## **Supplementary Figures**



Figure S1 Related to Figure 1 and "Regression-based normalization" Section of STAR Methods. Data filtering for three scRNA-seq datasets (Pollen et al., 2014; Gaublomme et al., 2015; Zheng et al., 2017). **(a-c)** Boxplot representing (in black) proportions of genes, cells and counts preserved after sample and gene filtering. Note in (a) that no samples were filtered in Pollen et al. 2014. **(d-f)** Per-cell zero rates before and after data filtering. Datasets are presented in the same order as (a-c). In the case of Gaublomme et al. 2015, bulk RNAseq samples from the same study were plotted in green along single-cell samples in (e). Point size corresponds to two-sided p-value of sample read count under log-normal model fit to single-cell samples passing filter. This is meant to highlight bulk samples with similar read coverage: other samples had very poor coverage and correspondingly high zero rates. **(g-i)** Per-gene zero rates before and after data filtering. Datasets are presented in the same order as (a-c).



Figure S2 Related to Figure 1. Exploratory data analysis of human cortex cells (Pollen et al., 2014). **(a)** PCA of the log-transformed, TC-normalized read count data using all genes passing quality filtering. Cells are color-coded by biological condition. Cells cluster partially by biological condition, with significant intracondition heterogeneity. The design of this study is fully confounded (one batch per biological condition): batch adjustment is not advisable in this case, as it would remove the biological effects of interest. **(b)** Absolute Spearman correlation coefficient between the first three PCs of the expression data (as computed in (a)) and a set of  $QC$  measures (Table S1).  $(c)$  Heatmap of pairwise Pearson correlation coefficients between QC measures. **(d)** PCA of the QC measures for all cells in (a). Single-cell QC profiles cluster by biological condition, suggestive of technical confounding. **(e)** Boxplot of the first qPC, stratified by biological condition. QC measures differ significantly between NPCs and other biological conditions / batches.



Figure S3 Related to Figure 1. Exploratory data analysis of human peripheral blood mononuclear cells (PBMCs) (Zheng et al., 2017). **(a)** tSNE of the first 10 PCs of the log-transformed, TC-normalized UMI count data for all genes and cells passing quality filtering. Cells are color-coded by a *Seurat*-based manual annotation of major PBMC subtypes; shape represents the 10x batch. Samples from both batches ("pmbc4k" and a larger "pbmc8k") originated from the same "healthy" human donor. Cells clearly cluster by data-derived biological condition, one consequence of being clustered jointly in *Seurat*. **(b)** Absolute Spearman correlation coefficient between the first ten PCs of the expression data (as computed in  $(a)$ ) and a set of QC measures (Table S2). **(c)** Heatmap of pairwise Pearson correlation coefficients between QC measures. **(d)** PCA of the QC measures for all cells in (a). Single-cell QC profiles partially cluster by data-derived biology (especially CD14+ monocytes), with no clear clustering by batch. **(e)** boxplot of the third qPC, stratified by batch. The third qPC is the qPC with the highest correlation with batch.



Figure S4 Related to Figure 2. Factors of unwanted variation in the Gaublomme et al. dataset (Gaublomme et al., 2015). (a) Heatmap of Pearson correlation coefficients between RUVg-derived factors of unwanted variation (Risso et al., 2014) and qPCs. Row and column clustering is generated from the R *hclust* function with default parameters. **(b)** Scatter plot of one anti-correlated pair of RUVg factor and qPC, selected based on their high correlation magnitude displayed in (a).



Figure S5 Related to Figure 2 and Figure 4. Stratified performance evaluation for human peripheral blood mononuclear cells (PBMCs) (Zheng et al., 2017). **(a)** Scatter plot representing *scone* performance scores for normalization procedures applied to the 10x PBMC data set. The x-axis measures the aggregation over non-stratified (default) performance scores. The y-axis measures the aggregation over scores computed via stratification by both batch and bio condition. Procedures are colored according to scaling method. Pearson correlation is denoted in the bottom-right corner of the plot. **(b)** ROC AUC vs. stratified *scone* performance score, as in 4c. Normalization procedures in the top-right corner are deemed best both by *scone* and by independent differential expression (DE) validation. Procedures are colored according to scaling method and batch adjustment.



Figure S6 Related to Figure 5. Fold-change estimates of the simulated datasets. **(a)** Boxplot of the average log-fold-change estimation bias across 10 *splatter* simulations (see Methods). All methods led to small bias, with the scran method A. Lun et al., 2016, especially pooling samples after clustering, performing best. **(b)** Scatterplot of average ARI versus the average log-fold-change estimation bias. The absence of strong correlation between these two measures suggests that the bias in log-fold-change estimation is not enough to predict the impact of normalization methods on subsequent analyses.



Figure S7 Related to Figure 6. Batch adjustment for the Tung et al. dataset (Tung et al., 2017). **(a)** PCA of ComBat (Leek et al., 2012) normalized data. Donor-specific effects are removed. (b) Histogram of *scone* performance scores recomputed to include ComBat (red arrow). **(c)** Boxplot of *scone* performance scores for various normalization procedures, excluding BIO\_SIL and BATCH\_SIL from the performance score calculation (see Methods).

## **Supplementary Tables**



Table S1 Related to Figure 1. Sample-level quality control (QC) measures (non-10x Genomics).

Table S2 Related to Figure 1. Sample-level quality control (QC) measures (10x Genomics).

