



Single-cell Multi-Omics integration

SinCellTE 2022

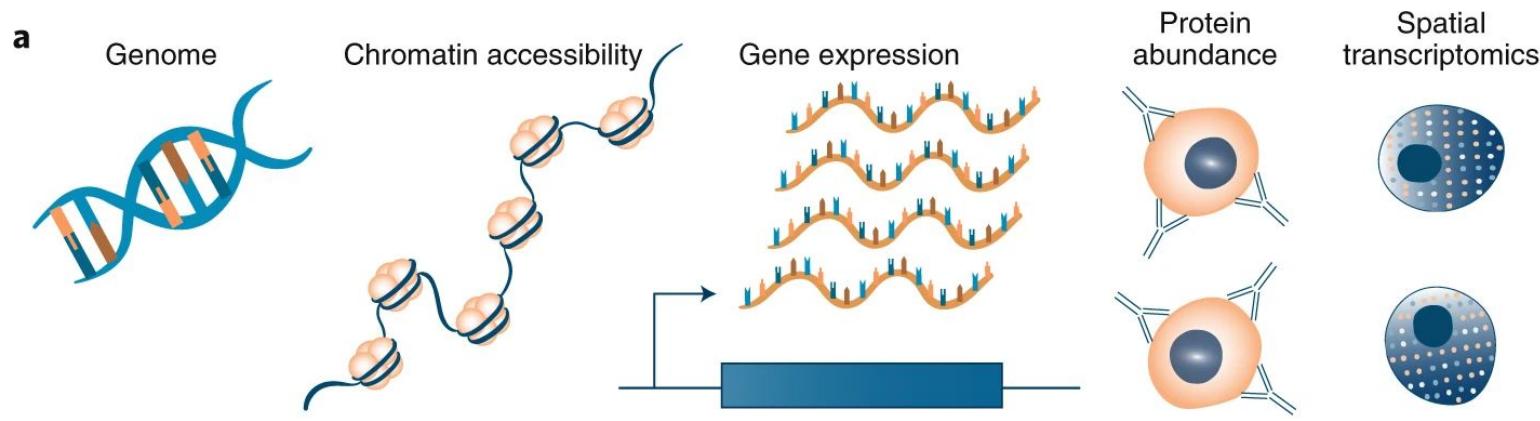
Andres Quintero
Carl Herrmann

Health Data Science Unit
Heidelberg University
13/01/2022
Roscoff, France

Content

- ❑ Single-cell multi-omics
- ❑ Integrating multiple single-cell datasets
- ❑ Single-cell multimodal profiling
- ❑ Single-cell multimodal analysis
- ❑ Inference of gene regulatory networks
- ❑ Perspectives

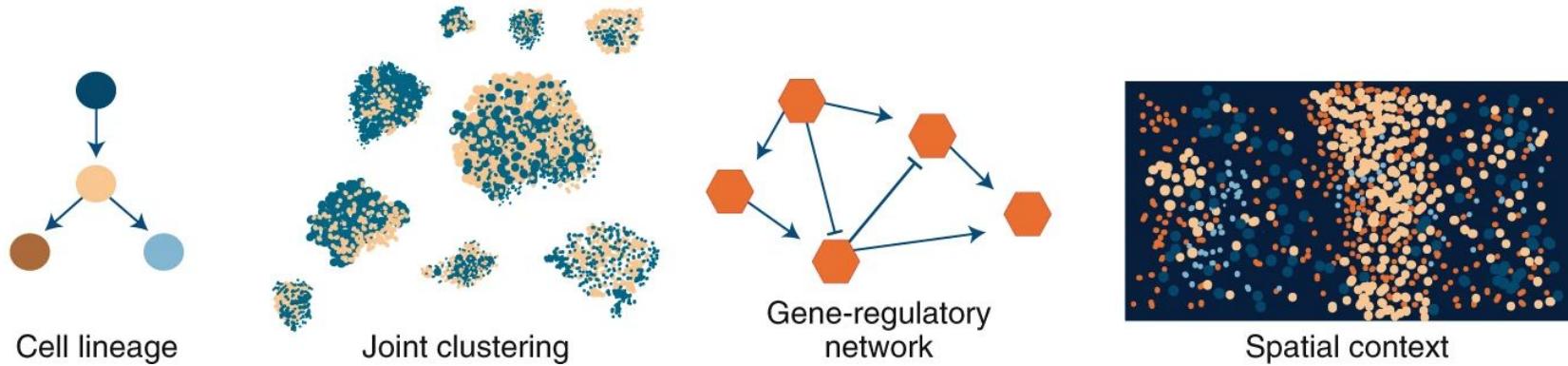
Single-cell multi-omics



To disentangle the complexity of gene-regulatory and cell–cell communication networks that drive cell functions and responses, measuring multiple modalities of the multivariate phenotypic and genetic cellular state is extremely powerful.

Single-cell multi-omics

c



To disentangle the complexity of gene-regulatory and cell–cell communication networks that drive cell functions and responses, measuring multiple modalities of the multivariate phenotypic and genetic cellular state is extremely powerful.

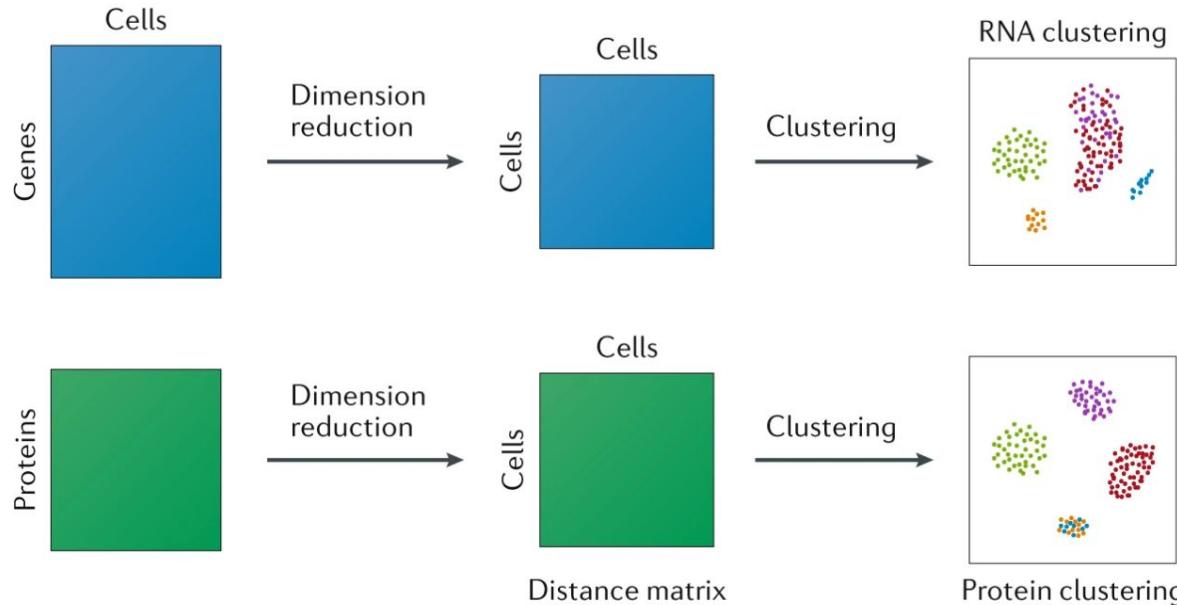
Single-cell multi-omics

	Shared dimension	Features
Multimodal experiment integration (different types of data for all samples/cells)	- samples - cells	- genes - pathways - genomic regions - interacting pairs
Multi-experiment integration (data from different samples/cells)	- genes - pathways - genomic regions - interacting pairs	- samples - cells

The integrative analysis of multi-omics data can be done in two different ways, integrating over cells for multimodal datasets or over molecular features.

Single-cell multi-omics

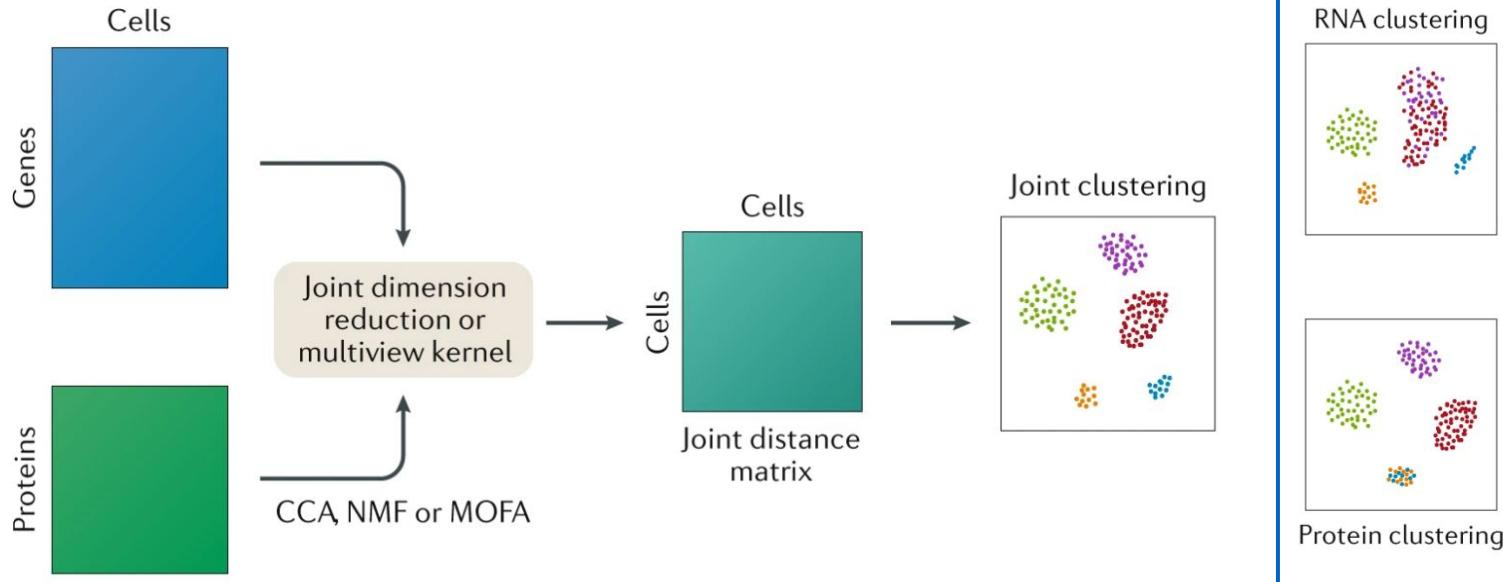
a Separate analysis of multiple modalities



Independent analysis of multiple modalities measured from the same group of cells can lead to conflicting identification of clusters of cells.

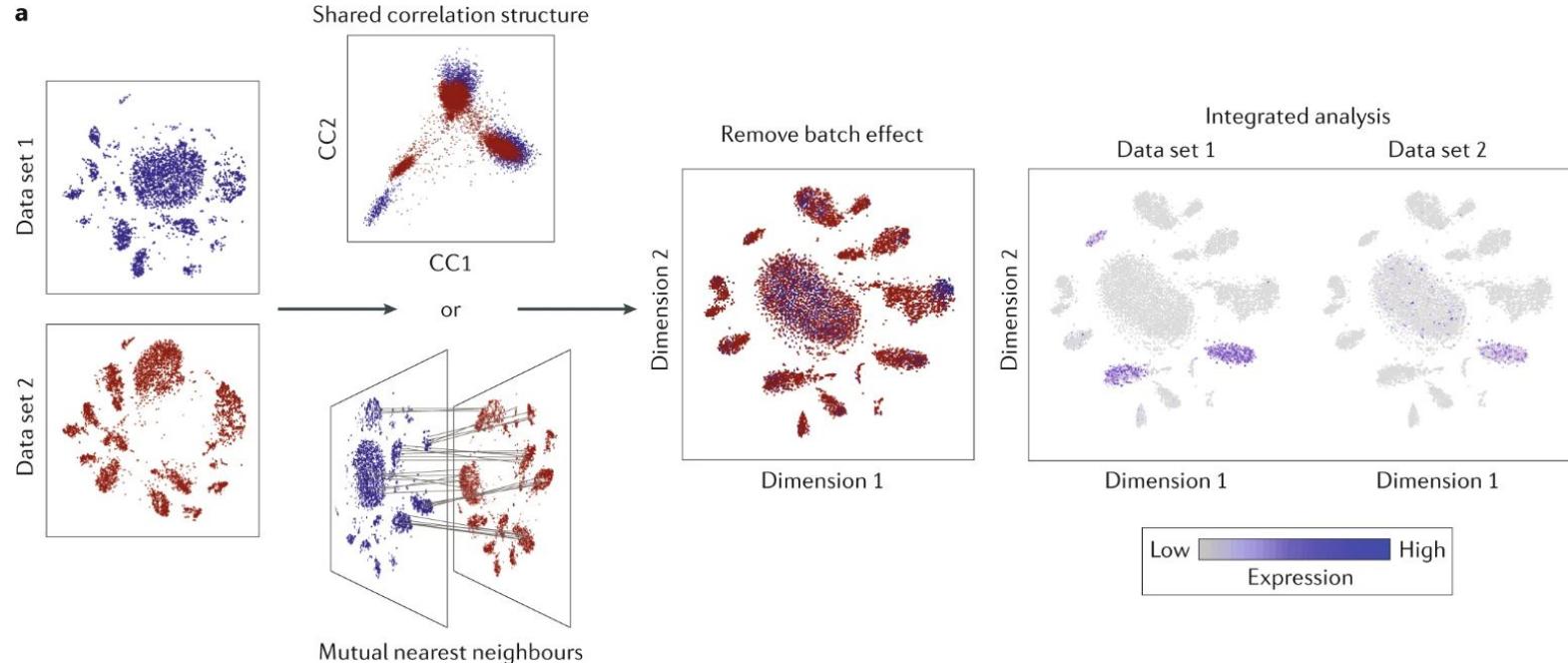
Single-cell multi-omics

b Joint analysis of multiple modalities



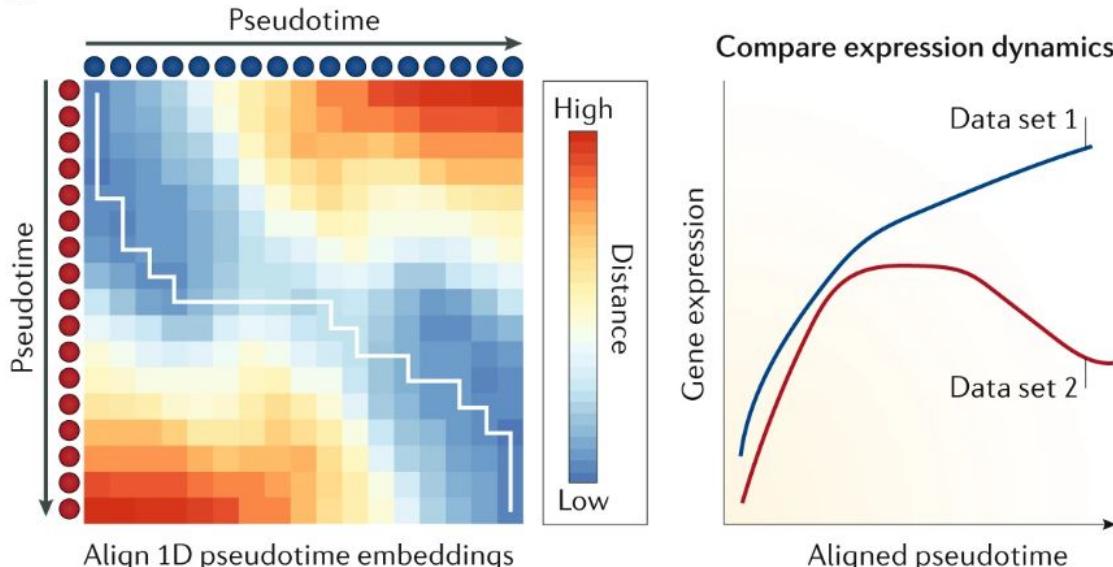
Joint analysis of multiple modalities measured from the same group of cells can have greater power to identify unique cell states.

Integrating multiple single-cell datasets



Multiple data sets can be integrated computationally to facilitate downstream comparative analysis. Shared correlation structure can be detected using canonical correlation analysis (CCA) or mutual nearest neighbours (MNNs) identified.

Integrating multiple single-cell datasets



The alignment of pseudotime vectors can allow temporal differences in cell trajectories to be removed and equivalent points in the trajectory across two data sets to be identified.

Gene expression can then be directly compared across the corrected pseudotime trajectories.

Integrating multiple single-cell datasets

Example: Projection of bulk and single-cell data onto a reference embedding *nature cancer*

Moritz Gartlgruber*, Ashwini Kumar Sharma*, Andrés Quintero*, Daniel Dreidax*, Selina Jansky, Young-Gyu Park, Sina Kreth, Johanna Meder, Daria Oncevic, Paul Saary, Umut H. Toprak, Naveed Ishaque, Elena Afanasyeva, Elisa Wecht, Jan Koster, Rogier Versteeg, Thomas G. P. Grünwald, David T. W. Jones, Stefan M. Pfister, Kai-Oliver Henrich, Johan van Nes, Carl Herrmann*, Frank Westermann*. Super enhancers define regulatory subtypes and cell identity in neuroblastoma. *Nature Cancer*. (December 2020).

Division of Neuroblastoma Genomics



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Research for a Life without Cancer

GERMAN
CANCER RESEARCH CENTER
IN THE HELMHOLTZ ASSOCIATION

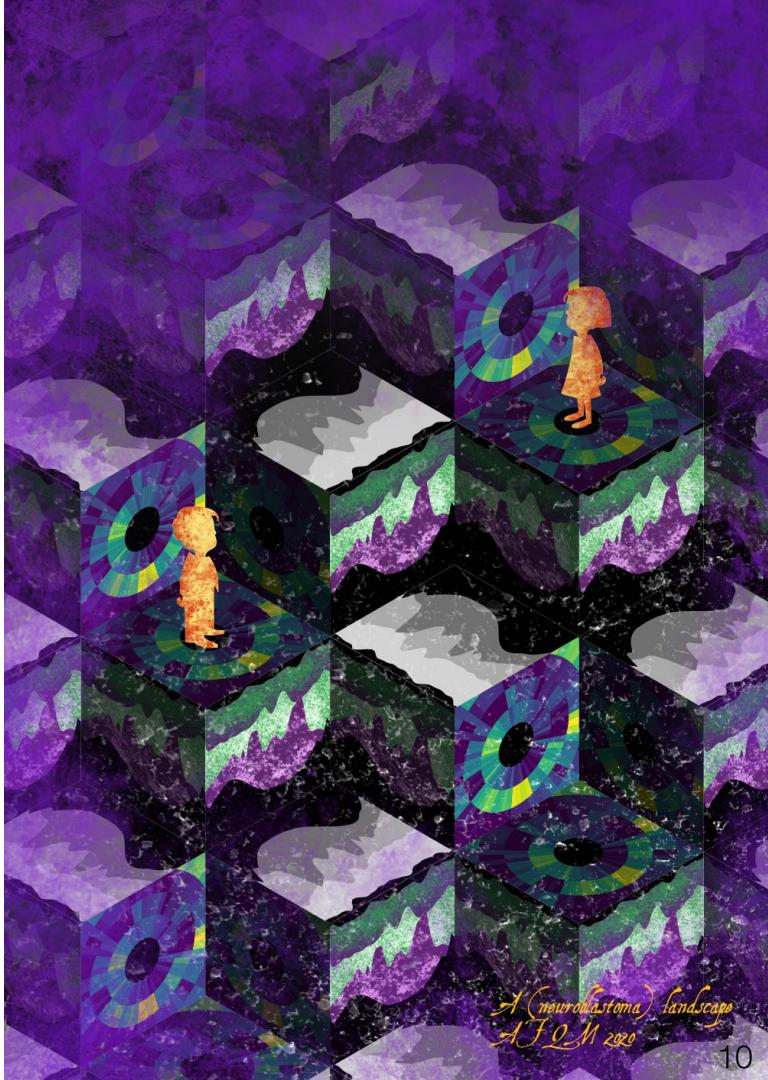


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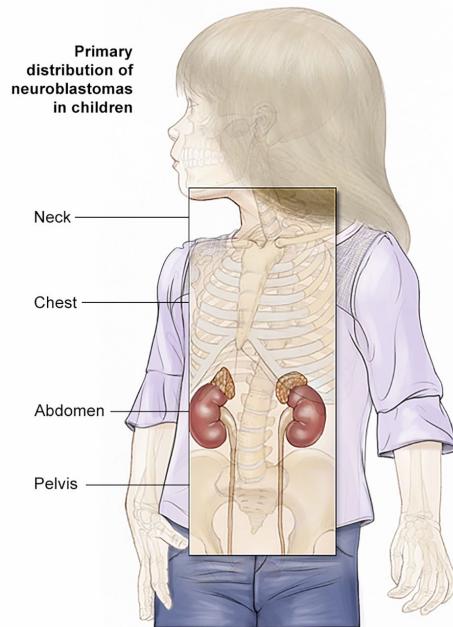


healthdata
scienceunit



A (neuroblastoma) landscape
AFQM 2020

NMF to Reveal Regulatory Subtypes in Neuroblastoma

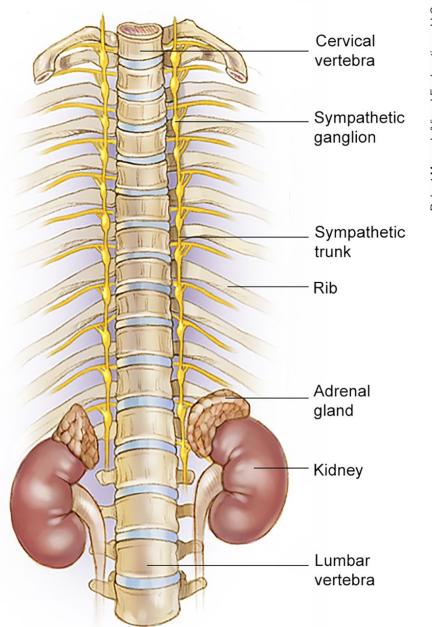


© 2005 American Society of Clinical Oncology

Taken from:

<https://www.cancer.net/cancer-types/neuroblastoma-childhood/medical-illustrations>

2005 American Society of Clinical Oncology



Robert Morreale/Visual Explanations, LLC

- Pediatric solid tumor of the sympathetic nervous system (SNS).
- Common place of origin is the adrenal gland.
- Is thought to develop from neural crest-derived precursor cells of the SNS.

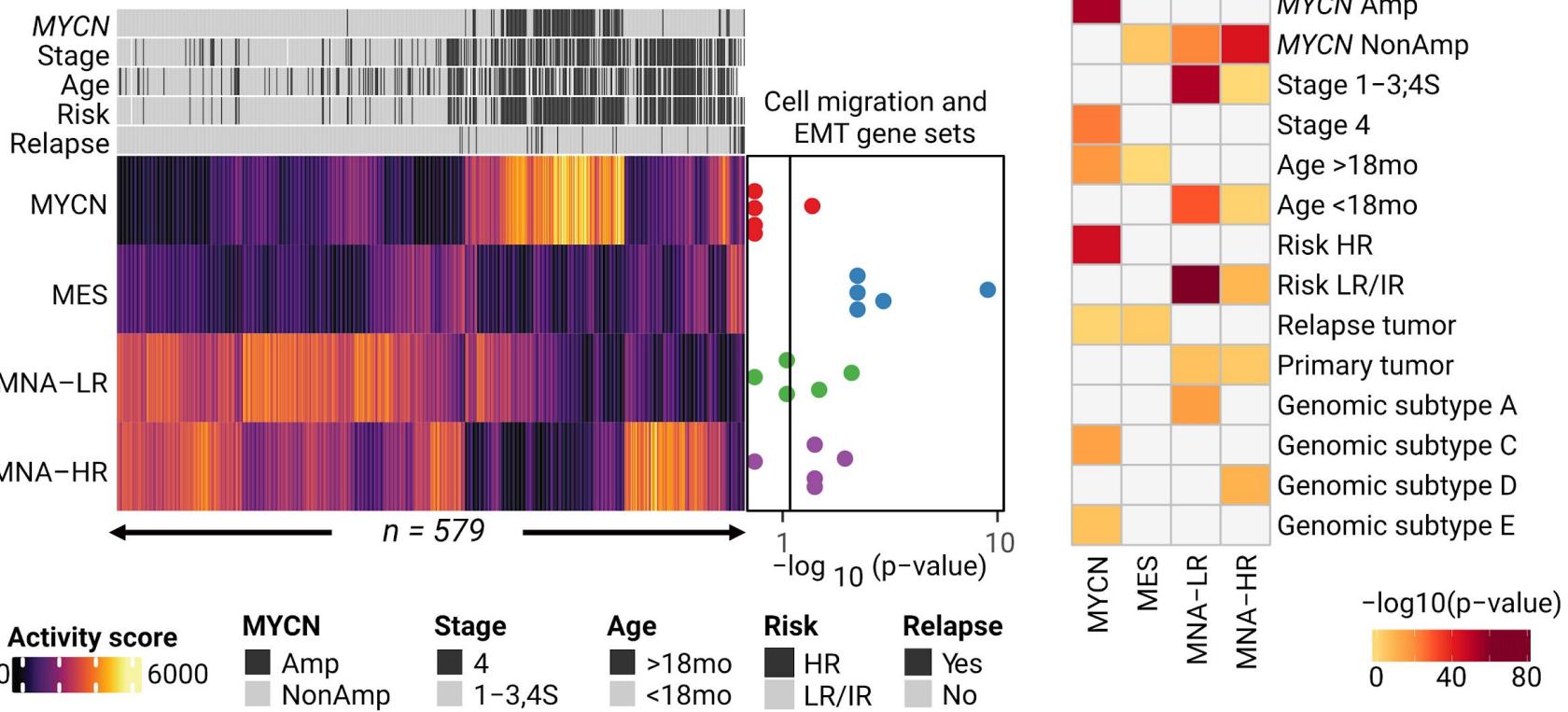


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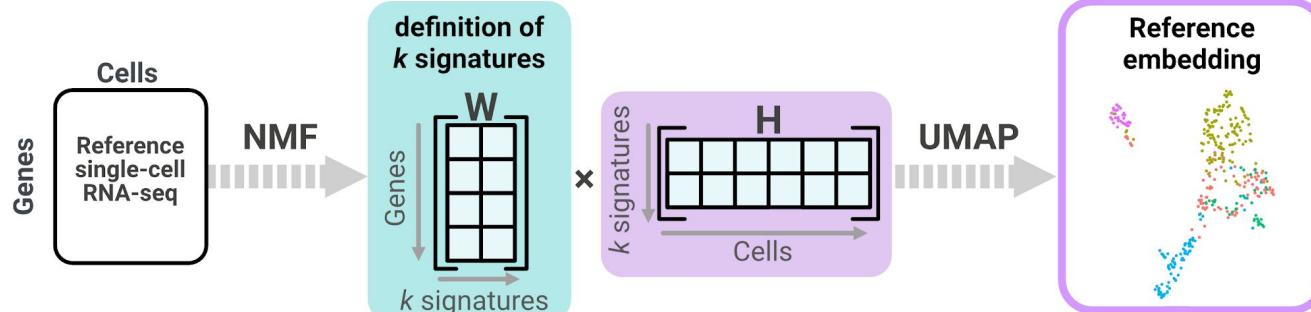
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Neuroblastoma transcriptomic signatures



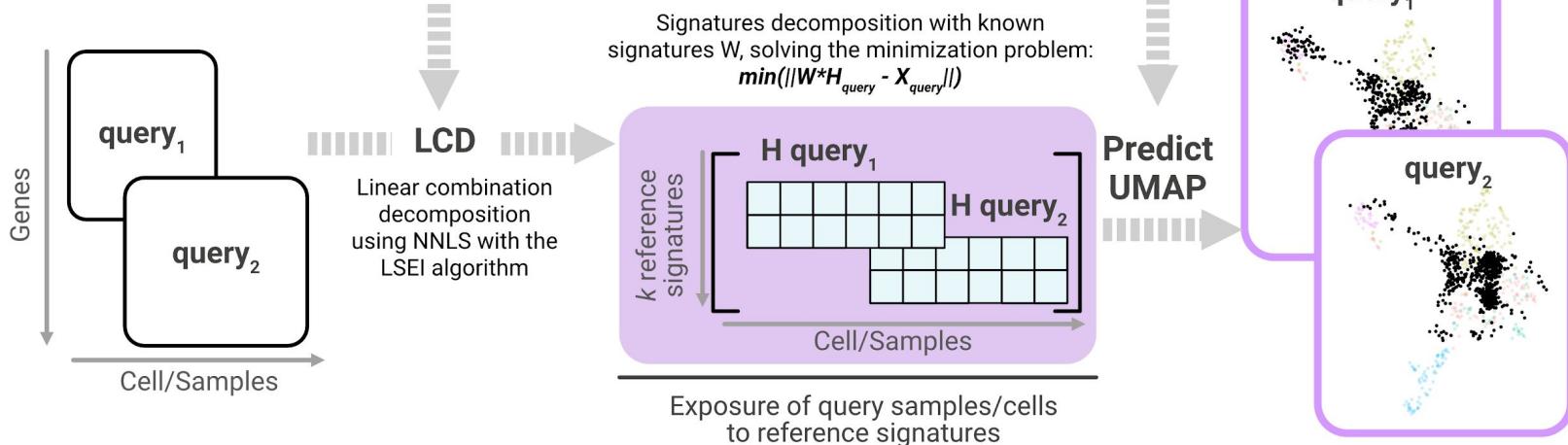
Projection onto reference dataset

Stage 1: Build reference embedding



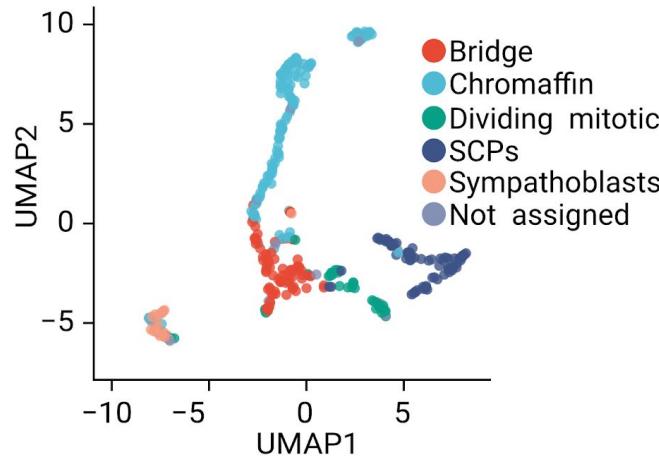
ButchR

Stage 2: Project query onto reference embedding



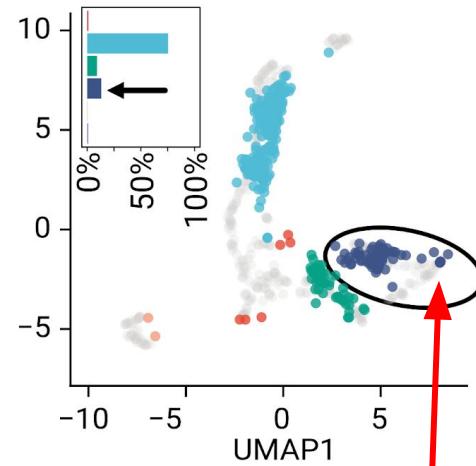
Projection of neuroblastomas onto mouse-developing adrenal sympathetic system

Mouse E12.5 developing adrenal medulla (Furlan et al. 2017)



Every point represents
one single-cell

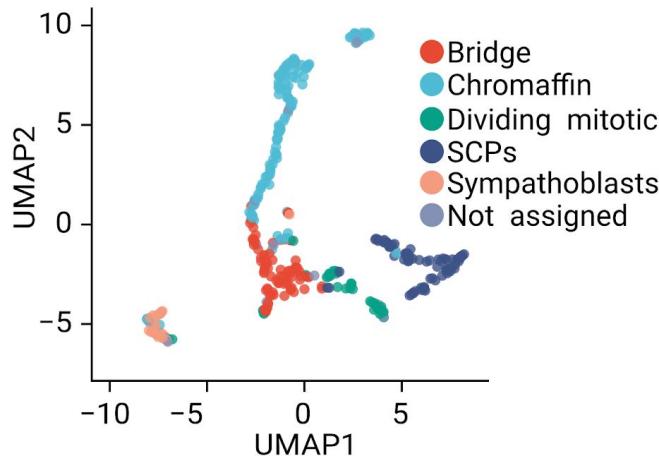
NB RNA-seq cohort projection
n = 573 projected samples



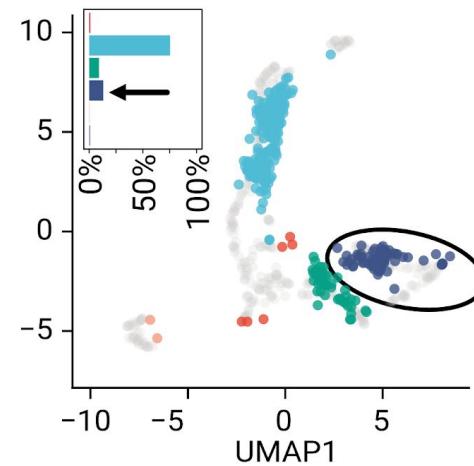
Every colored point
represents one bulk sample

Projection of neuroblastomas onto mouse-developing adrenal sympathetic system

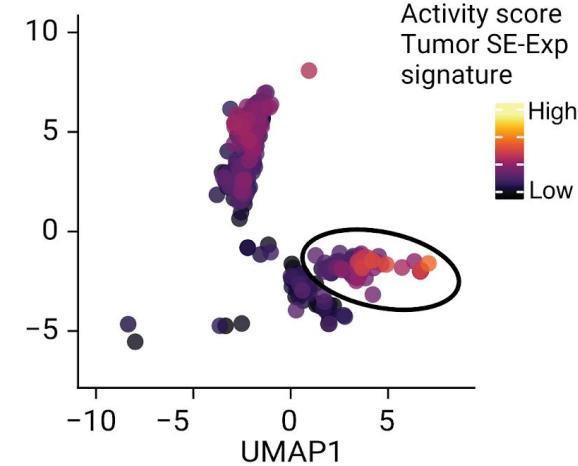
Mouse E12.5 developing adrenal medulla (Furlan et al. 2017)



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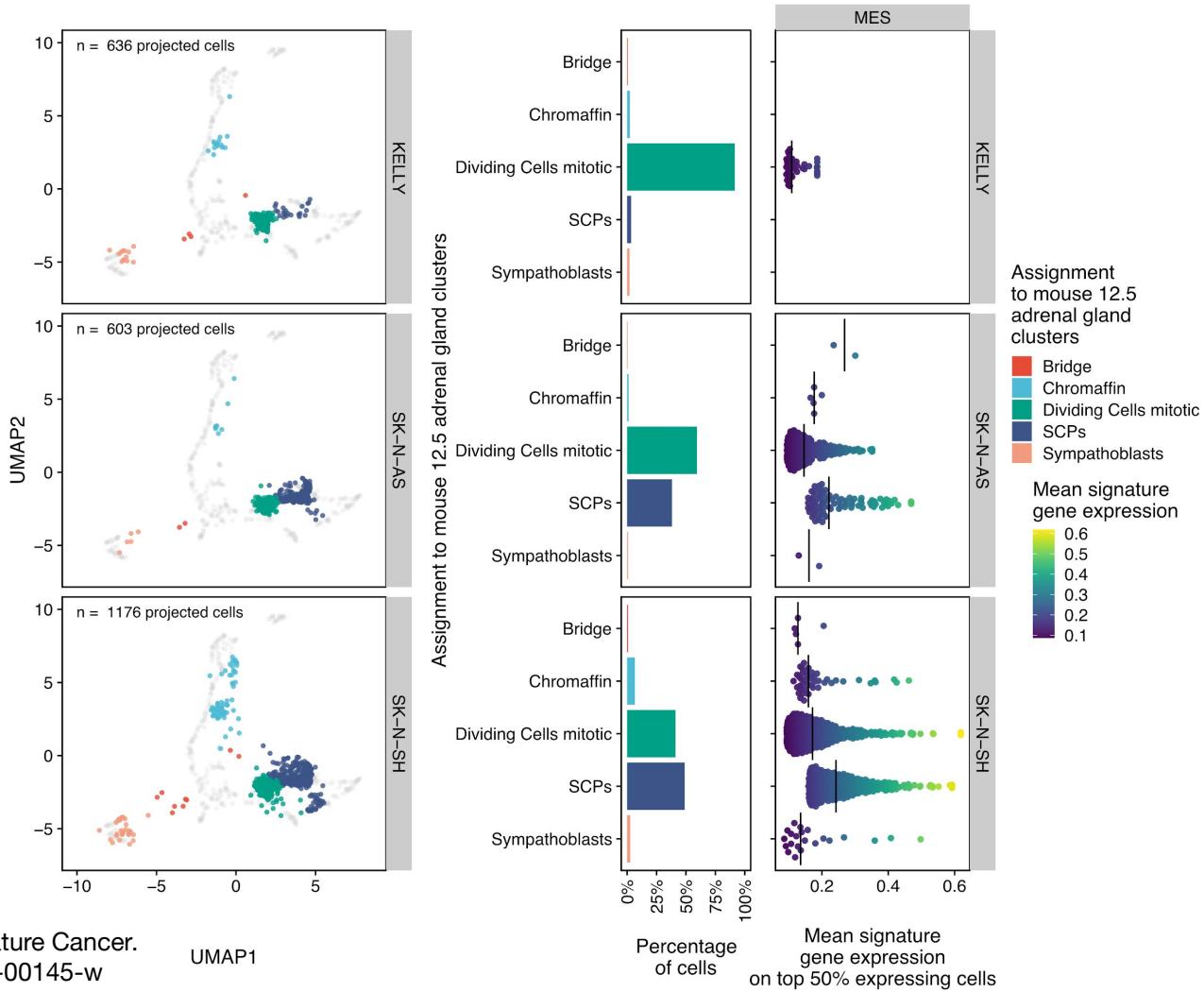
NB RNA-seq cohort projection
MES score



MES subtype associated with multipotent Schwann cell precursors



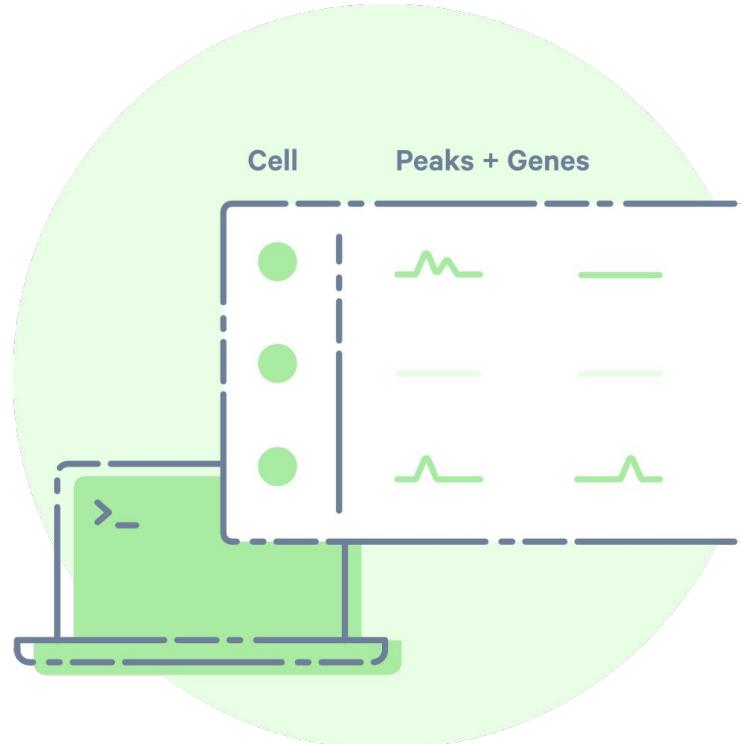
Projection of neuroblastoma cell lines onto mouse-developing adrenal sympathetic system



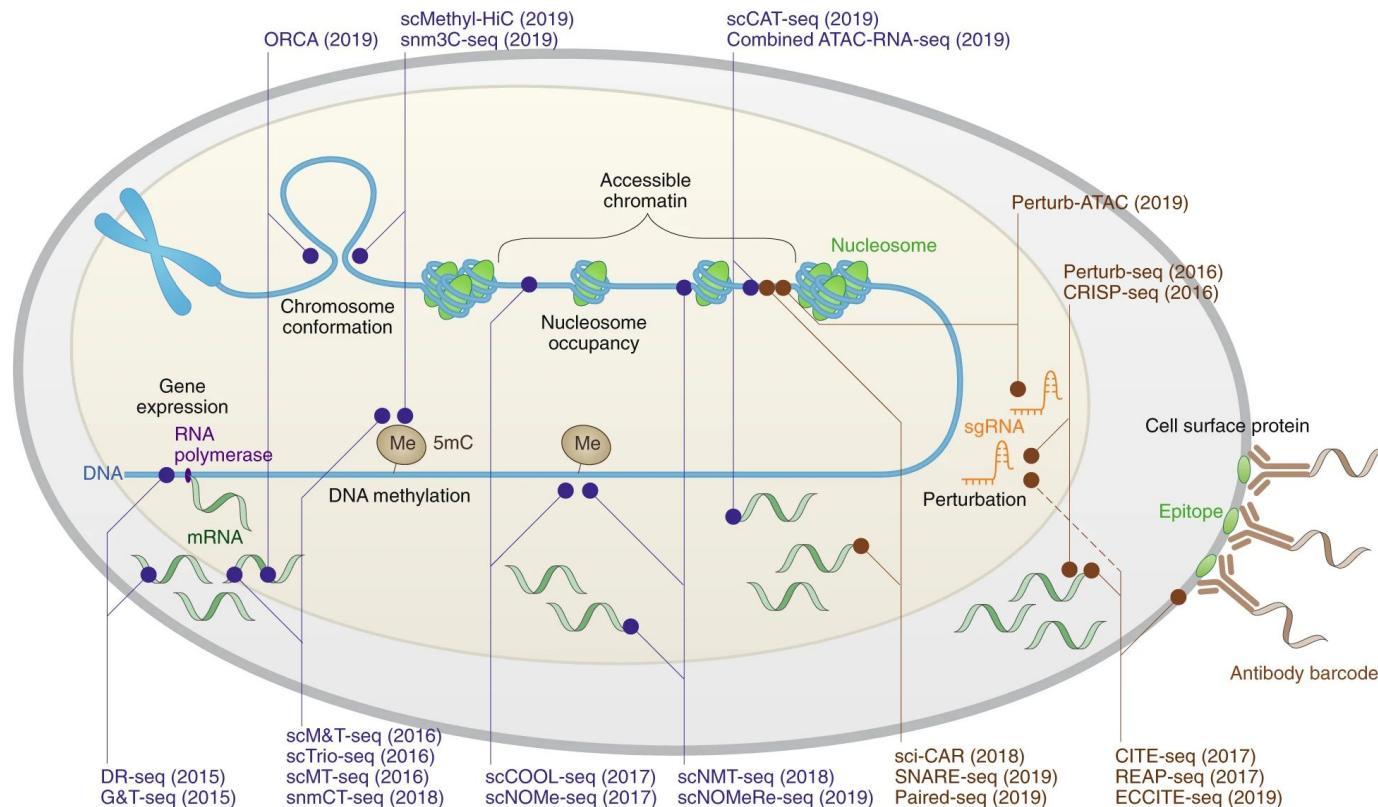
Gartlgruber et al. 2020. Nature Cancer.
DOI: 10.1038/s43018-020-00145-w

Andres Quintero

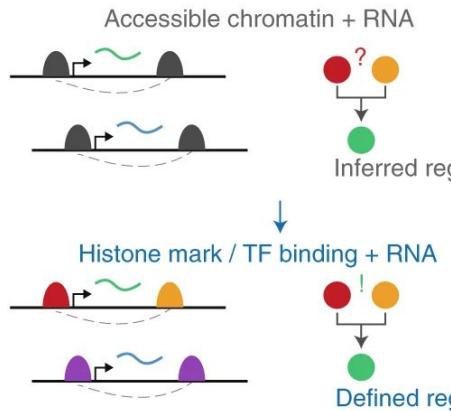
Single-cell multimodal integration



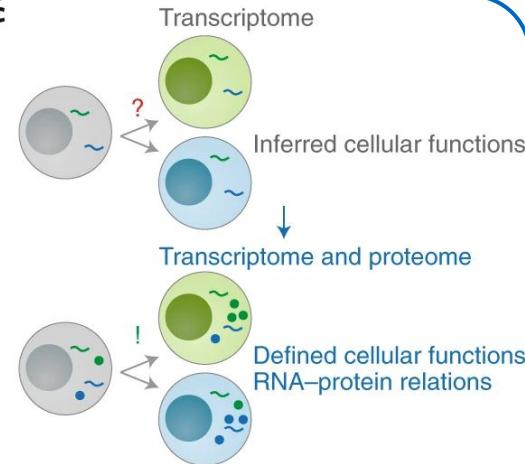
Single-cell multimodal profiling



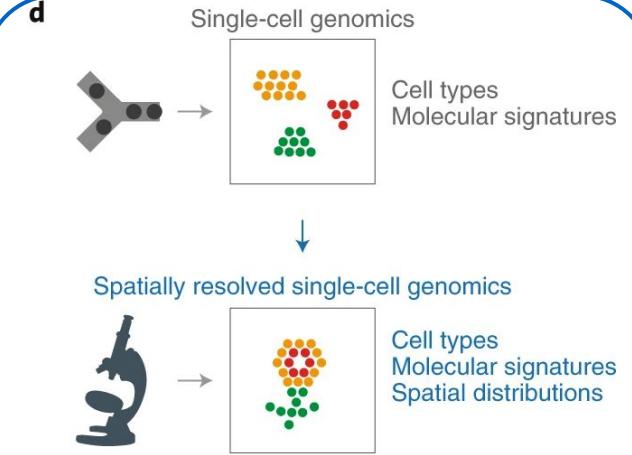
Single-cell multimodal profiling



Co-assays of histone marks or transcription-factor binding and gene expression will refine the understanding of gene regulatory networks.



Joint analysis of transcripts and proteins in single cells will reveal the dynamic relationships of transcripts and protein abundance

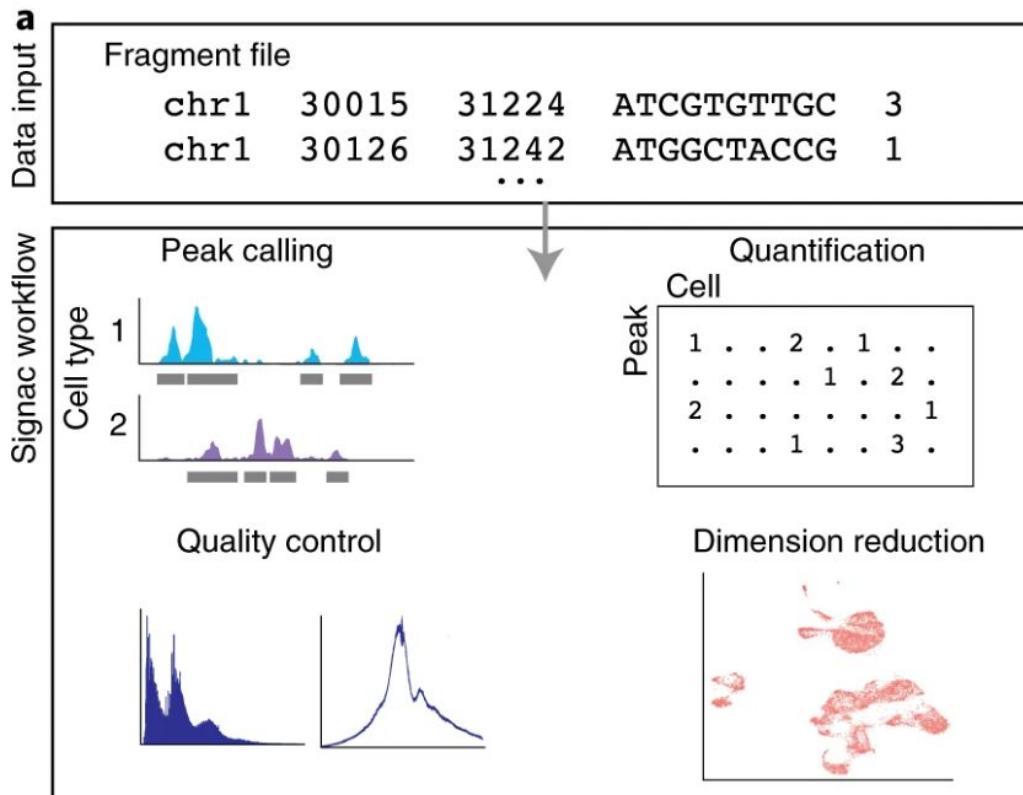


Extension of the spatial transcriptomics toolbox to epigenome analysis will facilitate the dissection of molecular and cellular networks in complex tissues.

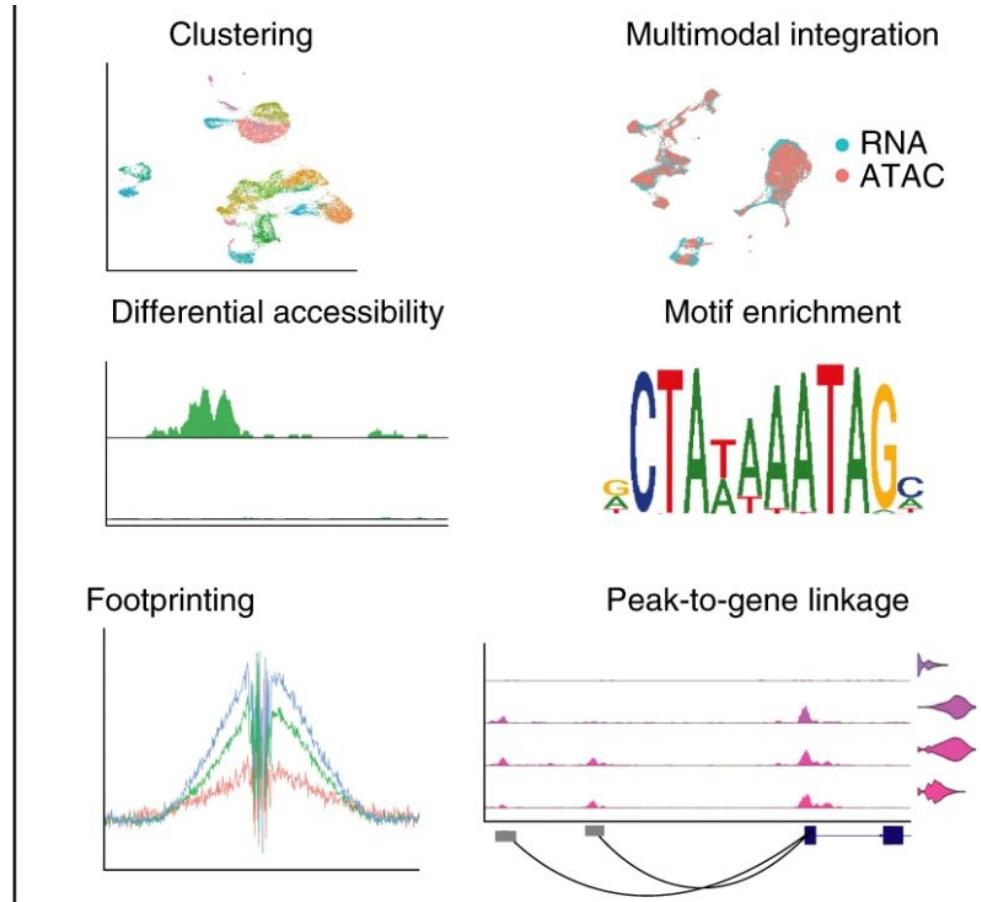
Single-cell Multimodal analysis



Single-cell multimodal analysis steps

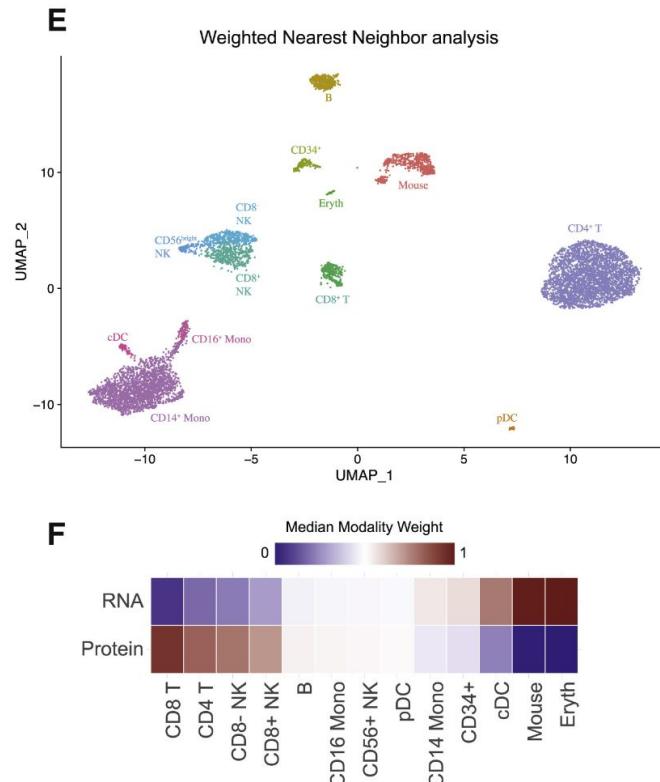
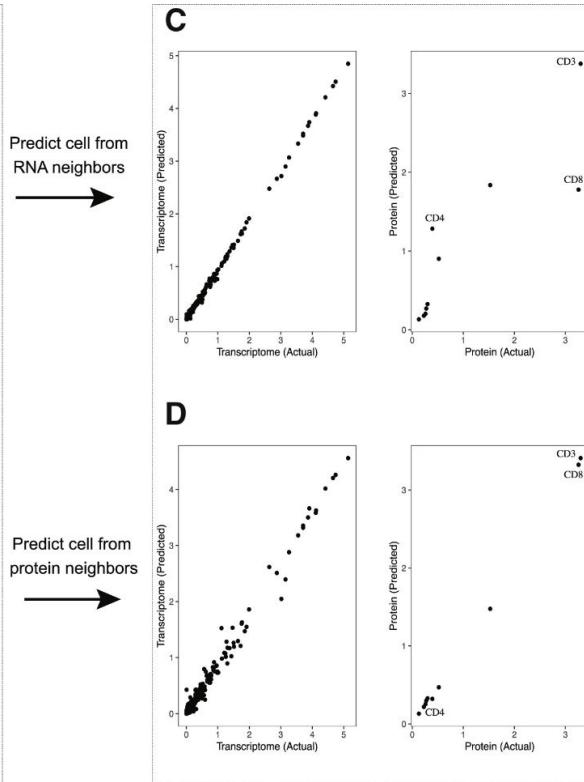
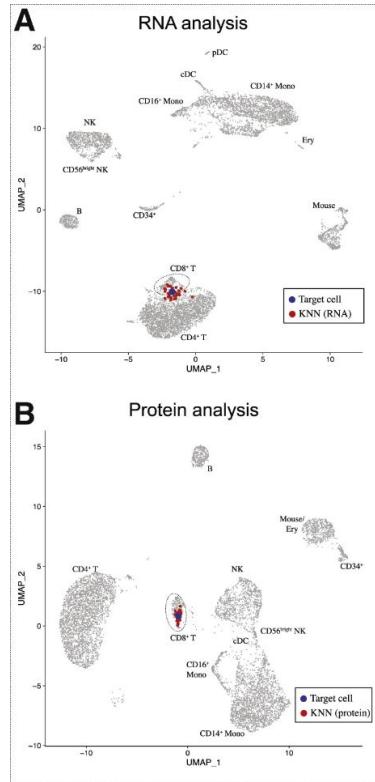


Single-cell multimodal analysis steps

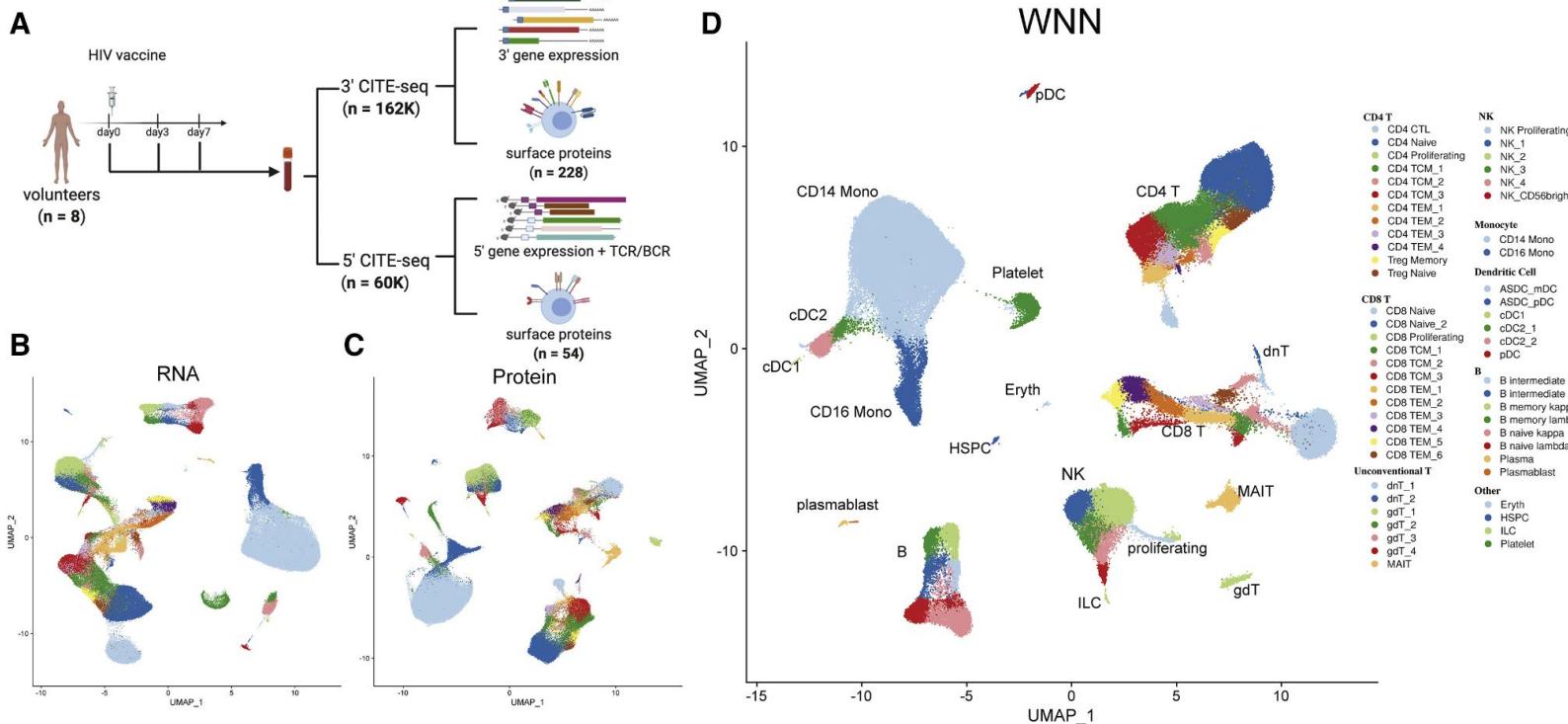


Single-cell multimodal analysis

Weighted nearest neighbors



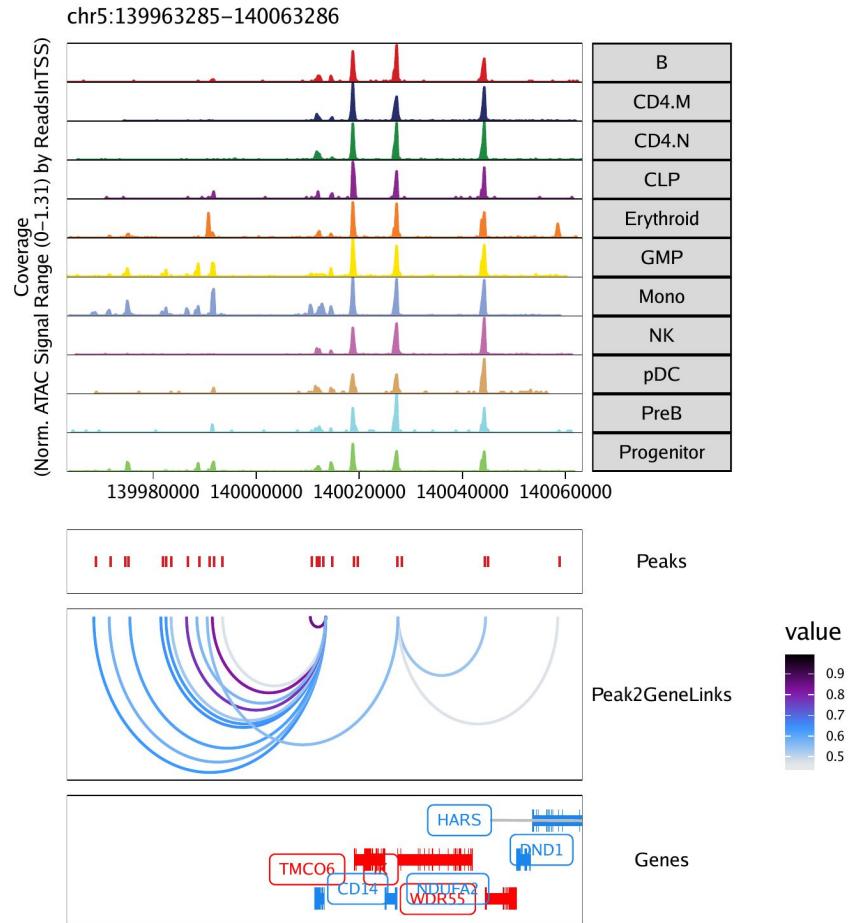
Weighted nearest neighbors



A multimodal atlas of human PBMC with CITE-seq data: 161,764 cells

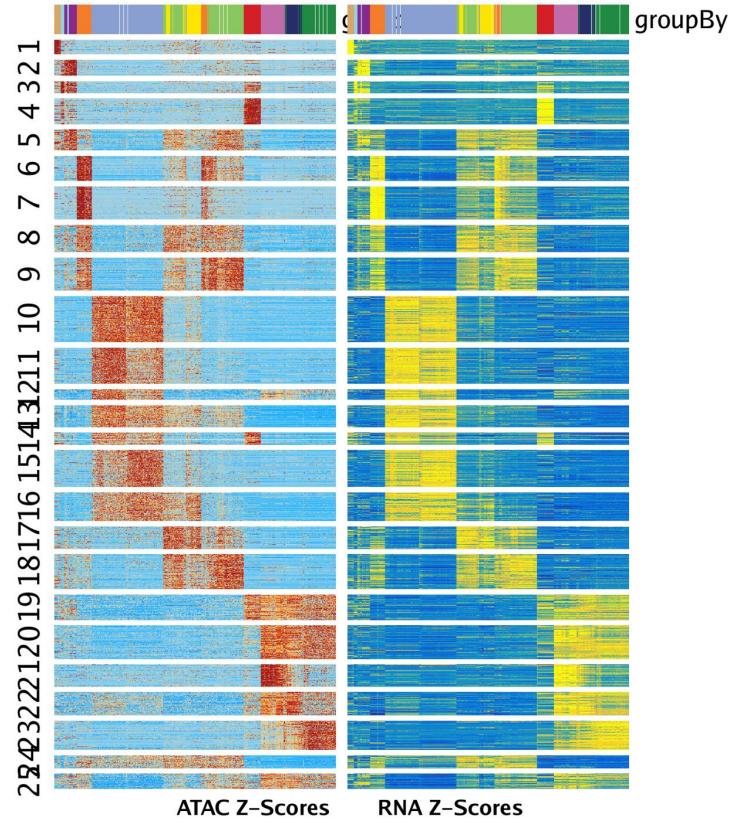
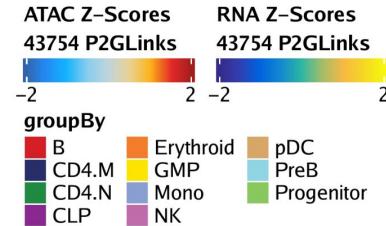
Finding peak-to-gene links

Peak-to-gene linkage leverages integrated scRNA-seq data to look for correlations between peak accessibility and gene expression.



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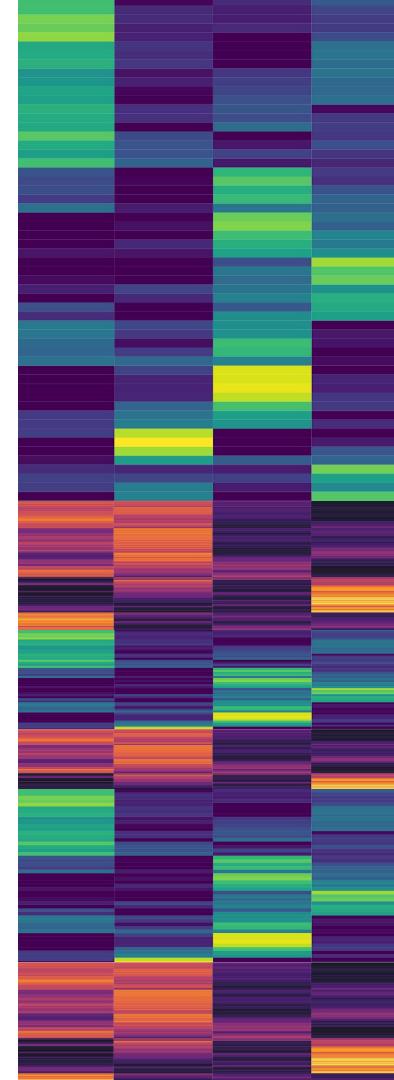


Single-cell multimodal analysis

Example: Prediction of gene regulatory networks using GRANet

nature communications

Longqi Liu*, Chuanyu Liu*, Andrés Quintero*, Liang Wu*, Yue Yuan*, Mingyue Wang, Mengnan Cheng, Lizhi Leng, Liqin Xu, Guoyi Dong, Rui Li, Yang Liu, Xiaoyu Wei, Jiangshan Xu, Xiaowei Chen, Haorong Lu, Dongsheng Chen, Quanlei Wang, Qing Zhou, Xinxin Lin, Guibo Li, Shiping Liu, Qi Wang, Hongru Wang, J. Lynn Fink, Zhengliang Gao, Xin Liu, Yong Hou, Shida Zhu, Huanming Yang, Yunming Ye, Ge Lin, Fang Chen, Carl Herrmann, Roland Eils, Zhouchun Shang & Xun Xu. **Deconvolution of single-cell multi-omics layers reveals regulatory heterogeneity.** *Nature Communications* 10, 470 (2019)



scCAT-seq multimodal data

a

Three different cell lines:



HCT116
n = 90



HeLa-S3
n = 42

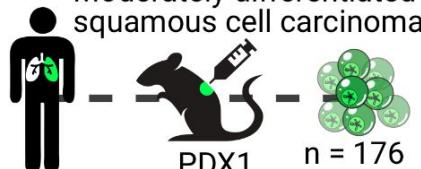


K562
n = 74

b

Two lung cancer patient-derived xenografts (PDX):

Moderately differentiated squamous cell carcinoma



PDX1 n = 176



PDX2 n = 167

Large-cell lung carcinoma

c

Pre-implantation human embryo:

Morula

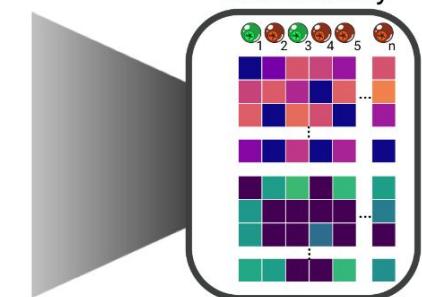


Blastocyst



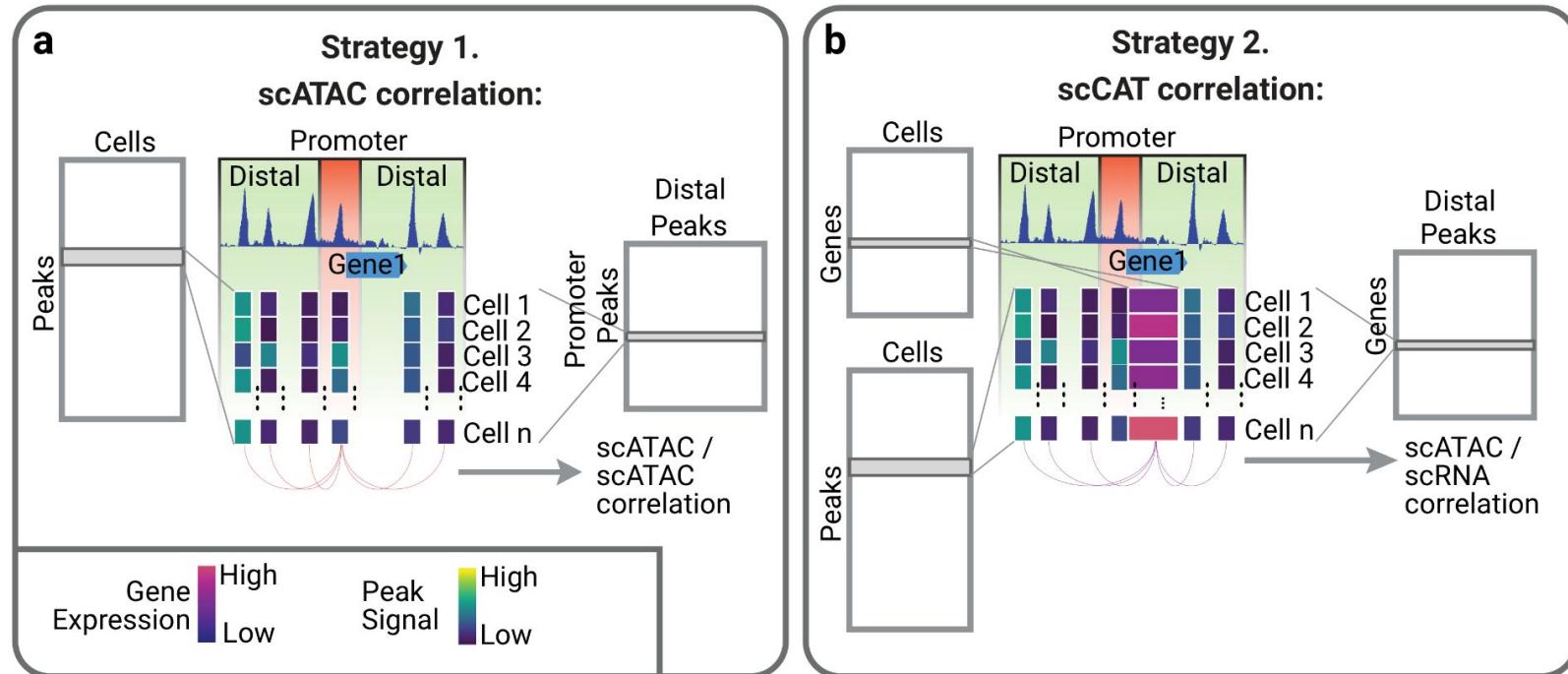
72 Cells

scCAT-seq data: gene expression and chromatin accessibility for every cell
Liu et al., 2019

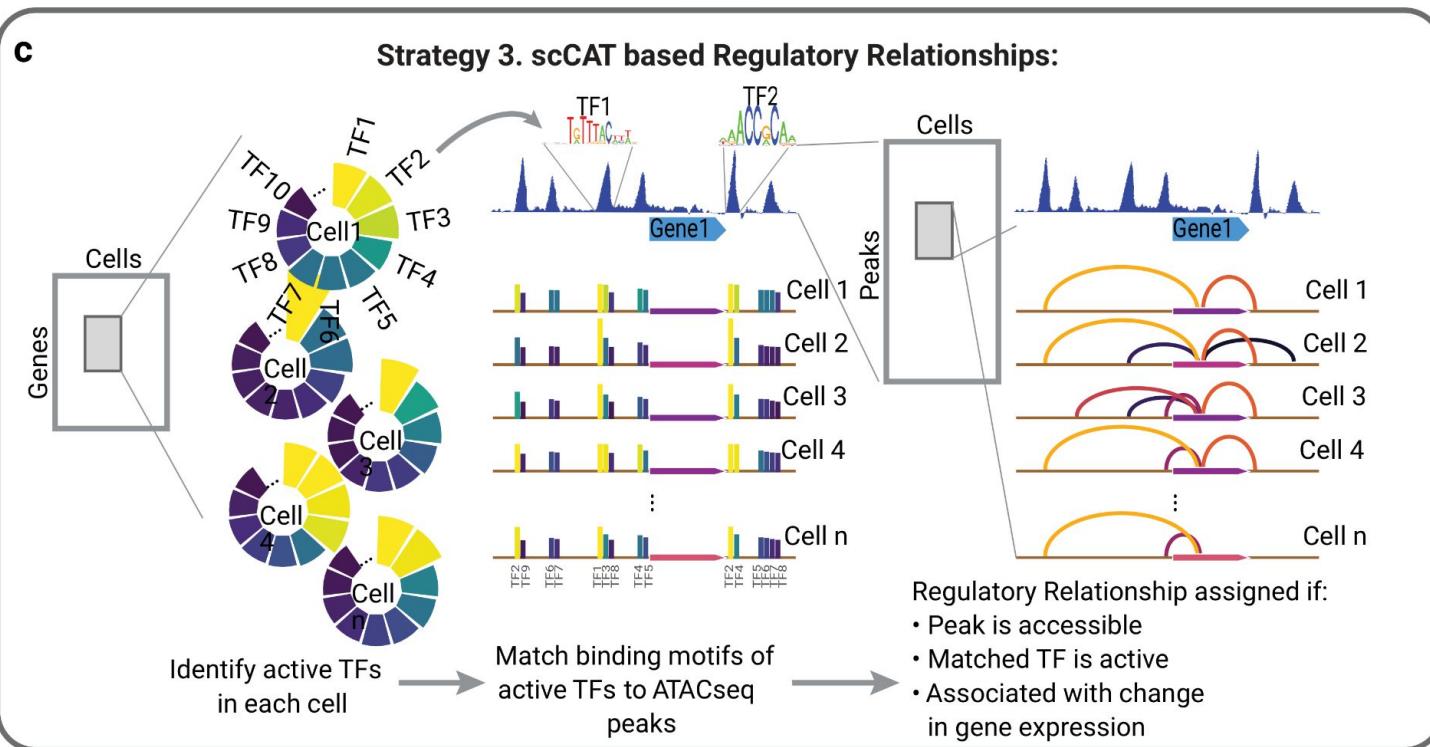


Chromatin accessibility
Gene expression

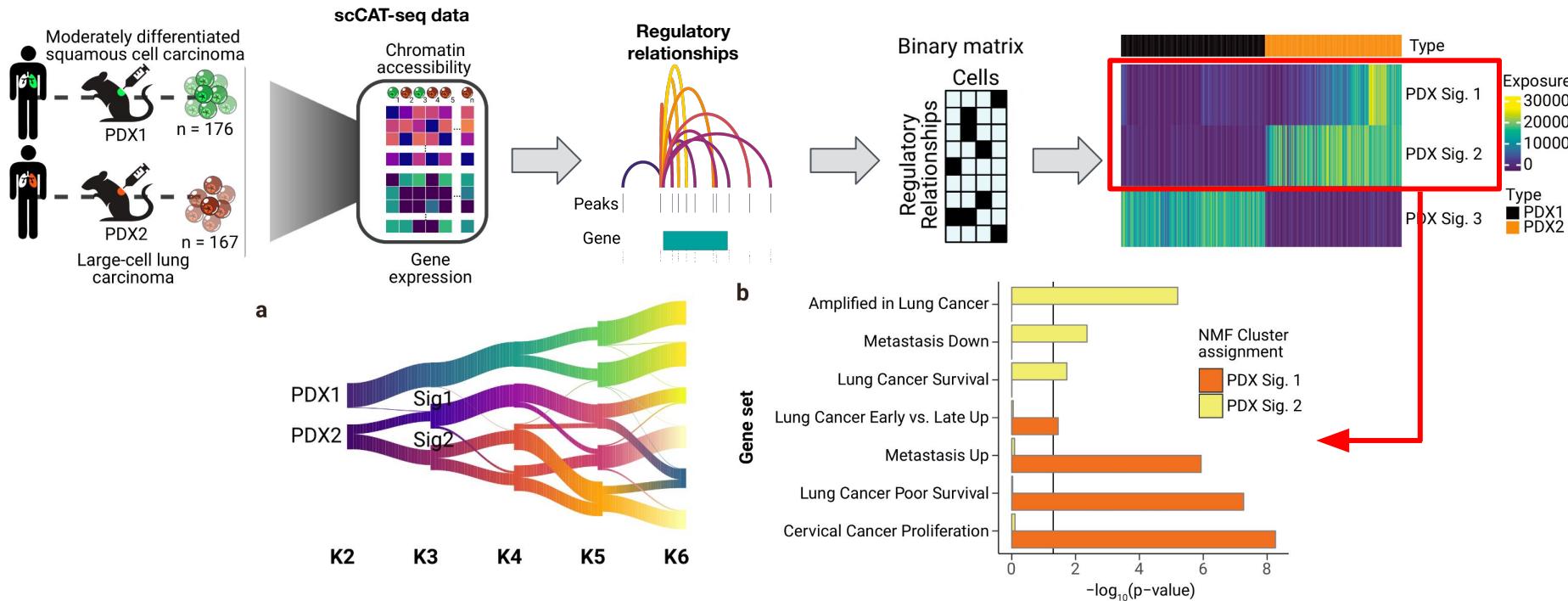
Strategies to infer regulatory interactions



Strategies to infer regulatory interactions



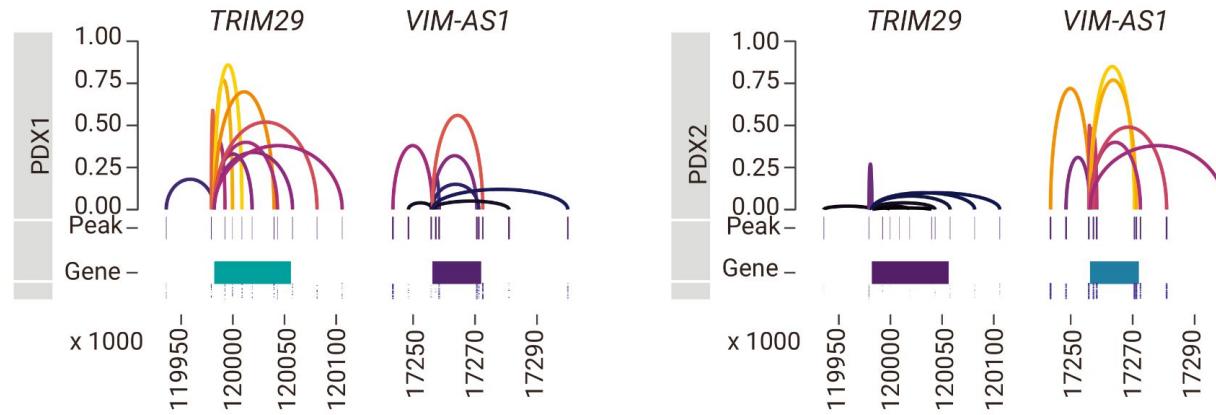
Regulatory relationships from multiomics scCAT-seq data



Regulatory signatures captured the intra- and inter-tumor regulatory variability

Inter and intra-tumor regulatory variability

b



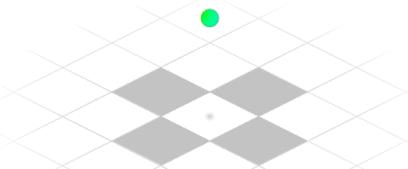
TRIM29: reported to mediate metastasis in lung squamous cell carcinoma via regulation of the autophagic degradation of E-cadherin (W. Xu et al. 2020).

VIM-AS1: It is a long noncoding RNA that promotes colorectal (Rezanejad bardaji, Asadi & Yaghoobi 2018) and prostate cancer (Z. Zhang et al. 2019) progression inducing EMT.

Perspectives

ArchR

<https://www.archrproject.com/>



muon
multimodal omics
Python framework

<https://github.com/scverse/muon>

Signac

<https://satijalab.org/signac/index.html>

Cell Ranger ARC

<https://support.10xgenomics.com/single-cell-multiome-atac-gex>

Session 2 - Multi-omics integration

Hands-on sessions:

https://www.hdsu.org/sincelITE_2022/

RStudio server:

<https://rstudio-singlecell.sb-roscoff.fr/>



Dr. Carl Herrmann

Dr. Carlos Ramirez

Dr. Andres Quintero

Daria Doncevic

Ana Luísa Costa

Youcheng Zhang





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Thank you!