

# SEMINAR

**Dr Jiadong Mao**, School of Math & Stats

$\Phi$ -Space ST: a platform-agnostic method to identify cell states in spatial transcriptomics studies



 [@jiadongm.bsky.social](https://bsky.app/profile/jiadongm.bsky.social)

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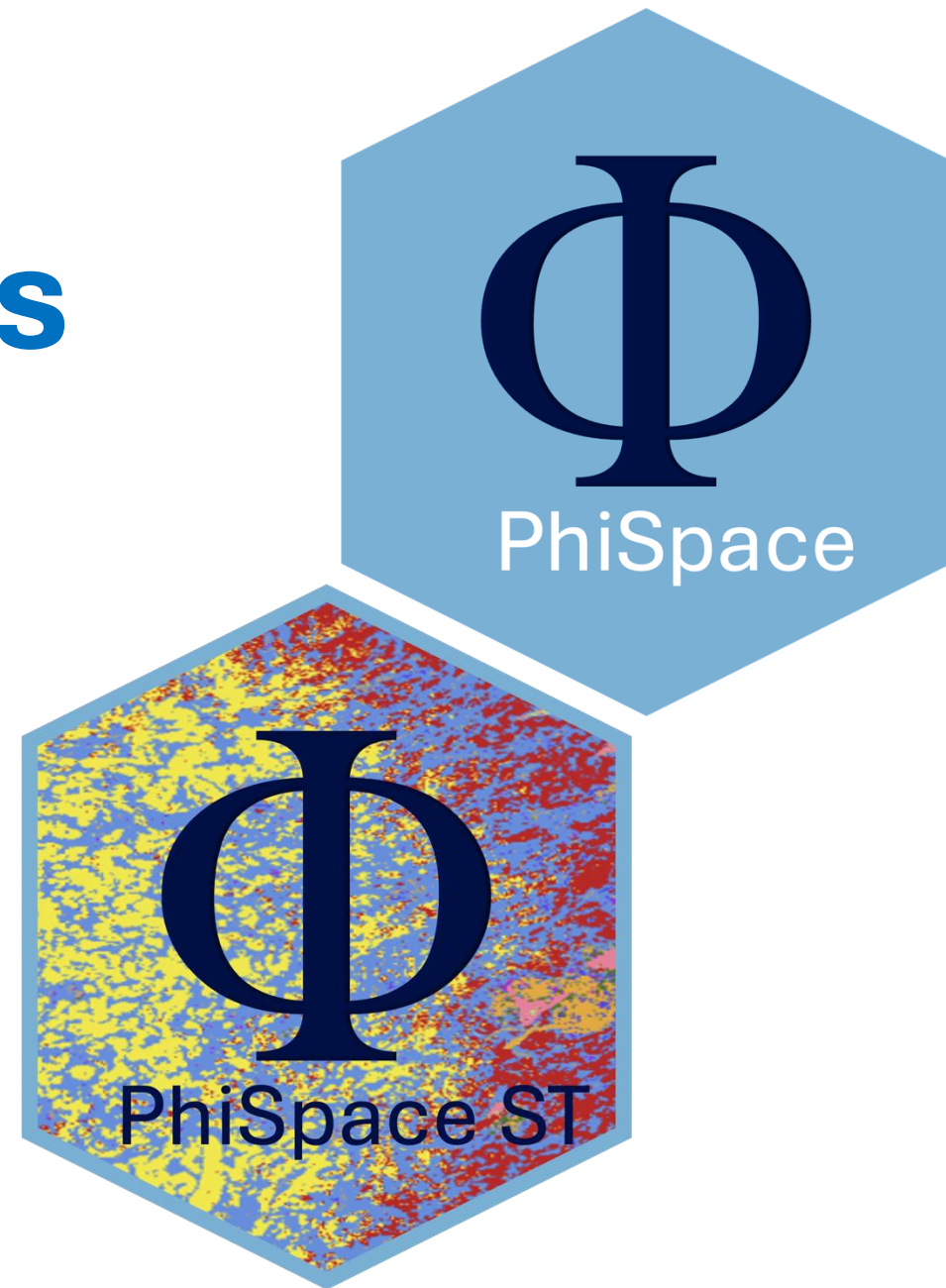
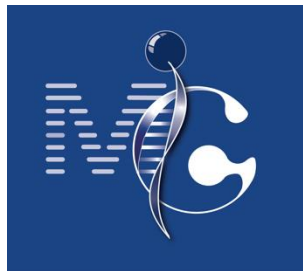
[@mig-unimelb.bsky.social](https://bsky.app/profile/mig-unimelb.bsky.social)

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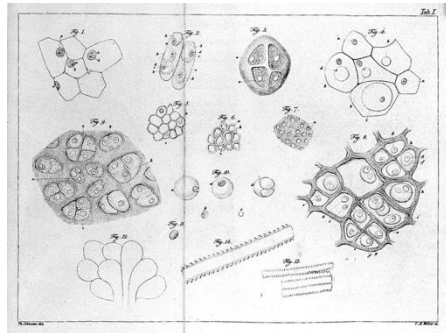
# A Tale of Two Spaces

Discovery of *spatial* biology in *phenotype space* by  
 $\Phi$ -Space ST

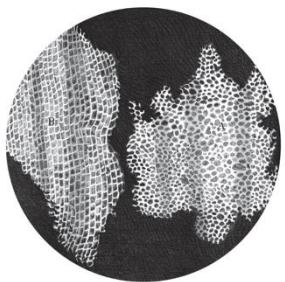
Dr Jiadong Mao  
Melbourne Integrative Genomics



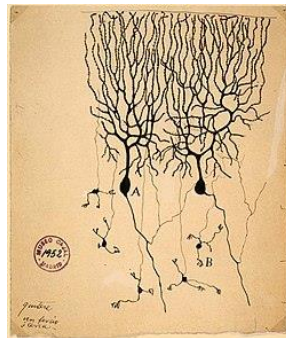
# 'Cell type'



Schwann's *Mikroskopie*, 1839, Wellcome Collection



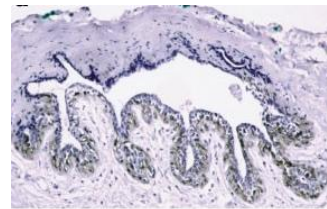
Dead cells in cork, from Hooke's *Micrographia*, 1665, Science Museum UK



Drawing of Purkinje (1787–1869) cells by Cajal (1852–1934), Wikipedia

Describe cell type by

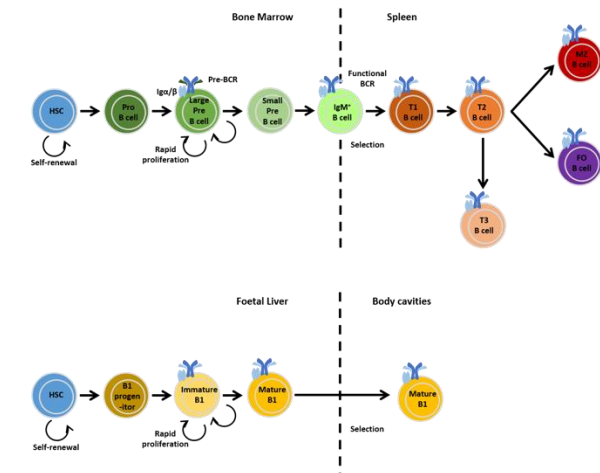
- Morphology
- function
- location



H&E staining, first introduced by Wissozky 1877, fig from Perou et al. (2000)

Describe cell type by

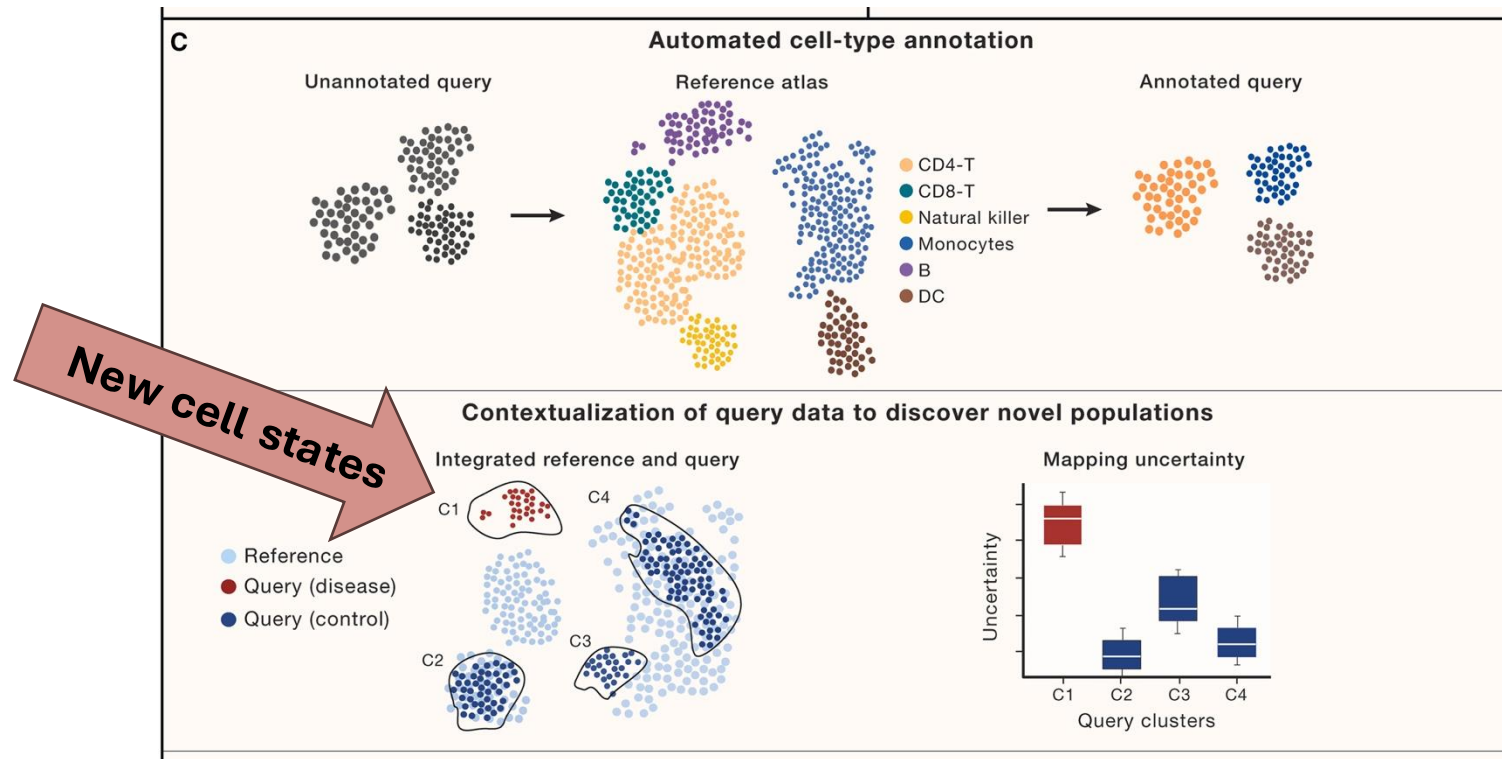
- Morphology
- function
- Location
- Gene expression
- Protein expression
- Chromatin accessibility
- Histone modification
- ...



B cells, Rebecca Newman, British Society for Immunology

# Cell type annotation using scRNA-seq

- Cell type: cells with similar gene expression profiles
- Reference based annotation
  - **Supervised:** train cell type classifier on **reference** data





# Adding spatial information

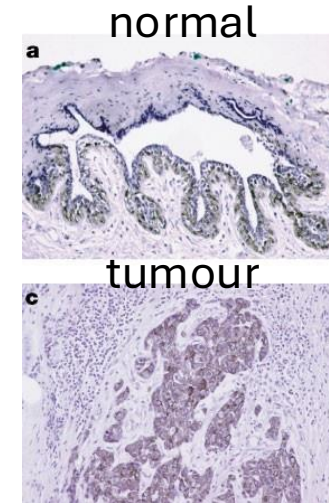
Biology has always been spatial

- 20-century tools: microscope, antibody staining
- But limited throughput (dimensionality)

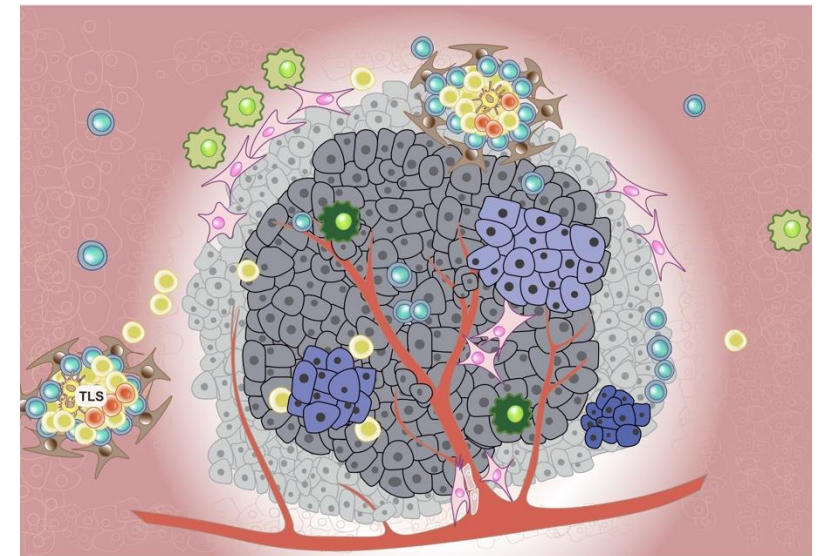
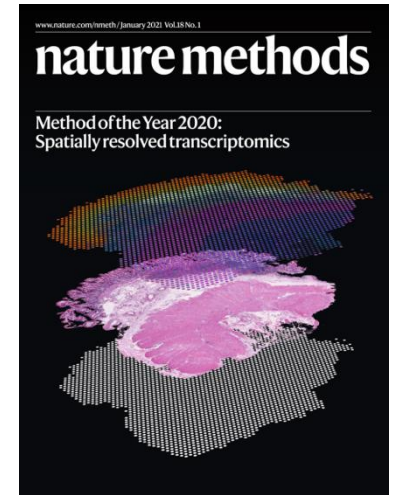
Why ST

- High-throughput measurement of RNA
- Retaining spatial locations of RNA
- scRNA-seq: which cells are doing what
- ST: which cells are doing what, and **where they are doing it**

Cell type annotation is still the key



Perou et al. (2000). *Nature*.

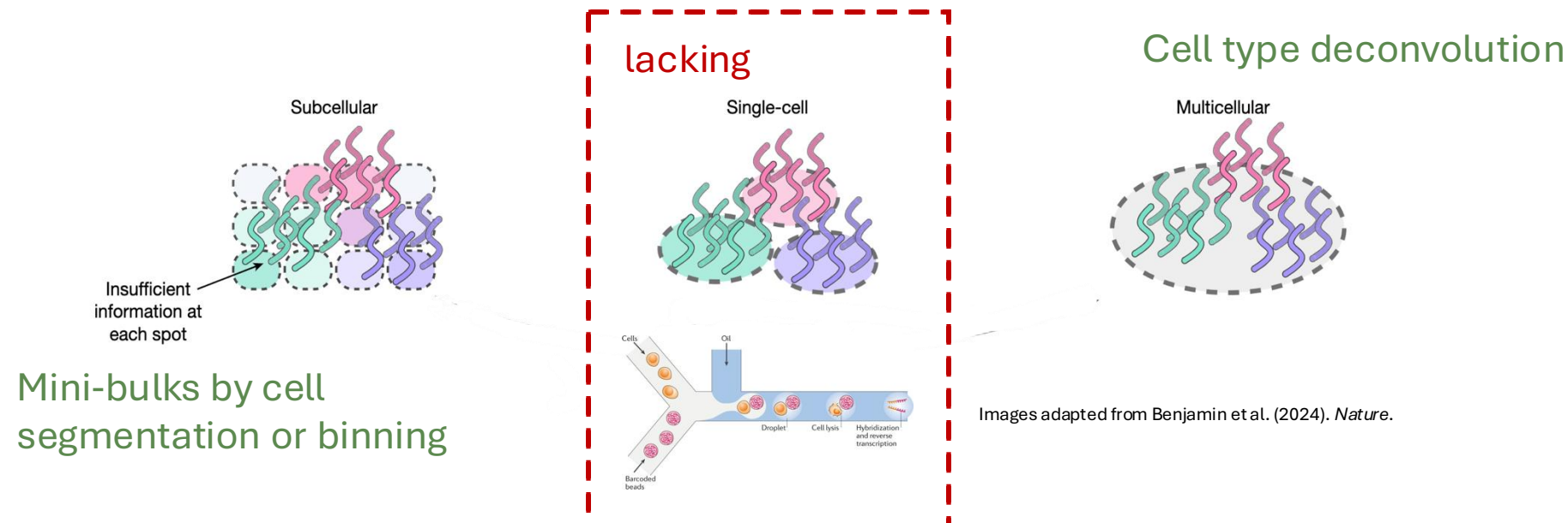


# Wait ... but what is a cell in ST?

- Fast evolving tech, different spatial resolutions
  - Super-cellular: Visium
  - Sub-cellular: Xenium, CosMx, Visium HD, Stereo-seq, ...
  - Nearly-cellular: Slide-seqV2
  - But lack of exact single cells
- Common problem: **mixture of cell identities**



<https://www.inveniagroup.com/blog/spatial-omics-technology/>



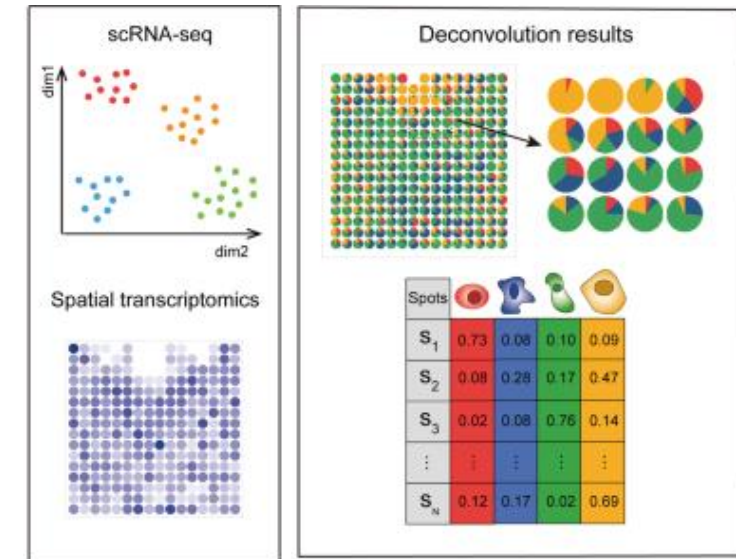
# Cell type deconvolution

## Conventional deconvolution

- Using scRNA-seq to decompose spot into cell type proportions, eg

$$1 = 0.7 \text{ CD4T} + 0.2 \text{ CD8T} + 0.1 \text{ NK}$$

- Goal: understanding spatial distribution of (known) cell types



Li et al. (2023). Nat Comms

## Φ-Space ST

- Use scRNA-seq to deconvolute every '**Cell-like objects**':  
Segmented cells, multi-cellular spots, spatial bins, ...

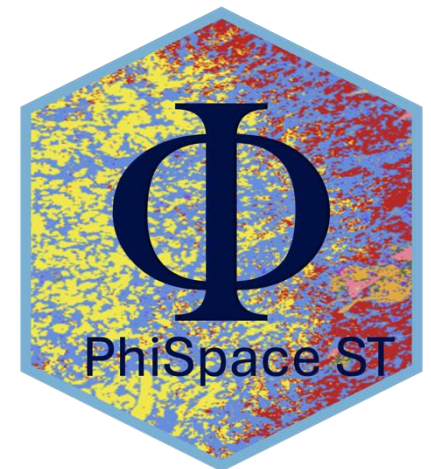
- Scoring without restriction, eg

$$1.5 = 0.8 \text{ Epithelial} + 0.5 \text{ Stem} + 0.2 \text{ Immune (tumour region)}$$

$$0.9 = 0.8 \text{ Epithelial} + 0.1 \text{ Immune (stromal region)}$$

- Goal: understanding spatial distribution of (known and unknown) **cell states**

Cell type divergence





# $\Phi$ -Space ST as unified approach

## Limitations of existing ST deconvolution methods

- Specialised in specific types of cell-like objects
- Reliance on a single reference dataset
- Specialised in well-defined cell types
- Computational efficiency 🐢
- Restrictive parametric assumptions (eg variational autoencoders)

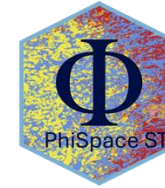
## $\Phi$ -Space ST:

- Platform-agnostic
  - Multi-reference
  - Divergent cell states
  - Very fast to compute
  - Nonparametric
- } Extension to emerging tech



$\Phi$ -Space: Continuous phenotyping of single-cell multi-omics data

Jiadong Mao<sup>1</sup>, Yidi Deng<sup>1</sup>, Kim-Anh Lê Cao<sup>1,\*</sup>



$\Phi$ -Space ST: a platform-agnostic method to identify cell states in spatial transcriptomics studies

Jiadong Mao<sup>1</sup>, Jarny Choi<sup>2,&</sup>, Kim-Anh Lê Cao<sup>1,\*,&</sup>



Capybara imitator Yidi



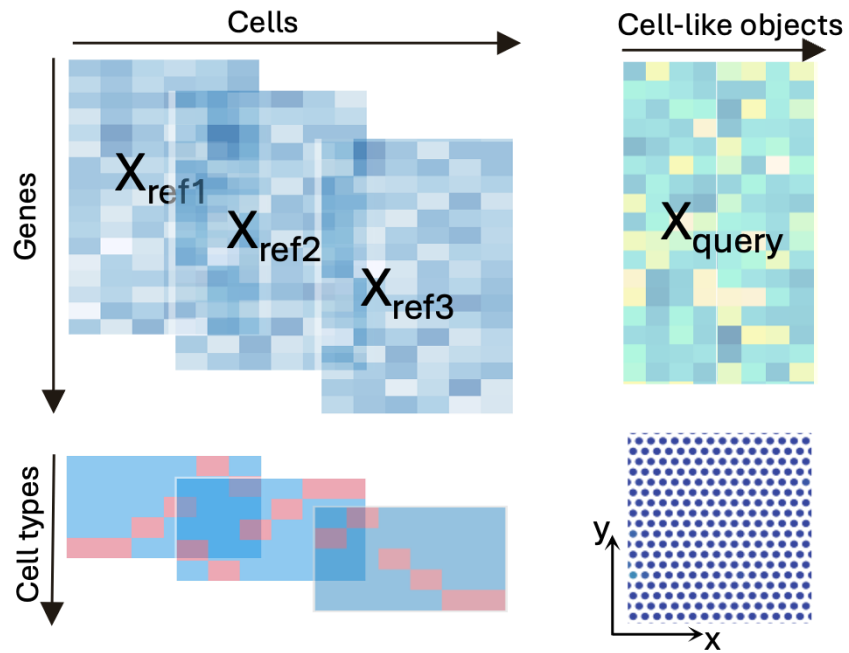
Tango dancer Jarny



Rock climber Kim-Anh

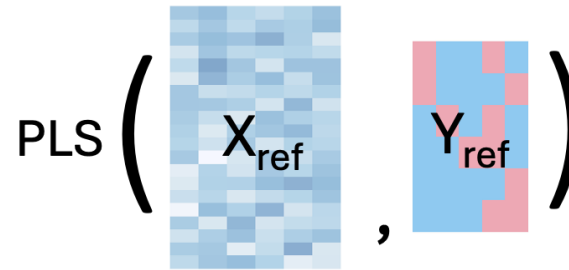


# How does it work



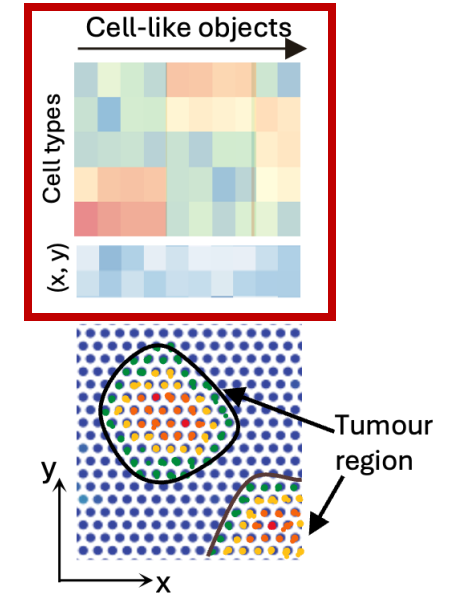
Input

- One or more annotated scRNA-seq datasets
- Query ST



Training

PLS regression (soft classification)  
model from each reference

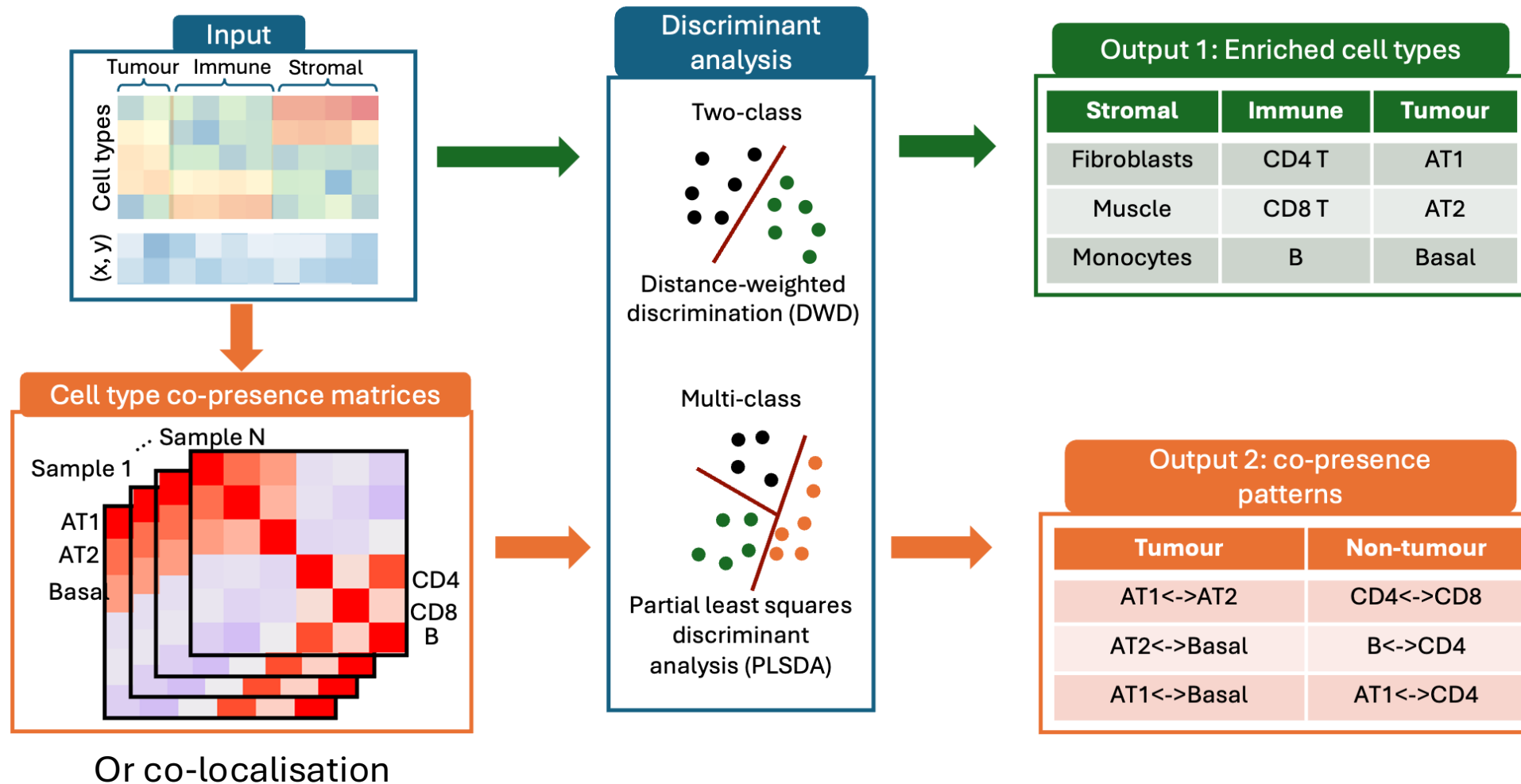


Output

‘Phenotype space embeddings’

Comparable across  
references and samples after  
*rescaling*

# Spatial biology in phenotype space



# Motivating example: Visium

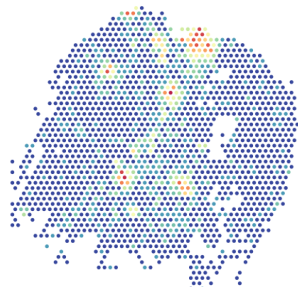
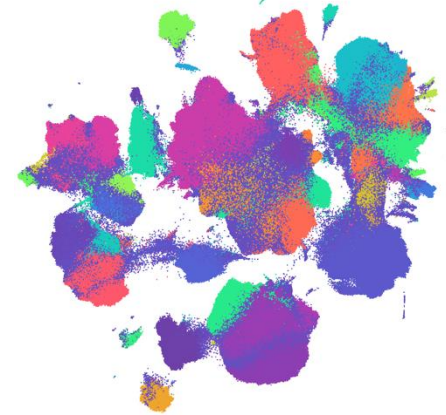
- *Platform*: 10x Visium
- *Cell like object*: spot with diameter 55 $\mu$ m
- *Sample info*: 18 healthy and cancerous lungs (NSCLC)
- *Reference*: integrated Human Lung Cell Atlas (HLCA)

## Challenges

- Interpretable deconvolution;
- Healthy reference, cancerous query

## Reference

HLCA with 61 healthy cell types



KRT19 (cancer)

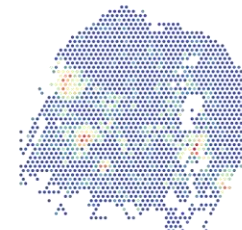


CD79A (B cell)

## Predicted B cell abundance



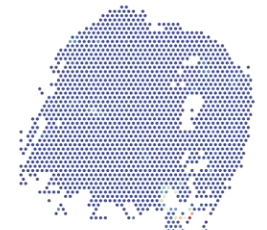
PhiSpace



RCTD



cell2location

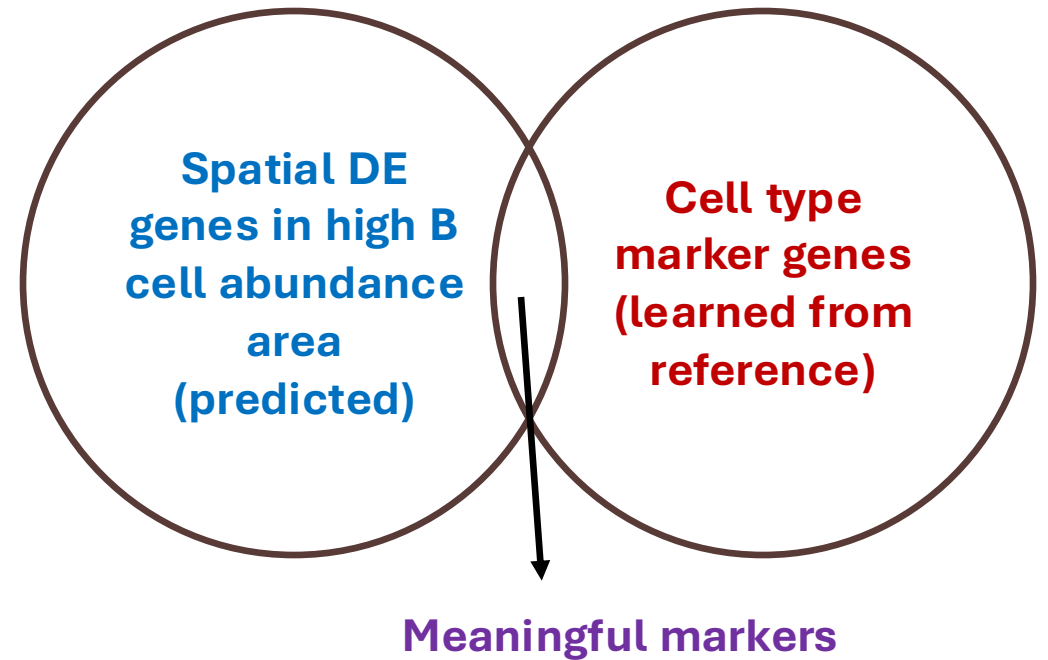


TACCO

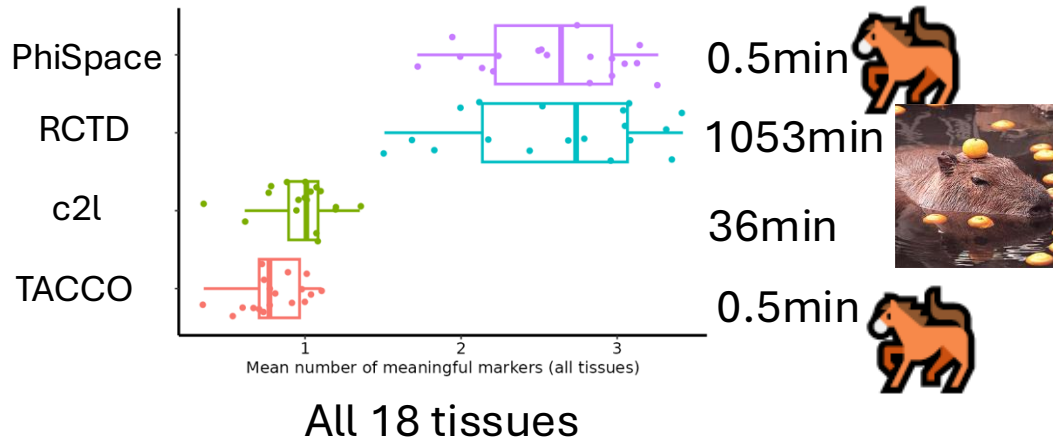
Which one should I trust?

# Meaningful markers

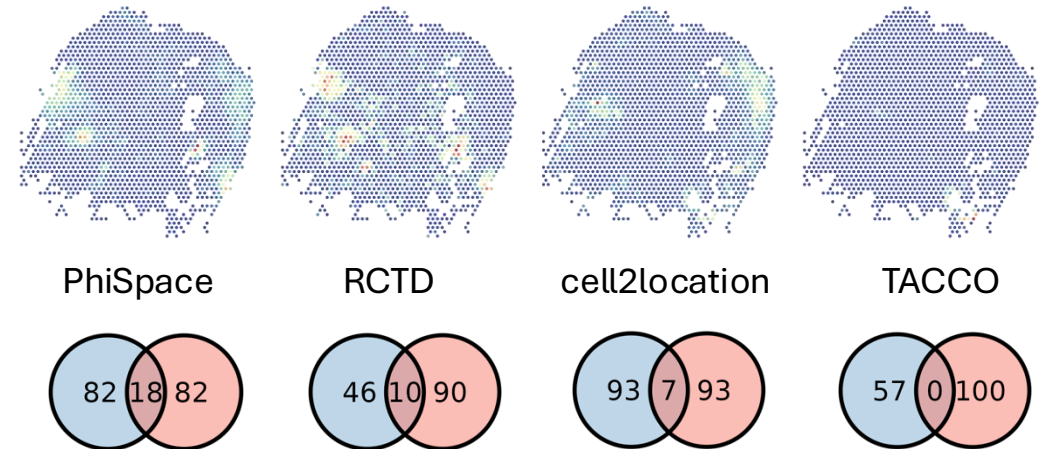
- No ground truth
- A proxy of truth:
  - If you say a spot has high B cell identity, spot should express B cell marker genes
  - ‘Meaningful markers’



$\Phi$ -Space ST annotation is **meaningful** and **fast**



Predicted B cell abundance





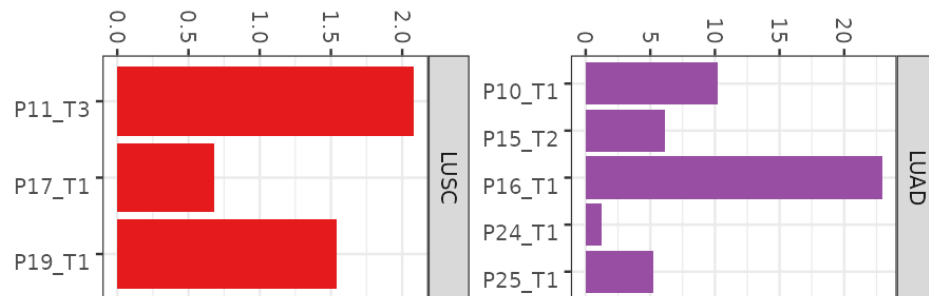
# Co-presence

18 tissues from

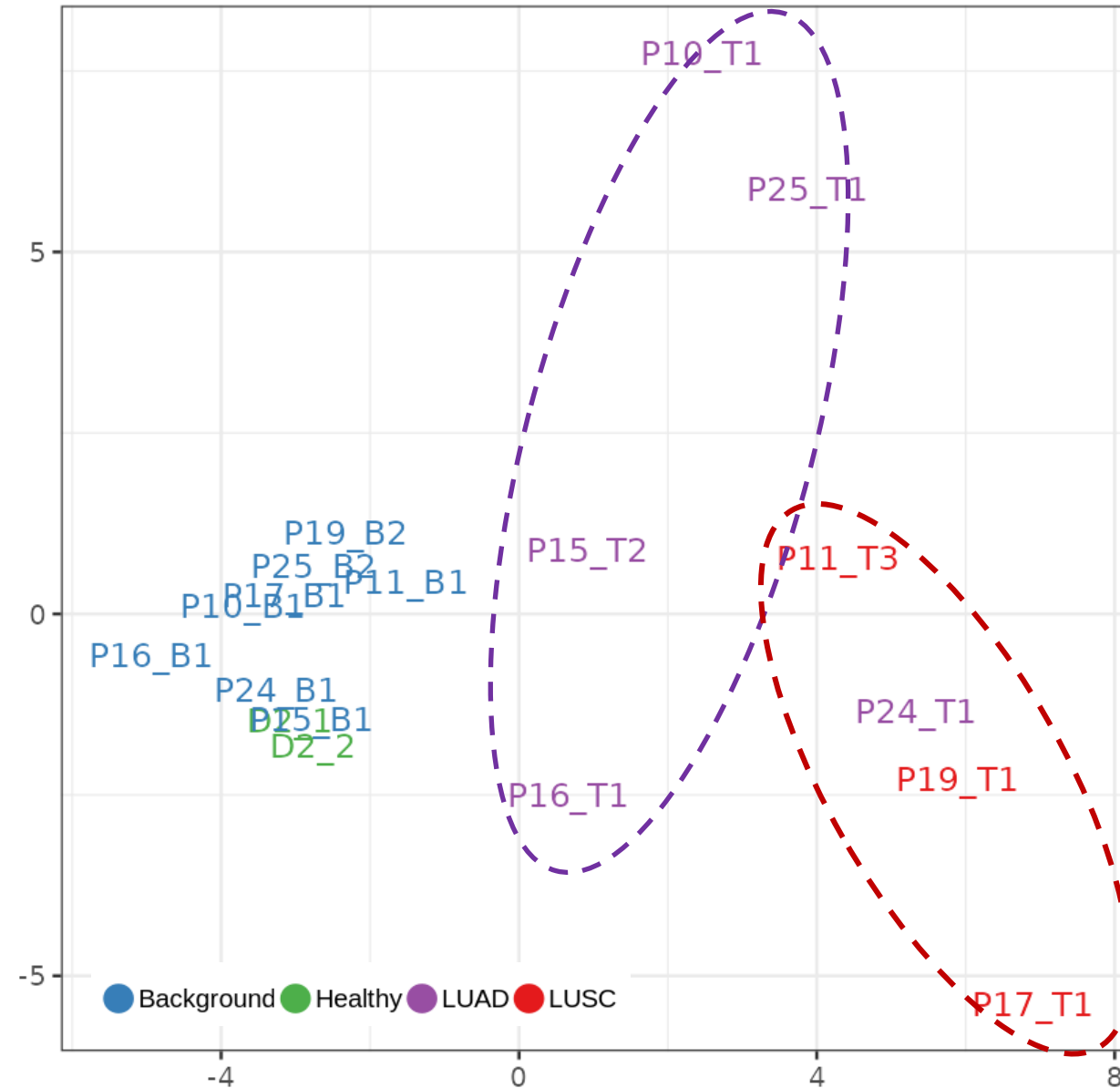
- **Healthy**: healthy donor
- **Background**: non-cancerous tissue from cancer patients
- **LUAD**: lung adenocarcinoma (better prog)
- **LUSC**: lung squamous cell carcinoma (worse prog)

Compute a co-presence matrix from each tissue.

**Favourable prognosis score**



**PCA of co-presence matrices**

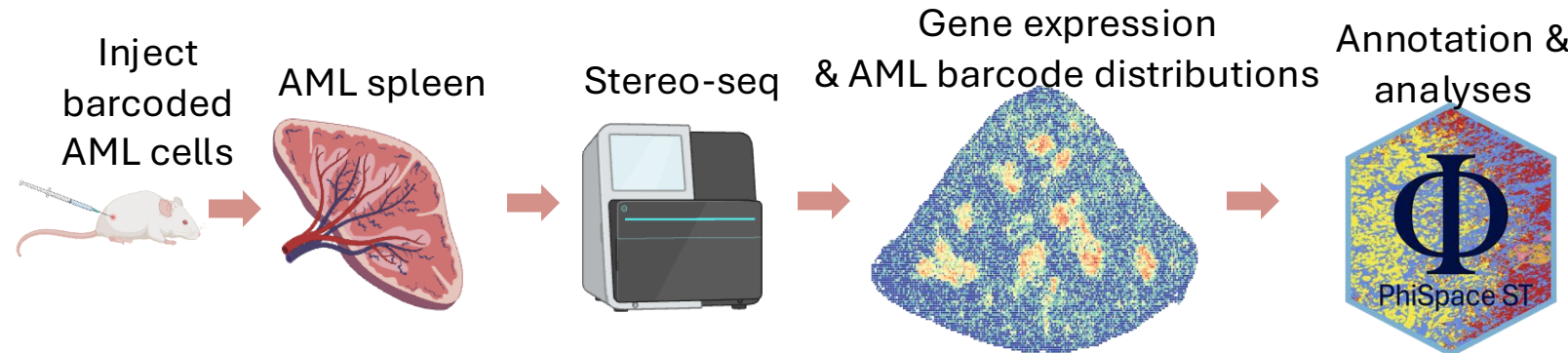


# Subcellular ST with cancer cell lineage tracing

- *Platform*: BGI Stereo-seq
- *Cell like object*: spatial bins side lengths ~25µm
- *Sample info*
  - 1 mouse spleen sample with AML cells
  - SPLINTR lineage tracing, same AML **clone** same **barcode**
- *References*: Spleen, BM, CITE, Neutro

## Challenges

- Lack of cell segmentation;
- Lack of reference atlas;
- Liquid tumour lacking structures.



Henrietta Holze



Dane Vassiliadis



Mark Dawson

## Article

### Non-genetic determinants of malignant clonal fitness at single-cell resolution

<https://doi.org/10.1038/s41586-021-04206-7>

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Katie A. Fennell<sup>1,2,3</sup>, Dane Vassiliadis<sup>1,2,3</sup>, Enid Y. N. Lam<sup>1,2</sup>, Luciano G. Marcelotto<sup>1</sup>, Jesse J. Balic<sup>1</sup>, Sebastian Holzeck<sup>1</sup>, Tom S. Weber<sup>1</sup>, Timothy Sempke<sup>1</sup>, Qing Wang<sup>1</sup>, Denise C. Milne<sup>1,2</sup>, Laura MacPherson<sup>1,2</sup>, Yu-Chih Chan<sup>1,2</sup>, Andrew A. Gillingham<sup>1,2</sup>, Lev M. Kats<sup>1,2</sup>, Emily S. Wong<sup>1</sup>, Sarah-Jane Dawson<sup>1,2,3</sup>, Shalin H. Nair<sup>1,2</sup> & Mark A. Dawson<sup>1,2,3,4</sup>✉

Cell Reports Methods

CellPress  
OPEN ACCESS

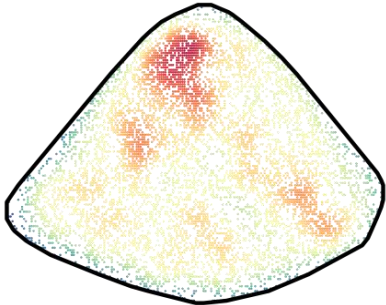
## Article

### Analysis of synthetic cellular barcodes in the genome and transcriptome with BARTab and bartools

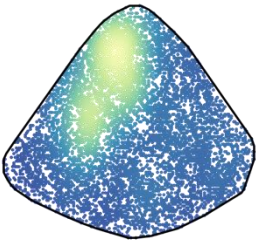
Henrietta Holze,<sup>1,2</sup> Laure Talarmin,<sup>1,2</sup> Katie A. Fennell,<sup>1,2</sup> Enid Y. N. Lam,<sup>1,2</sup> Mark A. Dawson,<sup>1,2,3,4</sup> and Dane Vassiliadis<sup>1,2,3,4</sup>✉  
<sup>1</sup>Peter MacCallum Cancer Centre, Melbourne, VIC 3000, Australia  
<sup>2</sup>Peter MacCallum Department of Oncology, The University of Melbourne, Melbourne, VIC 3000, Australia  
<sup>3</sup>The University of Melbourne Centre for Cancer Research, The University of Melbourne, Melbourne, VIC 3000, Australia  
<sup>4</sup>Lead contact  
✉Correspondence: mark.dawson@petermac.org (M.A.D.), dane.vassiliadis@petermac.org (D.V.)  
<https://doi.org/10.1016/j.crmeth.2024.100763>

# Cell states of ‘meta-clones’

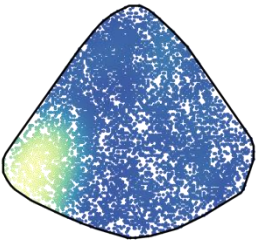
Density of all AML barcodes



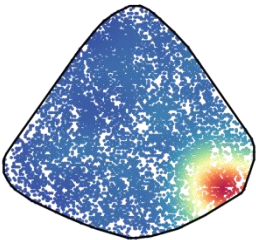
Barcode\_25



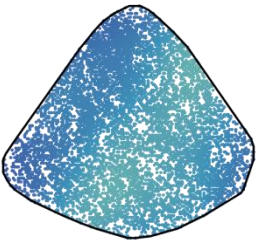
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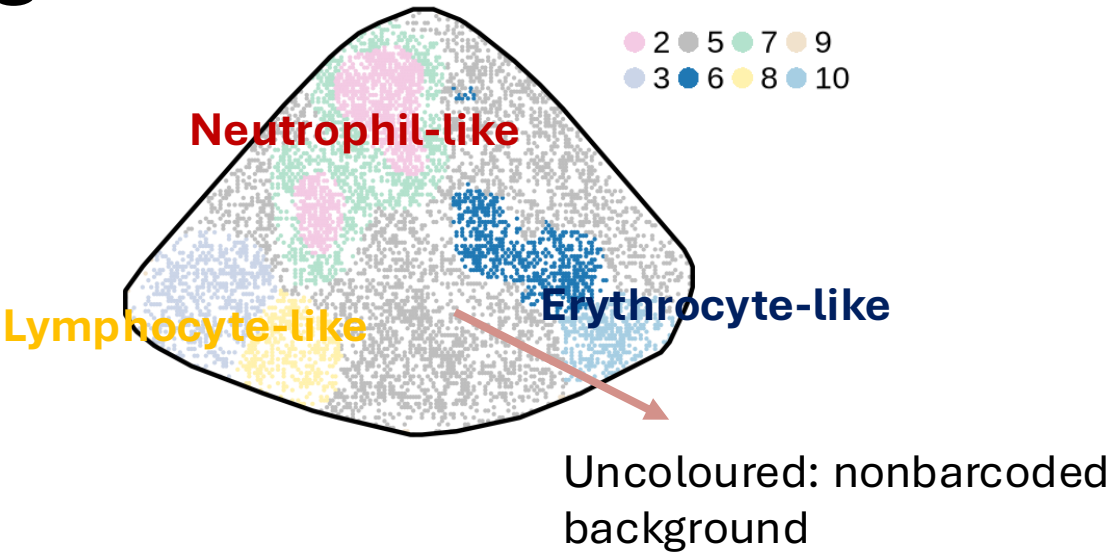
Barcode\_6595



Barcode\_19949



AML Meta-clones



Meta-clone-specific enriched cell types

	Meta-clone 2	Meta-clone 3	Meta-clone 6	Meta-clone 7	Meta-clone 8	Meta-clone 10
1	Granulo (BM)	Imm NK (BM)	RBC (CITE)	HPC (BM)	HPC (BM)	Naive B (BM)
2	Neutro (Spleen)	Trans B (Spleen)	RBC (Spleen)	IMM 1 (Neutro)	T (BM)	ProEryThBla (BM)
3	HPC (BM)	T (BM)	ErythBla (BM)	Neutro (Spleen)	Pre-B cycl (Spleen)	Pre-B cycl (Spleen)
4	T1 (Neutro)	MAT 3 (Neutro)	ProEryThBla (BM)	Pre-B cycl (Spleen)	Imm NK (BM)	ICOS+ Tregs (CITE)
5	Imm NK (BM)	CD8 T (Spleen)	IMM 2 (Neutro)	Pre-B (BM)	Pre-B (BM)	CD4 T (CITE)

# Discussion

- $\Phi$ -Space ST goes beyond single sample
- Cell segmentation can be skipped for some questions: try segmentation-free methods!
- $\Phi$ -Space is a simple and robust method for evolving technologies
  - Bulk RNA-seq
  - scRNA-seq
  - Single-cell multiomics
  - Spatial transcriptomics
  - Spatial multiomics?
  - Spatial developmental trajectories?
  - ...

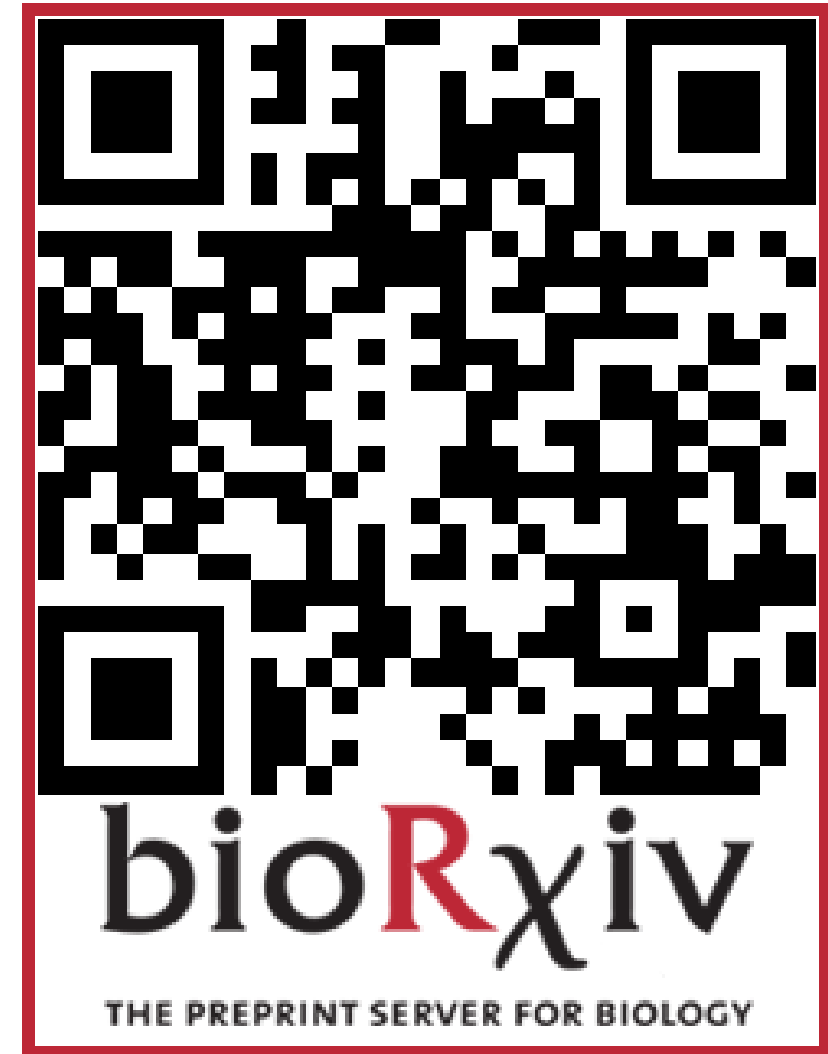
ance. In short, we shall have to treat ~~species~~ <sup>cells</sup> in the same manner as those naturalists treat genera, who admit that genera are merely artificial combinations made for convenience. This may not be a cheering

Darwin, *Origin of Species*, 1859, p 485



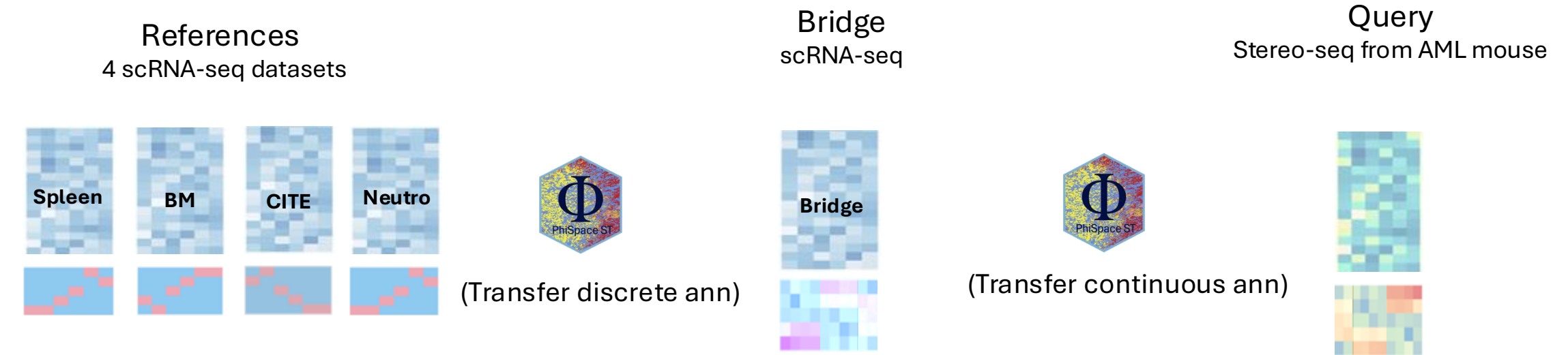
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# Questions



Mao, J., Choi, J., & Le Cao, K.-A. (2025).  *$\Phi$ -Space ST: a platform-agnostic method to identify cell states in spatial transcriptomics studies.* bioRxiv.

# Supp: Multi-reference bridging



- Spleen: mouse spleen
- BM: mouse bone marrow
- CITE: CITE-seq mouse spleen
- Neutro: mouse neutrophils

From same AML mouse spleen

# Supp: Co-presence results for Visium

Role of fibroblasts  
highlighted

