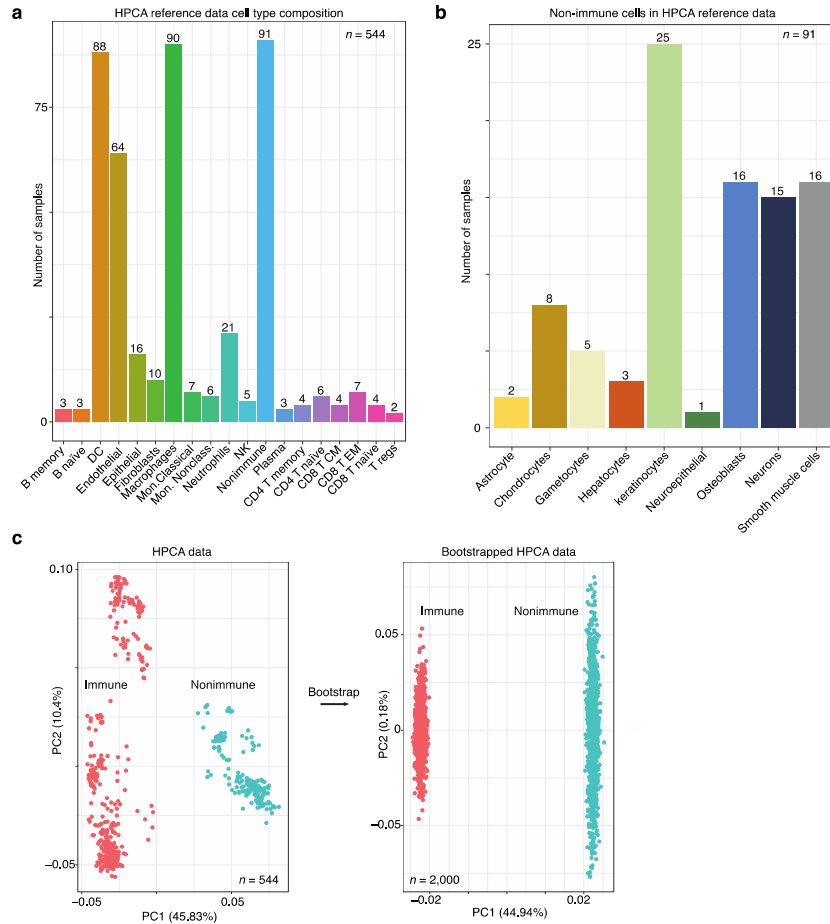
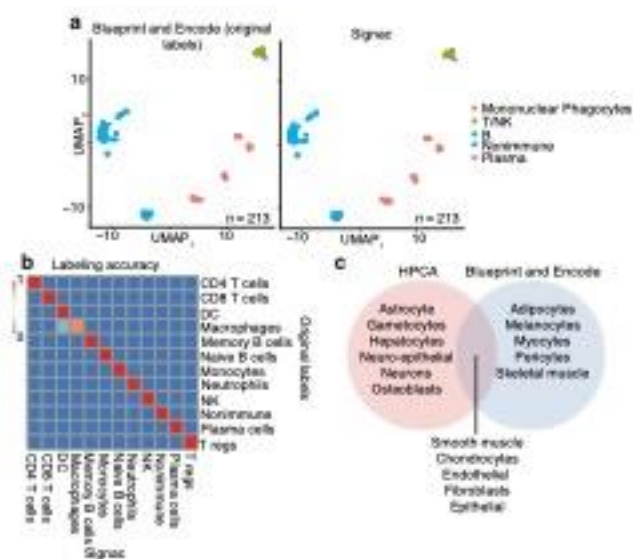


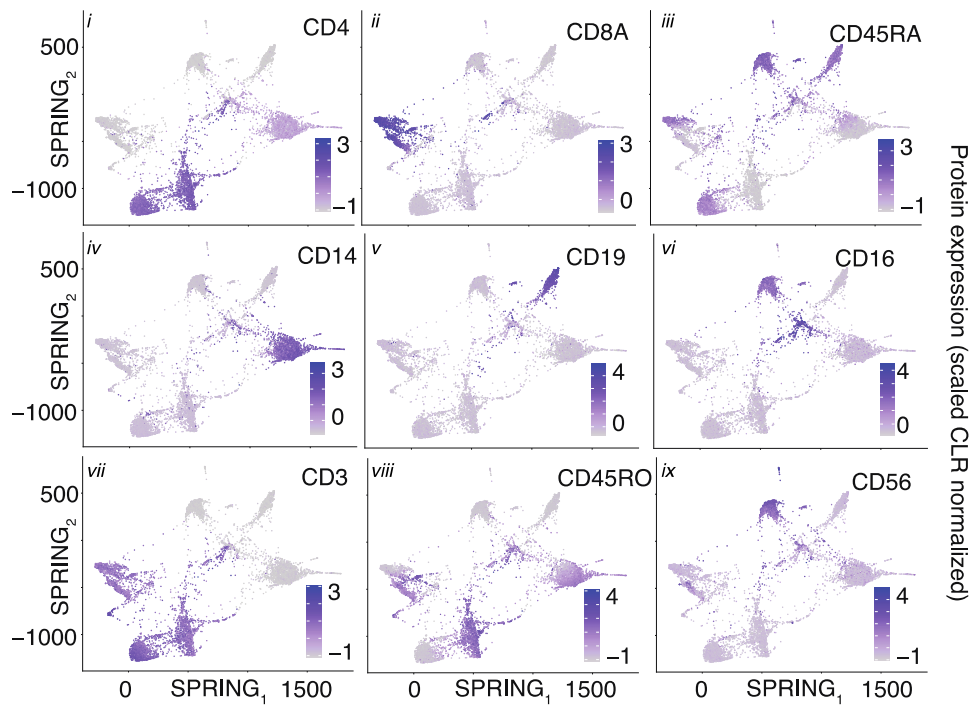


Supplemental Figure 1: Overview of the HPCA reference data. A, Number of samples bar plot for each annotated cell type. Bar plot indicates the number of samples (y-axis; numbers) for each cellular phenotype (x-axis) that was in the HPCA reference data set. **B, Number of samples bar plot for the “nonimmune” cellular phenotypes.** Bar plot as depicted in [Supplemental Figure 1A](#) for the $n = 91$ samples in the “nonimmune” cell type category. **C,** Principal component analysis (PCA) plots revealed that the HPCA reference data and the bootstrapped training data were separable by immune and nonimmune gene markers. PCA

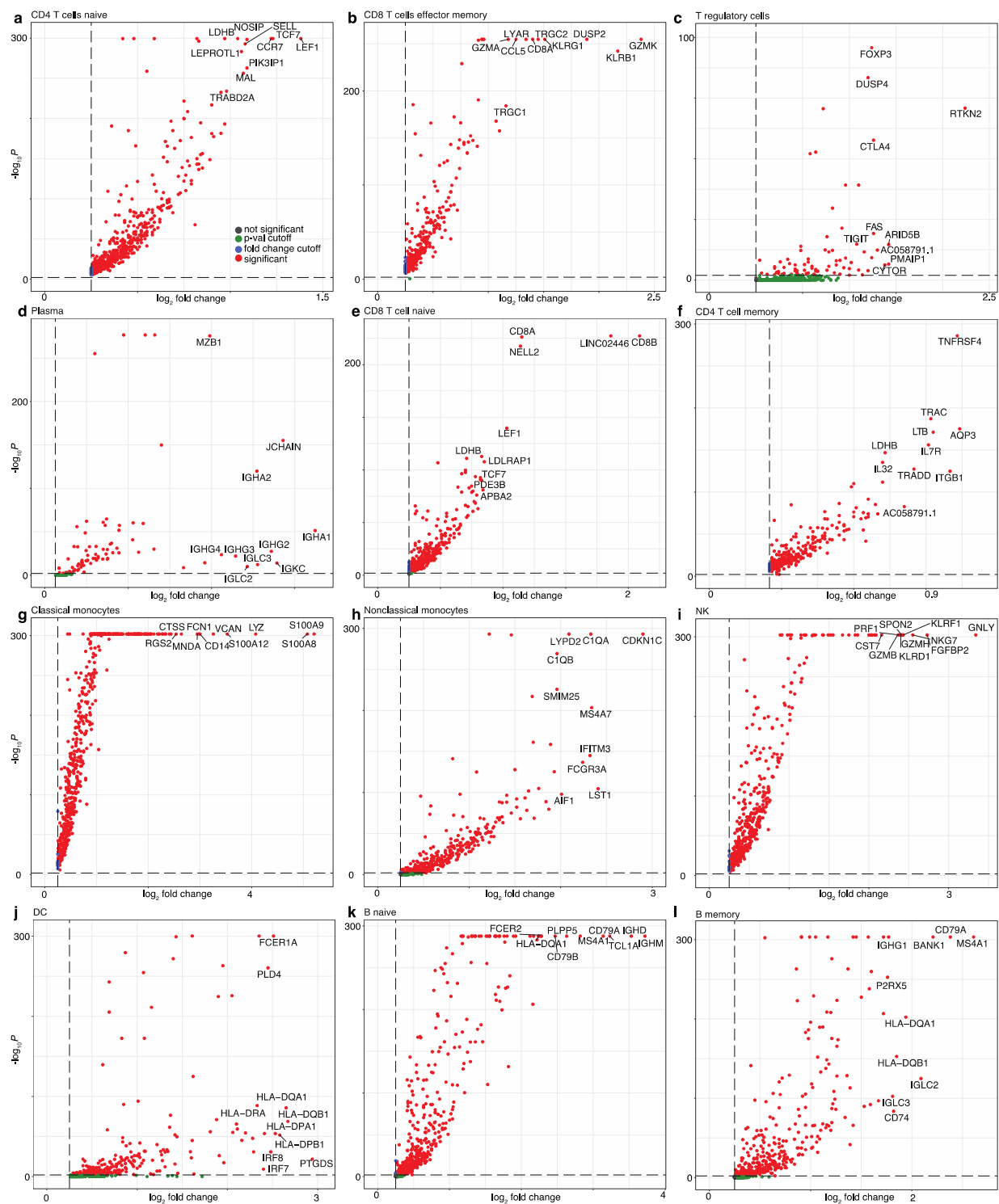
plot (left) shows a gene expression sample (each dot) from the HPCA reference data that is either labeled as immune (red) or nonimmune (teal) based on the classification hierarchy established here and the annotated cell type established experimentally ([Fig. 1A](#)). PCA was performed on the marker gene that were determined by differential gene expression analysis comparing the samples annotated as immune and nonimmune. After bootstrapping (arrow); PCA was performed with the same marker genes, except with data that was bootstrapped from the immune and nonimmune samples. We note that the structure in the PCA plot prior to bootstrapping was largely removed, consistent with the view that bootstrapping generated what can be thought of as composite or as average immune and nonimmune gene expression samples.



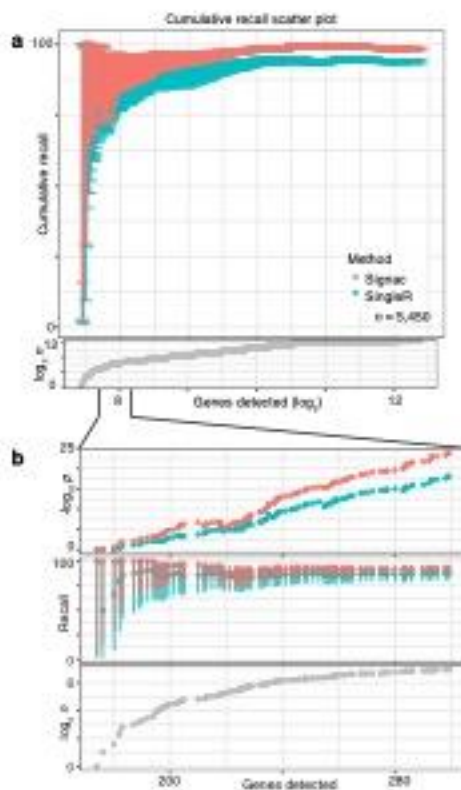
Supplemental Figure 2: Neural networks robustly classified validation data from the Blueprint and Encode consortia. A, UMAP plots show that cellular phenotypes were accurately classified by Signac. In the scatter plot (left), each dot is a sample of pure cell type gene expression data that was amended labels for cellular phenotypes (colors; see legend). The data represented here are in a two-dimensional embedding (axes), in which distances correspond to transcriptional similarities between samples (closer samples are more similar); we determined this embedding with UMAP. Cellular phenotype labels (colors) were established either by the Blueprint and Encode consortium (left) with empirical measurements or by our computational approach (right). **B, Heatmap shows that distinct immune cell phenotypes were accurately classified by Signac.** Heatmap displays the fraction of the samples within each cellular phenotype category (axes) that were accurately classified by our approach (scale bar; red is more accurate; blue is less accurate). **C, Venn diagram shows that Signac accurately identified the transcriptomes of nonimmune cellular phenotypes despite never being trained to recognize them.** Venn diagram depicts the nonimmune cellular phenotypes that were specific to the HPCA reference data (left; red), that were shared between the HPCA reference and the Blueprint and Encode data (middle; purple), and that were distinct to the Blueprint and Encode data (right; blue).



Supplemental Figure 3: Protein expression SPRING plots validated the cellular phenotypes classified by Signac for the CITE-seq PBMCs data. Each SPRING plot (*i-ix*) displays the z-score transformed CLR normalized protein expression (colors) generated for each individual cell.

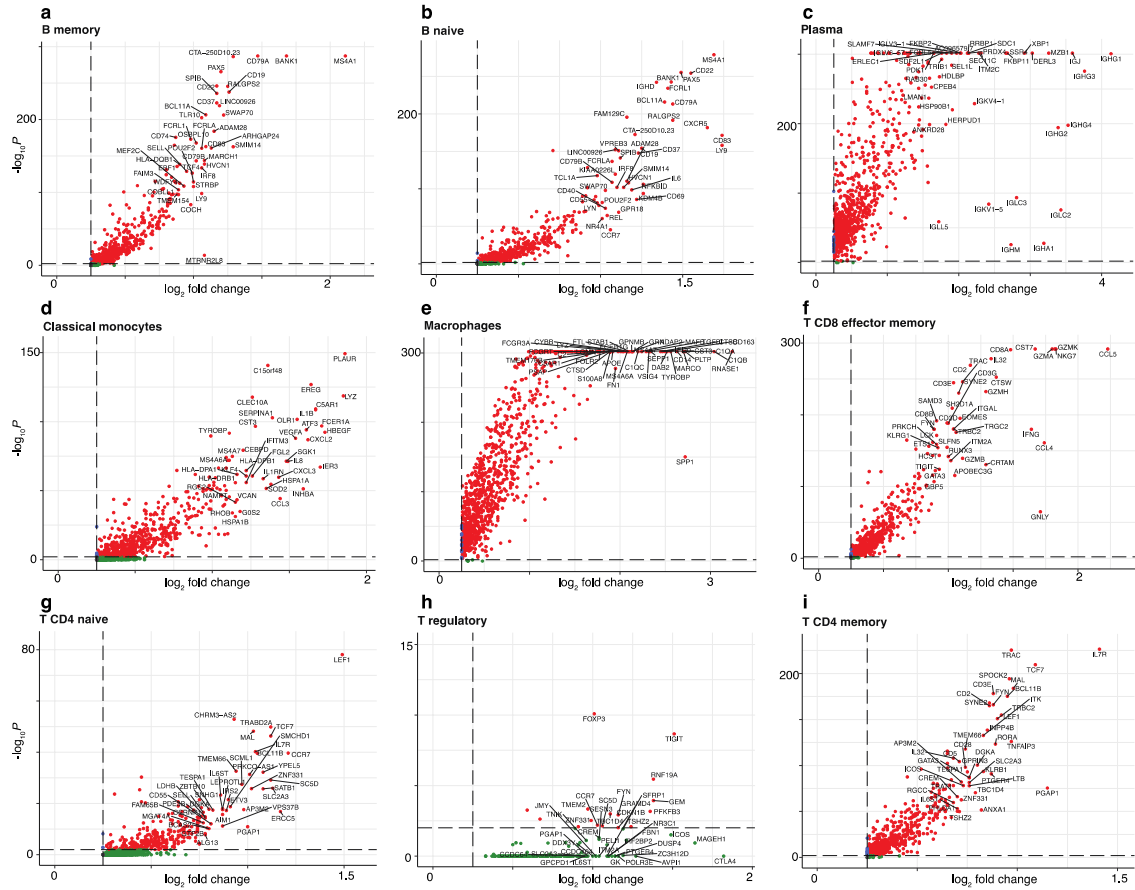


Supplemental Figure 4: IMAGES identified from immune phenotypes in CITE-seq PBMCs single cell transcriptomes. A-I, Volcano plots demonstrate the IMAGES identified in each cell population. Each scatter plot depicts the statistical association (y-axis) and the average fold-change of IMAGES (each dot is a unique gene) for immune cell phenotypes. Colors (red) indicate IMAGES that passed the thresholds applied to the fold-change and adjusted p-values.

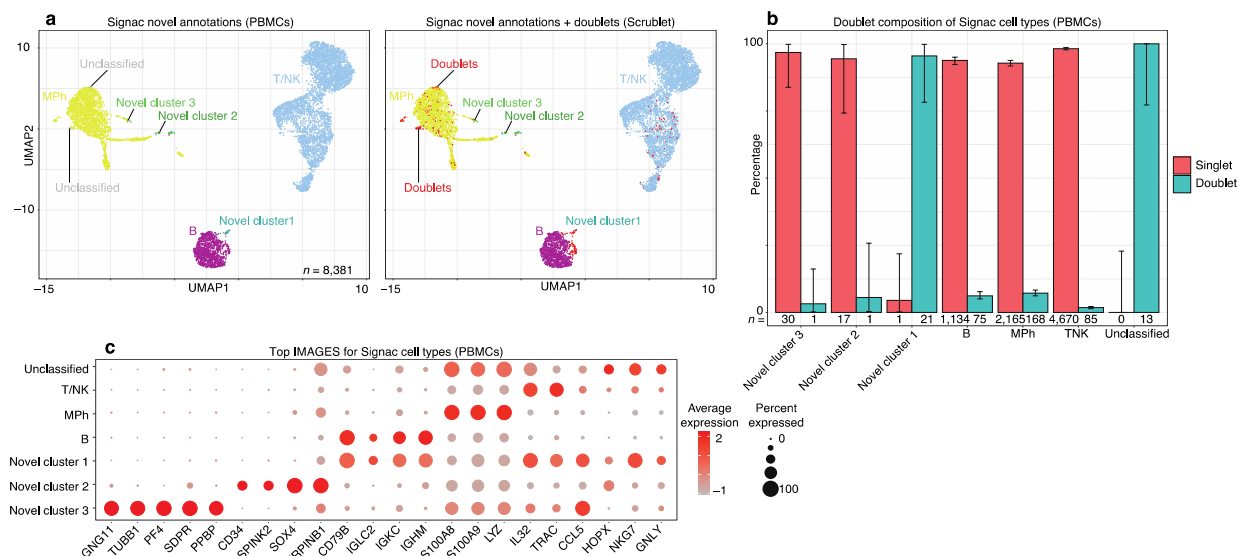


Supplemental Figure 5: Signac accurately recalled flow cytometry labels with few genes detected. A, Cumulative recall scatter plot showed that Signac outperformed SingleR as a function of genes detected in immune cell transcriptomes. Plot depicts the cumulative recall

(y-axis) of immune cell type labels. The labels were originally determined by flow cytometry (T cell, B cell or monocyte). Recall of these labels was calculated cumulatively as a function of the number of genes detected (x-axis) by either Signac (red) or SingleR (teal). Fibroblasts were omitted from this analysis due to broad misclassification by SingleR. Scatter plot, bottom depicts the number of single cell transcriptomes (n) as a function of genes detected. Error bars (top) are 95% C.I.s determined by two-sided binomial testing. **B, Inset shows stronger Signac performance at low genes detected.** Scatter plot (top) depicts the p -value for the two-sided binomial test and showed that Signac (red) outperformed SingleR (teal) at low sequencing depths. Scatter plots (middle; bottom) are close-ups of [Supplemental Figure 5A](#) for data with less than 300 genes detected.



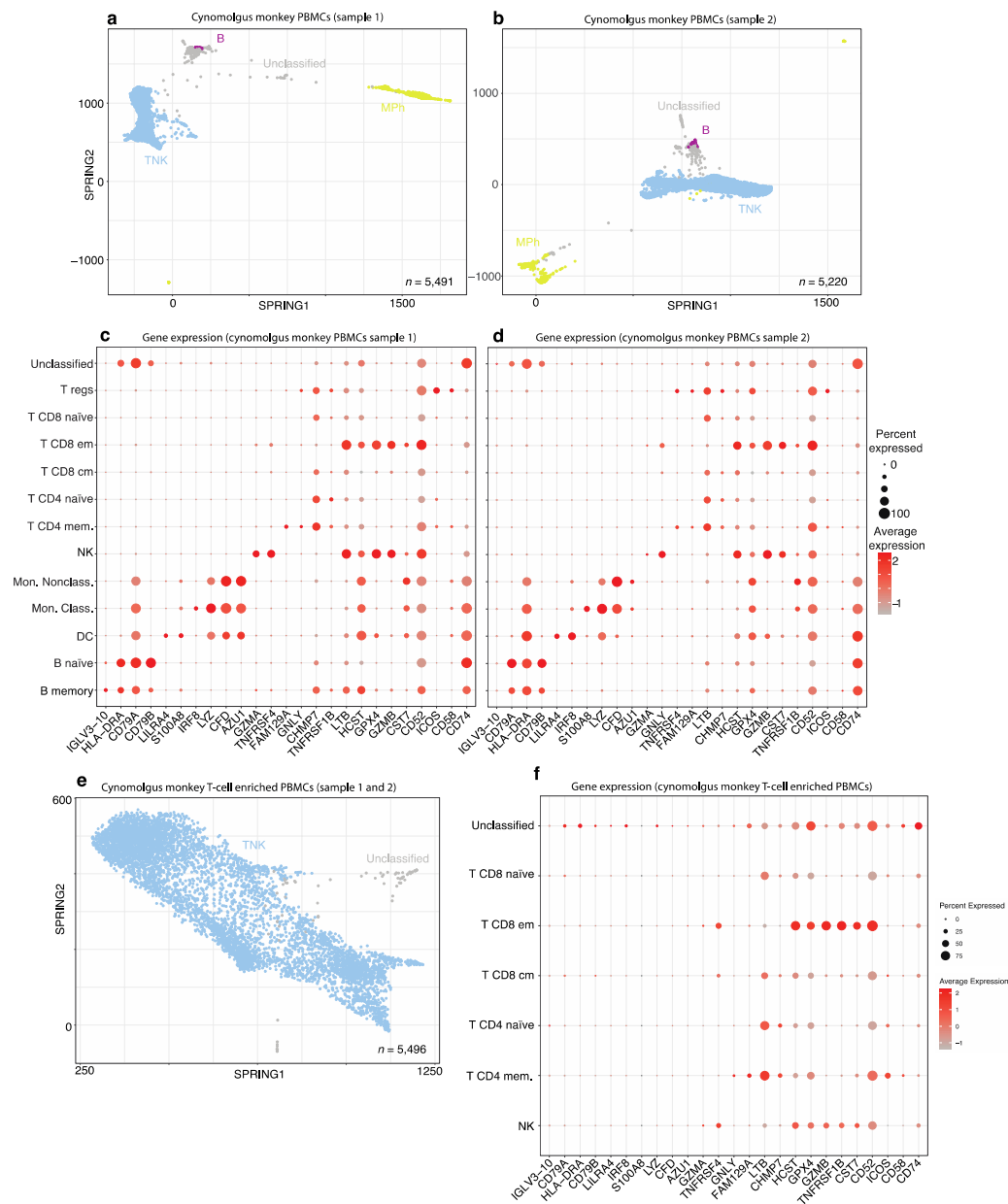
Supplemental Figure 6: IMAGES identified from immune phenotypes in synovium single cell transcriptomes. A-I, Volcano plots demonstrate the IMAGES identified in each cell population. Each scatter plot depicts the statistical association (y-axis) and the average fold-change of IMAGES (each dot is a unique gene) for immune cell phenotypes. Colors (red) indicate IMAGES that passed the thresholds applied to the fold-change and adjusted p-values.



Supplemental Figure 7: Signac-generated “unclassified” PBMCs were all identified as doublets (Scrublet), novel and classified cell type populations were mostly singlets. A-I,

Volcano plots demonstrate the IMAGES identified in each cell population. A, UMAP plot displays the cell type annotations of Signac for PBMCs (left), and the same data but with doublets classified by Scrublet (right). Each cell barcode ($n = 8,381$ from one human donor) was classified by Signac (left), and then doublet labels were amended to each cell with Scrublet (right; red); see [Methods: Signac classification](#). B, Bar plot reveals that unclassified cells were entirely composed of doublets, whereas novel cell populations and classified cells were mostly composed of singlets. Each bar shows the percentage (y-axis) of each cell type (x-axis) that is a doublet (teal) or a singlet (red). Error bars correspond to 95% confidence intervals, two-sided binomial test. C, IMAGE expression dot plot shows that unclassified cells and novel cluster 2 were doublet-like, whereas novel cluster 2 and 3 were singlet-like and enriched for

known platelet and hematopoietic stem-cell gene markers. Dot plot shows the percentage (size) of single-cell transcriptomes within a cell type (y-axis) for which non-zero expression of marker genes was observed (x-axis). Color displays the average gene expression (red indicates more expression) in each cell type category. Novel cluster 1 was enriched for IMAGES that were typically enriched in either B cells or T cells, but not both (i.e., these cells expressed both *CD79B* and *TRAC*), consistent with the view that these cells were doublets. Novel cluster 3 images ($\text{GNG11}^+ \text{TUBB1}^+$) suggested platelet-like cells, and novel cluster 2 images ($\text{CD34}^+ \text{SPINK2}^+$) suggested hematopoietic stem cell-like cells.



Supplemental Figure 8: Signac accurately classified primate PBMCs without any species-specific training. A, SPRING plot for PBMCs from cynomolgus monkey donor 3003. B, SPRING plot for PBMCs from cynomolgus monkey donor 3004. C-D, IMAGE expression dot plot shows that Signac classifications for immune phenotypes were consistent with known gene markers. E, SPRING plot for PBMCs from cynomolgus monkey samples that were enriched for T cells during sequencing. See Methods: Cross-species classification of single cell data from cynomolgus monkey PBMCs with human reference data. F, IMAGE expression dot plot shows that Signac classifications for immune phenotypes were consistent with T cell type enrichment assay.