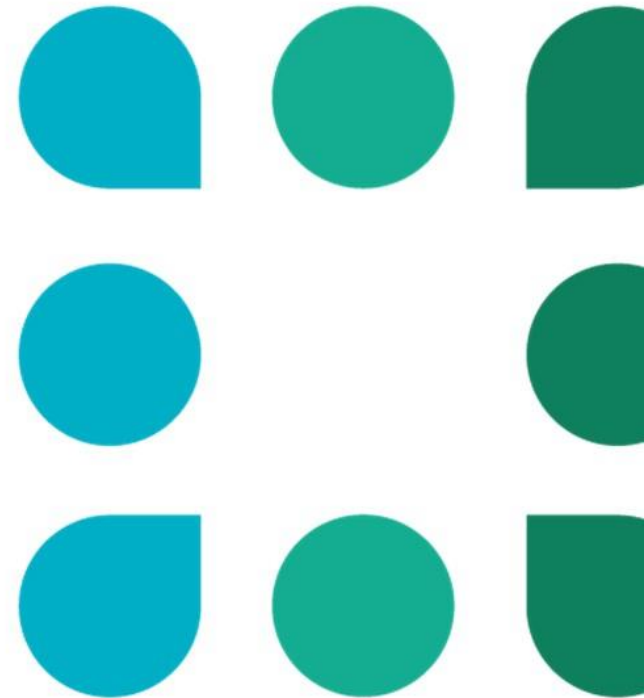




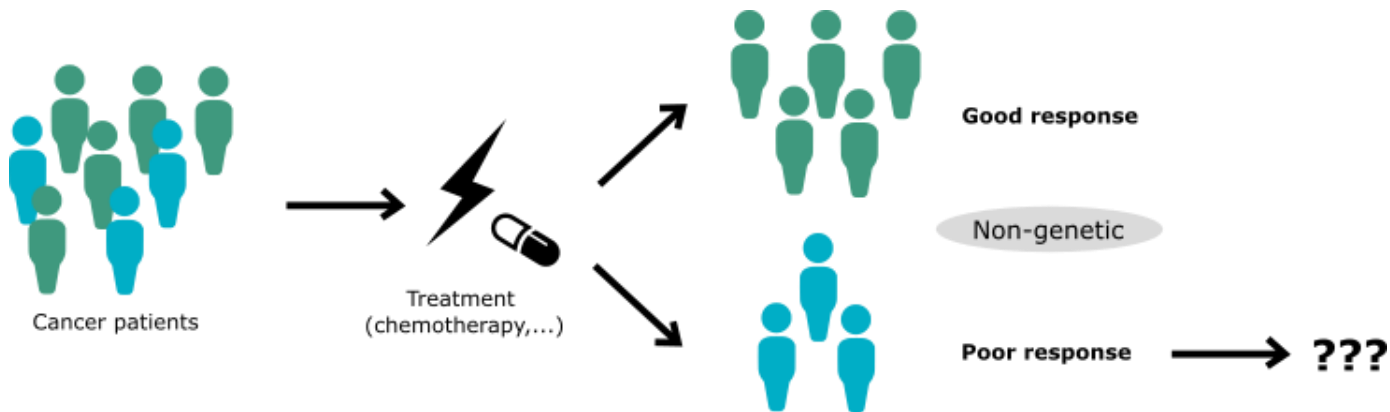
# Multi-modal quantification of pathway activity with MAYA

Yuna LANDAIS - 2<sup>nd</sup> year PhD student  
Dynamics of epigenetic plasticity in cancer (UMR3244)  
One Biosciences

02/05/2023



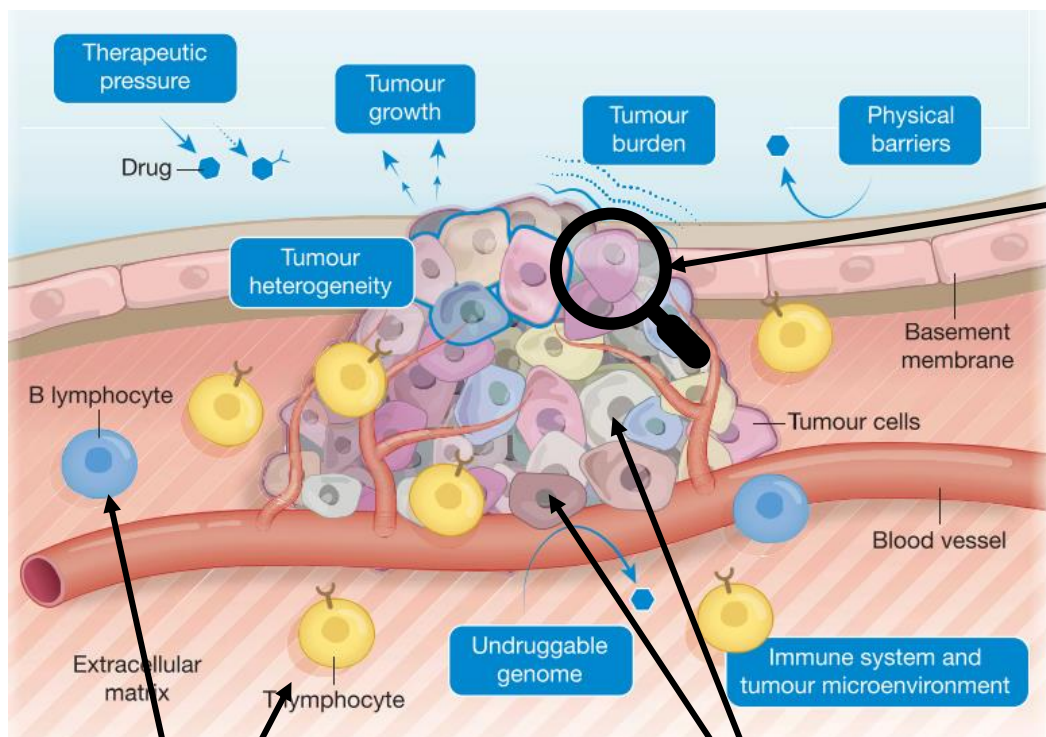
# Resistance is a major challenge for cancer treatment



**Can we predict patient's response to treatment?**

**Can we find new therapeutic approaches for non-responding patients?**

# Chemoresistance is a complex biological mechanism



Vasan et al., Nature, 2019

Regulated at different levels:

- Genetic
- Transcriptomic
- Epigenetic

+ How does the system change during the course of treatment?

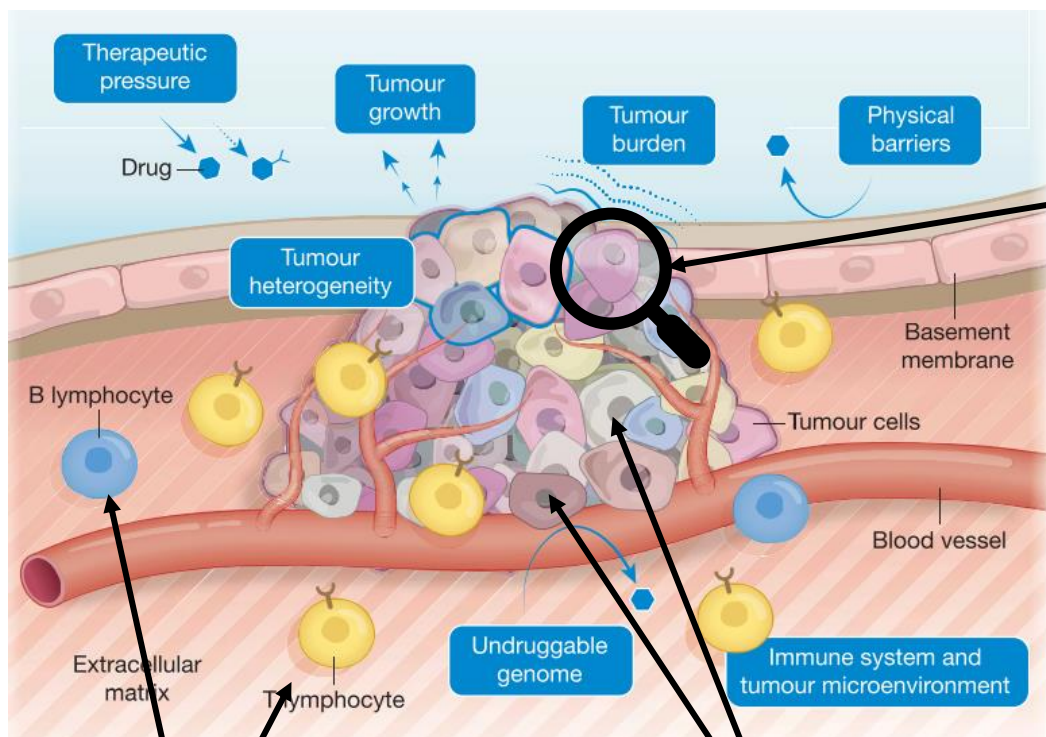
Different cell types

Inter-patient variability +  
Intra-tumoral heterogeneity

Single-cell technologies are a great opportunity to precisely describe the tumor ecosystem.

BUT many variables here,  
**where to start?**

# Chemoresistance is a complex biological mechanism



Regulated at different levels:

- Genetic
- **Transcriptomic**
- Epigenetic

+ How does the system change during the course of treatment?

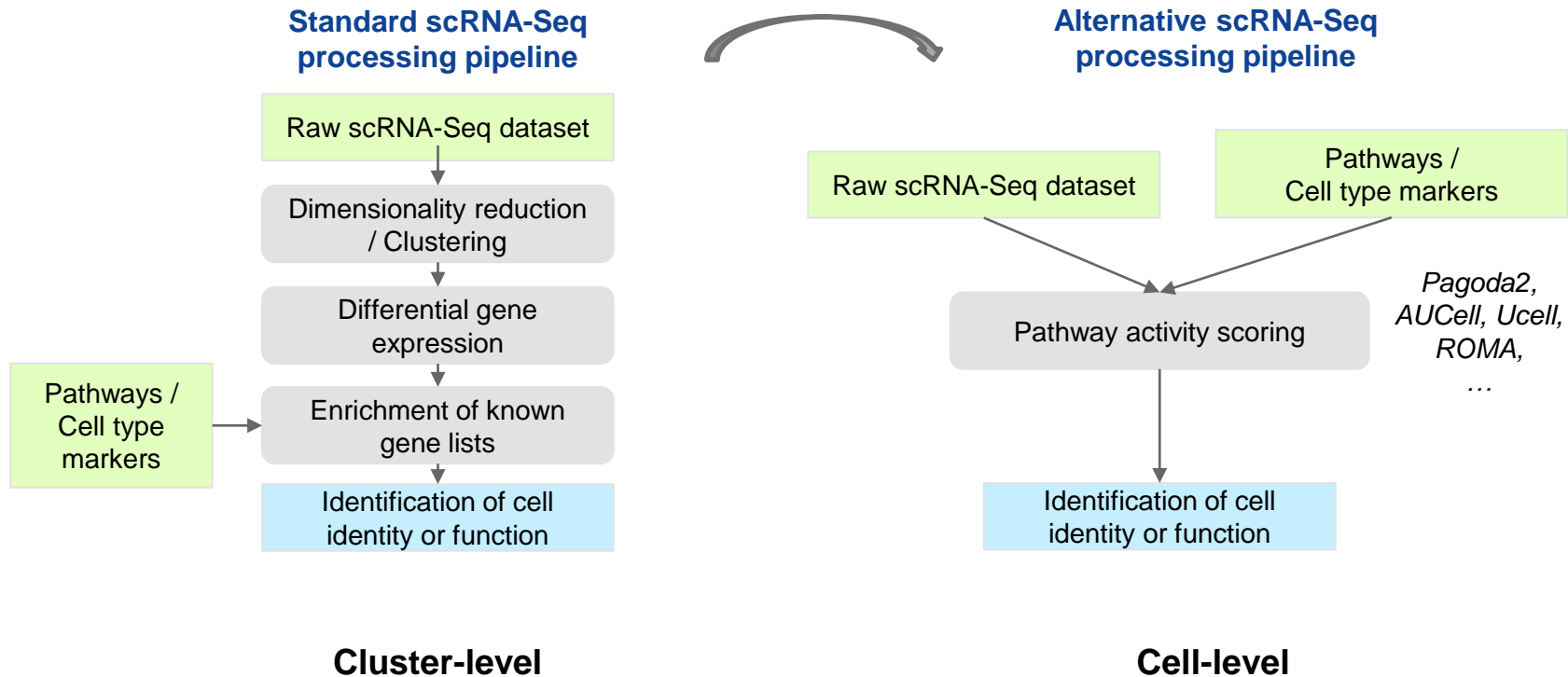
Different cell types

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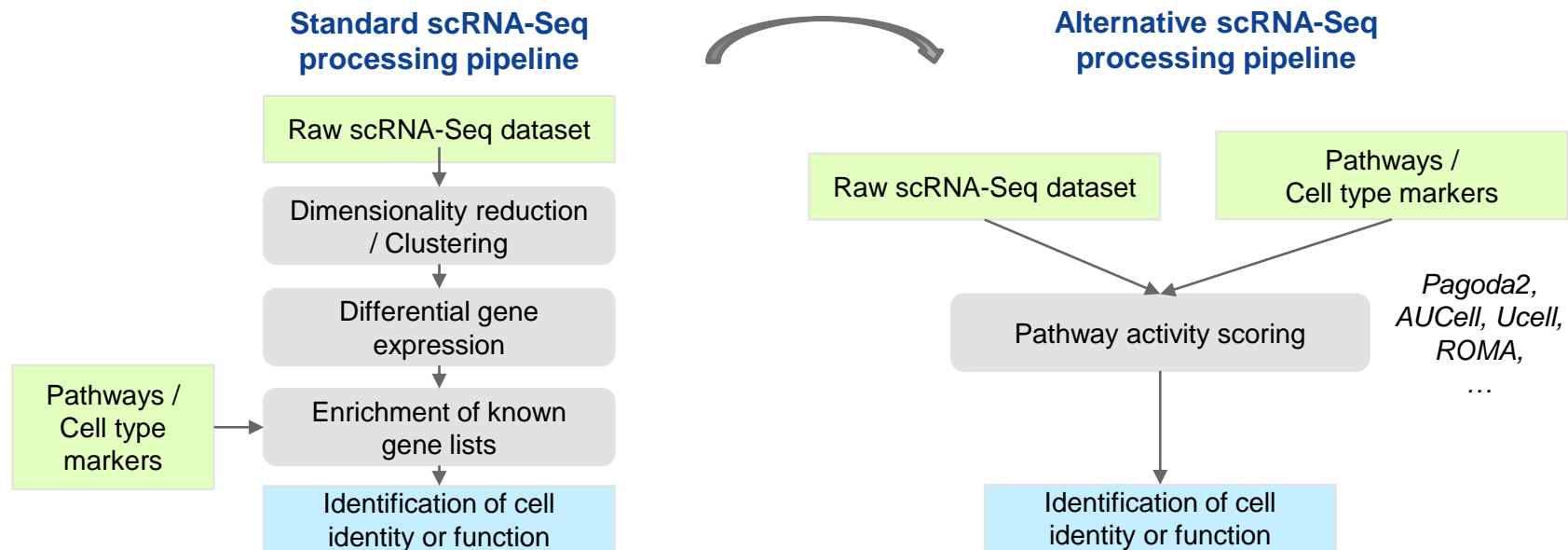
What does the tumor look like **before treatment** from **transcriptomic** perspective?

- **Who is who?**
- **Who does what?**
  - **How?**

# Current methods to study cell identity and function from scRNA-Seq data



# Current methods to study cell identity and function from scRNA-Seq data

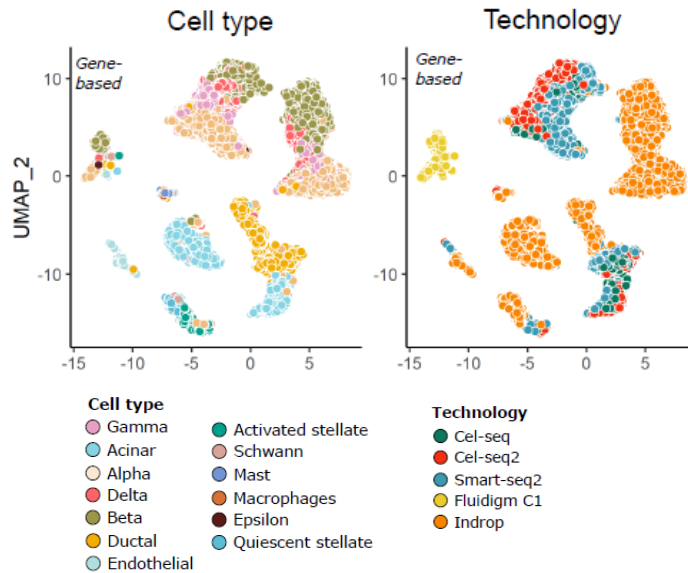


- *Dependence to clustering parameters*
- *Dependence to DEGs significance thresholds*

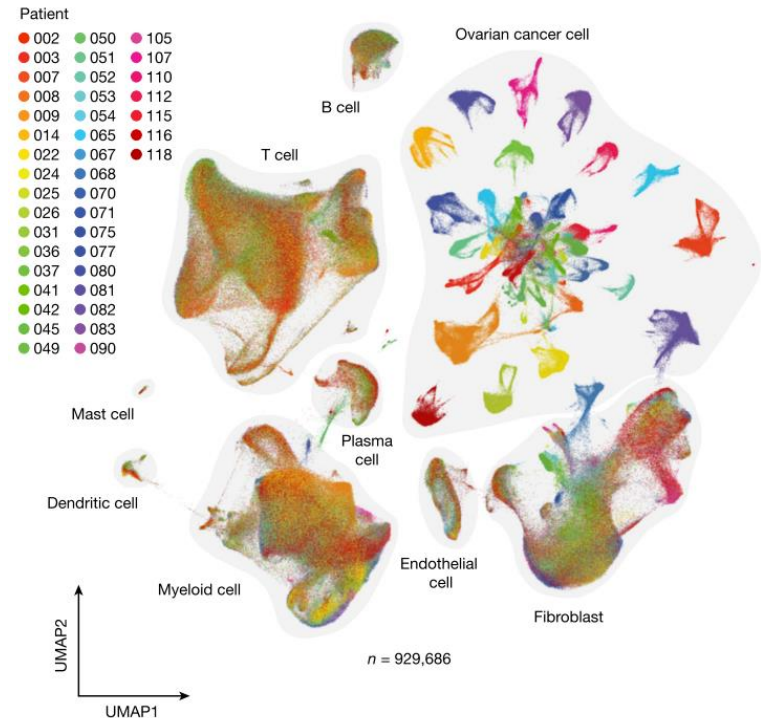
**Strong hypothesis:**  
**1 cluster = 1 cell identity = 1 cell function**

# Identity is not always the main driver of cell clustering

## Batch effect



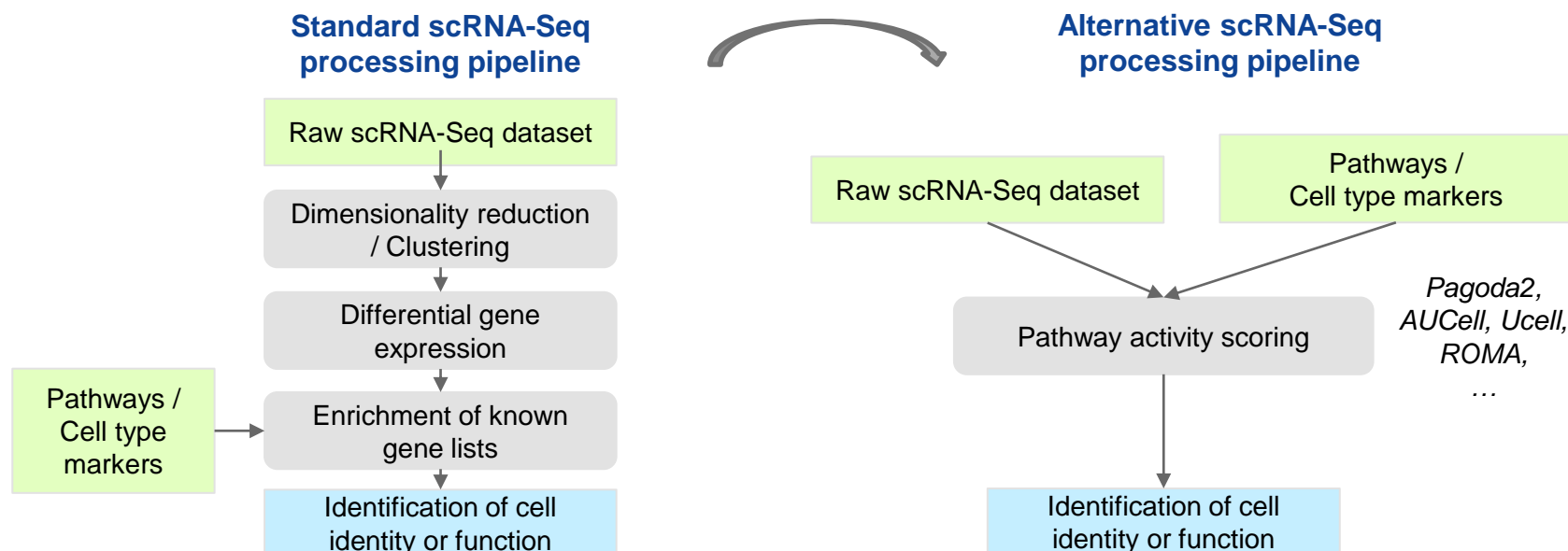
## Patient specificity of tumor cells



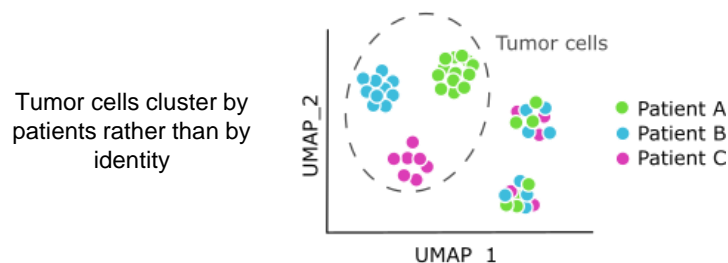
Vazquez-Garcia et al., Nature, 2022



# Current methods to study cell identity and function from scRNA-Seq data



- **Dependence to clustering parameters**
- **Dependence to DEGs significance thresholds**
  - **Inadequate for cancer datasets**



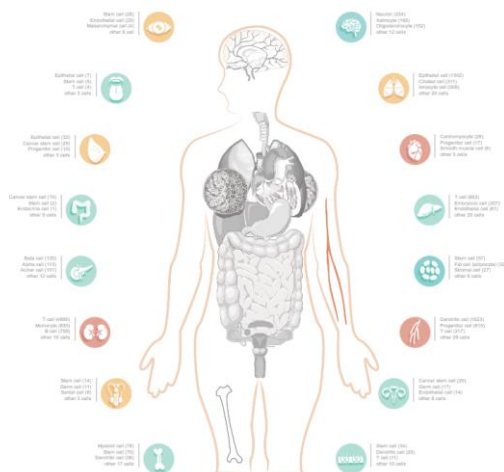
**Strong hypothesis:**  
**1 pathway = 1 group of genes with coordinated expression across all cell populations**



# Current knowledge does not meet the granularity reached by single-cell data

## Cell identity

PanglaoDB  CellMarker



Capture of CellMarker Home page

## Cell function

 BROAD  
INSTITUTE

 MSigDB  
Molecular Signatures  
Database



Category	Hallmarks
<b>Cellular component</b>	Apical_surface, apical_junction, peroxisome
<b>Development</b>	Adipogenesis, angiogenesis, epithelial_mesenchymal_transition, myogenesis,...
<b>DNA damages</b>	DNA_repair, UV_response_up, UV_response_down
<b>Immune system</b>	Coagulation, complement, allograft_rejection,...
<b>Metabolism</b>	Cholesterol_homeostasis, glycolysis...
<b>Pathway</b>	Apoptosis, hypoxia,...
<b>Proliferation</b>	G2M_checkpoint, MYC_targets,...
<b>Signaling</b>	Notch_signaling, KRAS_signaling_up,...

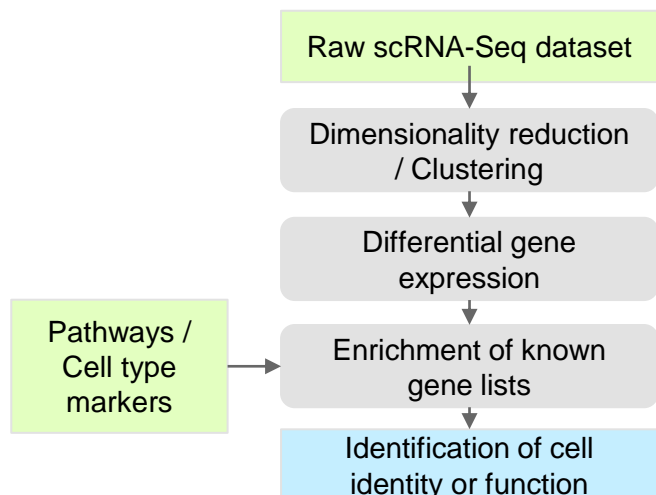
*Example of "HALLMARK" pathways*

### Issue:

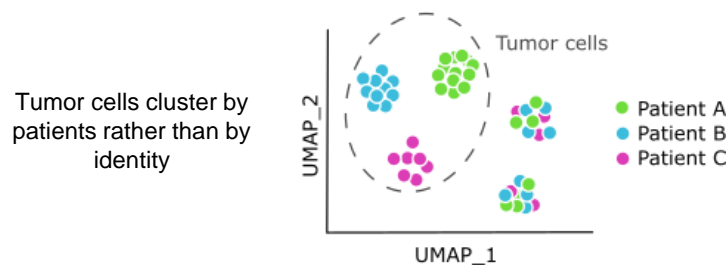
Pathway lists are often derived from bulk data  
→ they do not describe cell-type-specific biological processes

# Current methods to study cell identity and function from scRNA-Seq data

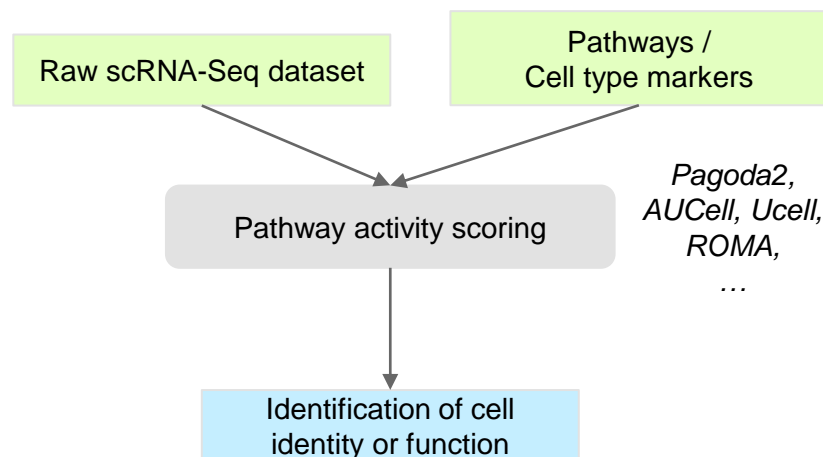
## Standard scRNA-Seq processing pipeline



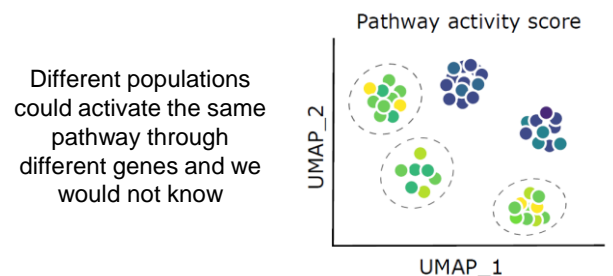
- **Dependence to clustering parameters**
- **Dependence to DEGs significance thresholds**
  - **Inadequate for cancer datasets**



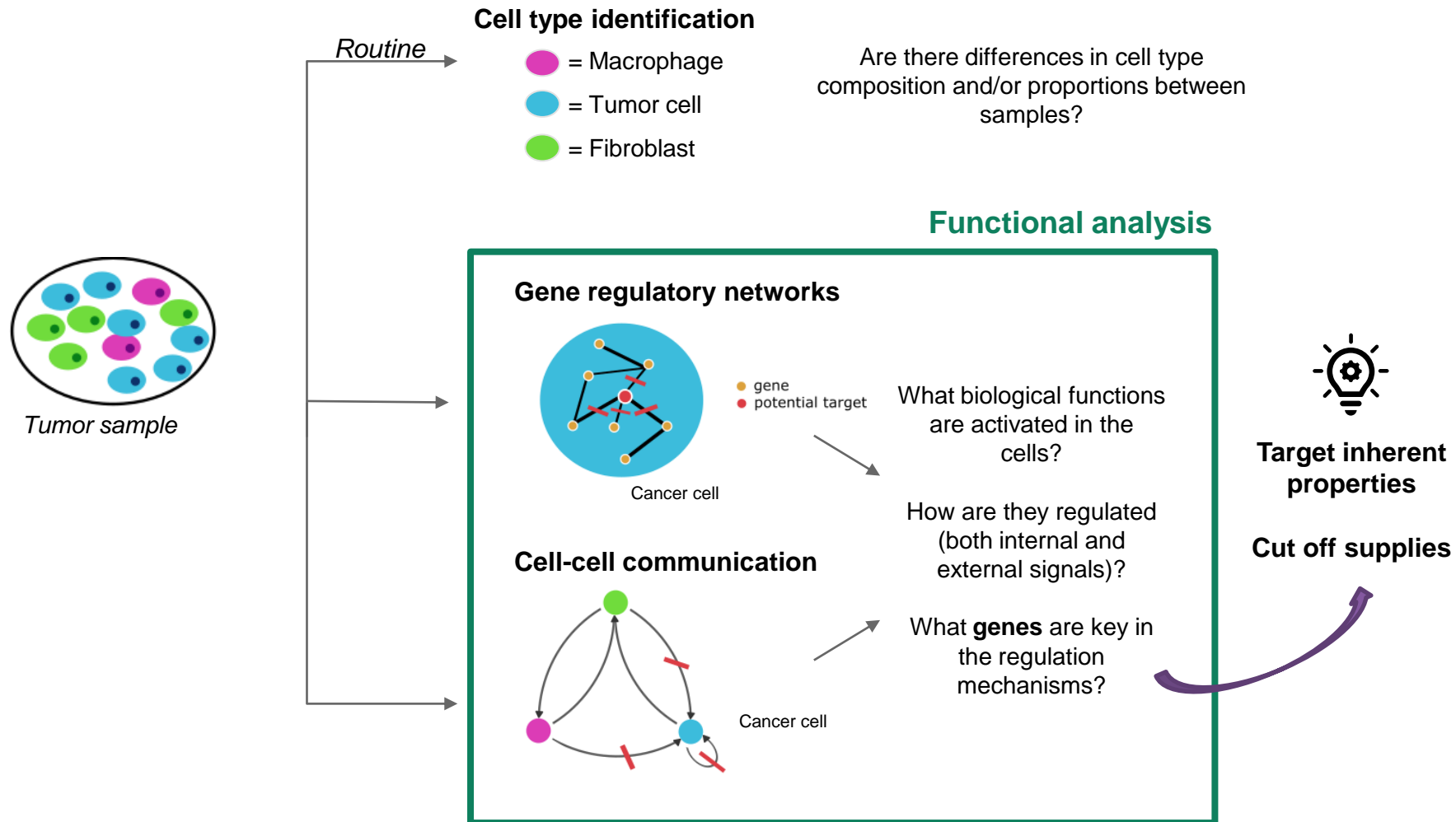
## Alternative scRNA-Seq processing pipeline



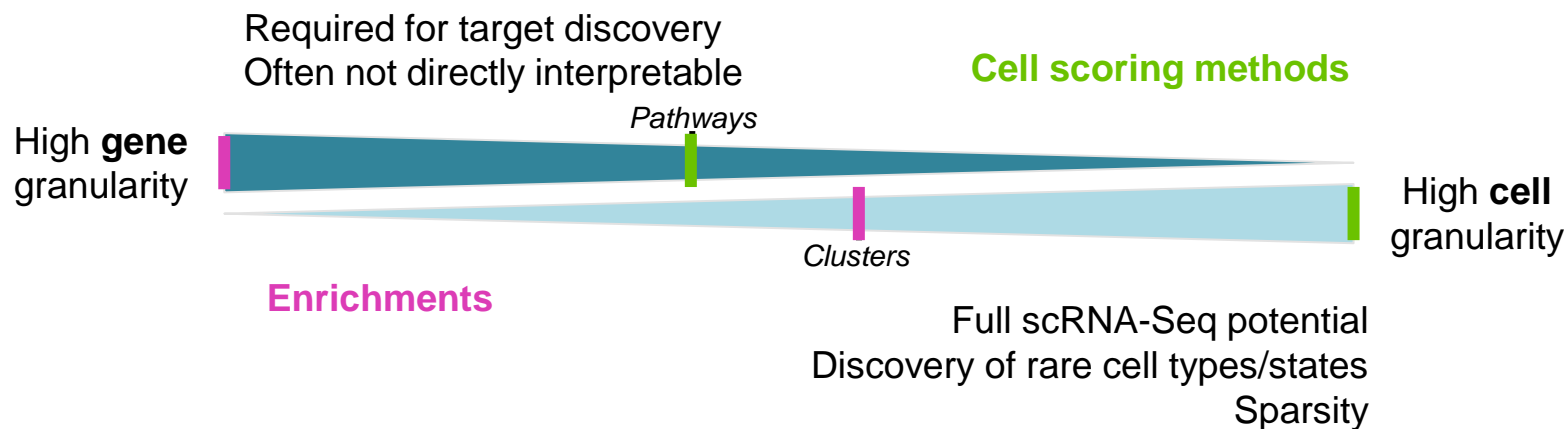
- **Current knowledge does not meet the granularity reached by single-cell data**
- **Information can be incomplete for drug discovery purposes**



# Precise description of pathway activation in specific populations is essential for drug discovery

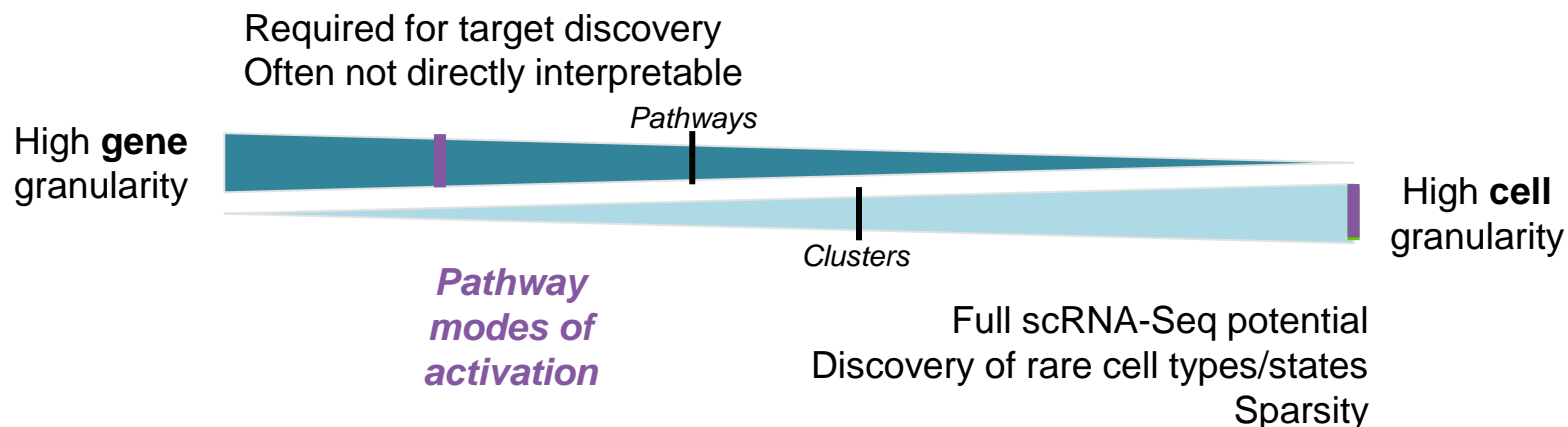


# Can we find a compromise?

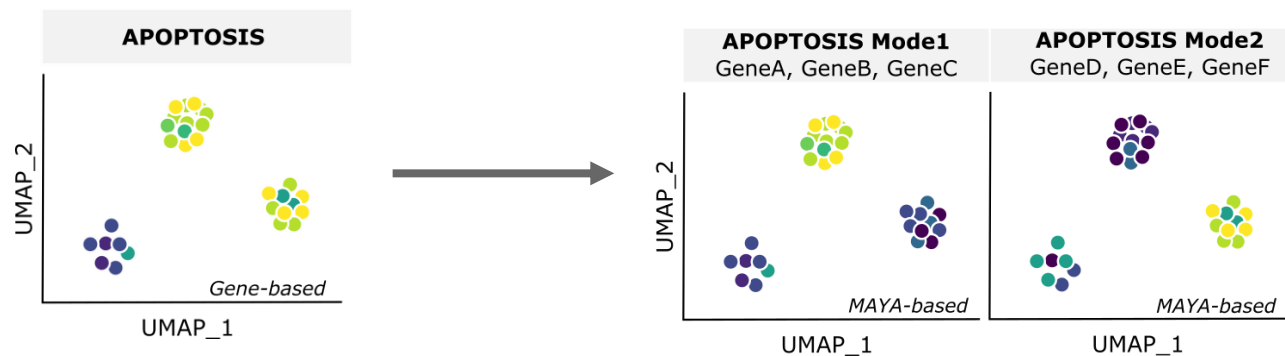


Difficult-to-reach balance between using the full potential of the **cell level granularity** of the data and having **precise information about pathway activation**

# Can we find a compromise?

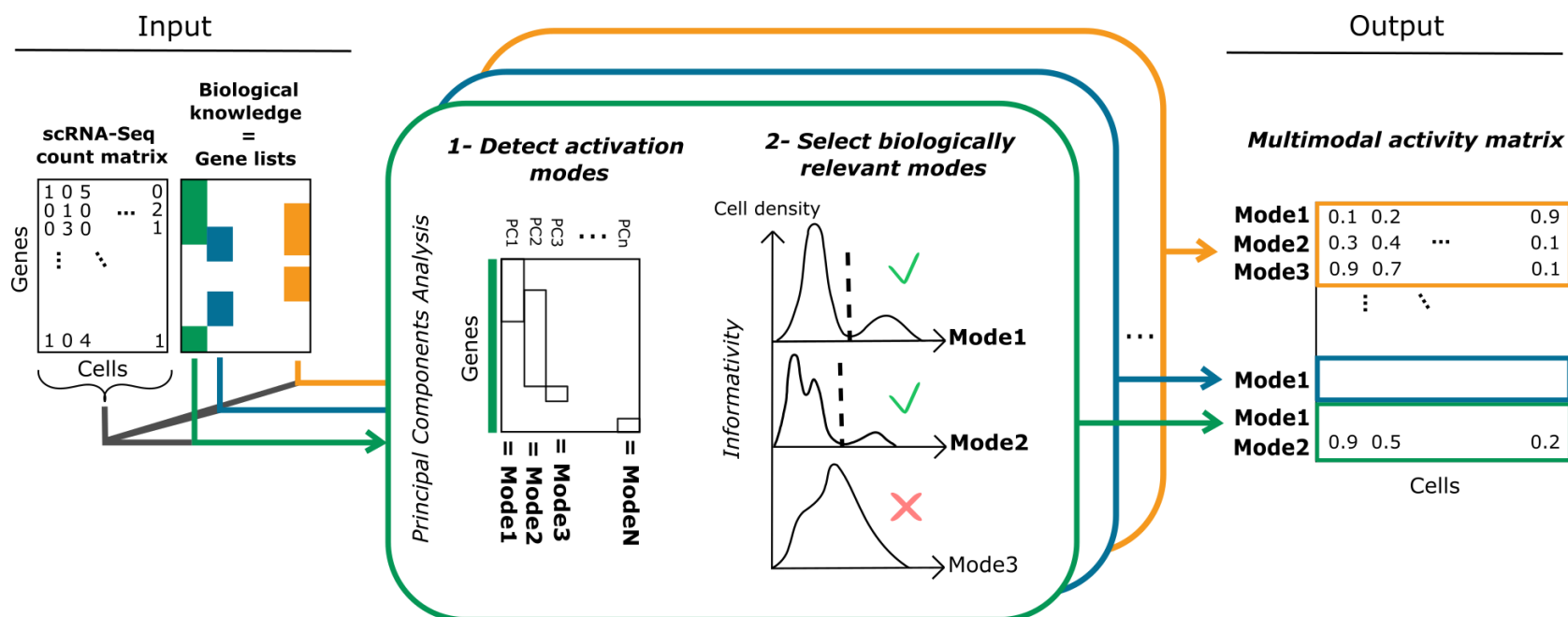


Difficult-to-reach balance between using the full potential of the **cell level granularity** of the data and having **precise information about pathway activation**





# MAYA: Multimodes of pathway Activation

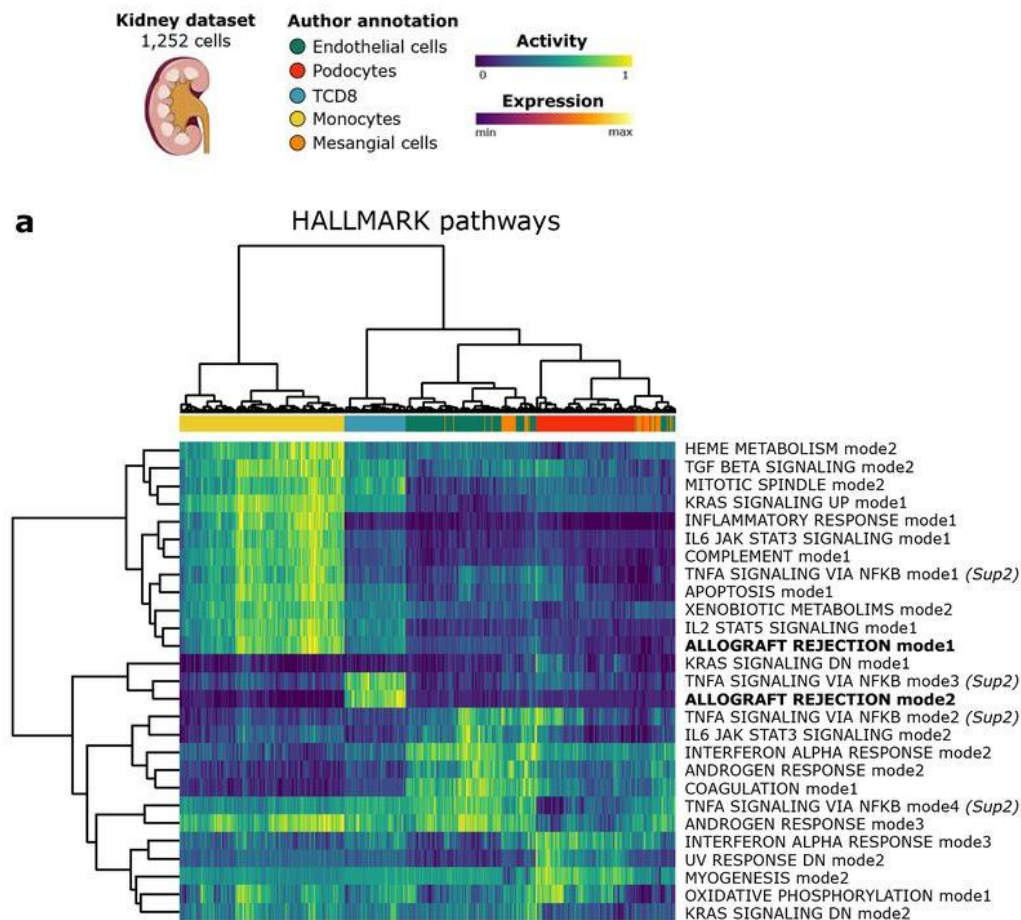


MAYA detects **subgroups of genes within reference pathways**, each characteristic of a cell population and how it activates a pathway.

MAYA's output can be used to:

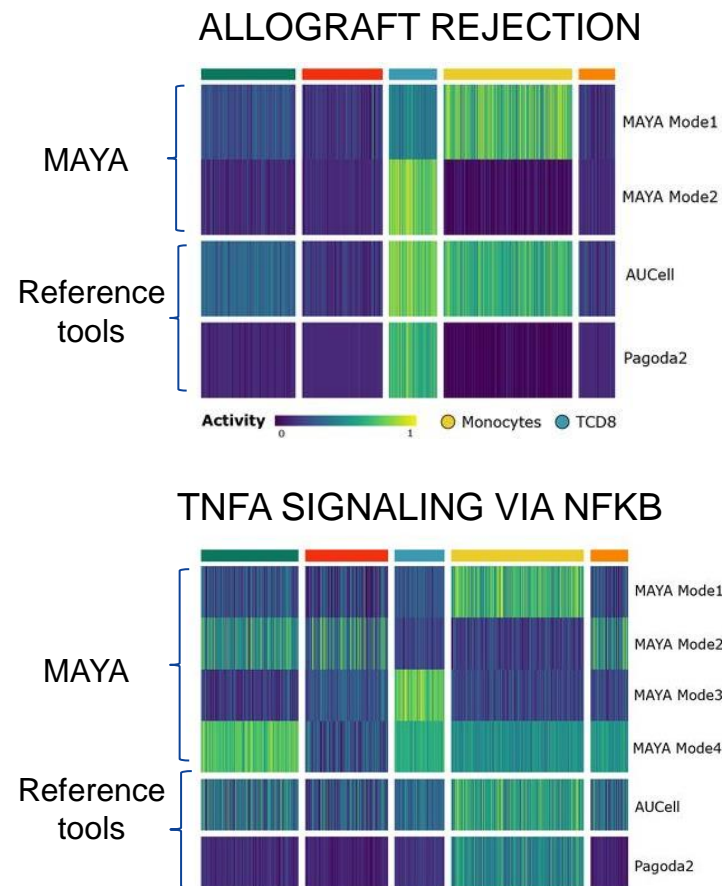
- Identify cell populations sharing similar modes of pathway activation → they can be different from the ones found with standard gene-based pipeline
  - Compute a **new visualization** of cells in 2D space

# MAYA detects biologically relevant **multimodal** pathway activity in kidney



Heatmap representing MAYA activity matrix

## Example of two multimodal pathways





# MAYA detects cell-type specific modes

Kidney dataset  
1,252 cells

Author annotation

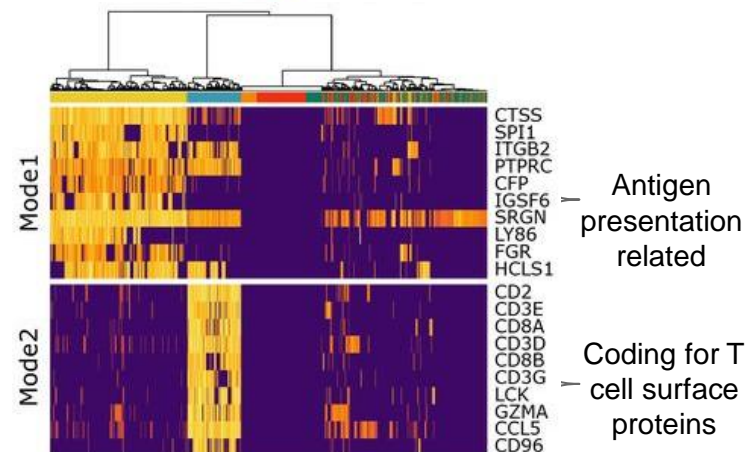
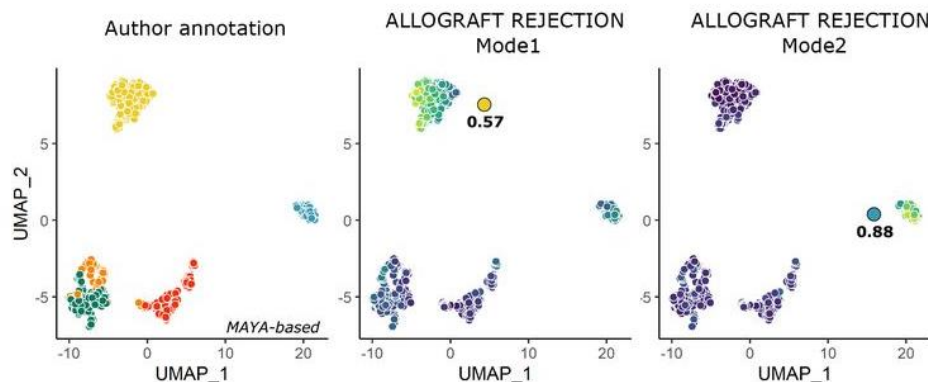
- Endothelial cells
- Podocytes
- TCDS
- Monocytes
- Mesangial cells

Activity  
0 1

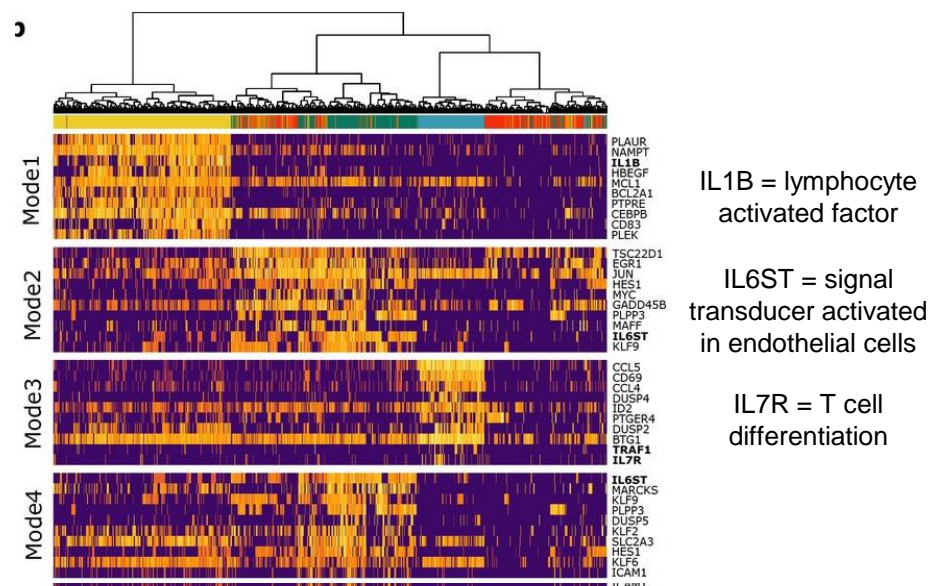
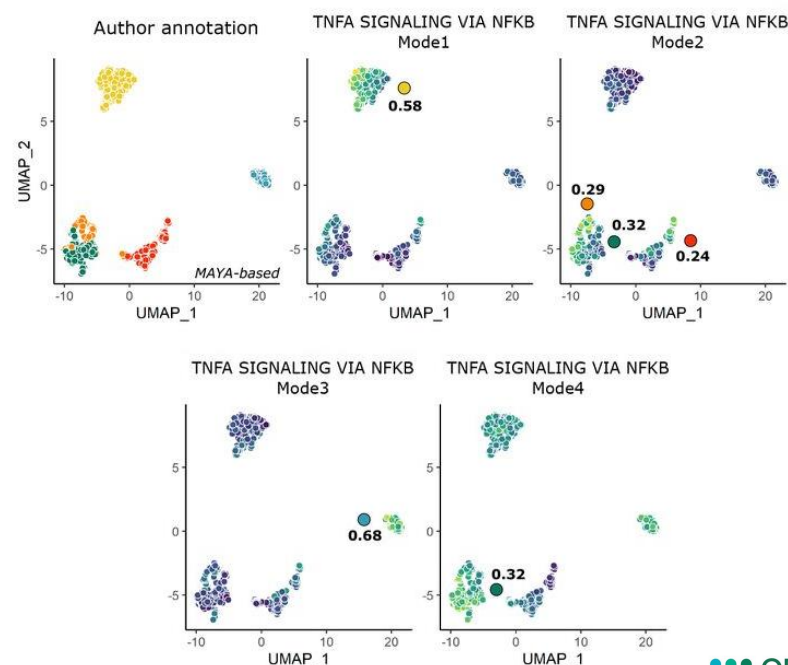
Expression  
min max



ALLOGRAFT REJECTION

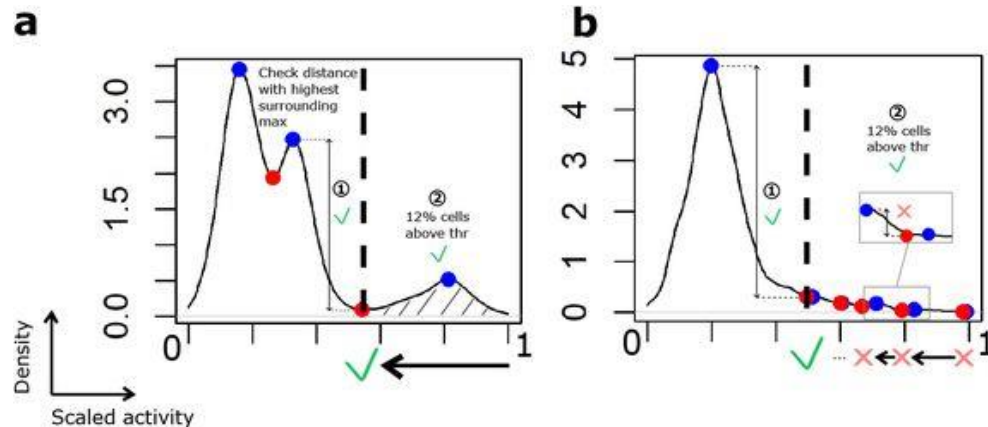


TNFA SIGNALING VIA NFKB

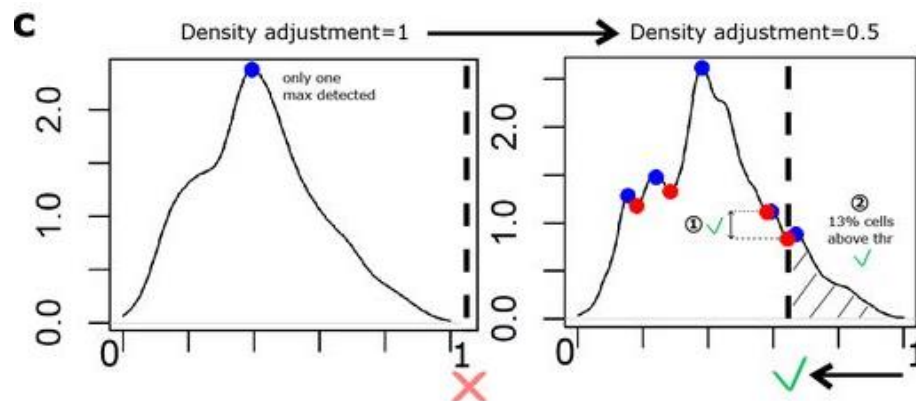


# Informativity to select modes: bimodal detection

*Identifying a density minima separating two cell populations with different activity levels*

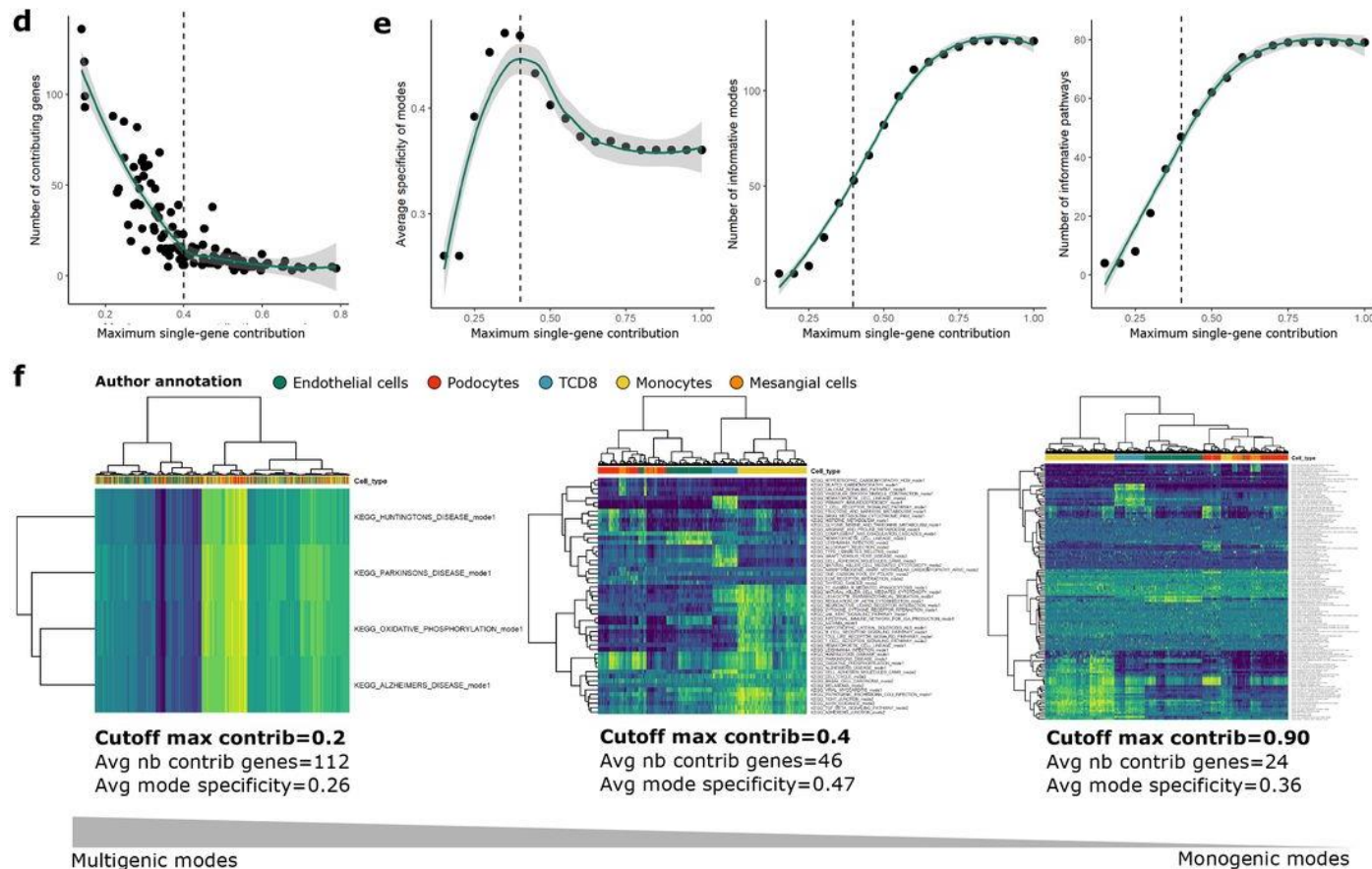


*Testing a more fitted density curve to ensure we don't miss more subtle variations in activity*



The minimal percentage of cells expected to activate a pathway is a parameter of the function and can be tuned by the user based on prior knowledge or arbitrarily.

# Informativity to select modes: maximum gene contribution as an indicator for monogenic modes



Users can also tune the cutoff on maximum single-gene contribution, depending on their tolerance to monogenic modes

# Testing MAYA robustness to noise

Kidney dataset  
1,252 cells



Author annotation

- Endothelial cells
- Podocytes
- TCD8
- Monocytes
- Mesangial cells



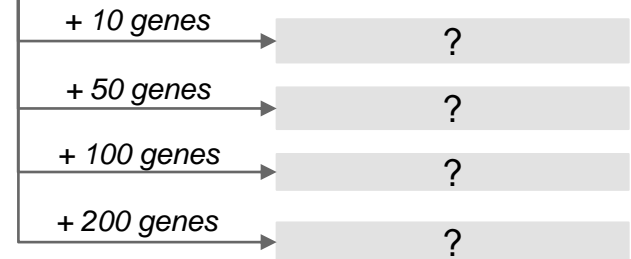
Allograft rejection  
pathway  
(200 genes)

2 cell-type specific  
modes

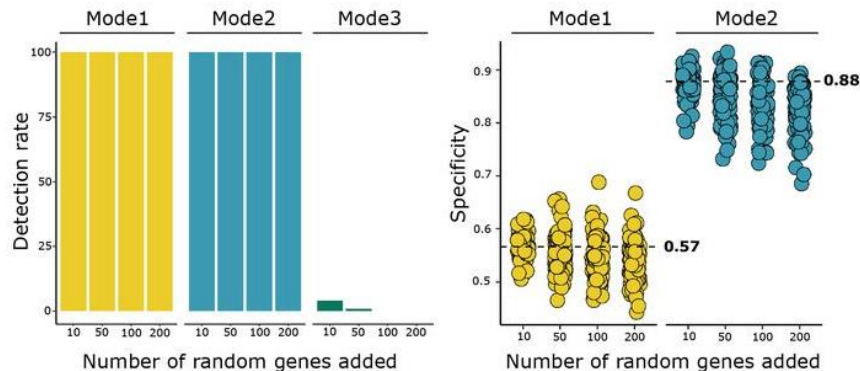


TNFA signaling  
pathway  
(200 genes)

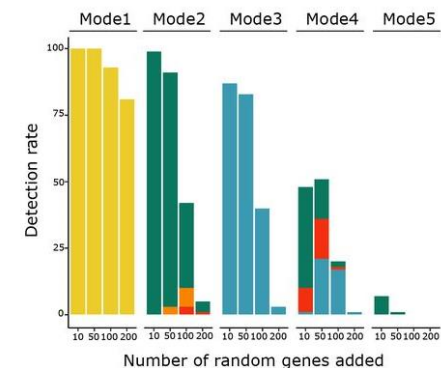
4 cell-type specific  
modes



## ALLOGRAFT REJECTION



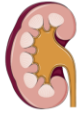
## TNFA SIGNALING VIA NFKB





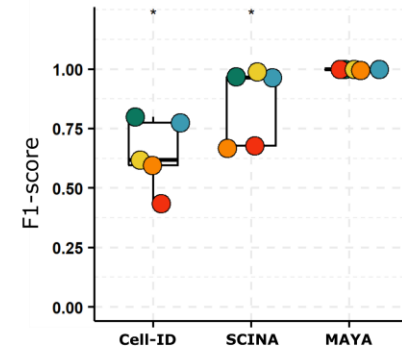
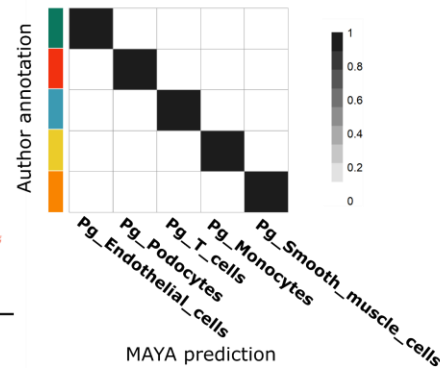
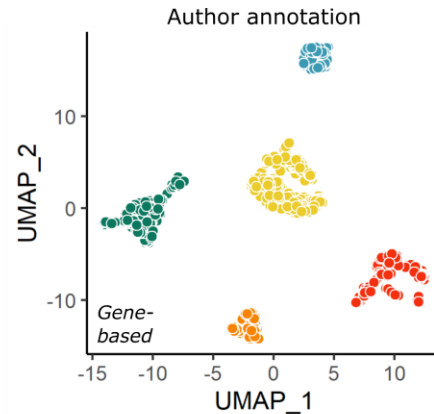
# MAYA annotates cell types

Kidney dataset  
1,252 cells  
5 cell types



## Author annotation

- Endothelial cells
- Podocytes
- TCD8
- Monocytes
- Mesangial cells

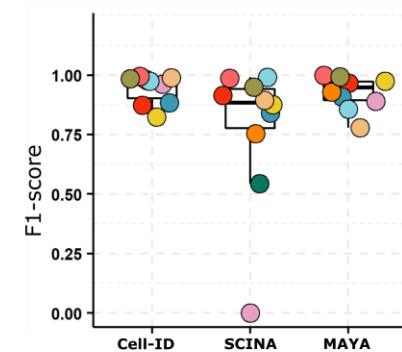
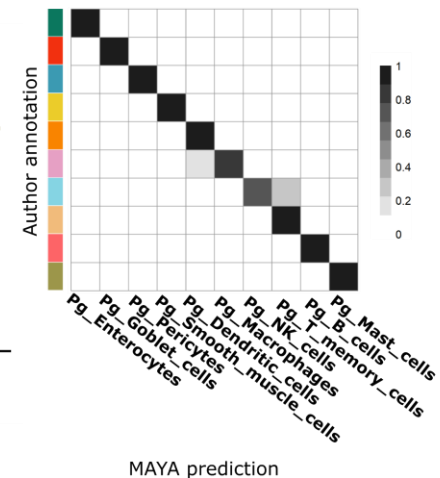
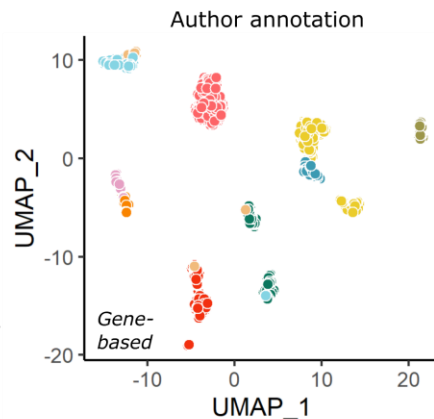


Colon dataset  
1,415 cells  
10 cell types



## Author annotation

- Mature enterocytes
- Goblet cells
- Pericytes
- Smooth muscle cells
- cDC
- Proliferating monocytes
- NK cells
- Regulatory T cells
- CD19+CD20+ B cells
- Mast cells



MAYA presents rates of precision and recall comparable to other specialized cell-type annotation methods.

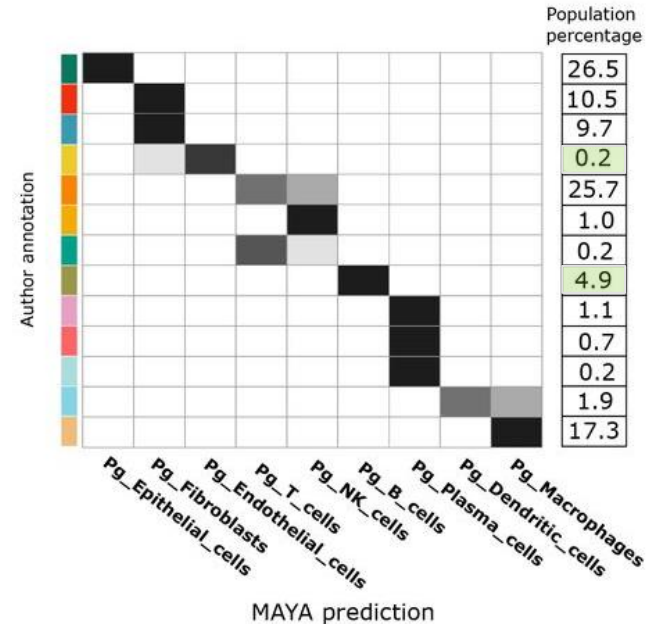
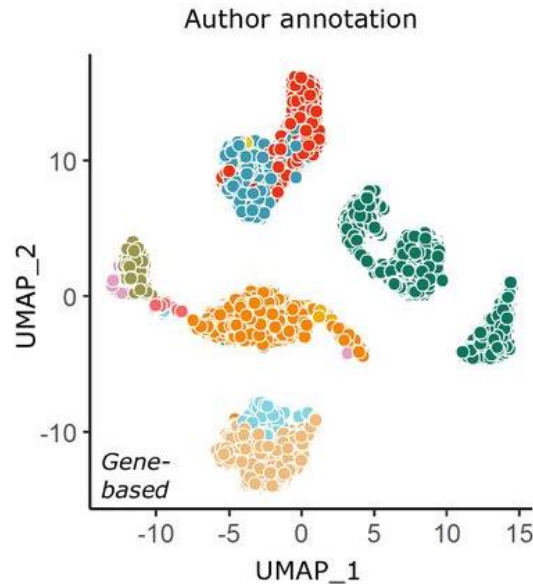
# MAYA detects and annotates rare cell populations



HGSOc dataset  
16,815 cells  
13 cell types

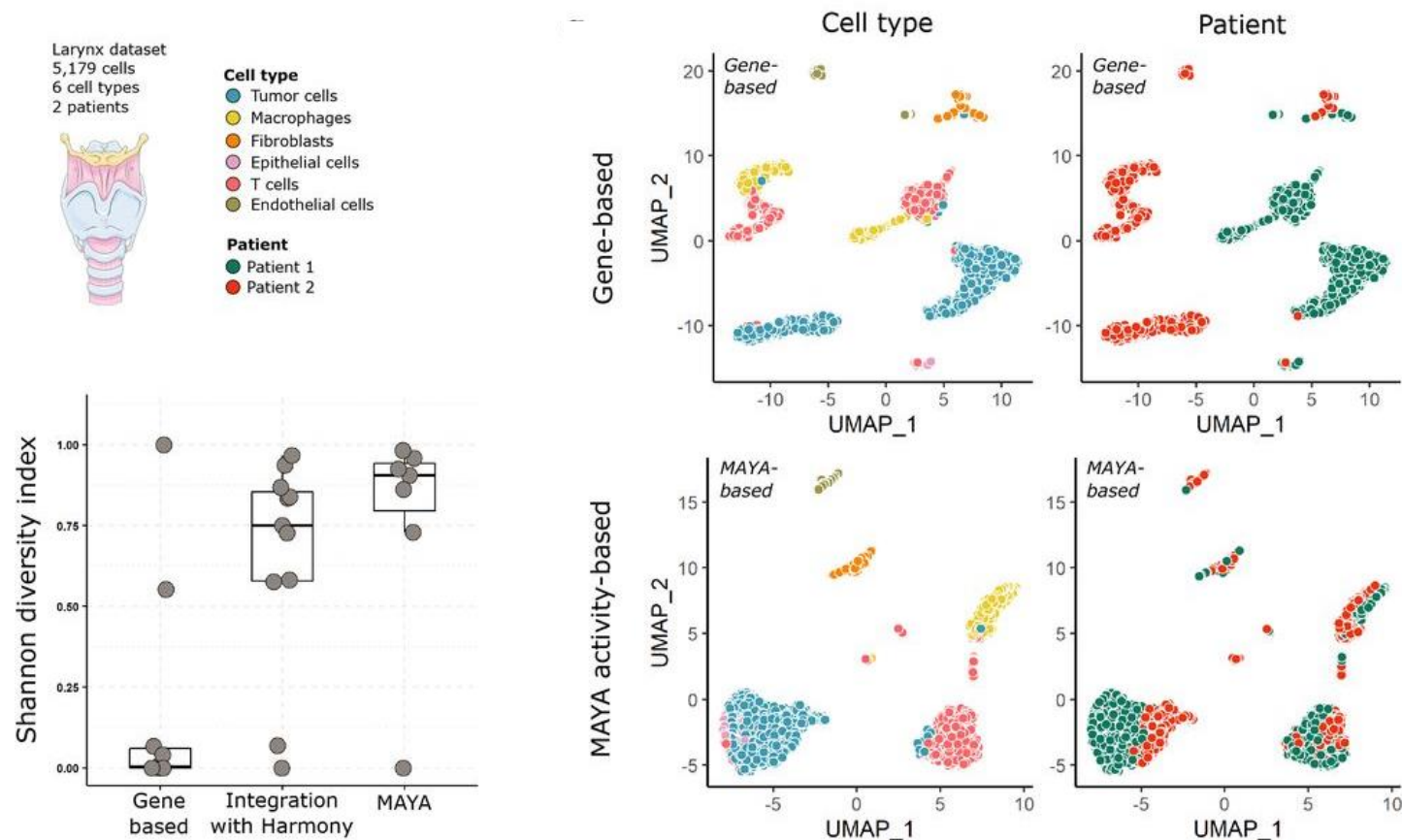
## Author annotation

- Epithelial cancer cells
- CAF
- Mesothelial cells
- Endothelial cells
- T cells
- Plasma cells
- Dendritic cells
- Macrophages
- Plasmacytoid dendritic cells
- B cells
- NK cells
- Mast cells
- Innate lymphoid cells



- MAYA can also accurately annotate very rare populations in a dataset.
- However, a limitation is the overlap between cell-type markers list that sometimes make it difficult to distinguish between two cell types (NK/T cells, DC/macrophages, endothelial/fibroblasts)

# MAYA allows batch effect free cell-type annotation

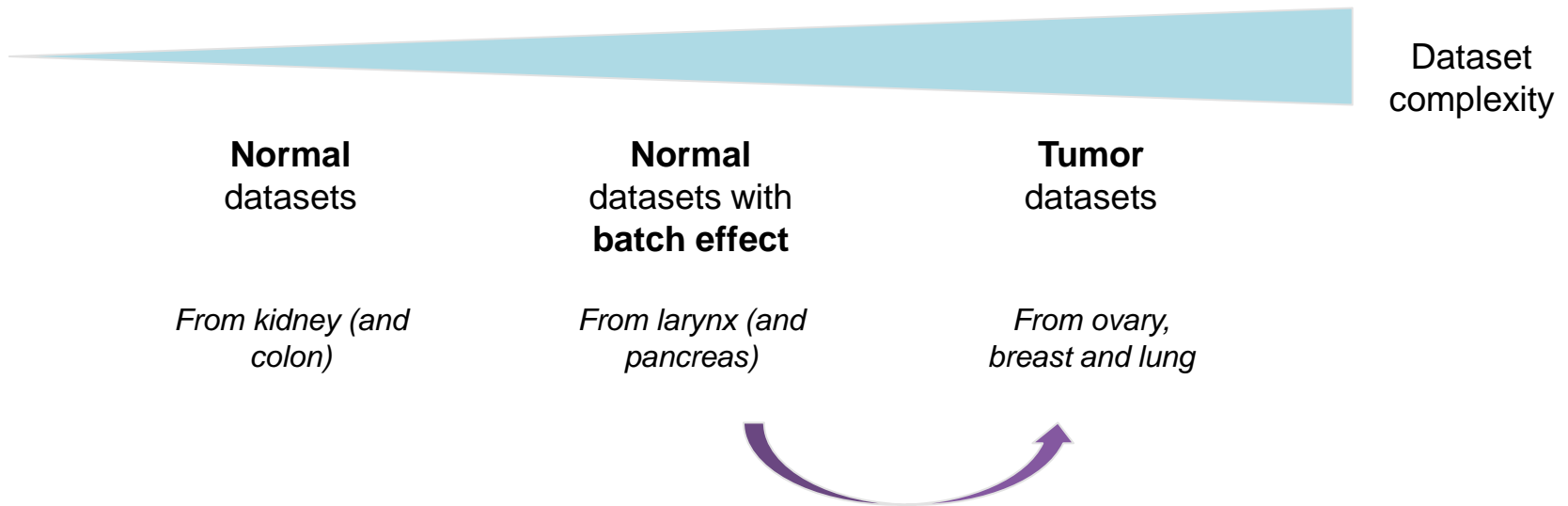


MAYA UMAP embeddings can be used for batch-effect-free visualization of datasets



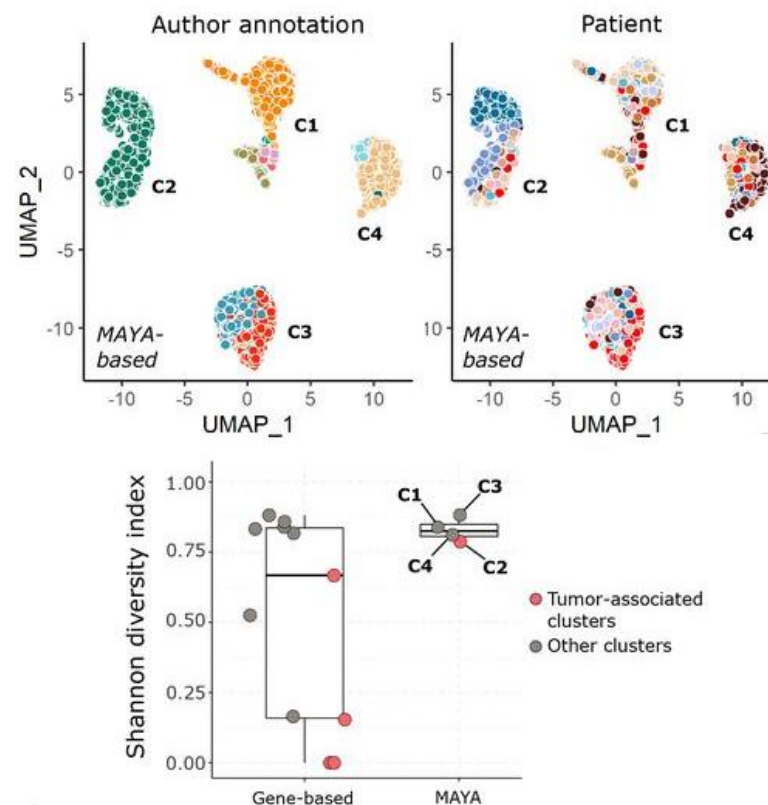
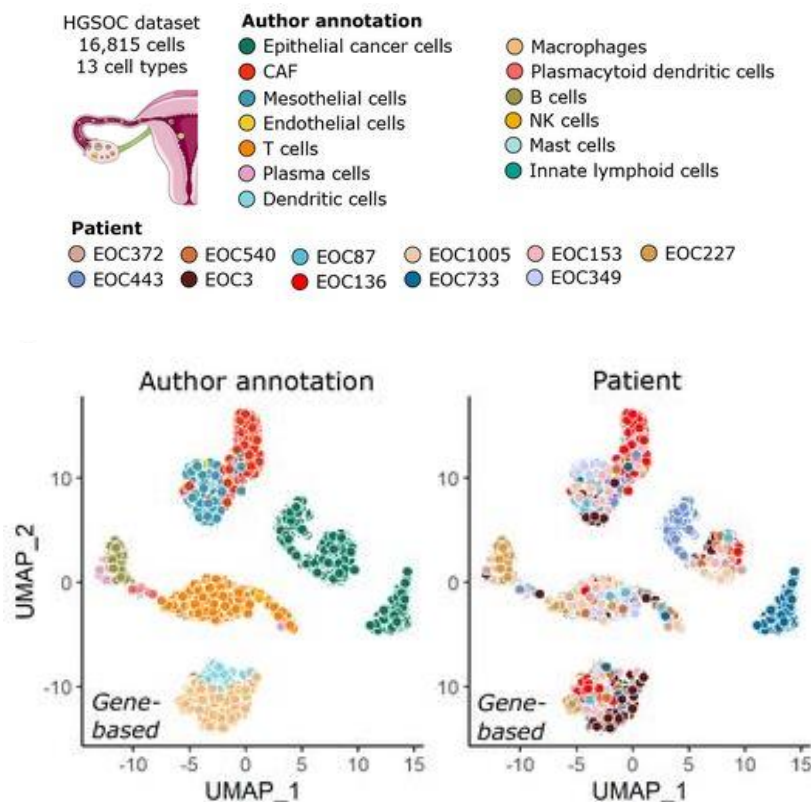
# Summary

- All-in-one tool for cell identity and pathway study and easy to use (few parameters, with default values)
- Robust to noise: very useful as manual curation of gene lists is time-consuming
- Scalable: annotation of 125,000 cells in ~15 minutes
- Interpretable way to correct batch effect for visualization



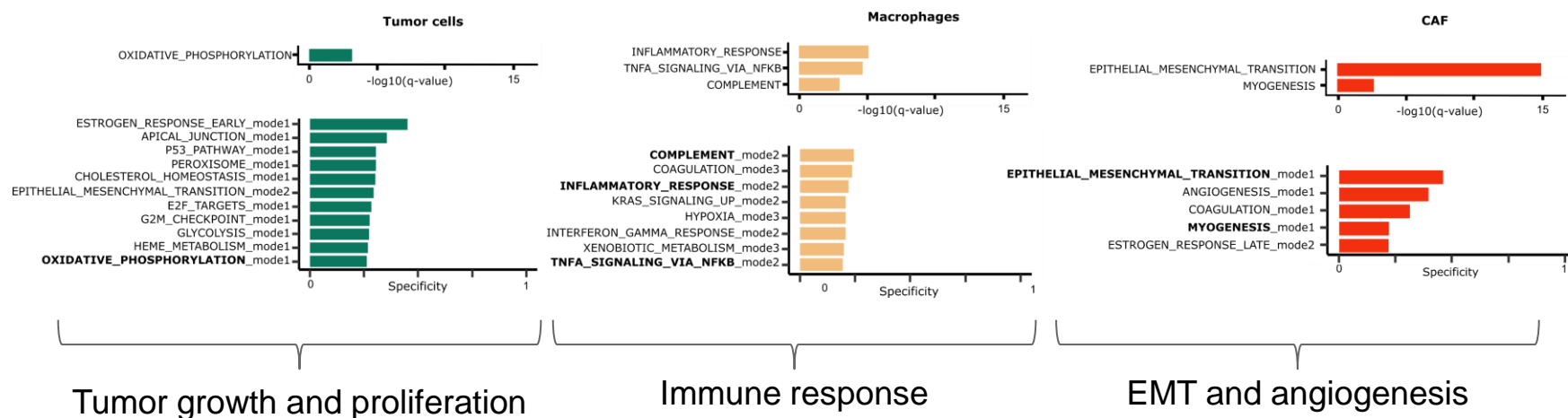
# MAYA detects common modes of pathway activation across patients

*With HALLMARK pathways*



Tumor cells tend to cluster by patient rather than by identity with standard analyses  
→ MAYA identifies shared modes of pathway activation across patient

# MAYA detects common modes of pathway activation across patients that are not detected by GSEA

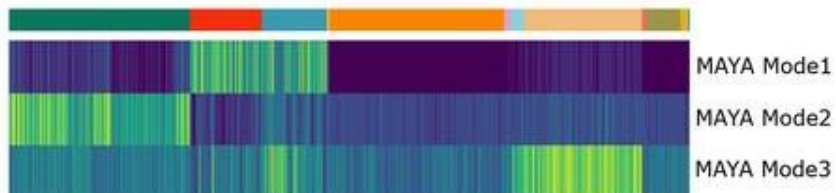
MAYA  
GSEA

Identification of relevant top-specific modes of pathway activation for both tumor cells and the microenvironment

Identification of more functions than with classical GSEA analysis

# MAYA detects three cell-type specific modes of EMT activation

## HALLMARK: EPITHELIAL MESENCHYMAL TRANSITION

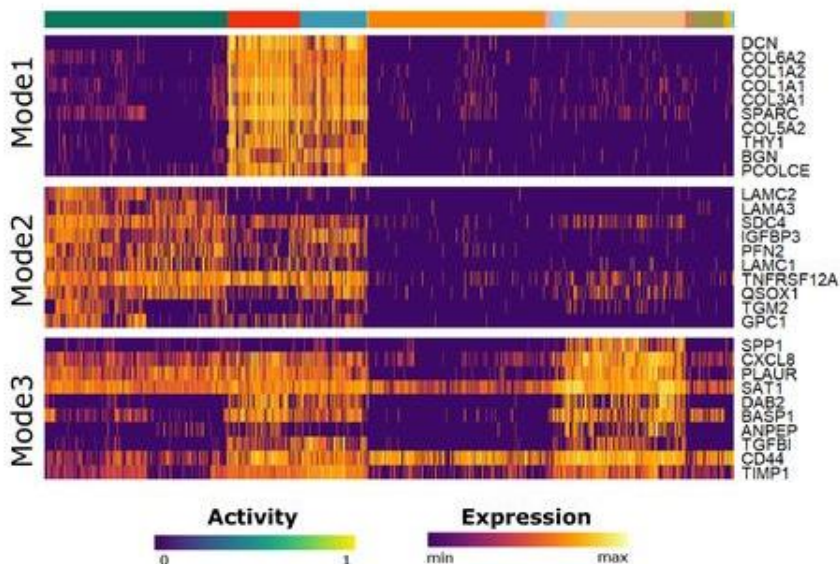


HGSOC dataset  
16,815 cells  
13 cell types



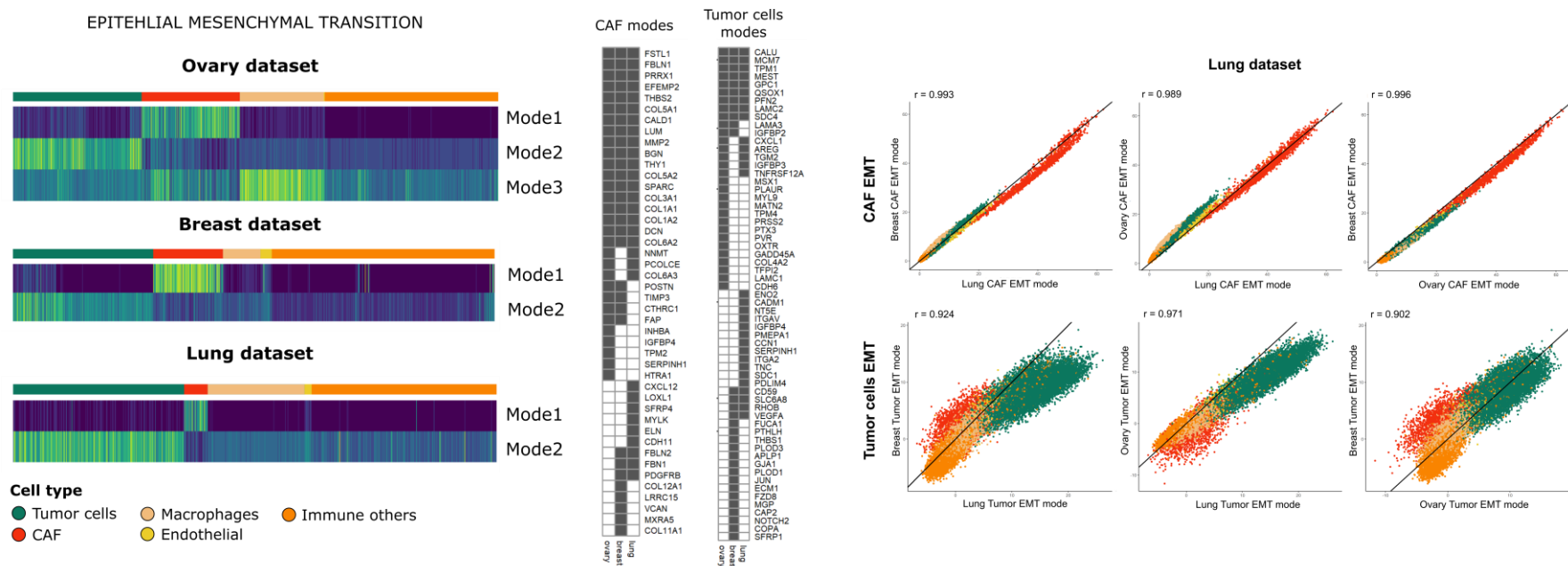
### Author annotation

- Epithelial cancer cells
- CAF
- Mesothelial cells
- Endothelial cells
- T cells
- Plasma cells
- Dendritic cells
- Macrophages
- Plasmacytoid dendritic cells
- B cells
- NK cells
- Mast cells
- Innate lymphoid cells



- Identification of a set of genes that characterizes EMT occurring in epithelial cells driven by genes coding for subunit of laminin 332 (component of epithelial basement membrane, that promotes tumor motility).
- EMT in fibroblasts driven mainly by ECM genes
- Macrophages shown to be involved in EMT in several cancer types.

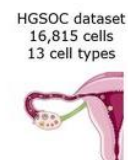
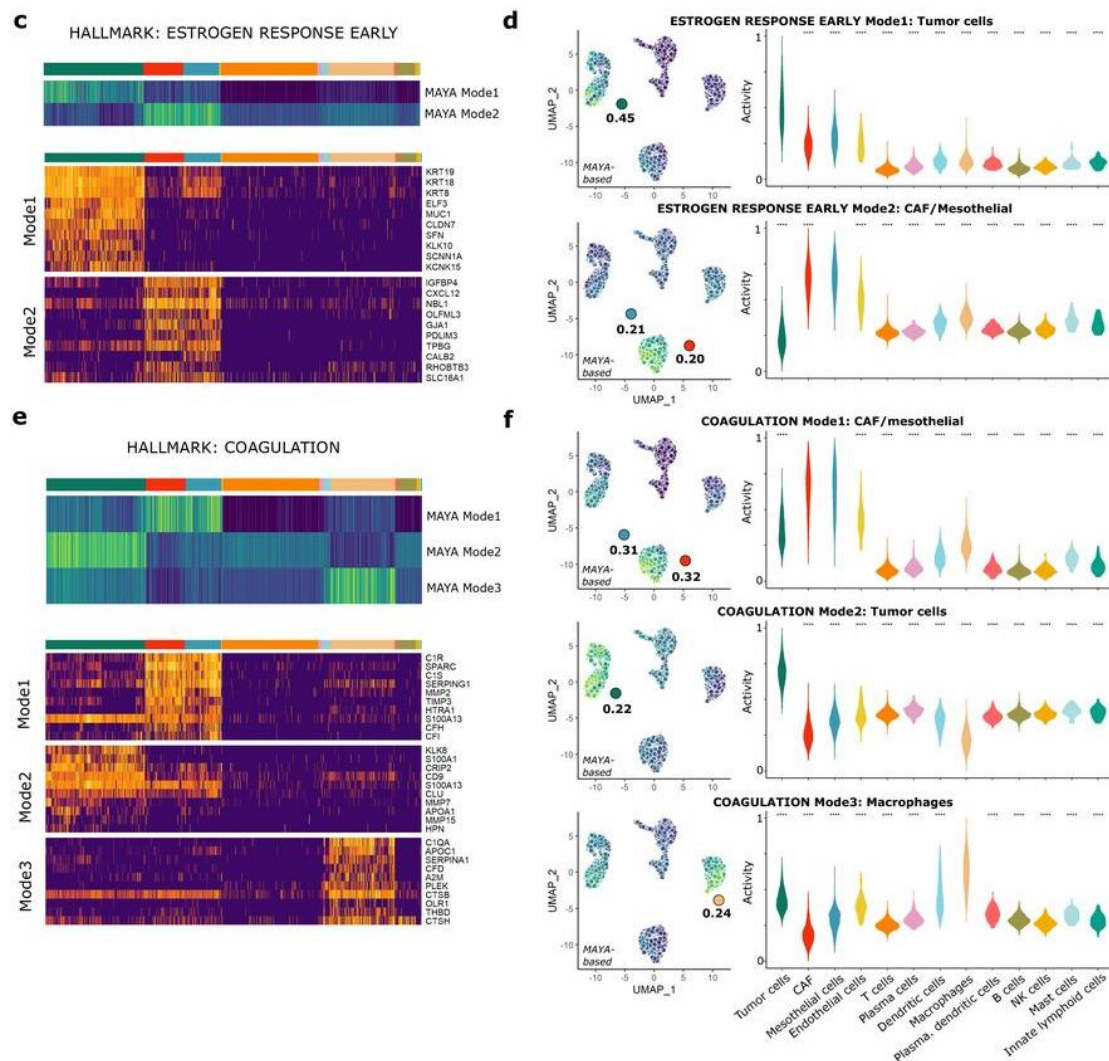
# MAYA EMT modes are reproducible across datasets



CAF and tumor cell specific modes of EMT were detected in two additional cancer datasets and display high correlation when evaluated in the same cells.



# Other examples of multimodal pathway activation



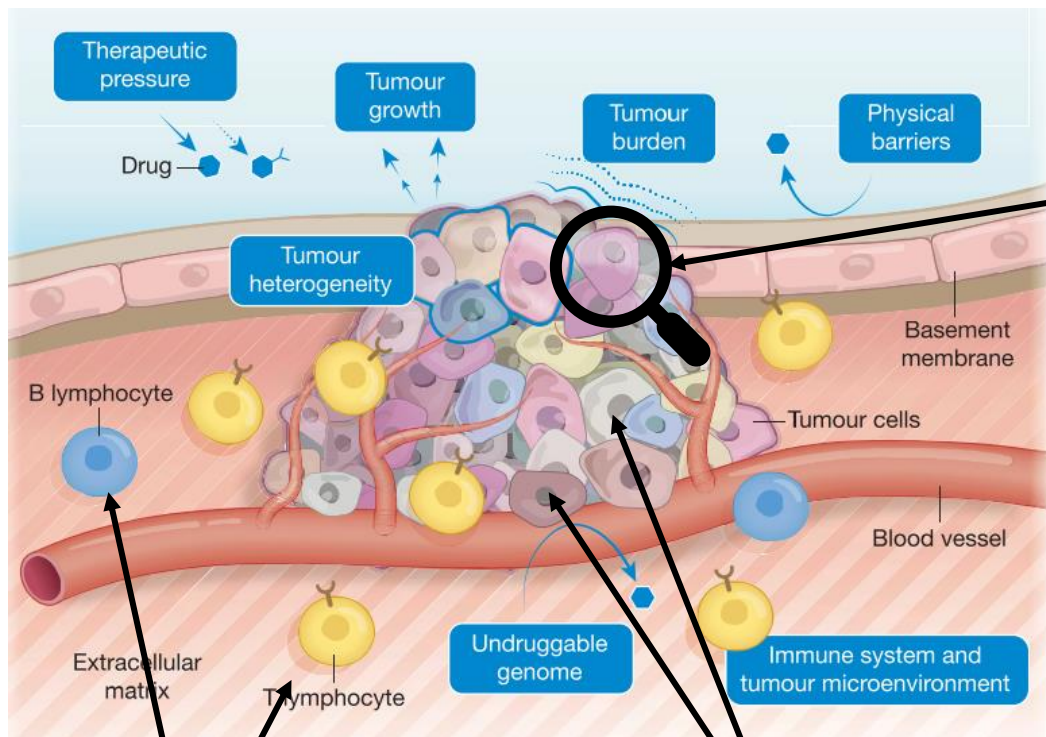
HGSOC dataset  
16,815 cells  
13 cell types

## Author annotation

- Epithelial cancer cells
- CAF
- Mesothelial cells
- Endothelial cells
- T cells
- Plasma cells
- Dendritic cells
- Macrophages
- Plasmacytoid dendritic cells
- B cells
- NK cells
- Mast cells
- Innate lymphoid cells

- CAFs can use ER-mediated pathways to promote tumor cell proliferation
- MAYA helps to untangle the respective contributions of cancer cells and its microenvironment to the hemostatic imbalance observed in cancer

# Can MAYA help us address other challenges related to the study of chemoresistance?



Vasan et al., Nature, 2019

Regulated at different levels:

- Genetic
- Transcriptomic
- Epigenetic

**+ How does the system change during the course of treatment?**

How far does MAYA precision go?

Can we detect subtle changes in pathway activation:

- within a tumor?
- Between paired samples pre/post-treatment?

**Different cell types**

**Inter-patient variability +  
Intra-tumoral heterogeneity**



# Acknowledgments

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*Pacôme Prompsy  
Camille Landragin*

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Marine Gaillard  
Cécile Hui-bon-hoa  
Marceau Quatreteniers  
Magali Richard  
Baptiste Simon  
**Céline Vallot**

*Paul Cadorin*

**Thank you for your attention !**

