

Analyzing Single-Cell RNA-sequencing Data to Classify Cell States



Shreya Sharma¹, Samantha A. O'Connor¹, Christopher L. Plaisier¹

¹School of Biological and Health Systems Engineering, Arizona State University, Tempe AZ, USA;

Introduction

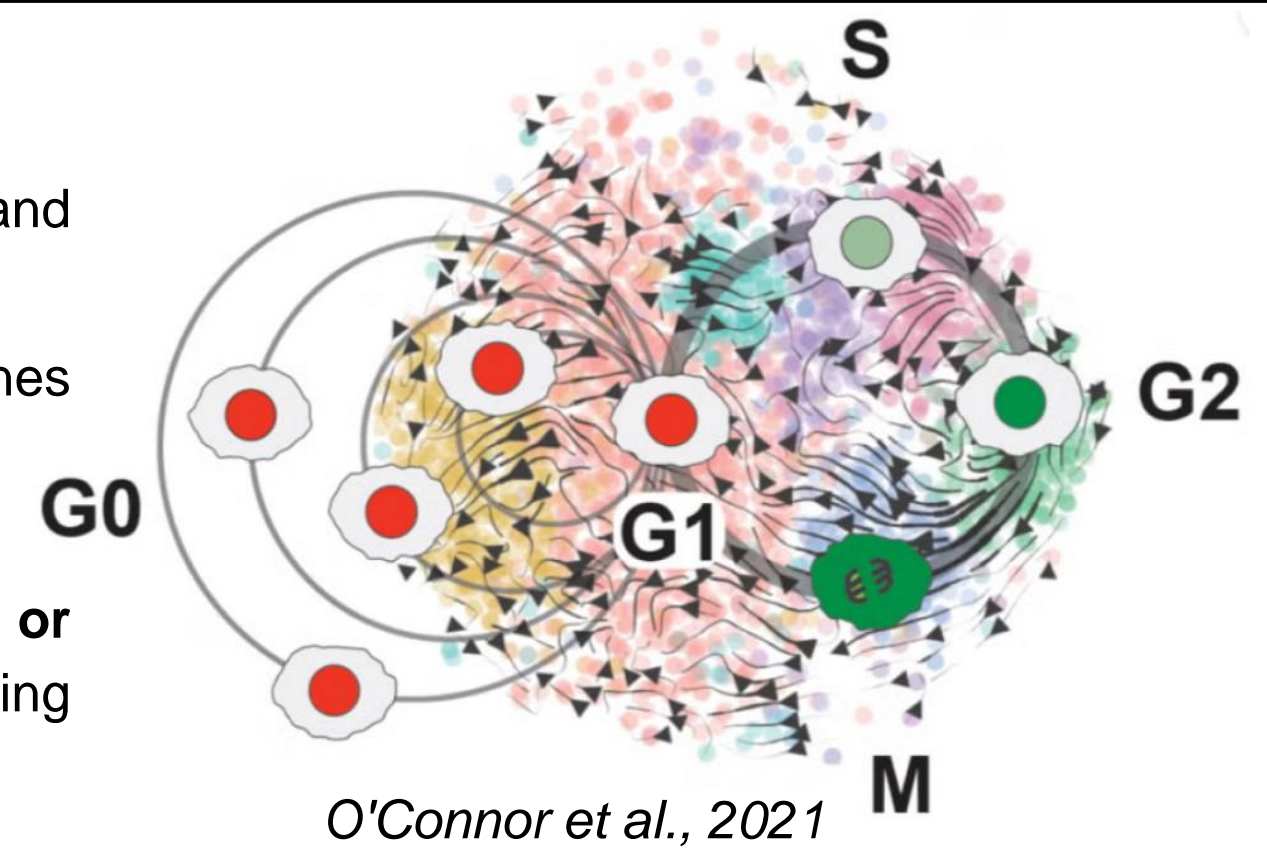
Single-cell RNA-sequencing (scRNA-seq) allows researchers to analyze gene expression at single-cell resolution, uncovering previously hidden subpopulations and dynamic cellular states.

As scRNA-seq use has grown, **computational classifiers** have been developed to efficiently annotate cell states across datasets. The **cell cycle** is a fundamental biological process often targeted by these classifiers. The **Plaisier Lab** developed **ccAF** (cell cycle classifier ASU/Fred Hutch), a cell cycle classifier trained on human neural stem cells, which predicts a novel **quiescent G0-like state** in neuroepithelial-derived glioma cells.

Cells in the G0-like state have exited the cell cycle and are found in neural stem and progenitor populations.

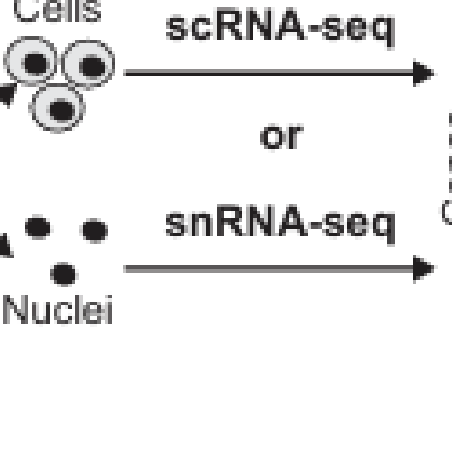
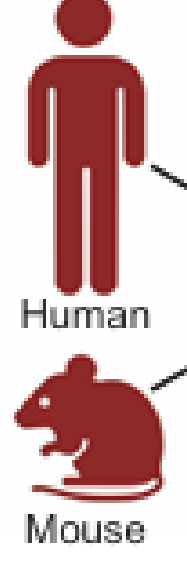
Higher expression of G0-like signature genes correlates with **better prognosis** in glioma patients.

G0-like states are present in multiple tissue types and are thought to represent **quiescence or dormancy**, making them promising targets for treating **tumors and neurodegenerative diseases**.



Pipeline

Tissue source

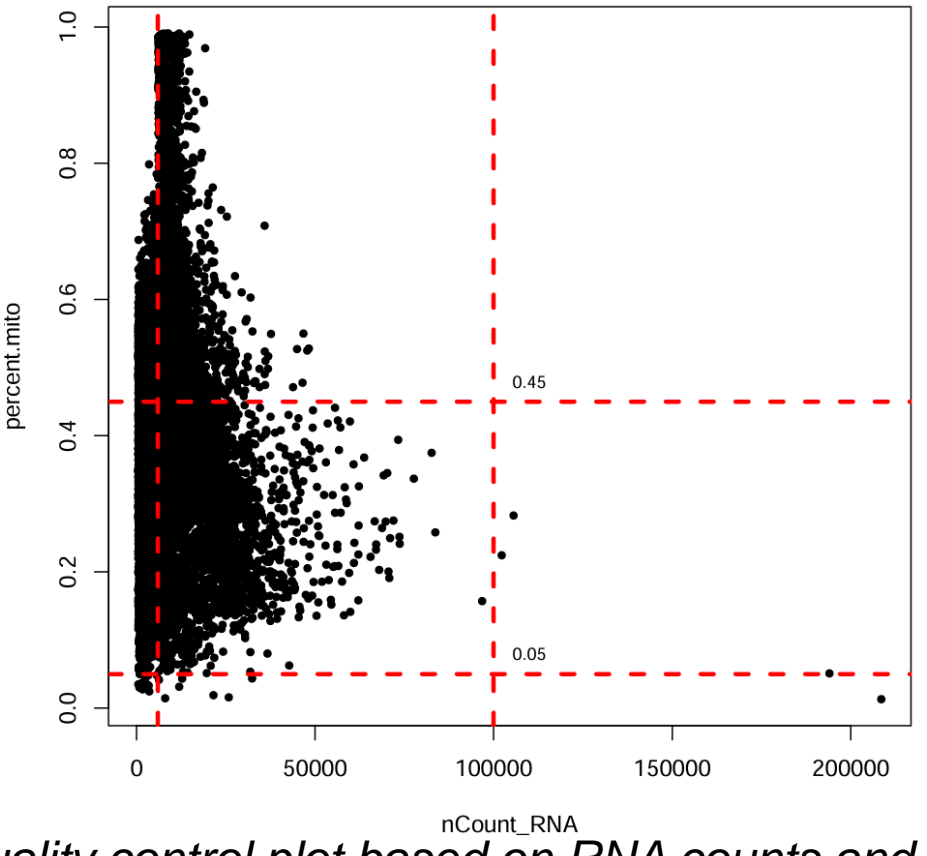


Stage 1: Test Dataset Discovery

- Identified 111 publicly available 10x Genomics scRNA-seq datasets from various published studies.
- Selected datasets with over 1,000 cells to ensure sufficient sampling for downstream analysis.

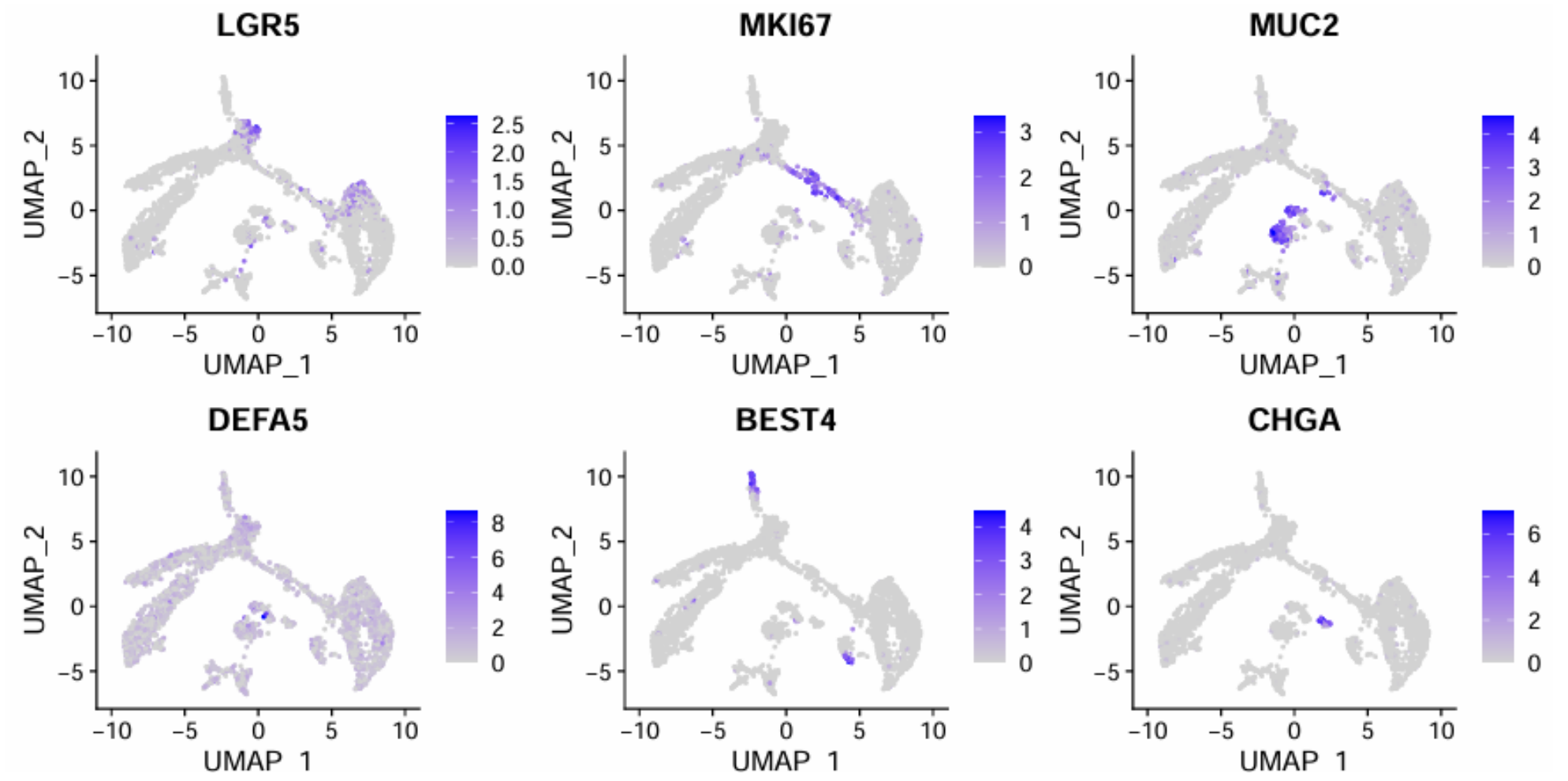
Stage 2: Quality Control

- Assessed cell quality based on the **percentage of mitochondrial gene expression** and the number of unique RNA molecules.
- Filtered out low-quality cells that did not meet **thresholds for mitochondrial content or RNA complexity**.
- Applied **SCTransform normalization** to reduce technical variability while preserving biological signal.



- Prioritized datasets with downloadable metadata, including source tissue, clinical context, applied perturbations, and previously inferred cell types.

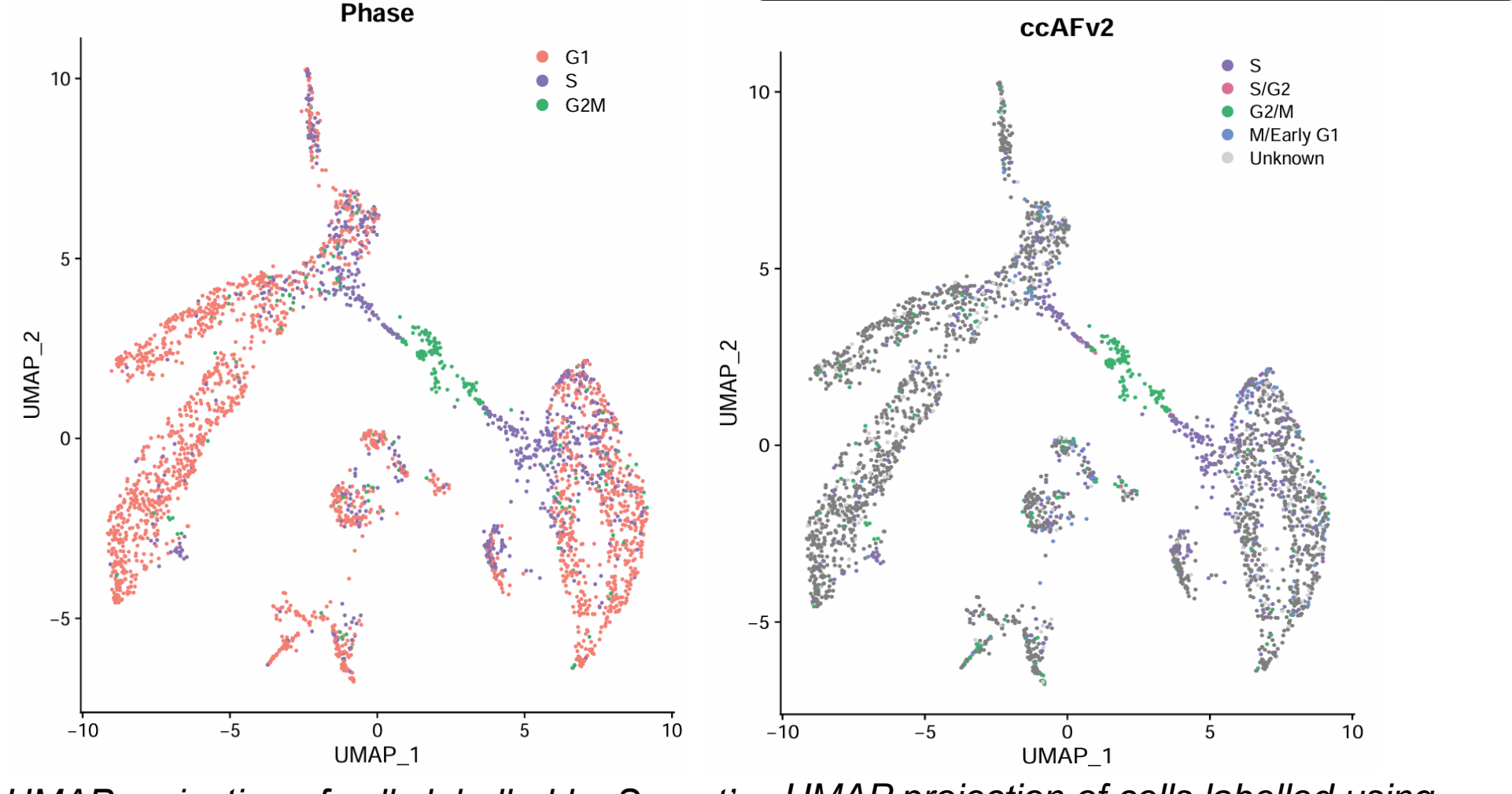
Stage 3: Clustering and Annotation



UMAPs showcasing upregulated gene expression

- Visualized marker gene expression** to identify and distinguish key intestinal cell types (e.g., stem, goblet, Paneth, tuft).
- Annotated clusters** by assigning biologically meaningful cell type labels based on known gene expression profiles.
- Compared clustering with annotations** using dimensionality reduction plots to assess accuracy of cell type identities.

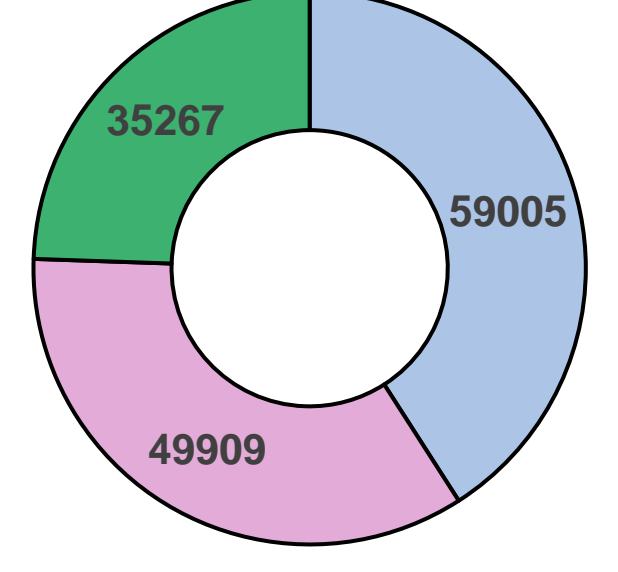
Stage 4: Cell Cycle Classification



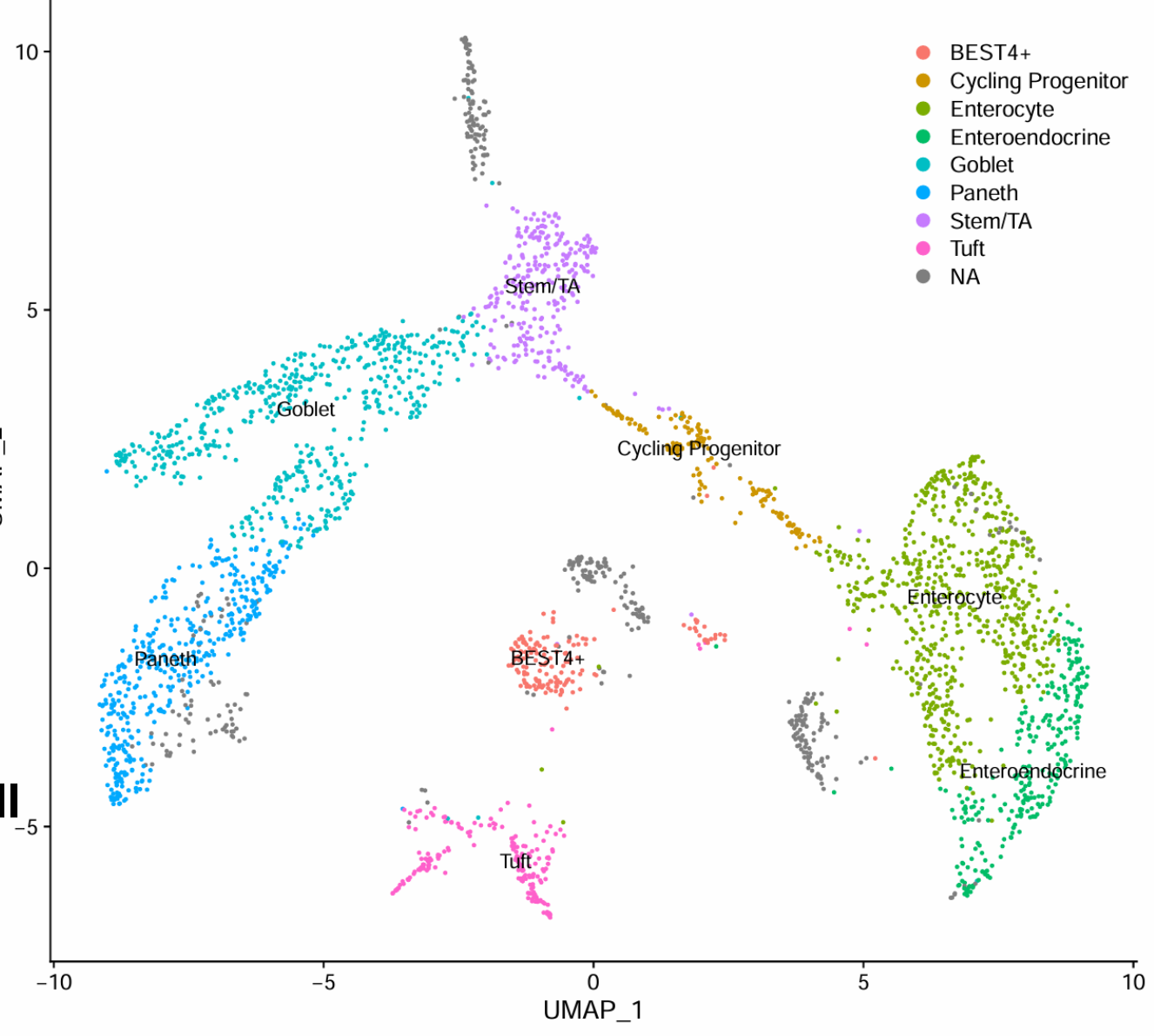
UMAP projection of cells labelled by Seurat's cell cycle scoring. UMAP projection of cells labelled using ccAFv2.

- Compared traditional Seurat annotations (Tirosh, I., et. al, (2016)) with ccAFv2-based classifications to evaluate prediction accuracy.

Cell Counts From Each Dermal Layer

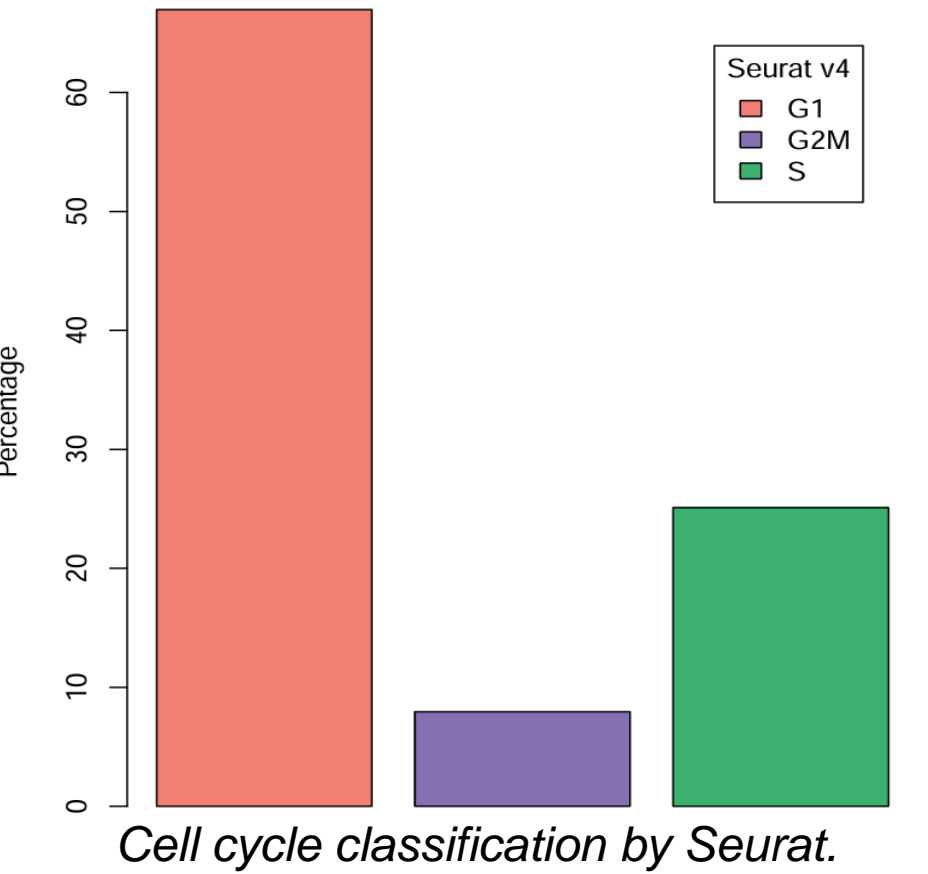


Results

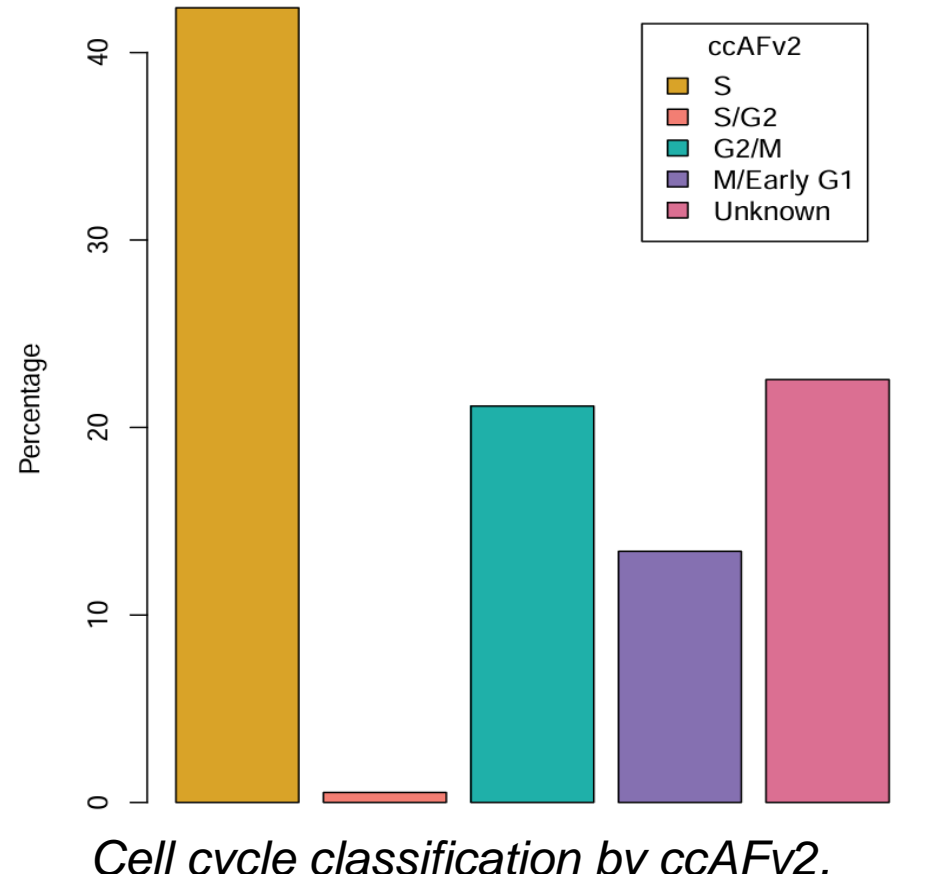


Annotated UMAP of cell types within a scRNA-seq sample.

- Quantified and visualized cell counts across annotated dermal layers from the 111 dataset to evaluate tissue representation and sampling consistency.
- Identified clusters of cell types based on gene expression.
- Defined more specific cell states than current publicly available classifiers.
- Identified "unknown" states that may hold relevance to a possible G0/ quiescent state.



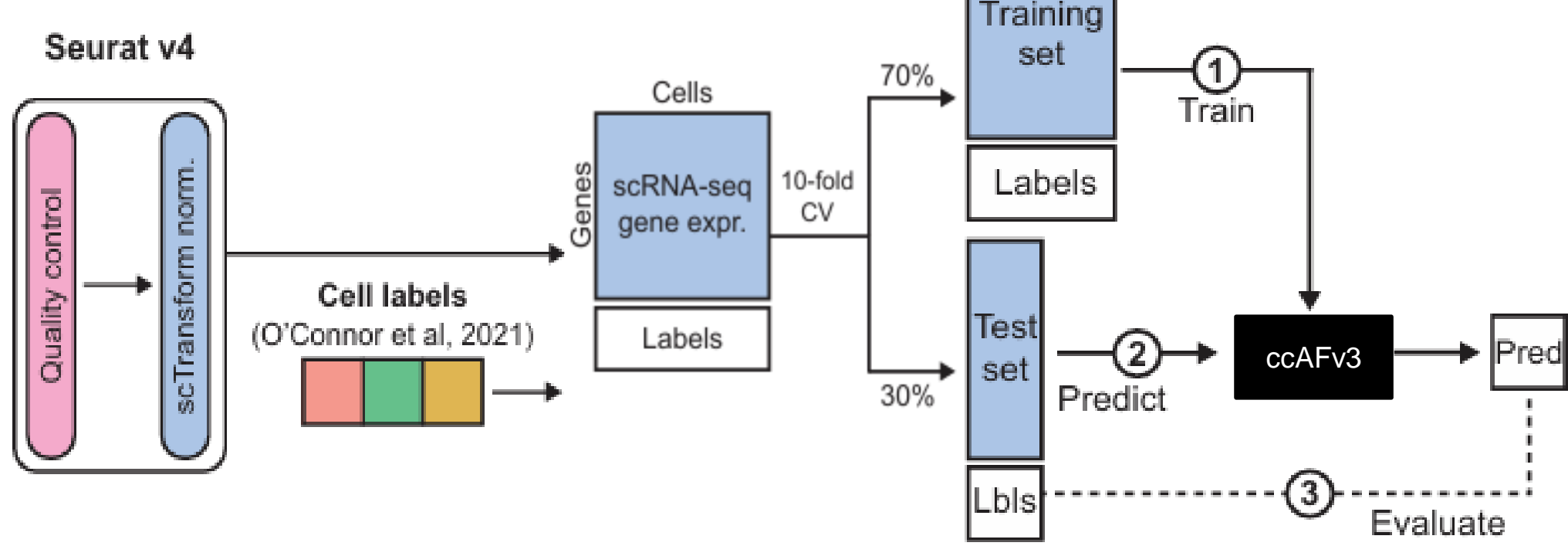
Cell cycle classification by Seurat.



Cell cycle classification by ccAFv2.

Future Directions and Acknowledgements

Stage 5: Testing and Training



Visualization of the integration of more markers for G0 in ccAFv3, found through datasets.

- Split cells into **testing and training datasets**.
- Analyze datasets by applying ccAFv3, **labelling** with previously established **cell cycle labels** (O'Connor et al. 2021)
- Assess accuracy** and compared with publicly available cell cycle classifiers (Seurat v5).

