Comparison of sequence processing methods

In this document, we evaluate how different clustering methods and denoising approach for long amplicon sequences influence microbial abundance at the genus level. Note that in the heatmaps, comparisons are made across rows, not columns. Though, genera is sorted in descending order, colors do not reflect abundance differences.

Libraries

```
library(mia)
library(pheatmap)
library(viridis)
library(kableExtra)
```

Import data

Data is reloaded from tse files

```
closedref <- readRDS("results/closedref/tse.rds")
openref <- readRDS("results/openref/tse.rds")
denovo <- readRDS("results/denovo/tse.rds")
denoise <- readRDS("results/denoised/tse.rds")</pre>
```

Rarefaction and transformation

Each object is rarefied to 114,000 counts to minimize the effect of varying sample sizes on comparison between methods.

Taxonomy is aggregated at the genus level, and abundance data is converted to relative abundance.

Closed vs Open reference

The first comparison pair is closed-reference and open-reference OTU picking. Since not all genera are found in both datasets, a value of 1e-6 is added to the empty columns.

```
assay_open <- assay(openref, "relabundance")
 assay_closed <- assay(closedref, "relabundance")
assay_closed < absay_closed.

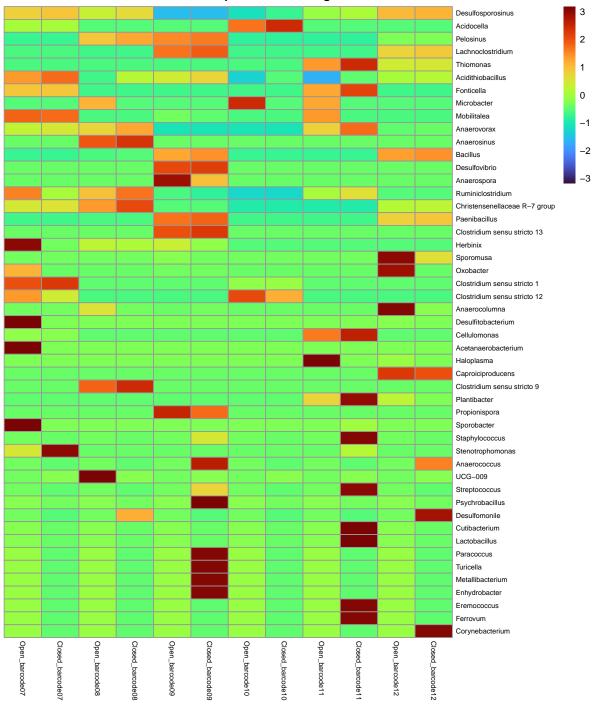
# Unify genera
unified <- union(rownames(assay_open), rownames(assay_closed))

# Create empty matrices with the full list of genera and existing samples

# Fill missing genera with pseudocounts (1e-6)
assay_open_filled <- matrix(1e-6, nrow = length(unified), ncol = ncol(assay_open),
dimnames = list(unified, colnames(assay_open)))

**Trick(1e-6, nrow = length(unified), ncol = ncol(assay_close)))
assay_closed_filled <- matrix(1e-6, nrow = length(unified), ncol = ncol(assay_closed), dimnames = list(unified, colnames(assay_closed)))
 # Fill in the original data for genera that are present
assay_open_filled[rownames(assay_open), ] <- assay_open assay_closed_filled[rownames(assay_closed), ] <- assay_closed
 # Combine the data matrices
merged <- cbind(assay_open_filled, assay_closed_filled)</pre>
 # Ensure column names are unique for clarity
 colnames(merged) <- c(</pre>
pasteO("Upen_", colnames(assay_open)),
pasteO("Closed_", colnames(assay_closed)))
# Reorder the columns so that each open-closed pair is next to each other
 sample_names <- colnames(assay_open)
ordered_columns <- unlist(lapply(sample_names, function(x) c(
   paste0("Open_", x),
   paste0("Closed_", x)</pre>
merged <- merged[, ordered_columns]</pre>
 # Calculate the sum of abundances for each genus across all samples
 abundance_sums <- rowSums(merged)
 # Order the rows based on descending abundance
merged_sorted <- merged[order(abundance_sums, decreasing = TRUE), ]</pre>
```

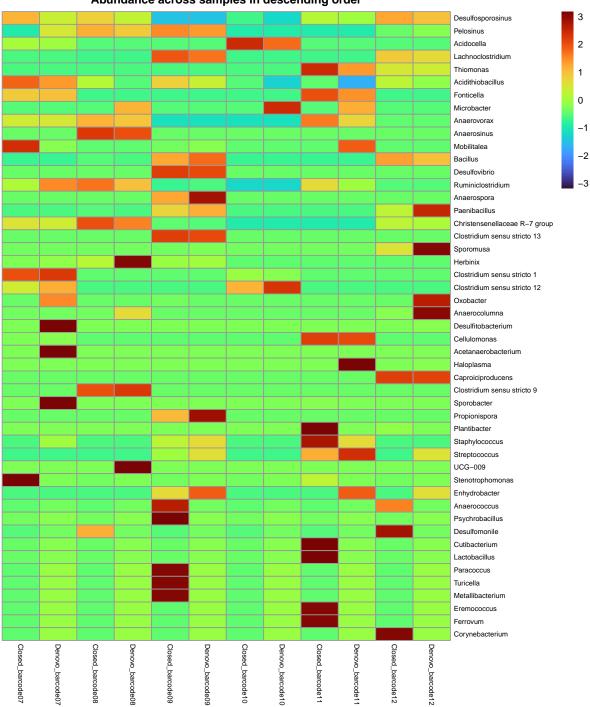
```
# Create the heatmap with sorted genera
pheatmap(
    merged_sorted,
    cluster_rows = FALSE,  # Disable clustering to keep the sorted order
    cluster_cols = FALSE,  # Keep open-closed pairs together
    main = "Abundance across samples in descending order",
    scale = "row",  # Scale the data across rows (genera)
    color = turbo(100),
    fontsize = 8,  # Adjust the overall font size
    fontsize_row = 6,  # Adjust the font size for row labels
    fontsize_col = 6  # Adjust the font size for column labels
)
```



Closed reference vs de-novo

```
# Extract the assay data
assay_closed <- assay(closedref, "relabundance")
assay_denovo <- assay(denovo, "relabundance")
# Unify all genera
unified <- union(rownames(assay_closed), rownames(assay_denovo))
# Create empty matrices with the full list of genera and existing samples
# Fill missing genera with pseudocounts (1e-6)
# Fill in the original data for genera that are present
assay_closed_filled[rownames(assay_closed), ] <- assay_closed assay_denovo_filled[rownames(assay_denovo), ] <- assay_denovo
# Combine the data matrices
merged <- cbind(assay_closed_filled, assay_denovo_filled)
# Ensure column names are unique for clarity
colnames(merged) <- c(
paste0("Closed_", colnames(assay_closed)),
paste0("Denovo_", colnames(assay_denovo))
# Reorder the columns so that each open-closed pair is next to each other
sample_names <- colnames(assay_closed)</pre>
ordered_columns <- unlist(lapply(sample_names, function(x) c( paste0("Closed_", x), paste0("Denovo_", x)
)))
merged <- merged[, ordered_columns]</pre>
# Calculate the sum of abundances for each genus across all samples
abundance_sums <- rowSums(merged)
\ensuremath{\text{\#}} Order the rows based on descending abundance
merged_sorted <- merged[order(abundance_sums, decreasing = TRUE), ]</pre>
```

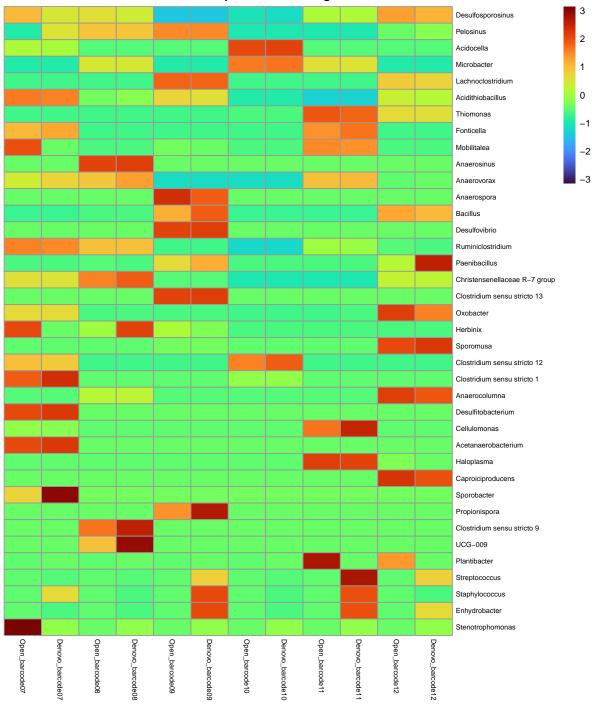
```
# Create the heatmap with sorted genera
pheatmap(
    merged_sorted,
    cluster_rows = FALSE,  # Disable clustering to keep the sorted order
    cluster_cols = FALSE,  # Keep open-closed pairs together
    main = "Abundance across samples in descending order",
    scale = "row",  # Scale the data across rows (genera)
    color = turbo(100),
    fontsize = 8,  # Adjust the overall font size
    fontsize_row = 6,  # Adjust the font size for row labels
    fontsize_col = 6  # Adjust the font size for column labels
)
```



Open reference vs de-novo

```
# Extract the assay data
assay_open <- assay(openref, "relabundance")
assay_denovo <- assay(denovo, "relabundance")</pre>
 # Unify all genera
unified <- union(rownames(assay_open), rownames(assay_denovo))
# Create empty matrices with the full list of genera and existing samples</pre>
# Fill missing genera with pseudocounts (1e-6)
assay_open_filled <- matrix(1e-6, nrow = length(unified), ncol = ncol(assay_open),
dimnames = list(unified, colnames(assay_open)))
# Combine the data matrices
merged <- cbind(assay_open_filled, assay_denovo_filled)
 # Ensure column names are unique for clarity
colnames(merged) <- c(
paste0("Open_", colnames(assay_open)),
paste0("Denovo_", colnames(assay_denovo))
# Reorder the columns so that each open-closed pair is next to each other
sample_names <- colnames(assay_closed)</pre>
ordered_columns <- unlist(lapply(sample_names, function(x) c(
   paste0("Open_", x),</pre>
   paste0("Denovo_", x)
)))
merged <- merged[, ordered_columns]</pre>
# Calculate the sum of abundances for each genus across all samples
abundance_sums <- rowSums(merged)</pre>
# Order the rows based on descending abundance
merged_sorted <- merged[order(abundance_sums, decreasing = TRUE), ]</pre>
```

```
# Create the heatmap with sorted genera
pheatmap(
   merged_sorted,
   cluster_rows = FALSE,  # Disable clustering to keep the sorted order
   cluster_cols = FALSE,  # Keep open-closed pairs together
   main = "Abundance across samples in descending order",
   scale = "row",  # Scale the data across rows (genera)
   color = turbo(100),
   fontsize = 8,  # Adjust the overall font size
   fontsize_row = 6,  # Adjust the font size for row labels
   fontsize_col = 6  # Adjust the font size for column labels
)
```

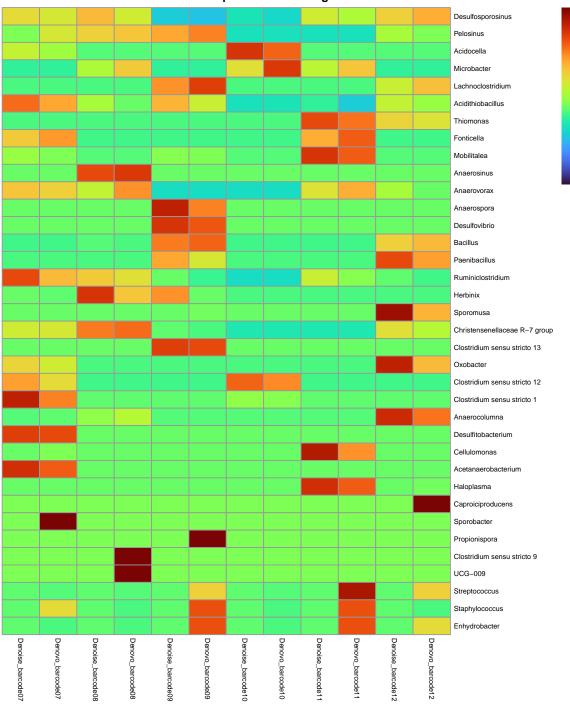


Denoise vs de-novo

```
# Extract the assay data
assay_denoise <- assay(denoise, "relabundance")</pre>
# Fix names discrepance
colnames(assay_denoise) <- c("barcode07", "barcode08", "barcode09", "barcode10", "barcode11", "barcode12")
assay_denovo <- assay(denovo, "relabundance")
# Unify all genera
unified <- union(rownames(assay_denoise), rownames(assay_denovo))
\# Create empty matrices with the full list of genera and existing samples \# Fill missing genera with pseudocounts (1e-6)
assay_denovo_filled <- matrix(le-6, nrow = length(unified), ncol = ncol(assay_denovo)))

# Fill in the original data for genera that are present
assay_denoise_filled[rownames(assay_denoise), ] <- assay_denoise
assay_denovo_filled[rownames(assay_denovo), ] <- assay_denovo
# Combine the data matrices
merged <- cbind(assay_denoise_filled, assay_denovo_filled)
# Ensure column names are unique for clarity
colnames(merged) <- c(</pre>
  paste0("Denoise_", colnames(assay_denoise)),
paste0("Denovo_", colnames(assay_denovo))
# Reorder the columns so that each open-closed pair is next to each other
sample_names <- colnames(assay_denoise)
colnames(assay_denoise) <- colnames(assay_denovo)</pre>
ordered_columns <- unlist(lapply(sample_names, function(x) c( paste0("Denoise_", x), paste0("Denovo_", x)
)))
merged <- merged[, ordered_columns]</pre>
# Calculate the sum of abundances for each genus across all samples
abundance_sums <- rowSums(merged)
\ensuremath{\text{\#}} Order the rows based on descending abundance
merged_sorted <- merged[order(abundance_sums, decreasing = TRUE), ]</pre>
```

```
# Create the heatmap with sorted genera
pheatmap(
    merged_sorted,
    cluster_rows = FALSE,  # Disable clustering to keep the sorted order
    cluster_cols = FALSE,  # Keep open-closed pairs together
    main = "Abundance across samples in descending order",
    scale = "row",  # Scale the data across rows (genera)
    color = turbo(100),
    fontsize = 8,  # Adjust the overall font size
    fontsize_row = 6,  # Adjust the font size for row labels
    fontsize_col = 6  # Adjust the font size for column labels
)
```



2

1

0

-1

-2

Comparing richness

Reloading original data

Calculating shannon values

Combine data to the table

Table 1: Alpha diversity

	Closed_Ref	Open_Ref	Denovo	Denoise
barcode07	2.48	2.85	3.46	5.08
barcode08	2.89	3.28	3.45	5.07
barcode09	2.23	2.59	2.41	5.22
barcode10	0.99	1.39	1.71	3.85
barcode11	2.38	2.78	2.80	4.87
barcode12	2.40	2.67	2.57	5.10

Analysis

Analysis of the complete genus information from the samples did not reveal significant differences between the various sequence processing methods, particularly given that the ten most abundant genera account for a vast majority of the communities. The most notable difference

observed is that the closed-reference approach fails to detect *Microbacter* due to its identity being lower than 97% compared to the reference database. Its frequent occurrence in this dataset makes it highly unlikely that this is an error.

The richness values suggest that the *de-novo* method is most effective for preserving taxonomic information. Conversely, the Shannon index indicates that denoising may struggle to correct sequencing errors in long amplicon products. But erroneous variants could cluster within the same genera, leading to taxonomic abundance patterns close to results from other methods. Denoising could be more effective with shorter amplicons, where a higher proportion of error-free sequences are present.

This also would explain why denoising yields nearly perfect results for mock community samples, which consist of a few microbes with known abundances.