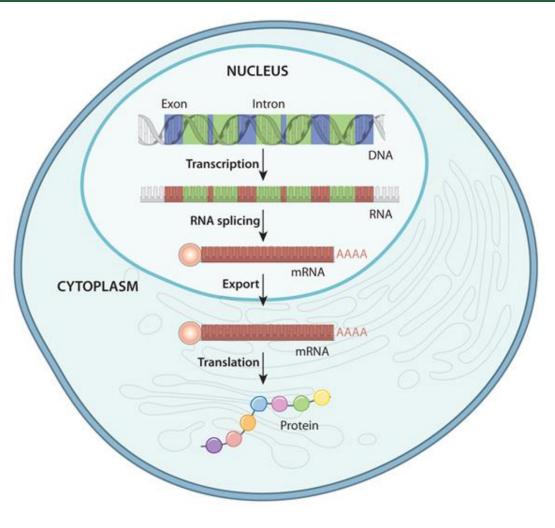
### THE POWER OF SINGLE CELL ANALYSIS: SINGLE CELL SEQ AND SPATIAL TRANSCRIPTOMICS

#### ADVANCED CELL EXPLORATION (ACE) CORE MIKE WONG

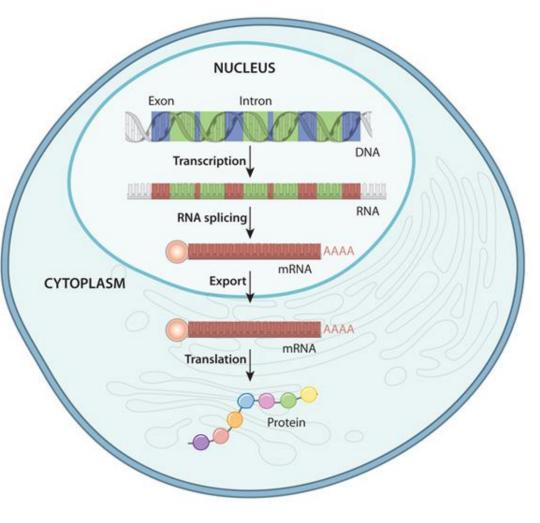


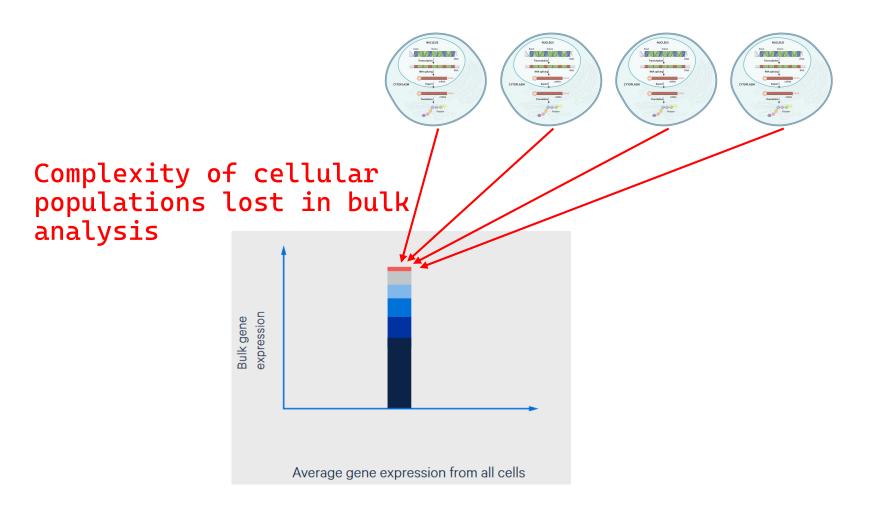




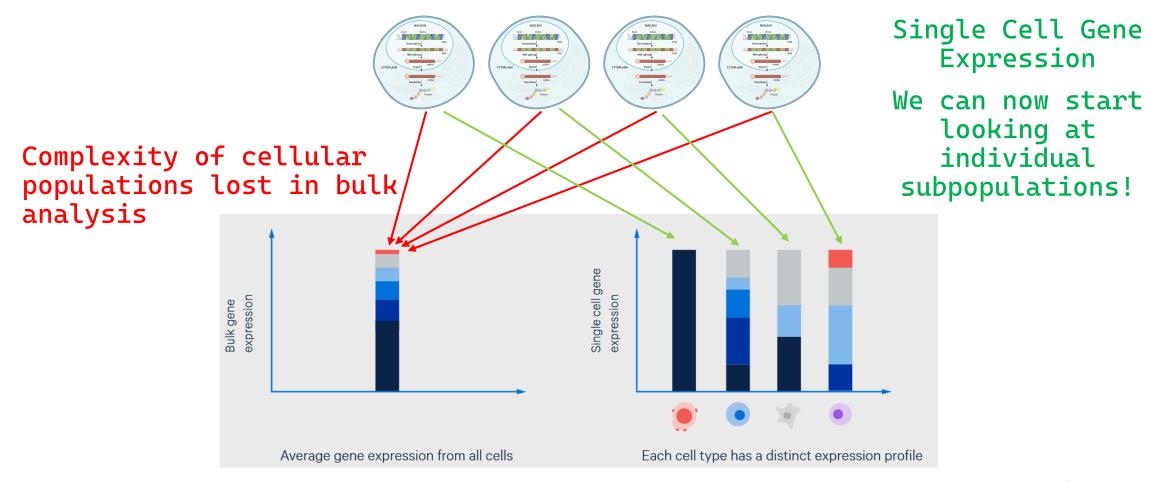
### Central Dogma of Biology

- DNA -> mRNA -> Protein
- Gene expression previously measured in 'bulk' methods where all RNA from a batch of cells is collected to analyze
  - Quantitative RTPCR
    - Target must be known
  - Bulk RNA Sequencing
    - Can only trace transcripts to whole input tissue or cell suspension
    - All population context lost





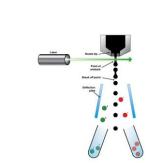
www.nature.com

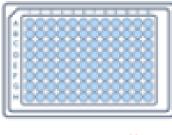


# Single Cell Sequencing Techniques

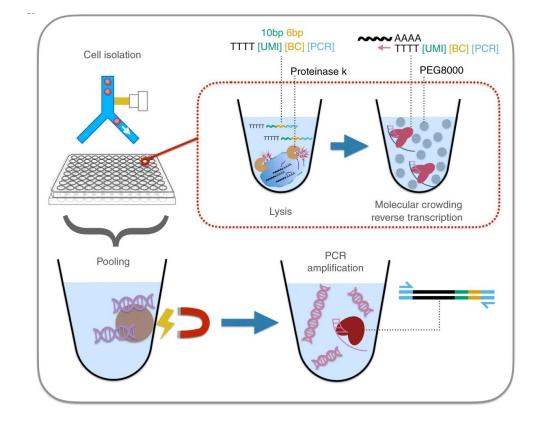
### True Single Cell Sequencing

- Glass pipette picked or FACS-Sorted Single Cells
- Similar processing steps to regular bulk RNA seq, but with ultra-low input
- Low throughput, high cost per cell
- Currently used for very specific purposes





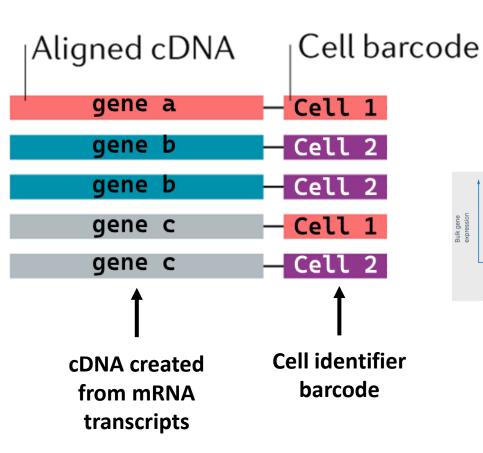
#### 1-384 Cells

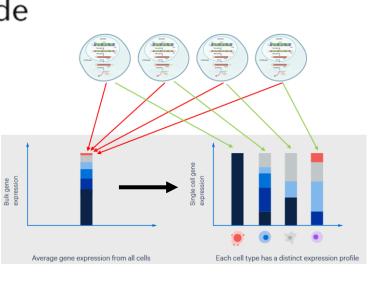


# Single Cell Sequencing Techniques

### Single Cell Barcoding techniques

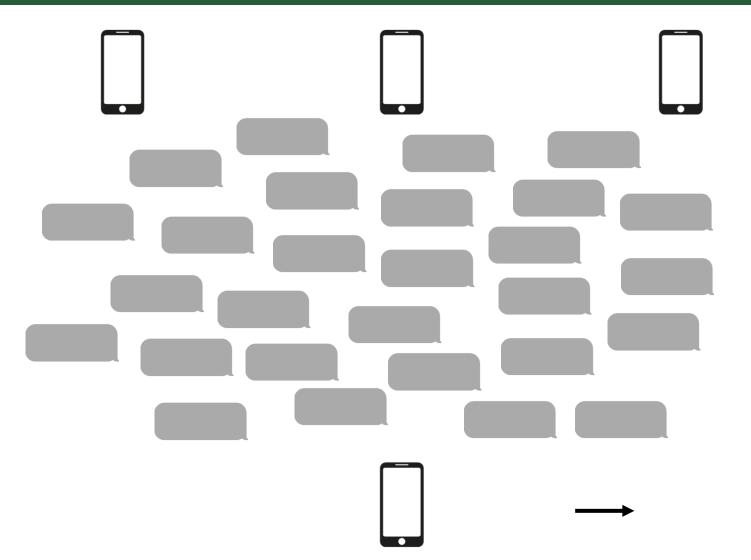
- Barcode the cDNAs from each cell with a cell identifier
- Process as bulk RNA
- Use the identifier to assign transcript counts to individual cells
- Moderate to high throughput
- Expensive, but low cost/cell



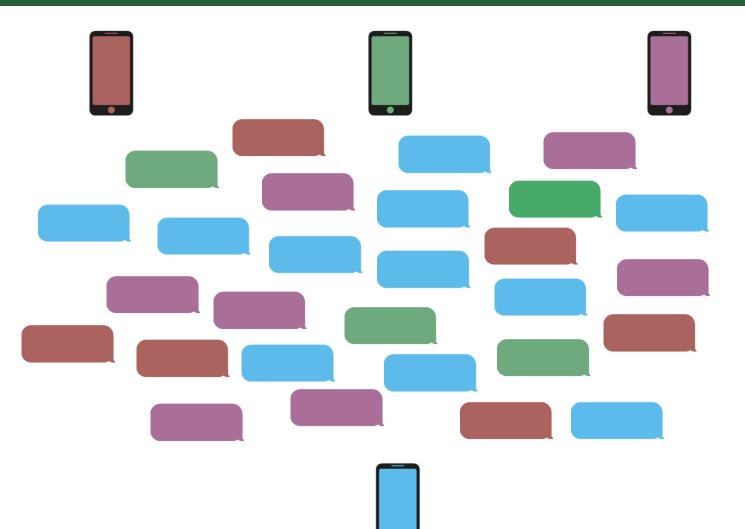


10X Genomics

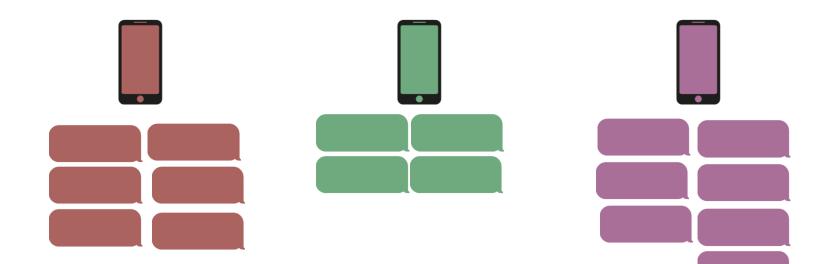
• With bulk RNA sequencing, all messages are mixed together!

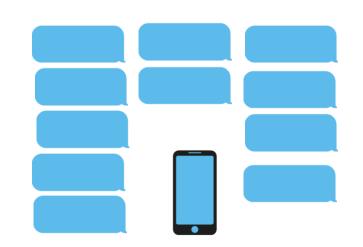


- With bulk RNA sequencing, all messages are mixed together!
- If we add handles, we can now figure out the source of each message

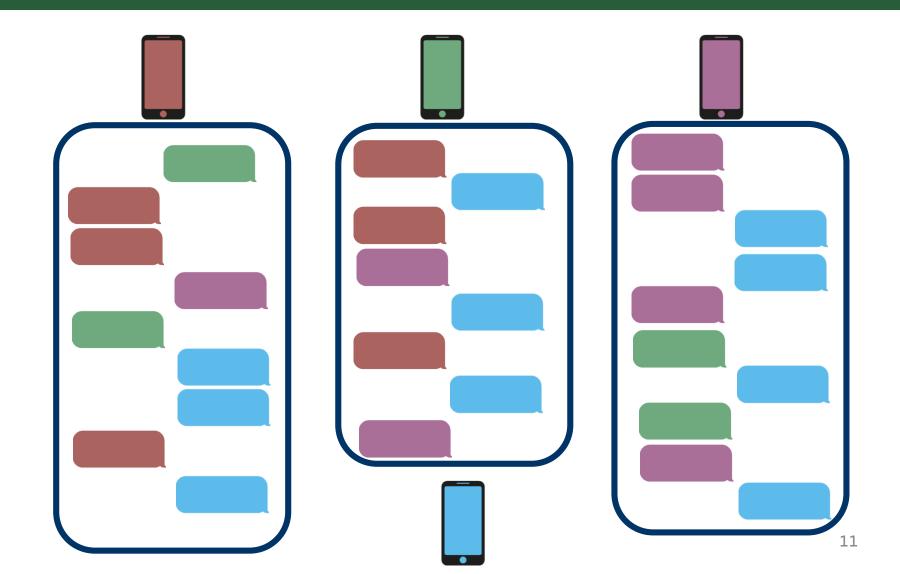


- With bulk RNA sequencing, all messages are mixed together!
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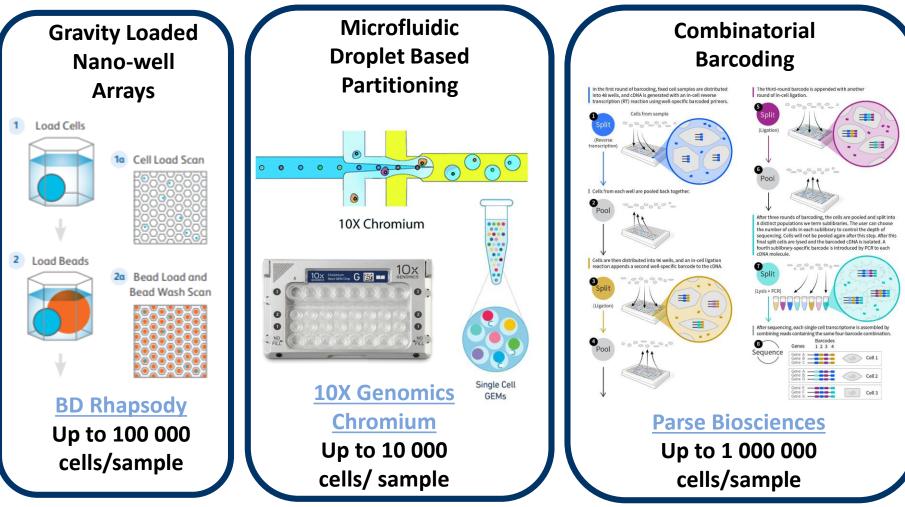
- With bulk RNA sequencing, all messages are mixed together!
- If we add handles, we can now figure out the source of each message
- Provide context to the groups of messages
- Determine contributions to each conversation



## Single Cell Sequencing Techniques

### Single Cell Barcoding techniques

- Use various methods to give cells unique barcodes when mRNA is captured
- Moderate to high throughput
- Expensive, but low cost/cell

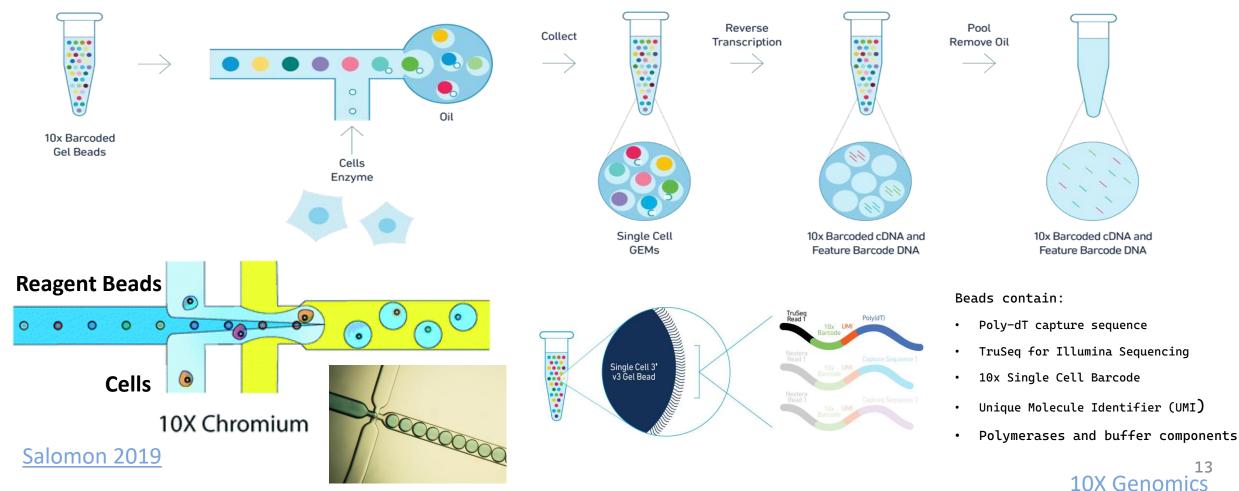


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## Droplet Microfluidic Partitioning scRNASeq

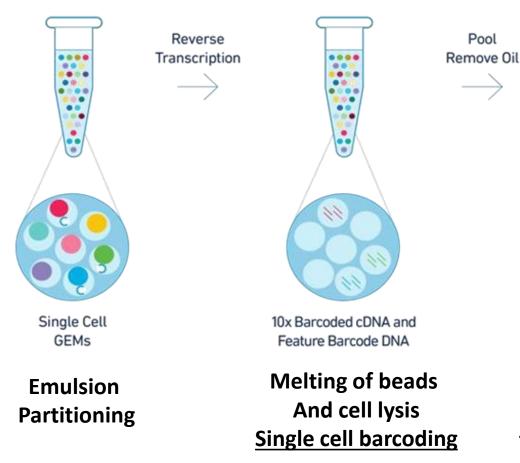
### Fluidic Partitioning

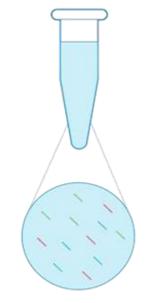
Create oil droplet 'chambers' that will contain single cell reactions



## Droplet Microfluidic Partitioning scRNASeq

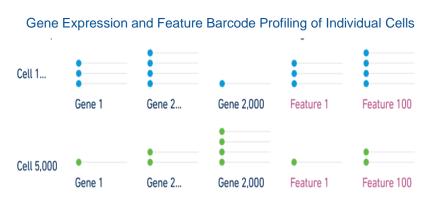
#### Fluidic Partitioning Reagent Beads with Individual Cells





10x Barcoded cDNA and Feature Barcode DNA

Remove partition process the sample the same as bulk RNA



#### Sequence and demultiplex



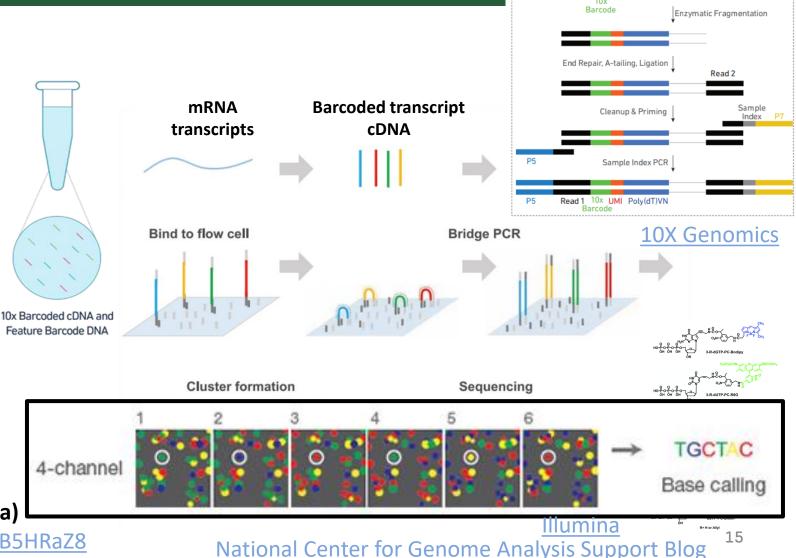
## Library Preparation and Sequencing

#### <u>Library prep:</u>

- Fragment and prepare the cDNA for sequencing.
- Sequencing by synthesis
- Adapters to support bridge amplification
- Build clusters of identical ٠ fragments
- Change the nucleotides to fluorescent tagged versions with chemical stops
  - Clusters emit the fluorescence of the current nucleotide
  - Chemically cleave the fluorescent and repeat

#### Primers on Next Gen Sequencing (illumina)

https://www.youtube.com/watch?v=fCd6B5HRaZ8



Pooled amplified cDNA processed in bulk UMI Poly(dT)VN

Read 1

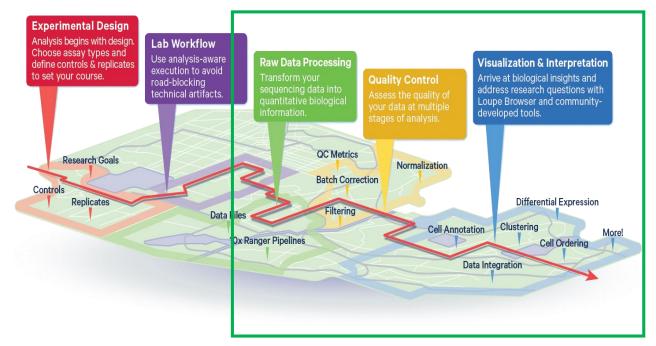
### Data Processing and Quality Control

#### Once Sequencing is complete, still a long way to go!

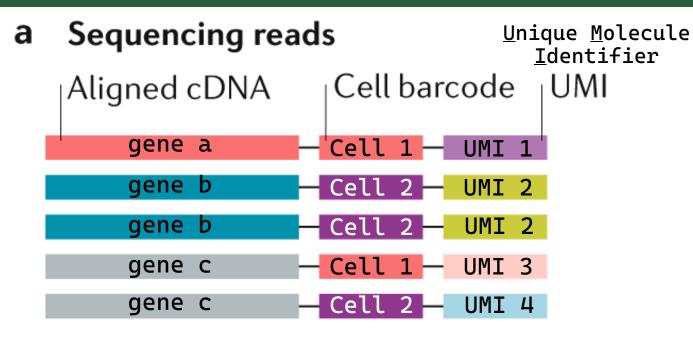
Quality control and downstream processing is a huge part of scRNAseq

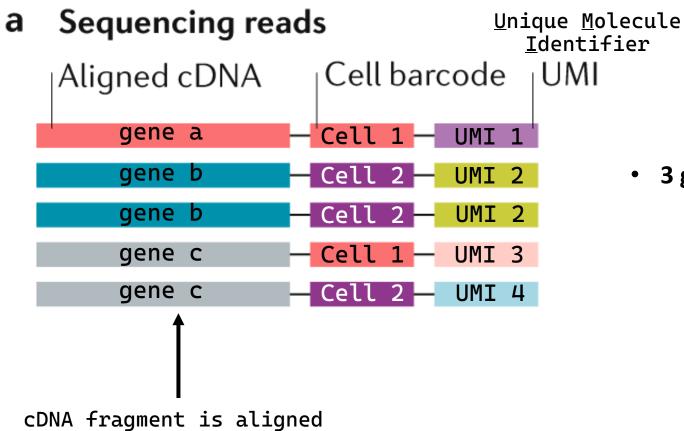
- Align sequences to identify genes
- De-multiplex all barcodes (samples, cells, UMI) and to create gene expression matrices
- Remove dead cells
- Empty Droplet Detection
- Adjust for ambient RNA
- Correct batch effects
  - Unsupervised clustering can be heavily impacted by batch effects before correction and aggregation





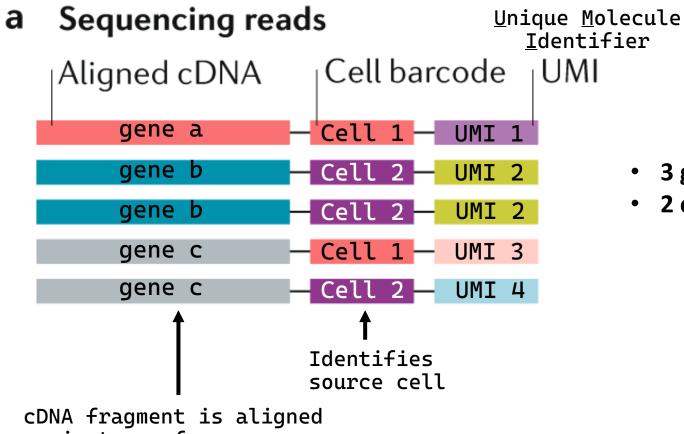






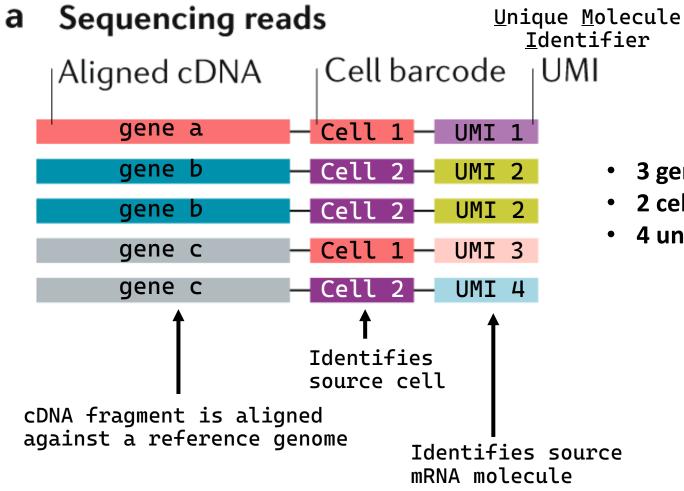
against a reference genome

3 genes detected



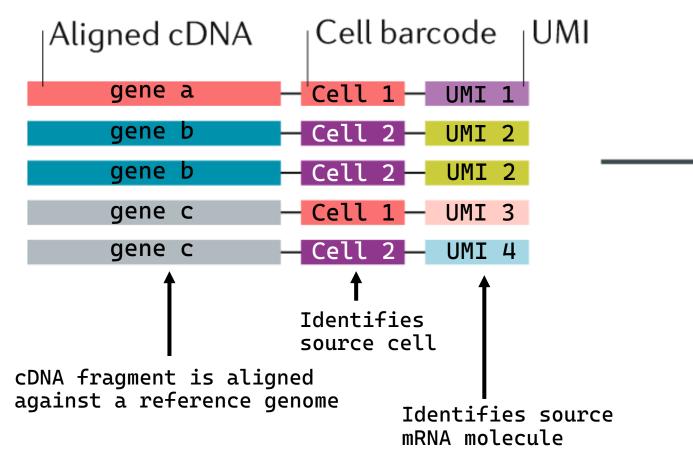
against a reference genome

- 3 genes detected
- 2 cells detected

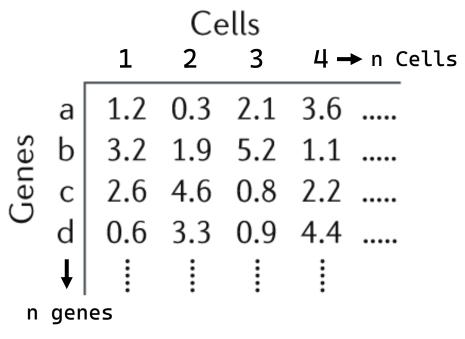


- 3 genes detected
- 2 cells detected
- 4 unique original transcript molecules

#### a Sequencing reads



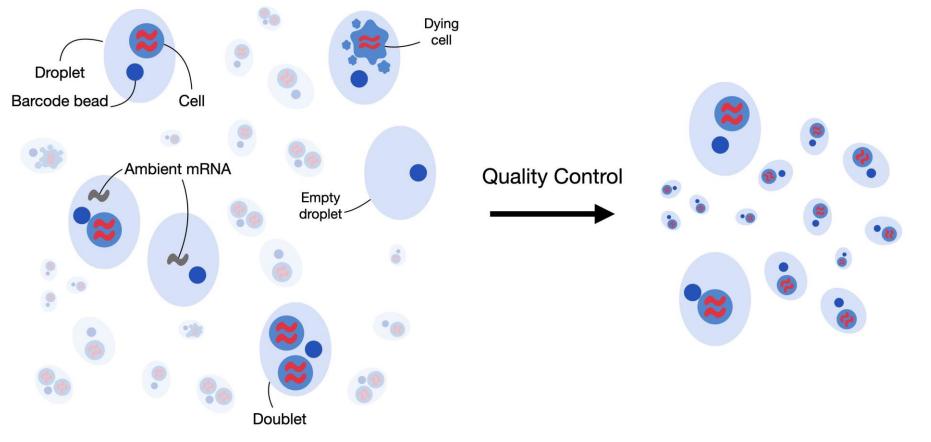
Gene expression matrix



20 000 gene dimensions!!! At 10 000 cells/ sample: 500 million data points per sample!!!

### Quality Control

Many scenarios of imperfect droplets that can affect your data!



sc-best-practices.org

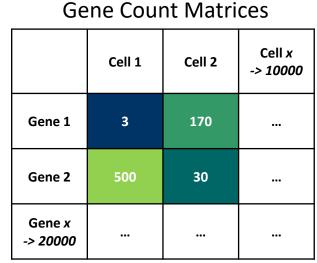
## Single Cell Gene Expression

### **Dimension Reduction**

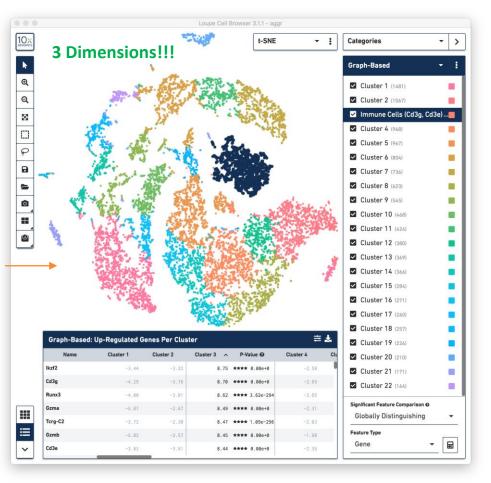
- Very difficult to visualize thousands of dimensions of data at once
- ٠ Use fancy stats and data science techniques (clustering) to find patterns and associations within the data to group
- Supervised (Semi) Clustering
  - Takes user input on cluster number
- Unsupervised
  - Will make as many clusters as it thinks exists, depending on variance 20 000 genes \*10 000 cells/ sample: limits for specific algorithms

Not necessary to understand the underlying data science mathematics in order to understand what the algorithm functions. This is an excellent resource for learning about data science and machine learning techniques without needing any coding or advanced mathematic knowledge:

https://machinelearningmastery.com/start-here/#algorithms



500 million data points per sample!!!



#### 10X Genomics

## Single Cell Gene Expression

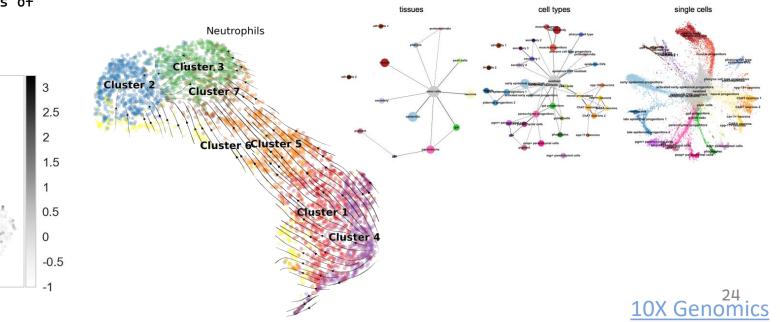
### Now can do some really interesting analyses!

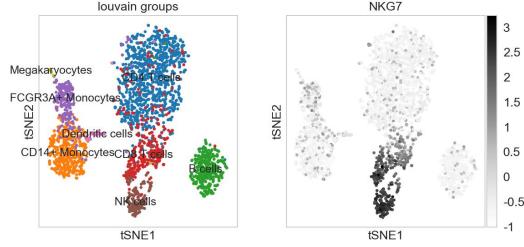
Analysis

- Clustering
- Differential expression
- Associated genes
- Endless data mining
  - Revisit previous experiments with new genes of interest

Trajectory Analysis

 What direction are progenitor cells differentiating to, in what proportions? How is this affected by experimental conditions?





## Additional Single Cell Assays

#### Protein Expression

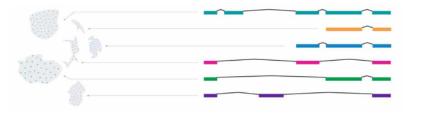
- Tag cell surface moieties with antibodies bound to a Capture Sequence and Feature Barcode CITE-Seq)
- Acts in place of a transcript once in the partitioned barcoding reaction





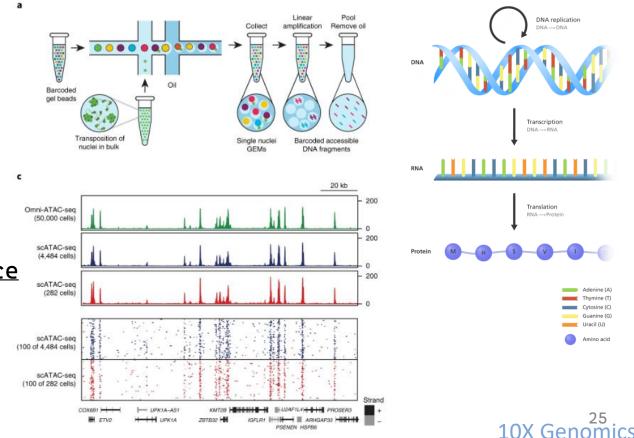
#### <u>B Cell and T Cell receptor sequencing</u>

Full length transcript sequencing for splice variants (PacBio long read sequencing)



#### DNA availability

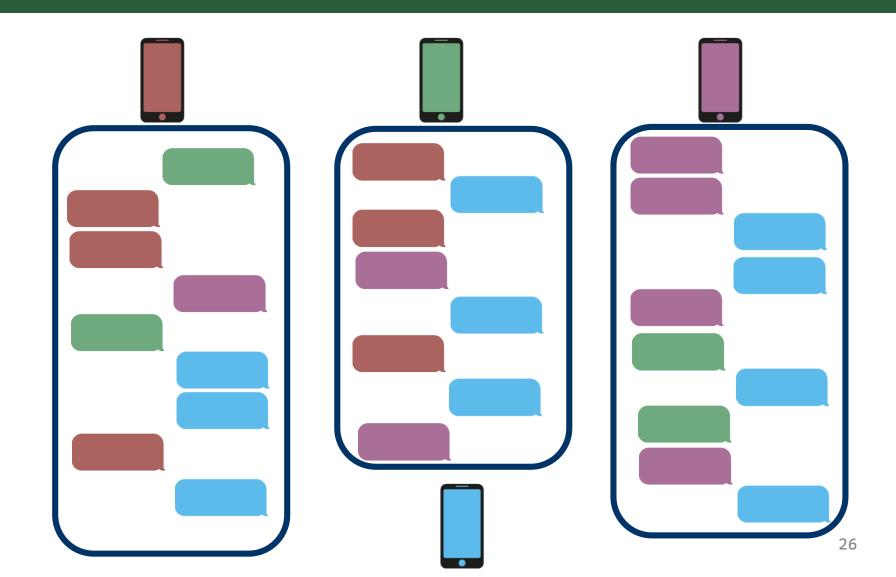
Transposase-accessible chromatin with sequencing (ATAC-Seq)



wmine (T Uracil (U)

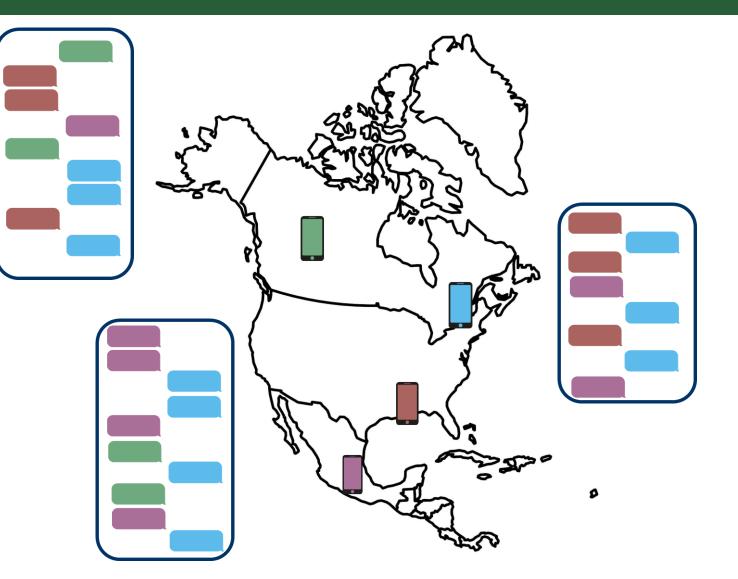
Amino acid

Now we can see which cells are contributing to the total gene expression conversation!

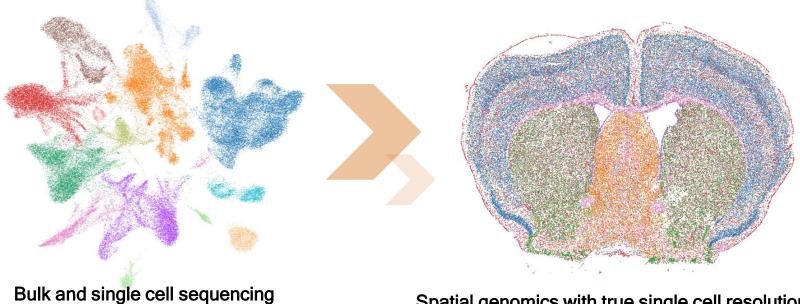


Now we can see which cells are contributing to the total gene expression conversation!

But what if we add spatial context as well!?



## Spatial Transcriptomics



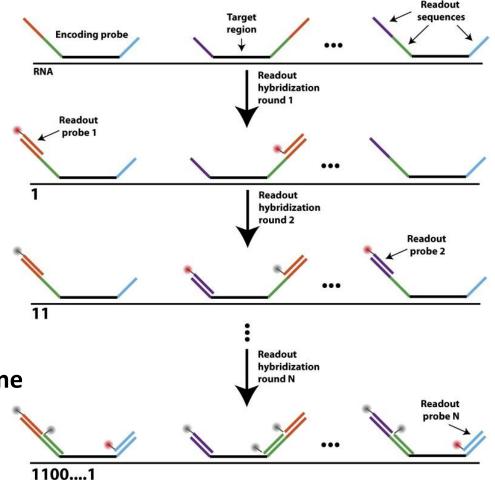
Spatial genomics with true single cell resolution

Next big field in genomics Many technologies available

## Fluorescence In-Situ Hybridization



1 gene transcript with a specific fluorophore captured with a microscope





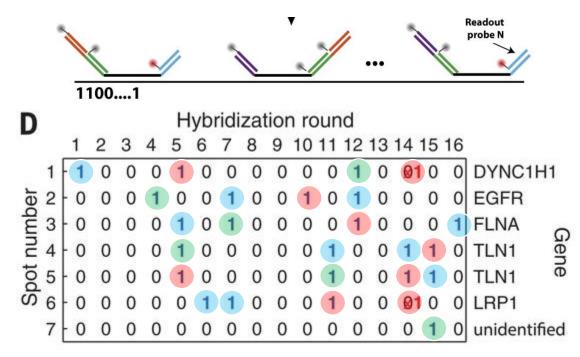
- Multiplexed Error-Robust (merFISH)
- Hundreds (thousands) of gene targets
- Probes designed along the length of a gene with multiple readout sequences

https://europepmc.org/article/MED/27625426

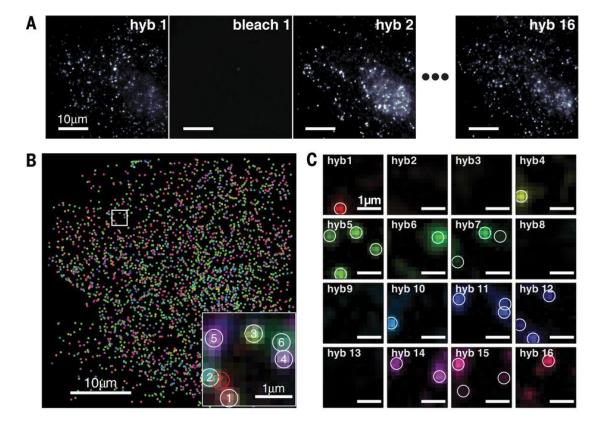
29

## merFISH - How it works

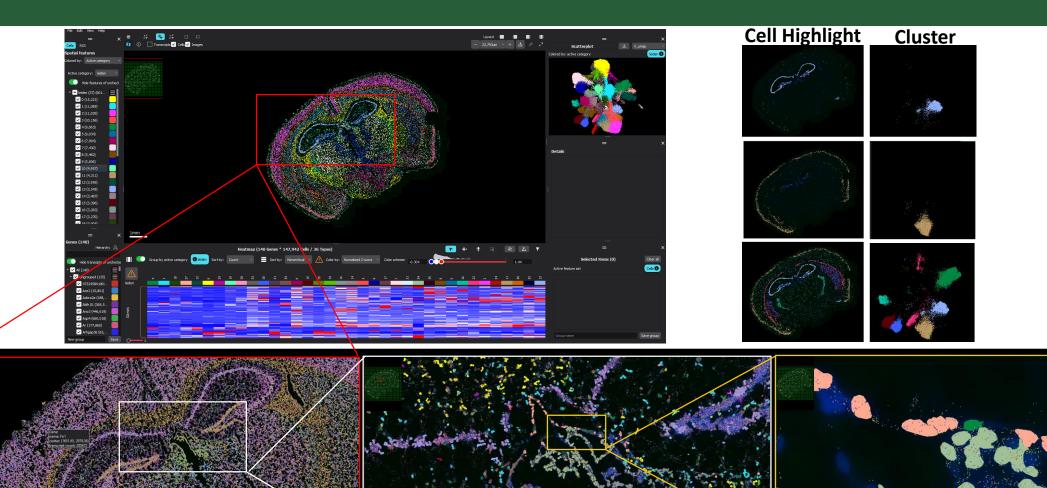
- Multiplexed Error-Robust Fluorescences In-Situ Hybridization
- Spots are read in sequence



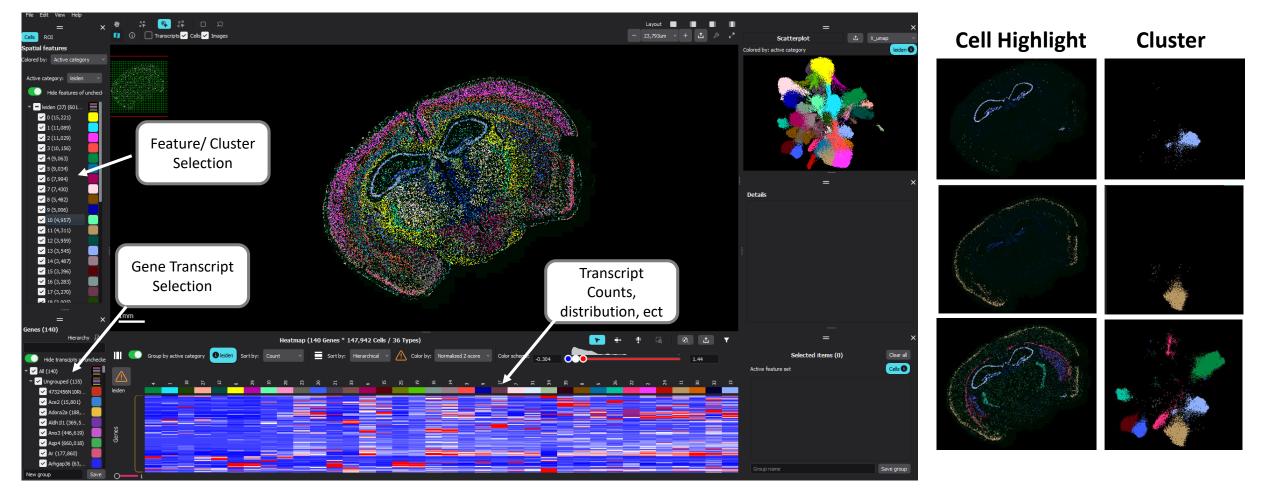
1 miss-call can be corrected



## Spatial Transcriptomics



## Spatial Transcriptomics



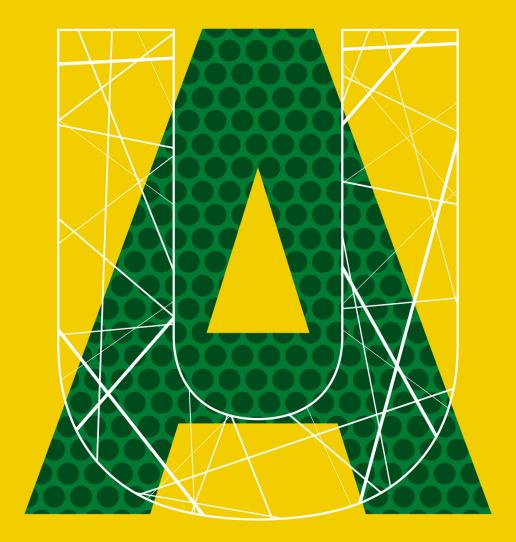
## THANKS!

#### ADVANCED CELL EXPLORATION CORE

### MIKE WONG

### MEWONG@UALBERTA.CA





### Doublet and Empty Droplet Removal

Gene counts, identified genes and mitochondrial gene expression all important

\*Can be heavily impacted by specific biology of cell Ambient mRNA populations Empty A 3000 в droplet 160 800 b 2500 140 700 120 100 2000 600 80 **S** 500. Dying 1500 -60 Mitochondrial fraction 20 cell 400 40 -20 -1000 300 0 1000 2000 3000 4000 200 15 500 -Count depth Doublet 100 0 2000 10000 20000 ò 1000 3000 4000 0 30000 40000 50000 Count depth Number of genes 10 Dead cells С D 4000 0.25 **S** 3000 -0.15 🕫 Count depth of gen 2000. 5.000 10,000 15,000 0 1000 0.05 10<sup>3</sup>-Number of UMIs

2000 4000 6000 8000 10000 12000 14000

Barcode rank

10000

20000

30000

Count depth

40000

50000

Leucken and Theis 2019