LINEAGE ESTIMATION WITH SINGLE CELL MRNA-SEQ DATA

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Associate Professor

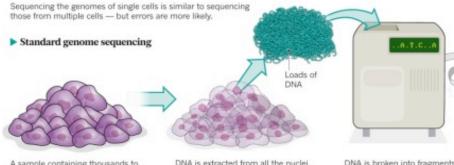
Department of Statistics, UC Berkeley

Statistical and Computational Challenges in Large Scale Molecular Biology Banff International Research Station March 28, 2017

Single Cell sequencing

 Standard mRNA-Seq on bulk populations

ONE GENOME FROM MANY



A sample containing thousands to millions of cells is isolated.

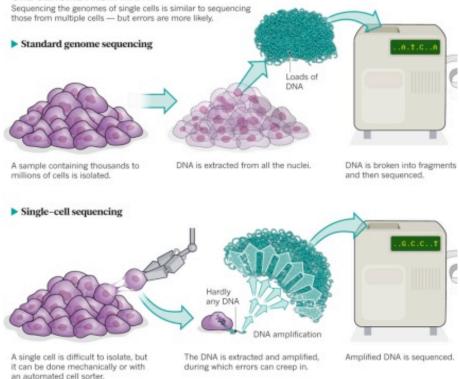
DNA is extracted from all the nuclei.

DNA is broken into fragments and then sequenced.

Single Cell sequencing

- Standard mRNA-Seq on bulk populations
- Single cell: allows to see diversity of individual cells

ONE GENOME FROM MANY



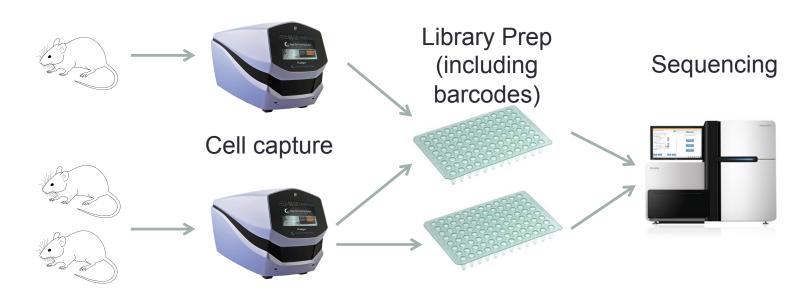
Owens (2012) "Genomics: The single life" Nature News

Experimental process

- Isolate cell
 - Micropipette
 - FACS : Fluidigm C₁
 ≤96 cells per run*,
 good: 60-70% capture rate

Droplet

- Library Prep
 - Amplification: small input material, high amplification
- Sequencing
 - Low seq. depth: e.g. 96 per lane (1M reads)

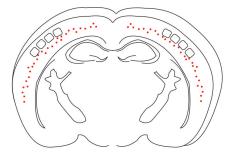


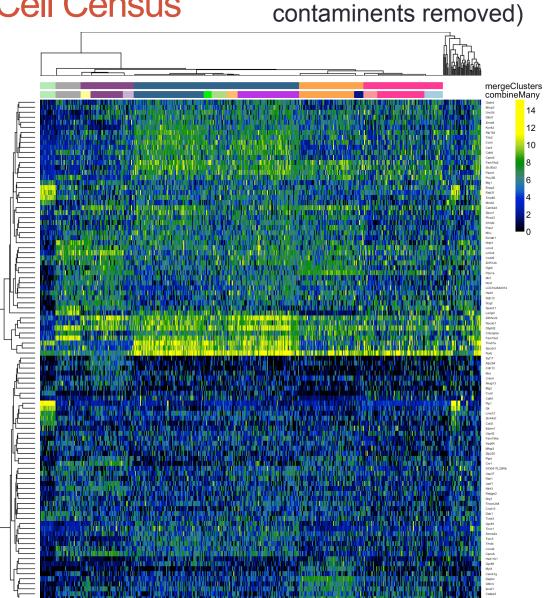
S1 cortex in mice (NIH BRAIN Initiative Cell Census Consortium)

 FACS sorting of the S1 cortex (Layer 4/5/6)



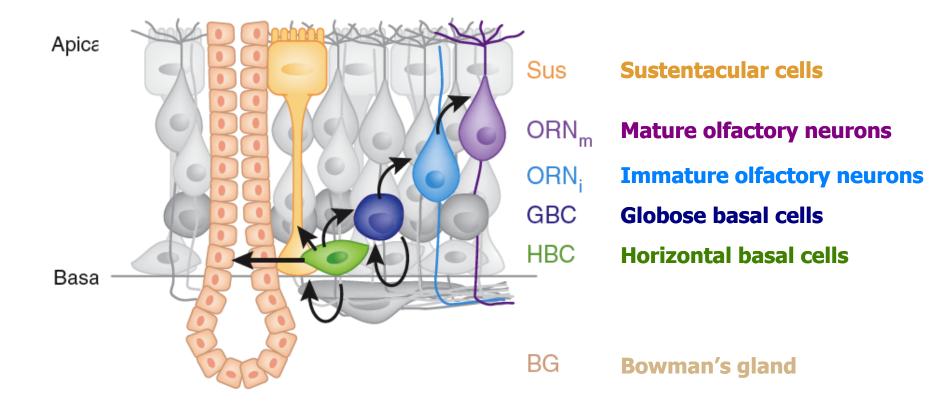
Layer 5 Cre x tdTomato reporter





Layer 5 cells (Glial

Olfactory Epithelium (OE)



Quick snapshot of the data

Data Set	Olefactory	Brain
# mice	51	41
# C1 Batches	61	40
# Illumina Lanes	19	7
# cells	2,627*	1,249
# cells pass QC	2,190	1,042
# Sequenced Reads	4,001 Million	1,500 Million

* Many conditions: in this talk, only 904 total (687 after sequencing)

Overview

SCONE

- Data specific choice of normalization strategy
- Via comprehensive comparison in every dataset
- Metrics to rank normalized data

RSEC

- Robust clustering strategy to find heterogeneity in scSeq data
- Subsampling and sequential clustering, merging of clusters, …
- Part of clusterExperiment package for common clustering tasks (e.g. pairwise DE, plotting with clustering information)
- Slingshot
 - Estimation of developmental lineages

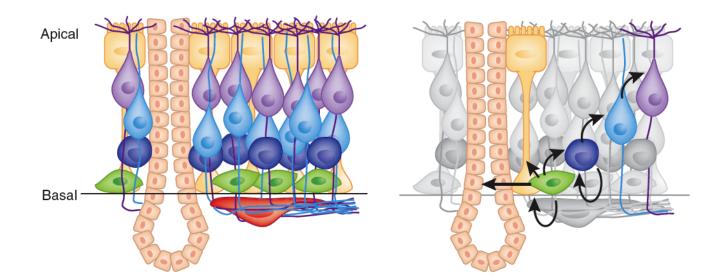
Overview

SCONE

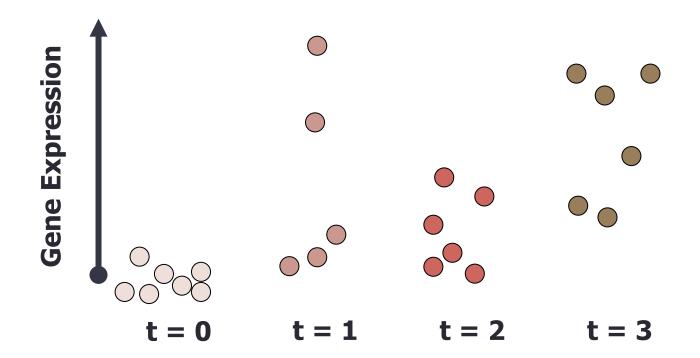
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Experiments (two):

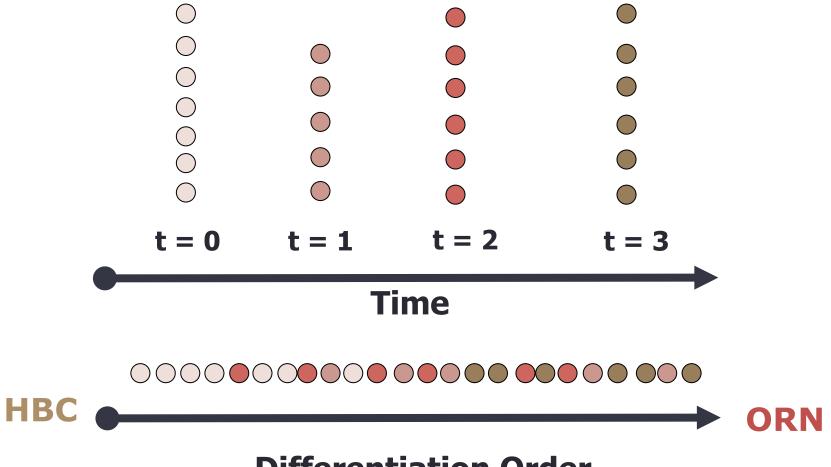
- Capture descendant cells at several time points after regeneration
 - Destroy all but HBC and watch them regenerate: 145 cells (of 175)
 - Lineage tracing after inducing HBC: 542 cells (of 729)
- Sequence the individual cells to determine what is changing
- Goal: characterize the differentiation process and at what point cell fate is chosen



Find genes related to differentiation

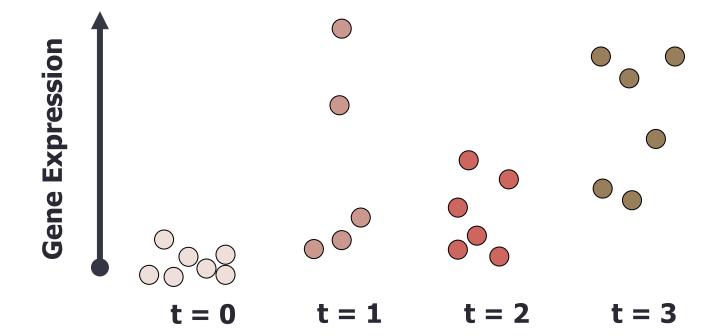


But observed time is not differential state

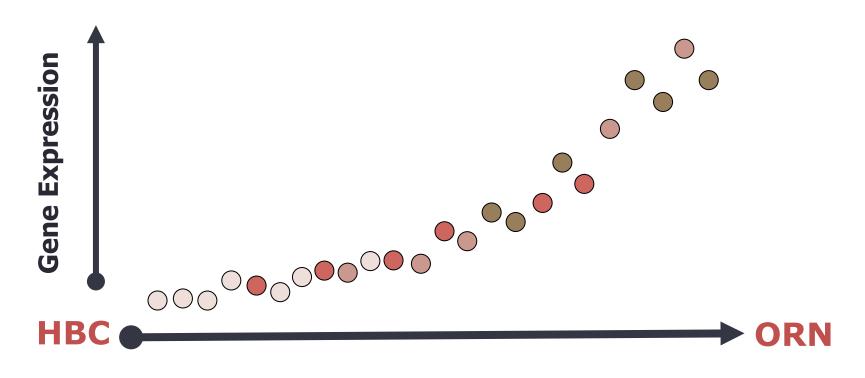


Differentiation Order

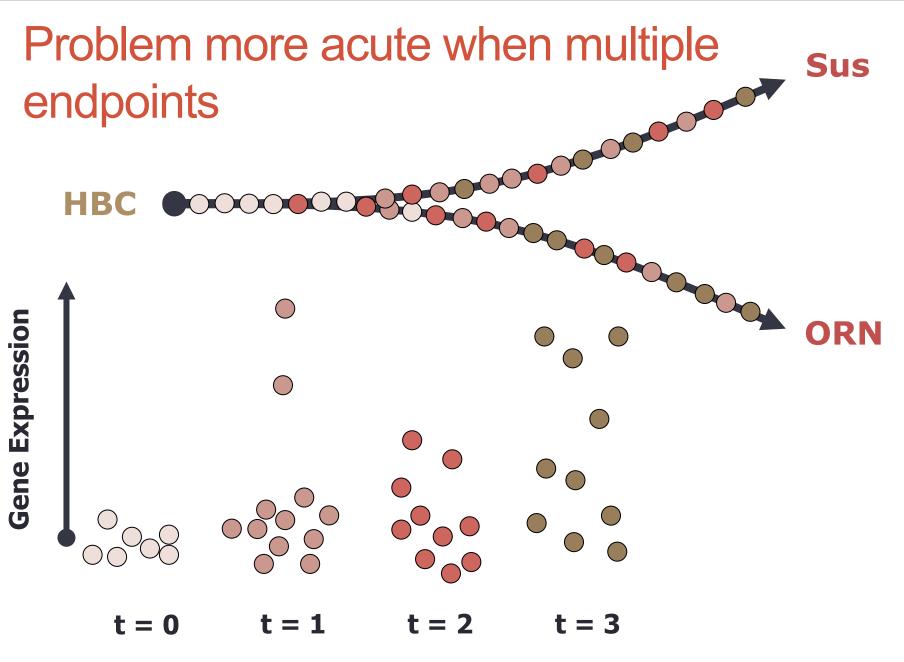
Better representation if order cells by differentiation state

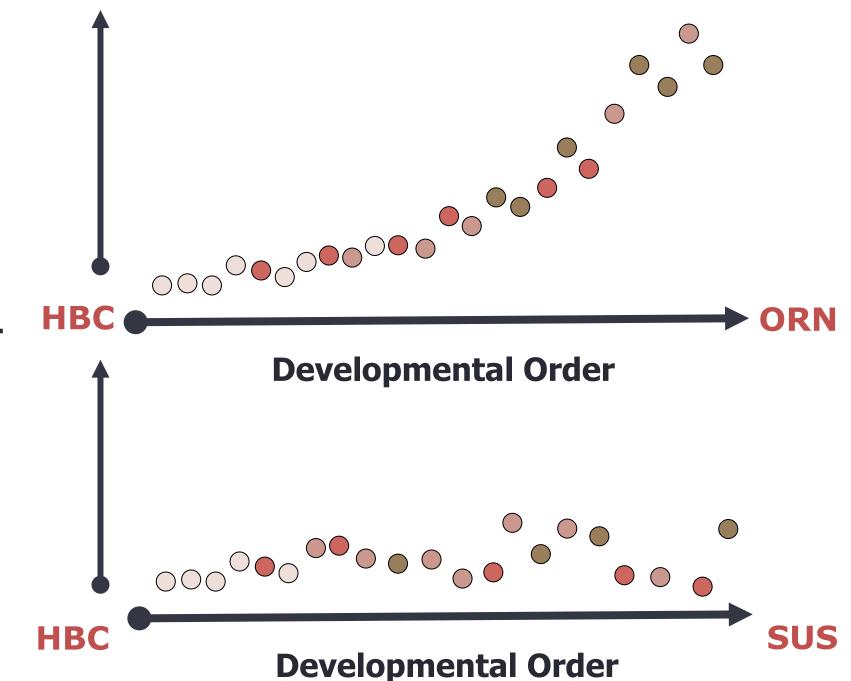


Better representation if order cells by differentiation state



Differentiation Order





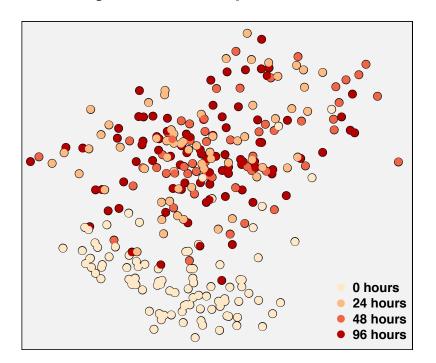
Gene Expression

Many Strategies for One lineage

- Assume distance gives differentiation order, at some level
- Find a 'path' (lineage) through space of gene expression data
- Order individual cells on the path
 - E.g. orthogonal projection
- Many "details" hard-coded in, make comparisons difficult
 - Dimensionality of space (e.g. 2 dimensions)
 - How find low dimensions (ICA / PCA / Laplacian Embedding)

Path Choices

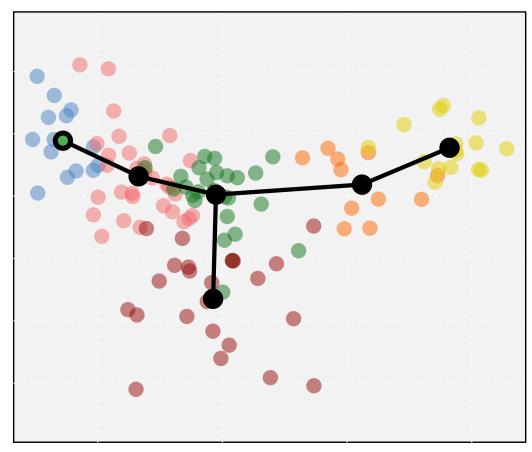
MST through individual cells, take longest path (Monocle)
 'Project' onto path via where branch off path





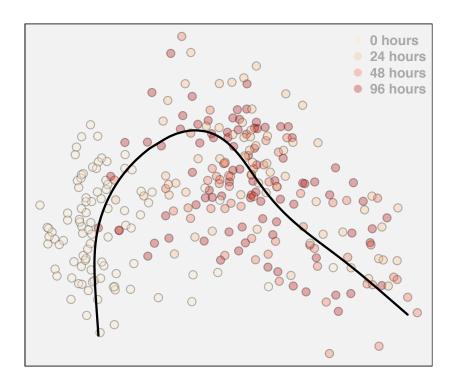
Path Choices

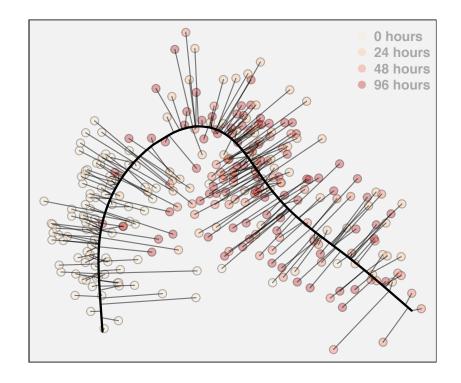
- MST through individual cells, take longest path (Monocle)
- MST on Clusters, orthogonal projection (Waterfall / TSCAN)



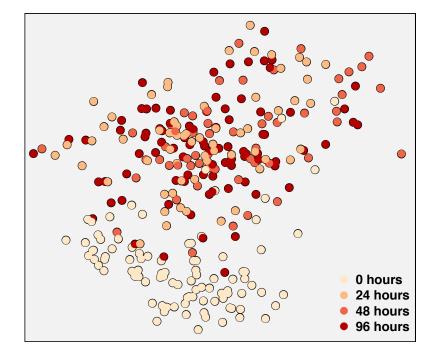
Path Choices

- MST through individual cells, take longest path (Monocle)
- MST on Clusters, orthogonal projection (Waterfall / TSCAN)
- Principal Curves, orthogonal projection (Embedder)



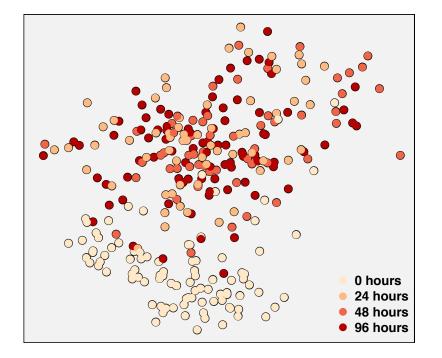


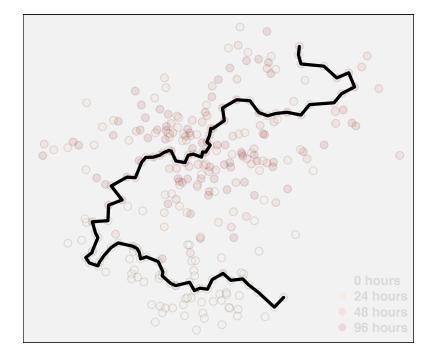
Monocle not robust





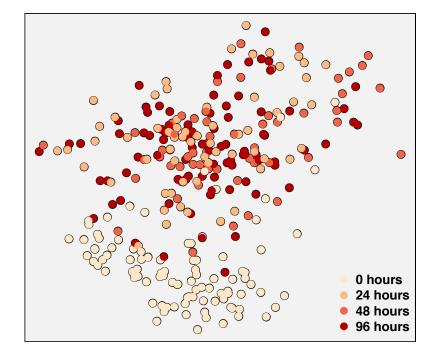
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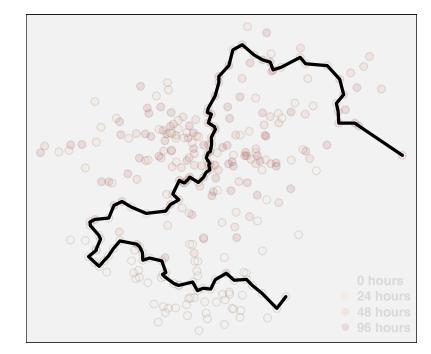




(Jittered)

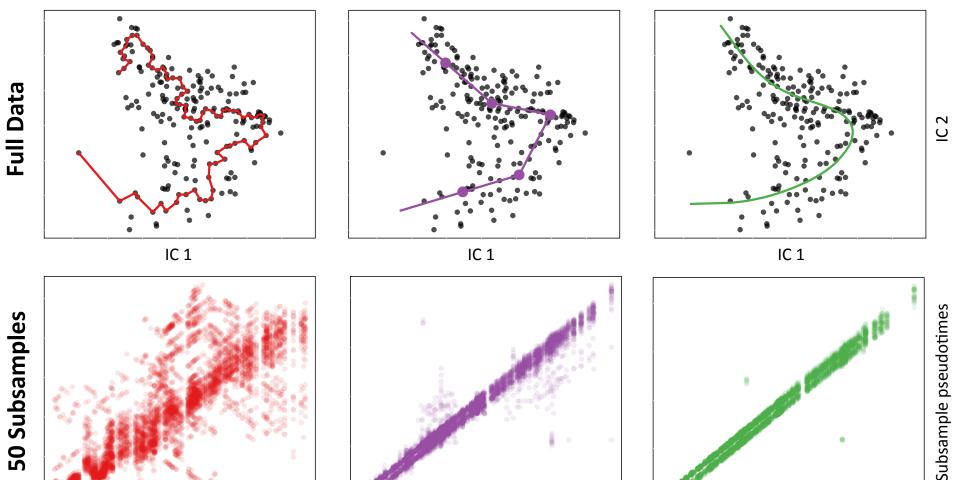
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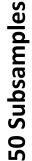


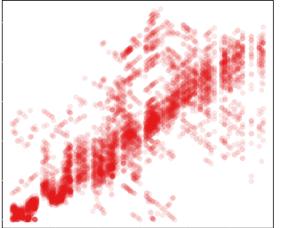


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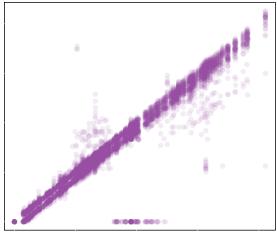
Principal Curves More Stable



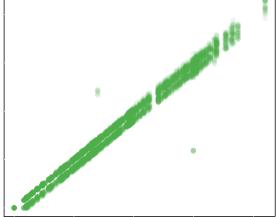




Original pseudotime



Original pseudotime

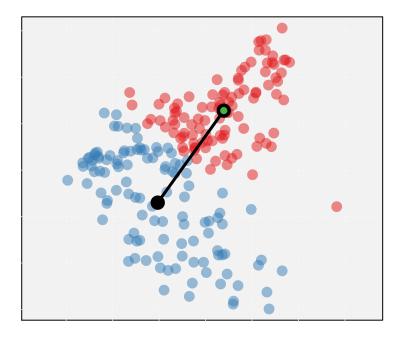


Original pseudotime

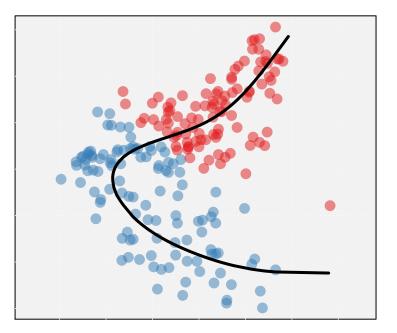
Principal Curves Not Reliant on Clustering

MST on clusters can be sensitive to choice of clusters

MST on Clusters



Principal curves



Monocle Data

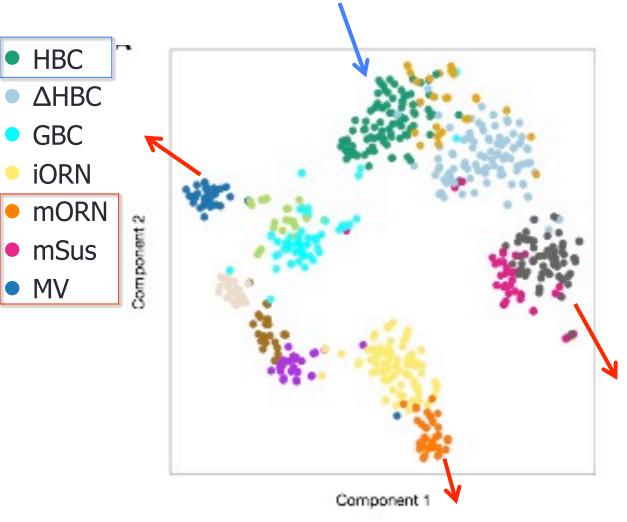
Slingshot: Multiple Lineages

- MST useful for broad shapes, finding branching Clustering often uses more dimensions – more information
- Principal curves more robust estimates of ordering
- Slingshot
 - → Use MST for assigning clusters of cells to lineages
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 - \rightarrow allow for supervision (constrained MST)

Importance of Constrained MST



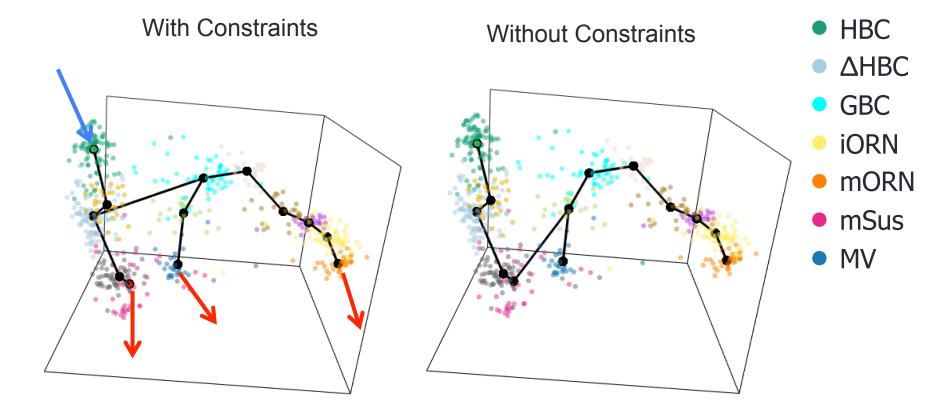
 Huge assumption distance in gene expression = order

 Clustering gives important information

 If know the end points of process, should guide estimation

PCA of Gene Expression, with clusters

Constraint keeps these lineages separate



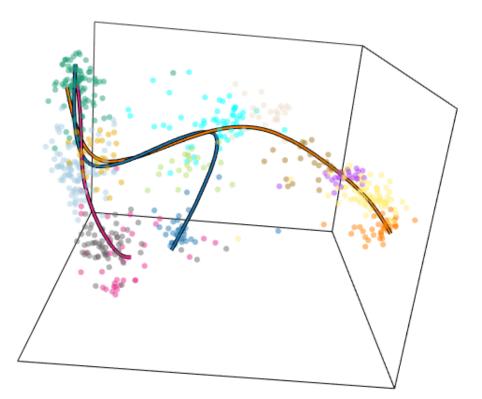
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→ simulataneous principal curve fitting for overlapping branches

Shrinkage

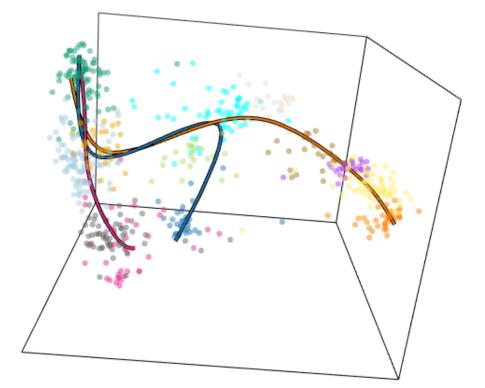
- Principal curves → multiple pseudotimes for same cells in multiple lineages
- Shrink curves to average based on the density of cells shared across lineages

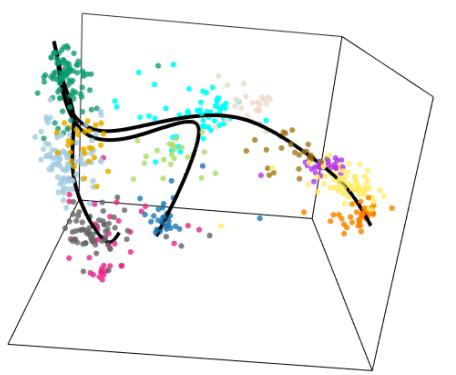


Shrinkage

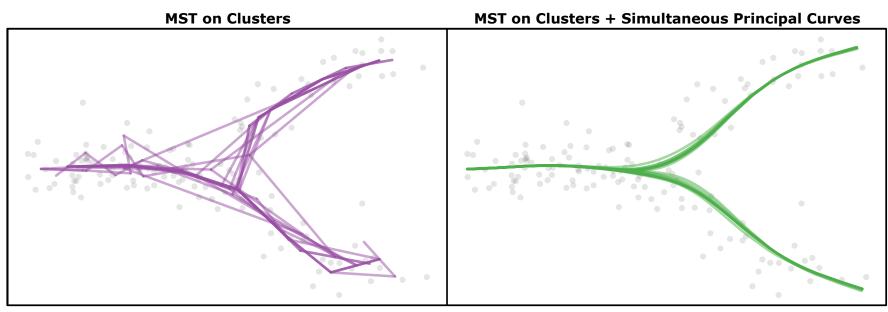
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With Shrinkage





Retain robustness of Principal Curves





k = 3-14

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Slingshot

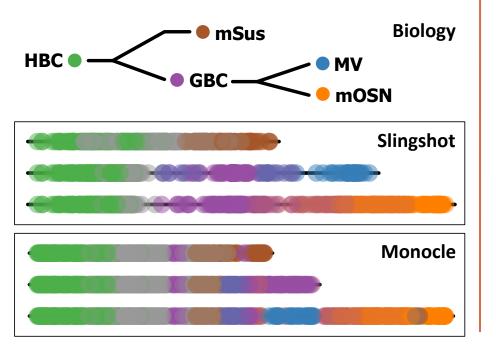
- → Use MST for assigning clusters of cells to lineages
 → Principal curves within lineages to give ordering
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 - \rightarrow simulataneous principal curve fitting for overlapping branches

 \rightarrow covariance based distance for MST to capture shape of cluster

Compare to Other Methods

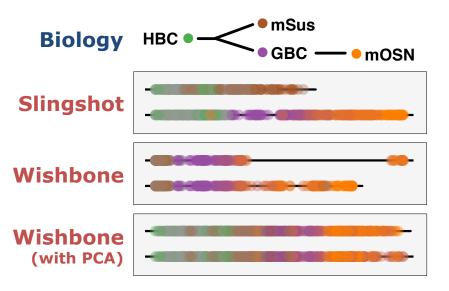
Monocle

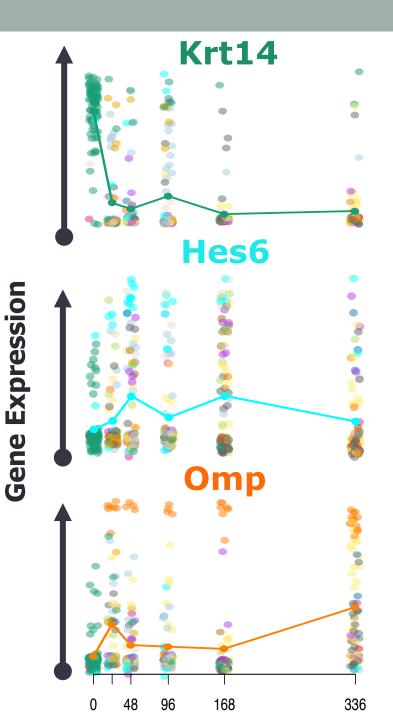
Must specify
 # lineages

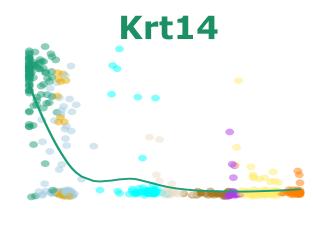


Wishbone

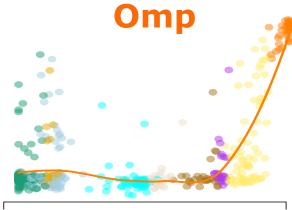
- Only two lineages
- Built-in Dimensionality Reduction

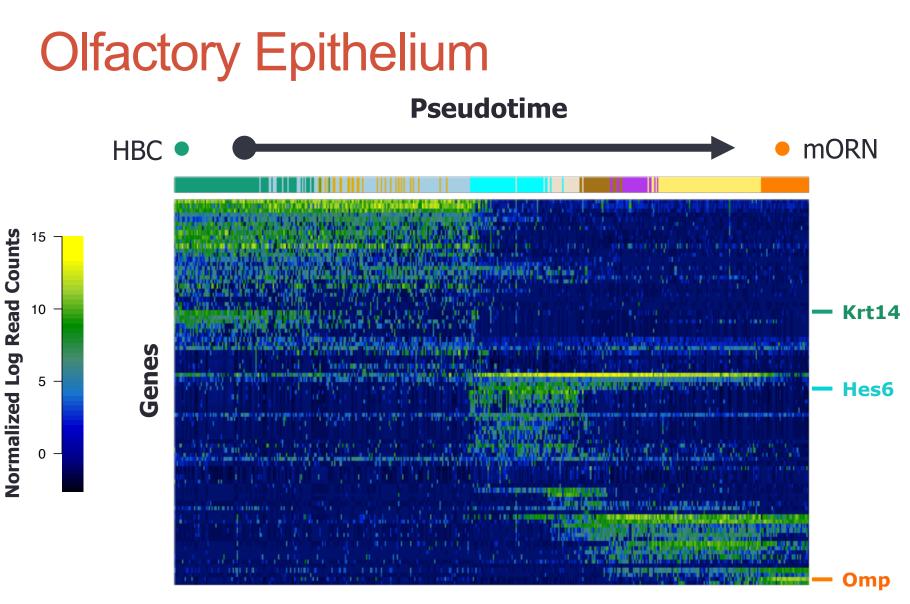












Neuronal Lineage Samples

Concluding Remarks

- Robust and flexible method for determining lineage of cells
- However, ...
- Very high expectations \rightarrow Many assumptions
- Processing and dimensionality reduction are also critical components

John Ngai David Stafford Jasper Visser Russell Fletcher Diya Das Levi Gadye Mike Sanchez Ariane Baudhuin

Hillel Adesnik

David Taylor Alex Naka Sandrine Dudoit Elizabeth Purdom Davide Risso Kelly Street

Nir Yosef Allon Wagner Michael Cole

Functional Genomics Lab Justin Choi

CRL Flow Cytometry Core Hector Nolla

RSEC available as part of clusterExperiment package on bioconductor SCONE available on bioconductor (dev) Slingshot available on https://github.com/kstreet13/slingshot

NIH BRAIN Initiative Cell Census Consortium National Institute on Deafness and Other Communication Disorders National Institute on Aging National Human Genome Resource Institute California Institute for Regenerative Medicine

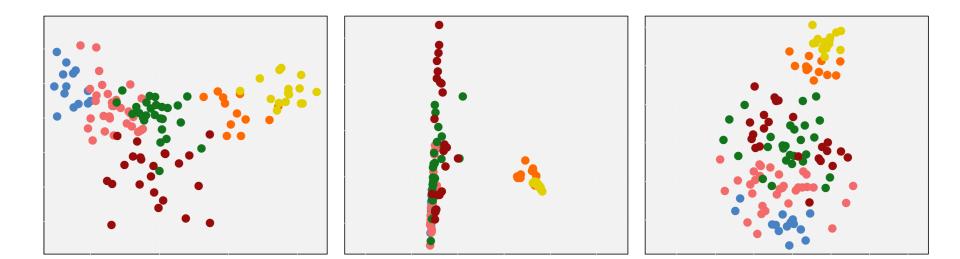
GRAVEYARD

Effect of dimensionality reduction is big

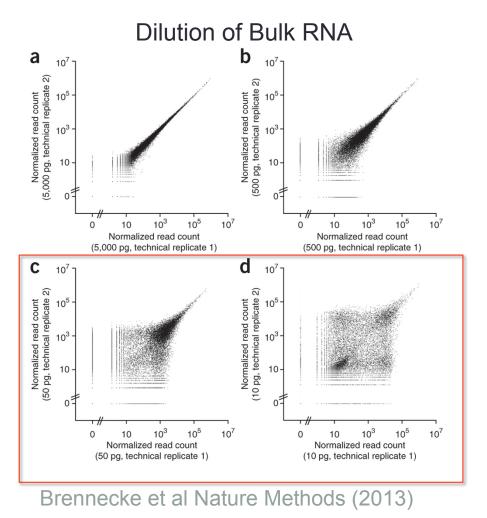


Laplacian Embedding

tSNE



Limitations: Noisy data



Because of low starting input (picograms), large amounts of amplification, other technical problems

