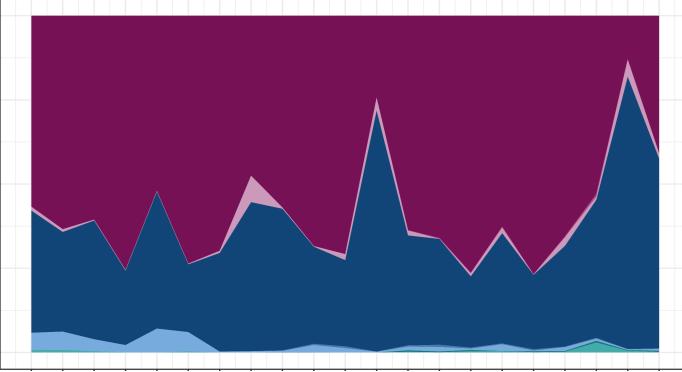
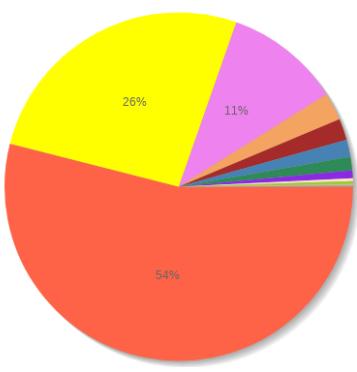
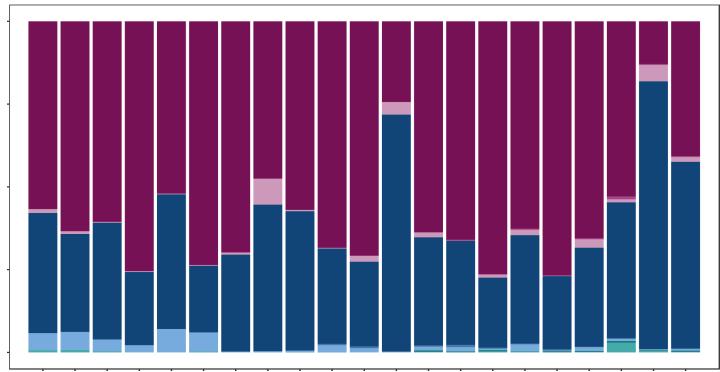
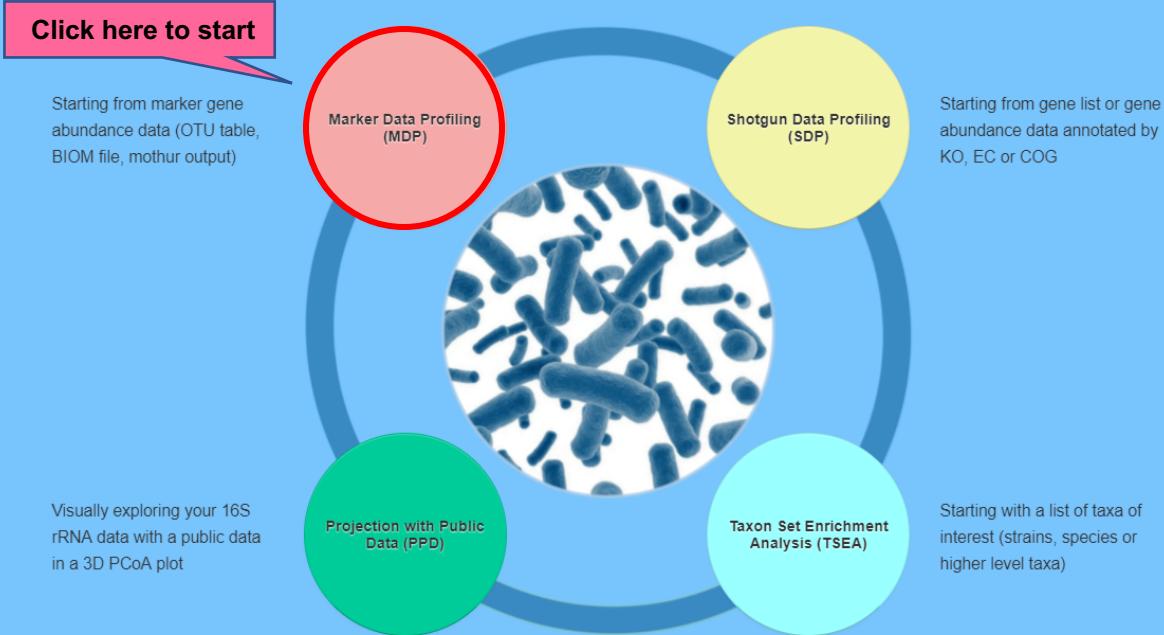


Marker Data Profiling (MDP)



Goal for this tutorial

- To perform a comprehensive analysis on a OTU table from 16S rRNA sequencing data, including:
 - ❖ **Diversity and compositional analysis**
 - ❖ **Comparative analysis**
 - ❖ **Predictions of metabolic potentials**



Data Formatting

- User can upload their 16S data in multiple formats :
 - ❖ **Tab-delimited text file** (abundance, taxonomy and metadata file)
 - ❖ **BIOM format** (containing at least abundance and taxonomy information)
 - ❖ **mothur** output files.

Details about each format are in the next few slides.

Data Formatting

1. Tab-delimited text file

- Manipulate data headings in a spreadsheet program like MS Excel
- Save as a **tab delimited (.txt) or comma-separated (.csv) file**
- The headings **#NAME** (all capital letters) must be used
 - ❖ #NAME is for sample names (first column in abundance; first row in metadata file)
 - ❖ 2nd Column of metadata file is for the clinical metadata.
 - ❖ Taxonomy information can be present within abundance table or uploaded separately.

For Example:

#NAME	Sample1	Sample2	Sample3	Sample4	Sample5	Sample6	Sample7	Sample8
#CLASS	Y	N	N	Y	N	Y	Y	N
Archaea;	219	49	42	50	6	17	22	21
Archaea;Crenarchaeota;Thermoprotei;				424	0	191	0	0
Bacteria;Acidobacteria;	32	4	4	22	76	16	1	0
Bacteria;Actinobacteria;	47	0	0	4	0	0	0	0

Taxonomic profiles with valid taxonomy identifier labelled names

#NAME	SampleType	Primer
Sample1	skin	ILBC_02
Sample2	gut	ILBC_06
Sample3	skin	ILBC_01
Sample4	gut	ILBC_07
Sample5	gut	ILBC_05
Sample6	gut	ILBC_09
Sample7	skin	ILBC_08
Sample8	skin	ILBC_03

Metadata file

Data Formatting

2. BIOM format

- General-use format (**standard**) for representing biological sample by observation contingency tables.
 - For details, please check BIOM format page (<http://biom-format.org/>)
- **QIIME** and **mothur** can also generate output in this format.
 - Must contain at least abundance and taxonomy information. (metadata file can be uploaded separately.)

3. Mothur output file

- Two files needed: a **consensus taxonomy** (taxonomy) file and a **.shared** (abundance) file.
- Metadata file can be uploaded separately.
 - For details, please visit the mothur home page (https://mothur.org/wiki/Main_Page).

1. Data Upload

Upload your data or try our example data below:

Plain text table format

OTU table (.txt or .csv) No file chosen Taxonomy labels included

Metadata file (.txt or .csv) No file chosen

Taxonomy table (.txt or .csv) No file chosen

Taxonomy labels

BIOM format

MOTHUR outputs

Example data sets for testing

Step 4 : Click "Submit" to proceed

Submit

You can try our example also

Example data sets for testing

Data Type	Format	Annotation	Description
<input checked="" type="radio"/> Aging Mouse Gut	BIOM	Greengenes	16S read counts (.biom file) of 21 samples from the fecal microbiome of mice (Langille, et al.). Group label: Young, Mid and Old - indicating the age group.
<input type="radio"/> Mammalian Gut	Plain text	SILVA	16S read counts (.txt file) of 38 samples from different mammalian (excluding human) species (Muegge, et al.) analyzed using QIIME. Group label: Herbivores, Carnivores and Omnivores - indicating the diet group.
<input type="radio"/> Human Stool	Mothur	RDP	24 pyrosequenced samples derived from human stool and analyzed in mothur (Costello, et al.). Group Label: Male (M), Female (F).

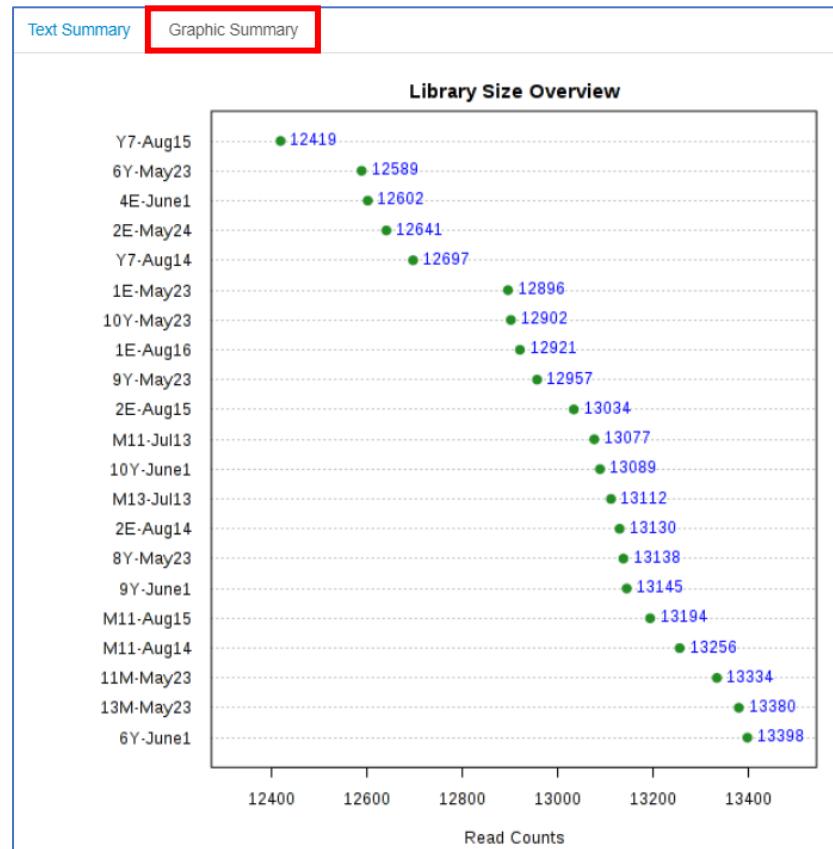
Submit

2. a) Data Integrity Check

Text Summary	Graphic Summary
Data type:	OTU abundance table
File format:	biom
OTU annotation:	greengene_id
OTU number:	3238
OTU with ≥ 2 counts:	3238
Sample number:	21
Number of experimental factors:	1
Total read counts:	272911
Average counts per sample:	12995
Maximum counts per sample:	13398
Minimum counts per sample:	12419

- Provides processing and summary information for user uploaded data.

2. b) Graphic Summary



- Provides user the information about library size or total number of reads present in each sample and help in identifying the potential outliers due to undersampling or sequencing errors.

3. a) Data Filtering (Features)

The screenshot shows a software interface titled 'Feature Filter' (highlighted with a red box). It has two main sections: 'Low count filter' and 'Low variance filter'.
Low count filter: Minimum count: 2. Prevalence in samples (%): 20 (radio button selected). Options: Mean abundance value, Median abundance value.
Low variance filter: Percentage to remove (%): 10. Inter-quartile range (radio button selected). Based on: Standard deviation, Coefficient of variation.
A 'Submit' button is at the bottom.

Identifying and removing variables or features that are unlikely to be of use when modeling the data.

- **Features that are of low quality or low confidence**
 - All zeros, singleton or detected in only sample
- **Features that are of low abundance**
 - May be less functionally important
- **Features that are of low variance**
 - Less informative for comparative analysis
- **6 different approaches: on the basis of count (abundance) or using statistical approaches such as mean, median, IQR, standard deviation or C.V.**

3. b) Sample Filtering (Editor)

The screenshot shows a user interface for sample filtering. At the top, there are two tabs: "Feature Filter" (disabled) and "Sample Editor" (selected, highlighted with a red border). A note below the tabs states: "Note you must click the **Submit** button below to complete sample removal. After data updates, you need to re-perform the data filtering normalization and analysis again." The main area is divided into two sections: "Available" on the left and "Exclude" on the right. The "Available" section contains a list of sample names, and the "Exclude" section is currently empty. Between the two sections are four buttons: a standard arrow pointing right, a double-headed arrow, a left arrow, and a double-headed arrow. At the bottom of the interface is a "Submit" button.

User can select samples to remove from downstream analysis

Available	Exclude
9Y-June1	
10Y-June1	
8Y-May23	
10Y-May23	
6Y-June1	
9Y-May23	
Y7-Aug14	
Y7-Aug15	
6Y-May23	
M11-Aug14	
M11-Aug15	
M11-Jul13	
11M-May23	
M13-Jul13	

- Users can remove samples that are detected as outlier via graphical summary result or downstream analysis. (e.g. Beta-diversity analysis)

4. Data Normalization

The screenshot shows a user interface for configuring data normalization parameters. It consists of three sections: 'Data rarefying', 'Data scaling', and 'Data transformation'. Each section contains a list of options with radio buttons. In each section, the first option ('Do not rarefy my data', 'Do not scale my data', and 'Do not transform my data' respectively) is selected.

Data rarefying

- Do not rarefy my data
- Rarefy without replacement to the minimum library size
- Rarefy with replacement to the minimum library size

Data scaling

- Do not scale my data
- Total sum scaling (TSS)
- Cumulative sum scaling (CSS)
- Upper-quantile normalization (UQ)

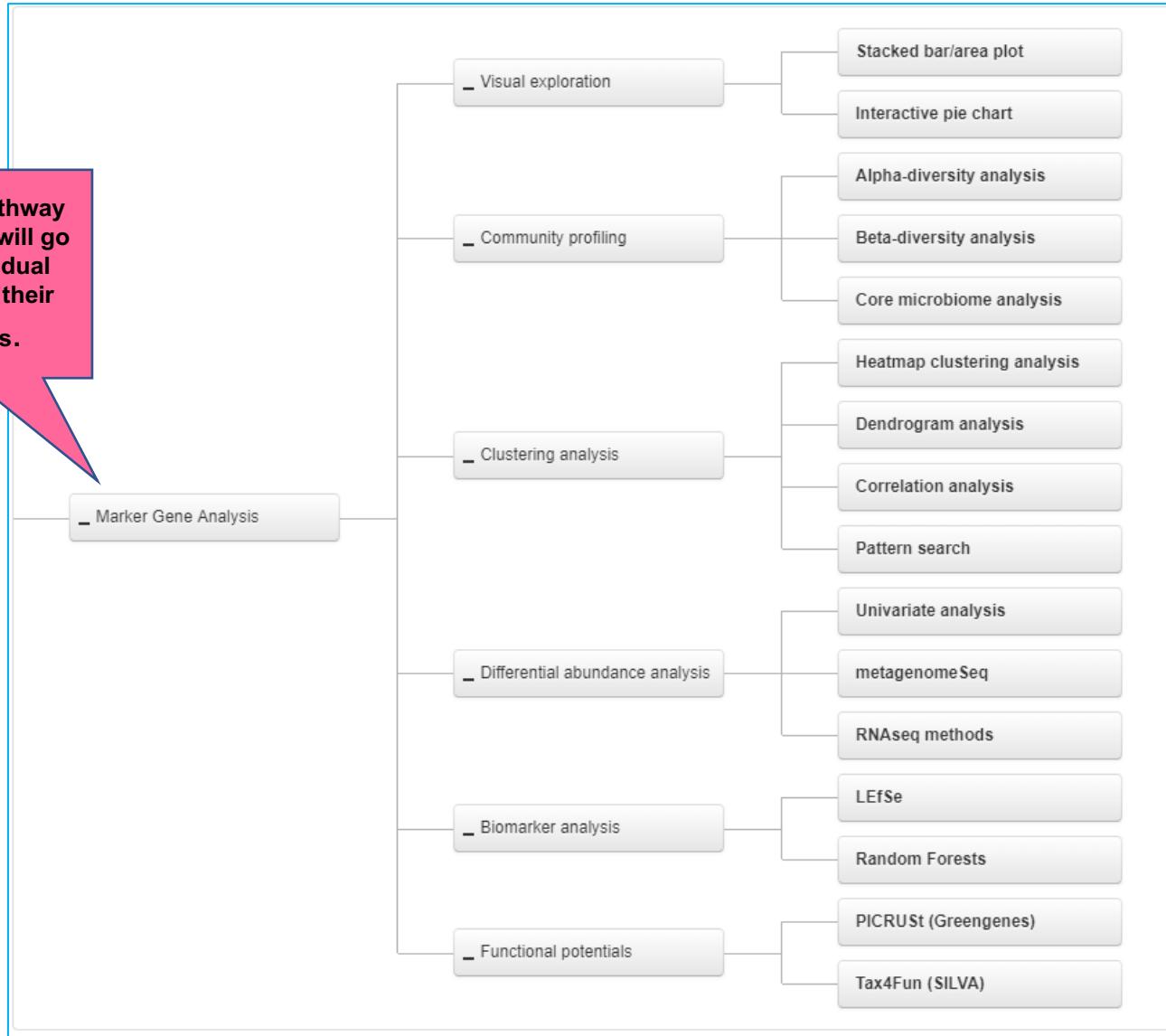
Data transformation

- Do not transform my data
- Relative log expression (RLE)
- Trimmed mean of M-values (TMM)
- Centered log ratio (CLR)

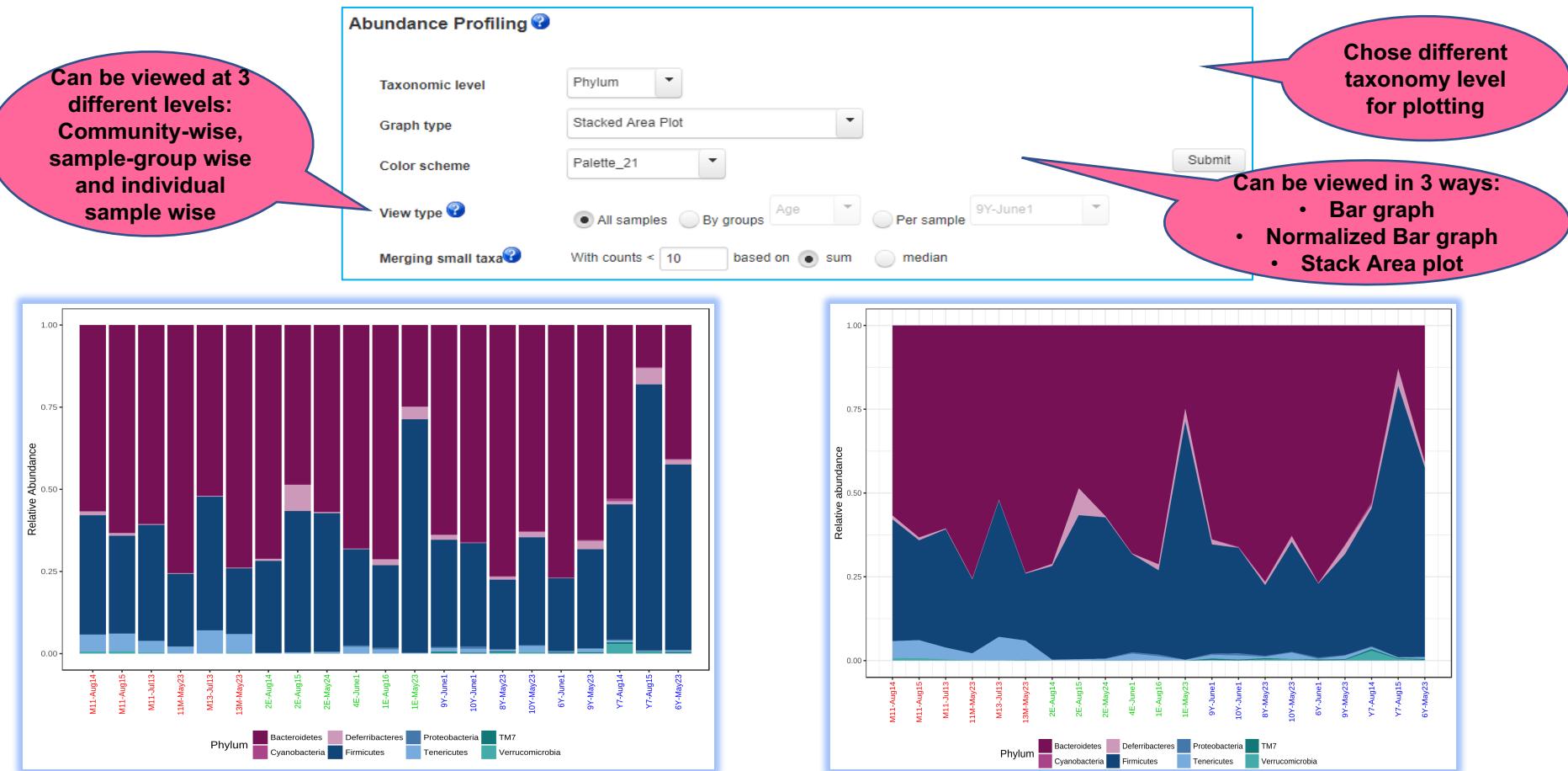
- Normalizing is required to account for **uneven sequencing depth, undersampling and sparsity** present in such data. (useful before any meaningful comparison)
- Several normalization methods which have been commonly used in the field are present. (3 categories: **rarefaction, data scaling and data transformation**)

5. Data Analysis

Six analysis pathway supported. We will go through individual pathways and their components.



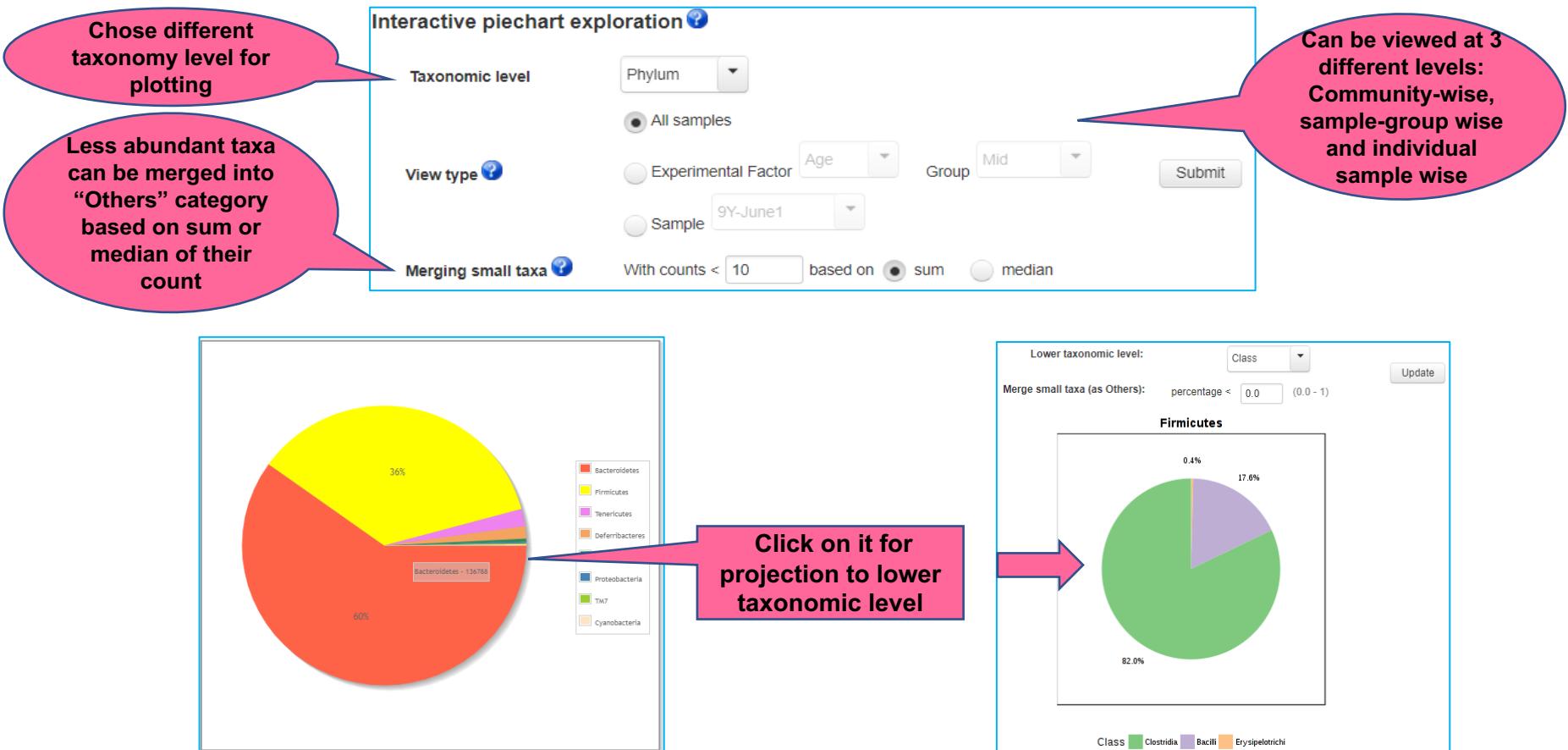
A. Visual Exploration



1. Stacked Bar/Area plot

- Provides exact composition of each community through direct quantitative comparison of abundances.
- It can be created for **all samples, sample-group wise or individual sample-wise** at multiple **taxonomic level** present in data.(i.e. phylum to OTU)

A. Visual Exploration



2. Pie Chart

- Helps in visualizing the taxonomic compositions of microbial community.
- It can also be created for **all samples, sample-group wise or individual sample-wise** at multiple **taxonomic level** present in data.(i.e. phylum to OTU)

B. Community Profiling

Alpha diversity profiling & significance testing

Taxonomic level: OTU-level

Diversity measure: Chao1

Statistical method: T-test / ANOVA

Experimental factor: Age

Submit

p-value: 5.3031e-05; [ANOVA] F-value: 17.872

Sample-wise diversity measure

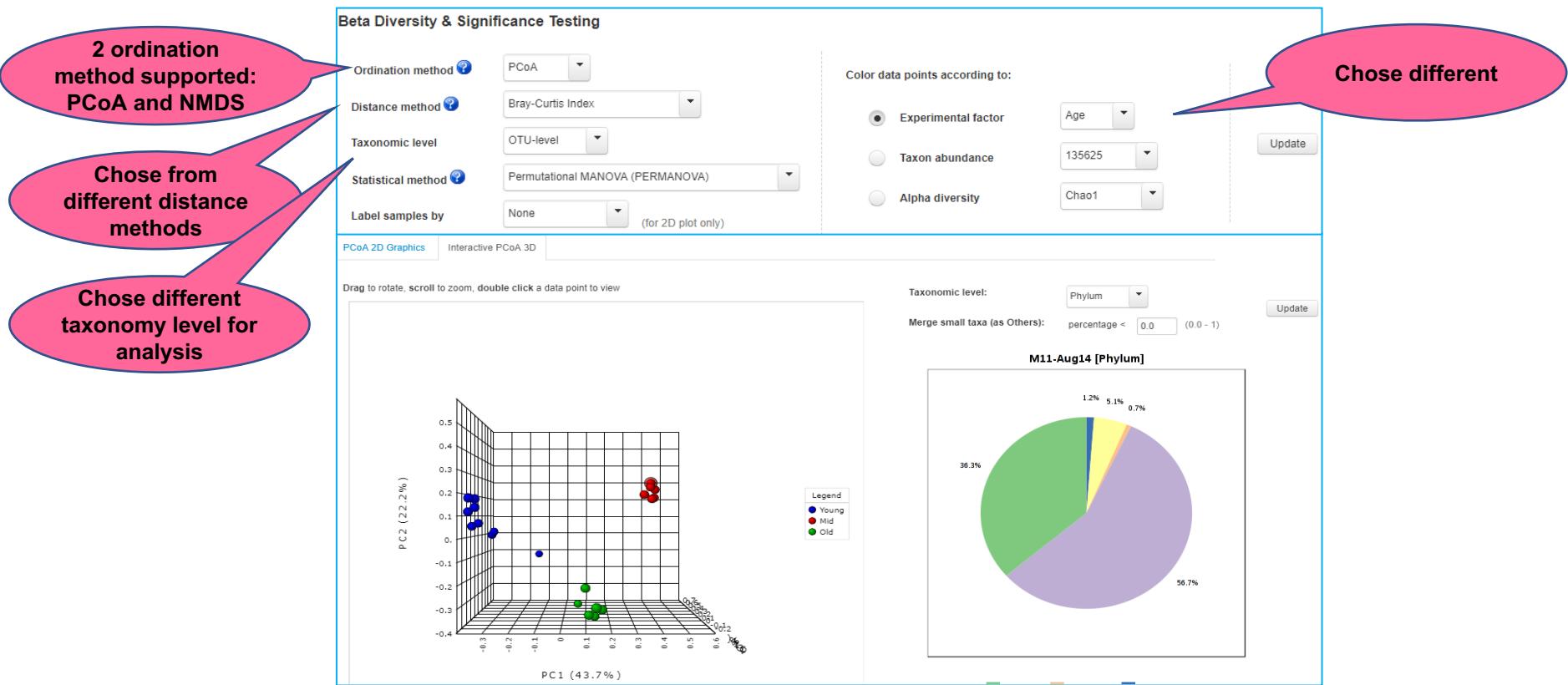
significance testing result

Sample group-wise diversity measure

1. **Alpha-diversity analysis & significance testing:** assessing diversity within community or sample.

- Supporting **6** widely used metrics to calculate the alpha diversity supported such as **Chao1** (evenness), **Observed** (richness), **Shannon** (account for both evenness and richness).
 - Statistical significance testing between groups using parametric and non-parametric tests.

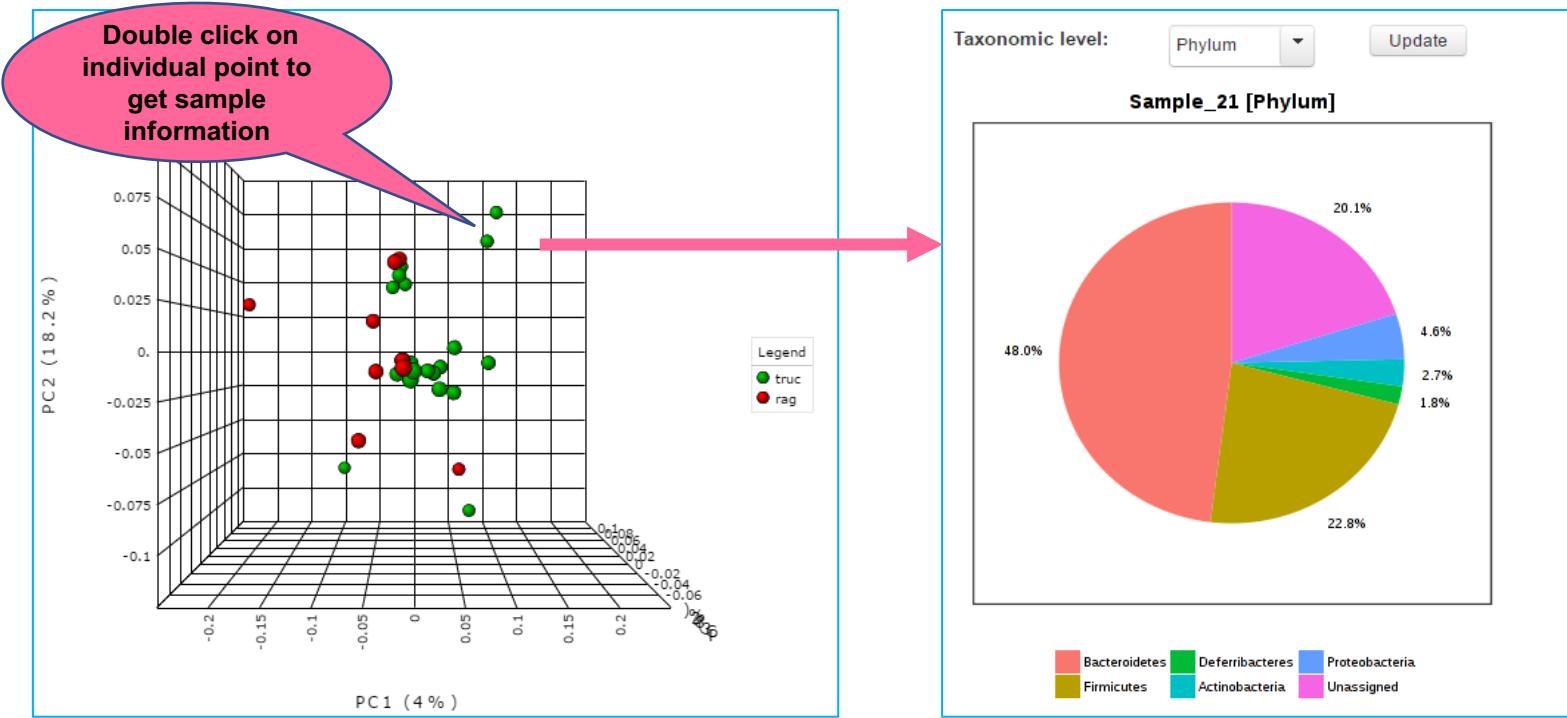
B. Community Profiling



2. Beta diversity analysis & significance testing: assessing the differences between microbial communities.(between samples)

- Dissimilarity matrix can be calculate via multiple distance method and can be visualized using **PCoA** (Principal Coordinate Analysis) or **NMDS** (Nonmetric Multidimensional Scaling)
- 5 widely used methods: **compositional-based** distance metrics such as **Bray-Curtis** or phylogenetic-based (**Unweighted Unifrac**) supported.

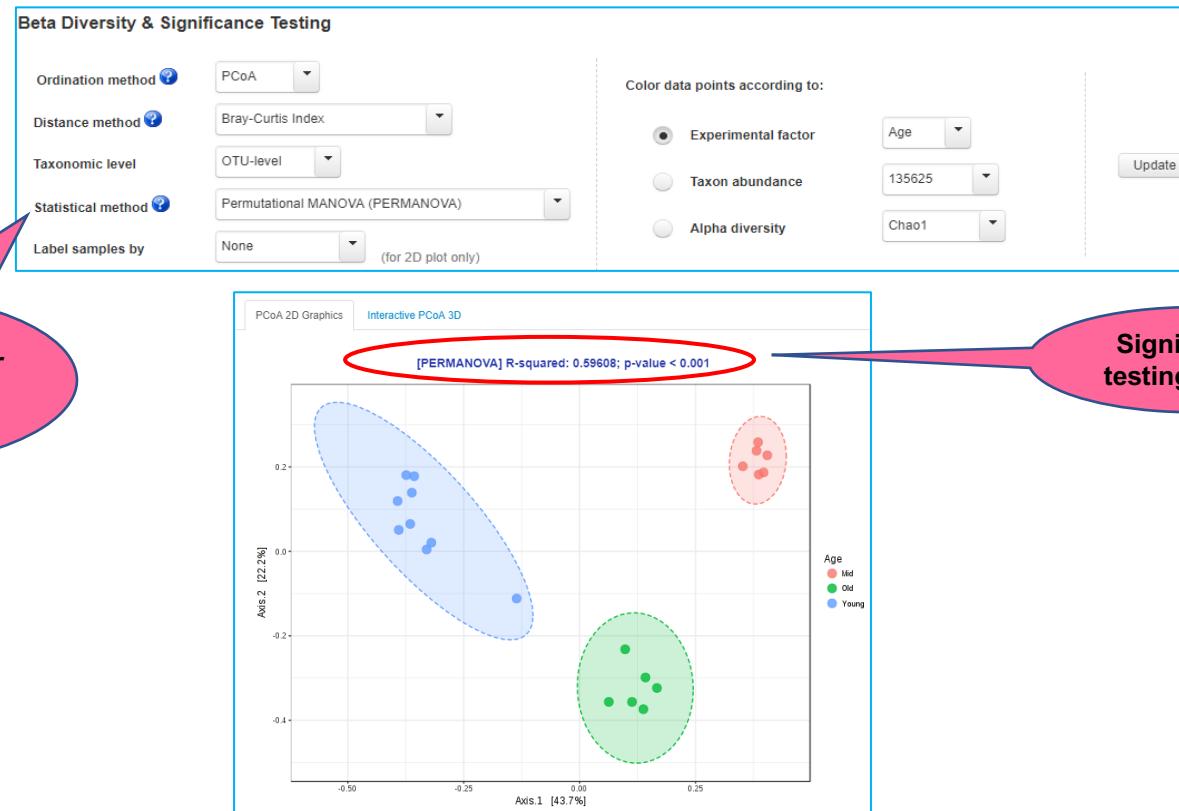
B. Community Profiling



2. Beta diversity analysis & significance testing

- Results of PCoA/NMDS analysis can be visualized in 3D using **ordination-based** distances supported.

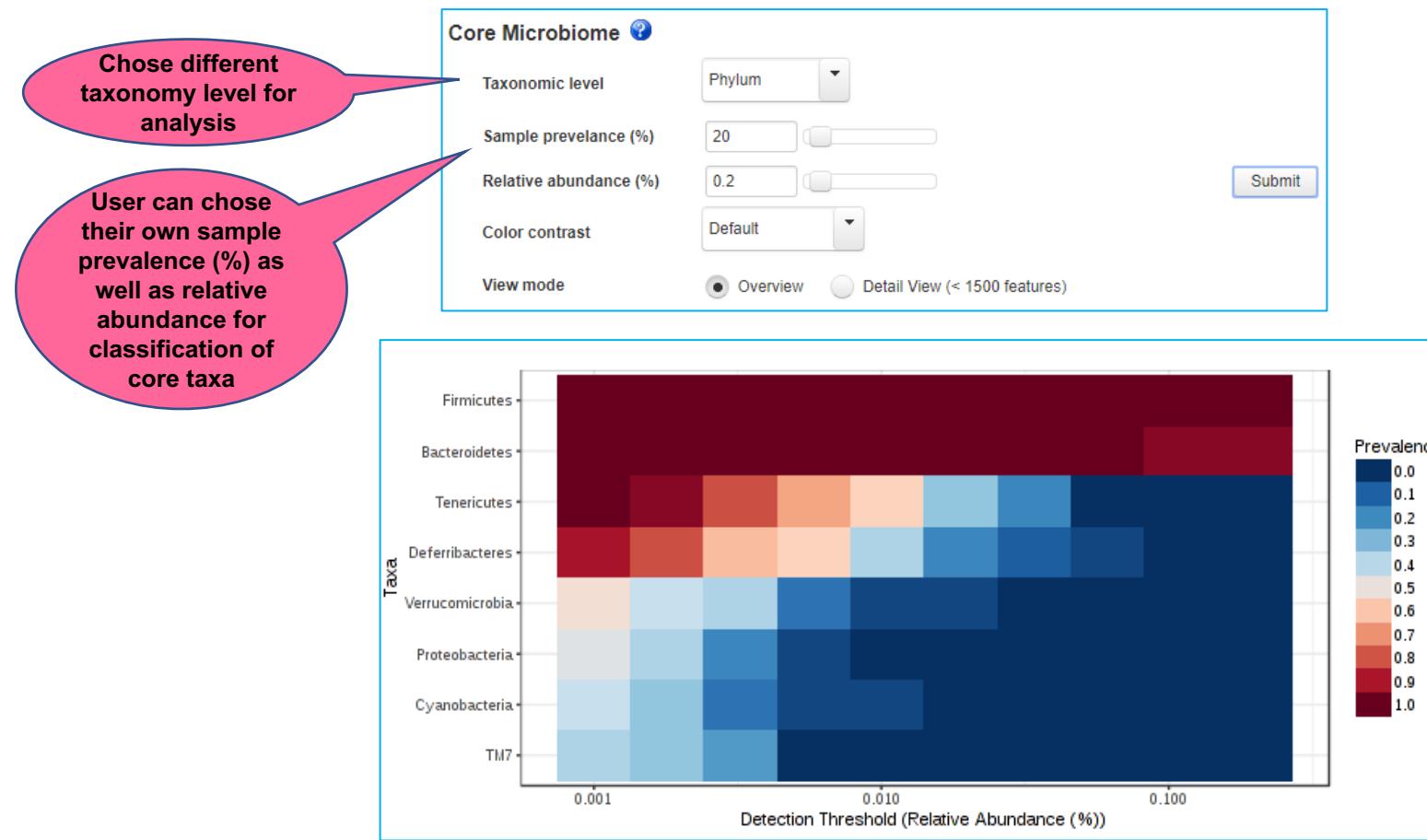
B. Community Profiling



2. Beta diversity analysis & significance testing

- 3 statistical methods supported to tests the strength and statistical significance of sample groupings based on ordination based distances.
- **ANOSIM/adonis, PERMANOVA and PERMDISP** supported.
- Helps in understanding the underlying reasons for pattern present in PCoA or NMDS plot.

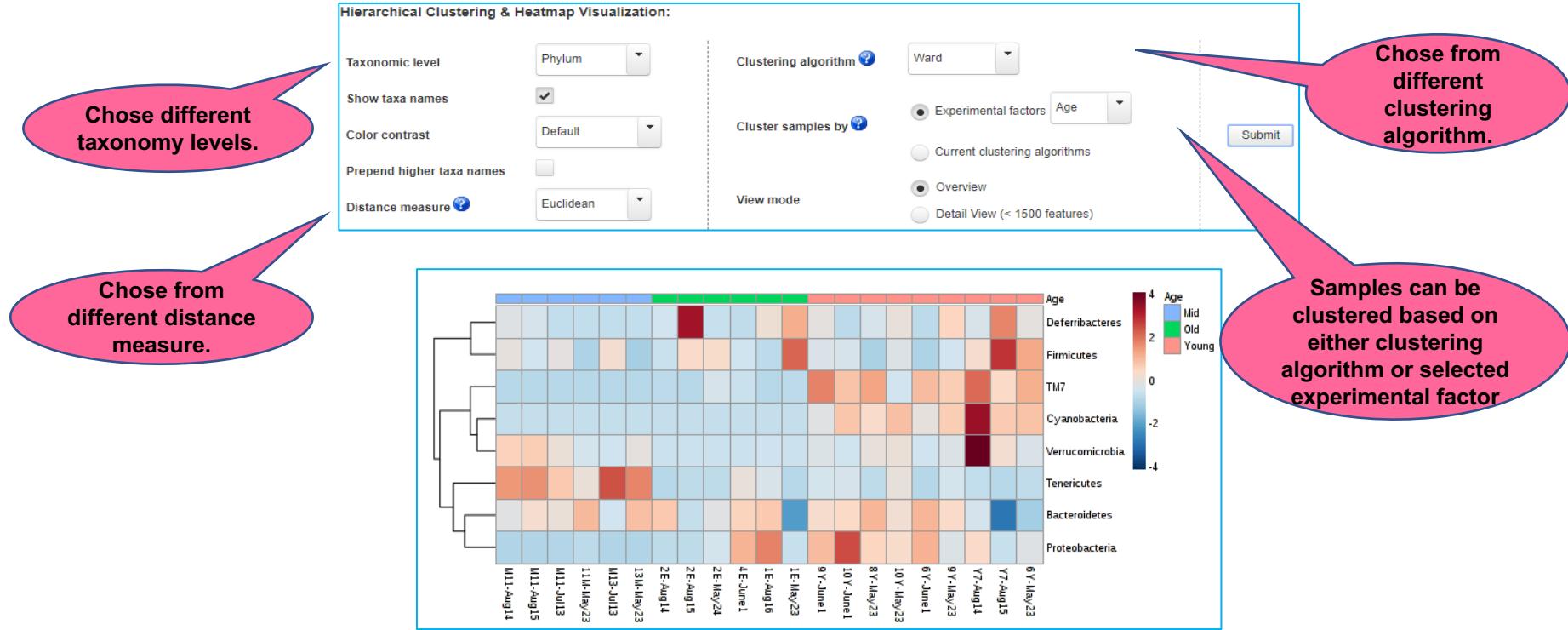
B. Community Profiling



3. Core microbiome analysis

- Helps in identifying core taxa or features that remain unchanged in their composition across different sample groups based on sample prevalence and relative abundance.
- Can be performed at various taxonomical level. (Phylum to OTU)

C. Clustering analysis



1. Heatmap and clustering analysis

- Visualize the relative patterns of high-abundance features against a background of features that are mostly low-abundance or absent.
- Various distance and clustering methods supported.(both sample and feature-wise)
- Features can be merged at multiple taxonomic levels also.(can also be visualized at individual OTU-level)

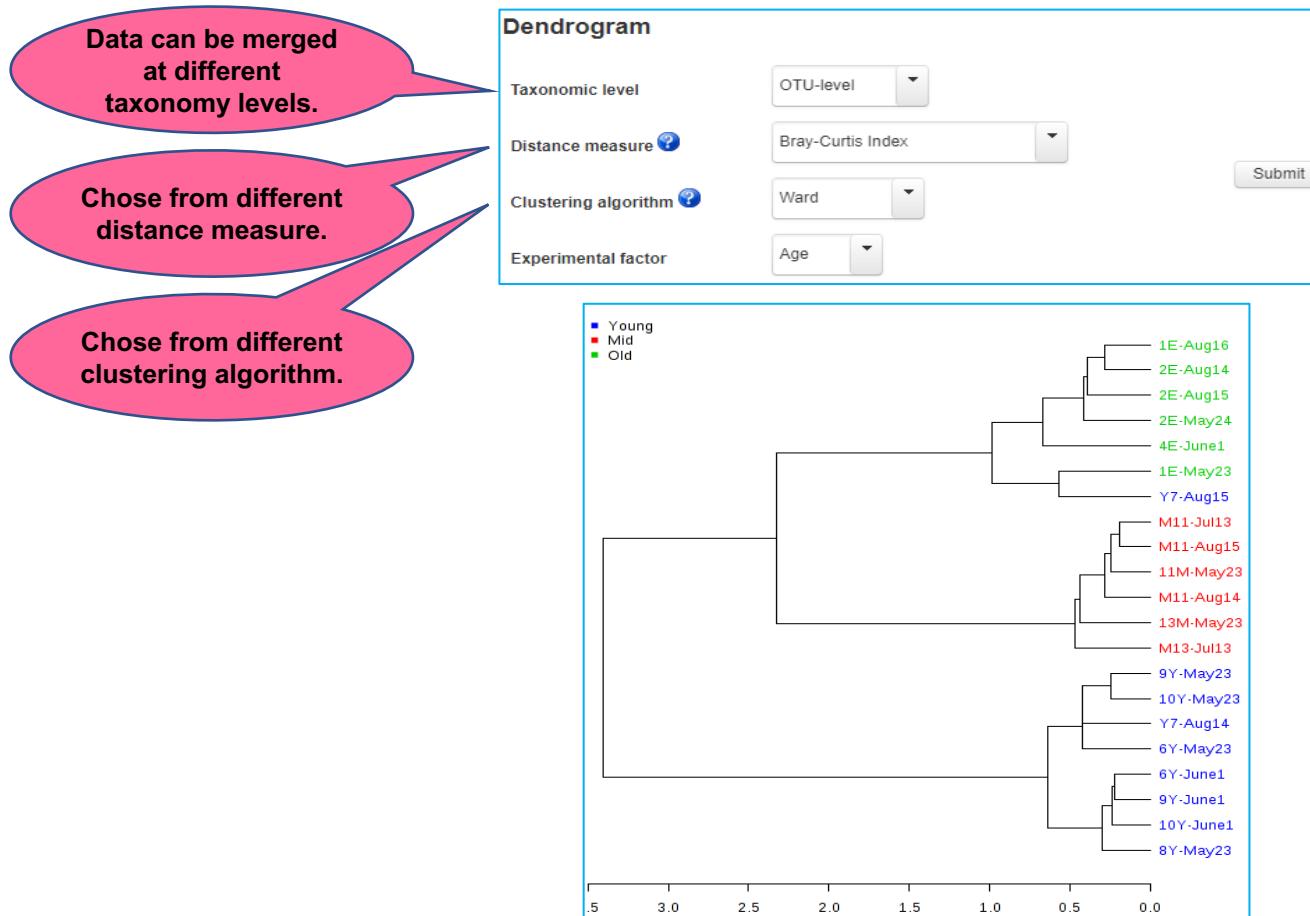
C. Clustering analysis



2. Correlation analysis

- Helps in identifying biologically or biochemically meaningful relationship or associations between taxa or features.
- Can be analyzed at various level (Phylum to OTU) by merging data based on taxonomic rank.

C. Clustering analysis



3. Dendrogram and clustering analysis

- Performs phylogenetic analysis on samples using either various phylogenetic or non-phylogenetic distance measures. (support for 5 most widely used)

C. Clustering analysis

3 most common method supported for performing correlation analysis

User can define their own pattern based on their interest

Pattern Search

Taxonomic level: Phylum

Define pattern using: Specific taxon (Firmicutes), Predefined profile (Mid-Old-Young), Custom profile

Distance measure: Pearson r

Experimental factor: Age

Result Table

Top 8 phylum correlated with the Bacteroidetes

Phylum	Correlation Coefficient
Bacteroidetes	1.0
Proteobacteria	0.4
Tenericutes	0.2
TM7	0.1
Verrucomicrobia	-0.2
Cyanobacteria	-0.3
Deferrribacteres	-0.6
Firmicutes	-0.8

Name	correlation	t-stat	p-value	FDR	View
Firmicutes	1.0	0.0	0.0	0.0	
Bacteroidetes	-0.9916	-33.417	2.4167E-18	9.6666E-18	
Deferrribacteres	0.56531	2.9873	0.0075719	0.020192	
Proteobacteria	-0.27973	-1.27	0.21942	0.41031	
Tenericutes	-0.25925	-1.1701	0.25644	0.41031	
Cyanobacteria	0.18181	0.80591	0.43027	0.57369	
Verrucomicrobia	0.075474	0.32992	0.74507	0.80747	
TM7	0.0566	0.24711	0.80747	0.80747	

4. Pattern Search

- Helps in identifying or search for a pattern based on correlation analysis on defined pattern.
- Pattern can be defined based on either feature (gene) of interest or based on predefined or custom profile of experimental factors.

D. Differential abundance analysis

Univariate Statistical Comparisons

Features can be merged at different taxonomic level

Chose from different Experimental factors

Taxonomic level: Phylum

Experimental factor: Age

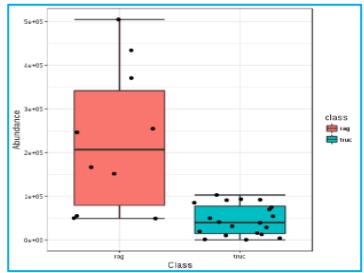
Statistical method: Mann-Whitney/Kruskal-Wallis

Adjusted p-value cutoff: 0.05

Submit

Name	Pvalues	FDR	Statistics	Action
Cyanobacteria	1.1821E-4	9.4567E-4	18.086	
TM7	2.6973E-4	0.0010789	16.436	
Proteobacteria	0.001339	0.0033499	13.232	
Verrucomicrobia	0.0019605	0.0033499	12.469	
Tenericutes	0.0020937	0.0033499	12.338	
Deferribacteres	0.25647	0.34196	2.7215	
Firmicutes	0.67634	0.77296	0.78211	
Bacteroidetes	0.94596	0.94596	0.11111	

Click on “Details” to see group-wise data distribution for each individual feature



Differential abundant taxa are highlighted in orange color

1. Univariate Statistical Comparisons

- t-test/ANOVA (parametric) or Mann-Whitney/KW test (non-parametric) can be done.
- Depending upon no. of sample groups, statistical test is chosen from parametric or non parametric test options.
- P-values adjusted using **FDR** method.

D. Differential Abundance analysis

Features can be merged at different taxonomic level

Chose from 2 statistical models based on number of groups

metagenomeSeq: statistical analysis for sparse high-throughput sequencing data

Taxonomic level: Phylum

Experimental factor: Age

Statistical model: zero-inflated Gaussian fit

Adjusted p-value cutoff: 0.05

Submit

Chose from different Experimental factors

Click on “Details” to see group-wise data distribution for each individual feature

Name	Pvalues	FDR	View
Tenericutes	3.5853E-4	0.0028683	[Details]
Proteobacteria	0.010273	0.037245	[Details]
Verrucomicrobia	0.013967	0.037245	[Details]
Deferribacteres	0.050285	0.10057	[Details]
Cyanobacteria	0.075187	0.1203	[Details]
TM7	0.16447	0.2193	[Details]
Bacteroidetes	0.28385	0.3244	[Details]
Firmicutes	0.72836	0.72836	[Details]

Figure showing differential abundance distribution for Firmicutes and Bacteroidetes across two experimental classes.

2. metagenomeSeq

- Detect differential abundant features in microbiome experiments with an explicit design.
- Accounts for **under-sampling** and **sparsity** in such data.
- Performs zero-inflated Gaussian fit (**fitZIG**) or fit-Feature (**fitFeature**) on data after normalizing the data through **cumulative sum scaling** (CSS) method (novel approach)
- **fitFeature** model is recommended over **fitZIG** for two groups comparison.
- Very sensitive and specific in nature (fails with very low sample size)

D. Differential Abundance analysis

Features can be merged at different taxonomic level

Chose from different Experimental factors

Click on “Details” to see group-wise data distribution for each individual feature

Name	log2FC	logCPM	Pvalues	FDR	View
Tenericutes	-3.0802	14.845	3.1447E-7	2.5158E-6	
Verrucomicrobia	-4.3271	11.439	4.9827E-6	1.9931E-5	
Proteobacteria	3.2594	10.795	7.4467E-5	1.9858E-4	
Deferribacteres	2.9655	14.22	8.2952E-4	0.001659	
TM7	1.5455	10.093	0.12029	0.19247	
Firmicutes	0.45802	18.745	0.28217	0.37623	
Bacteroidetes	-0.24242	19.455	0.60068	0.68649	
Cyanobacteria	0.26256	9.9525	1.0	1.0	

Differential abundant taxa are highlighted in orange color

3. EdgeR

- Developed for RNAseq data analysis.
- Powerful statistical method (outperforms others methods with appropriate data filtration and normalization techniques)
- By default, RLE (Relative Log Expression) normalization is performed on the data.

D. Differential Abundance analysis

Features can be merged at different taxonomic level

Chose from different Experimental factors

Click on “View Data” to see group-wise data distribution for each individual feature

Differential abundance analysis methods

Taxonomic level: Phylum

Experimental factor: Age

Algorithm: DESeq2

Adjusted p-value cutoff: 0.05

Submit

Name	log2FC	IfcSE	Pvalues	FDR	View
Cyanobacteria	6.569	0.9275	1.4165E-12	1.1332E-11	
TM7	6.5625	0.9592	7.8265E-12	3.1306E-11	
Tenericutes	-3.0843	0.51155	1.6464E-9	4.3904E-9	
Proteobacteria	4.4767	0.8567	1.7383E-7	3.4726E-7	
Bacteroidetes	-0.70234	0.41298	0.089006	0.14241	
Firmicutes	-0.42471	0.35972	0.23773	0.2917	
Deferribacteres	0.83264	0.73185	0.25524	0.2917	
Verrucomicrobia	-0.25039	0.74011	0.73513	0.73513	

A differential abundance plot showing abundance on the y-axis (log scale, 0.5e-03 to 5e-03) versus Class (Hfq vs Dmc) on the x-axis. The plot shows two box plots: one for Hfq (red) with a median around 2.5e-03 and one for Dmc (blue) with a median around 1e-03. Individual data points are overlaid on the box plots.

Differential abundant taxa are highlighted in orange color

4. DESeq2

- Developed for RNAseq data analysis.
- Uses negative binomial generalized linear models to estimate **dispersion** and **logarithmic fold changes**.

E. Biomarker Analysis

Features can be merged at different taxonomic level

Chose from different Experimental factors

Linear Discriminant Analysis (LDA) Effect Size (LEfSe)

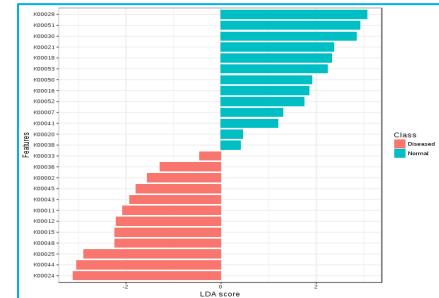
Taxonomic level: Phylum

Experimental factor: Age

Adjusted p-value cutoff: 0.05

Log LDA score: 1.0

Submit



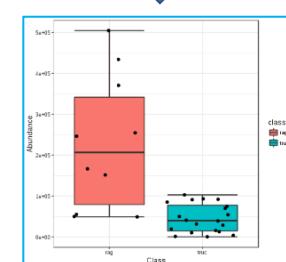
Click here to view Effect size of differential features

Result Table Graphical Summary

The table below shows at most 500 features ranked by their p values, with significant ones highlighted in orange

Name	Pvalues	FDR	Mid	Old	Young	LDAscore	View
Cyanobacteria	1.1821E-4	9.4567E-4	0.0	0.0	29117.4	4.16	
TM7	2.9855E-4	0.0011942	0.0	1839.34	28874.8	4.16	
Proteobacteria	0.001339	0.0035707	707.651	19471.6	28375.5	4.14	
Verrucomicrobia	0.0019605	0.003921	38722.3	499.922	53121.3	4.42	
Tenericutes	0.0025495	0.0040792	481002.0	78233.2	84400.0	5.3	
Deferribacteres	0.25647	0.34196	47773.8	248583.0	152698.0	5.0	
Firmicutes	0.68667	0.78477	3071660.0	3964320.0	3876590.0	5.65	
Bacteroidetes	0.94596	0.94596	6360140.0	5687060.0	5747020.0	5.53	

Click on “Details” to see group-wise data distribution for each individual feature



1. LEfSe

- Compare the metagenomics (16S or shotgun) abundance profiles between samples in different state.
- Performs a set of statistical tests for detecting differentially abundant features (**KW sum-rank test**: statistical significance) and biomarker discovery. (**Linear Discriminant analysis**: Effect Size)

E. Biomarker Analysis

Features can be merged at different taxonomic level

User can choose from no. of trees to be used for classification

No. of predictors for each node

Random Forests ?

Taxonomic level: Phylum

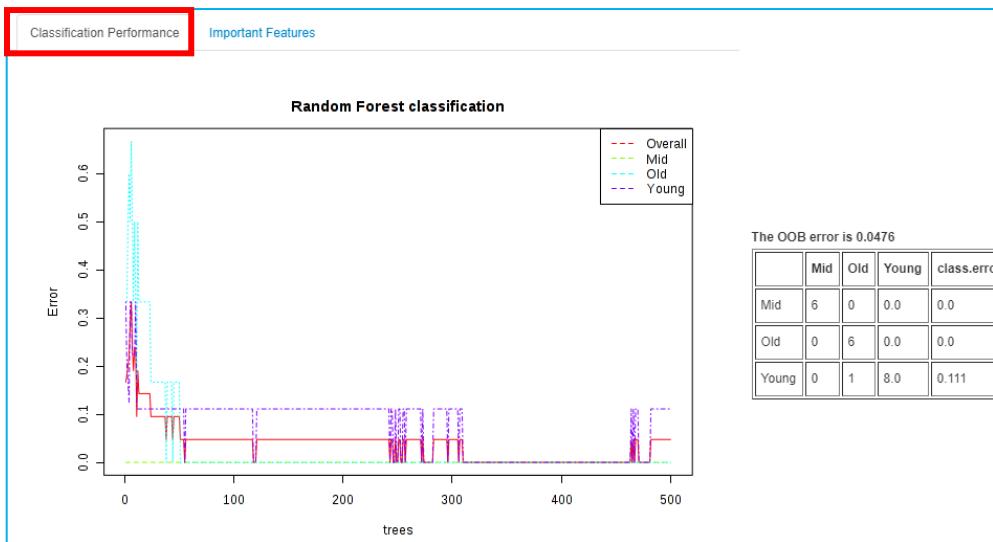
Experimental factor: Age

Number of trees to grow: 500

Number of predictors to try: 7

Randomness setting: On

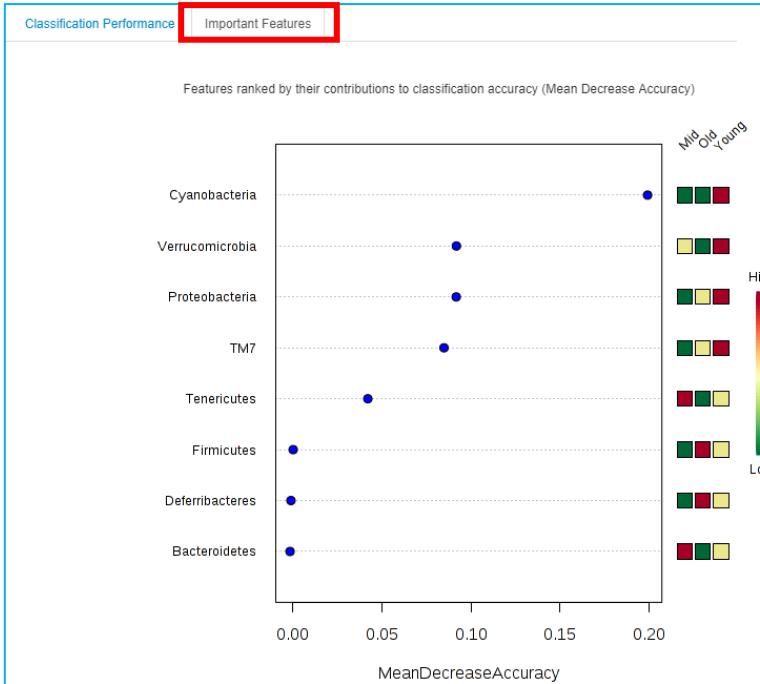
Submit



2. Random forests

- Ensemble learning method used for classification, regression and other tasks.
- It operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) of the individual trees.
- Random forests correct for decision trees habit of overfitting to their training set.

E. Biomarker Analysis



Most important features for classification of data into provided class groups

2. Random Forest

- It provides estimates of what variables are important in the classification of data.
- It computes proximities between pairs of cases that can be used in clustering, locating outliers, or give interesting views of the data.

F. Functional potential

Prediction for Greengenes Annotated OTUs (PICRUSt)

PICRUSt (phylogenetic investigation of communities by reconstruction of unobserved states) estimates the properties of ancestral organisms from living relatives by performing gene content inference and metagenome inference. More details about this algorithm can be found from [MGI Langille et al.](#) Please make sure you have used closed-reference OTU picking protocol to search sequences against the Greengenes reference OTUs (18May2012 version) to a specified percent identity.

You can perform functional profiling if only your features or OTUs are annotated using greengene or SILVA database

Predicting the functional capabilities of microbial communities using Tax4Fun

Tax4Fun is designed for functional prediction based on minimum 16SrRNA sequence similarity. It is applicable to output as obtained from the SILVAngs web server or the application of QIIME against the SILVA database. Note, the process is time consuming and may take ~2 min to complete. There will be an error with the box plots if the counts are relative. The result table can be used for functional profiling using our *Shotgun Data Profiling* module.

Annotation Pipeline

QIIME against SILVA database

Functional potential prediction: inferring functional (metabolic) profile from taxonomic profile.

- 2 methods available:
 - ❖ **PICRUSt:** It's an **evolutionary modeling algorithm**. Its predictions based on **topology** of the tree and phylogenetic **distance** to next sequenced organism. It is based on **Greengenes** annotated OTUs.
 - ❖ **Tax4Fun:** Prediction based on minimum **16SrRNA sequence similarity** using **SILVA** annotated OTUs.

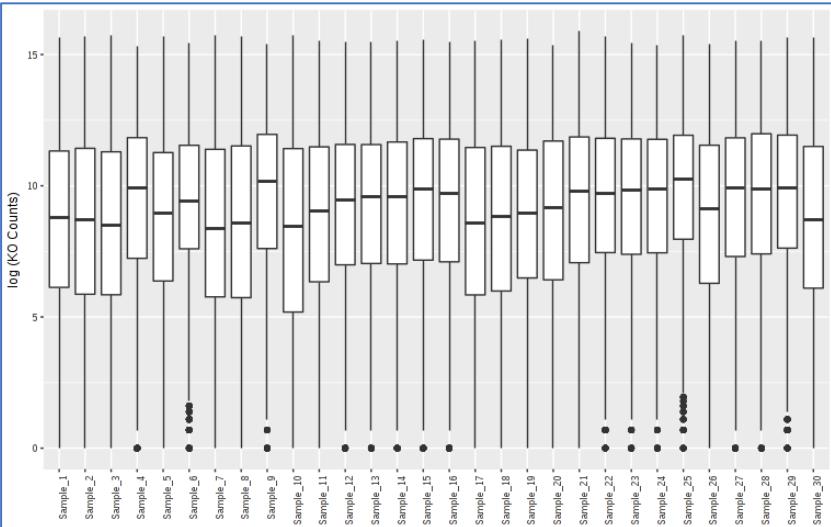
F. Functional potential

Prediction for Greengenes Annotated OTUs (PICRUSt)

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Predict Metabolic Potential

**Click on “Predict”
for profiling**



Count distribution od predicted metagenomic abundance data (KO counts) [log-scale]

	Sample_1	Sample_2	Sample_3	Sample_4	Sample_5	Sample_6	Sample_7
K00001	250909	233567	216513	470693	270248	246187	221069
K00002	8509	2834	4060	11144	4332	6965	3428
K00003	1114897	1153876	1154249	981943	1128078	1005126	1165678
K00004	530	604	372	4249	946	921	231
K00005	30894	30435	22192	61806	32201	38726	29505
K00007	1371	175	1184	7180	1971	5938	349
K00008	52714	54522	32976	257301	77995	59550	37235
K00009	24321	68586	41373	127192	58857	131226	32610
K00010	51165	52906	41571	63596	53110	64203	55787
K00011	372	37	136	323	102	264	85
K00012	303002	266747	251261	360465	260342	440048	246247
K00013	1013642	1047238	1020036	872323	1043993	997186	1036895
K00014	803730	808773	813423	781430	811373	764087	809040
K00015	8102	6526	4413	52508	12419	9214	2931
K00016	721909	738355	695982	811983	766730	602250	734496
K00018	99781	86186	90984	93518	73678	122128	90908
K00019	16779	13996	16526	66896	23543	32695	10703
K00020	49409	40655	51099	158991	52683	62358	39725
K00021	2717	22	50	99	137	3801	11
K00023	8123	1590	6532	44293	11733	13100	2000

Result KO table

F. Functional potential

#NAME	Sample_1	Sample_2	Sample_3	Sample_4	Sample_5	Sample_6
#CLASS	truc	truc	truc	truc	truc	truc
Archaea;	0	0	0	0	0	0
Archaea;Crenarchaeota;	0	0	0	0	0	0
Archaea;Crenarchaeota;Thermoprotei;	0	0	0	0	0	0
Archaea;Crenarchaeota;Thermoprotei;Desulfurococcales;	0	0	0	0	0	0
Archaea;Crenarchaeota;Thermoprotei;Sulfolobales;	0	0	0	0	0	0
Archaea;Crenarchaeota;Thermoprotei;Sulfolobales;Sulfolobaceae;	0	0	0	0	0	0
Archaea;Crenarchaeota;Thermoprotei;Thermoproteales;	0	0	0	0	0	0
Archaea;Crenarchaeota;Thermoprotei;Thermoproteales;Thermoproteaceae;	0	0	0	0	0	0
Archaea;Crenarchaeota;Thermoprotei;Thermoproteales;Thermoproteaceae;Caldivirga;	0	0	0	0	0	0
Archaea;Euryarchaeota;	0	0	0	0	0	0
Archaea;Euryarchaeota;Halobacteria;	0	0	0	0	0	0
Archaea;Euryarchaeota;Halobacteria;Halobacteriales;	0	0	0	0	0	0
Archaea;Euryarchaeota;Halobacteria;Halobacteriales;Halobacteriaceae;	0	0	0	0	0	0
Archaea;Euryarchaeota;Methanomicrobia;	0	0	0	0	0	0
Archaea;Euryarchaeota;Methanopyri;	0	0	0	0	0	0
Archaea;Euryarchaeota;Methanopyri;Methanopyrales;	0	0	0	0	0	0
Archaea;Euryarchaeota;Methanopyri;Methanopyrales;Methanopyraceae;	0	0	0	0	0	0
Archaea;Euryarchaeota;Methanopyri;Methanopyrales;Methanopyraceae;Methanopyrus;	0	0	0	0	0	0
Bacteria;	99.92767599	99.99021909	99.95954365	100	99.98081351	99.91038279
Bacteria;Acidobacteria;	0	0	0	0	0	0
Bacteria;Actinobacteria;	0.072324012	0.088028169	0.121369043	0.232045481	0.134305449	0.307258994
Bacteria;Actinobacteria;Actinobacteria;	0.072324012	0.088028169	0.121369043	0.232045481	0.134305449	0.307258994

OTU table

Functional profiling



	Sample_1	Sample_2	Sample_3	Sample_4	Sample_5	Sample_6	Sample_7
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KO table

- After, prediction the result data is similar as **shotgun metagenomic** data.
- User have to go through the **Shotgun Data Profiling** module to perform comprehensive analysis.
- Please check, **Tutorial II** on (**Shotgun data profiling**) for stepwise detailed analysis on such data.

Gene (KO) abundance profile



MicrobiomeAnalyst
Shotgun Data Profiling
(SDP)



Download Results



- The analysis results (images and tables) can be downloaded from east panel present at every individual analysis page.
- Images can be downloaded in SVG and PDF format.
- Tables are available in CSV format to download.

==END==