Phase 1A: RNA-seq data analysis

David Amar, Archana Raja

Phase 1A raw data was preprocessed at the BIC using our pipeline, which was implemented according to the MOP. Here we present QC analyses performed on the output of the pipeline.

1 Input data

Read the data from both sites - FPKMs, counts, and metadata (including the QC scores).

```
setwd("/Users/David/Desktop/MoTrPAC/data/pass_1a/rnaseq/")
library(data.table)
library(DESeq2)
library(preprocessCore)
library(ggplot2)
# Data paths
site2fpkm path = list(
  stanford = "./stanford/rsem_genes_fpkm_pass1a_batch1_Stanford.csv",
  sinai = "./sinai/rsem_genes_fpkm_pass1a_batch1_Sinai.csv"
site2genecount_path = list(
  stanford = "./stanford/rsem_genes_count_pass1a_batch1_Stanford.csv",
  sinai = "./sinai/rsem_genes_count_pass1a_batch1_Sinai.csv"
)
# load the metadata of the samples
# this is a data frame called rnaseq_meta that contains
# the qc and sample metadata from both sites
load("./rnaseg meta.RData")
rnaseq_meta$Tissue = tolower(rnaseq_meta$Tissue)
rnaseq_meta$Tissue = gsub(" powder","",rnaseq_meta$Tissue)
rnaseq_meta[rnaseq_meta=="N/A"] = NA
print("Number of samples flagged according to the MOP's thersholds:")
print(sum(rnaseq_meta$IsFlagged))
# Metadata of the animals
# This is a merged data frame containing the animal key and
# registry data from dmaqc
load("/Users/David/Desktop/MoTrPAC/data/pass_1a/animal_metadata.RData")
# Show some fields
print("Animal metadata, time label table:")
print(table(animal_metadata$ANIRandGroup))
print("Animal metadata, sex table:")
print(table(animal_metadata$sex))
# read the data in
site2fpkm = list()
site2counts = list()
for(site in names(site2fpkm_path)){
```

2 PCA plots

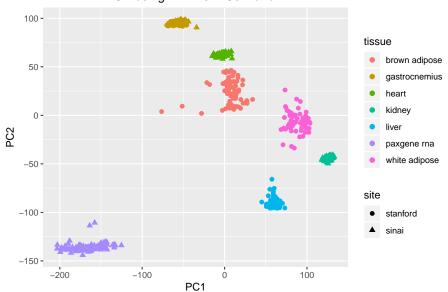
We tested two simple ways to normalize the count data: (1) FPKM, and (2) factor normalized counts with and without variance stabilizing transformations (to accound for gene dispersion).

2.1 FPKM data

```
#' Takes an FPKM matrix, removes lowly expressed genes and log transform
#' the remaining matrix
#' @return A matrix of log transformed FPKMs
process_fpkm1 <-function(fpkm_matrix, intensity_threshold=0,intensity_pct=0.2){</pre>
  lowly_expressed_genes = rowSums(
    fpkm_matrix==intensity_threshold)/ncol(fpkm_matrix) > intensity_pct
  fpkm_matrix = fpkm_matrix[!lowly_expressed_genes,]
  fpkm_matrix = log(fpkm_matrix+1,base = 2)
  return(fpkm_matrix)
}
#' A wrapper for preprocessCore's quantile normalization.
#' Comment: we do not use this by default
run quantile normalization<-function(x){</pre>
  x = as.matrix(x)
  mode(x) = "numeric"
  newx = preprocessCore::normalize.quantiles.robust(x)
  rownames(newx) = rownames(x)
  colnames(newx) = colnames(x)
  return(newx)
# Process the FPKM matrix from each site separately
site_proc_fpkms = lapply(site2fpkm,process_fpkm1)
# Check the dimension of the reduced data
print("FPKM processing done for each site, matrix dim:")
## [1] "FPKM processing done for each site, matrix dim:"
print(sapply(site_proc_fpkms,dim))
        stanford sinai
## [1,]
           13616 11951
```

```
## [2,]
             320
                   320
# Get the shared genes
shared_genes = intersect(rownames(site_proc_fpkms[[1]]),
                         rownames(site_proc_fpkms[[2]]))
print("Number of shared genes that survive the filter above:")
## [1] "Number of shared genes that survive the filter above:"
print(length(shared genes))
## [1] 11711
proc_fpkms = cbind(site_proc_fpkms[[1]][shared_genes,],
                   site_proc_fpkms[[2]][shared_genes,])
# QC: make sure the metadata and the expression matrix have the same sample id:
print("do we have the same samples in the expression and metadata matrices?")
## [1] "do we have the same samples in the expression and metadata matrices?"
print(all(colnames(proc fpkms) %in% rownames(rnaseq meta)))
## [1] TRUE
# Run the PCA: try all genes first
fpkm_all = cbind(site2fpkm[[1]],site2fpkm[[2]])
fpkm_all = log(fpkm_all+1,base=2)
fpkm_pca = prcomp(t(fpkm_all))
fpkm_pcax = fpkm_pca$x
df = data.frame(fpkm_pcax[,1:10],
                tissue = rnaseq_meta[rownames(fpkm_pcax), "Tissue"],
                site = rnaseq_meta[rownames(fpkm_pcax), "site"])
ggplot(df,aes(x=PC1, y=PC2,shape=site, color=tissue)) +
  geom_point(size=2) + ggtitle("PCA using FPKMs: PCs 1 and 2") +
  theme(plot.title = element_text(hjust = 0.5))
```

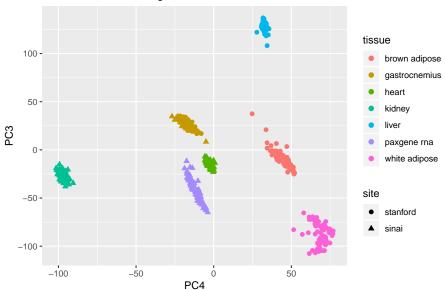




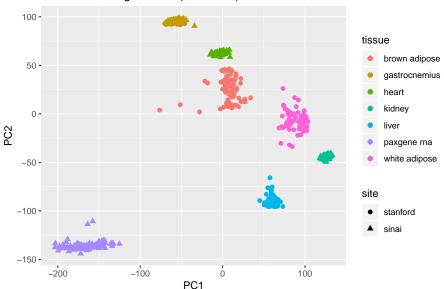
```
ggplot(df,aes(x=PC4, y=PC3,shape=site, color=tissue)) +
geom_point(size=2) + ggtitle("PCA using FPKMs: PCs 3 and 4") +
```

theme(plot.title = element_text(hjust = 0.5))

PCA using FPKMs: PCs 3 and 4

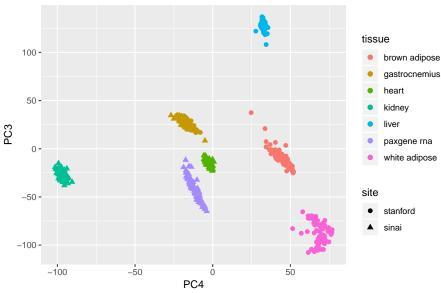






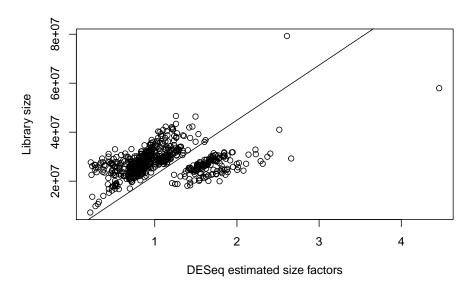
```
ggplot(df,aes(x=PC4, y=PC3,shape=site, color=tissue)) +
  geom_point(size=2) + ggtitle("PCA using FPKMs (after filter): PCs 3 and 4") +
  theme(plot.title = element_text(hjust = 0.5))
```





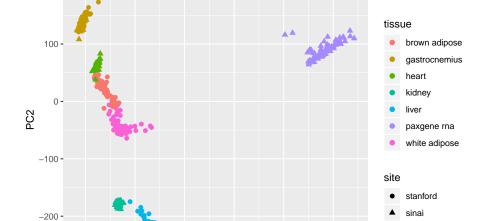
2.2 Normalized counts

```
# Pipeline 2: work with count data
# Combine the two count matrices
count_matrix = as.matrix(cbind(site2counts[[1]],site2counts[[2]]))
#' Use DESeq2 to estimate sample factors and gene dispersion
#' @return a DESeqDataSet
process_counts<-function(count_matrix,plotFactors=T){</pre>
  mode(count_matrix) = "integer"
  se <- SummarizedExperiment(count_matrix)</pre>
  dds <- DESeqDataSet(se, design = ~ 1 )</pre>
  #Estimate size factors
  dds <- estimateSizeFactors( dds )</pre>
  if(plotFactors){
      # Plot the size factors
    plot(sizeFactors(dds), colSums(counts(dds)),ylab="Library size",
         xlab = "DESeq estimated size factors")
    abline(lm(colSums(counts(dds)) ~ sizeFactors(dds) + 0))
  dds <- estimateDispersions(dds)</pre>
  return(dds)
}
# Process the counts and normalize
dds = process_counts(count_matrix)
```



```
# Simple normalization and log transform
# The argument normalized equals true, divides each column by its size factor.
logcounts <- log2( counts(dds, normalized=TRUE) + 1 )</pre>
pc <- prcomp( t( logcounts ) )</pre>
counts_pcax1 = pc$x
# Try variance stabilizing transformation instead
vsd <- varianceStabilizingTransformation(dds)</pre>
pc2 <- prcomp( t( assay(vsd) ) )</pre>
counts_pcax2 = pc2$x
# PCA plots
df = data.frame(counts_pcax1[,1:10],
                tissue = rnaseq_meta[rownames(counts_pcax1), "Tissue"],
                site = rnaseq_meta[rownames(counts_pcax1),"site"])
ggplot(df,aes(x=PC1, y=PC2,shape=site, color=tissue)) +
  geom_point(size=2) + ggtitle("PCA using normalized counts") +
  theme(plot.title = element_text(hjust = 0.5))
```

PCA using normalized counts



200

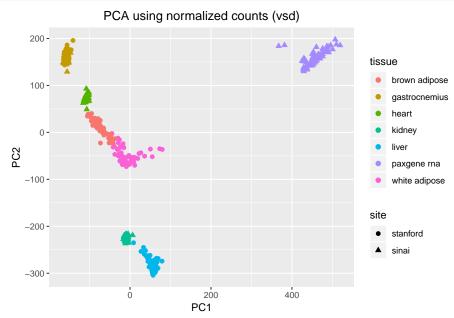
PC1

300

400

100

-100



3 Site comparison using the Gastrocnemius samples

3.1 Load the data

```
# tissue vector - used below for getting the subset of
# Gastrocnemius samples
tissue = rnaseq_meta$Tissue
names(tissue) = rownames(rnaseq meta)
# get the Gastrocnemius samples from each site
Gastrocnemius_fpkm = lapply(site2fpkm,
    function(x,y)x[,grepl("Gastrocnemius",y[colnames(x)],ignore.case = T)],y=tissue)
print("Gastrocnemius samples, data dim:")
## [1] "Gastrocnemius samples, data dim:"
print(sapply(Gastrocnemius_fpkm,dim))
        stanford sinai
## [1,]
           32883 32883
## [2,]
              80
# Process the FPKM data matrix from each site separately
Gastrocnemius_fpkm_processed = lapply(Gastrocnemius_fpkm,process_fpkm1)
print("Filtered FPKM data (separately for each site):")
## [1] "Filtered FPKM data (separately for each site):"
```

```
print(sapply(Gastrocnemius_fpkm_processed,dim))
        stanford sinai
## [1,]
           12977 14218
## [2,]
              80
shared_genes = intersect(rownames(Gastrocnemius_fpkm_processed[[1]]),
                         rownames(Gastrocnemius_fpkm_processed[[2]]))
print("Number of shared genes that survive the filter above:")
## [1] "Number of shared genes that survive the filter above:"
print(length(shared_genes))
## [1] 12966
# Merge the datasets, store in a single data frame
Gastrocnemius_fpkm_mat = cbind(Gastrocnemius_fpkm_processed[[1]][shared_genes,],
                        Gastrocnemius fpkm processed[[2]][shared genes,])
# Analysis of the metadata
Gastrocnemius_metadata = rnaseq_meta[colnames(Gastrocnemius_fpkm_mat),]
# We by default keep the vial sample id, which is different even if
# the biospecimen id is the same.
# This vector keeps the BID+PIDs
sample_id = paste(Gastrocnemius_metadata$BID,Gastrocnemius_metadata$PID,sep=";")
names(sample_id) = rownames(Gastrocnemius_metadata)
print("Do we have a copy from each site?")
## [1] "Do we have a copy from each site?"
all(table(sample_id)==2) # QC: make sure we have two copies for each id
## [1] TRUE
# Reorder the data by the site and sample id
Gastrocnemius_metadata = Gastrocnemius_metadata[order(Gastrocnemius_metadata$site,sample_id),]
sample_id = sample_id[rownames(Gastrocnemius_metadata)]
```

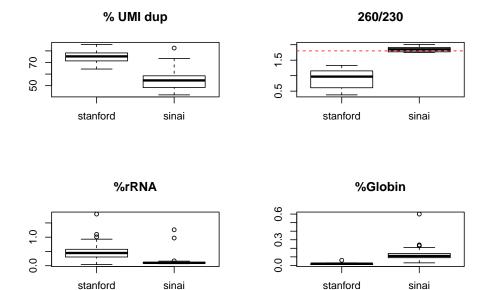
3.2 QC scores: site comparison

Here we compare the two sites by taking all numeric qc scores. We compare the two sites using a paired non-parametric test (Wilcoxon).

```
metadata2site_pval = c()
site_ind = Gastrocnemius_metadata$site==Gastrocnemius_metadata$site[1]
# We go over all numeric columns in the metadata matrix and use
# a paired Wilcoxon test to estimate site differences
for(col in names(Gastrocnemius_metadata)){
    x = Gastrocnemius_metadata[[col]]
    if(! mode(x)=="numeric"){next}
    # data are ordered by site and sample id, which keeps the correct
# order for the paired test
    x1 = x[site_ind];x2 = x[!site_ind] # define the two vectors
    if(!is.numeric(x1) || !is.numeric(x2)){next}
    sd1 = sd(x1,na.rm = T);sd2=sd(x2,na.rm = T)
    if(is.na(sd1)||is.na(sd2)){next}
```

```
# Need to try, some numeric columns are constants or have NAs
  metadata2site_pval[col] = wilcox.test(x1,x2,paired=T) p.value
}
# Take the top 30 significant columns
selected_qc_comparisons = sort(metadata2site_pval)[1:30]
# Some of the columns are not informative (e.g., date)
# Take the "pct " columns and print the p-values
print("Top pct_ qc scores that differ between sites:")
## [1] "Top pct_ qc scores that differ between sites:"
print(selected_qc_comparisons[grepl("pct_",names(selected_qc_comparisons))])
##
        pct_unmapped_other
                                         pct_globin
                                                       pct_adapter_detected
##
              4.280729e-15
                                       7.749430e-15
                                                                7.985442e-15
                   pct_utr
##
                                 pct_trimmed_bases
                                                             pct_picard_dup
              7.989667e-15
##
                                       7.993189e-15
                                                                8.628287e-15
##
          pct_dup_sequence
                                        pct_umi_dup
                                                                  pct_coding
              8.957509e-15
##
                                       1.003521e-14
                                                                1.081158e-14
##
                  pct_chrX pct_multimapped_toomany
                                                                    pct_rRNA
##
              1.790211e-13
                                       1.014781e-12
                                                                2.552097e-12
##
       pct_uniquely_mapped
                                    pct_multimapped
                                                                    pct_mrna
##
              3.844703e-12
                                       7.674417e-12
                                                                3.366564e-10
##
              pct_intronic
                                     pct_intergenic
                                                                    pct_chrM
##
              5.172570e-10
                                       6.216488e-09
                                                                4.088722e-08
##
               pct_chrAuto
                             pct_unmapped_tooshort
                                                                  pct_contig
##
              3.172734e-07
                                       4.687337e-07
                                                                4.814240e-03
##
                    pct_GC
##
              6.067464e-02
The plot below shows the site differences for selected scores.
# Comparison 1: selected qc scores
par(mfrow=c(2,2))
boxplot(pct_umi_dup~site,data=Gastrocnemius_metadata,main="% UMI dup")
boxplot(r_260_230~site,data=Gastrocnemius_metadata,main = "260/230")
abline(h = 1.8, lty=2, col="red")
boxplot(pct_rRNA~site,data=Gastrocnemius_metadata,main="%rRNA")
abline(h = 20, lty=2, col="red")
boxplot(pct_globin~site,data=Gastrocnemius_metadata,main="%Globin")
```

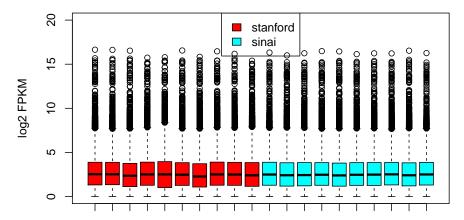
if(sd1==0 || sd2==0){next}



3.3 FPKM data comparison

We next compare the sites by looking at the boxplot of the sample data (after removing lowly expressed genes).

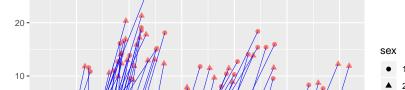
```
# Comparison 2: boxplots
#' Helper function to get a color set by a discrete vector
get_cols_vector_from_names<-function(v,pl_func = topo.colors){</pre>
 v = as.character(v)
 vals = unique(v)
  cols = pl_func(length(vals))
  names(cols) = vals
 newv = cols[v]
  return(list(newv,cols))
}
currcols = get_cols_vector_from_names(
 rnaseq_meta[colnames(Gastrocnemius_fpkm_mat), "site"], rainbow)
# Select a set of samples for the plot (too many samples otherwise)
inds_for_boxplot = c(1:10,81:90)
x_for_boxplot = Gastrocnemius_fpkm_mat[,inds_for_boxplot]
boxplot(x_for_boxplot,names=rep("",ncol(x_for_boxplot)),
        col=currcols[[1]][inds_for_boxplot],
        ylim = c(0,20), ylab="log2 FPKM") # extend lim to have room for legend
legend(x="top",names(currcols[[2]]),fill=currcols[[2]])
```



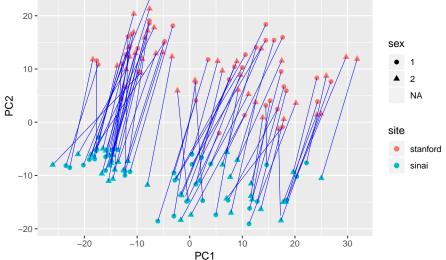
We next plot the PCA of the Gastrocnemius data, coloring the samples by site, shaper corresponds to sex. Two samples had NA for PID (controls?) and where excluded.

```
# Comparison 3: PCA
# Attempt 1: Take the FPKM data and run the PCA
Gastrocnemius_fpkm_pca = prcomp(t(Gastrocnemius_fpkm_mat))
Gastrocnemius_fpkm_pcax = Gastrocnemius_fpkm_pca$x
df = data.frame(Gastrocnemius_fpkm_pcax[,1:10],
                shape=Gastrocnemius_metadata$site, site=Gastrocnemius_metadata$site,
                sample = sample_id[rownames(Gastrocnemius_fpkm_pcax)],
                sex = as.factor(animal_metadata[Gastrocnemius_metadata$PID, "sex"]))
df = df[order(df$sample),]
# Add lines between matching samples (i.e., same sample, different site)
ggplot(df,aes(x=PC1, y=PC2, shape=sex, color=site,group=sample)) +
  geom_point(size=2) + geom_path(size=0.02,color="blue") +
  ggtitle("PCs 1 and 2: Gastrocnemius samples") +
  theme(plot.title = element_text(hjust = 0.5))
```

Warning: Removed 4 rows containing missing values (geom_point).



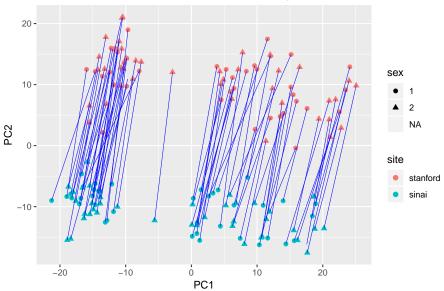
PCs 1 and 2: Gastrocnemius samples



```
# Retry - quantile normalization before PCA (slightly cleaner)
Gastrocnemius_fpkm_mat_q = run_quantile_normalization(Gastrocnemius_fpkm_mat)
```

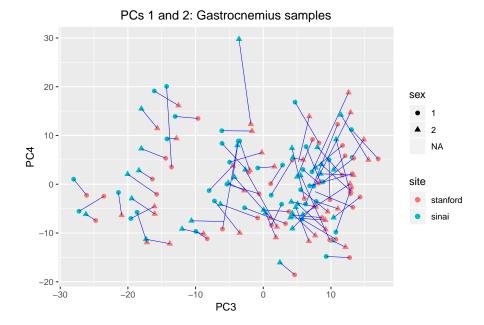
Warning: Removed 4 rows containing missing values (geom_point).





```
ggplot(df,aes(x=PC3, y=PC4, shape=sex, color=site,group=sample)) +
geom_point(size=2) + geom_path(size=0.02,color="blue") +
ggtitle("PCs 1 and 2: Gastrocnemius samples") +
theme(plot.title = element_text(hjust = 0.5))
```

Warning: Removed 4 rows containing missing values (geom_point).



3.4 Look at the sample correlation

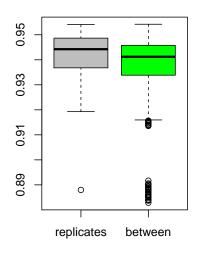
We next compute the Spearman correlation between the samples (with and without filterling lowly expressed genes). We separate the correlations to those between different samples and those between cross-site replicates.

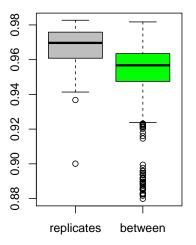
```
par(mfrow=c(1,2))
# Raw FPKMs
x1 = site2fpkm[[1]][,colnames(Gastrocnemius_fpkm_processed[[1]])]
x2 = site2fpkm[[2]][,colnames(Gastrocnemius_fpkm_processed[[2]])]
x1 = x1[,order(sample_id[colnames(x1)])]
x2 = x2[,order(sample_id[colnames(x2)])]
print("Do we have the same mapped sample id in the matrices?")
## [1] "Do we have the same mapped sample id in the matrices?"
print(all(sample_id[colnames(x1)] == sample_id[colnames(x2)]))
## [1] TRUE
corrs = cor(x1,x2,method="spearman")
l = list(
 replicates = diag(corrs),
  between = corrs[lower.tri(corrs,diag = F)]
boxplot(1,col=c("gray", "green"),
        main="Sample corr (Spearman), raw FPKM",
        cex.main=0.9)
# Processed FPKMs - take the expressed genes
corrs = cor(x1[shared_genes,],x2[shared_genes,],method="spearman")
l = list(
 replicates = diag(corrs),
  between = corrs[lower.tri(corrs,diag = F)]
)
boxplot(1,col=c("gray", "green"),
```

```
main="Sample corr (Spearman), filtered FPKM",
cex.main=0.9)
```

Sample corr (Spearman), raw FPKM

Sample corr (Spearman), filtered FPKM



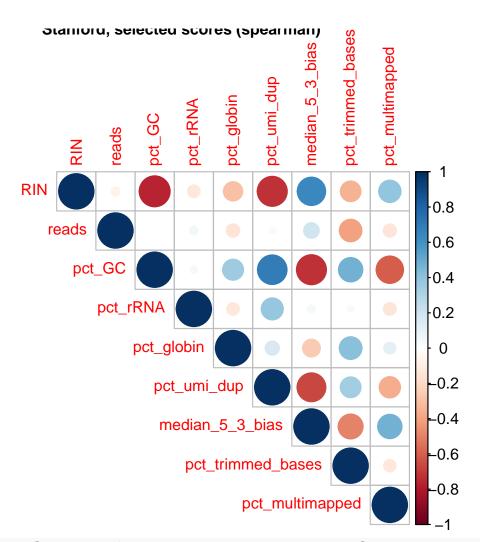


4 In progress

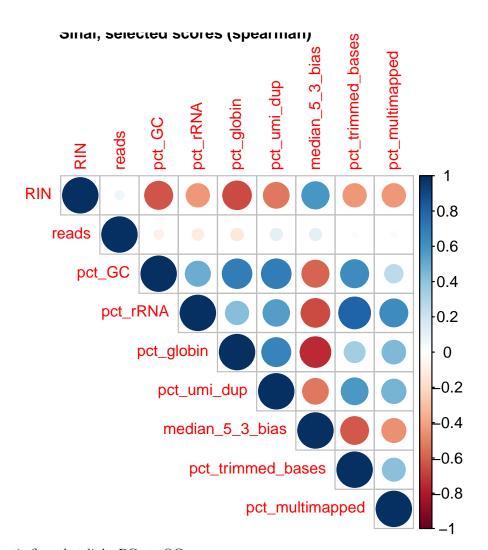
1. Looking at qc scores correlation (assay specific), for example for RNA-seq:

```
library(corrplot)
```

```
## corrplot 0.84 loaded
```



x = rnaseq_meta[rnaseq_meta\$site=="sinai",cols_for_qc_analysis]
corrplot(cor(x,method="spearman"),tl.cex = 0.8,type = "upper", main="Sinai, selected scores (spearman)"



- 2. Automatic flow that links PCs to QC scores
- 3. Differential abundance analysis using LMMs
- 4. Site comparison by differential genes