

# Untitled

## Project 3

### Import packages

```
library(tidyverse)
```

```
-- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
v dplyr      1.1.4      v readr      2.1.6
v forcats    1.0.1      v stringr    1.6.0
v ggplot2    4.0.1      v tibble     3.3.0
v lubridate  1.9.4      v tidyr      1.3.1
v purrr      1.2.0
-- Conflicts ----- tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()     masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become
```

```
library(igraph)
```

Attaching package: 'igraph'

The following objects are masked from 'package:lubridate':

%--%, union

The following objects are masked from 'package:dplyr':

as\_data\_frame, groups, union

The following objects are masked from 'package:purrr':

`compose, simplify`

The following object is masked from 'package:tidyr':

`crossing`

The following object is masked from 'package:tibble':

`as_data_frame`

The following objects are masked from 'package:stats':

`decompose, spectrum`

The following object is masked from 'package:base':

`union`

```
library(pheatmap)
library(brainGraph)
library(reticulate)
library(ggpubr)
```

## Import data and experimental design

### Load sample data

```
counts_raw <- read.csv("data/expression_matrix.csv",
                      row.names = 1, header=FALSE)
col_meta <- read.csv("data/columns_metadata.csv", header = TRUE)
row_meta <- read.csv("data/rows_metadata.csv", header = TRUE)
```

### Parse data

### Create unique identifier

```
col_meta <- col_meta %>% mutate(
  uid = paste0(donor_id, "_", structure_id)
)
```

### Format row and column names in expression matrix

```
row.names(counts_raw) <- make.unique(row_meta$gene_symbol)
colnames(counts_raw) <- col_meta$uid
```

### Add Life Stage and System info to column metadata

```
col_meta <- col_meta %>%
  mutate(
    LifeStage = case_when(
      # 1. PRENATAL (Conception to Birth)
      grepl("pcw", age) ~ "Prenatal",

      # 2. INFANCY (Birth to 4 yrs)
      age %in% c("4 mos", "10 mos", "1 yrs", "2 yrs", "3 yrs", "4 yrs") ~ "Infancy",

      # 3. ADOLESCENCE (8 yrs to 21 yrs)
      age %in% c("8 yrs", "11 yrs", "13 yrs", "15 yrs", "18 yrs", "19 yrs", "21 yrs") ~ "Ado.",

      # 4. ADULTHOOD (23+ yrs)
      age %in% c("23 yrs", "30 yrs", "36 yrs", "37 yrs", "40 yrs") ~ "Adult",
    )
  )
```

```
col_meta <- col_meta %>%
  mutate(
    Fine_System = case_when(
      # --- SENSORY SYSTEMS ---
      structure_acronym %in% c("V1C", "Ocx", "ITC") ~ "Visual",
      structure_acronym %in% c("M1C", "S1C", "M1C-S1C") ~ "Somatomotor",
      structure_acronym %in% c("A1C", "STC", "TCx") ~ "Auditory_Temporal",

      # --- ASSOCIATION SYSTEMS ---
      structure_acronym %in% c("DFC", "VFC", "MFC") ~ "Frontal_Executive",
      structure_acronym %in% c("IPC", "PCx") ~ "Parietal_Attn",
    )
  )
```

```

# --- DEEP BRAIN SYSTEMS ---
structure_acronym %in% c("OFC", "AMY", "HIP") ~ "Limbic System",
structure_acronym %in% c("STR", "MD", "DTH") ~ "Core_Subcortex",
structure_acronym %in% c("CB", "CBC") ~ "Cerebellum",

# --- FETAL ONLY ---
structure_acronym %in% c("MGE", "LGE", "CGE", "URL") ~ "Fetal_Transient",
)
)

```

```

systems <- c("Visual", "Somatomotor", "Auditory_Temporal",
            "Frontal_Executive", "Parietal_Attn", "Limbic System",
            "Core_Subcortex")
stage <- c("Prenatal", "Infancy", "Adolescence", "Adult")

col_meta$LifeStage <- factor(col_meta$LifeStage, levels = stage)
col_meta$Fine_System <- factor(col_meta$Fine_System, levels = systems)

```

```

col_meta %>% group_by(donor_id, Fine_System, LifeStage) %>%
  summarise(Count = n()) %>%
  filter(Count >=3) %>% group_by(Fine_System, LifeStage) %>%
  summarize(n())

```

`summarise()` has grouped output by 'donor\_id', 'Fine\_System'. You can override using the `.groups` argument.

`summarise()` has grouped output by 'Fine\_System'. You can override using the `.groups` argument.

```

# A tibble: 9 x 3
# Groups:   Fine_System [3]
  Fine_System LifeStage `n()`
  <fct>       <fct>    <int>
1 Frontal_Executive Prenatal    14
2 Frontal_Executive Infancy      4
3 Frontal_Executive Adolescence  7
4 Frontal_Executive Adult        3
5 Limbic_System    Prenatal    13
6 Limbic_System    Infancy      3
7 Limbic_System    Adolescence  5
8 Limbic_System    Adult        5
9 <NA>             Prenatal     2

```

```
validDonors <- col_meta %>% group_by(donor_id, LifeStage, Fine_System) %>% summarise(Count =
```

`summarise()` has grouped output by 'donor\_id', 'LifeStage'. You can override using the `.groups` argument.

```
head(validDonors)
```

```
# A tibble: 6 x 4
# Groups:   donor_id, LifeStage [4]
  donor_id LifeStage Fine_System Count
  <int> <fct> <fct> <int>
1 12287 Prenatal Frontal Executive 3
2 12288 Prenatal Frontal Executive 3
3 12288 Prenatal Limbic System 3
4 12289 Adolescence Frontal Executive 3
5 12289 Adolescence Limbic System 3
6 12290 Adult Frontal Executive 3
```

```
validDonors_meta <- data.frame()

for (system in systems) {
  donors_sys <- validDonors %>% filter(Fine_System == system)
  sys_data <- col_meta %>% filter(
    Fine_System == system,
    donor_id %in% donors_sys$donor_id)

  validDonors_meta <- rbind(validDonors_meta, sys_data)
}
```

```
grouping_info <- validDonors_meta %>%
  mutate(
    SampleID = paste0(donor_id, LifeStage, Fine_System, sep="_")
  )
```

```
global_counts <- counts_raw[, validDonors_meta$uid]
```

```
keep_genes <- rowSums(global_counts >= 1) >= 8 # >=1 because data is already Log2
```

```
clean_counts <- global_counts[keep_genes, ]
```

## Quality check data

### Data clustering

```
vsd_mat <- log2(clean_counts + 1)
gene_vars <- apply(vsd_mat, 1, var)
top_genes <- order(gene_vars, decreasing=TRUE)[1:1000]
vsd_mat <- vsd_mat[top_genes, ]
```

### PCA

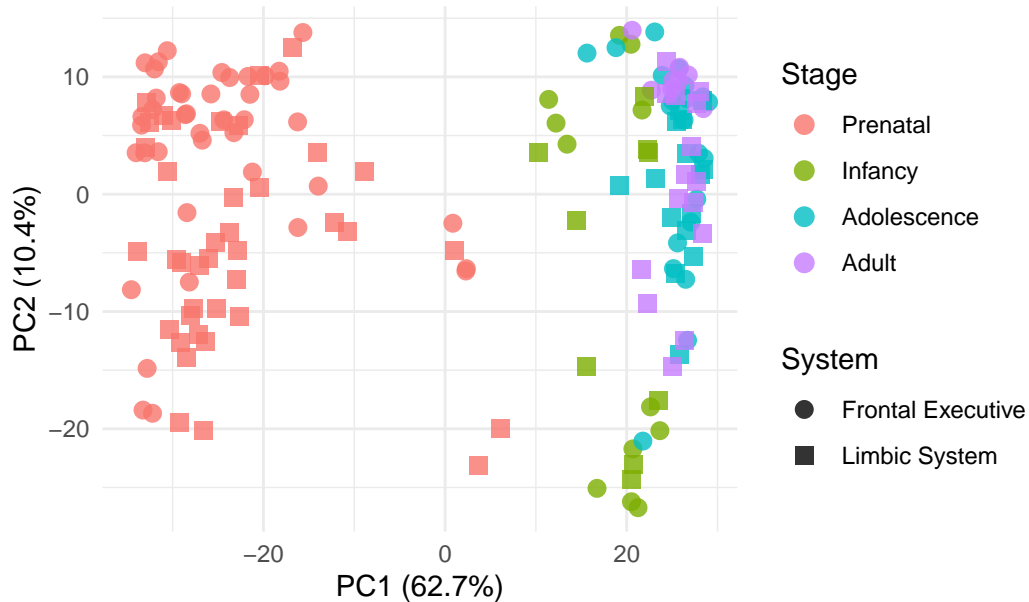
```
pca_res <- prcomp(t(vsd_mat), scale. = TRUE)
var_explained <- round(100 * summary(pca_res)$importance[2, 1:2], 1)

pca_df <- data.frame(PC1 = pca_res$x[,1],
                     PC2 = pca_res$x[,2],
                     Donor = as.character(validDonors_meta$donor_id),
                     Stage = validDonors_meta$LifeStage,
                     System = validDonors_meta$Fine_System)

p <- ggplot(pca_df, aes(x = PC1, y = PC2, color = Stage, shape = System)) +
  geom_point(size = 3, alpha = 0.8) +
  scale_shape_manual(values = c(16, 15, 17, 18, 3, 4, 8, 6)) +
  guides(color = guide_legend(order = 1),
         shape = guide_legend(order = 2)) +
  labs(title = "PCA of Brain Development",
       x = paste0("PC1 (", var_explained[1], "%)"),
       y = paste0("PC2 (", var_explained[2], "%)")) +
  theme_minimal()
```

p

## PCA of Brain Development



```
# save image
ggsave(filename = "results/global_PCA.png",
        plot = p, width = 6, height = 4)
```

## PCA per systems

```
system_pca <- list()
for (sys in unique(validDonors_meta$Fine_System)) {
  system_samples <- validDonors_meta %>%
    filter(Fine_System == sys)

  sys_counts <- clean_counts[, system_samples$uid]

  vsd_sys <- log2(sys_counts + 1)
  gene_vars_sys <- apply(vsd_sys, 1, var)
  top_genes_sys <- order(gene_vars_sys, decreasing=TRUE)[1:1000]
  vsd_sys <- vsd_sys[top_genes_sys,]

  pca_res <- prcomp(t(vsd_sys), scale. = TRUE)

  var_explained <- round(100 * summary(pca_res)$importance[2, 1:2], 1)

  pca_df <- data.frame(PC1 = pca_res$x[,1],
```

```

        PC2 = pca_res$x[,2],
        Structure = as.character(system_samples$structure_acronym),
        Stage = system_samples$LifeStage)

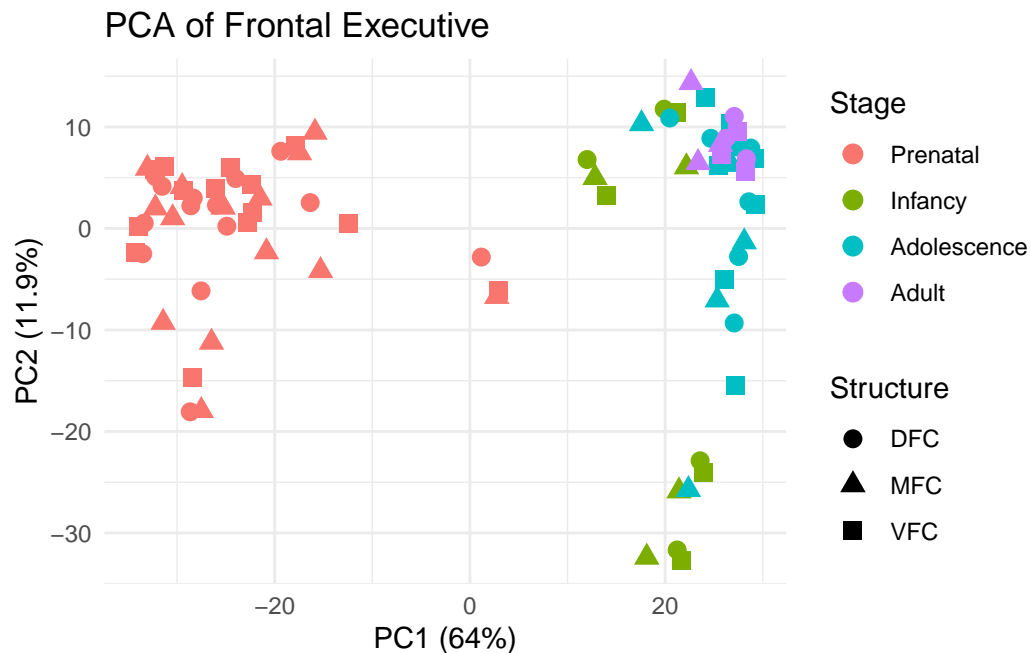
p<- ggplot(pca_df, aes(x = PC1, y = PC2, color = Stage, shape = Structure)) +
  geom_point(size = 3) +
  theme_minimal() +
  guides(color = guide_legend(order = 1),
         shape = guide_legend(order = 2)) +
  labs(title = paste("PCA of", sys),
       x = paste0("PC1 (", var_explained[1], "%)"),
       y = paste0("PC2 (", var_explained[2], "%)"))
  )

#save image
ggsave(filename = paste0("results/", sys, "_PCA.png"),
       plot = p, width = 6, height = 4)
system_pca[[sys]] <- p
}

system_pca

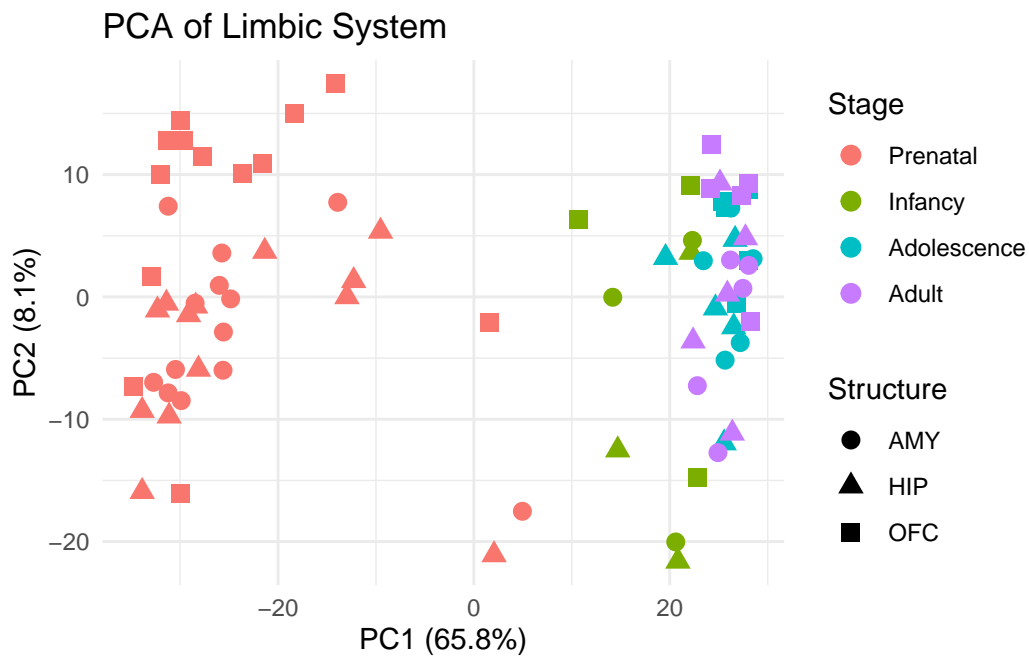
```

\$`Frontal Executive`





\$`Limbic System`



### PCA plots without prenatal

```
system_pca_no_prenatal <- list()
for (sys in unique(validDonors_meta$Fine_System)) {
  system_samples <- validDonors_meta %>%
    filter(Fine_System == sys, LifeStage != "Prenatal")
  sys_counts <- clean_counts[, system_samples$uid]

  vsd_sys <- log2(sys_counts + 1)
  gene_vars_sys <- apply(vsd_sys, 1, var)
  top_genes_sys <- order(gene_vars_sys, decreasing=TRUE)[1:1000]
  vsd_sys <- vsd_sys[top_genes_sys,]

  pca_res <- prcomp(t(vsd_sys), scale. = TRUE)

  var_explained <- round(100 * summary(pca_res)$importance[2, 1:2], 1)

  pca_df <- data.frame(PC1 = pca_res$x[,1],
                      PC2 = pca_res$x[,2],
```

```

        Structure =
        as.character(system_samples$structure_acronym),
        Stage = system_samples$LifeStage)
p<- ggplot(pca_df, aes(x = PC1, y = PC2, color = Stage, shape = Structure)) +
  geom_point(size = 3) +
  theme_minimal() +
  labs(title = paste("PCA of", sys, " (No Prenatal)"),
       x = paste0("PC1 (", var_explained[1], "%)" ),
       y = paste0("PC2 (", var_explained[1], "%)" )
  )

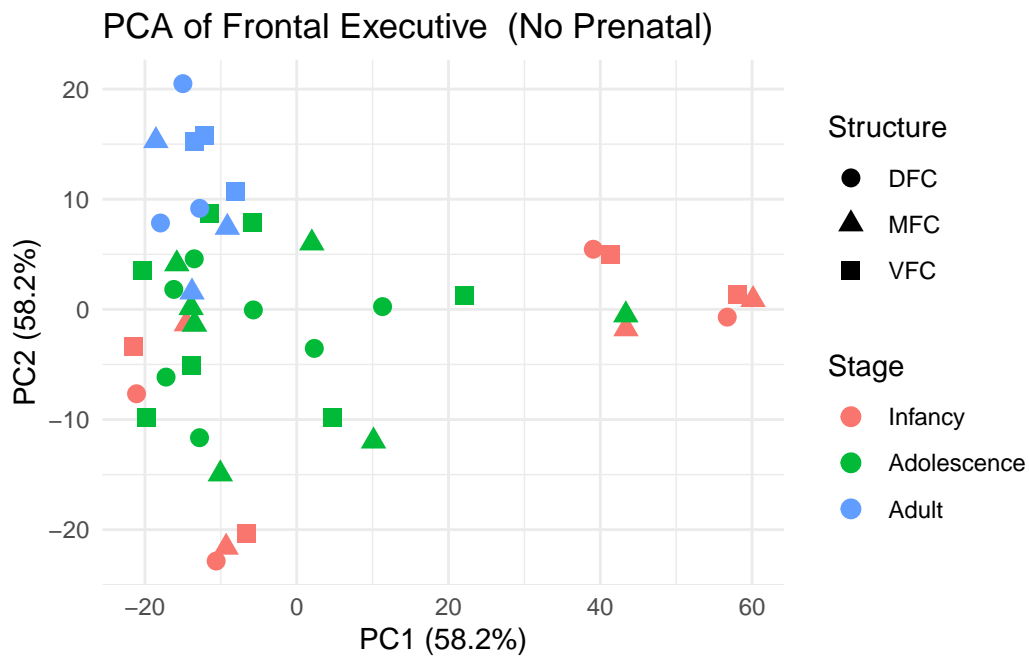
#save image
ggsave(filename = paste0("results/", sys, "_PCA_no_prenatal.png"),
       plot = p, width = 6, height = 4)

system_pca_no_prenatal[[sys]] <- p
}

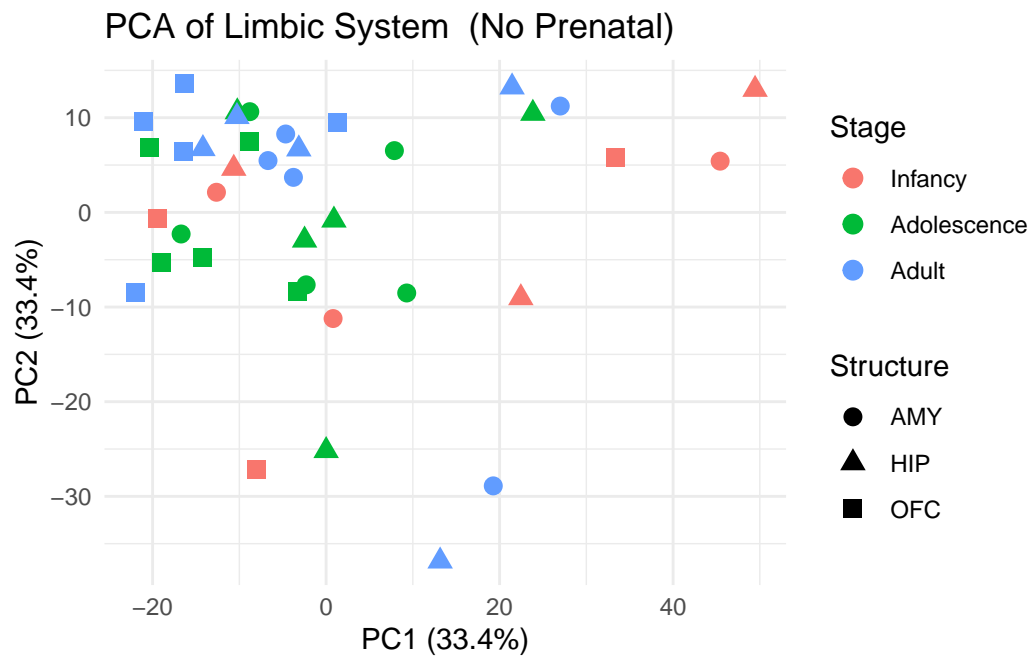
system_pca_no_prenatal

```

\$`Frontal Executive`



\$`Limbic System`



### Sample-to-sample correlation

```
# Calculate Sample-to-Sample Correlation
sample_dist <- cor(vsd_mat)

# Create Annotation Bar for the side
# Again, use validDonors_meta to ensure alignment
anno_col <- data.frame(
  Stage = validDonors_meta$LifeStage,
  System = validDonors_meta$Fine_System
  #donorID = as.character(validDonors_meta_grouped$donor_id)
)
rownames(anno_col) <- colnames(sample_dist)

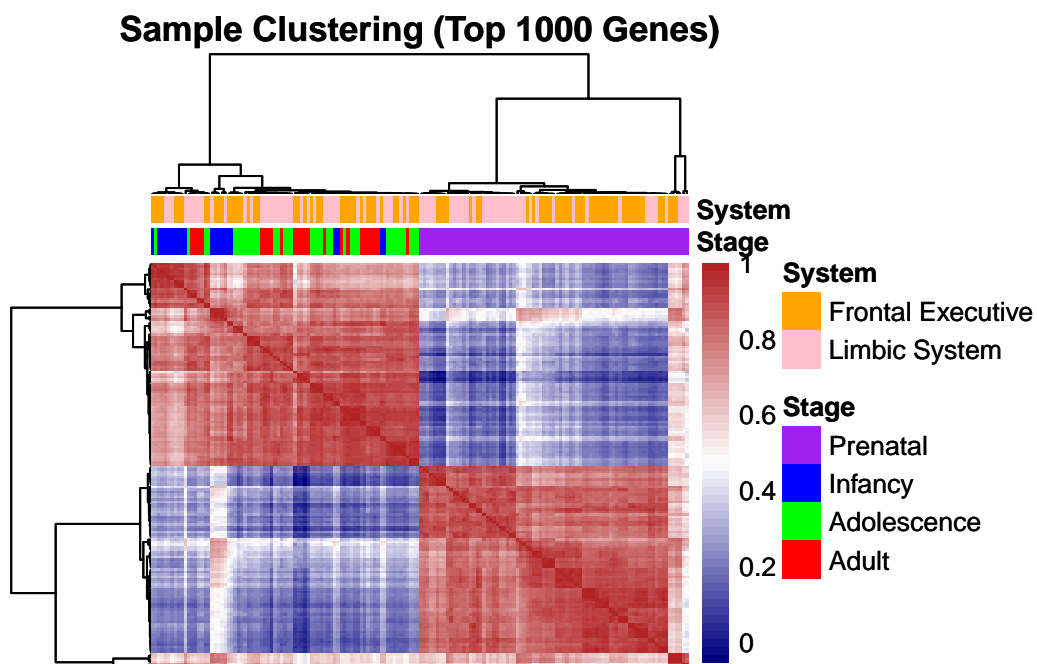
# Plot
map <- pheatmap(sample_dist,
  main = "Sample Clustering (Top 1000 Genes)",
  annotation_col = anno_col,
  annotation_colors = list(
```

```

Stage = c("Prenatal" = "purple",
          "Infancy" = "blue",
          "Adolescence" = "green",
          "Adult" = "red"),
System = c("Frontal Executive" = "orange",
          "Limbic System" = "pink"
          )),
show_rownames = FALSE,
show_colnames = FALSE,
clustering_distance_rows = "correlation",
clustering_distance_cols = "correlation",
color = colorRampPalette(c("navy", "white", "firebrick"))(50))

```

map



```

# save image
ggsave(filename = "results/sample_correlation_heatmap.png",
        plot = map, width = 6, height = 4)

```

## Build individual networks and measure topology and controllability

```
vsd_systems <- list()
topology_results <- data.frame()

for (sys in unique(validDonors_meta$Fine_System)) {

  print(paste("Processing System:", sys))

  system_samples <- validDonors_meta %>%
    filter(Fine_System == sys)

  system_counts <- clean_counts[, system_samples$uid]
  vsd_systems[[sys]] <- log2(system_counts + 1)
  gene_vars <- apply(vsd_systems[[sys]], 1, var)
  top_genes <- order(gene_vars, decreasing=TRUE)[1:300]
  vsd_systems[[sys]] <- vsd_systems[[sys]][top_genes, ]

  for (stage in unique(validDonors_meta$LifeStage)) {
    print(paste(" Processing Stage:", stage))
    stage_samples <- system_samples %>%
      filter(LifeStage == stage)

    for (d in stage_samples$donor_id) {
      contains_d <- grepl(d, stage_samples$uid)
      sub_vsd <- vsd_systems[[sys]][,
        stage_samples$uid[contains_d],
        drop = FALSE]

      stage_vars <- apply(sub_vsd, 1, var)
      valid_genes <- stage_vars > 0

      sub_vsd <- sub_vsd[valid_genes, ]

      adj <- cor(t(sub_vsd), method = "pearson")

      adj <- abs(adj)^2
      diag(adj) <- 0
      adj[is.na(adj)] <- 0

      #edge_weights <- adj[upper.tri(adj)]
      #cutoff <- quantile(edge_weights, 0.75)
      #adj[adj < cutoff] <- 0
    }
  }
}
```

```

# Network topology metrics

g <- graph_from_adjacency_matrix(adj,
                                mode = "undirected",
                                weighted = TRUE)

g_dist <- g
E(g_dist)$weight <- 1 / E(g)$weight
glob_eff <- efficiency(g_dist, type = "global")

clust_coeff <- transitivity(g, type = "global")

comm <- cluster_louvain(g)
mod_score <- modularity(comm)

topology_results <- rbind(topology_results, data.frame(
  Donor = d,
  System = sys,
  Stage = stage,
  #Clustering = clust_coeff,
  Efficiency = glob_eff,
  Modularity = mod_score
))
}
}
}

```

```

[1] "Processing System: Frontal Executive"
[1] " Processing Stage: Prenatal"
[1] " Processing Stage: Infancy"
[1] " Processing Stage: Adolescence"
[1] " Processing Stage: Adult"
[1] "Processing System: Limbic System"
[1] " Processing Stage: Prenatal"
[1] " Processing Stage: Infancy"
[1] " Processing Stage: Adolescence"
[1] " Processing Stage: Adult"

```

```

py_require("nctpy")
nct <- import("nctpy.metrics")
utils <- import("nctpy.utils")

```

```

control_results <- data.frame()

for (sys in unique(validDonors_meta$Fine_System)) {

  print(paste("Processing System:", sys))

  system_samples <- validDonors_meta %>% filter(Fine_System == sys)
  system_counts <- clean_counts[, system_samples$uid]

  vsd_temp <- log2(system_counts + 1)
  gene_vars <- apply(vsd_temp, 1, var)
  top_genes <- order(gene_vars, decreasing=TRUE)[1:300]
  vsd_sys <- vsd_temp[top_genes, ]

  for (stag in unique(validDonors_meta$LifeStage)) {

    stage_samples <- system_samples %>% filter(LifeStage == stag)

    for (d in stage_samples$donor_id) {

      contains_d <- grepl(d, stage_samples$uid)

      sub_vsd <- vsd_sys[, stage_samples$uid[contains_d], drop = FALSE]

      # Filter constant genes for this specific donor
      valid_genes <- apply(sub_vsd, 1, var) > 0
      sub_vsd <- sub_vsd[valid_genes, ]

      adj <- cor(t(sub_vsd), method = "pearson")

      adj <- abs(adj)^2
      diag(adj) <- 0
      adj[is.na(adj)] <- 0

      if (max(adj) > 0) {

        # Normalize for Control Theory
        A_norm <- utils$matrix_normalization(adj, system = "discrete")

        # Average Controllability
        ac_vector <- nct$ave_control(A_norm, system = "discrete")
        mean_avg_ctrl <- mean(as.numeric(ac_vector))
      }
    }
  }
}

```

```

# Modal Controllability
mc_vector <- nct$modal_control(A_norm)
mean_mod_ctrl <- mean(as.numeric(mc_vector))

control_results <- rbind(control_results, data.frame(
  Donor = d,
  System = sys,
  Stage = stag,
  Avg_Controllability = mean_avg_ctrl,
  Mod_Controllability = mean_mod_ctrl
))
}
}
}
}

```

```

[1] "Processing System: Frontal Executive"
[1] "Processing System: Limbic System"

```

```

ev <- eigen(adj)$values
max_lambda <- max(Re(ev))

if(max_lambda > 0) {
  A_norm <- adj / (max_lambda * 1.00001)
} else {
  A_norm <- adj
}

```

### Combine topology and controllability results

```

results <- topology_results %>%
  left_join(control_results,
    by = c("Donor", "System", "Stage"))

```

```

Warning in left_join(., control_results, by = c("Donor", "System", "Stage")): Detected an un
i Row 1 of `x` matches multiple rows in `y`.
i Row 1 of `y` matches multiple rows in `x`.
i If a many-to-many relationship is expected, set `relationship =
  "many-to-many"` to silence this warning.

```



```
head(results)
```

	Donor		System	Stage	Efficiency	Modularity	Avg_Controllability
1	13058	Frontal	Executive	Prenatal	0.5930697	0.2099931	1.26371
2	13058	Frontal	Executive	Prenatal	0.5930697	0.2099931	1.26371
3	13058	Frontal	Executive	Prenatal	0.5930697	0.2099931	1.26371
4	13058	Frontal	Executive	Prenatal	0.5930697	0.2026925	1.26371
5	13058	Frontal	Executive	Prenatal	0.5930697	0.2026925	1.26371
6	13058	Frontal	Executive	Prenatal	0.5930697	0.2026925	1.26371
							Mod_Controllability
1							0.9952612
2							0.9952612
3							0.9952612
4							0.9952612
5							0.9952612
6							0.9952612

## Statistics and Plots

```
stage <- c("Prenatal", "Infancy", "Adolescence", "Adult")

for (sys in unique(results$System)) {
  system_data <- results %>%
    filter(System == sys)

  stages <- unique(system_data$Stage)
  comparison_list <- combn(stages, 2, simplify = FALSE)

  for (met in colnames(system_data[4:ncol(system_data)])) {
    nameMetrics <- case_when(
      met == "Avg_Controllability" ~ "Average Controllability",
      met == "Mod_Controllability" ~ "Modal Controllability",
      TRUE ~ met
    )

    p <- ggplot(system_data, aes(x = Stage, y = .data[[met]],
                                fill = Stage, color = Stage)) +
      geom_violin(alpha = 0.15) +
      geom_point(position=position_jitter(h=0.0,w=0.15)) +
```

```

stat_compare_means(comparisons = comparison_list,
                    label = "p.signif",
                    method = "t.test",
                    p.adjust.method = "bonferroni",
                    show.legend = FALSE) +

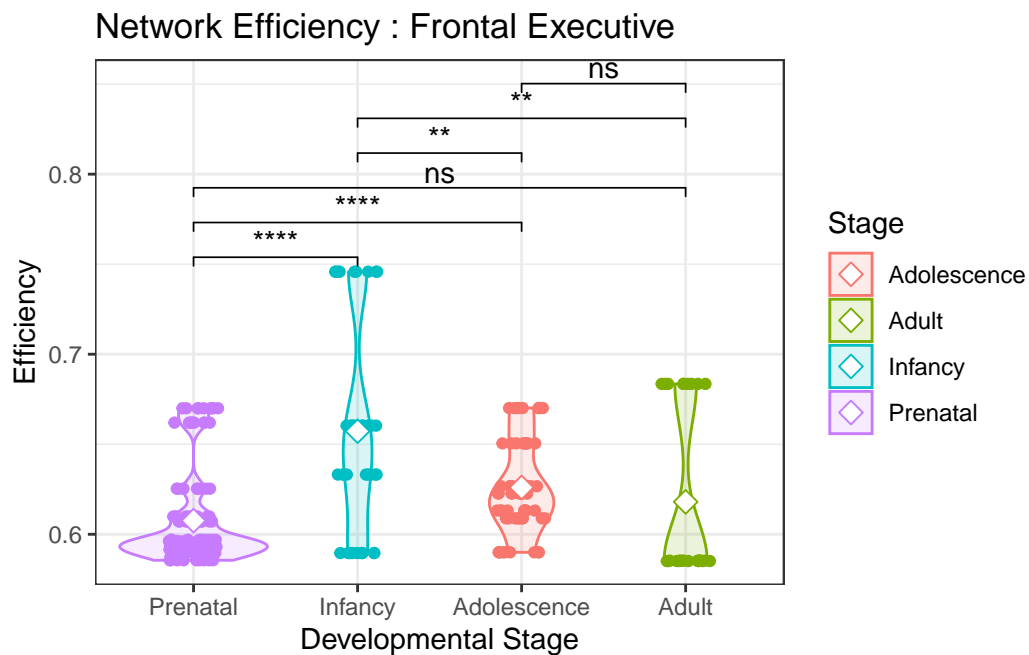
# add mean
stat_summary(fun = mean, geom = "point", shape = 23, size = 3,
             fill = "white") +

scale_x_discrete(limits = stages) +

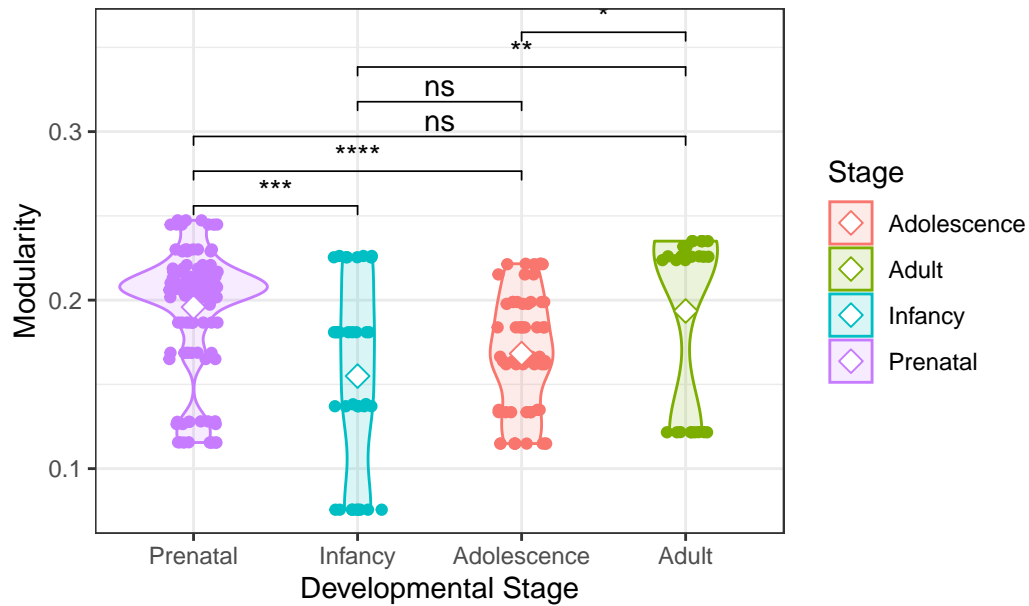
theme_bw() +
labs(title = paste("Network", nameMetrics, ":", sys),
     x = "Developmental Stage",
     y = paste0(met))
print(p)

#save image
ggsave(filename = paste0("results/", sys, "_", met, "_violin_plot.png"),
        plot = p, width = 6, height = 4)
}
}

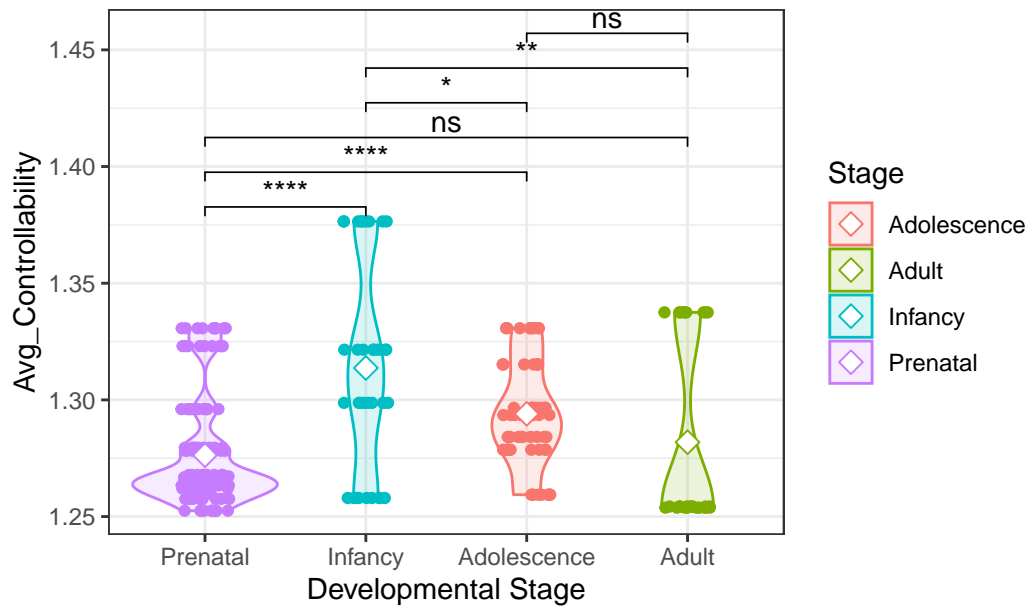
```

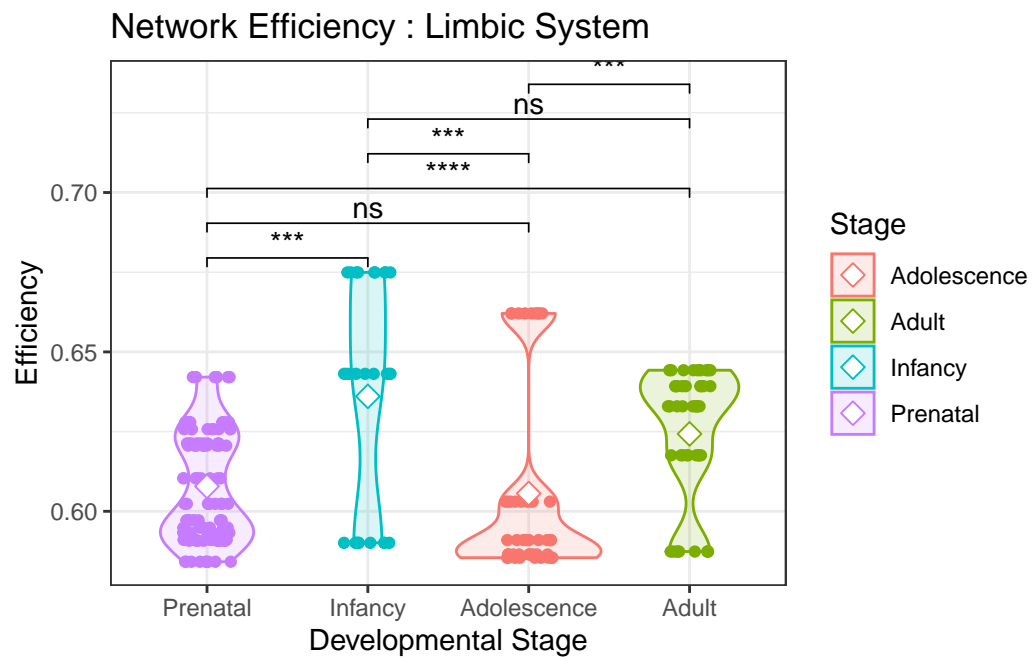
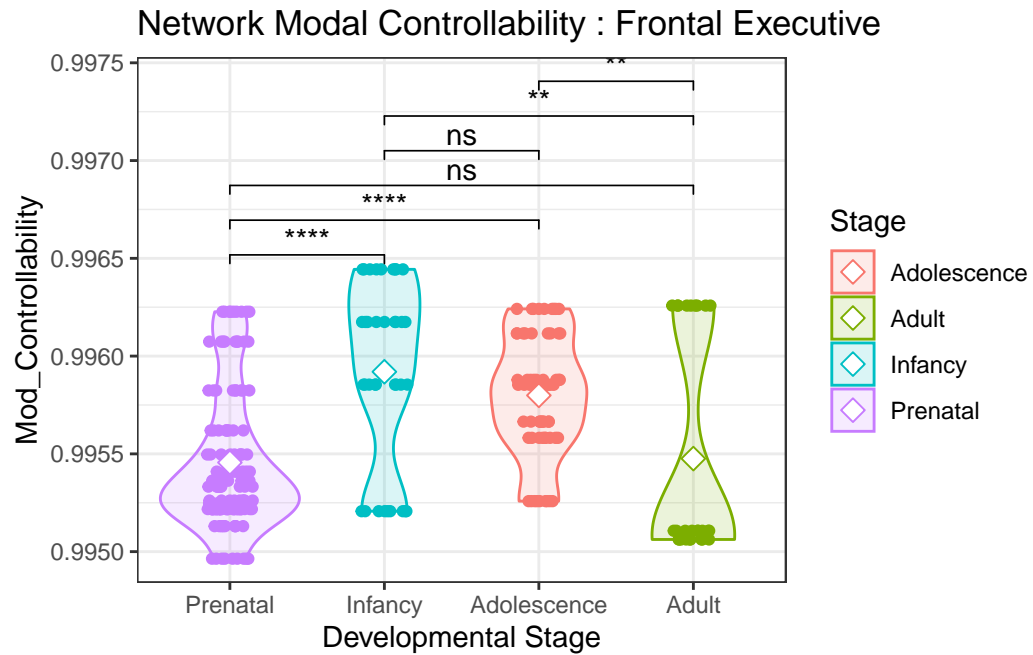


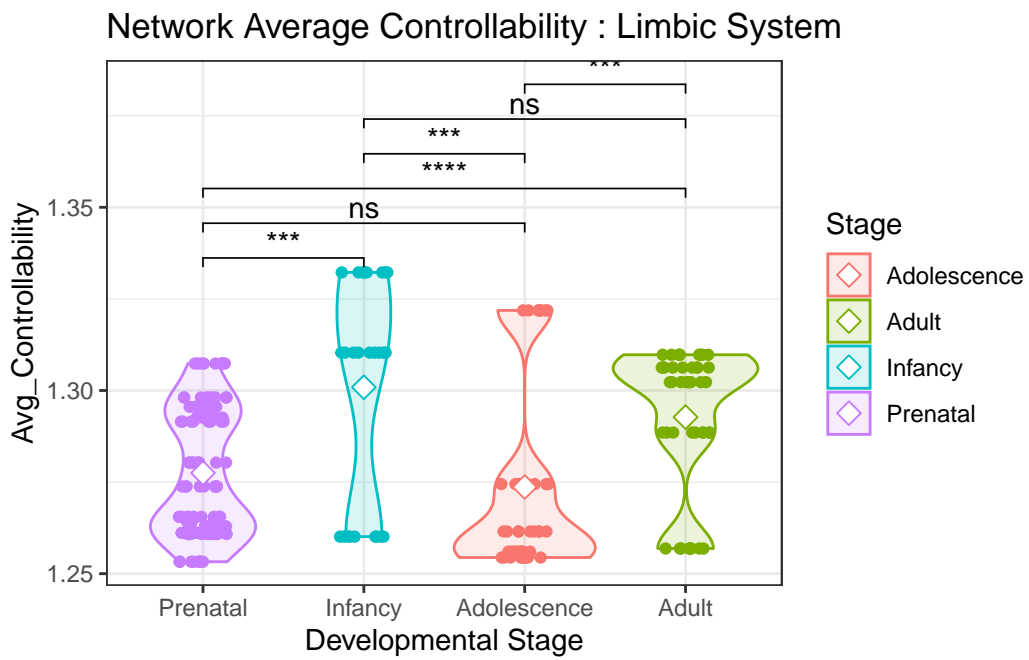
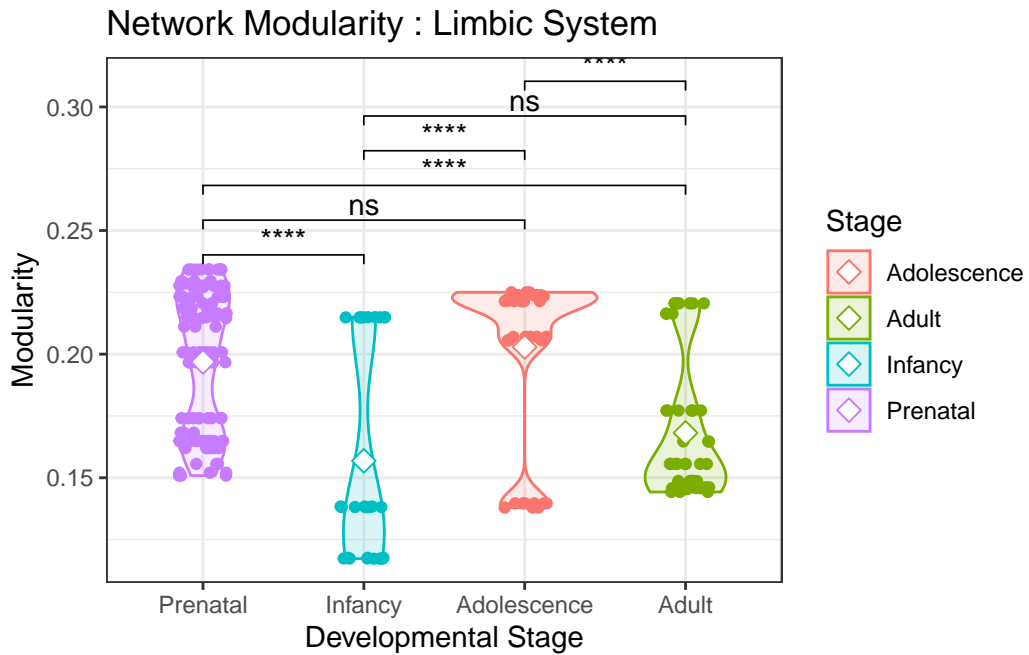
Network Modularity : Frontal Executive

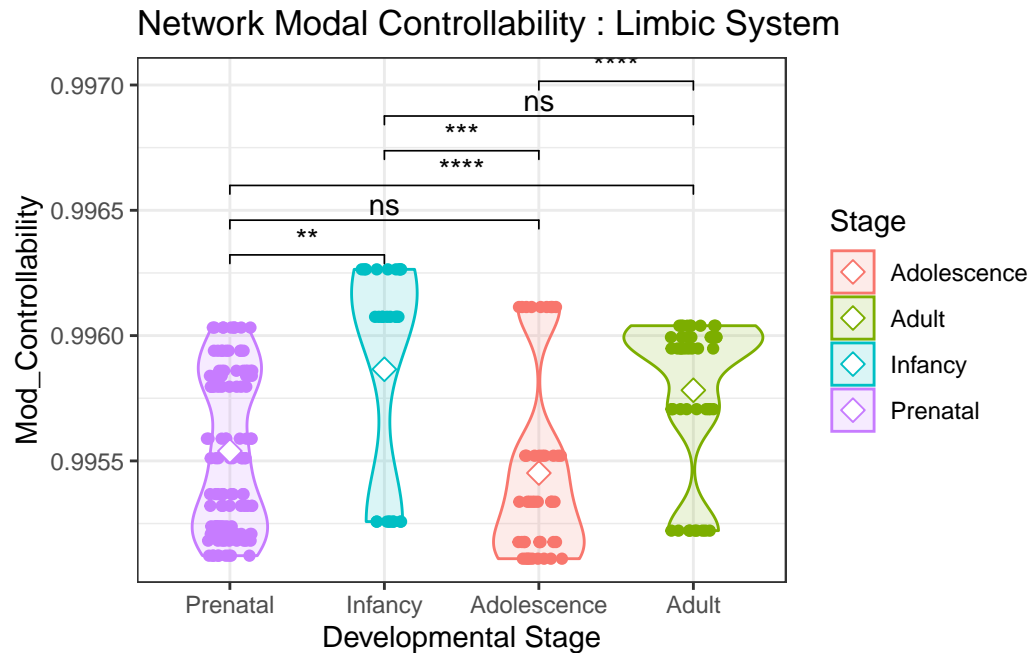


Network Average Controllability : Frontal Executive









## Visualize networks

```
for (sys in unique(validDonors_meta$Fine_System)) {
  system_samples <- validDonors_meta %>%
    filter(Fine_System == sys)

  system_counts <- clean_counts[, system_samples$uid]
  vsd_systems[[sys]] <- log2(system_counts + 1)
  gene_vars <- apply(vsd_systems[[sys]], 1, var)
  top_genes <- order(gene_vars, decreasing=TRUE)[1:100]
  vsd_systems[[sys]] <- vsd_systems[[sys]][top_genes, ]

  for (stag in unique(validDonors_meta$LifeStage)) {
    system_stage_samples <- system_samples %>%
      filter(LifeStage == stag)

    sub_vsd <- vsd_systems[[sys]][,system_stage_samples$uid]
    stage_vars <- apply(sub_vsd, 1, var)
    valid_genes <- stage_vars > 0

    sub_vsd <- sub_vsd[valid_genes, ]
  }
}
```

```

adj <- cor(t(sub_vsd), method = "pearson")

adj <- abs(adj)^2
diag(adj) <- 0
adj[is.na(adj)] <- 0

map <- pheatmap(adj,
  main = paste("Transcriptomic Network Architecture:",
    stag, " ", sys),
  cluster_rows = TRUE, # Cluster similar systems together
  cluster_cols = TRUE,
  display_numbers = TRUE, # Show the correlation values
  fontsize_number = 12,
  color = colorRampPalette(c("white", "firebrick"))(50))

map

g <- graph_from_adjacency_matrix(adj,
  mode = "undirected",
  weighted = TRUE)

E(g)$width <- E(g)$weight * 10
edge_colors <- sapply(E(g)$weight,
  function(w) alpha("firebrick", w^3))

p <- plot(g,
  vertex.label = NA,
  vertex.size = 15,

  edge.width = E(g)$weight * 5,
  main = paste("Transcriptomic Network:",
    stag, "", sys),
  edge.color = edge_colors
)

p

}

}

```





Heatmap showing the correlation of gene expression profiles between two sets of genes. The top set of genes is labeled on the right, and the bottom set is labeled on the left. A color scale on the right indicates correlation values from 0 (white) to 0.8 (red).

Top set of genes (labeled on the right):

- LOC101928148
- LOC101928147
- LOC101928146
- LOC101928145
- LOC101928144
- LOC101928143
- LOC101928142
- LOC101928141
- LOC101928140
- LOC101928139
- LOC101928138
- LOC101928137
- LOC101928136
- LOC101928135
- LOC101928134
- LOC101928133
- LOC101928132
- LOC101928131
- LOC101928130
- LOC101928129
- LOC101928128
- LOC101928127
- LOC101928126
- LOC101928125
- LOC101928124
- LOC101928123
- LOC101928122
- LOC101928121
- LOC101928120
- LOC101928119
- LOC101928118
- LOC101928117
- LOC101928116
- LOC101928115
- LOC101928114
- LOC101928113
- LOC101928112
- LOC101928111
- LOC101928110
- LOC101928109
- LOC101928108
- LOC101928107
- LOC101928106
- LOC101928105
- LOC101928104
- LOC101928103
- LOC101928102
- LOC101928101
- LOC101928100
- LOC101928099
- LOC101928098
- LOC101928097
- LOC101928096
- LOC101928095
- LOC101928094
- LOC101928093
- LOC101928092
- LOC101928091
- LOC101928090
- LOC101928089
- LOC101928088
- LOC101928087
- LOC101928086
- LOC101928085
- LOC101928084
- LOC101928083
- LOC101928082
- LOC101928081
- LOC101928080
- LOC101928079
- LOC101928078
- LOC101928077
- LOC101928076
- LOC101928075
- LOC101928074
- LOC101928073
- LOC101928072
- LOC101928071
- LOC101928070
- LOC101928069
- LOC101928068
- LOC101928067
- LOC101928066
- LOC101928065
- LOC101928064
- LOC101928063
- LOC101928062
- LOC101928061
- LOC101928060
- LOC101928059
- LOC101928058
- LOC101928057
- LOC101928056
- LOC101928055
- LOC101928054
- LOC101928053
- LOC101928052
- LOC101928051
- LOC101928050
- LOC101928049
- LOC101928048
- LOC101928047
- LOC101928046
- LOC101928045
- LOC101928044
- LOC101928043
- LOC101928042
- LOC101928041
- LOC101928040
- LOC101928039
- LOC101928038
- LOC101928037
- LOC101928036
- LOC101928035
- LOC101928034
- LOC101928033
- LOC101928032
- LOC101928031
- LOC101928030
- LOC101928029
- LOC101928028
- LOC101928027
- LOC101928026
- LOC101928025
- LOC101928024
- LOC101928023
- LOC101928022
- LOC101928021
- LOC101928020
- LOC101928019
- LOC101928018
- LOC101928017
- LOC101928016
- LOC101928015
- LOC101928014
- LOC101928013
- LOC101928012
- LOC101928011
- LOC101928010
- LOC101928009
- LOC101928008
- LOC101928007
- LOC101928006
- LOC101928005
- LOC101928004
- LOC101928003
- LOC101928002
- LOC101928001

Bottom set of genes (labeled on the left):

- LOC101928148
- LOC101928147
- LOC101928146
- LOC101928145
- LOC101928144
- LOC101928143
- LOC101928142
- LOC101928141
- LOC101928140
- LOC101928139
- LOC101928138
- LOC101928137
- LOC101928136
- LOC101928135
- LOC101928134
- LOC101928133
- LOC101928132
- LOC101928131
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- LOC101928126
- LOC101928125
- LOC101928124
- LOC101928123
- LOC101928122
- LOC101928121
- LOC101928120
- LOC101928119
- LOC101928118
- LOC101928117
- LOC101928116
- LOC101928115
- LOC101928114
- LOC101928113
- LOC101928112
- LOC101928111
- LOC101928110
- LOC101928109
- LOC101928108
- LOC101928107
- LOC101928106
- LOC101928105
- LOC101928104
- LOC101928103
- LOC101928102
- LOC101928101
- LOC101928100
- LOC101928099
- LOC101928098
- LOC101928097
- LOC101928096
- LOC101928095
- LOC101928094
- LOC101928093
- LOC101928092
- LOC101928091
- LOC101928090
- LOC101928089
- LOC101928088
- LOC101928087
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- LOC101928082
- LOC101928081
- LOC101928080
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- LOC101928076
- LOC101928075
- LOC101928074
- LOC101928073
- LOC101928072
- LOC101928071
- LOC101928070
- LOC101928069
- LOC101928068
- LOC101928067
- LOC101928066
- LOC101928065
- LOC101928064
- LOC101928063
- LOC101928062
- LOC101928061
- LOC101928060
- LOC101928059
- LOC101928058
- LOC101928057
- LOC101928056
- LOC101928055
- LOC101928054
- LOC101928053
- LOC101928052
- LOC1



Heatmap showing the correlation of gene expression between two sets of genes. The top set of genes is labeled on the right, and the bottom set is labeled on the left. A color scale on the right indicates correlation values from 0 (white) to 0.8 (red).

Top set of genes (labeled on the right):

- 18.9
- 5
- 11.10
- G11.3
- A
- 7K21.6
- 7M14.2-001
- 1

Bottom set of genes (labeled on the left):

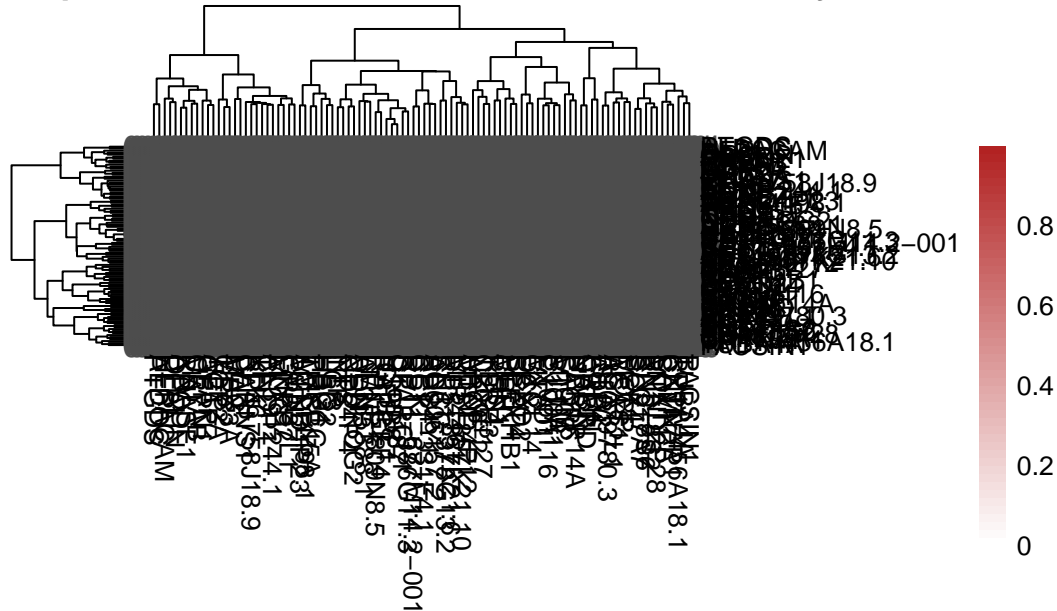
- 18.9
- 5
- 11.10
- G11.3
- A
- 7K21.6
- 7M14.2-001
- 1

Heatmap visualization showing gene expression data across 100 samples (rows) and 100 genes (columns). The color scale ranges from 0 (white) to 0.8 (red). The heatmap shows a dense pattern of expression levels, with a color bar on the right indicating the scale.

[illegible]



scriptomic Network Architecture: Adult Limbic System



Transcriptomic Network: Adult Limbic System

