

Teaching unit “non-coding RNAs and epigenetics”

Single cell omics in oncology

Justine Marsolier

Group Dynamic of Epigenetic Alterations in Cancer

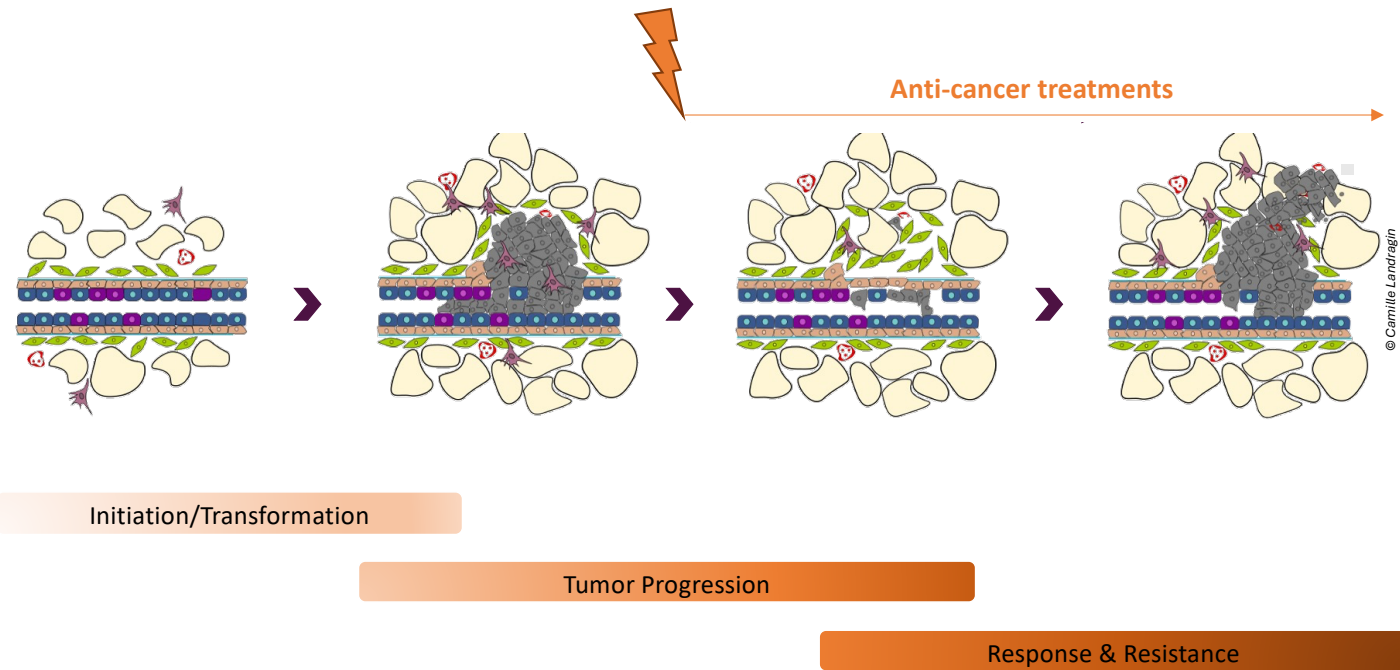
Céline Vallot

Translational Department & UMR3244

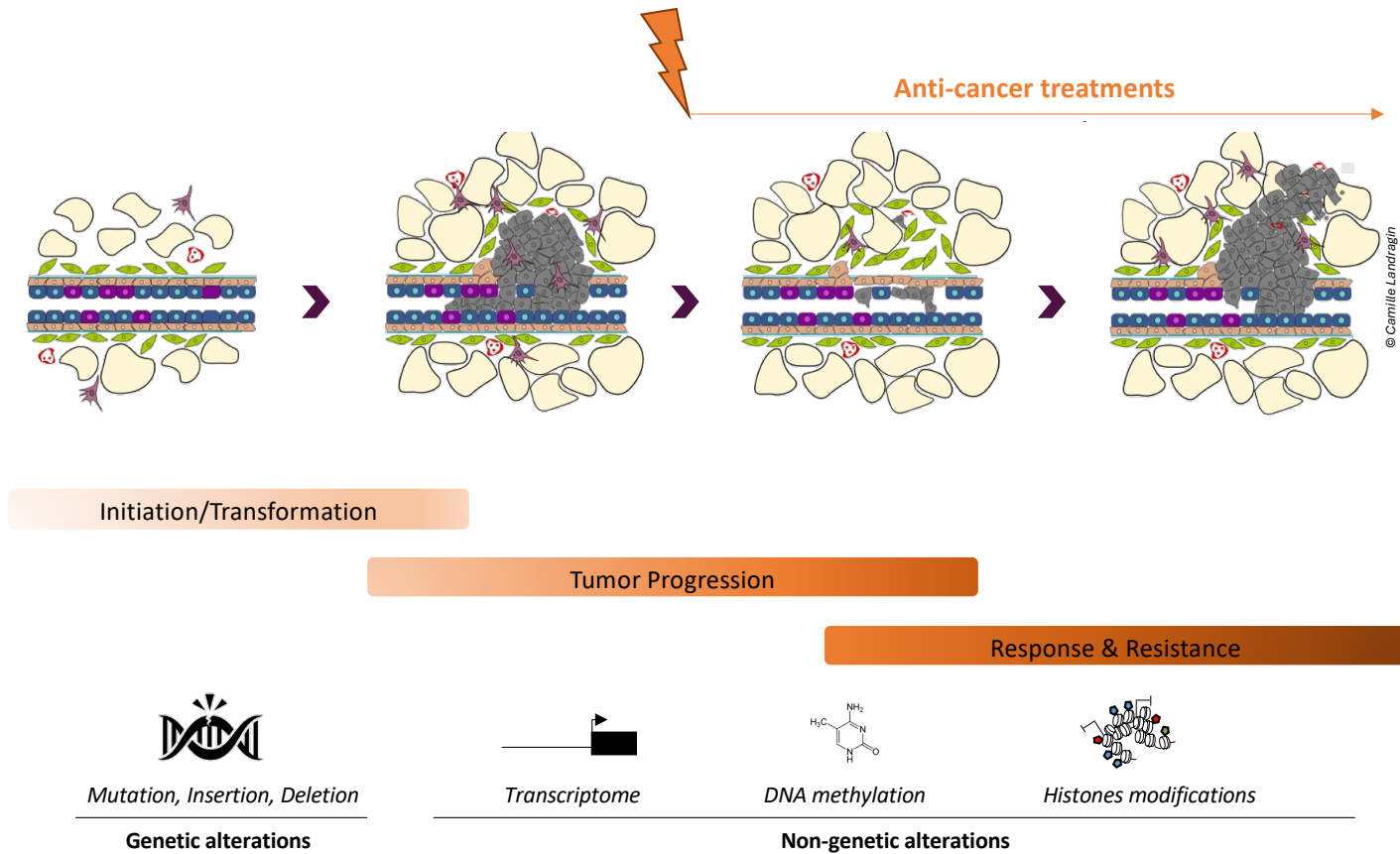
Institut Curie, Paris, France



Tumor evolution is a multi-step process



Plasticity of the cells during tumor evolution



LETTER

doi:10.1038/nature22794

Rare cell variability and drug-induced reprogramming as a mode of cancer drug resistance

Sydney M. Shaffer^{1,2}, Margaret C. Dunagin¹, Stefan R. Torborg^{1,3}, Eduardo A. Torre^{1,2}, Benjamin Emert^{2,4}, Clemens Krepler⁵, Marilda Beqiri⁵, Katrin Sproesser⁵, Patricia A. Brafford⁵, Min Xiao⁵, Elliott Eggen², Ioannis N. Anastopoulos², Cesar A. Vargas-Garcia⁶, Abhyudai Singh^{6,7}, Katherine L. Nathanson², Meenhard Herlyn⁵ & Arjun Raj^{1,8}

Model: Melanoma (V600E mutation - BRAF protein)

Therapy: Vemurafenib = BRAF inhibitor (inhibits the mutated BRAF protein)

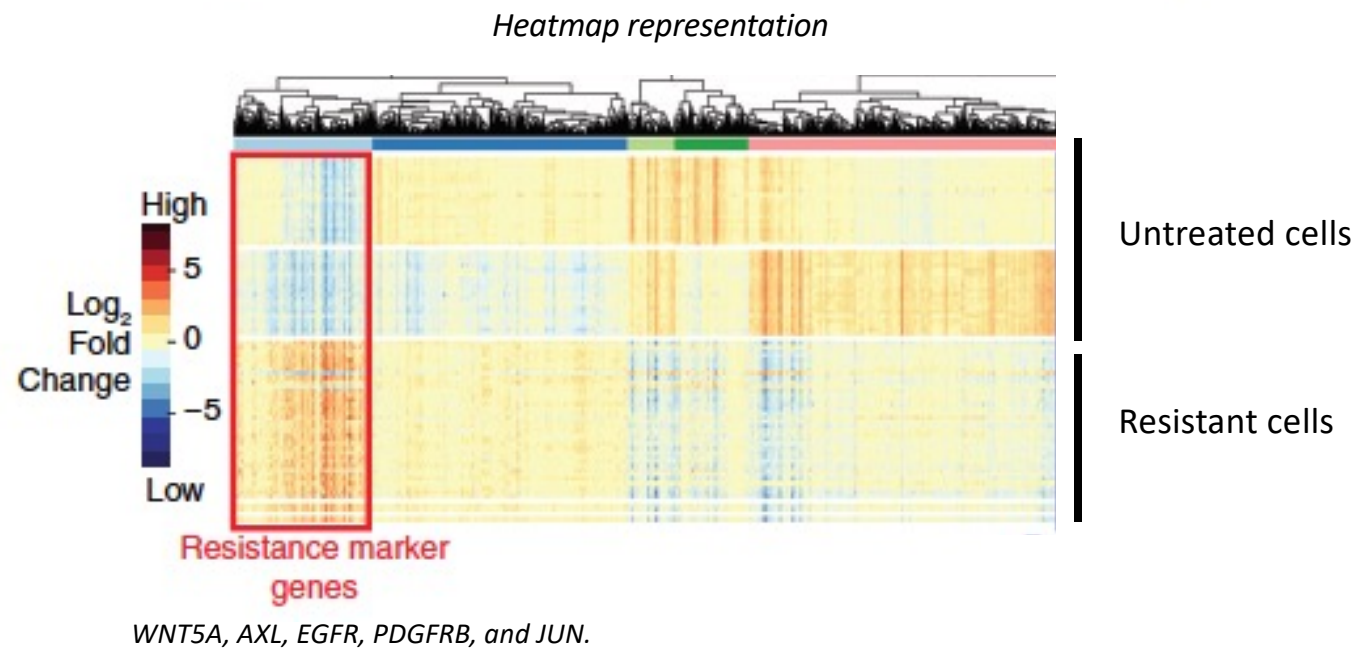
-> a small subset of cancer cells develop drug resistance

Objectif: To understand resistance at the single-cell level (cultured patient-derived melanoma cells)

Hypothesis: Single-cell gene expression differences marked pre-resistant cells in the population before treatment.

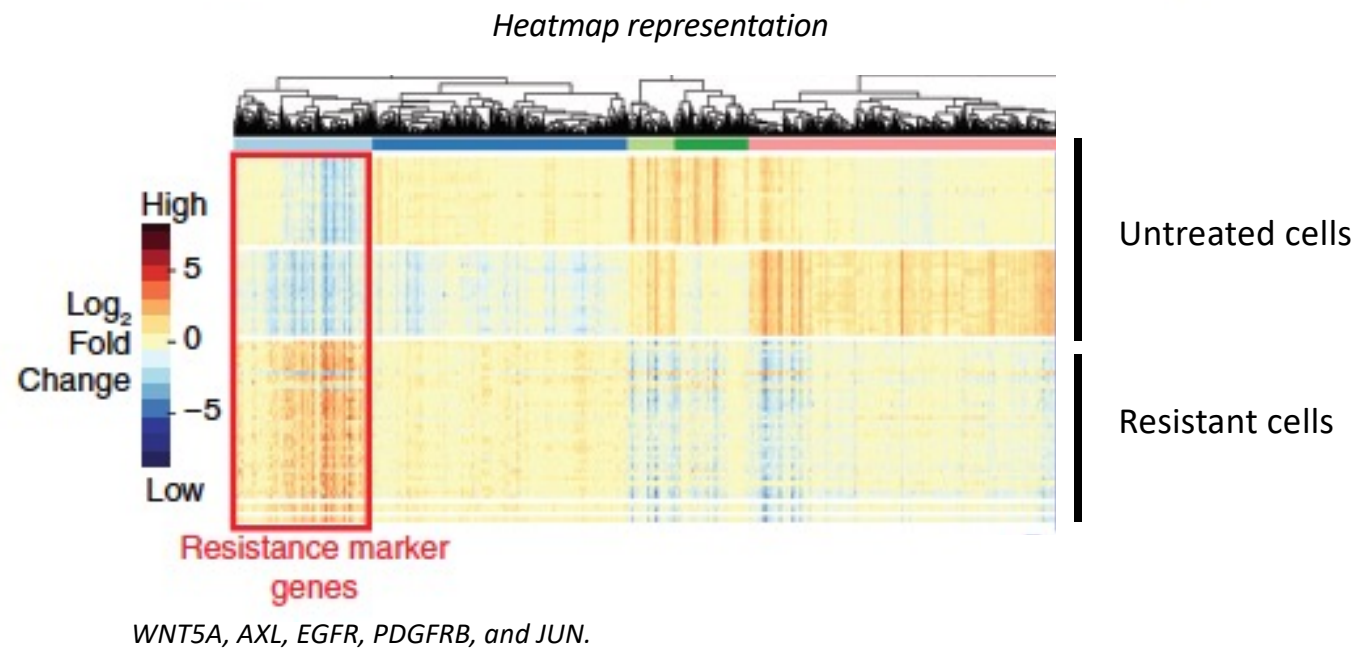
Expression of marker genes increased in resistant cells

Transcriptomic profiles (bulk-RNA-seq)



Expression of marker genes increased in resistant cells

Transcriptomic profiles (bulk-RNA-seq)

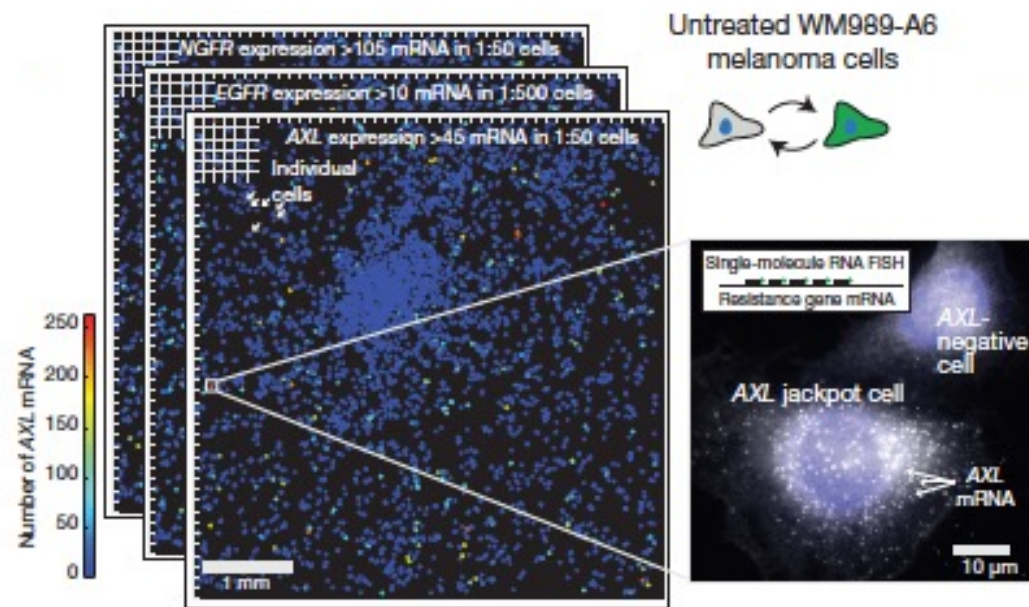


Can the low average expression of these markers in untreated cells mask rare individual cells with high expression for these resistant markers ?

Shaffer et al., 2017

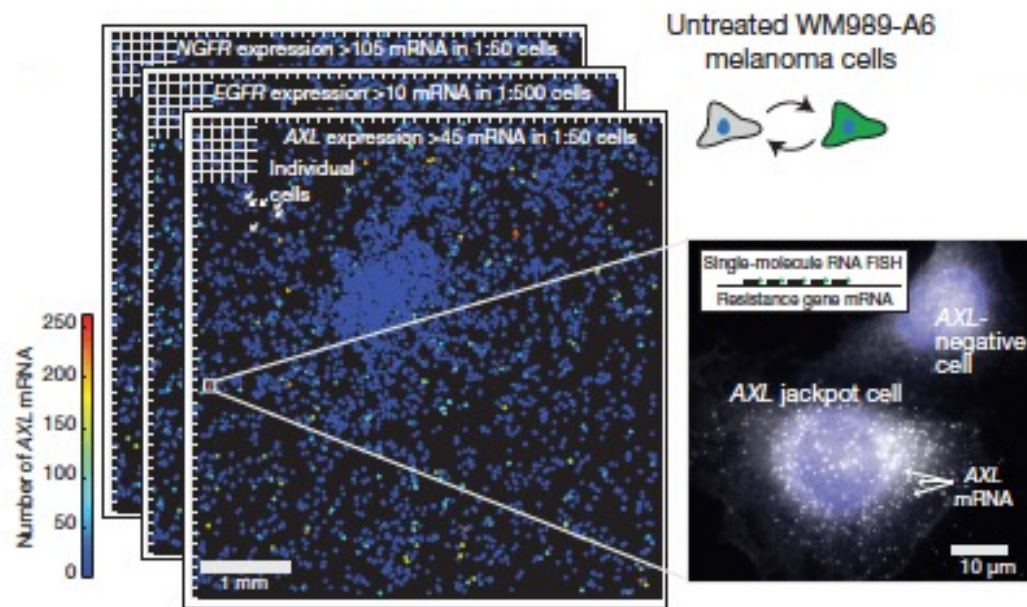
A population of rare cells expressed resistance genes at high levels before drug exposure

High-throughput single-molecule RNA FISH



A population of rare cells expressed resistance genes at high levels before drug exposure

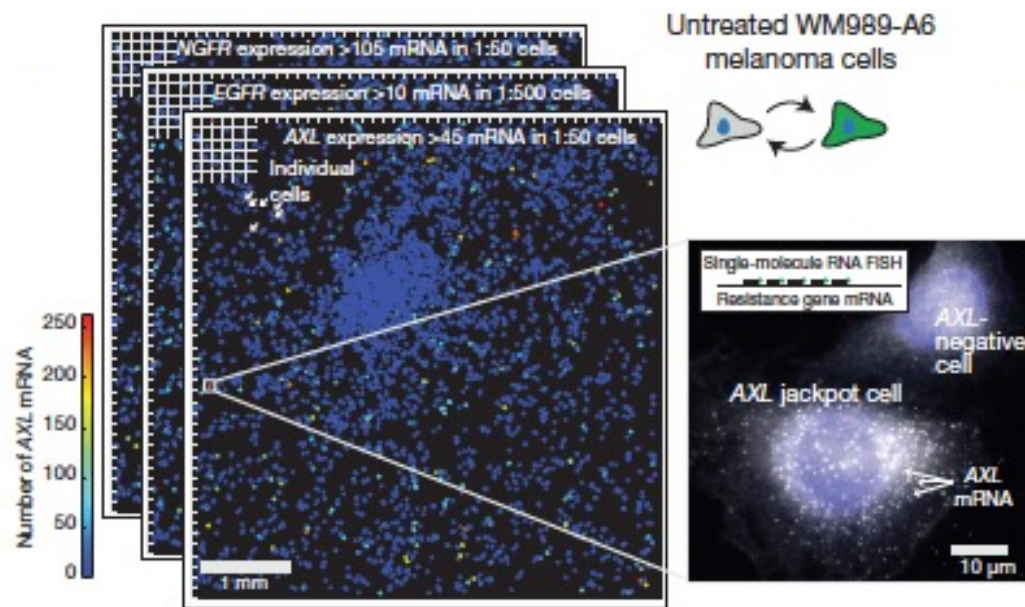
High-throughput single-molecule RNA FISH



After 4 weeks of treatment with vemurafenib
= resistant colonies expressed these markers at more uniformly high levels

A population of rare cells expressed resistance genes at high levels before drug exposure

High-throughput single-molecule RNA FISH

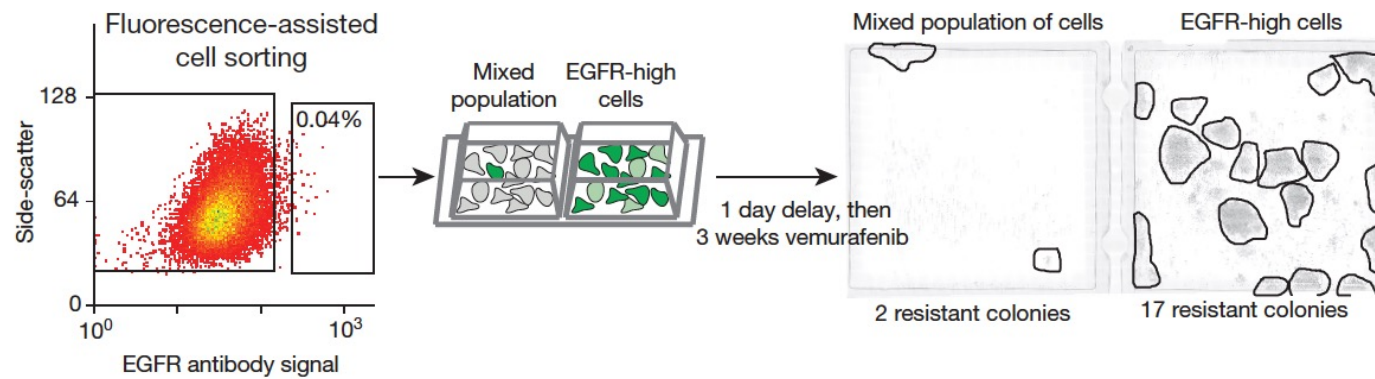


Did sporadic marker gene expression marked untreated cells that ultimately become resistant after drug exposure ?

Shaffer et al., 2017

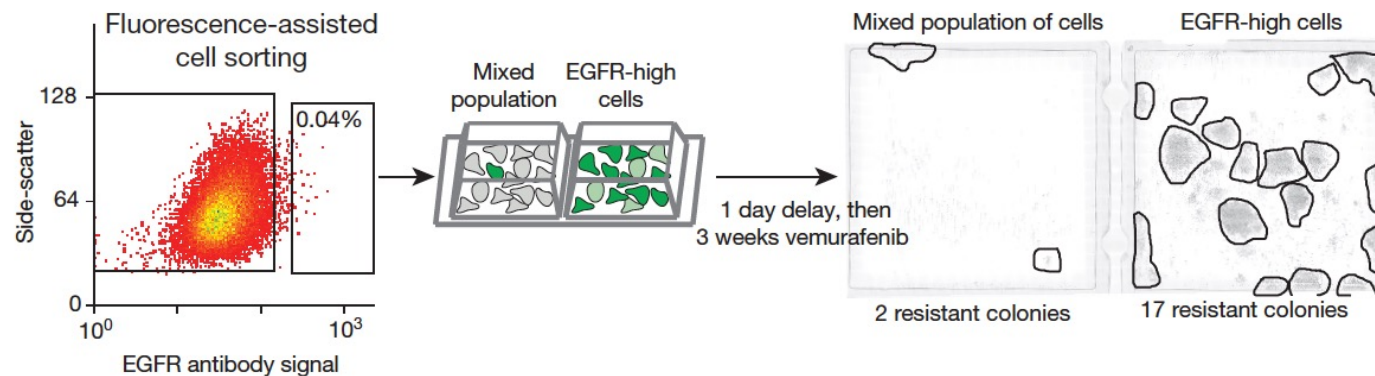
EGFR-high cells produced more resistant colonies than EGFR-mixed cells

Fluorescence-activated cell sorting of EGFR expressing cells – 3 weeks of treatment



EGFR-high cells produced more resistant colonies than EGFR-mixed cells

Fluorescence-activated cell sorting of EGFR expressing cells – 3 weeks of treatment



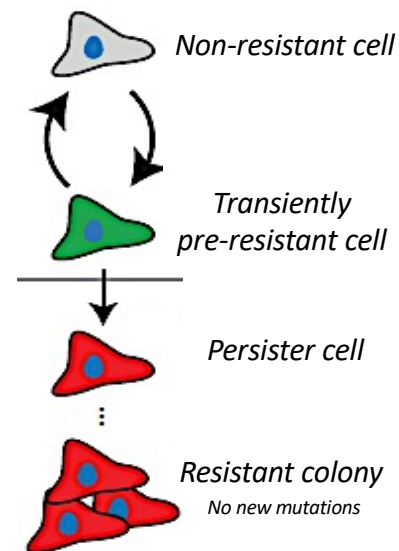
Human melanoma cells can display transcriptional variability at the single cell level
(i.e. infrequent, semi-coordinated transcription of a limited number of resistance markers at high levels in a very small percentage of cells in the initial population = jackpot cells)

=

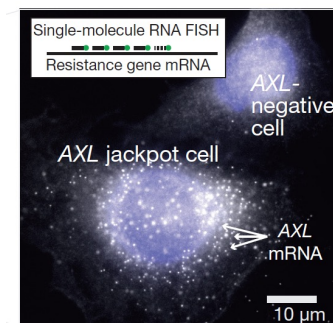
Prediction of which cells will ultimately resist drug treatment.

Rare cell variability and drug-induced reprogramming as a mode of cancer drug resistance

Melanoma and BRAFi targeted therapy



Pre-resistant cells = cells that give rise to resistant colonies upon addition of drug.



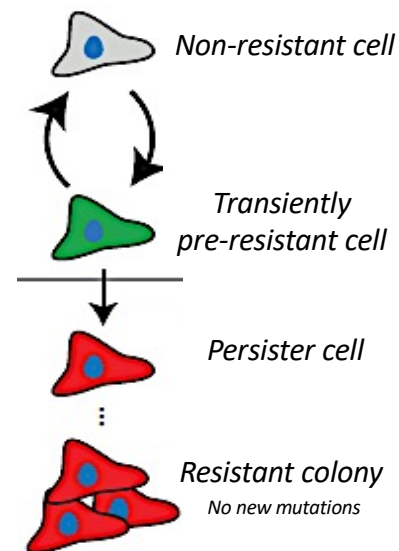
Rare cell diversity = **HETEROGENEITY** of the initial population

+

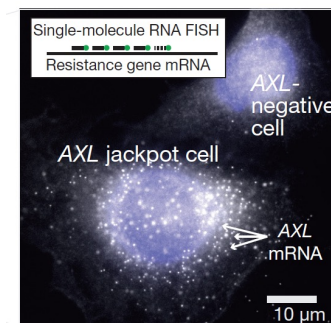
Acquisition of new transcriptomic features = **PLASTICITY**

Rare cell variability and drug-induced reprogramming as a mode of cancer drug resistance

Melanoma and BRAFi targeted therapy



Pre-resistant cells = cells that give rise to resistant colonies upon addition of drug.

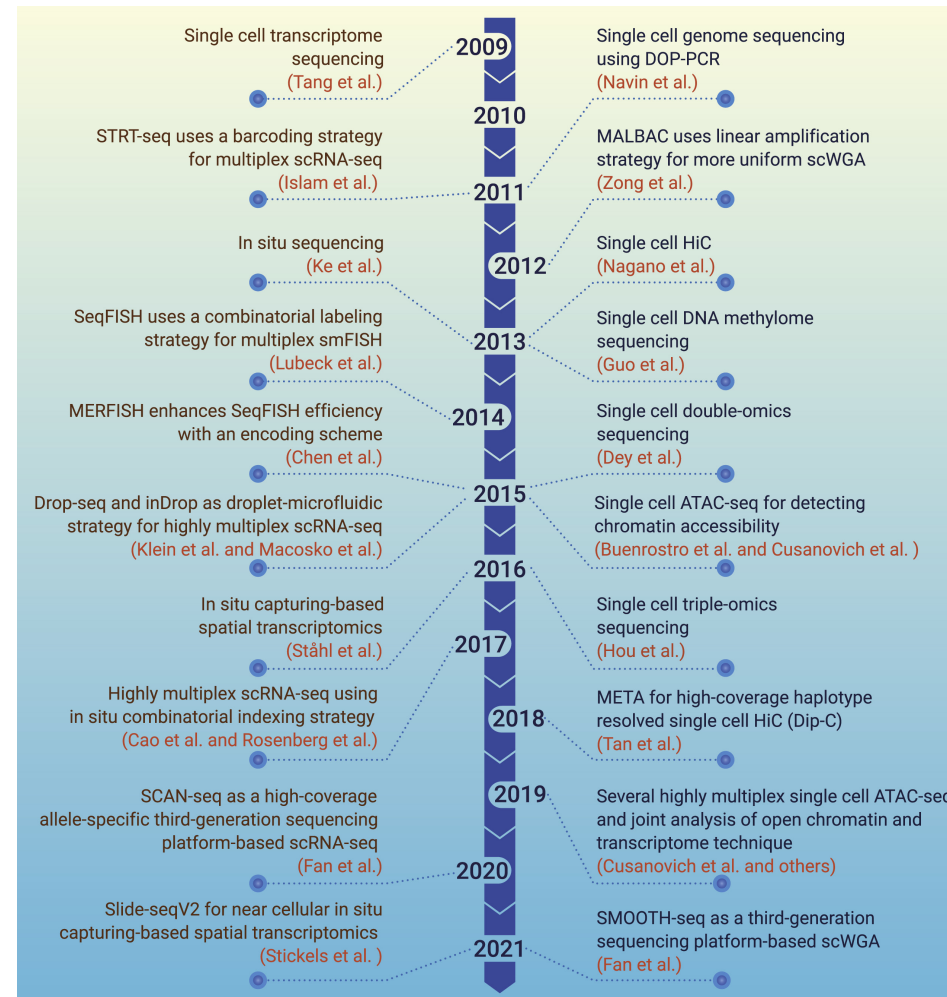


RNA-FISH ~ 1000 cells

How can we study non-genetic alterations on several thousands of cells at the same time, at the single cell level to study heterogeneity and detect rare cell subpopulations?

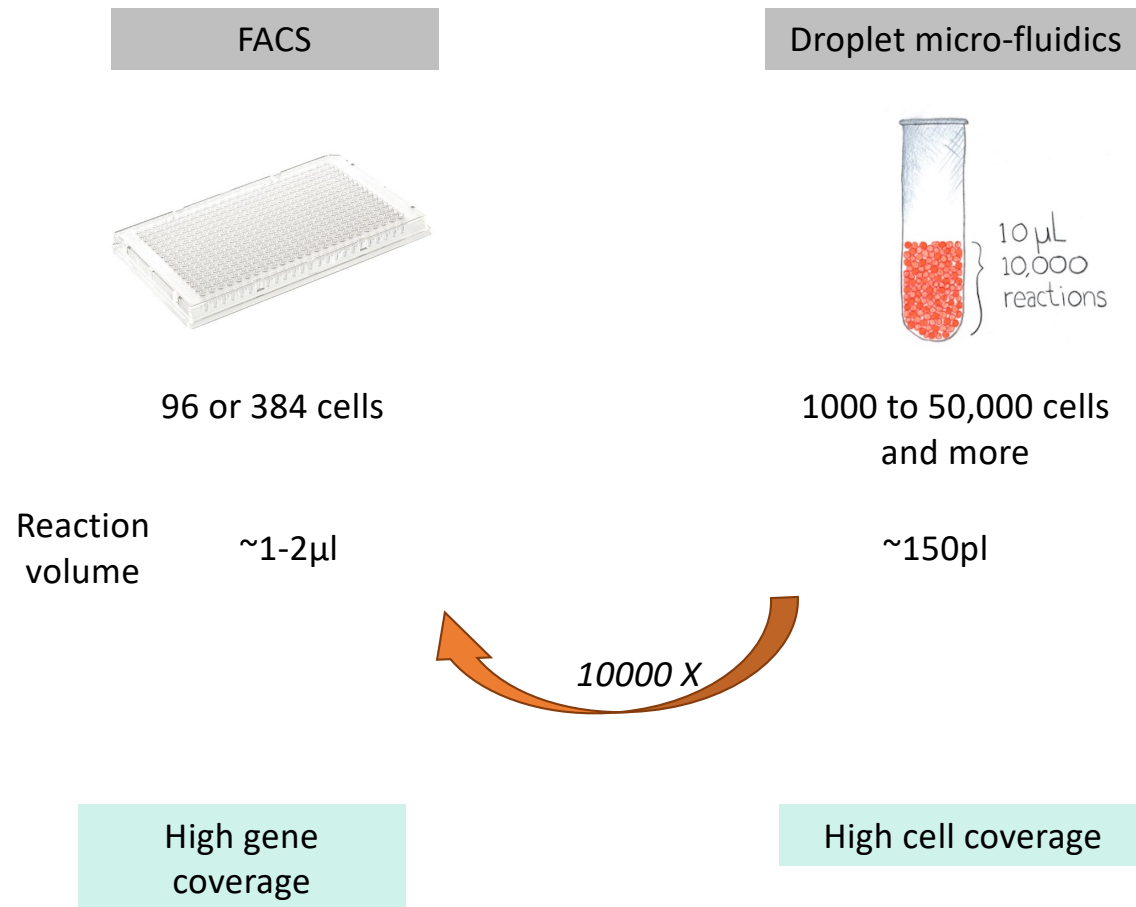
Shaffer et al., 2017

Single-cell transcriptomic technologies : A rapidly-evolving field

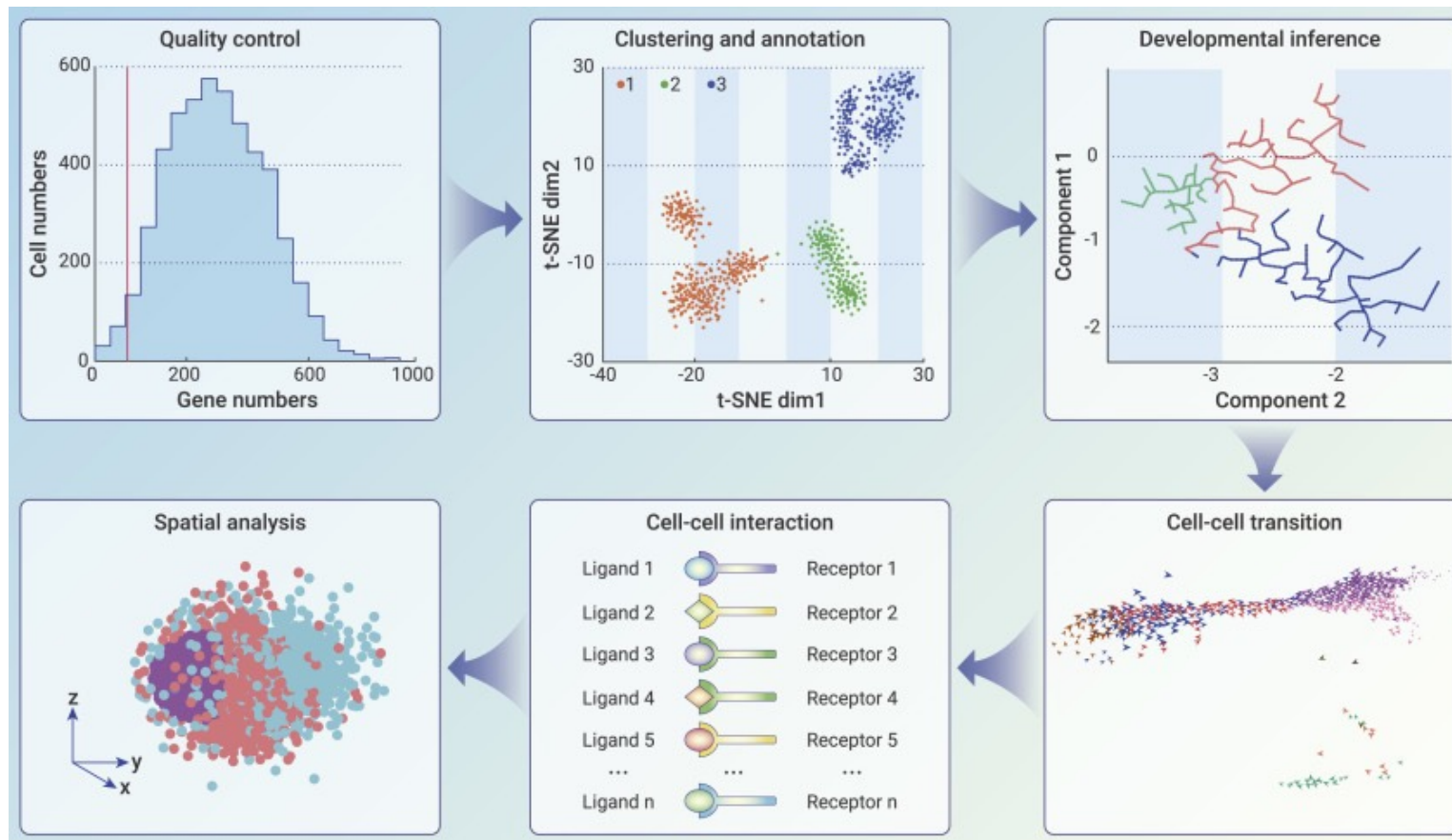


Weng et al.,2022

How to make reactions with one cell?



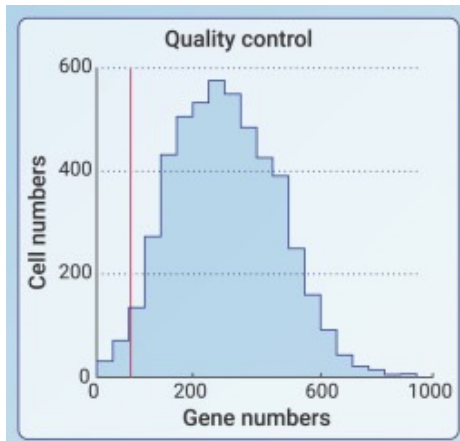
Bioinformatics analysis of single-cell sequencing data



Algorithm and software development in bioinformatics are critical to translate scRNA-seq data into biological and medical data and further applications.

Weng et al., 2022

1- Quality Control



Limited RNA content of single cells
+ the stochastic nature of current scRNA-seq techniques



mRNAs within one cell cannot be fully captured and sequenced

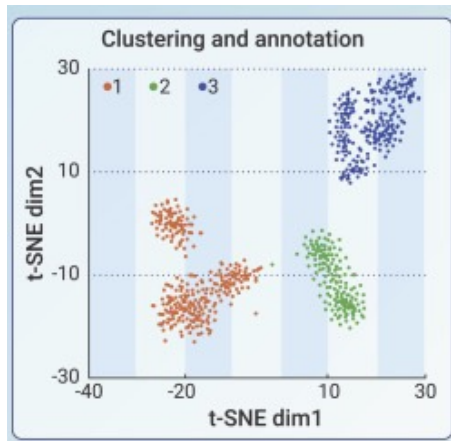
Indices for quality control during scRNA-seq data analysis:

- Low or high gene numbers
- Percentage of mitochondrial genes

The aim of quality control
= to control the rates of empty cells, doublets or multiplets, and
cells with bad states.

-> such quality control metrics vary across different biological
specimens, and thus no consistent cutoffs exist.

2 – Visualization, clustering and cell-type annotation



Critical task of scRNA-seq data analysis:

Visualization of cell clusters and their mutual relationships.

PCA - principal-component analysis

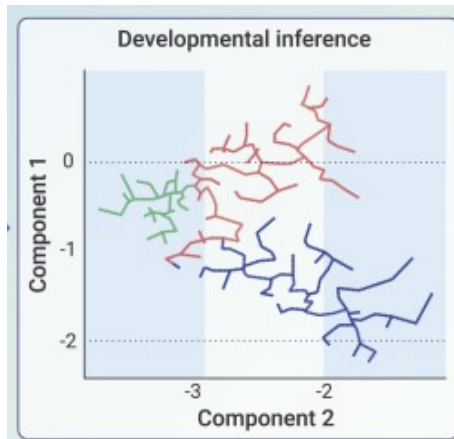
T-SNE - t-distributed stochastic neighbor embedding

UMAP - Uniform Manifold Approximation and Projection

After clustering, the cell type of each cluster can be predicted:

- with artificial intelligence-based methods (SingleR),
- with cell marker-based methods (CellAssign).

3 - Trajectory analysis



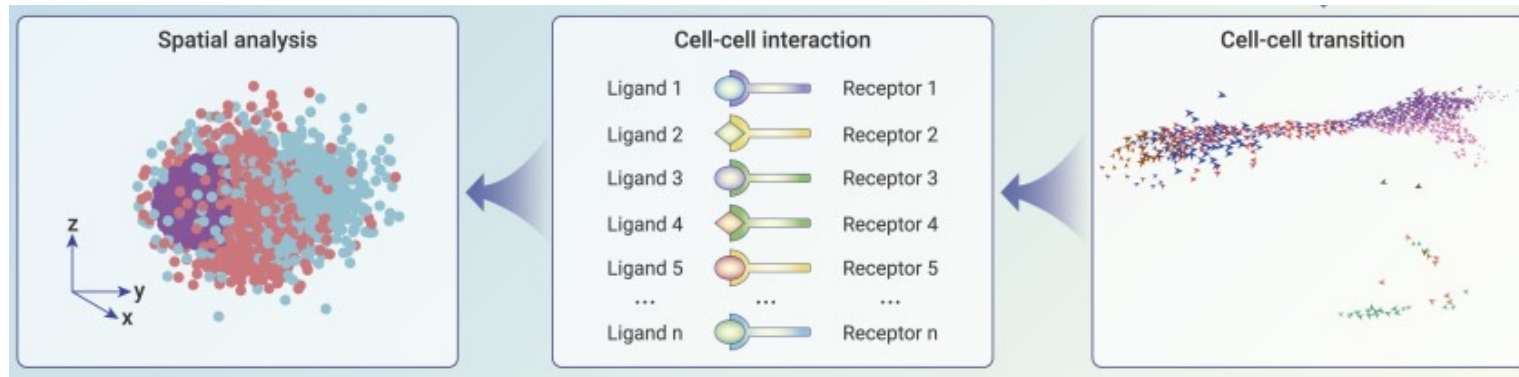
Developmental inference = cells along a specific developmental trajectory were sampled by scRNA-seq and thus could be reconstructed via examining the similarity of cellular expression profiles.

Monocle infers cellular developmental trajectories based on gene expression similarity.

RNA velocity derives the probability and direction of cell-to-cell transitions.

Results are predictive and validations are needed to confirm the predictions.

4 - Single-cell regulatory network & Cell-cell communication



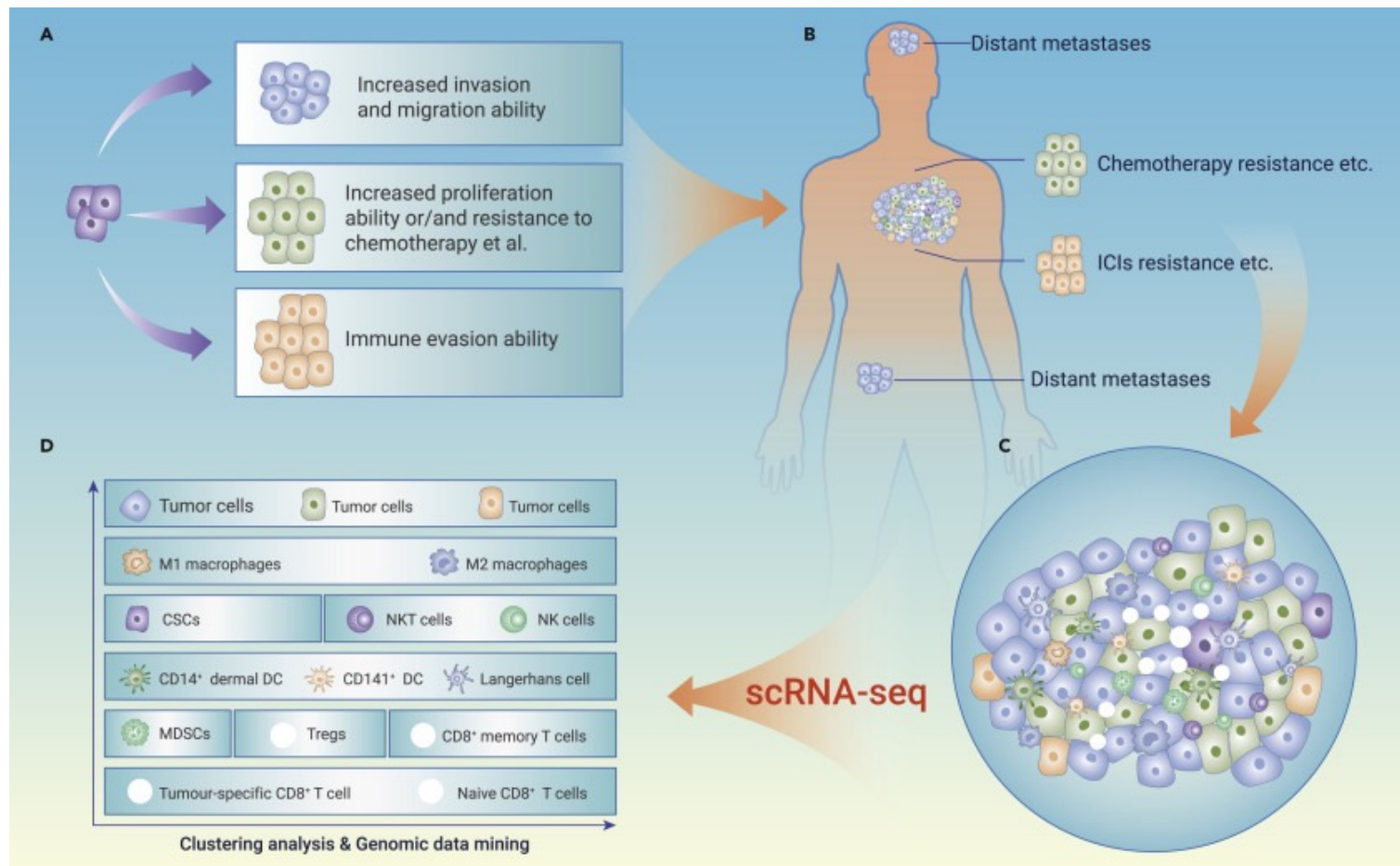
To construct the single-cell regulatory network:

- SCENIC conducts regulon analysis based on scRNA-seq data and can provide quantitative analysis of the roles of diverse transcription factors in shaping the observed scRNA-seq data.
- NicheNet compiles a ligand-target database and tries to prioritize those extrinsic factors critical to the observed gene expression profiles.

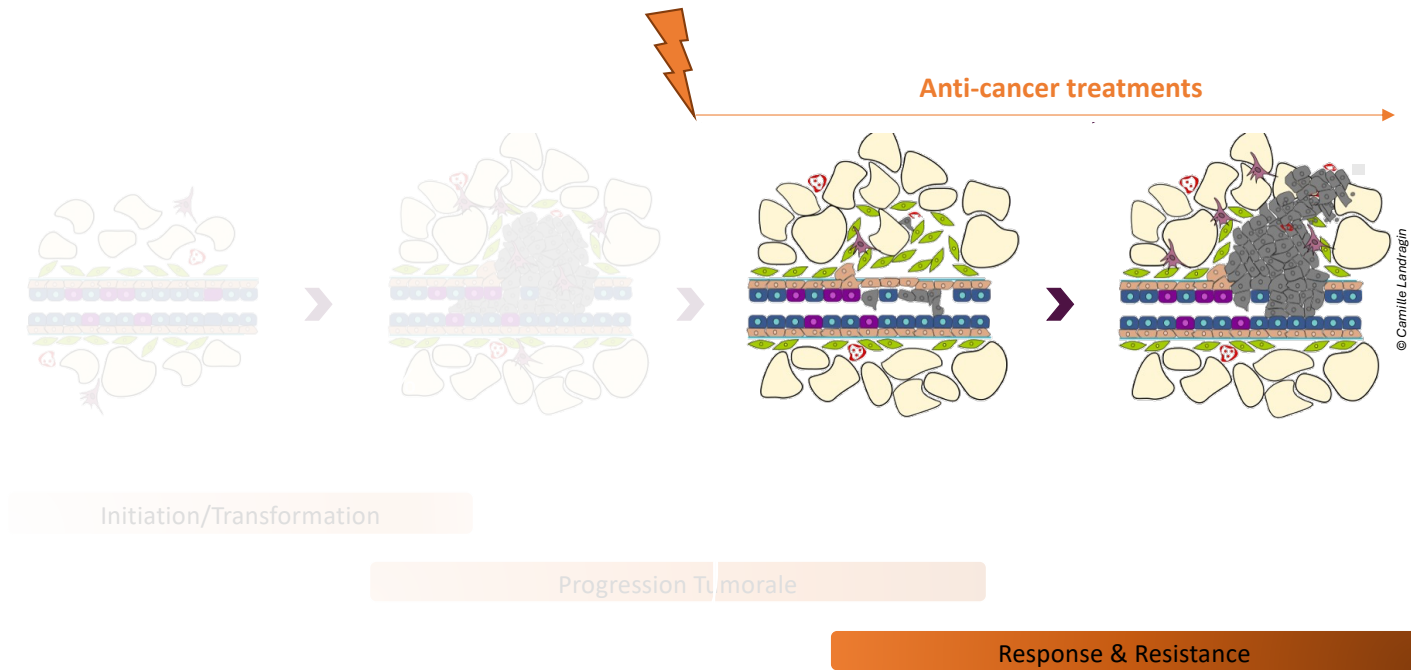
To interrogate the potential cell-to-cell crosstalks and even spatial relationships:

- CellphoneDB and CSOmap are two typical methods of the ligand-receptor interaction-dependent cell-cell communication algorithms.
- NovoSpaRc derives cellular spatial relationships only based on scRNA-seq data without ligand-receptor interactions (Cells with similar gene expression profiles should have a high probability to share spatial niches).

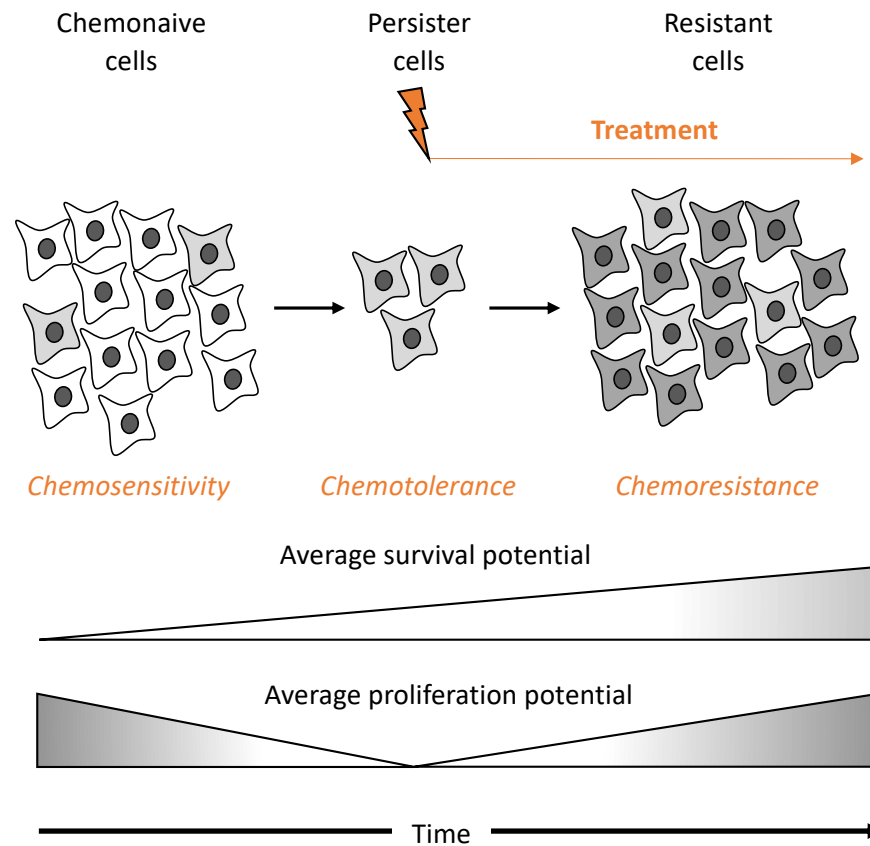
The applications of sc technologies in oncology



Plasticity of the cells during tumor evolution

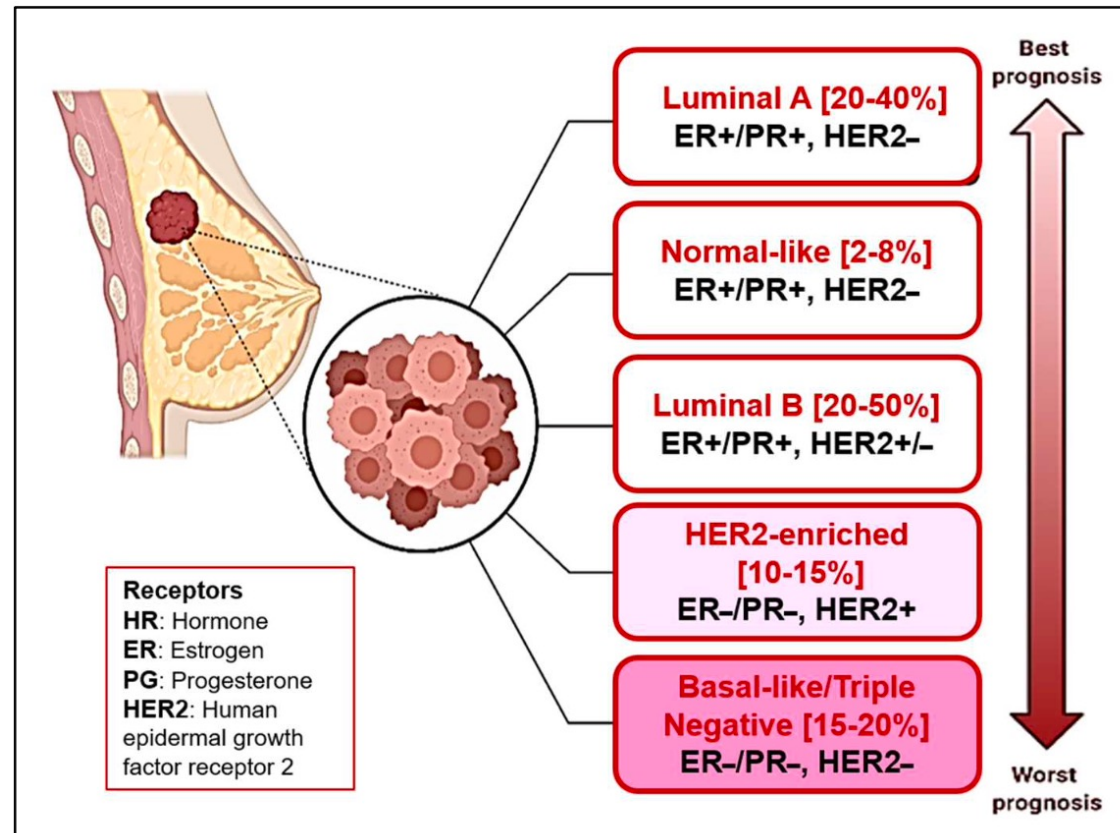


Drug persister cells constitute a reservoir of cells from which drug resistant cells will emerge



Adapted from Chisholm et al., 2015

Clinical setting: Triple Negative Breast Cancers



Drug resistance develops following use of chemotherapies

Chemoresistance Evolution in Triple-Negative Breast Cancer Delineated by Single-Cell Sequencing

Charissa Kim,^{1,2,6} Ruli Gao,^{1,6} Emi Sei,¹ Rachel Brandt,¹ Johan Hartman,³ Thomas Hatschek,³ Nicola Crosetto,⁴ Theodoros Foukakis,^{3,*} and Nicholas E. Navin^{1,2,5,7,*}

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⁵Department of Bioinformatics and Computational Biology, UT MD Anderson Cancer Center, Houston, TX 77030, USA

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<https://doi.org/10.1016/j.cell.2018.03.041>

Model: TNBC

Therapy: Neo-adjuvant chemotherapy

An unresolved question:

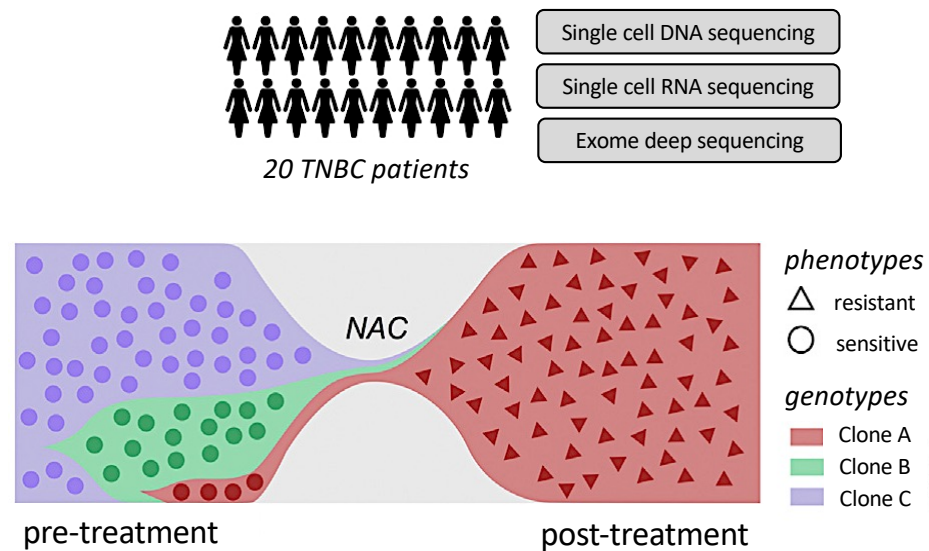
Chemoresistance -> selection and expansion of rare pre-existing subclones (adaptive resistance)
-> induction of new mutations that confer a chemoresistant phenotype (acquired resistance)

Author's hypothesis:

Genomic aberrations associated with chemoresistance are pre-existing in the tumor mass and adaptively selected in response to chemotherapy.

Chemoresistance evolution in TNBC is driven by genetic & transcriptomic mechanisms through combined selective and adaptive modes of evolution

Breast cancer and NAC therapy



Adaptive genome evolution
+
Transcriptional reprogramming
= **SELECTION + PLASTICITY**

CANCER

Resistance to neoadjuvant chemotherapy in triple-negative breast cancer mediated by a reversible drug-tolerant state

Gloria V. Echeverria¹, Zhongqi Ge^{1,2}, Sahil Seth^{3,4,5}, Xiaomei Zhang¹, Sabrina Jeter-Jones¹, Xinhui Zhou¹, Shirong Cai¹, Yizheng Tu¹, Aaron McCoy¹, Michael Peoples^{4,5}, Yuting Sun^{4,5}, Huan Qiu⁶, Qing Chang^{4,5}, Christopher Bristow^{4,5}, Alessandro Carugo^{4,5}, Jiansu Shao¹, Xiaoyan Ma^{4,5}, Angela Harris^{4,5}, Prabhjot Mundi⁷, Rosanna Lau⁸, Vandhana Ramamoorthy^{4,5}, Yun Wu⁸, Mariano J. Alvarez^{7,9}, Andrea Califano⁷, Stacy L. Moulder¹⁰, William F. Symmans⁸, Joseph R. Marszalek^{4,5}, Timothy P. Heffernan^{4,5}, Jeffrey T. Chang^{2,6}, Helen Piwnica-Worms^{1*}

Model: TNBC

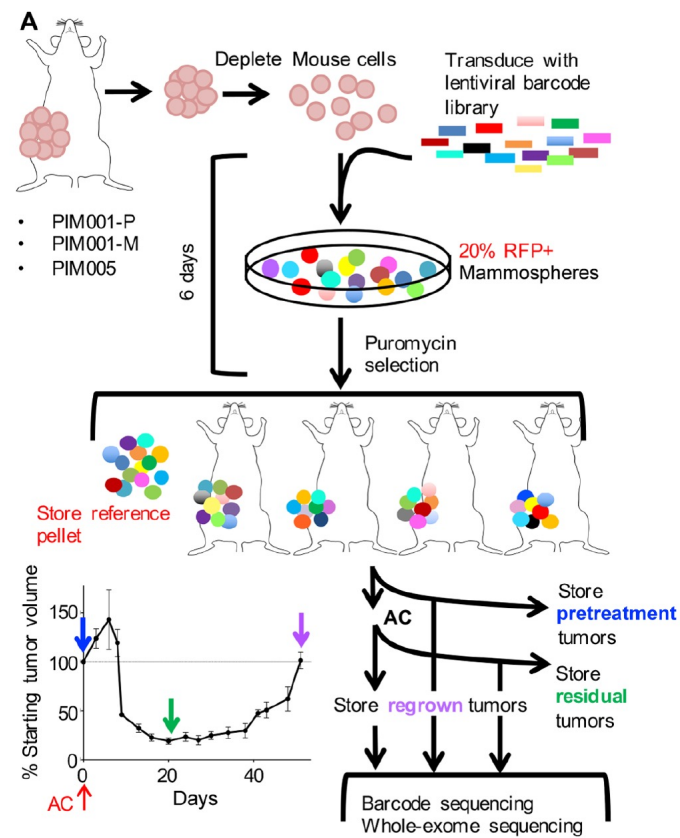
Therapy: Neo-adjuvant chemotherapy

Objectif:

To understand the earliest steps of chemoresistance

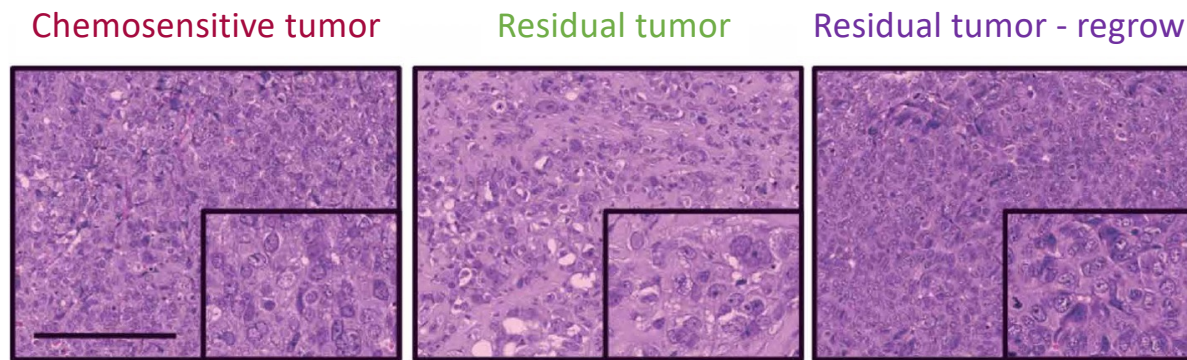
Resistance to chemotherapy in breast cancer is mediated by a reversible drug-tolerant state

Breast cancer and neo-adjuvant chemotherapy

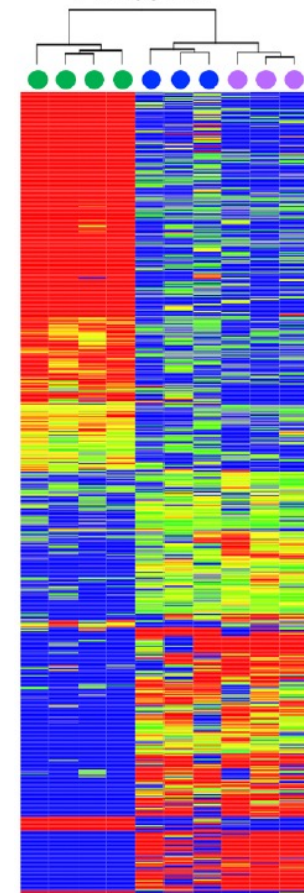


The reversible drug-tolerant state involved transcriptional reprogramming

Histological features



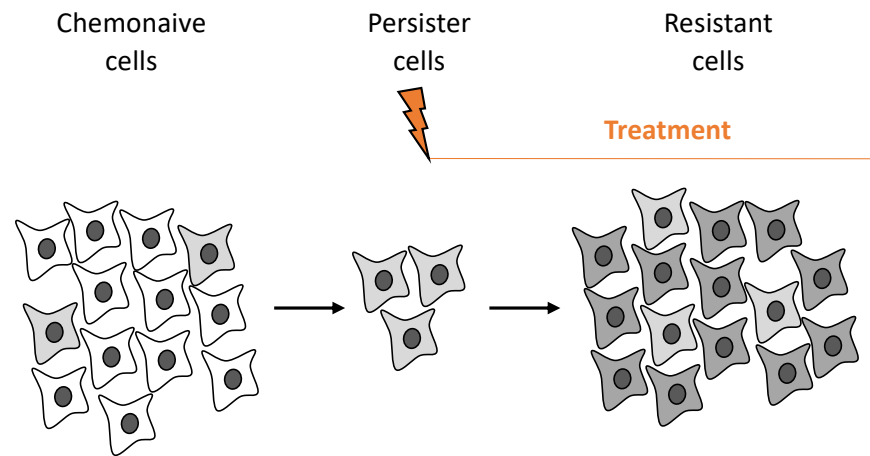
Transcriptomic profiles (bulk-RNA-seq)



Reversibility of the drug-tolerant state
+
Transcriptional reprogramming
= **PLASTICITY**

Echeverria et al., 2019

Genetic and transcriptomic mechanisms drive cancer evolution towards drug tolerance/resistance



Molecular basis of drug tolerance ?

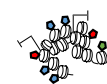


Mutation, Insertion, Deletion

Genetic alterations



Transcriptome



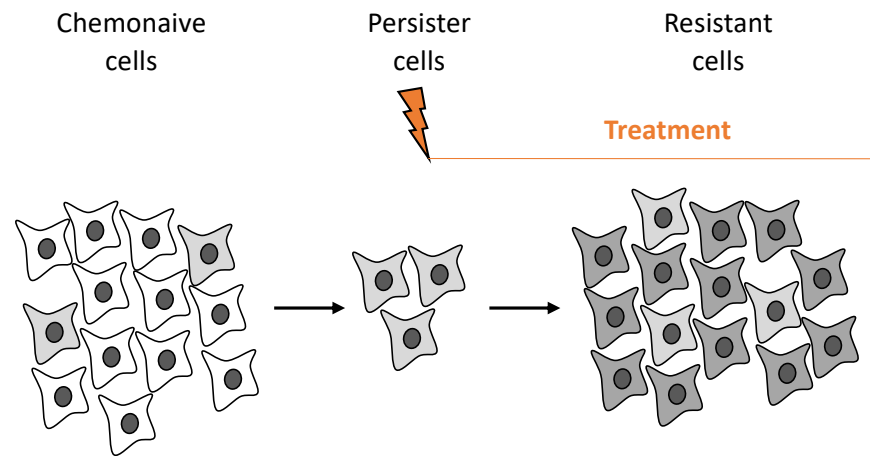
Histones modifications

Non-genetic alterations

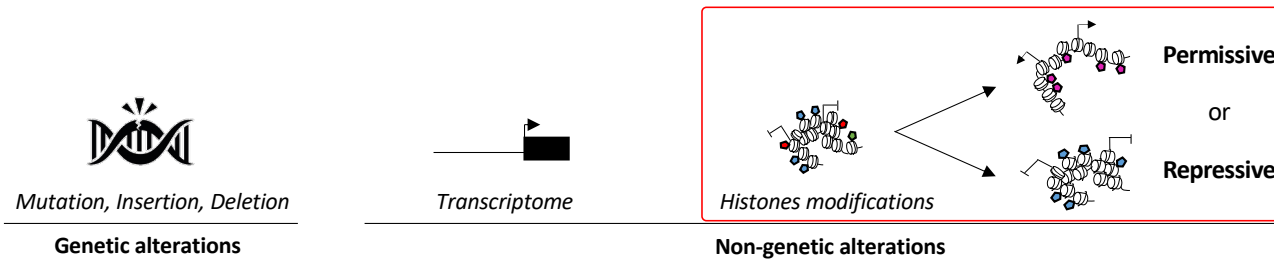


DNA methylation

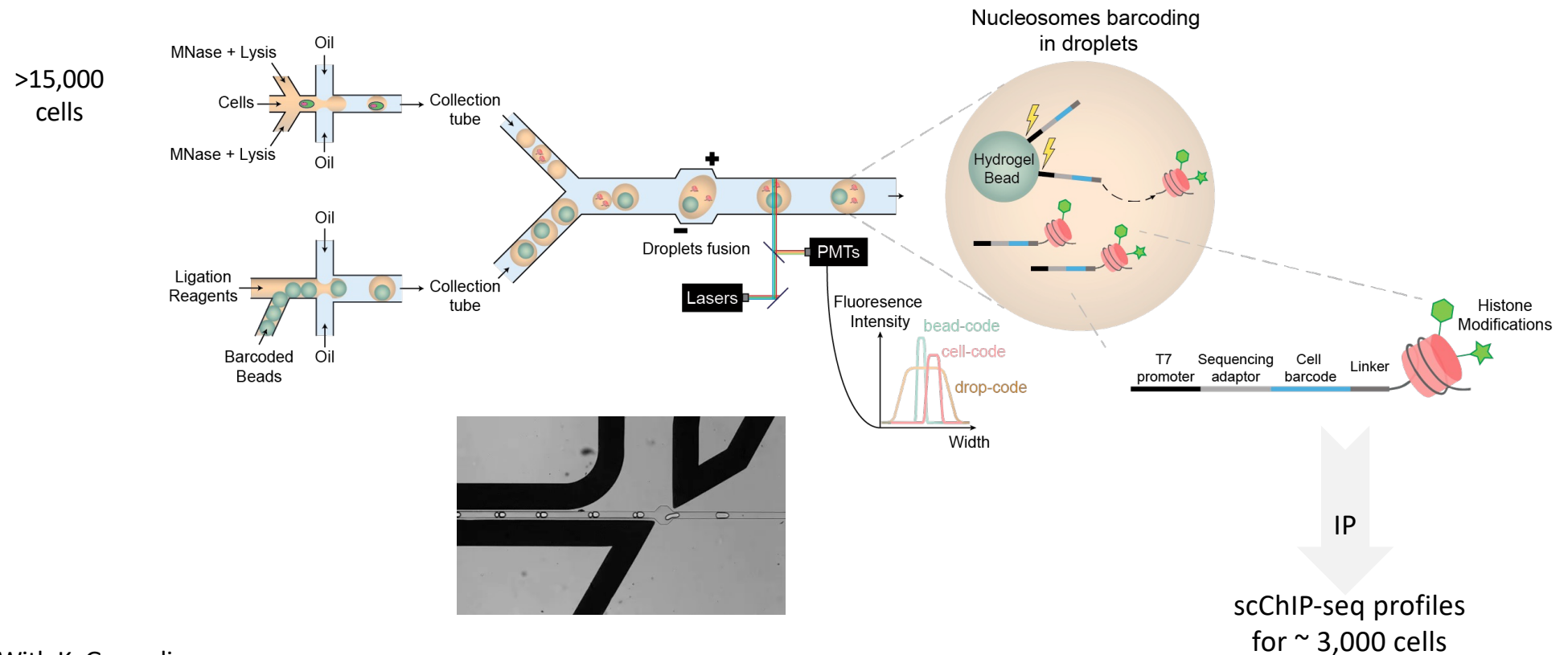
Genetic and transcriptomic mechanisms drive cancer evolution towards drug tolerance/resistance



Molecular basis of drug tolerance ?



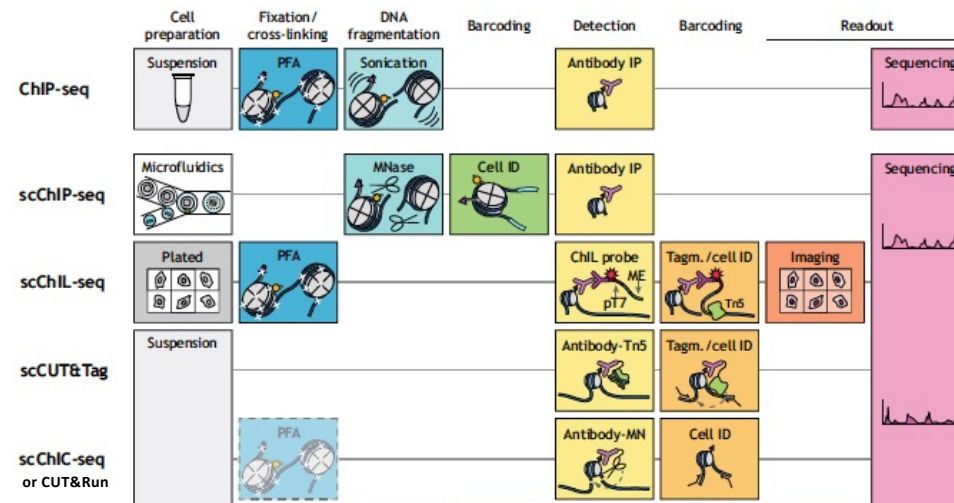
High-throughput single-cell chromatin profiling of complex biological samples



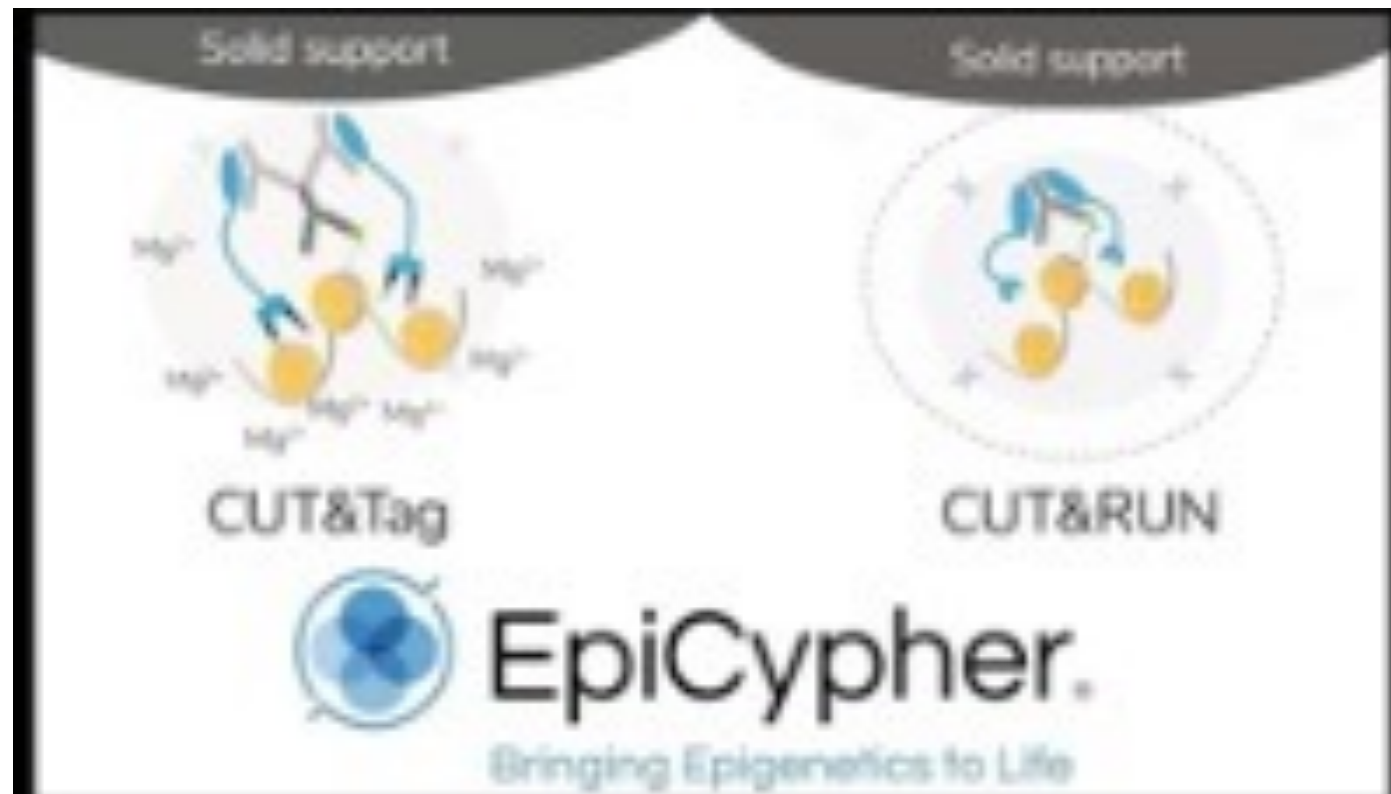
With K. Grosselin,
A. Griffiths (ESPCI)
A. Gérard (HiFiBio)

Grosselin et al., Nat Genet 2019

Mapping chromatin modifications at the single-cell level

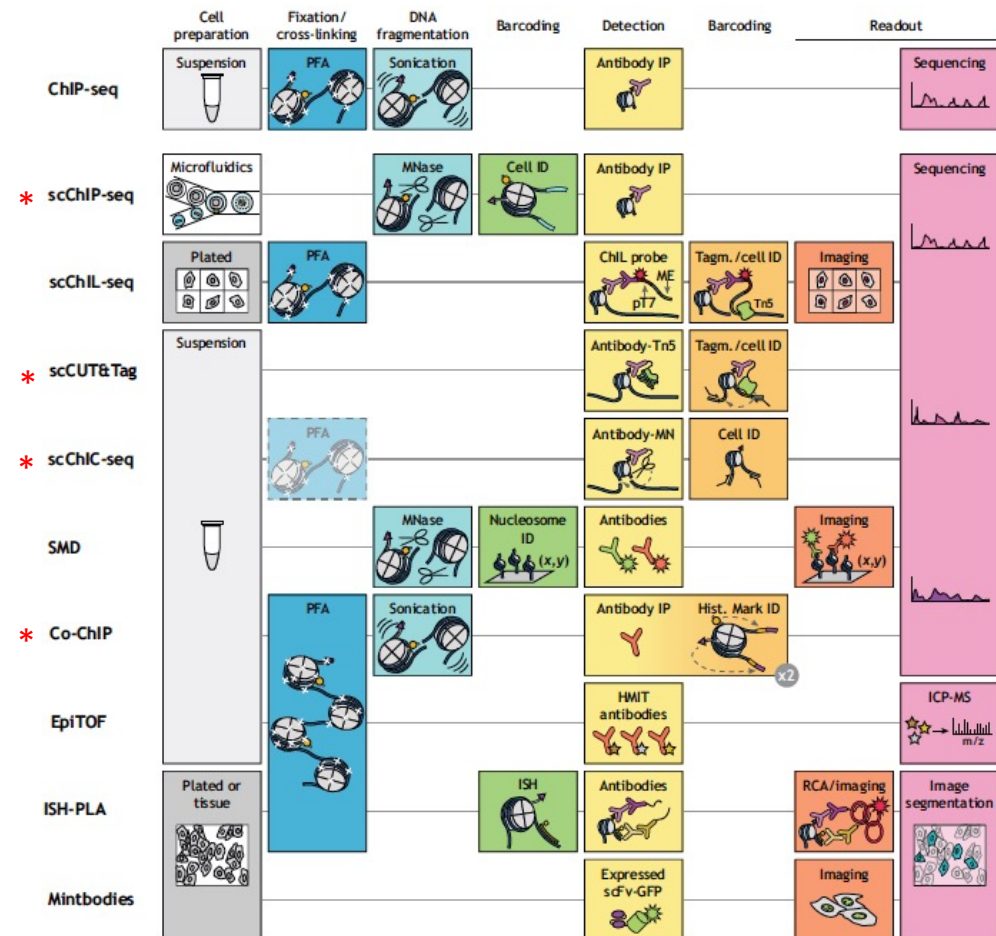


CUT&Tag and CUT&Run technologies



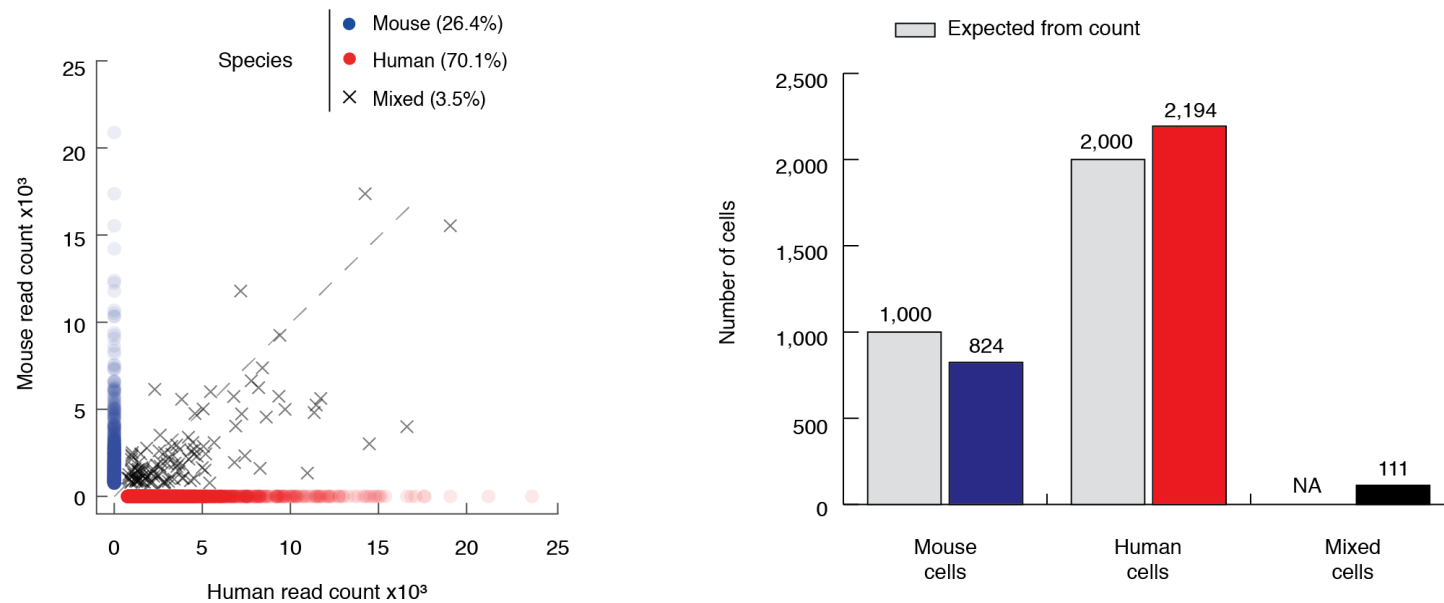
<https://youtu.be/LxnNnlnEs8>

Mapping chromatin modifications at the single-cell level



Human and mouse cells mixture confirmed single-cell resolution

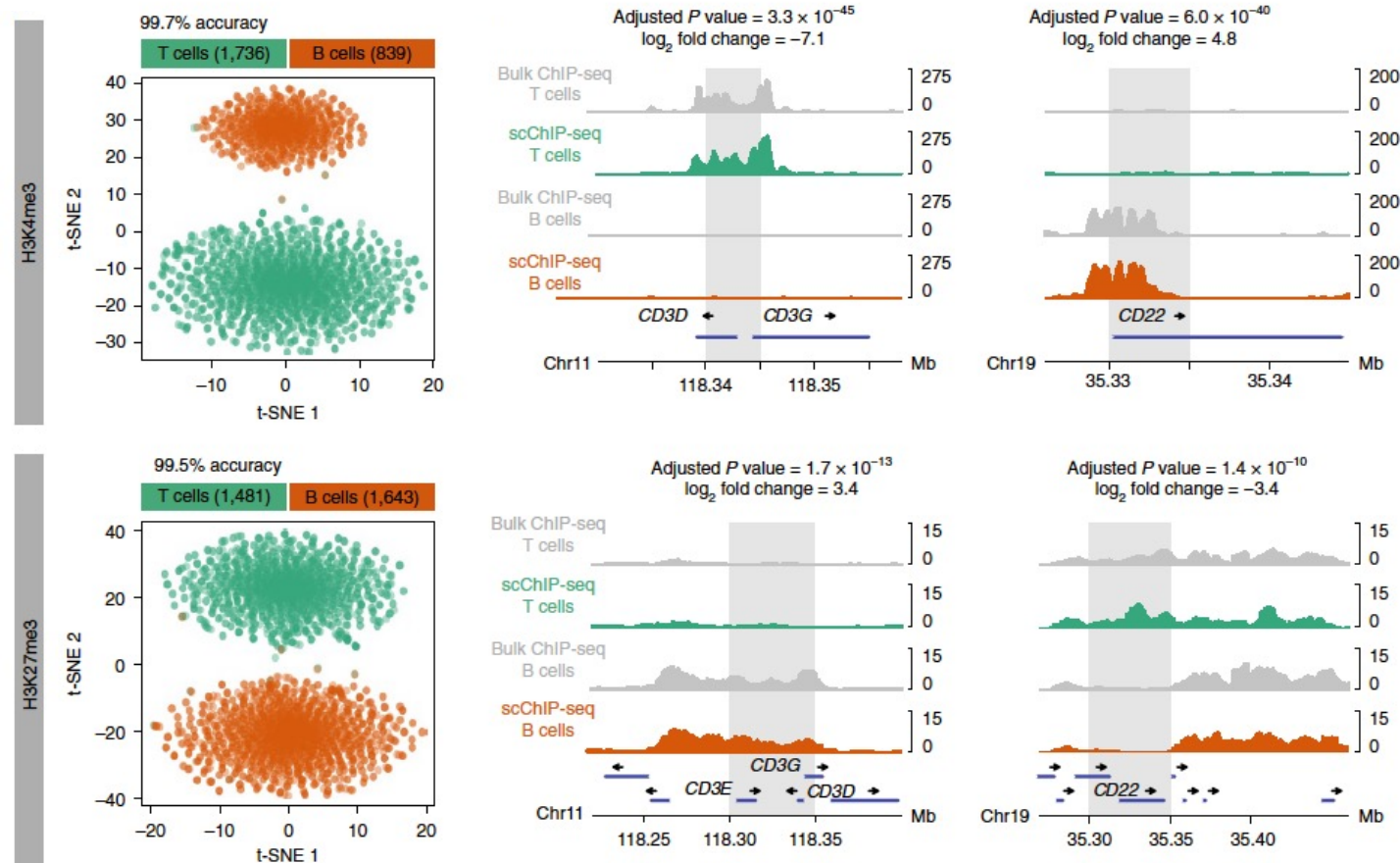
Microfluidic QC



Mixture : 1/3 mouse cells and 2/3 of human cells

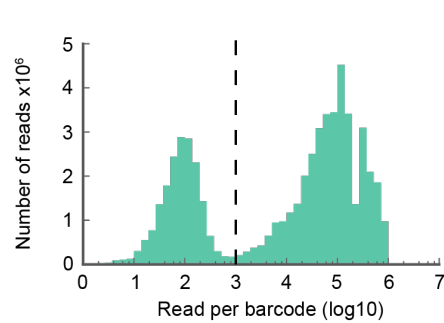
Reconstructing cell-type-specific chromatin states from single-cell ChIP-seq profiles

Chromatin profiles



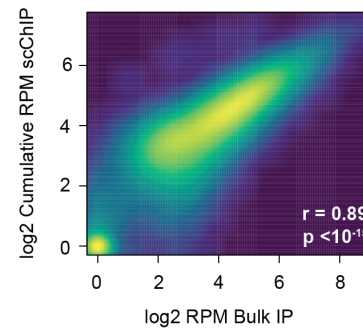
Single-cell chromatin profiling by drop-seq achieves high coverage and similarities to bulk

Data QC analysis

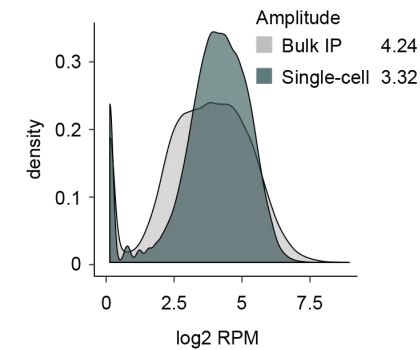


**An average coverage of up to
10,000 loci/cell**

Previously <1,000 loci
(Rotem *et al.*, 2015)



**Recapitulates bulk histone
enrichment profiles for active and
repressive histone marks
H3K4me3, H3K27me3**

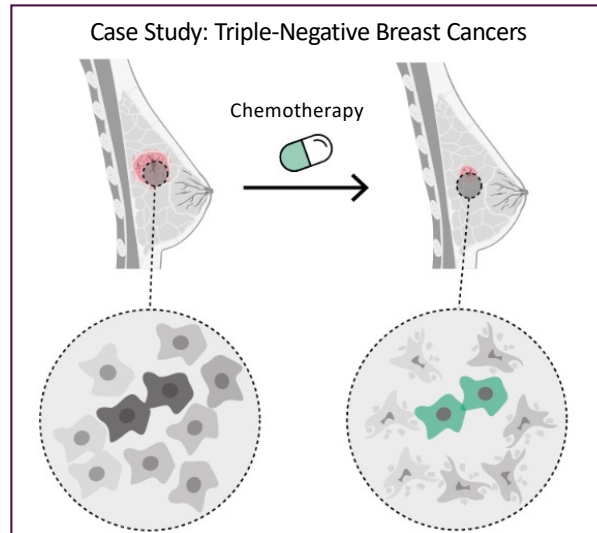


**Similar amplitude of signal
Log2fold-change 1.89**

Persister cells share a common expression program

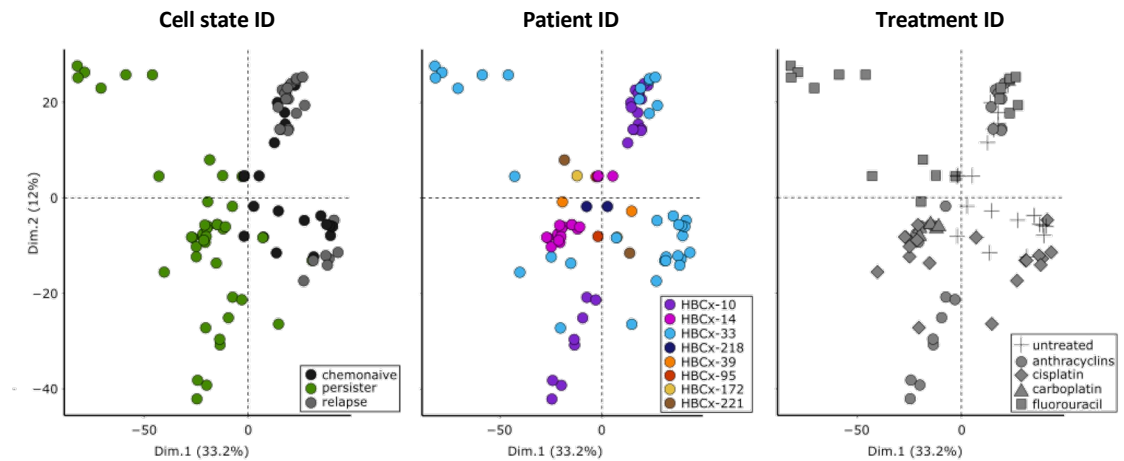


© Marthe Laisné



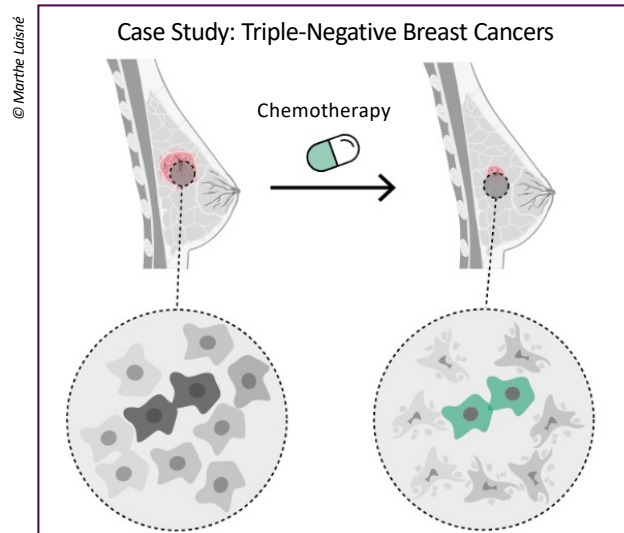
	Primary tumors Neoadjuvant chemotherapy				Residual tumors Adjuvant chemotherapy			
	HBCx-10	HBCx-33	HBCx-14	HBCx-218	HBCx-39	HBCx-95	HBCx-172	HBCx-221
Anti-tumor antibiotics	●		●	●				
Alkylating agents		◆	◆					
		△	△					
Antimetabolites		□			□	□	□	□
	24	35	18	12	15	7	5	11

Gene expression

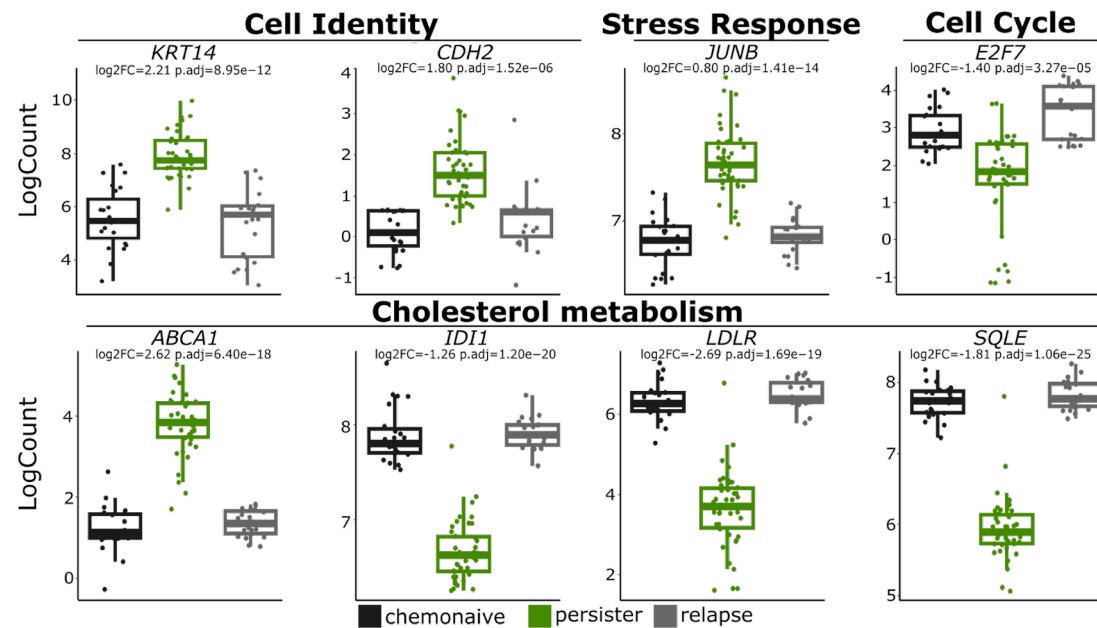


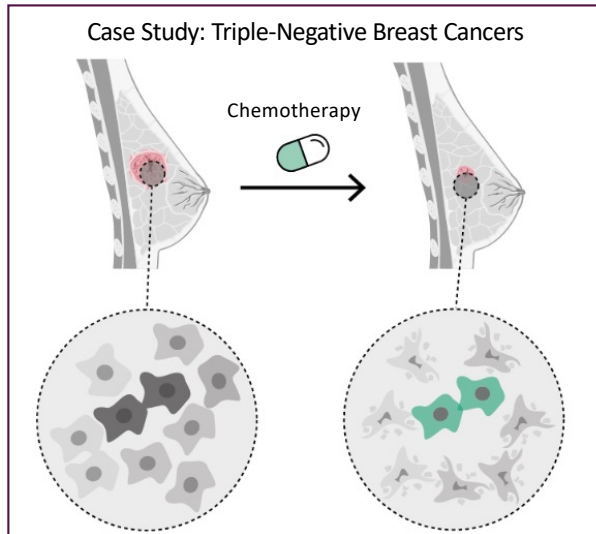
Marsolier & Prompsy et al., 2022
Baudre & Jouault et al., 2025

Persister cells share a common expression program



Gene expression

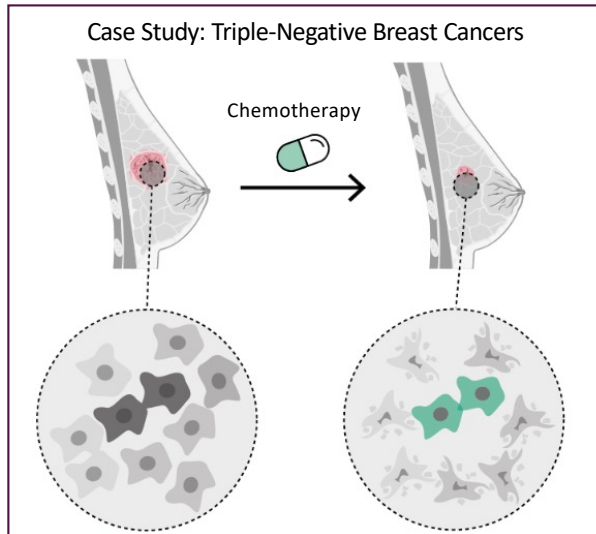




Mechanisms regulating the activation of persister genes?

Chromatin landscapes

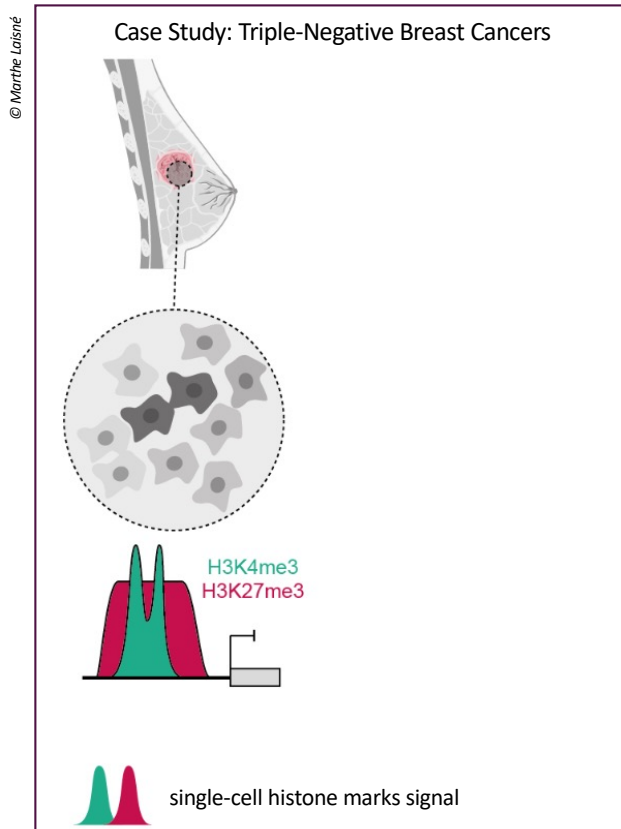
Transcription factors



Mechanisms regulating the activation of persister genes?

Chromatin landscapes

A fraction of the persister genes is in a bivalent chromatin configuration before treatment



Histone marks profiles

H3K4me3

untreated

persister

ns

4.2

H3K27me3

untreated

persister

**

0.7

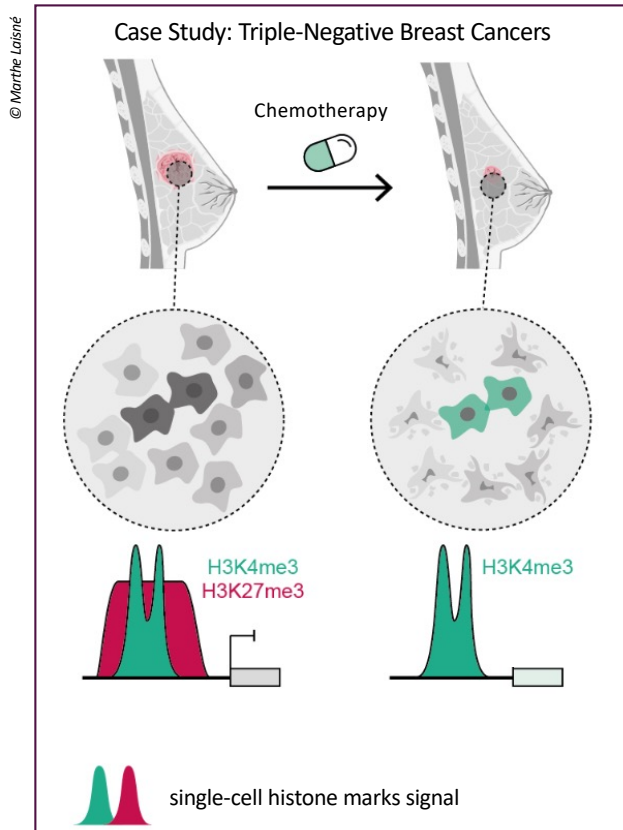
65,895 Kb

65,900 Kb

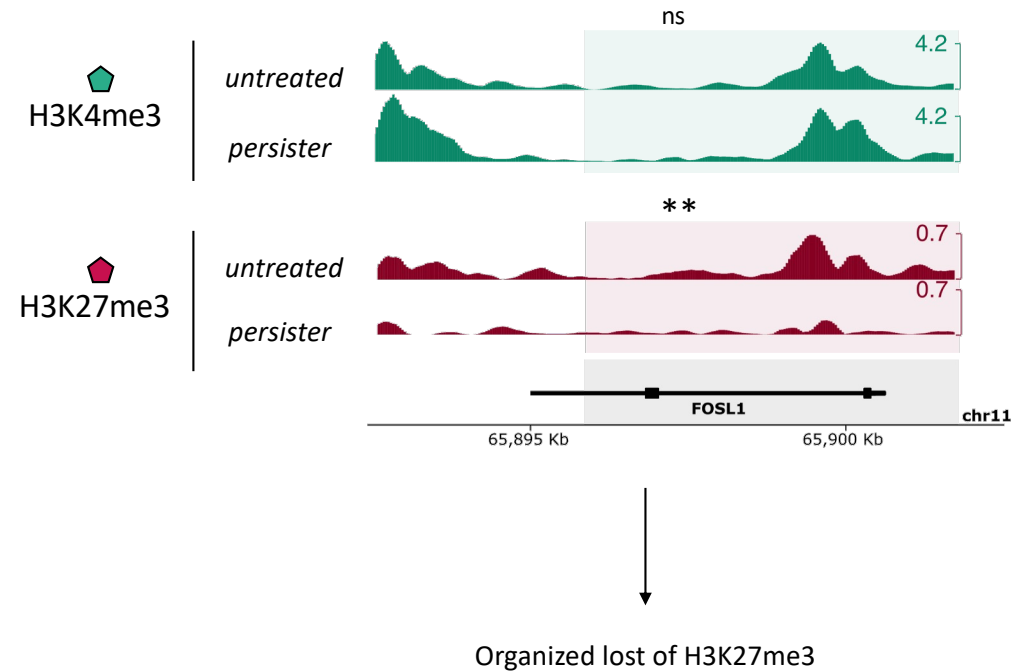
FOSL1

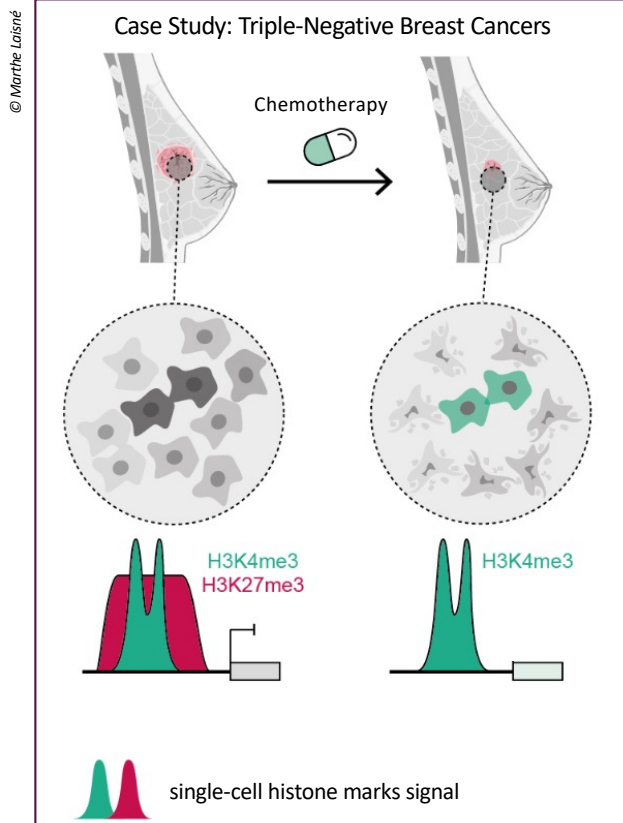
chr11

Recurrent redistribution of H3K27 methylation under chemotherapy treatment

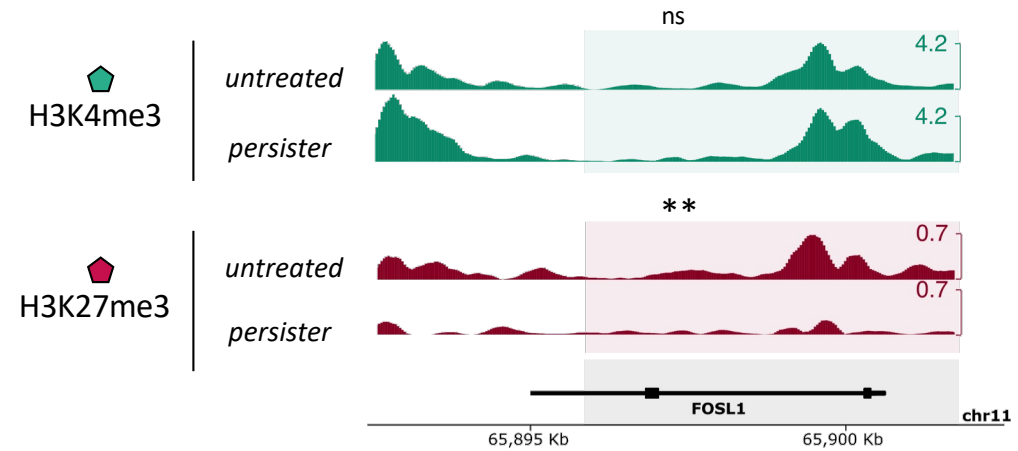


Histone marks profiles





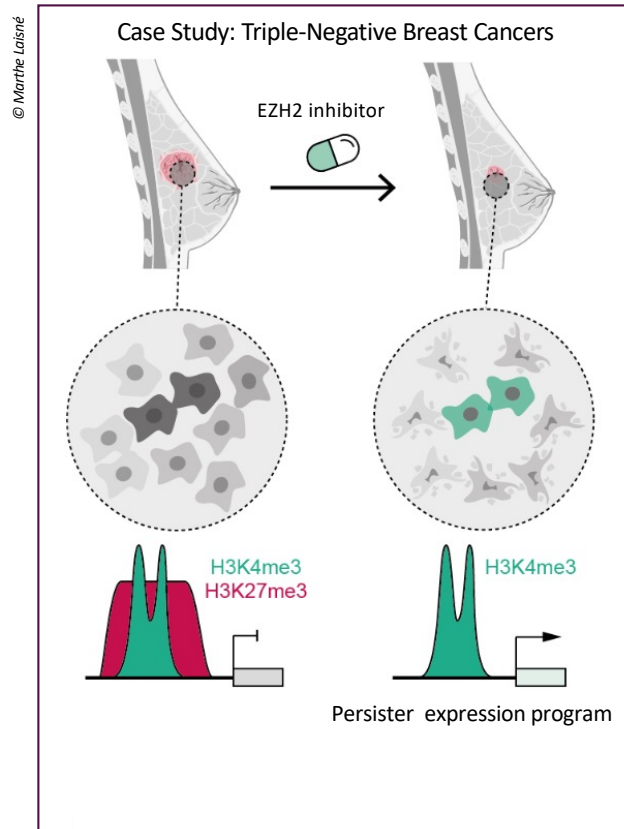
Histone marks profiles



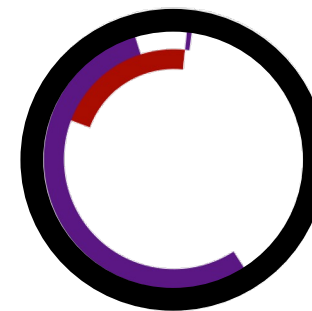
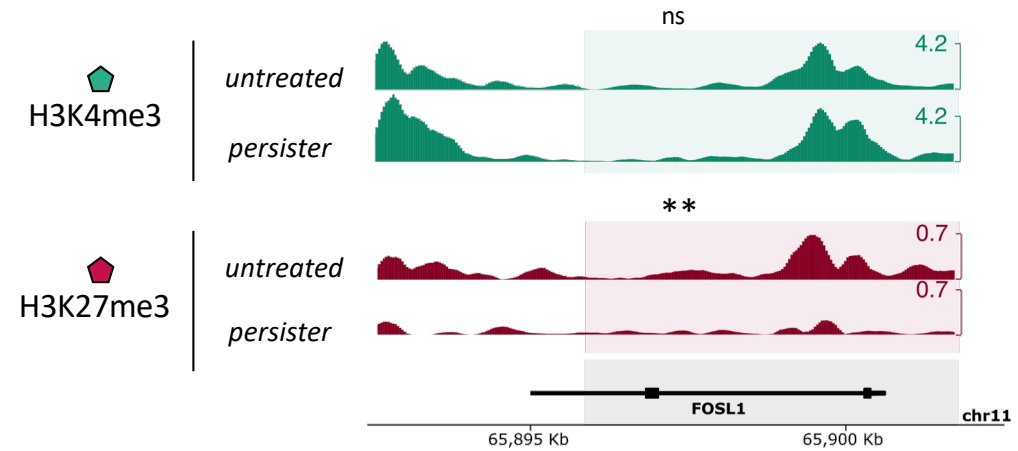
Organized lost of H3K27me3

Activation of the persister expression program?

Persister expression program is locked by H3K27me3

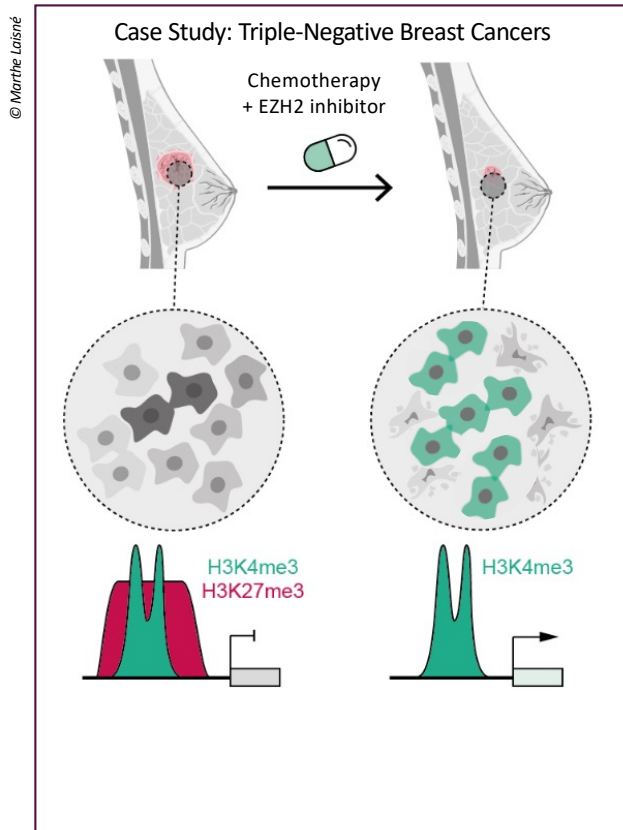


Histone marks profiles

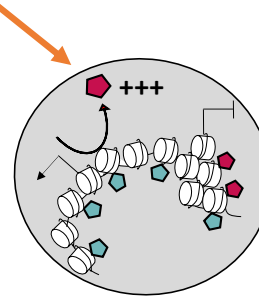


- Persister genes (168)
- Depleted of H3K27me3 upon 5-FU (37)
- Expressed with EZH2i-1 (101)

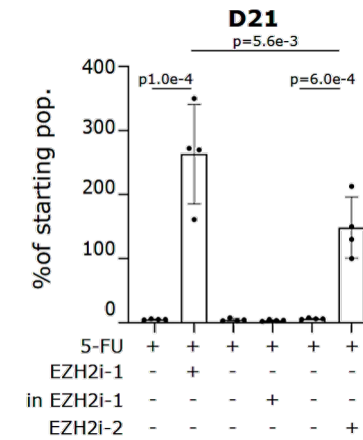
Erasing H3K27me3 increases the chemopersistence



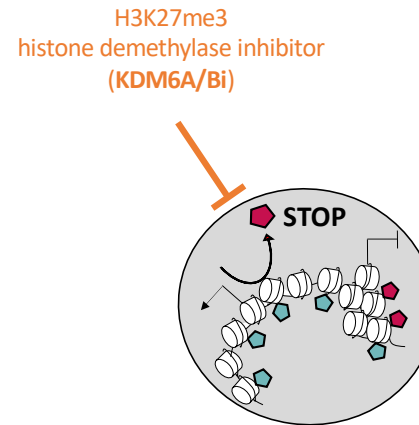
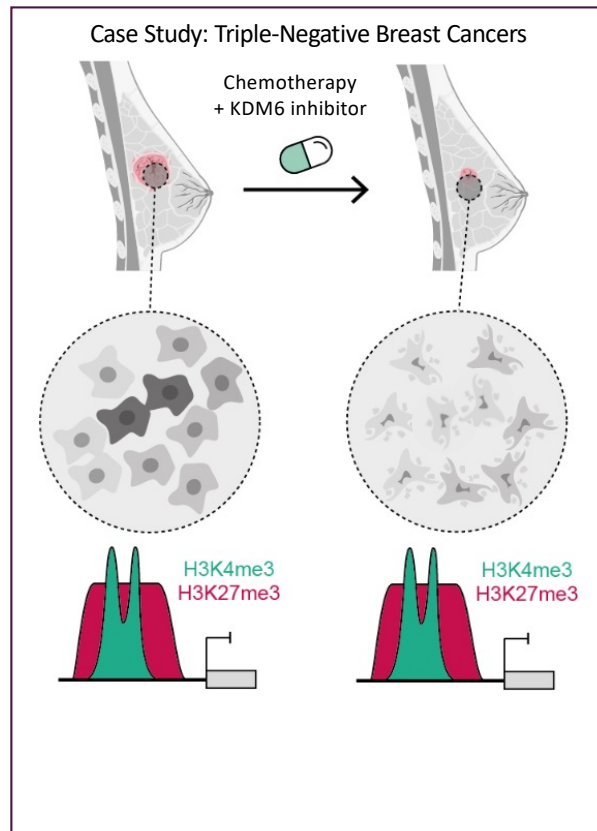
H3K27me3
histone methyltransferase
inhibitor
(EZH2i)



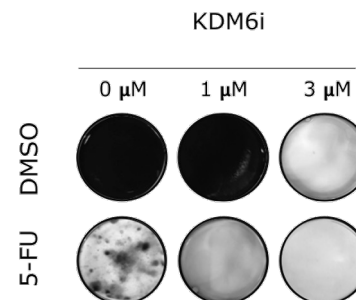
Number of persister cells



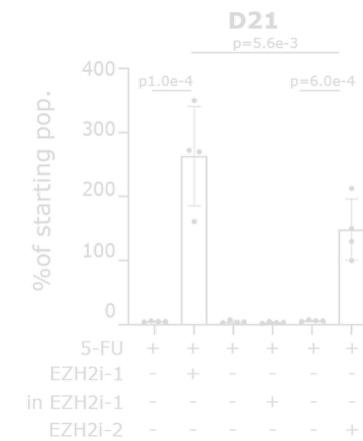
Co-treatment with KDM6A/Bi delays the emergence of persister cells



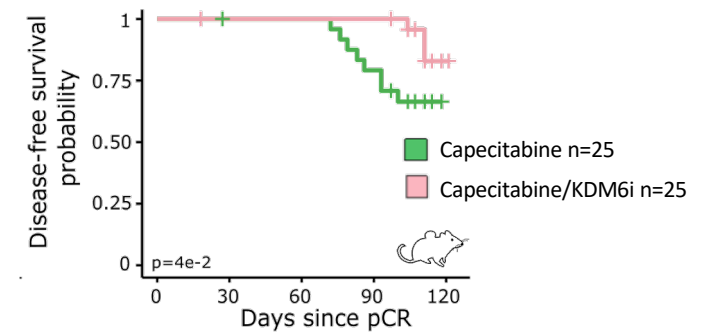
Colony forming assay



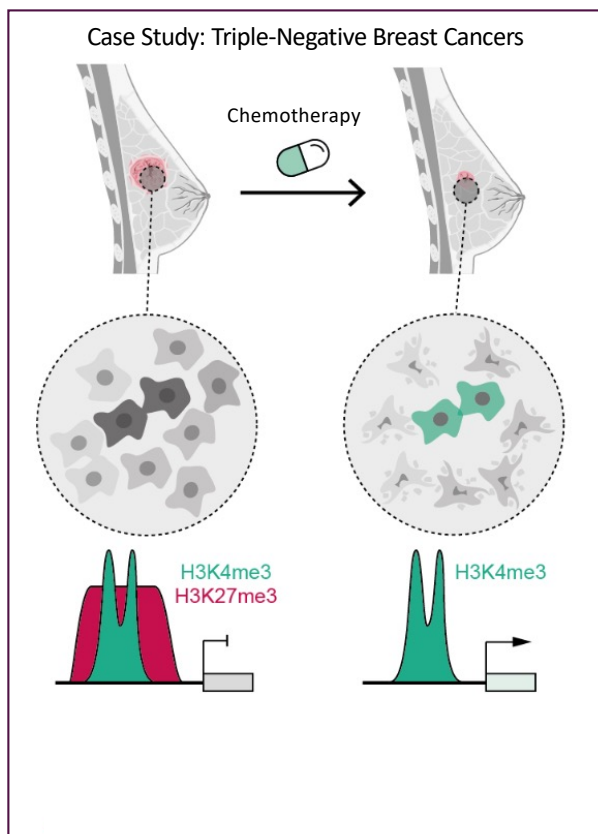
Number of persister cells



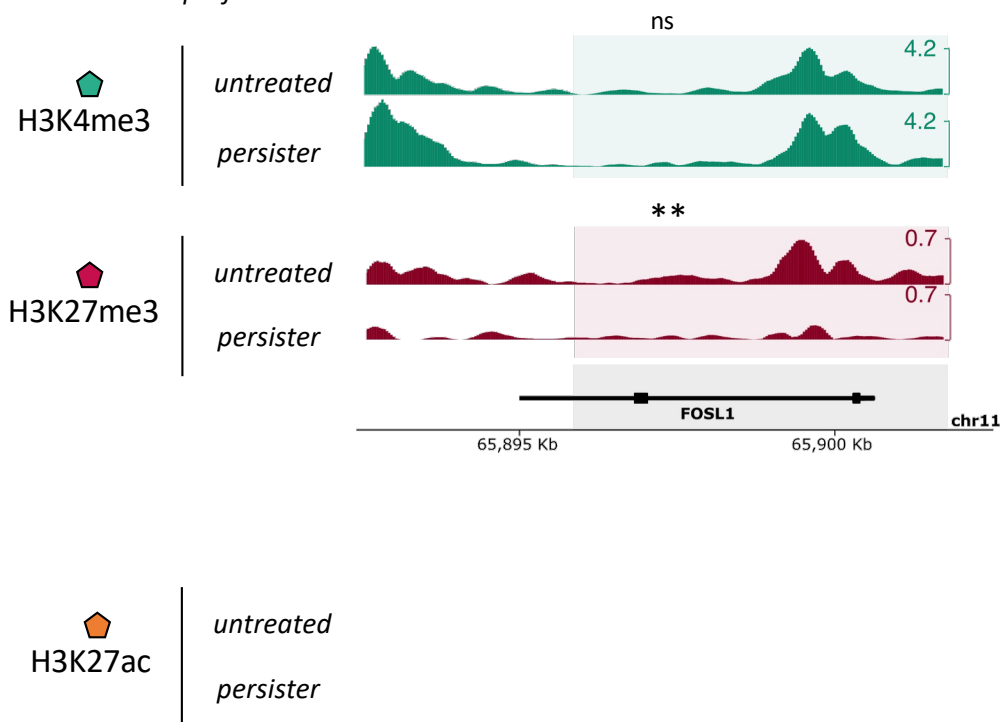
Recurrence



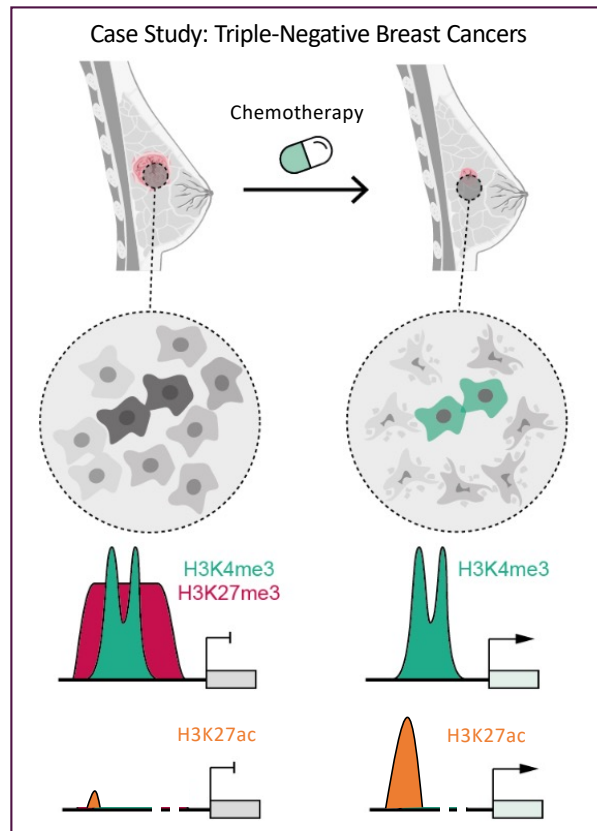
Profiling of additional histone marks in response to chemotherapy treatment



Histone marks profiles



Rewiring of the H3K27ac landscape in persister cells



Histone marks profiles

H3K4me3

untreated

persister

ns

4.2

4.2

H3K27me3

untreated

persister

**

0.7

0.7

FOSL1

chr11

65,895 Kb

65,900 Kb

H3K27ac

untreated

persister

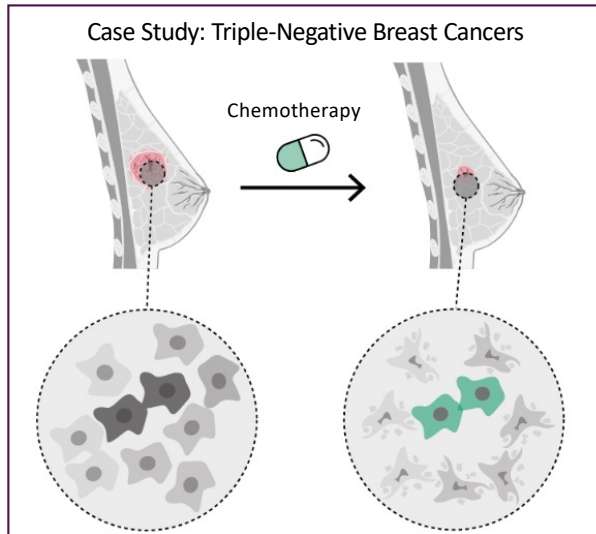
FOSL1

chr11

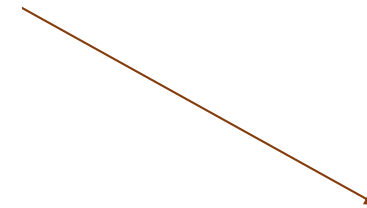
65,895 Kb

65,905 Kb

Localized gains of H3K27ac

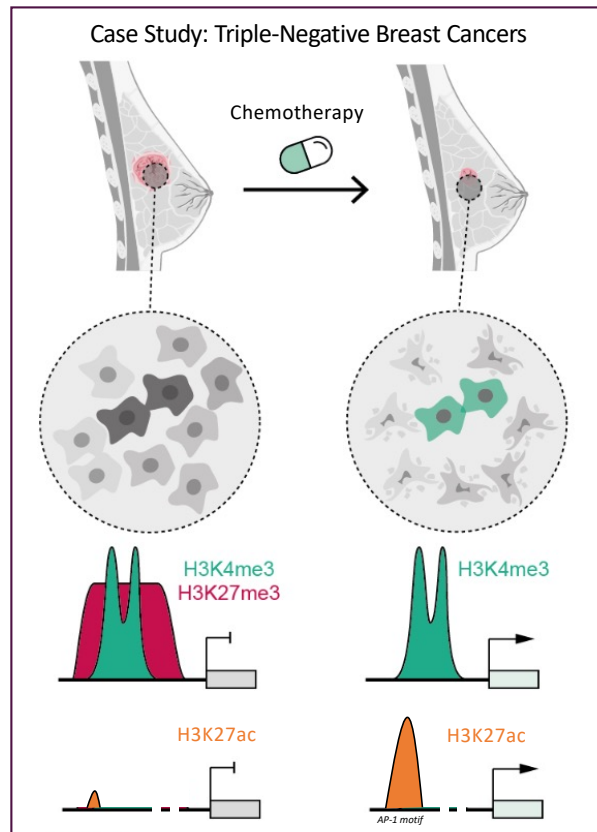


Mechanisms regulating the activation of persister genes?



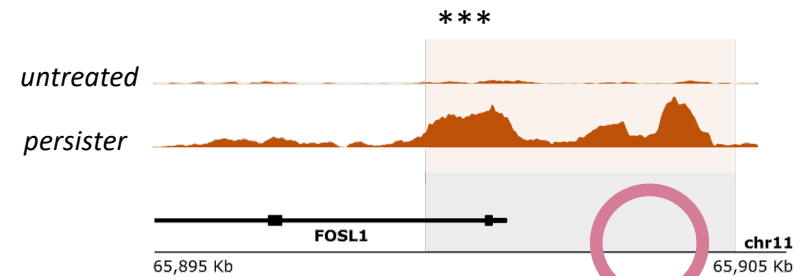
Transcription factors

Epigenomic remodeling of enhancers in persister cells is dedicated to AP-1 sites

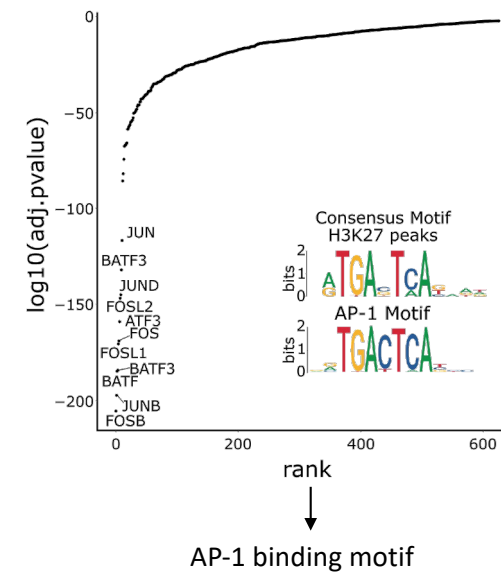


Histone marks profiles

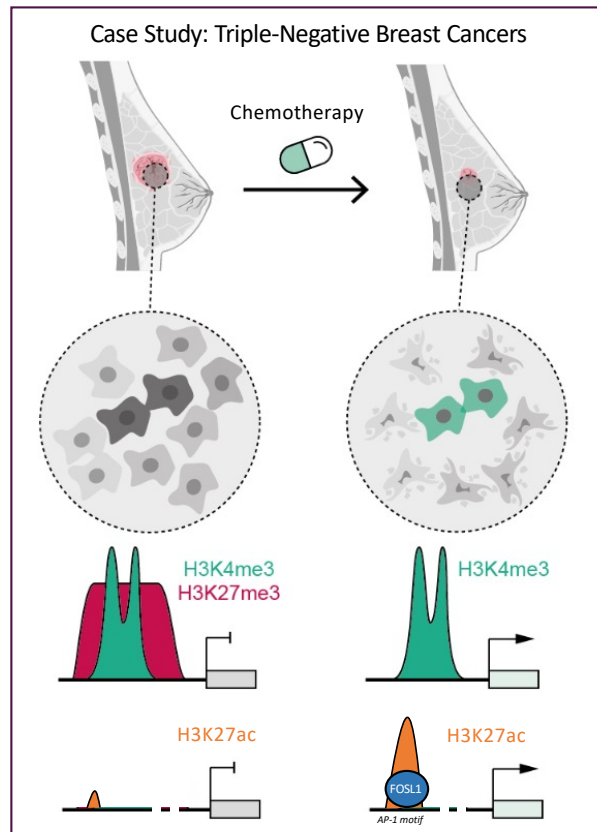
H3K27ac



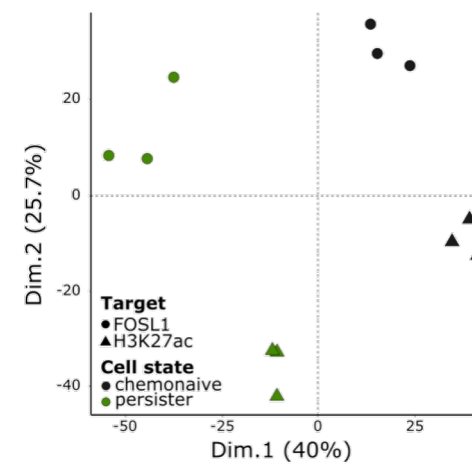
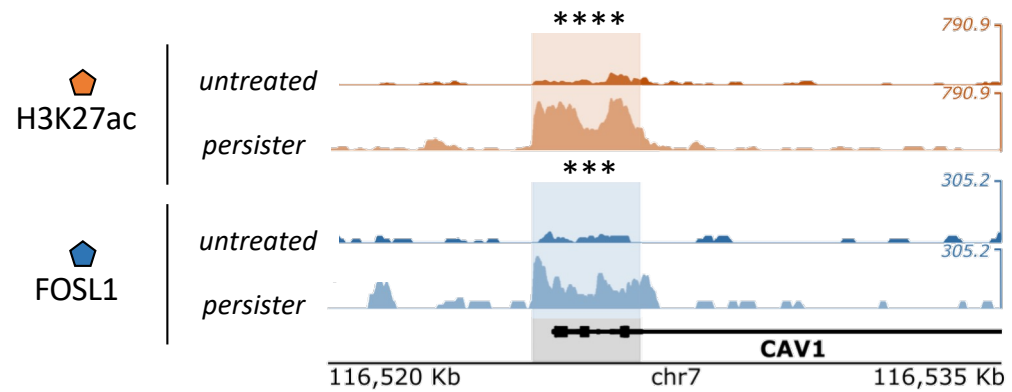
Motif enrichment analysis



FOSL1 is overexpressed upon treatment and binds activated enhancers



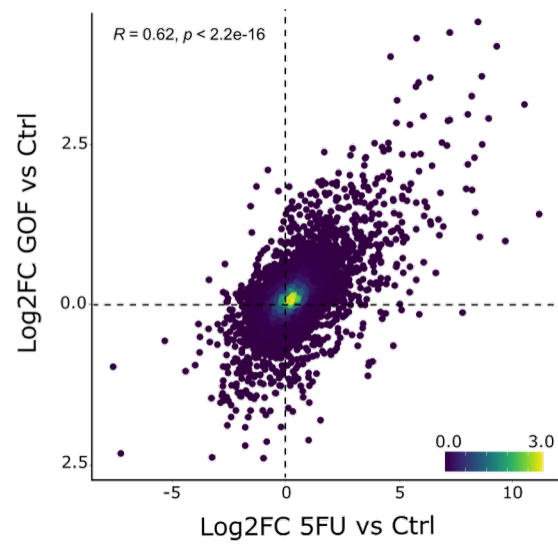
H3K27ac & FOSL1 genomic profiling



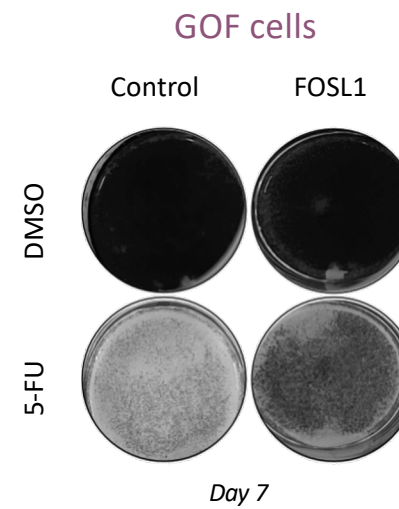
FOSL1 is sufficient to reach the persister state



Transcriptome correlation



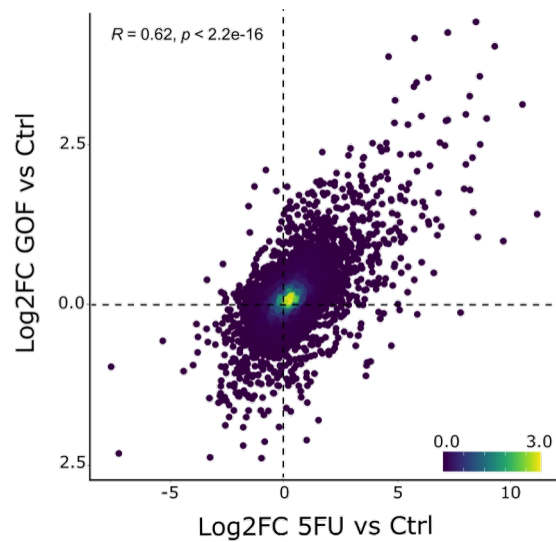
Colony forming assay



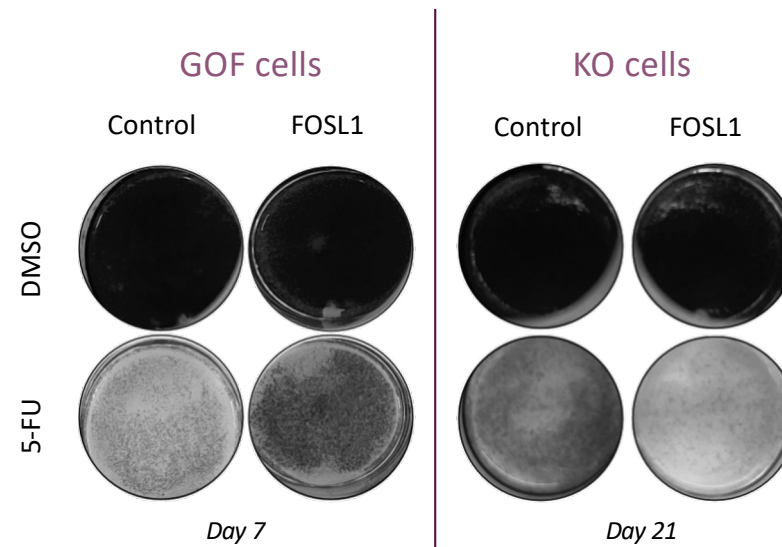
Preventing the activation of FOSL1 expression upon treatment leads to a decrease of persister cells



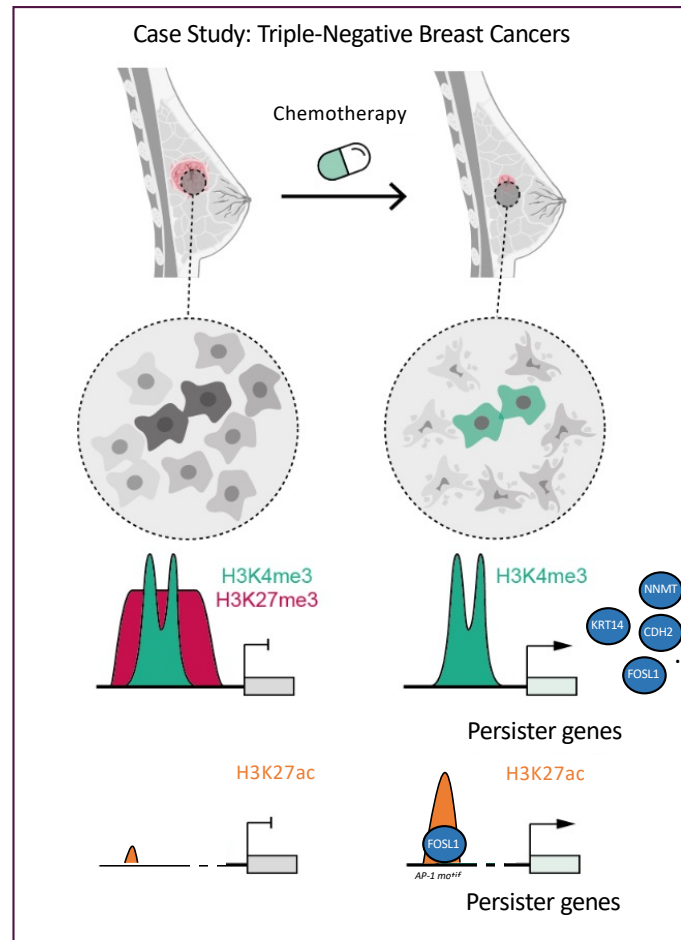
Transcriptome correlation



Colony forming assay



Understanding & fighting drug persistence in breast cancer



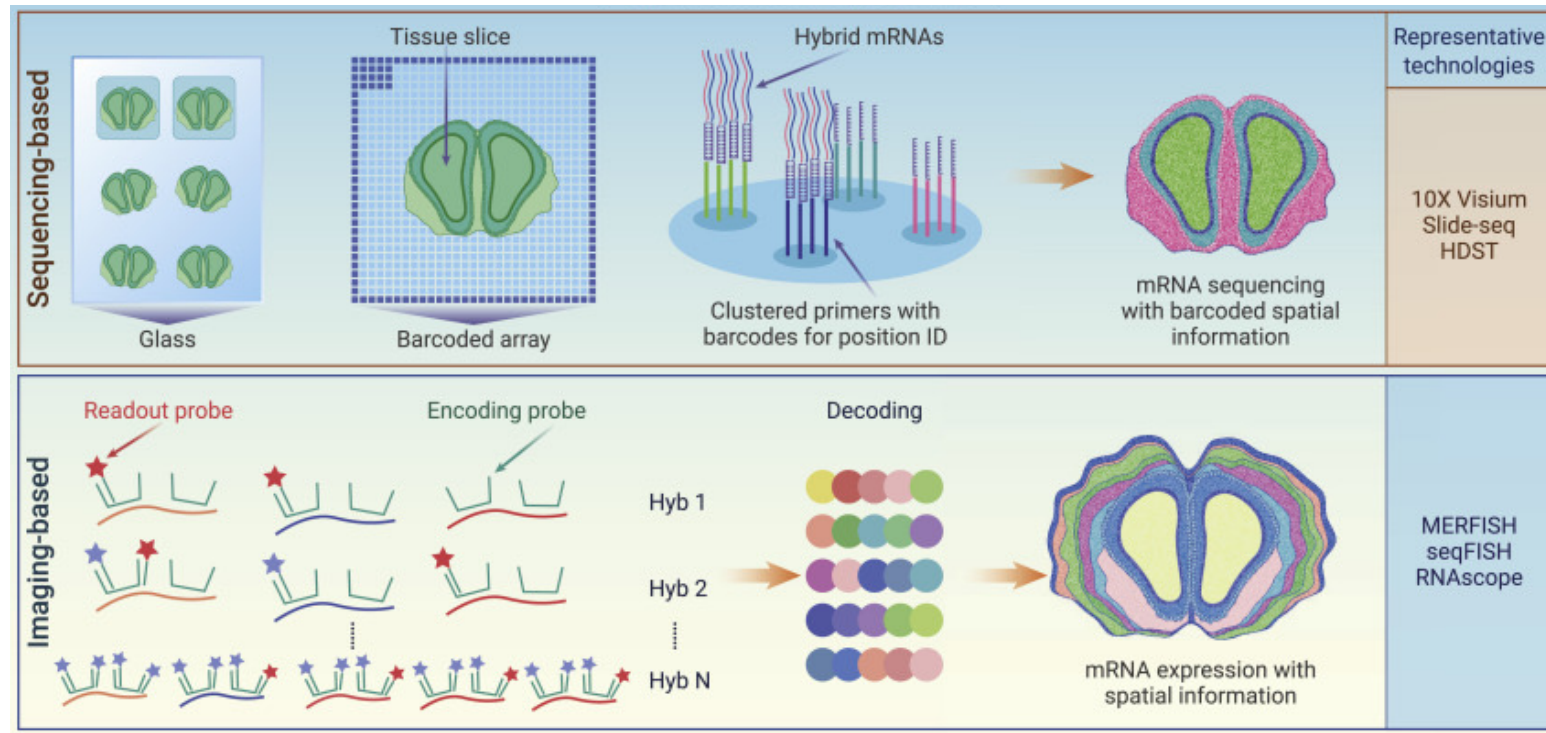
Marsolier & Prompsy et al., 2022
Baudre & Jouault et al., 2025

Single-cell multi-omics

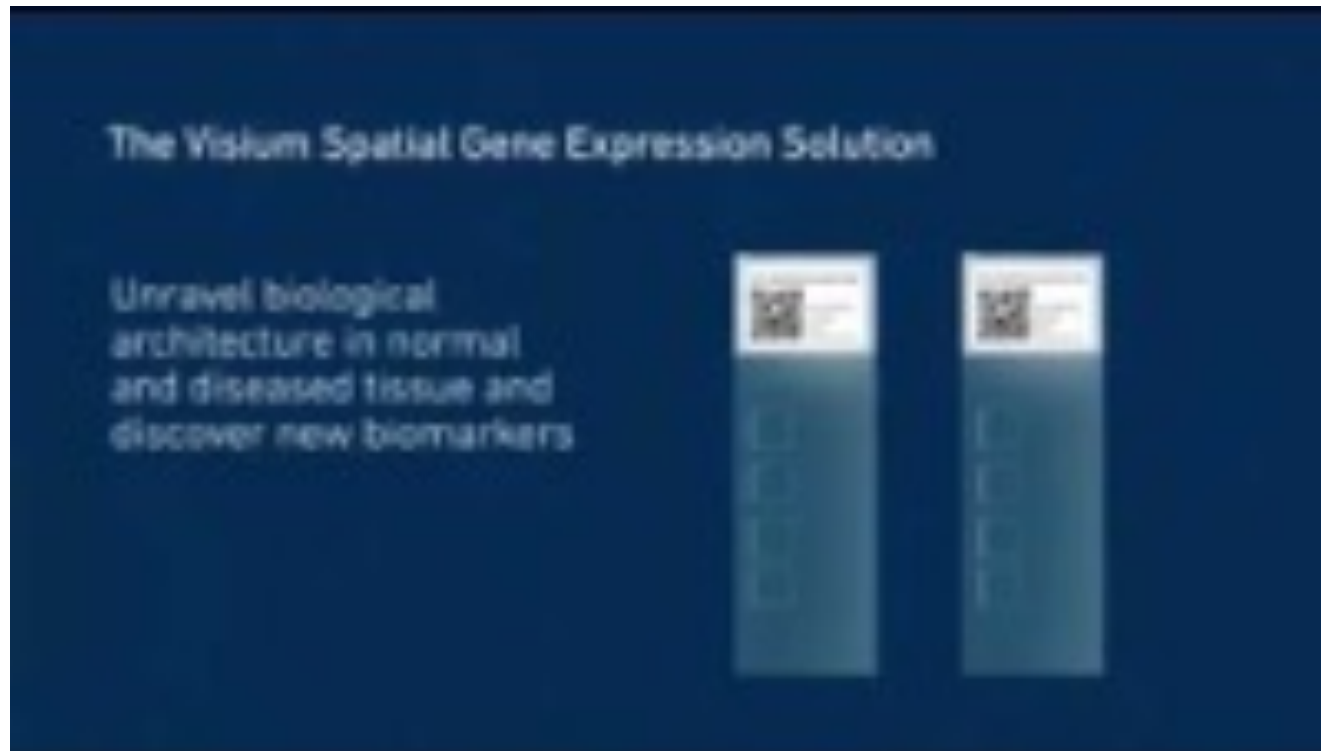


<https://youtu.be/rjke1BWcyBA>

Spatial transcriptomics



Spatial transcriptomics: sequencing-based approach



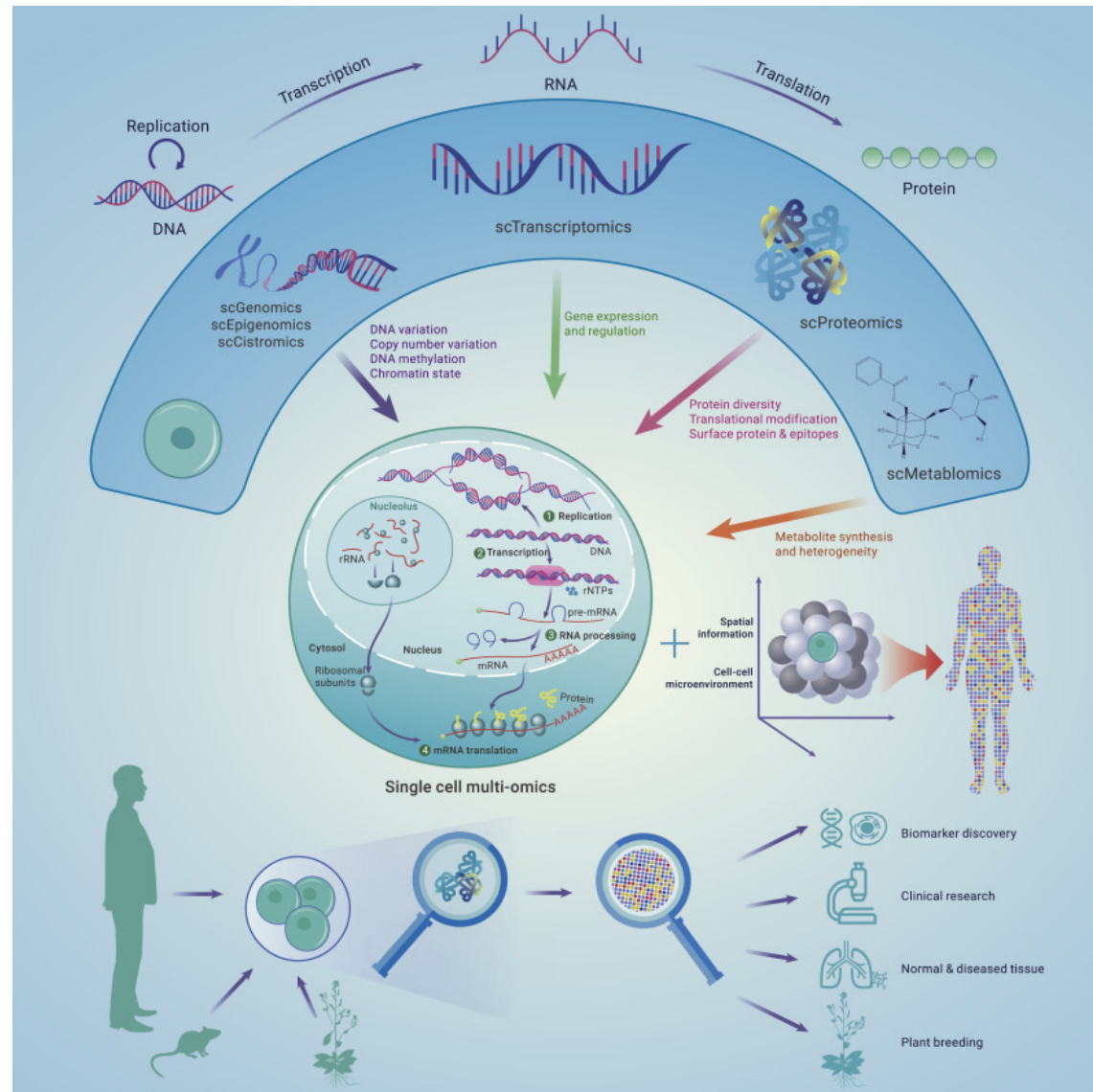
<https://youtu.be/VwNk4d-0RJc>

Spatial transcriptomics: imaging-based approach



<https://youtu.be/O0QekKSscjA?si=zKvWvGTSZoD7HzaF>

Future directives



Weng et al.,2022