## Batch effects

## Looking for batch effects

This document provides some analyses looking for unwanted data trends (batch effects).

```
library(mbtools)
```

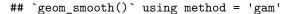
#### Based on IDs

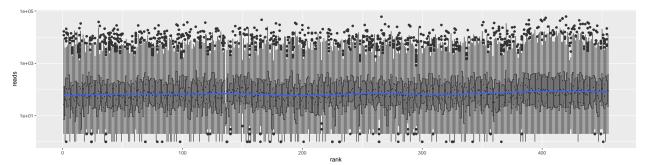
IDs are sometimes a proxy for the temporal order of samples since many researches assign IDs consecutively to subjects. For that we will first get the reads stratified by sequence and ID.

```
ps <- readRDS("../data/taxonomy.rds")
reads <- taxa_count(ps, lev=NA)[order(sample)]</pre>
```

Now we can plot the marginal distributions of the ordered samples. IDs are not evenly spaced so we will rather use their rank.

```
library(ggplot2)
reads$rank <- as.numeric(factor(reads$sample))
ggplot(reads[reads > 0], aes(x=rank, y=reads)) +
        geom_boxplot(aes(group=rank)) + stat_smooth() + scale_y_log10()
```

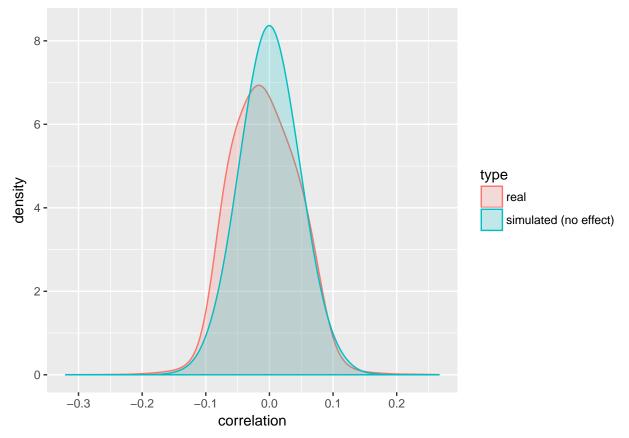




There is nothing striking here. Maybe a tiny effect where low IDs have a higher fraction of low abundance sequences.

We can check whether individual sequences are correlated with their IDs. To get an idea how those correlations would distribute under a model with no association between ID rank and reads we will also simulate read counts under a Poisson model.





Maximum correlations are  $\sim 0.2$  which is not really substantial.

#### Based on Runs

Runs are identified from the directory structure in our DADA2 pipeline. We can use the same function here.

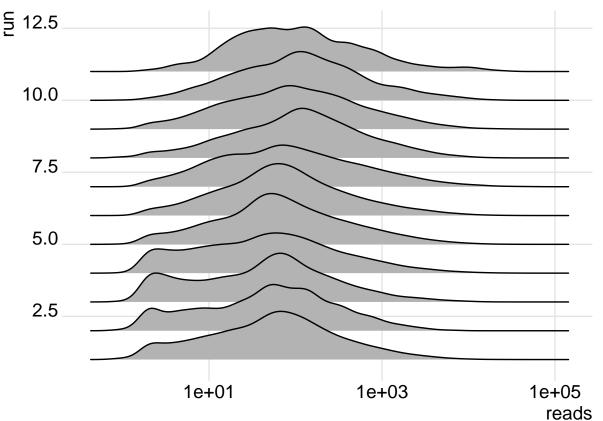
```
files <- annotate_files("../data/filtered")
files[, sample := basename(forward)]
reads <- reads[files, on="sample"]
reads[, run := as.integer(run)]</pre>
```

Now we can stratify the samples by run.

```
library(ggridges)

ggplot(reads[reads > 0], aes(x=reads, y=run, group=run)) +
  geom_density_ridges() + scale_x_log10() + theme_ridges()
```

## Picking joint bandwidth of 0.123

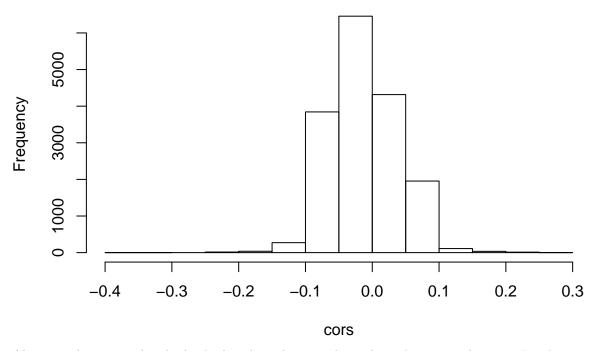


Again nothing really striking. The first 4 runs have a bit higher fractions of low abundance sequences again. Might be noteworthy that those are removed prior to the association analysis anyways.

We can also check the correlation again.

```
cors <- reads[, cor(reads, run, method="spearman"), by=taxa][, V1]
hist(cors)</pre>
```

# **Histogram of cors**



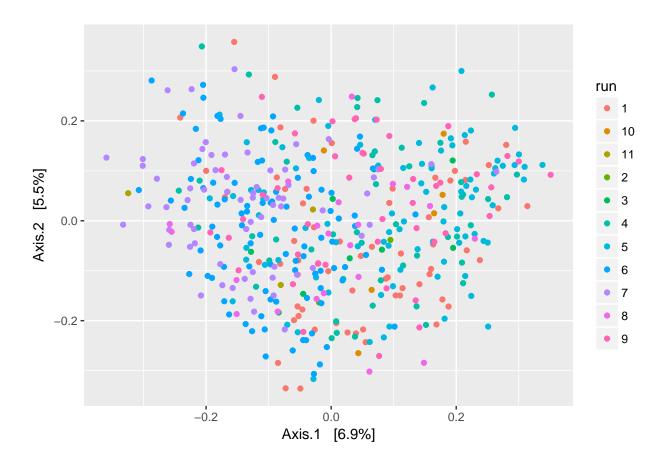
Alternatively we can also check whether the ordination shows dependencies on the runs. For that we will first add our file metadata to the phyloseq object.

```
files <- as.data.frame(files)
rownames(files) <- files$sample
sample_data(ps) <- files</pre>
```

## With PCoA

First using a linear transformation.

```
ord <- ordinate(ps, "PCoA")
plot_ordination(ps, ord, color="run")</pre>
```

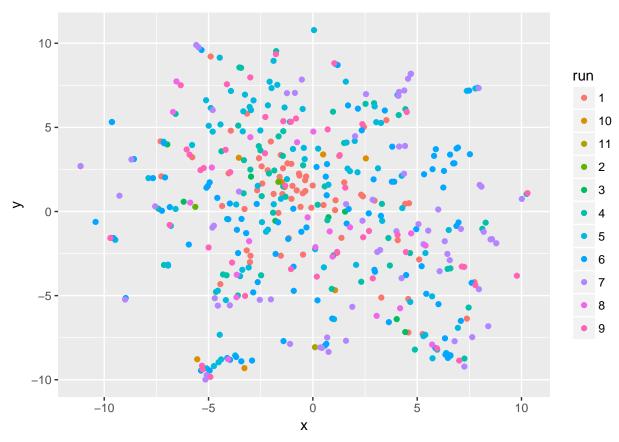


#### With t-SNE

And also with a non-linear transformation. t-SNE essentially searches for a spatial arrangement of the points in 2 dimensions that has the same distribution of inter-point distances as the original data.

```
library(Rtsne)

tsne <- Rtsne(otu_table(ps), pca=FALSE)
data <- data.frame(x=tsne$Y[, 1], y=tsne$Y[,2], run=files$run)
ggplot(data, aes(x=x, y=y, col=run)) + geom_point()</pre>
```



There is no obvious separation of points by run.