



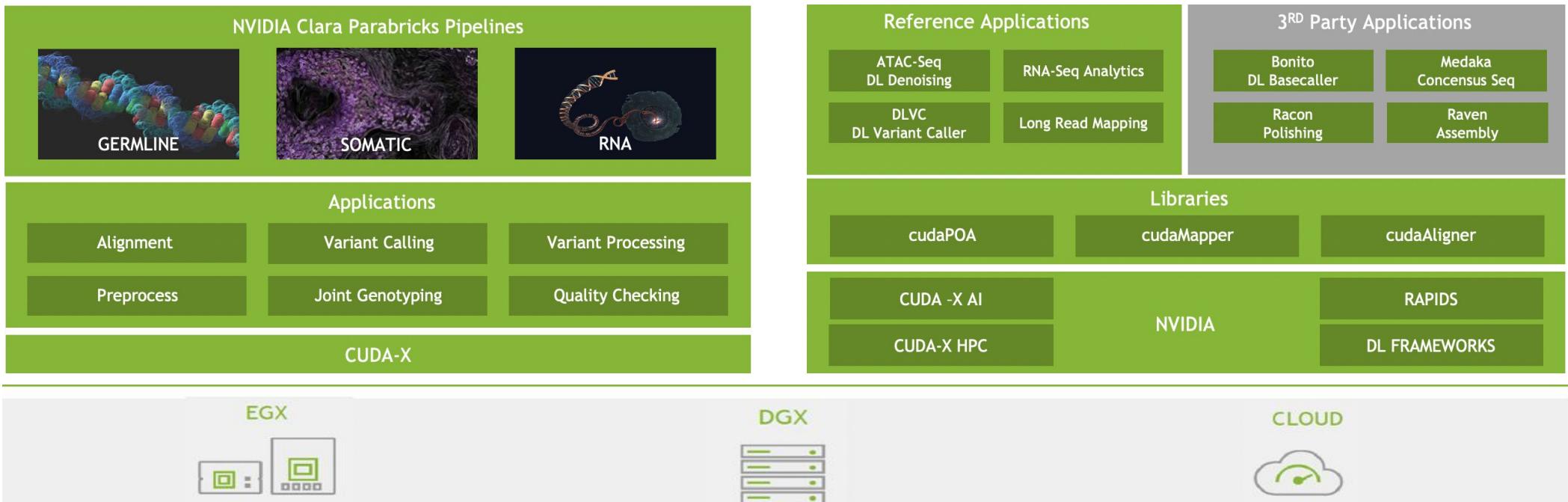
Machine Learning Tools to Analyze Gene Expression and Regulation

Avantika Lal, 07/15/2021

Outline

- GPU-accelerated genomic analysis at NVIDIA
- Gene expression and multimodal data integration
- Single-cell sequencing
- Variational autoencoders
- Predicting gene expression from sequence
- Deep learning to improve data quality

GPU-accelerated genomics at NVIDIA



Parabricks v3.6 Release- July 2021

WGS Pipeline for 30x Human Genome in 22 Minutes on an DGX A100

Update referenced mapped data / re-analysis of legacy data

- > 10x acceleration of BAM2FastQ

More Comprehensive Somatic Calling

- LoFreq addition, expanding to 4 callers
- Vote-based merge tool for fast variant filtering (e.g. allele frequency)
- VCF Annotation Tool for better quality variants (+ BAM QC)

De novo germline mutation pipeline

- Supports trio sequencing and uses Google's DeepVariant1.0

Two Structural Variant Callers

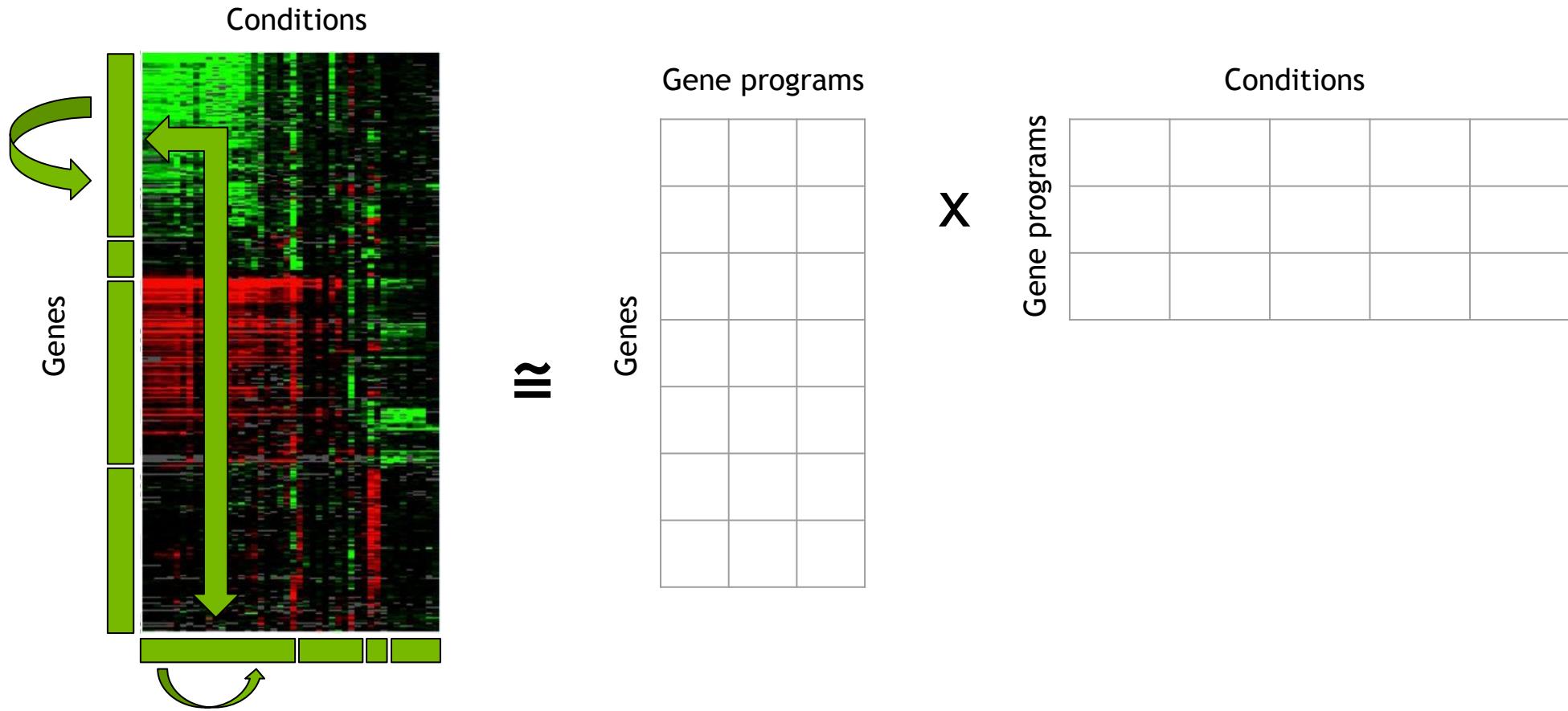
- Manta and Smoove (Lumpy)



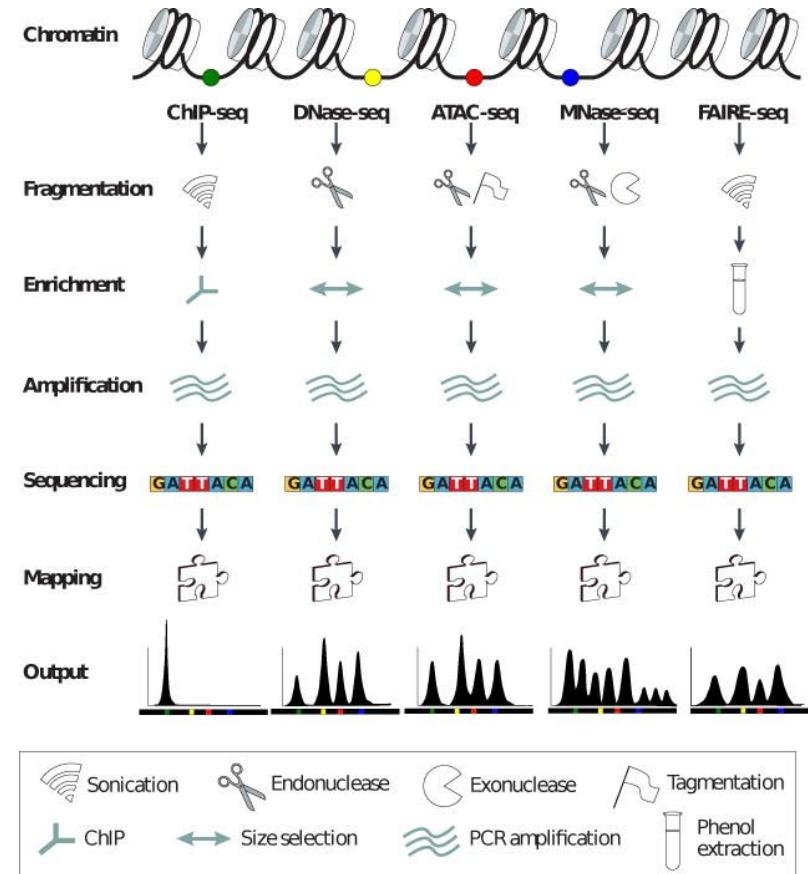
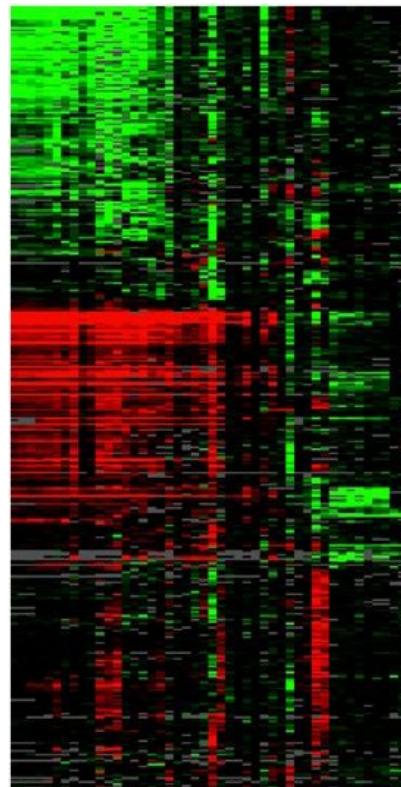
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<https://www.nvidia.com/en-us/docs/nvidia-parabricks-general/>

Gene expression profiling and multi-omic integration

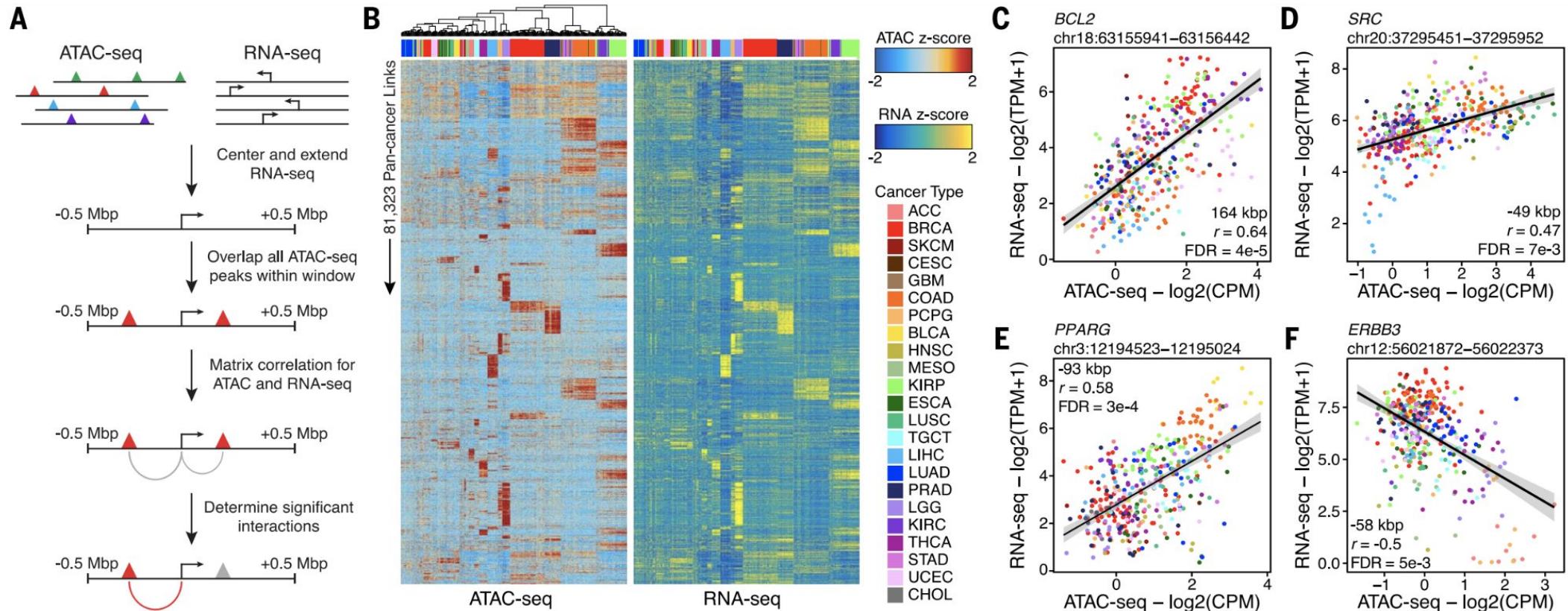


Gene expression profiling and multi-omic integration

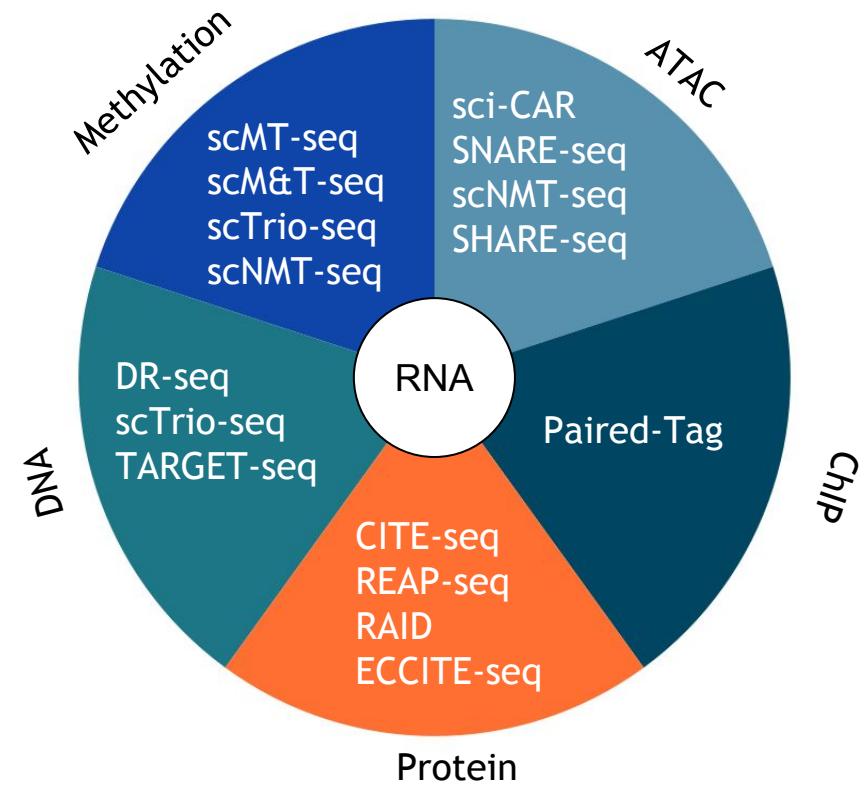
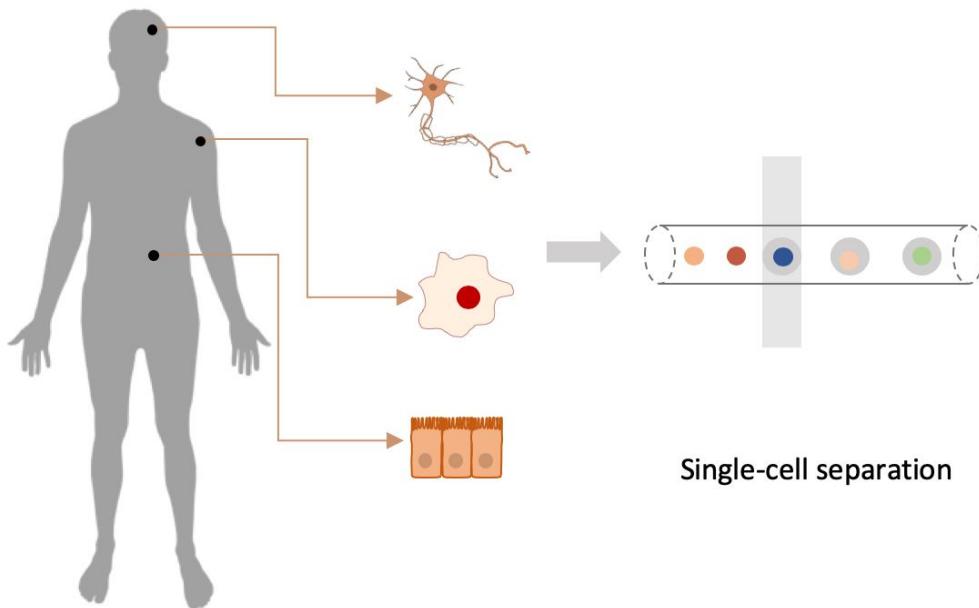


Meyer, C., Liu, X.
Identifying and
mitigating bias in
next-generation
sequencing methods
for chromatin biology.
Nat Rev Genet 15,
709-721 (2014).

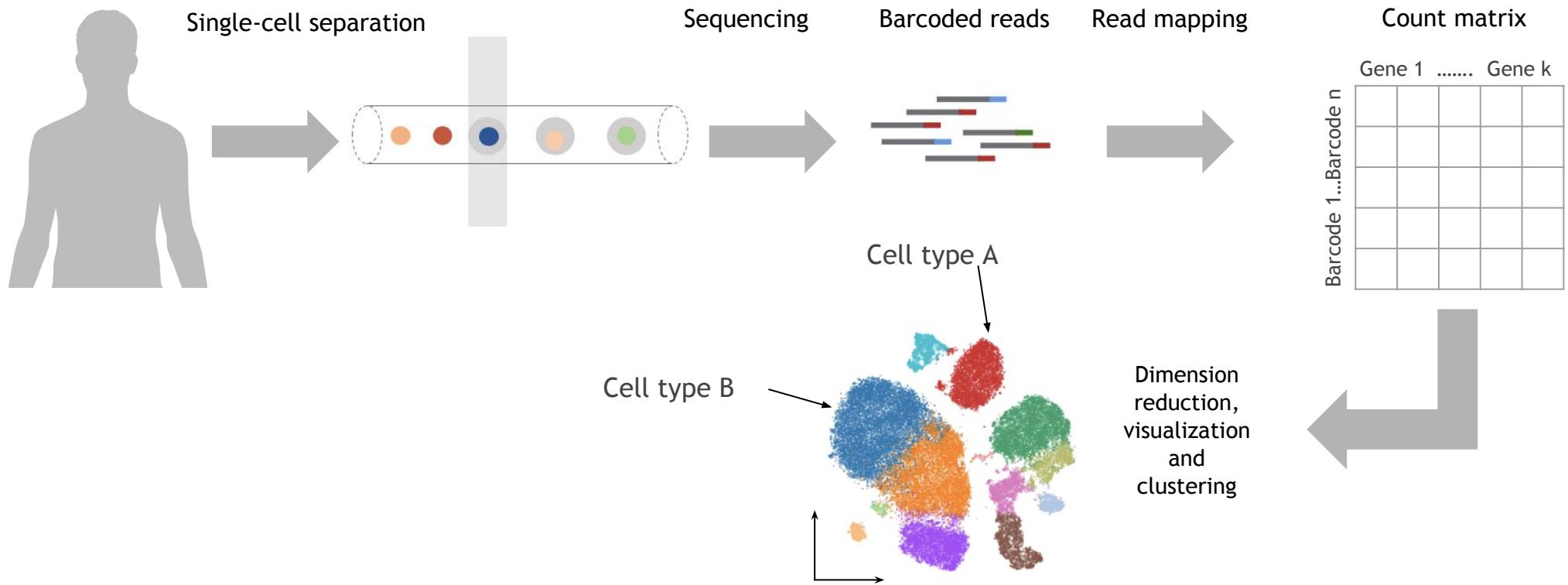
Multi-omic data integration



Single-cell sequencing



Single-cell data analysis



Analytical challenges in single-cell data

Doublets & multiplets

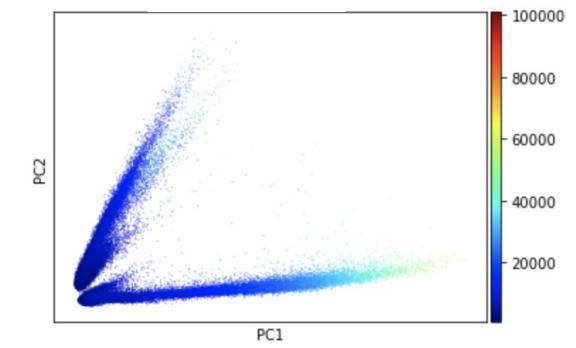
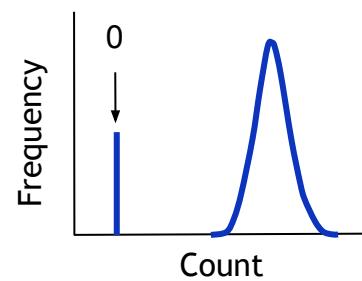
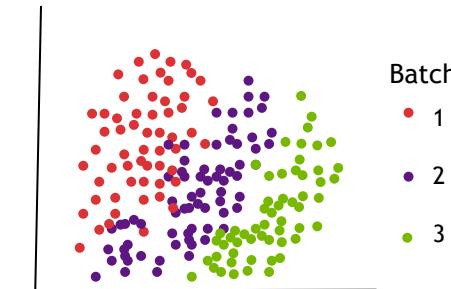
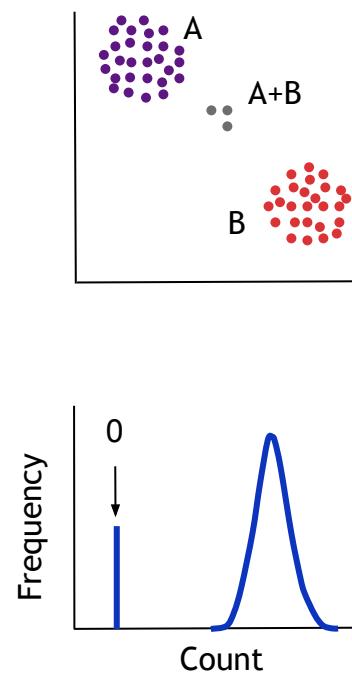
Library size

Batch effects

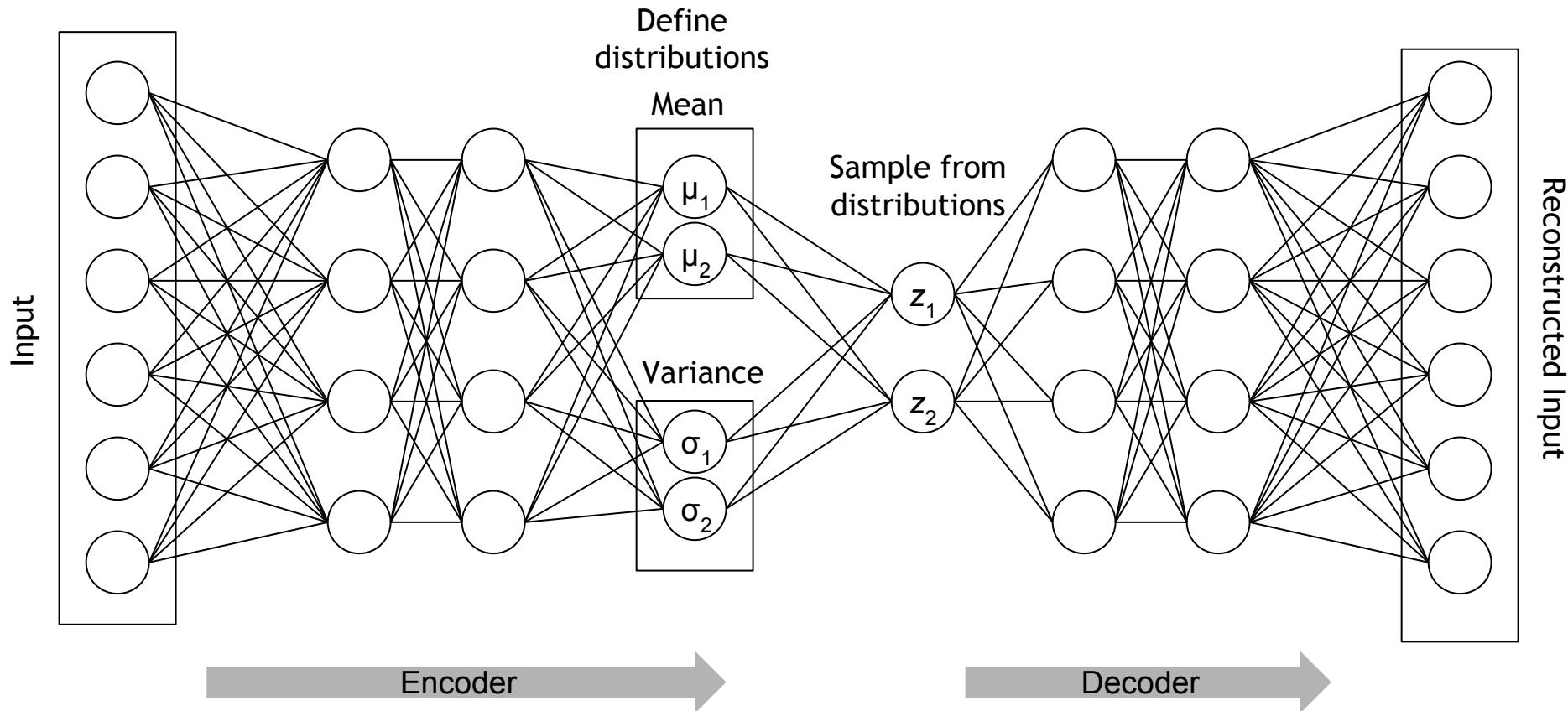
Noise

Dropout

Dimension reduction, clustering and differential expression

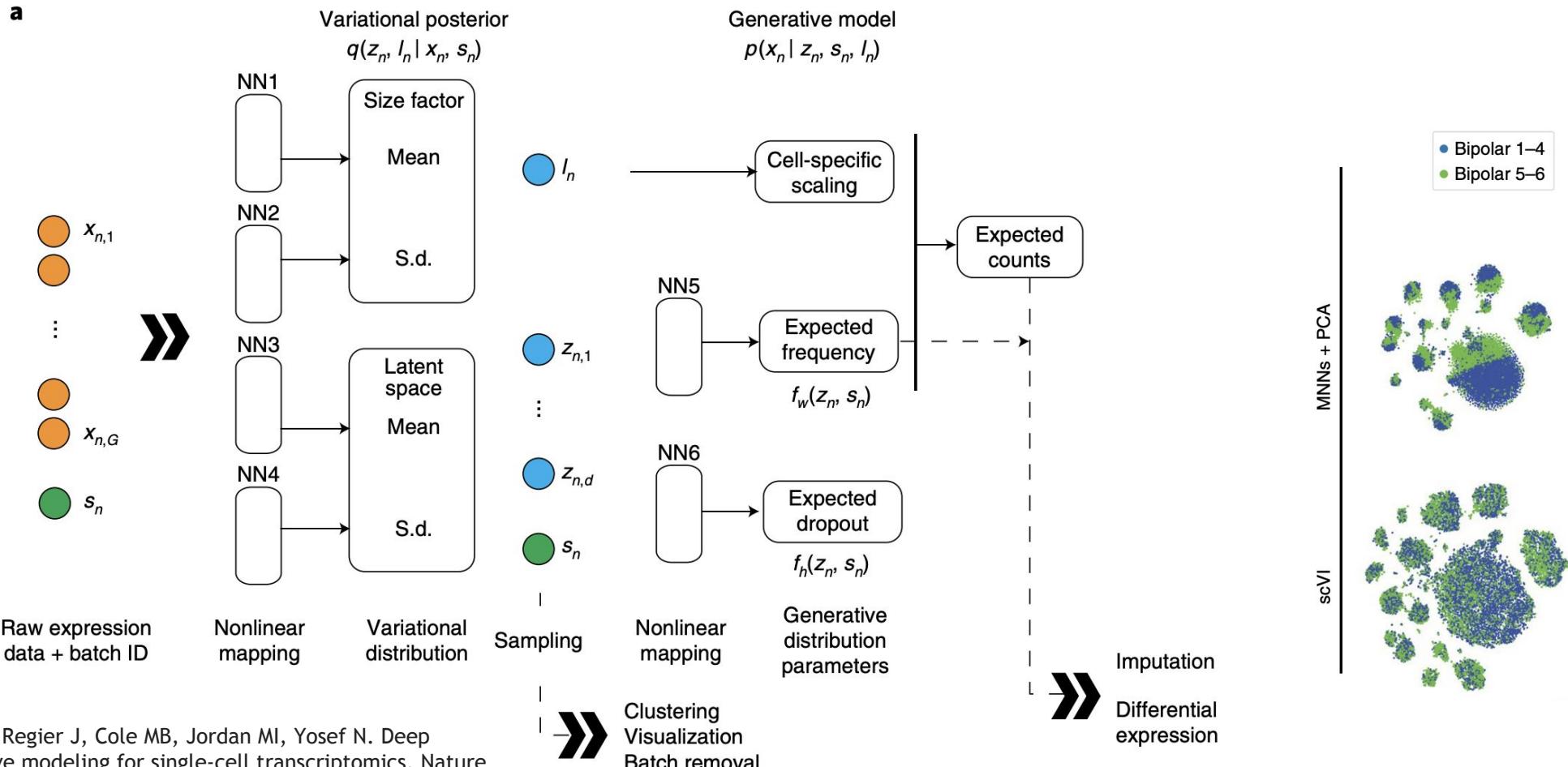


Variational Autoencoder (VAE)

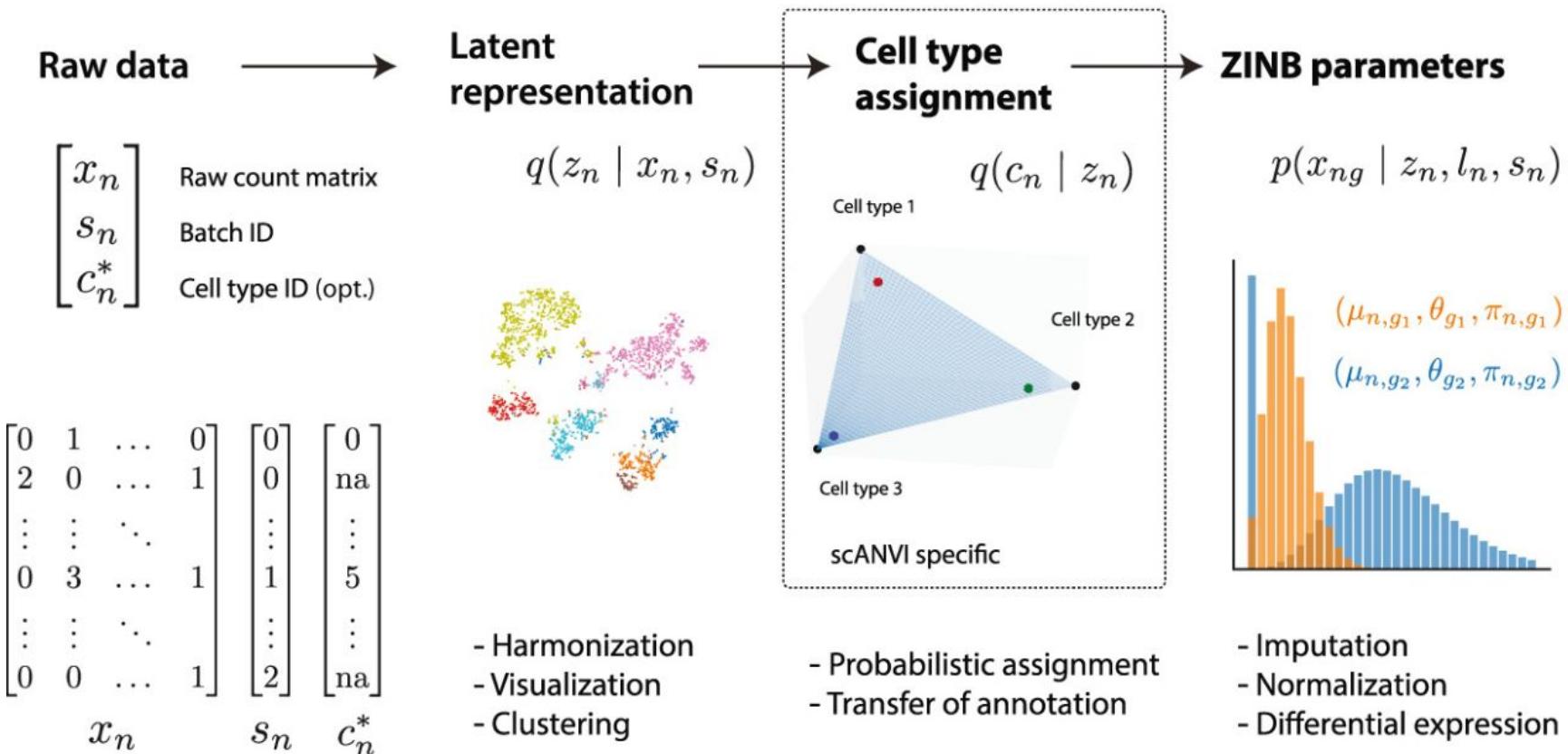


scVI

a

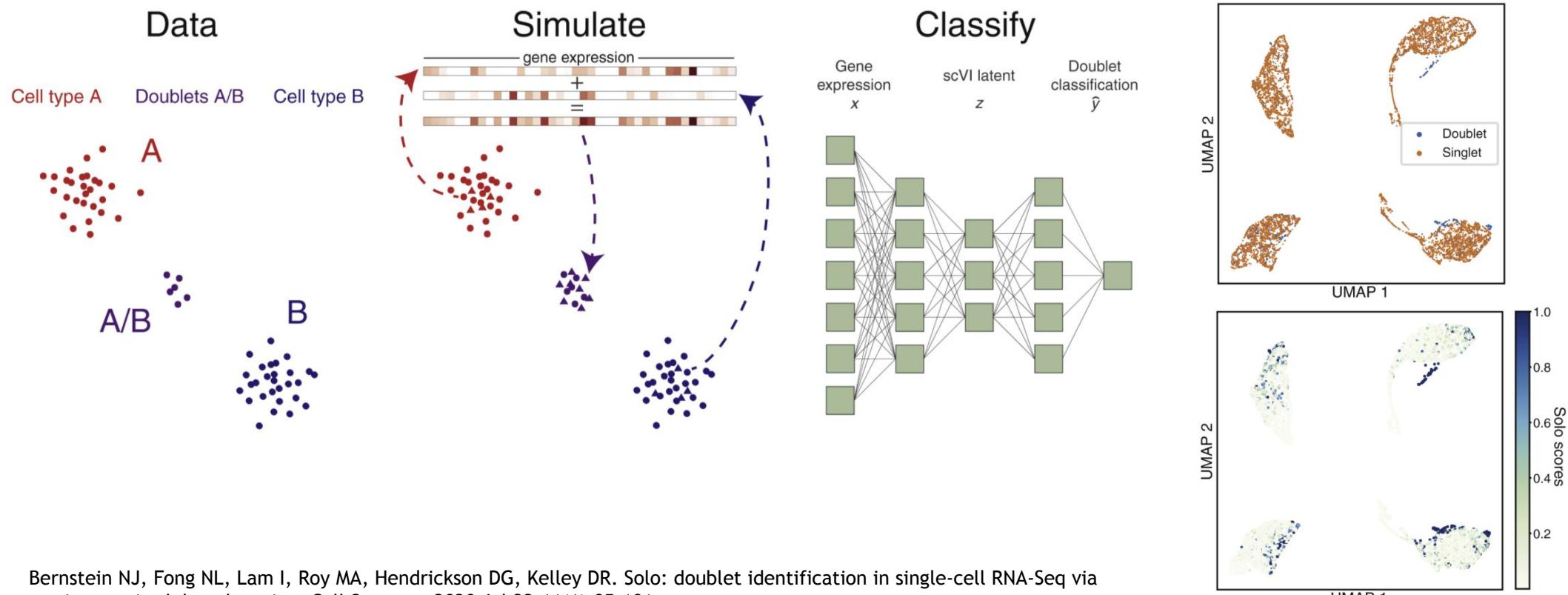


Cell type annotation



Xu C, Lopez R, Mehlman E, Regier J, Jordan MI, Yosef N. Probabilistic harmonization and annotation of single-cell transcriptomics data with deep generative models. Molecular systems biology. 2021 Jan;17(1):e9620.

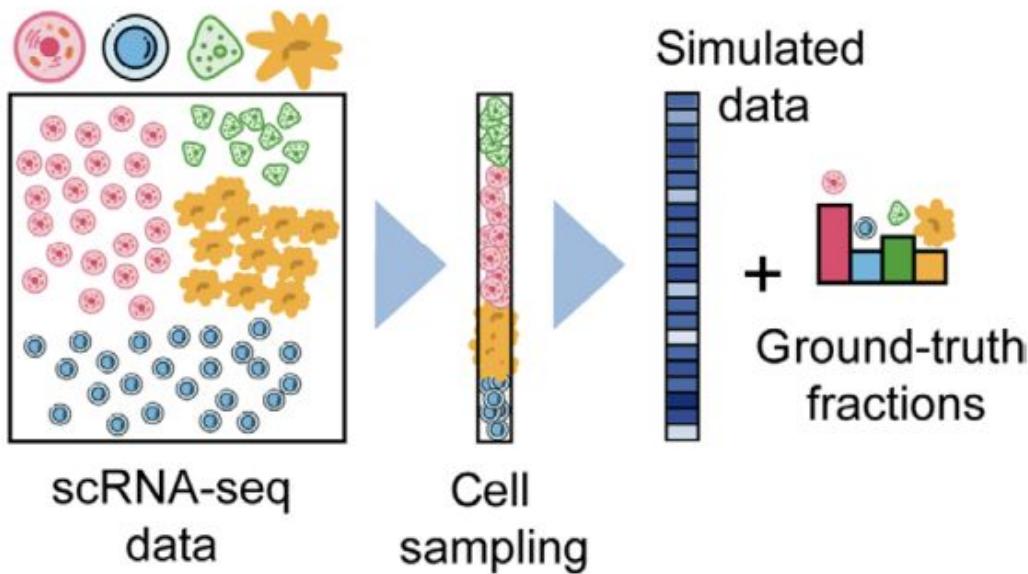
Doublet identification



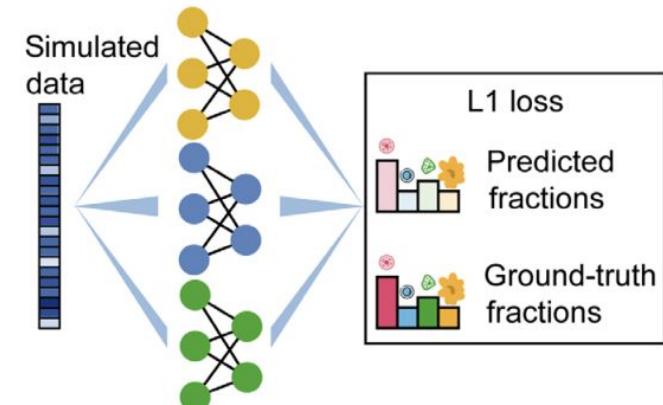
Bernstein NJ, Fong NL, Lam I, Roy MA, Hendrickson DG, Kelley DR. Solo: doublet identification in single-cell RNA-Seq via semi-supervised deep learning. *Cell Systems*. 2020 Jul 22;11(1):95-101.

Bulk deconvolution

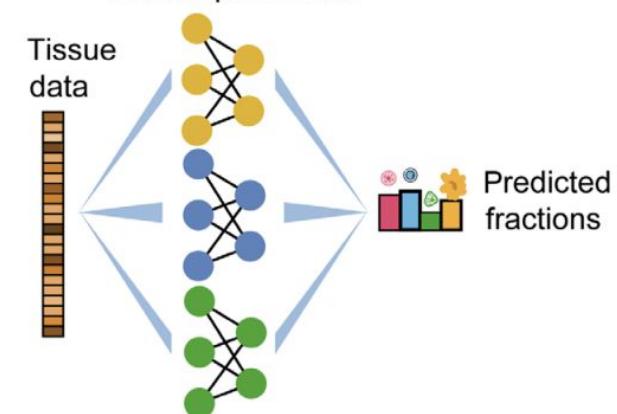
A Simulated training data



B Scaden training

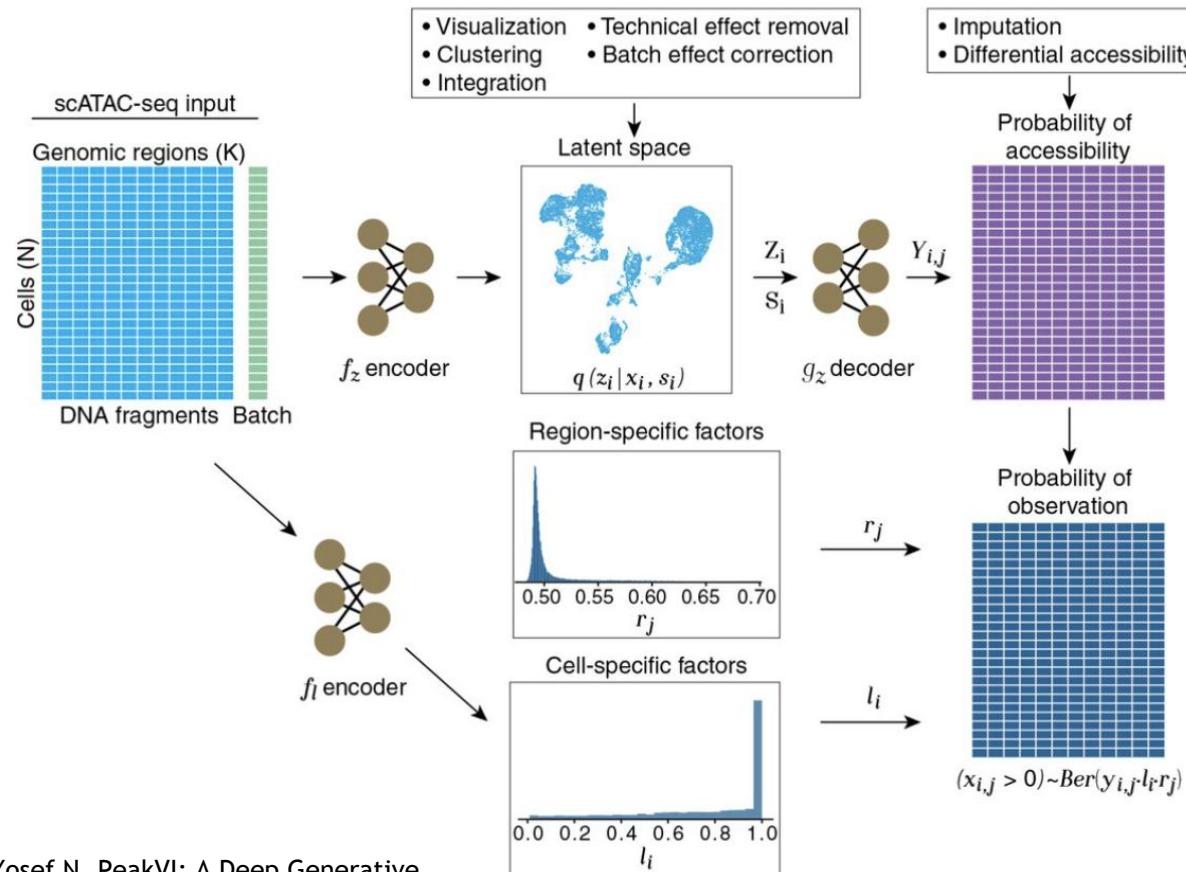


C Scaden predictions

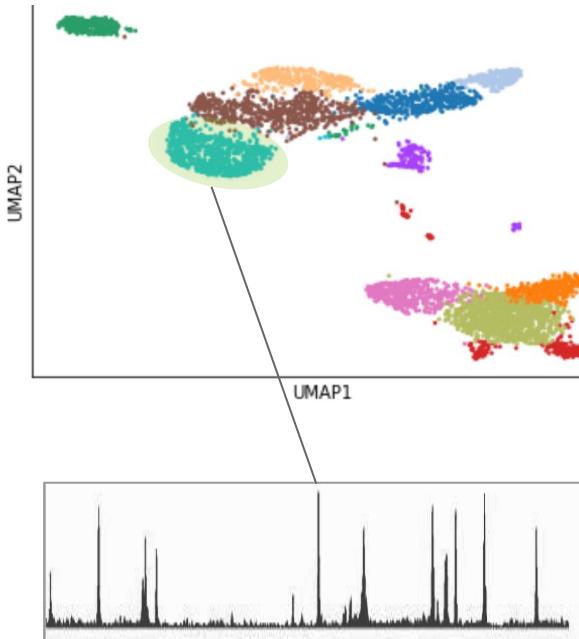


Menden K, Marouf M, Oller S, Dalmia A, Magruder DS, Kloiber K, Heutink P, Bonn S. Deep learning-based cell composition analysis from tissue expression profiles. *Science advances*. 2020 Jul 1;6(30):eaba2619.

VAEs for other single-cell modalities



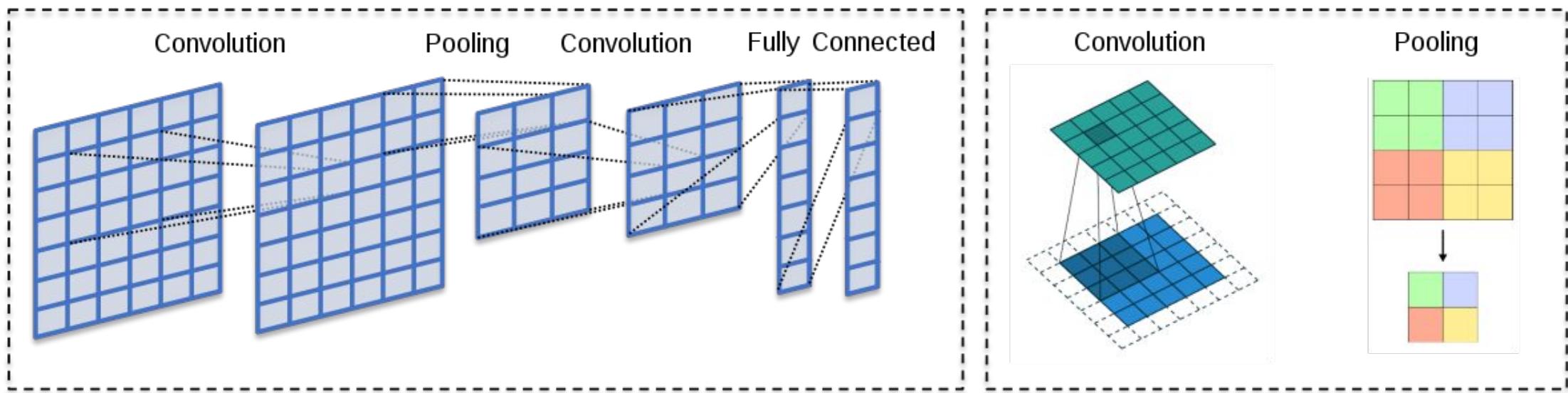
Modeling cell-type specific profiles



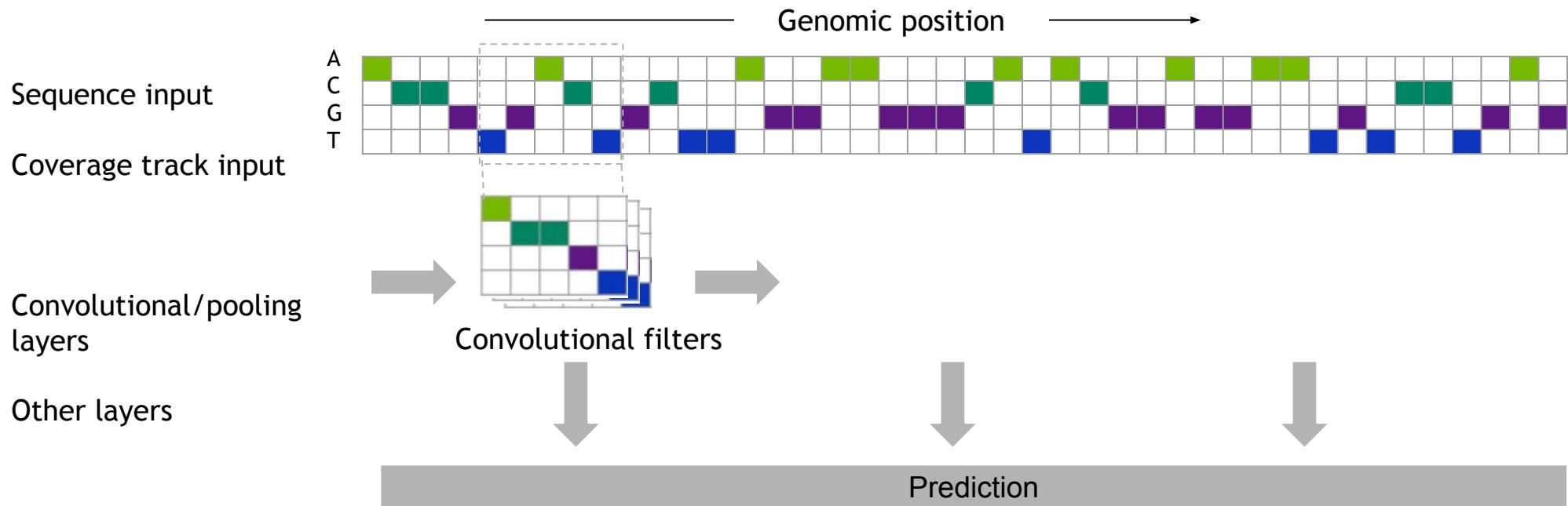
Given DNA sequence, can we predict gene expression and/or functional profiles in different cell types?

Based on these learned rules, can we predict the cell-type specific effect of sequence variation and mutations?

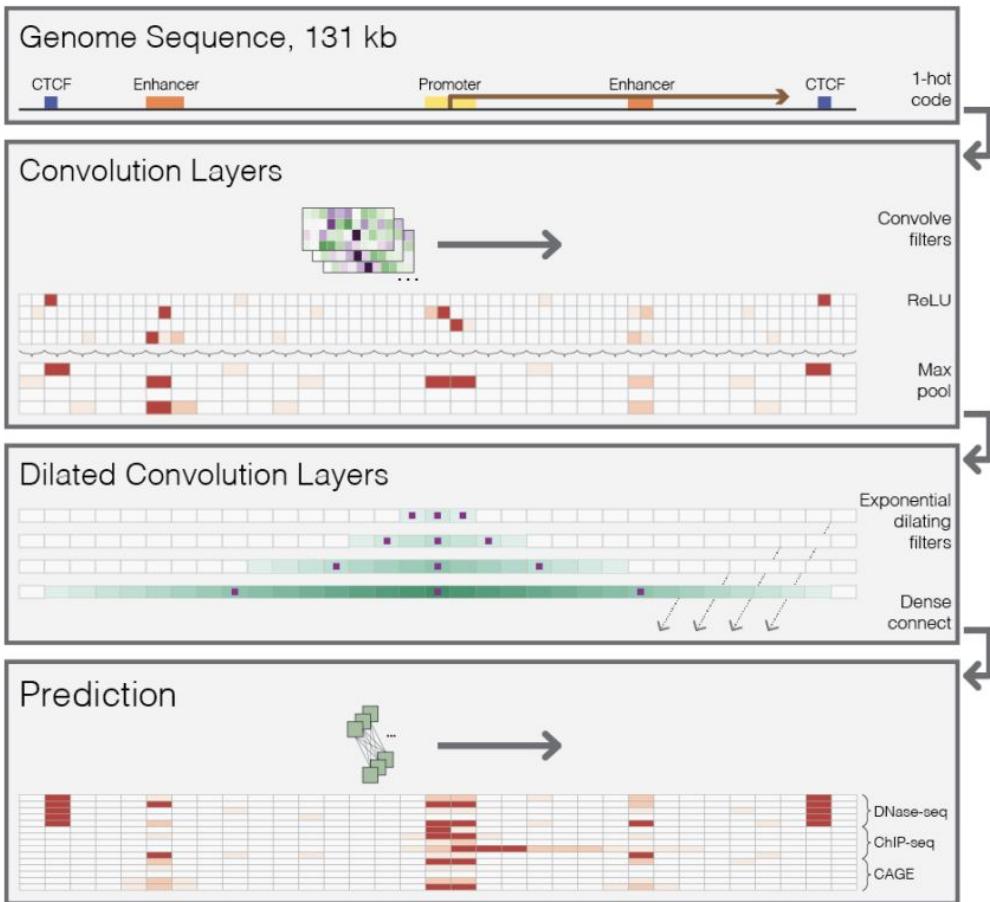
Convolutional neural networks



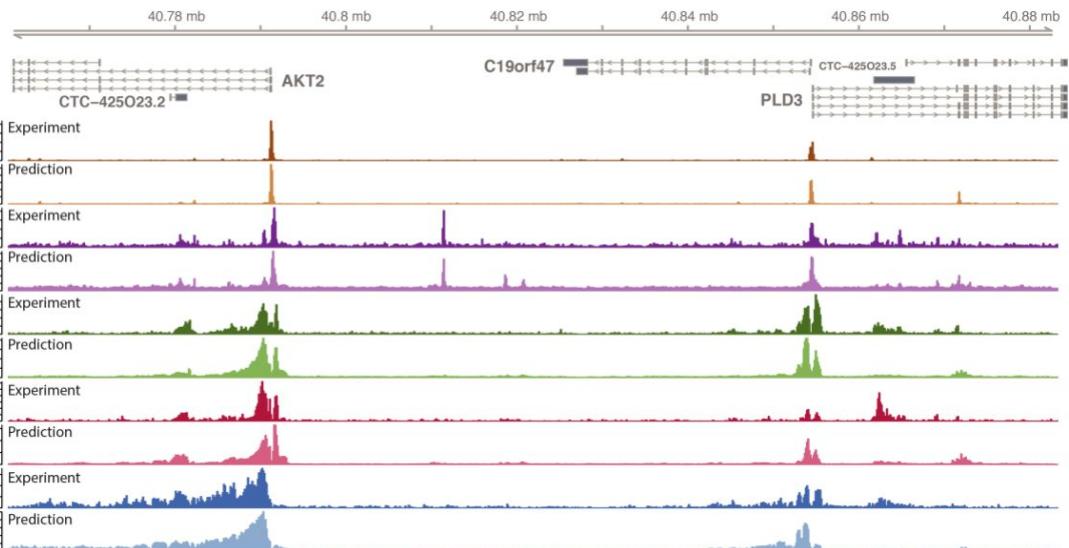
CNNs for genomics



Basenji

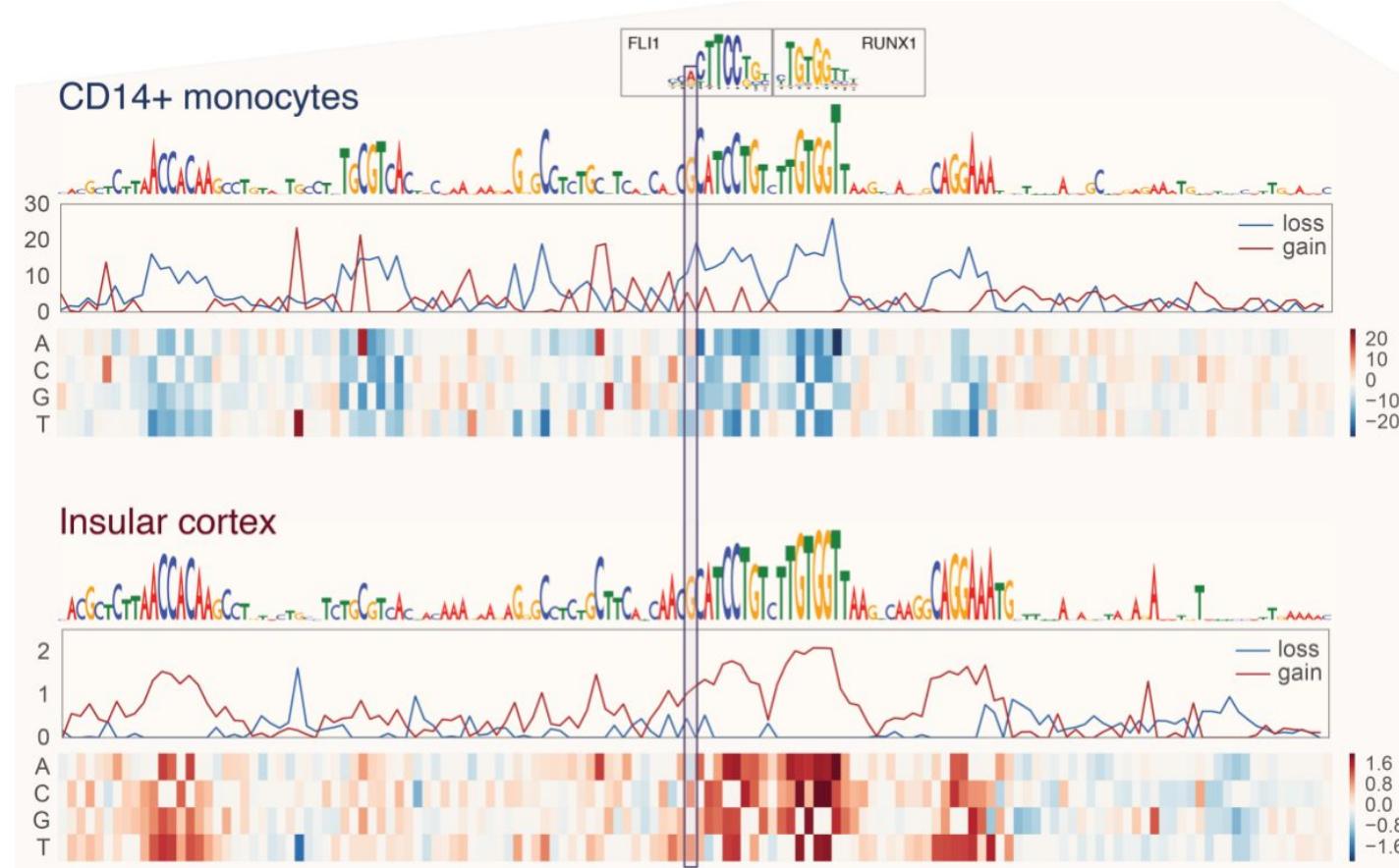


A



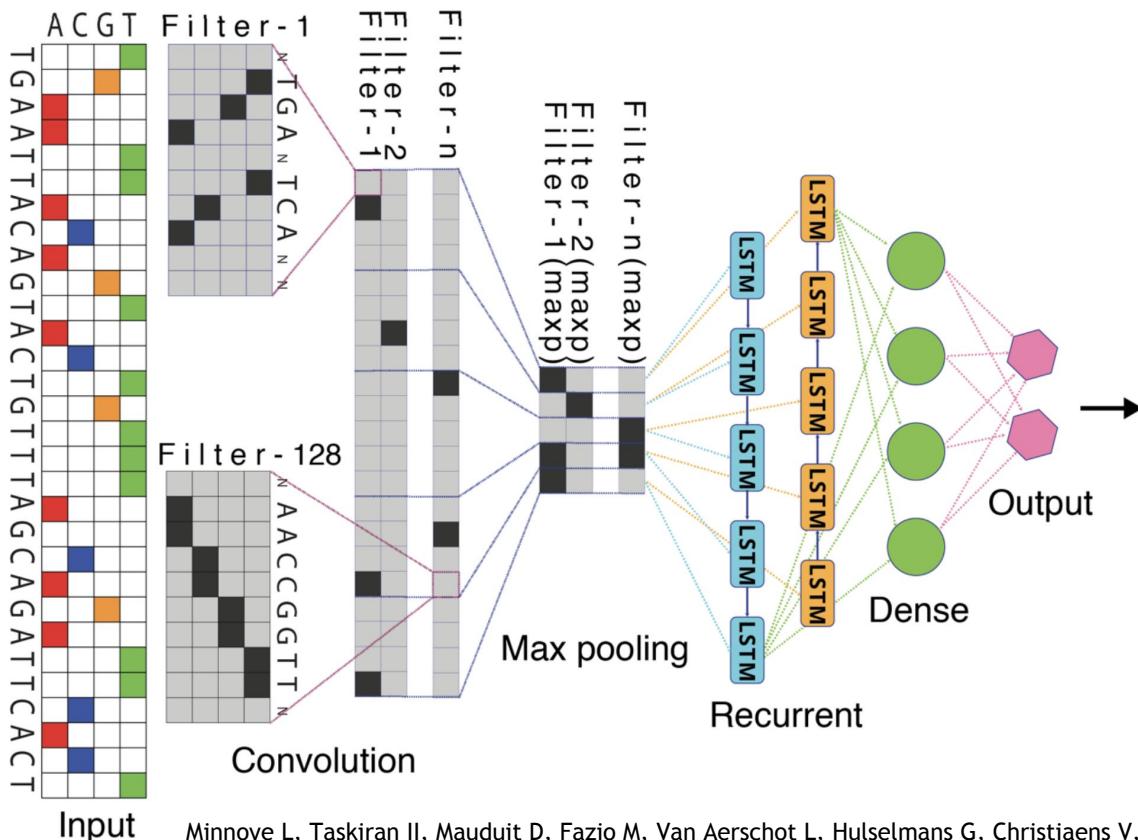
Kelley DR, Reshef YA, Bileschi M, Belanger D, McLean CY, Snoek J. Sequential regulatory activity prediction across chromosomes with convolutional neural networks. *Genome research*. 2018 May 1;28(5):739-50.

Predicting the impact of genetic variation

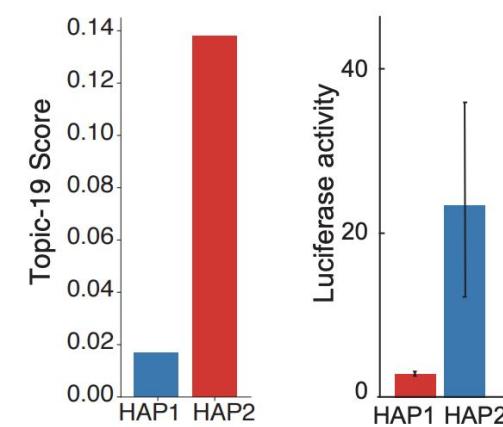
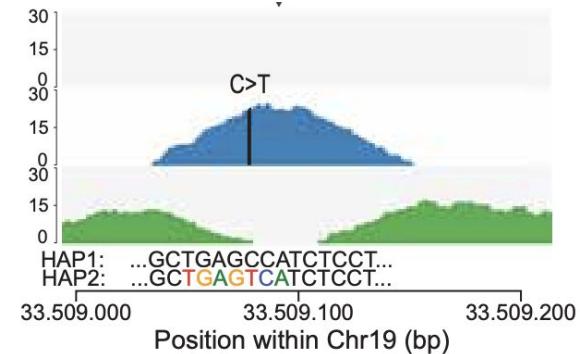


Kelley DR, Reshef YA, Bileschi M, Belanger D, McLean CY, Snoek J. Sequential regulatory activity prediction across chromosomes with convolutional neural networks. *Genome research*. 2018 May 1;28(5):739-50.

Predicting somatic mutation effects



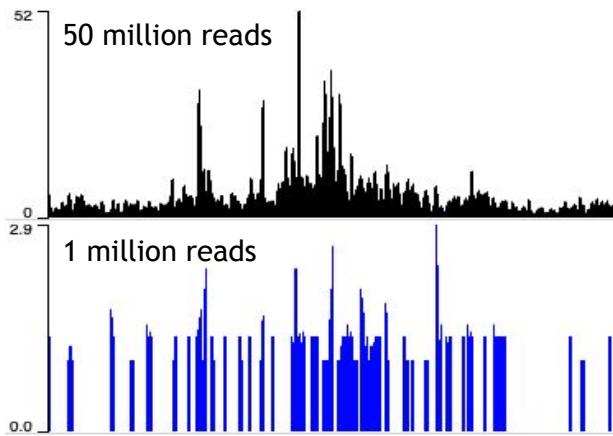
Minnoye L, Taskiran II, Mauduit D, Fazio M, Van Aerschot L, Hulselmans G, Christiaens V, Makhzami S, Seltenhammer M, Karras P, Primot A. Cross-species analysis of enhancer logic using deep learning. *Genome research*. 2020 Dec 1;30(12):1815-34.



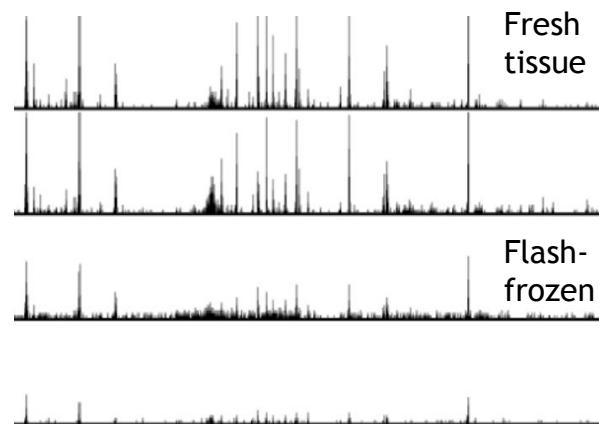
Atak ZK, Taskiran II, Demeulemeester J, Flerin C, Mauduit D, Minnoye L, Hulselmans G, Christiaens V, Ghanem GE, Wouters J, Aerts S. Interpretation of allele-specific chromatin accessibility using cell state-aware deep learning. *Genome research*. 2021 Jun 1;31(6):1082-96.

Epigenomic data quality

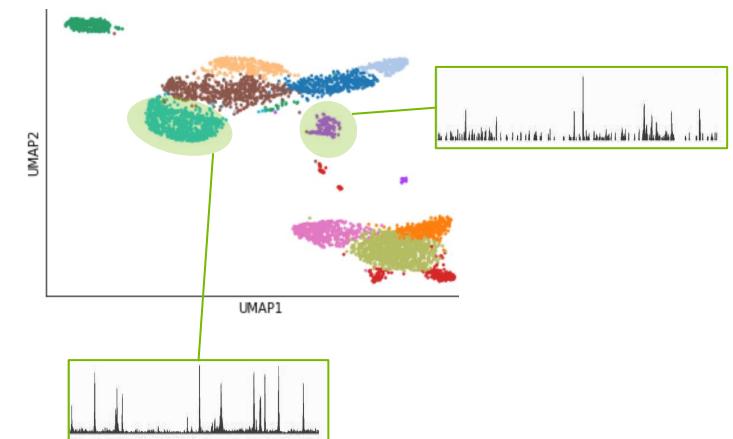
Low sequencing depth



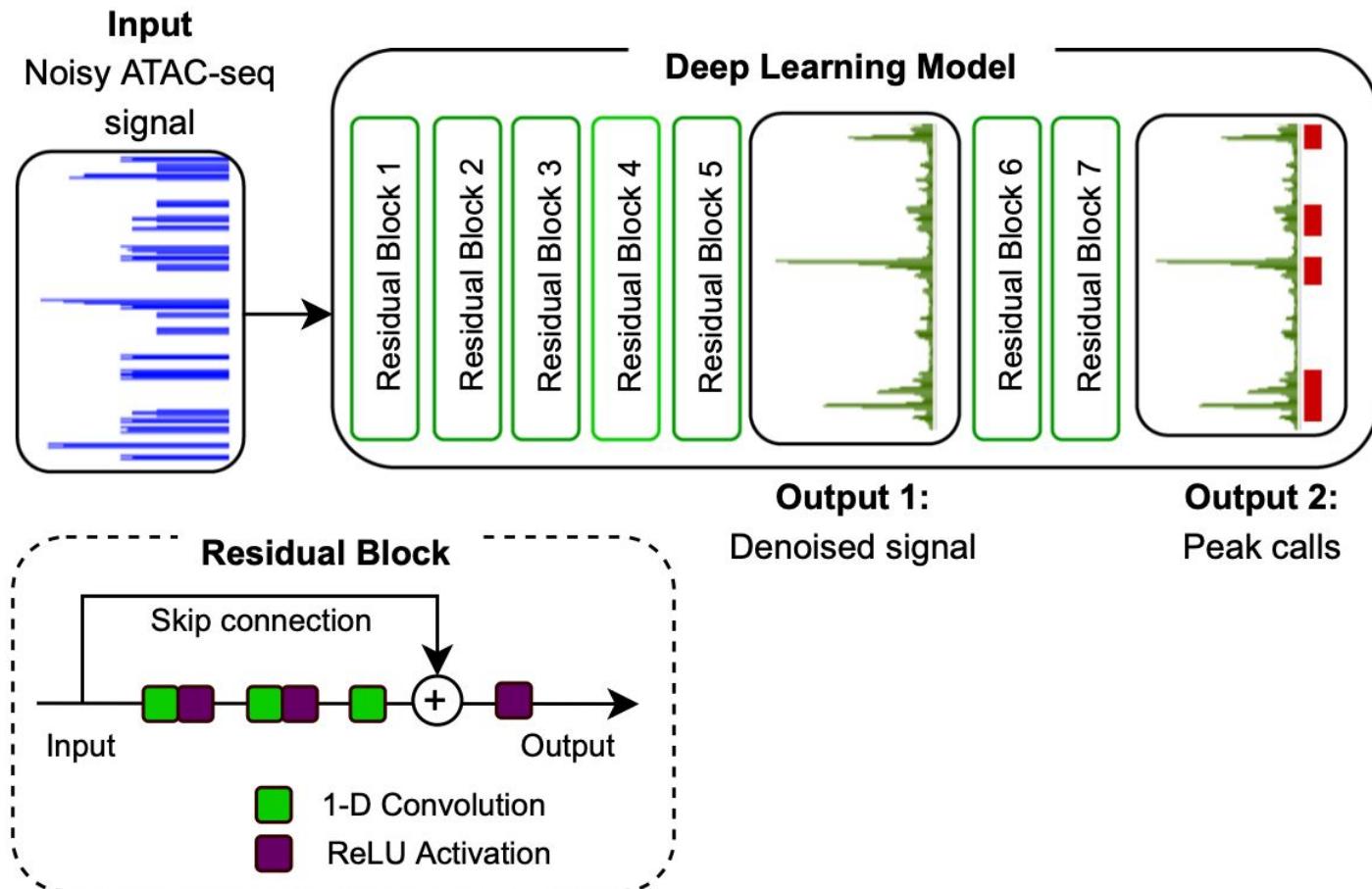
Sample/experimental factors



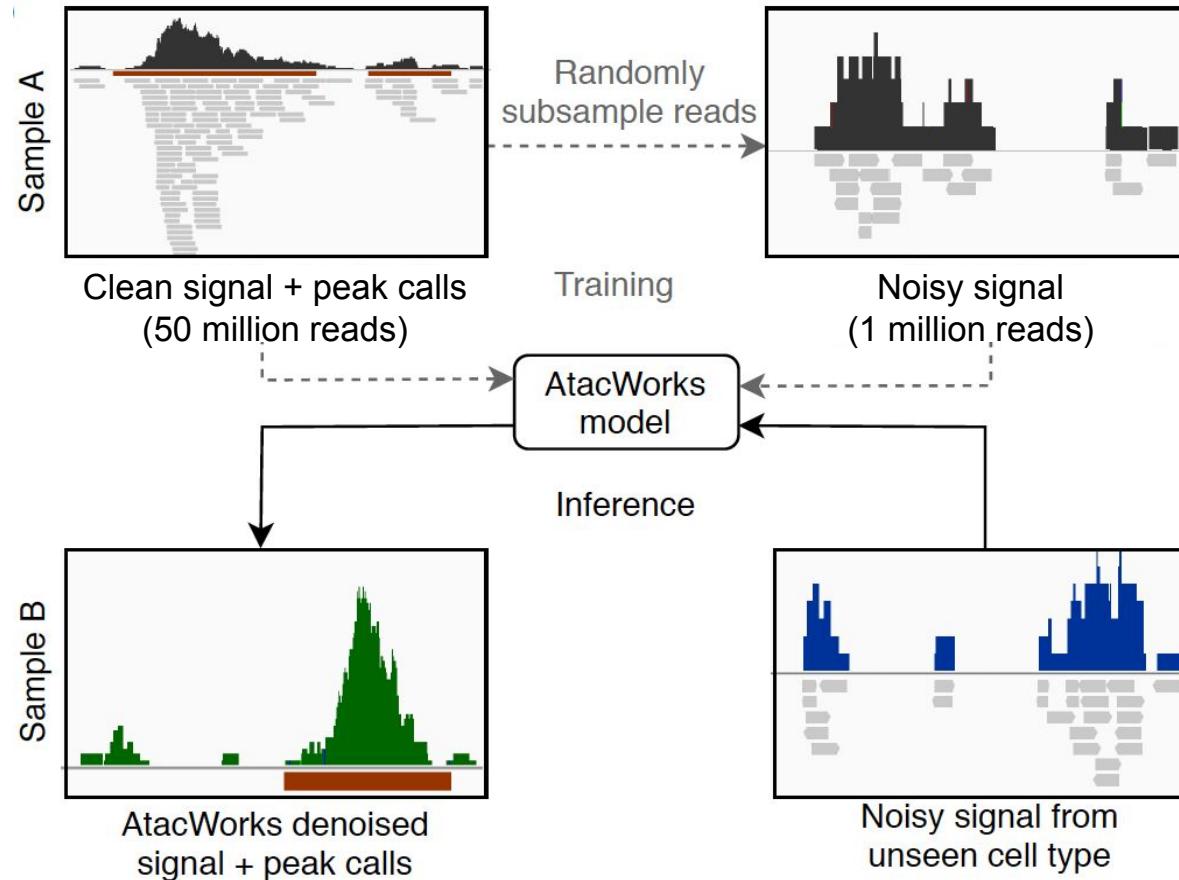
Low aggregate cell count



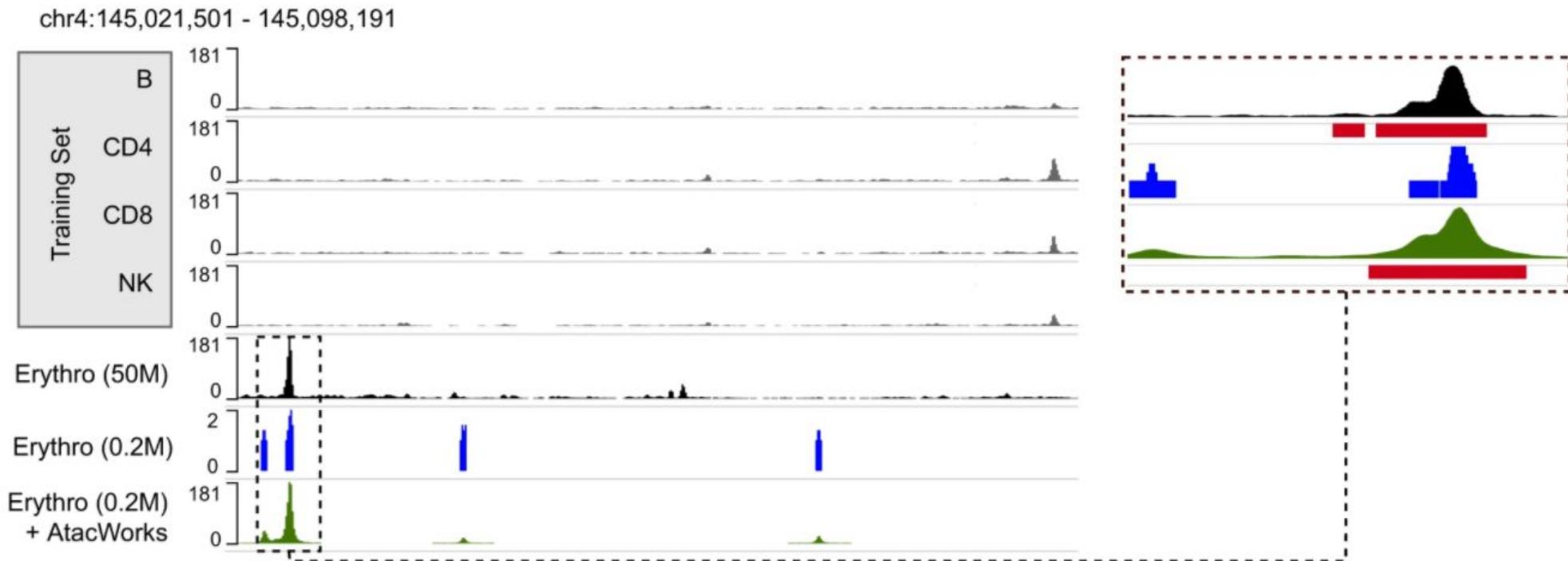
AtacWorks



Training models to enhance low-coverage ATAC-seq

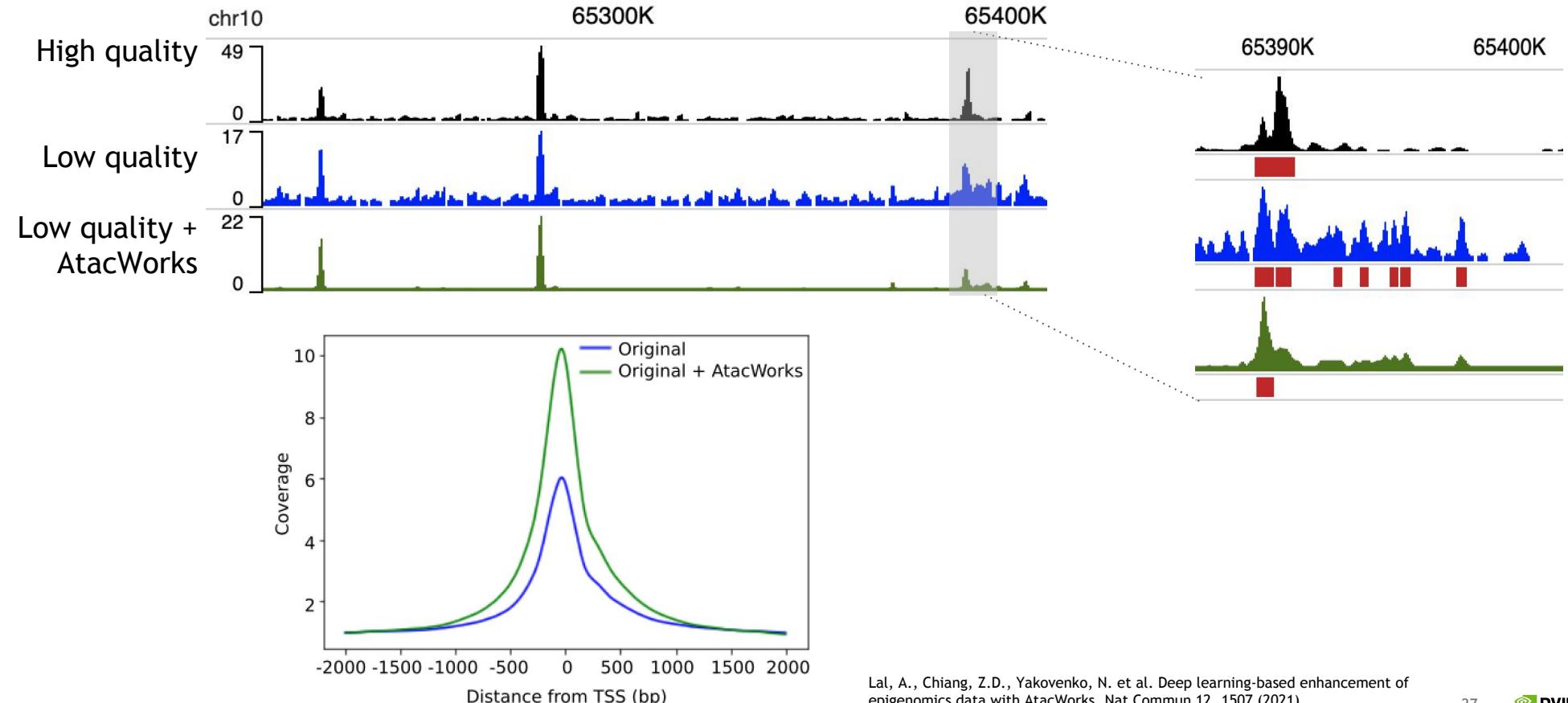


Denoising and peak calling from low-coverage ATAC-seq



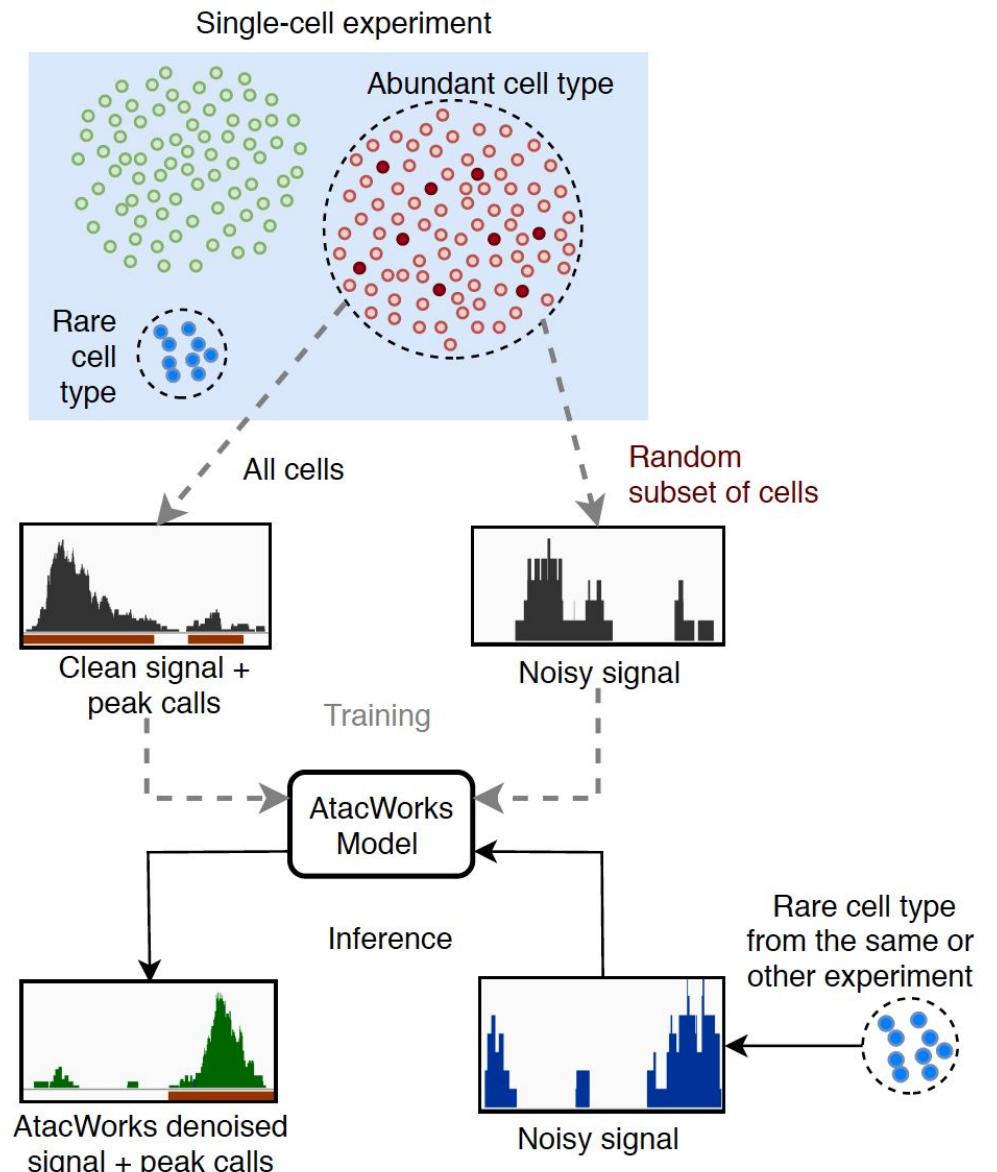
Rescuing low-quality data

Bulk ATAC-seq data from human Erythroblasts

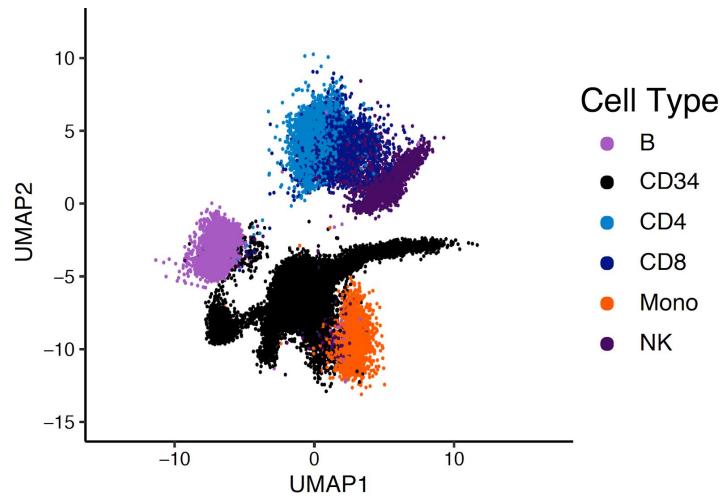


Lal, A., Chiang, Z.D., Yakovenko, N. et al. Deep learning-based enhancement of epigenomics data with AtacWorks. *Nat Commun* 12, 1507 (2021).

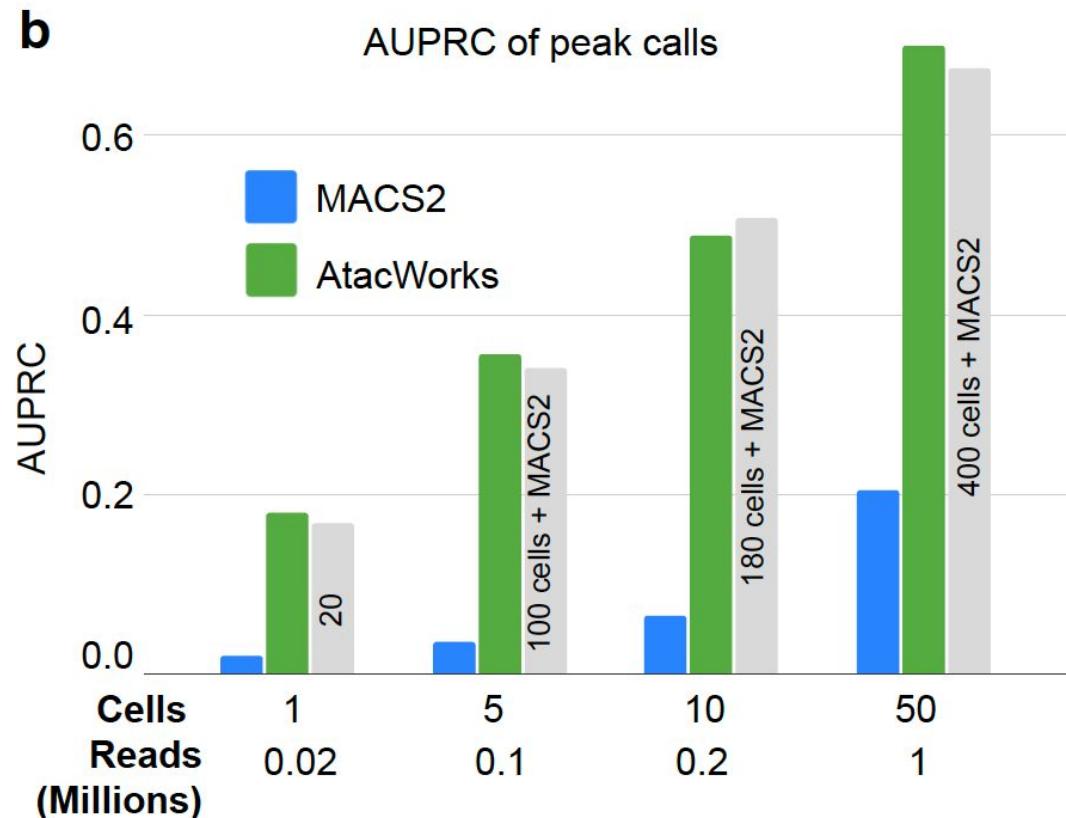
Applying AtacWorks to scATAC-seq



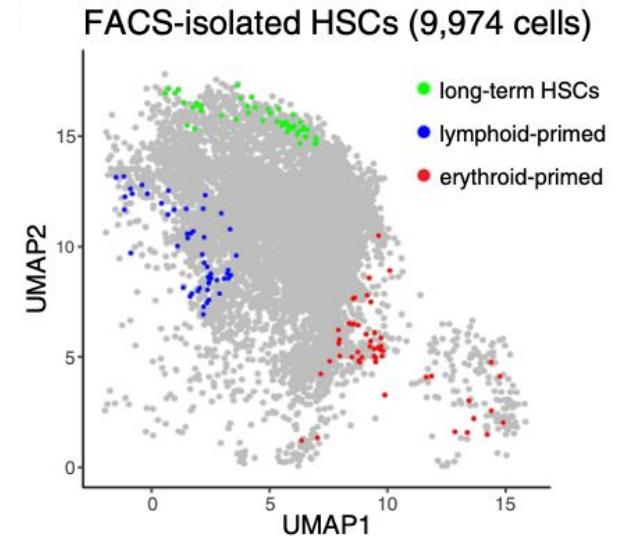
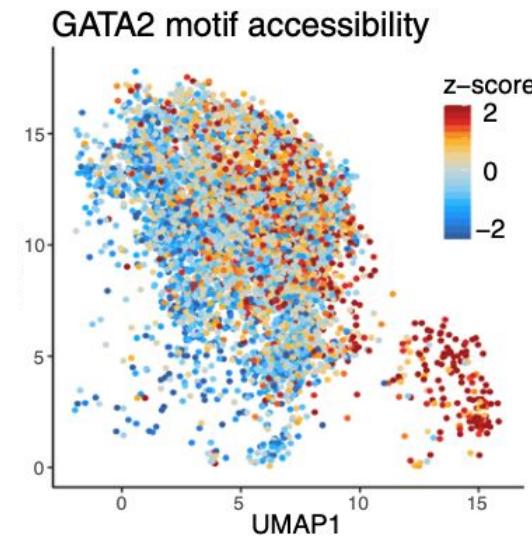
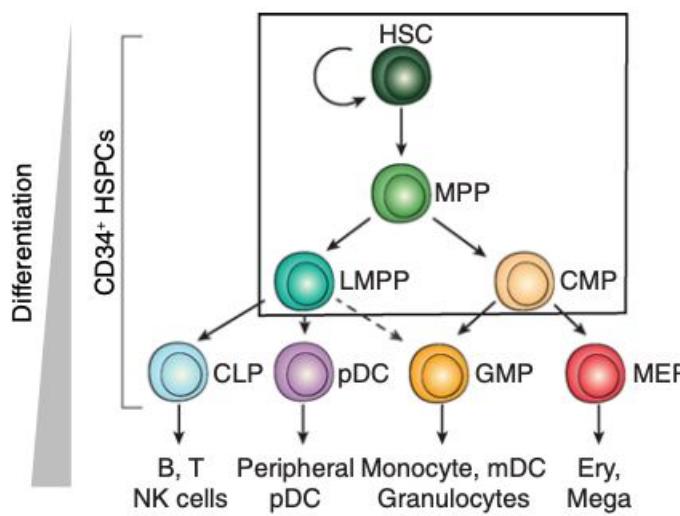
Increasing single-cell resolution



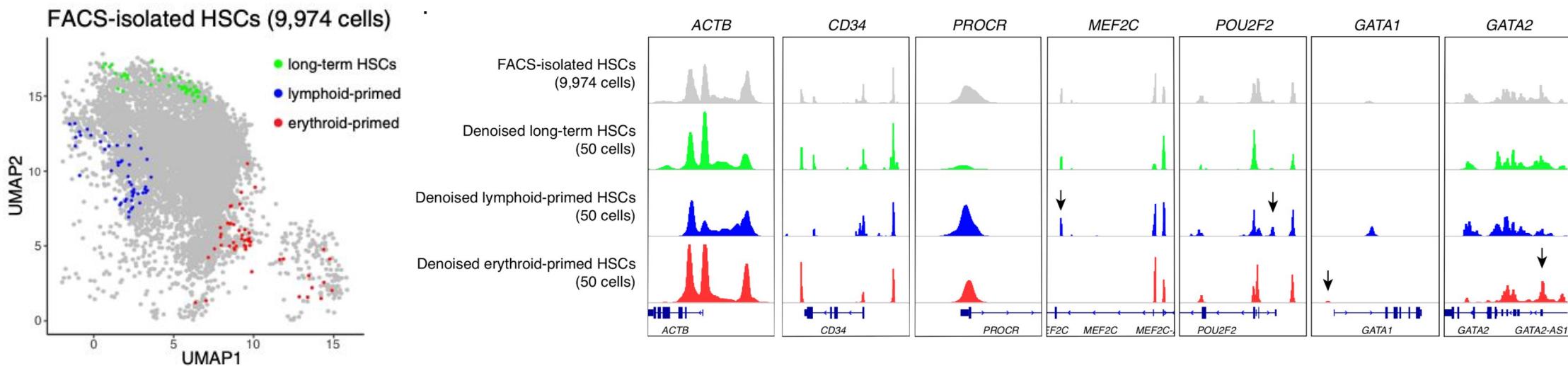
AtacWorks can obtain the same quality results from ~10x fewer cells, increasing the resolution of single-cell chromatin accessibility profiling by an order of magnitude.



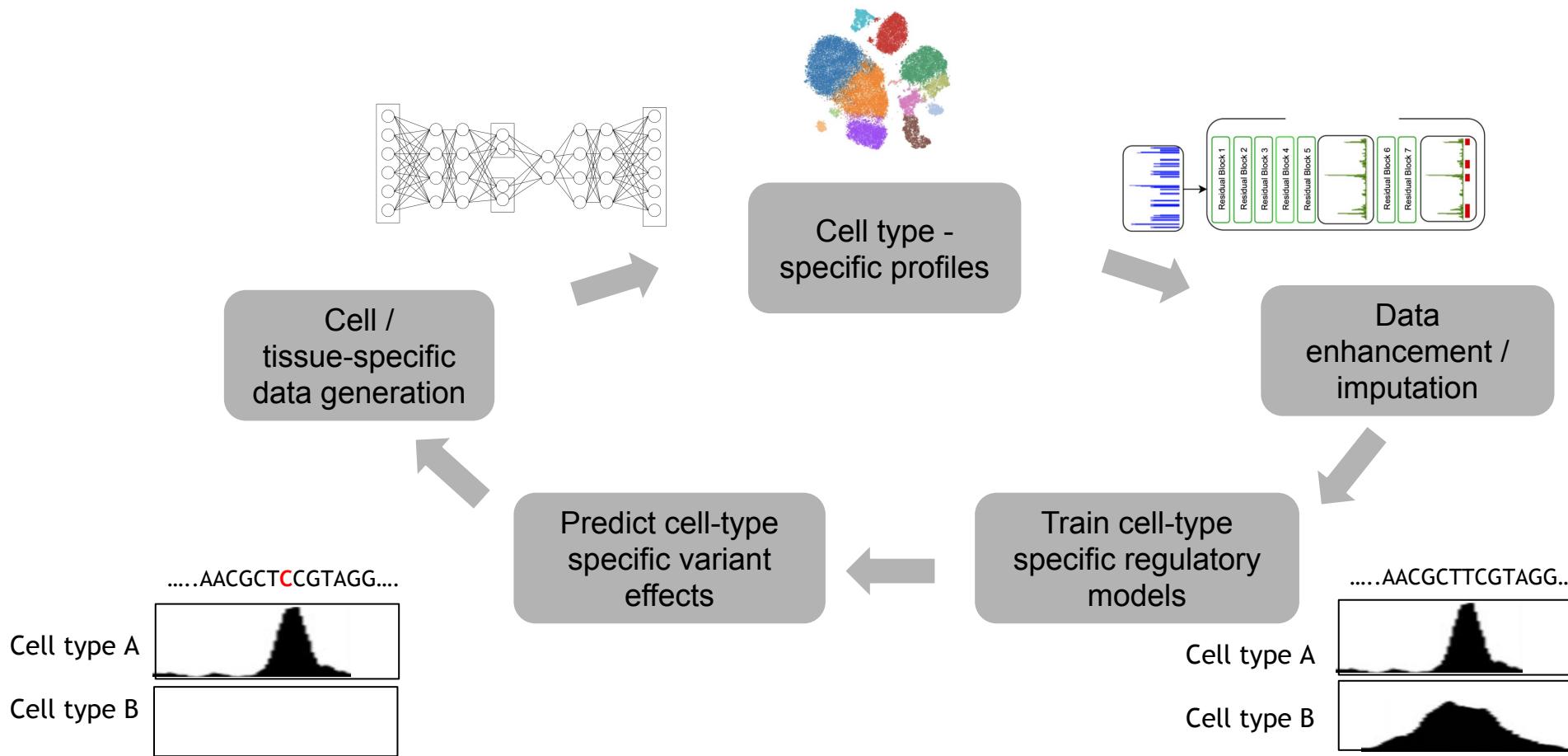
Identifying regulatory DNA associated with lineage priming



Identifying regulatory DNA associated with lineage priming



Regulatory modeling with deep learning





NVIDIA®

