

Spatial transcriptomics 1

- Why spatial transcriptomics?



Bulk

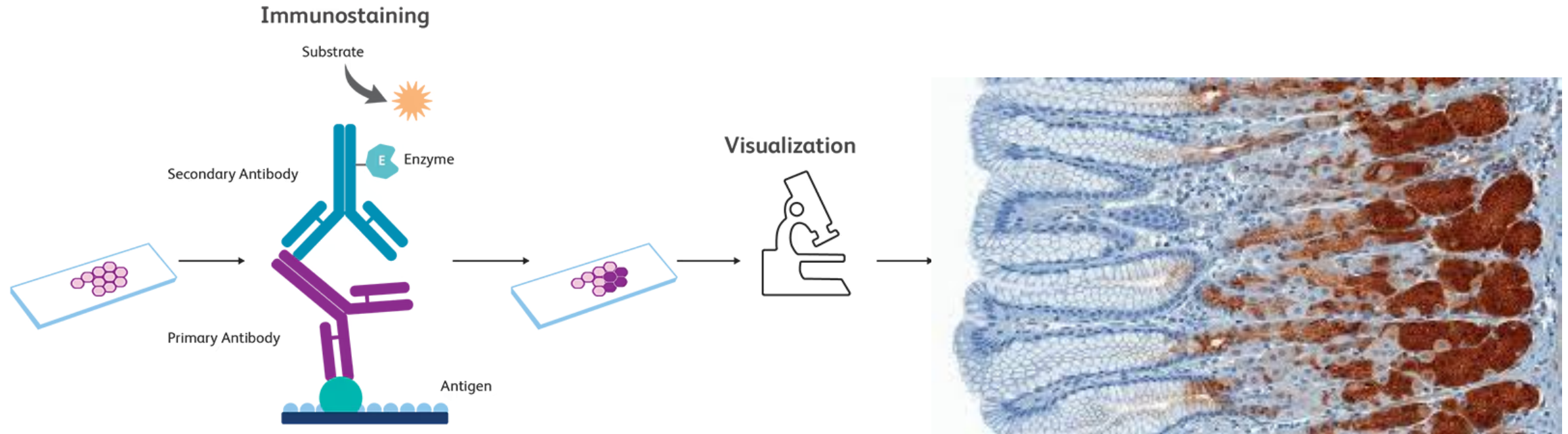


Single Cell



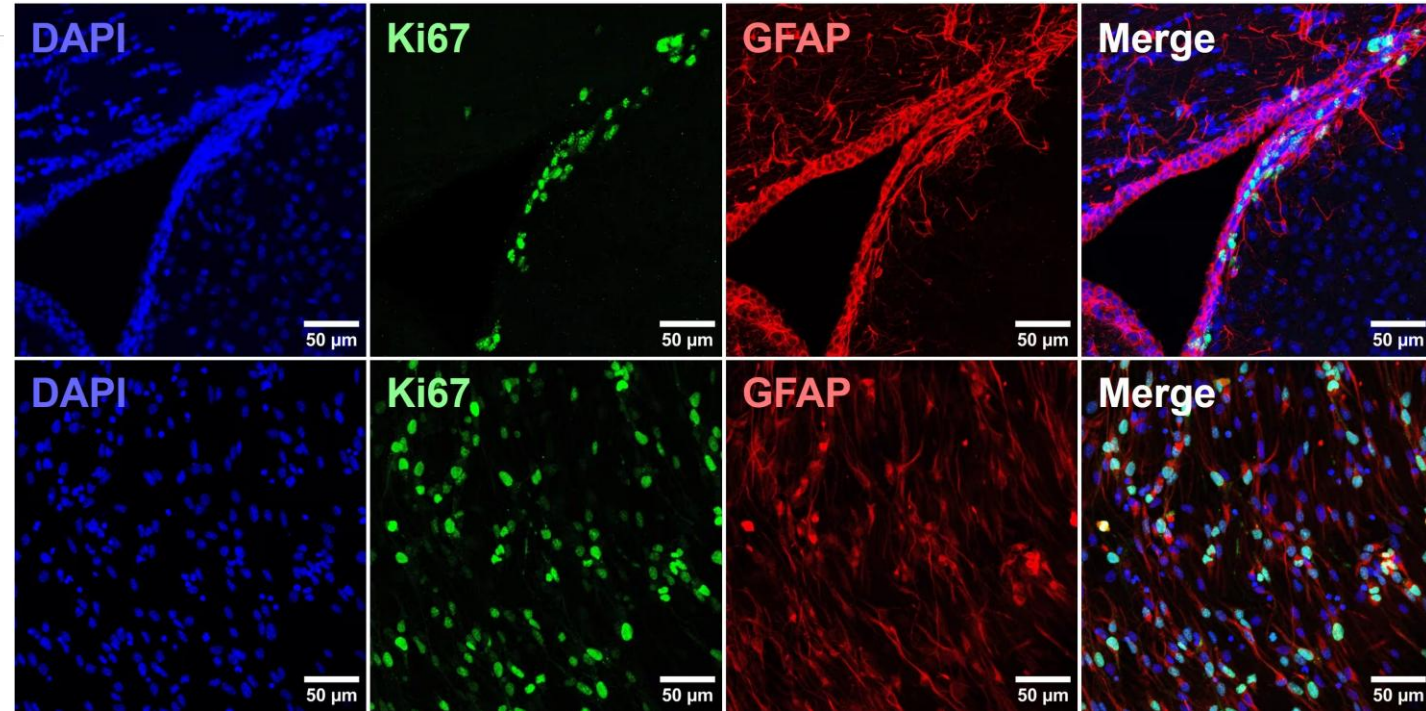
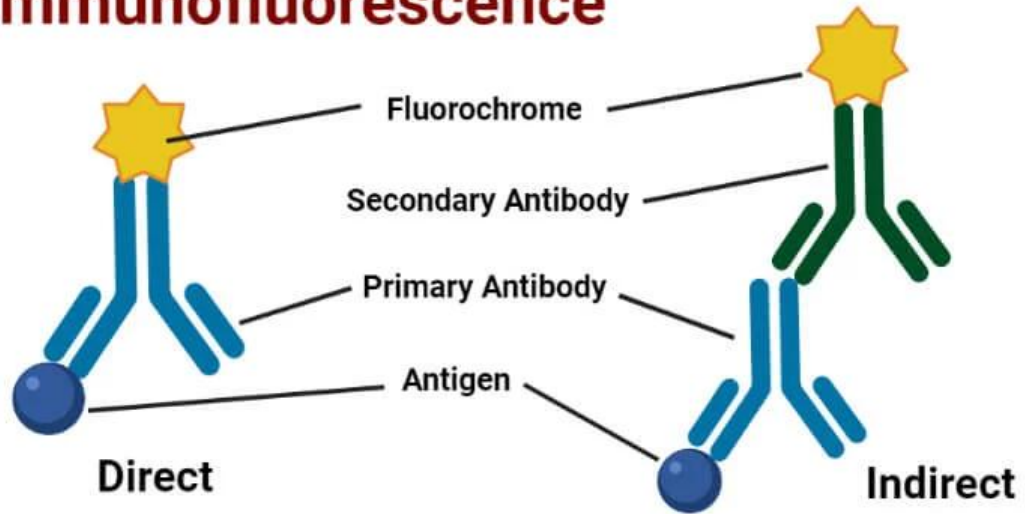
Spatial

- Previous method
- Immunohistochemistry



- Previous method
- ImmunoFluorescence

Immunofluorescence

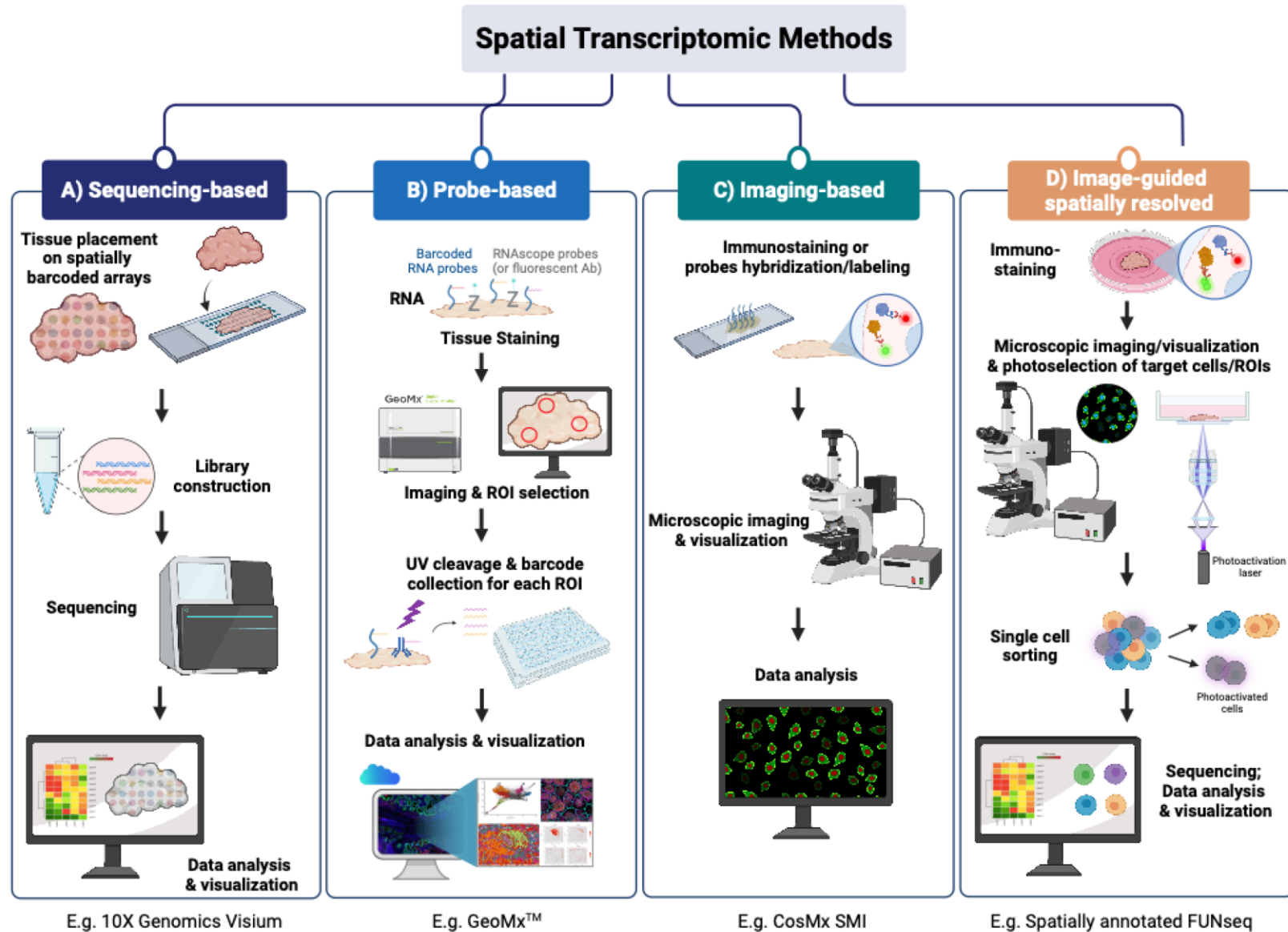


- Previous method

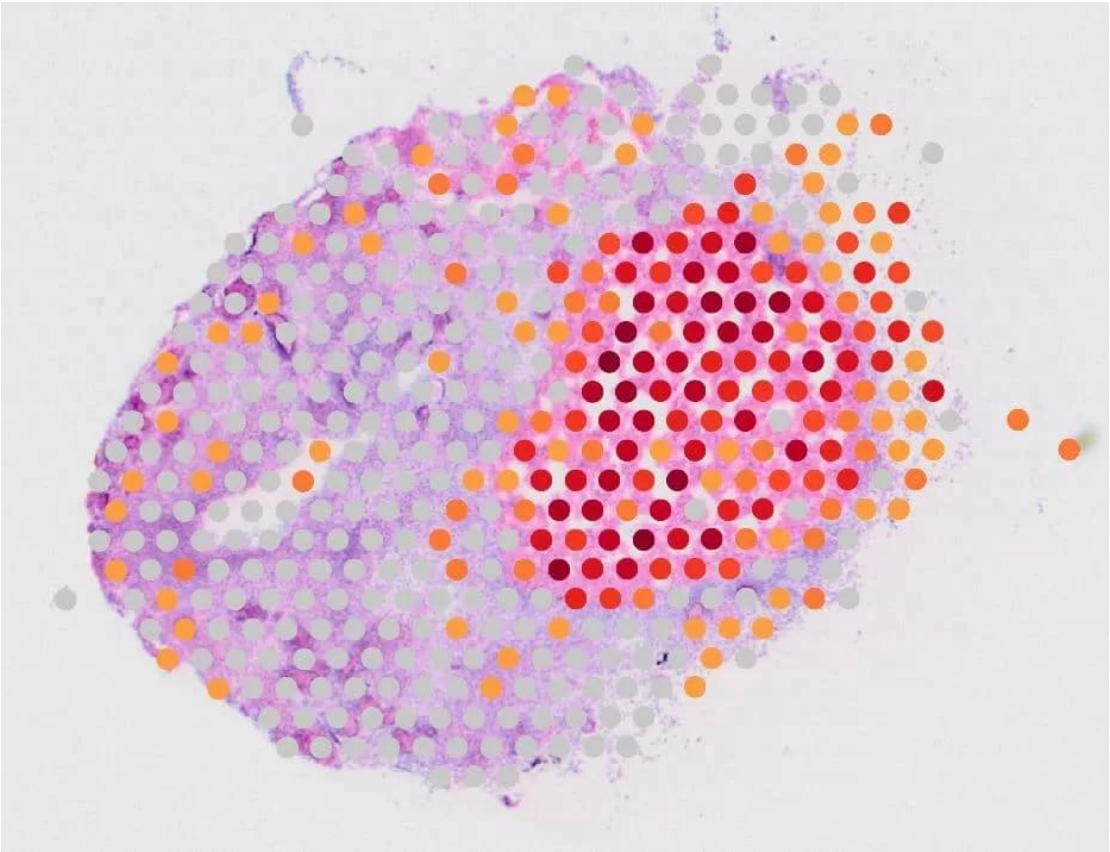
-IHC vs IF

Feature	Immunofluorescence (IF)	Immunohistochemistry (IHC)
Visualization	Fluorescence microscope	Light microscope
Detection	Fluorescent dyes	Enzyme-substrate reaction
Sensitivity	Generally higher	Generally lower
Multiplexing	Easier	More challenging
Equipment	Specialized	Standard

- Various techniques



- Spot-based spatial transcriptomics
 - Visium (10x), GeoMx (NanoString)



Geometric



Segmentation



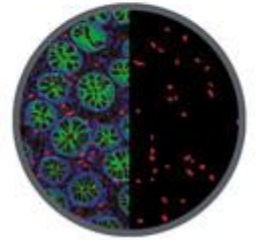
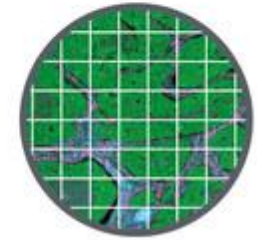
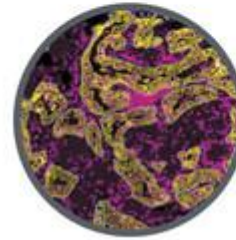
Contour



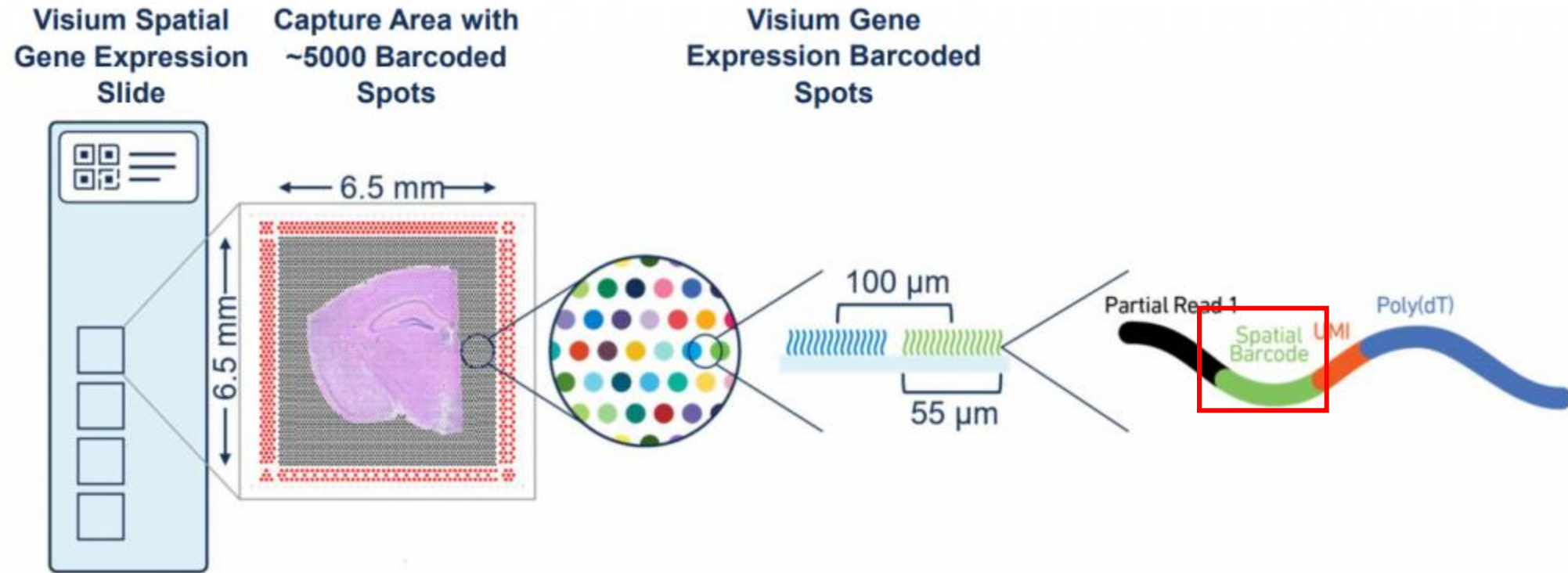
Gridded



Cell-Type Specific

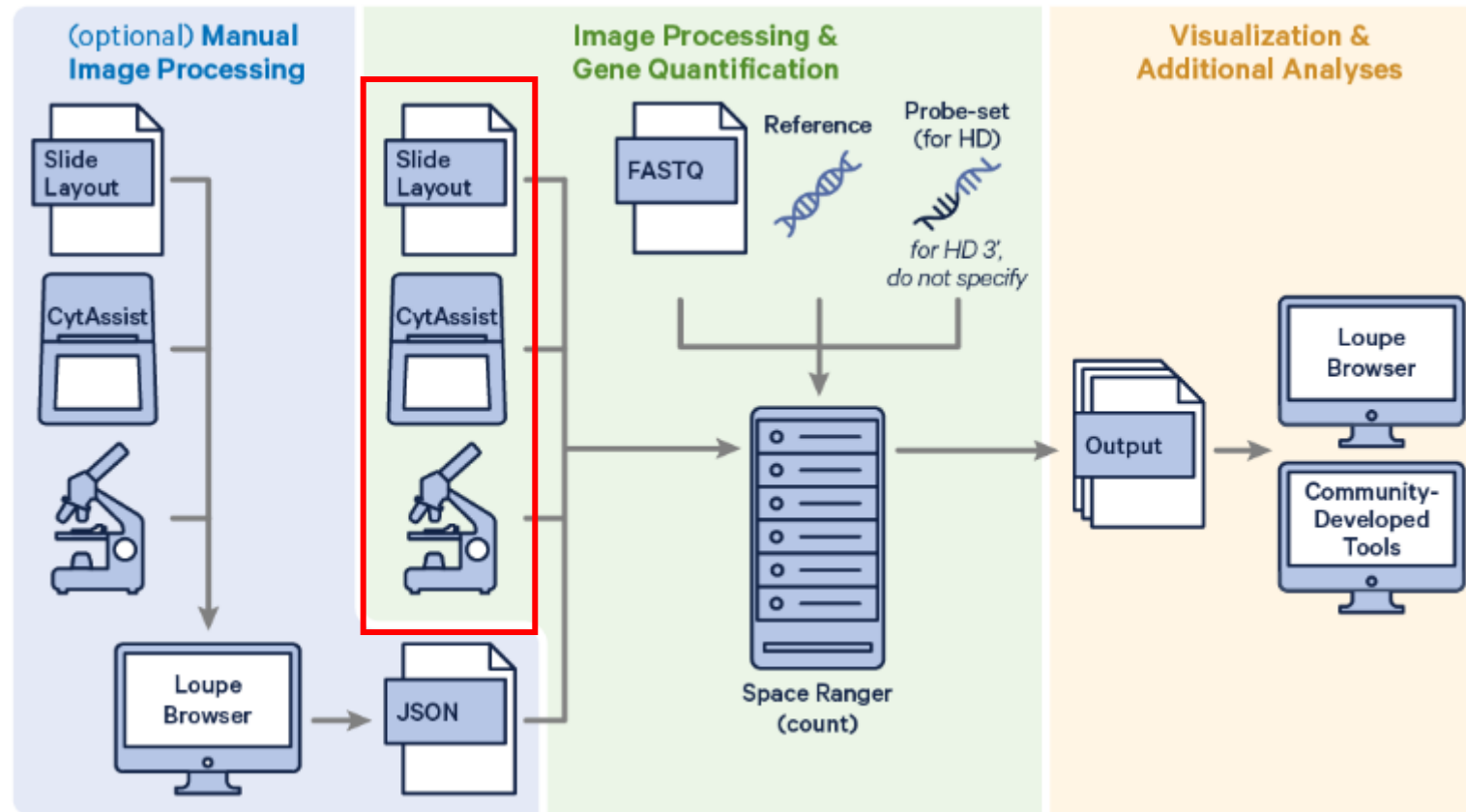


- Visium



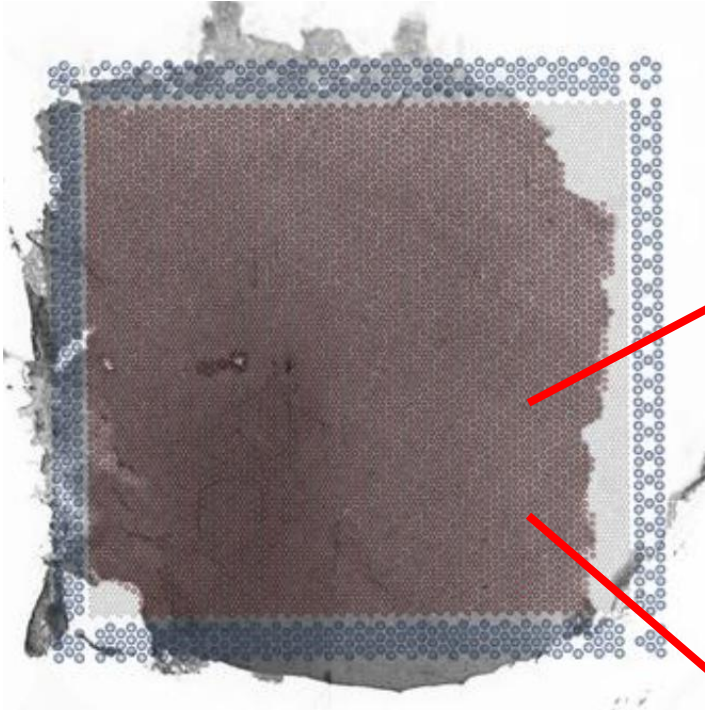
-Spatial barcode on each spot → instead of cell barcode, we could detect each spot (spatial location)
Center – center: 100 μm

- Visium

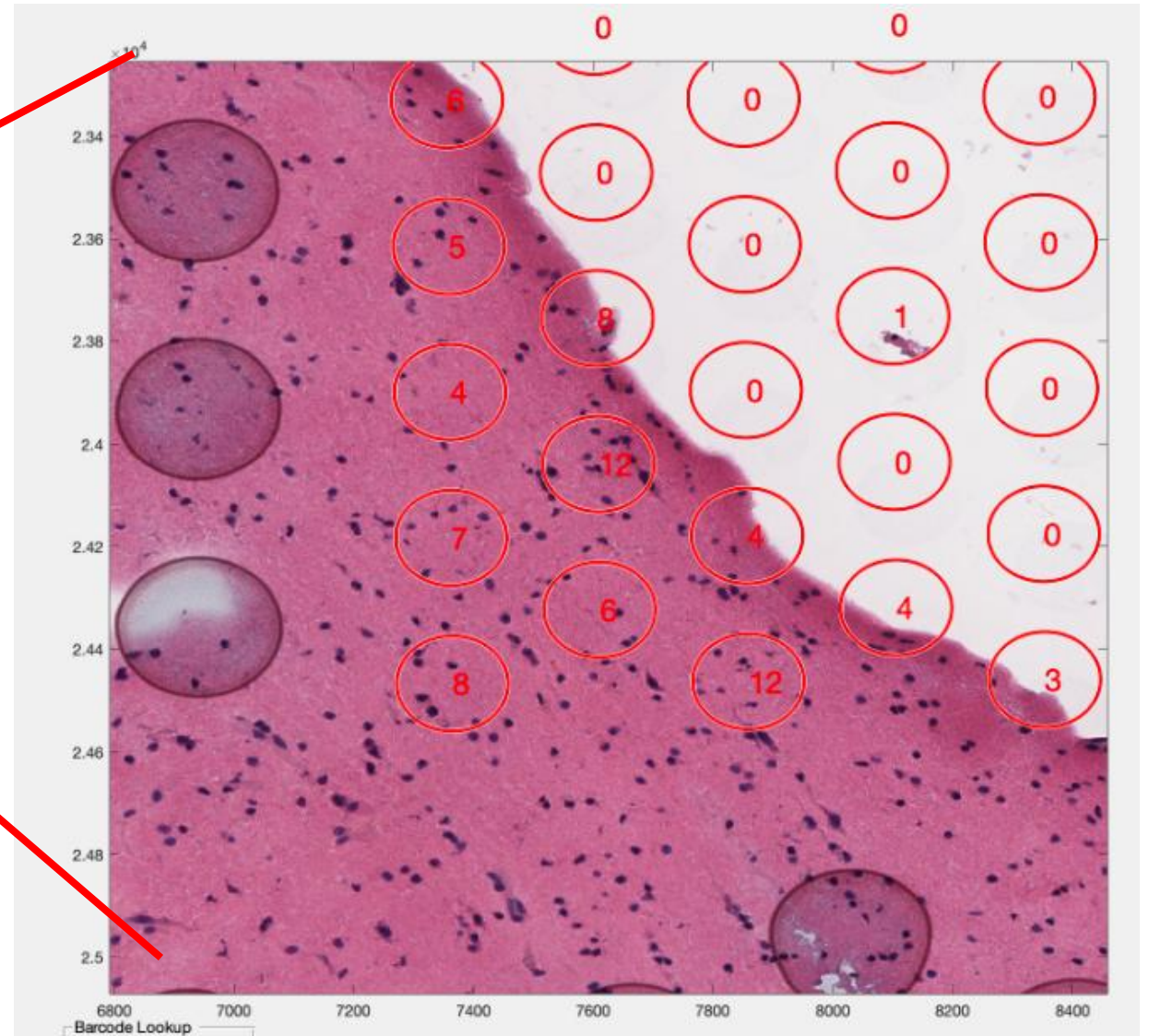


- Spatial data require **spatial images** for processing
- spaceranger count
- Count matrix (same as scRNA-seq) + spatial information

- Visium

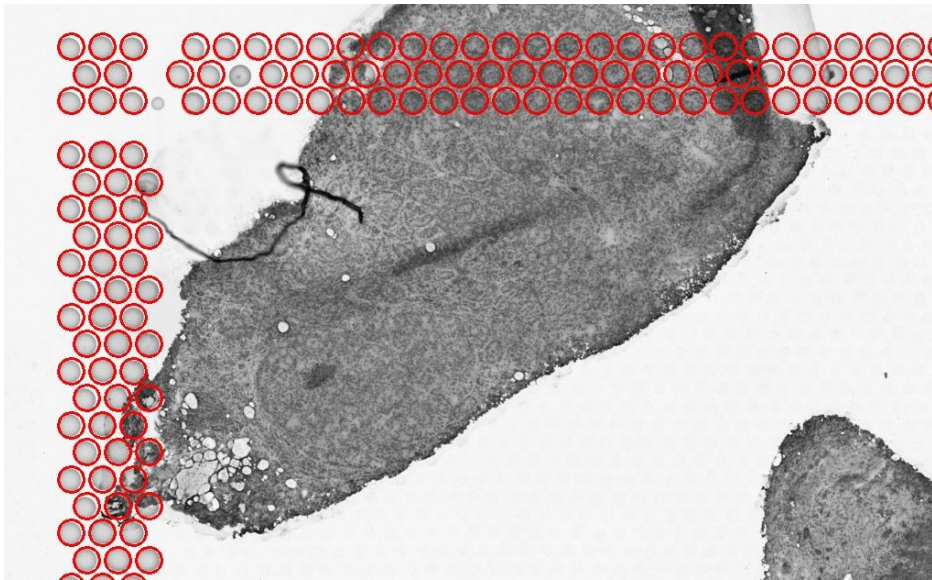


- Depends on the tissue size
- Usually, overlay with H&E results

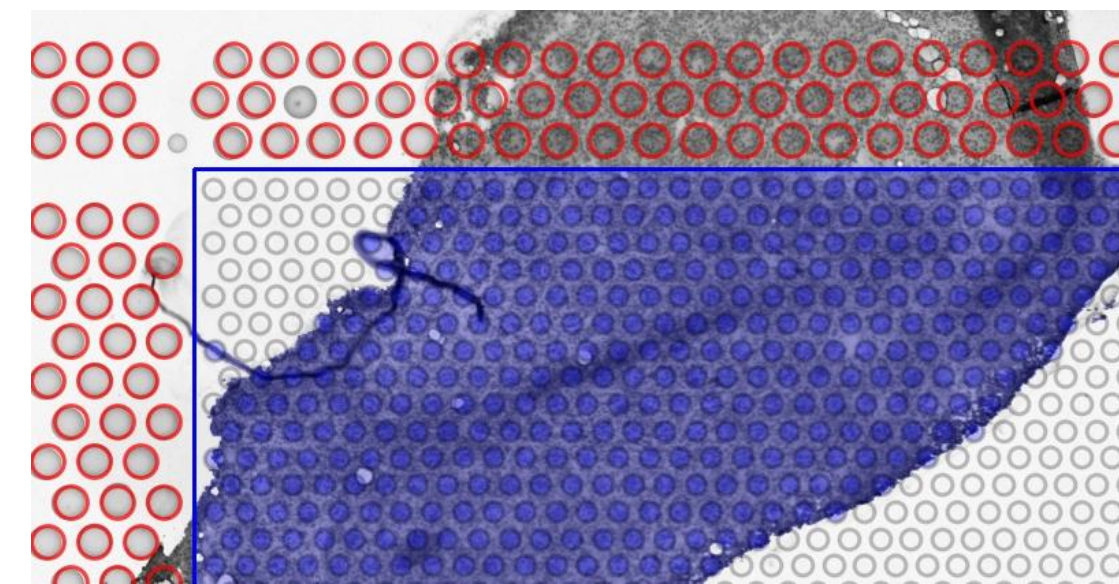


- Visium

- Aligned_fiducial: bullet point of the imaging focusing → boundary of the sample



- Detected_tissue_image → detected spots

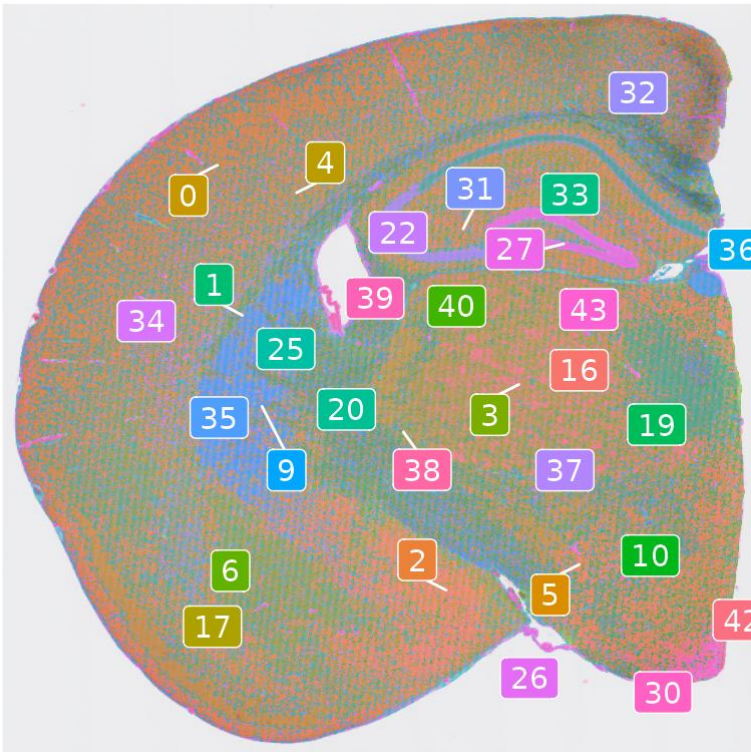


- Tissue_image: H&E staining
(high or low resolution)



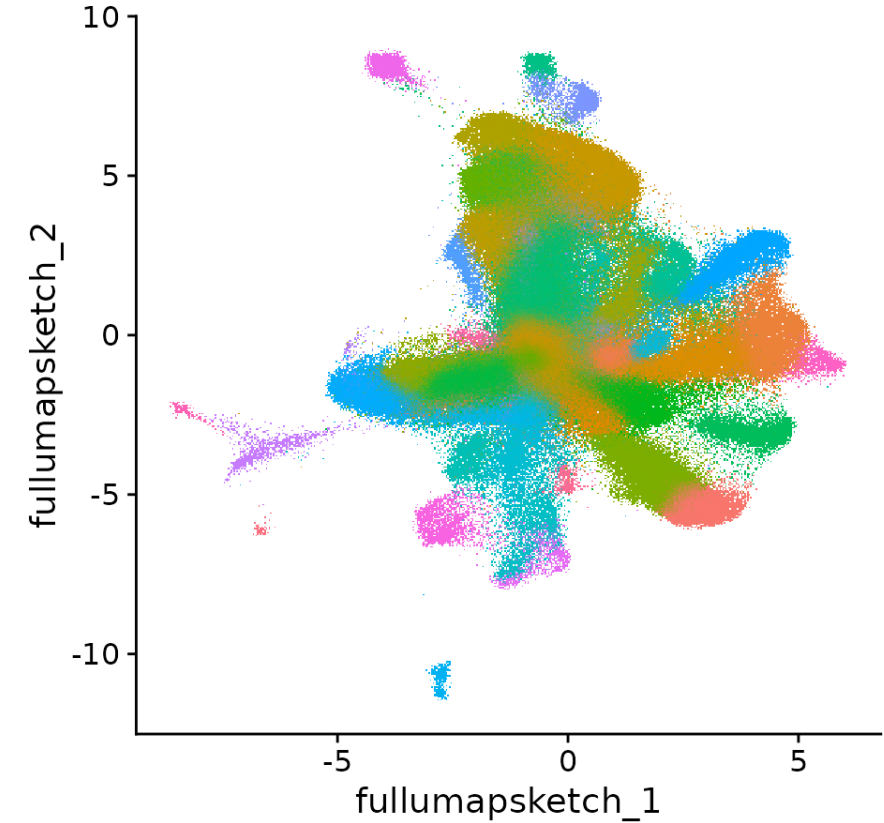
• Visium (Data processing)

- Normalization (log-norm) or SCTransform
- FindVariableFeatures
- ScaleData
- PCA, neighbor graph, clustering, UMAP ...



ident		
• 16	• 14	• 31
• 23	• 19	• 32
• 2	• 1	• 37
• 12	• 33	• 22
• 5	• 20	• 34
• 8	• 25	• 26
• 0	• 29	• 27
• 4	• 15	• 21
• 17	• 13	• 43
• 7	• 28	• 30
• 18	• 24	• 39
• 3	• 36	• 38
• 6	• 11	• 41
• 40	• 9	• 42
• 10	• 35	

Projected clustering (full dataset)



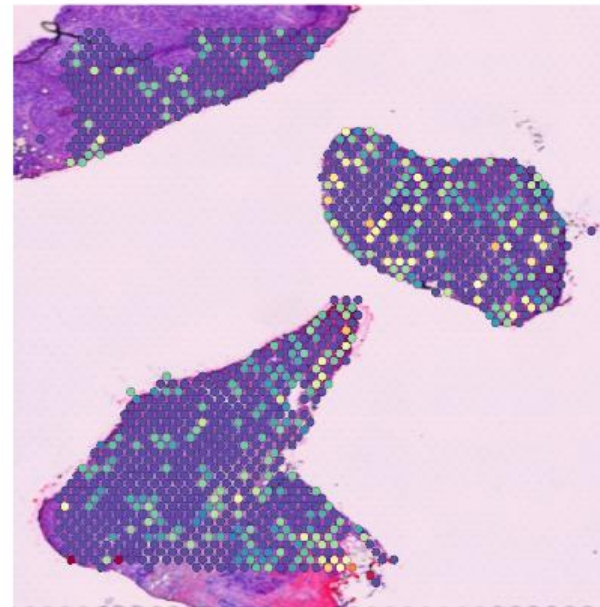
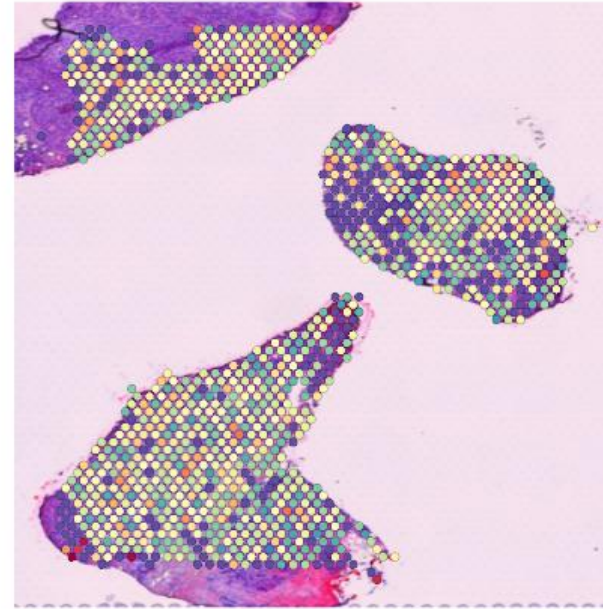
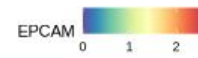
• 16	• 7	• 33	• 11	• 27
• 23	• 18	• 20	• 9	• 21
• 2	• 3	• 25	• 35	• 43
• 12	• 6	• 29	• 31	• 30
• 5	• 40	• 15	• 32	• 39
• 8	• 10	• 13	• 37	• 38
• 0	• 14	• 28	• 22	• 41
• 4	• 19	• 24	• 34	• 42
• 17	• 1	• 36	• 26	

- Visium (Data processing)

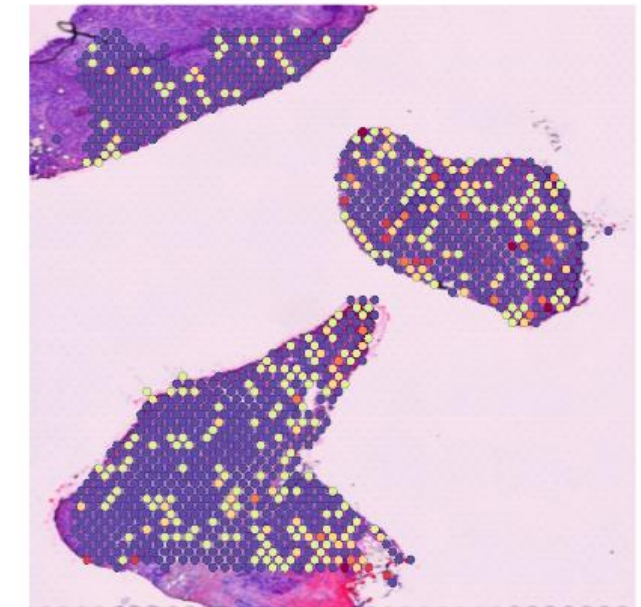
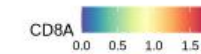
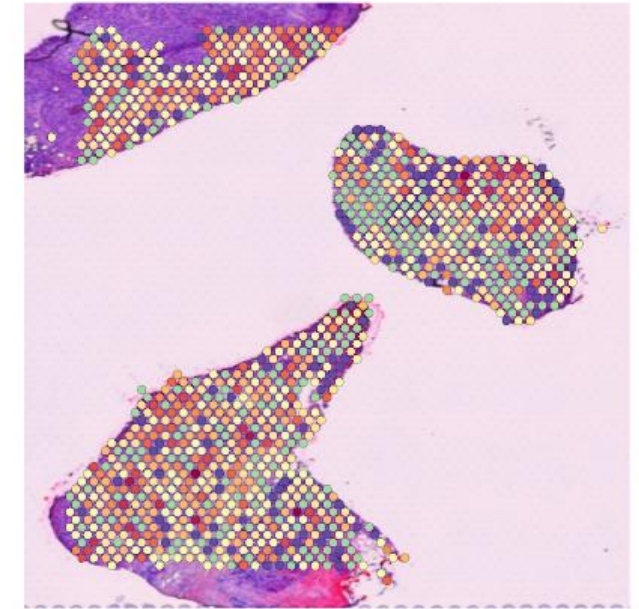
Log norm vs SCTransform

→ SCTransform make low signal → high
(higher sensitivity)

Log-norm



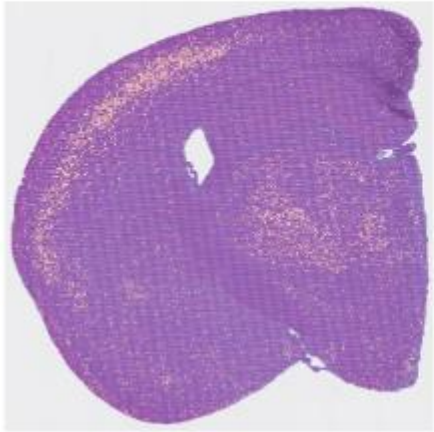
SCT



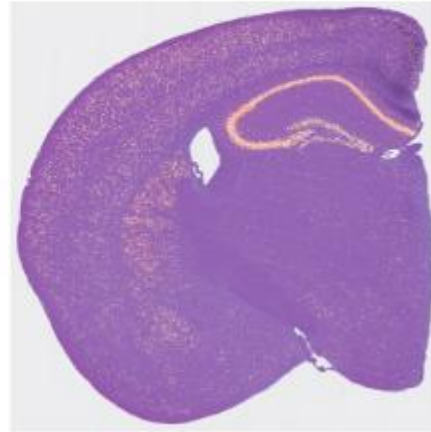
- Visium (Data processing)

-SpatialFeaturePlot

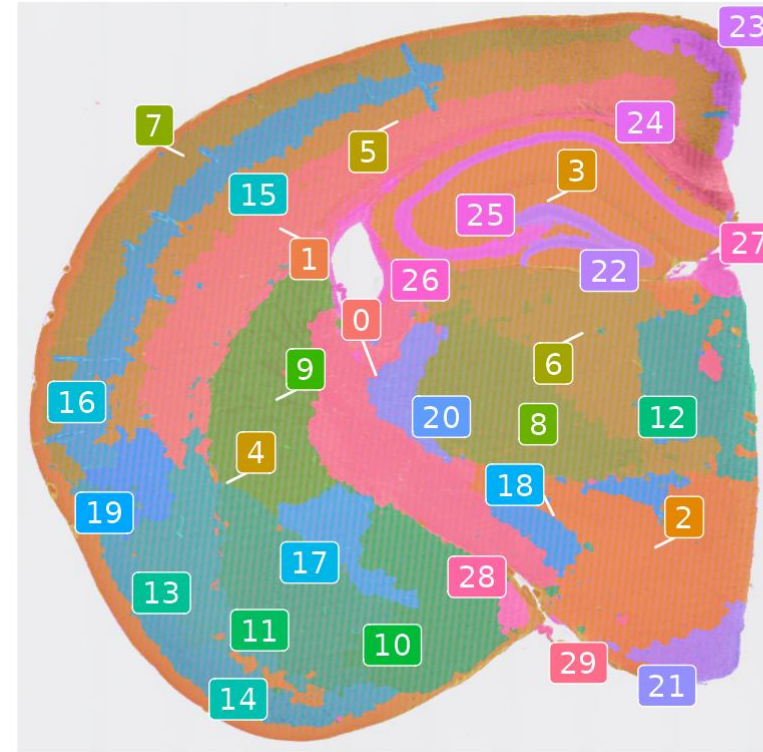
Rorb expression (16um)



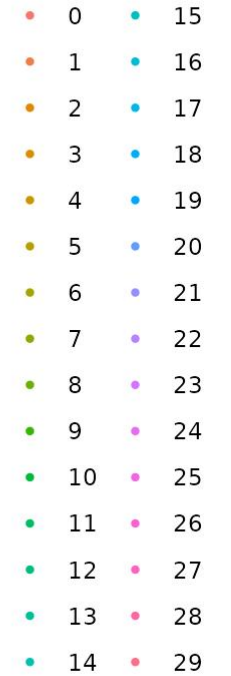
Hpca expression (8um)



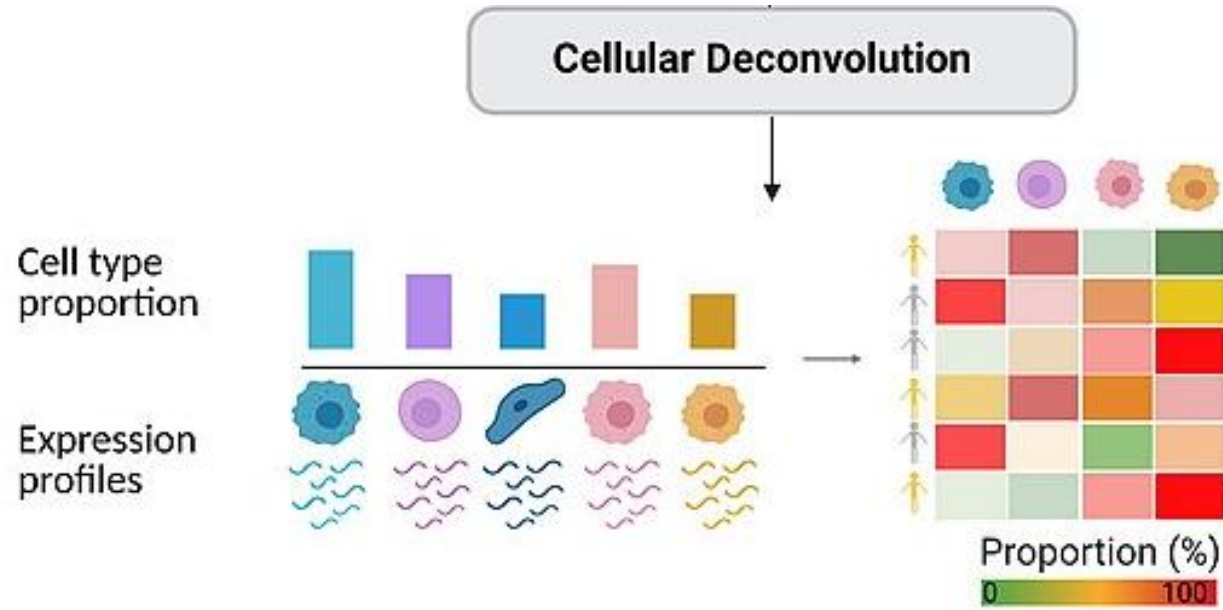
-Spatialcluster



banksy_cluster



- Visium (Deconvolution)

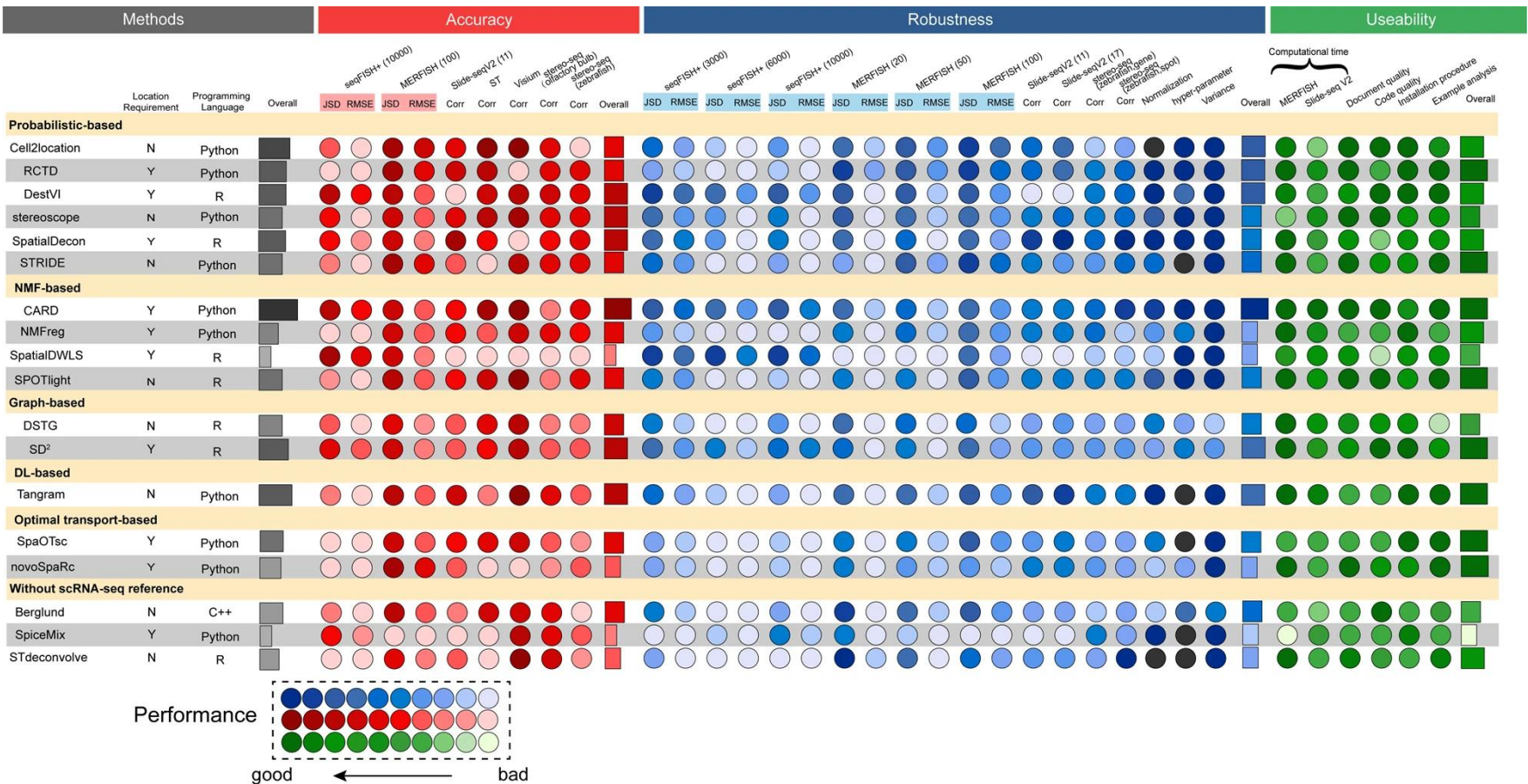


Spatial data for each spot

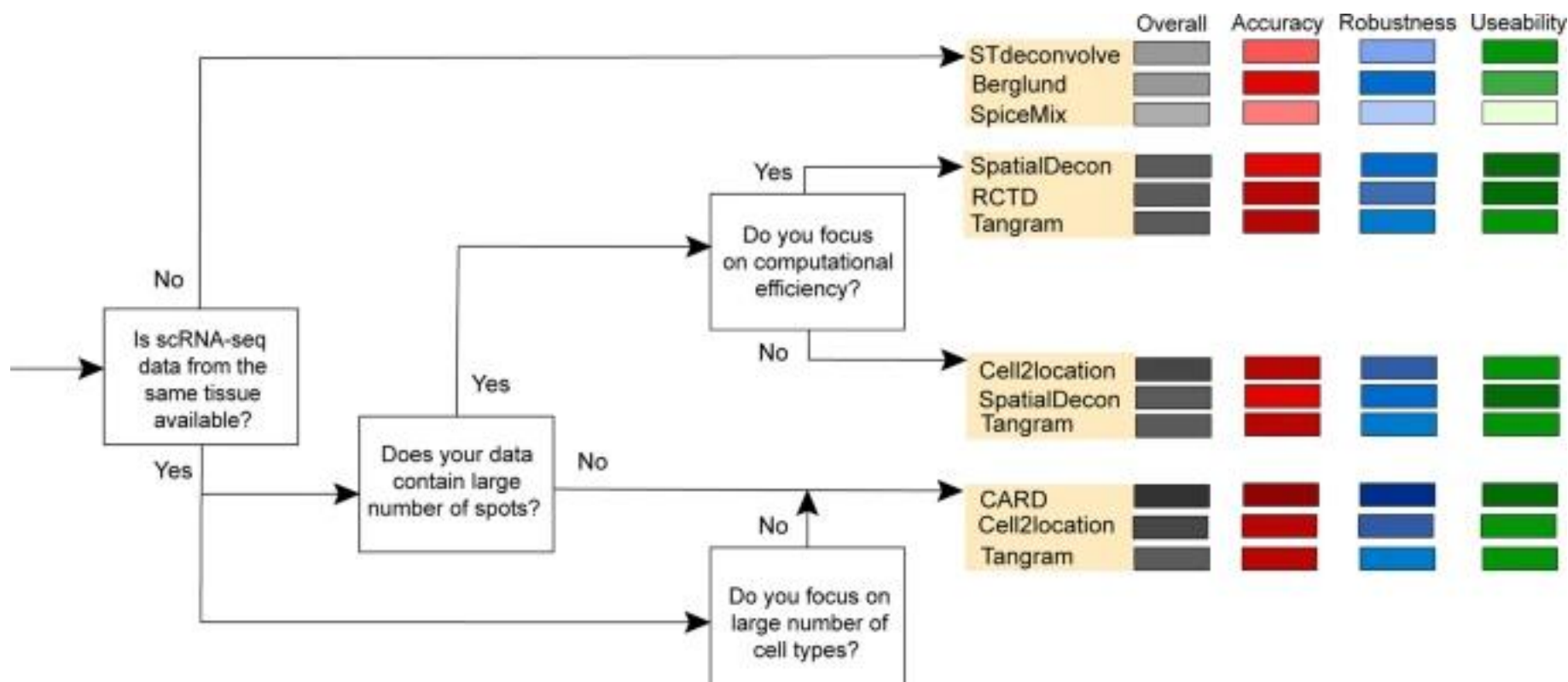
→ Aggregate of a few cells

→ Deconvolute the signals into each cell type

A comprehensive benchmarking with practical guidelines for cellular deconvolution of spatial transcriptomics



• Visium (Deconvolution)



experimental conditions. Nevertheless, each method category contained at least one high-performing method. **In general, CARD, Cell2location, Tangram, and RCTD were the best performing methods.** Compared with the existing benchmarking studies^{8,9}, our study included most number of existing methods. More importantly, we provided a full-scale



• Visium (Deconvolution)

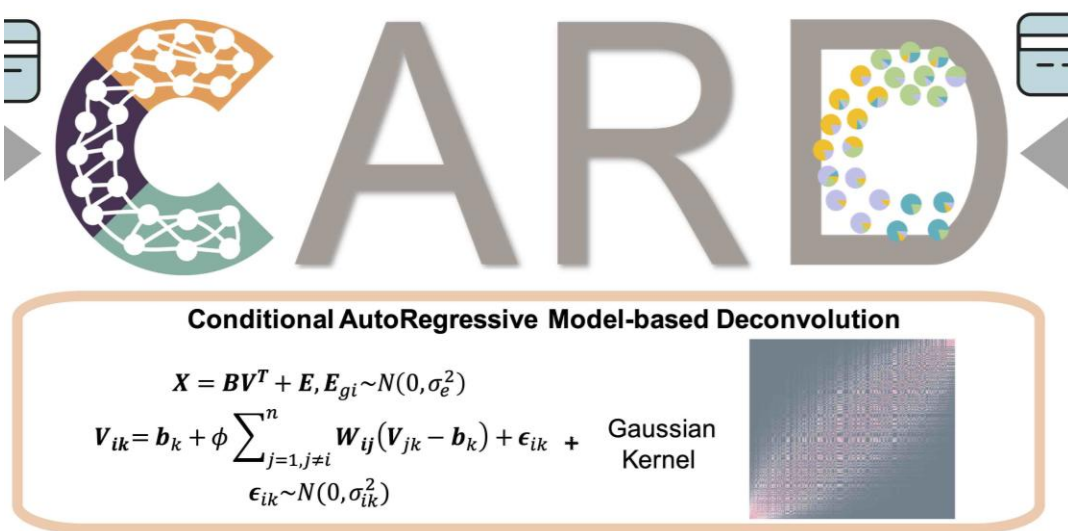
-scRNA-seq based

→ generate reference cell type specific signature matrix

Article | Published: 02 May 2022

Spatially informed cell-type deconvolution for spatial transcriptomics

[Ying Ma](#) & [Xiang Zhou](#) 



scRNA: K celltype * G informative gene

B: mean exp per celltype

V: N(spot) ~ celltype (proportion)

X: spatial data, E: error (gaussian)

$$X = BV^T + E$$

X: real gene expression (scRNA-seq)

$$V_{ik} = b_k + \phi \sum_{j=1, j \neq i}^n W_{ij} (V_{jk} - b_k) + \epsilon_{ik},$$

V: overall cell-composition +
autocorrelation (high autocorrelation → similar cell composition)

• Visium (Deconvolution)

Yang et al. *Genome Biology* (2024) 25:304
<https://doi.org/10.1186/s13059-024-03441-1>

Genome Biology

METHOD

Open Access



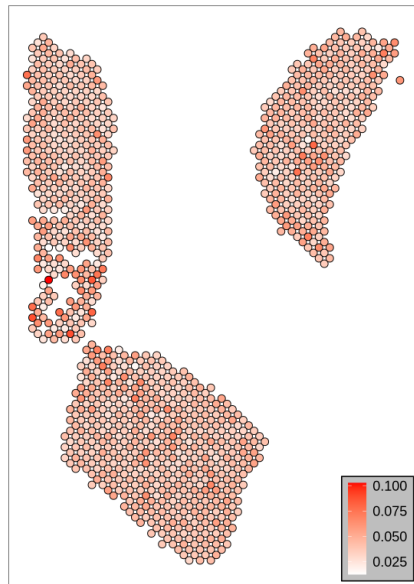
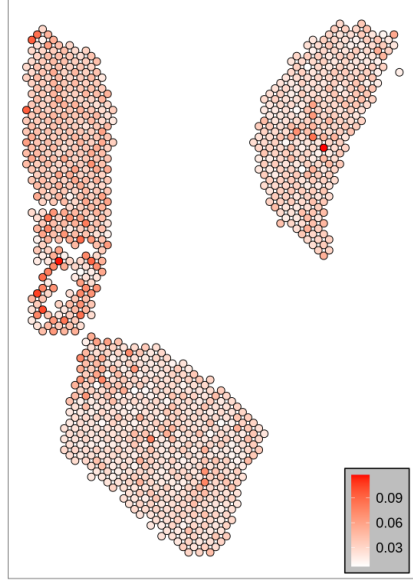
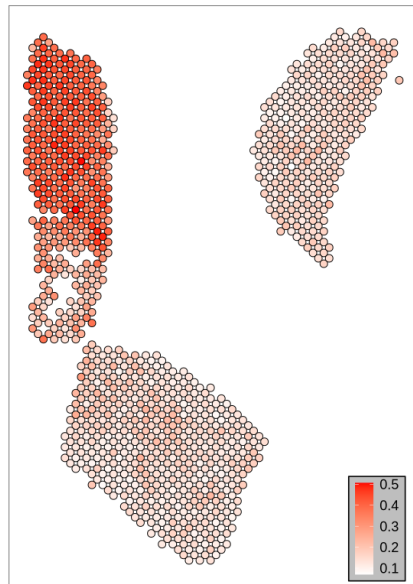
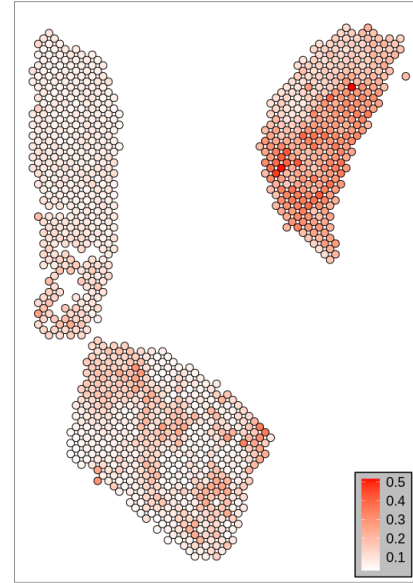
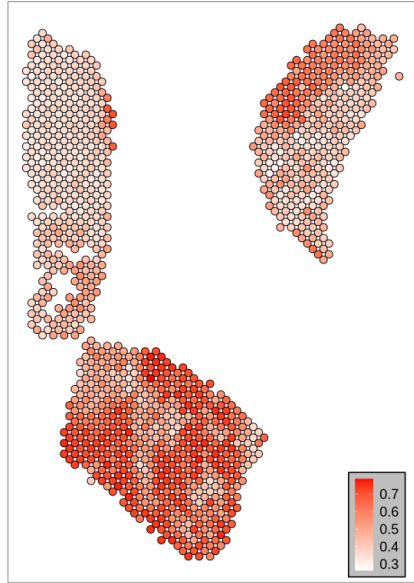
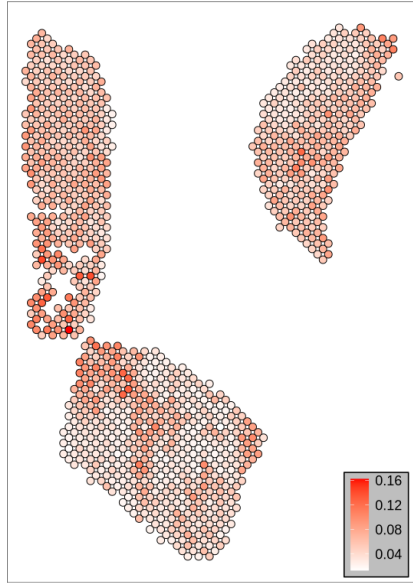
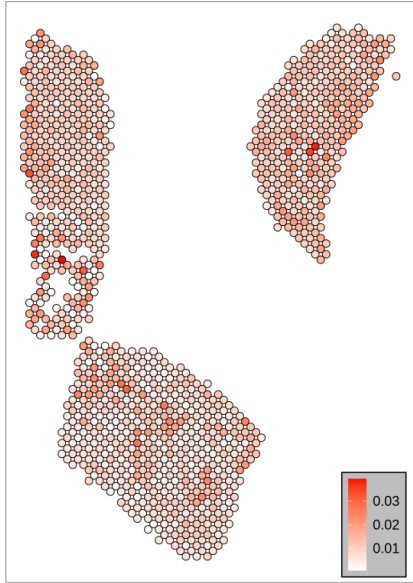
SMART: spatial transcriptomics
deconvolution using marker-gene-assisted
topic model

MARker-gene-assisted Topic model (SMART)

-scRNA-seq based → batch problem (ex: scRNA-seq & spatial data is not paired sample)

→ Marker-based (celltype-specific marker gene list)

• Visium (Deconvolution)

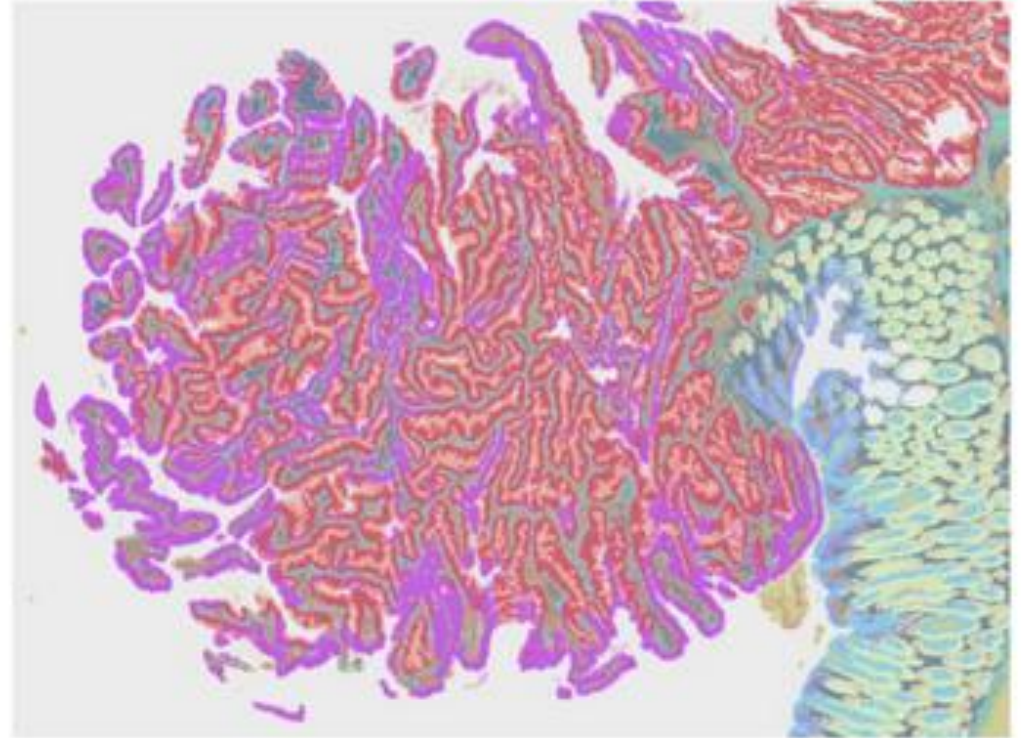


- Visium

Visium



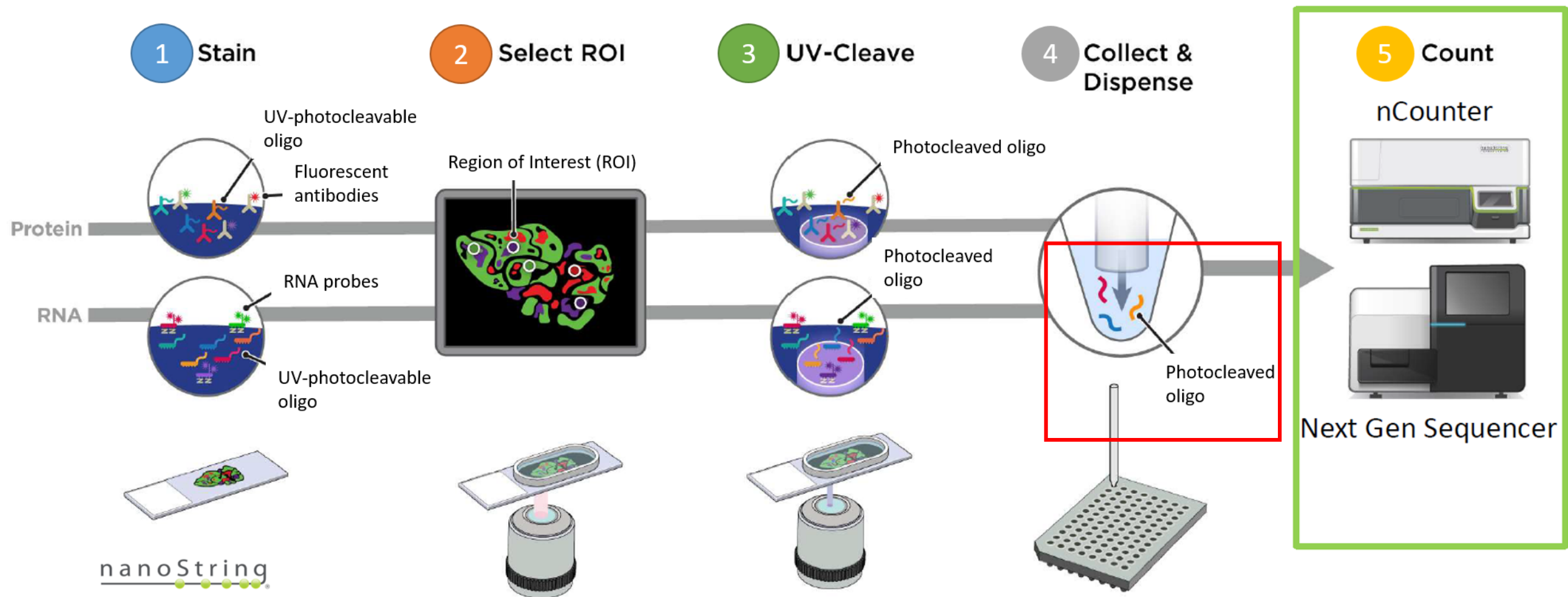
Visium HD



- Visium: 55um spot → multiple cells
- Visium HD: 2um → subcellular

- GeoMx

GeoMx DSP with nCounter or Next Gen Sequencer Workflow



- GeoMx



Geometric



Segmentation



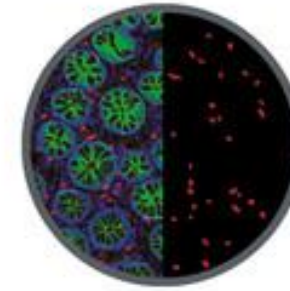
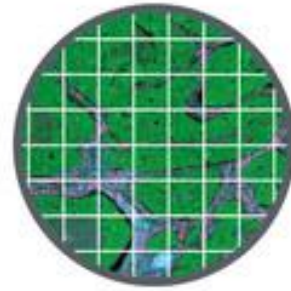
Contour



Gridded



Cell-Type Specific



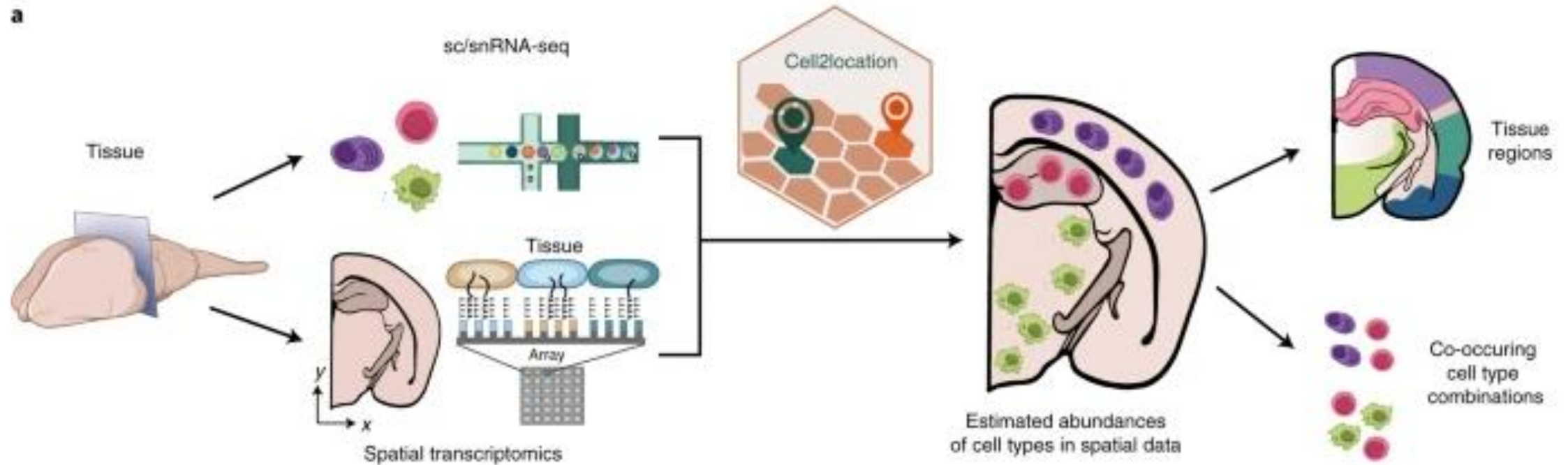
- Region of Interest (ROI)
- 10~600um: typically, 20~300 cells

- GeoMx (deconvolution)

- Cell2location

- scRNA-seq based (reference cell type specific signature matrix)

- negative binomial regression



• Cell size

cell type	average volume (μm^3)	BNID
sperm cell	30	109891, 109892
red blood cell	100	107600
lymphocyte	130	111439
neutrophil	300	108241
beta cell	1,000	109227
enterocyte	1,400	111216
fibroblast	2,000	108244
HeLa, cervix	3,000	103725, 105879
hair cell (ear)	4,000	108242
osteoblast	4,000	108088
alveolar macrophage	5,000	103566
cardiomyocyte	15,000	108243
megakaryocyte	30,000	110129
fat cell	600,000	107668
oocyte	4,000,000	101664

-Lymphocyte: diameter: ~10 μm

→ Cell size is important for spatial transcriptomics

→ Spot size is fixed

→ Variability between different spots for cellular content

Macrophage: too big!

-Visium: ~20 cells

Center-to-center: 100 μm

-GeoMx: 20~300 cells

→ only spatial profiling

→ No cellular analysis

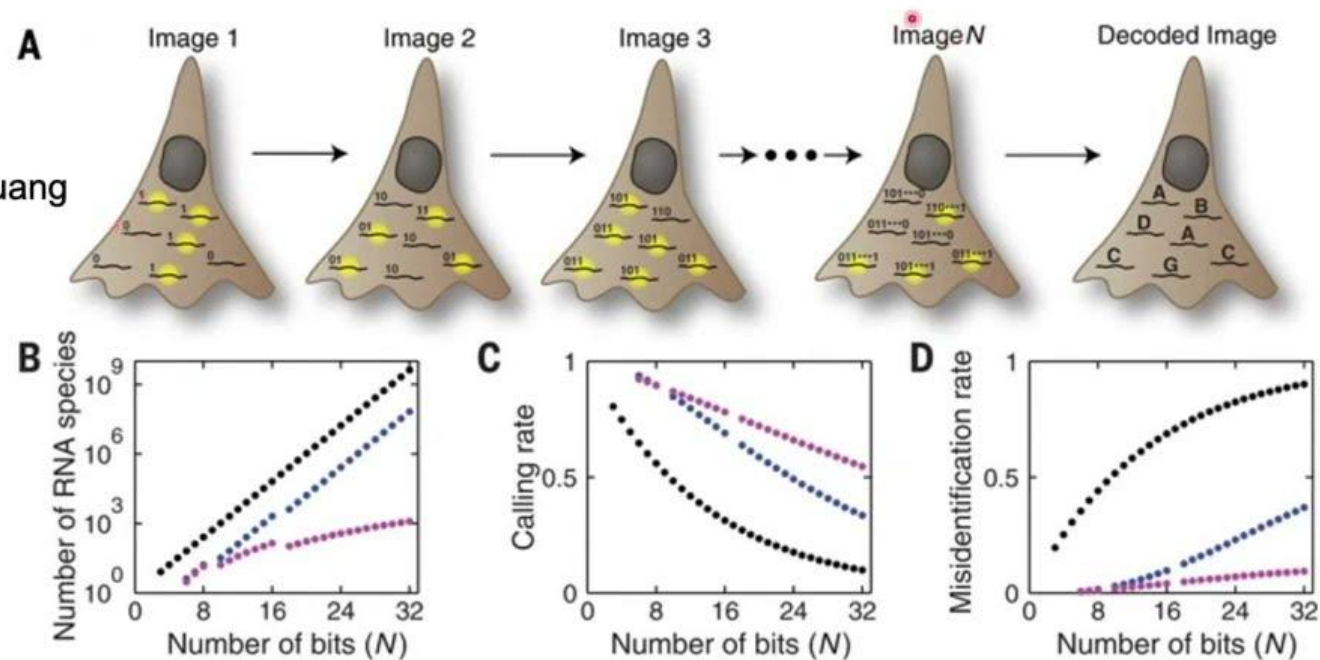
- Probe-based spatial transcriptomics

How MERFISH Works



Prof. Xiaowei Zhuang

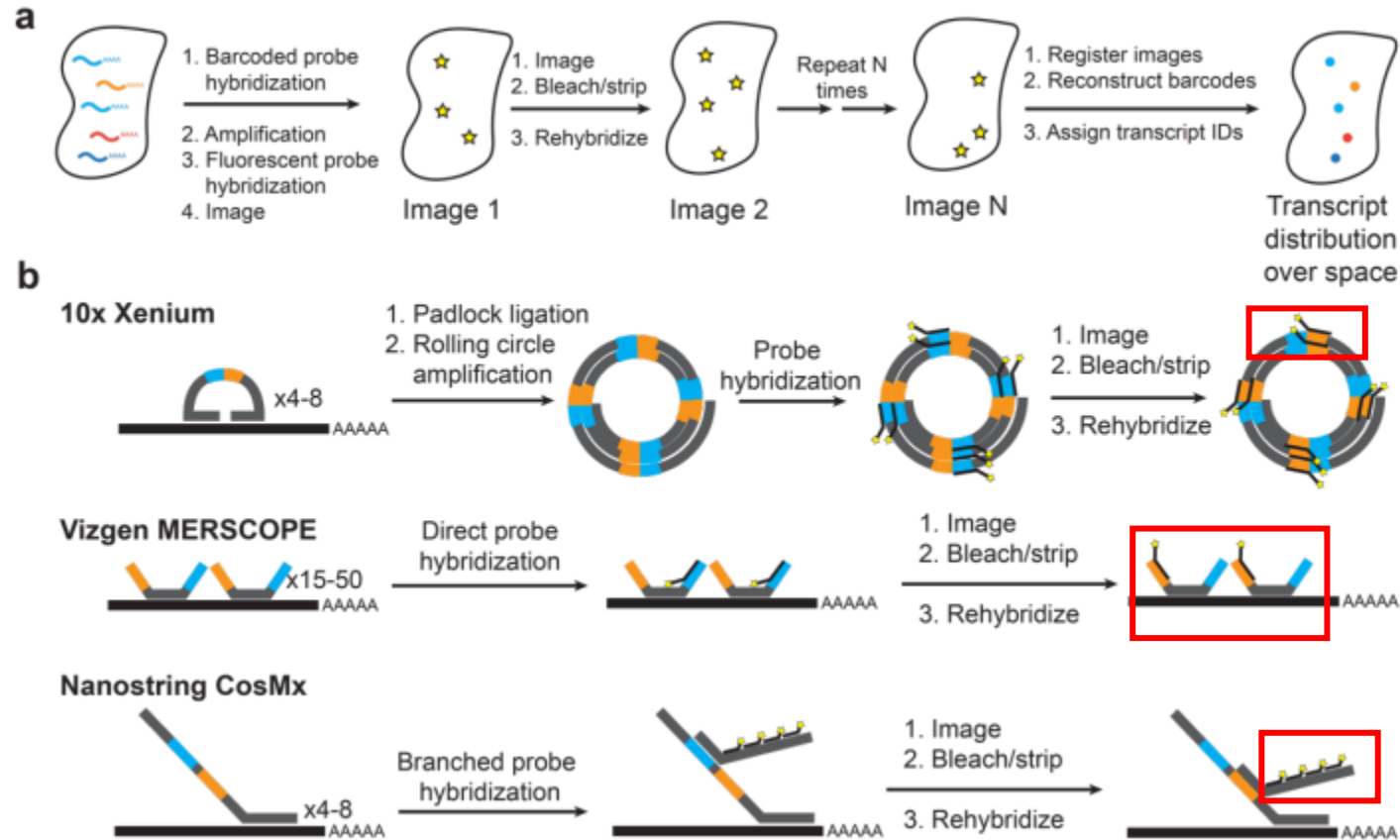
- Multiplex-Error-Robust-FISH (MERFISH)



Chen et al. Science 2015

- MERFISH, , MERSCOPE, COSMX, XENIUM
- Subcellular resolution → cellular analysis is possible

• Probe-based spatial transcriptomics



Imaging strategy

→ Different amplification method

Xenium: Rolling amplification

Merscope: Direct probe amplification

Cosmx: Branched probe amplification

cf) typically: FFPE blocks → may lead to poor RNA integrity

• CosMx

nature biotechnology

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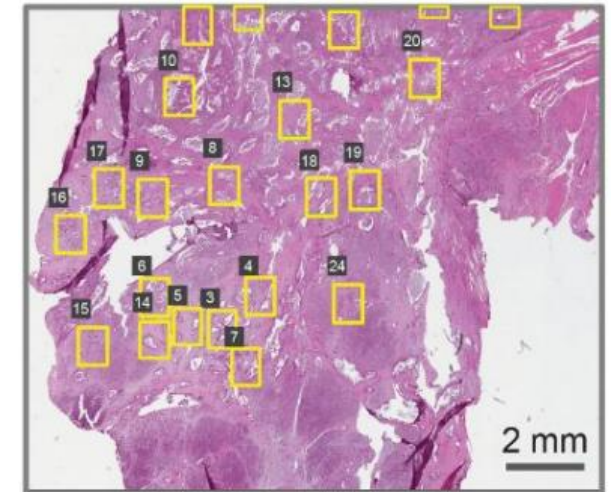
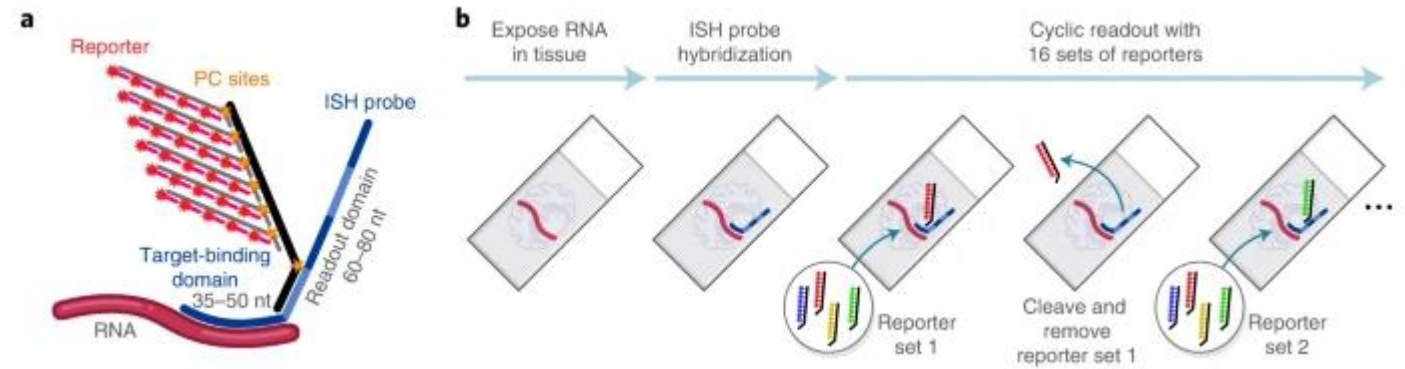
[nature](#) > [nature biotechnology](#) > [articles](#) > [article](#)

Article | [Published: 06 October 2022](#)

High-plex imaging of RNA and proteins at subcellular resolution in fixed tissue by spatial molecular imaging

*Technical procedure

- Wide field laser
- Stage moving system → each FOV imaging (Field of view)
- Objective (water → trash)

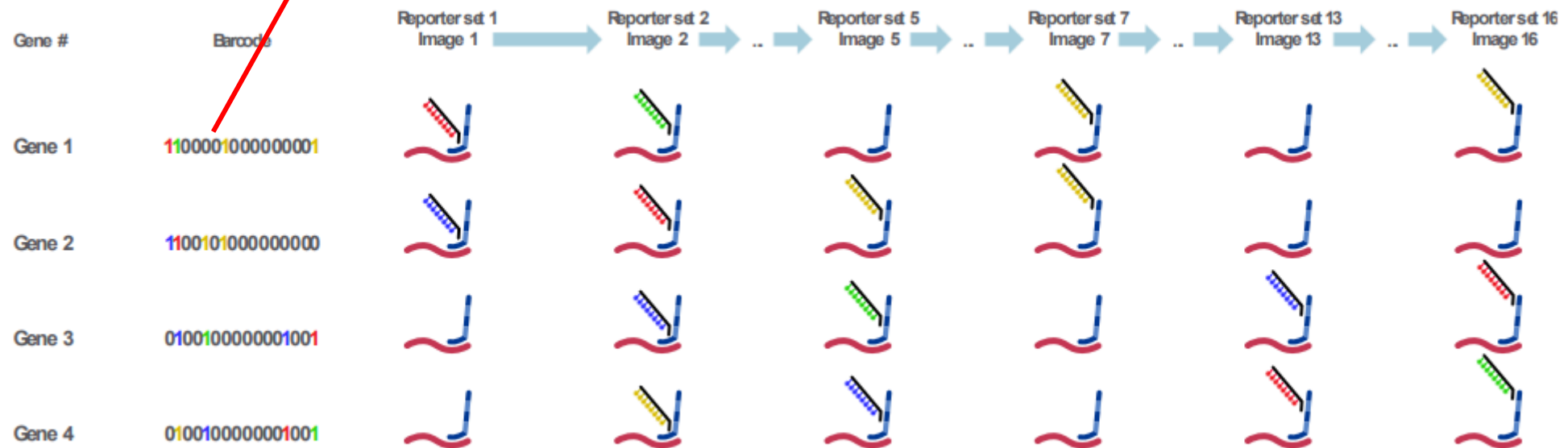


• CosMx

*RNA barcode

-4 reporter + “off” (16round \rightarrow 16-serial barcode) \rightarrow UV fluorescence

-Hamming distance (barcode similarity) > 4 (HD4) \rightarrow 1210 barcode



• CosMx

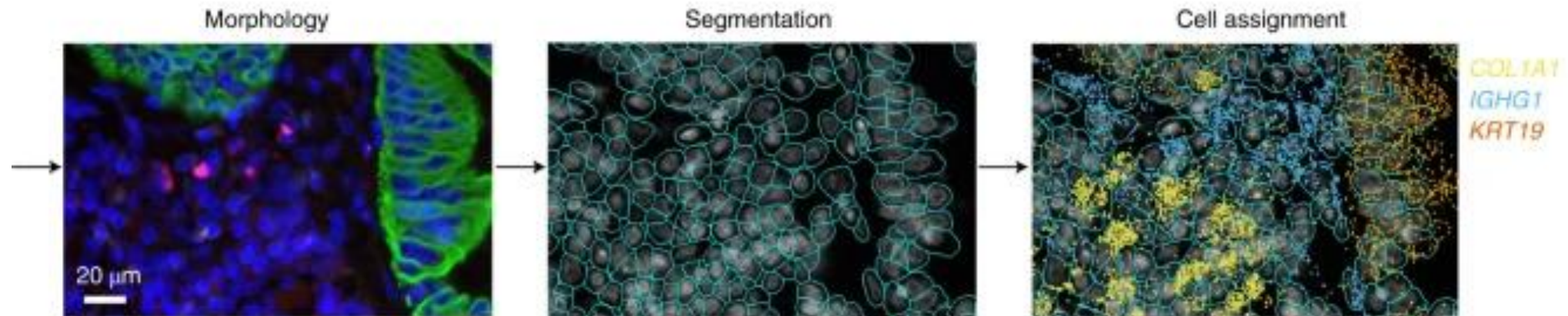
*Image reconstruction

1) Image stacking (z-direction) → 2D Laplacian of Gaussian filter (increase optical resolution) → fluorescence background correction

2) Gene assignment: integrate the signals within 0.5 pixel (90nm)

3) cell segmentation: DAPI (nucleus), PANCK (epithelial cell), CD3, CD298

+ Cellpose



- Benchmarking of image-based spatial transcriptomics

Systematic benchmarking of imaging spatial transcriptomics platforms in FFPE tissues

Broad Institute, BWH
bioRxiv: 20231208

Huan Wang^{1,*}, Ruixu Huang^{2,*}, Jack Nelson^{1,*}, Ce Gao³, Miles Trans³, Anna Yeaton⁴, Kristen Felt⁵, Kathleen L. Pfaff⁶, Teri Bowman⁷, Scott J. Rodig^{6,7}, Kevin Wei^{3,7}, Brittany A. Goods^{2,**},
Samouil L. Farhi^{1,**}

A Comparative Analysis of Imaging-Based Spatial Transcriptomics Platforms

South Australia
bioRxiv: 20231214

David P. Cook¹, Kirk B. Jensen^{2,3,4}, Kellie Wise^{2,3}, Michael J. Roach^{2,3}, Felipe Segato Dezem^{6,7},
Natalie K. Ryan^{3,5}, Michel Zamojski⁹, Ioannis S. Vlachos^{10,11,12}, Simon R. V. Knott^{13,14}, Lisa M.
Butler^{3,5}, Jeffrey L. Wrana^{1,15}, Nicholas E. Banovich¹⁶, Jasmine T. Plummer^{6,7,8*}, Luciano G.
Martelotto^{2,3*}

- Benchmarking of image-based spatial transcriptomics

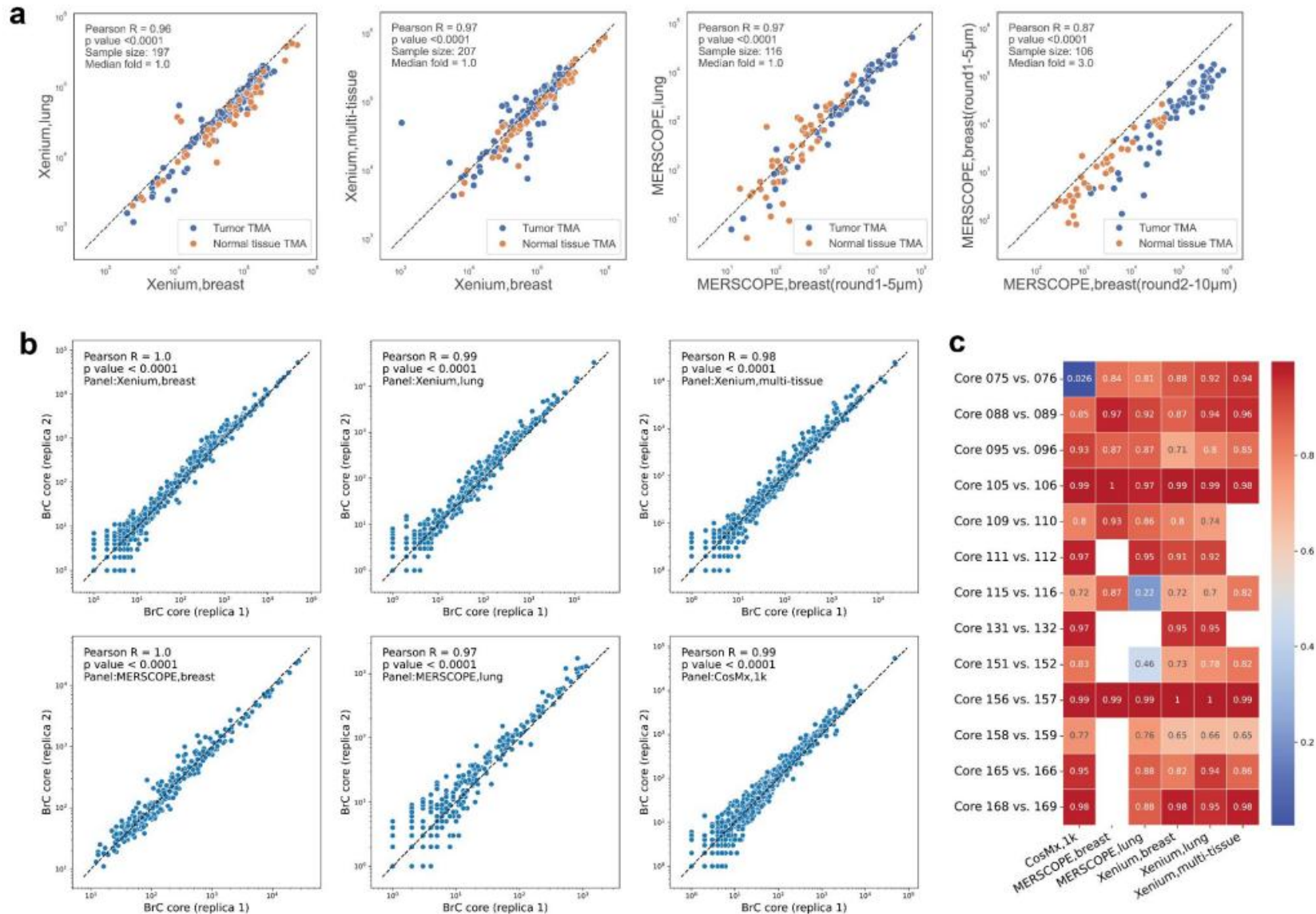
Total transcript: Xenium > Cosmx > Merscope

Number of cells: Xenium > Merscope > Cosmx

A

	Xenium Rep 1	Xenium Rep 2	CosMx Rep 1	CosMx Rep 2
Gene target #	377	377	1000	1000
Total cell count	99,852	102,508	96,139	98,767
Median gene count per cell	33	34	75	71
Median transcript count per cell	88	92	113	99
Median transcript count gene target count	0.23	0.24	0.11	0.10
Median transcript count (intersecting targets only)	23	24	8	7

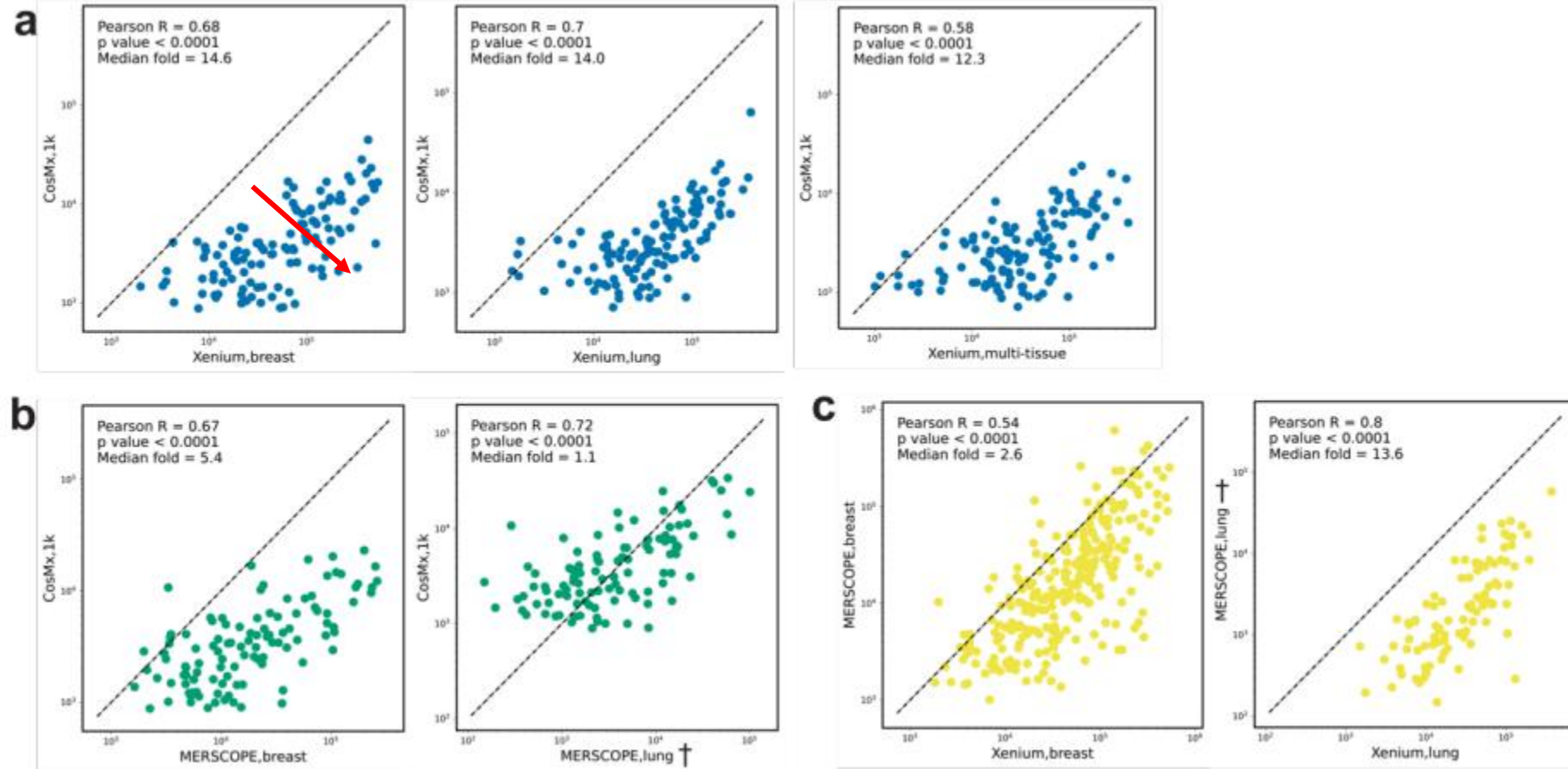
• Benchmarking of image-based spatial transcriptomics



Total transcript / gene \leftarrow pseudo-bulk from each core

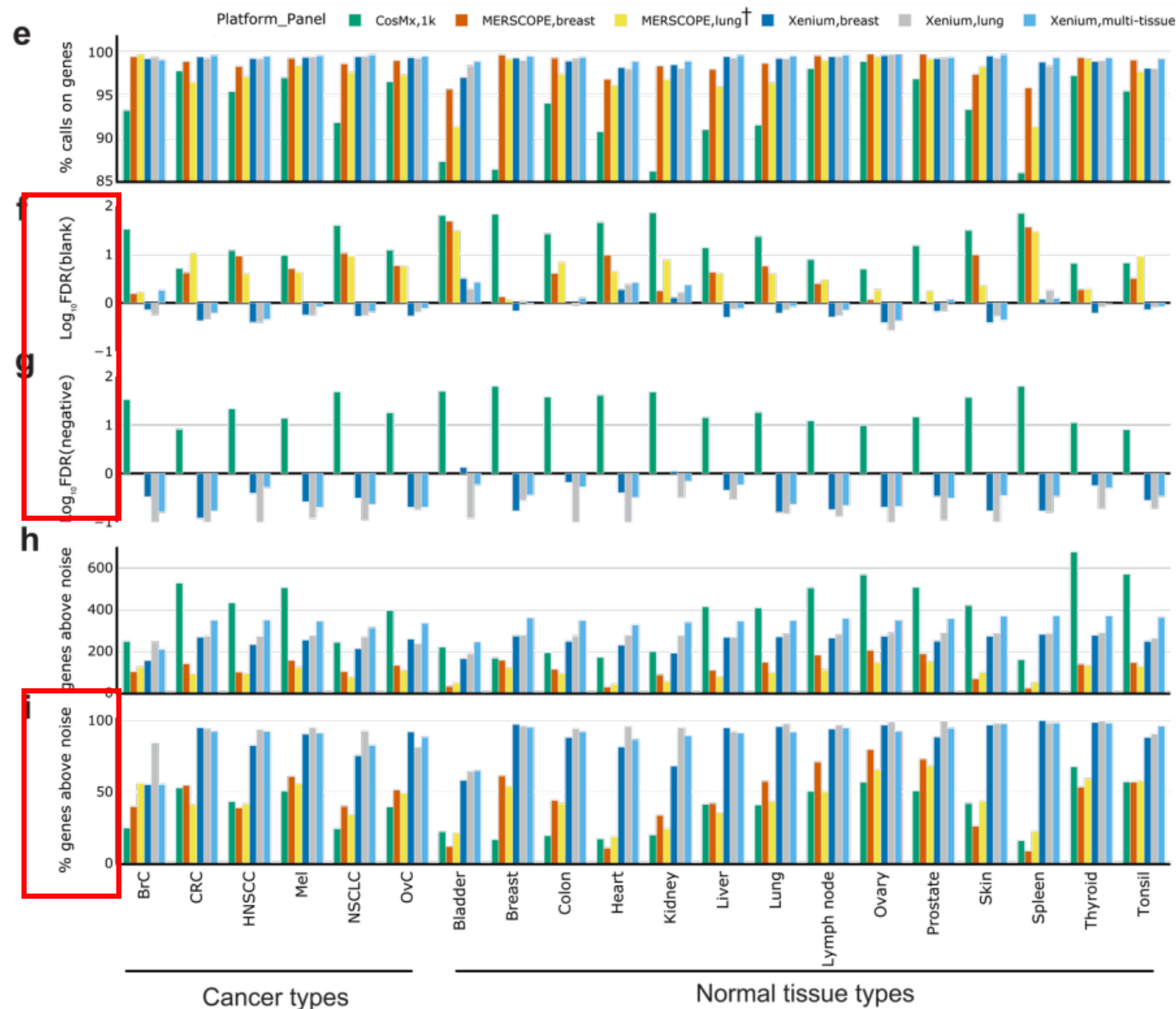
Intra-platform reproducibility (same patient, different core) \rightarrow very good

- Benchmarking of image-based spatial transcriptomics



Xenium is always better

• Benchmarking of image-based spatial transcriptomics

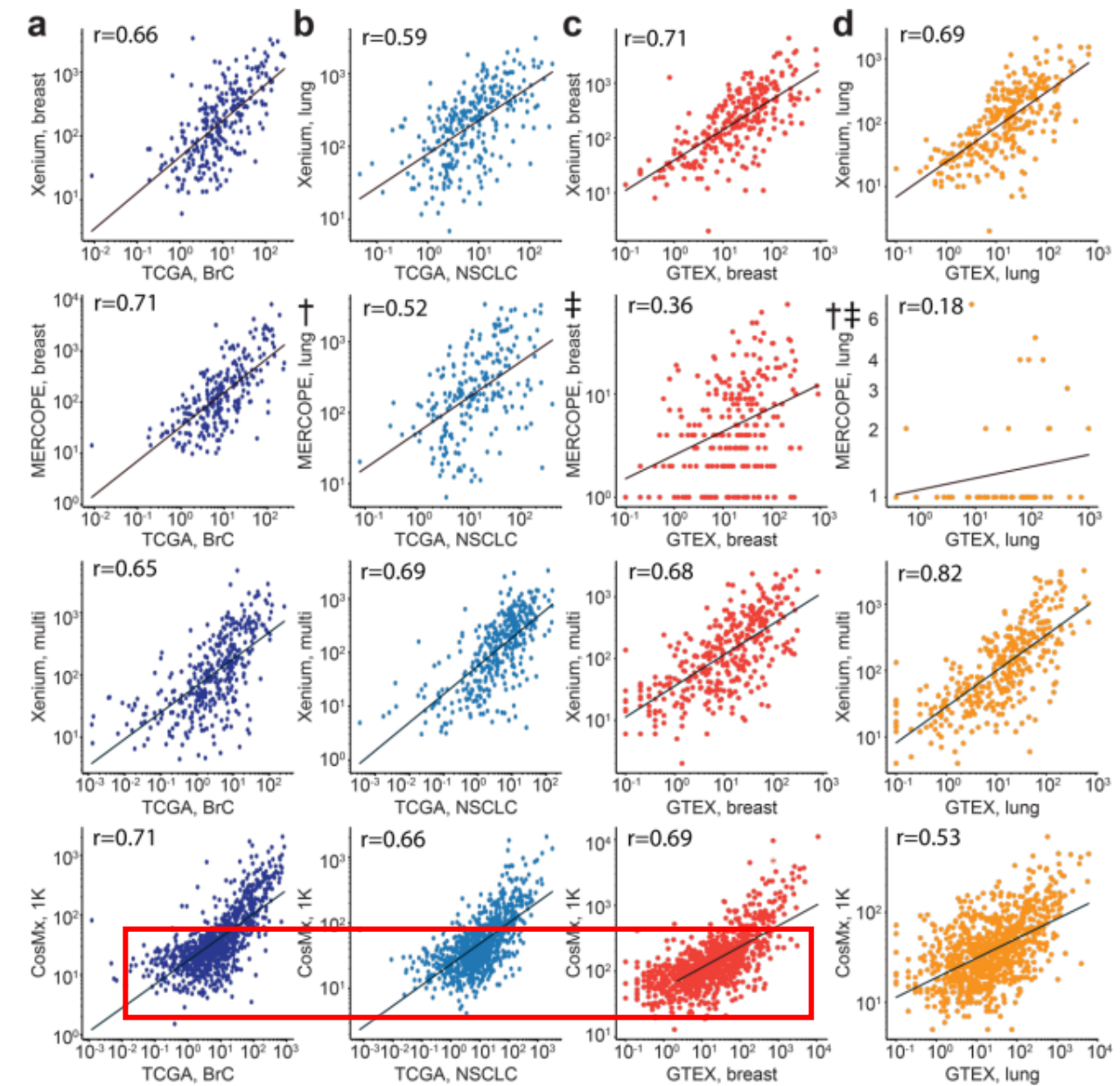


- Probe specificity: negative probe (experimental probe: does not present in human) (cf: Merscope: X) & negative barcode (computational barcode: algorithmically)

- On target / total
- above noise (2 S.D. > Avg)

→ Xenium is the best

• Benchmarking of image-based spatial transcriptomics

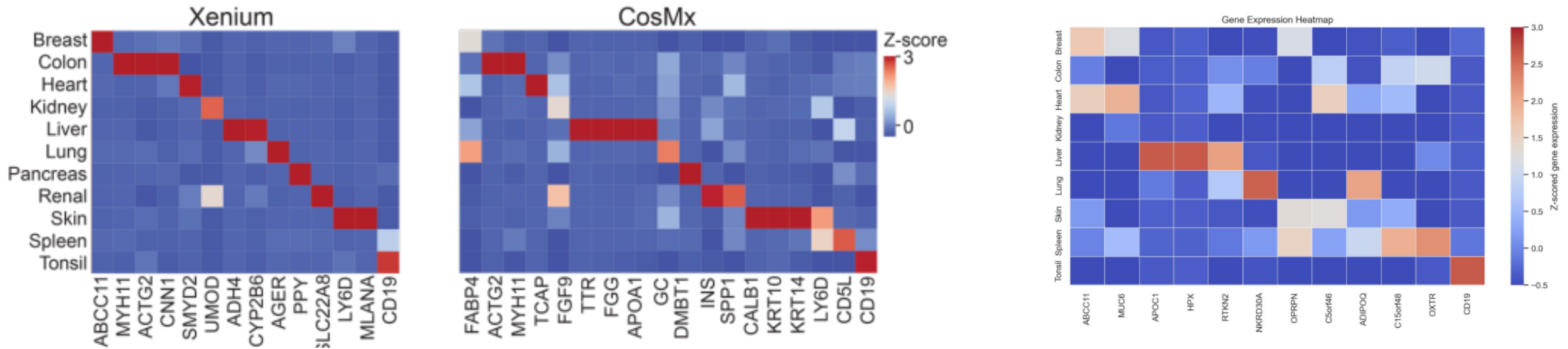


-Specificity assessment by TCGA and GTEX:
gene-gene correlation

→ Cosmx: low exp: skewed

→ (low expression → non-specific binding high)

- Benchmarking of image-based spatial transcriptomics

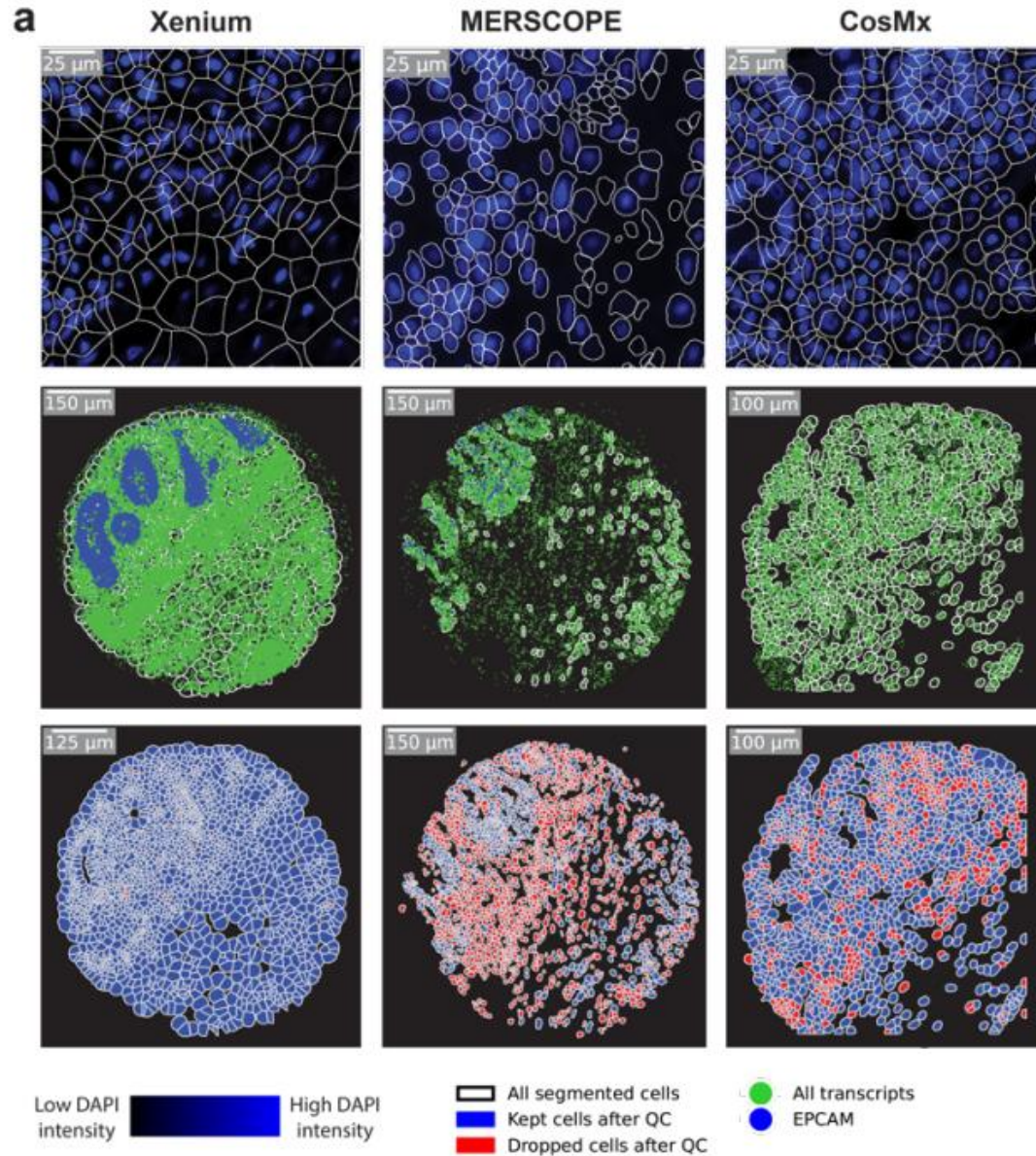


*Specificity assessment by TCGA and GTEX

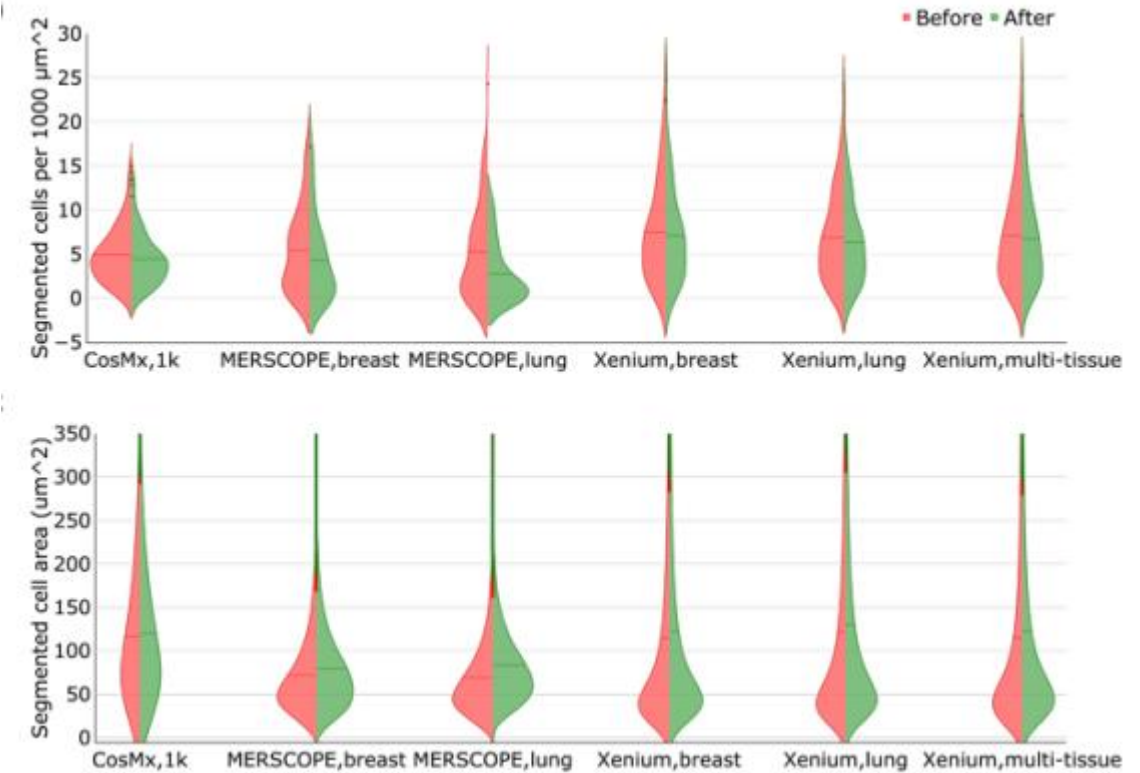
- Tissue-specific marker (> 20 fold btw other tissues)

→ Xenium > Cosmx

Benchmarking of image-based spatial transcriptomics

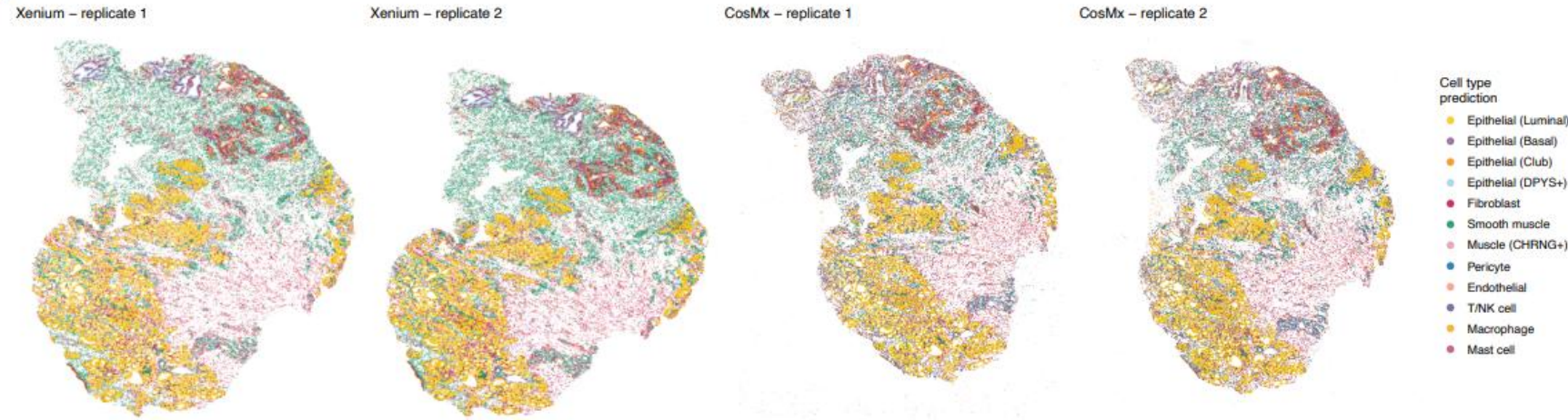


Xenium: large boundary
(though less dropped cells after QC)

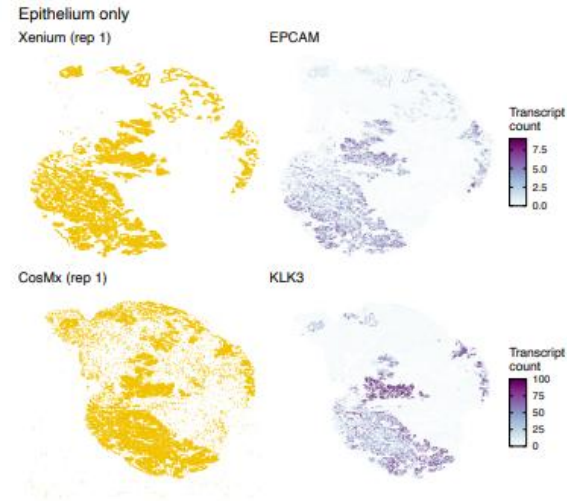


• Benchmarking of image-based spatial transcriptomics

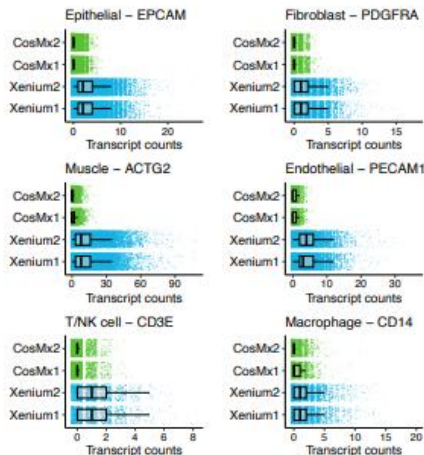
A



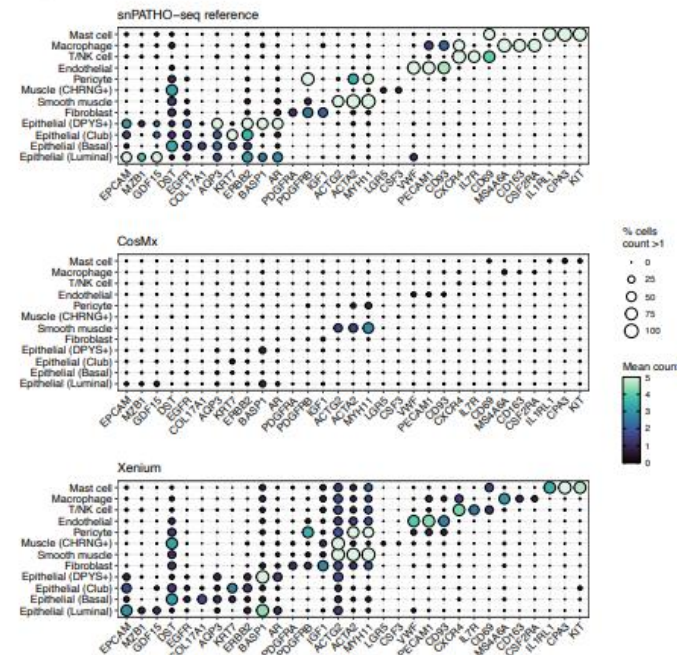
B



C



D



Marker gene: Xenium > Cosmx (Sensitivity)
Marker plot: Xenium is similar to snRNA-seq

