

Microbiota-Analysis

Jacqueline Wyss, 21.06.2023

Overview

1. Definitions
2. Sample processing
3. Data analysis
 - Alpha diversity
 - Beta diversity
 - Taxonomy
 - Differential abundance
 - Correlation
 - Models/classification

Introduction: Microbiology vs Microbiota-Studies



Culturing based



Sequencing based

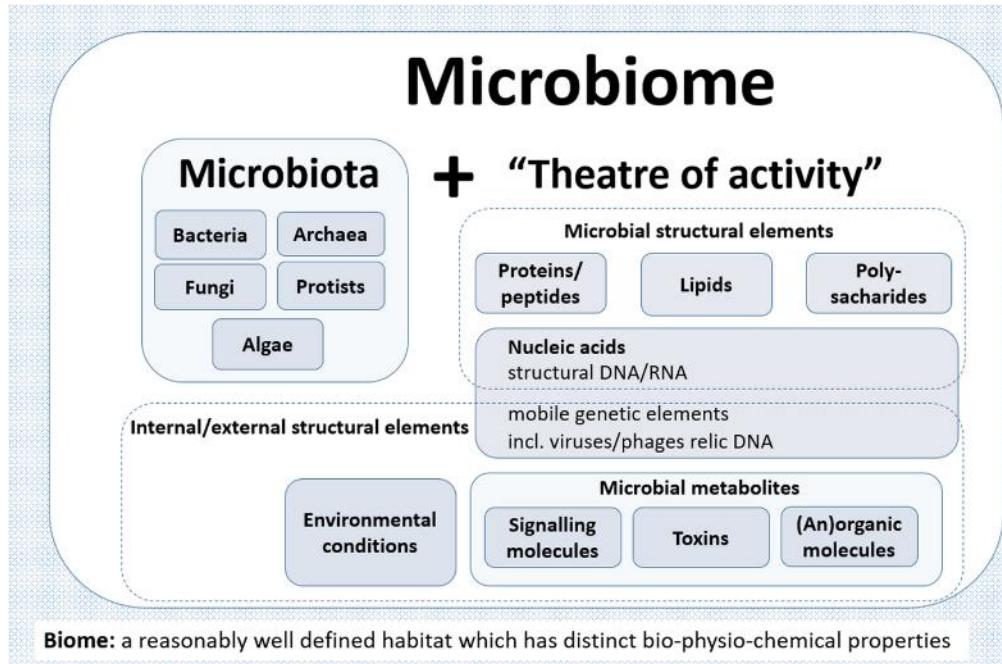
Introduction: Definitions

Microbiota:

Microbiome:

Meta

- Genomics
- Transcriptomics
- Metabolomics



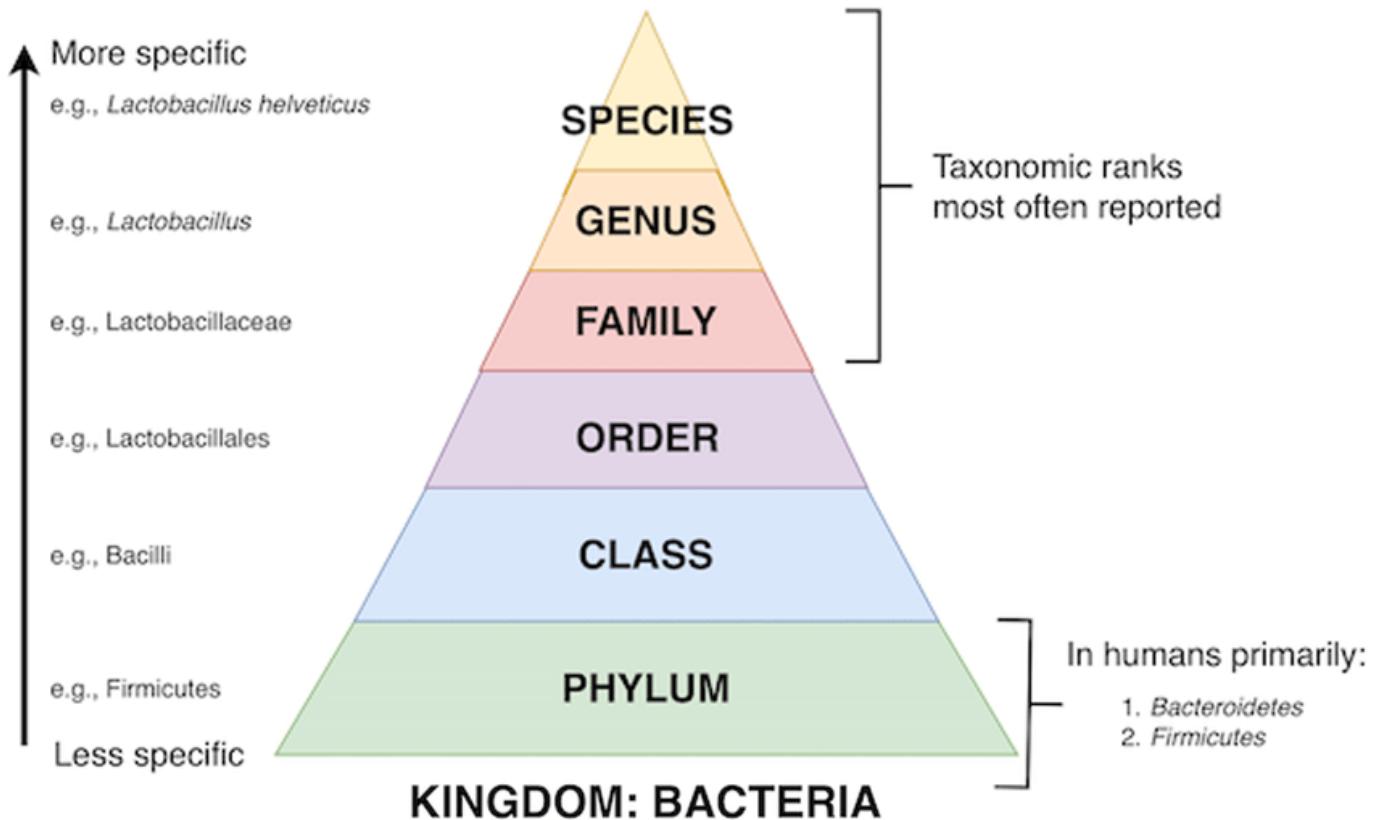
Berg et al. Microbiome 2020

Introduction: Definitions

Taxonomy:

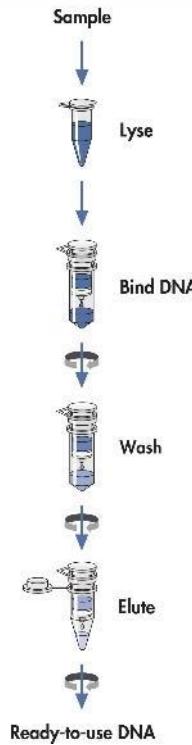
- Species: Strains
- Substrains

Taxa: no definition of the taxonomic level



Ameringen et al. Depression and Anxiety 2019

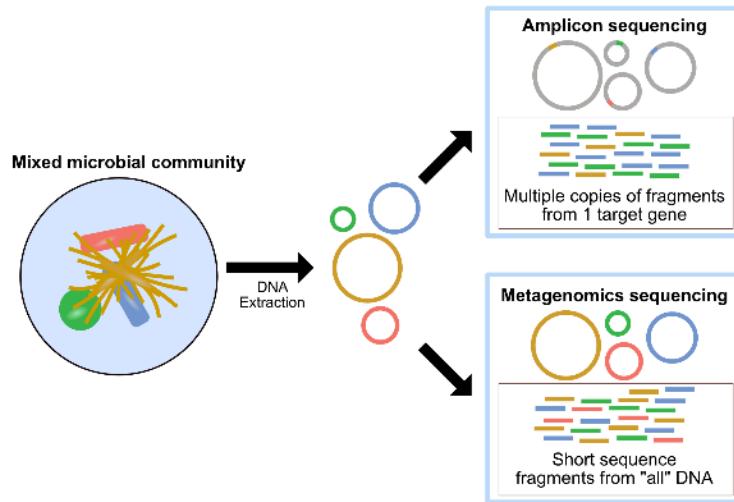
Workflow: Sample preparation



DNA is extracted from the samples

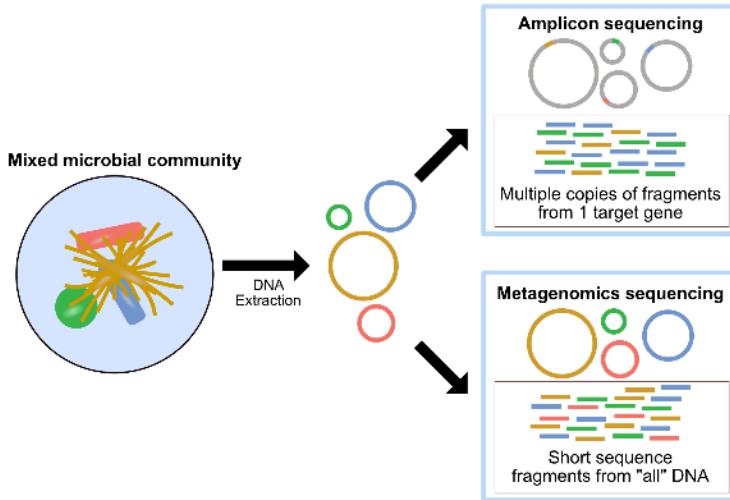
DNA can then be used for sequencing

Workflow: Amplicon vs full metagenomic sequencing



<https://astrobiomike.github.io>

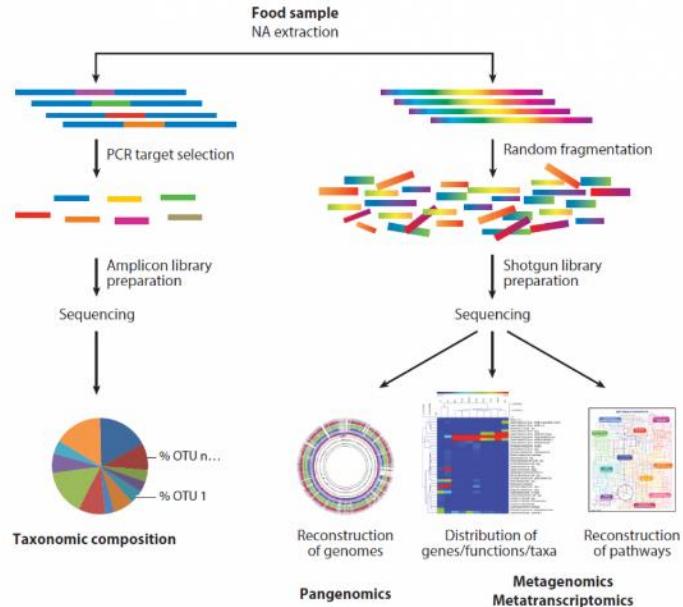
Workflow: Amplicon vs full metagenomic sequencing



In microbiota studies most often a hypervariable region of the 16S subunit is used as a target gene for amplification

<https://astrobiomike.github.io>

Workflow: Amplicon vs full metagenomic sequencing



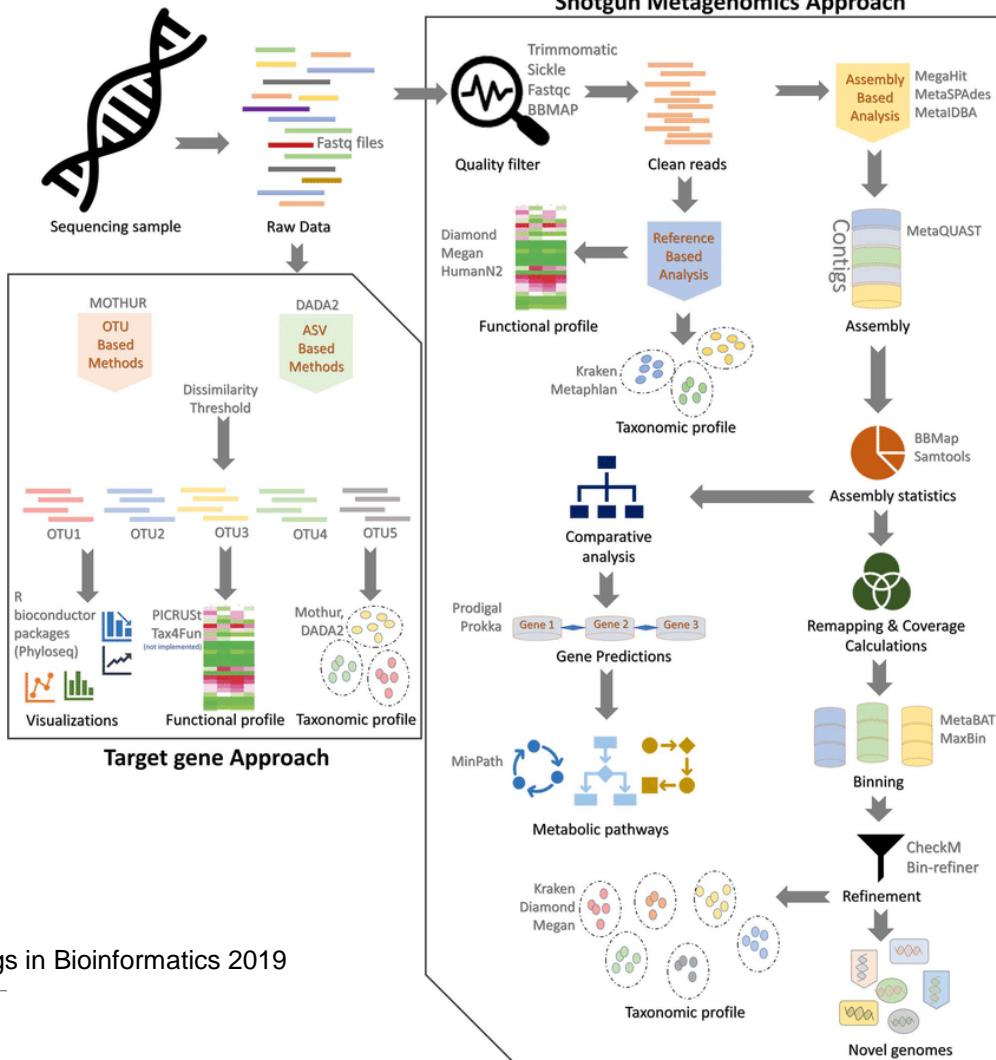
16S sequencing =
amplicon sequencing

We mainly get
information about the
taxa composition

De Filippis F., et al, 2018

Workflow: Sequencing analysis

Raw sequencing data
is analysed by
bioinformatic pipelines
and packages



Bharti et al. *Briefings in Bioinformatics* 2019

Raw sequencing data: FASTQ files

```
@DMJVU:00004:00006  
TTCAATTGGCATTAGATACCCCTGGTAGTCCACGCCGTAACGATGTCGAC  
TTGGAGGTTGTGCCCTTG  
+  
;75505057;66ACDCCCCC?DC6<;;666;606666,6666666666606066060666--  
)-)  
@DMJVU:00004:00009  
CTAGGAACCGCATTAGATACCCCTGGTAGTCCACGCCGTAACGATGAGT  
GCTAGGTGTTAGACCCTTCCGGGGTTAGTGCCGCAGCTAACGCATTA  
AGCACTCCGCCTGGGGAGTACGACCGCAAGGTTGAAACTCAAAGGAATT  
GACGG  
+  
;:5D0;7606=66;@CD???B::;7;B@ @B7<<  
A>A;::;6@ @;6>;4==@0;;05;49C  
*44*4.4==*44*4444EAC?5:8//)--  
//:3@39@<;;7;C6;;@B7@CBACC::4:@ @<@=B5:::/:::2*2.239.-----
```

Sample identifier

Sequencing result

Quality score

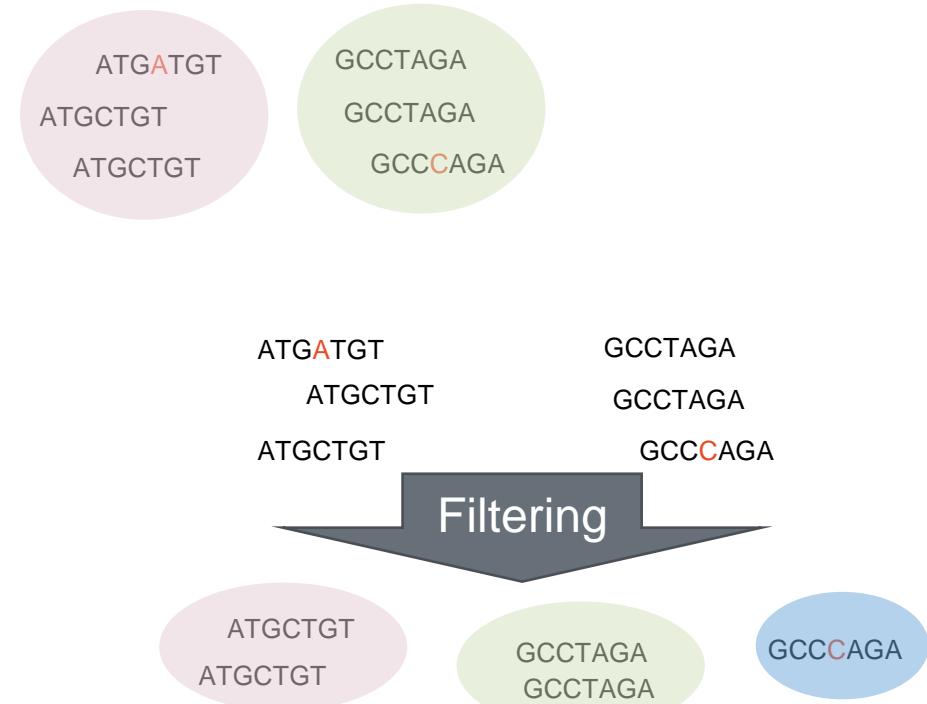
Workflow: Grouping reads

OTU: operational taxonomic units

Grouping by consensus (e.g. 97%)

ASV: amplicon sequencing variants

Denoising and quality filtering before
grouping exact matches



Workflow: Scripts and Server

```
*MicroCarbComb.sh - Editor
Datei Bearbeiten Format Ansicht Hilfe
#!/bin/sh
#!/bin/bash
#SBATCH --job-name="Iontorrent"
#SBATCH --mail-user=jacqueline.wyss@dbmr.unibe.ch
#SBATCH --mail-type=end,fail
#SBATCH --nodes=1
#SBATCH --time=72:00:00
#SBATCH --mem-per-cpu=32G
#SBATCH --partition=epyc2

##SBATCH --output=~/MicroCarb/Combined
##SBATCH --error=~/MicroCarb/Combined

#### Your shell commands below this line ####

## QIIME pipeline shell script ##

# set language
export LC_CTYPE=en_US.UTF-8
export LC_ALL=en_US.UTF-8
# source activate qiime2-2020.2
source activate qiime2-2023.2
cd /storage/workspaces/dbmr_sg/microbarb/MicroCarb/MicroCarbComb

qiime feature-table merge \
--i-tables /storage/workspaces/dbmr_sg/microbarb/MicroCarb/MC001_002/table_Chip_MC001_002.qza \
--i-tables /storage/workspaces/dbmr_sg/microbarb/MicroCarb/MC004_005/table_Chip_MC004_005.qza \
--i-tables /storage/workspaces/dbmr_sg/microbarb/MicroCarb/MC008_007/table_Chip_MC008_007.qza \
--i-tables /storage/workspaces/dbmr_sg/microbarb/MicroCarb/MC008_009/table_Chip_MC008_009.qza \
--o-merged-table table_MicroCarb.qza

qiime feature-table merge-seqs \
--i-data /storage/workspaces/dbmr_sg/microbarb/MicroCarb/MC001_002/rep-seqs_Chip_MC001_002.qza \
--i-data /storage/workspaces/dbmr_sg/microbarb/MicroCarb/MC004_005/rep-seqs_Chip_MC004_005.qza \
<
```

Zeil 1, Spalte 2 100% Unix (LF) UTF-8

```
jw21z307@submit02:/storage/workspaces/dbmr_sg/microbarb/MicroCarb/MicroCarbComb
drwxrwsr-x 3 jw21z307 microbarb 4096 Apr 16 22:27 MC006_007
drwxrwsr-x 3 jw21z307 microbarb 4096 Apr 27 13:13 MC008_009
drwxrwsr-x 2 jw21z307 microbarb 4096 Jun 14 15:58 MicroCarbComb
drwxrwsr-x 2 jw21z307 microbarb 4096 Jun 14 15:57 SILVA
drwxrwsr-x 7 jw21z307 microbarb 4096 May 19 12:23 picrust
-rw-rw-r-- 1 jw21z307 microbarb 531637835 Mar 10 21:15 silva-138-99-nb-classifier.qza
(base) [jw21z307@submit02 MicroCarb]$ cd MicroCarbComb/
(base) [jw21z307@submit02 MicroCarbComb]$ ls
total 10131
-rw-rw-r-- 1 jw21z307 microbarb 31602 Apr 27 14:34 MicroCarb.tsv
-rw-rw-r-- 1 jw21z307 microbarb 2630 Jun 14 15:58 MicroCarbComb.sh
-rw-rw-r-- 1 jw21z307 microbarb 399485 May 5 11:21 aligned-rep-seqs_MicroCarb.qza
-rw-rw-r-- 1 jw21z307 microbarb 387187 May 5 11:21 masked-aligned-rep-seqs_MicroCarb.qza
-rw-rw-r-- 1 jw21z307 microbarb 302098 May 5 11:19 rep-seqs_MicroCarb.qza
-rw-rw-r-- 1 jw21z307 microbarb 268761 May 5 11:21 rooted-tree_MicroCarb.qza
-rw-rw-r-- 1 jw21z307 microbarb 12251 Mar 29 11:31 slurm-51411561.out
-rw-rw-r-- 1 jw21z307 microbarb 12272 Mar 29 11:37 slurm-514211897.out
-rw-rw-r-- 1 jw21z307 microbarb 13981 Mar 30 10:24 slurm-51479728.out
-rw-rw-r-- 1 jw21z307 microbarb 6277 Mar 30 11:21 slurm-51481500.out
-rw-rw-r-- 1 jw21z307 microbarb 523 Mar 30 12:15 slurm-51482570.out
-rw-rw-r-- 1 jw21z307 microbarb 523 Apr 18 18:41 slurm-52604372.out
-rw-rw-r-- 1 jw21z307 microbarb 3698 Apr 27 15:52 slurm-52283720.out
-rw-rw-r-- 1 jw21z307 microbarb 1752 May 5 12:24 slurm-53871881.out
-rw-rw-r-- 1 jw21z307 microbarb 457406 May 5 11:19 table_MicroCarb.qza
-rw-rw-r-- 1 jw21z307 microbarb 5730638 May 5 12:24 taxonomy_bar-plots_MicroCarb.qzv
-rw-rw-r-- 1 jw21z307 microbarb 378674 May 5 12:24 taxonomy_MicroCarb.qza
-rw-rw-r-- 1 jw21z307 microbarb 2925093 May 5 12:24 taxonomy_MicroCarb.qzv
-rw-rw-r-- 1 jw21z307 microbarb 268195 May 5 11:21 unrooted-tree_MicroCarb.qza
(base) [jw21z307@submit02 MicroCarbComb]$ sbatch MicroCarbComb.sh
```

Sequences are filtered, demultiplexed
grouped and assigned to known sequences
in taxonomy databases

Workflow:

Feature table

	Sample 1	Sample 2	Sample 3
Taxa 1	0	0	2
Taxa 2	1	0	0
Taxa 3	10	2	15
Taxa 4	0	1	0

Feature tables are sometimes filtered (rare taxa, low abundance, rarefaction)

Microbiota data: analytic challenges

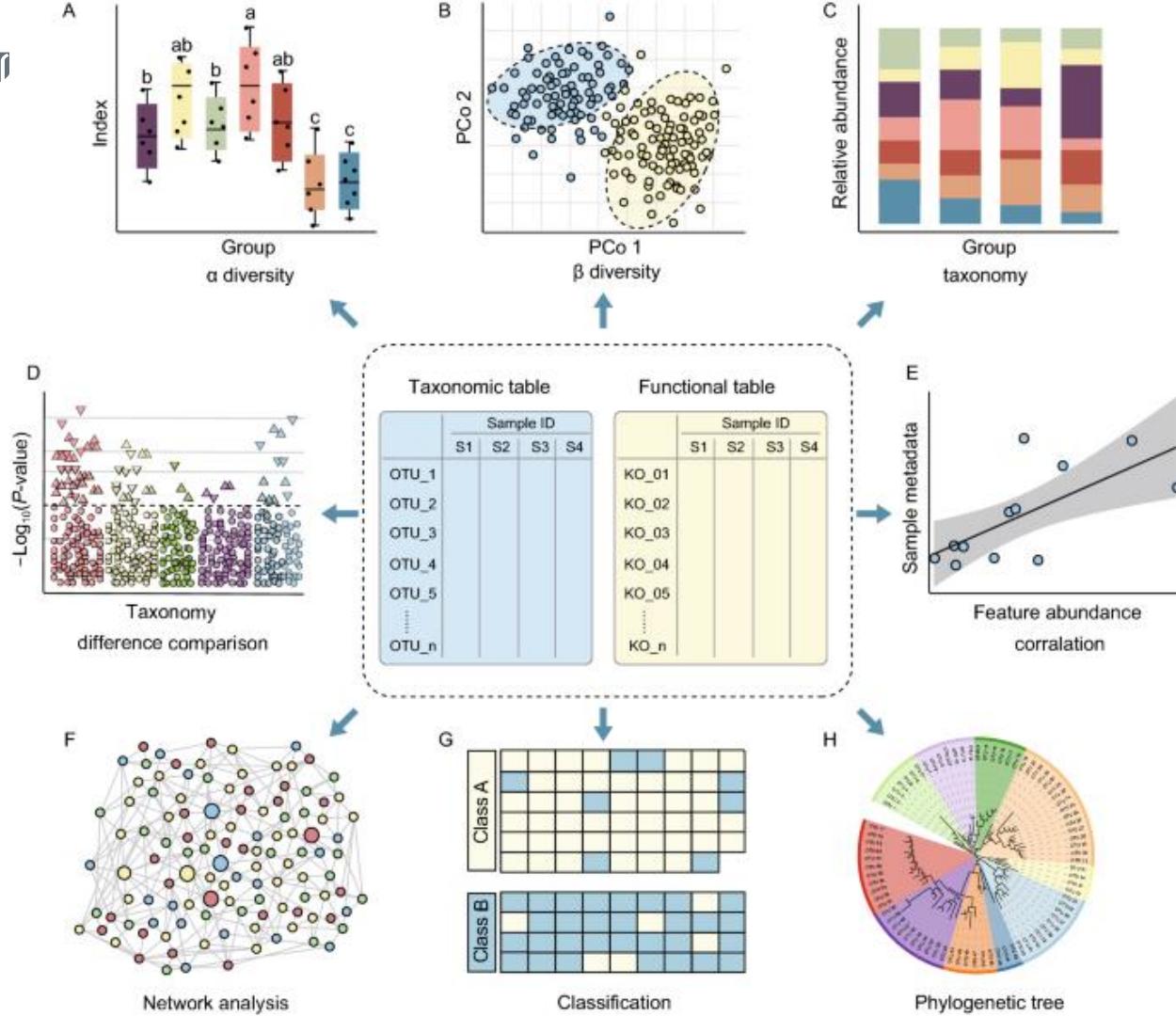
Taxonomic table		Functional table			
	Sample ID				
	S1	S2	S3	S4	
OTU_1					
OTU_2					
OTU_3					
OTU_4					
OTU_5					
⋮					
OTU_n					
		Sample ID			
		S1	S2	S3	S4
KO_01					
KO_02					
KO_03					
KO_04					
KO_05					
⋮					
KO_n					

Microbiota data is:

multivariable (= because every taxon is a variable)

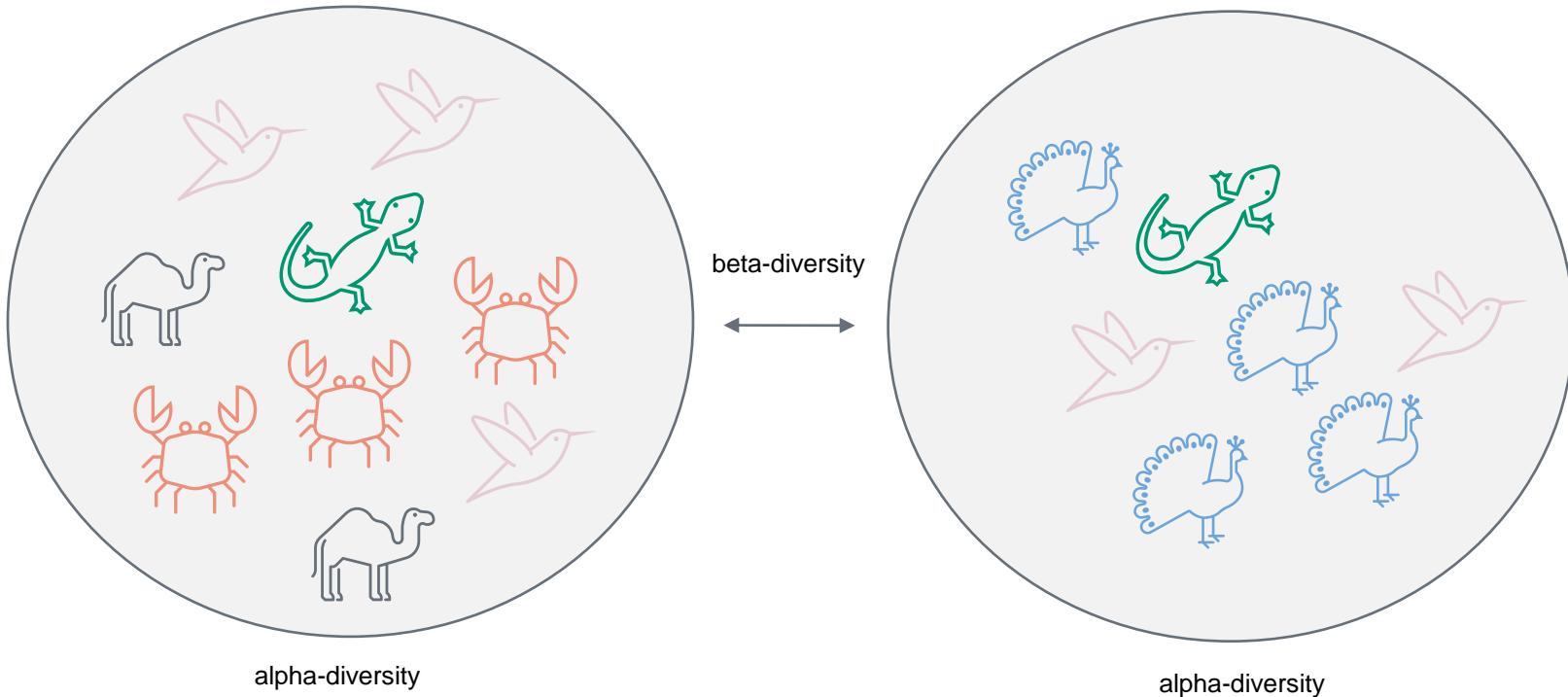
sparse (= have many zeros, because taxa are often only present in few samples)

compositional (= are not absolute measurements but are proportions)



Liu et al. Protein & Cell 2021

Microbiota as an ecosystem



Diversity measures

alpha diversity

Most simple: Species richness= total number of species at a site

Most popular alpha diversity measures:

- Simpson: between 0 and 1
$$D = 1 - \sum_{i=1}^s \frac{n_i(n_i - 1)}{n(n - 1)}$$
- Shannon: max= $\ln S$
$$H' = - \sum_i p_i \cdot \ln p_i \quad \text{mit } p_i = \frac{n_i}{N}$$
- Others: Chao1, ACE, ..

Simpson diversity example calculation:

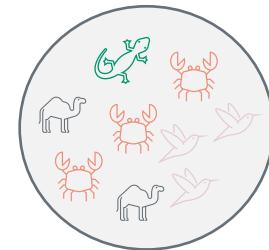
$$1*0/9*8 = 0$$

$$2*1/9*8 = 0.027$$

$$3*2/9*8 = 0.083$$

$$3*2/9*8 = 0.083$$

$$1-(2*0.083+0.027) = 0.8$$

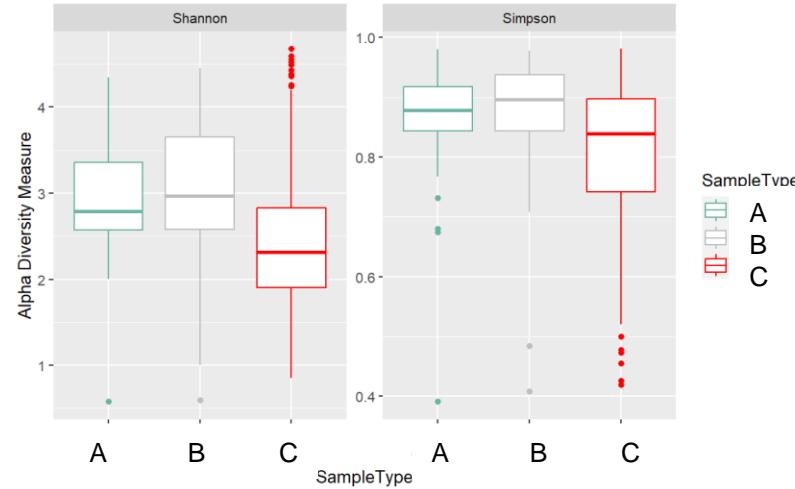


Alpha diversity Visualisation

Often visualised as boxplots per groups

Alpha diversity differences statistically evaluated like any other measurement:

- Wilcox-test, ANOVA



Diversity measures

beta diversity

Popular beta-diversity measures:

- Euclidean distance
- Aitchinson distance: central log transform + euclidean distance
- Bray-curtis dissimilarity
- UniFrac + weighted UniFrac: includes phylogenetic information
- Jaccard, Chao, Mahalobani, etc.



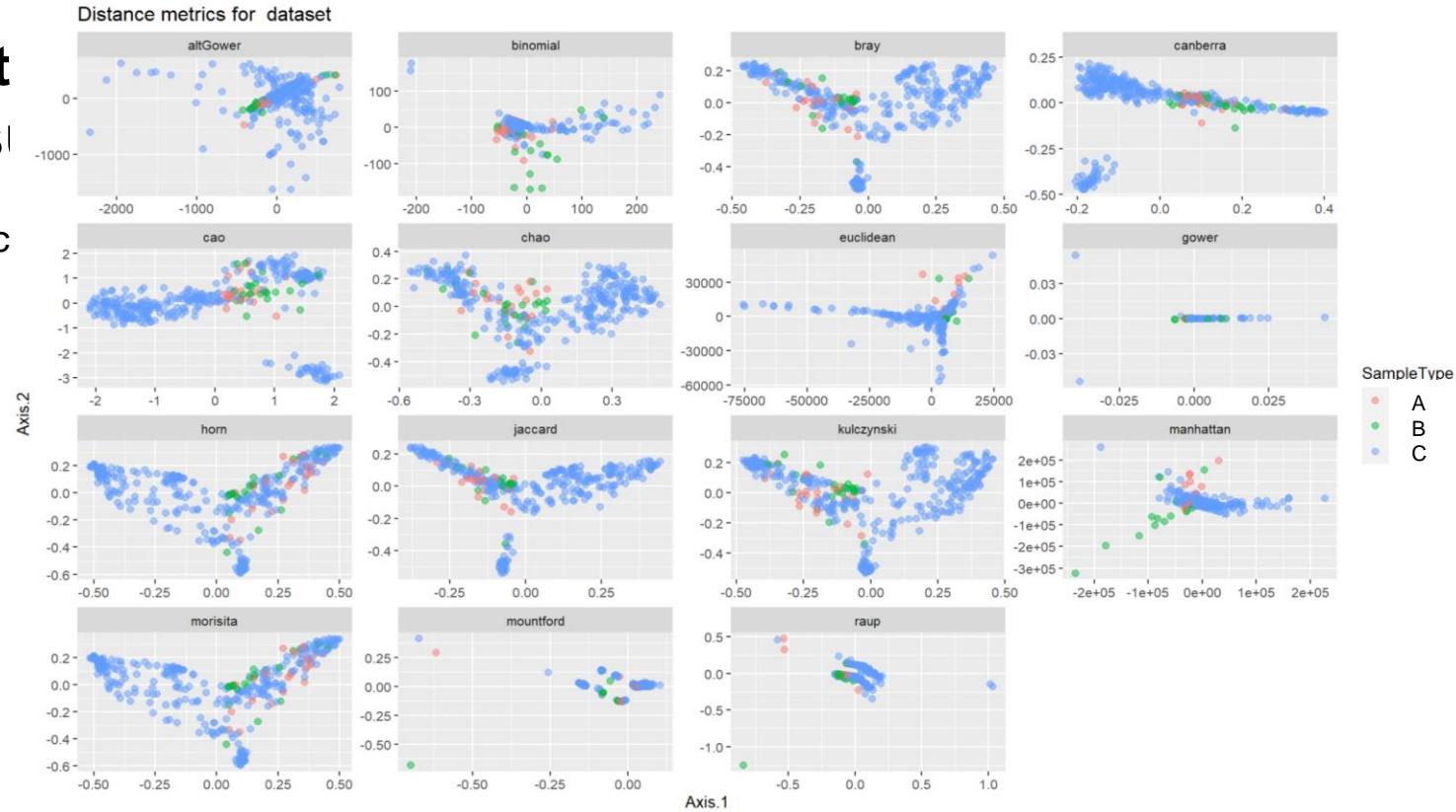
$$BC_{ij} = 1 - \frac{2C_{ij}}{S_i + S_j}$$

C= common species
S= total species at a site

$$\left(\frac{\text{sum of unshared branch lengths}}{\text{sum of all tree branch lengths}} \right) = \text{fraction of total unshared branch lengths}$$

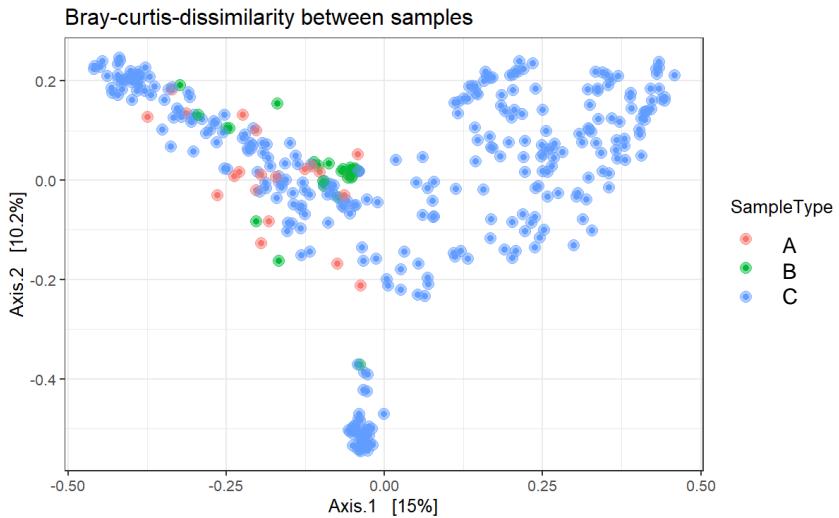
Bet Vis

Choic



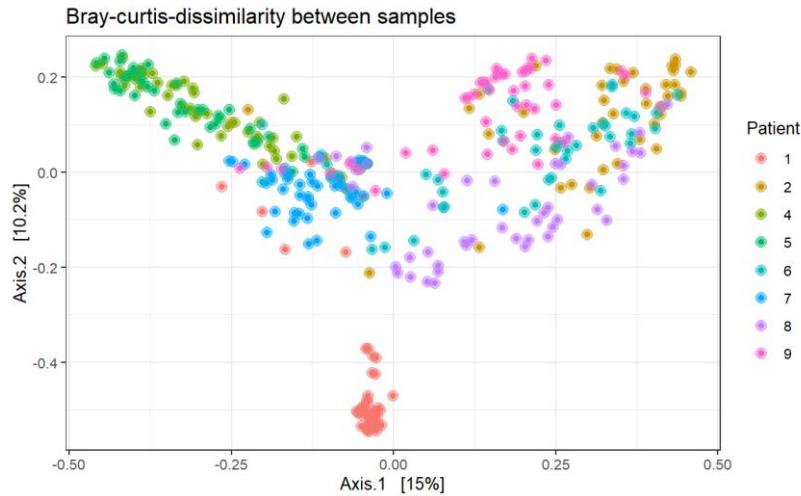
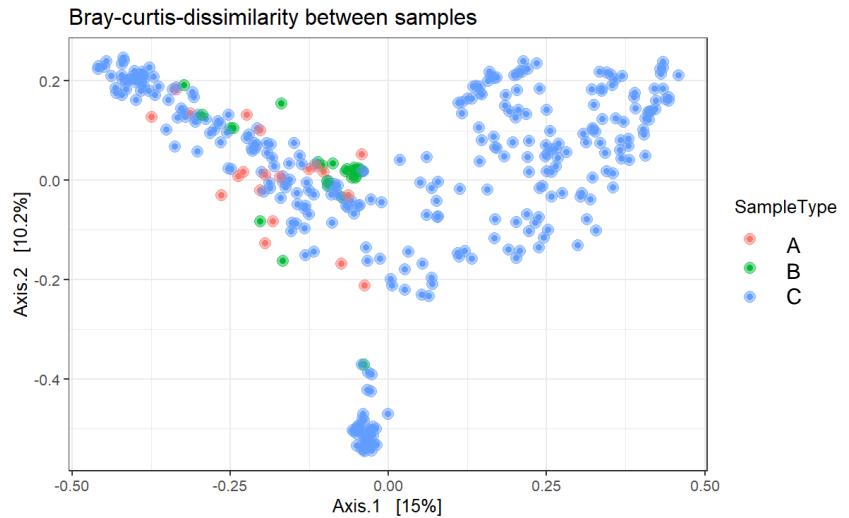
Beta diversity

Pitfall: Batch effects



Beta diversity

Pitfall: Batch effects



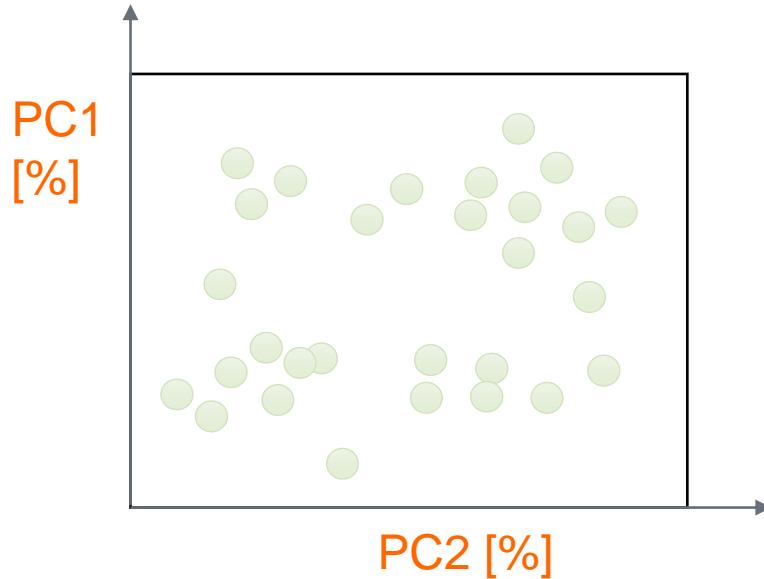
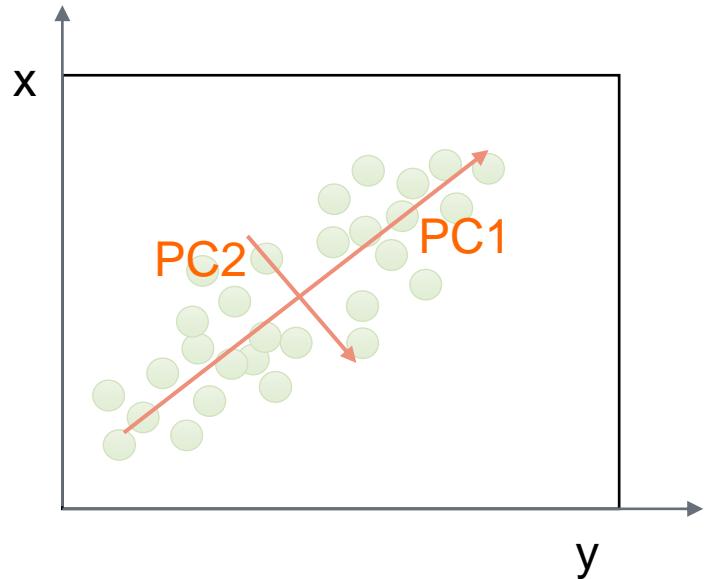
Beta diversity Ordination

Multivariate data can be plotted in a 2D way using dimensionality reduction techniques

- PCA: for any multivariate data set, characterizing the main axes of variance in the data
- PCoA: main axes of variance for distance matrices

Principal components

Idea



Beta diversity Ordination

Multivariate data can be plotted in a 2D way using dimensionality reduction techniques

- PCA: for any multivariate data set, characterizing the main axes of variance in the data
- PCoA: main axes of variance for distance matrices
- NMDS (Non-Metric Multidimensional Scaling): iterative process, axes can not be interpreted
- Other: correspondance analysis (CA), redundancy analysis (RDA): uses metadata variables for scaling

Beta diversity Visualisation

Choice of distance method is variable, ultimate goal is to see separation of groups

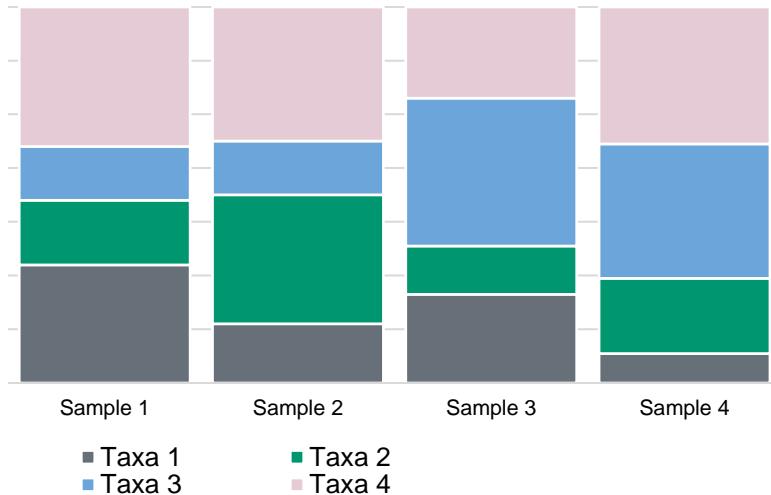
Beta diversity Visualisation

Significant differences between groups need to be tested by methods assessing multivariable data

- ANOSIM, ADONIS, PERMANOVA, MRPP

Taxonomy

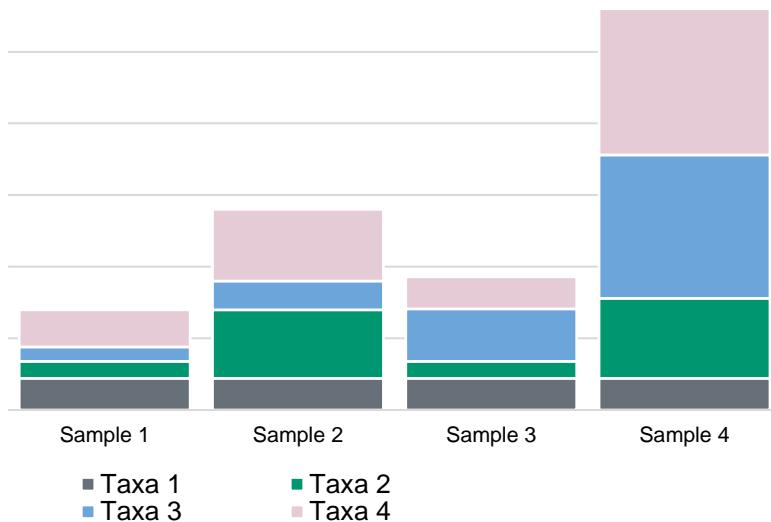
Taxa composition



Taxonomy results are not absolute,
taxa composition are proportions

Taxonomy

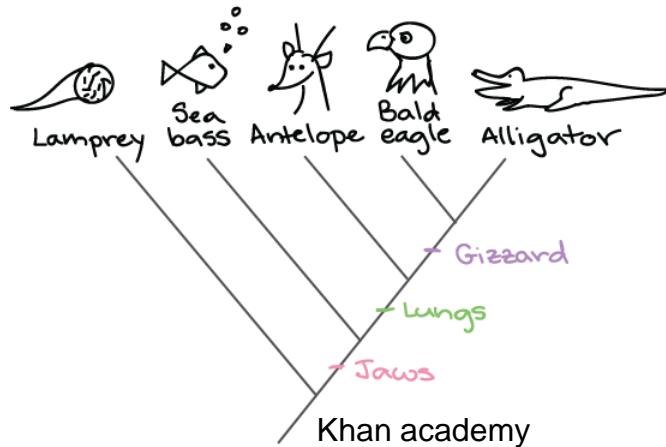
Taxa absolute numbers



This can lead to distortions if the overall bacterial count fluctuates between samples

Taxonomy

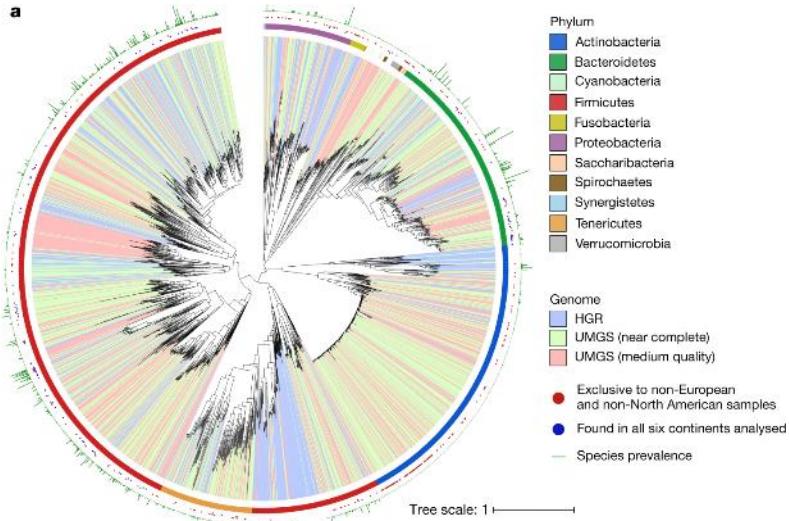
Phylogenetic trees



Phylogenetic trees can be built with reference databases or with information from the sequencing reads

Taxonomy

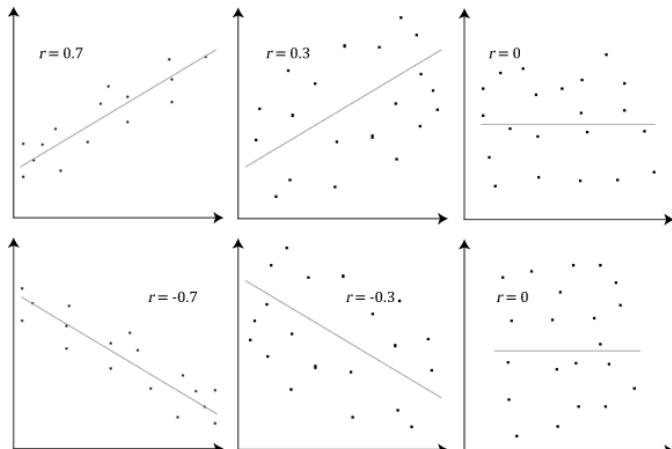
Phylogenetic trees



Phylogenetic trees can be built with reference databases or with information from the sequencing reads

Almeida et al. Nature, 2019

Analysis: Correlation analysis



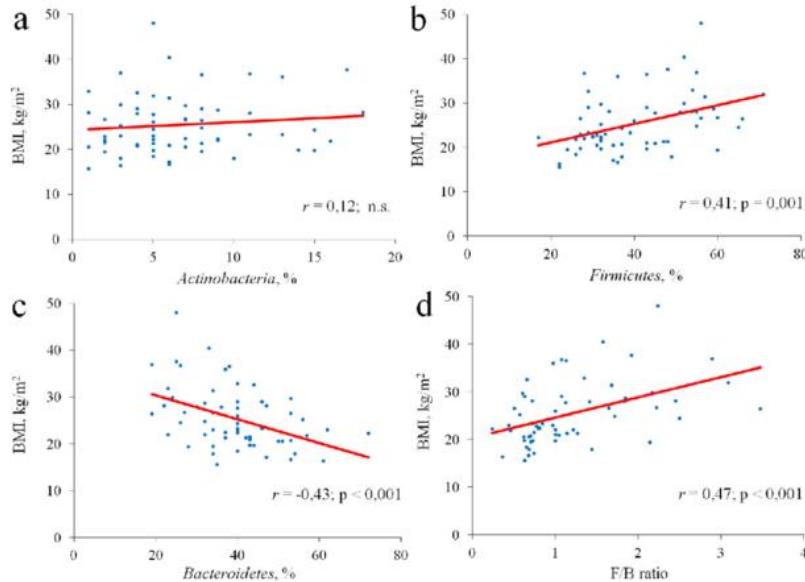
Wikipedia: Correlation

Data can be assessed for correlation structure

- Between microbiota
- Between microbiota and metadata

Because every taxa is tested separately results have to be adjusted by multiple testing correction

Correlation analysis: Visualisation

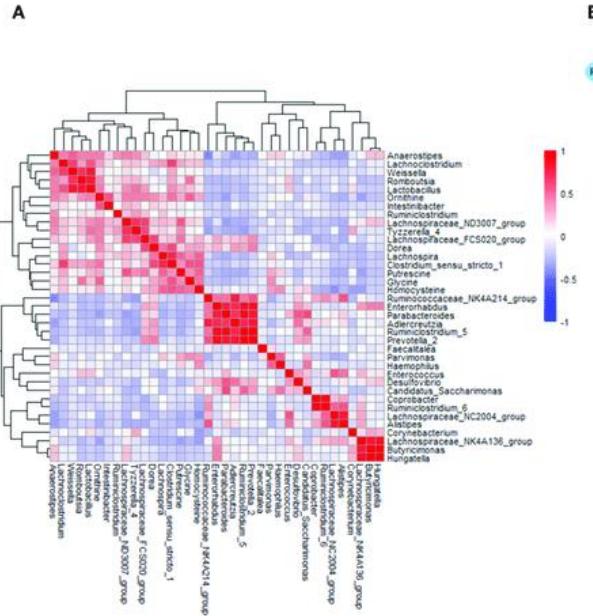


Correlations with one predictor can be depicted as a regression

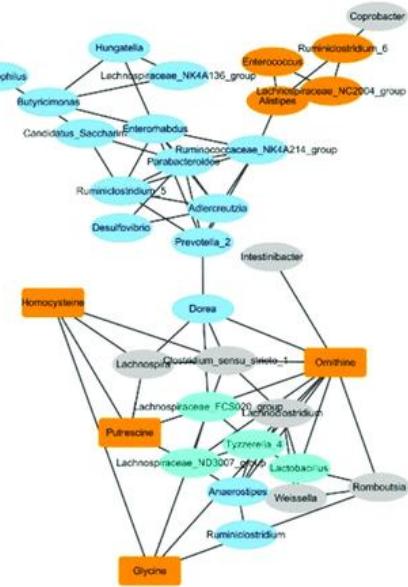
Multiple correlations can be depicted as a network analysis or in a correlation plot

Koliada et al. BMC Microbiology 2017

Correlation analysis: Visualisation



B



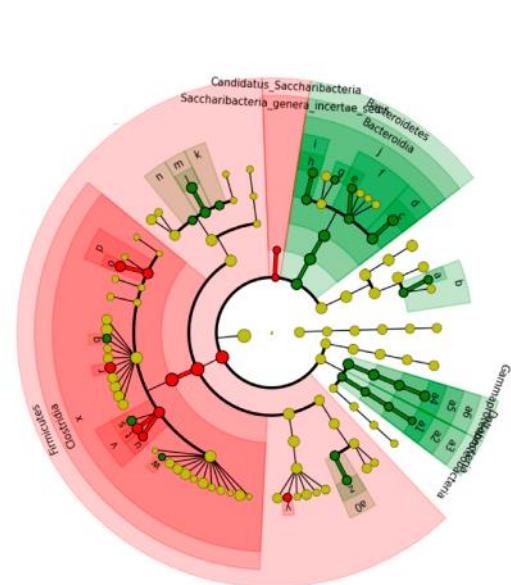
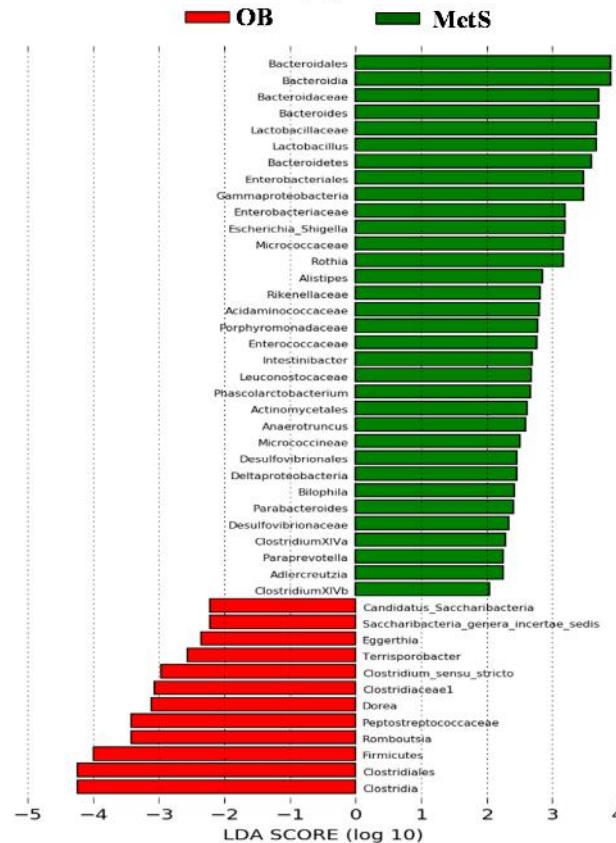
Correlations with one predictor can be depicted as a regression

Multiple correlations can be depicted as a network analysis or in a heatmap

Analysis

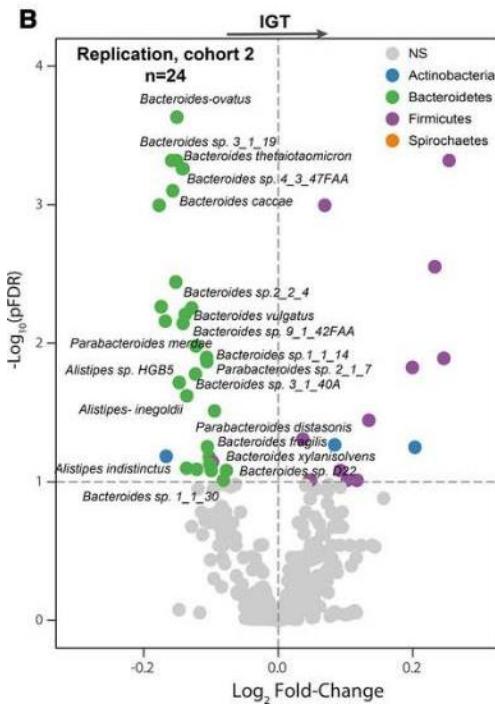
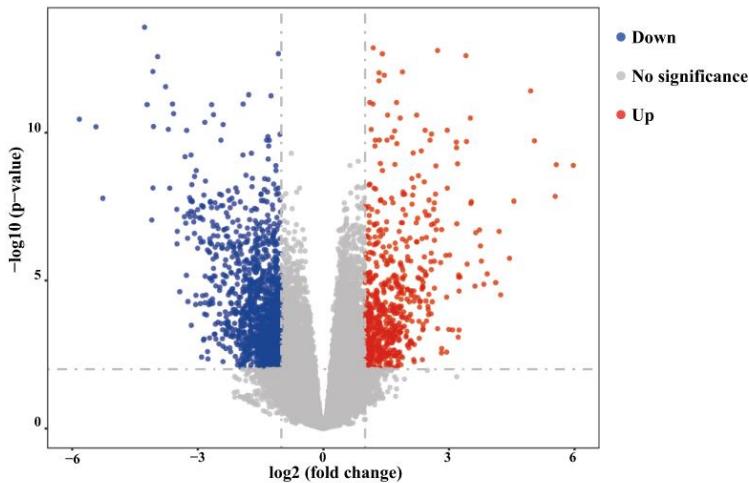
Differential abundance

Differential abundance tells us
which taxa differ significantly
between groups



Differential abundance Visualisation

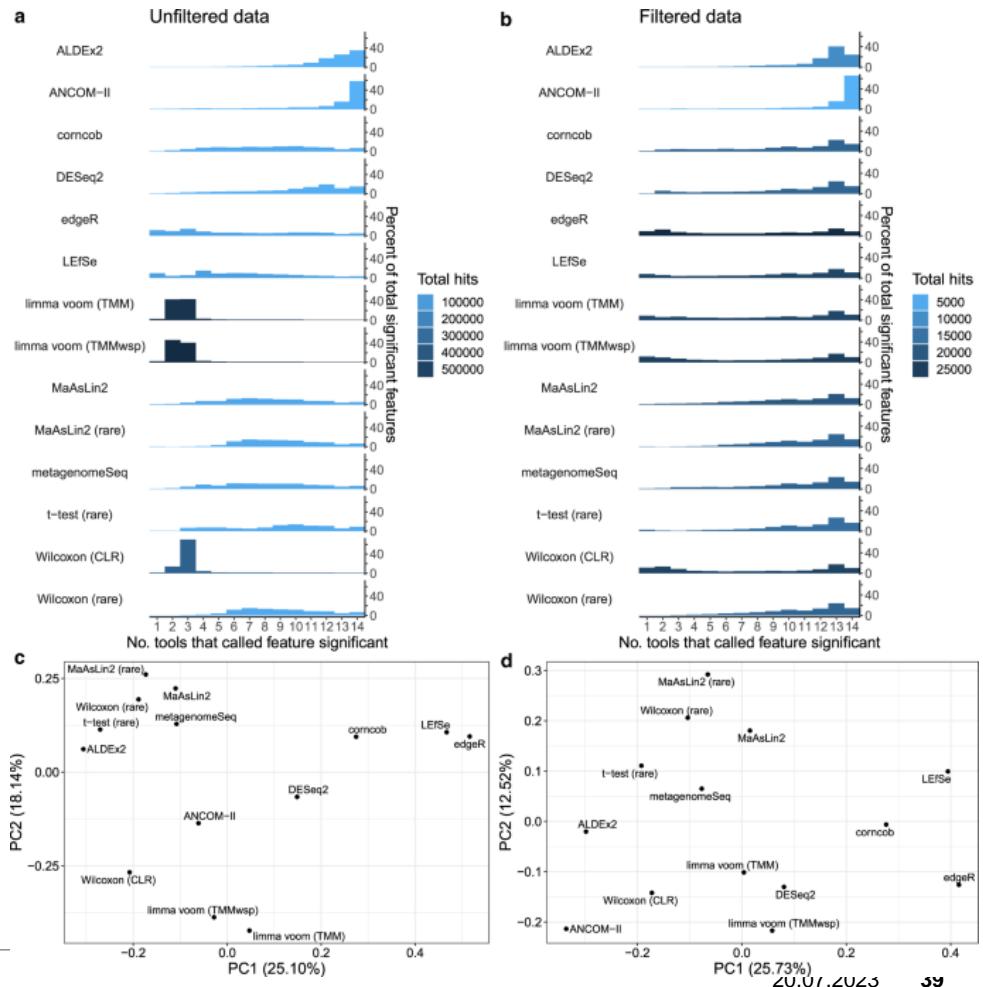
Volcano plot



Arnoriaga-Rodríguez et al., Gut, 2021

Analysis Differential abundance

Methods are not standardised and can output different results



Nearing et al. Nature communications 2022

Classification: Model fitting

If we have some hypothesis about the underlying structure of the data we can try to fit a model

- e.g. classification into two disease groups
- Model parameters can give information about which features (=e.g. taxa) are important

Classification: Model fitting

If we have some hypothesis about the underlying structure of the data we can try to fit a model

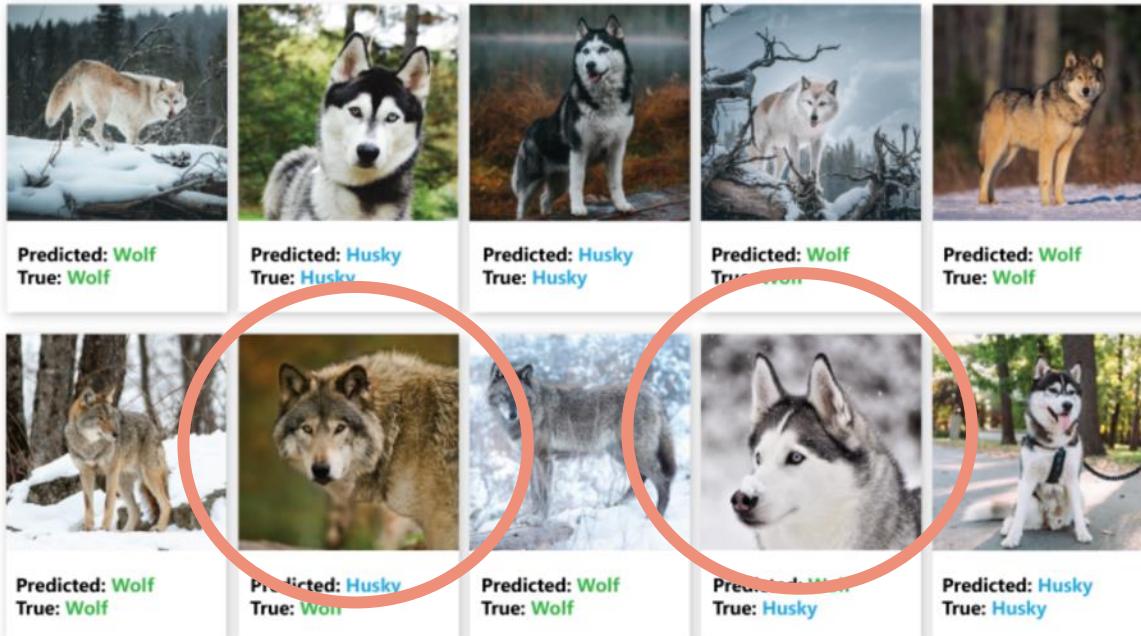
- e.g. classification into two disease groups
- Model parameters can give information about which features (=e.g. taxa) are important

Examples:

- Multiple linear regression
- Random forest
- Partial Least-Squares Discriminant Analysis (PLS-DA)
- Neural networks

Model fitting: pitfalls

Explain the Prediction



<https://carpentries-incubator.github.io/data-science-ai-senior-researchers/05-Problems-with-AI/index.html>

Overfitting

Overfitting: If a model uses a lot of features it can be fitted very well to a training data set

- Extreme: one variable classifies one samples -> perfect fit
- Problem: **This model will not be informative for a new unrelated data**

Solution: Validation with new data

- Cross-validation
- Splitting of data before analysis
- Second evaluation cohort



Model evaluation: AUC-ROC-curves

Good AUC results

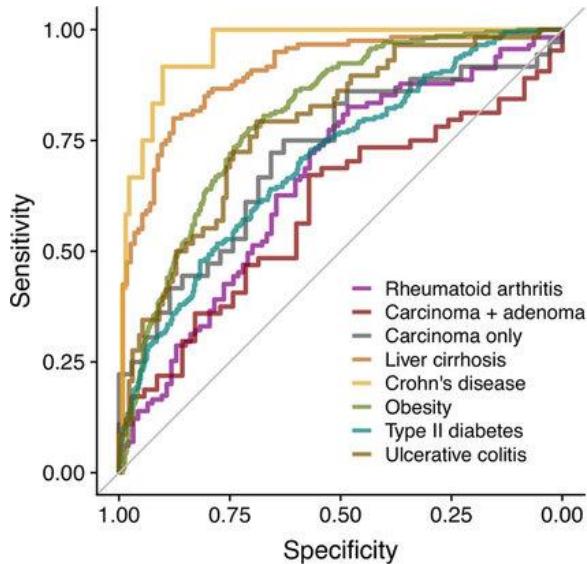
- Over 0.7: acceptable
- Over 0.8: excellent
- Over 0.9: outstanding

True positive rate (Precision) = $TP/(TP+FN)$

False positive rate = $FP/(FP+TN)$

Sensitivity (Recall): $1 - TPR$

Specificity: $1 - FPR$



Random Forest by Disease				
Level	Disease	Color	OOB error	AUC
Module	Crohn's Disease	Yellow	5.56%	0.954
Module	Liver cirrhosis	Orange	17.09%	0.902
Module	Obesity	Green	22.57%	0.803
Module	Ulcerative colitis	Brown	25.26%	0.783
Module	Type II diabetes	Blue	31.58%	0.708
Module	Rheumatoid arthritis	Purple	35.58%	0.664
Module	Colorectal carcinoma	Red	36.36%	0.596
Module	Carcinoma (without adenoma)	Grey	35.21%	0.715

Armour et. al, mSystems, 2019

Metagenomic analysis: Functional potential

Metagenomic sequencing analyses
the whole genome of bacteria

This includes bacterial enzymes:

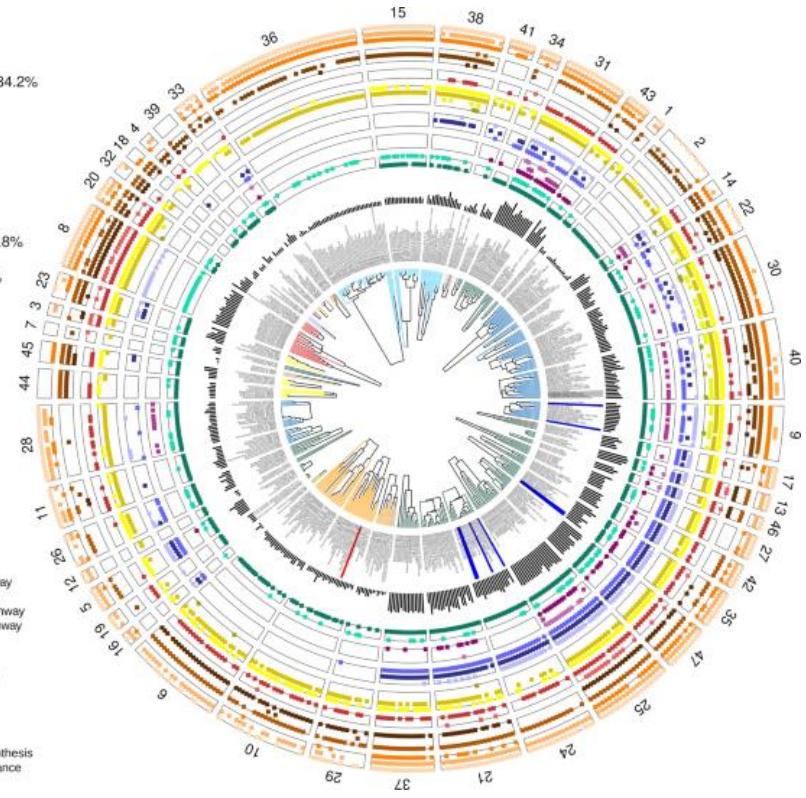
- Analysis of functional potential

Taxonomy:

Firmicutes	– 4%
Bdellovibrionota	– 0.6%
Gammaproteobacteria	– 34.2%
Actinobacterita	– 4.7%
Deinococotta	– 0.6%
Thermotogota	– 1.7%
Spirochaetota	– 0.6%
Others	– 3%
Desulfobacterota	– 1.1%
Cyanobacteria	– 15%
Aquificota	– 0.6%
Alphaproteobacteria	– 21.8%
Bacteroidota	– 11.4%
Campylobacterota	– 0.6%

Interaction-traits:

Vitamin B1 biosynthesis
Vitamin B7 biosynthesis
Vitamin B12 biosynthesis
Vitamin B1 transport
Vitamin B7 transport
Vitamin B12 transport
Fe-Siderophore
Fe-Siderophore transporter
Auxin: Indole-3-pyruvate pathway
Auxin: Tryptamine pathway
Auxin: Indole-3-acetonitrile pathway
Auxin: Indole-3-acetamide pathway
Quorum sensing
Chemotactic behavior
Motility and adhesion apparatus
Type III secretion system
Type IV secretion system
Type VI secretion system
Antimicrobial compounds biosynthesis
Antimicrobial compounds resistance



Zoccarato et. al, communications biology, 2022

Metagenomic analysis: Functional potential

Metagenomic sequencing analyses
the whole genome of bacteria

This includes bacterial enzymes:

- Analysis of functional potential

Because of higher resolution also:

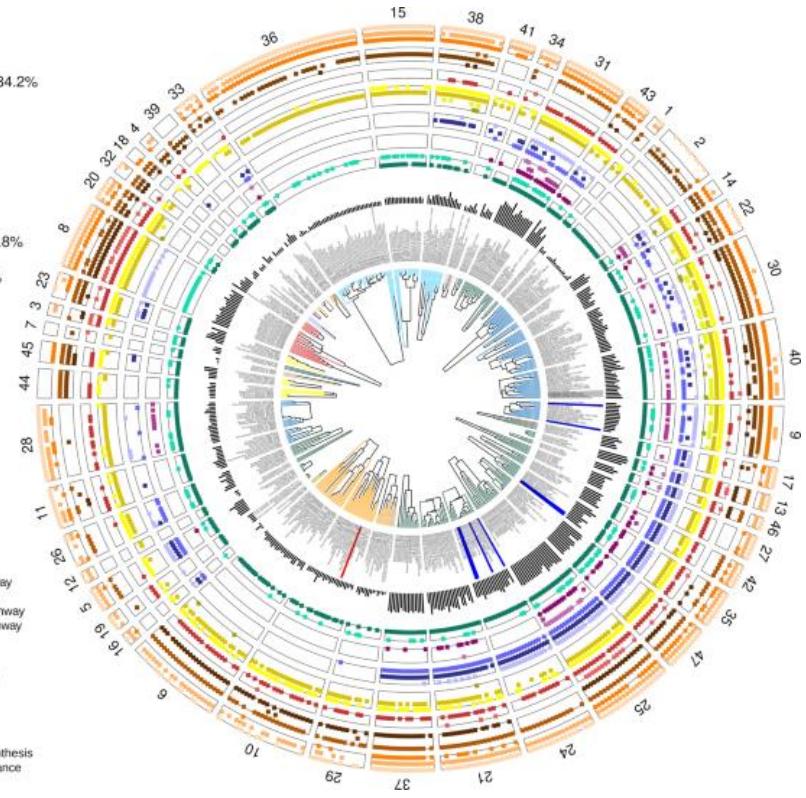
- Species level taxonomic profiling

Taxonomy:

Firmicutes	4%
Bdellovibrionota	0.6%
Gammaproteobacteria	34.2%
Actinobacterita	4.7%
Deinococotta	0.6%
Thermotogota	1.7%
Spirochaetota	0.6%
Others	3%
Desulfobacterota	1.1%
Cyanobacteria	15%
Aquificota	0.6%
Alphaproteobacteria	21.8%
Bacteroidota	11.4%
Campylobacterota	0.6%

Interaction-traits:

Vitamin B1 biosynthesis	
Vitamin B7 biosynthesis	
Vitamin B12 biosynthesis	
Vitamin B1 transport	
Vitamin B7 transport	
Vitamin B12 transport	
Fe-Siderophore	
Fe-Siderophore transporter	
Auxin: Indole-3-pyruvate pathway	
Auxin: Tryptamine pathway	
Auxin: Indole-3-acetonitrile pathway	
Auxin: Indole-3-acetamide pathway	
Quorum sensing	
Chemotactic behavior	
Motility and adhesion apparatus	
Type III secretion system	
Type IV secretion system	
Type VI secretion system	
Antimicrobial compounds biosynthesis	
Antimicrobial compounds resistance	



Zoccarato et. al, communications biology, 2022

Type of analysis depends on the research question

What questions can we answer?

- We can identify if specific taxa are present
- We can compare if a sample has reduced alpha diversity (e.g. after antibiotic therapy)
- We can compare samples with others (e.g. is a sample more similar to other from healthy people or from a disease group)
- We can establish taxa signatures that are diagnostic or predictive for clinical variables
- Metagenomic sequencing can give answers about metabolic functions of taxa: pathways, metabolites, bacterial signalling molecules, ..

Questions?