

Controllability Metrics in Markov Decision Linear Models of Gene Networks

Dan Goreac¹

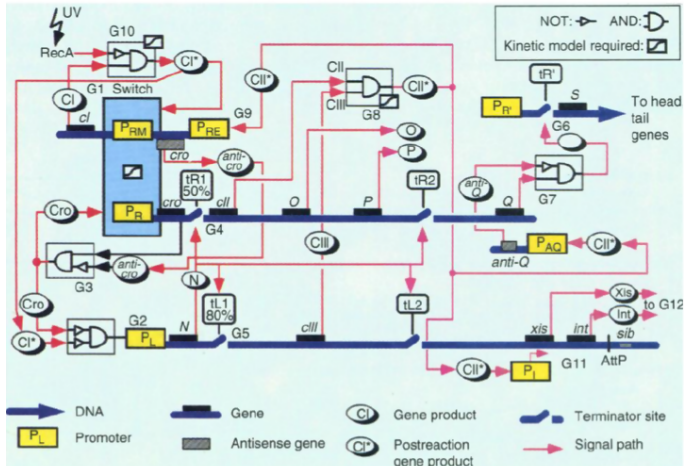
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¹UPEM. Based on papers joint with T. Diallo, M. Martinez (UPEM), E. -P. Rotenstein (UAIC, Iasi, Romania), C. A. Grosu (UAIC, Iasi, Romania)

Outline

- 1 The model
 - Biochemical Reactions
 - Mathematical Model
 - The Questions
- 2 Controllabilities
 - Metric By Observability
 - Riccati Formulation of the Metric
 - Main Theoretical Results
- 3 Minimal Intervention
 - Optimization Problems
 - Back to Lambda

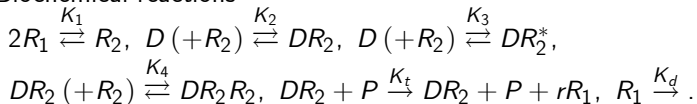
Lambda Phage



from McAdams and Shapiro, Science 1995

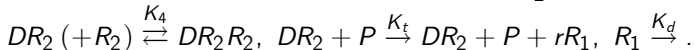
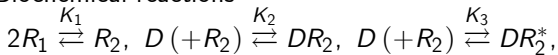
Reference Model

- Biochemical reactions



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- Biochemical reactions



- Groups of reaction

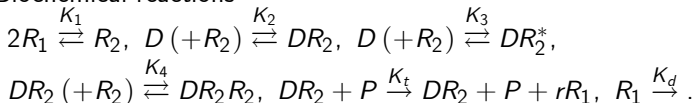
trend : DNA mechanism of the host E-Coli $(D, DR_2, DR_2^*, DR_2R_2)^T$

update : $2R_1 \xrightleftharpoons{K_1} R_2, R_1 \xrightarrow{K_d}$

rare : $DR_2 + P \xrightarrow{K_t} DR_2 + P + rR_1$

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- Some mathematical models $(d_1, d_2, d_3, d_4, x_1, x_2)$:
pure jump, 2-scale PDMP, Marked-point, discrete model
Reaction speeds can be "chosen".

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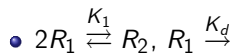
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- In general, since only one type of occupation, one gets basis vectors $e_1 (D), e_2 (DR_2) \dots e_p$
- Take $\Delta M_{n+1} = L_{n+1} -$ "average" (in fact $\mathbb{E}[L_{n+1}/\mathcal{F}_n]$)
To make it simple, assume L_{n+1} is completely independent of L_n and has 0-mean
 $\Delta M_{n+1} = L_{n+1}$

Update



Update

- $2R_1 \xrightleftharpoons{K_1} R_2, R_1 \xrightarrow{K_d}$
- continuous with choice of speed (u) :
$$x_1' = -k_1(u) x_1^2 - k_d(u) x_1 + k_{-1}(u) x_2$$
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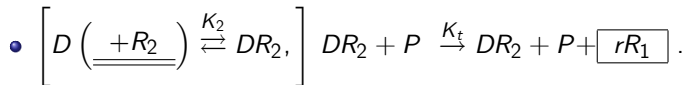
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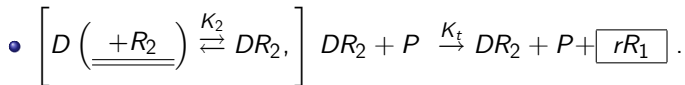
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- or, again $dX_s^{x,u} = [A(\gamma_s) X_s^{x,u} + B_s u_s] ds$
- discrete $X_{n+1}^{x,u} = A_n(\omega) X_n^{x,u} + B u_{n+1}$

Rare (and Synthesis)



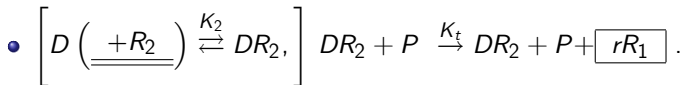
Rare (and Synthesis)



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$$\begin{pmatrix} x_{1,n+1} \\ x_{2,n+1} \end{pmatrix} = \begin{pmatrix} x_{1,n} \\ x_{2,n} \end{pmatrix} + \begin{pmatrix} 0 & r \\ 0 & 0 \end{pmatrix} \begin{pmatrix} x_{1,n} \\ x_{2,n} \end{pmatrix}$$

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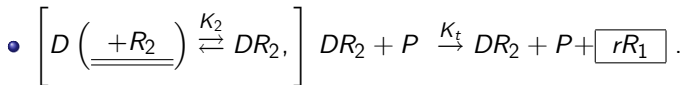


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- Continuous f (config. DNA γ , reaction speeds u , fast variable X)
 $dX_s^{X,u} = [A(\gamma_s) X_s^{X,u} + B_s u_s] ds + \int_E C(\gamma_{s-}, \theta) X_{s-}^{X,u} \tilde{q}(d\theta ds)$

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- Discrete

$$X_{n+1}^{X,u} = A_n(\omega) X_n^{X,u} + B u_{n+1} + \sum_{i=1}^p \langle \Delta M_{n+1}, e_i \rangle C_{i,n}(\omega) X_n^{X,u}$$

Rare (and Synthesis)

- $$\bullet \left[D \left(\underline{\underline{+R_2}} \right) \xrightleftharpoons{K_2} DR_2, \right] DR_2 + P \xrightarrow{K_t} DR_2 + P + \boxed{rR_1} .$$
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- The "expected" behavior is similar ... (is it?)

The Questions

- For the reference model, one has bistability
E.g. lytic : for some choice of speeds, lysis occurs (say at time T or N) i.e. $X_T = 0$ (or, more general $X_T = \text{target}$).
- from arbitrary x to "almost" 0
- from arbitrary x exactly to 0
- from arbitrary x exactly/almost to any "possible" target

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A Hint to the Metric

- In deterministic update
$$X_{n+1}^{x,u} = AX_n^{x,u} + Bu_{n+1}.$$
- "the dual" $Y_N=y, Y_n^{N,y} := A^T Y_{n+1}^{N,y}$
$$\langle X_N, Y_N \rangle = \langle x, Y_0^{N,y} \rangle + \sum_{n=0}^{N-1} \left[\langle u_{n+1}, B^T Y_{n+1}^{N,y} \rangle \right].$$
- In order for $X_N^{x,u} = 0$, whenever all $B^T Y_{n+1}^{N,\tilde{c}} = 0$, should have
$$Y_0^{N,y} = 0$$
- If "reversible" dynamics, $Y_{n+1} = (A^T)^{-1} Y_n$
$$B^T (A^T)^{-k} y_0 = 0 \text{ for all } k \leq N \text{ should imply } y_0 = 0.$$
- controllability to 0 iff metric (\cdot^2)
$$y \mapsto y^T \left[\sum_{k=1}^N A^{-k} B B^T (A^T)^{-k} \right] y$$
- (in continuous case, application to power electronic actuator placement Summers, Cortesi, Lygeros '14)

Towards Riccati-like Formulation

- Recall that

$$X_{n+1}^{x,u} = A_n(\omega) X_n^{x,u} + Bu_{n+1} + \sum_{i=1}^p \langle \Delta M_{n+1}, e_i \rangle C_{i,n}(\omega) X_n^{x,u}$$

- Let us look at $\sum_{k=1}^N A^{-k} BB^T (A^T)^{-k}$

Recursively computed as $P_N = BB^T$,

$$P_n = A^{-1} (P_{n+1} + BB^T) (A^T)^{-1}$$

- How to deal with non-homogeneity (dependence on n)?

Well ... $P_n = A_n^{-1} (P_{n+1} + BB^T) (A_n^T)^{-1}$

- How to deal with with stochasticity?

Problem : too much information in p_{n+1} which is not available at time n

Solution : decompose P_{n+1} in what is known at time n and some random variation

Couple (p, q) .

Riccati-like Formulation

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 P_n has some noise, and so does the process \Rightarrow some correction
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- One "corrects" by subtracting "horrible terms" $-\alpha_n^T \eta_n^{-1} \alpha_n$
 $\alpha_n := -q_n \times \text{bruit}^2 \times \left[A_n^T \right]^{-1}$
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- Problem η_n is only semi-positive definite.
- Solution : penalize by adding εI

Horrible Terms (you may look away for 2 minutes)

- In fact, $P_{n+1}^\varepsilon = \underbrace{\mathbb{E} [P_{n+1}^\varepsilon / \mathcal{F}_n]}_p + \underbrace{Q_n^\varepsilon \text{diag} (\Delta M_{n+1})}_q$,
- $P_n^\varepsilon = A_n^{-1} \left(\mathbb{E} [P_{n+1}^\varepsilon / \mathcal{F}_n] + BB^T \right) \left[A_n^T \right]^{-1} - \alpha_{n,\varepsilon}^T \eta_{n,\varepsilon}^{-1} \alpha_{n,\varepsilon}$,
- $\alpha_{n,\varepsilon}^j := -Q_n^\varepsilon \mathbb{E} [\langle \Delta M_{n+1}, e_j \rangle \text{diag} (\Delta M_{n+1}) / \mathcal{F}_n] \left[A_n^T \right]^{-1}$
- $\eta_{n,\varepsilon}^{j,k} :=$
 $\varepsilon \delta_{j,k} I_{m \times m} + \frac{1}{2} Q_n^\varepsilon \mathbb{E} [\langle \Delta M_{n+1}, e_k \rangle \langle \Delta M_{n+1}, e_j \rangle \text{diag} (\Delta M_{n+1}) / \mathcal{F}_n]$
 $+ \frac{1}{2} \mathbb{E} [\langle \Delta M_{n+1}, e_k \rangle \langle \Delta M_{n+1}, e_j \rangle (\text{diag} (\Delta M_{n+1}))^T / \mathcal{F}_n] (Q_n^\varepsilon)^T$
 $+ \mathbb{E} [\langle \Delta M_{n+1}, e_k \rangle \langle \Delta M_{n+1}, e_j \rangle / \mathcal{F}_n] \mathbb{E} [P_{n+1}^\varepsilon / \mathcal{F}_n]$
- If C is present, even more "horrible terms" α, η .
- JUST A,B condition does not suffice (R)

Theorem

i. System is controllable to 0 \Leftrightarrow almost to 0 $\Leftrightarrow \liminf_{\varepsilon \rightarrow 0^+} P_0^\varepsilon \gg 0$ (positive definite).

ii. The norm is $\|y_0\|_{ctrl}^2 = \liminf_{\varepsilon \rightarrow 0} \langle P_0^\varepsilon y_0, y_0 \rangle$.

Existence results :

iii. If A_n, C_n are non-random, $\exists P^\varepsilon \geq 0$ (explicit).

iv. If $C_n = 0$, $\exists P^\varepsilon \geq 0$ (explicit).

v. continuous and discrete conditions are NOT the same.

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Scenarios, Efficiency

- Several (r) scenarios $(B_i)_{i \in \{1, \dots, r\}} : \|\cdot\|_{ctrl, \boxed{B}}$
- $\|B\|_{ctrl}^{spec} := \inf_{y \neq 0} \frac{\|y\|_{ctrl, B}}{\|y\|}$
- $\|B\|_{ctrl}^{rank} := Rank \left(\liminf_{\varepsilon \rightarrow 0} P_0^\varepsilon(B) \right)$
- controllable using $B \Leftrightarrow \|B\|_{ctrl}^{spec} > 0 \Leftrightarrow \|B\|_{ctrl}^{rank} = m$.

Definitions

1) \mathcal{I} is minimal spectral-efficient intervention :

(i) $\|B(\mathcal{I})\|_{ctrl}^{spec} > 0$;

(ii) $\forall \mathcal{J} \subset \{1, \dots, r\}, |\mathcal{J}| < |\mathcal{I}|$, one has $\|B(\mathcal{J})\|_{ctrl}^{spec} = 0$;

(iii) $\forall \mathcal{J} \subset \{1, \dots, r\}, |\mathcal{J}| = |\mathcal{I}|$, one has $\|B(\mathcal{J})\|_{ctrl}^{spec} \leq \|B(\mathcal{I})\|_{ctrl}^{spec}$.

2) \mathcal{I} is minimal rank-efficient intervention :

(i) $\|B(\mathcal{I})\|_{ctrl}^{rank} = m$;

(ii) $\forall \mathcal{J} \subset \{1, \dots, r\}, |\mathcal{J}| < |\mathcal{I}|$, one has $\|B(\mathcal{J})\|_{ctrl}^{rank} < m$.

Optimization Problems

- $\max_{\substack{\mathcal{I} \subset \{1, \dots, r\} \\ |\mathcal{I}|=k}} \|B(\mathcal{I})\|_{ctrl}, 1 \leq k \leq r,$
- rank-based set functions are submodular (Lovasz '83) :
 $f(S_1 \cap S_2) + f(S_1 \cup S_2) \leq f(S_1) + f(S_2)$
- submodularity is "a combinatorial analogue of concavity"
(Nemhauser '78)
problem is NP-hard BUT a greedy approach provides good results.
- SO : use $\|\cdot\|_{ctrl}^{rank}$ and greedy heuristic \Rightarrow minimal k
then, use $\|\cdot\|_{ctrl}^{spec}$ for such k .

Back to the Initial Model

- $X_{n+1}^{x,u} = A_n(\omega) X_n^{x,u} + Bu_{n+1} + \sum_{i=1}^p \langle \Delta M_{n+1}, e_i \rangle C_{i,n}(\omega) X_n^{x,u}$
- $A = \begin{pmatrix} \frac{1}{4} & \frac{1}{2} \\ \frac{1}{4} & \frac{3}{4} \end{pmatrix}$, $C_2 = \begin{pmatrix} 0 & r \\ 0 & 0 \end{pmatrix}$
- $b_1 = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$, respectively $b_2 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$
- direct control on dimer fails to work
- one needs SIMULTANEOUS control on monomer/dimer
BUT altering ONE external factor suffices.

Thank you for your patience !