



SINGLE CELL TRANSCRIPTOMICS IN SCHIZOPHRENIA POSTMORTEM BRAIN: MOVING BEYOND BULK LYSATE

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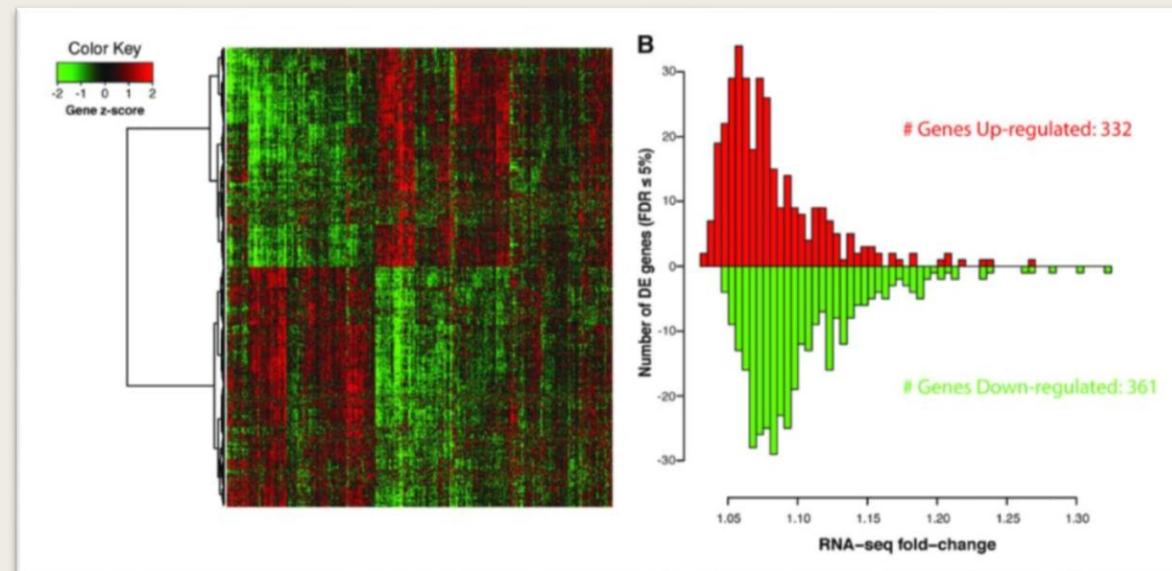
Schizophrenia Transcriptomics

- Microarray and RNA sequencing
- Differentially expressed genes across many cortical and sub-cortical regions
 - *Dorsolateral prefrontal cortex (dlPFC)* (Fillman et al, 2013)
 - *Anterior Cingulate Cortex* (Zhao et al, 2015; Hong et al, 2013)
 - *Superior temporal gyrus* (Wu et al, 2012)
 - *Hippocampus* (Hwang et al, 2013; Kohen et al, 2014)
 - *Amygdala* (Chang et al, 2017)
- Enrichment of pathways and gene networks
 - *Neural development*
 - *Axon guidance*
 - *Inflammation and immune-related proteins*

CommonMind Consortium

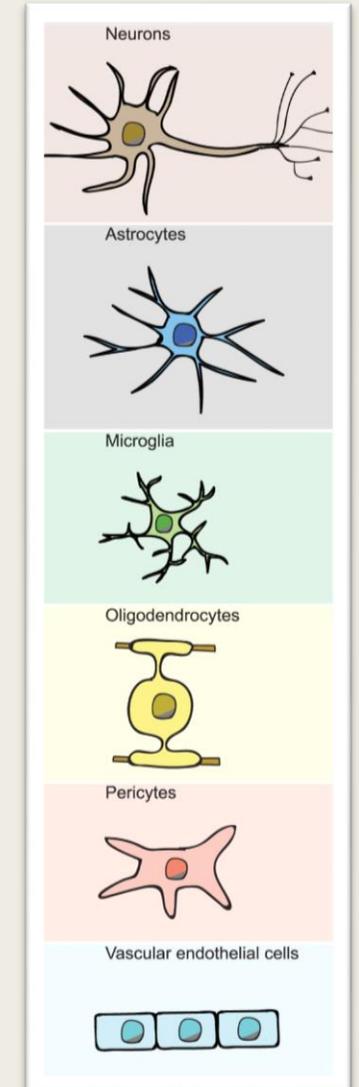
- Largest transcriptomic analysis of schizophrenia
 - 258 cases/279 controls
 - RNAseq in dIPFC

- 693 differentially expressed genes



Cell Diversity in Postmortem Brain

- Brain, like all tissues, consists of many cell types
 - *Major cell populations (e.g. astrocytes)*
 - *Distinct sub-populations (e.g. PVALB+ interneurons)*
- Problems in assessing differential expression in bulk lysate
 - *Inability to identify which cells are affected*
 - *Missed expression changes in less common cell types*



Schizophrenia Single Cell Transcriptomics

- Immunofluorescence and laser capture microdissection to collect individual populations of cells
- Layer III/V pyramidal neurons (Arion et al, 2017)
 - *72 PFC samples – 36 cases/36 controls*
 - *100 cells per layer for each sample*
 - *Expression assessed by microarray*
 - *1,783 differentially expressed probe sets corresponding to 1,420 genes*
- Parvalbumin positive (PVALB+) interneurons (Enwright et al, 2018)
 - *Same samples and methods*
 - *1,044 differentially-expressed probe sets corresponding to 872 genes*

Technical Hurdles with Single Cells

- Laser capture microdissection
 - *Low-throughput*
 - *Targeted*
- Pooling cells
 - *Lost information on variability between cells*
 - *Collapses sub-populations*
- Frozen human brain tissue
 - *Freeze/thaw ruptures cell membranes making single cell methods impossible*
 - *Single cells and nuclei have similar transcriptomes*
 - Same relative levels of **98% of transcripts** (Grindberg et al, 2013)

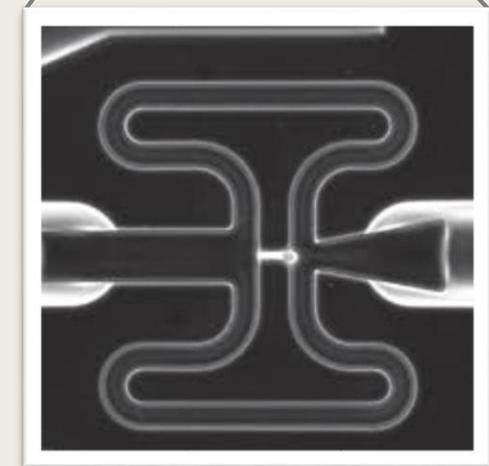
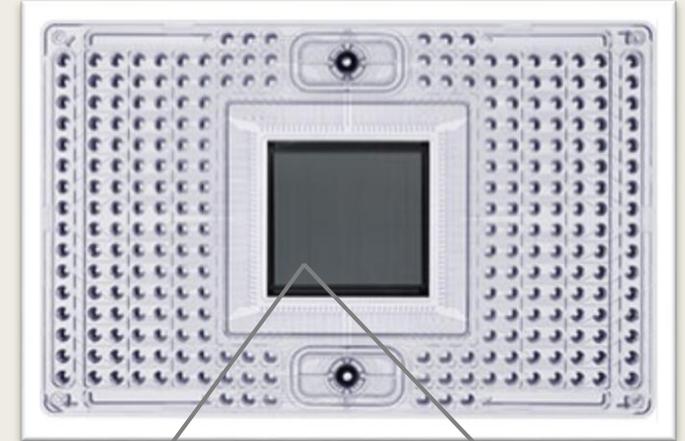
snRNAseq in Human Brain

REPORTS | GENETICS

Neuronal subtypes and diversity revealed by single-nucleus RNA sequencing of the human brain

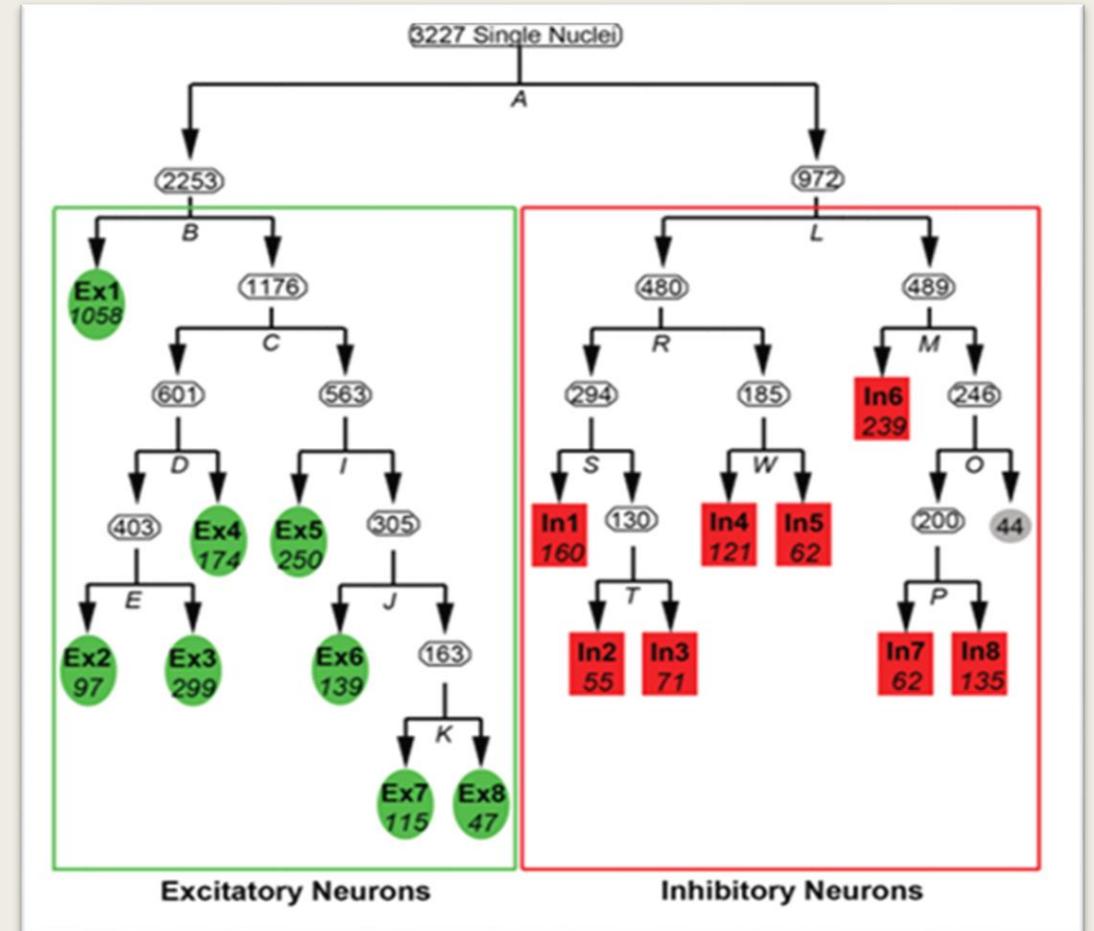
Blue B. Lake^{1,*}, Rizi Ai^{2,*}, Gwendolyn E. Kaeser^{3,4,*}, Neeraj S. Salathia^{5,*}, Yun C. Yung³, Rui Liu¹, Andre Wildberg², Derek Ga...

- Single nuclei isolated from frozen human brain
 - *FACS sort after staining for NeuN*
 - *One brain, multiple regions, multiple methods*
- Fluidigm C1 platform for capture and library preparation
 - *Microfluidics chip designed for single cell*
 - *96 nuclei per chip*

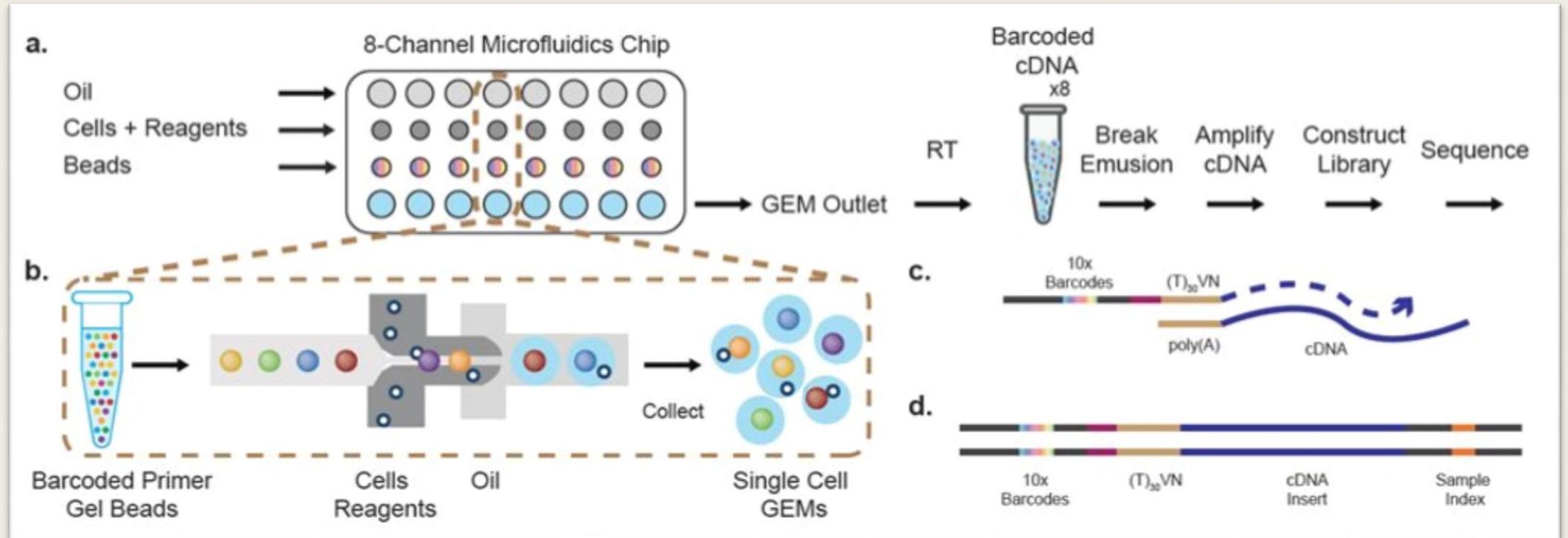


snRNAseq in Human Brain

- Different layers of excitatory neurons
 - *PVALB+*, *SST+*, etc
- Distinct interneuron populations
 - *PVALB+*, *SST+*, etc
- Regional differences
 - e.g. *Ex2* and *Ex3* are layer 4 neurons from rostral and caudal areas, respectively



10x Genomics Chromium Controller



10x Genomics

■ Pros

- *High-throughput*
- *Indexing at three levels: sample, nucleus/cell, transcript*
- *Performs equally well on cells and nuclei*
- *Theoretically cell type agnostic*

■ Cons

- *Expensive/fixed costs*
- *Splicing not addressed (mostly)*
- *Possibly not cell type agnostic?*

10x Genomics in Human Brain

- Five studies using 10x in postmortem human brain samples
 - *Alzheimer's* (Mathys et al, 2019)
 - *Autism* (Velmeshev et al, 2019)
 - *MS* (Schirmer et al, 2019)
 - *MDD* (Nagy et al, 2020)
 - *Huntington's* (Al-Dalahmah et al, 2020)
- Successfully distinguished cell populations using snRNAseq data

Single-nucleus transcriptomics of the prefrontal cortex in major depressive disorder implicates oligodendrocyte precursor cells and excitatory neurons

Corina Nagy^{1,9}, Malosree Maitra^{1,9}, Arnaud Tanti¹, Matthew Suderman², Jean-Francois Th  roux¹,

Article | Published: 17 July 2019

Neuronal vulnerability and multilineage diversity in multiple sclerosis

Lucas Schirmer, Dmitry Velmeshev, Staffan Holmqvist, Max Kaufmann, Sebastian

REPORT

Single-cell genomics identifies cell type-specific molecular changes in autism

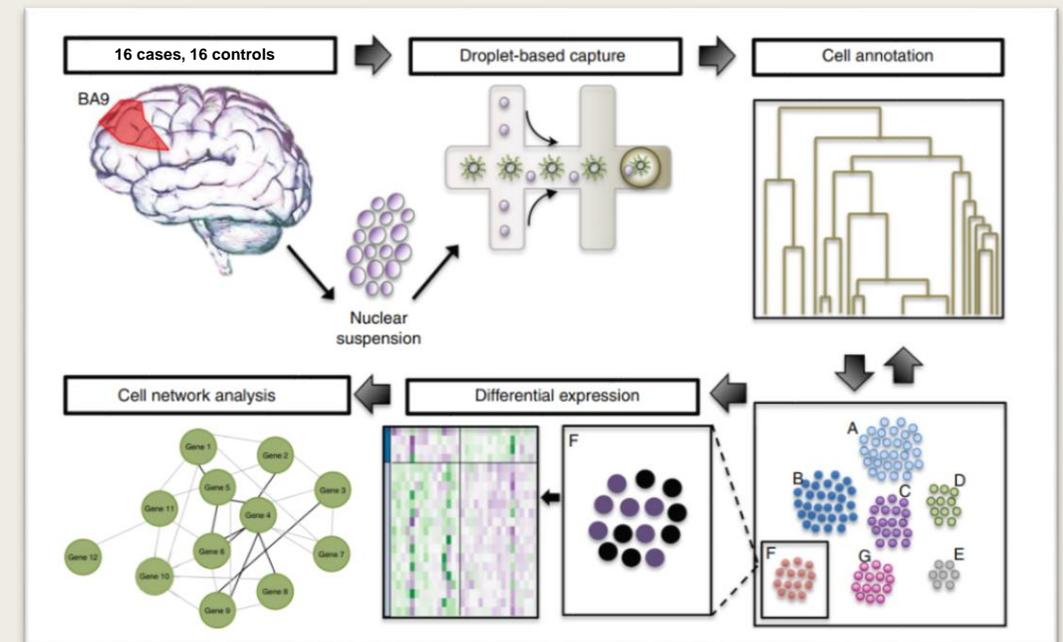
 Dmitry Velmeshev^{1,2,*},  Lucas Schirmer^{1,3,4}, Diane Jung^{1,2},  Maximilian Haeussler⁵, Yonatan Perez^{1,2},  Si

Single-cell transcriptomic analysis of Alzheimer's disease

Hansruedi Mathys^{1,2,10}, Jose Davila-Velderrain^{3,4,10}, Zhuyu Peng^{1,2}, Fan Gao^{1,2}, Shahin Mohammadi^{3,4}, Jennie Z. Young^{1,2}, Madhvi Menon^{4,5,6}, Liang He^{3,4}, Fatema Abdurrob^{1,2}, Xueqiao Jiang^{1,2}, Anthony J. Martorell^{1,2}, Richard M. Ransohoff⁷, Brian P. Hafler^{4,5,6,8}, David A. Bennett⁹, Manolis Kellis^{3,4,11*} & Li-Huei Tsai^{1,2,4,11*}

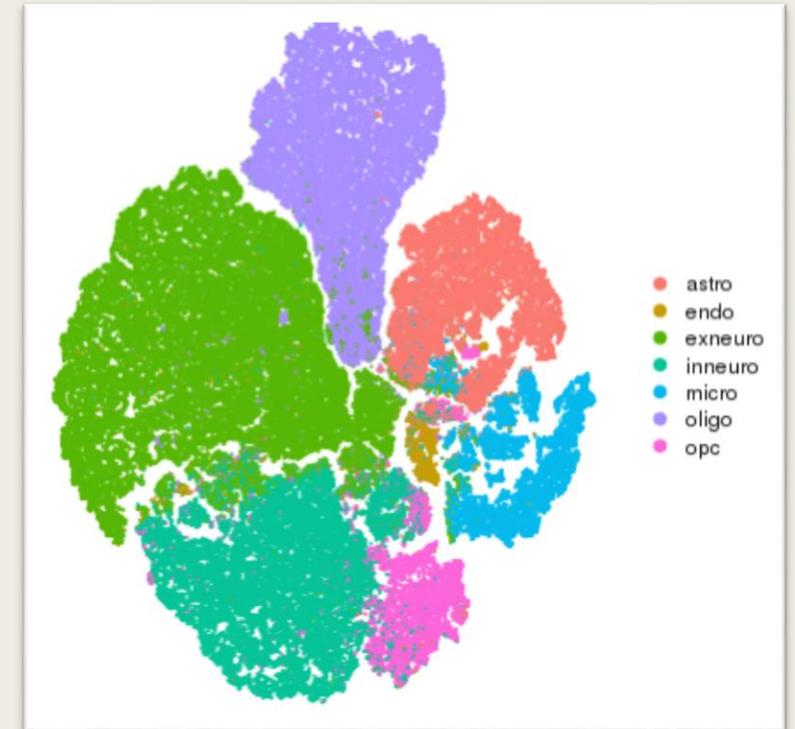
Experimental Design

- 32 postmortem dIPFC (BA9)
 - 16 cases (14M/2F)
 - 16 controls (14M/2F)
 - European ancestry
- Nuclei isolated using a modified version of previous protocol (Nagy et al 2020)
 - Homogenization, 2x wash and filter, resuspend $\sim 1,000$ nuclei/ μl
- 10x library production and sequencing
 - CHOP Center for Applied Genomics
- Sequencing on NovaSeq 6000

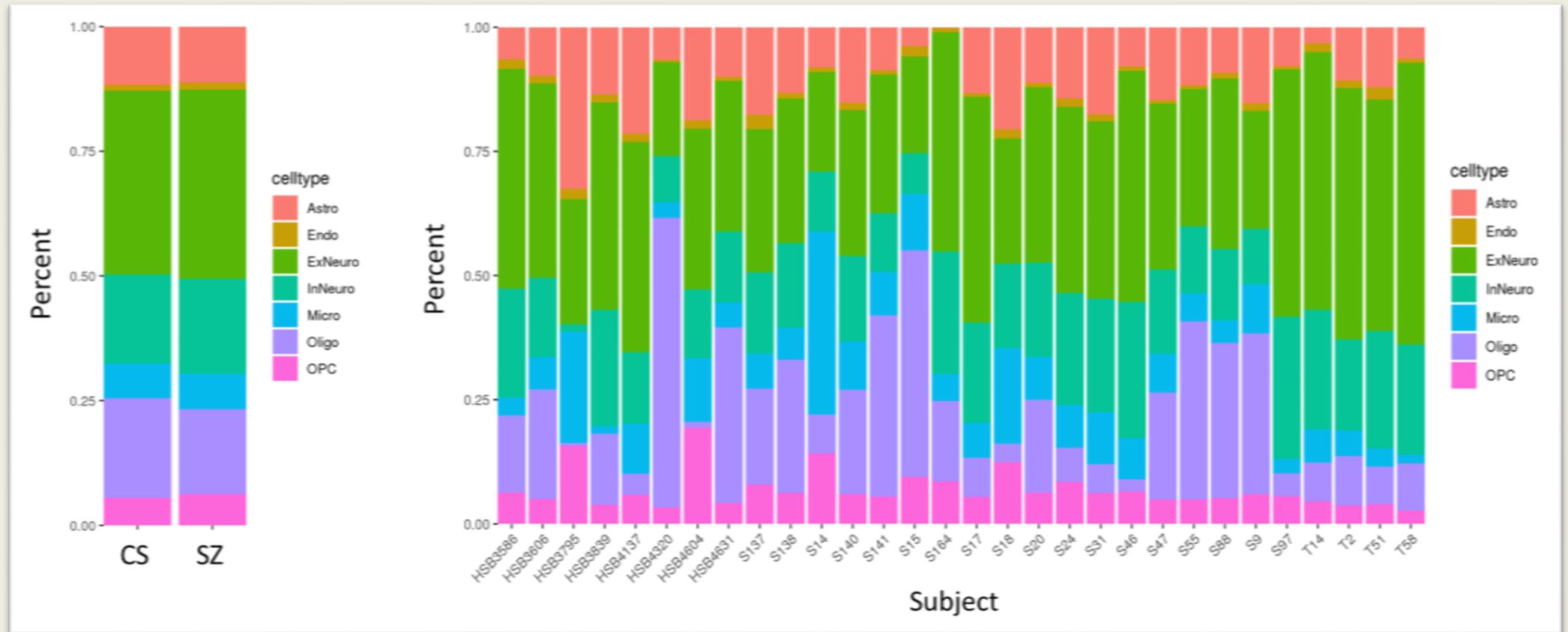


Quality Control and Clustering

- Deconvolution and alignment with 10x CellRanger
- QC using Seurat package
 - *Genes <3 nuclei, nuclei <200 genes, nuclei with high or low UMI*
 - *Normalize to 10,000 counts/nucleus*
- Clustering
 - *First 50 PCs calculated from 2215 “highly variable genes”*
 - *Low resolution first run, remove additional low UMI clusters and two SZ samples*
 - *High resolution second run, remove clusters specific to only a few individuals*
- Final results: ~323,821 nuclei in 27 clusters
 - *Previous 4 papers: ~313k total*

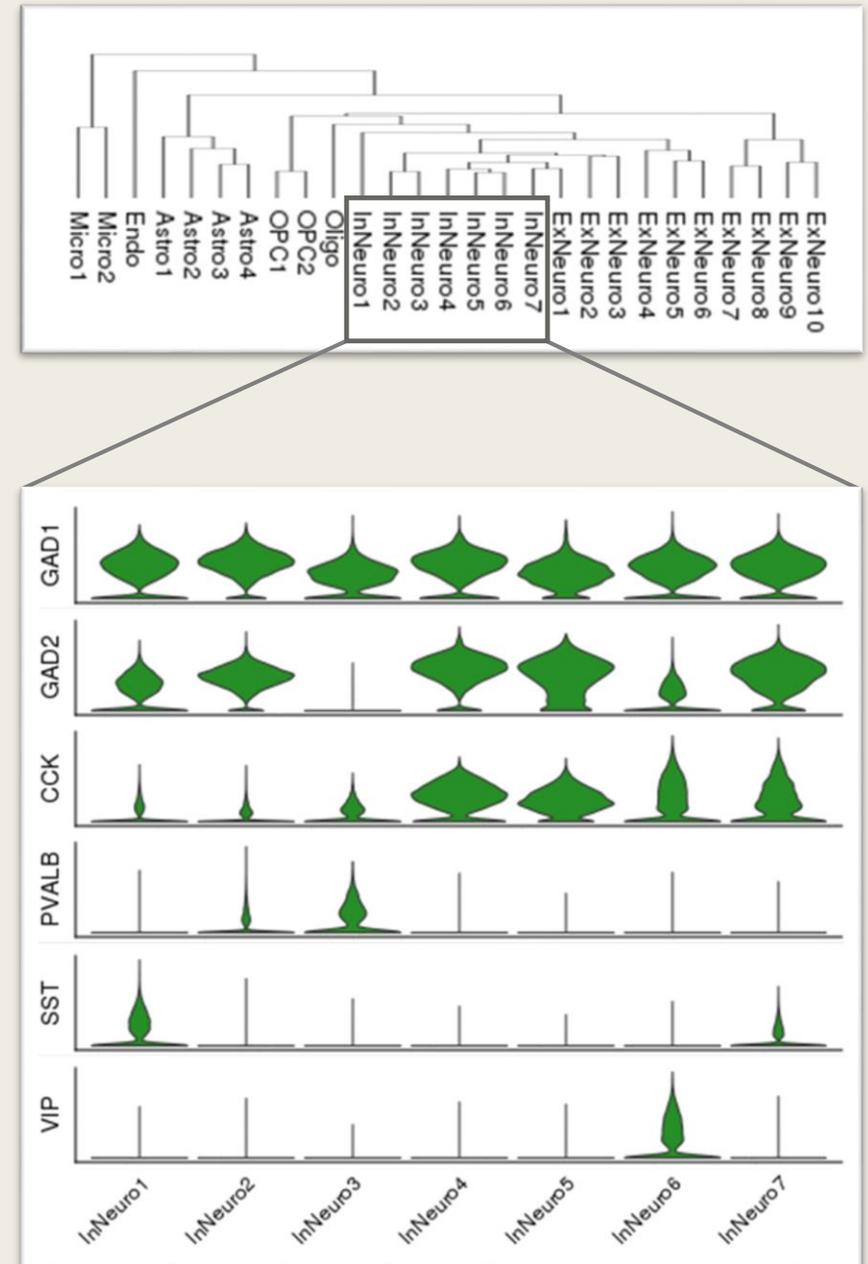


Cell Type Proportions



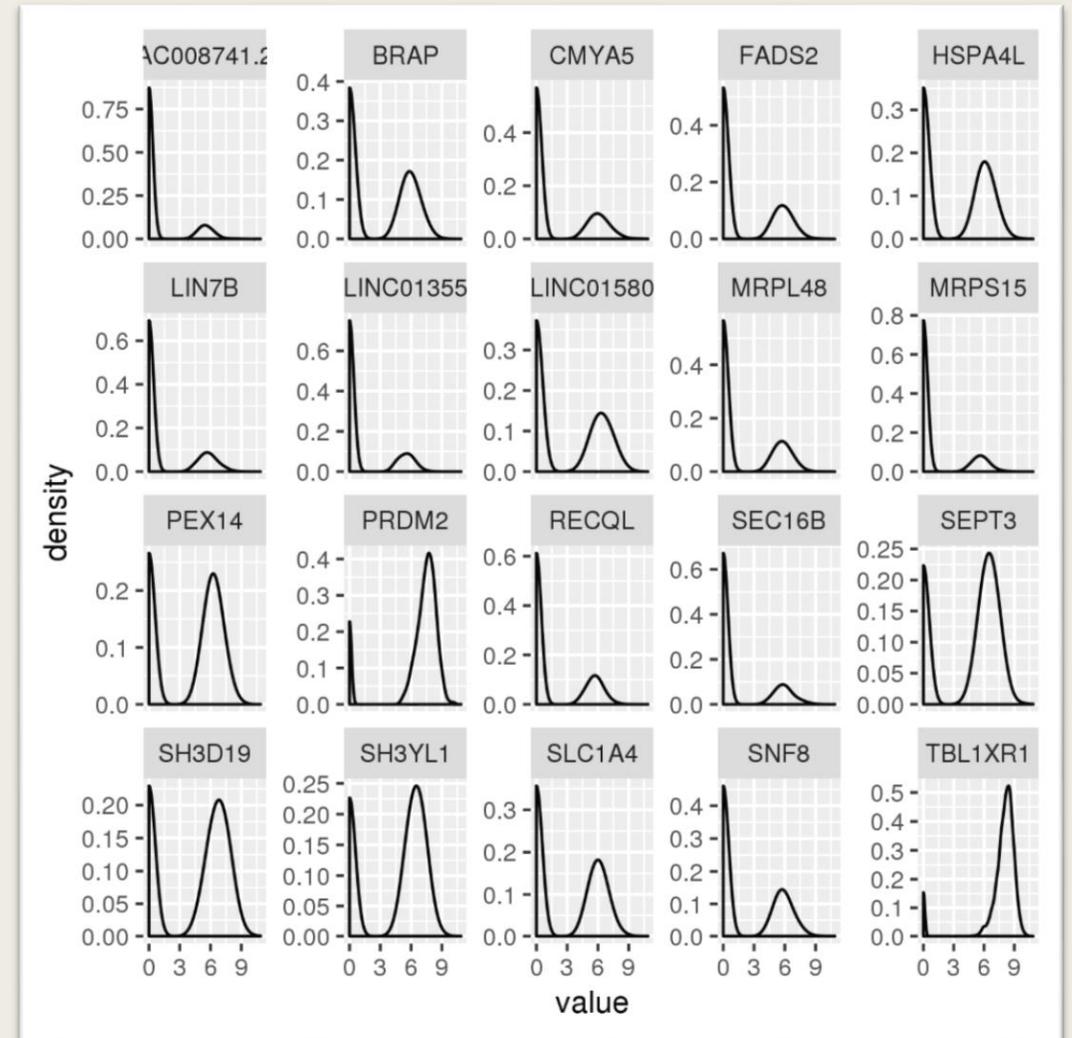
Sub-populations

- Our single nuclei transcriptomic data differentiates known sub-populations
 - *Multiple interneuron types*
 - *Layer markers*
- How many clusters is the correct number?
 - *Sample size*
 - *Number of nuclei*
 - *Sequencing depth*



Expression Data in snRNAseq

- Single cell/nuclei RNAseq data forms a bimodal distribution for each gene
 - *Genes will not be detected in all cells or nuclei*
 - *Large number of zeroes*
- What is the best way to handle this in a statistical model?

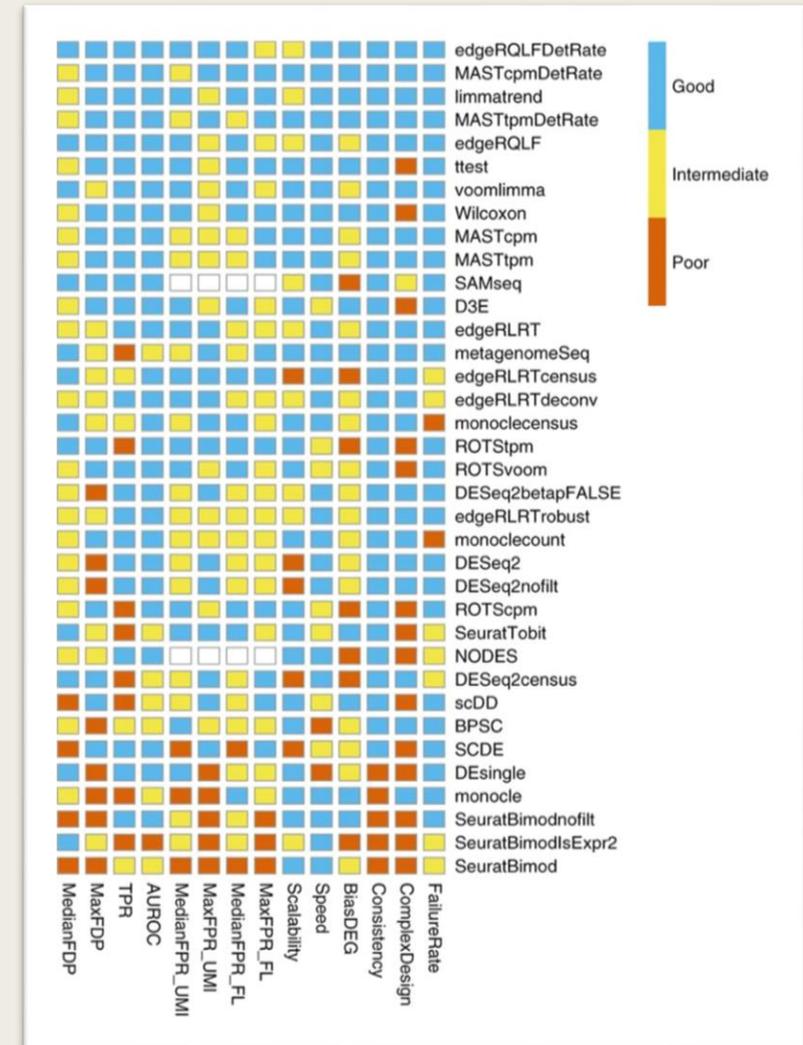


Analyzing snRNAseq: The Wild West

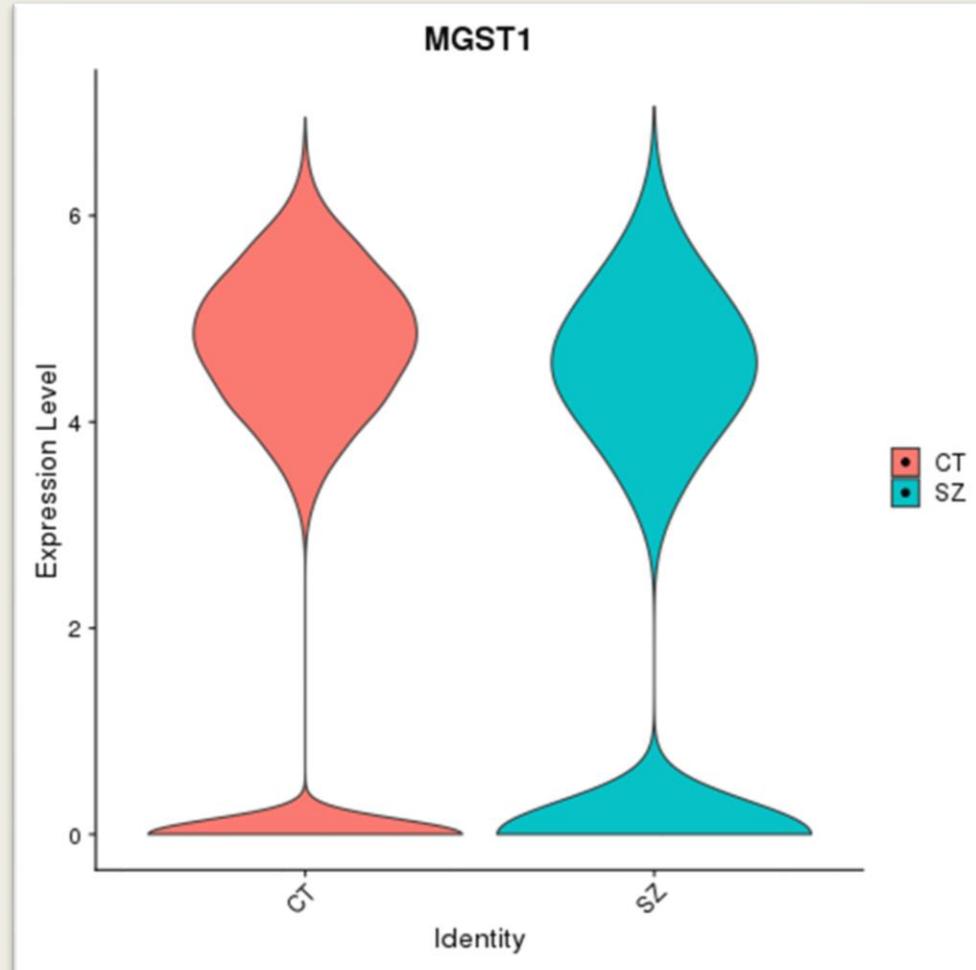
- There is no consensus yet on the best methods for analyzing snRNAseq data
 - *Mathys – LMM/Wilcoxon*
 - *Velmeshev/Schirmer – MAST*
 - *Nagy – LMM*
- The methods for those manuscripts in the field also include different:
 - *Covariates*
 - *FDR – 0.05 vs 0.1*
 - *logFC Cutoff – 0.25 vs 0.14 vs none*

Analyzing snRNAseq: The Wild West

- Systematic analysis of statistical methods
 - *Wide variation in efficacy*
 - *Single cell methods on average were not better than other methods*
- May be specific to the data set being analyzed or the questions being asked



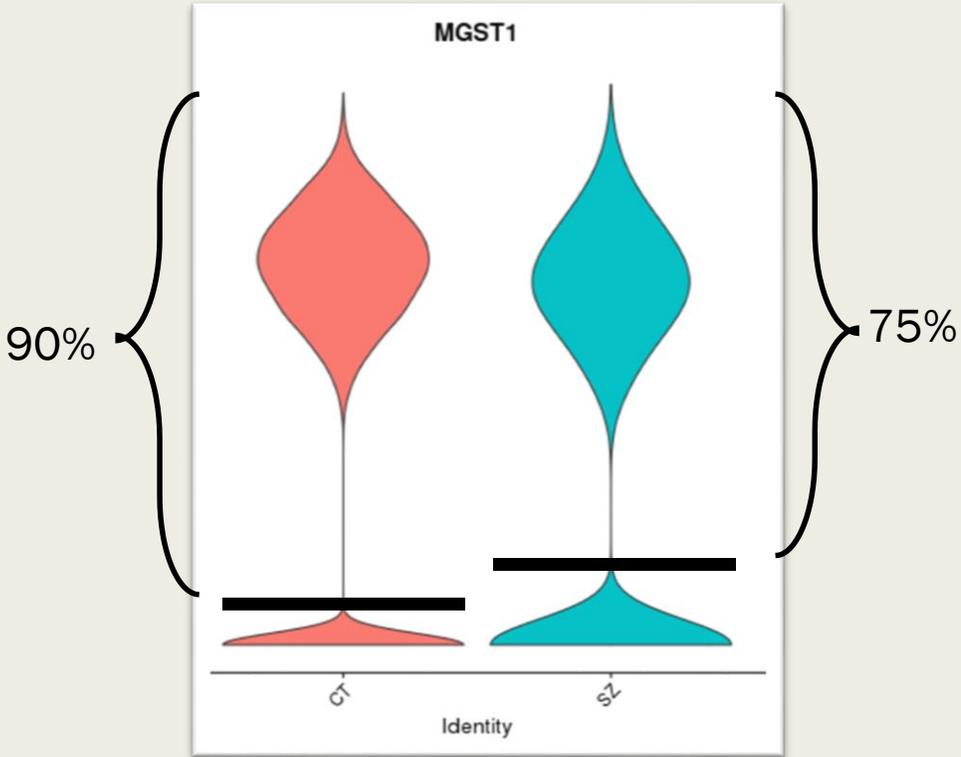
The *MAST* Hurdle Model



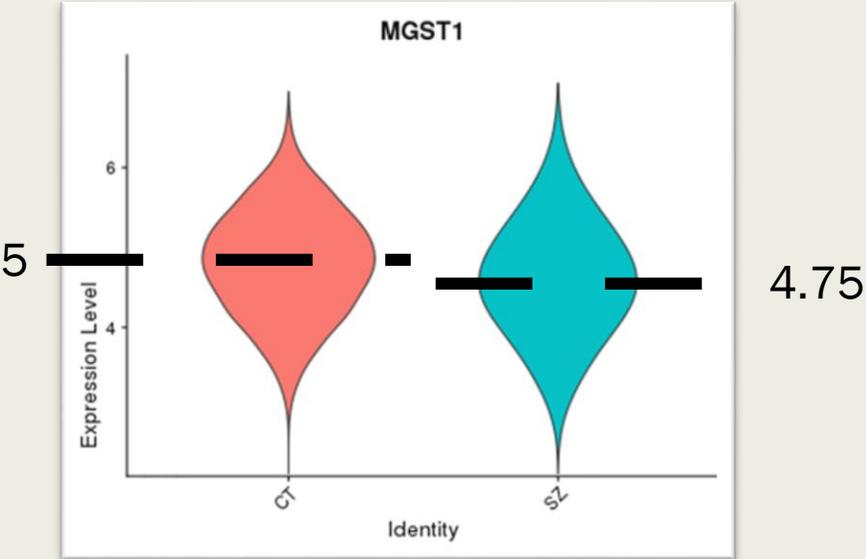
- Hurdle model is a combination of two different models to address the bimodal distribution of snRNAseq data
- Discrete model
 - *Is the gene detected in a larger percentage of nuclei in cases compared to controls?*
- Continuous model
 - *In non-zero nuclei, is expression of the gene higher in cases compared to controls?*

The *MAST* Hurdle Model

Discrete Model

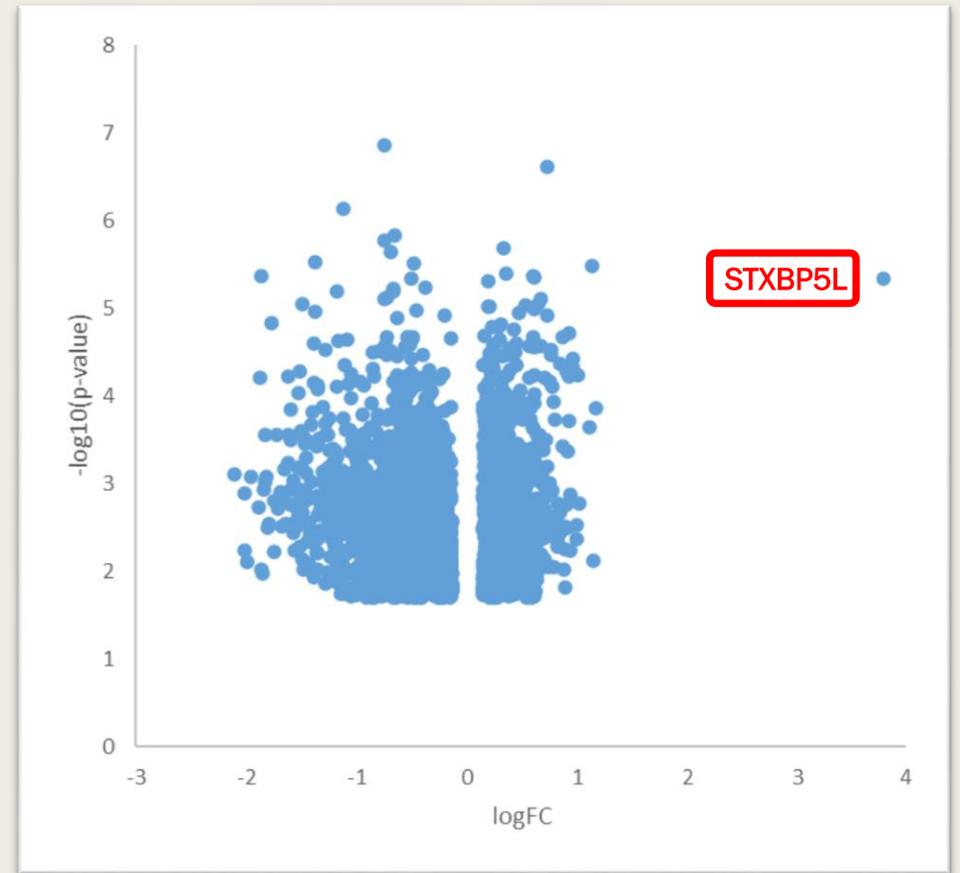


Continuous Model



Differential Expression Analysis

- MAST – Hurdle Model
- Fixed effects
 - *Case/control status, sex, age, batch*
 - *Gene detection rate*
- Random effect
 - *Subject*
- Significance
 - FDR = 0.1
 - $\text{Log}_2\text{FC} \geq 0.14$ (10% difference)



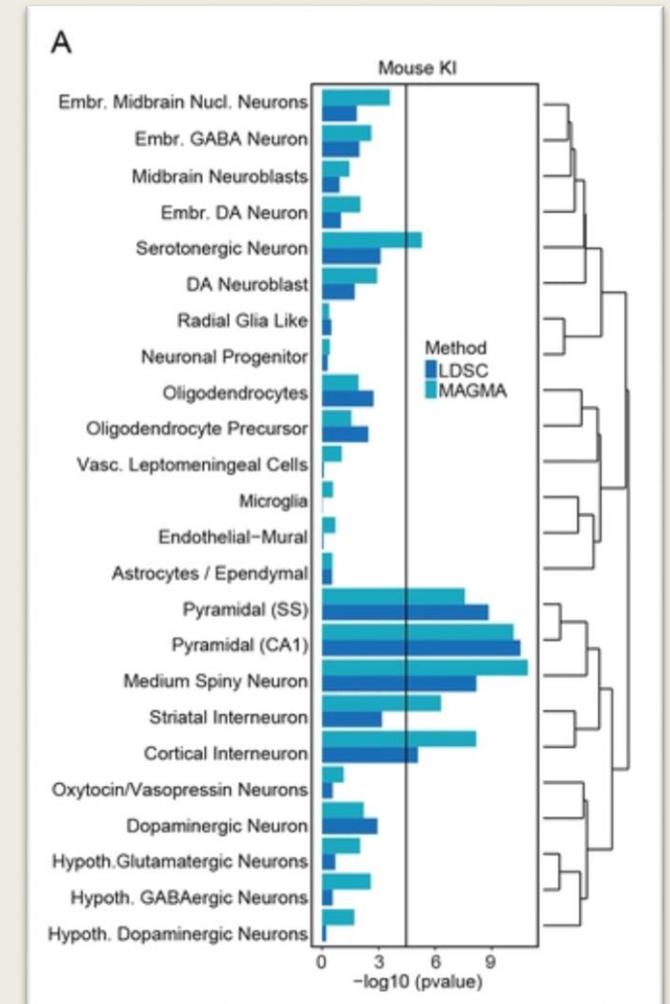
Differentially Expressed Genes

- Differential genes found in 21/27 clusters
- 2,853 differentially expressed genes
 - 957 upregulated, 1896 downregulated
- 2,196 unique genes
- Top 5 clusters accounted for 95.9% of differentially expressed genes

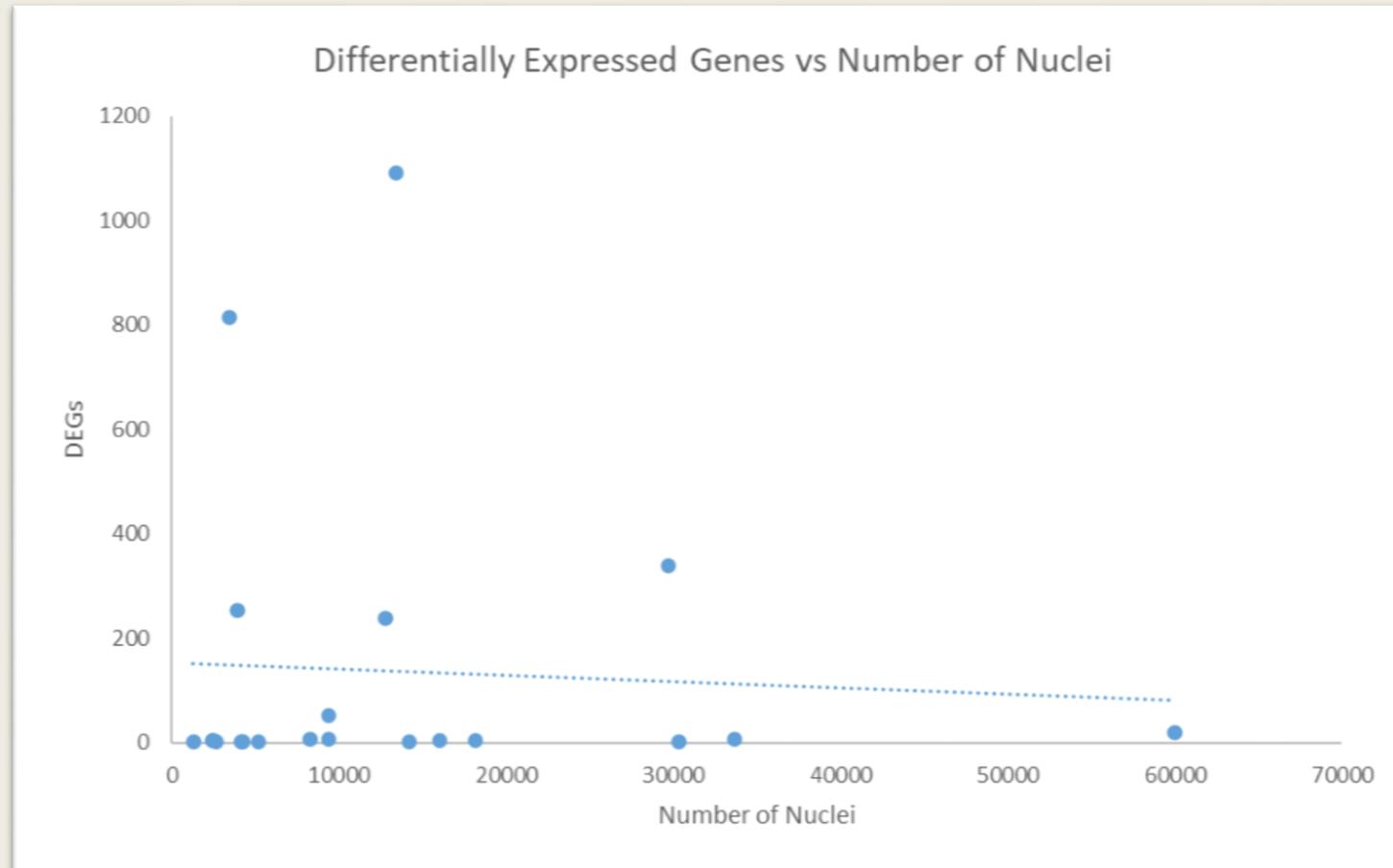
Cell Type	# DEGs
Inhibitory Neuron #2 - PVALB+	1092
Excitatory Neuron #1 - Layer V HTR2C+	814
Excitatory Neuron #4 - Layer II/III	340
Inhibitory Neuron #5	254
Excitatory Neuron #3 - Layer IV	237
Excitatory Neuron #6 - Layer VI	53
Oligodendrocyte	18
Excitatory Neuron #9 - Layer V	7
Microglia #2	6
Excitatory Neuron #5 - Layer II/III	6
Astrocyte #4	5
Inhibitory Neuron #6 - VIP+	4
Excitatory Neuron #2 - Layer IV/V	4
Excitatory Neuron #10 - Layer VI	3
Inhibitory Neuron #4	2
Inhibitory Neuron #7	2
Inhibitory Neuron #3 - PVALB+	2
Endothelial	1
Astrocyte #3	1
Excitatory Neuron #7	1
Inhibitory Neuron #1 - SST+	1

Neurons and Schizophrenia

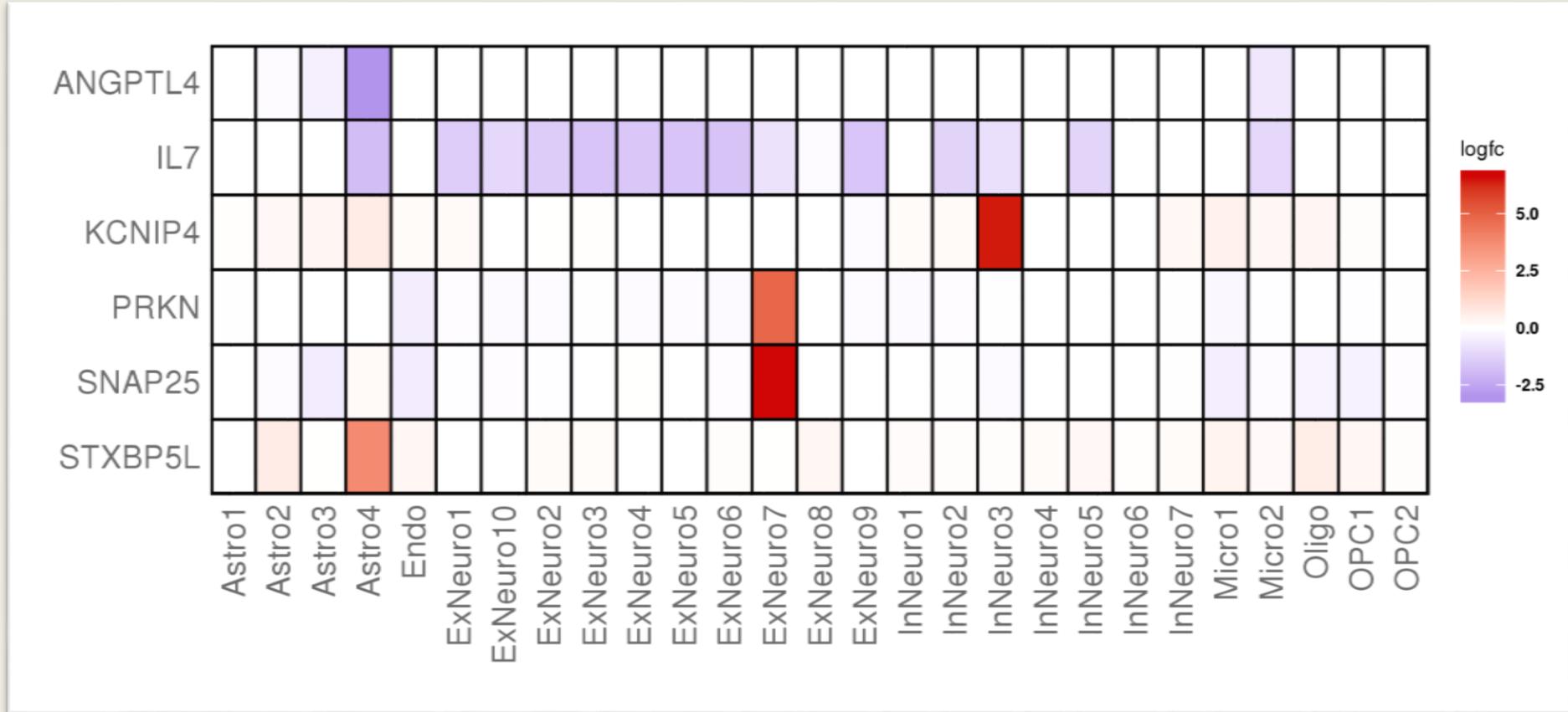
- Schizophrenia GWAS hits are enriched for genes expressed in mouse neurons (Skene et al, 2018)
 - *Medium spiny neurons*
 - *Pyramidal cells in hippocampal CA1*
 - *Pyramidal cells in somatosensory cortex*
 - *Cortical interneurons*
- Similar results from limited human data (Skene et al, 2018)
- PVALB+ interneurons have reduced density or altered gene expression in schizophrenia (Chung et al. 2016; Enwright et al. 2018; Fung et al. 2014; Hashimoto et al. 2008; Joshi et al. 2015; Volk et al. 2016)



Larger Clusters Do Not Have More Differentially Expressed Genes

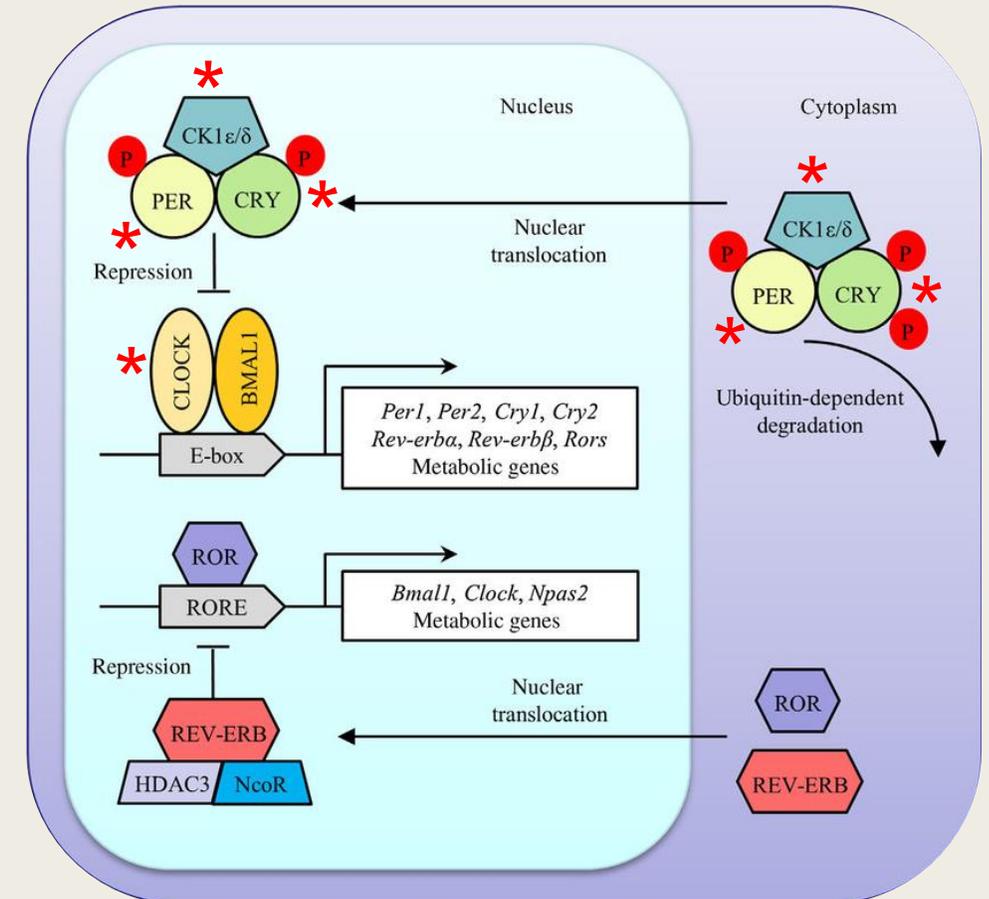


Cell Type Specificity



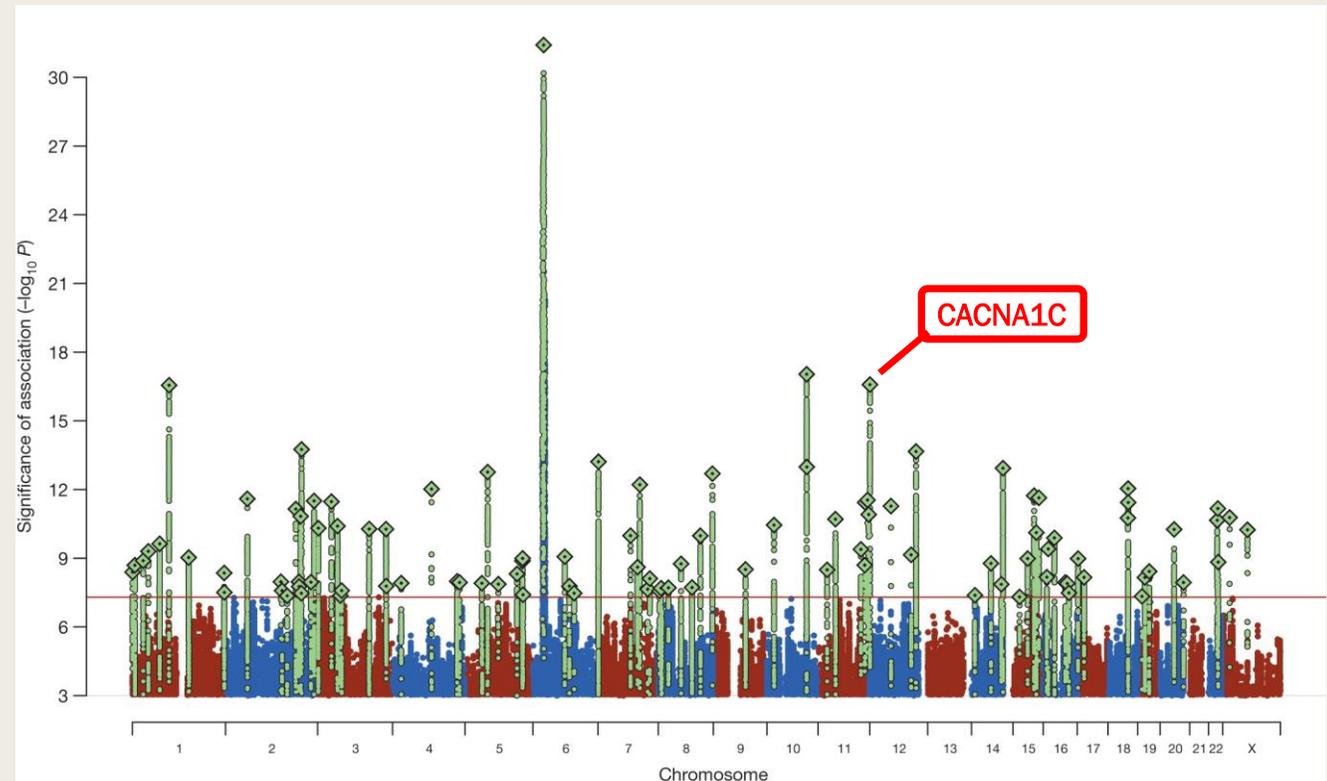
Molecular Clocks and Circadian Rhythm

- Schizophrenia patients frequently report sleep abnormalities (Kaskie et al, 2017)
- Evidence for altered rhythmic expression of clock genes in schizophrenia (Johansson et al, 2016)
- Inhibitory Neuron #2 - PVALB+
 - Upregulated - *CLOCK*, *CRY1*, *NPAS3*
 - Downregulated - *PER2*, *CSNK1D*
- Other Clusters
 - *CLOCK*, *ARNTL*, *BHLHE41*



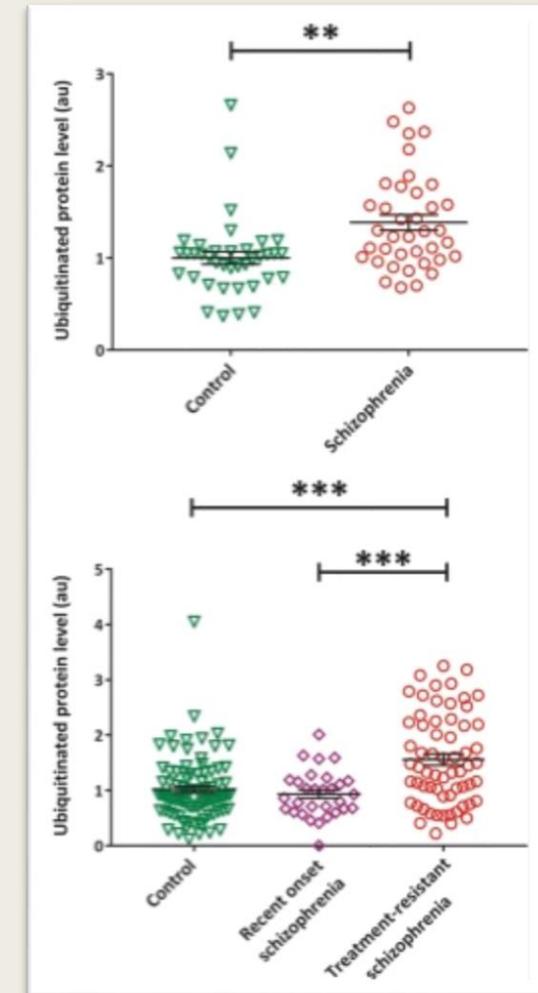
Schizophrenia as a “Channelopathy”

- Calcium channel genes
 - CACNA1C, CACNA1L, CACNB1, CACNB3
- Potassium channel genes
 - KCNAB2, KCNC4, KCNJ3, KCNJ9, KCNK12, KCNK3, KCNQ5, KCNV1, KCTD2
- Sodium channel genes
 - SCN2B, SCN3B



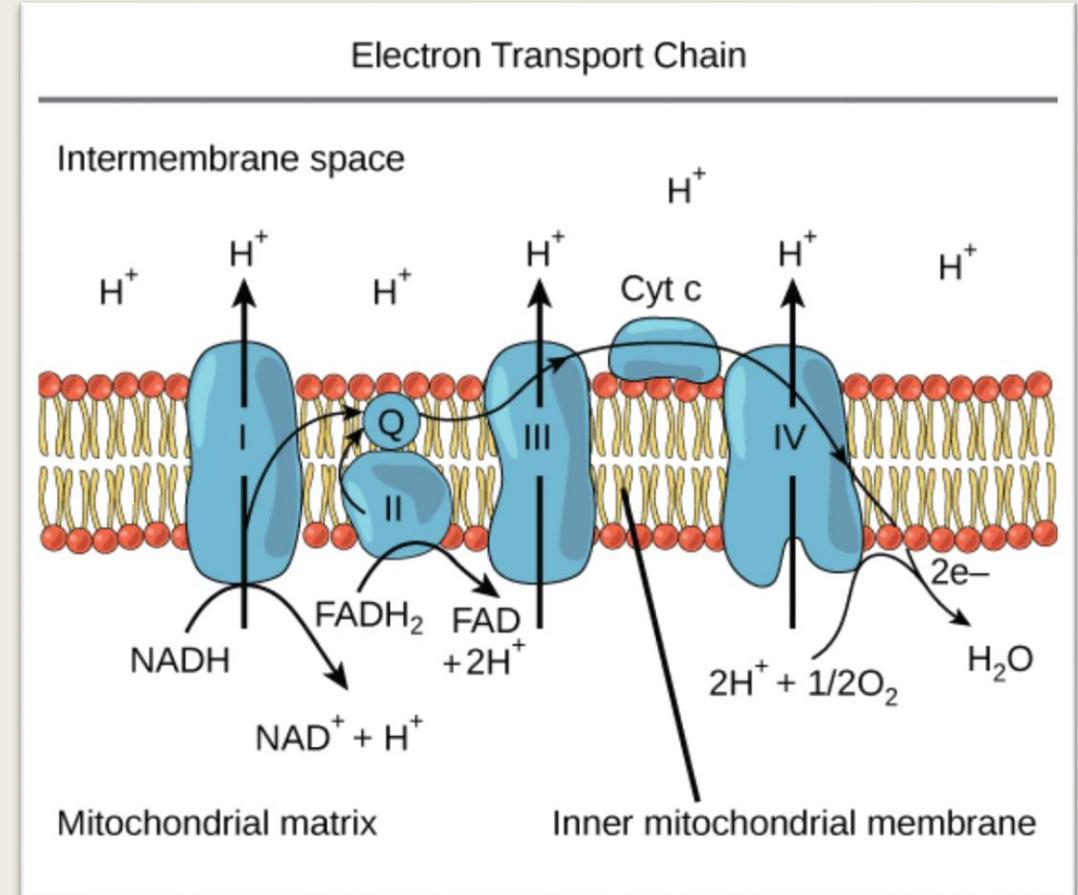
Gene Ontology Term Enrichment

- Inhibitory Neuron #2 - PVALB+
 - Ubiquitin-Dependent Protein Catabolic Process
 - Intracellular Transport
 - Mitochondrion
 - Spliceosomal snRNP Complex
- Excitatory Neuron #1 - Layer V HTR2C+
 - ATP Synthesis Coupled Electron/Protein Transport
 - Ribonucleoprotein Complex Assembly
 - Vesicle Fusion to Plasma Membrane



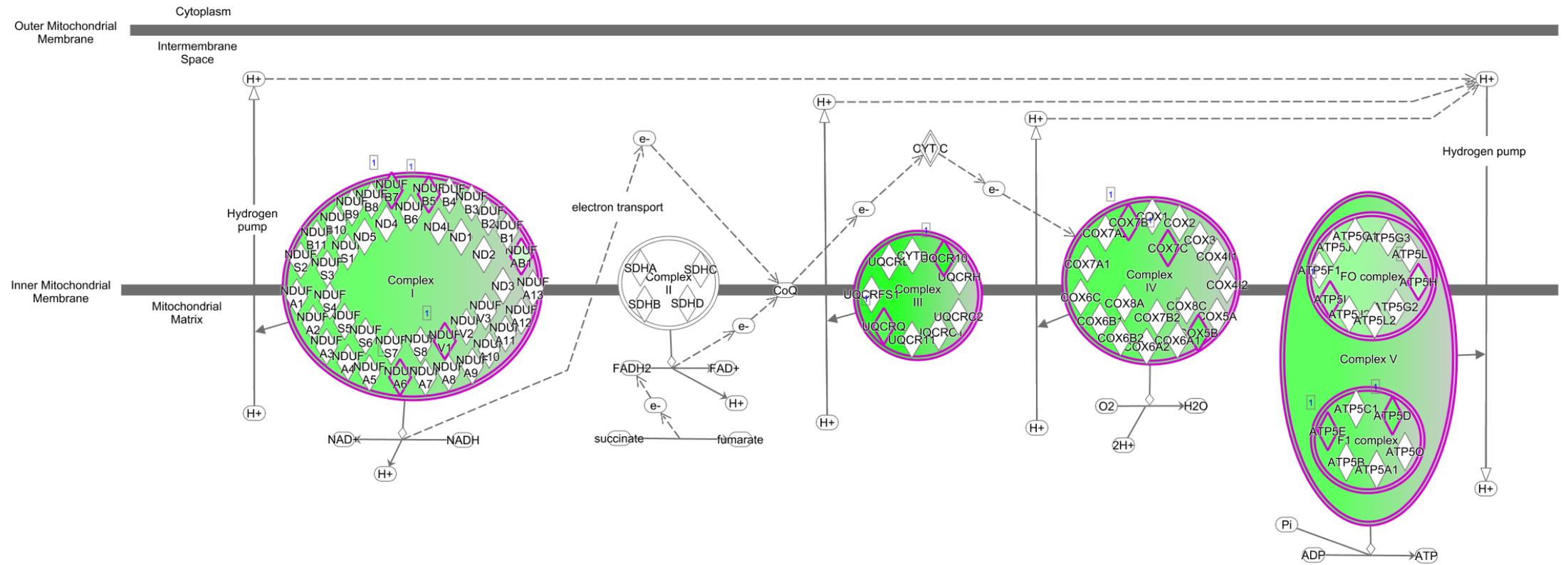
Mitochondria and Schizophrenia

- *NDUFV1* downregulated in five clusters
 - *Previously linked to schizophrenia*
- Genes encoding mitochondrial proteins
 - *NDUFAB1, NDUFAF5, NDUFAF7, NDUFB2, NDUFB5, NDUFB7, NDUFB9, NDUF1, NDUF2, NDUF3, NDUF4, NDUF5, NDUF6, NDUF7, NDUF8*
 - *UQCC1*, *UQCC2, UQCR10, UQCRC1, UQCRC2, UQCRH, UQCRQ*
 - *COX18, COX20, COX4I1, COX5B, COX6B1, COX7B, COX7C*
 - *MTFR1*



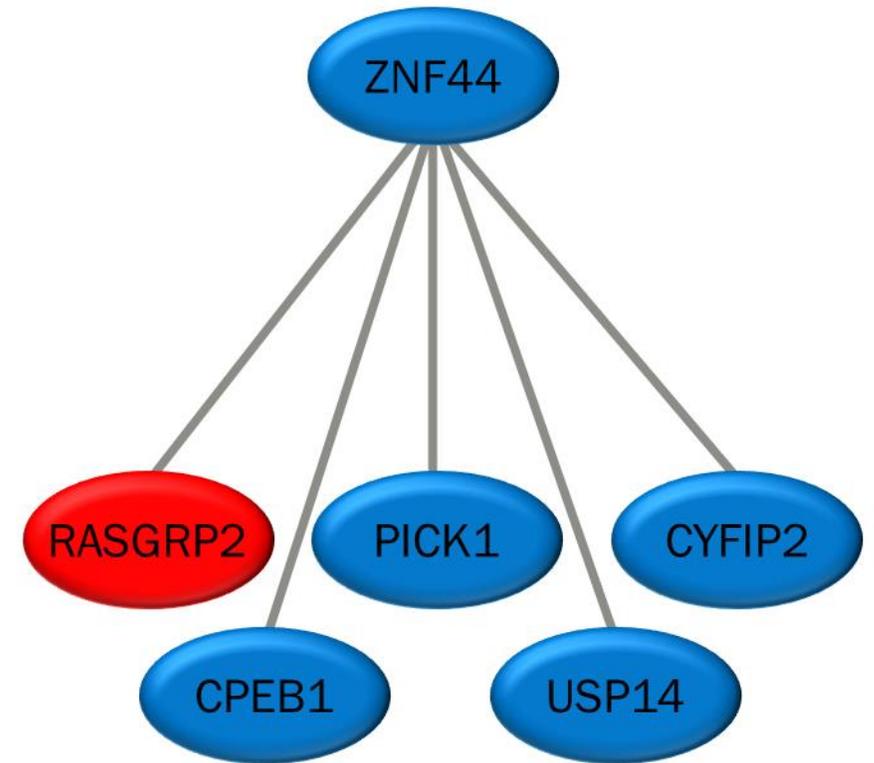
Ingenuity Pathway Analysis

Oxidative Phosphorylation : SZ_10x_Cluster27 : Expr Log Ratio



Transcription Factor Analysis

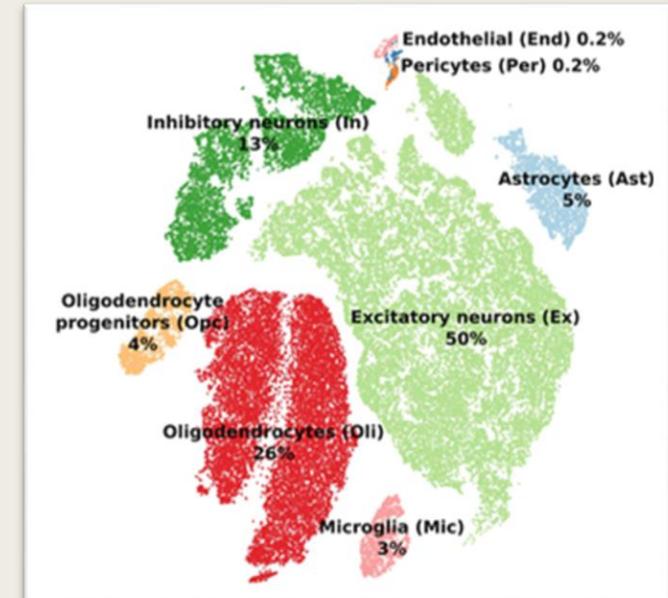
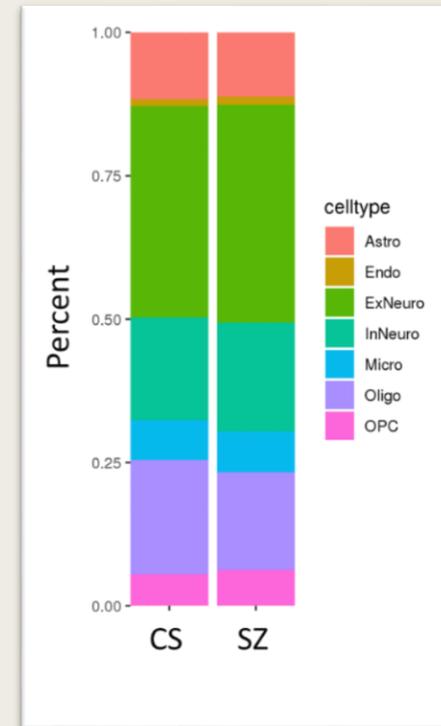
- A number of transcription factors appear in our list of differentially expressed genes
 - *Do the genes they regulate also appear?*
 - *Are those target genes enriched for particularly GO terms or pathways?*
- Target genes identified using TF2DNA
- Enrichment analyzed using DAVID



GO Cellular Compartment: Synapse

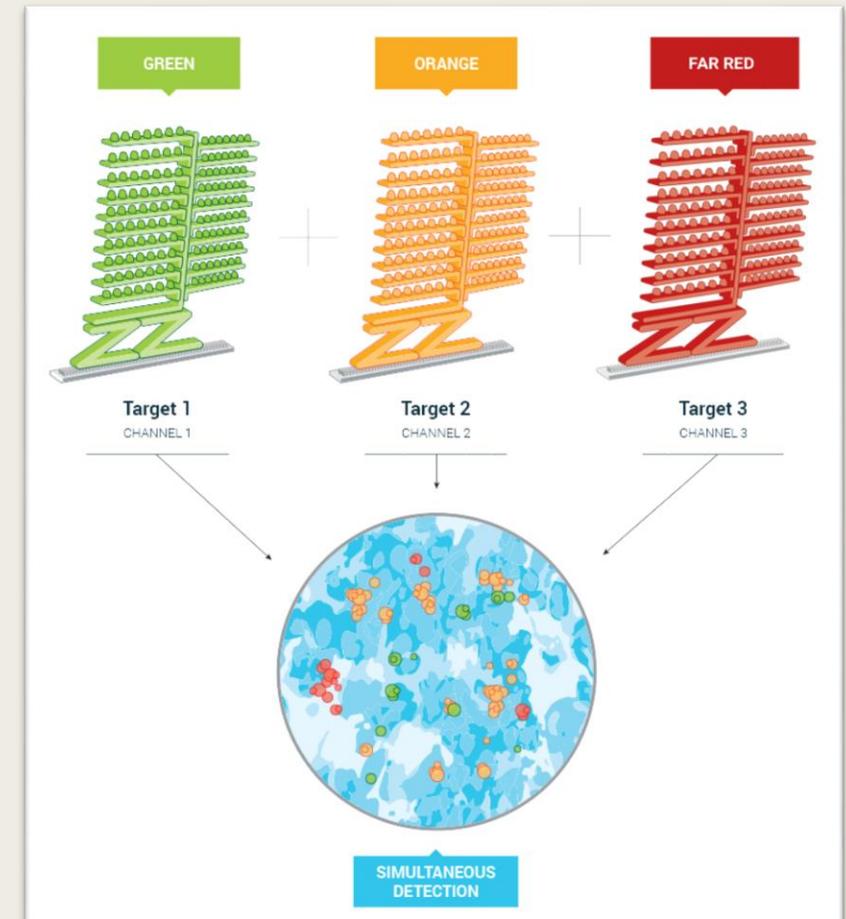
The Missing Glia

- Gray matter from the cortex contains more glia than neurons
 - *1.48 ratio* (Azevedo et al, 2009)
- snRNAseq from postmortem human brain has found the reverse
- Technical issues
 - *Nuclear isolation*
 - *Glia have fewer UMIs than neurons*



Future Directions

- Non-sequencing Validation
 - *RNAscope with Dr. Lauren Stein*
- Replication
 - *Sample size and individual variation*
- Expand Into Substance Use Disorders
 - *Opioid use disorder*
 - *Animal models*



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