

# EGY-SEJT FUNKCIONÁLIS GENOMIKA



2018. 11. 29.

# AZ ELŐADÁS FELÉPÍTÉSE



I. Egy-sejt funkcionális genomika áttekintése és jelentősége

II. Egy-sejt funkcionális genomika alkalmazása

1. Humán Sejt Atlasz (2016 – 2024)

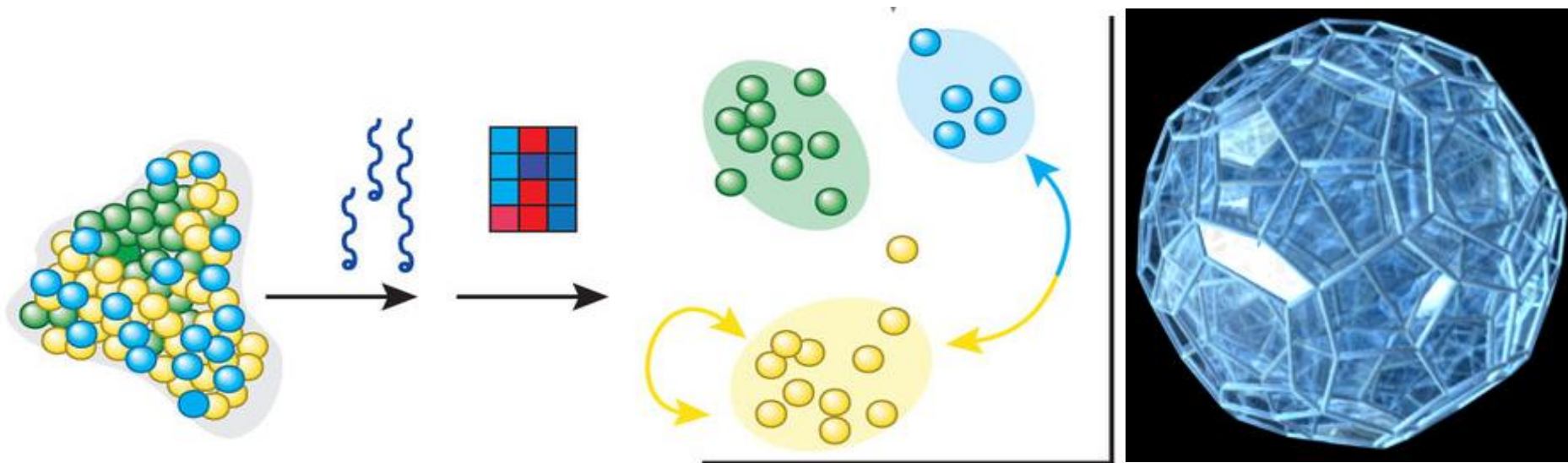
2. Heterogén sejtpopulációk

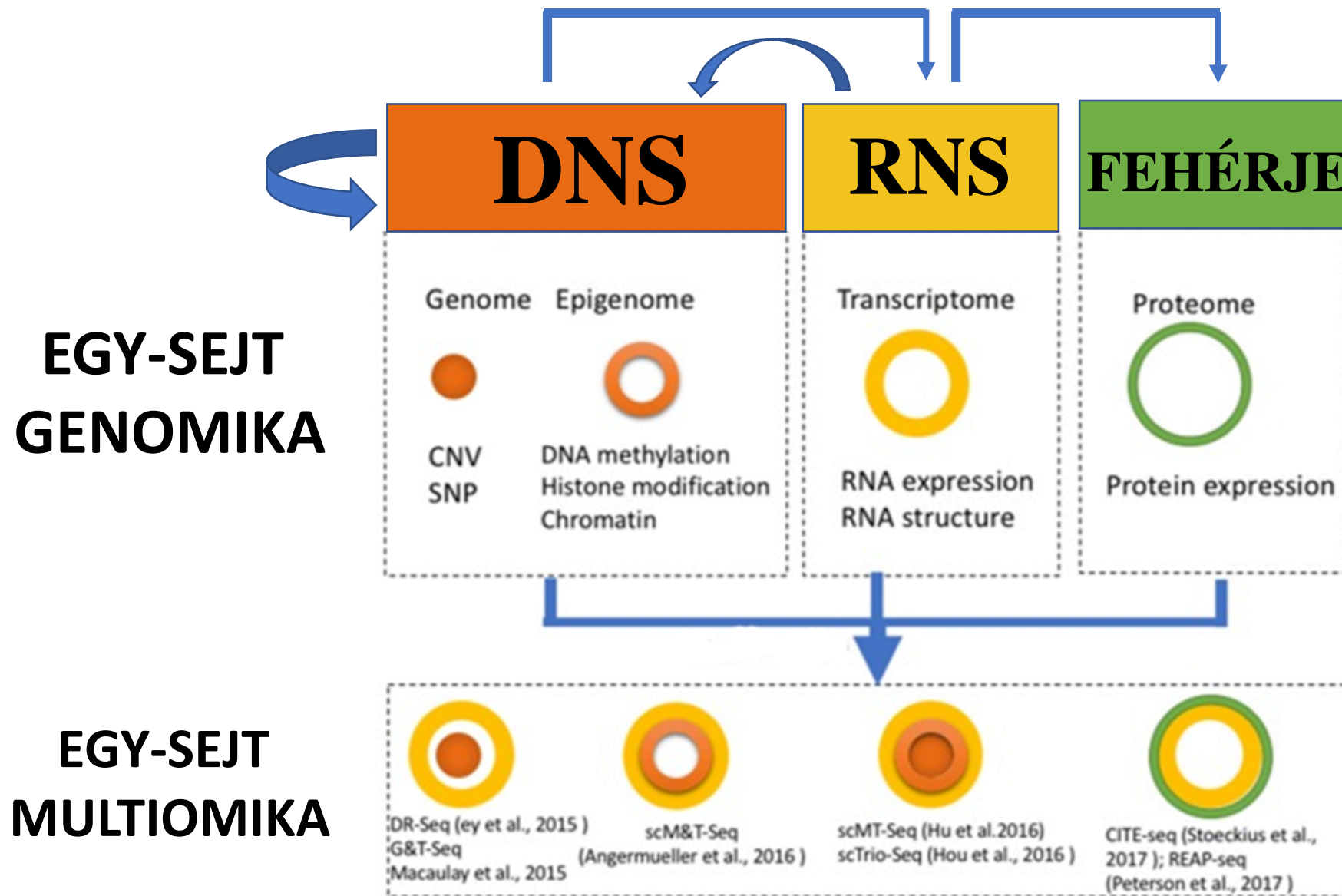
3. Transzkripciós dinamika

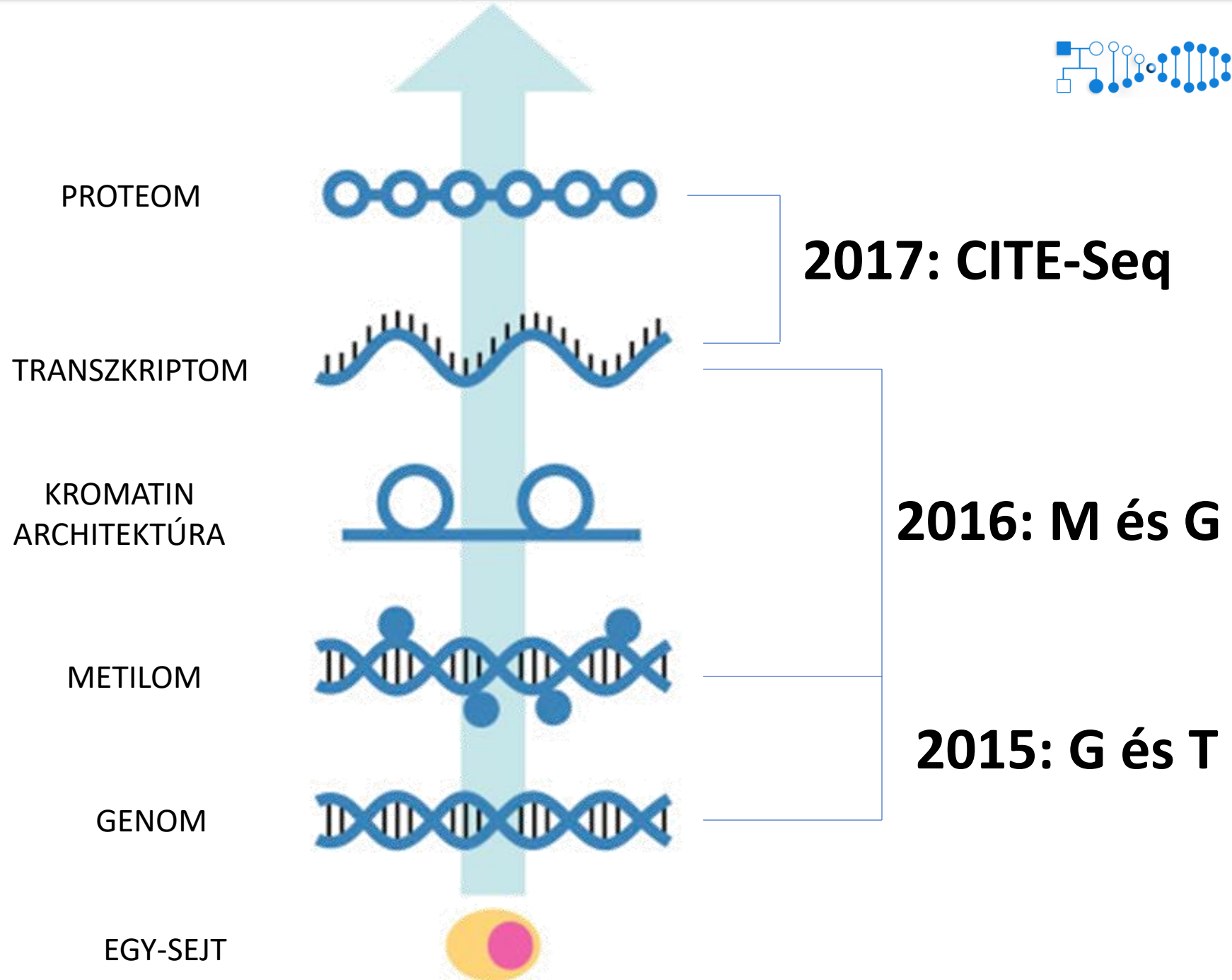
4. Hálózat interferencia

} részletgazdag elemzése

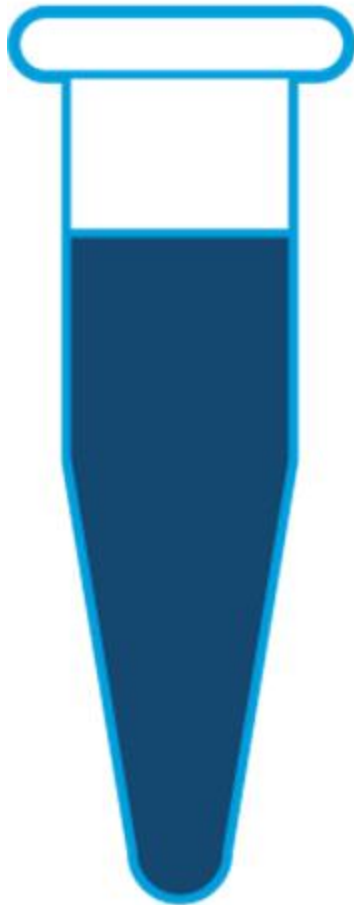
## AZ EGY-SEJT TRANSZKRIPTOMIKAI MÓDSZERTAN ELVÉNEK ISMERTETÉSE, KUTATÁSI ÉS KLINIKAI VETÜLETE





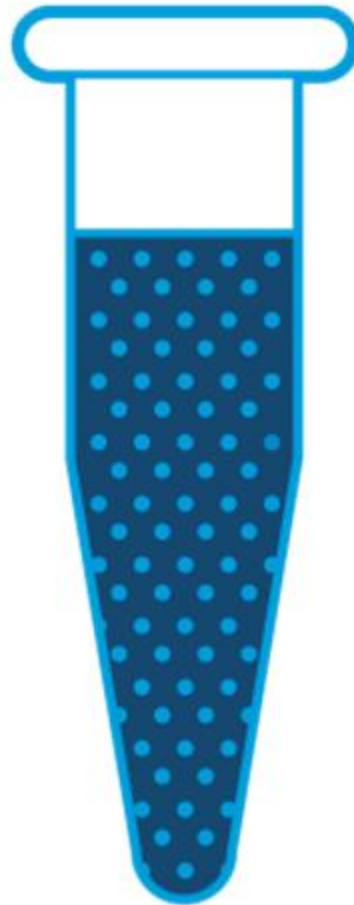


HOMOGENIZÁLT  
MINTA



ÁTLAGOS TRANSZKRIPTOM

EGY-SEJT  
SZUSZPENZIÓ



SEJTENKÉNTI  
TRANSZKRIPTOM

EGYEDI SEJTTÍPUS



TRANSZKRIPTOM



RITKA SEJT TRANSZKRIPTOM



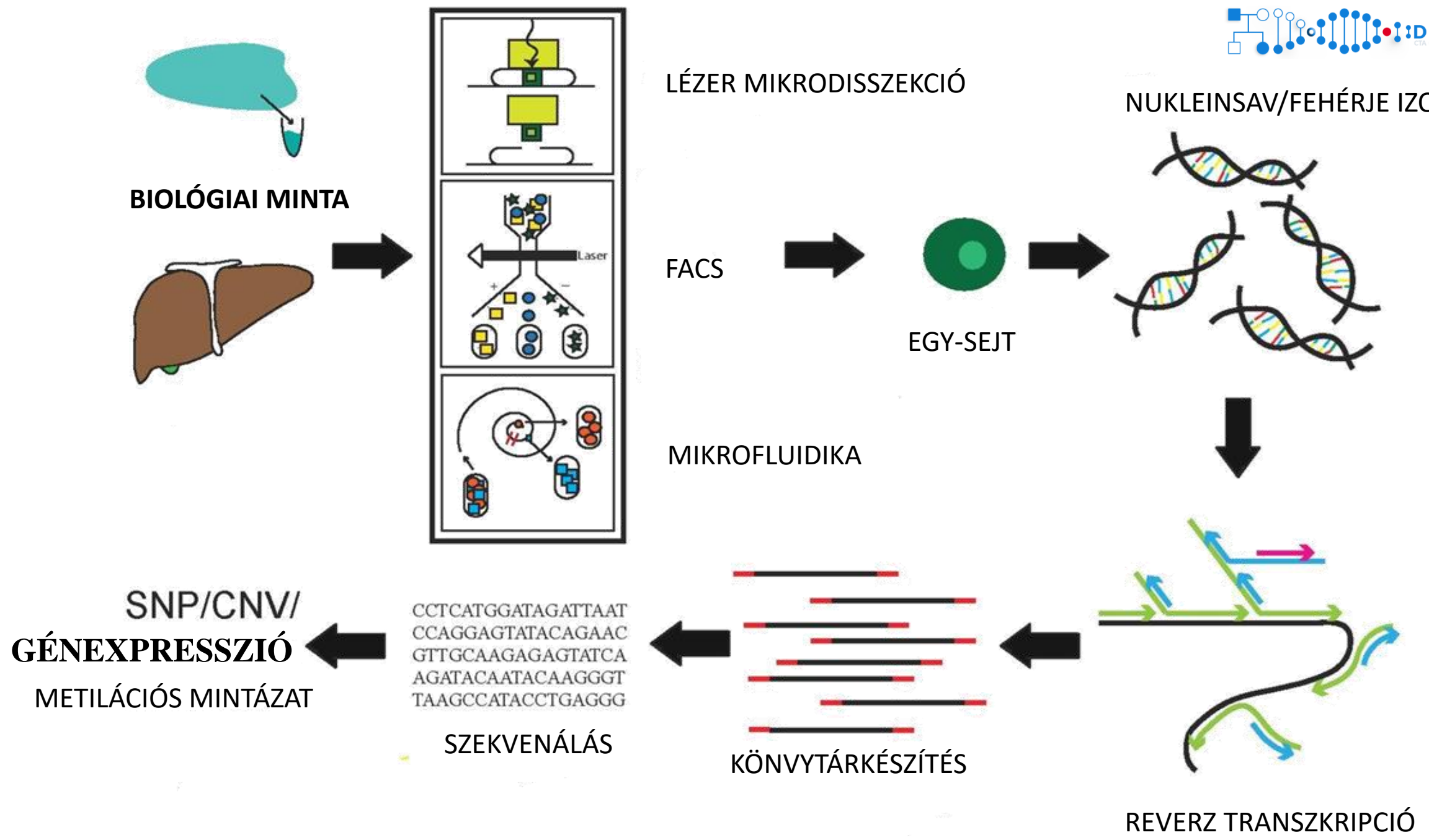
TRANSZKRIPTOM



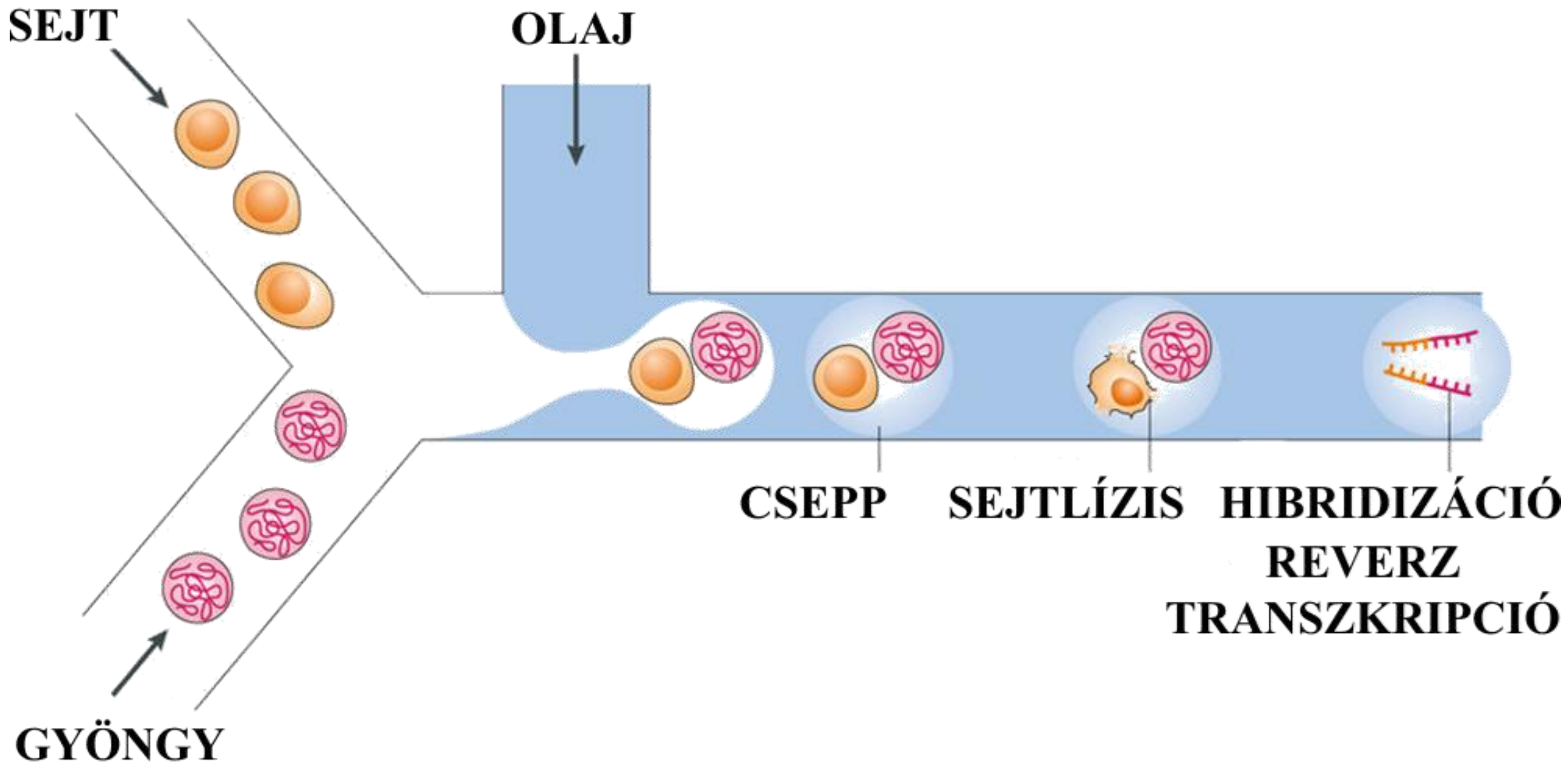
TRANSZKRIPTOM



TRANSZKRIPTOM

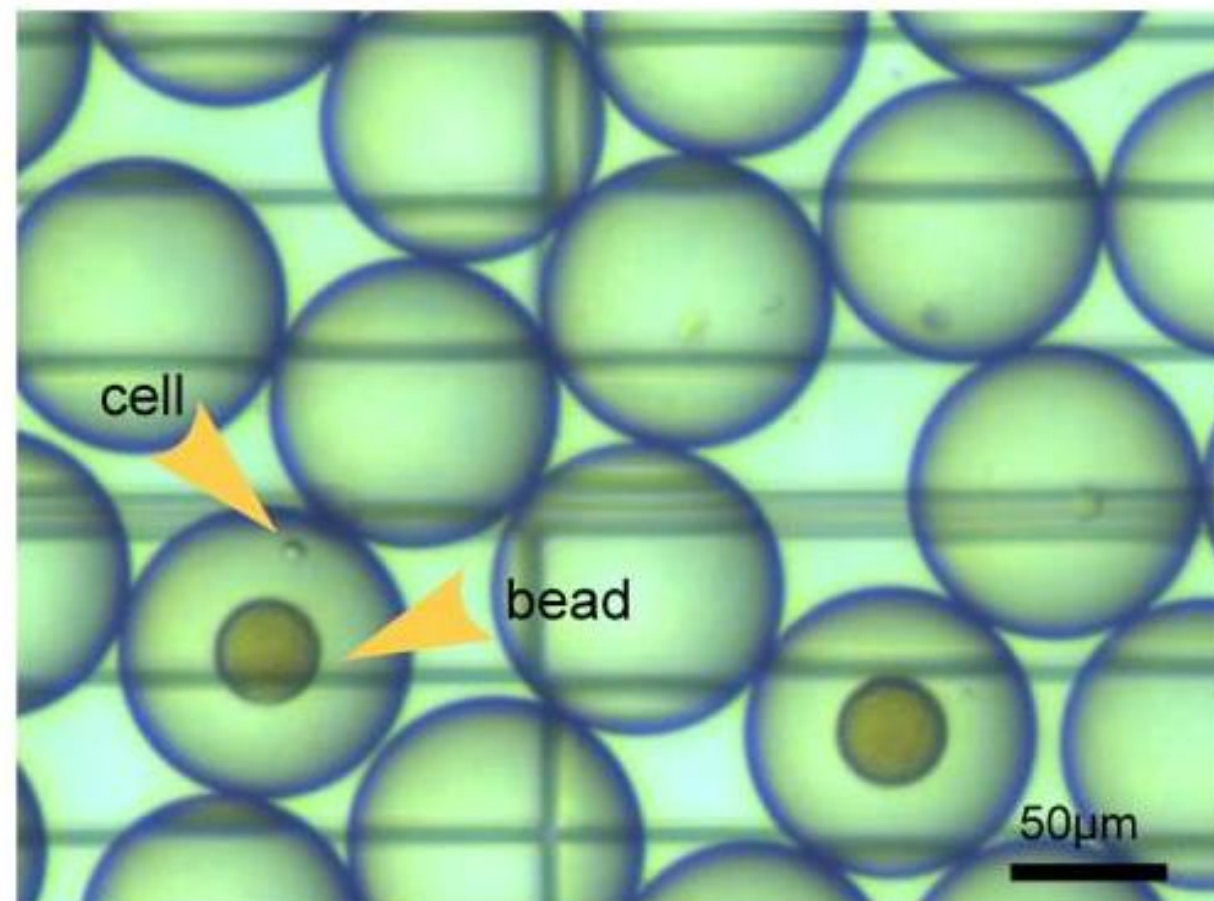
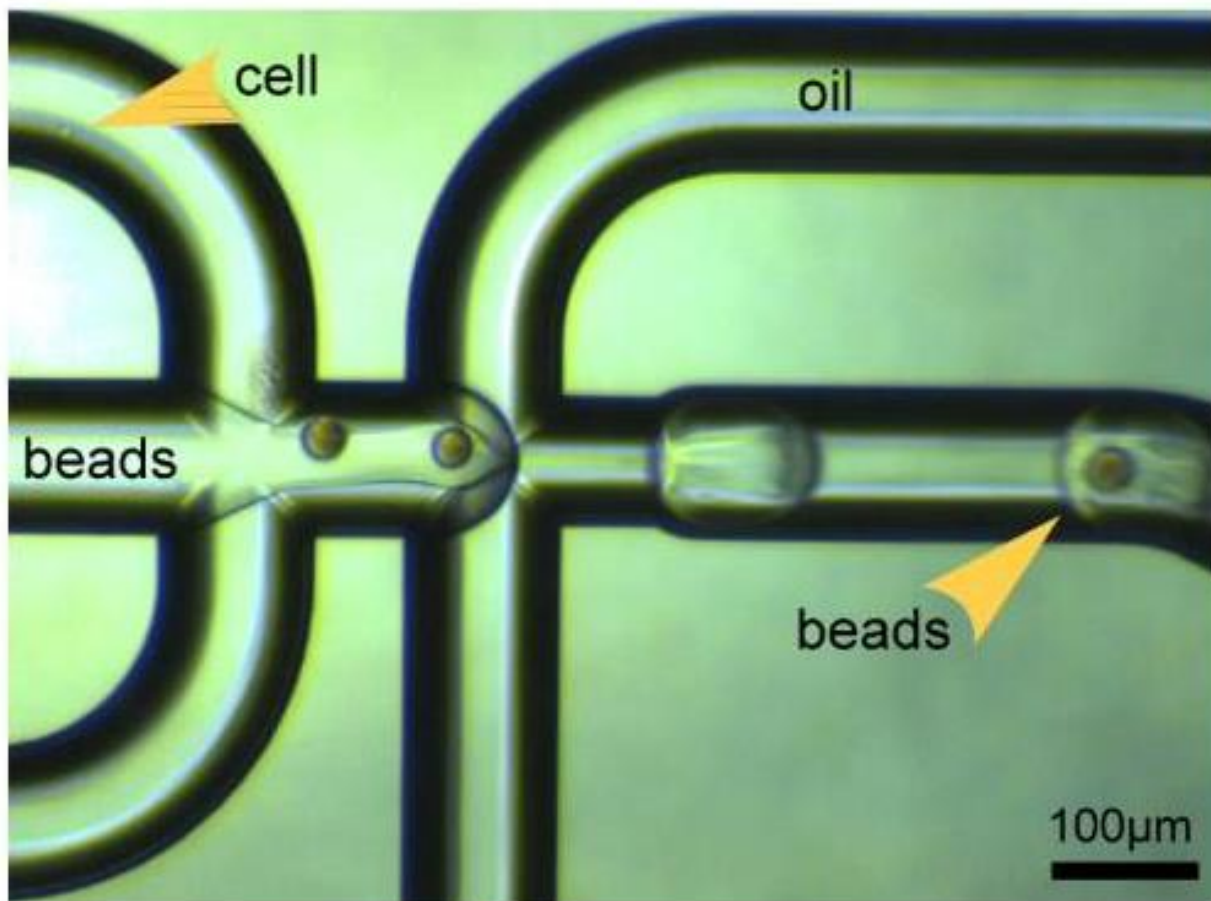


# SEJTEK EGY-SEJT TRANSZKRIPTOMIKAI VIZSGÁLATA

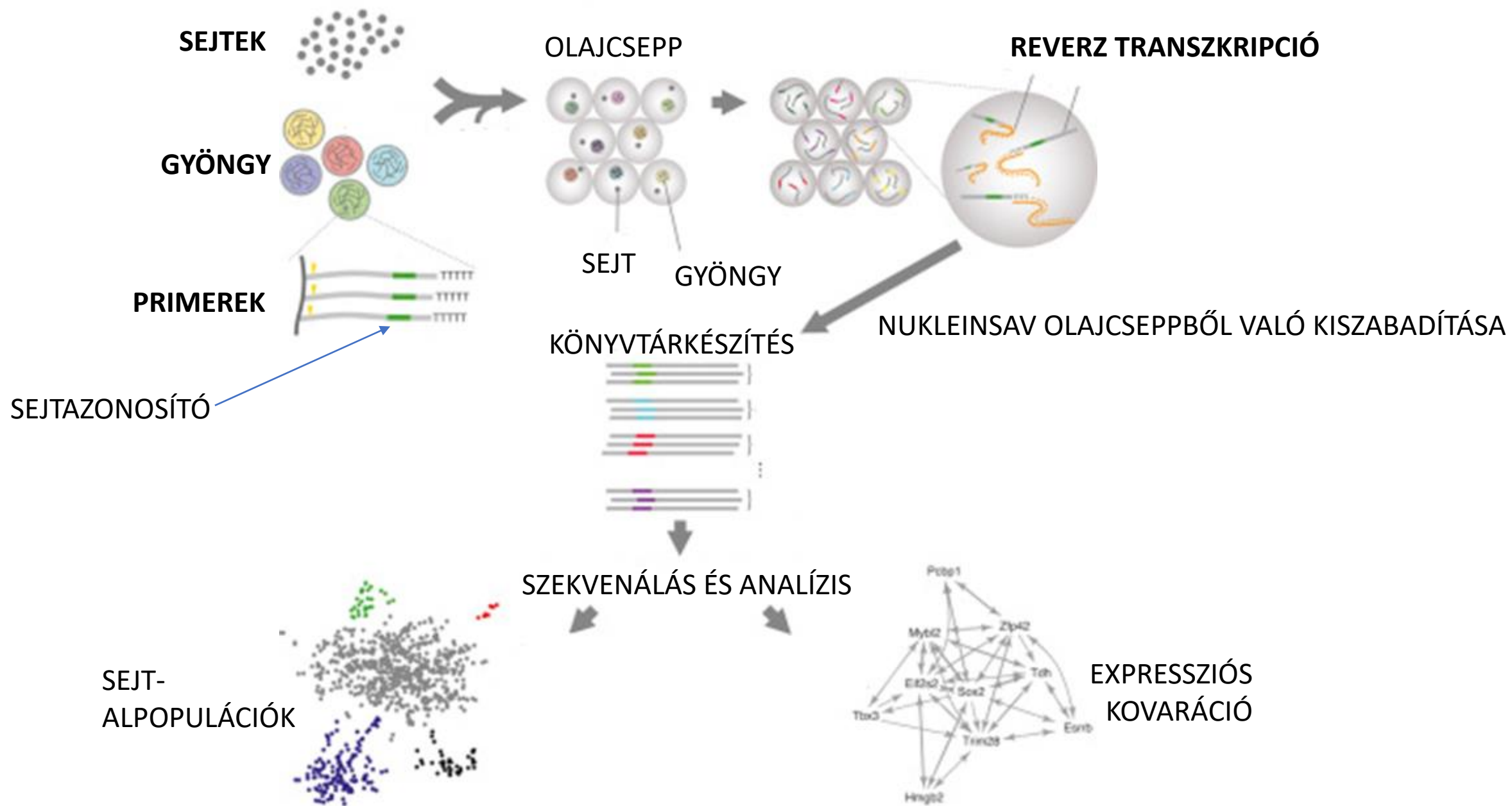


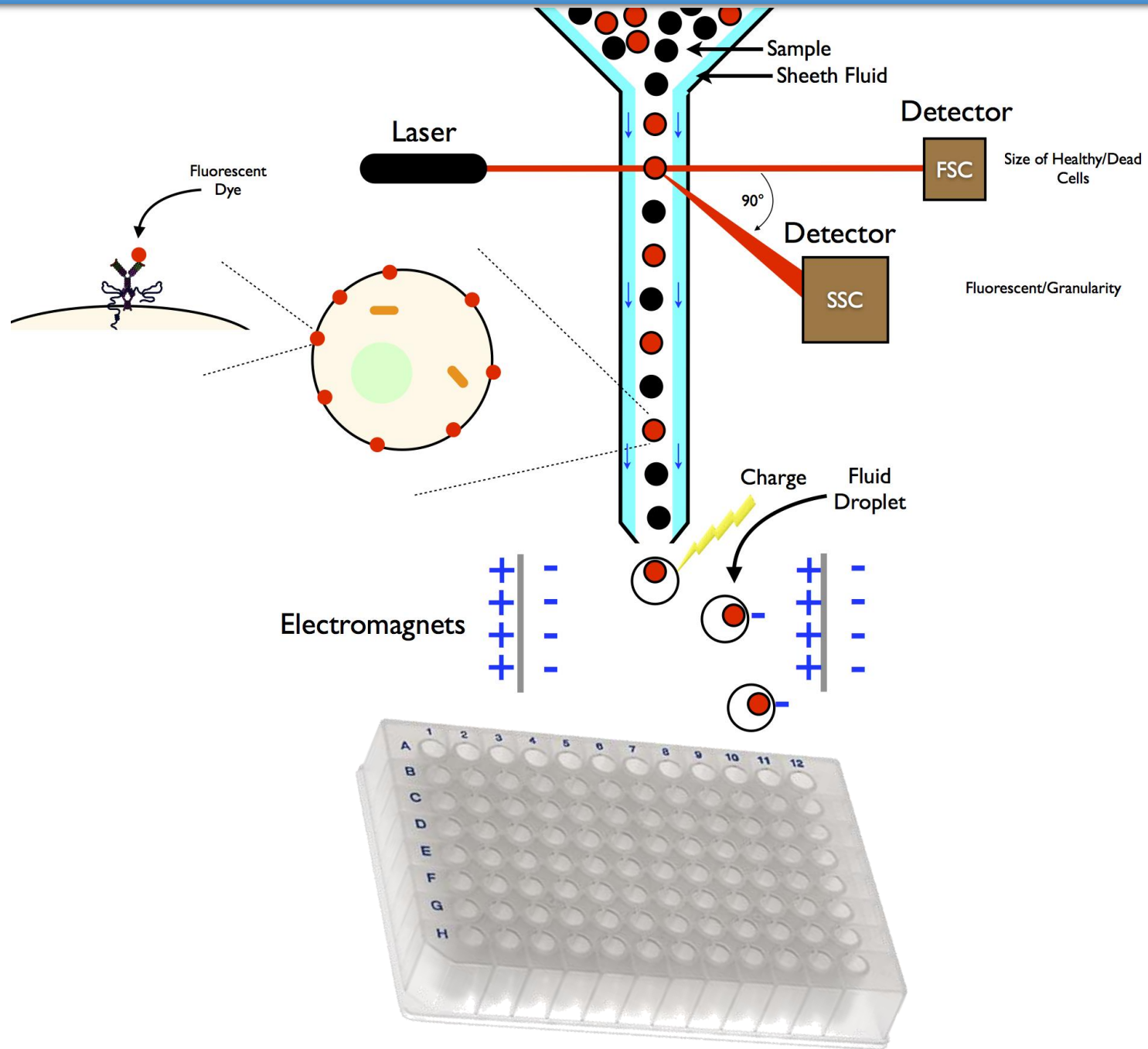


# SEJTEK EGY-SEJT TRANSZKRIPTOMIKAI VIZSGÁLATA



# SEJTEK EGY-SEJT TRANSZKRIPTOMIKAI VIZSGÁLATA





# Heterogén SEJTEK EGY-SEJT TRANSZKRIPTOMIKAI VIZSGÁLATA



Unravel heterogeneity to decipher dynamic cell state transition

Combinatorial indexing may also facilitate the scalable generation of “joint” single-cell molecular profiles (e.g., RNA-seq and ATAC-seq from each of many single cells).

Multi-omics on single-cells

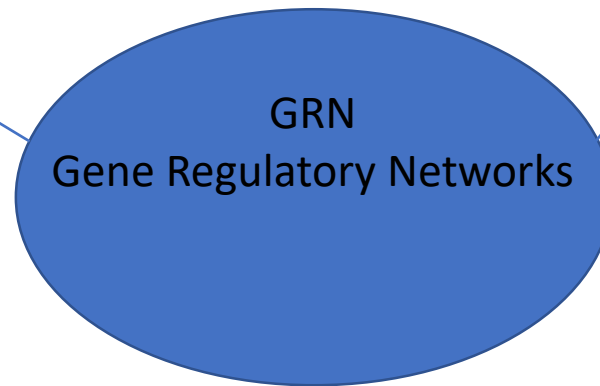
Single-cell **EPIGENOMICS**: scATAC-seq, DHS-seq, sc-methylation-seq

Single-cell active Transcription Factors

Target genes

Single-cell Transcribed genes scRNAseq

Egy-sejt transzkriptom



Genome architecture mapping  
Hi-C (TAD)

Single-cell

Sorting

FACS or microfluidics

BIOLOGICAL SAMPLE

Dual-sequencing

Sc-transcriptogenomics

Sc-G&Tseq

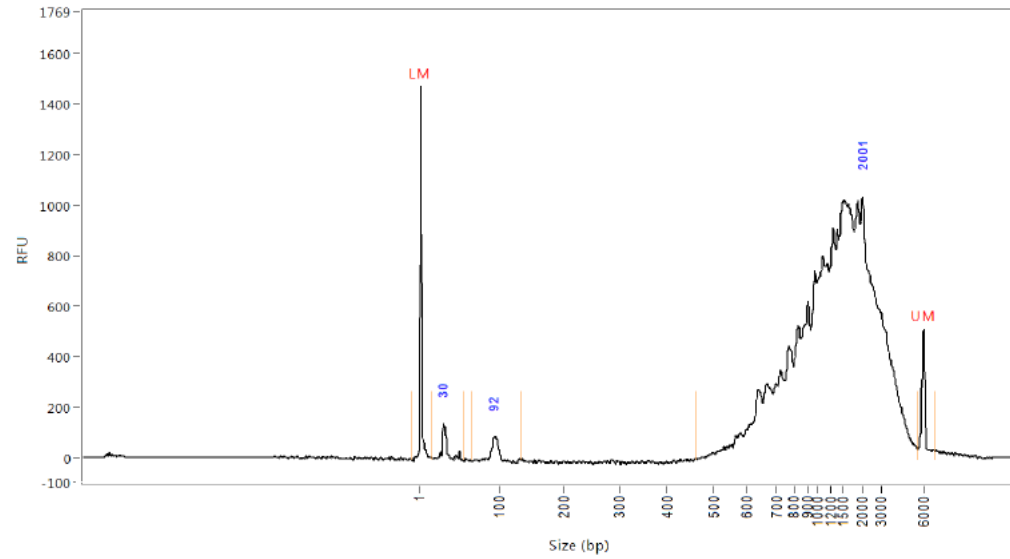
Sc-M&Tseq

**Proteomics**

Mass cytometry, CyTOF

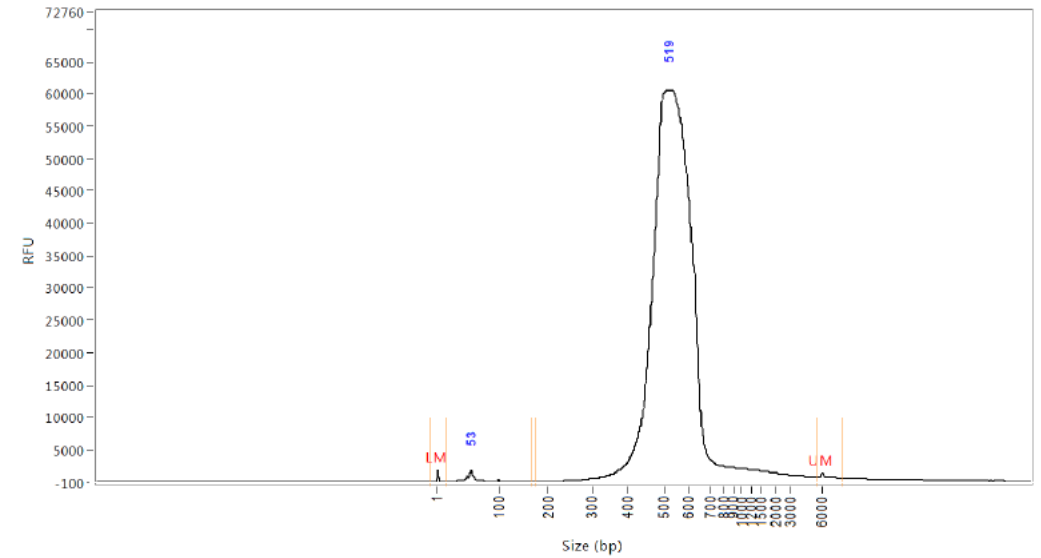
# PBMC SEJTEK EGY-SEJT TRANSZKRIPTOMIKAI VIZSGÁLATA

## Preamplification



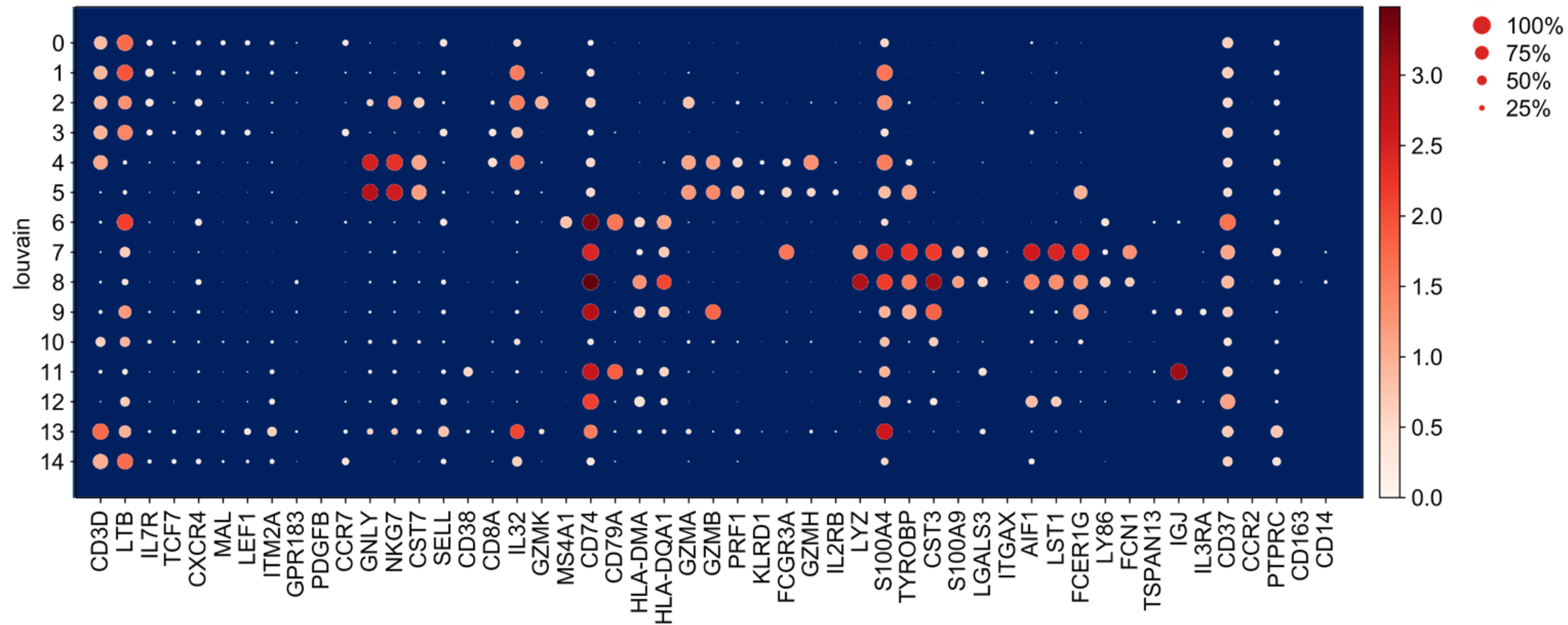
Peak	Size (bp)	Conc. (ng/uL)	From (bp)	To (bp)	Avg. Size (bp)	CV%	RFU
1	1 (LM)	0.0132	0	16	1	156.15	1469
2	30	0.0259	16	56	31	14.28	135
3	92	0.0241	64	133	92	3.01	80
4	2001	2.4261	463	5622	1599	57.72	1033
5	6000 (UM)	0.0042	5622	6886	6033	3.65	506
TIC:		2.4760	ng/uL				
TIM:		4.2912	nmole/L				
Total Conc.:		2.4760	ng/uL				

## Postamplification



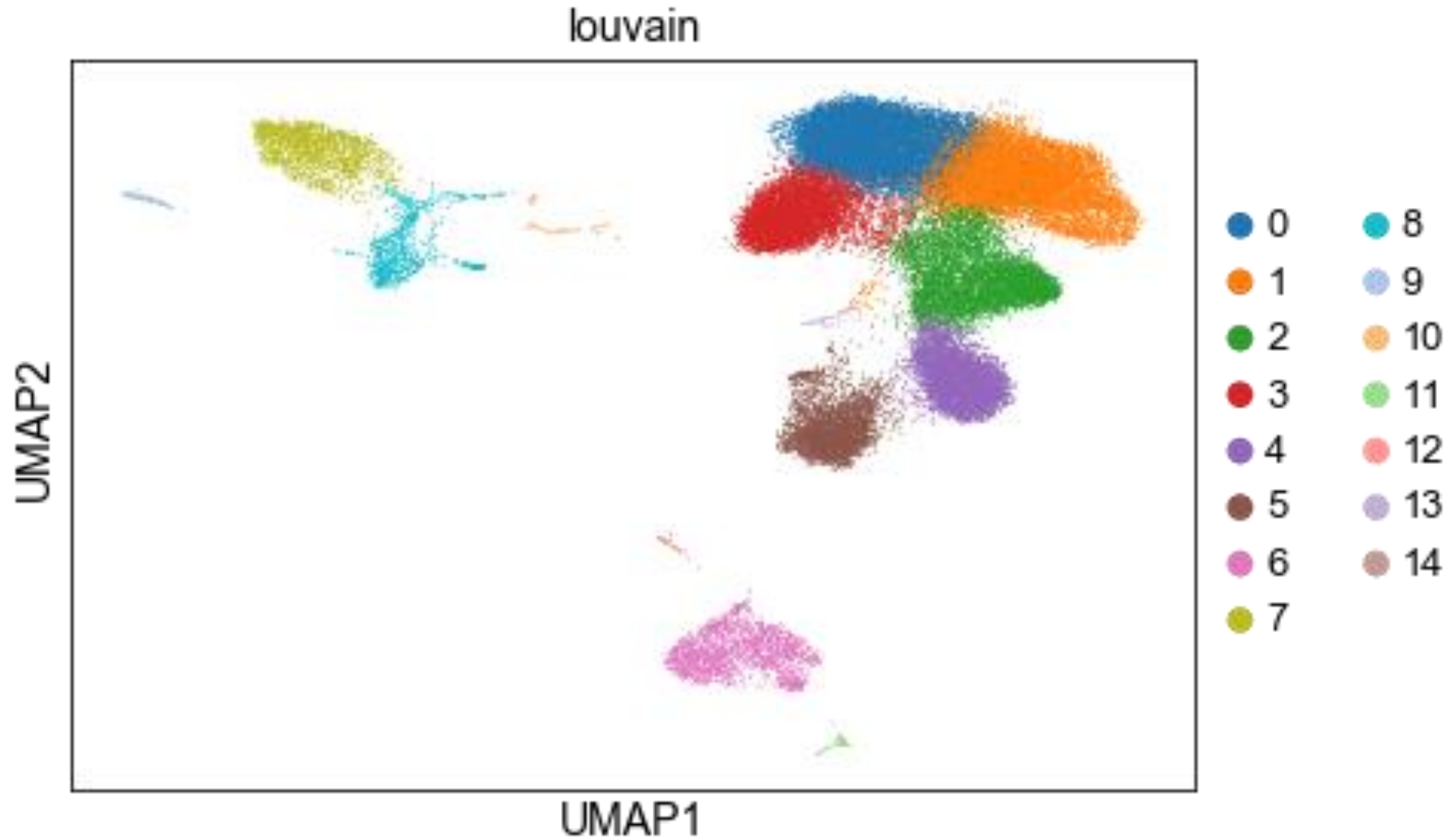
Peak	Size (bp)	Conc. (ng/uL)	From (bp)	To (bp)	Avg. Size (bp)	CV%	RFU
1	1 (LM)	0.0138	0	15	1	155.91	1738
2	53	0.6924	15	164	52	17.96	1755
3	519	105.0950	175	5449	584	59.23	60615
4	6000 (UM)	0.0491	5449	8068	6632	11.27	1400
TIC:		105.7873	ng/uL				
TIM:		317.9549	nmole/L				
Total Conc.:		105.7873	ng/uL				

# PBMC SEJTEK EGY-SEJT TRANSZKRIPTOMIKAI VIZSGÁLATA

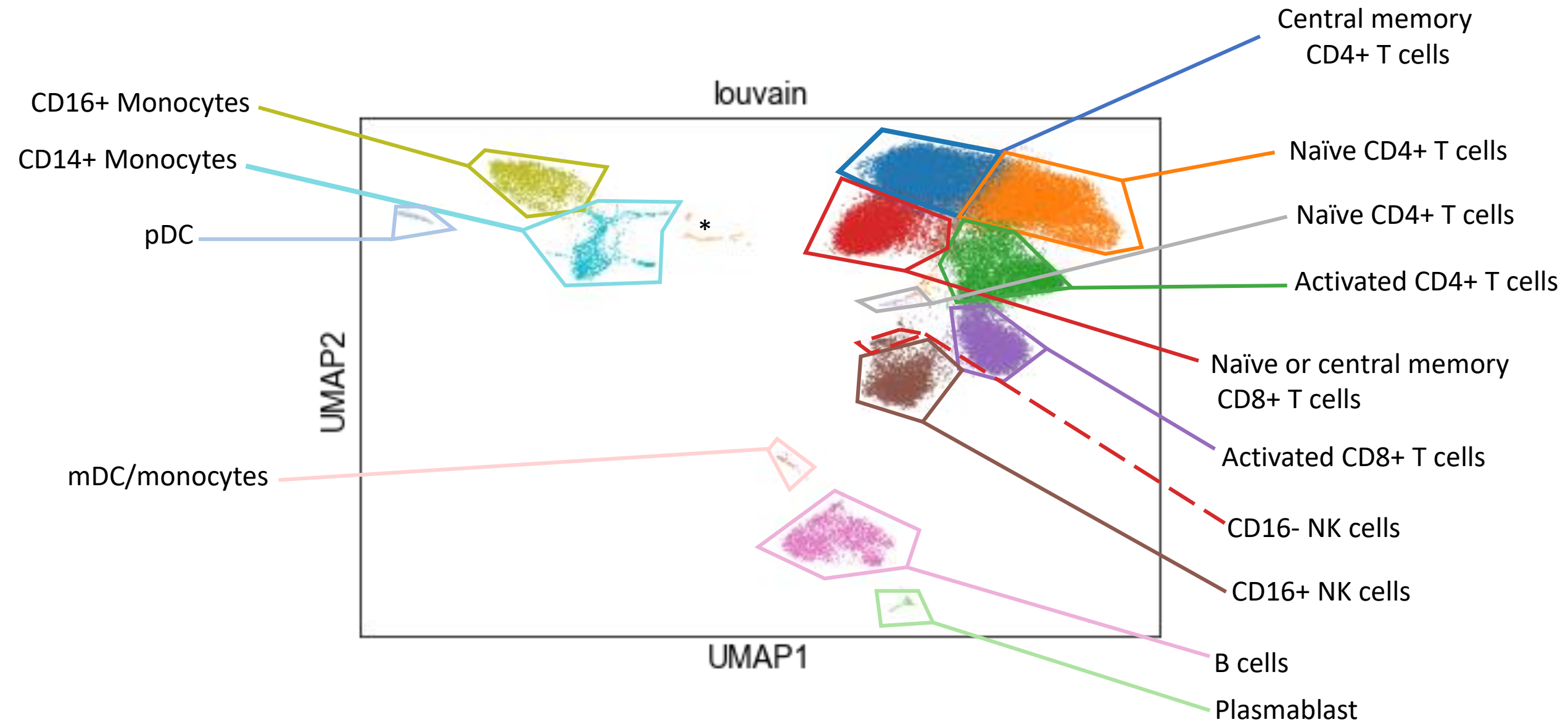


SIZE OF THE BULLETS IS PROPORTIONAL TO THE NUMBER OF CELLS EXPRESSING THE GENE, THE COLOR IS PROPORTIONAL WITH THE LEVEL OF GENE EXPRESSION

SAMPLE	PLATFORM	SOFTWARE	PROTOCOL	UMAP	tSNE	CELL NUMBER
68K PBMC	10X	SCANPY 1.2.2	SEURAT	YES	YES	68 000

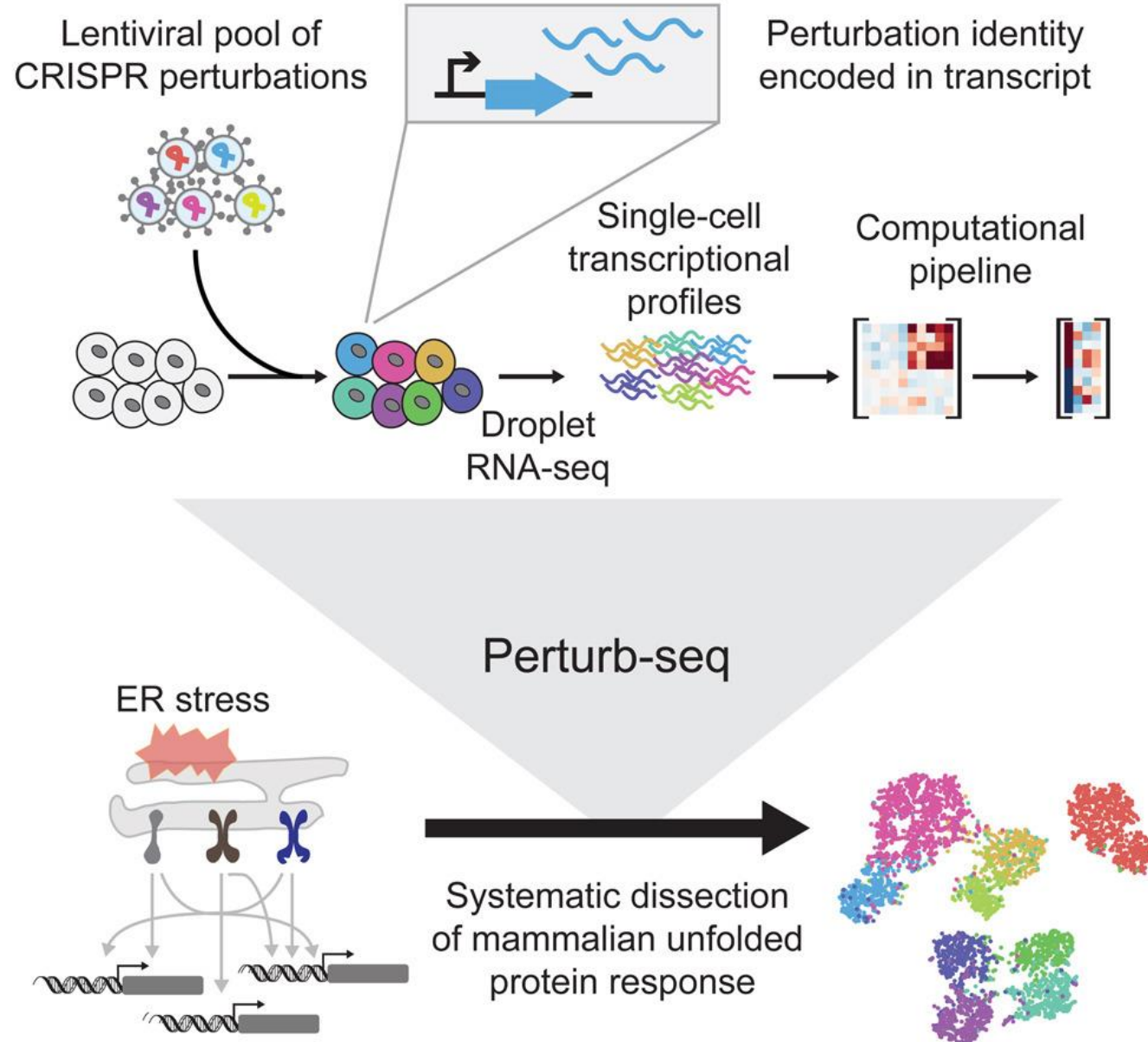


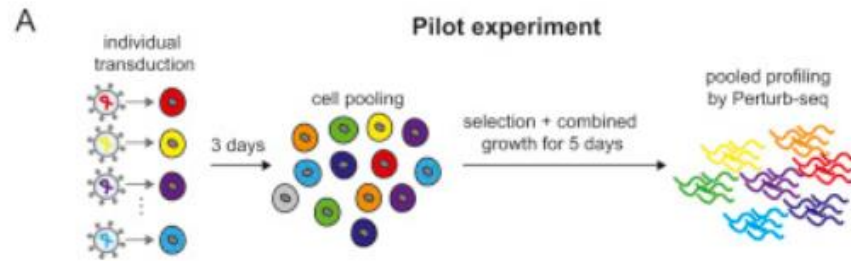
SAMPLE	PLATFORM	SOFTWARE	PROTOCOL	UMAP	tSNE	CELL NUMBER
68K PBMC	10X	SCANPY 1.2.2	SEURAT	YES	YES	68 000



\* Putative doublets

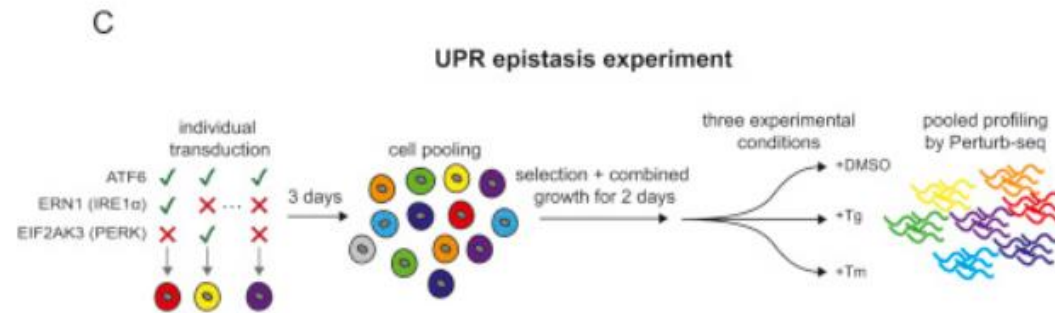






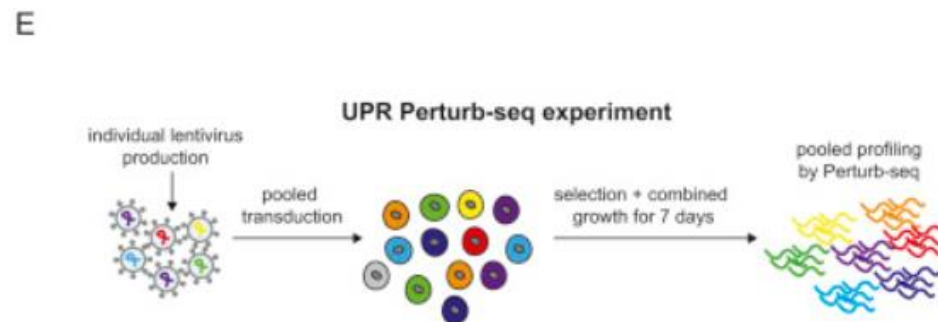
**B**

Perturbation complexity	8 sgRNAs
Cell count	5,768
Unique sgRNA	92%
Multiplet	6%
Unidentifiable	2%
Mean read depth	22,911 per cell
Median UMI depth	9,969 per cell
Median unique genes	2,580



**D**

Perturbation complexity	9 three-guide vectors, 3 conditions
Cell count	15,006
Unique sgRNA	90%
Multiplet	5%
Unidentifiable	5%
Mean read depth	122,670 per cell
Median UMI depth	25,082 per cell
Median unique genes	4,304



**F**

Perturbation complexity	91 sgRNAs, 2 control sgRNAs
Cell count	65,337
Unique sgRNA	77%
Multiplet	13%
Unidentifiable	9%
Mean read depth	66,950 per cell
Median UMI depth	15,355 per cell
Median unique genes	3,690

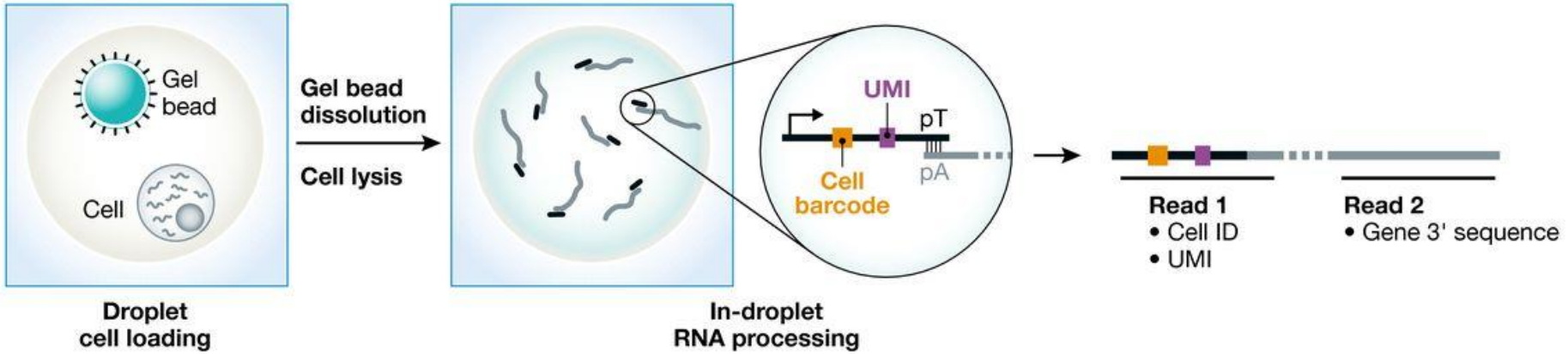
### DROPLET-BASED METHODS

e.g. Drop-seq  
10X Chromium

**+** Extremely high cell throughput  
( $>10^4$  cells per experiment)

**+** Low cost per cell  
( $< \$0.01$ )

**-** Smaller cell libraries  
( $\sim 10^4$  molecules per cell)



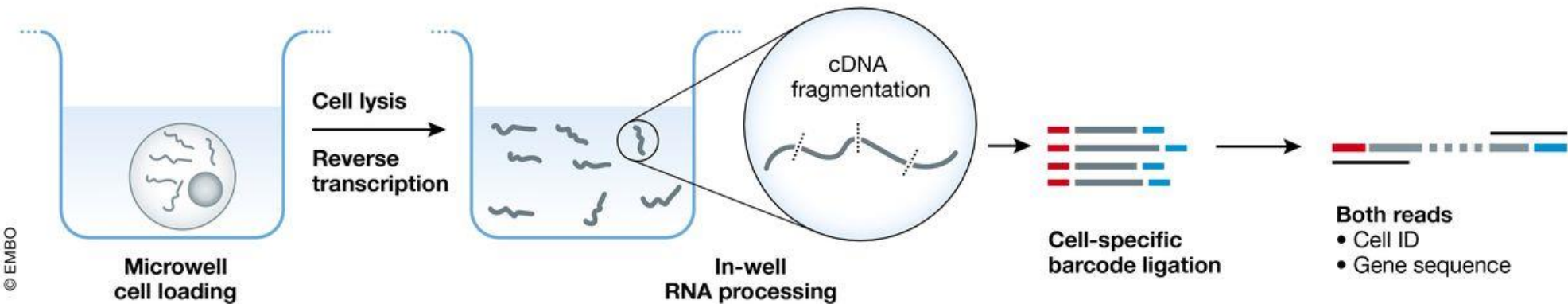
### PLATE-BASED METHODS

e.g. Smart-Seq2  
MARS-seq

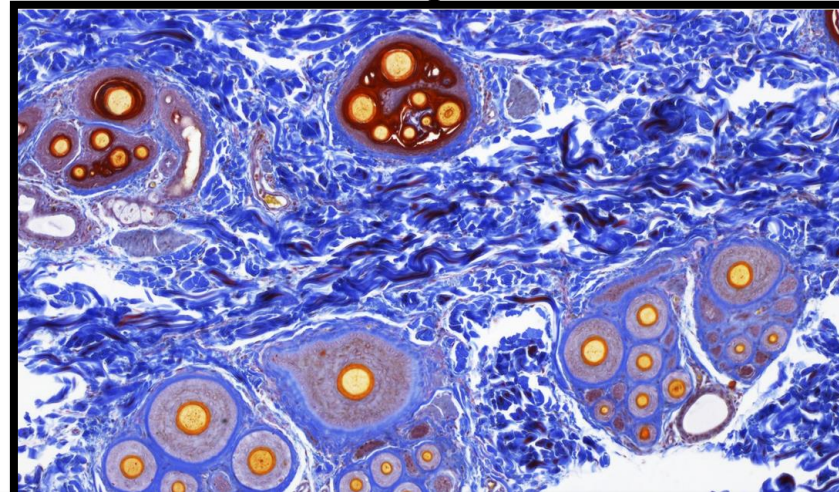
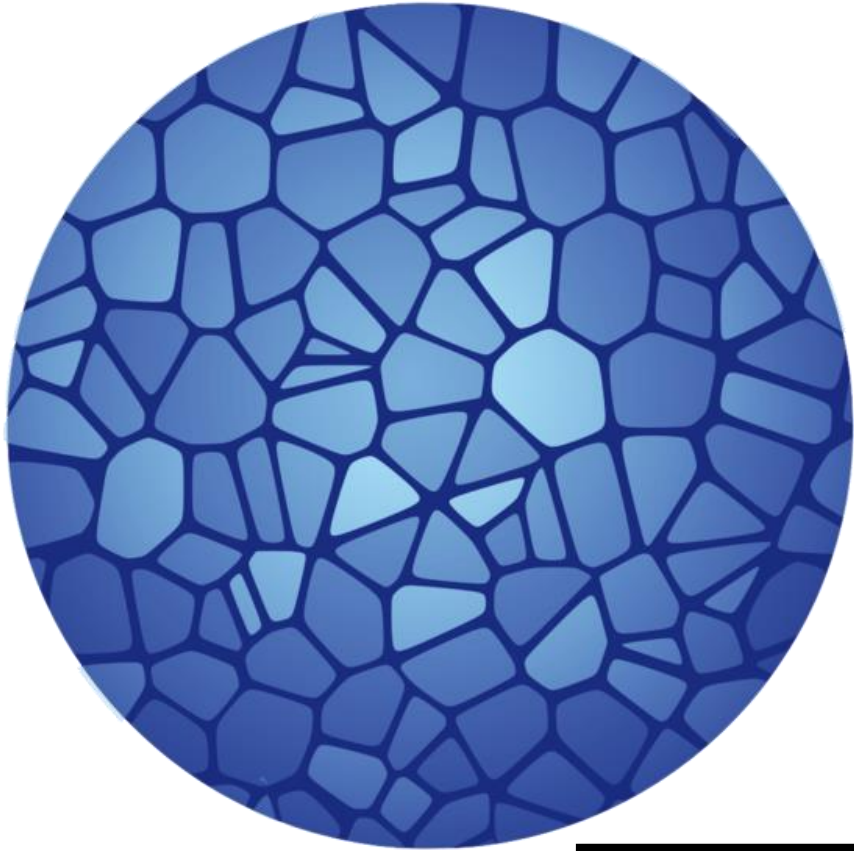
**+** High read-depth per cell  
( $>10^6$  reads per cell)

**+** Reads may be generated across  
whole transcript length

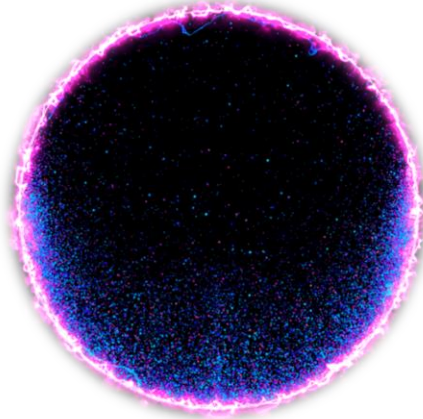
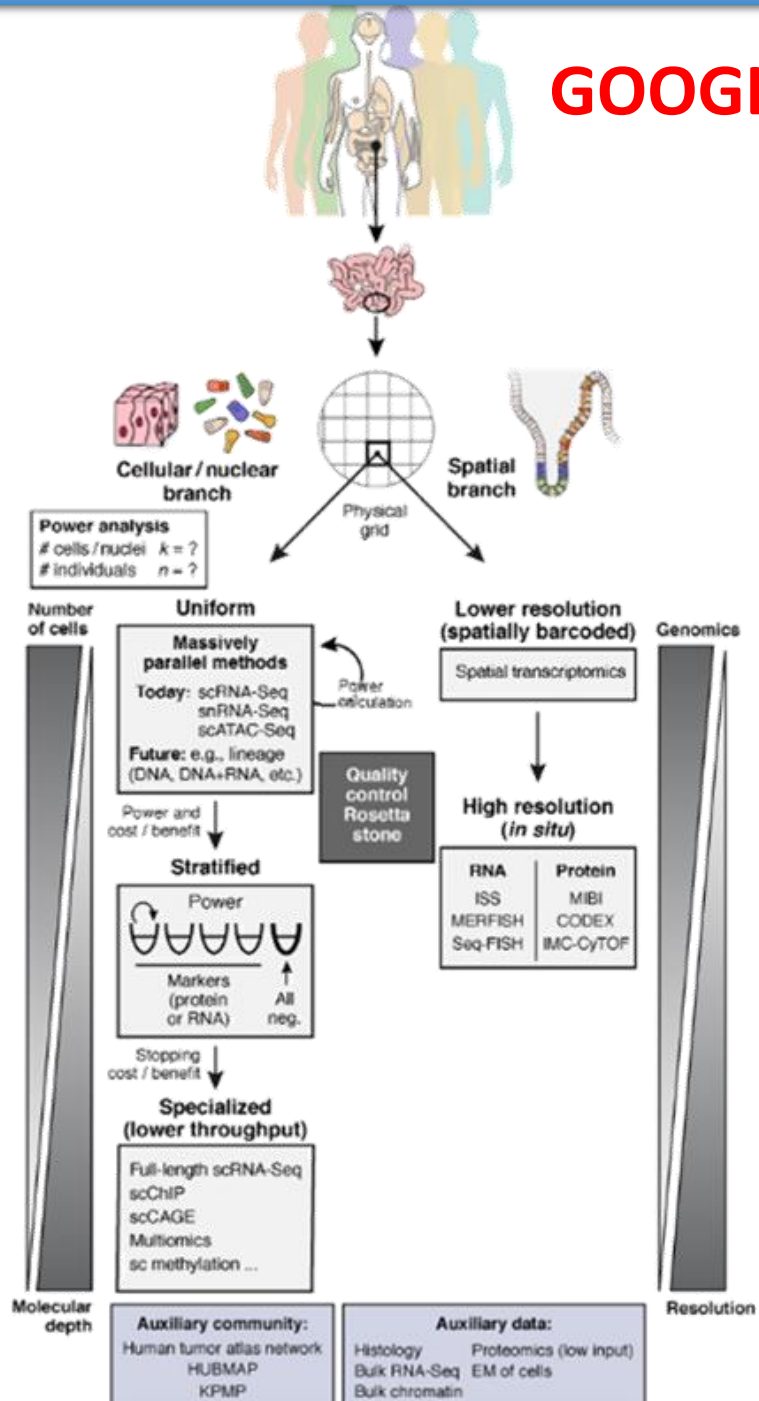
**-** Moderate cell throughput  
( $10^2 - 10^3$  cells per experiment)



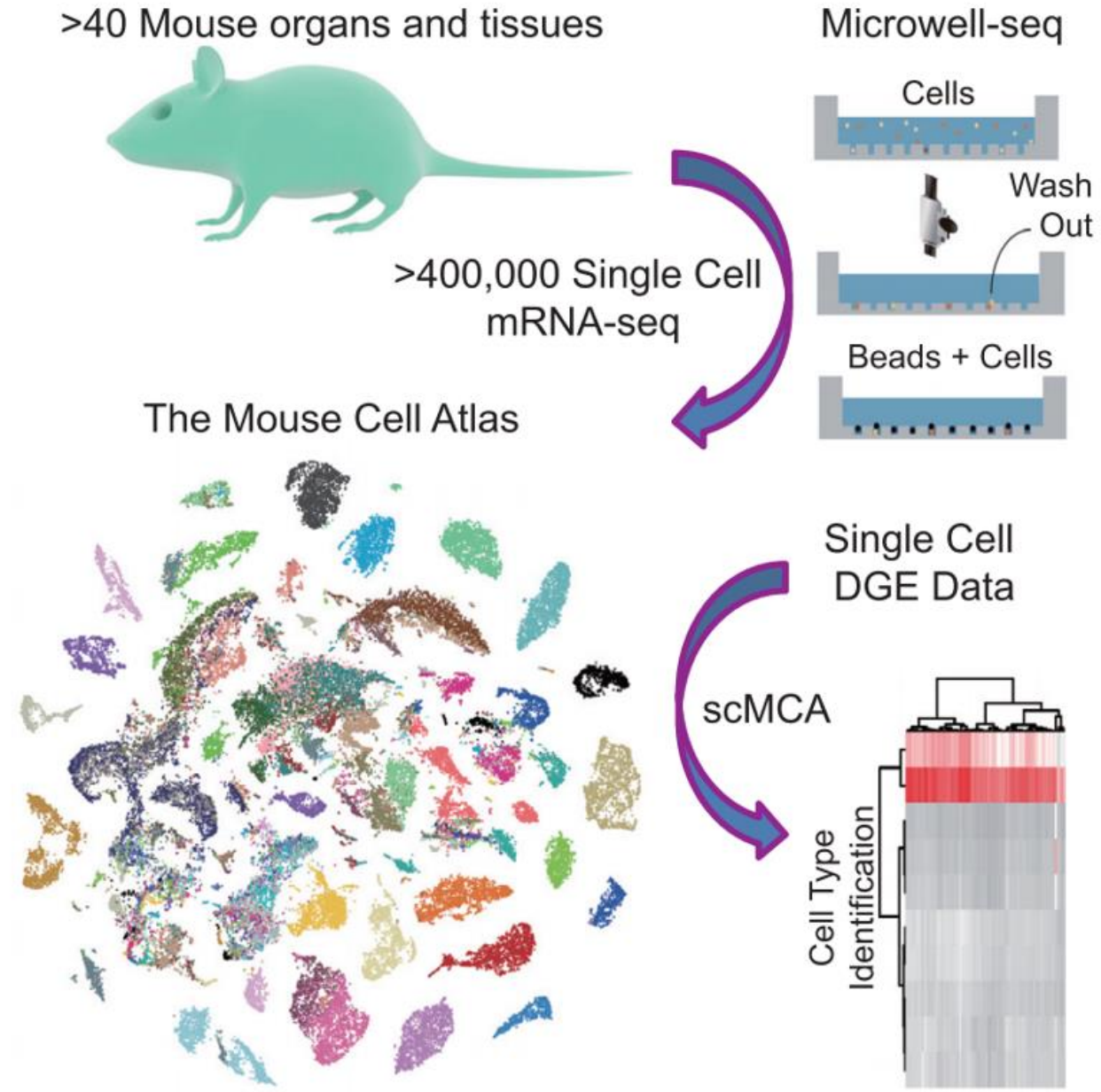
# HUMAN CELL ATLAS



# GOOGLE TÉRKÉPE A HUMÁN TESTNEK

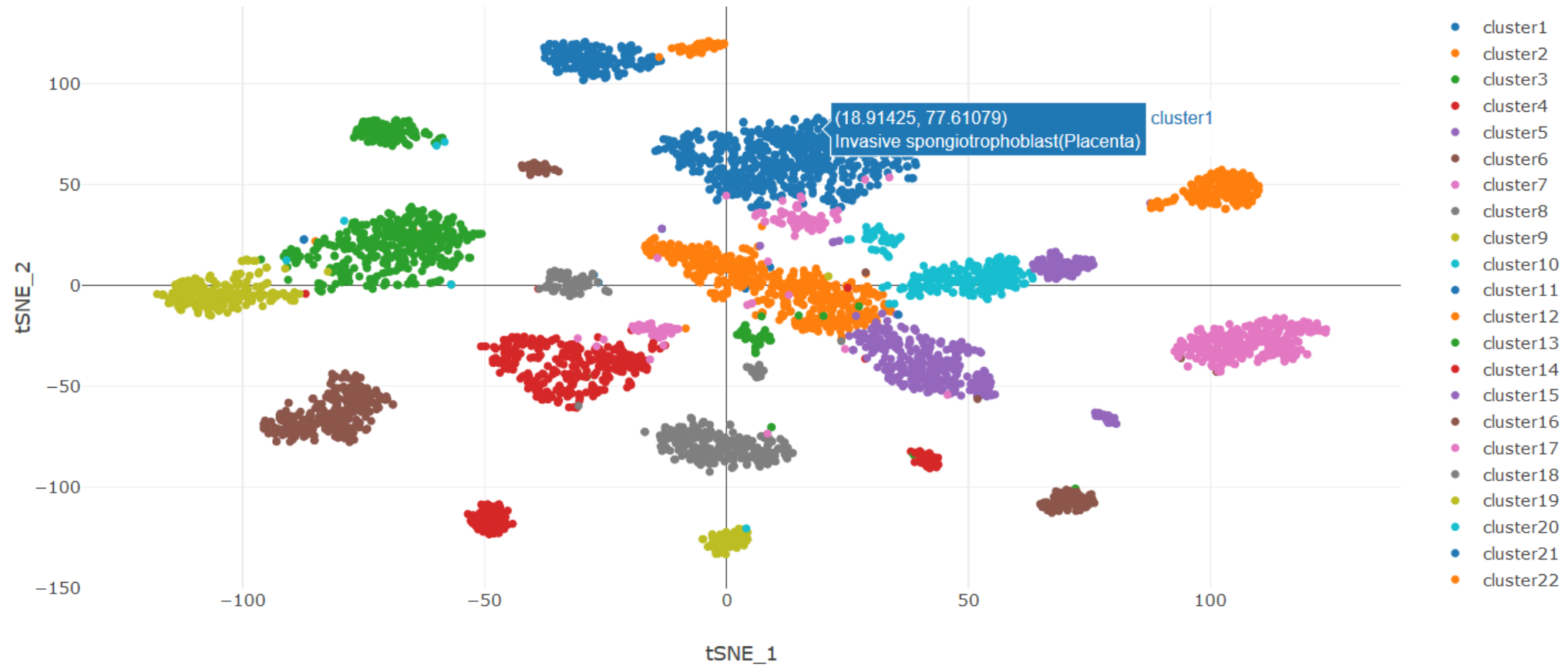


# A PROJEKT MEGVALÓSÍTHATÓSÁGA: EGÉR SEJT-ATLASZ LÉTREHOZÁSA



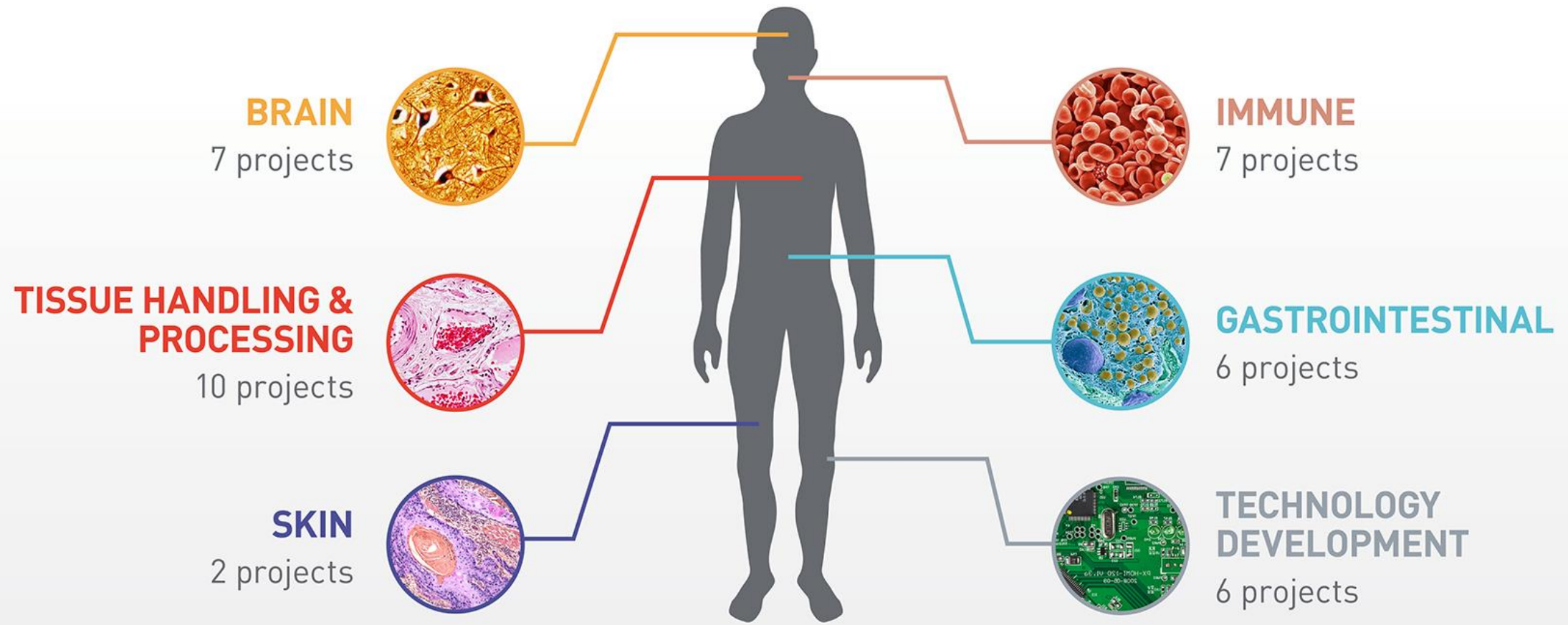


tSNE map for Placenta



# MAPPING THE BASIC UNITS OF LIFE

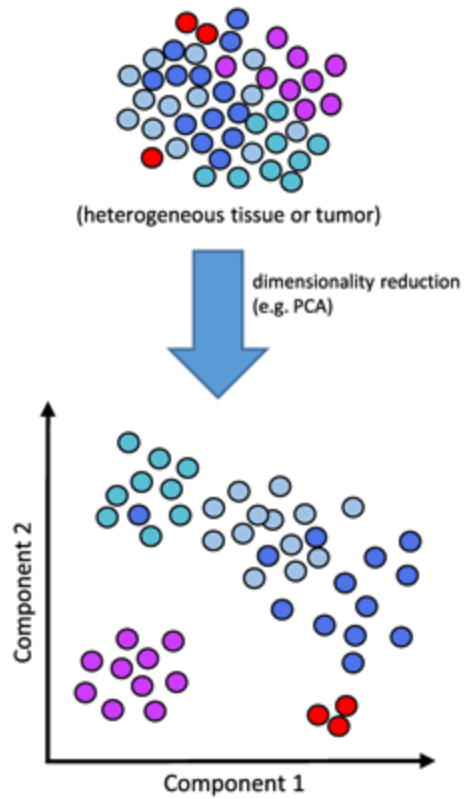
CZI proudly supports **38 new projects** in these six areas for the **Human Cell Atlas**.



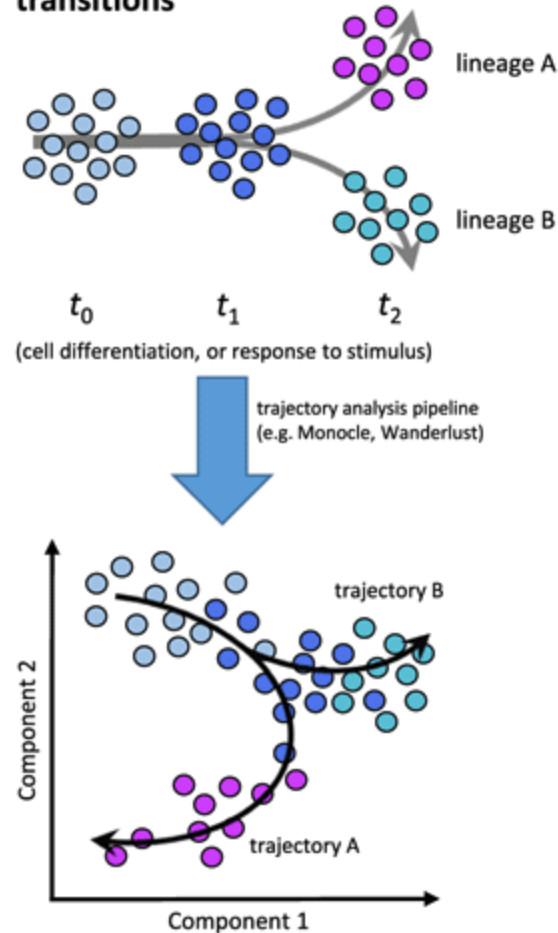


# EGY-SEJT TRANSZKRIPTOMIKA ALKALMAZÁSA

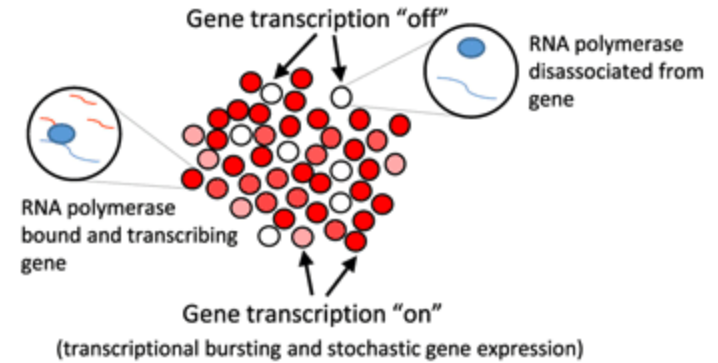
## a) Deconvolving heterogeneous cell populations



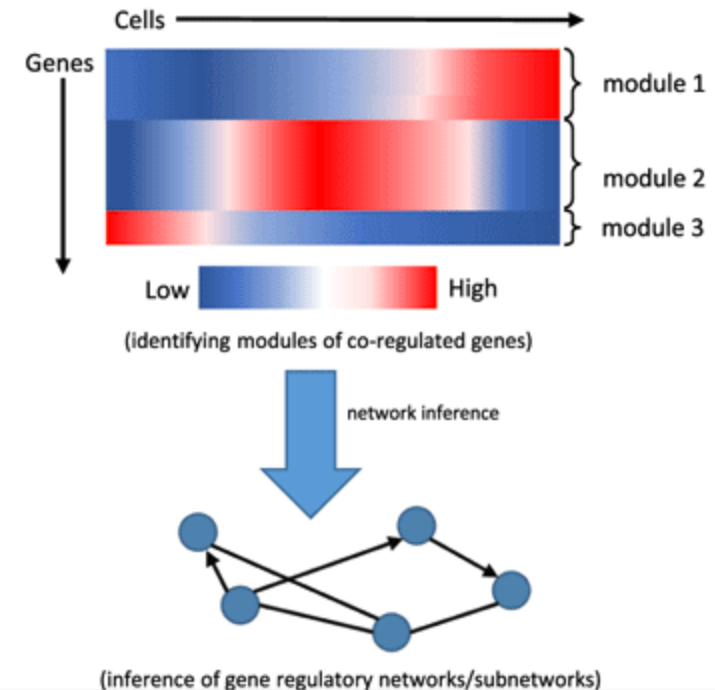
## b) Trajectory analysis of cell state transitions

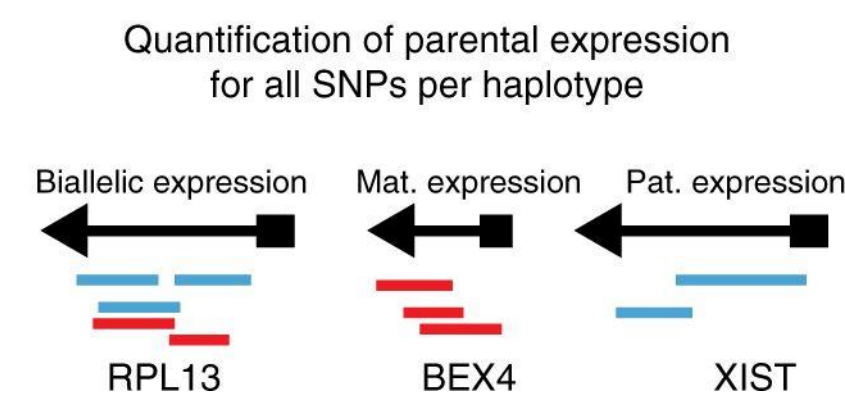
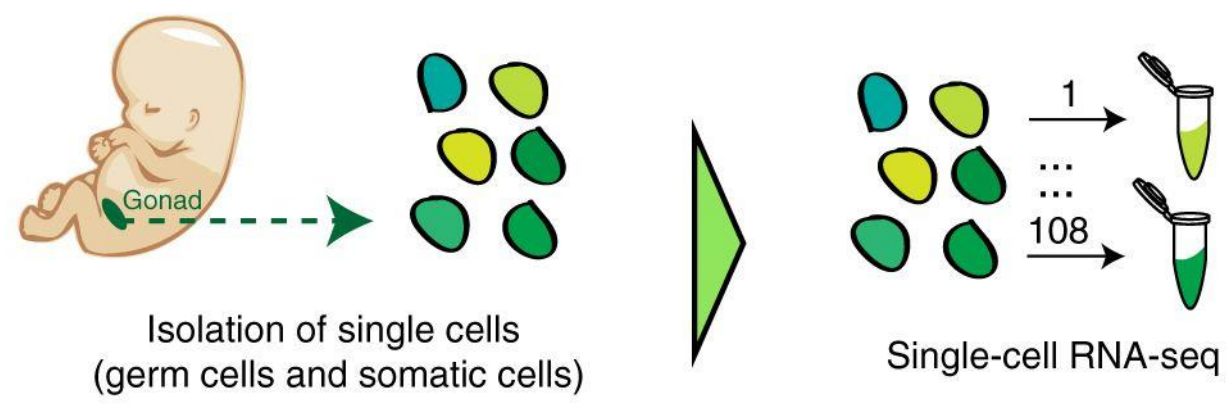
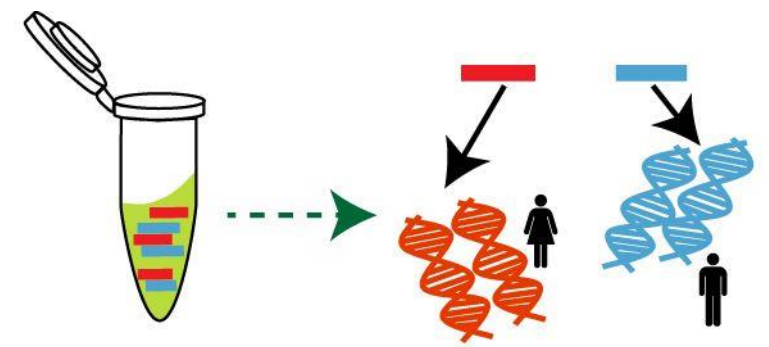
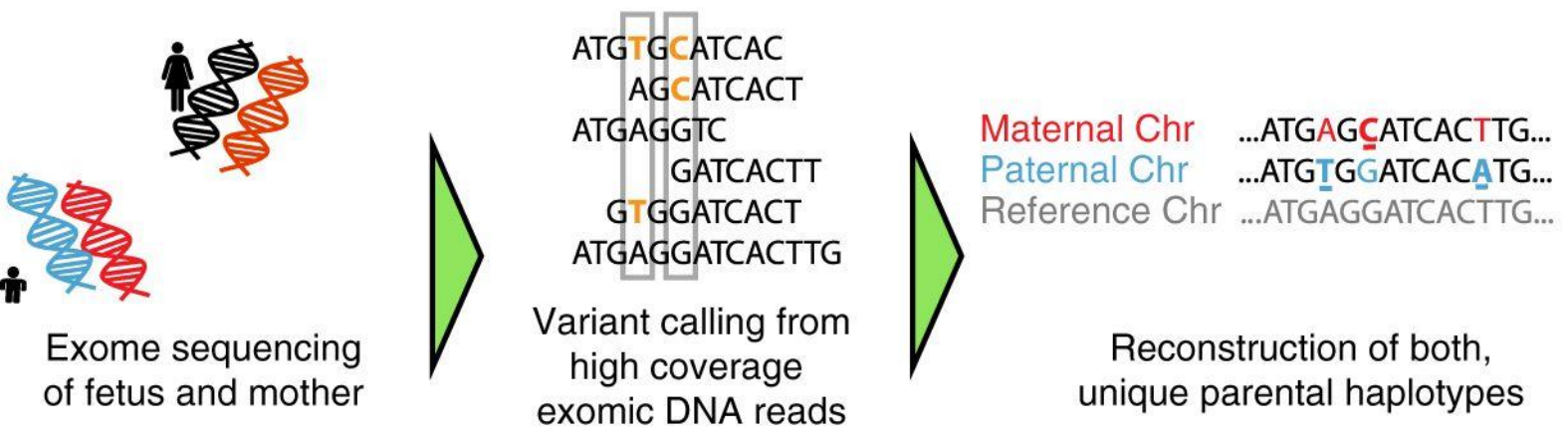


## c) Dissecting transcription mechanics

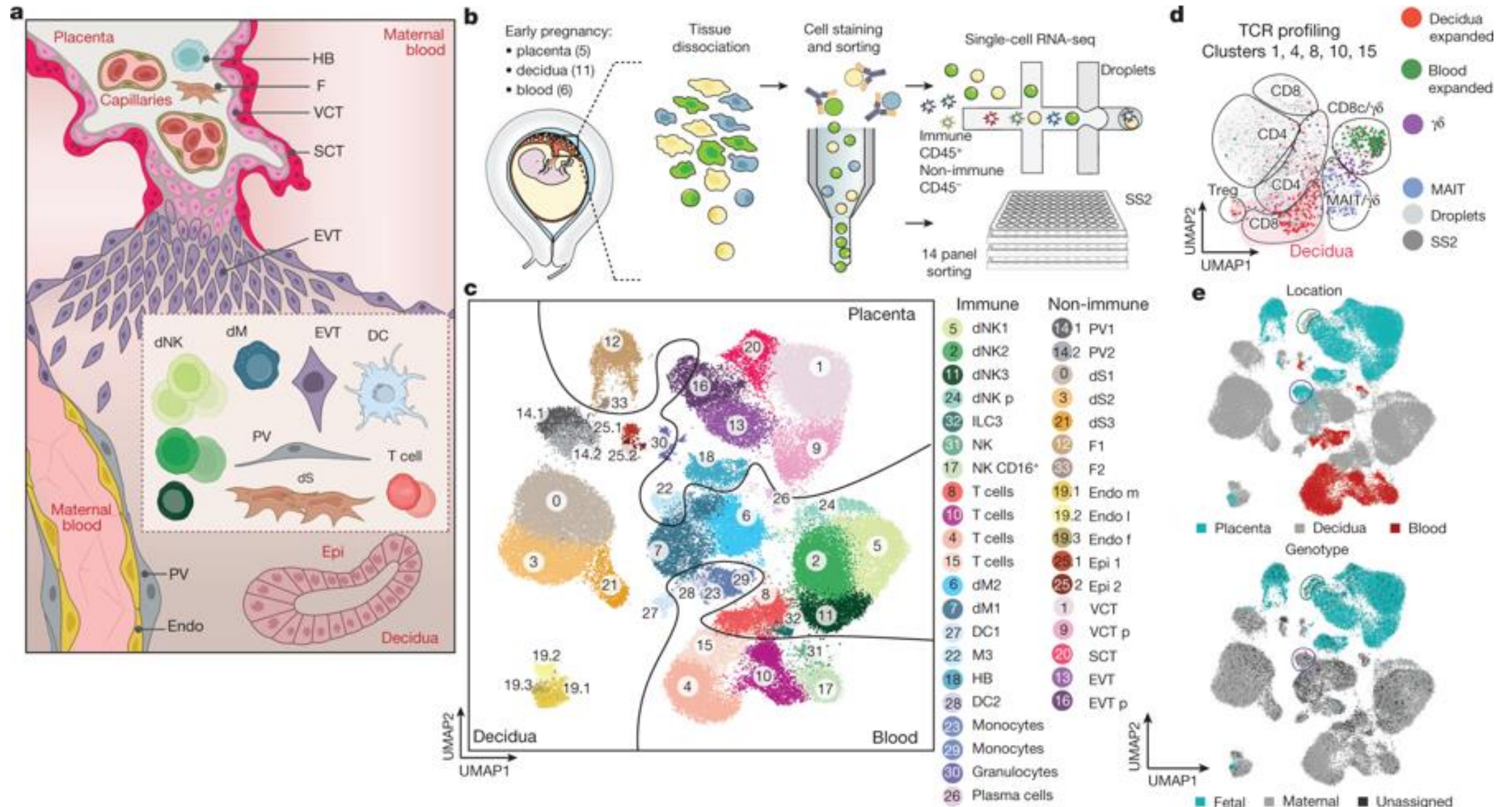


## d) Network inference



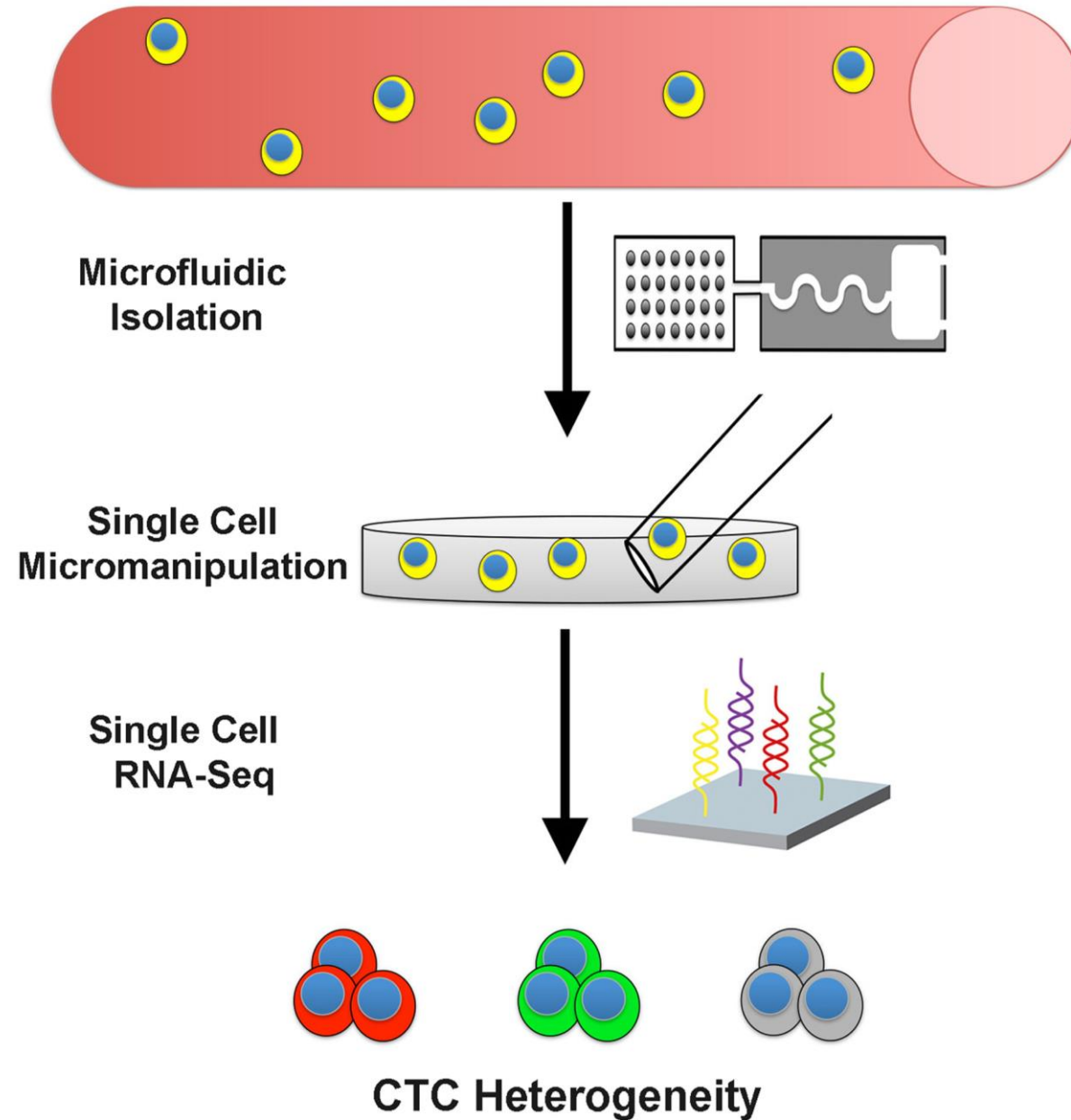


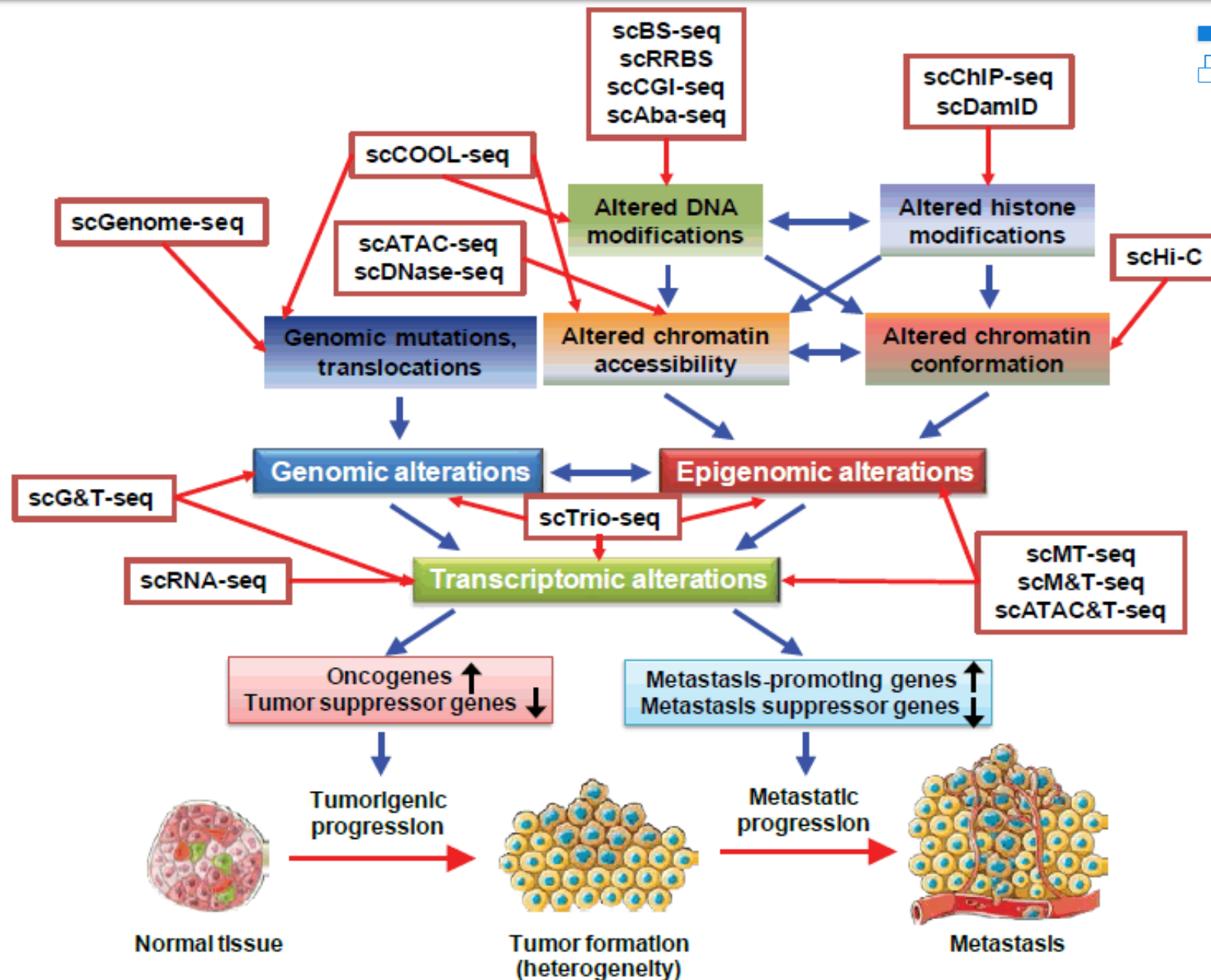
# HUMÁN ANYAI-MAGZATI HATÁRFELÜLET ATLASZA





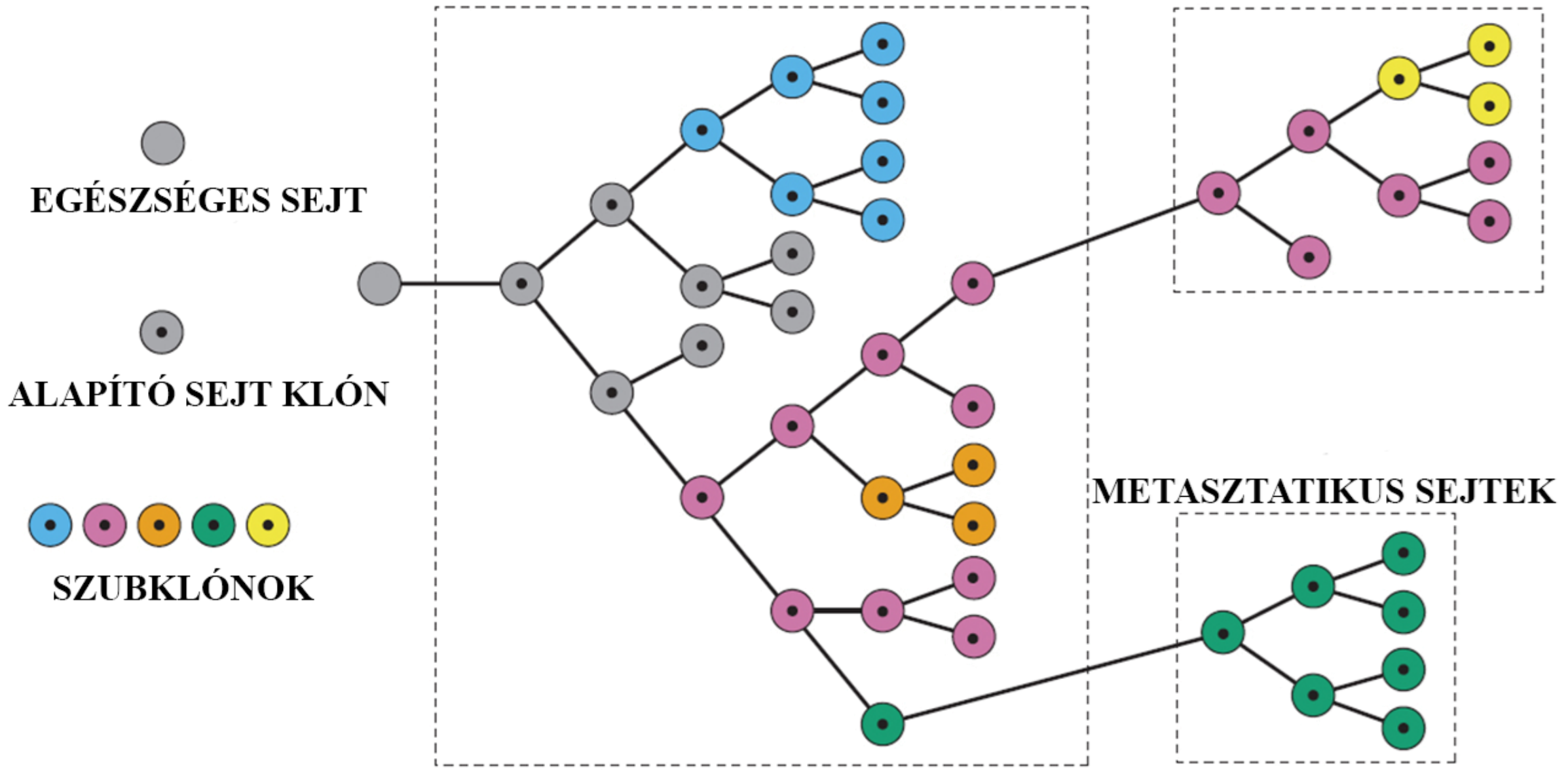
# KERINGŐ METASZTATIZÁLÓ TUMORSEJTEK





**Figure 5:** The diagram for illustrating the roles of genomic, epigenomics and transcriptomic alterations in tumorigenesis and metastasis. The current established single-cell genomics, epigenomics, transcriptomics and their derived multi-omics methods are also shown in the diagram to indicate their applications.

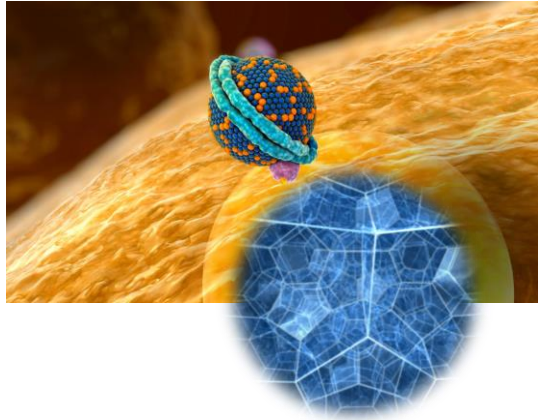
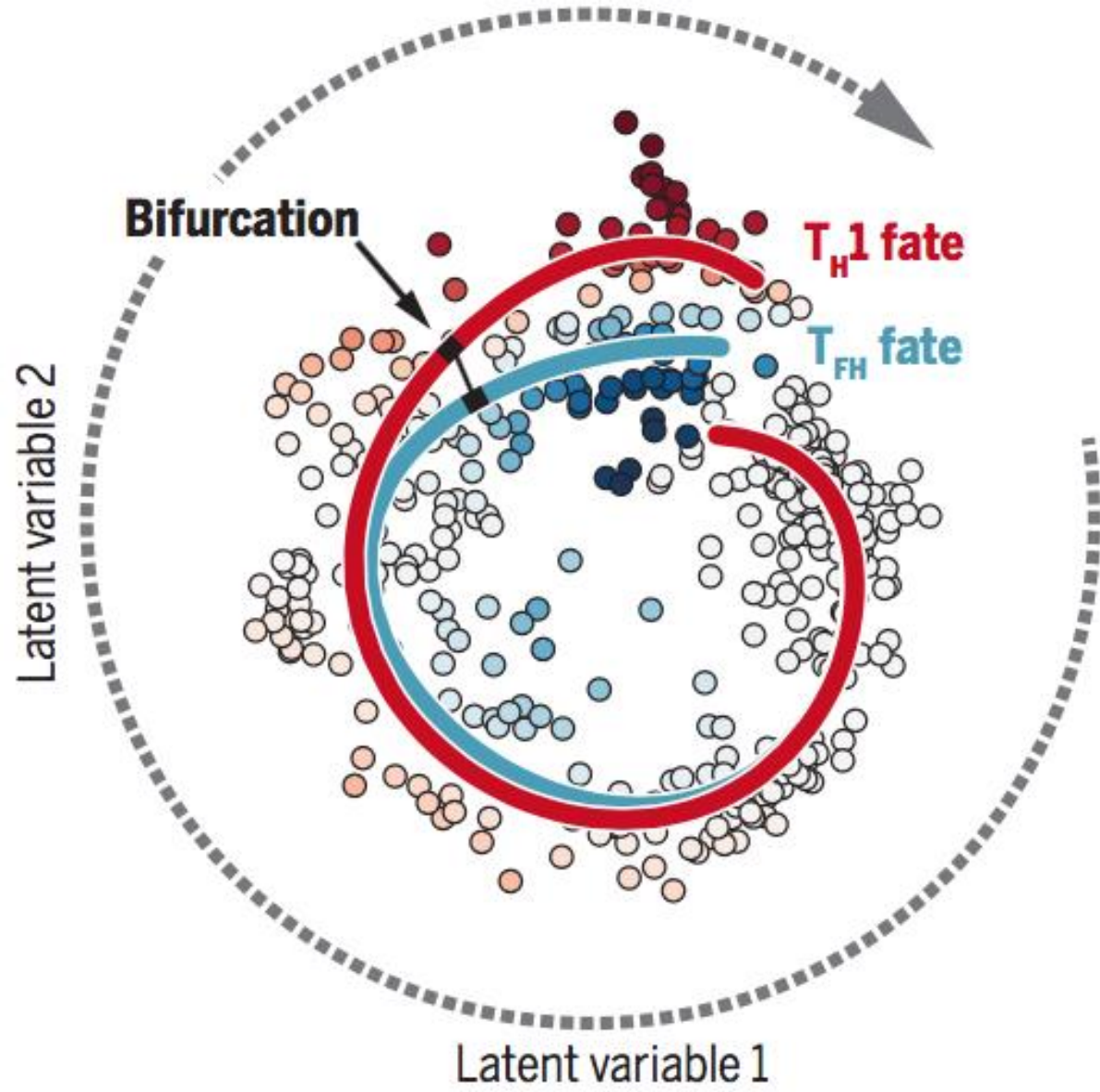
# SEJTEK MOLEKULÁRIS PORTRÉJÁNAK FESTÉSE (1)



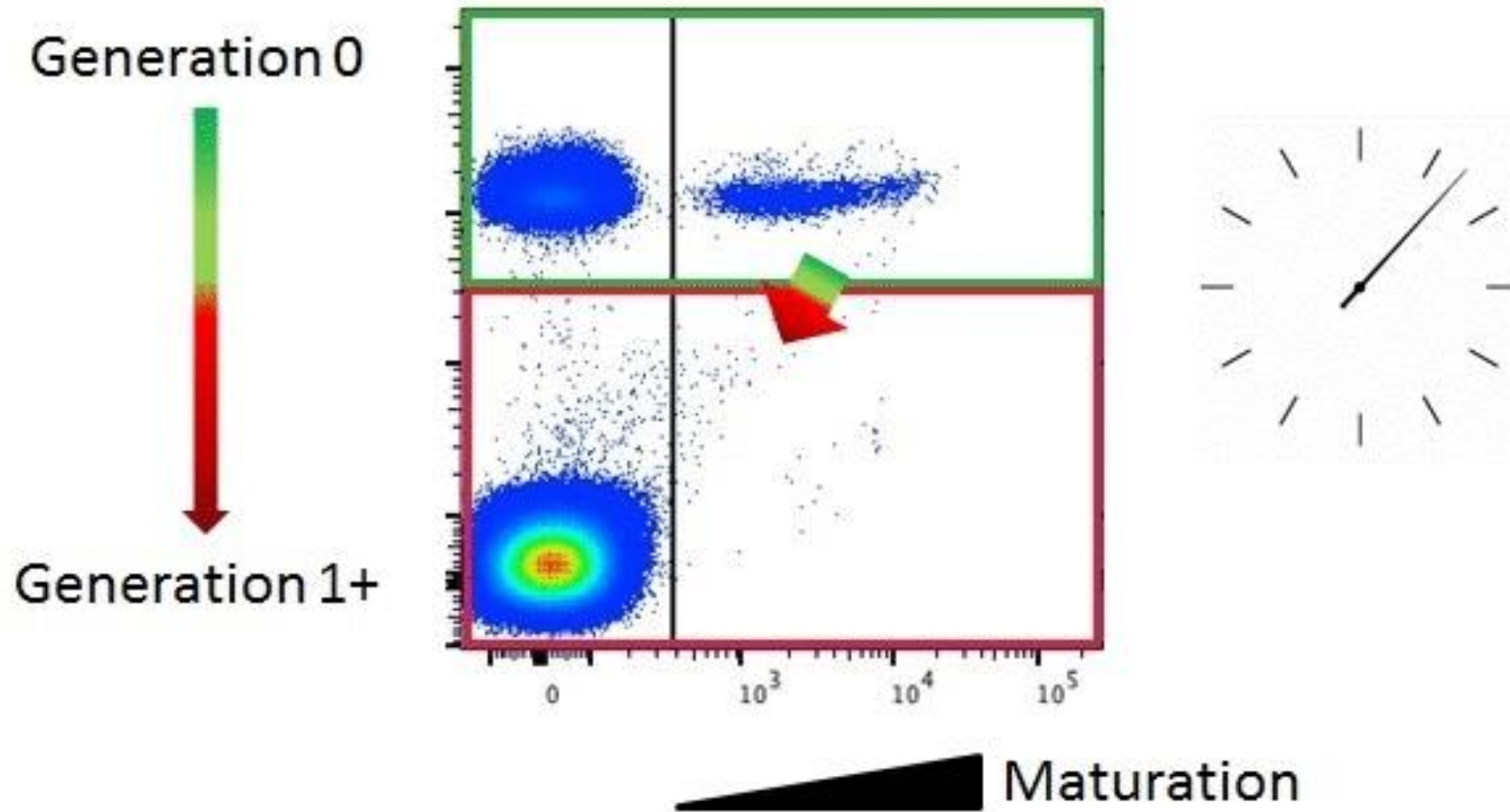




# SEJTEK MOLEKULÁRIS PORTRÉJÁNAK FESTÉSE (3)

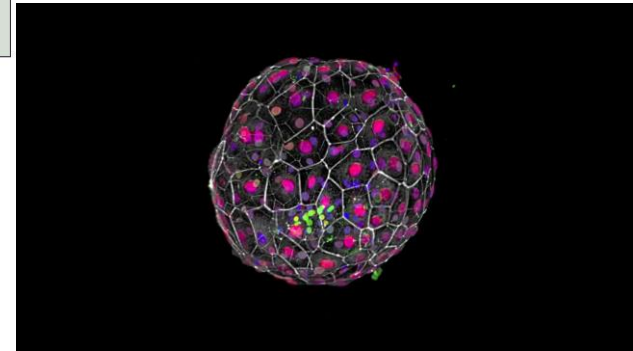
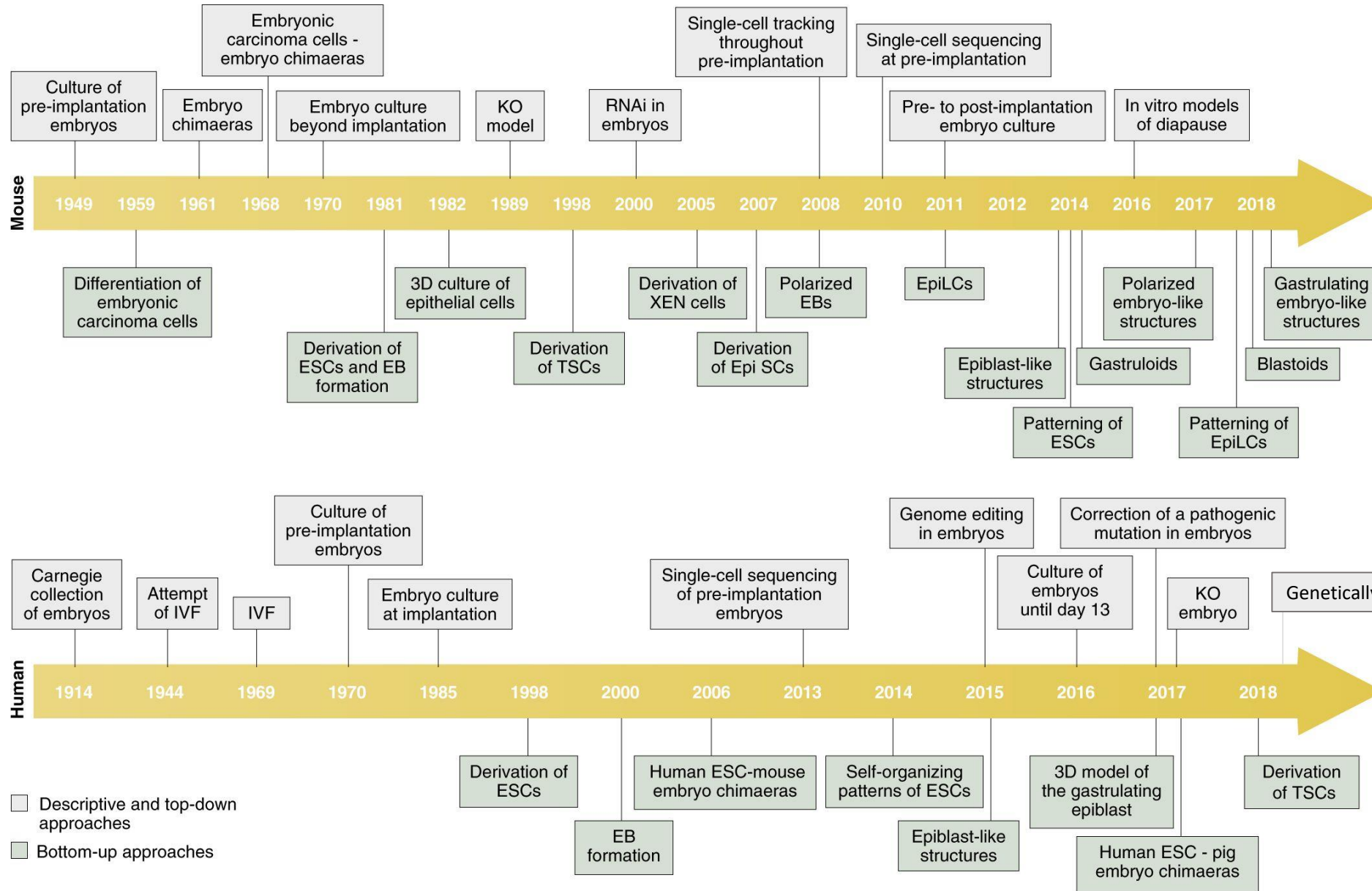


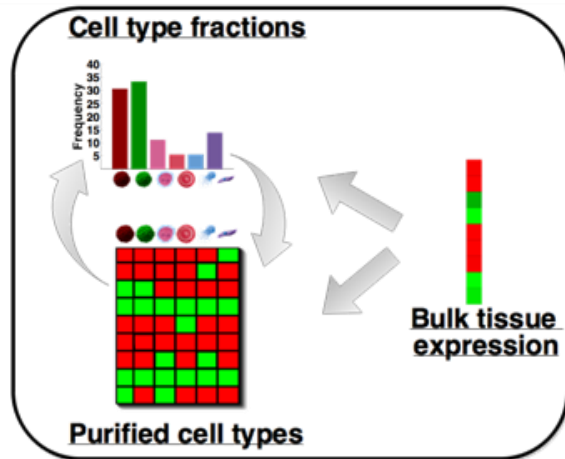
# SEJTEK MOLEKULÁRIS PORTRÉJÁNAK FESTÉSE (4)



## THE MODEL

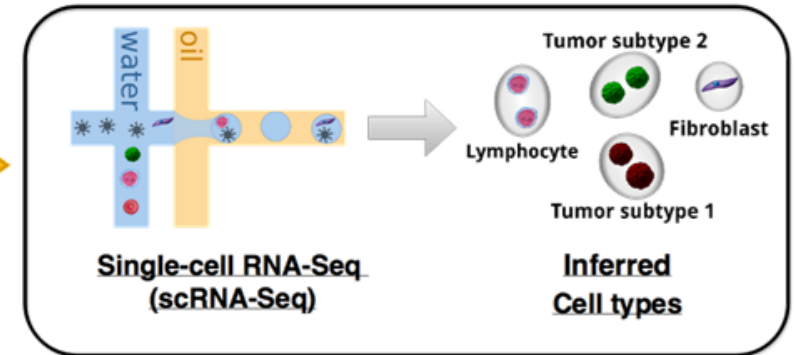
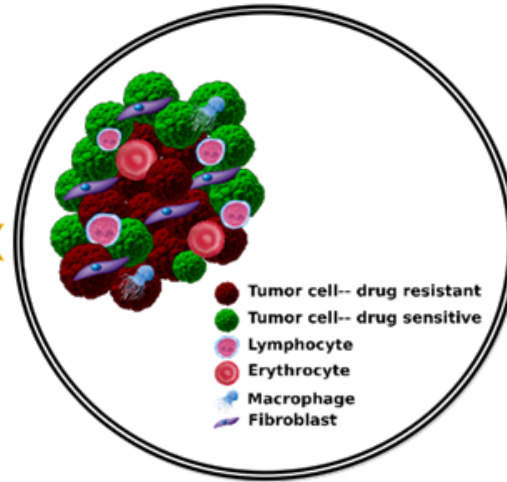
$$\frac{\partial P}{\partial t} + \lambda \frac{\partial P}{\partial x} = -c(x)P(t, x), \quad P(0, x) = P_0 f(x; \mu, \sigma), \quad P(t, 0) = \beta P(t, x_r)$$





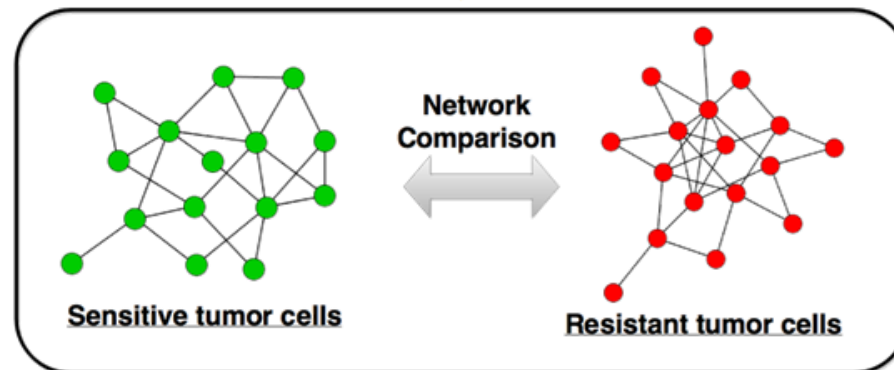
## Deconvolving gene expression profiles

*A Comprehensive Survey of Deconvolution Methods for Separating Cell types in Complex Tissues, 2016*



## Identifying cell types from single-cell profiles

*Take ACTION to identify high-resolution cell types and associated transcriptional pathways, 2016*



## Constructing cell type-specific networks

*A convex optimization approach for identification of human tissue-specific interactomes, 2016*

