# ABIDEI PINT FC mat stats

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This is an analysis of the FC Mats

```
library(dplyr)
library(tidyr)
library(broom)
library(igraph)
library(corrplot)
library(effsize)
library(knitr)
library(ggplot2)
library(gridExtra)
```

## Reading in the data

A couple things to note here about the how the clinical data is being parsed:

- 1. all catergorical variables are being set to Factors
- Note that sex.x still needs descriptive labels
- 2. Education is being very basically impluted when it is not available so that we do not lose data

## Some functions we're using

```
## functions
read_subject_meants <- function(subid, pint_dir, vertex_type) {
  meants <- read.csv(file.path(pint_dir,</pre>
```

```
paste(subid, vertex_type, "meants.csv", sep="_")),
                      header=FALSE)
  return(meants)
}
load_all_subject_matrices <- function(subids, myedgenames, pint_dir,</pre>
                                        vertex type) {
  ## use these parameters to set up a blank dataframe to hold all the correlations
  theZs <- as.data.frame(cbind("subid" = subids,
                                matrix(numeric(),
                                        nrow = length(subids),
                                        ncol = numedges,
                                        dimnames = list(1:length(subids),
                                                        myedgenames))))
  theZs[,2:ncol(theZs)] <- numeric(nrow(theZs)*(ncol(theZs)-1))
  ## now correlate everyones ts and write the correlations to a massive data frame
  for (i in 1:nrow(theZs)) {
    ## get the subid from the dataframe and read in the meants
    meants <- read_subject_meants(theZs$subid[i], pint_dir, vertex_type)</pre>
    ## correlate and graph
    cormat <- cor(t(meants))</pre>
    g<-graph_from_adjacency_matrix(cormat, mode="upper",
                                    weighted=T, diag=F)
    # take the eqde list as a vector
    thecorrs <- E(g)$weight
    # apply the Z transform (so we can do stats)
    theseZ <- atanh(thecorrs)</pre>
    # save the output to the data.frame
    theZs[i,2:ncol(theZs)] <- theseZ
  }
 return(theZs)
make_corrplot <-function(data, attrtoplot, graph_title) {</pre>
  forplot <- as.data.frame(data)</pre>
  forplot <- forplot %>% separate(Edge, into = c("V1", "V2"), sep = '\\.')
  g <- graph_from_data_frame(forplot, directed=F)</pre>
  g.mat <- get.adjacency(g, attr=attrtoplot)</pre>
  corrplot(as.matrix(g.mat),
           is.corr = F, tl.cex = 0.3, tl.col = "black",
           title = graph_title)
}
#new circle graph function
radian.rescale <- function(x, start=0, direction=1) {</pre>
  c.rotate <- function(x) (x + start) %% (2 * pi) * direction</pre>
  c.rotate(scales::rescale(x, c(0, 2 * pi), range(x)))
```

```
draw_circle_graph <- function(data, Yeo7_80verts) {</pre>
  CircleOrder <- as.character(Yeo7_80verts$SHORTNAME)</pre>
  CircleOrder <- c(CircleOrder[75:length(CircleOrder)], CircleOrder[1:74])</pre>
  g <- graph.data.frame(data, directed = F)</pre>
  Yeo7_80verts$wnetname <- substr(Yeo7_80verts$SHORTNAME,3,6)
  Yeo7 80verts$Vhex <- NA
  Yeo7_80verts$Vhex[Yeo7_80verts$NETWORK==2] <- "#781286"
  Yeo7_80verts$Vhex[Yeo7_80verts$NETWORK==3] <- "#00760E"
  Yeo7_80verts$Vhex[Yeo7_80verts$NETWORK==4] <- "#C43AFA"
  Yeo7_80verts$Vhex[Yeo7_80verts$NETWORK==5] <- "#4682B4"
  Yeo7_80verts$Vhex[Yeo7_80verts$NETWORK==6] <- "#E69422"
  Yeo7_80verts$Vhex[Yeo7_80verts$NETWORK==7] <- "#CD3E3A"
  V(g)$color <- Yeo7_80verts$Vhex
  g$layout <- layout_in_circle(g,order = CircleOrder)</pre>
  lab.locs <- radian.rescale(x=1:80, direction=-1, start=0)
  d <-as.matrix(dist(g$layout, method = "euclidean",</pre>
                      upper = TRUE, diag = TRUE, p = 2))
  gdist <-graph_from_adjacency_matrix(as.matrix(dist(g$layout, method = "euclidean",</pre>
                                                        upper = TRUE, diag = TRUE, p = 2)),
                                        mode="upper", weighted=T, diag=F)
  dist.df <- cbind(data, E(gdist) $ weight)</pre>
  dist.df$scaledD <- (dist.df$`E(gdist)$weight`/(-2)) + 1</pre>
  dist.df$scaleDc <- dist.df$scaledD</pre>
  dist.df\$netcombo <- paste(substr(dist.df\$V1,1,2), substr(dist.df\$V2,1,2), sep =".")
  switchlist <- c("DA.VI", "DA.SM")</pre>
  dist.df$scaleDc[dist.df$netcombo %in% switchlist] <- dist.df$scaleD[dist.df$netcombo %in% switchlist]
  plt <- plot(g, edge.width=E(g)$logp*5,</pre>
       edge.curved=dist.df$scaleDc,
       edge.color = E(g)$posneg,
       vertex.size = 3.5,
       vertex.label.family="sans",
       vertex.label.font=1,
       vertex.label.cex = 0.5,
       vertex.label = Yeo7_80verts$wnetname,
       vertex.label.dist=0.5,
       vertex.label.degree=lab.locs,
       vertex.label.color = V(g)$color)
  return(plt)
}
```

### Load the ivertex and tvertex Zs for all subjects

```
## read in one examplar to get some parameters we want
meants1 <- read_subject_meants(qced_sublists$subid[1], pint_dir, 'ivertex')
## sort the meants into the order from the new naming scheme
names(meants1) <- paste0("TR_",1:ncol(meants1))
Yeo_meants <- cbind(Yeo7_80verts,meants1)
## correlate and graph from the first one</pre>
```

```
cormat <- cor(t(select(Yeo_meants,starts_with("TR_"))))</pre>
rownames(cormat) <- Yeo_meants$SHORTNAME</pre>
colnames(cormat) <- Yeo_meants$SHORTNAME</pre>
g<-graph_from_adjacency_matrix(cormat, mode="upper",
                                 weighted=T, diag=F,
                                 add.rownames = "code")
g.df <- as.data.frame(get.edgelist(g), names=T)</pre>
# take the egde list as a vector
thecorrs \leftarrow E(g)$weight
# apply the Z transform (so we can do stats)
theseZ <- atanh(thecorrs)</pre>
## get two variables of interest.. edgenames and the number of edges
myedgenames <- paste(g.df[ ,1],g.df[ ,2],sep=".") ## the V1.V2 name
                                                    ## the number of edges
numedges <- length(myedgenames)</pre>
## get all the Z's from ivertex
theZs_ivertex <- load_all_subject_matrices(as.character(qced_sublists$subid),</pre>
                                             myedgenames, pint_dir, 'ivertex')
## merge all those correlations back with the demographics
alldemZs_i_m <- merge(pheno,theZs_ivertex,by="subid") %>%
    gather_("Edge", "FC", myedgenames)
## get all the Z's from tvertex
theZs_tvertex <- load_all_subject_matrices(as.character(qced_sublists$subid),</pre>
                                             myedgenames, pint_dir,
                                             'tvertex')
## merge all those correlations back with the demographics
alldemZs_t_m <- merge(pheno,theZs_tvertex,by="subid") %>%
 gather_("Edge", "FC", myedgenames)
```

# Run the linear model for all Template and Personalized FC edges

Note: one trick here (but justified by Saba's thesis and Graces work, is to add a DX\*Sex interation term of all models)

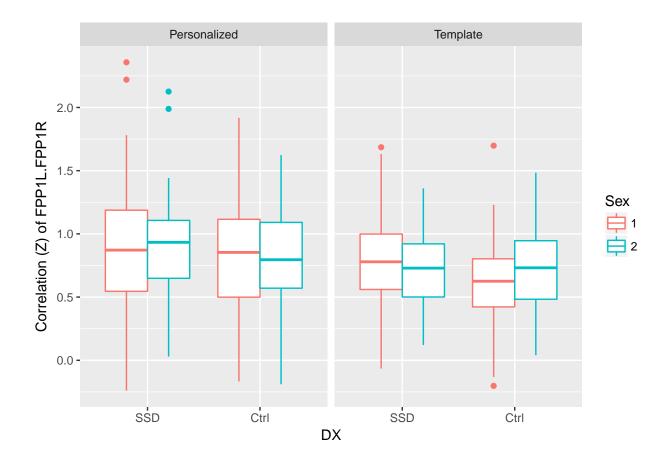
## looking at all FDR corrected results..

Most results are for the linear effect of age..but there is one significant effect of Diagnosis in the FP network (contralateral partietal areas..)

```
FC_lmres %>%
  filter(term %in% c("DXCtrl","Sex2", "DXCtrl:Sex2","age")) %>%
  arrange(p.value) %>%
  select(Edge, vertex_type, term, statistic, p.value, p.FDR) %>%
  filter(p.value < 0.0001) %>%
  kable()
```

Edge	vertex_type	term	statistic	p.value	p.FDR
DAP2R.DMP2L	Personalized	age	-4.911880	1.30e-06	0.0081221
VI04L.VI04R	Template	age	-4.514794	8.20 e-06	0.0259097
FPP1L.FPP1R	Template	$\mathrm{DXCtrl}$	-4.514494	8.20 e-06	0.0518894
DAP2L.SMF2L	Personalized	age	4.279925	2.31e-05	0.0439448
DAP1L.VAP2R	Template	age	4.236437	2.78e-05	0.0439448
DMP1R.DMT1R	Template	Sex2	4.111470	4.71e-05	0.2486655
DAP2R.VAI1R	Personalized	age	4.027573	6.66e-05	0.0721185
DAP2L.VAI1R	Template	age	4.008427	7.21e-05	0.0721185
DMP1L.VAF3R	Personalized	Sex2	3.986851	7.87e-05	0.2486655
${\rm DAP2R.DMP2R}$	Personalized	age	-3.941623	$9.45\mathrm{e}\text{-}05$	0.0721185

# Looking at the significant effect in FP network



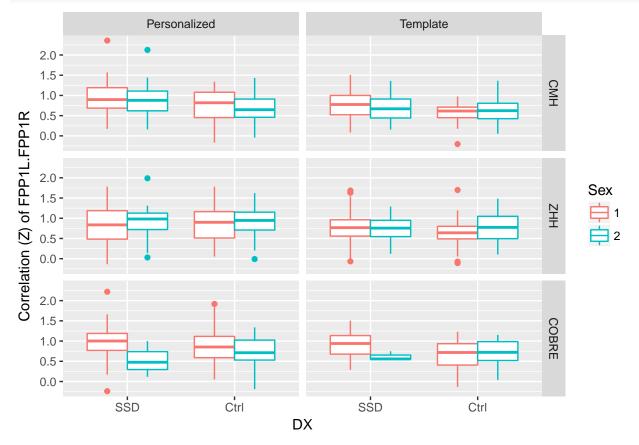
# all the model terms within this edge

```
FC_lmres %>%
filter(Edge == "FPP1L.FPP1R") %>%
  select(Edge, vertex_type, term, statistic, p.value, p.FDR) %>%
  kable()
```

Edge	vertex_type	term	statistic	p.value	p.FDR
FPP1L.FPP1R	Personalized	(Intercept)	4.9027915	0.0000013	0.0000456
FPP1L.FPP1R	Personalized	DXCtrl	-0.5152849	0.6066194	0.9261453
FPP1L.FPP1R	Personalized	Sex2	-0.0991067	0.9210998	0.9981405
FPP1L.FPP1R	Personalized	$mean\_fd$	0.6063966	0.5445722	0.7798235
FPP1L.FPP1R	Personalized	age	1.3504356	0.1775882	0.7334033
FPP1L.FPP1R	Personalized	Edu	-0.4112220	0.6811151	0.9970032
FPP1L.FPP1R	Personalized	SiteZHH	1.6322088	0.1033693	0.3993238
FPP1L.FPP1R	Personalized	SiteCOBRE	0.3332637	0.7390981	0.9129909
FPP1L.FPP1R	Personalized	DXCtrl:Sex2	-0.1388769	0.8896126	0.9977319
FPP1L.FPP1R	Template	(Intercept)	4.9213744	0.0000012	0.0000424
FPP1L.FPP1R	Template	DXCtrl	-4.5144944	0.0000082	0.0518894
FPP1L.FPP1R	Template	Sex2	-1.3698671	0.1714449	0.8081463
FPP1L.FPP1R	Template	$mean\_fd$	-0.7201338	0.4718348	0.7280264
FPP1L.FPP1R	Template	age	-0.4186586	0.6756752	0.9377793
FPP1L.FPP1R	Template	Edu	1.7905168	0.0740758	0.9970032
FPP1L.FPP1R	Template	SiteZHH	1.1552492	0.2486314	0.5937746
FPP1L.FPP1R	Template	${\bf Site COBRE}$	2.4661057	0.0140492	0.1587799

Edge	vertex_type	term	statistic	p.value	p.FDR
FPP1L.FPP1R	Template	DXCtrl:Sex2	1.9149833	0.0561593	0.8467977

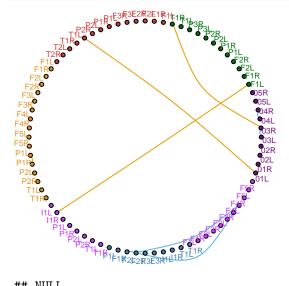
## splitting the plot by Site



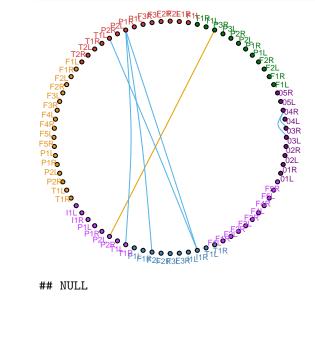
# building circle plots of the subthreshold effects

```
mutate(thres_statistic = if_else(p.value <= p_thres,</pre>
                                     true = statistic,
                                     false= 0)) %>%
  mutate(posneg = case_when(.$thres_statistic < -0.01 ~ 1,</pre>
                              .$thres_statistic > 0.01 ~ 2,
                              TRUE ~ NA_real_),
        log_p = case_when(.$p.value <= p_thres ~ log(.$p.value),</pre>
                           TRUE \sim 0)
  plot <- draw_circle_graph(forgraph, Yeo7_80verts)</pre>
  return(plot)
thresholded_circle_plot(FC_lmres, p_thres = 0.001,
```

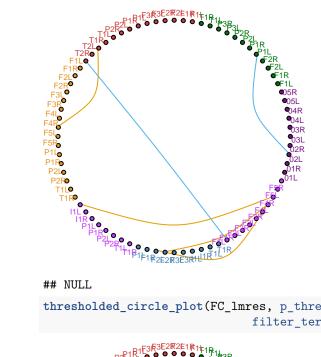
```
filter_term = "DXCtrl", filter_vtype = "Template")
```



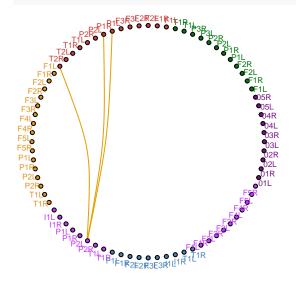
```
thresholded_circle_plot(FC_lmres, p_thres = 0.001,
                              filter_term = "DXCtrl", filter_vtype = "Personalized")
```



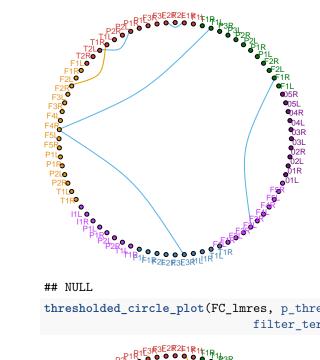
```
thresholded_circle_plot(FC_lmres, p_thres = 0.001,
                              filter_term = "DXCtrl:Sex2", filter_vtype = "Template")
```



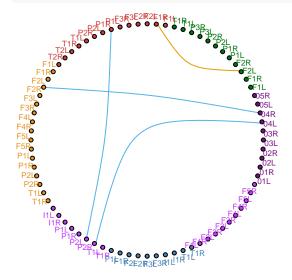
```
thresholded_circle_plot(FC_lmres, p_thres = 0.001,
                              filter_term = "DXCtrl:Sex2", filter_vtype = "Personalized")
```



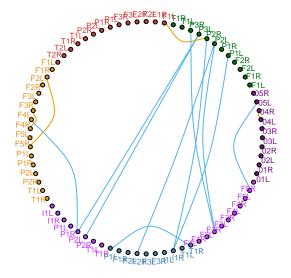
```
thresholded_circle_plot(FC_lmres, p_thres = 0.001,
                              filter_term = "Sex2", filter_vtype = "Template")
```



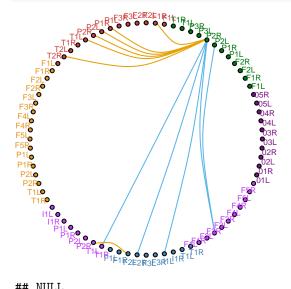
```
thresholded_circle_plot(FC_lmres, p_thres = 0.001,
                              filter_term = "Sex2", filter_vtype = "Personalized")
```



```
thresholded_circle_plot(FC_lmres, p_thres = 0.001,
                              filter_term = "age", filter_vtype = "Template")
```



```
thresholded_circle_plot(FC_lmres, p_thres = 0.001,
                              filter_term = "age", filter_vtype = "Personalized")
```



## NULL

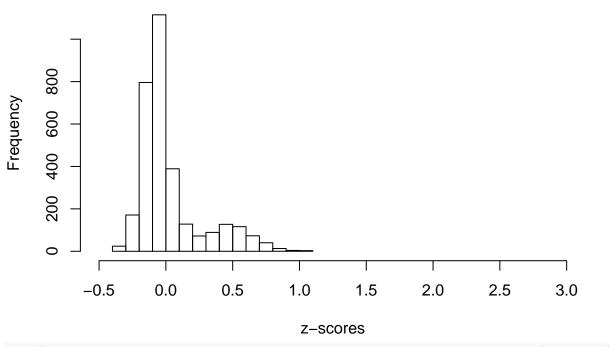
New stuff for graph theory - 30 July 2017

```
# New stuff for graph theory - 30 July 2017
## merge all those correlations back with the demographics
alldemZs_i_m <- merge(qced_sublists,theZs_ivertex,by="subid")</pre>
alldemZs_t_m <- merge(qced_sublists,theZs_tvertex,by="subid")</pre>
# Averaging z-scores for each diagnostic group for the i vertices
aggregate_all_i <- aggregate(alldemZs_i_m[, 14:3173], list(alldemZs_i_m$DX_GROUP), mean)
# Subsetting into patients and controls so I can make separate adjacency matrices
```

```
aggregate_all_i_SCZ <- aggregate_all_i[1,2:3161]</pre>
aggregate_all_i_HC <- aggregate_all_i[2,2:3161]</pre>
# Averaging z-scores for each diagnostic group for the t vertices
aggregate_all_t <- aggregate(alldemZs_t_m[, 14:3173], list(alldemZs_t_m$DX_GROUP), mean)
# Subsetting into patients and controls so I can make separate adjacency matrices
aggregate_all_t_SCZ <- aggregate_all_t[1,2:3161]</pre>
aggregate_all_t_HC <- aggregate_all_t[2,2:3161]</pre>
## Thresholding the values here
\#\ aggregate\_all\_i\_SCZ[aggregate\_all\_i\_SCZ\ <\ 0.60]\ <-\ 0
{\it \# Creating \ an \ iGraph - will \ change \ weights \ to \ represent \ different \ diagnostic \ groups}
g<-graph_from_adjacency_matrix(cormat, mode="upper",
                                 weighted=T, diag=F,
                                 add.rownames = "code")
# Color coding the networks
V(g) color <- ifelse(substr(V(g) name, 0,2) == "DM", "#CD3E3A", (ifelse(substr(V(g) name, 0,2) == "EX",
# Creating labels for the vertices - just the lobe and the hemisphere as the network is color-coded
V(g) $label_name <- substr(V(g) $name, 3,5)
# Creating adjacency matrices for i vertices
aggregate_all_i_SCZ_data <- as.matrix(aggregate_all_i_SCZ)</pre>
aggregate_all_i_SCZ_data <- as.vector(aggregate_all_i_SCZ_data)</pre>
E(g)$weight <- aggregate_all_i_SCZ_data</pre>
SCZ_i_vertex <- get.adjacency(g, type="both", attr="weight", sparse=FALSE)</pre>
aggregate_all_i_HC_data <- as.matrix(aggregate_all_i_HC)</pre>
aggregate_all_i_HC_data <- as.vector(aggregate_all_i_HC_data)</pre>
E(g)$weight <- aggregate_all_i_HC_data</pre>
HC_i_vertex <- get.adjacency(g, type="both", attr="weight", sparse=FALSE)</pre>
# Creating adjacency matrices for t vertices
aggregate_all_t_SCZ_data <- as.matrix(aggregate_all_t_SCZ)</pre>
aggregate_all_t_SCZ_data <- as.vector(aggregate_all_t_SCZ_data)</pre>
E(g)$weight <- aggregate_all_t_SCZ_data</pre>
SCZ_t_vertex <- get.adjacency(g, type="both", attr="weight", sparse=FALSE)</pre>
aggregate_all_t_HC_data <- as.matrix(aggregate_all_t_HC)</pre>
aggregate_all_t_HC_data <- as.vector(aggregate_all_t_HC_data)</pre>
E(g)$weight <- aggregate_all_t_HC_data</pre>
HC_t_vertex <- get.adjacency(g, type="both", attr="weight", sparse=FALSE)</pre>
# # Writing the adjacency matrices to use in MATLAB
# write.csv(SCZ_i_vertex, "..//projects/saba/HCP_fMRI_SCZ/new_analyses_20170412/FC_analyses/Graph_Theor
# write.csv(HC_i_vertex, "/projects/saba/HCP_fMRI_SCZ/new_analyses_20170412/FC_analyses/Graph_Theory/HC
\# write.csv(SCZ_t_vertex, "/projects/saba/HCP_fMRI_SCZ/new_analyses_20170412/FC_analyses/Graph_Theory/S
# write.csv(HC_t_vertex, "/projects/saba/HCP_fMRI_SCZ/new_analyses_20170412/FC_analyses/Graph_Theory/HC
```

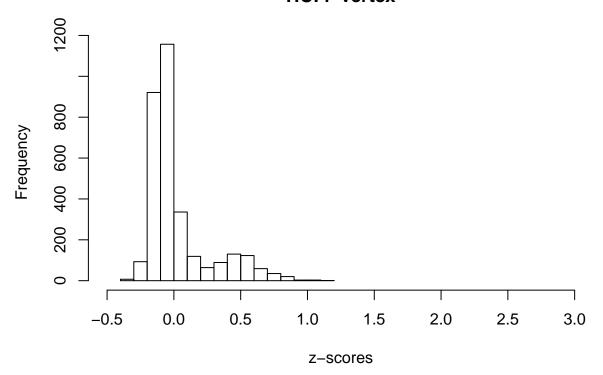
#plot.igraph(g,vertex.label=V(g)\$name,layout=layout.fruchterman.reingold, edge.color="black",edge.width
hist(aggregate\_all\_i\_SCZ\_data, main="SCZ: i-vertex", xlab = "z-scores", xlim=c(-0.5, 3.0))

SCZ: i-vertex

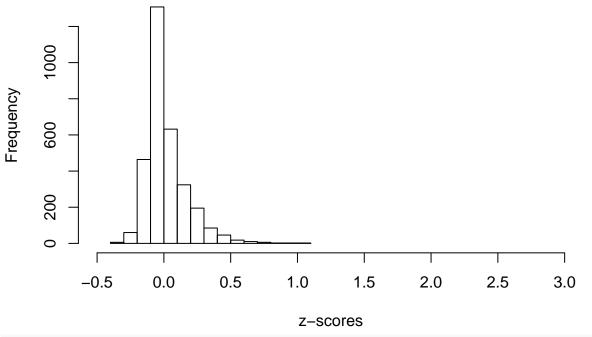


hist(aggregate\_all\_i\_HC\_data, main="HC: i-vertex", xlab = "z-scores", xlim=c(-0.5, 3.0))

# HC: i-vertex

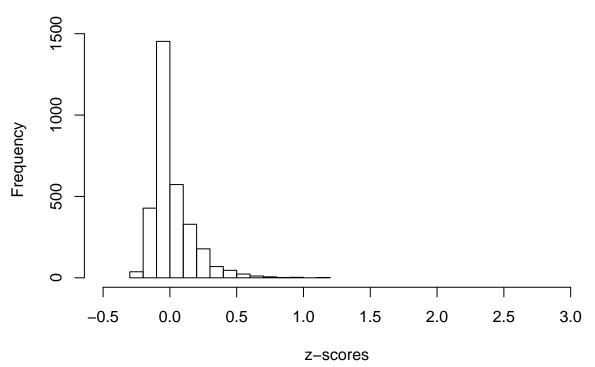


# SCZ: t-vertex



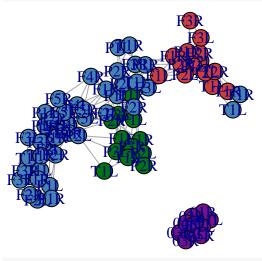
hist(aggregate\_all\_t\_HC\_data, main="HC: t-vertex", xlab = "z-scores", xlim=c(-0.5, 3.0))

# **HC**: t-vertex

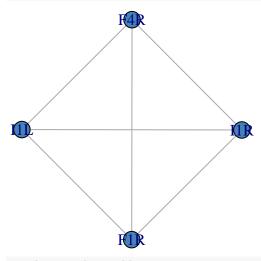


```
# Reassigning weights to the igraph
E(g)$weight <- aggregate_all_i_SCZ_data
E(g)$weight <- aggregate_all_i_HC_data
E(g)$weight <- aggregate_all_t_SCZ_data
E(g)$weight <- aggregate_all_t_HC_data

# Using 0.65 for i-vertex, and 0.35 for t-vertex
# Using 0.2 for i-vertex, and 0.19 for t-vertex</pre>
g_few=delete.edges(g, which(E(g)$weight <=0.20))
plot(g_few, vertex.label=V(g_few)$label_name)
```



g\_few\_vert=delete.vertices(g\_few,which(degree(g\_few)<15))
plot(g\_few\_vert, vertex.label=V(g\_few\_vert)\$label\_name)</pre>



sum(degree(g\_few))

## [1] 680

degree(g\_few)

## DAF1L DAF1R DAF2L DAF2R DAP1L DAP1R DAP2L DAP2R DAP3L DAP3R DAT1L DAT1R ## 9 7 13 11 8 7 7 5 8 8 3 7 ## DMF1L DMF1R DMF2L DMF2R DMF3L DMF3R DMP1L DMP1R DMP2L DMP2R DMT1L DMT1R

```
8 8 9 9 5 2 11 11
                                                 10
                                                       10
## DMT2L DMT2R FPF1L FPF1R FPF2L FPF2R FPF3L FPF3R FPF4L FPF4R FPF5L FPF5R
                  8
                       8
                             6
                                   6
                                         6
                                              8
                                                   10
                                                          6
## FPP1L FPP1R FPP2L FPP2R FPT1L FPT1R VAF1L VAF1R VAF2L VAF2R VAF3L VAF3R
            5
                 11
                       9
                             5
                                   3
                                        14
                                              17
                                                    9
                                                         11
## VAF4L VAF4R VAF5L VAF5R VAI1L VAI1R VAP1L VAP1R VAP2L VAP2R VAT1L VAT1R
                 11
                       7
                            19
                                  21
                                         8
                                              10
                                                   14
                                                         12
           15
## SMF1L SMF1R SMF2L SMF2R SMF3L SMF3R SMI1L SMI1R SMT1L SMT1R VIO1L VIO1R
      7
            5
                6
                       7
                             6
                                   9
                                        10
                                              10
                                                    7
                                                                7
## VIO2L VIO2R VIO3L VIO3R VIO4L VIO4R VIO5L VIO5R
                       7
betweenness(g_few_vert)
## VAF1R VAF4R VAI1L VAI1R
##
      0
           0
degree(g_few_vert)
## VAF1R VAF4R VAI1L VAI1R
                 3
##
      3
            3
# Ratio of the number of edges and the number of possible edges
edge_density(g_few)
## [1] 0.1075949
## rm the extra object in memory
#rm(cormat, meants1, theZs_tvertex, theZs_ivertex, Yeo_meants, g)
```