

# Training on Galaxy: Statistics to explore metagenomics

Find, Rapidly, Otus with Galaxy Solution

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## Goals

- Exploratory Data Analysis
  - $\alpha$ -diversity: how diverse is my community?
  - $\blacksquare$   $\beta$ -diversity: how different are two communities?
  - Visual assessment of the data
    - Barplots: what is the composition of each community?
    - Multidimensional Scaling: how are communities related?
    - Heatmaps: are there interactions between species and (groups of) communities?
  - Use a distance matrix to study structures:
    - Hierarchical clustering: how do the communities cluster?
    - Permutational ANOVA: are the communities structured by some known environmental factor (pH, height, etc)?

## FROGSSTAT with Phyloseq R package

 R package (McMurdie and Holmes, 2013) to analyse community composition data in a phylogenetic framework

#### It uses other R packages:

- Community ecology functions from vegan, ade4, picante
- Tree manipulation from ape
- Graphics from ggplot2
- (Differential analysis from DESeq2)

## Overview

- 1. Part A: We play together on a first dataset
- 2. Part B: You play alone with our guideline on a 2<sup>nd</sup> dataset

## PART A

## Training Data1

A real analysis provided by Stéphane Chaillou et al.

Comparison of meat and seafood bacterial communities.

8 environment types (EnvType) :

- Meat → Ground Beef, Ground veal, Poultry sausage, Diced bacon
- Seafood → Cooked schrimps, Smoked salmon, Salmon filet, Cod filet













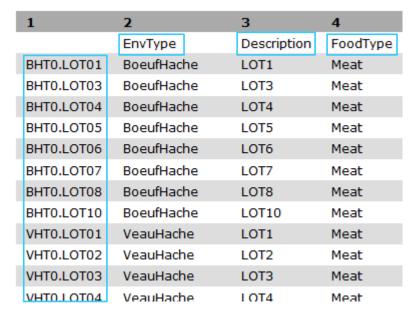




- 64 samples of 16S V1-V3
- Taxonomic affiliations was made with the Greengenes database

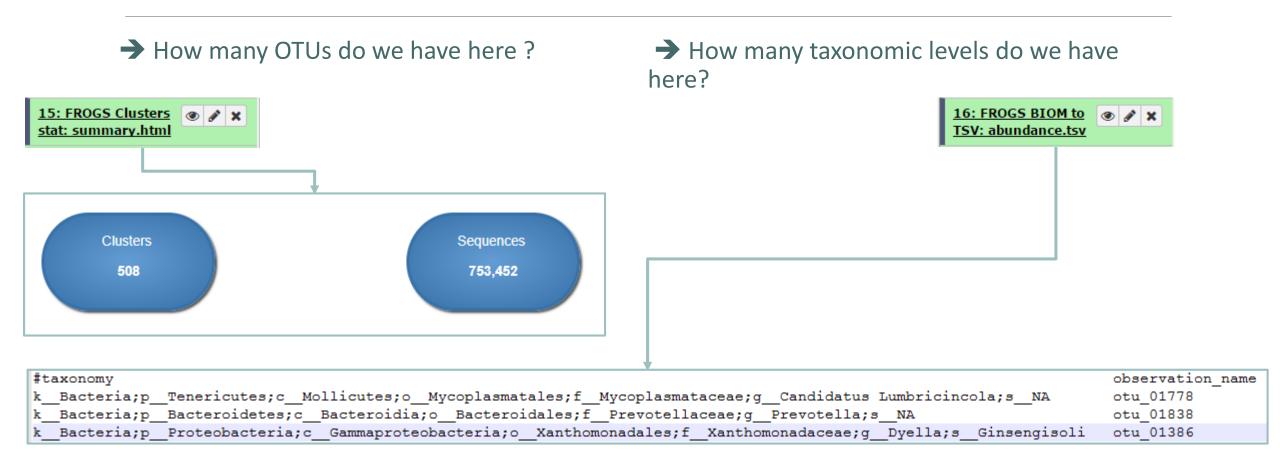
- 1. Create a new history : « food »
- → At the end of FROGS pipeline, what kind of data do we have ?
- → What supplementary data do we need to perform statistical analysis?

- 1. Create a new history: « food »
- → At the end of FROGS pipeline, what kind of data do we have ?
- → What supplementary data do we need to perform statistical analysis?
- 2. Upload data
  - chaillou/sample\_metadata.tsv
  - 2. chaillou/chaillou.biom
  - 3. chaillou/tree.nwk (datatype nhx)
- → Take a look at the data



→ How many OTUs do we have here ?

→ How many taxonomic levels do we have here?



# Data import tool

PHYLOSEQ OBJECT CREATION

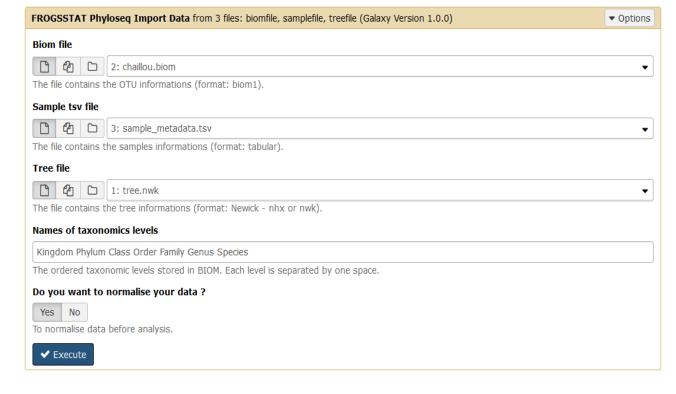
## Phyloseq: Data import

The FROGS biom format contains:

- OTU count tables (required)
- OTU description : taxonomy

Others informations used in FROGSSTAT are:

- sample description in TSV file
- phylogenetic tree in Newick format (nwk or nhx)



- 1. Use FROGSSTAT Phyloseq Import Data, with and without samples normalization (rename datasets in consequence).
  - → What is the difference?

2. Guess what is a Rdata file?

3. Explore the HTML results

#### FROGS Phyloseq: Import Data

Phyloseq 1.20.0



Ranks Names

Sample metadata

Plot tree

R code

Number of sequences in each sample after normalization: 11718

#### 3. Explore the HTML results

#### FROGS Phyloseq: Import Data

Phyloseq 1.20.0

Summary

Ranks Names

Sample metadata



R code

Warning: Taxonomic affiliations come from Greengenes database, user specified ranks names are ignored.

Rank names : Kingdom, Phylum, Class, Order, Family, Genus, Species

# Phylum Actinobacteria Bacteroidetes Candidate division TM: CK-1C4-19 Cyanobacteria Firmicutes Fusobacteria GN02 Proteobacteria Spirochaetes Tenericutes

Phylogenetic tree colored by Phylum

#### 3. Explore the HTML results

#### FROGS Phyloseq: Import Data

Phyloseq 1.20.0

Summary Ranks Names

Sample metadata

Plot tree

R code

Sample variables: EnvType, Description, FoodType

EnvType : BoeufHache, VeauHache, DesLardons, SaucisseVolaille, Crevette, SaumonFume, FiletSaumon, FiletCabillaud

Description: LOT1, LOT3, LOT4, LOT5, LOT6, LOT7, LOT8, LOT10, LOT2, LOT9

FoodType : Meat, Seafood

#### FROGS Phyloseq: Import Data

Phyloseq 1.20.0

Summary F

Ranks Names

Sample metadata

Plot tree

R code

#### Loading packages

library(phyloseq)
library(ape)
library(ggplot2)

#### Warning!

Metadata order (in each sample variable) are used to organised graphics.

So take extra care when you construct your sample\_metadata file

# Biodiversity analysis

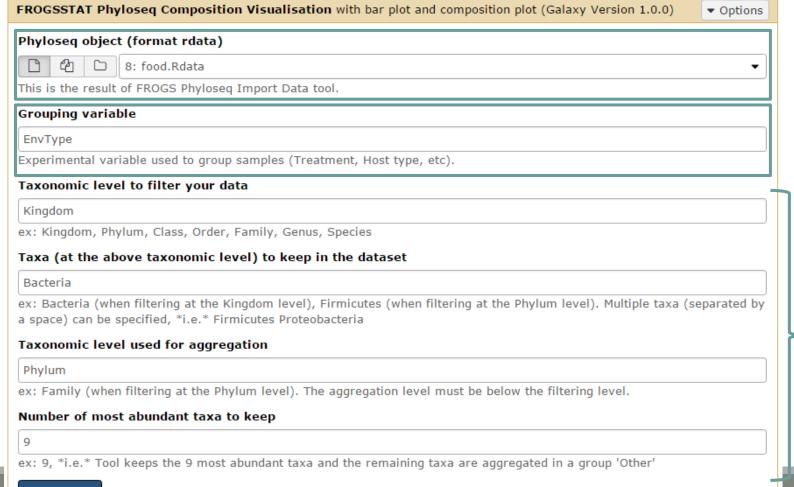
## Biodiversity analysis

- 1. Exploring the sample composition
- 2. Notions of biodiversity
- 3.  $\alpha$ -diversity analysis
- 4. β-diversity analysis

# I. Biodiversity analysis

COMPOSITION VISUALISATION

## Exploring biodiversity: visualisation



Explore the sample raw count

Choose a sample variable to organise graphics: either EnvType or FoodType

For the first usage, let the default parameters, but :

- Take care of your taxonomic level name
- Is the Taxon « Bacteria » in your data?

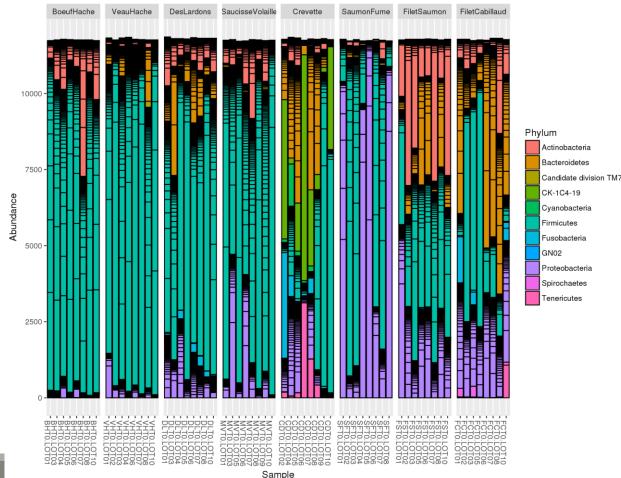
- → Interpretations ?
- Firmicutes and Proteobacteria are presents in all samples, but with a wide range of abundance
- Meat type share common Phylum composition with a majority of Firmicutes
- Seafoods seem to be much more variable

#### FROGS Phyloseq: Visualize Data Composition

Phyloseq 1.20.0

Bar plot Composition plot R code

#### Bar plot colored by Phylum



## Exploring biodiversity: visualisation

- → Limitations:
  - Plot bar works at the OTU-level...
  - ...which may lead to graph cluttering and useless legends
  - No easy way to look at a subset of the data
  - Works with absolute counts (beware of unequal depths or used normalized function)



## Exploring biodiversity: visualisation

#### Customisation: plot\_composition function:

- Works with relative abundances
- Subsets OTUs at a given taxonomic level

Aggregates OTUs at another taxonomic level

Shows only a given number of OTUs

#### Taxonomic level to filter your data

Kingdom

ex: Kingdom, Phylum, Class, Order, Family, Genus, Species

#### Taxa (at the above taxonomic level) to keep in the dataset

Bacteria

ex: Bacteria (when filtering at the Kingdom level), Firmicutes (when filtering at the Phylum level). Multiple taxa (separated by a space) can be specified, i.e. Firmicutes Proteobacteria

#### Taxonomic level used for aggregation

Phylum

ex: Family (when filtering at the Phylum level). The aggregation level must be below the filtering level.

#### Number of most abundant taxa to keep

9

ex: 9, i.e. Tool keeps the 9 most abundant taxa and the remaining taxa are aggregated in a group 'Other'

Look at the « Composition plot » tab

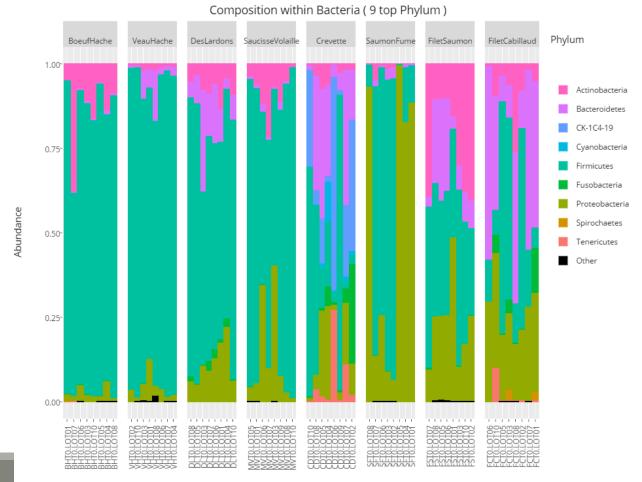
Based on these results what would be interesting to look into?

- → What are the composition of the 9 most abundant Families of Firmicutes ?
- → What are the composition of the 9 most abundant Families of Proteobacteria?

#### FROGS Phyloseq: Visualize Data Composition

Phyloseq 1.20.0

plot Composition plot R code



#### THE 9 MOST ABUNDANT FAMILIES OF FIRMICUTES

#### Taxonomic level to filter your data

Phylum

ex: Kingdom, Phylum, Class, Order, Family, Genus, Species

#### Taxa (at the above taxonomic level) to keep in the dataset

Firmicutes

ex: Bacteria (when filtering at the Kingdom level), Firmicutes (when filtering at the Phylum level). Multiple taxa (separated by a space) can be specified, i.e. Firmicutes Proteobacteria

#### Taxonomic level used for aggregation

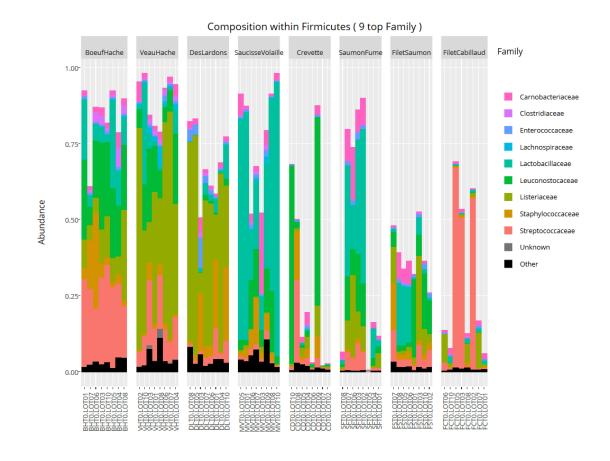
Family

ex: Family (when filtering at the Phylum level). The aggregation level must be below the filtering level.

#### Number of most abundant taxa to keep

9

ex: 9, i.e. Tool keeps the 9 most abundant taxa and the remaining taxa are aggregated in a group 'Other'



#### THE 9 MOST ABUNDANT FAMILIES OF PROTEOBACTERIA

#### Taxonomic level to filter your data

Phylum

ex: Kingdom, Phylum, Class, Order, Family, Genus, Species

#### Taxa (at the above taxonomic level) to keep in the dataset

Proteobacteria

ex: Bacteria (when filtering at the Kingdom level), Firmicutes (when filtering at the Phylum level). Multiple taxa (separated by a space) can be specified, i.e. Firmicutes Proteobacteria

#### Taxonomic level used for aggregation

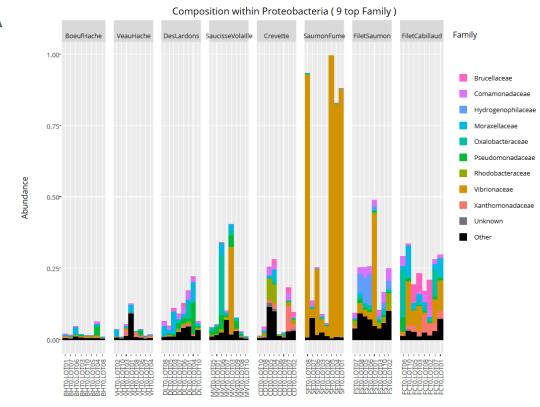
Family

ex: Family (when filtering at the Phylum level). The aggregation level must be below the filtering level.

#### Number of most abundant taxa to keep

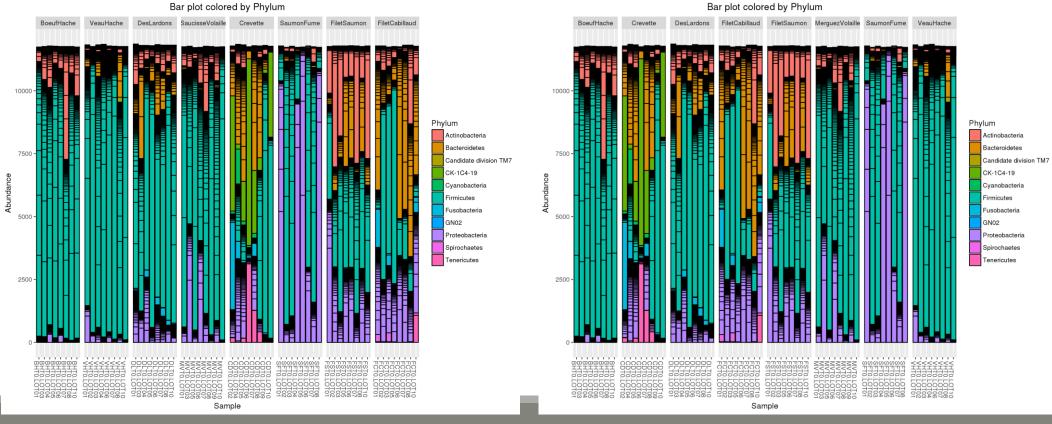
9

ex: 9, i.e. Tool keeps the 9 most abundant taxa and the remaining taxa are aggregated in a group 'Other'



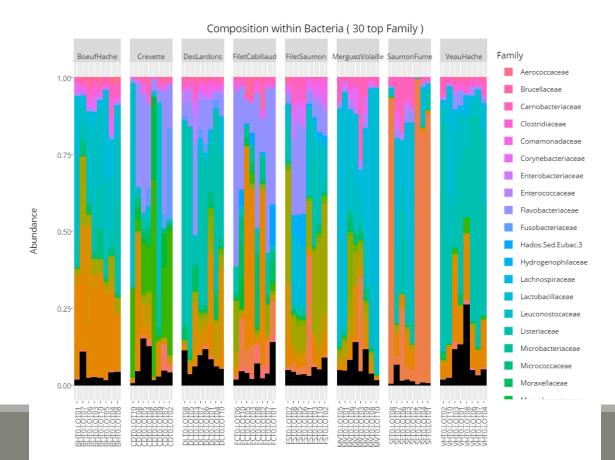
## Exploring biodiversity: visualisation

Remark 1: An example of what happens when sample\_metadata file is not sorted in a meaning full way



## Exploring biodiversity: visualisation

Remark 2: Keep in mind that human eye cannot distinguish more than 12 colours at the same time. Example of the 30 most abundant Families among Bacteria

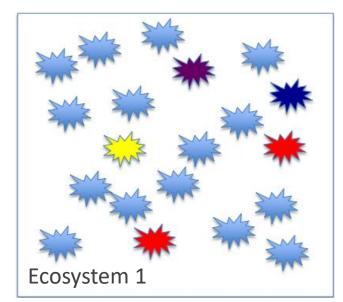


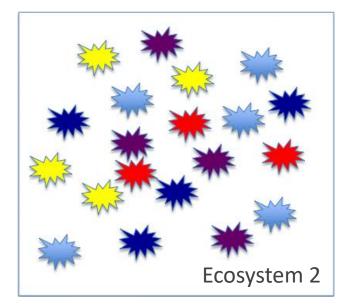
# II. Biodiversity analysis

**DIVERSITY INDICES** 

## Exploring biodiversity: descriptors

- The richness corresponds to the number of OTUs or functional groups present in communities. It caracterises the composition.
- The diversity takes into account the relative abundancy of species. It caracterises the structure





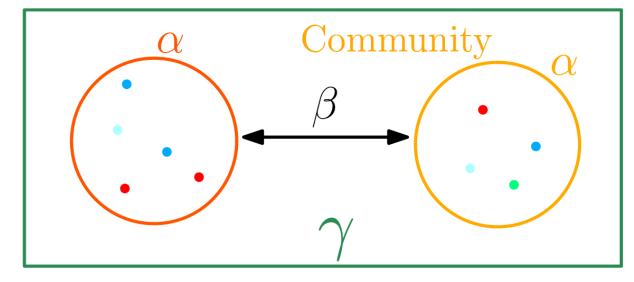
Richness : Eco1 = Eco2

Diversity: Eco2 > Eco1

## Exploring biodiversity: statistical indices

Compute and compare diversity indices. 3 levels of diversity:

- $\bullet$  **\alpha-diversity**: diversity within a community;
- β-diversity: diversity between communities;
  - β-dissimilarities/distances
    - dissimilarities between pairs of communities
    - often used as a first step to compute diversity
- γ-diversity: diversity at the landscape scale (blurry for bacterial communities);



Landscape

## Exploring biodiversity: statistical indices

#### Qualitative (Presence/Absence) vs. Quantitative (Abundance)

- Qualitative gives less weight to dominant species;
- Qualitative is more sensitive to differences in sampling depths;
- Qualitative indices emphasize differences in taxa diversity while quantitative are more sensitive to raise differences in composition.

#### Compositional vs. Phylogenetic

- Compositional does not require a phylogenetic tree;
- Compositional is more sensitive to erroneous OTU picking;
- Compositional gives the same importance to all OTUs.

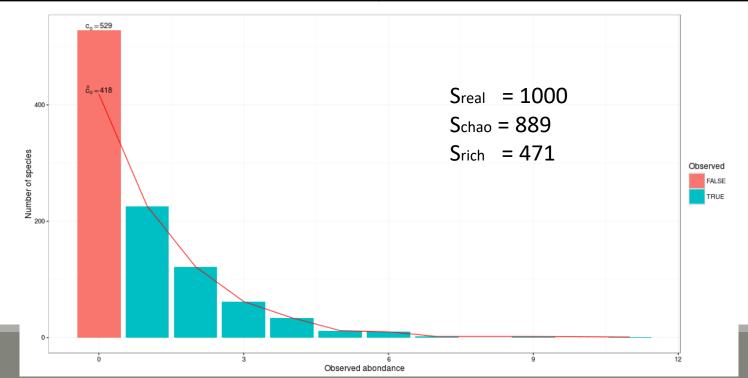
# III. Biodiversity analysis

α-DIVERSITY INDICES

## Exploring biodiversity: $\alpha$ -diversity

 $\alpha$ -diversity is equivalent to the richness : number of species

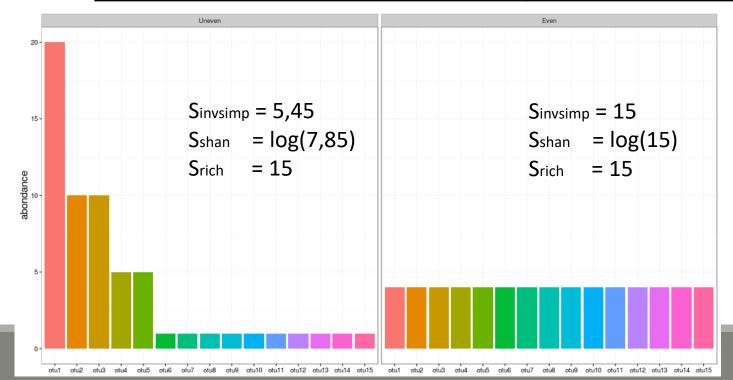
Richness	Chao
Number of observed species	Richness + (estimated) number of unobserved species



## Exploring biodiversity: $\alpha$ -diversity

 $\alpha$ -diversity is equivalent to the richness : number of species

Shannon	Inv-Simpson
Evenness of the species abundance distribution	Inverse probability that two sequences sampled at random come from the same species



#### <u>Interpretation</u>:

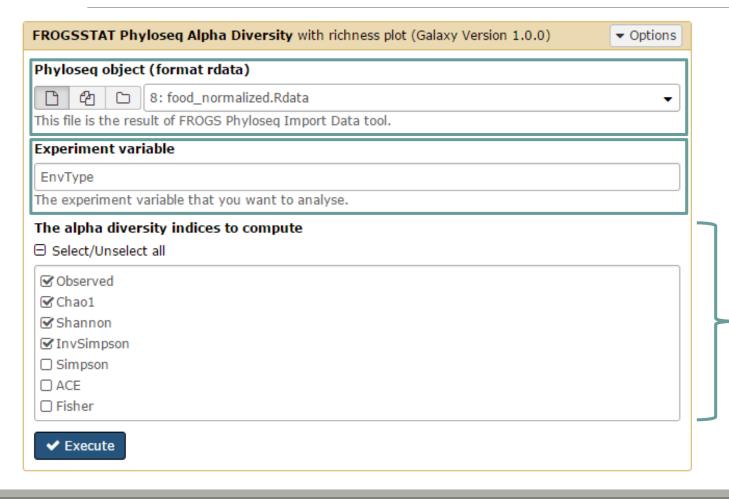
15 observed species, but according to Shannon, the left example acts like there is 7.85 equally abundant species (5.45 for invSimp) It is called effective diversities

## Exploring biodiversity : $\alpha$ -diversity

#### $\alpha$ -diversity indices available in phyloseq :

- Species richness: number of observed OTU
- Chao1: number of observed OTU + estimation of the number of unobserved OTU
- **Shannon** entropy / **Jensen** : the width of the OTU relative abundance distribution. Roughly, it reflects our (in)ability to predict OTU of a randomly picked bacteria.
- Simpson: 1 probability that two bacteria picked at random in the community belong to different OTU.
- Inverse Simpson: inverse of the probability that two bacteria picked at random belong to the same OTU.

## Exploring biodiversity: $\alpha$ -diversity



Select R workspace including phyloseq object

Choose a sample variable to organise graphics

Choose which  $\alpha$ -diversity indices you want to compute

#### Test it on EnvType

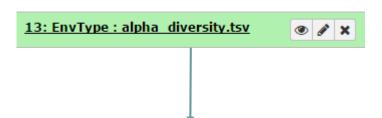
- → What are the resulting datasets?
- → Which interpretation could you make on the boxplot results?
- $\rightarrow$  Have EnvType got an impact on  $\alpha$ -diversity indice ?

→ What are the resulting datasets?

Report HTML file with graphical and statistical results

14: EnvType: alpha diversity.html

Tabular file containing the detailed value of each indice in each sample

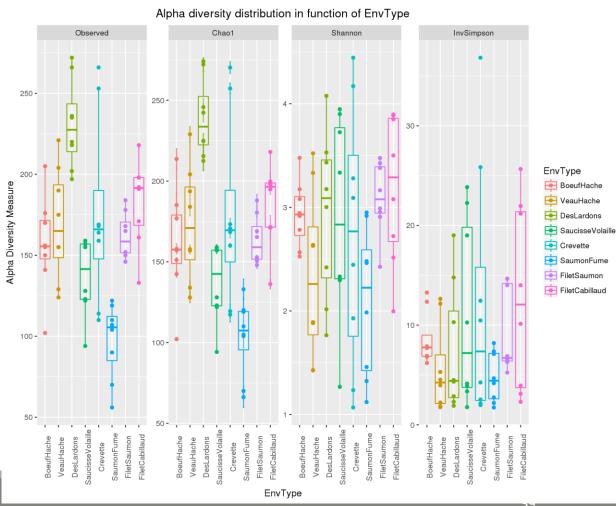


1	2	3	4	5	6
	Observed	Chao1	se.chao1	Shannon	InvSimpson
DLT0.LOT08	205	215.344827586207	5.63455654866184	2.01591714100393	2.31393432719116
DLT0.LOT05	197	215.454545454545	9.04924368908291	1.76545015179311	1.90925718747888
DLT0.LOT03	219	226.916666666667	4.86003372343409	3.4340155003954	14.786255213252
DLT0.LOT07	220	224.714285714286	3.77924481885382	3.00227529842681	4.33279579199353

#### **Boxplot interpretations**

- Observed and Chao1 are very similar
  - → All species have been detected

- Many taxa observed in Deslardons (high Chao1, high Observed)...
- ...but low Shannon and Inverse-Simpson
  - communities are dominated by few abundant taxa

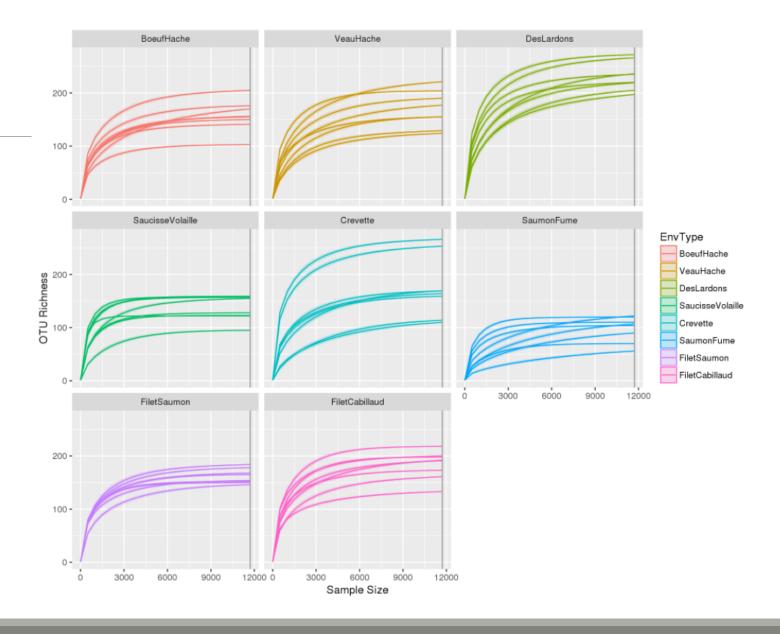


#### **Anova interpretations**

- Environments differ a lot in terms of richness...
- ...but not so much in terms of Shannon diversity
  - → Effective diversities are quite similar

```
#Perform ANOVA on Observed, which effects are significant
  anova.Observed <-aov( Observed ~ Depth + EnvType, anova data)
 summary(anova.Observed)
             Df Sum Sq Mean Sq F value Pr(>F)
             7 82142 11735 11.64 5.02e-09 ***
 EnvType
 Residuals
             56 56472 1008
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#Perform ANOVA on Shannon, which effects are significant
anova.Shannon <-aov( Shannon ~ Depth + EnvType, anova data)
summary (anova. Shannon)
           Df Sum Sq Mean Sq F value Pr(>F)
            7 7.91 1.1300 1.771 0.111
EnvType
Residuals 56 35.72 0.6379
```

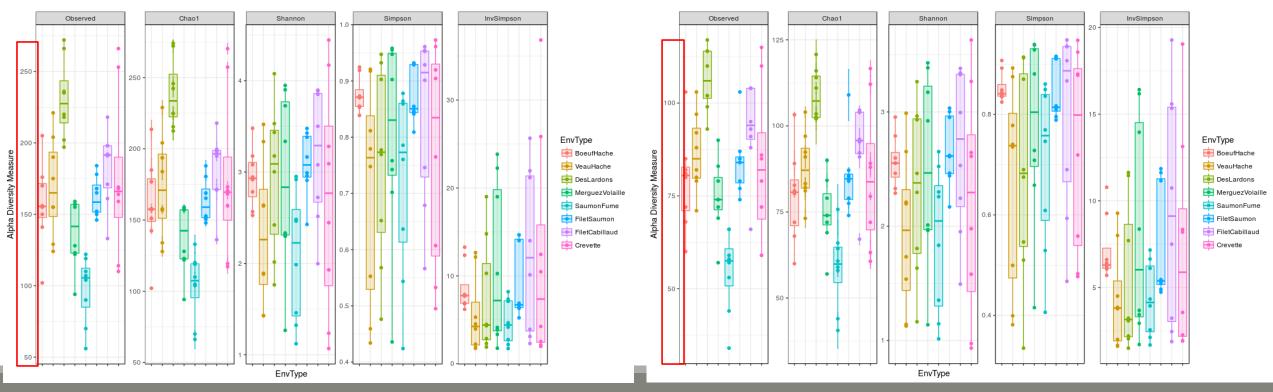
Rarefaction curves interpretation



# Exploring biodiversity : $\alpha$ -diversity

WARNING: Many diversity indices (richness, Chao) depend a lot on rare OTUs. Do not trim rare OTUs before computing them as it can drastically alter the result.

 $\alpha$ -diversity: without (left) and with (right) trimming on rare OTU (total abundance < 500)



# IV. Biodiversity analysis

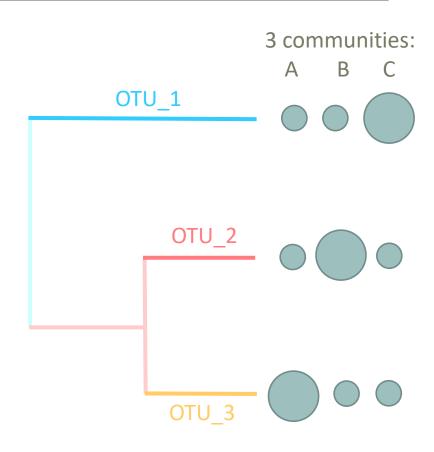
β-DIVERSITY INDICES

Many diversity indices (both compositional and phylogenetic) are available with the Phyloseq package through the generic distance function.

Different dissimilarities capture different features of the communities.

#### In this example:

- qualitatively, communities are very similar
- quantitatively, communities are very different
- phylogenetically, two communities seem to be closer than the third one.



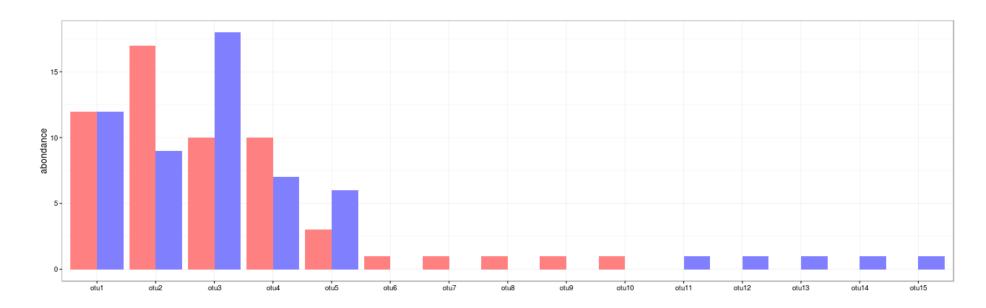
#### Jaccard:

Fraction of <u>species</u> specific to either 1 or 2

#### Bray-Curtis:

Fraction of the <u>community</u> specific to either 1 or 2

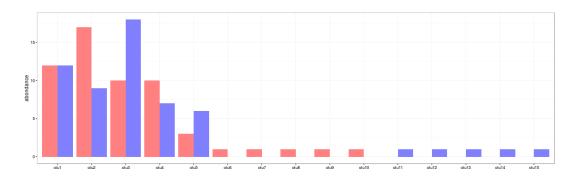
- 2 communities
- 15 OTUs

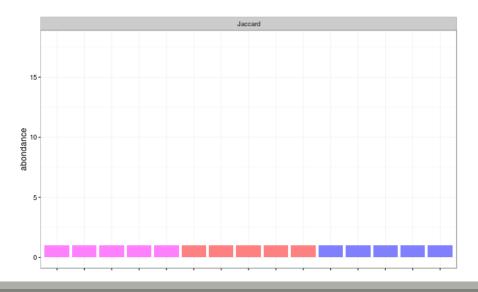


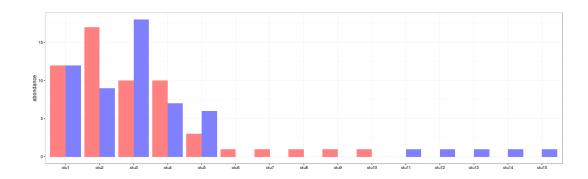
#### Jaccard:

Fraction of <u>species</u> specific to either 1 or 2

$$D_{jac} = 10/15 = 0.667$$



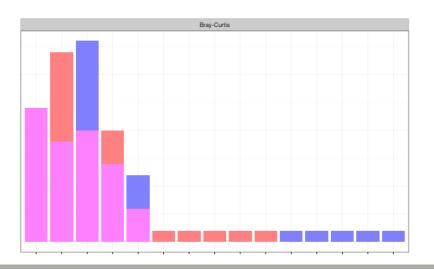


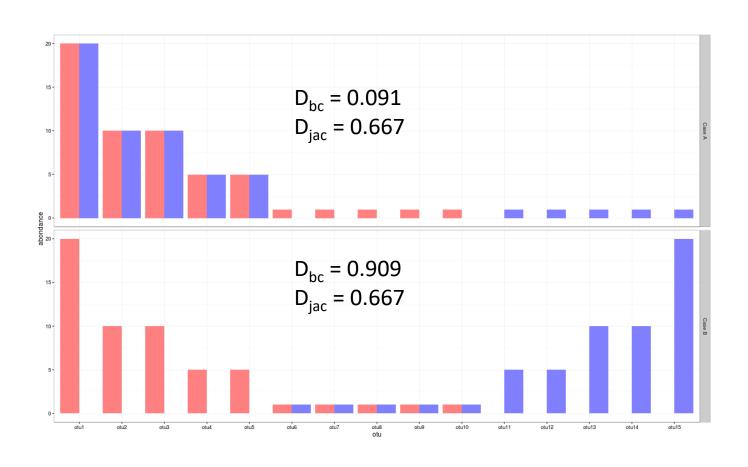


#### **Bray-Curtis:**

Fraction of the <u>community</u> specific to either 1 or 2

$$D_{bc} = (8+8+3+3+10) / (24+26+28+17+9+10) = 0.281$$

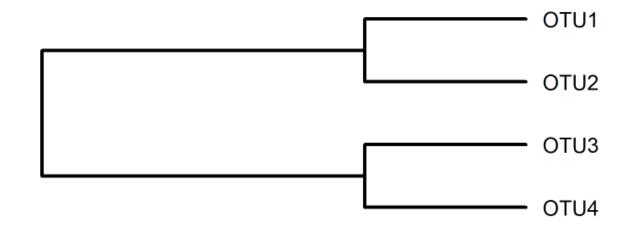




#### Unifrac:

Fraction of the tree specific to either 1 or 2

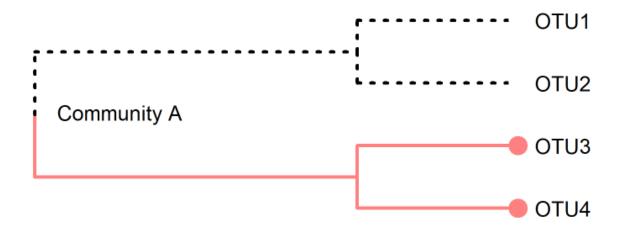
#### Weigthed-Unifrac:

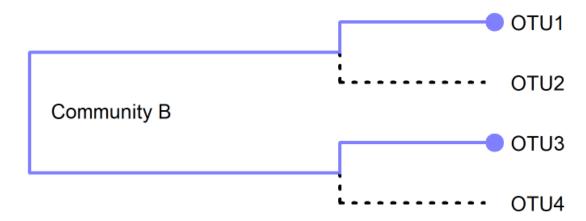


#### Unifrac:

Fraction of the tree specific to either 1 or 2

$$Unifrac = \frac{\sum specific\_branch\_length}{\sum all\_branch\_length}$$



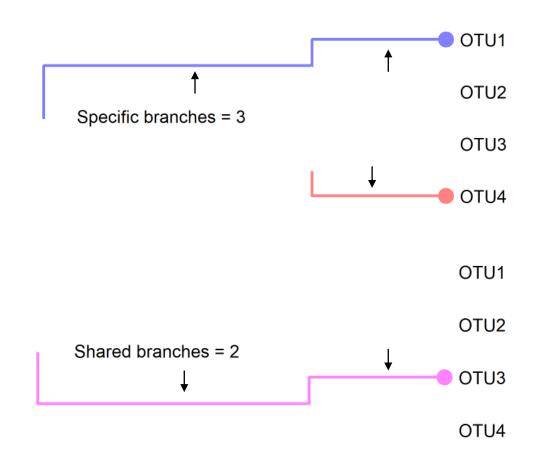


#### Unifrac:

Fraction of <u>the tree</u> specific to either 1 or 2

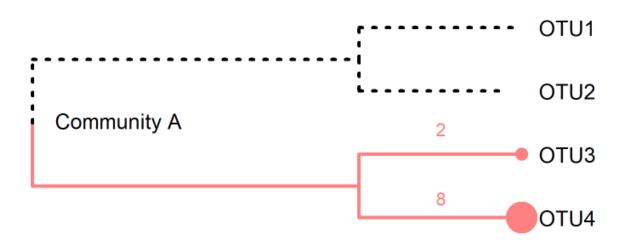
If all branch lengths are equal to 1, only branches present in at least one community are taken into account:

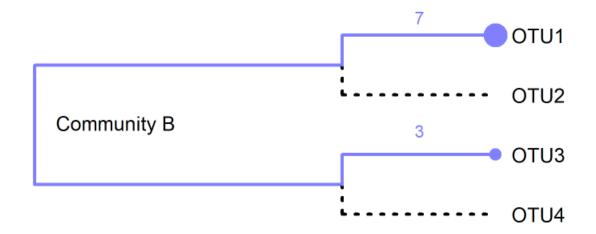
$$Unifrac = \frac{\sum specific\_branch\_length}{\sum all\_branch\_length} = 0.6$$



#### Weigthed-Unifrac:

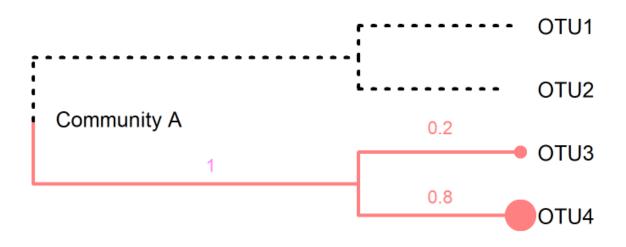
$$WUnifrac = \frac{\sum reduced\_branch\_length}{\sum non\_reduced\_branch\_length}$$

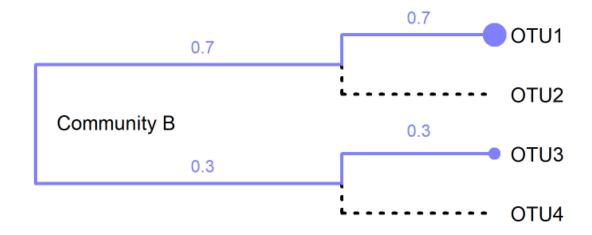




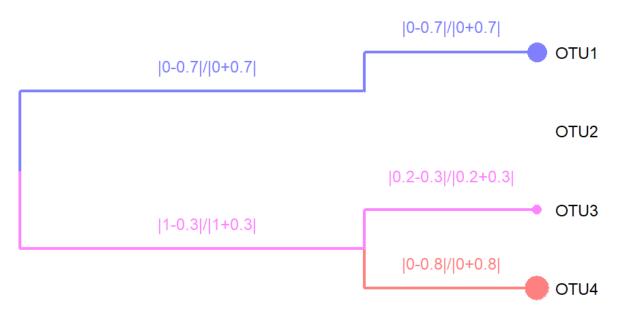
#### Weigthed-Unifrac:

$$WUnifrac = \frac{\sum reduced\_branch\_length}{\sum non\_reduced\_branch\_length}$$





#### Weigthed-Unifrac:

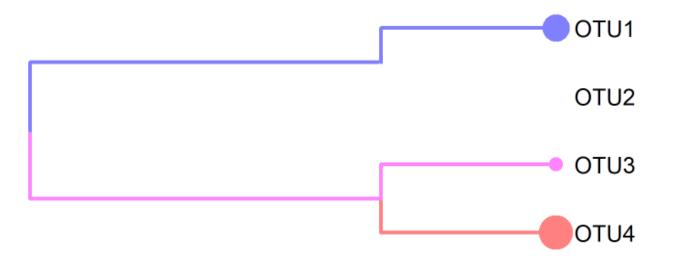


$$WUnifrac = \frac{\sum reduced\_branch\_length}{\sum non\_reduced\_branch\_length}$$

Blue branches = 
$$\frac{|0-0.7|}{|0+0.7|} + \frac{|0-0.7|}{|0+0.7|} = 1 + 1 = 2$$
  
Red branches =  $\frac{|0-0.8|}{|0+0.8|} = 1$   
Pink branches =  $\frac{|1-0.3|}{|1+0.3|} + \frac{|0.2-0.3|}{|0.2+0.3|} = \frac{0.7}{0.3} + \frac{0.1}{0.5} = 0.73$   
 $\sum \text{reduced branch length} = 3.73$ 

#### Weigthed-Unifrac:

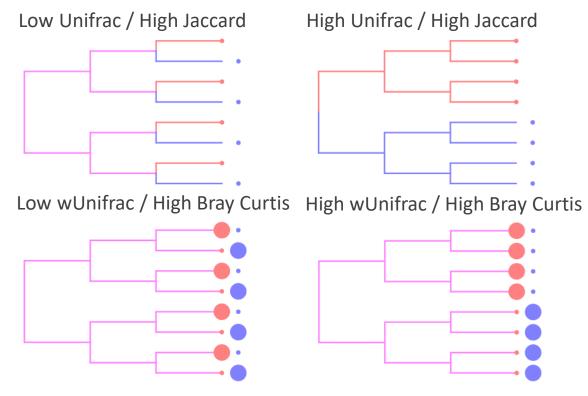
$$WUnifrac = \frac{\sum reduced\_branch\_length}{\sum non\_reduced\_branch\_length}$$



$$\sum$$
 non reduced branch length = 5

$$WUnifrac = \frac{\sum reduced\_branch\_length}{\sum non\_reduced\_branch\_length} = \frac{3,73}{5} = 0,75$$

→ What do you conclude in terme of Jaccard, Bray Curtis, Unifrac and weighted Unifrac values?



Phyloseq supports currently 43 beta diversity distance methods, see <a href="phyloseq distanceMethodList">phyloseq distanceMethodList</a> <a href="documentation">documentation</a> :

```
"unifrac" "wunifrac"

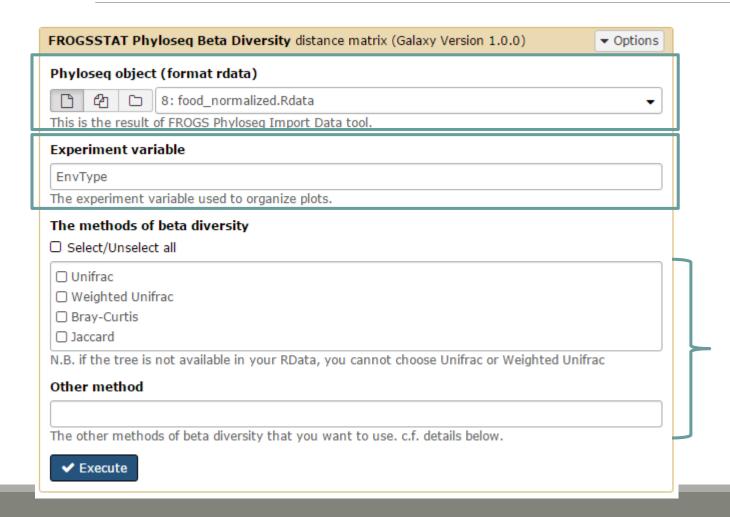
"dpcoa"

"jsd"

"manhattan" "euclidean" "canberra" "bray" "kulczynski " "jaccard" "gower" "altGower" "morisita"

"horn" "mountford" "raup" "binomial" "chao" "cao"

"w" "-1" "c" "wb" "r" "l" "e" "t" "me" "j" "sor" ...
```



Explore the sample normalised count

Choose a sample variable to organise graphics.

Choose which beta diversity distances you want to compute

Try it with the 4 most commonly used distance methods

- → What are the output datasets?
- → A priori, abundant OTU are they shared among samples?
- Considering that Jaccard is higher than Unifrac, what can you conclude ?
- Considering that Unifrac is higher than weighted Unifrac, what can you conclude?

→ What are the output datasets ?

Report HTML file with graphical and statistical results

One tabular file per distance method containing the all samples againt all beta diversity distance : a matrix

DLT0.LOT08 DLT0.LOT05 DLT0.LOT03

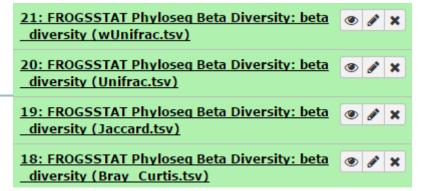
DLT0.LOT08 0 0.239033964840416 0.724185014507595

DLT0.LOT05 0.239033964840416 0 0.817716333845366

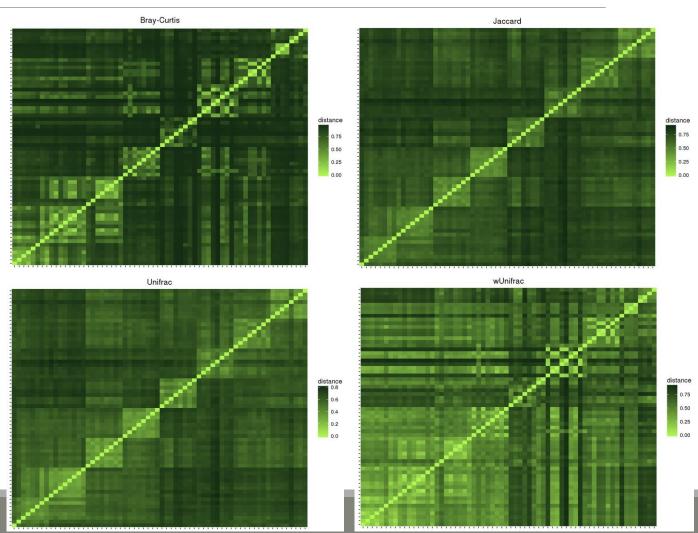
DLT0.LOT03 0.724185014507595 0.817716333845366 0

17: FROGSSTAT Phyloseq Beta Diversity: beta diversity

947.7 KB
format: html, database: ?



- Jaccard lower than Bray-Curtis
- → abundant taxa are not shared
- Jaccard higher than Unifrac
- communities' taxa are distinct but phylogenetically related
- Unifrac higher than weighted Unifrac
- → abondant taxa in both communities are phylogenetically closed.



- In general, qualitative diversities are more sensitive to factors that affect presence/absence of organisms (such as pH, salinity, depth, etc) and therefore useful to study and define bioregions (regions with little of no flow between them)...
- •... whereas quantitative distances focus on factors that affect relative changes (seasonal changes, nutrient availability, concentration of oxygen, depth, etc) and therefore useful to monitor communities over time or along an environmental gradient.

Different distances capture different features of the samples.

There is no "one size fits all"

# Exploring the structure

# I. Exploring the structure

ORDINATION AND HEATMAP PLOTS

# Exploring the structure: Ordination plot

- Each community is described by OTU abundances
- OTU abundances may be correlated
- PCA finds linear combinations of OTUs that
  - are uncorrelated
  - capture well the variance of community composition

But variance is not a very good measure of  $\beta$ -diversity

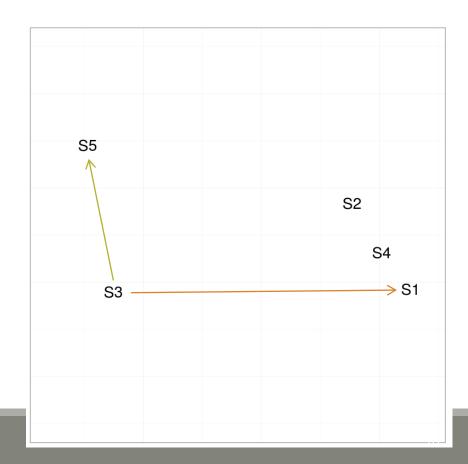
# Exploring the structure: Ordination plot

The Multidimensional Scaling (MDS or PCoA) is equivalent to a Principal Component Analysis (PCA) but preserves the  $\beta$ -diversity instead of the variance.

The MDS tries to represent samples in two dimensions

→ The samples ordination.

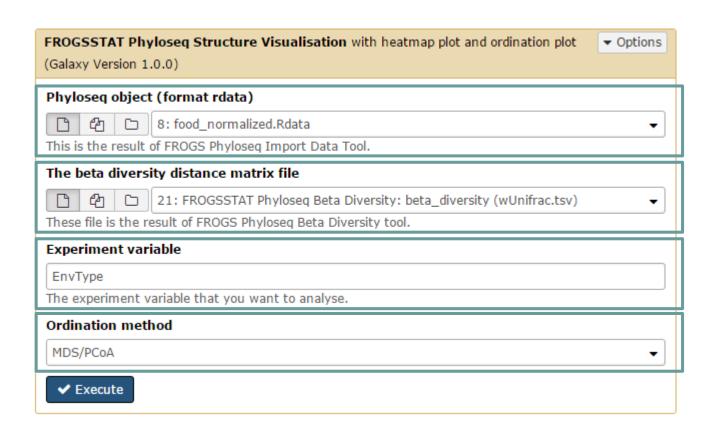
	Distance Matrix							
	S1	S2	S3	S4	S5			
S1	0.00	2.21	6.31	0.99	7.50			
S2	2.21	0.00	5.40	1.22	5.74			
S3	6.31	5.40	0.00	5.75	3.16			
S4	0.99	1.22	5.75	0.00	6.64			
S5	7.50	5.74	3.16	6.64	0.00			



## Exploring the structure: Heatmap

- Heatmap is an other representation of the abundance table.
- It tries to reveal if there is a structure between a group of OTUs and a group of samples.
- It
  - Finds a meaningful order of the samples and the OTUs
  - Allows the user to choose a custom order (in R)
  - Allows the user to change the colour scale (in R)
  - Produces a ggplot2 object, easy to manipulate and customize

# Exploring the structure: Ordination plot and Heatmap



Explore the sample normalised count

Choose the beta diversity distance matrix

Choose a sample variable to organise graphics.

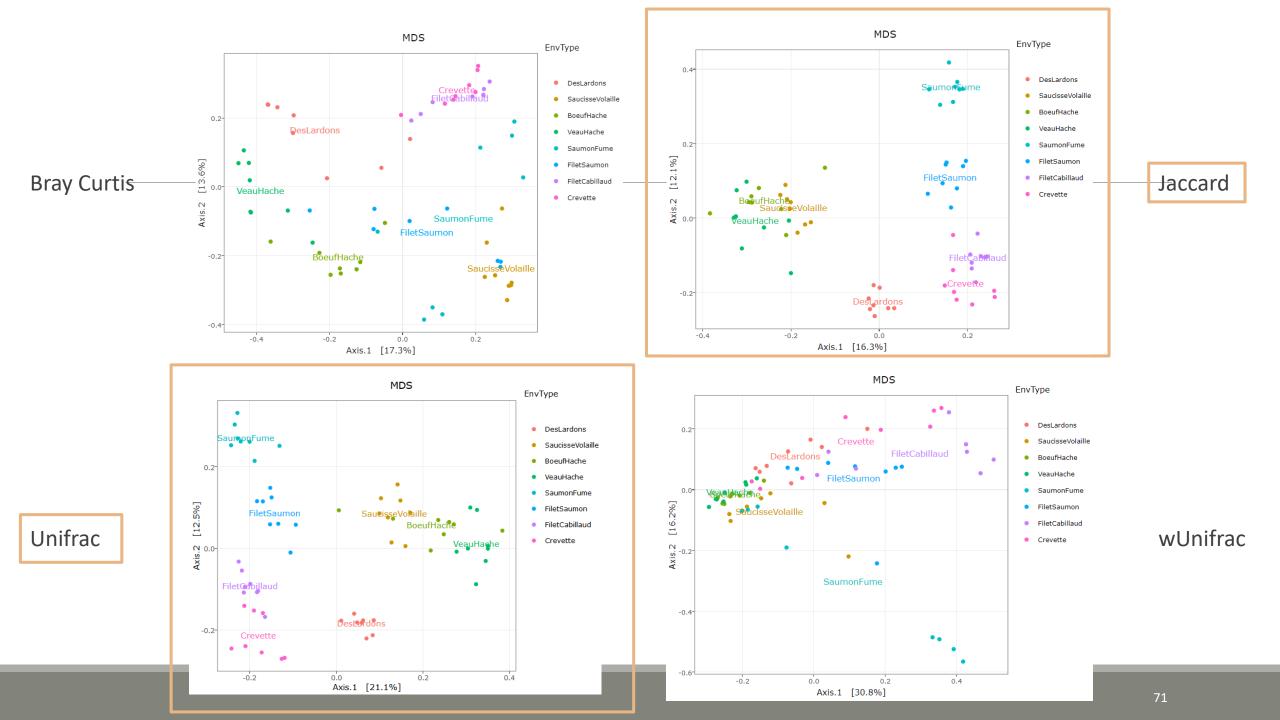
Choose the ordination method (most commonly used is MDS/Pcoa)

Try it with one distance method matrix

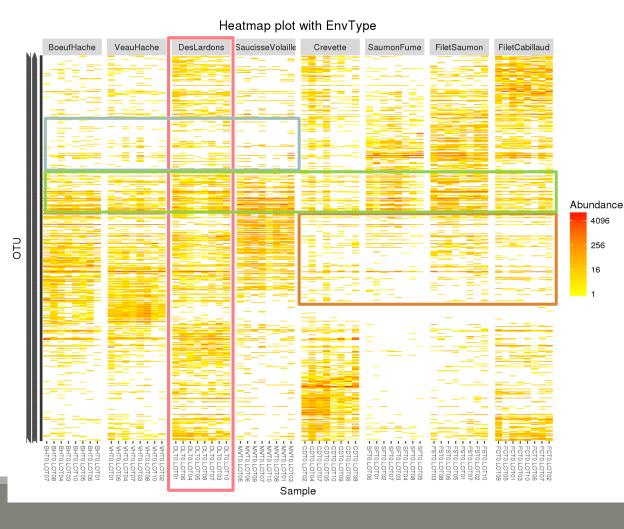
→ Are you satisfied of your ordination plot ?

Try with the other distance matrix

- → What is the best distance matrix to use to better separate samples?
- Guess why Lardon are somewhere between Meat and Seafood ?
- → Based on your preferred distance matrix, what can you conclude on the heatmap?



- Qualitative distances (Unifrac, Jaccard) separate meat products from seafood ones
- detected taxa segregate by origin.
- DesLardons is somewhere in between
- contamination induced by sea salt.
- Quantitative distances (weighted Unifrac) exhibit a gradient meat seafood (on axis 1) with DesLardons in the middle and a gradient SaumonFume - everything else on axis 2.
- Note the difference between weighted UniFrac and Bray-Curtis for the distances between BoeufHache and VeauHache
- Warning
  - The 2-D representation captures only part of the original distances.
  - Ellipse are not always an advantage for visualisation



- Block-like structure of the abundance table
- Interaction between (groups of) taxa and (groups of) samples
- Core and condition-specific microbiota
- Classification of taxa and use of custom taxa order to highlight structure

# II. Exploring the structure

HIERARCHICAL CLUSTERING

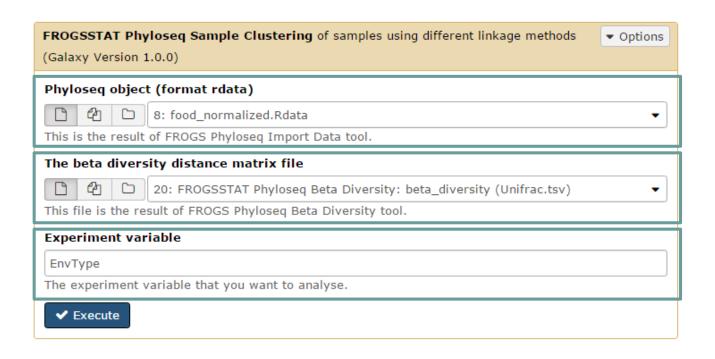
## Exploring the structure: clustering

Clustering aims to represent samples in a tree based on a distance matrix and a linkage function:

- Complete linkage: tends to produce compact, spherical clusters and guarantees that all samples in a cluster are similar to each other.
- Ward: tends to also produce spherical clusters but has better theoretical properties than complete linkage.
- single: friend of friend approach, tends to produce banana-shaped or chains-like clusters.

Complete	Ward	Single
$\begin{array}{c c} A & B \\ \hline \bullet & d(A,B) & \hline \bullet & \\ \hline \end{array}$	$A \qquad B \qquad B$	$ \begin{array}{c c} A & B \\ \bullet & \bullet & d(A,B) & \bullet \\ \bullet & \bullet & \bullet \end{array} $

## Exploring the structure: clustering



Explore the sample normalised count

Choose the beta diversity distance matrix

Choose a sample variable to organise graphics.

The tree different linkage functions will be used, generating three different trees

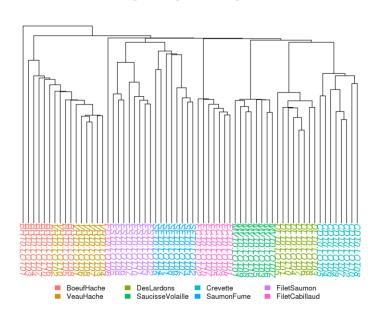
Try it with « a good » distance method matrix on EnvType and on FoodType

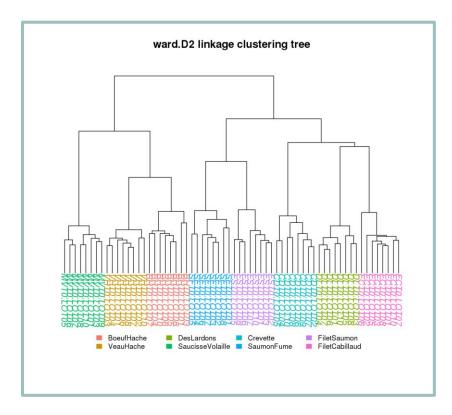
→ Which linkage method seems better to fit the data?

Try with « a bad » distance matrix

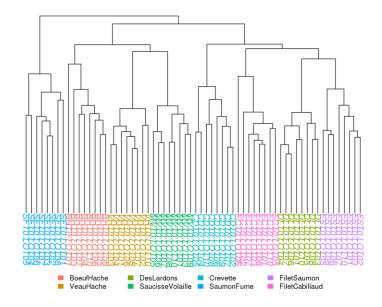
→ Is there a big difference?

#### single linkage clustering tree





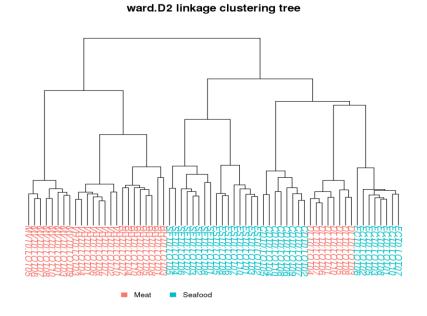
#### complete linkage clustering tree



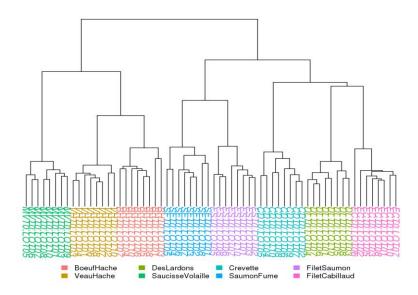
#### Remarks

- Consistent with the ordination plots, clustering works quite well for the UniFrac distance for some linkage (Ward)
  - DesLardons seems to be much closer to Seafood than Meat.
- Clustering is based on the whole distance whereas ordination represents parts of the distance (the most it can with 2 dimensions)

Ward linkage on Unifrac distance matrix



#### ward.D2 linkage clustering tree



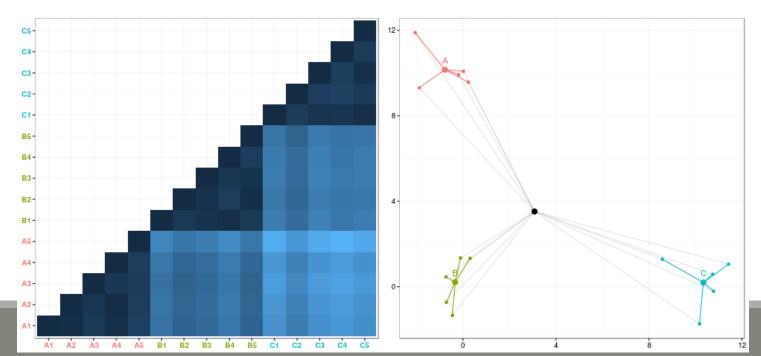
# Diversity partitioning

## Diversity partitioning

Are the structures seen linked to metadata? Have the metadata got an effect on our communities composition?

To answer these questions, **multivariate analyses** that :

- tests composition differences of communities from different groups using a distance matrix
- compares within group to between group distances

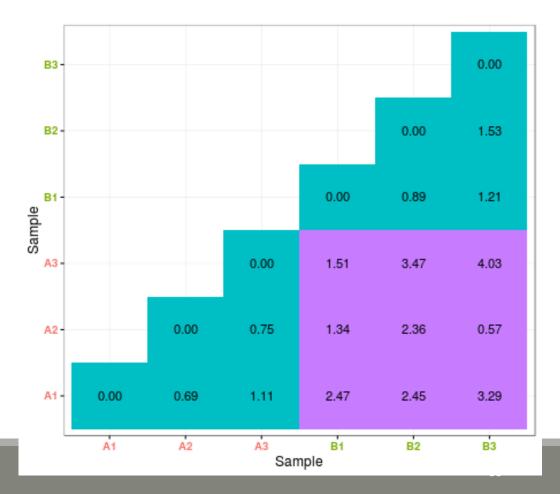


## Diversity partitioning: Multivariate ANOVA

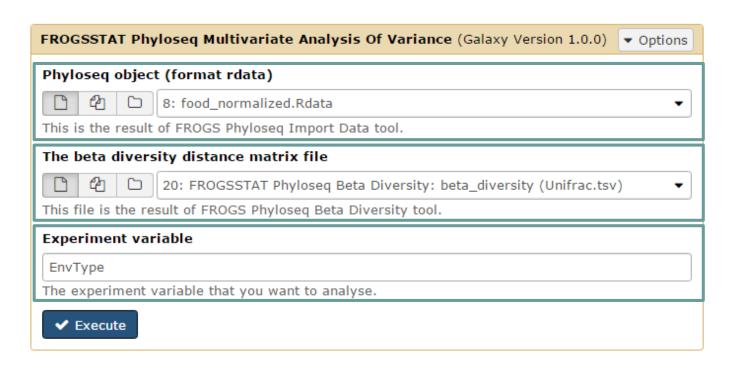
Idea: Test differences in the community composition from different groups using a distance matrix.

#### How it works?

- Computes sum of square distance
- Variance analysis



## Diversity partitioning: Multivariate ANOVA



Explore the sample normalised count

Choose the beta diversity distance matrix

Choose a sample variable to organise graphics.

Try it with a good beta distance matrix with EnvType and FoodType

- → Does EnvType have an influence on the beta diversity variance?
- → What about FoodType?

Environment type explains roughly **62%** of the total variation

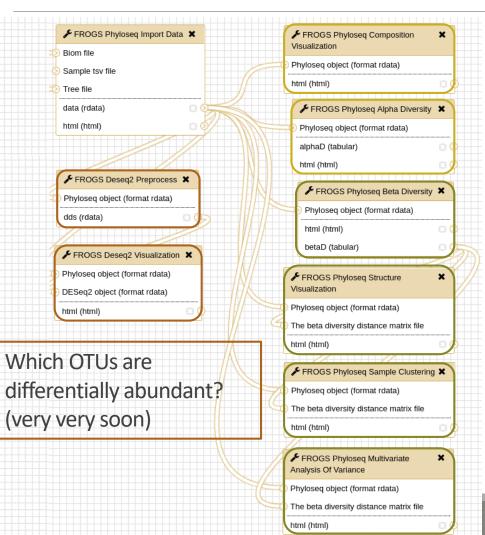
```
With Unifrac distance
```

```
Call:
adonis(formula = dist ~ EnvType, data = metadata, permutations = 9999)
Permutation: free
Number of permutations: 9999
Terms added sequentially (first to last)
         Df SumsOfSqs MeanSqs F.Model
                                           R2 Pr(>F)
               7.6445 1.09207 12.858 0.61645 1e-04 ***
EnvType
Residuals 56
               4.7564 0.08494
                                      0.38355
Total
         63 12.4009
                                     1.00000
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

## Food type explains only **18** % of the total variation

```
Call:
adonis(formula = dist ~ FoodType, data = metadata, permutations = 9999)
Permutation: free
Number of permutations: 9999
Terms added sequentially (first to last)
          Df SumsOfSqs MeanSqs F.Model
                                            R2 Pr(>F)
               2.2609 2.26092 13.824 0.18232 1e-04 ***
Residuals 62
               10.1400 0.16355
                                       0.81768
Total
          63
              12,4009
                                       1.00000
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

## FROGSStat Summary



What is the sample composition?

What are the sample diversities?

Composition analysis

What is the samples dissimilarity?

Is there any relation between species or communities?

how do the communities cluster?

Which variable influence the diversity?

Structure analysis

# Conclusion and advices reminder

#### FROGSTAT advices

- Before starting, check taxonomy format : how many levels? Possibly level name ?
- Well construct your sample\_metadata TSV file, after import check that variable order is meaning full
- Keep in mind that :
  - Phyloseq composition and structure analysis need to be perform on normalised/rarefied counts
  - Different indices or distance methods will give different information
  - Test different distances or choose which one fits better our data
  - Richness indices depend lot on rare OTUs

## PART B. Your turn!

## Training Data2

A real analysis provided by Núria Mach et al.

16S survey of gut microbiomes from early life swines. Used (among others) to study the impact of weaning (Time and Weaned) on bacterial communities.

Along a kinetic of time 31 samples are analysed:

- Time: D14 (before weaning), D36, D48, D60, D70
- Weaned : TRUE, FALSE (Weaned is TRUE for TIME D14, else FALSE )
- sex : 1 (male), 2 (female)

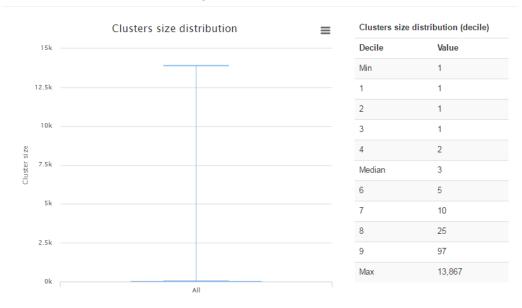
155 samples of 16S V3-V4, and taxonomic affiliations was made with the Greengenes database

#### Upload this new dataset:

- kinetic.biom
- kinetic\_sample\_metadata.tsv
- tree.nwk
- → How can you simply caracterise this dataset ?
- → What is happening when you rarefy the counts?

- → How can you simply caracterise this dataset ?
  - Number of OTUs and size / sample distribution with FROGS Clusters Stat
- → More than 30% of OTUs are composed of just 1 sequence.
- → But a small number of OTUs is specific to each sample.
  - Number of taxonomic level, by converting biom to a tsv file with FROGS Biom to TSV
- → Taxonomy are composed of 6 levels, from Kingdom to Genus

#### Clusters size summary



Root; Bacteroidetes; Bacteroidia; Bacteroidales; Prevotellaceae; Prevotella

→ What is happening when you rarefy the counts?

#### Import of raw counts

```
phyloseq-class experiment-level object
otu_table() OTU Table: [ 4031 taxa and 155 samples ]
sample_data() Sample Data: [ 155 samples by 8 sample variables ]
tax_table() Taxonomy Table: [ 4031 taxa by 6 taxonomic ranks ]
phy_tree() Phylogenetic Tree: [ 4031 tips and 4030 internal nodes ]
```

#### Import of rarefying counts

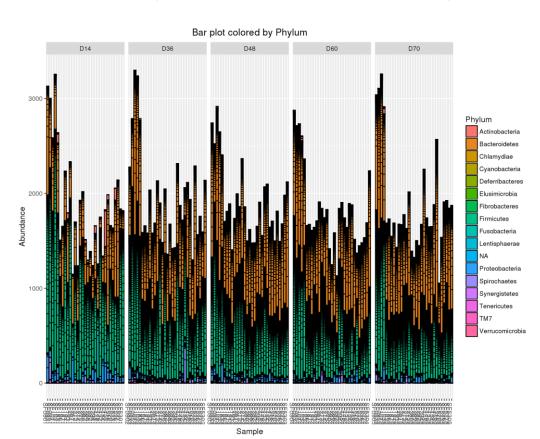
```
phyloseq-class experiment-level object
  otu_table()   OTU Table:        [ 3002 taxa and 155 samples ]
  sample_data()   Sample Data:        [ 155 samples by 8 sample variables ]
  tax_table()   Taxonomy Table:        [ 3002 taxa by 6 taxonomic ranks ]
  phy_tree()   Phylogenetic Tree:   [ 3002 tips and 3001 internal nodes ]
```

Number of sequences in each sample after normalization: 1056

→ 4031 – 3002 = 1029 OTUs have been deleted, probably most of the singleton OTU

- → What can you conclude with the composition plots?
- → What can you tell about alpha diversity indices ? Try it on raw counts and on rarefied counts.

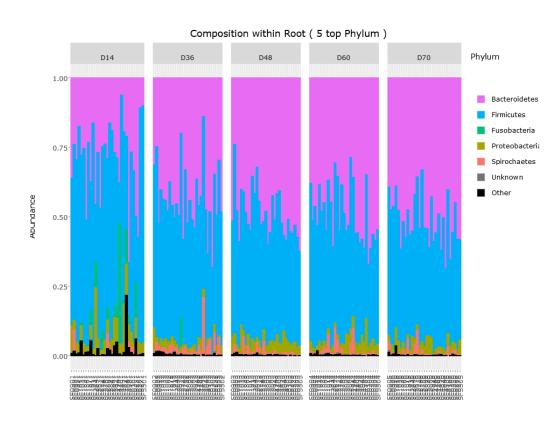
→ What can you conclude with the composition plots?



Plot bar coloured at the Phylum level on raw counts

- → Clearly, samples are not sequenced at the same depth
- → Data have to be rarefied

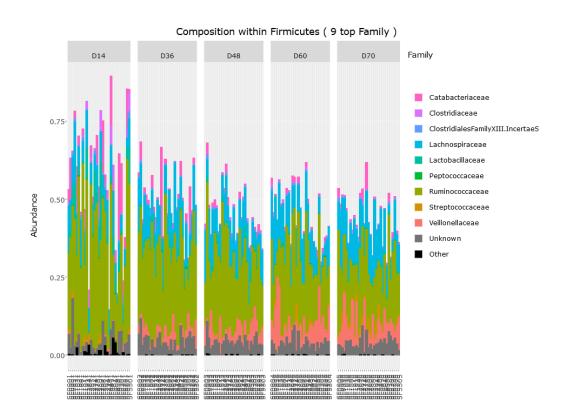
→ What can you conclude with the composition plots?



Composition plot of the 5 top Phylum coloured at the Phylum level on rarefied counts

→ The 2 most abundant Phylum are the Firmicutes and the Bacteroidetes

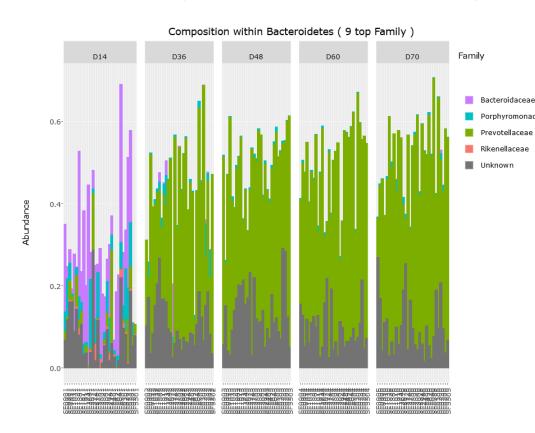
→ What can you conclude with the composition plots?



Composition plot of the 9 top Firmicutes families coloured at the Family level on rarefied counts

→ Veillonellaceae seems to rise after weaning, but the Firmicutes are not drastically change

→ What can you conclude with the composition plots?



Composition plot of the 9 top Bacteroidetes families coloured at the Family level on rarefied counts

→ After weaning Bacteroidetes composition has clearly changed.

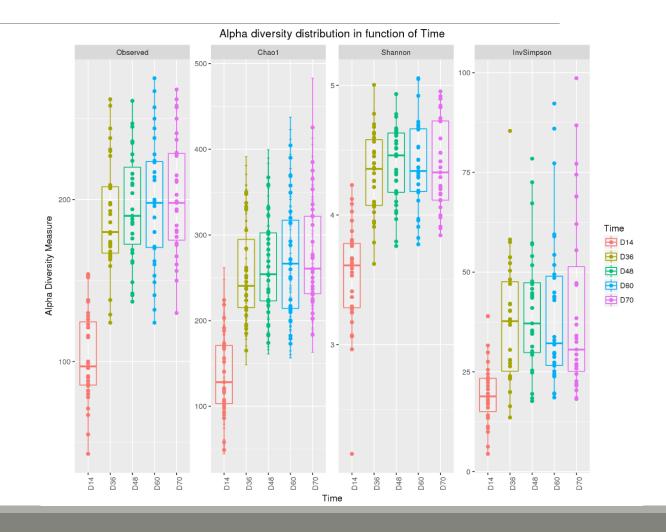
→ What about alpha diversity indices?

#### **Interpretation**

Diversity increases with time (with strong housing effect)

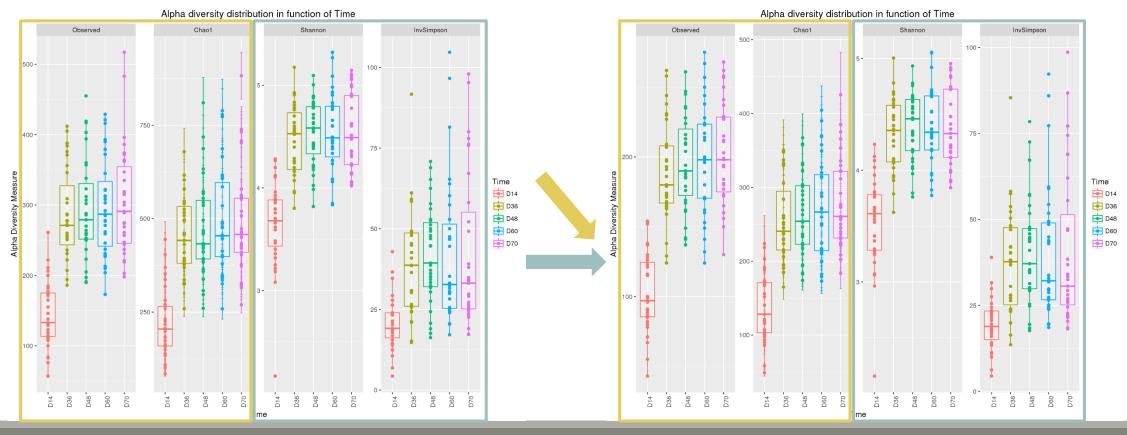
Low shannon/InvSimpson diversities compared to Observed, Chao1

→ communities are dominated by a moderate number of abundant taxa



Effective diversities are more robust to depth bias

→ Either correct for depth or perform rarefaction before comparing diversities



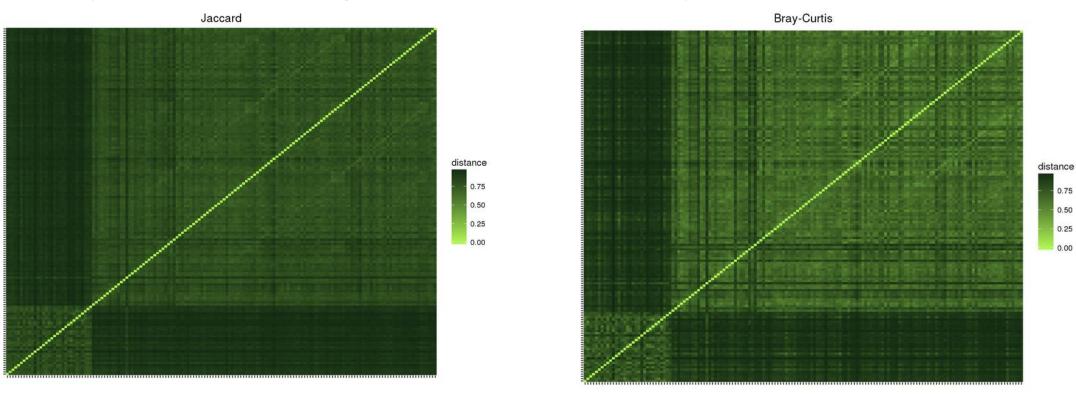
- → Now, how to analyse the OTU/sample structure?
  - → First step is to compute distance matrix : beta diversities also called dissimilarities
  - Then use it to:
    - represent samples in a 2D graphic that best respect this distance matrix.
    - test that clustering samples based on dissimilarities looks like expected.
    - construct heatmap to discover if samples/OTUs are connected.

Test the 4 most common distances.

→ Can you conclude something based on distance matrix comparison

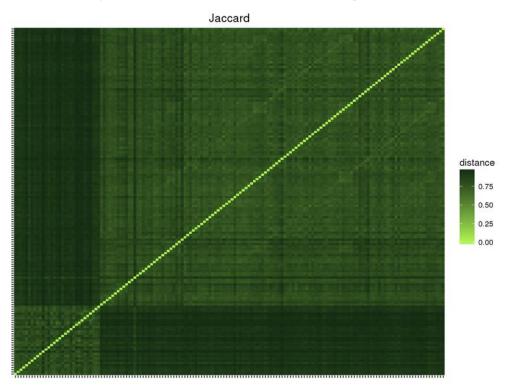
→ Can you conclude something based on the graphical representations of samples/OTUs, which type of distance fit the most our data?

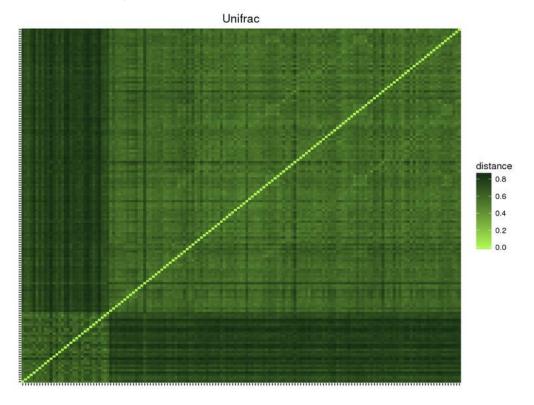
→ Can you conclude something based on distance matrix comparison



Jaccard higher than Bray-Curtis → abundant taxa are shared

→ Can you conclude something based on distance matrix comparison

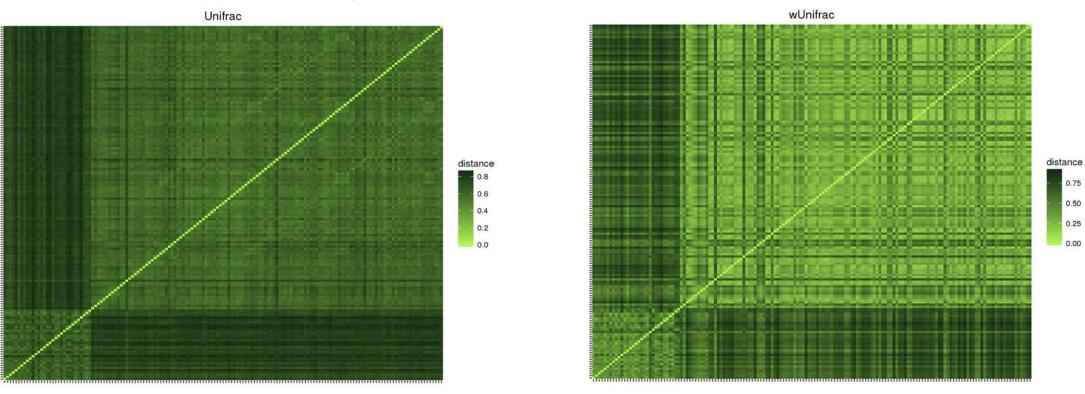




Jaccard higher than Unifrac

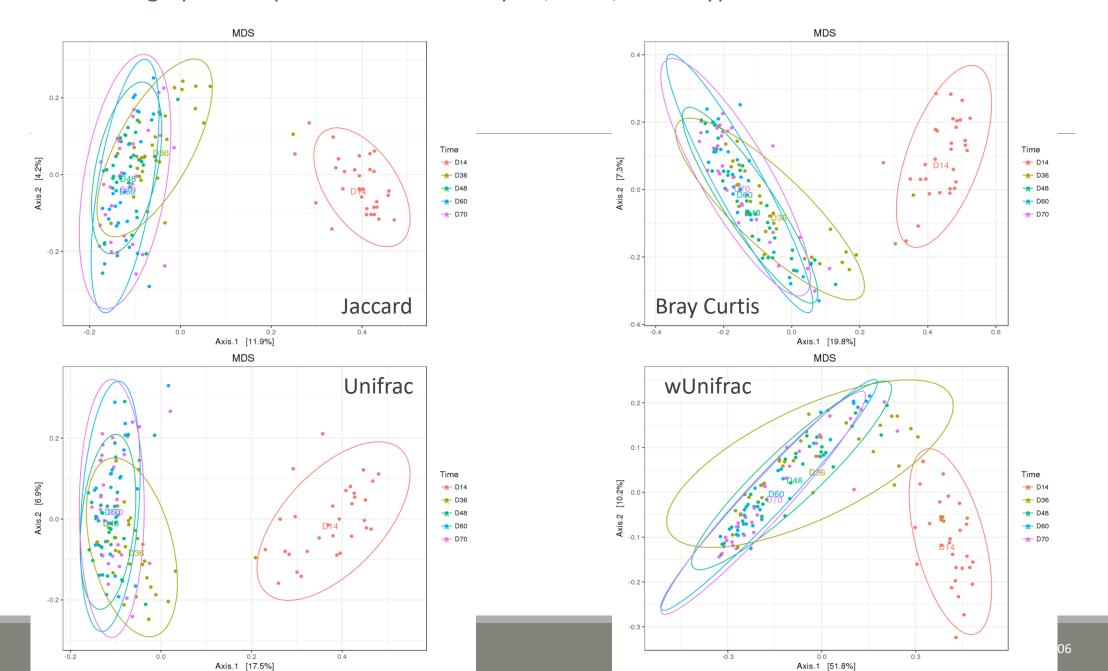
→ community taxa are distinct but phylogenetically related

→ Can you conclude something based on distance matrix comparison



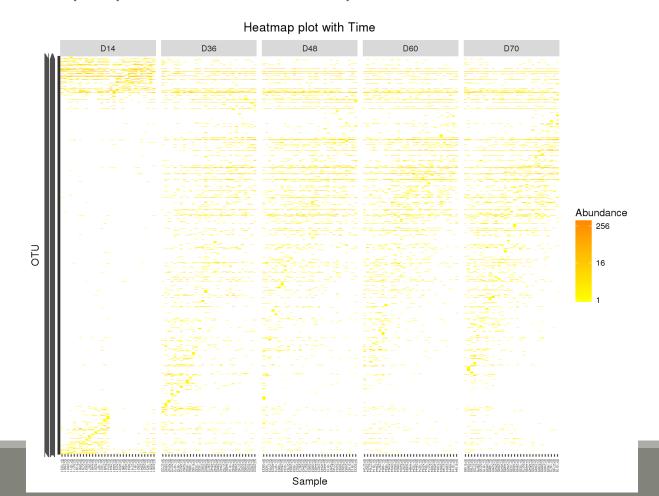
Unifrac higher than weighted Unifrac → abundant taxa in communities are phylogenetically close

→ Based on the graphical representations of samples/OTUs, which type of distance fit the most our data?



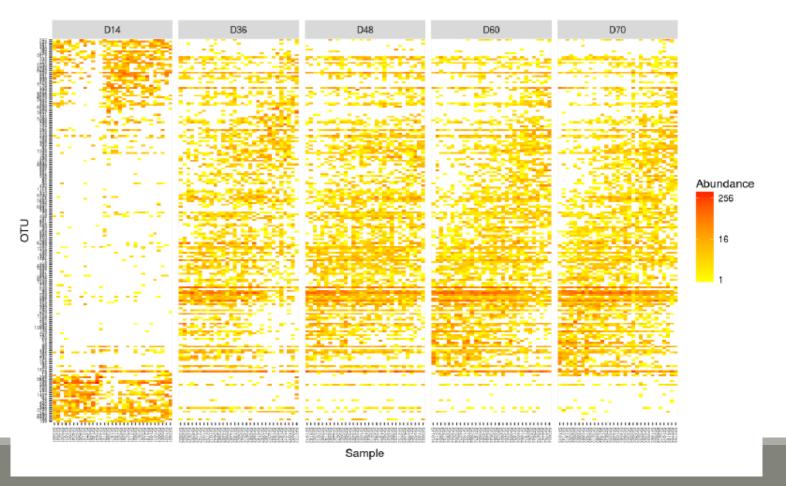
- → Based on the graphical representations of samples/OTUs, which type of distance fits the most our data?
- Qualitative distances (Unifrac, Jaccard) separate D14 and the rest.
- weighted Unifrac mixes up some samples: the taxa separating D14 from the rest may be replaced by (phylogenetically) close siblings.
- All distances (weighted Unifrac) exhibit a high gradient corresponding to high heterogeneity of samples on axis 2.
- Distance between groups seems to be smaller with qualitative distances (Jaccard/Unifrac) than quantitative distance → specific species before or after weaning must be pretty rare.
- Warning: The 2-D representation capture only part of the original distances.

→ Based on the heatmap representation are samples/OTUs connected?



→ Based on the heatmap representation are samples/OTUs connected?

Heatmap on 200 most abundant OTU

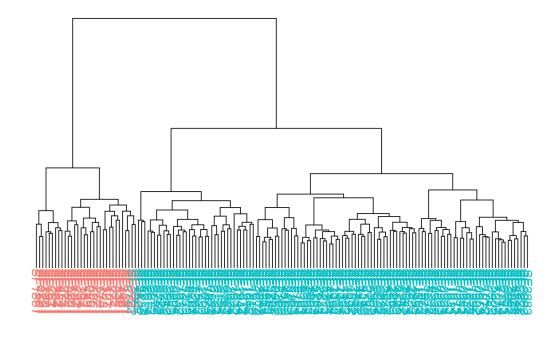


→ Based on the graphical representations of samples/OTUs, which type of distance fit the most our data?

#### **Hierarchical clustering plots:**

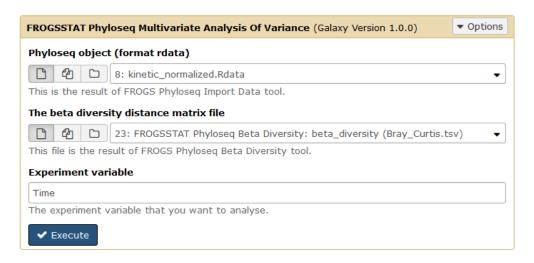
- Consistent with the ordination plots, clustering shows a good structure (D14 vs. rest or Weaned FALSE vs TRUE) for the Bray-Curtis distance for the Ward linkage
- Different distances would result (in this case)
   in similar results.
- Clustering is based on the whole distance whereas ordination represents parts of the distance (the most it can with 2 dimensions)

#### Sample Clustering with Ward.D2 linkage



We found that Time or Weaned seems to have an effect on sample diversities.

- → How can we measure this effect ?
  - > by performing a multivariate analysis of the variance



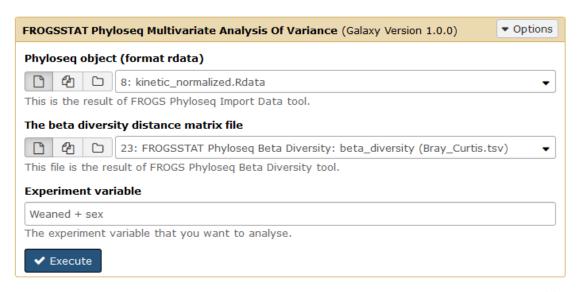
```
Call:
adonis(formula = dist ~ Time, data = metadata, permutations = 9999)
Permutation: free
Number of permutations: 9999
Terms added sequentially (first to last)
           Df SumsOfSqs MeanSqs F.Model
                                            R2 Pr(>F)
                  9.560 2.3899 9.6484 0.20464 1e-04 ***
Time
Residuals 150
                 37.155 0.2477
                                       0.79536
Total
          154
                46.714
                                       1.00000
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Time explains significantly around 20% of the beta diversity variance

#### **Comment:**

You can use more complexe formula:

to analyse multiple variable at the same time



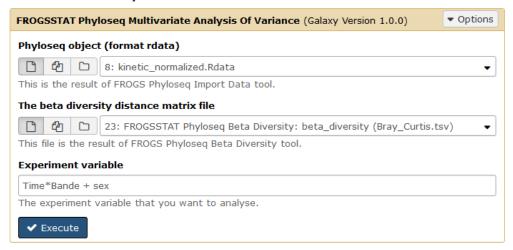
```
Call:
adonis(formula = dist ~ Weaned + sex, data = metadata, permutations = 9999)
Permutation: free
Number of permutations: 9999
Terms added sequentially (first to last)
          Df SumsOfSqs MeanSqs F.Model
                                             R2 Pr(>F)
                 7.840 7.8397 30.9042 0.16782 0.0001 ***
Weaned
                 0.315 0.3155 1.2437 0.00675 0.1583
Residuals 152
                38.559 0.2537
                                        0.82542
          154
                46.714
                                       1.00000
Total
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Only Weaned has an effect and it explains significantly around 17% of the beta diversity variance

#### **Comment:**

You can use more complexe formula:

- to analyse multiple variable at the same time
- to analyse variable interaction



```
Call:
adonis(formula = dist ~ Time * Bande + sex, data = metadata,
                                                                  permutations = 9999)
Permutation: free
Number of permutations: 9999
Terms added sequentially (first to last)
            Df SumsOfSqs MeanSqs F.Model
                                              R2 Pr(>F)
Time
                   9.560 2.38988 10.3916 0.20464 0.0001 ***
Bande
                   2.804 0.56076 2.4383 0.06002 0.0001 ***
                   0.302 0.30170 1.3118 0.00646 0.1233
                   5.531 0.27656 1.2025 0.11841 0.0116 *
Residuals 124
                  28.518 0.22998
                                         0.61048
                                         1.00000
Total
          154
                  46.714
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Time and Bande have independently an effect as well as their combination which explains significantly around 37% of the beta diversity variance

# Annexes

#### References

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- Shade, A., Jones, S. E., Caporaso, J. G., Handelsman, J., Knight, R., Fierer, N., and Gilbert, J. A. (2014). Conditionally rare taxa disproportionately contribute to temporal changes in microbial diversity. MBio, 5(4):e01371{e01314.