

RNA Velocity of Single Cells

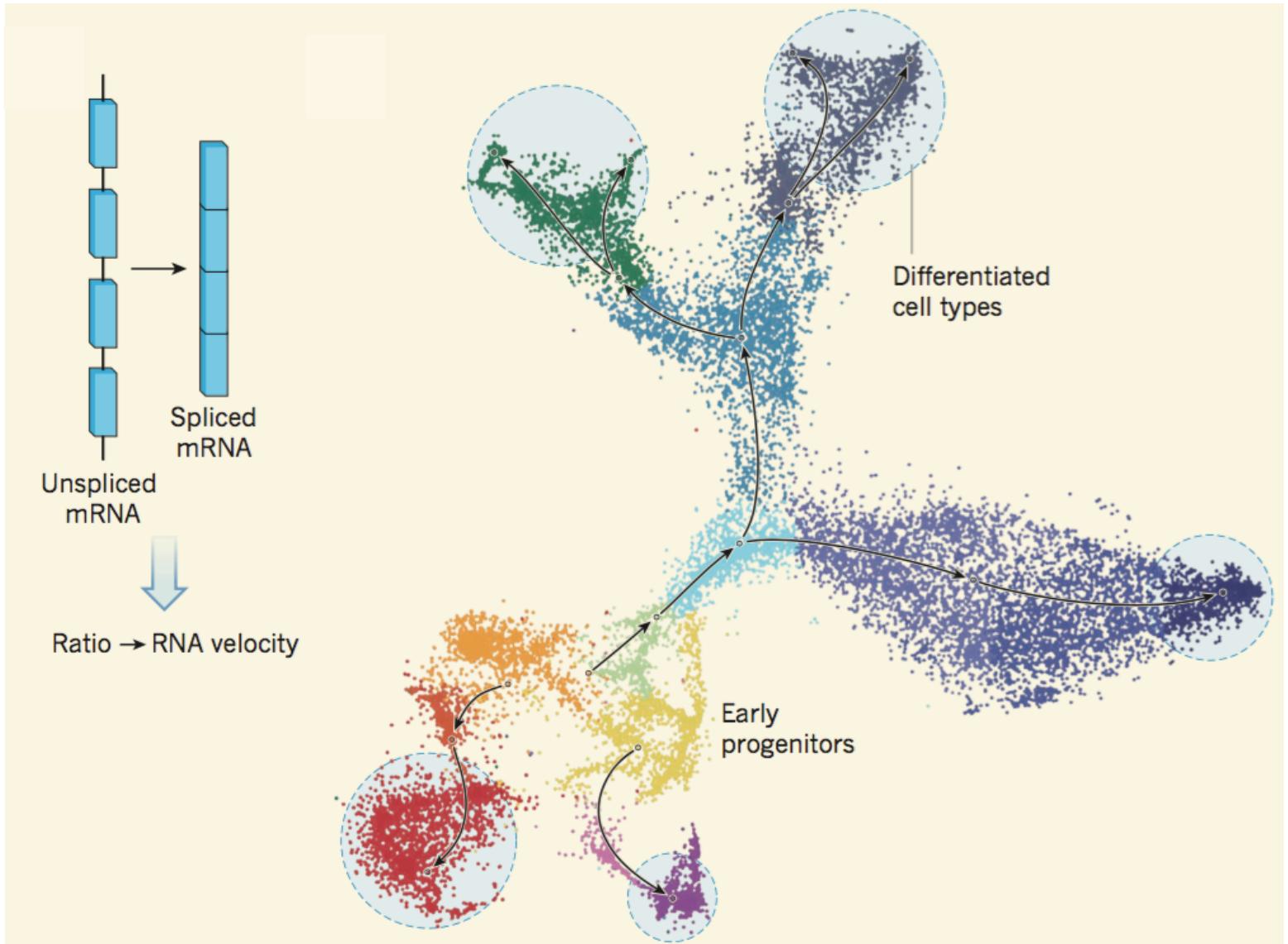
Min Dai

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daimin@zju.edu.cn

Outline

- Description
- Estimation
- Extrapolation
- Visualization
- Application



New Results

RNA velocity in single cells

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LETTER

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RNA velocity of single cells

Gioele La Manno^{1,2}, Ruslan Soldatov³, Amit Zeisel^{1,2}, Emelie Braun^{1,2}, Hannah Hochgerner^{1,2}, Viktor Petukhov^{3,4}, Katja Lidschreiber⁵, Maria E. Kastriti⁶, Peter Lönnerberg^{1,2}, Alessandro Furlan¹, Jean Fan³, Lars E. Borm^{1,2}, Zehua Liu³, David van Bruggen¹, Jimin Guo³, Xiaoling He⁷, Roger Barker⁷, Erik Sundström⁸, Gonçalo Castelo-Branco¹, Patrick Cramer^{5,9}, Igor Adameyko⁶, Sten Linnarsson^{1,2*} & Peter V. Kharchenko^{3,10*}

Peter Kharchenko



Making sense of genomics data!

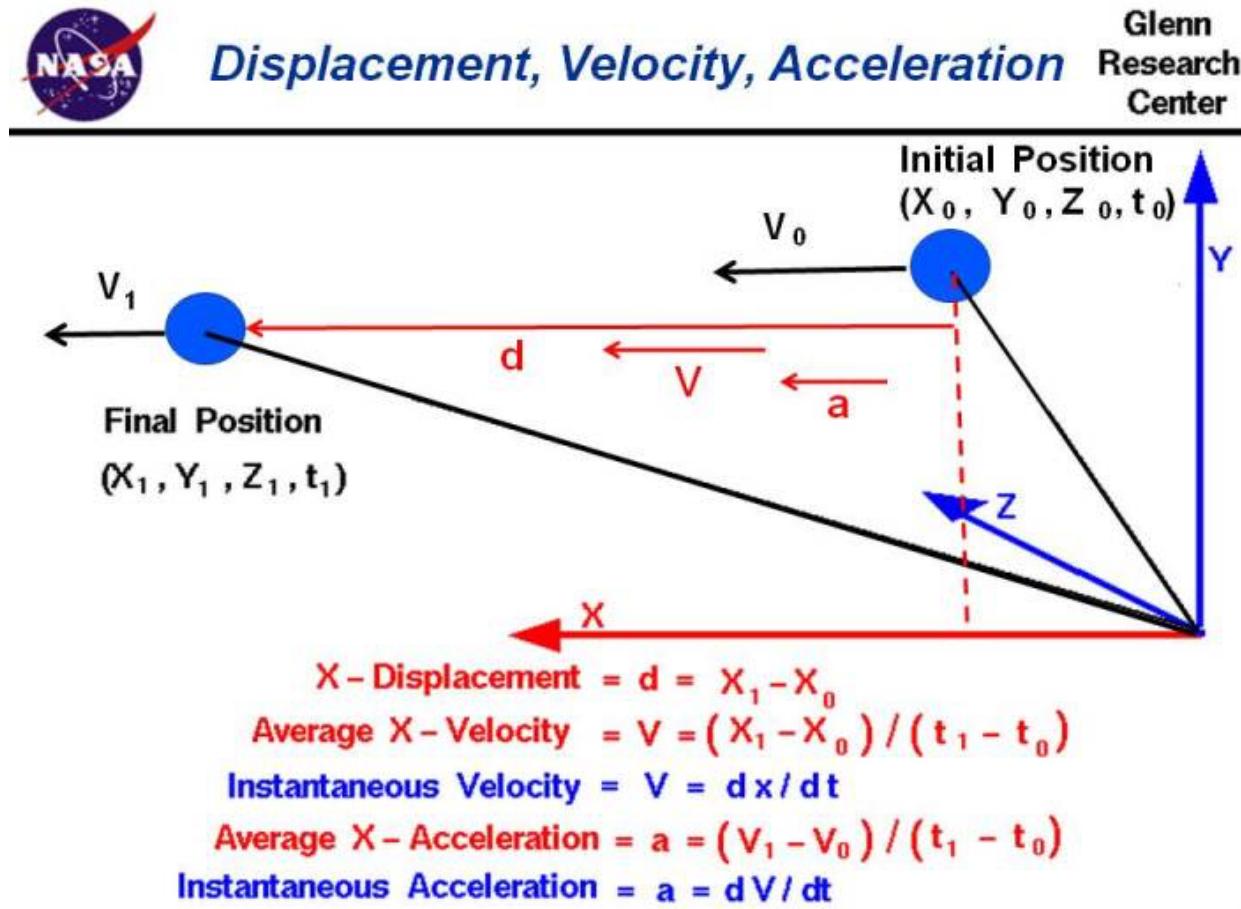
- Department of Biomedical Informatics
- Harvard Medical School
- PhD in Biophysics at Harvard University (studying gene regulation and metabolic networks under the advisement of George Church)

Research interest:

- Intratumoral heterogeneity in different cancer types
- Statistical modeling of the biological tissue from single-cell measurements
- Automating and scaling up key functional genomics assays using microfluidics

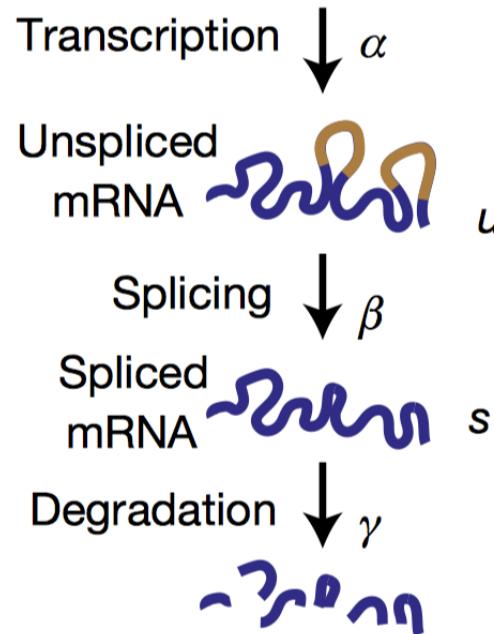
What is velocity?

- Velocity: a vector quantity that designates how fast and in what direction a point is moving
- Can we predict future states of a point with estimated velocity?

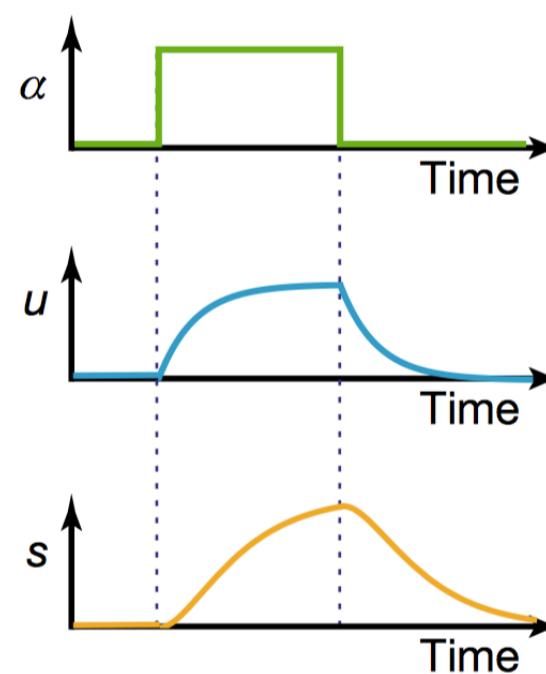


Theoretical description of RNA velocity

- The rate equations for a single gene describes how the expected number of unspliced mRNA molecules u , and spliced molecules s , evolve over time
- $\alpha(t)$ is the time-dependent rate of transcription, $\beta(t)$ is the rate of splicing, $\gamma(t)$ is the rate of degradation



The transcriptional dynamics



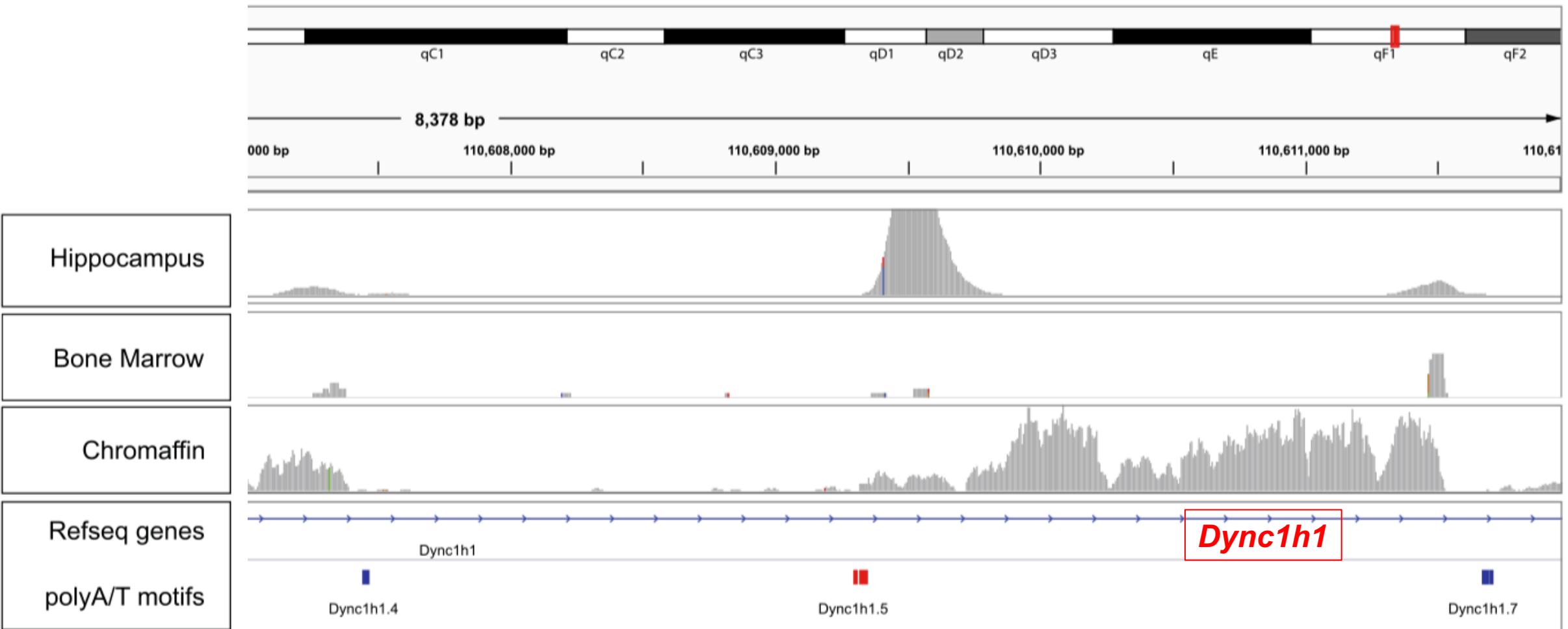
$$\frac{du}{dt} = \alpha(t) - \beta(t)u(t)$$

$$\frac{ds}{dt} = \beta(t)u(t) - \gamma(t)s(t)$$

The rate equations for a single gene

Most of the intronic reads arise due to internal priming from stable positions

- 15–25% of reads contained unspliced intronic sequences
- Track: 10x Chromium (top), inDrop (the second), Smart-seq2 (the third)



Simplify the model with assumptions

- Under an assumption of constant (time-independent) rates $\alpha(t) = \alpha$, $\gamma(t) = \gamma$, and setting $\beta(t) = 1$, the rate equations can be simplified
- The solution can be used to extrapolate mRNA abundance s to a future timepoint t_1

$$\frac{du}{dt} = \alpha(t) - \beta(t)u(t)$$

$$\frac{ds}{dt} = \beta(t)u(t) - \gamma(t)s(t)$$

$$u(t) = \alpha(1 - e^{-t}) + u_0 e^{-t}$$

$$\frac{du}{dt} = \alpha - u(t)$$

$$\frac{ds}{dt} = u(t) - \gamma s(t)$$

$$s(t) = \frac{e^{-t(1+\gamma)} [e^{t(1+\gamma)} \alpha(\gamma - 1) + e^{t\gamma} (u_0 - \alpha)\gamma + e^t (\alpha - \gamma(s_0 + u_0 + s_0\gamma))]}{\gamma(\gamma - 1)}$$

(where $u(0) = u_0$ and $s(0) = s_0$ are initial conditions)

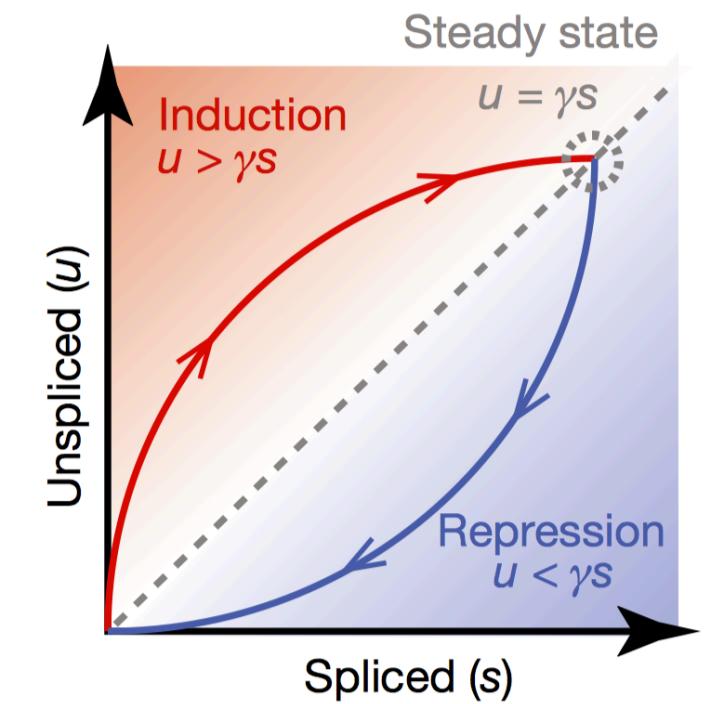
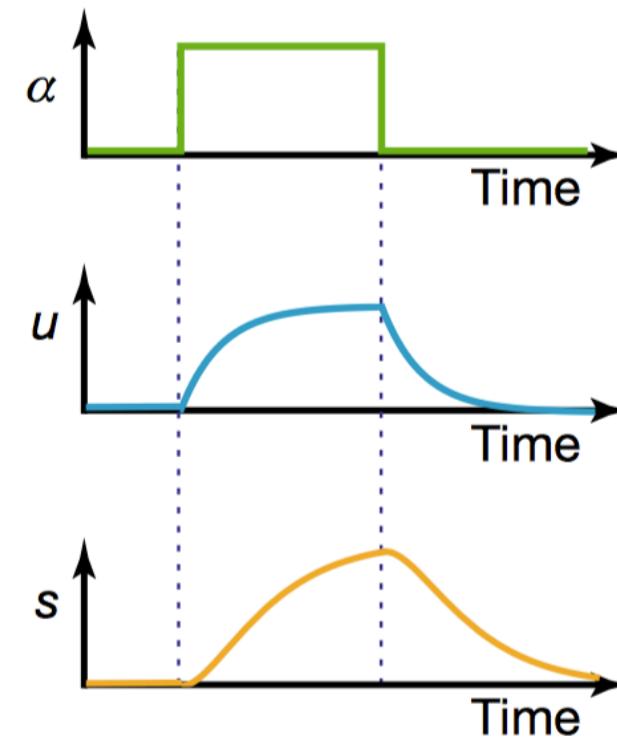
Estimate γ with the steady-state assumption

- The normalized degradation rate γ varies among genes and needs to be estimated in a gene-specific manner
- In steady-state populations, where $ds/dt = 0$, γ of a given gene can be determined as the ratio of unspliced to spliced mRNA molecules
- The equilibrium slope γ combines degradation and splicing rates, capturing gene-specific regulatory properties, the ratio of intronic and exonic lengths, and the number of internal priming sites

$$\frac{du}{dt} = \alpha - u(t), \frac{ds}{dt} = u(t) - \gamma s(t)$$

\downarrow

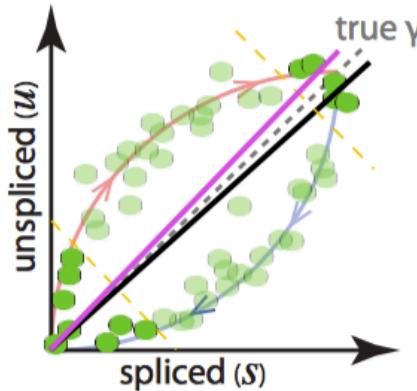
$$\frac{ds}{dt} = 0 \text{ (steady state)}$$
$$\gamma = \frac{u}{s}, \alpha = u$$



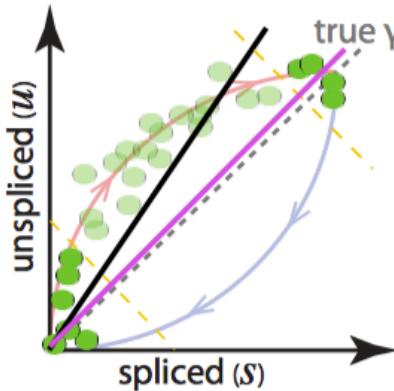
Estimate γ with the steady-state assumption

- Use a least squares fit of $u \sim \gamma * s$ to estimate γ for each gene
 - u and s are the size-normalized unspliced and spliced abundances observed for given gene across the cells
- An offset can optionally be included (baseline intronic counts that might be driven by unannotated transcripts)

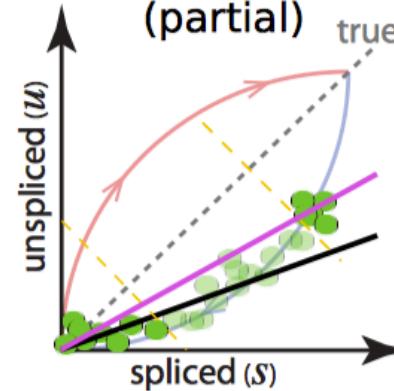
a full observation



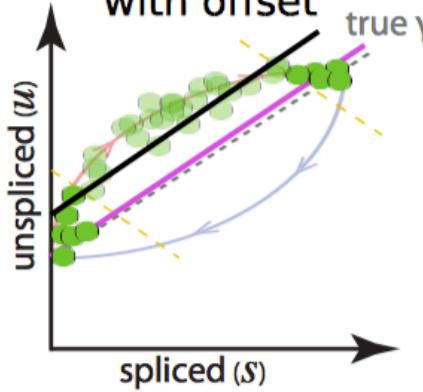
b upregulation



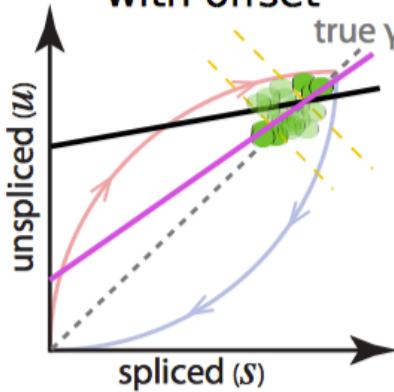
c downregulation (partial)



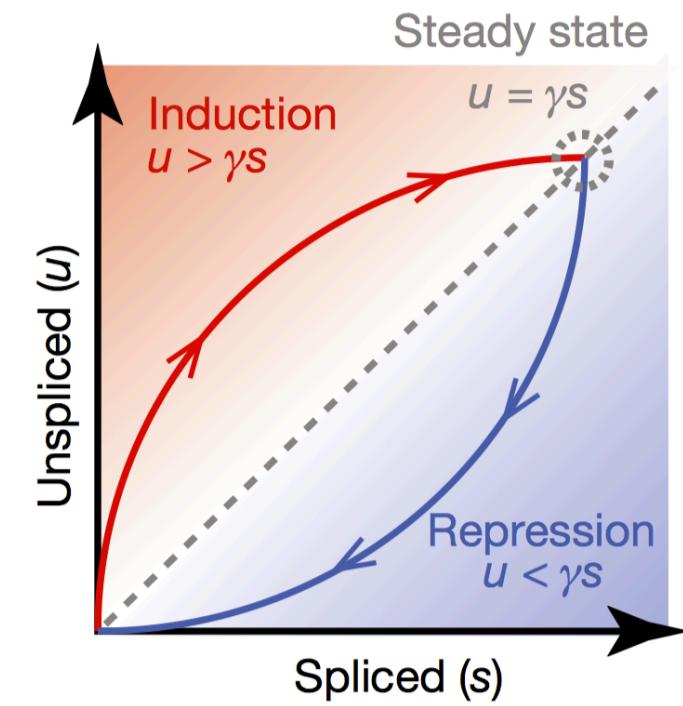
d upregulation with offset



e steady state with offset



- extreme quantile cell
- other cell
- - true slope
- regular fit
- quantile fit



Estimate $s(t)$ with two alternative assumptions

Model I. Constant velocity assumption

- The rate of change of the spliced molecules remains constant, i.e. that $\frac{ds}{dt} = v$ is constant

$$s(t) = s_0 + vt$$

- This assumption works well in practice as long as the time step is short

Model II. Constant unspliced molecules assumption

- The number of unspliced molecules stays constant, i.e. that $u(t) = u_0$. This reduces the problem to a single rate equation:

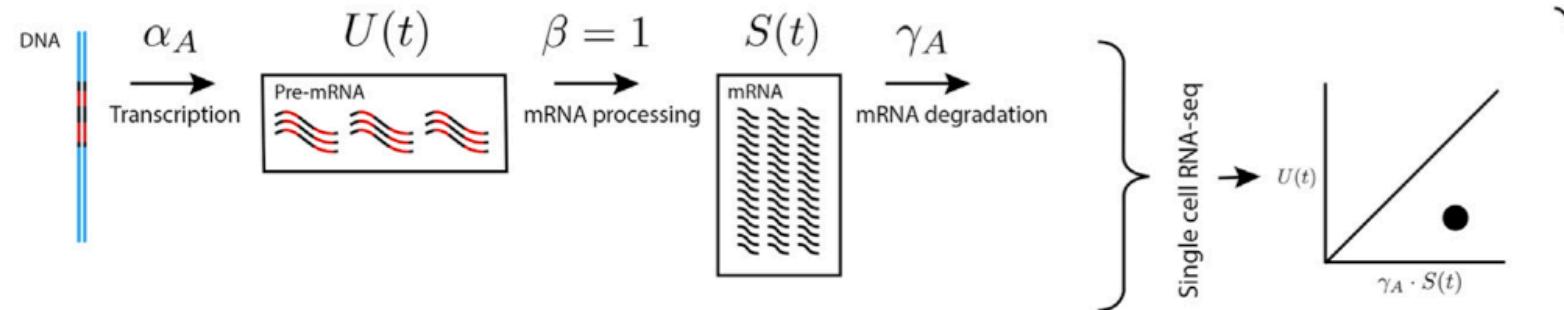
$$\frac{ds}{dt} = u_0 - \gamma s(t)$$

- The solution then becomes:

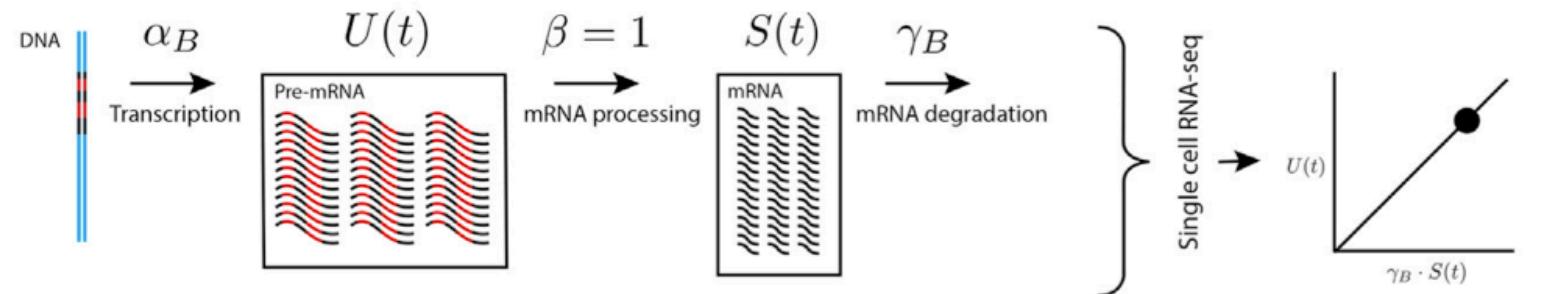
$$s(t) = s_0 e^{-\gamma t} + \frac{u_0}{\gamma} (1 - e^{-\gamma t})$$

Illustration of the relation between pre-mRNA and mRNA in a single cell

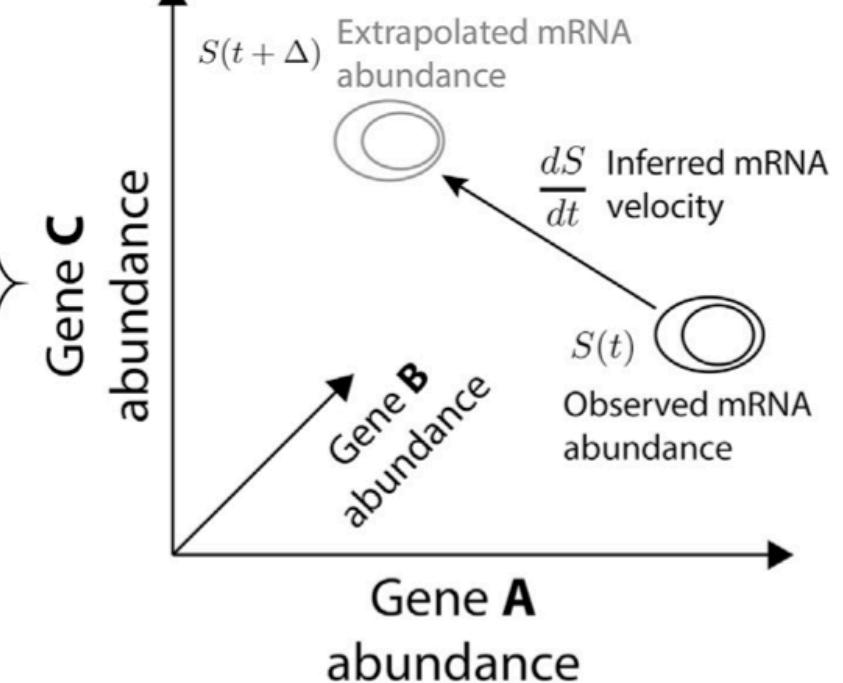
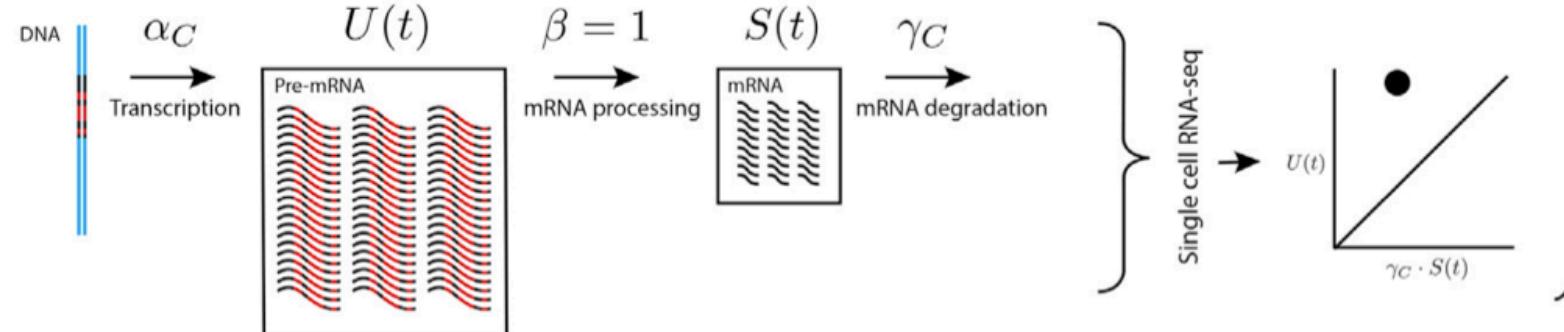
Gene **A** Downregulation, pre-mRNA pool refills slower than mRNA degradation.



Gene **B** Steady, pre-mRNA pool keeps up with mRNA degradation.

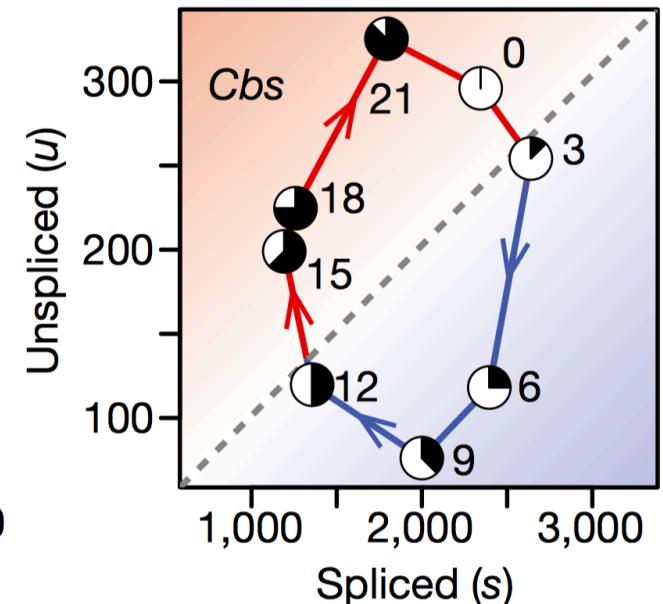
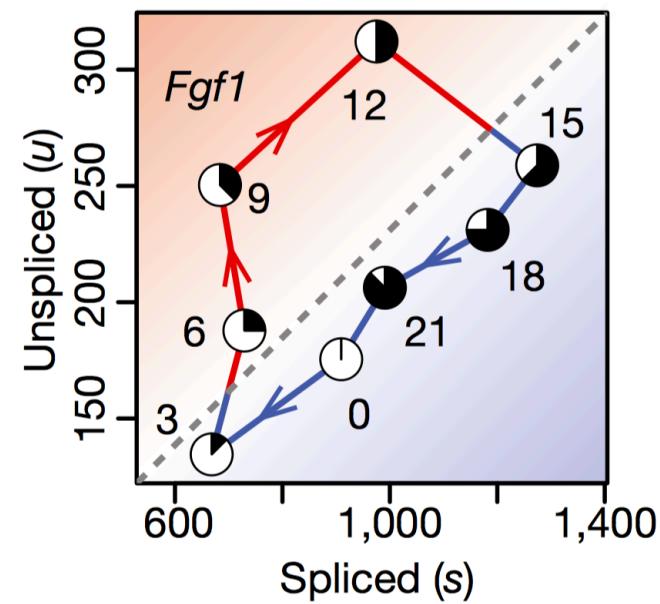
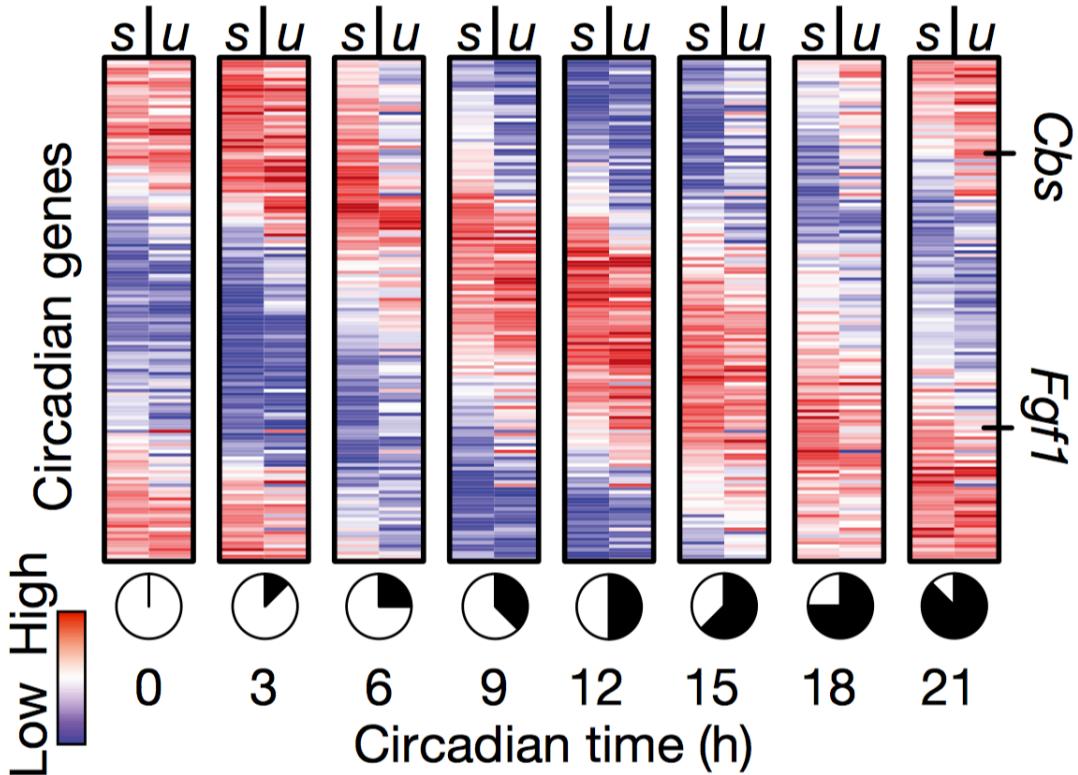


Gene **C** Upregulation, pre-mRNA pool grows faster than mRNA degradation.



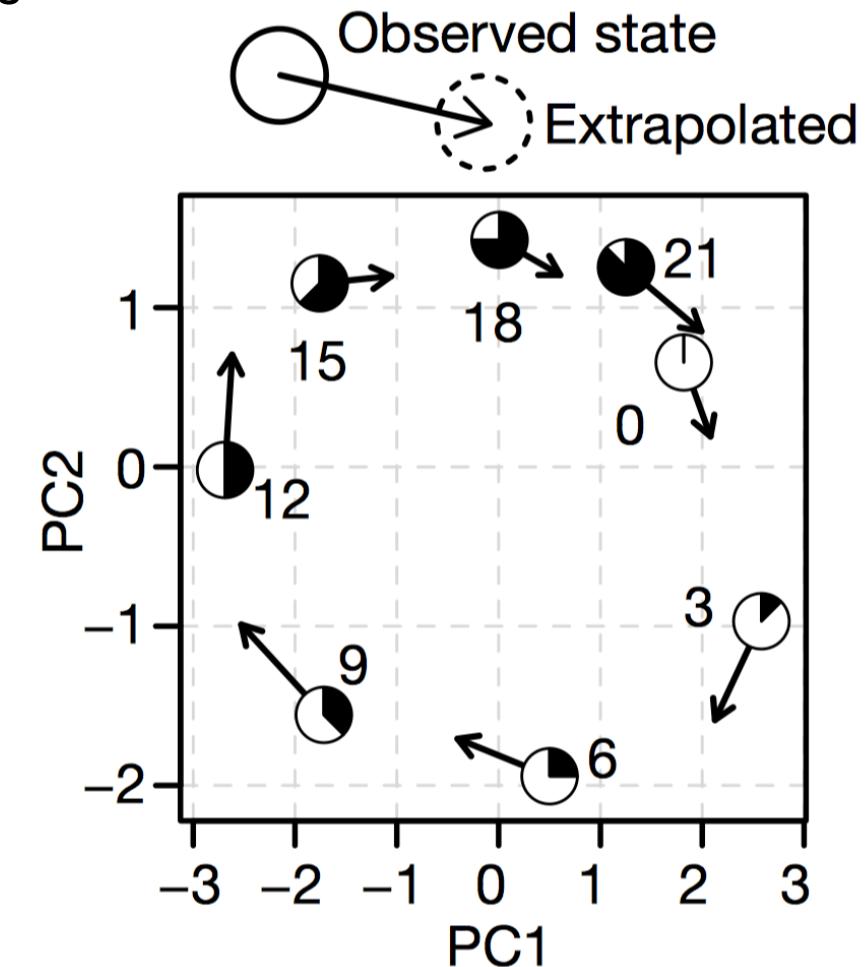
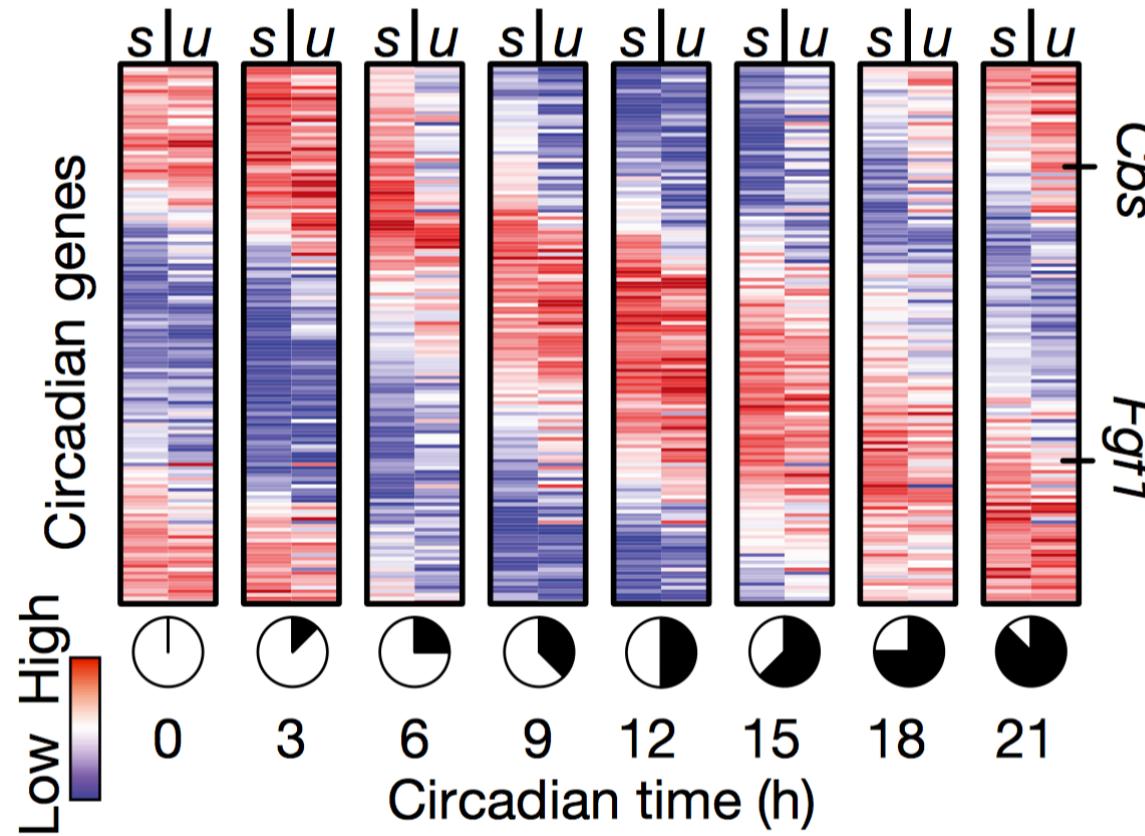
Abundance of spliced (s) and unspliced (u) mRNAs for circadian-associated genes

- A time course of bulk RNA-seq measurements of the circadian cycle in the mouse liver
- The unspliced mRNAs are predictive of spliced mRNA at the next time point
- The dashed diagonal line shows the steady-state relationship, as predicted by γ fit



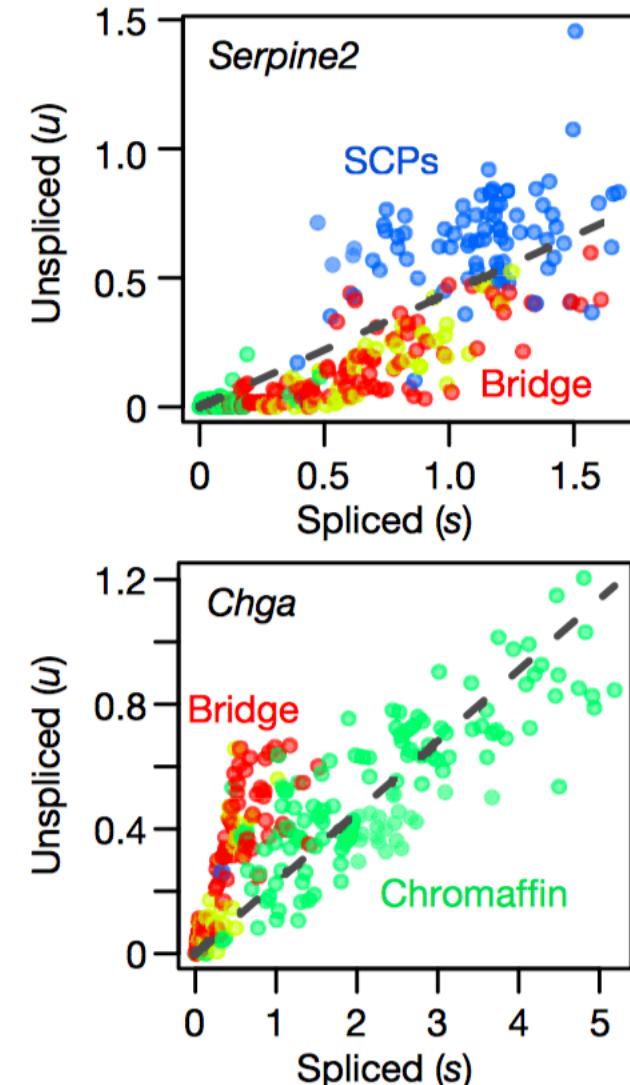
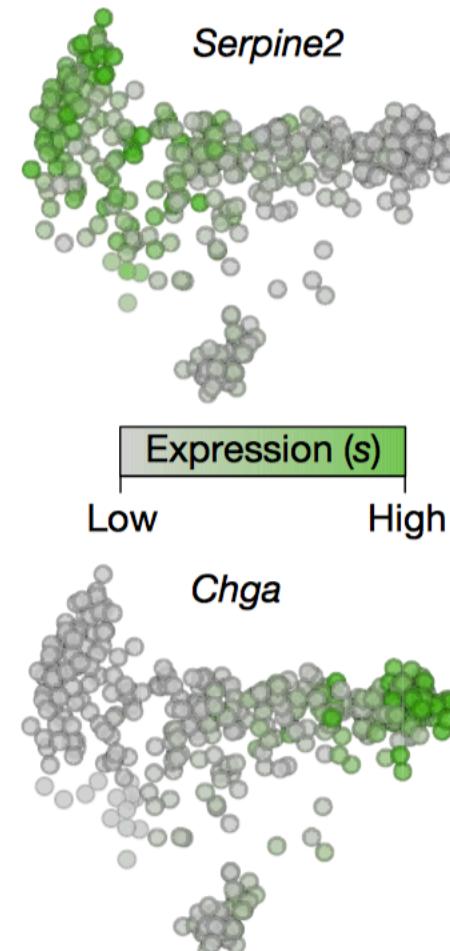
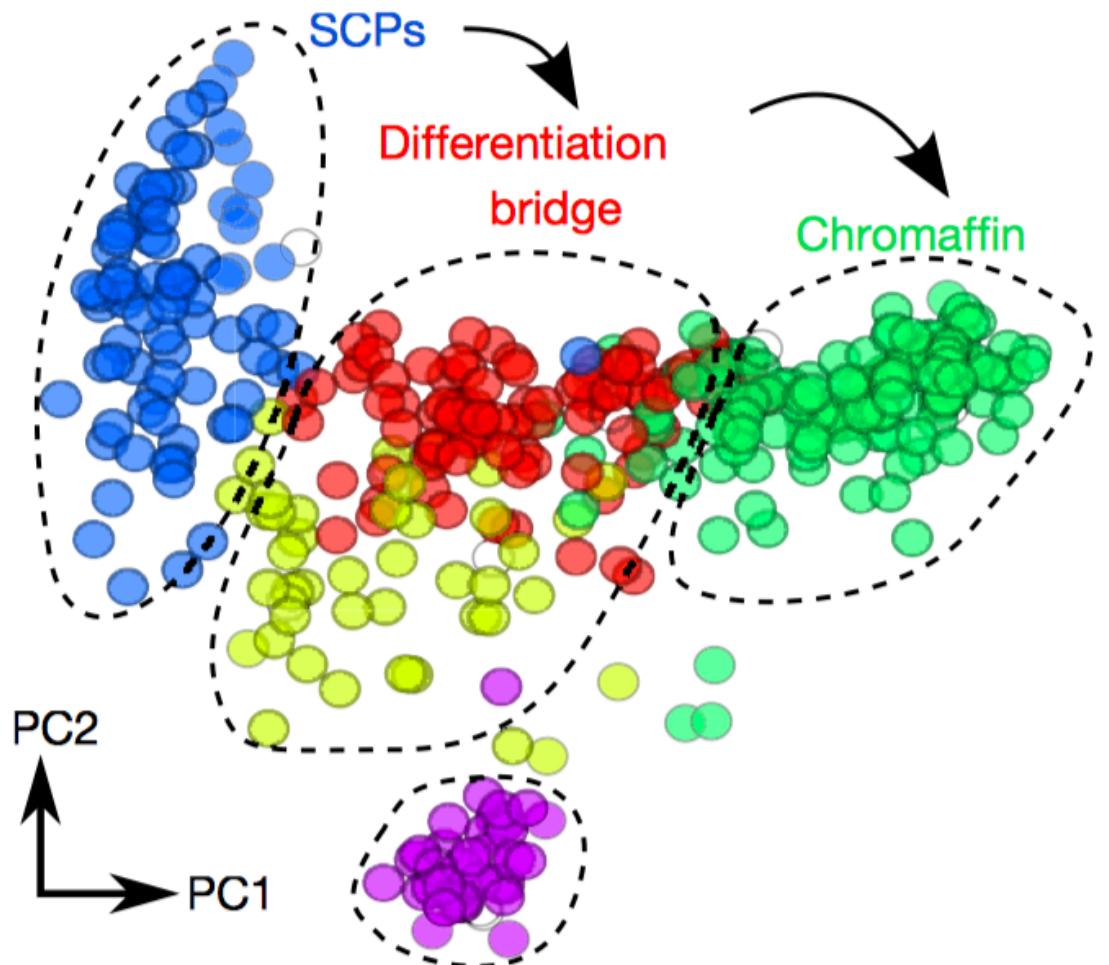
Balance between unspliced and spliced mRNAs is predictive of cellular state progression

- Assuming gene independence, the overall RNA velocity of the cell is a multidimensional vector comprised of the individual gene velocities



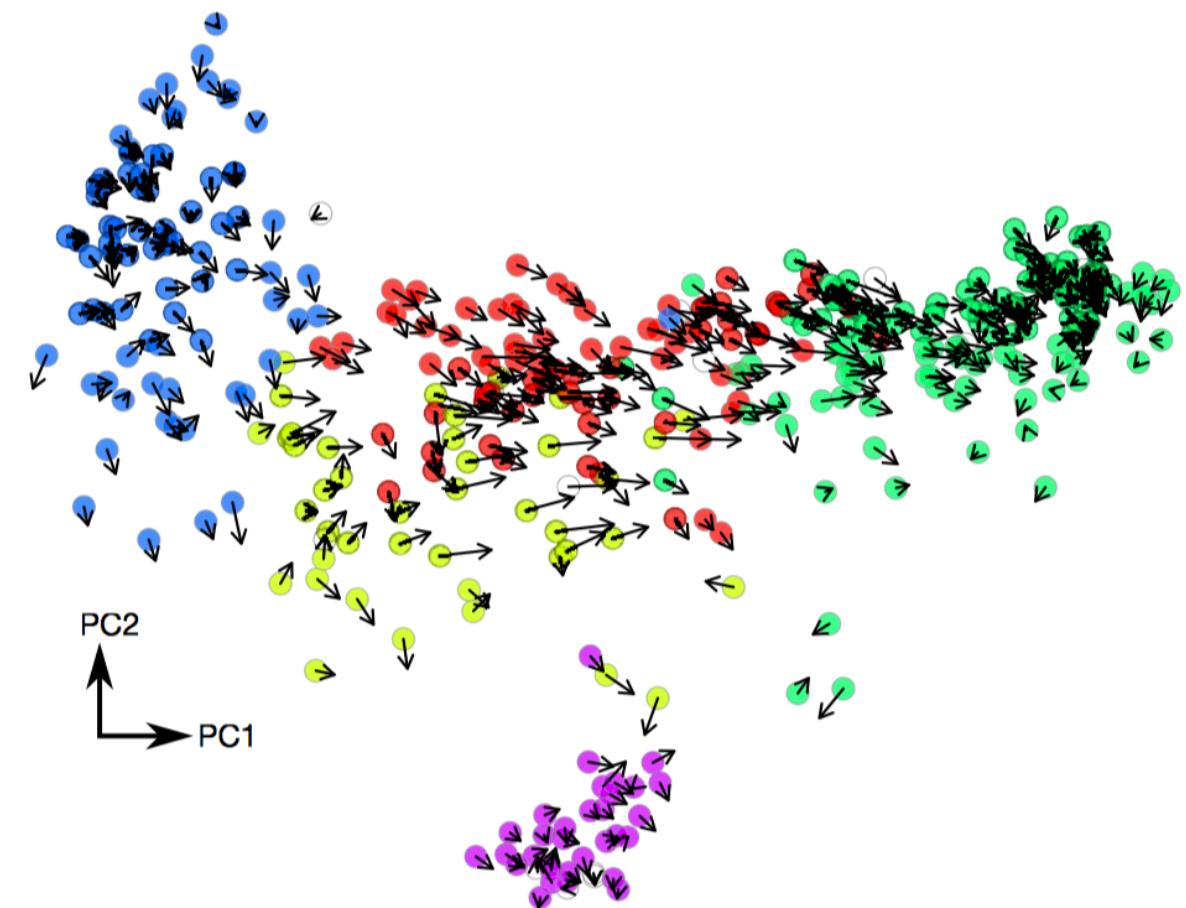
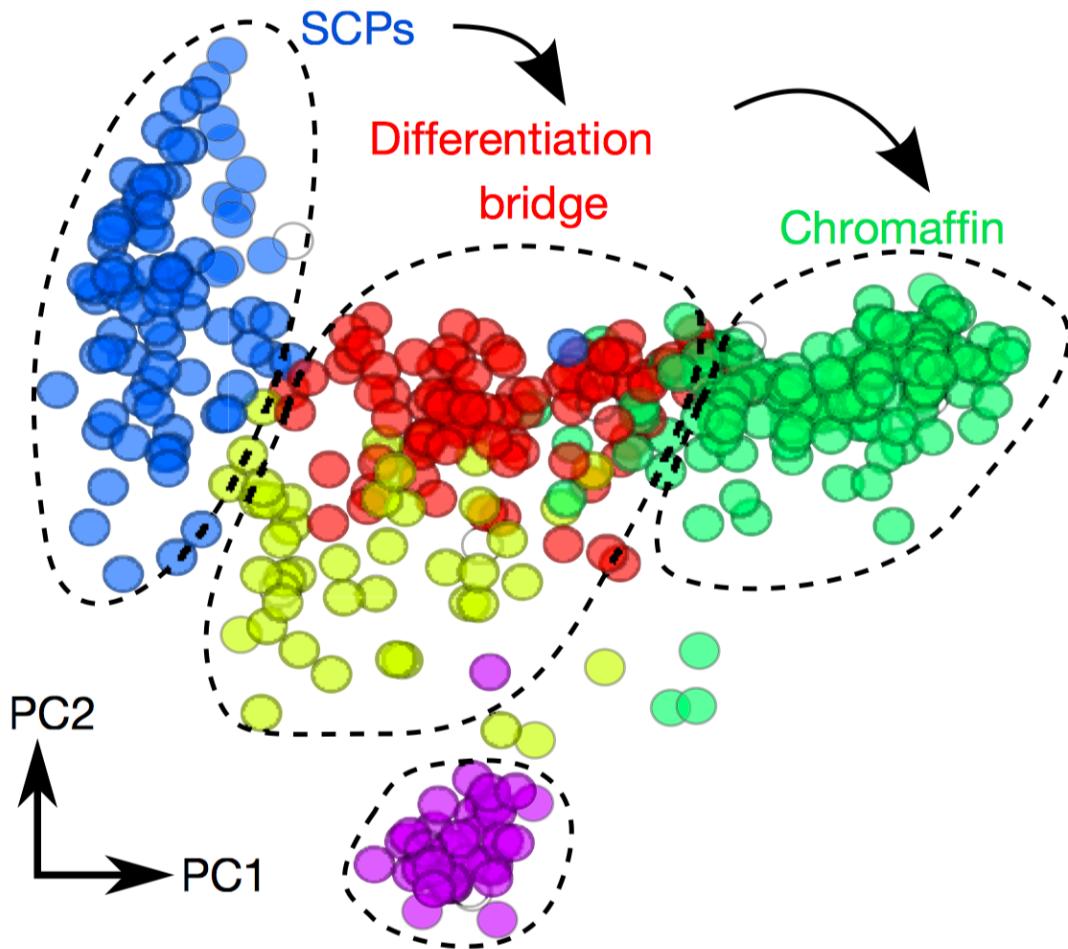
Major subpopulations of Schwann cell precursors (SCPs) differentiate into chromaffin cells

- Single-cell mRNA-seq data of mouse chromaffin cells (SMART-seq2), E12.5 mice (385 cells)
- The direction of differentiation can be validated by lineage tracing



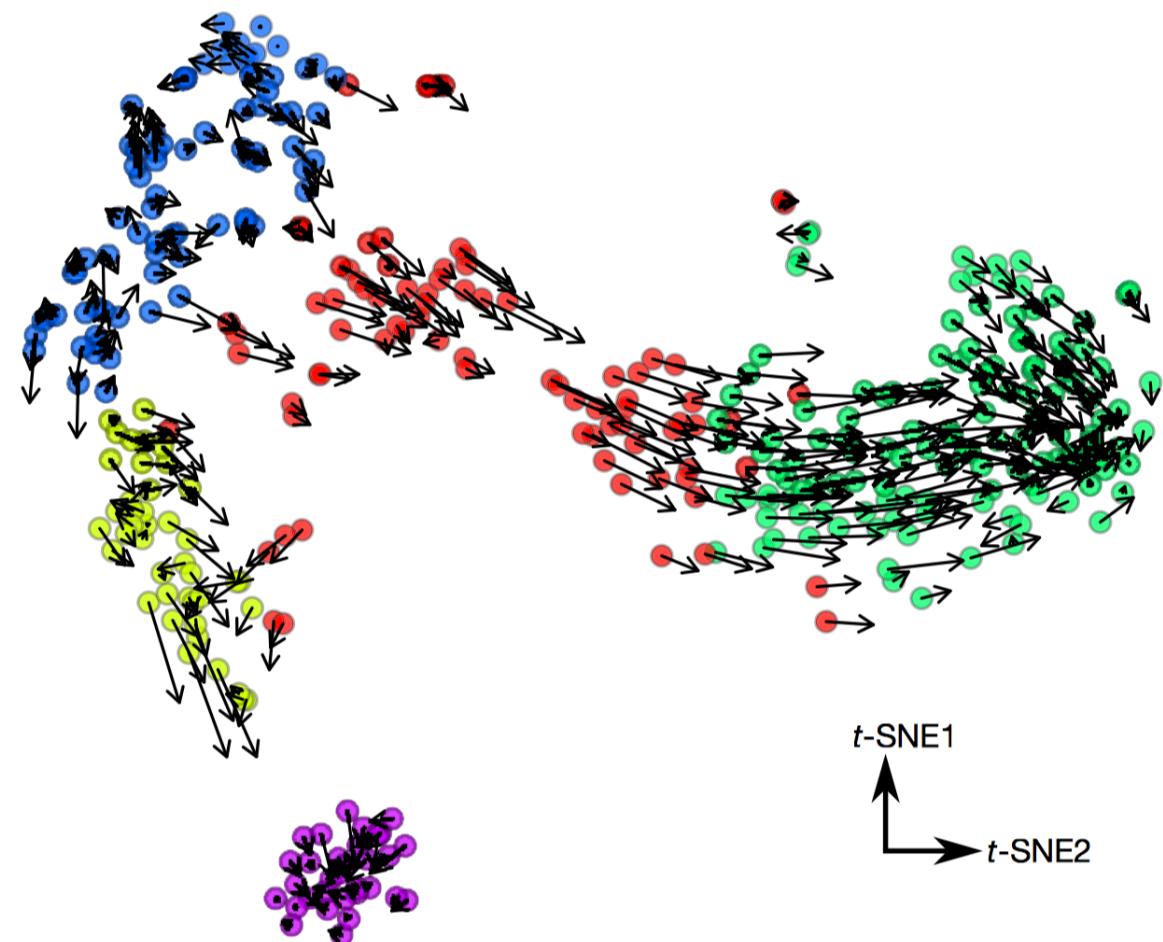
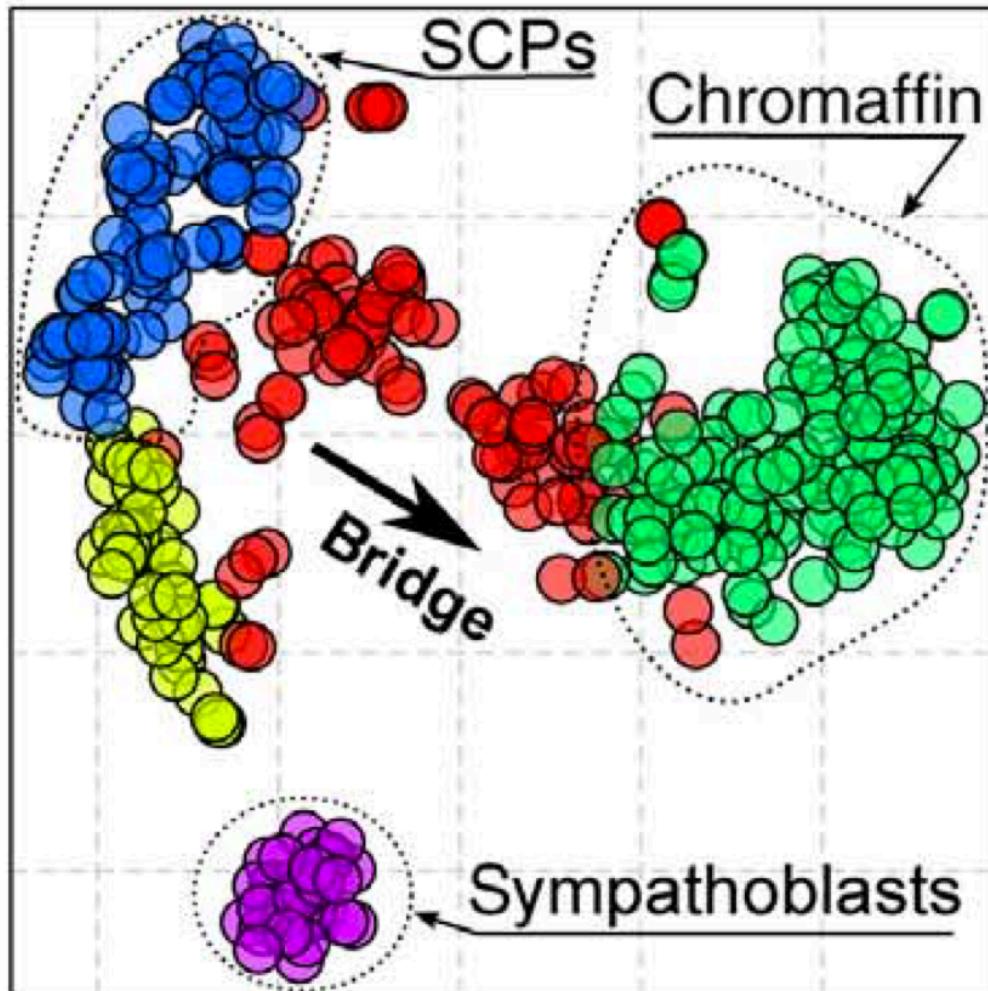
RNA velocity recapitulates dynamics of chromaffin cell differentiation

- The observed and extrapolated cell states can be jointly embedded in a common low-dimensional space



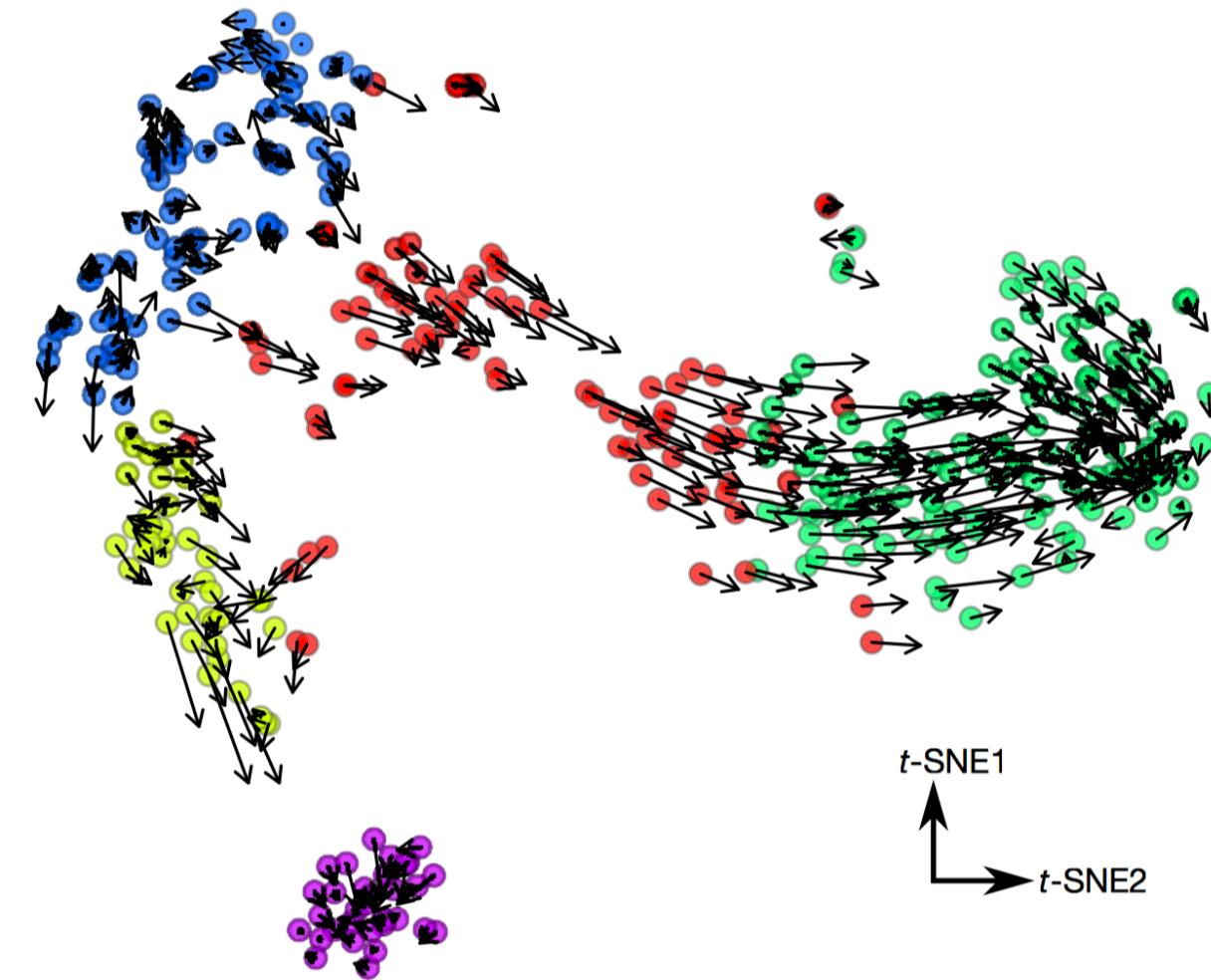
Velocities can be projected onto existing low-dimensional representations (e.g. t-SNE)

- Based the similarity of the extrapolated state to other cells in the local neighbourhood

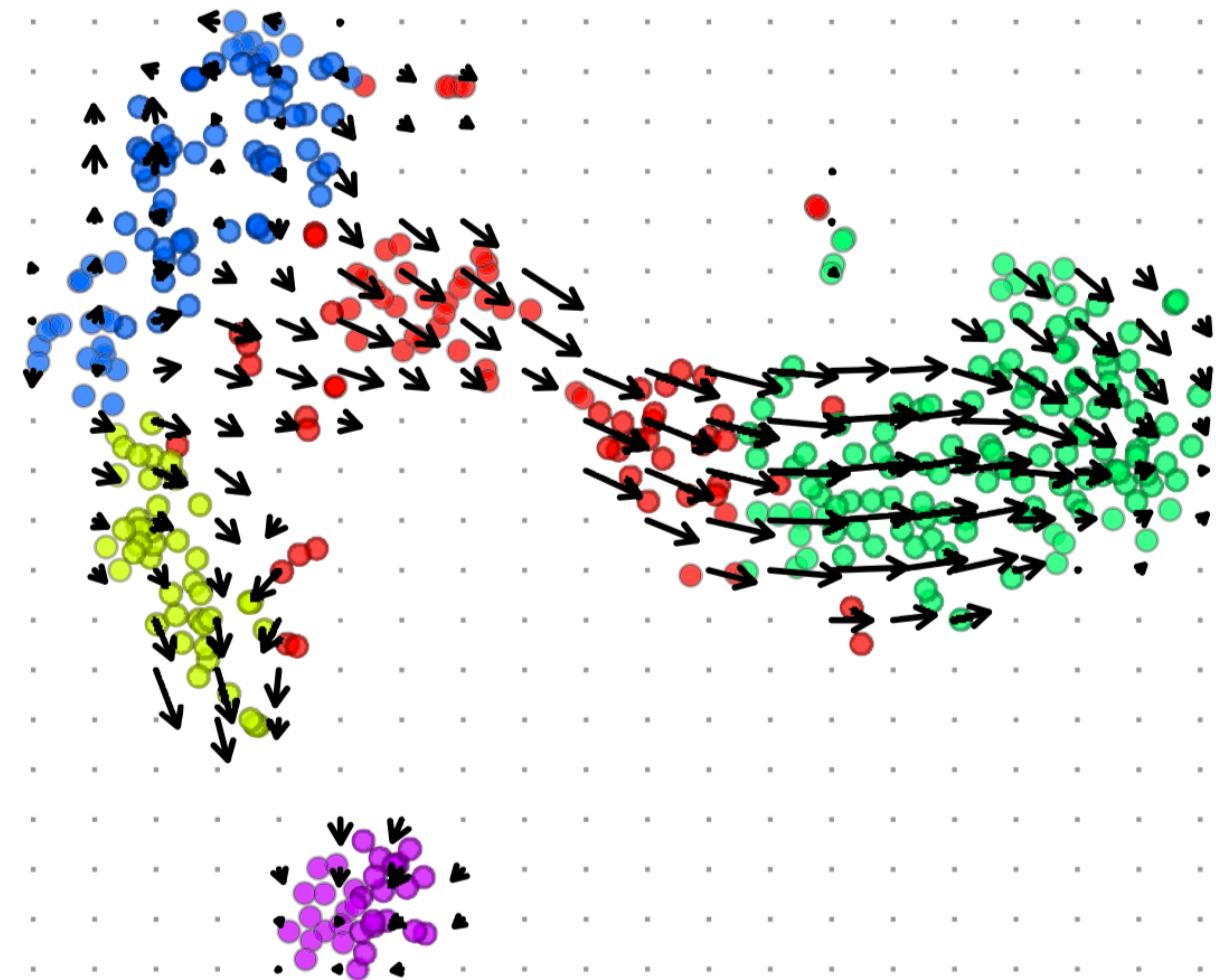


Visualize the prevalent pattern of cell velocities with locally averaged vector fields

- Suitable for large datasets

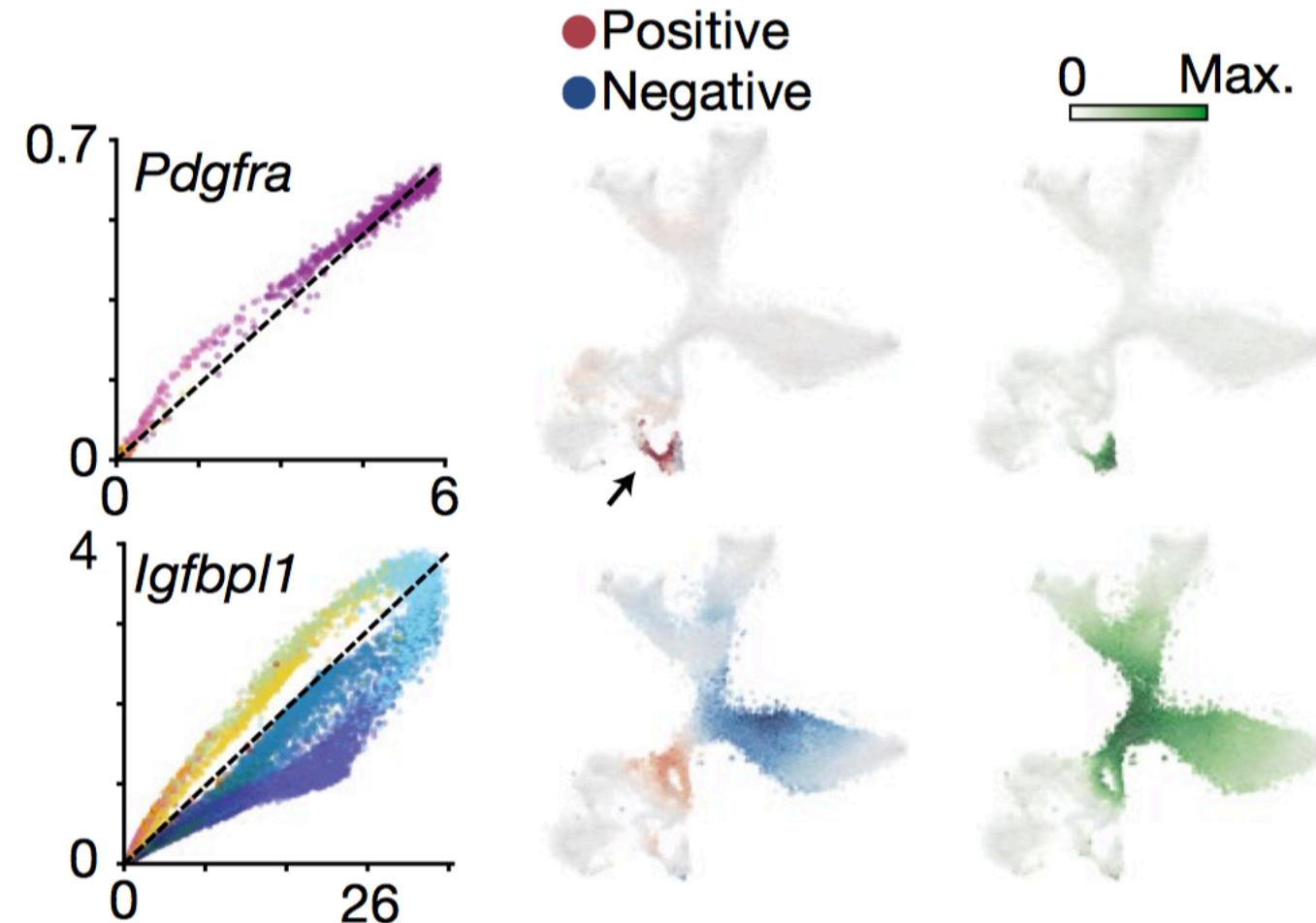
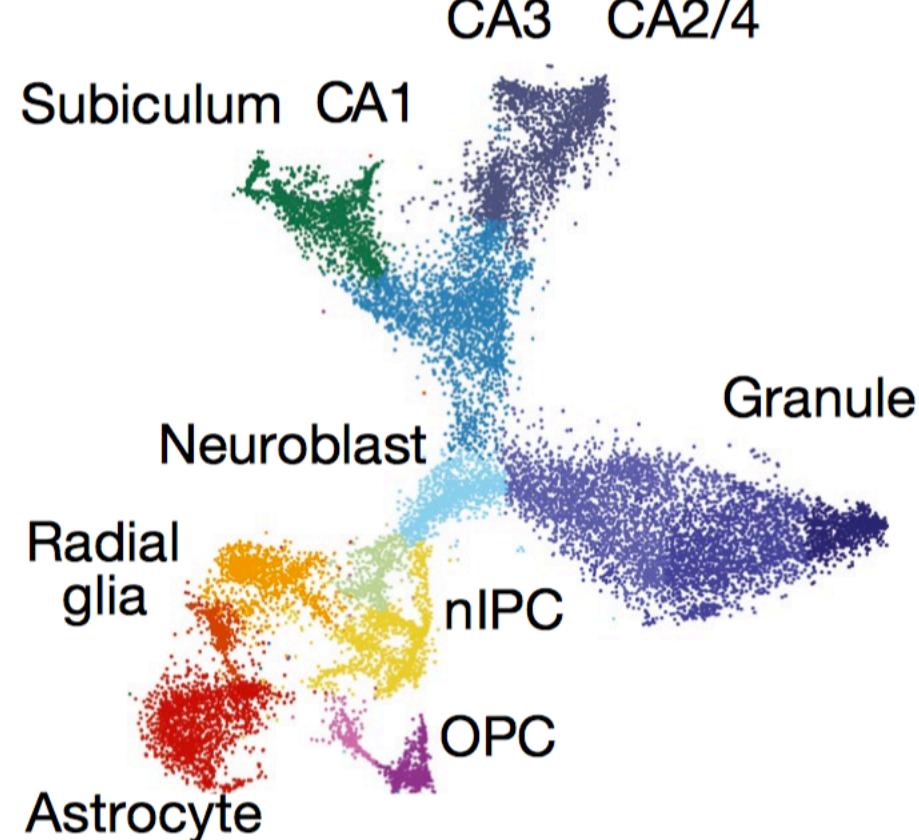


$t\text{-SNE1}$
↑
 $t\text{-SNE2}$



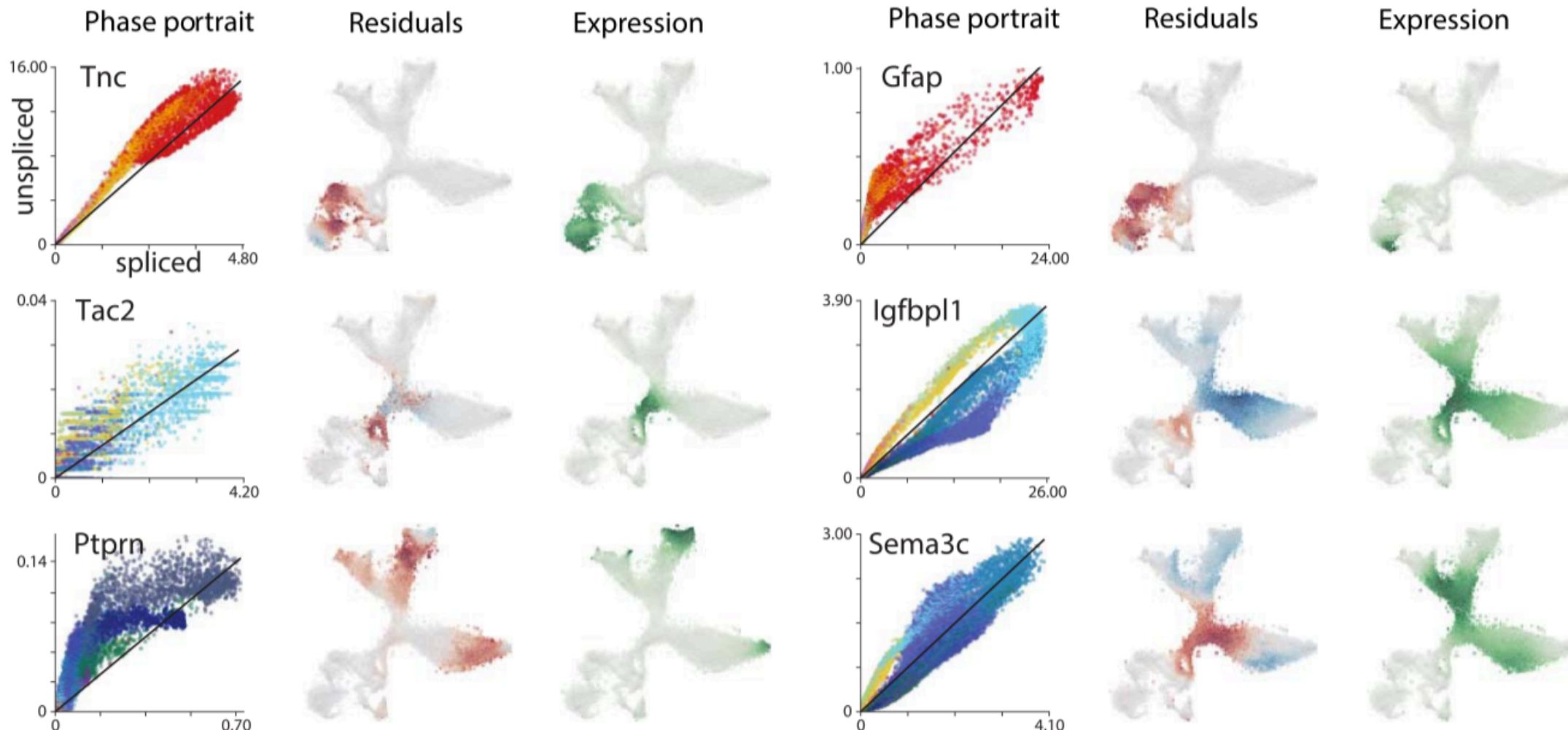
Apply RNA velocity to the branching lineage of the developing mouse hippocampus

- t-SNE plot reveals a complex manifold with multiple branches
- Phase portraits of individual genes showed specific induction and repression of gene expression along the manifold



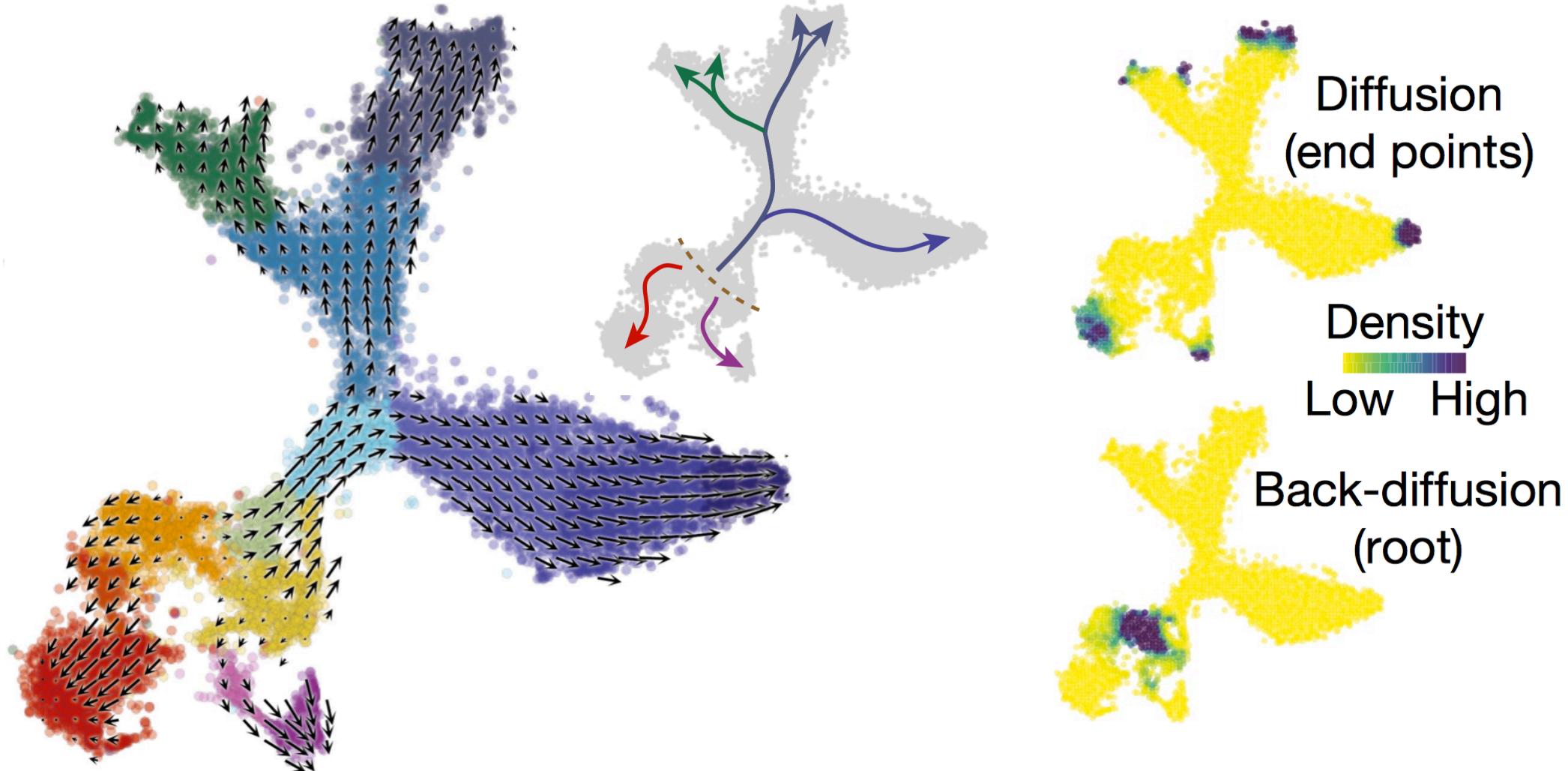
Selected phase portraits and fits of the equilibrium slope (γ) for the developing cells

- The residuals are the difference between observed and expected unspliced abundance, which closely tracks with velocity



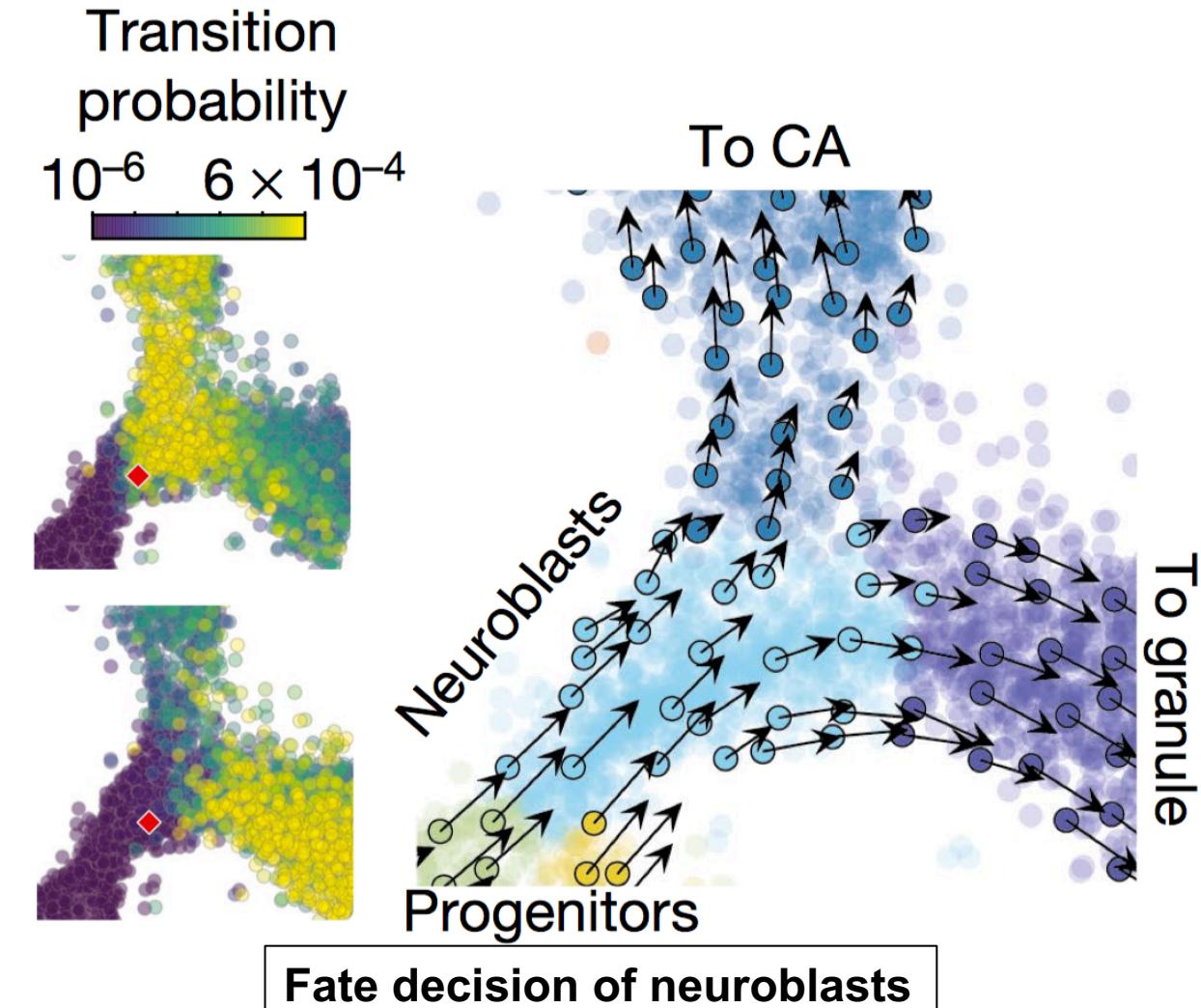
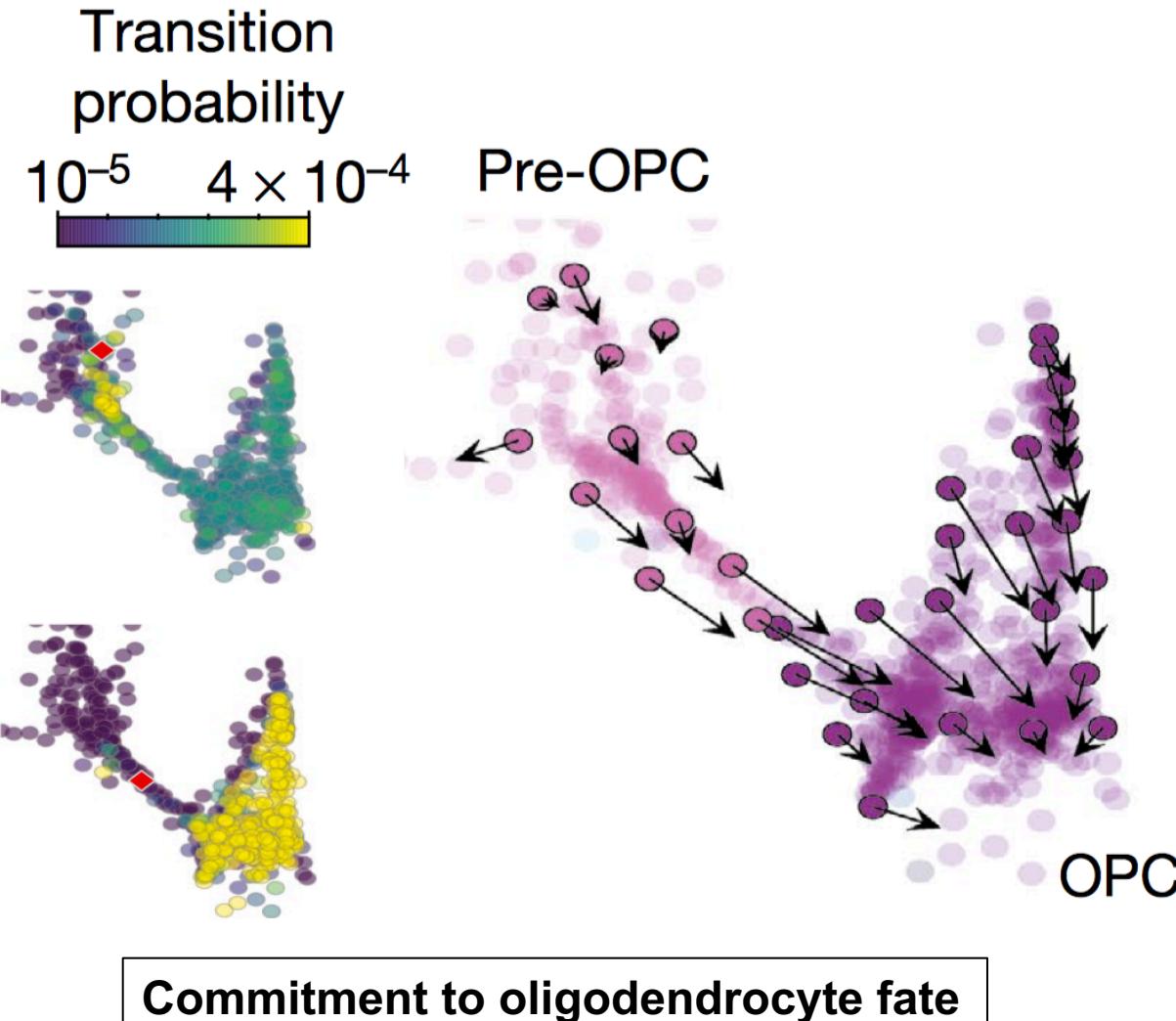
RNA velocity shows a strong directional flow towards each of the main branches

- Using a Markov random-walk model on the velocity field, the terminal and root states could be automatically identified



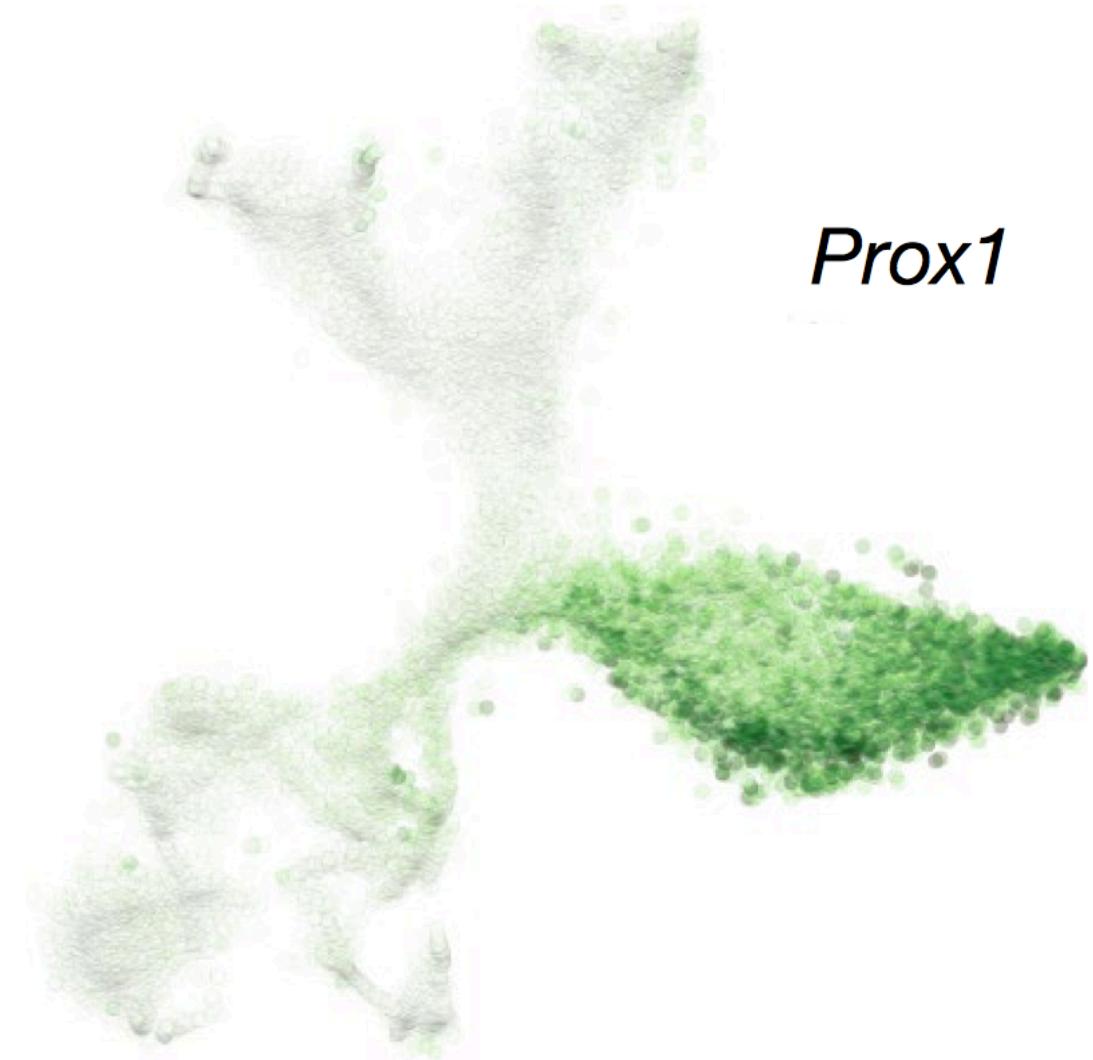
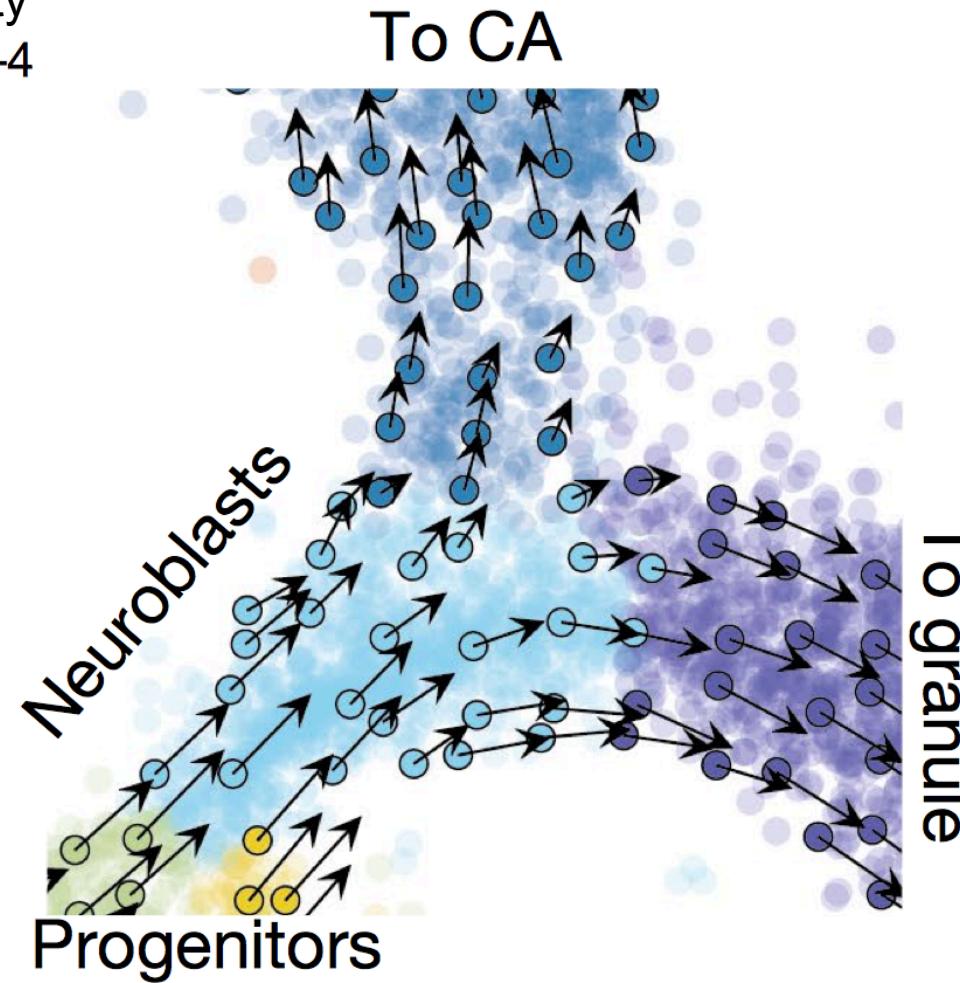
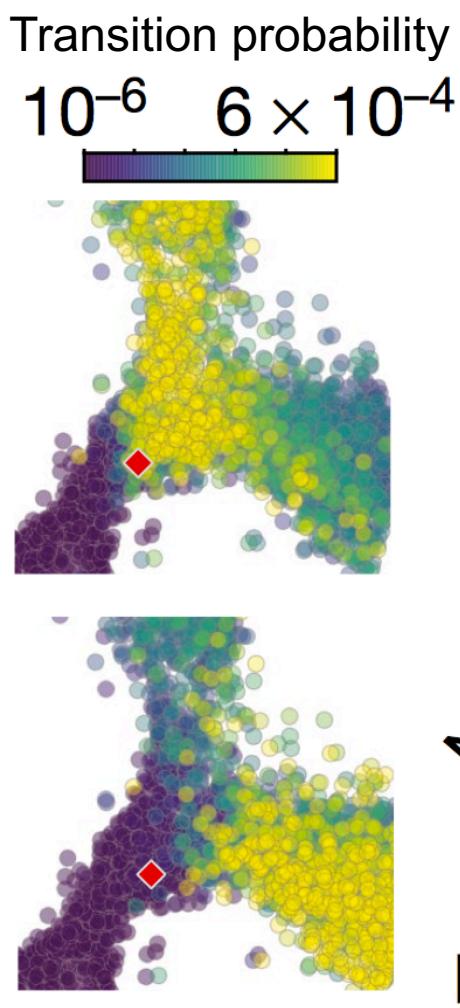
Visualization of single-step transition probabilities from two starting cells (red) to neighbouring cells

- The detailed, single-cell view of a branching lineage allowed us to interrogate fate choice



Two neighbouring cells with different fates are distinguished by activation of *Prox1*

- *Prox1* is required for the formation of granule neurons and that, when *Prox1* is deleted, neuroblasts instead adopt a pyramidal neuron fate



Summary

- Across diverse scRNA-seq pipelines, 15–25% of reads originated from priming in the intronic regions of unspliced molecules
- RNA velocity leverages nascent unspliced RNA to deduce the future transcriptional states of cells, thus providing insights into developmental trajectories
- RNA velocity showed the expected developmental trajectory and helped deduce potentially key developmental transition genes that are responsible for driving cell fate choices

Thank you!



Discussion