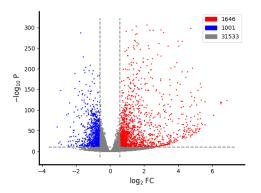
## Establishing a quantitative framework for analyzing IFN $\gamma$ induction in HeLa cells

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## Interferon- $\gamma$ induces differential gene expression in HeLa cells

Single cell transcriptome measurements of polyA mRNA for naïve HeLa cells (N=90), induced with interferon gamma (50 ng/mL) for 24h



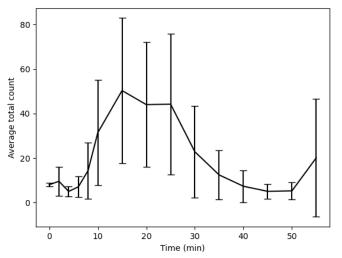
Siwek et al. Activation of Clustered IFN Target Genes Drives Cohesin-Controlled Transcriptional Memory Cell 2020

## Key questions

- lacktriangle Does IFN $\gamma$  induce transcriptional bursts in HeLa cells?
- ► Which genes?
- What are the parameters of the burst (size, frequency, etc.)?
- ▶ In general, it possible to correlate spatial patterning with transcriptional bursting, using only ensemble snapshots (FISH)?

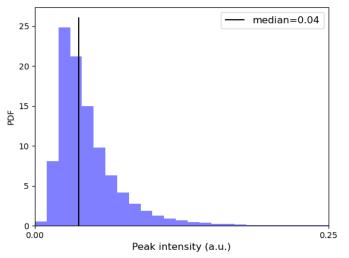
Need to establish analysis methods on a testing dataset...

## Significant variability in STL1 mRNA counts per cell at 0.4M NaCl



Error bars represent standard deviations from the mean Cells marked ON for > 3 STL1 mRNA in yeast

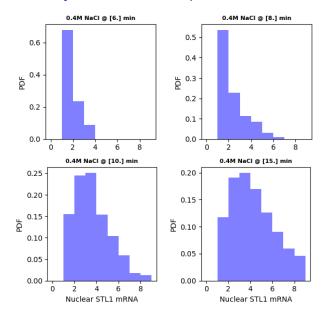
## Assessing STL1 mRNA count variability at the transcription site



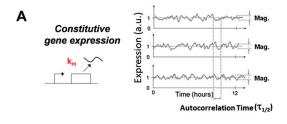
The median of the mRNA intensity distribution is used to determine the number of nascent RNA at the transcription site (TS)

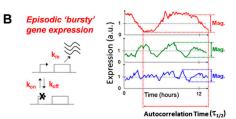
### Assessing STL1 mRNA count variability at the transcription site

- Brightest spot in the nucleus defined as putative TS
- ► TS marked ACTIVE if 1 > 2 \* med
- Nascent mRNA count is round(I/med)
- Count variability suggests asynchrony



## Gene expression is stochastic and non-constitutive





#### Single-state models

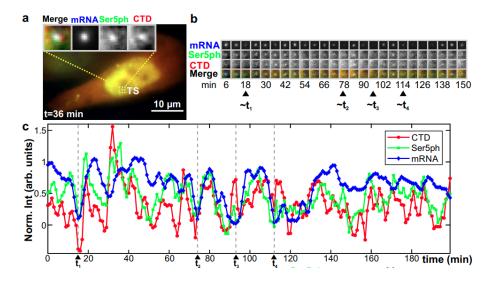
- RNAs are 'born' at a fixed rate
- RNA counts are Poisson

#### Multi-state models

- Promoter can be in multiple states (switching behavior)
- ► RNA counts are not Poissonian

Single-state models tend to underestimate variance in RNA counts

## Gene expression is stochastic and non-constitutive (live-cell MS2-MCP)



Forero-Quintero, et al. Live-cell imaging reveals the spatiotemporal organization of endogenous RNAPII phosphorylation at a single gene. Nat Commun 2021

# Ensemble averages and variances do not fully explain underlying transcription dynamics

- ► Transcription is stochastic, meaning that RNA counts can only be understood in terms of a probability distribution
- ► High variance in mRNA counts suggests more complicated underlying dynamics which are not evident in ensemble averages
- We cannot assume that cells are bursting synchronously
- Bursting phase has implications for correlating bursting with spatial organization via ensemble data (FISH)
  - ► Classification of cells based on  $P(X_{nuc}, X_{cyto}, X_{TS})$ ?
  - Can also look at the evolution of the spatial feature distributions

## A compartment model for IFN $\gamma$ induced gene expression

Let X represent an arbitrary RNA transcript of IFN $\gamma$  induced gene G. Assume two chromatin 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 :  $X_{\text{nuc}} \stackrel{k_{\text{exp}}}{\to} X_{\text{cyt}}$ 

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

Raw data collected post induction can be used to infer parameters

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

## Bayesian parameter inference using ensemble snapshots

Likelihood-based methods can infer  $\theta$  from ensemble snapshots (FISH data)

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

One way is through maximum a posteriori estimation (MAP):

$$\theta^* = \underset{\theta}{\operatorname{argmax}} P(X|\theta)$$

A more robust (but harder) way is via Bayesian inference, which lets us infer  $\theta$  from X while quantifying the uncertainty in our estimate:

$$P(\theta|\mathbf{x}) \propto P(\mathbf{x}|\theta)\pi(\theta) = \pi(\theta) \prod_t P(\mathbf{x}_t|\theta)$$

The likelihood P(X, t) is the solution to the chemical master equation at time t

## Kolmogorov's forward equation (chemical master equation)

Dynamics on biochemical reaction networks are inherently stochastic and the state space is discrete. We can only write probabilities over the state space

$$P(x_i, t) = \sum_j T_{ji}(x_i, t|x_j, t - \Delta t)P(x_j, t - \Delta t)$$

$$= \sum_k T_k(x_i, t|x_i - \nu_k, t - \Delta t)P(x_i - \nu_k, t - \Delta t)$$

where  $T_k$  is the probability of a reaction channel k firing in the interval  $(t, t + \Delta t)$ .

Taking the limit  $\Delta t \to 0$  one can derive the forward Kolmogorov equation or chemical master equation (CME)

$$\frac{dP(x,t|x_0)}{dt} = \sum_k T_k(x-\nu_k)P(x-\nu_k,t) - T_k(x)P(x,t)$$