Advanced Topics in Single Cell Omics

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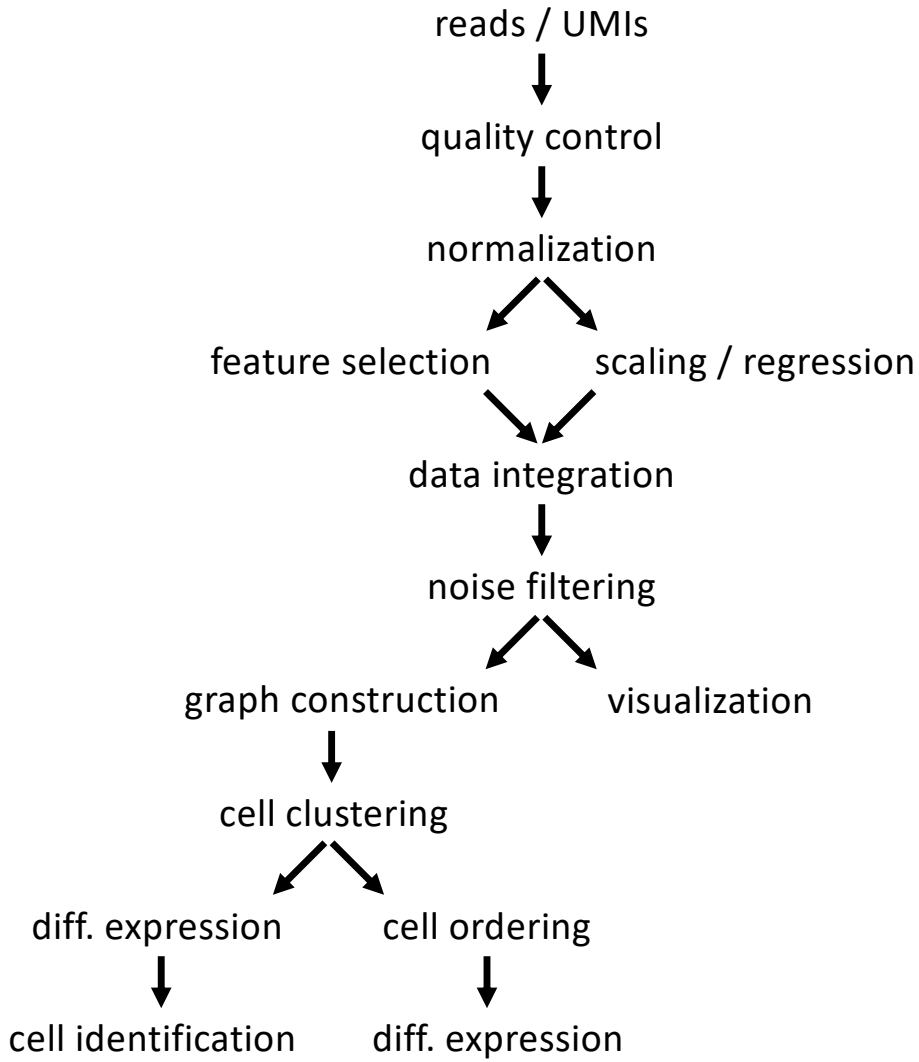
2021-08-30

scRNA-seq analysis workflow



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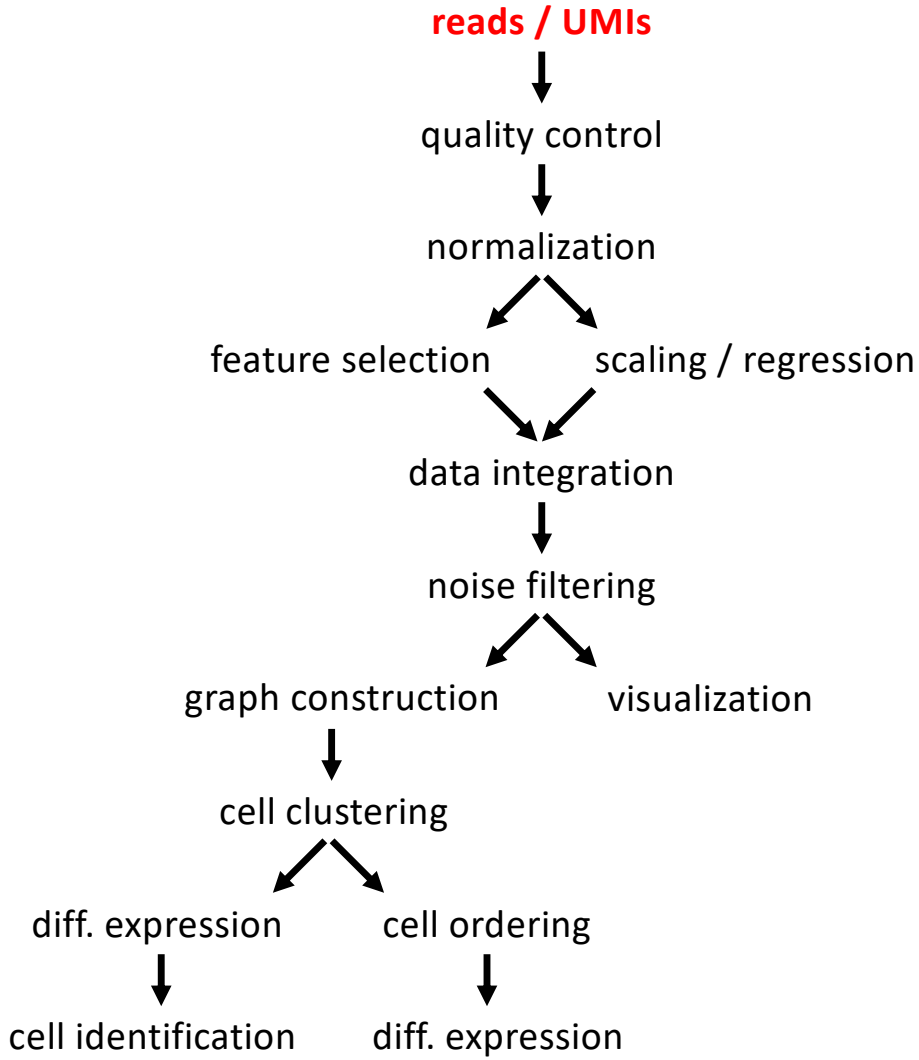
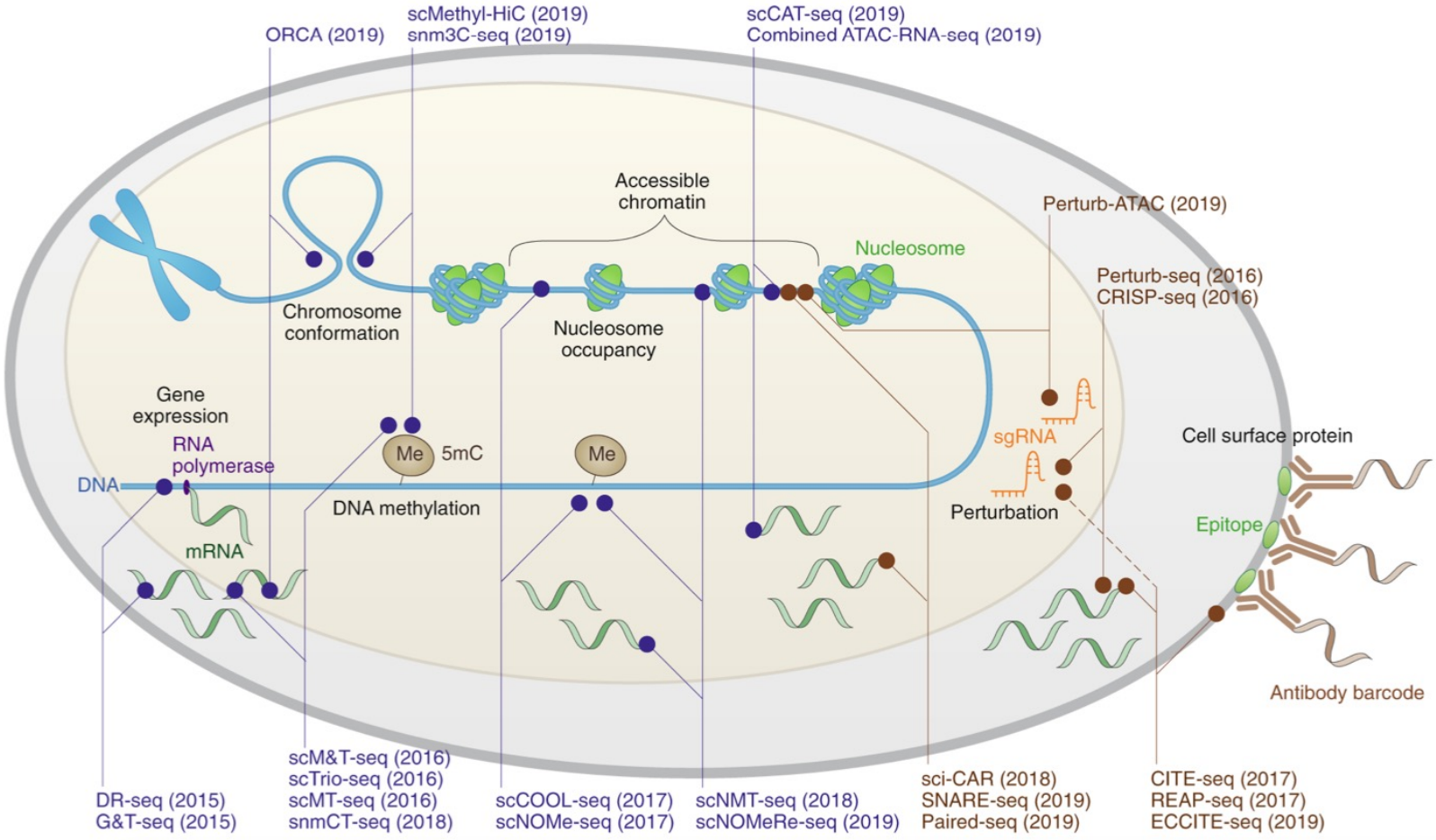
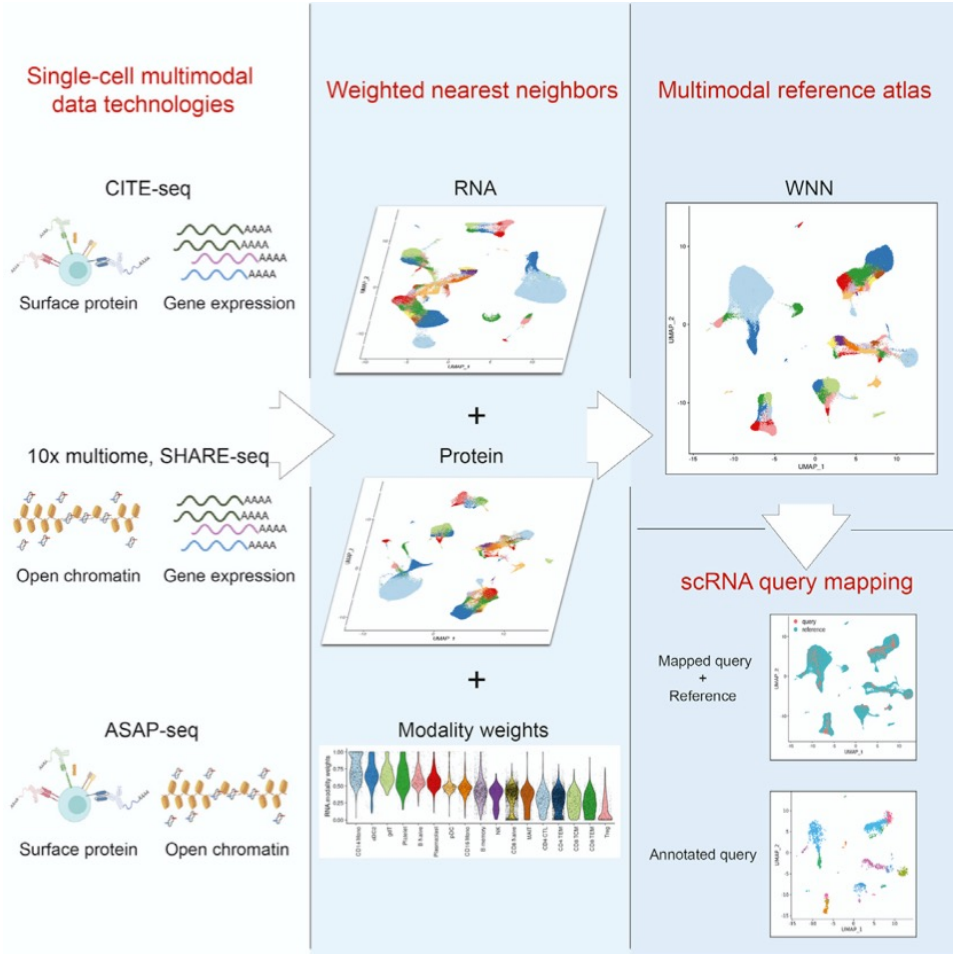


scRNA-seq technologies



Zhu et al, Comment in Nature Methods, 2020

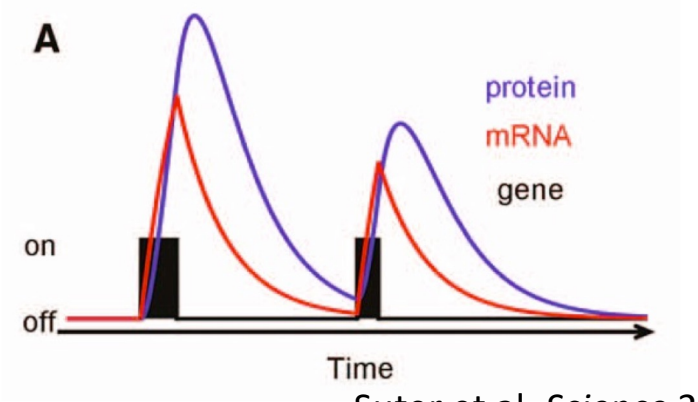
scRNA-seq technologies



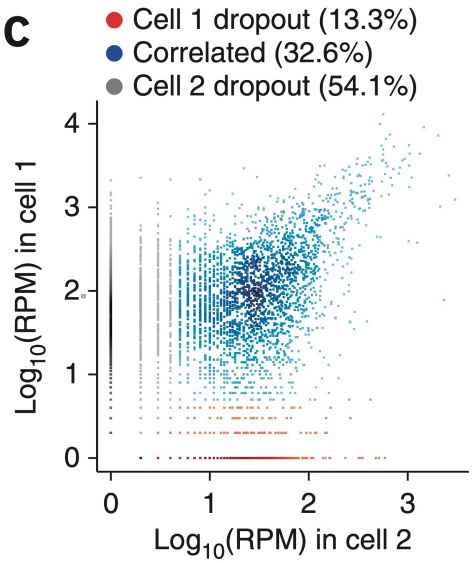
Hao et al, Cell, 2021

scRNA-seq biases

- Amplification bias
- Drop-out rates
- Transcriptional bursting
- Background noise
- Bias due to cell-cycle, cell size and other factors
- Often clear batch effects
- Dissociation protocols may introduce transcriptional artifacts
- Ambient RNA

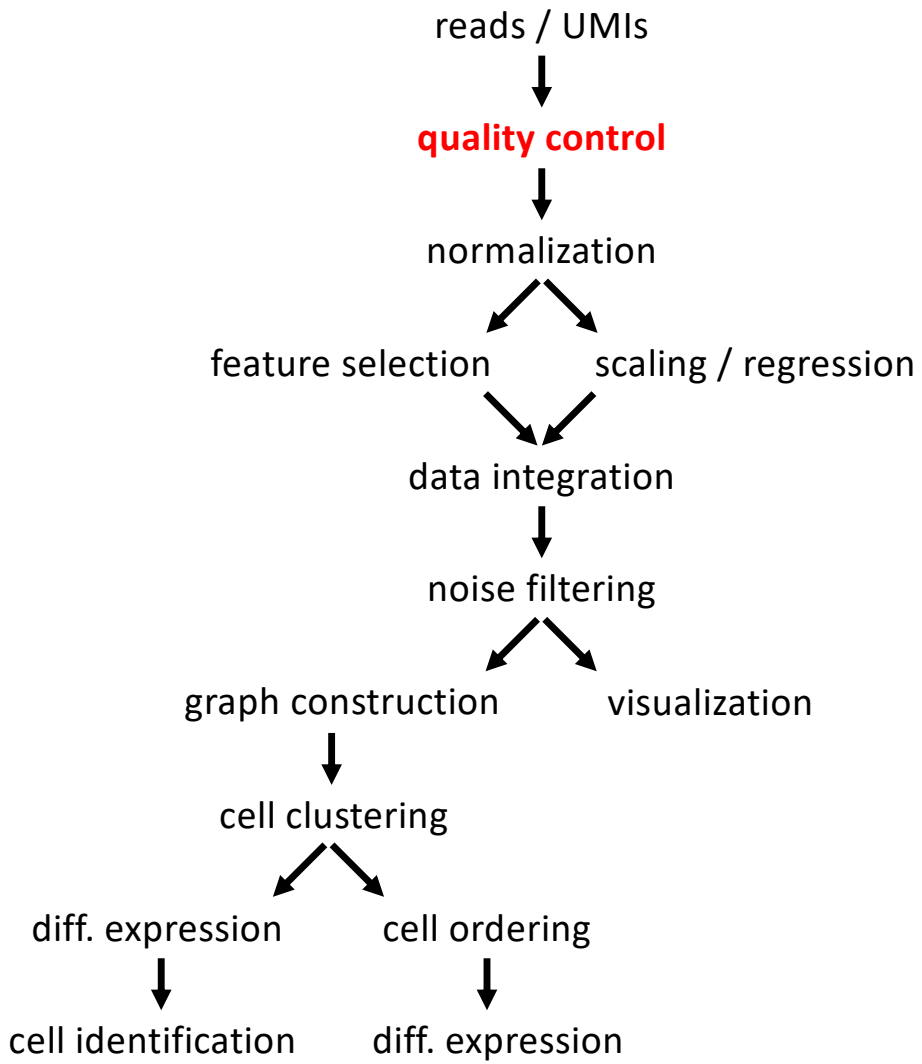


Suter et al. *Science* 2011



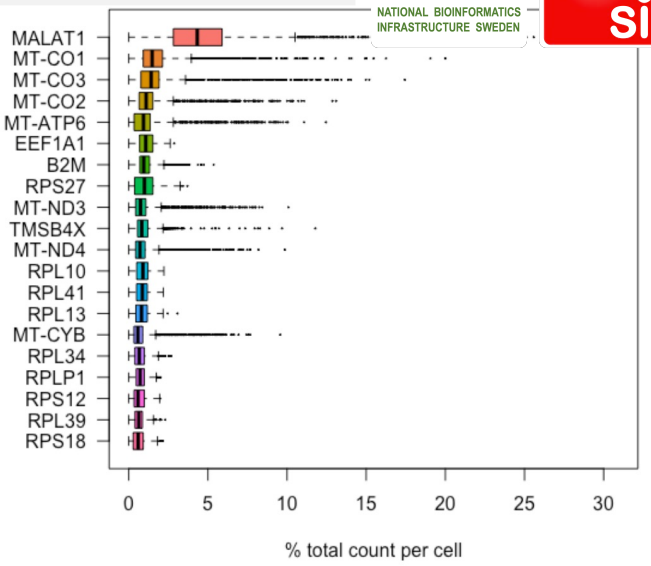
Karchenko et al. *Nature Methods* 2014

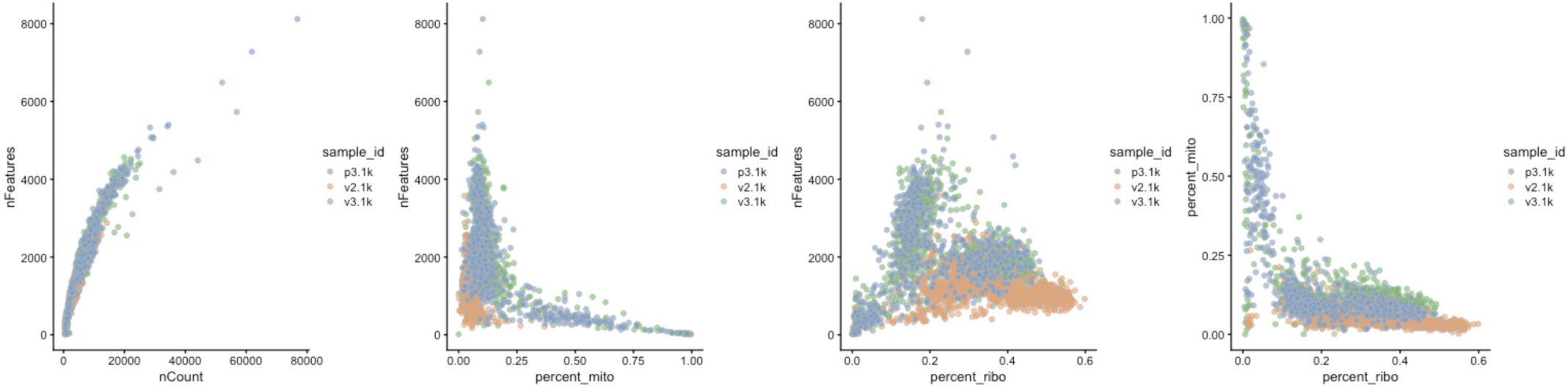
scRNA-seq analysis workflow



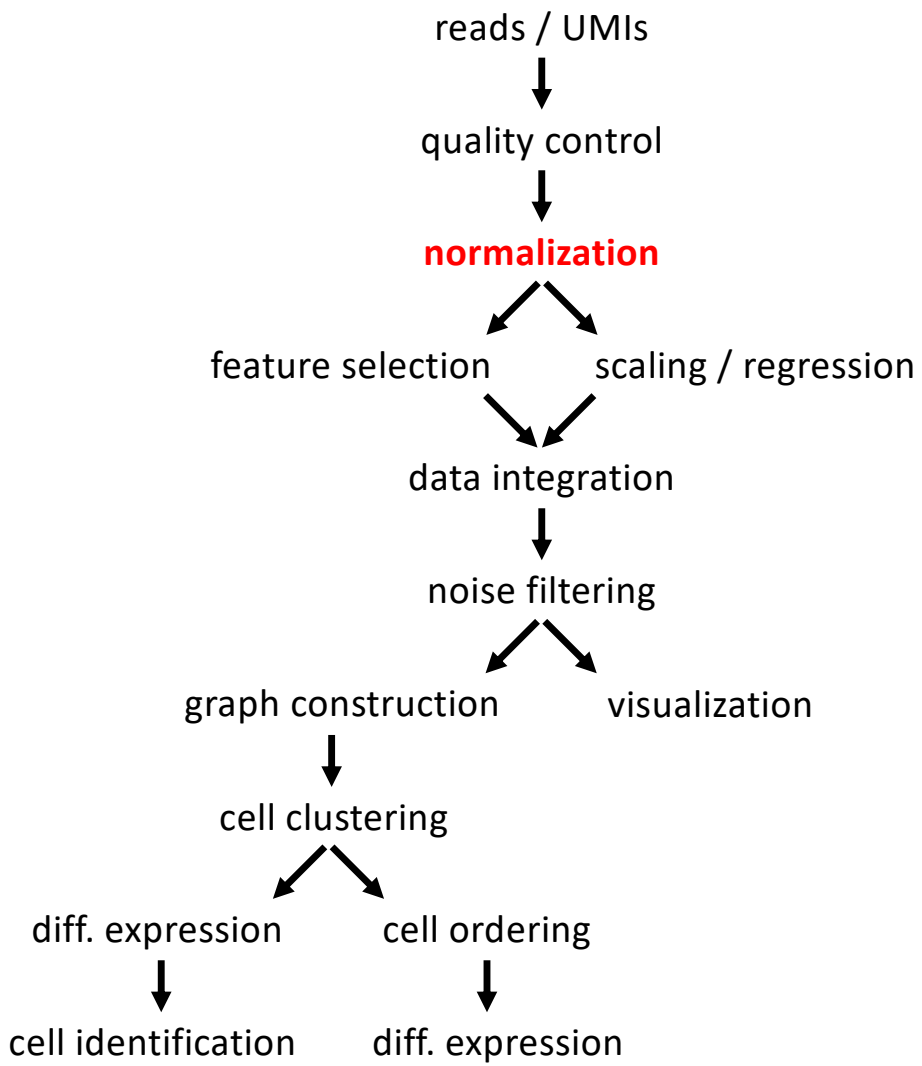
scRNA-seq quality control

- Mapping statistics (% uniquely mapping)
- Cell cycle biases
- 3’ bias – for full length methods like SS2
- mRNA-mapping read percentage
- Number of UMIs/read counts
- Number of detected genes
- Spike-in detection
- Mitochondrial percentage
- ribosomal percentage
- Protein-coding percentage





scRNA-seq analysis workflow



scRNA-seq normalization

Count normalization (UMI and read counts)
for uneven sequencing depth
- CPM - log[CP10K+1]

Gene length normalization (read counts)
for differences in gene detection due to gene length
- TPM (closer to UMI counts)
- FPKM

Drop-out rate normalization (UMI and read counts)
for differences in RNA content / drop-out rates
- Deconvolution/Scran(Pooling-Across-Cells)
- SCnorm(Expression-DepthRelation)
- SCTransform
- Census
- Linnorm
- ZINB-WaVE
- …

bulk

$$CPM = \log\left(\frac{counts}{library_{size}} \cdot 10^{6} + 1\right)$$

single-cell

$$log[TP10K + 1] = \log\left(\frac{counts}{library_{size}} \cdot 10^{4} + 1\right)$$

Most common for UMI data / fast

$$FPKM = \log\left(\frac{counts}{library_{size} \cdot transcript_{length}} \cdot 10^{4} + 1\right)$$

$$TPM = \log\left(\frac{counts}{transcript_{length}} \cdot \frac{10^{4}}{\sum \frac{counts}{transcript_{length}}} + 1\right)$$

scRNA-seq analysis workflow

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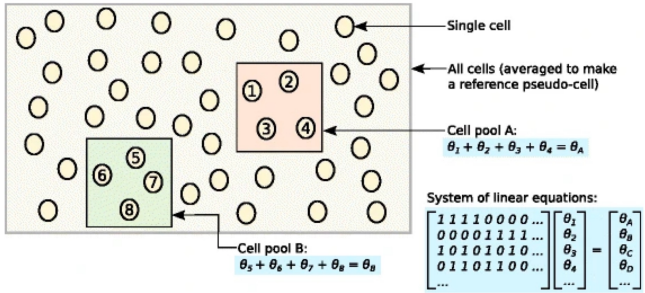
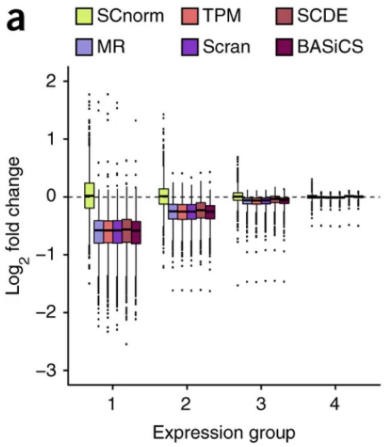
- …

Deconvolution



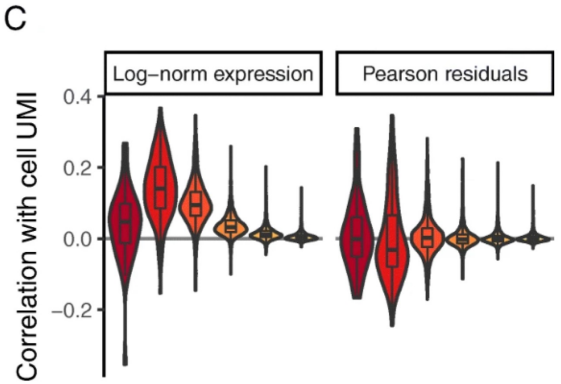
Lun et al. Genome Biol. 2016

SCnorm



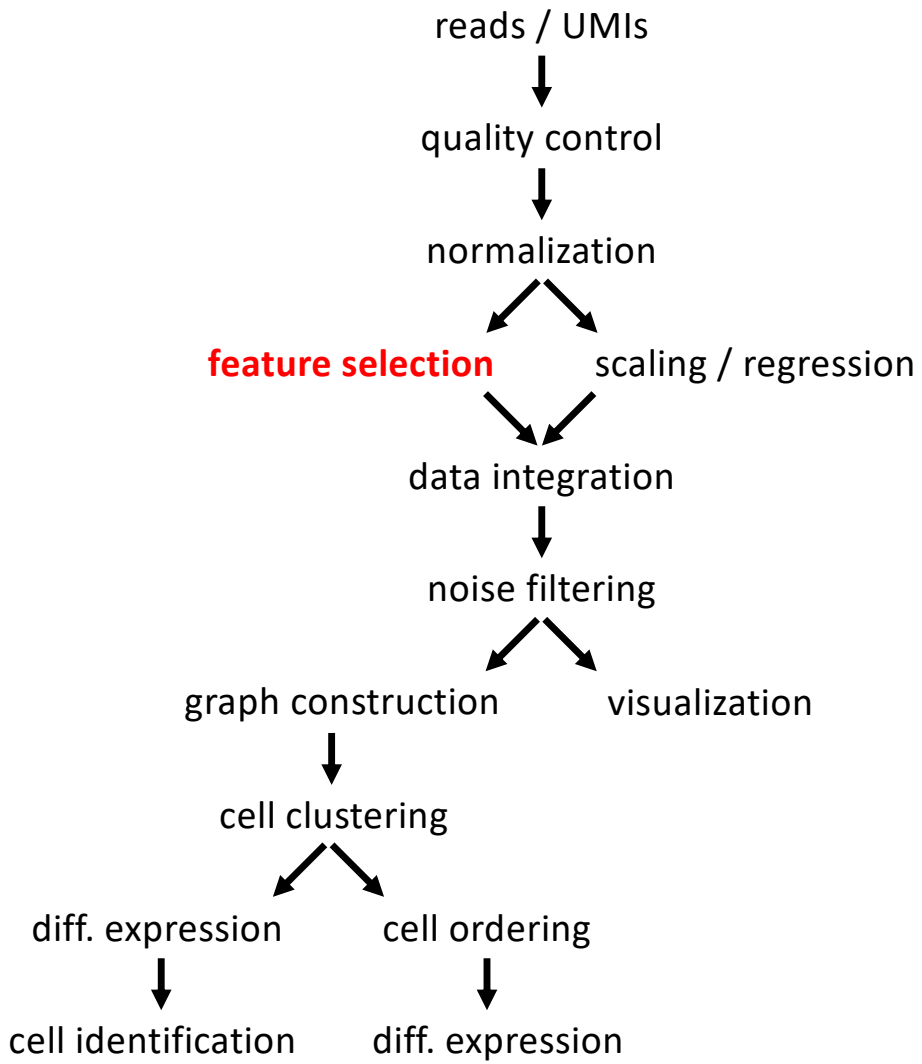
Bacher et al. Nature Methods 2017

SCTransform



Hafmeister &
Satija Genome Biology 2019

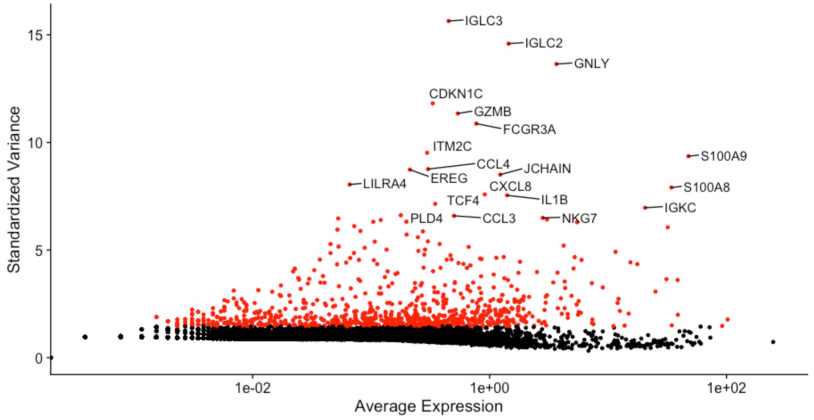
scRNA-seq analysis workflow



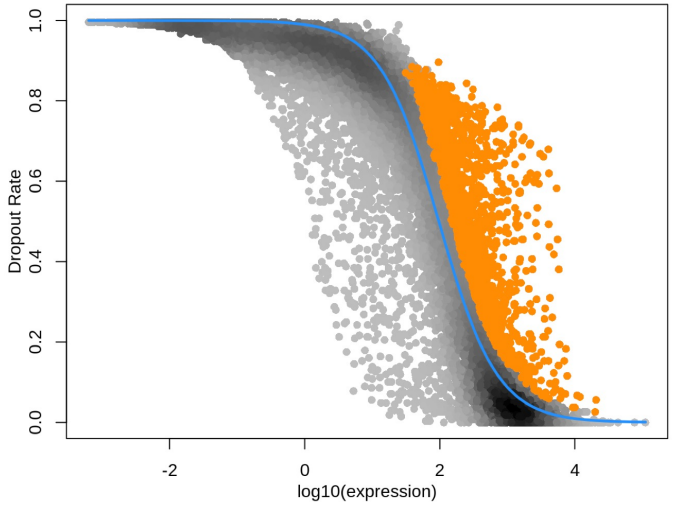
scRNA-seq feature selection

Not all genes are important to define you cell types

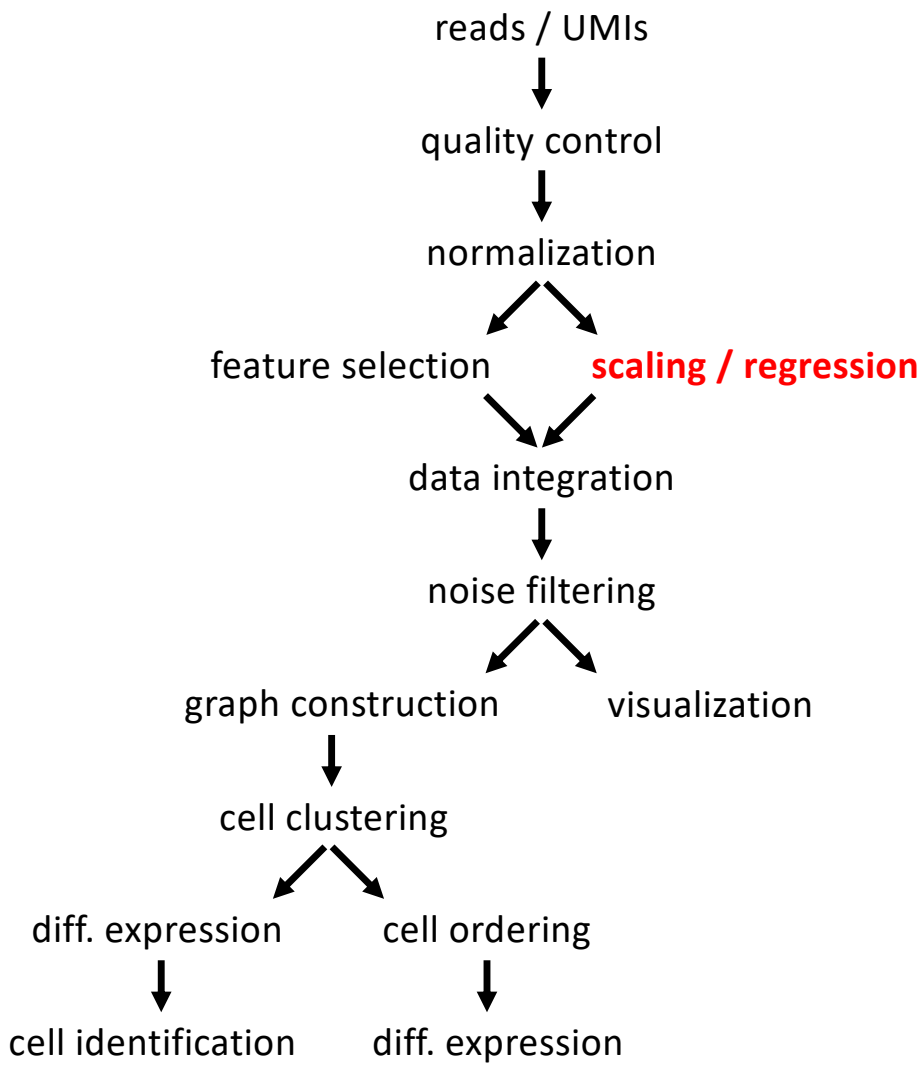
$$HVG = \frac{variance}{\log(meanExpression)}$$



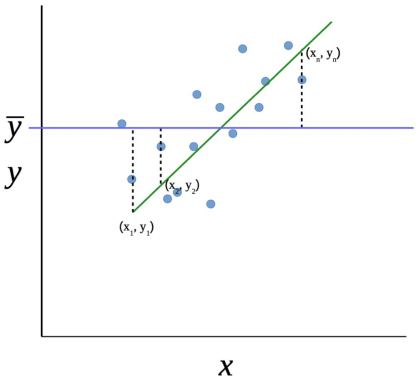
$$HVG = \frac{\log(meanExpression)}{dropout_{rate}}$$



scRNA-seq analysis workflow



scRNA-seq scaling and regression of biases



Any source of variation that you do not expect to give separation of the cell types can be regressed out.

- Fit a line to the gene expression *vs* variable of interest
- Calculate residuals
- Remove variance explained by the variable of interest by taking the residuals.
- Linear / Negative Binomial / Poisson distributions

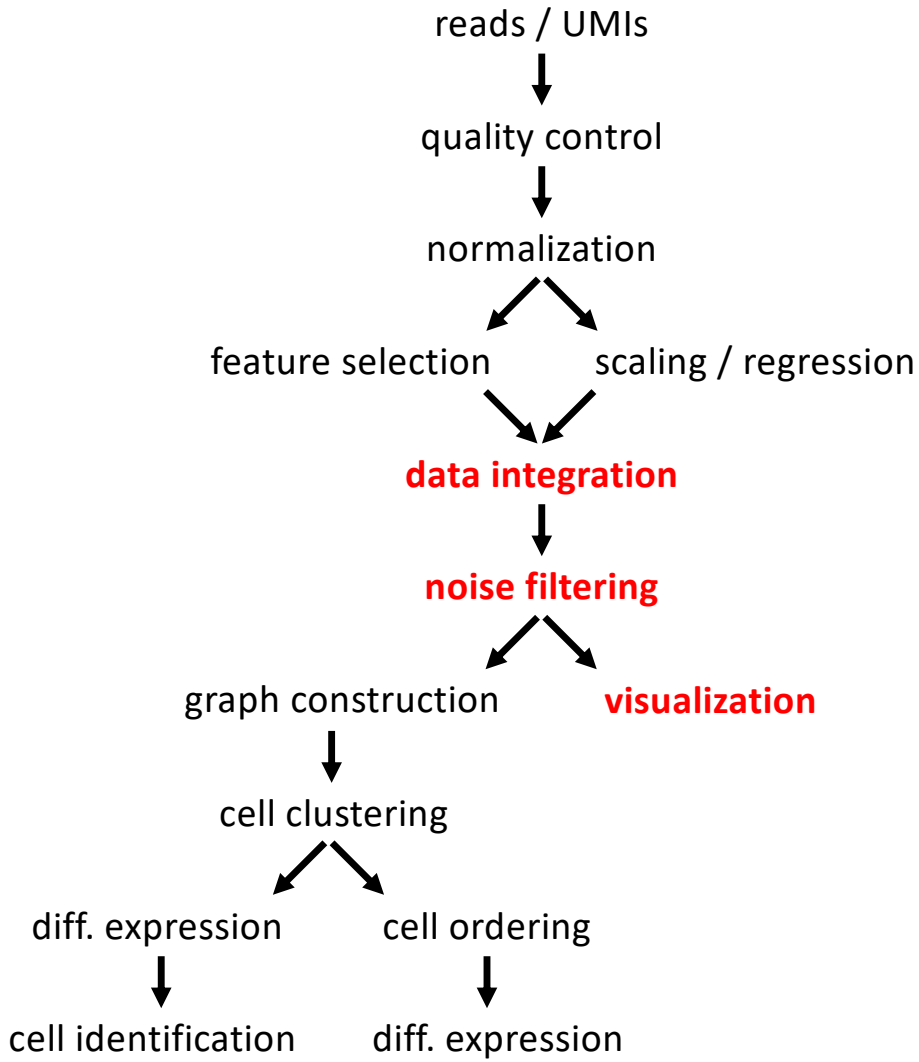
fast

logNormalized counts follows a log-linear distribution

slower (but more accurate)

Regressing counts directly is better with count-based distributions

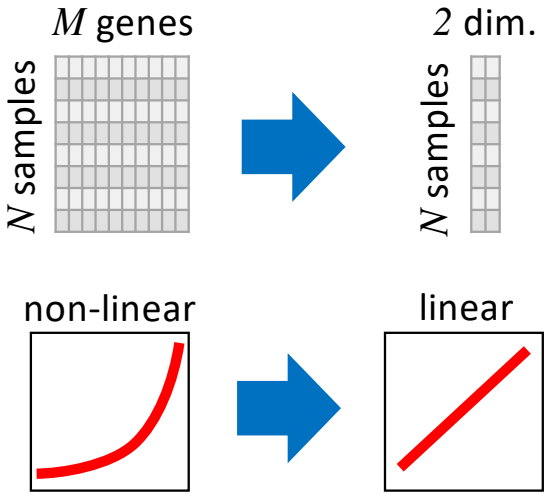
scRNA-seq analysis workflow

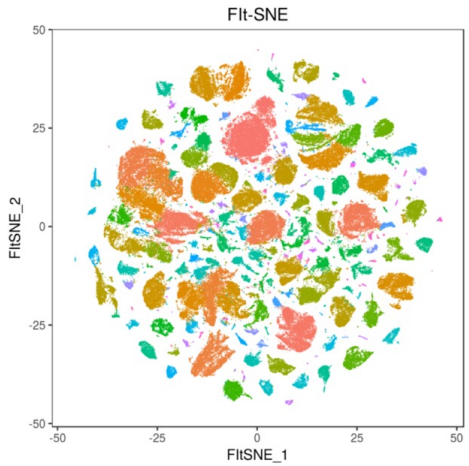


scRNA-seq dimensionality reduction

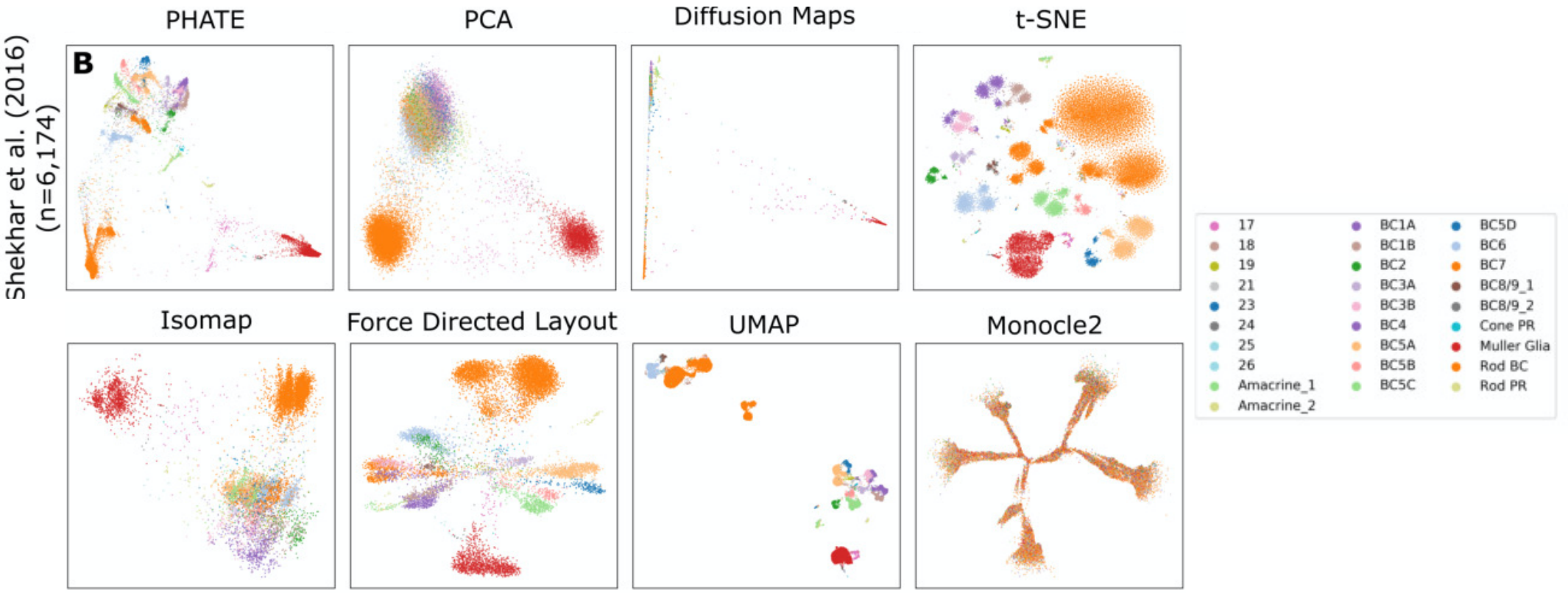
- Simplify complexity, so it becomes easier to work with.
  - Reduce number of features (genes)
  - In some: Transform non-linear relationships to linear
- "Remove" redundancies in the data
- Identify the most relevant information (find and filter noise)
- Reduce computational time for downstream procedures
- Facilitate clustering, since some algorithms struggle with too many dimensions
- Data visualization

… and more …



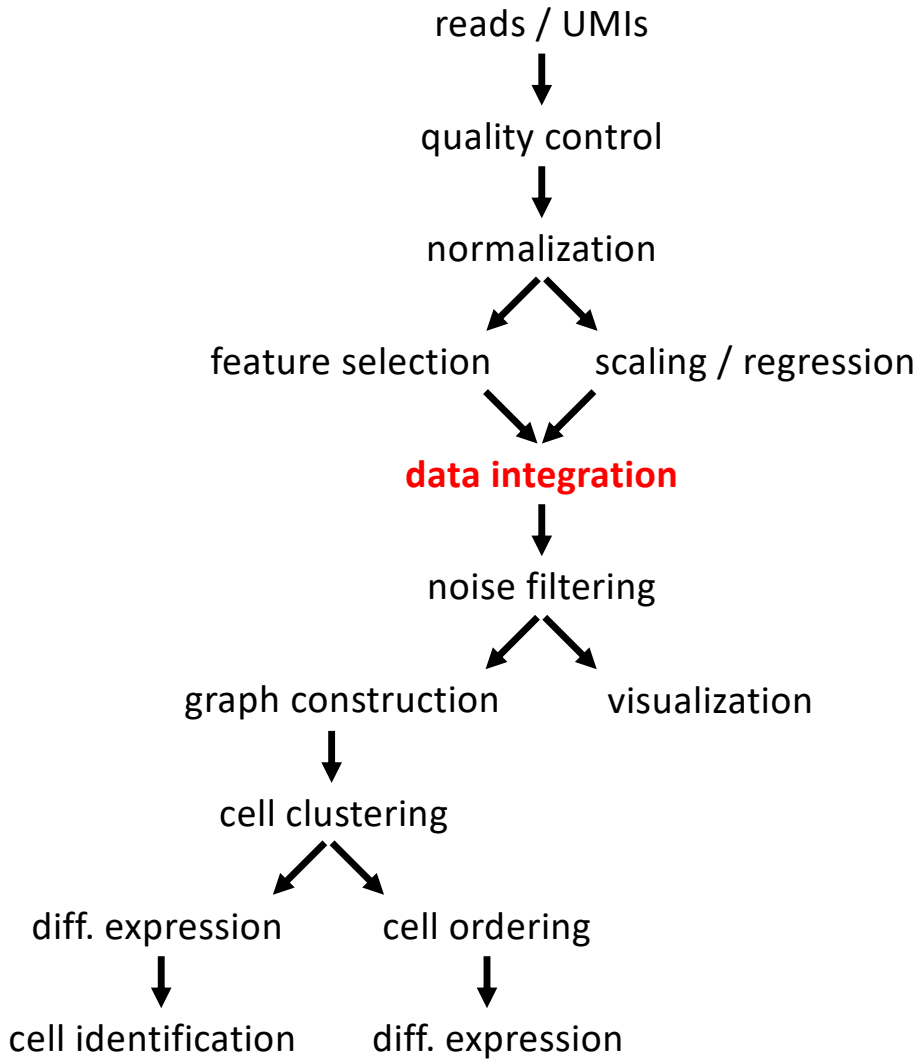


Some dimensionality reduction methods



Moon et al (2019) *BioRxiv*

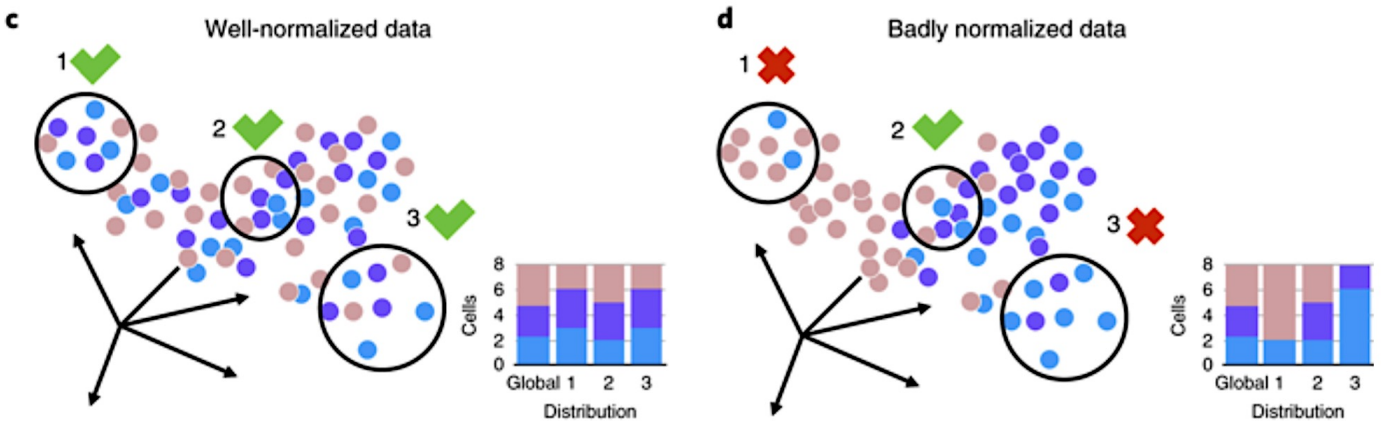
scRNA-seq analysis workflow



scRNA-seq data integration

We wish to obtain corrected data where the following goals are met:

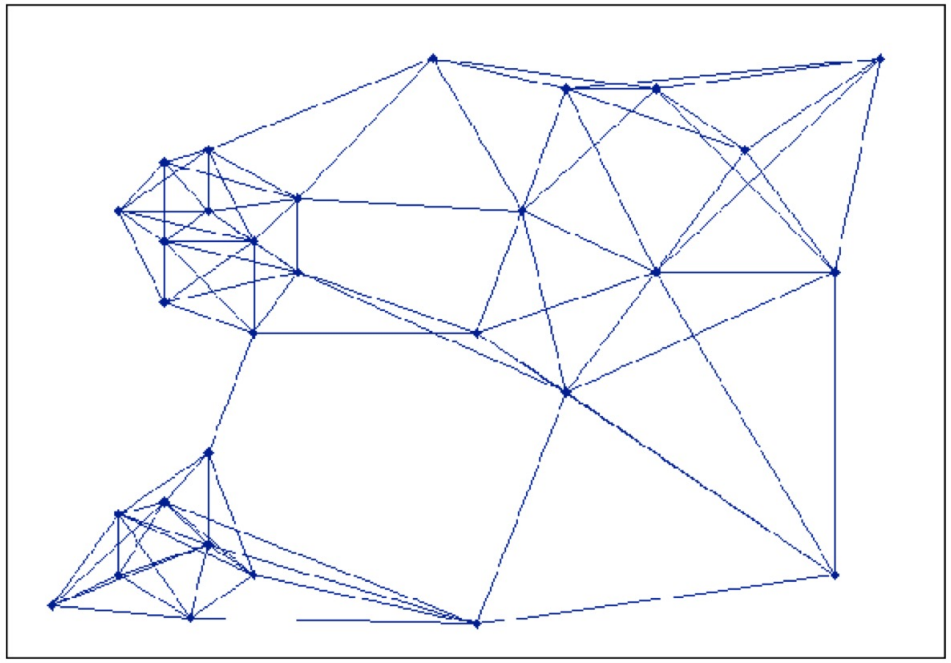
Goal:	**What it practically means:**
1.The batch-originating variance is erased	Similar cell types are intermixed across batches
2.Meaningful heterogeneity is preserved	We are not mixing distinct cell types (across or within batches)
3.No artefactual variance is introduced	We do not separate similar cells within batches



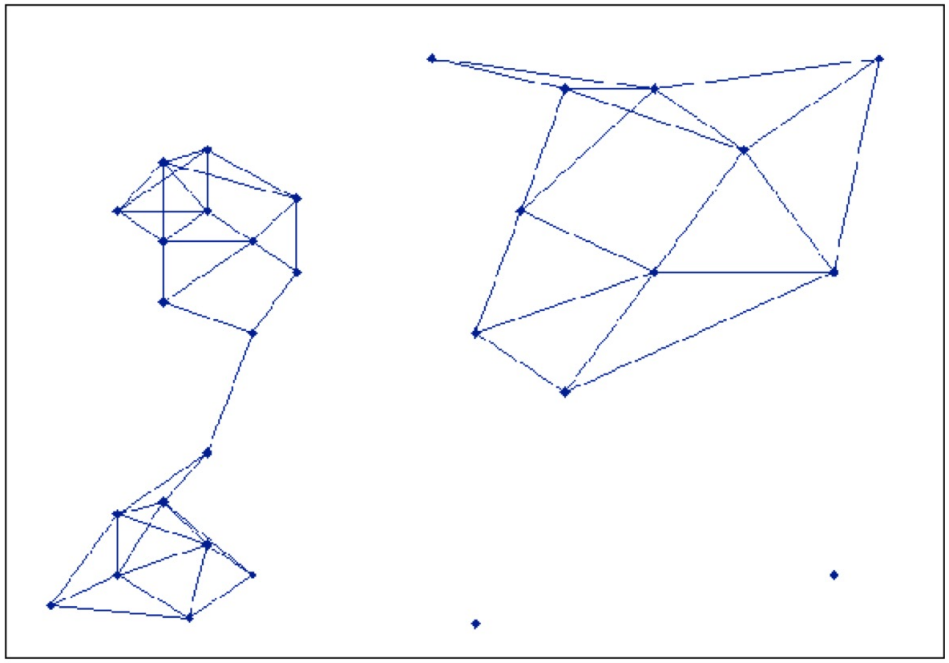
Büttner, et al (2019) *Nat Methods*

scRNA-seq graph construction

The ***k*-Nearest Neighbor** (***k*NN**) graph is a graph in which two vertices *p* and *q* are connected by an edge, if the distance between *p* and *q* is among the *k*-th smallest distances from *p* to other objects from *P*.



The **Shared Nearest Neighbor** (**SNN**) graph has weights that defines proximity, or similarity between two edges in terms of the number of neighbors (i.e., directly connected vertices) they have in common.

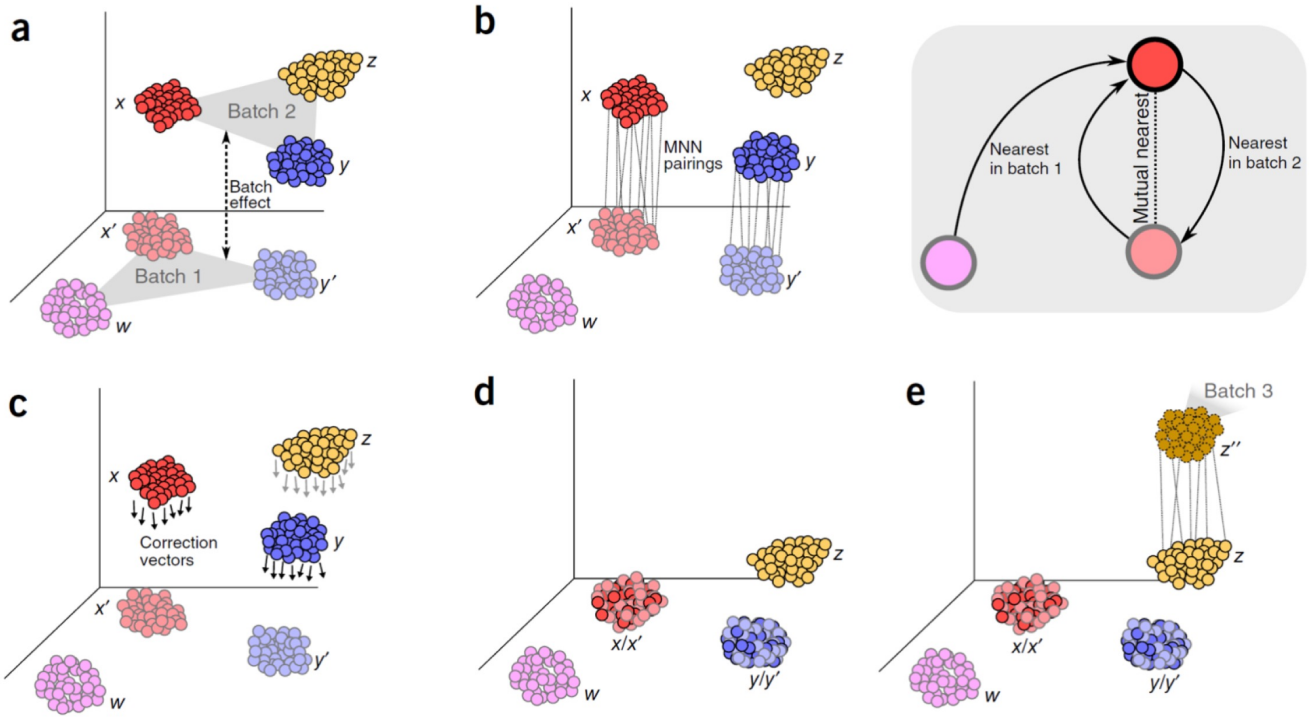


scRNA-seq analysis workflow

Regression based bulk-RNAseq batch correction methods are slow and assume the batch is constant across cells

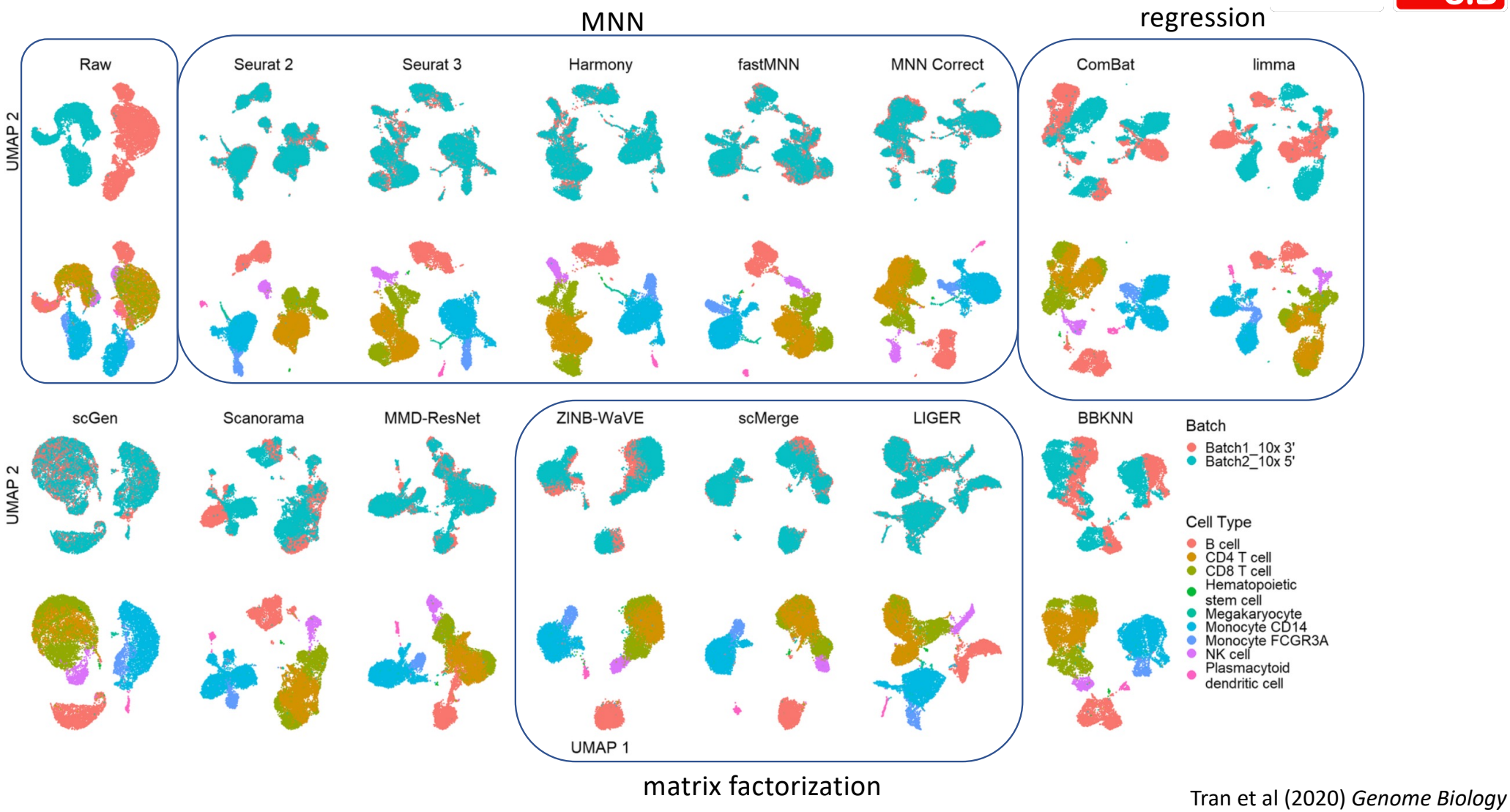
Modern data integration methods are based on the same principle:

- find MNN (mutual nearest neighbours) across datasets and correct each cell individually
- Done on a graph: much faster



Haghverdi et al (2017) Nat Biotechnology

scRNA-seq analysis workflow



Tran et al (2020) *Genome Biology*

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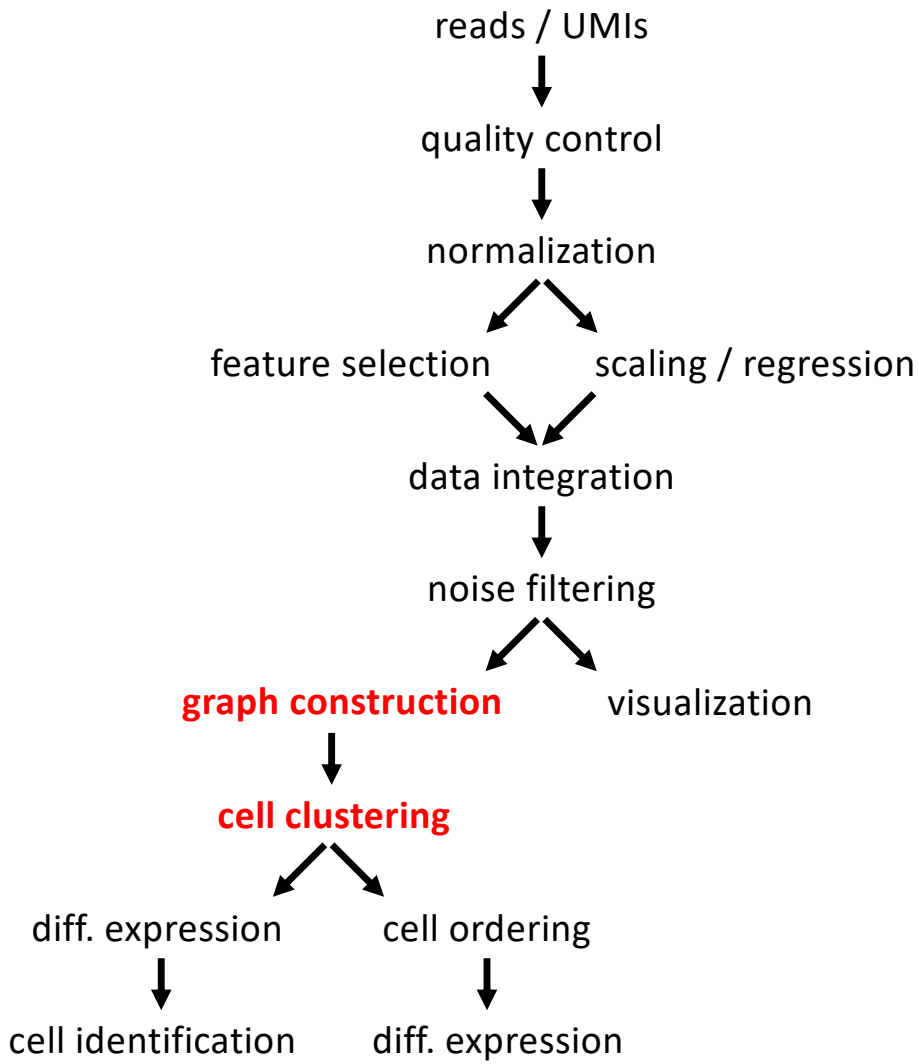
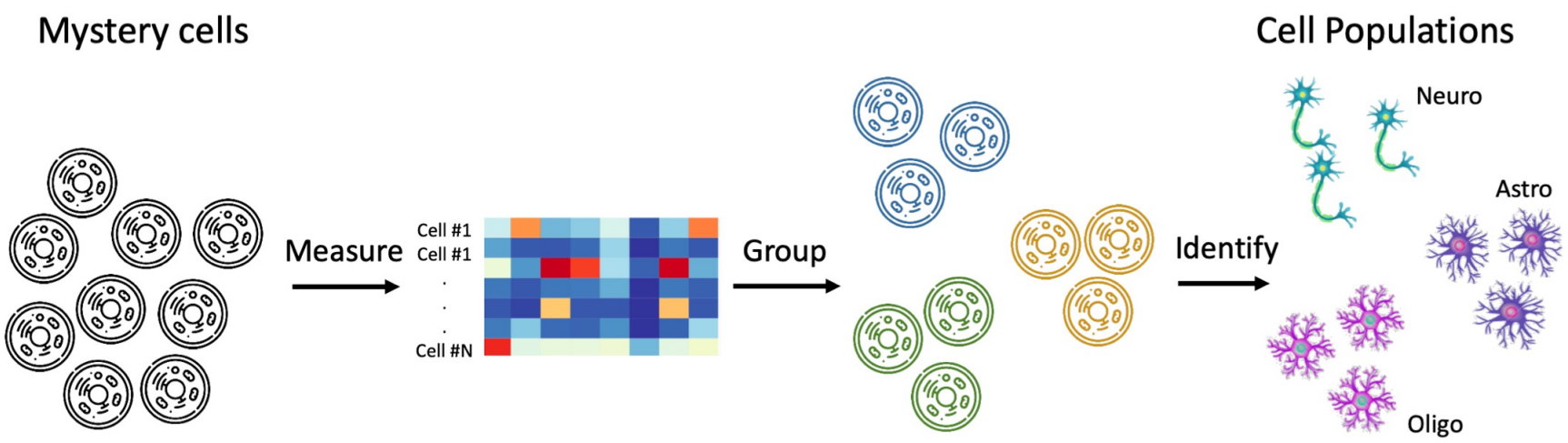


scRNA-seq clustering



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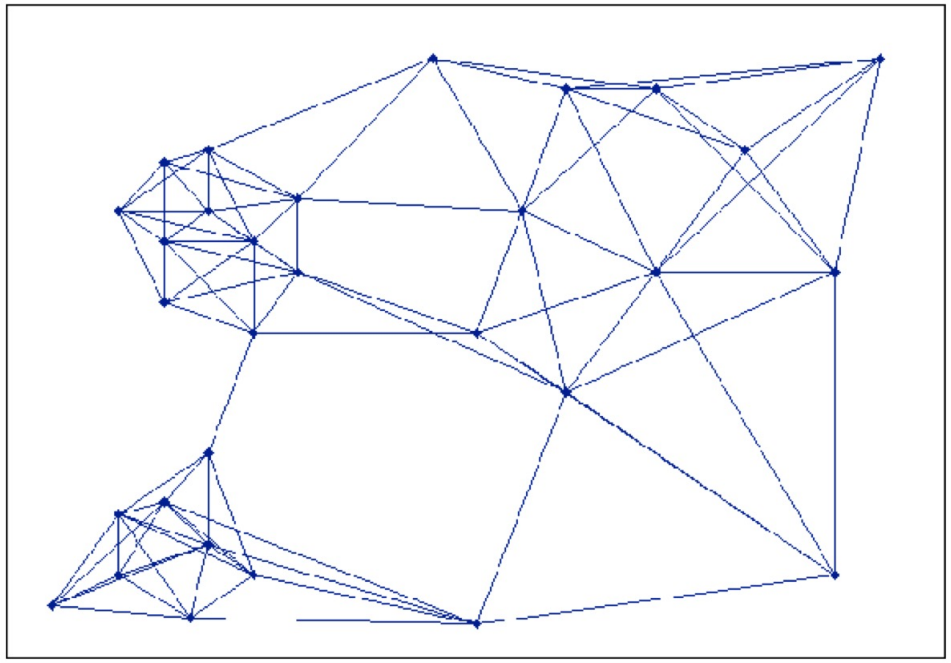

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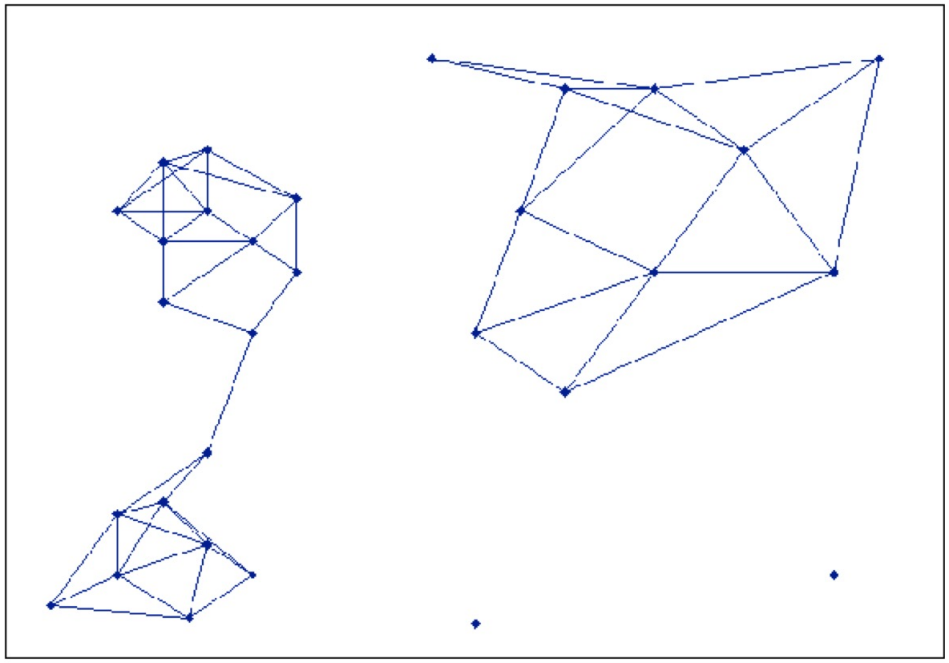
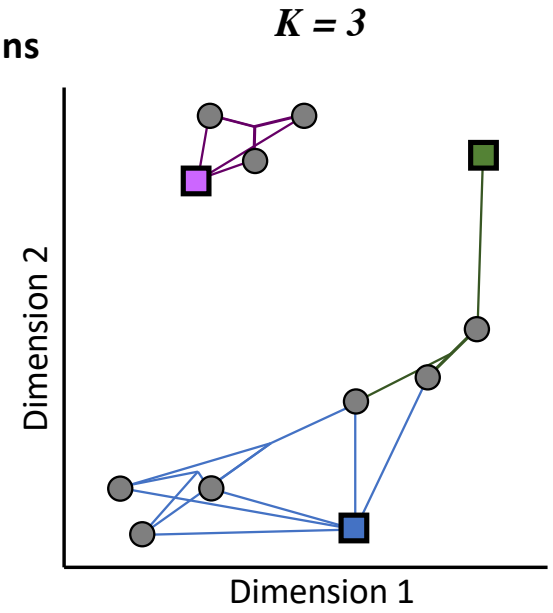
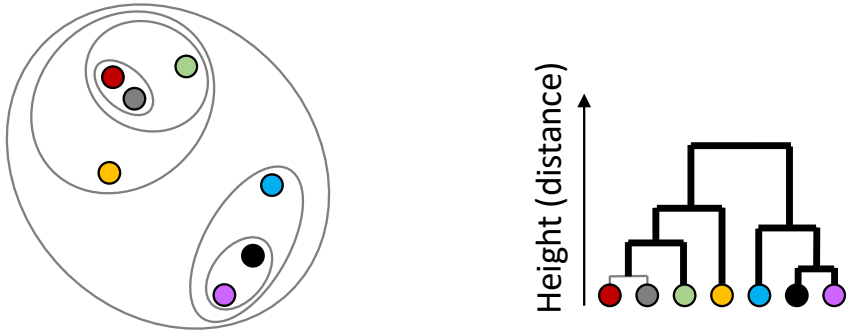


scRNA-seq clustering

K-means

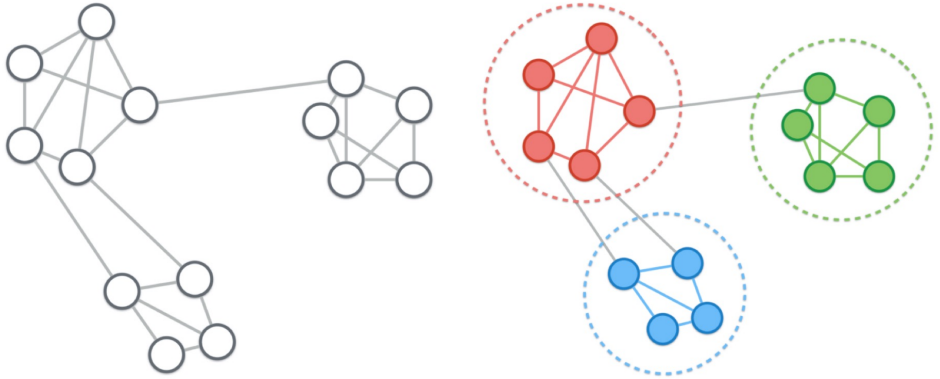


Hierarchical Clustering

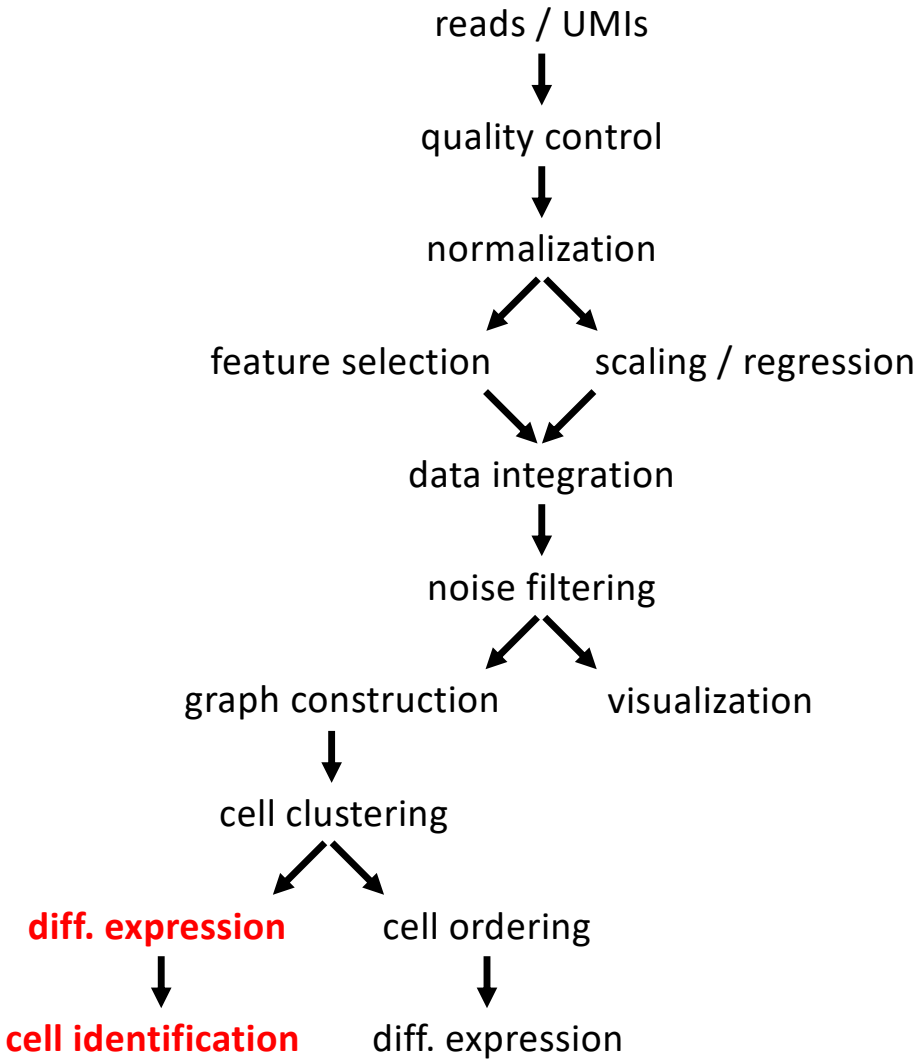


GRAPH
Louvain / Leiden community detection

Communities, or clusters, are usually groups of vertices having higher probability of being connected to each other than to members of other groups.



scRNA-seq analysis workflow

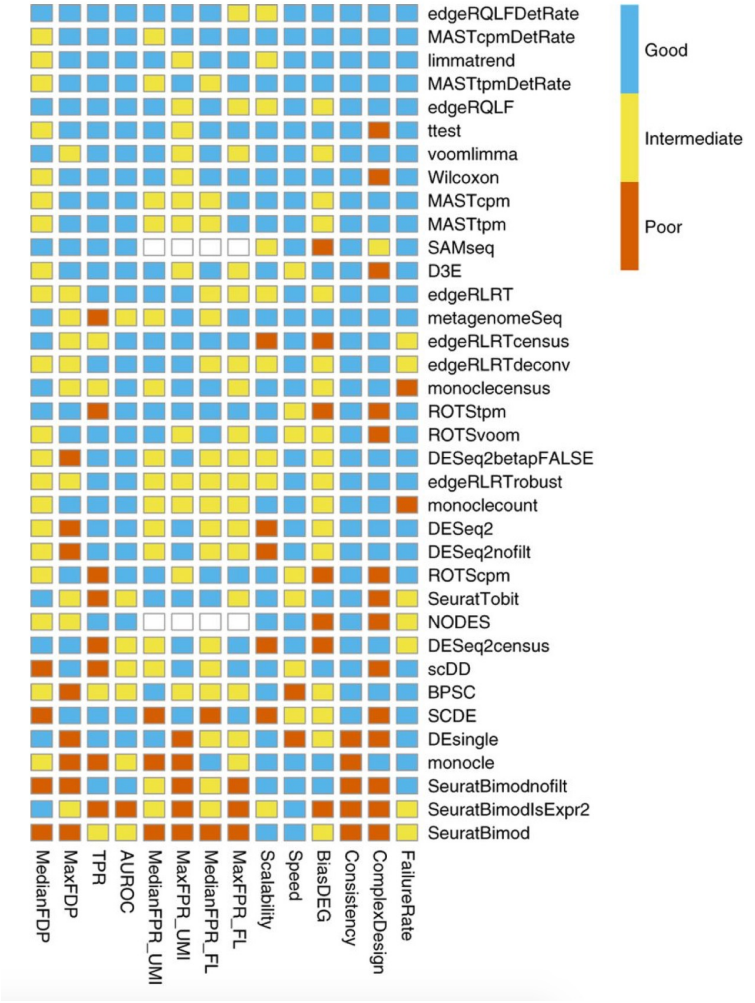


scRNA-seq differential gene expression

Typically we have more than two clusters in a data set

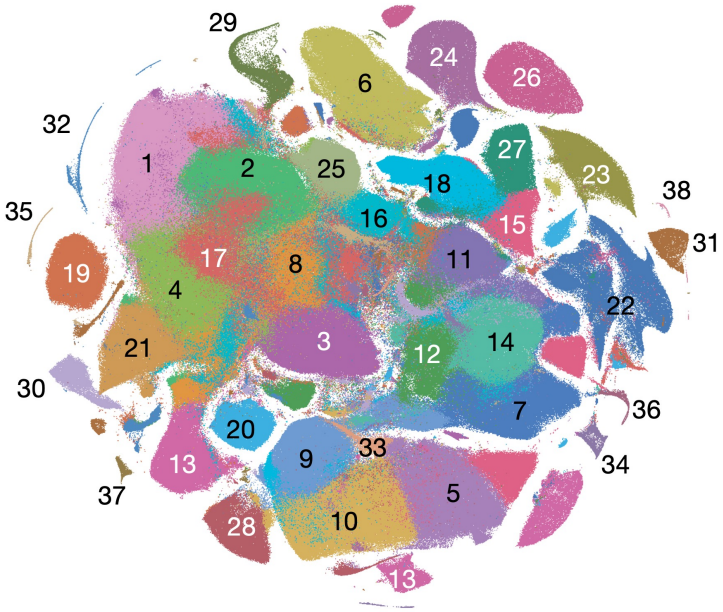
For a given cluster, are we interested in “marker genes” that are:

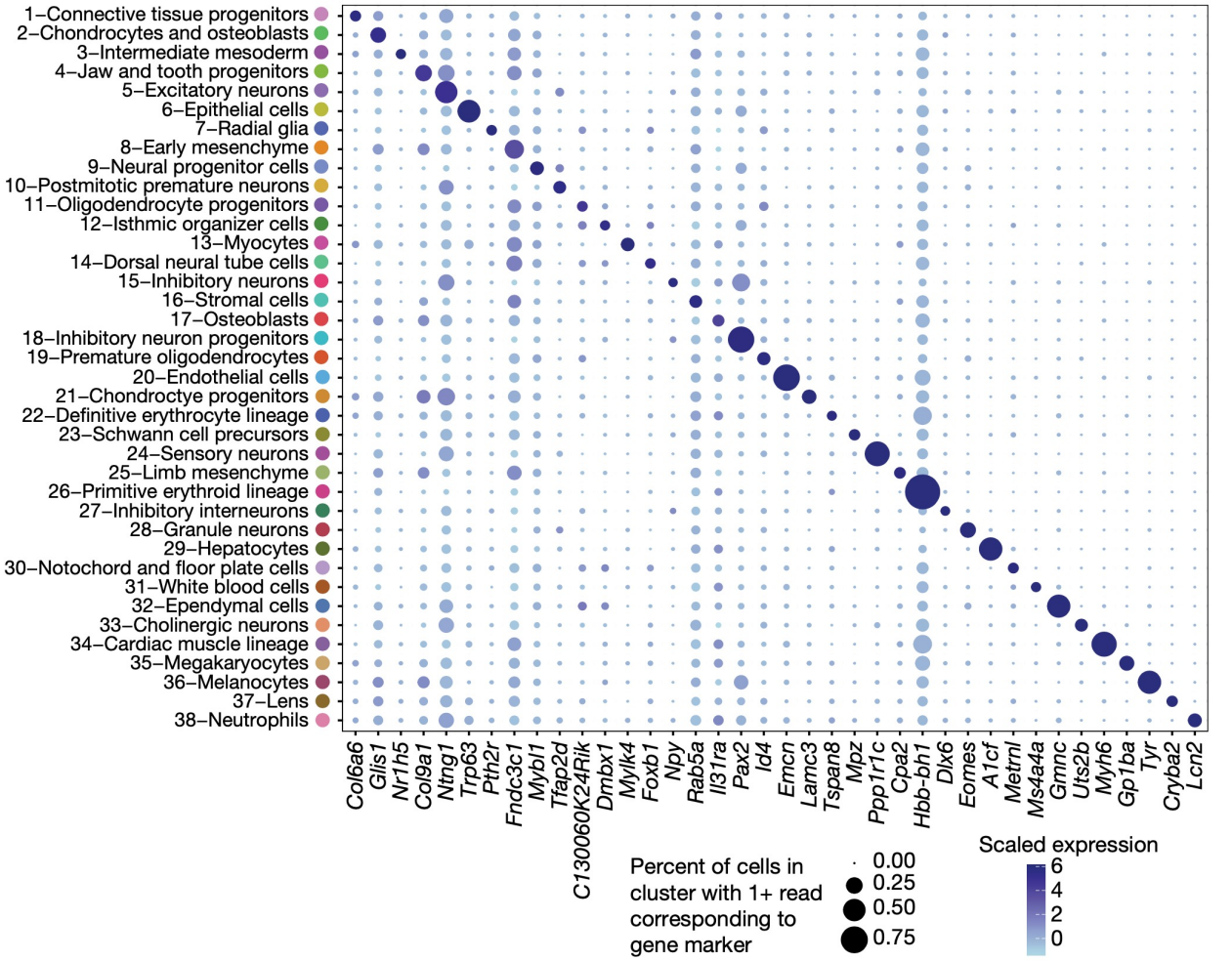
- **DE compared to all cells outside of the cluster (most common)**
- DE compared to at least one other cluster
- DE compared to *each* of the other clusters
- DE compared to “most" of the other clusters



Soneson et al 2018 *Nat Methods*

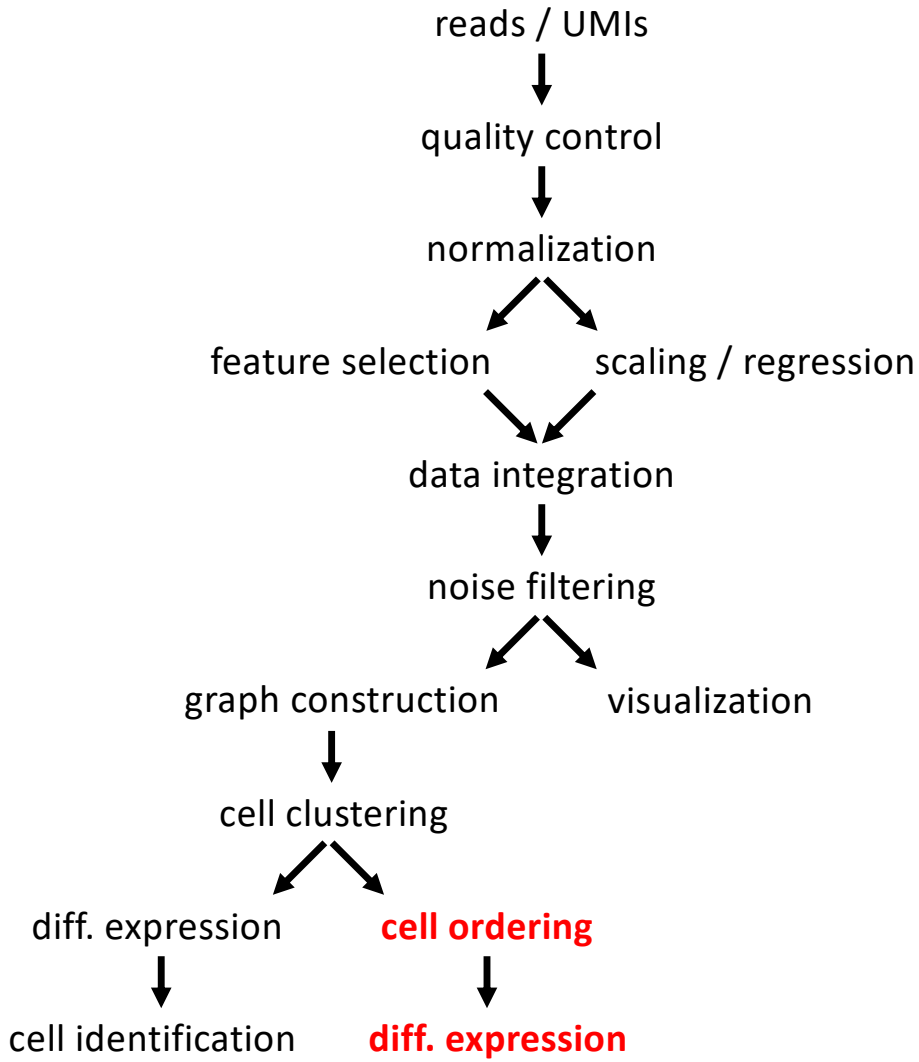
scRNA-seq differential gene expression



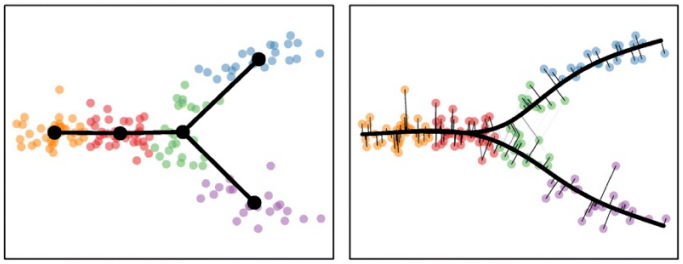


Cao et al 2019 *Nature*

scRNA-seq analysis workflow



scRNA-seq trajectory inference



Street et al (2018) *BMC Genomics*

Are you sure that you have a trajectory?

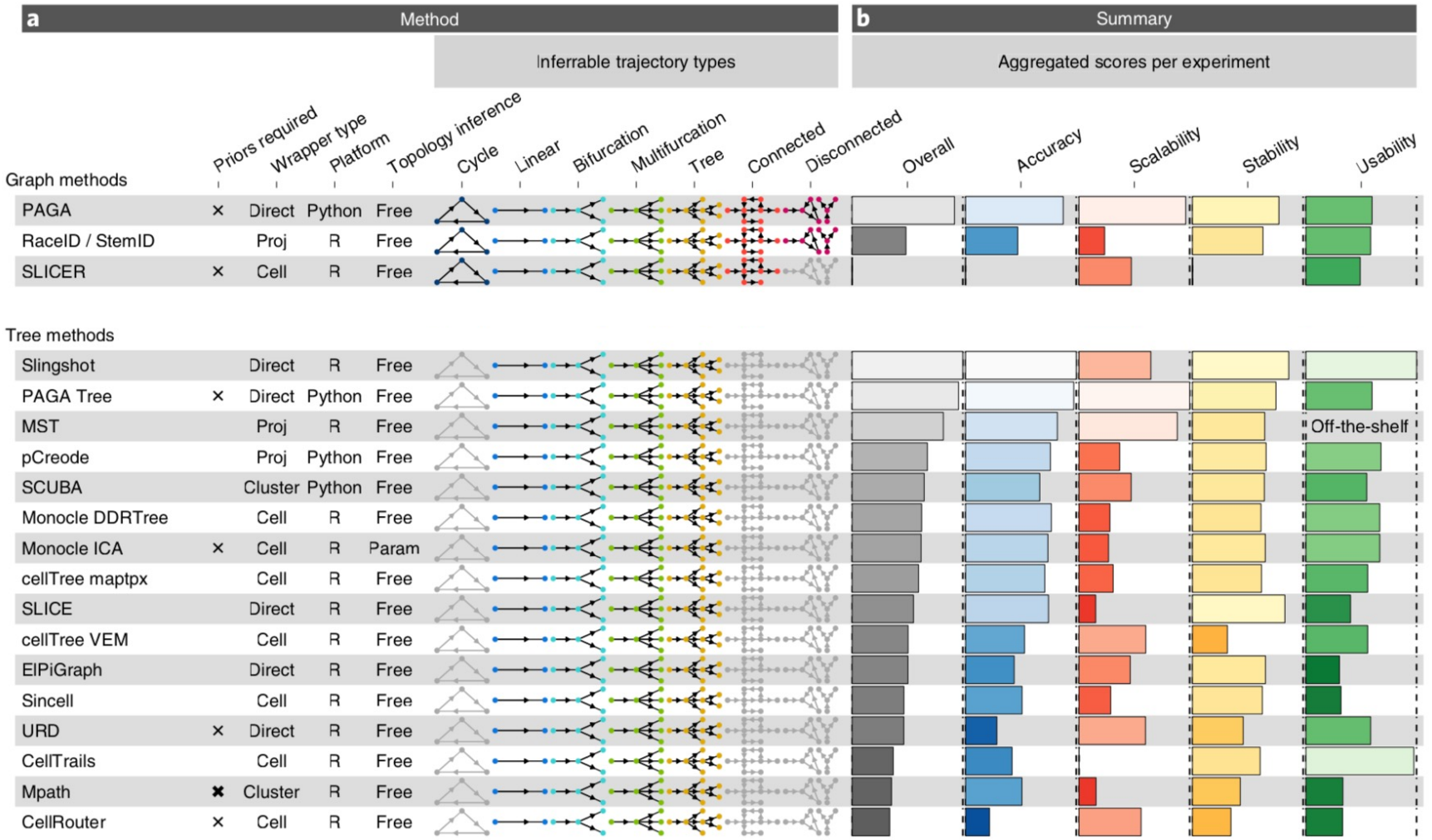
Do you have intermediate states?

Do you believe that you have branching in your trajectory?

! Be aware, any dataset can be forced into a trajectory without any biological meaning!

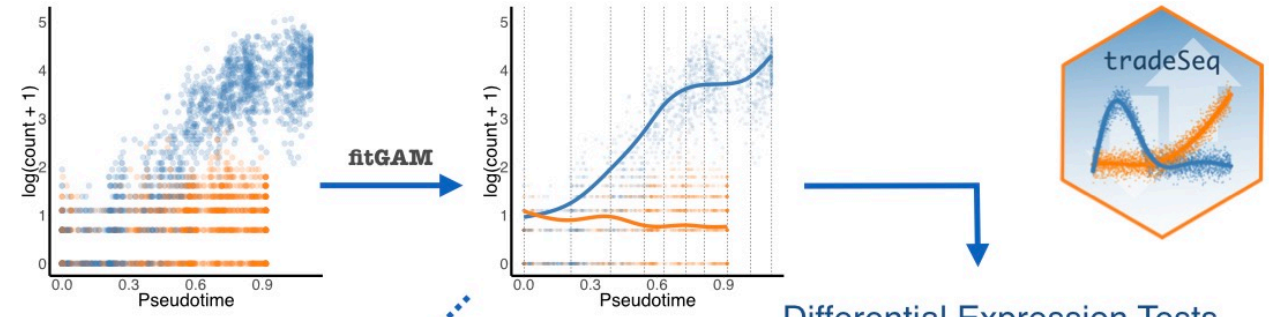
! First make sure that gene set and dimensionality reduction captures what you expect.

scRNA-seq trajectory inference

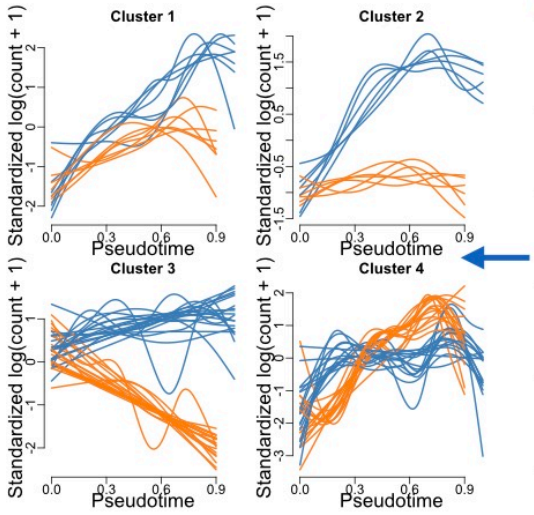


Saelens et al 2019 *Nat Biotechnology*

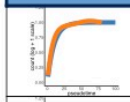
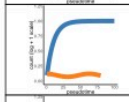
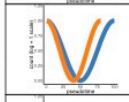
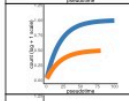
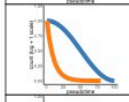
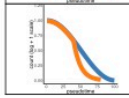
scRNA-seq trajectory inference



Clustering

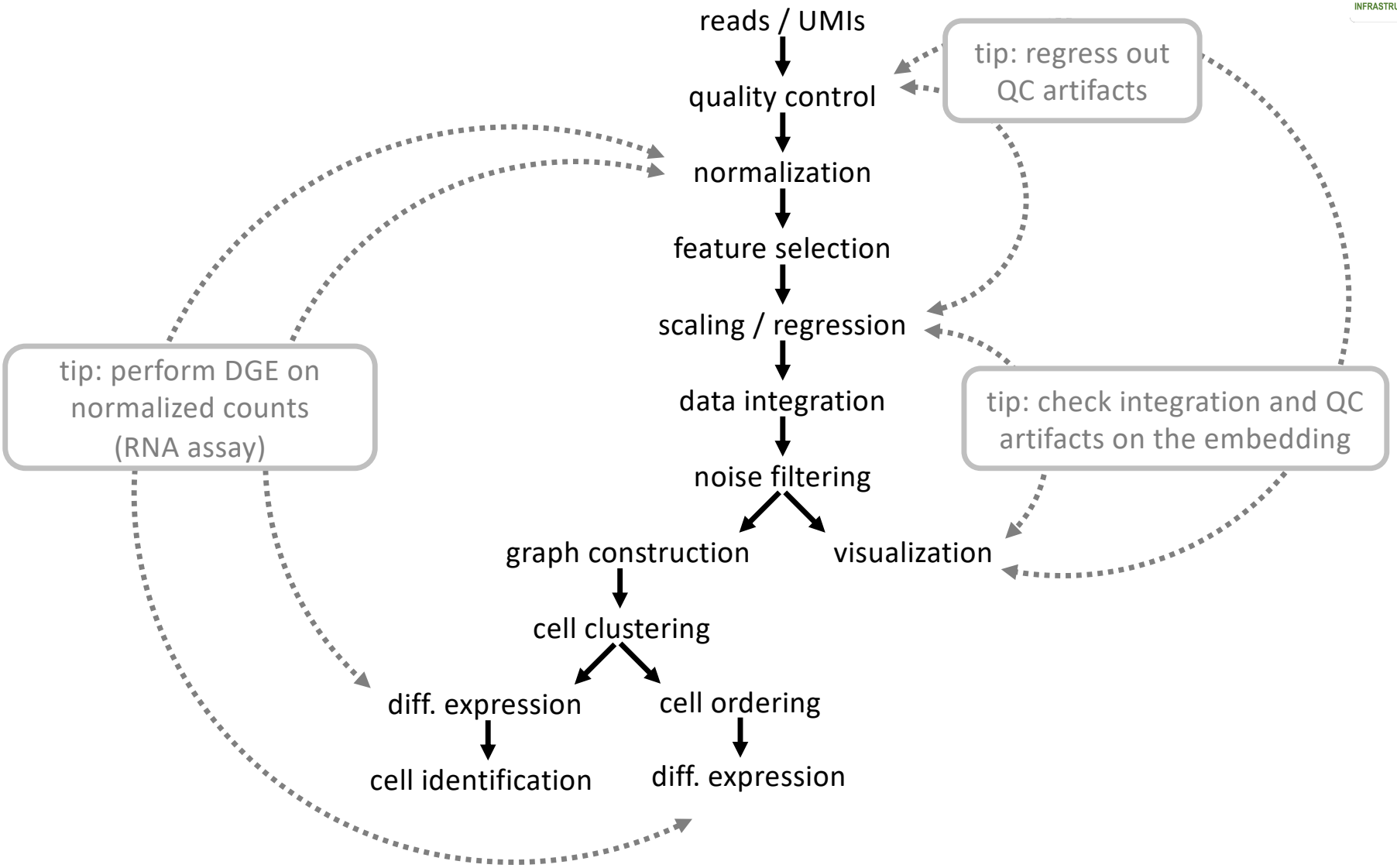


Differential Expression Tests

Lineages	Within the orange lineage		Between the orange and blue lineages		
	association Test	**startVsEnd Test**	**diffEnd Test**	**pattern Test**	**earlyDE Test**
	DE	DE	Not DE	Not DE	Not DE
	Not DE	Not DE	DE	DE	DE
	DE	Not DE	Not DE	Not DE	Not DE
	DE	DE	DE	DE	Not DE
	DE	DE	Not DE	DE	DE
	DE	DE	Not DE	DE	Not DE

Berge et al 2020 *Nat Communication*

scRNA-seq analysis workflow



scRNA-seq mini projects

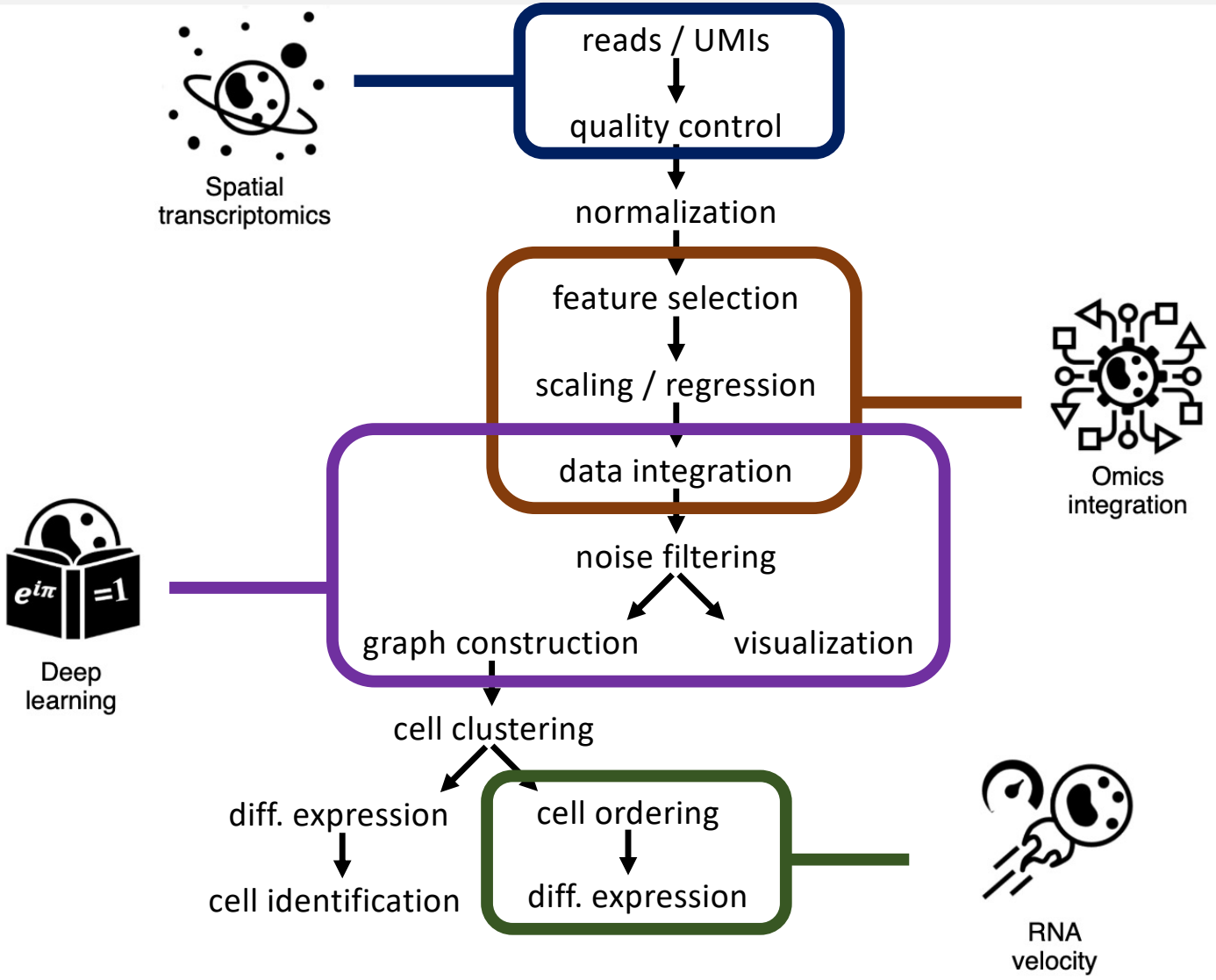
Spatial transcriptomics

RNA velocity

Omics integration

Deep learning

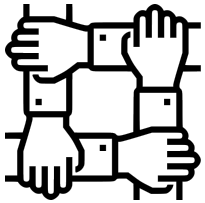
scRNA-seq analysis workflow



Project-based learning (PBL)

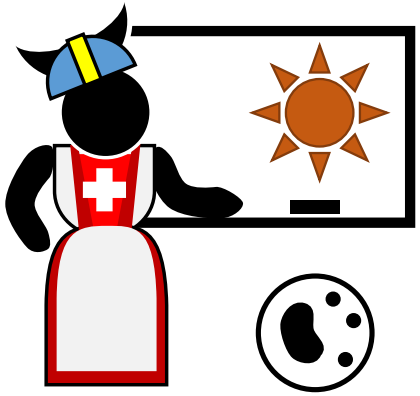
Please read the material at:
https://nbisweden.github.io/single-cell_sib_scilifelab_2021/projects.html

Learning Strategy



Working in Groups

Tips for a good dynamic



Project-based learning (PBL)

Report.Rmd

Load and merge datasets

- Consult the Glossary or additional sources for help
- Which file format do we have the data in?
- Describe in form of text the rational for this step in your markdown report.

Report.Rmd

```
# Loading data

We first load the single cell RNA-seq dataset
supplied from the `.h5` format in order to create
a Seurat object.

```{r}
data <- Seurat::Read10X_h5( filename =
"data/colon_dataset.h5", use.names = T)
```
```

Glossary

Reading files

There are many formats available in which one can store single cell information, many of which cannot all be listed here. The most common formats are:

[...]

How to run it:

```
# From .csv .tsv .txt format
raw_matrix <- read.delim(
          file = "data/folder_sample1.csv",
          row.names = 1 )

# From .mtx format
sparse_matrix <- Seurat::Read10X(
          data.dir = "data/folder_sample1")

# From .h5 format
sparse_matrix <- Seurat::Read10X_h5(
          filename = "data/matrix_file.h5",
          use.names = T)
```

[...]

Thank you!

https://czarnewski.github.io/czarnewski/index.html