

Stochastic Analysis of Retroactivity in Transcriptional Networks through Singular Perturbation

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Introduction

Stochastic
modeling

Stationary analysis

Singular
perturbation
analysis

Analysis of
Transient Behavior

Conclusion

Network of elements



Computer motherboard.

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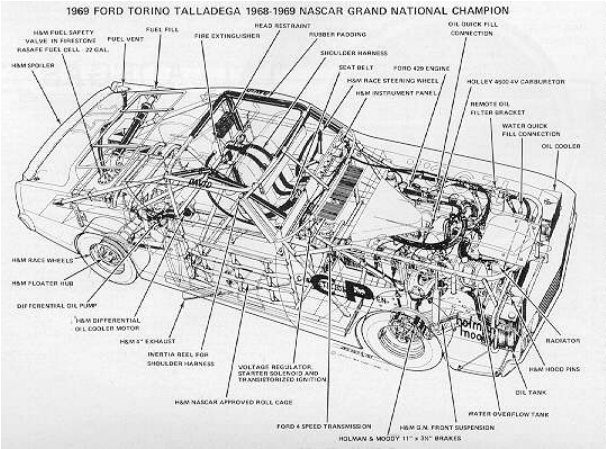
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An old car.

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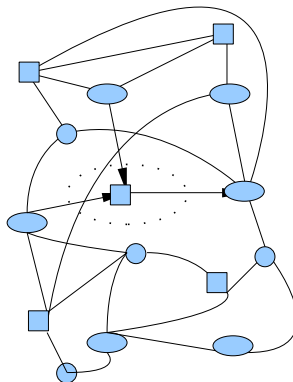
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In isolation vs in a network

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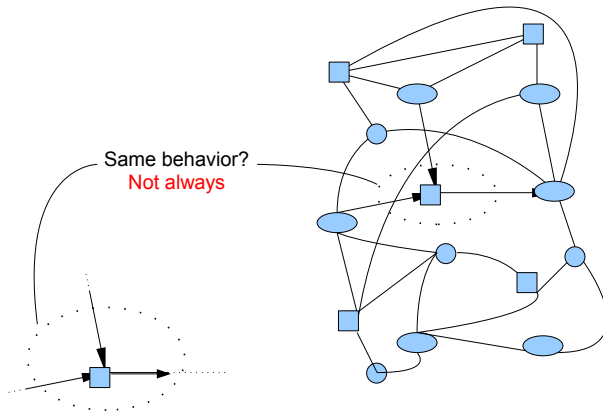
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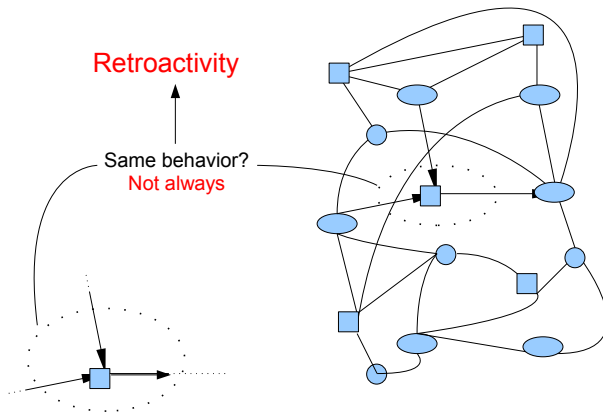
Component behaves differently when isolated

In isolation vs in a network



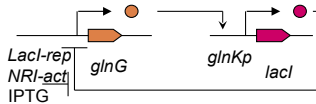
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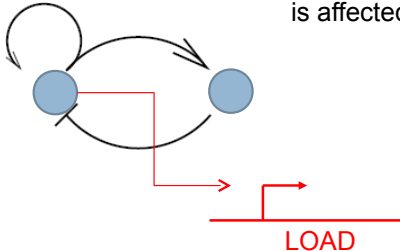


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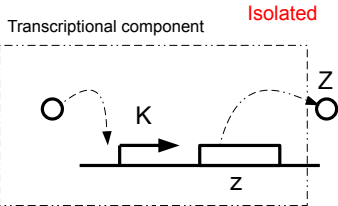
In isolation vs in a network



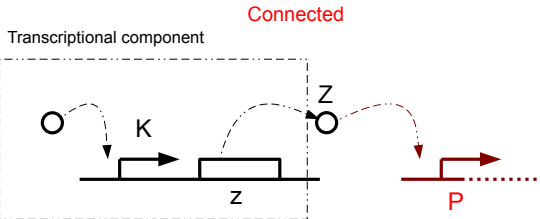
The oscillating behavior is affected by load



In isolation vs in a network



The dynamic of the upstream system slows down according to ODE model.



Stochastic modeling

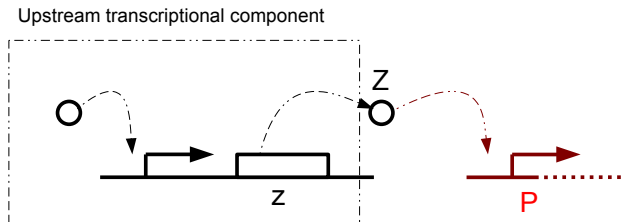
- Biological networks exhibit stochastic behavior and fluctuations → inherently stochastic systems.
- Stochastic models are valid even for very low molecule numbers.

→ to have a complete and general characterization of retroactivity, we need to perform stochastic analysis.

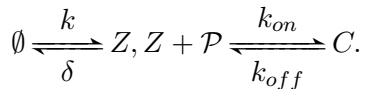
Outline

- Introducing stochastic model of interconnected transcriptional component: Master equation
- Stationary analysis
- Singular perturbation analysis
- Analysis of Transient Behavior

Transcriptional System

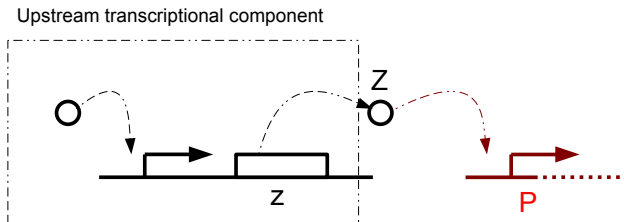


Interconnected transcriptional components.

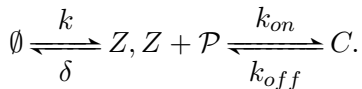


Total amount of DNA is conserved, i.e., $\mathcal{P} + C = p_T$

Transcriptional System

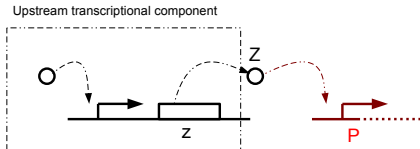


Interconnected transcriptional components.



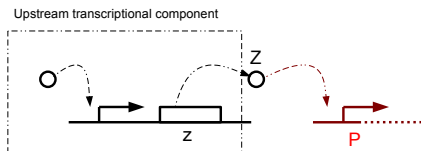
Total amount of DNA is conserved, i.e., $\mathcal{P} + C = p_T$

Deterministic retroactivity



- Analyzing the effect of downstream system on upstream: retroactivity.
- A deterministic approach is performed which analyzes the steady state as well as transient behavior of the concentration of Z [Del Vecchio et. al.]

Stochastic retroactivity

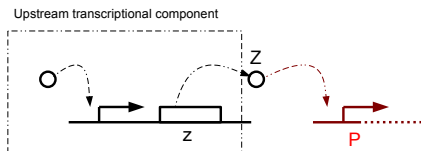


However

- The deterministic approach requires the number of molecules to be large.
- The deterministic approach does not provide an insight on how the load affects the intrinsic noise that is present in the system.

→ Stochastic analysis.

Stochastic retroactivity

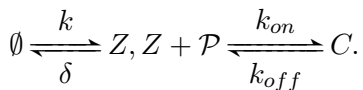


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→ Stochastic analysis.

Stochastic modeling



C , Z , and \mathcal{P} : stochastic processes

What we are looking for:

Starting in state $m_0 = (c_0, z_0, p_0)$ at time zero,

$$\begin{aligned} P_{C,Z,\mathcal{P}}(c, z, p; t, m_0) \\ = P(M(t) = m = (c, z, p) \mid M(0) = m_0) \end{aligned}$$

Master equation

A linear differential equation characterizes the evolution of $P_{C,Z,P}(c, z, p; t, m_0)$ over time:

$$\frac{d}{dt} P_{C,Z,P}(c, z, p; t, m_0) = A(P_{C,Z,P}(\cdot, \cdot, \cdot; t, m_0))$$

where A is a linear operator.

Probability distribution of a single molecule X with finite number of molecules is

$$\frac{d}{dt} P_X(x; t) = A(P_X(\cdot; t)) \quad (1)$$

or

$$\frac{d}{dt} P_X(\cdot; t) = A P_X(\cdot; t)$$

where $P_X(\cdot; t) = [P_X(0; t), P_X(1; t), \dots, P_X(x_{max}; t)]$ and A is matrix.

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Master equation

$$\begin{aligned} & \frac{d}{dt} P_{C,Z,\mathcal{P}}(c, z, p; t, m_0) \\ &= \Omega [k(t) P_{C,Z,\mathcal{P}}(c, z - 1, p; t, m_0) \\ &+ \delta \frac{(z + 1)}{\Omega} P_{C,Z,\mathcal{P}}(c, z + 1, p; t, m_0) \\ &+ k_{on} \frac{(z + 1)}{\Omega} \frac{(p + 1)}{\Omega} P_{C,Z,\mathcal{P}}(c - 1, z + 1, p + 1; t, m_0) \\ &+ k_{off} \frac{(c + 1)}{\Omega} P_{C,Z,\mathcal{P}}(c + 1, z - 1, p - 1; t, m_0) \\ &- (k + \delta \frac{z}{\Omega} + k_{on} \frac{zp}{\Omega^2} + k_{off} \frac{c}{\Omega}) P_{C,Z,\mathcal{P}}(c, z, p; t, m_0)]. \end{aligned}$$

Keep in mind:

$$C(t) + \mathcal{P}(t) = p_T = C(0) + \mathcal{P}(0) = c_0 + p_0$$

Master equation

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Keep in mind:

$$C(t) + \mathcal{P}(t) = p_T = C(0) + \mathcal{P}(0) = c_0 + p_0$$

Master equation: Modified

$$\begin{aligned} & \dot{P}_{C,Z}(c, z; t, m_0) \\ &= \Omega [k P_{C,Z}(c, z-1; t, m_0) + \delta \frac{(z+1)}{\Omega} P_{C,Z}(c, z+1; t, m_0) \\ &+ k_{on} \frac{(z+1)}{\Omega} \frac{(p_T - c + 1)}{\Omega} P_{C,Z}(c-1, z+1; t, m_0) \\ &+ k_{off} \frac{(c+1)}{\Omega} P_{C,Z}(c+1, z-1; t, m_0) \\ &- \left(k + \delta \frac{z}{\Omega} + k_{on} \frac{z(p_T - c)}{\Omega^2} + k_{off} \frac{c}{\Omega} \right) P_{C,Z}(c, z; t, m_0)], \end{aligned}$$

where

$$P_{C,Z}(c, z; t, m_0) = P(C(t) = c, Z(t) = z \mid C(0) = c_0, Z(0) = z_0).$$

Stationary analysis

What would happen if we wait for a long time?

$$P((C(t), Z(t)) = (c, z)) \rightarrow \pi_{C,Z}(c, z) \text{ as } t \rightarrow \infty$$

$\pi_{C,Z}(c, z)$ is the unique *stationary distribution* of (C, Z) , which is the product of *stationary distribution* of the random process Z , $\pi_Z(z)$, and *stationary distribution* of the random process C , $\pi_C(c)$, i.e.,

$$\pi_{C,Z}(c, z) = \pi_C(c)\pi_Z(z).$$

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- C has binomial *stationary distribution* as follows

$$\pi_C(c) = \frac{p_T!}{c!(p_T - c)!(k_d k_z)^c} \left(1 + \frac{1}{k_d k_z}\right)^{-p_T}, \quad (2)$$

$$k_d := \frac{k_{off}}{k_{on}}, \quad k_z := \frac{\delta}{k},$$

- Z has Poisson *stationary distribution* given by

$$\pi_Z(z) = \frac{\Omega_z^z}{z!} e^{-\Omega_z}, \quad \Omega_z := \frac{\Omega}{k_z}. \quad (3)$$

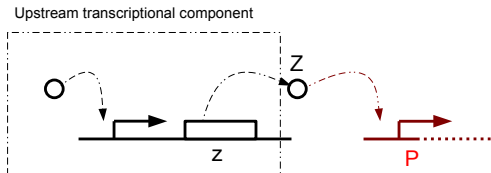
Implication of the stationary analysis

At steady state, the downstream and upstream systems are statistically independent.

Namely, $Z(\infty)$ and $C(\infty)$ are independent random variables.

$$E(Z) = \Omega_z = \frac{k}{\delta} \Omega$$

$$Var(Z) = \Omega_z$$

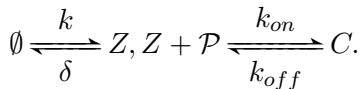
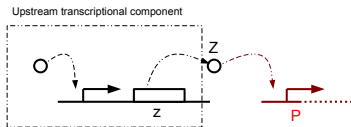


Singular perturbation analysis

We want to characterize the transient behavior of mean and variance of Z .

Define $Y := C + Z$.

$P_{C,Y}(c, y; t, m_0) := P(C(t) = c, Y(t) = y \mid C(0) = c_0, Y(0) = y_0)$



Singular perturbation analysis

Defining $\epsilon := \frac{\delta}{k_{off}}$, $k_d := \frac{k_{off}}{k_{on}}$, $\bar{k}_{on} := \frac{\delta}{k_d}$, and $\bar{k}_{off} := \delta$, the Master equation can be written in the following form:

$$\begin{aligned} \dot{P}_{C,Y}(c, y; t, m_0) = & \Omega[kP_{C,Y}(c, y - 1; t, m_0) \\ & + \delta \frac{(y - c + 1)}{\Omega} P_{C,Y}(c, y + 1; t, m_0) \\ & + \frac{1}{\epsilon} \bar{k}_{on} \frac{(y - c + 1)}{\Omega} \frac{(p_T - c + 1)}{\Omega} P_{C,Y}(c - 1, y; t, m_0) \\ & + \frac{1}{\epsilon} \bar{k}_{off} \frac{(c + 1)}{\Omega} P_{C,Y}(c + 1, y; t, m_0) \\ & - \left(k + \delta \frac{y - c}{\Omega} + \frac{1}{\epsilon} \bar{k}_{on} \frac{(y - c)(p_T - c)}{\Omega^2} \right. \\ & \left. + \frac{1}{\epsilon} \bar{k}_{off} \frac{c}{\Omega} \right) P_{C,Y}(c, y; t, m_0)]. \end{aligned} \quad (4)$$

Singular perturbation analysis

Equivalently:

$$\frac{d}{dt}P_{C,Y}(c, y; t, m_0) = (A + \frac{1}{\epsilon}B)(P_{C,Y}(\cdot, \cdot; t, m_0)) \quad (5)$$

Singular perturbation analysis

Slowly varying Prob. Dist $P_Y(y; t)$

$$\sum_y \left(\frac{d}{dt} P_{C,Y}(c, y; t, m_0) = (A)(P_{C,Y}(\cdot, \cdot; t, m_0)) \right).$$

Define $P_Y^s(y; t)$ as the solution of the following forward equation:

$$\begin{aligned} \dot{P}_Y^s(y; t) = & \Omega[kP_Y^s(y-1; t) \\ & + \delta \frac{(y+1 - E^s(C|Y=y+1))}{\Omega} P_Y^s(y+1; t) \\ & - (k + \delta \frac{y - E^s(C|Y=y)}{\Omega}) P_Y^s(y; t)], \end{aligned}$$

with initial distribution $P_Y^s(y; 0) = P_Y(y; 0)$.

$E^s(C|Y=y)$: conditional expectation at stationary distribution.

Singular perturbation analysis

Slowly varying Prob. Dist $P_Y(y; t)$

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$E^s(C|Y=y)$: conditional expectation at stationary distribution.

Singular perturbation analysis

Fast varying Prob. Dist

$$\sum_y \left(\frac{d}{dt} P_{C,Y}(c, y; t, m_0) = \left(\frac{1}{\epsilon} B \right) (P_{C,Y}(\cdot, \cdot; t, m_0)) \right).$$

Let $P_{C,Y}^f(c, y; \tau)$ denote the solution to the following forward equation

$$\begin{aligned} & \frac{d}{dt} P_{C,Y}^f(c, y; t) \\ &= \Omega \left[\bar{k}_{on} \frac{(y-c+1)}{\Omega} \frac{(p_T-c+1)}{\Omega} P_{C,Y}^f(c-1, y; t) \right. \\ &+ \bar{k}_{off} \frac{(c+1)}{\Omega} P_{C,Y}^f(c+1, y; t) \\ &\left. - \left(\bar{k}_{on} \frac{(y-c)(p_T-c)}{\Omega^2} + \bar{k}_{off} \frac{c}{\Omega} \right) P_{C,Y}^f(c, y; t) \right]. \end{aligned}$$

with initial distribution

$$P_{C,Y}^f(c, y; 0) = P_{C,Y}(c, y; 0) - P_Y^s(y; 0) \pi_{C|Y}(c|y).$$

Singular perturbation analysis

Fast varying Prob. Dist

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Singular perturbation analysis

$$P_{C,Y}^e(c, y; t, \epsilon) := P_Y^s(y; t)\pi_{C|Y}(c|y) + P_{C,Y}^f(c, y; \frac{t}{\epsilon})$$

approximates

$$P_{C,Y}(c, y; t)$$

of order of $O(\epsilon)$ over $[0, T]$ for any T .

Moreover, there exists $\kappa > 0$ and $\alpha > 0$ such that

$$\|P_{C,Y}^f(\cdot, \cdot; \tau)\|_1 < \kappa e^{-\alpha\tau}.$$

Analyzing the reduced Master equation

Now we have reduced Master equation to analyze the transient behavior of system:

$$\begin{aligned}\dot{P}_Y^s(y; t) = & \Omega[kP_Y^s(y-1; t) \\ & + \delta \frac{(y+1 - E^s(C|Y=y+1))}{\Omega} P_Y^s(y+1; t) \\ & - (k + \delta \frac{y - E^s(C|Y=y)}{\Omega}) P_Y^s(y; t)],\end{aligned}$$

We need to characterize $E^s(C|Y=y)$

Analyzing the reduced Master equation

$E^s(C|Y = y)$ can be written as follows

$$\begin{aligned} E^s(C|Y = y) &= \sum_{c=0}^{\min y, p_T} c \pi_{C|Y}(c|y) \\ &= \frac{\sum_{c=0}^{\min(p_T, \Omega)} \frac{c}{c!(p_T-c)!(\Omega k_d)^c (y-c)!}}{\sum_{c=0}^{\min(p_T, \Omega)} \frac{1}{c!(p_T-c)!(\Omega k_d)^c (y-c)!}}. \end{aligned} \tag{6}$$

Hard to characterize in this form

Analyzing the reduced Master equation

$$\begin{aligned} E^s(C|Y = y) &= \frac{[p_T - E^s(C|Y = y - 1)]y}{p_T + k_d\Omega - E^s(C|Y = y - 1)} \\ &=: \Upsilon(E^s(C|Y = y - 1), y), \end{aligned}$$

with $E^s(C|Y = 0) = 0$.

Analyzing the reduced Master equation

\hat{f} that is the fixed point of the map Υ at y , i.e.,
 $\hat{f}(y) = \Upsilon(\hat{f}(y), y)$, is a good approximation of
 $E^s(C|Y = y)$. with some algebraic manipulation:

$$\hat{f}(y) = \frac{y + p_T + k_d\Omega - \sqrt{(y + p_T + k_d\Omega)^2 - 4yp_T}}{2}$$
$$\approx E^s(C|Y = y).$$

Analyzing the reduced Master equation

Assuming that k_d is sufficiently large compared to $\frac{p_T}{\Omega}$ and $\frac{y}{\Omega}$, which is often a reasonable assumption, we have

$$\begin{aligned}\hat{f}(y) &= \frac{2yp_T}{y + p_T + k_d\Omega + \sqrt{(y + p_T + k_d\Omega)^2 - 4yp_T}} \\ &\approx \frac{p_T}{p_T + k_d\Omega}y.\end{aligned}\quad (7)$$

Analyzing the reduced Master equation: $E(Y)$

Defining $\beta := \frac{k_d \Omega}{k_d \Omega + p_T}$,

$$E^s(C|Y = y) \approx (1 - \beta)y. \quad (8)$$

with

$$\begin{aligned} \dot{P}_Y^s(y; t) = & \Omega[kP_Y^s(y - 1; t) \\ & + \delta \frac{(y + 1 - E^s(C|Y = y + 1))}{\Omega} P_Y^s(y + 1; t) \\ & - (k + \delta \frac{y - E^s(C|Y = y)}{\Omega}) P_Y^s(y; t)], \end{aligned}$$

we have

$$\frac{d}{dt} E^s(Y; t) = -\delta \beta E^s(Y; t) + k\Omega. \quad (9)$$

with $\beta < 1$. For isolated system we have $\beta = 1$.

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with $\beta < 1$. For isolated system we have $\beta = 1$.

Analyzing the reduced Master equation: $Var(Y)$

$$\begin{aligned} \frac{d}{dt} E^s(Y^2; t) &= E^s(2Y(k\Omega - \delta\beta Y); t) + E^s(\delta\beta Y + k\Omega; t) \\ &\quad - 2\delta\beta E^s(Y^2; t) + (2k\Omega + \delta\beta) E^s(Y; t) + k\Omega. \end{aligned} \tag{10}$$

$E^s(Y^2; t)$ with time constant $\frac{1}{2\delta\beta}$, \rightarrow time constant of the variance.

Analyzing the reduced Master equation:

$$E(Z), \text{Var}(Z)$$

$$E^s(Z^2; t) \approx \beta^2 E^s(Y^2; t) + \beta(1 - \beta) E^s(Y; t). \quad (11)$$

and

$$E^s(Z; t) \approx \beta E^s(Y; t) \quad (12)$$

→ the dynamics of $E(Z)$ and $\text{Var}(Z)$ slows down when interconnected with downstream component.

Analyzing the reduced Master equation:

$$E(Z), \text{Var}(Z)$$

$$E^s(Z^2; t) \approx \beta^2 E^s(Y^2; t) + \beta(1 - \beta) E^s(Y; t). \quad (11)$$

and

$$E^s(Z; t) \approx \beta E^s(Y; t) \quad (12)$$

→ the dynamics of $E(Z)$ and $\text{Var}(Z)$ slows down when interconnected with downstream component.

Conclusion

we studied the stochastic effects of retroactivity in a transcriptional module connected to downstream systems:

- We developed singular perturbation analysis for the Master equation.
- We provided a reduced Master equation describing the slow processes and demonstrated that the solution of the original Master equation fast approaches a neighbor of the solution of the reduced Master equation.
- We mathematically analyzed how retroactivity impacts both transient and stationary behavior of the system
- We observed that the upstream system and the downstream one are statistically independent at the steady state.
- The interconnection slows down the dynamics of both the expectation and the variance of the output of the upstream transcriptional module.

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