Predicting Drug Effects on Single Cell State

Zeinab Navidi

CSC2431 Project Proposal

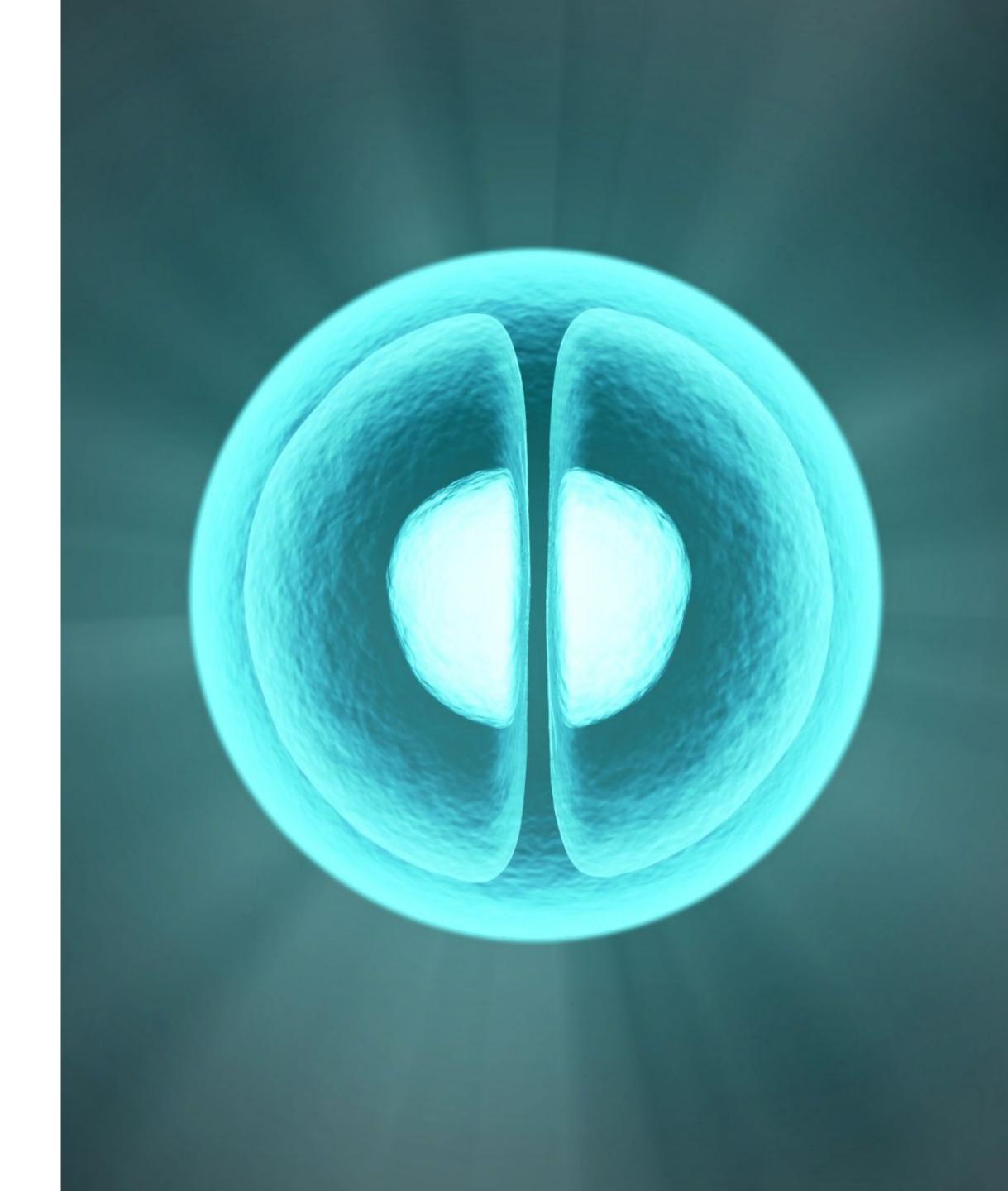
University of Toronto

Supervised: Dr. Bo Wang,

Co-supervised: Dr. Benjamin Haibe-kains

October 12, 2022

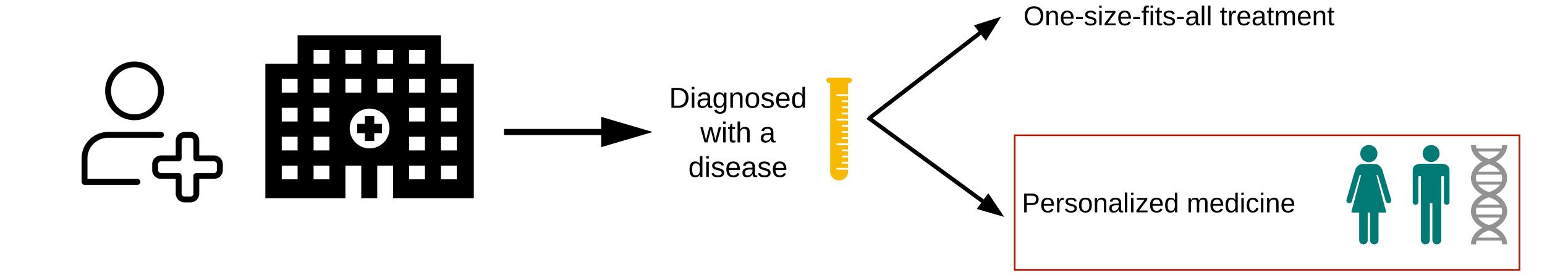




Overview

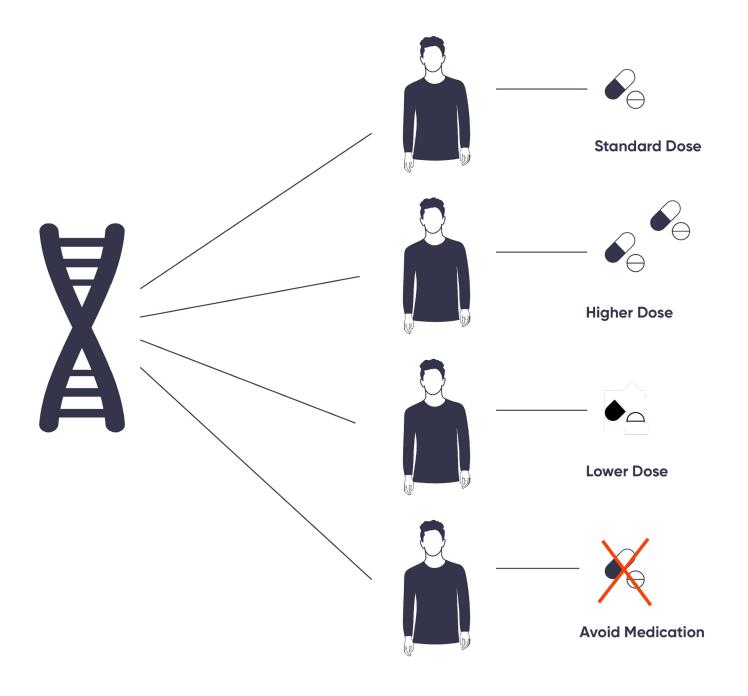
- Motivation
- Introduction to single-cell sequencing data
- Project proposal:
 - Optimal dimensionality reduction of single-cell data
 - Robust drug response prediction
- Who can join this project? Learning opportunities!

Motivation



Motivation

- How to find the most effective treatment for a patient?
 - Apply many possible treatment on the patient sample to select the best approach
- Challenge:
 - Testing many different treatments are impractical



There is a need for computational tools for predicting cell's response to different treatments

1. Patient pre-treatment genetic information

> Al Model

Effect of input treatment on the patient sample

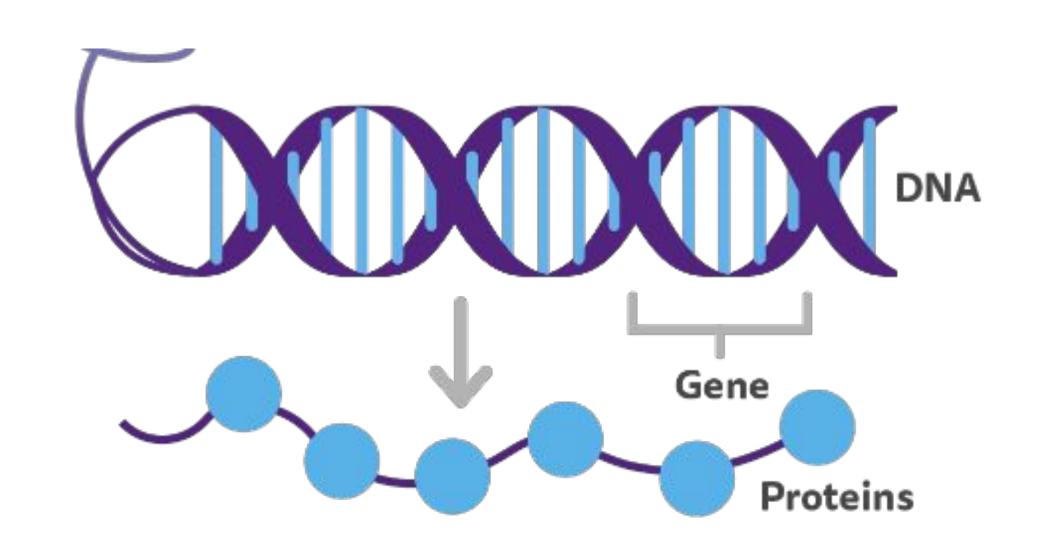
Shortlist the most effective treatments to be tested in clinic

2. Treatment information

• **DNA** (or deoxyribonucleic acid) is a long molecule that contains our unique genetic code. Like a recipe book it holds the instructions for making all the **proteins** in our bodies.

• Proteins are the functional units of cells!

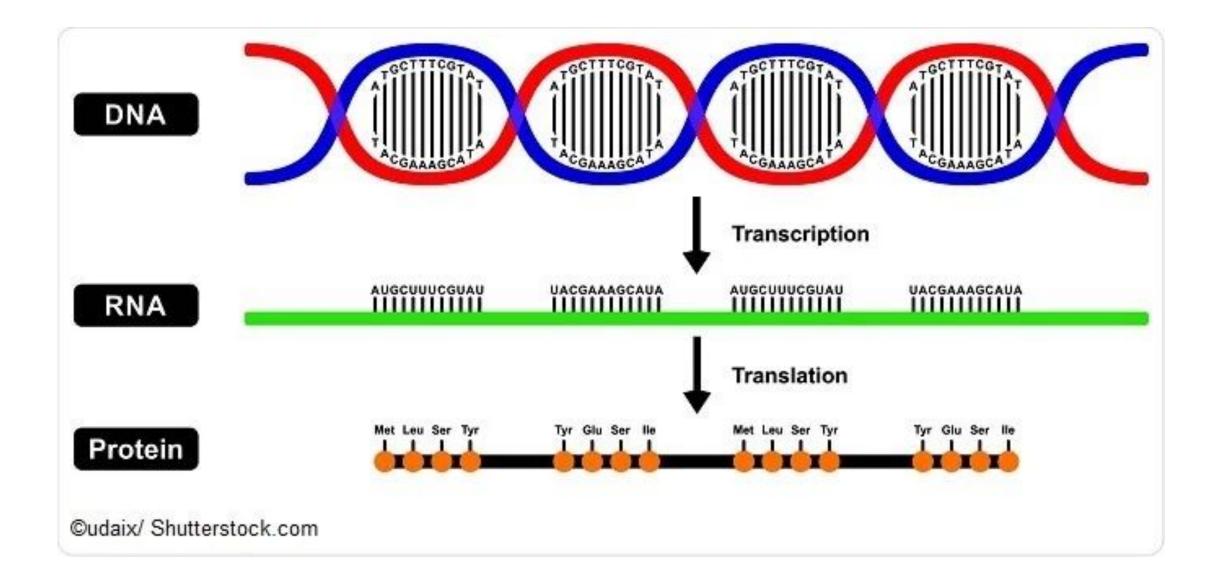
• How proteins are created? **genes** are segments of the DNA that encodes the information for making these proteins!



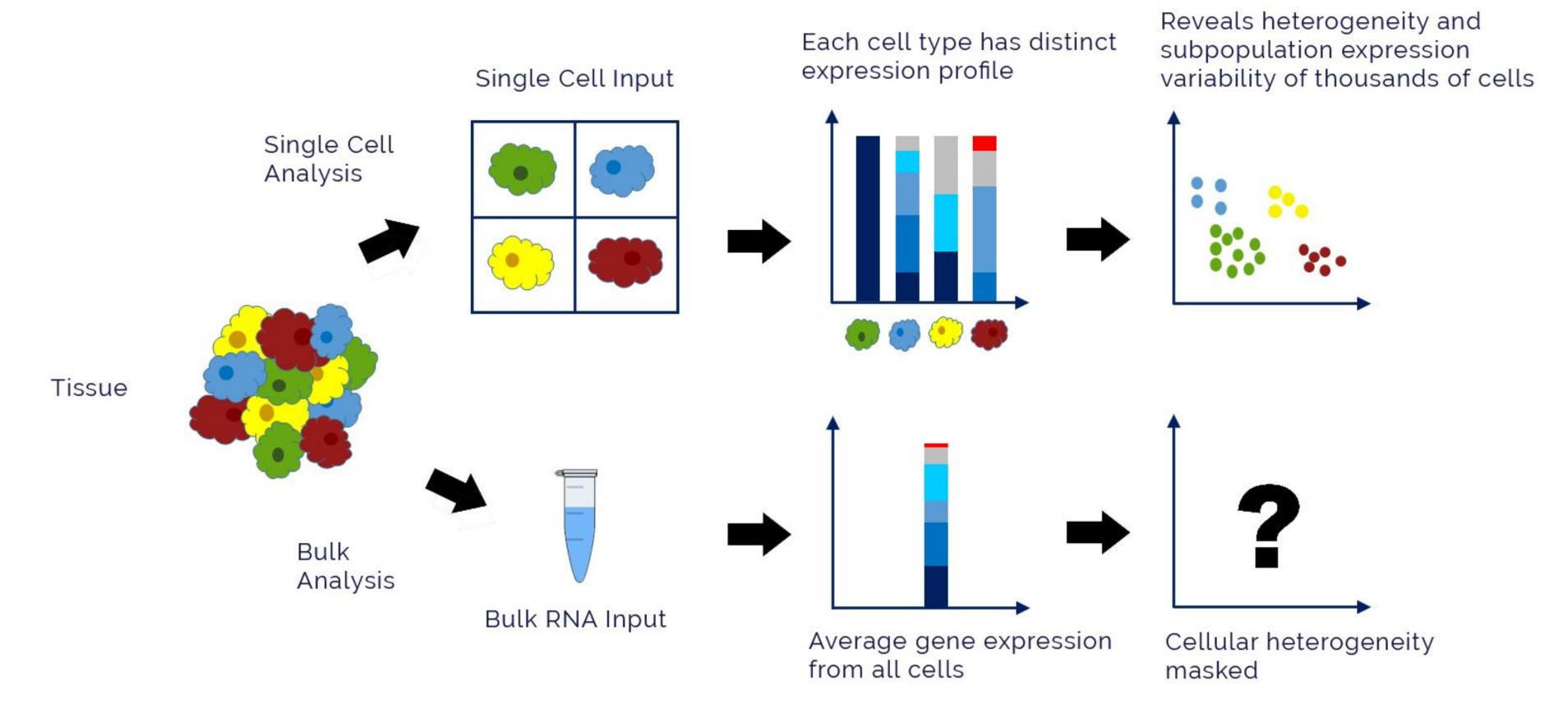
- Genes are transcribed into RNA
- RNA (intermediate message) are translated into proteins

 We focus on RNA data, which provide information about gene expression

 Gene expression controls how much RNA is made



RNA-sequencing technology measures the number of RNA for each gene (gene expression profile)

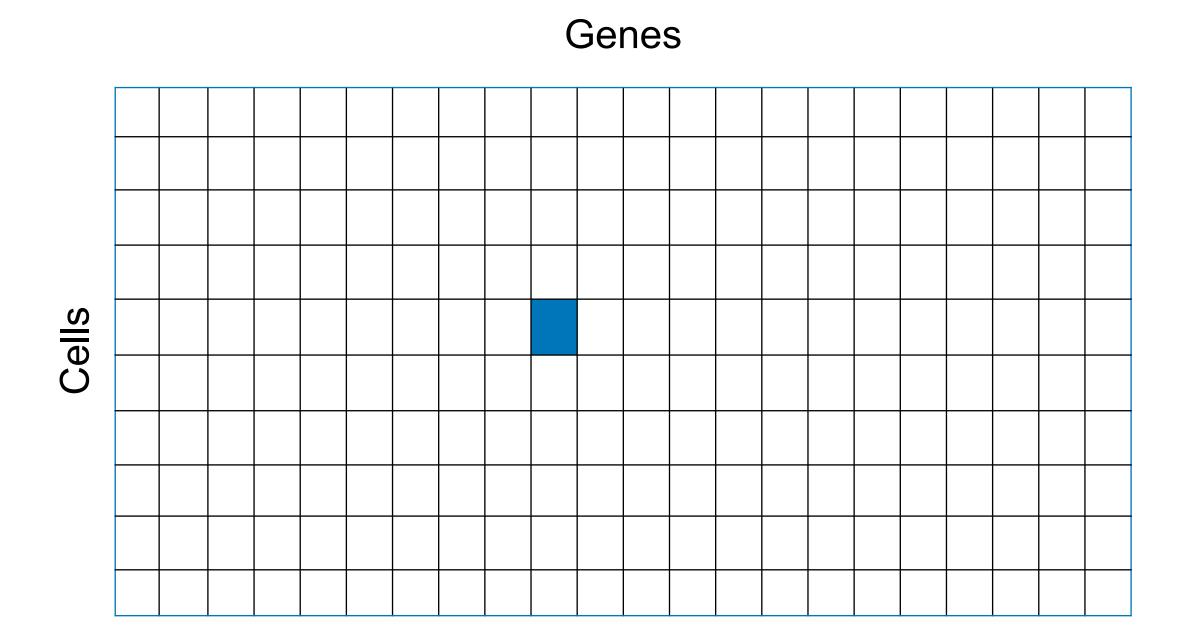


Data:

 We will work with single-cell gene expression data for pre-treatment and post-treatment samples

 Each element of this matrix indicate the number of RNA sequenced for a gene in each individual cell

Gene Expression Matrix



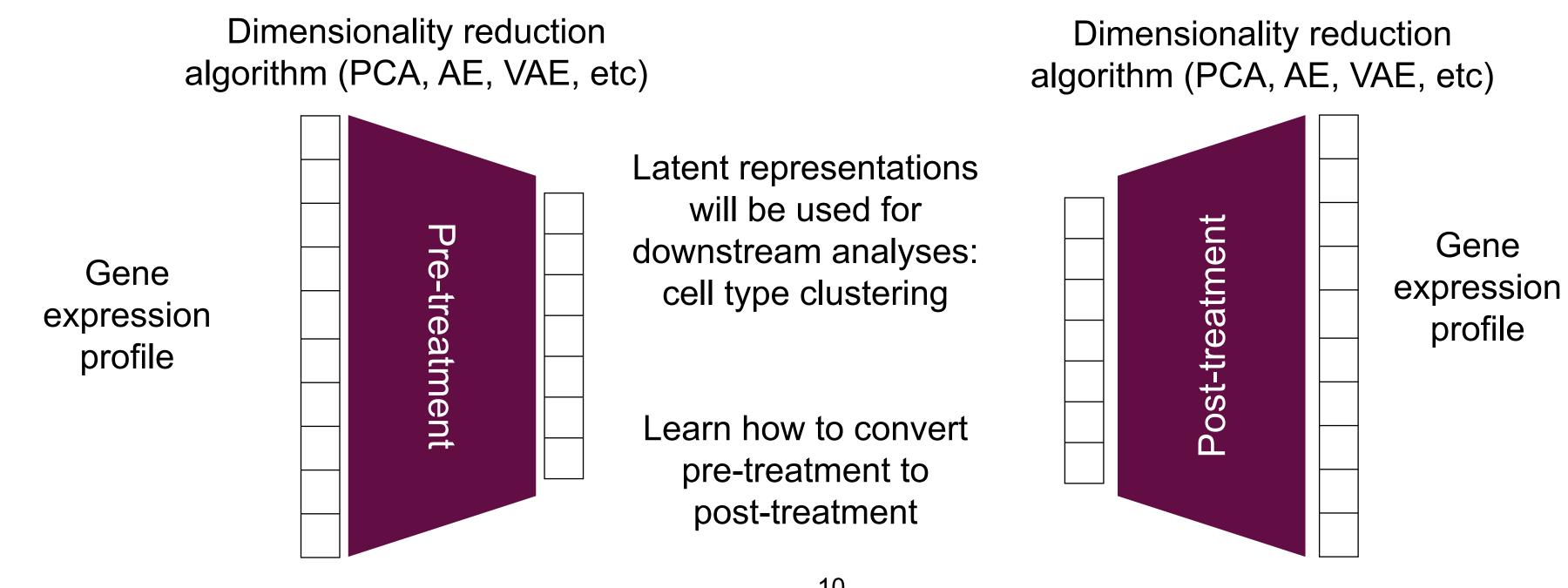
Problem: Developing a novel Machine Learning model for predicting a cell's post-treatment gene expression from pre-treatment gene expression

Two interesting proposed tasks:

- 1. Optimal dimensionality reduction of post-treatment gene expression profile
- 2. Effective post-treatment gene expression prediction from pre-treatment data

These analyses will give insight about what factors help training more robust and effective machine learning models for post-treatment cell state prediction

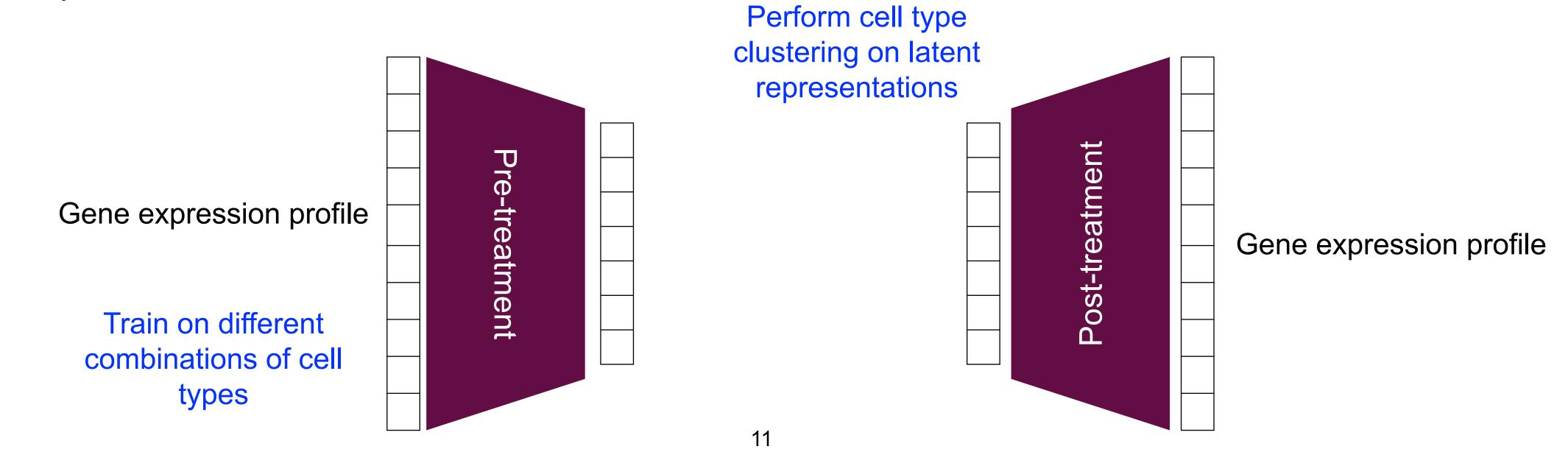
- Dimensionality reduction is a common task in high dimensional single-cell gene expression analysis
- First step in both tasks: Deploy an existing tool OR implement a Machine Learning model for post-treatment gene expression prediction from pre-treatment expression profile



Task 1: Optimal dimensionality reduction of high dimensional gene expression profiles

• **Objective**: To investigate the effect of cell type diversity and proportion in training samples on maintaining cell-type-specific characteristics in post-treatment lower dimension representation

 Proposed approach: Train ML model (Variational Autoencoder) on data with different cell type combinations and compare their cell type clustering performance on post-treatment latent representation



Task 1: Optimal dimensionality reduction of high dimensional gene expression profiles

• Data:

- Kang et al.
- Includes two groups of pre-treatment and post-treatment cells
- 8 cell types
- 18,868 cells, 6,998 genes
- 23M

- Task 2: Effective post-treatment gene expression profile prediction from pre-treatment data
- **Objective**: To investigate how the effectiveness of drugs would affect learning drug response prediction
- A metric was recently introduced for each drug, indicating how strong the effect of each drug is (Peidli et al.)
- Proposed approach: Train ML model (Variational Autoencoder) on data treated with different drugs and effectiveness, and compare the performance on post-treatment expression prediction

Task 2: Effective post-treatment gene expression profile prediction from pre-treatment data

• Data:

- Srivatsan et al.
- Includes two groups of pre-treatment and post-treatment cells
- Treated with 4 different drugs
- 14811 cells, 58347 genes
- 173.7M

Resources Estimation

- One GPU
- 8 CPUs
- 32G memory

Who can join this project?

- No biology background is required!
- Experience with Python (preferably PyTorch) is super helpful!
- Understanding Variational Autoencoder is helpful!
- Any motivated student interested in the drug response prediction can join!

Learning opportunities

- Learn about single-cell data and its features
- Get hands-on experience with Pytorch and using Python packages for running existing tools
- Learn about dimensionality reduction algorithms, generative model (Variational Autoencoder), clustering algorithms
- Learn and practice teamwork and collaboration!

Thanks for listening!

Any questions?