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# Computational Biology For Novel Targets and Novel Therapeutics: A Multiscale-Modeling Approach

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# Pre-read of the lecture

- [Multiscale modeling of drug mechanism and safety](#), Drug Discovery Today (2020)
- [An introduction to machine learning](#), Clinical Pharmacology & Therapeutics (2020)
- [Causal inference in drug discovery and development](#), arXiv, 2022

# Acknowledgements

- **Predictive Modeling and Data Analysis (PMDA) team members**, especially for the work introduced here performed by Fabian Birzele, Iakov Davydov, Petra Schwalie, Daniel Marbach, Guido Steiner, Roland Schmucki, Laura Badi, Klas Hatje, Martin Ebeling, Marco Berrera, Nikolaos Bertenis, Tony Kam-Thong, Alex Seitz, Sophia Maedler, Luis Wyss, Rafael Mueller, Miroslav Phan, Andrea Ciuprina, and Anthony Sonrel.
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# Computational biology transforms drug discovery and development

Integrating  
public &  
internal  
knowledge  
and data



Optimizing  
molecules by data-  
and model-driven  
approaches



Understanding  
mechanism and  
safety profiles



Translating clinical  
findings to better  
targets, preclinical  
models, and  
molecules



**Drug Discovery and Development**

Target  
Identification

Lead  
Discovery

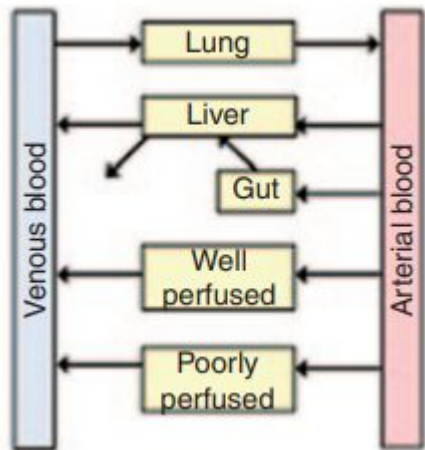
Medicinal  
Chemistry

In vitro  
studies

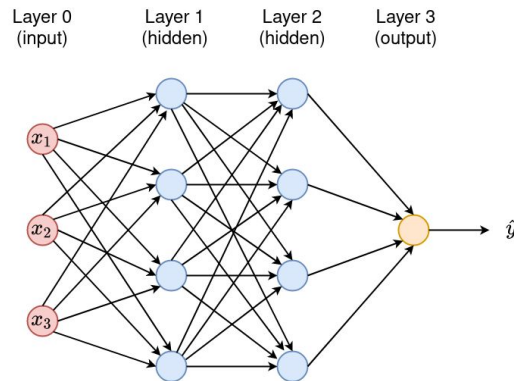
In vivo  
studies

Clinical  
Trials

# Three types of computational models

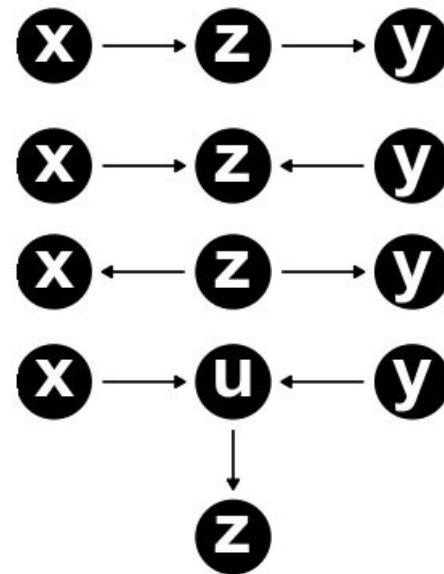


Mechanistic models



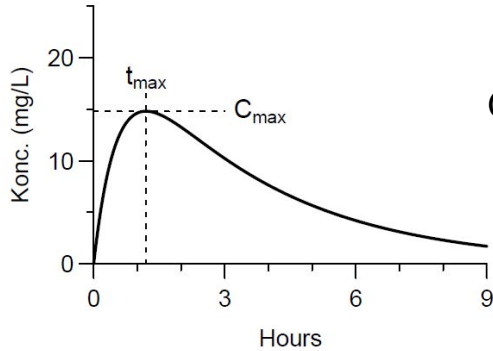
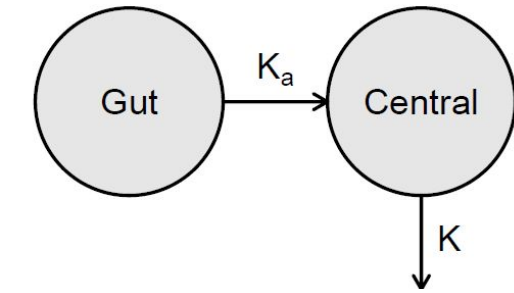
$$y \sim f(x)$$

Statistical and  
machine-learning models

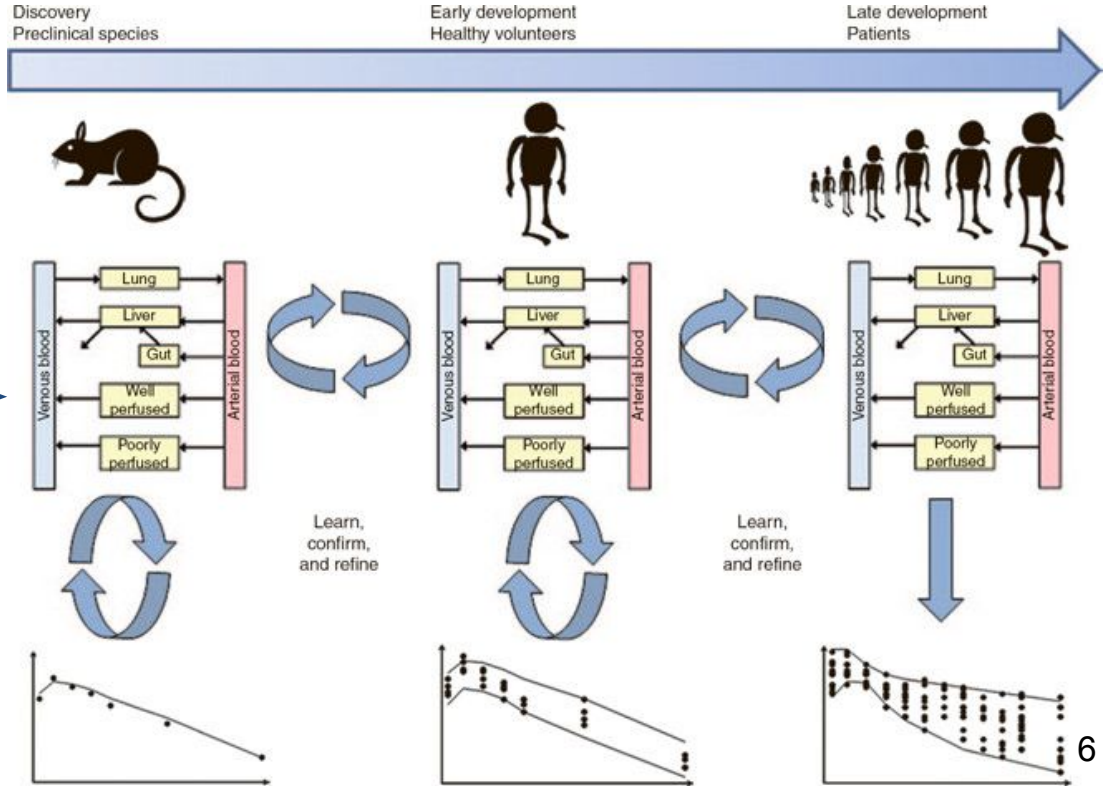


Causal models

# A mechanistic model: physiologically based pharmacokinetic modeling



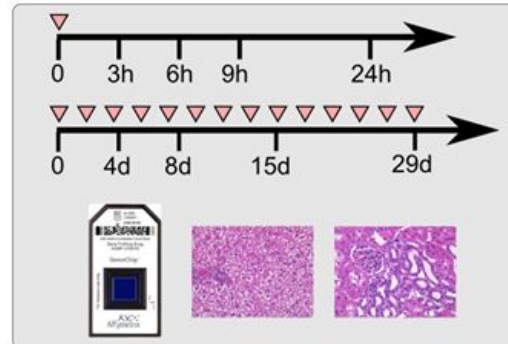
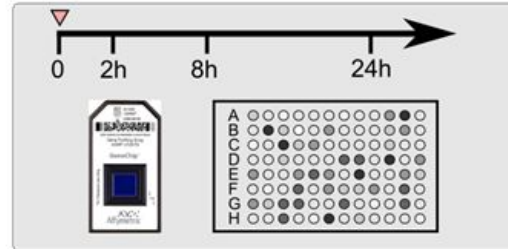
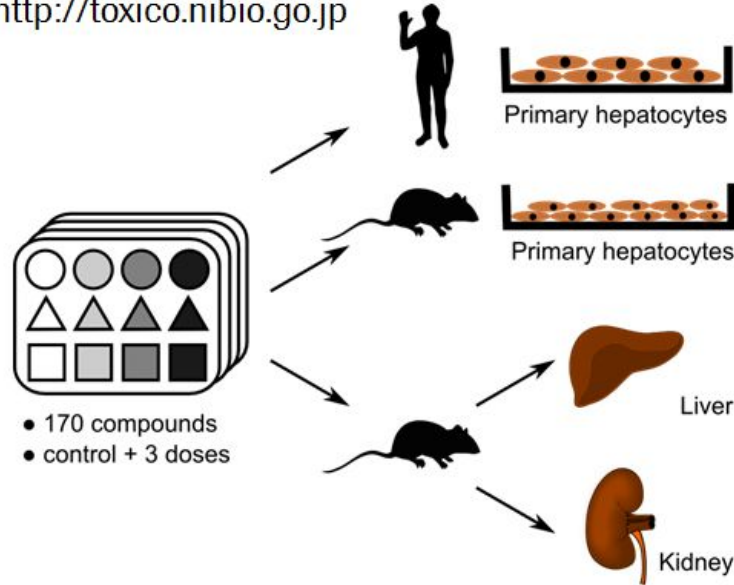
Generalization



# No mechanistic models are available for huge amount of data



<http://toxico.nibio.go.jp>



170

Compounds

>2000

Cellular assays

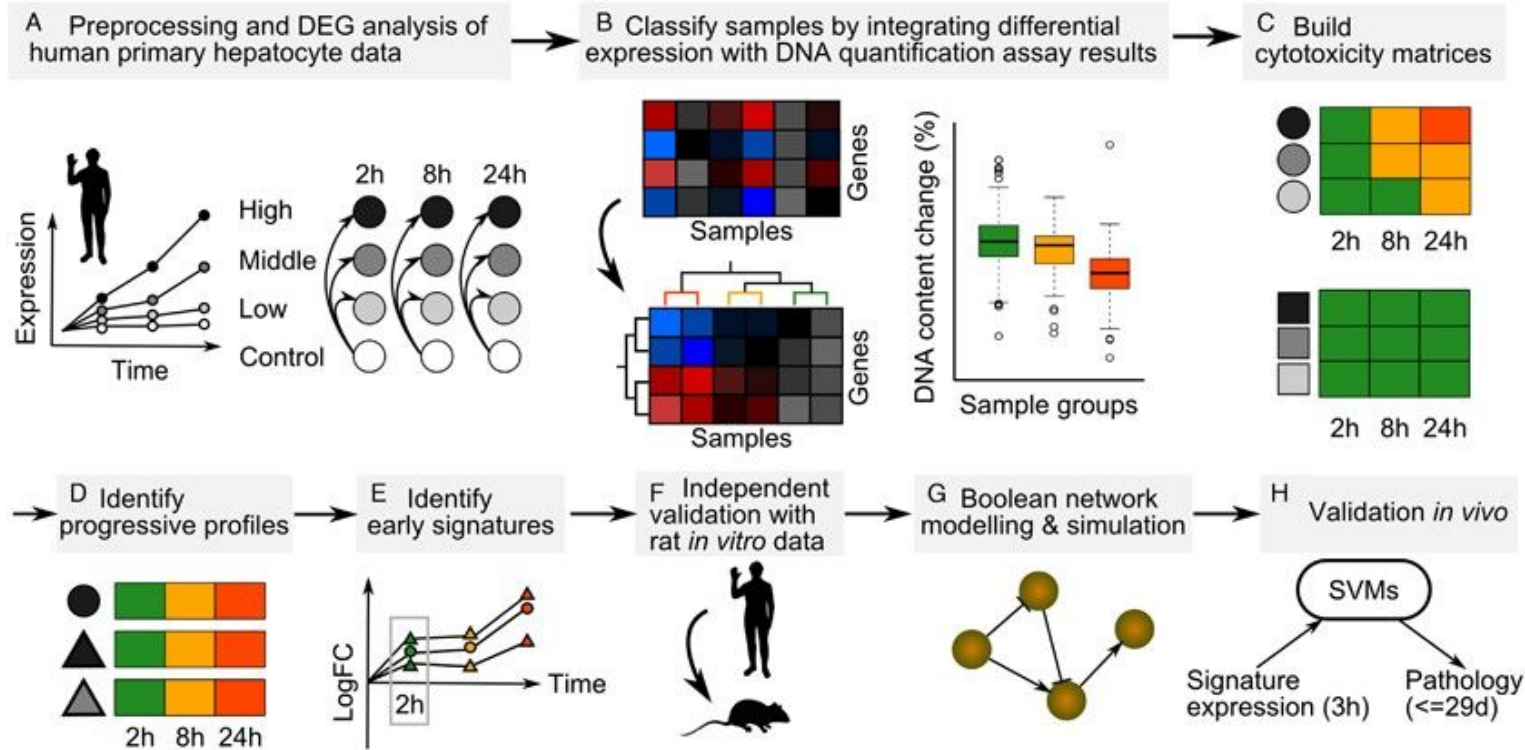
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Pathology records

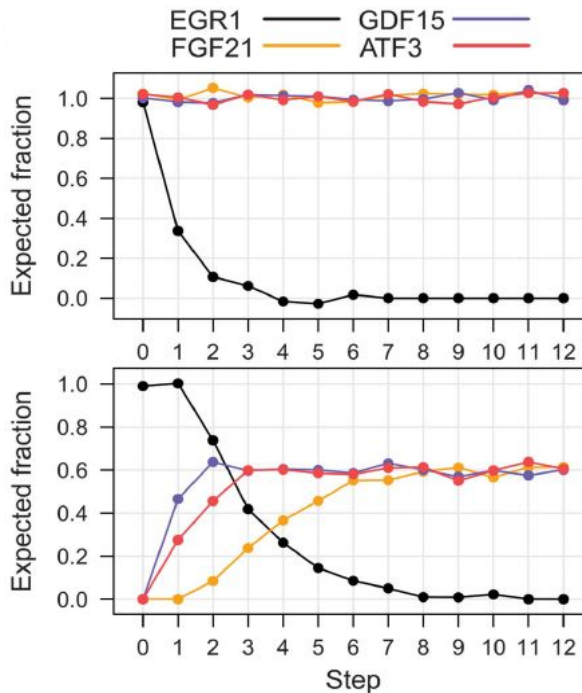
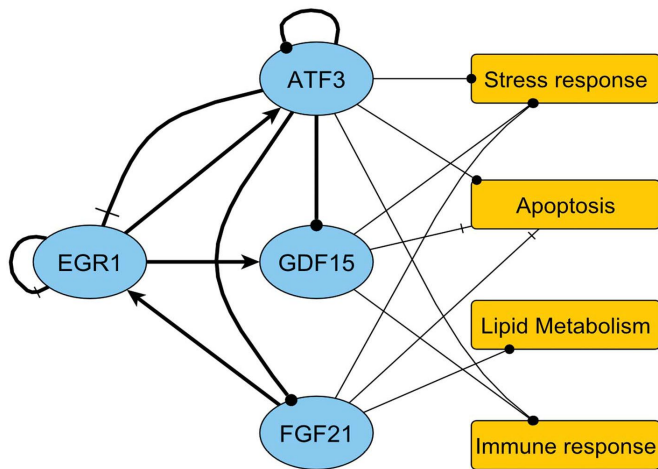
>24000

Expression profiles

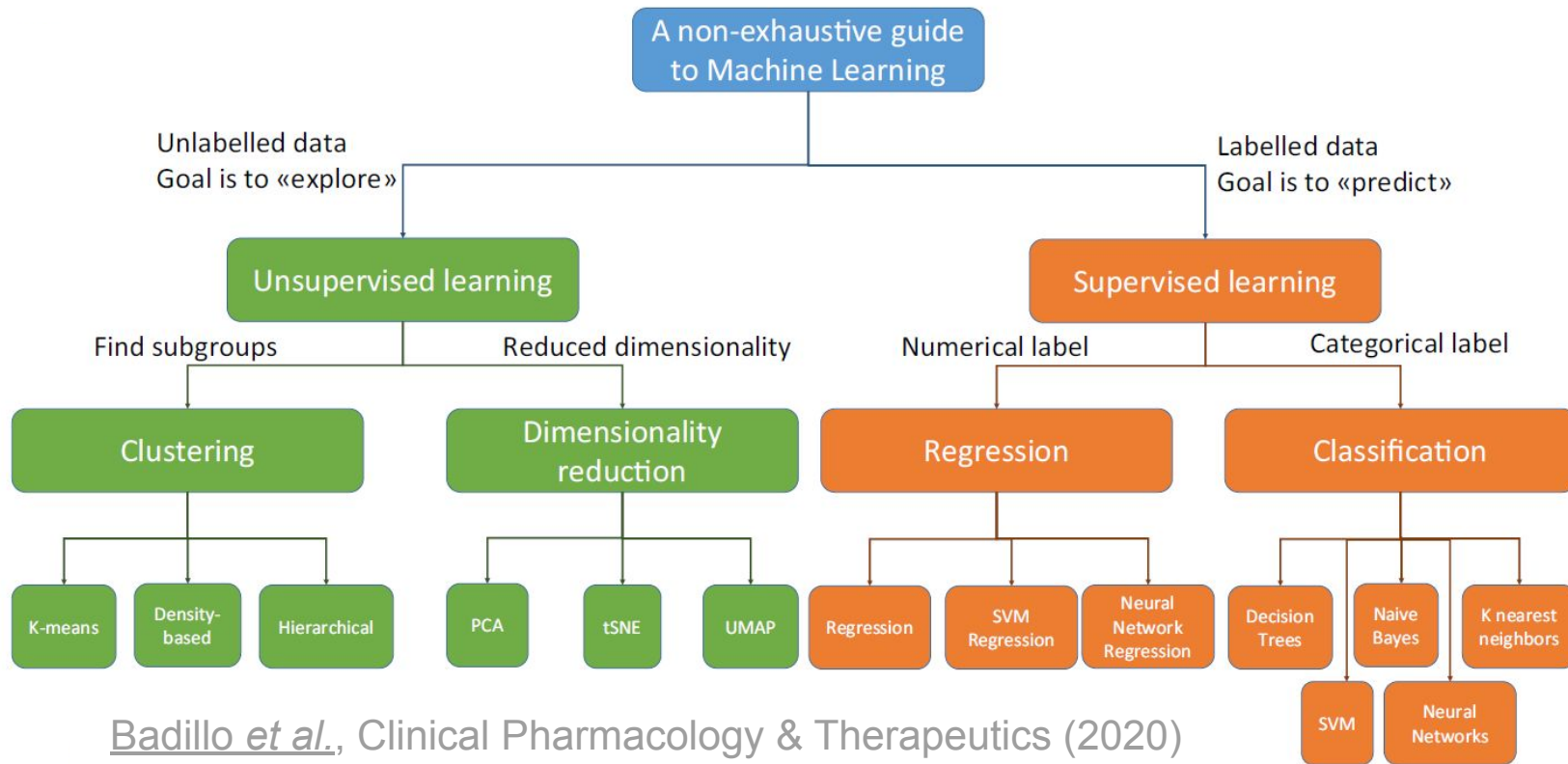
# Statistical models identify hidden patterns and discover correlations



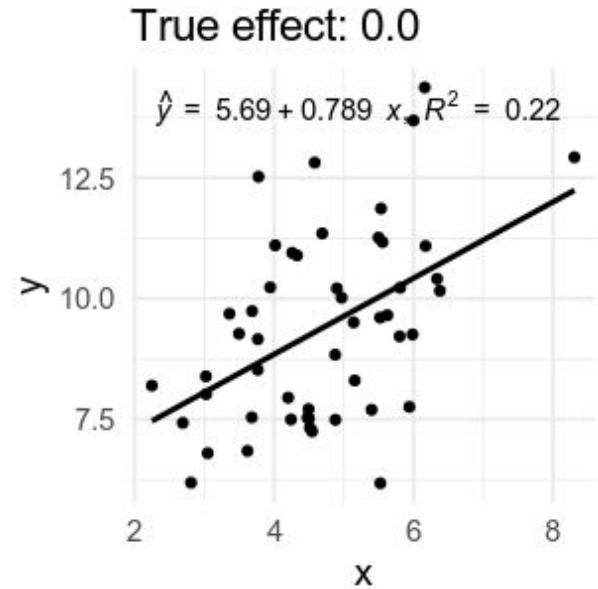
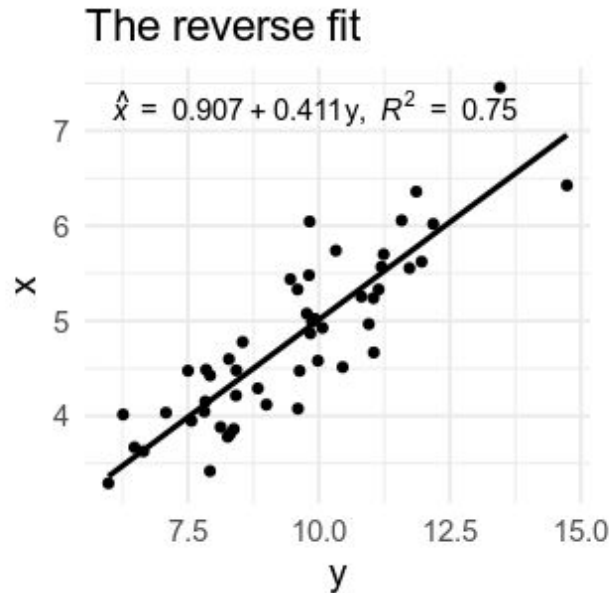
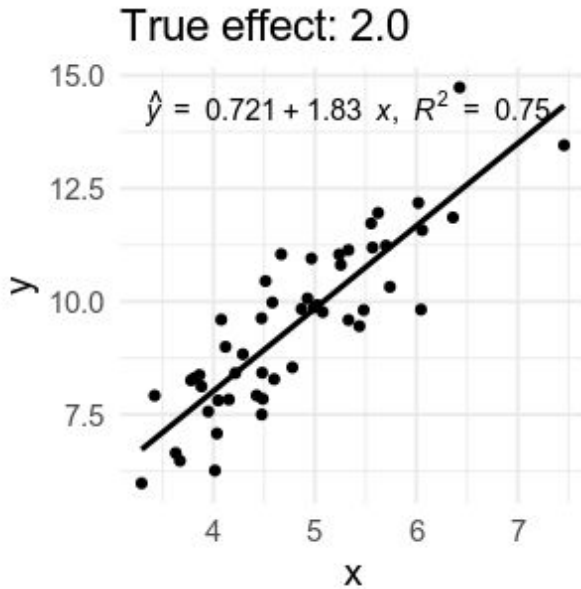
# Statistical models and prior knowledge can give rise to mechanistic/causal models



# Machine learning expands and enhances statistical models

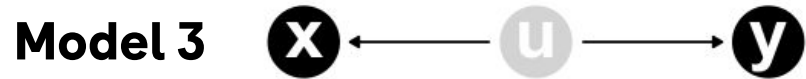


# Correlation is caused by causation or confounding



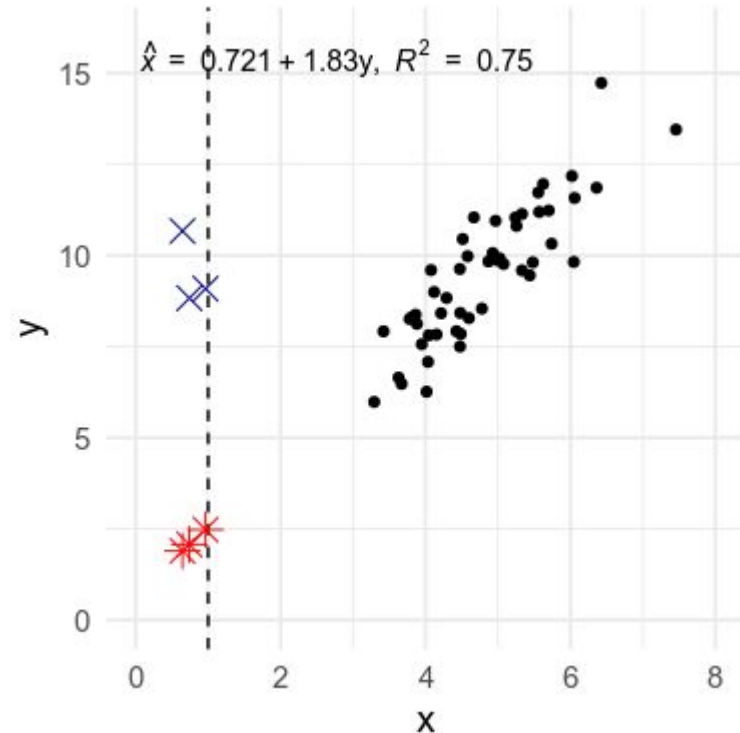
**Statistical models alone cannot derive causality from correlation**

# We learn causality by (1) listing models explicitly and (2) manipulating a variable and observe the outcomes



Assume that the data is generated by either Model 1, or Model 2, or Model 3. And assume that we can manipulate the value of X by setting it to 1.0 (the dash line).

**Question: which outcomes (red stars or blue crosses) would support which models? Why?**

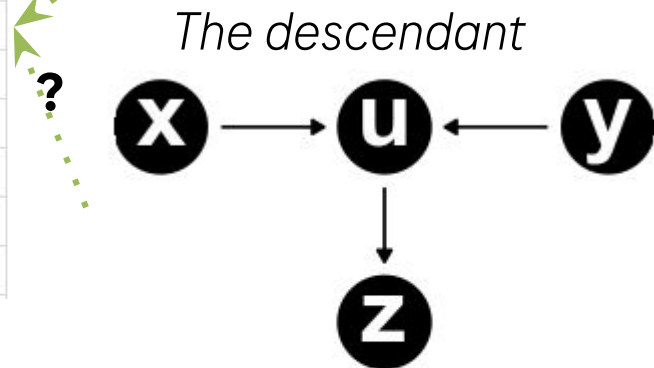


# Causality is crucial for drug discovery



Biomarker, tox study, pathology,  
omics data, real-world data, EHR, ...

|    | x            | z  | y           |
|----|--------------|----|-------------|
| 1  | 0.835386320  | 1  | -0.73897252 |
| 2  | -0.005354014 | -1 | -0.82972315 |
| 3  | 0.058788286  | 1  | 0.76213369  |
| 4  | -1.015602246 | -1 | -0.05951719 |
| 5  | -0.339569780 | -1 | -0.11745910 |
| 6  | -0.041077979 | -1 | -1.28243716 |
| 7  | 0.363740407  | 1  | -0.30570762 |
| 8  | 0.119496314  | -1 | -1.19932461 |
| 9  | 0.257108454  | -1 | -1.06044066 |
| 10 | 0.304537158  | -1 | -0.43396492 |

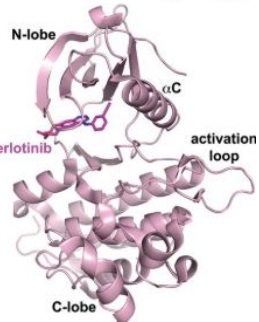


**We need both models (knowledge + assumptions) and data to infer causality.**

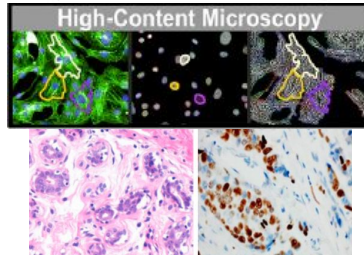
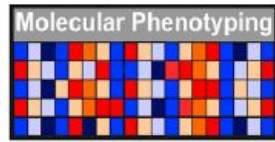
# Multiscale Modelling of Drug Mechanism and Safety

Forward translation

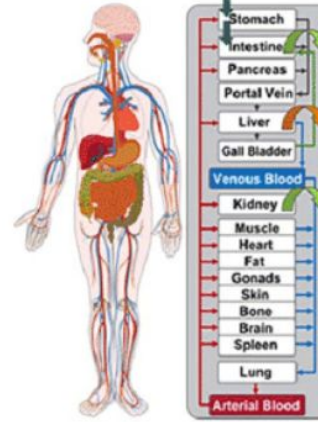
CCAUCAAUAAGGAAGAAGCCC  
GGTAGTTATTCTTCTCGGG



Molecular modeling



Omics & cellular modeling



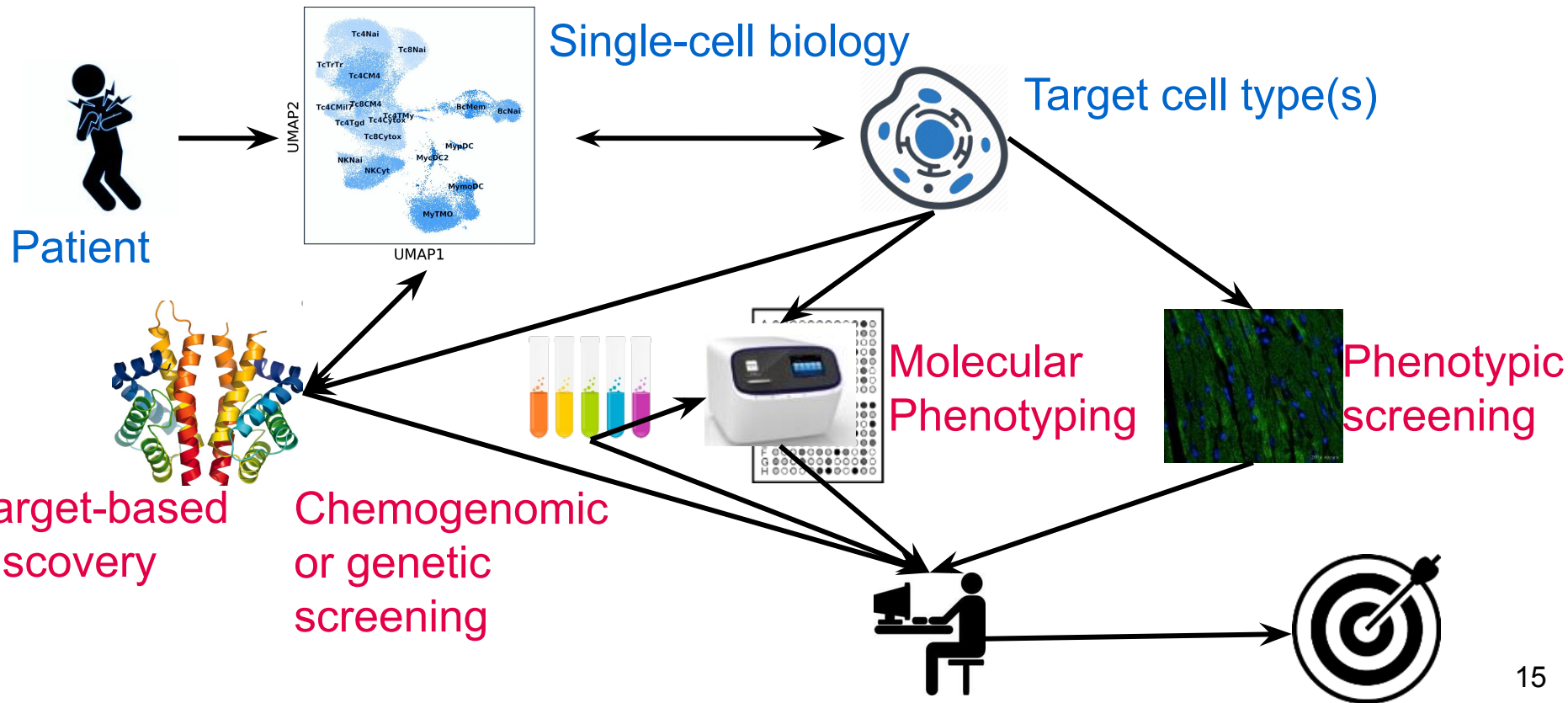
Organ & system modeling



Populational modeling

Reverse translation

# Computational biologists work with experimentalists to empower drug discovery



# Conclusions

- Computational biologists in drug discovery build and use mechanistic, causal, and statistical/machine-learning models.
- Model and data offer insights into disease biology, as well as into pharmacology and safety profiles of drug candidates.
- We experiment with a multiscale-modeling approach to drug discovery by integrating data and models at molecular, cellular, organ and system, and population levels.

# Interested in learning more about quantitative aspects of drug discovery?

- Fall Semesters: *Applied Mathematics and Informatics In Drug Discovery* (AMIDD): an introductory course.
  - See more information at <http://AMIDD.ch>.
- Spring Semesters: *Mathematical and Computational Biology in Drug Discovery* (MCBDD), an advanced course.
  - See more information at <http://MCBDD.ch>.

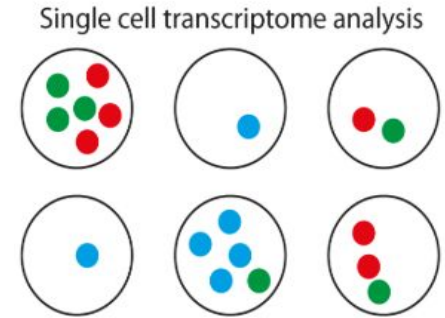
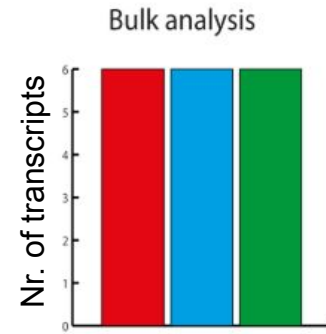
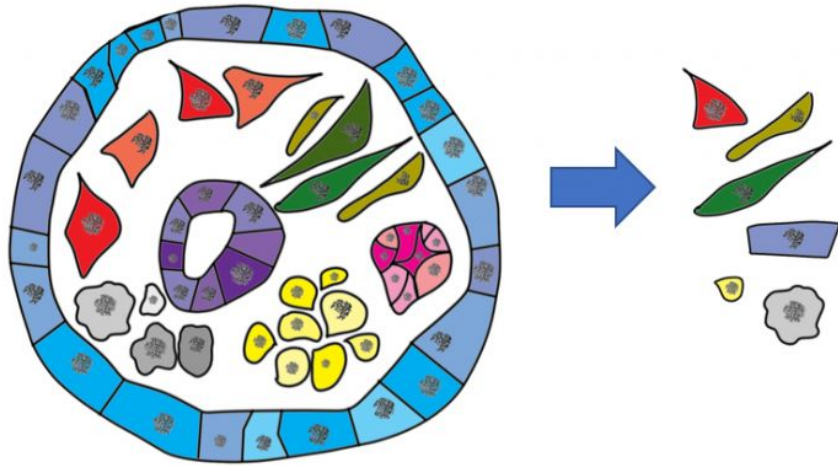
*Doing now what patients need next*

# *Backup material*

# Types of computational models

|                           | Prediction for independent and identically distributed samples | Prediction under changing distributions or intervention | Answer counterfactual questions | Obtain physical insight | Learn from data (data-driven discovery) |
|---------------------------|----------------------------------------------------------------|---------------------------------------------------------|---------------------------------|-------------------------|-----------------------------------------|
| <b>Mechanistic models</b> | yes                                                            | yes                                                     | yes                             | yes                     | maybe                                   |
| <b>Causal models</b>      | yes                                                            | yes                                                     | maybe                           | maybe                   | maybe                                   |
| <b>Statistical models</b> | yes                                                            | no                                                      | no                              | no                      | yes                                     |

# Target identification and mechanism & safety understanding benefits from single-cell biology



# Single-cell biology fuels drug discovery

**Disease understanding:**  
disease-specific cell types  
and states



**Target identification:**  
expression pattern in  
health and disease across  
cell types



**Biomarker and patient stratification:** which  
genes should we measure  
in which cell type(s)?

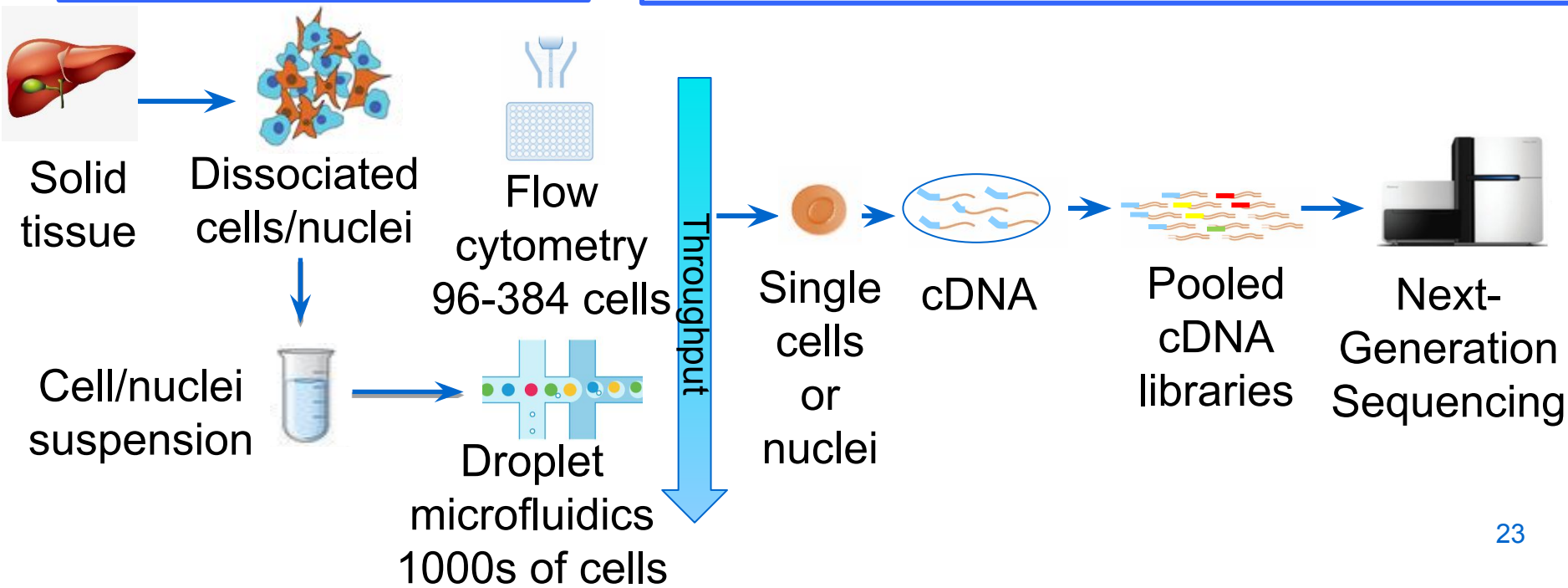


**MoA and safety modeling:** perturbation  
effect at single-cell level

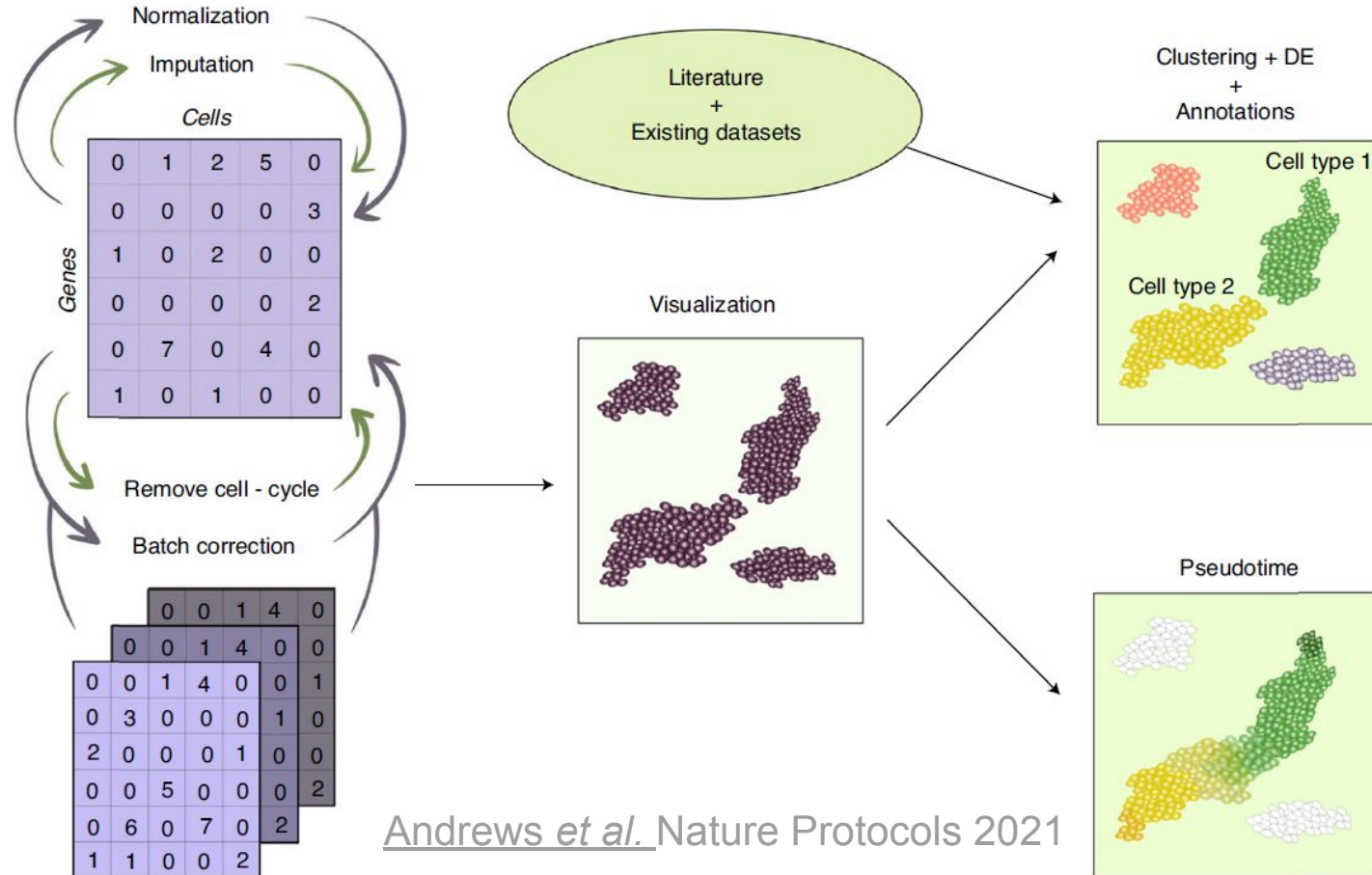
# Single-cell sequencing (scSeq) workflow

## Tissue dissociation

## Single cell capture and transcriptome sequencing



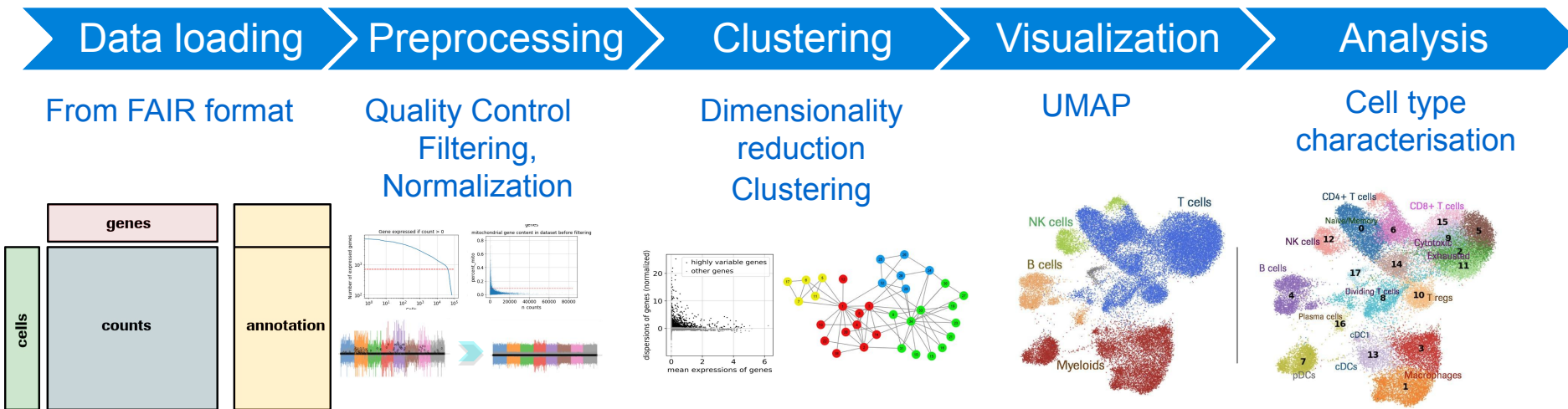
# Overview of the computational workflow



Andrews *et al.* Nature Protocols 2021

# Open-source BESCA (BEDA's single cell analysis)

## An automatized standard workflow



Maedler et al., NAR Genomics and Bioinformatics, 2021

<https://github.com/bedapub/besca>

*Doing now what patients need next*