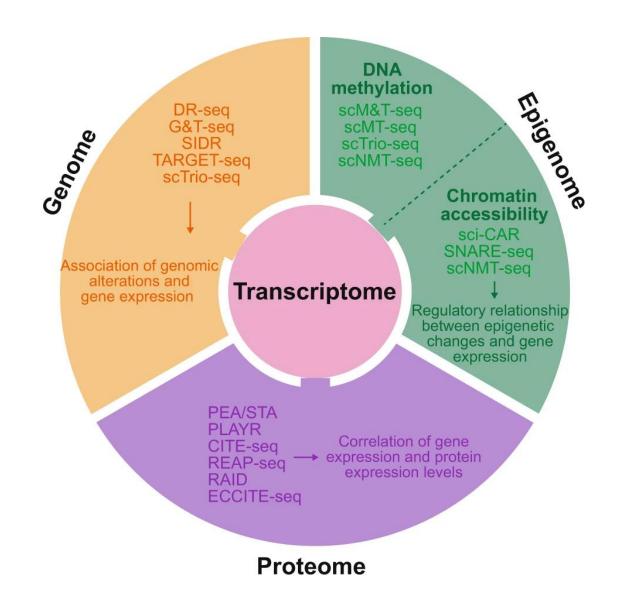
Transcription Factor Activity Analysis Using Multi-Omic Single Cell Data

BMI 585 Final Project Hope Mumme

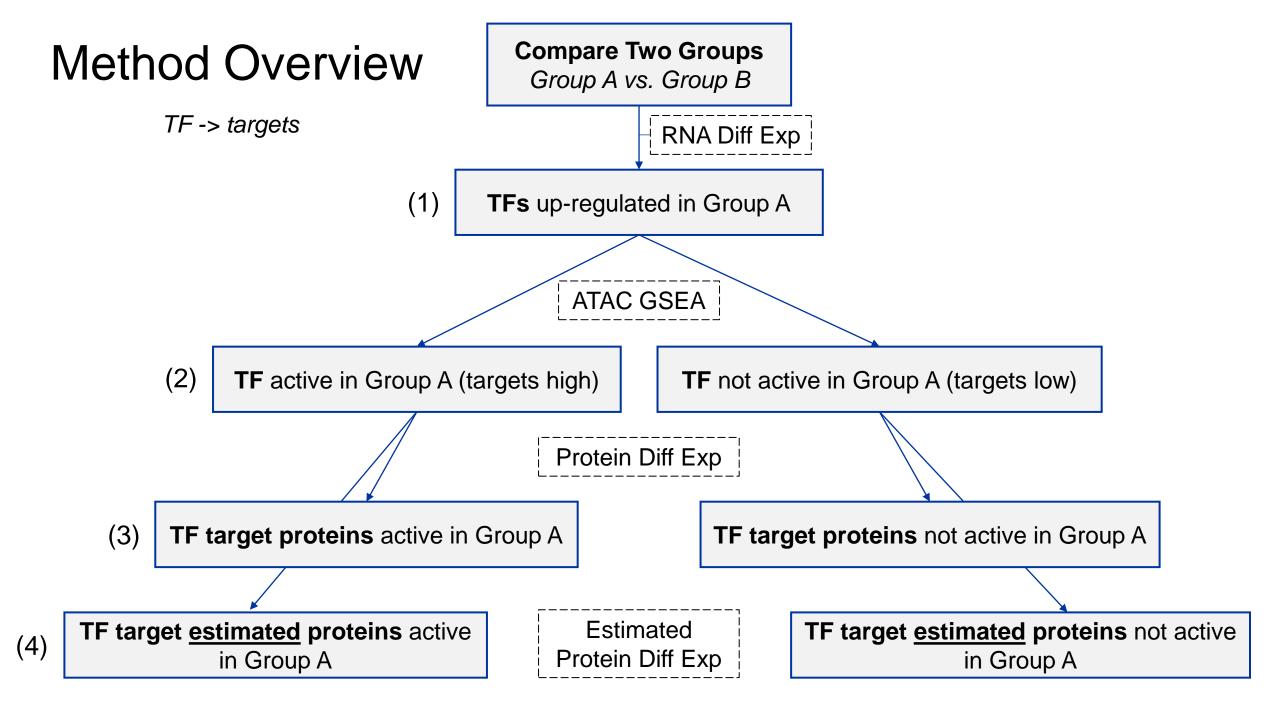
Background

Integration of genomic, epigenomic, or proteomic data with transcriptomic data:

- Association of genomic alterations + gene expression (mRNA-genome)
- Regulatory relationship between epigenetic changes and gene expression (mRNAepigenome)
- Correlation of gene expression and protein expression levels (mRNA-proteome)



[1] Single-cell multiomics: technologies and data analysis methods (Lee, Hyeon, and Hwang – 2020 Experimental & Molecular Medicine)



TF Dataset

ENCODE Transcription Factor Targets Dataset:

https://maayanlab.cloud/Harmonizome/dataset/ENCODE+Transcription+Factor+Targets

Contains 181 TFs and all known gene targets,

1,651,393 gene-transcription factor associations

CITE/ATAC Dataset

Mixed Phenotype Acute Leukemia (MPAL) bone marrow from adults at diagnosis (CITE-seq and scATAC-seq)

2 T-Myeloid MPAL

Healthy Adult bone marrow (CITE-seq and scATAC-seq)

2 samples

data from GSE139369 by Granja et al [2]

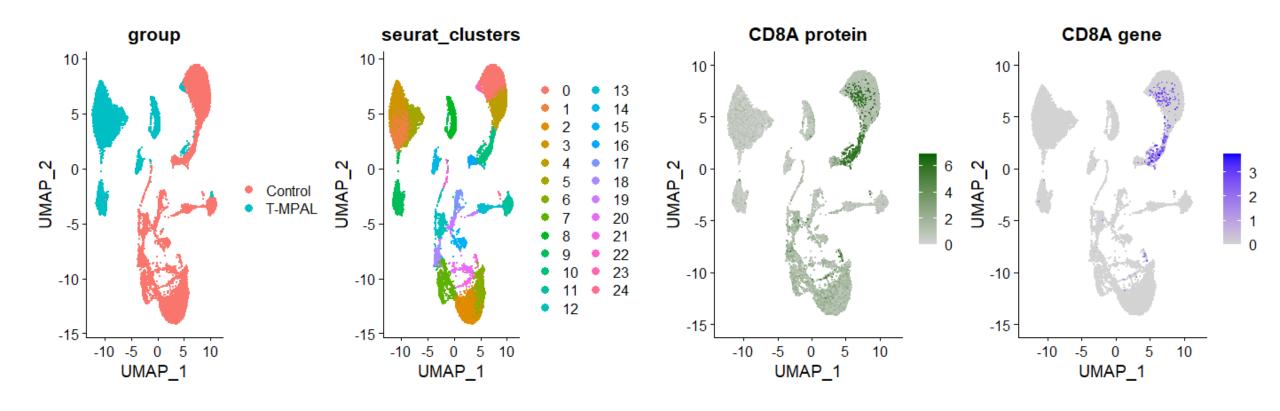
Pre-Processing

- Build Seurat objects using CITE-seq data (scADT + scRNA)
 - ADT assay
 - RNA assay
- Build ArrowProject (ArchR) using scATAC-seq fragment files
 - ATAC assay

Filtering, Normalization, Clustering (RNA-ADT)

Differentially expressed genes and gene activity regions between T-MPAL and Control groups

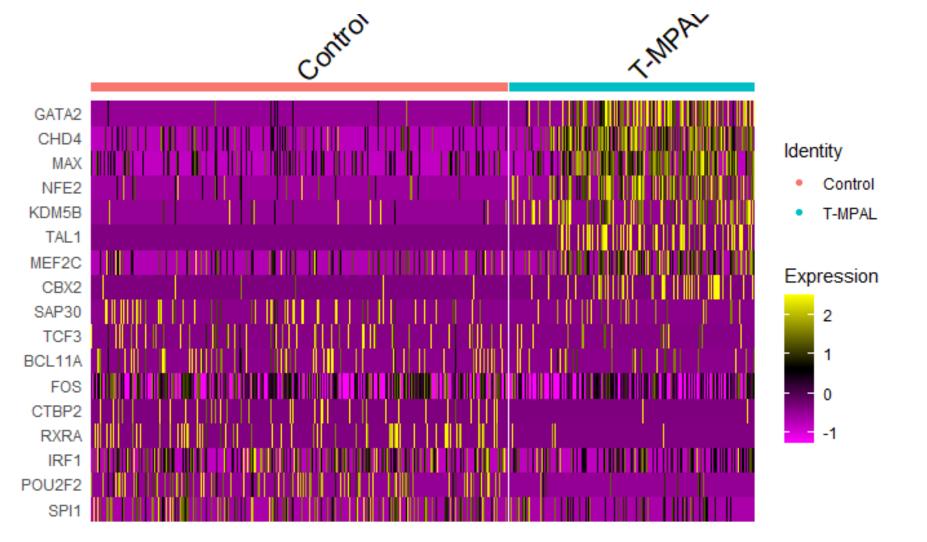
Pre-Processing



(1) Identify top up/down regulated TFs for T-MPAL

Analysis

tfMap(seuratObject, rnaMarkers, tf_list, type = up)
DoHeatmap(obj, features = unlist(topTFs), group.by = group)



(2) Identify active/non-active gene targets

tfs = getTFs(obj, rnaMarkers, db, num = all)[[T-MPAL]] db.filt = db[names(db) %in% tfs] en = tfEnrichment(atacMarkers[[T-MPAL]], db.filt) head(en)

pathway <chr></chr>	pval <dbl></dbl>	padj <dbl></dbl>	log2err <dbl></dbl>	ES <dbl></dbl>	NES <dbl></dbl>	size <int></int>	leadingEdge <list></list>
ATF3	9.616904e-37	4.039100e-36	1.5763736	-0.2618345	-2.156421	1977	<chr [1,341]=""></chr>
BATF	6.596011e-26	2.308604e-25	1.3188888	-0.2846389	-2.250415	1085	<chr [647]=""></chr>
BDP1	1.234257e-01	1.619962e-01	0.2020717	-0.3139491	-1.320581	29	<chr [25]=""></chr>
CBX2	3.786982e-01	4.678037e-01	0.1752040	-0.1403863	-1.031677	406	<chr [94]=""></chr>
CEBPZ	6.007067e-01	7.008245e-01	0.1009906	-0.1465165	-0.945335	161	<chr [107]=""></chr>
CHD1	NA	NA	NA	-0.1582863	NA	4806	<chr [2,052]=""></chr>

6 rows

posTFs = en %>% filter(NES > 0 & padj < 0.05) %>% select(pathway) negTFs = en %>% filter(NES < 0 & padj < 0.05) %>% select(pathway)

Only significant negatively enriched TF target sets.

pathway <chr></chr>	NES <dbl></dbl>
ATF3	-2.156421
BATF	-2.250415
CHD4	-1.300768
CUX1	-2.251888
FLI1	-1.989872
KDM1A	-1.667133
MAFF	-1.503808
MEF2C	-1.729570
NFE2	-2.211867
SMARCC1	-1.655428

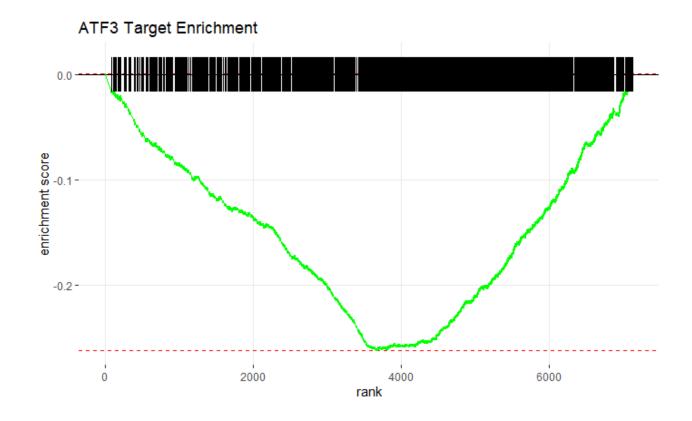
(2) Identify active/non-active gene targets

plotEn(atacMarkers[[T-MPAL]], db.filt, ATF3)

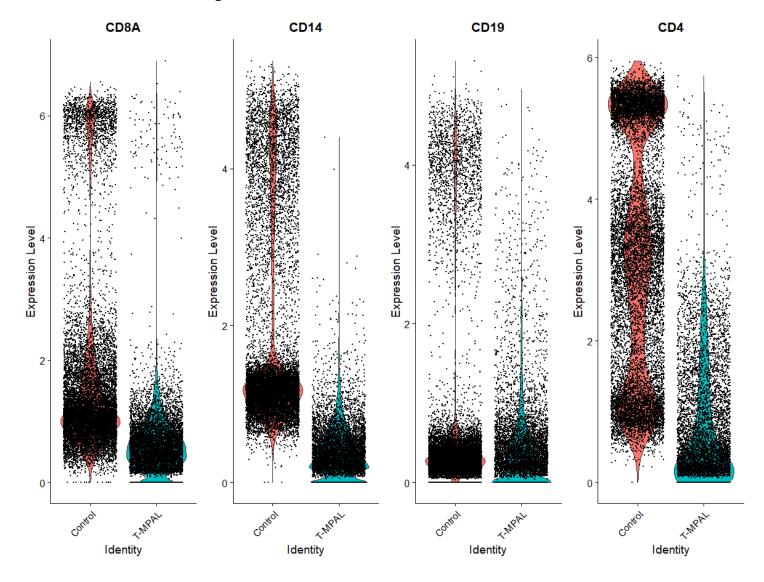
Analysis

pathway <chr></chr>	pval <dbl></dbl>	padj <dbl></dbl>	log2err <dbl></dbl>	ES <dbl></dbl>	NES <dbl></dbl>	size <int></int>	leadingEdge <list></list>
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CHD1	NA	NA	NA	-0.1582863	NA	4806	<chr [2,052]=""></chr>

6 rows



(3) Identify up/down regulated protein targets of TFs in T-MPAL protein_targets = getProteins(adtMarkers, db.filt)



[1] CD8A

[1] ATF3 CBX2 CHD1 CHD2 CUX1 ELF1 GATA2 GTF2F1 HDAC2 HMGN3 KDM4A MAFF MAX MYC [15] REST SMC3 STAT5A TAL1 TBL1XR1 WRNIP1 ZKSCAN1 ZMIZ1

[1] CD14

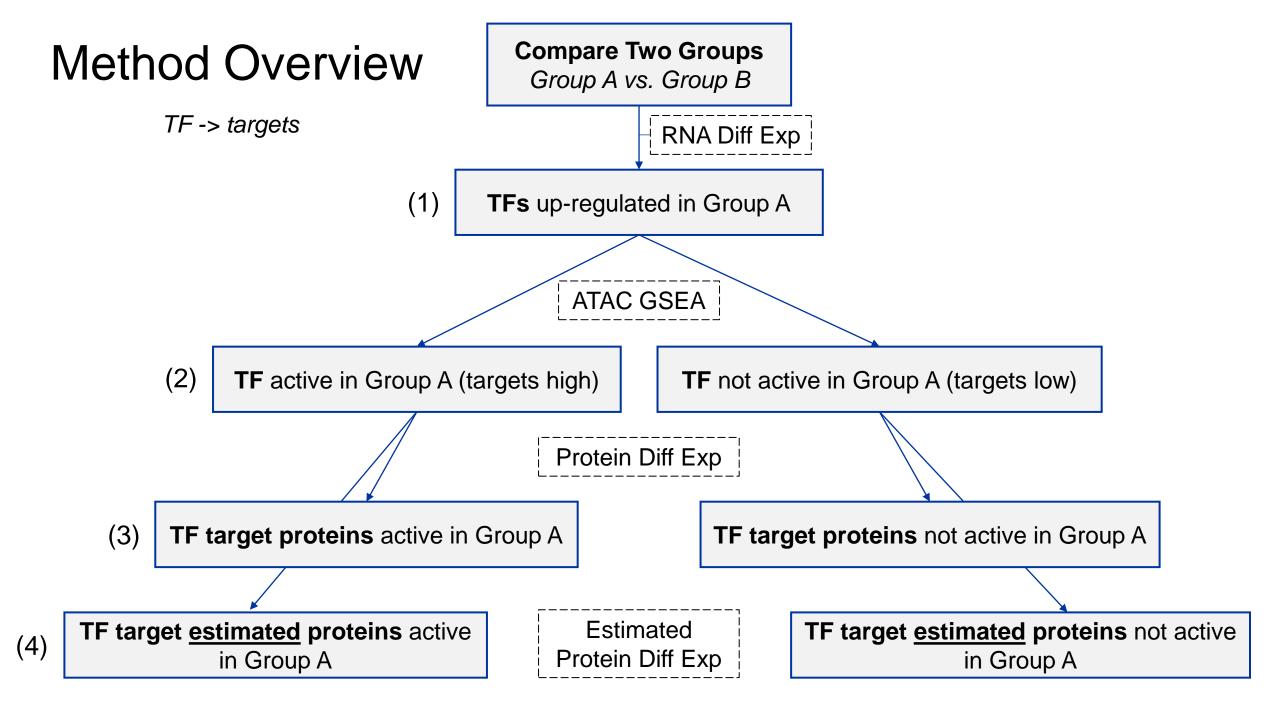
[1] CHD1 ELF1 HDAC2 MAFF MAX MYC REST SMC3 STAT3 TAL1 TBL1XR1 WRNIP1

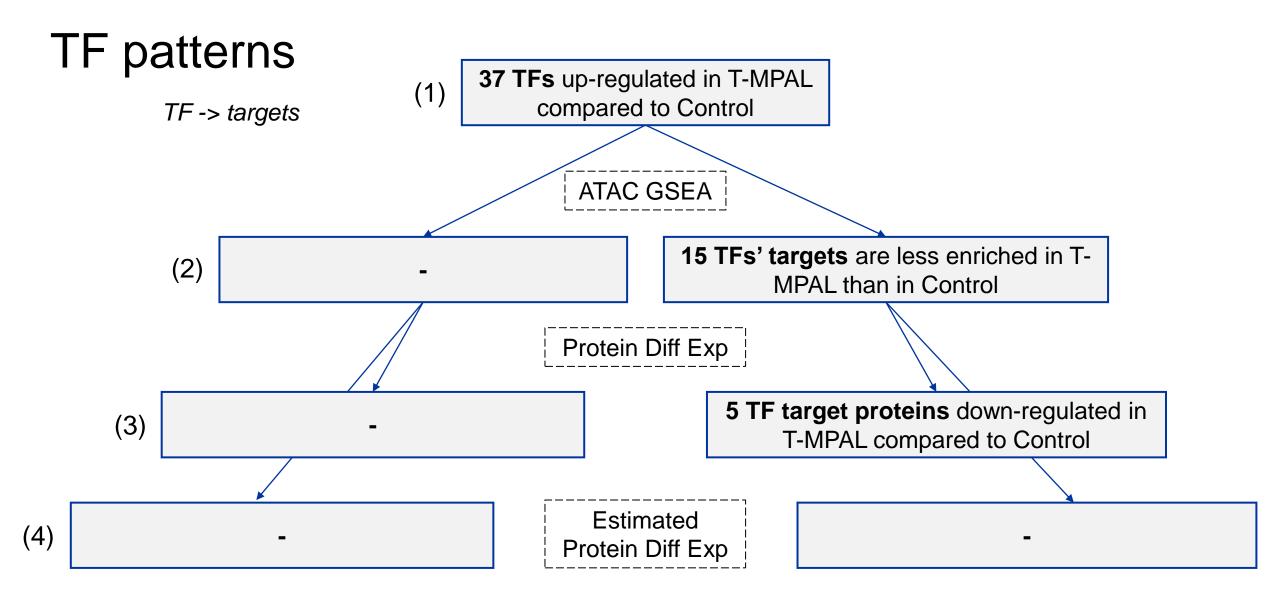
[1] CD19

[1] CHD1 CHD2 CUX1 ELF1 HDAC2 KDM5B MAX MYC REST SMC3 STAT5A TAL1 TBL1XR1 WRNIP1 [15] ZMIZ1

[1] CD4

[1] CHD1 KDM5A KDM5B MAFF MAX MYC REST





TF patterns

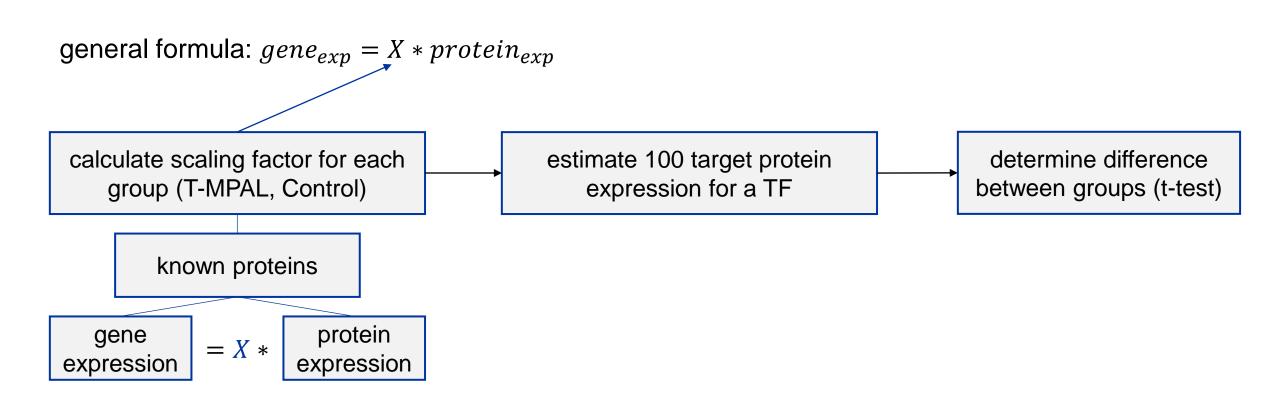
TF -> targets

- (1) **37 TFs** up-regulated in T-MPAL compared to Control
- (2) **15 TFs' targets** are less enriched in T-MPAL than in Control
- (3) **5 TF target proteins** down-regulated in T-MPAL compared to Control
- (4) TF target <u>estimated</u> proteins targets have lower expression in T-MPAL

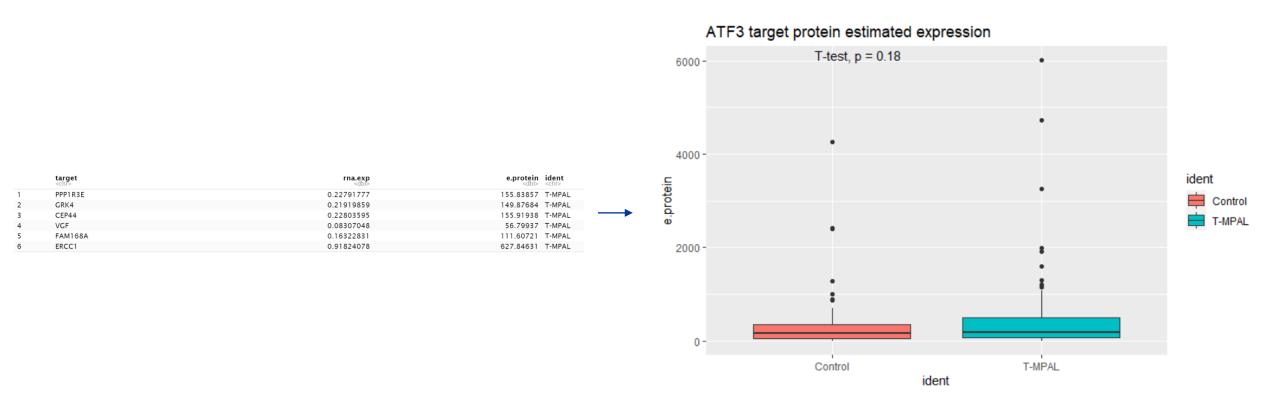
TFs for 5 target proteins (step 3)

ATF3 CBX2 CHD1 CHD2 CUX1 ELF1 GATA2 GTF2F1 HDAC2 HMGN3 KDM4A KDM5A KDM5B MAFF MAX MYC REST SMC3 STAT3 STAT5A TAL1 TBL1XR1 WRNIP1 ZKSCAN1 ZMIZ1

(4) Identify up/down regulated <u>estimated</u> protein targets of TFs in T-MPAL



(4) Identify up/down regulated <u>estimated</u> protein targets of TFs in T-MPAL



36

37

ZKSCAN1

ZMIZ1

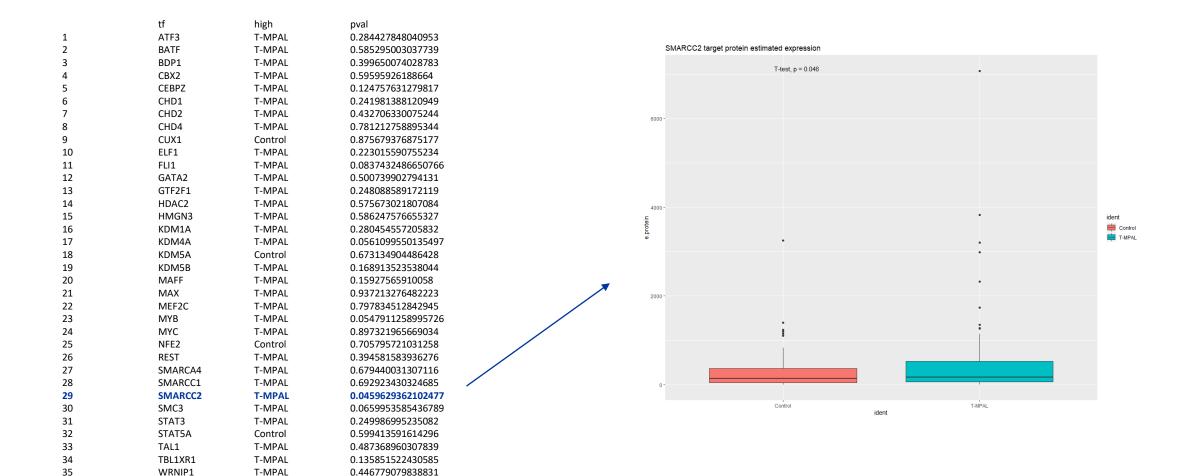
T-MPAL

Control

0.57282629752689

0.980607392815335

(4) Identify up/down regulated <u>estimated</u> protein targets of TFs in T-MPAL



TF patterns

TF -> targets

Goal

Identify transcription factors that meet the following requirements:

- 1. up-regulated in T-MPAL compared to control
- 2. have higher enriched targets in T-MPAL versus control
- 3. have target proteins active in T-MPAL versus control
- 4. estimated protein targets are significantly higher in T-MPAL versus control

R Package - github.com/hmumme/finalProjectMUMME

Provide functions to predict transcription factor and target activities using Seurat (CITE) and ArchR (ATAC)

Functions:

- buildCITE(rna, adt)
- getTFs(object, rna.markers, tf.db, num = all)
- tfEnrichment(atac.markers, db.filt)
- plotEn(atac.markers, db.filt, TF.name)
- getProteins(adt.markers, db.filt)
- getScale(object, ident)
- estProtein(x, object, db.filt, TF.name, ident)
- tfBar(est, TF.name)

Demo: demo.Rmd, demo.RData

Future Improvements

- Compare individual cell types
- Separate analysis for inhibitory/promotive targets of TFs
- Refine protein estimation
- Perform analysis on larger dataset

References

- [1] Lee, J., Hyeon, D.Y. & Hwang, D. Single-cell multiomics: technologies and data analysis methods. Exp Mol Med 52, 1428–1442 (2020). https://doi.org/10.1038/s12276-020-0420-2
- [2] Granja JM, Klemm S, McGinnis LM, Kathiria AS et al. Single-cell multiomic analysis identifies regulatory programs in mixed-phenotype acute leukemia. Nat Biotechnol 2019 Dec;37(12):1458-1465. PMID: 31792411