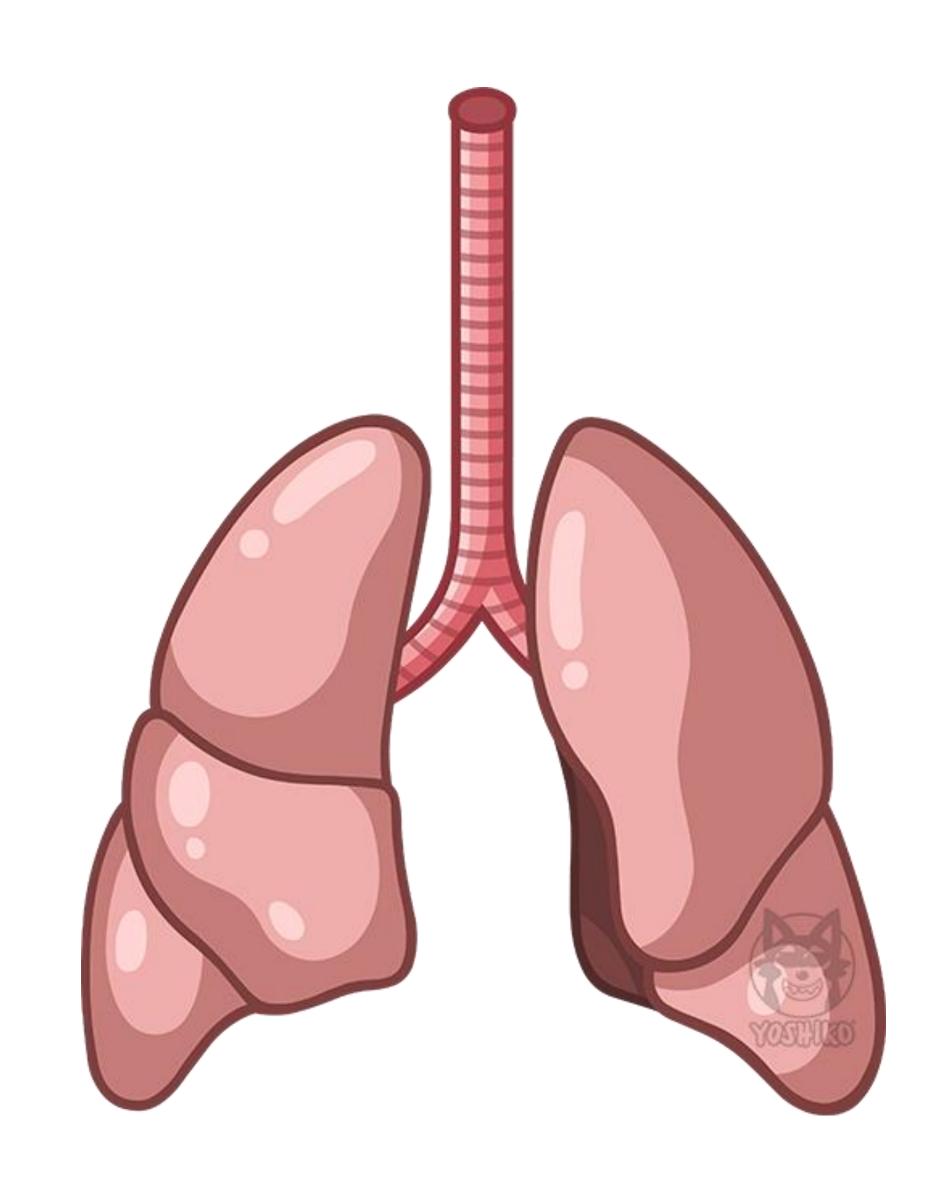
Predicting molecular biomarkers for cancer therapeutic response

Aubhishek Zaman, PhD

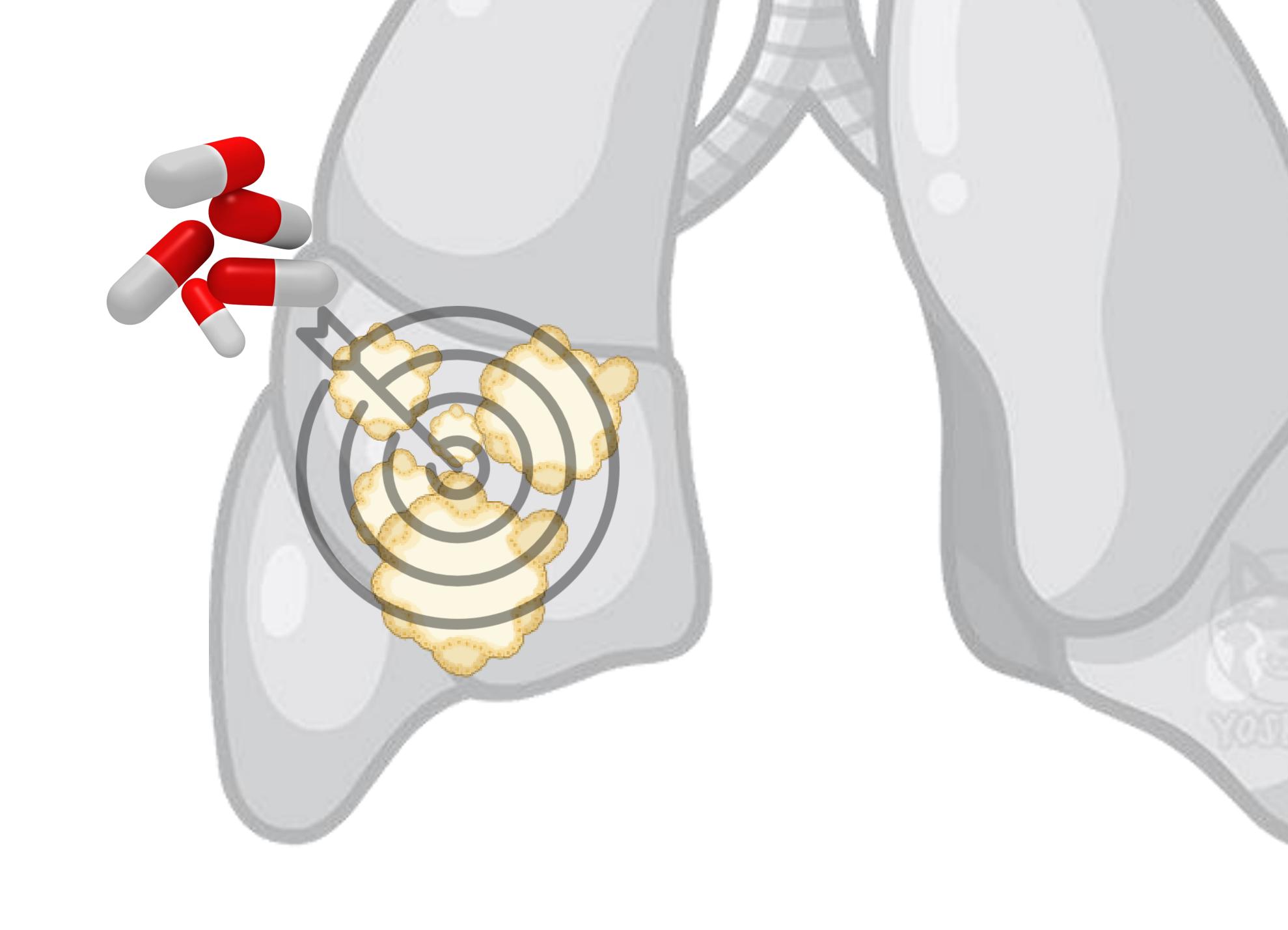




Lung Cancer

- leading cause of Cancer related death in the United States
- aggressive solid with molecular difference from normal cells
- cancer specific molecular difference is targetable

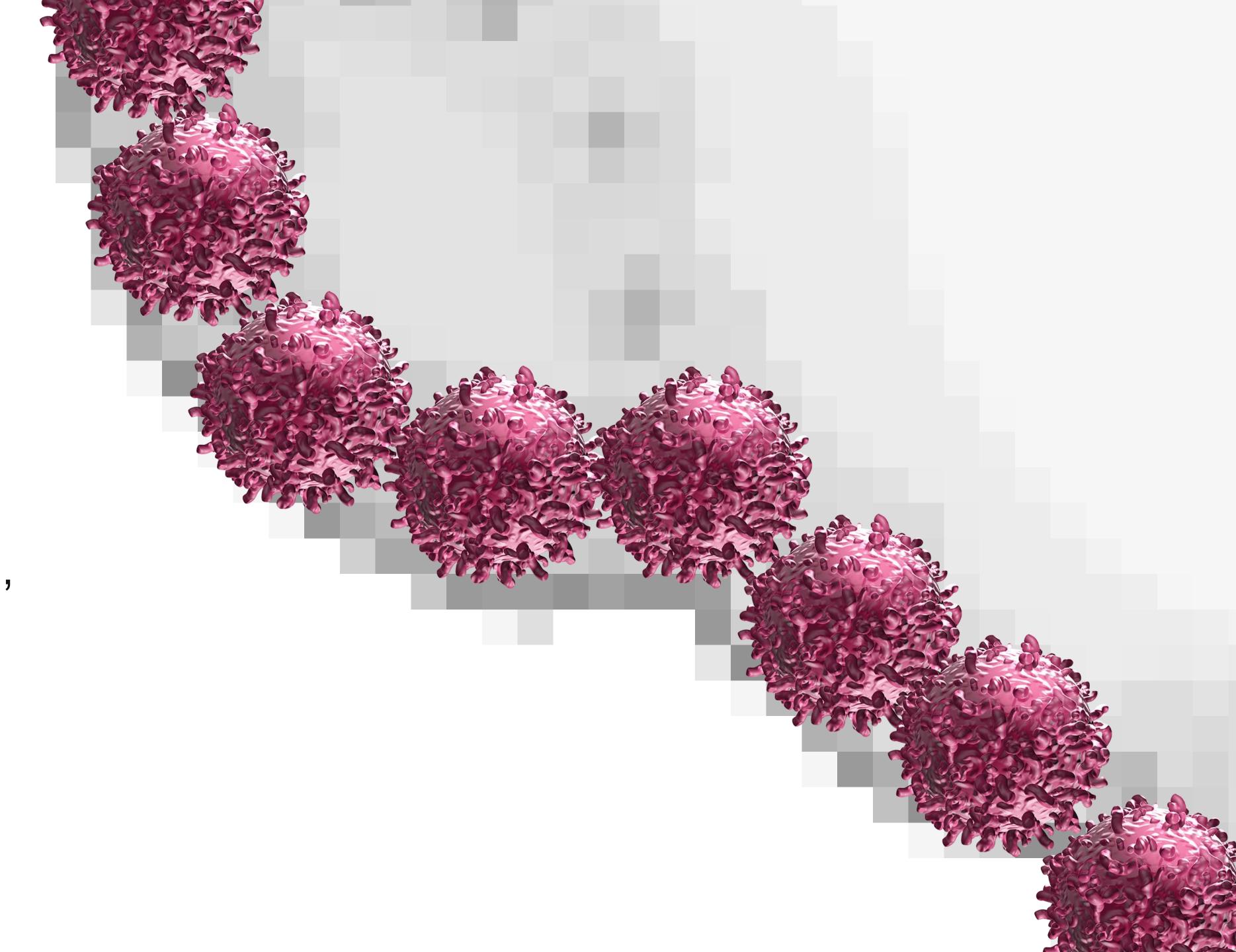


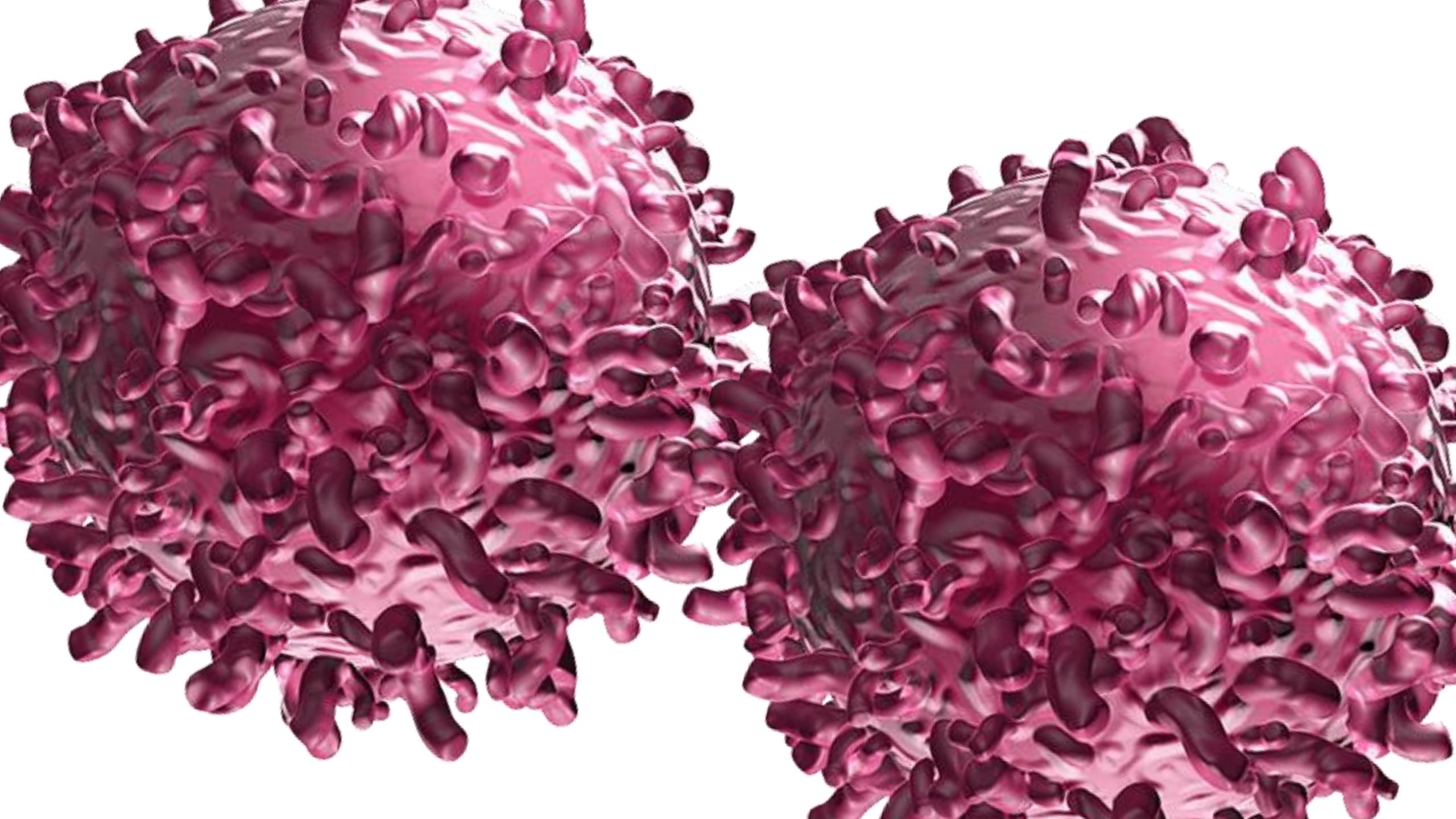


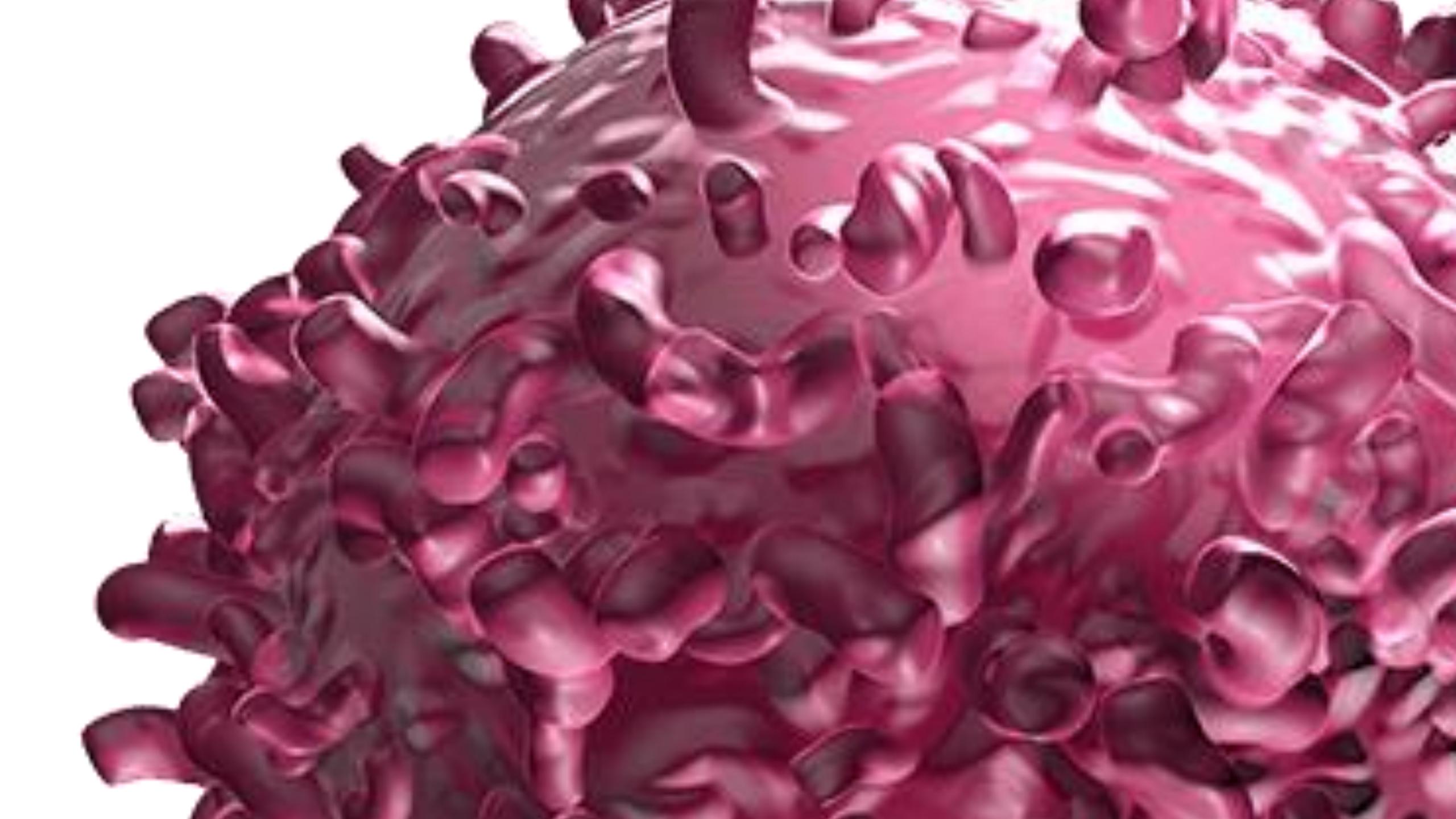


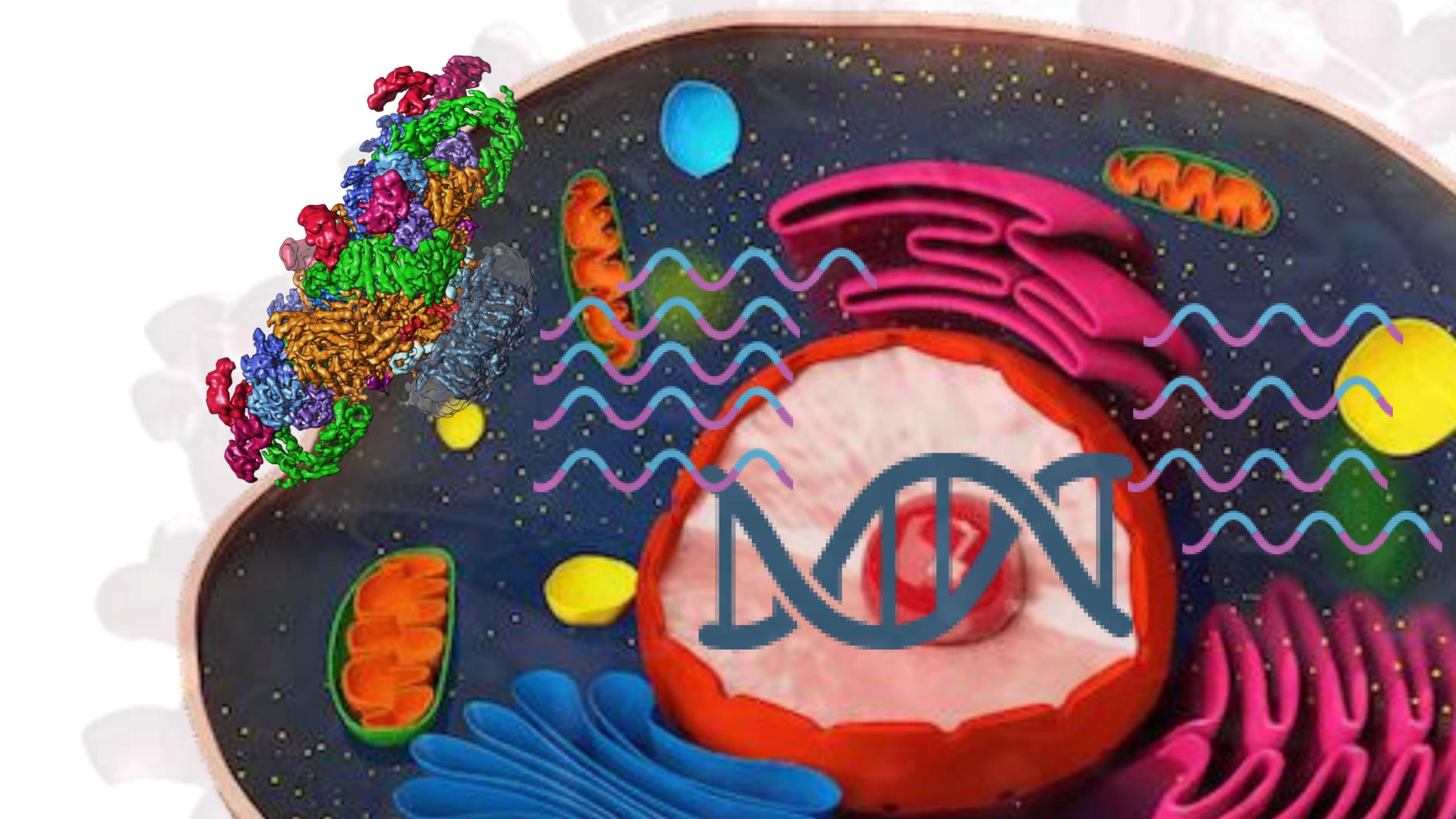
Molecular Features

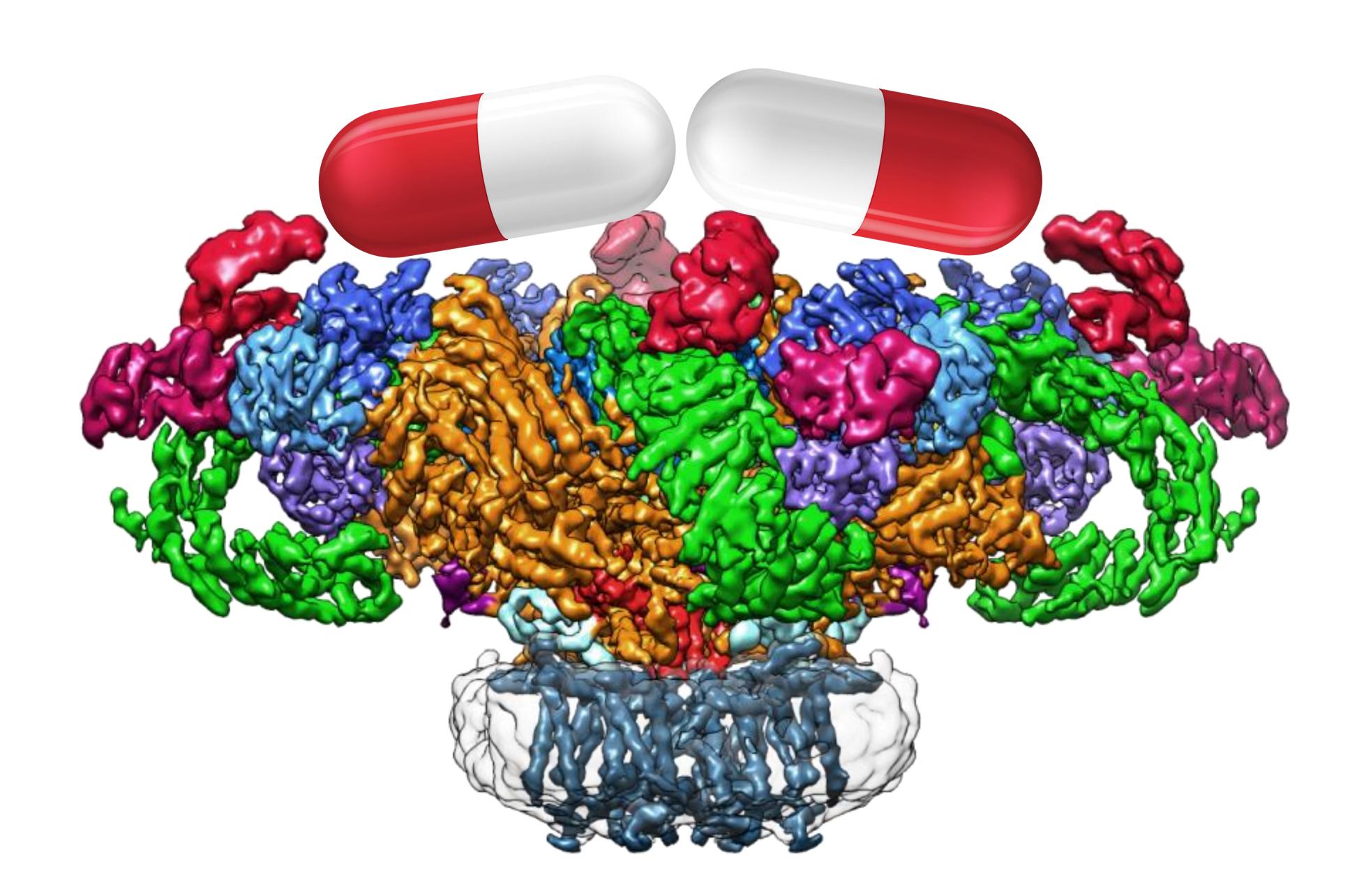
- Human cells (also cancer cells) have DNA, RNA, Portein, Carbohydrate and Lipid intracellular macromolecule
- Proteins are cells' functional coins







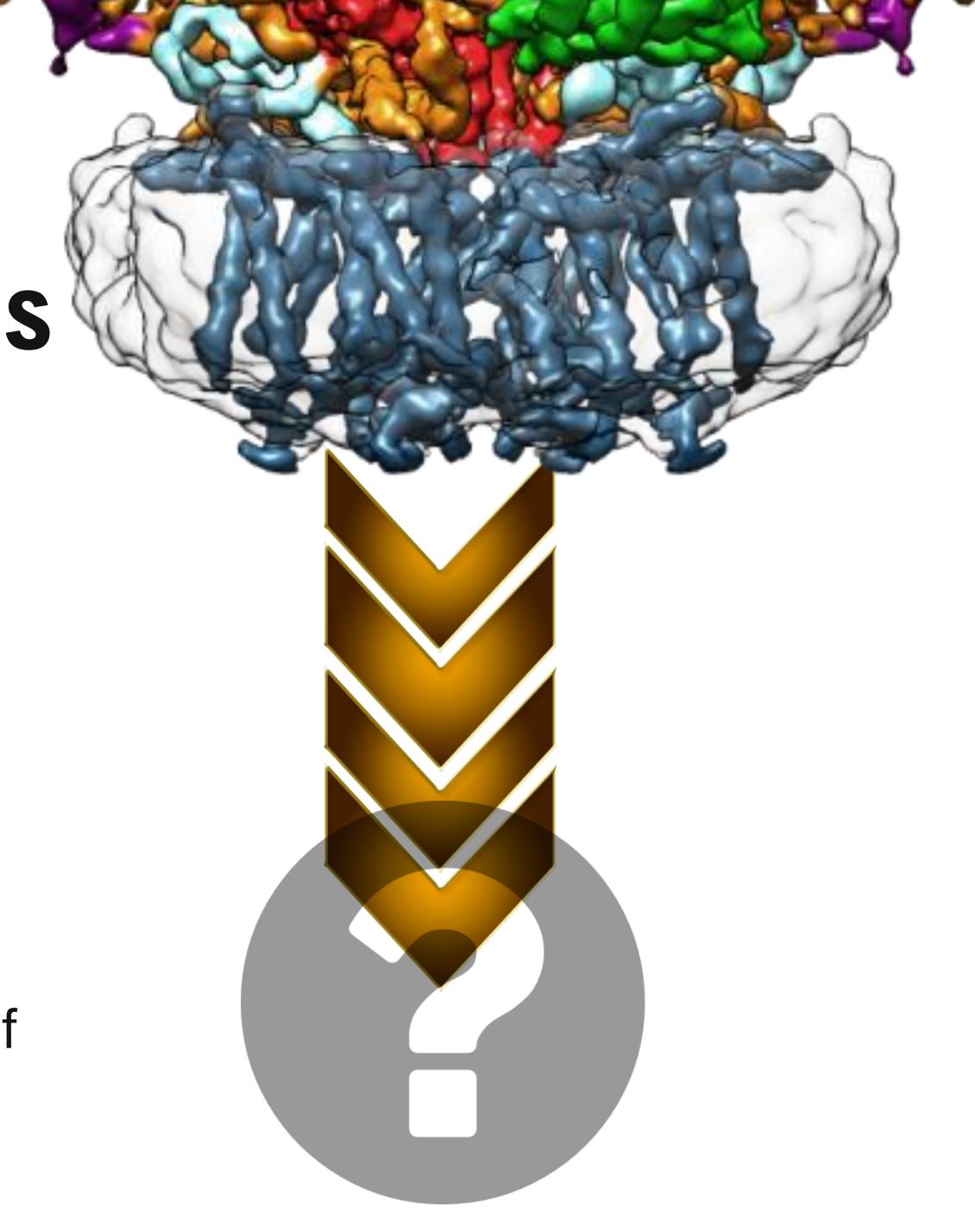






Targeted therapeutics

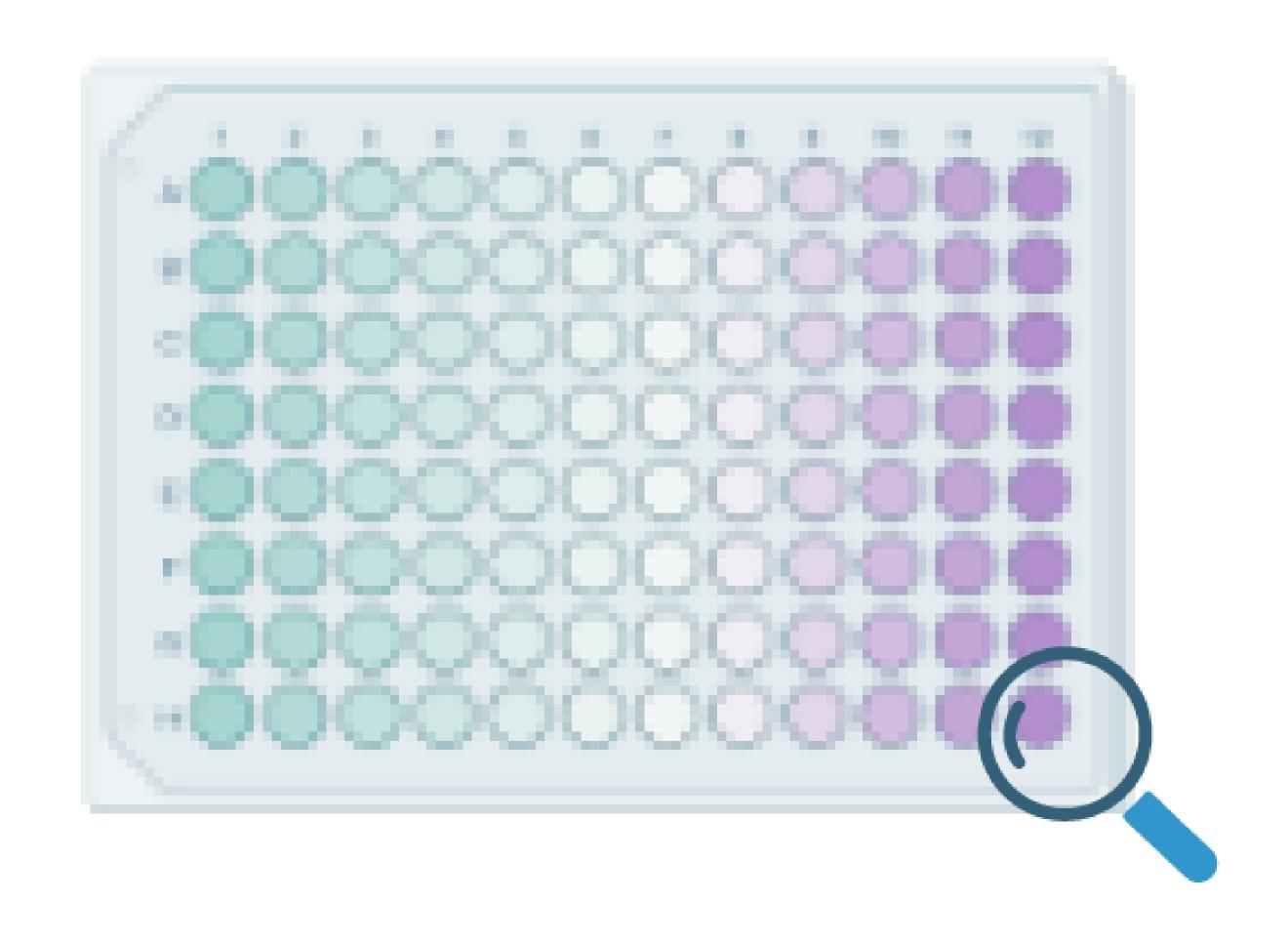
- Specific small molecules can be toxic in a cancer targeted manner
- Candidate small molecule to drug approval requires understanding of exact mechanism of action (MOA) for toxicity



- 1. Bioactive compound screenings:
- Easy to perform
- Combinatorial
 compound libraries
 are easy to scale



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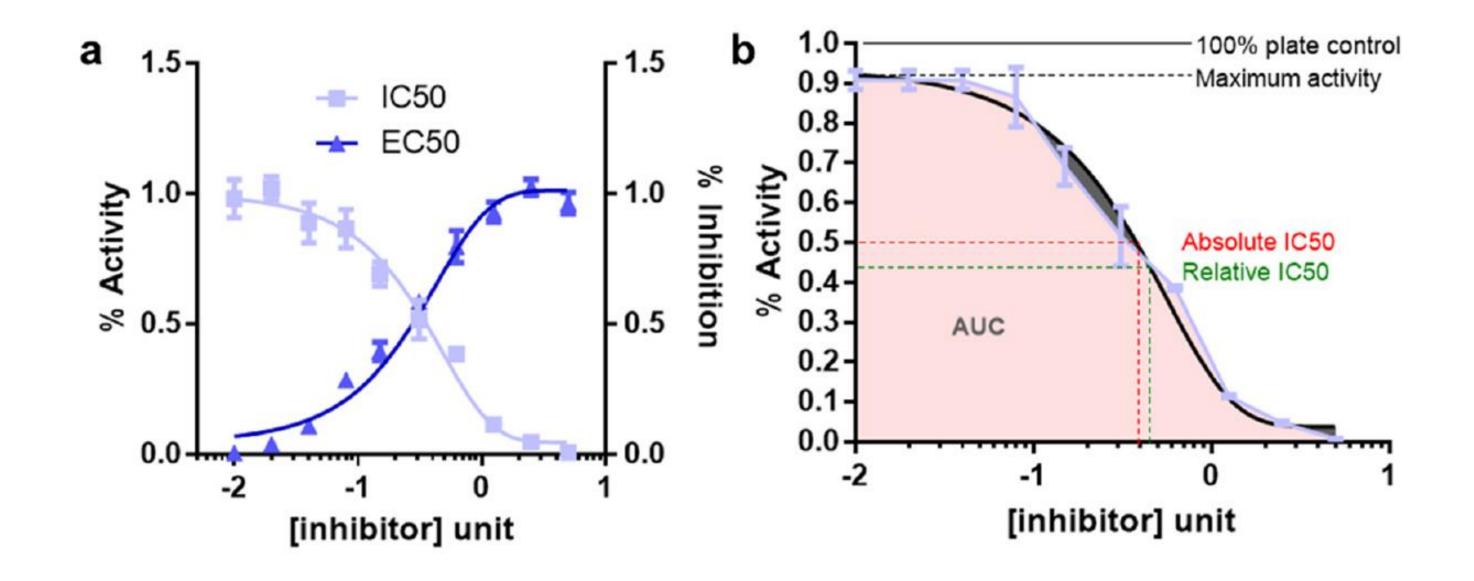
1. Bioactive compound screenings:

- Easy to perform
- Combinatorial
 compound libraries
 are easy to scale
- MOA studies answer
 how cells are
 sensitive to the drugs



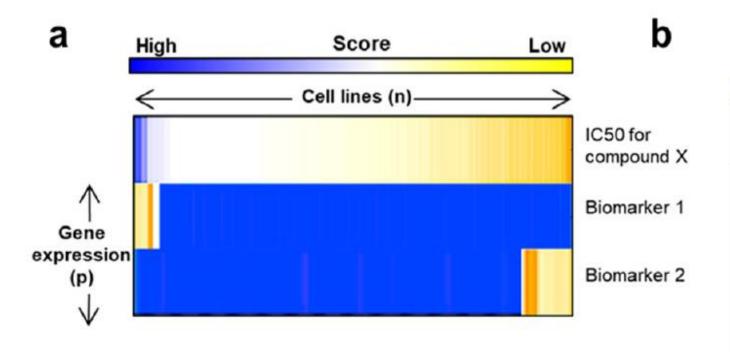
Compare sensitive vs resistant cells:

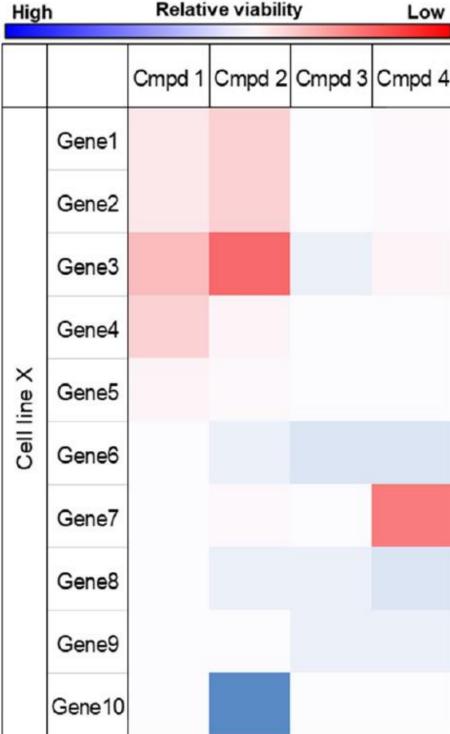
- Gene set enrichment analysis
- Weights are much less comprehensive
- Less quantitative more qualitative
- A group of gene prediction



Multiple elastic net regression (MLR):

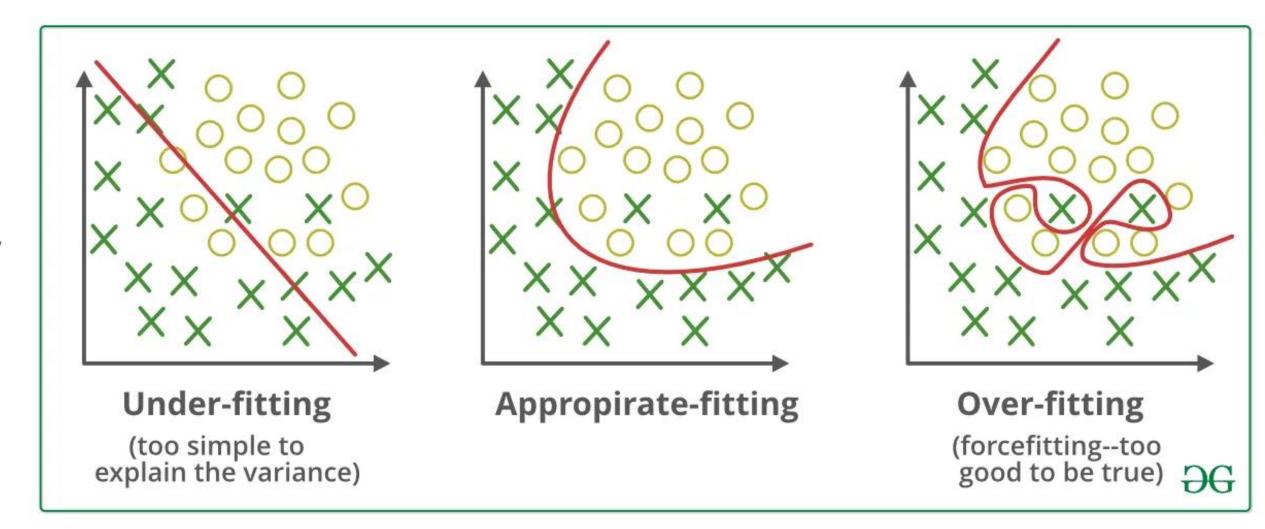
- Quantitative
- Deep learning methodology
- Train and test needs to be optimized often
- Individual biomarker nomination
- Compared to OMICS features
- N/P ratio problem
- Results in overfitting: the solution is unique for the dataset and fails on unknown test data

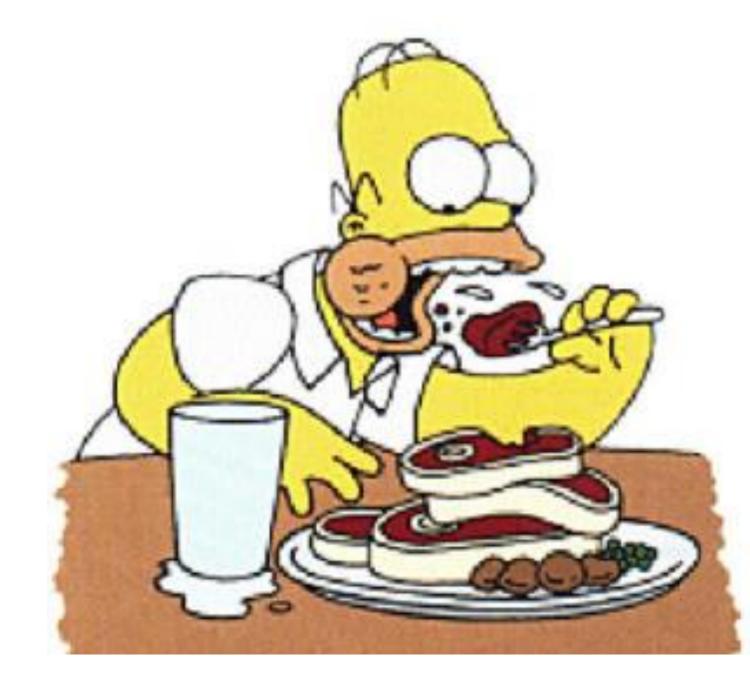




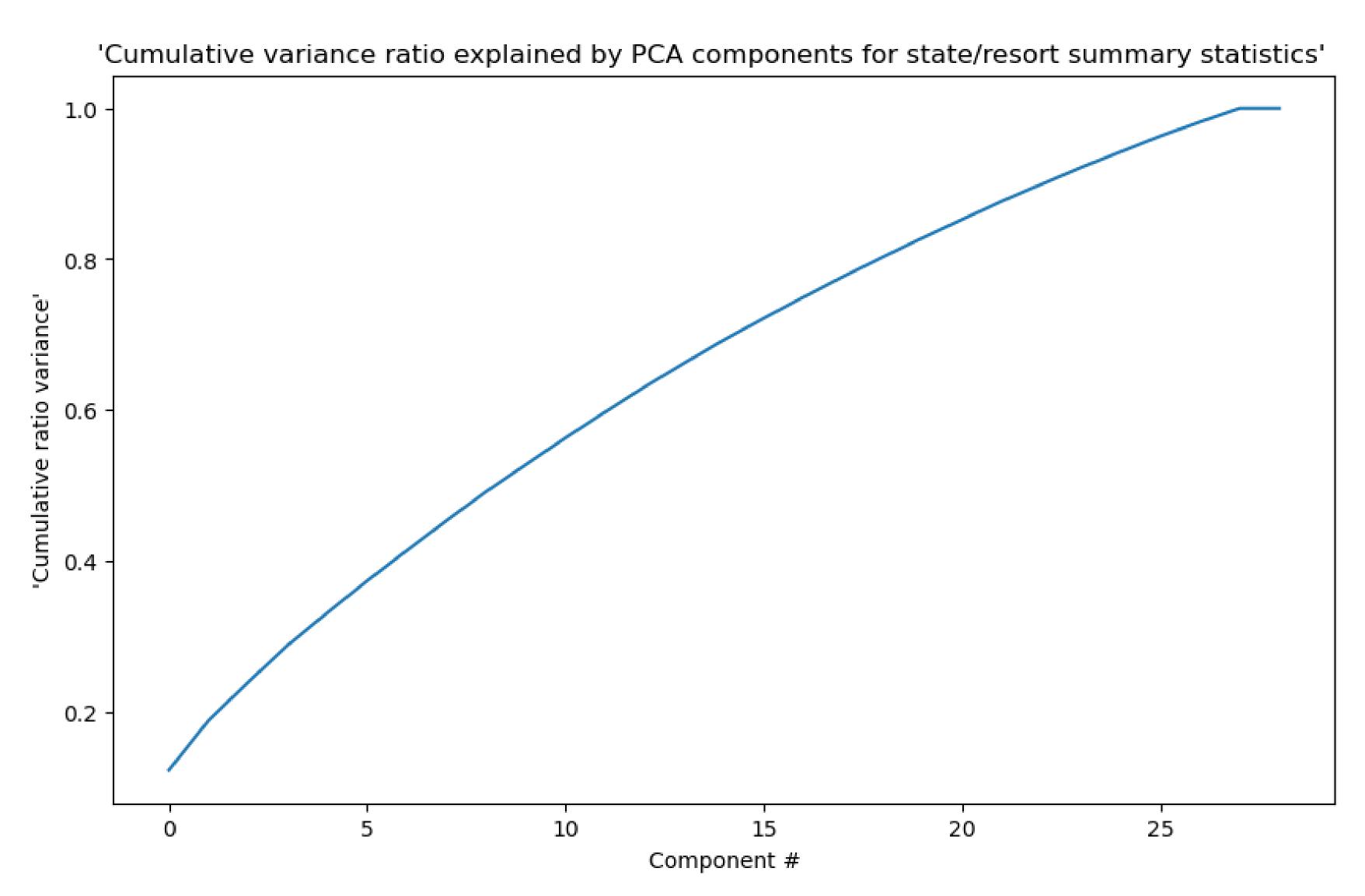
Elastic net regularization curbs overfitting

- L1 (Lasso) regularization: penalty term that lowers the complexity by minimizing the number of non-zero coefficients (note the w term being zero nullifies wx)
- L2 (Ridge) regularization: penalty term that lowers the complexity by making the weights more homogenous (note the squared term for weights, which are fractions)



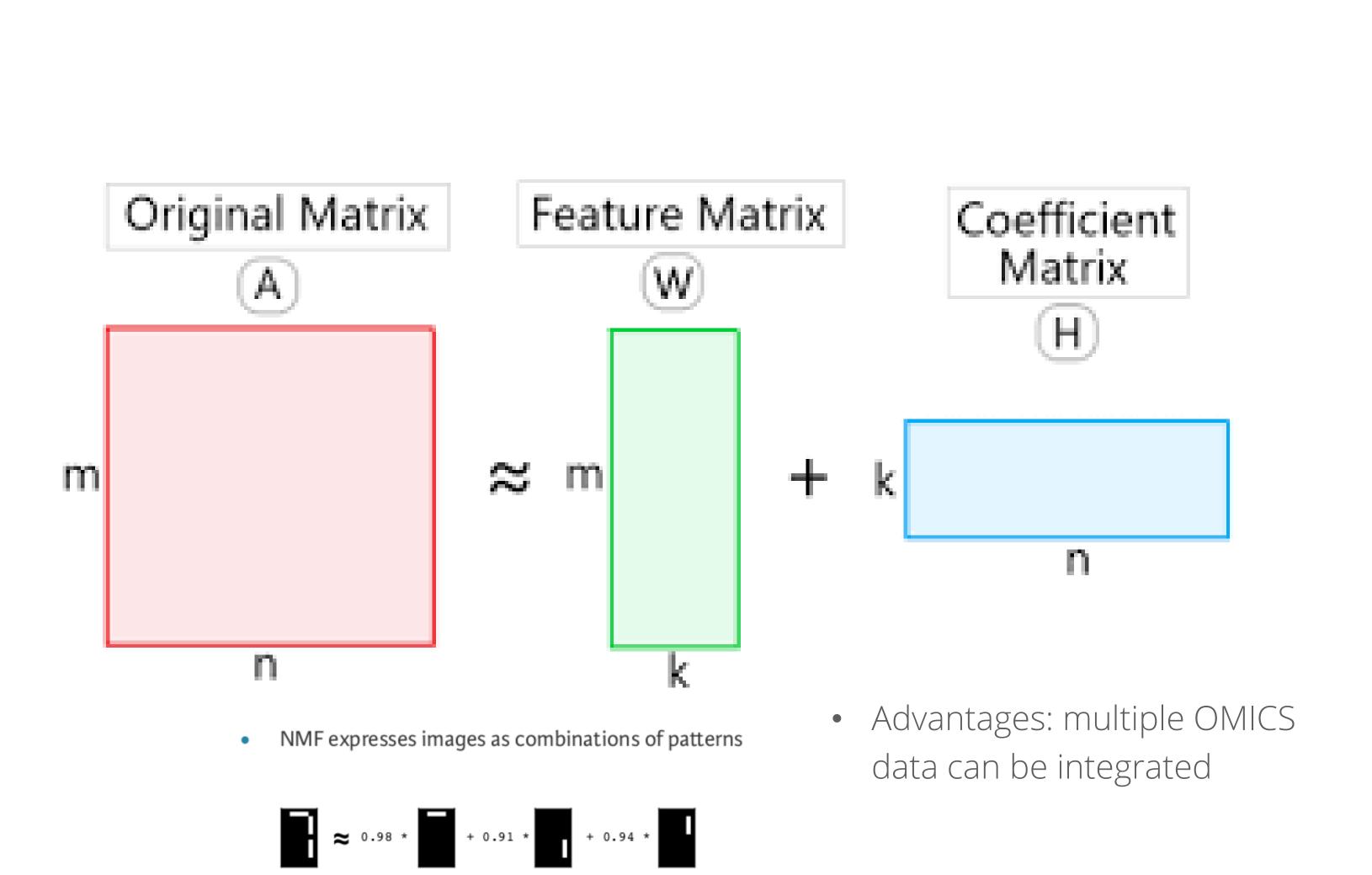


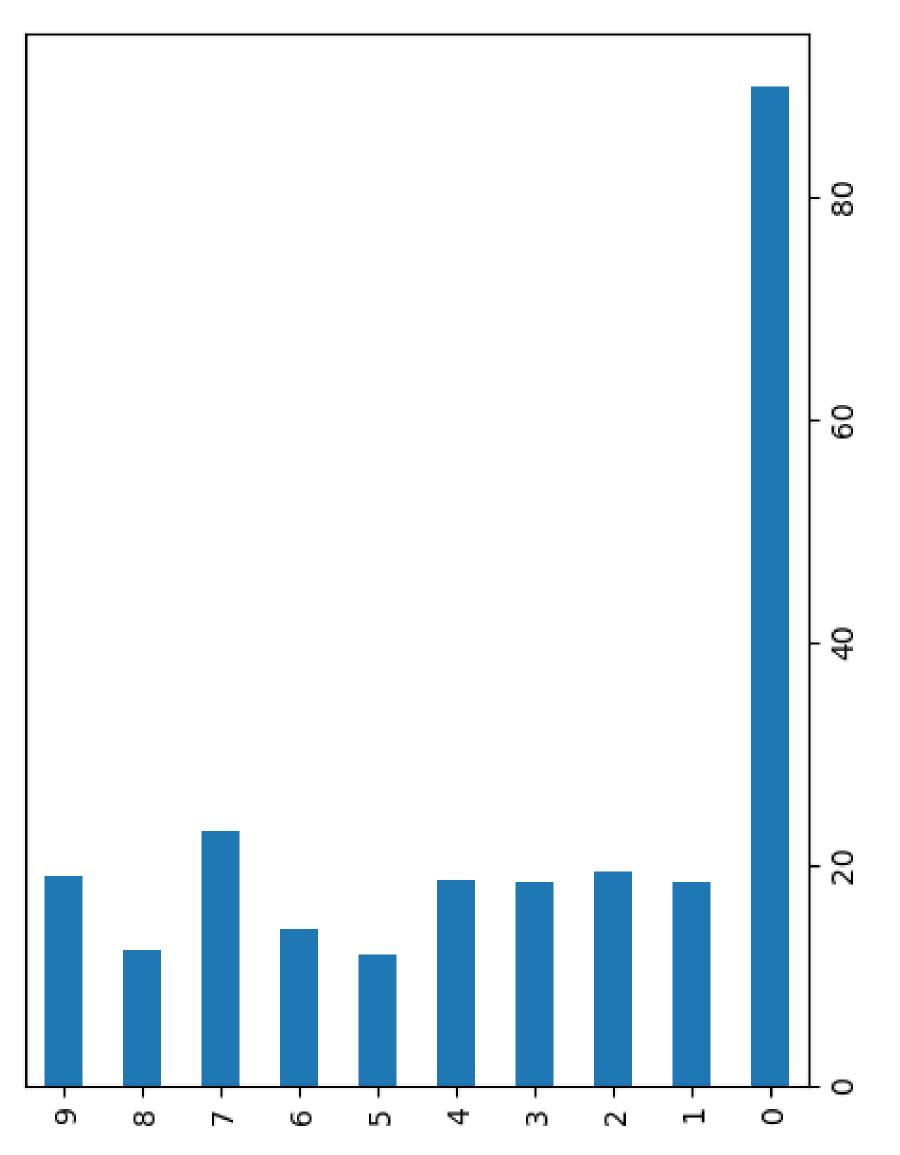
Data complexity is not contributed by a handful of exempler components/ outliers



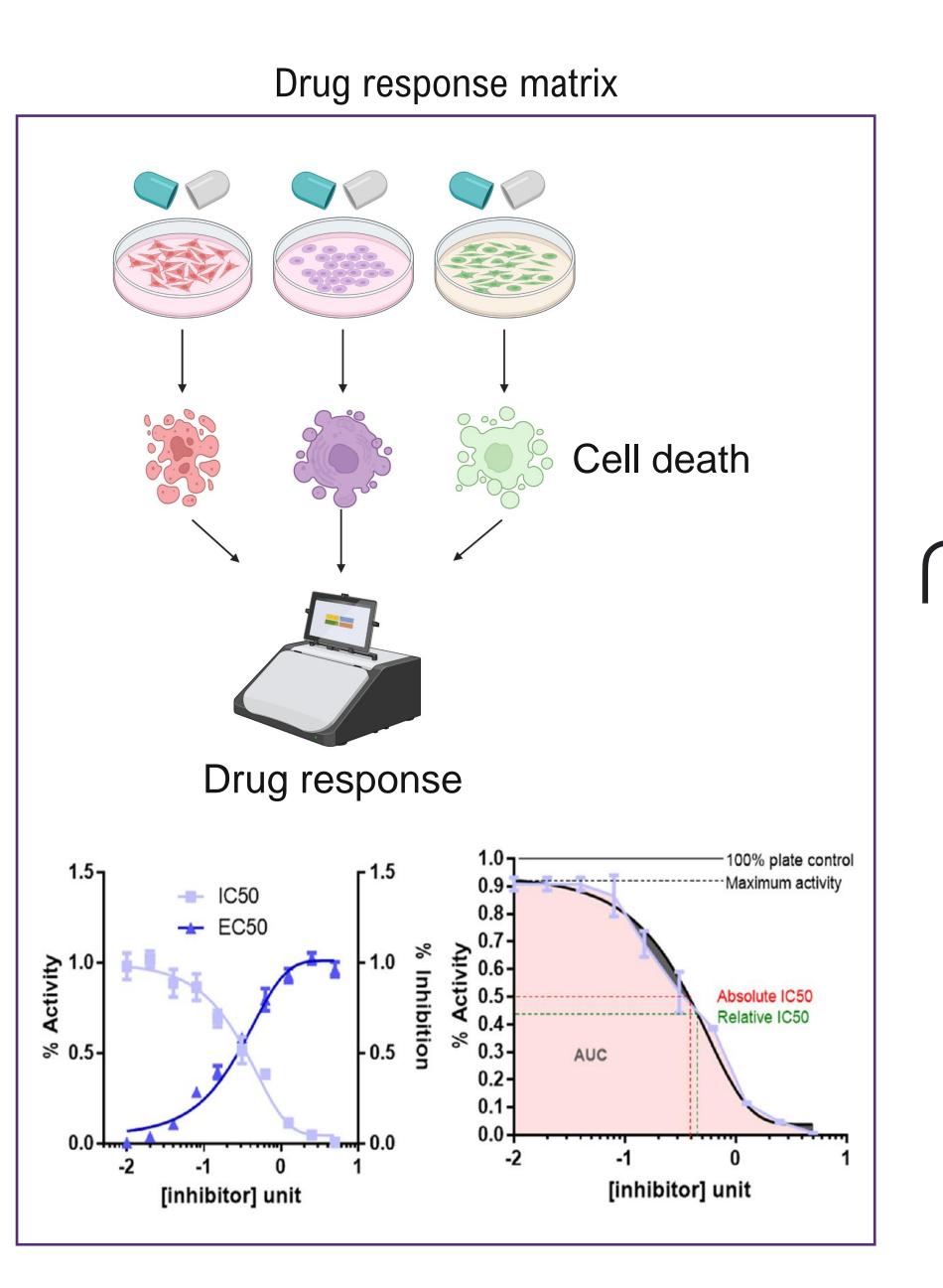
Alternative modeling: NMF (non-negative matrix

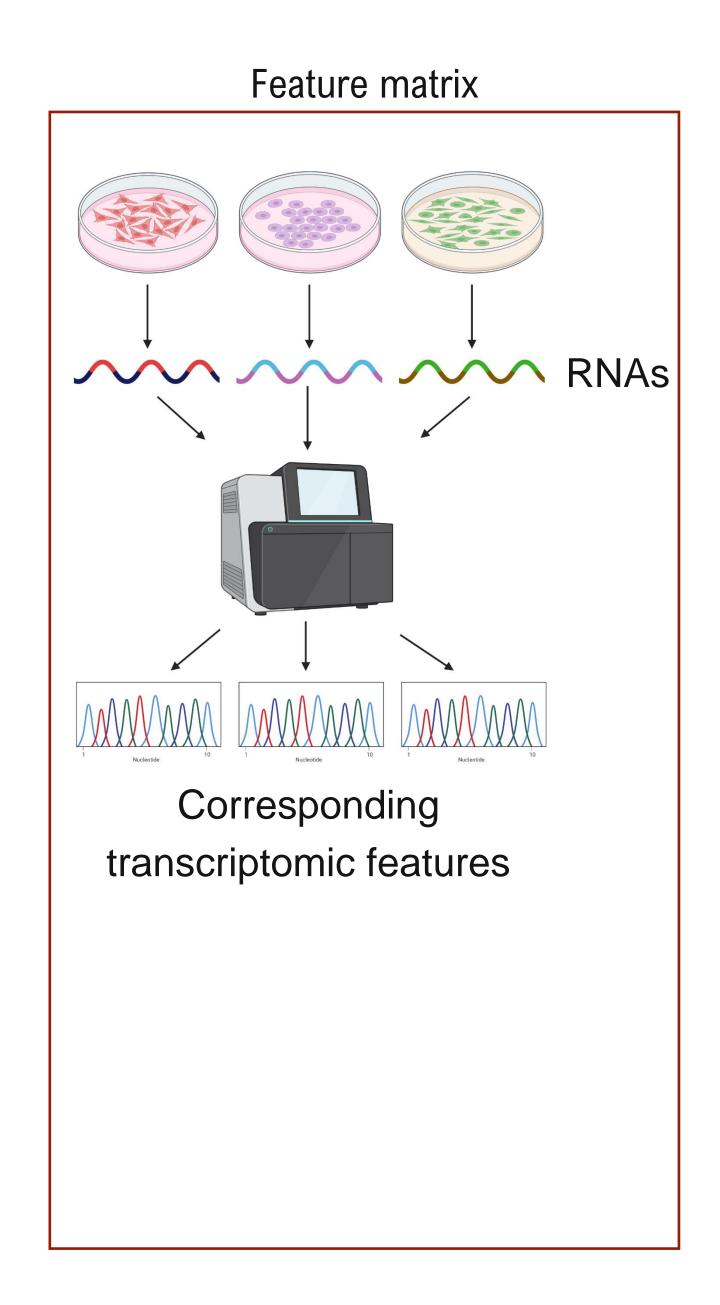
factorization)

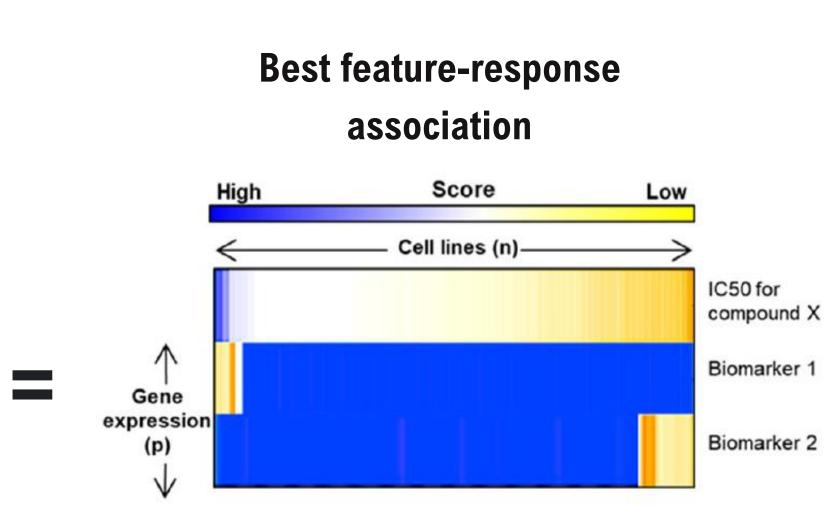




Data wrangling: dataset merging, cleanup and structuring







Modeling

Train-test split:

- 75-25
- No validation set

Hyperparameter tuning:

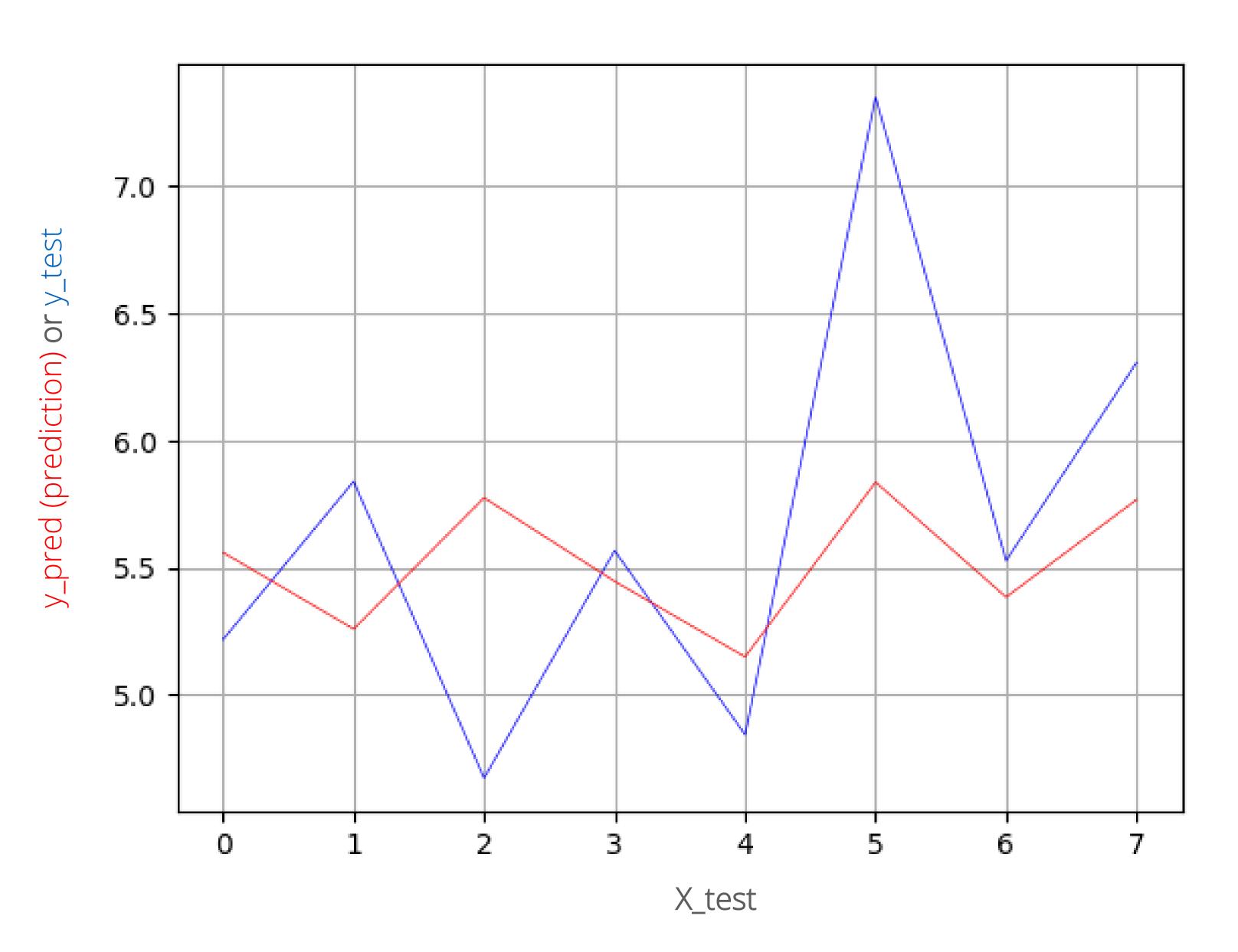
- Gridsearch:
- "max_iter" {1, 5, 10, 100, 500, 1000, 5000, 10000}
- "alpha" {0.0001, 0.001, 0.01, 0.1, 1, 10, 100}
- "I1_ratio" {0.0, 1.0, 0.1

K-fold cross-validation:

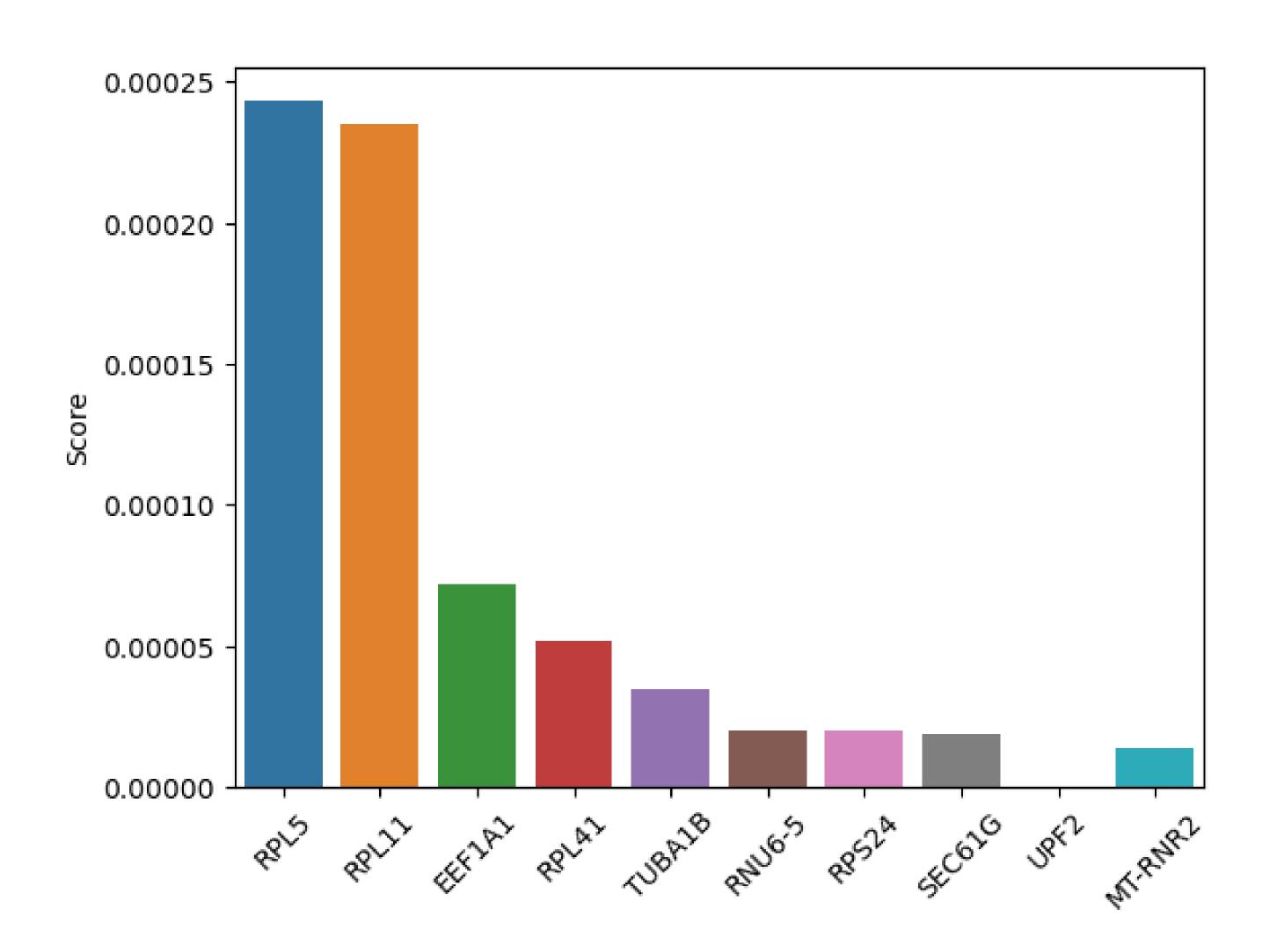
- Randomize (with seed)
- Repeat train test split and subsequent analysis

RMSE and MAE:

Accuracy check: ~0.7

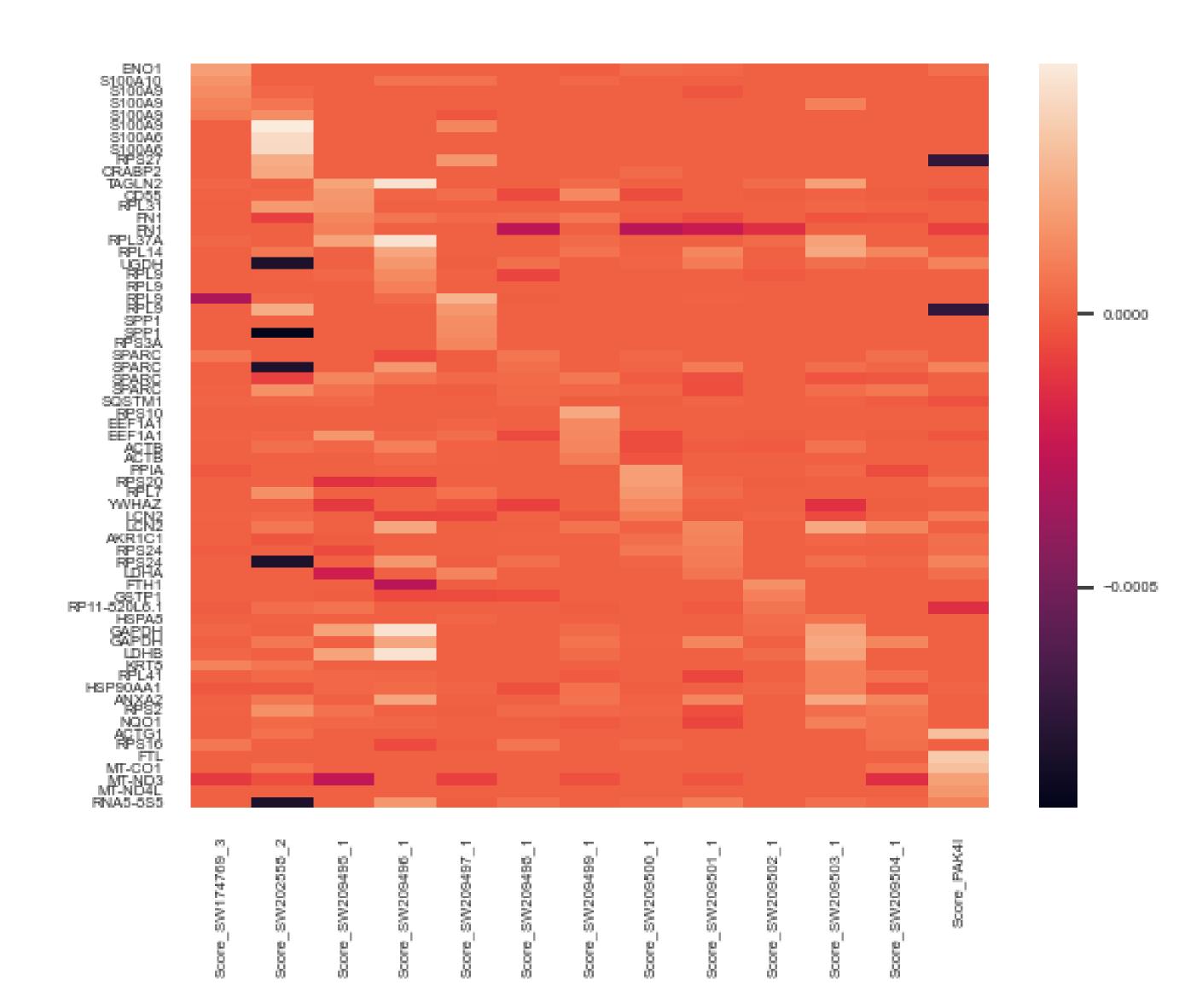


Result for feature importance for chemotherapeutic agent PAK4i

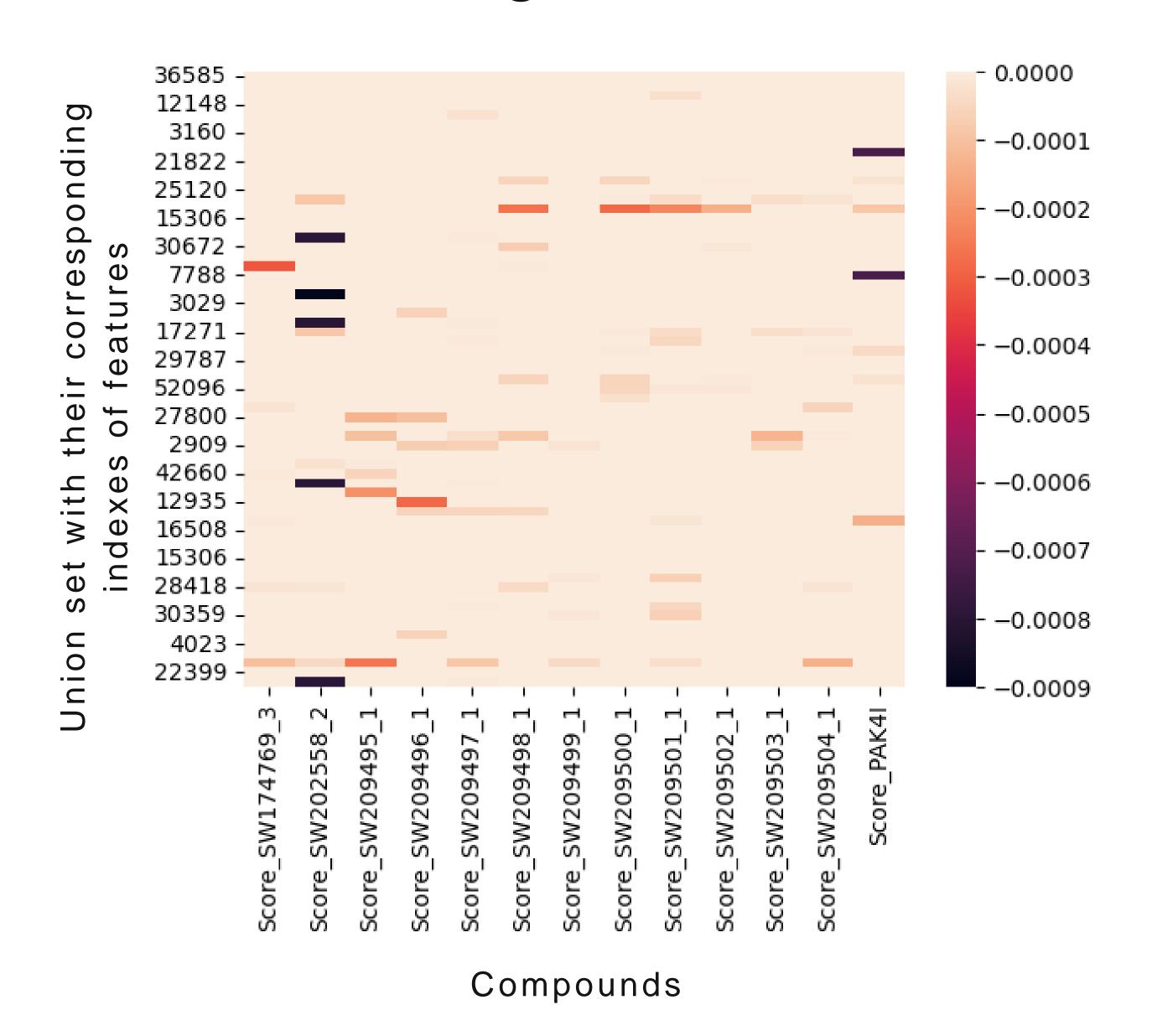


Heatmap for the result: positive correlators

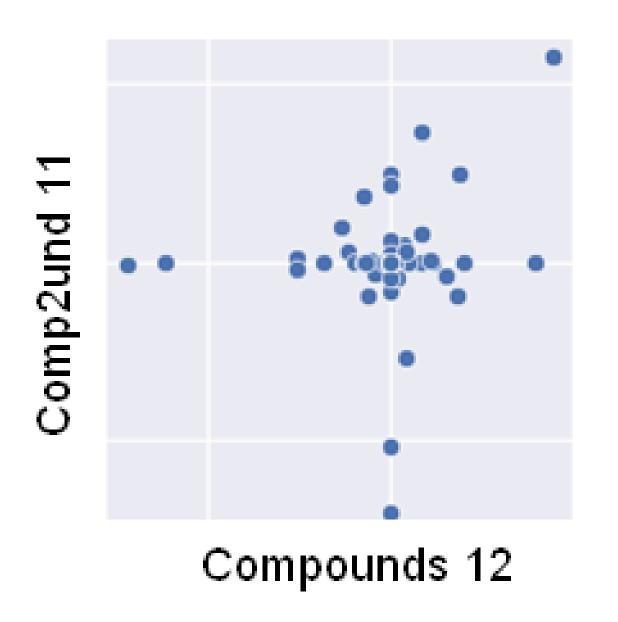
- For PAK4 inhibitor, the best biomarker was ACTG1 which has similar functionality to PAK4 (drug target)
- For the 2nd compound \$100 identified as a biomarkers
- For the 4th compound GAPDH was identified. The 3rd, 11th and 12th compounds also were predicting this as somewhat of a candidate biomarker

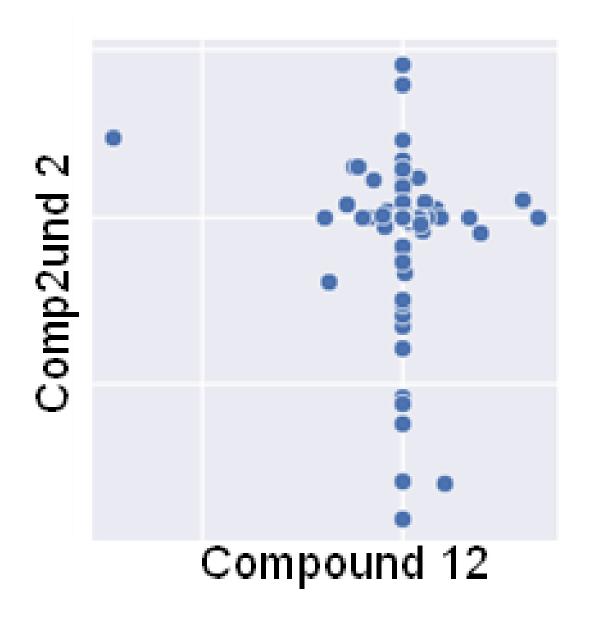


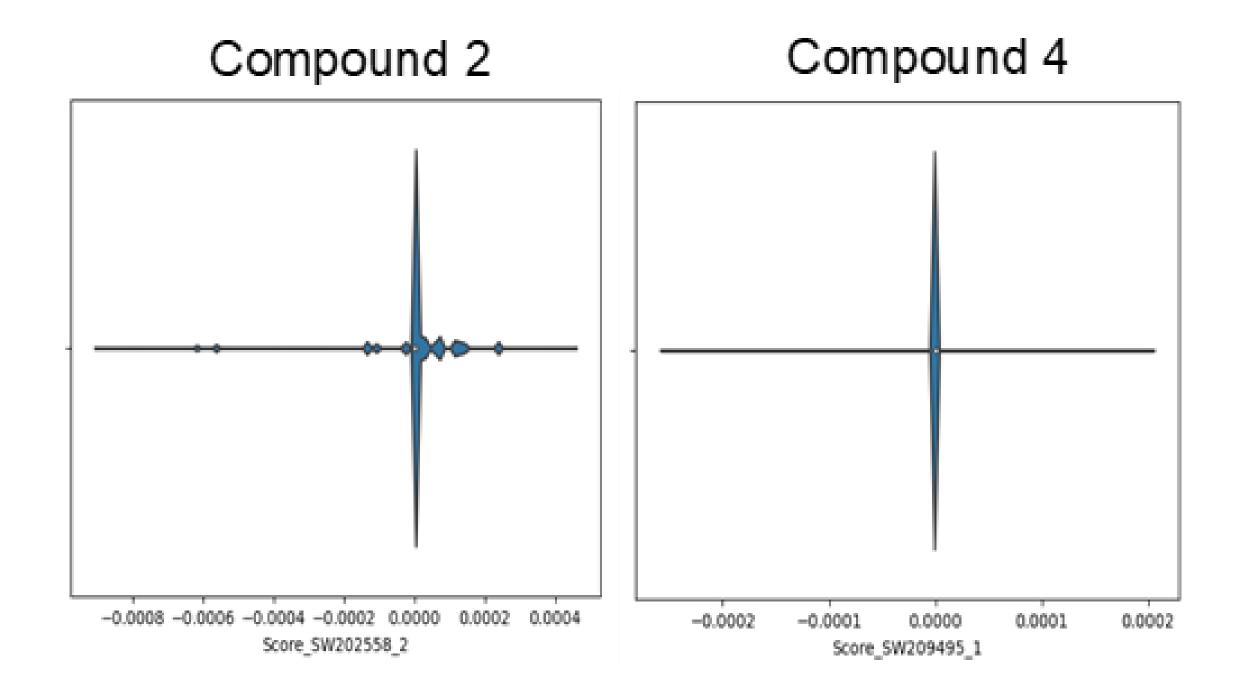
Heatmap for the result: negative correlators



Nonspecific vs specific hits







Future directions

Hybrid model: Classification followed by regression

Improved datasets: Dataset with validation set/gold standard and bigger datapoints should. SHAP and LIME methods to compare model accuracy

Multi-OMICS analysis: Couple transcriptomics with genomics and proteomics

