Bayesian inference of transcription dynamics from population snapshots of single-molecule RNA FISH in single cells

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A spatial model for induced gene expression

Let X represent an arbitrary RNA transcript of an induced gene G. Assume two promoter states (on and off)

Gene activation : $G_{off} \stackrel{k_{on}}{\rightarrow} G_{on}$

Gene inactivation : $G_{on} \stackrel{k_{off}}{\rightarrow} G_{off}$

Transcription : $G_{on} \stackrel{k_t}{\rightarrow} G_{on} + X_{\text{nuc}}$

RNA Export : $X_{\text{nuc}} \stackrel{k_{exp}}{\rightarrow} X_{\text{cyt}}$

RNA degradation : $X_{\text{cyt}} \stackrel{\gamma}{\to} \emptyset$

Raw data collected post induction can be used to infer parameters

$$\theta = (k_{on}, k_{off}, k_t, k_{exp}, \gamma)$$

Bayesian inference of model parameters

It is well-known that using just means and variances gives poor estimates of the model parameters (Munsky et al. PNAS 2018)

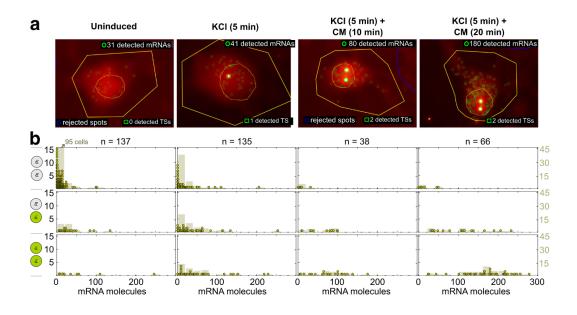
Let $\theta = (k_{on}, k_{off}, k_t, k_{exp}, \gamma)$. Using Bayes Rule:

$$P(\theta|X) = \frac{P(X|\theta)P(\theta)}{\int P(X|\theta)P(\theta)} \propto P(X|\theta)P(\theta)$$

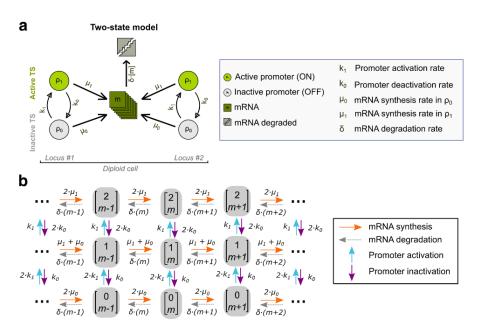
Can infer θ if we know the likelihood $P(X|\theta)$ and specify a prior $P(\theta)$

Generally we have to resort to Monte Carlo methods to find $P(X|\theta)$

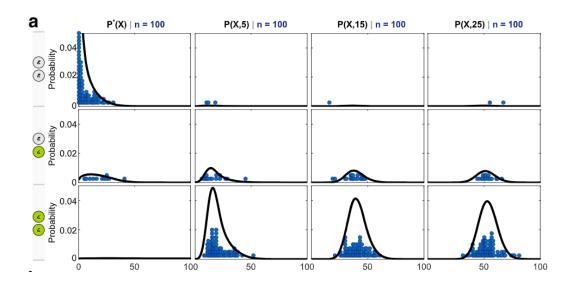
smFISH data of Npas4 mRNA in primary neurons after membrane depol.



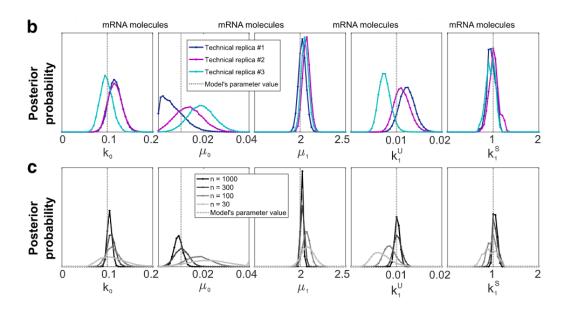
Two-state model of gene expression



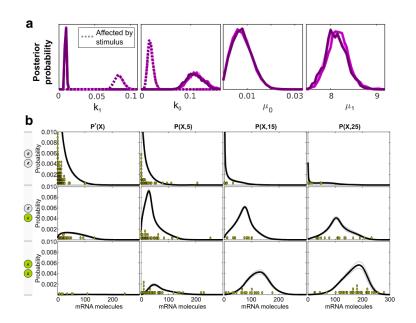
Validating BayFish on synthetic smFISH data



Validating BayFish on synthetic smFISH data



Model selection using BayFish and information criteria



Bayesian posterior distribution for (k1,k0)-stimulus model run on Npas4 data

