

INTRODUCTION

Melanoma affects over 100,000 Americans every year. We can combine more granular insights from single cell biology with clinical information from bulk RNA sequencing data. Using drug-labelled single cell data alongside melanoma clinical data from The Cancer Genome Atlas (TCGA) we extract promising general and drug response specific gene markers and examine their relationship with patient survival. We found gene signatures related to cell type, treated with drugs, and survival that will help design treatments to kill cancer cells rather than normal cells. We also generated a pipeline to do this analysis.

RESEARCH METHODOLOGIES

- Download** single cell RNA-seq melanoma data (Jerby-Arnon et. al, 2019) and bulk TCGA data with survival data.
- Process Data** Using R, Scanpy, and Seurat - normalize data and correct data for inconsistencies
- Analyze Data**
 - Use MSigDB to find gene sets that overlap with differentially expressed genes between treated and non-treated cells
 - Use STREAM to find cell state progression

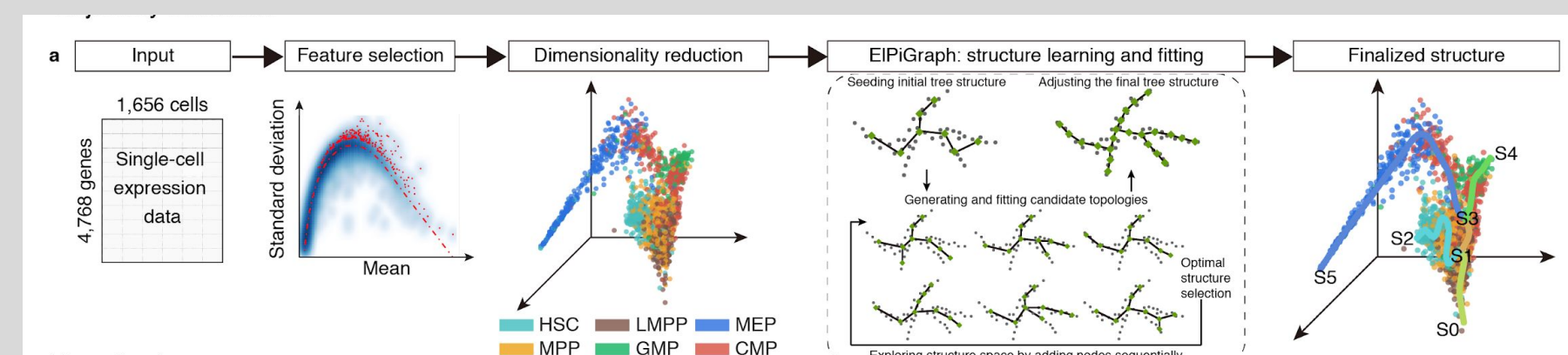


Figure 1. STREAM pipeline

- Use Multi-subject Single Cell deconvolution (MuSiC) to deconvolve data from TCGA, connecting single cell drug treated dataset to bulk RNA-seq data.

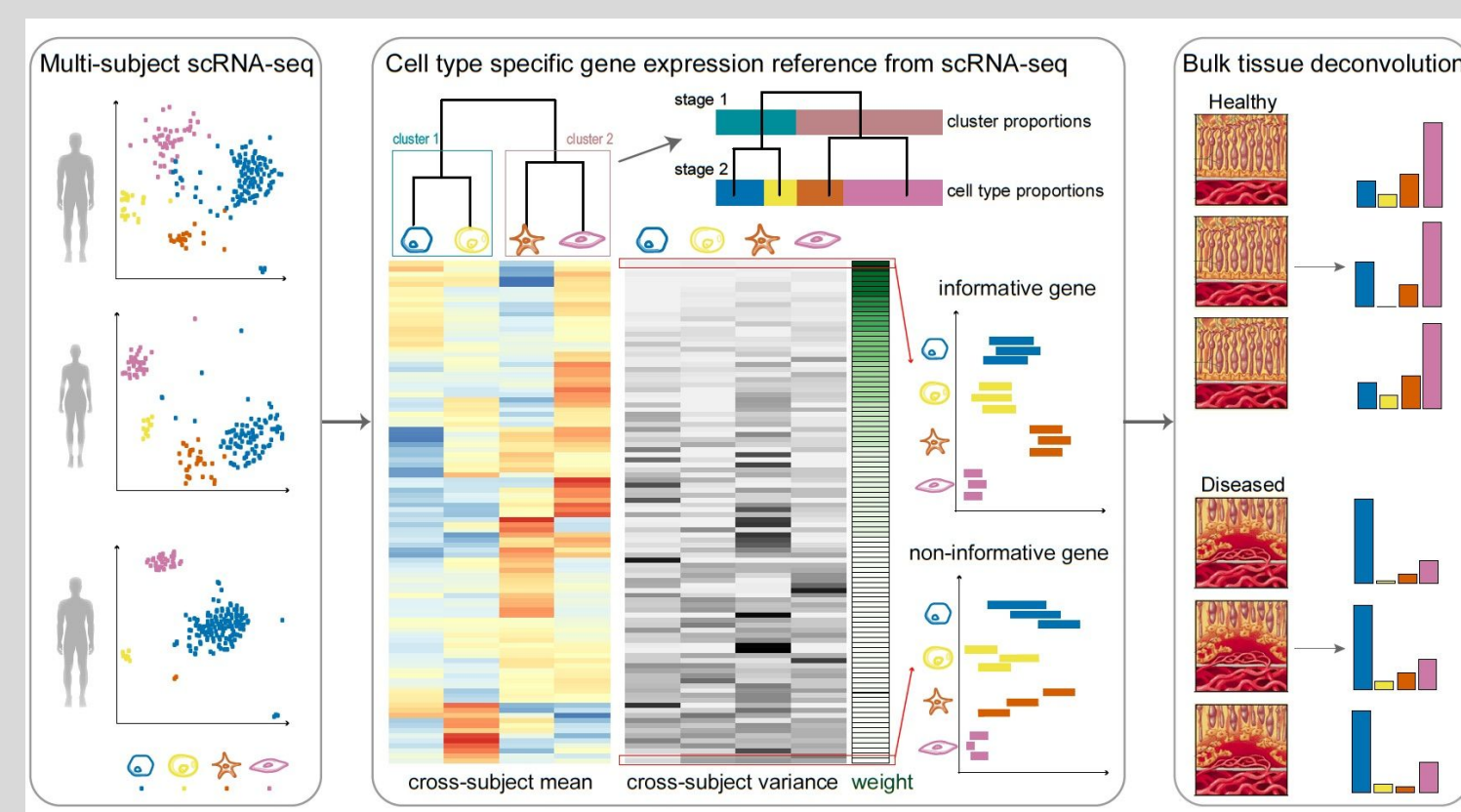


Figure 2. MuSiC pipeline to find fractions of different cell types within the bulk data

- Use Kaplan-Meier plot to generate relationship between expression of malignant cell gene markers and survival
- Plot heatmap of differentially expressed genes as well as marker genes found from CellMarker



IMPLICATIONS

These results are important because researchers can target differentially expressed genes and manipulate drugs to alter the pathways associated with those genes. We can extend this analysis to other cell types.

DATA AND FINDINGS

STEP 1: Curate Gene Markers from sc-RNA-seq Melanoma data

Gene Set Name (# Genes (K))	Description	Genes Overlap	p-value	FDR	Gene Set Name (# Genes (K))	Description	Genes Overlap	p-value	FDR
GO_CYTOSOLADRIC_VESICLE_TRAFF [449]	Any constituent part of cytoplasmic vesicle, including a vesicle, vacuole, or inclusion body, that is a site of storage or transport of a substance.	12	1.21e-13	3.79e-29	GO_CELL_ACTIVATION [424]	A change in the morphology of a cell resulting from an activating factor or signal.	26	2.38e-13	3.79e-11
GO_XEROCYTOSIS [898]	A process of a cell that results in the release of melanin granules from the cytoplasm of a melanocyte.	31	7.68e-27	6.11e-23	MSIGDB_41 [860]	Whole blood genes.	17	1.78e-13	1.42e-9
					GO_CELL_ACTIVATION_INVOLVES_TUMORINE_RESPONSE [205]	A change in the morphology of a cell resulting from an activating factor such as a cytokine or growth factor.	18	3.23e-13	1.76e-9
					GO_MYELOID_LEUKOCYTE_MEDIATED_IMMUNITY [518]	Any process involving an immune response that is mediated by myeloid leukocytes.	16	1.09e-12	4.35e-9
					GO_MYELOID_LEUKOCYTE_ACTIVATION [650]	A change in the morphology of a myeloid leukocyte resulting from an activating factor.	16	1.33e-11	4.24e-8

Figure 3. Top 5 MSigDB gene sets that overlap with 100 most differentially expressed genes for treated and untreated A) malignant cells and B) B cells

STEP 2: Analyze single cell data

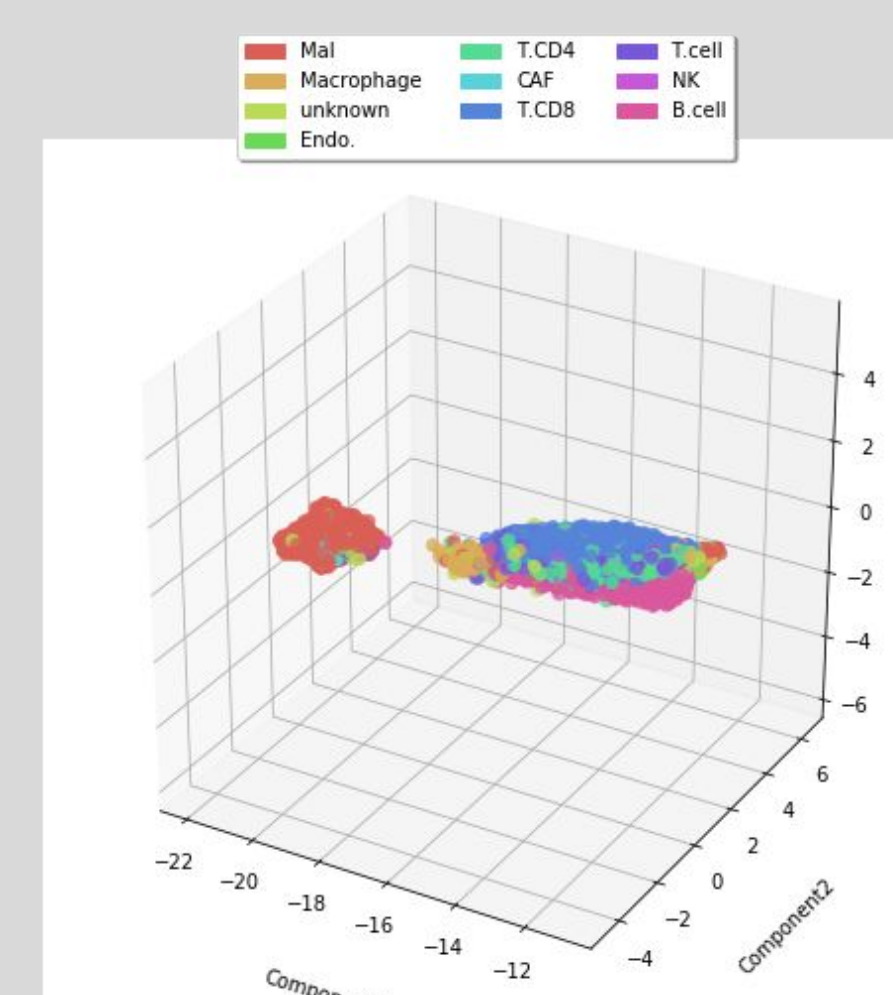


Figure 6. STREAM plot showing time trajectories for CD8 and B cells.

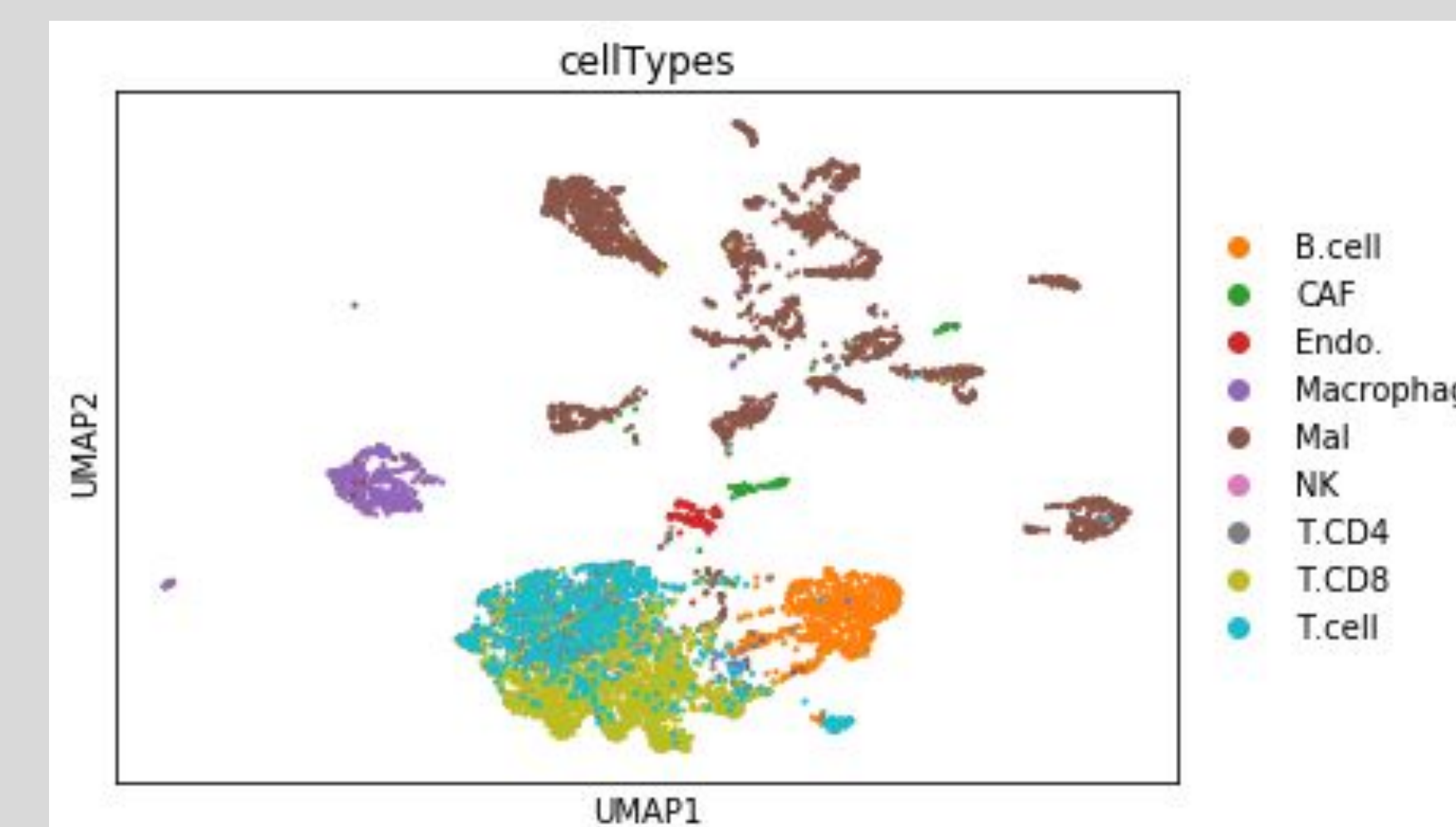


Figure 7. Clusters of cells generated through UMAP, showing distinctions between cell type

STEP 3: Combine single cell data with bulk data to get clinical insights

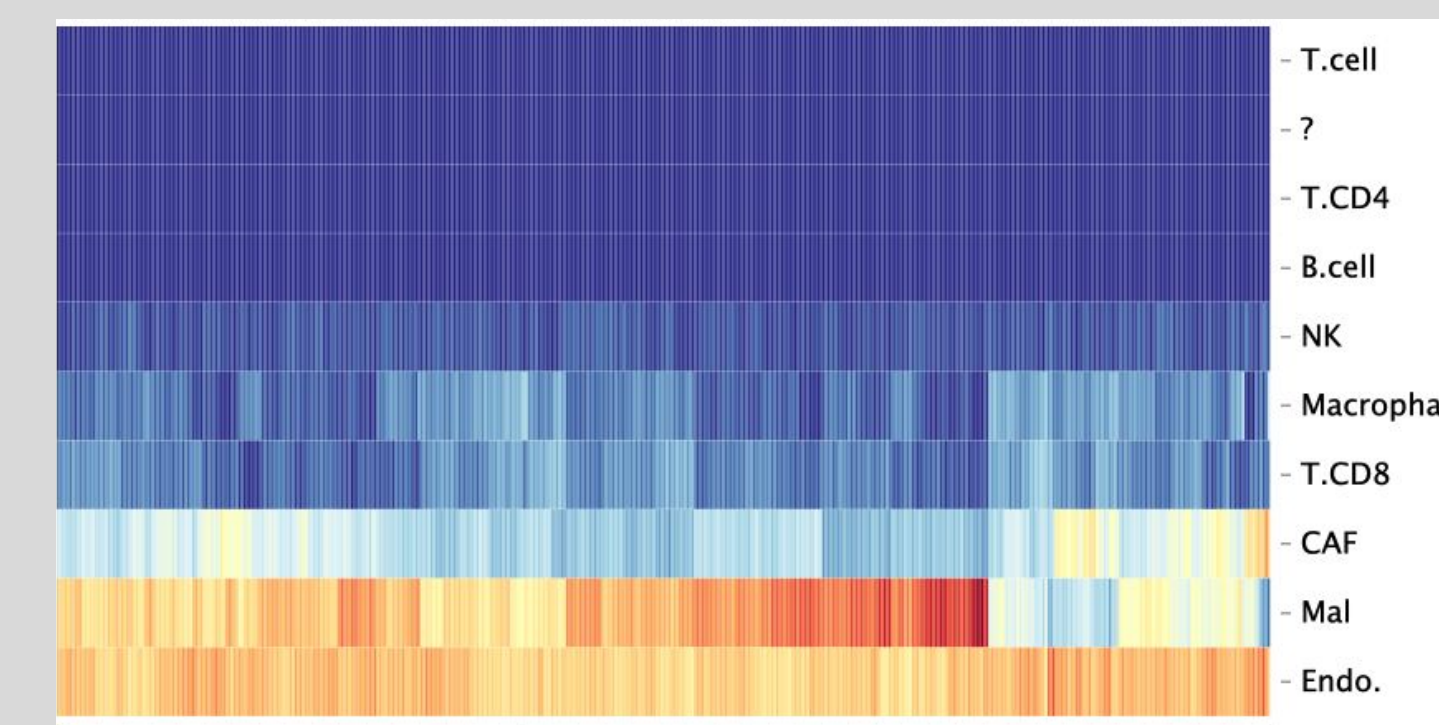


Figure 9. Deconvoluted TCGA data with two apparent malignant cell groups with differing expression

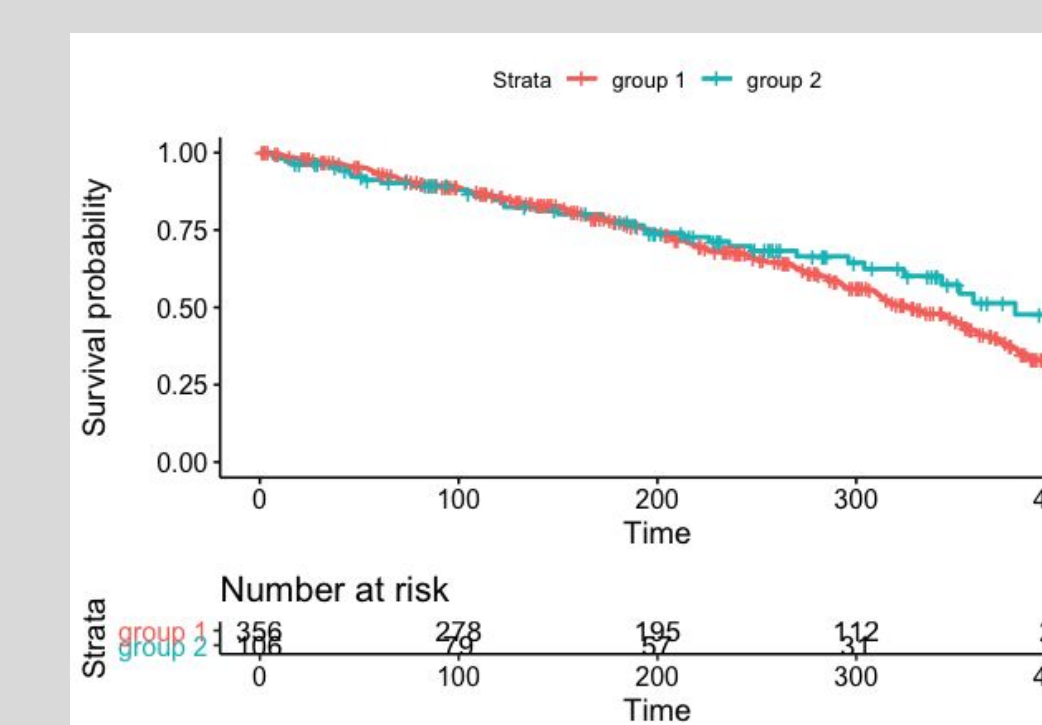


Figure 10. Kaplan-Meier Plot showing differences in survival between two malignant groups of cells

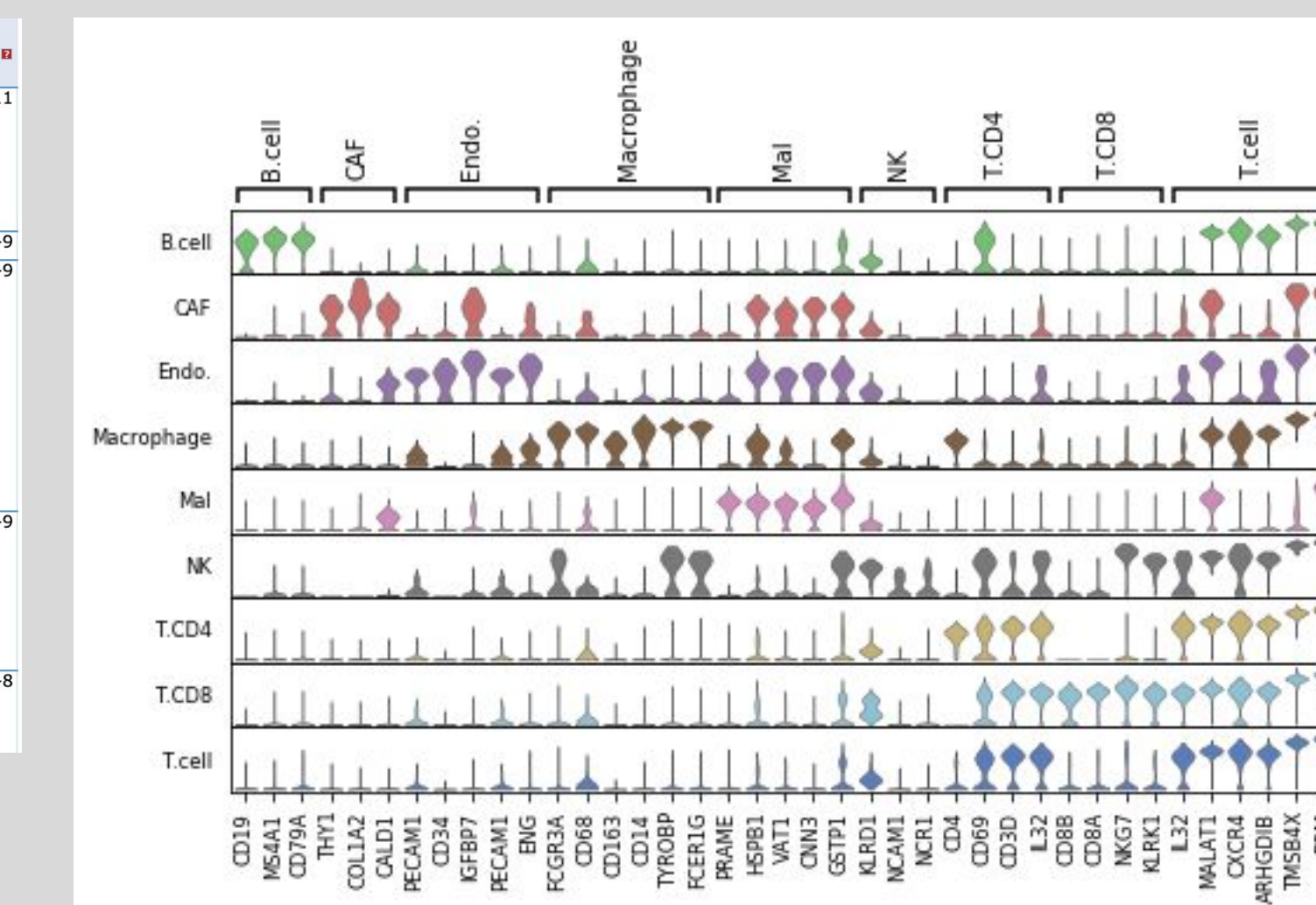


Figure 4. Violin plot that shows the distribution of the gene expression values of marker genes across cell types. Top 3 differentially expressed between the cell type and all other cell types

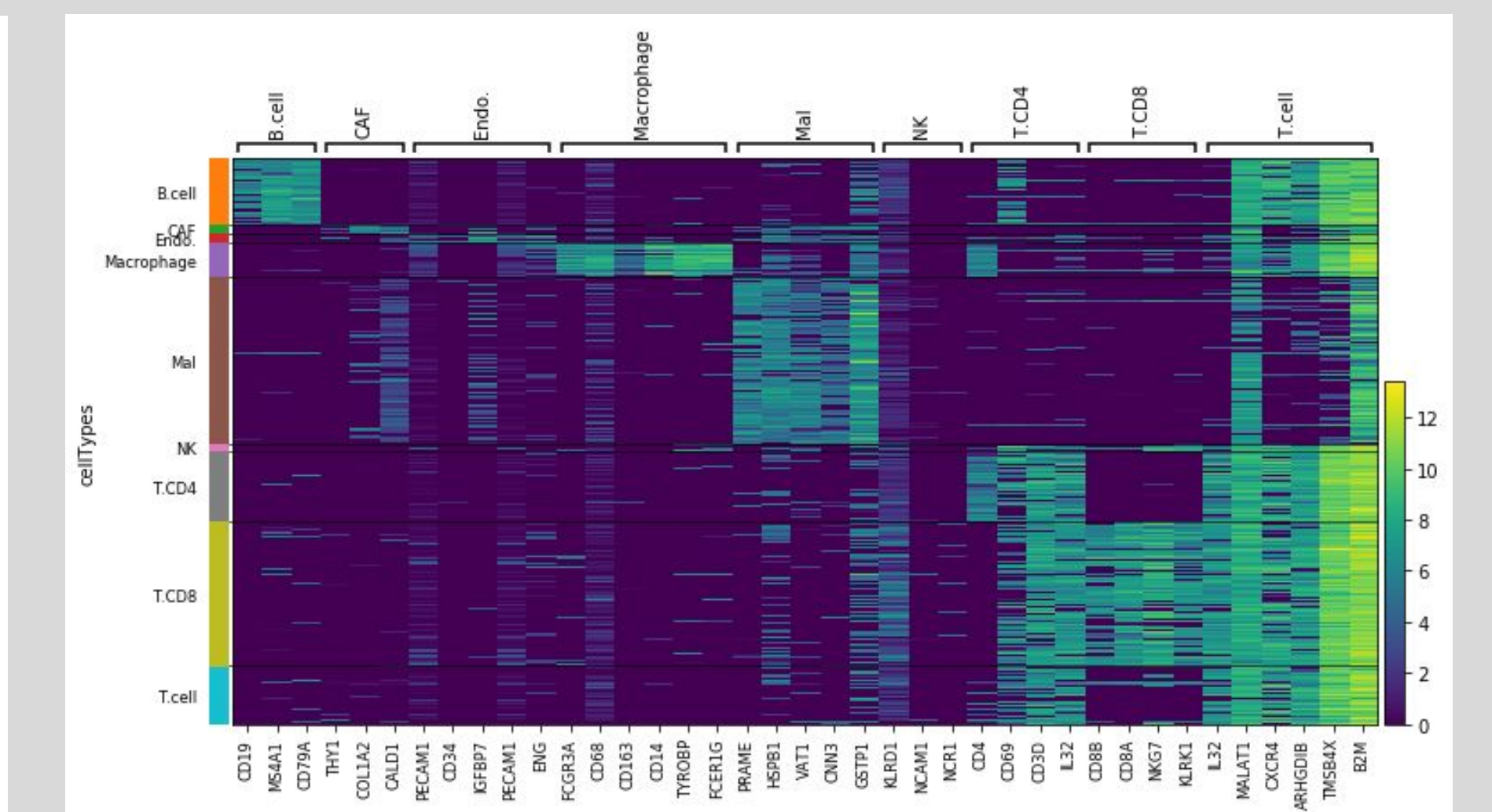


Figure 5. Heatmap that shows the expression of marker genes which consist of the top 3 differentially expressed between the cell type and all the other cell types as well as cell specific markers.

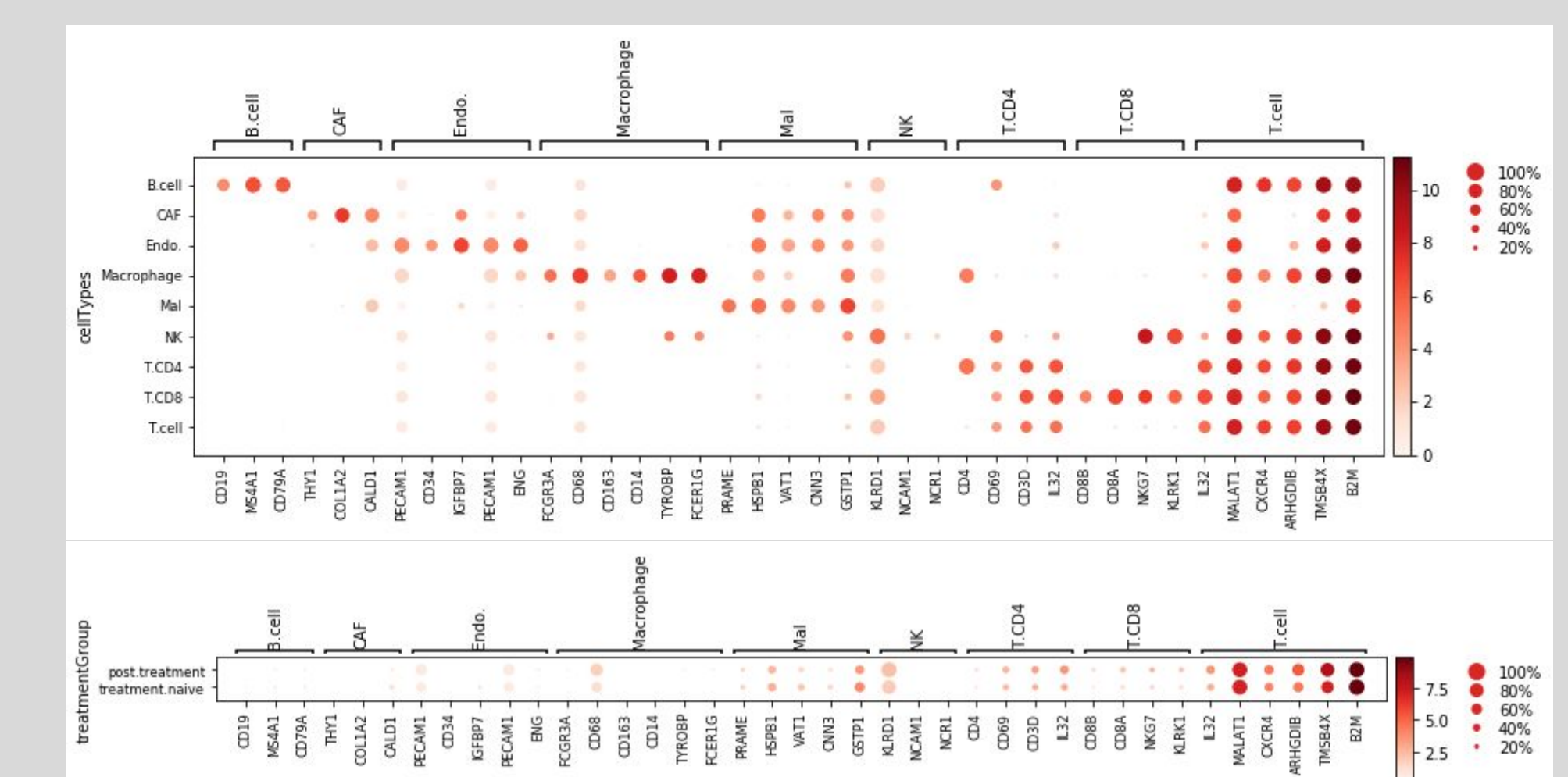


Figure 8. Dotplot that shows the fraction of cells with expression of each marker gene. The top graph shows a comparison between expression between cell types, while the bottom graph shows the expression of genes based on whether the cells were treated.

CONCLUSION

The genes that are most differentially expressed play a role in exocytosis, which suggests that there is a link between anti-PDL-1 therapy and altering the mechanism of exocytosis in malignant cells. The 34 clusters created suggest that there is some link to cancer associated fibroblasts as well as the differentially expressed genes between clusters. The Kaplan Meier Plot shows survival probability differences between two malignant groups of cells.

ACKNOWLEDGEMENTS

Special thanks to Alborz Bejnood, Ms. Angell, and the AAR program for making this project possible.

Works cited:

Alsaab, H. O., Sau, S., Alzhrani, R., Tatiparti, K., Bhishe, K., Kashaw, S. K., & Iyer, A. K. (2017). PD-1 and PD-L1 Checkpoint Signaling Inhibition for Cancer Immunotherapy: Mechanism, Combinations, and Clinical Outcome. *Frontiers in Pharmacology*, 8. <https://doi.org/10.3389/fphar.2017.00561>

Chen, K.-Y., Srinivasan, T., Lin, C., Tung, K.-L., Gao, Z., Hsu, D. S., ... Shen, X. (2018). Single-cell transcriptomics reveals heterogeneity and drug response of human colorectal cancer organoids. *Conference Proceedings: ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE Engineering in Medicine and Biology Society, Annual Conference*, 2018, 2378-2381. <https://doi.org/10.1109/EMBC.2018.8512784>

Elyada, E., Bolisetty, M., Laise, P., Flynn, W. F., Courtis, E. T., Burkhart, R. A., ... Tuveson, D. A. (2019). Cross-species single-cell analysis of pancreatic ductal adenocarcinoma reveals antigen-presenting cancer-associated fibroblasts. *Cancer Discovery*, 9(8), 1102-1123. <https://doi.org/10.1158/2157-9790.CCR-19-0094>

Gong, J., Chehrzad-Raffie, A., Reddi, S., & Salgia, R. (2018). Development of PD-1 and PD-L1 inhibitors as a form of cancer immunotherapy: A comprehensive review of registration trials and future considerations. *Journal for Immunotherapy of Cancer*, 6. <https://doi.org/10.1186/s40425-018-0316-z>

Jerby-Arnon, L., Shah, P., Cuomo, M. S., Rodman, C., Su, M.-J., Melms, J. C., ... Regev, A. (2018). A Cancer cell program promotes T cell exclusion and resistance to checkpoint blockade. *Cell*, 175(4), 984-997.e24. <https://doi.org/10.1016/j.cell.2018.09.006>

Li, H., Courtis, E. T., Sengupta, D., Tan, Y., Chen, K. H., Goh, J. J. L., ... Prabhakar, S. (2017). Reference component analysis of single-cell transcriptomes elucidates cellular heterogeneity in human colorectal tumors. *Nature Genetics*, 49(5), 708-718. <https://doi.org/10.1038/ng.3818>

Patel, A. P., Tirosh, I., Trombetta, J. J., Shalek, A. K., Gillespie, S. M., Wakimoto, H., ... Bernstein, B. E. (2014). Single-cell RNA-seq highlights intratumoral heterogeneity in primary glioblastoma. *Science (New York, N.Y.)*, 344(6190), 1396-1401. <https://doi.org/10.1126/science.1254257>

Tirosh, I., Izar, B., Prakadan, S. M., Wadsworth, M. H., Treacy, D., Trombetta, J. J., ... Garraway, L. A. (2016). Dissecting the multicellular ecosystem of metastatic melanoma by single-cell RNA-seq. *Science*, 352(6282), 189-196. <https://doi.org/10.1126/science.1254257>