Single cell RNA - seq analysis for muscle samples

1. Results:

a. t-SNE:

In my analysis, the t-SNE plot (fig. 1)) closely aligns with the configuration observed in the reference paper. Specifically, the expected clustering of Endothelial Cells is evident, underscoring the reliability of the t-SNE analysis. Notably, T and B cells, alongside NK cells, exhibit close spatial affinity, reflecting their shared immune cell features. Furthermore, distinct separation is apparent among Satellite, LUM+FAP, and FBN1+FAP cells, delineating clear distinctions from both Endothelial and Immune cell groups. Importantly, the t-SNE plot unveils a distinct connection between Smooth Muscle Cells and Pericytes, akin to observations in the reference t-SNE plot. This congruence emphasizes the robustness of the t-SNE analysis in uncovering meaningful cellular relationships within the single-cell RNA sequencing dataset. The visualization details are derived from the t-SNE plot generated using sc.pl.tsne in Scanpy, with cell types indicated by color and a legend placed on data points for clarity.

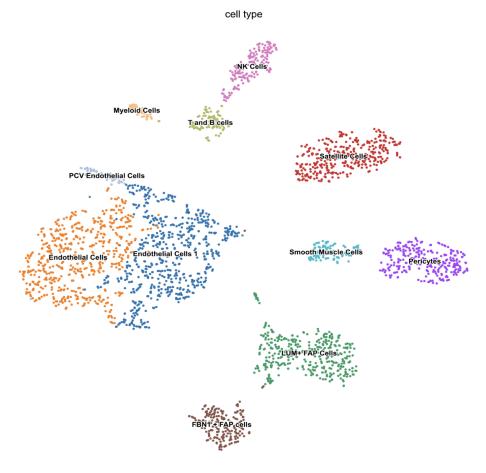


Figure. 1: t-SNE plot

b. Heatmap:

In my analysis using sc.pl.heatmap in Scanpy, the heatmap (fig. 2) provides a visual representation of marker gene expression patterns (marker_genes_dict) across diverse cell types (groupby='cell_type'). The color map is specifically tailored to capture varying expression levels, employing a 'Reds' palette (cmap='Reds'). Both row and column hierarchical clustering are incorporated into the heatmap, as indicated by the presence of dendrograms (dendrogram=True). Adjusting the figure size to 12 by 8 inches (figsize=(12, 8)) enhances the clarity of the heatmap, offering a comprehensive depiction of gene expression across different cell types. It's important to note that the Y-axis dendrogram orientation in Python reflects the convention of placing variables along columns, differing from the X-axis dendrogram used in R. Despite this distinction, the heatmap closely aligns with the expression patterns observed in the reference paper.

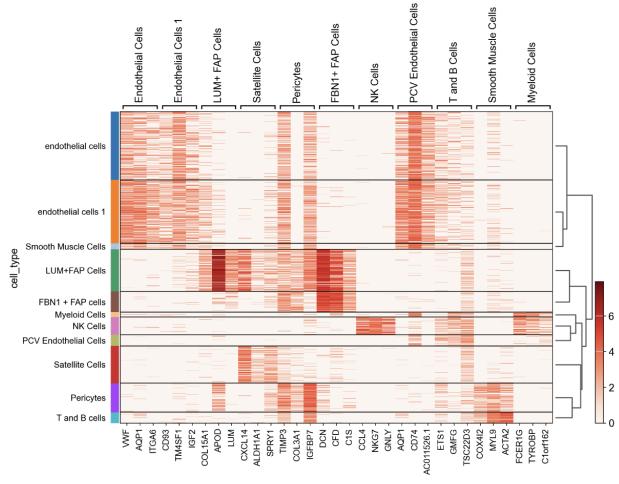


Figure. 2: Heatmap

2. References:

1. Rubenstein, A.B., Smith, G.R., Raue, U. *et al.* Single-cell transcriptional profiles in human skeletal muscle. *Sci Rep* 10, 229 (2020).

https://doi.org/10.1038/s41598-019-57110-6

2. Scanpy: Preprocessing and clustering 3k PBMCs https://scanpy-tutorials.readthedocs.io/en/latest/pbmc3k.html

3. Scanpy: Core plotting functions https://scanpy-tutorials.readthedocs.io/en/latest/plotting/core.html

4. Seurat's guided clustering tutorial (Satija et al., 2015) https://satijalab.org/seurat/articles/pbmc3k_tutorial

5. anndata: Annotated data

Isaac Virshup, Sergei Rybakov, Fabian J. Theis, Philipp Angerer, F. Alexander Wolf *bioRxiv* 2021 Dec 19. doi:10.1101/2021.12.16.473007. https://anndata.readthedocs.io/en/latest/

6. The severse project provides a computational ecosystem for single-cell omics data analysis.

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Nat Biotechnol. 2023 Apr 10. doi: <u>10.1038/s41587-023-01733-8</u>. https://www.nature.com/articles/s41587-023-01733-8