# Some mathematical aspects of RNA velocity 

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Purpose: summary of the mathematical aspects of the paper "RNA velocity of single cells" ([1])


Some recalls

A mathematical model

RNA velocity

Estimation of parameters and prediction

Appendix

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The notion of derivatives
Let $f$ be a function and $t_{0}$ a point of its domain.

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(if this limit exists and is finite).

## Variations with respect to time

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\frac{d f}{d t}\left(t_{0}\right):=\lim _{t \rightarrow 0} \frac{\overbrace{f\left(t_{0}+t\right)-f\left(t_{0}\right)}^{t}}{t}
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v(t):=\frac{d x}{d t}(t)
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- In 3D: likewise! If $\vec{x}(t):=(x(t), y(t), z(t))$ is the position of a particle in the space, then its velocity is

$$
\vec{v}(t):=\frac{d \vec{x}}{d t}(t):=\left(\frac{d x}{d t}(t), \frac{d y}{d t}(t), \frac{d z}{d t}(t)\right) .
$$

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## RNA dynamics: the idea

In one cell, for one gene...

## Transcription

## Unspliced RNA

## DNA



## RNA dynamics: the idea

In one cell, for one gene...

## Transcription Rate $\alpha(t)$ <br> Unspliced RNA

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Degradation

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## RNA dynamics: the idea

In one cell, for one gene...


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## Transcription <br> Rate $\alpha(t)$

Unspliced RNA
DNA
Quantity $u(t)$

| $\left\{\begin{array}{l}\frac{d u}{d t}(t)=\alpha(t)-\beta(t) u(t) \\ \frac{d s}{d t}(t)=\beta(t) u(t)-\gamma(t) s(t)\end{array}\right.$ | Splicing <br> Rate $\beta(t)$ |
| :---: | :---: |
| $\emptyset<$ | Spliced RNA |
| Degradation Rate $\gamma(t)$ | Quantity $s(t)$ |

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In this context

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Our equations

$$
\left\{\begin{aligned}
\frac{d u}{d t}(t) & =\alpha(t)-\beta(t) u(t) \\
\frac{d s}{d t}(t) & =\beta(t) u(t)-\gamma(t) s(t)
\end{aligned}\right.
$$

## RNA dynamics

## Assumptions

- The rates $\alpha, \beta, \gamma$ are constant: $\alpha \geq 0, \beta>0, \gamma>0$.


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"(Linear) differential equations"

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$u_{0}>\alpha$



In all cases, $\lim _{t \rightarrow \infty} u(t)=\alpha$, i.e. $u(t) \approx \alpha$ if $t \gg 0$.

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Many graphical possibilities... But we always have

$$
\lim _{t \rightarrow \infty} s(t)=\frac{\alpha}{\gamma}
$$

i.e. $s(t) \approx \frac{\alpha}{\gamma}$ if $t \gg 0$.

## Solution of the second equation: graphical examples






## RNA dynamics: summary

There exist solutions $u, s$, depending on $u_{0}, s_{0}$ (initial conditions) and on $\alpha, \gamma$ (parameters), with

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Steady state
When $t \gg 0$, the system reaches a steady state, with

$$
u(t) \approx \alpha, \quad s(t) \approx \frac{\alpha}{\gamma}, \quad \text { and } \quad u(t) \approx \gamma s(t)
$$

## Phase portrait

Graphic "spliced vs. unspliced"



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$\beta_{j}=1$ for all $j$ : the rates of splicing are equal for all genes!

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Definition
The RNA velocity of the cell (at time $t$ ) is

$$
\frac{d \vec{s}}{d t}(t):=\left(\frac{d s_{1}}{d t}(t), \ldots, \frac{d s_{p}}{d t}(t)\right)
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## Representation: an unreal world...

- A cell with 2 genes...
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"Physical velocity" in RNA's space!


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- Principle component analysis: quite natural, projection on P.C.;
- t-SNE? Possible, but more tricky...


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Example: Schwann cell precursors (coming from [1])


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## Estimation of $\gamma$

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## Assumptions

- The sample of cells is sufficiently large to cover all the "RNA cycle" (from beginning of production to steady state).
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$\sim$ Estimation of $\gamma$ with phase portraits...

Theoritical estimation of $\gamma$


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$u=\gamma s$
- 400 cells, uniformly generated in time.

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Here, estimation of $\gamma$ (slope): 0.73493

## Difficulties of estimation for $\gamma \ldots$

Assumption 1 not respected...


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Corrections?
Estimation on very correlated genes, filtering some cells...

## Multiple splicing

- In [1], $\pm 89 \%$ of studied genes showed a unique degradation rate $\gamma \ldots$


## Multiple splicing

- In [1], $\pm 89 \%$ of studied genes showed a unique degradation rate $\gamma \ldots$ but $11 \%$ showed several degradation rates!
- Example from [1]:

- Then the model fails...


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According to [1], it is very difficult to estimate $\alpha \ldots$... Two approximations are considered:

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- Model I: $v:=\frac{d s}{d t}$ is assumed to be constant; then,

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s(t)=v t+s_{0}
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$$
\text { with } v:=u_{0}-\gamma s_{0} .
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with $v:=u_{0}-\gamma s_{0}$.

- Model II: $u$ is assumed to be constant; then,

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s(t)=\frac{u_{0}}{\gamma}+\left(s_{0}-\frac{u_{0}}{\gamma}\right) e^{-\gamma t} .
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These two models are correct in the short term; they have to be used "step by step" to predict the future (Markov process).

Thank you for your attention!

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## And if the parameters are non-constant?

Much more complex...
Example
Assume that $\alpha(t)=1-\cos (t), \beta=1$, and $\gamma>0$ is constant.


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RNA equations

$$
\left\{\begin{aligned}
\frac{d u}{d t}(t) & =[1-\cos (t)]-u(t) \\
\frac{d s}{d t}(t) & =u(t)-\gamma s(t)
\end{aligned}\right.
$$

## Solutions

Unspliced RNA

$$
\begin{array}{cc}
u(t)=1-\frac{1}{2}(\cos (t)+\sin (t))+\left(u_{0}-\frac{1}{2}\right) e^{-t} . \\
u_{0}=0 & u_{0}=3
\end{array}
$$




## Solutions

Spliced RNA
If $\gamma \neq 1$,

$$
\begin{aligned}
s(t) & =\frac{1}{\gamma}-\frac{1}{2\left(1+\gamma^{2}\right)}((\gamma-1) \cos (t)+(\gamma+1) \sin (t)) \\
& +\frac{u_{0}-1 / 2}{\gamma-1} e^{-t}+\left(s_{0}-\frac{1}{\gamma}+\frac{1 / 2-u_{0}}{\gamma-1}+\frac{\gamma-1}{2\left(1+\gamma^{2}\right)}\right) e^{-\gamma t}
\end{aligned}
$$

and, if $\gamma=1$,

$$
s(t)=1-\frac{1}{2} \sin (t)+\left(\left(u_{0}-\frac{1}{2}\right) t+s 0-1\right) e^{-t} .
$$

## Solutions




$u_{0}=20, s_{0}=5, \gamma=1$


## Phase portraits



$$
u_{0}=1, s_{0}=2, \gamma=2.5
$$


$u_{0}=7, s_{0}=5, \gamma=0.2$

$u_{0}=20, s_{0}=5, \gamma=1$


## References I

R. La Manno et al. RNA velocity of single cells. Nature, 560:494-516, 2018.

