
Single Cell Applications - Pseudotime Cell Trajectories

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Outline



What is pseudotime



Monocle

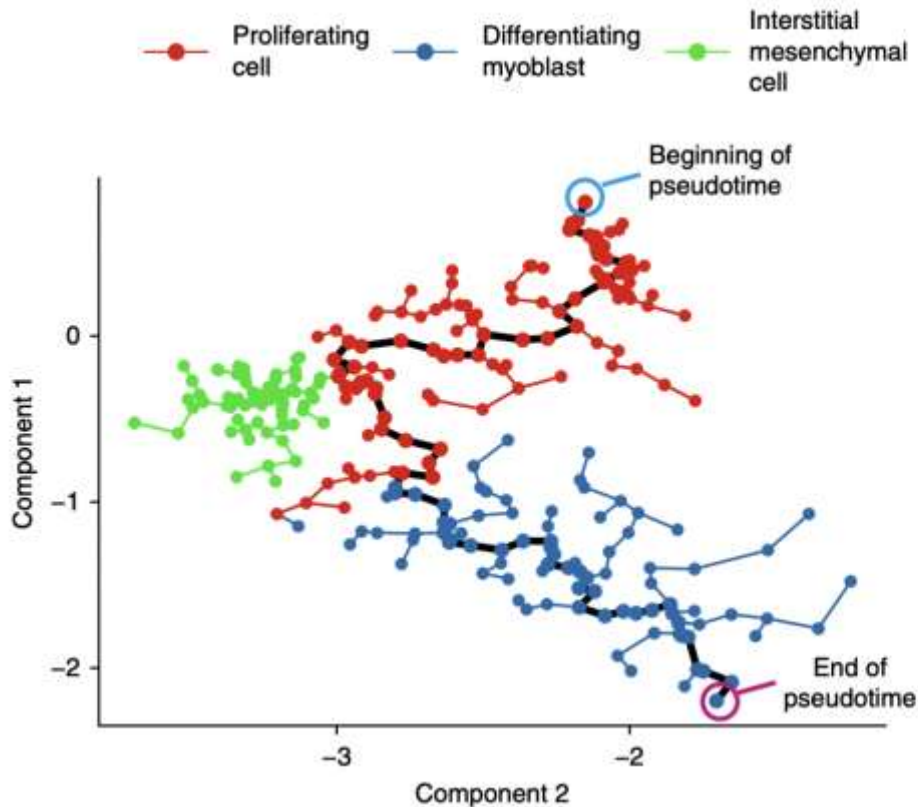


RNA Velocity



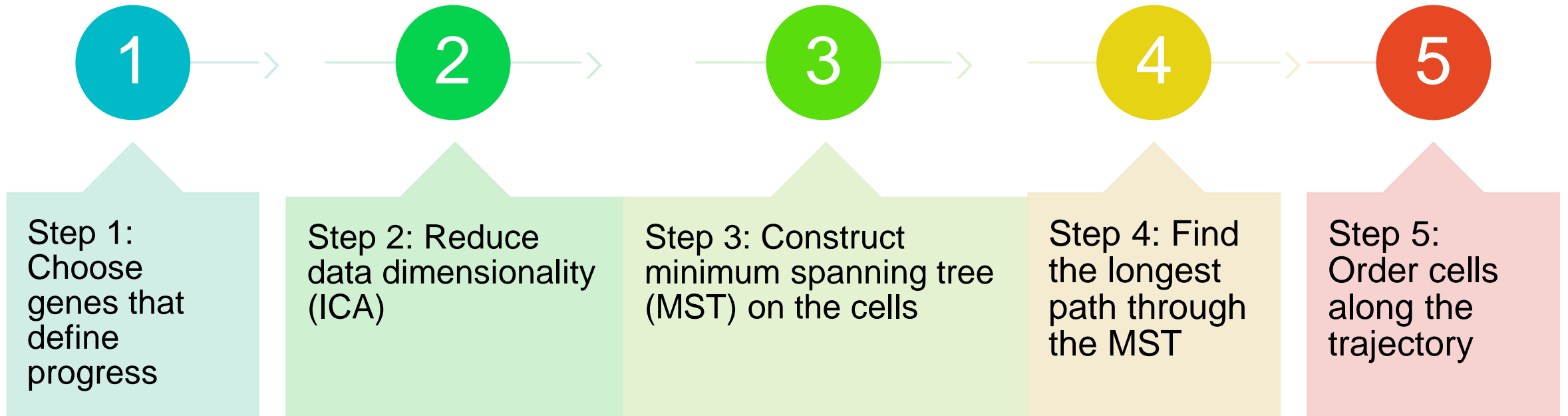
Challenges of Computational Inferences

What is Pseudotime/Trajectory



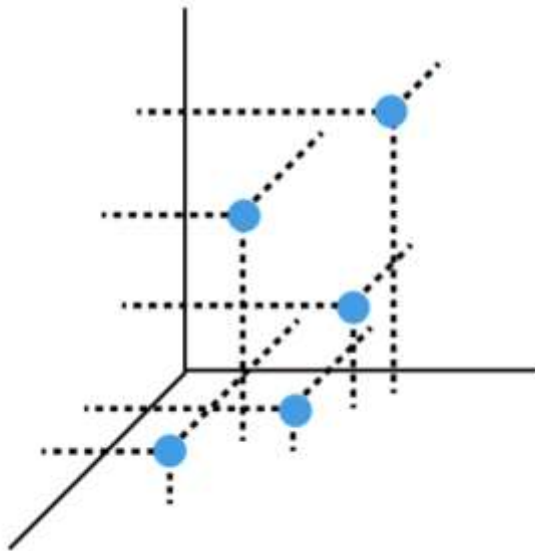
- 1) Cell differentiation occurs through dynamic developmental processes
- 2) Pseudotime orders cells along trajectories that represent these process
- 3) Trajectory inference (TI) reconstructs these cellular transitions

Monocle 2



Step 1: Identify genes that define the progress

Cells represented as points in expression space



- 1) Cells exist in a high-dimensional space
 - Each cell X_i is a point in d dimensional space

$$x_i = (g_1, g_2, \dots, g_d)$$

- 2) Select high variance genes or based on differential expression patterns

- A. High variability across cells

- Compute the variance across cells for each gene

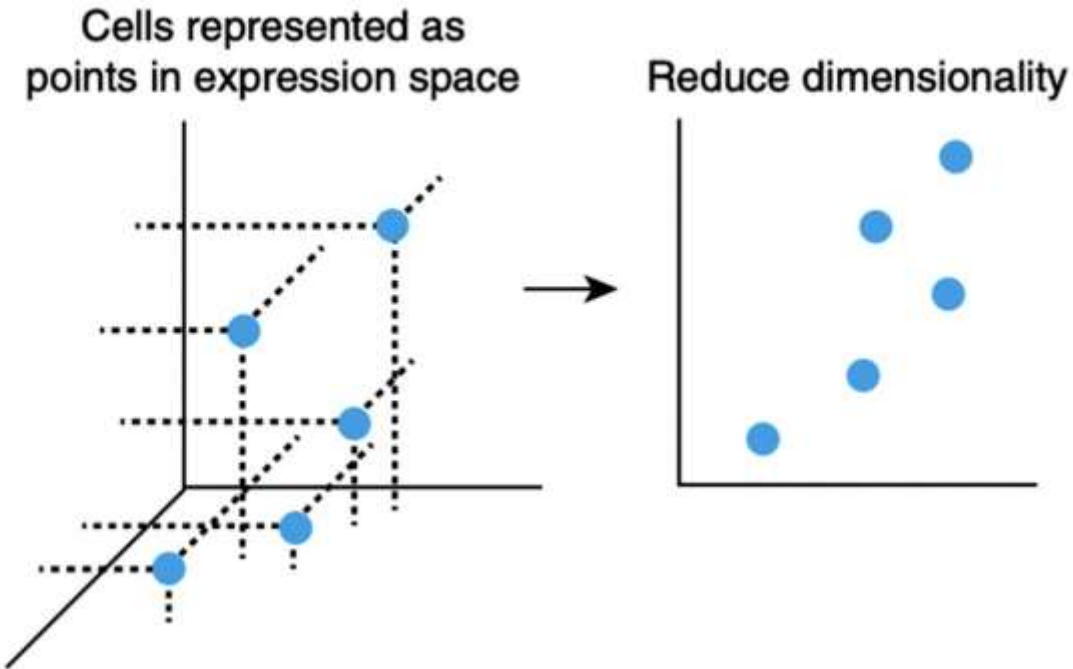
$$\text{Var}(g) = \frac{1}{n} \sum_{i=1}^n (X_{i,g} - \bar{X}_g)^2$$

- B. Genes that define biologically relevant processes (e.g., stem cell markers)

- C. Differer $H_0 : \mu_1 = \mu_2, \quad H_A : \mu_1 \neq \mu_2$ tes

Step 2: Reduce data dimensionality

ICCA



1) Mathematical equations:

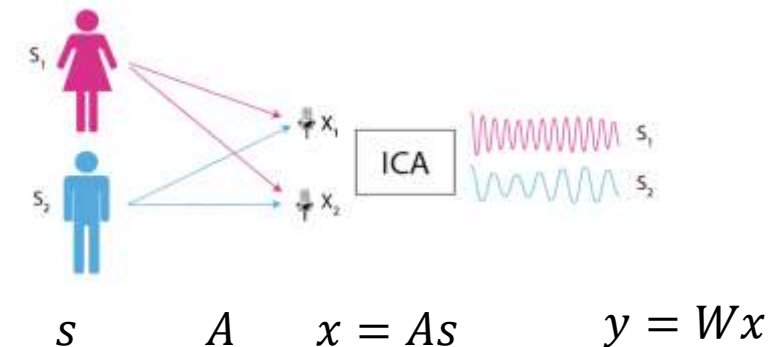
$$x = As$$

- x is the observed mixed signals
- A is the mixing matrix
- s is the original independent source signals

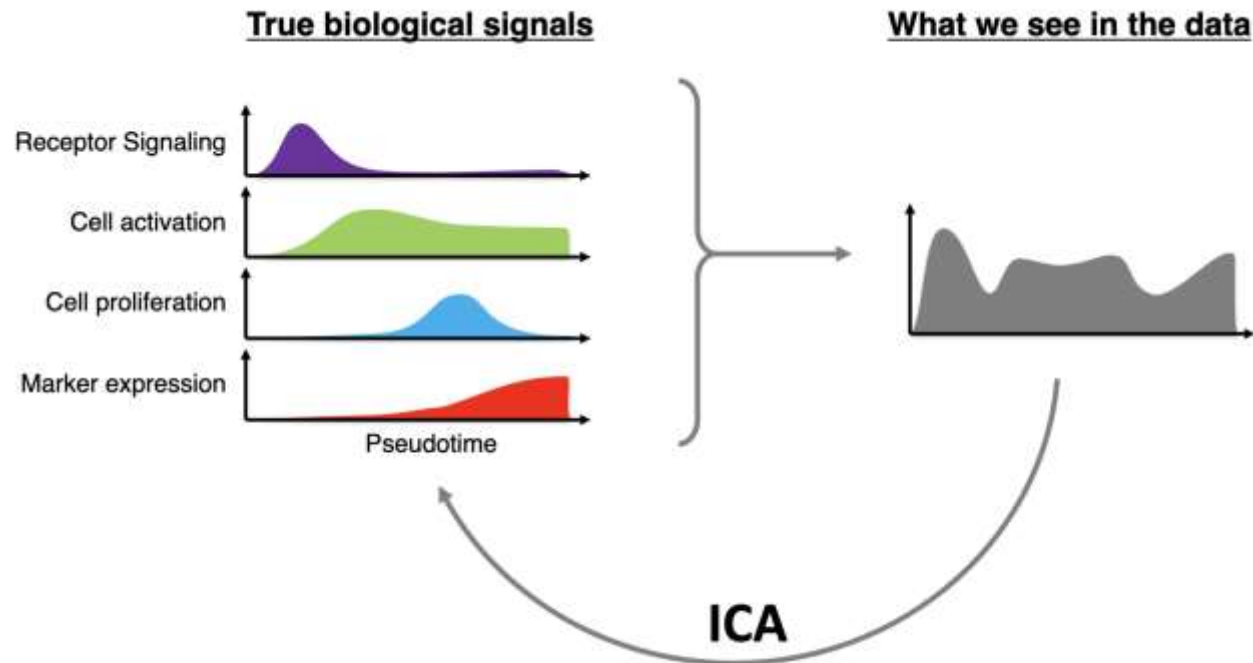
2) Goals:

$$y = Wx = WAs$$

- y is the estimated independent components
- W is the unmixing matrix, computed by ICA



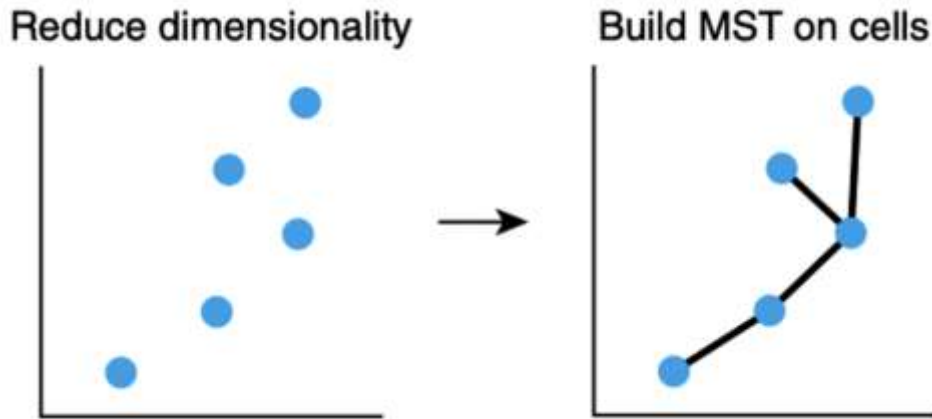
Why ICA



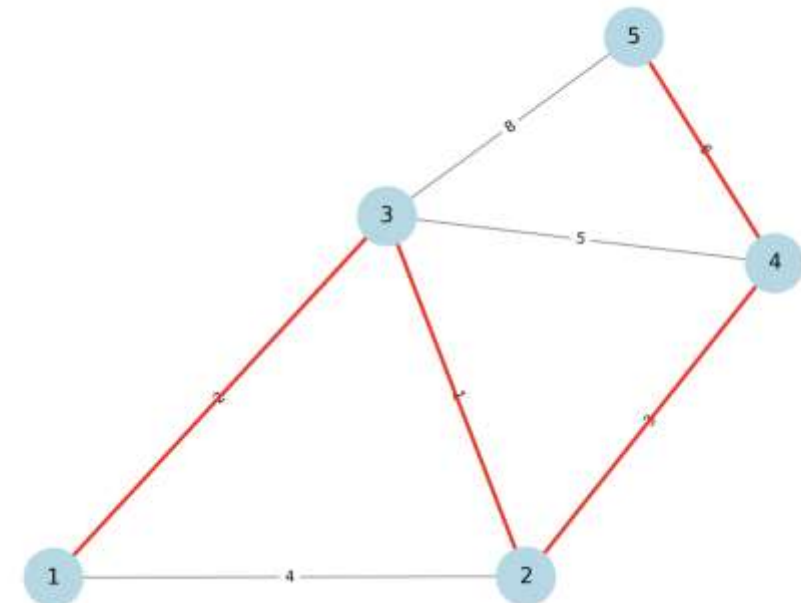
- 1) PCA : find the directions of maximal variance
 - Find the loudest sound in the room (dominant but may be mixed)
- 2) ICA: find the direction of maximal independence
 - Find individual voices in a conversation

Step 3: Construct minimum spanning tree (MST) on the cells

- Connect all vertices (cells) in V in $G = (V, E)$
 - Has no cycles
 - Minimizes the total sum of edge weights
- 1) Compute the pairwise distance in reduced-dimensional space
 - 2) Prim's algorithm

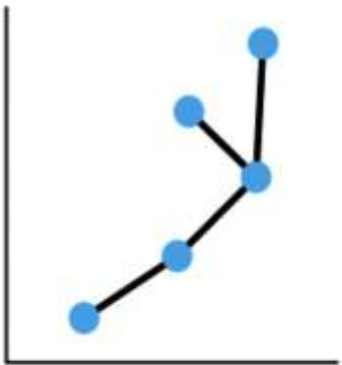


Minimum Spanning Tree using Prim's Algorithm

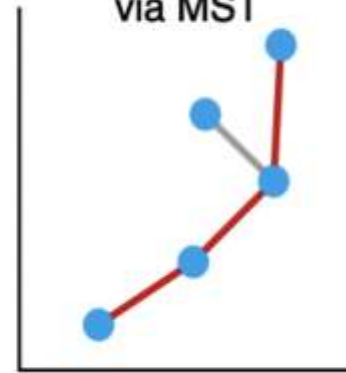


Step 4: Find the longest path through the MST

Build MST on cells



Order cells in pseudotime
via MST



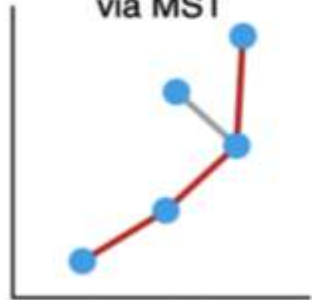
- 1) The longest continuous path is the best proxy for the differentiation timeline
 - Longest path is called the diameter

Step 5: Order cells along the trajectory

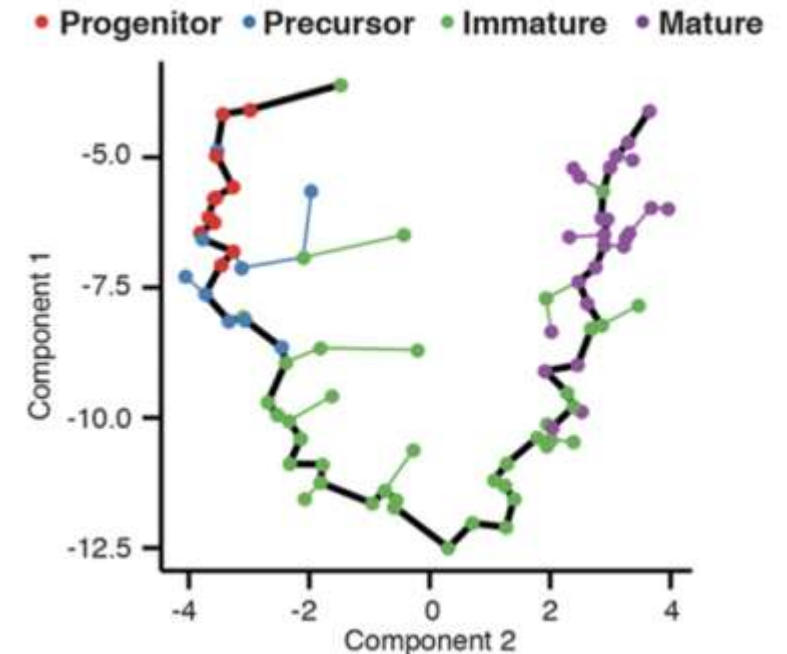
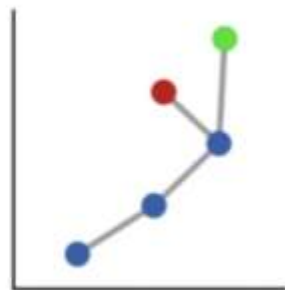
- 1) Assign a pseudotime value to each cell
 - Cells early in the path: undifferentiated states
 - Cells later in the path: fully differentiated states

Developmental trajectory of olfactory neurons in mice

Order cells in pseudotime via MST



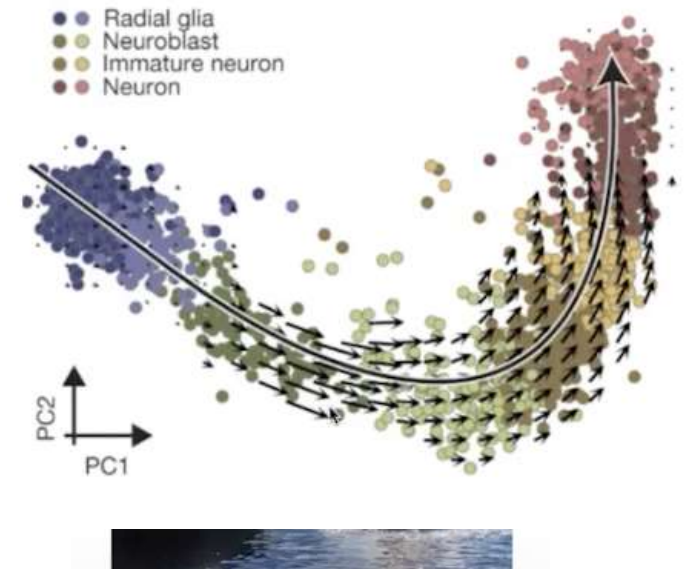
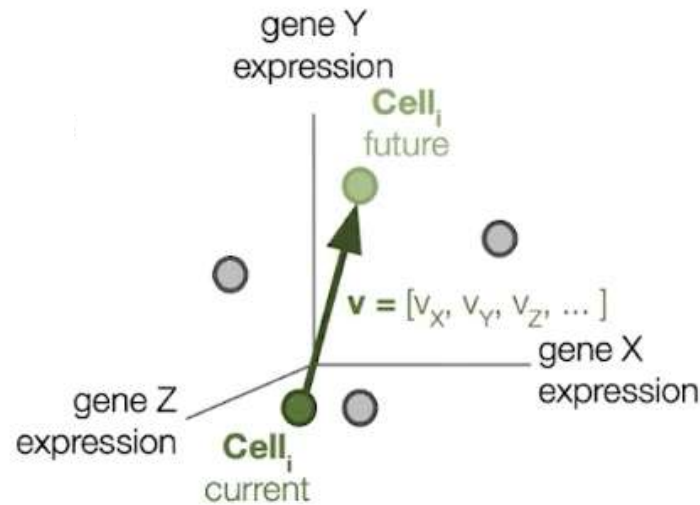
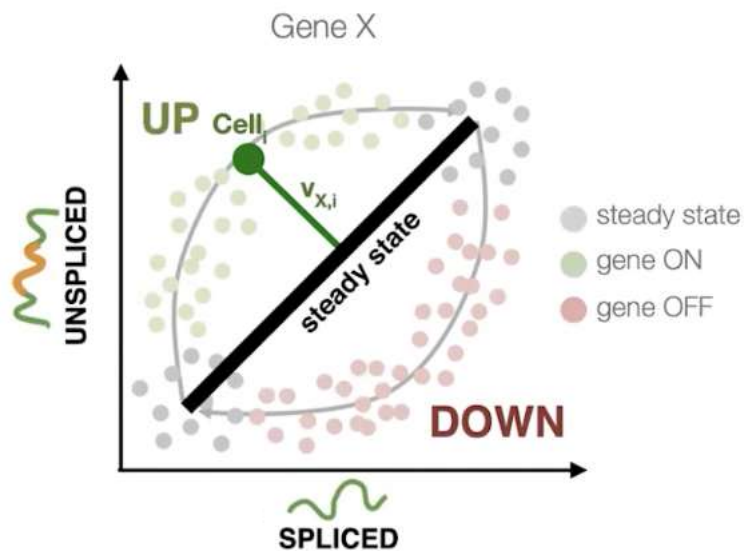
Label cells by type



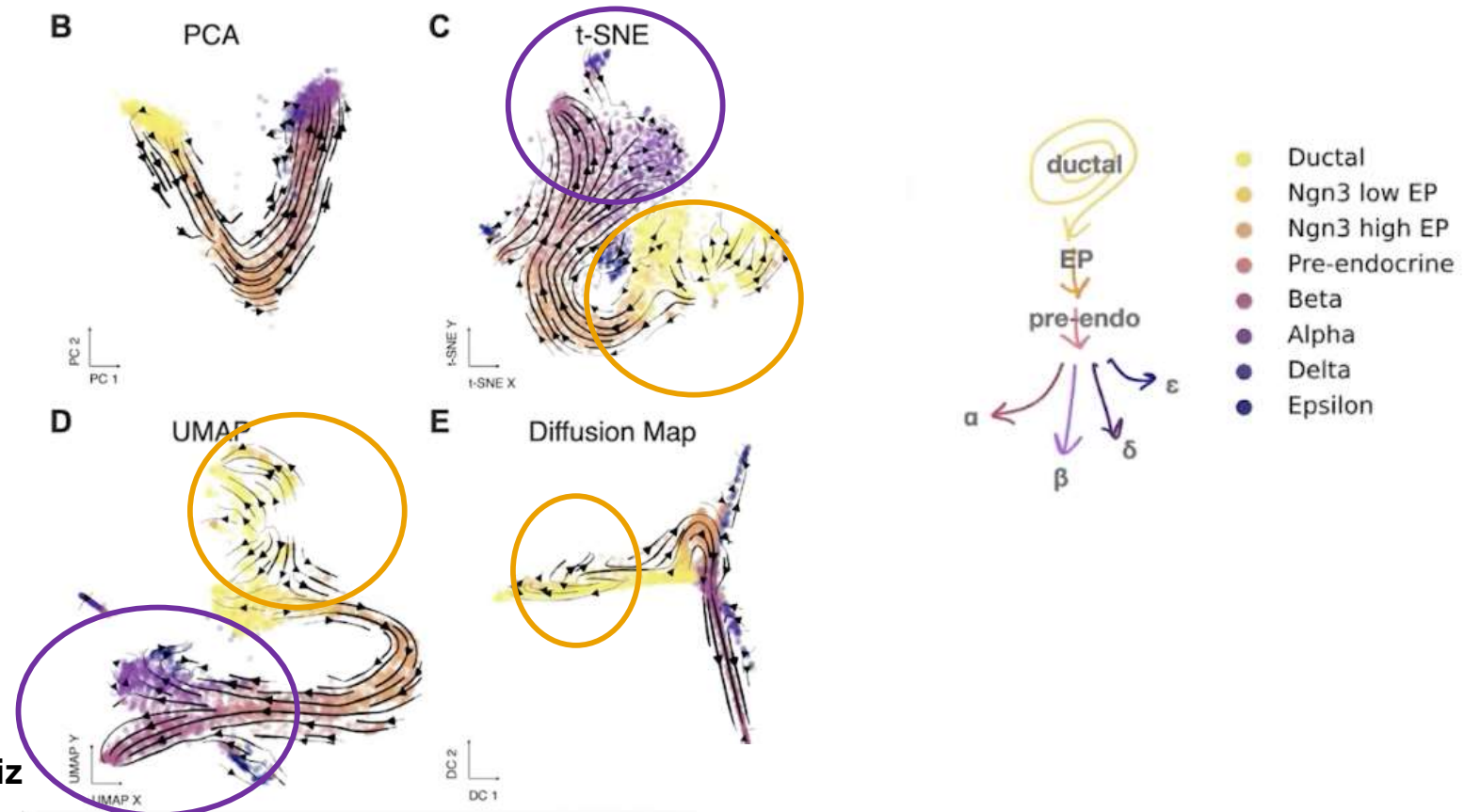
RNA Velocity: spliced and unspliced RNA levels indicate changing gene expression



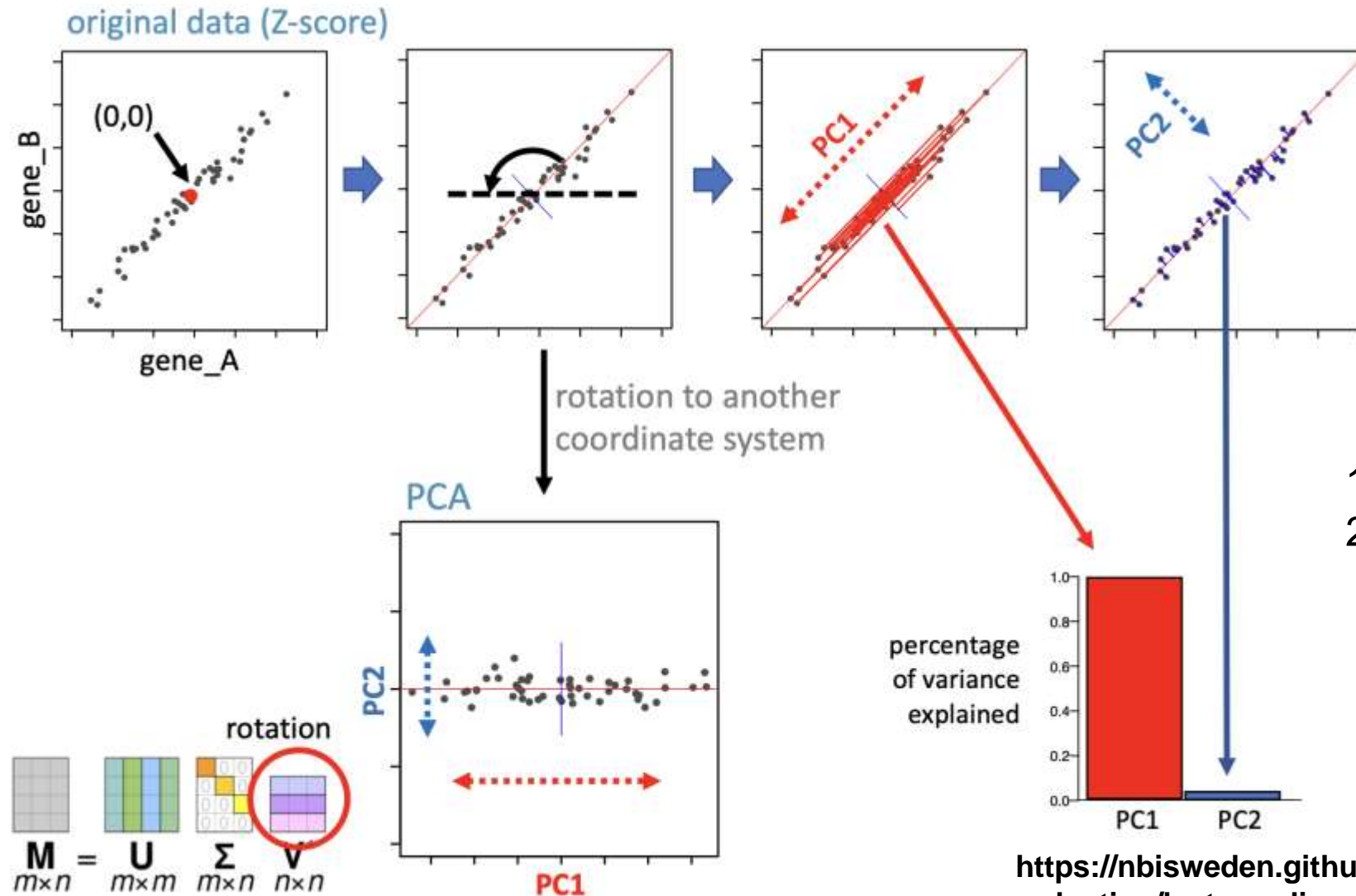
RNA Velocity: spliced dynamics predict future cell state



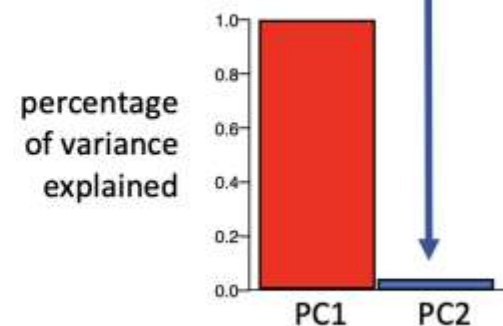
Visualizing RNA velocity trends: projecting onto existing 2D-embeddings



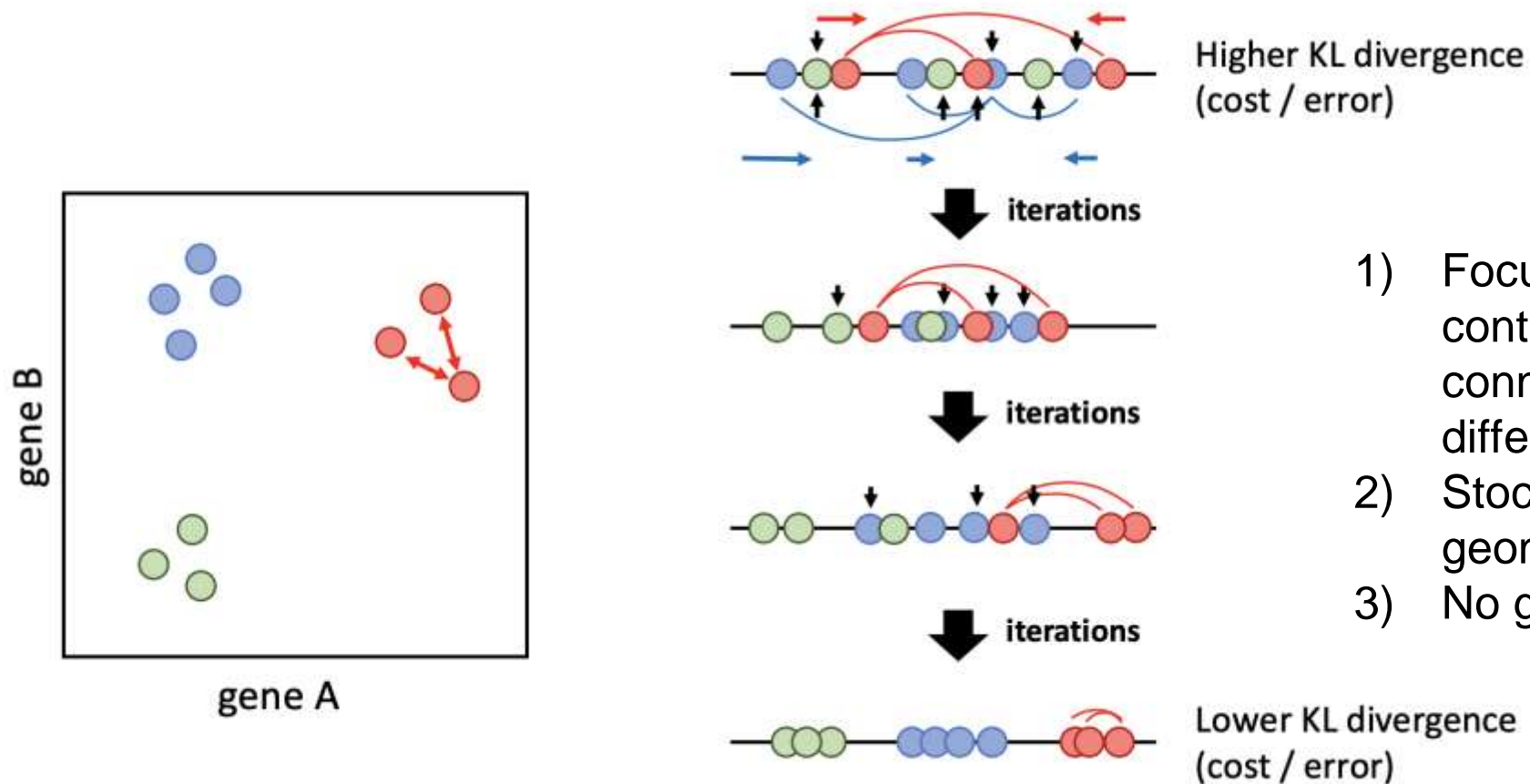
Limitations of PCA for RNA velocity



- 1) Only capture linear trends
- 2) PCA prioritizes global variance and ignores local trajectories

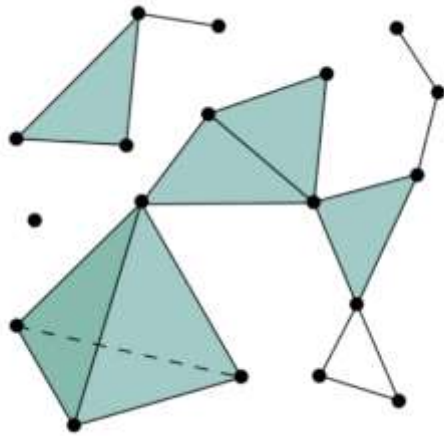


Limitations of t-SNE for RNA velocity



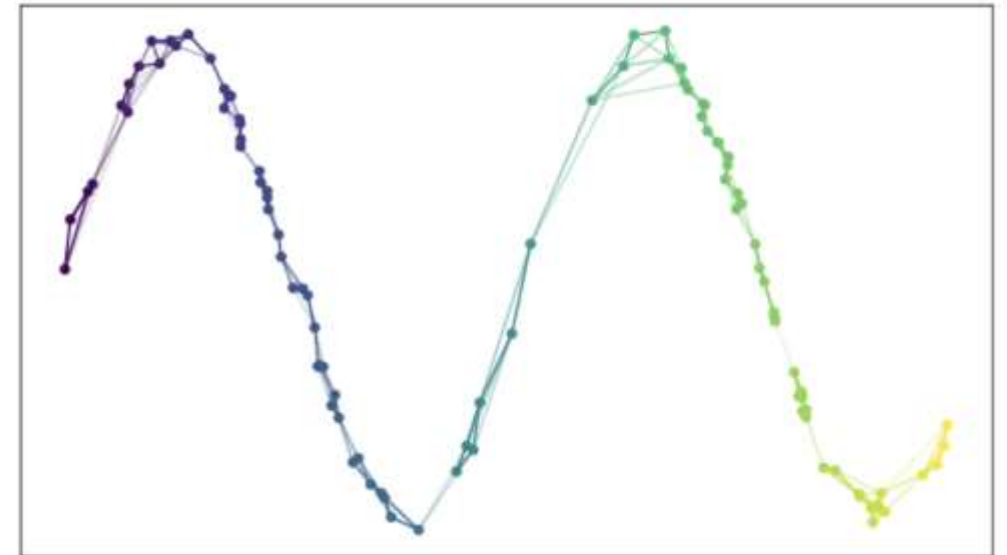
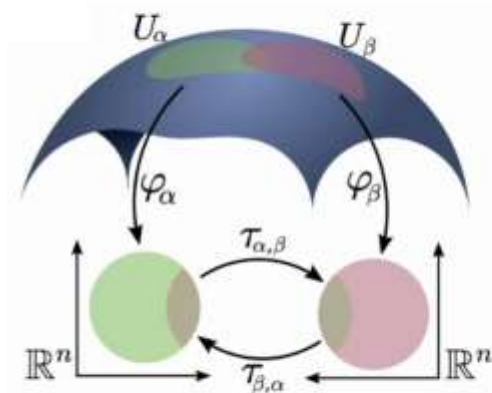
- 1) Focus on clustering rather than continuity (cells should be connected may end up in different clusters)
- 2) Stochastic and no fixed geometric structure
- 3) No global structure

Limitations of UMAP for RNA velocity



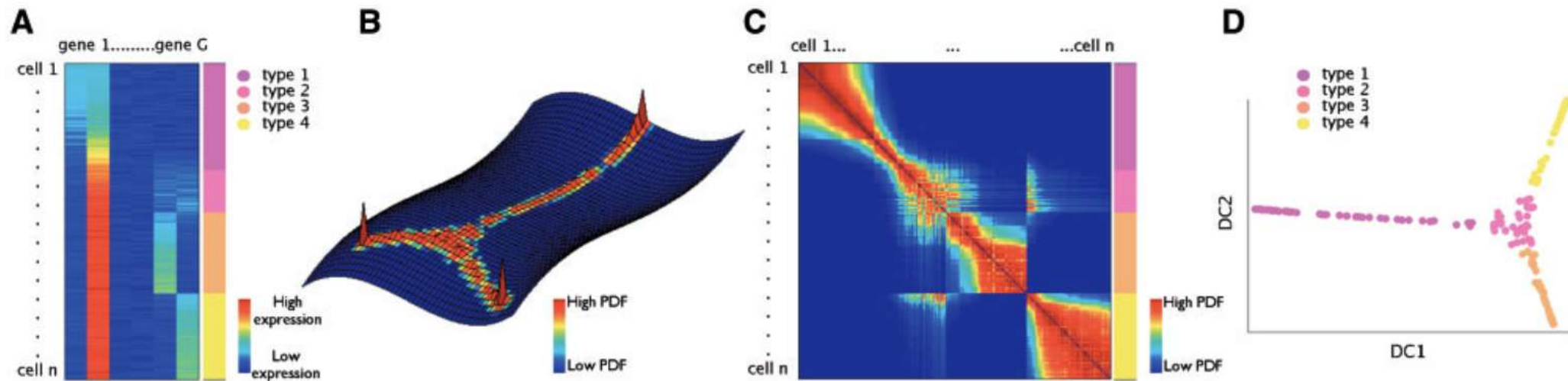
- Based on topological structures
- Points are connected if the distance is below a threshold
- Manifold alignment while preserving topology

1) Distance-based but not descriptive of directional process and transcriptional dynamics

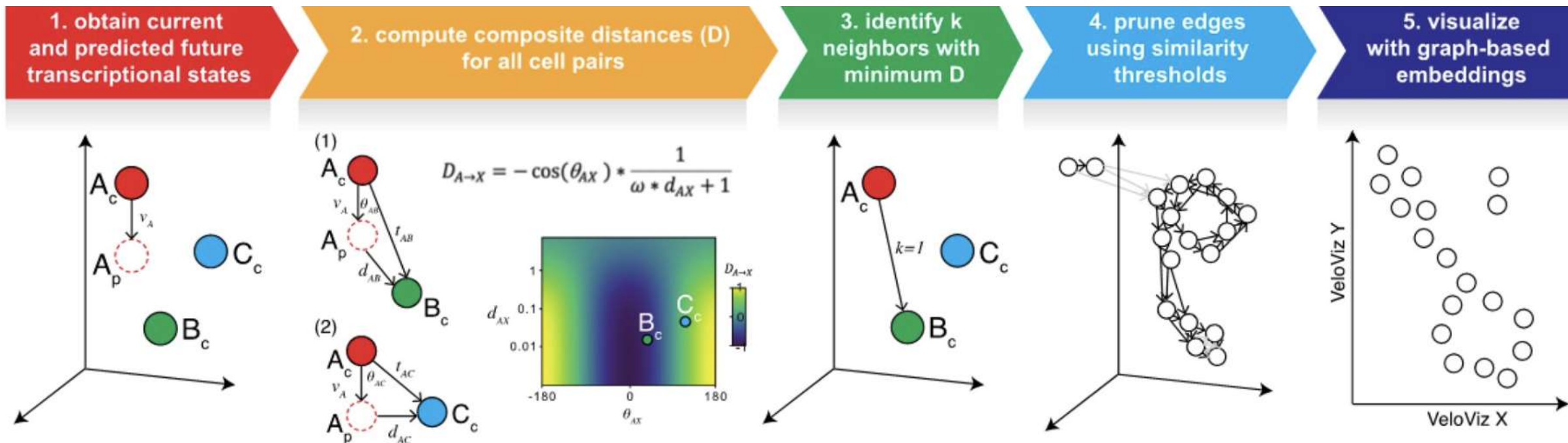


Limitations of diffusion maps for RNA velocity

- 1) Diffusion maps assume Markovian diffusion (reversible transitions) while RNA velocity is irreversible
- 2) Global manifold structure and they tend to over smooth local velocity variations



Visualizing RNA velocity: RNA-velocity informed 2D-embeddings using VeloViz



A_c the observed transcriptomic profile
 A_p the predicted future state

transition vectors A_c to B_c
 Cells with small composite distances are more likely transitions

Challenges in Inferring cellular time



1) Learning 'pseudo time' trajectories

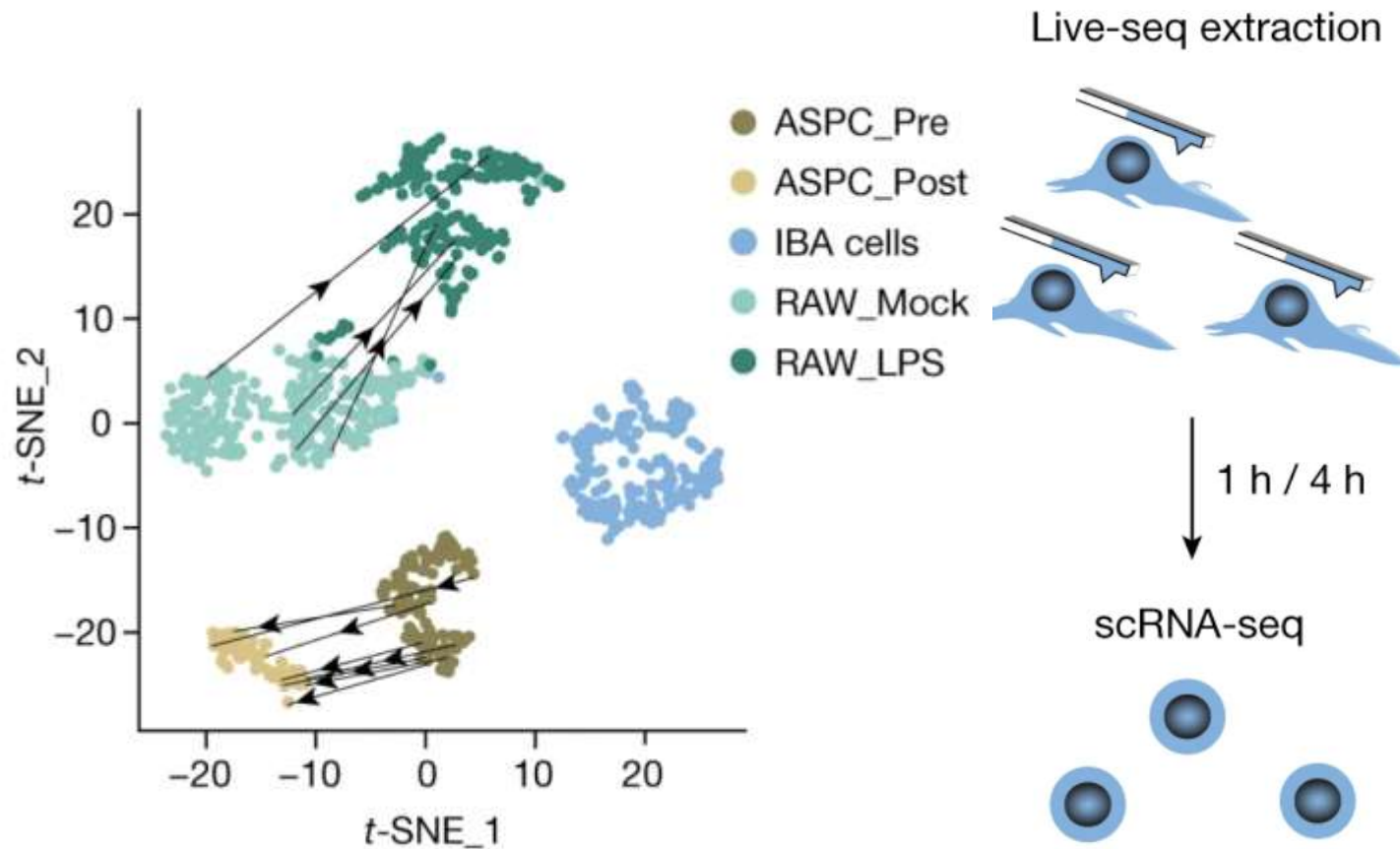


Assume cells take smooth paths



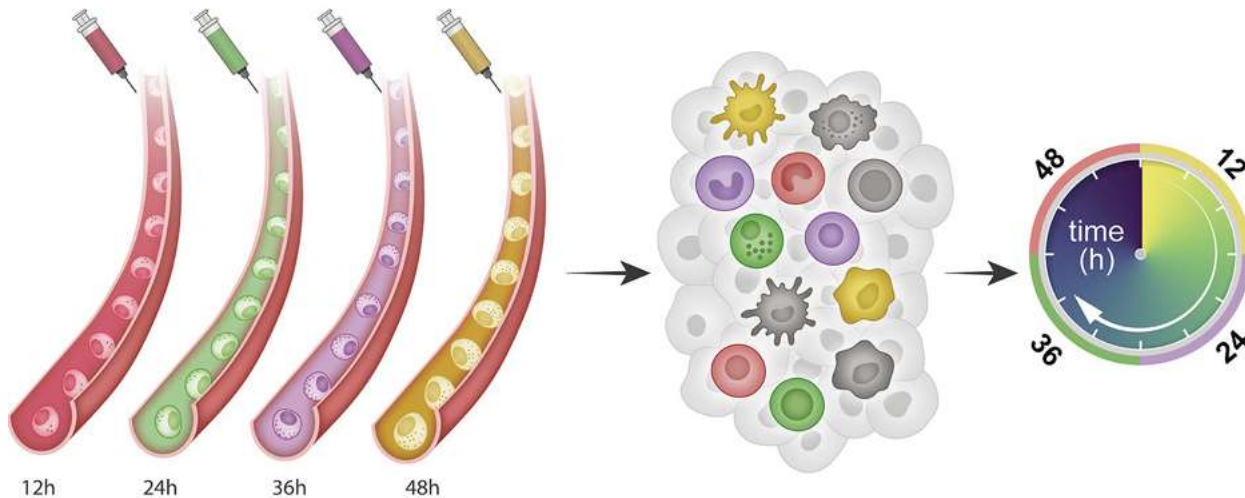
Does the learnt trajectory reflect real biological path?

LIVE-seq



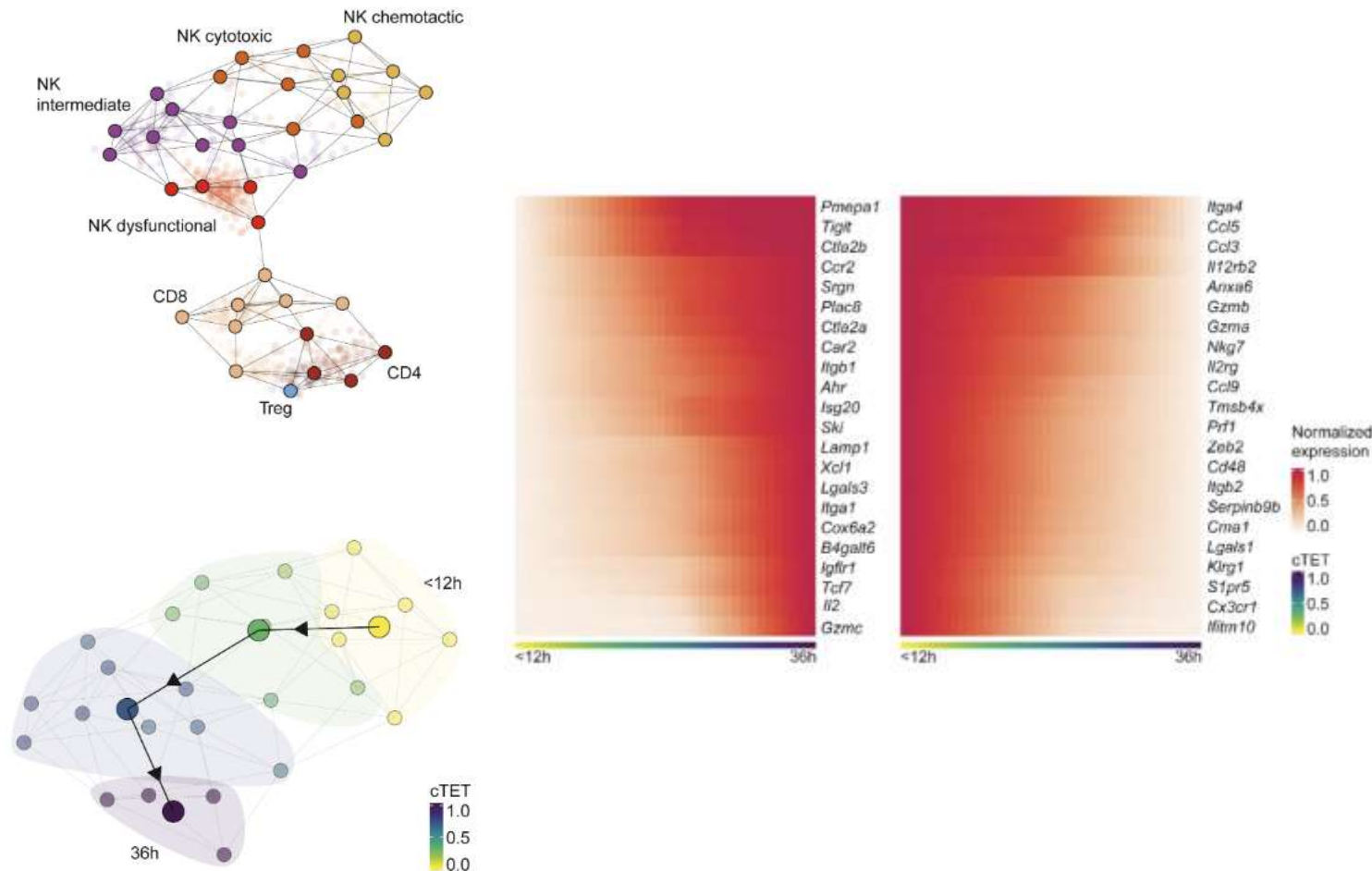
- 1) Cytoplasmic cellular biopsies
 - miniaturized RNA-seq protocols for profiling gene expression
- 2) Repeated cellular sampling
 - time-lapse microscopy enables sequential extractions and profiling
 - challenging to scale protocol to large numbers of cells

Zman-seq



- 1) Barcoding cellular time in-vivo
 - use fluorescent pulse labels
- 2) Time-stamped cellular dynamics
 - cells retain their fluorescent label as a temporal barcode
 - can build cellular trajectories with ground truth time-stamps

Zman-seq



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Thank you!