

# Multi-Omics Factor Analysis (MOFA)

A generalisation of principal component analysis to  
multi-omics data

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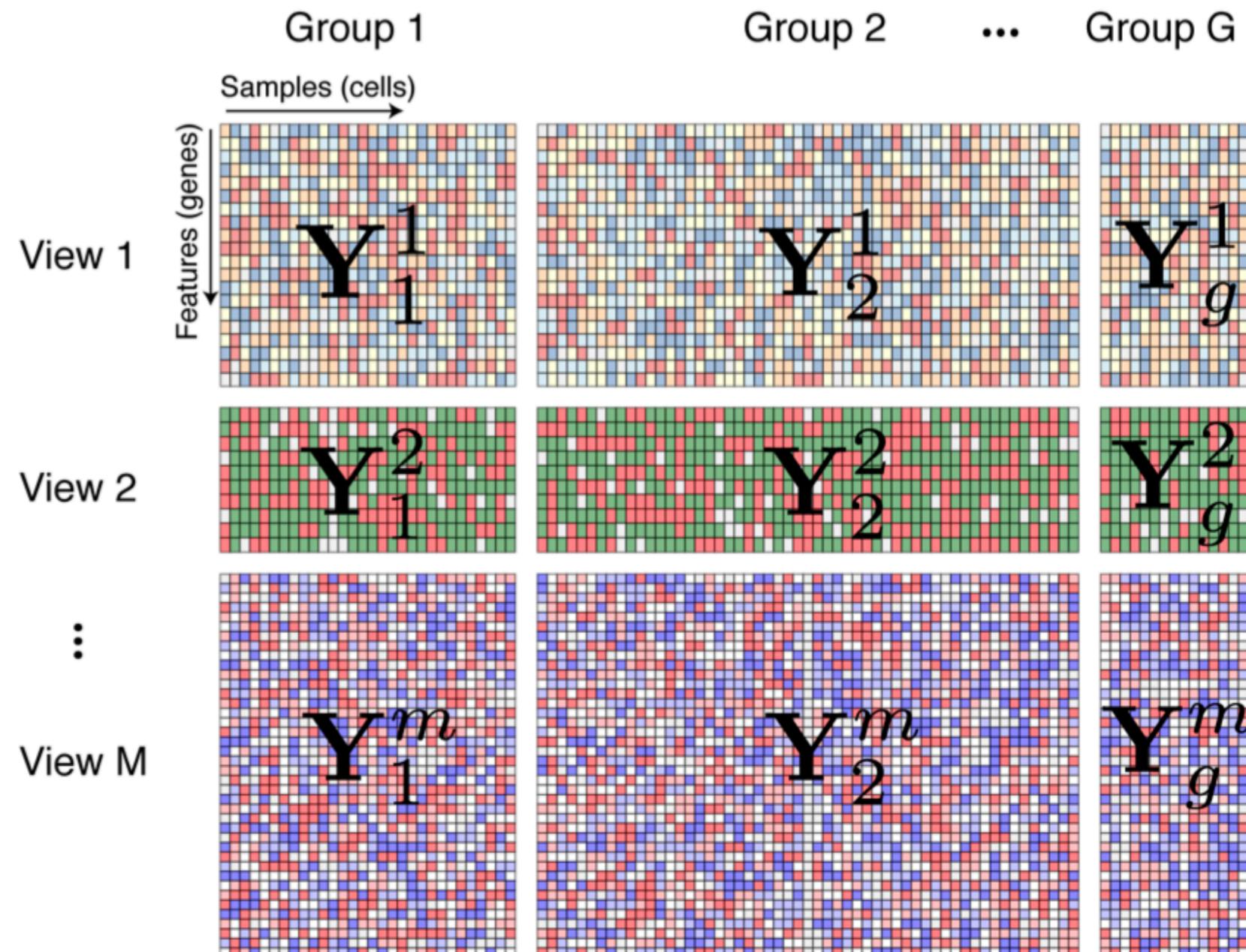
PhD at EMBL-EBI  
John Marioni & Oliver Stegle groups

Postdoctoral scientist at Babraham Institute  
Wolf Reik group

Senior Research scientist, AI/ML  
Altos Labs

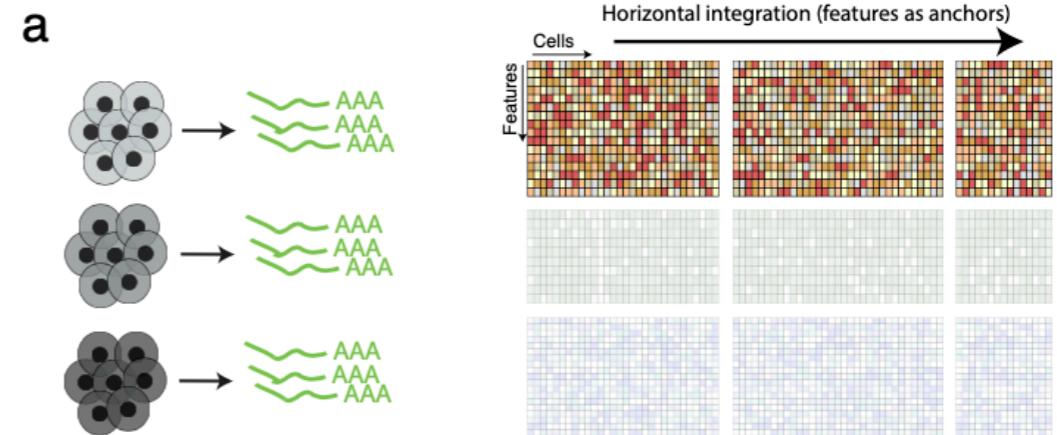


RArgelaguet

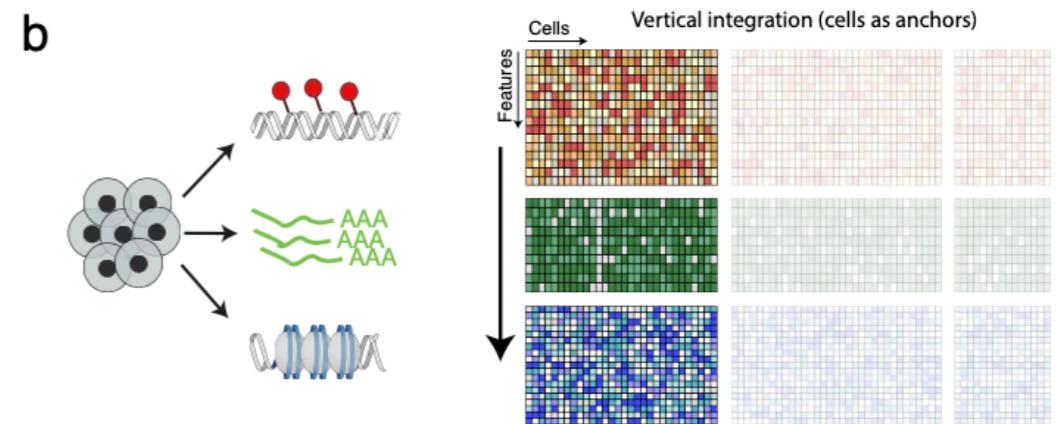


# Choosing the integration anchor

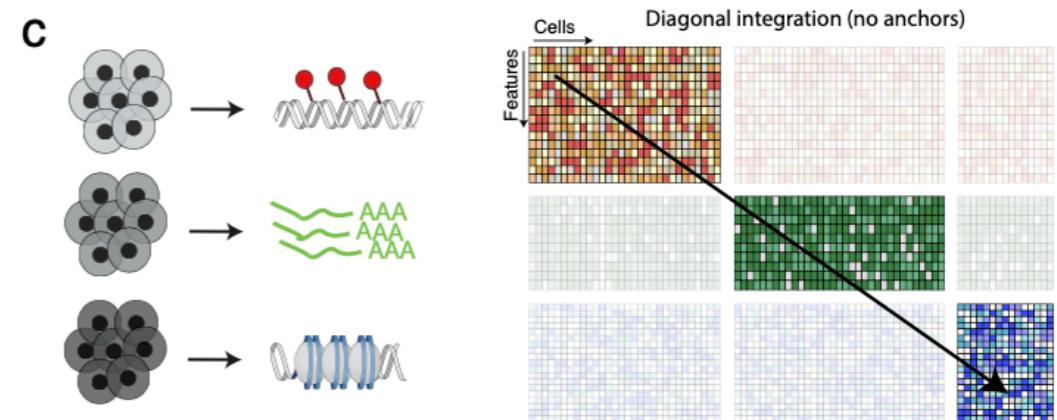
**(a) Genomic features as the anchor (horizontal integration): same data modality profiled from independent groups of samples**



**(b) Samples as the anchor (vertical integration): multiple data simultaneously profiled from the same sample**



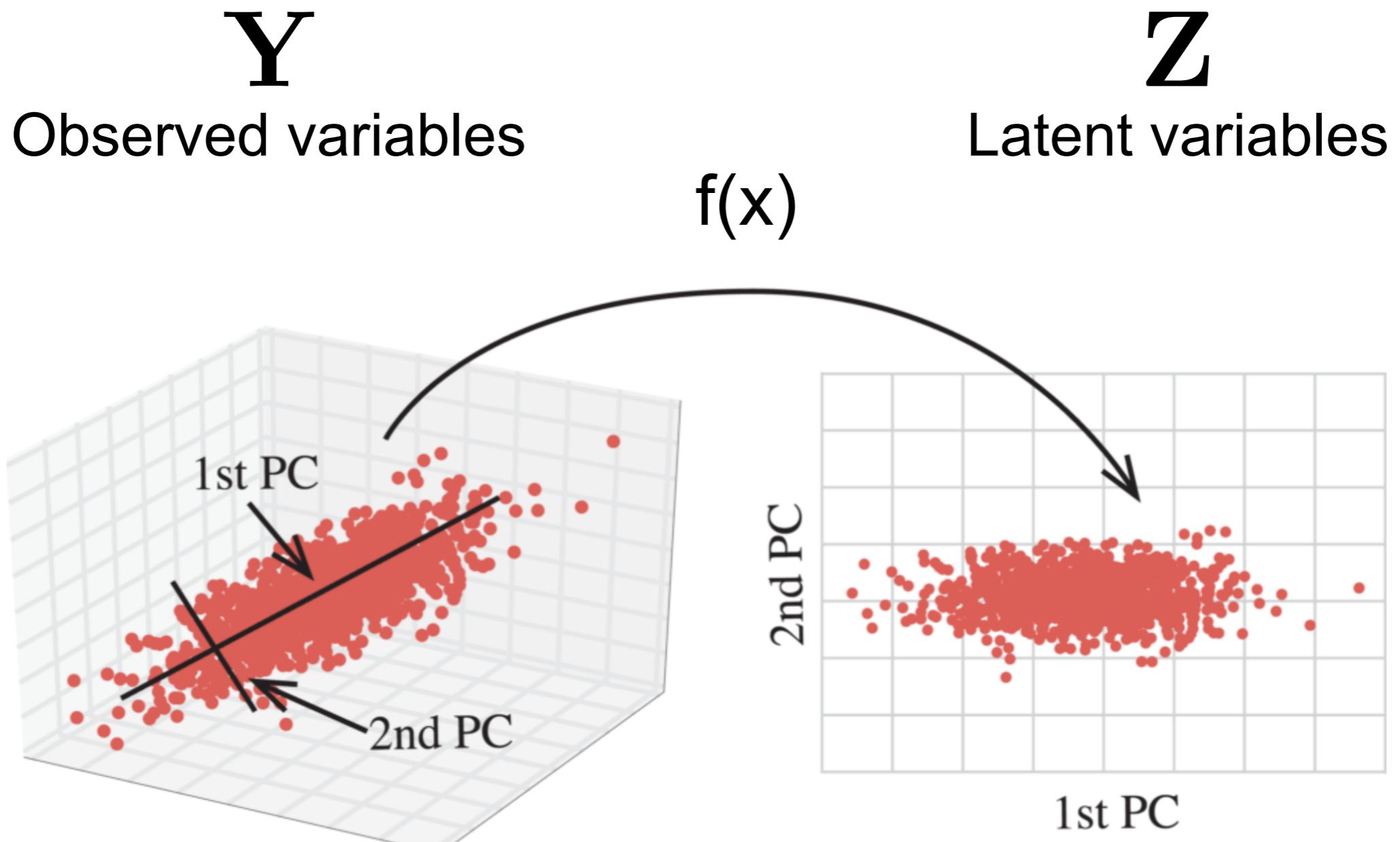
**(c) No anchor in the high-dimensional space (diagonal integration): both samples and data modalities are different between experiments.**



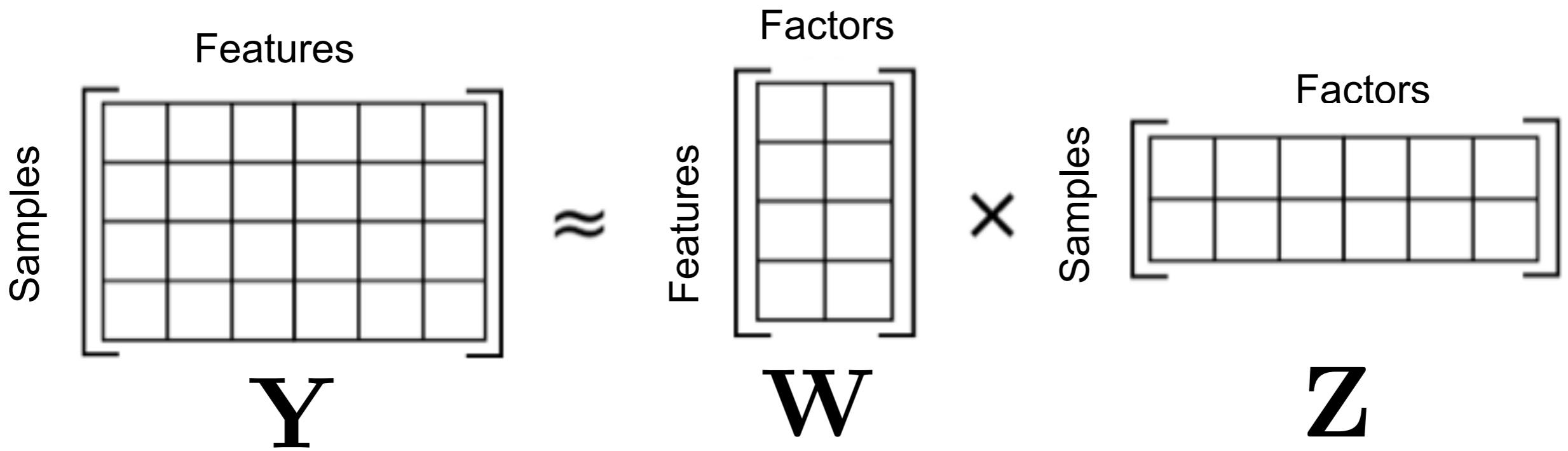
# Challenges in vertical multi-omics data integration

- Data collected using different techniques (i.e. data modalities) generally exhibit heterogeneous statistical properties
- Large amounts (and different patterns) of missing values
- Undesired sources of heterogeneity
- Overfitting
- Complexity of the data requires unsupervised interpretable approaches

# Latent variable models



# Matrix factorisation



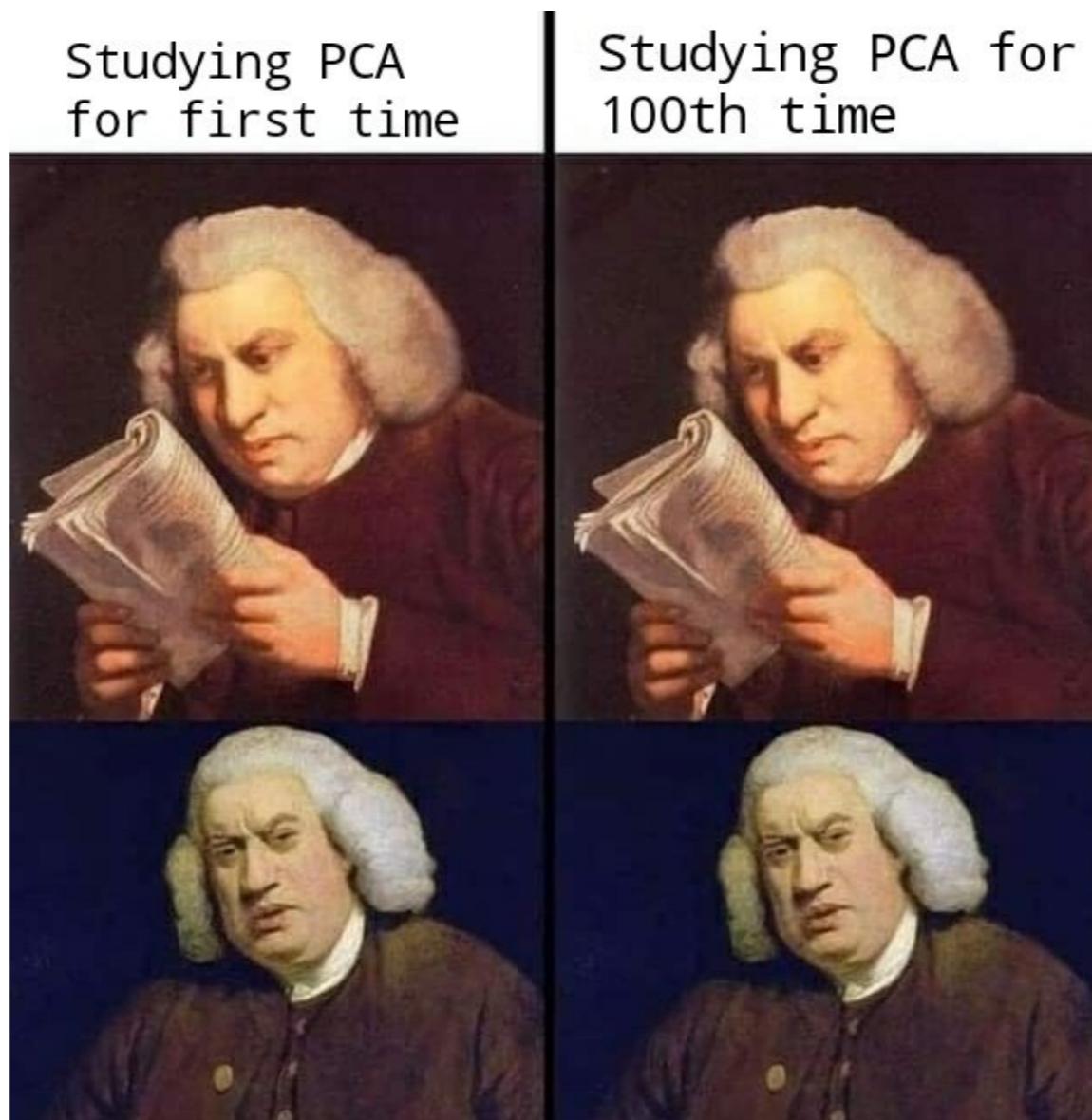
$Y$  is the observed measurements

$W$  is the inferred feature weights

$Z$  is the inferred latent factors

Principal Component Analysis is  
an instance of matrix factorisation!

# Principal Component Analysis



# Problems of using principal component analysis for multi-omics data

- Does not generalise to an arbitrary number of data modalities
- No natural way to combine different data modalities (binary data with continuous data)
- Can't handle missing values
- Non-sparse loadings: challenges in interpretability and risk of overfitting

## Canonical Correlation Analysis (CCA)

Canonical Correlation Analysis (CCA) is a simple extension of PCA to find linear components that capture correlations between **two** datasets<sup>3</sup>.

Given two data matrices  $\mathbf{Y}_1 \in \mathbb{R}^{N \times D_1}$  and  $\mathbf{Y}_2 \in \mathbb{R}^{N \times D_2}$  CCA finds a set of linear combinations  $\mathbf{U} \in \mathbb{R}^{D_1 \times K}$  and  $\mathbf{V} \in \mathbb{R}^{D_2 \times K}$  with maximal cross-correlation.

For the first pair of canonical variables, the optimisation problem is:

$$(\hat{\mathbf{u}}_1, \hat{\mathbf{v}}_1) = \underset{\|\mathbf{u}_1\|=1, \|\mathbf{v}_1\|=1}{\arg \max} \text{corr}(\mathbf{u}_1^T \mathbf{Y}_1, \mathbf{v}_1^T \mathbf{Y}_2)$$

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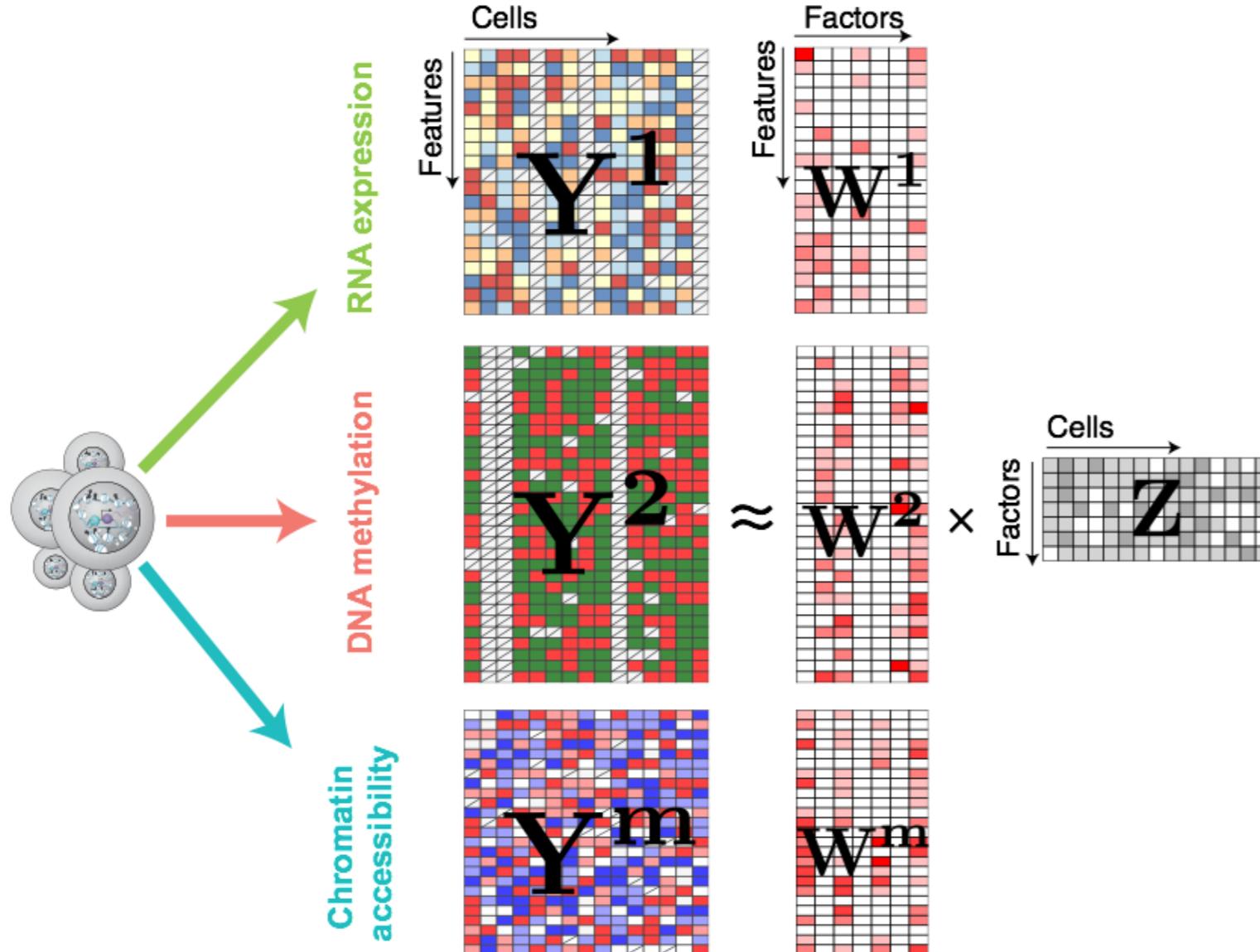
<sup>3</sup>Hotelling, H. "Relations between two sets of variates" *Biometrika* 1936.

## What are the problems of CCA for multi-omics data integration?

The canonical components are defined as linear combinations of features that maximise the cross-correlation between the two data sets. This implies that:

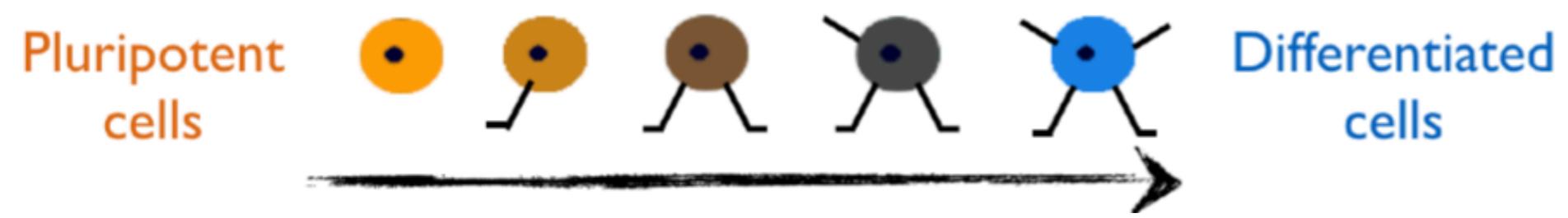
- It only works for the integration of 2 data sets
- It only finds sources of covariation between the two data sets. CCA is not able to find the sources of variation that are present within individual data sets

# Multi-omics Factor Analysis (MOFA)

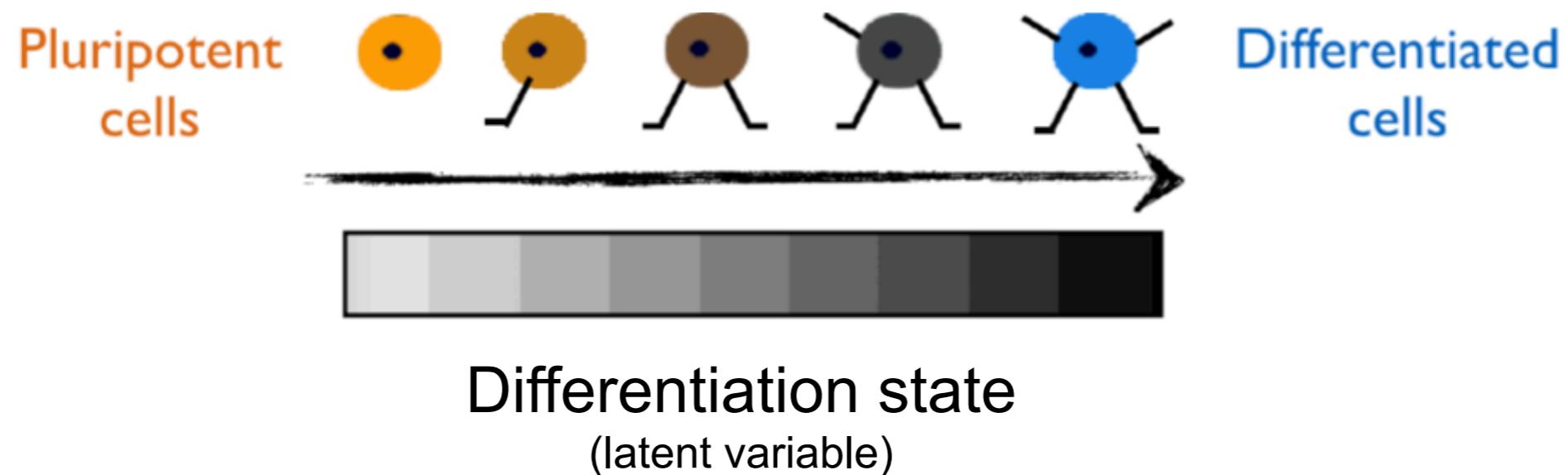


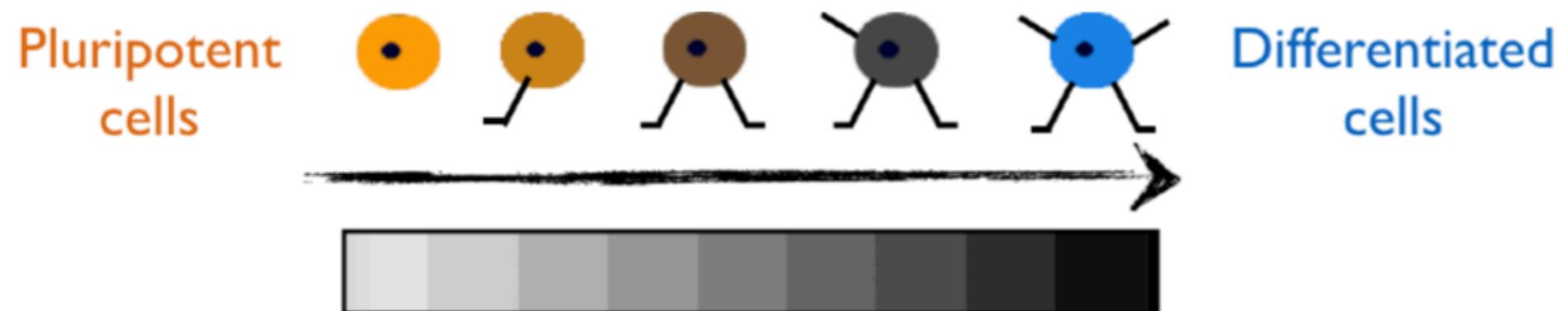
$$\mathbf{Y}^m = \mathbf{Z}\mathbf{W}^{mT}$$

- MOFA is a probabilistic generalisation of PCA to multiple data modalities
- The structure of the data is specified in the prior distributions of the Bayesian model
- The critical part of the model is the use sparsity priors



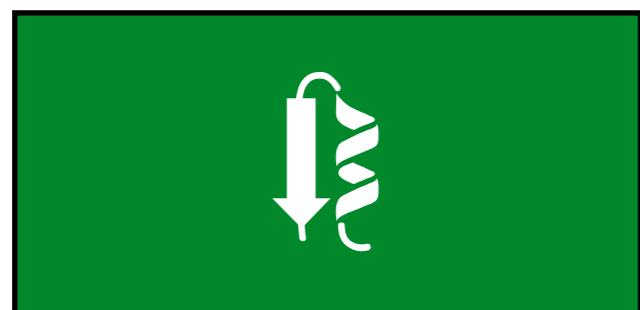
## Illustrative example





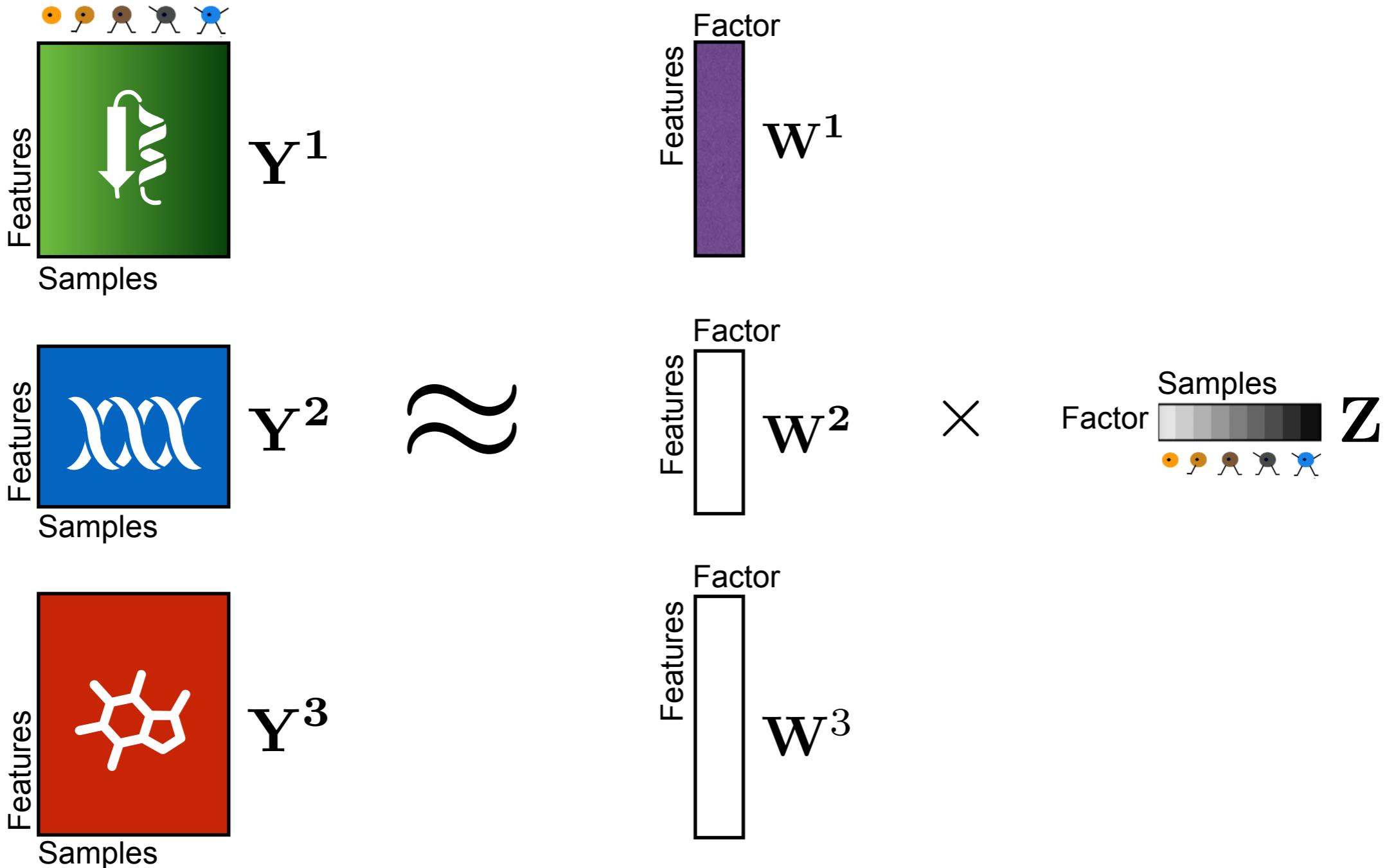
Differentiation state

(latent variable)

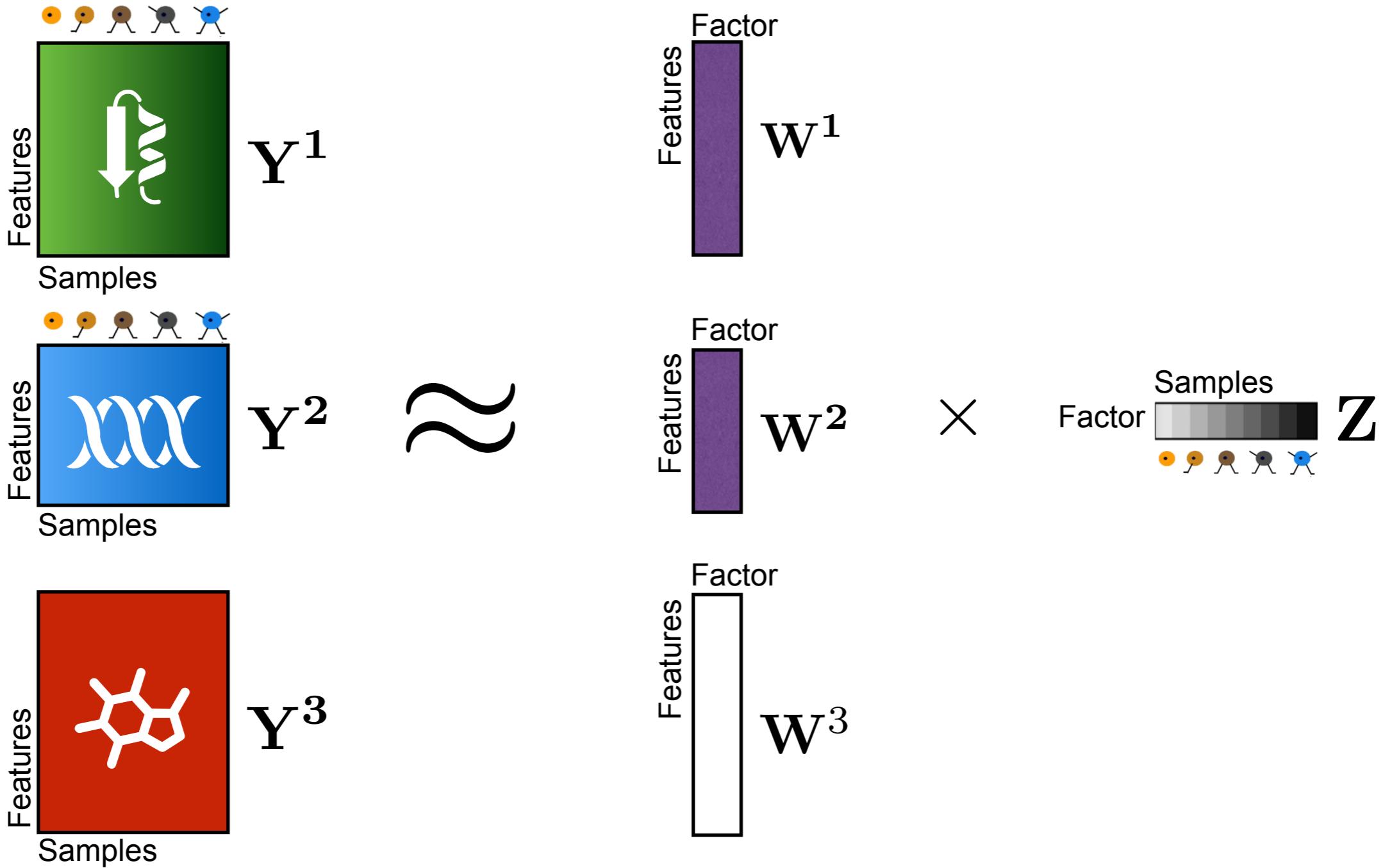


Omics  
(observed variables)

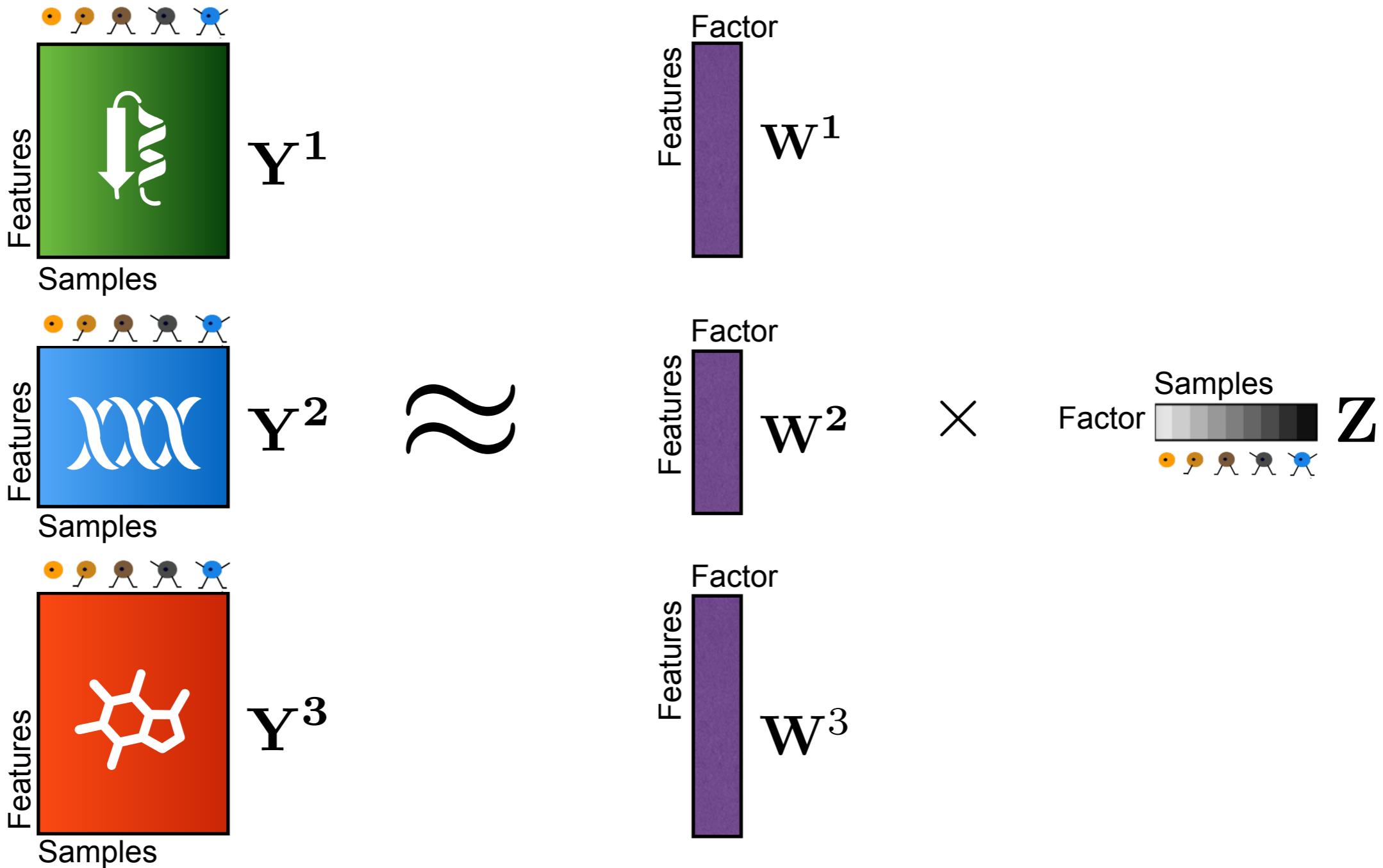
# The differentiation state is the only driver of variation in transcriptomics



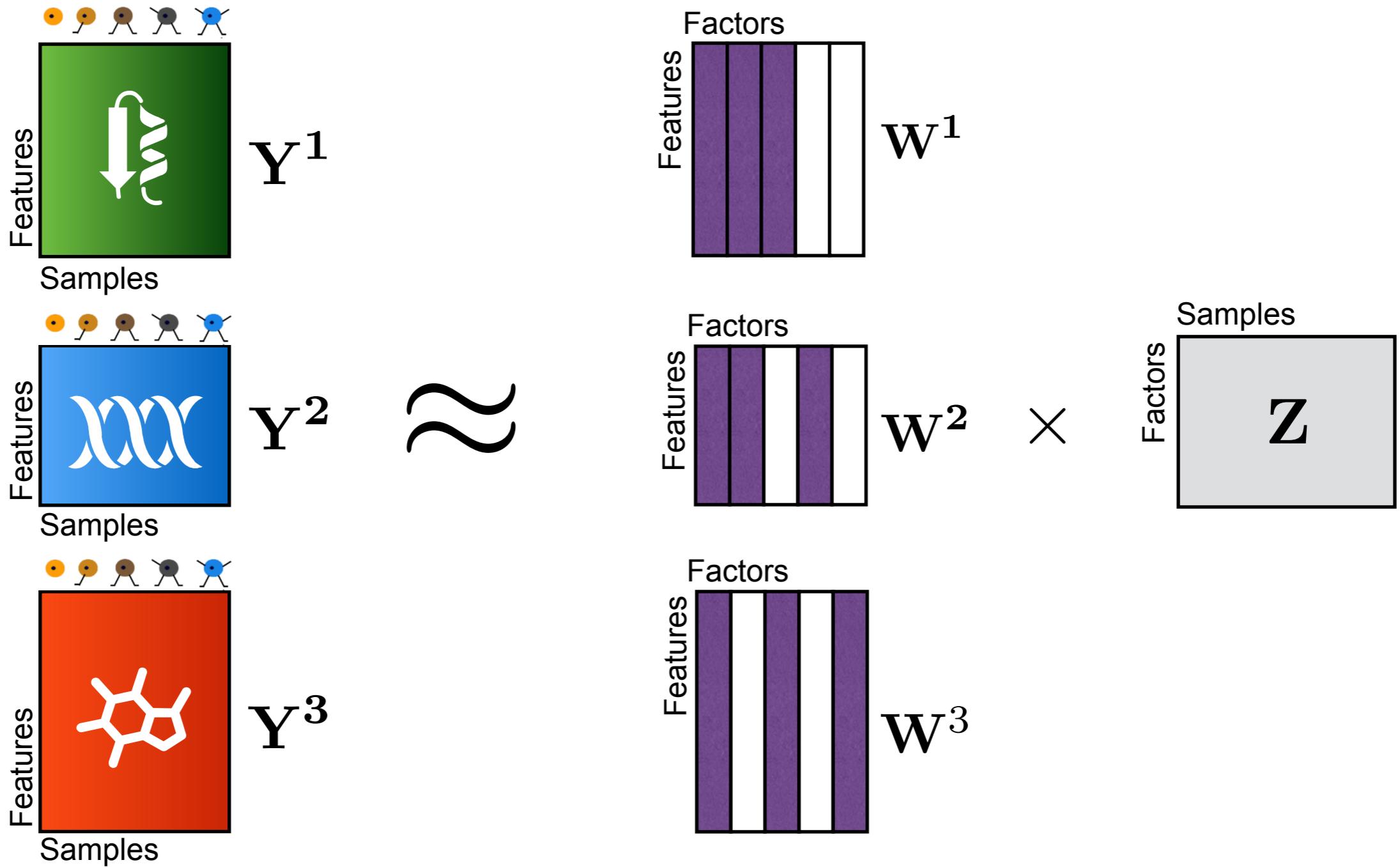
# The differentiation state is the only driver of variation in **transcriptomics** and genetics



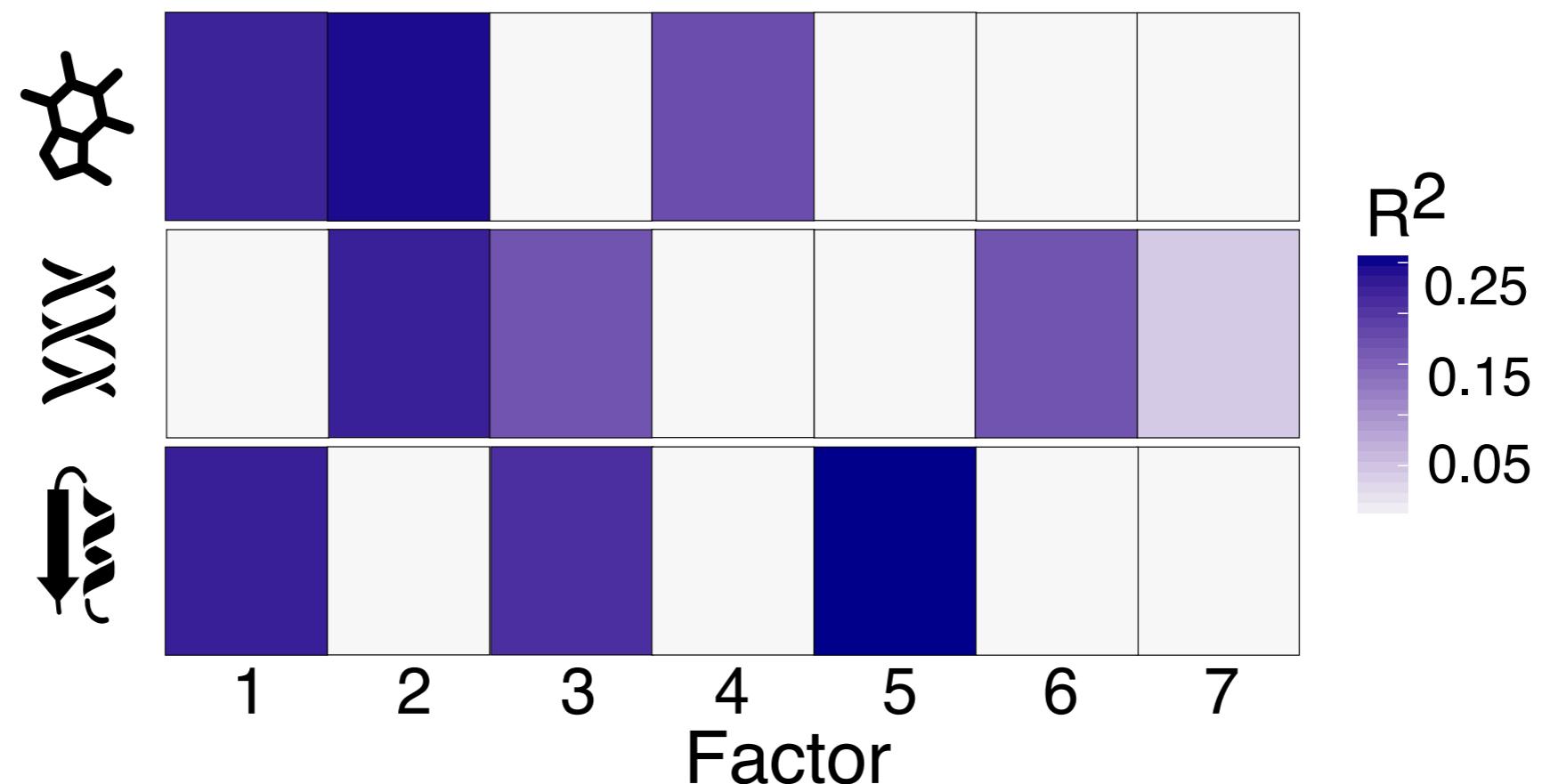
# The differentiation state is the only driver of variation in **all** omics



# A more realistic solution...

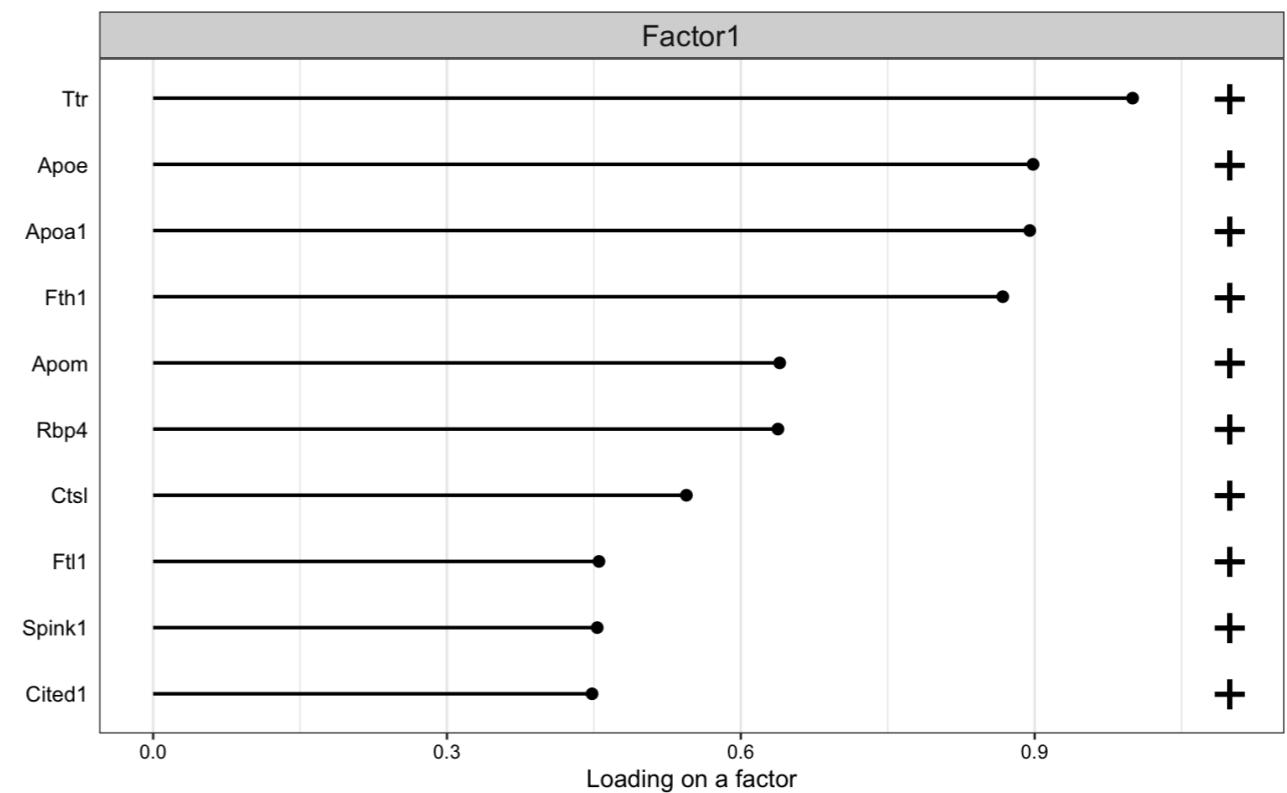
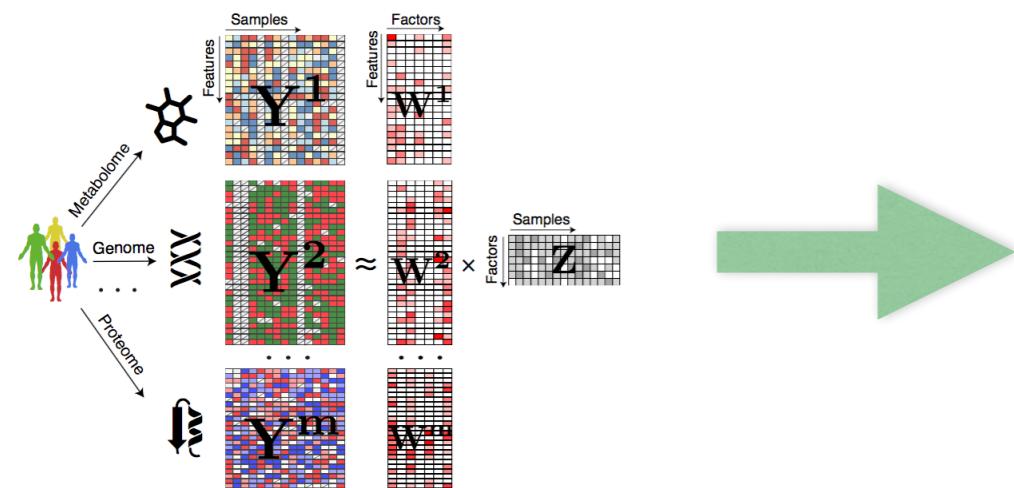


# Variance decomposition by factor

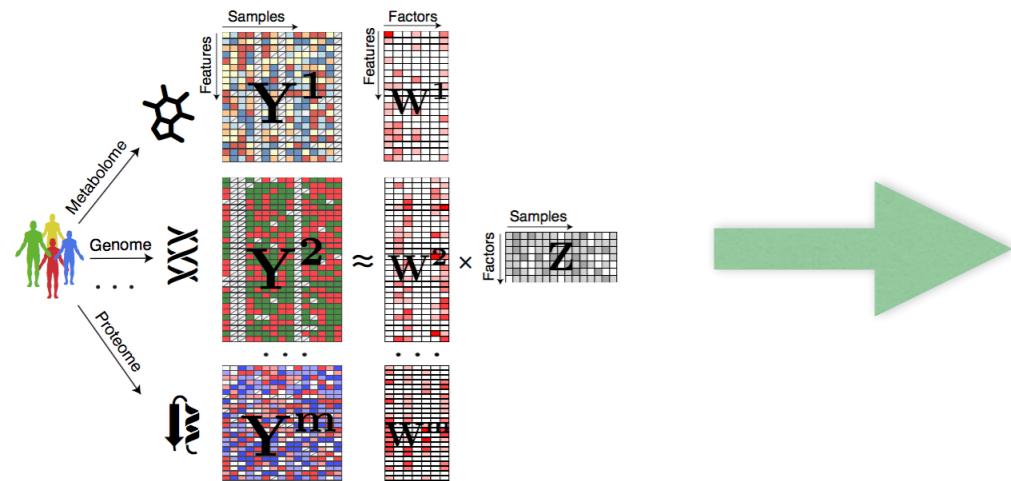


# Downstream analysis

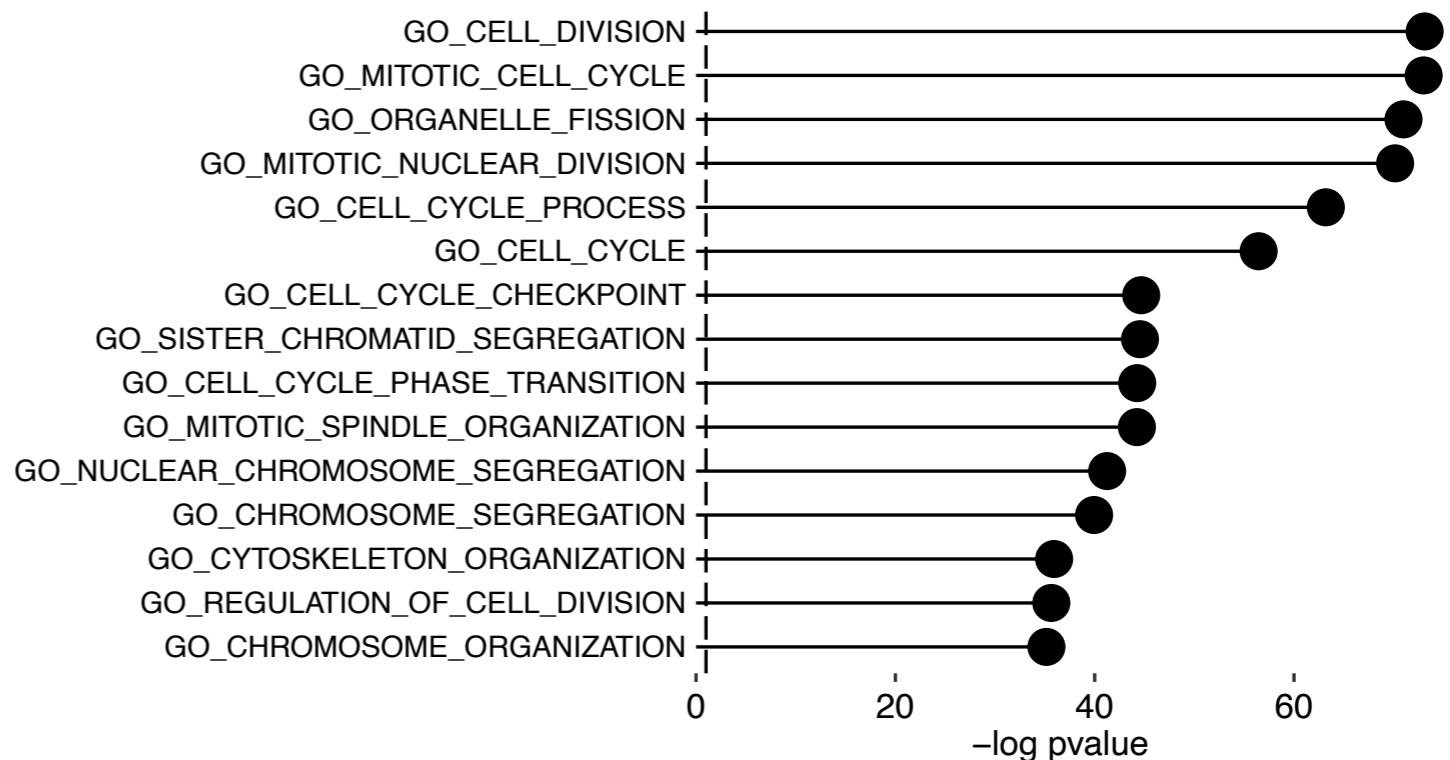
## Inspection of feature weights



# Downstream analysis

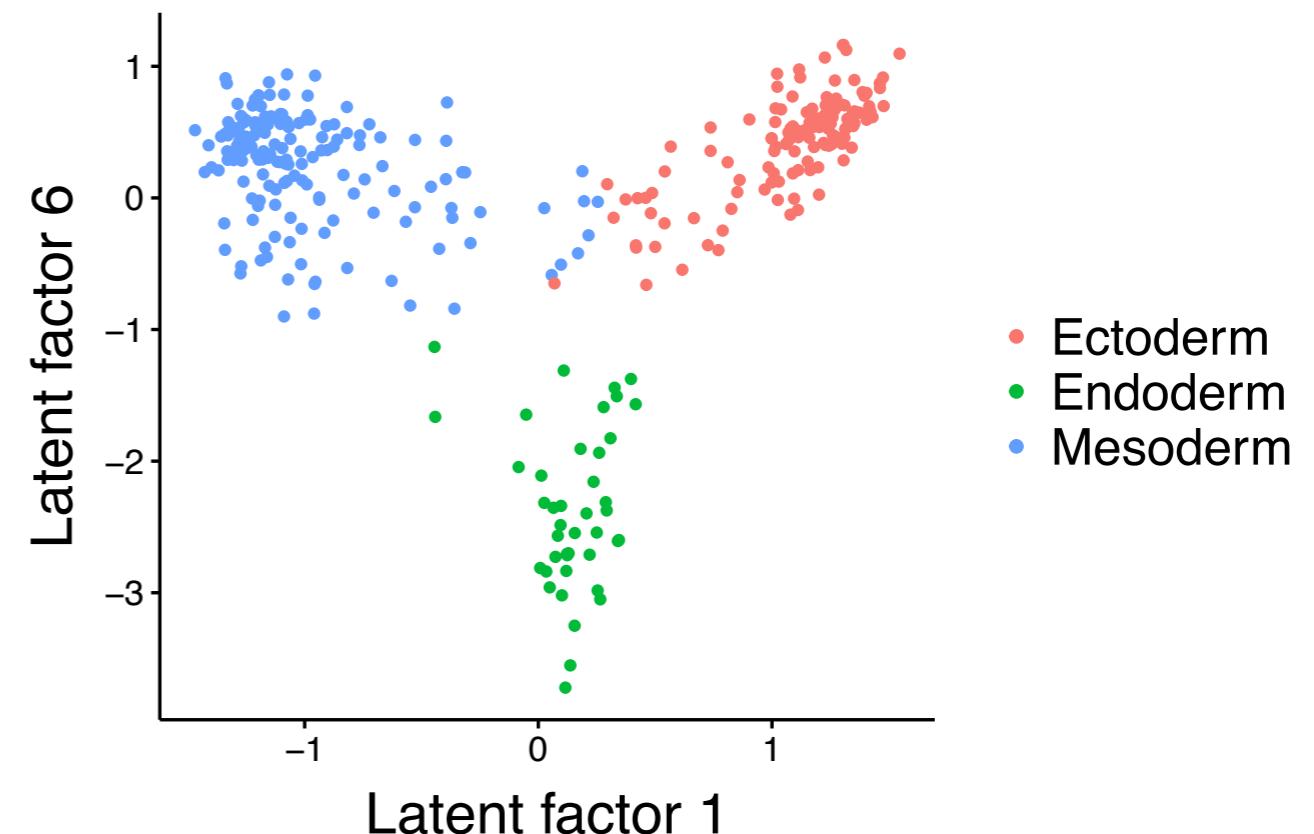
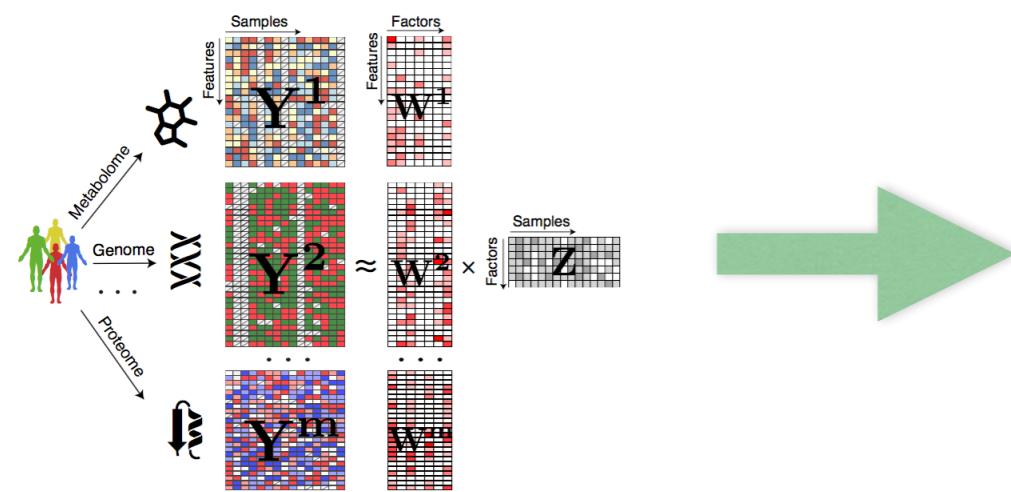


## Gene set enrichment analysis

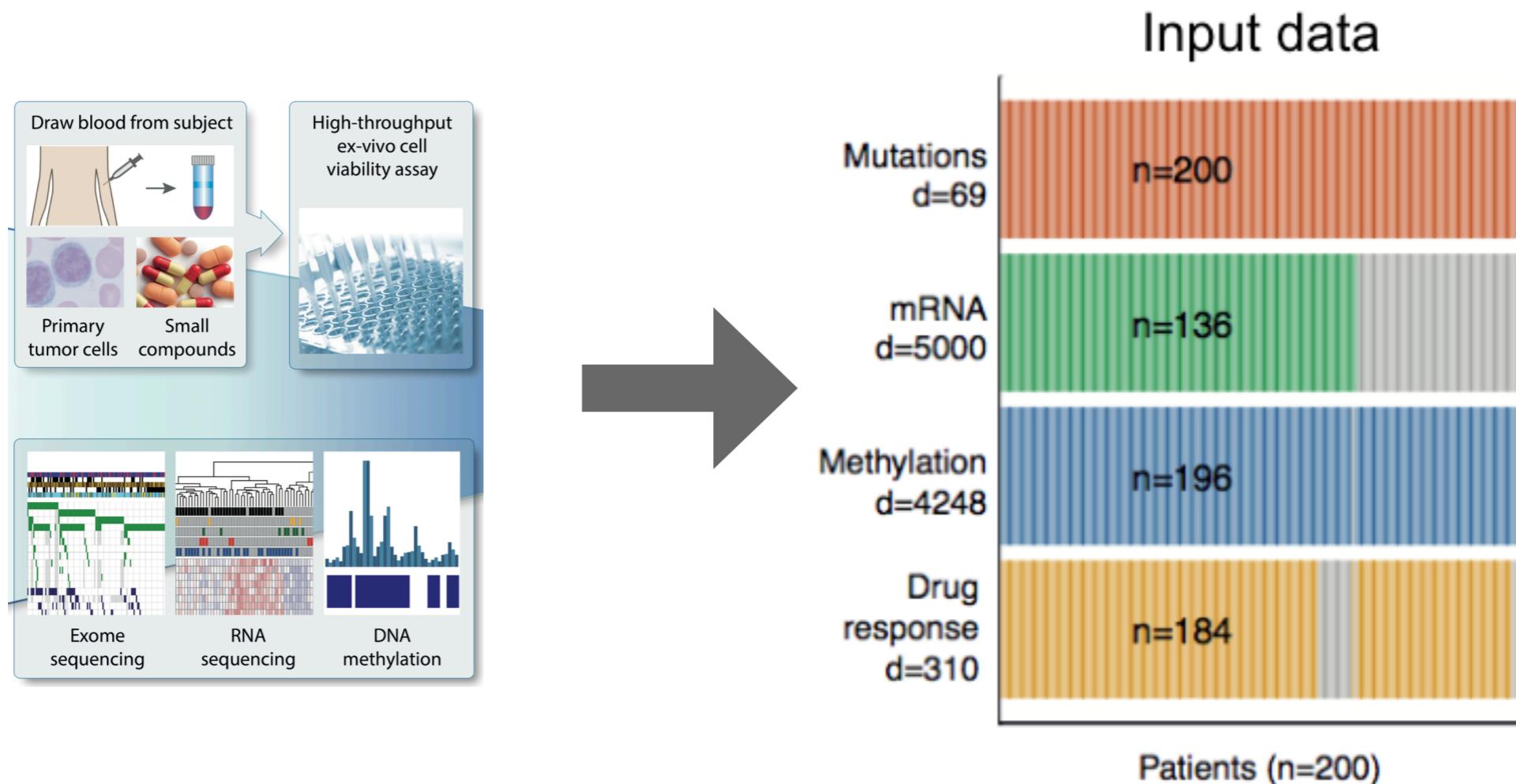


# Downstream analysis

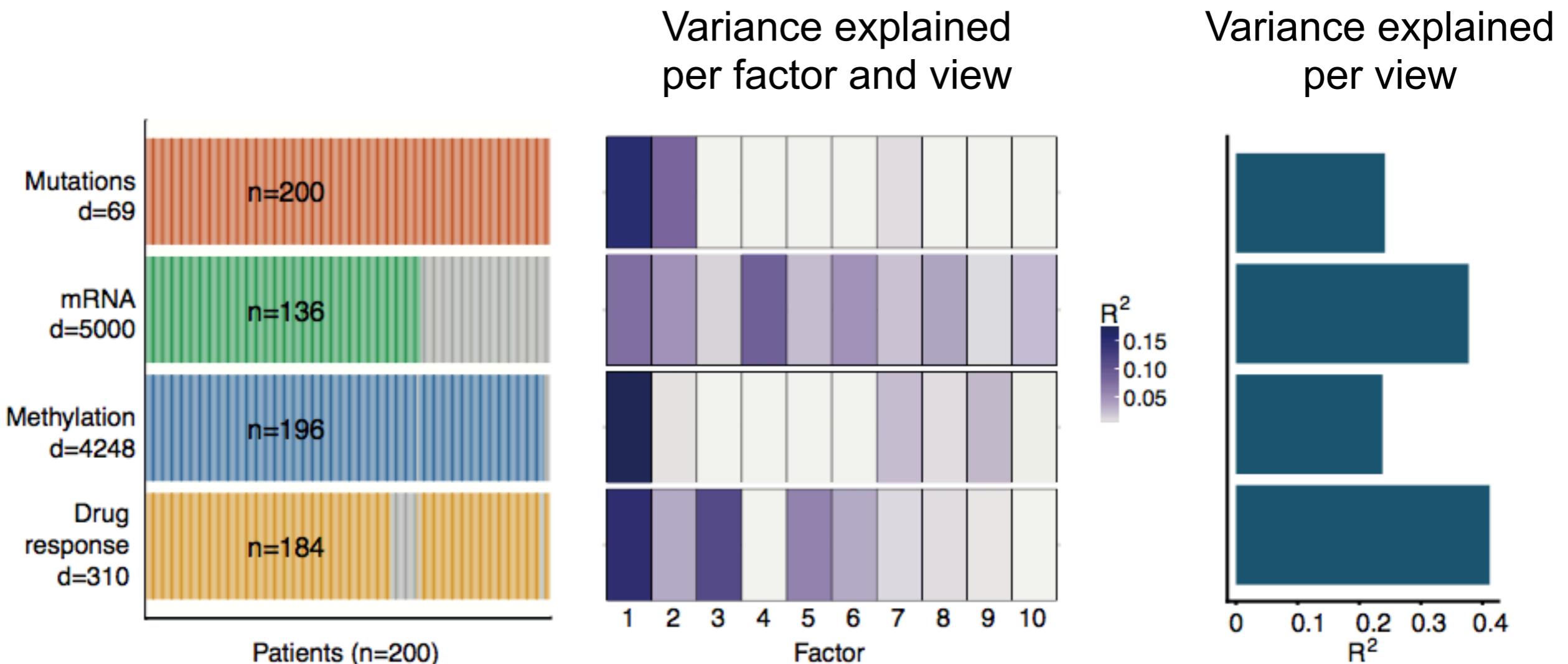
## Visualisation of samples in the latent space



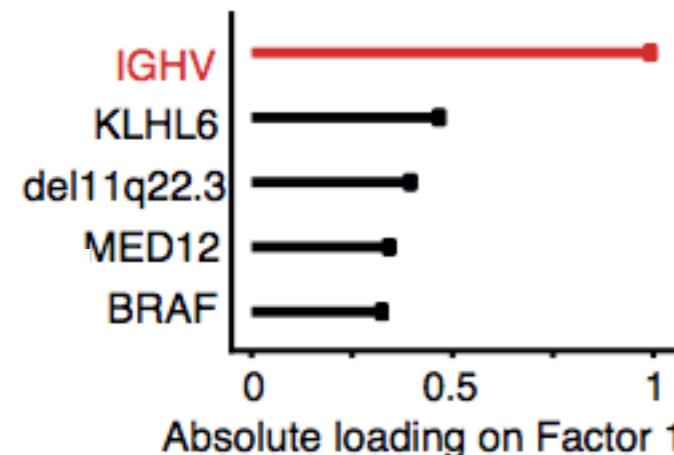
# Personalised medicine application, a cohort of Chronic Lymphocytic Leukemia patients



# Personalised medicine application, a cohort of Chronic Lymphocytic Leukemia patients



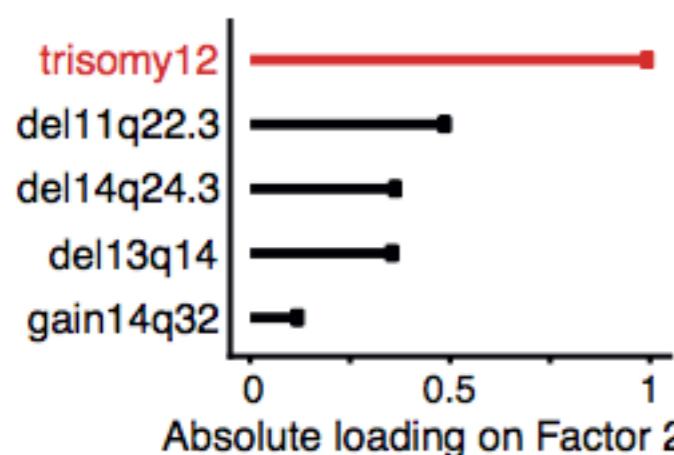
# Inspection of Somatic mutation weights for Factors 1 and 2



CLINICAL PEARLS IN BLOOD DISEASES

*IGHV* mutational status testing in chronic lymphocytic leukemia

Jennifer Crombie, Matthew S. Davids [✉](#)



Trisomy 12 chronic lymphocytic leukemia cells

John C. Riches, Conor J. O'Donovan, Sarah J. Kingdon, Fabienne McClanahan, Andrew J. Clear, Laura Z. Rassenti, Thomas J. Kipps, and John G. Gribben

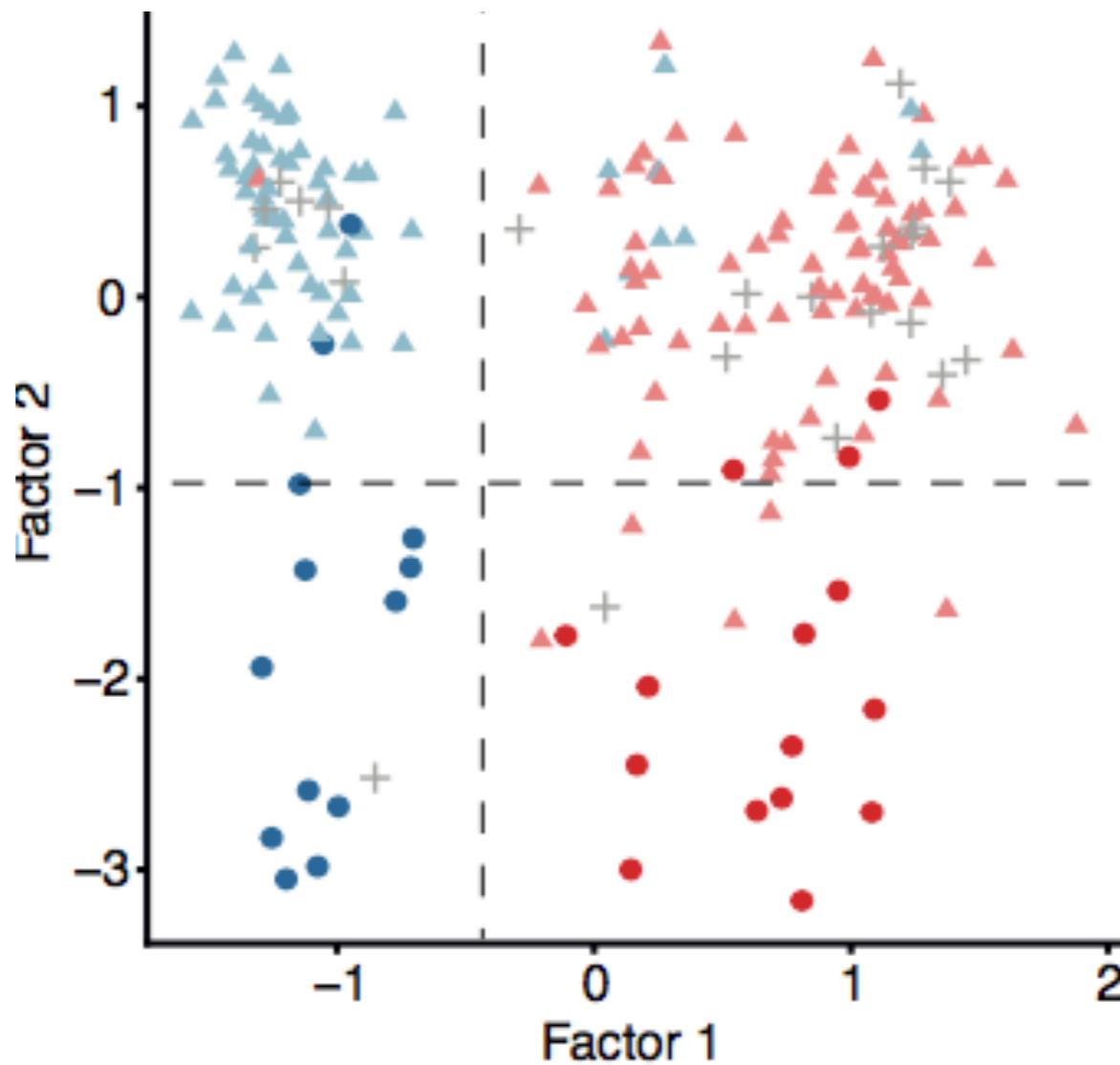
Blood 2014 123:4101–4110; doi: <https://doi.org/10.1182/blood-2014-01-552307>

*IGHV*: Immunoglobulin heavy chain variable region

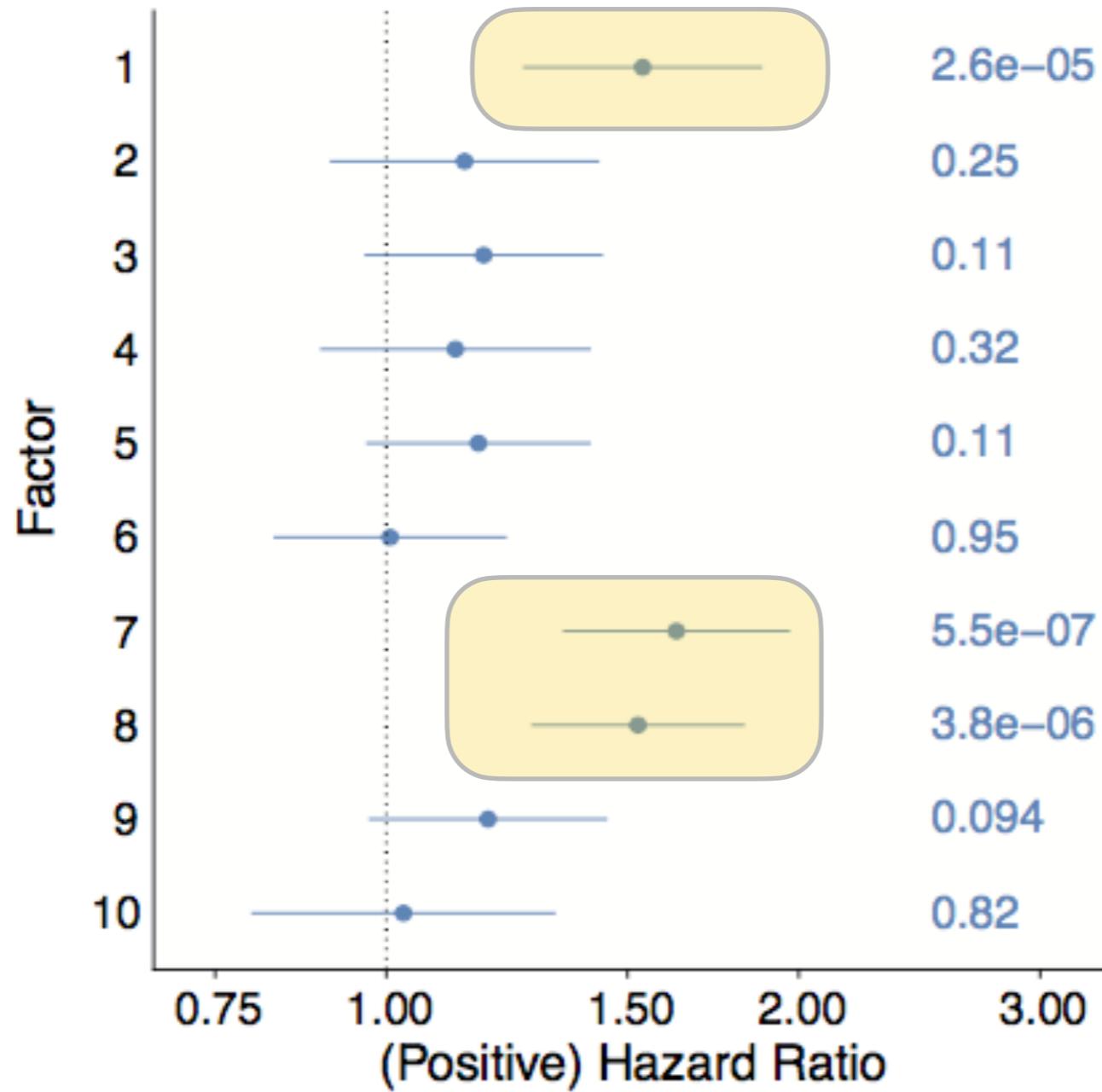
## Visualisation of samples in the latent space

Factor 1: IGHV+ vs IGHV-

Factor 2: tr12+ (circle) vs tr12- (triangle)



# Association of Factors with clinical covariates



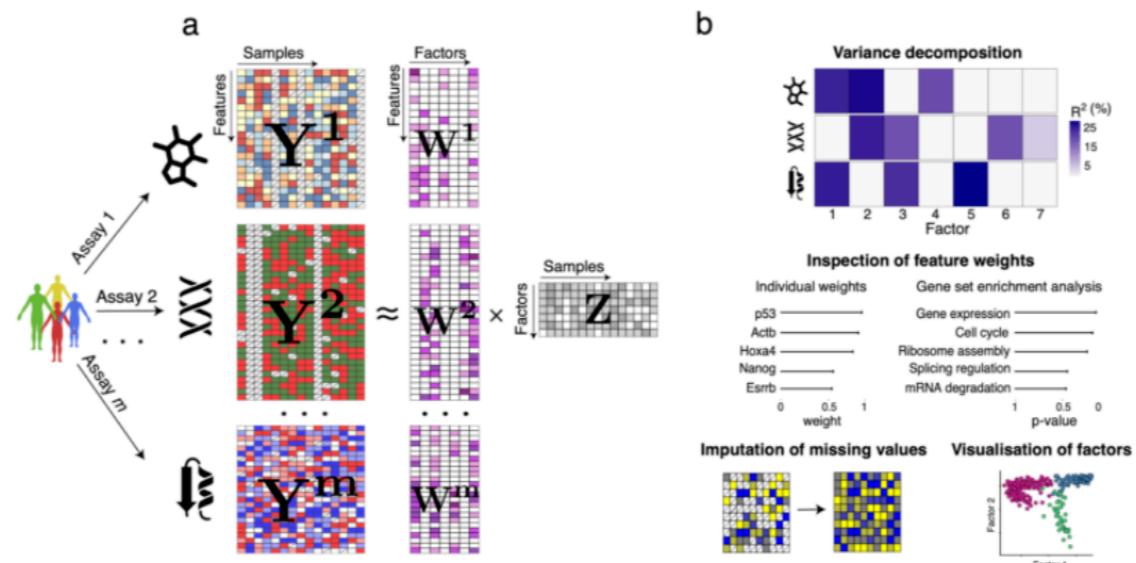
# MOFA

Multi-Omics Factor Analysis V2 (MOFA+)

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MOFA is a factor analysis model that provides a **general framework for the integration of multi-omic data sets** in an unsupervised fashion.

Intuitively, MOFA can be viewed as a versatile and statistically rigorous generalization of principal component analysis to multi-omics data. Given several data matrices with measurements of multiple -omics data types on the same or on overlapping sets of samples, MOFA infers an **interpretable low-dimensional representation in terms of a few latent factors**. These learnt factors represent the driving sources of variation across data modalities, thus facilitating the identification of cellular states or disease subgroups.



## Case examples using real data (in R)

- **(authors' favourite) Analysis of chronic lymphocytic leukaemia cohort for personalised medicine:** a bulk multi-omics data set. Figure 2 and 3 of the MOFA v1 paper.
- **(authors' favourite) Integrative analysis of the Chromium Single Cell Multiome ATAC + Gene Expression assay:** this is the result of a collaboration between the MOFA team and the 10x Genomics R&D team to provide a downstream analysis pipeline for the new RNA+ATAC multi-modal technology.
- **Analysis of a time course scRNA-seq data set using the multi-group framework:** Figure 2 of the MOFA+ paper. Demonstrates the multi-group functionality and how to train a MOFA model from a Seurat object.
- **Integration of scNMT-seq data (single-cell multi-omics):** Figure 4 of the MOFA+ paper. Demonstrates the simultaneous multi-view and multi-group functionality using the scNMT-seq mouse gastrulation atlas.
- **Integration of SNARE-seq data (single-cell multi-omics):** Demonstrates how MOFA can be used for the analysis of paired scRNA+scATAC data (from the same cell) using a multi-modal Seurat object. This data set is very noisy and the results are not fantastic, we suggest you have a look at the Chromium Single Cell Multiome ATAC + Gene Expression vignette instead.
- **Analysis of multi-modal microbiome data:** we demonstrate how to systematically integrate viral, fungal and bacterial sequence data.

# Statistical methods for the integrative analysis of single-cell multi-omics data



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European Bioinformatics Institute  
University of Cambridge

This dissertation is submitted for the degree of  
*Doctor of Philosophy*

## Practical session

```
git clone https://github.com/rargelaguet/mofa_training
```