

Welcome to

ResistXplorer

- a web-based tool for visualization and exploratory analysis of resistome data

The key features include:

- Support for a wide array of common as well as advanced methods for **composition profiling**, **visualization** and **exploratory data analysis**;
- Comprehensive support for various **data normalization** methods coupled with standard as well as more recent **statistical** and **machine learning algorithms**;
- Support for a variety of methods for performing **vertical data integrative analysis** on paired metagenomic datasets (i.e. taxonomic and resistome abundance profiles);
- Comprehensive support for **ARG functional annotations** along with their **microbe** and **phenotype** associations based on data collected from more than **10 reference and curated databases**;
- A powerful and fully featured **network visualization** for intuitive exploration of **ARG-microbial host** associations, incorporated with **functional annotations enrichment analysis** support.

In this manual, we will go through the analysis of resistome data using **INTEGRATION** data as input.

Please cite:

Dhariwal A, Junges R, Chen T, Petersen FC.

ResistoXplorer: a web-based tool for visualization and exploratory analysis of resistome data.

In this manual, you will encounter **blue** and **red** dialog boxes.



Blue dialogs indicate explanations and details for different functions in each page, while **red dialogs** indicate actions that will move forward with the analysis to a new screen or a download option for a visualization/analysis.



The question mark icons are available in ResistoXplorer. If you hove over it, a short explanation about that item will appear.

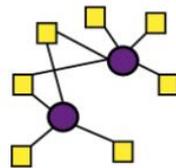


Throughout this manual you will also find additional explanations about the functionalities of ResistoXplorer following this icon.

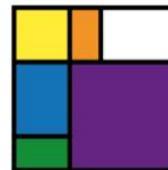
In the front page of ResistoXplorer, you can select one of the three options for input data:
ARG list /// ARG table /// Integration



Features



ARG-MICROBE
NETWORK
EXPLORATION



INTERACTIVE
EXPLORATION



COMPREHENSIVE
DATABASE

1. Upload both your microbiome and resistome abundance profile

A. Taxonomic profile (Taxon abundance and taxonomy information)

1. **Taxon abundance table:** * (.txt or .csv format) No file chosen

2. **Annotation file:** (.txt or .csv format) No file chosen

B. Resistome profile (ARGs abundance and annotation information)

1. **ARG abundance table:** * (.txt or .csv format) No file chosen

2. **Annotation file:** (.txt or .csv format) No file chosen

C. Metadata (Sample metadata information)

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

2. Try our example data set

Data Type	Description
<input checked="" type="radio"/> Beef feedlot cattle	Gut microbiota (bacteriome) and resistome profile of 60 samples from commercial beef feedlot cattle treated with therapeutic doses of tulathromycin (E Doster, et al.). Group label: Untreated and Treated- indicating the treatment group; Day1 and Day11 - indicating the timepoint group.

Here you can upload your data in .txt or .csv formats, and you will need to upload the taxonomic, resistome, and metadata.

Optional: You can also upload the annotation files, if you have them.

If you click on the dataset, you will be able to download it as well.

Optional: Alternatively, you can use an example dataset to explore the functionalities of ResistoXplorer.

To proceed with the example dataset of your choice, click on 'Submit'. If you want to continue with your own data, click on the 'Submit' button above this one, after you have added your data.

Data Integrity check

Please review the **Text Summary** below from your uploaded **microbiome** and **resistome** data. Click the **Library Size Overview** for a detailed visual summary of read count calculated for each sample. Kindly note:

- Features with zeros across all the samples and features that are present only in one sample (considered artifacts) will be excluded from further analysis from both the datasets

[Taxonomic profile](#) [Resistome profile](#) [Metadata](#) [Library Size Overview](#)

You can click on the other tabs to browse through the details of the dataset.

Total no of features (taxa):	4600
Features with ≥ 2 counts:	4600
Total read counts:	170218008
Average counts per sample:	2836966
Maximum counts per sample:	5792417
Minimum counts per sample:	598700
Sparsity (%):	16
Compositional:	No

In this manual, we will use the example dataset called 'Beef feedlot cattle', and as you select the option, a text and graphic summaries of the data will be available. This step named 'Data Integrity Check' will also take place when you upload your own data.

Data Integrity check

Please review the **Text Summary** below from your uploaded **microbiome** and **resistome** data. Click the **Library Size Overview** for a detailed visual summary of read count calculated for each sample. Kindly note:

- Features with zeros across all the samples and features that are present only in one sample (considered artifacts) will be excluded from further analysis from both the datasets

[Taxonomic profile](#) [Resistome profile](#) [Metadata](#) [Library Size Overview](#)

Total no of features (ARGs):	134
Features with ≥ 2 counts:	134
Sparsity (%):	51
Compositional:	No
Total read counts:	3773873
Average counts per sample:	62897
Maximum counts per sample:	132644
Minimum counts per sample:	18177

Data Integrity check

Please review the **Text Summary** below from your uploaded **microbiome** and **resistome** data. Click the **Library Size Overview** for a detailed visual summary of read count calculated for each sample. Kindly note:

- Features with zeros across all the samples and features that are present only in one sample (considered artifacts) will be excluded from further analysis from both the datasets

[Taxonomic profile](#) [Resistome profile](#) [Metadata](#) [Library Size Overview](#)

No. of samples in microbiome data:	60
No. of samples in resistome data:	60
No. of experimental factor:	3
No. of discrete experimental factor:	3
Sample names match (resistome vs microbiome):	Yes
No. of samples matched (microbiome vs resistome):	60
No. of samples that will be processed:	60

Data Integrity check

Please review the **Text Summary** below from your uploaded **microbiome** and **resistome** data. Click the **Library Size Overview** for a detailed visual summary of read count calculated for each sample. Kindly note:

- Features with zeros across all the samples and features that are present only in one sample (considered artifacts) will be excluded from further analysis from both the datasets

Taxonomic profile Resistome profile Metadata **Library Size Overview**

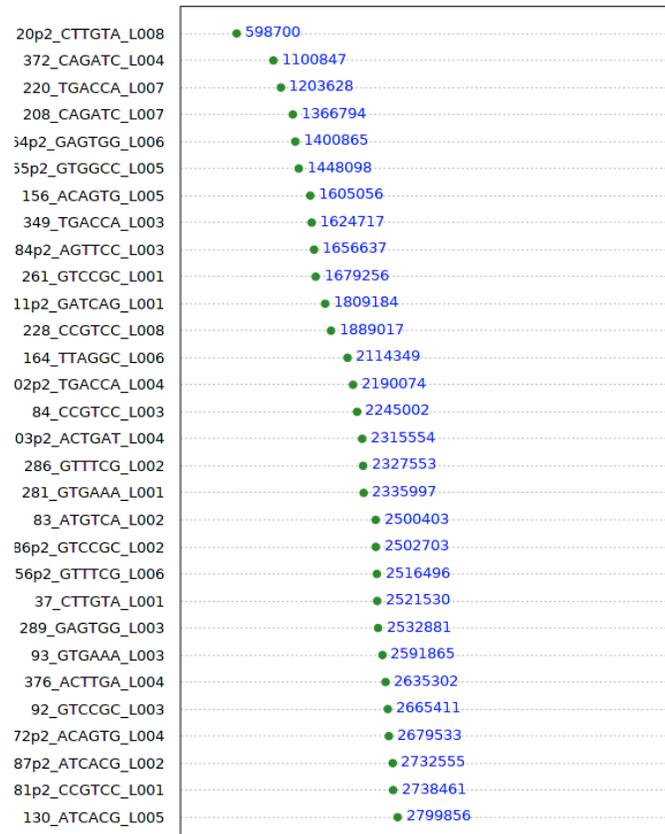
Dataset: Taxonomic profile

Update

PDF

SVG

Library Size Overview



Previous

If the details seem fine,
go ahead and click on
'Proceed'.

Proceed

Data Filtration

Data Filtration aims at removing or filtering low quality or uninformative features from the data to improve the downstream statistical testing. Uninformative features can be filtered through two main ways:

- **Low count filter:** features that are present in a few samples with a very low read count are difficult to distinguish from sequencing errors. User need to set a minimum count (default value: 2). A 20% prevalence filter means that at least 20% of the values of a feature should contain at least 2 counts. You can also filter based on *mean* and *median* values.
- **Low variance filter:** features that do not vary or remain constant throughout the experiment conditions are not likely to be associated with the conditions under study. Feature variances can be calculated using *inter-quantile range (IQR)*, *standard deviation* or *coefficient of variation (CV)*.

We generally recommend users to use **more stringent filtration** criteria for taxonomic data due to larger size (more no. of features) and more abundance (higher library sizes) as compared to resistome data.

Taxonomic Feature Filter Resistome Feature Filter

Note: If you want to choose different filtering parameters for both datasets, please perform data filtration of resistome data first.

Use same filtration parameters for both dataset

Low count filter ?

Minimum count:

Prevalence in samples (%)

Mean abundance

Median abundance

Low variance filter ?

Percentage to remove (%):

Based on: Inter-quantile range

Standard deviation

Coefficient of variation

Submit

For integrative data analysis, you can choose to either use the same filters for both taxonomic and resistome data, or you can set specific filters for each. If you would like to treat them separately, uncheck this box, and set the details by browsing in the tabs above.

Features with very small counts in very few samples are likely due to sequencing errors. You need to first specify a minimum count (default value is 2).

If you use 20% prevalence filter, meaning for any feature to be retained, at least 20% of its values should contain at least 2 counts.

In addition, you can also filter low abundance features based on their mean or median values below the minimum count.

Features that are close to constant throughout the experiment conditions can also be filtered, especially for comparative analysis. The variance can be measured using inter-quantile range (IQR), standard deviation or coefficient of variation (CV). The lowest percentage based on the cutoff will be excluded.

Feel free to set the parameters of your preference. In this manual, we will move forward with the default values. Click on 'Submit'.

Please notice that you cannot move forward with the analysis without clicking on 'Submit'.

Data Filtration

Data Filtration aims at removing or filtering low quality or uninformative features from the data to improve the downstream statistical testing. Uninformative features can be filtered through two main ways:

- **Low count filter:** features that are present in a few samples with a very low read count are difficult to distinguish from sequencing errors. User need to set a minimum count (default value: 2). A 20% prevalence filter means that at least 20% of the values of a feature should contain at least 2 counts. You can also filter based on *mean* and *median* values.
- **Low variance filter:** features that do not vary or remain constant throughout the experiment conditions are not likely to be associated with the conditions under study. Feature variances can be calculated using *inter-quantile range (IQR)*, *standard deviation* or *coefficient of variation (CV)*.

We generally recommend users to use **more stringent filtration** criteria for taxonomic data due to larger size (more no. of features) and more abundance (higher library sizes) as compared to resistome data.

Taxonomic Feature Filter

Resistome Feature Filter

Note: If you want to choose different filtering parameters for both datasets, please perform data filtration of resistome data first.

Use **same** filtration parameters for both dataset

Minimum count:

Low count filter

Prevalence in samples (%)

Mean abundance

Median abundance

Low variance filter

Percentage to remove (%):

Inter-quantile range

Based on: Standard deviation

Coefficient of variation

Submit

You will then receive messages indicating how many features were removed and how many remain after the filtering process, for both taxonomic and resistome data.

Taxonomic Data Filtering- OK

A total of 174 low abundance features were removed based on prevalence. A total of 443 low variance features were removed based on iqr. The number of features remains after the data filtering step: 3983

Resistomic Data Filtering- OK

A total of 28 low abundance features were removed based on prevalence. A total of 11 low variance features were removed based on iqr. The number of features remains after the data filtering step: 95

You can now proceed with the analysis. Click on 'Proceed'.

Previous

Proceed



Why should I use the data filtering option?

Data filtering is important because features having very low counts or abundance across all the samples cannot be discriminated from sequencing errors, and they can interfere with some statistical and biological approximations. Thus, such features should be removed from the data before performing any downstream analysis.



Which category should I choose to perform data filtering?

ResistoXplorer automatically removes features that comprise of all zeros or that are only present in one sample.

However, for all other types of analysis, further data filtration is required. By default, features are filtered based on their sample prevalence and abundance levels. You can also choose to remove features having low variance across samples.

All analyses for integrative data are performed on filtered and normalized data.

Data Normalization

Data Normalization aims to address the high level of systematic variability (uneven sampling depth), sparsity and heterogeneity present in the metagenomic data to enable more biologically meaningful comparisons and interpretations. There are wide variety of methods available and their performance have been evaluated in terms of methods ability to identify differentially abundant genes (see [MB Pereira et al.](#)) in metagenomic count data. All these methods require "raw count data" as input. You can rarefy your data followed by either data scaling or data transformation. However, both data scaling and data transformation cannot be applied together, because scaled or transformed data is no longer valid count data. To account for compositionality, two CoDA recommended **log-ratio** transformations have been also implemented. Please note, zero have been replaced with a small **pseudocount** (*i.e.*, $\min(\text{non zero value in table}) * 0.01$) before performing log-ratio transformations.

For integrative data analysis, both the datasets (taxonomic and resistome) are normalized using the **same** approach

Data rarefying ?

- Do not rarefy my data
- Rarefy to the minimum library size

Data scaling ?

- Do not scale my data
- Count per Million (CPM)
- Log Count per Million (logCPM)
- Cumulative sum scaling (CSS)
- Upper-quantile normalization (UQ)
- Relative proportion

Data transformation ?

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

All samples will be rarefied to even sequencing depth based on the sample having the lowest sequencing depth. If this sample contains extremely low reads, you may need to manually exclude this sample (using the Sample Editor) to avoid significant data loss. You can find out if this is the case from View Sample Size from the Data Summary page.

Data scaling aims to bring all samples to the same scale by dividing the samples by a scaling factor. Some common choices include total sum scaling (TSS), cumulative sum scaling (CSS), and upper-quantile scaling (UQ).

Variance stabilization transformation such as log-ratio transformation and its variations. Some common choices include centered log-ratio (CLR) transformation, relative log expression (RLE) normalization, or weighted trimmed mean of M-values (TMM).

Compositional data analysis (CoDA) recommended normalization approaches.

Submit

For this manual, we will go ahead with the default options as shown above. Click on 'Submit'.

Please notice that you cannot move forward with the analysis without clicking on 'Submit'.

No data rarefaction was performed. Performed count per million (CPM) normalization. No data transformation was performed.

Data Normalization

Data Normalization aims to address the high level of systematic variability (uneven sampling depth), sparsity and heterogeneity present in the metagenomic data to enable more biologically meaningful comparisons and interpretations. There are wide variety of methods available and their performance have been evaluated in terms of methods ability to identify differentially abundant genes (see [MB Pereira et al.](#)) in metagenomic count data. All these methods require "raw count data" as input. You can rarefy your data followed by either data scaling or data transformation. However, both data scaling and data transformation cannot be applied together, because scaled or transformed data is no longer valid count data. To account for compositionality, two CoDA recommended **log-ratio** transformations have been also implemented. Please note, zero have been replaced with a small **pseudocount** (*i.e.*, $\min(\text{non zero value in table}) * 0.01$) before performing log-ratio transformations.

For integrative data analysis, both the datasets (taxonomic and resistome) are normalized using the **same** approach

Data rarefying 

Do not rarefy my data

Rarefy to the minimum library size

Data scaling 

Do not scale my data

Count per Million (CPM)

Log Count per Million (logCPM)

Cumulative sum scaling (CSS)

Upper-quantile normalization (UQ)

Relative proportion

Data transformation 

Do not transform my data

Relative log expression (RLE)

Trimmed mean of M-values (TMM)

Hellinger transformation

Centered log ratio (CLR)

Additive log ratio (ALR)

Submit

You will then receive a message indicating the normalization procedures that were performed.

You can now proceed with the analysis. Click on 'Proceed'.

Analysis Panel

Here we have several options including Global Similarity analysis, Ordination-based integrative analysis, and pair-wise correlation analysis. In the next slides, we will go through important aspects of each, including some common questions.

1. Global Similarity analysis

Procrustes
analysis

Co-inertia
analysis

rCCA

sPLS

2. Ordination-based integrative analysis

3. Pair-wise correlation analysis

Spearman

Pearson

MIC

CCLasso

Analysis Panel

The first type of analysis is 'Global Similarity analysis'.

1. Global Similarity analysis

Procrustes
analysis

Co-inertia
analysis

rCCA

sPLS

2. Ordination-based integrative analysis

3. Pair-wise correlation analysis

Spearman

Pearson

MIC

CCLasso



What are Global Similarity analysis methods and what are the differences between them?

The two methods for Global Similarity analysis employed in ResistoXplorer are:

- 'Procrustes analysis' and
- 'Co-Inertia analysis'.

Both are symmetric methods which aim to analyze the covariance matrices. They differ in the form of presentation for the joint data ordination. Both are appropriate for community composition data. While Procrustes analysis creates a "compromise" ordination of two matrices measured on the same objects in order to visualize differences between two matrices, Co-inertia creates an ordination based on two covariance between two data matrices and plots both matrices in the same ordination space along with their variables.

Remember that you can always browse and go back to different steps of the process by utilizing the links provided here.

Let's start by looking at 'Procrustes analysis' – click here.

Analysis Panel

1. Global Similarity analysis

Procrustes analysis

Co-inertia analysis

rCCA

sPLS

2. Ordination-based integrative analysis

3. Pair-wise correlation analysis

Spearman

Pearson

MIC

CCLasso

Procrustes analysis

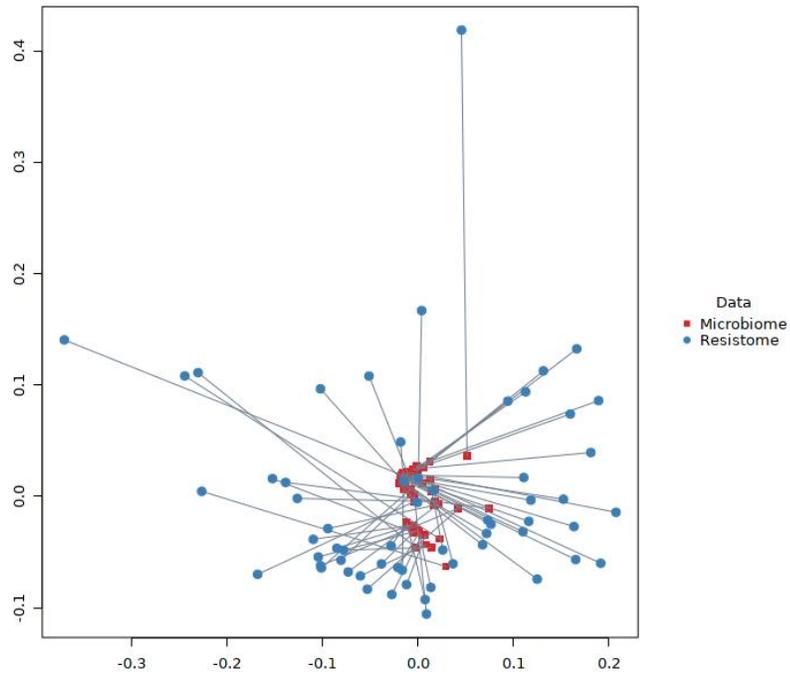
General options: Taxonomic level: Feature (Rownames) Profile level: Feature (Rownames)
Ordination method: PCoA Distance method: Bray-Curtis Index No. of Permutations: 999 [Submit](#) [Downloads](#)

View options: Color data points according to: Data (Omics) Experimental factor Time Color Palette: Set1 Label samples by: None (for 2D plot only)

2D Graphics 3D Graphics

[Procrustes] Sum of Squares = 0.6014; Correlation coefficient (squared m12) = 0.6313; P-value < 0.506

The statistical data is available here.



Procrustes analysis allows you to integrate omics data, and to analyze how these are spatially organized in dimensional shape analysis. Ordination and distance methods can be changed.

Ordination is an approach to display 'high dimensional' data into lower numbers of dimensions (2-3D). Currently, three common ordination based methods are supported in ResistoXplorer:

- Principal Coordinates Analysis (PCoA);
- Nonmetric Multidimensional Scaling (NMDS);
- Principal Component Analysis (PCA).

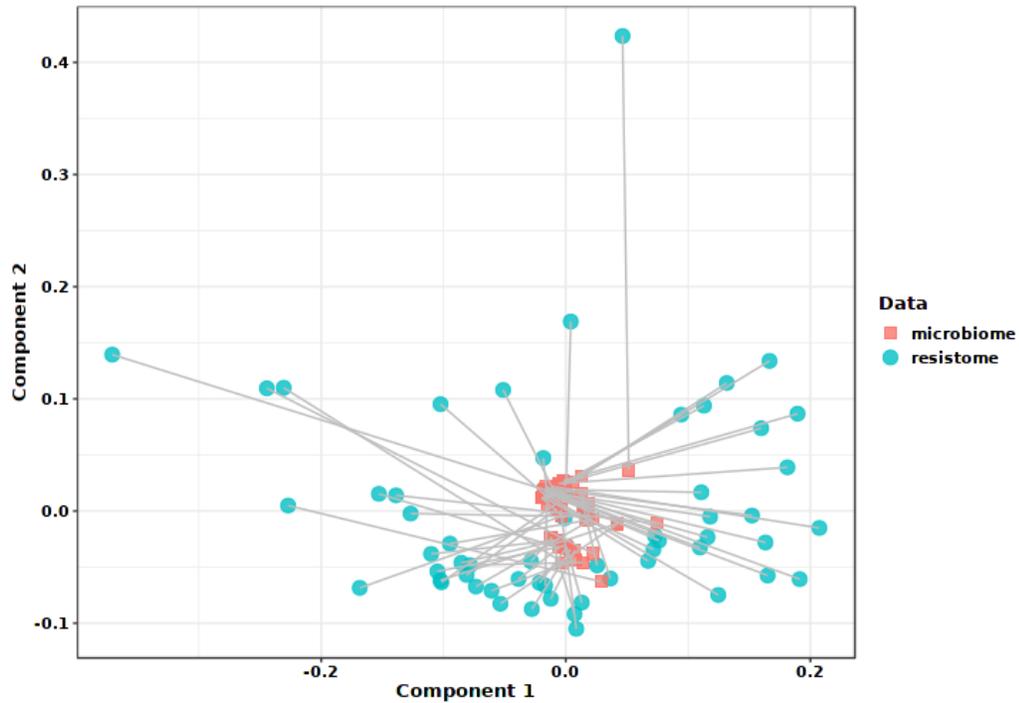
Procrustes analysis

General options: Taxonomic level: Feature (Rownames) | Ordination method: PCoA | Distance method: Bray-Curtis Index | No. of Permutations: 999 | [Submit](#) | [Downloads](#)

View options: Color data points according to: Data (Omics) | Experimental factor | Time | Color Palette: Set1 | Label samples by: None (for 2D plot only)

2D Graphics | 3D Graphics

[Procrustes] Sum of Squares = 0.6014; Correlation coefficient (squared m12) = 0.6313; P-value < 0.499



Procrustes analysis

General options:

Taxonomic level: Feature (Rownames) Profile level: Feature (Rownames)

Ordination method: PCoA Distance method: Bray-Curtis Index No. of Permutations: 999 [Submit](#) [Downloads](#)

View options:

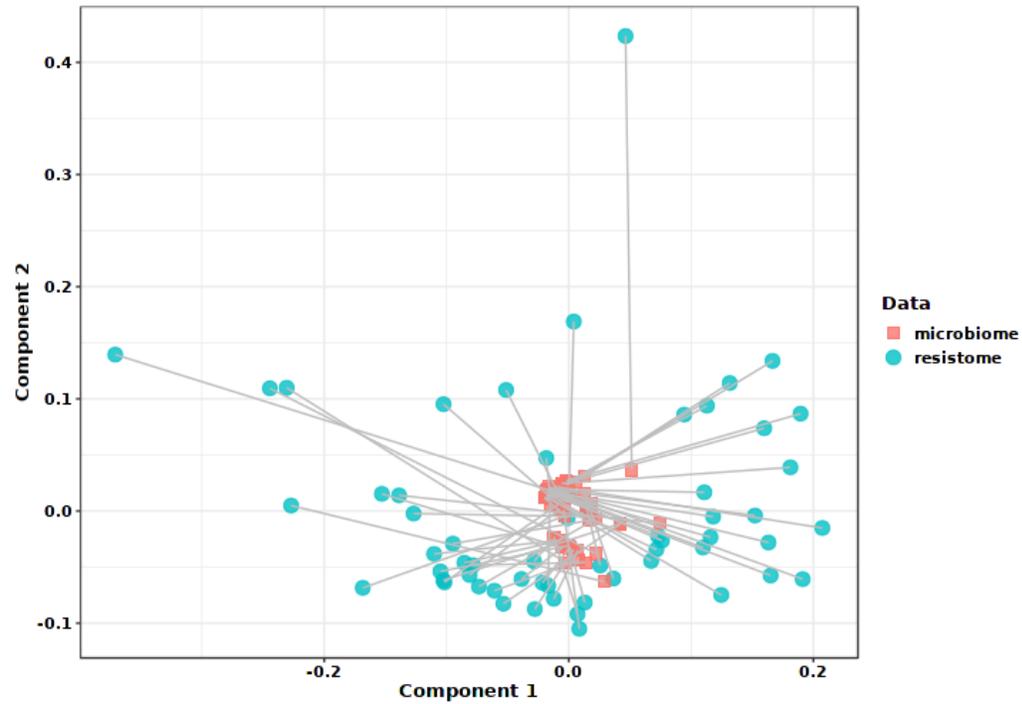
Color data points according to: Data (Omics) Experimental factor Time Color Palette: Set1 Label samples by: None (for 2D plot only)

2D Graphics

3D Graphics

If you click here, you will be able to see the same graph but in 3D.

[Procrustes] Sum of Squares = 0.6014; Correlation coefficient (squared m12) = 0.6313; P-value < 0.499



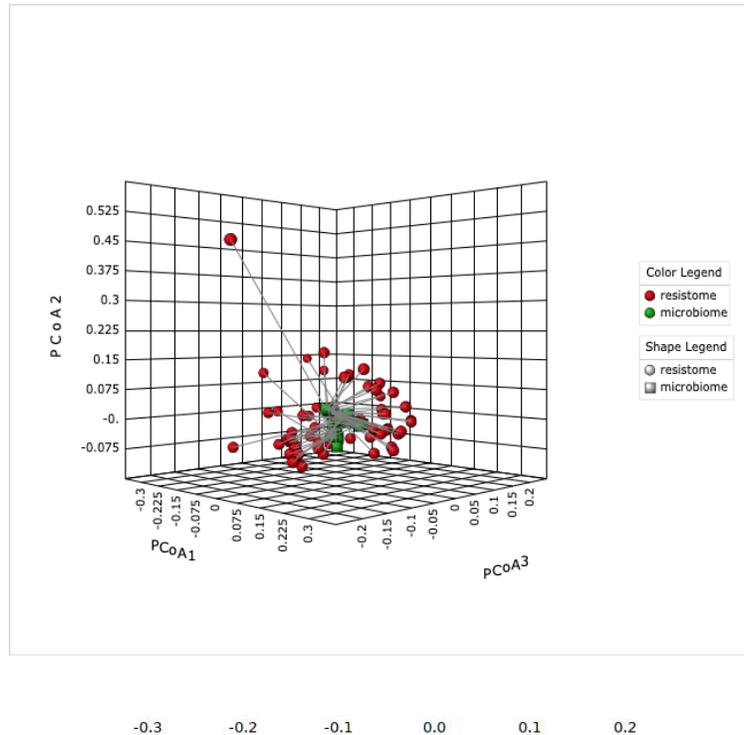
Procrustes analysis

General options: Taxonomic level: Feature (Rownames) Profile level: Feature (Rownames)
Ordination method: PCoA Distance method: Bray-Curtis Index No. of Permutations: 999 [Submit](#) [Downloads](#)

View options: Data (Omics) Experimental factor
Color data points according to: Time Color Palette: Set1 Label samples by: None (for 2D plot only)

2D Graphics [3D Graphics](#)

Drag to rotate, scroll to zoom, hover on a data point to view



You can click and drag to move the angle of the graph. If you hover over data points, information about them will be given. In addition, you can scroll to zoom in or out.

Procrustes analysis

General options: Taxonomic level: Feature (Rownames) Profile level: Feature (Rownames)
Ordination method: PCoA Distance method: Bray-Curtis Index No. of Permutations: 999

View options: Color data points according to: Data (Omics) Experimental factor Time Color Palette: Set1 Label samples by: None (for 2D plot only)

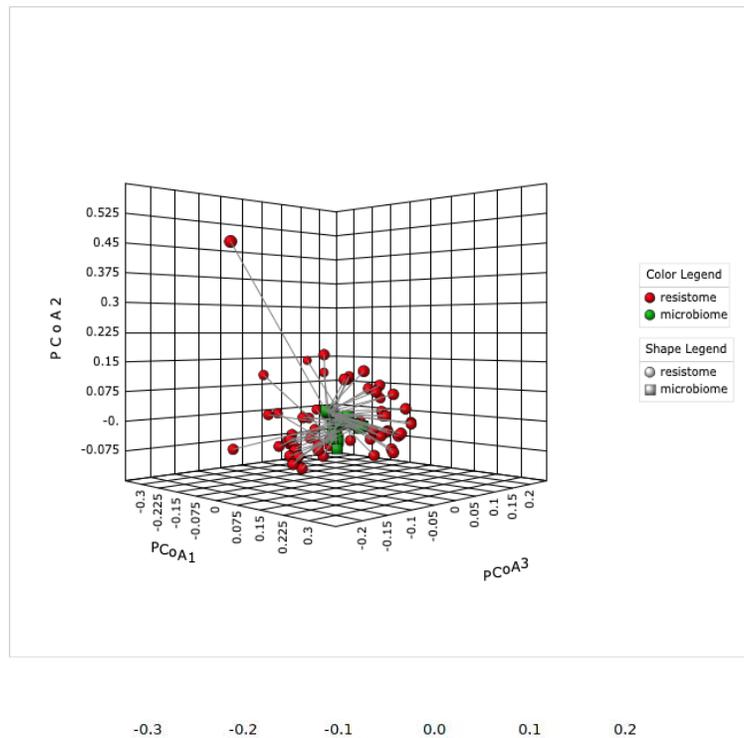
Submit

Downloads

You can choose to download the analyses and/or graphs in a number of different formats by clicking here.

2D Graphics 3D Graphics

Drag to rotate, scroll to zoom, hover on a data point to view



Once you are finished, you can click on 'Integrative Analysis' to go back to the previous page.

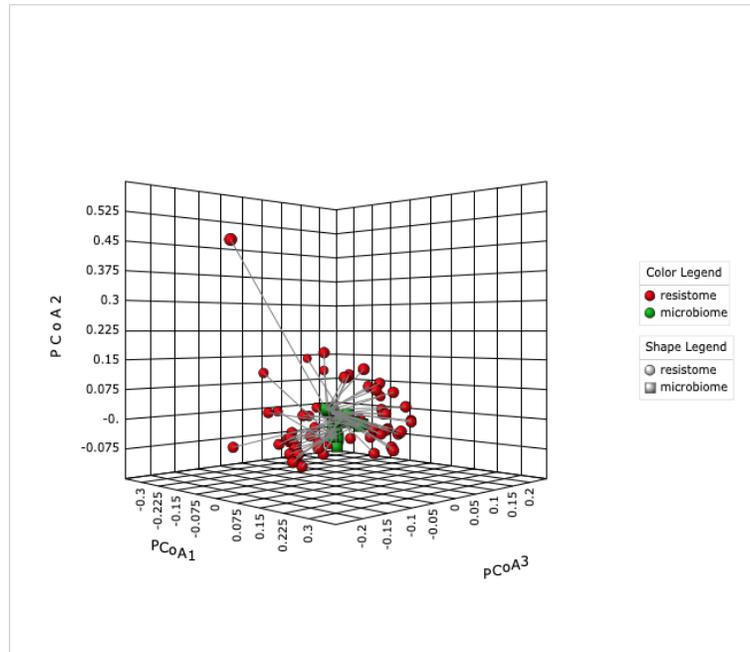
Procrustes analysis

General options: Taxonomic level: Feature (Rownames) Profile level: Feature (Rownames)
Ordination method: PCoA Distance method: Bray-Curtis Index No. of Permutations: 999 [Submit](#) [Downloads](#)

View options: Data (Omics) Experimental factor
Color data points according to: Time Color Palette: Set1 Label samples by: None (for 2D plot only)

2D Graphics [3D Graphics](#)

Drag to rotate, scroll to zoom, hover on a data point to view



-0.3 -0.2 -0.1 0.0 0.1 0.2

Analysis Panel

1. Global Similarity analysis

Procrustes

Co-inertia
analysis

rCCA

sPLS

Let's now look at
'Co-inertia analysis'
- click here.

3. Pair-wise correlation analysis

Spearman

Pearson

MIC

CCLasso

Co-inertia analysis (CIA) ?

General options:

Taxonomic level: Profile level:

Ordination method: Distance method: No. of Permutations:

View options:

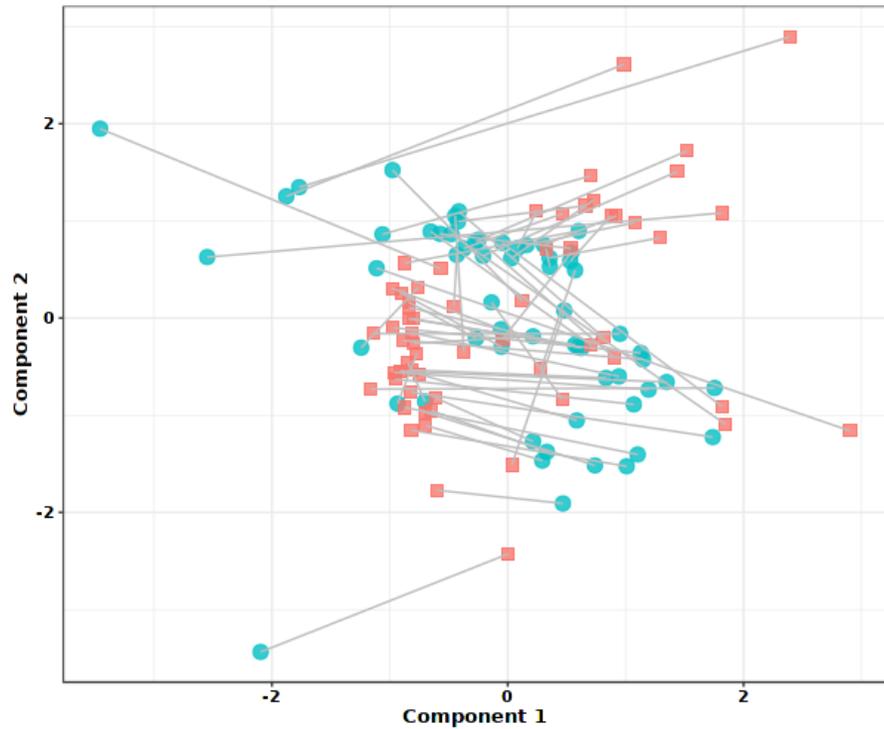
Color data points according to: Data (Omics) Experimental factor Color Palette: Label samples by: (for 2D plot only)

2D Graphics

3D Graphics

The statistical data is available here.

[Coinertia] RV coefficient = 0.59813; P-value = 0.01



Data
■ microbiome
● resistome

Similarly to Procrustes analysis, Co-inertia aims to compare the distribution of a set of shapes based on the input data. As previously, we can also visualize this in 3D.

Co-inertia analysis (CIA) [?](#)

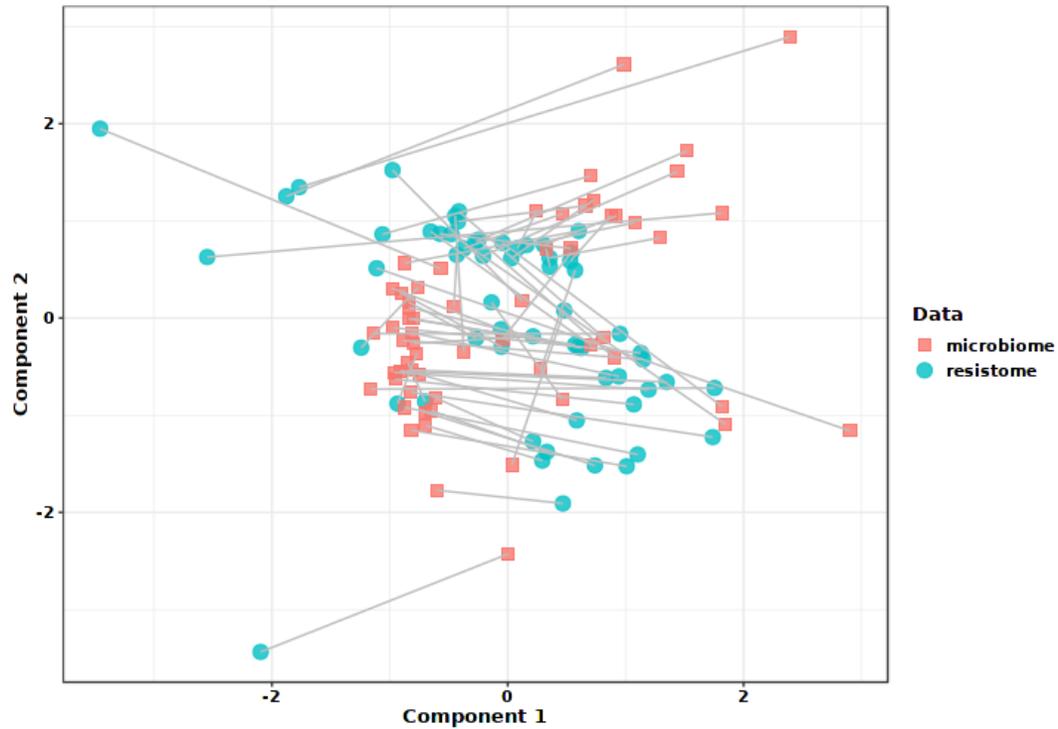
General options:
Taxonomic level: Feature (Rownames) Profile level: Feature (Rownames)
Ordination method: [?](#) PCoA Distance method: [?](#) Bray-Curtis Index No. of Permutations: 99

View options:
Color data points according to: Data Experimental factor

Ordination is an approach to display 'high dimensional' data into lower numbers of dimensions (2-3D). Currently, the two common ordination based methods supported in ResistoXplorer for Co-inertia are:
- Principal Coordinates Analysis (PCoA);
- Principal Component Analysis (PCA).

2D Graphics 3D Graphics

[Coinertia] RV coefficient = 0.59813; P-value = 0.01



Co-inertia analysis (CIA) [?]

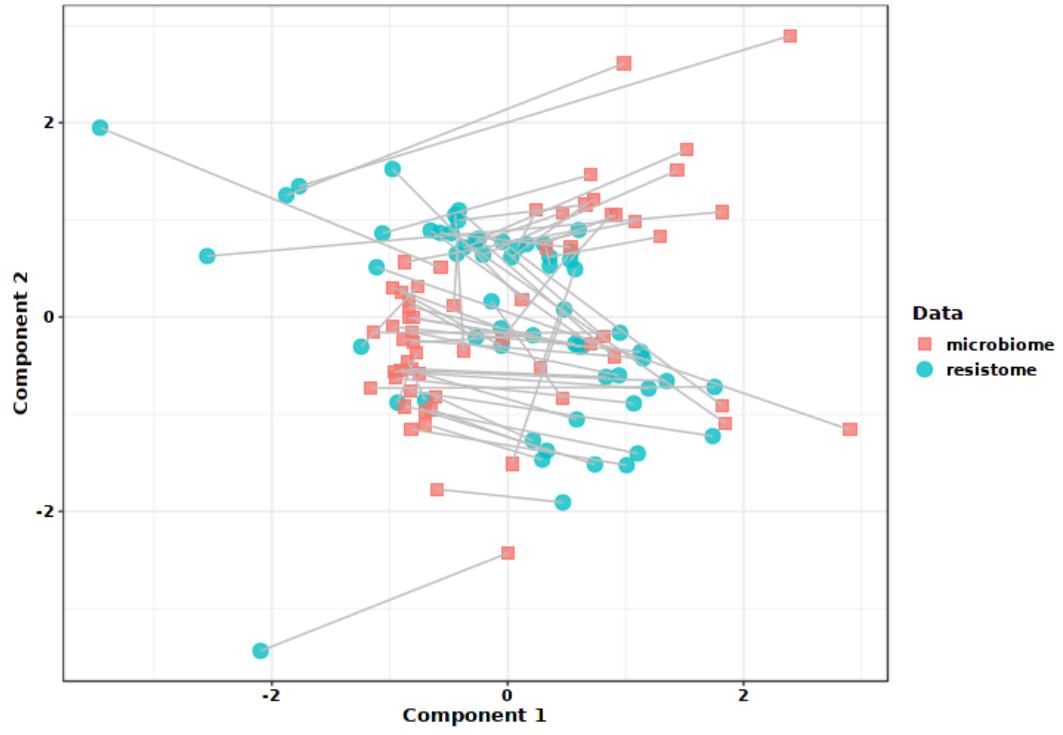
General options: Taxonomic level: Profile level:
Ordination method: Distance method: No. of Permutations:

View options: Color data points according to: Data (Omics) Experimental factor Color Palette: Label samples by: (for 2D plot only)

You can customize your options regarding the calculation such as ordination and distance methods. And you can also change the visualization.

If you click here, you will be able to see the same graph but in 3D.

[Coinertia] RV coefficient = 0.59813; P-value = 0.01



Co-inertia analysis (CIA) ?

General options: Taxonomic level: Feature (Rownames) Profile level: Feature (Rownames)

Ordination method: ? PCoA Distance method: ? Bray-Curtis Index No. of Permutations: 99

View options: Color data points according to: Data (Omics) Experimental factor Time Color Palette: Set1 Label samples by: None (for 2D plot only)

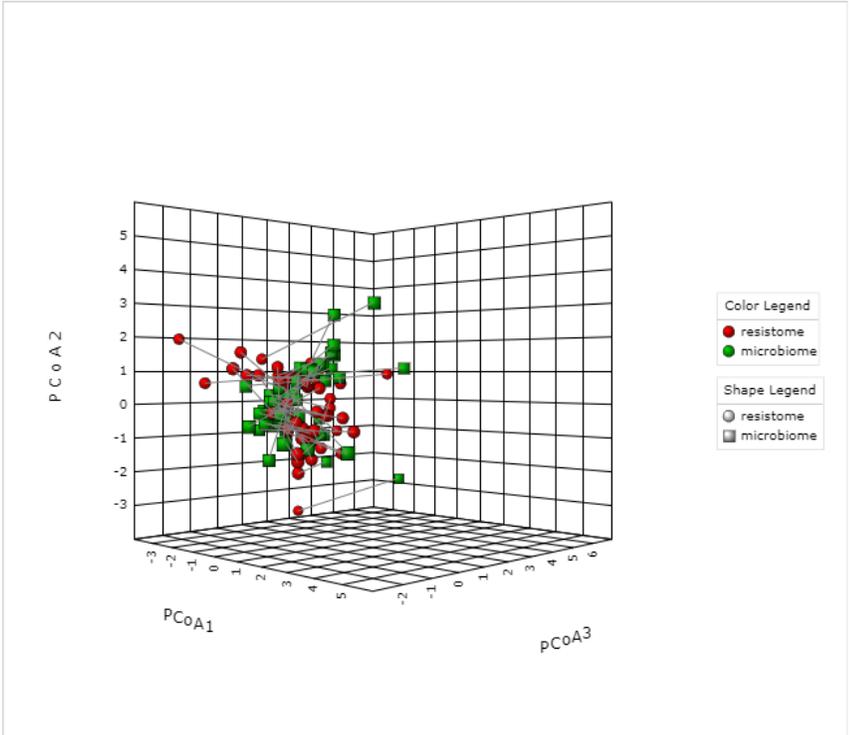
Submit

Downloads

You can choose to download the analyses and/or graphs in a number of different formats by clicking here.

2D Graphics 3D Graphics

Drag to rotate, scroll to zoom, hover a data point to view



Co-inertia analysis (CIA) ?

Once you are finished, you can click on 'Integrative Analysis' to go back to the previous page.

General options:

Taxonomic level: Profile level:

Ordination method: Distance method: No. of Permutations:

[Submit](#) [Downloads](#)

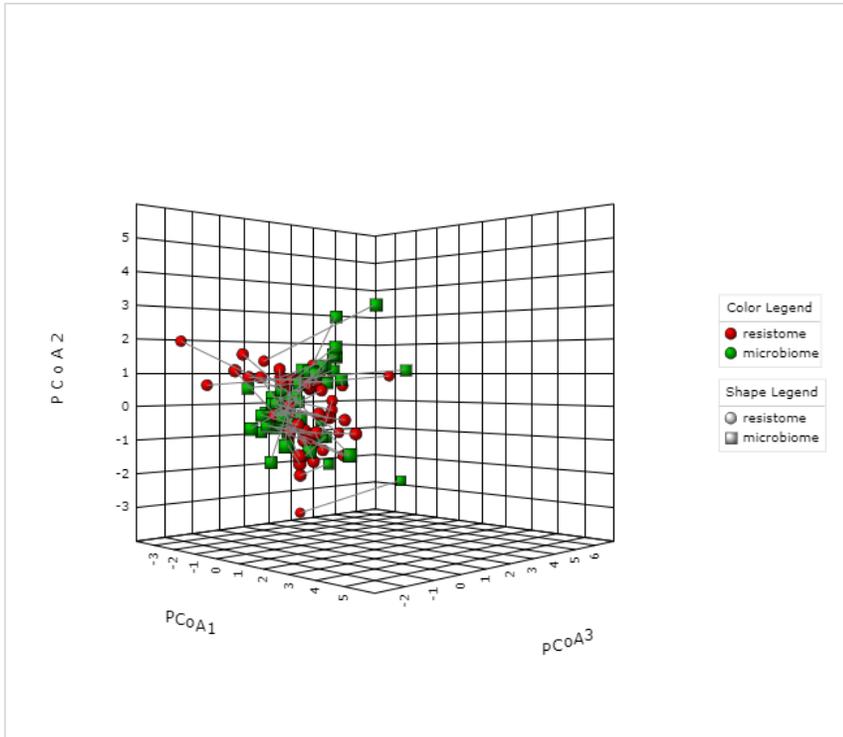
View options:

Color data points according to: Data (Omics) Experimental factor

Color Palette: Label samples by: (for 2D plot only)

[2D Graphics](#) [3D Graphics](#)

Drag to rotate, scroll to zoom, hover a data point to view



Analysis Panel

1. Global Similarity analysis

Procrustes
analysis

Co-inertia
analysis

rCCA

sPLS

2. Ordination-based integrative analysis

3. Pair-wise correlation analysis

Spearman

Pearson

MIC

CCLasso

Let's move to 'Ordination-based integrative analysis' now.



What are the options for 'Ordination-based integrative analysis' in ResistoXplorer?

ResistoXplorer offers two options of techniques to perform Ordination-based integrative analysis:

- regularized Canonical Correlation Analysis (rCCA).
- Sparse Partial Least Squares regression (sPLS).



What are the main differences between rCCA and sPLS?

Canonical Correlation Analysis (CCA) and Partial Least Squares regression (PLS) are methods that focus on the integration and exploration of two datasets. While their purpose and application is very similar, they differ in the method utilized for such. While CCA maximizes the correlation between linear combinations regarding variables in each dataset, PLS focuses on maximizing the covariance. Despite the underlying differences in the algorithms, if the components are scaled, both methods should give similar results. Importantly, CCA will calculate all components directly without deflation, and PLS presents different deflation modes. The decision regarding which technique to use will depend on your preference and data.

For more details, please refer to the original [mixOmics R package](#) publication.

Analysis Panel

1. Global Similarity analysis

2. Ordination-based integrative analysis

Procrustes
analysis

Co-inertia
analysis

rCCA

sPLS

Let's navigate
through 'rCCA' -
click here.

correlation analysis

Spearman

Pearson

MIC

CCLasso

Regularized Canonical Correlation Analysis (rCCA) ?

General options:

Taxonomic level: Profile level:

No of components: Regularization method: Validation method:

View options:

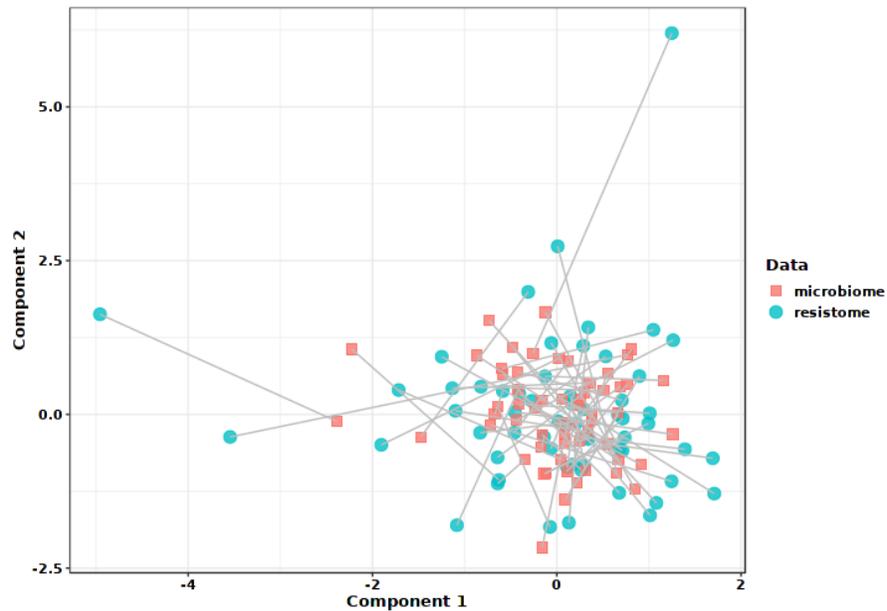
Color data points according to: Data (Omics) Experimental factor Color Palette: Label samples by:

(for score plot only)

Please Note: The *Color Palette* and *Label samples by* options are applicable for sample score plot (2D) only.

[Submit](#) [Downloads](#)

[Sample score plot \(2D\)](#) [Sample score plot \(3D\)](#) [Scree plot](#) [Clustered Image Map \(CIM\)](#) [Correlation Circle Plot](#)



As we have seen, Regularized Canonical Correlation Analysis (RCCA) is a statistical technique that extracts correlations between two types of data to construct a homogeneous, uniform representation of heterogeneous data channels.

Regularized

Here you can change the number of canonical variates pairs (components) to include in the model.

General options:

Taxonomic level: Profile level:

No of components: Regularization method: Validation method:

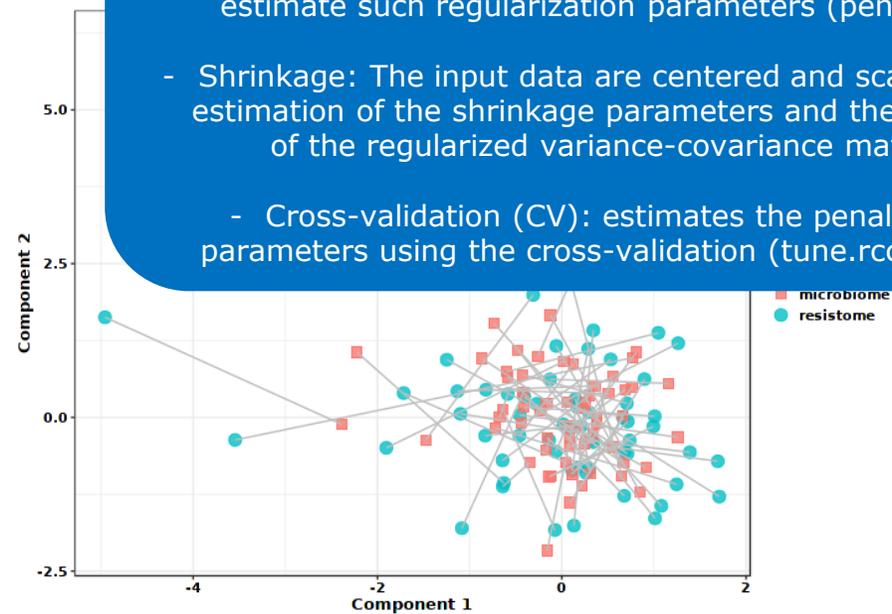
View options:

Color data: (Omics) Color Palette: Label samples by:

Due to the collinearities or near-collinearities in high-dimensional omics datasets, rCCA includes a regularization step in the computations of CCA. Before running rCCA, the regularization parameters λ_1 and λ_2 need to be tuned or estimated for both the datasets. There are two methods to estimate such regularization parameters (penalties):

- Shrinkage: The input data are centered and scaled for the estimation of the shrinkage parameters and the calculation of the regularized variance-covariance matrices;
- Cross-validation (CV): estimates the penalization parameters using the cross-validation (tune.rcc function).

To estimate the regularization parameters using Cross-validation, you can choose from either 5-fold CV (5-fold Cross-validation) or LOOCV (Leave One Out Cross-validation) (internal) cross-validation method.



Regularized Canonical Correlation Analysis (rCCA) ?

General options:

Taxonomic level: Profile level:

No of components: Regularization method: Validation method:

View options:

Color data points according to: Data (Omics) Experimental factor

Color Palette: Label samples by:

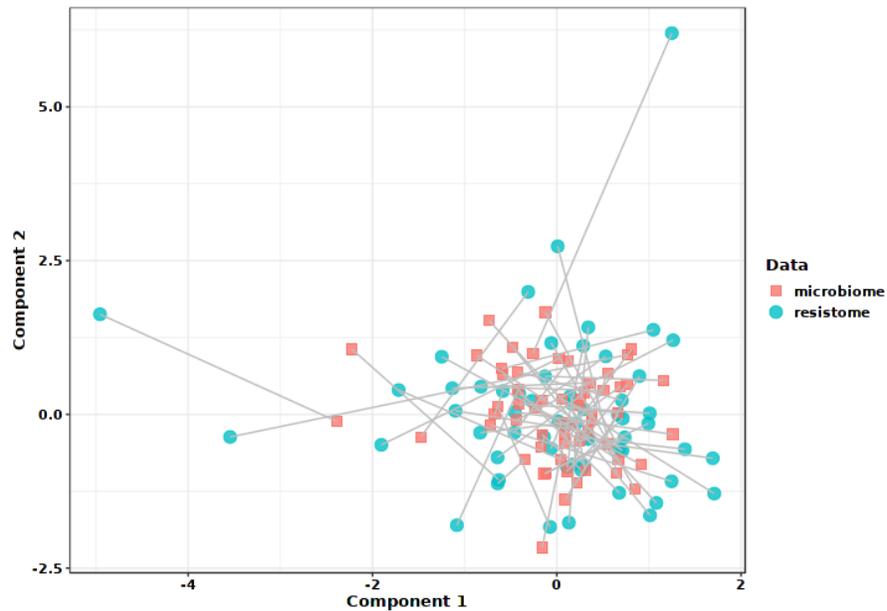
(for score plot only)

[Submit](#) [Downloads](#)

Please Note: The *Color Palette* and *Label samples by* options are applicable for sample score plot (2D) only.

[Sample score plot \(2D\)](#) [Sample score plot \(3D\)](#) [Scree plot](#) [Clustered Image Map \(CIM\)](#) [Correlation Circle Plot](#)

There are four options to visualize the data including Clustered Image Map (CIM), Correlation Circle Plot, Sample score plot (2D), and Sample score Plot (3D).



Regularized Canonical Correlation Analysis (rCCA) ?

General options:

Taxonomic level: Profile level:

No of components: Regularization method: Validation method:

View options:

Color data points according to: Data (Omics) Experimental factor

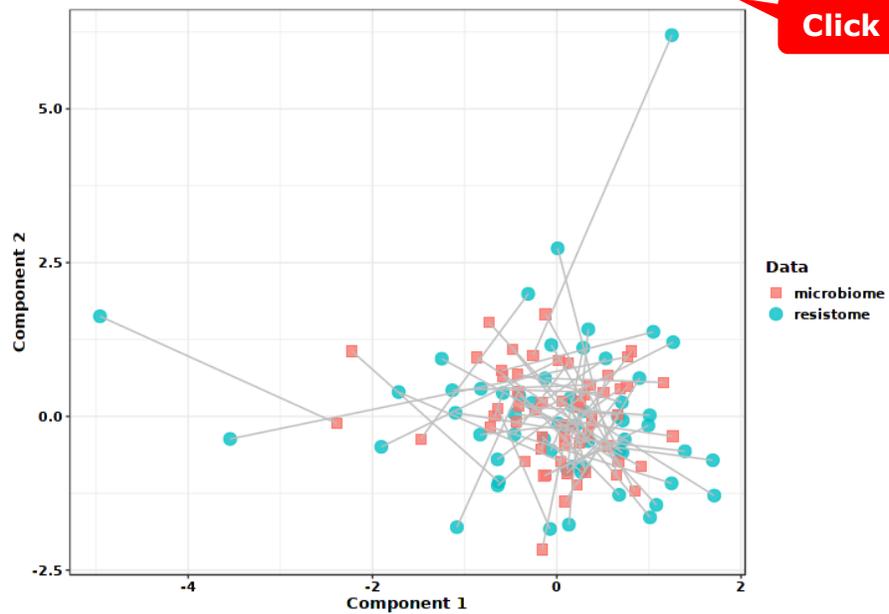
Color Palette: Label samples by:

(for score plot only)

Submit **Downloads**

Please Note: The *Color Palette* and *Label samples by* options are applicable for sample score plot (2D) only.

- Sample score plot (2D)
- Sample score plot (3D)
- Scree plot
- Clustered Image Map (CIM)**
- Correlation Circle Plot



Click on Clustered Image Map (CIM).

Regularized Canonical Correlation Analysis (rCCA) ?

General options:

Taxonomic level: Profile level:

No of components: Regularization method: Validation method:

View options:

Color data points according to: Data (Omics) Experimental factor

Time: Color Palette: Label samples by:

(for score plot only)

[Submit](#)

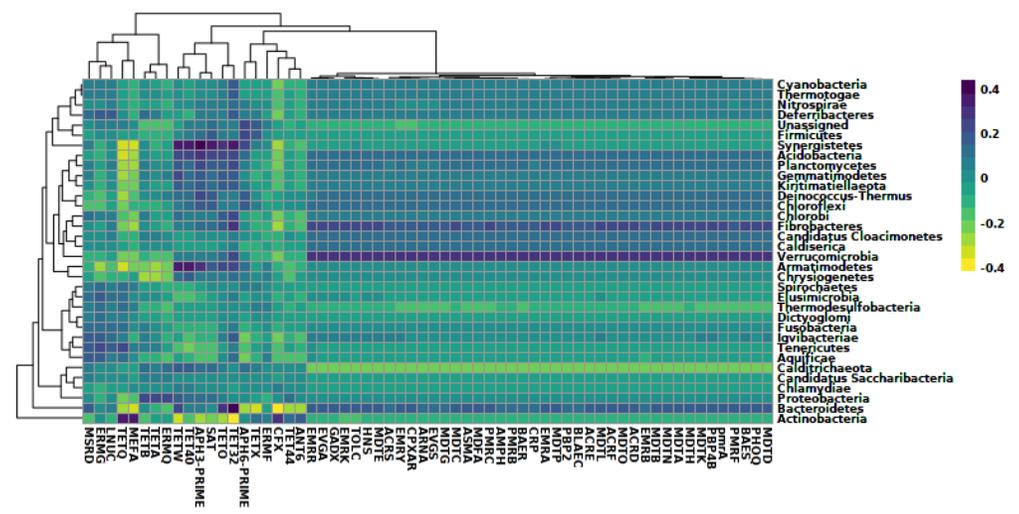
[Downloads](#)

Please Note: The *Color Palette* and *Label samples by* options are applicable for sample score plot (2D) only.

Sample score plot (2D) | Sample score plot (3D) | Scree plot | **Clustered Image Map (CIM)** | Correlation Circle Plot

Distance measure: Color contrast:

Clustering algorithm: View mode: [Update](#)



Here we can see a heatmap showing the correlation between taxonomic and resistome features. Distance measures and clustering algorithm can be changed as well as the color scheme and visualizing mode. As the values range from -0.3 to 0.3, in this case, strong features were not observed.

Regularized Canonical Correlation Analysis (rCCA) ?

General options:
Taxonomic level: Profile level:
No of components: Regularization method: Validation method:

View options: Data (Omics) Experimental factor
Color data points according to: Color Palette: Label samples by:

Submit

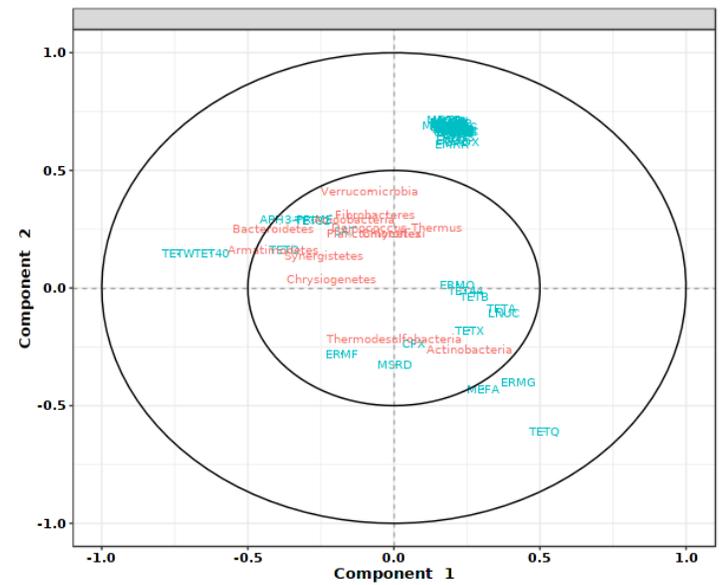
Downloads

Please Note: The **Color Palette** and **Label samples by** options are applicable for sample score plot (2D) only.

You can choose to download the analyses and/or graphs in a number of different formats by clicking here.

Sample score plot (2D) | Sample score plot (3D) | Scree plot | Clustered Image Map (CIM) | **Correlation Circle Plot**

Component on X-axis:
Component on Y-axis:
Correlation threshold:



Features
● Resistome
● Microbiome

Analysis Panel

1. Global Similarity analysis

Procrustes
analysis

Co-inertia
analysis

rCCA

sPLS

2. Ordination-based integrative analysis

3. Pair-wise correlation analysis

Spearman

Pearson

MIC

CCLasso

Moving forward
to sPLS. Click
here.

Sparse Partial Least Squares (sPLS) ?

General options:

Taxonomic level: Profile level:

No of components: Mode:

View options: Color data points according to: Data (Omics) Experimental factor

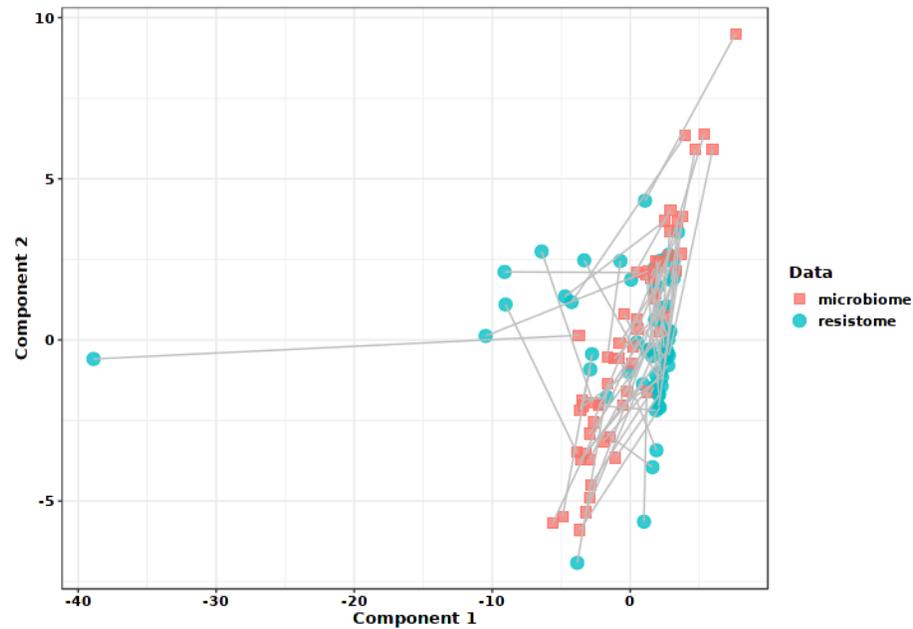
(for score plot only)

Color Palette: Label samples by:

[Submit](#) [Downloads](#)

Please Note: The *Color Palette* and *Label samples by* options are applicable for sample score plot (2D) only.

- Sample score plot (2D)
- Sample score plot (3D)
- Clustered Image Map (CIM)
- Correlation Circle Plot



Sparse Partial Least Squares (sPLS) is a multivariate methodology which integrates two omics datasets, in ResistoXplorer it is employed to combine metagenomics and resistome data. It acts by maximizing the covariance between components from these datasets. It combines both integration and variable selection simultaneously on two high-dimensional datasets in a one-step strategy.

The number of latent variables (components) to include in the model.

Sparse Partial Least Squares (sPLS)

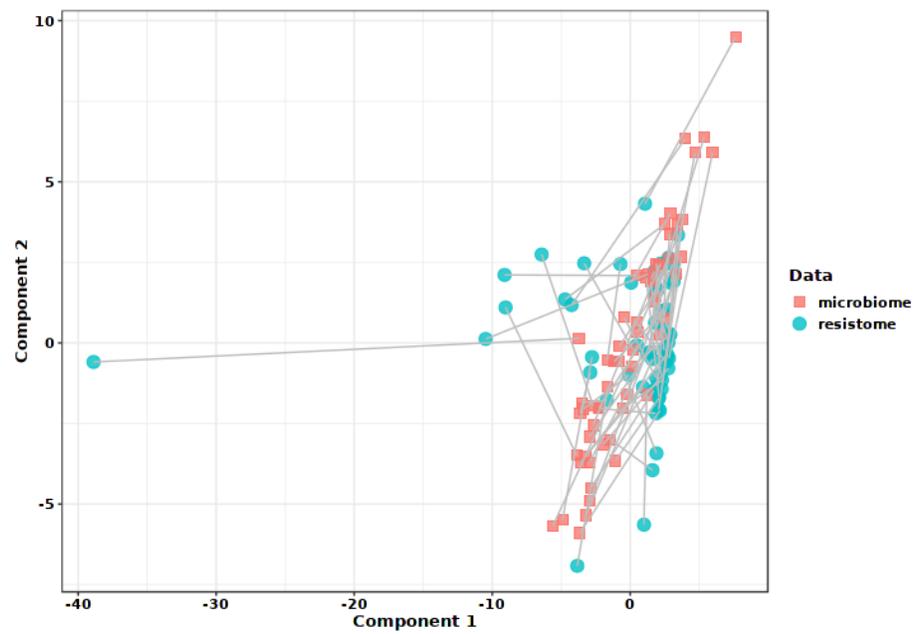
General options:
Taxonomic level: Profile level:
No of components: Mode:

Submit

Downloads

View options:
Color data points according to: Data (Omics) Experimental factor
(for score plot only)

Please Note: The *Color Palette* and *Label samples by* options are applicable for sample score plot.



Different modes relate on how the Y matrix (taxonomic profile) is deflated across iterations of the algorithms – *i.e.* the different components.

- Regression mode: the Y matrix is deflated with respect to the information extracted/modelled from the local regression on X (resistome profile). The goal is to predict Y from X (Y and X play an asymmetric role). Consequently, the latent variables computed to predict Y from X are different from those computed to predict X from Y.
- Canonical mode: the Y matrix is deflated to the information extracted/modelled from the local regression on Y. Here X and Y play a symmetric role and the goal is similar to a Canonical Correlation type of analysis.
- Invariant mode: the Y matrix is not deflated and perform a redundancy analysis.
- Classic mode: similar to a regression mode. It gives identical results for the loading vectors associated to the Y dataset.

Sparse Partial Least Squares (sPLS) [?]

General options:

Taxonomic level: Profile level:

No of components: Mode:

View options: Color data points according to: Data (Omics) Experimental factor

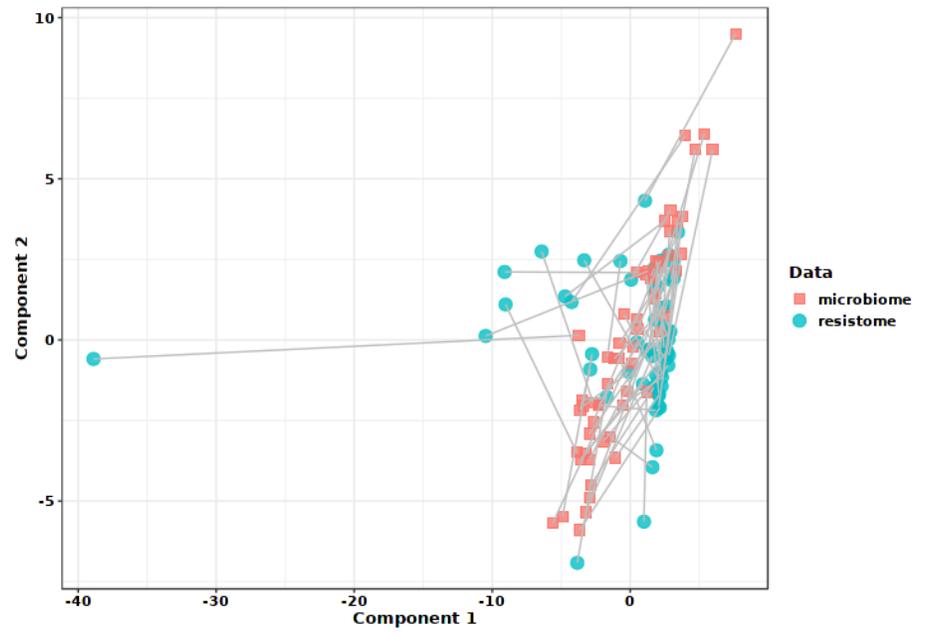
(for score plot only)

Color Palette: Label samples by:

Please Note: The **Color Palette** and **Label samples by** options are applicable for sample score plot (2D) only.

- Sample score plot (2D)
- Sample score plot (3D)
- Clustered Image Map (CIM)
- Correlation Circle Plot

Same as with rCCA, data can be visualized with Clustered Image Map (CIM), Correlation Circle Plot, and Sample score Plots (2D and 3D).



Sparse Partial Least Squares (sPLS) [?]

General options:

Taxonomic level: Profile level:

No of components: Mode:

Submit

Downloads

View options:

Color data points according to: Data (Omics) Experimental factor

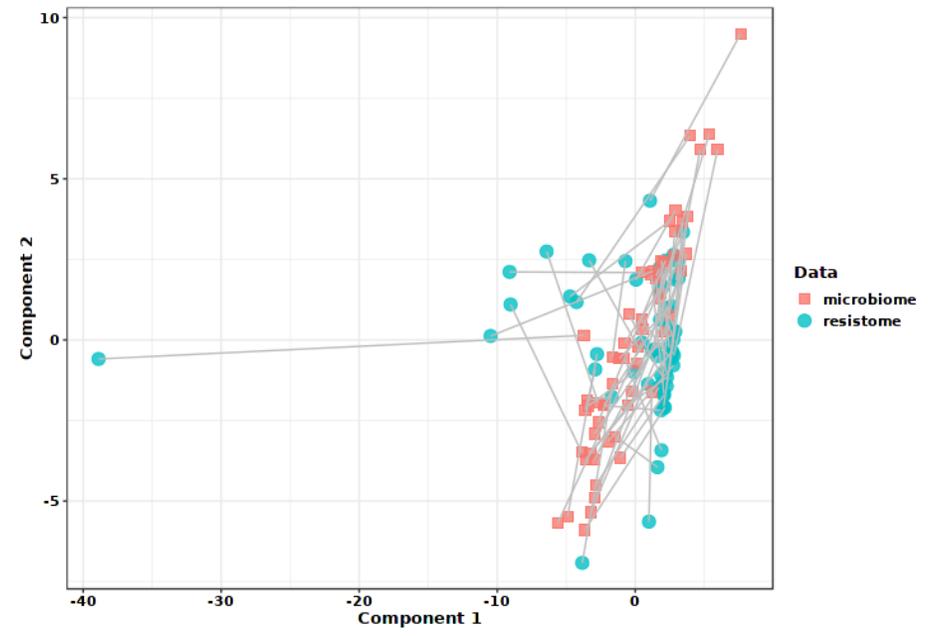
(for score plot only)

Color Palette: Label samples by:

Please Note: The *Color Palette* and *Label samples by* options are applicable for sample score plot (2D) only.

You can choose to download the analyses and/or graphs in a number of different formats by clicking here.

Sample score plot (2D) | Sample score plot (3D) | Clustered Image Map (CIM) | Correlation Circle Plot



Once you are finished, you can click on 'Integrative Analysis' to go back to the previous page.

Sparse Partial Least Squares (sPLS) [?]

General options:

Taxonomic level: Profile level:

No of components: Mode:

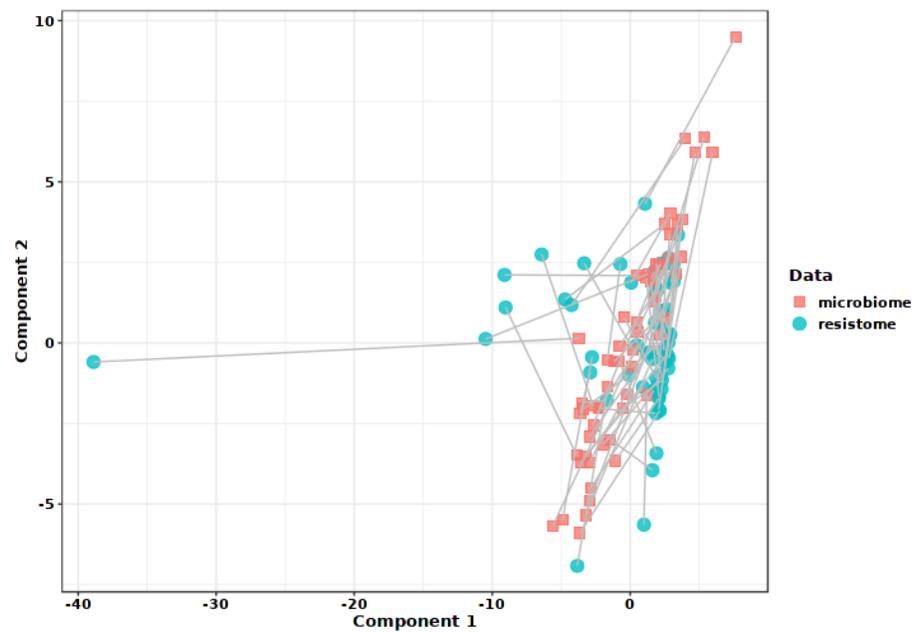
View options:

Color data points according to: Data (Omics) Experimental factor

(for score plot only)

Color Palette: Label samples by:

Please Note: The *Color Palette* and *Label samples by* options are applicable for sample score plot (2D) only.



Analysis Panel

1. Global Similarity analysis

Procrustes
analysis

Co-inertia
analysis

rCCA

sPLS

2. Ordination-based integrative analysis

Finally, let's move to pair-wise correlation analysis.

3. Pair-wise correlation analysis

Spearman

Pearson

MIC

CCLasso



What are the options for 'Pair-wise correlation analysis' in ResistoXplorer?

ResistoXplorer offers four options of to perform pair-wise correlation analysis between microbiome and resistome data. The methods are:

- Spearman correlation analysis;
- Pearson correlation analysis;
- Maximal Information Coefficient (MIC) analysis; and
- Correlation inference for compositional data through Lasso (CCLasso).



What information can the 'Pair-wise correlation analysis' methods provide?

ResistoXplorer provides four types of correlation analyses, namely Spearman, Pearson, Maximal Information Coefficient (MIC) and Correlation inference for compositional data through Lasso (CCLasso). These methods can be used to determine if there are any strong associations between individual taxa (microbiome) and ARGs (resistome).

Both sets of data (microbiome and resistome) can be analyzed at different taxonomic levels such as phylum, genus and species, and at different functional levels such as class and mechanism (based on available annotations). The level of significance to be considered can also be adjusted.

Analysis Panel

1. Global Similarity analysis

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analysis

Co-inertia
analysis

rCCA

sPLS

2. Ordination-based integrative analysis

3. Pair-wise correlation analysis

Spearman

Pearson

MIC

CCLasso

Let's look at the potential outputs of pair-wise correlation analyses. We will start with Spearman.

Spearman rank correlation

It is the most widely used method to perform pair-wise correlation analysis between microbiome and resistome abundance profile. **Please Note:** The microbiome and resistome count data (after data filtering) have been transformed to their relative abundances (proportion) in order to perform such analysis. Also, features (i.e., ARGs and species) that are not found (zero count) in more than half of the samples are removed from both datasets before merging and performing correlation to alleviate the bias from potential joint-ranking of zero values.

General options:

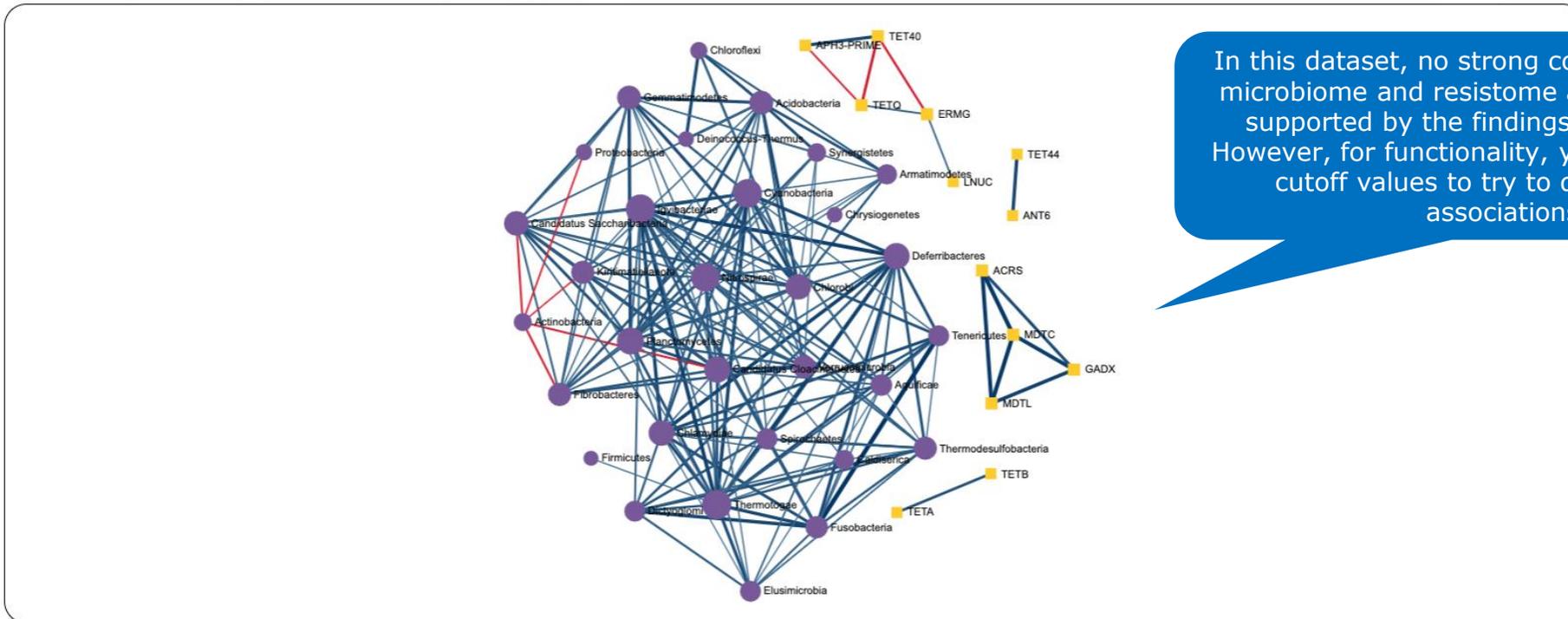
Taxonomic level: Profile level: Corr. coefficient cutoff:

Adjusted p-value cutoff: p-value correction method:

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the magnitude and strength of correlation between them (**Red**: negative; **Blue**: positive). **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.

Network Layout: Node size based on:



In this dataset, no strong correlation between microbiome and resistome are seen, which is supported by the findings of the authors. However, for functionality, you can reduce the cutoff values to try to detect weaker associations.

Spearman rank correlation

It is the most widely used method to perform pair-wise correlation analysis between microbiome and resistome abundance profile. **Please Note:** The microbiome and resistome count data (after normalization) have been transformed to their relative abundances (proportion) in order to perform such analysis. Also, features (i.e., ARGs and species) that are not found (zero count) in more than half of the samples are removed from both datasets before merging and performing correlation to alleviate the bias from potential joint-ranking of zero values.

General options:

Taxonomic level: Profile level: Corr. coefficient cutoff:

Adjusted p-value cutoff: p-value correction method:

Submit

Downloads

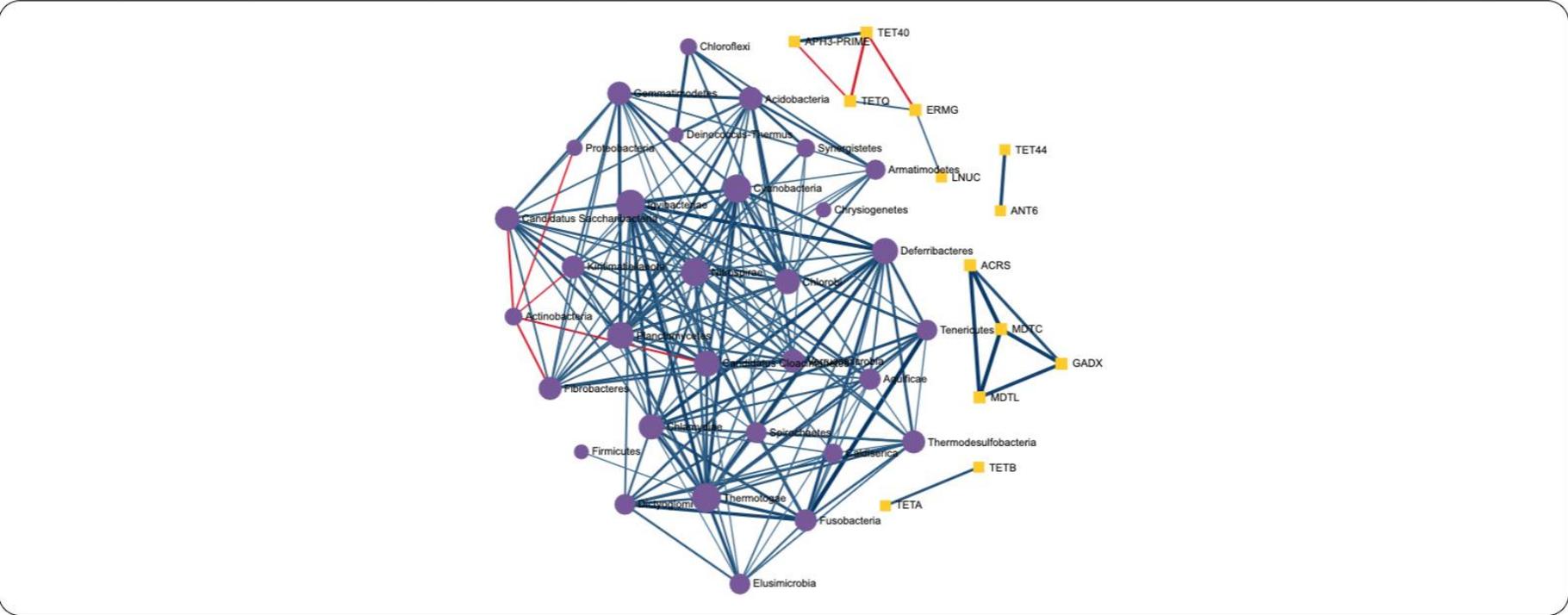
To try to detect weaker correlations, you can select the cutoff to be 0.3.

After you changed the cutoff, click on 'Submit'.

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality (degree measure). The color and width of edges shows the magnitude and strength of correlation between them (**Red**: negative; **Blue**: positive). **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.

Network Layout: Node size based on:



Spearman rank correlation

It is the most widely used method to perform pair-wise correlation analysis between microbiome and resistome abundance profile. **Please Note:** The microbiome and resistome count data (after data filtering) have been transformed to their relative abundances (proportion) in order to perform such analysis. Also, features (i.e., ARGs and species) that are not found (zero count) in more than half of the samples are removed from both datasets before merging and performing correlation to alleviate the bias from potential joint-ranking of zero values.

General options:

Taxonomic level: Profile level: Corr. coefficient cutoff:

Adjusted p-value cutoff: p-value correction method:

Submit

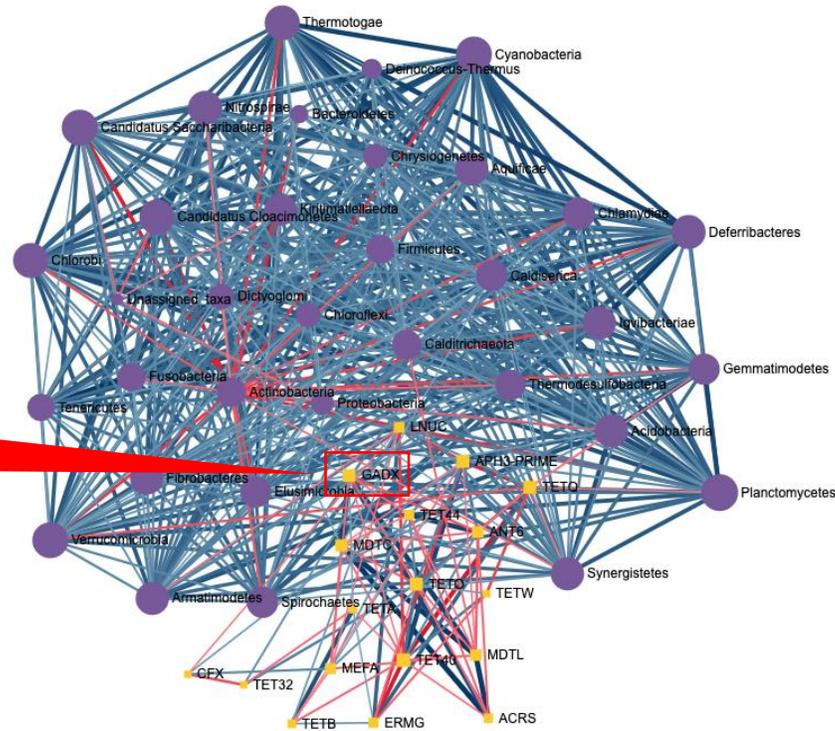
Downloads

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the magnitude and strength of correlation between them (**Red**: negative; **Blue**: positive). **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.

Network Layout: Node size based on: Submit

Refresh



Try to double-click GADX.

As you lowered the cutoff, more correlations appear as expected.

Spearman rank correlation

It is the most widely used method to perform pair-wise correlation analysis between microbiome and resistome abundance profile. **Please Note:** The microbiome and resistome count data (after data filtering) have been transformed to their relative abundances (proportion) in order to perform such analysis. Also, features (i.e., ARGs and species) that are not found (zero count) in more than half of the samples are removed from both datasets before merging and performing correlation to alleviate the bias from potential joint-ranking of zero values.

General options:

Taxonomic level: Profile level: Corr. coefficient cutoff:

Adjusted p-value cutoff: p-value correction method:

Submit

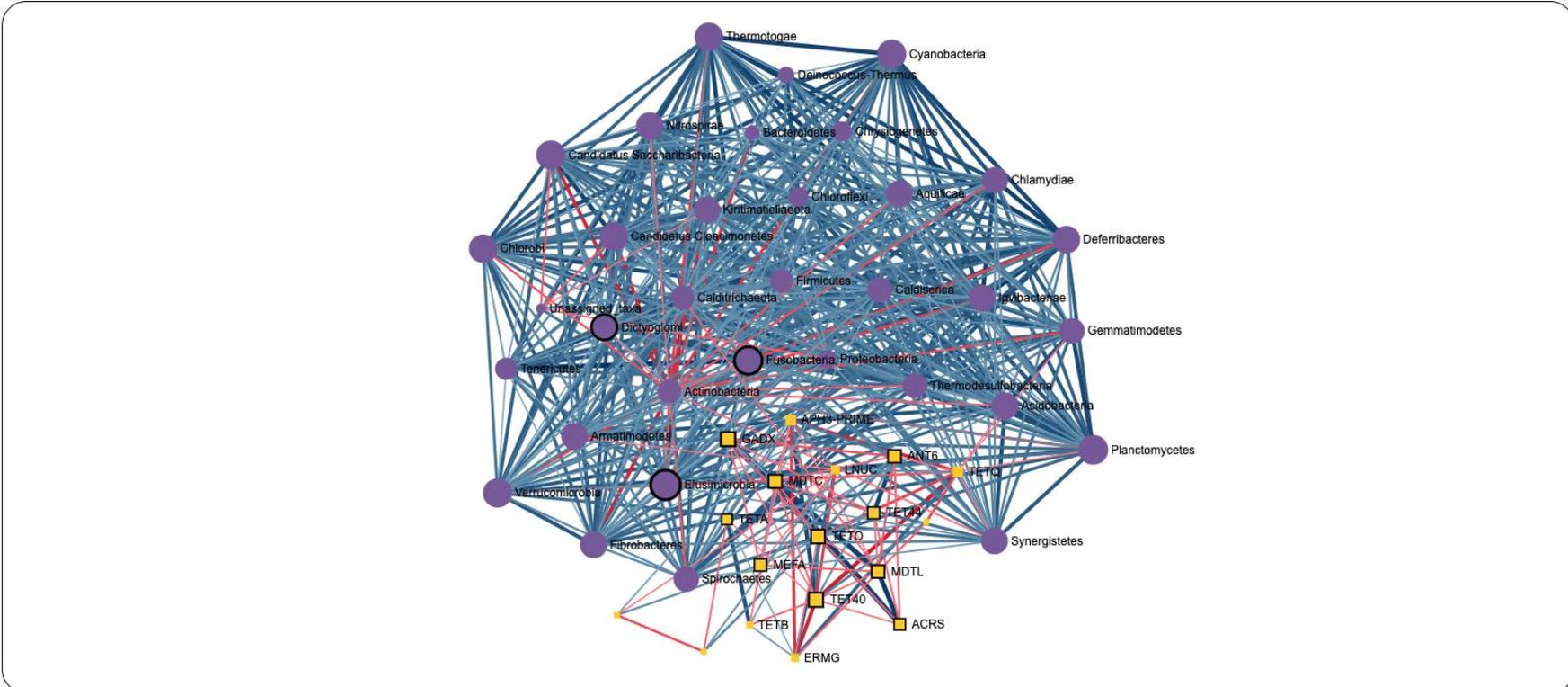
Downloads

You can choose to download the analyses and/or graphs in a number of different formats by clicking here.

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the magnitude and strength of correlation between them (**Red**: negative; **Blue**: positive). **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.

Network Layout: Node size based on:



Once you are finished, you can click on 'Integrative Analysis' to go back to the previous page.

Spearman rank correlation

It is the most widely used method to perform pair-wise correlation analysis between microbiome and resistome abundance profile. **Please Note:** The microbiome and resistome count data (after data filtering) have been transformed to their relative abundances (proportion) in order to perform such analysis. Also, features (i.e., ARGs and species) that are not found (zero count) in more than half of the samples are removed from both datasets before merging and performing correlation to alleviate the bias from potential joint-ranking of zero values.

General options:

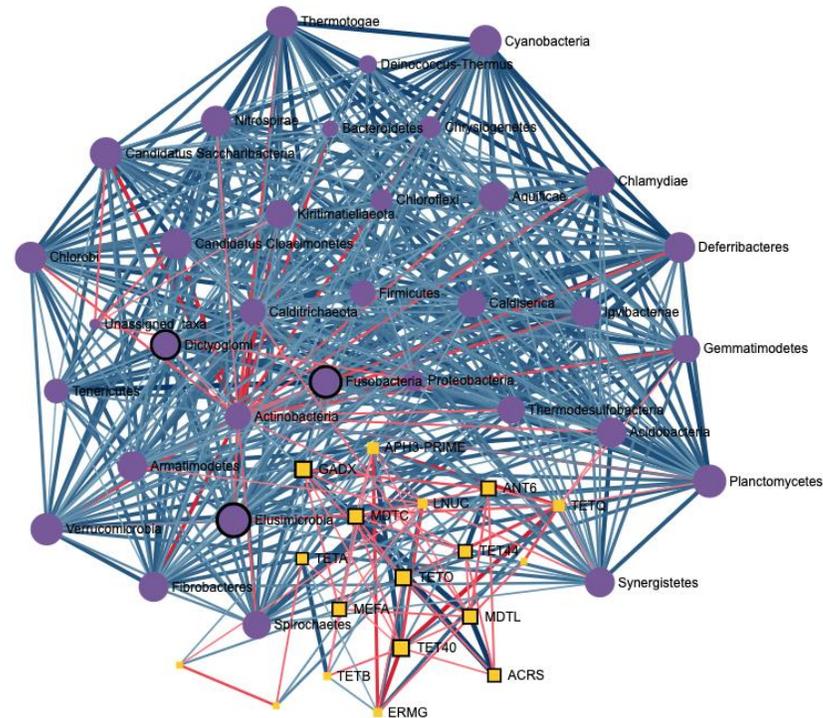
Taxonomic level: Profile level: Corr. coefficient cutoff:

Adjusted p-value cutoff: p-value correction method:

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the magnitude and strength of correlation between them (**Red**: negative; **Blue**: positive). **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.

Network Layout: Node size based on:



Analysis Panel

1. Global Similarity analysis

Procrustes
analysis

Co-inertia
analysis

rCCA

sPLS

2. Ordination-based integrative analysis

3. Pair-wise correlation analysis

Spearman

Pearson

MIC

CCLasso

Let's proceed with
'Pearson correlation
analysis'. Click here.

Pearson correlation

Please Note: The microbiome and resistome count data (after data filtering) have been transformed to their relative abundances (proportion) in order to perform pair-wise pearson correlation. Features with zero count in more than half of the samples are removed from both datasets before merging and performing such analysis.

General options:

Taxonomic level: Profile level: Corr. coefficient cutoff:

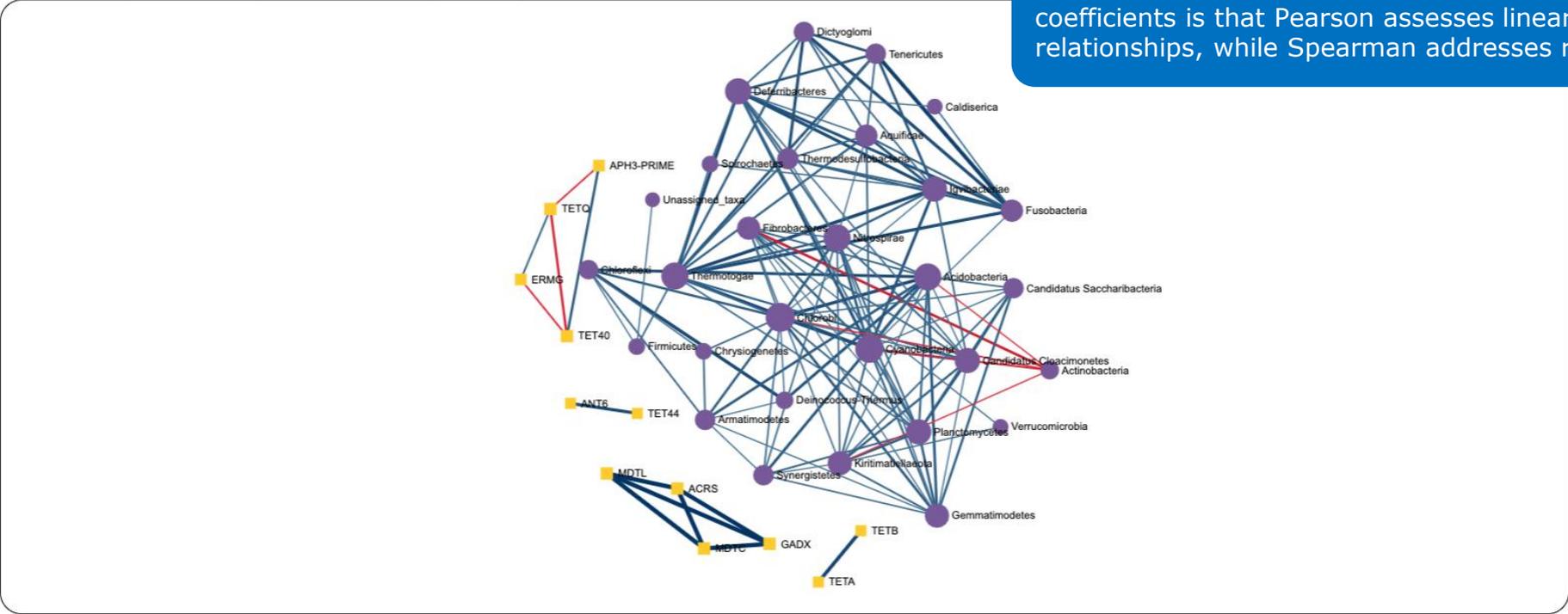
Adjusted p-value cutoff: p-value correction method:

Here you will be able to set up the different options for the correlation analysis. Once selections are made, remember to click on 'Submit'.

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure. The color and width of edges shows the magnitude and strength of correlation between them (**Red**: negative; **Blue**: positive). **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.

Network Layout: Node size based on:



The main difference between Pearson and Spearman correlation coefficients is that Pearson assesses linear and continuous relationships, while Spearman addresses rank relationships.

Pearson correlation

Please Note: The microbiome and resistome count data (after data filtering) have been transformed to their relative abundances (proportion) in order to perform pair-wise pearson correlation analysis. Also, an additional data filtering i.e., features (ARGs and species) that are missing (zero count) in more than half of the samples are removed from both datasets before merging and performing such analysis.

General options:

Taxonomic level: Profile level: Corr. coefficient cutoff:

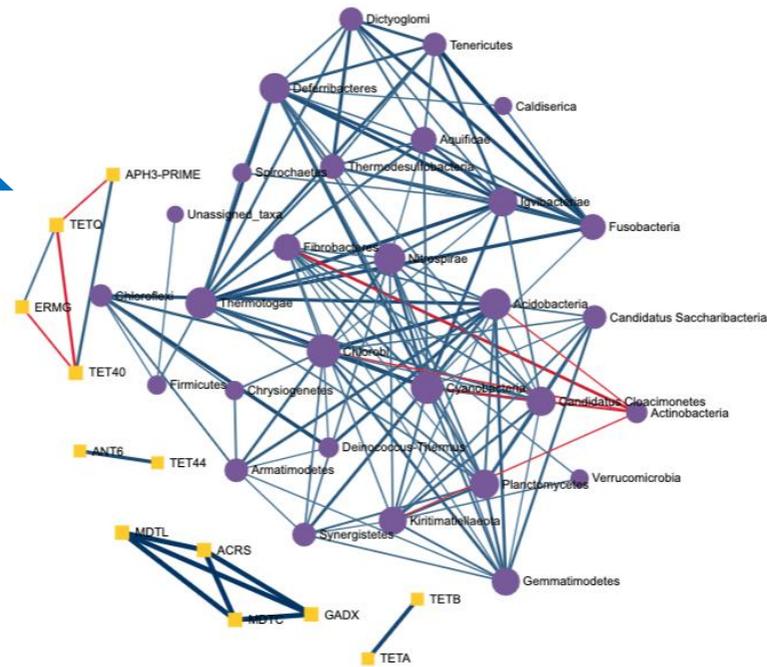
Adjusted p-value cutoff: p-value correction method:

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the magnitude and strength of correlation between them (**Red**: negative; **Blue**: positive). **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.

Network Layout: Node size based on:

The size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the magnitude and strength of correlation between them. If you double-click a node, it will highlight all the associated or correlated neighbour nodes.



Likewise, the results can be visualized in the 'co-occurrence network'. Resistome data is shown in yellow squares, while microbiome data are purple dots. Positive correlations are marked as blue lines, while negative correlations are in red.

Pearson correlation

Please Note: The microbiome and resistome count data (after data filtering) have been transformed to their relative abundances (proportion) in order to perform pair-wise pearson correlation analysis. Also, an additional data filtering i.e., features (ARGs and species) that are missing (zero count) in more than half of the samples are removed from both datasets before merging and performing such analysis.

General options:

Taxonomic level: Profile level: Corr. coefficient cutoff:

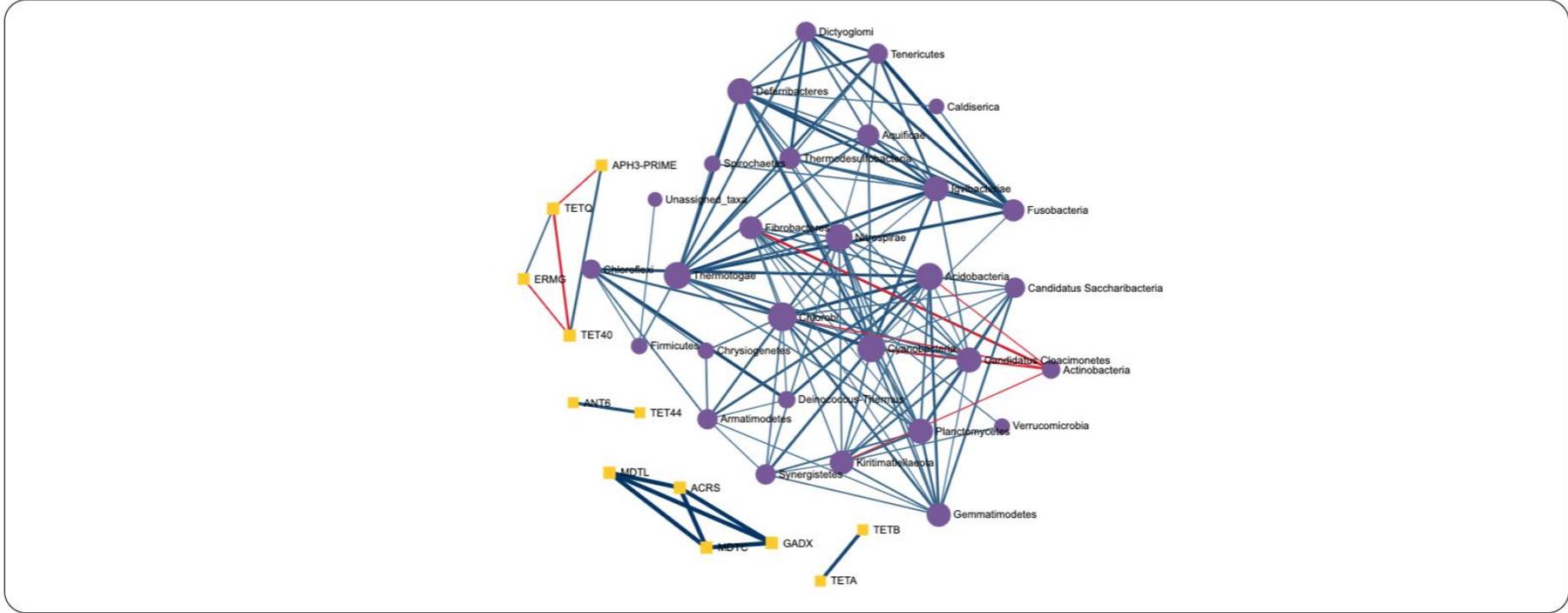
Adjusted p-value cutoff: p-value correction method:

You can choose to download the analyses and/or graphs in a number of different formats by clicking here.

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the magnitude and strength of correlation between them (**Red**: negative; **Blue**: positive). **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.

Network Layout: Node size based on:



Analysis Panel

1. Global Similarity analysis

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analysis

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analysis

rCCA

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2. Ordination-based integrative analysis

3. Pair-wise correlation analysis

Spearman

Pearson

MIC

CCLasso

Now we will look at
MIC. Click here.

Maximal Information Coefficient (MIC) analysis

General options:

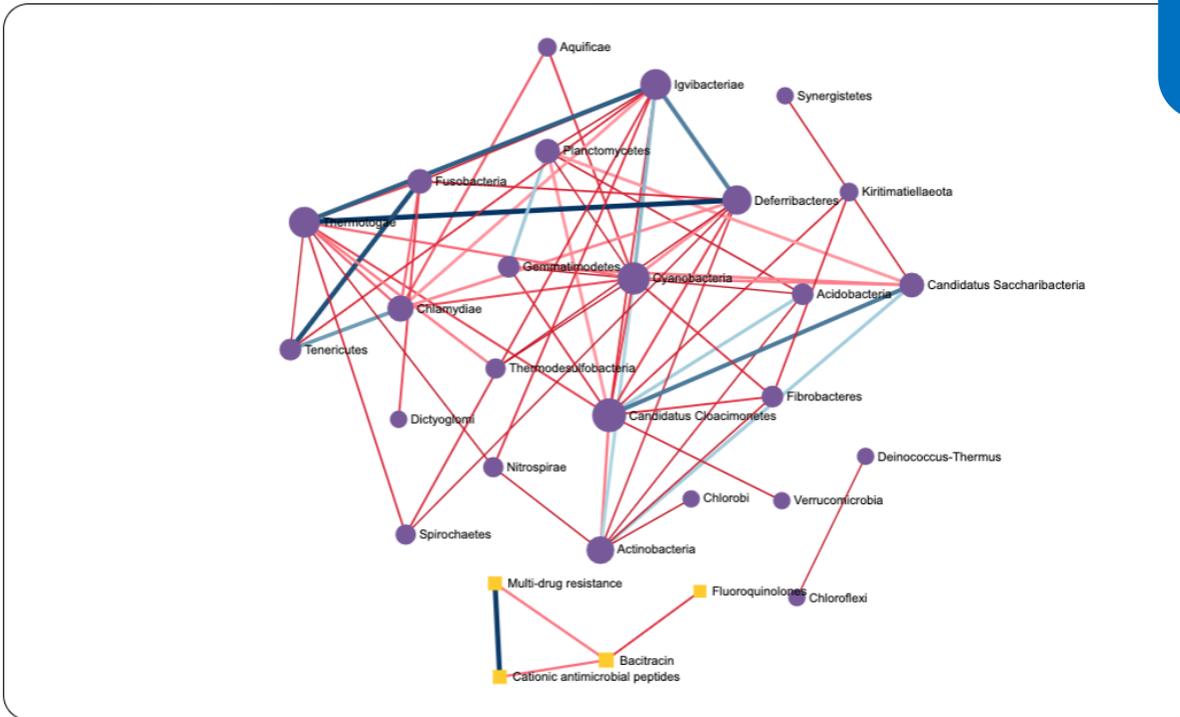
Taxonomic level: Profile level: No. of permutations:

Corr. coefficient cutoff: Adjusted p-value cutoff: p-value correction method:

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the strength of correlation between them (**MIC**: varies from 0 to 1). User can **zoom** in and out the network along with **dragging** nodes. Also, **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.

Network Layout: Node size based on:



Maximal Information Coefficient (MIC) is a measure of two-variable dependence designed specifically for rapid exploration of many dimensional data sets. MIC is part of a larger family of maximal-information-based nonparametric exploration (MINE) statistics, which can be used not only to identify important relationships in data sets but also to characterize them.

Maximal Information Coefficient (MIC) analysis

General options:

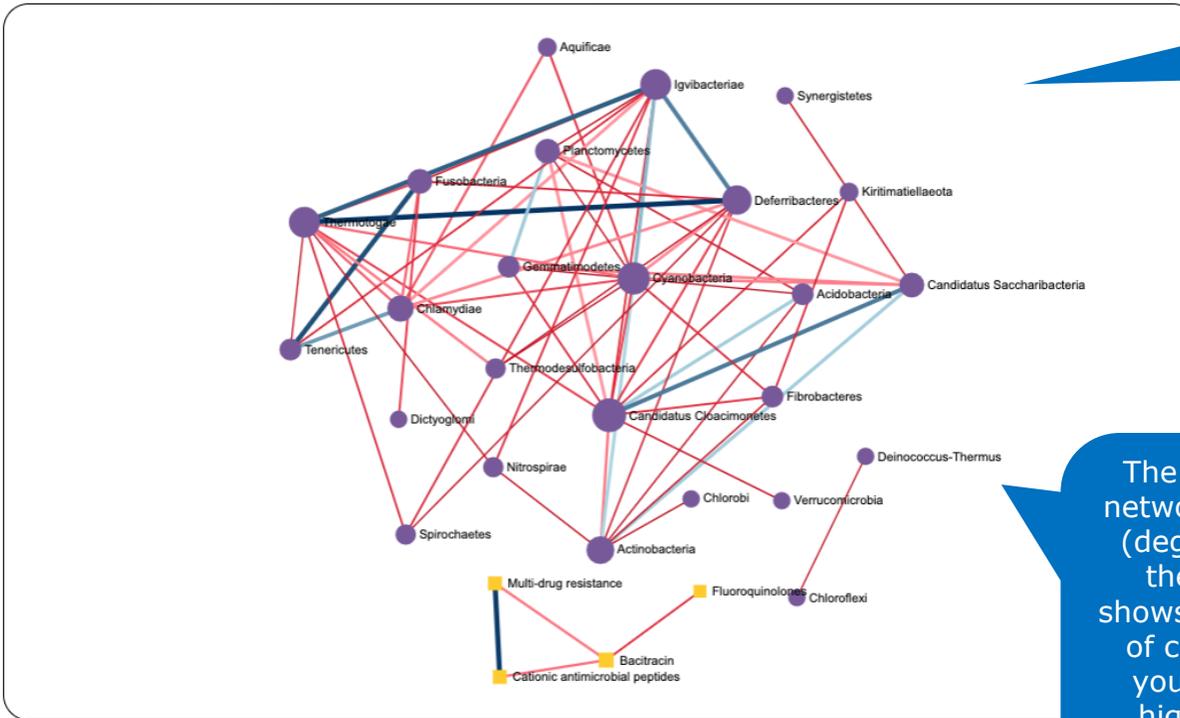
Taxonomic level: Profile level: No. of permutations:

Corr. coefficient cutoff: Adjusted p-value cutoff: p-value correction method:

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the strength of correlation between them (**MIC**: varies from 0 to 1). User can **zoom** in and out the network along with **dragging** nodes. Also, **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.

Network Layout: Node size based on:



Likewise, the results can be visualized in the 'co-occurrence network'. Resistome data is shown in yellow squares, while microbiome data are purple dots. Positive correlations are marked as blue lines, while negative correlations are in red.

The size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the magnitude and strength of correlation between them. If you double-click a node, it will highlight all the associated or correlated neighbour nodes.

Maximal Information Coefficient (MIC) analysis

General options:

Taxonomic level: Profile level: No. of permutations:

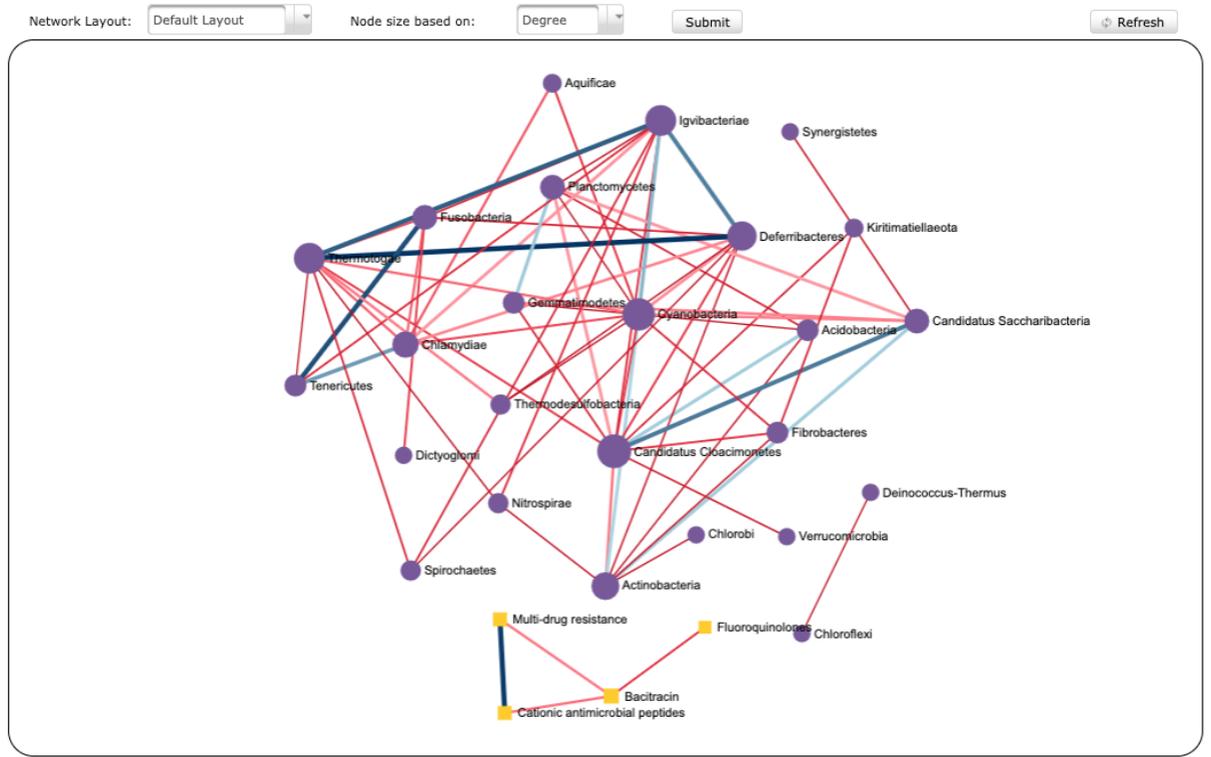
Corr. coefficient cutoff: Adjusted p-value cutoff: p-value correction method:

[Submit](#) [Downloads](#)

You can choose to download the analyses and/or graphs in a number of different formats by clicking here.

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the strength of correlation between them (**MIC**: varies from 0 to 1). User can **zoom** in and out the network along with **dragging** nodes. Also, **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.



Once you are finished, you can click on 'Integrative Analysis' to go back to the previous page.

Maximal Information Coefficient (MIC) analysis

General options:

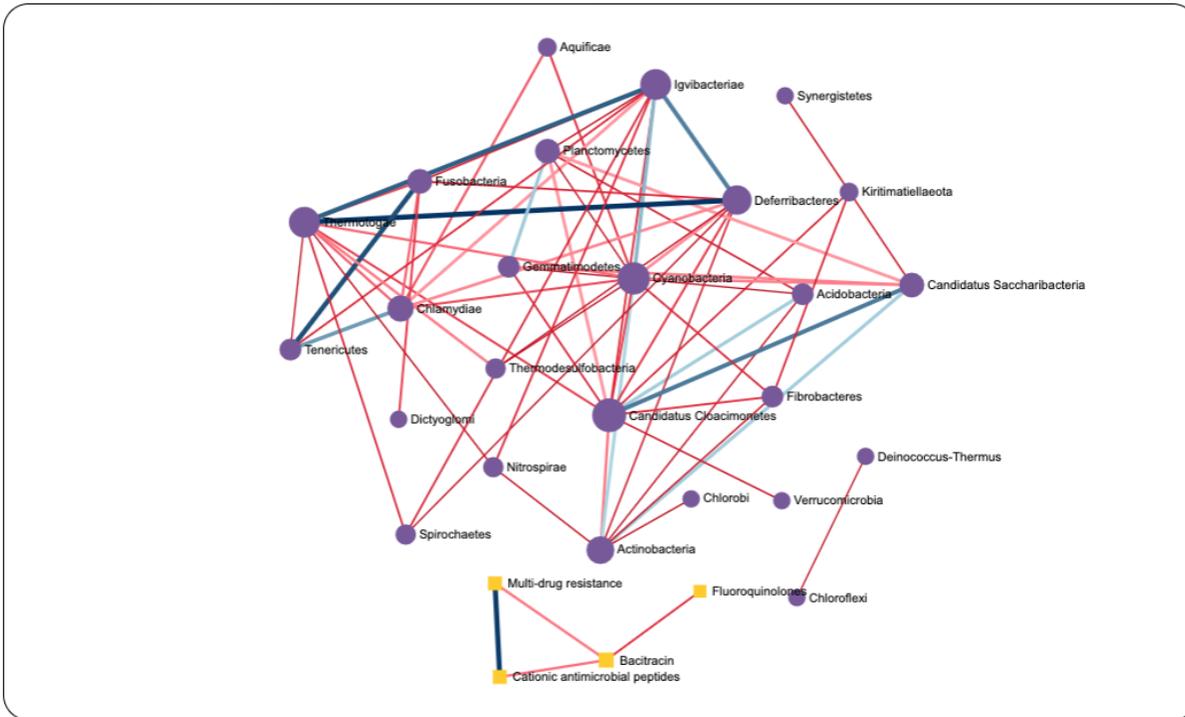
Taxonomic level: Profile level: No. of permutations:

Corr. coefficient cutoff: Adjusted p-value cutoff: p-value correction method:

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the strength of correlation between them (**MIC**: varies from 0 to 1). User can **zoom** in and out the network along with **dragging** nodes. Also, **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.

Network Layout: Node size based on:



Analysis Panel

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analysis

Co-inertia
analysis

rCCA

sPLS

2. Ordination-based integrative analysis

3. Pair-wise correlation analysis

Spearman

Pearson

MIC

CCLasso

As the last step
in this manual,
let's look at
CCLasso.

Correlation inference for compositional data through Lasso (CCLasso)

General options:

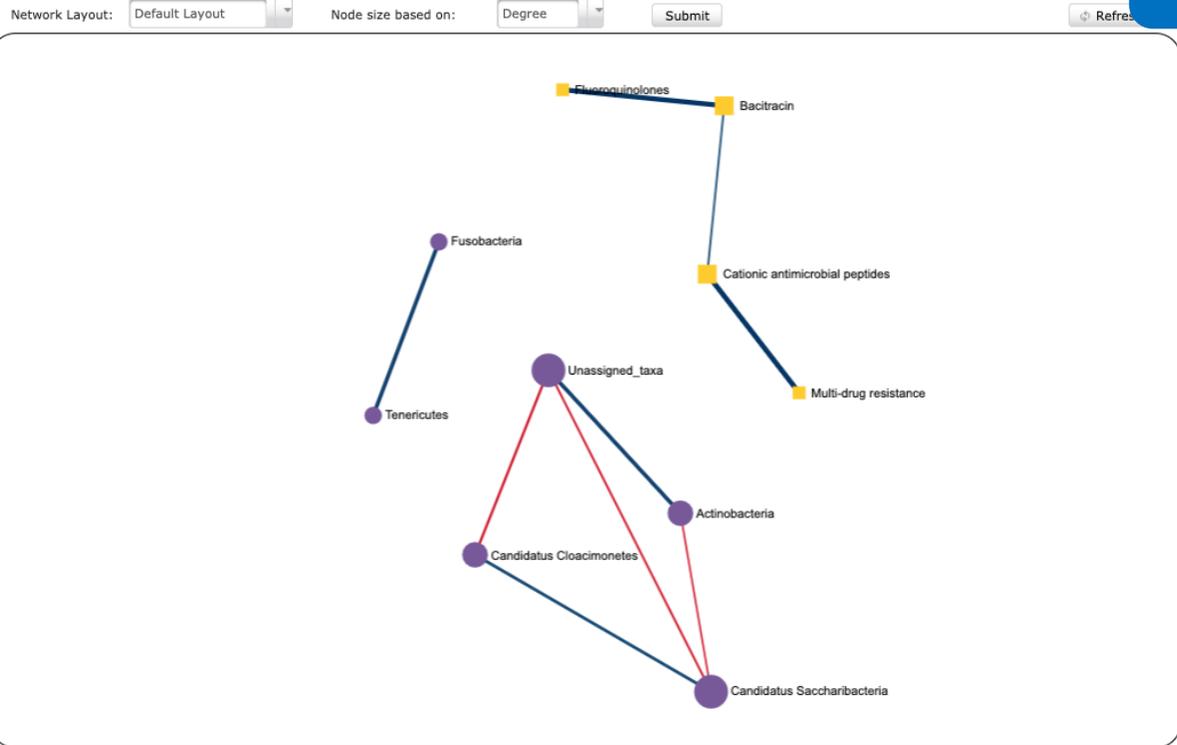
Taxonomic level: Profile level: p-value cutoff:

Corr. coefficient cutoff: No. of max. iterations: No. of Bootstraps:

CCLasso is based on least squares with L1 penalty after log ratio transformation for compositional (metagenomic) data to infer the correlations among features through a latent variable model.

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the magnitude and strength of correlation between them (**Red**: negative; **Blue**: positive). **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.



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Results can be visualized in the 'co-occurrence network'. Resistome data is shown in yellow squares, while microbiome data are purple dots. Positive correlations are marked as blue lines, while negative correlations are in red.

The size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the magnitude and strength of correlation between them. If you double-click a node, it will highlight all the associated or correlated neighbour nodes.

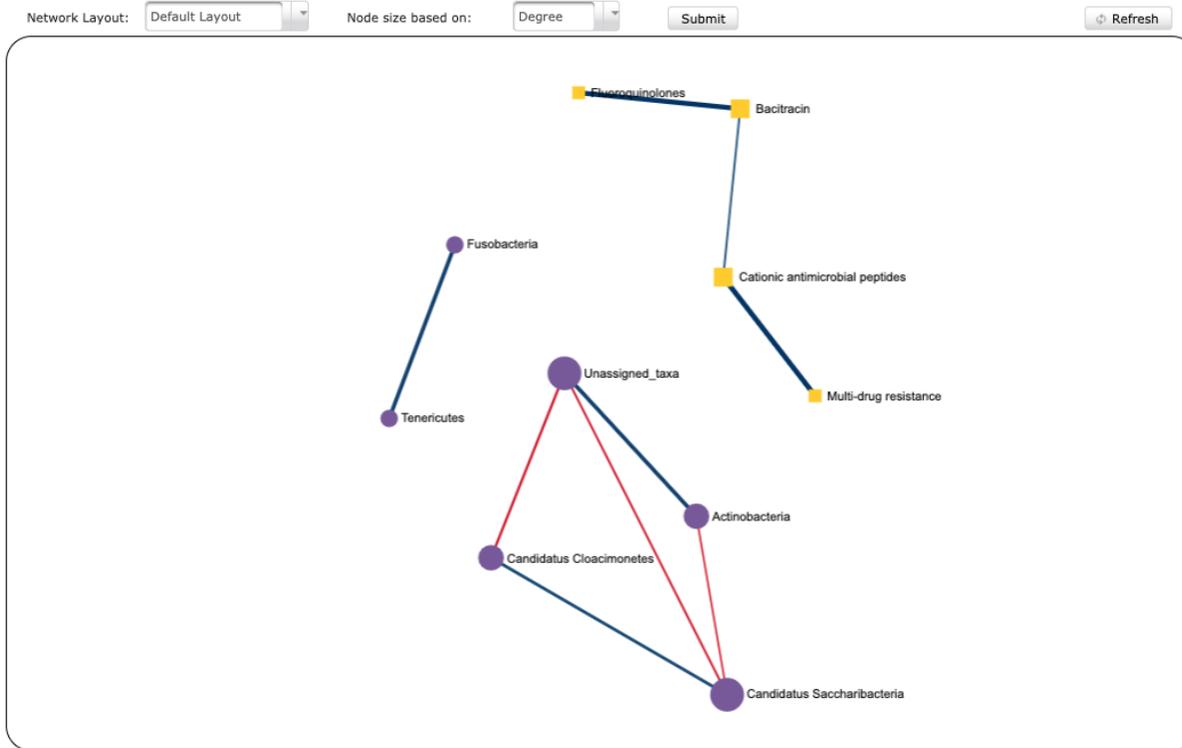
Correlation inference for compositional data through Lasso (CCLasso)

General options: Taxonomic level: Profile level: p-value cutoff:
Corr. coefficient cutoff: No. of max. iterations: No. of Bootstraps:

Let's change the coefficient cutoff to 0.3

After you have made the selection, click on 'Submit'.

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the magnitude and strength of correlation between them (**Red**: negative; **Blue**: positive). **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.



Correlation inference for compositional data through Lasso (CCLasso)

General options:

Taxonomic level: Profile level: p-value cutoff:

Corr. coefficient cutoff: No. of max. iterations: No. of Bootstraps:

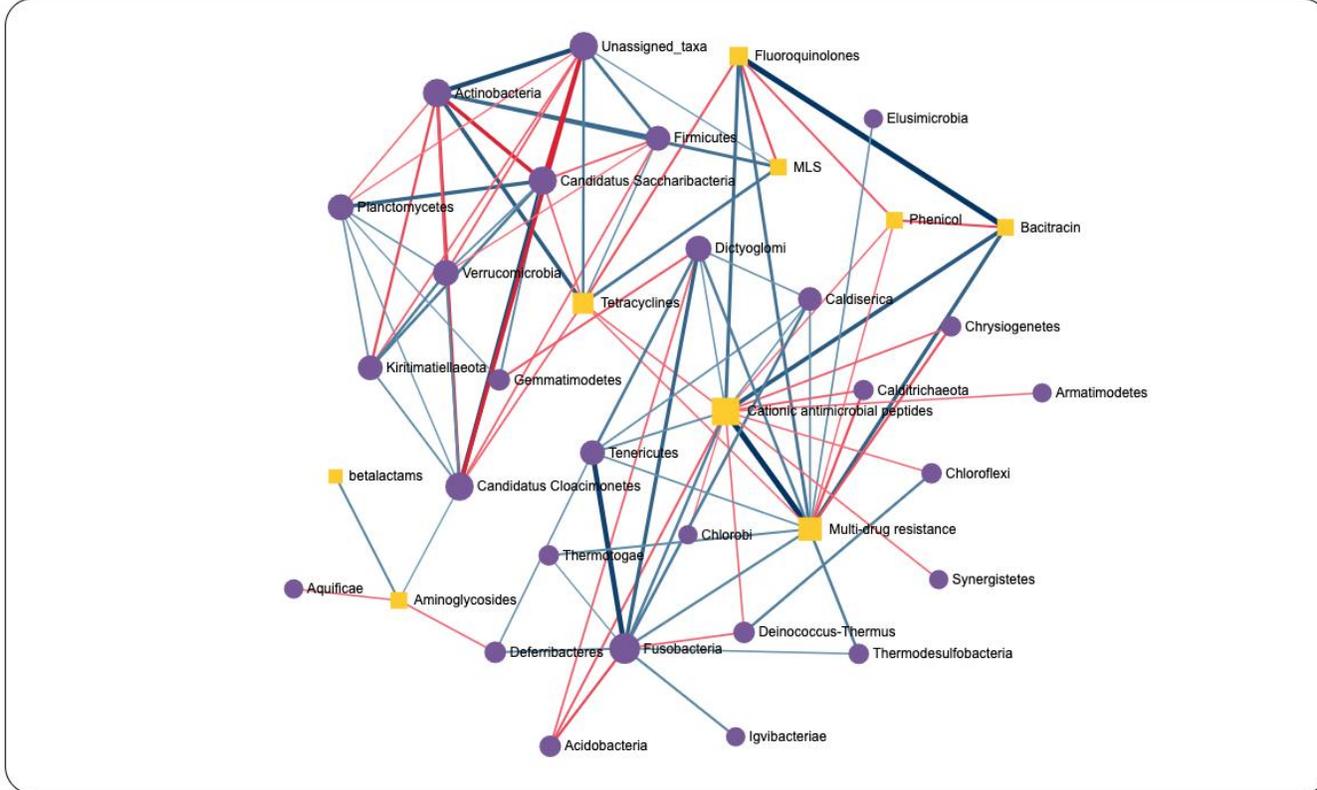
Submit

Downloads

Co-occurrence Network

The color and shape of nodes are based on the type of data or profile (**Resistome**: yellow square; **Microbiome**: purple circle). In the network, the size of node represents the network centrality-based measure (degree or betweenness). While the color and width of edges shows the magnitude and strength of correlation between them (**Red**: negative; **Blue**: positive). **Double click** on the respective node will highlight all the associated or correlated neighbour nodes.

Network Layout: Node size based on:



You can choose to download the analyses and/or graphs in a number of different formats by clicking here.

THIS MANUAL IS FINISHED.

To explore more features of ResistoXplorer based on different input data, please check our manuals for **ARG list** and **ARG table**.

Thank you for using

Resist**st** **Xplorer**

Please cite:

Dhariwal A, Junges R, Chen T, Petersen FC.

ResistoXplorer: a web-based tool for visualization and exploratory analysis of resistome data.