# Lab 8

Single-cell RNA seq Maarten de Vries

slides adapted from Qing Zhang, Aviv Regev exercises adapted from Harvard Chan Bioinformatics Core

### **Outline**

- HW5 on scRNA-seq released, due April 11th
  - o scRNA analysis with Seurat
- Today:
  - Brief review of scRNA-seq
  - Hands-on practice with Seurat
- Office hours
  - Maarten: Saturday 3/27 & 4/3 @ 10:30 am + Thursday @ 8 pm
  - Philip: Friday 3/26 & 4/2 @ 4:30 pm

# Why scRNA-seq



**Bulk genomics** 

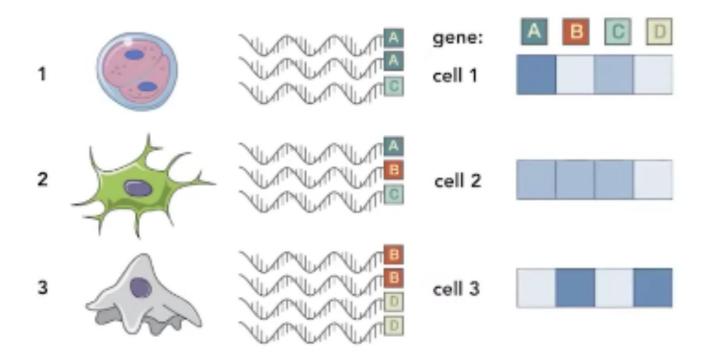


Single cell genomics

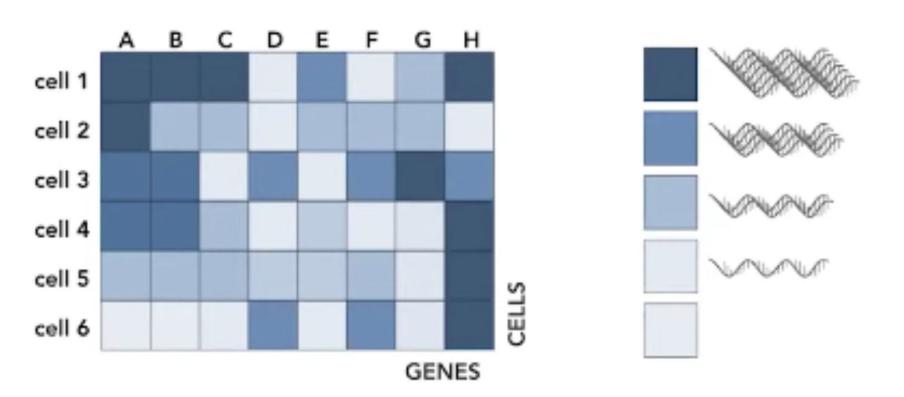


Spatial genomics

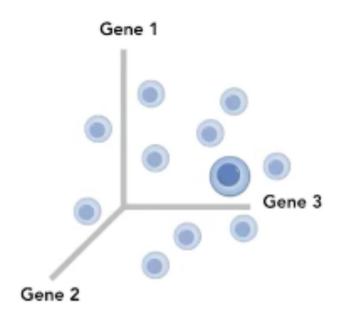
### Cells express the genes they need at the right quantities

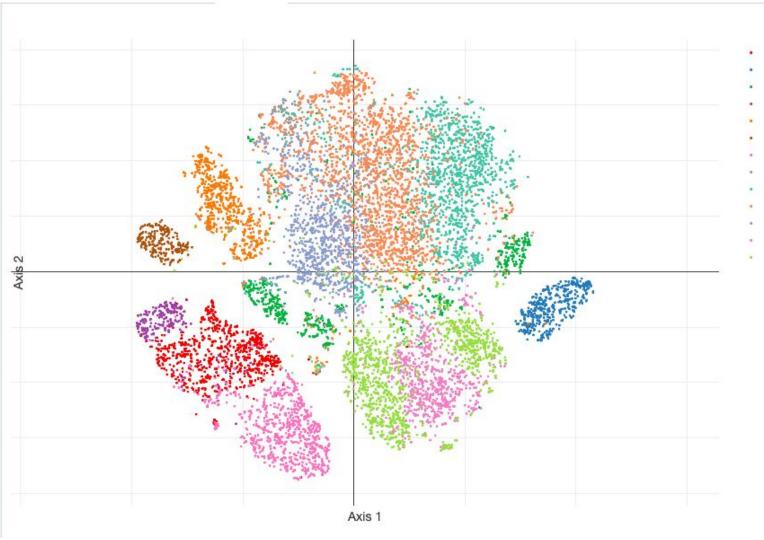


### Gene expression profile is the calling card of a cell



### Cell as a point in 20,000+ dimensional gene expression space



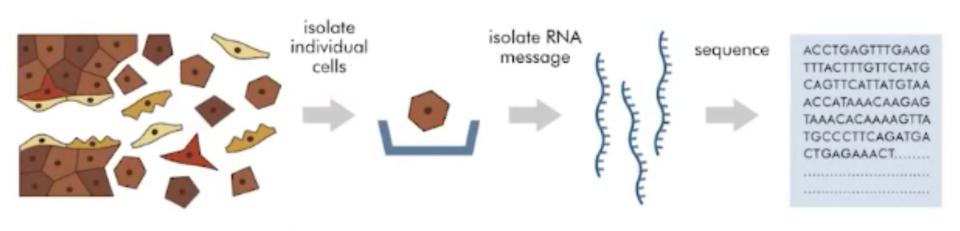


- Endothelial (773 points) Glia (415 points)
- Inflammatory Fibroblasts (715 points)
- Myofibroblasts (606 points) Pericytes (226 points)
- Post-capillary Venules (756 points) RSPO3+ (118 points)

Microvascular (208 points)

- 18 points)
- WNT2B+ Fos-hi (1349 points) WNT2B+ Fos-lo 1 (2008 points)
- WNT2B+ Fos-lo 2 (952 points) WNT5B+ 1 (736 points)
- WNT5B+ 2 (1138 points)

### Capturing a single cell



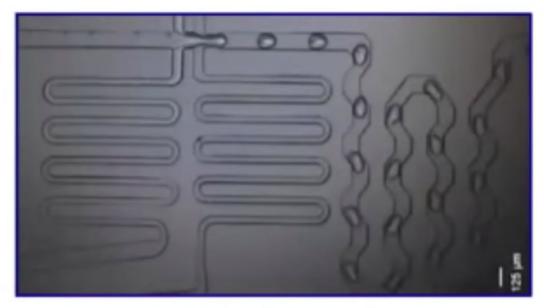
Tissue

Dissociated cells

Single cell

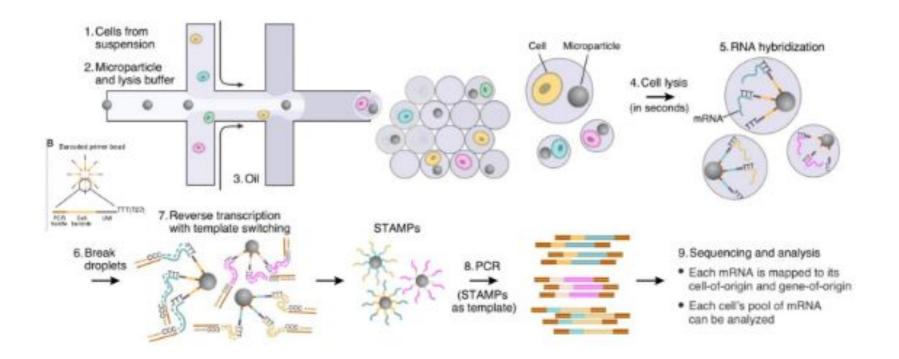
RNA from active genes Transcriptome active genes in that cell

# **Droplet sequencing**

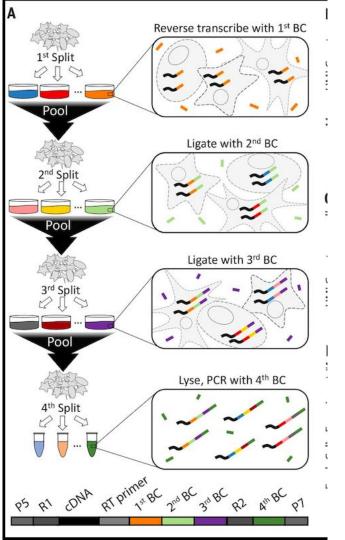


5,000 cells/second

# **Droplet sequencing**



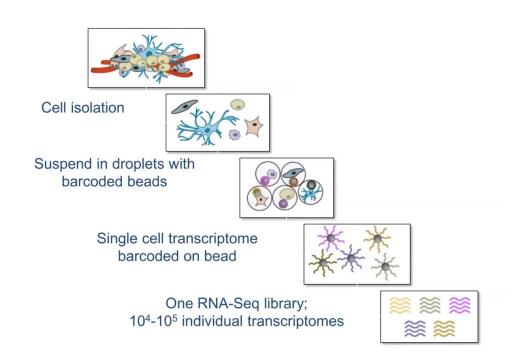
# **SPLIT-seq**

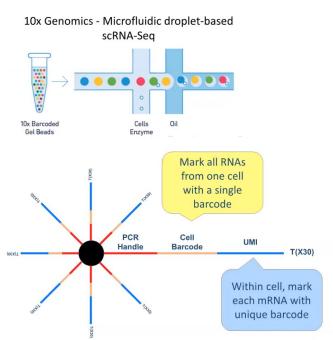


# **SPLIT-seq: the movie**



### Recap: Single cell RNA seq





UMI: distinguish multiple copies of a transcript vs PCR artifacts

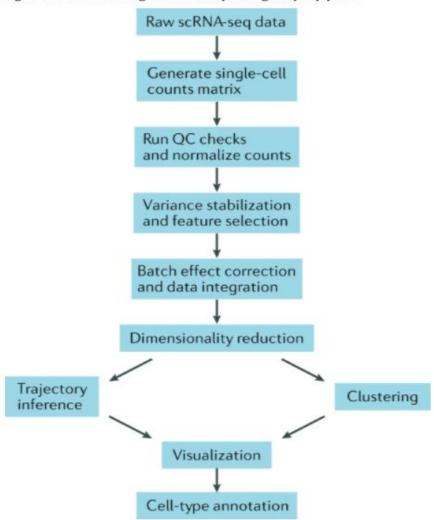
Macosko et al, Cell, 161, 2015

scRNA-seg analysis

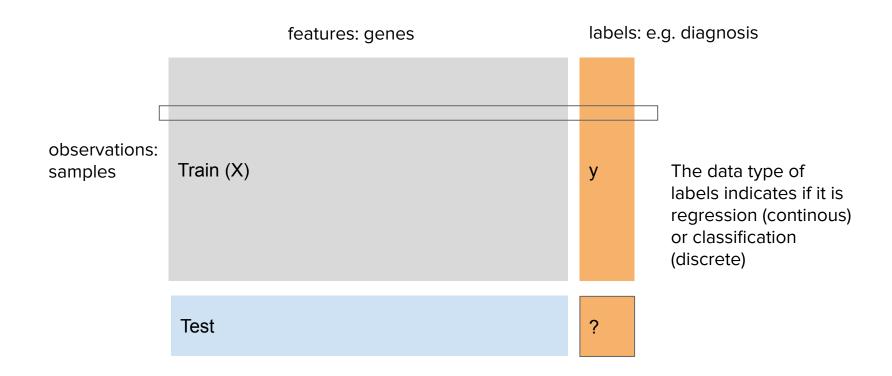
Wu & Zhang

Nature Rev Neph 2020

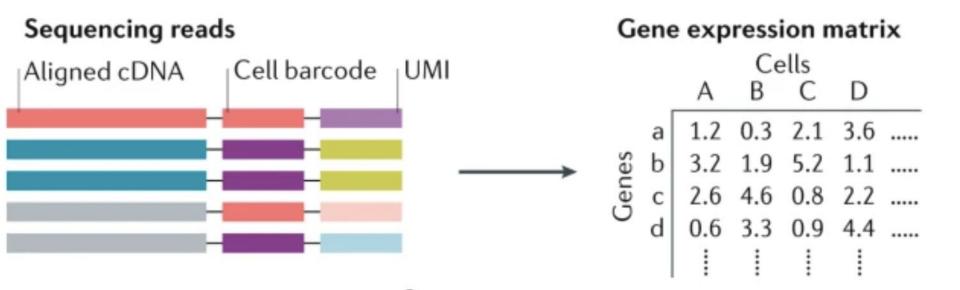
Fig. 1: Overview of the single-cell RNA sequencing analysis pipeline.



### **Dataset**

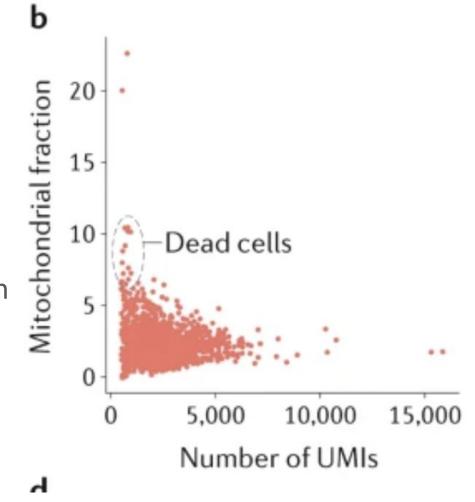


### **Generating the counts matrix**

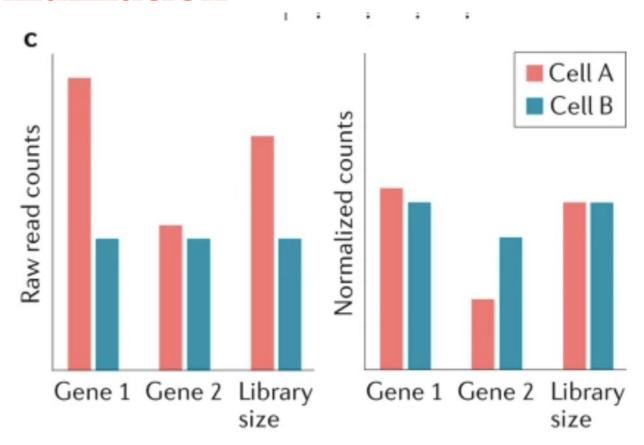


QC

- Detect cells with
  - Low read count
  - Low % of mapped reads
  - Too few/many genes
  - High mitochondrial fraction



### **Normalization**



### **Dimensionality reduction**

- Dimensionality reduction
  - Curse of dimensionality
  - Linear: Principal Component Analysis (PCA)
    - Finds linear combinations of genes that best capture the variance in data
    - Zero-inflated factor analysis (ZIFA) is a version of PCA designed to explicitly model the high expected count of zero values in scRNA-seq data.
  - Nonlinear: t-SNE, UMAP, Deep neural networks
- Imputation of zero-values
  - Technical limitations in RNA capture lead to zero-inflation
  - o In part biological variance, in part noise
  - o Imputation methods are available
    - MAGIC uses information from neighboring cells
    - Lots of deep learning methods recently developed

### Clustering & Visualization

Fig. 4: Cell clustering in datasets with discrete cell types.

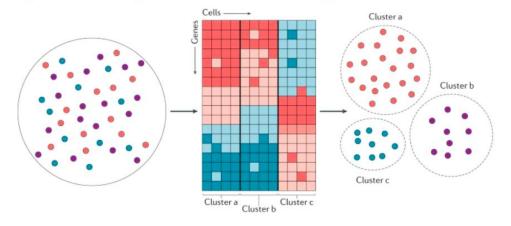


Fig. 6: Local and global structure in a dataset.

a Local structure (neighbourhood distances)

b Global structure (cell type and cluster distances)

Cluster distances

### **Cell-type annotation**

- Time-consuming if done manually
- Find genes that are uniquely expressed in each cluster
- Match those genes to lists of canonical cell-type markers
- To accelerate this, use functional pathways and gene ontology terms
- New (semi-)automated cell-type classification methods are being developed.
- Novel cell types and states still need to be manually annotated, or do they?

### Workflows

Conveniently, there exist toolkits that enable all of the aforementioned steps within a single workflow.

- Seurat (in R)
- SCANPY (in Python)
- MAESTRO (Philip's Lab next week)

# Seurat [v4.0]

https://satijalab.org/seurat/

R package for single cell analysis

Great vignettes!

Make sure you have Seurat 4.0 and R version >4.0 installed





# **Further reading**

https://hbctraining.github.io/scRNA-seq\_online/schedule/