

Applications of Single Cell Sequencing

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Disclosures

Consultant/Honoraria: Merck, AstraZeneca, Illumina, Chrysalis Biomedical Advisors, Canada Pension Plan Investments, PACT Therapeutics

Research funding: Roche/Genentech imCORE

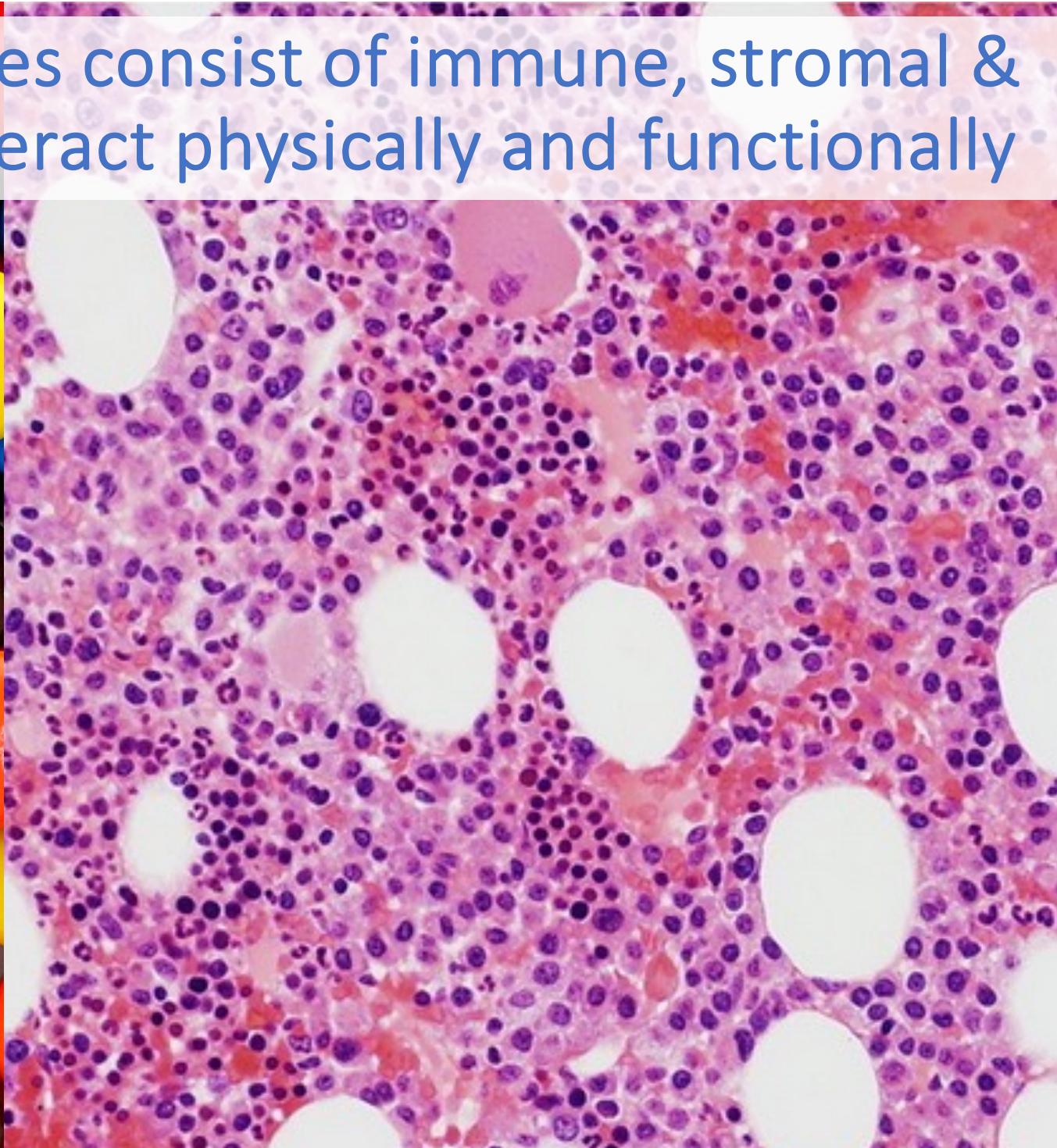
Inventor on patents filed by University Health Network “Hybrid-capture sequencing for determining immune cell clonality”

Director of an academic research core offering single cell profiling (10X Genomics Certified Service Provider, www.pmgenomics.ca)

Learning Objectives

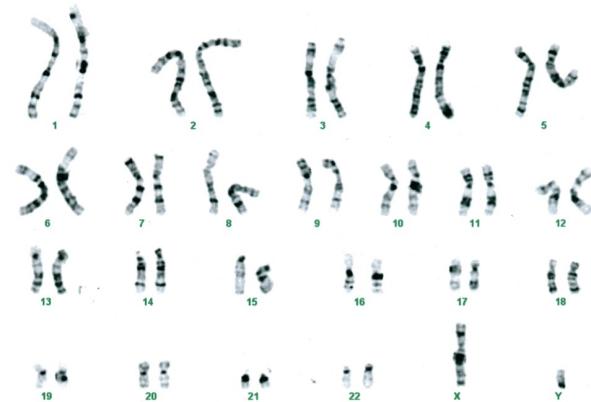
- 1) Understand the conceptual shift in moving from bulk to single cell profiling
- 2) Become acquainted with types, parameters and trade-offs of various single cell technologies
- 3) Using cancer as an example, be exposed to scientific questions and experimental designs utilizing single cell analysis
- 4) Appreciate new scientific and translational opportunities enabled by integrative single cell molecular profiling

We are all made of cells: tissues consist of immune, stromal & many other cell types that interact physically and functionally

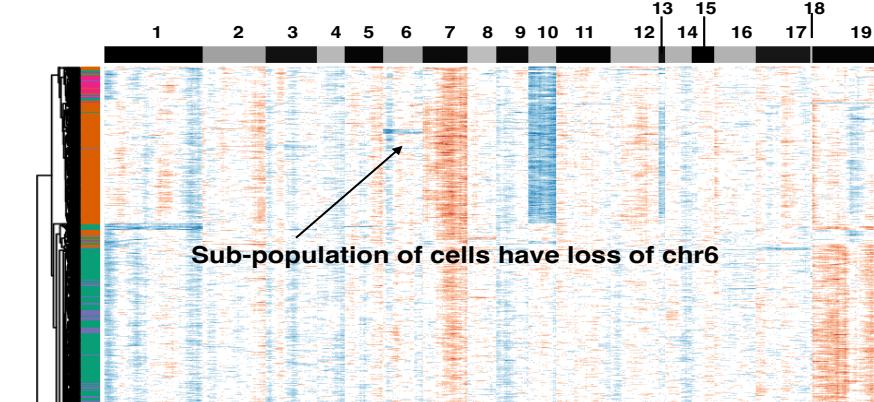


Single cell analysis is not new...the revolution is in the scale, completeness, & quantitative nature of genomic technologies

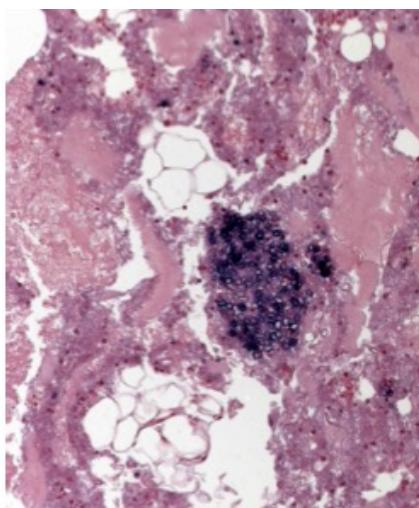
One karyotype in one cell



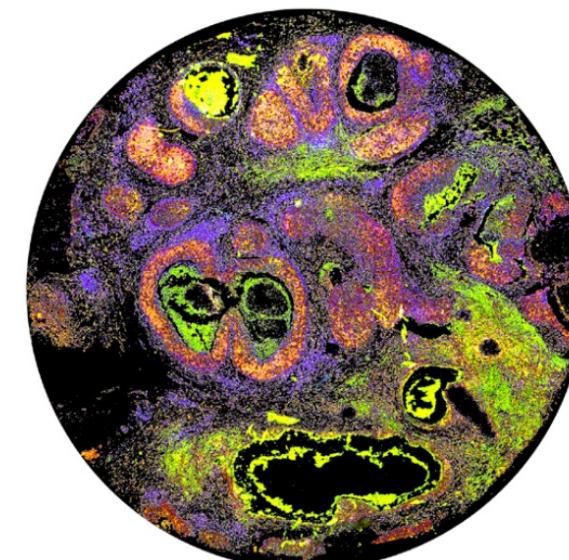
Quantification of all chromosomes in all cells



In situ hybridization of one transcript

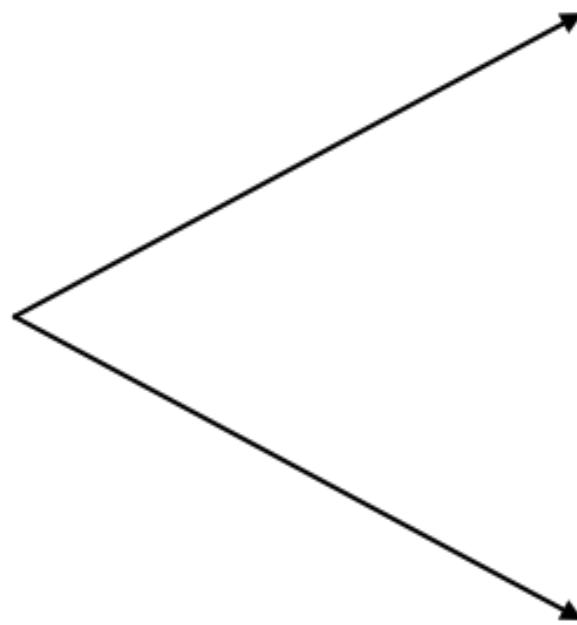
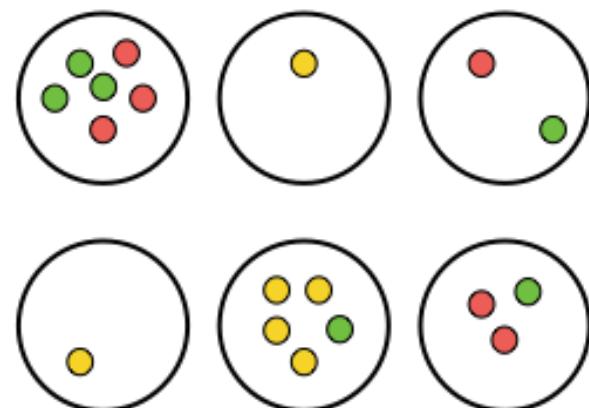


Visualization of 1,000s of genes expressed in all cells

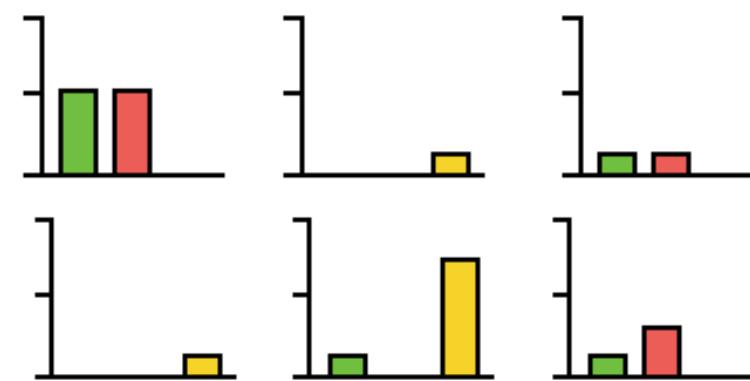
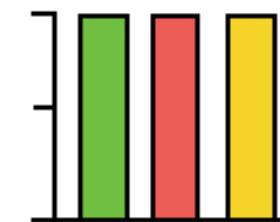


Single-cell analysis reveals heterogeneity in molecular profiles at resolution bulk analysis may not permit

e.g. Six cells with heterogeneous expression of three genes

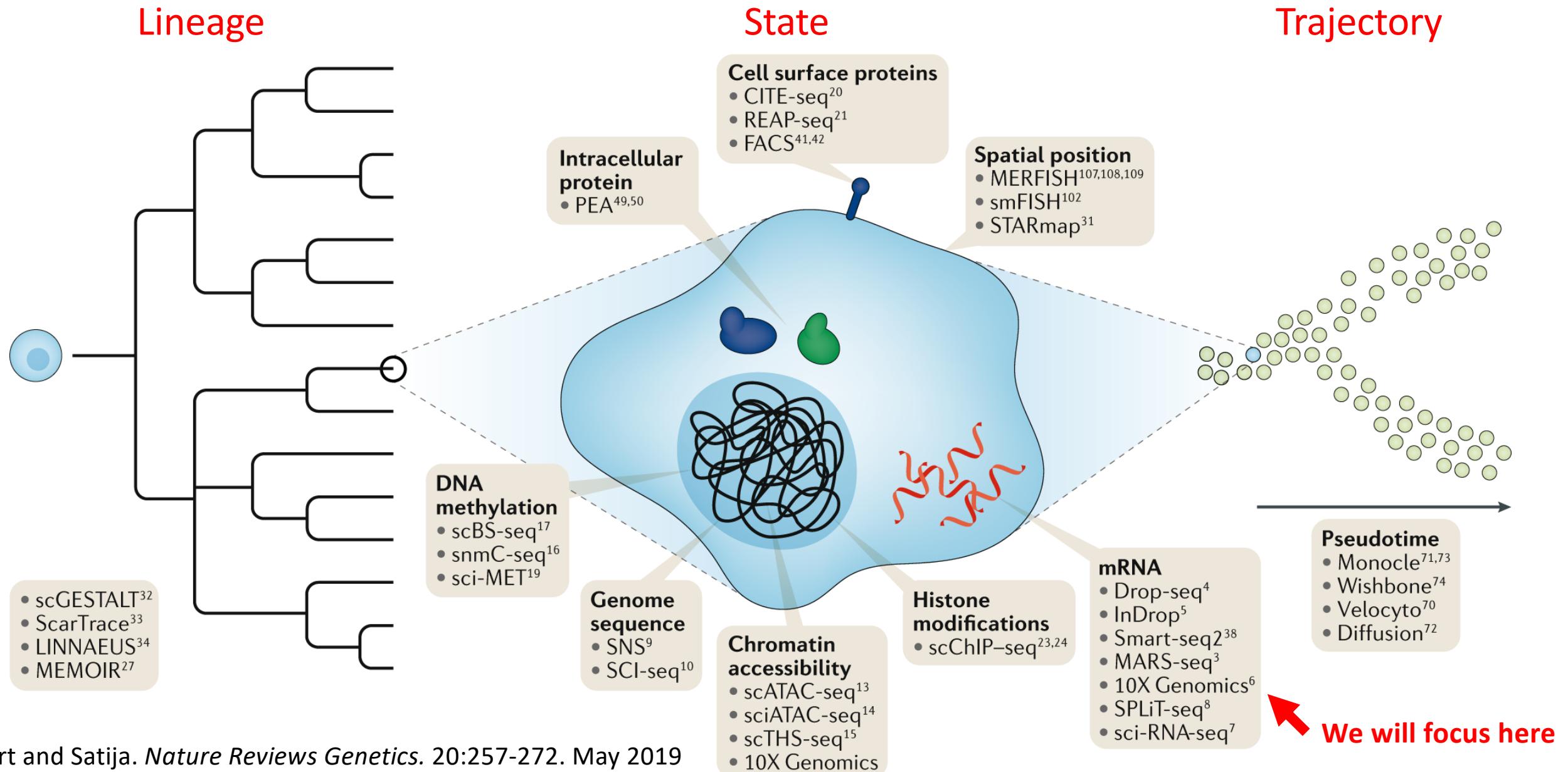


Bulk analysis detects uniform expression of all three genes



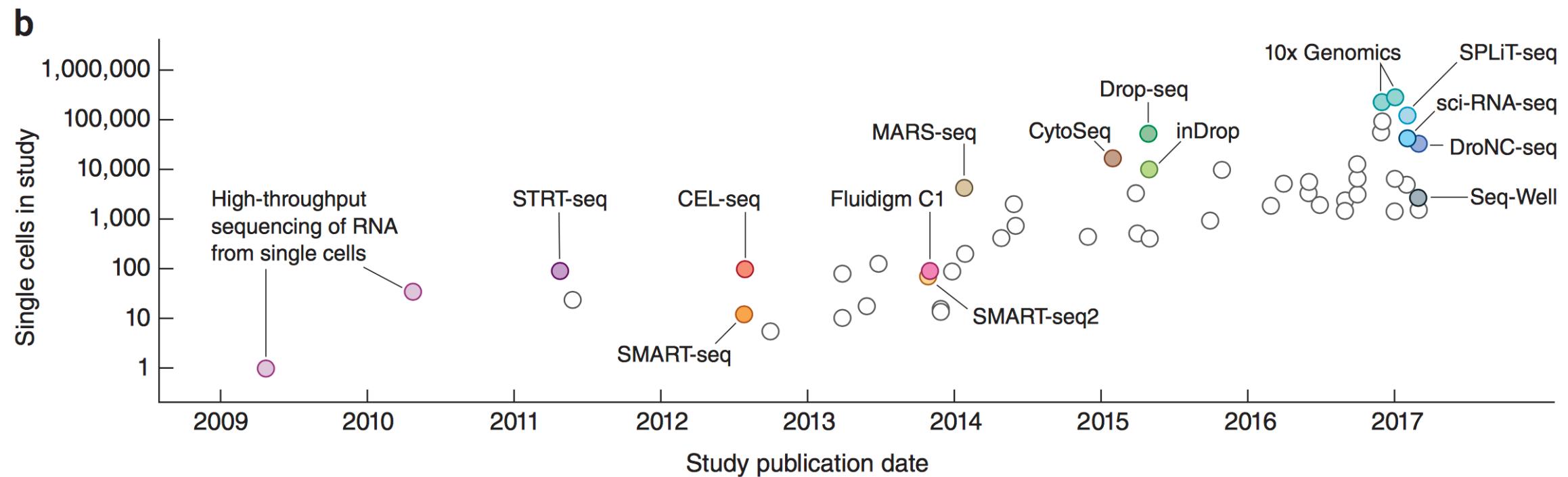
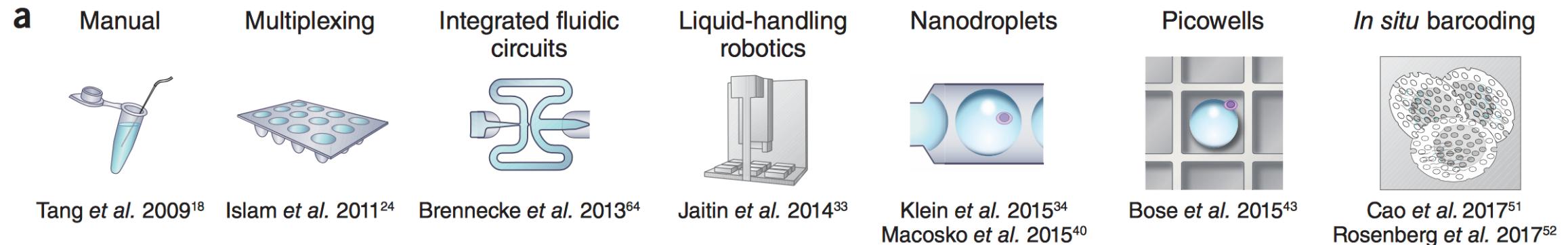
Single-cell analysis directly measures diversity of expression

“A wide variety of single-cell methods have now been developed to measure a broad range of cellular parameters”



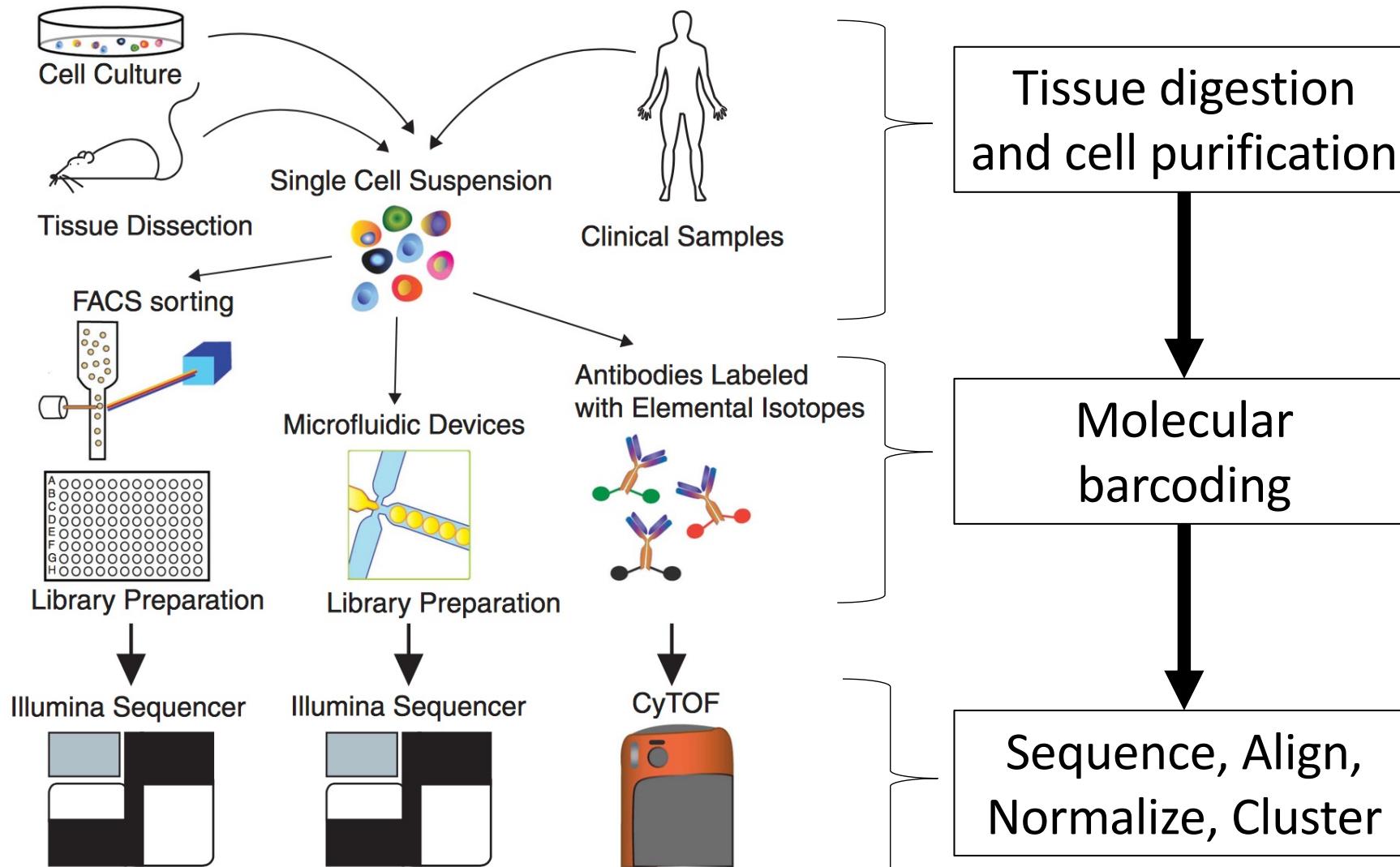
Considerations and capabilities for generation of single cell data

“Exponential scaling of single-cell RNA-seq in the past decade”



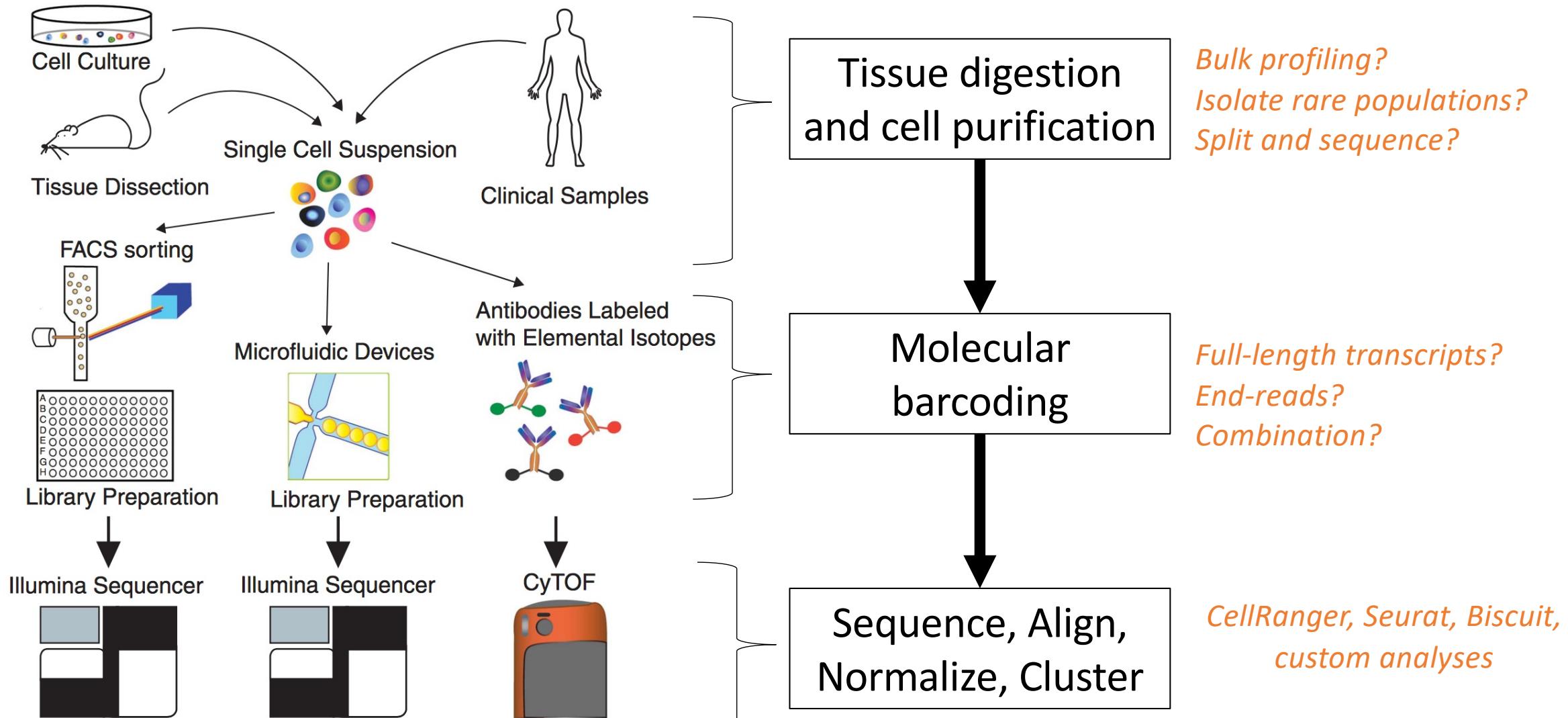
Svensson, Vento-Tormo, and Teichmann. *Nat Protoc.* 2018 Apr;13(4):599-604.

Multiple pathways and technology options to analyze 100s-100,000s of single cells from a variety of sources

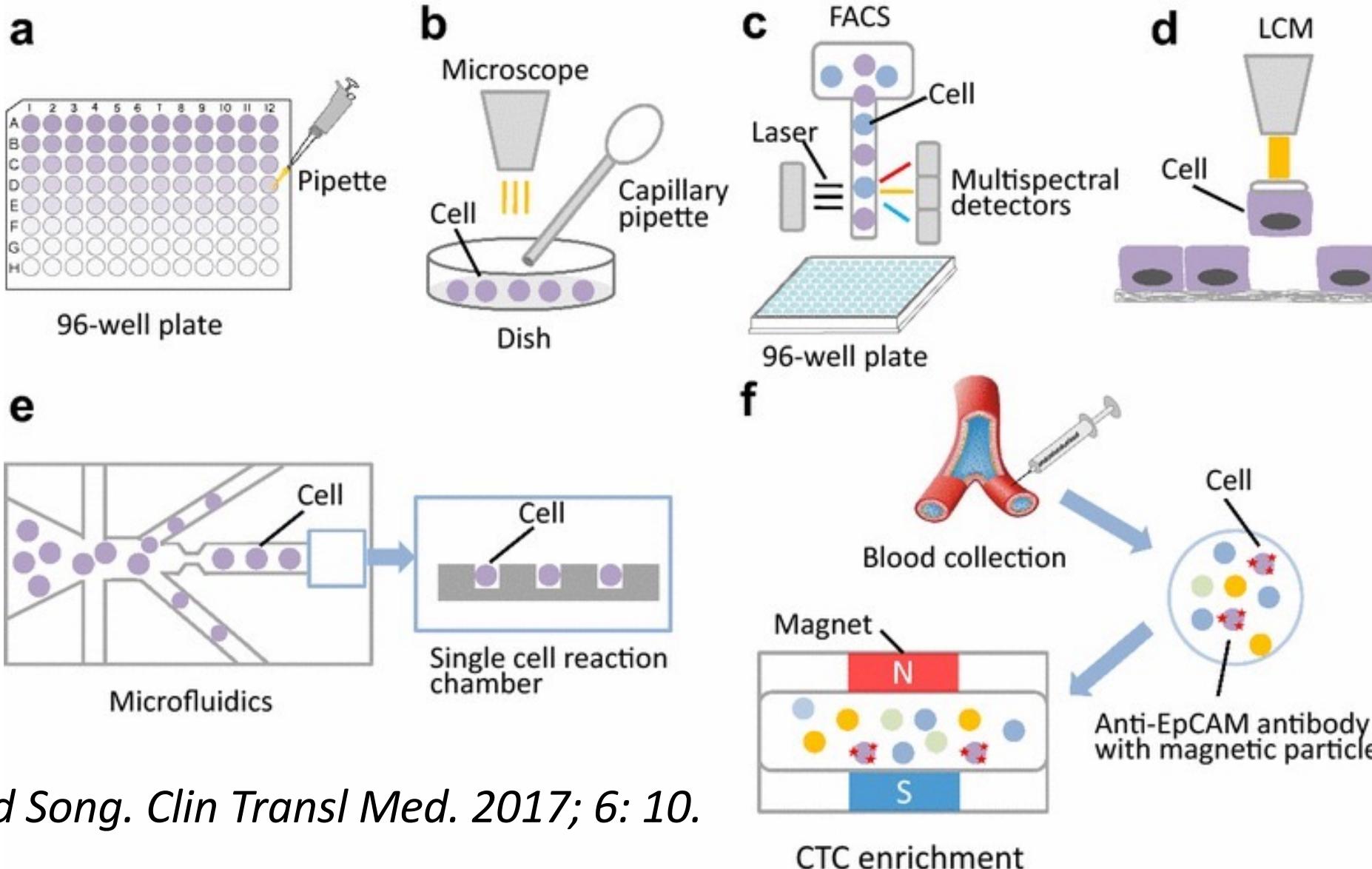


Proserpio and Lönnberg. *Immunol Cell Biol*. 2016 Mar;94(3):225-9.

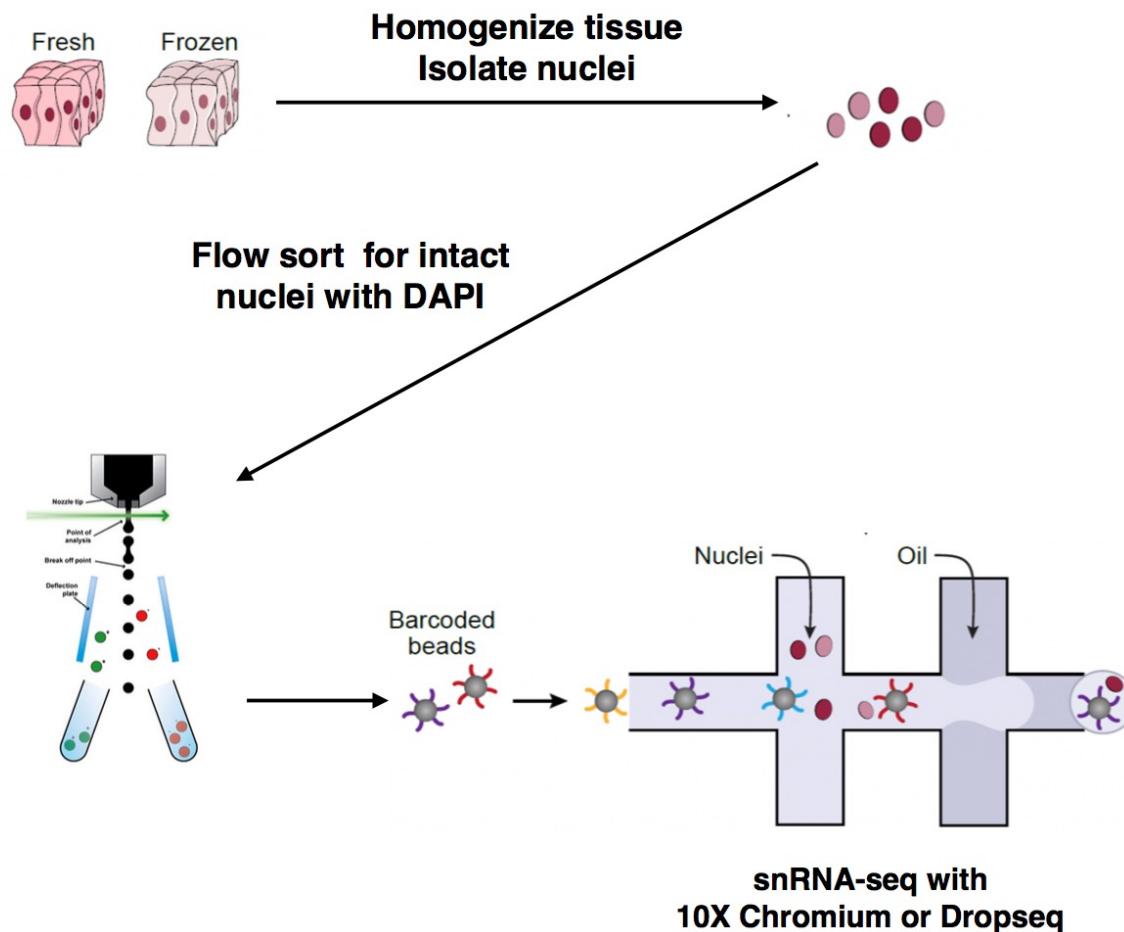
Multiple pathways and technology options to analyze 100s-100,000s of single cells from a variety of sources



Numerous methods to isolate single cells, some more scalable than others



Single nuclei sequencing of snap frozen cells overcomes viability problem in primary tumours



Permits use of frozen, banked samples

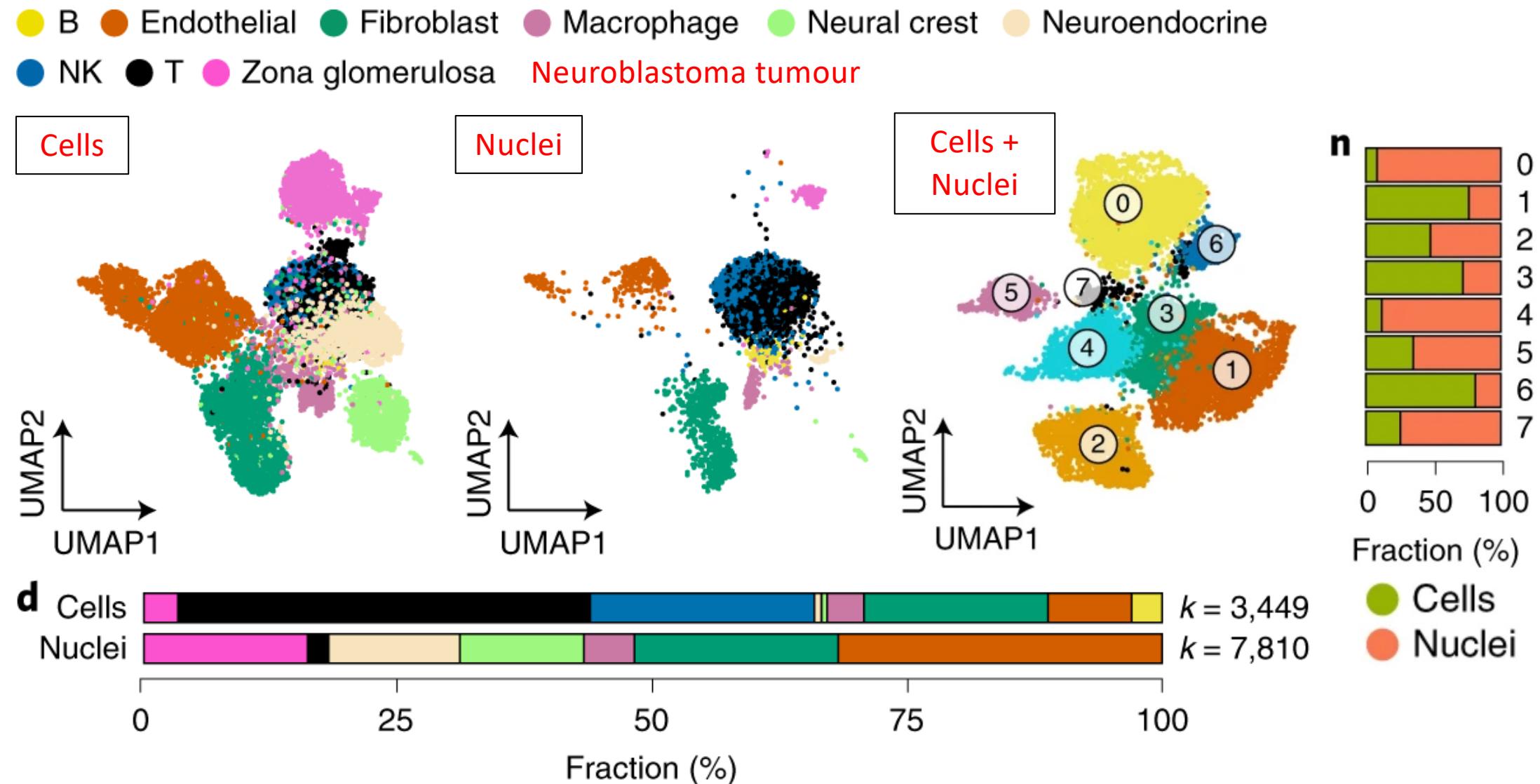
Avoids potential dissociation/processing-induced transcriptional shifts and cell-type depletion

Lower transcript and gene counts compared to live cell cytoplasmic RNA-seq

Increased mapping to ironic regions compared to mature cytoplasmic mRNA

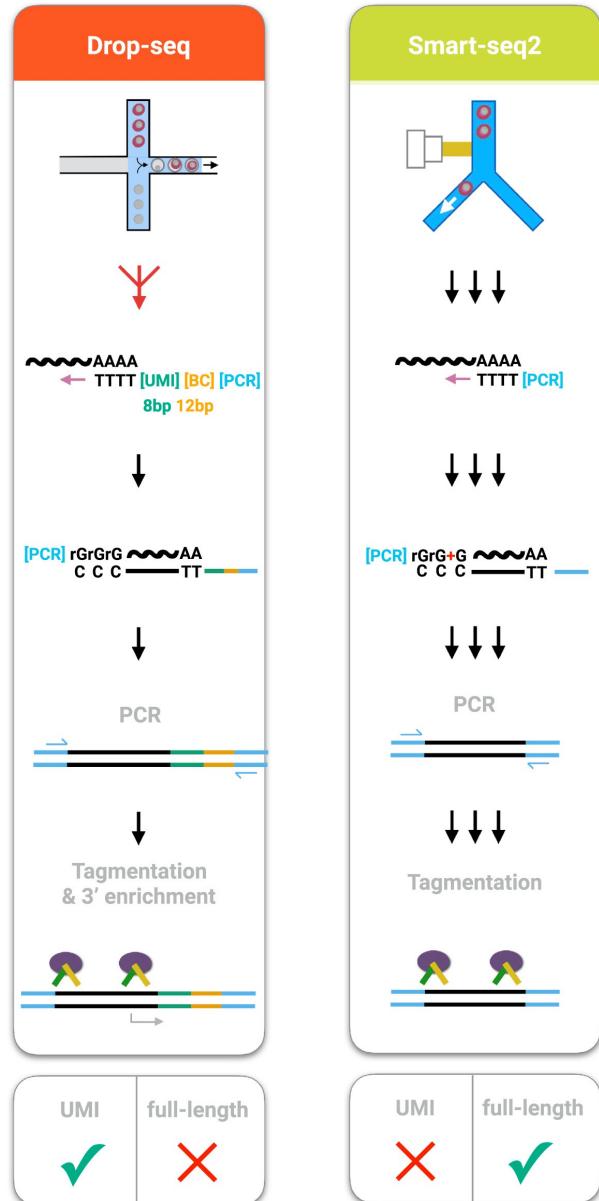
Able to recapitulate clusters and cell-type marker genes using nuclei

Nuclei RNA sequencing now routine: use frozen tissues but drawbacks of no cytoplasm, fewer transcripts, more introns, no cell enrichment



Two commonly-employed RNA-seq strategies: 10X Genomics End-reads versus Smart-Seq2 Full-length transcripts

10x Genomics Chromium
\$2-4/cell including sequencing
100–100,000 cells
3'- or 5'-tag method in droplets
Tagmentation, 3' or 5'
enrichment, Illumina sequencing

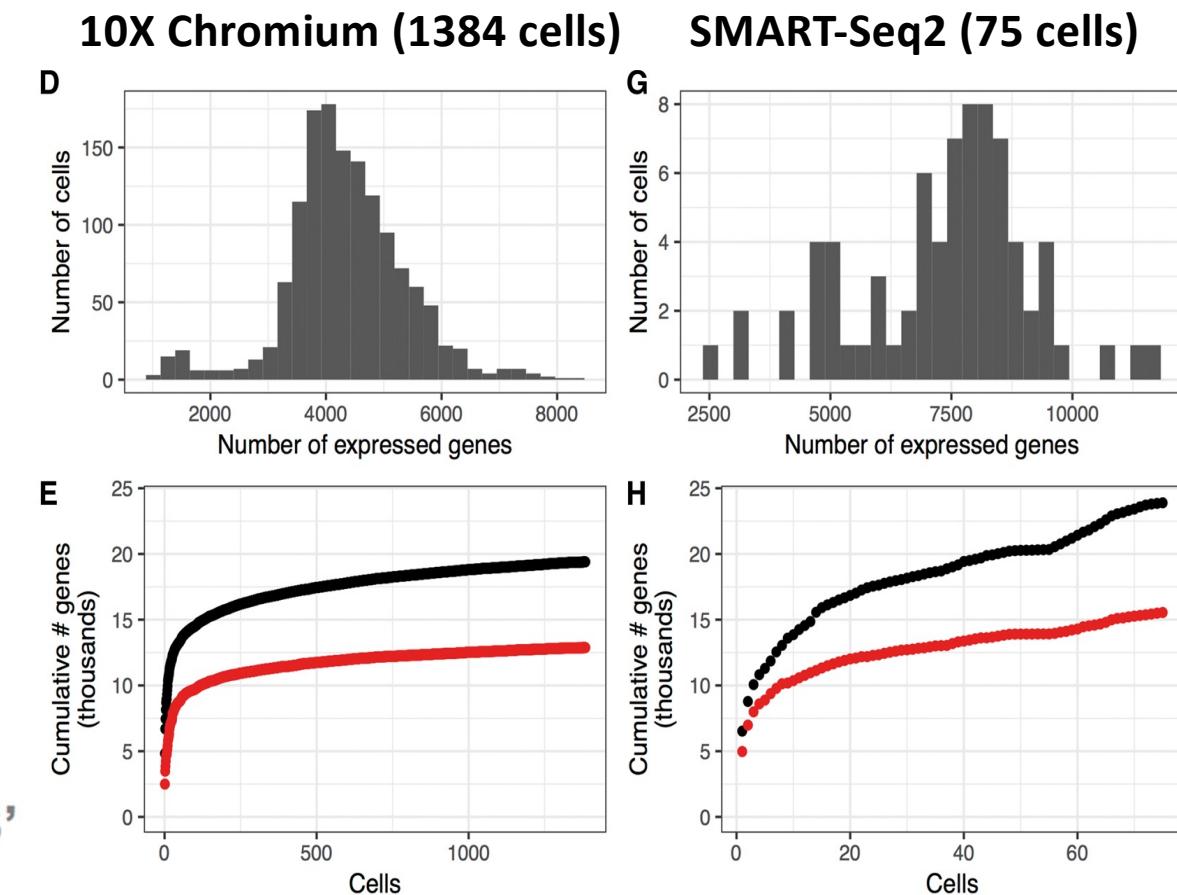
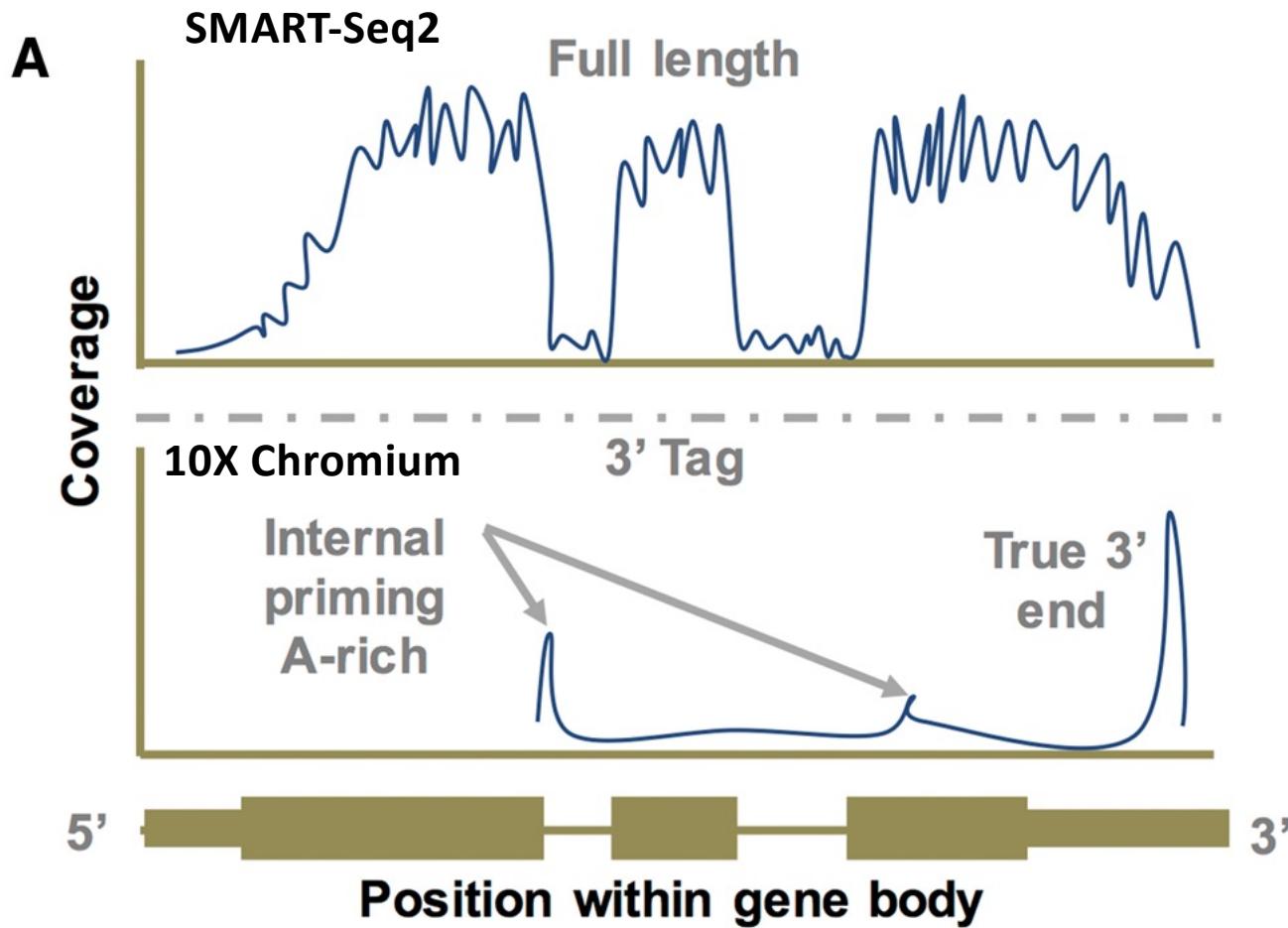


SmartSeq2
\$28-69/cell including sequencing
96–384 cells
Full length capture in plates
Tagmentation, Illumina sequencing

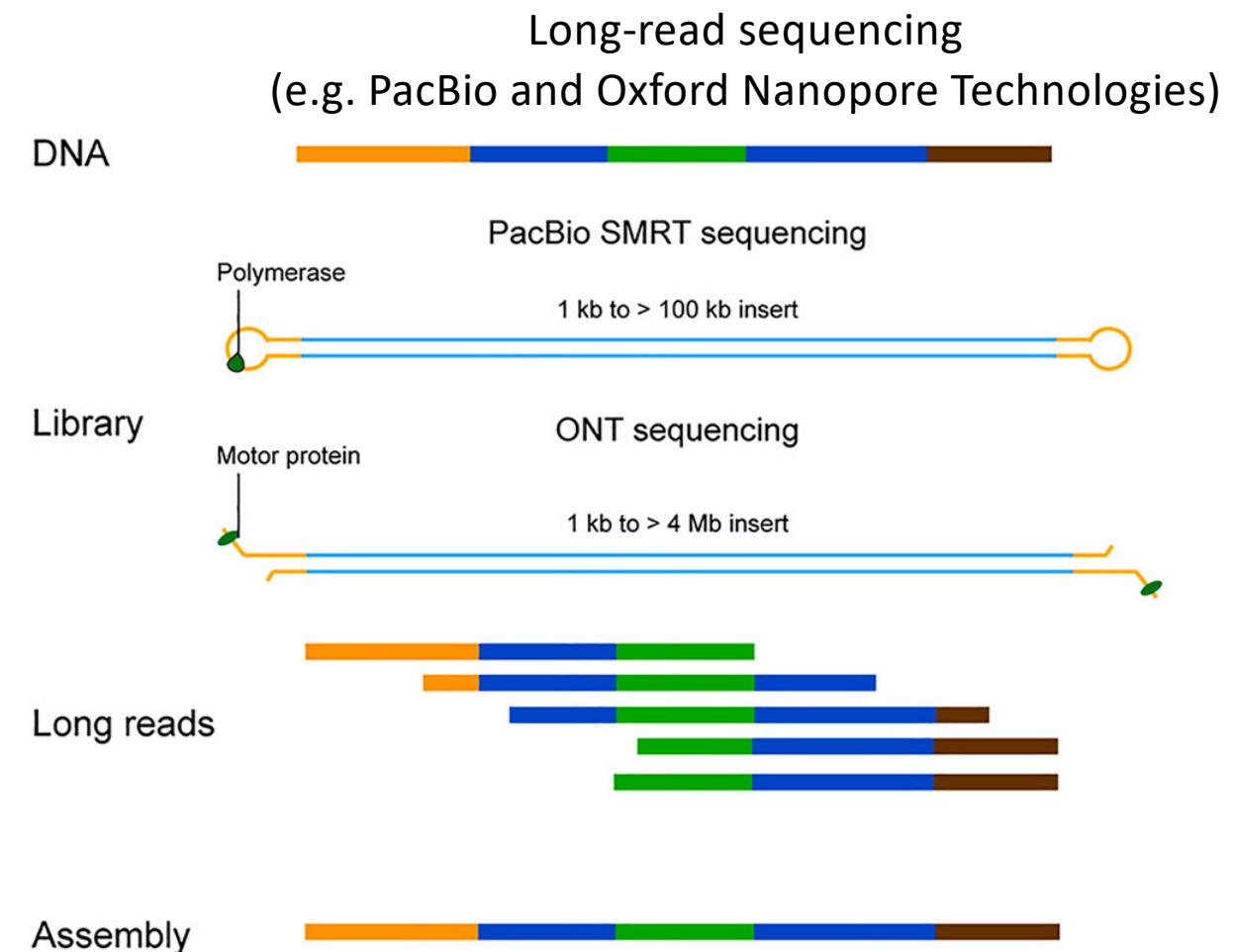
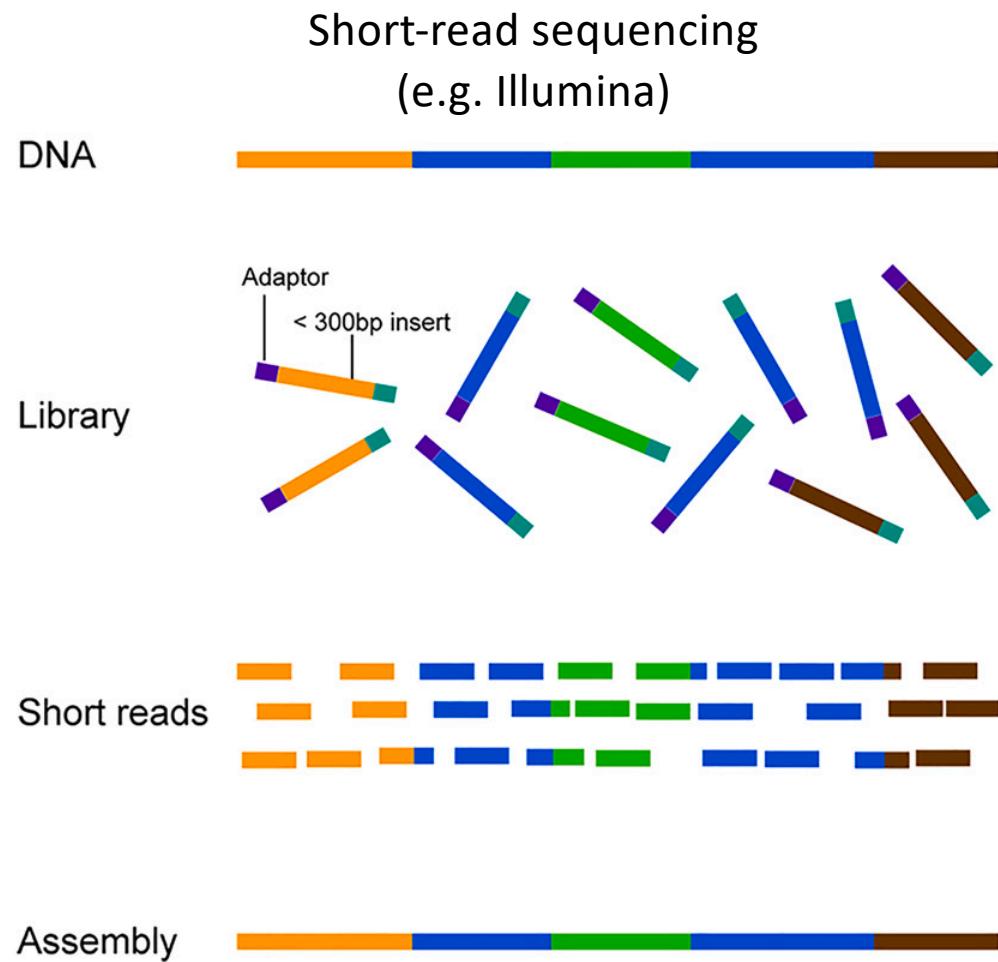
Figure modified from:
Ziegenhain et al. Mol Cell. 2017
Feb 16;65(4):631-643.e4.

Baran-Gale, Chandra, and
Kirschner K. Brief Funct
Genomics. 2017 Nov 8.

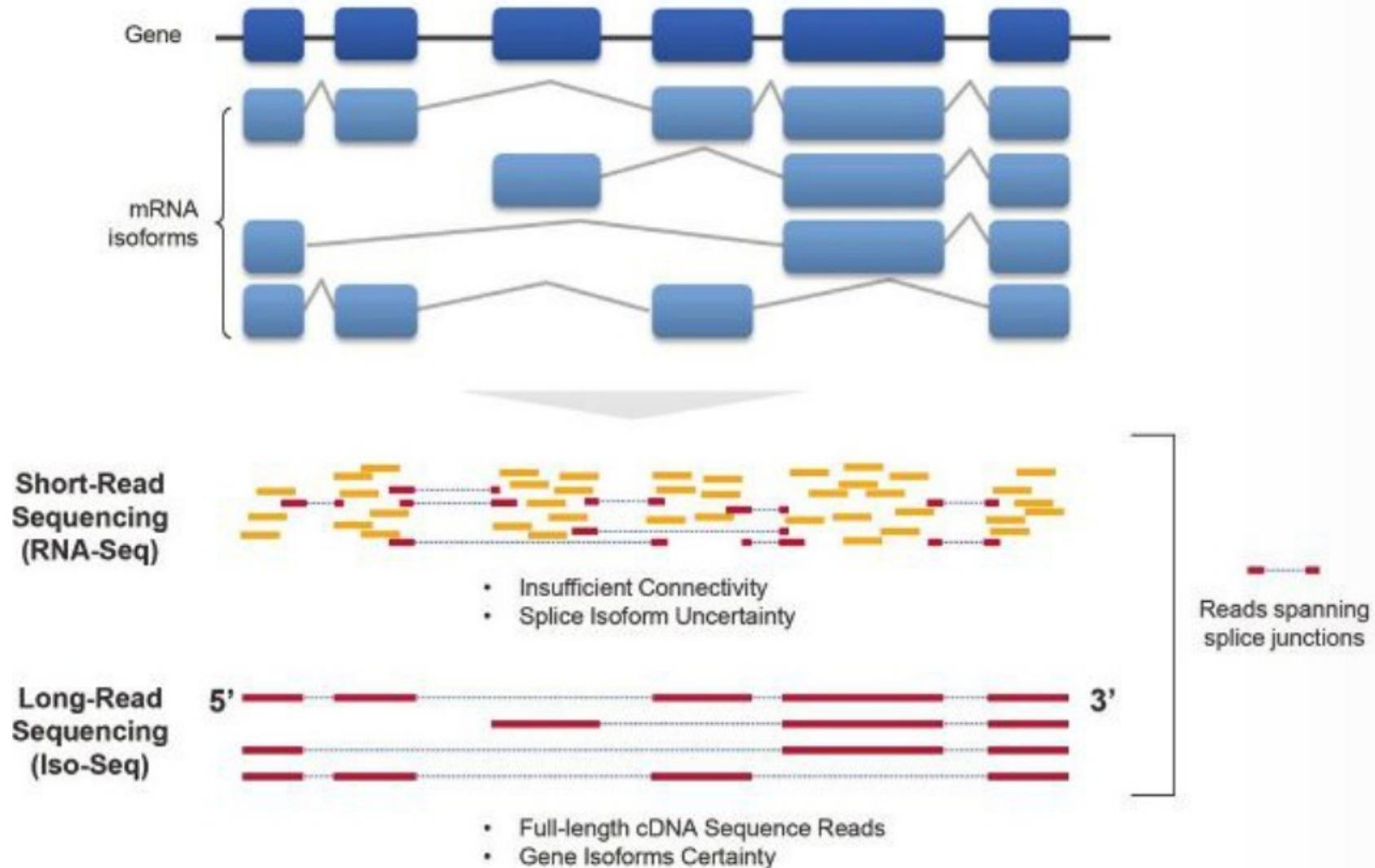
Experimental design balancing transcript coverage, number of genes detected, and library complexity



Long-read sequencing technologies are applicable to DNA and RNA libraries barcoded at the single cell level

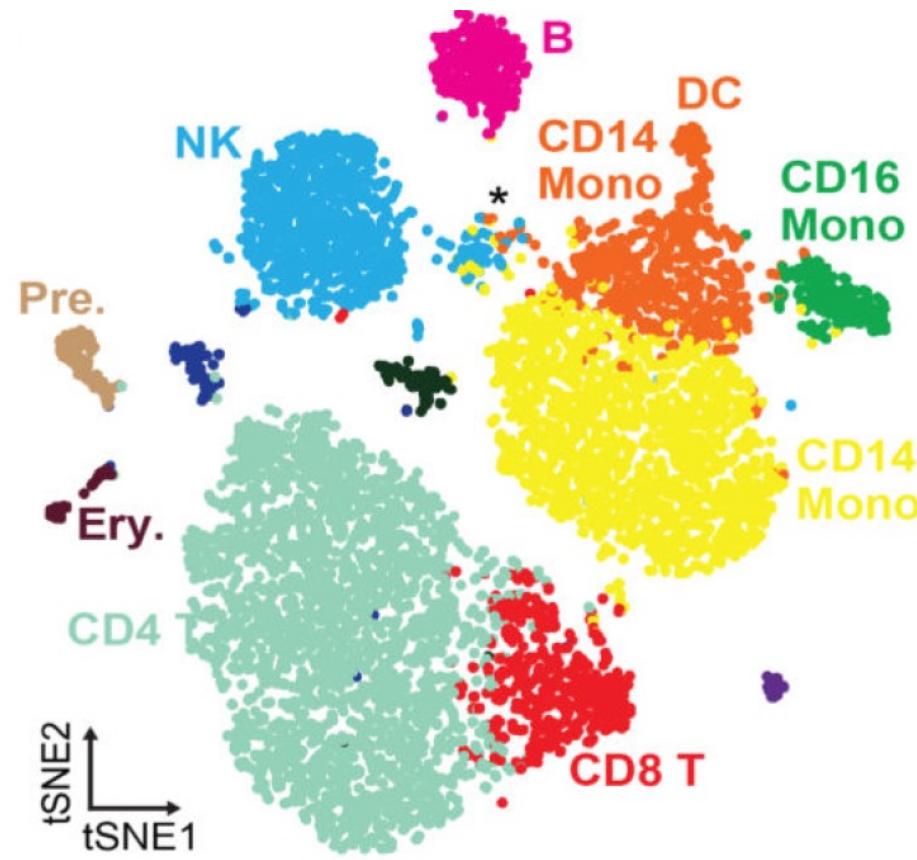


Long-read sequencing technologies can enable complete reconstruction of transcript isoforms at the single cell level

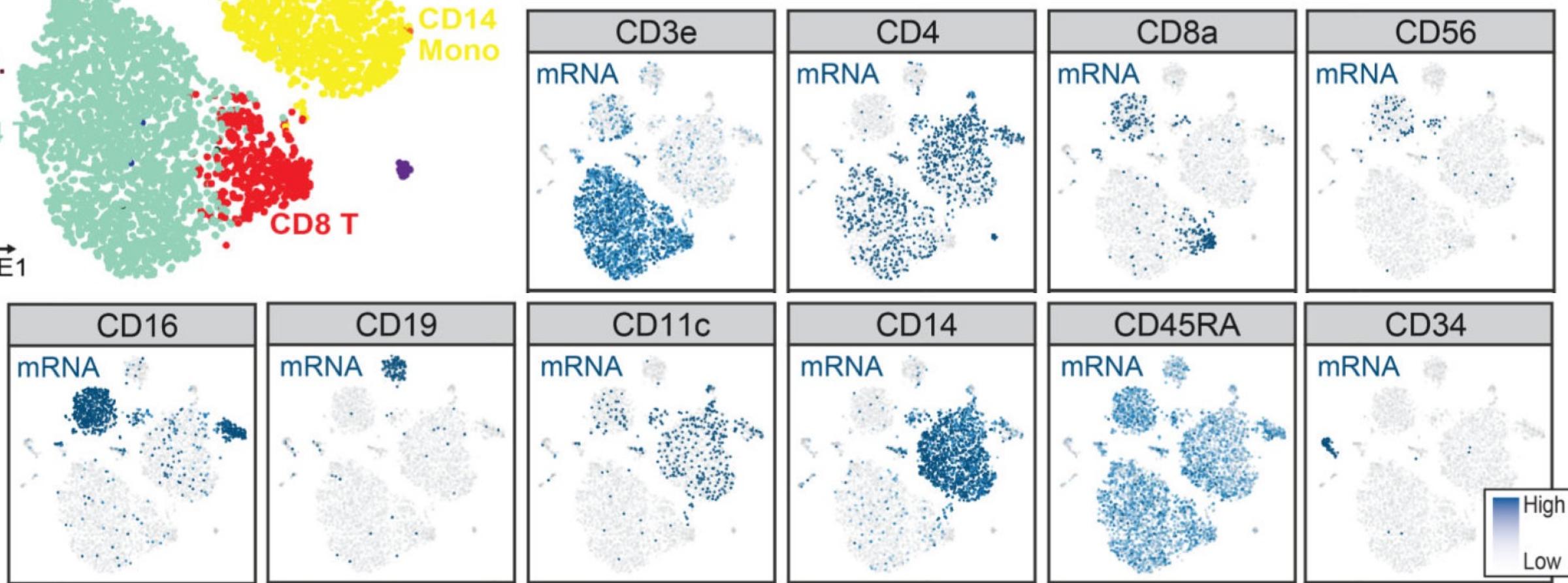


Chen and He. *Medical Review*. <https://doi.org/10.1515/mr-2021-0013>

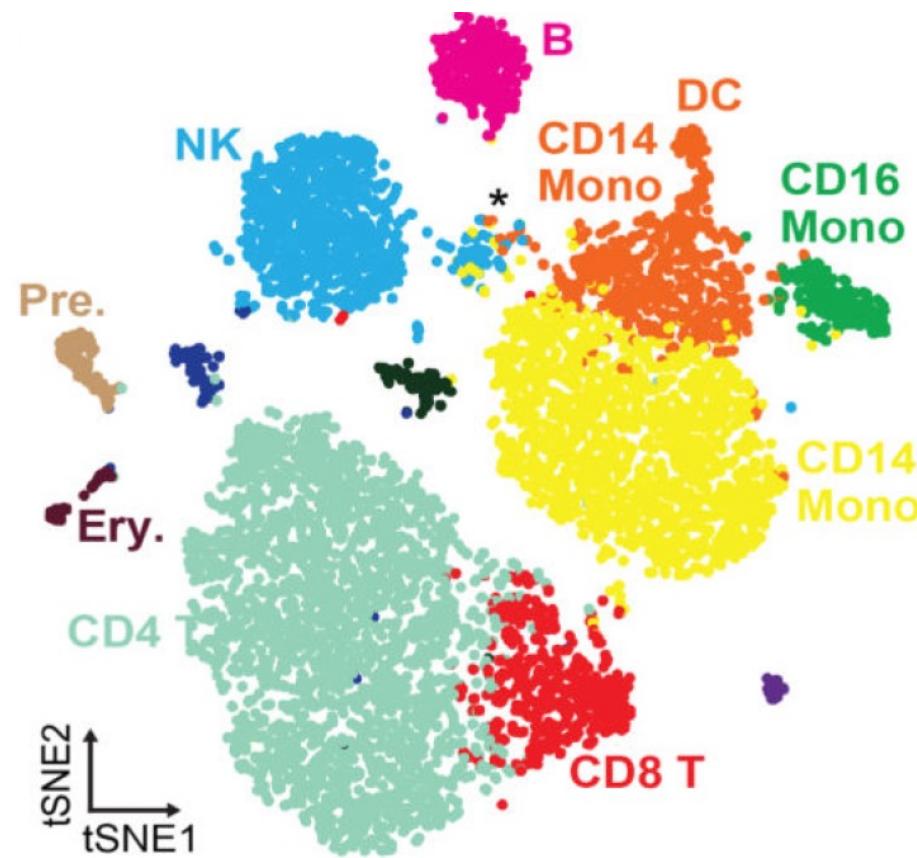
<https://www.ddw-online.com/full-length-isoform-sequencing-iso-seq-yields-a-more-comprehensive-view-of-gene-activity-1586-201608/>



Canonical single-gene markers may not be expressed at high level for detection in all cells → consider gene sets or protein measurements

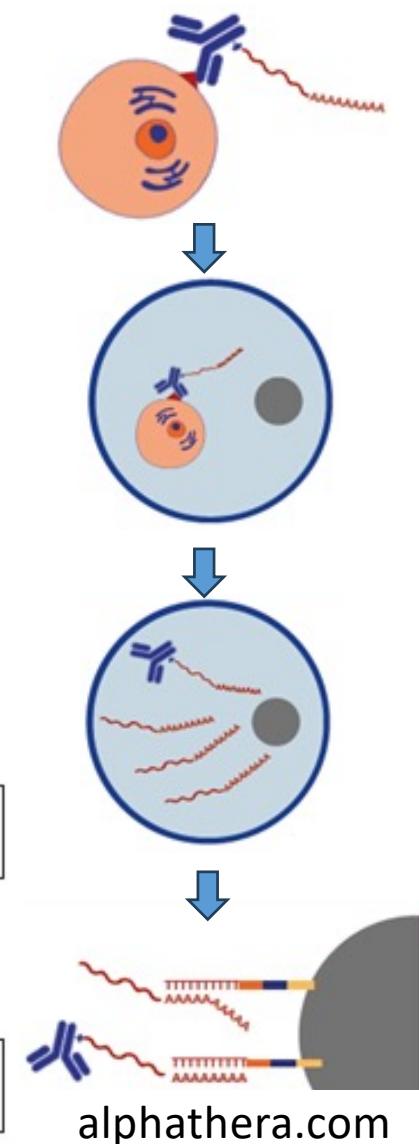
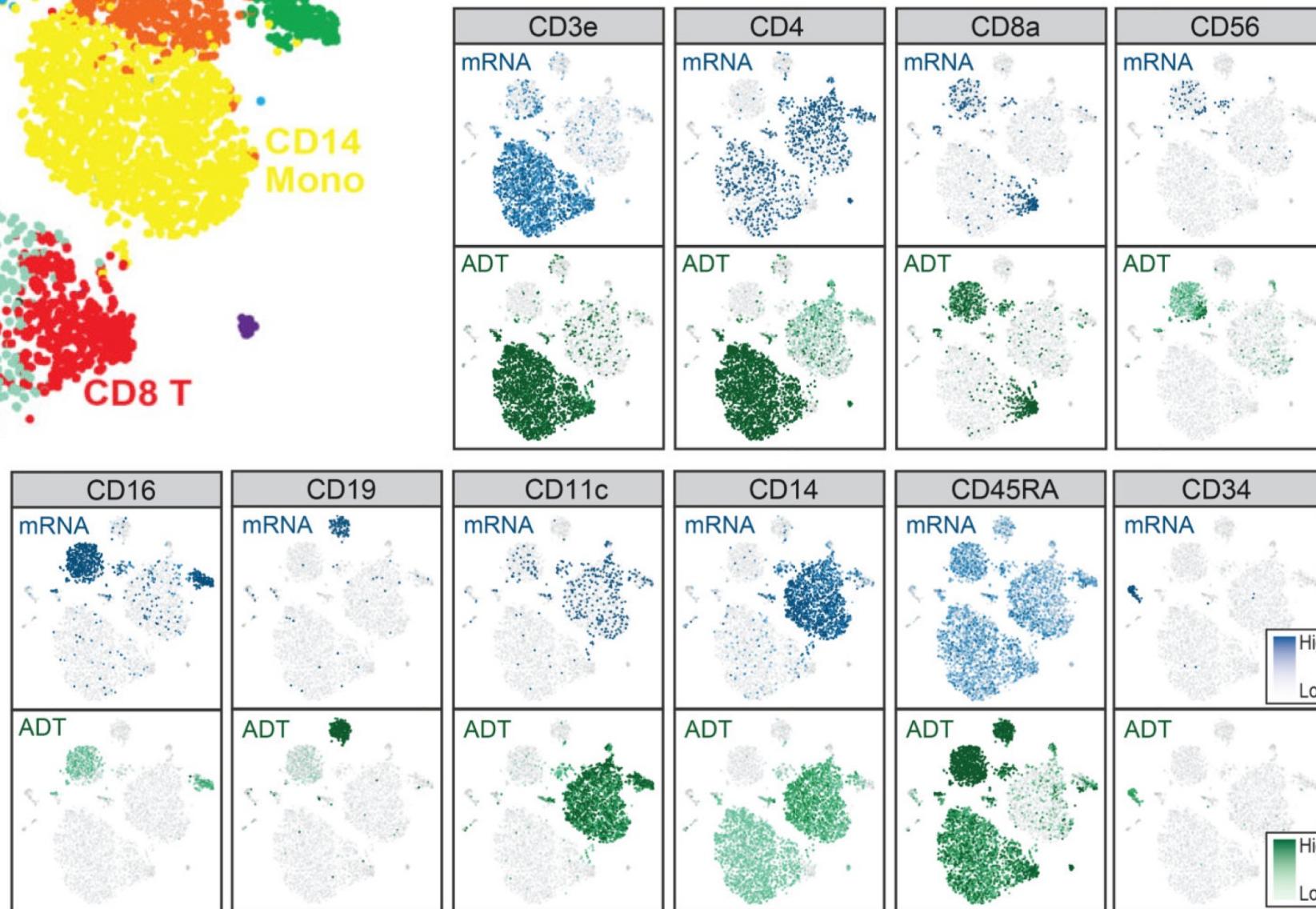


Modified from Stoeckius et al. Nat Methods. 2017 Sep;14(9): 865-868.



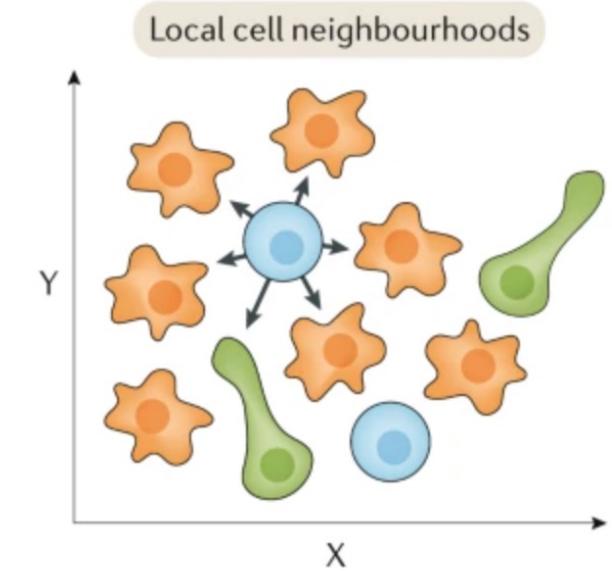
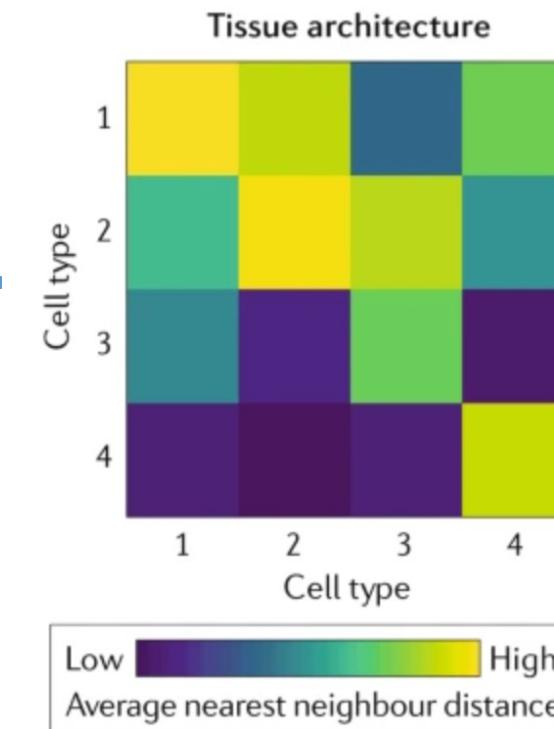
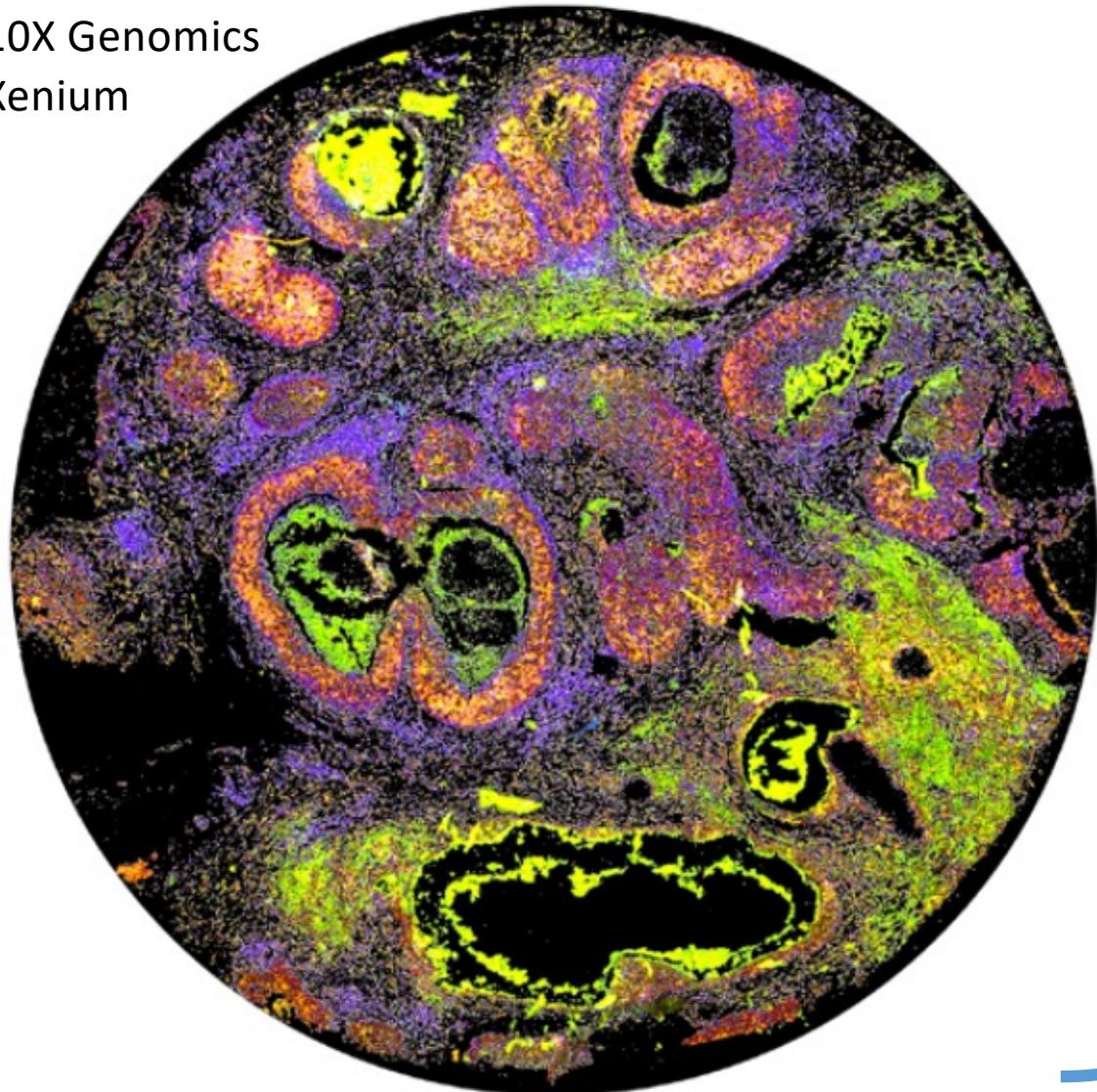
*Stoeckius et
Nat Methods
2017 Sep;14
865-868.*

Protein & RNA expression can be measured simultaneously by CITE-seq (Cellular Indexing of Transcriptomes & Epitopes by S



New spatial technologies enable additional cellular metadata describing physical distances between cell types and cell states

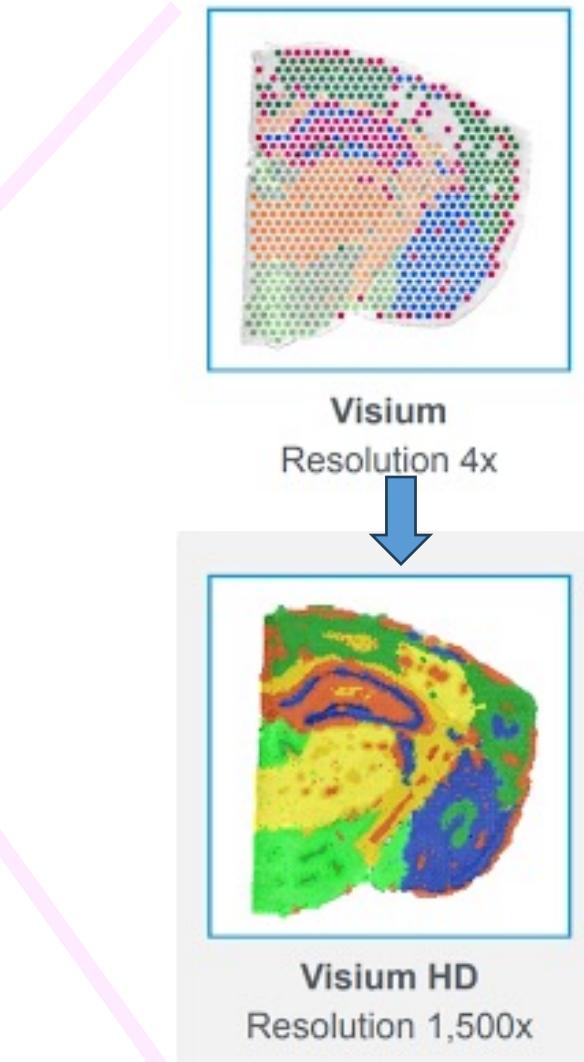
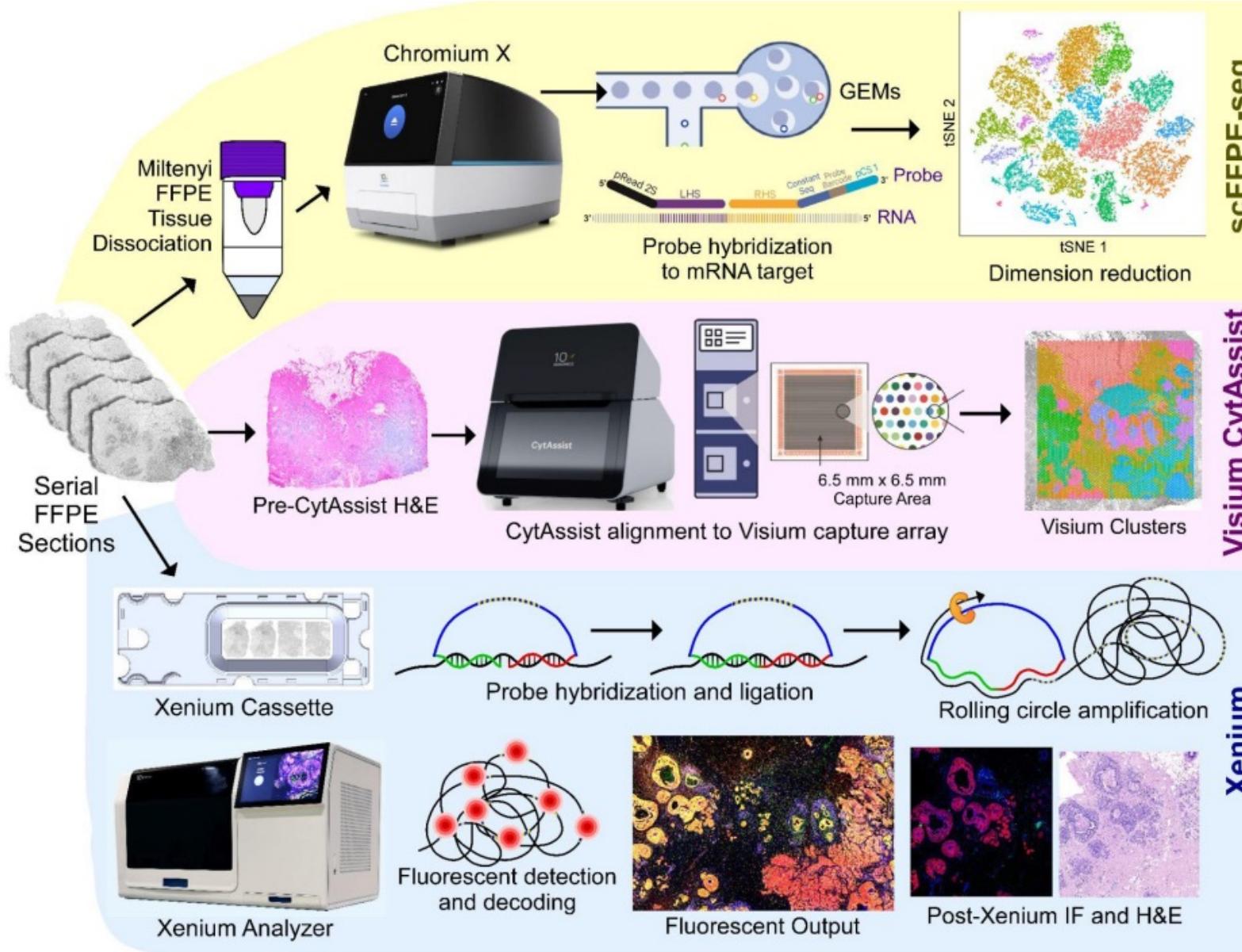
10X Genomics
Xenium



<https://www.10xgenomics.com/in-situ-technology>

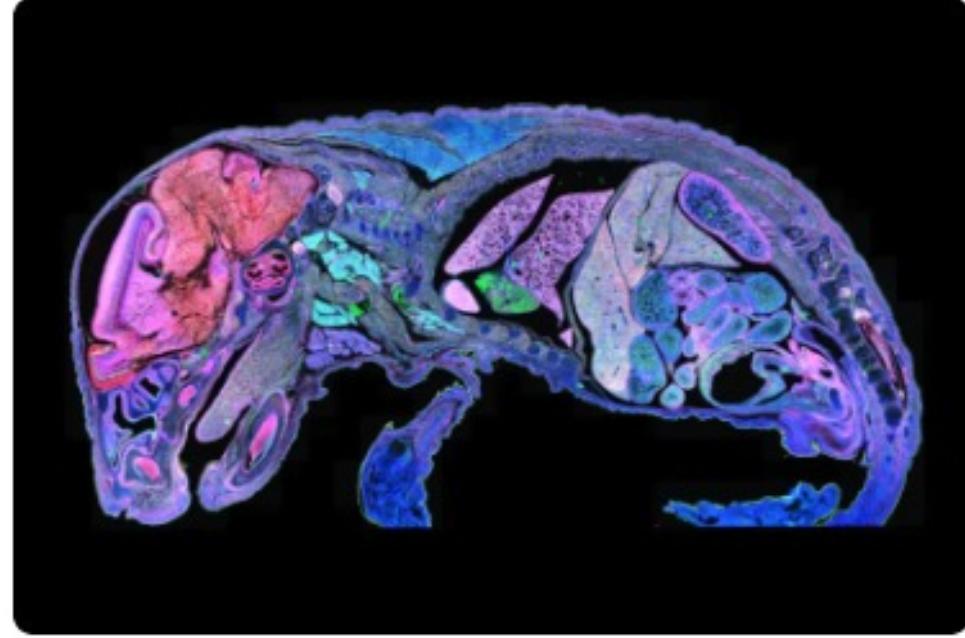
Stuart and Satija. *Nature Reviews Genetics*. 20:257-272. May 2019

Spatial technologies are currently panel-based, but moving rapidly to whole transcriptome + protein at subcellular resolution



<https://omicsomics.blogspot.com/2021/02/more-details-on-10xs-sample-profiling.html>

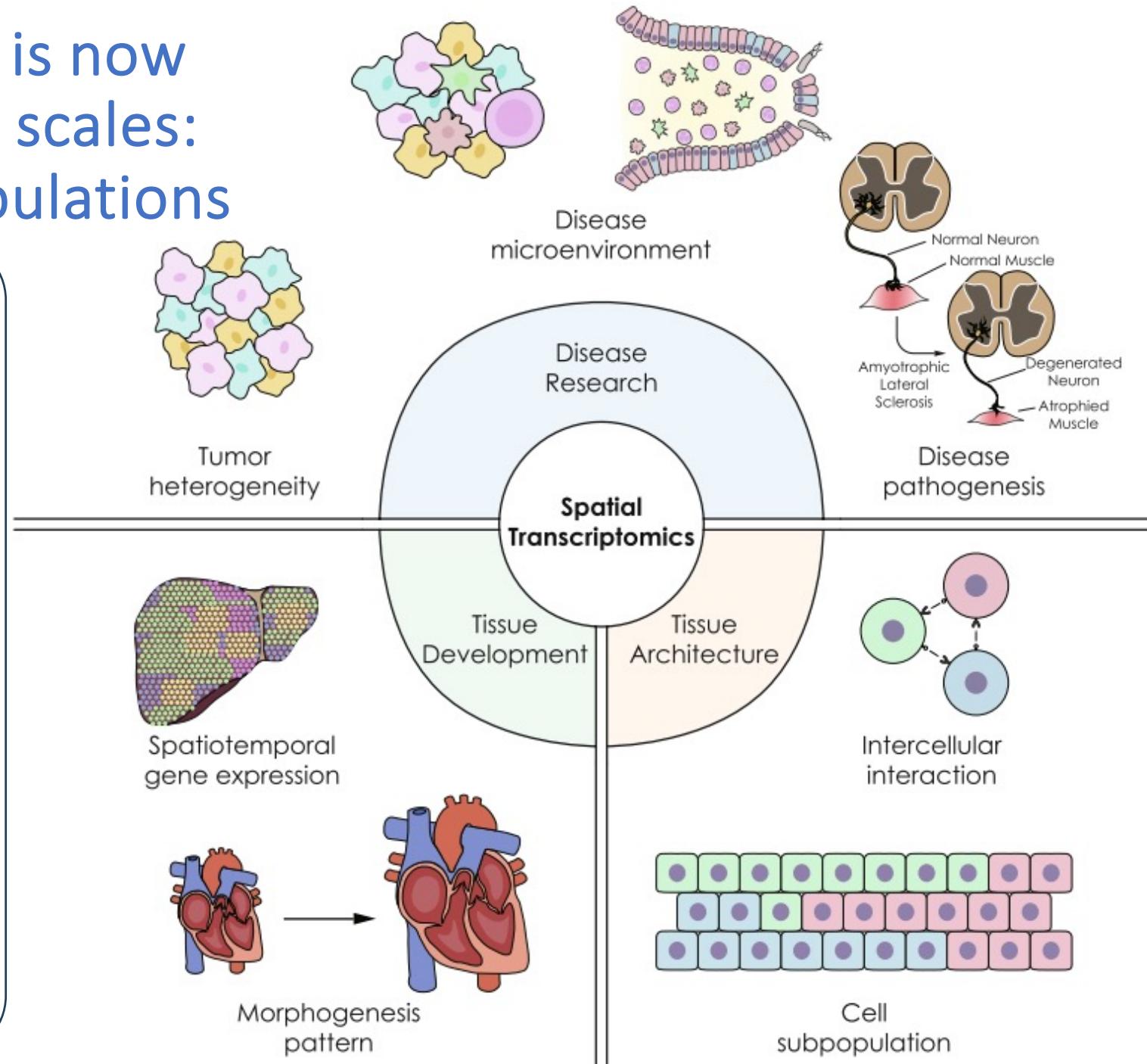
Cell organization & cell state is now measureable at all biological scales: cells, tissues, organisms, populations



Mouse Tissue Atlassing (379 genes)

Includes gene markers for bladder, bone marrow, brain, heart, kidney, limb muscle, lung, pancreas, thymus, etc.

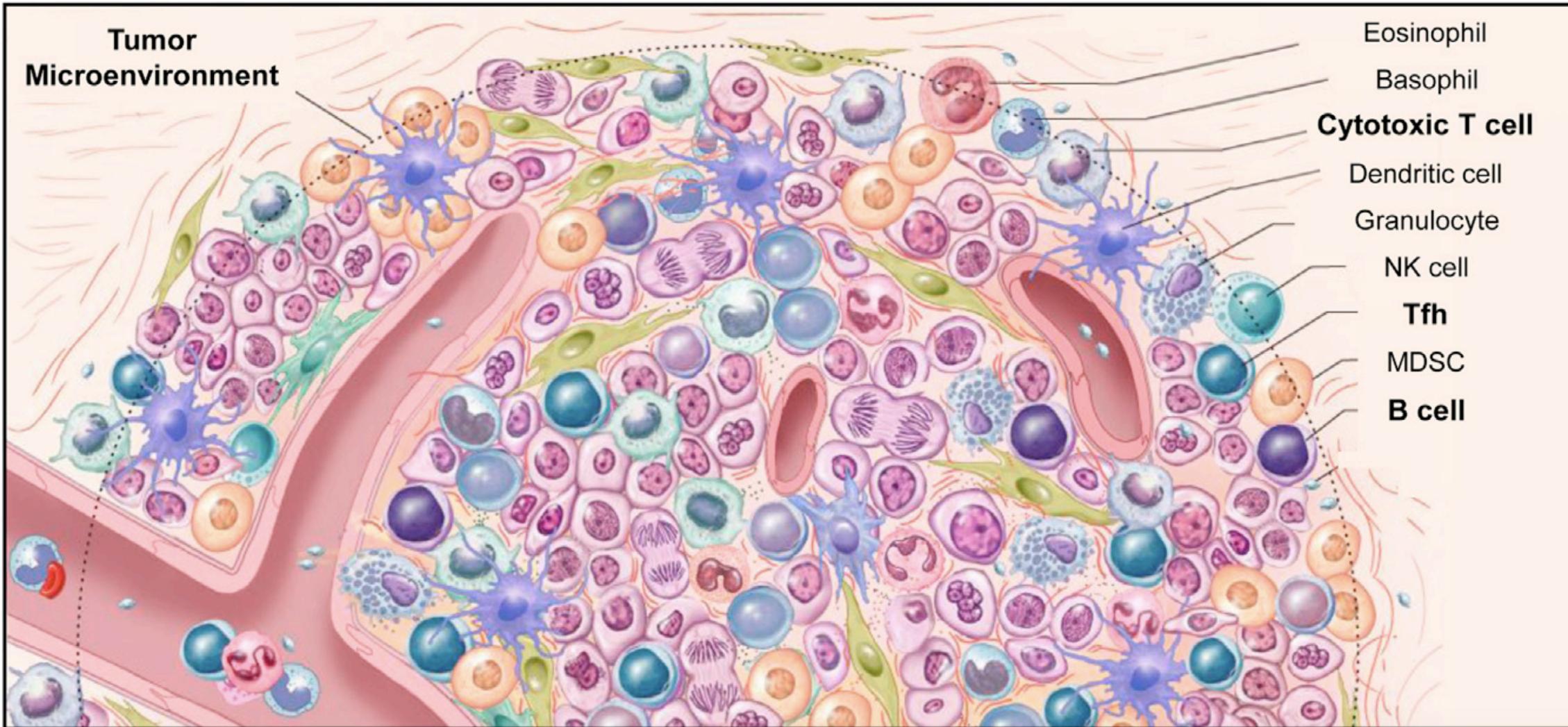
<https://www.10xgenomics.com/products/xenium-panels>



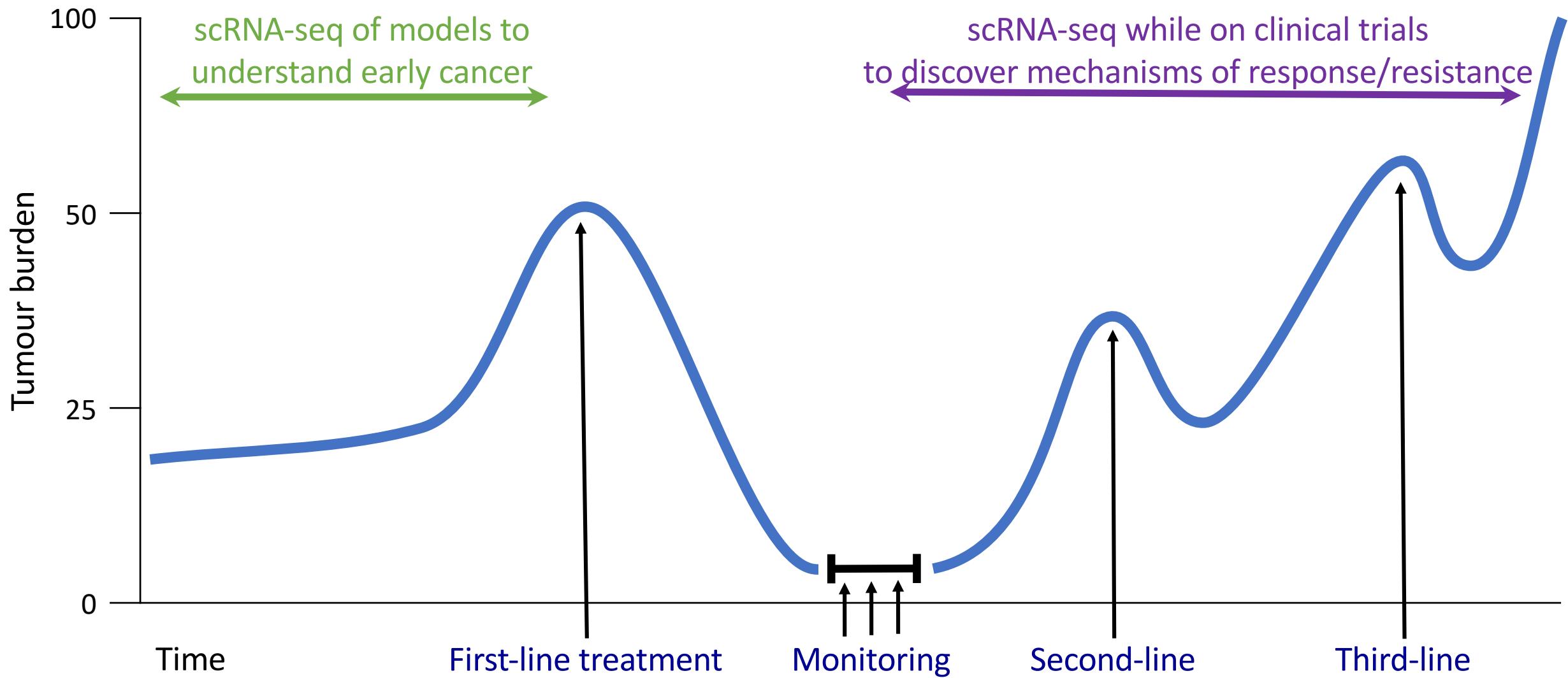
Du, Yang et al. *J Transl Med.* 2023; 21: 330.

Cancer as an example

Tumours are dynamic populations of cancer, immune, and other cells that change in frequency and function over the course of treatment



scRNA-seq in practice: How do cancer and immune systems change over time? Is there clinical relevance?



Watching immune systems evolve at the single cell level as cancer develops

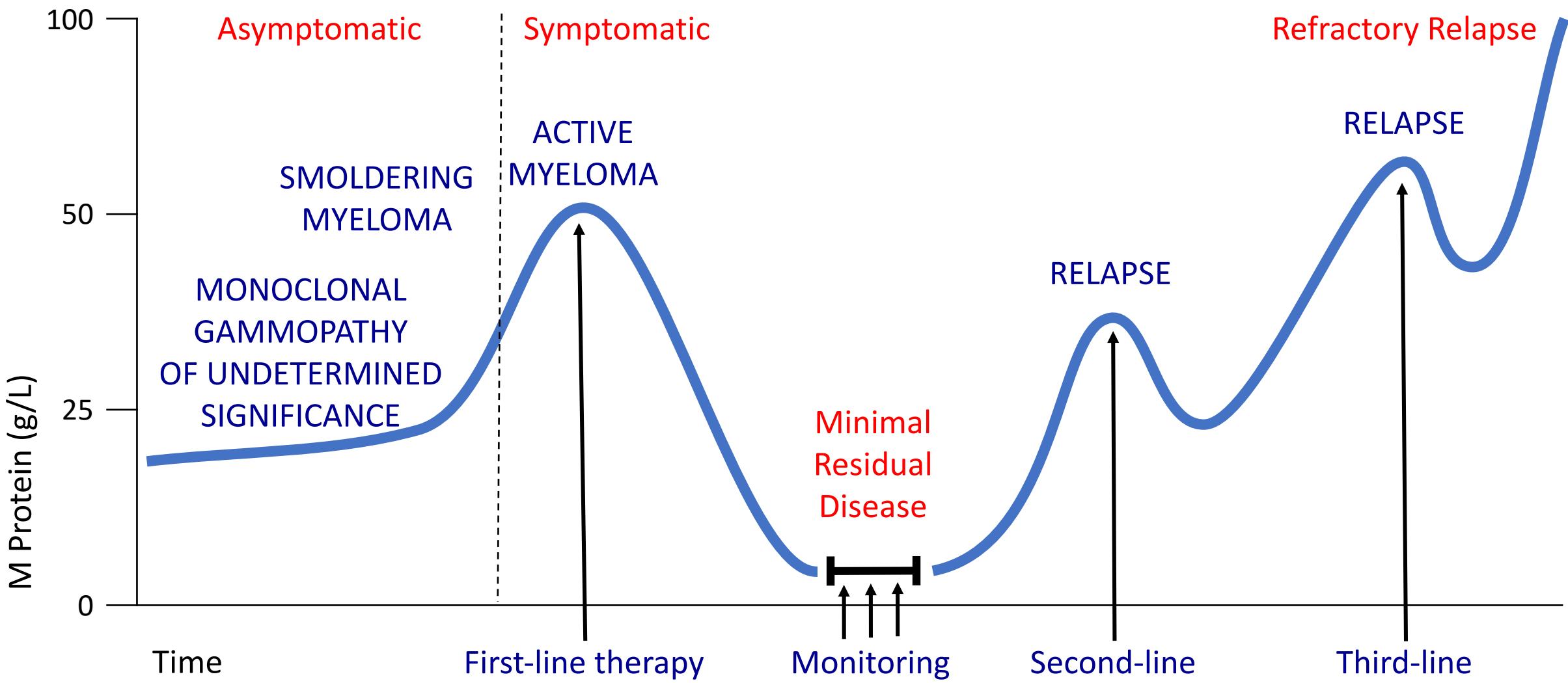
Croucher et al. *bioRxiv*. 2021 Jan. 10.22.464971

Single-cell transcriptional analysis of the immune tumour microenvironment during myeloma disease evolution.

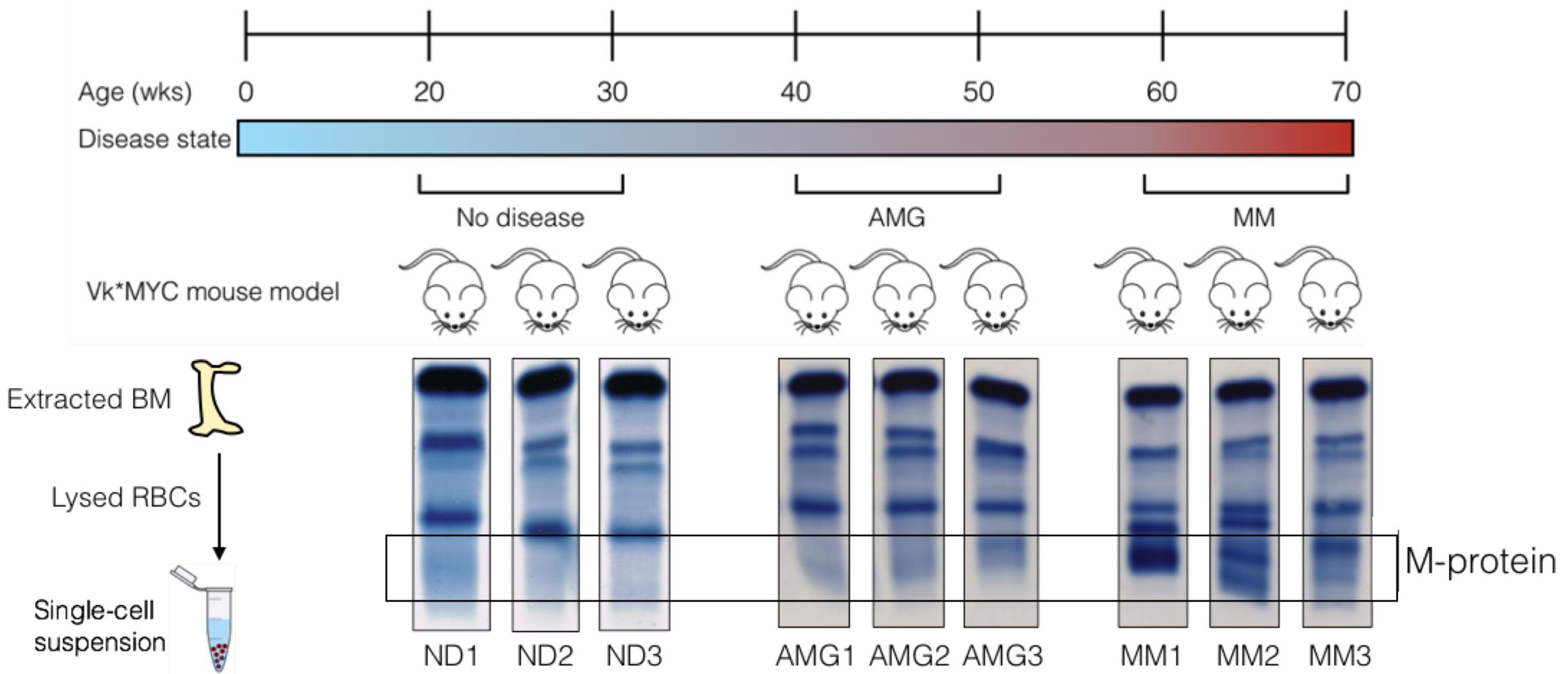
Croucher et al. *Nature Communications*. 2021 Nov; 12(6322).

Longitudinal single-cell analysis of a myeloma mouse model identifies subclonal molecular programs associated with progression.

Myeloma begins as a benign condition that progresses to incurable malignancy that tides during treatment and can be tolerated as MRD

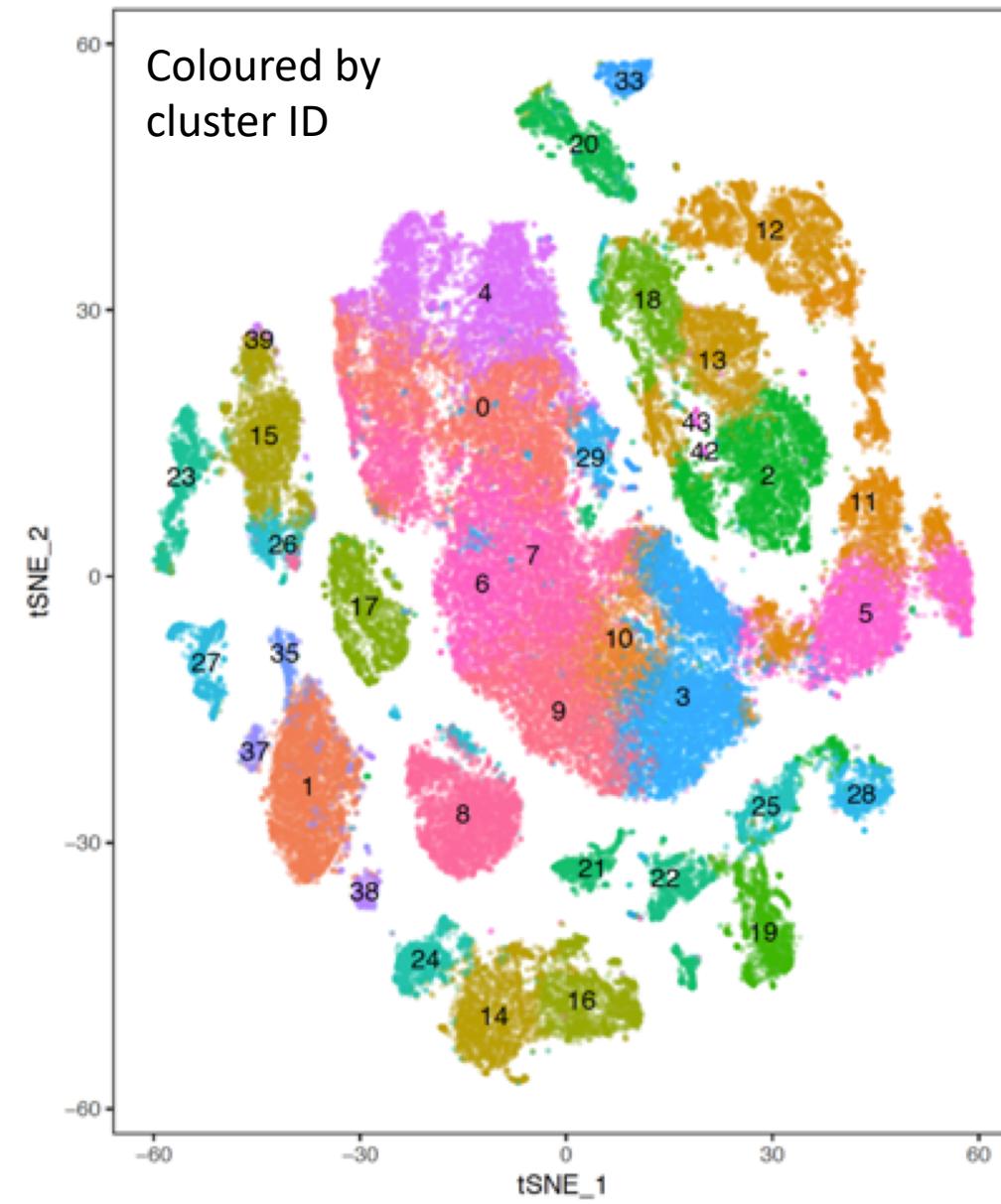
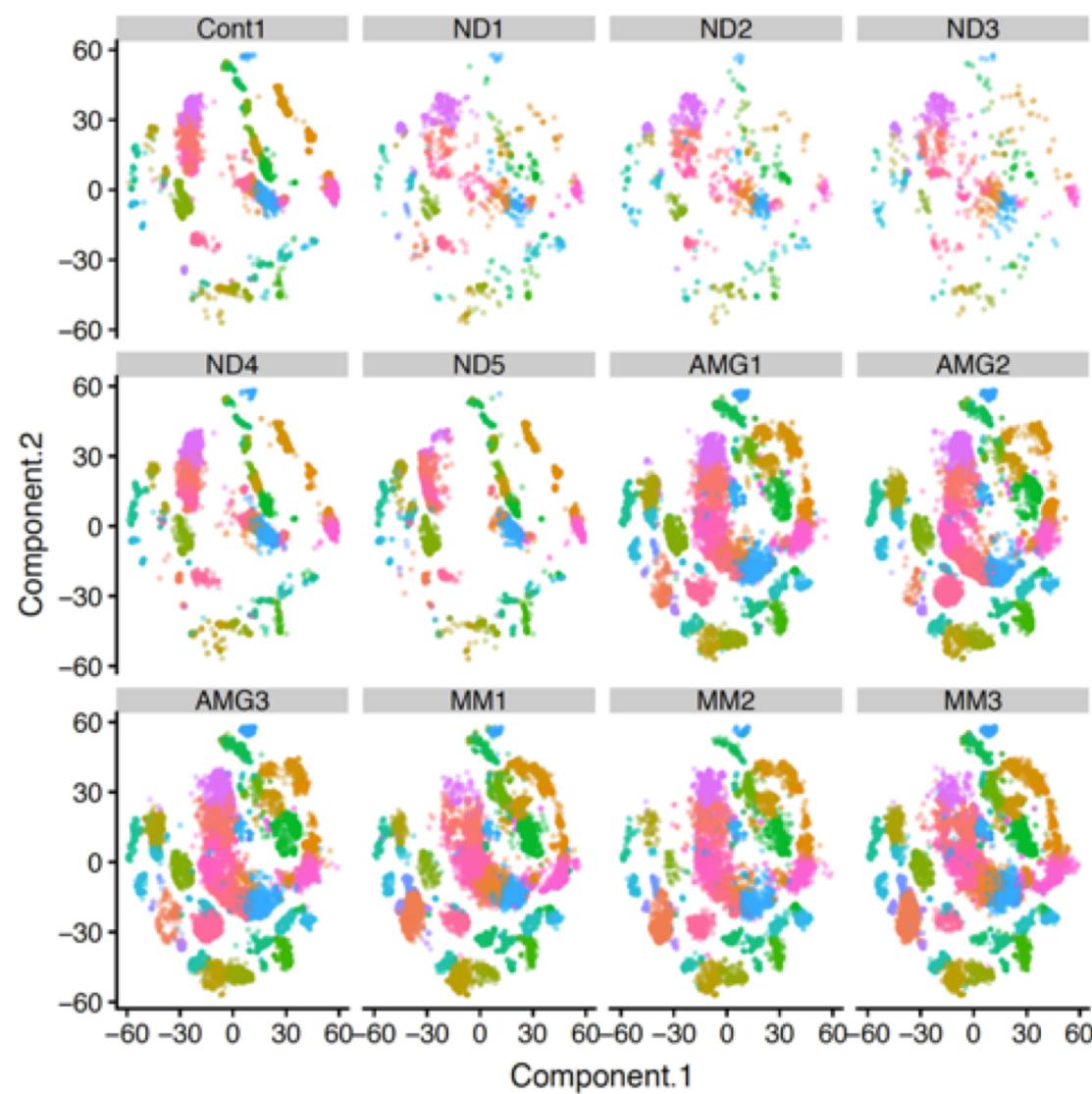


$V\kappa^*MYC$ mouse model enables serial dissection of bone marrow microenvironments during transition from MGUS to MM

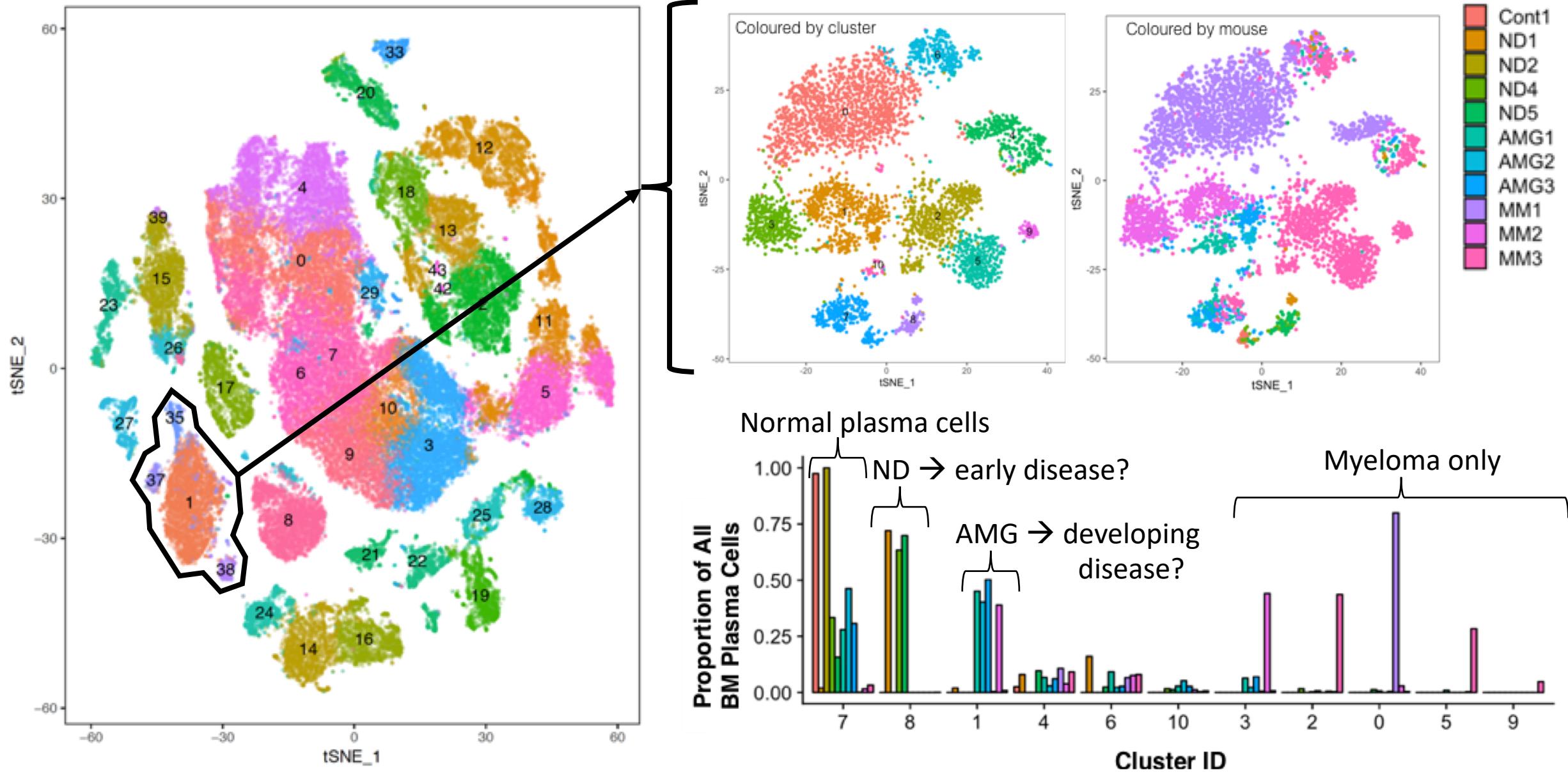


Collaboration with Michael Sebag (McGill) and Leif Bergsagel (Mayo)
Mouse model published by Chesi et al. Cancer Cell. 2008 Feb; 13(2): 167–180.

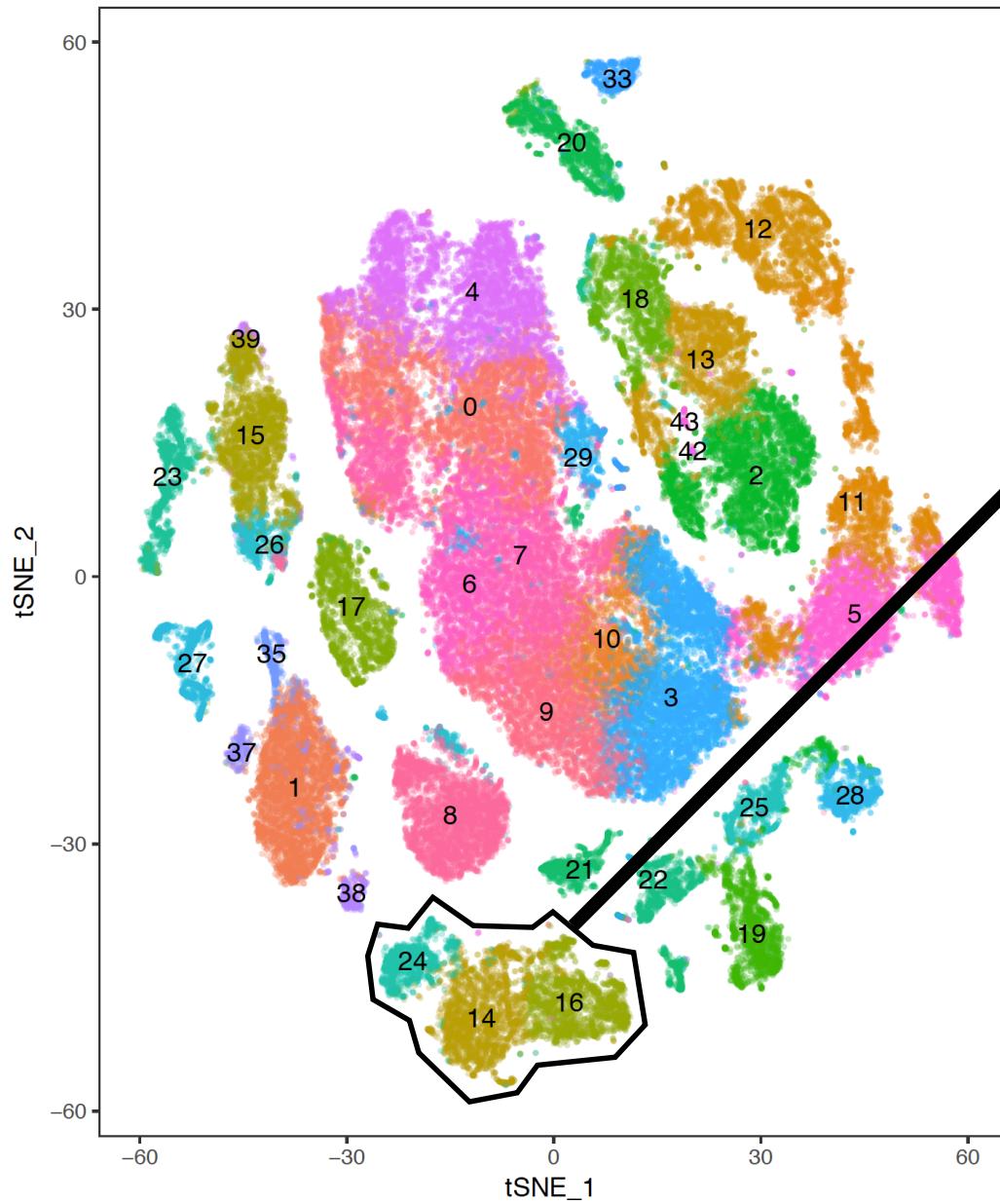
Integrated data from >90k cells from 12 mice during disease evolution



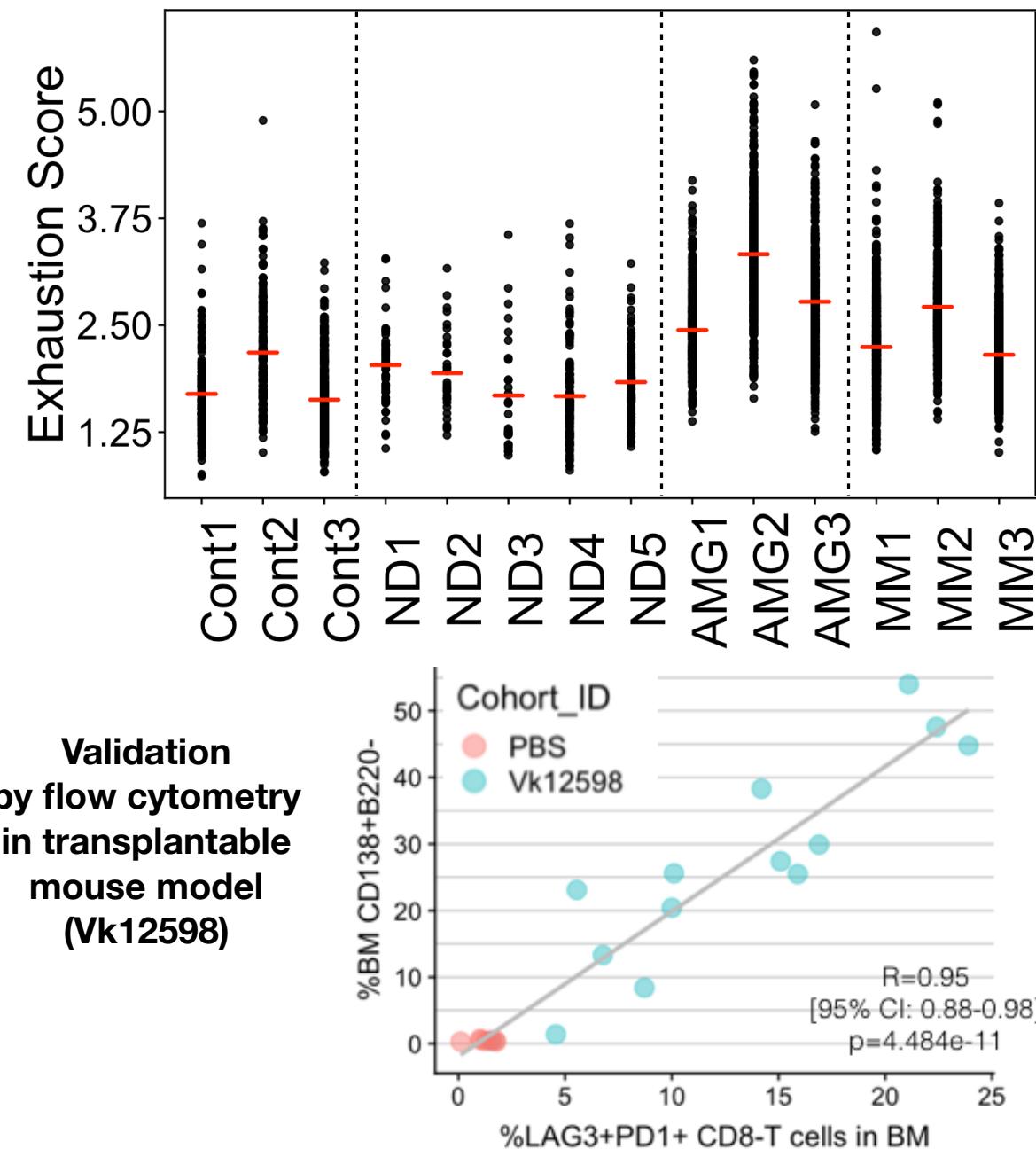
Focused re-analysis of plasma cells found A) normal plasma cells in all mice, B) evolving disease in ND & AMG mice, C) cells unique to each MM



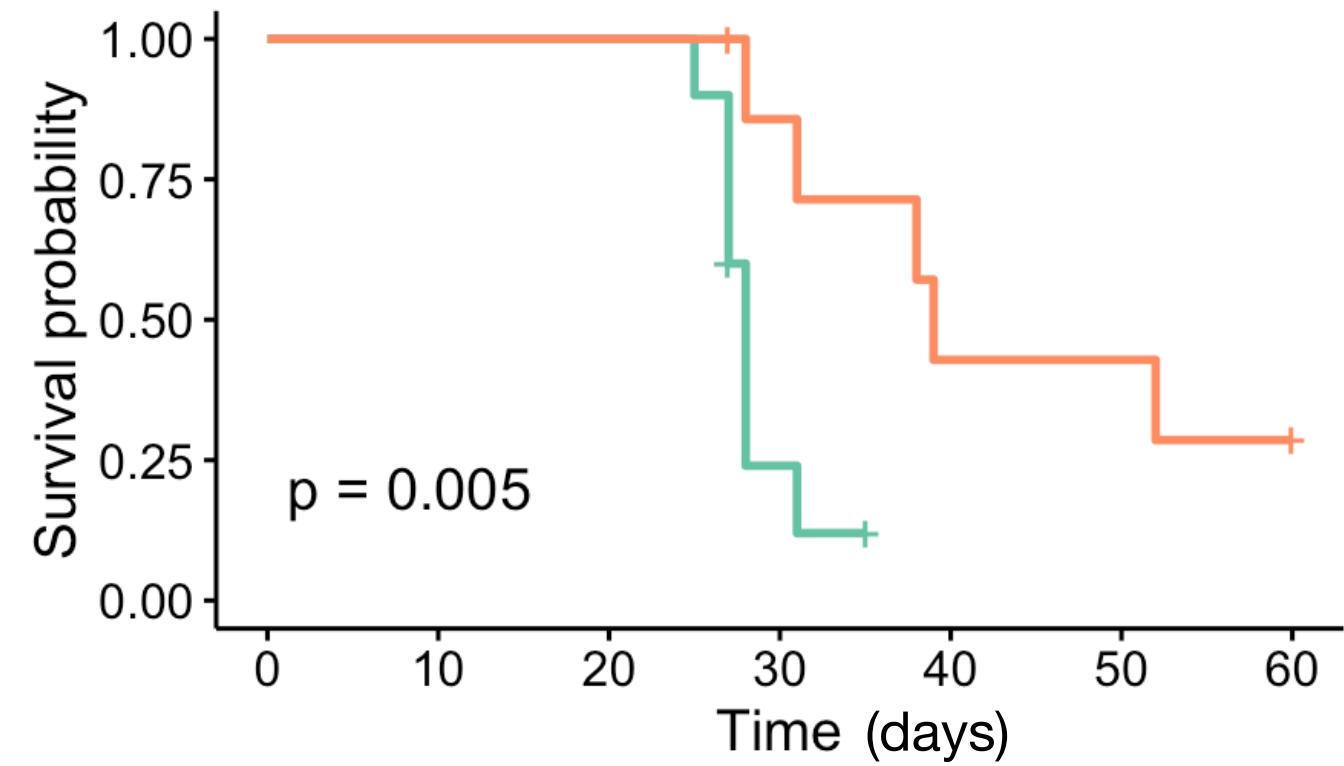
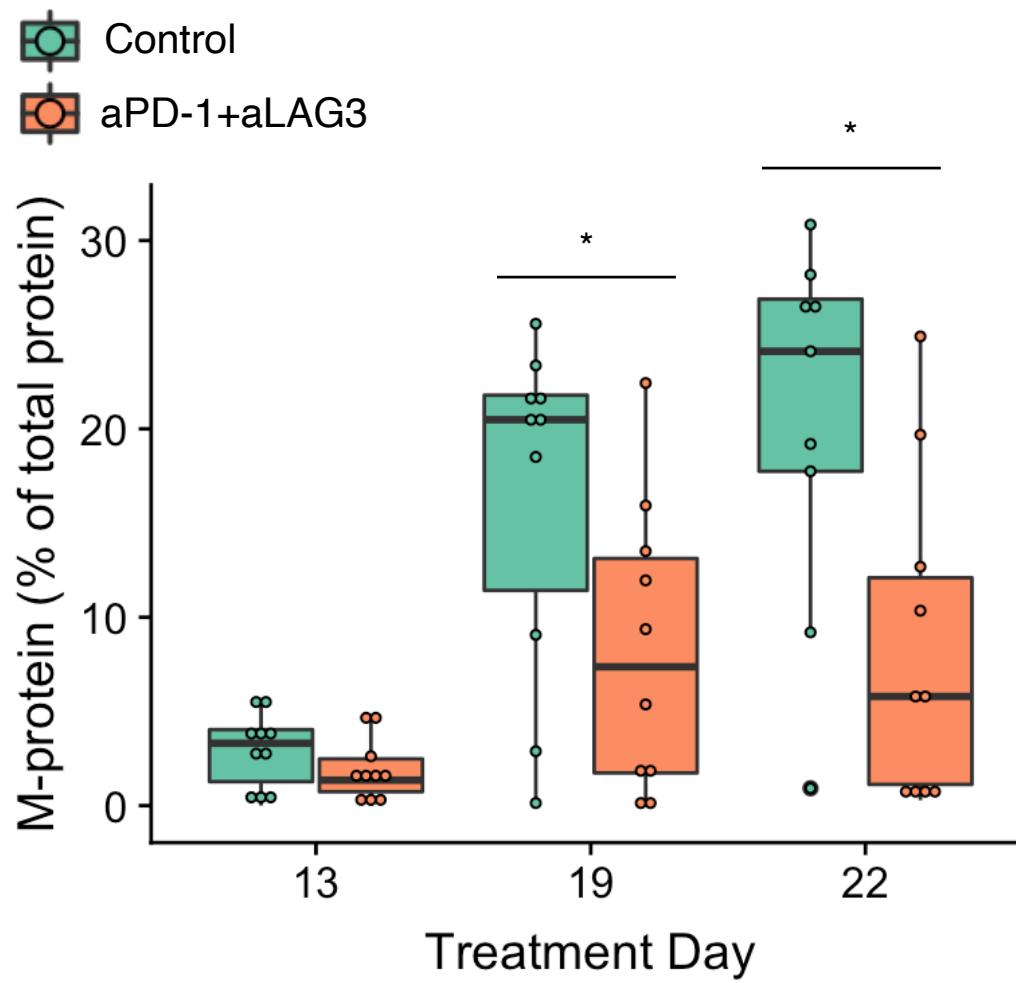
T-cells display increased exhaustion signatures as myeloma develops



**Validation
by flow cytometry
in transplantable
mouse model
(Vk12598)**



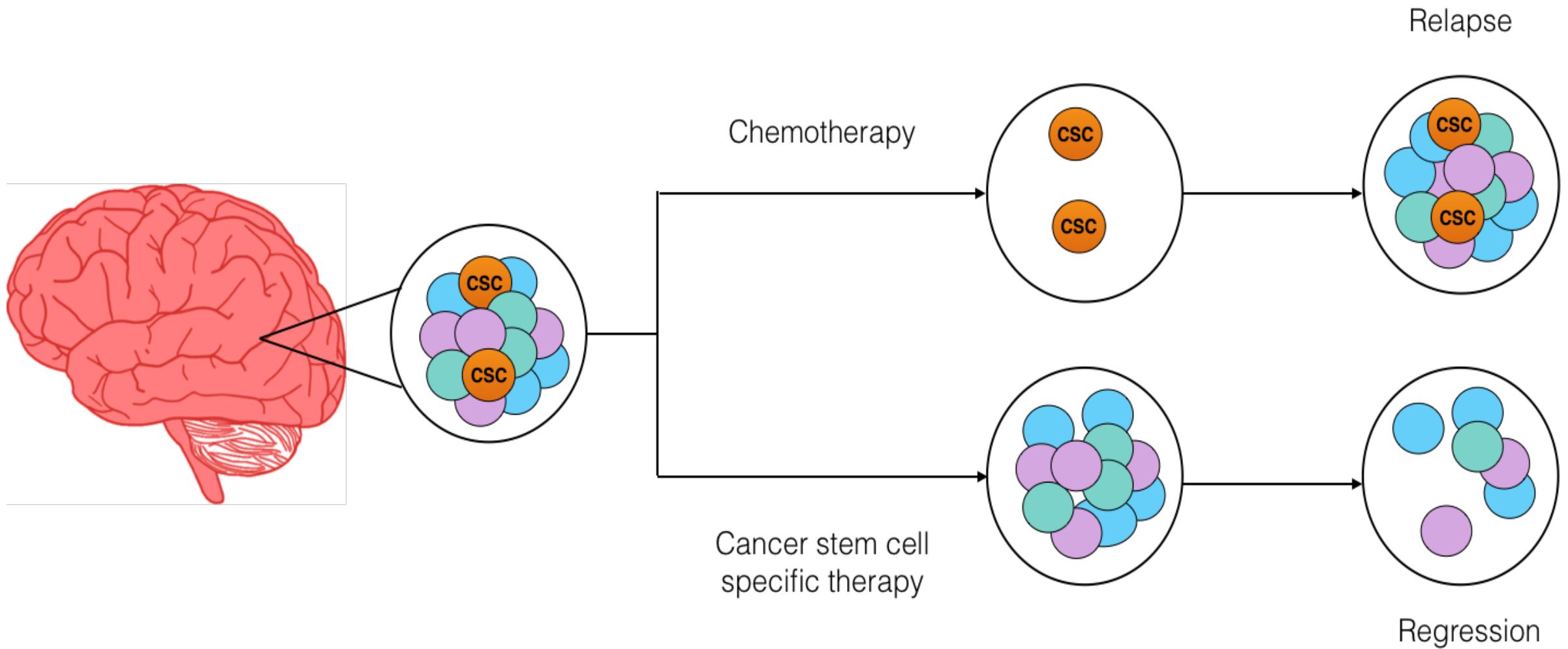
Combinatorial treatment with anti-LAG3 + anti-PD-1 antibodies delays myeloma progression in transplantable mouse model



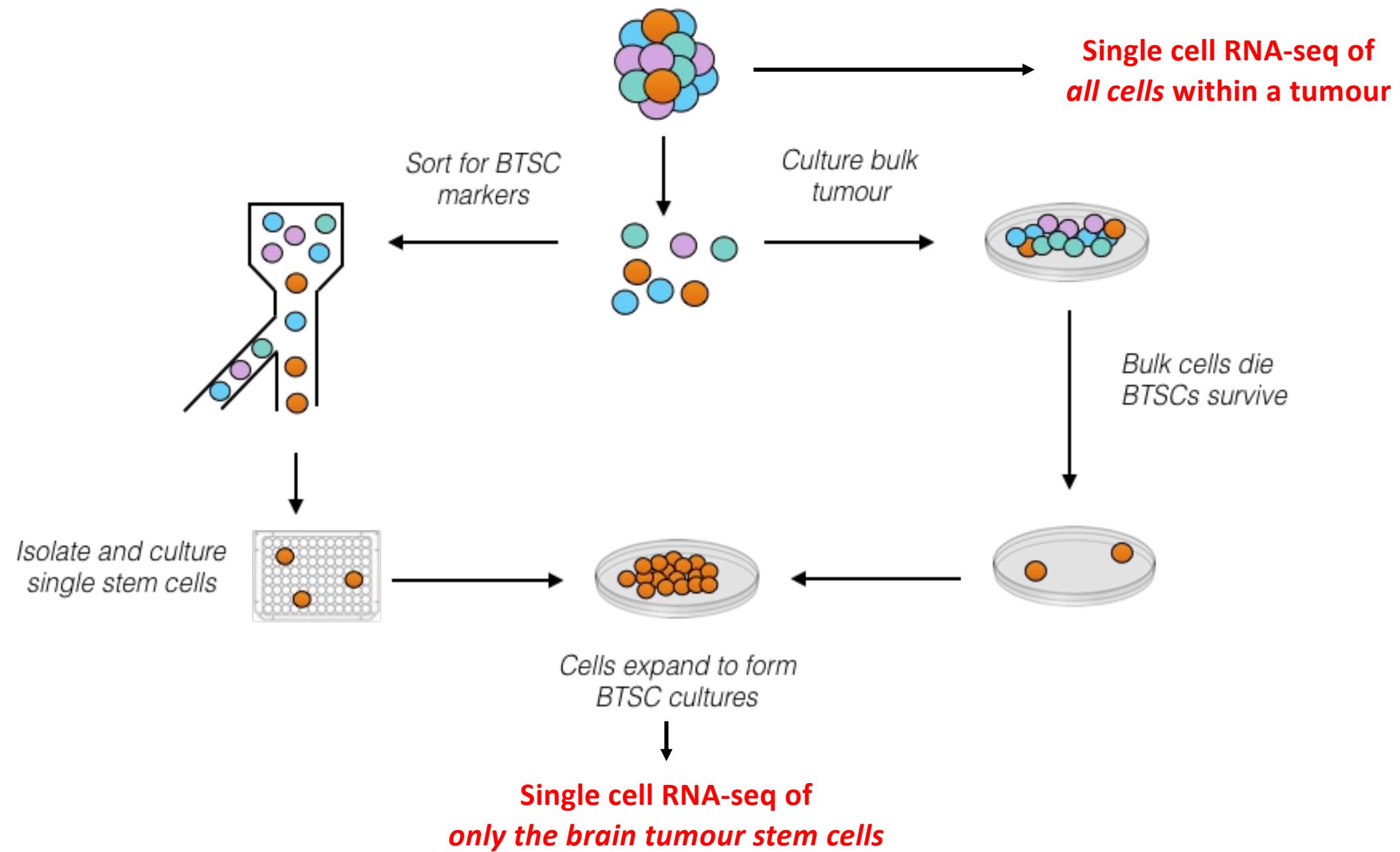
Cancer stem cells & subclones inform tumour development & treatment outcome

Richards, Whitley et al. *Nature Cancer*. 2021 Feb.
Gradient of developmental and injury-response transcriptional states defines
functional vulnerabilities underpinning glioblastoma heterogeneity

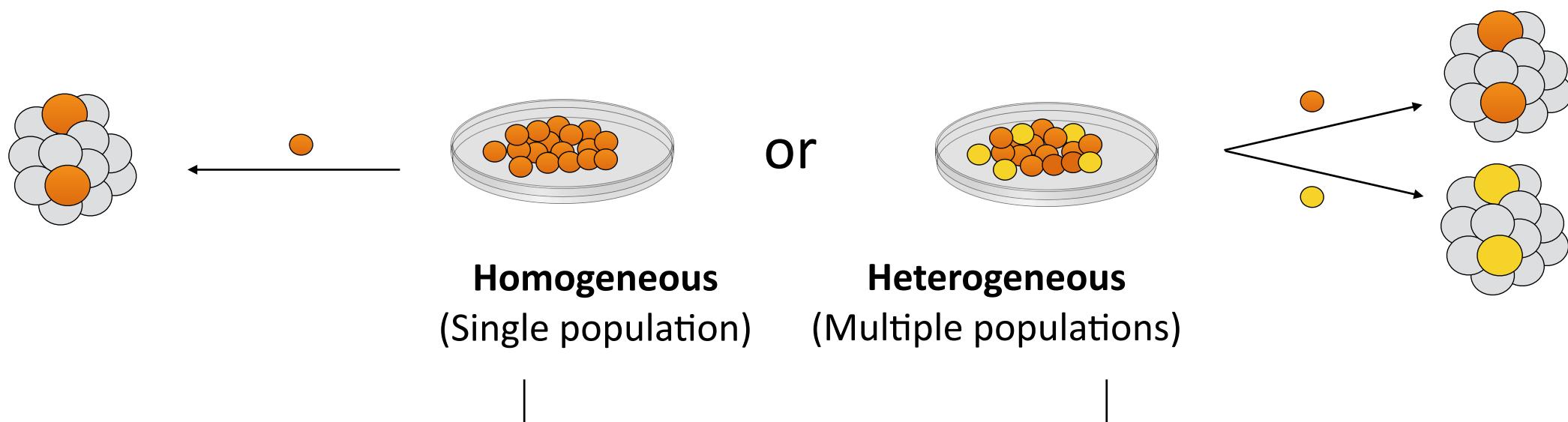
Glioblastomas contain self-renewing cancer stem cells that contribute to tumour initiation and therapeutic resistance



Brain tumour stem cell cultures derived from primary GBMs



Are Brain Tumour Stem Cells comprised of genetic and transcriptional subpopulations?



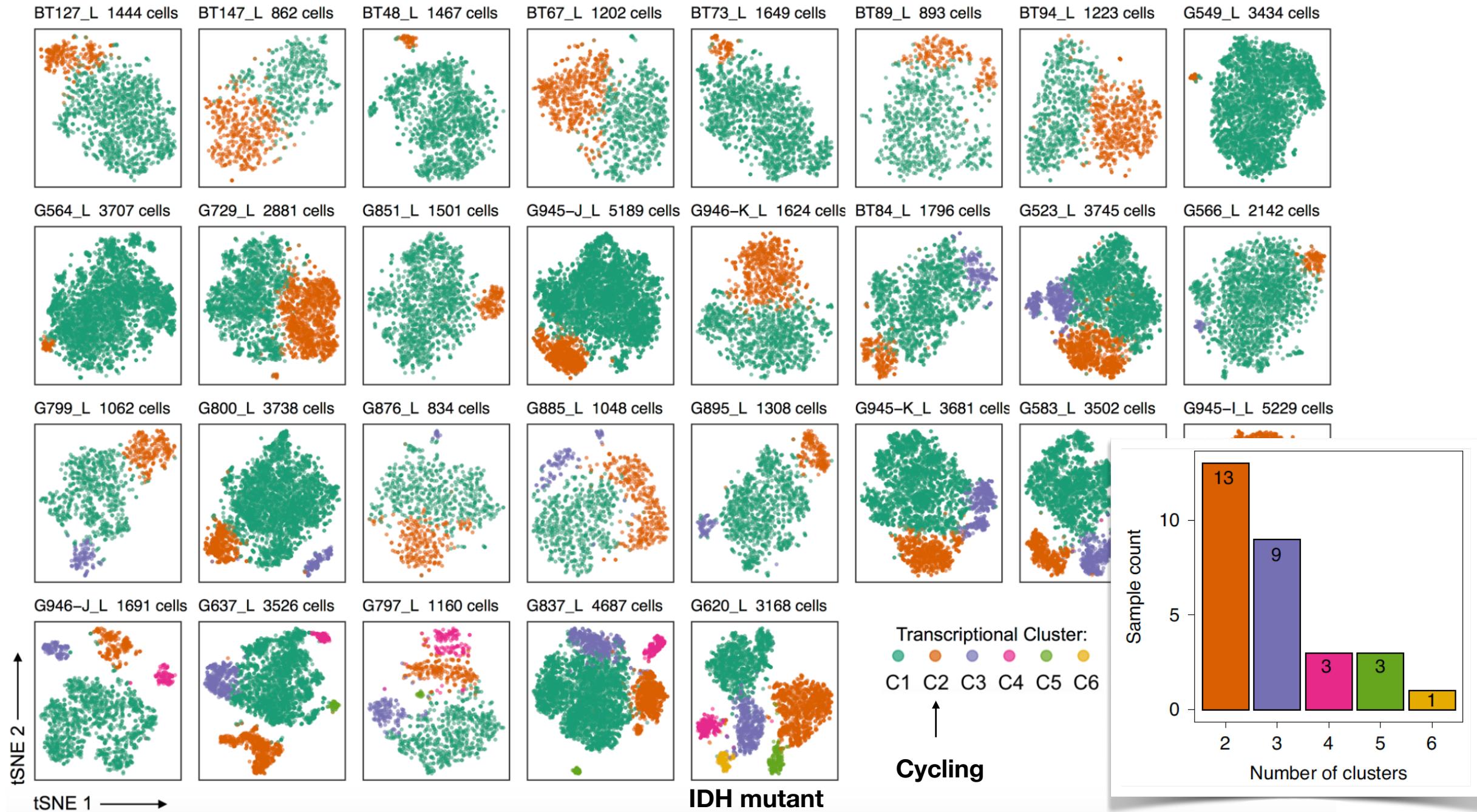
Homogeneous **Heterogeneous**

(Single population)

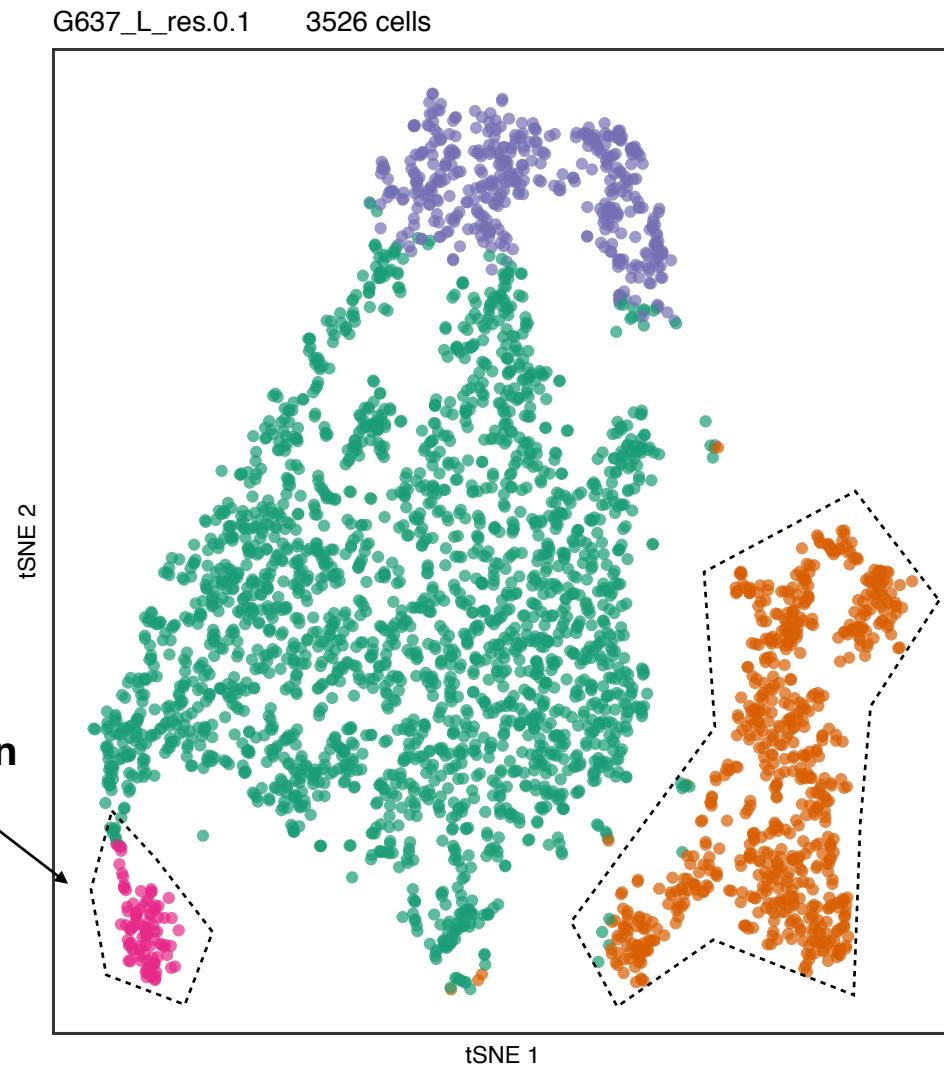
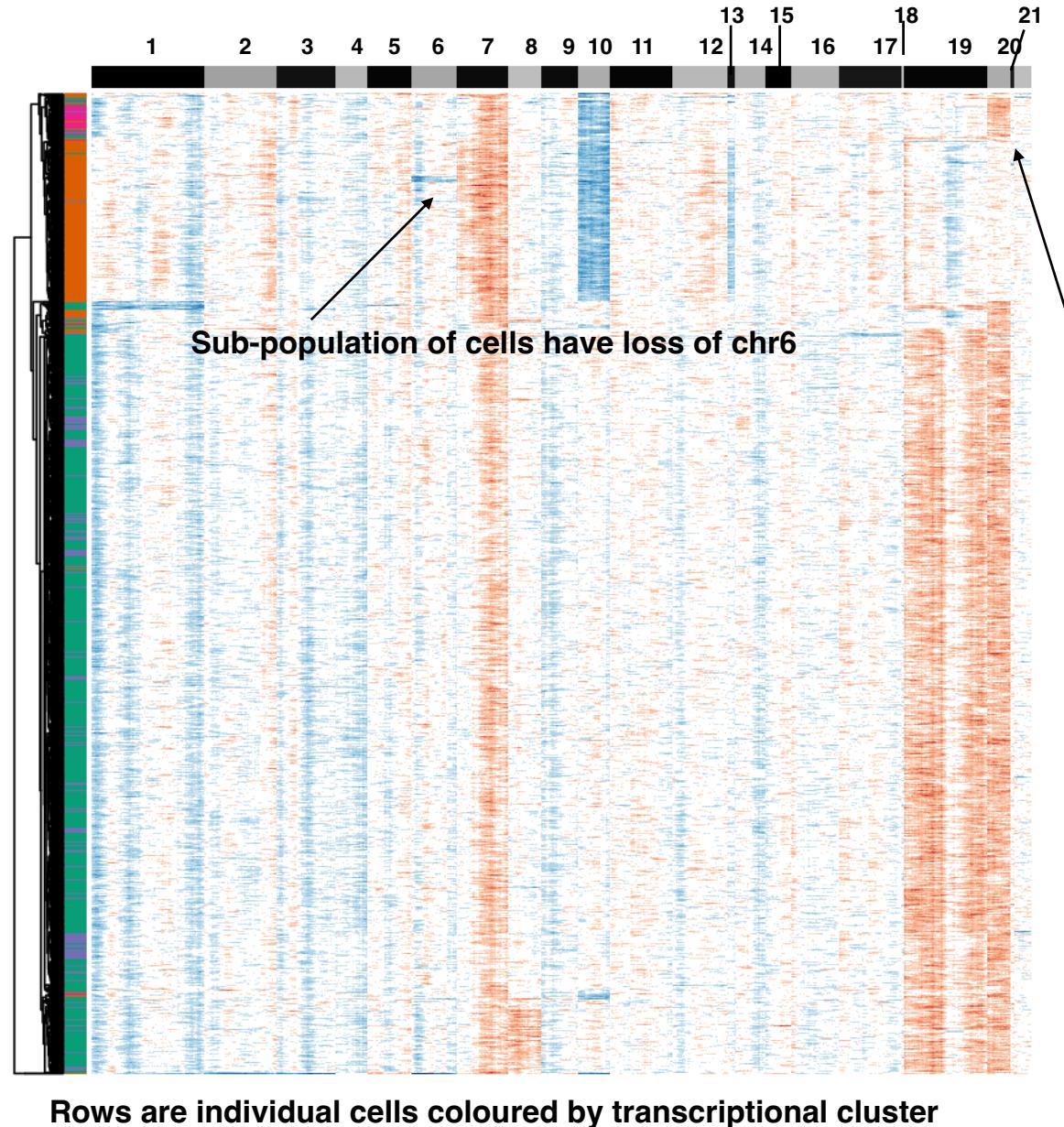
(Multiple populations)

Single cell RNA-sequencing of 29 patient-derived glioblastoma stem cell cultures

Within each stem cell culture, we find a range of distinct subpopulations



Genome-wide analysis using normal oligodendrocytes as controls uncovers CNVs that *partially* distinguish clusters

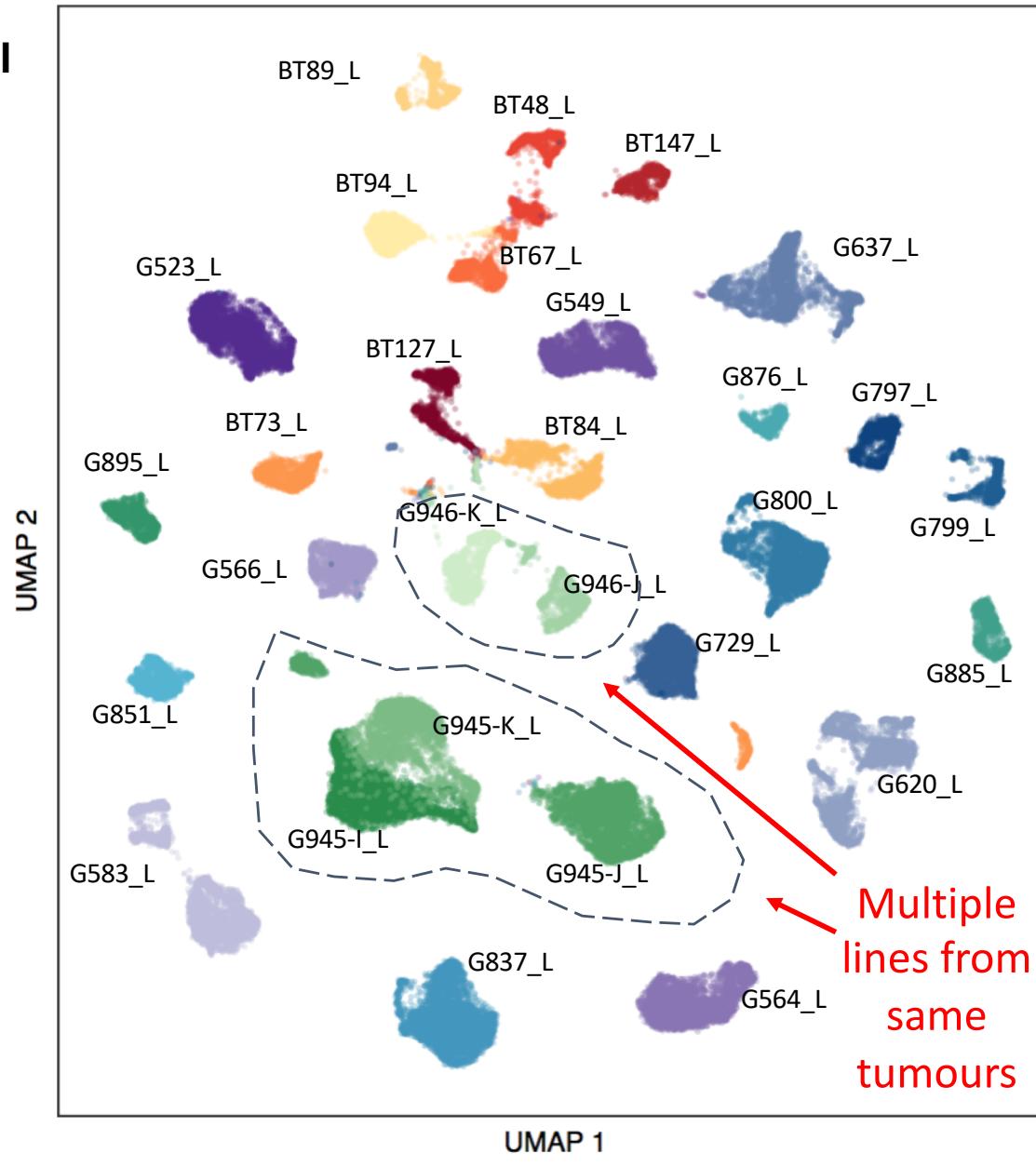


Patients' GSCs are all different...do they share any common biology?

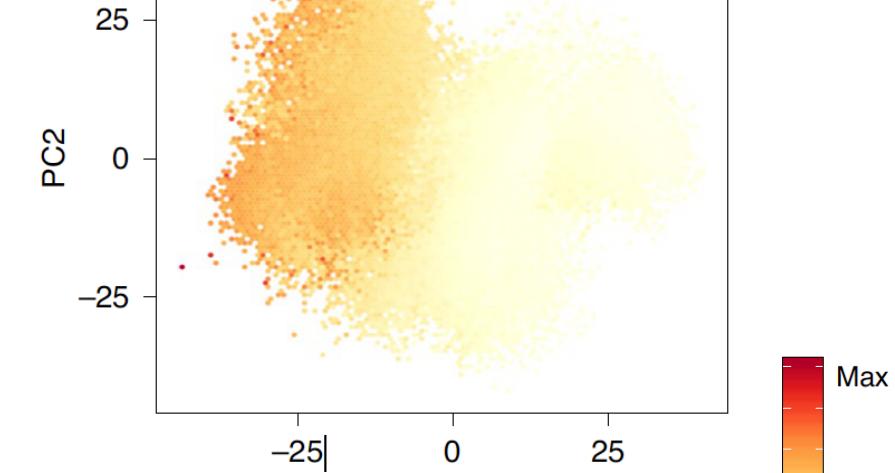
Developmental
Programs



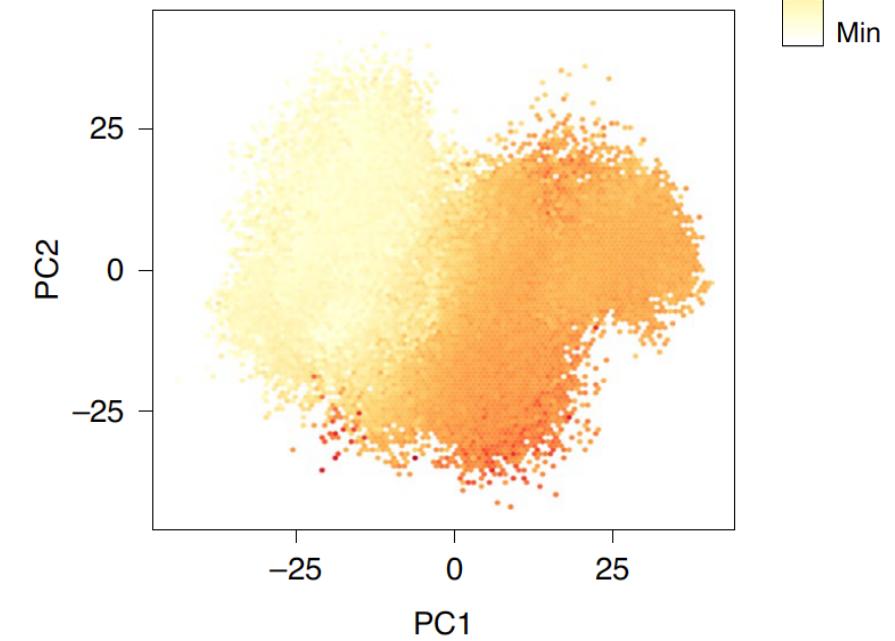
Injury-
response
Programs



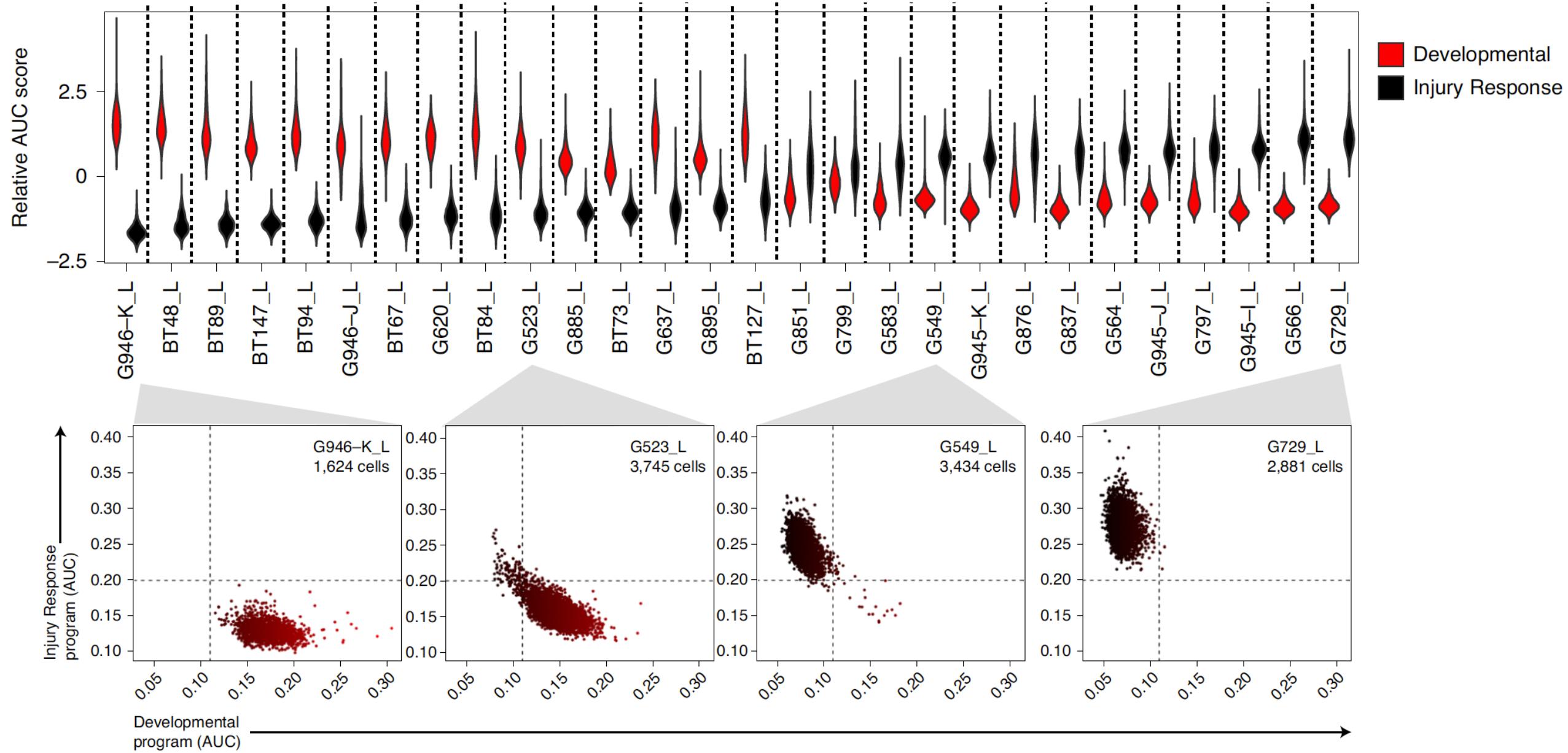
Developmental program (PC1-low)



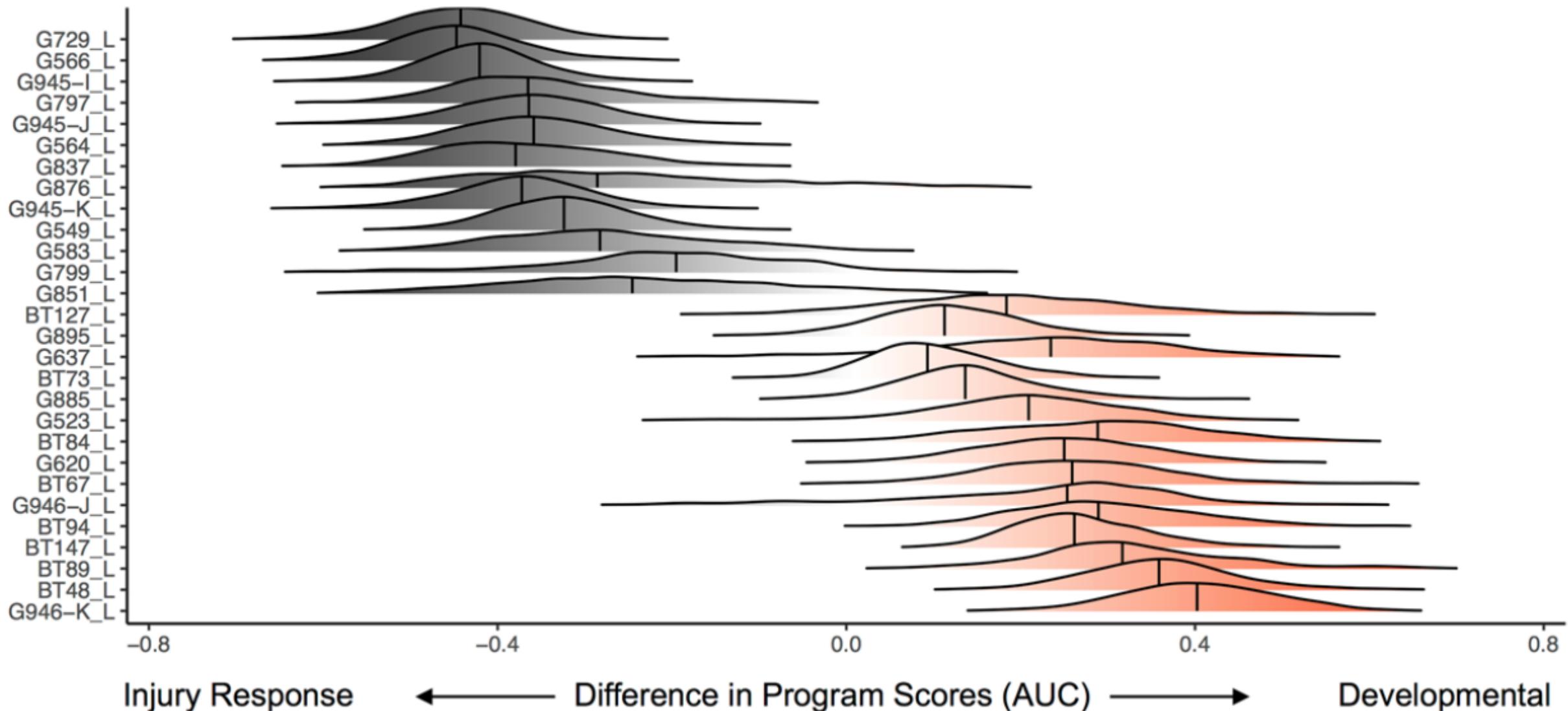
Injury Response program (PC1-high)



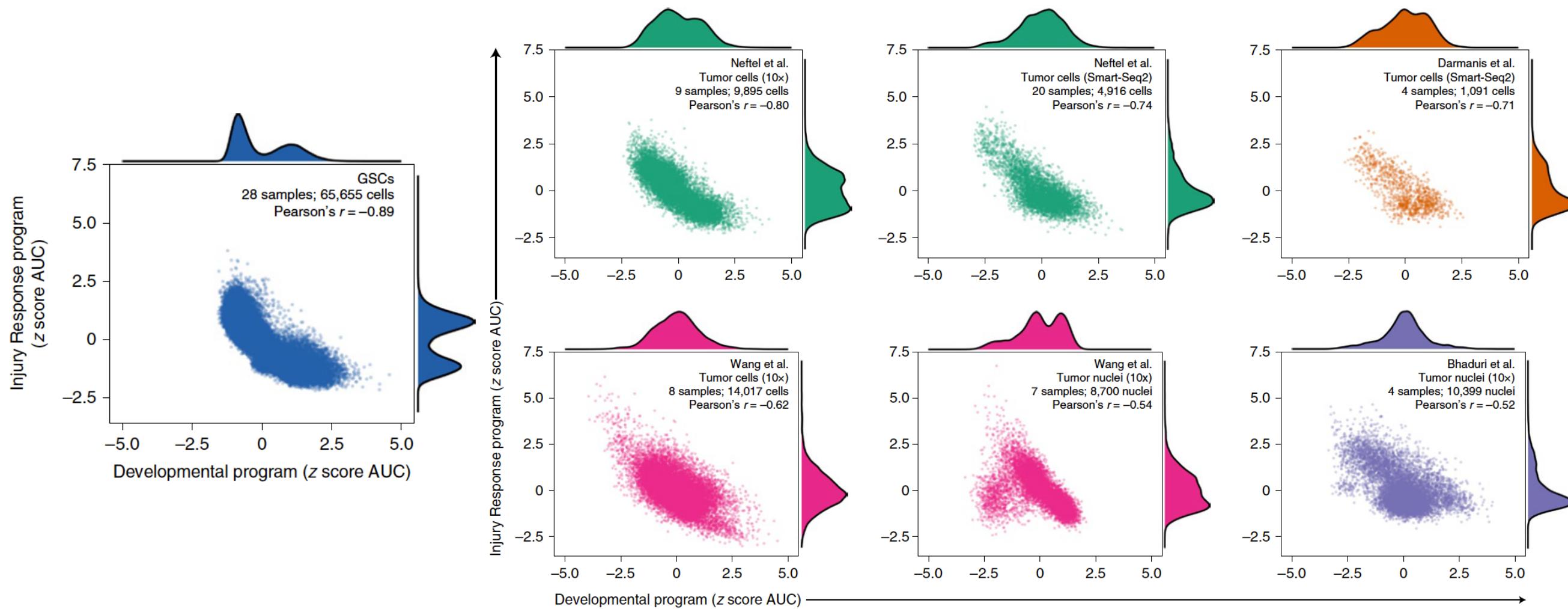
Subpopulations within brain tumour stem cells maintain relative position within the initial developmental/injury-response gradient



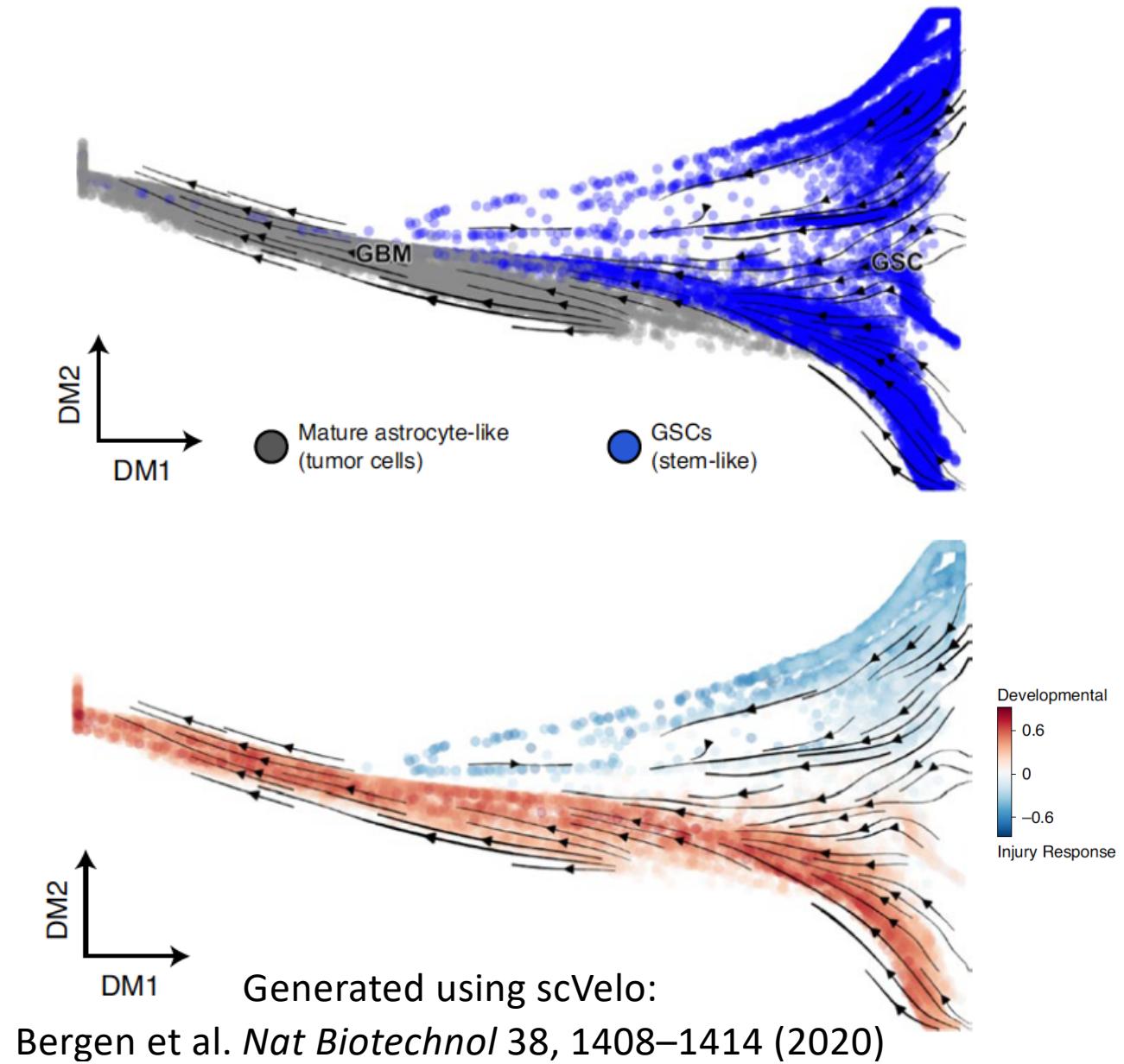
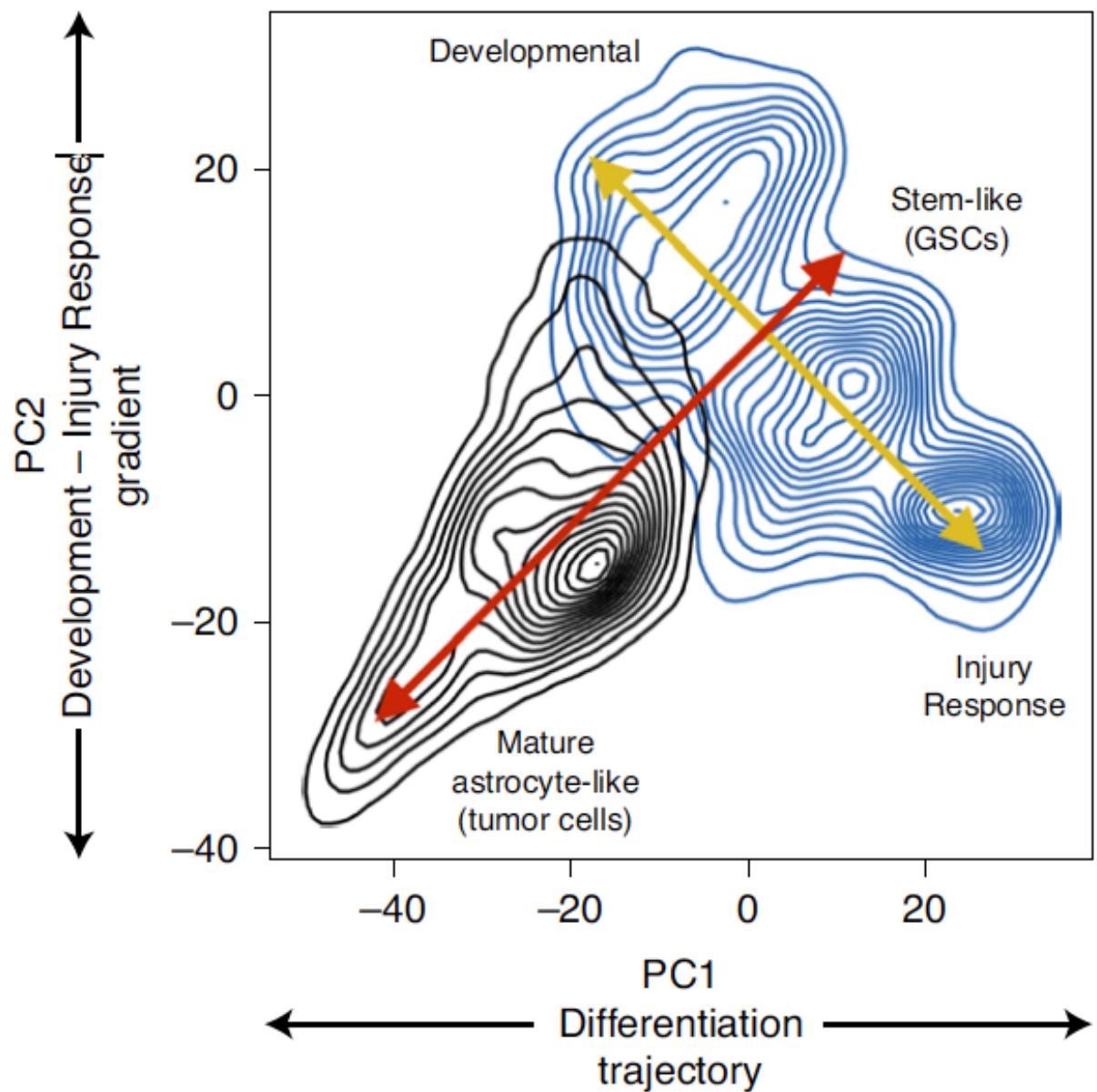
Profiling GSCs from many samples is necessary to characterize the full spectrum of possible transcriptional states giving rise to bulk GBM.



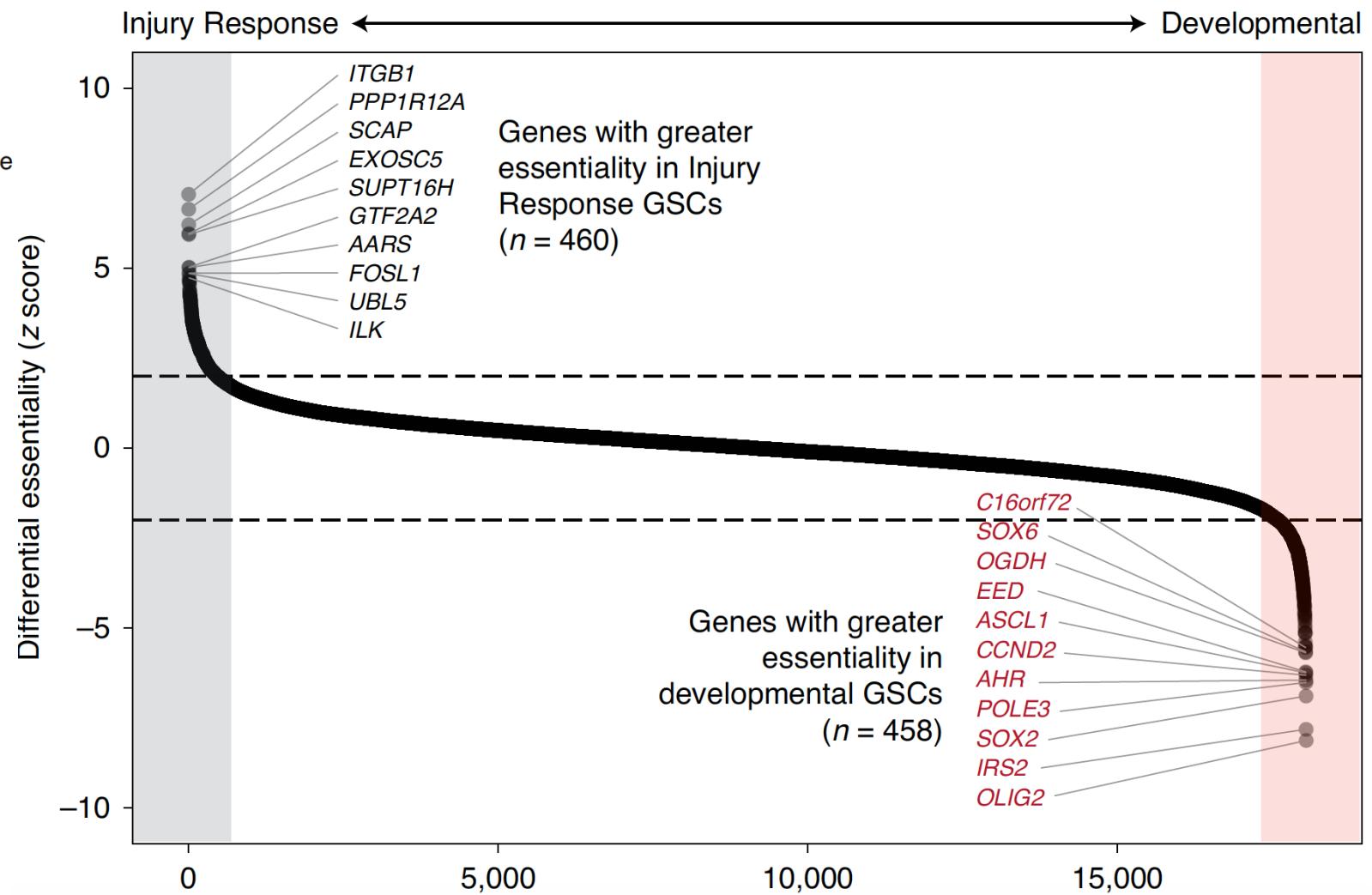
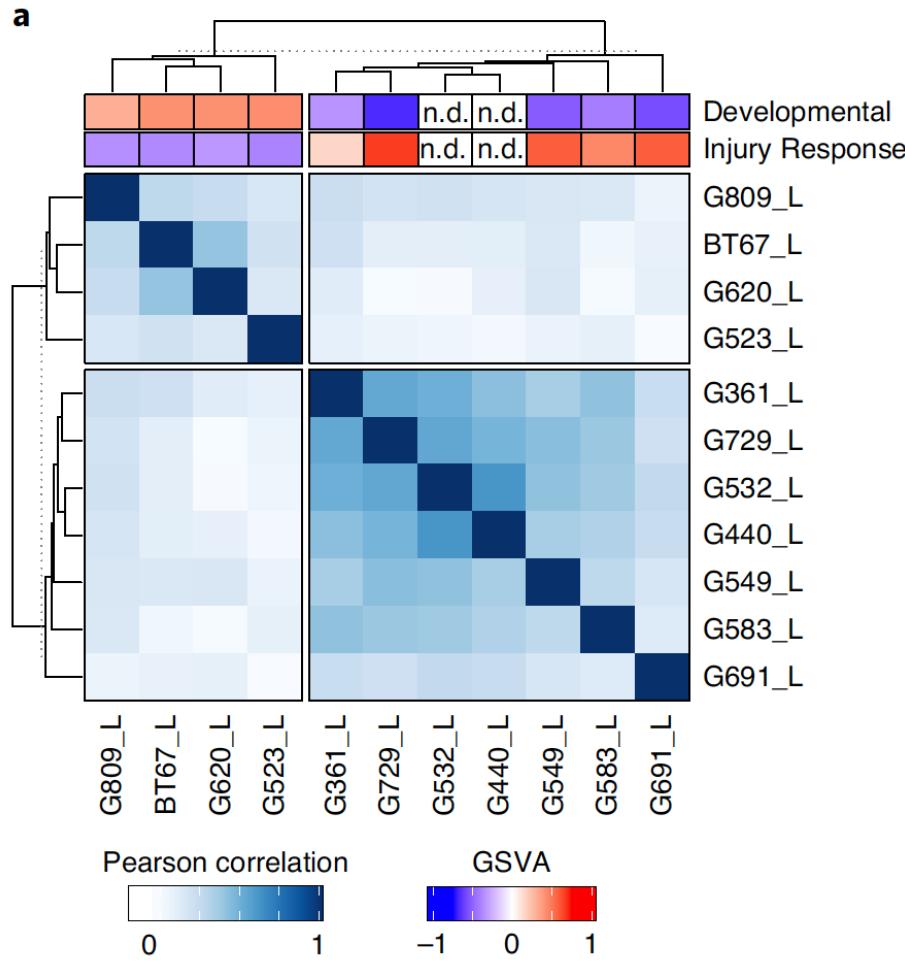
GSC gradient between Developmental and Injury Response is recapitulated in cells or nuclei from primary tumors, but bulk tumour cells can obscure



Bulk tumour cells “flow” from their progenitor GSCs’ position on the Developmental/Injury Response Gradient

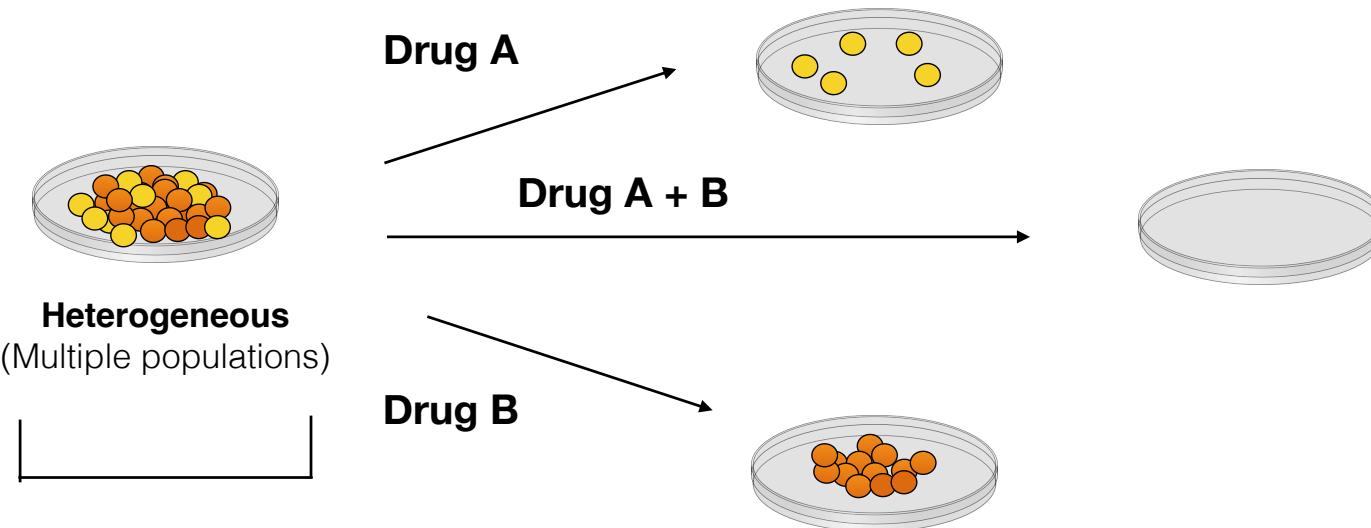


Functional dependencies identified by genome-wide CRISPR screens reflect Developmental–Injury Response gradient position



TKOv3 library: 70,948 guides targeting 18,053 protein-coding genes in 11 GSCs

Gradients and clusters may be biologically interesting, but is there application for patients?



Single cell RNA-sequencing of 25 patient-derived
BTSC cultures

PharmacoDB aggregates gene expression, copy number, and pharmacogenomic profiles of cell lines from multiple high-throughput drug screening studies

The screenshot shows the homepage of the PharmacoDB website. At the top, there is a navigation bar with links for "ABOUT", "DOCUMENTATION", "CITE USI", "GITHUB", "DOWNLOAD", and "NEWS". To the right of the navigation bar is a menu icon consisting of three horizontal lines. Below the navigation bar, the main title "PHARMACODB" is displayed in large white letters. Underneath the title, the subtitle "MINE MULTIPLE CANCER PHARMACOGENOMIC DATASETS" is visible. A search bar at the bottom left contains the placeholder text "Dataset (eg. 'ccle')". To the right of the search bar is a magnifying glass icon. At the very bottom of the page, there is a footer bar with the following statistics: "7 DATASETS", "41 TISSUES", "1,691 CELL LINES", "19,933 GENES", "759 COMPOUNDS", and "650,894 EXPERIMENTS".

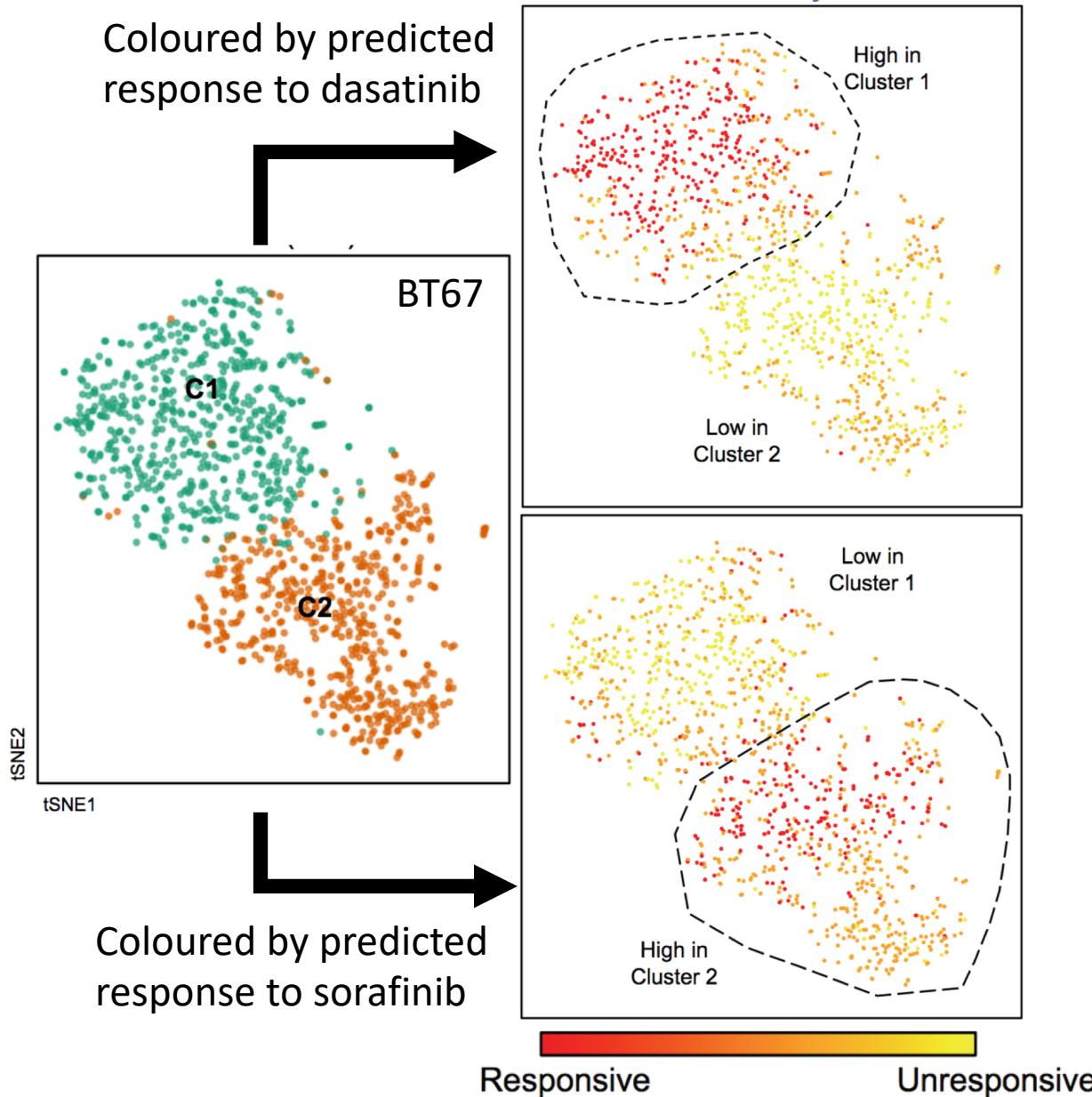
www.pharmacodb.ca

Smirnov, Petr, et al. "PharmacoDB: an integrative database for mining in vitro anticancer drug screening studies." Nucleic Acids Research (2017).

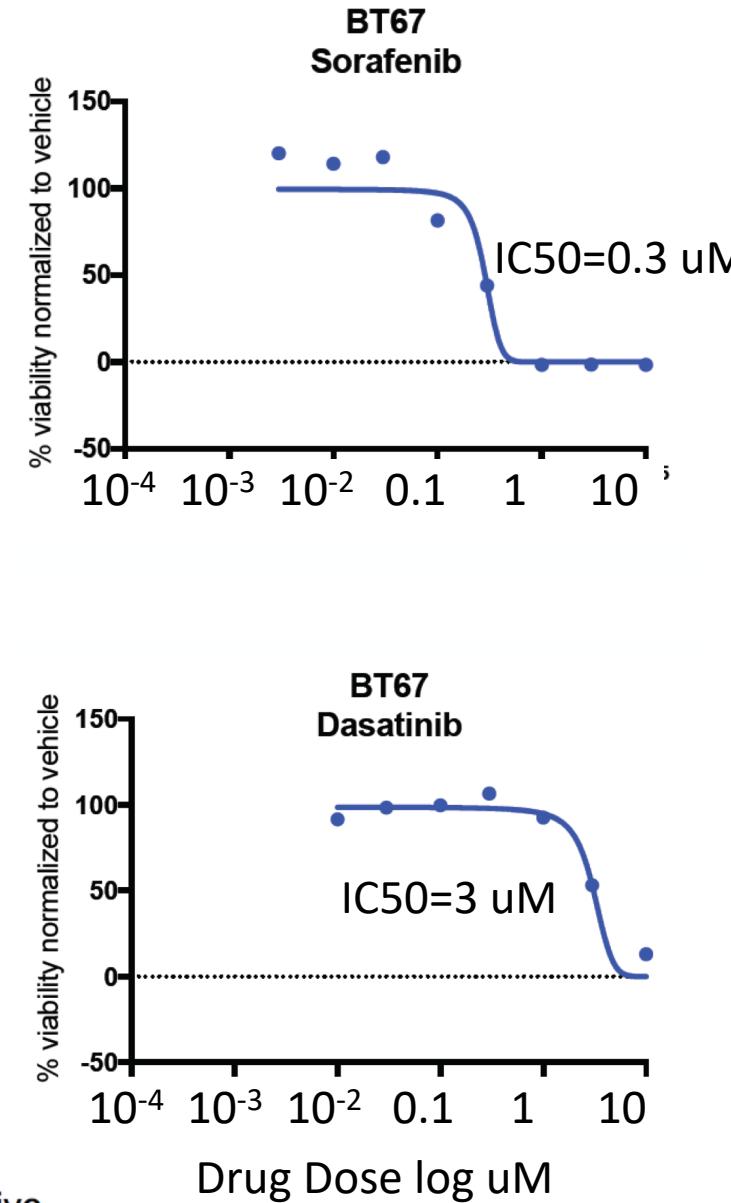
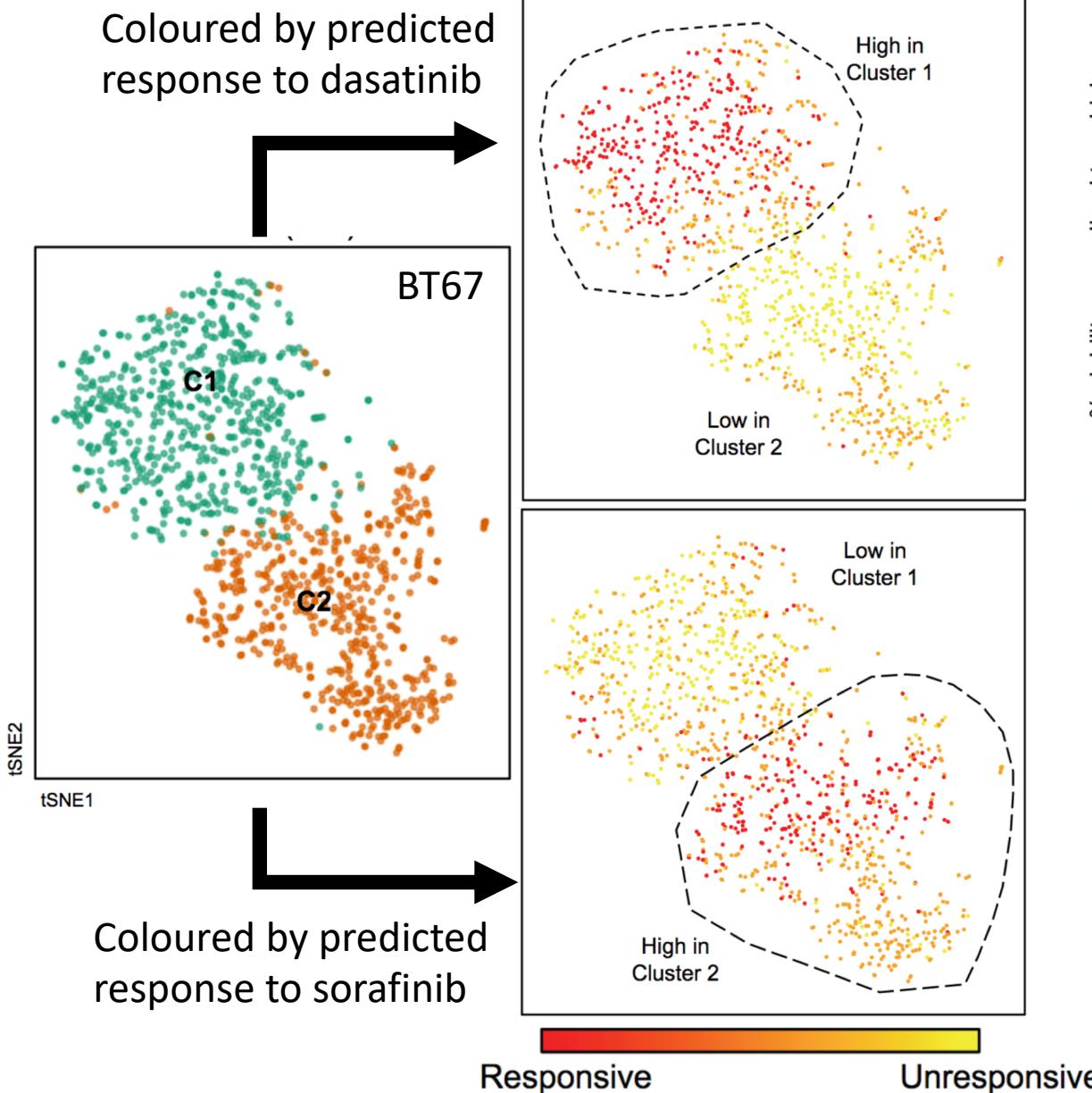
Smirnov, Petr, et al. "PharmacoGx: an R package for analysis of large pharmacogenomic datasets." Bioinformatics 32.8 (2015): 1244-1246.

Laboratory of Benjamin Haibe-Kains

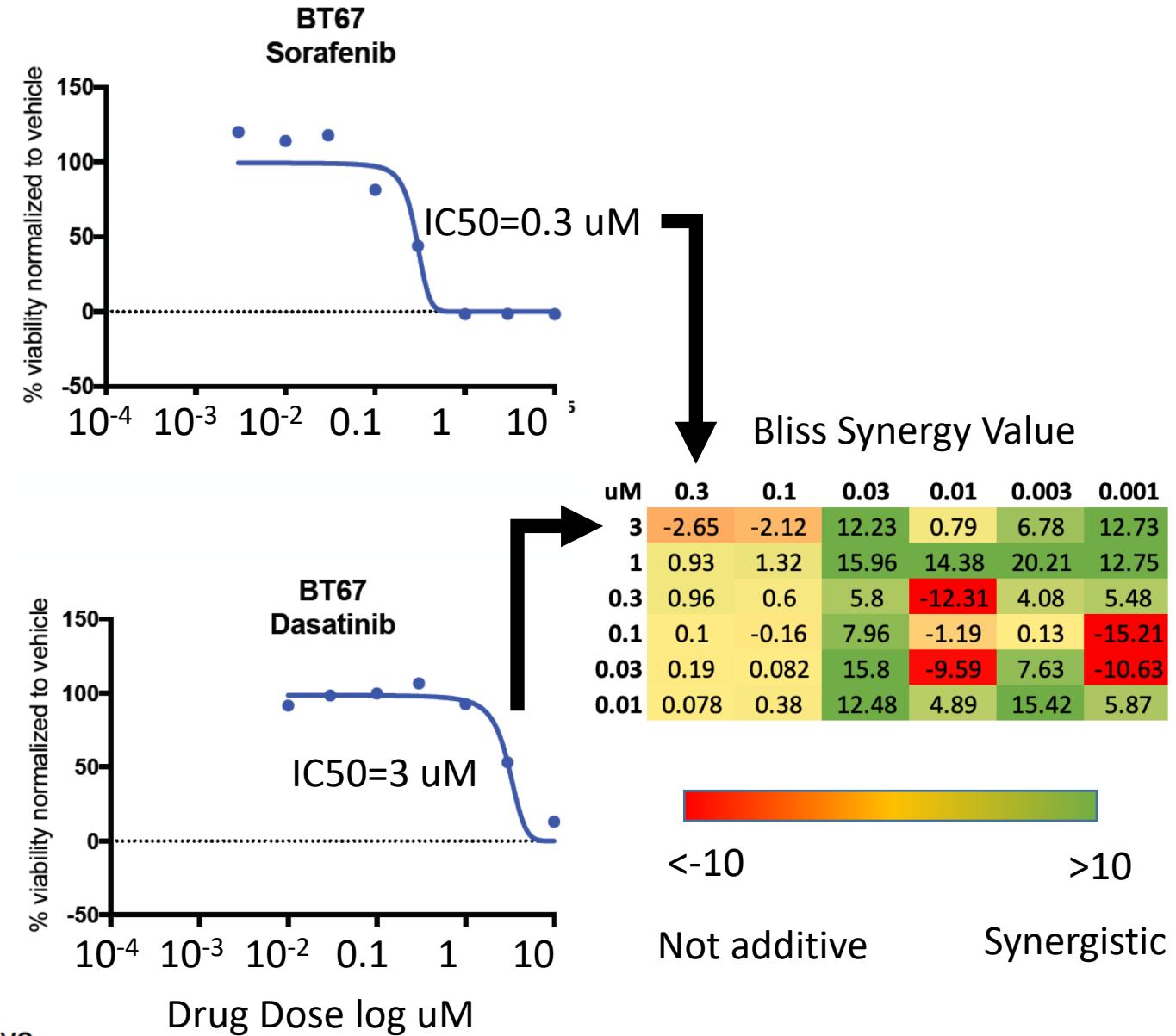
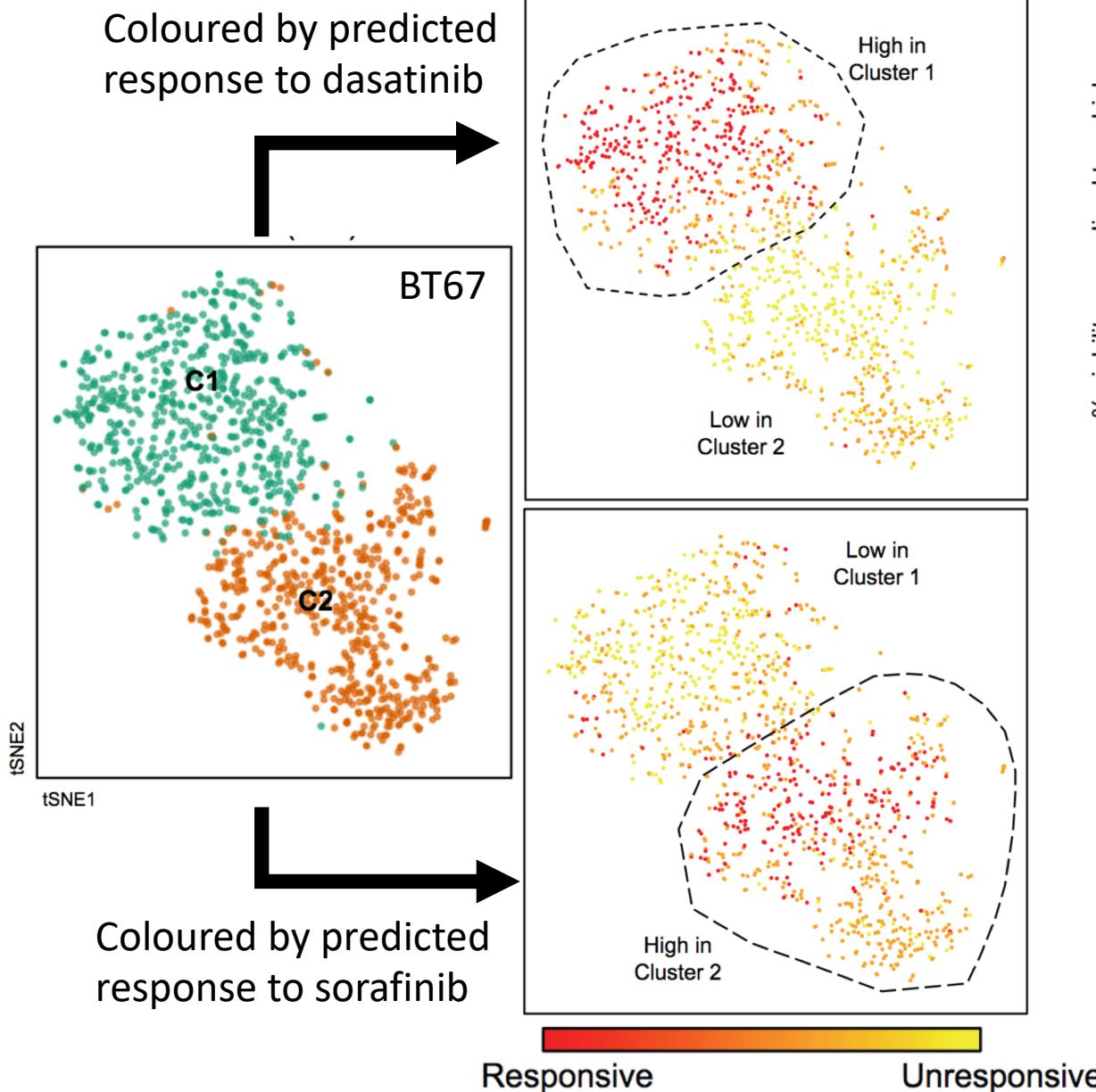
Predict drug efficacy score for each cluster, calculate variation of score across each cell, establish dose/response, synergy assay



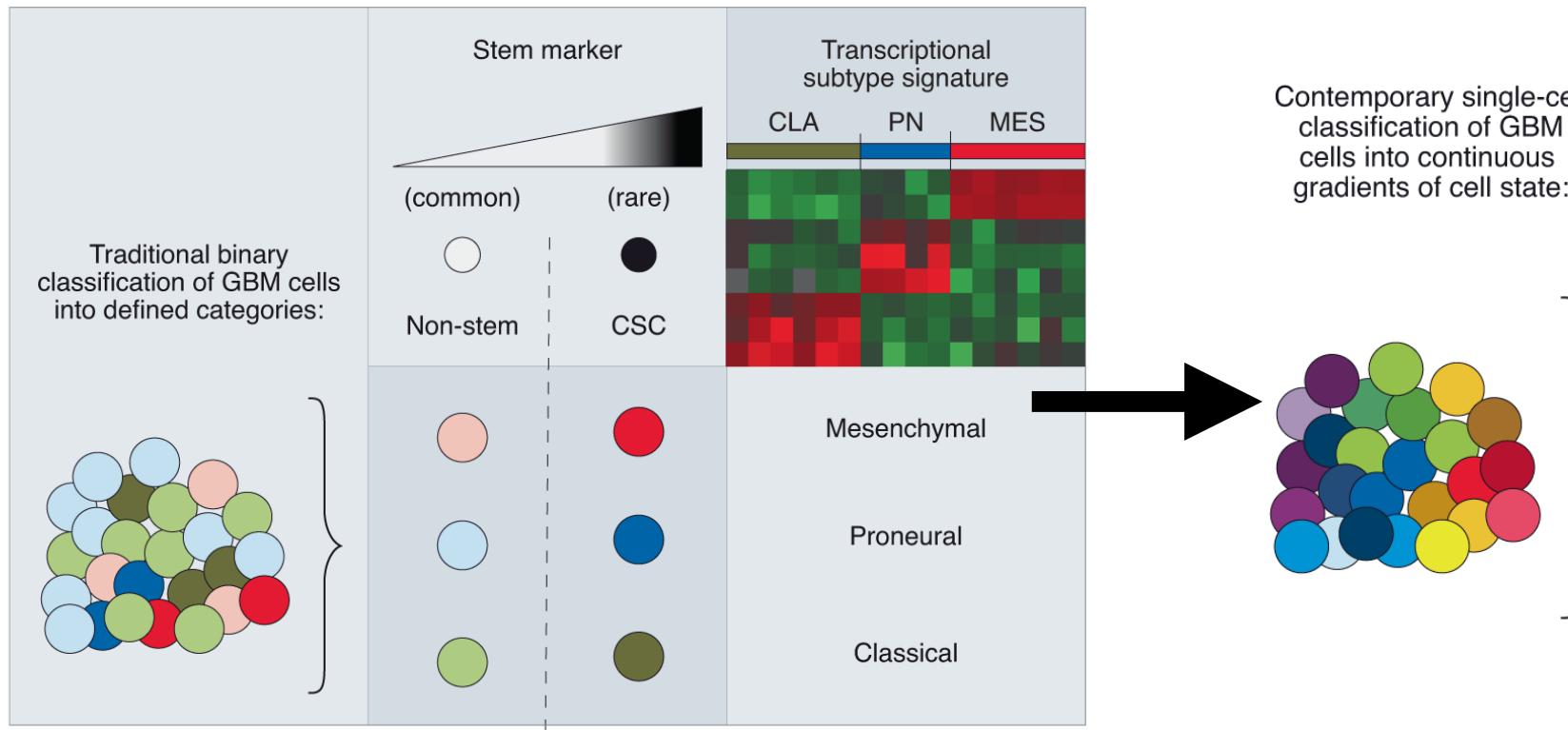
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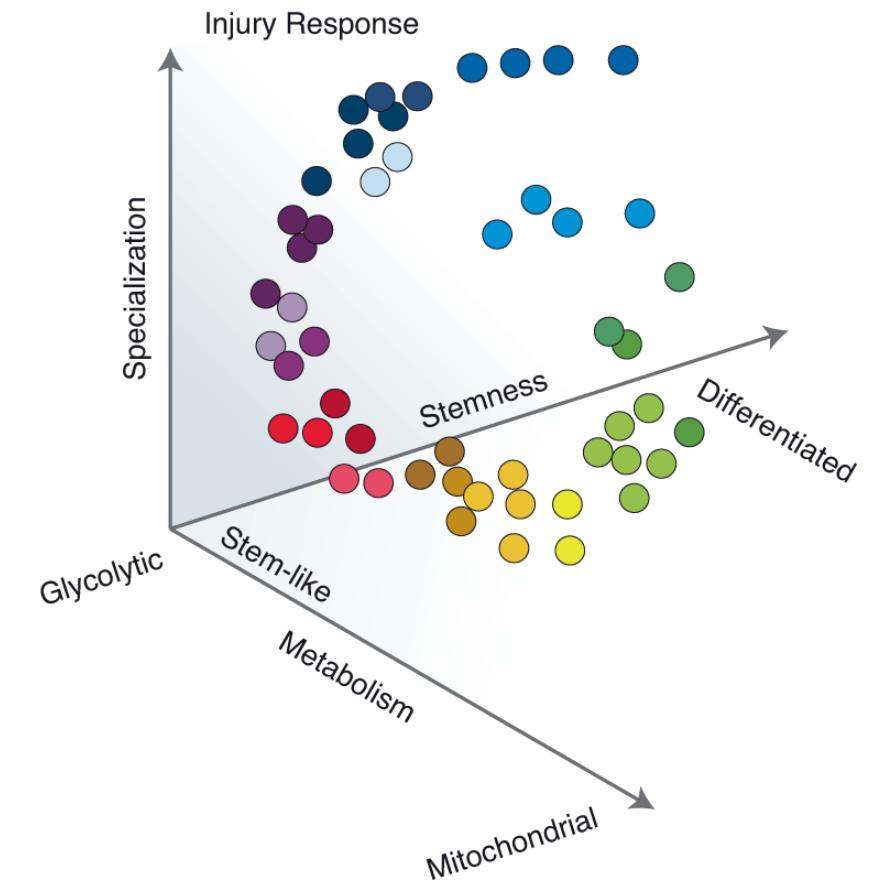
Predict drug efficacy score for each cluster, calculate variation of score across each cell, establish dose/response, synergy assay



Gradients galore: RNA, metabolic, & proteomic profiling all identified continuous biological gradients in glioblastoma



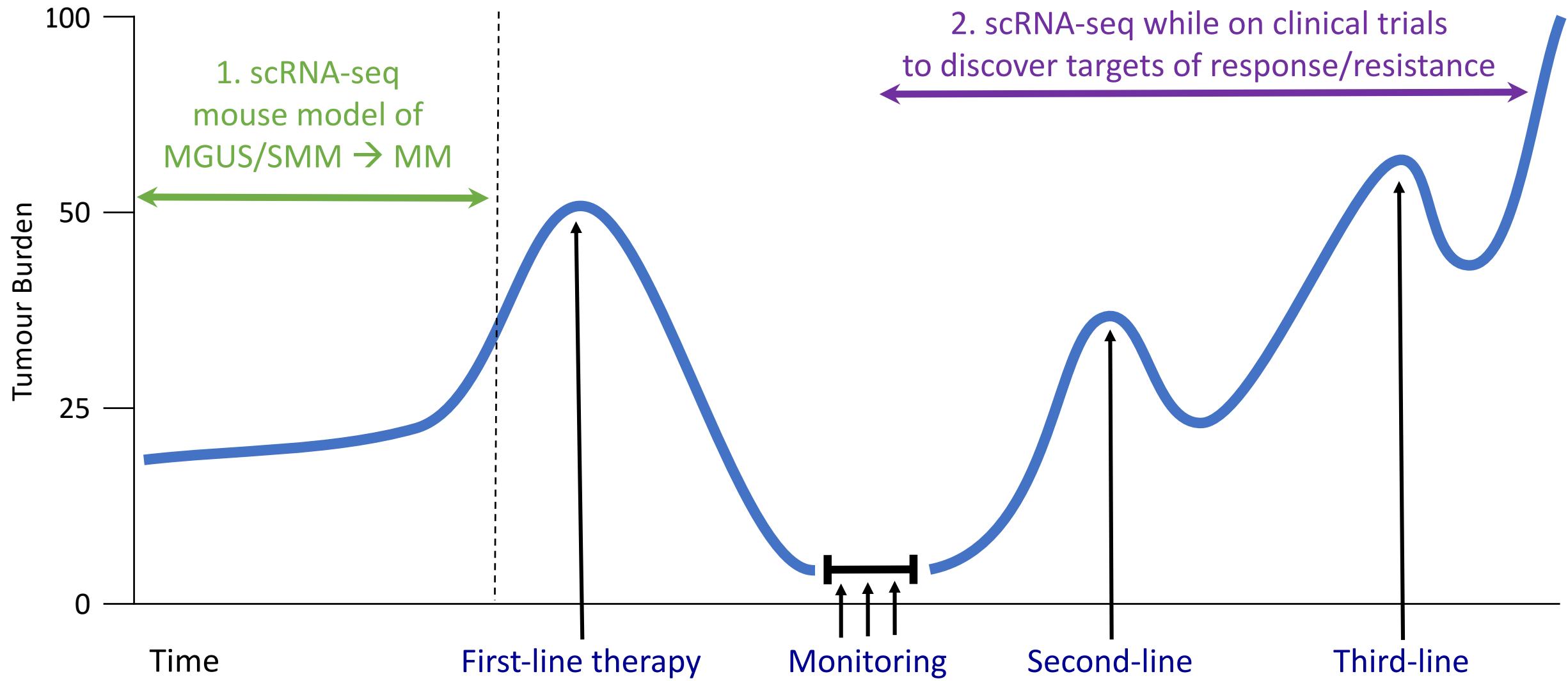
Hubert and Lathia. Nature Cancer 2021.



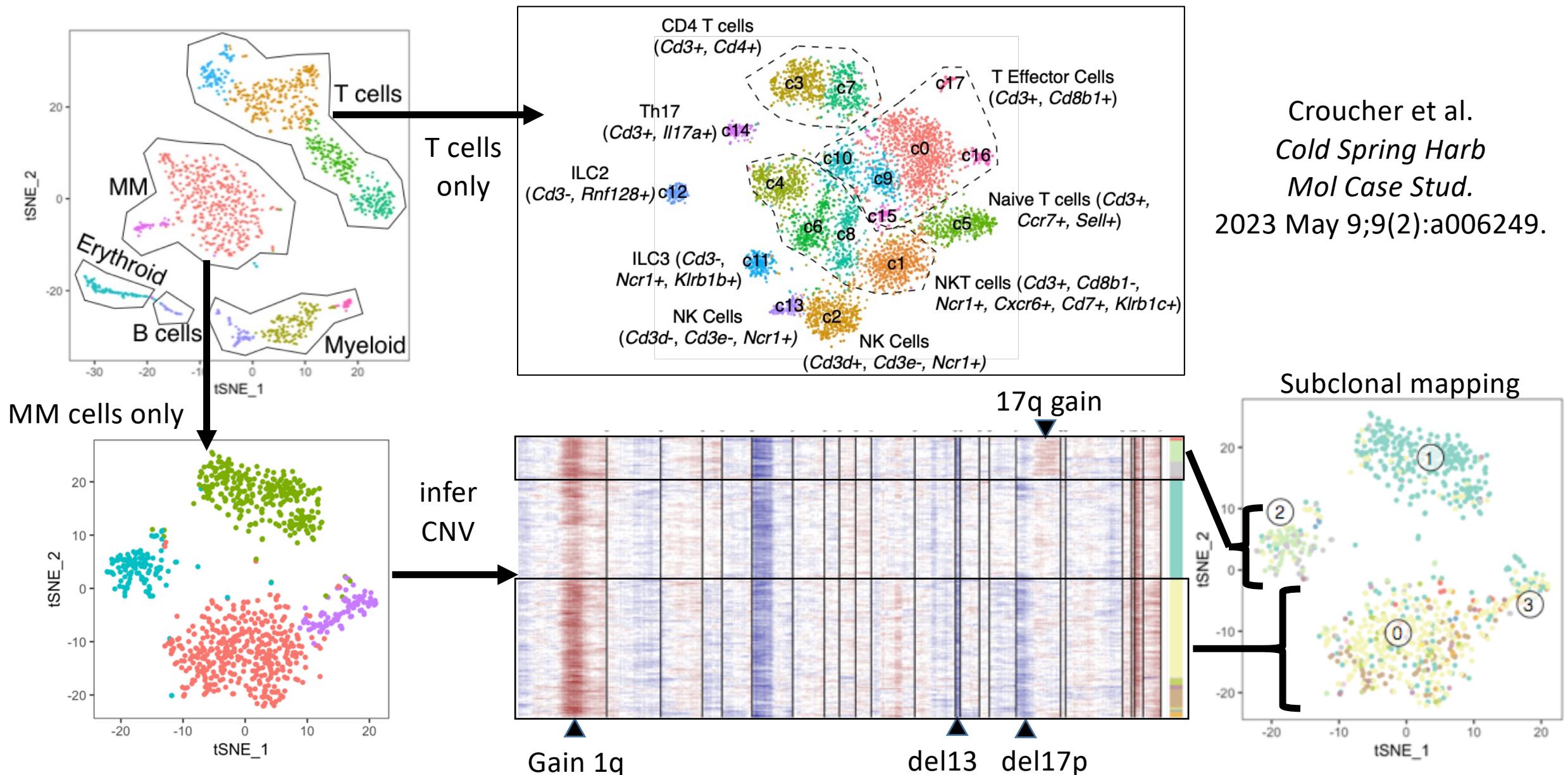
Multiple, single cell approaches can converge and cross-validate biological signals

Single cell technologies can reveal biology not apparent from bulk approaches

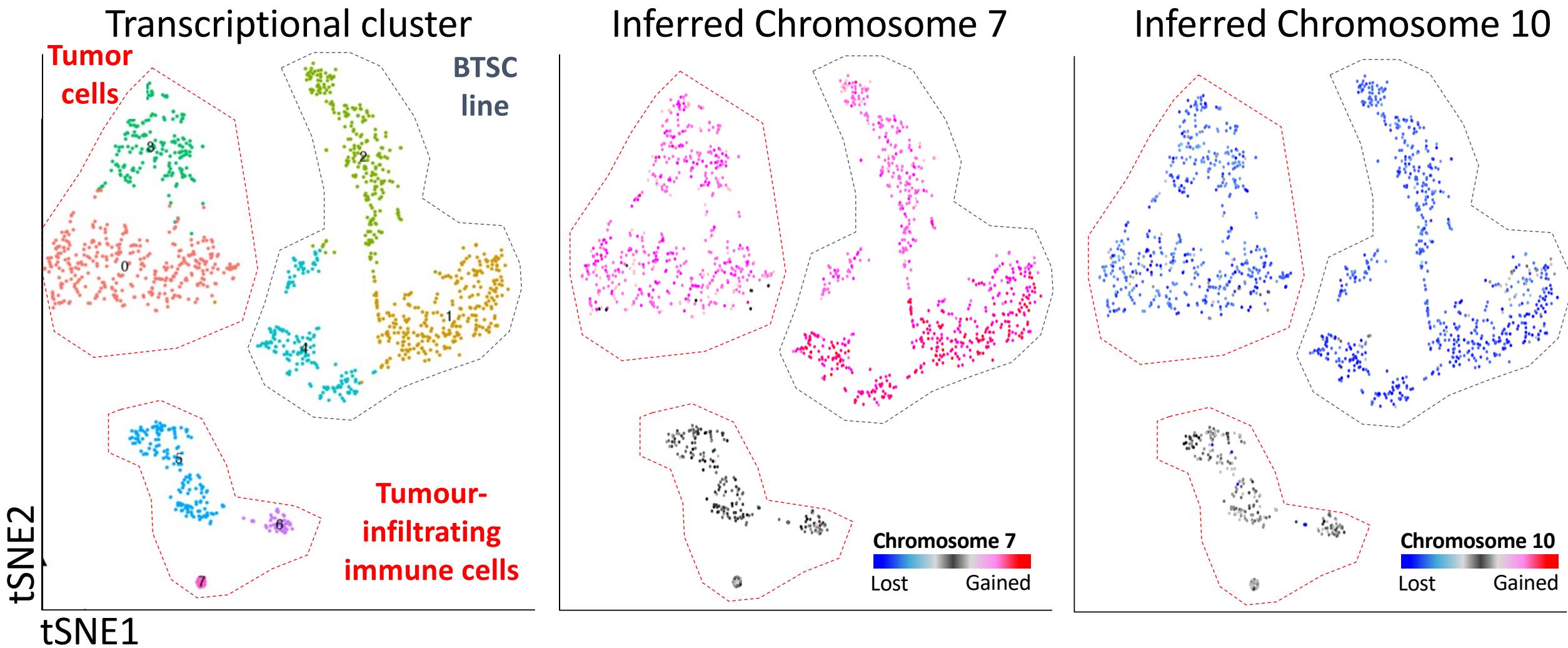
Putting it into practice: Can we prevent early cancer or observe subclonal drug responses in patients?



Computational dissection of cells from a patient with multiple myeloma: direct analysis of cell type, cell state, TCR/BCR, & subclonal copy number

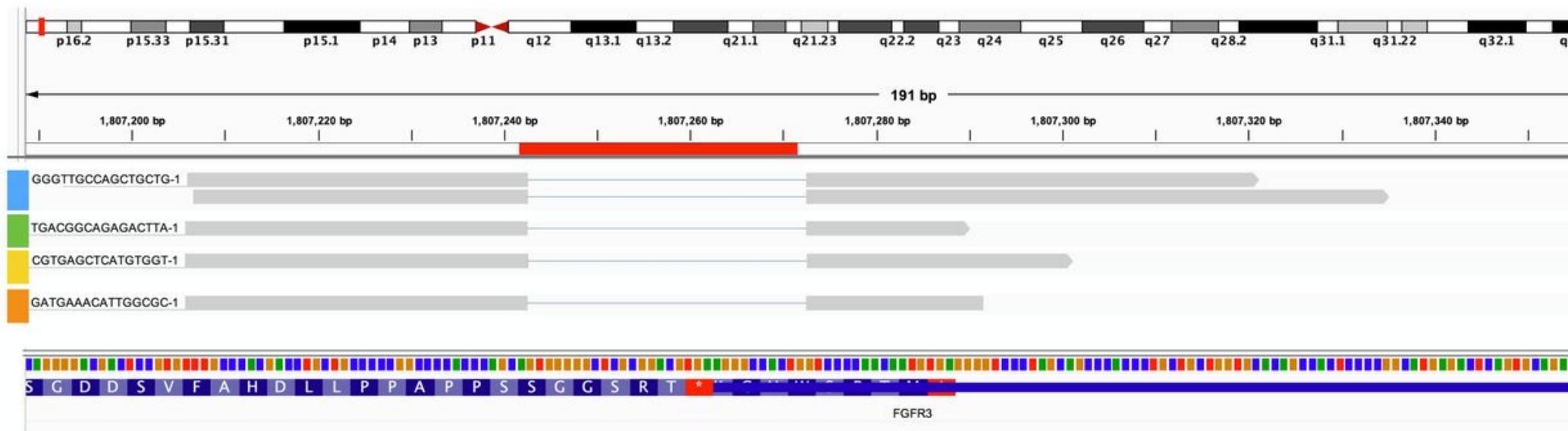


Copy number variants called from 10X Genomics single cell RNA-seq using chromosomal “pathway” enrichment

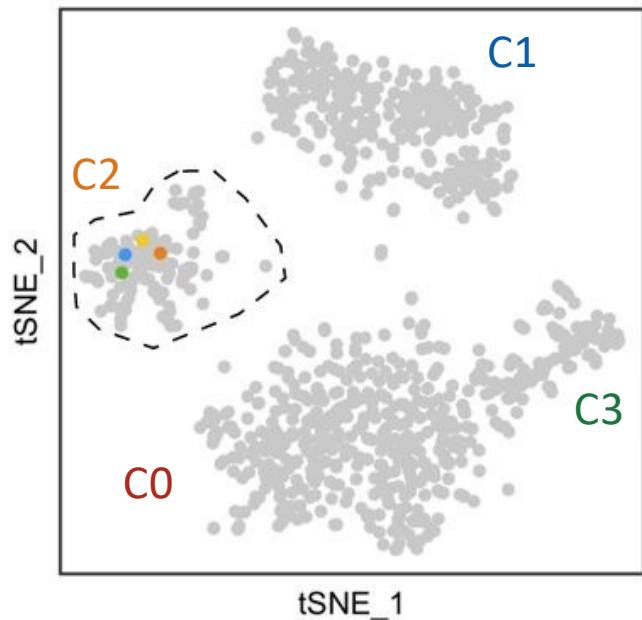


Somatic mutations in scRNA-seq data explain clonal responses

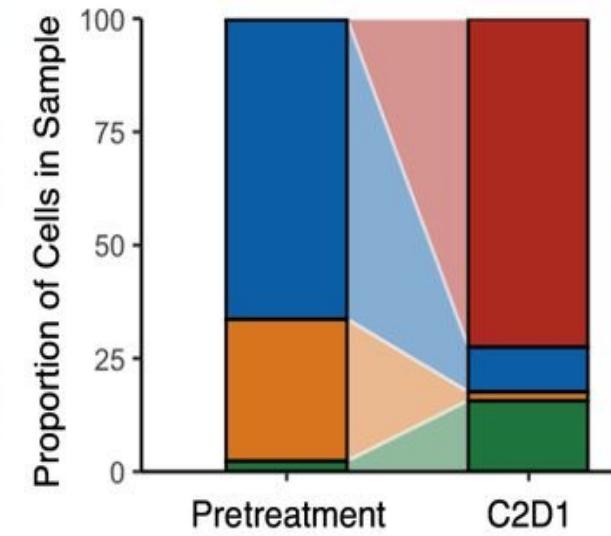
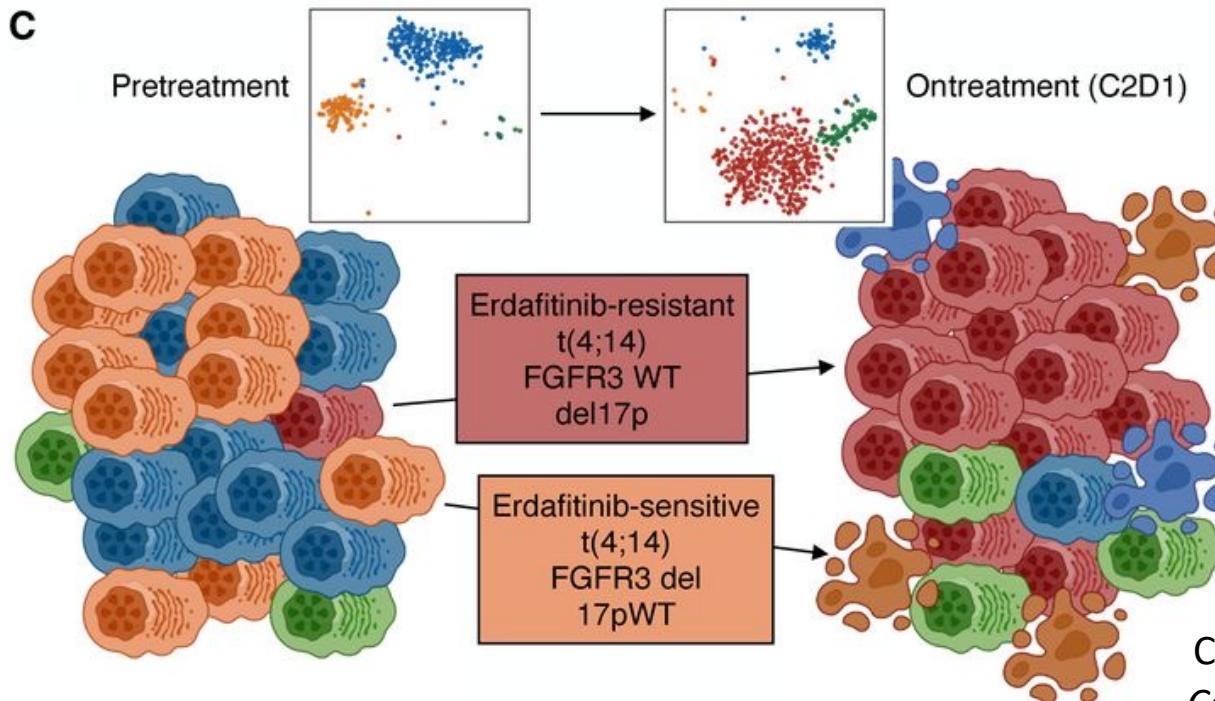
A



B



C



Croucher et al. *Cold Spring Harb Mol Case Stud.* 2023 May 9;9(2):a006249.

Revisiting the Learning Objectives

- 1) A plethora of single cell technologies have opened windows into cell biology that were closed to bulk approaches that “average out” signal
- 2) The same biology may be measurable using multiple methods
→ tailor experimental approaches to specific scientific questions answerable by available samples & technologies
- 3) Multiple cellular components can be queried from one single cell experiment, e.g. immune & cancer cells inhabiting tumours
- 4) “Fact-check” data quality, integrations, & conclusions using orthogonal experiments, external data sets, & clinical outcomes

Citations - Single Cell RNA-seq (trevor.pugh@utoronto.ca)

Tumour microenvironment
Immune inference
Experimental design
Cell isolation
Technology scaling
10X vs SMART-SEQ2
scRNA-seq technologies
Bioinformatics
Myeloma mouse immune
Myeloma mouse cancer
Glioblastoma stem scRNA-seq

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Broad Single Cell Portal
10X Genomics TCR/Ig poster
Human Cell Atlas
Chan-Zuckerberg Initiative
Princess Margaret Genomics

portals.broadinstitute.org/single_cell/
www.10xgenomics.com/resources/posters
www.humancellatlas.org
www.chanzuckerberg.com
www.pmgenomics.ca

Panoramics A Vision:
Single Cell Analysis Working Group
panoramics-a-vision.slack.com
<https://www.panoramics-a-vision.com>