## *Supplementary information for*

# **Metabolite annotation from knowns to unknowns through knowledge-guided multi-layer metabolic networking**

*Zhiwei Zhou1,† , Mingdu Luo1,2,† , Haosong Zhang1,2, Yandong Yin<sup>1</sup> , Yuping Cai<sup>1</sup> , and Zheng-Jiang Zhu1,3, \**

<sup>1</sup> Interdisciplinary Research Center on Biology and Chemistry, Shanghai Institute of Organic Chemistry, Chinese Academy of Sciences, Shanghai, 200032 China

<sup>2</sup> University of Chinese Academy of Sciences, Beijing, 100049 China

<sup>3</sup>Shanghai Key Laboratory of Aging Studies, Shanghai, 201210 China

*†* These authors contributed equally

## **Corresponding Author**

Correspondence should be addressed to Z.J.Z (jiangzhu@sioc.ac.cn)

## **List for Supplementary Figures**

**Supplementary Figure 1.** Curation of knowledge-based metabolic reaction network (KMRN) with *insilico* enzymatic reactions.

**Supplementary Figure 2.** Statistics of linked nodes in MS/MS similarity network or knowledge-guided MS/MS similarity network.

**Supplementary Figure 3.** The construction and optimization of global peak annotation network.

**Supplementary Figure 4.** Flowchart for the optimization and filtering of subnetworks in the global peak correlation network.

**Supplementary Figure 5.** The workflow of accuracy evaluation with a manually curated data set.

**Supplementary Figure 6.** Comparison between MetDNA1 and KGMN in different biological samples, including NIST human urine, NIST human plasma, BV2 cells, head tissues of fruit fly, and 200STD spiked mouse liver tissues.

**Supplementary Figure 7.** Benchmark comparison between CAMERA and KGMN for annotating ion forms of metabolic peaks.

**Supplementary Figure 8.** KGMN recognized the in-source fragments of N4-Acetylcytidine.

**Supplementary Figure 9.** Examples of different ion form recognition and peak assignment in KGMN.

**Supplementary Figure 10.** Knowledge-guided multi-layer networks of 46std\_mix data sets.

**Supplementary Figure 11.** Validation examples of annotated unknowns in 46std mix data sets.

**Supplementary Figure 12.** Knowledge-guided MS/MS similarity network of NIST human urine sample.

**Supplementary Figure 13.** Global peak correlation network of NIST human urine sample.

**Supplementary Figure 14.** Global annotation of unknown metabolites in negative mode and validation examples of unknowns using *in-silico* MS/MS tools.

**Supplementary Figure 15.** The repository-mining and structural validations of 3 recurrent unknown metabolites.

**Supplementary Figure 16.** Curated unknown metabolites and reaction pairs in the knowledge-based metabolic reaction network (KMRN).

## **List for Supplementary Table**

**Supplementary Table 1.** The supported data processing tools with KGMN

**Supplementary Table 2.** Statistics of global peak annotation optimization to improve annotation accuracy.

**Supplementary Table 3.** Statistics of biotransformation types in 46std mix data set.

**Supplementary Table 4**. Statistics of annotated peaks in different biological samples.

**Supplementary Table 5.** Statistics of unknown biotransformation types in NIST urine data set.

## **List for Supplementary Notes**

**Supplementary Note 1**: Tutorial of KGMN result visualization and analysis.

**Supplementary Note 2**: Tutorial of validating KGMN unknowns with repository mining.

**Supplementary Note 3**: Tutorial of integrating KGMN results with other in-silico MS/MS workflows.



**Supplementary Figure 1.** Curation of knowledge-based metabolic reaction network (KMRN) with *insilico* enzymatic reactions. (**a**) Examples for the curation of unknown metabolites through *in-silico* enzymatic reaction; (**b**) The workflow to curate the knowledge-based metabolic reaction network with *in-silico* enzymatic reactions. The known metabolites and reaction pairs were downloaded from the KEGG database, while the unknown metabolites were curated through *in-silico* enzymatic reactions. The reactant and product were paired and filtered with structural similarity. The knowledge-based metabolic reaction network was linked to the known metabolic reaction network. (**c**-**d**) Knowledgebased metabolic reaction networks: (**c**) known metabolites are connected through known reactions (6,397 nodes and 8,129 edges); (**d**) known and unknown metabolites are connected with known or *in-silico* reactions (41,336 nodes and 52,137 edges). The largest subnetwork is shown here.



**Supplementary Figure 2.** Statistics of linked nodes in MS/MS similarity network or knowledge-guided MS/MS similarity network in positive (**a**) and negative modes (**b**), respectively. The linked nodes from seed metabolites in NIST human urine sample (N=181 and 163 in positive and negative modes, respectively) were included here. The cutoff of MS/MS similarity score is defined as 0.5. Neighbor metabolites within 3 steps were considered in knowledge-guided MS/MS similarity network. The lower, middle and upper lines in box plots (a, b) correspond to 25<sup>th</sup>, 50<sup>th</sup> and 75<sup>th</sup> quartiles, and the whiskers extend to the most extreme data point within 1.5 interquartile range (IQR).



**Supplementary Figure 3.** The construction and optimization of global peak annotation network. **Step 1**: co-eluted peaks are extracted as one peak group according to the putative metabolite annotations in knowledge-guided MS/MS similarity network; **Step 2**: recognition of different ion forms to build the subnetwork, including adducts, isotopes, in-source fragments and neutral losses; **Step 3**: all recognized subnetworks are merged as a global peak correlation network; **Step 4**: global optimization and conflict resolving to improve the peak annotation accuracy. Three types of conflict annotations are checked and resolved, including empirical rule, removal of conflict peaks and annotations, and consolidation of redundant ion form peaks.



**Supplementary Figure 4**. Flowchart for the optimization and filtering of subnetworks in the global peak correlation network.



**Supplementary Figure 5.** The workflow of accuracy evaluation with a manually curated data set. (**a**) Curation of manually checked table; (**b**) Comparison of annotation results with manually checked results.



**Supplementary Figure 6.** Comparison between MetDNA1 and KGMN in different biological samples, including NIST human urine, NIST human plasma, BV2 cells, head tissues of fruit fly, and 200STD spiked mouse liver tissues. (**a**-**b**) Comparison of annotation coverages and correct/error percentages between MetDNA1 and KGMN in positive (**a**) and negative modes (**b**), respectively. (**c**-**d**) Correct and error rates among top n (n = 1 to 10) annotations in different biological samples in positive (**c**) and negative modes (**d**), respectively.



**Supplementary Figure 7.** Benchmark comparison between CAMERA and KGMN for annotating ion forms of metabolic peaks. (**a**) Percentages of annotation coverage and correct/error rates for annotating ion forms of metabolic peaks. (**b**) Annotation percentages for different types of ion forms. The R package "CAMERA" (v1.46.0) and the same rule table were used for evaluation.



**Supplementary Figure 8.** KGMN recognized the in-source fragments of N4-Acetylcytidine. (**a**) Peak M286T283 and peak M112T282 were annotated as N4-Acetylcytidine and cytosine in MetDNA1, respectively. (**b**-**c**) MS/MS spectral match between experimental MS/MS spectra and the standard spectral libraries for N4-Acetylcytidine (**b**) and cytosine (**c**). (**d**) Peak correlation subnetwork recognized M112T282 as an in-source fragment of M286T283. (**e**) The parallel acquisition of NIST human urine sample and chemical standards confirmed that peak M112T282 is an in-source fragment of M286T283.



**Supplementary Figure 9.** Examples of different ion form recognition and peak assignment in KGMN. (**a-c**) Different ion form peaks and putative annotations for (**a**) M372T650, (**b**) M218T573 and (**c**) M218T484. The left panel is the table for the reduction of putative annotations; the middle panel is the conflicted peak correlation subnetworks; the right panel is the pseudo MS1 spectrum after resolving the conflict peak correlations. The examples were retrieved from NIST human urine samples.



**Supplementary Figure 10.** Knowledge-guided multi-layer networks of 46std\_mix data sets. (**a**) Knowledge-based metabolic reaction network of 46 seed metabolites and unknown metabolites. The orange and red nodes represent seed and unknown metabolites, respectively. The unknown metabolites were curated via *in-silico* enzymatic reactions. The edges represent a biotransformation from known reactions or *in-silico* reactions. This network contains 531 unknown structures and 642

reaction pairs. (**b**) Knowledge-guided MS2 similarity network of 46 seed metabolites and unknown metabolites. The black and red edges represent the biotransformation and MS/MS spectral similarity. The edge of biotransformation represents two nodes can be transformed within 3-step reactions. The edge of MS/MS spectral similarity represents two nodes having MS/MS similarity (dot product score ≥0.5) or shared fragments (n≥4). Only linked peaks are showed here. (**c**) Global peak correlation network of 46std\_mix data sets. The orange, red and green nodes represent seed, unknown and different ion form peaks. The edge represents an ion form relationship (isotope, adduct, neutral loss or in-source fragment) between two nodes. A total of 700 and 741 peaks are included in positive and negative modes, respectively.







**Supplementary Figure 11.** Validation examples of annotated unknowns in 46std\_mix data sets. (**ab**) Validation of unknowns using standards: (**a**) M156T683 (Exd007045, L-Histidine); and (**b**) M259T844 (Exd001651, D-Fructose 6-phosphate) in positive and negative modes, respectively; (**c**-**d**) validation of unknowns using public spectral databases: (**c**) M228T355 (Exd000286, Deoxycytidine), and (**d**) M433T203 (Exd001267, Naringenin 7-O-beta-D-glucoside) through MoNA and Metlin databases, respectively.



**Supplementary Figure 12.** Knowledge-guided MS/MS similarity network of NIST human urine sample: (**a**) positive mode; (b) negative mode. The positive mode network contains 1,100 nodes, and 3,170 edges. The negative mode contains 1,444 nodes, and 7,810 edges. The orange, blue, and red nodes represent seed, known and unknown metabolites, respectively. The black and red edges represent the biotransformation edge and the MS/MS similarity edge, respectively. The edge of biotransformation represents two nodes can be transformed within 3-step reactions. The edge of MS/MS similarity represents two nodes having MS/MS similarity (dot product score ≥ 0.5) or shared fragments ( $n \geq 4$ ). Only linked peaks are showed here.

 $\mathsf{b}$ a 

**Supplementary Figure 13.** Global peak correlation network of NIST human urine sample in positive (**a**) and negative (**b**) modes. It contains 3,301 nodes and 4,374 edges in positive mode, and 4,117 nodes and 5,750 edges in negative mode. The orange, blue, and red nodes represent seed, known and unknown metabolites from network 2, which were used as base peaks here. The green nodes represent different ion form peaks.

urbit. L



**Supplementary Figure 14.** Global annotation of unknown metabolites in negative mode and validation examples of unknowns using *in-silico* MS/MS tools. (**a**) The annotated known and unknown metabolites in NIST human urine samples in negative mode. The left panel is the statistics of annotated peaks in the multi-layer networks, and the right panel is the statistics of annotated known and unknown peaks. (**b**) Validations of annotated unknown metabolites in urine samples with different *in-silico* MS/MS tools. (**c**) Global annotations of metabolites in different biological samples in negative mode. The left panel is the statistics of annotated peaks in the multi-layer network, and the right panel is the statistics of known and unknown metabolites. (**d**-**h**) Validation examples of unknown metabolites using *in-silico* MS/MS tools.



**Supplementary Figure 15.** The repository-mining and structural validations of 3 recurrent unknown metabolites. (**a**-**c**) a recurrent unknown metabolite (M196T388, 3-hydroxyhippuric acid); (**d**-**g**) a recurrent unknown metabolite (M233T407, protocatechuic acid 3-O-sulfate); (**g**-**i**) a recurrent unknown metabolite (M217T395, 3-hydroxybenzoic acid-3-O-sulphate). The panels **a**, **d**, **g** are recurrent distributions of species and sample types; the inner and outer pie plots are the distributions in species and sample types, respectively. The panels **b**, **e**, **h** are the details of unknown annotations using KGMN. The panels **c**, **f**, **i** are the structural validations using the synthetic standards by matching the retention time and MS/MS spectra.



**Supplementary Figure 16.** Curated unknown metabolites and reaction pairs in the knowledge-based metabolic reaction network (KMRN). (**a**) Distribution of natural product likeness score of unknown metabolites in KMRN, KEGG metabolites, and PubChem compounds. 100,000 PubChem compounds were randomly retrieved to represent the PubChem database. (**b**) Natural product likeness score of unknown metabolites in KMRN (n=159,083), KEGG metabolites (n=16,085), and PubChem compounds (n=100,000). (**c**-**d**) MS/MS spectral similarity comparison among KEGG reaction pairs, *in-silico* curated unknown reaction pairs (i.e., constructed RP), and non-reaction pairs in positive (**c**) and negative (**d**), respectively. The lower, middle and upper lines in box plots (**b**) correspond to 25<sup>th</sup>, 50<sup>th</sup> and 75<sup>th</sup> quartiles, and the whiskers extend to the most extreme data point within 1.5 interquartile range (IQR).



### **Supplementary Table 1. The supported data processing tools with KGMN**

[https://github.com/ZhuMetLab/MetDNA2\\_Web/blob/main/Tutorials/Tutorial\\_KGMN\\_and\\_MASS](https://github.com/ZhuMetLab/MetDNA2_Web/blob/main/Tutorials/Tutorial_KGMN_and_MASST.pdf) [T.pdf](https://github.com/ZhuMetLab/MetDNA2_Web/blob/main/Tutorials/Tutorial_KGMN_and_MASST.pdf)

## $\bullet$  Link 6:

[https://github.com/ZhuMetLab/MetDNA2\\_Web/blob/main/Tutorials/Tutorial\\_visualization.pdf](https://github.com/ZhuMetLab/MetDNA2_Web/blob/main/Tutorials/Tutorial_visualization.pdf)



**Supplementary Table 2.** Statistics of global peak annotation optimization to improve annotation accuracy.

No.	<b>Biotransformation</b>	<b>Positive mode</b>	<b>Negative mode</b>
1	C6H8O6	6	47
$\overline{2}$	SO <sub>3</sub>	10	44
3	HPO <sub>3</sub>	24	30
4	O	7	17
5	<b>H2O</b>	3	11
6	C2H2O	0	4
7	CH <sub>3</sub>	0	4
8	C2H3NO	0	3
9	C4H4O3	1	$\overline{2}$
10	C3H5NO	2	
11	C10H10N4O3	0	
12	C6H10O4	0	
13	C6H9O6	0	
14	H <sub>2</sub>	0	
15	CO <sub>2</sub>		

**Supplementary Table 3.** Statistics of biotransformation types in 46std\_mix data set.



**Supplementary Table 4**. Statistics of annotated peaks in different biological samples

No.	<b>Biotransformation</b>	Pos	<b>Neg</b>	No.	<b>Biotransformation</b>	Pos	<b>Neg</b>
1	SO <sub>3</sub>	322	1045	31	H	$\overline{2}$	3
$\overline{2}$	C6H8O6	353	905	32	C19H20N3O11P	$\overline{2}$	$\overline{2}$
3	H <sub>2</sub>	251	505	33	C29H49N3O17P2	$\mathbf 0$	$\overline{2}$
4	O	71	160	34	C3H3O5P	$\mathbf 0$	$\overline{2}$
5	HPO <sub>3</sub>	15	119	35	C5H8NO3	$\mathbf 0$	$\overline{2}$
6	<b>H2O</b>	100	108	36	CO	6	$\overline{2}$
$\overline{7}$	C2H2O	60	105	37	C12H22N2O7	$\mathbf 0$	$\mathbf 1$
8	C2H3NO	57	83	38	C14H26O	$\mathbf 0$	$\mathbf 1$
9	CH <sub>2</sub>	41	59	39	C15H9O4	4	$\mathbf 1$
10	isomer	33	56	40	C18H14N2O7	$\mathbf 0$	$\mathbf{1}$
11	CH <sub>3</sub>	10	38	41	C2H4O	$\mathbf 0$	$\mathbf{1}$
12	C7H12O6	20	34	42	C30H25O12	6	$\mathbf 1$
13	C6H9O6	3	29	43	C30H48O2	1	$\mathbf 1$
14	C6H10O5	33	22	44	C3H2O	0	$\mathbf 1$
15	C6H11O5	17	20	45	C61H100O11P2	0	$\mathbf{1}$
16	CO <sub>2</sub>	10	19	46	C67H110O16P2	$\mathbf 0$	$\mathbf{1}$
17	C11H18O10	0	10	47	C6H13N4O	0	$\mathbf 1$
18	C7H10O6	8	10	48	C8H13NO	$\mathbf 0$	$\mathbf{1}$
19	C <sub>2</sub> O <sub>3</sub>	$\mathbf 0$	6	49	HO3S	$\mathbf 0$	$\mathbf 1$
20	C15H9O5	3	4	50	$-2O+H$	12	0
21	C23H34N4O19P2	7	4	51	C3H2O3	6	0
22	C <sub>2</sub> H <sub>4</sub>	$\overline{2}$	4	52	C33H50O8	5	$\boldsymbol{0}$
23	C5H7NO3	0	4	53	C27H40O2	3	$\boldsymbol{0}$
24	C10H15N3O6S	$\overline{2}$	$\ensuremath{\mathsf{3}}$	54	C6H10O4	$\overline{2}$	$\boldsymbol{0}$
25	C12H16O10	3	3	55	C7H4O4	1	0
26	C12H20O10	5	3	56	C7H5NO	1	$\pmb{0}$
27	C15H8O2	6	$\ensuremath{\mathsf{3}}$				
28	C3H6NO	1	$\ensuremath{\mathsf{3}}$				
29	C8H12O7	$\overline{\mathbf{4}}$	$\ensuremath{\mathsf{3}}$				
30	CH6N7O15P3S	0	3				

**Supplementary Table 5.** Statistics of unknown biotransformation types in NIST urine data set

## **Tutorial of KGMN result visualization and analysis**

Zhiwei Zhou

2022-06-05

#### **Introduction**

Unknown metabolite annotation is one of long-standing challenges in untargeted metabolomics. We develop an approach, namely, knowledge-guided multi-layer network (KGMN), to enable global metabolite annotation from knowns to unknowns in untargeted metabolomics. The KGMN approach integrates three-layer networks, including knowledge-based metabolic reaction network (Network 1), knowledge-guided MS/MS similarity network (Network 2), and global peak correlation network (Network 3). This tutorial will help users to visualize, reproduce and investigate putatively annotated known and unknown metabolites from KGMN.

#### **1. Installation**

The analysis and visualization of KGMN results mainly relies on R package – MetDNA2Vis, and its depended R packages; The Cytoscape software is used for manually visualize networks, and interactively investigate results of KGMN; The ChemDraw software is involved for drawing chemical structures.

```
• Install R packages
# Install related packages
if(!require(devtools)){
install.packages("devtools")
}
```

```
if(!require(BiocManager)){
install.packages("BiocManager")
```
}

```
# Install CRAN/Bioconductor packages
required_pkgs <- c("dplyr","tidyr","readr","CHNOSZ","igraph",
   "magrittr","ggplot2","ggraph","tidygraph")
```

```
list_installed <- installed.packages()
```
new pkgs <- required pkgs[!(required pkgs %in% list installed[, Package'])]

**if** (length(new pkgs)  $> 0$ ) {

BiocManager::install(new\_pkgs)

#### } **else** {

cat('Required CRAN/Bioconductor packages installed\n')

}

#### *# Install ZhuLab packages*

devtools::install\_github("ZhuMetLab/SpectraTools") devtools::install\_github("ZhuMetLab/MetDNA2Vis")

- Cytoscape software (Version 3.8 or higher required):<https://cytoscape.org/>
- ChemDraw software (Version 19.0 or higher required): <https://perkinelmerinformatics.com/products/research/chemdraw>

#### **2. Step-by-step instruction for visualization**

In this part, we introduce how to visualize multi-layer networks from KGMN. It will help users to reproduce figures in KGMN manuscripts. Here, the Human NIST urine (Positive data, used in KGMN manuscript) is used as a demo dataset. This data set have been processed and exported by **MetDNA2 web server** (version 1.0.4). The raw data files and results can be downloaded at **[here](https://mega.nz/file/8v50iL6T#oILf8wlVJU_iqTfjcOtH1TRHhnP1GGbvG_ZNb1xniGc)** (https://mega.nz/file/8v50iL6T#oILf8wlVJU\_iqTfjcOtH1TRHhnP1GGbvG\_ZNb1xniGc). The more details of sample extraction and data preprocessing can be found in our KGMN manuscript.

#### **The step-by-step demonstration is provided as below.**

#### *2.1 Download demo data and unzip the archive.*

All required intermediate files for visualization is provided in '06 visualization' folder.



#### *2.2 Preparing.*

• Set the working directory ('your path/06 visualization') and load required packages. Then, please check required files whether existed.

#### *# load packages*

library(MetDNA2Vis)

library(CHNOSZ)

library(dplyr)

#### *# check required files*

checkFiles4Vis()

## Check required files ... ## Check required files: done!

#### *2.3 Reconstruct and export global multi-layer networks.*

#### **2.3.1 Network 1**

The network 1 is the knowledge-guided metabolic reaction network. For knowns, the KEGG reaction pair network is directly used. For unknowns, an extended KEGG reaction pair network is used. The network expansion is performed with in-silico enzymic reactions (via Biotransformer), and further connected with KEGG reaction pair network. The details of network construction and expansion are described in our KGMN manuscript. It should be note that the KEGG reaction pair network and extended network are built in advance.

To export the network 1, it is easily to run reconstructNetwork1 function as below:

## *# export network 1 for visualization* reconstructNetwork1(is\_unknown\_annotation = TRUE)

The networks files will be exported in '00 network1' folder. It contains two files, including "edge\_table.tsv" and "node\_table.tsv" (Figure 2.3.1). These tables can be import into Cytoscape software for visualization.



#### **2.3.2 Network 2**

The network 2 is a knowledge-guided MS/MS network. Although it calls MS/MS network, differing to MS/MS network (mainly based on MS2), the linkage (edge) of network2 has a prerequisite. It requires a reasonable reaction relationship and definitive structure candidate first. As a result, their retention time can also be predicted. In other words, two linked nodes indicate 4 messages. Their candidates of these nodes have (1) reasonable reaction relationships, (2) low m/z errors, (3) low RT error against with predicted RT values, and (4) MS/MS similarity. It should be note that optimized network2 required to be reconstructed from KGMN exported results, because the global peak correlation network remove and collapse some error nodes and edges in prior analysis. This process usually requires 10- 20 min to complete.

To export the network 2, it is easily to run reconstructNetwork2 function as below:

*# Modify format of KGMN result*

annotation table <- reformatTable1()

#### *# Export global network2 files*

reconstructNetwork2(annotation table = annotation table,

is\_unknown\_annotation = TRUE)

The networks files will be exported in '01 network2' folder. The "edge table.tsv" and "node table.tsv" in this folder can be imported to Cytoscape.



#### **2.3.3 Network 3**

The network 3 is the global peak correlation network. This network recognized different ion form peaks derived from peaks from network 2, including adducts, isotopes, neutral losses, and in-source fragments (ISF). The network 3 is used to optimize the annotation and linkage of network 2. The optimization has been completed in KGMN analysis. The details of network 3 construction and optimization can be found in our manuscript.

To export the network 3, it is easily to run reconstructNetwork3 function as below:

# export network3 reconstructNetwork3()

The networks files will be exported in '**02\_files\_network3**' folder. The "edge\_table.tsv" and "node table.tsv" in this folder can be imported to Cytoscape for visualization.



#### *2.4 Visualize global networks with Cytoscape*

Above networks (Network 1-3) can be imported to Cytoscape software tool for visualization. The process of network visualization is generally similar. Here, we use the above network 1 as a demonstration. The version of Cytoscape used here is 3.8.2.

#### **Below is the step-by-step instruction:**

1. **Import edge file.** Select the "edge\_table.tsv" file and open it in the box.



2. **Assign column attributes.** Click the 'from' column and select it as "source node". Similarly, click the "to" column and select it as "target node". After assigning attributes, click **OK** to construct a network.



3. **Import node file.** Select the "node\_table.tsv" file and open it in the box.



4. Select the "name" column as a key. Then, click the **OK** button.



5. **Modify the style for visualization.** Click the Style type, you can adjust node shapes and colors, edge types and colors.



To help users reproduce our plot quickly, users can directly import our style file. The styles of different networks are provided **[here](https://mega.nz/file/tnp1nKjT#LS1oPzcFzw6bbdsLSqGoW4Qggrl_lM2LsPgsyZXilzQ)**

(https://mega.nz/file/tnp1nKjT#LS1oPzcFzw6bbdsLSqGoW4Qggrl\_lM2LsPgsyZXilzQ).



#### *2.5 Select and export interesting subnetwork*

Through above procedures, users can easily visualize global network 1-3. With such global networks, users can find interesting subnetworks in Cytoscape. The Cytoscape supports interactively investigation. **It should be note that the targeted subnetwork selection is customized.** Users can directly find interesting nodes from KGMN annotation results, or considering more information, like insilico MS/MS, chemical structure and/or statistics analysis. For example, in KGMN manuscript, we combined MASST to select an unknown subnetwork of M262T526 (**Figure 5e in manuscript**). This unknown peak was putatively annotated as O-sulfotyrosine, and this annotation was from M182T541- Tyrosine. This subnetwork consisted of 2 peaks and 2 metabolites. Here, we mainly introduce how to export and visualize this subnetwork. First, export network 1 of this subnetwork. **Note:** the export and visualization require intermediate results from global networks. Therefore, please run global peaks export first. To export the subnetwork 1, please directly run retrieveSubNetwork1 function as below.

*# network 1 of unknown peak subnetwork*

*# Note: the folder\_output should keep same among different layer subnetworks* retrieveSubNetwork1(centric\_met = c('C00082', 'KeggExd000923'),

is\_unknown\_annotation = TRUE,

folder\_output =  $c('M182T541~M262T526'))$ 



The networks files will be exported in '03\_subnetworks/your\_defined\_folder/network 1' folder. Here, the exported folder is "M182T541 M262T526". The "edge table.tsv" and "node table.tsv" in this folder can be imported to Cytoscape for visualization. **Note:** if you run in RStudio, the preview plot of subnetwork 1 will be directly shown in the plot panel.

Similarly, export network 2 and network 3 of this subnetwork can be completed through running retrieveSubNetwork2 and retrieveSubNetwork3 functions, respectively. The preview plots of subnetwork 2 and subnetwork 3 will be shown in the plot panel if you run in RStudio.

```
# network 2 of unknown peak subnetwork
retrieveSubNetwork2(from_peak = 'M182T541', 
   end_peak = 'M262T526', 
   folder_output = c('M182T541_M262T526'))
```
## Using `sugiyama` as default layout



*# network 3 of unknown peak subnetwork* retrieveSubNetwork3(base\_peaks = c('M182T541', 'M262T526'), base\_adducts =  $c('[M+H]+', '[M+H]+'),$ folder\_output = c('M182T541\_M262T526'))

## Using `stress` as default layout



The network 2 and network 3 of the subnetwork can be further merged through running mergeSubnetwork function. The 'network\_merge' folder contains node table and edge table for reproduce the merged network.



## Using `stress` as default layout



Finally, the folder of subnetwork is organized like below. Each folder contains related files of each network for further visualization in other tools (e.g. Cytoscape).



#### **3. The script for visualization**

Here is a script which contains above codes to help to reproduce above analysis quickly.

*# load packages* library(CHNOSZ) library(dplyr) library(MetDNA2Vis)

#### *# set working directory*

setwd('D:/project/00\_zhulab/01\_metdna2/00\_data/20220602\_visualization\_kgmn/Demo\_MetDNA2\_ NIST urine pos/06 visualization/')

*# Export global networks* 

#### *# construct network 1*

reconstructNetwork1(is\_unknown\_annotation = TRUE)

#### *# construct network 2*

annotation table <- reformatTable1() reconstructNetwork2(annotation\_table = annotation\_table)

#### *# construct network 3*

reconstructNetwork3()

*# Export subnetworks --- # network 1 of unknown peak subnetwork # Note: the folder\_output should keep same among different layer subnetworks* retrieveSubNetwork1(centric\_met = c('C00082', 'KeggExd000923'),

is\_unknown<sub>\_</sub>annotation = TRUE,

folder\_output = c('M182T541\_M262T526'))

*# network 2 of unknown peak subnetwork* retrieveSubNetwork2(from\_peak = 'M182T541', end\_peak = 'M262T526',

folder\_output = c('M182T541\_M262T526'))

```
# network 3 of unknown peak subnetwork
retrieveSubNetwork3(base peaks = c('M182T541', 'M262T526'),
 base_adducts = c([M+H]+', [M+H]+'), folder_output = c('M182T541_M262T526'))
```
*# merge subnetwork* mergeSubnetwork(from peak = 'M182T541', end\_peak = 'M262T526', folder\_output = 'M182T541\_M262T526')

# Tutorial of validating KGMN unknowns with repository mining

Zhiwei Zhou

2022-06-13

This tutorial aims to help users to select and validate their interesting unknown peaks from KGMN through repository mining. In the manuscript, we mainly used **MASST** to perform repository mining. The MASST<sup>1</sup> is a tool to query spectrum in context of where it occurs against all GNPS data sets. In this tutorial, we focus on demonstrating how to combine KGMN results and MASST. The detail instructions of MASST can be found in **[GNPS document](https://ccms-ucsd.github.io/GNPSDocumentation/masst/)** (https://ccmsucsd.github.io/GNPSDocumentation/masst/).

The step-by-step instruction has been provided below.

#### **1. Data preparing.**

In this workflow, the data files require KGMN (MetDNA2) processed firstly. Here, we utilized NIST human urine data set as example. The data set has been analyzed with KGMN (v1.0.4), and the results can be downloaded **[here](https://mega.nz/file/8v50iL6T#oILf8wlVJU_iqTfjcOtH1TRHhnP1GGbvG_ZNb1xniGc)** (https://mega.nz/file/8v50iL6T#oILf8wlVJU\_iqTfjcOtH1TRHhnP1GGbvG\_ZNb1xniGc).

The folders should look like as below:



The users can browser and select interesting known/unknown peaks in the **annotation table**  "table1\_identification.csv" in the "00 annotation table" folder. It should be note that the selection of targeted peak is customized.

For demonstration, we utilized the unknown peak M262T526 as an example (Figure 5d in manuscript). The MS/MS spectrum of this peak can be found in the **"ms2\_data.msp"** in "06\_visualization" folder. You can open it with text tool (e.g. Notepad++).



#### **2. Upload and analysis in MASST.**

Users can upload this file to MASST (https://gnps.ucsd.edu/ProteoSAFe/static/gnpssplash.jsp?redirect=auth) to perform repository mining. The users need to login first. Then, click the "**query spectrum**" button in MASST panel to start the analysis. Copy **related texts from MSP** file to "title", "precursor m/z", "spectrum input" panel in the web server, respectively.



Modify the search parameters and click "submit" button. The **used parameters** in KGMN manuscript have been provided below.



When the job finished, you will receive an email with a link. You can view and download results in the webserver.

• Matched data set: Dataset Matches → View File Matches → Download Job Status



• Matched files: Dataset Matches → View File Matches → Download



#### **3. Result interpretation and visualization.**

The downloaded results include 2 ZIP files, "view all-datasets-matched.zip" and "view all file datasets matched.zip". The files in packages can be further opened with Microsoft Office Excel or other program tools (e.g. R, Python).

• The table of "view all datasets matched" contains meta information of appeared data sets, like "dataset description", "dataset id", "dataset organisms" and "files count".

Furthermore, we can conclude the species and sample information based on the dataset description. For our examples, it was appeared in 7 datasets, and 3 organisms (where genipapo is from human urine actually according to the data set description).



• The table of "view all file datasets matched" contains names of matched files. Each file can be viewed online through the filename in GNPS dashboard [\(https://gnps-lcms.ucsd.edu/\)](https://gnps-lcms.ucsd.edu/), while the files and dataset can be accessed in GNPS datasets [\(https://gnps.ucsd.edu/ProteoSAFe/datasets.jsp\)](https://gnps.ucsd.edu/ProteoSAFe/datasets.jsp).



With above information, it would be easy to reproduce figures of repository validation. The result of



# **Tutorial of integrating KGMN results with other in-silico MS/MS workflows**

Zhiwei Zhou

2022-06-10

#### **Introduction**

**Knowledge-guided multi-layer network (KGMN)** is a new approach leveraging knowledge-guided multi-layer networks to annotate known and unknown metabolites in untargeted metabolomics data. Although KGMN is an independent software tool, it can further integrate with other workflows to help users discover and validate metabolites. This tutorial aims to provide an easy instruction to integrated KGMN results with 3 common in-silico MS/MS tools (MetFrag, CFM-ID, MS-FINDER).

Here, we mainly focus on providing ways to help users linking KGMN with other tools. It should be note that the parameters need to be adjusted according to their instrument settings and experimental designs. **The detailed usage please refer their own tutorials.** 

#### **Tutorials:**

- MetFrag:<https://ipb-halle.github.io/MetFrag/>
- CFM-ID:<https://cfmid.wishartlab.com/>
- MSFINDER:<https://mtbinfo-team.github.io/mtbinfo.github.io/MS-FINDER/tutorial.html>

#### **Demo datasets:**

• NIST urine set (Positive mode, processed by KGMN): **[Download](https://mega.nz/file/w7ZnjLAa#u4Dj5lhkYyEhOZHH4BX_HUHvGMkjZ_ti5bn986tgyrY)** (https://mega.nz/file/w7ZnjLAa#u4Dj5lhkYyEhOZHH4BX\_HUHvGMkjZ\_ti5bn986tgyrY)

If you use these tools, please cite their papers (MetFrag<sup>2</sup>, CFM-ID<sup>3</sup>, MSFINDER<sup>4</sup>).

#### **1. Installation.**

This integration of KGMN and in-silico MS/MS tools is mainly performed by R package "MetDNA2InSilicoTool". It can be downloaded as below:

```
# Install required packages
if(!require(devtools)){
install.packages("devtools")
}
if(!require(BiocManager)){
install.packages("BiocManager")
}
# Install CRAN/Bioconductor packages
required_pkgs <- c("dplyr","tidyr","readr","stringr","rcdk")
list installed <- installed.packages()
new_pkgs <- required_pkgs[!(required_pkgs %in% list_installed[,'Package'])]
if (length(new pkgs) > 0) {
   BiocManager::install(new_pkgs)
} else {
   cat('Required CRAN/Bioconductor packages installed\n')
}
```

```
# Install GitHub packages - call MetFrag
devtools::install_github("schymane/ReSOLUTION")
```

```
# Install GitHub packages
devtools::install_github("ZhuMetLab/MetDNA2InSilicoTool")
```
#### **2. MetFrag**

**MetFrag** is a common in-silico MS/MS tool developed by *Dr. Sebastian Wolf* and *Dr. Christoph Ruttkies*. It provides multiple ways to use it, including web server (MetFragWeb), MetFrag commandline tool (MetFragCL) and R package (MetFragR). In this workflow, we mainly use **MetFragCL (version 2.4.5)** to demonstrate the connection between KGMN and MetFrag.

#### *2.1 Download MetFragCL program.*

MetFragCL is a Java Archive File. It can be downloaded from GitHub. [https://github.com/ipb](https://github.com/ipb-halle/MetFragRelaunched/releases/tag/v2.4.8)[halle/MetFragRelaunched/releases/tag/v2.4.8](https://github.com/ipb-halle/MetFragRelaunched/releases/tag/v2.4.8)



**Note:** The MetFragCL program is depended on **Java**. Please install java and set environment variable first.

#### *2.2 Load required packages, and setting the working directory.*

We use MetDNA2InSilicoTool to call MetFragCL. Please set the working directory at 07 insilico msms, which is localized at KGMN result folder. Then, load some required packages.

```
# set working directory
setwd('G:/00_projects/03_MetDNA2/00_data/20220609_insilico_ms2_demo/NIST_urine_pos/07_in
silico_msms/')
```
*# load packages* library(dplyr) library(MetDNA2InSilicoTool)

```
# reformat identification_table
reformatTable1(dir path =
'G:/00_projects/03_MetDNA2/00_data/20220609_insilico_ms2_demo/NIST_urine_pos/07_insilico
msms/')
```
It looks like as below:



#### *2.3 Generate input files for your interested peak.*

In this workflow, users need generate necessary files for different in-silico tools. Here, we use an interesting peak **M196T420** as example (Figure 4c). This peak is annotated as an unknown peak in KGMN, while it has 6 possible metabolite candidates.

First, generate necessary file for M196T420.

```
# generate files for in-silico MS/MS match
# peak 'M196T420' as example
generateFiles4InsilicoMsMs(peak_id = 'M196T420', 
                            dir path ='G:/00_projects/03_MetDNA2/00_data/20220609_insilico_ms2_demo/NIST_urine_pos/07_insilico_
msms/')
```
A folder "M196T420" will be created as blow:



It contains two files, candidate\_list and MS/MS file. The **candidate list** is a list of chemical structures for in-silico MS/MS tool validation. The **MS/MS file** is a experimental spectrum of the targeted peak. The MS/MS file can be used for other in-silico tools if needed.

#### *2.4 Run MetFrag.*

We provide a R function (runMetFragMatch) to call MetFragCL. Here, the path of MetFragCL should be given. Other parameters can be adjusted. In MetDNA2InSilicoTool package, we only open limited parameters. For advanced users, the parameters can be adjusted according to [MetFragCL tutorial.](https://ipb-halle.github.io/MetFrag/)

#### *# run MetFrag*

*# parameters # peak\_id: name of interested peak # metfrag\_path: path of metfrag program # ppm: relative error of precursor MS1. 25 ppm # mzabs: absolute error or MS1. 0.01 Da # frag\_ppm: relative error of precursor MS1. 25 ppm*

runMetFragMatch(peak\_id = 'M196T420',

```
dir path =
```
'G:/00\_projects/03\_MetDNA2/00\_data/20220609\_insilico\_ms2\_demo/NIST\_urine\_pos/07\_insilico msms/',

> metfrag\_path = 'F:/software/metfrag/MetFrag2.4.5-CL.jar',  $ppm = 25$ ,  $mzabs = 0.01$ frag  $ppm = 25$ )

#### *2.5 Output of MetFrag.*

A folder "01 metfrag" is created in the "M196T420" folder. It contains results of MetFrag. For candidate with different adducts, they are divided into different folders. The rank results localize at the subfolder "results".



#### **3. CFM-ID**

.

CFM-ID is a machine-learning based MS/MS prediction tool, which developed by *Prof. David S Wishart Lab*. It provides several access ways, including web server and command lines. In this workflow, we mainly use CFM-ID (version 2.4) to demonstrate the connection between KGMN and CFM-ID

#### *3.1 Download and Set CFM-ID program.*

#### Here, we utilize CFM-ID (v2.4). The program can be downloaded at [here](https://sourceforge.net/projects/cfm-id/files/)

(https://sourceforge.net/projects/cfm-id/files/). The new docker image of CFM-ID4 is available at [here](https://bitbucket.org/wishartlab/cfm-id-code/src/master/) (https://bitbucket.org/wishartlab/cfm-id-code/src/master/).



#### **Note:**

• The prediction model is required for CFM-ID. Users can train their own model or directly use the pre-trained model. The predicted model can be downloaded at **[here](https://sourceforge.net/p/cfm-id/code/HEAD/tree/supplementary_material/trained_models/esi_msms_models/)** (https://sourceforge.net/p/cfmid/code/HEAD/tree/supplementary\_material/trained\_models/esi\_msms\_models/).

#### *3.2 Load required packages, and setting the working directory.*

Similar with MetFrag, we use MetDNA2InSilicoTool to call CFM-ID. Please set the working directory at 07 insilico msms, which is localized at KGMN result folder. Then, load some required packages.

*# set working directory* setwd('G:/00\_projects/03\_MetDNA2/00\_data/20220609\_insilico\_ms2\_demo/NIST\_urine\_pos/07\_in silico\_msms/')

#### *# load packages*

library(dplyr) library(MetDNA2InSilicoTool)

### *# reformat identification\_table*

reformatTable1( $dir$  path =

'G:/00\_projects/03\_MetDNA2/00\_data/20220609\_insilico\_ms2\_demo/NIST\_urine\_pos/07\_insilico msms/')

#### *3.2 Generate input files for your interested peak.*

**This step is consistent with MetFrag.** We use an interesting peak M196T420 as example.

*# generate files for in-silico MS/MS match # peak 'M196T420' as example* generateFiles4InsilicoMsMs(peak\_id = 'M196T420',  $dir$  path = 'G:/00\_projects/03\_MetDNA2/00\_data/20220609\_insilico\_ms2\_demo/NIST\_urine\_pos/07\_insilico msms/')

### *3.3 Run CFM-ID.*

*# run CFM-ID*

#### *# parameters*

*# cfmid\_path: path of cfm-id*

*# config\_file: config file of prediction model. It should be selected according to ionzation polairty. Pos: metab\_se\_cfm/param\_config.txt; Neg: negative\_metab\_se\_cfm/param\_config.txt # param\_file: parameter file of prediction model. It should be selected according to ionzation polairty. Pos: metab\_se\_cfm/param\_output0.log; Neg: negative\_metab\_se\_cfm/param\_output0.log # score\_type: rank score of CFM-ID. Default: 'jaccard' # ppm: relative mz tolerance*

*# mzabs: absolute mz tolerance*

#### runCfmIdMatch(peak\_id = 'M196T420',

dir  $path =$ 

'G:/00\_projects/03\_MetDNA2/00\_data/20220609\_insilico\_ms2\_demo/NIST\_urine\_pos/07\_insilico msms/',

> cfmid\_path = 'F:/software/cfm\_id/cfm-id.exe', config file = 'F:/software/cfm\_id/metab\_se\_cfm/param\_config.txt', param\_file = 'F:/software/cfm\_id/metab\_se\_cfm/param\_output0.log', score\_type = 'Jaccard',  $ppm = 25$ ,  $mzabs = 0.01$

#### *3.4 Output of CFM-ID.*

A folder "02\_cfmid" will be created in the "M196T420" folder. It contains results of CFM-ID. The "cfmid\_result.txt" is the CFM-ID rank result. The "cfmid\_pred\_spec.msp" is the predicted MS/MS spectra of candidates.

∧ Name	Date modified	Type	Size			
01 metfrag	6/10/2022 12:23 PM	File folder				
02 cfmid	6/10/2022 1:07 PM	File folder				
candidate_list	6/10/2022 12:40 PM	File	1 KB			
xai candidate_list.csv	6/10/2022 12:40 PM	Microsoft Excel C	2 KB			
ms2	6/10/2022 12:40 PM	File	1 KB			
ms2.mgf	6/10/2022 12:40 PM	<b>MGF</b> File	1 KB			
> 00_projects > 03_MetDNA2 > 00_data > 20220609_insilico_ms2_demo > NIST_urine_pos > 07_insilico_msms > M196T420 > 02_cfmid						
Α Name	Date modified	Type Size				
Ë candidate list.txt	6/10/2022 1:07 PM	<b>Text Document</b>	1 <sub>KB</sub>			
碍 cfmid pred spec.msp	6/10/2022 1:07 PM	Windows Installer	9 KB			
Ë cfmid_result.txt	6/10/2022 1:07 PM	<b>Text Document</b>	1 <sub>KB</sub>			
Eì peak list.txt	6/10/2022 1:07 PM	<b>Text Document</b>	1 KB			

00\_projects > 03\_MetDNA2 > 00\_data > 20220609\_insilico\_ms2\_demo > NIST\_urine\_pos > 07\_insilico\_msms > M196T420 >

#### **4. MS-FINDER**

MS-FINDER is a rule-based fragmentation tool, which developed by *Prof. Hiroshi Tsugawa* and *Prof. Masanori Arita* Lab. It usually is combined with MS-DIAL. In this tutorial, we mainly used it command tool (version 3.2.4) to evaluate KGMN metabolites.

#### *4.1 Download MS-FINDER program.*

We used the MS-FINDER v3.24. The newest version can be downloaded from [here.](http://prime.psc.riken.jp/compms/msfinder/main.html)

**Note:** The instruction of MetDNA2InSilicoTool is only supported and tested in Windows System.

software > MSFINDER > MSFINDER\_ver\_3.24



#### *4.2 Load required packages, and setting the working directory.*

Repeat procedures in MetFrag and CFIM-ID. Set the working directory at 07\_insilico\_msms, which is localized at KGMN result folder. Then, load some required packages.

#### *# set working directory*

```
setwd('G:/00_projects/03_MetDNA2/00_data/20220609_insilico_ms2_demo/NIST_urine_pos/07_in
silico_msms/')
```
## *# load packages*

library(dplyr) library(MetDNA2InSilicoTool)

#### *# reformat identification\_table*

reformatTable1( $dir$  path =

'G:/00\_projects/03\_MetDNA2/00\_data/20220609\_insilico\_ms2\_demo/NIST\_urine\_pos/07\_insilico msms/')

#### *4.3 Generate input files for your interested peak.*

Consist with **MetFrag** and **CFM-ID**, generate related files for targeted peaks. The example M196T420 is here.

*# generate files for in-silico MS/MS match # peak 'M196T420' as example* generateFiles4InsilicoMsMs(peak\_id = 'M196T420', dir  $path =$ 'G:/00\_projects/03\_MetDNA2/00\_data/20220609\_insilico\_ms2\_demo/NIST\_urine\_pos/07\_insilico\_ msms/')

#### *4.4 Run MS-FINDER*

*# run MS-FINDER*

We provided a R function (runMsFinderMatch) to call MS-FINDER. Here, we use the command tool of MS-FINDER (MsfinderConsoleApp.exe). The path of MS-FINDER should be given.

```
# parameters
# 
runMsFinderMatch(peak_id = 'M196T420',
                 dir path ='G:/00_projects/03_MetDNA2/00_data/20220609_insilico_ms2_demo/NIST_urine_pos/07_insilico_
msms',
                 msfinder path ='F:/software/MSFINDER/MSFINDER_ver_3.24/MsfinderConsoleApp.exe')
```
#### *4.5 Output of MS-FINDER.*

A folder "03\_msfinder" will be created in the "M196T420" folder. It contains results of MS-FINDER. The result of MS-FINDER is organized as adduct types. The rank result will be 03\_msfinder -> [M+H]+ -> result -> Structure result-2055.txt.



#### **Note:**

• The parameter file of MS-FINDER is in '/03\_msfinder/[M+H]+/MsfinderConsoleAppparam.txt'. Advanced users can adjust this file, and rerun MS-FINDER.

#### **5. The script for connection KGMN and in-silico MS/MS tools**

Here is a script contains above codes to help to connect KGMN and in-silico MS/MS tools quickly.

*# set working directory* setwd('G:/00\_projects/03\_MetDNA2/00\_data/20220609\_insilico\_ms2\_demo/NIST\_urine\_pos/')

*# load packages* library(dplyr) library(MetDNA2InSilicoTool)

*# copy files* copyFiles4InsilicoTool(dir\_path = '.')

*# set working directory* setwd('G:/00\_projects/03\_MetDNA2/00\_data/20220609\_insilico\_ms2\_demo/NIST\_urine\_pos/07\_in silico\_msms/')

*# reformat identification\_table* reformatTable1(dir path =  $'$ .')

*# generate files for in-silico MS/MS match # peak 'M196T420' as example* generateFiles4InsilicoMsMs(peak\_id = 'M196T420')

#### *# run MetFrag*

runMetFragMatch(peak\_id = 'M196T420',

metfrag\_path = 'F:/software/metfrag/MetFrag2.4.5-CL.jar',

 $ppm = 25$ ,

 $mzabs = 0.01$ 

 $frag\_ppm = 25$ 

#### *# run CFM-ID*

runCfmIdMatch(peak\_id = 'M196T420',

cfmid\_path = 'F:/software/cfm\_id/cfm-id.exe',

config\_file = 'F:/software/cfm\_id/metab\_se\_cfm/param\_config.txt', param\_file = 'F:/software/cfm\_id/metab\_se\_cfm/param\_output0.log', score\_type = 'Jaccard', ppm = 25,  $mzabs = 0.01$ 

*# run MS-FINDER*

*# note: the dir\_path must be given* 

runMsFinderMatch(peak\_id = 'M196T420',

dir  $path =$ 

'G:/00\_projects/03\_MetDNA2/00\_data/20220609\_insilico\_ms2\_demo/NIST\_urine\_pos/07\_insilico msms',

msfinder  $path =$ 

'F:/software/MSFINDER/MSFINDER\_ver\_3.24/MsfinderConsoleApp.exe')

#### **Supplementary References:**

- 1. Wang, M. et al. Mass spectrometry searches using MASST. *Nat. Biotechnol.* **38**, 23–26 (2020).
- 2. Ruttkies, C., Schymanski, E. L., Wolf, S., Hollender, J. & Neumann, S. MetFrag relaunched: incorporating strategies beyond in silico fragmentation. *J. Cheminform.* **8**, 3 (2016).
- 3. Wang, F. et al. CFM-ID 4.0: More Accurate ESI-MS/MS Spectral Prediction and Compound Identification. *Anal. Chem.* **93**, 11692-11700 (2021).
- 4. Tsugawa, H. et al. Hydrogen Rearrangement Rules: Computational MS/MS Fragmentation and Structure Elucidation Using MS-FINDER Software. *Anal. Chem.* **88**, 7946–7958 (2016).