Final Project - Differential Expression Analysis in sporadic Alzheimer's disease patients

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Introduction

One of the pathologies of **Alzheimers disease** is dysfunctional/disrupted BBB. **Pericytes** are cells that belong to the Blood-Brain Barrier and play an important role in maintaining the **blood brain barrier** integrity as well as in the functioning of the barrier. I want to identify differentially expressed genes in primary brain pericytes from sAD (Sporadic AD) patients compared to normal/WT pericytes. RNA seq data was obtained from Normal/Healthy patients and two sAD patients. The goal is to identify if the genetic basis of this disease is similar and what could be the major players in Alzheimers Disease

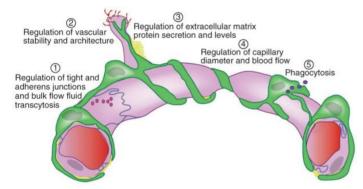


Figure 1: Shows the localization of pericytes and its role in the blood brain barrier (Green represents pericytes and the pink represents endothelial cells)

Datasets used:

RNA Sequence data in FASTQ format are available from 2 sAD patients(in duplicates) and 1 WT.

Data Retrieval and Alignment

Get gene annotation files for STAR aligner (In Bash/Terminal)

```
mkdir Finalproject
cd Finalproject
wget ftp://igenome:G3nom3s4u@ussd-ftp.illumina.com/Homo_sapiens/NCBI/GRCh38/Homo_sapi
ens_NCBI_GRCh38.tar.gz
gunzip Homo_sapiens_NCBI_GRCh38.tar.gz
mkdir Homo_sapiens_NCBI_GRCh38/Homo_sapiens/NCBI/GRCh38/Sequence/STAR_Index
```

Transfer the files from local computer to remote server (In Bash/Terminal)

scp /Users/varshaneelakantan/Desktop/TRGN510\ FINAL\ PROJECT/044_sAD_PC_002.fastq.gz varsha@trgn.bioinform.io:./Finalproject

It is easier to have all the files in one folder so running it would be simpler for example:

```
total 21G
drwxrwxr-x
             9 varsha varsha 4.0K Nov 16 19:26
1 varsha varsha 271M Nov 14 04:19
drwx----
             1 varsha varsha 284M Nov 14 04:20
1 varsha varsha 282M Nov 14 04:21
-rwxrwxr-x
               varsha varsha 257M Nov 14 04:20
-rwxrwxr-x
             1 varsha varsha
                                97M Nov 14 04:13
 rwxrwxr-x
             1 varsha varsha 102M Nov 14 04:11
                                91M Nov 14 04:14
             1 varsha varsha 349M Nov 14 03:58
             1 varsha varsha 338M Nov 14 03:52
 rwxrwxr-x
                varsha varsha 343M Nov 14 03:59
             1 varsha varsha 337M Nov 14 03:59
             1 varsha varsha 432M Nov 14 05:22
 rwxrwxr-x
             1 varsha varsha 429M Nov 14 05:20
             1 varsha varsha 372M Nov 14 05:16
                varsha varsha
             1 varsha varsha 364M Nov 14 05:09
             3 varsha varsha
                                18 Nov 14 05:32
15G Nov 13 22:36
                                                                   _NCBI_GRCh38.tar.gz
             1 yarsha yarsha 5.3K Jun 17
                                              2014
                varsha varsha 4.0K Nov 16 06:31
```

Run STAR (In Bash/Terminal)

Troubleshooting: STAR Requires upto 32GB of RAM. So the alignment was done in the TRGN server.

STAR --runThreadN 6 --genomeDir /home/varsha/Finalproject/Homo_sapiens/NCBI/GRCh38/Se quence/STAR_Index --readFilesIn 131_sAD_PC_001.fastq.gz,131_sAD_PC_002.fastq.gz,131_s AD_PC_003.fastq.gz,131_sAD_PC_004.fastq.gz --readFilesCommand zcat --outFileNamePref ix /home/varsha/Finalproject/bamfiles/131_sAD --outSAMtype BAM Unsorted SortedByCoord inate

Saved all the output to another folder called bamfiles. In the output, the data we are interested in are the ones in pink labelled as XXXAligned.out.bam

These bam files are then transferred back to my local computer using "sftp" command

```
(05:45 varsha@trgn510 Finalproject) > cd bamfiles/
(05:45 varsha@trgn510 bamfiles) > ls -la

total 166
drwxrwxr-x 2 varsha varsha 4.0K Nov 16 06:31
drwxrwxr-x 5 varsha varsha 4.0K Dec 5 05:43
-rw-rw-r-- 1 varsha varsha 1.7G Nov 16 06:13 044_b_sADAligned.out.bam
-rw-rw-r-- 1 varsha varsha 1.9K Nov 16 06:13 044_b_sADAligned.sortedByCoord.out.bam
-rw-rw-r-- 1 varsha varsha 1.9K Nov 16 06:13 044_b_sADLog.out
-rw-rw-r-- 1 varsha varsha 28K Nov 16 06:13 044_b_sADLog.out
-rw-rw-r-- 1 varsha varsha 600 Nov 16 06:13 044_b_sADLog.out
-rw-rw-r-- 1 varsha varsha 600 Nov 16 06:13 044_b_sADLog.out
-rw-rw-r-- 1 varsha varsha 635M Nov 16 06:13 044_b_sADLog.out.tab
-rw-rw-r-- 1 varsha varsha 635M Nov 16 06:13 044_b_sADLog.out.bam
-rw-rw-r-- 1 varsha varsha 635M Nov 16 06:16 044_sADAligned.out.bam
-rw-rw-r-- 1 varsha varsha 635M Nov 16 06:16 044_sADAligned.sortedByCoord.out.bam
-rw-rw-r-- 1 varsha varsha 364 Nov 16 06:16 044_sADLog.final.out
-rw-rw-r-- 1 varsha varsha 364 Nov 16 06:16 044_sADLog.progress.out
-rw-rw-r-- 1 varsha varsha 2.7G Nov 16 06:16 044_sADLog.progress.out
-rw-rw-r-- 1 varsha varsha 1.8G Nov 16 06:24 131_b_sADAligned.sortedByCoord.out.bam
-rw-rw-r-- 1 varsha varsha 1.8K Nov 16 06:24 131_b_sADLog.final.out
-rw-rw-r-- 1 varsha varsha 28K Nov 16 06:24 131_b_sADLog.final.out
-rw-rw-r-- 1 varsha varsha 366 Nov 16 06:24 131_b_sADLog.progress.out
-rw-rw-r-- 1 varsha varsha 6.6M Nov 16 06:24 131_b_sADLog.progress.out
-rw-rw-r-- 1 varsha varsha 6.6M Nov 16 06:24 131_b_sADLog.progress.out
-rw-rw-r-- 1 varsha varsha 1.9K Nov 16 06:31 131_sADLog.progress.out
-rw-rw-r-- 1 varsha varsha 1.9K Nov 16 06:31 131_sADLog.progress.out
-rw-rw-r-- 1 varsha varsha 1.9K Nov 16 06:31 131_sADLog.progress.out
-rw-rw-r-- 1 varsha varsha 1.9K Nov 16 06:31 131_sADLog.final.out
-rw-rw-r-- 1 varsha varsha 1.9K Nov 16 06:31 131_sADLog.progress.out
-rw-rw-r-- 1 varsha varsha 1.9K Nov 16 06:00 wtAligned.sortedByCoord.out.bam
-rw-rw-r-- 1 varsha varsha 2.1G Nov 16 06:00 wtAligned.sortedByCoord.out.bam
-rw-rw-r-- 1 varsha varsha 2.1G Nov 16 06:00
```

Install and Load Libraries required for Featurecounts

```
BiocManager::install("Rsubread")
BiocManager::install("DESeq2")
BiocManager::install("Biobase")
BiocManager::install("limma")
BiocManager::install("EnhancedVolcano")
```

```
library(BiocManager)
library(Rsubread)
library(DESeq2)
library(RColorBrewer)
library(gplots)
library(ggplot2)
library(grid2)
library(grid)
library(grid library(gridExtra)
library(genefilter)
```

Set working Directory

```
setwd("/Users/varshaneelakantan/Desktop/test")
```

RunFeatureCounts

Note: my gtf file has the Gene names already. In cases where the gtf file only has the gene ID you need to get the gene names from some other resource like NCBI.

The Subread package allows us to analyse next gen sequencing data. The featurecounts function is for counting reads to genomic features

```
featureCounts(files=c("wtAligned.out.bam", "044_b_sADAligned.out.bam", "044_sADAligned.out.bam", "131_sADAligned.out.bam", "131_b_sADAligned.out.bam"),annot.ext="genes.gtf", isGTFAnnotationFile=TRUE,GTF.featureType="exon",GTF.attrType="gene_id")
fc <- featureCounts(files=c("wtAligned.out.bam", "044_b_sADAligned.out.bam", "044_sAD
Aligned.out.bam", "131_sADAligned.out.bam", "131_b_sADAligned.out.bam"),annot.ext=
"genes.gtf", isGTFAnnotationFile=TRUE,GTF.featureType="exon",GTF.attrType="gene_id")
```

Save data as a txt file

```
write.table(x=data.frame(fc$annotation[,c("GeneID","Length")],fc$counts,stringsAsFact
ors=FALSE),file="readcounts.txt",quote=FALSE,sep="\t",row.names=FALSE)
```

Differential Analysis using DESeq

Reading Data

Make "Coldata" as a table that contains the sample names and the type/condition (example: WT/Control, Sample1/Test etc). You may get an error because of dupplicates in the featurecounts file. In order to go past that you need to look for those duplicates and delete them.

```
dds <- read.delim("featurecounts_output.txt" , sep = "\t" , header=TRUE, row.names =
1) #Removed Duplicates from the file or else error keeps popping up
dds <- dds[-c(1)] #Ignoring the Length column
data <- as.data.frame(dds)
coldata <- read.delim("coldata.txt", sep = "\t") #Made an excel with the column names
    of the different samples
coldata <- as.data.frame(coldata)
head(coldata)</pre>
```

```
## X Condition
## 1 WT Control
## 2 sAD1 test1
## 3 sAD2 test1
## 4 sAD3 test2
## 5 sAD4 test2
```

Run DESEQ2

Run the libararies first.

Size factors or normalization factors for stabilizing the variance in the samples

```
sizeFactors(deseq_dds)
```

```
## WT sAD1 sAD2 sAD3 sAD4
## 1.1636215 1.0305322 0.3502768 1.4225433 1.7041582
```

Reordering based on Lowest p value

Showing and example of how the data looks like as a data frame

```
resOrdered_1 <- res_test1[order(res_test1$pvalue),]
resOrdered_2 <- res_test2[order(res_test2$pvalue),]
resOrdered_sAD1vsctr1 <- resa[order(resa$pvalue),]
resOrdered_sAD2vsctr1 <- resb[order(resb$pvalue),]
resOrdered_sAD2vssAD1 <- res_sad1_sad2[order(res_sad1_sad2 $pvalue),]
head(resOrdered_sAD2vsctr1)</pre>
```

```
## log2 fold change (MLE): Condition test2 vs Control
## Wald test p-value: Condition test2 vs Control
## DataFrame with 6 rows and 6 columns
##
                   baseMean
                               log2FoldChange
                                                          lfcSE
##
                  <numeric>
                                    <numeric>
                                                      <numeric>
## APOE
           2768.01794915885 -6.80076247248609 0.186422171547044
## COL11A1 3557.97961520115 -6.28152590065817 0.18516383465743
## IGFBP1 2917.73668218714 5.85824992910463 0.211900048724944
           4148.1372313505 -4.15399864838396 0.168099986897092
## FBLN2
## FRZB
           739.167133623431 -6.11591288236176 0.248191304163045
## CX3CL1 575.737859500636 -6.68475510162572 0.285019654411804
##
                                            pvalue
                        stat
                                                                    padj
                                         <numeric>
##
                   <numeric>
                                                               <numeric>
## APOE
           -36.4804380082543 2.26543295529474e-291 3.47426798024001e-287
## COL11A1 -33.9241510756113 2.93481598524462e-252 2.25041689748557e-248
## IGFBP1
            27.6462887307256 3.09277386184194e-168 1.5810259981736e-164
## FBLN2
           -24.7114751467944 8.05099422312859e-135 3.0867511851475e-131
## FRZB
           -24.6419305583085 4.49133817174888e-134 1.37758324403882e-130
## CX3CL1 -23.4536636268859 1.2128824016795e-121 3.1001274186928e-118
```

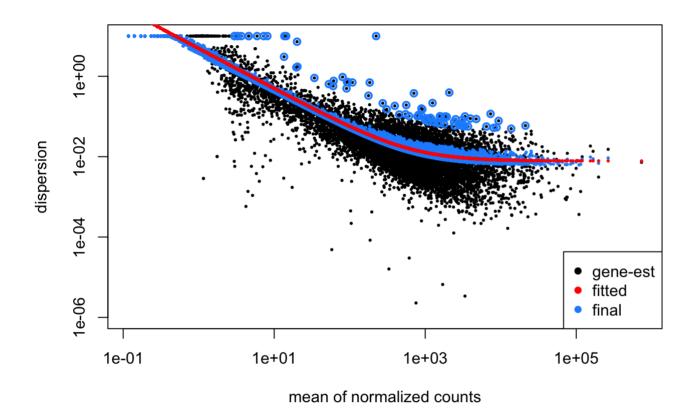
Exporting data into csv files

```
write.csv(as.data.frame(resOrdered_1), file="dds_ctrlvssAD1.csv")
write.csv(as.data.frame(resOrdered_2), file="dds_ctrlvssAD2.csv")
write.csv(as.data.frame(resOrdered_sAD1vsctrl), file="dds_sAD1vsctrl.csv")
write.csv(as.data.frame(resOrdered_sAD2vsctrl), file="dds_sAD2vsctrl.csv")
write.csv(as.data.frame(resOrdered_sAD2vssAD1), file="dds_sAD2vssAD1.csv")
```

Plot for how the data is dispersed

This shows how deseg runs the program to give you a final data point

```
plotDispEsts(deseq_dds, ylim = c(1e-6, 1e1) )
```



To make it rlog transformed data

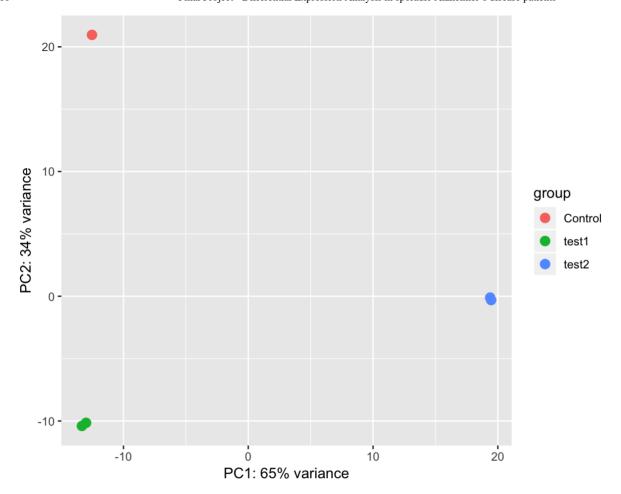
Showing and example of how the data looks like as a data frame

```
rld <- rlog(deseq dds)
head( assay(rld) )
                    WT
                            sAD1
                                      sAD2
                                                sAD3
                                                          sAD4
                       3.901767
                                  4.090172
                                            4.085234
## DDX11L1
              4.238392
                                                      4.124920
## WASH7P
              9.795133
                        9.270708 9.526410
                                            9.649355
                                                      9.447682
## MIR6859-1
              3.551767
                        3.353717
                                 3.440006
                                            3.368766
## MIR1302-2 -1.874578 -1.860017 -1.866338 -1.875957 -1.877196
## FAM138A
             -1.861909 -1.873430 -1.866812 -1.875407 -1.876515
## OR4F5
              0.000000 0.000000 0.000000
                                            0.000000
                                                      0.00000
```

PCA - To know how different are the patient pericytes in comparison to wild type or control

The PCA shows that there is very little variance in the replicates but there is not too much variance between the replicates of the patient RNA but they are different from each other and the wild type.

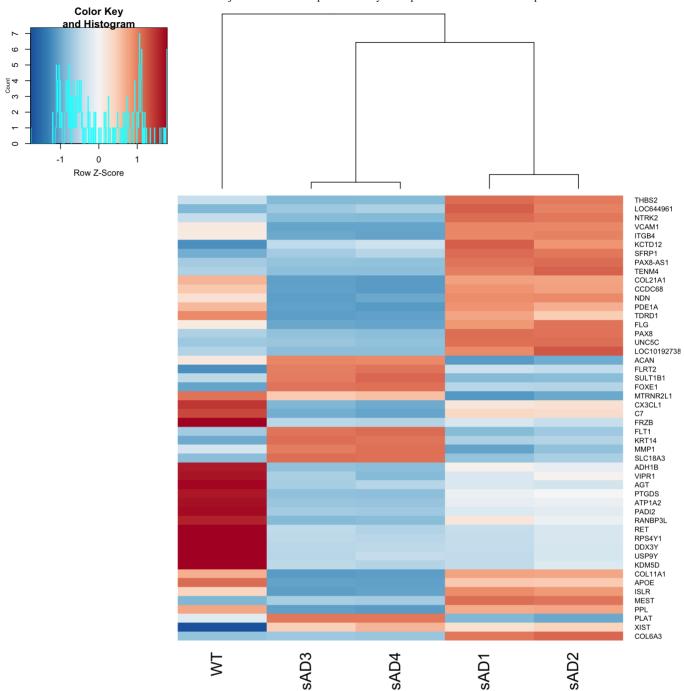
```
plotPCA(rld, intgroup = "Condition")
```



Generating Plots

Heatmap for top 50 variable genes

Data used is rlog transformed



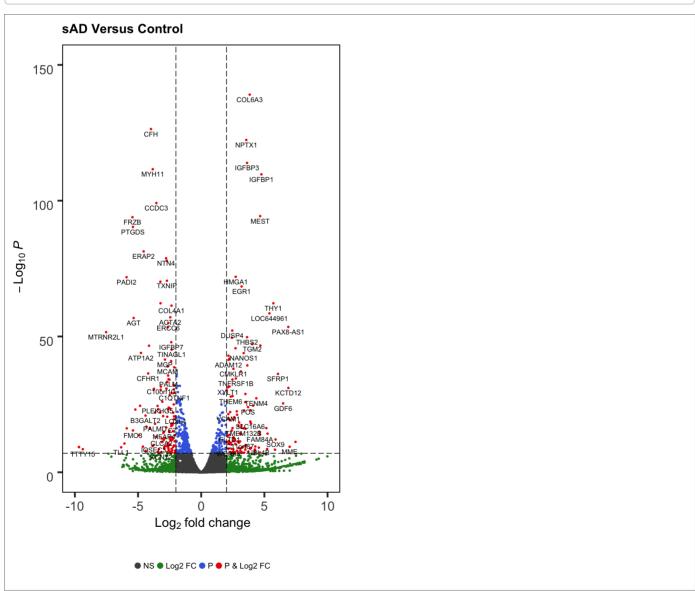
Volcano plot

(Using Enhanced volcano plots package by Kevin Blighe)

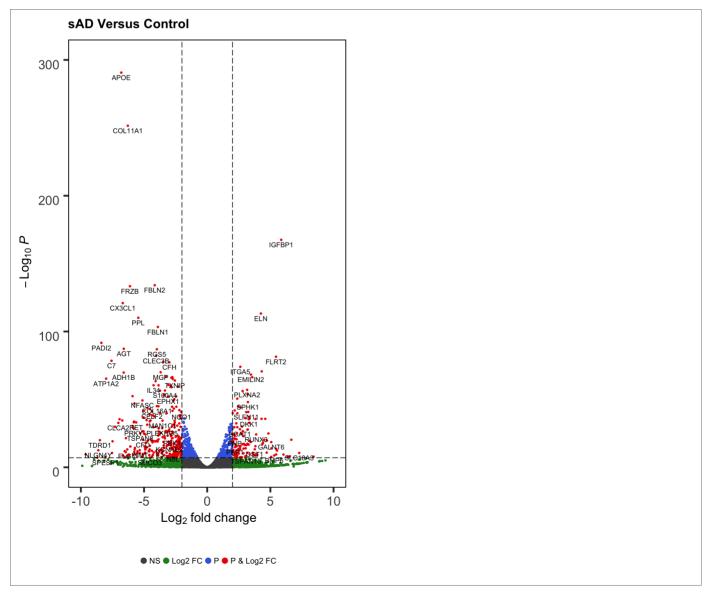
NOTE: sADa refers to sAD 1 and 2 in the heatmap data. sADb refers to sAD 3 and 4

Data used is the original results from deseq analysis

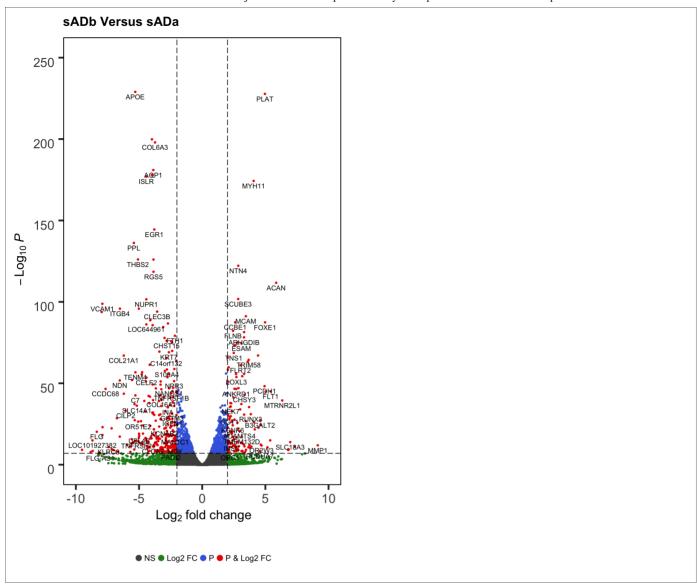
```
p1 <- EnhancedVolcano(resa,</pre>
                       lab = rownames(resa),
                       x = "log2FoldChange",
                       y = "pvalue",
                       pCutoff = 10e-8,
                       FCcutoff = 2.0,
                       xlim = c(-10, 10),
                       ylim = c(0, 150),
                       transcriptLabSize = 3.0,
                       title = "sAD Versus Control",
                       colAlpha = 1,
                       legendPosition = "bottom",
                       legendLabSize = 10,
                       legendIconSize = 3.0,
                       border = "full",
                       borderWidth = 1,
                       borderColour = "black",
                       gridlines.major = FALSE,
                       gridlines.minor = FALSE)
grid.arrange(p1, ncol=2)
grid.rect(gp=gpar(fill=NA))
```



```
p2 <- EnhancedVolcano(resb,</pre>
                       lab = rownames(resb),
                       x = "log2FoldChange",
                       y = "pvalue",
                       xlab = bquote(~Log[2]~ "fold change"),
                       ylab = bquote(~-Log[10]~italic(P)),
                       pCutoff = 10e-8,
                       FCcutoff = 2.0,
                       xlim = c(-10, 10),
                       ylim = c(0, 300),
                       transcriptLabSize = 3.0,
                       title = "sAD Versus Control",
                       colAlpha = 1,
                       legend=c("NS","Log2 FC","P","P & Log2 FC"),
                       legendPosition = "bottom",
                       legendLabSize = 10,
                       legendIconSize = 3.0,
                       border = "full",
                       borderWidth = 1,
                       borderColour = "black",
                       gridlines.major = FALSE,
                       gridlines.minor = FALSE)
grid.arrange(p2, ncol=2)
grid.rect(gp=gpar(fill=NA))
```



```
p3 <- EnhancedVolcano(res sad1 sad2,
                      lab = rownames(res_sad1_sad2),
                      x = "log2FoldChange",
                      y = "pvalue",
                      xlab = bquote(~Log[2]~ "fold change"),
                      ylab = bquote(~-Log[10]~italic(P)),
                      pCutoff = 10e-8,
                      FCcutoff = 2.0,
                      xlim = c(-10, 10),
                      ylim = c(0, 250),
                      transcriptLabSize = 3.0,
                      title = "sADb Versus sADa",
                      colAlpha = 1,
                      legend=c("NS","Log2 FC","P","P & Log2 FC"),
                      legendPosition = "bottom",
                      legendLabSize = 10,
                      legendIconSize = 3.0,
                      border = "full",
                      borderWidth = 1,
                      borderColour = "black",
                      gridlines.major = FALSE,
                      gridlines.minor = FALSE)
grid.arrange( p3, ncol=2)
grid.rect(gp=gpar(fill=NA))
```



Results:

Amongst the highly varying genes, we see many genes that have an assiciation with AD. APOE-ApolipoproteinE which is known to be associated with Alzheimer's Disease

FBLN2- Is a protein that is involved in calcium ion binding and ECM binding. Pericytes are contractile cells that contract in response to calcium and potassium levels and defect in this gene could affect the pericyte function.

THBS2 - Thrombospondin 2, is a glycoprotein that is involved in cell-cell adhesion. Pericytes are usually wrapped around endothelial cells in capillaries and need to establish a strong cell contact for maintaining the blood-brain barrier.

PDE1A- is a phosphodiesterase enzyme, and is known to be involved in learning and is found in brain regions that subserve memory and learning, including frontal cortex, hippocampus.

NTRK2 - Neurotrophic tyrosine kinase receptor type 2: The NTRK family encodes the receptors TRKA, TRKB, and TRKC, to which the neurotrophins, nerve growth factor (NGF), BDNF and neurotrophin-3 (NT-3) (regulates neuronal development and plasticity, long-term potentiation, and apoptosis) bind with high affinity.

PADI2-Peptidylarginine deiminases, has been shown to be associated with amyloid beta processing.

Conclusion:

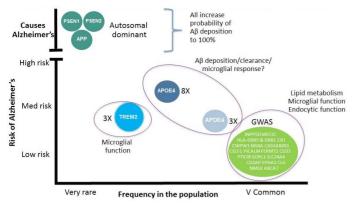


Figure 2: GWAS analysis of AD patients for potential high risk genes.

From our data, we see that the genetic profiles of the two AD patients are quite different from each other and APOE (which is one of the prominent risk factors of AD) is clearly downregulated in one of the patients but the physiological effects are similar - Blood-brain barrier leakiness and amyloid beta accumulation. So this could mean that more than one gene is responsible for the disease.

References:

- 1. "Exome Sequencing of Extended Families with Alzheimer's Disease Identifies Novel Genes Implicated in Cell Immunity and Neuronal Function". Cukier HN (2017)
- 2. "Preclinical profile of ITI-214, an inhibitor of phosphodiesterase 1, for enhancement of memory performance in rats" Gretchen L. Snyder (2016)
- 3. "Genetic association of neurotrophic tyrosine kinase receptor type 2 (NTRK2) With Alzheimer's disease" Chen Z(2008)
- 4. "Increased expression of PAD2 after repeated intracerebroventricular infusions of soluble Abeta(25-35) in the Alzheimer's disease model rat brain: effect of memantine" Arif.M (2009)