



TO LYSE OR NOT TO LYSE: TRANSIENT-MEDIATED STOCHASTIC FATE DETERMINATION IN CELLS INFECTED BY BACTERIOPHAGES



w/Richard Joh (GA Tech, left), Yuriy Mileyko (GA Tech/Duke, right) & others

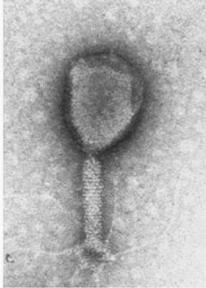


Joshua S. Weitz, Georgia Tech, School of Biology & Physics

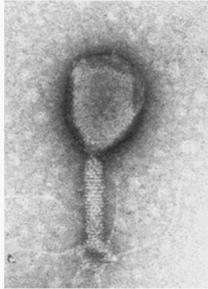
Email: jsweitz@gatech.edu,

Web: <http://ecothery.biology.gatech.edu>, KITP, March 1, 2011

Wanna go lyse
some cells?



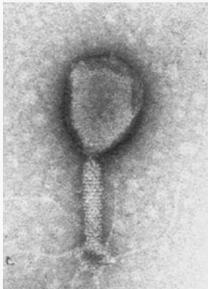
About time
you asked.

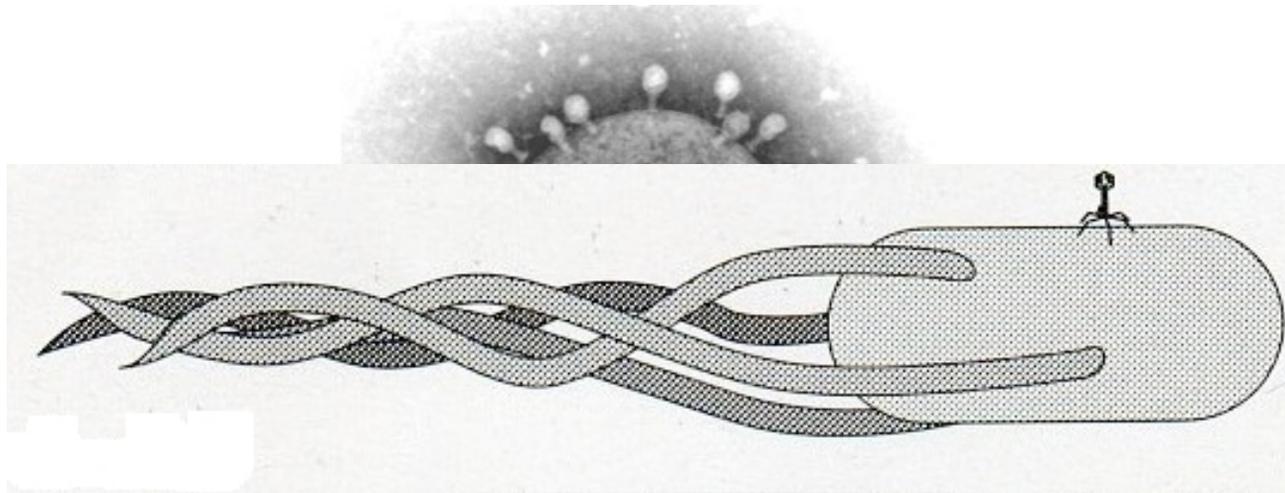


... hey, what
about me?



Yeah,
let's go!





Copyright: CIMC

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Central Questions in Today's Talk

- 1) Does co-infection alter cell fate, and if so, in what way?

Yes, lysis and lysogeny depend on co-infection

- 2) How can viral genomes interact intracellularly to collectively determine cell fate?

Coupling of transcription with viral protein pool

- 3) How can a simple model of fate determination be reconciled with observed single-cell level data?

Stochastic dynamics & a gene dosage compensation mechanism provide an alternative explanation for cell fate determination in co-infected hosts

Experimental work: Kourilsky (Mol Ge. Genet, 1973), Kobilier et al. (PNAS, 2005), St. Pierre and Endy (PNAS, 2008), Zeng et al. (Cell 2010)

Theoretical work: Weitz et al. (Biophys J., 2008), Mileyko et al. (PNAS 2008), Joh & Weitz (PLoS Comp Biol, in press)

From intracellular mechanisms to traits

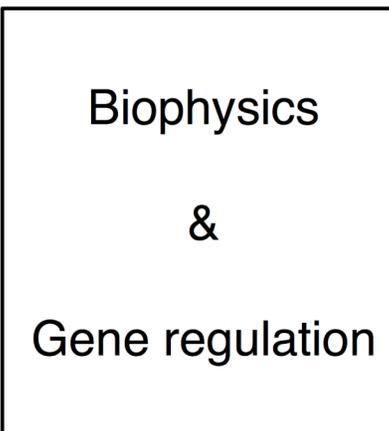
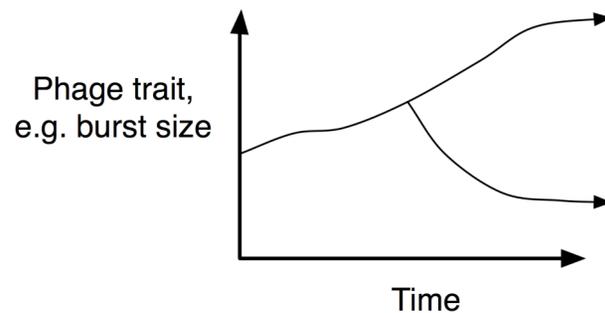
Ecological Model

$$\frac{dV}{dt} = \overbrace{\beta\phi NV}^{\text{Phage production}} - \overbrace{mV}^{\text{Phage decay}}$$

Trait space

$$\{\dots, \beta_1, \beta_2, \beta_3, \dots\}$$

Evolutionary model



Outline



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- Determination of alternative cell fates
- Quantitative model of lysis-lysogeny decisions
- Heterogeneity of decisions: gene dosage effect on lysis-lysogeny

Stochastic cell fates in unicellular organisms

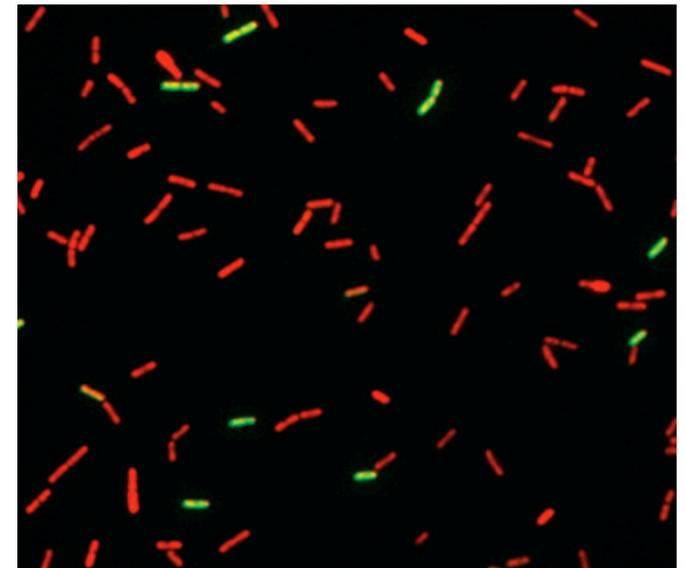


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- Eukaryotes
 - ▣ *S. cerevisiae* mating

- Bacteria
 - ▣ Bacterial persistence to antibiotics
 - ▣ Competence: *Bacillus subtilis*

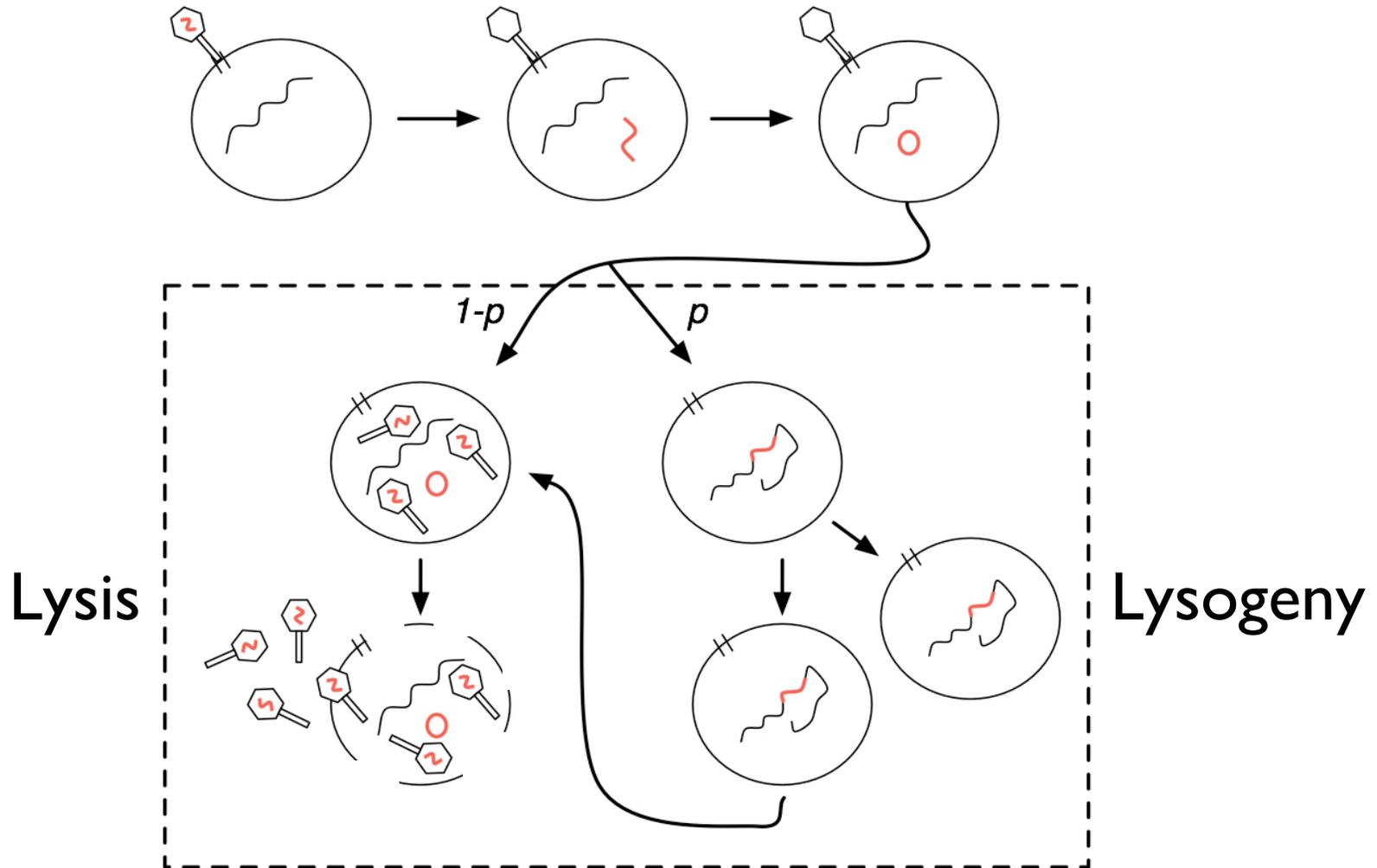
- Viruses?



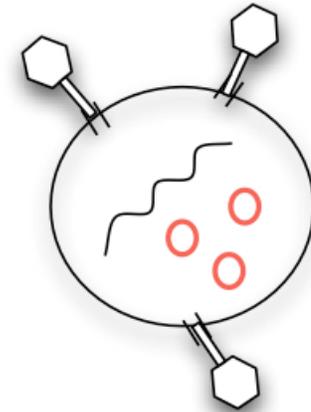
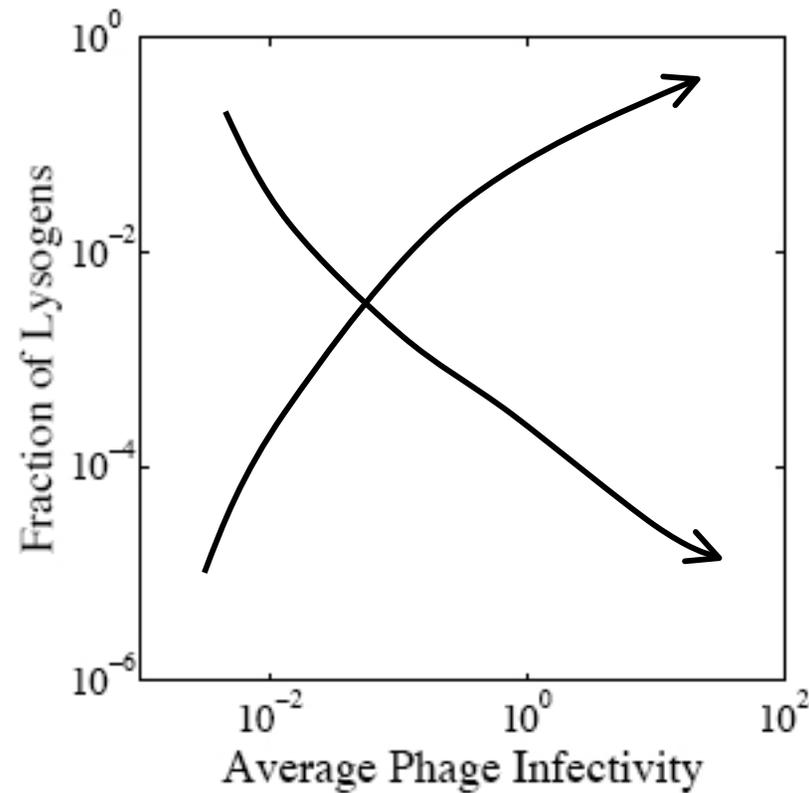
Viruses also drive alternative cell fates: lysis or lysogeny



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Strategies and the Cellular Multiplicity of Infection

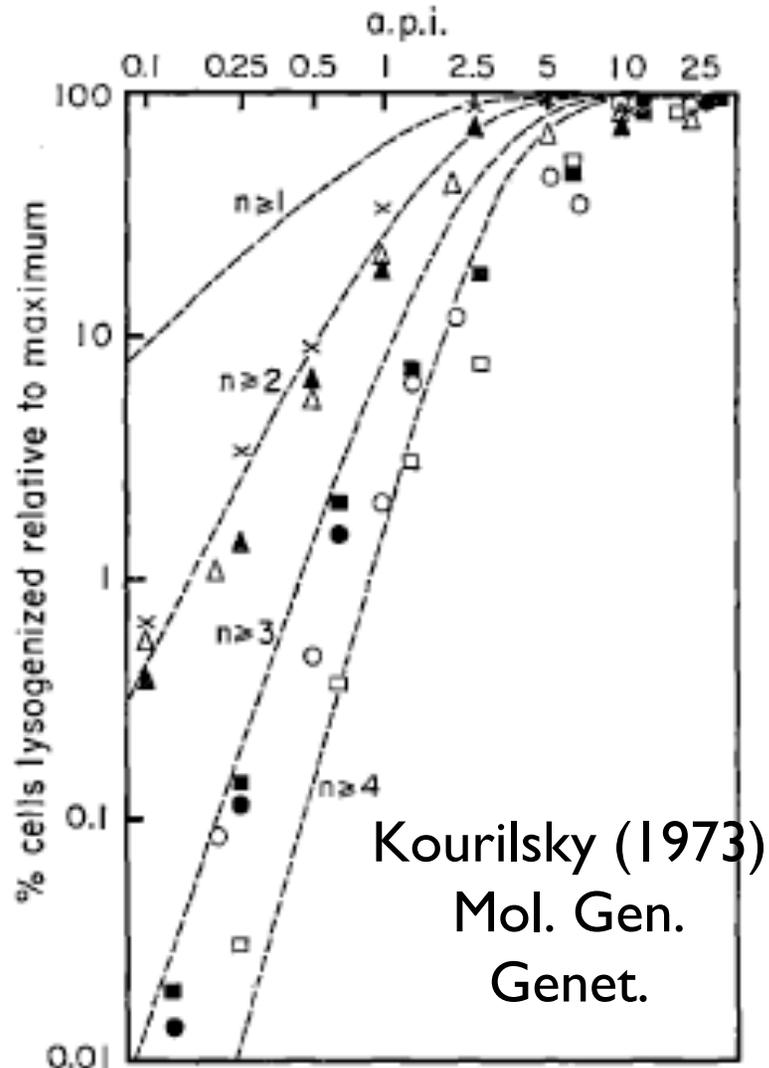


Which of these is what phages really do?

Chance of lysogeny critically depends on cellular multiplicity of infection (MOI)

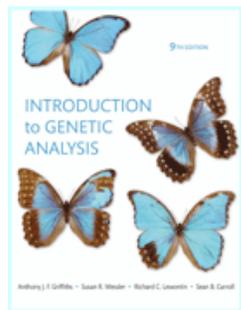
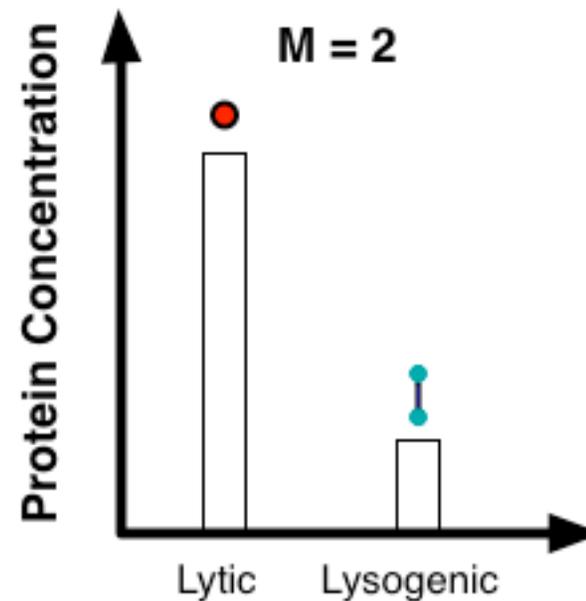
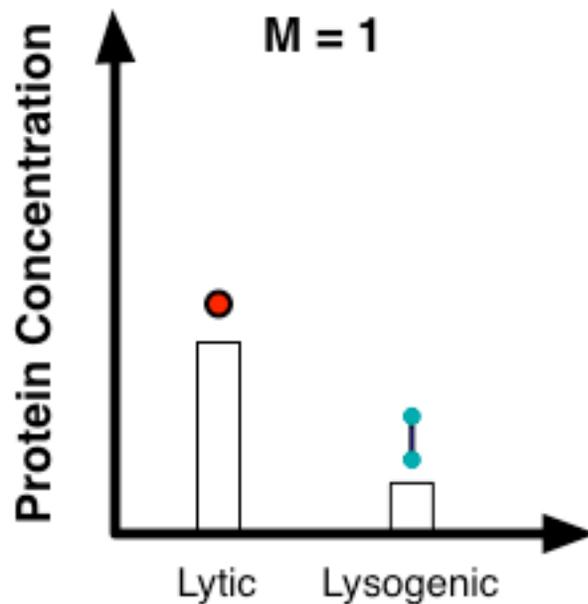


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- $API = \# \text{ phage} / \# \text{ host}$
- Lysogeny is more likely when a host cell is multiply infected

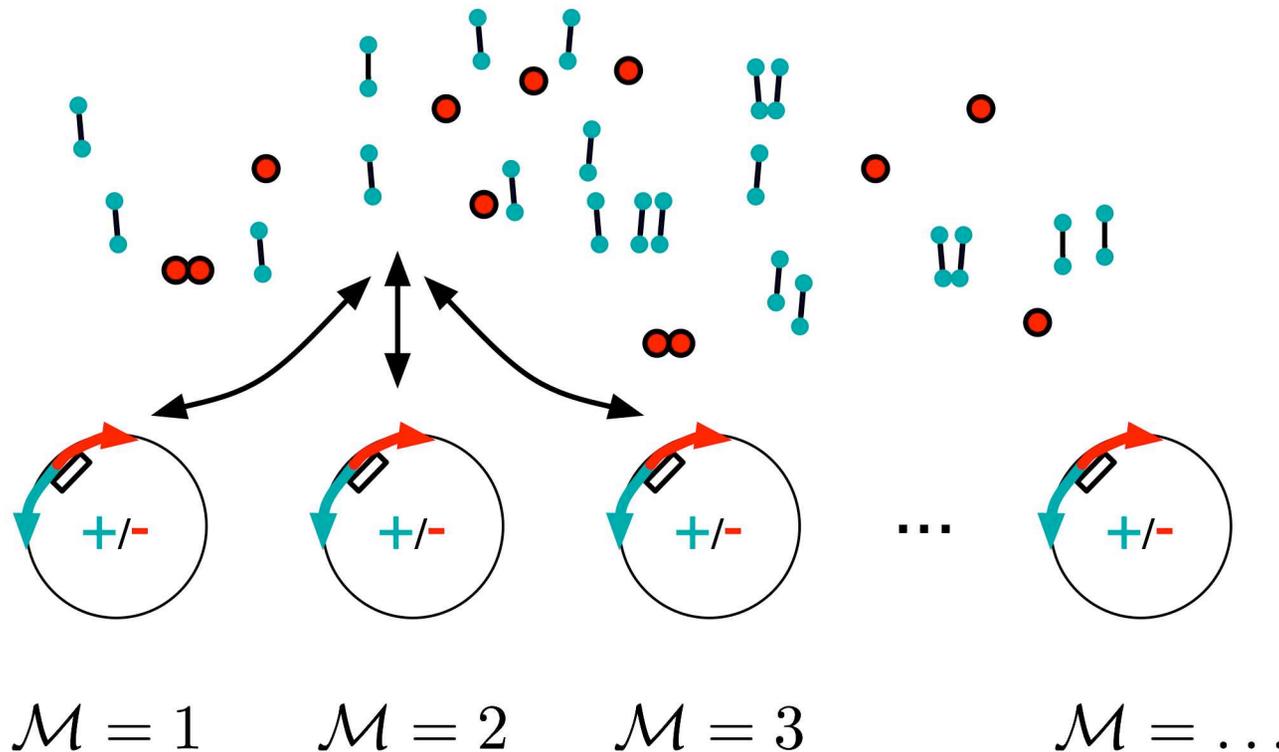
Intuition from Classic Gene Dosage Expectation: Expression is Linearly Related to Viral Copy Number



“In general, the amount of transcript produced by a gene is directly proportional to the number of copies of that gene in a cell.”

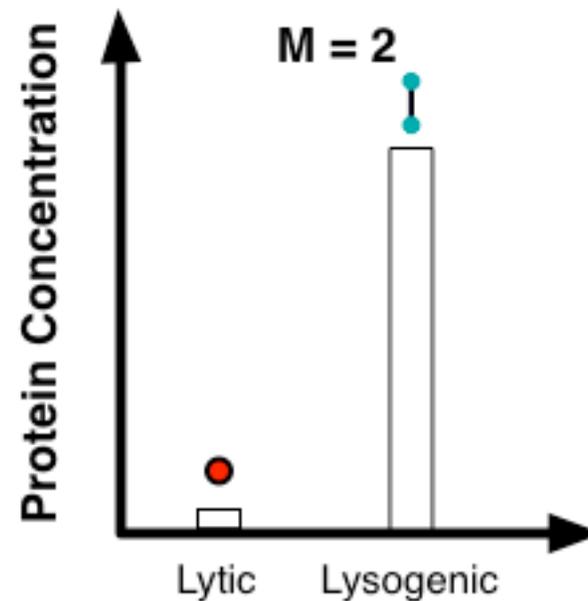
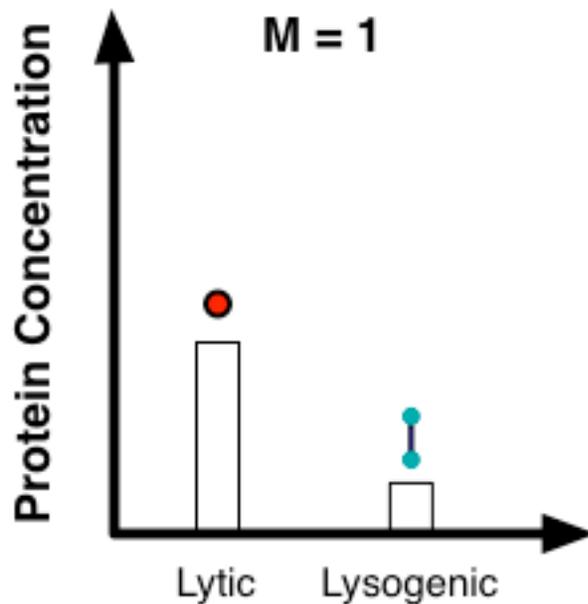
Griffiths et al., Intro. to Genetic Analysis

A “Simple” Decision Switch: In Reality, a Coupled Set of Regulatory Networks



Communal gene products form the basis for “viral communication”

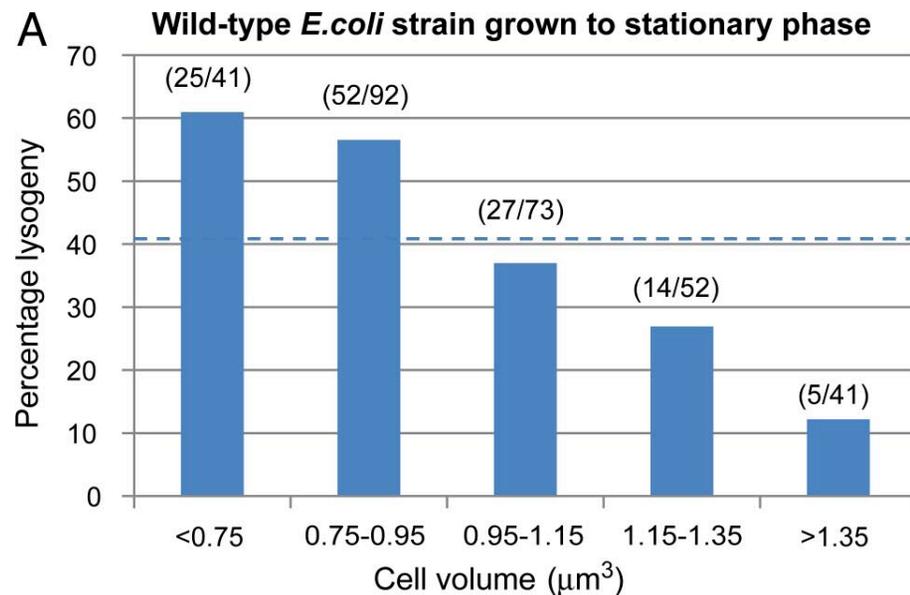
SO, Gene Expression May be Nonlinearly Related to Gene Copy Number:



Cell volume is another critical parameter



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St. Pierre and Endy
(2008) PNAS

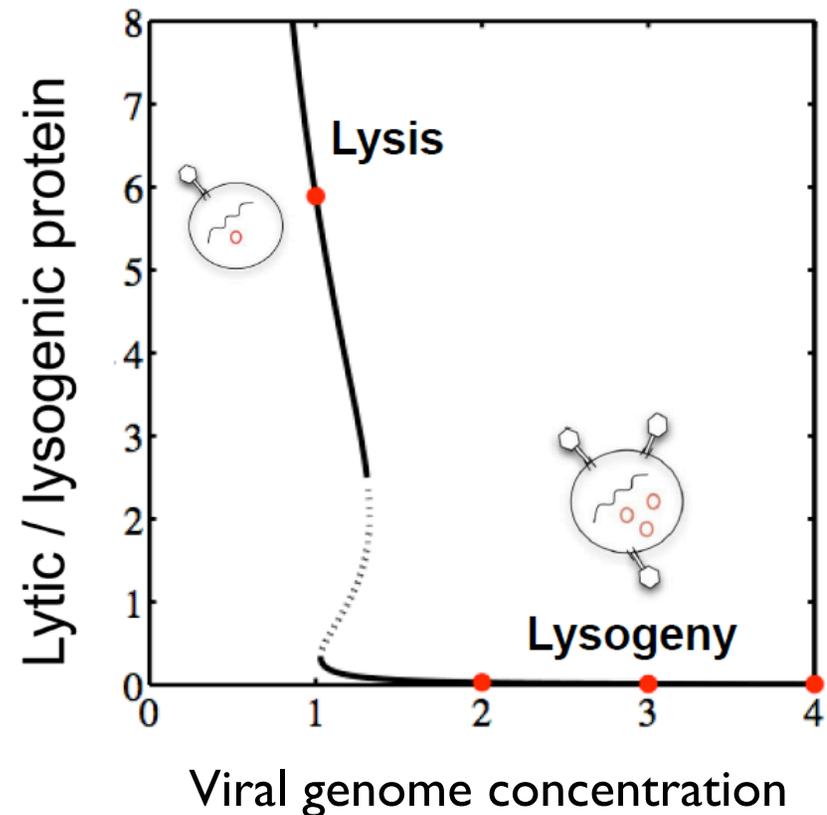
- Lysis-lysogeny is stochastic
- Cell fate determination depends on concentration of viral genome



Viral concentration is key to lysis-lysogeny switch

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- Explicit consideration of viral genome concentration
- Based on asymptotic behaviors of gene regulation
- Small change in viral copy number can shift between lysis and lysogeny

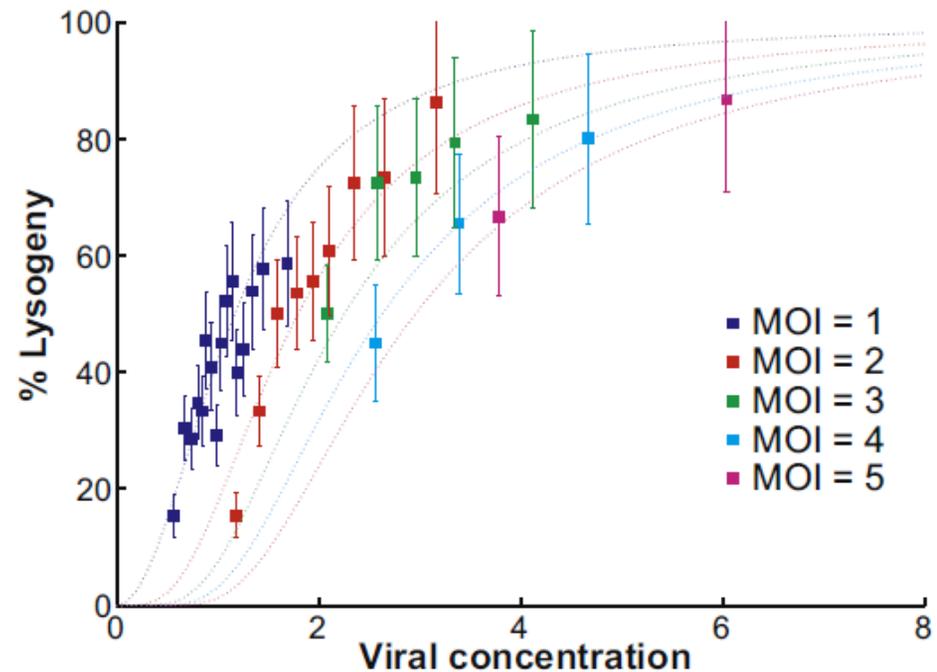
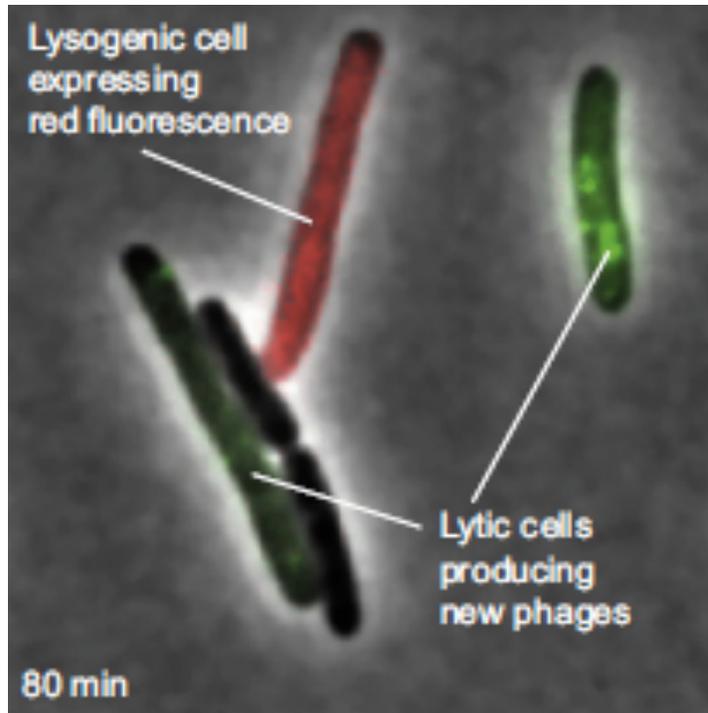


Weitz, Mileyko, Joh and Voit (2008) Biophys J

Experiments confirmed concentration dependence



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Zeng et al (2010) Cell

A stochastic model of phage lambda is necessary



Outline

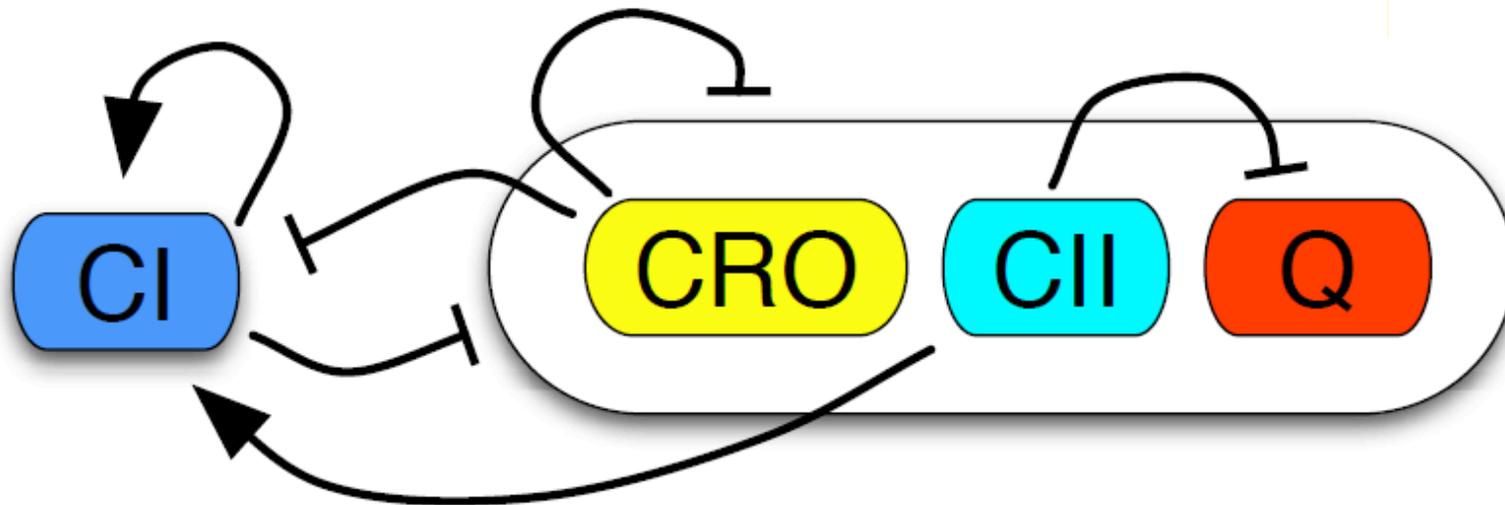
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- Determination of alternative cell fates
- Quantitative model of lysis-lysogeny decisions
- Heterogeneity of decisions: gene dosage effect on lysis-lysogeny



Core GRN for lysis-lysogeny

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- CI (repressor): lead to and maintain lysogeny
- CRO: control repressor
- CII: transcription activator
- Q: activate late lytic genes

Cumulative work of many (Ptashne, Kobiler, Oppenheim, and many more).

Quantitative model of lysis-lysogeny



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$$\begin{aligned} [cro \ mRNA] \quad \frac{dm_y}{dt} &= \underbrace{\frac{\mathcal{M}}{V} \alpha_y f_R}_{\text{Transcription}} - \underbrace{\gamma_m m_y}_{\text{Degradation}} \\ [CRO] \quad \frac{dY}{dt} &= \underbrace{\sigma m_y}_{\text{Translation}} - \underbrace{\gamma_y Y}_{\text{Degradation}} \end{aligned}$$



Full model of lysis-lysogeny

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of coinfecting phages

$$[cI \text{ mRNA}] \quad \frac{dm_x}{dt} = \frac{\mathcal{M}}{V} \alpha_x f_{RM}^{basal} + \frac{\mathcal{M}}{V} \beta_x f_{RM}^{act} + \frac{\mathcal{M}}{V} \delta_x f_{RE} - \gamma_m m_x,$$

$$[cro \text{ mRNA}] \quad \frac{dm_y}{dt} = \frac{\mathcal{M}}{V} \alpha_y f_R - \gamma_m m_y,$$

$$[cII \text{ mRNA}] \quad \frac{dm_z}{dt} = \frac{\mathcal{M}}{V} \alpha_z f_R - \gamma_m m_z,$$

$$[Q \text{ mRNA}] \quad \frac{dm_Q}{dt} = \frac{\mathcal{M}}{V} \alpha_Q f_R - \gamma_m m_Q - \zeta m_Q m_{aQ},$$

$$[aQ \text{ mRNA}] \quad \frac{dm_{aQ}}{dt} = \frac{\mathcal{M}}{V} \delta_{aQ} f_{aQ} - \gamma_m m_{aQ} - \zeta m_Q m_{aQ},$$

$$[CI] \quad \frac{dX}{dt} = \sigma m_x - \gamma_x X,$$

$$[CRO] \quad \frac{dY}{dt} = \sigma m_y - \gamma_y Y,$$

$$[CII] \quad \frac{dZ}{dt} = \sigma m_z - \gamma_z Z,$$

$$[Q] \quad \frac{dQ}{dt} = \sigma m_Q - \gamma_Q Q,$$

Host cell volume



Parameters for lysis-lysogeny

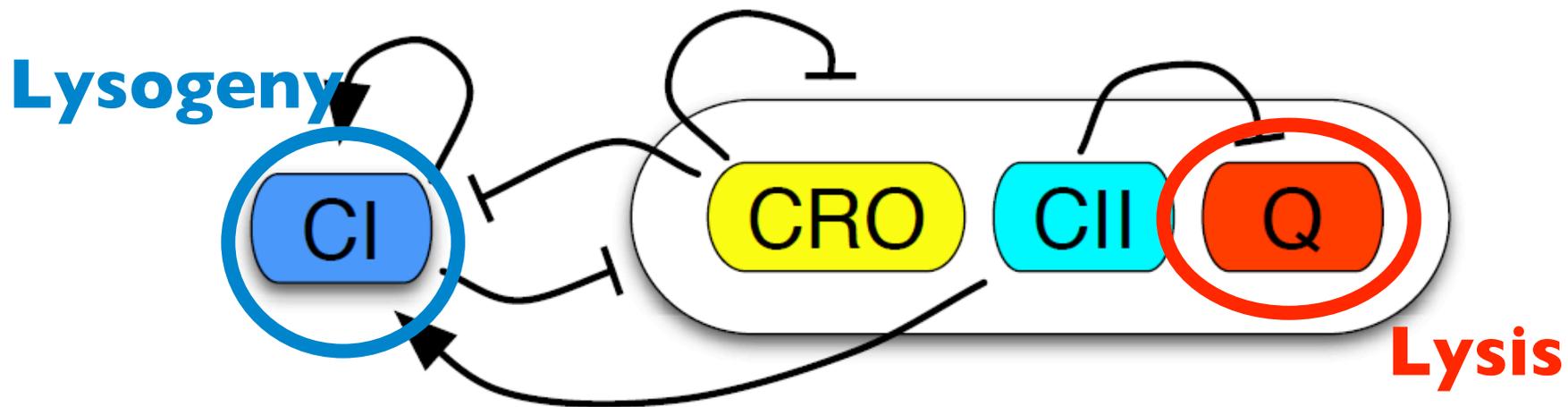
| Parameter | Reference value | Reference |
|---------------|---------------------------|------------------------------|
| γ_x | 0.01 (min^{-1}) | ≈ 0 [62], 0.042 [25] |
| γ_y | 0.06 (min^{-1}) | 0.016 [63] |
| γ_z | 0.10 (min^{-1}) | 0.16 w/o CIII [64] |
| γ_q | 0.01 (min^{-1}) | |
| γ_m | 0.1 (min^{-1}) | 0.12 [65] |
| α_x | 0.06 (min^{-1}) | 0.06 [36] |
| α_y | 0.84 (min^{-1}) | 0.84 [36], 3 [62] |
| α_z | 0.8 (min^{-1}) | $< \alpha_y$ |
| α_q | 0.75 (min^{-1}) | $< \alpha_z$ |
| β_x | 0.66 (min^{-1}) | 0.66 [36], 3.42 [66] |
| δ_x | 0.9 (min^{-1}) | 0.9 [25] |
| δ_{aQ} | 2 (min^{-1}) | |
| c_d^x | 0.05 (nM^{-1}) | 0.05 [67], 0.18 [68] |
| c_d^y | 5.8 (nM^{-1}) | 5.8 [69], 307 [70] |
| c_d^z | 0.05 (nM^{-1}) | |
| c_t^z | 0.05 (nM^{-1}) | |
| c_p^{aQ} | 0.2 (nM^{-1}) | |
| σ | 0.5 (min^{-1}) | |
| ζ | 0.1 ($nM^{-1}min^{-1}$) | 0.02 [71] |
| V | 1 (μm^3) | 0.5~2.0 |



Stochastic simulations by Gillespie algorithm

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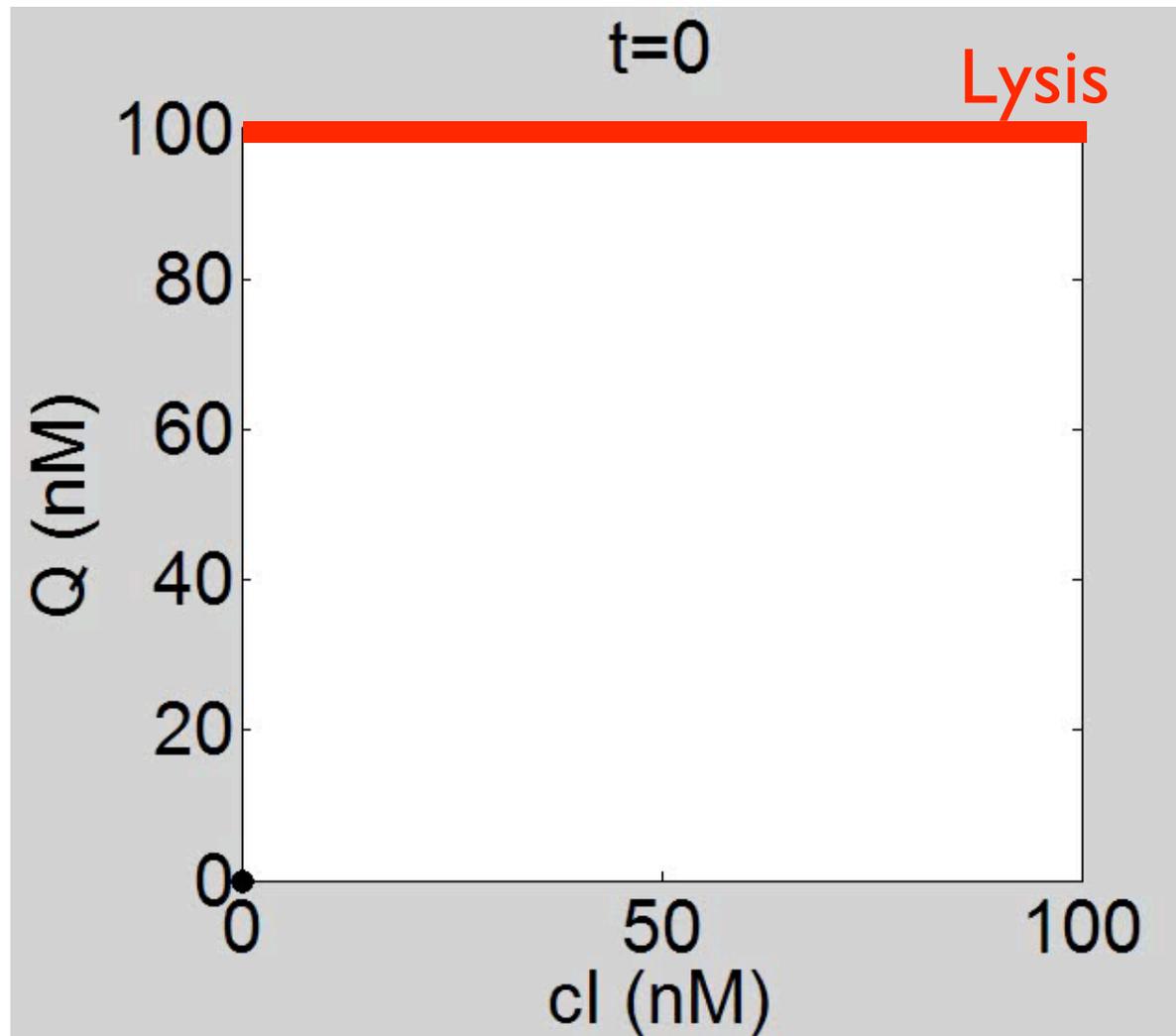
- Stochastic simulation: time evolution trajectory using Gillespie algorithm



- Threshold concentrations for decisions
 - Reaching CI threshold: lysogeny
 - Reaching Q threshold: lysis

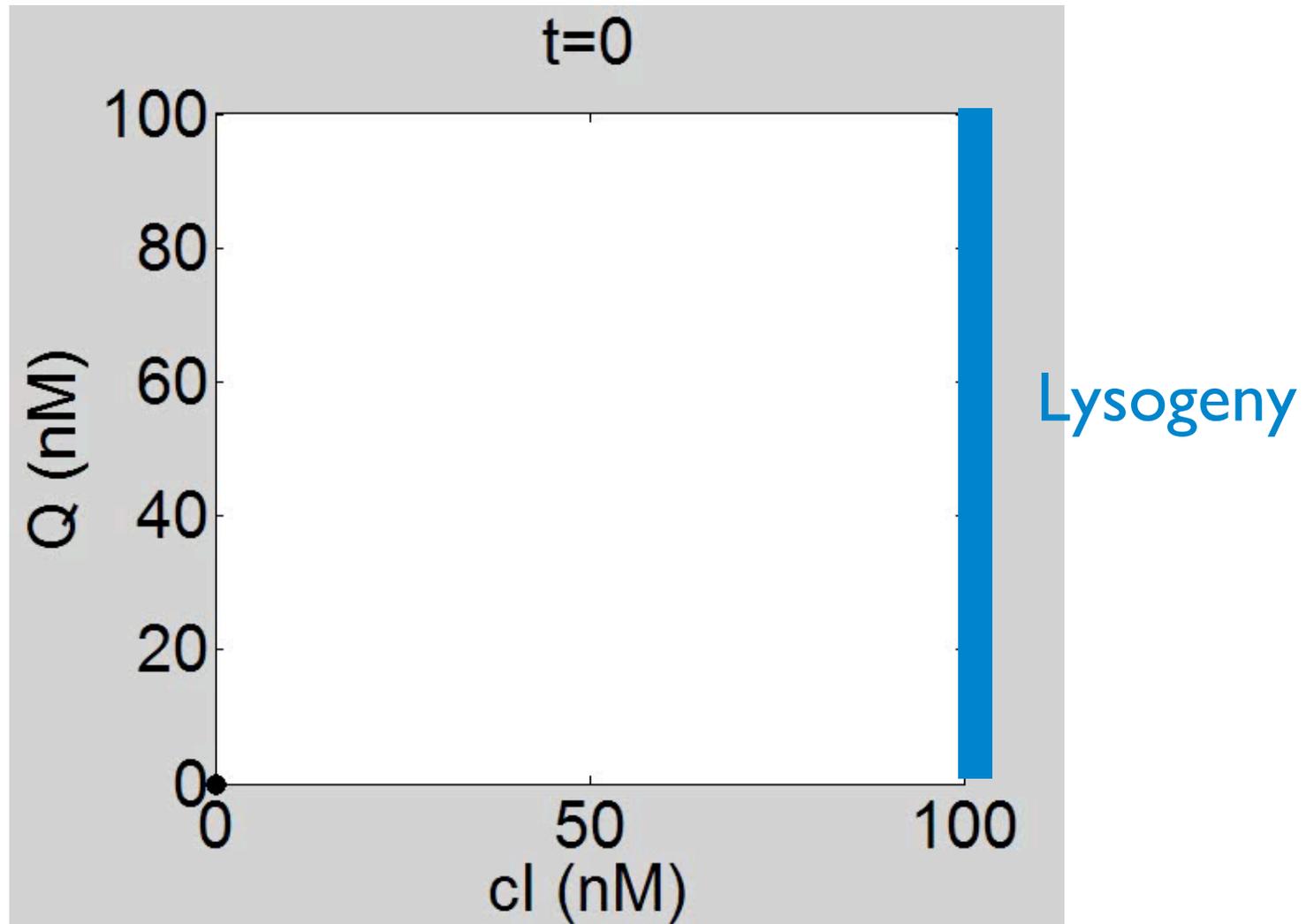


First passage: lysis

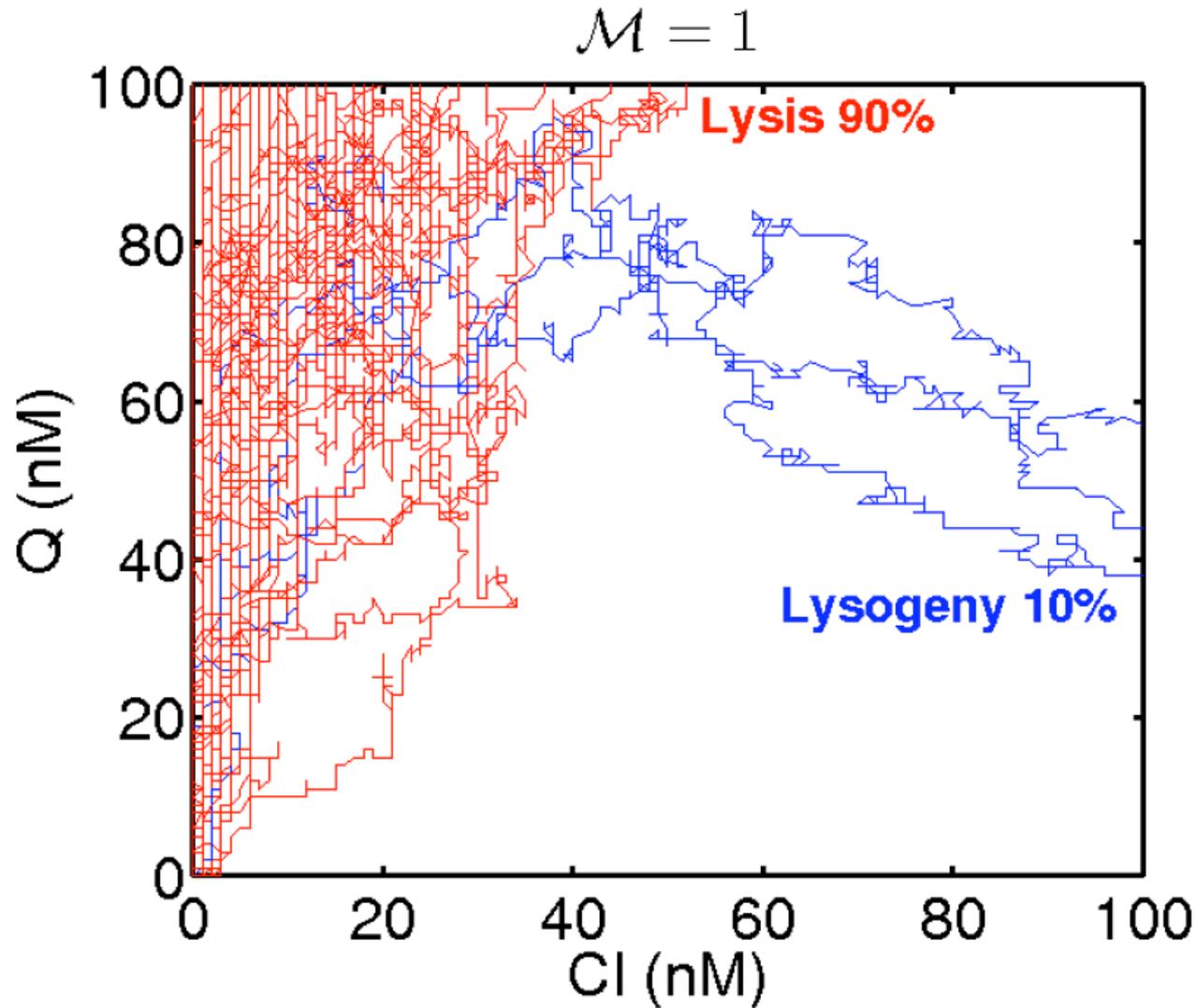




First passage: lysogeny



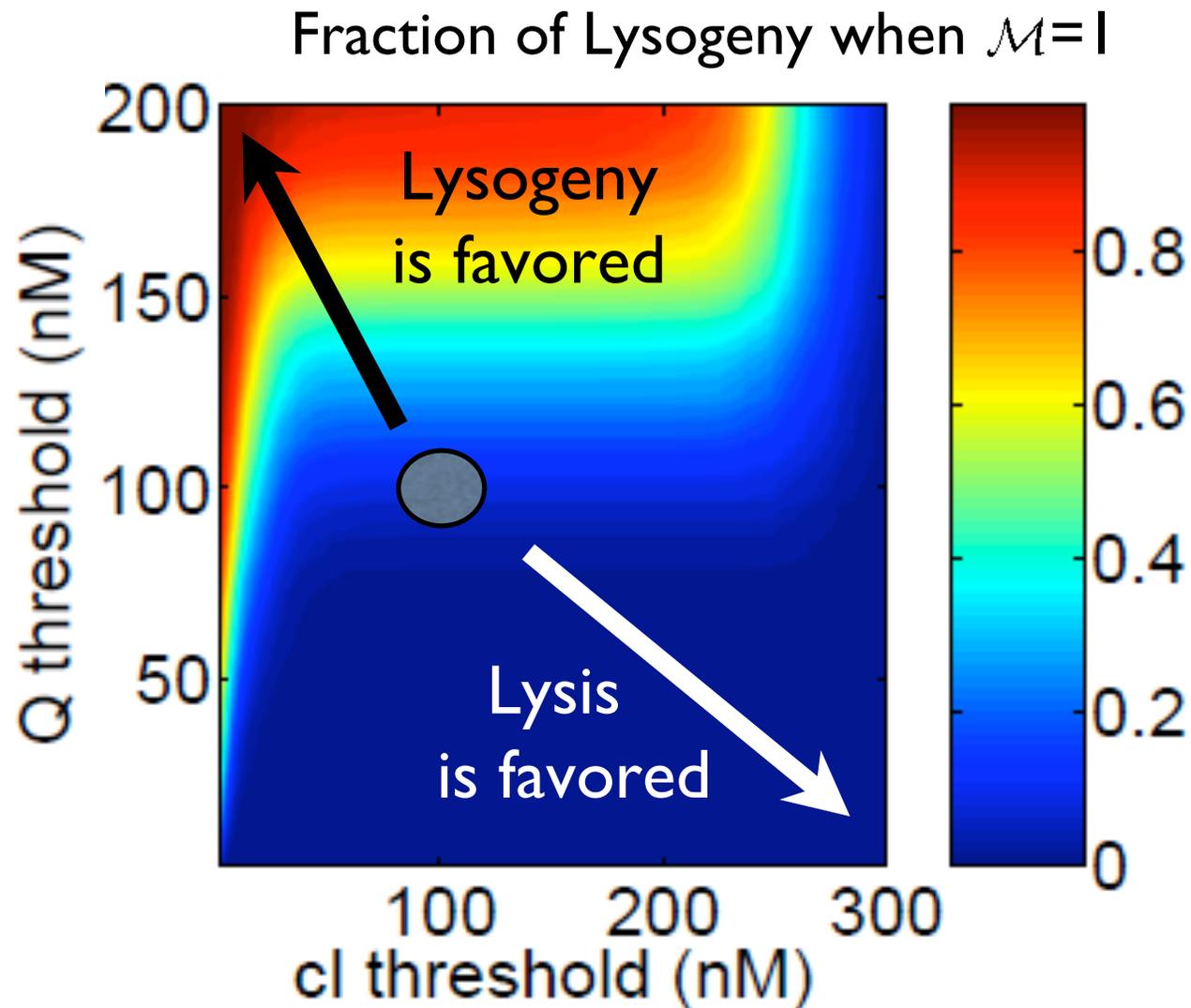
Fraction of lysogeny determined by multiple stochastic simulations



Thresholds as evolvable traits



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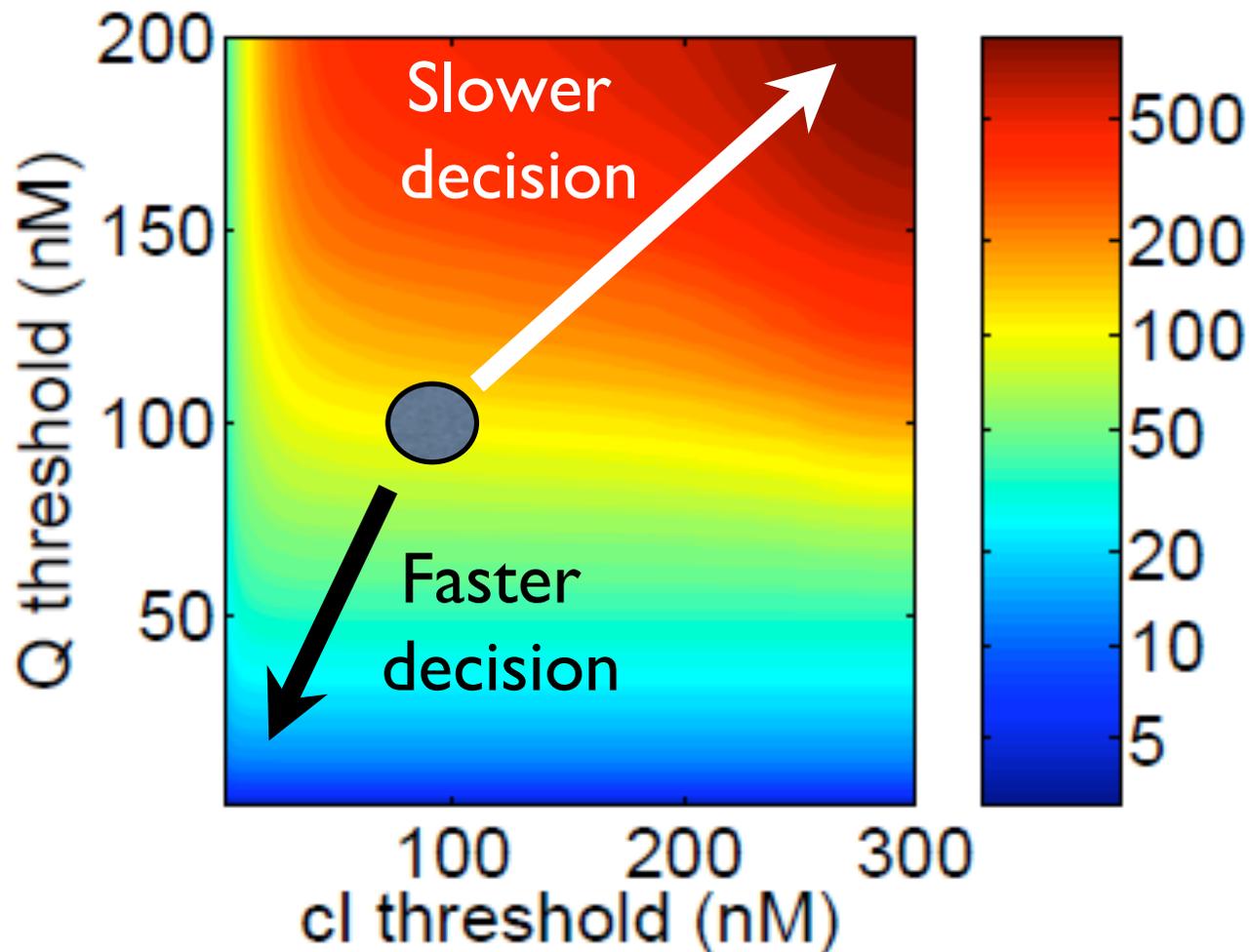


Average decision time can also be tuned by thresholds



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Average decision time when $\mathcal{M} = 1$



What are essential features of alternative decisions?



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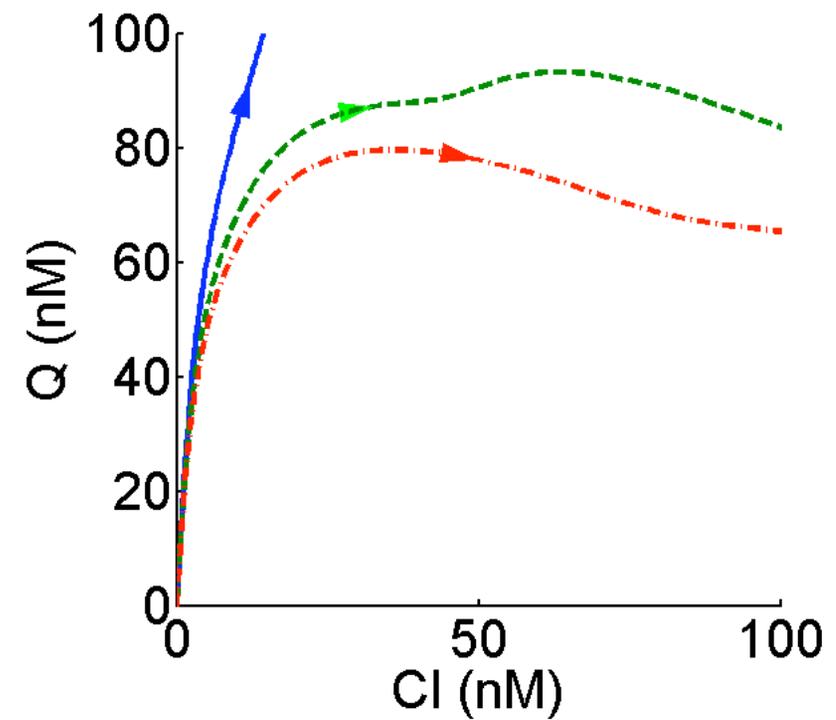
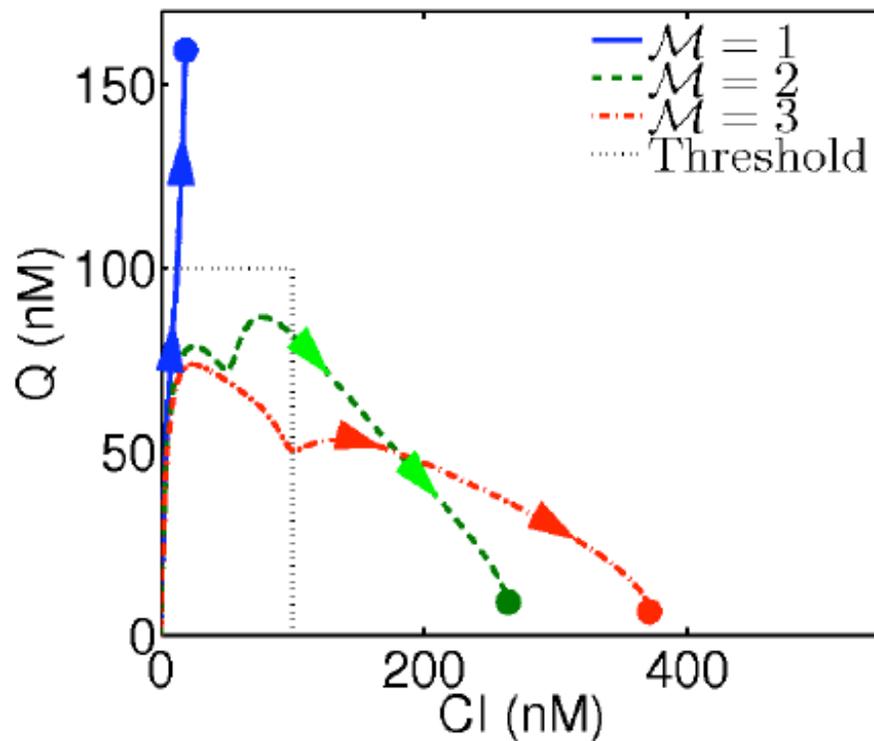
- Is bistability necessary for alternative decisions?
- Can two systems behave the same way due to similarity of transient dynamics?



Asymptotically divergent GRN

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Asymptotically divergent



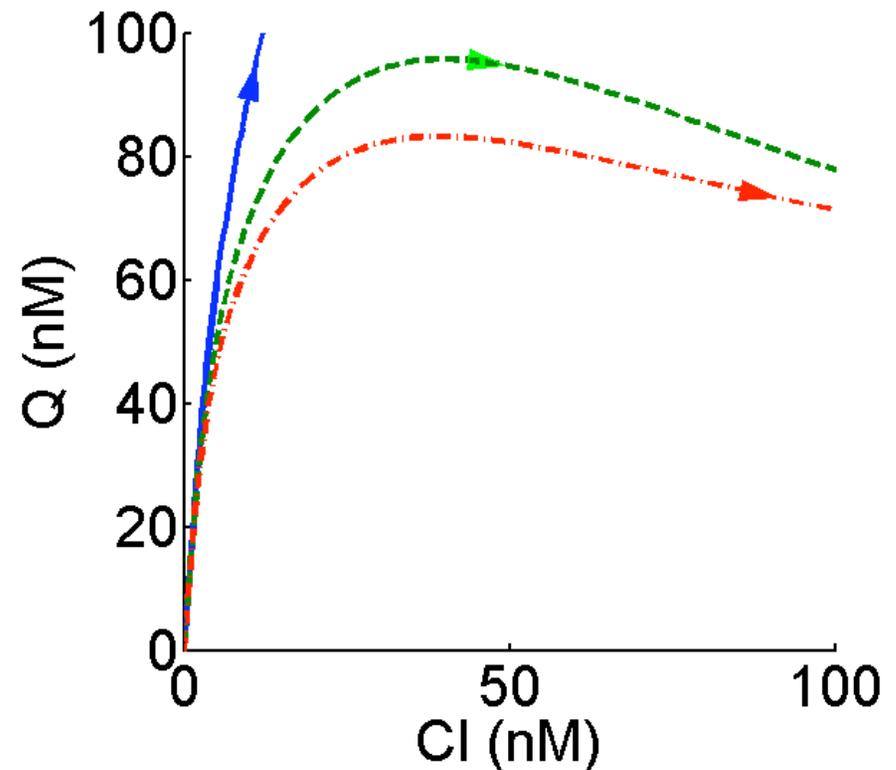
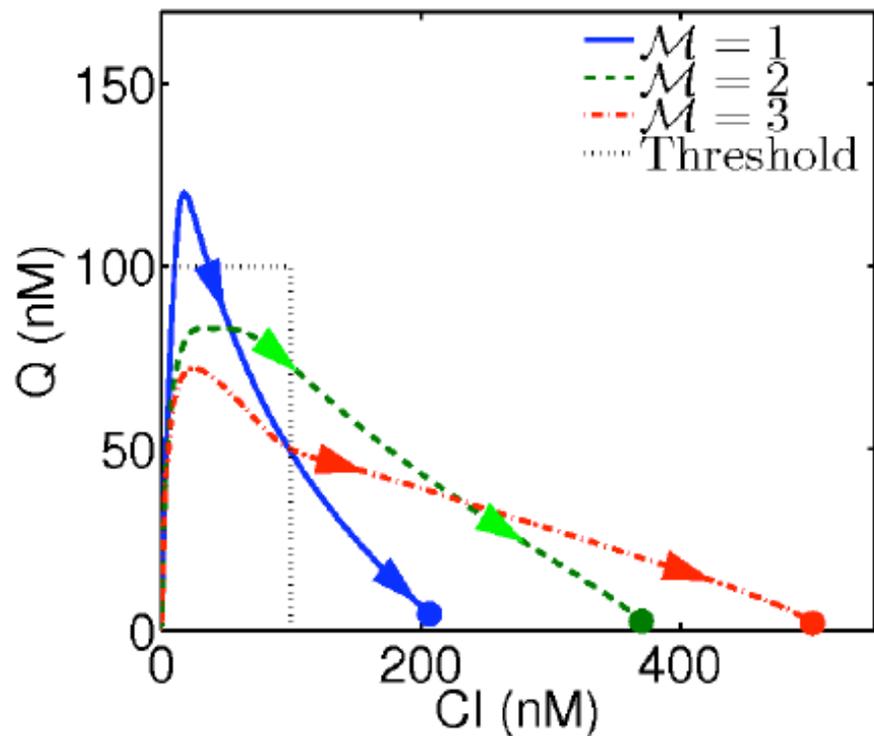
- $\mathcal{M}=1$: Q expression level stays high.
- $\mathcal{M} > 1$: $Q \rightarrow 0$.



Transiently divergent GRN

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Transiently divergent

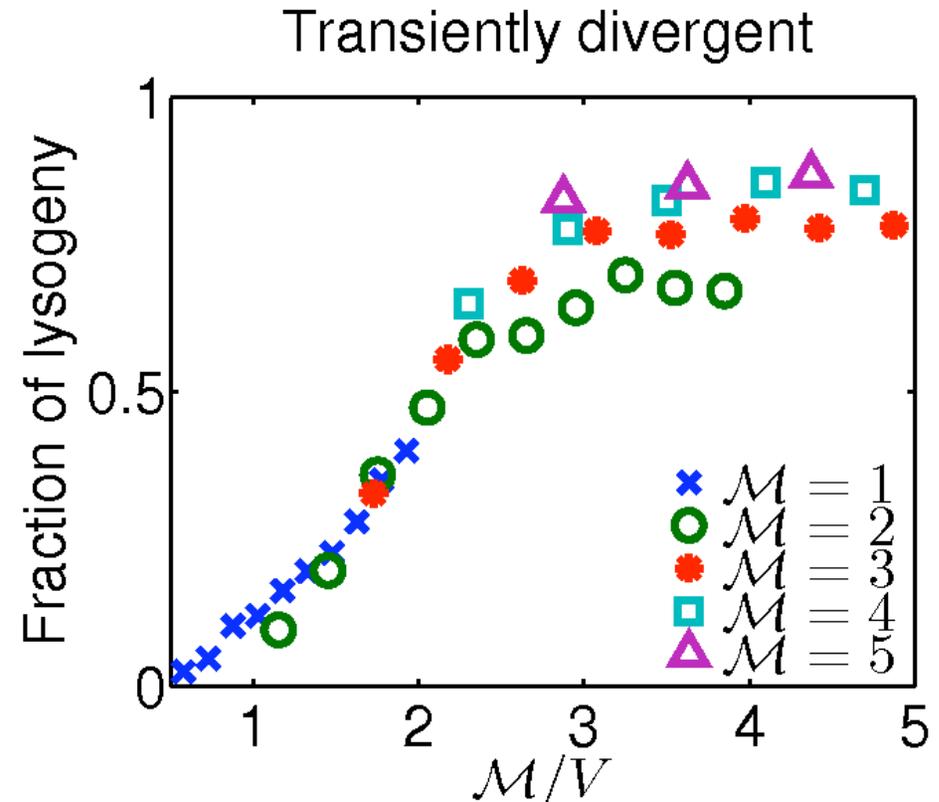
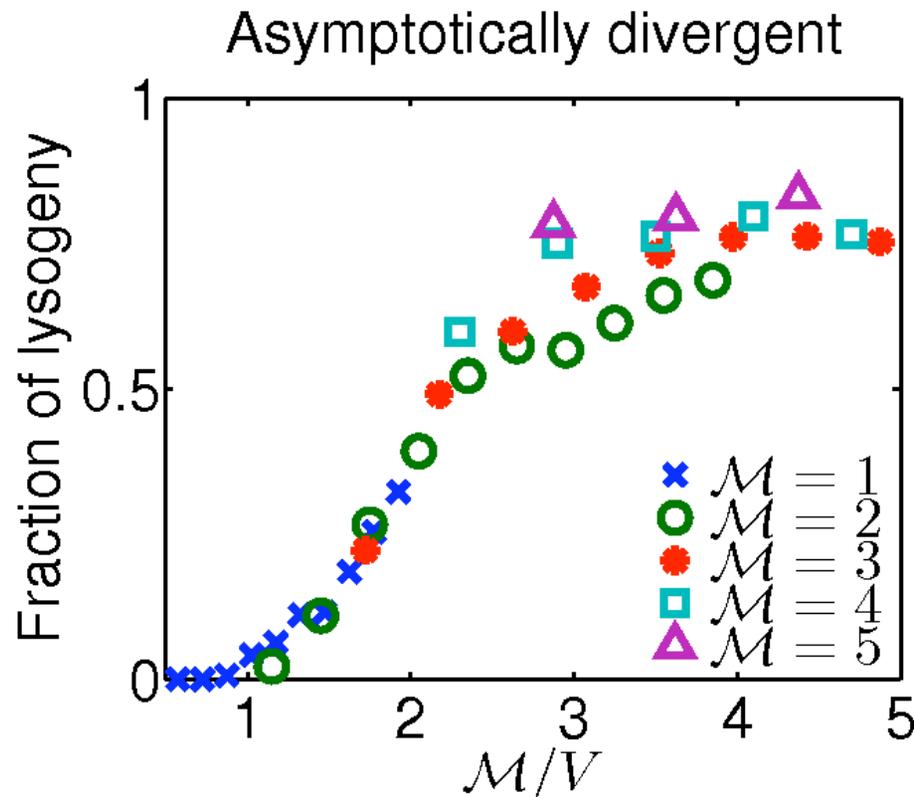


- At all \mathcal{M} s, $Q \rightarrow 0$.
- Maximum transient levels of Q are different.

Similarity of transient dynamics leads to same response



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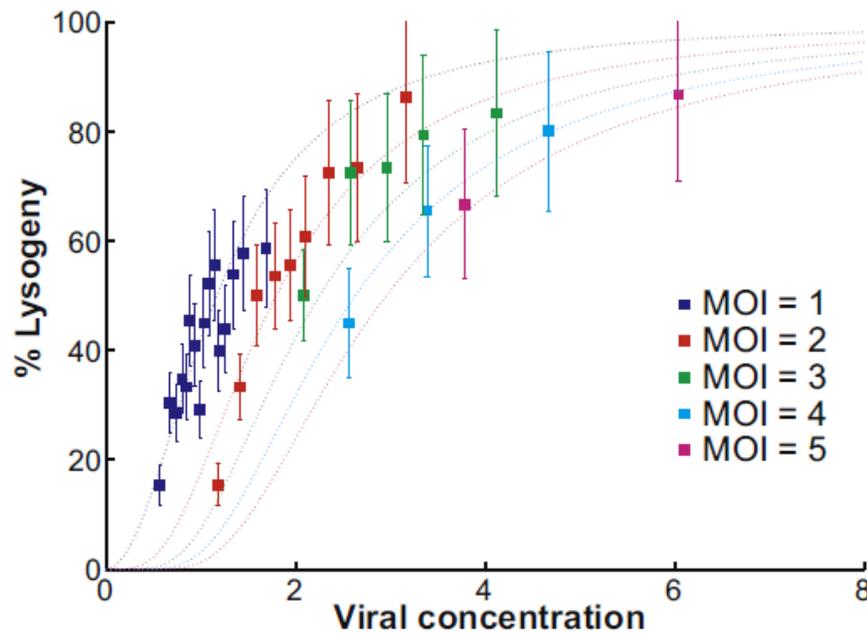


- Responses can be very similar even if steady-state behaviors are qualitatively distinct

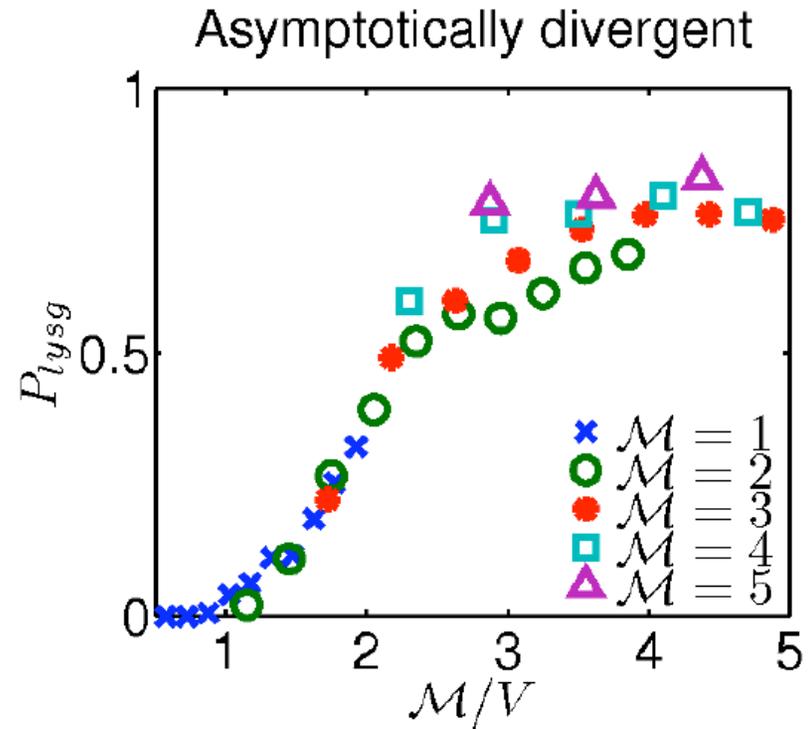
Experiments show much more heterogeneity than simulations



Data



Simulation



Zeng et al (2010) Cell

How can we explain this discrepancy?

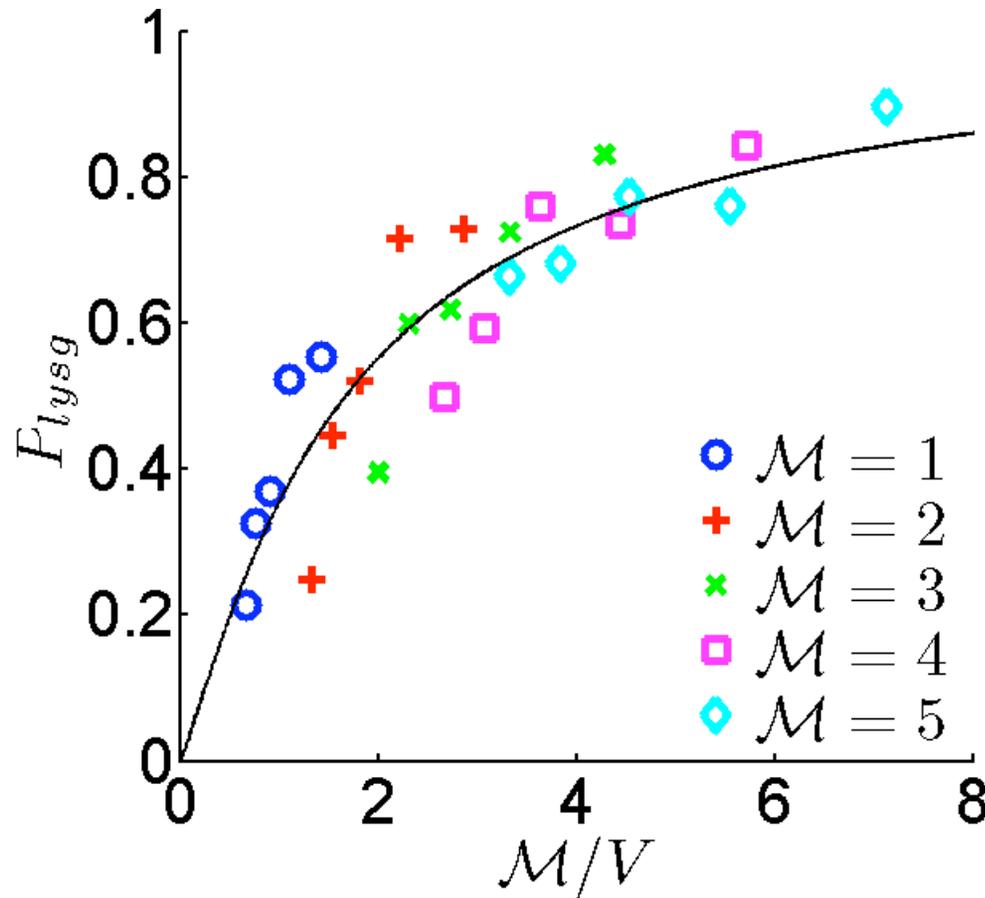


Outline

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- Determination of alternative cell fates
- Quantitative model of lysis-lysogeny decisions
- Heterogeneity of decisions: gene dosage effect on lysis-lysogeny

What can explain the variance of lysogeny?



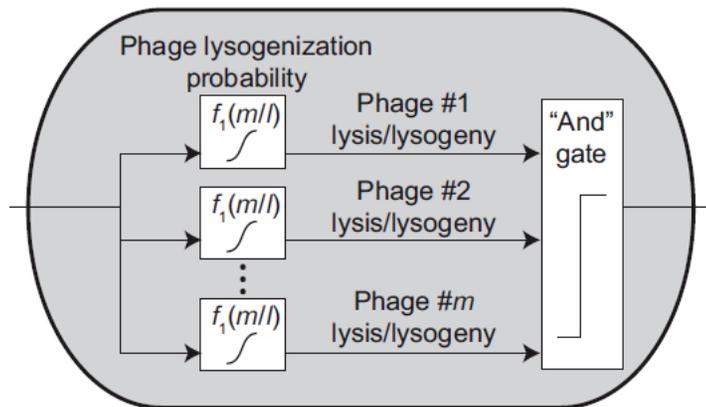
- At same M/V , a singly infected cell has much higher probability of lysogeny than a doubly infected cell

Data taken from Zeng et al (2010) Cell

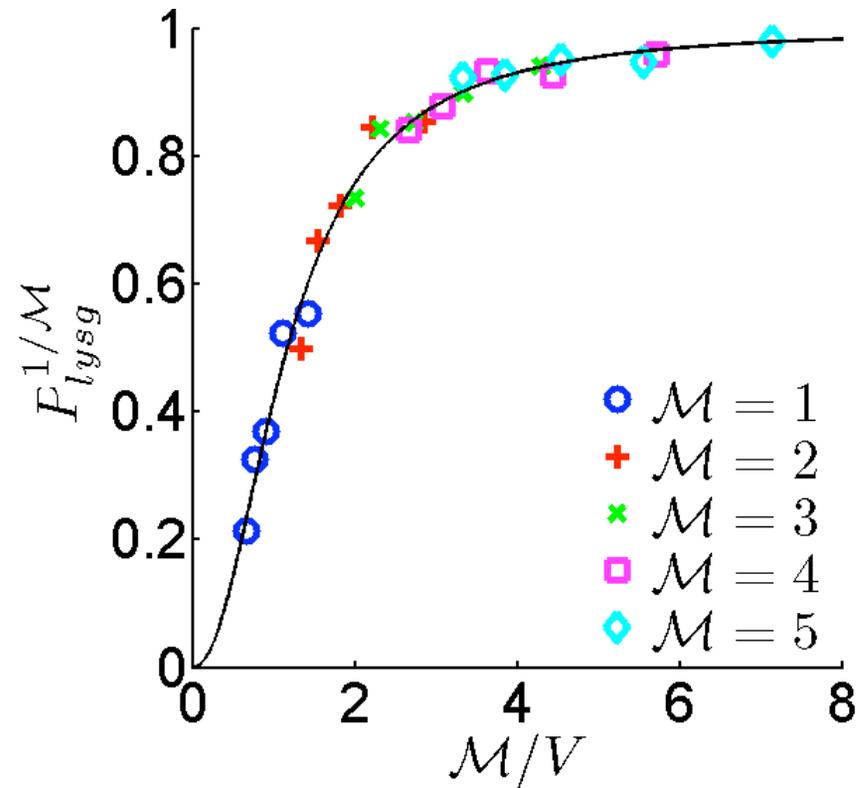
Quasi-independent decision proposed by Zeng et al (2010)



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$$P_{lysg} = (P_{1 \text{ phage}})^{\mathcal{M}}$$



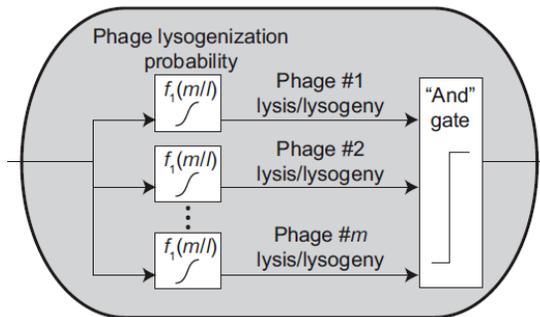
- Phages are independent
- Phages know the presence of other phages



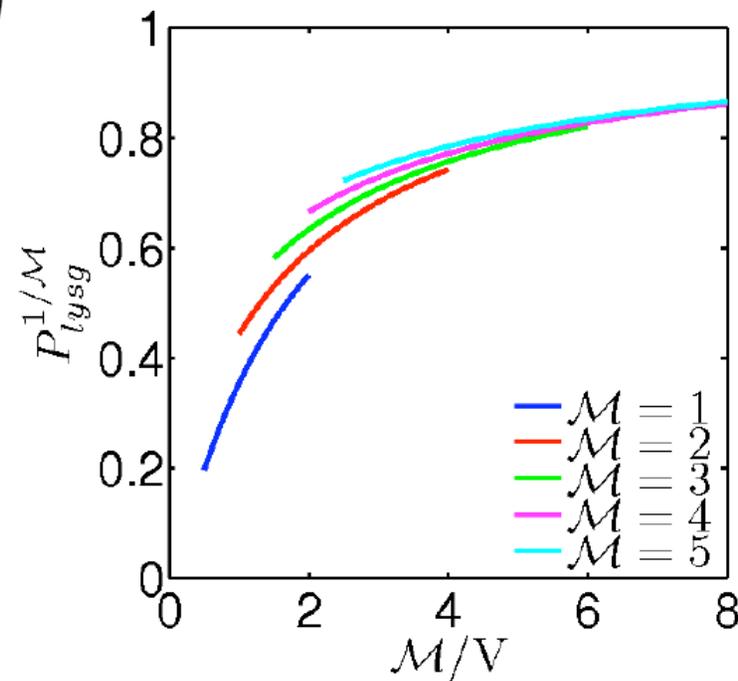
When phages are totally independent

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- Assume phages have no way of detecting other phages within a host



$$f\left(\frac{\mathcal{M}}{V}\right) \rightarrow f\left(\frac{1}{V}\right)$$

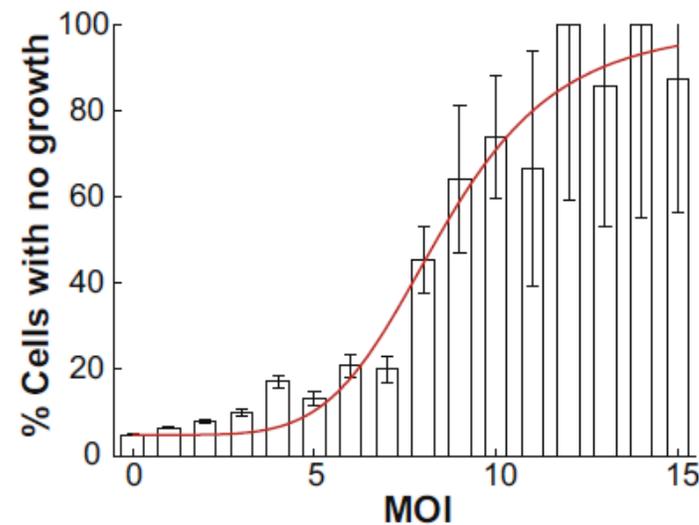
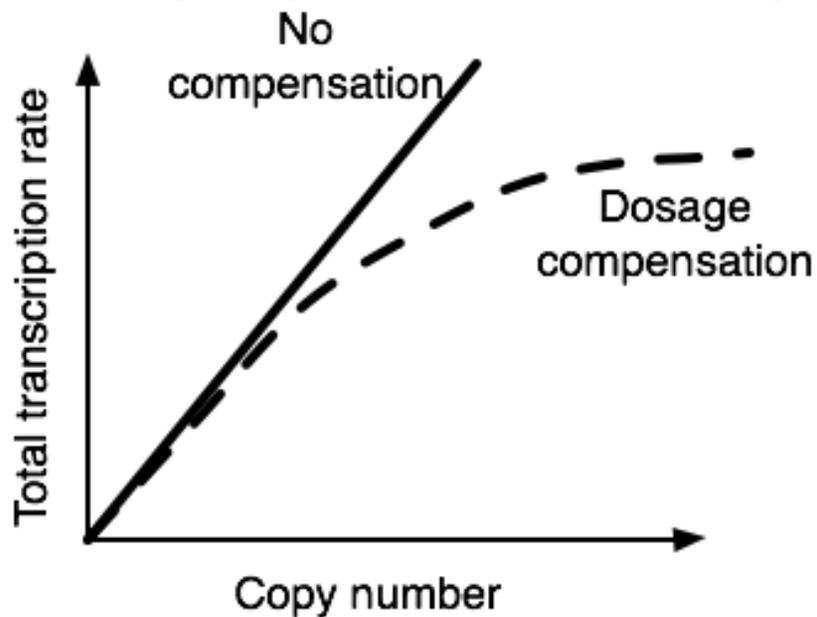




Gene dosage compensation

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- Gene expressions is not always proportional to copy number



Zeng et al (2010) Cell

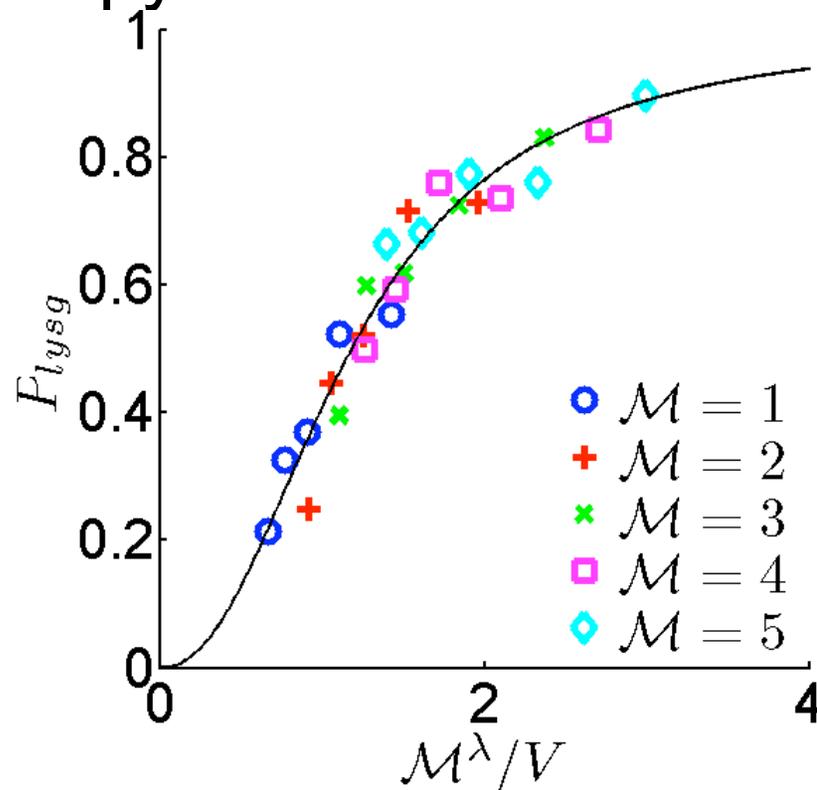
$$\text{Tot transcription} = M^\lambda \text{ transcription/copy}$$

Data can also be collapsed by partial dosage compensation



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- Effective copy number is smaller than actual copy number



Data supports $\lambda = 0.5$

Comparison of different rescaling schemes



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- Quasi-independent decisions:
 - ▣ Decision for each phage is independent
 - ▣ However, the decision rule for each phage depends on the concentration of all phages

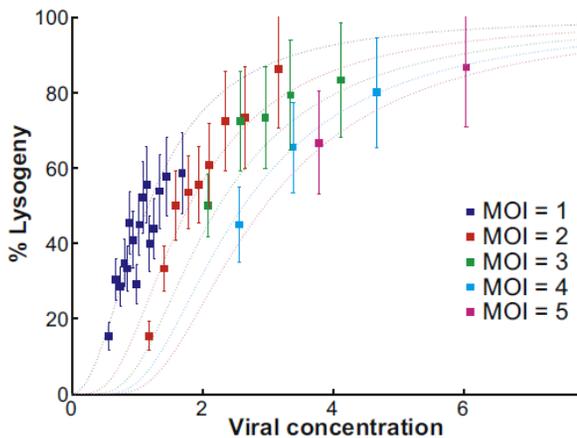
- Gene dosage compensation
 - ▣ Mechanism by which resource limitation impacts viral gene production
 - ▣ Effective number of viral genomes is predicted to be less than the actual number

Stochastic simulations support effect of dosage compensation

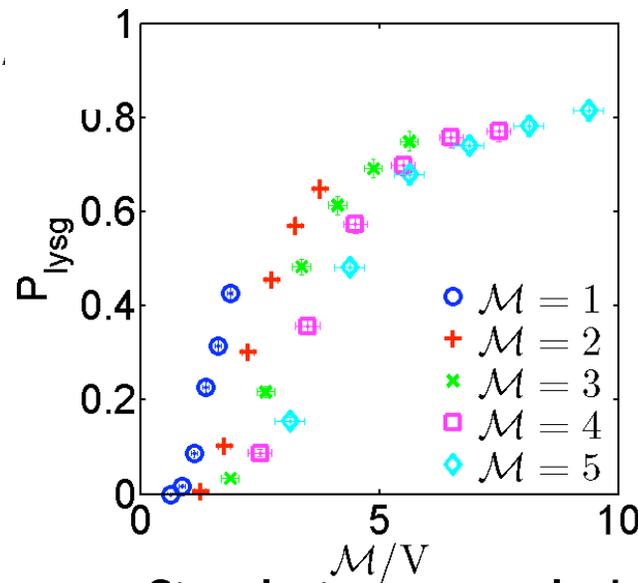


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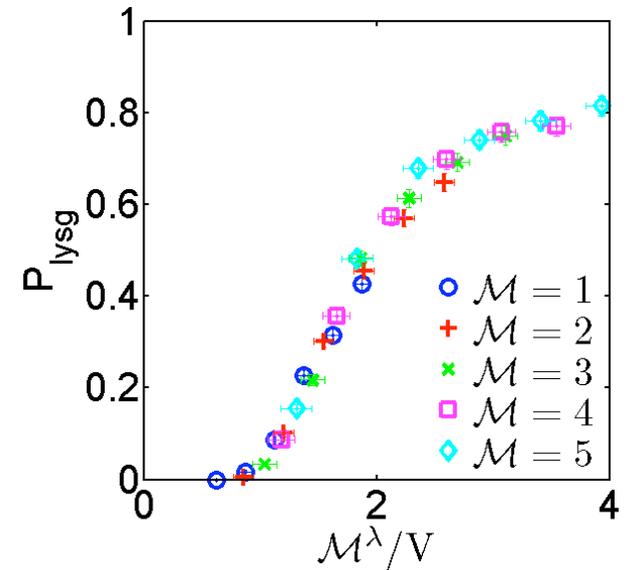
- Replace \mathcal{M} with \mathcal{M}^λ in our simulation



Data



Simulation, unscaled



Simulation, rescaled

Stochastic simulations supports partial gene dosage compensation

Conclusions

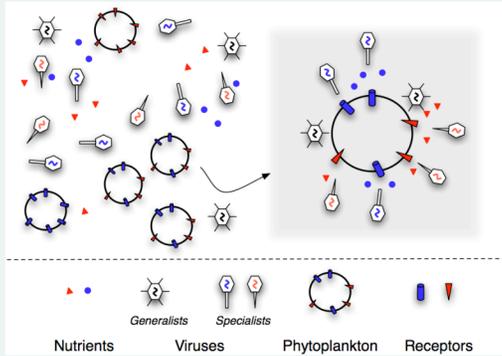


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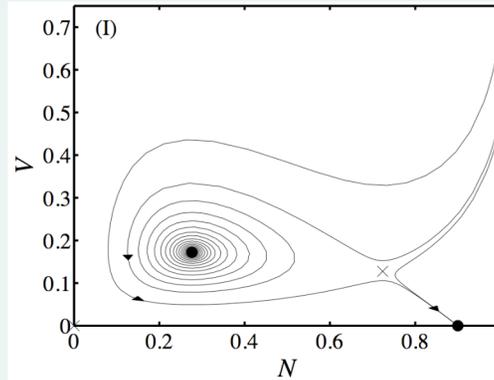
- ❑ Feedback and transient dynamics of gene regulation are sufficient for lysis and lysogeny
- ❑ Systems with qualitatively distinct steady state behaviors might lead to similar decisions if their transient dynamics are similar
- ❑ Gene dosage compensation can explain observed variation of MOI dependence
- ❑ Future work involves predicting cell fate based on partial information of gene regulatory state

Other Things We Do

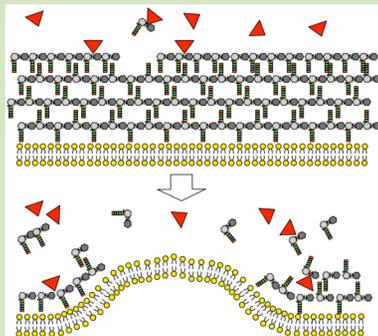
Eco-evolutionary dynamics of phages and their hosts



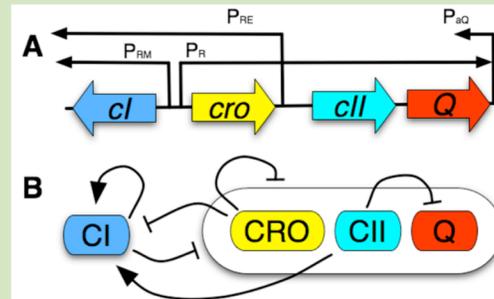
Dangerous nutrients: top-down vs. bottom up forces impact evolution of resource uptake
 Menge & Weitz (2009) JTB 257: 104



Host-state impacts phage effectiveness and subsequent host-phage dynamics
 Dushoff & Weitz (2008). Theor Ecol 1:13



Quantifying enzymatic lysis
 Mitchell et al. (2010) Physical Biology 7:046002

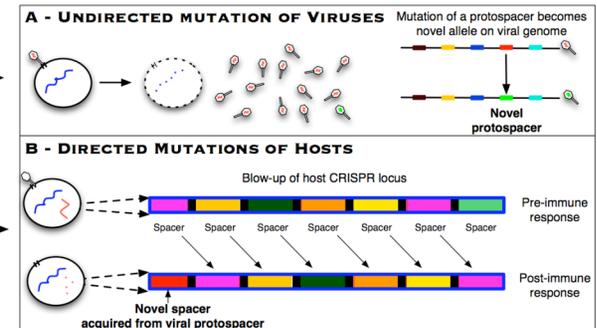


Cell fate determination by viruses
 Joh & Weitz (in press) PLoS Comp Biol

Systems biology and biophysics of phage traits

CRISPR-induced co-evolutionary dynamics

Weitz & collaborators (in prep)





Acknowledgments

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Weitz Lab

- Richard Joh
- Tae Lee
- Yuriy Mileyko (Duke)

Russell Monds, Stanford

- Selwyn Quan, Stanford
- Harold Kim, GATech
- Eberhard Voit, GATech

Ido Golding, Baylor College of Medicine

- Lanying Zeng, UIUC
- NESCENT Working Group

References

Weitz, Mileyko, Joh and Voit (2008) *Collective decision making in bacterial viruses*, **Biophys. J.**, 95:2673-2860.

Mileyko, Joh and Weitz(2008) *Small-scale copy number variation and large-scale changes in gene expression*, **PNAS**, 105:16659-16664.

Gudelj, Weitz et al (2010). *An integrative approach to understanding microbial diversity: from intracellular mechanisms to community structure*. **Ecology Letters**. 13:1073-1084.

Joh and Weitz (in press) *To lyse or not to lyse: transient-mediated stochastic fate determination in cells infected by bacteriophages*. **PLoS Computational Biology**

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Questions?



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