Metabolomics of bacterial-fungal pairwise interactions reveal conserved molecular mechanisms

Gordon T. Luu^{1,}^Ξ, Jessica C. Little^{2,Ξ}, Emily C. Pierce³, Manon Morin³, Celine A. Ertekin¹,

Benjamin E. Wolfe^{5,6}, Oliver Baars⁷, Rachel J. Dutton^{3,4}, Laura M. Sanchez^{1,*}

¹ Department of Chemistry and Biochemistry, University of California Santa Cruz, Santa Cruz, California, 95064

² Department of Pharmaceutical Sciences, University of Illinois at Chicago, Chicago, Illinois,

60612

³ Division of Biological Sciences, University of California San Diego, La Jolla, California, 92093

⁴Center for Microbiome Innovation, Jacobs School of Engineering, University of California San

Diego, La Jolla, 92093

⁵ Department of Biology, Tufts University, Medford, Massachusetts, 02155

⁶ Tufts University Sensory and Science Center, Medford Massachusetts, 02155

⁷ Department of Entomology and Plant Pathology, North Carolina State University, Raleigh,

North Carolina, 27607

* Corresponding Author

Email: Imsanche@ucsc.edu

Table of Contents

BLANKA2: an Updated Algorithm for Blank Subtraction in Mass Spectrometry of	S3
Complex biological Samples	
Data Preprocessing in MZmine	S4
Using IDBac and antiSMASH to Prioritize Alternative Bacterial Growth Partners	S10
Equation S1. Formula used to score strains based on IDBac results	S10
Figure S1. Graphic depiction of co-culture inoculation layout	S11
Figure S2. Predicted biosynthetic gene clusters in select fungal species	S12
Figure S3. Molecular networks generated through GNPS	S13-14
Figure S4. Bacterial-fungal co-culture strains possess different amounts of	S15
biomass	
Figure S5. sPLS-DA plot for nitrocellulose culture dataset	S16
Figure S6. Hierarchical clustering heatmap for nitrocellulose culture dataset	S17
Figure S7. Hierarchical clustering of the fungal metabolites putatively identified	S18
using GNPS	
Figure S8. CAS assay with bacterial and fungal monoculture extracts	S19
Figure S9. Pseudo-phylogenetic tree created in IDBac	S20
Figure S10. Molecular association network (MAN) created in IDBac	S21
Table S1. Scores for each group of strains as determined by IDBac	S22
Table S2. Metabolites identified from fungal species	S23-24
Table S3. P. psychrophila JB418 species specific gene sets with enriched function	S25
Table S4. E. coli K12 species specific gene sets with enriched function	S26
Table S5. Metabolites identified from Actinobacteria species	S27-28
References	S29

BLANKA2: an Updated Algorithm for Blank Subtraction in Mass Spectrometry of Complex Biological Samples

More recently, development of new tools for handling MS/MS data have led to the reevaluation of the previously developed approach to blank subtraction. Here, BLANKA2 and its updated approach to performing blank detection and subtraction from input datasets with an output format that is supported by a variety of downstream analysis tools is described.

BLANKA2 is written in Python 3.8 as a command line tool for Linux that takes LC-MS/MS sample and blank datasets in mzML format. Importantly, BLANKA2 only acts on MS/MS spectra, as methods and processing pipelines highlighted above (i.e. MZmine3) are better suited to performing blank subtraction on MS¹ spectra. Blank detection is performed using cluster based methods and relies heavily on falcon, a tool that performs scalable clustering of large amounts of MS/MS spectra (1). Clustering is performed in falcon by 1) binning and hashing spectral features, 2) constructing nearest neighbor indexes, 3) computing a pairwise distance matrix based on cosine distance, and 4) performing density-based clustering. Bittremieux *et al.* discuss the process in more detail and have also benchmarked falcon to compare its performance to similar clustering tools(1). Following MS/MS spectra that are found in blank dataset files. Since blank subtraction performance is directly tied to MS/MS clustering performance, users are able to pass parameters to falcon to ensure the correct settings for their dataset are used. Blank subtraction from sample files is performed using the *MZMLTransformer* provided by the psims API (2).

BLANKA2 is available at https://github.com/gtluu/blanka2 as a command line tool for Linux, where documentation on its installation and usage is also available. Due to falcon's use of the Faiss library, which lacks a Windows implementation, BLANKA2 is not available on Windows (3). However, users may run BLANKA2 and other Linux based software in the Windows Subsystem for Linux environment.

Data Preprocessing in MZmine

S3

LC-MS data were preprocessed in MZmine 2.53 prior to analysis in MetaboAnalyst 5.0 using a preprocessing workflow adapted from Cleary as follows (4,5). A custom R script was then used to convert the exported CSV file to a format compatible with MetaboAnalyst 5.0 Statistical Analysis (one factor) workflow (6).

- 1. Import recalibrated LC-MS mzML files (3 biological replicates per condition)
- 2. Filter: crop filter
 - 1. RT range: 0.30 14.00
 - 2. m/z range: 100 2000
- 3. Scan smoothing
 - 1. Time: 0.10 min
 - 2. Scan span: 10
 - 3. m/z tolerance: 0
 - 4. m/z min points: 0
 - 5. Min height: 200
- 4. Mass Detection
 - 1. MS level: 1
 - 2. Mass detector: centroid
 - 3. Centroid noise level: 200
- 5. ADAP chromatogram builder
 - 1. Scans: MS level: 1
 - 2. Min group size: 5
 - 3. Group intensity threshold: 500
 - 4. Min highest intensity: 500
 - 5. m/z tolerance: 0.05 Da or 10 ppm
- 6. Chromatogram smoothing

- 1. Filter width: 25
- 7. Chromatogram deconvolution
 - 1. Algorithm: wavelets (ADAP)
 - 1. Signal-to-noise threshold: 6
 - 2. Signal-to-noise estimator: intensity window SN
 - 3. Min feature height: 500
 - 4. coefficient/area threshold: 50
 - 5. Peak duration range: 0.00 2.00
 - 6. RT wavelet range: 0.00 2.00
 - 2. m/z center calculation: median
 - 3. m/z range: 0.05 Da
 - 4. RT range: 0.15 min
- 8. Isotope Peak Grouper
 - 1. m/z tolerance: 0.05 Da or 10 ppm
 - 2. RT tolerance: 0.15 min
 - 3. Maximum charge: 4
 - 4. Representative isotope: lowest m/z
- 9. Alignment: Join Aligner MS1
 - 1. m/z tolerance: 0.05 Da or 10 ppm
 - 2. Weight for m/z: 75
 - 3. RT tolerance: 0.15 min
 - 4. Weight for RT: 25
- 10. Gap-Filling: Peak Finder
 - 1. Intensity tolerance: 50%
 - 2. m/z tolerance: 0.05 Da or 10 ppm
 - 3. RT tolerance: 0.15 min

- 4. RT correction
- 11. Duplicate peak filter
 - 1. Filter mode: New Average
 - 2. m/z tolerance: 0.05 Da or 10 ppm
 - 3. RT tolerance: 0.15 min
- 12. Normalization
 - 1. Linear normalizer
 - 2. Normalization type: average intensity
 - 3. Peak measurement type: Peak area
- 13. Export to CSV
 - 1. Export row m/z, RT, and peak area

LC-MS and LC-MS/MS datasets were processed in MZmine2.53 as a combined dataset prior to analysis via GNPS FBMN using a preprocessing workflow adapted from Cleary as follows (4,7). A custom R script was then used to generate the metadata file required for FBMN in the format described by Phelan (8).

- 1. Import recalibrated LC-MS and LC-MS/MS mzML files (3 biological replicates per condition)
- 2. Filter: crop filter
 - 1. RT range: 0.30 14.00
 - 2. m/z range: 100 2000
- 3. Scan smoothing (MS¹ files only)
 - 1. Time: 0.10 min
 - 2. Scan span: 10
 - 3. m/z tolerance: 0
 - 4. m/z min points: 0

- 5. Min height: 200
- 4. Mass Detection MS¹
 - 1. MS level: 1
 - 2. Mass detector: centroid
 - 3. Centroid noise level: 200
- 5. Mass Detection MS/MS
 - 1. MS level: 2
 - 2. Mass detector: centroid
 - 3. Centroid noise level: 100
- 6. ADAP chromatogram builder (MS¹ files only)
 - 1. Scans: MS level: 1
 - 2. Min group size: 5
 - 3. Group intensity threshold: 100
 - 4. Min highest intensity: 200
 - 5. m/z tolerance: 0.05 Da or 10 ppm
- 7. ADAP chromatogram builder (MS/MS files only)
 - 1. Scans: MS level: 1
 - 2. Min group size: 2
 - 3. Group intensity threshold: 100
 - 4. Min highest intensity: 200
 - 5. m/z tolerance: 0.05 Da or 10 ppm
- 8. Chromatogram smoothing (MS¹ files only)
 - 1. Filter width: 25
- 9. Chromatogram smoothing (MS/MS files only)
 - 1. Filter width: 11
- 10. Chromatogram deconvolution

- 1. Algorithm: wavelets (ADAP)
 - 1. Signal-to-noise threshold: 6
 - 2. Signal-to-noise estimator: intensity window SN
 - 3. Min feature height: 500
 - 4. coefficient/area threshold: 50
 - 5. Peak duration range: 0.00 2.00
 - 6. RT wavelet range: 0.00 2.00
- 2. m/z center calculation: median
- 3. m/z range: 0.05 Da
- 4. RT range: 0.15 min

11. Isotope Peak Grouper

- 1. m/z tolerance: 0.05 Da or 10 ppm
- 2. RT tolerance: 0.15 min
- 3. Maximum charge: 5
- 4. Representative isotope: lowest m/z

12. Alignment: Join Aligner

- 1. m/z tolerance: 0.05 Da or 10 ppm
- 2. Weight for m/z: 75
- 3. RT tolerance: 0.15 min
- 4. Weight for RT: 25
- 13. Duplicate peak filter
 - 1. Filter mode: New Average
 - 2. m/z tolerance: 0.05 Da or 10 ppm
 - 3. RT tolerance: 0.15 min
- 14. Feature list rows filter
 - 1. Minimum peaks in a row: 2

2. Keep only peaks with MS2 scan (GNPS)

15. Export/Submit to GNPS-FBMN

1. Filter rows: ONLY WITH MS2

Using IDBac and antiSMASH to Prioritize Alternative Bacterial Growth Partners

Glutamicibacter arilaitensis JB182 and various Brevibacterium and Brachybacterium sp. (total 16 strains) were selected for co-culture experiments. Niccum et al. have previously observed genotypic differences at the strain level in the cheese rind microbiome, which implies there are also differences in the biosynthetic potential of different Brevibacterium and Brachybacterium strains (9). Furthermore, analysis of Dataset 2, containing LC-MS/MS data processed with BLANKA2, using Global Natural Products Social (GNPS) classical molecular networking showed that these species potentially made a variety of known specialized metabolites or structurally related analogues of known specialized metabolites (Table S5). The IDBac workflow was used alongside a modified rapid extraction sampling method to prioritize for cheese rind microbes producing unique chemistry (10). Intact microprotein profiles and small molecule data collected via matrix-assisted laser desorption/ionization time-of-flight mass spectrometry (MALDI-TOF MS) was used to create a pseudo-phylogenetic tree and molecular association network (MAN), respectively (Figure S9 & S10). A two-step strain prioritization algorithm was then used to group strains based on their pseudo-phylogeny and score each strain based on the amount of unique and shared chemistry with other strains in the dataset (Equation S1; Table S1). Brevibacterium linens JB5 and G. arilaitensis JB182 were chosen due to having high scores in addition to slightly above average number of BGCs relative to the other Actinobacteria that were screened. All data here constitutes Dataset 8.

Equation S1: Formula used to score strains based on IDBac results.

strain score = \sum (weight of edges connected to strain node ** 2)

Figure S1: Graphic depiction of co-culture inoculation layout for alternating "t streaks" in pairwise microbial co-cultures. Here, fungal colonies are denoted by the green and white streaked colony, while bacterial colonies are denoted by the gray-beige streaked colony. Streaks were performed perpendicular to each other.



Figure S2: Predicted biosynthetic gene clusters (BGCs) found in select fungal species. Only fungal species included in this study with genome data available are shown here. The reported % known for each species refers to the % of BGCs represented here that have 100% similarity to BGCs that have been assigned to known metabolites. The *P. camemberti* genome is a publicly available complete genome and this likely accounts for the much higher number of identified BGCs. *P. atramentosum, P. solitum*, and *Scopulariopsis* sp. JB370 results are based on draft genomes compiled by the Dutton Lab.



Figure S3: Molecular networks generated through GNPS of metabolites found in (A) all microbial cultures and (B) fungi derived metabolites. (A) The metabolites represented within the molecular network were assigned as either bacterial, fungal, or microbial according to the monocultures in which they were found. If they are present in fungal monocultures and co-cultures but not in bacterial monocultures, they are labeled as fungal and vice versa. If metabolites (represented as gray nodes). Network clusters containing different structural classes (i.e. amino acids, coprogens, etc.) can be identified. A majority of the nodes appear to be of fungal origin. (B) Features found in fungal monocultures are color coded to represent the specific fungal species in which they are present. The number of nodes found in the network that are specific to the yeast species suggests that their metabolites are not as diverse and abundant as those of filamentous fungi. Based on the structural classes of nodes found in different clusters, fungi are able to produce a variety of unique chemistry.

А



amino acids - 1, peptides - 2, fatty acids - 3, phospholipids - 4, coprogens - 5, terpenoids - 6, alkaloids - 7, cyclic depsipeptides - 8

В

peptides - 1, fatty acids - 2, phospholipids - 3, lipopeptides - 4, polyketides - 5, misc. library matches - 6



Figure S4: Monoculture and pairwise bacterial-fungal co-culture images demonstrate the large inequality in colony biomass at 7 days of growth immediately prior to chemical extraction.



Figure S5: sPLS-DA plot showing solvent and media blanks, *E. coli* K12 and *P. solitum* #12 monocultures, and pairwise co-culture grown in the dark with and without the use of nitrocellulose filters. sPLS-DA was performed with five components and five-fold cross-validation using the top 1000 features.



Scores Plot

Component 1 (26.3 %)

Figure S6: Hierarchical clustering of features and samples is displayed in this heatmap. Cultures grown here were grown in the dark. The top 1000 most significant features as determined by ANOVA are plotted by intensity in the sample, and only group averages are shown here with a group referring to the average of all biological replicates across one sample condition. Sample and feature clustering was performed using the unweighted pair group method with arithmetic mean (UPGMA) algorithm based on Euclidean distance.



Figure S7: Hierarchical clustering of the fungal metabolites containing only features that were putatively identified using GNPS and DEREPLICATOR. *In silico* predictions from DEREPLICATOR are only included if fragmentation patterns from the raw data were indicative of the predicted compound class. For simplicity of visualization, features are shown here as a presence or absence map. The features have been parsed out to show different classes based on molecular structure (i.e. phenols, peptides) or known functions of molecules (i.e. siderophores) in the heatmap generated in MetaboAnalyst. The pie chart lists approximate percentages of the total identified features described here as found in each culture of fungal monoculture.



Figure S8: CAS assay with bacterial and fungal monoculture extracts. Deferoxamine standard was used for comparison in various concentrations and extracts were normalized to concentrations of 1 mg/mL and 0.1 mg/mL. * denotes a positive test result as indicated by visual inspection and OD_{630} .

1400 LO hyou I' P. psychrophila P. solitum * E. coli P. camemberti * CCA media P. atramentosum * 1µM Deferoxamine Scop. JB370 * 5µM Deferoxamine Scop. 165-5 10µM Deferoxamine F. domesticum * 100µM Deferoxamine C. catenulata Solvent blank D. hansenii

*

Figure S9: Pseudo-phylogenetic tree created in IDBac. Protein profiles for each strain were processed in IDBac and the dendrogram was created using peaks above a signal to noise ratio of 6 that were present in greater than 80% of replicate spectra (n = 4) in the mass range of *m*/z 3000 - 15,000. Hierarchical clustering was performed using cosine distances clustered by the unweighted pair group method with arithmetic mean (UPGMA) algorithm. At a tree height of 0.9, the dendrogram can be cleanly cut to yield two groups: one containing *Brevibacteria* and *Brachybacteria* and one containing all other bacteria.



Figure S10: Molecular association network (MAN) created in IDBac. Small molecule profiles for each strain were processed in IDBac and the MAN was created using peaks above a signal to noise ratio of 3 that were present in greater than 80% of replicate spectra (n = 4) in the mass range of *m*/*z* 100 - 3000. Strains are color coded at the genus level. Here, *G. arilaitensis* JB182 and *E. coli* K12, being a couple of the most distant outgroups, are shown to produce the most unique chemistry in the dataset based on their vastly different biosynthetic capabilities relative to other strains analyzed here.



Table S1: Scores for each group of strains as determined by pseudo-phylogeny and detected small molecules via IDBac. Groups were determined by cutting the dendrogram in **Figure S2A** at a height of 0.9. Scores (rounded to 2 decimal places) were then calculated for each strain using **Equation S1** based on the network shown. Strains selected for further analysis were selected and highlighted based on their scores and antiSMASH results as predicted using draft genomes.

Group 1			Group 2					
Strain	Score	Num of Predicted BGCs	Strain	Score	Num of Predicted BGCs			
G. arilaitensis JB182	6.18	7	Brevibacterium sp. EP18	2.48	7			
E. coli K12	3.04	2	Brevibacterium sp. EP26	2.43	7			
Hafnia alvei JB232	1.15	-	Brachybacterium sp. EP1	2.40	6			
P. psychrophila JB418	0.11	7	Brevibacterium linens JB5	2.33	9			
			Brevibacterium sp. EP38	1.68	4			
			Brevibacterium sp. EP24	1.44	6			
			Brevibacterium sp. EP6	1.35	3			
			Brachybacterium sp. EP7	1.28	3			
			Brevibacterium sp. EP34	1.01	7			
			Brevibacterium sp. EP20	0.58	7			
			Brevibacterium sp. EP29	0.52	5			
			Brevibacterium sp. EP13	0.42	10			
			Brevibacterium sp. EP31	0.26	12			
			Brevibacterium sp. EP10	0.08	6			
			Brachybacterium sp. JB7	0.01	5			

Species	Compound Name	Molecular Formula	Calculated [M+H]	Measured [M+H]	ppm Error	PubChem CID	Level ID	Reference
Scopulariopsis sp. JB370 and 165-5	Isariin A	$C_{33}H_{59}N_5O_7$	638.4493	638.4506	2.1	73424	4	Saabareesh et al. 2007
Scopulariopsis sp. JB370 and 165-5	Isariin G2	$C_{31}H_{56}N_5O_7$	610.4180	610.4195	2.5	44423145	3	Saabareesh et al. 2007
P. atramentosum	NBRI23477 A (Atpenin Analogue)	$C_{15}H_{21}CI_2NO_5$	366.0875	366.0872	0.8	54741826	2	Natural Products Atlas: NPA008775
P. atramentosum	NBRI23477 B (Atpenin Analogue)	$C_{15}H_{21}NO_5$	296.1498	296.1498	0	5474182	3	Natural Products Atlas: NPA009059
P. atramentosum	Atpenin A4*	$C_{15}H_{23}CINO_5$	322.1265	322.1269	1.2	54676867	2	Natural Products Atlas: NPA008981
P. atramentosum	Atpenin A5*	$C_{15}H_{21}CI_2NO_5$	366.0875	366.0873	0.6	54676868	2	Natural Products Atlas: NPA015919
P. atramentosum	Atpenin B	$C_{15}H_{24}NO_5$	298.1655	298.1648	2.2	54676869	3	Natural Products Atlas: NPA018005
P. atramentosum	Glandicoline A	$C_{22}H_{21}N_5O_3$	404.1723	404.1732	2.3	91820007	3	
P. atramentosum	Glandicoline B	$C_{22}H_{21}N_5O_4$	420.1672	420.1656	3.7	124079399	3	
P. atramentosum	Roquefortine C	$C_{22}H_{23}N_5O_2$	390.1930	390.1940	2.6	21608802	3	
P. atramentosum	Andrastatin A	C ₂₈ H ₃₈ O ₇	487.2696	487.2684	2.4	6712564	2	GNPS: CCMSLIB00004713231 CCMSLIB00004713240
P. atramentosum	Citreohybridonol	C ₂₈ H ₃₆ O ₈	501.2489	501.2486	0.4	101252260	2	GNPS: CCMSLIB00004711830
P. atramentosum	Meleagrin	$C_{23}H_{23}N_5O_4$	434.1828	434.1827	0.3	23728435	2	GNPS:

Table S2: Metabolites identified from fungal species and their level of identification as defined by Sumner et al. (11).

								CCMSLIB00000852096
P. atramentosum	Oxaline	$C_{24}H_{25}N_5O_4$	448.1985	448.1982	0.6	70698220	2	MassBank EU: AC000745
P. solitum	Atlantinone A	$C_{26}H_{34}O_{6}$	443.2434	443.2436	0.5	101516467	2	GNPS: CCMSLIB00000853278
P. solitum	Cyclopenol	$C_{17}H_{14}N_2O_4$	311.1032	311.1021	3.5	101201	2	GNPS: CCMSLIB00000852686
P. solitum	Viridicatol	$C_{15}H_{11}NO_3$	254.0817	254.0819	0.7	115033	2	GNPS: CCMSLIB00000845922
P. solitum	Pyripyropene O (Putative Adduct)	C ₂₉ H ₃₅ NO ₇	[M+NH ₄] = 527.2757	[M+NH ₄] = 527.2861	18	10553713	3	GNPS: CCMSLIB00000848971
P. solitum	Pyripyropene Analog	$C_{29}H_{35}NO_{6}$	[M+NH ₄] = 511.2808	[M+NH ₄] = 511.2906	19		3	GNPS: CCMSLIB00000848971
P. solitum	ML-236A	$C_{18}H_{26}O_4$	307.1909	307.1901	2.6	173651	2	GNPS: CCMSLIB00000478442
P. solitum	Cyclopeptine	$C_{17}H_{16}N_2O_2$	281.1290	281.1284	2.1	15649435	2	GNPS: CCMSLIB00000854845
P. atramentosum, P. camemberti, P. solitum	Desferrichrome	$C_{27}H_{45}N_9O_{12}$	688.3266	688.3234	4.6	169636	1	GNPS: CCMSLIB00005435755
P. atramentosum, P. camemberti, P. solitum	Desferricoprogen	C ₃₅ H ₅₆ N ₆ O ₁₃	769.3984	769.3976	1	23636677	1	
F. domesticum	Desferricoprogen B	$C_{33}H_{54}N_6O_{12}$	727.3878	727.3882	0.5	122198275	2	GNPS: CCMSLIB00004679227
F. domesticum	Palmitoylcoprogen	C ₄₉ O ₁₃ H ₈₂ N ₆ Fe	1018.5289	1018.5243	4.5		3	

Table S3: Number of genes in species specific gene sets with enriched functions in pairwise cocultures of native cheese rind fungi and *P. psychrophila* JB418 as reported by Pierce *et al.* (12).

Fungal Growth Partner	Number of Genes
Scopulariopsis sp. JB370	85
Scopulariopsis sp. 165-5	269
Penicillium atramentosum RS17	328
Penicillium camemberti SAM3	516
Penicillium solitum #12	463
Fusarium domesticum 554A	56
Diutina catenulata 135E	80
Debaromyces hansenii 135B	34

Table S4: Number of genes in species specific gene sets with enriched functions in pairwise cocultures of native cheese rind fungi and *E. coli* K12 as reported by Pierce *et al.* (12).

Fungal Growth Partner	Number of Genes
Scopulariopsis sp. JB370	260
Scopulariopsis sp. 165-5	130
Penicillium atramentosum RS17	-
Penicillium camemberti SAM3	12
Penicillium solitum #12	51
Fusarium domesticum 554A	220
Diutina catenulata 135E	185
Debaromyces hansenii 135B	124

Table S5: Metabolites identified from Actinobacteria species and their level of identification as defined by Sumner et al. (11). Note that
ppm error is only reported for library matches that were not determined to be analogues. Otherwise, the mass differences are reported
instead. Although the timsTOF fleX is capable of reaching four significant features, only three have been reported due to being the
default in GNPS. The GNPS job can be found at
https://gnps.ucsd.edu/ProteoSAFe/status.jsp?task=570905801277433a88add3bb735c963c.

Species	Compound Name	Molecular Formula	Calculated [M+H]	Measured [M+H]	ppm Error	Mass Difference	Pubchem CID	Level ID	Reference
Arthonia endlicheri	Arthonin Analogue	$C_{25}H_{32}N_2O_4$	Arthonin = 425.244	340.166		85.078	11101959	3	Natural Products Atlas: NPA009730
Aspergillus versicolor	Cyclo-(D)-Tyr- (D)-Pro Analogue	C ₁₄ H ₁₆ N ₂ O ₃	Cyclo-(D)- Tyr-(D)-Pro = 261.124	327.135		66.011	28125534	3	Natural Products Atlas: NPA000159
Streptomyces sp. KH29	Cyclo-(L)-Trp- (L)-Trp Analogue	$C_{22}H_{20}N_4O_2$	Cyclo-(L)- Trp-(L)-Trp = 373.166	286.155		87.011	7091706	3	Natural Products Atlas: NPA002698
Streptomyces sp. KH29	Cyclo-(L)-Trp- (L)-Trp Analogue	C ₂₂ H ₂₀ N ₄ O ₂	Cyclo-(L)- Trp-(L)-Trp = 373.166	284.14		89.026	7091706	3	Natural Products Atlas: NPA002698
Fungus	Laxaphycin D	C ₆₃ H ₁₁₀ N ₁₄ O ₁ 9	[M+2H] ²⁺ = 684.414	[M+2H] ²⁺ = 684.393	30.7	0.021	101632355	3	Natural Products Atlas: NPA014810
Sponge	Makaluvamine I Analogue		Makaluvami ne I = 188.080	226.098		38.018	135474607	3	GNPS: CCMSLIB00004679175
Bacillus pumilus	N- Acetyltryptoph an Analogue	C ₁₃ H ₁₄ N ₂ O ₃	N- Acetyltrypto phan = 247.108	323.139		76.031	2002	3	Natural Products Atlas: NPA015473

Bacillus pumilus	N- Acetyltryptoph an Analogue	C ₁₃ H ₁₄ N ₂ O ₃	N- Acetyltrypto phan = 247.108	339.134		92.026	2002	3	Natural Products Atlas: NPA015473
Xenorhabdus nematophilus	Nematophin Analogue	$C_{16}H_{20}N_2O_2$	Nematophin = 273.160	189.103		84.057	9881952	3	Natural Products Atlas: NPA007705
Xenorhabdus sp. PB62.7	Nevaltophin A Analogue		Nevaltophin A = 347.230	383.176		35.946	132509308	3	GNPS: CCMSLIB00000840595
Xenorhabdus sp. PB62.7	Nevaltophin D Analogue	$C_{22}H_{31}N_3O_3$	Nevaltophin D = 386.244	422.187		35.943	132509319	3	Natural Products Atlas: NPA0028349 and GNPS: CCMSLIB00000840594
Candida albicans	Tryptophol Analogue	C ₁₀ H ₁₁ NO	Tryptophol = 162.092	203.118		41.026	10685	3	Natural Products Atlas: NPA006412
Candida albicans	Tryptophol Analogue	C ₁₀ H ₁₁ NO	Tryptophol = 162.092	261.124		99.032	10685	3	Natural Products Atlas: NPA006412
Rhizopogon roseolus	Zeatin Riboside	$C_{15}H_{21}N_5O_5$	352.162	352.162	0	0	6440982	2	Natural Products Atlas: NPA009273
Rhizopogon roseolus	Zeatin Riboside Analogue	$C_{15}H_{21}N_5O_5$	Zeatin Riboside = 352.162	398.15		45.988	6440982	3	Natural Products Atlas: NPA009273

References

- 1. Bittremieux W, Laukens K, Noble WS, Dorrestein PC. Large-scale tandem mass spectrum clustering using fast nearest neighbor searching. Rapid Commun Mass Spectrom. 2021 Jun 25;e9153.
- 2. Klein J, Zaia J. psims A Declarative Writer for mzML and mzIdentML for Python. Mol Cell Proteomics. 2019 Mar;18(3):571–5.
- 3. Johnson J, Douze M, Jegou H. Billion-scale similarity search with GPUs. IEEE Trans Big Data. 2021 Jul 1;7(3):535–47.
- Cleary J. Chemotype to phenotype studies of bacterial-fungal interactions [Internet]. University of Illinois at Chicago; 2021. Available from: https://indigo.uic.edu/articles/thesis/Chemotype_to_Phenotype_Studies_of_Bacterial-Fungal_Interactions/14134604/1
- 5. Pluskal T, Castillo S, Villar-Briones A, Oresic M. MZmine 2: modular framework for processing, visualizing, and analyzing mass spectrometry-based molecular profile data. BMC Bioinformatics. 2010 Jul 23;11:395.
- 6. Pang Z, Zhou G, Ewald J, Chang L, Hacariz O, Basu N, et al. Using MetaboAnalyst 5.0 for LC-HRMS spectra processing, multi-omics integration and covariate adjustment of global metabolomics data. Nat Protoc. 2022 Aug;17(8):1735–61.
- Nothias LF, Petras D, Schmid R, Dührkop K, Rainer J, Sarvepalli A, et al. Feature-based molecular networking in the GNPS analysis environment. Nat Methods. 2020 Sep;17(9):905–8.
- 8. Phelan VV. Feature-Based Molecular Networking for Metabolite Annotation. Methods Mol Biol. 2020;2104:227–43.
- Niccum BA, Kastman EK, Kfoury N, Robbat A Jr, Wolfe BE. Strain-Level Diversity Impacts Cheese Rind Microbiome Assembly and Function. mSystems [Internet]. 2020 Jun 16;5(3). Available from: http://dx.doi.org/10.1128/mSystems.00149-20
- Clark CM, Costa MS, Sanchez LM, Murphy BT. Coupling MALDI-TOF mass spectrometry protein and specialized metabolite analyses to rapidly discriminate bacterial function. Proc Natl Acad Sci U S A. 2018 May 8;115(19):4981–6.
- Sumner LW, Amberg A, Barrett D, Beale MH, Beger R, Daykin CA, et al. Proposed minimum reporting standards for chemical analysis Chemical Analysis Working Group (CAWG) Metabolomics Standards Initiative (MSI). Metabolomics. 2007 Sep;3(3):211–21.
- 12. Pierce EC, Morin M, Little JC, Liu RB, Tannous J, Keller NP, et al. Bacterial-fungal interactions revealed by genome-wide analysis of bacterial mutant fitness. Nat Microbiol. 2021 Jan;6(1):87–102.