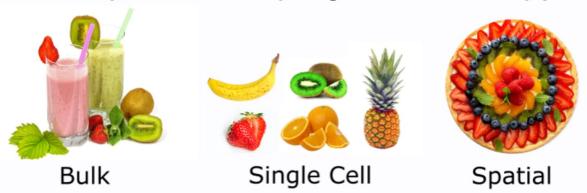
Single-Cell Transcriptomics: From Bulk to Precision Biology

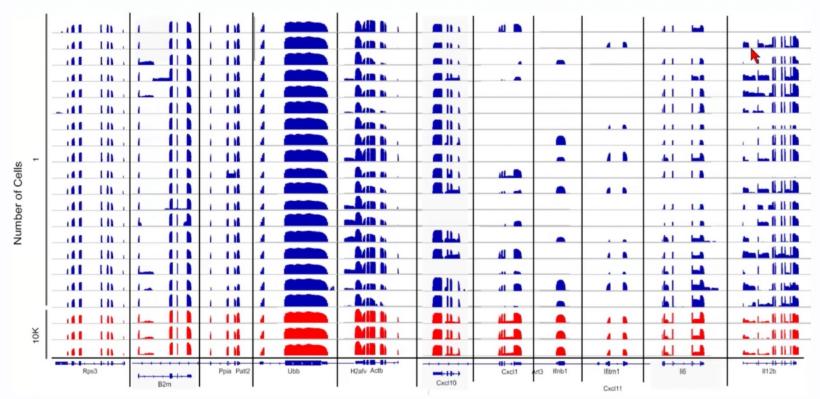
Resolving Cellular Heterogeneity, One Cell at a Time Jiekun (Jackie) Yang, Department of Genetics, Rutgers University, 2/26/2025

Why Single Cells? Bulk RNA-seq Limitations

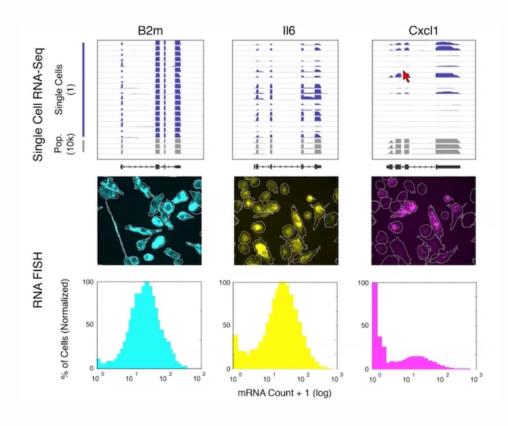
- Loss of Cellular Heterogeneity
- Difficulty in Identifying Rare Cell Types



- Inability to Study Cell-State Transitions
- Limited Resolution for Cell-Type-Specific Signatures
- Difficulty in Detecting Lowly Expressed Genes



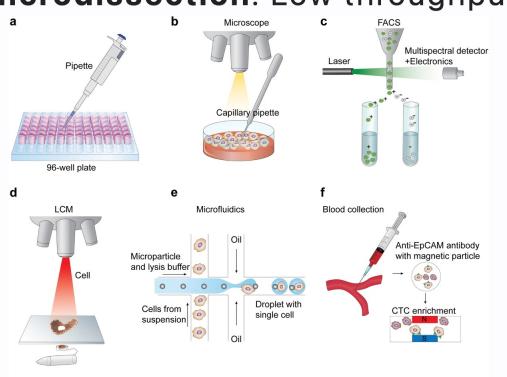
RNA FISH validates scRNA-seq cell to cell variability



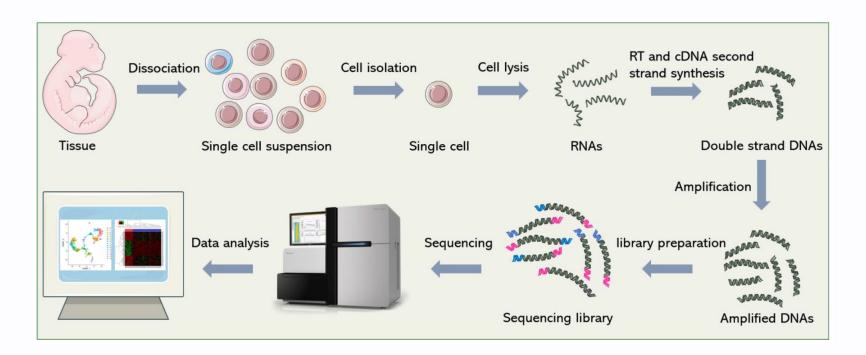
Traditional Approaches

FACS: Limited to known markers, heterogeneity exists

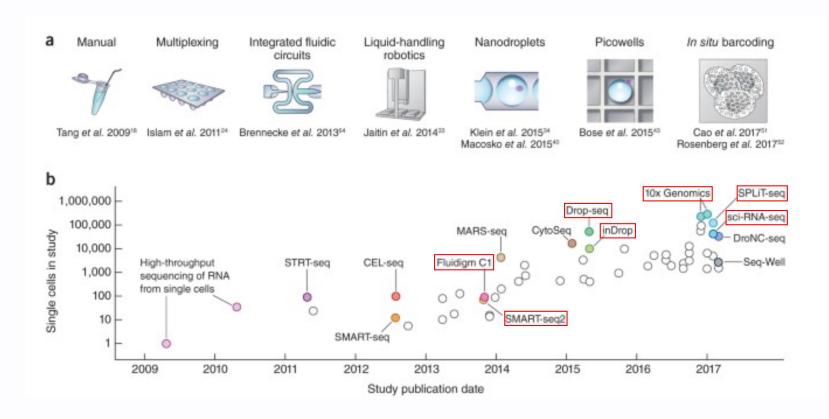
Microdissection: Low throughput



scRNA-seq Workflow

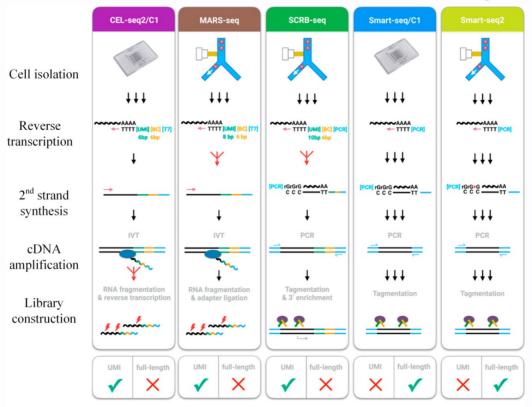


Technology Evolution

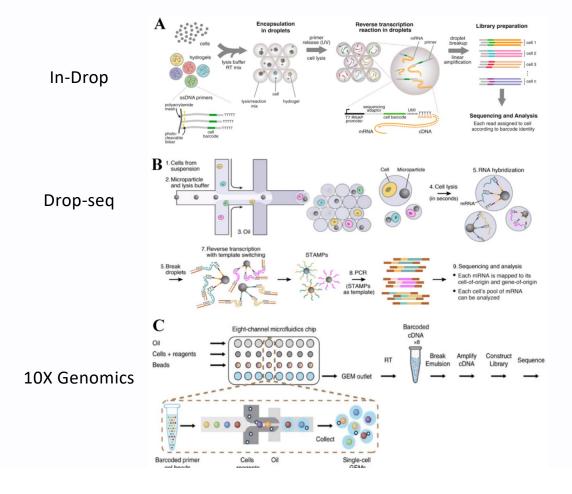


Conventional scRNA-seq

Plate-based platforms: low throughput



High-Throughput Revolution

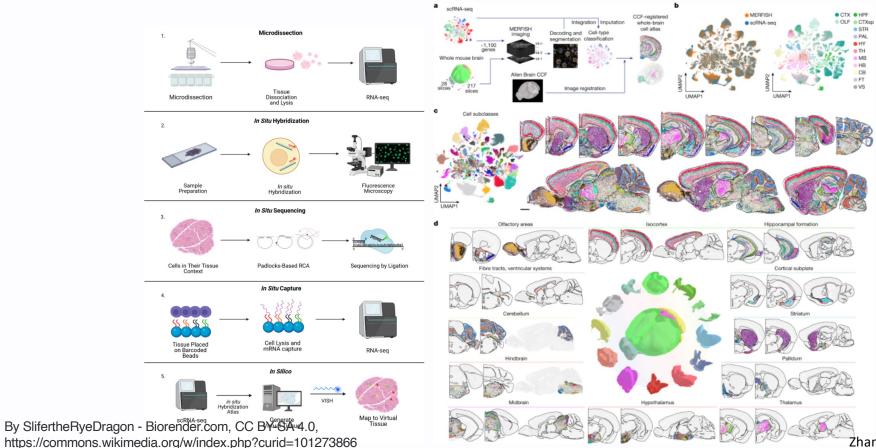


Sequential combinatorial barcoding

SPLIT-seq/sci-RNA-seq



Spatial Transcriptomics



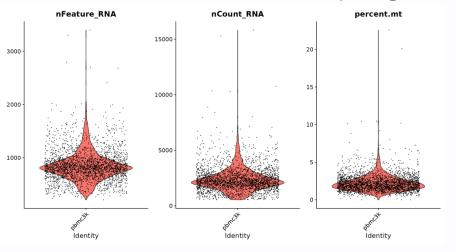
12

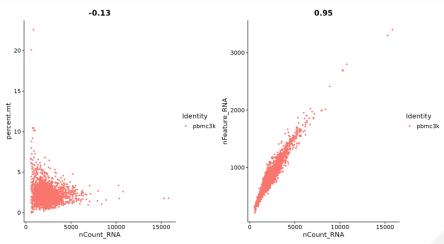
Zhang et al., Nature (2023)

Computational Challenges

Data Preprocessing

Quality control (Seurat, CellBender)
Normalization (Log-normalize, SCTransform).



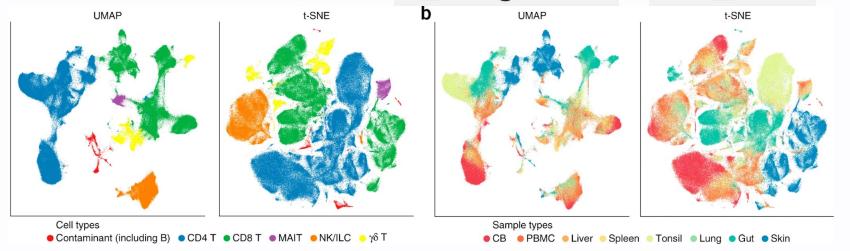


Dimensionality Reduction

PCA: Linear projection, preserves global variance.

t-SNE/UMAP: Constructs neighbor graph → optimizes

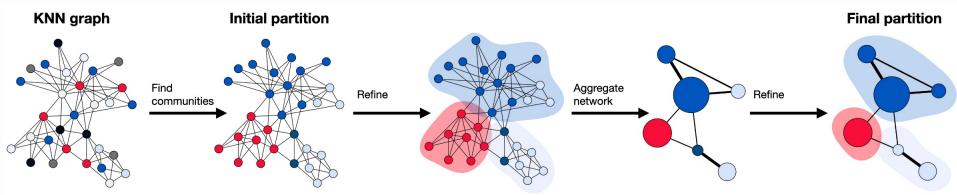
low-dimensional layout (n_neighbors , min_dist).



Clustering

Leiden: Avoids disconnected communities.

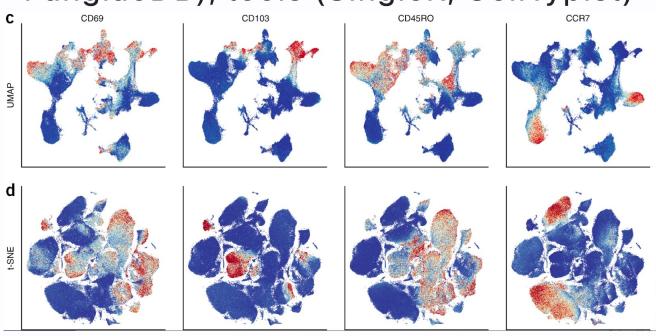
Louvain: Maximizes modularity.



Resolution: 0.2 (broad) vs. 1.0 (fine-grained).

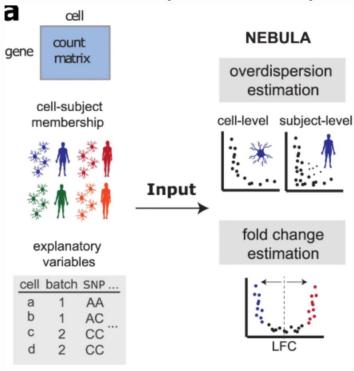
Cell Type Annotation

Marker genes, reference databases (CellMarker, PanglaoDB), tools (SingleR, CellTypist)



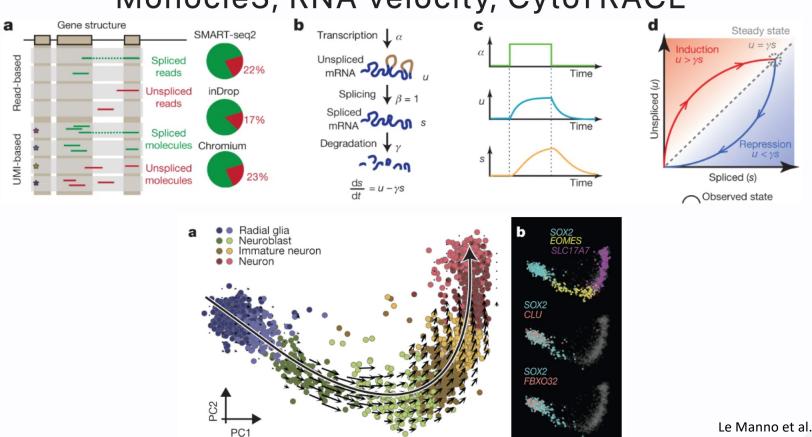
Differential expression

Cell-based (MAST), Pseudobulk (DESeq2), Linear-Mixed Models (NEBULA)



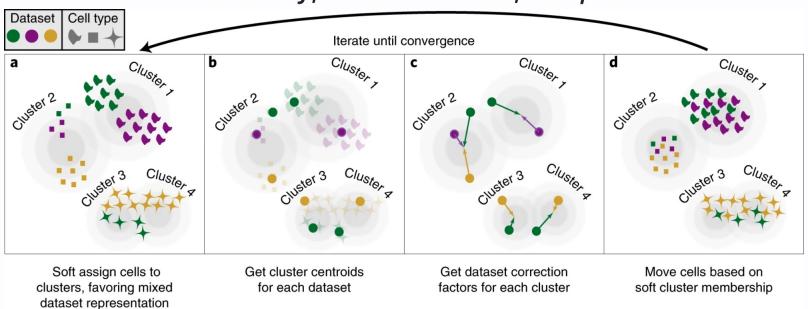
Trajectory inference

Monocle3, RNA velocity, CytoTRACE



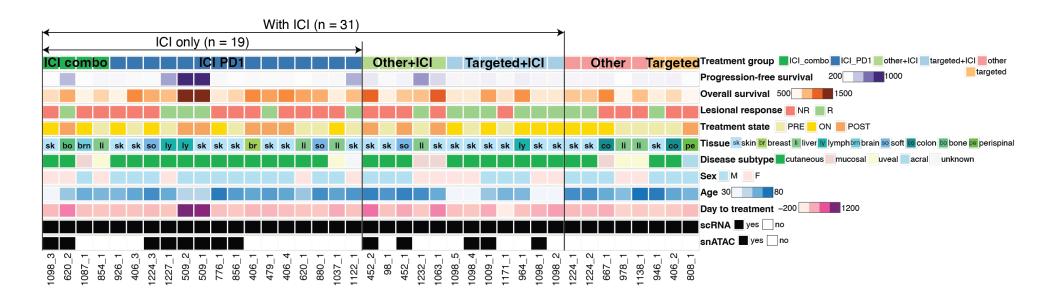
Multi-Dataset Integration

Harmony, Seurat CCA, ML/DL

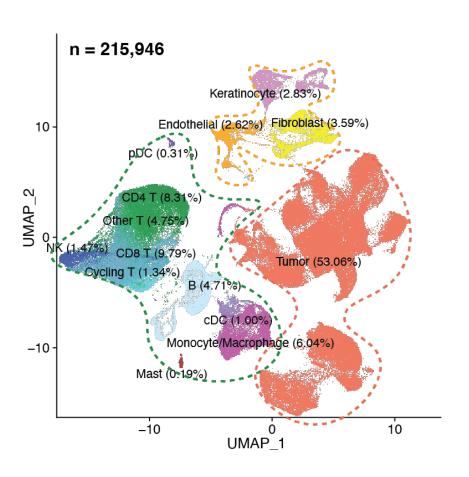


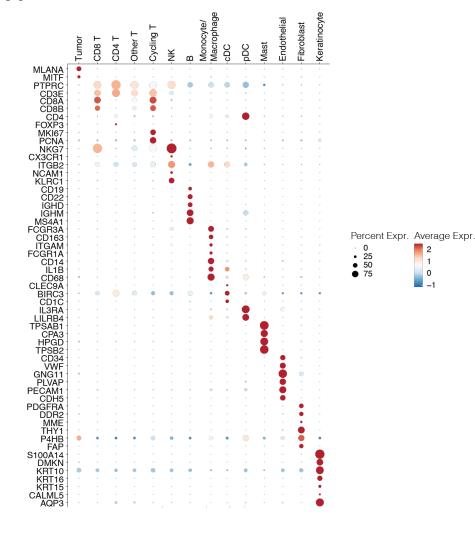
Case Studies: Single-cell Dissection of Immunotherapy Response in Metastatic Melanoma

We used 39 scRNA-seq and 15 paired snATAC-seq samples

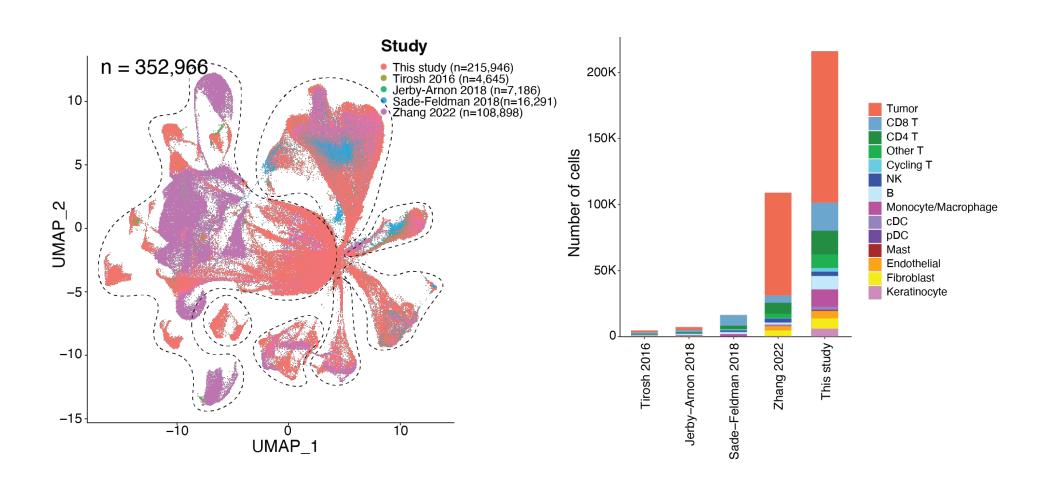


We annotated 14 cell types for ~216K cells

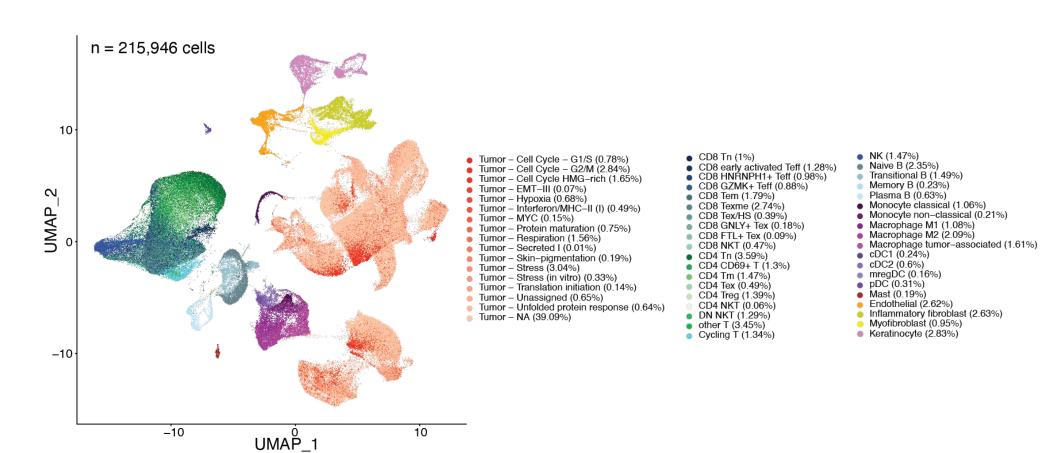




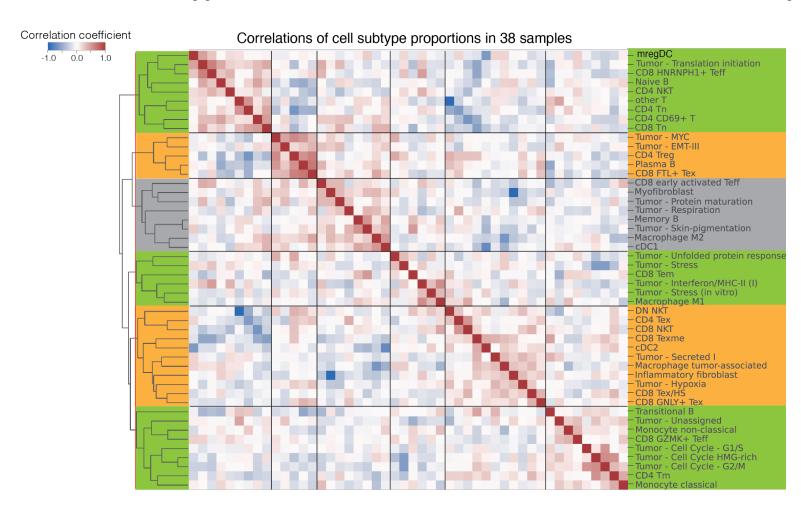
We contributed more cells than all previous studies combined



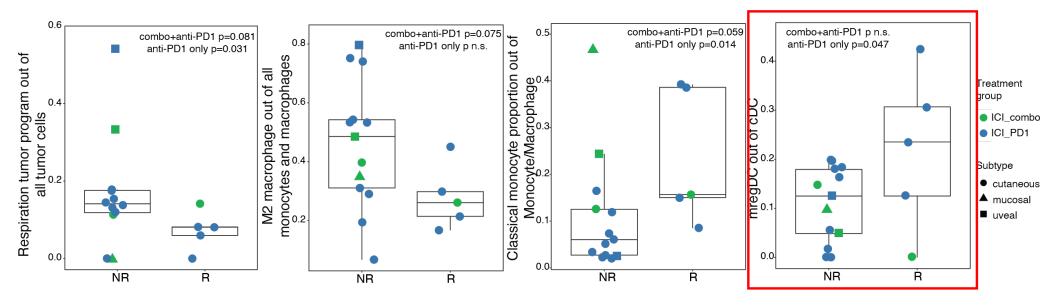
We identified 55 cell subtypes for ~216K cells



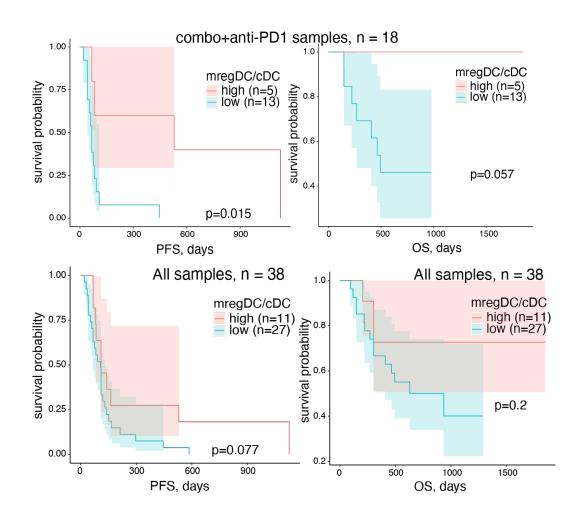
We revealed 6 cell subtype correlation modules with varied tumor responses



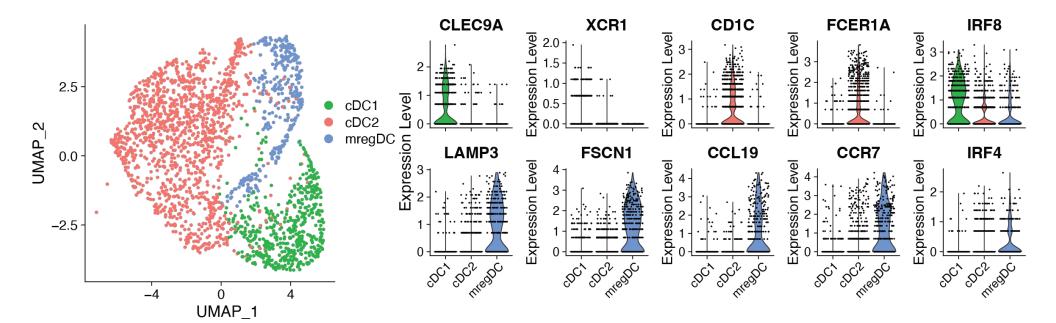
We detected cell subtypes associated with ICI response



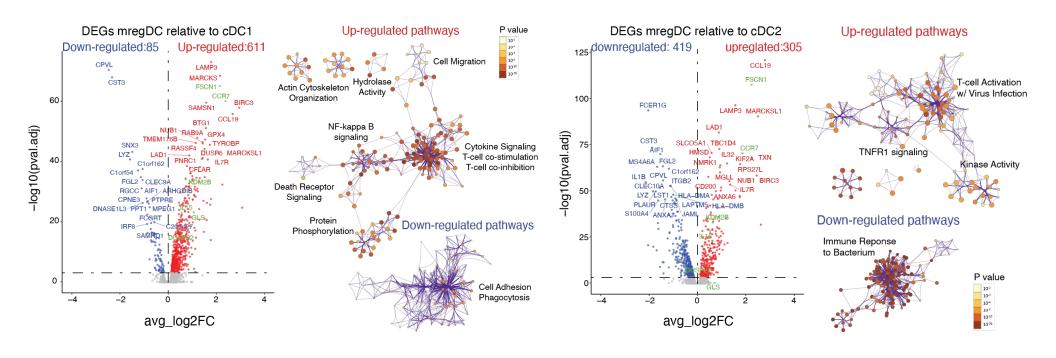
We observed PFS benefit for ICI-treated mregDC-high samples



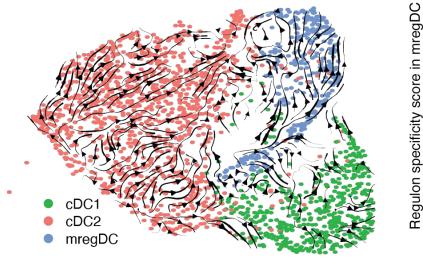
Conventional Dendritic Cell subtypes and markers

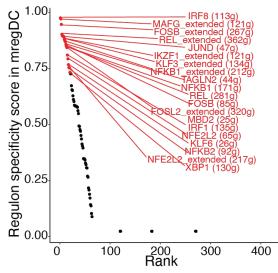


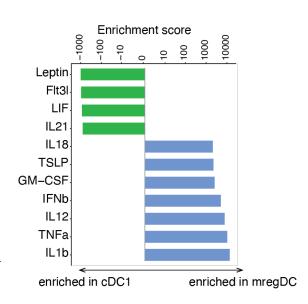
mregDC likely derives from cDC1, with certain gene programs activated



Trajectory, gene-regulatory network and immune response inference

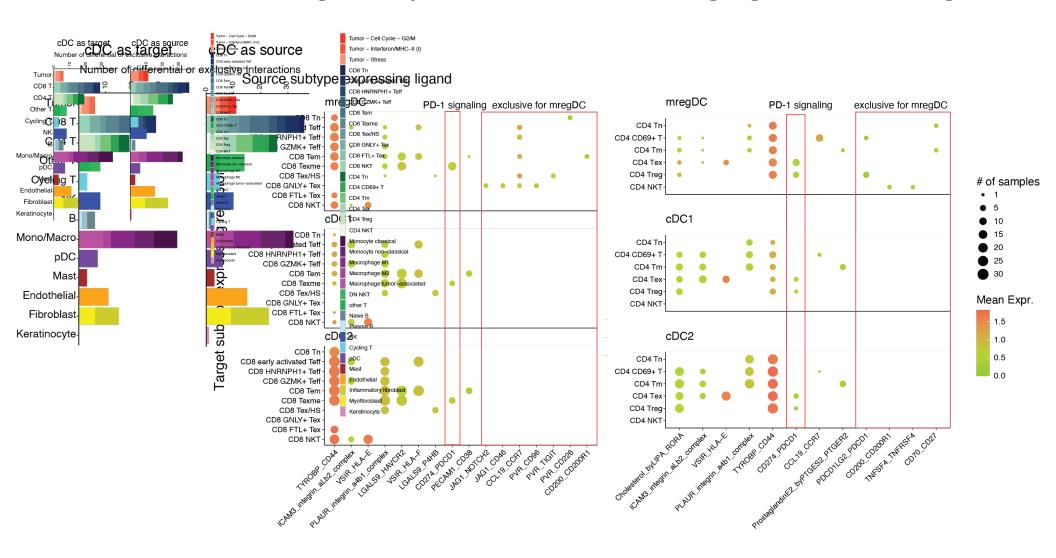






Cui et al. (2024) Nature

Increased immunoregulatory and immune recruiting signals from mregDCs



Deep Learning in scRNA-seq

• Why DL?

Handling high-dimensional data, non-linear patterns.

Key Methods:

- Autoencoders (scVI, scANVI) for denoising.
- Graph Neural Networks (GNNs) for cell-cell interactions.
- Transformers for gene-gene relationships.

Applications:

 Cell type prediction, data integration, synthetic data generation.

Beyond scRNA-seq: Multi-Omics & scATAC-seq

• scATAC-seq:

Chromatin accessibility, regulatory element mapping.

• Multi-Omics Integration:

- CITE-seq (RNA + protein), SNARE-seq (RNA + ATAC).
- Challenges: Technical noise, data harmonization.

Future Directions:

Spatial multi-omics, live-cell imaging integration.

Conclusion & Future Directions

- Key Takeaways:
 - Single-cell tech enables unprecedented resolution.
 - Computational methods are critical for interpretation.
 - Multi-omics and DL are shaping the future.
- Challenges: Scalability, benchmarking.

Thank You!

Questions?

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Website: yangcompbio.org