

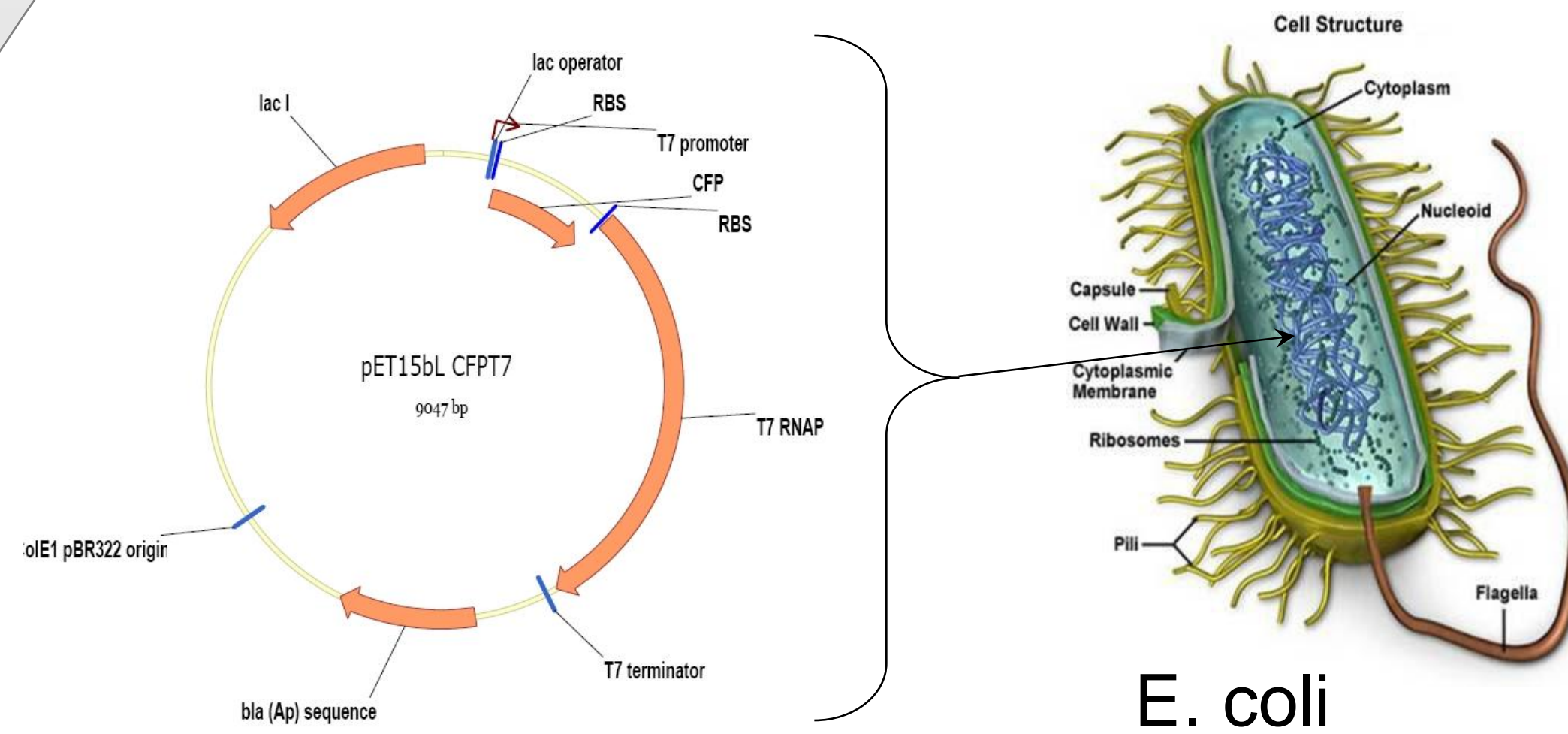
# Nonlinear Dynamic Models for Single-Cell Time-Lapse Microscopy

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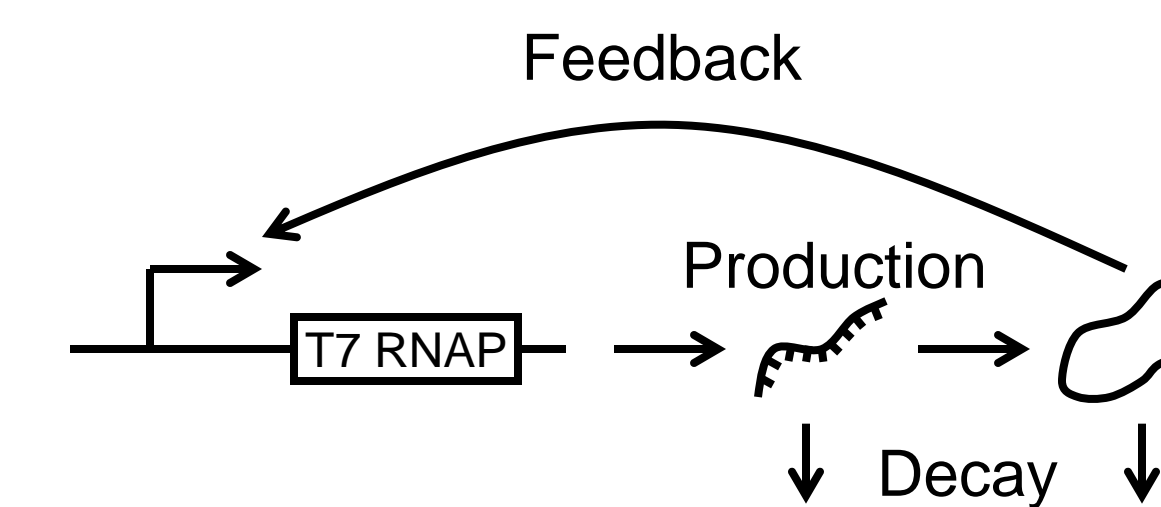
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## Case Study: T7 RNA polymerase bistability

Hypothesis: T7 RNAP level is driven by effective degradation rate.

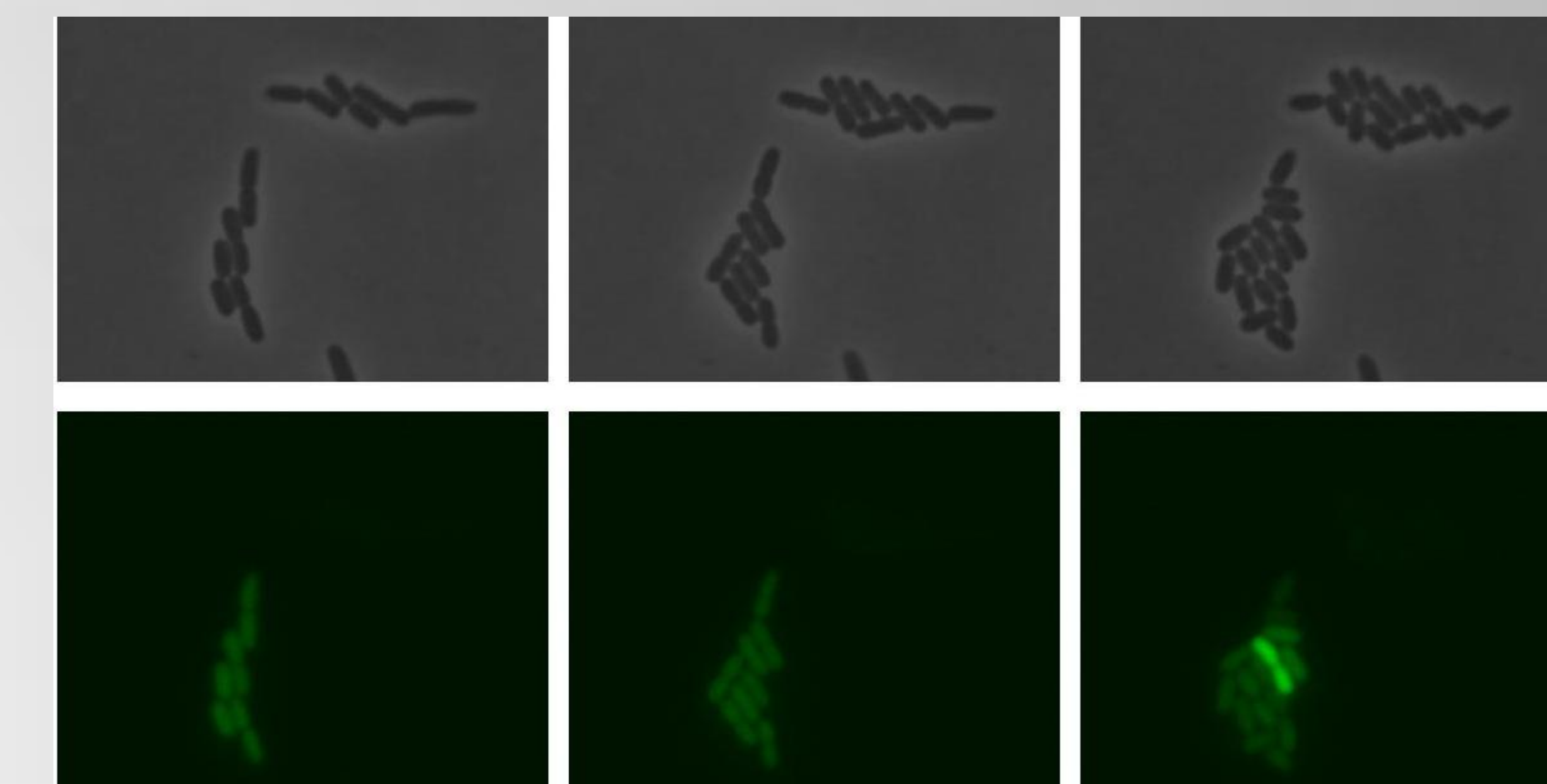


### Circuit Schematic



E. coli

## Time-Lapse Fluorescent Microscopy



Phase Image (top row):

- Used for imaging as described below

Fluorescent Image (bottom row):

- Provides a measure of the level of the target protein in the system.

Details:

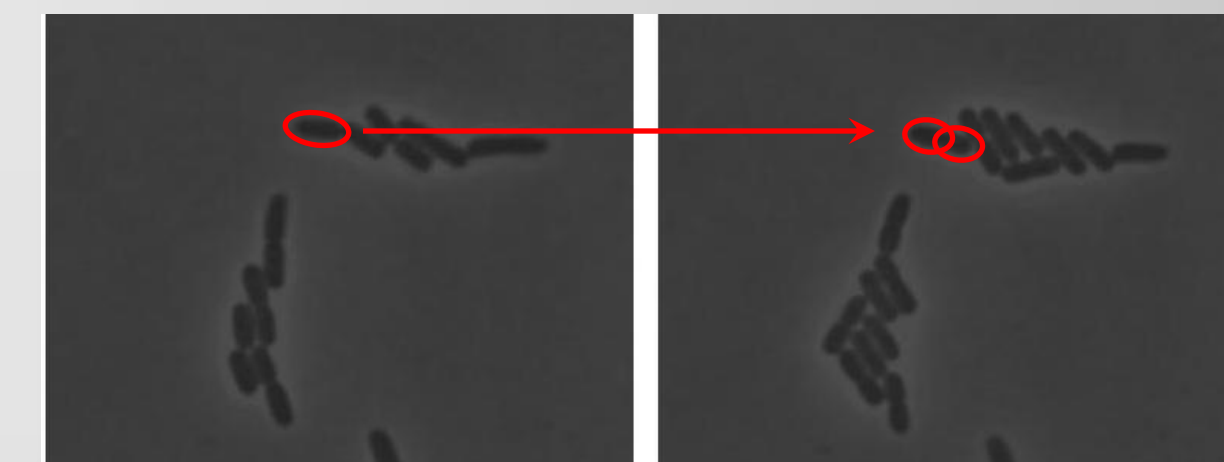
- Pictures taken every 10 minutes to avoid photobleaching
- Recorded for ~7 hrs
- Multiple proteins simultaneously

## Imaging by CellTracer

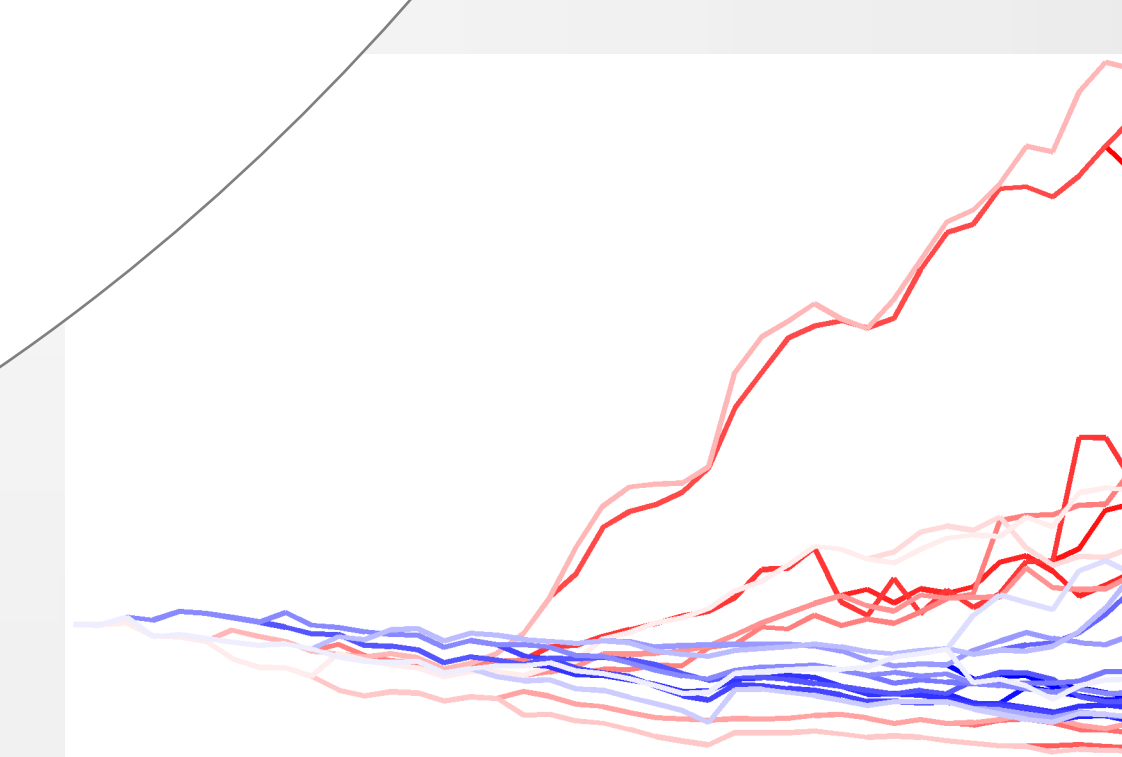
Segmentation



Tracking



## Lineage Reconstruction



Fluorescence

Color indicates descension from a common ancestor.

Time

## Nonlinear Dynamic Models

Observations (data)

Observation error

$$y_{c,t} = f(x_{c,t}) + \nu_{c,t}$$

System noise

$$x_{c,t} = g_c(x_{c,t-1}) + \omega_{c,t}$$

Unobserved true state

$f(\cdot)$  Observation function

$g_c(\cdot)$  State evolution function

Unknown parameters in:

- observation function,
- state evolution function,
- observation error, and
- system noise.

$\theta$

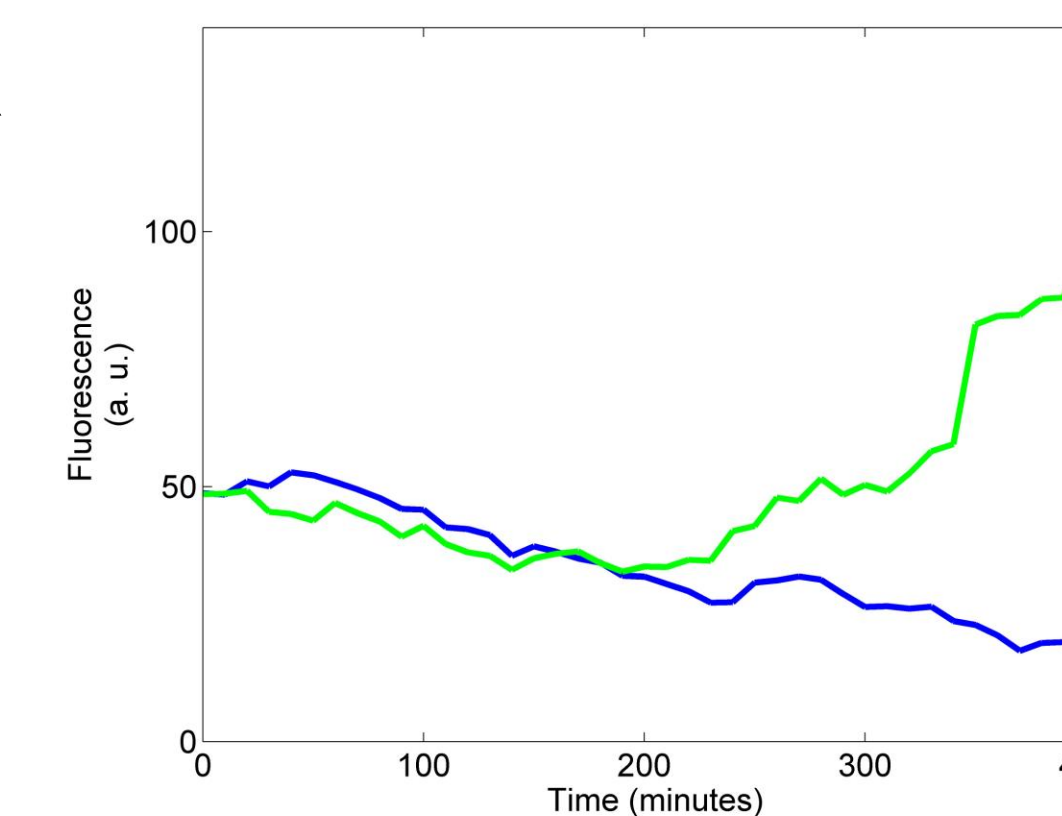
**Goal:** Inference about unknown parameters based on data.

## Positive-Feedback Model

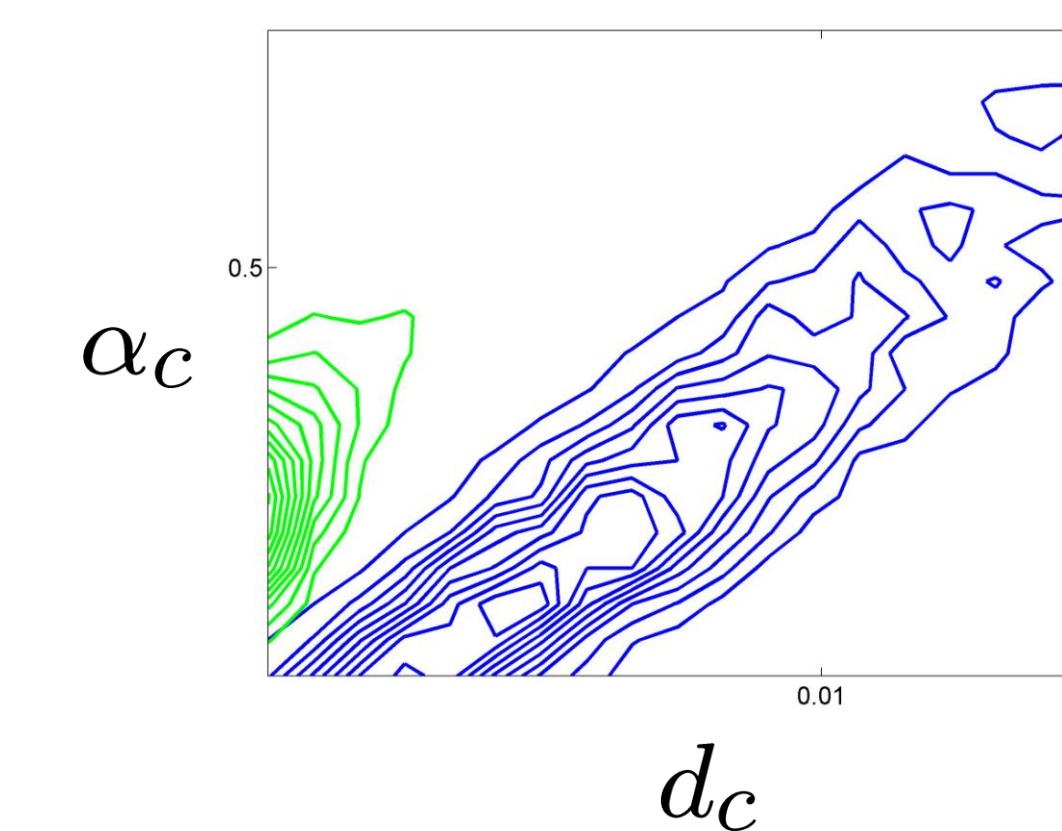
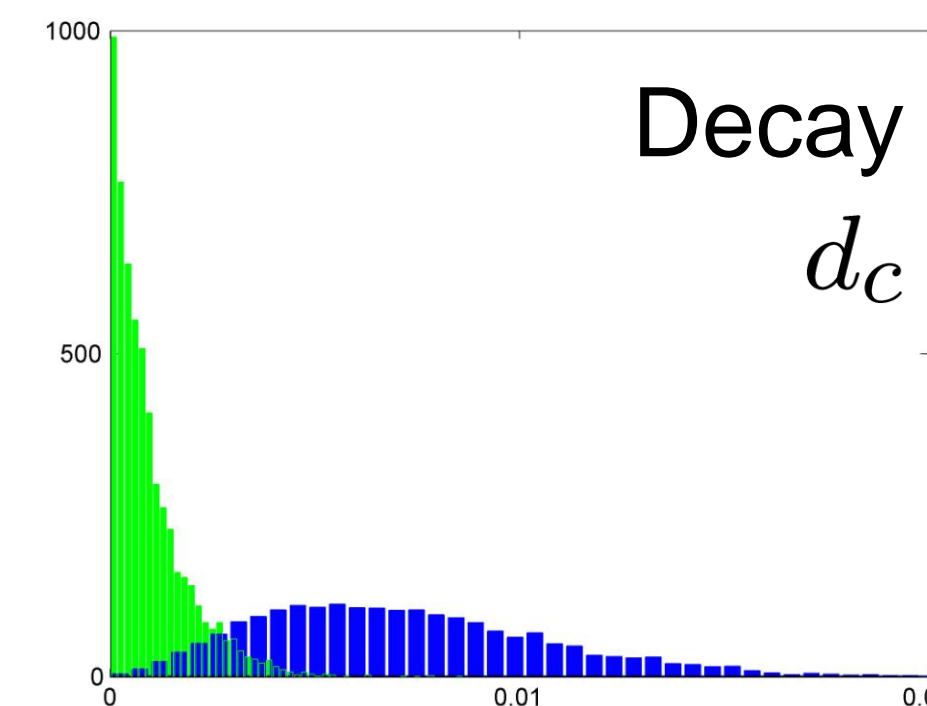
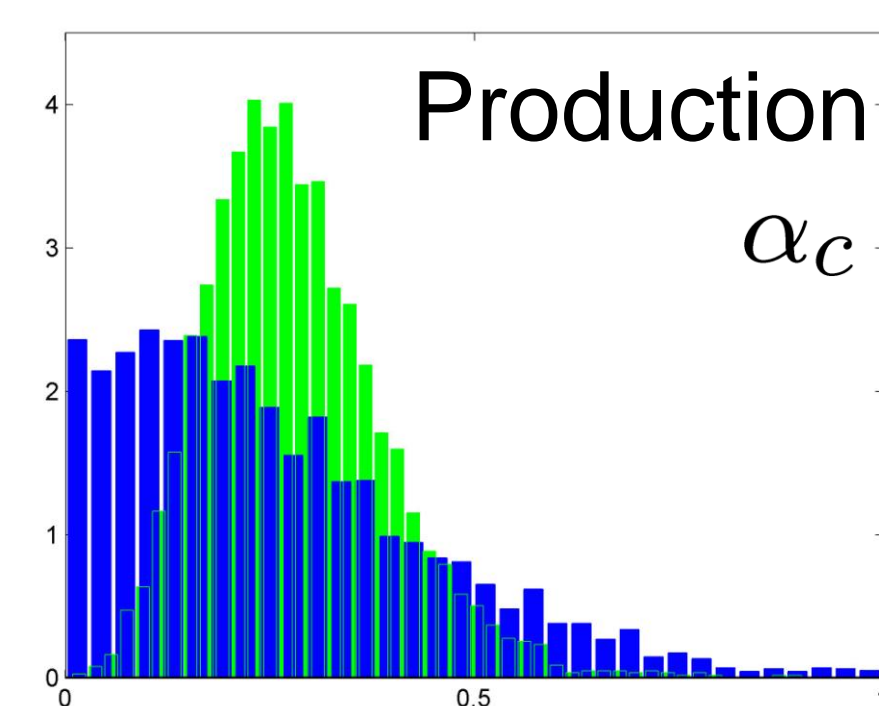
$$f(x) = x$$

$$g_c(x) = x + \frac{k_c + \alpha_c x}{\beta_c + x} - d_c x$$

## Data



## Results



## Conclusions:

- Time-lapse fluorescent microscopy allows for studying in vitro cellular processes.
- Dynamic models with Bayesian methods are powerful tools for understanding these processes.
- Case study: T7 RNAP level appears driven by decay rate, although the combination of production and decay is important.

## Bayesian Inference

$$p(\theta, x_{1:C,1:T} | y_{1:C,1:T})$$

$$\theta = (\theta_1, \theta_2, \dots, \theta_p)'$$

Markov chain Monte Carlo

AM4

$$x_{1:C,1:T} \sim p(\cdot | \theta, y_{1:C,1:T})$$

$$\theta_1 \sim p(\cdot | \theta_{-1}, y_{1:C,1:T}, x_{1:C,1:T})$$

$$\theta_2 \sim p(\cdot | \theta_{-2}, y_{1:C,1:T}, x_{1:C,1:T})$$

⋮

$$\theta_p \sim p(\cdot | \theta_{-p}, y_{1:C,1:T}, x_{1:C,1:T})$$