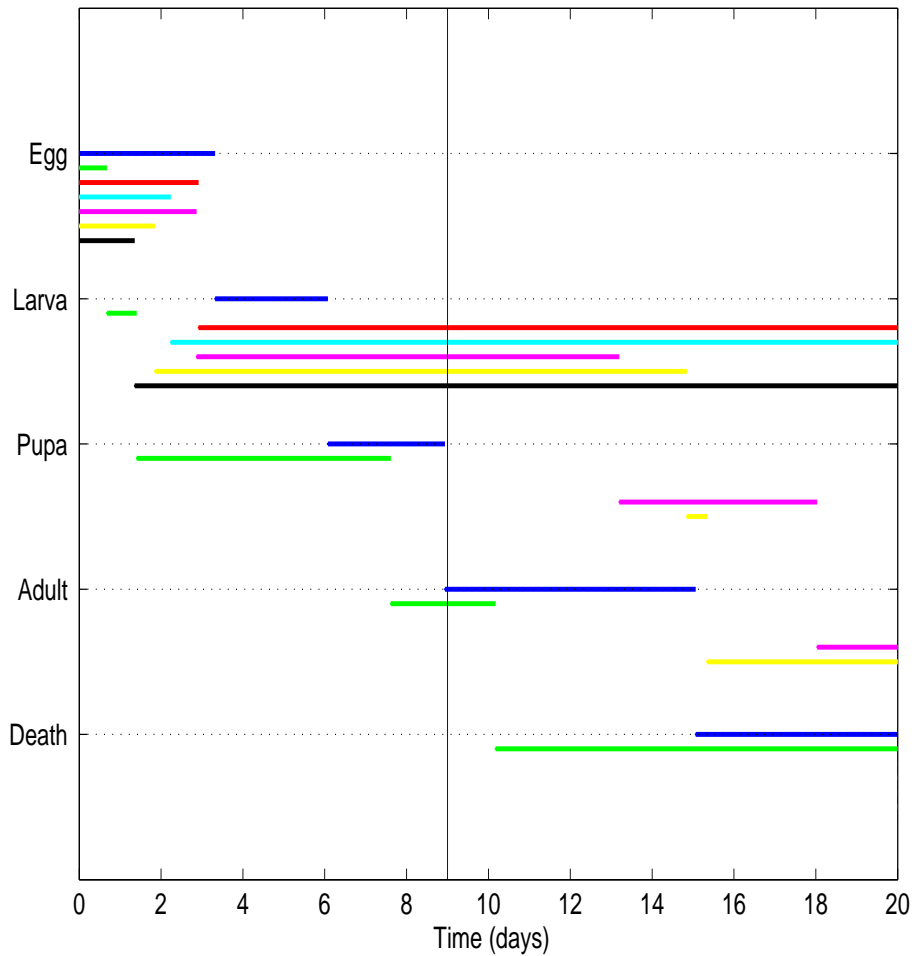


Numbers at $t = 8$ days ($n = 7$ butterflies)

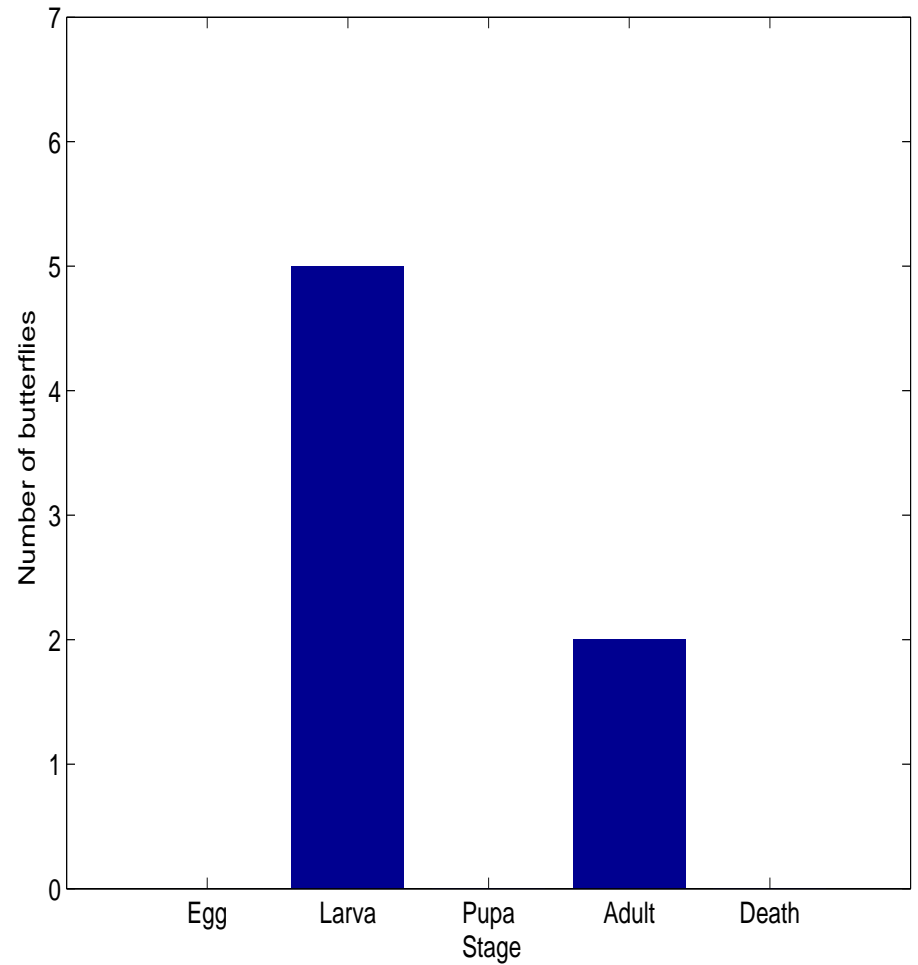


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

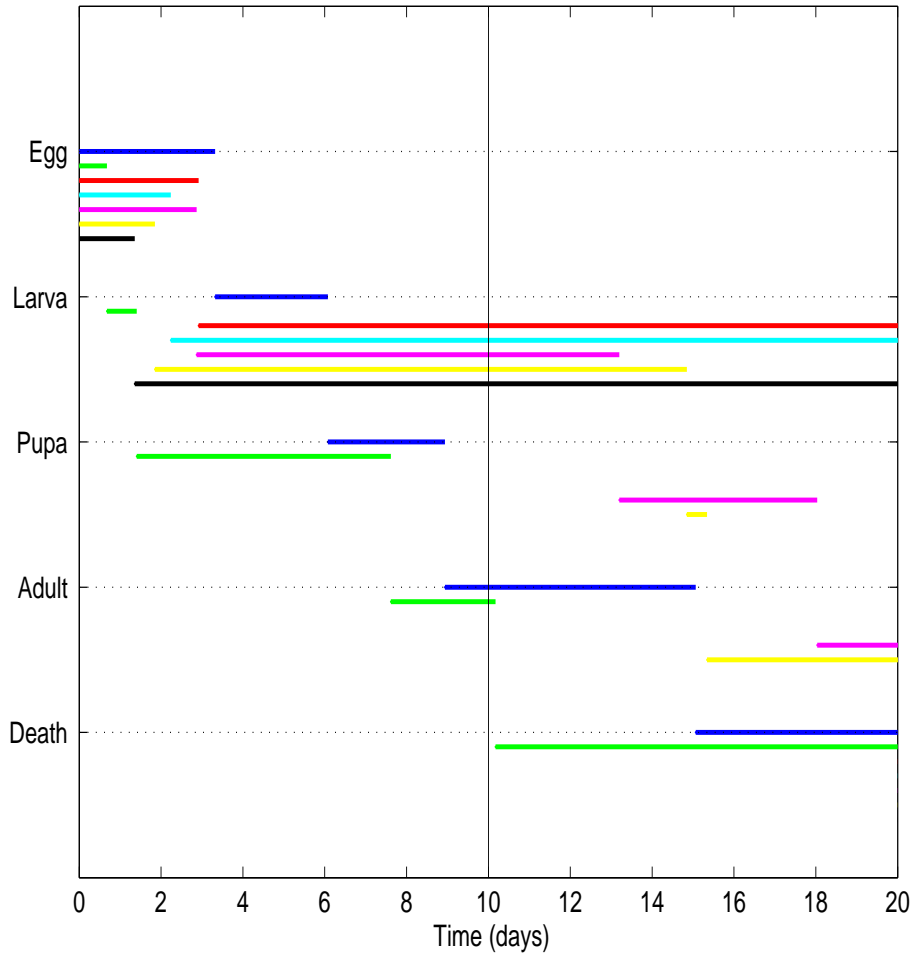


Numbers at $t = 9$ days ($n = 7$ butterflies)

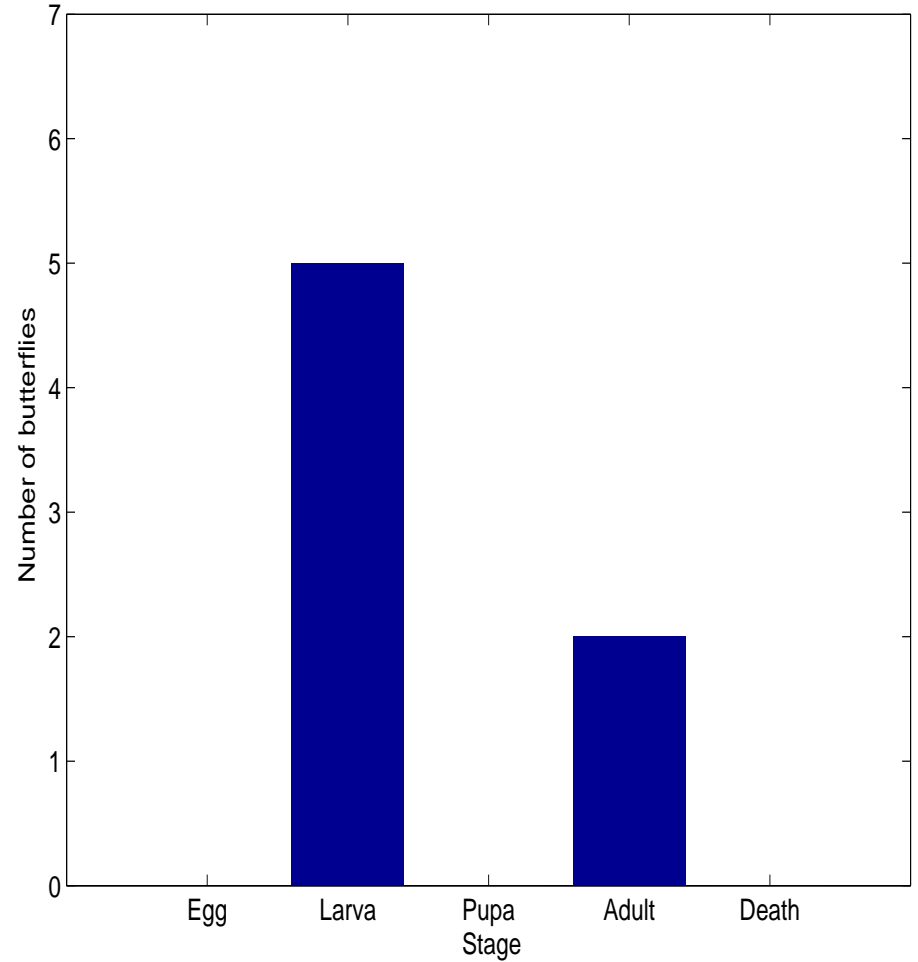


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

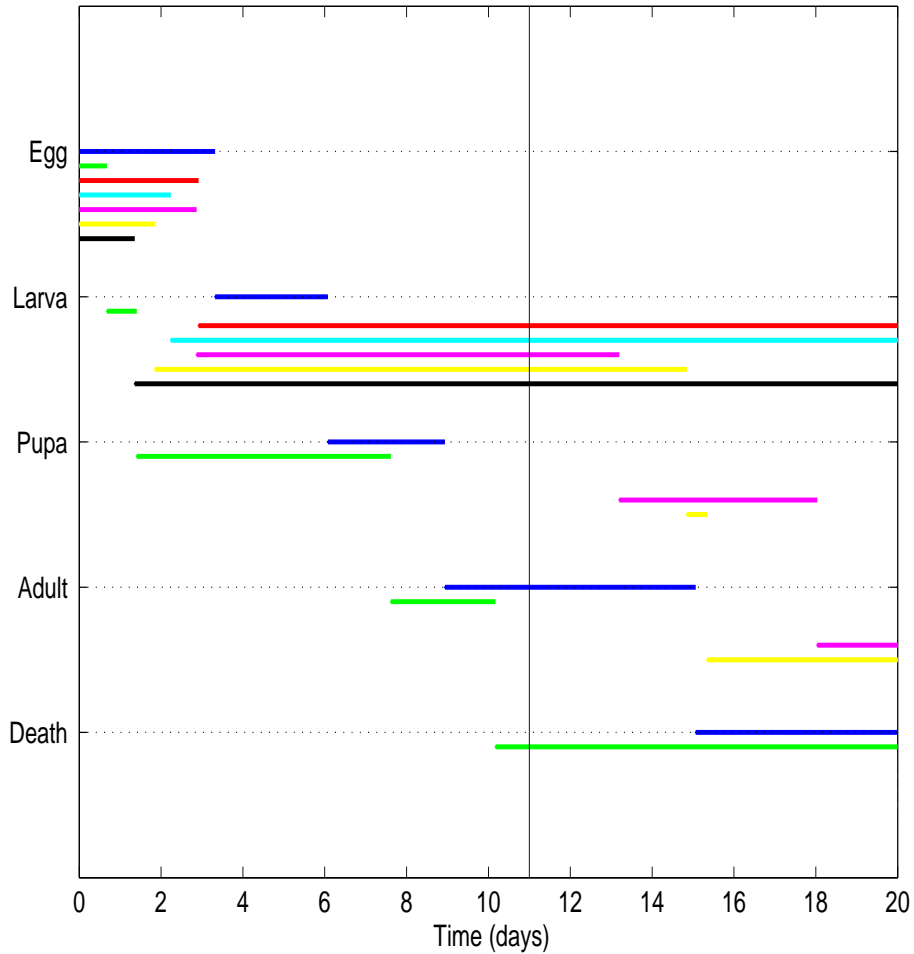


Numbers at $t = 10$ days ($n = 7$ butterflies)

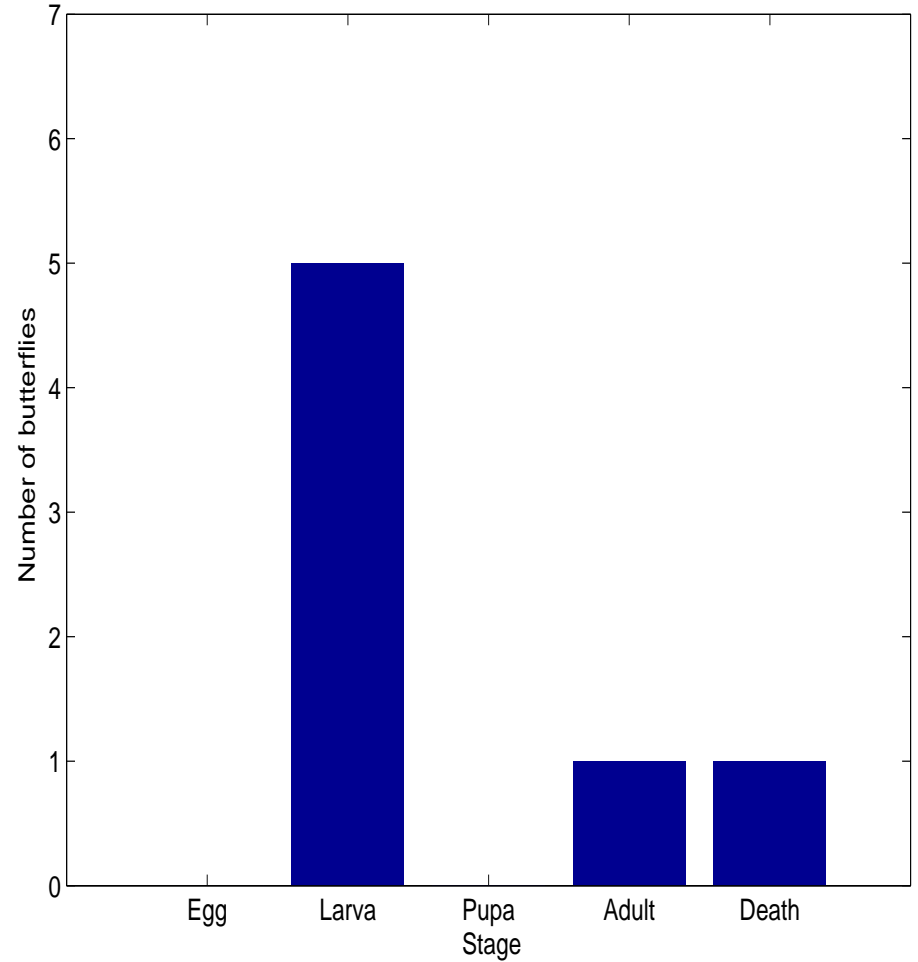


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

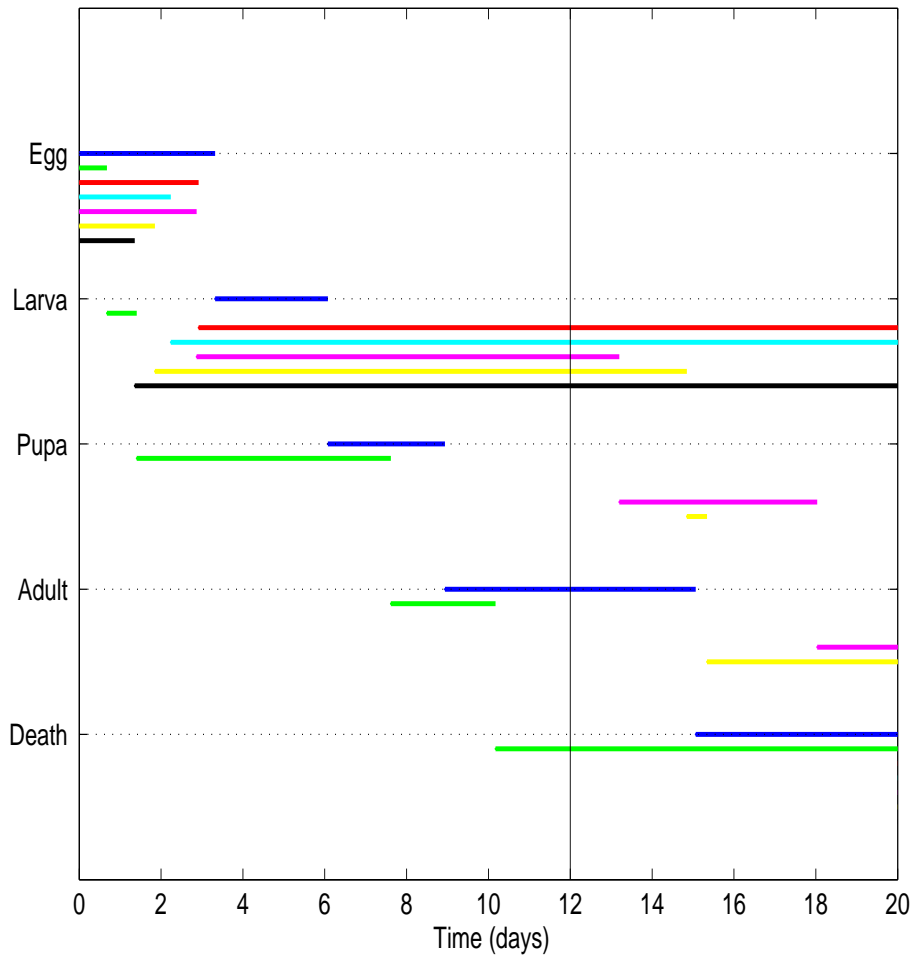


Numbers at $t = 11$ days ($n = 7$ butterflies)

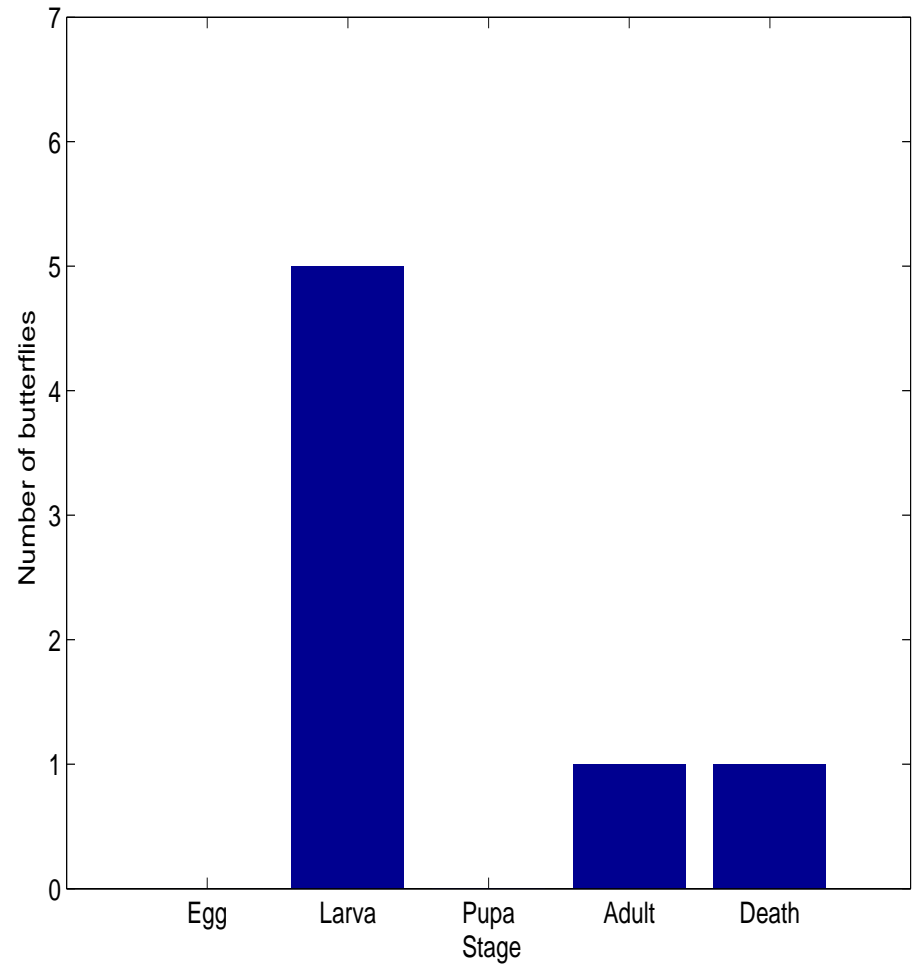


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

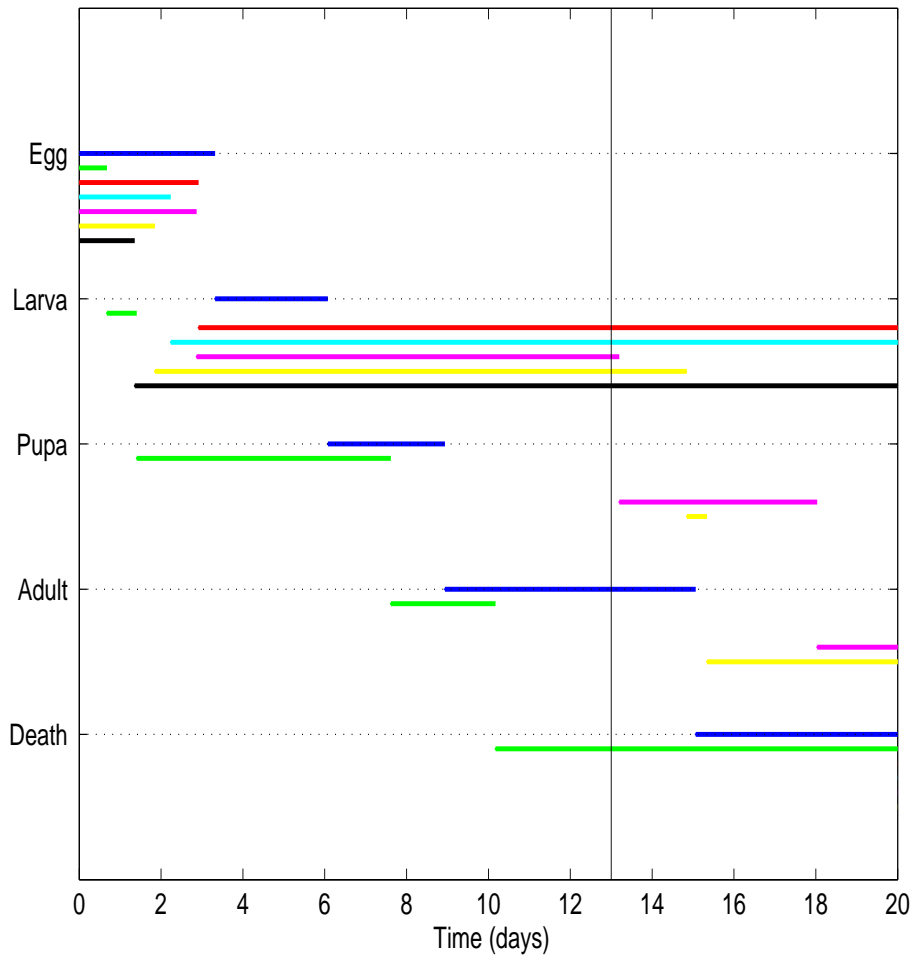


Numbers at $t = 12$ days ($n = 7$ butterflies)

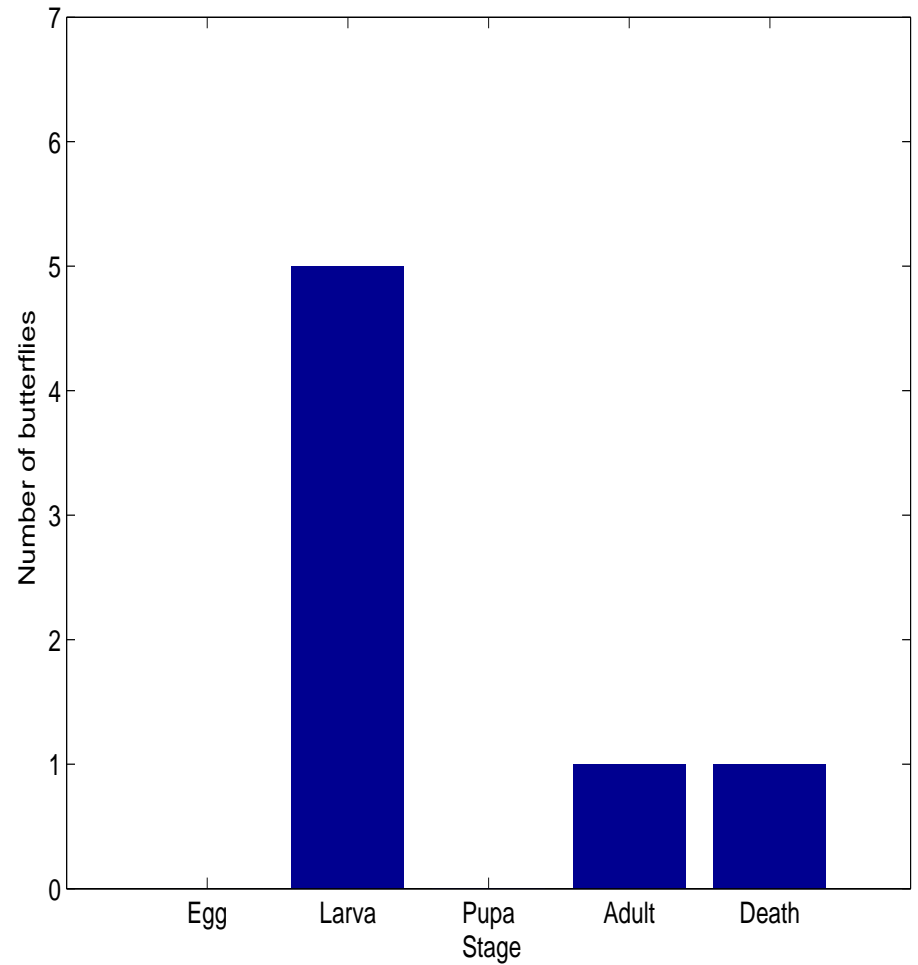


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

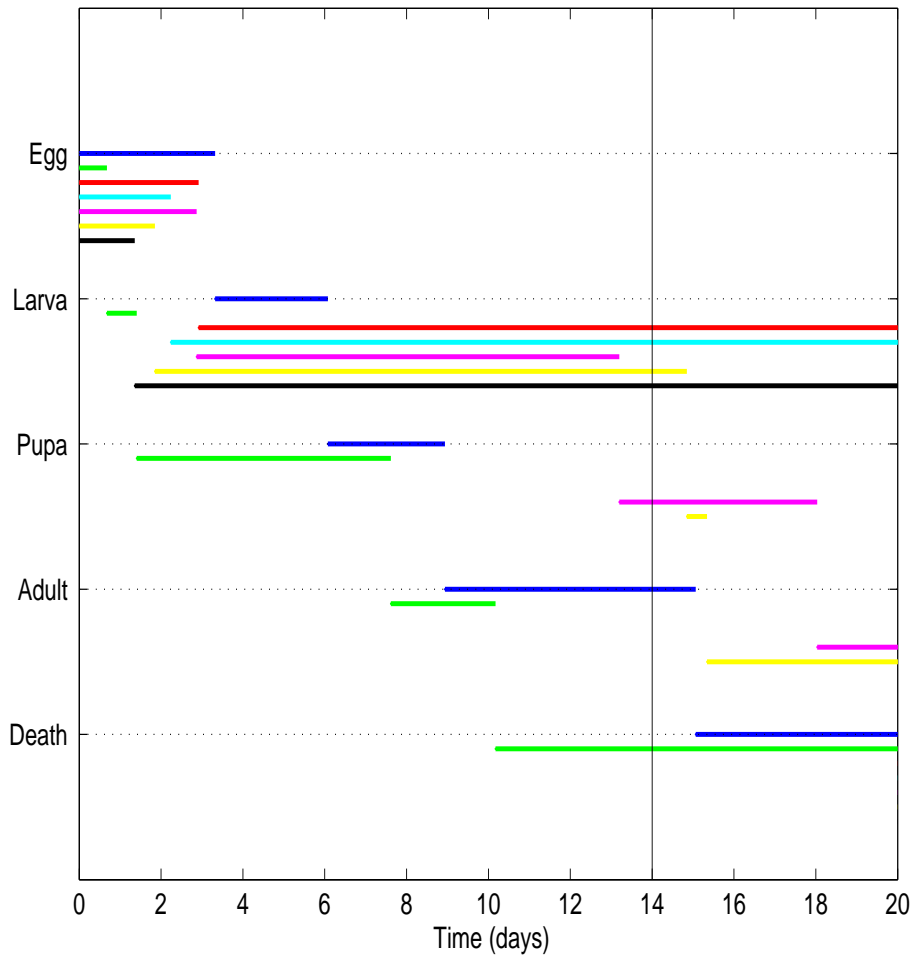


Numbers at $t = 13$ days ($n = 7$ butterflies)

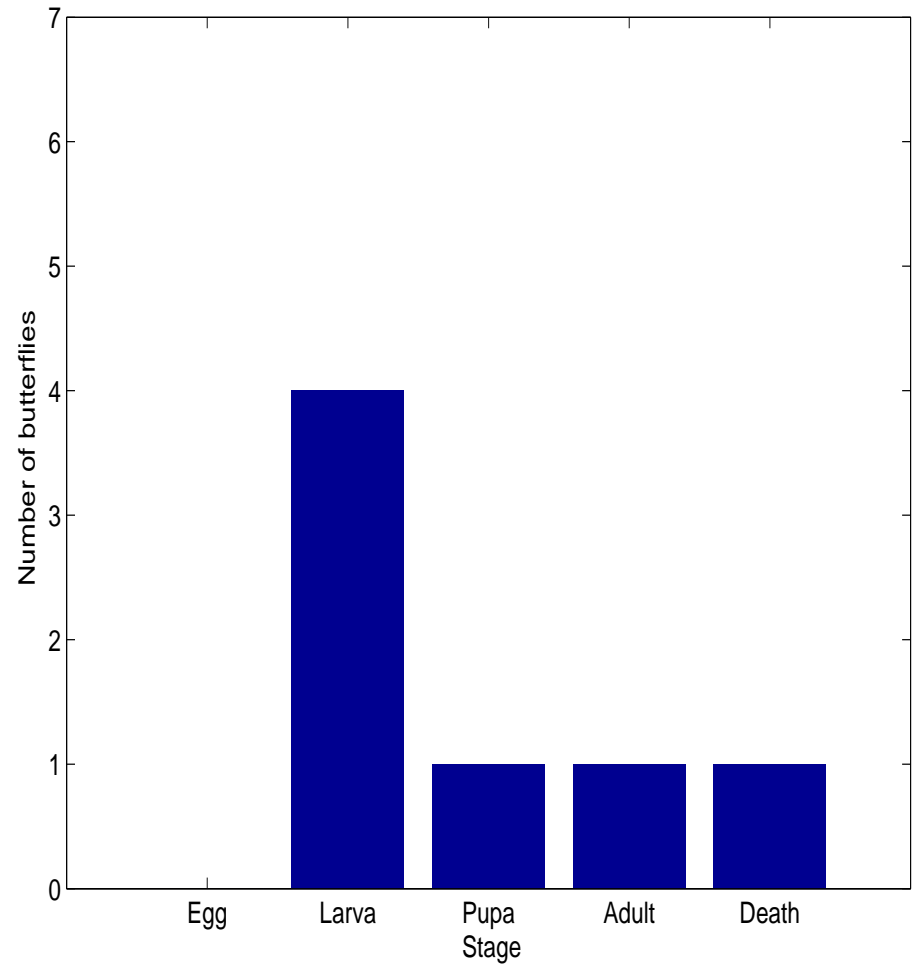


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

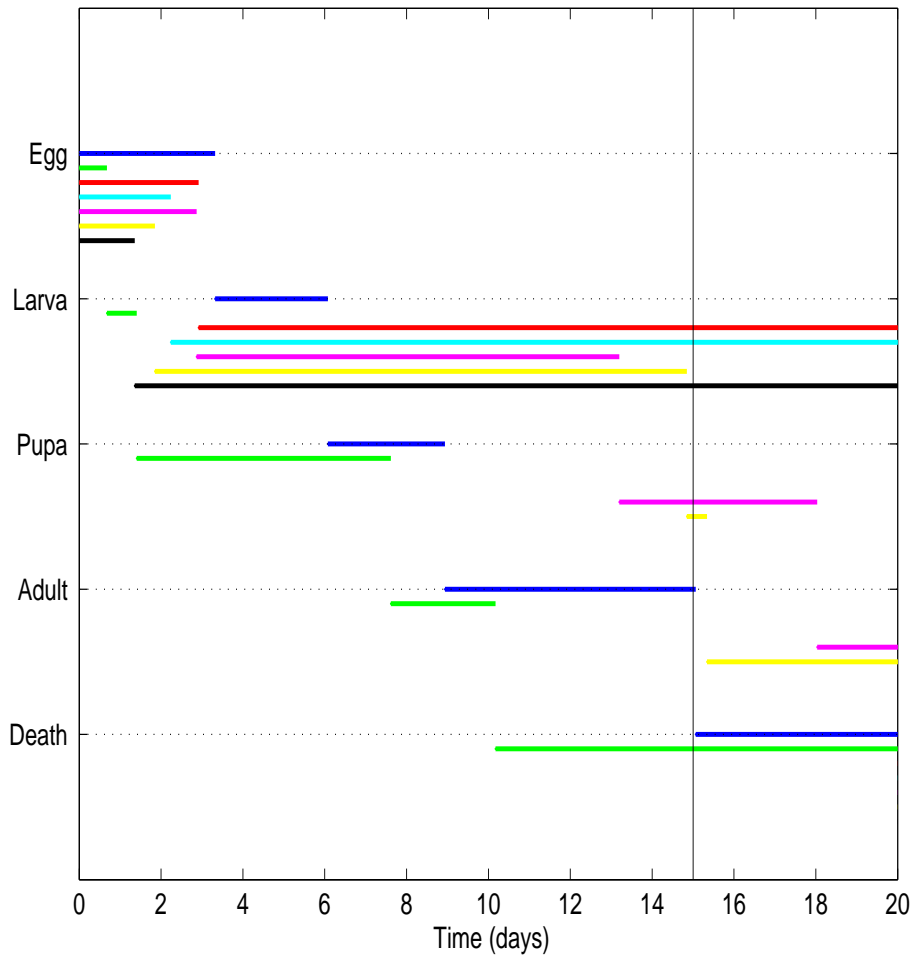


Numbers at $t = 14$ days ($n = 7$ butterflies)

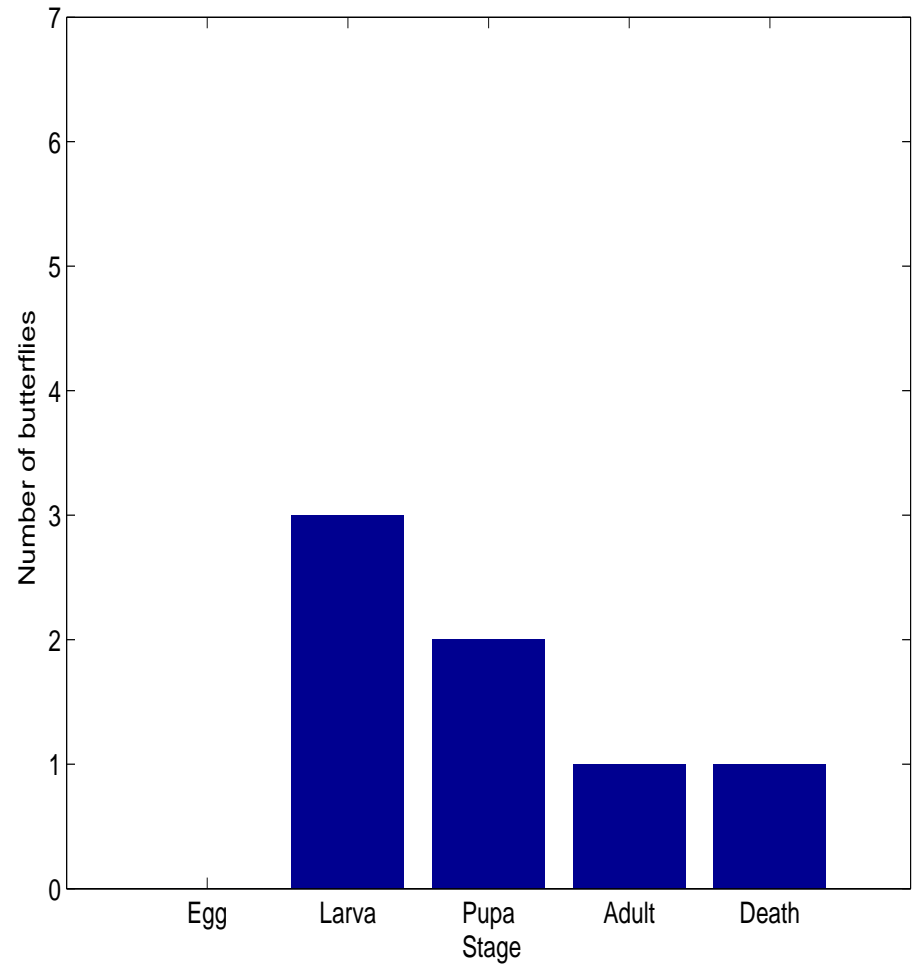


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

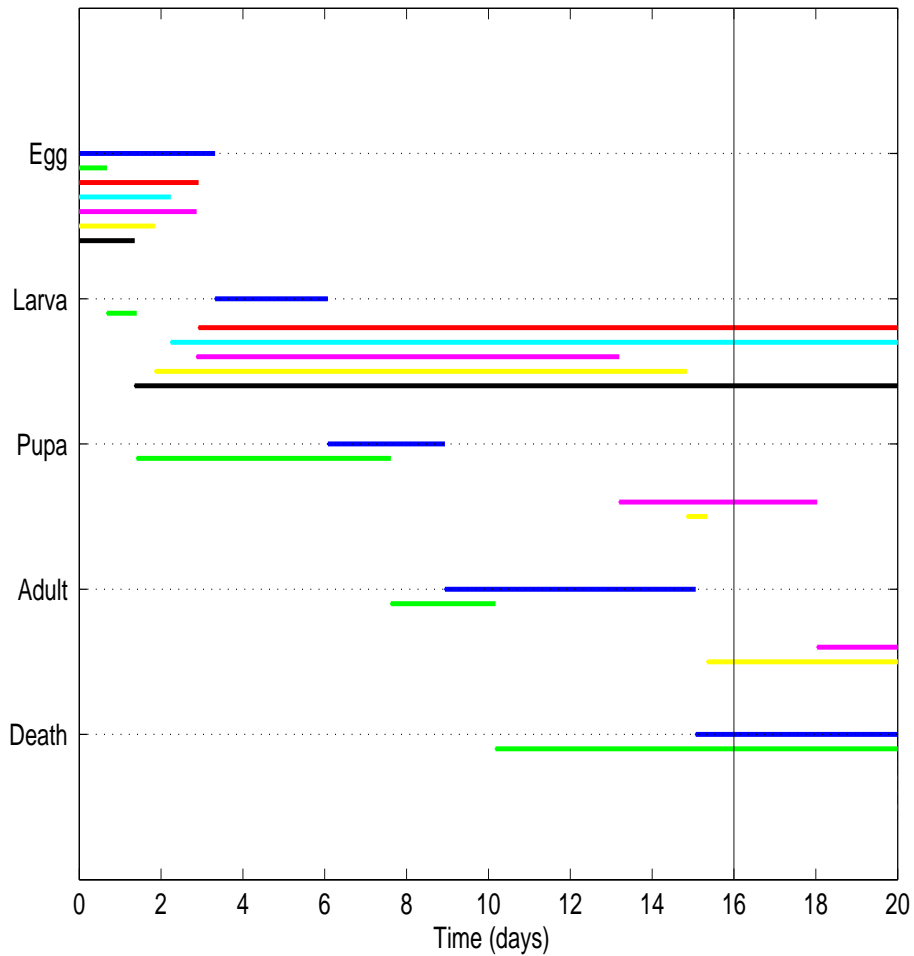


Numbers at $t = 15$ days ($n = 7$ butterflies)

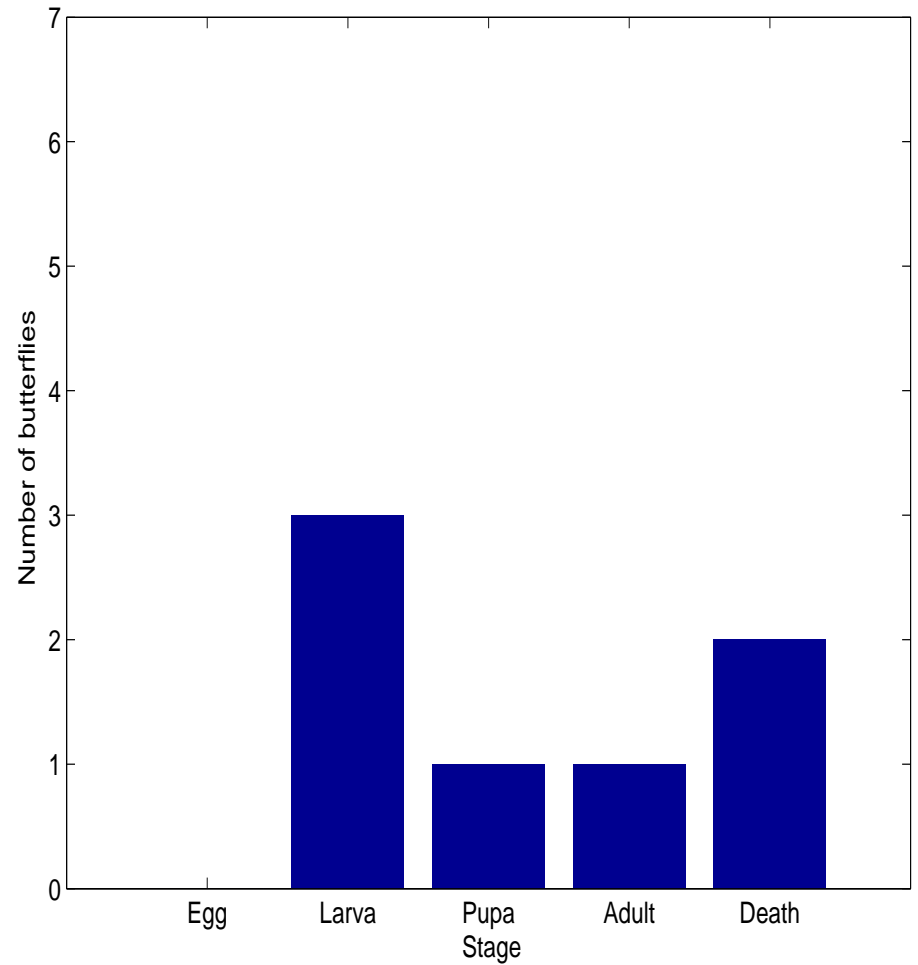


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

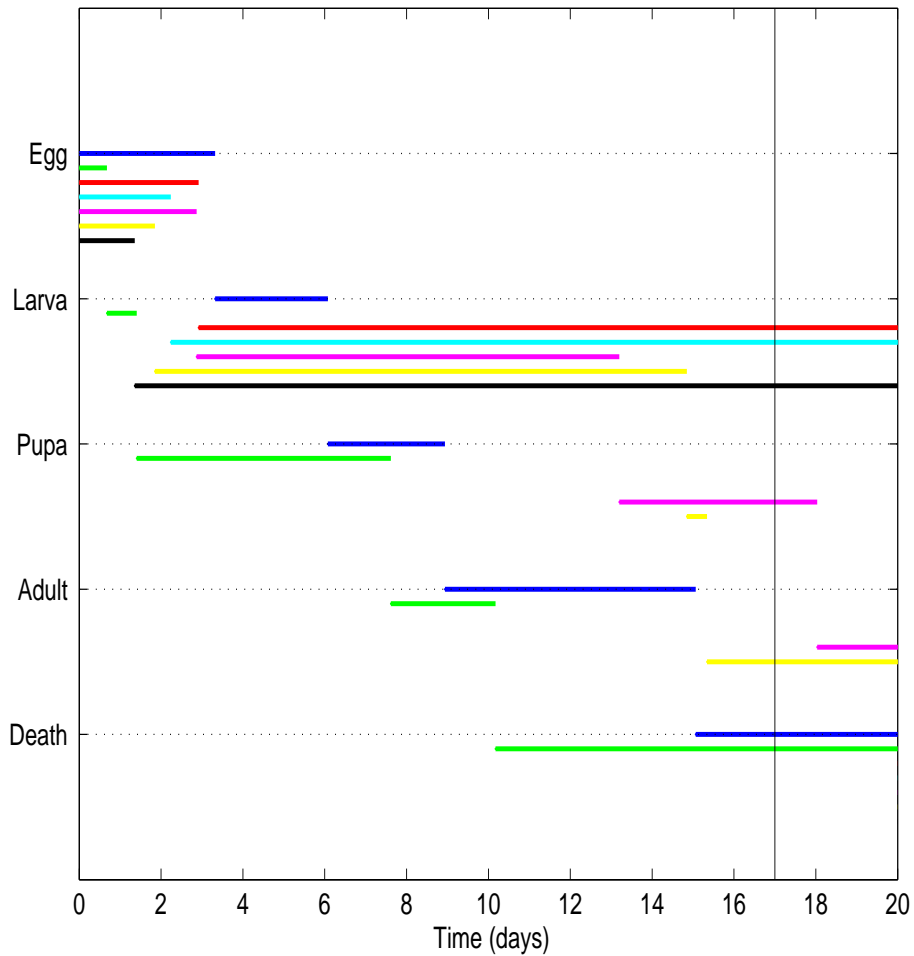


Numbers at $t = 16$ days ($n = 7$ butterflies)

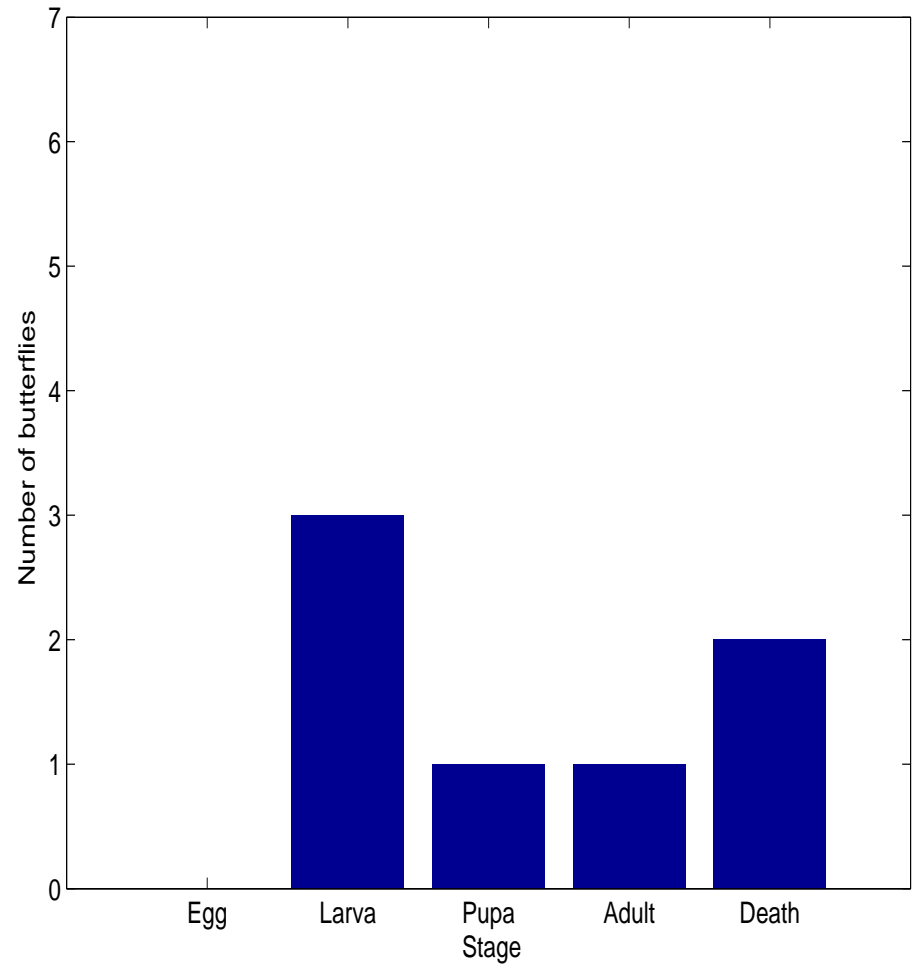


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

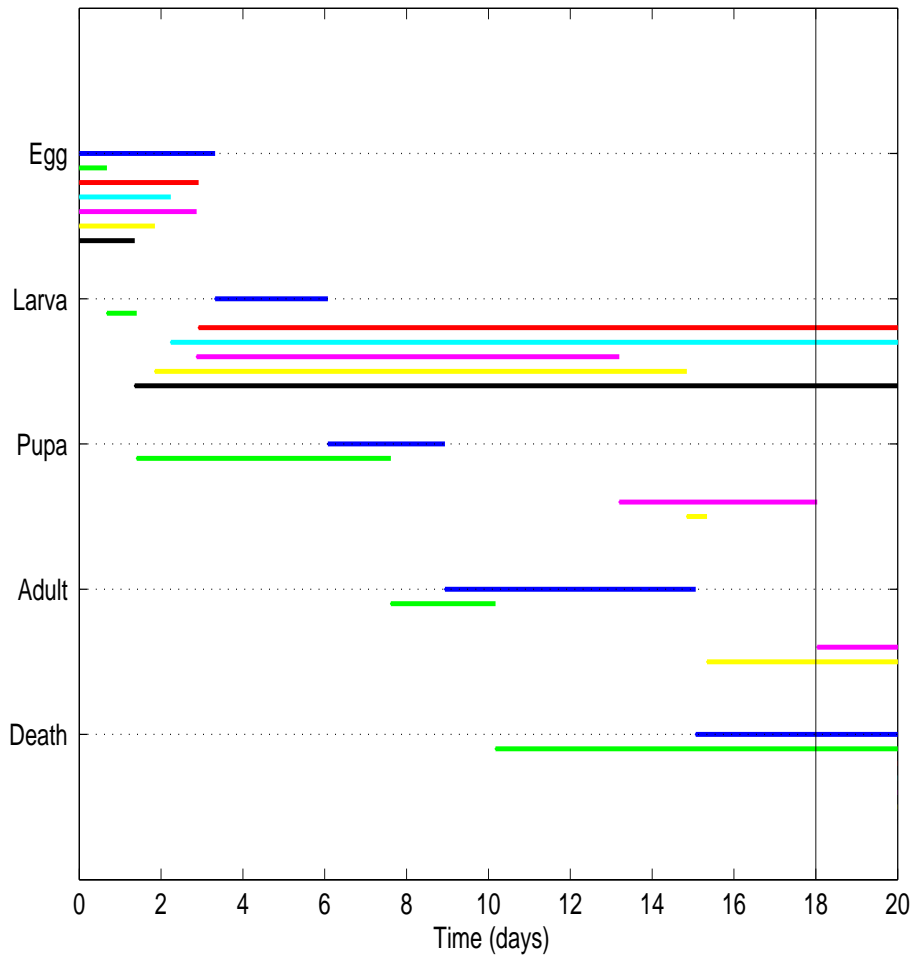


Numbers at $t = 17$ days ($n = 7$ butterflies)

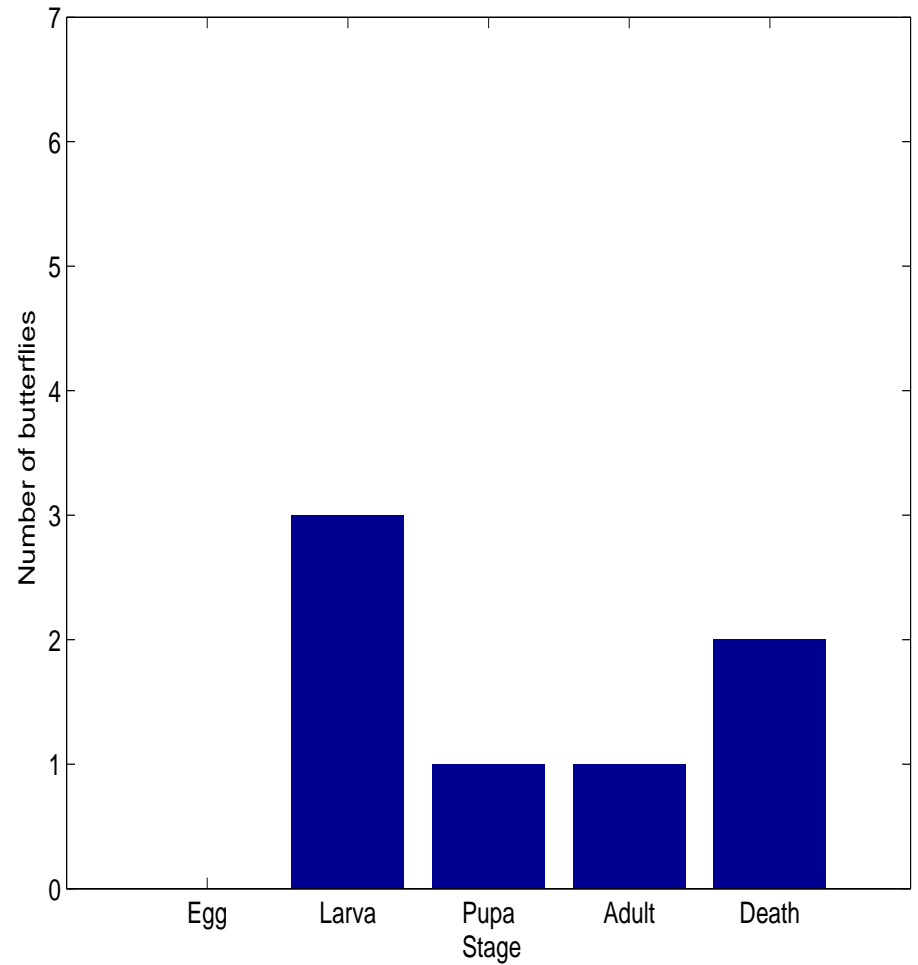


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

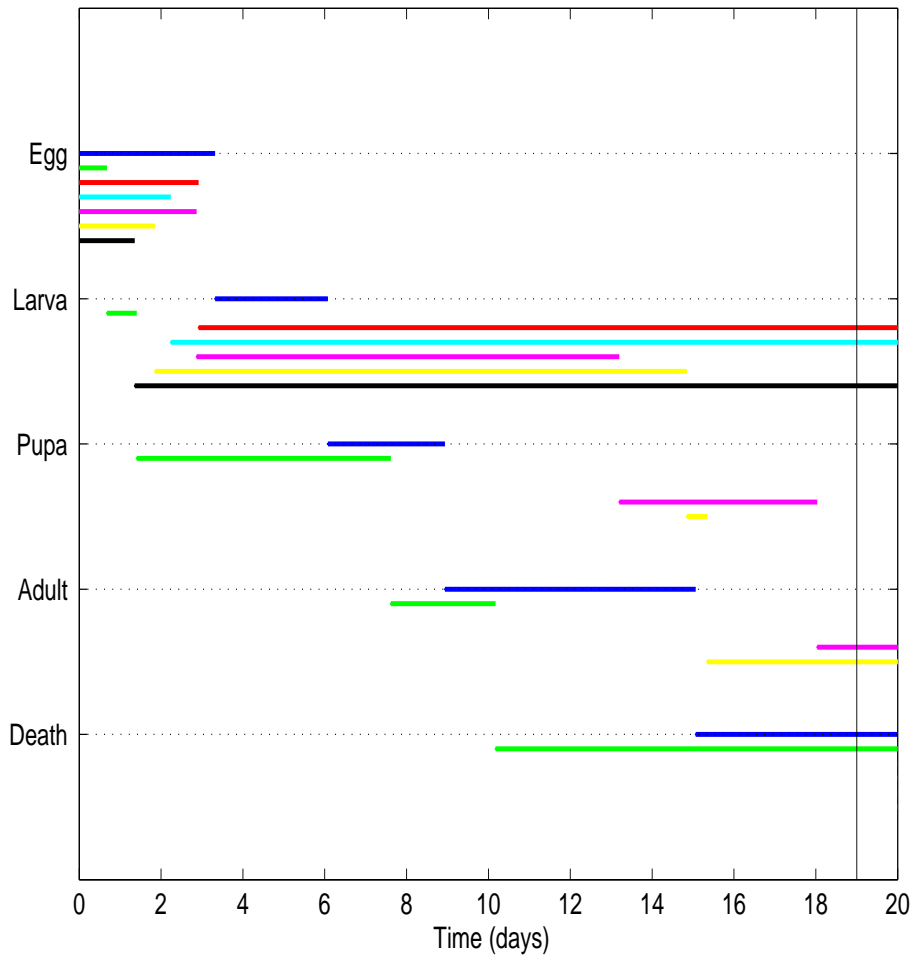


Numbers at $t = 18$ days ($n = 7$ butterflies)

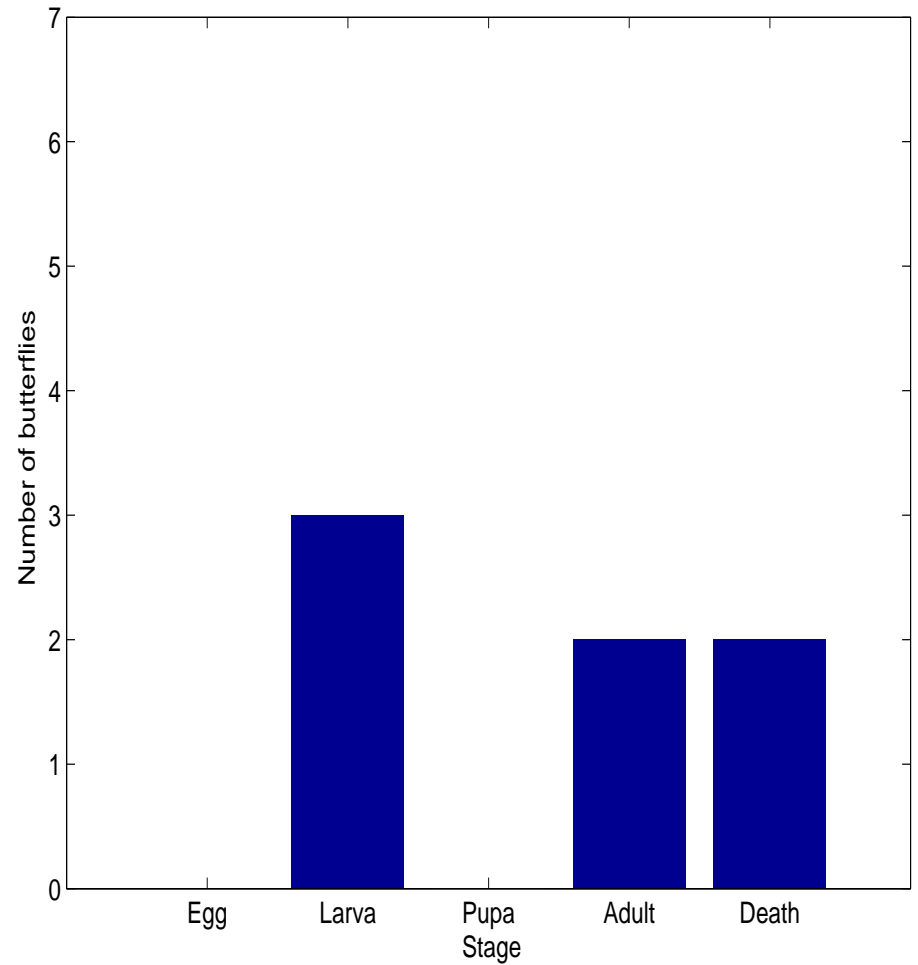


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)

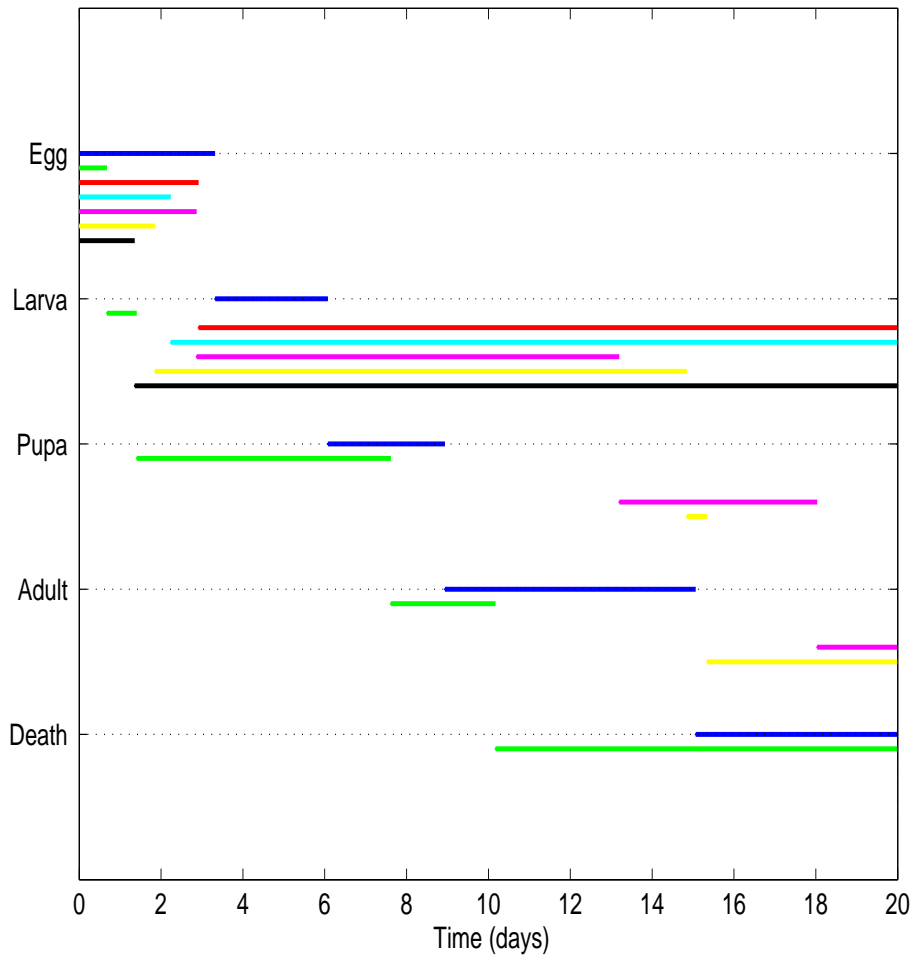


Numbers at $t = 19$ days ($n = 7$ butterflies)

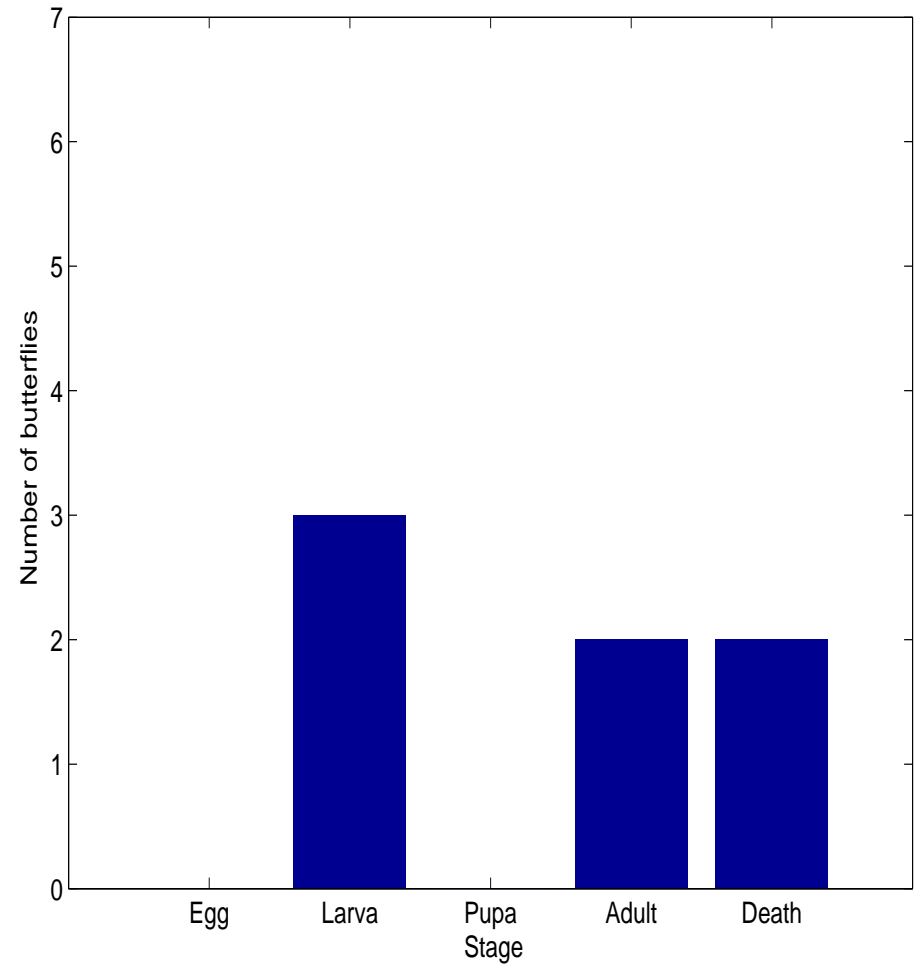


Ensemble state description

Life cycle simulation ($n = 7$ butterflies)



Numbers at $t = 20$ days ($n = 7$ butterflies)



The closed ensemble

The closed ensemble. We suppose that there is a *fixed* number n of individuals, each moving according to Q .

The process takes values in

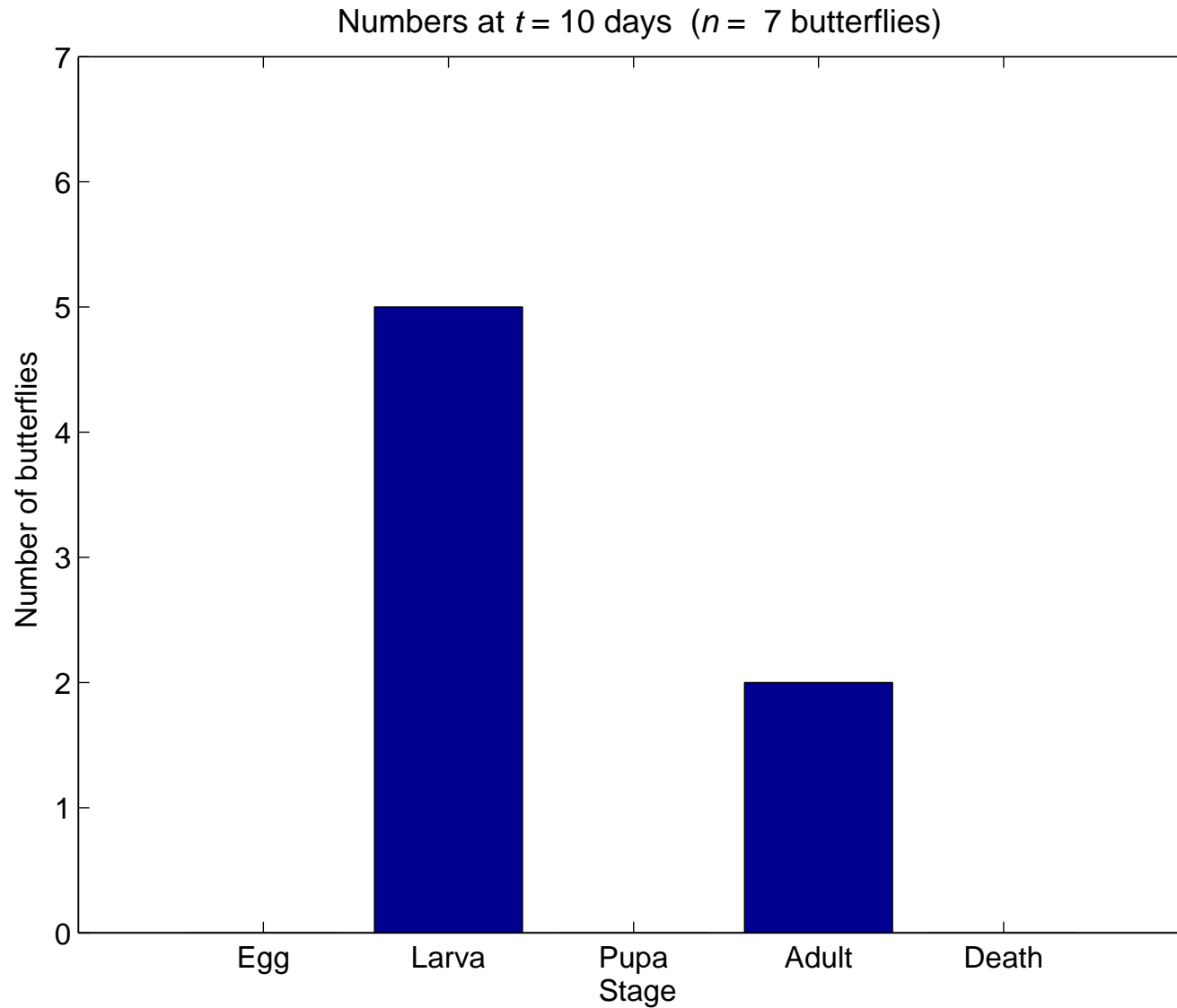
$$E = \{\mathbf{n} \in \{0, \dots, n\}^S : \sum_{j \in S} n_j = n\},$$

and its transition rates $Q_E = (q(\mathbf{n}, \mathbf{m}), \mathbf{n}, \mathbf{m} \in E)$ are given by

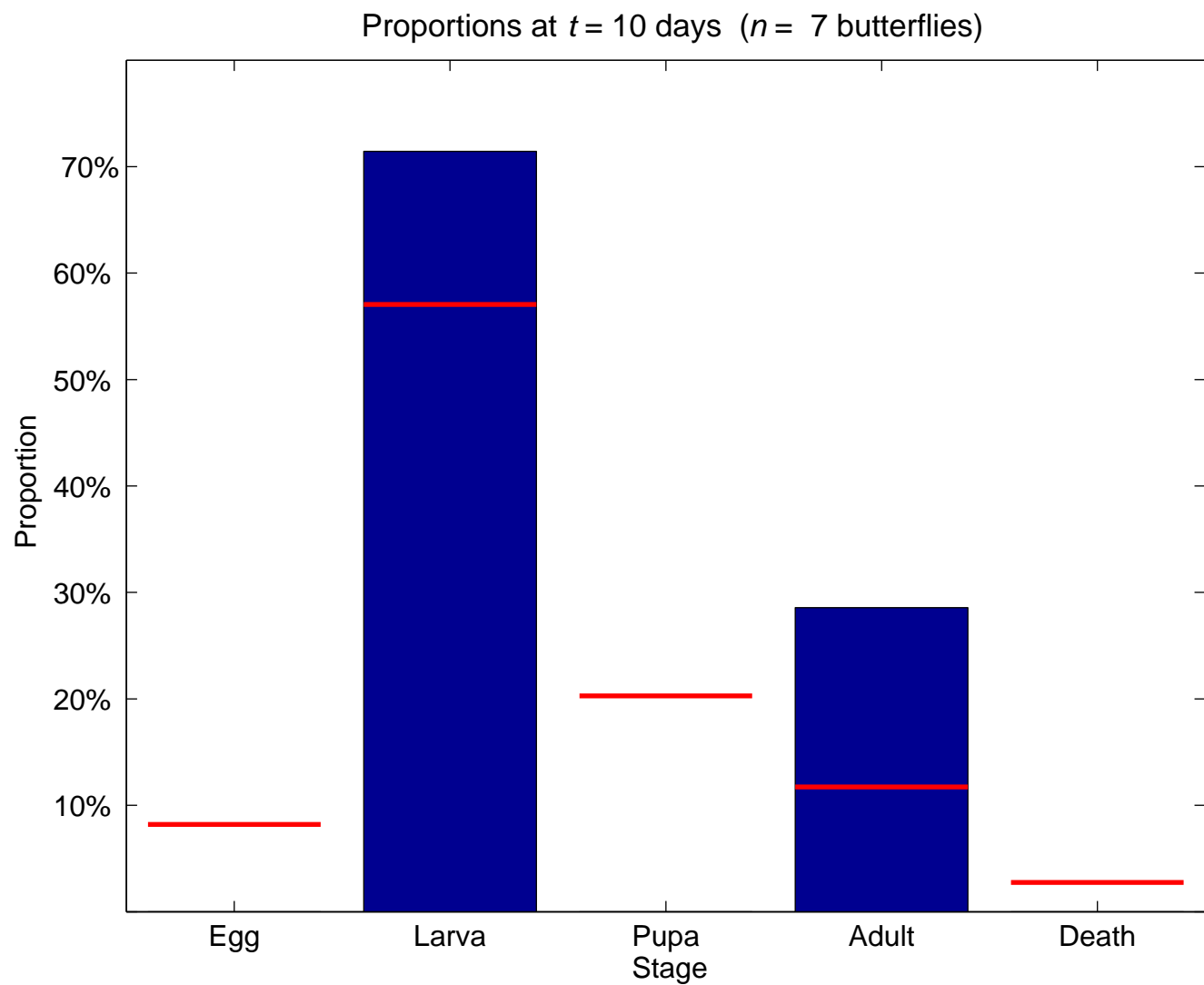
$$q(\mathbf{n}, \mathbf{n} + \mathbf{e}_j - \mathbf{e}_i) = n_i q_{ij},$$

for all states $j \neq i$ in S , where $\mathbf{e}_j = (0, \dots, 0, 1, 0, \dots, 0)$ is the unit vector with a 1 as its j -th entry (this transition corresponds to a single individual moving from state i to state j).

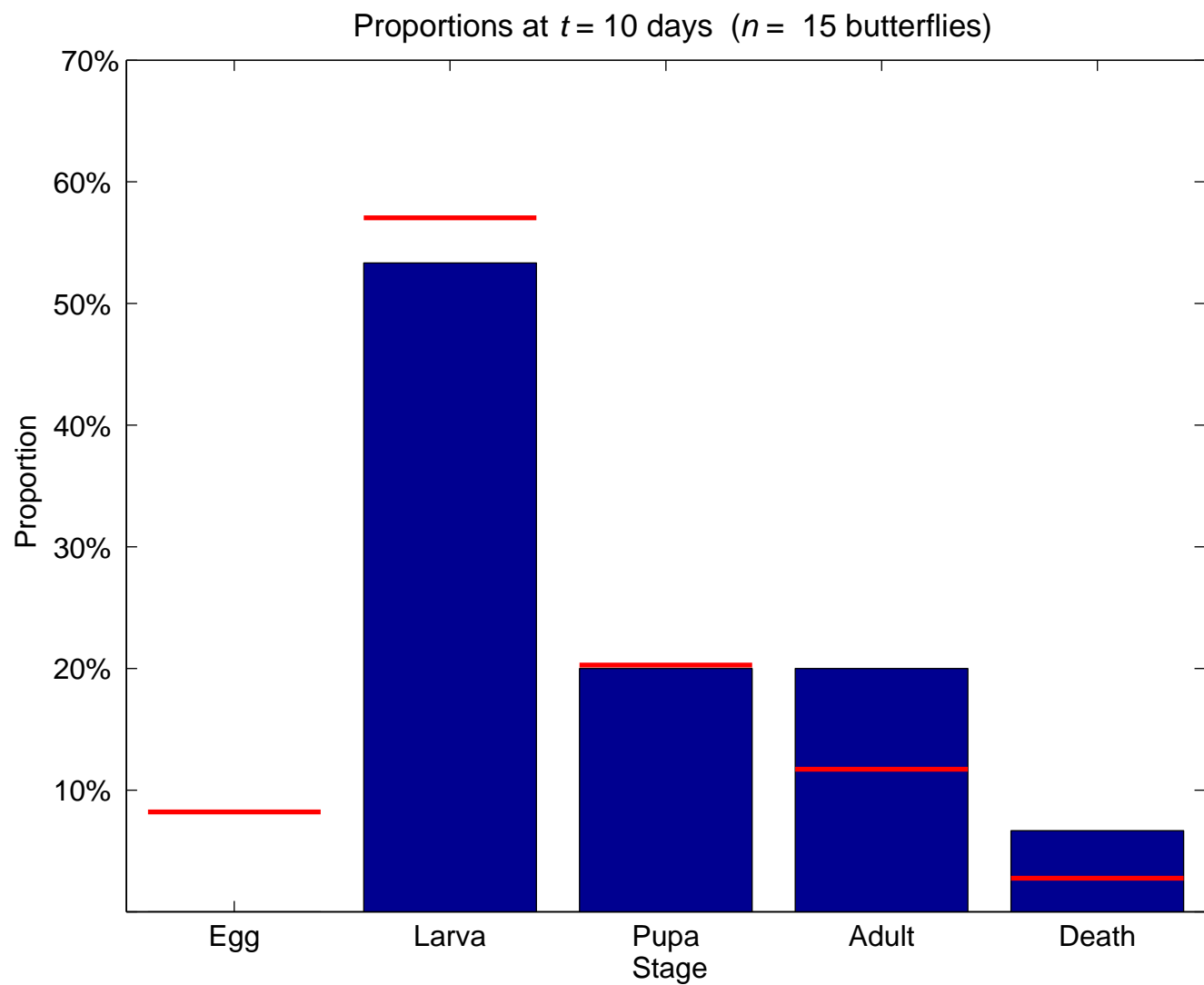
Ensemble proportions (simulation)



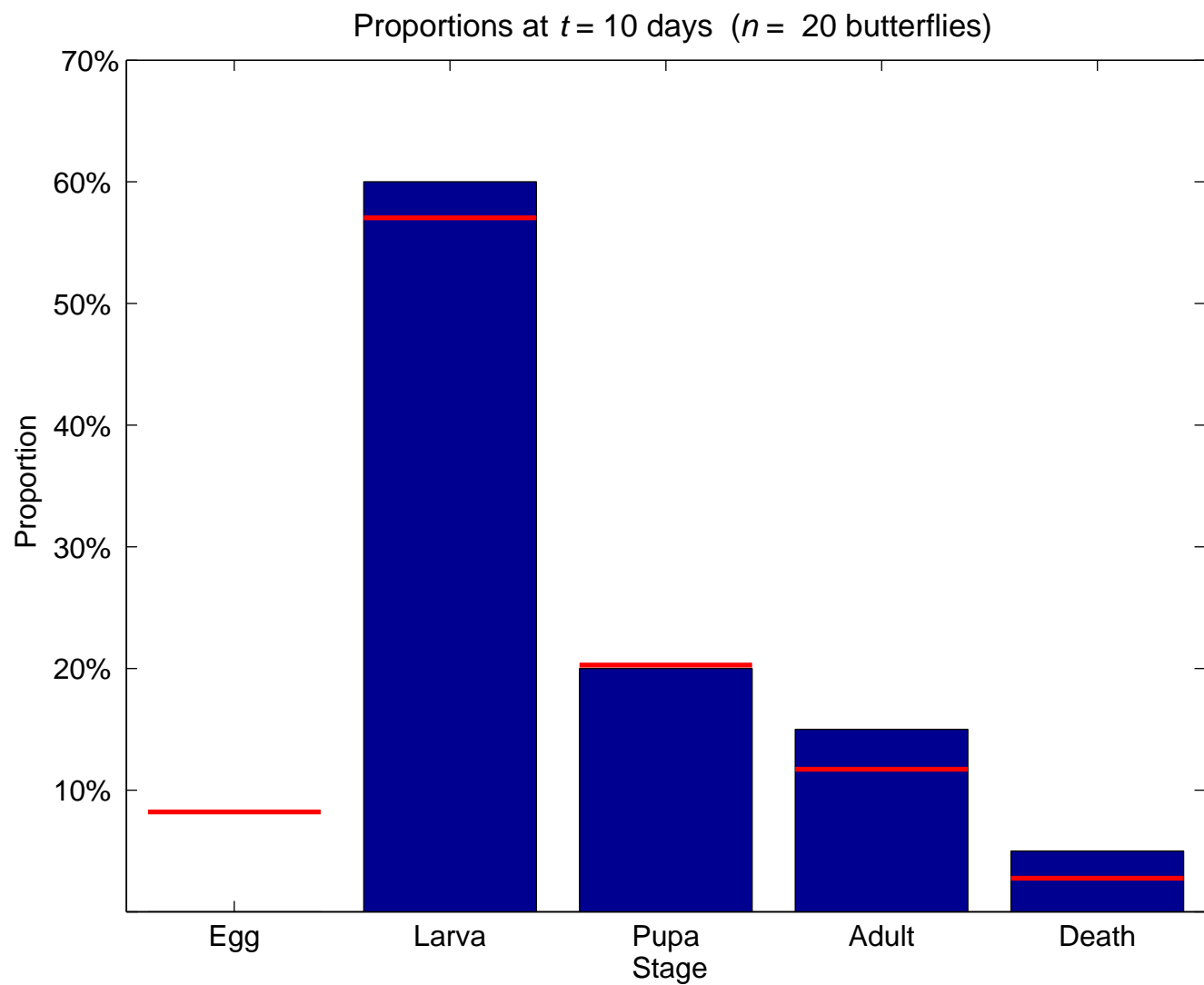
Ensemble proportions (simulation)



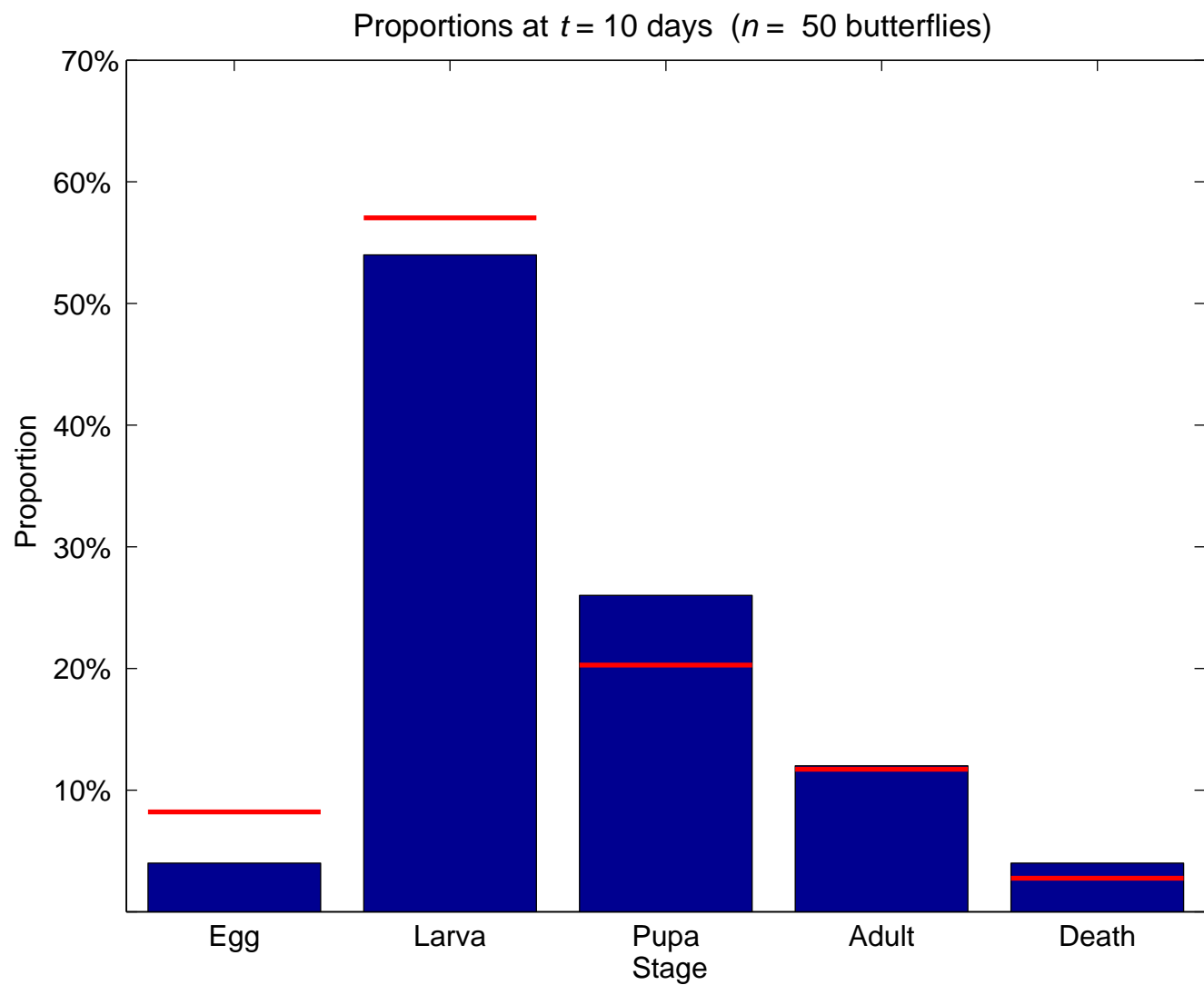
Ensemble proportions (simulation)



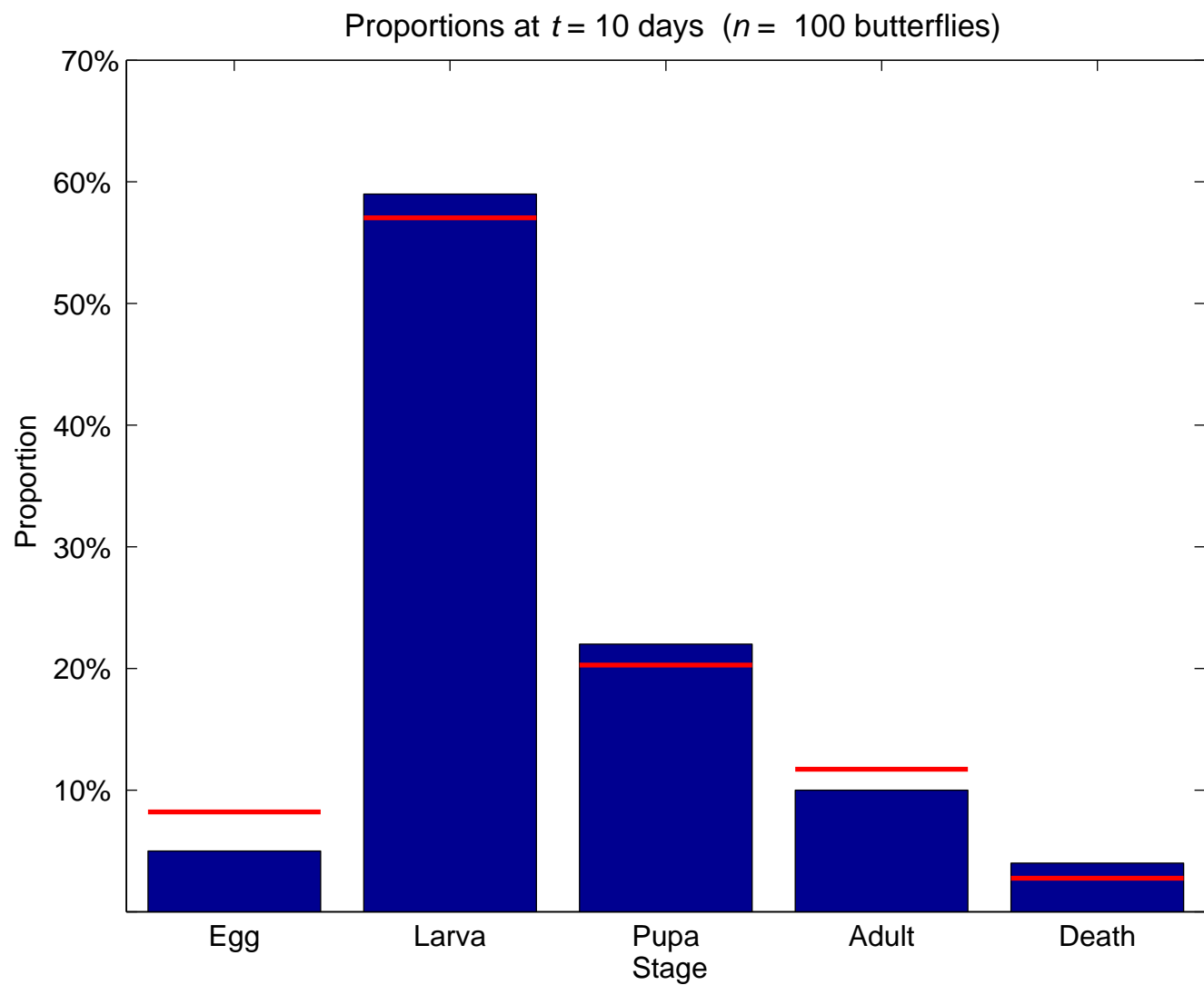
Ensemble proportions (simulation)



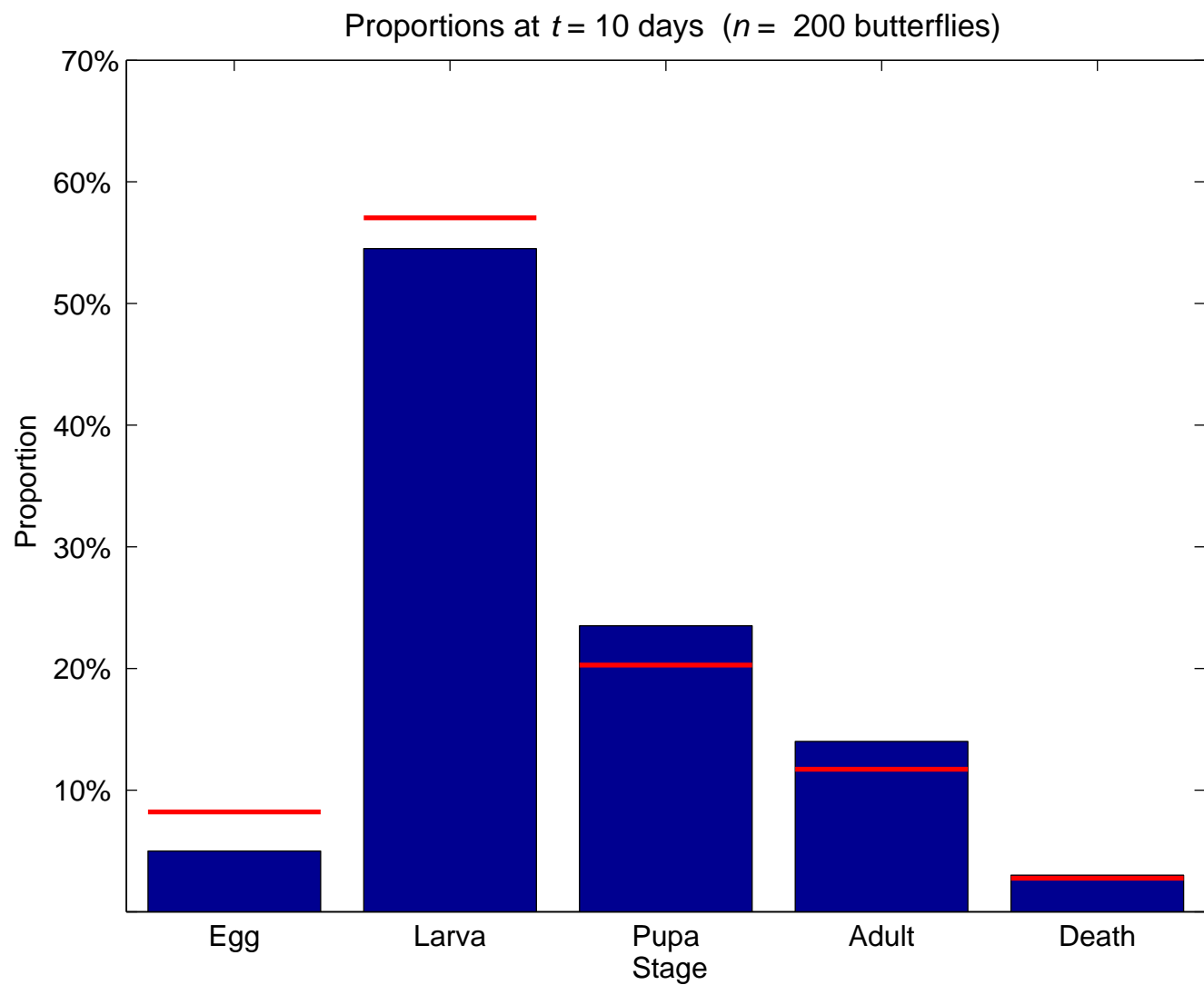
Ensemble proportions (simulation)



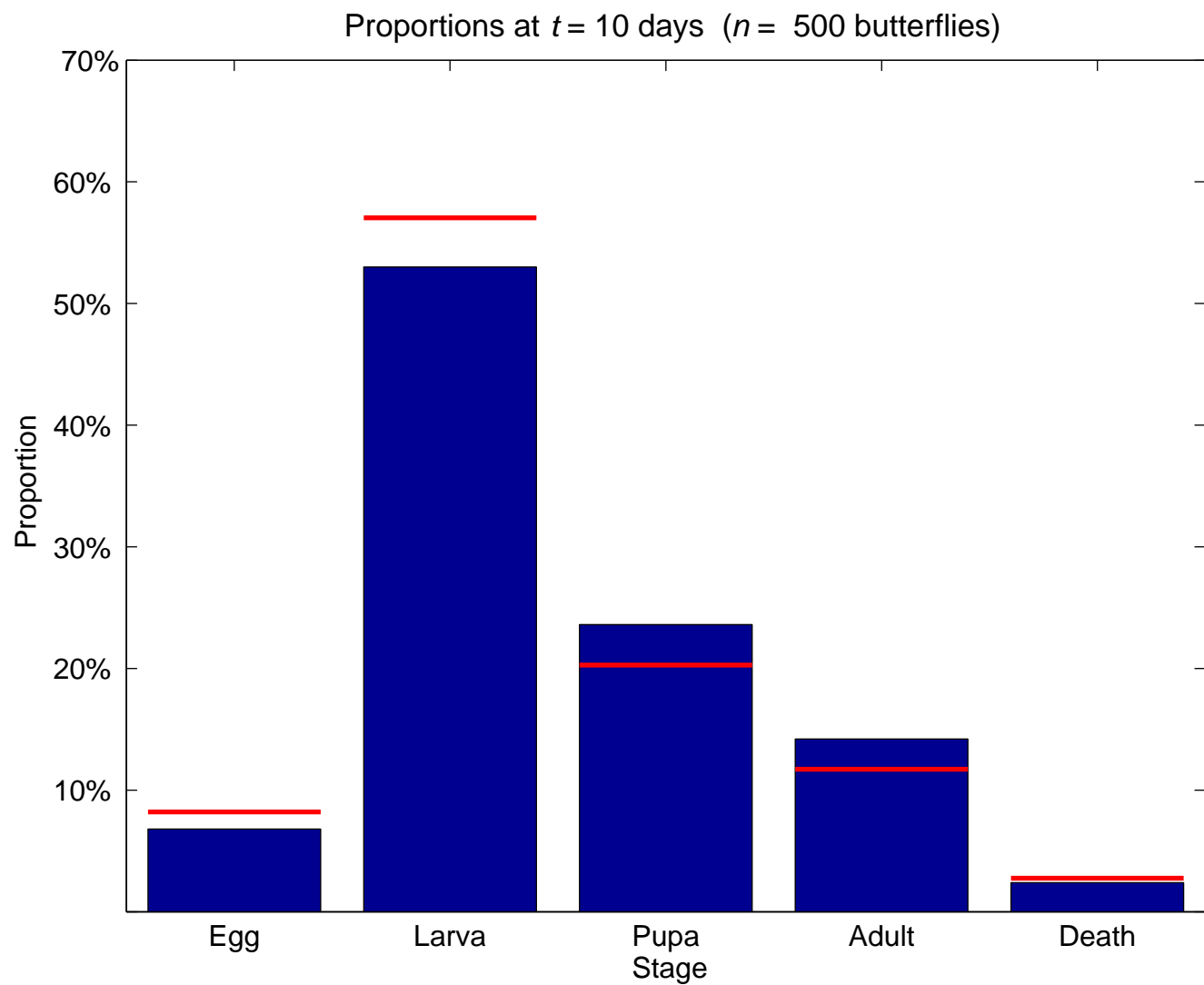
Ensemble proportions (simulation)



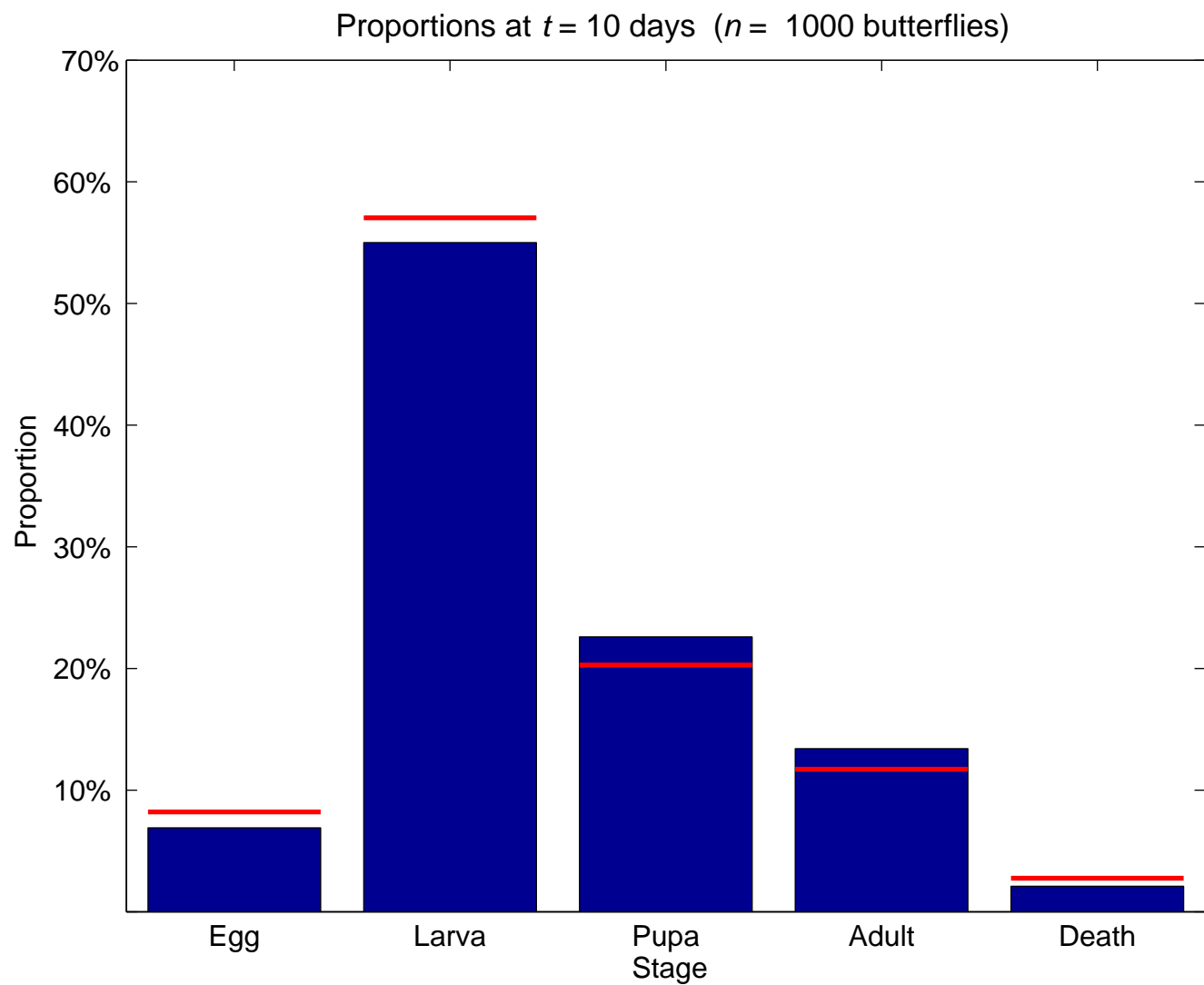
Ensemble proportions (simulation)



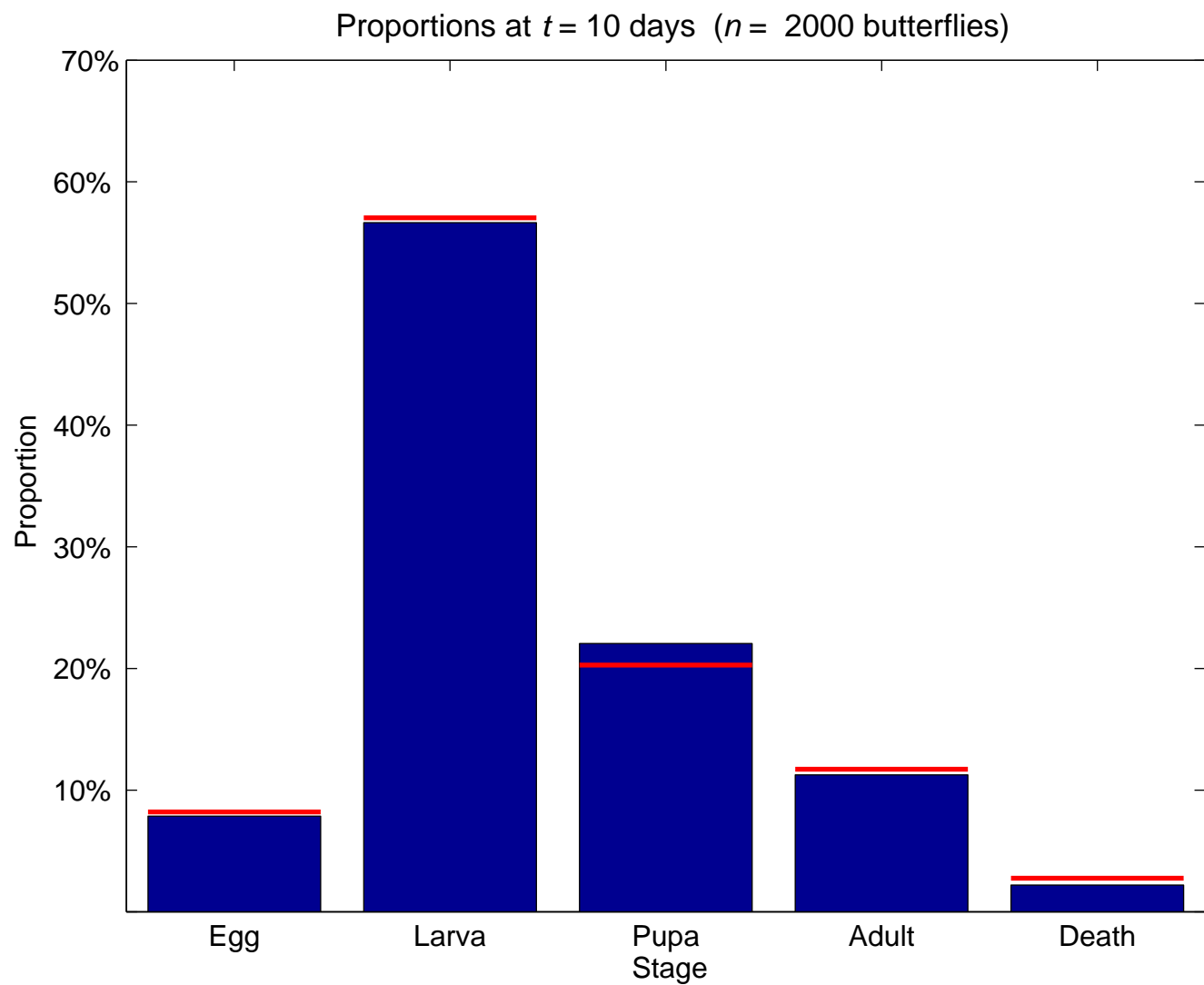
Ensemble proportions (simulation)



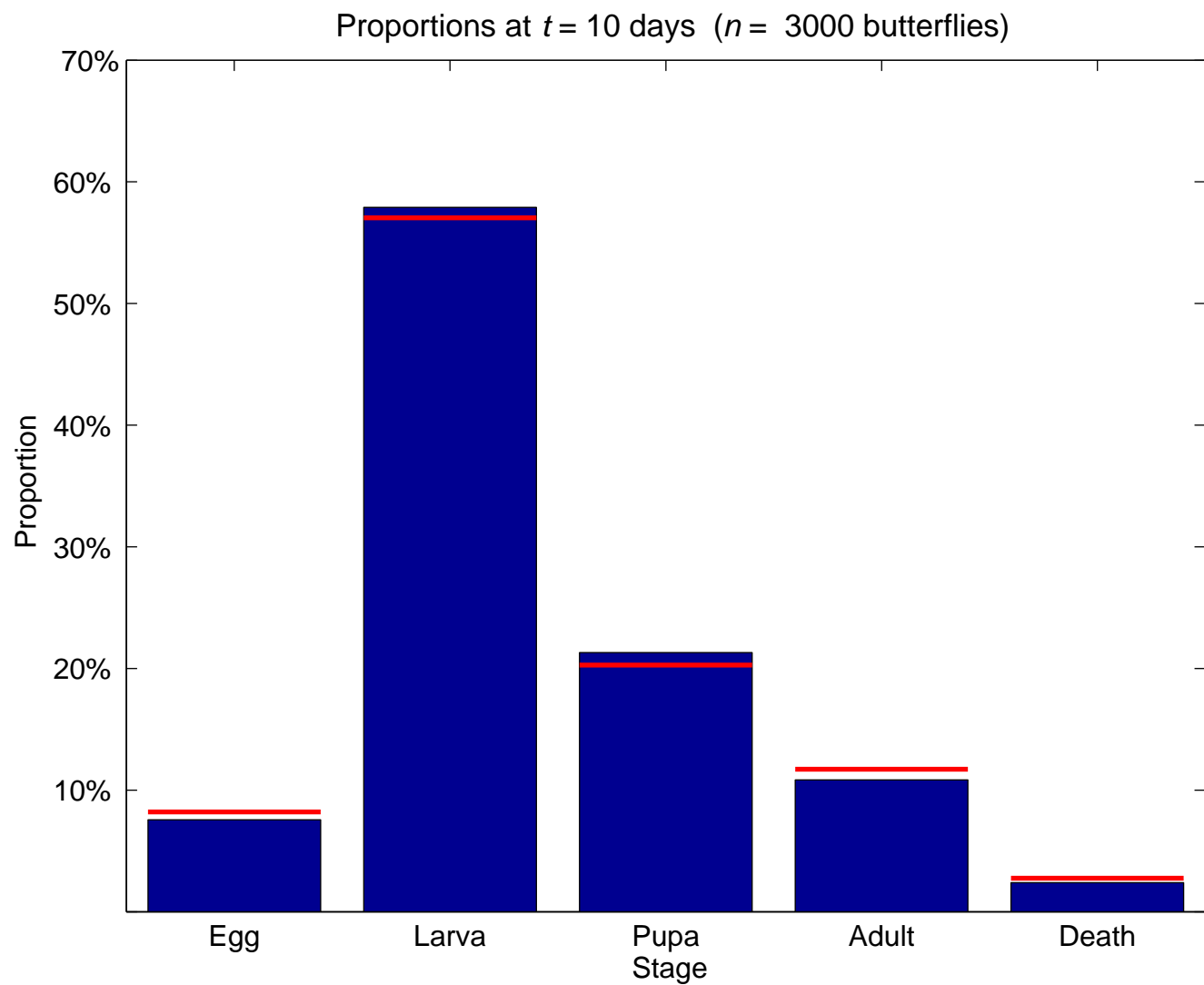
Ensemble proportions (simulation)



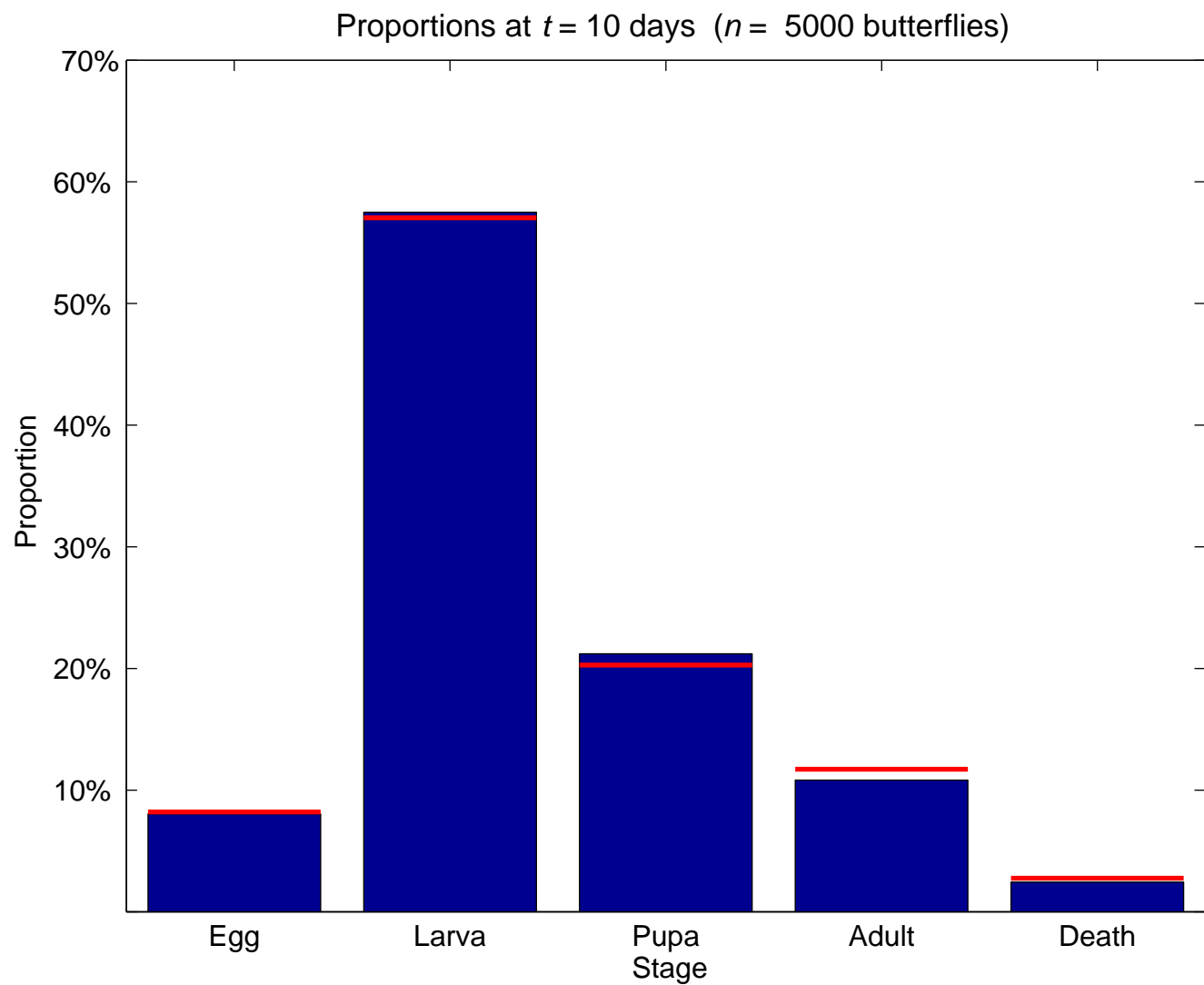
Ensemble proportions (simulation)



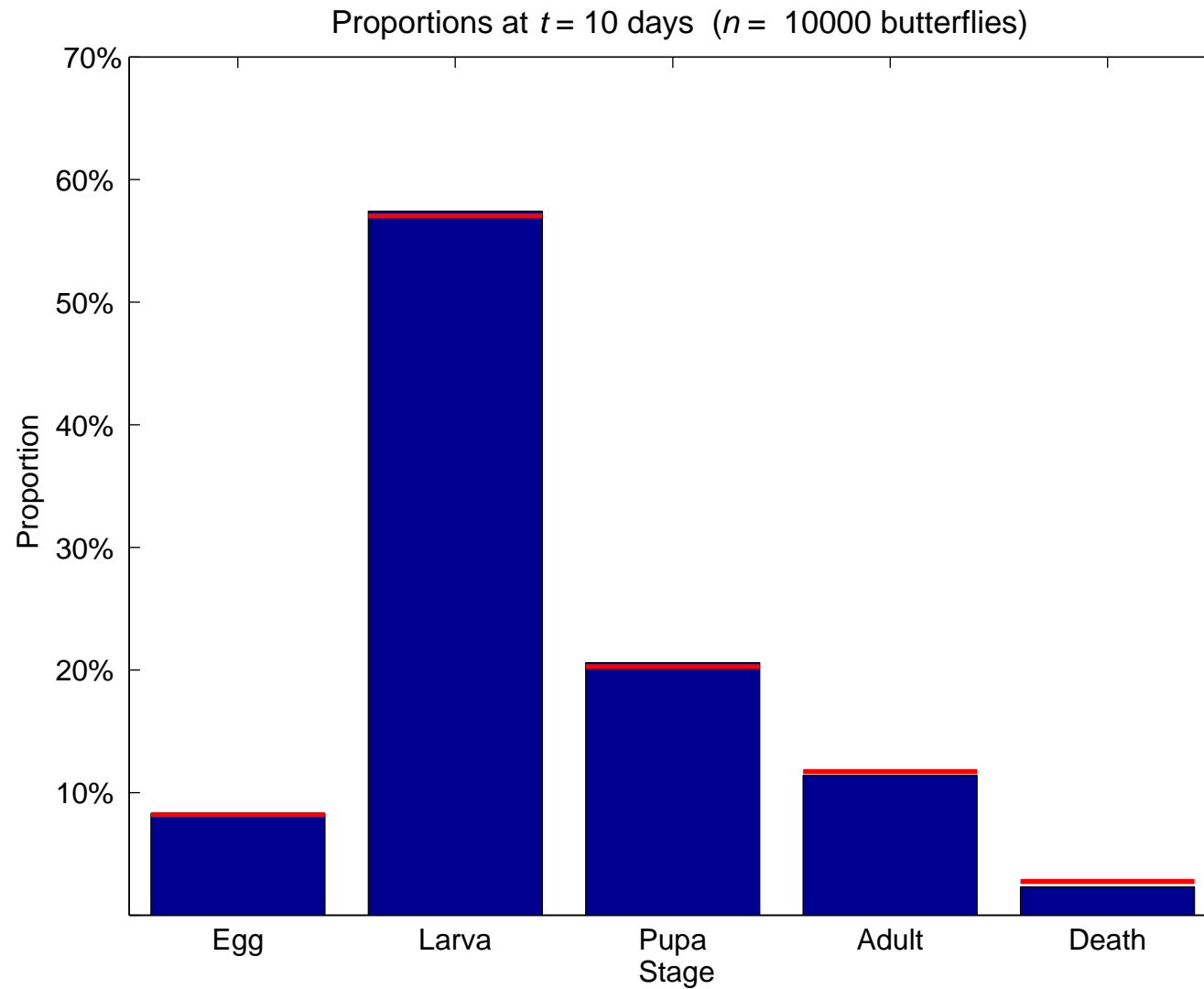
Ensemble proportions (simulation)



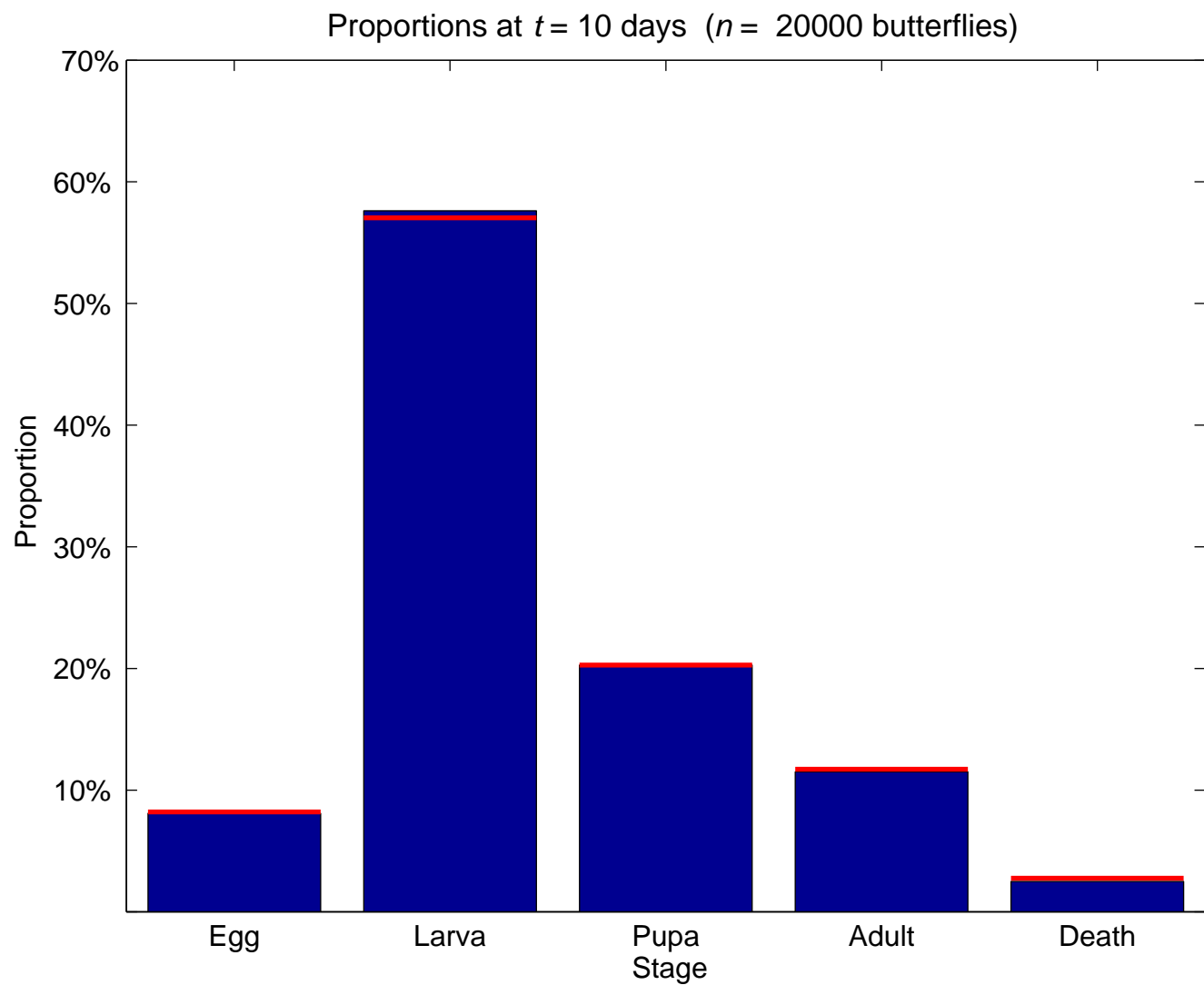
Ensemble proportions (simulation)



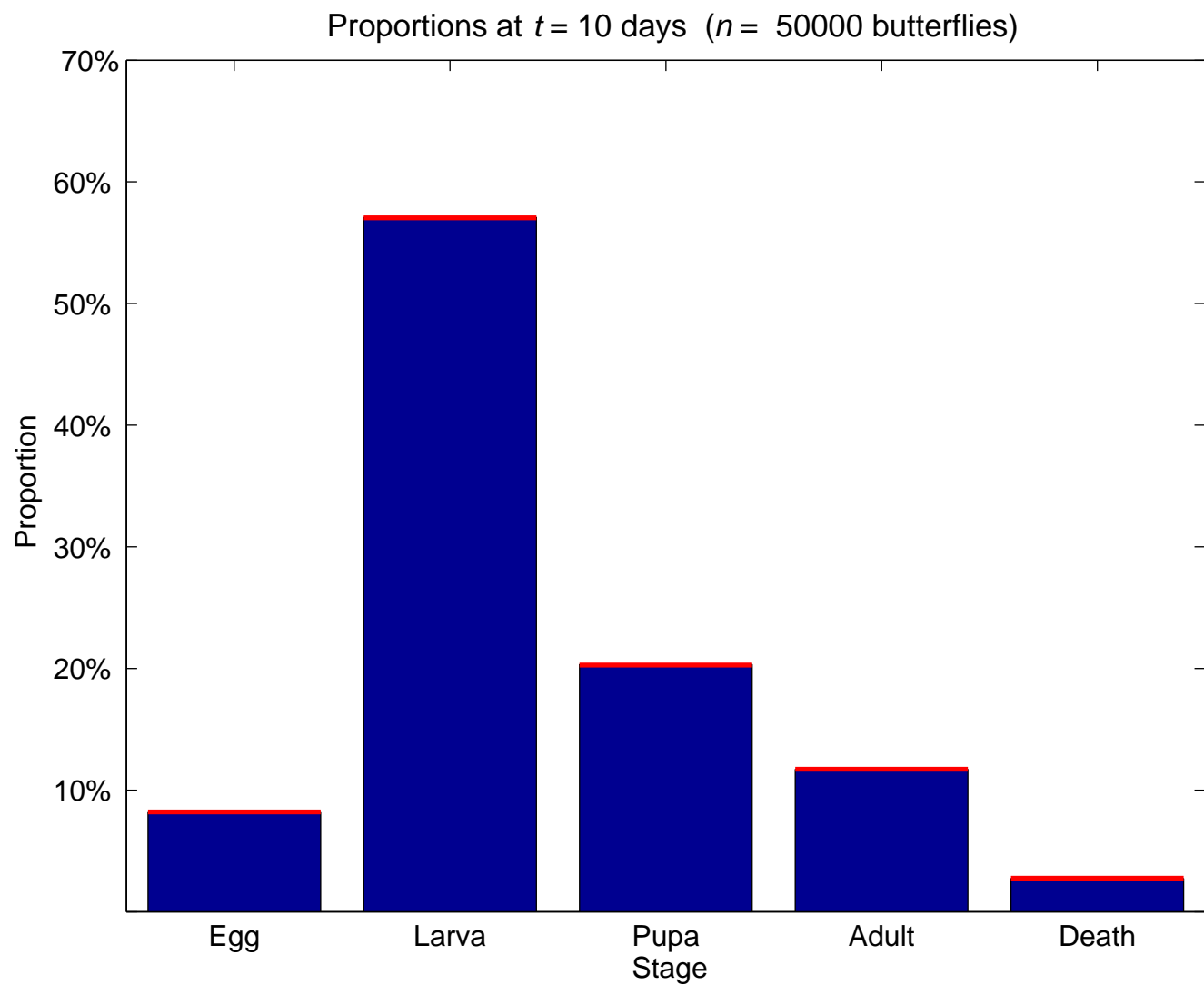
Ensemble proportions (simulation)



Ensemble proportions (simulation)



Ensemble proportions (simulation)



Convergence of ensemble proportions

Let $\mathbf{X}^{(n)}(t) = \mathbf{N}(t)/n$, where n is the number of individuals, so that $X_j^{(n)}(t)$ is the proportion of individuals in state j .

Convergence of ensemble proportions

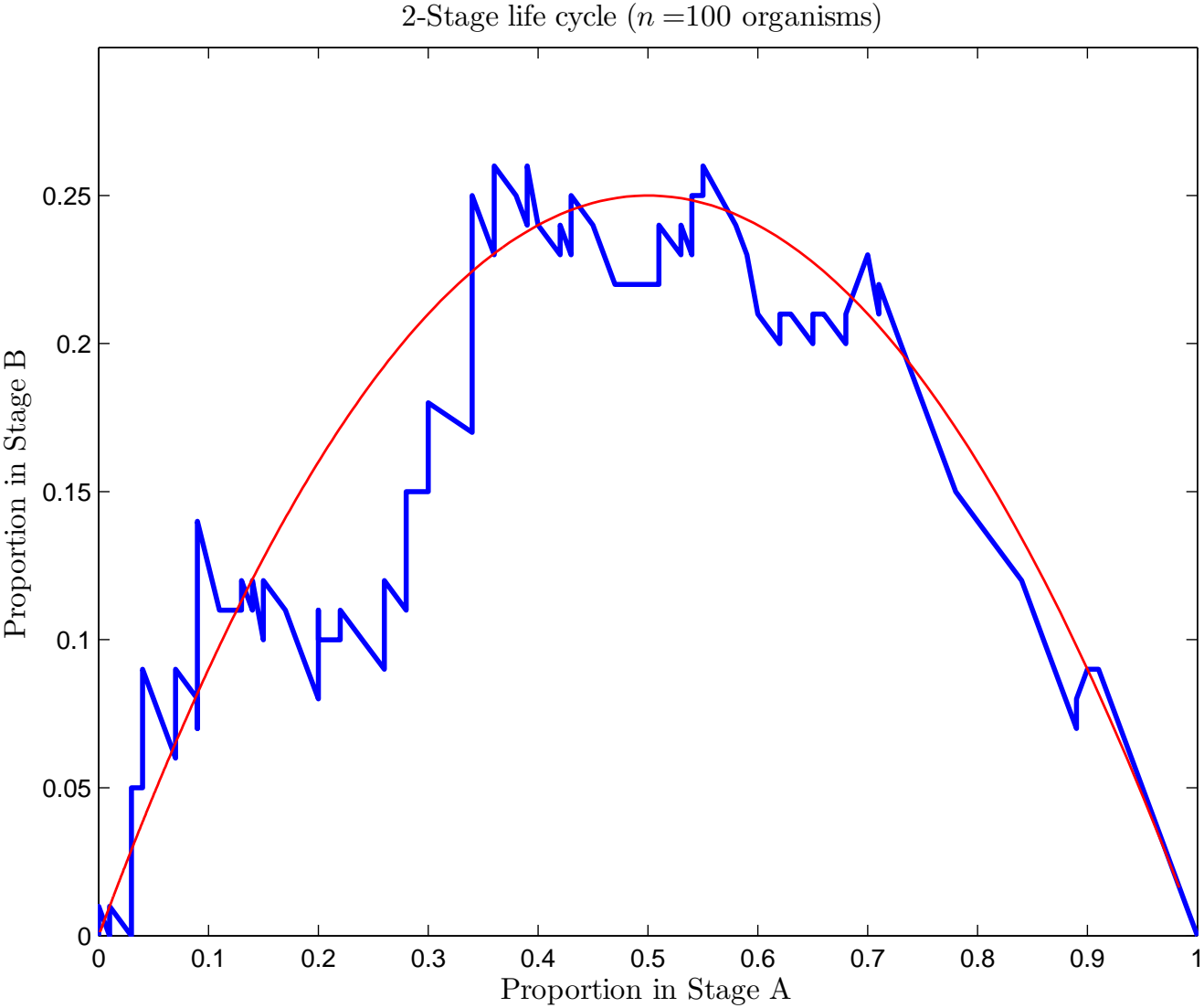
Let $\mathbf{X}^{(n)}(t) = \mathbf{N}(t)/n$, where n is the number of individuals, so that $X_j^{(n)}(t)$ is the proportion of individuals in state j .

Theorem 1. If $\mathbf{X}^{(n)}(0) \rightarrow \mathbf{a}$ as $n \rightarrow \infty$, then, for all $u > 0$, and for every $\epsilon > 0$,

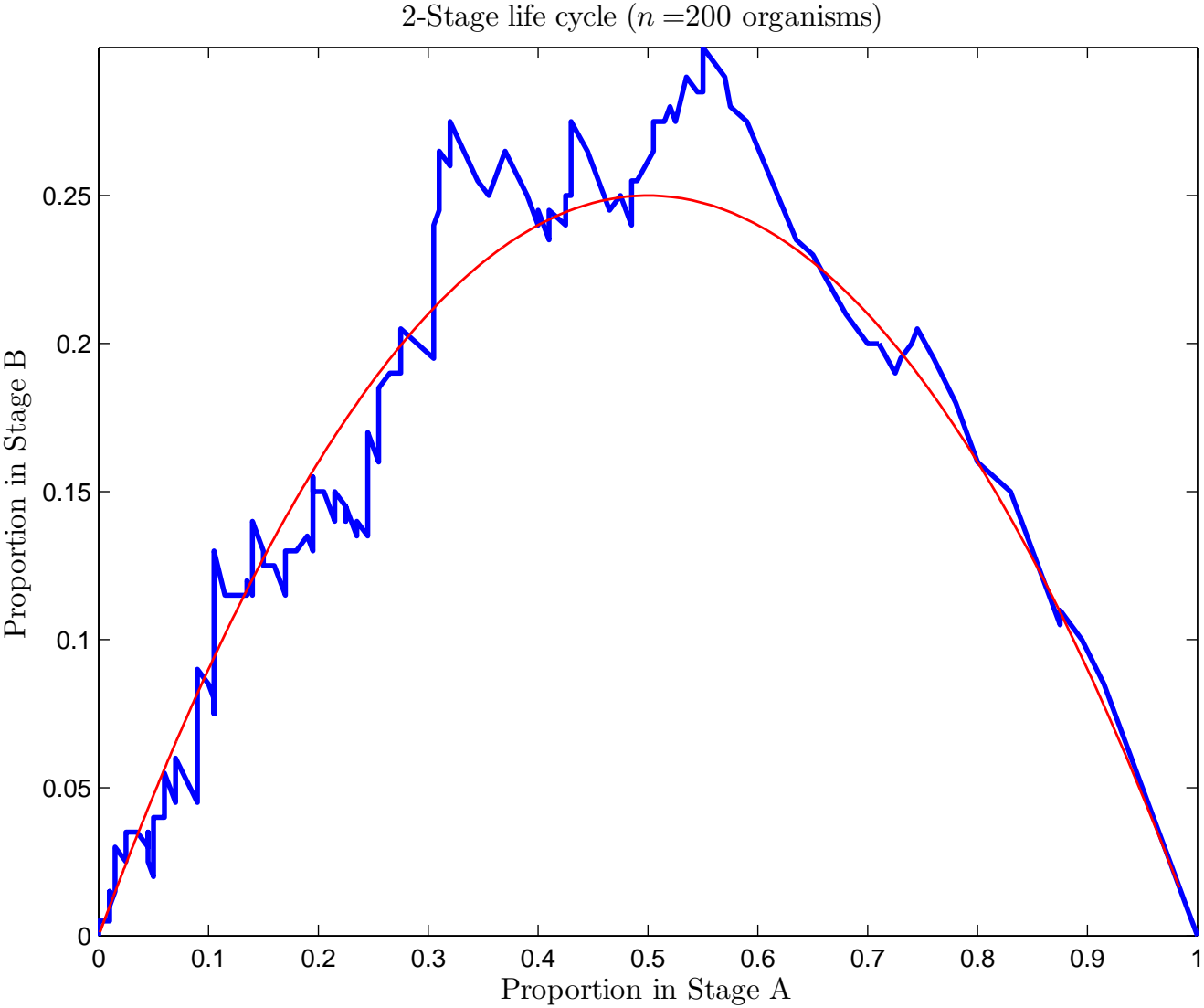
$$\Pr \left(\sup_{0 \leq t \leq u} \left| \mathbf{X}^{(n)}(t) - \mathbf{p}(t) \right| > \epsilon \right) \rightarrow 0 \quad \text{as } n \rightarrow \infty,$$

where $\mathbf{p}(t) = (p_j(t), j \in S)$ is the unique solution to $\mathbf{p}'(t) = \mathbf{p}(t) Q$ satisfying $\mathbf{p}(0) = \mathbf{a}$, namely $\mathbf{p}(t) = \mathbf{a} \exp(tQ)$, where $\exp(\cdot)$ is the matrix exponential.

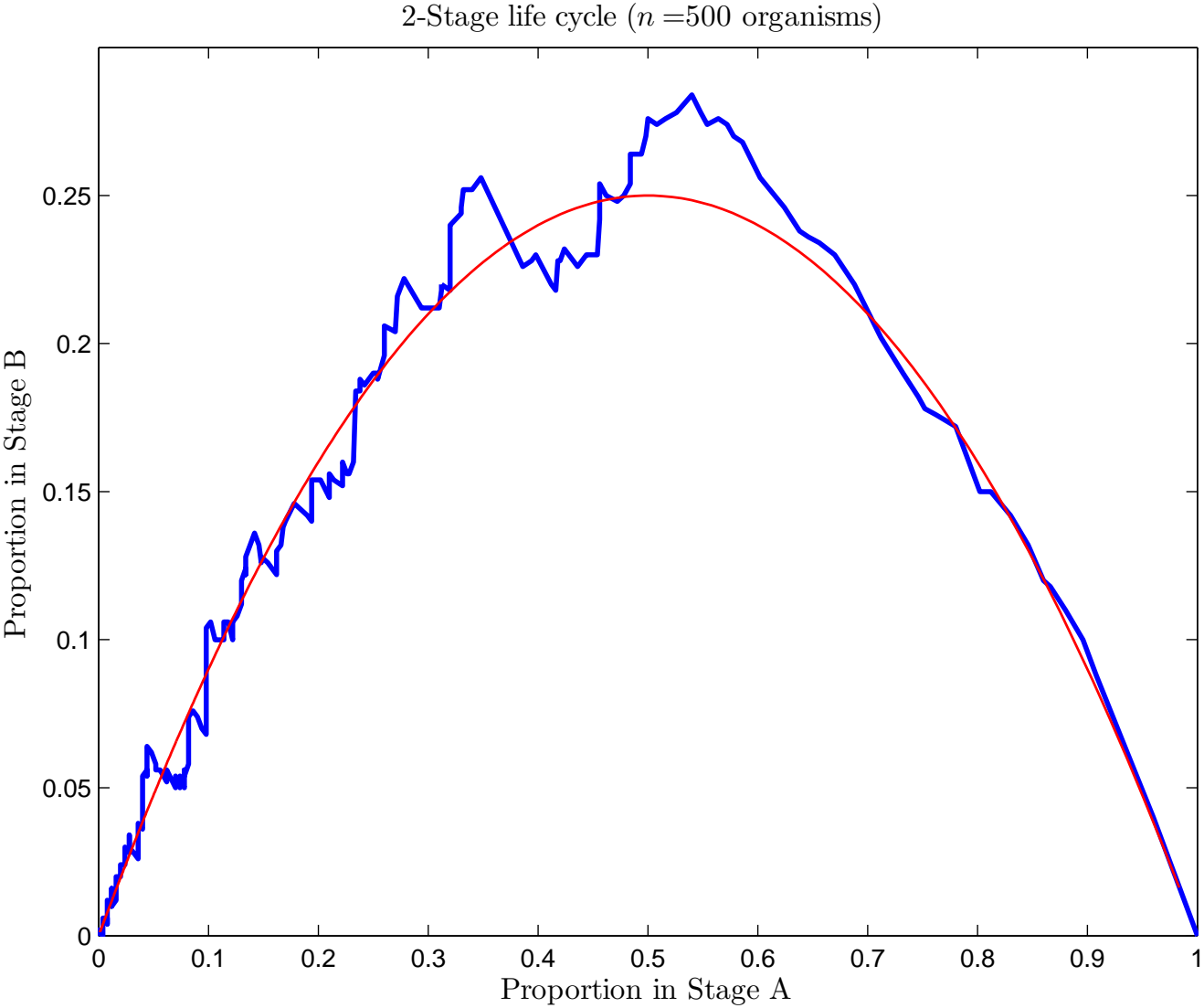
Convergence of ensemble proportions



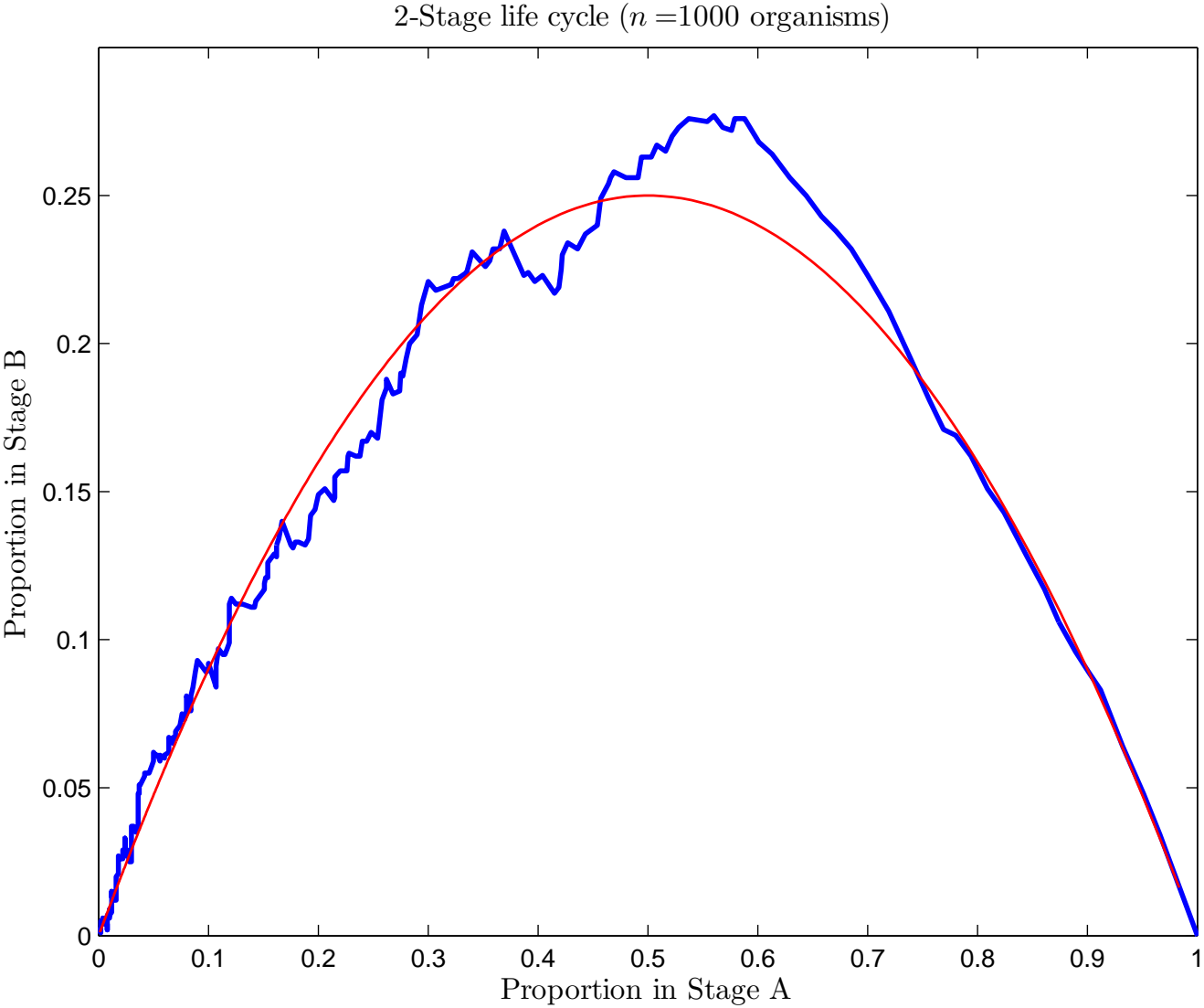
Convergence of ensemble proportions



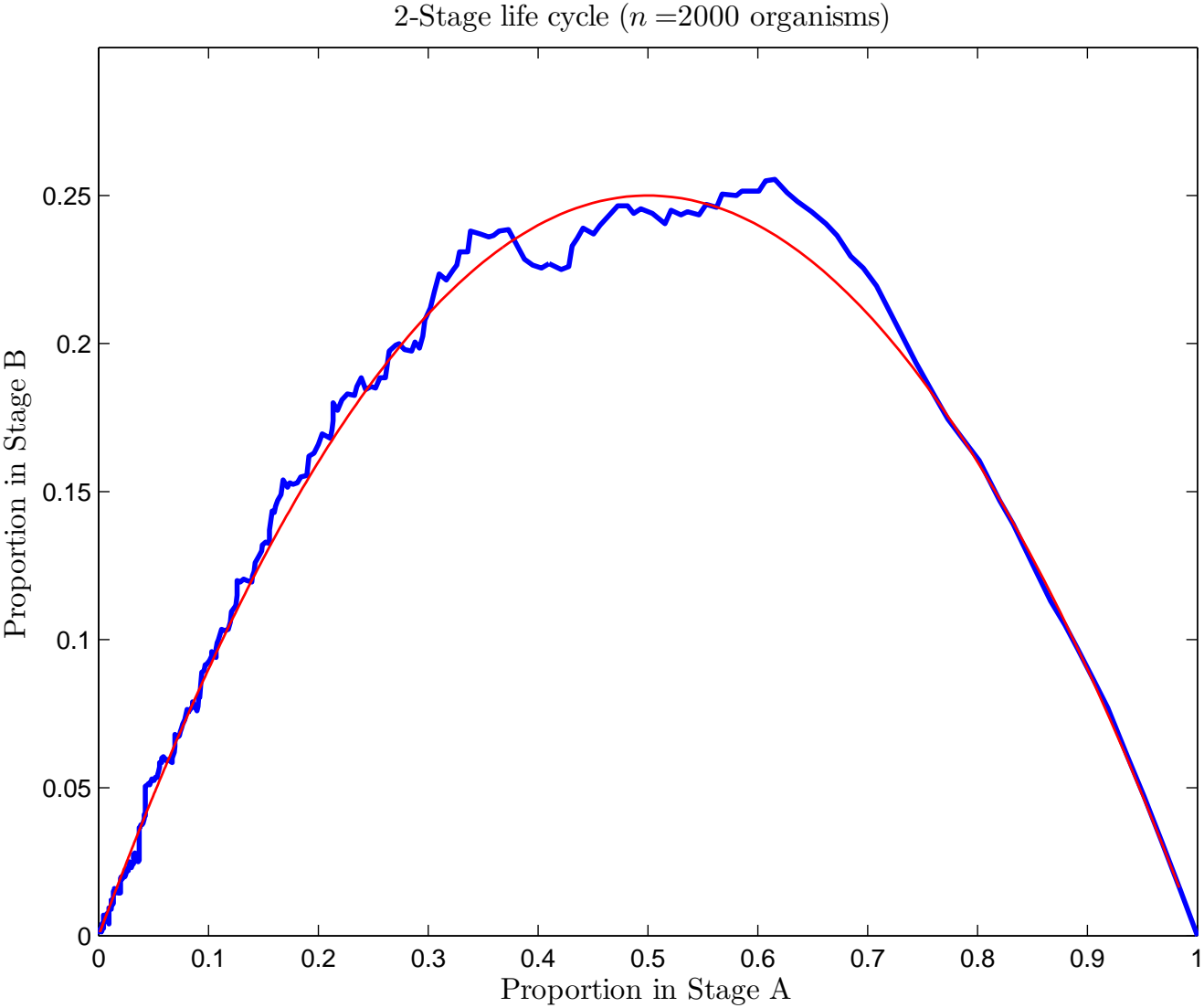
Convergence of ensemble proportions



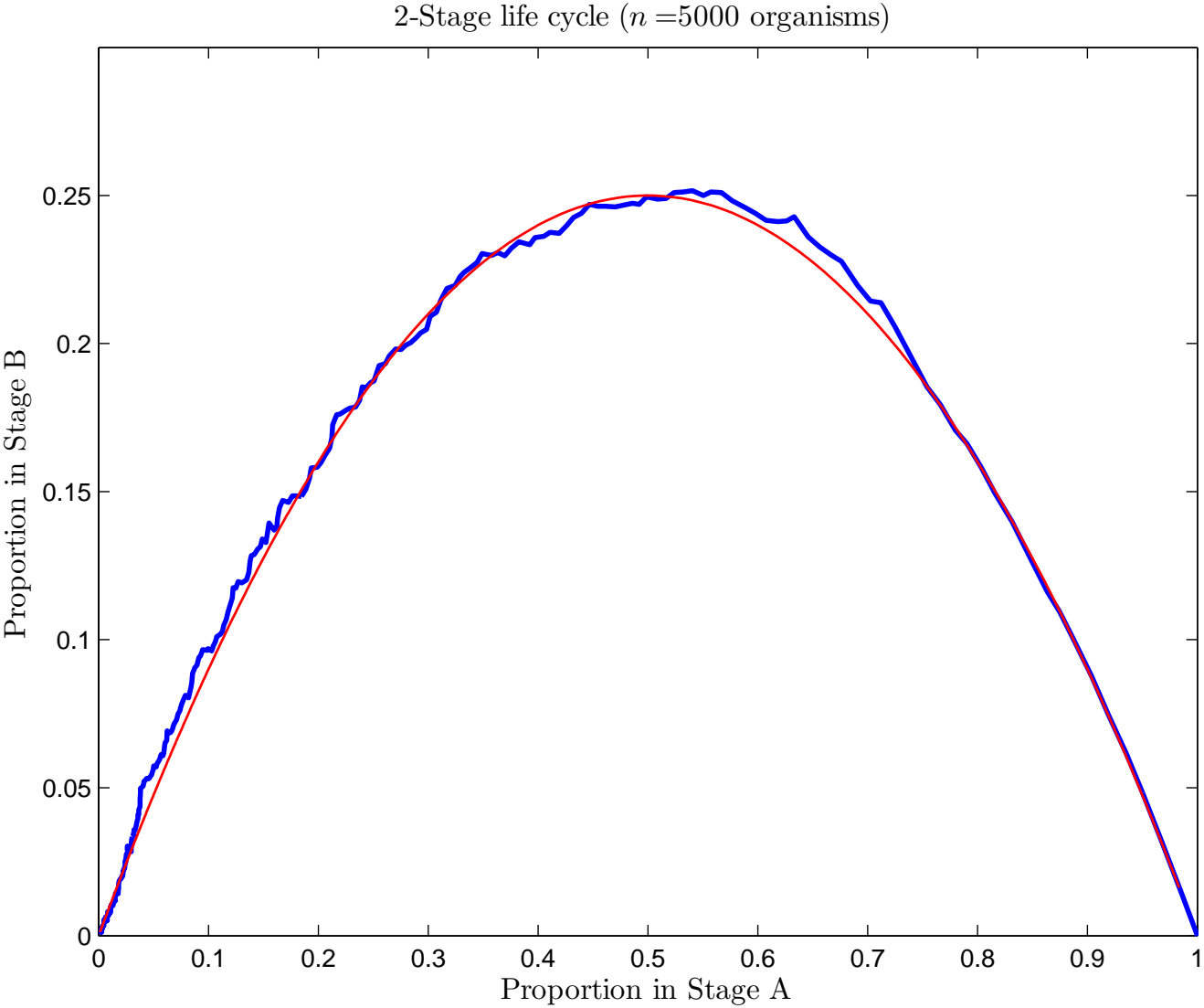
Convergence of ensemble proportions



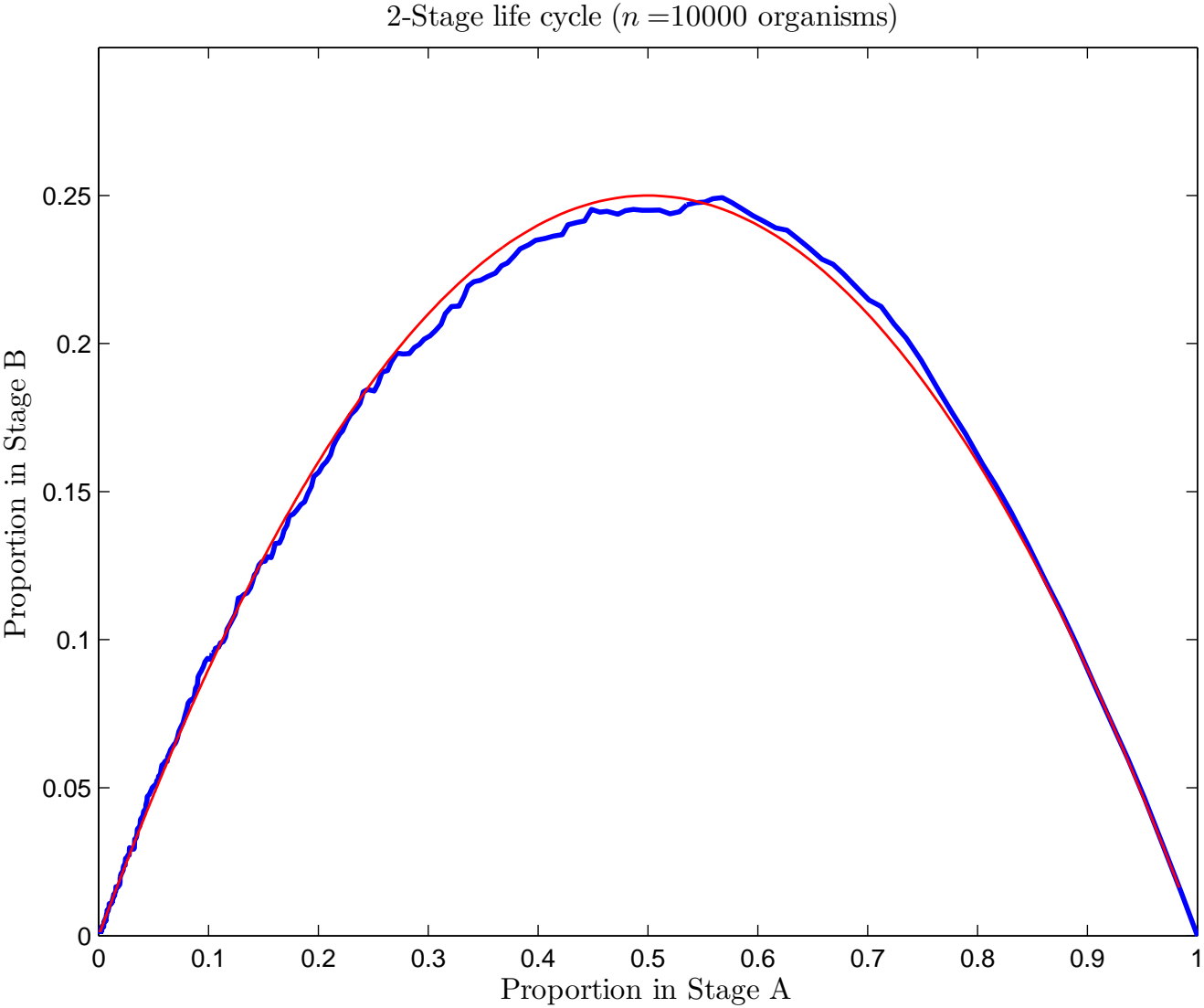
Convergence of ensemble proportions



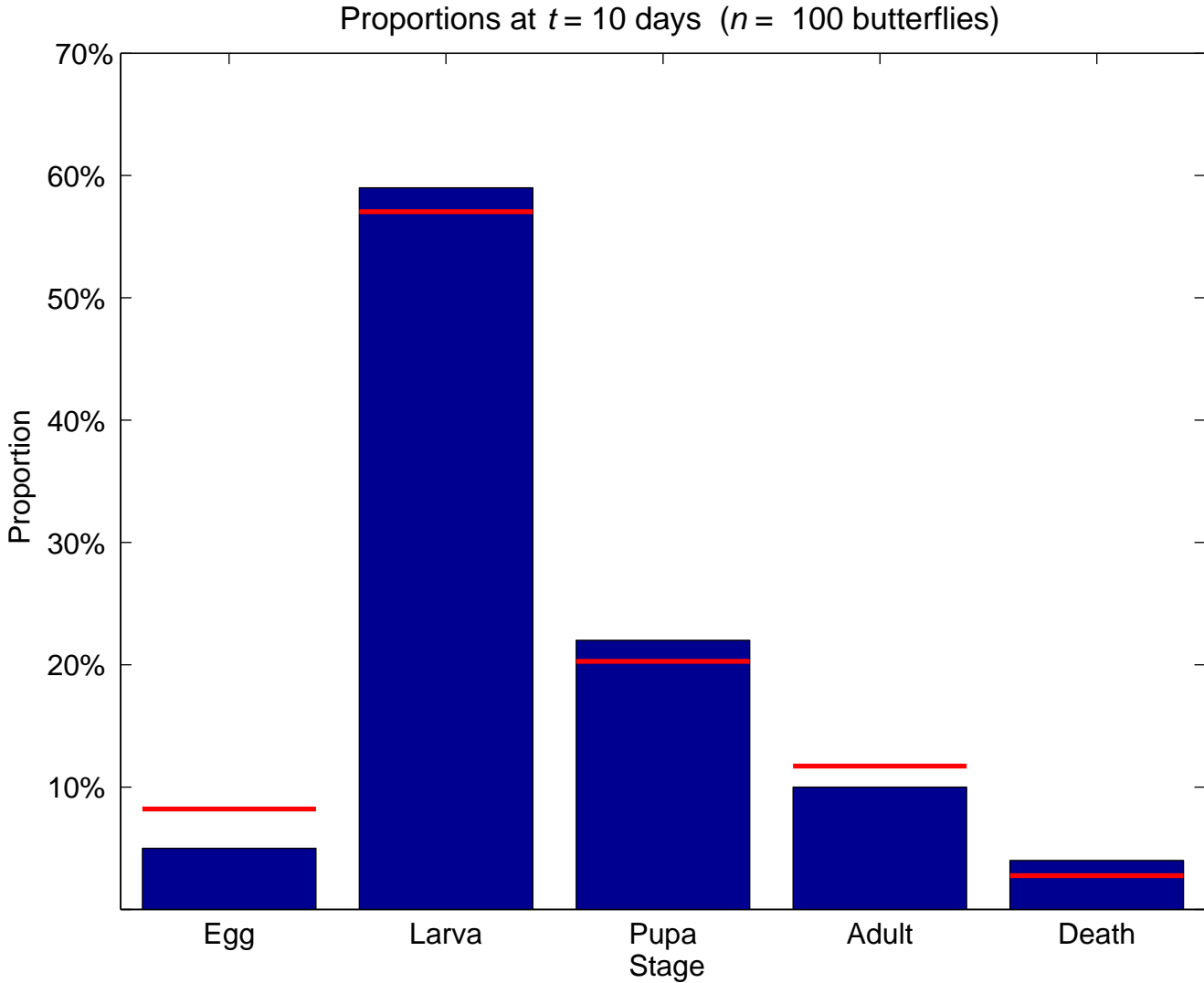
Convergence of ensemble proportions



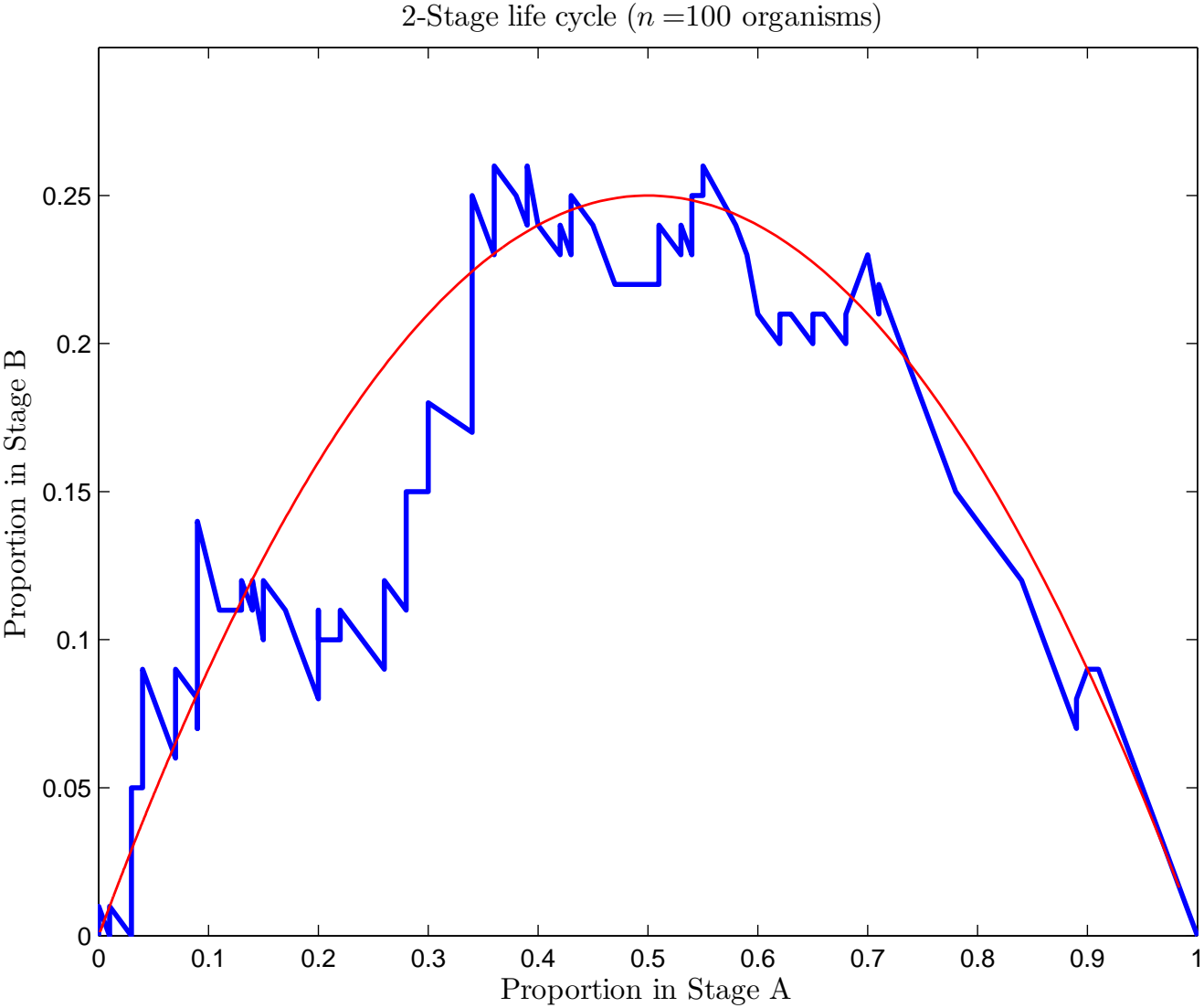
Convergence of ensemble proportions



Convergence of ensemble proportions



Convergence of ensemble proportions



A Central Limit Theorem

Theorem 2. In the setup of Theorem 1, let

$$\mathbf{Z}^{(n)}(t) = \sqrt{n}(\mathbf{X}^{(n)}(t) - \mathbf{p}(t)).$$

If $\mathbf{Z}^{(n)}(0) \rightarrow \mathbf{z}$ as $n \rightarrow \infty$, then $(\mathbf{Z}^{(n)}(t))$ converges weakly in $D[0, t]$ (the space of right-continuous, left-hand limits functions on $[0, t]$) to a *Gaussian diffusion* $(\mathbf{Z}(t))$ with initial value $\mathbf{Z}(0) = \mathbf{z}$ and with mean and covariance given by $\mu_s := \mathbb{E}(\mathbf{Z}(s)) = e^{sQ^\top} \mathbf{z}$ and

$$V_s := \text{Cov}(\mathbf{Z}(s)) = e^{sQ^\top} \left(\int_0^s e^{-uQ^\top} G(\mathbf{p}(u)) e^{-uQ} du \right) e^{sQ},$$

A Central Limit Theorem

Theorem 2 (continued).

... where the matrix $G(\boldsymbol{x})$ has entries

$$G_{kk}(\boldsymbol{x}) = x_k q_k + \sum_{i \neq k} x_i q_{ik} \text{ and } G_{kl}(\boldsymbol{x}) = -(x_l q_{lk} + x_k q_{kl}).$$

A Central Limit Theorem

Theorem 2 (continued).

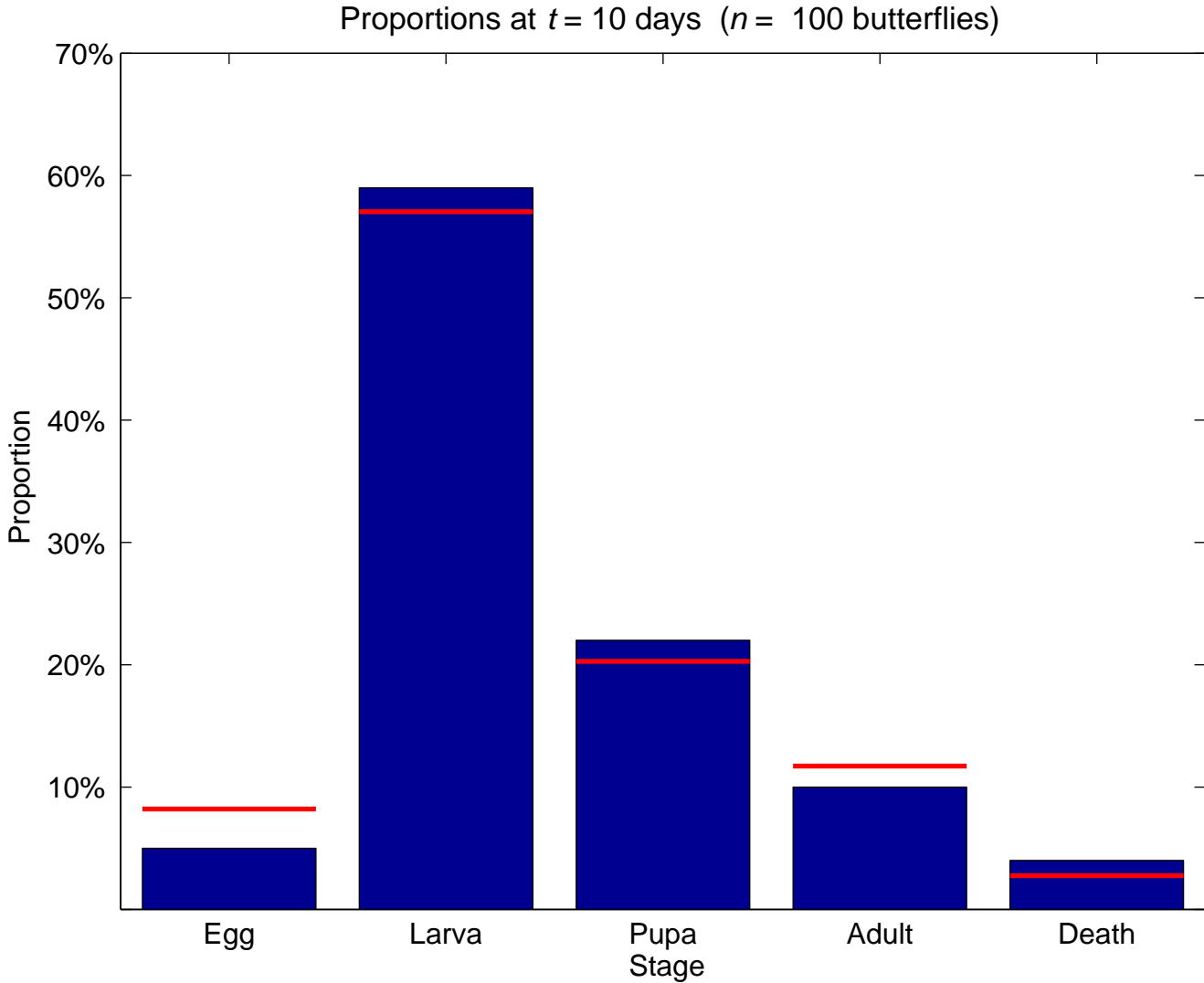
... where the matrix $G(\boldsymbol{x})$ has entries

$$G_{kk}(\boldsymbol{x}) = x_k q_k + \sum_{i \neq k} x_i q_{ik} \text{ and } G_{kl}(\boldsymbol{x}) = -(x_l q_{lk} + x_k q_{kl}).$$

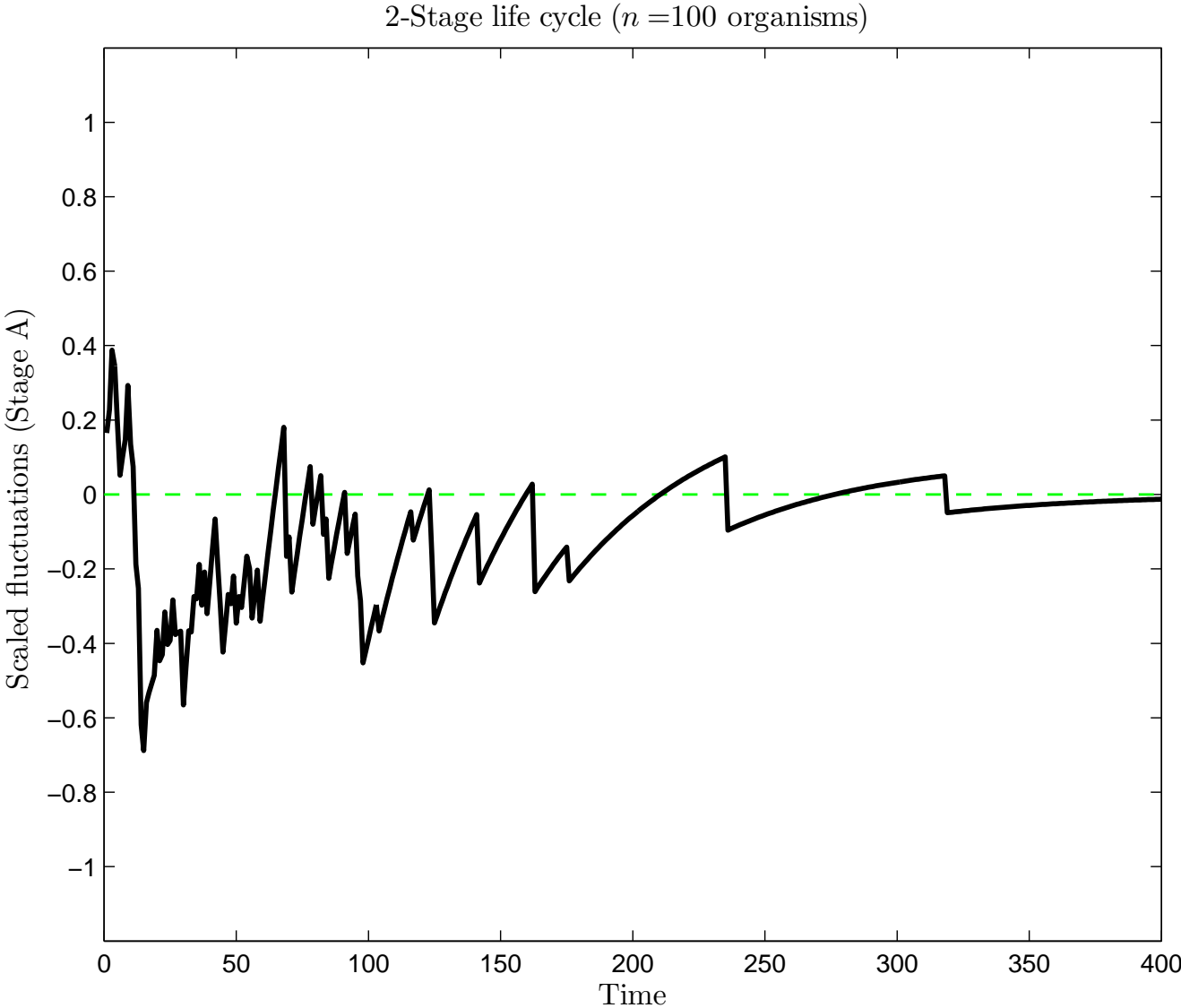
Theorem 2 has many implications. One immediate one is that the population proportions $\boldsymbol{X}^{(n)}(t)$ have an approximate multivariate Gaussian (normal) distribution with known mean vector and covariance matrix.

This helps explain the observed fluctuations (now seen to be of order $1/\sqrt{n}$) of $\boldsymbol{X}^{(n)}(t)$ about $\boldsymbol{p}(t)$.

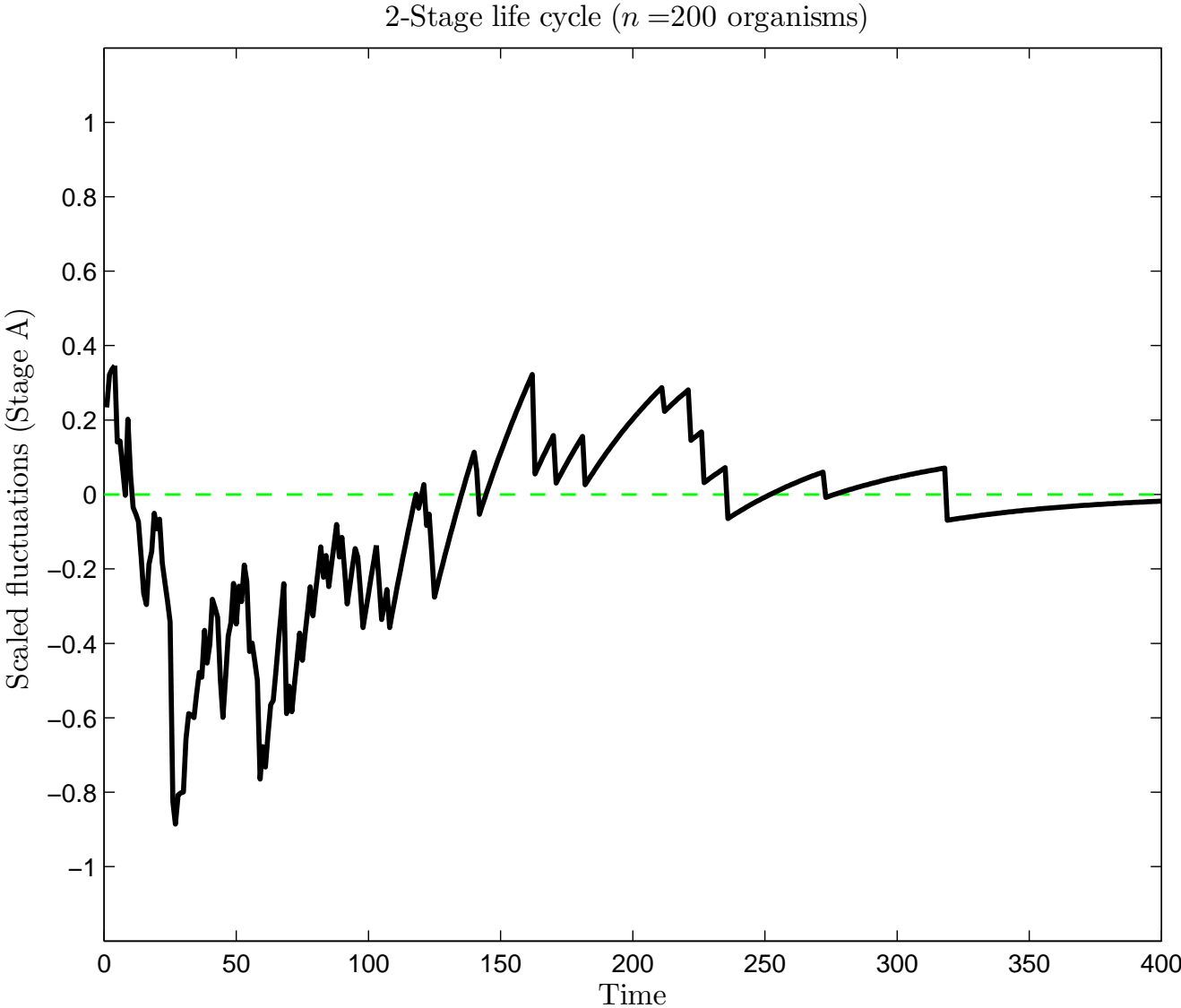
A Central Limit Theorem



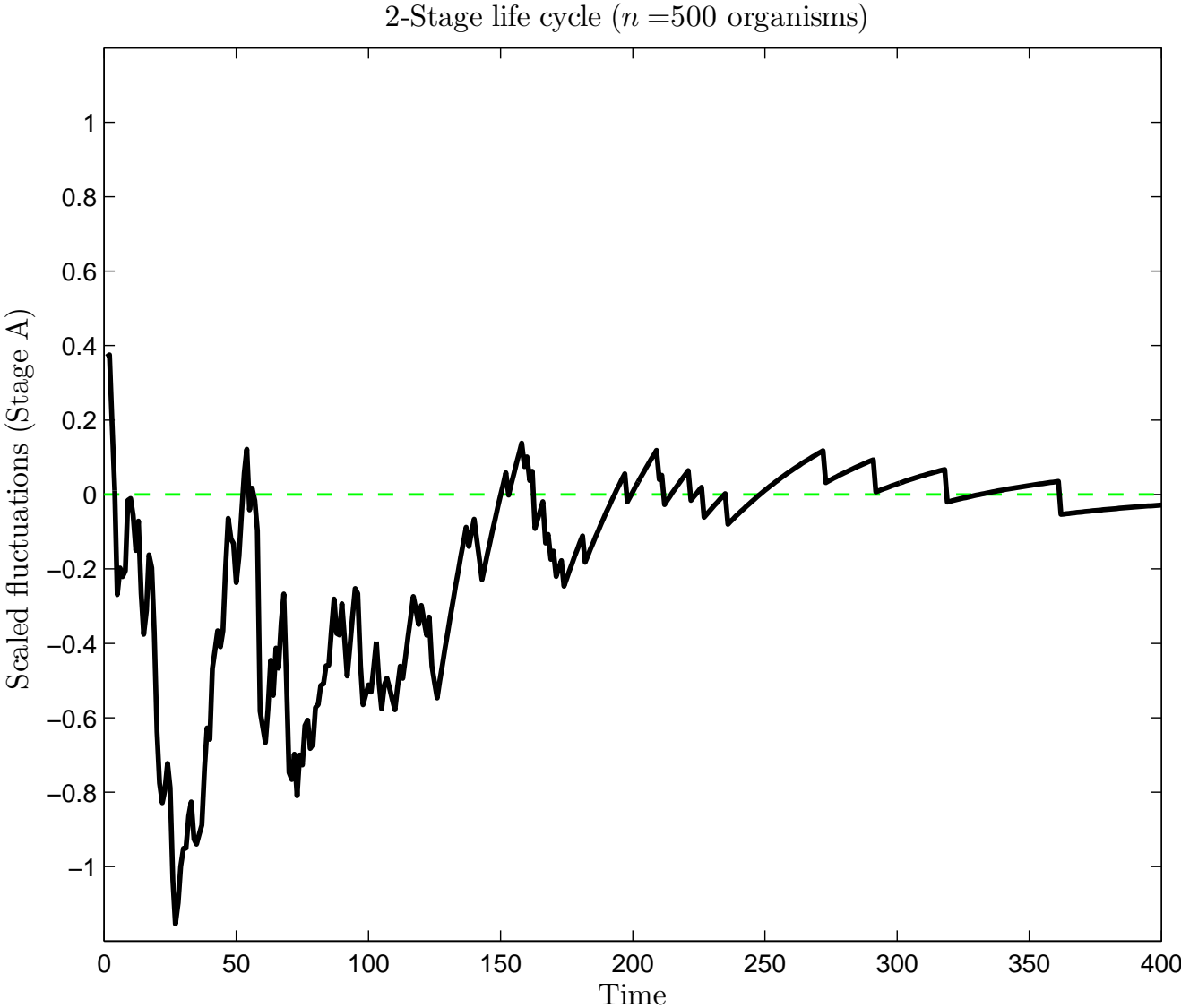
Convergence of scaled fluctuations



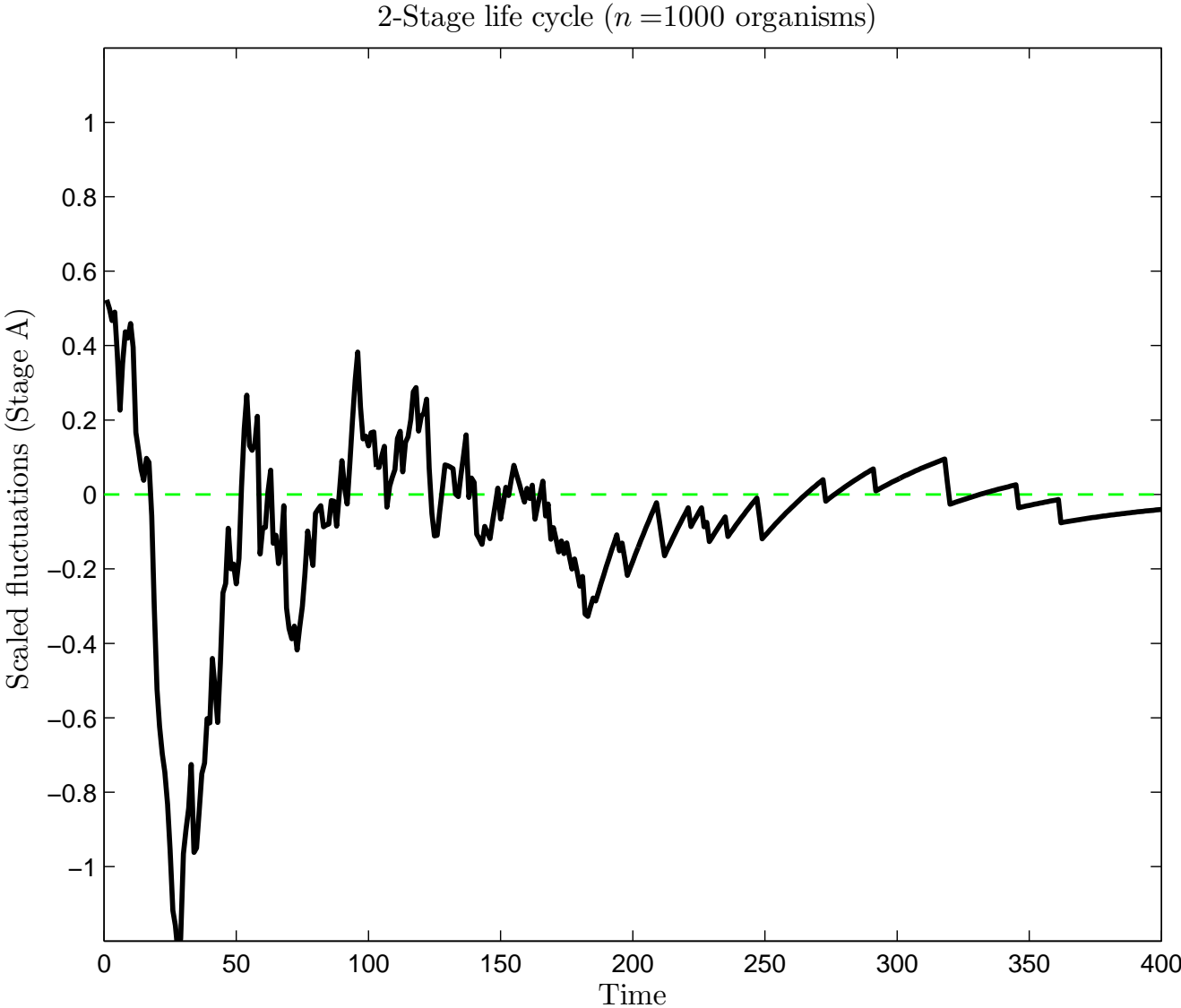
Convergence of scaled fluctuations



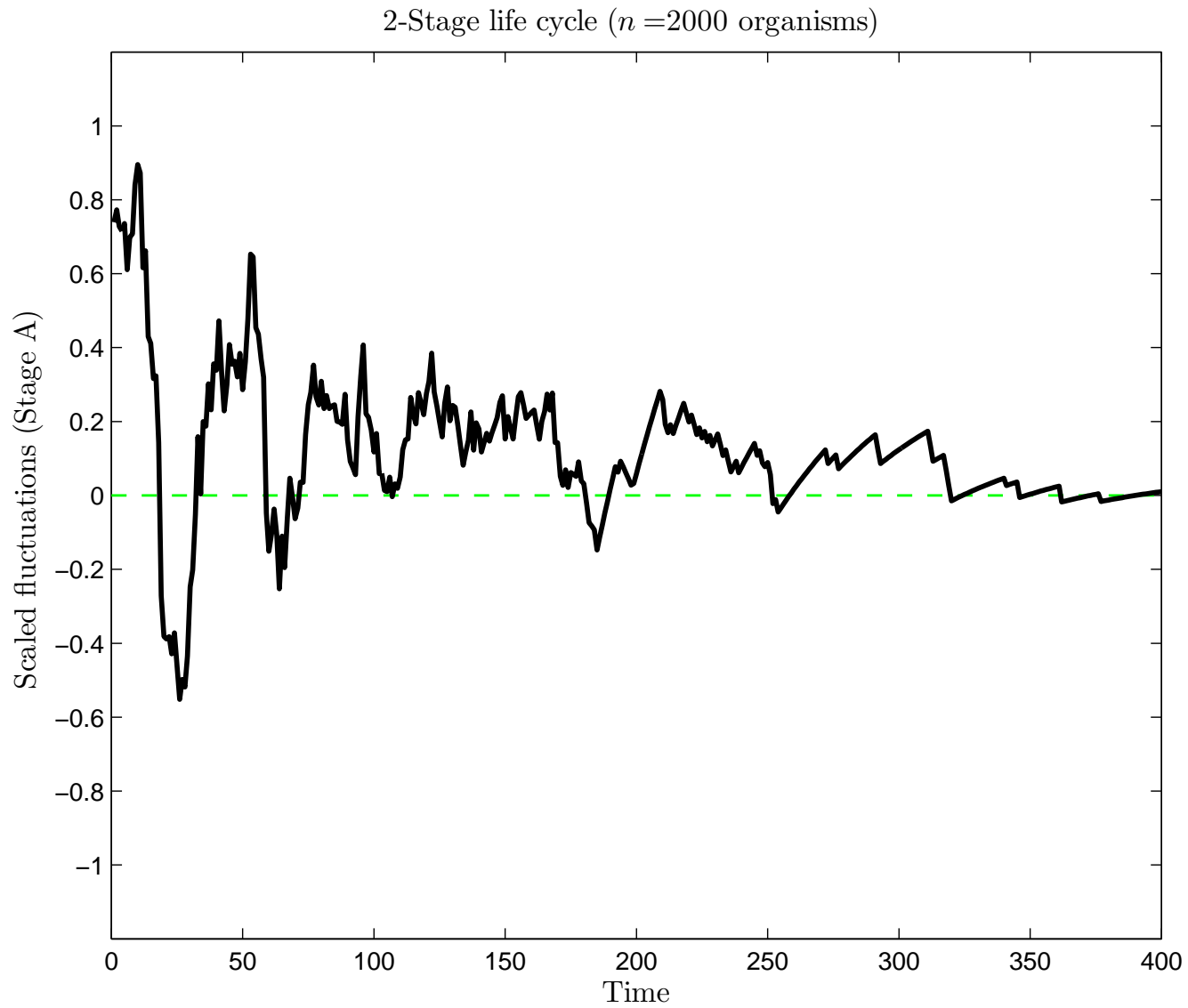
Convergence of scaled fluctuations



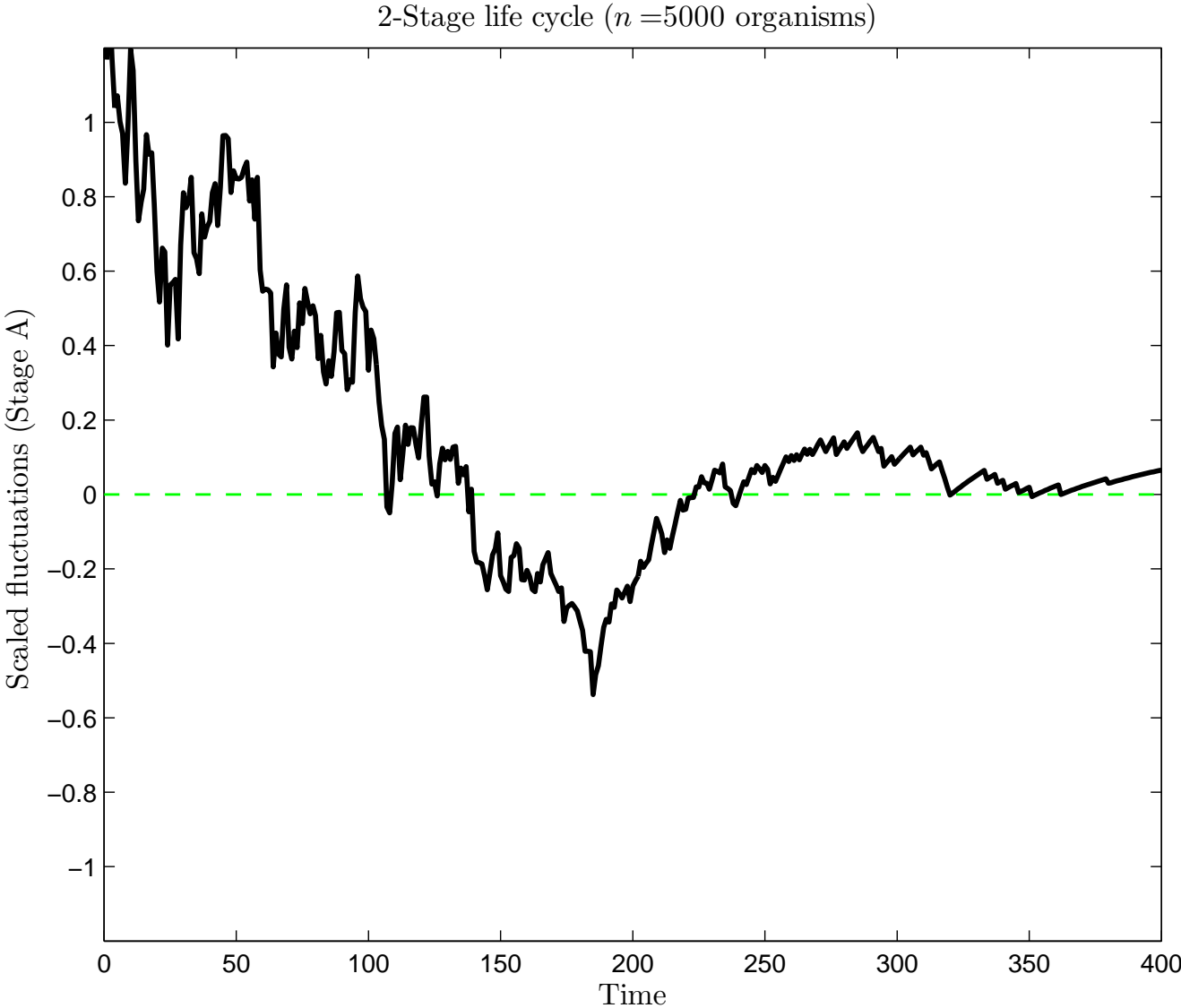
Convergence of scaled fluctuations



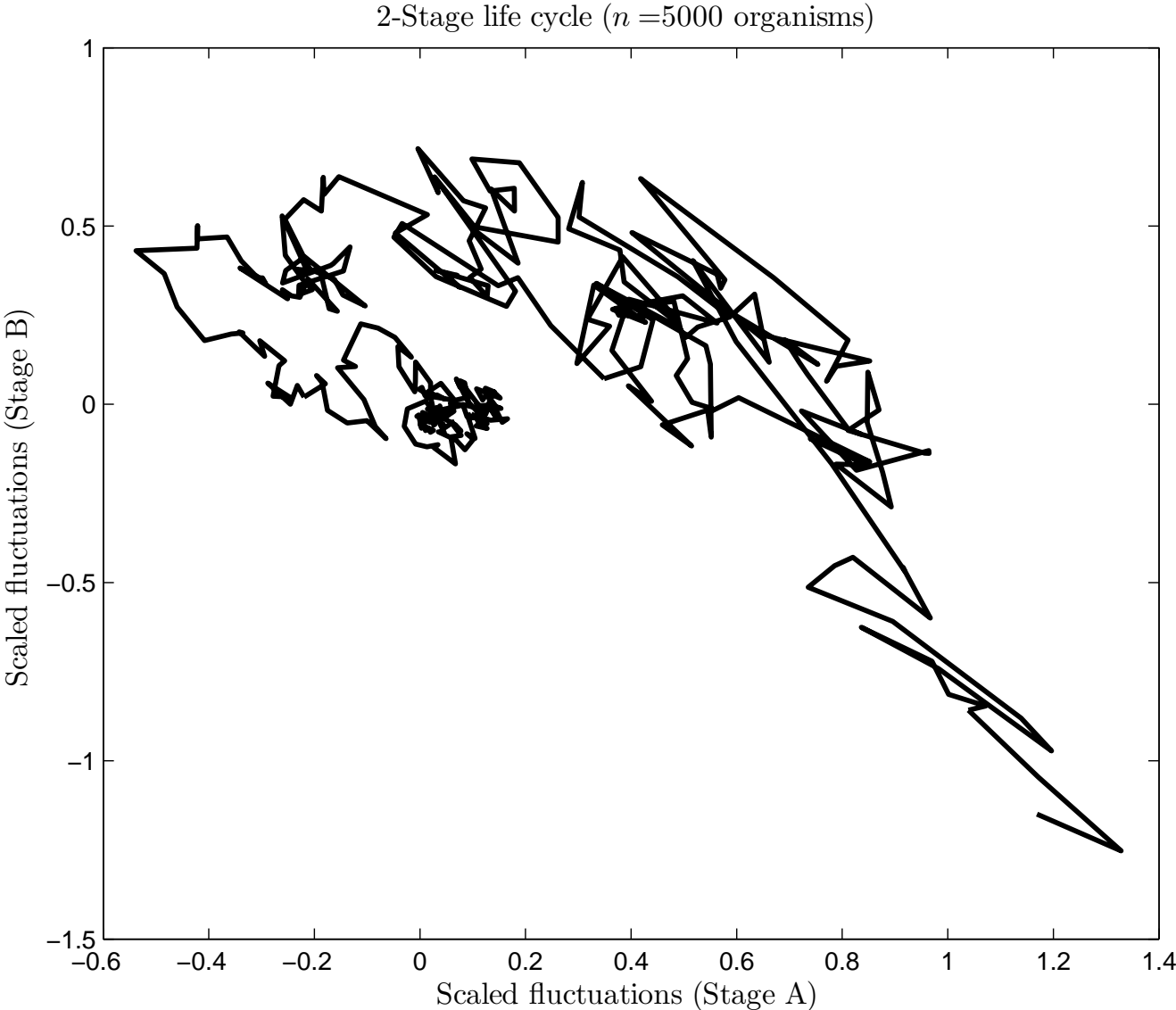
Convergence of scaled fluctuations



Convergence of scaled fluctuations



Convergence of scaled fluctuations



Further details

Pollett, P.K. (2008) Ensemble behaviour in population processes with applications to ecological systems.
Environmental and Ecological Statistics (to appear).

- Open ensembles

Further details

Pollett, P.K. (2008) Ensemble behaviour in population processes with applications to ecological systems. *Environmental and Ecological Statistics* (to appear).

- Open ensembles
- Stationary behaviour

Further details

Pollett, P.K. (2008) Ensemble behaviour in population processes with applications to ecological systems. *Environmental and Ecological Statistics* (to appear).

- Open ensembles
- Stationary behaviour
- Quasi-stationary behaviour

Further details

Pollett, P.K. (2008) Ensemble behaviour in population processes with applications to ecological systems. *Environmental and Ecological Statistics* (to appear).

- Open ensembles
- Stationary behaviour
- Quasi-stationary behaviour
 - Quasi-stationary distributions (QSDs) for *reducible* Markov chains
 - QSDs for ensemble processes

Bonus theorem

In our general setup (with C being the set of transient states and α being the *decay parameter*) ...

Theorem 3. Let $\pi = (\pi_j, j \in C)$ be the QSD of the individual process. If the initial numbers $N_j(0)$, $j \in C$, are chosen independently with $N_j(0)$ having a Poisson distribution with mean π_j , then, for all $t > 0$, $N_j(t)$, $j \in C$, are independent with $N_j(t)$ having a Poisson distribution with mean $\pi_j e^{-\alpha t}$.

For aficionados. This result holds in much greater generality; C need not be finite, Q could be explosive, $\pi = (\pi_j, j \in C)$ could be any α -subinvariant measure and, more remarkably still, π need not be finite (we could have $\sum_{j \in C} \pi_j = \infty$).